

Principles and Practice of

P₃

Extracting Entrepreneurial Innovation Opportunities for Social Businesses Pursuing Ethical Profitability

Shoumen Palit Austin Datta



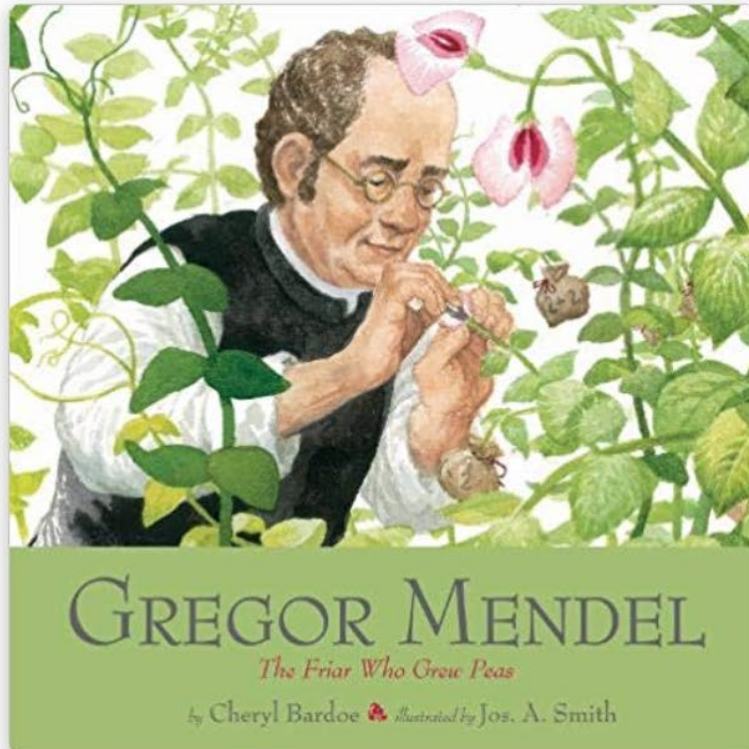
PLATFORM

PEAS is mnemonic borrowed from the literature on Agent based systems (ABS) designed (modeled) to address systems performance (P) in the context of environment (E) of operation, events or processes or systems, to be actuated (A), based on information from primary sources, for example, sensor (S) data.

<http://bit.ly/P-E-A-S> and https://link.springer.com/chapter/10.1007/978-981-10-8258-0_8



Gregor Mendel: The Friar Who Grew Peas



PEAS for P3

Platforms for Ecosystems

Shoumen Palit Austin Datta

Auto-ID Labs, Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139

MDPnP Lab, Department of Anesthesiology, Massachusetts General Hospital, Harvard Medical School, Cambridge, MA 02139

Nano-Bio Sensors Lab, Department of Agricultural and Biological Engineering, University of Florida, Gainesville, FL 32611

NSF Center for Robots and Sensors for Human Well Being (RoSeHuB), School of Technology, Purdue University, West Lafayette, IN 47907

Metaphors and Conceptual Umbrellas

IoT

SUGAR, SNAPS, PEAS, SARA

DIDAS, KIDS, ART, DIYBOT, PAPPU

SENSEE, SENSEM, SENSYN, SENSICS

IoT – Internet of Things

SUGAR – Simple User Guided Activity Report

SNAPS – Sensor Analytics Point Solutions

PEAS – Percept Environment Actuators Sensors

SARA – Sense Analyze Respond Actuate

DIDAS – Data Informed Decision as a Service

KIDS – Knowledge Informed Decision as a Service

ART – Artificial Reasoning Tools

DIYBOT – Digital Proxy of a BioReactor

PAPPU – Pay A Penny Per Use / Pay A Price Per Unit

SENSEE – Sensor Search Engine

SENSEM – Sensor Semantics

SENSYN – Sensor Retrosynthesis

SENSICS – Sensor Informatics

- **P**erformance
- **E**nvironment
- **A**ctuators
- **S**ensors

PEAS PLATFORM for Agro-Ecosystems

Decision Sciences for Social Businesses Practicing Ethical Profitability

Knowledge-Informed Decision as a Service

– Performance



– Sensors

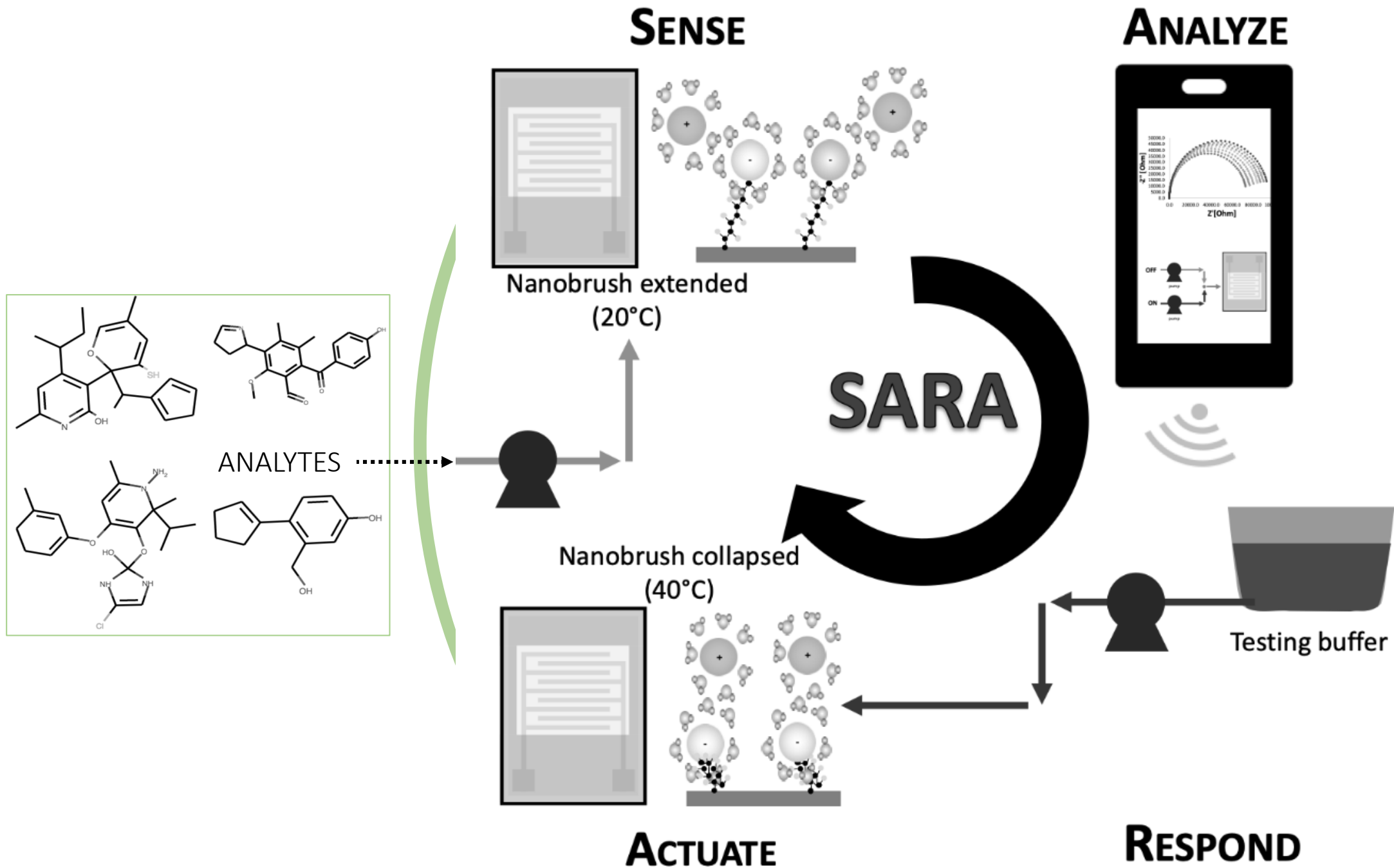
Sensor as a Service – SARA – Sense, Analyze, Respond, Actuate

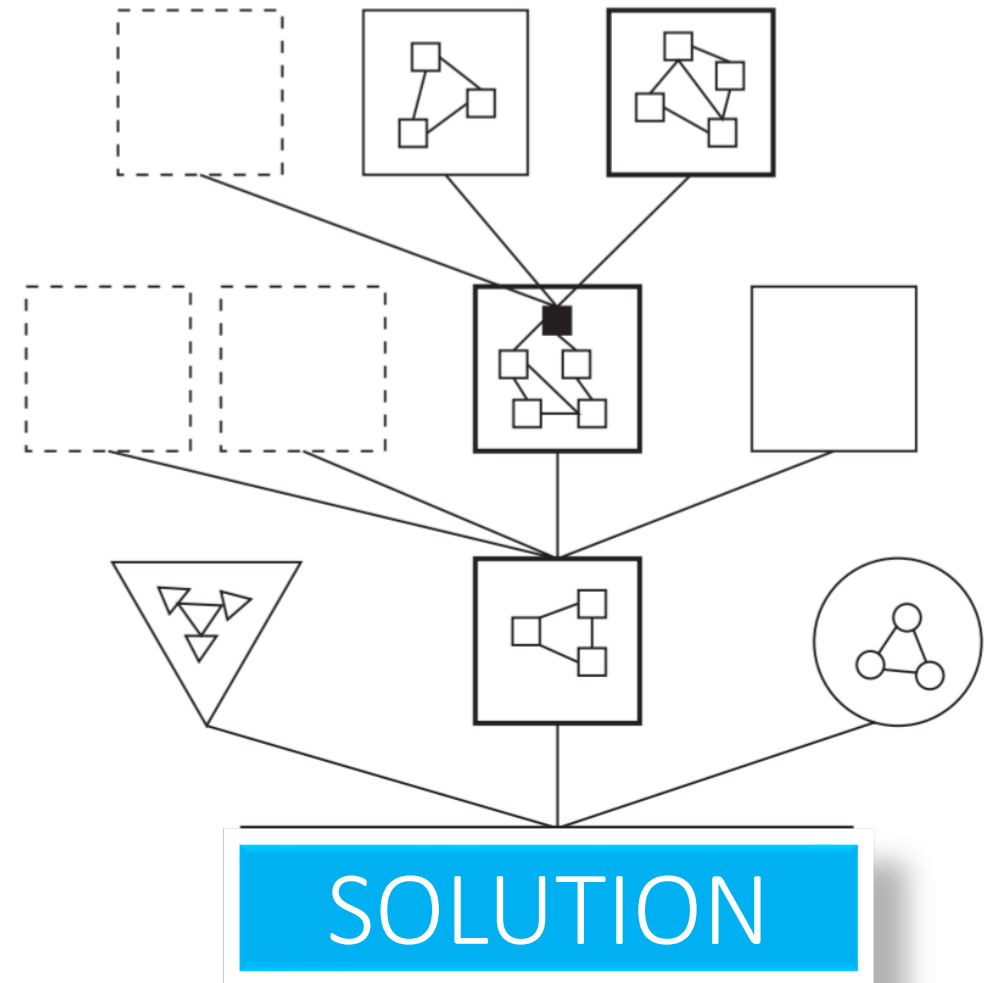
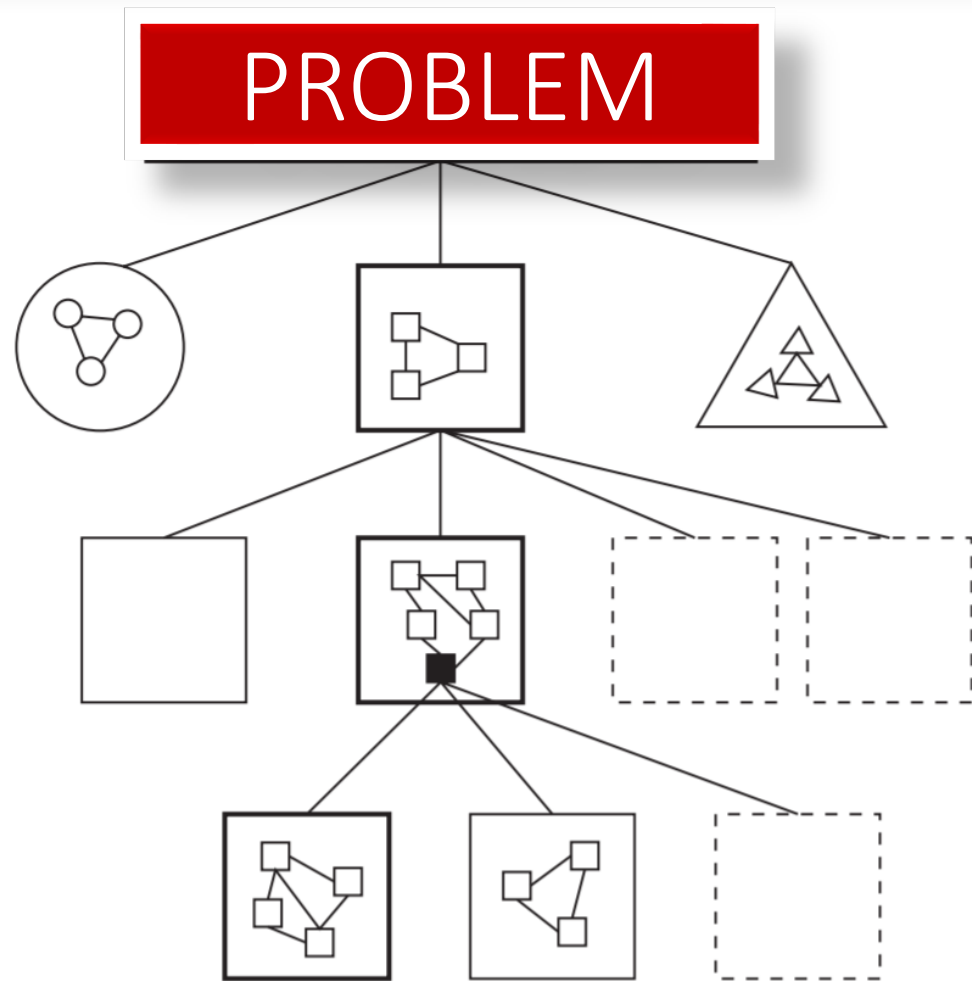
Knowledge-Informed Decision as a Service

KIDS

The outcome and the value of the service is the key performance indicator.

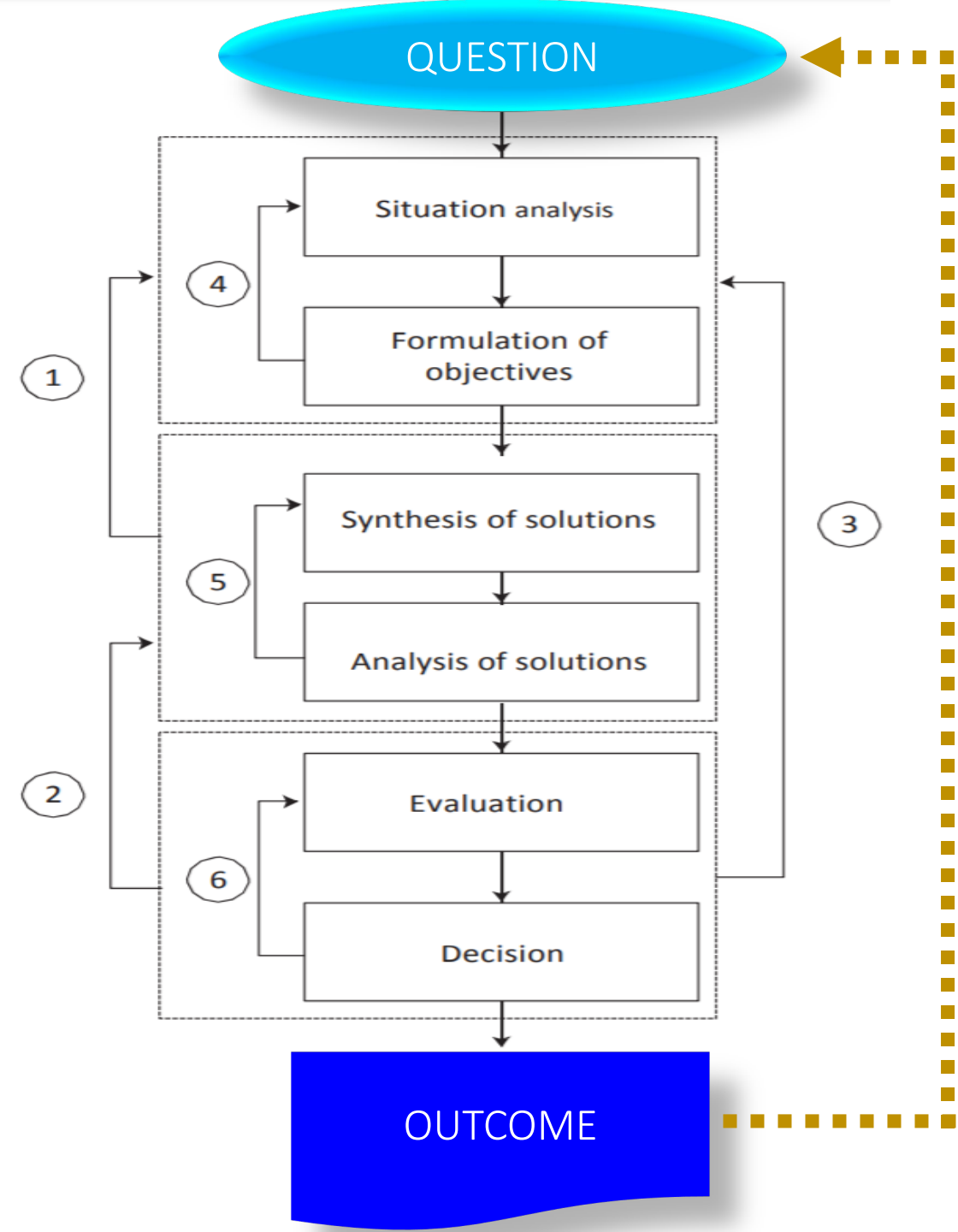
Sense, **A**nalyze, **R**espond, **A**ctuate





A Systems Engineering Approach?

- What is the problem? Is it the correct problem to address?
- Boundaries of the problem space (dynamic vs static).
- Principal influences/mechanisms relative to the context of the problem and problem space.
- Needs a new or re-configured solution?
- What are the solution/system boundaries?
- Requirements of the solution space (system, design goals)
- Feasibility (contextual, technical, economic, social, ecological)
- Solution space to be reconstructed based on existing system or create/innovate architecture to execute solution system?



TRIGGER

SENSE

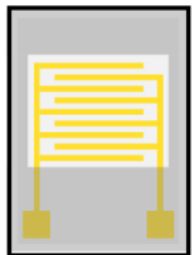
ANALYZE

SARA

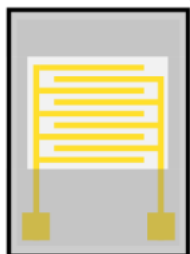
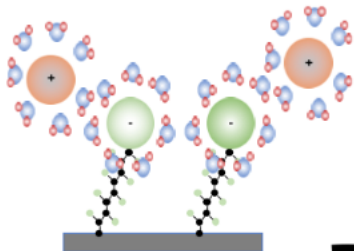
ACTUATE

RESPOND

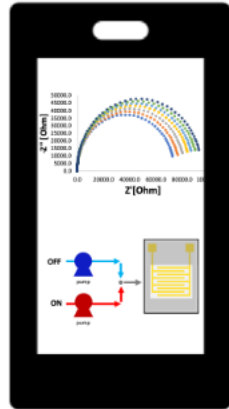
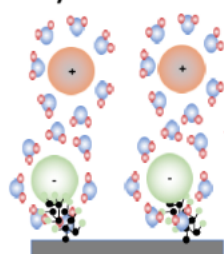
EXECUTE



Nanobrush extended
(20°C)



Nanobrush collapsed
(40°C)



Testing buffer

QUESTION

1

4

5

2

6

3

Situation analysis

Formulation of objectives

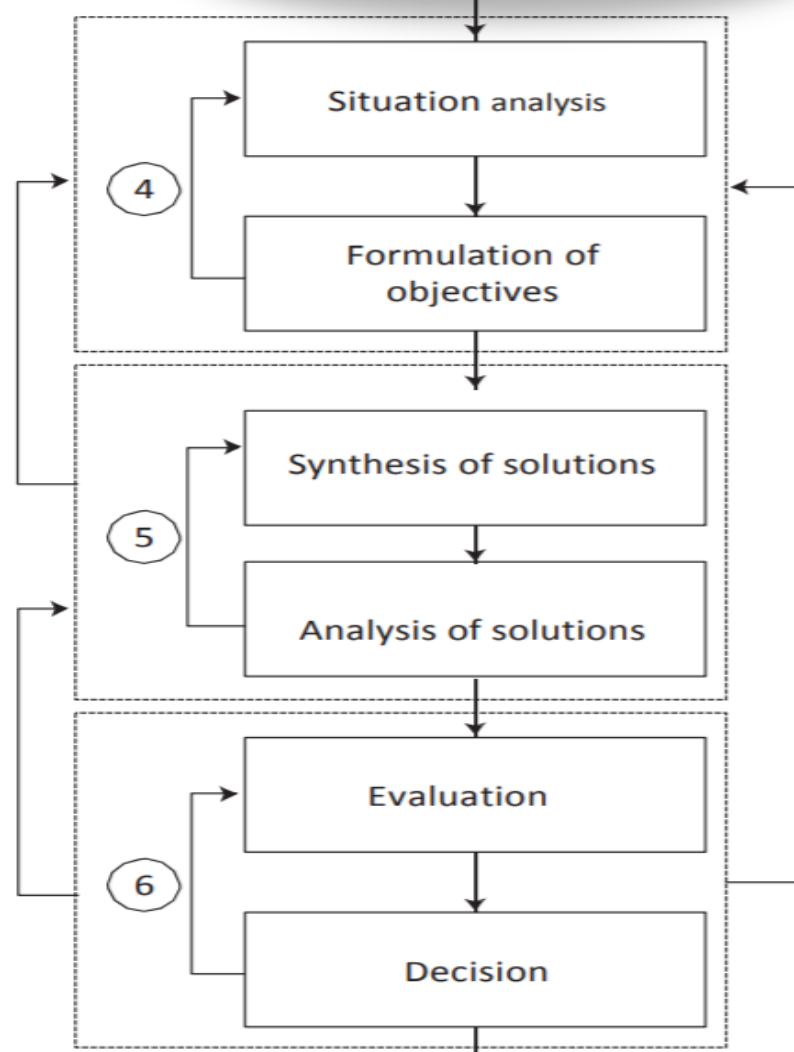
Synthesis of solutions

Analysis of solutions

Evaluation

Decision

OUTCOME

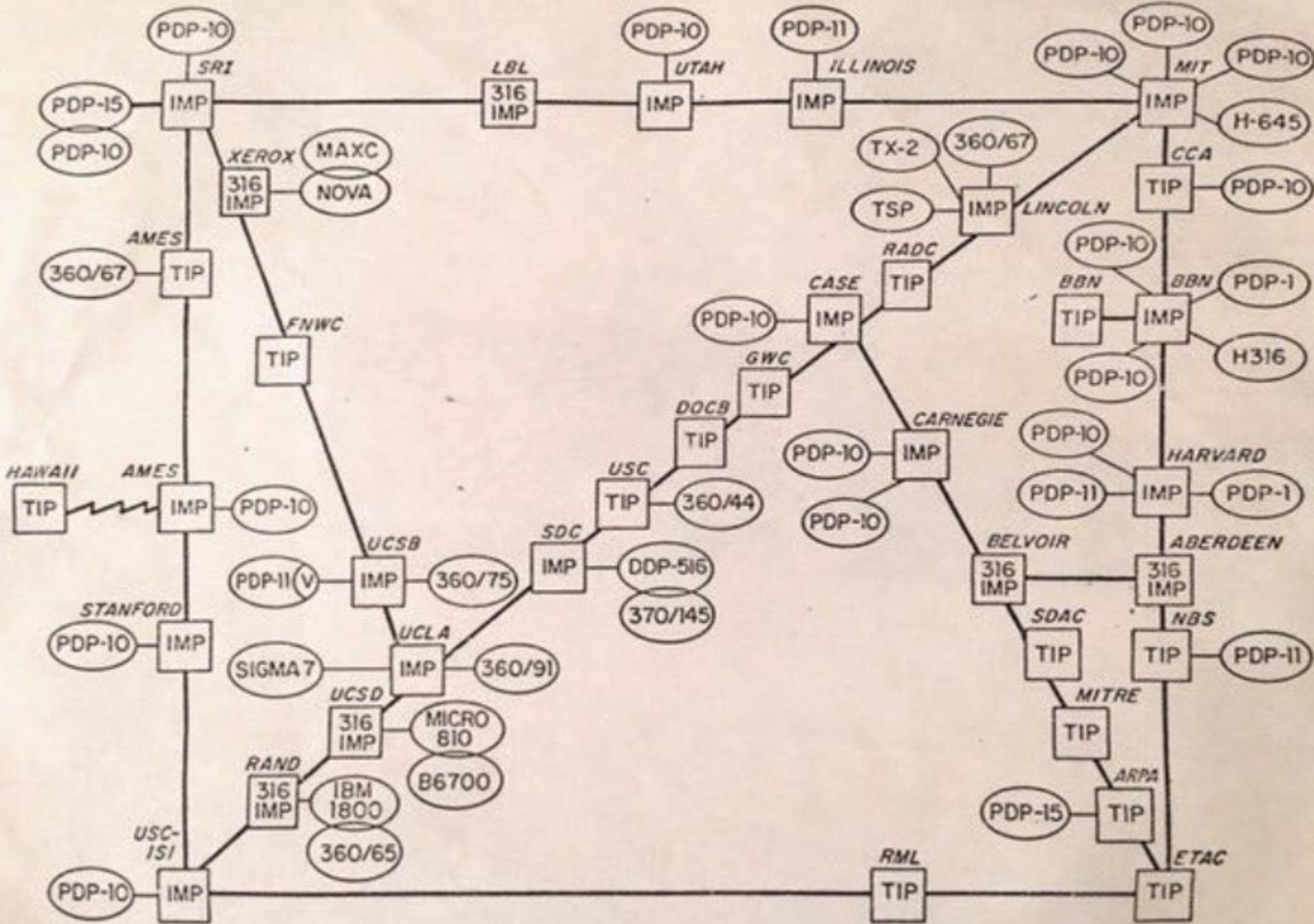


What is

KIDS

Knowledge-Informed Decision as a Service

ARPA NETWORK, LOGICAL MAP, MAY 1973



Information

Computer

Locations
 HARVARD STANFORD
 RAND MIT

Connecting devices

TIP **IMP**
 Terminal Interface Processor Interface Message Processor

Phone Lines

Satellite Link

PLATEFORM

KIDS

Knowledge-Informed Decision as a Service

KIDS is an open plan platform concept. Platforms are comprised of multiple applications and integrated solutions with embedded tools and databases that function as complete, seamless environments. Product innovation platforms are intended to support groups of users collaborating across various levels, domains, business units, and the ecosystem. These capabilities are increasingly needed throughout the entire extended enterprise in almost every vertical, agnostic of the type of application or function or users, including farmers, meat packers, produce growers, retail stores, customers, suppliers, and business partners. Developing open platform tools and technologies are not limited to any one domain because graph networks can overlay and configured for use, almost anywhere. KIDS also includes error correction, search engine algorithms, NLU/NLP (natural language processing), automated feature engineering, drag and drop functions, data analytics, workflows, and open services with plug & play interfaces. Human-computer interactions and data interoperability between system of systems are key elements in the KIDS model.

PLATFORM

Case-based reasoning ?

ABOUT AGRO-ECOSYSTEM

This discussion is about FEWS. But we focus on a tiny part of the science and engineering issues at the nexus of food, energy, water and sanitation (FEWS). Our emphasis is on agriculture and food.

KIDS aims to answer questions from end-users.

For KIDS, food growers and farmers in the field, are the customers.



Dilbert.com DilbertCartoonist@gmail.com



2-25-14 ©2014 Scott Adams, Inc. /Dist. by Universal Uclick



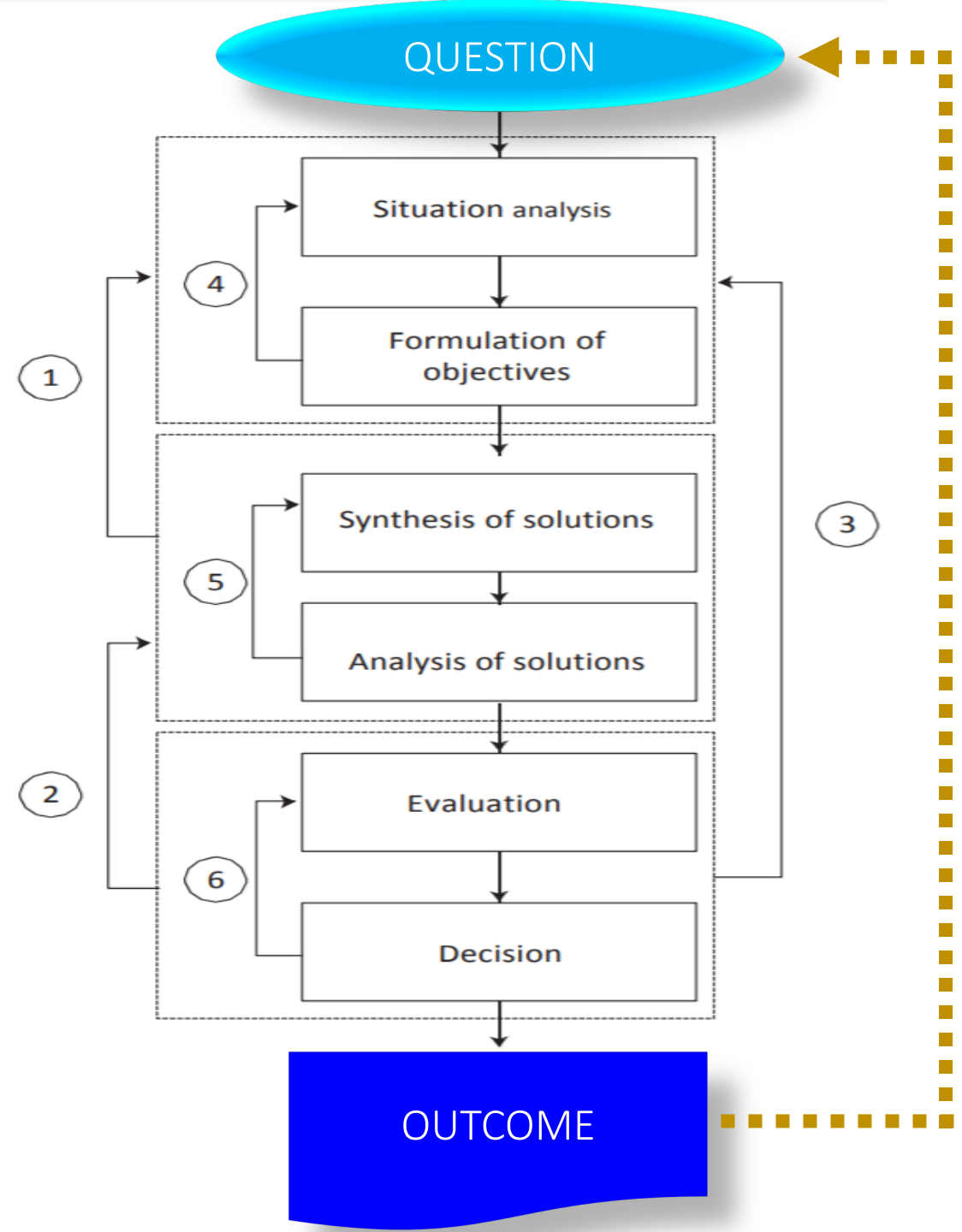
An educated consumer is the best customer.

Example of question from end-user

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Systems engineering approach can guide but it is woefully inadequate. Cannot stay in the “box” if we wish to answer.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

The complexity of this question indicates the challenge for decision support systems

Systems engineering may need several cycles of deconstruction and reconstruction to analyze the question and disassemble the sub-systems, components and data, necessary to attempt to answer the question. This question is quite difficult in terms of computation. It was chosen to illustrate the layers of complexity. In most cases users may benefit from SUGAR or simple case based reasoning tools, such as, SNAPS or some combination of SUGAR and SNAPS with ART.

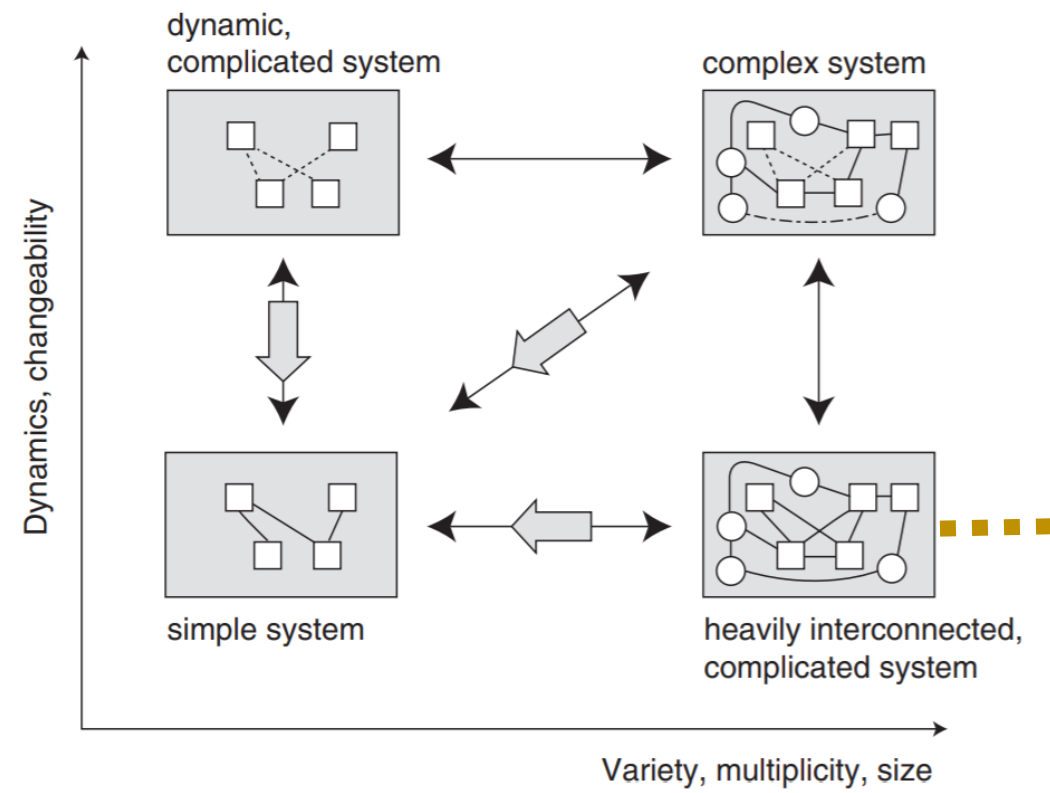
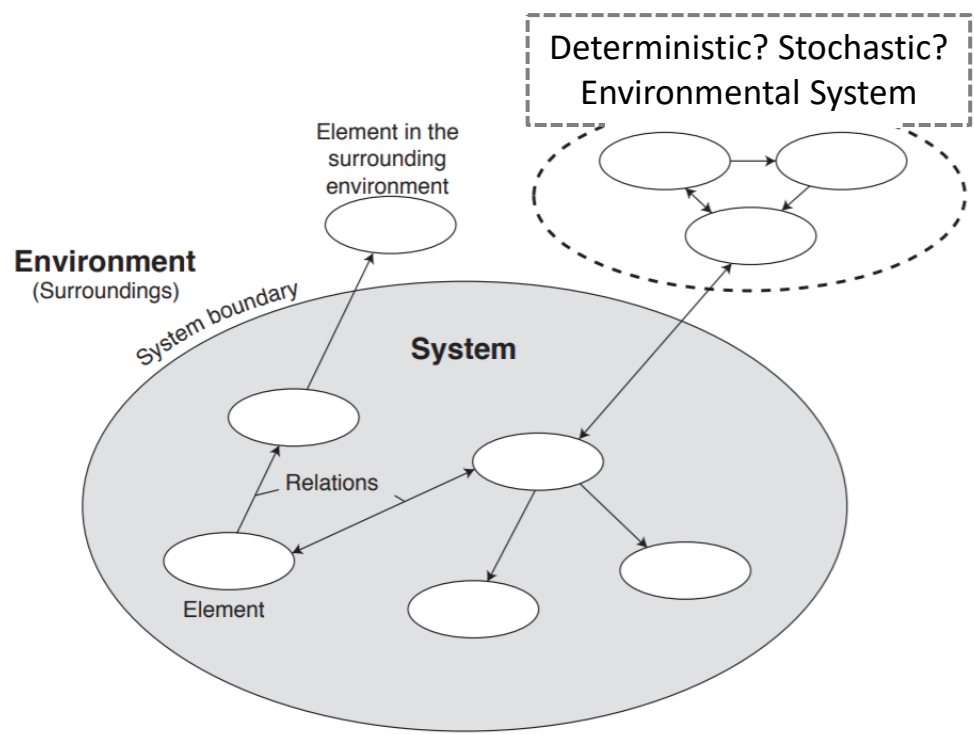
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

“sacrificing my values”

Prevailing decision systems are **data-informed**. Even extraction of actionable “information” stretches the reality. The semantics of this question represents an ecosystem of social “values” with respect to “sacrifices” which are personal in context of the user and her community. There are no tools or systems that can even attempt to answer the first part of the question to any degree of user satisfaction. In the short term, any answer may fail to meet an appreciable quality of service [QoS] level for which the user may recognize the value and may be willing to pay a fee (to receive the service). The best we are capable of delivering is the data-informed decision as a service (**DIDA’S**) which may be relevant to the cost and quality of the waste water which the user is seeking.

Beyond the horizon of data-informed decision as a service (decision support system)

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?



From a systems perspective, we have a heavily interconnected, complicated system

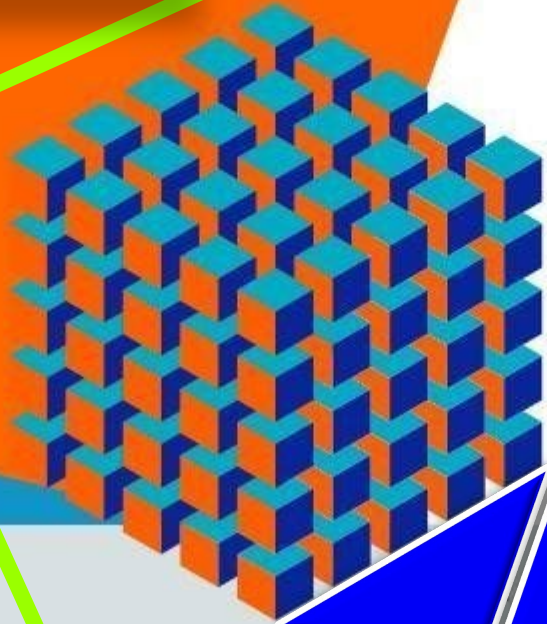
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

What happened to KIDS?

We initiated this discussion with **KIDS**, knowledge-informed decision as a service, but the user's question is compelling us to admit systemic inadequacies. Hence, we are stepping down, considerably, to recognize that the best outcome, at the present, may be limited to **DIDA'S** or data-informed decision as a service and stretch (?) our abilities to extract actionable information.

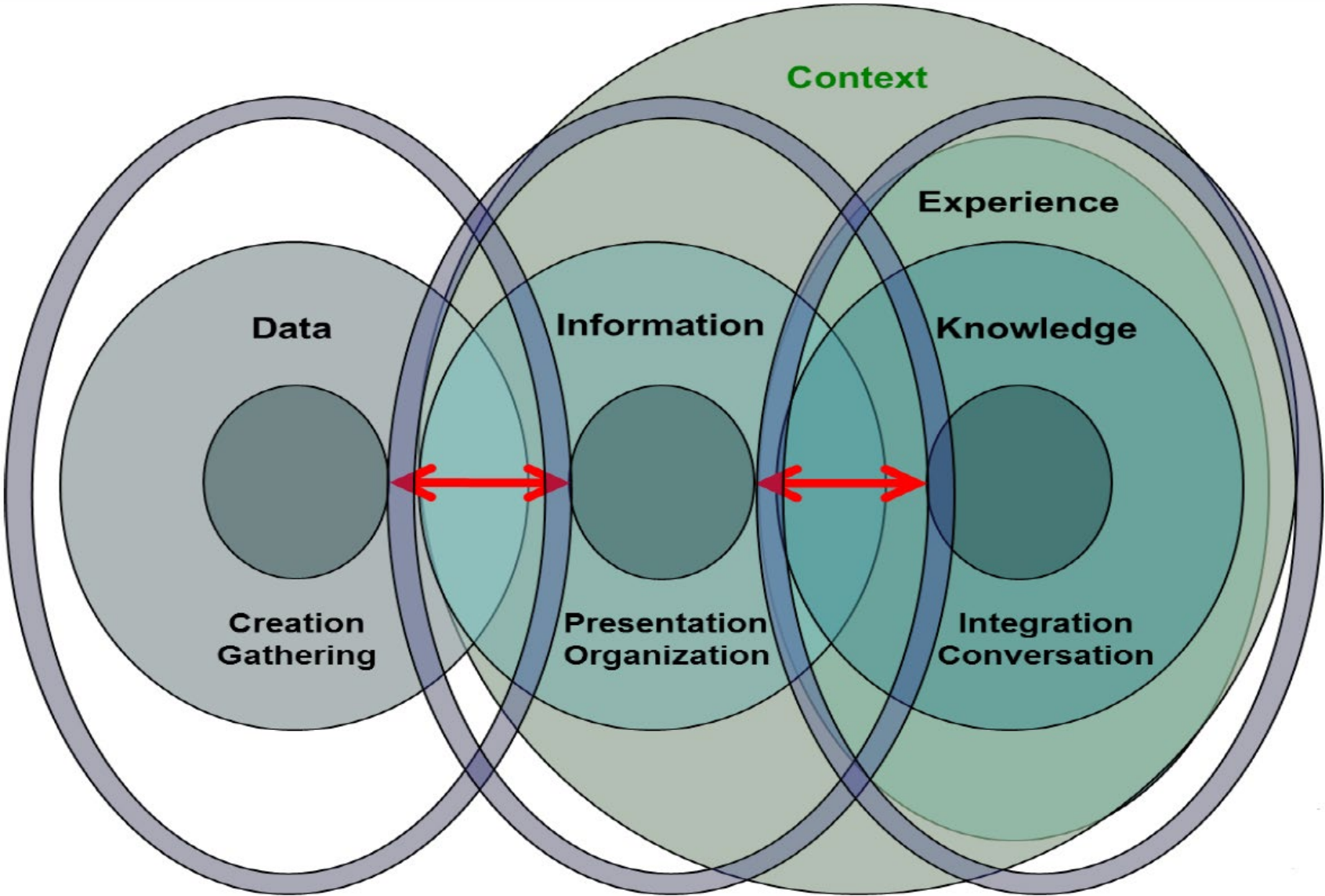
SUMMARY

- 1) Data ≠ Information ≠ Knowledge
- 2)
- 3)
- 4)



**DATA IS NOT
INFORMATION
GENERATING
DATA OR DATA
ACQUISITION
IS NOT INFO**

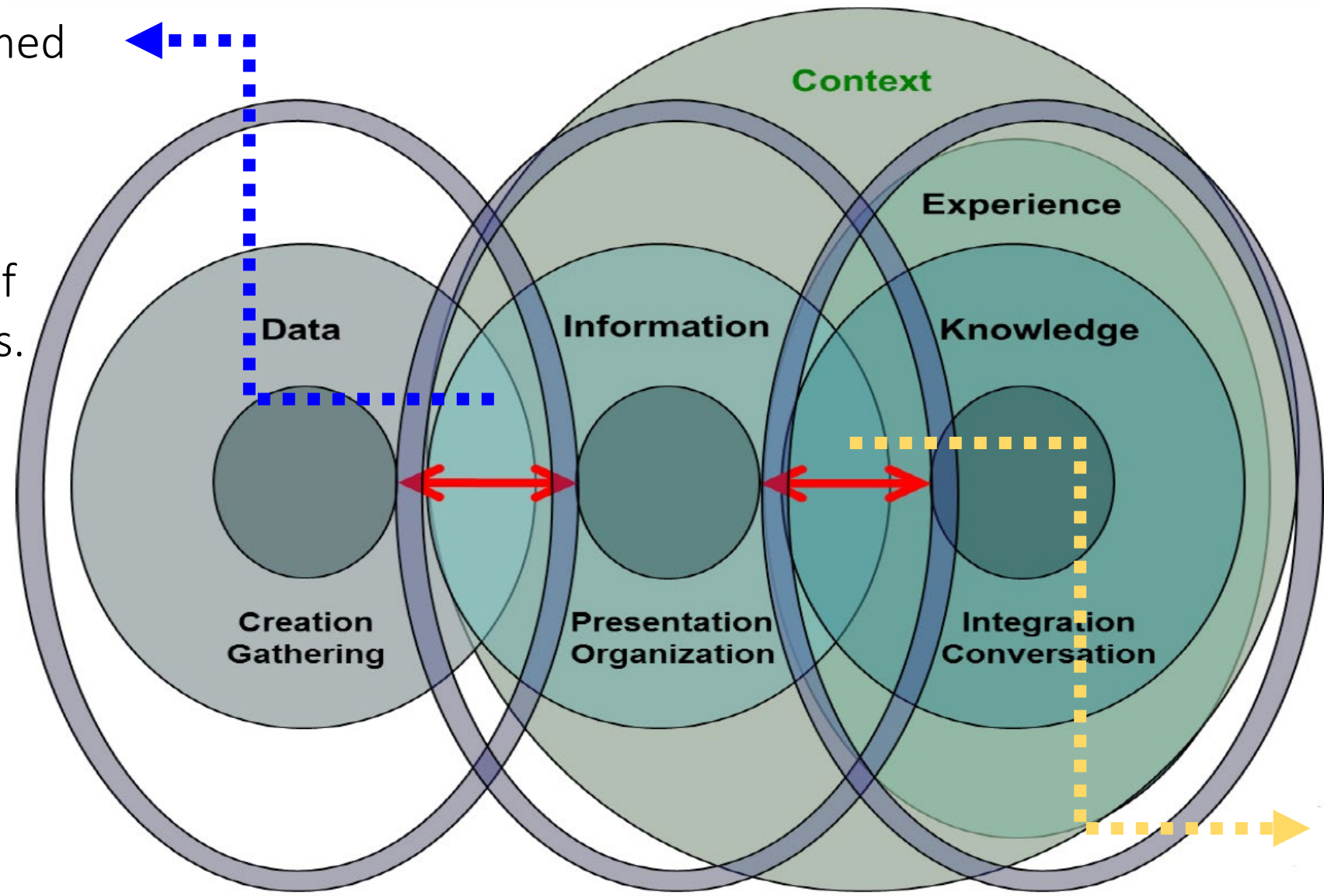
In terms of knowledge from data, our current status is analogous to 1950's, when TV was fuzzy black, greyish white, grainy & dull.



Cartoon: Jim Hendler

In terms of knowledge from data, our current status is analogous to 1950's, when TV was fuzzy black, greyish white, grainy & dull.

Data-informed may be the best case scenario at this stage of our systems.



Knowledge-informed is the Holy Grail. It may be decades away from reality. KIDS may aspire to reach this zone if artificial reasoning can escape the AI mis-information assault and move beyond classical expert systems.



Mind the Gap

There is a
vast
chasm between

data-informed

vs
knowledge-informed

<https://www.forbes.com/sites/joshlinkner/2016/02/08/mind-the-gap>

<http://www.kr.tuwien.ac.at/staff/tkren/pub/2008/rowschool2008.pdf>

KIDS

Knowledge-Informed Decision as a Service

Convergence → *A Sense of the Future*

PLATFORM

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

DIDA'S

Data-Informed Decision as a Service

First, successfully deploy DIDA'S and create tools to extract actionable information. Then we may re-visit how to create KIDS, knowledge-informed decision as a service.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to cost, quality of wastewater and wastewater treatment.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to cost, quality of wastewater and wastewater treatment.

If we dissect deeper with our reductionist approach, we determine the need to answer the user's question in terms of water quality. What data DIDA'S may require for water quality?

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to cost, quality of wastewater and wastewater treatment.

If we dissect deeper with our reductionist approach, we determine the need to answer the user's question in terms of water quality. What data DIDA'S may require for water quality?

SENSOR DATA



In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to performance, environment, actuators and sensors (PEAS).



- **P**erformance
- **E**nvironment
- **A**ctuators
- **S**ensors

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to performance, environment, actuators and sensor data.

DIDA'S

- Performance
- Environment
- Actuators
- Sensors

DIDA'S

- Performance
- Environment
- Actuators
- Sensors

KIDS

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to cost, quality of wastewater and wastewater treatment.

If we dissect deeper with our reductionist approach, we determine the need to answer the user's question in terms of water quality. What data DIDA'S may require for water quality?

1. Data from multiple sensors for water quality monitoring
2. Cost and pricing data for comparative analysis
3. Wastewater treatment tools and technologies

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Even the apparently simpler part of the question requires **multiple** sources of **data** and **convergence** of information to provide a sufficiently data-informed service to the user.

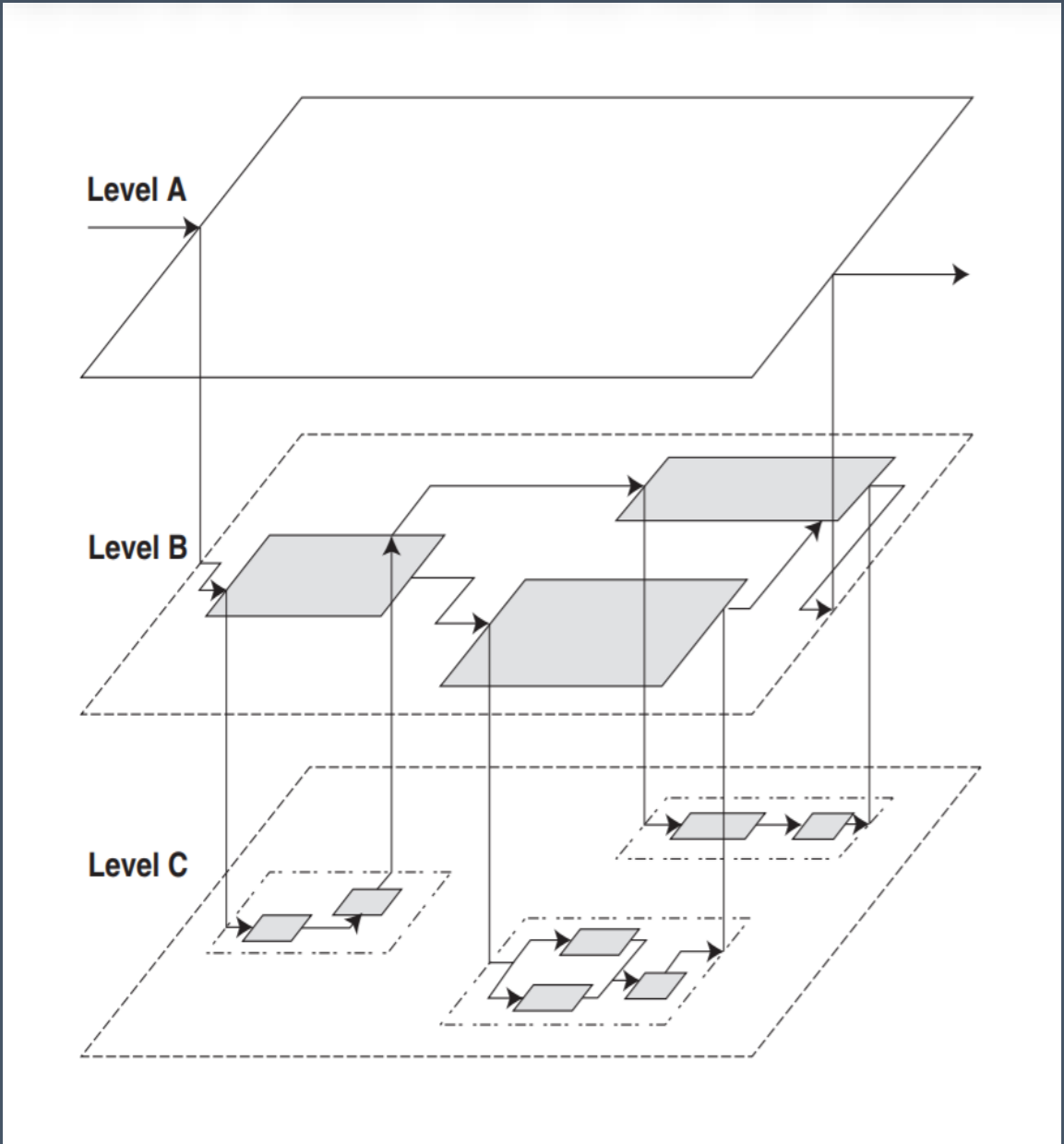
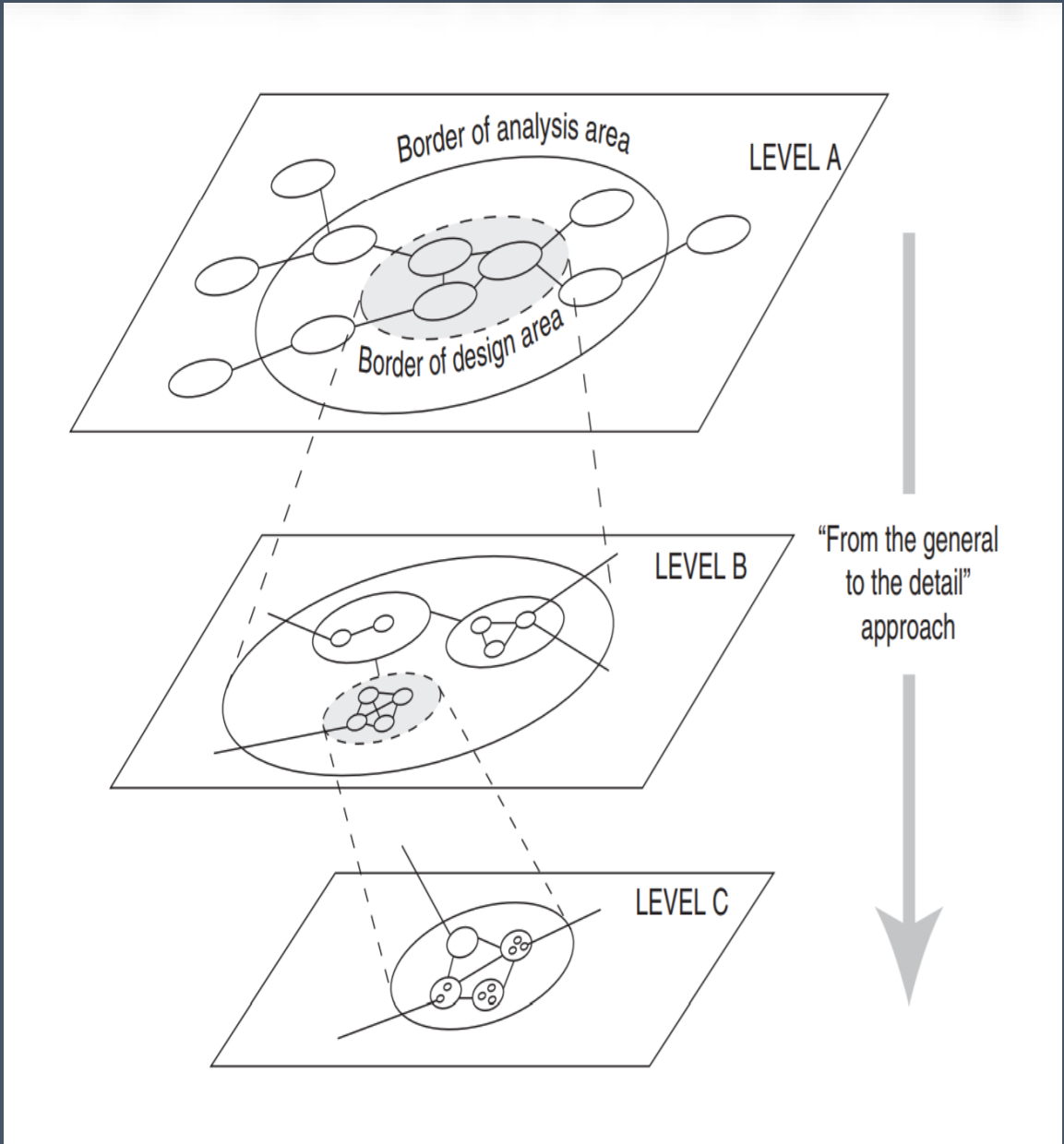
1. Data from multiple sensors for water quality monitoring
2. Cost and pricing data for comparative analysis
3. Wastewater treatment tools and technologies

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Data fusion and convergence of information are only a part of the data-informed *service* users expect. The tasks are to delineate relationships germane to the question, select relevant data, connect, catalyze data fusion, synthesize information, extract “actionable” information, and deliver to a mobile device, in time, contextually relevant recommendation, of value, to the end-user.

1. Data from multiple sensors for water quality monitoring
2. Cost and pricing data for comparative analysis
3. Wastewater treatment tools and technologies

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?



From a systems engineering approach, deconstruct the question in terms of data granularity.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

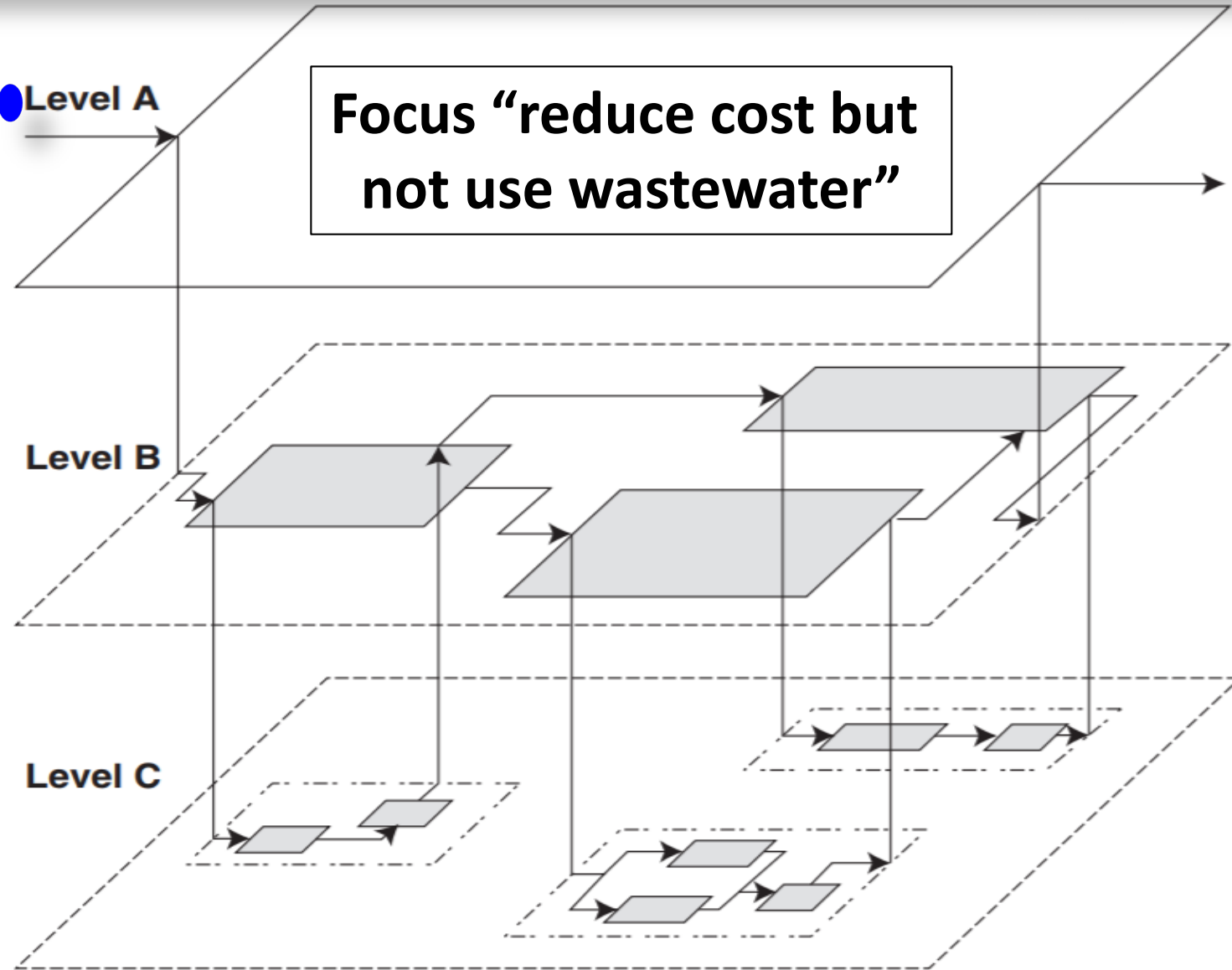
Focus “reduce cost but not use wastewater”

Level A

Focus “reduce cost but not use wastewater”

Level B

Level C



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Focus “reduce cost but not use wastewater”

Level A

Focus “reduce cost but not use wastewater”

- Factors affecting cost
- Sensors to determine water quality
- Tools necessary for treatment of wastewater

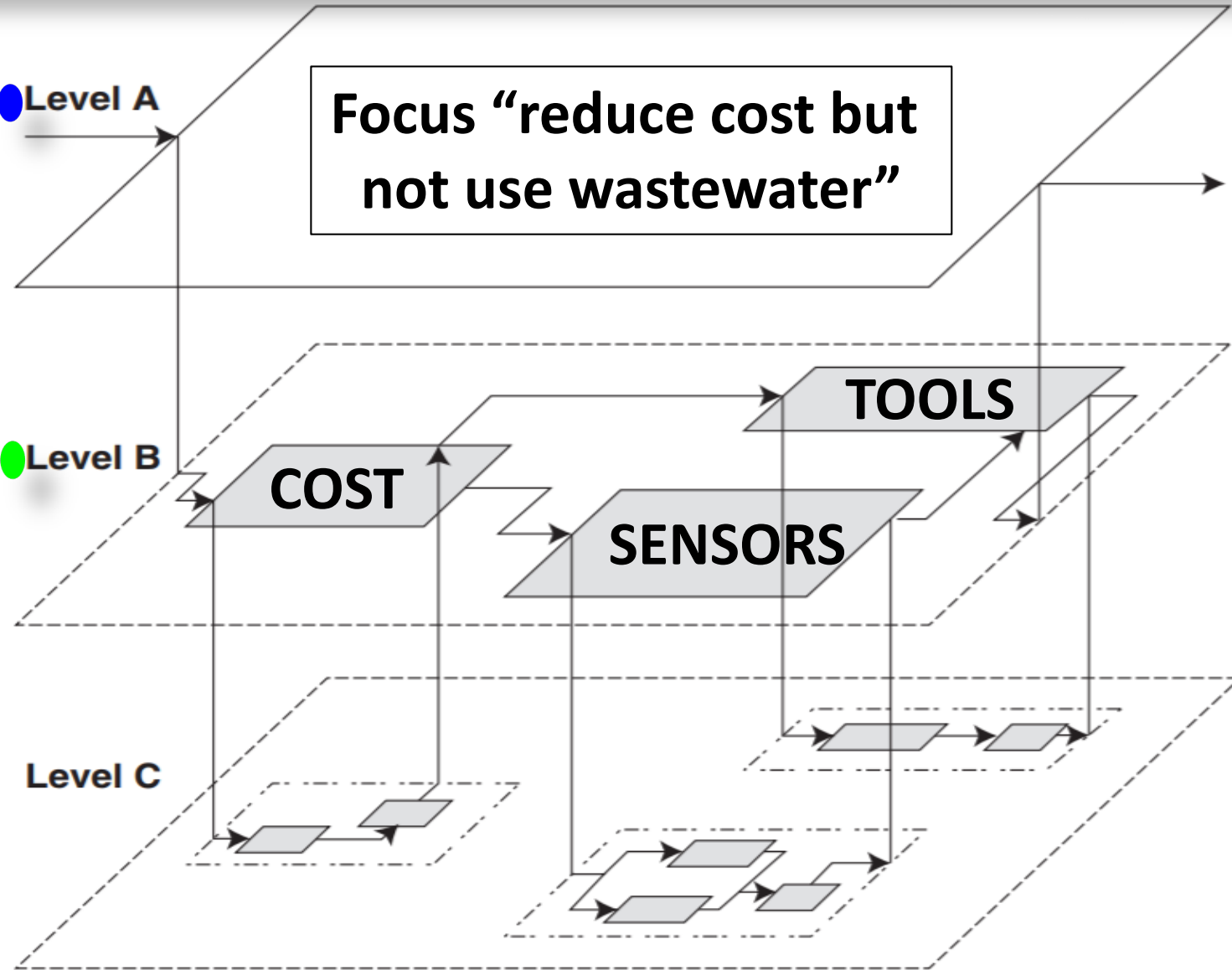
Level B

COST

SENSORS

TOOLS

Level C



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Focus “reduce cost but not use wastewater”

Level A

Focus “reduce cost but not use wastewater”

-Factors affecting cost
-Sensors to determine water quality
-Tools necessary for treatment of wastewater

Level B

COST

SENSORS

TOOLS

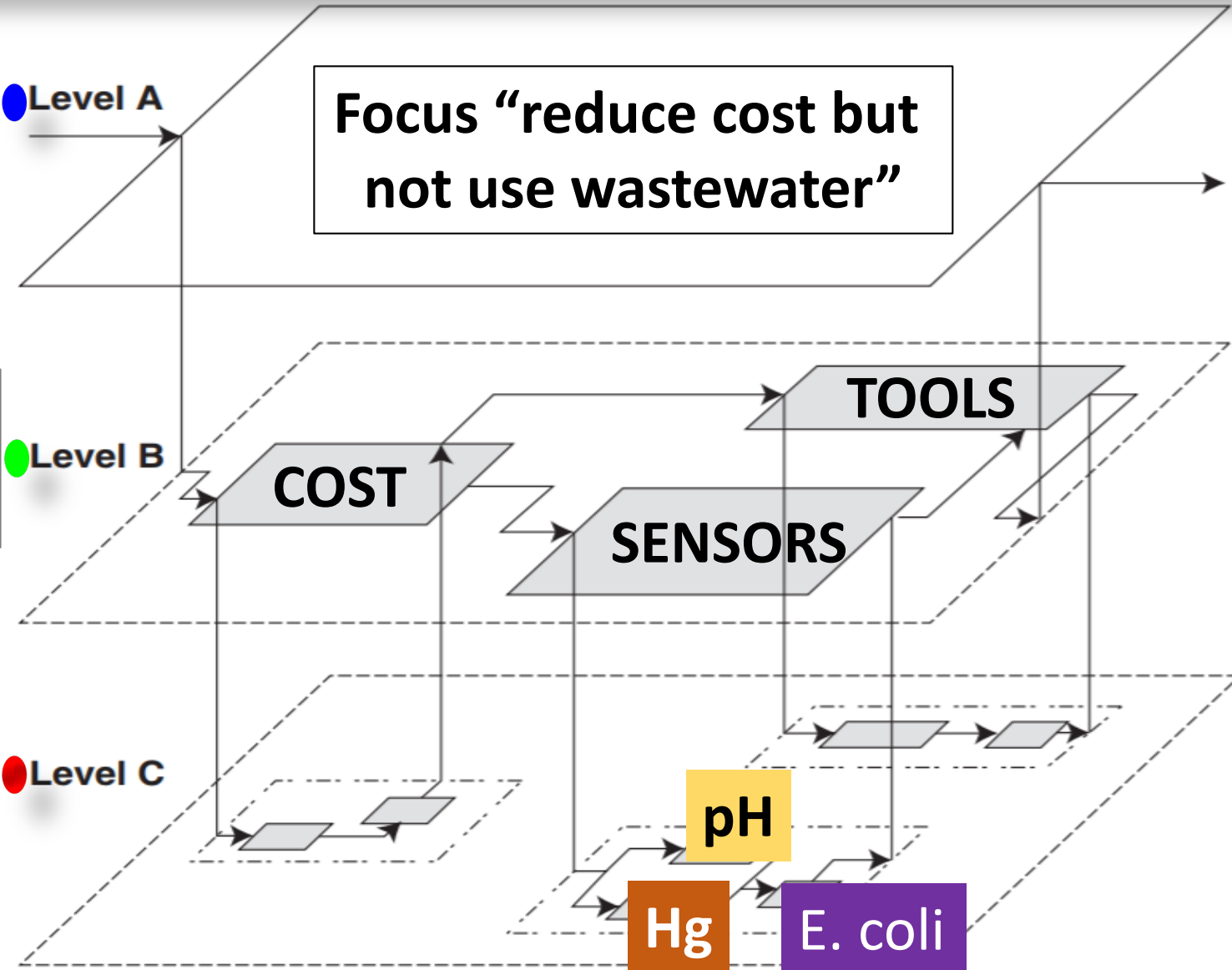
▪ Sensors to determine water quality
- Heavy metal pollution (Mercury)
- Microbial contaminants (E. coli)
- Chemical characteristics (pH)

Level C

pH

Hg

E. coli



Raw Data Source

Denominator

Granularity of Deconstruction – Where is the data source?

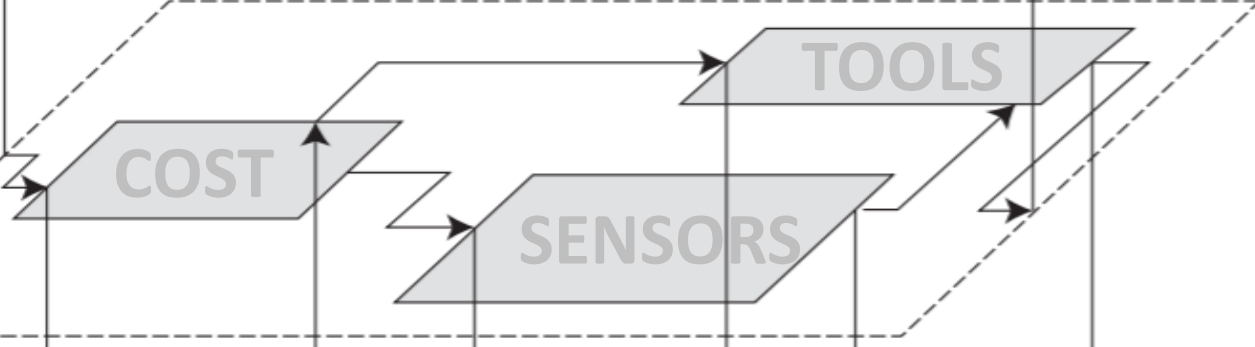
Focus “reduce cost but not use wastewater”

Level A

Focus “reduce cost but not use wastewater”

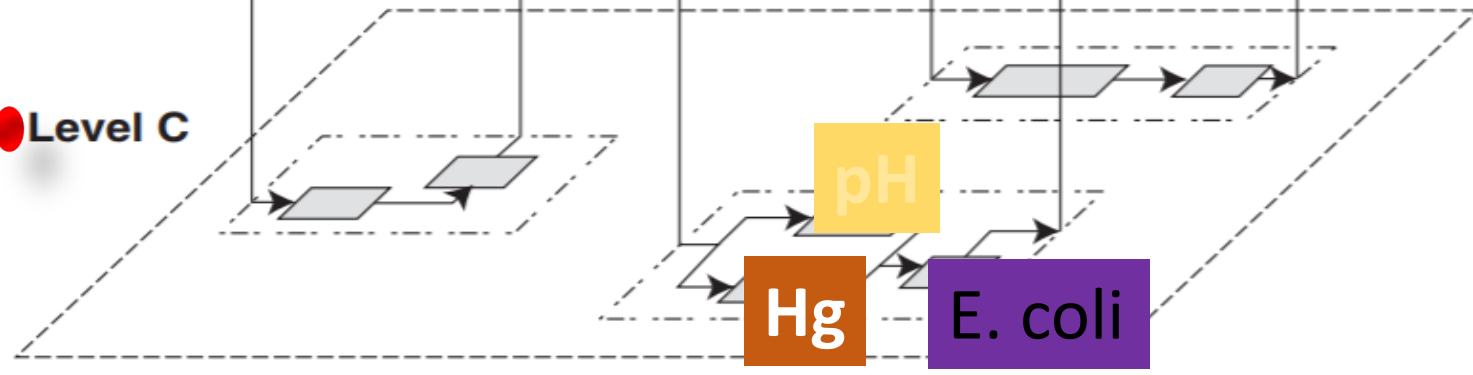
-Factors affecting cost
-Sensors to determine water quality
-Tools necessary for treatment of wastewater

Level B



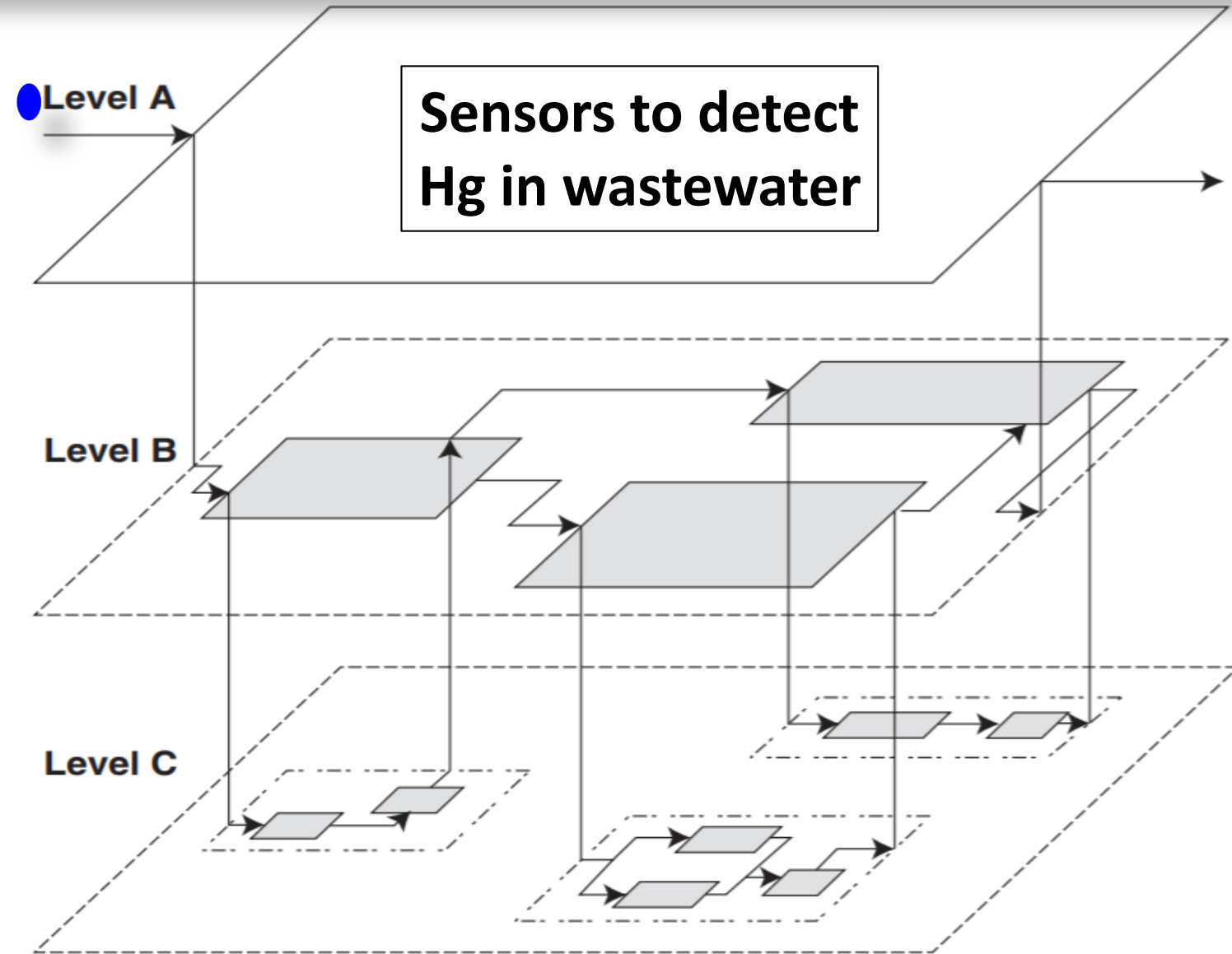
▪ Sensors to determine water quality
- Heavy metal pollution (Mercury)
- Microbial contaminants (E. coli)
- Chemical characteristics (pH)

Level C



Granularity of Deconstruction – Sensors to Detect Mercury

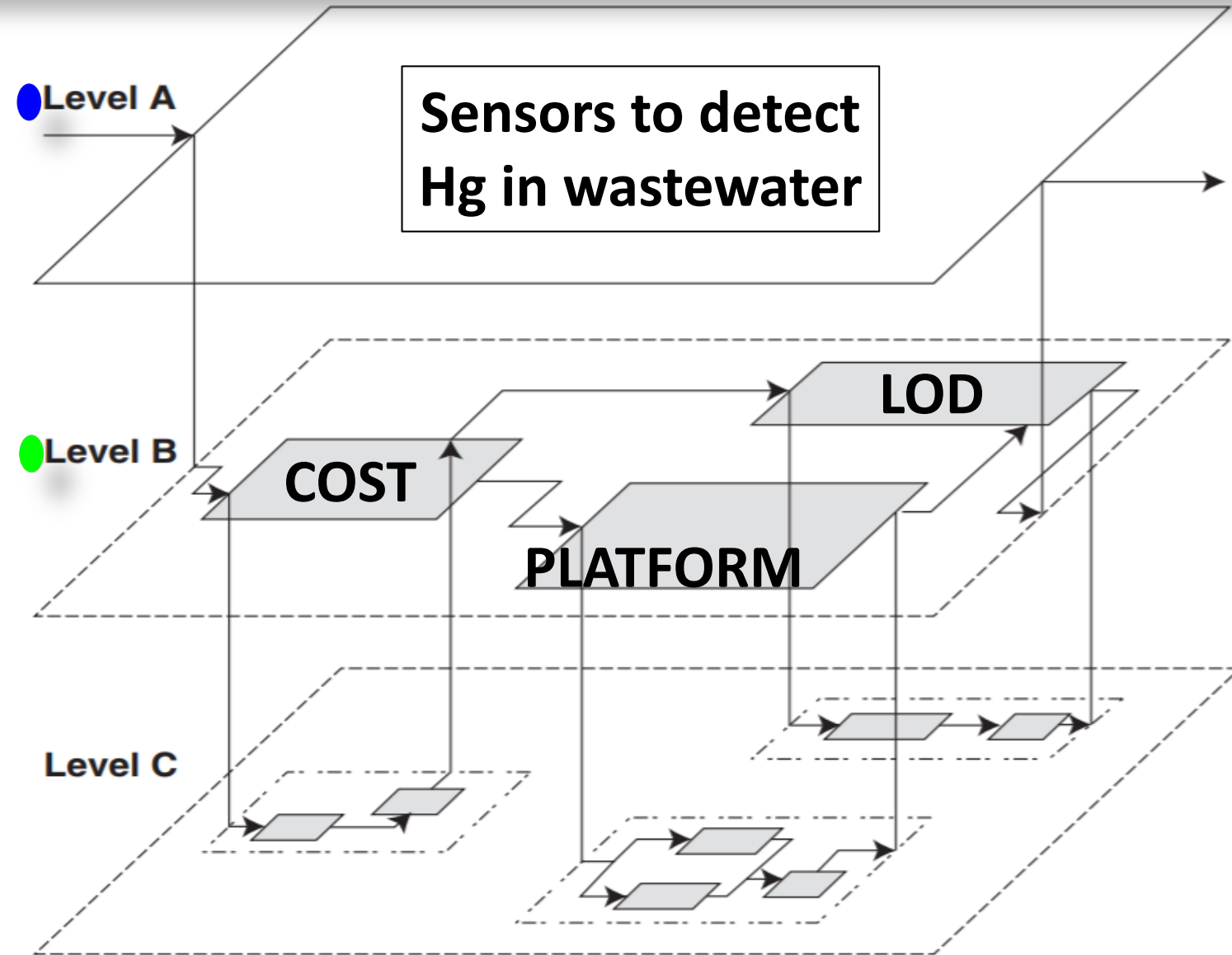
Sensors to detect Mercury (Hg) in wastewater



Granularity of Deconstruction – Sensors to Detect Mercury

Sensors to detect Mercury (Hg) in wastewater

- Cost of sensors
- Limit of Detection (LOD) necessary for use
- Which platform is best for the specific use

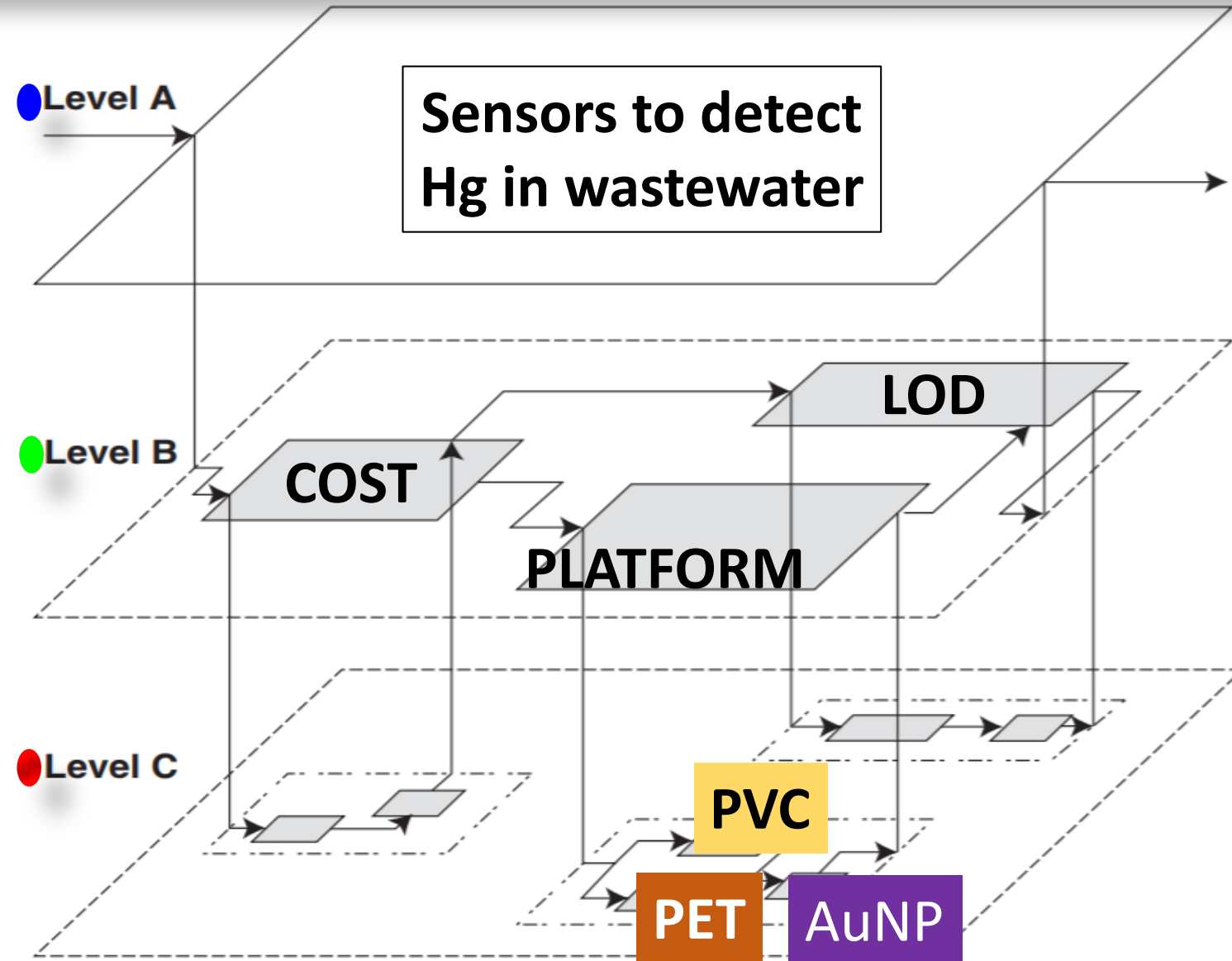


Granularity of Deconstruction – Sensors to Detect Mercury

Sensors to detect Mercury (Hg) in wastewater

- Cost of sensors
- Limit of Detection (LOD) necessary for use
- Which platform is best for the specific use

- Platforms for Mercury (Hg) sensor
 - Poly(vinyl chloride) (PVC) membrane
 - Photoinduced electron transfer (PET)
 - Gold-nanoparticle (AuNP)



Granularity of Deconstruction: Several types of sensors to detect Mercury

A	B	C	D	E	F	G	H	I	J
Device number	MW [Da]	Category	Target	Recognition-transduction scheme	Platform	Range (LOD)	Range (max tested)	Selectivity (interferent species tested)	Response time [sec]
1	201	heavy metal	mercury (Hg2+)	AuNP		1.00E-08	NR	NR	60
2	201	heavy metal	mercury (Hg2+)	MIP??	Sol gel	5.00E-06	NR	NR	600
3	201	heavy metal	mercury (Hg2+)	Rhodamine		1.00E-07	NR	NR	60
4	201	heavy metal	mercury (Hg2+)			5.00E-07	NR	95%	60
5	201	heavy metal	mercury (Hg2+)	foldamer	micelle	5.00E-07	NR	99%	60
6	201	heavy metal	mercury (Hg2+)	corroloe derivative	PVC	5.60E-06	NR	NR	300
7	201	heavy metal	mercury (Hg2+)	tetraarylborate		3.00E-07	NR	NR	60
8	201	heavy metal	mercury (Hg2+)			1.00E-07	NR	poor over Ag+	60
9	201	heavy metal	mercury (Hg2+)	polythiophene		3.00E-05	NR	90%	60
10	201	heavy metal	mercury (Hg2+)	thiosemicarbazone		5.00E-06	NR	NR	60
11	201	heavy metal	mercury (Hg2+)	dansylcarboxamide		1.00E-05	5.00E-04	NR	60
12	201	heavy metal	mercury (Hg2+)	quenching		3.00E-06	5.50E-05	excellent	60
13	201	heavy metal	mercury (Hg2+)	DNAzyme		2.40E-09	NR	excellent (transition/heavy metals)	60
14	201	heavy metal	mercury (Hg2+)	chromo-ionophore assembly	PVC	3.40E-08	NR	poor (heavy metals)	60
15	201	heavy metal	mercury (Hg2+)	AuNP		5.00E-09	1.00E-05	excellent (transition/heavy metals)	600
16	201	heavy metal	mercury (Hg2+)			1.00E-08	2.00E-04	excellent (transition/heavy metals)	60
17	201	heavy metal	mercury (Hg2+)	Rhodamine 6G	AuNP	6.00E-11	3.60E-08	excellent (transition/heavy metals)	60
18	201	heavy metal	mercury (Hg2+)	Cholic acid		5.00E-08	NR	good (MeHg/transition/heavy metals)	60
19	201	heavy metal	mercury (Hg2+)	thiacalixarene		2.00E-06	8.50E-06	good (poor over Ag+)	60
20	201	heavy metal	mercury (Hg2+)			7.00E-07	NR	poor over Cu+	60
21	201	heavy metal	mercury (Hg2+)	anthraquinone/urea		5.0E-05	2.0E-04	poor	60
22	201	heavy metal	mercury (Hg2+)	anthracene/ionophore hybrid	PET	1.0E-06		poor over Fe3+	60
23	201	heavy metal	mercury (Hg2+)	oligonucleotide	AuNP	1.0E-07	1.0E-06	poor over Pb3+	60
24	201	heavy metal	mercury (Hg2+)	oligonucleotide		4.2E-08	6.7E-07	moderate	60
25	201	heavy metal	mercury (Hg2+)			5.0E-08		excellent (transition/heavy metals)	60
26	201	heavy metal	mercury (Hg2+)	phosphorescent iridium(III) complex		2.0E-05		excellent (transition/heavy metals)	60
27	201	heavy metal	mercury (Hg2+)	MerR protein		1.0E-08		NR	60
28	201	heavy metal	mercury (Hg2+)			1.0E-06		NR	60

Which sensor to choose? Which sensor has the lowest limit of detection?

Which sensor to choose? Which sensor has the lowest limit of detection?

Users wish to explore sensor categories and attributes ?

Which sensor to choose? Which sensor has the lowest limit of detection?

Users wish to explore sensor categories and attributes ?

End-users, as well as experts, may benefit from information about different sensors, by categories and list of attributes, which may be suitable for use.

Which sensor to choose? Which sensor has the lowest limit of detection?

SENsor SEarch Engine

Which sensor to choose? Which sensor has the lowest limit of detection?

SENsensor **SE**arch Engine

SENSEE

Delving deeper into the granularity of the data necessary for DIDA'S to be sufficiently data-informed, we arrive at one data source:

SENSORS for DIDA'S

Sensor data as a source of data for data-informed decision as a service (DIDA'S)

Sensor data still remains a key denominator when we move from data-informed (DIDA'S) to knowledge-informed (KIDS)

SENSORS for DIDA'S KIDS

Sensors for knowledge-informed decision as a service (KIDS)

SKIDS



In granular terms, DIDA'S and KIDS, still needs to choose sensor type.

SENsor **SE**arch Engine

SENSEEE

In granular terms, the outcome from DIDA'S and KIDS, depends on data.

Data from Sensors

SENSEEE

At the most granular level, first we need to *choose the sensor* and then proceed to harvest *data* from specific sensor(s).

FOR SOME OF THE QUESTIONS, THIS IS A PRE-REQUISITE FOR DIDA'S and KIDS.

Hence, we start searching for suitable sensor categories and attributes.

SENsor SEarch Engine

SENSEEE

Then, we seek data from sensors (relevant to the real world questions).

Data from Sensors

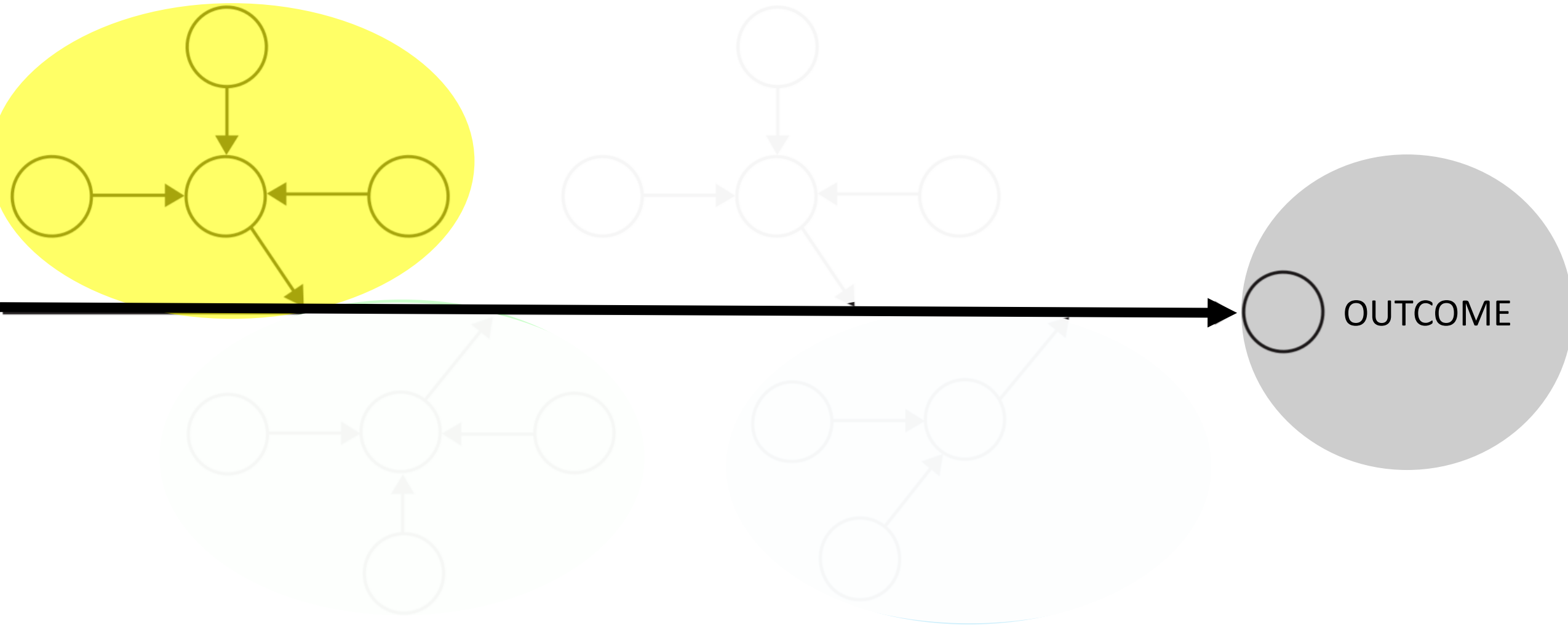
SENSEEE

We need sensors, and sensor data, to fuel the outcome.

Data-informed (DIDA'S)

Knowledge-informed (KIDS)

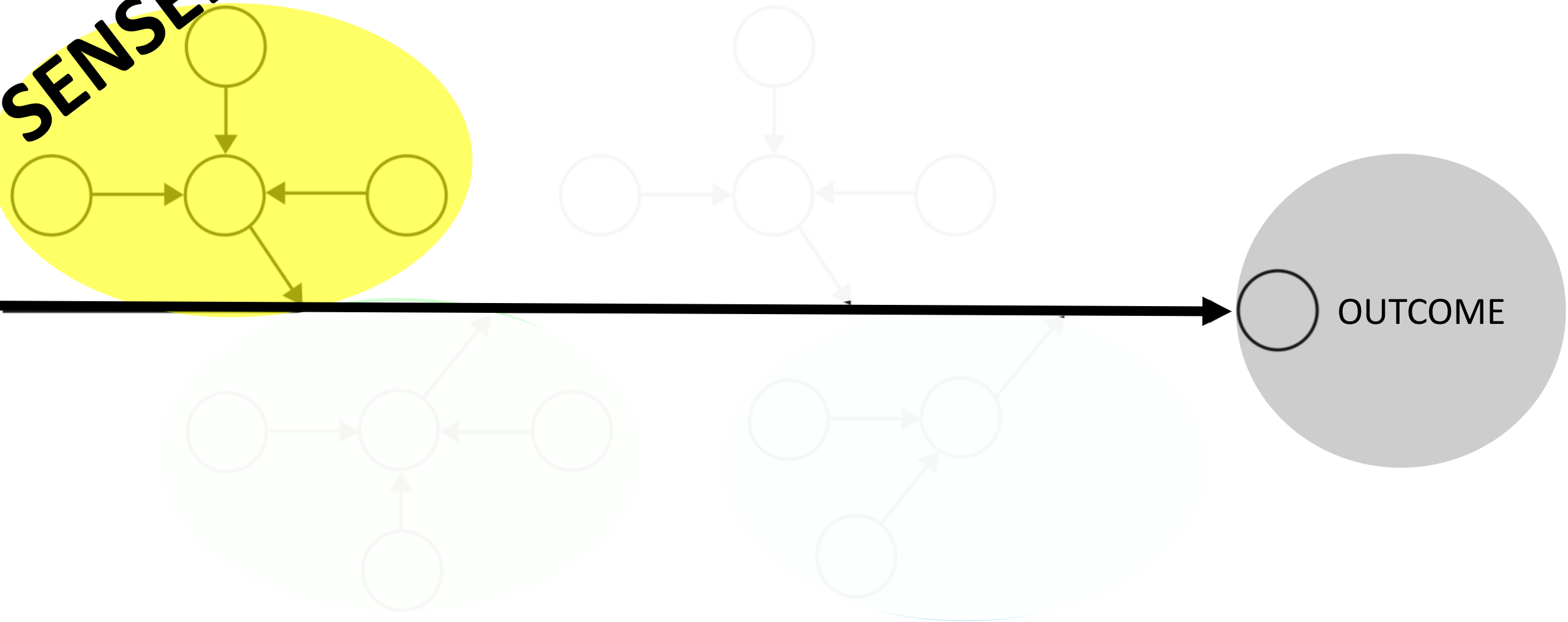
Sensor & sensor data



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

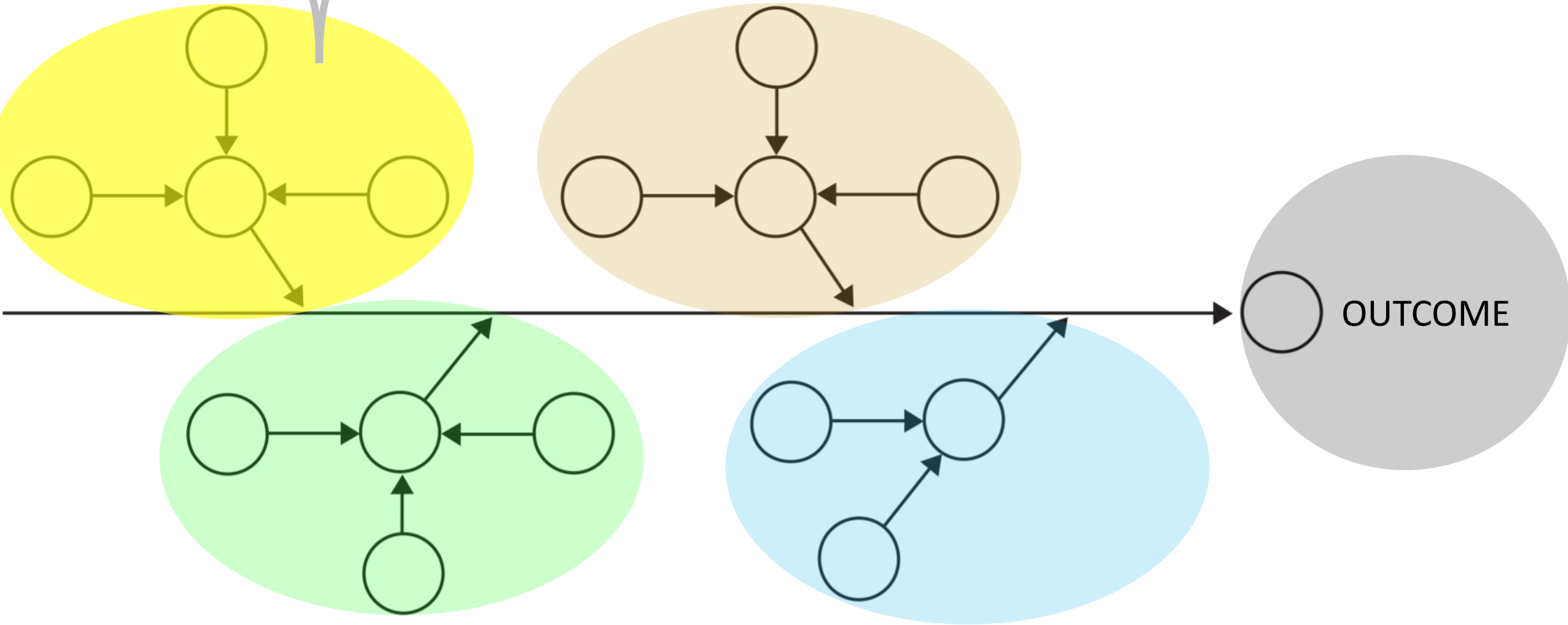
Sensor & sensor data

SENSEE



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Sensor & sensor data may be long way from information



http://www.ihl.org/education/IHIOpenSchool/resources/Assets/CauseandEffect_Instructions.pdf

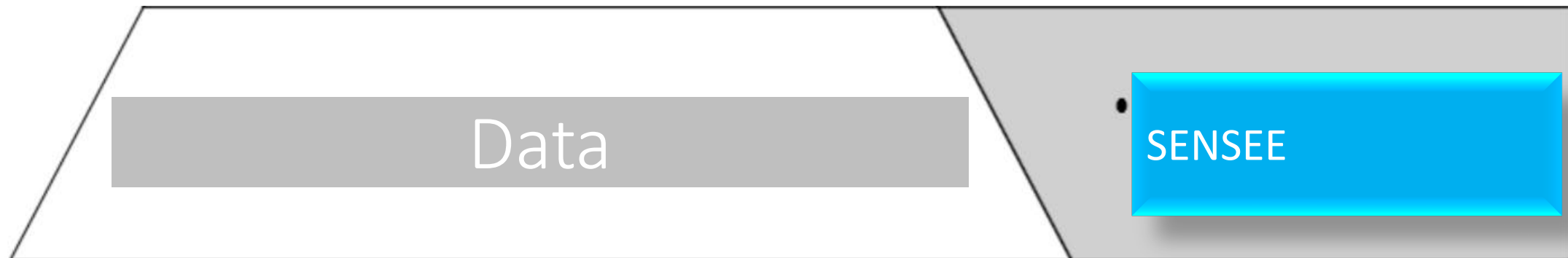
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

To summarize the steps

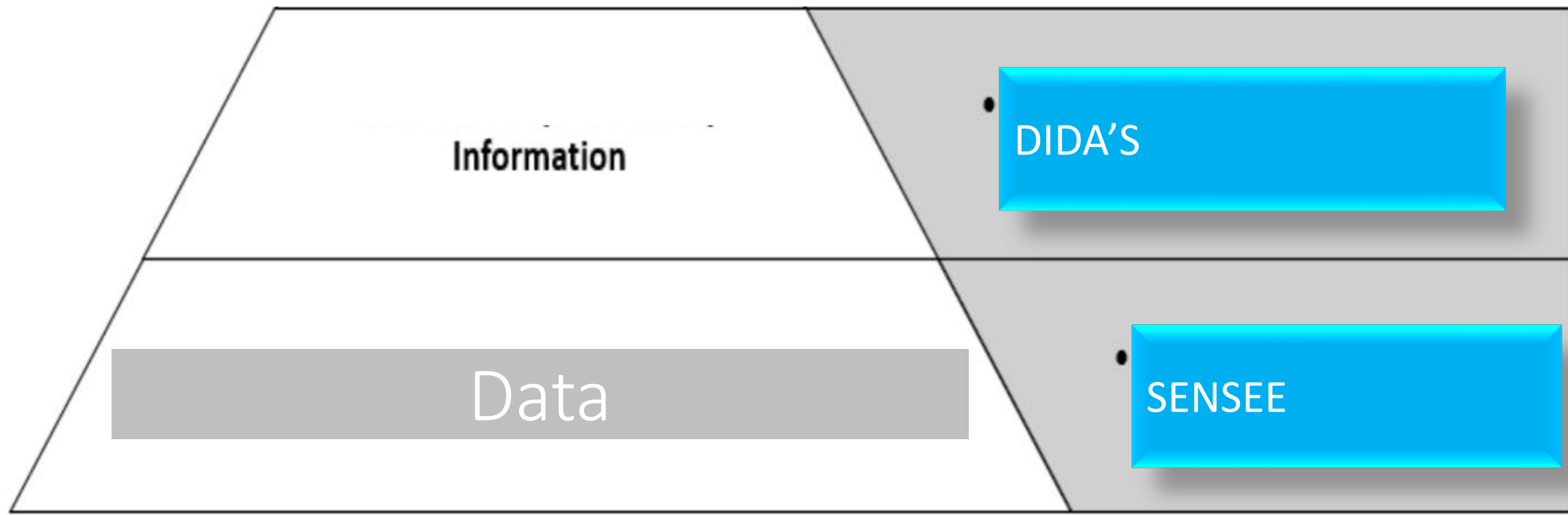


Data

DIKW



DIKW



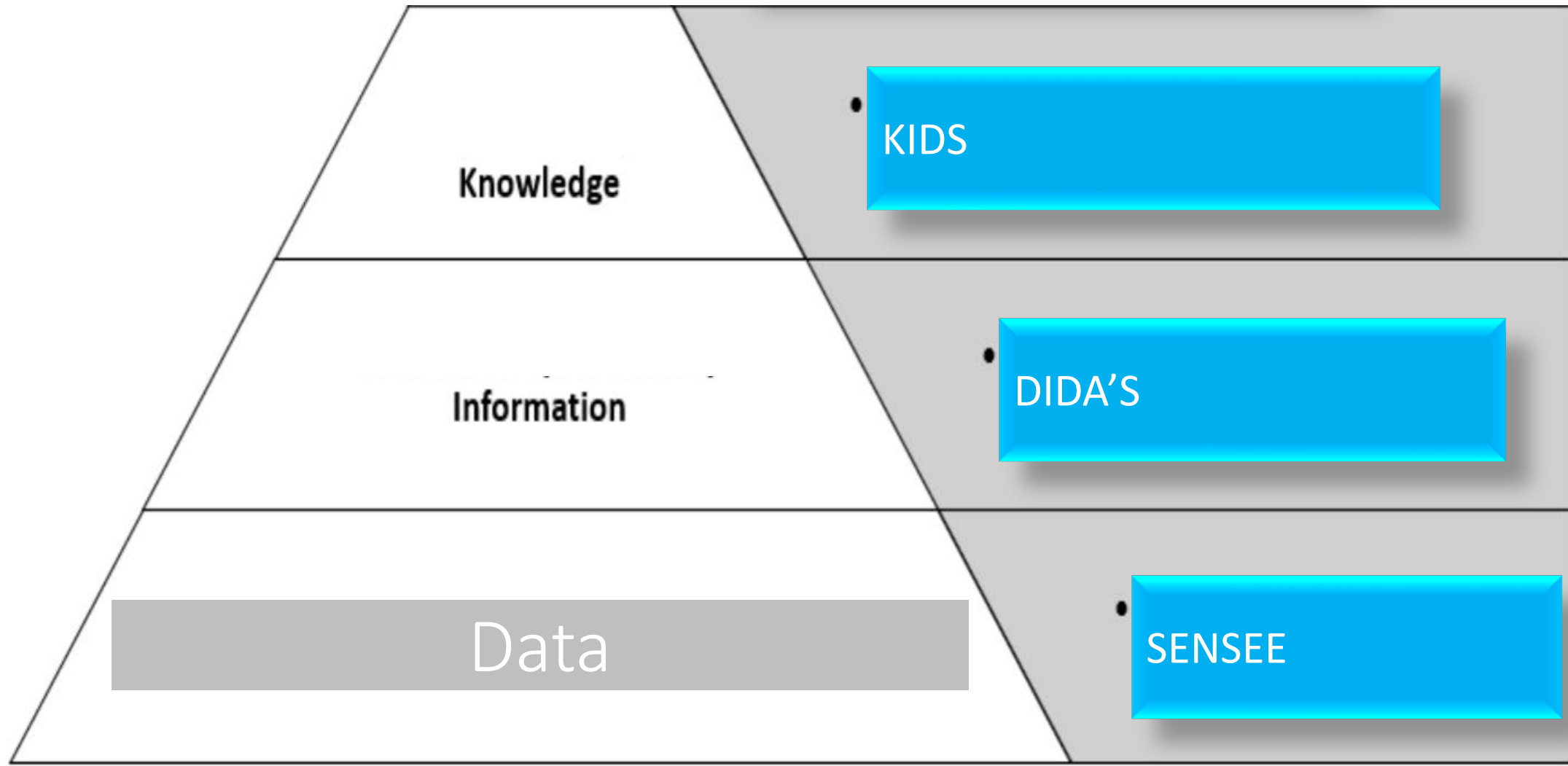
Information

• DIDA'S

Data

• SENSEE

DIKW



Knowledge

KIDS

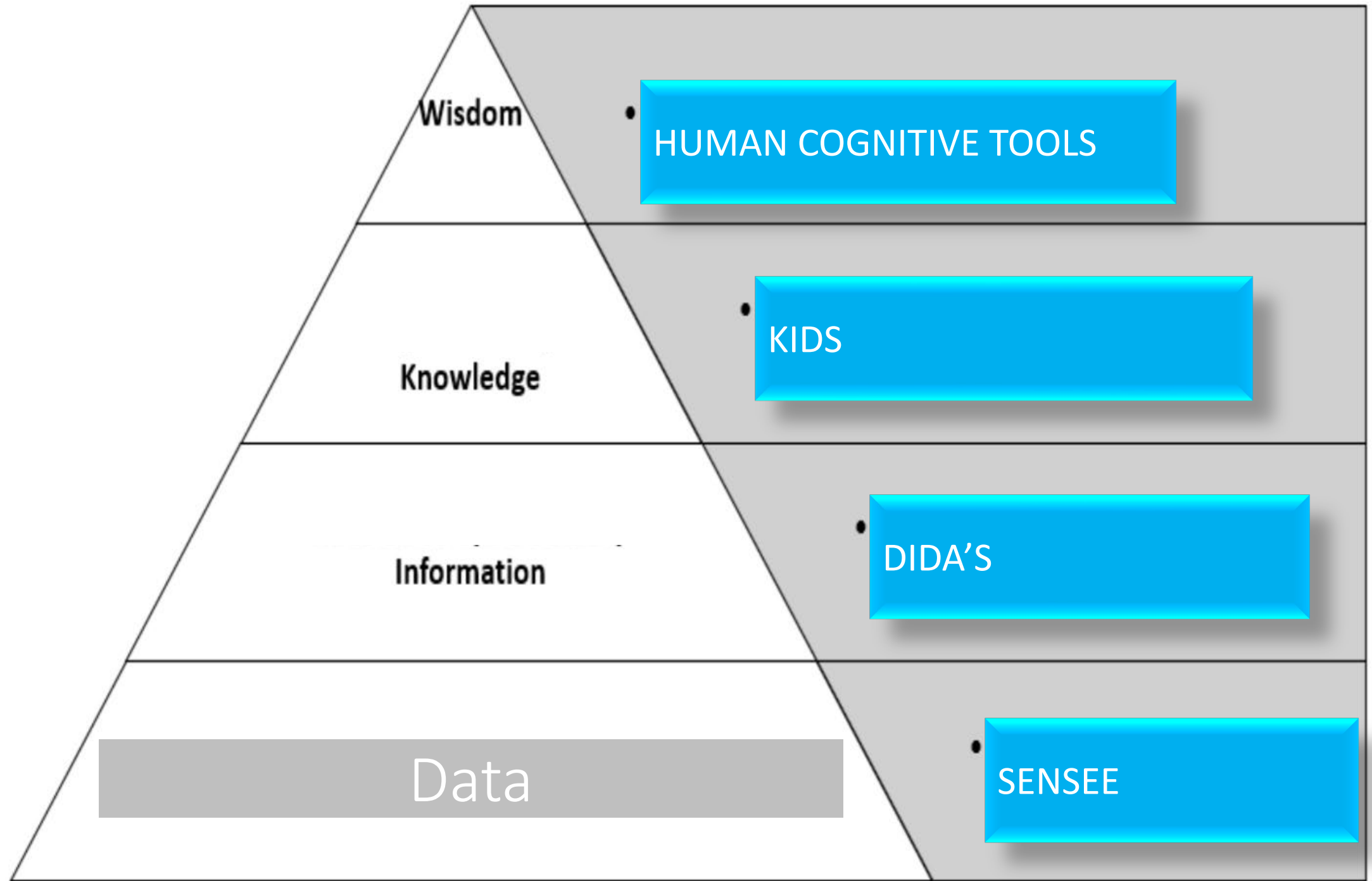
Information

DIDA'S

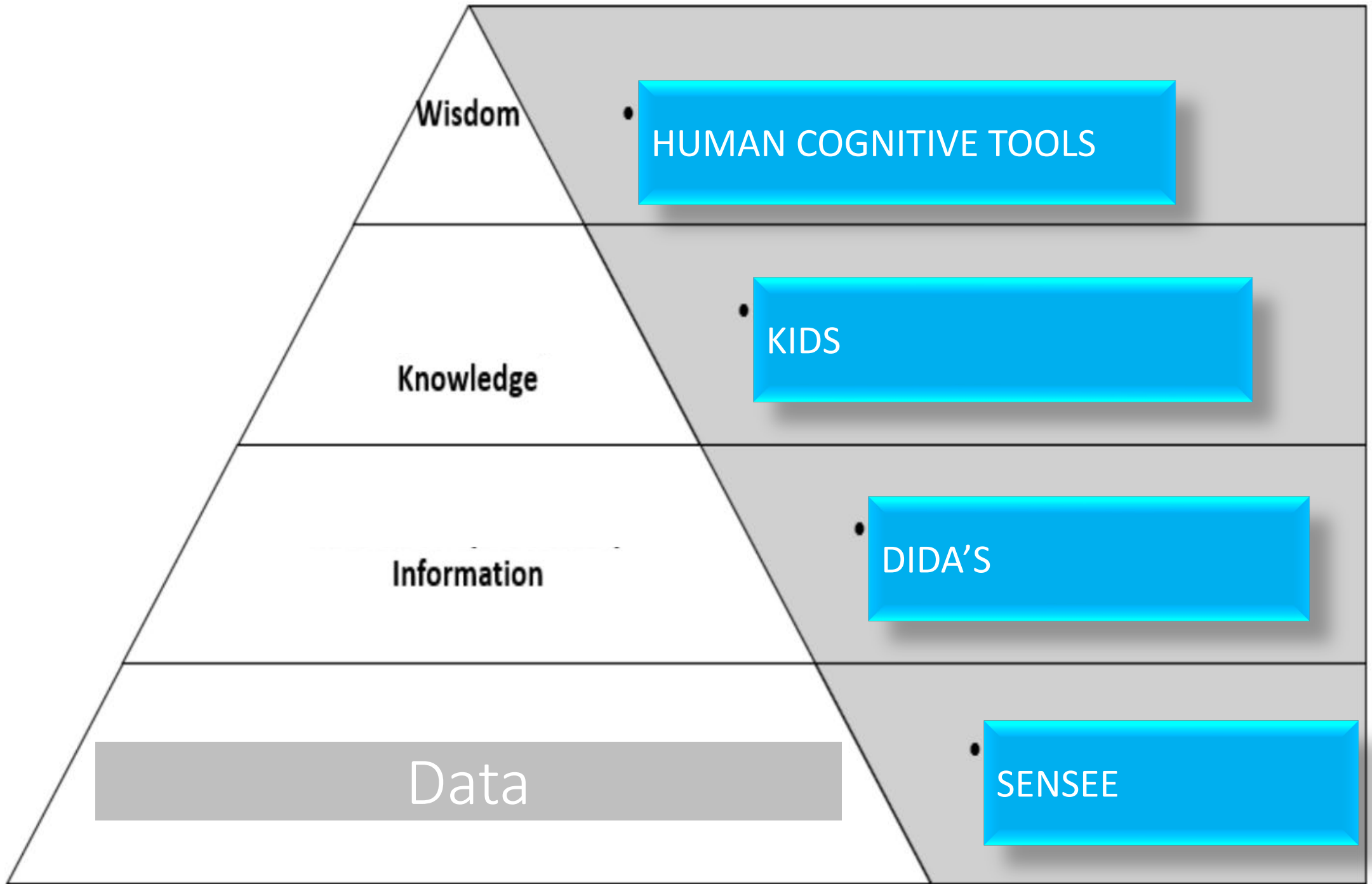
Data

SENSEE

SYNERGISTIC INTEGRATION



PEAS PLATFORM



Digital Transformation

is about the life cycle of data as it transforms to information and contributes to better decisions

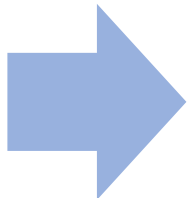
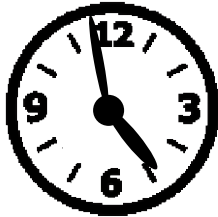
Are we immersed in **data** swamps?
Actions depend on **information**.
Informed by **knowledge**.
Learn from **experience**.

Unbeknownst to us, we are in a perpetual quest for knowledge. Every day, in every action, we undertake the journey from data and information to knowledge. In the process we are learning, in each step, from our experiences, no matter how small and agnostic of the scenarios (social actions, academic activities, business pursuits, ideas and opinions).

Convergence

every step of the journey

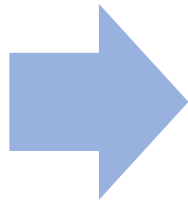
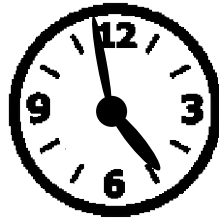
Social Domain



Situation

Time constraint

Social Domain



Situation

Time constraint

Engineering Domain

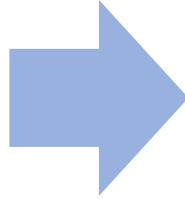
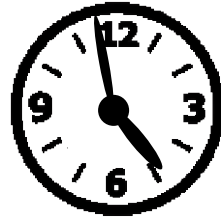


Sensor reading



Local knowledge

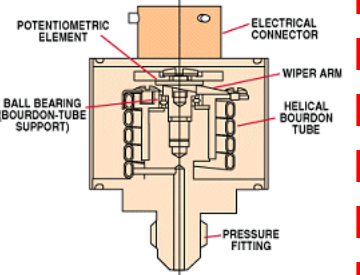
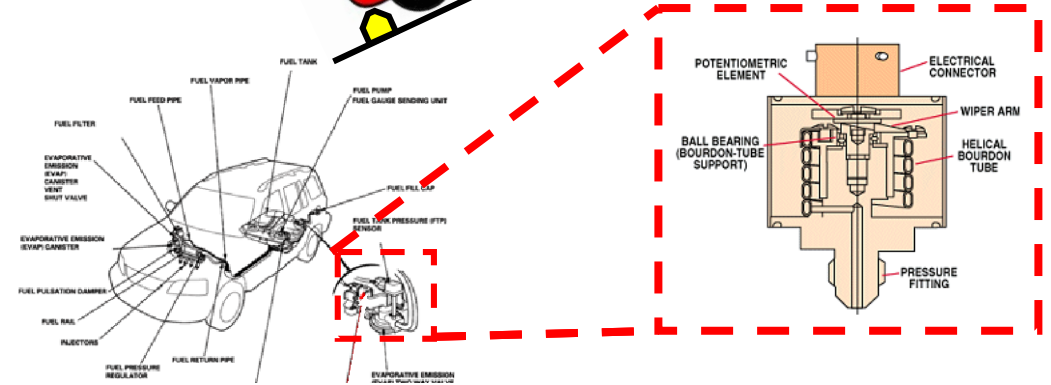
Social Domain



Situation

Time constraint

Information domain



Engineering Domain

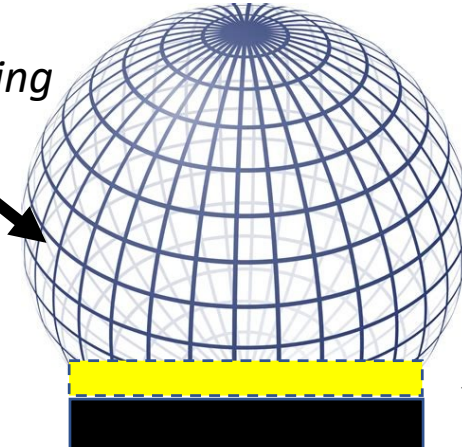


Sensor reading

Local knowledge

Scientific domain

Functional working space



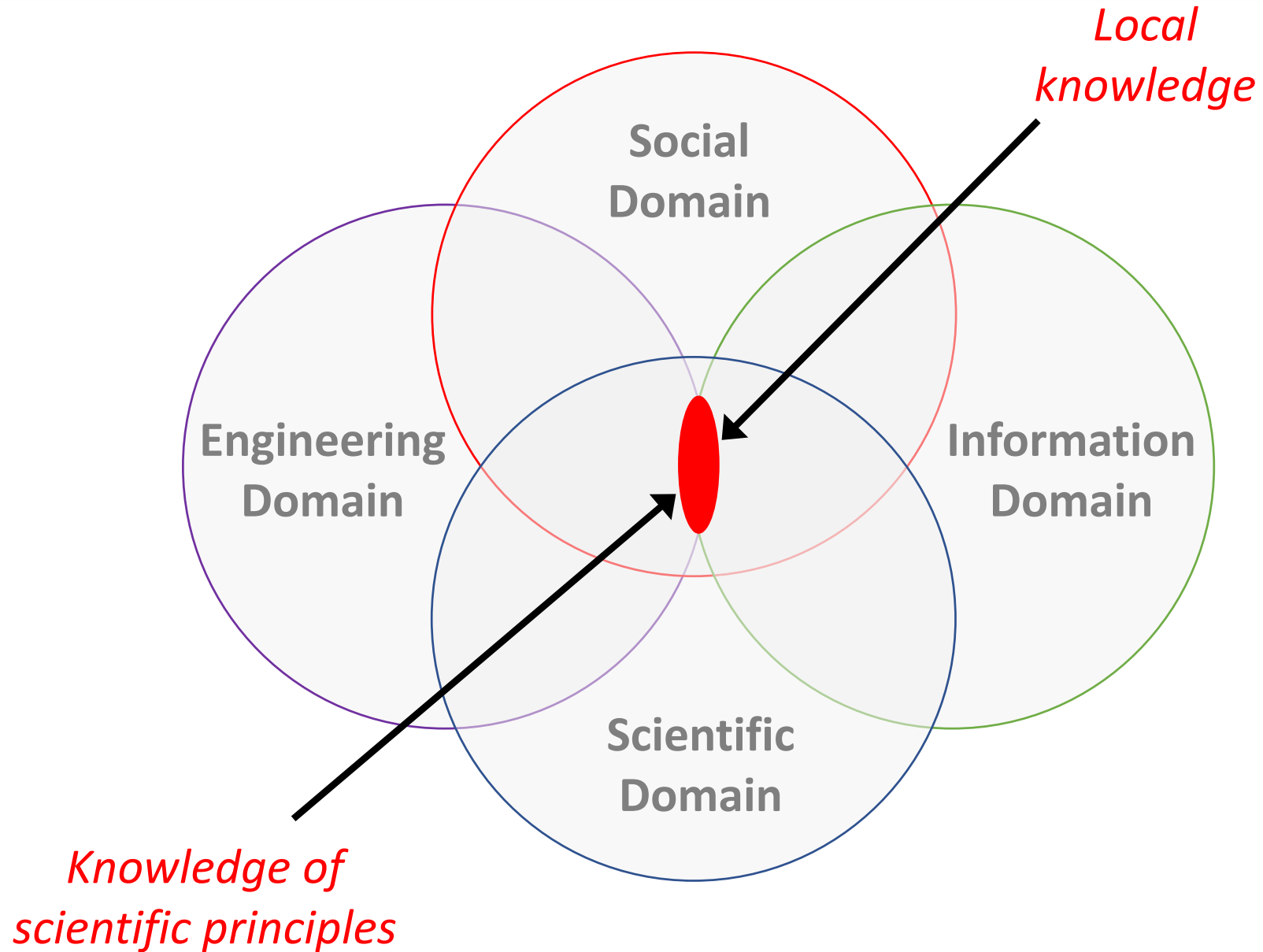
Knowledge of scientific principles

Sensor surface

$$\frac{\partial C}{\partial t} = \chi \frac{\partial^2 C}{\partial x^2}$$

$$Z = \frac{E(t)}{I(t)} = Z_o (\cos \psi + j \sin \psi)$$

Convergence



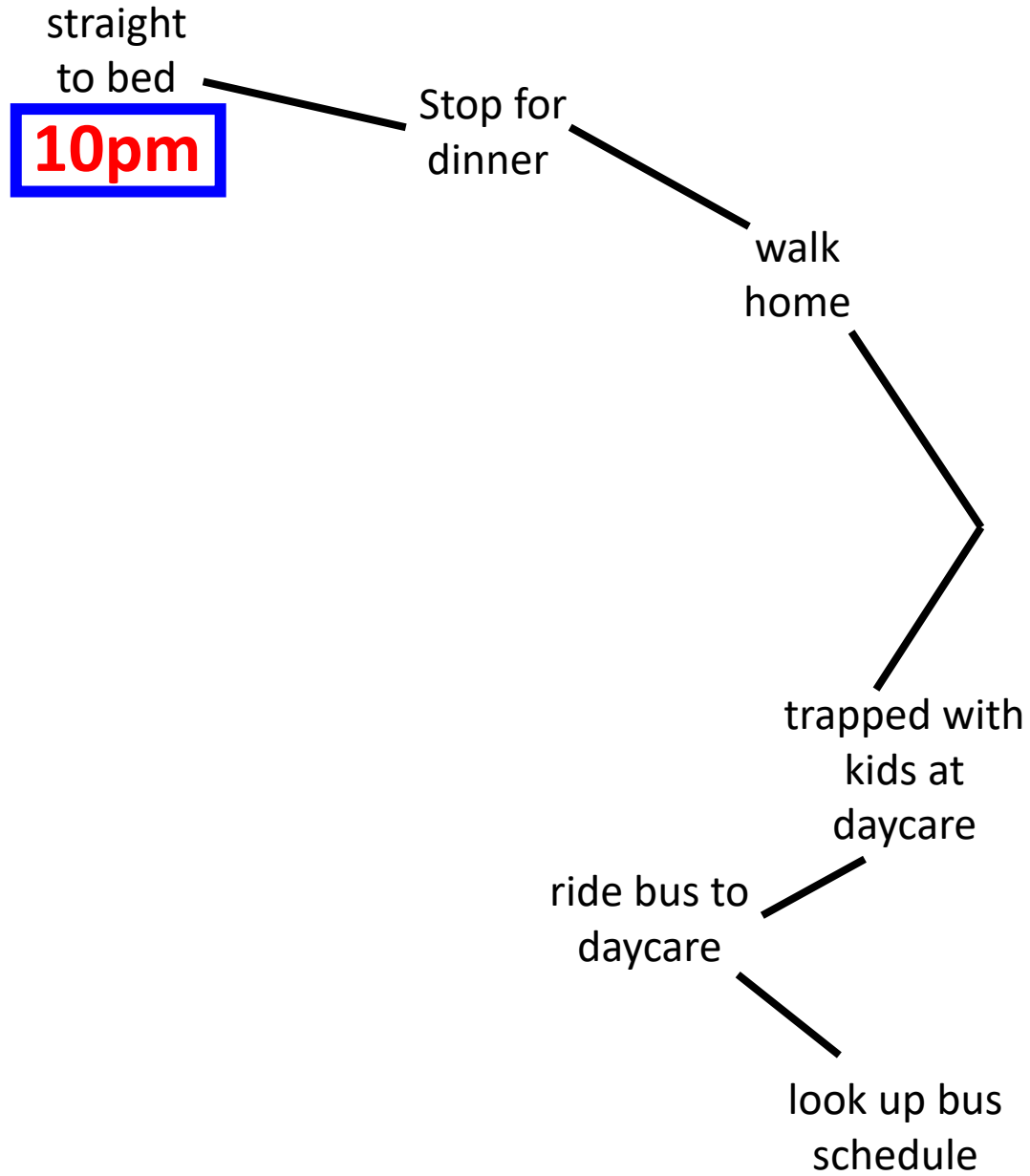
For humans, it is child's play

For systems, it's still a difficult task to select what is relevant, relative to the context, and connect (**R2C2**), distributed data, to extract information, to aid decisions or execute action for the situation, based on actionable knowledge.

Child Happiness Scale

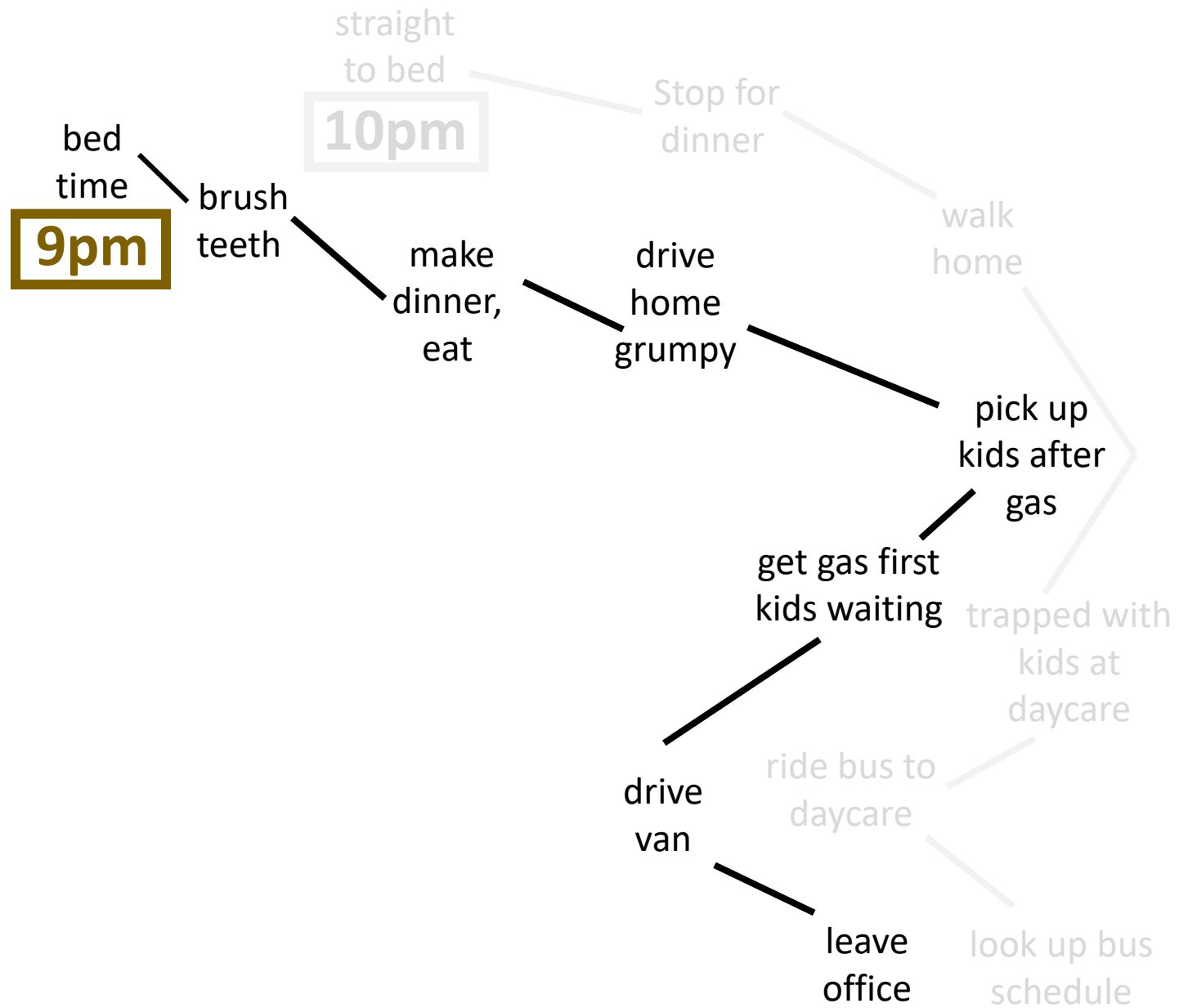


Time



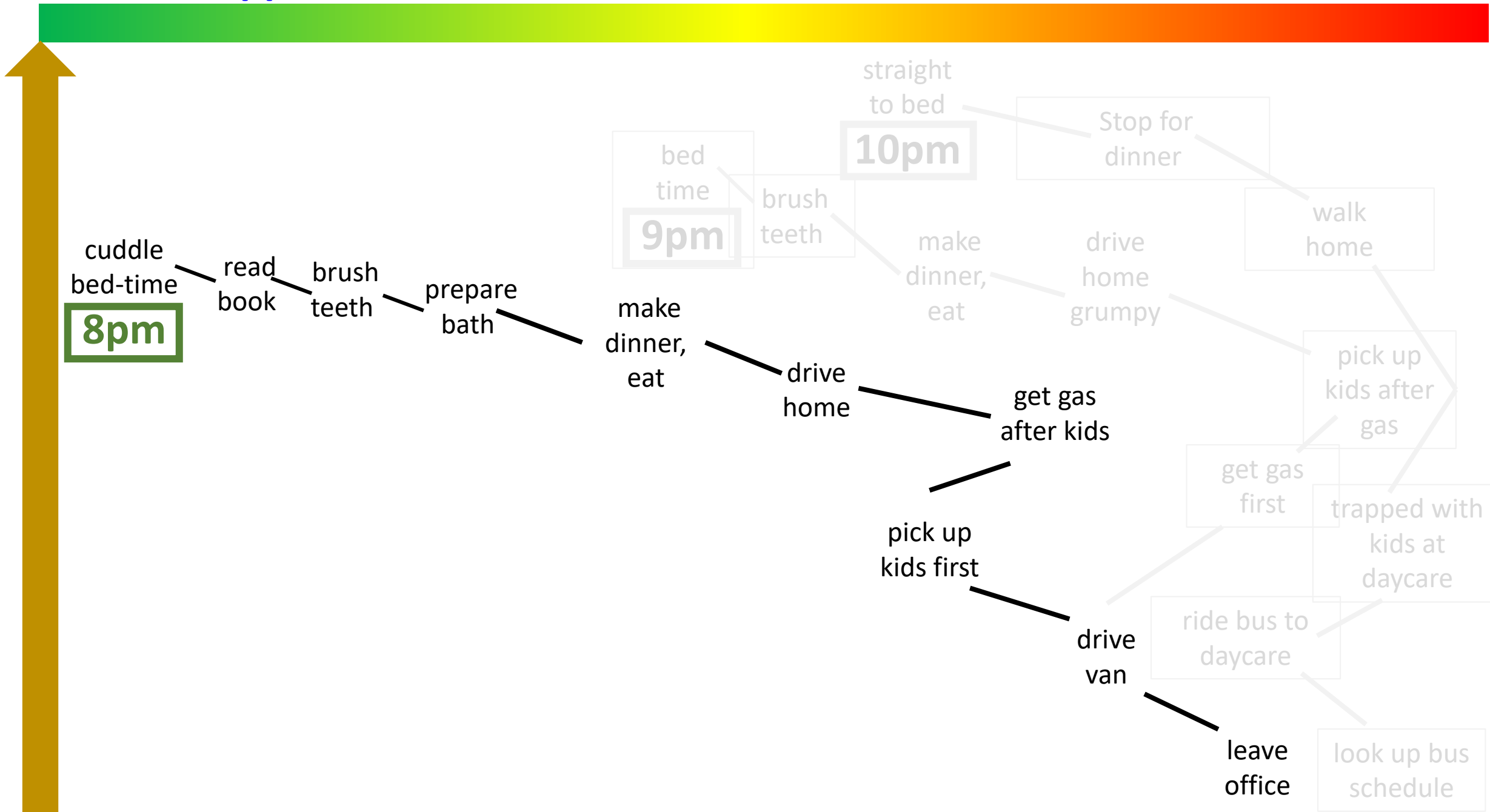
Child Happiness Scale

Time



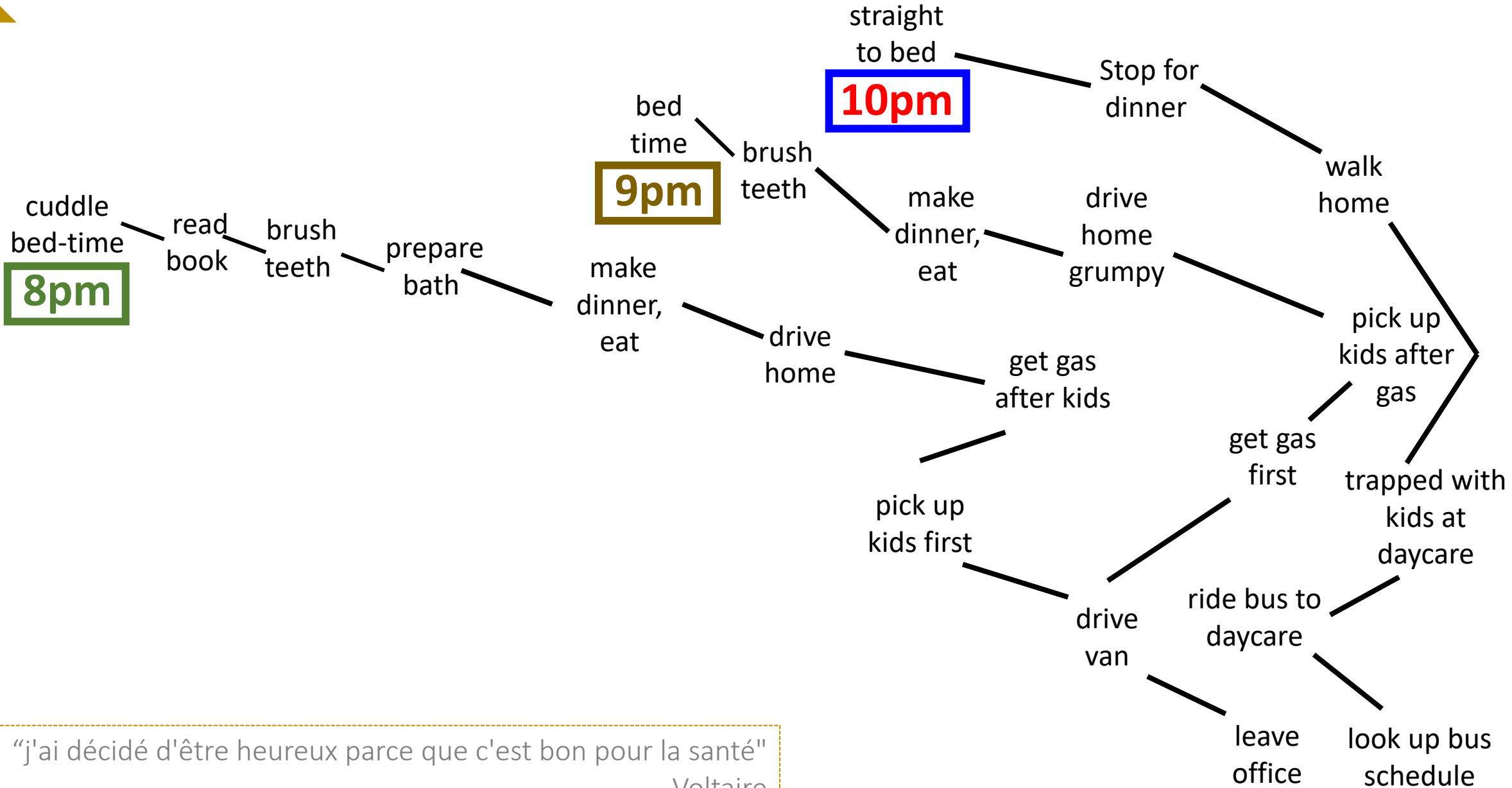
Child Happiness Scale

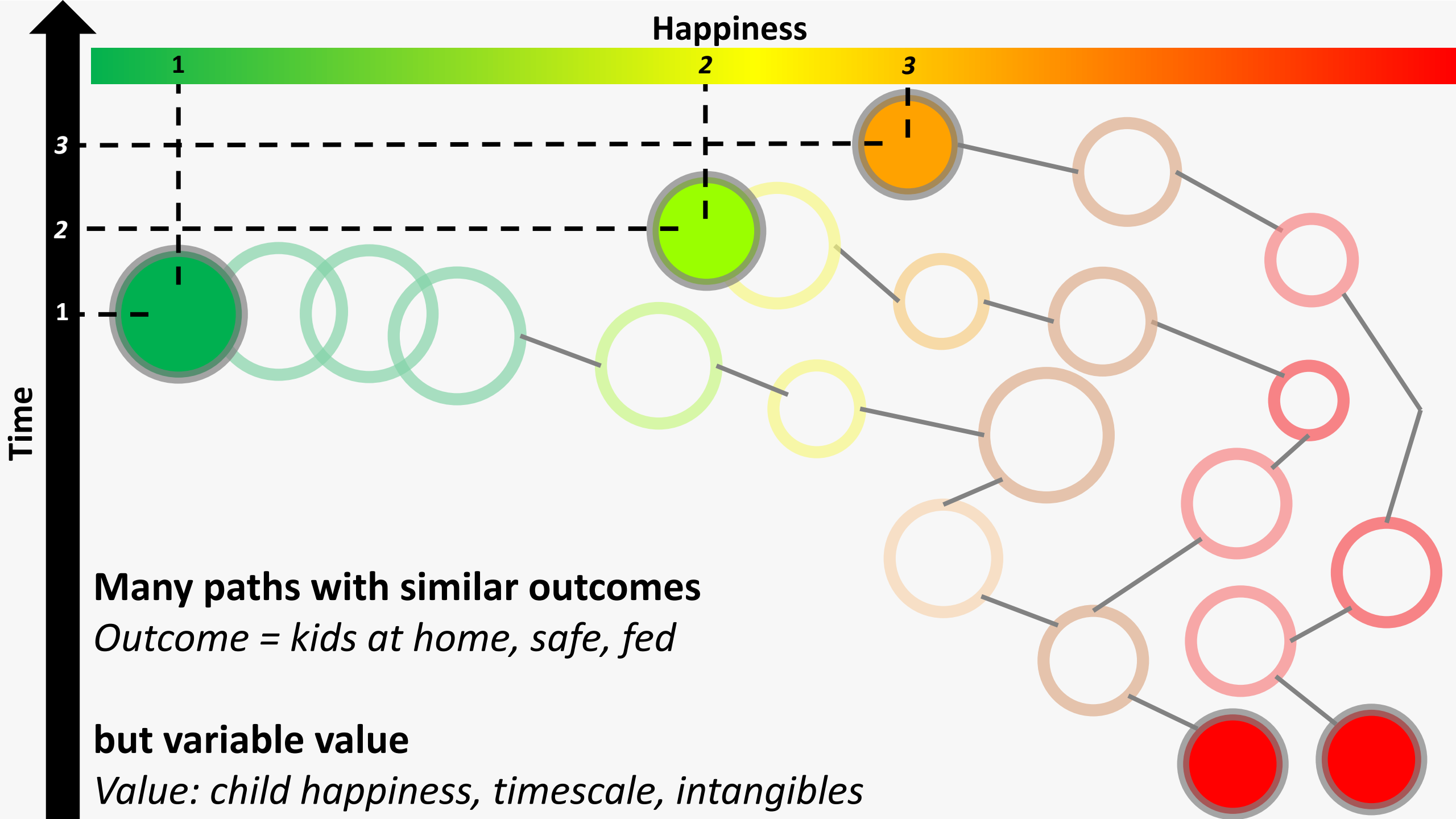
Time

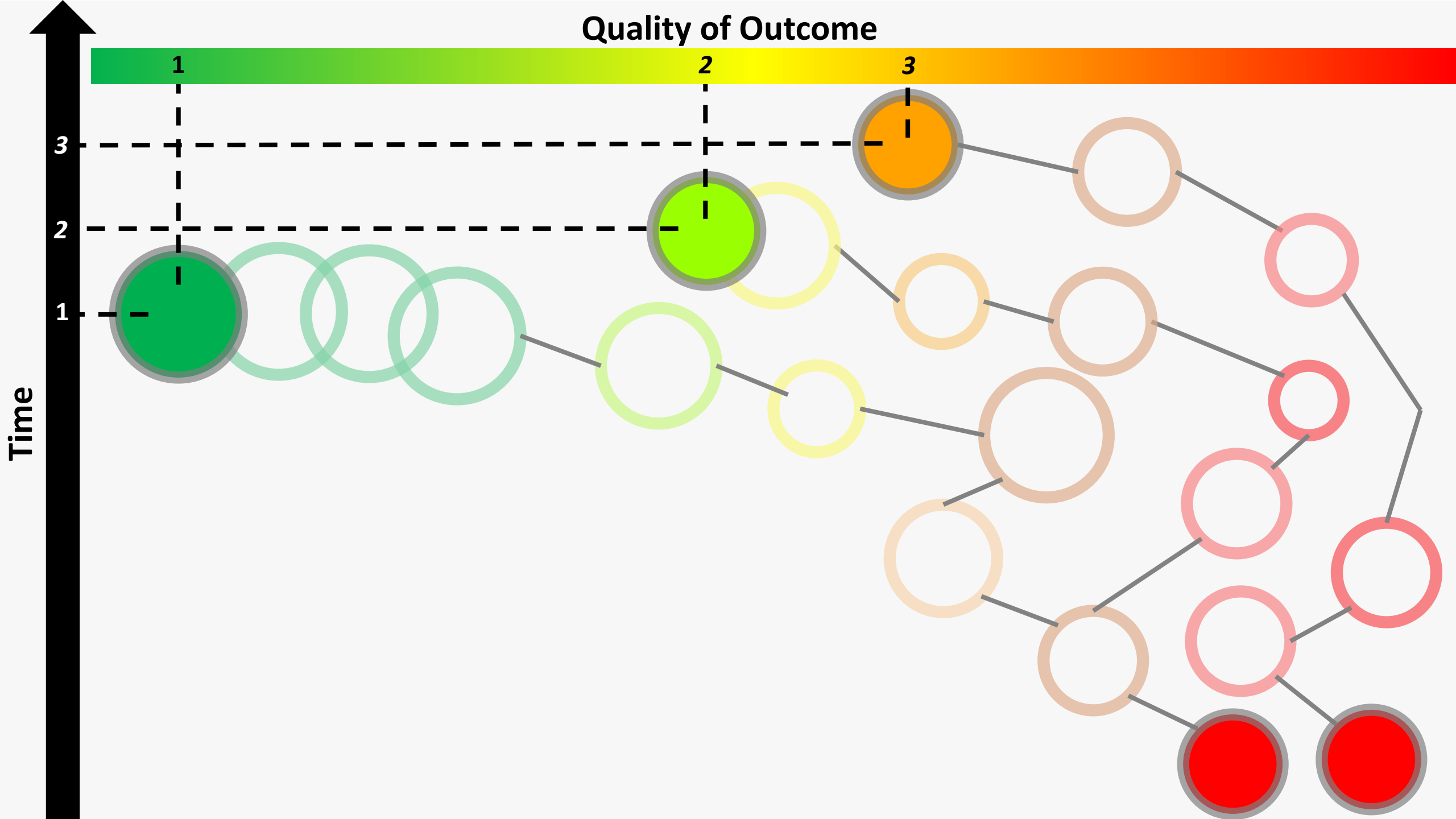


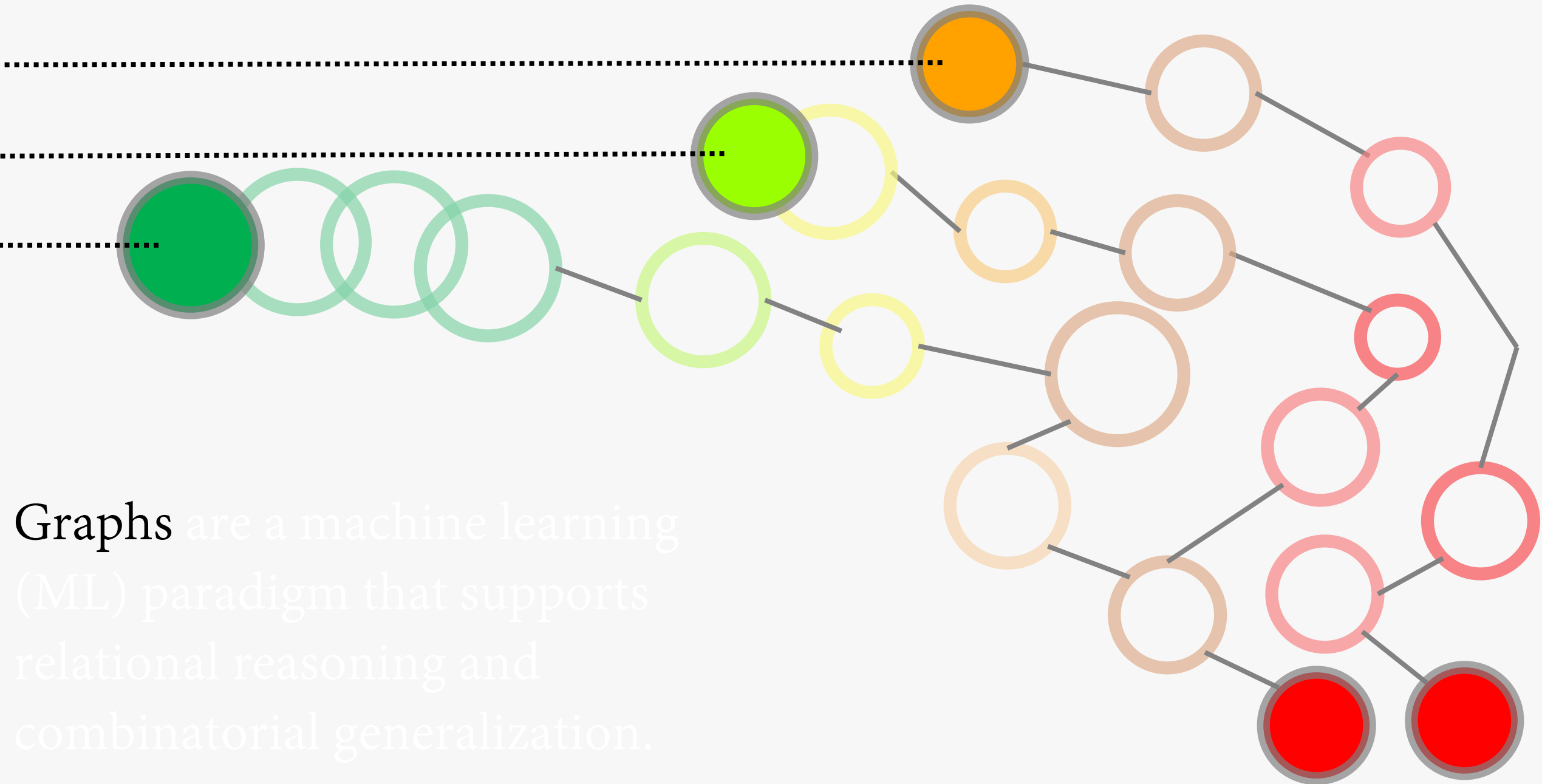
Child Happiness Scale (clap along if you feel like happiness is the truth)

Time



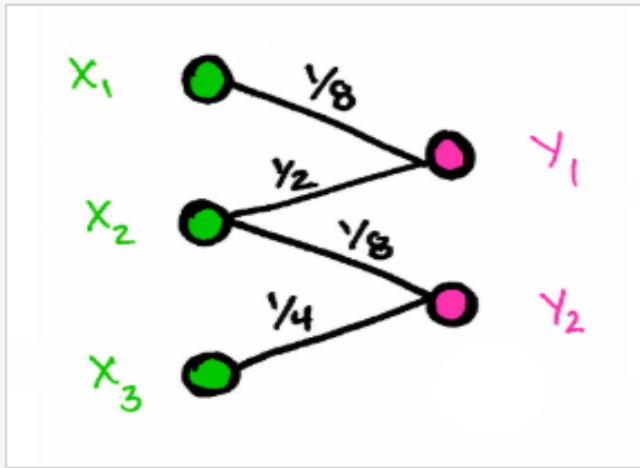
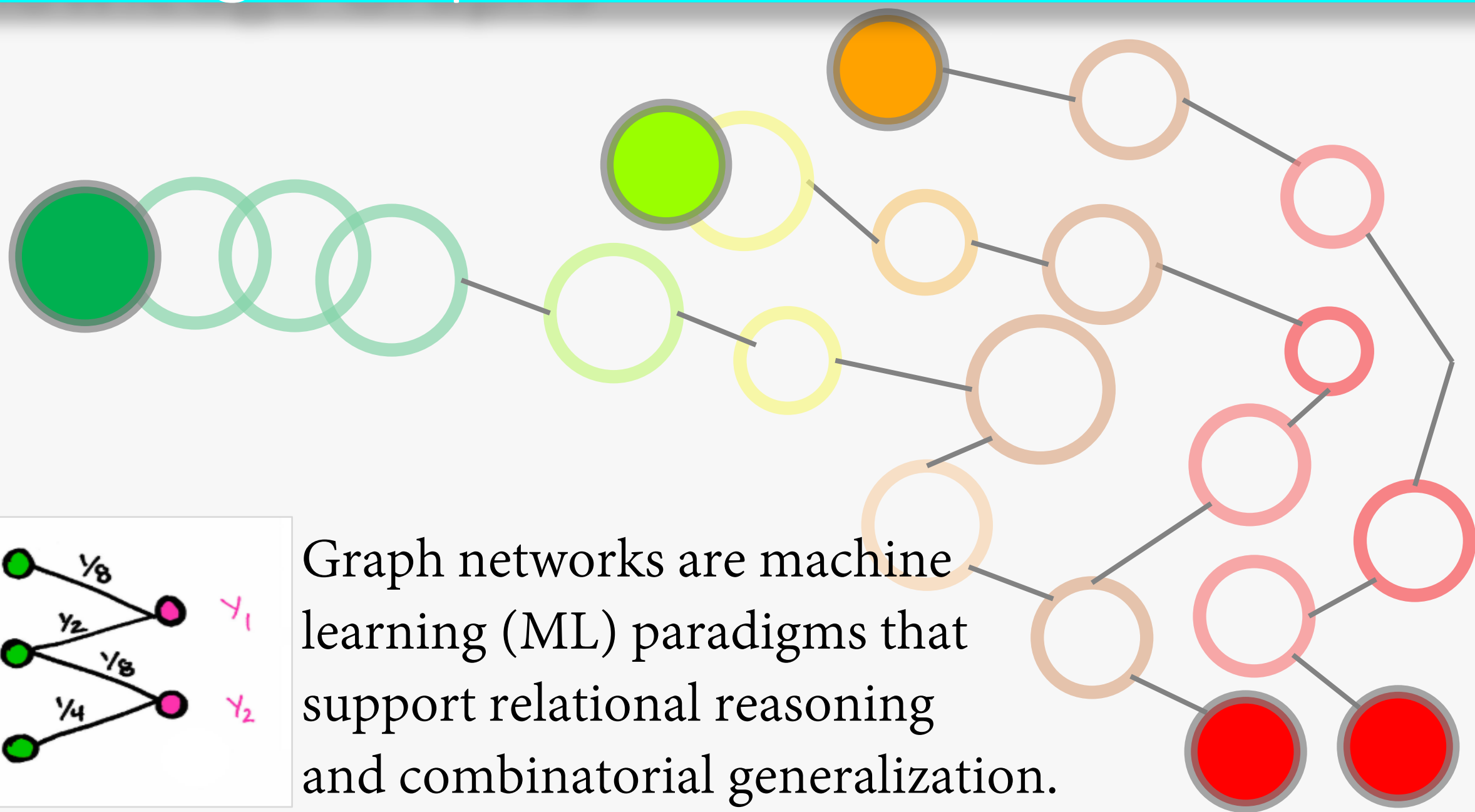






Graphs are a machine learning (ML) paradigm that supports relational reasoning and combinatorial generalization.

Knowledge Graphs



Graph networks are machine learning (ML) paradigms that support relational reasoning and combinatorial generalization.

BOOK - <http://bit.ly/Knowledge-Representation>

<http://www.mkbergman.com/2244/a-common-sense-view-of-knowledge-graphs/>

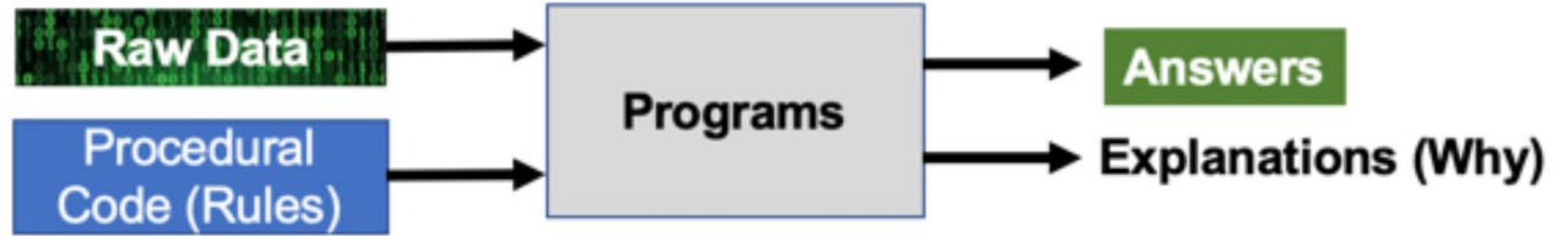


<https://www.springer.com/gp/book/9783319980911>

http://www.mkbergman.com/wp-content/themes/ai3v2/images/2012Posts/ontology_build.gif

Knowledge Graphs: The core of the 3rd era of computing

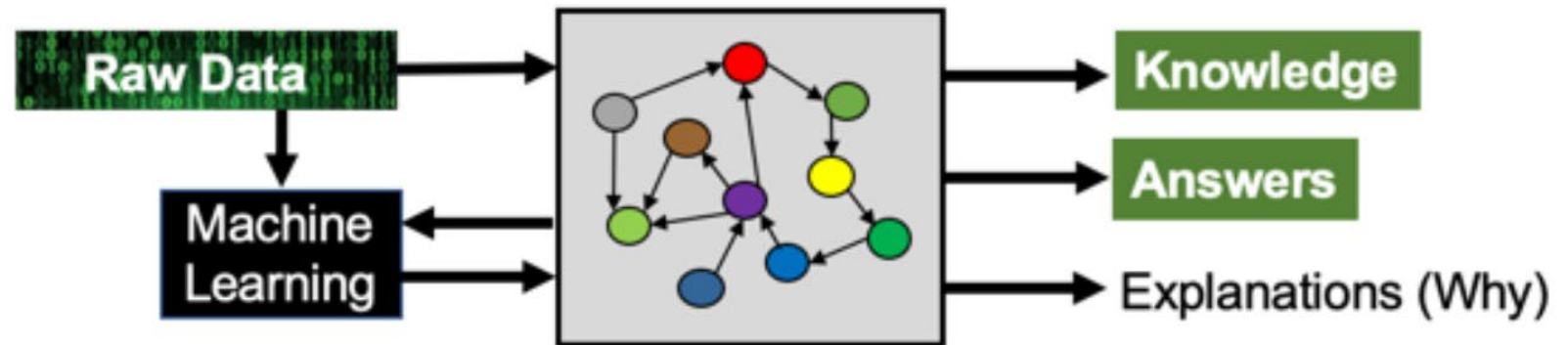
The Procedural Era



The Machine Learning Era



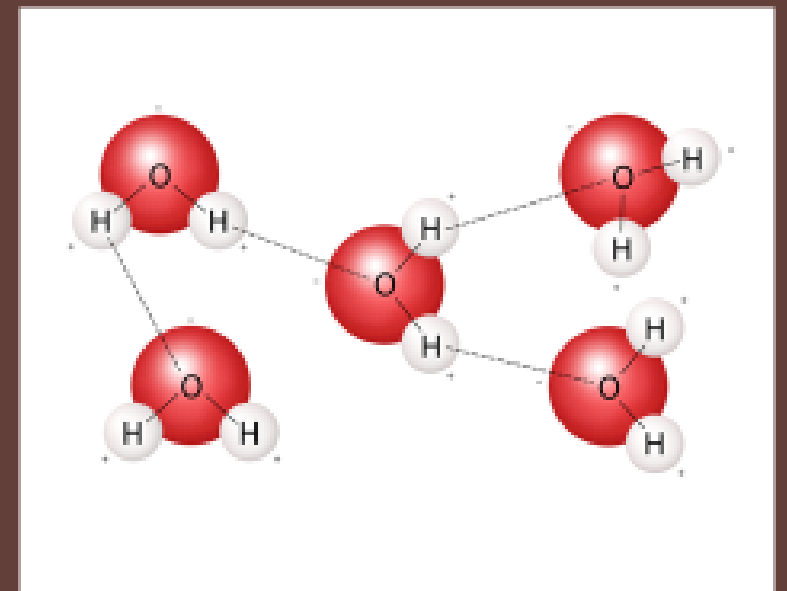
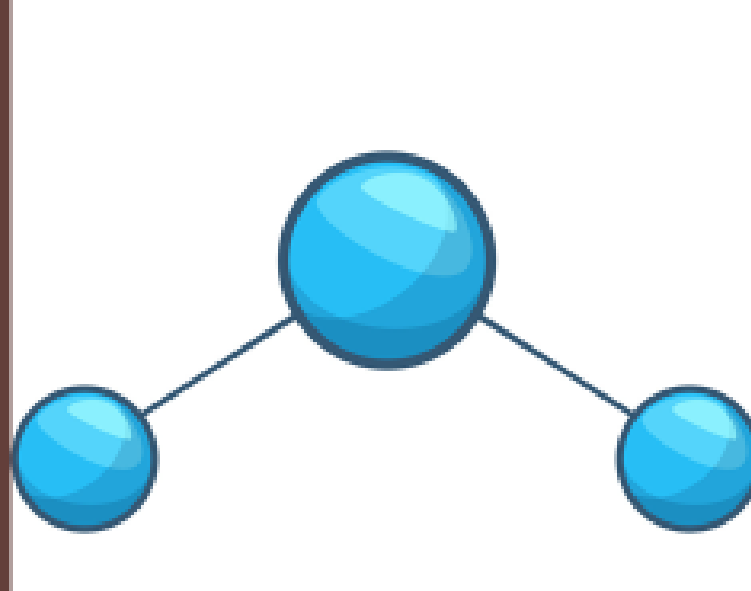
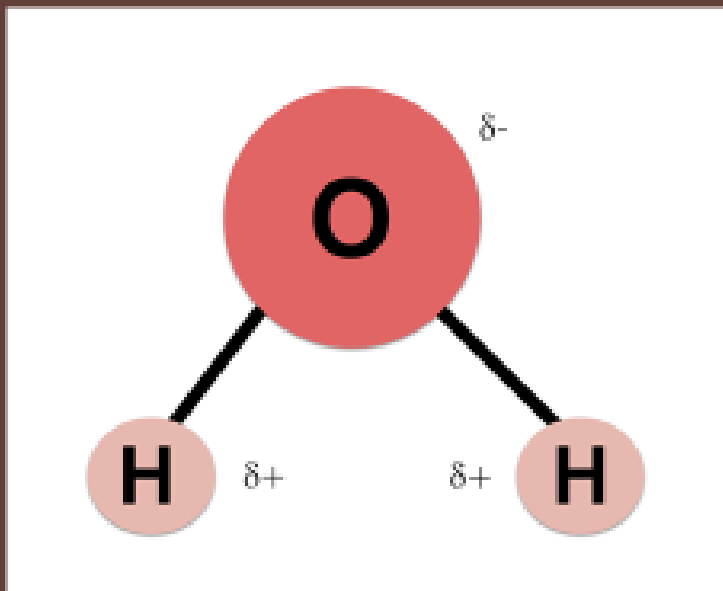
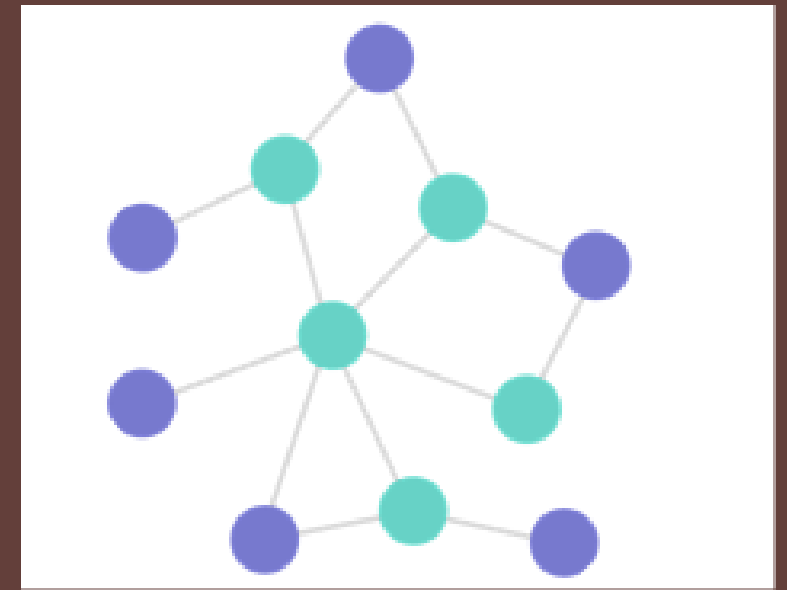
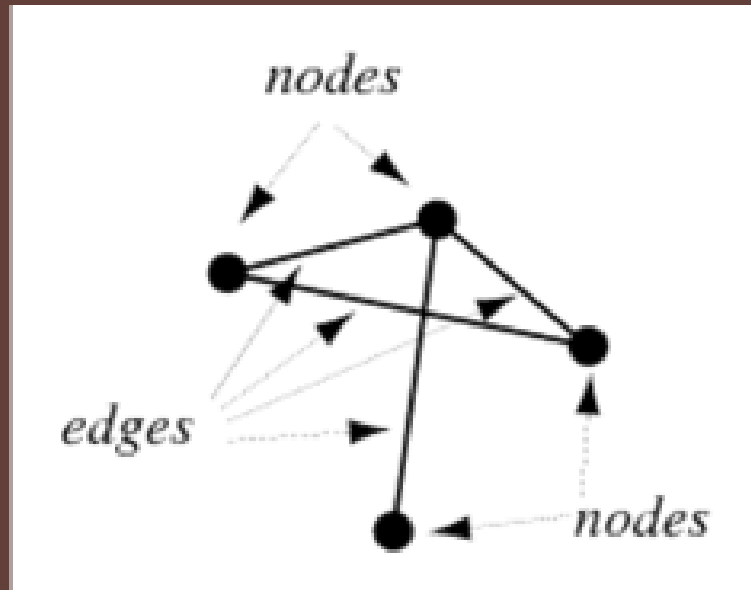
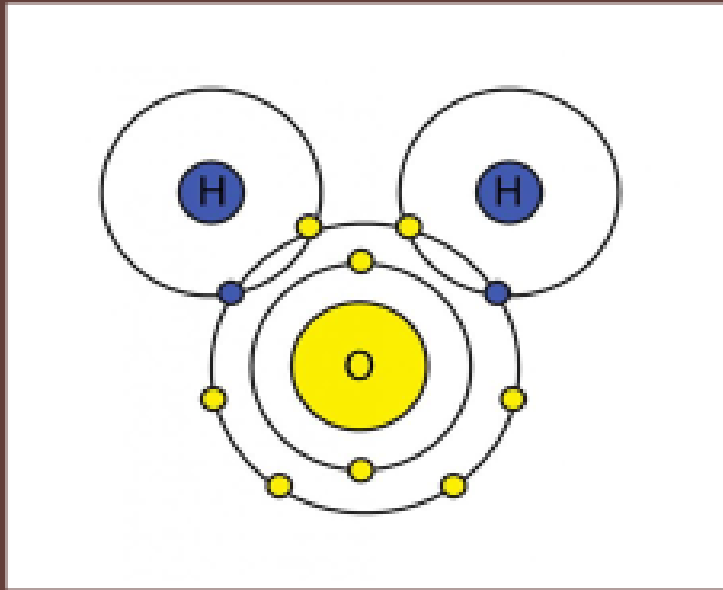
The Knowledge Graph Era



@dmccreary

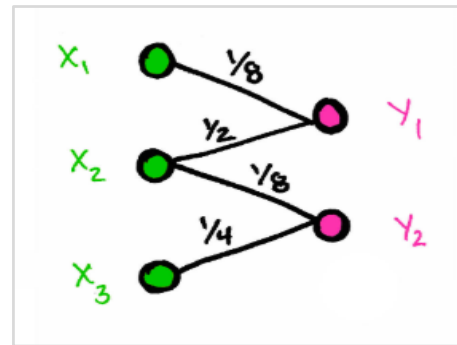
Use machine learning to continuously enrich knowledge

Knowledge Graphs: Chemistry of computing with molecules

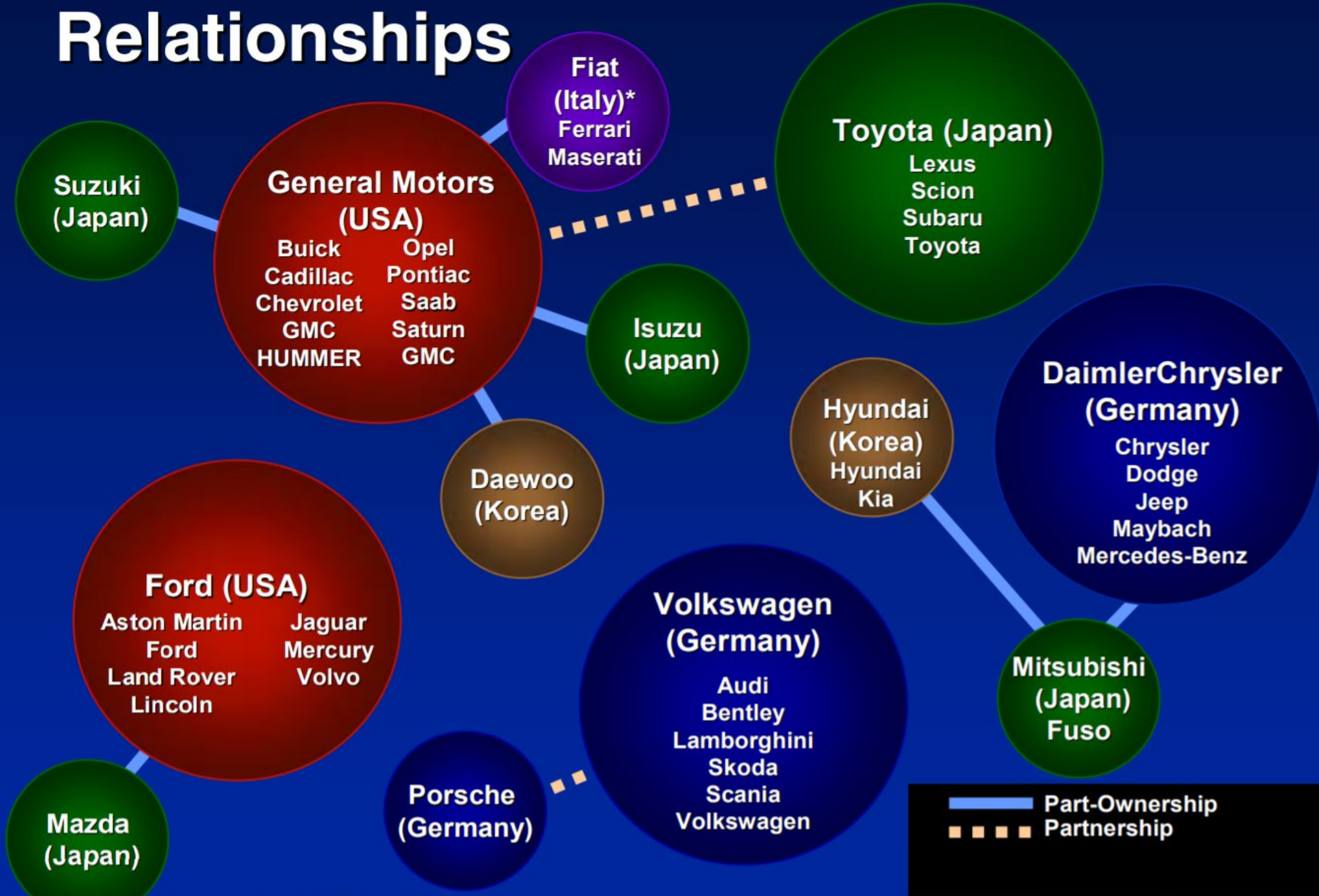


RELATIONSHIPS

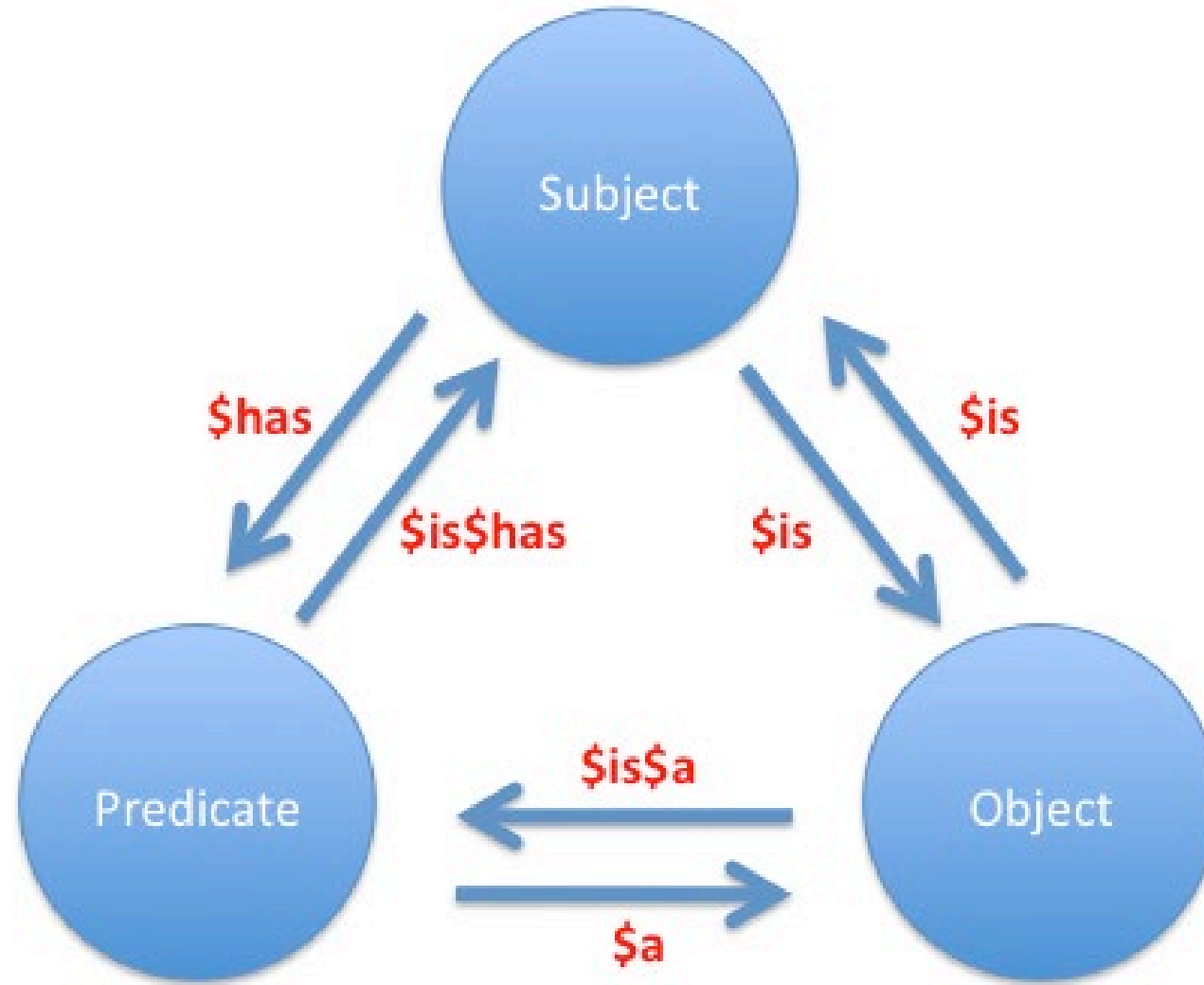
between entities are critical in the context of making decisions. Data available to the human mind (or the system) in the context of entities or objects or processes, under consideration, are used directly (as data) or converted to information (by humans) to fuel decisions (outcomes). Knowledge graphs are a form of **bio-mimicry** tool, to enable non-human computer systems to understand relationships between entities, objects, processes, people, and things (think IoT, internet of things). Resource Description Framework (**RDF**) is a standard to describe resources and is based on principles of linguistics (noun, verb, subject, predicate).



Relationships



RDF expresses RELATIONSHIPS as “triples” which are based on principles of linguistics (noun, verb, subject, predicate).

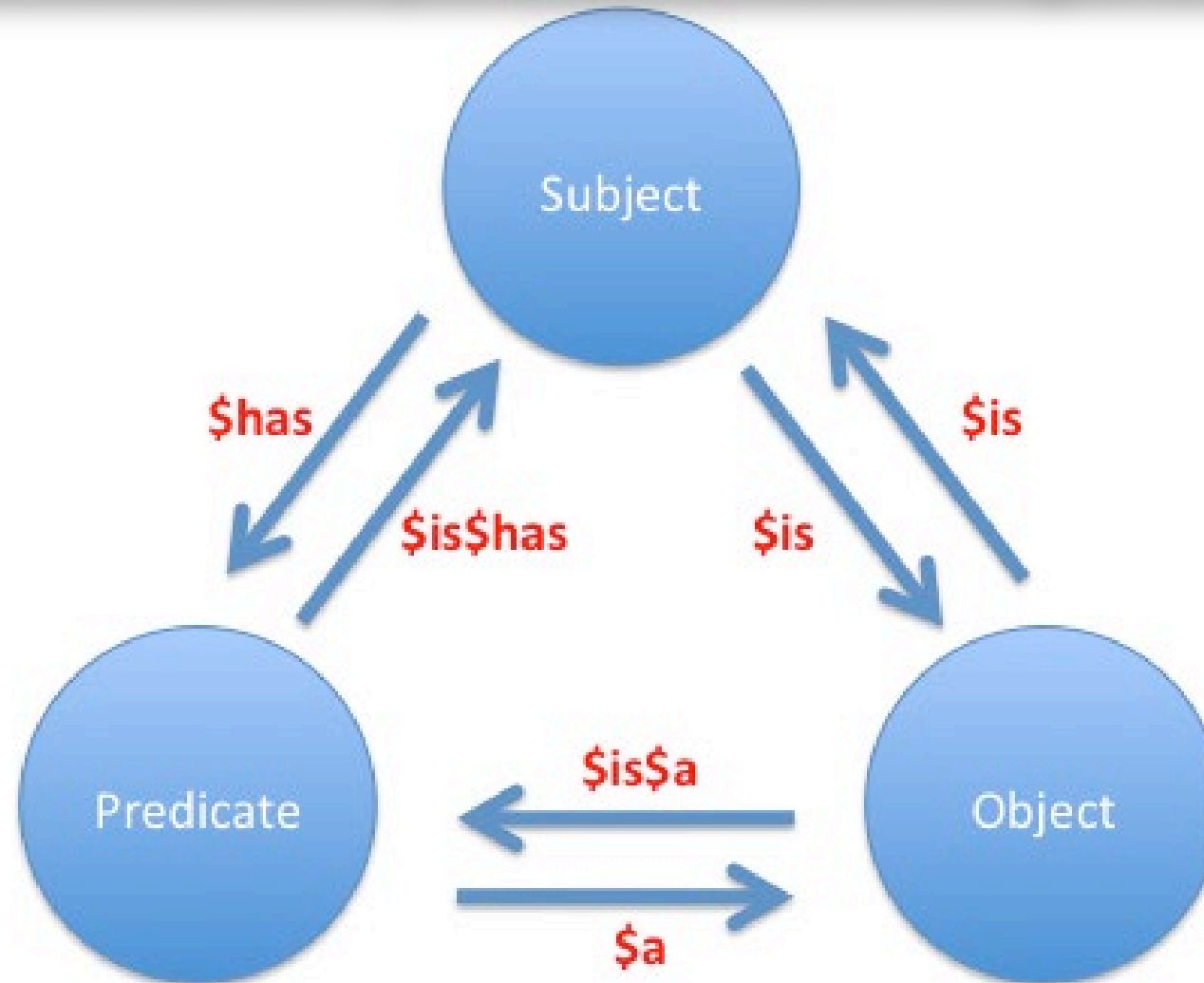


Drummond Reed

Resource Description Framework (RDF) is a standard to describe resources. It is written in XML and machine-readable.

Linguistics, Relationships and Knowledge Graph Networks

In the "Golden Triangle" of metagraph relationships: $\$has\a (which is literally $\$has/\$has/\$a$) defines a subset of $\$has$ relationships in which the predicate is also an object. Asserting a predicate **as an object** is different than asserting it **as a predicate**. Neither implies that the other exists. They have a logical relationship, it is the same predicate involved in both cases, but asserting it as a predicate does not mean it is also an object, and asserting is as an object does not need it to be also a predicate.



$\$$ is a subsegment delimiter (Global Context Symbols)
<https://wiki.oasis-open.org/xri/XriThree/GcsDelimiter>

Are computational standards, syntax semantics and ontologies influenced by linguistic bias?

Subject	Predicate	
	linking verb	subject complement noun or adjective
The aliens	were	killers.
The rats	are	ugly.
The griff	is	grafunkulous.

- The predicate is the action
- Action verbs are easy to identify, but remember **verbs of being**: am, is, are, were, was
- A sentence *can* have more than one predicate

Subject and Predicate



What is a Subject?

- *A subject is the person or thing that is doing an action, or the person or thing that is the focus of the sentence*

What is a Predicate?

- *The predicate of the sentence is the part that contains the action.*

What happens when the RDF ontology creator speaks a language where the rules of English grammar are not applicable?



At the heart of the predicate is a **verb**. In addition to the verb, a predicate can contain **direct objects, indirect objects, and various kinds of phrases**.

A sentence has two parts: the subject and the predicate. The subject is what the sentence is about, and the predicate is a comment about the subject.

www.grammar-monster.com/glossary/predicate.htm

Examples of Predicates of Sentences

Here are some examples of predicates. In each example, the predicate of the sentence is shaded and the verb in the predicate is in bold.

- Elvis **lives**.
- Adam **lives** in Bangor.
- The telegram **contained** exciting news.
- The girls in our office **are** experienced instructors.
- They **are** experienced instructors, who acquired their experience in France.

Predicates in Clauses

A **clause** contains a subject and predicate too. The examples below are all clauses not sentences. The predicate is shaded and the verb of the clause is in bold.

- who **lives** with her mother
(The subject is the **relative pronoun** *who*.)
- which **was** somewhat unexpected
(The subject is the **relative pronoun** *which*.)
- that **points** to the North Pole
(The subject is the **relative pronoun** *that*.)

www.grammar-monster.com/glossary/predicate.htm

Why RDF may be just a part of the solution: Is linguistic bias embedded in the grammatical context of RDF triples?

https://lists.w3.org/Archives/Public/www-archive/2005Feb/att-0050/eswc-i18n.pdf

Semantic Standards in other languages?

概念词关联导航

基本属性 全选

Current Class 中成药 清除查询条件

1

序号	属性名称	选择当前列	查询条件	查询内容
1	OTC分类	<input checked="" type="checkbox"/>	包含	
2	中药保护品种	<input checked="" type="checkbox"/>	包含	2
3	临床应用	<input checked="" type="checkbox"/>	包含	
4	主治症	<input checked="" type="checkbox"/>	包含	心脏病
5	别名	<input checked="" type="checkbox"/>	包含	
6	制备方法	<input type="checkbox"/>		
7	剂型	<input type="checkbox"/>		
8	功效	<input type="checkbox"/>		
9	包装规格	<input type="checkbox"/>		

Properties

3

OTC分类
 中药保护品种
 临床应用
 主治症
 包含 心脏病
 别名

提交查询

序号	属性名称	选择当前列	查询条件	查询内容
1	原发病	<input type="checkbox"/>	包含	
2	并发症	<input type="checkbox"/>	包含	
3	疾病名称	<input type="checkbox"/>	包含	
4	疾病症状	<input type="checkbox"/>	包含	5
5	病症候类型	<input type="checkbox"/>	包含	

提交查询 **添加条件**

4

相关概念属性

序号	概念名称	查看概念属性
1	药品销售状况	→
2	疾病	→
3	药物成分	→

Related Classes

Figure 4
DartSearch. The default user interface for DartSearch.

Knowledge Graphs relevant to SENSEE, ART, & DIDA'S KIDS

When data is mapped against an OWL/RDF ontology, instances of the data are expressed based upon the idea of making statements about resources in the form of **subject–predicate–object** expressions. These expressions are known as *triples* in RDF terminology. The ‘Subject’ denotes the object, and the predicate denotes a single semantic trait or aspect of the object that can be a literal value or expressed as a relationship between the subject and another object that is the target of the relationship. For example, the notion “The soil has a pH of 8” in RDF triple is **subject** denoting “soil” and **predicate** denoting “pH” and an **object** denoting “8” which is the OWL/RDF take on using the object as the subject from the classical entity–attribute–value model within object-oriented design: object (soil), attribute (pH) and value (8). The object (soil) can also have another attribute (contains) that can point to another object (phosphate). The object (phosphate) might have an attribute (produces) another object (acidity). Yet again, the object (soil) might have an attribute (contains) another object (microbes). This is one reason why RDF triples, despite their shortcomings and potential for linguistic bias, enables the formation, to link a series of relationships, between two or more objects. The latter is the foundation on which directed graphs can be built. Hence, knowledge graphs.

Subject – predicate – direct object.

Ex: Mateo quiere comprar un bate nuevo.

subject

predicate
with two
verbs

direct object phrase.

Ontology Languages

https://www.slideshare.net/don_willems/what-are-ontologies

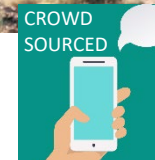
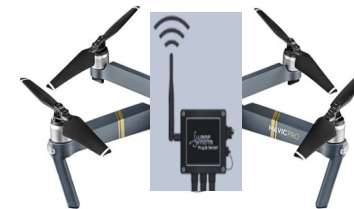
SUBJECT	PREDICATE	OBJECT
Elstar	sub class of	Apple
Elstar	label	“Elstar”
Apple	label	“Apple”
Apple	total production	69,569,612

Which / what nodes are the graphs connecting?

Which / what nodes are the graphs connecting?



Nodes connected by graphs



PORTABLE SPEC

Must be connected to a mobile device?



<https://www.aac.or.at/smart-farming>

<https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/>

http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Connected KIDS



<https://www.aac.or.at/smart-farming>

<https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/>

http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Connect KIDS PEAS to other ecosystems



Web of Knowledge Graph Networks are necessary for ART, DIDA'S, KIDS

Chromosomes of Knowledge



<https://www.aac.or.at/smart-farming>

<https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/>

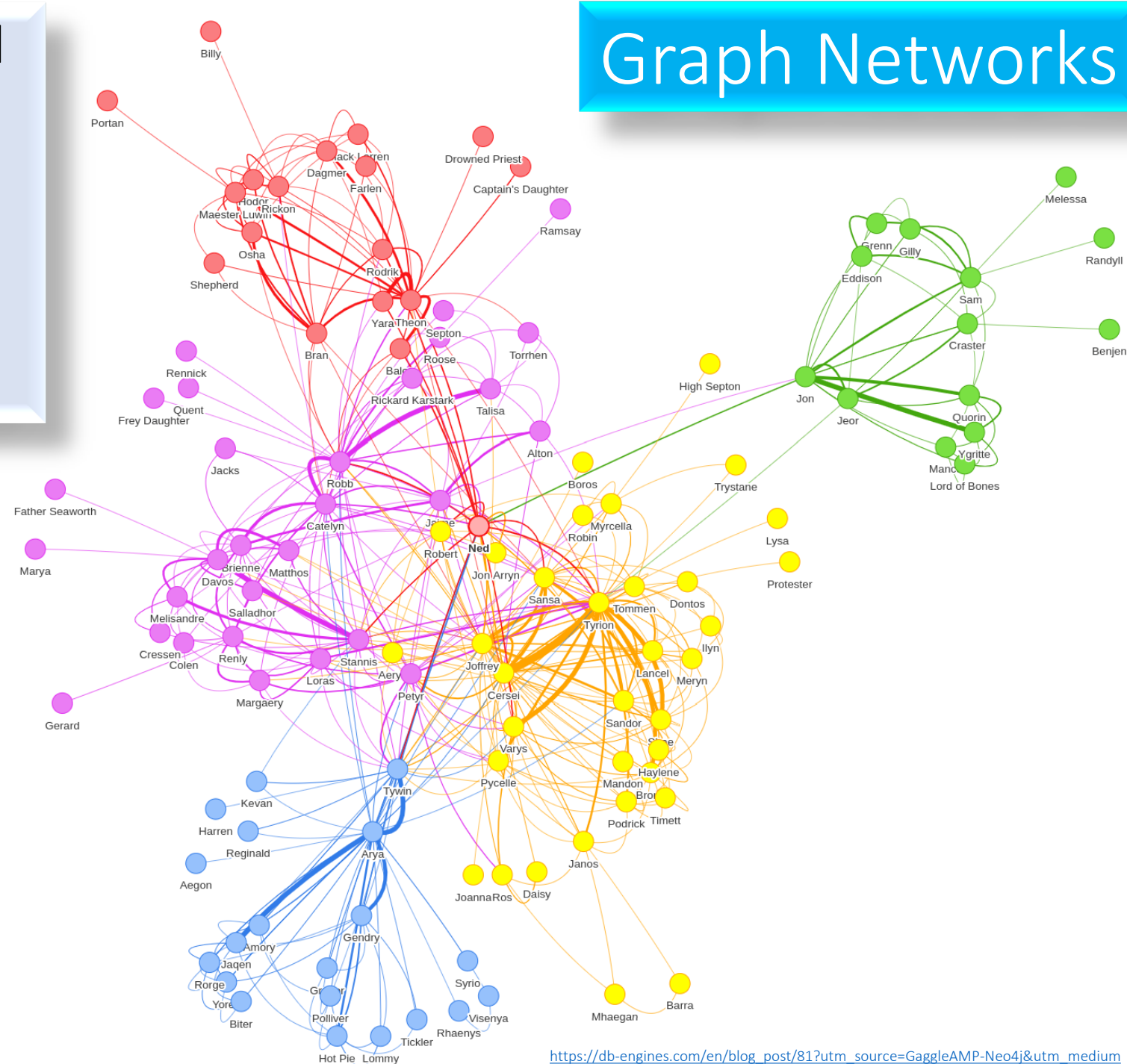
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Graph Networks

Increased adoption of tools based on graph theory. HTAP integrates graph transactions (OLTP) and analytic processing (OLAP) using graph databases and graph algorithms (relationships are key).

Graph algorithms provide one of the most potent approaches to analyzing connected data because their mathematical calculations are specifically built to operate on relationships. There are many types of graph algorithms and categories. The three classic categories consider the overall nature of the graph: pathfinding, centrality, and community detection. However, other graph algorithms such as similarity and link prediction algorithms consider and compare specific nodes.

- Pathfinding (and search) algorithms are fundamental to graph analytics and algorithms and explore routes between nodes. These algorithms are used to identify optimal routes for uses such as logistics planning, least cost routing, and gaming simulation.
- Centrality algorithms help us understand the roles and impact of individual nodes in a graph. They're useful because they identify the most important nodes and help us understand group dynamics such as credibility, accessibility, the speed at which things spread, and bridges between groups.
- Community algorithms evaluate related sets of nodes, finding communities where members have more relationships within the group. Identifying these related sets reveals clusters of nodes, isolated groups, and network structure. This helps infer similar behavior or preferences of peer groups, estimate resiliency, find nested relationships, and prepare data for other analyses.
- Similarity algorithms look at how alike individual nodes are. By comparing the properties and attributes of nodes, we can identify the most similar entity and score differences. This helps build more personalized recommendations as well as develop ontologies and hierarchies.
- Link Prediction algorithms consider the proximity of nodes as well as structural elements, such as potential triangles between nodes, to estimate the likelihood of a new relationship forming or that undocumented connections exist. This class of algorithms has many applications from drug repurposing to criminal investigations.



Web of Knowledge Graph – Select List of References

[0] BOOK - <http://bit.ly/Knowledge-Representation>

[1] P. Bonatti, S. Decker, A. Polleres and V. Presutti. Knowledge Graphs: New Directions for Knowledge Representation on the Semantic Web, Dagstuhl Seminar 18371, 2019.

[2] E. Marchi and O. Miguel. On the Structure of the Teaching-learning Interactive Process, International Journal of Game Theory, 3 (2), 1974.

[3] R. Bakker. Knowledge Graphs: Representation and Structuring of Scientific Knowledge, Ph.D. Thesis, University of Twente, Enschede. 1987.

[4] L. Ehrlinger and W. Wöß. Towards a Definition of Knowledge Graphs. SEMANTiCS, 2016.

[5] A Common Sense View of Knowledge Graphs. July 2019. <http://www.mkbergman.com/2244/a-common-sense-view-of-knowledge-graphs/>

[6] P. Domingos. "A Few Useful Things to Know about Machine Learning." Communications of the ACM 55(10): 78 – 87, 2012

[7] A. Sheth, S. Parera, S. Wijaratne, K. Thirunarayan. "Knowledge will propel machine understanding of content: extrapolating from current examples." Proceedings of the International Conference on Web Intelligence. ACM, 2017.

[8] M. Noura, A. Gyrard, S. Heil, M. Gaedke. Automatic Knowledge Extraction to build Semantic Web of Things Applications. IEEE IoT Journal 2019

[9] S. Bhatt, S. Padhee, A. Sheth, K. Chen, V. Shalin, D. Doran, B. Minnery. "Knowledge Graph Enhanced Community Detection and Characterization." Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining. ACM, 2019.

[10] M. Nickel, K. Murphy, V. Tresp, and E. Gabrilovich. A review of relational ML for knowledge graphs. IEEE Proceedings 104(1), 11-33, 2015

[11] H. Paulheim. Knowledge graph refinement: A survey of approaches and evaluation methods. Semantic web, 8(3), pp.489-508, 2017

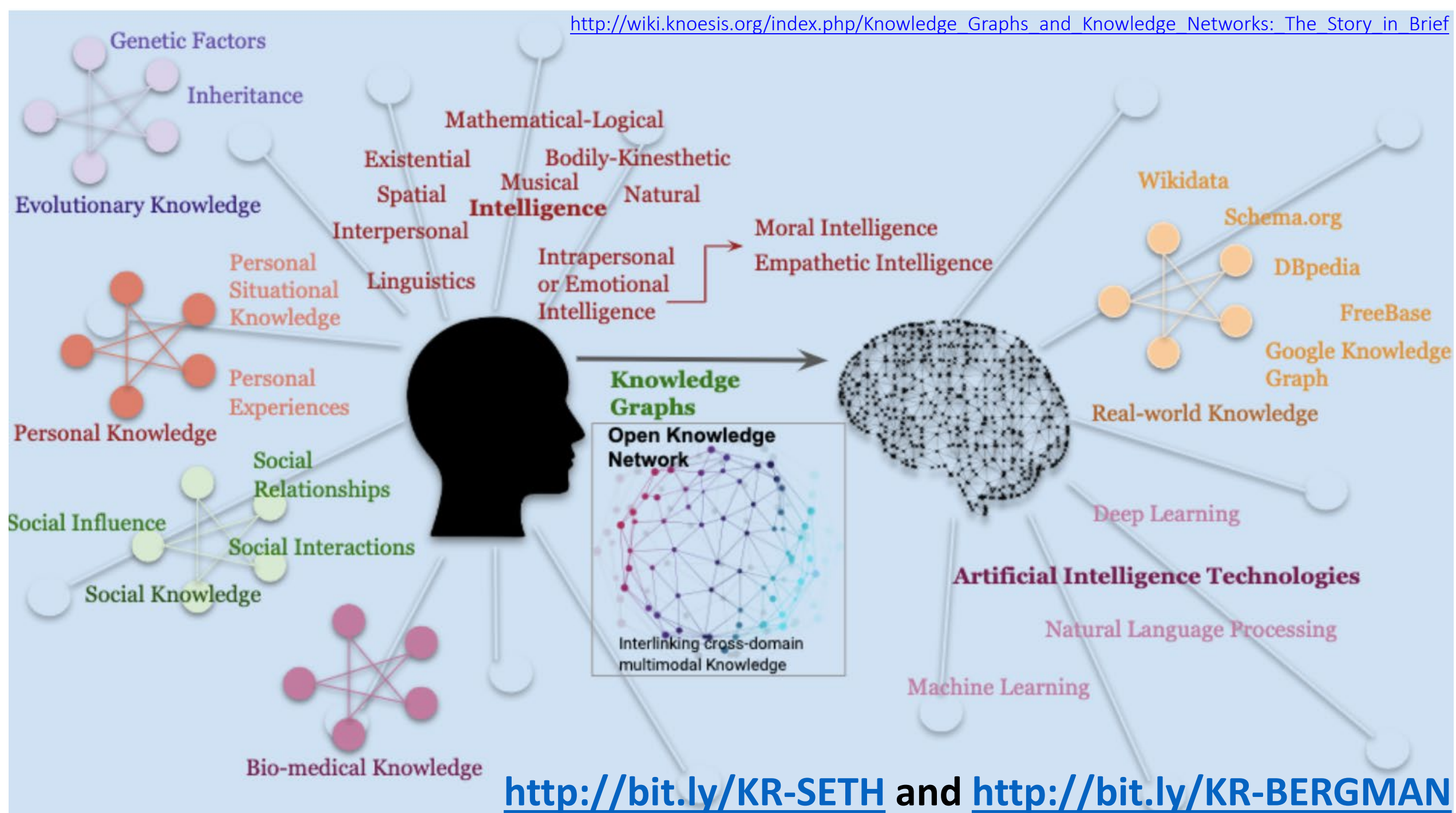
[12] S. Lalithsena, S. Perera, P. Kapanipathi, and A. Sheth. Domain-specific hierarchical subgraph extraction: A recommendation use case. In IEEE International Conference on Big Data (Big Data) (pp. 666-675). IEEE, 2017.

[13] R. Trivedi, H. Dai, Y. Wang, L. Song. "Know-evolve: Deep temporal reasoning for dynamic knowledge graphs. In Proceedings of the 34th International Conference on Machine Learning-Volume 70 (pp. 3462-3471). JMLR. org, 2017.

[14] OKN: Open Knowledge Network: Creating the Semantic Information Infrastructure for the Future (Summary of the Big Data IWG Workshop), October 4–5, 2017. November 2018. <https://www.nitr.gov/news/Open-Knowledge-Network-Workshop-Report-2018.aspx>

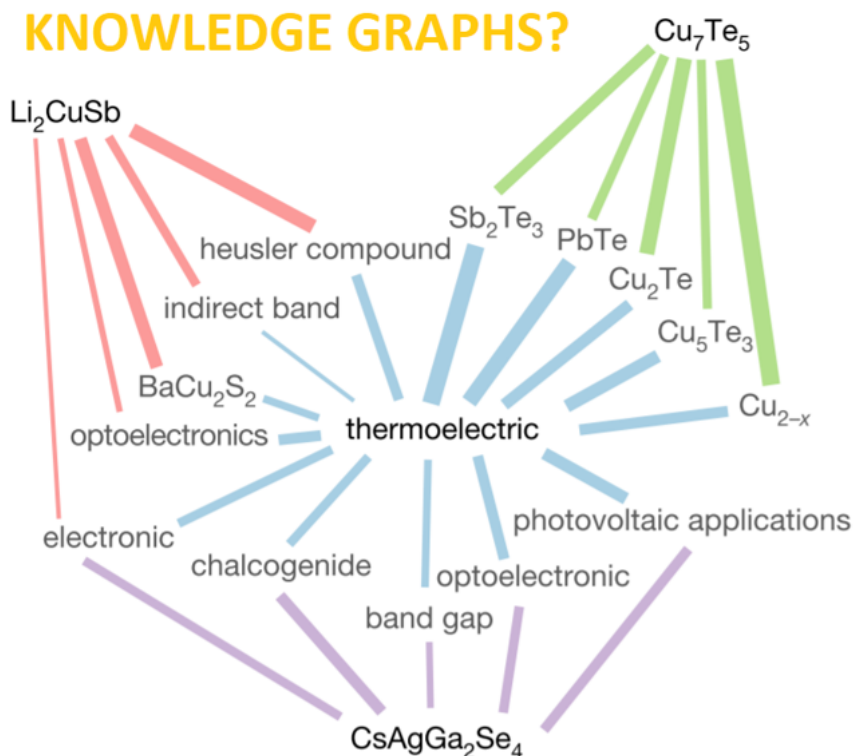
[15] P. Ekman. "Basic Emotions", in Dalgleish, T; Power, M (eds.), Handbook of Cognition and Emotion, Sussex, UK: John Wiley & Sons, 1999.

[16] Amit Sheth, Swati Padhee, Amelie Gyrard, 'Knowledge Graphs and Knowledge Networks - The Story in Brief,' IEEE Internet Computing, July-Aug 2019 http://wiki.knoesis.org/index.php/Knowledge_Graphs_and_Knowledge_Networks:_The_Story_in_Brief



Novel Paradigm for Machine-Assisted Graph Theoretic Approach to Mine Non-Obvious Relationships

The width of the edges between 'thermoelectric' and the context words (blue) is proportional to the cosine similarity between the word embeddings of the nodes, whereas the width of the edges between the materials and the context words (red, green and purple) is proportional to the cosine similarity between the word embeddings of context words and the output embedding of the material. The context words are top context words according to the sum of the edge weights between the material and the word 'thermoelectric'.



<https://doi.org/10.1038/s41586-019-1335-8>

Unsupervised word embeddings capture latent knowledge from materials science literature

Vahe Tshitoyan^{1,3*}, John Dagdelen^{1,2}, Leigh Weston¹, Alexander Dunn^{1,2}, Ziqin Rong¹, Olga Kononova², Kristin A. Persson^{1,2}, Gerbrand Ceder^{1,2*} & Anubhav Jain^{1*}

<https://www.nature.com/articles/s41586-019-1335-8>

Novel Paradigm for Machine-Assisted Graph Theoretic Approach to Mine Non-Obvious Relationships

KNOWLEDGE GRAPHS?

Scientific progress relies on the confluence of efficient assimilation of existing knowledge in order to minimize re-invention. The methodology in this paper may create a tool to plumb the depths of the unknown unknowns, where catalysts for scientific breakthroughs often reside. The authors are incisive to point out that this approach may be "generalized to other language models, such that the probability of an entity (a material or molecule) co-occurring with words, that represent a target application or property, can be treated as an indicator of performance."

Entity-relationship mode remains the "bread and butter" of context-awareness while RDF is a more general model of entities (nodes) and relationships. Thus, the paper strengthens the notion that knowledge graphs may aid in unleashing new ideas. Context-aware embeddings such as NLP BERT or ELMo may improve predictions. This document (PEAS) and the accompanying ideas (SIGNALS) are in quest of these tools. The paper indicates the potential for new research at the nexus of natural language processing, linguistics, semantics, and science, to advance knowledge discovery.

Artificial Reasoning Outcomes → Reasonable Expectations

It is easy to illustrate, but quite difficult for systems to claim real 'knowledge' discovery.

Can graph networks catalyze data to reveal information?

But, beware of snake oil sales and stupidity

**BEWARE
OF
STUPIDITY**

<https://emoshape.com/emoshape-enhances-its-cutting-edge-emotion-chip-with-the-addition-of-cloud-service/>

EMOSHAPE
EMOTIONS NEXT FRONTIER

[Emotion Synthesis](#)

[Products](#)

[Order](#)

[News](#)

Emoshape Enhances Its Cutting Edge Emotion Chip with the Addition of Cloud Service

On: [Jun 03](#) / Author: [Patrick Levy-Rosenthal](#) / Categories: [Uncategorized](#) /

**EPU III
CLOUD
TECHNOLOGY
2019**

256 EPU's instances per rack

unity

**UNREAL
ENGINE**

EMOSHAPE
EMOTIONS NEXT FRONTIER

The Lowest Common Denominator

We are immersed in **data** swamps.
Actions depend on **information**.
Informed by **knowledge**.
Learn from **experience**.

*SENSEE → Choose sensors and then
harvest DATA from specific SENSORS*

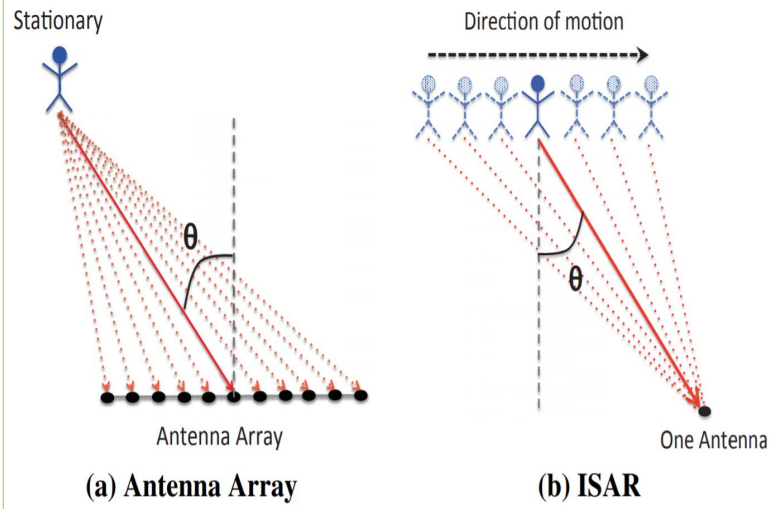
SENSE



SENSE

Don't bind.
Reflect

C
O
N
V
E
R
G
E



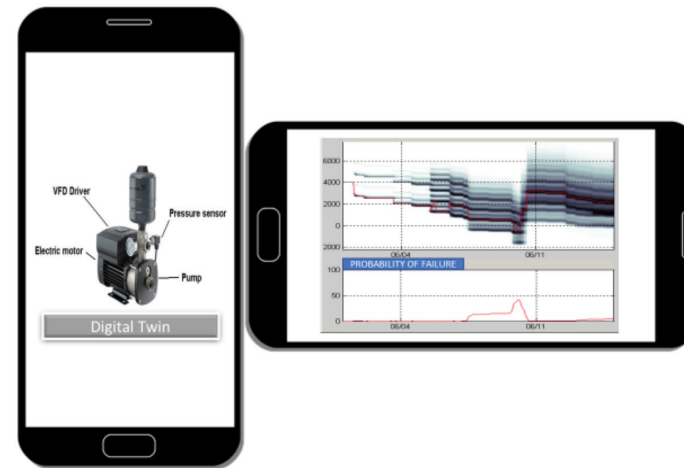
SENSE RF REFLECTION



TRANSMIT



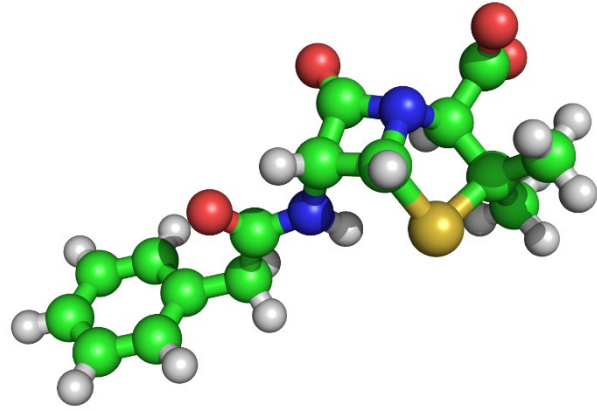
ANALYZE



DECISION SUPPORT

S
Y
N
E
R
G
I
Z
E

C
O
N
V
E
R
G
E



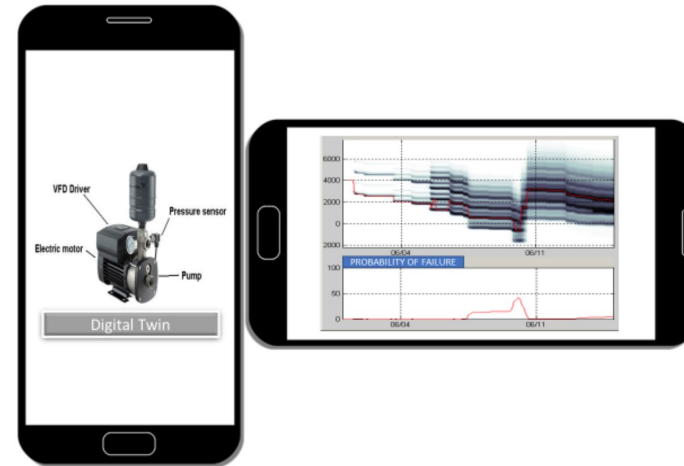
SENSE
BINDING OF ANALYTE



ANALYZE



TRANSMIT



DECISION SUPPORT

S
Y
N
E
R
G
I
Z
E

How does a sensor work? Sensors that bind analytes.

← → ↻ <https://onlinelibrary-wiley-com.libproxy.mit.edu/doi/pdf/10.1002/anie.199423751>

The Key–Lock Theory and the Induced Fit Theory

1 / 4

REVIEWS

There are sensors that may not bind analytes but are activated by reflected radio waves (WiFi, radar, sonar)

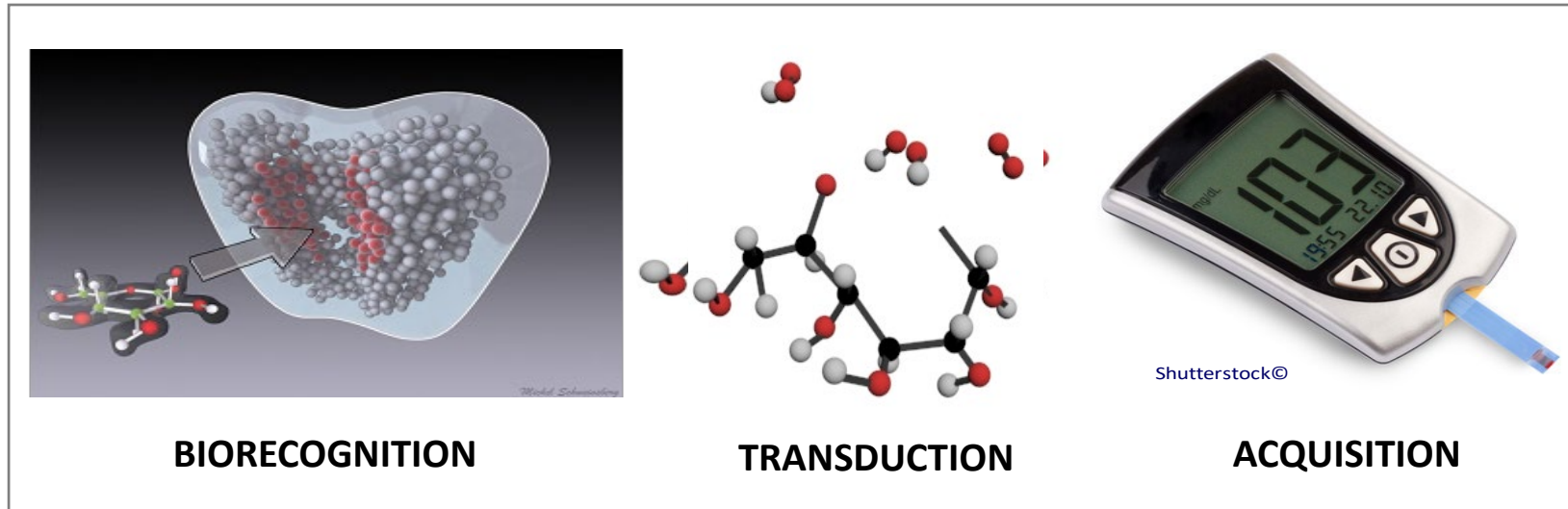
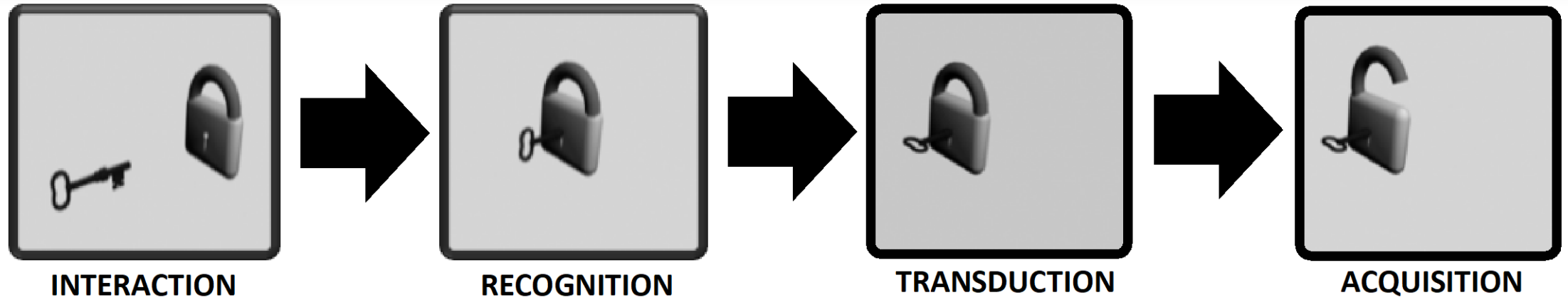
The Key–Lock Theory and the Induced Fit Theory

Daniel E. Koshland, Jr.

It is a great pleasure for me to contribute to this symposium honoring the great scientist Emil Fischer. My graduate thesis required me to synthesize [1-¹⁴C]glucose, which introduced me to the famous Fischer–Kiliani synthesis of glucose and mannose from arabinose and HCN.^[1] I was also particularly intrigued with his classic key–lock (or template) theory of enzyme specificity,^[2, 3] which like all great theories seemed so obvious once one understood it.

<https://onlinelibrary.wiley.com/doi/abs/10.1002/anie.199423751>

How does a sensor work? The classical glucometer.



- Step 1)** Biorecognition
- Step 2)** Binding and transduction
- Step 3)** Acquisition and data analytics

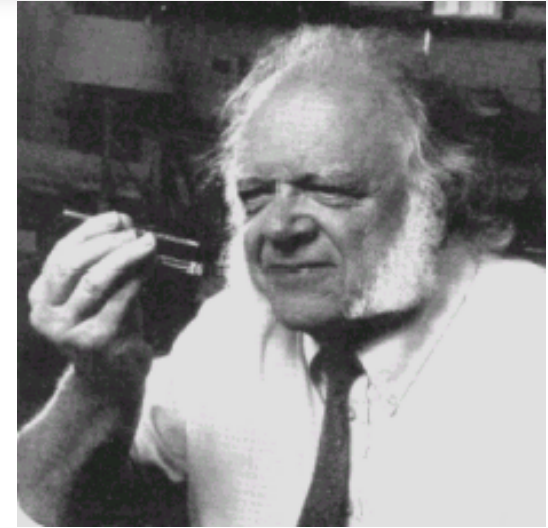
Unchanged: 1962 Classical Chemistry of Clark and Lyons

<https://nyaspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1749-6632.1962.tb13623.x>

ELECTRODE SYSTEMS FOR CONTINUOUS MONITORING IN CARDIOVASCULAR SURGERY

Leland C. Clark, Jr., and Champ Lyons
Medical College of Alabama, Birmingham, Ala.

Instruments capable of continuously indicating the chemical composition of blood have proved to be useful in controlling heart-lung machines, in regulating operative and postoperative management of patients, and in teaching and research. At first, such instruments were used with sensors mounted directly in the extracorporeal blood circuit that is used for perfusion of open-heart surgery patients.¹ Later, continuous monitoring of both machine and patients was conducted by means of continuous withdrawal of blood pumped into external cuvettes equipped with appropriate sensors.



Leland C. Clark, Jr. (1959)

Unchanged: 1962 Classical Chemistry of Clark and Lyons

<https://nyaspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1749-6632.1962.tb13623.x>

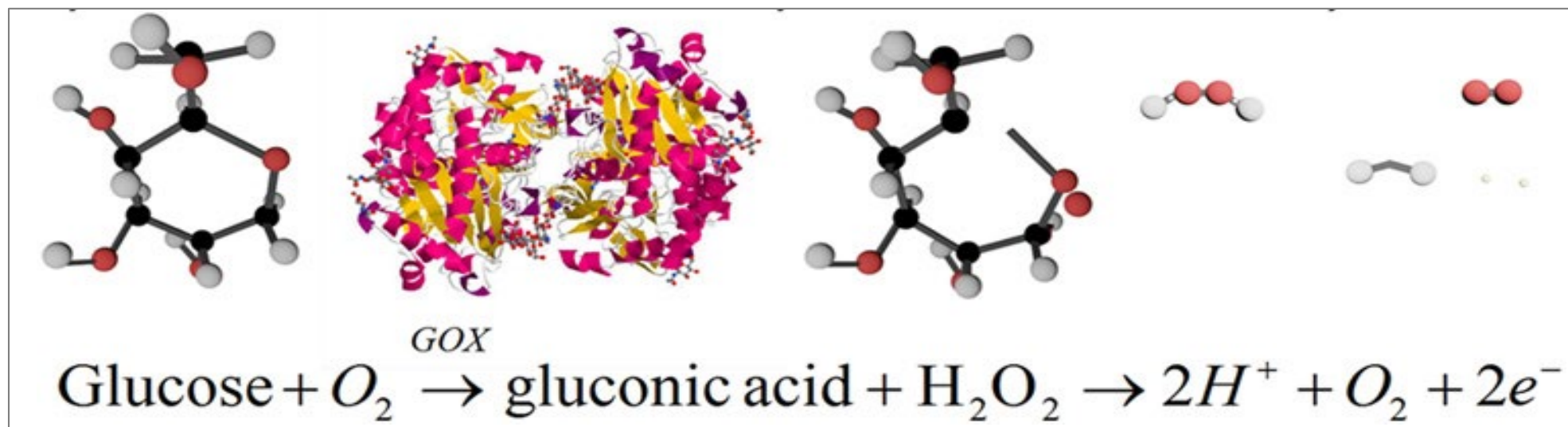
ELECTRODE SYSTEMS FOR CONTINUOUS MONITORING IN CARDIOVASCULAR SURGERY

Leland C. Clark, Jr., and Champ Lyons
Medical College of Alabama, Birmingham, Ala.

Instruments capable of continuously indicating the chemical composition of blood have proved to be useful in controlling heart-lung machines, in regulating operative and postoperative management of patients, and in teaching and research. At first, such instruments were used with sensors mounted directly in the extracorporeal blood circuit that is used for perfusion of open-heart surgery patients.¹ Later, continuous monitoring of both machine and patients was conducted by means of continuous withdrawal of blood pumped into external cuvettes equipped with appropriate sensors.



Leland C. Clark, Jr. (1959)



Glucometer – The Evolution of its Form and Function



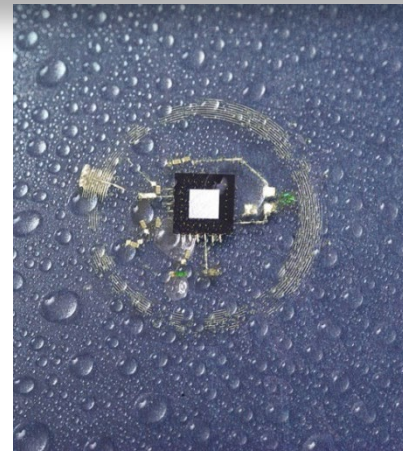
Paper based
(Whitesides)



Noninvasive
glycemic
monitoring
(Wang)



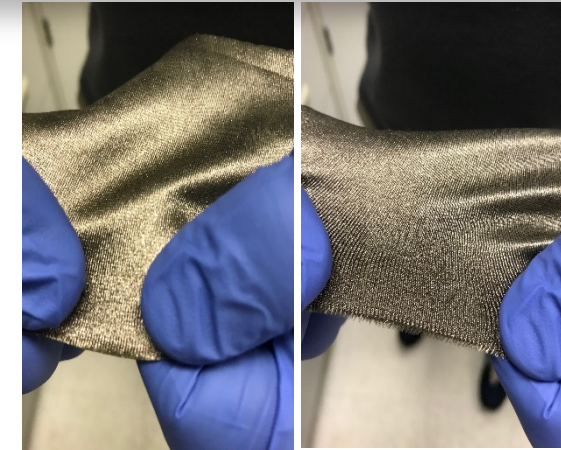
WISP: Wearable
Interactive
Stamp Platform
(MC10)



Resorbable
(Rogers)



Contact lens
(Google, Inc.)



Stretchable fabric
(Bhargava-UF)

Function	Form (elements and structure)
What a system does/could do	What a system is/could be
Creates behavior	Is aggregated and decomposed
Is a source of benefit/value	Is a source of costs
Requires form	Enables function

Source: E. Crawley, MIT Course Material

Glucometer – The Evolution of its Form and Function

https://onlinelibrary.wiley.com/doi/abs/10.1002/ami.200603817



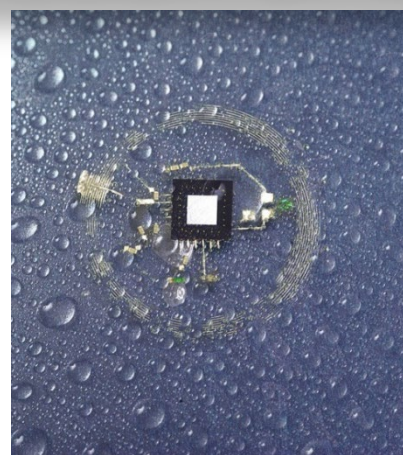
Paper based
(Whitesides)



Noninvasive
glycemic
monitoring
(Wang)



WISP: Wearable
Interactive
Stamp Platform
(MC10)



Resorbable
(Rogers)

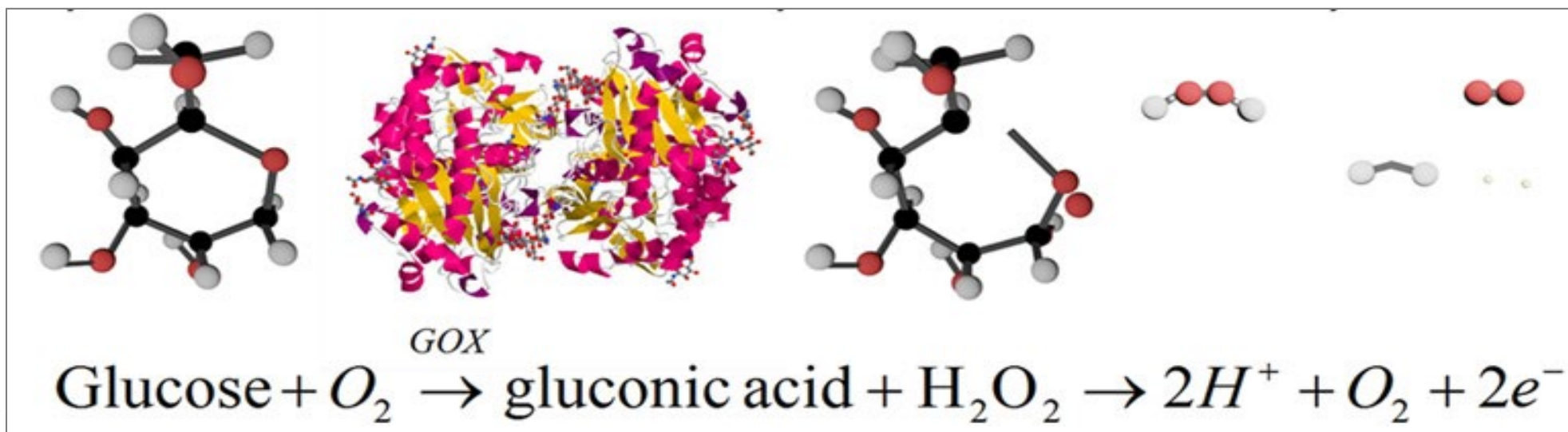


Contact lens
(Google, Inc.)



Stretchable fabric
(Bhargava-UF)

<https://www.cientperiodique.com/article/CPQME-2-1-40.pdf>

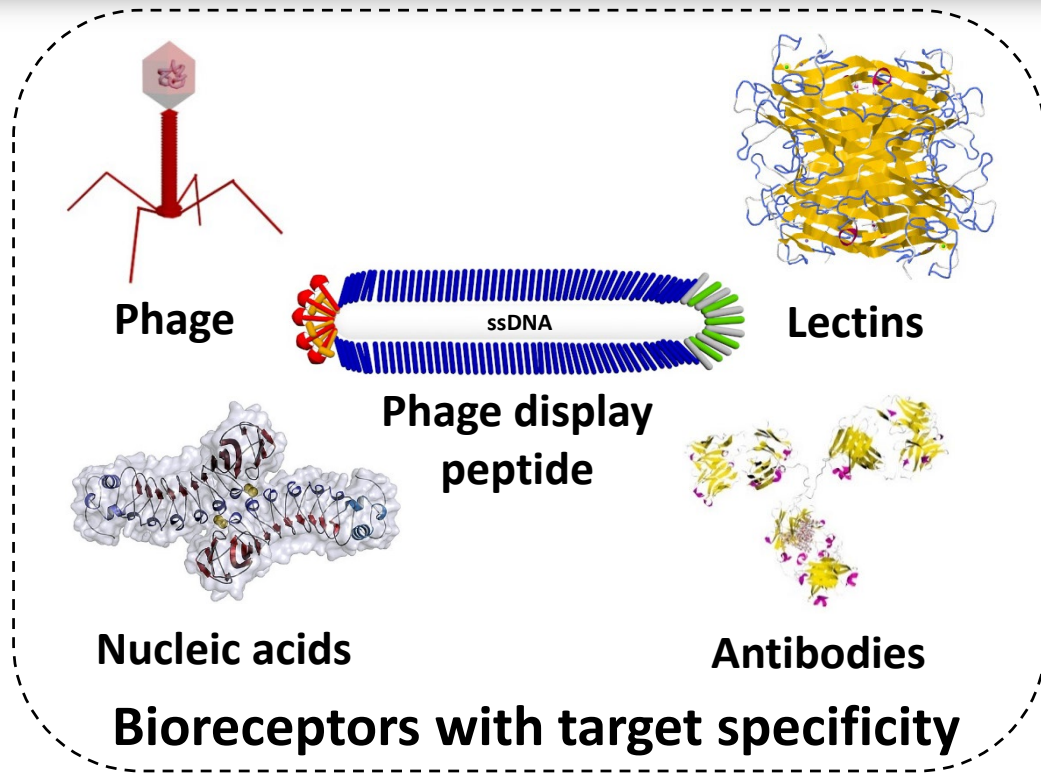


The core chemistry
developed by Clark
and Lyons has not
changed since 1962.

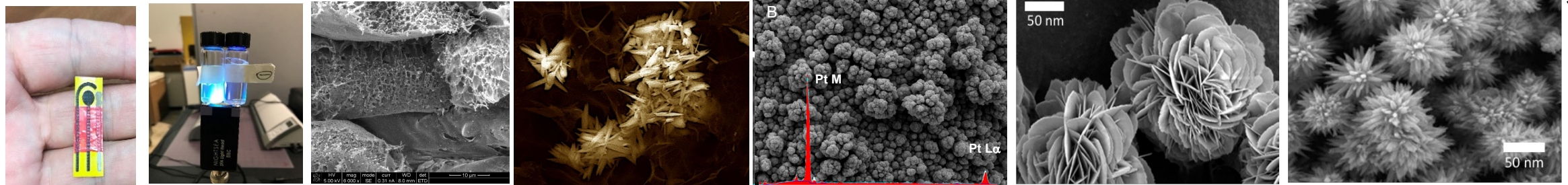
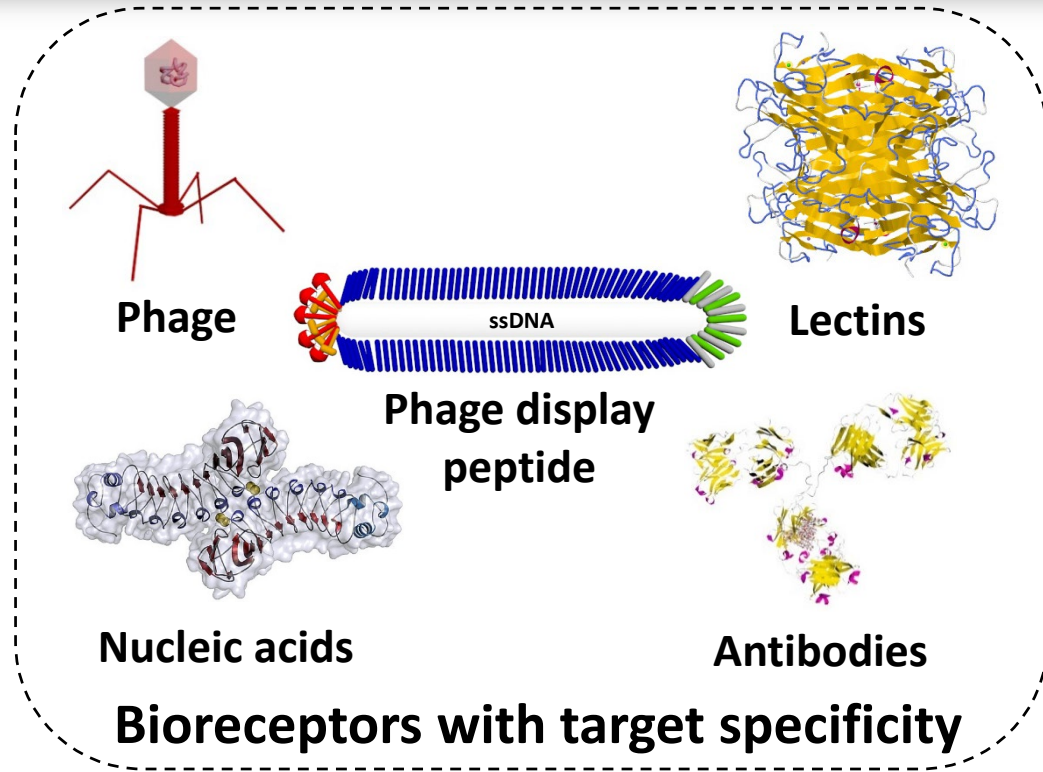
Evolution of Sensors ♦ Nano-bio Sensors

<https://emclamor.wixsite.com/mclamorelab>

Evolution of Sensors ♦ Nano-bio Sensors

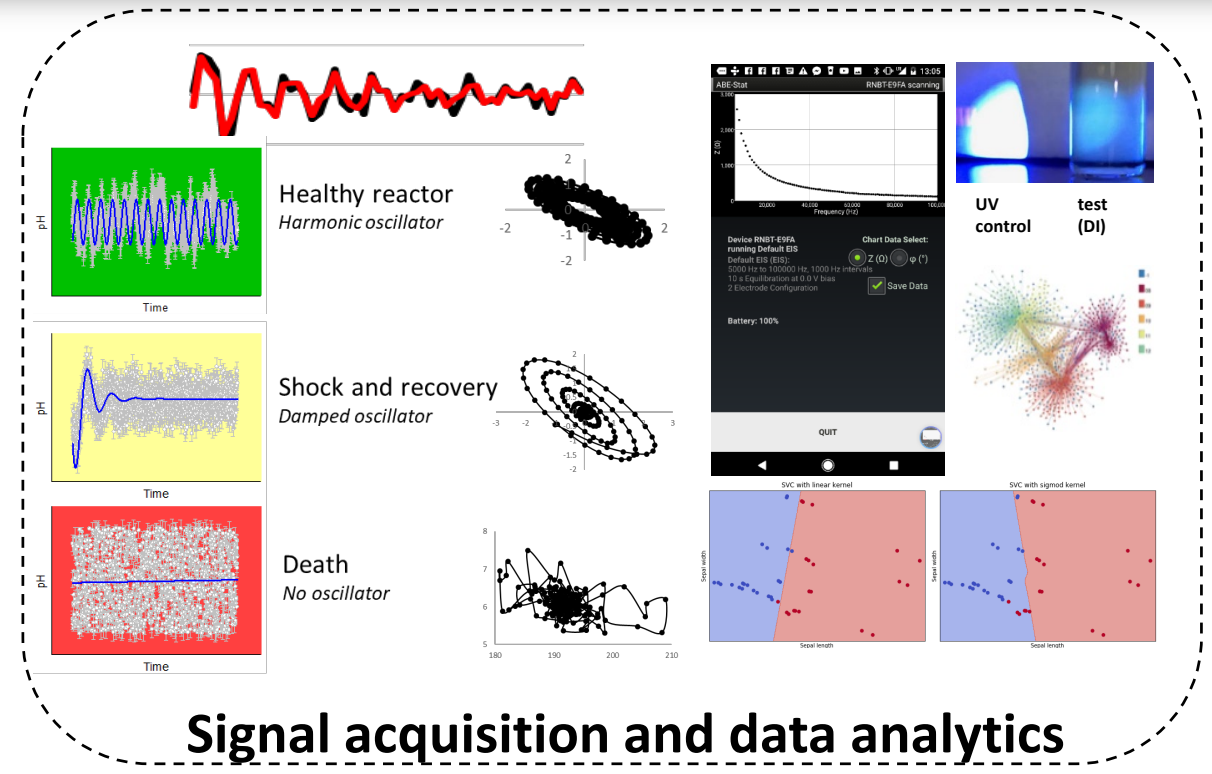
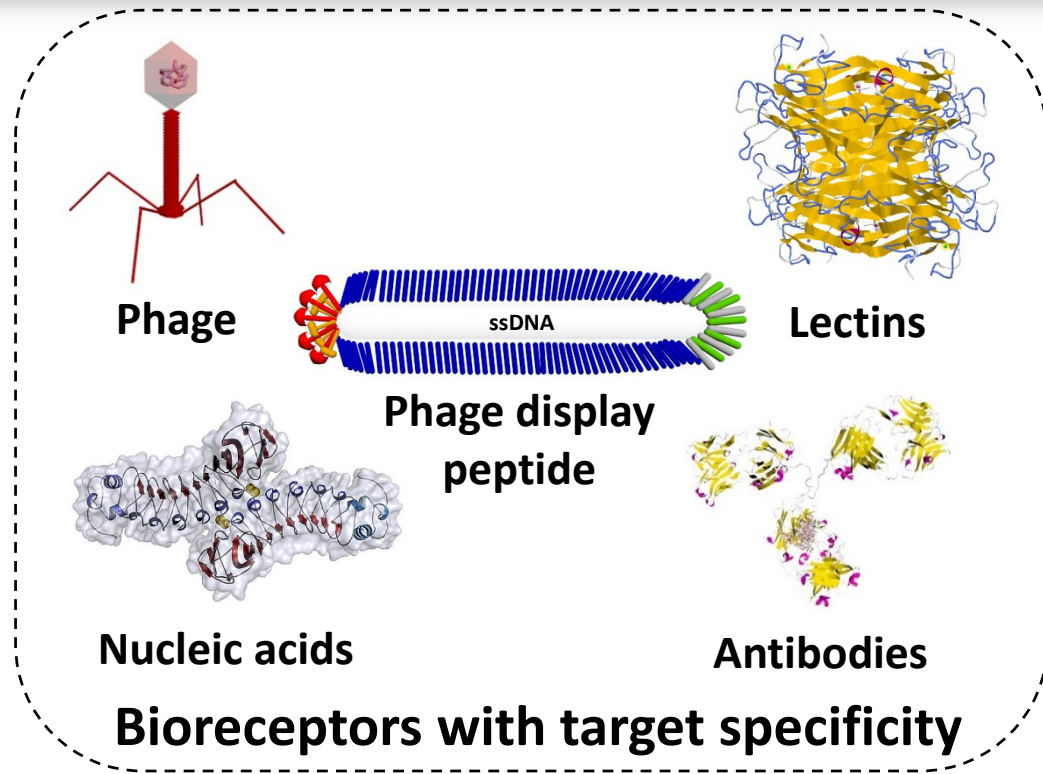


Evolution of Sensors ♦ Nano-bio Sensors

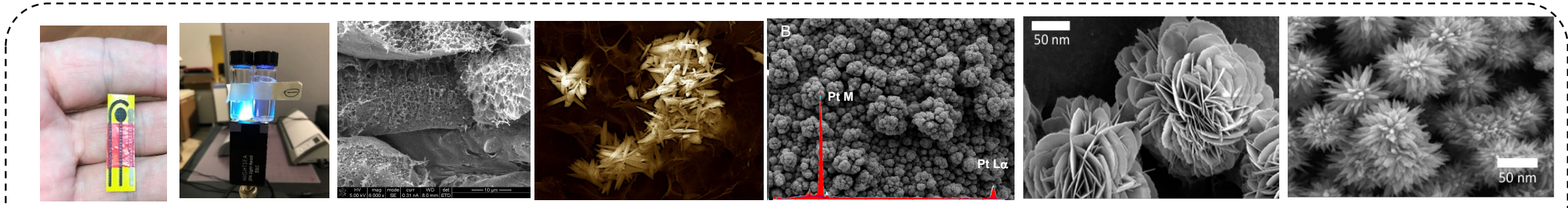


Nanomaterials improve signal transduction

Evolution of Sensors ♦ Nano-bio Sensors

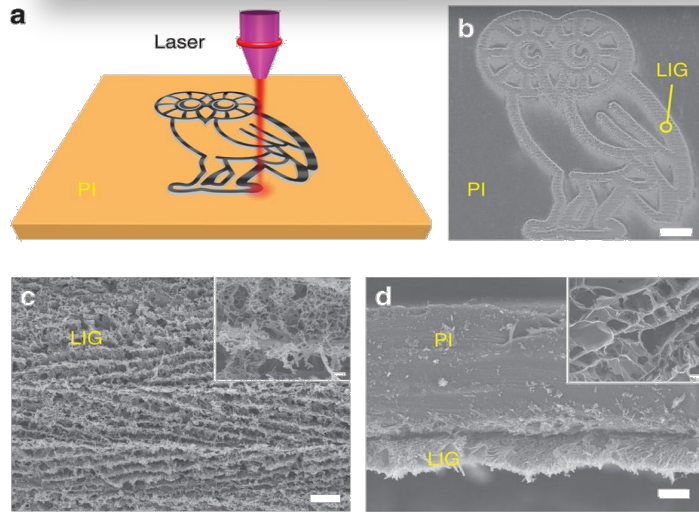


<https://emclamor.wixsite.com/mclamorelab>



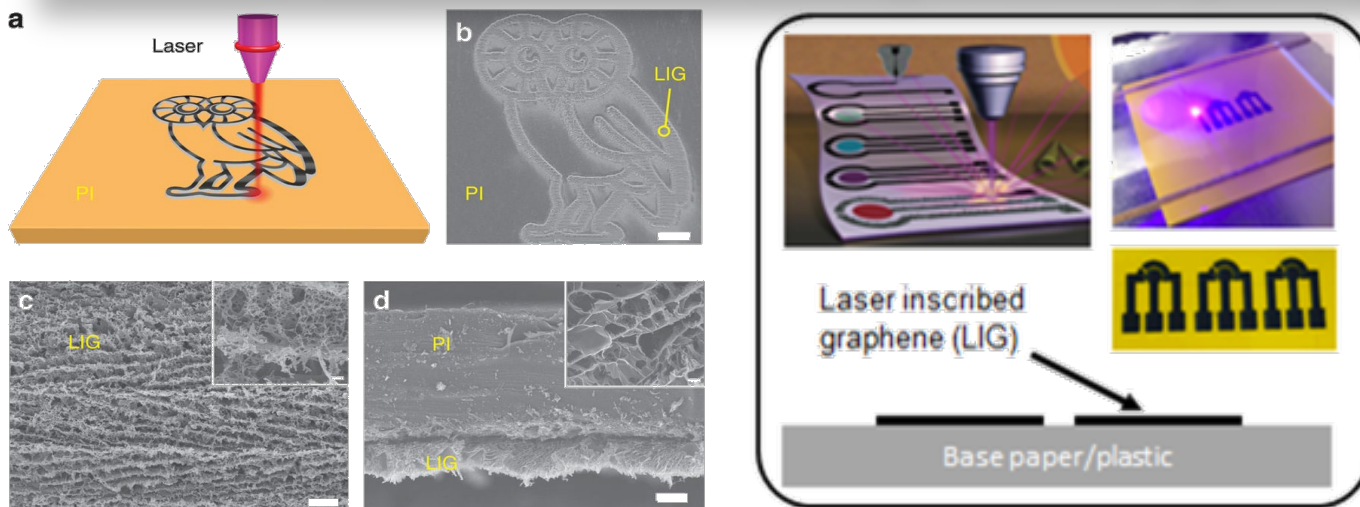
Nanomaterials improve signal transduction

Laser Inscribed Graphene (LIG)



Lin et. al. (2014) develops LIG for supercapacitors

Laser Inscribed Graphene (LIG)



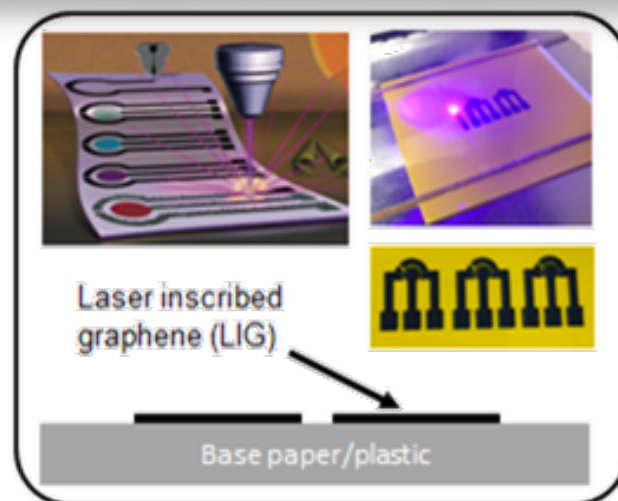
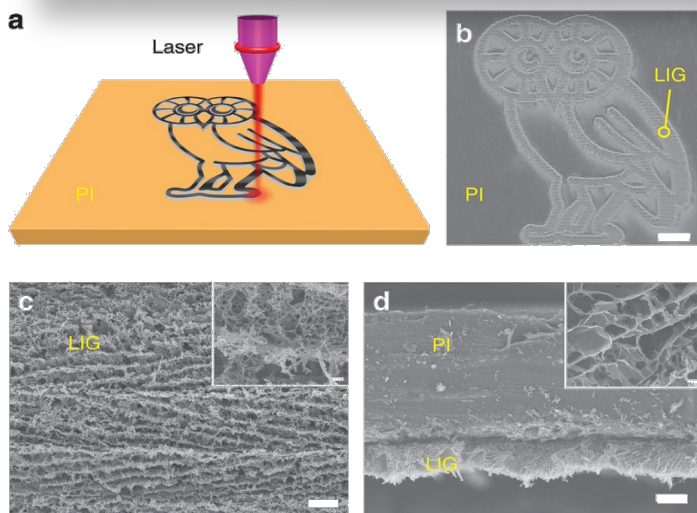
Lin et. al. (2014) develops LIG for supercapacitors

LIG for Sensing

- Sugars, organics
 - Tehrani et. al. (2016);
 - Nayak et. al. (2016);
 - Vanegas et al (2018)
- Ions
 - Garland et al (2019)

Evolution of Sensors ♦ 3D Printed Nano-bio Sensors

Laser Inscribed Graphene (LIG)

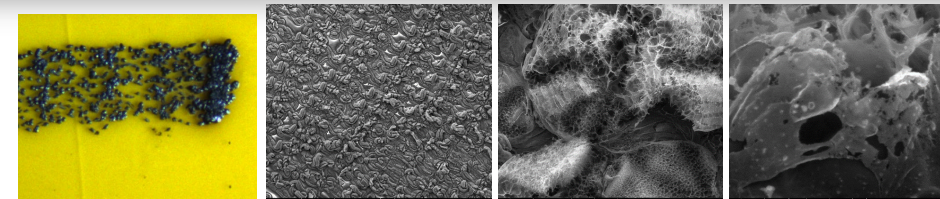


Lin et. al. (2014) develops LIG for supercapacitors

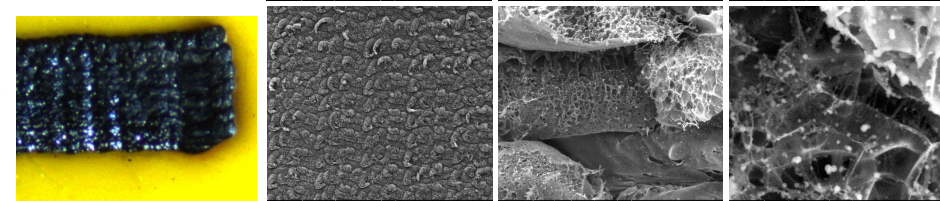
LIG for Sensing

- Sugars, organics
 - Tehrani et. al. (2016);
 - Nayak et. al. (2016);
 - Vanegas et al (2018)
- Ions
 - Garland et al (2019)

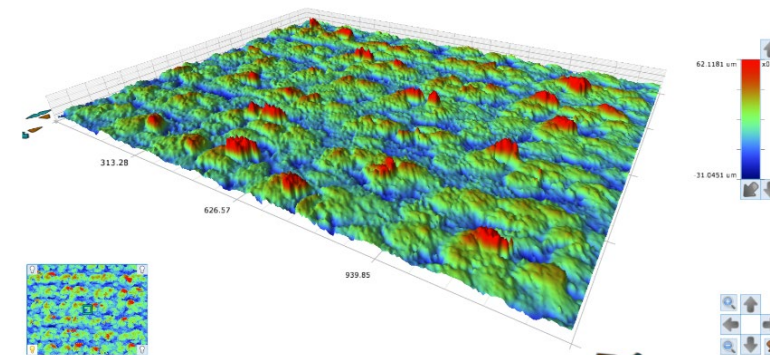
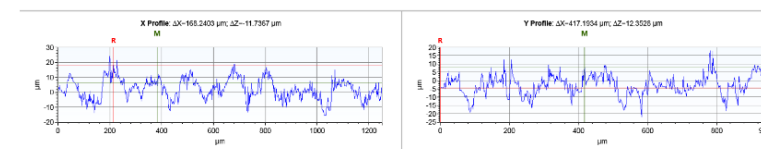
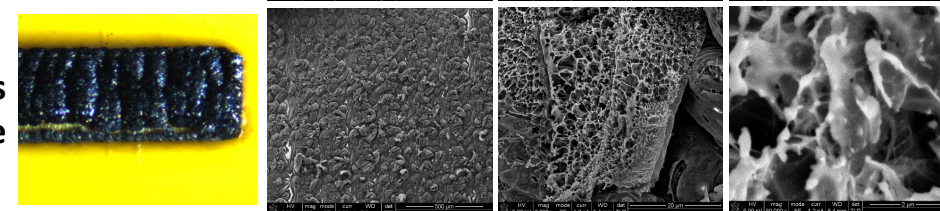
10 ms pulse



30 ms pulse



50 ms pulse



Problem

Platform

Coating

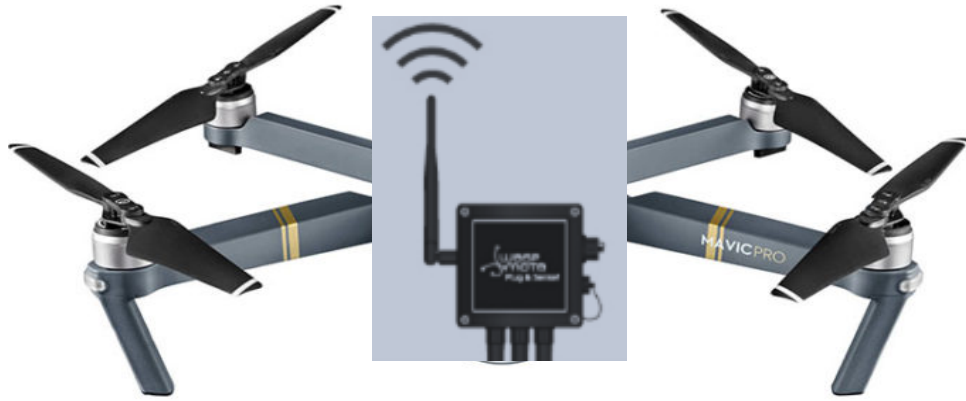
Proof of concept

Field validation

Data analytics

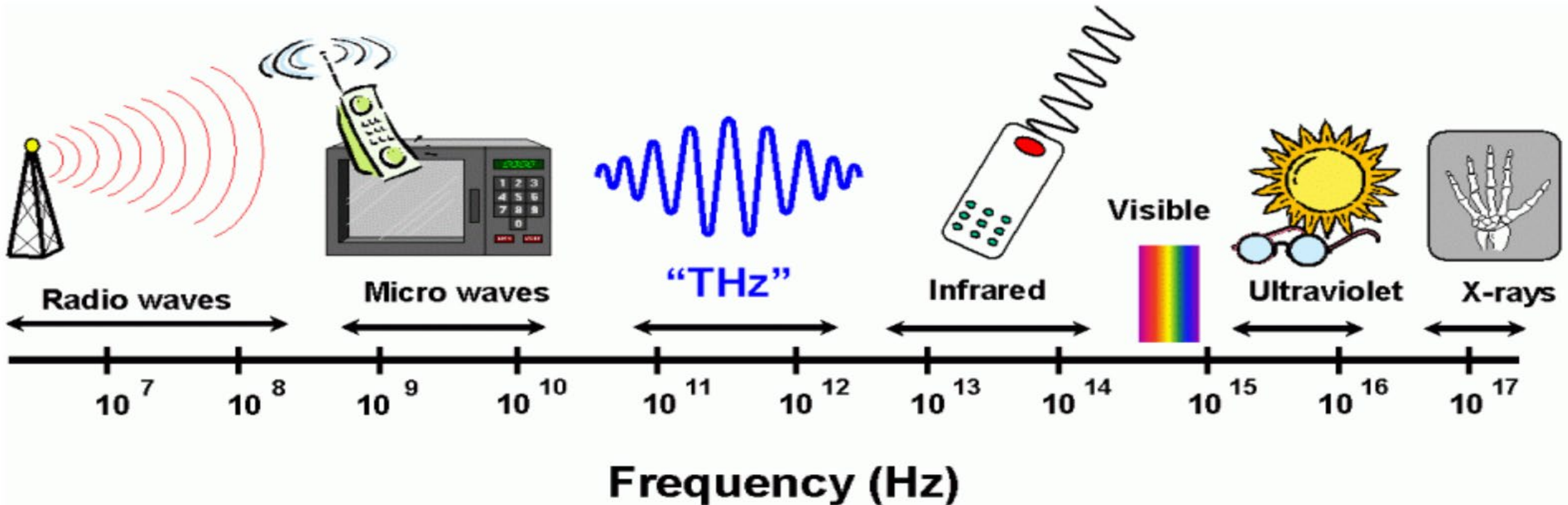
Decision support

Drones carrying Mobile Sensors acquire Reflected RF Signals

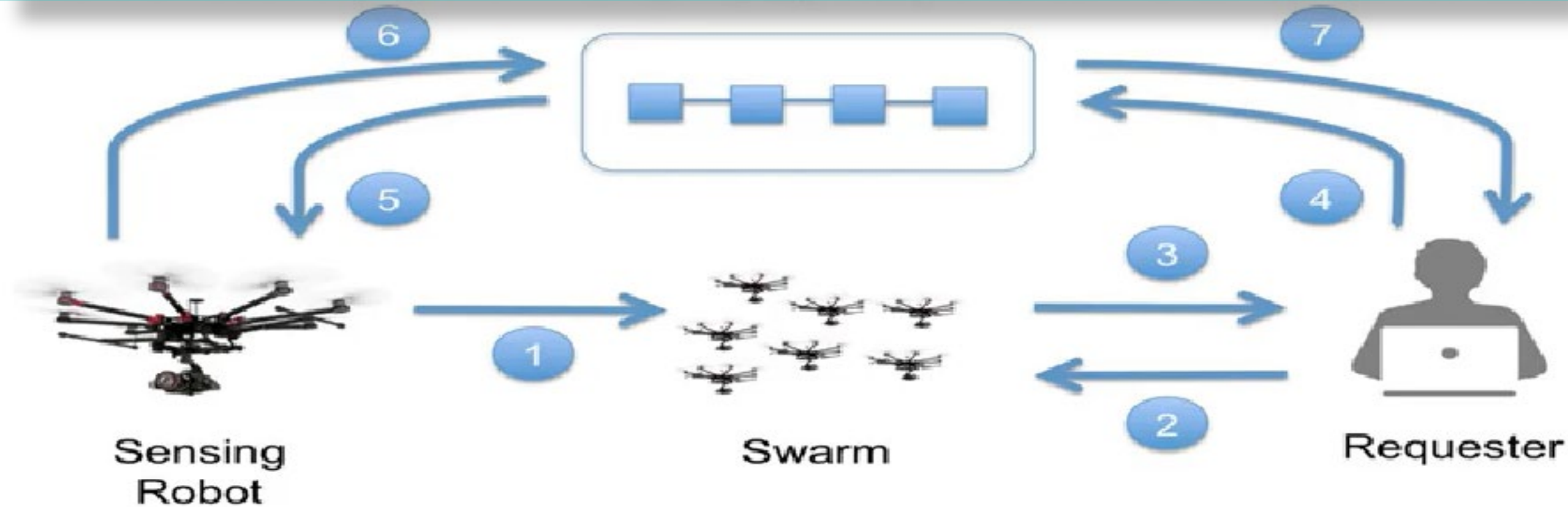


Terahertz (THz) spectrum, occupying frequency range between 0.3 and 3 THz, has potential for transformative applications in communication, sensing, spectroscopy, and imaging due to its desirable properties such as non-ionizing photon energy, penetration capability through optically opaque materials, unique spectral signatures for macro-molecules and chemicals.

<https://www.nature.com/articles/s41467-019-09868-6>



Rent-a-Robot drone-swarm "plug & play" remote sensors to collect desired data



- 1** Robot subscribes
- 2** User requests info
- 3** Robot's address is sent

- 4** Payment is sent
- 5** Payment is received

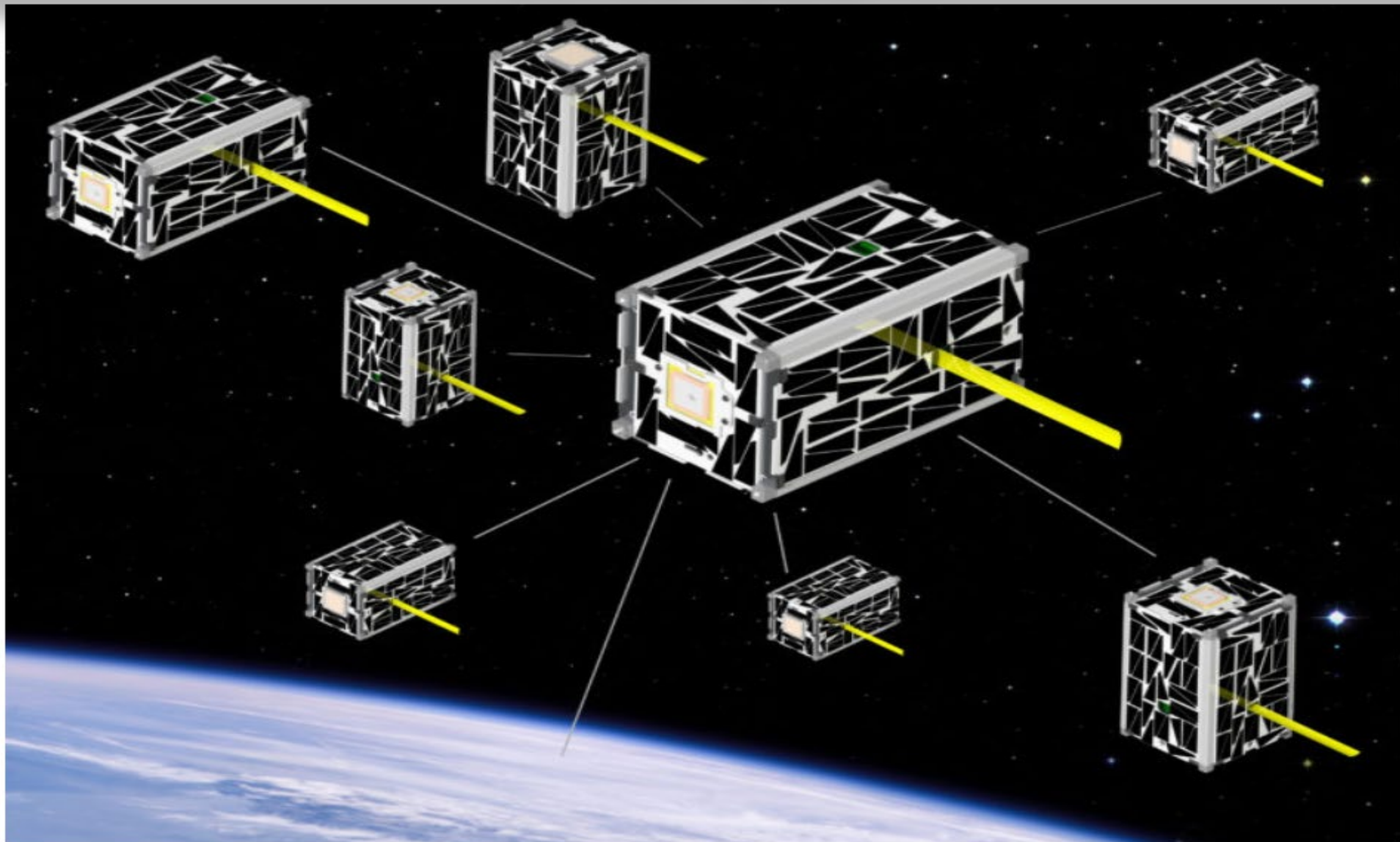
- 6** Info is sent
- 7** Info is received

Mobile Sensor Swarms deployed on Drones-on-Demand



Swarm Intelligence, Swarm Robotics, Mobile Robotics

Sensor Swarm



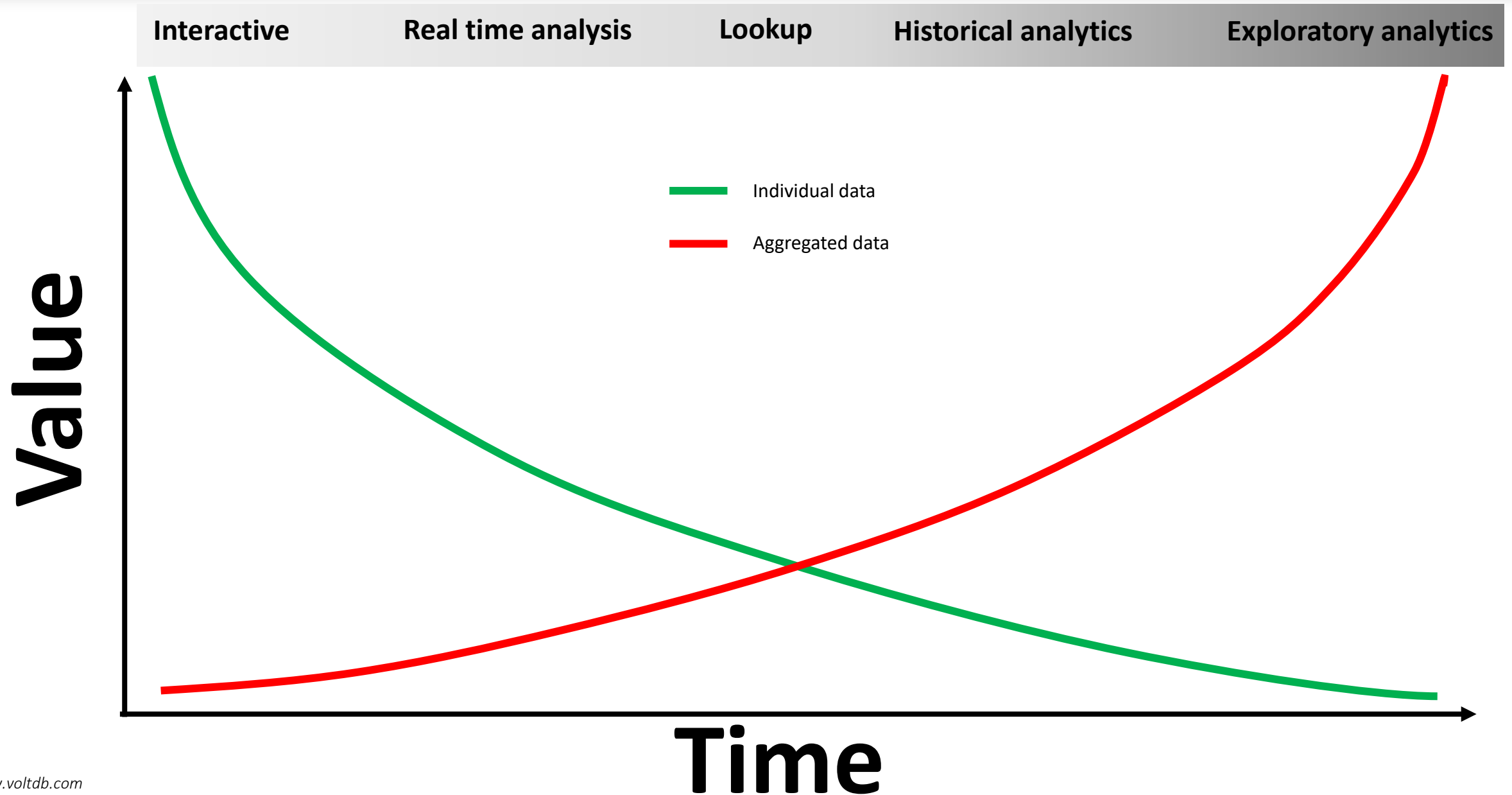
NASA and Lockheed Martin have been studying how small satellites could be knit together into a distributed swarm. (NASA Illustration)

Crowd-sourced radiation sensor data after the explosion Fukushima Daiichi Nuclear Power Plant in Ōkuma (2013)

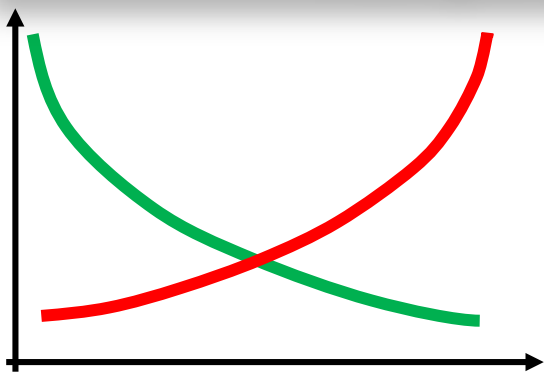


DATA from SENSORS

Is data perishable?

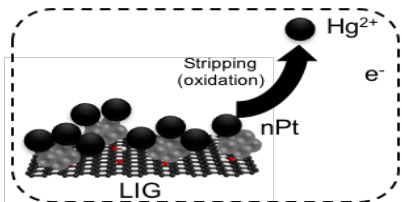


Varying Time-Sensitivity of Data from Sensors

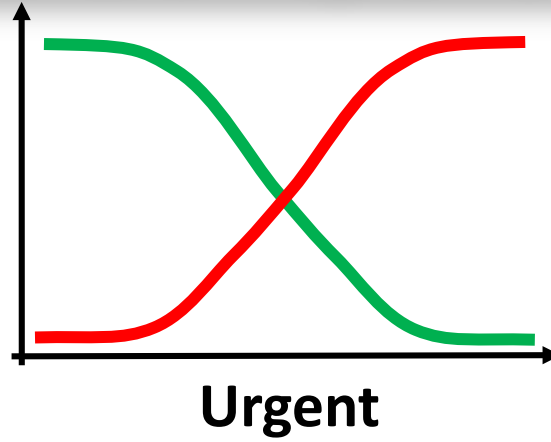
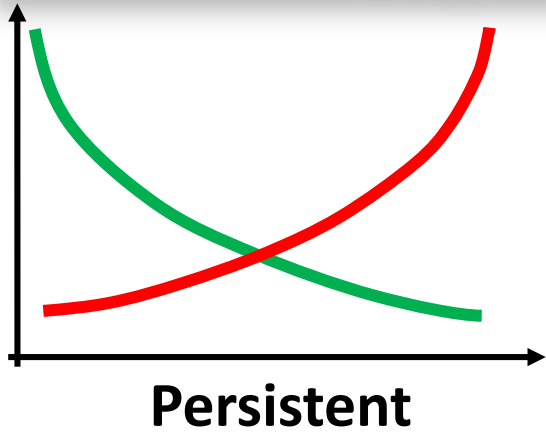


Persistent

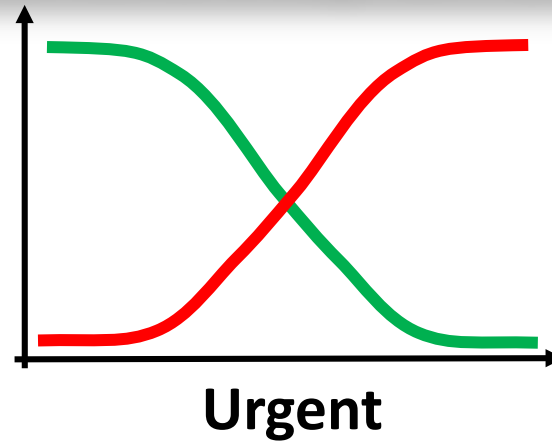
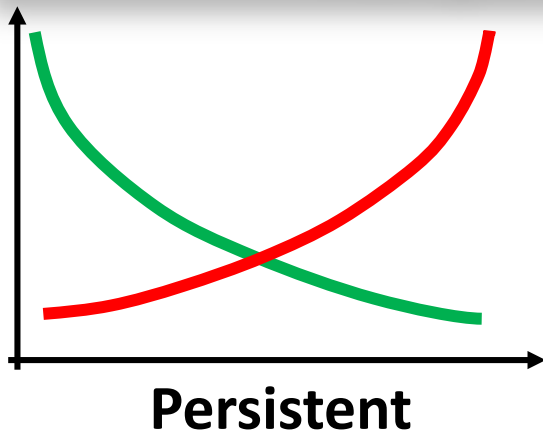
- Soil health
 - Erosion, degradation
- Agrochemical runoff
 - Nutrients, agrochemicals
- Land use change
 - Deforestation, mining



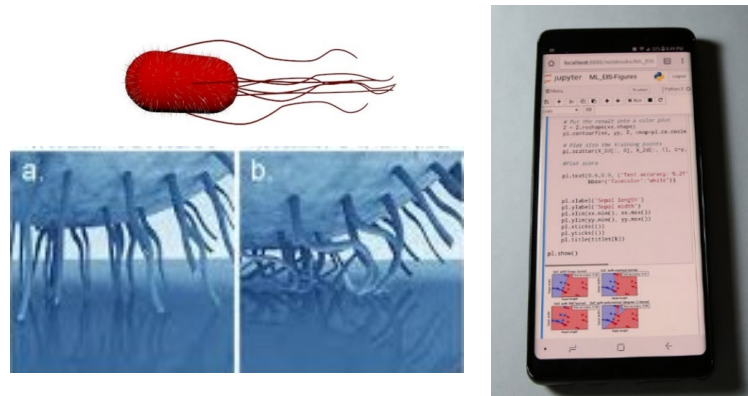
Varying Time-Sensitivity of Data from Sensors



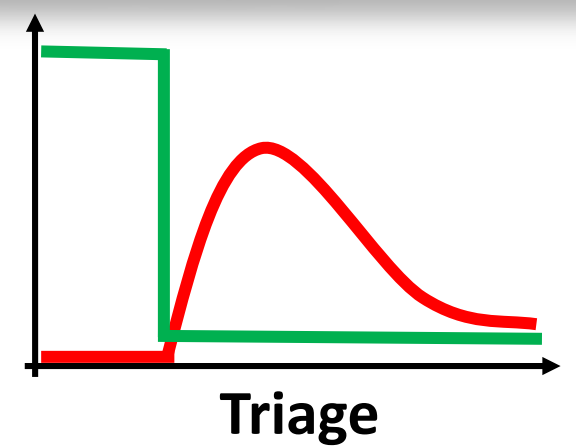
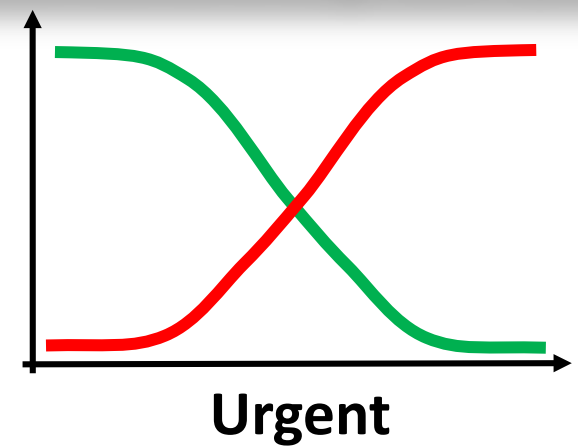
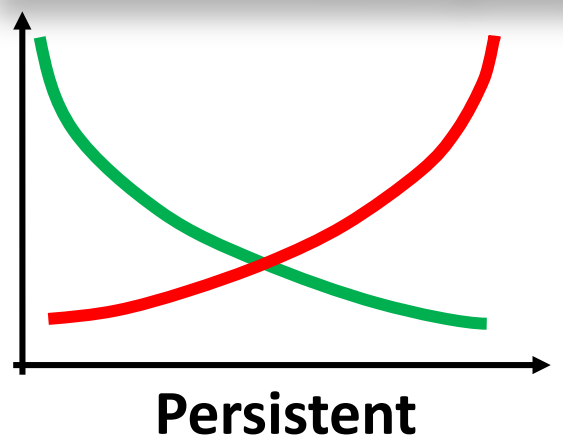
Varying Time-Sensitivity of Data from Sensors



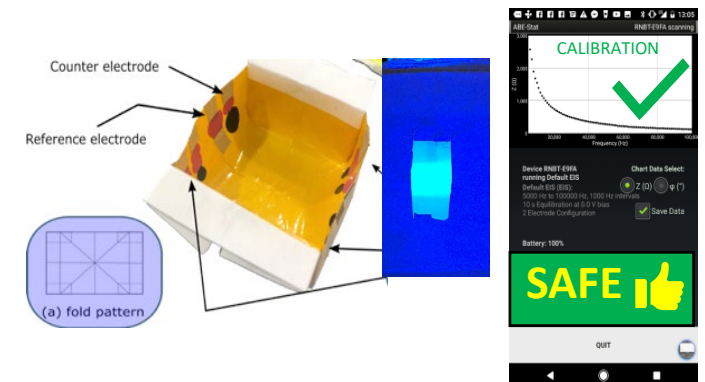
- Water scarcity
 - Quantity, quality
- Climate change
- Solid waste/wastewater
 - Pathogens, heavy metals



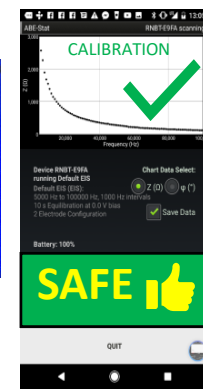
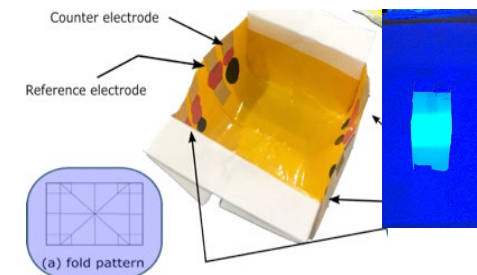
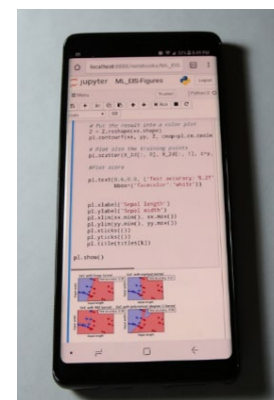
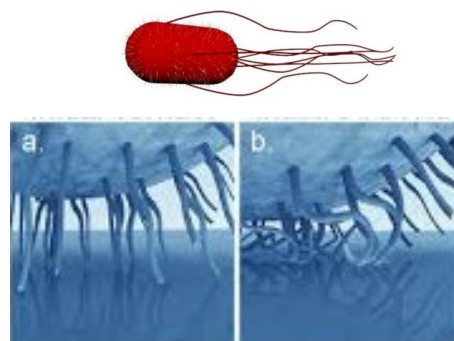
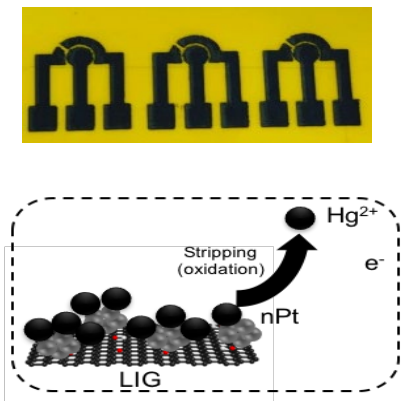
Varying Time-Sensitivity of Data from Sensors



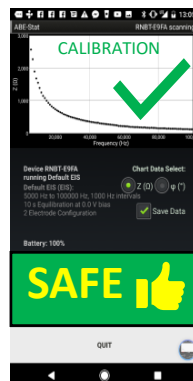
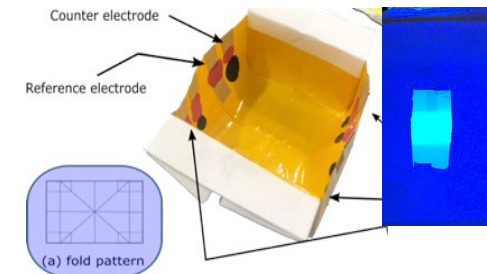
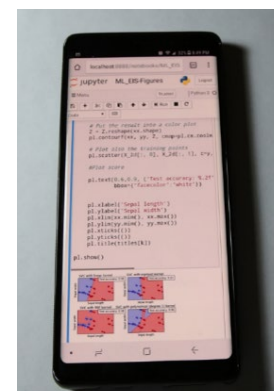
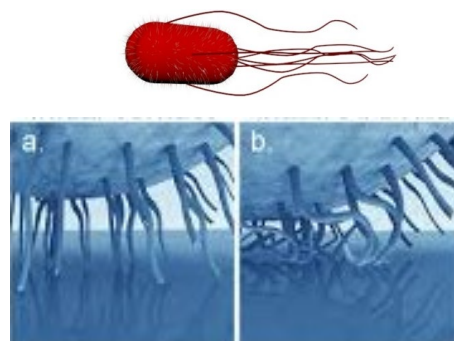
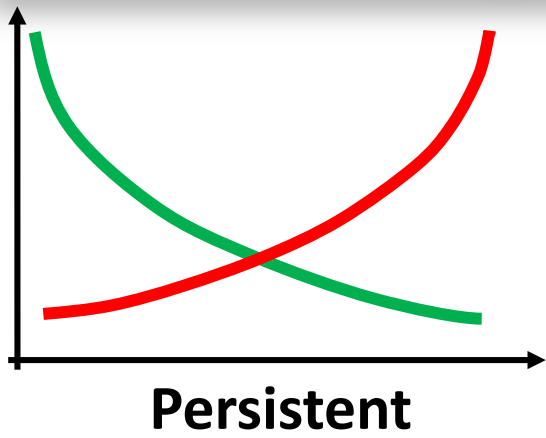
- Natural disaster
- Attack on infrastructure



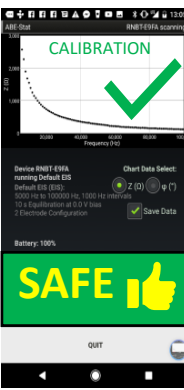
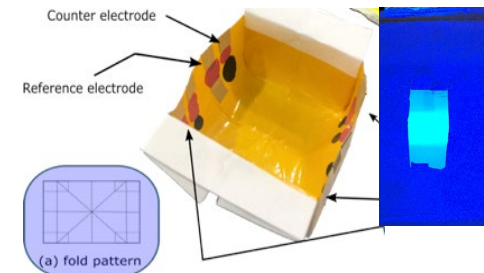
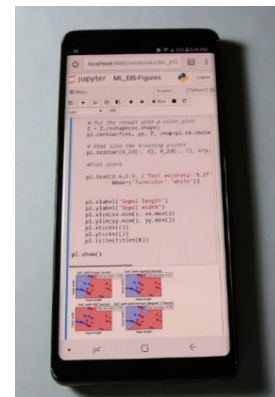
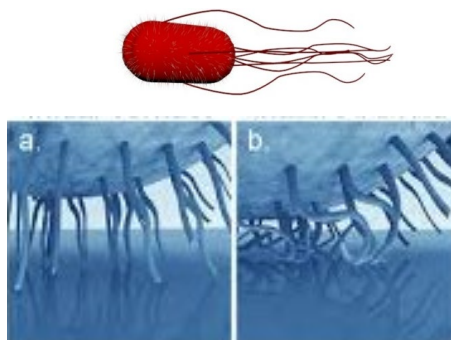
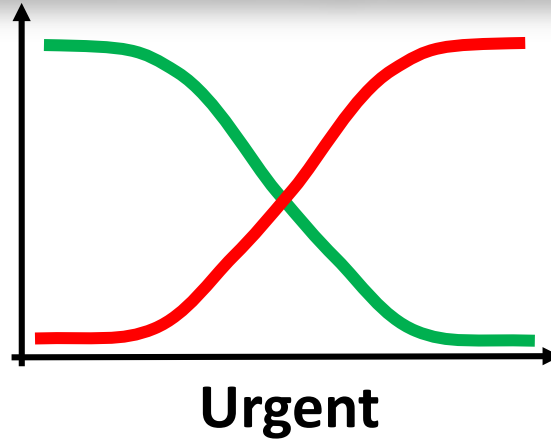
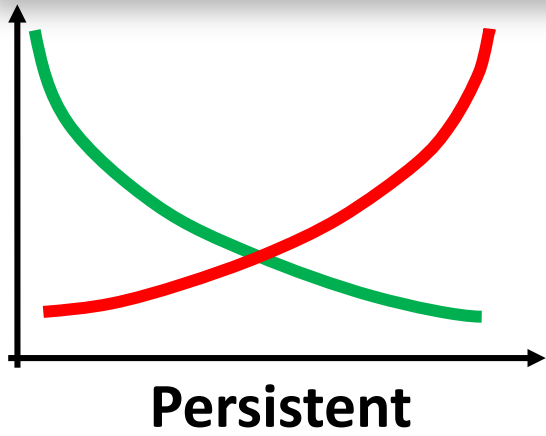
Data from the Perspective of Sensors



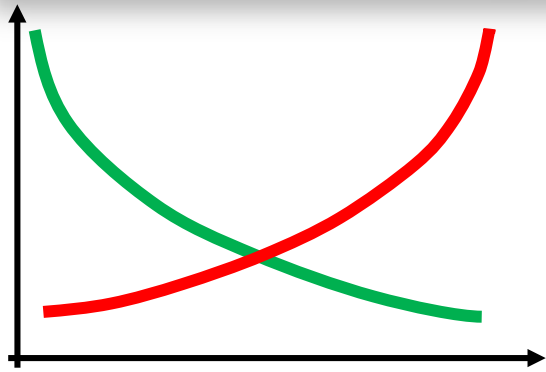
Data from the Perspective of Sensors



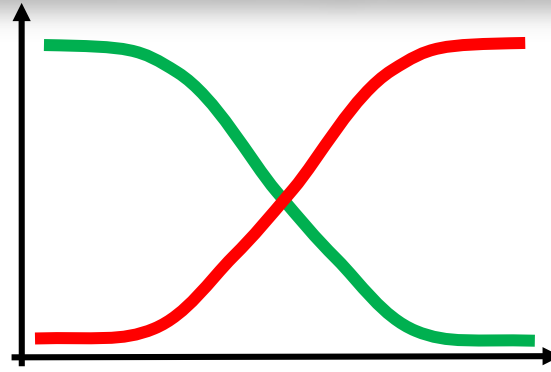
Data from the Perspective of Sensors



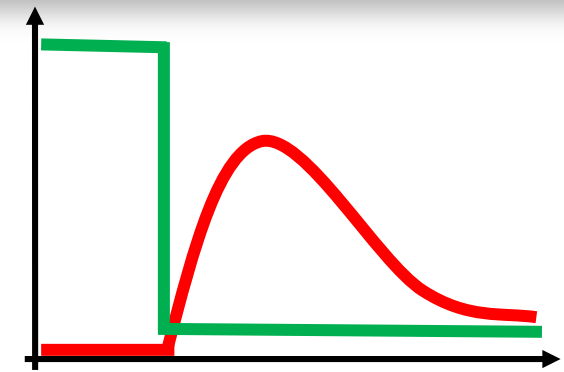
Data from the Perspective of Sensors



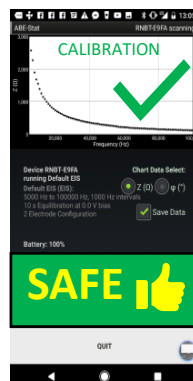
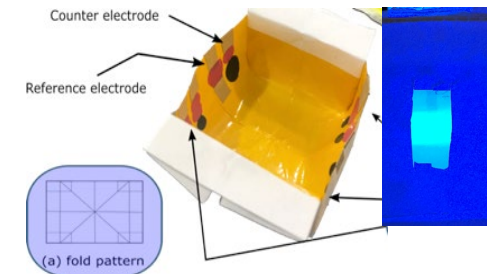
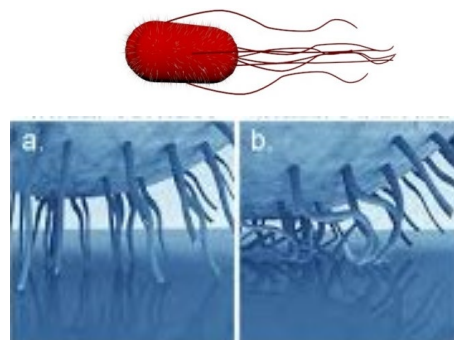
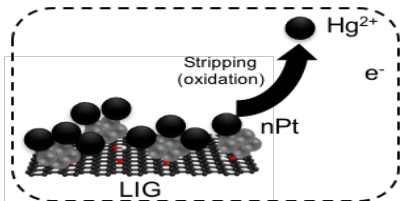
Persistent



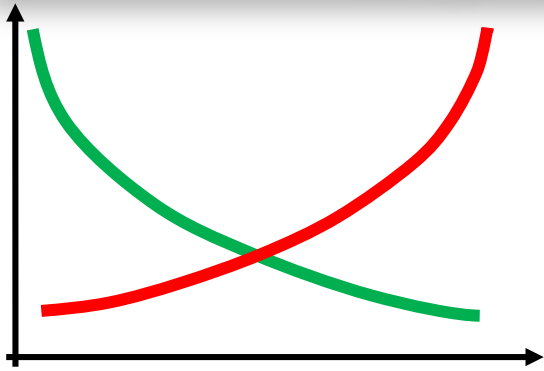
Urgent



Triage

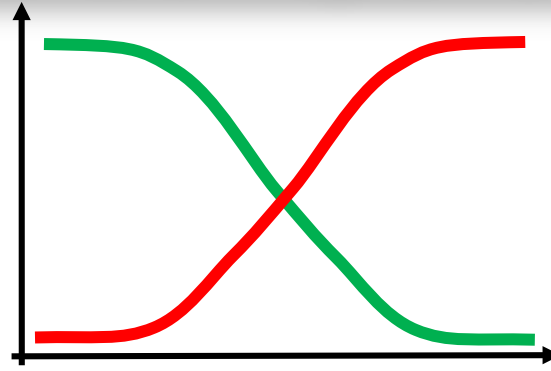


Varying Time-Sensitivity of Data from Sensors



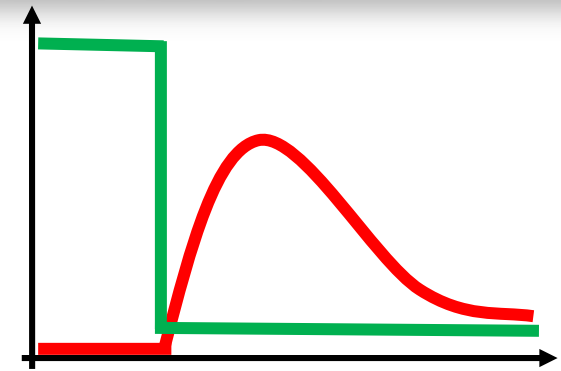
Persistent

- Soil health
 - Erosion, degradation
- Agrochemical runoff
 - Nutrients, agrochemicals
- Land use change
 - Deforestation, mining



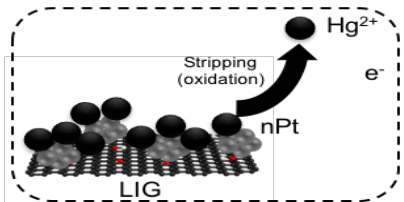
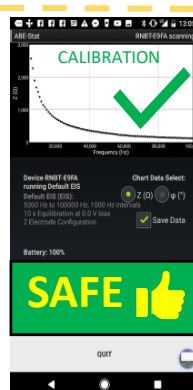
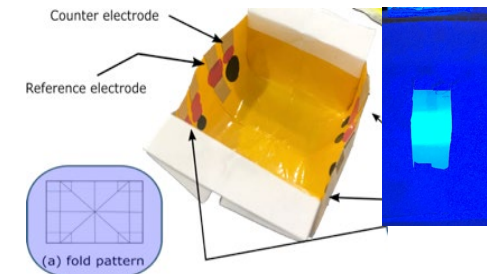
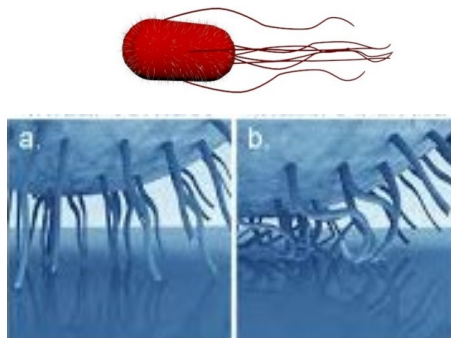
Urgent

- Water scarcity
 - Quantity, quality
- Climate change
- Solid waste/wastewater
 - Pathogens, heavy metals

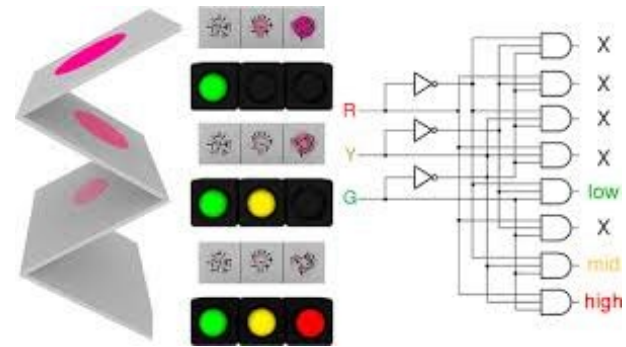
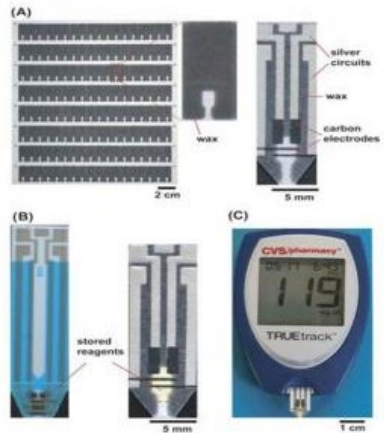
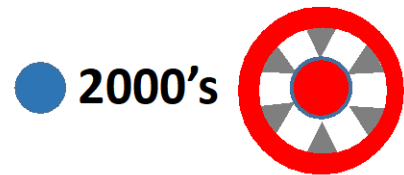
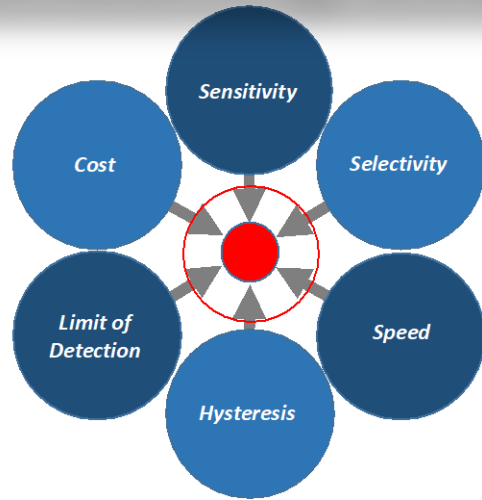
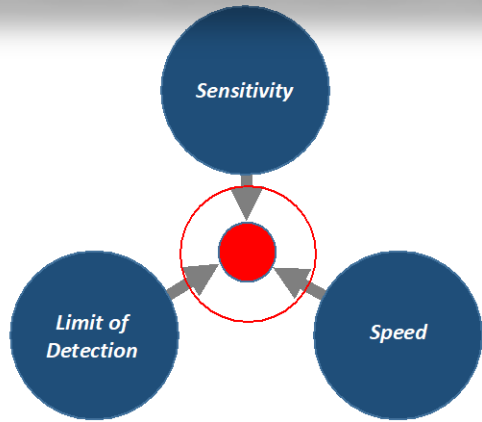


Triage

- Natural disaster
- Attack on infrastructure



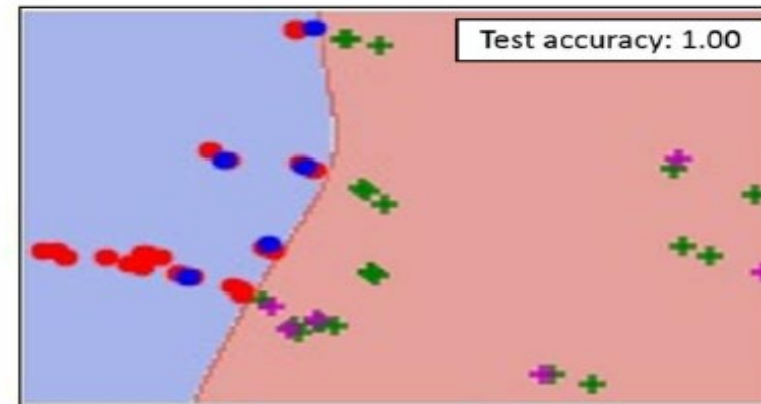
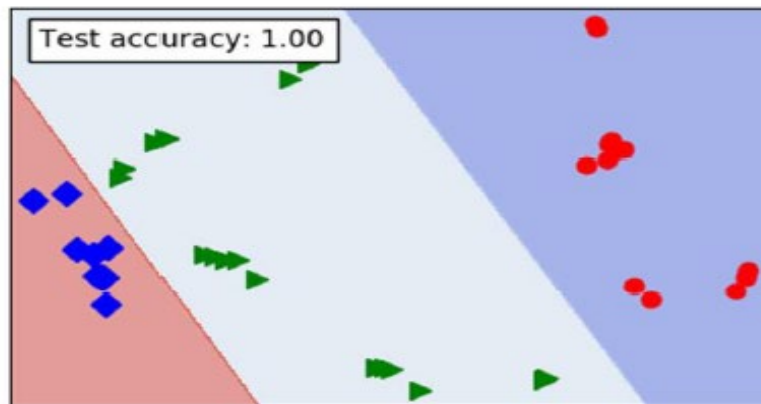
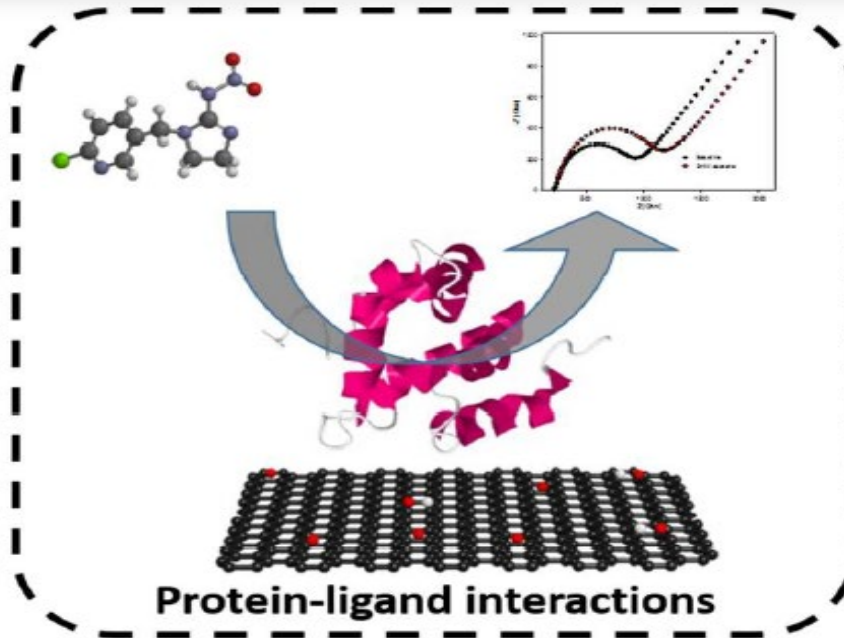
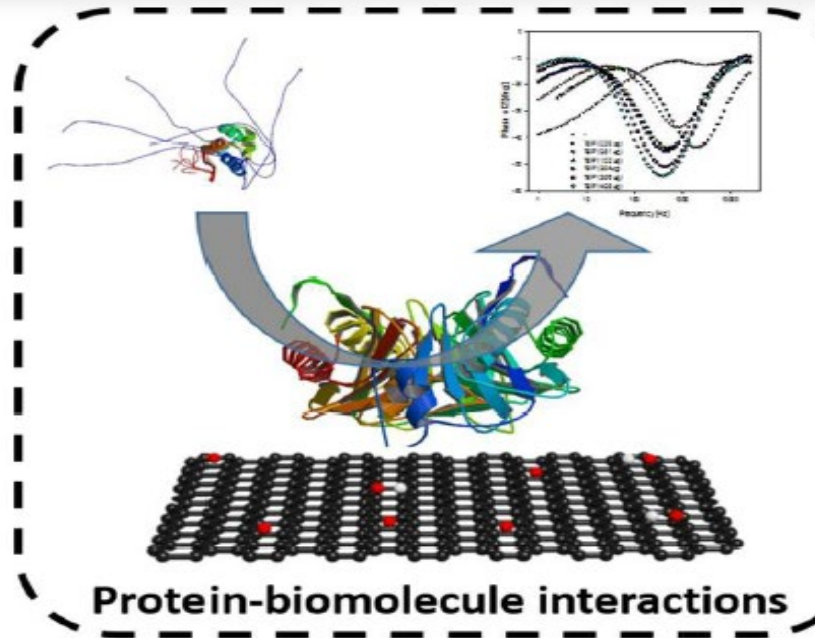
Has sensor engineering evolved with digital transformation



Original innovation



Water Polluted by Mercury (Hg)



Microbial Contamination of Water

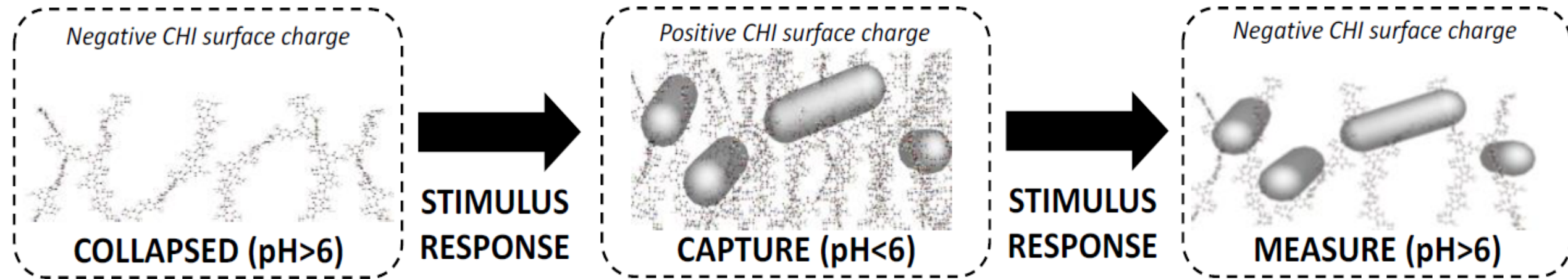
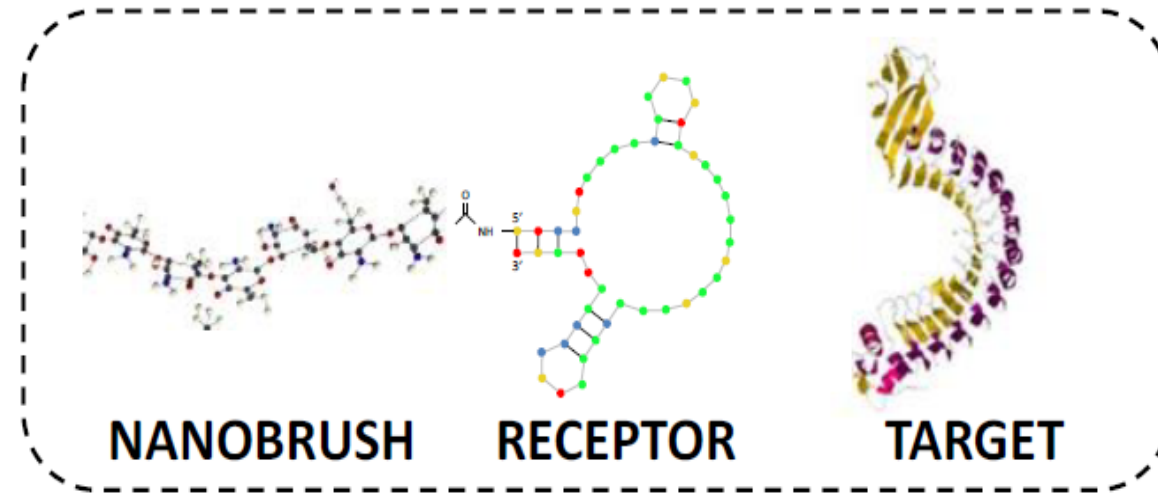


Image courtesy of [Hills et al \(2018\), Analyst](#), 143(7): 1650-1661.

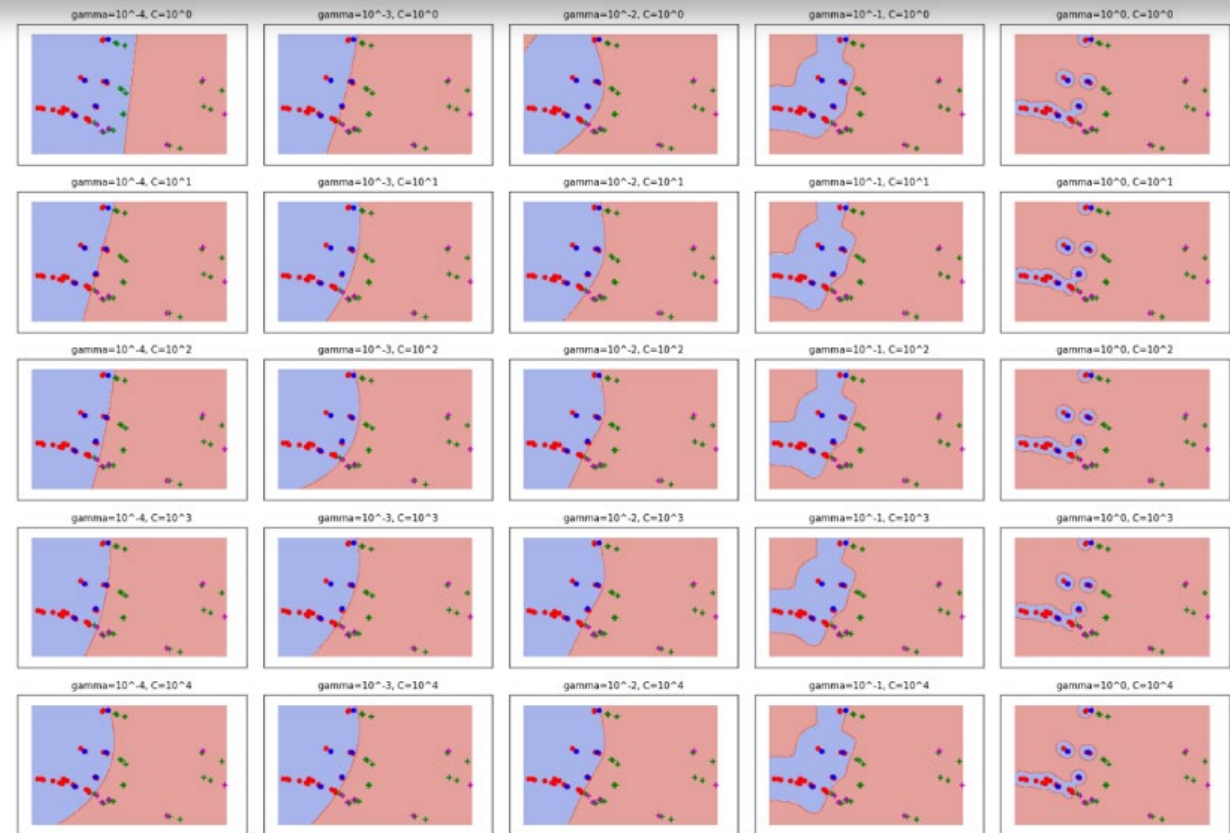
Water Contamination Data Analysis

Prior to running the support vector machine (SVM) algorithm, PCA (principal component analysis) was applied through singular value decomposition (SVD) to reduce 152 features to 2 principal components. PCA was used to reduce the dimension of 152 features in the raw EIS data to a two-dimensional principal components matrix. Depending on number of components to extract, full or randomized truncated SVD was used. To ensure general applicability across other application-specific biosensors, code screens were prepared for four types of SVM: kernels (linear, sigmoidal, radial basis function, polynomial) to identify which approach best segregates the training data.

Tuning of Gaussian radial base function (RBF) hyper-parameters (C and γ) for chemo-sensory proteins (CSP) acetone interactions. Recombinant insect chemosensory proteins (CSP) derived from *Glossina morsitans* (Gmm, tsetse fly) were heterologously expressed and purified from *E. coli* hosts. Representative support vector machine (SVM) classification results for one training and testing set show the effects of parameters C and γ in the output of the RBF kernels. Red and blue circles represent the baseline samples in training and testing sets; green and purple plus symbols represent the positive signals in training and testing sets. The background blue and red region indicated the classifier decision surface, where all data fall into the red region are predicted as positive.

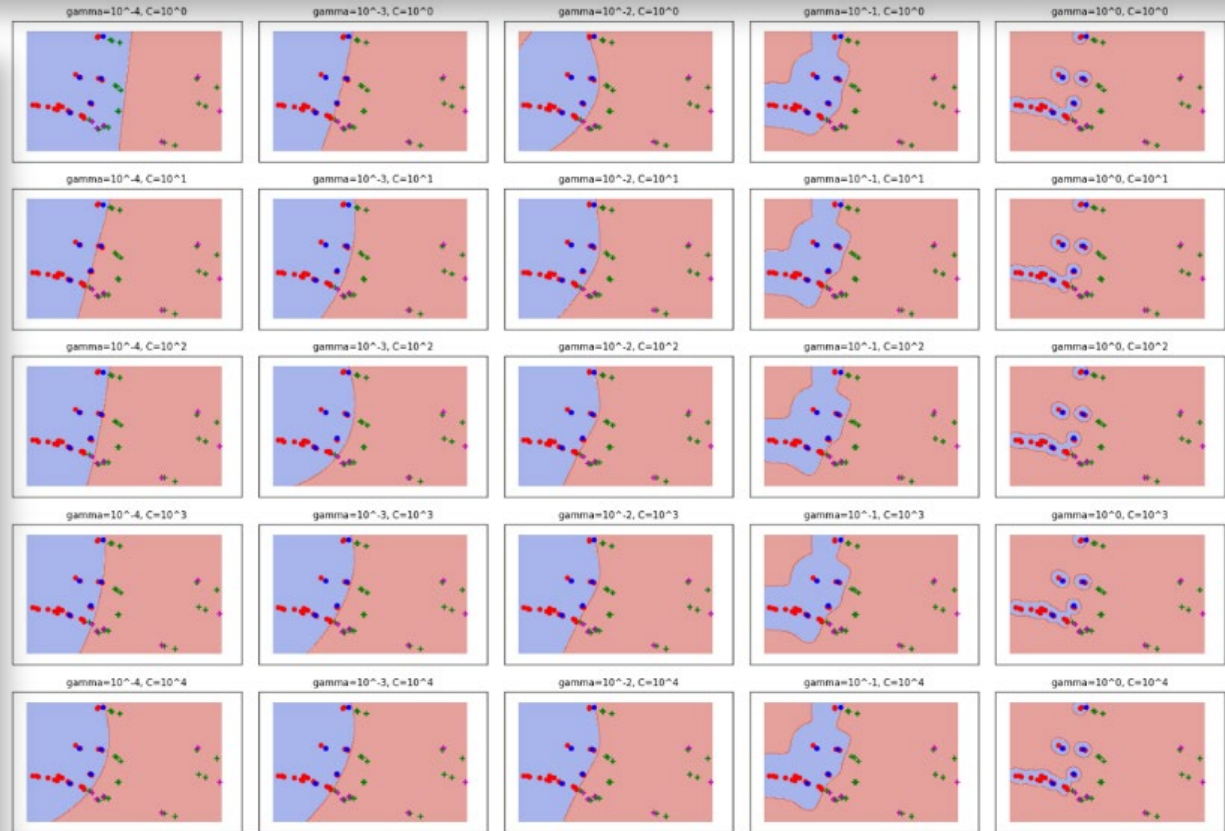


What is the value of this data analysis to the user ?



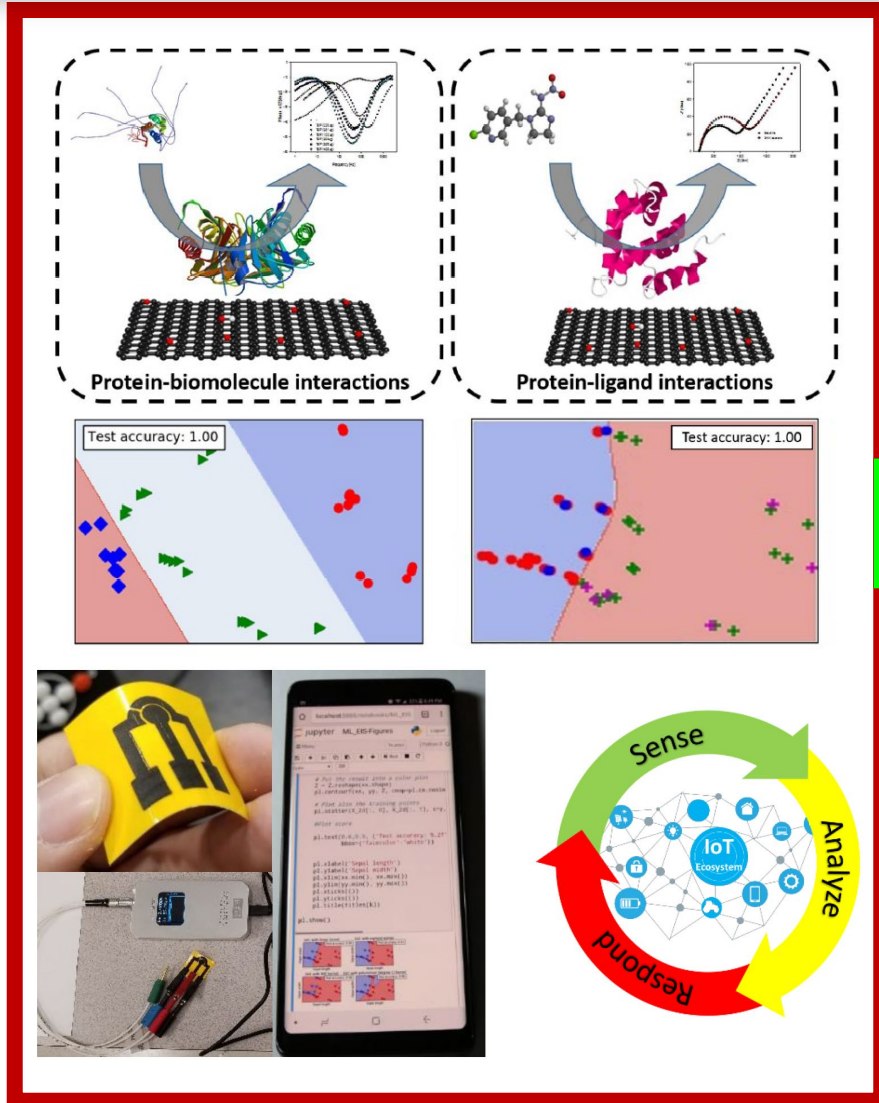
What is the value of this data analysis to the user ?

0

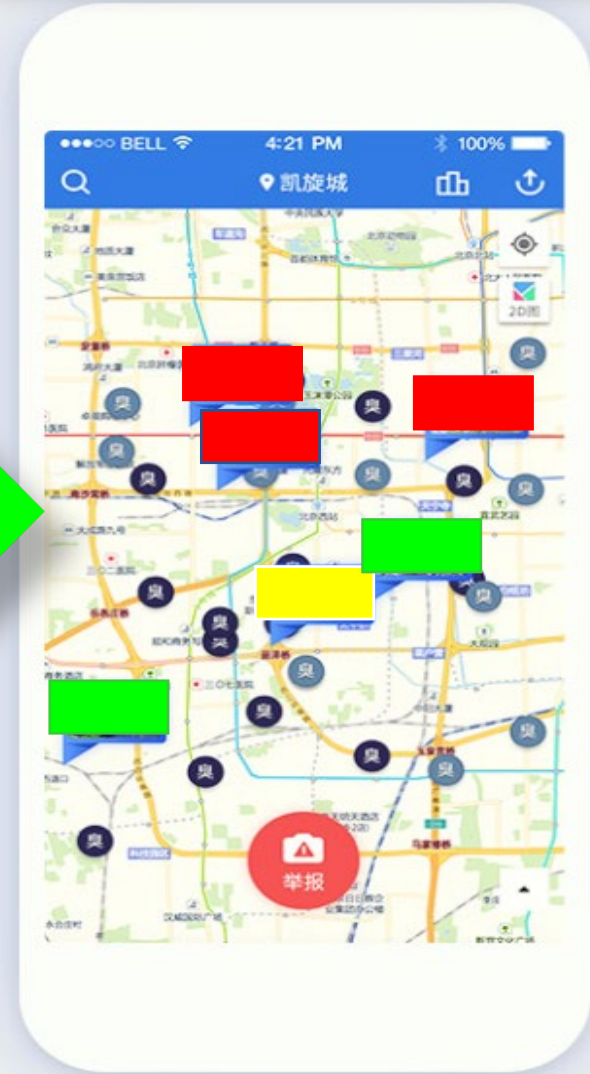


Z E R O

IoT-by-design: Data Analytics of Value to End-User



VALUE

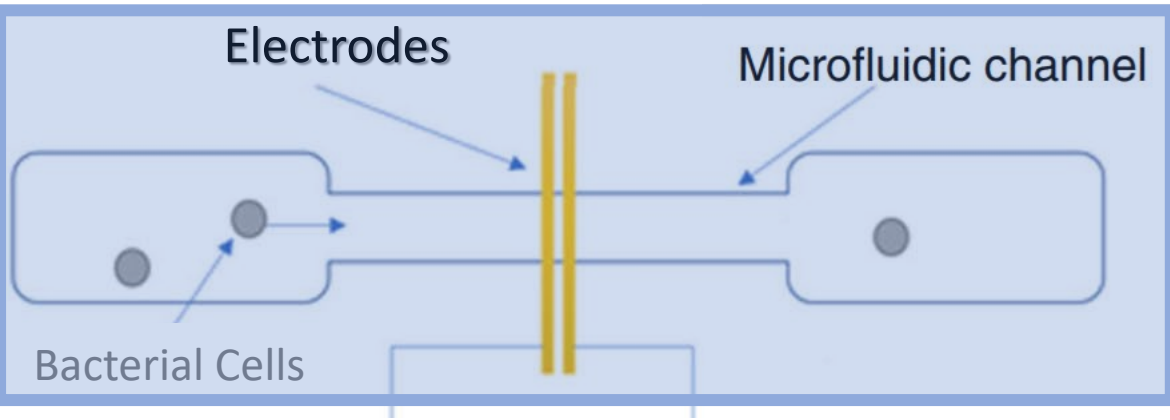


Near Real-Time Analytics: Data-Informed Services at the Edge

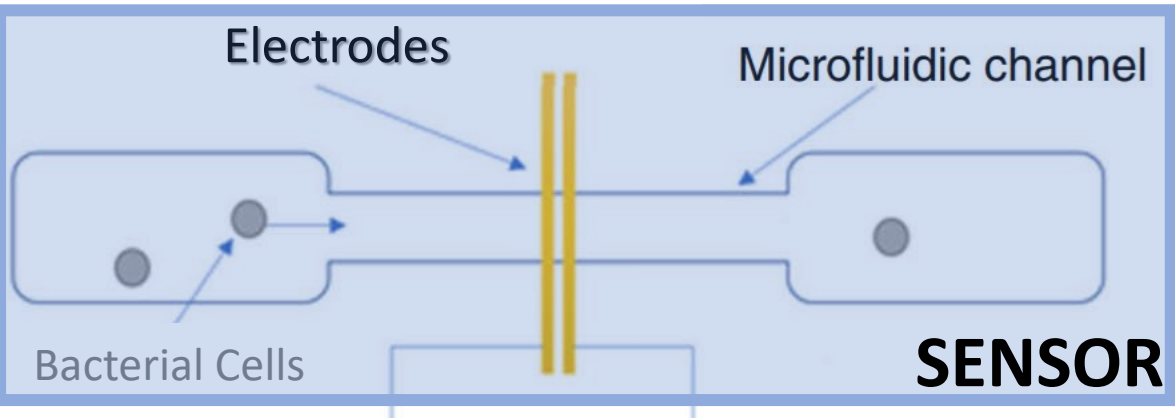
**Bacterial
Cells**

IoT-by-design: Data Analytics of Value to End-User

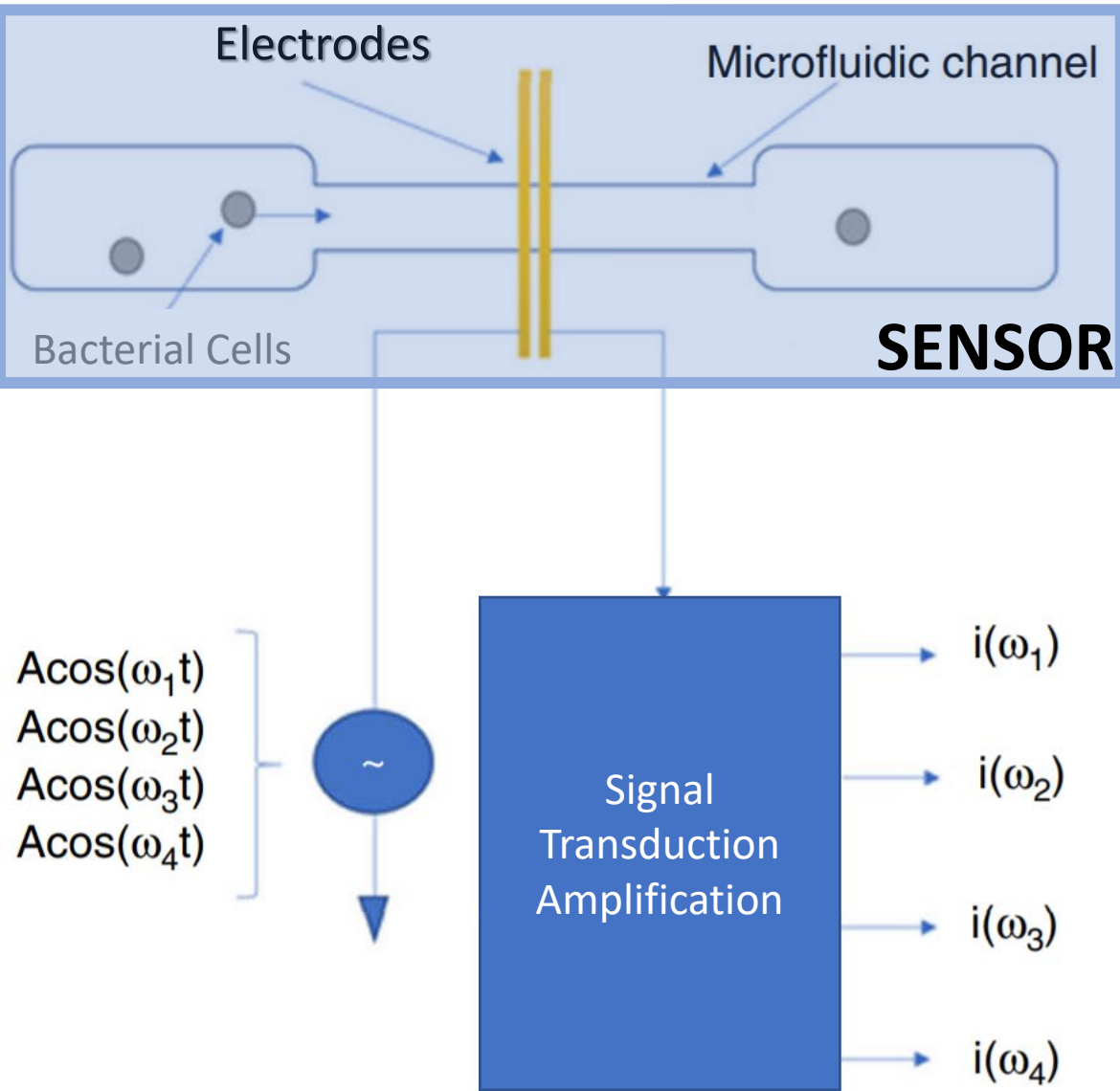
Near Real-Time Analytics: Data-Informed Services at the Edge



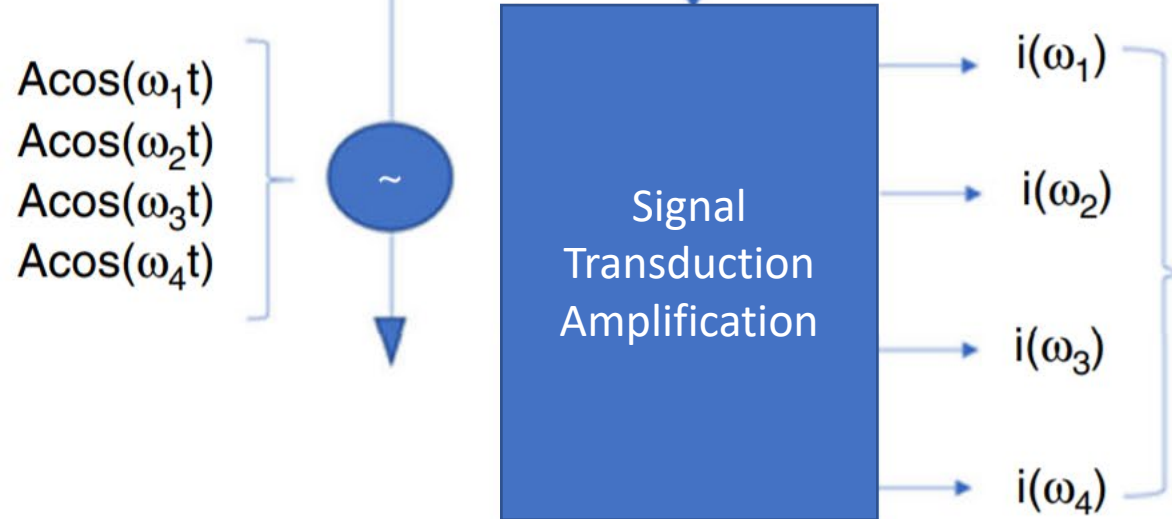
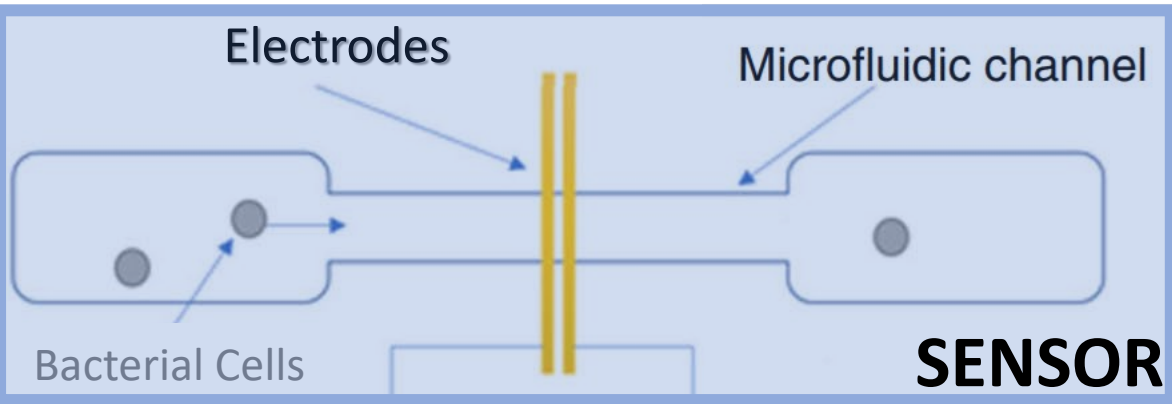
Near Real-Time Analytics: Data-Informed Services at the Edge



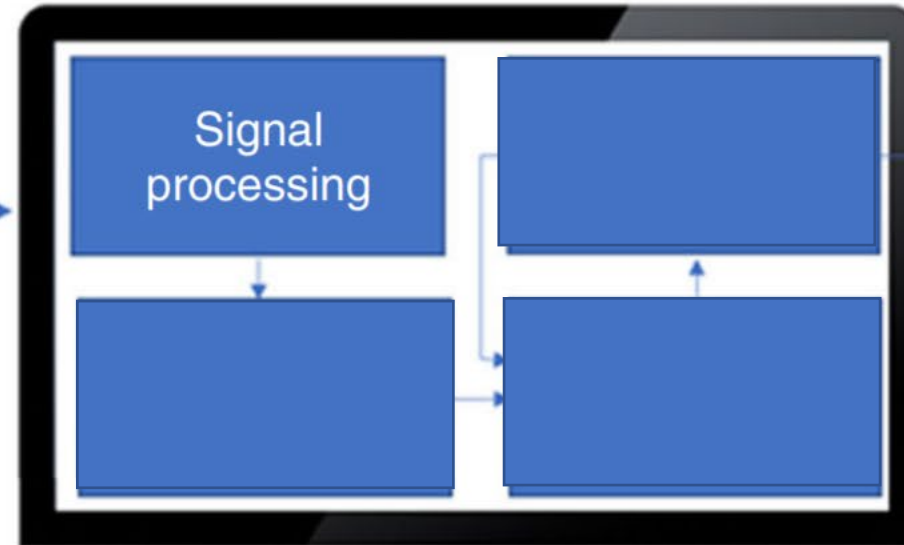
Near Real-Time Analytics: Data-Informed Services at the Edge



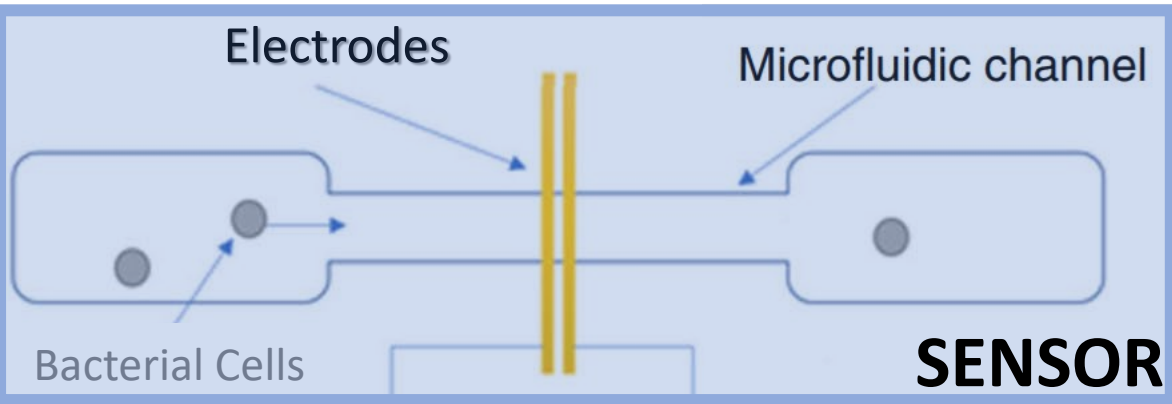
Near Real-Time Analytics: Data-Informed Services at the Edge



Mobile Device Tool-Kit at Point of Use



Near Real-Time Analytics: Data-Informed Services at the Edge

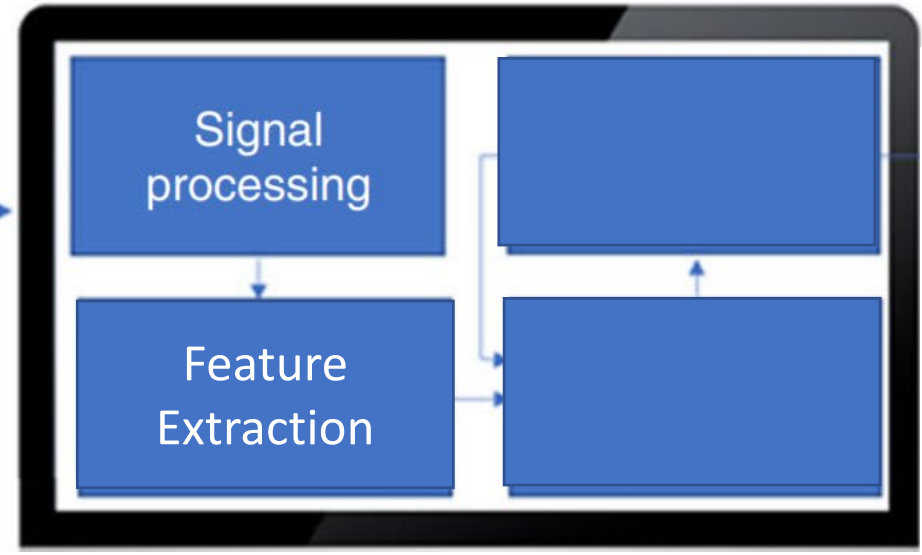


$A\cos(\omega_1 t)$
 $A\cos(\omega_2 t)$
 $A\cos(\omega_3 t)$
 $A\cos(\omega_4 t)$

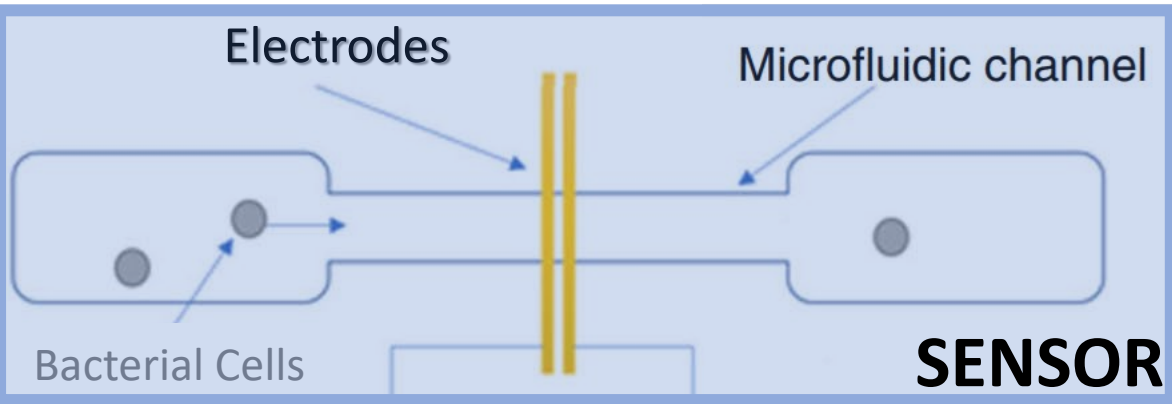


$i(\omega_1)$
 $i(\omega_2)$
 $i(\omega_3)$
 $i(\omega_4)$

Mobile Device Tool-Kit at Point of Use



Near Real-Time Analytics: Data-Informed Services at the Edge

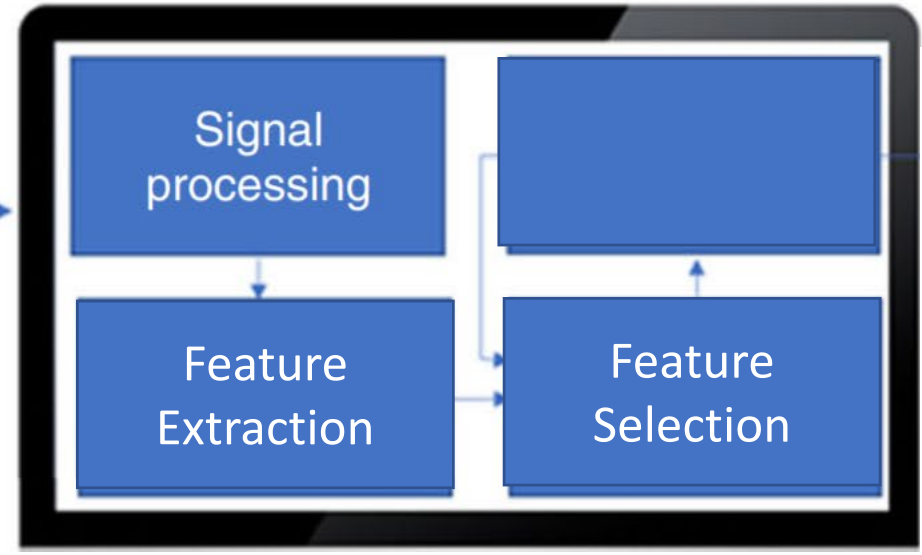


$A\cos(\omega_1 t)$
 $A\cos(\omega_2 t)$
 $A\cos(\omega_3 t)$
 $A\cos(\omega_4 t)$

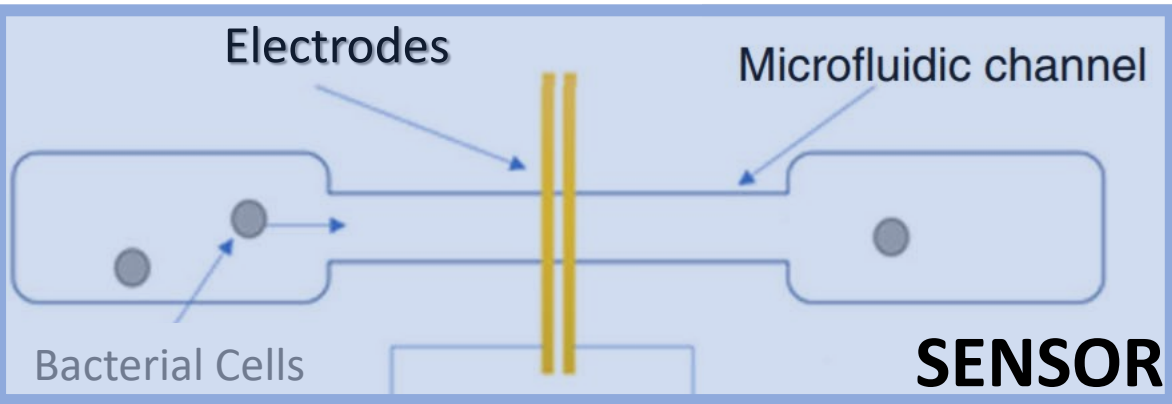


$i(\omega_1)$
 $i(\omega_2)$
 $i(\omega_3)$
 $i(\omega_4)$

Mobile Device Tool-Kit at Point of Use



Near Real-Time Analytics: Data-Informed Services at the Edge

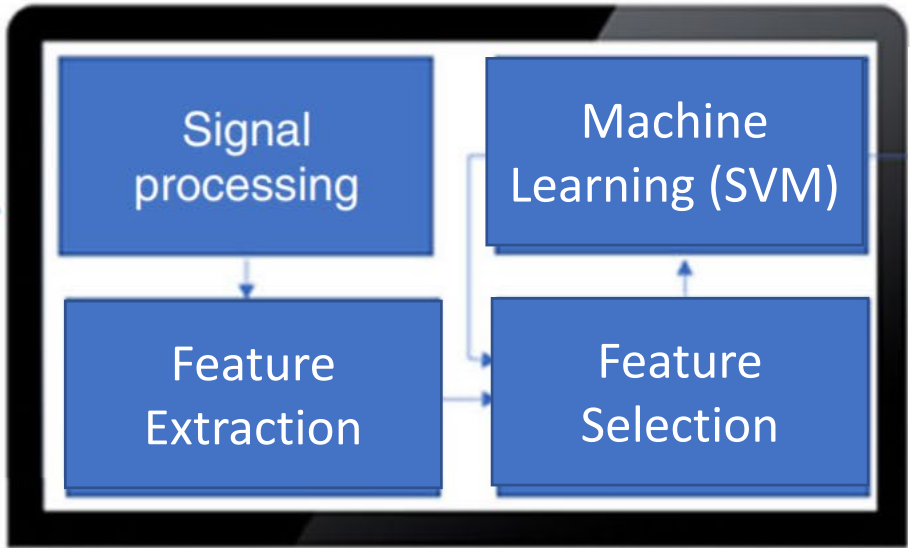


$A\cos(\omega_1 t)$
 $A\cos(\omega_2 t)$
 $A\cos(\omega_3 t)$
 $A\cos(\omega_4 t)$

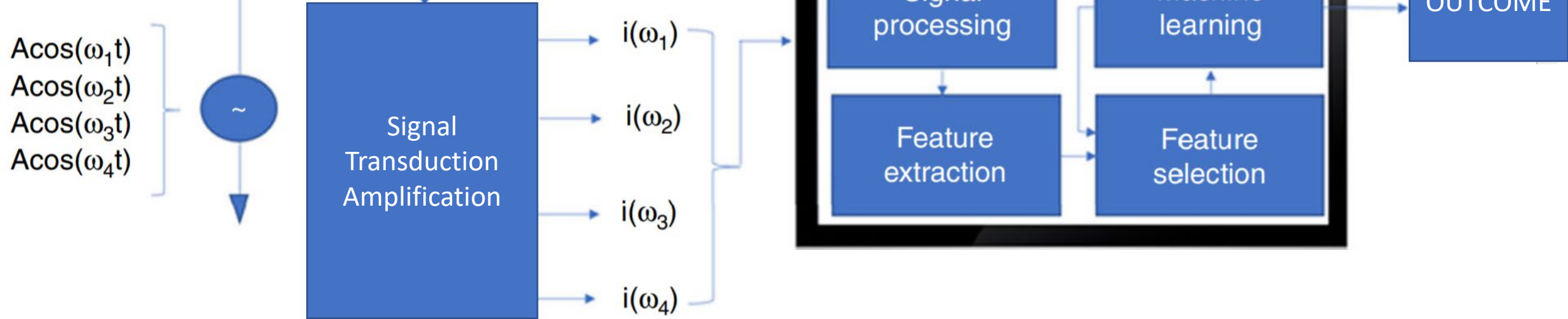
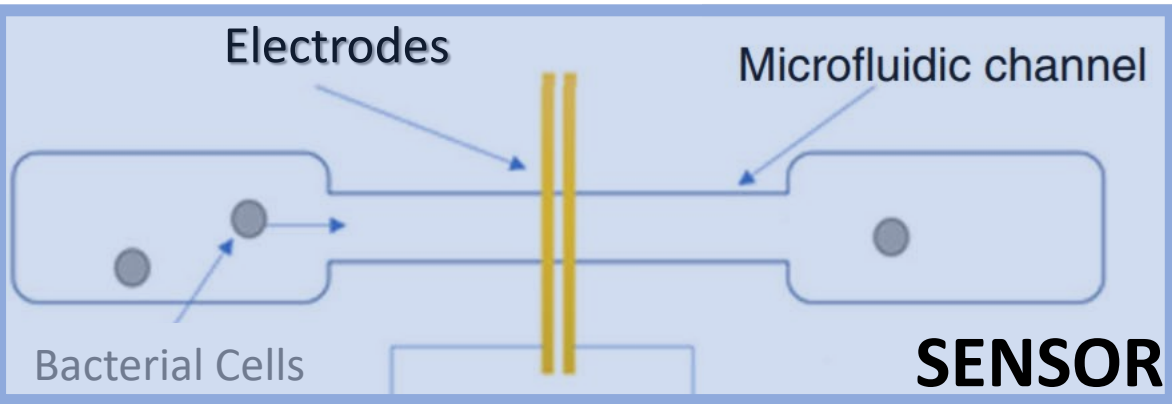


$i(\omega_1)$
 $i(\omega_2)$
 $i(\omega_3)$
 $i(\omega_4)$

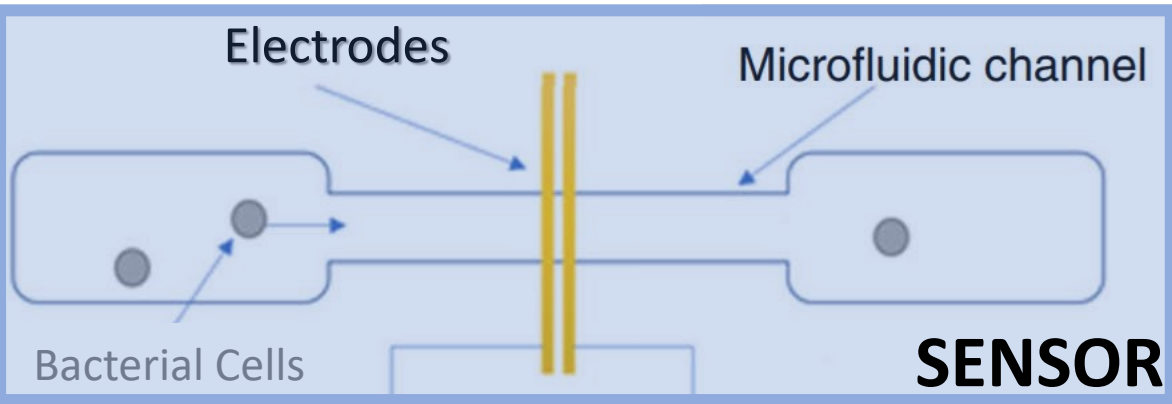
Mobile Device Tool-Kit at Point of Use



Near Real-Time Analytics: Data-Informed Services at the Edge



Near Real-Time Analytics: Data-Informed Services at the Edge

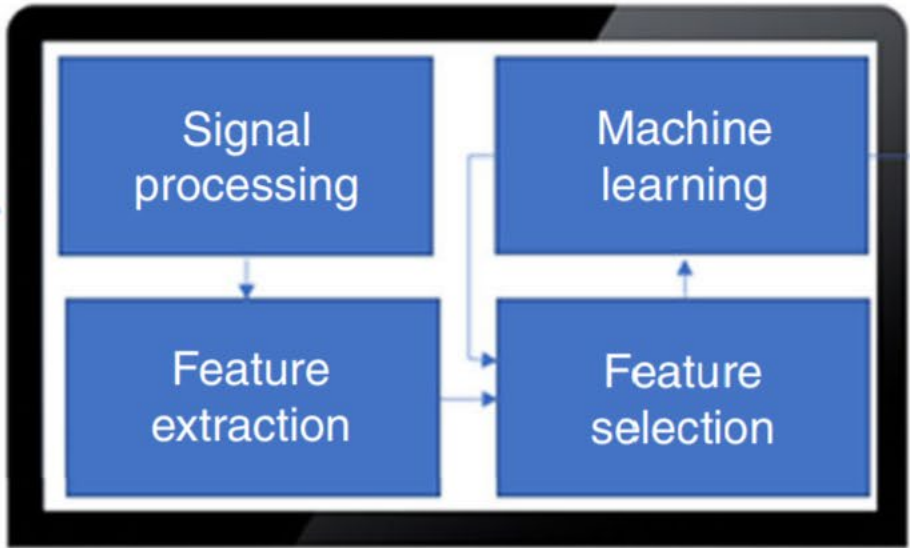


$A\cos(\omega_1 t)$
 $A\cos(\omega_2 t)$
 $A\cos(\omega_3 t)$
 $A\cos(\omega_4 t)$

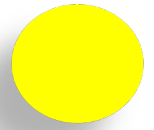


$i(\omega_1)$
 $i(\omega_2)$
 $i(\omega_3)$
 $i(\omega_4)$

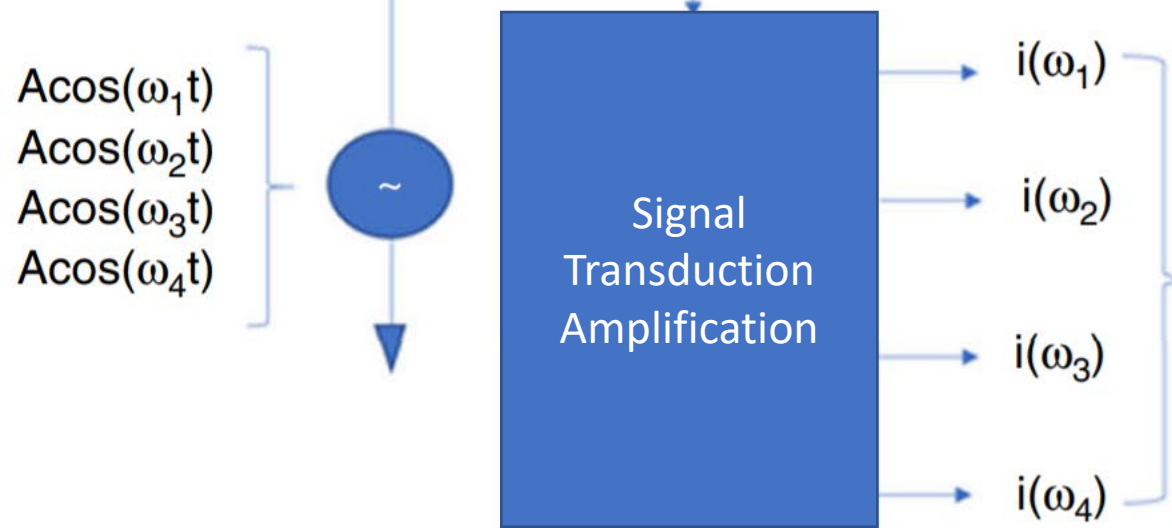
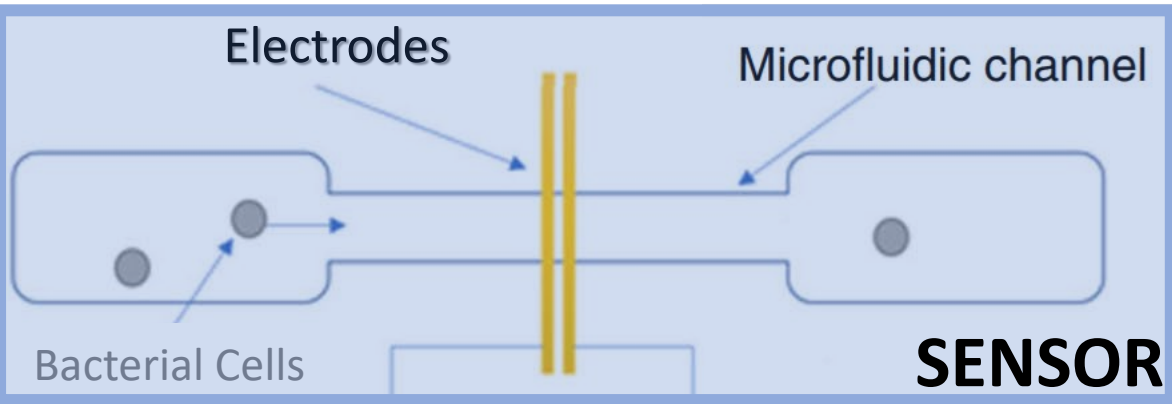
Mobile Device Tool-Kit at Point of Use



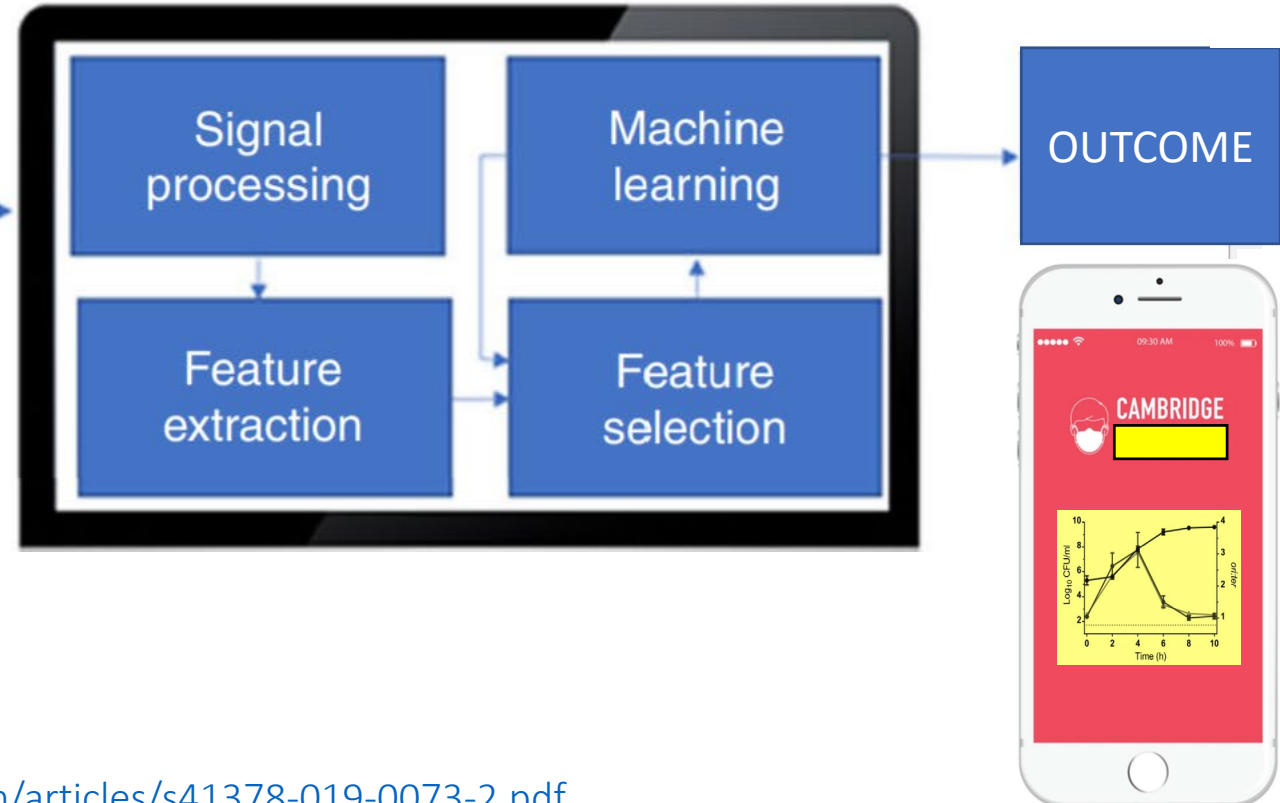
OUTCOME



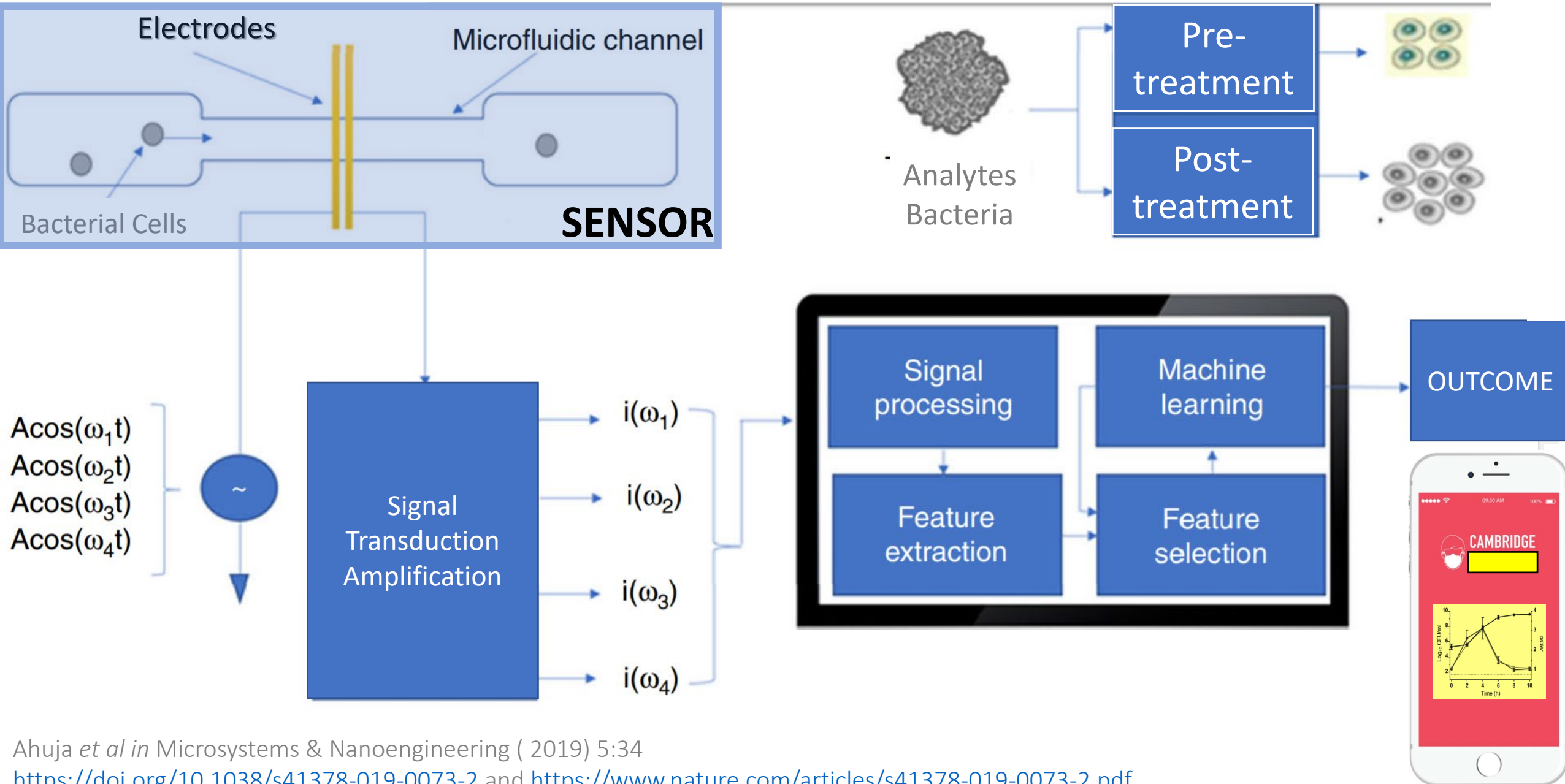
Near Real-Time Analytics: Data-Informed Services at the Edge



Mobile Device Tool-Kit at Point of Use

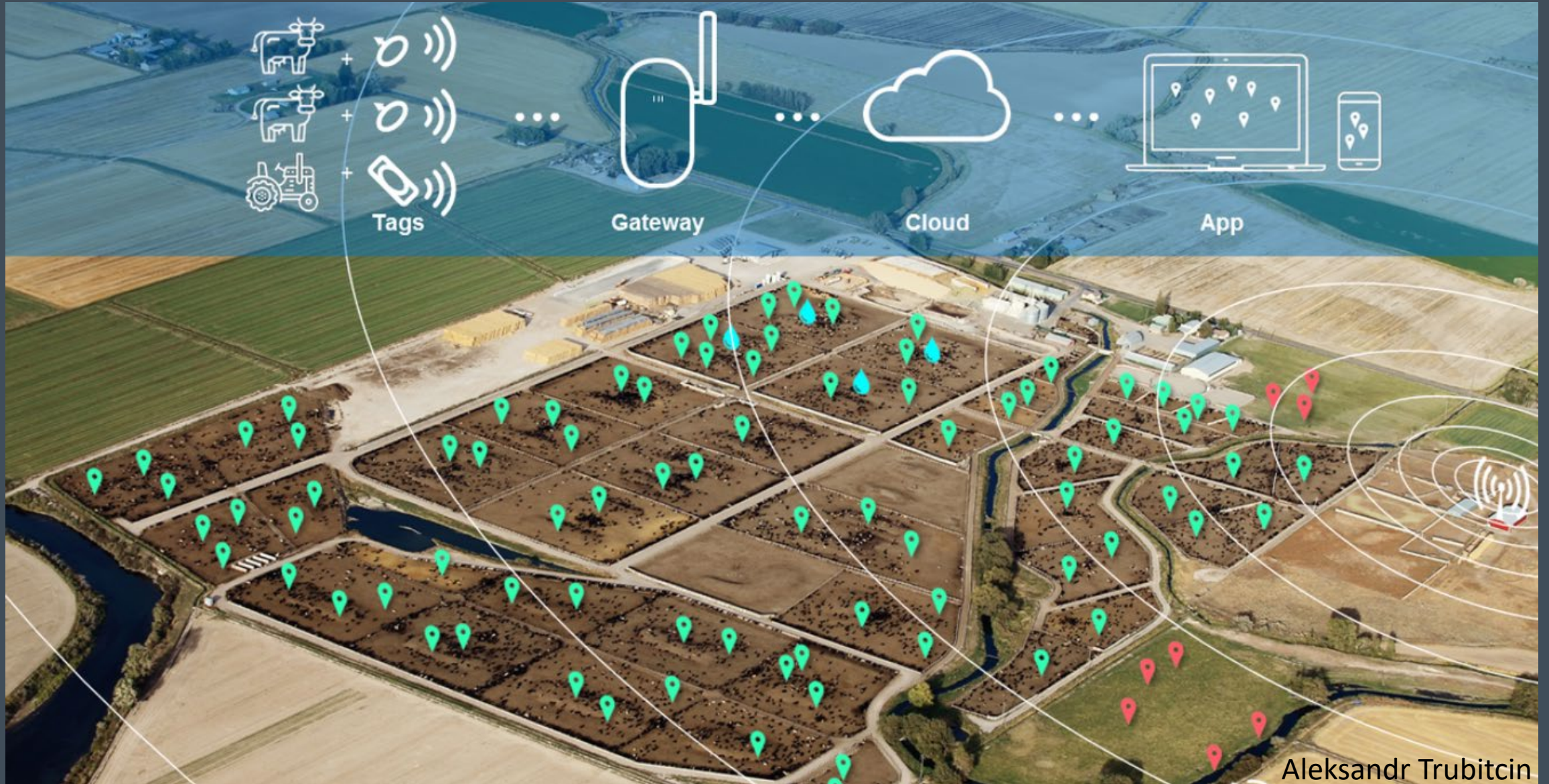


Near Real-Time Analytics: Data-Informed Services at the Edge



IoT-by-design: Data Analytics of Value to End-User

See SIGNALS - <https://dspace.mit.edu/handle/1721.1/1111021>



LoRaWAN Cattle Ear Tags: 200 acre feed-lot for 10,000 cows

IoT-BY-DESIGN: PAY A PENNY PER UNIT (PAPPU) PARADIGM ?

Fill in the details of your deployment.

Install Address

421 N 3200 E, Lewisville, ID 8343

Install Environment

Rural

Gateway Height

50 ft

Select Gateway

Field 64c

SF 7 | SF 8 | SF 9 | SF 10

Sensor Placement

Outdoor

Sensor Height

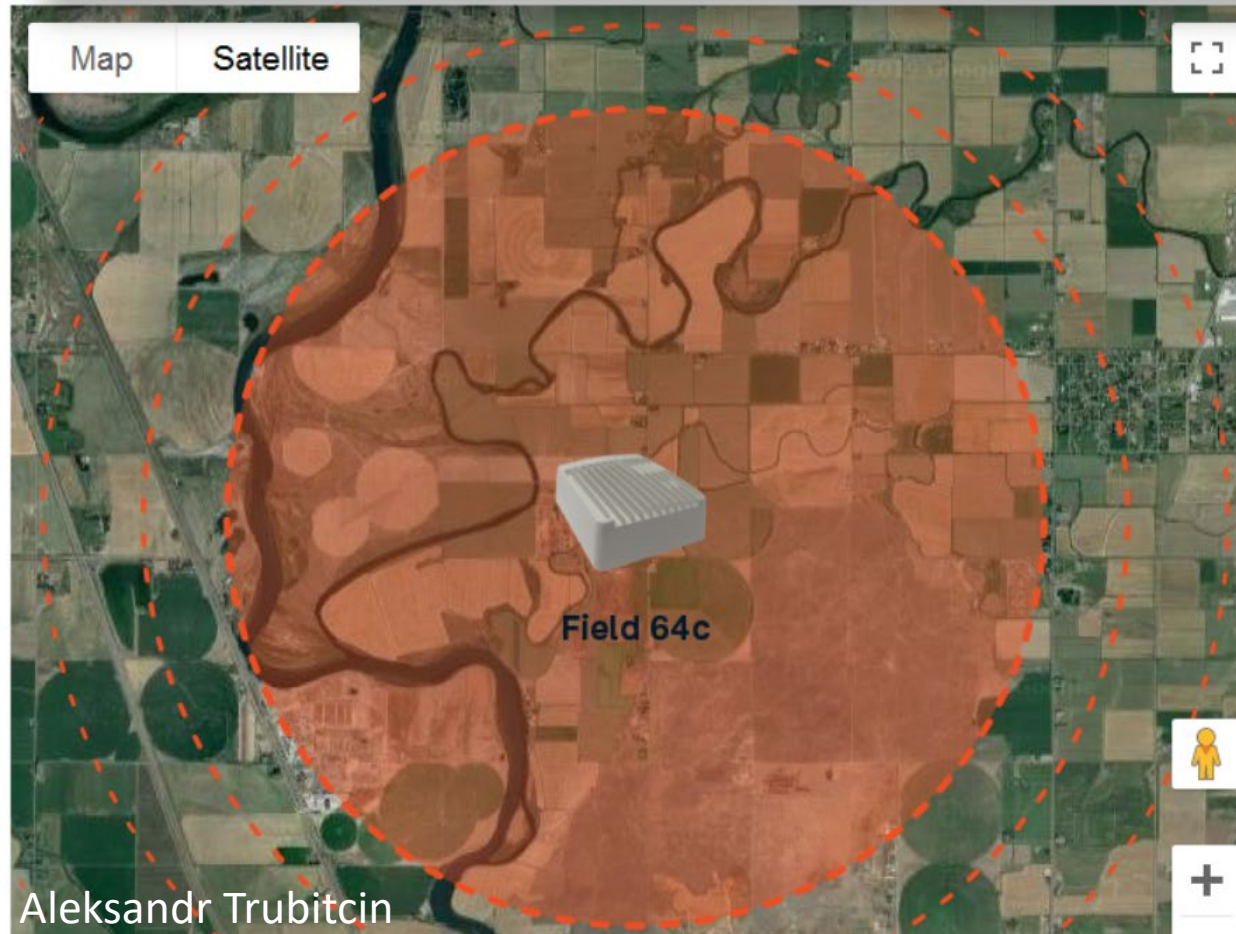
1 ft

Sensor Tx Power

14 dBm

Estimated Gateway Range
3.5 miles

CONNECTIVITY costs \$0.00137 per cow per day



Field 64c gateway with 64 channels of LoRaWAN connectivity and Ethernet/cellular backhaul manufactured by Tektelic, Canada.
MachineQ prices:
Gateway Field 64c \$2800 (CAPEX)
Software License \$4979 pa (OPEX)
Cell \$119 per gateway pa (OPEX)
Connectivity fee per animal (10,000) US \$0.50 per year (50 cents pa)

**0.001
cents**

LoRaWAN Cattle Ear Tags: 200 acre feed-lot for 10,000 cows

IoT SYSTEMS: HOW NANO-FEES MAY GENERATE MEGA-MILLIONS

The user will also need access to the cattle tracking and monitoring web application. For example, the cost of an annual subscription to the Cattle Tags Technologies app will be \$5 per animal.



0.12
cents

Software subscription cost \$0.0137 per cow per day



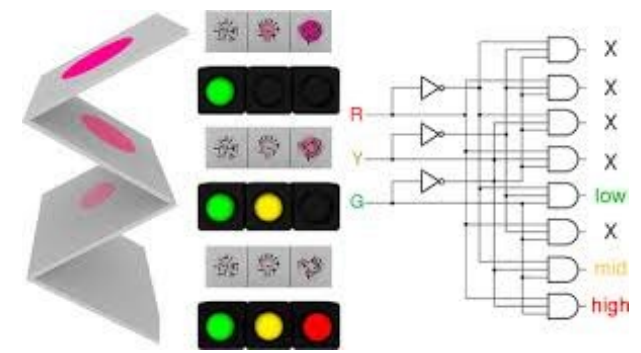
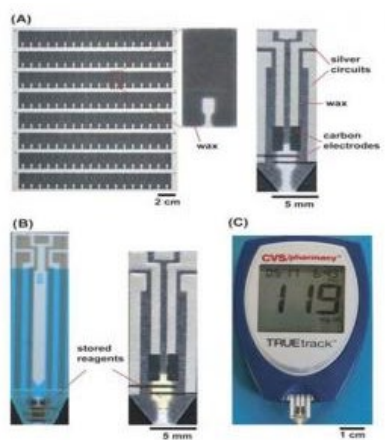
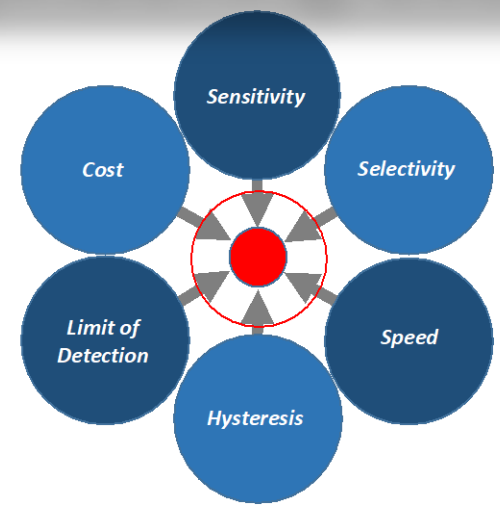
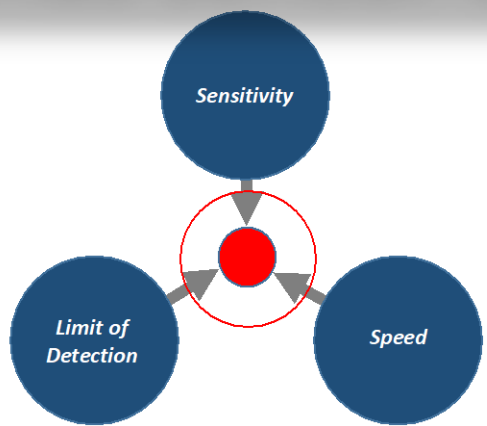
- End-User Needs (farmers, feedlots owners)
- Animal location, geo-fencing, theft alert
 - Health alerts and birthing status alert
 - Water and feeding related behavior
 - Activity monitoring for selection
 - Landscape utilization control

Aleksandr Trubitcin

LoRaWAN ear tag from Cattle Tags Technologies starts from \$39. Tags have embedded GPS receiver, accelerometer, temperature sensor and replaceable battery. Operator reads RFID-tag with Bluetooth reader (ID sent to ERP system). Installation of activated LoRaWAN ear tag follows. alex.trubitcin@gmail.com

Digital Transformation (Connectivity+App+Tag) Cost \$0.12 per cow per day

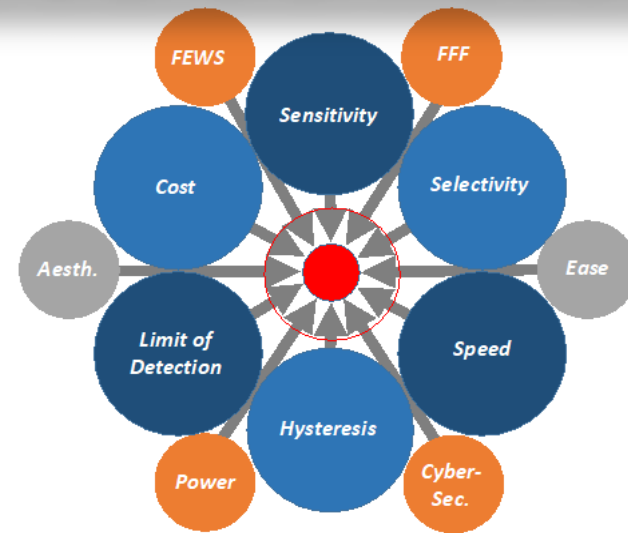
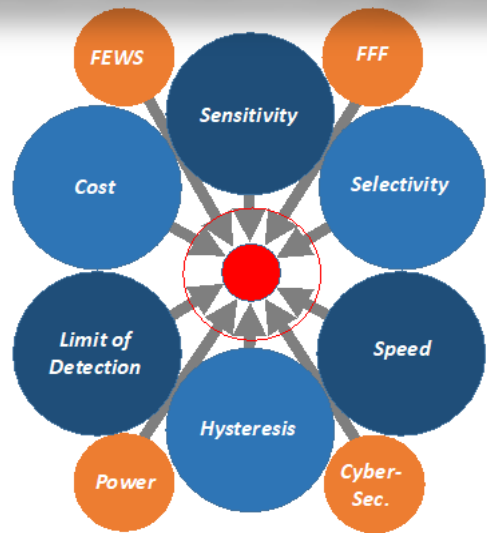
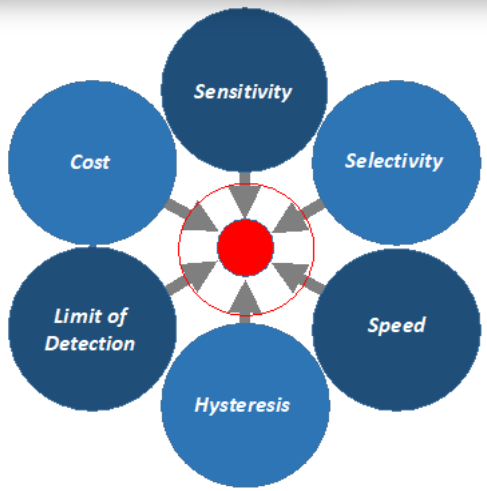
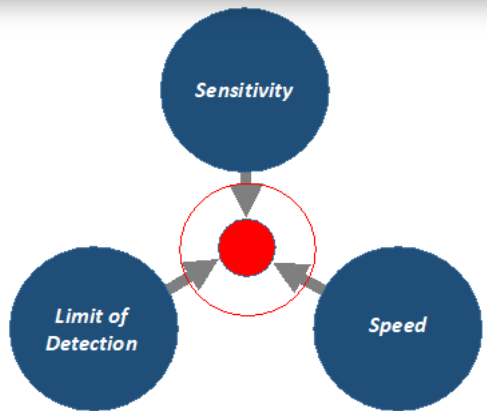
Has sensor engineering evolved with digital transformation



Original innovation



Has sensor engineering evolved with digital transformation

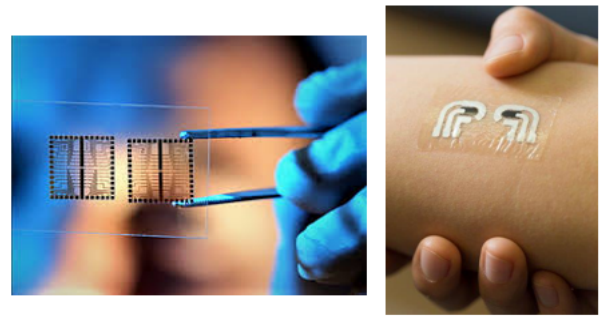
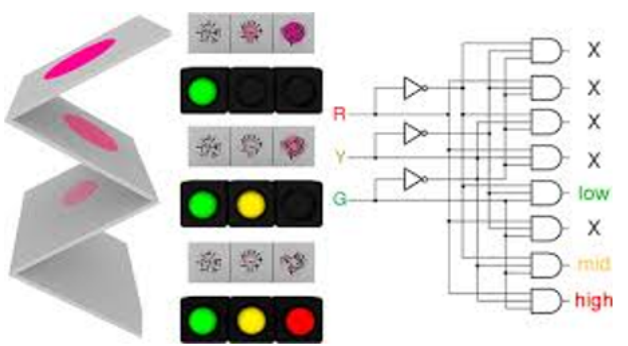
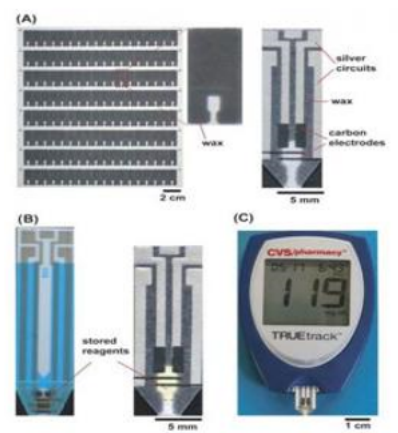


● 1990's

● 2000's

● 2010's

● 2020's



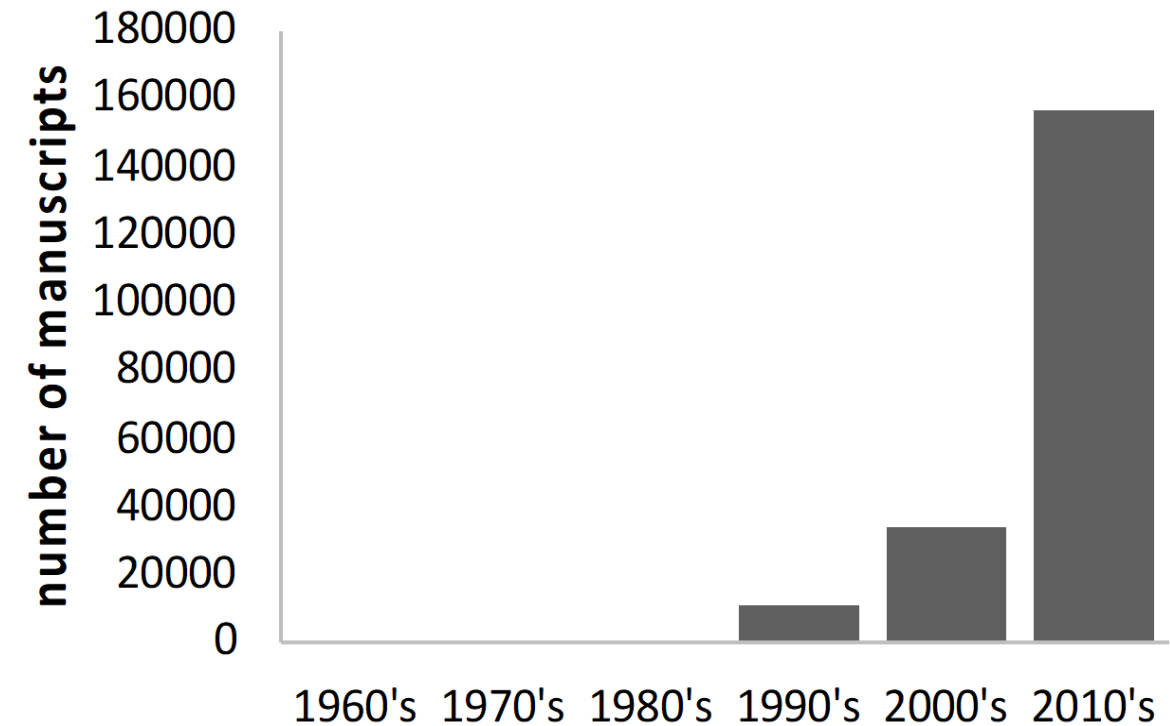
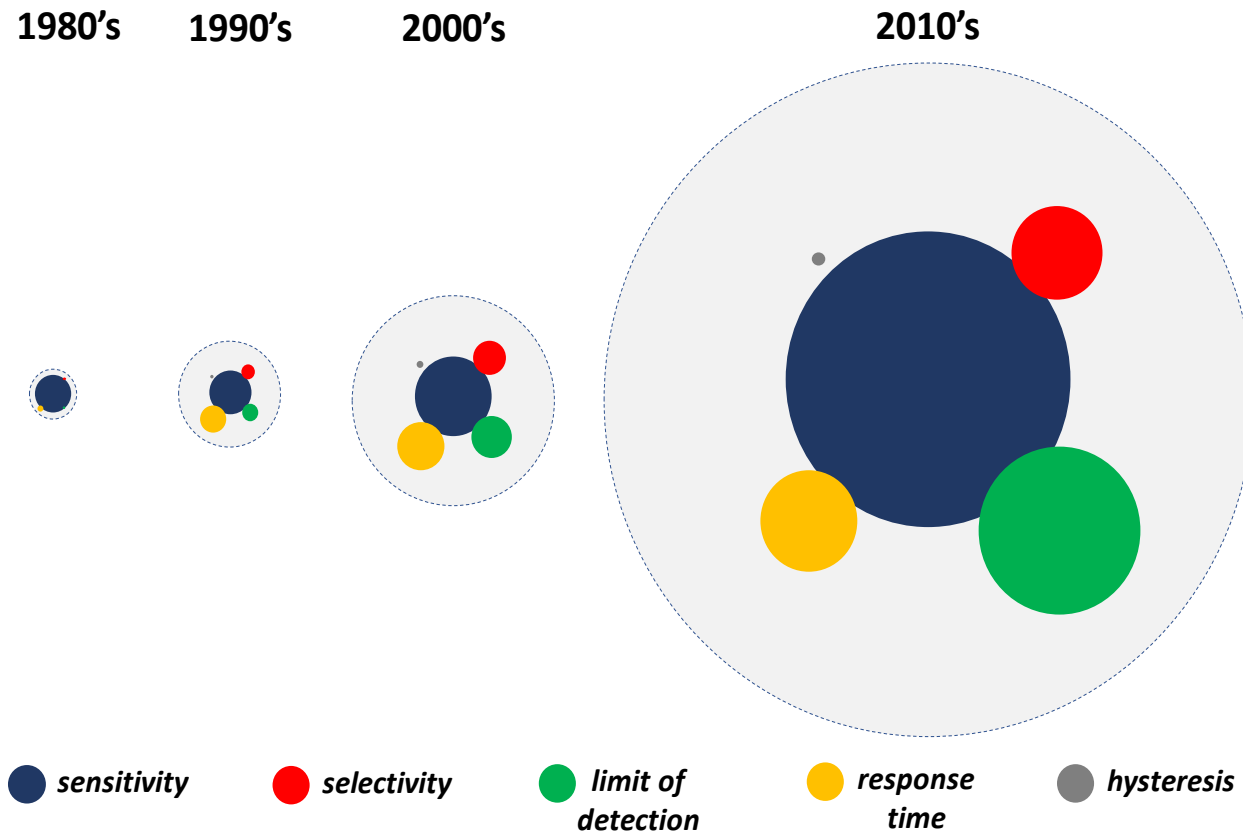
Original innovation

Digital transformation

Activate Windows
Go to Settings to activate Windows.

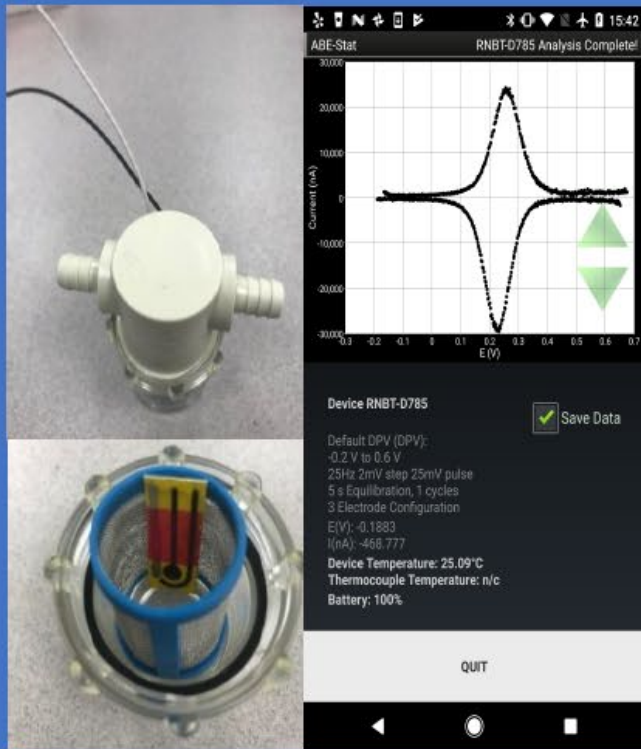
Sensor engineering has evolved with digital transformation

Sensor characteristics evolved (based on 50 yrs of papers)



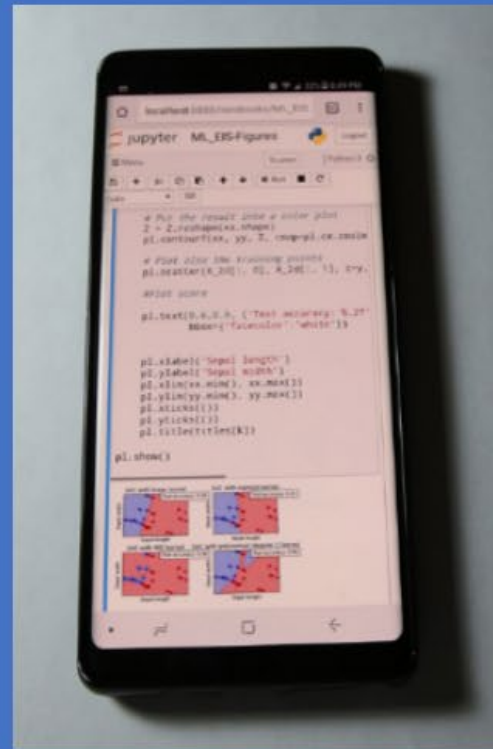
Sensor engineering has evolved with digital transformation

Sense



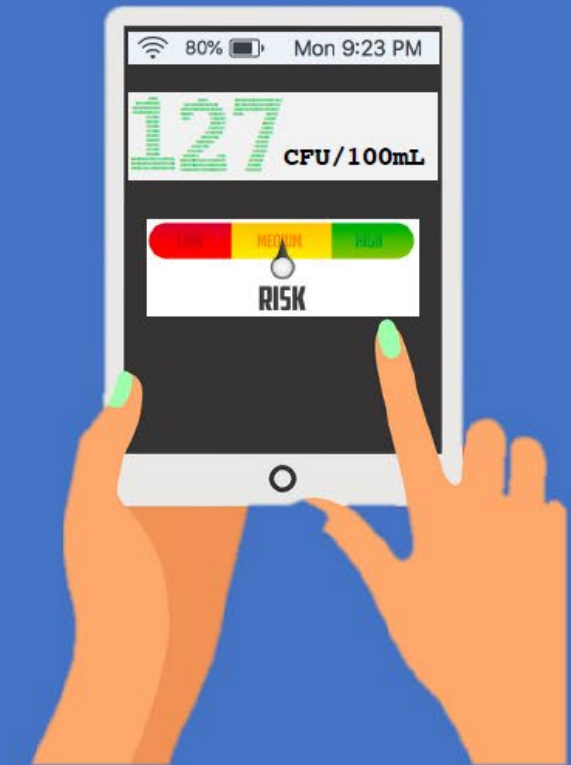
E. coli sensor

Analyze



Analysis

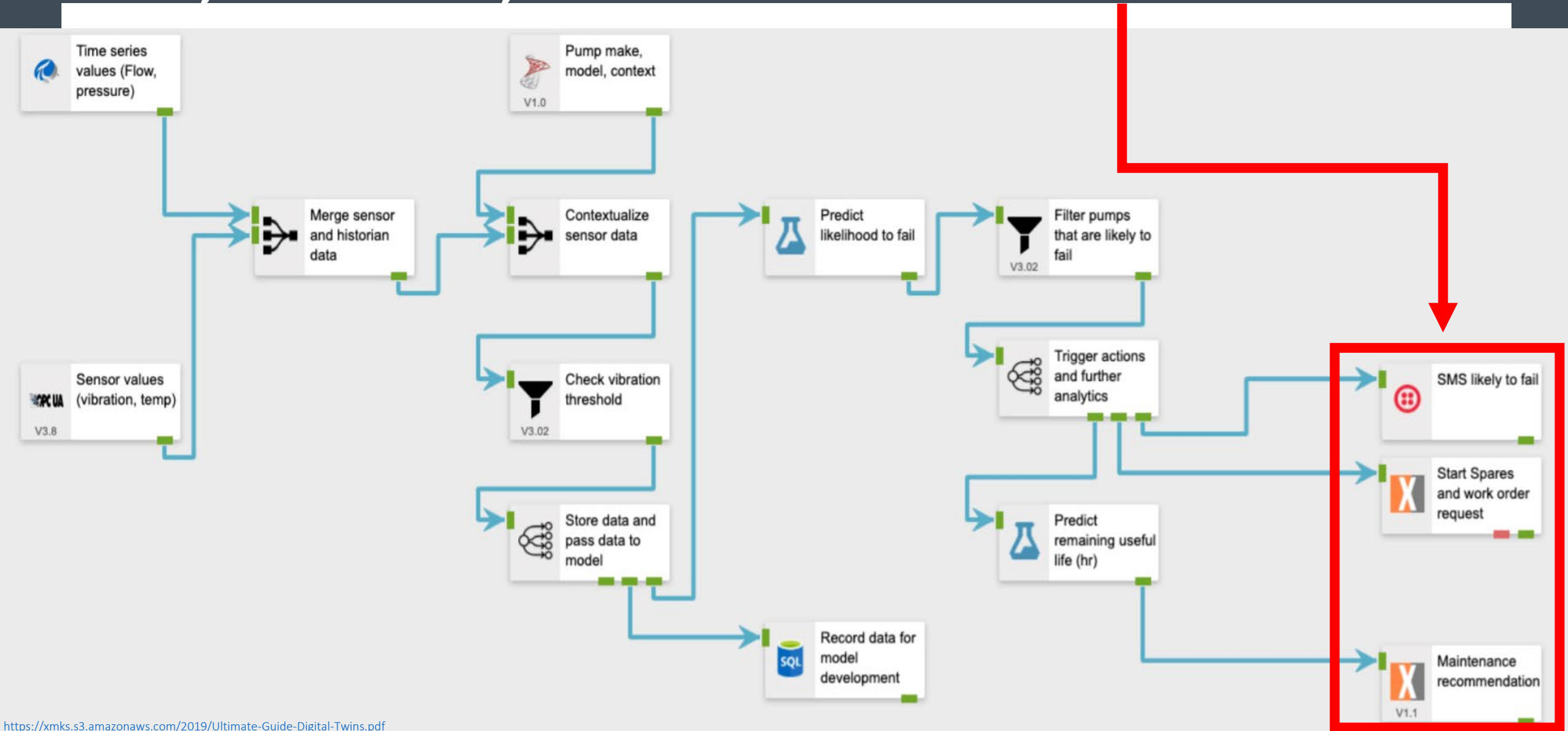
Respond



ART feature

SENSE, ANALYZE, RESPONSE SYSTEMS – SARS

SENSE, ANALYZE, RESPOND – MAY NOT BE ENOUGH



<https://xmks.s3.amazonaws.com/2019/Ultimate-Guide-Digital-Twins.pdf>

SENSE, ANALYZE, RESPOND, AUTO-ACTUATE → SARA

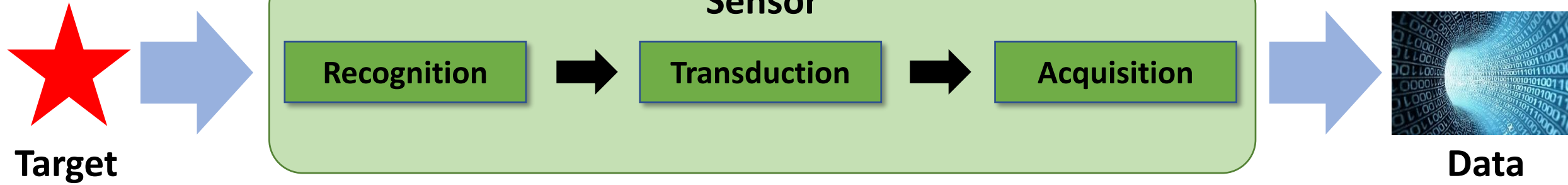
Role of Sensors and Sensor Data in Decision as a Service



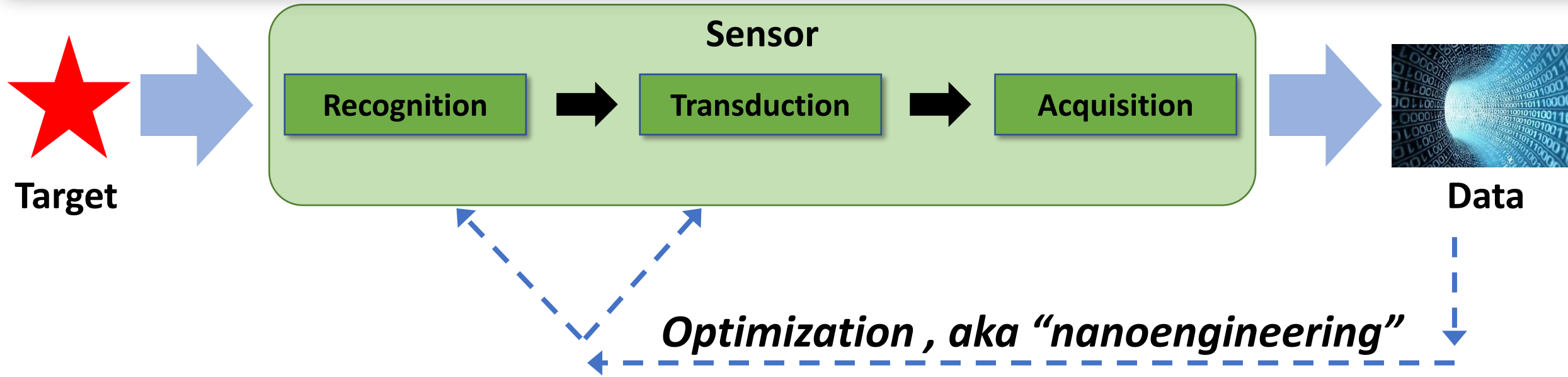
Target

Sensor

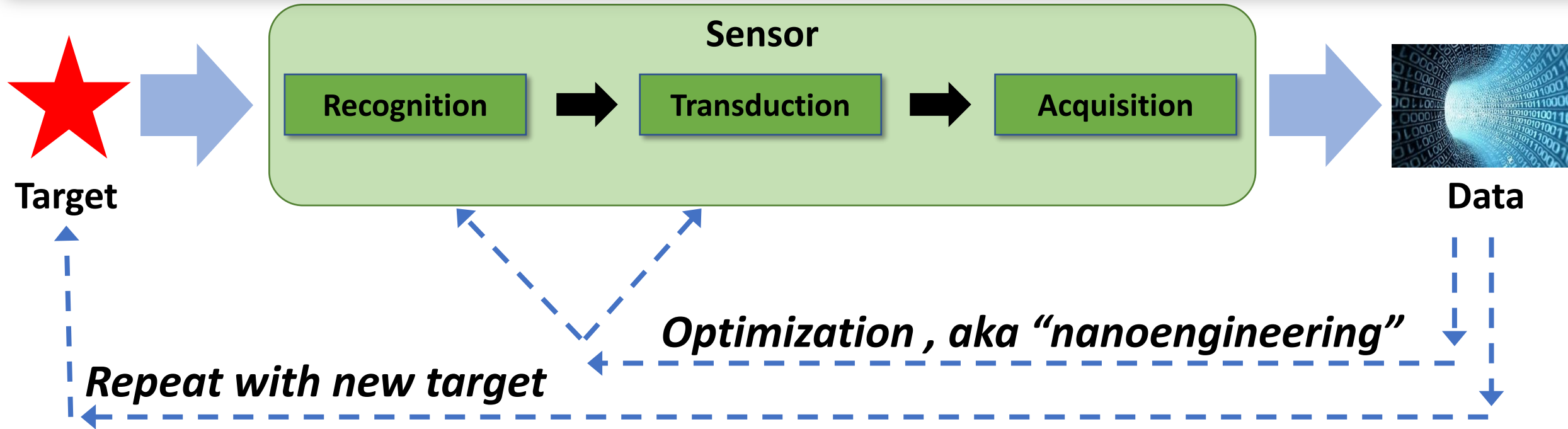
Role of Sensors and Sensor Data in Decision as a Service



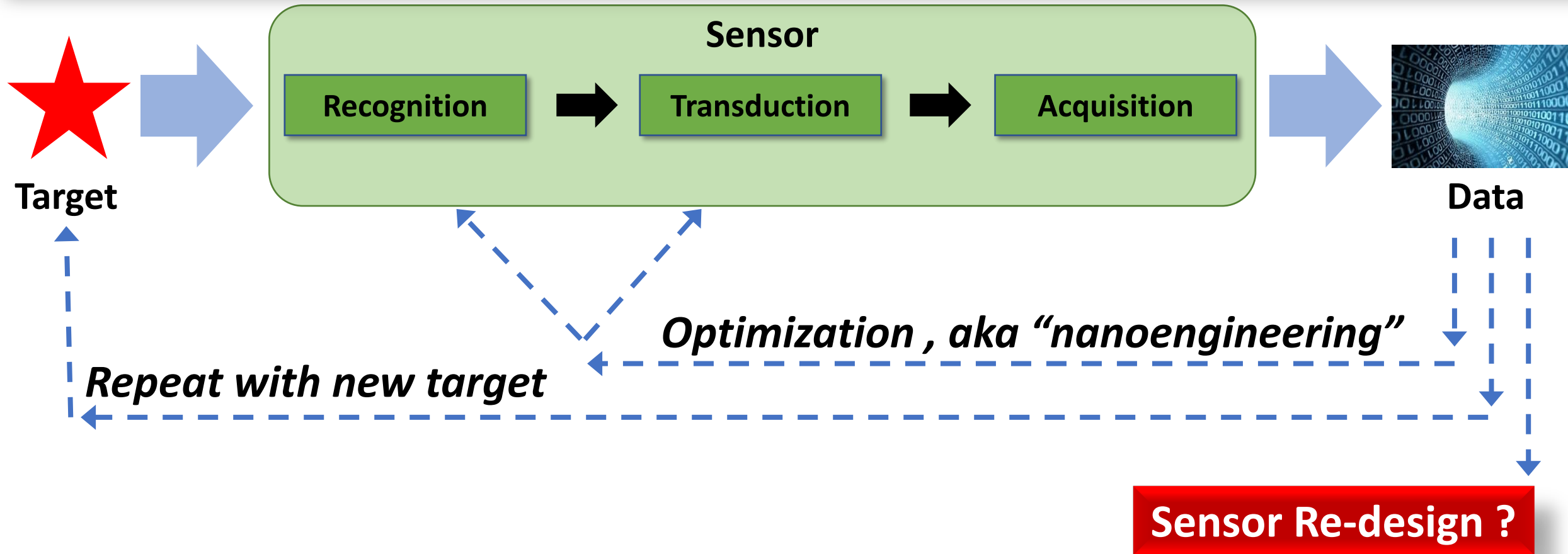
Role of Sensors and Sensor Data in Decision as a Service



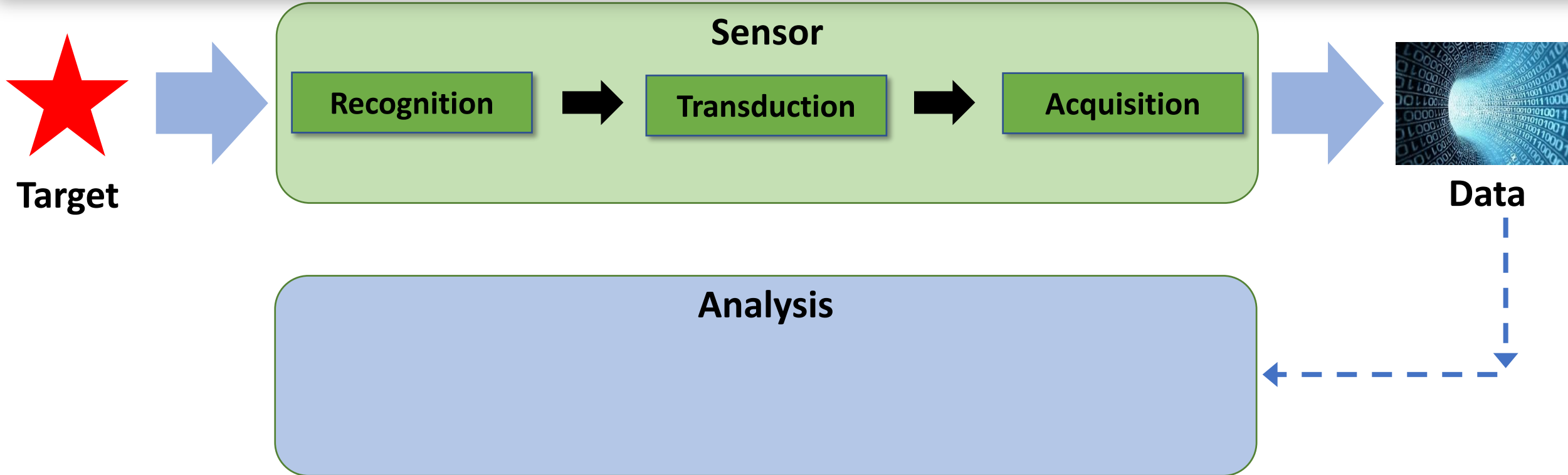
Role of Sensors and Sensor Data in Decision as a Service



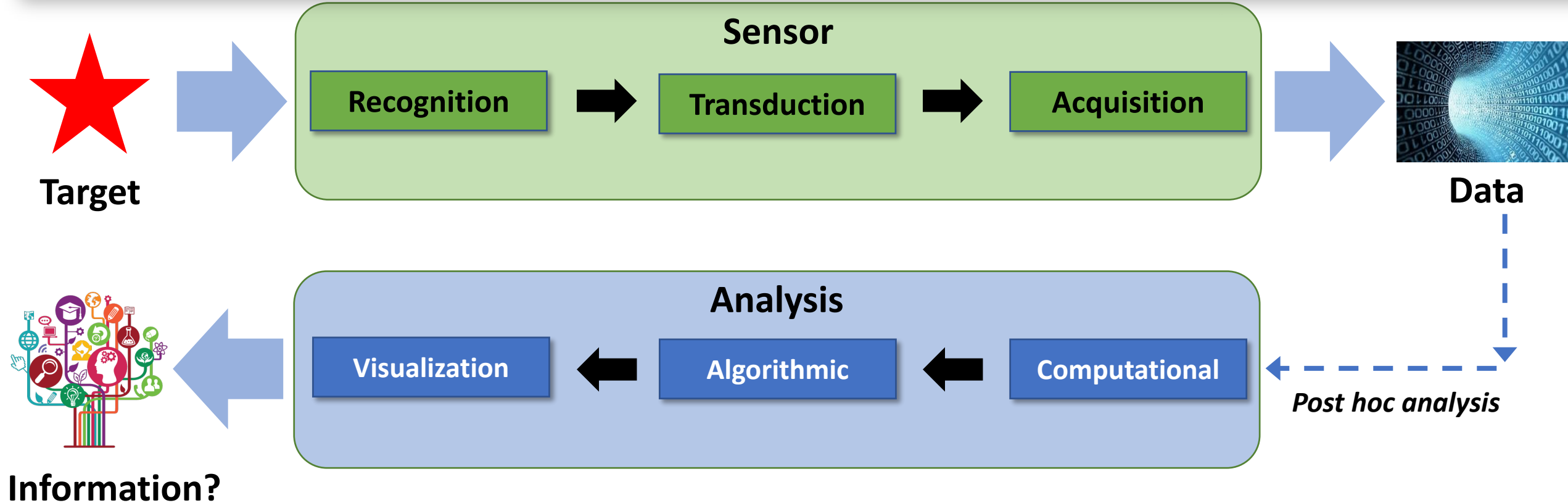
Role of Sensors and Sensor Data in Decision as a Service



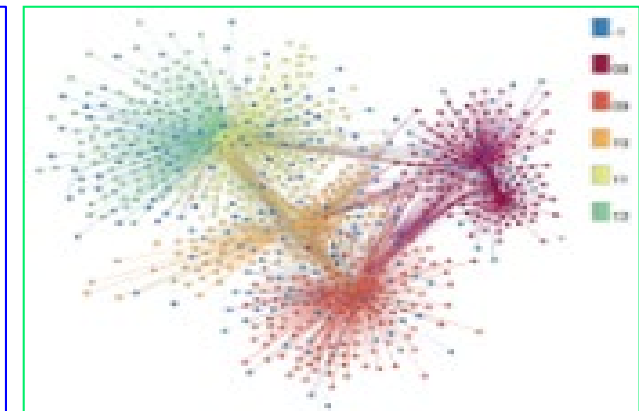
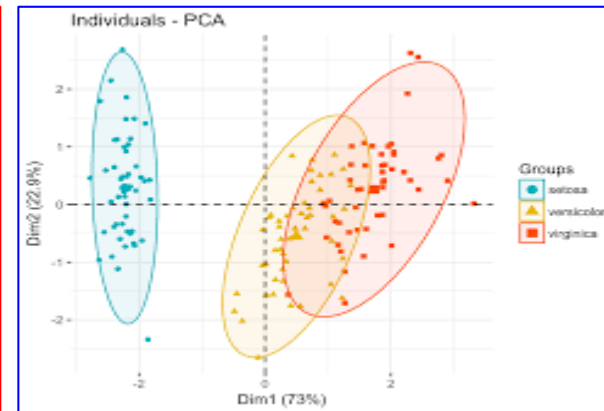
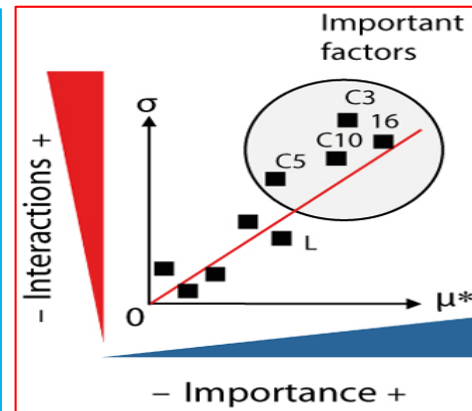
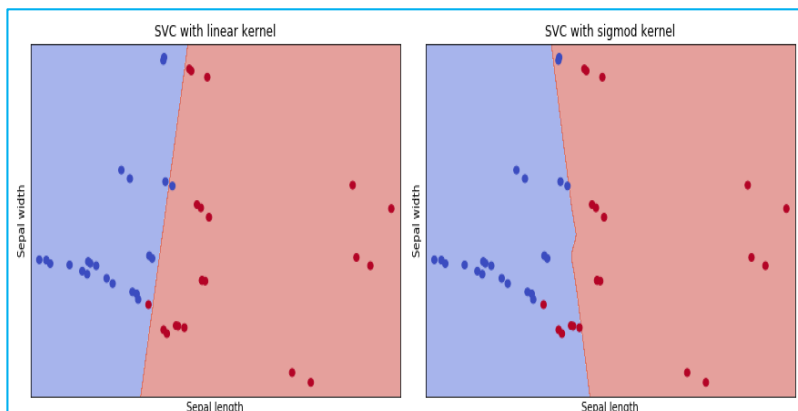
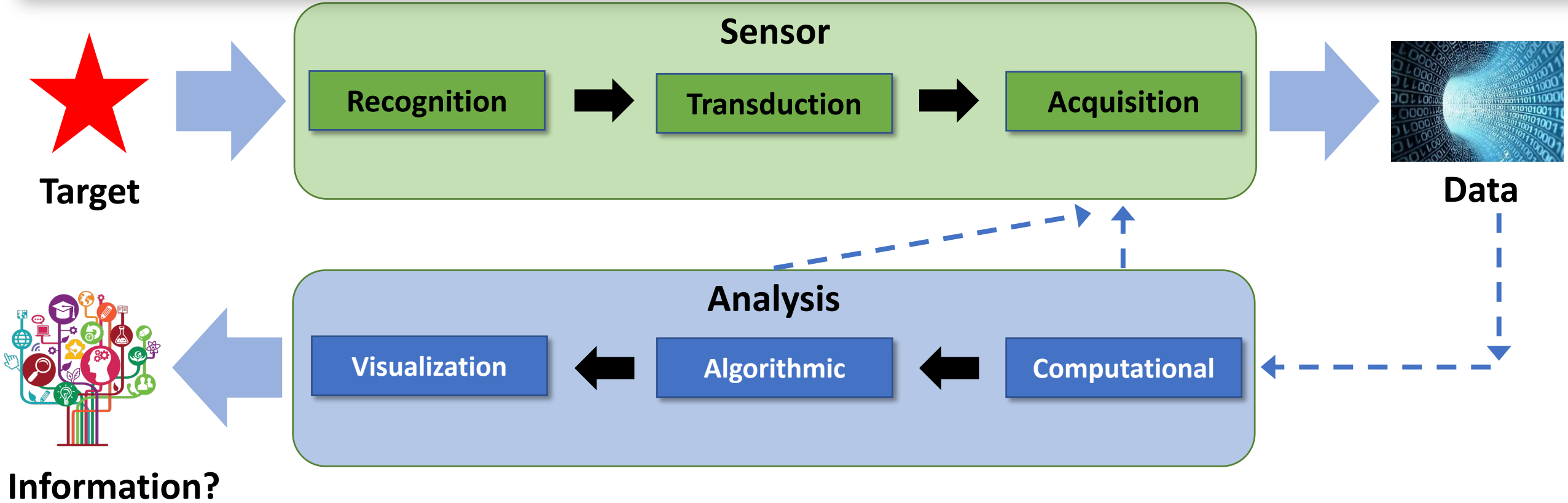
Role of Sensors and Sensor Data in Decision as a Service



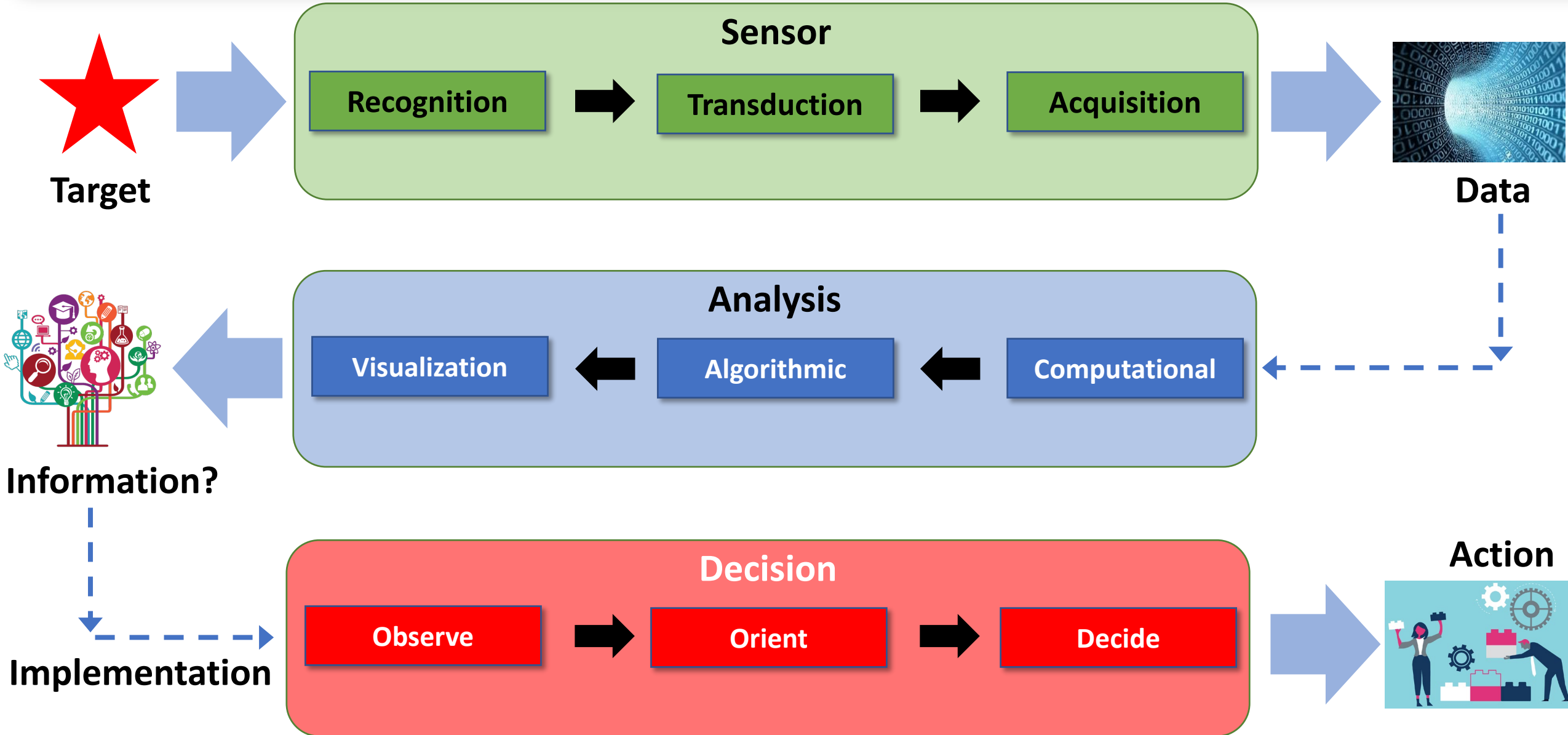
Role of Sensors and Sensor Data in Decision as a Service



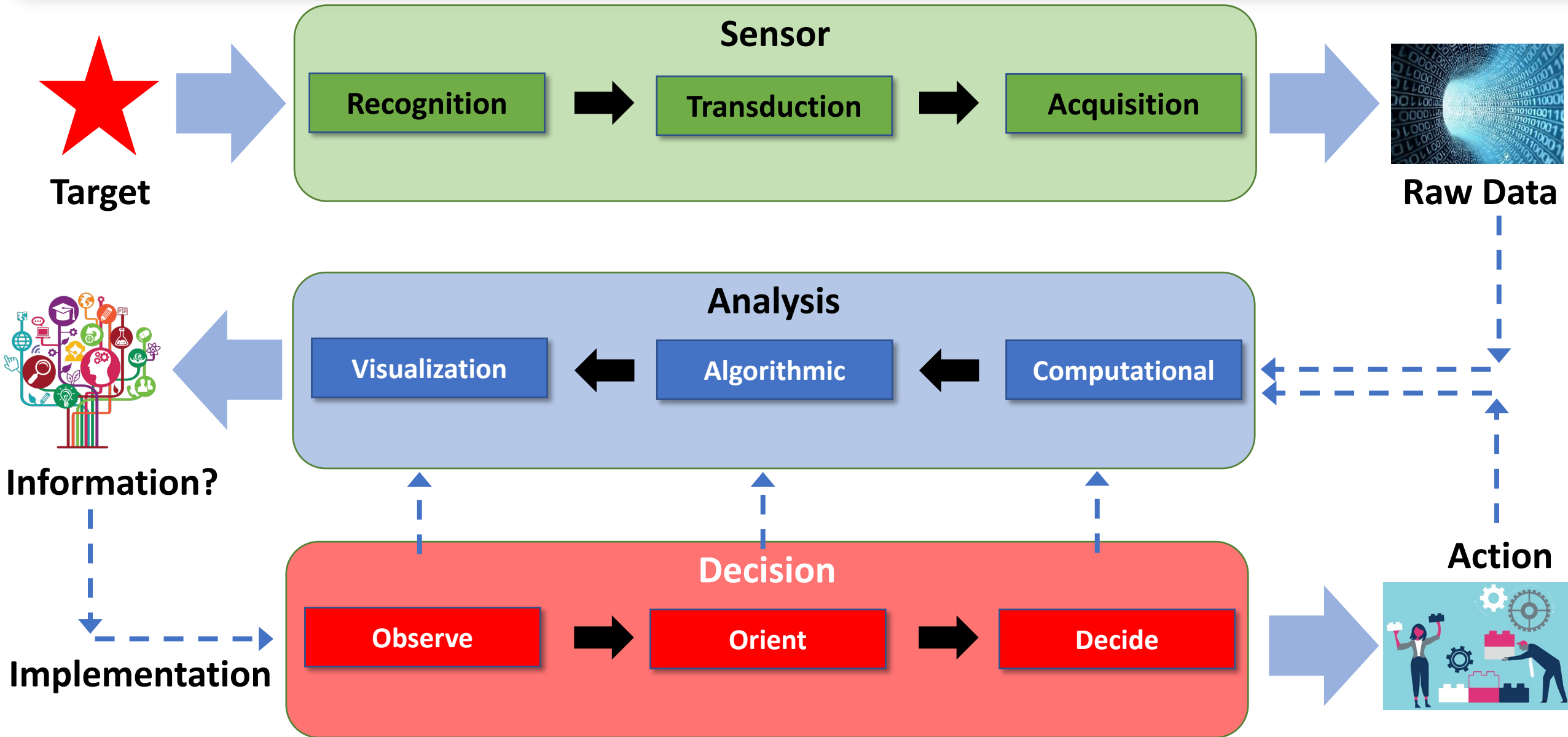
Role of Sensors and Sensor Data in Decision as a Service



Role of Sensors and Sensor Data in Decision as a Service



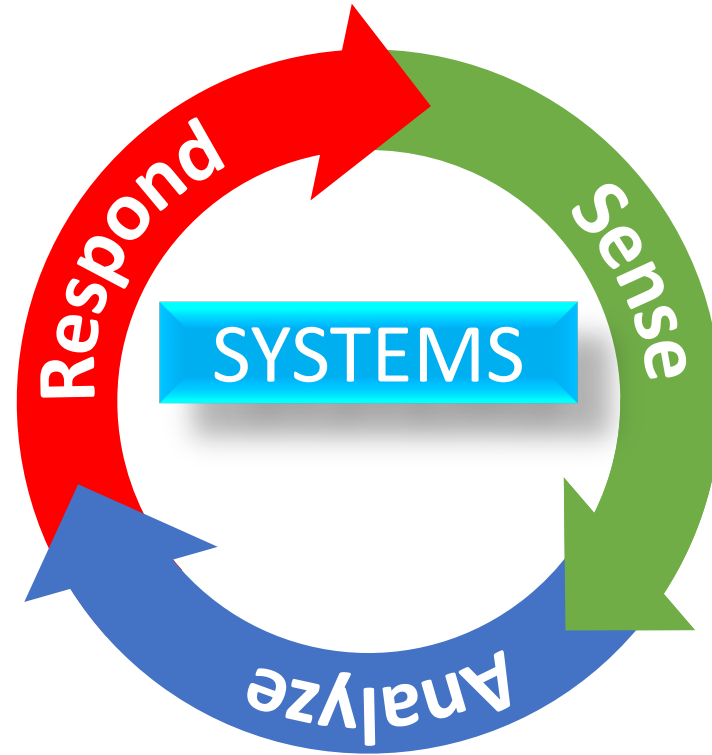
Data-Informed Decision as a Service



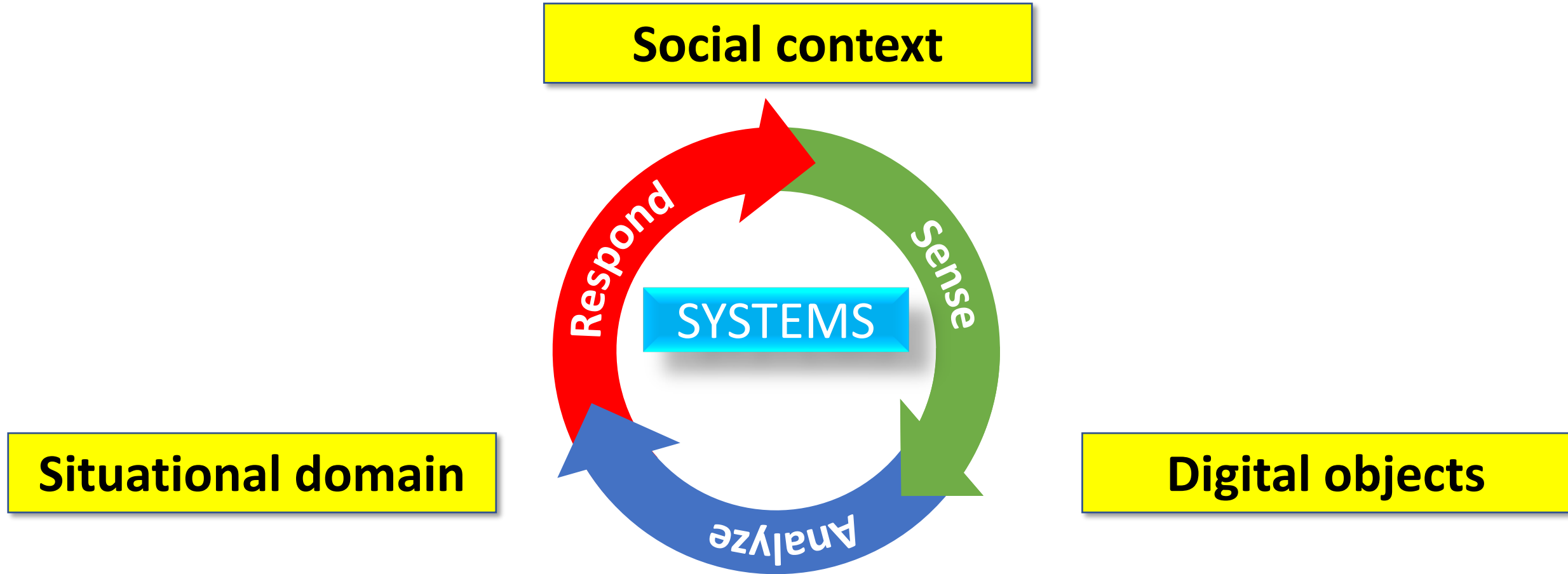
DIDA'S

Data-Informed Decision as a Service

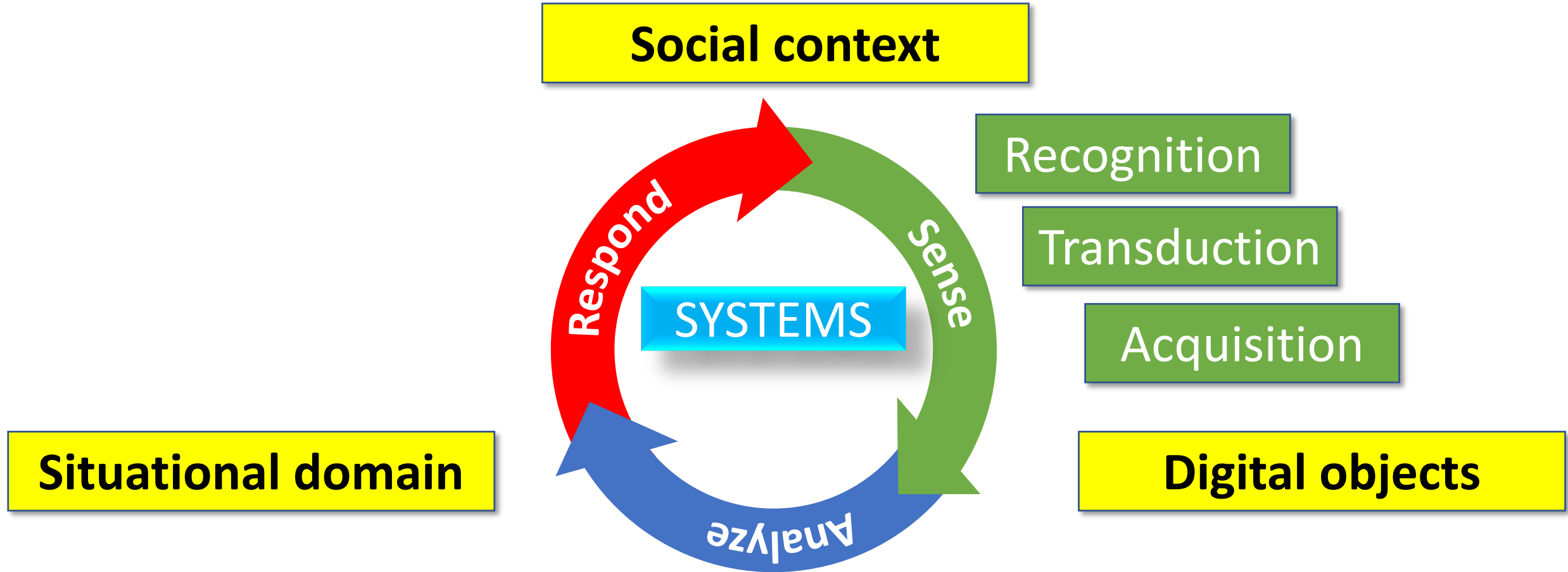
DIDA'S includes Sense, Analyze, Response, Systems (SARS)



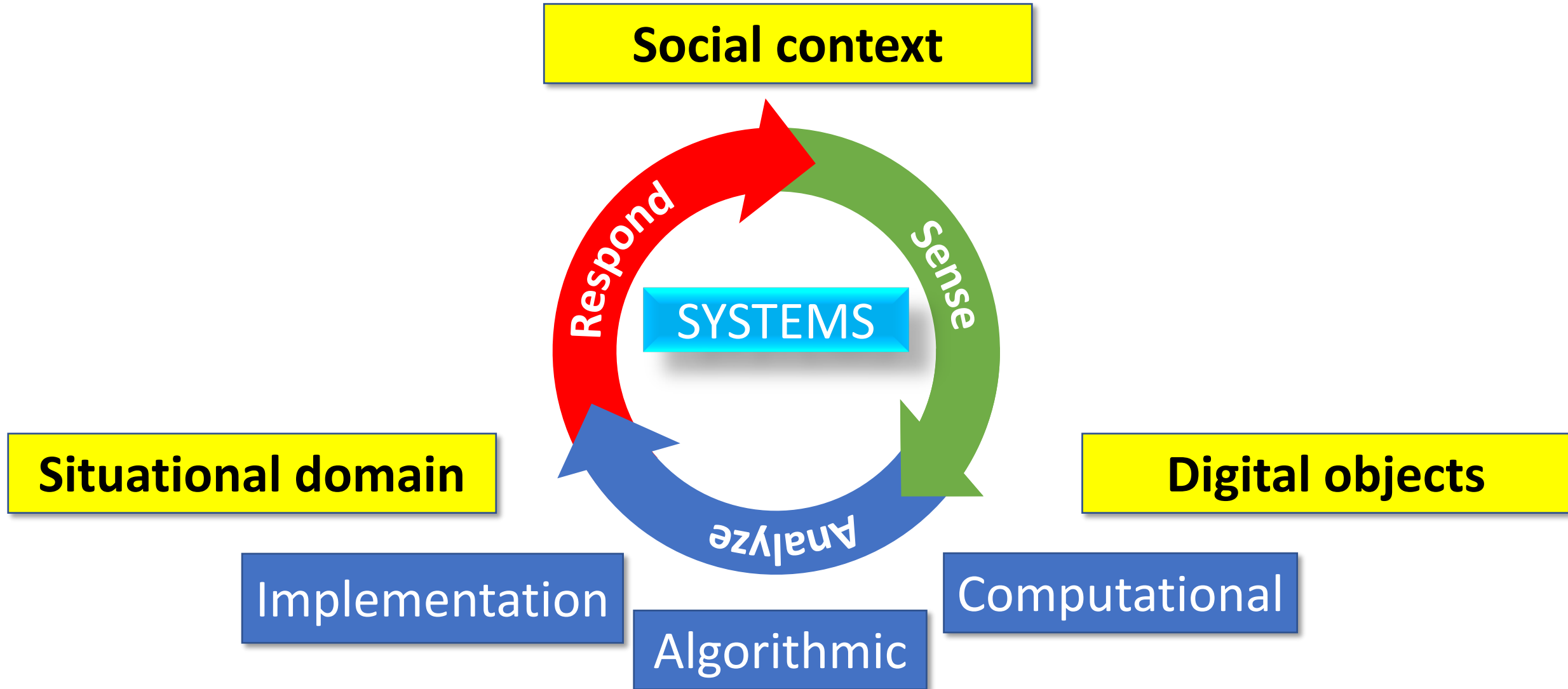
DIDA'S includes SARS context, objects and domains



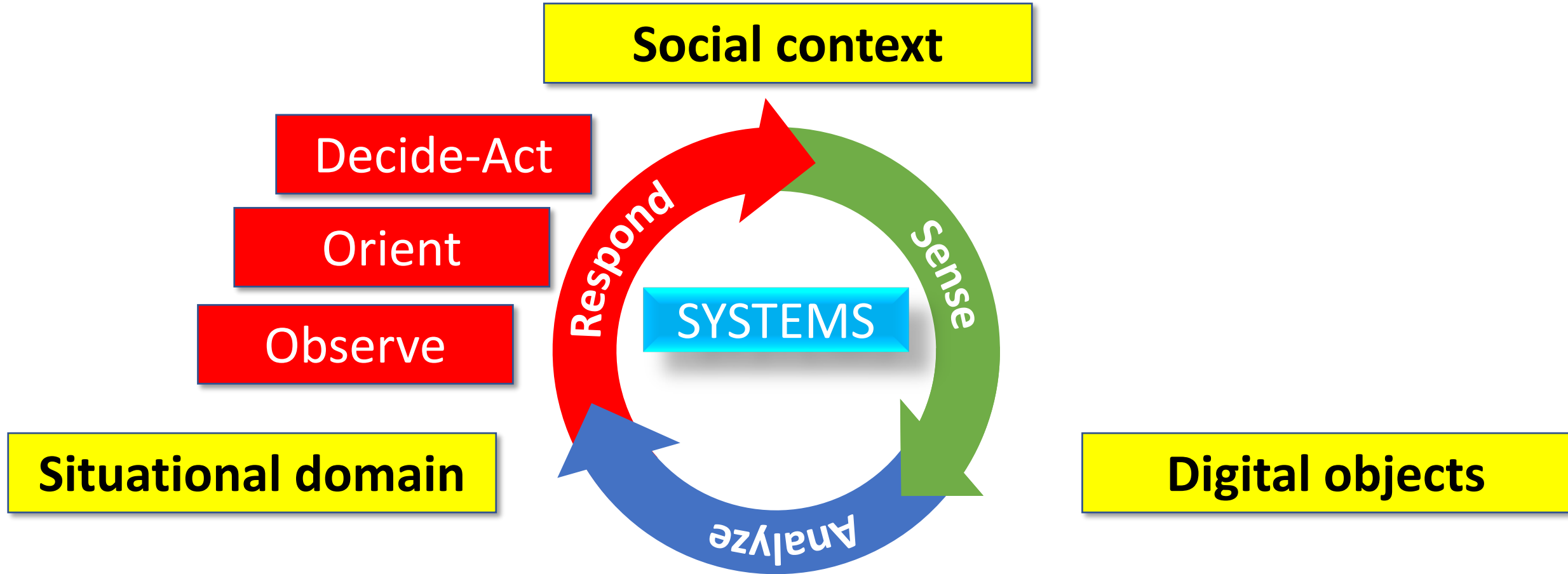
Granularity of the Data-Informed Decision as a Service



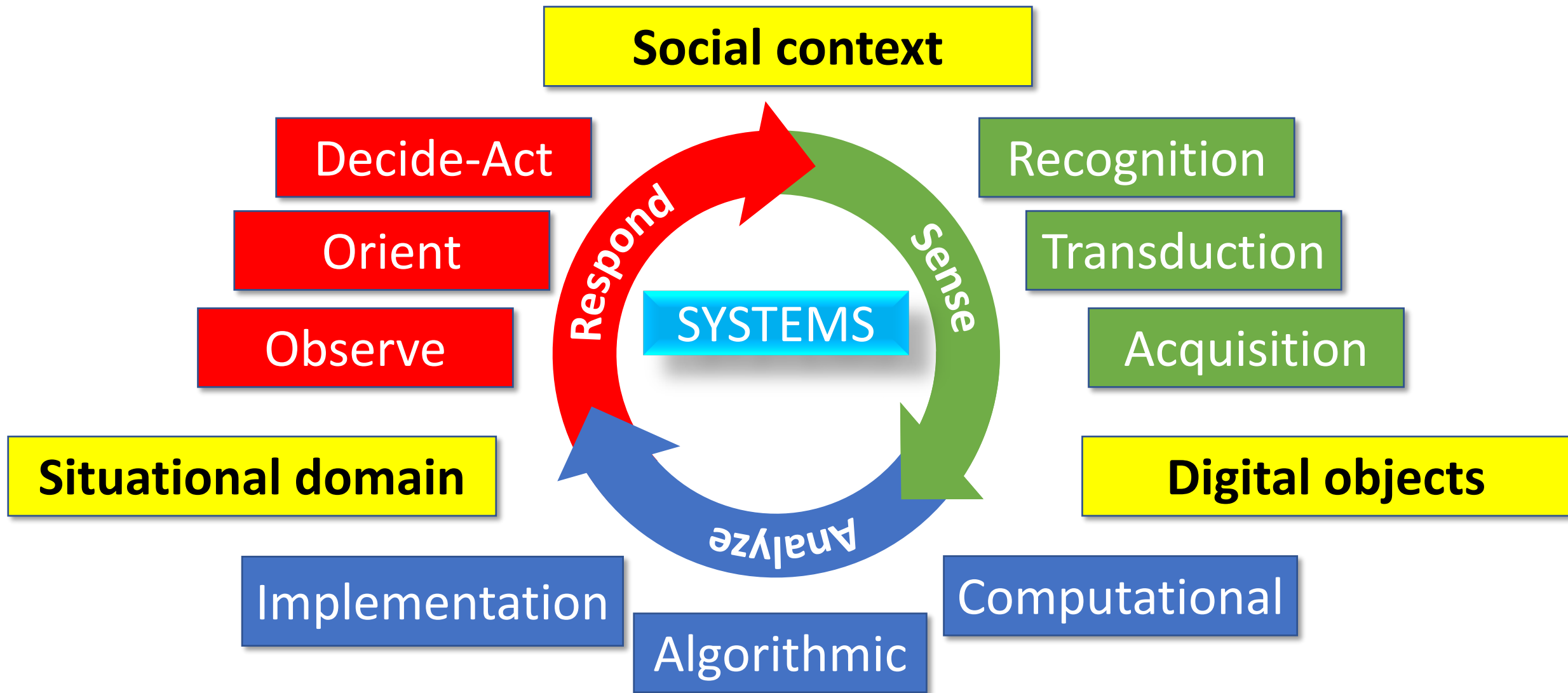
Granularity of the Data-Informed Decision as a Service



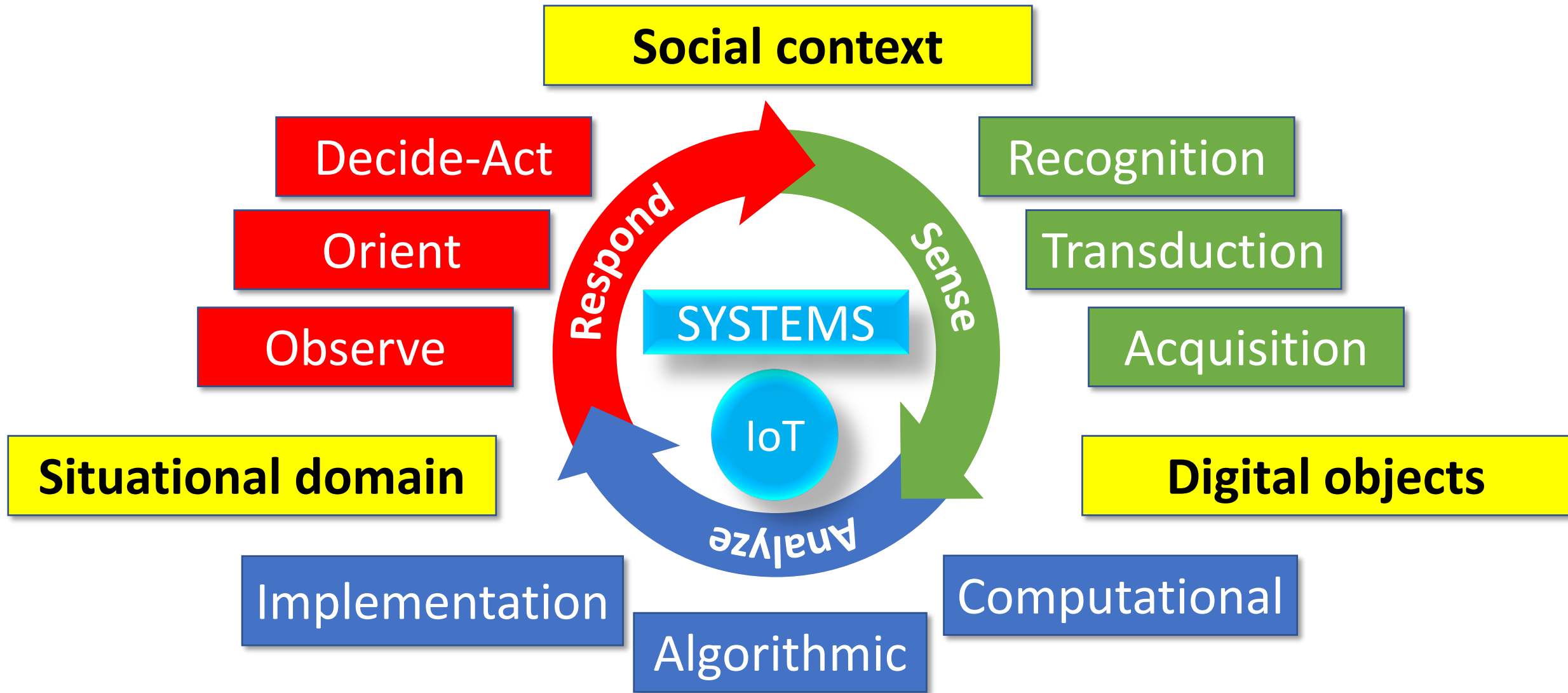
Granularity of the Data-Informed Decision as a Service



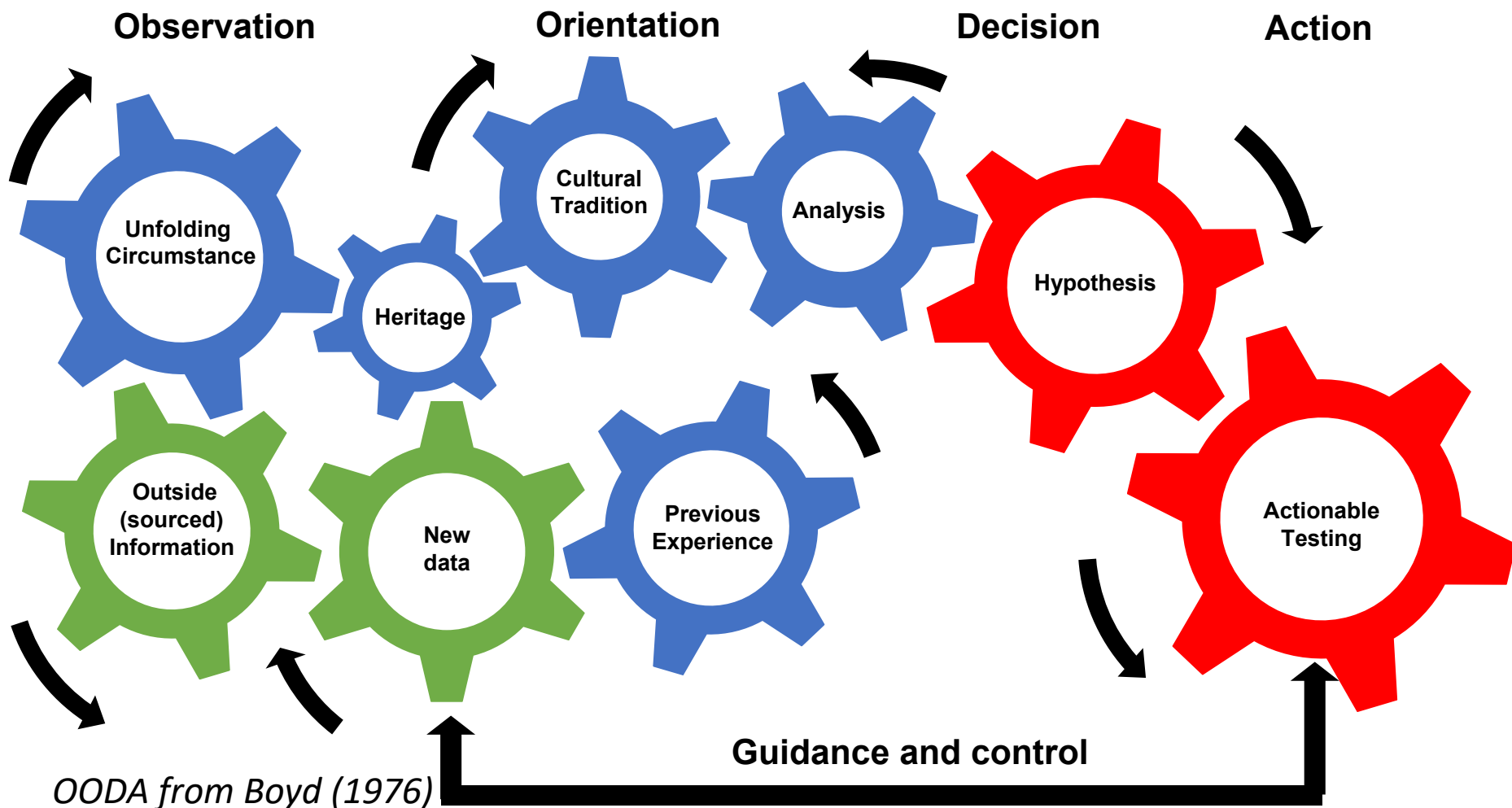
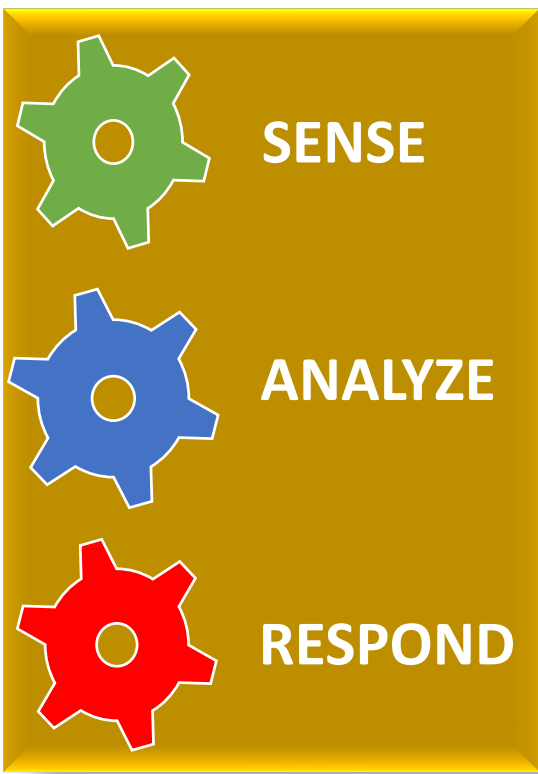
DIDA'S : Data-Informed Decision as a Service with SARS



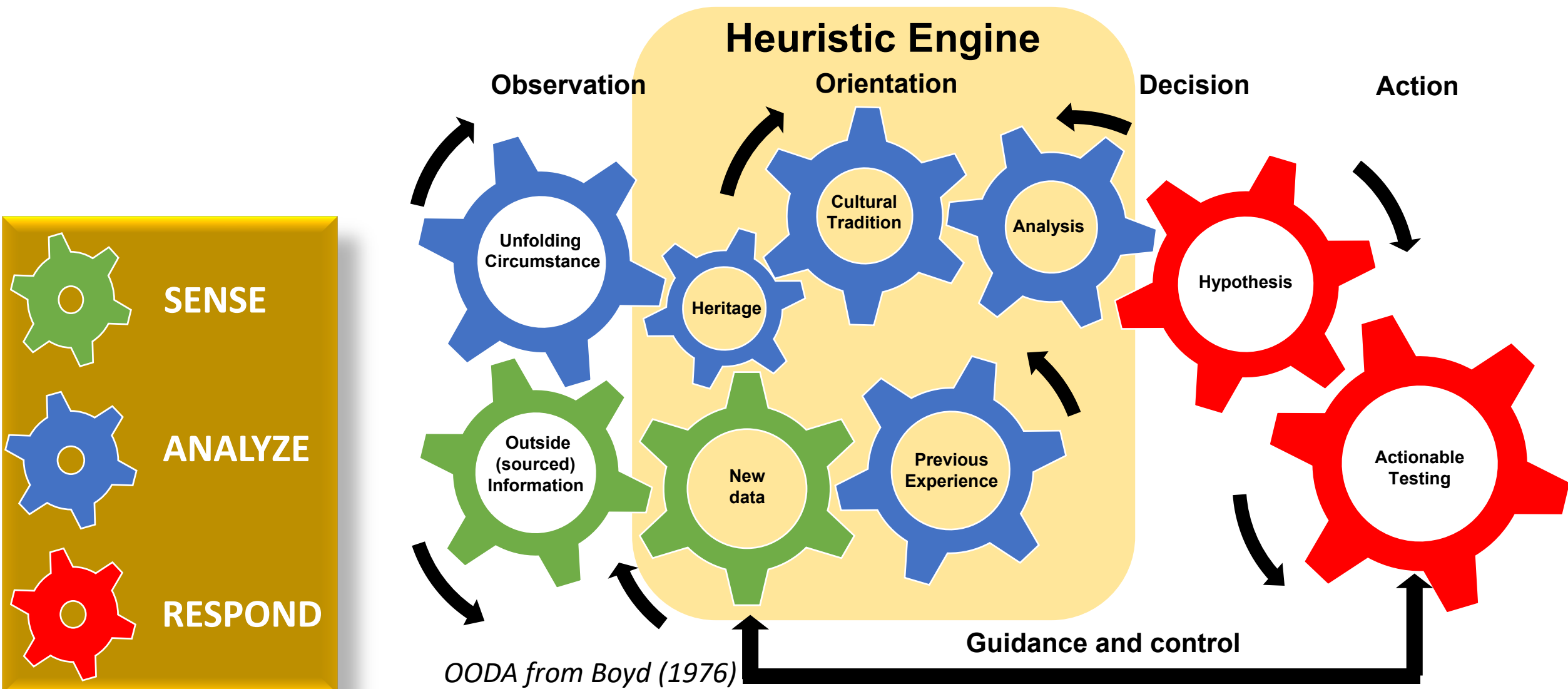
DIDA'S : Data-Informed Decision as a Service



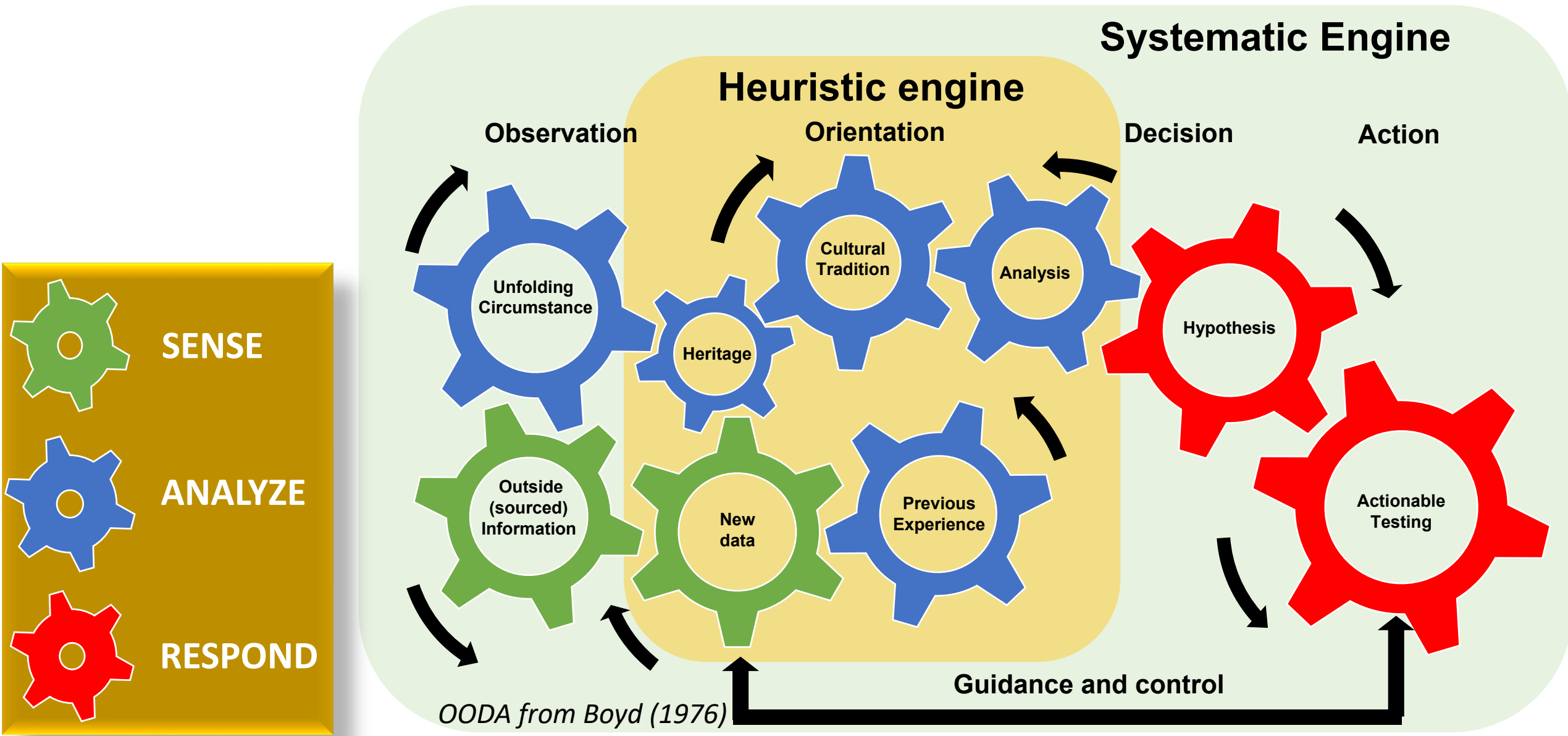
DIDA'S ENGINES : Data-Informed Decision Engines



DIDA'S ENGINES : Data-Informed Decision Engines



DIDA'S ENGINES : Data-Informed Decision Engines



The Value of DIDA'S (Data-Informed Decision as a Service)



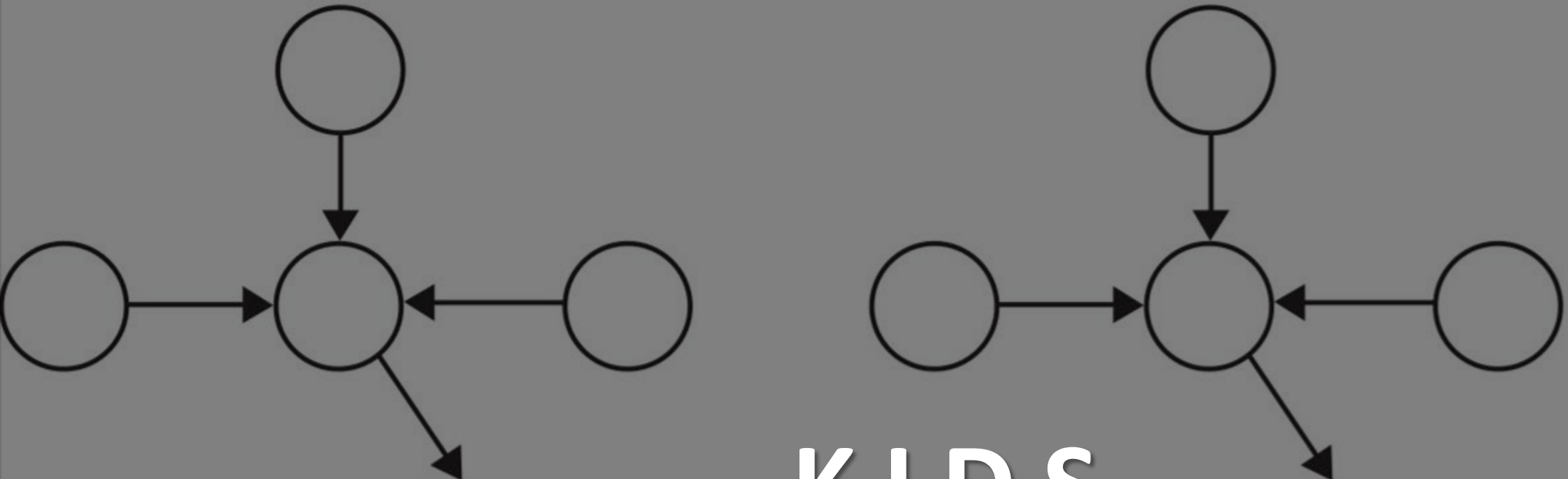
Is there consumer demand for this vegetable?



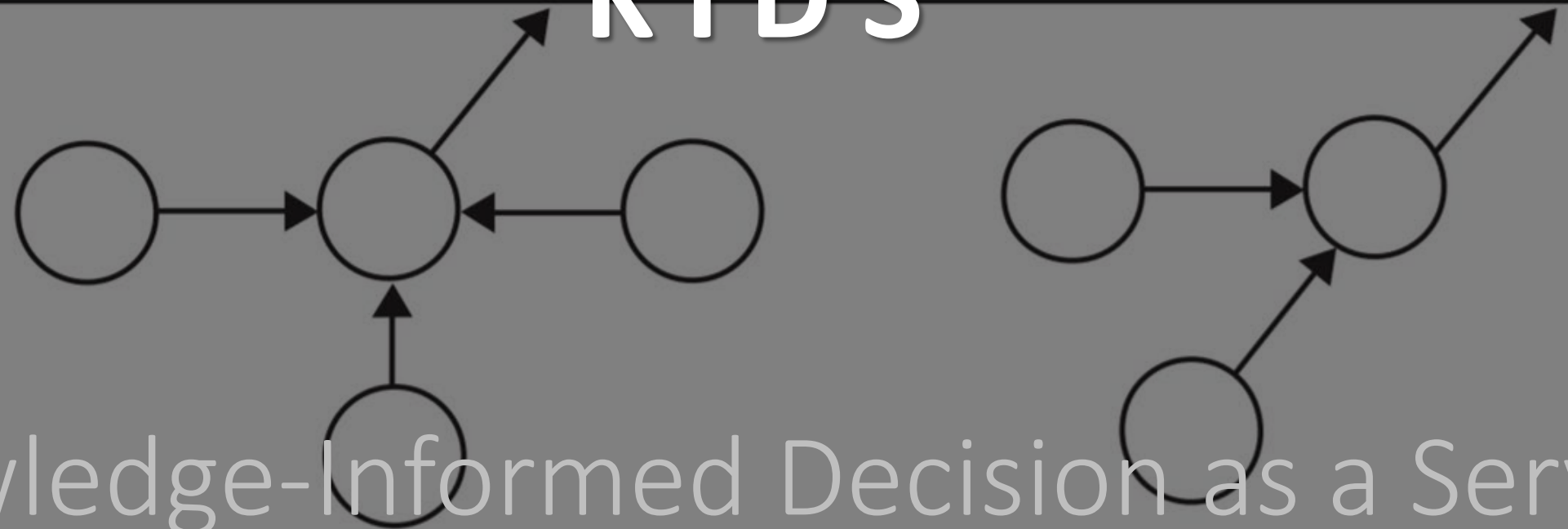
The Value of DIDA'S (Data-Informed Decision as a Service)

To realize the actual value of DIDA'S, the tool must be useful to end-users, if they can use the tool to ask questions and receive actionable information or if it can support the decision making process

The journey to DIDA'S must include and/or create and/or connect a multitude of domains to source data and synthesize relevant information. DIDA'S may lead to knowledge-informed decision as a service.



KIDS

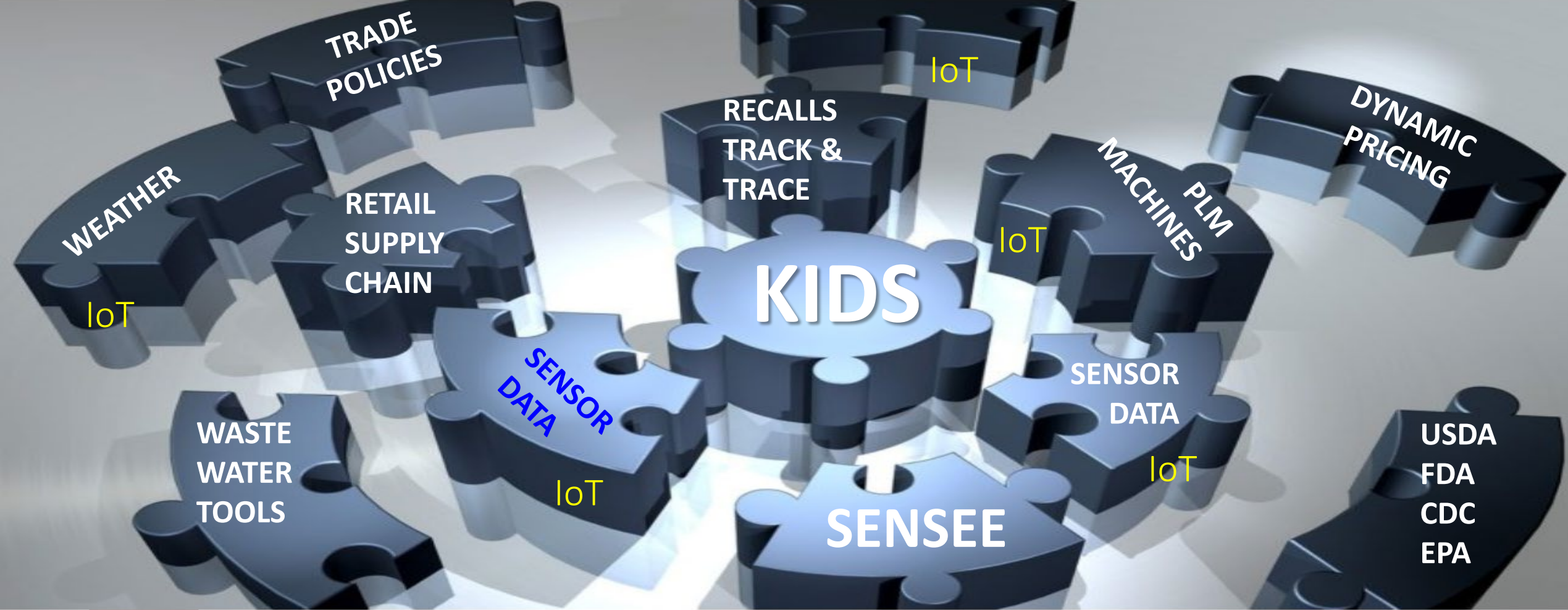


Knowledge-Informed Decision as a Service

KIDS

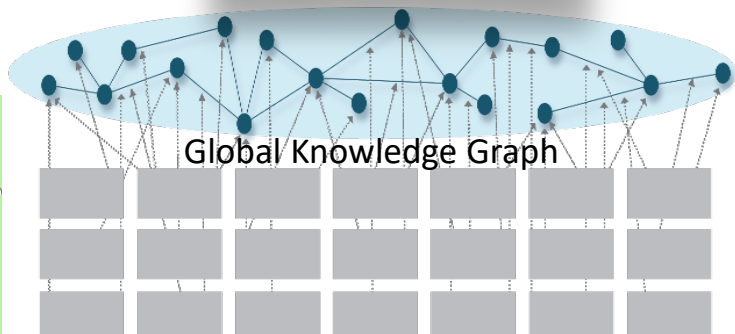
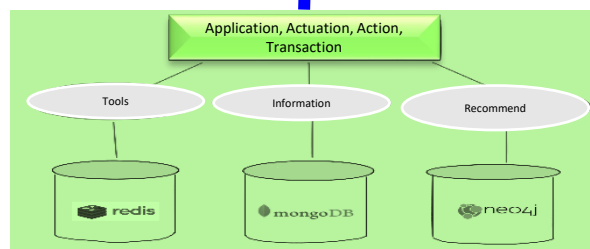
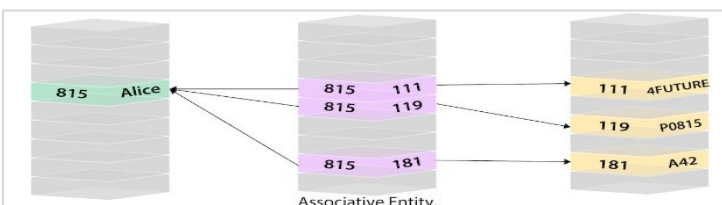
Knowledge-Informed Decision as a Service

KIDS is an open plan platform concept. Platforms are comprised of multiple applications and integrated solutions with embedded tools and databases that function as complete, seamless environments. Product innovation platforms are intended to support groups of users collaborating across various levels, domains, business units, and the ecosystem. These capabilities are increasingly needed throughout the entire extended enterprise in almost every vertical, agnostic of the type of application or function or users, including farmers, meat packers, produce growers, retail stores, customers, suppliers, and business partners. Developing open platform tools and technologies are not limited to any one domain because these modular tools can be applied, used and re-configured for re-use, almost anywhere, for example: error correction, search engine algorithms, NLU/NLP (natural language processing), automated feature engineering, drag and drop functions, analytics, workflows, and services, such as KIDS, where “open” means ‘plug & play’ user friendly human-computer interactions and interoperability between system of systems.

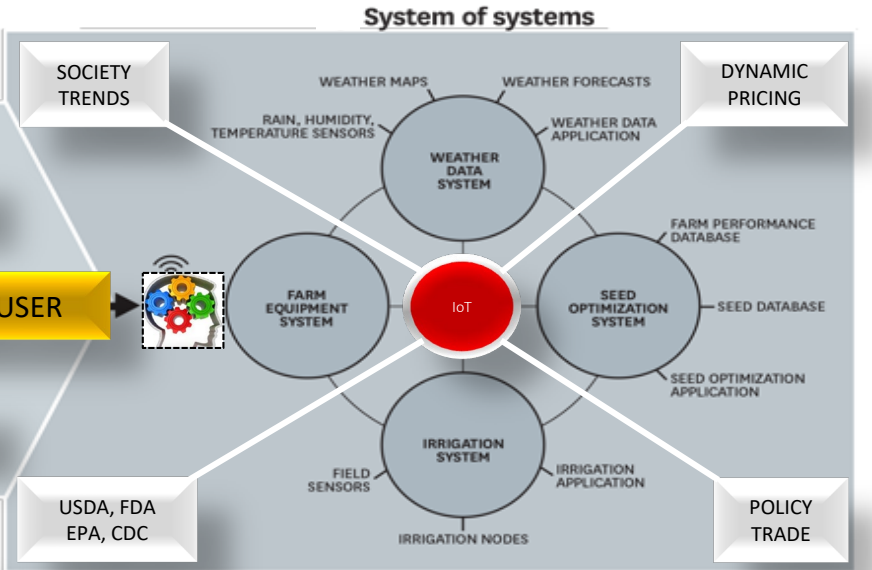
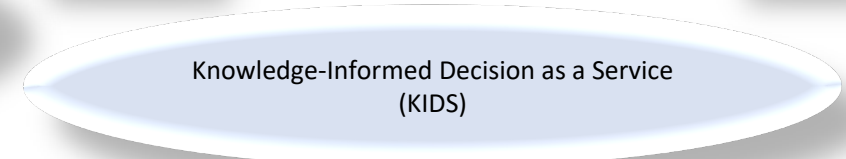
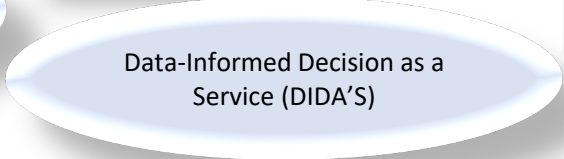
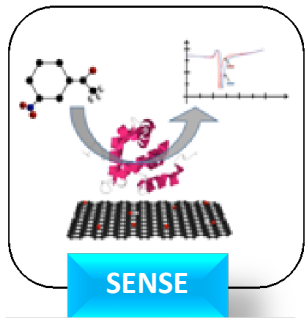


DATA

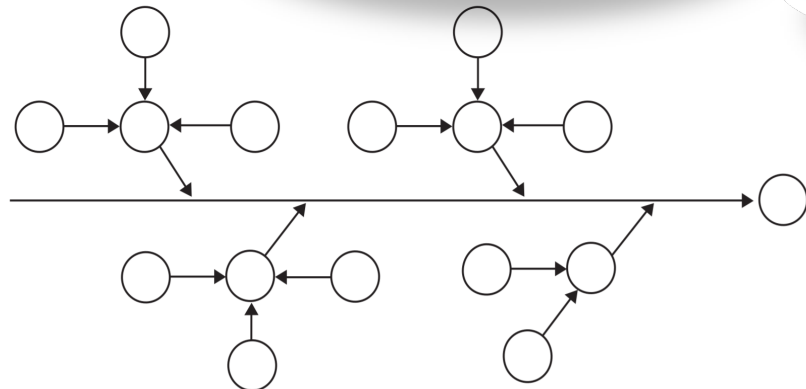
KNOWLEDGE



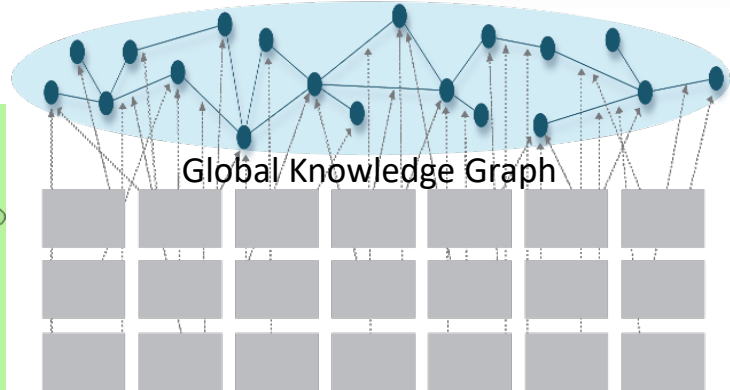
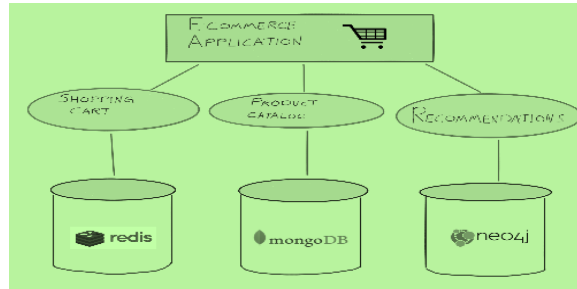
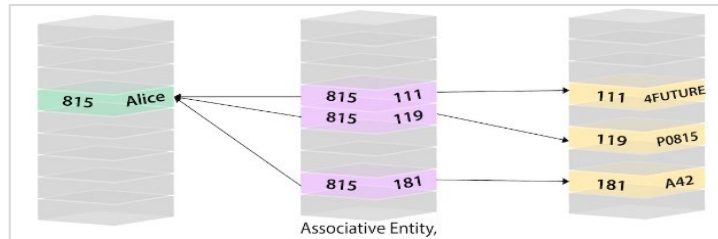
At the end, it is really all about KIDS



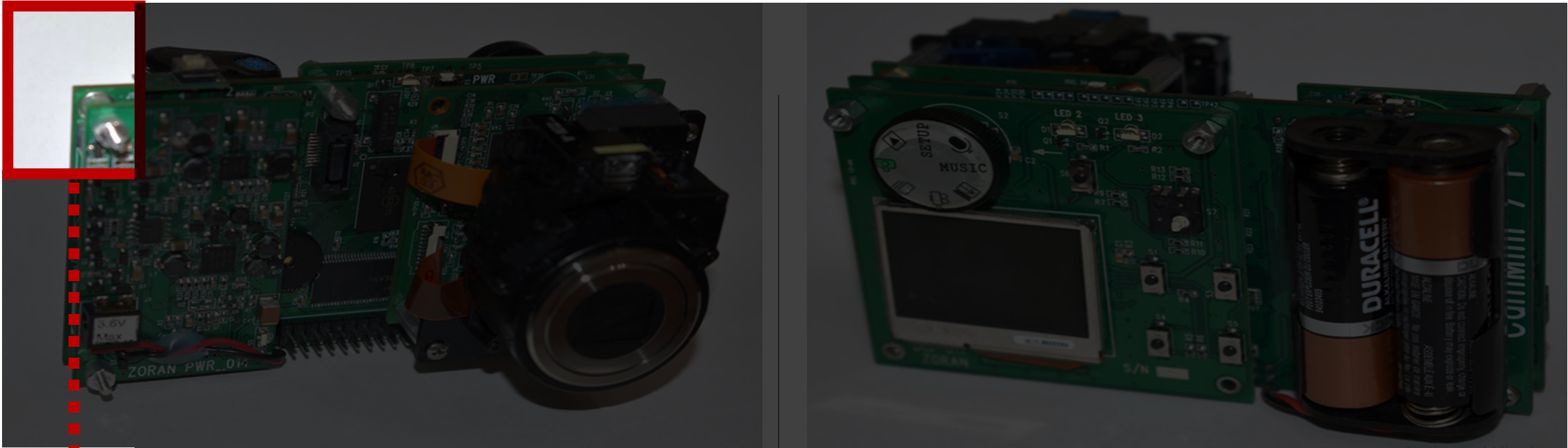
DATA

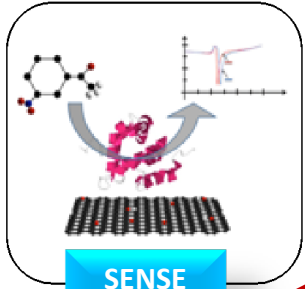


KNOWLEDGE

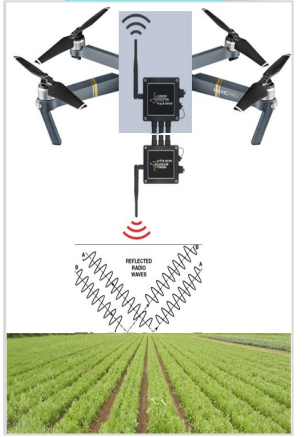


We are not even close



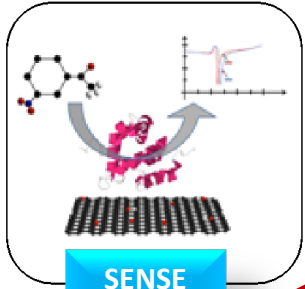


SENSE

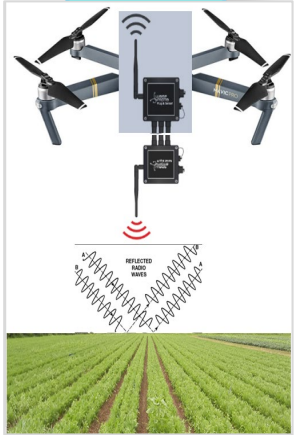


We are just starting here

SENSEE

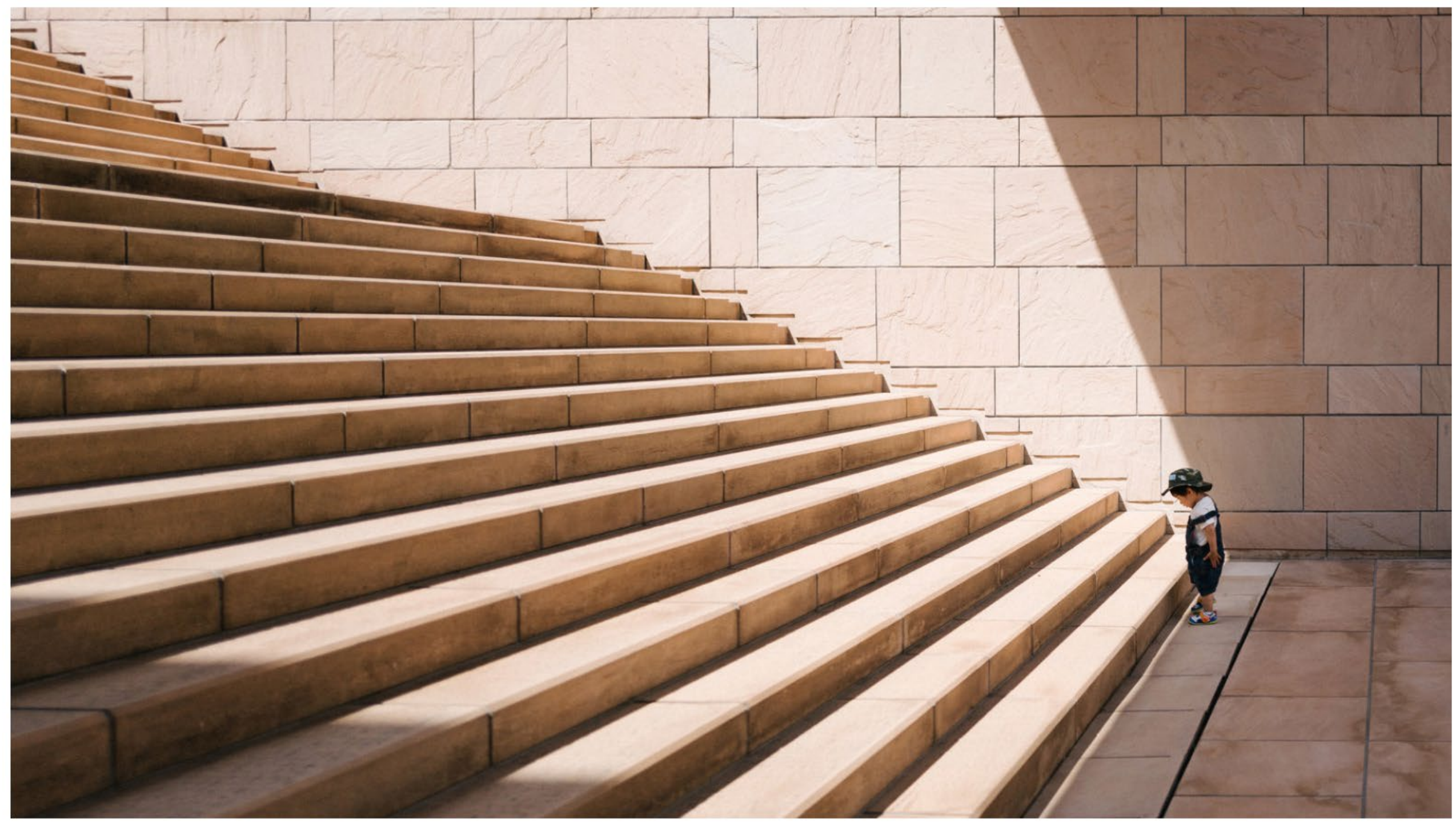


SENSE



We are just starting here

SENsor **SE**arch **Eng**ine





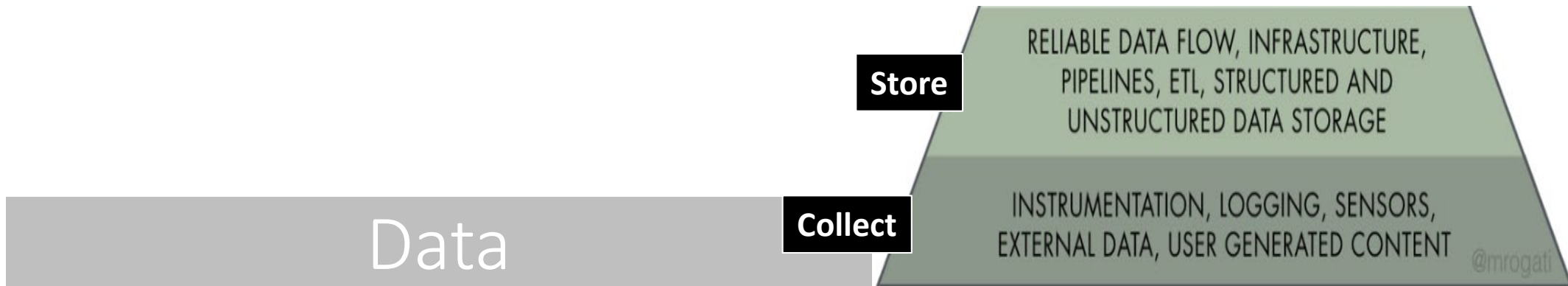
Data

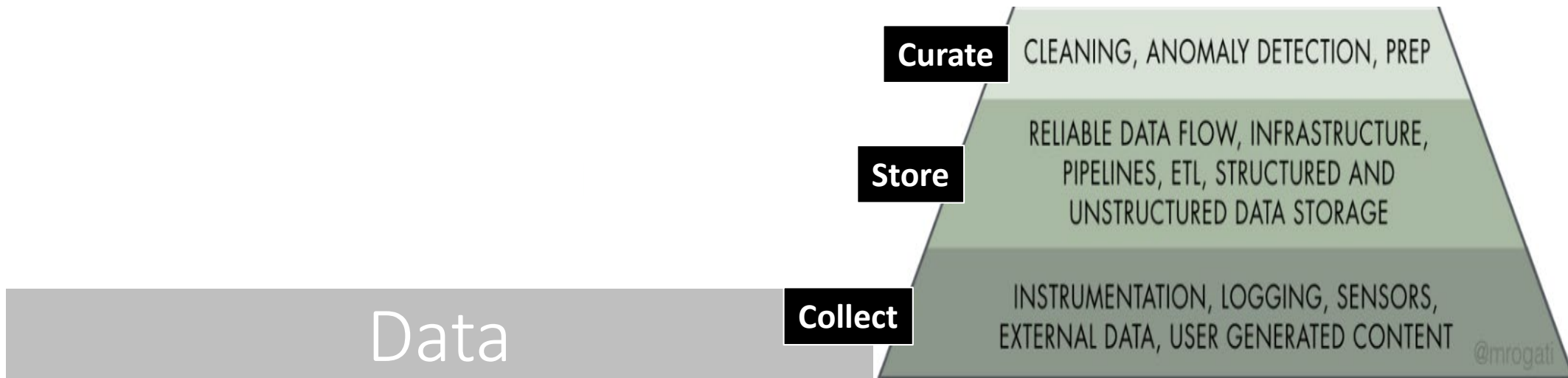


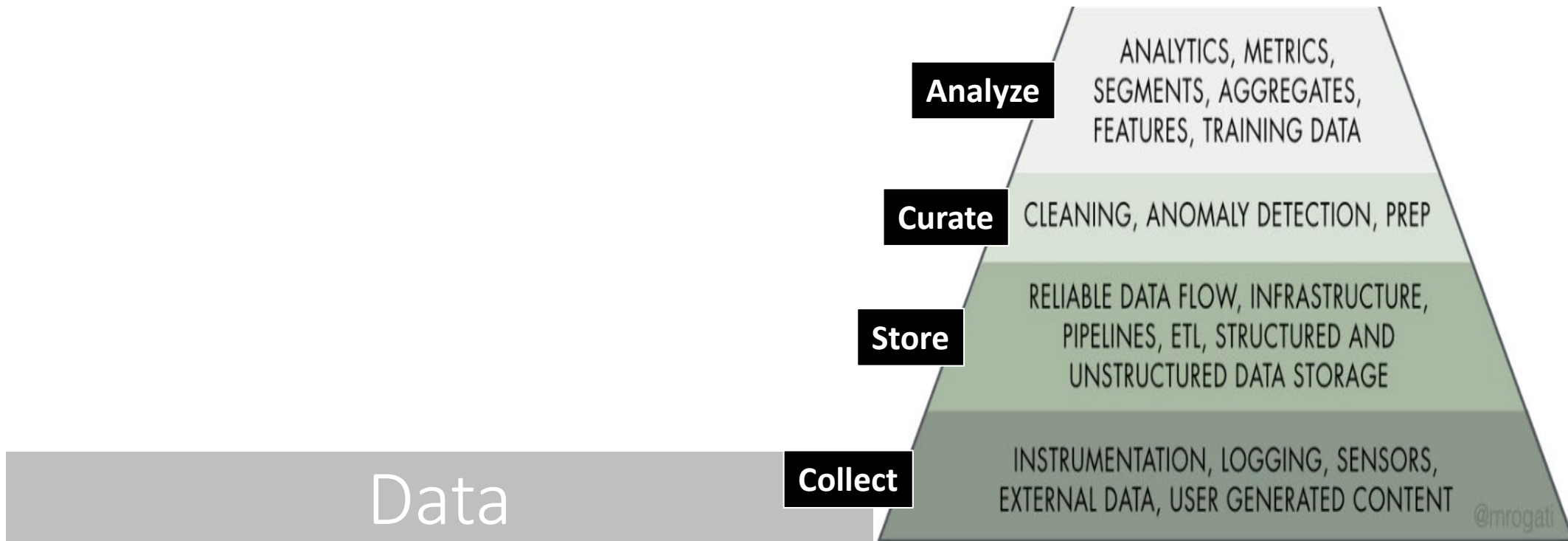
Data

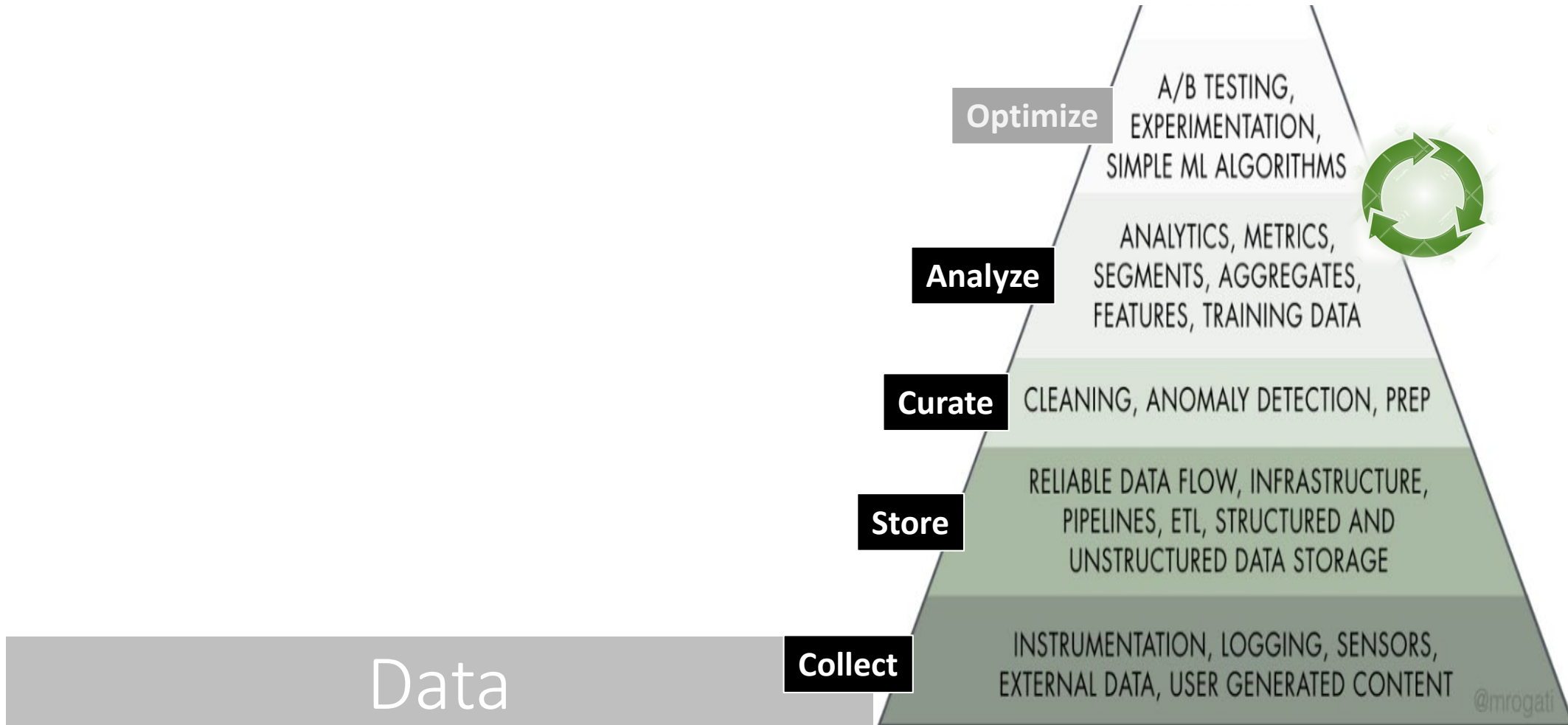
Collect

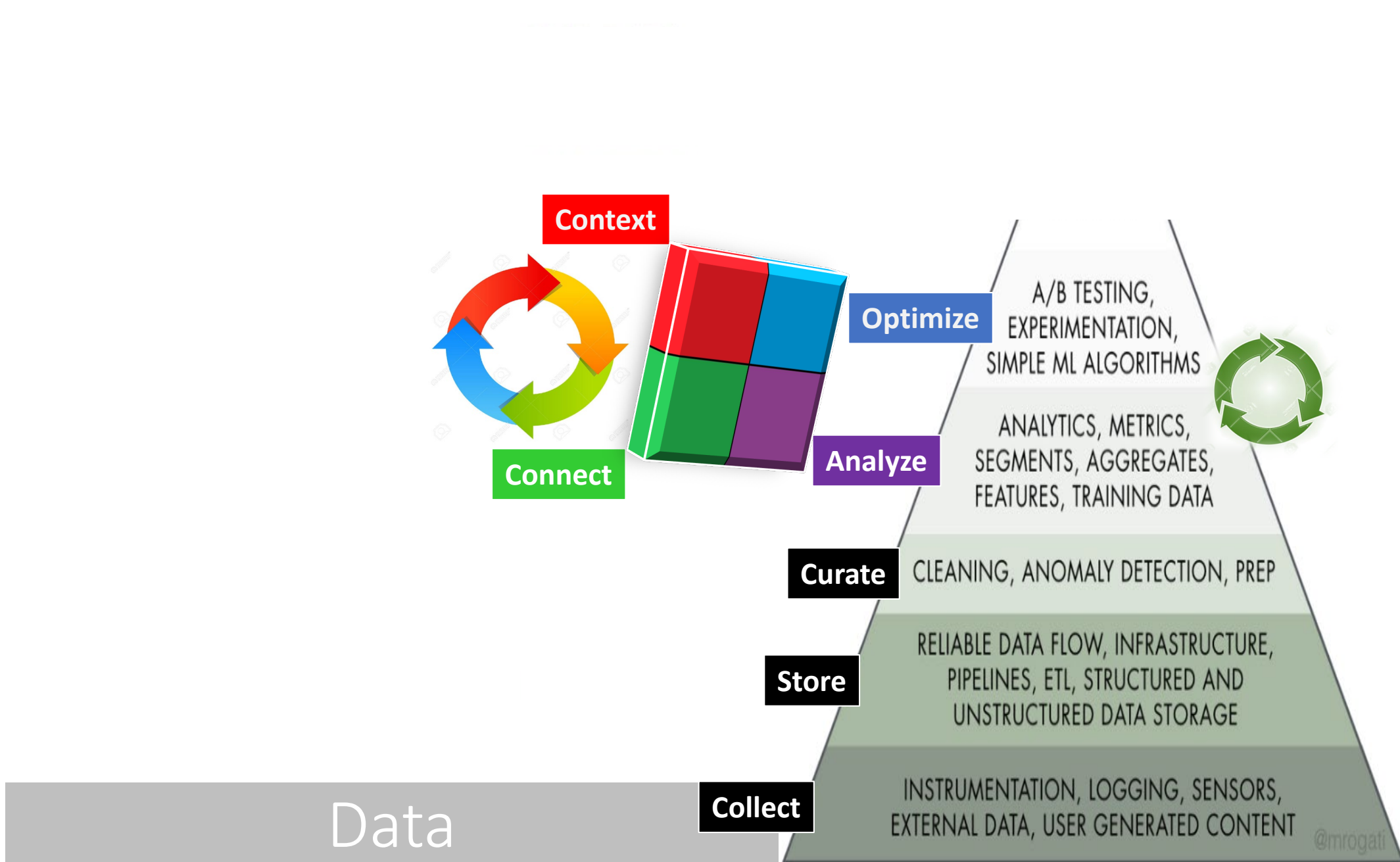
INSTRUMENTATION, LOGGING, SENSORS,
EXTERNAL DATA, USER GENERATED CONTENT
@mrogati

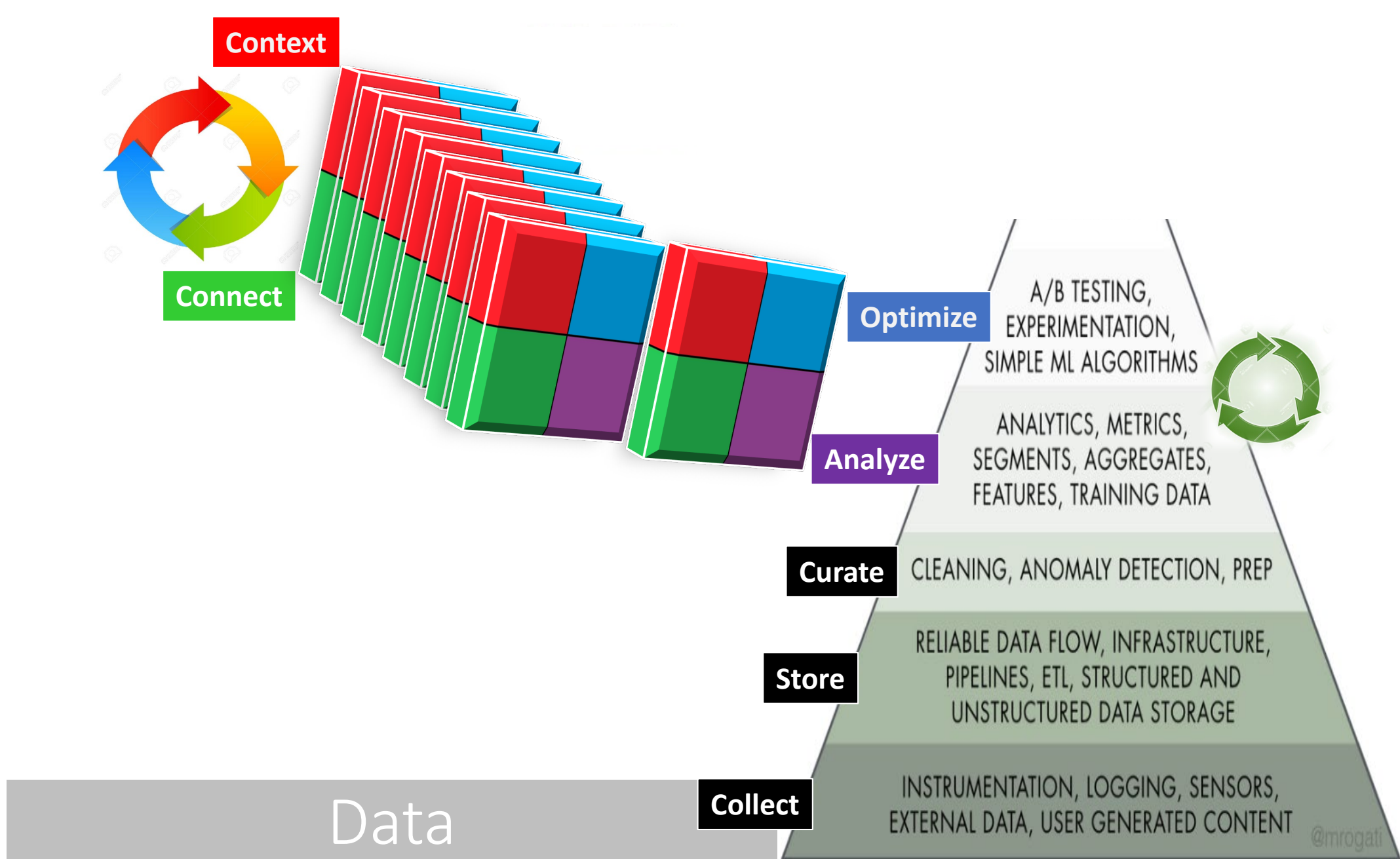


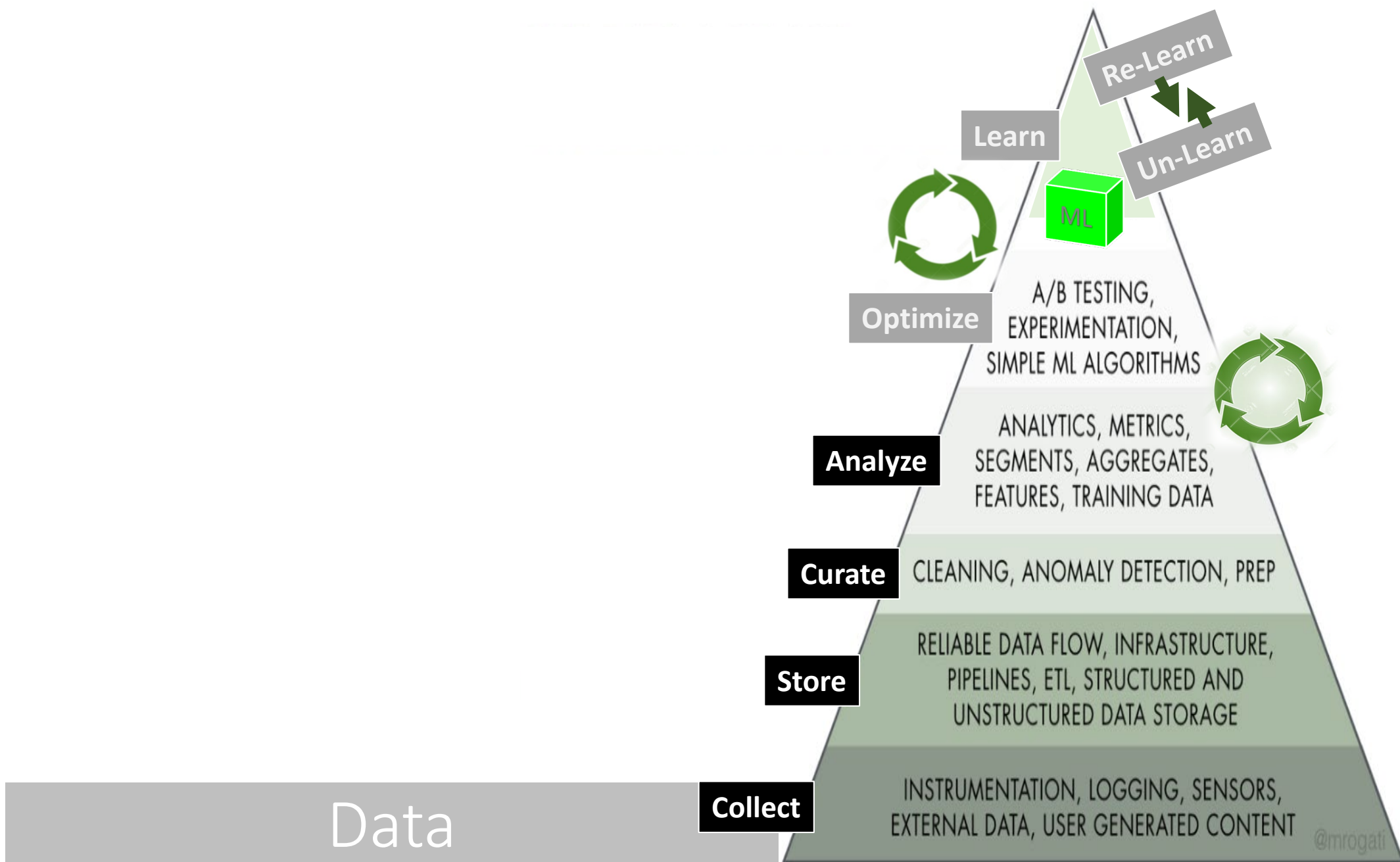


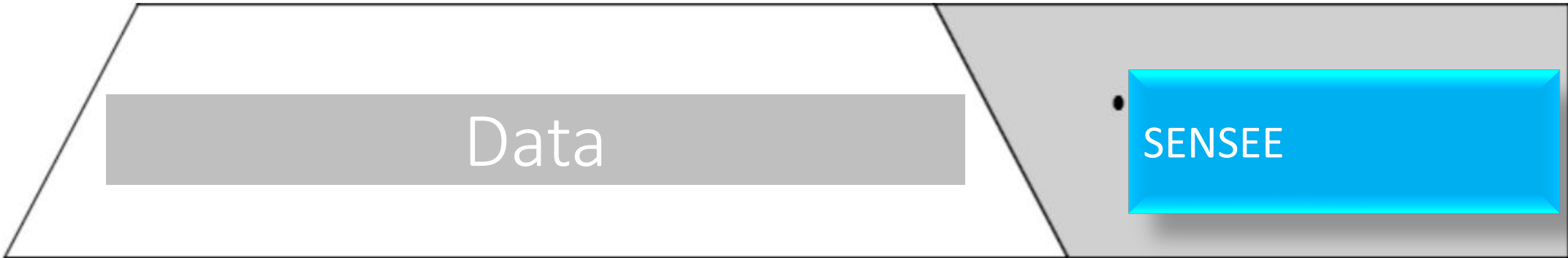


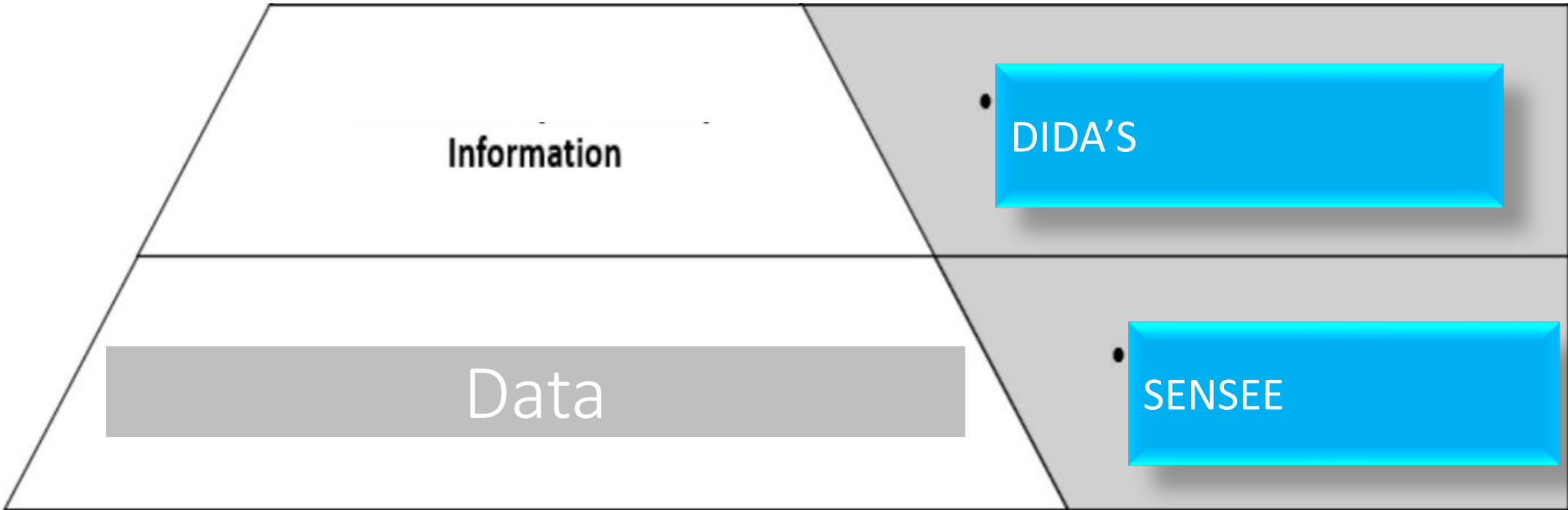










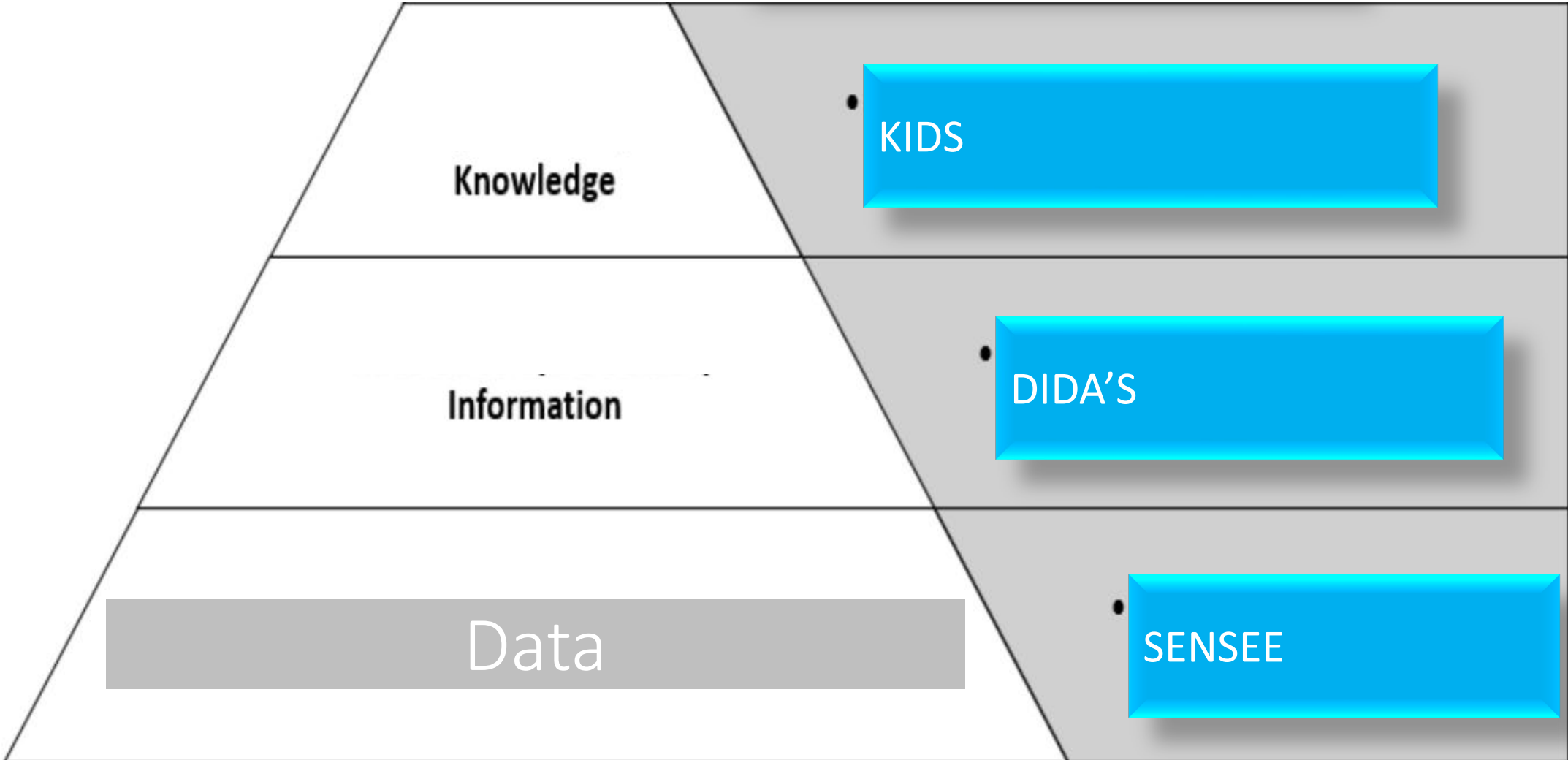


Information

DIDA'S

Data

SENSEE



Knowledge

KIDS

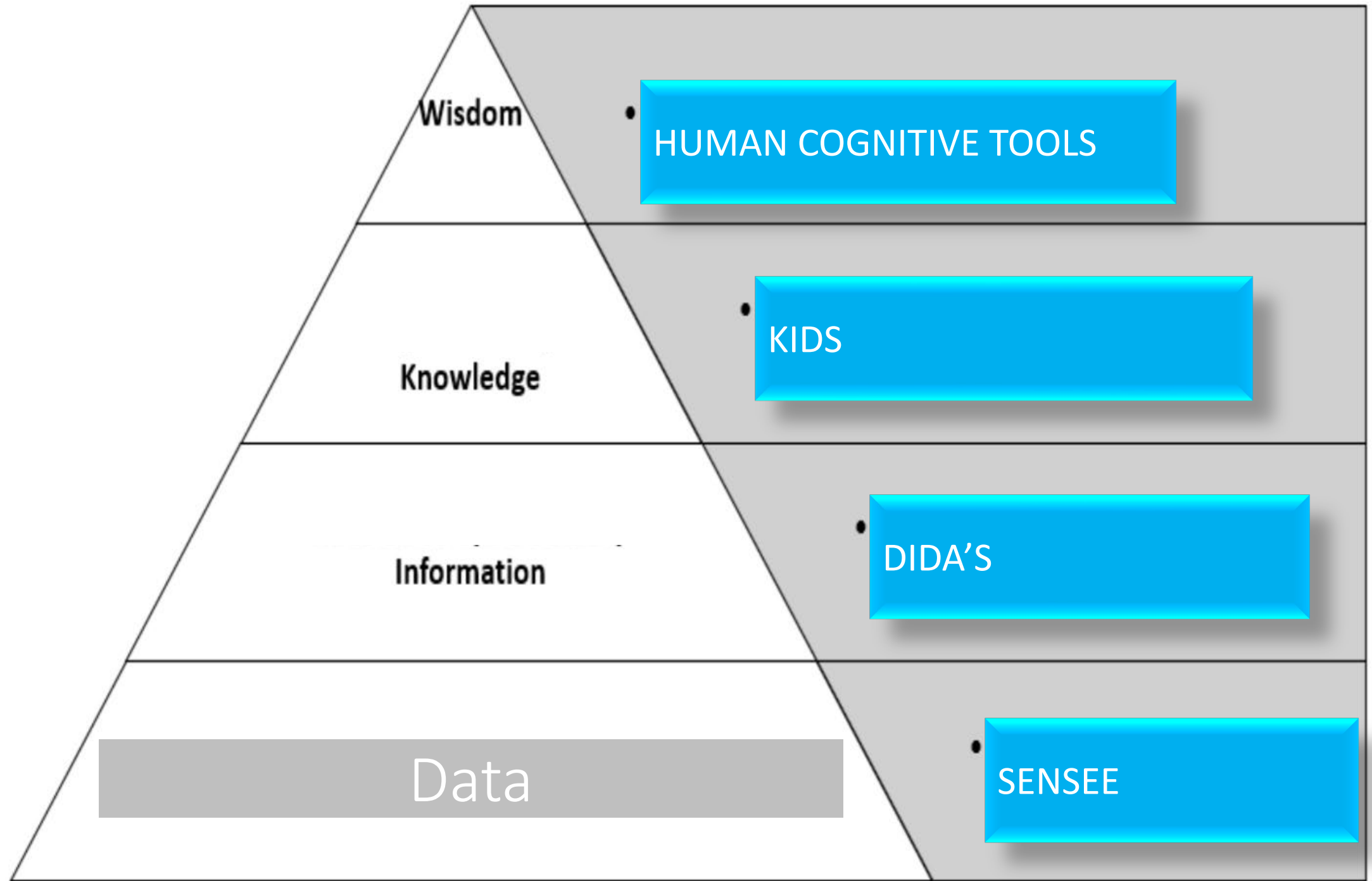
Information

DIDA'S

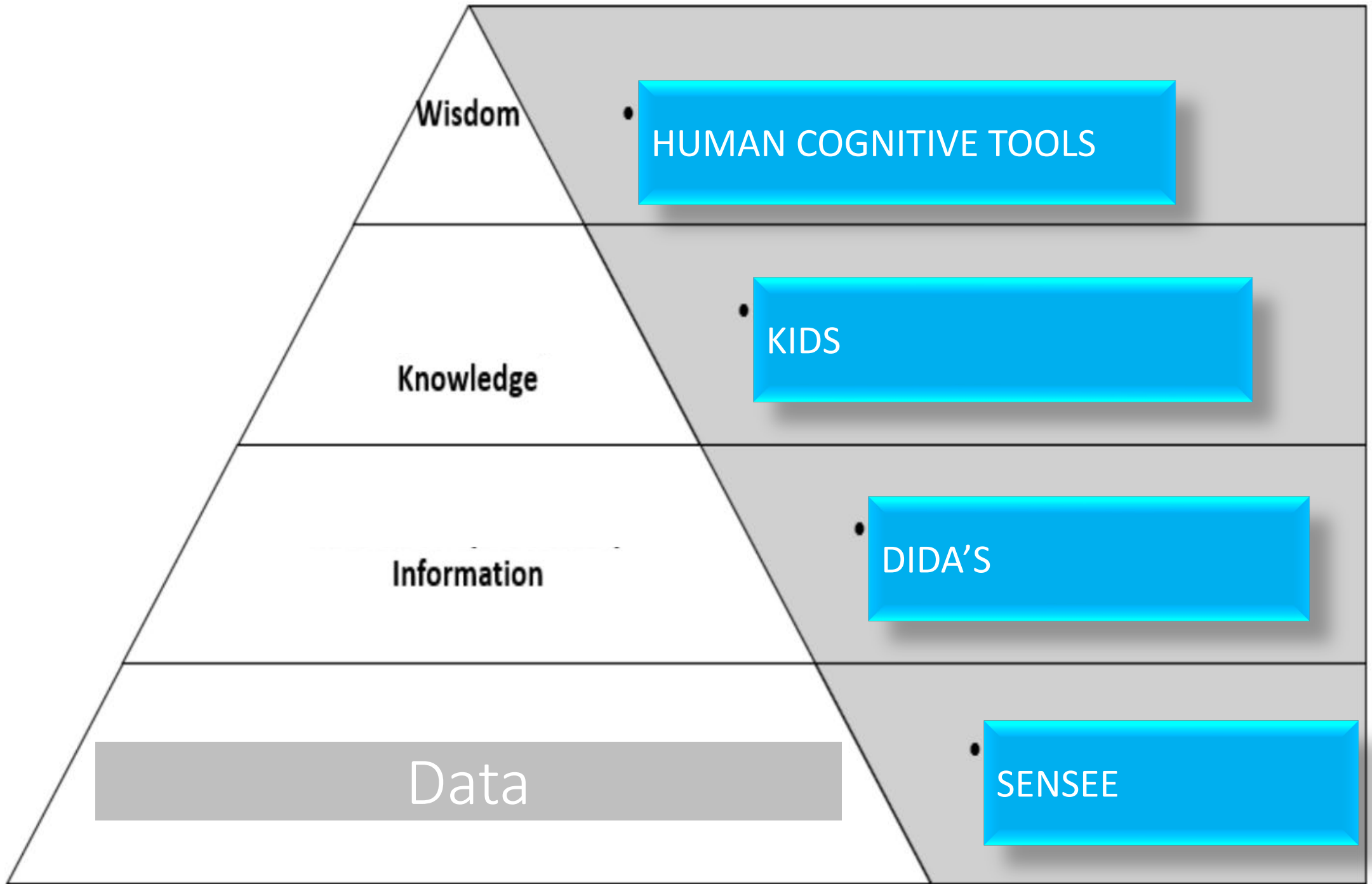
Data

SENSEE

SYNERGISTIC INTEGRATION

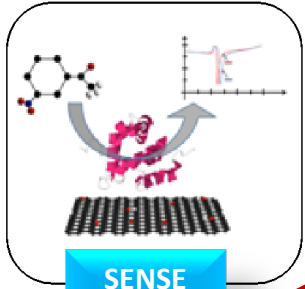


PEAS PLATFORM

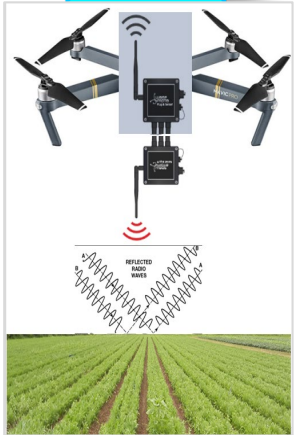


SENSEE

SENsor SEarch Engine



SENSE



Attempt to create an open source curated repository for different types of sensors created by academic and industrial labs, globally. Expect to connect with similar data from sensor manufacturers.

SENSEE

The curated repository containing descriptions of sensors may also serve as an unit or module for the hypothetical open source library to contain information about tools or technologies related to management of agricultural wastewater systems (AWS).

The purpose of the AWS library is to serve end-users (farmers, growers) who may ask questions pertaining to AWS for irrigation. Questions may be related to the detection of heavy metals and microbes (thus, sensors) or waste water treatment technologies (separate module to be developed by USDA SmartPath Project, not a part of SENSEE).

Development of an open source AWS technology repository (with mobile access)

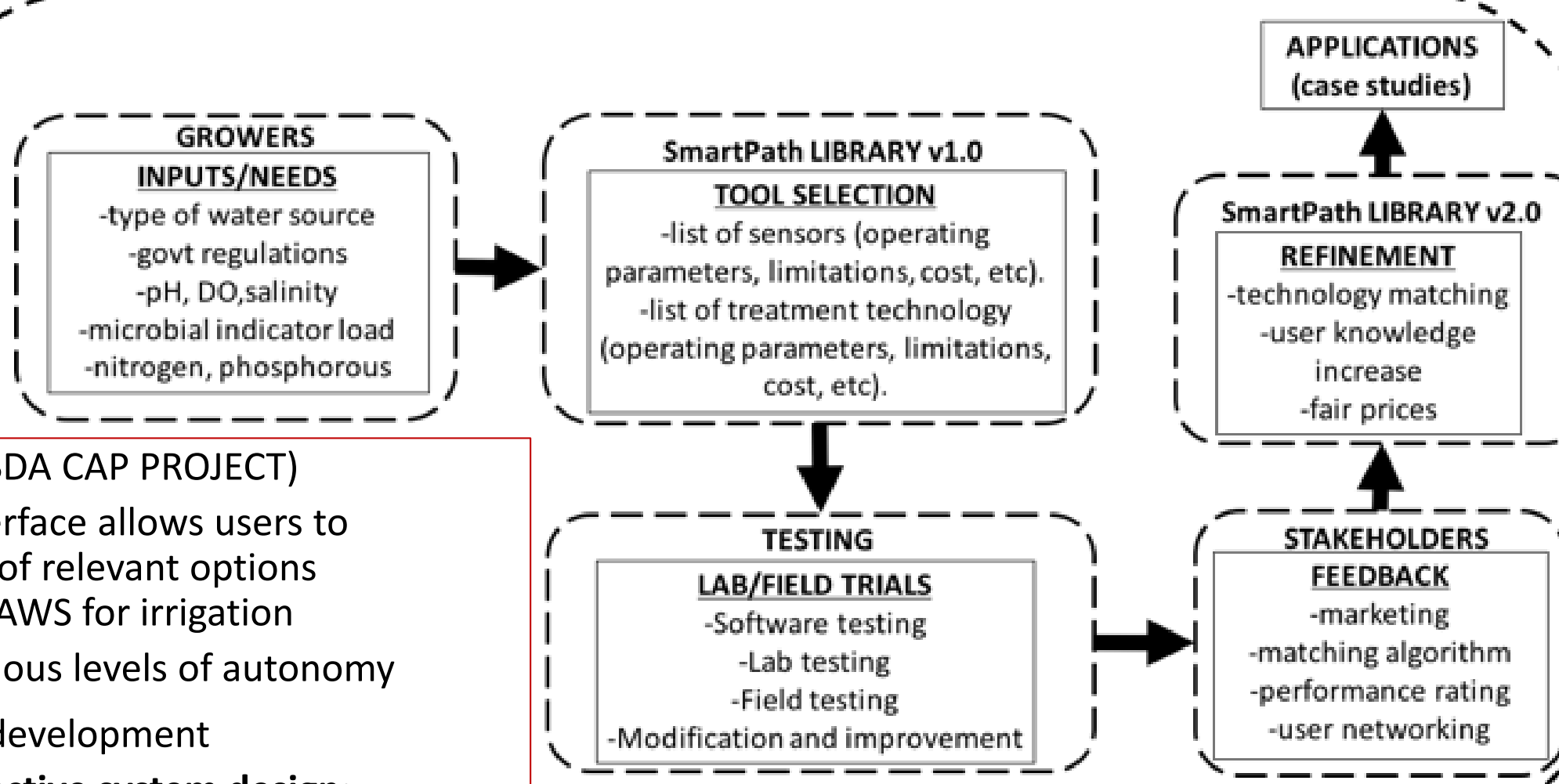


Development of an open source AWS technology repository (with mobile access)

- SmartPath Library (USDA CAP PROJECT)
 - User-friendly interface allows users to explore a variety of relevant options related to use of AWS for irrigation
 - Open source, various levels of autonomy
- Tools/widgets under development
 - Software for **proactive system design**; selection of appropriate technologies (sensors from SENSEE and treatment module)
 - Software for assisting growers with **technology adoption** and assist with trade policies, pricing
 - Software for providing **decision support** for monitoring/treatment (SENSEE, DIDA'S, KIDS)



Development of an open source AWS technology repository (with mobile access)



- SmartPath Library (USDA CAP PROJECT)
 - User-friendly interface allows users to explore a variety of relevant options related to use of AWS for irrigation
 - Open source, various levels of autonomy
- Tools/widgets under development
 - Software for **proactive system design**; selection of appropriate technologies (sensors from SENSEE and treatment module)
 - Software for assisting growers with **technology adoption** and assist with trade policies, pricing
 - Software for providing **decision support** for monitoring/treatment (SENSEE, DIDA'S, KIDS)



SENSEE

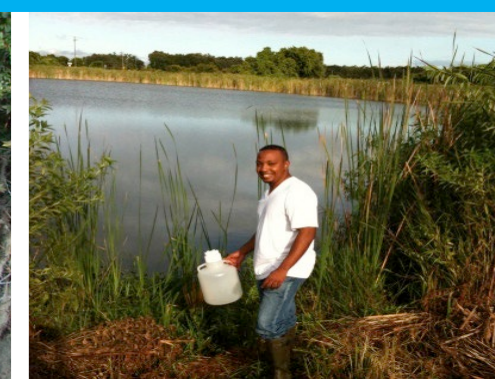
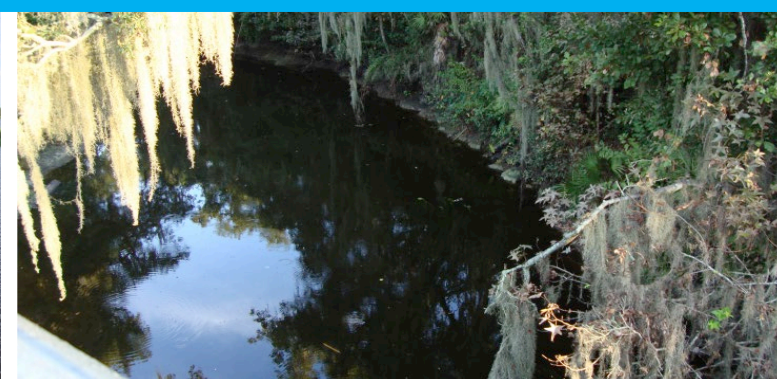
Expert users (academics, students, industrial labs) may be the short term beneficiary from the curated descriptions of sensors, if SENSEE contains a critical mass of sensor descriptions (expectation: sensor descriptions from 1,000 to 10,000 labs, globally).

Google search may reveal millions of documents. SENSEE presents a curated list.

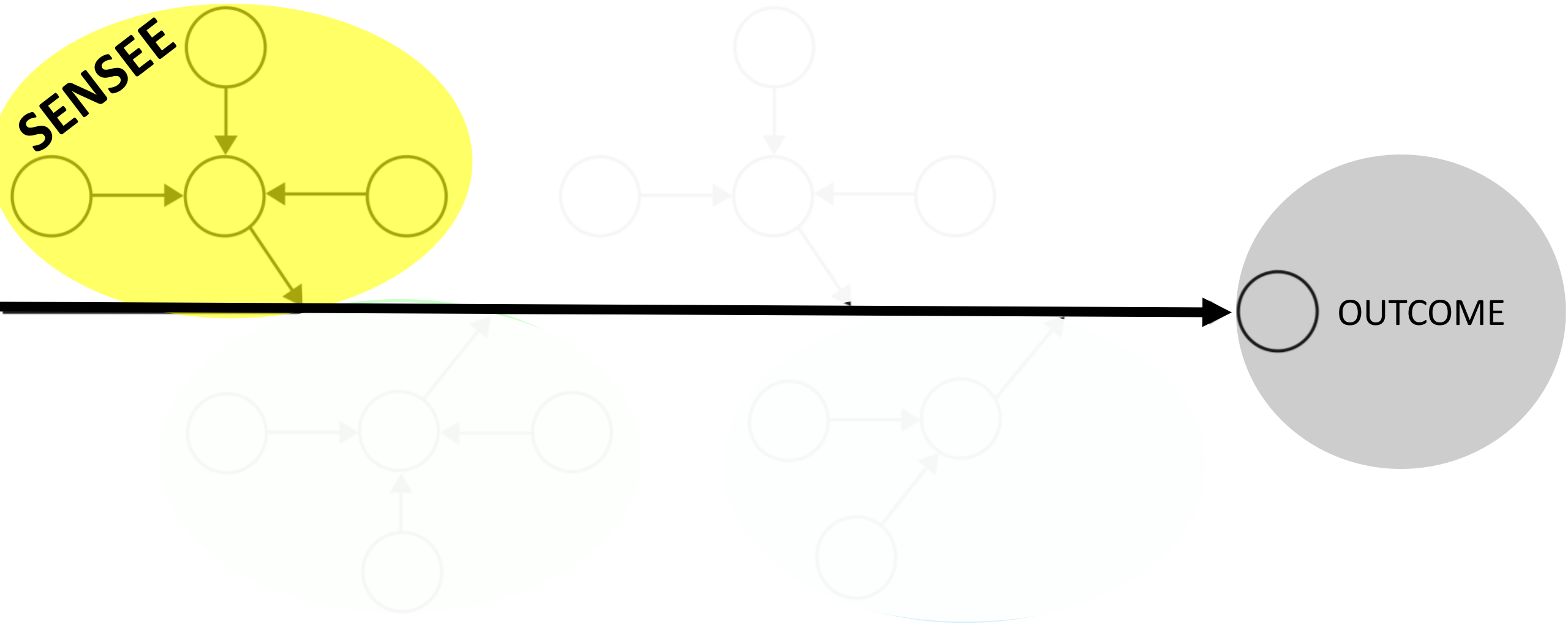
In the future, SENSEE will contain sensor descriptions (categories, attributes) **and** select data from specific sensors. Sensor data ingested in SENSEE will be determined by use cases for specific end-users (farms, grocery stores, food warehouse, food processing plant, packaging operations, retail distribution, food logistics, global transportation).

SENSEE is a start ... but woefully inadequate as a solution

- End-user perspective and questions from the field (agro-ecosystem) are complex:
 - Is my **water quality in compliance** with FSMA produce safety rule (PSR)?
 - What are the **costs** associated with agricultural wastewater (AWS) reuse?
 - Does reuse of AWS add excessive **management** issues?
 - **Who monitors** return flows, aquifer recharge, and water quality?
 - What are the perceived and real **health risks** associated with AWS for irrigation?
 - Can **technologies** (sensors + treatment systems) add **quantifiable** value?
 - Are there **legal implications** of real time water quality data acquisition?
 - Are there **economic penalties** for buyers if data log shows poor water quality?



SENSEE is a start ... but woefully inadequate as a solution



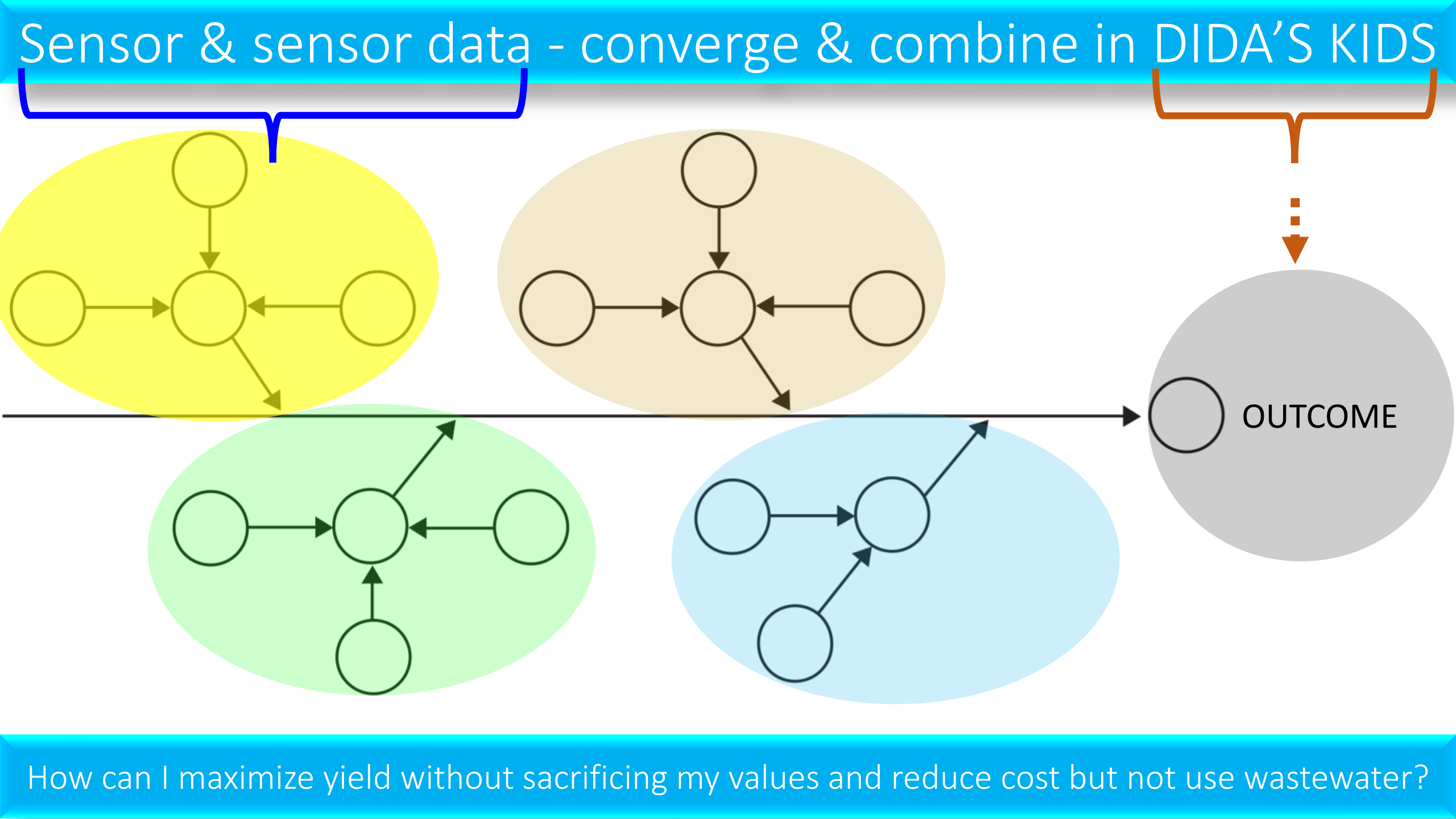
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

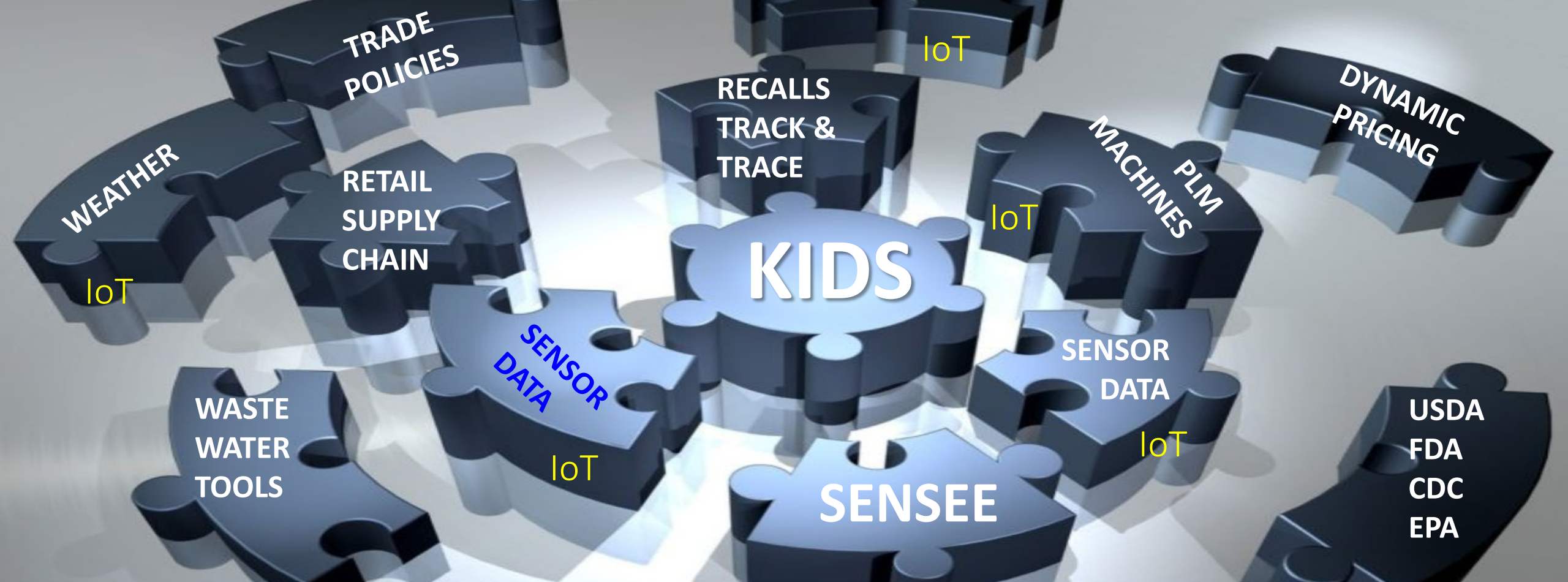
End-user perspective and questions from the field (agro-ecosystem) are complex

KIDS

Do you sense the convergence?

WHY SENSEE IS JUST A TINY STEP IN OUR JOURNEY TO KNOWLEDGE-INFORMED DECISIONS (KIDS)

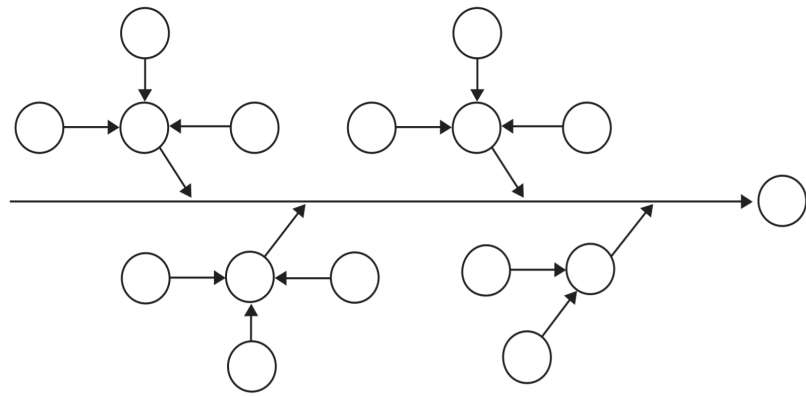


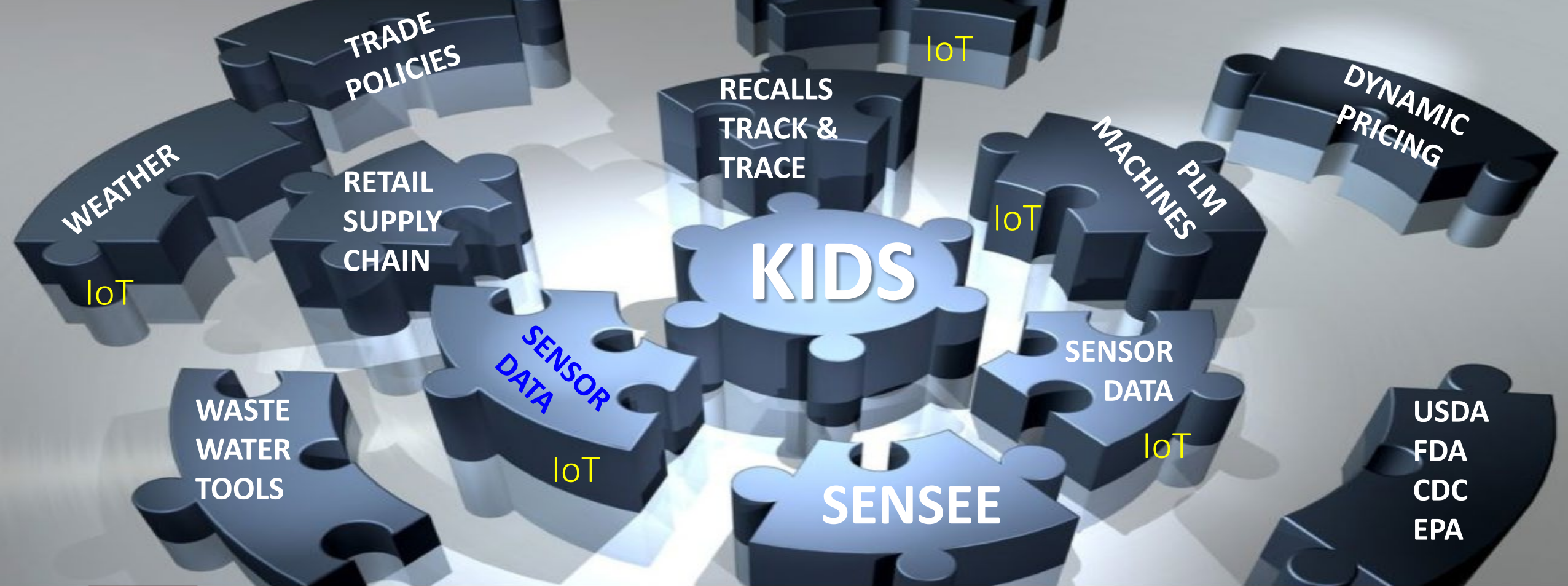


DATA



KNOWLEDGE





DATA

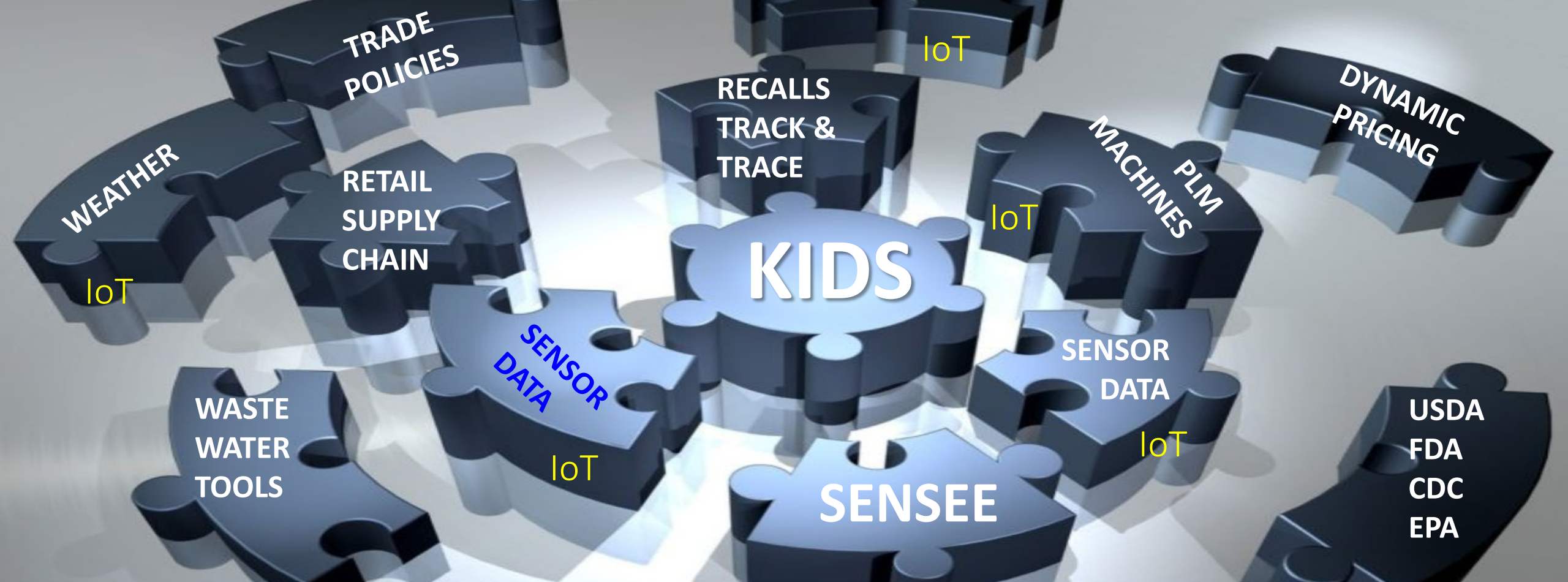
KNOWLEDGE

KIDS IS NOT A "THING"

ONE SIZE WILL NOT FIT ALL

KIDS IS A CONCEPTUAL DESIGN METAPHOR

KIDS IS A SYNERGISTIC KNOWLEDGE INTEGRATION PLATFORM



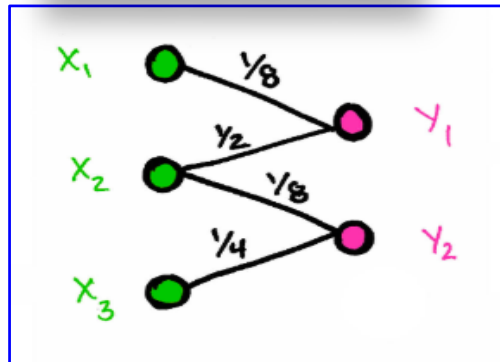
DATA



End-user perspective and questions from the field (agro-ecosystem) are complex:

- Is my **water quality in compliance** with FSMA produce safety rule (PSR)?
- What are the **costs** associated with agricultural wastewater (AWS) reuse?
- Does reuse of AWS add excessive **management** issues?
- Who monitors** return flows, aquifer recharge, and water quality?
- What are the perceived and real **health risks** associated with AWS for irrigation?
- Can **technologies** (sensors + treatment systems) add **quantifiable** value?
- Are there **legal implications** of real time water quality data acquisition?
- Are there **economic penalties** for buyers if data log shows poor water quality?

KNOWLEDGE



WHY SENSEE IS A TINY PART OF A SYSTEM

It may not be difficult to grasp that the questions from field users demand immense cross-pollination of data and information to converge with knowledge, logic and reasoning, to generate even a basic response.

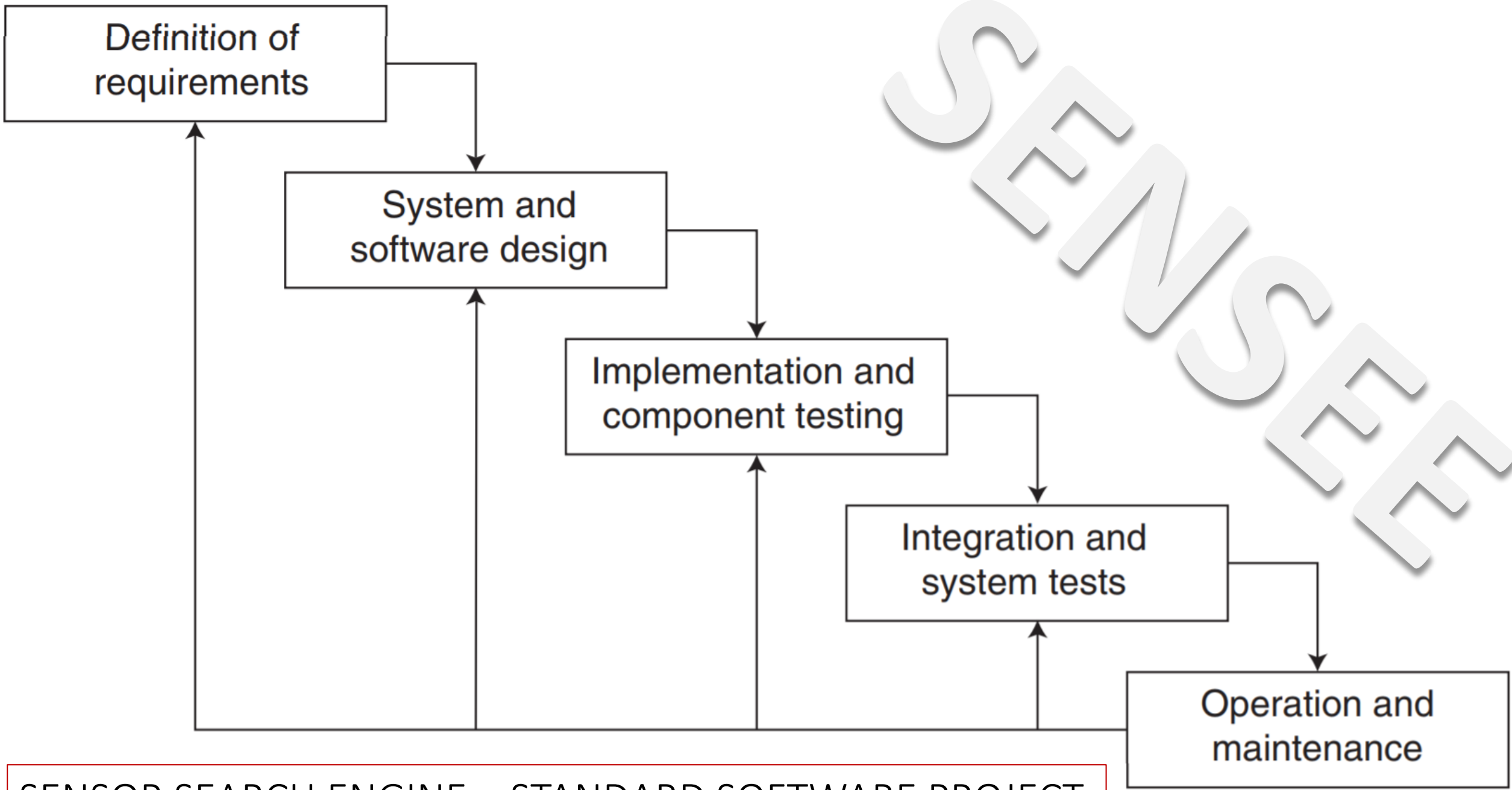
SENSEE

AT THIS TIME, SENSEE 1.0 CONTAINS ONLY SENSOR DESCRIPTIONS (CATEGORIES, ATTRIBUTES). SENSEE CAN ANSWER SELECT QUESTIONS.

Expert users (academics, students, industrial labs) may benefit from the curated descriptions of sensors. In future, SENSEE may contain a critical mass of sensor descriptions. Google search reveal millions of docs but SENSEE is a curated list.

In the future, SENSEE will contain sensor descriptions (categories, attributes) **and** select **data** from specific sensors. Sensor data ingested in SENSEE will be determined by use cases for specific end-users (farms, grocery stores, food warehouse, food processing, packaging, retail distribution, logistics, agri-business, machine tools, supply chain).

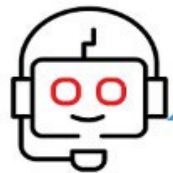
SENSOR SEARCH ENGINE



SENSOR SEARCH ENGINE – STANDARD SOFTWARE PROJECT

Experts can query SENSEE and perhaps receive a decent answer, in the near future

SENSEE



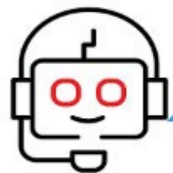
Show 3 molecules (10Da, 100Da and 200Da)
for which there are sensors on LSG platform

Submit

SENSEE WEB SERVICE (MOBILE APP EQUIVALENT)

Experts can query SENSEE and perhaps receive a decent answer, in the near future

SENSEE

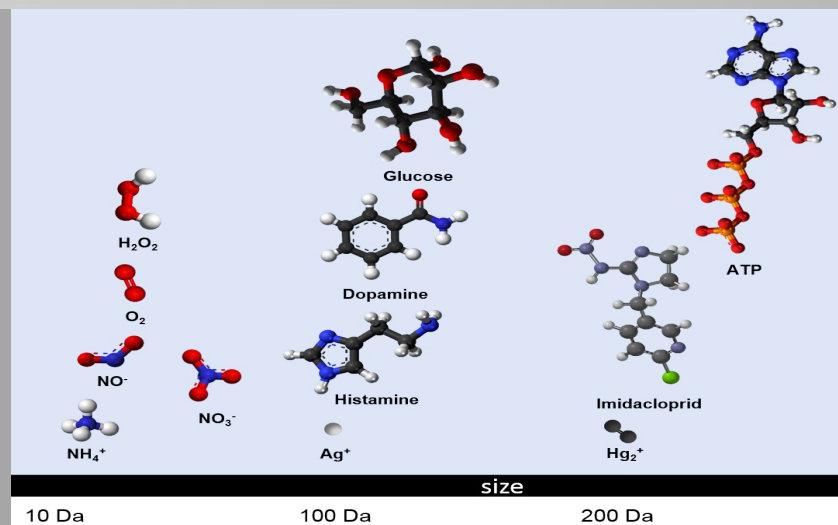


I found 3 classes of molecules. See results.



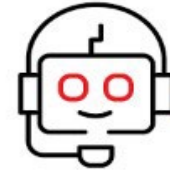
Show 3 molecules (10Da, 100Da and 200Da) for which there are sensors on LSG platform

Submit



Experts can query SENSEE and perhaps receive a decent answer, in the near future

SENSEE

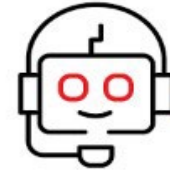


Which types of microbes are most used by sensor labs to create lectin based recognition?

Submit

Experts can query SENSEE and perhaps receive a decent answer, in the near future

SENSEE



I found two types of bacteria. See display.

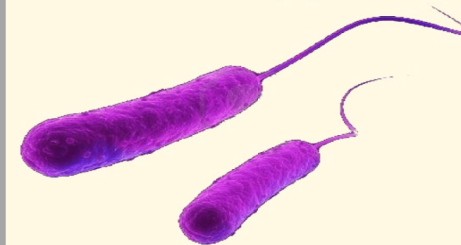


Which types of microbes are most used by sensor labs to create lectin based recognition?

Submit



Listeria monocytogenes



Escherichia coli

Experts may query SENSEE but is SENSEE capable of facing complex questions?

SENSEE

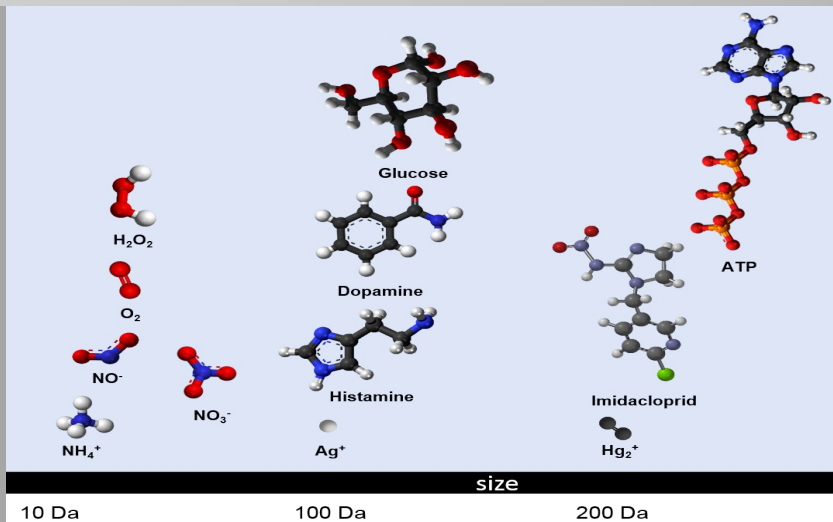


I found 3 classes of molecules. See results.

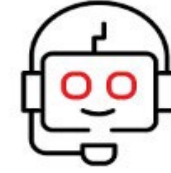


Show 3 molecules (10Da, 100Da and 200Da) for which there are sensors on LSG platform

Submit



SENSEE

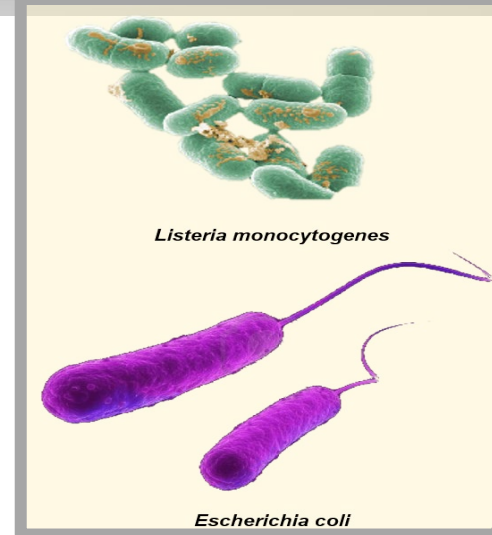


I found two types of bacteria. See display.



Which types of microbes are most used by sensor labs to create lectin based recognition?


Submit



End-user perspective and questions from the field (agro-ecosystem) are complex

SENSEE




 How can I maximize yield without sacrificing my values & reduce cost without using wastewater?

Submit




End-user perspective and questions from the field (agro-ecosystem) are complex

SENSEE



This question does not exist. I am not able to understand the query.



How can I maximize yield without sacrificing my values & reduce cost without using wastewater?

Submit





SENSEE 1.0 CANNOT HELP

CAN ART HELP? CAN KIDS HELP?

End-user perspective and questions from the field (agro-ecosystem) are complex

SENSEE




 How can I disseminate the health benefit of our fresh cilantro sauce for lowering blood pressure?


Submit



End-user perspective and questions from the field (agro-ecosystem) are complex

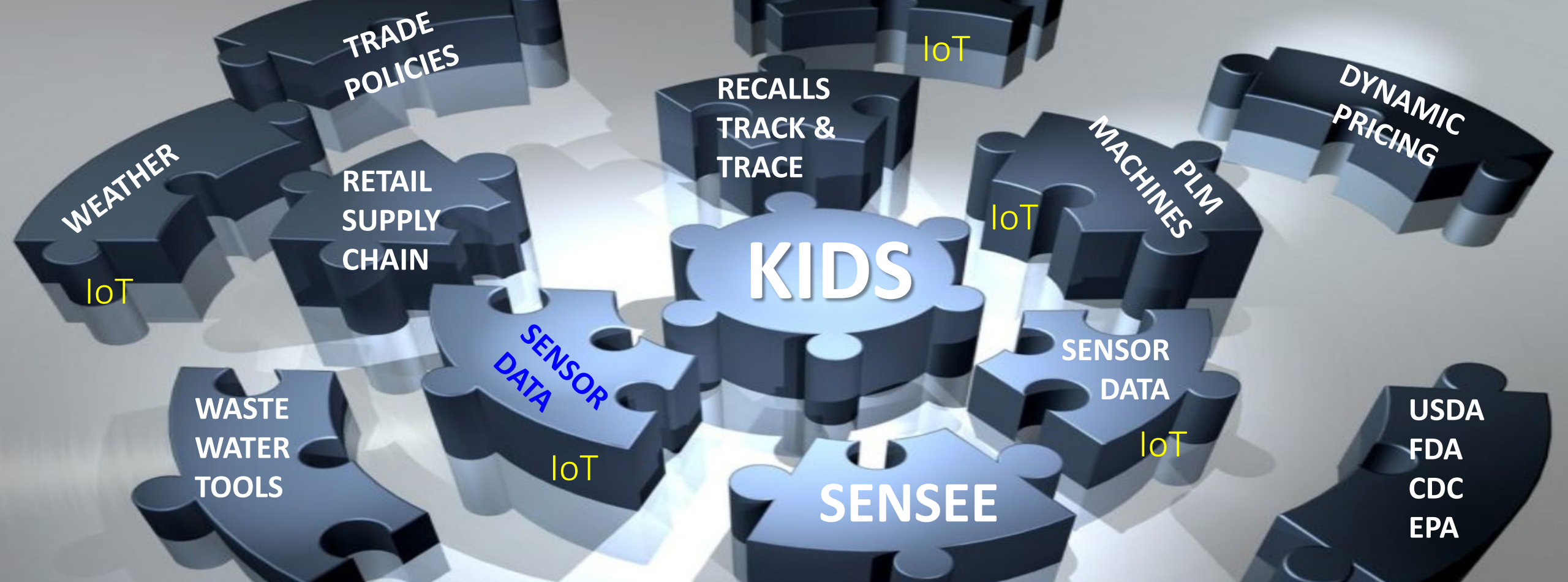
SENSEE

 Go to KIDS to request Agent to connect with Citizen Science Service

 How can I disseminate the health benefit of our fresh cilantro sauce for lowering blood pressure?

Submit





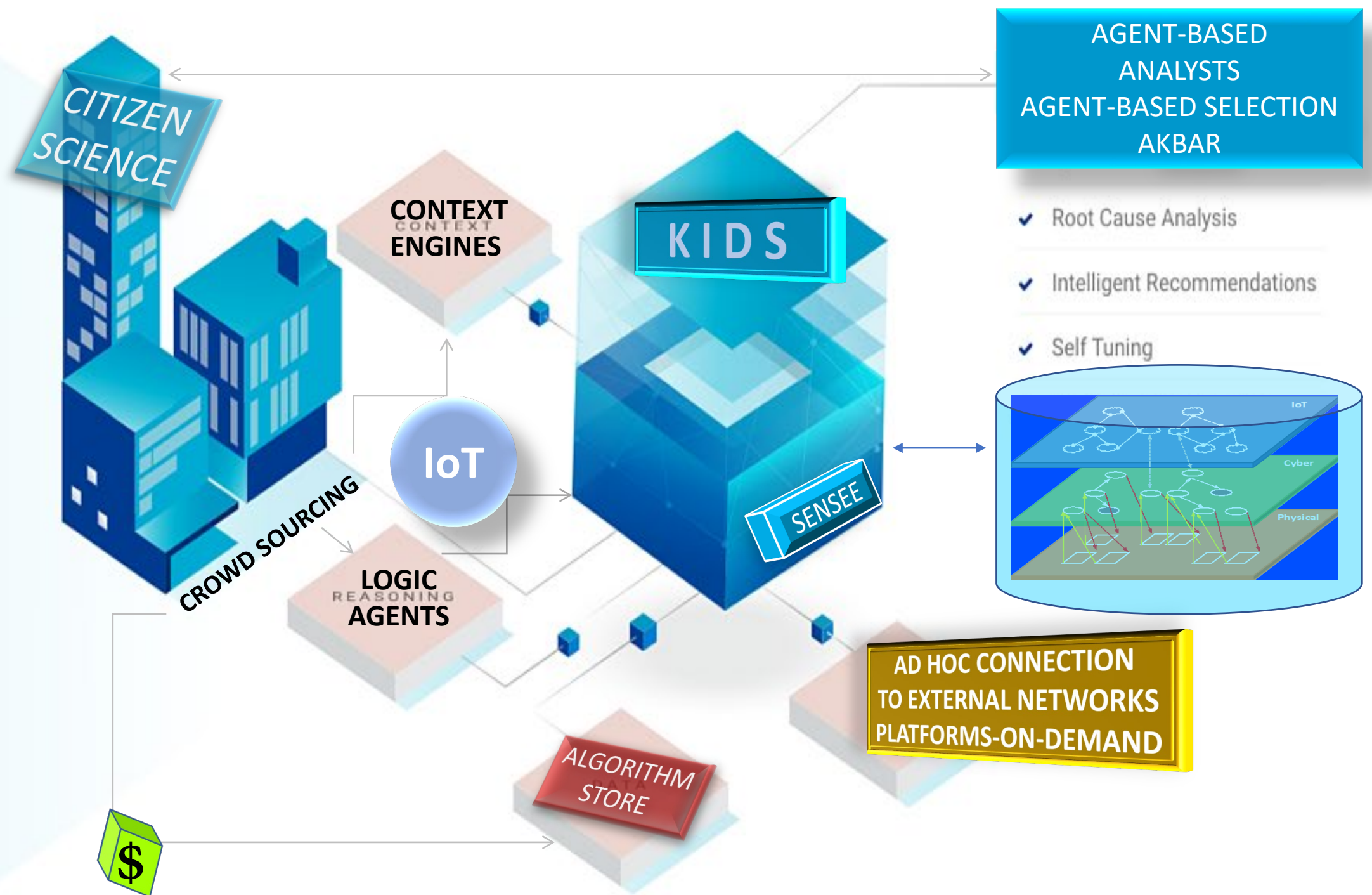
DATA



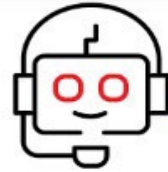
KNOWLEDGE

HOW KIDS IS DESIGNED TO ADDRESS COMPLEXITY. LET US TAKE ANOTHER LOOK.

KIDS



KIDS

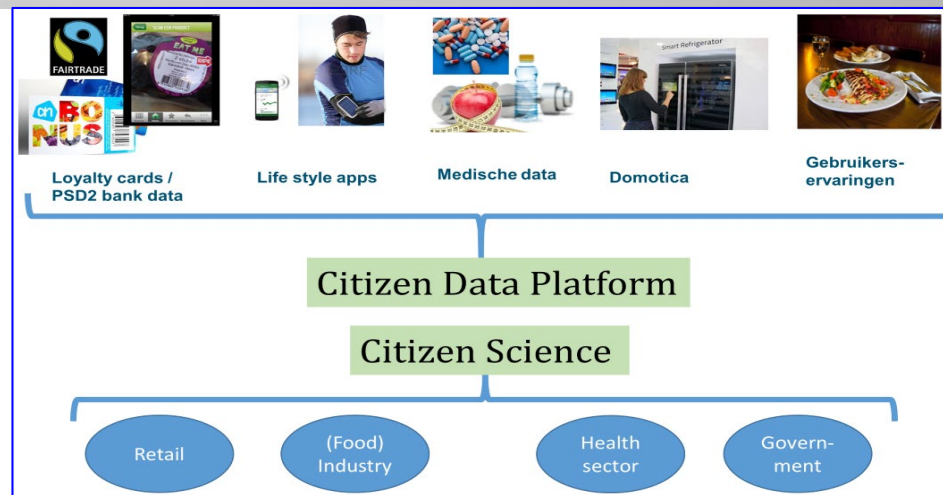


Referring you to Agent Analyst working with Citizen Science Service



How can I disseminate the health benefit of our fresh cilantro sauce for lowering blood pressure?

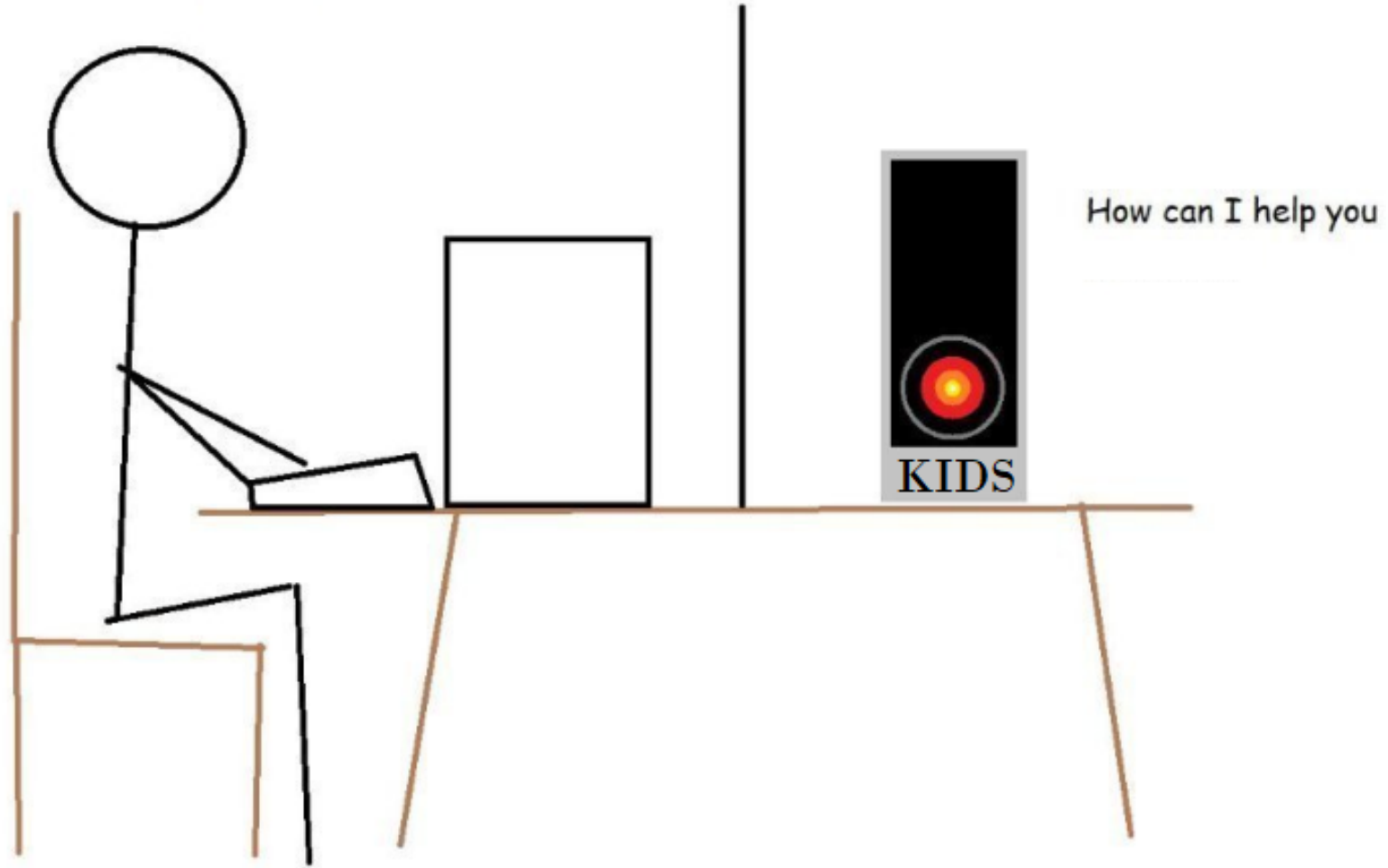
Submit



CITIZEN SCIENCE

The use of Agents as virtual chat bots are common and may be modified for the agro-ecosystem.

K
I
D
S



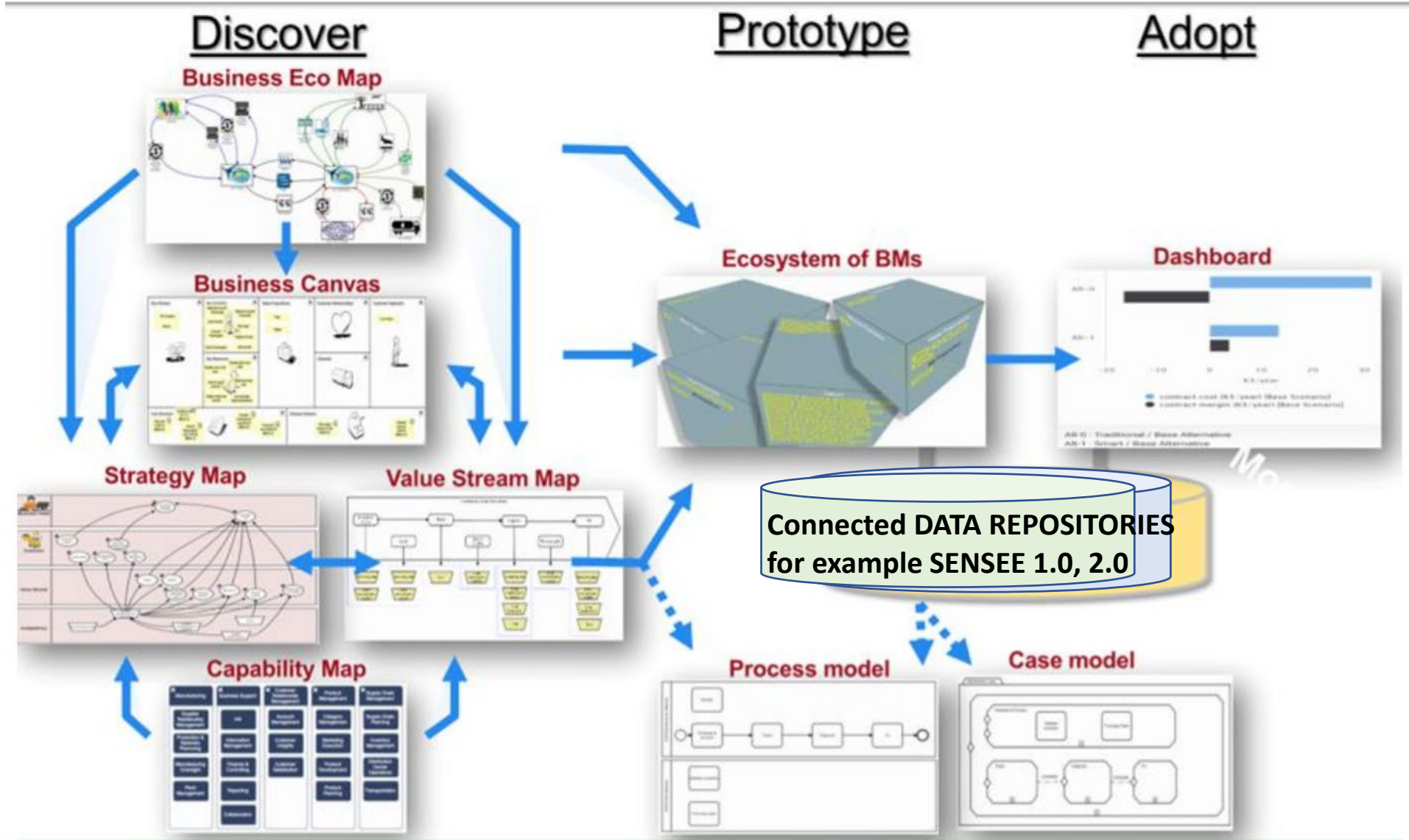
Microsoft Virtual Agent and Dynamics 365 for Finance and Operations

K

I

D

S

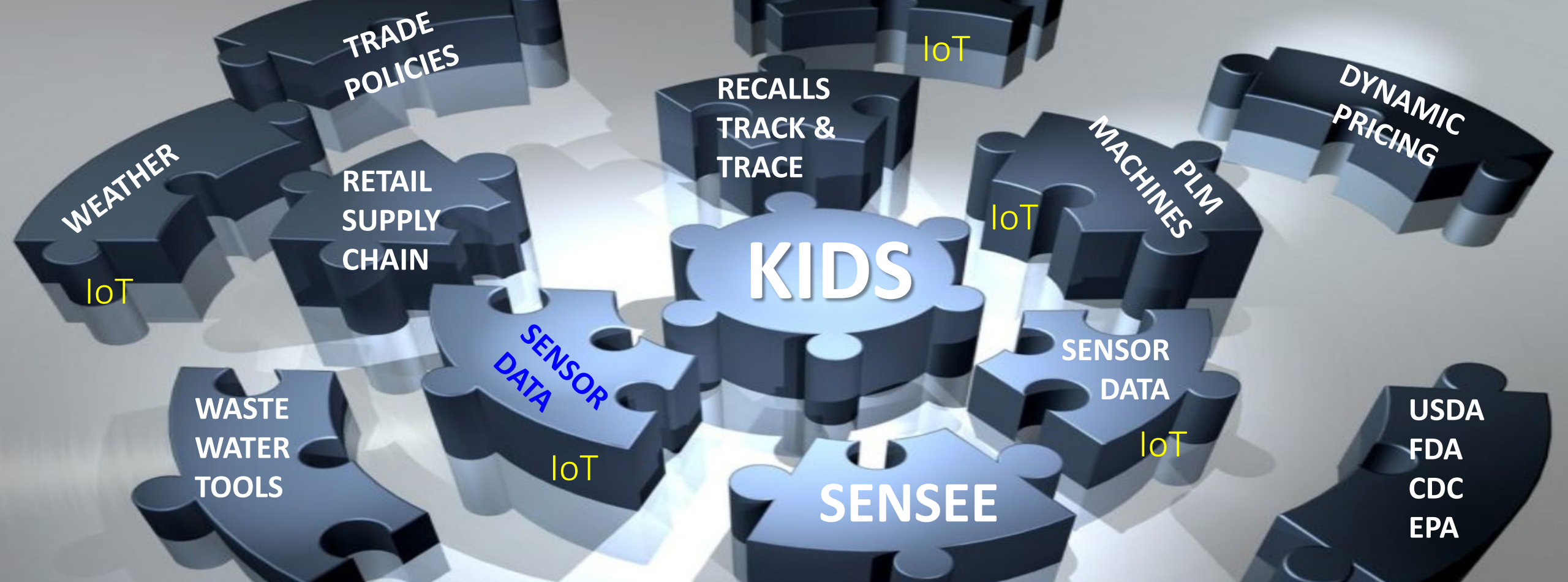


End-user perspective and questions from the field (agro-ecosystem) are complex

PEAS, KIDS

makes sense?

WHY SENSEE IS JUST A TINY STEP IN OUR JOURNEY TO KNOWLEDGE-INFORMED DECISIONS (KIDS)



DATA



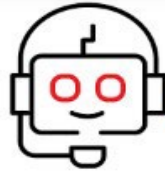
KNOWLEDGE



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Can KIDS answer end-user questions? We don't know but that is the expectation.

KIDS



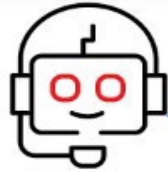
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Submit



Can KIDS answer end-user questions? We don't know but that is the expectation.

KIDS



Explore CropX system.
Monitor soil nitrogen
& moisture every day.



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Submit



SENSEE

A journey of a thousand miles begins with a single step.

Developing SENSEE 1.0

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Spreadsheet

Sensor Properties

Library
PoC
DB

Development of SENSEE 1.0 (SENsor SEArch Engine)

Spreadsheet

Sensor Properties

	A	B	C	D	E	F	G	H	I	J	K	L
1	MW [Da]	Category	Target	Recognition-transduction scheme	Platform	LOD [M]	Max range [M]	Selectivity (interferent species tested)	Response time [sec]	Durability	USECAT1	Link to paper(s)
2	1	small molecule	H+	H+ ionophore (liquid)	glass capillary	1.00E-13	1.00E-04	excellent (K+, Na+, Ca2+, Mg2+)	2	High	hydroponics	https://www.ncbi.nlm.nih.gov/pubmed/26088926
3	1	small molecule	H+	anthocyanin/nanocellulose	paper filter	1.00E-15	1.00E-02	excellent	2	high	irrigation water	https://www.ncbi.nlm.nih.gov/pubmed/28884510
4	18	small molecule	Ammonium	NH4+ ionophore (liquid)	glass capillary	5.00E-09	1.00E-01	excellent	5	medium	wastewater	http://www.allelopathyjournal.org/archives/?Year=2016&Vol=37&Issue=2&Month=3
5	18	small molecule	Ammonium	NH4+ ionophore (solid)	LSG	2.80E-05	5.00E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
6	30	small molecule	N/O radicals	nanoplatinum/nanoceria	Pt electrode	1.00E-08	3.00E-06	medium	1	medium	ocean water	https://pubs.rsc.org/en/Content/ArticleLanding/2017/AY/C7AY01964F#divAbstract
7	32	small molecule	DO	Pt porphyrin-nTiO2	fiber optic	1.00E-06	5.00E-06	excellent, temp sens	1	High	hydroponic media	https://www.sciencedirect.com/science/article/pii/S0925540051400117
8	32	small molecule	DO	Pt porphyrin	96 well	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	https://www.sciencedirect.com/science/article/pii/S016770121300331X
9	32	small molecule	DO	Pt porphyrin	glass vial	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	
10	34	small molecule	H2O2	fractal nPt	Pt electrode	5.00E-09	5.00E-05	excellent	1	high	ocean water	https://www.ncbi.nlm.nih.gov/pubmed/27121177
11	39	small molecule	K+	K+ ionophore (liquid)	glass capillary	1.00E-06	2.50E-01	excellent	2	low	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/24961073
12	41	small molecule	Ca2+	Ca2+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-01	excellent	1	low	Hoaglands media	https://onlinelibrary.wiley.com/doi/full/10.1002/jipln.201700319
13	58	small molecule	acetone	chemosensory proteins-nPt	Pt electrode	5.00E-06	1.00E-05	high	10	low	buffer	https://pubs.rsc.org/en/content/articlelanding/2018/an/c8an00065d#divAbstract
14	62	small molecule	Nitrate	NO3- ionophore (liquid)	glass capillary	1.00E-06	2.00E-01	excellent	2	medium	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/18985610
15	62	small molecule	Nitrate	NO3- ionophore (solid)	LSG	2.00E-05	1.50E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
16	108	small molecule	Ag+	Ag+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-02	excellent	2	high	wound dressing	https://link.springer.com/article/10.1007/s11356-014-3058-6
17	111	small molecule	histamine	diamine oxidase-nCu	LSG	6.30E-05	1.00E-03	excellent	2	medium	fermented fish	https://www.mdpi.com/2079-6374/8/2/42
18	147	small molecule	Glutamate	CNT/nPt/GlOx	Pt electrode	1.00E-06	1.00E-03	excellent	2	low	INS1 tissue culture	https://www.sciencedirect.com/science/article/pii/S0165027010001196
19	147	small molecule	Glutamate	CNT/nPt/GlOx	Si biochip	1.00E-06	5.00E-01	excellent	2	low	INS1 tissue culture	https://pubs.rsc.org/en/content/articlelanding/2011/im/c1im11561h#divAbstract
20	154	small molecule	catecholamines	nPt	LSG	5.00E-07	3.00E-03	excellent	2	high	ocean water	
21	154	small molecule	catecholamines	graphene anchored nCuO	LSG	3.00E-07	3.00E-03	high	2	medium	buffer	https://pubs.acs.org/doi/abs/10.1021/acssuschemeng.8b02510
22	176	small molecule	indole acetic acid	fractal nPt	Pt/Ir microwire	1.00E-06	1.00E-03	high	1	high	root growth media	https://link.springer.com/article/10.1007/s00344-017-9688-4
23	181	small molecule	Glucose	nPt/GOx	graphene paper	8.00E-08	1.00E-03	excellent	2	medium	buffer	https://www.ncbi.nlm.nih.gov/pubmed/27209574
24	181	small molecule	Glucose	nPt/GOx	Pt/Ir microwire	1.00E-07	5.00E-06	excellent	1	medium	blood	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166557
25	181	small molecule	Glucose	nPt/nCe/GOx	Pt electrode	1.00E-07	3.00E-06	excellent	1	medium	buffer	https://www.sciencedirect.com/science/article/pii/S0956566314000992

Development of SENSEE 1.0 (SENsor SEArch Engine)

Spreadsheet

Sensor Properties

	A	B	C	D	E	F	G	H	I	J	K	L
1	MW [Da]	Category	Target	Recognition-transduction scheme	Platform	LOD [M]	Max range [M]	Selectivity (interferent species tested)	Response time [sec]	Durability	USECAT1	Link to paper(s)
2	1	small molecule	H+	H+ ionophore (liquid)	glass capillary	1.00E-13	1.00E-04	excellent (K+, Na+, Ca2+, Mg2+)	2	High	hydroponics	https://www.ncbi.nlm.nih.gov/pubmed/26088926
3	1	small molecule	H+	anthocyanin/nanocellulose	paper filter	1.00E-15	1.00E-02	excellent	2	high	irrigation water	https://www.ncbi.nlm.nih.gov/pubmed/28884510
4	18	small molecule	Ammonium	NH4+ ionophore (liquid)	glass capillary	5.00E-09	1.00E-01	excellent	5	medium	wastewater	http://www.allelopathyjournal.org/archives/2Year=2016&Vol=37&Issue=2&Month=3
5	18	small molecule	Ammonium	NH4+ ionophore (solid)	LSG	2.80E-05	5.00E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
6	30	small molecule	N/O radicals	nanoplatinum/nanoceria	Pt electrode	1.00E-08	3.00E-06	medium	1	medium	ocean water	https://pubs.rsc.org/en/Content/ArticleLanding/2017/AY/C7AY01964E#divAbstract
7	32	small molecule	DO	Pt porphyrin-nTiO2	fiber optic	1.00E-06	5.00E-06	excellent, temp sens	1	High	hydroponic media	https://www.sciencedirect.com/science/article/pii/S0925400514001117
8	32	small molecule	DO	Pt porphyrin	96 well	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	https://www.sciencedirect.com/science/article/pii/S016770121300331X
9	32	small molecule	DO	Pt porphyrin	glass vial	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	
10	34	small molecule	H2O2	fractal nPt	Pt electrode	5.00E-09	5.00E-05	excellent	1	high	ocean water	https://www.ncbi.nlm.nih.gov/pubmed/27121177
11	39	small molecule	K+	K+ ionophore (liquid)	glass capillary	1.00E-06	2.50E-01	excellent	2	low	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/24961073
12	41	small molecule	Ca2+	Ca2+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-01	excellent	1	low	Hoaglands media	https://onlinelibrary.wiley.com/doi/full/10.1002/jpln.201700319
13	58	small molecule	acetone	chemosensory proteins-nPt	Pt electrode	5.00E-06	1.00E-05	high	10	low	buffer	https://pubs.rsc.org/en/content/articlelanding/2018/an/c8an00065d#divAbstract
14	62	small molecule	Nitrate	NO3- ionophore (liquid)	glass capillary	1.00E-06	2.00E-01	excellent	2	medium	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/18985610
15	62	small molecule	Nitrate	NO3- ionophore (solid)	LSG	2.00E-05	1.50E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
16	108	small molecule	Ag+	Ag+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-02	excellent	2	high	wound dressing	https://link.springer.com/article/10.1007/s11356-014-3058-6
17	111	small molecule	histamine	diamine oxidase-nCu	LSG	6.30E-05	1.00E-03	excellent	2	medium	fermented fish	https://www.mdpi.com/2079-6374/8/2/42
18	147	small molecule	Glutamate	CNT/nPt/GlOx	Pt electrode	1.00E-06	1.00E-03	excellent	2	low	INS1 tissue culture	https://www.sciencedirect.com/science/article/pii/S0165027010001196
19	147	small molecule	Glutamate	CNT/nPt/GlOx	Si biochip	1.00E-06	5.00E-01	excellent	2	low	INS1 tissue culture	https://pubs.rsc.org/en/content/articlelanding/2011/im/c1im11561h#divAbstract
20	154	small molecule	catecholamines	nPt	LSG	5.00E-07	3.00E-03	excellent	2	high	ocean water	
21	154	small molecule	catecholamines	graphene anchored nCuO	LSG	3.00E-07	3.00E-03	high	2	medium	buffer	https://pubs.acs.org/doi/abs/10.1021/acssuschemeng.8b02510
22	176	small molecule	indole acetic acid	fractal nPt	Pt/Ir microwire	1.00E-06	1.00E-03	high	1	high	root growth media	https://link.springer.com/article/10.1007/s00344-017-9688-4
23	181	small molecule	Glucose	nPt/GOx	graphene paper	8.00E-08	1.00E-03	excellent	2	medium	buffer	https://www.ncbi.nlm.nih.gov/pubmed/27209574
24	181	small molecule	Glucose	nPt/GOx	Pt/Ir microwire	1.00E-07	5.00E-06	excellent	1	medium	blood	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166557
25	181	small molecule	Glucose	nPt/nCe/GOx	Pt electrode	1.00E-07	3.00E-06	excellent	1	medium	buffer	https://www.sciencedirect.com/science/article/pii/S0956566314000992

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Sensor R&D
Community

Spreadsheet

High Quality Description

Sensor Properties

Contributed by
Experts

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch Engine)

Sensor R&D
Community

Spreadsheet

High Quality Description

Basic Search, DB Tools

Sensor Properties

Contributed by
Experts

Elasticsearch, UI
DevOps, Web Host



SENSEE



Response time for
superoxide dismutase is
1200 seconds

what is the response time for superoxide dismutase?

Submit

<http://139.162.7.63/SENSEE/>

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Sensor R&D
Community

Spreadsheet

High Quality Description

Search Tools

Training



Sensor Properties

Contributed by
Experts

Elasticsearch, UI
DevOps, Web Host

NLU – BERT NLP
Error Correction

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Sensor R&D
Community

Spreadsheet

High Quality Description

Search Tools

Training

Scaling



Sensor Properties

Contributed by
Experts

Elasticsearch, UI
DevOps, Web Host

NLU – BERT NLP
Error Correction

Auto-upload,
Auto-config, Check

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Sensor R&D
Community

Spreadsheet

High Quality Description

Search Tools

Training

Scaling



Sensor Properties

Contributed by
Experts

Elasticsearch, UI
DevOps, Web Host

NLU – BERT NLP
Error Correction

Auto-upload,
Auto-config, Check

Users

Library
PoC
DB

SENSEE 1.0 PROOF OF CONCEPT – TEST QUESTIONS

- 155) What molecules can be detected in breast milk using biosensors?
- 156) What is the difference in sensitivity between glucose biosensors based on graphene or platinum foil?
- 157) What is the most sensitive biosensor based on carbon nanotubes?
- 158) How many biosensors have been proposed for glucose determination?
- 159) Anthocyanin is used as a target for which biosensor?
- 160) Which biosensors can be used for hydroponic medium?
- 161) In which samples, glutamate and/or glutamine was determined using biosensors?
- 162) Which biosensors were proposed for catecholamine determination?
- 163) What is the lowest limit of detection for graphene-based biosensors?
- 164) What is the maximal range for nitrate biosensors?
- 165) What platforms can be used for ammonium detection and mercury detection?
- 166) Most durable recognition-transduction scheme for interferon gamma biosensors?
- 167) Best limit of detection achieved with phosphotriesterase-based biosensors?
- 168) How many biosensors were described for ATP determination?
- 169) What platforms were proposed for ATP-sensitive biosensors?
- 170) What is the average LOD of K⁺ sensors?
- 171) Which platform could be used for selective glutamate analysis?
- 172) What is largest analyte/molecule for which there is a sensor in the database?
- 173) Is there any cost associated with any type of sensor?
- 174) How many labs are making sensors to detect lead in water?
- 175) Are there sensors to detect air-borne viruses in the air?

Development of SENSEE 1.0 (SENsor SEArch Engine)

Sensor R&D
Community

Spreadsheet

High Quality Description

Search Tools

Training

Scaling

Sensor Properties

Contributed by
Experts

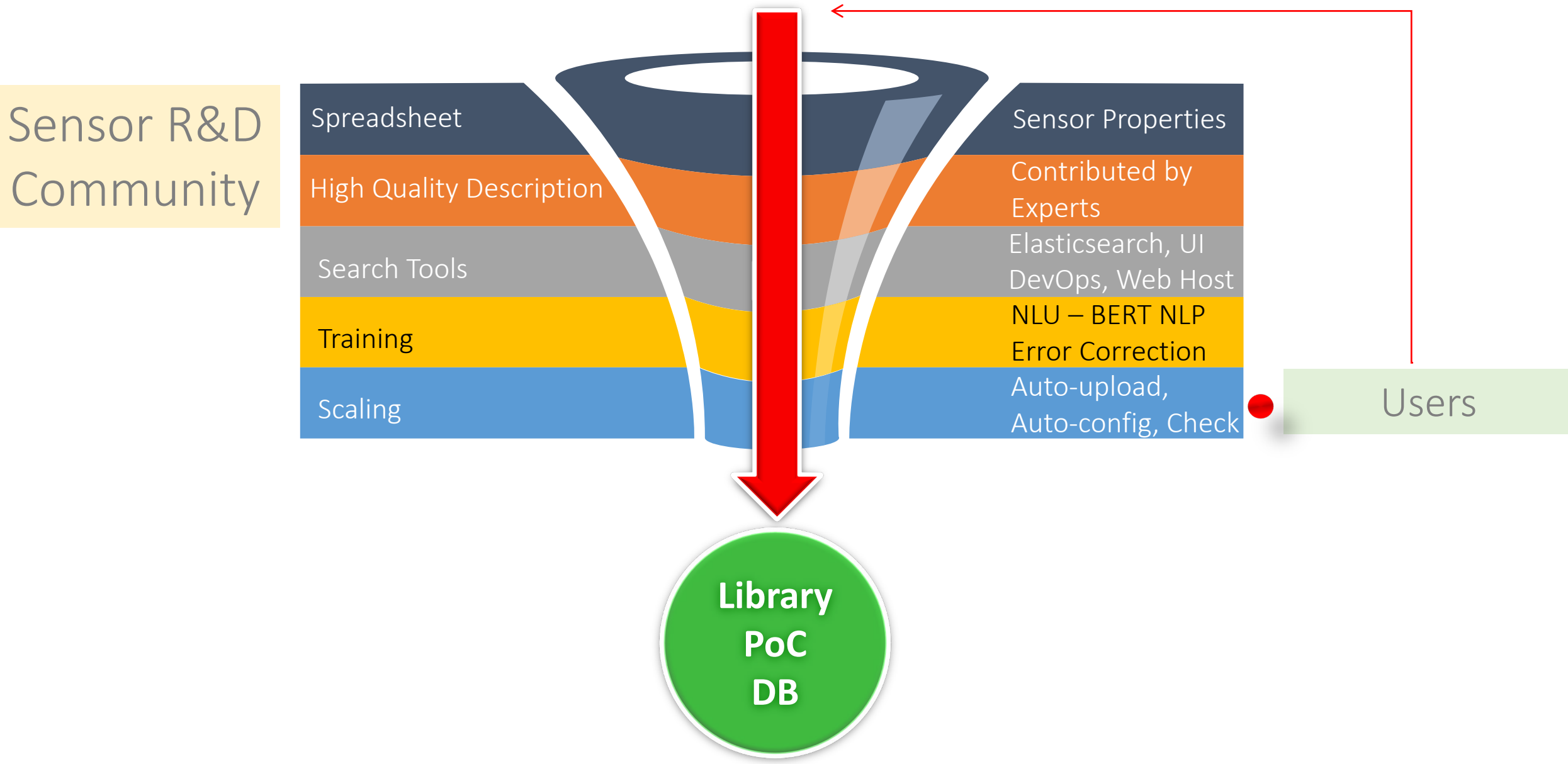
Elasticsearch, UI
DevOps, Web Host

NLU – BERT NLP
Error Correction

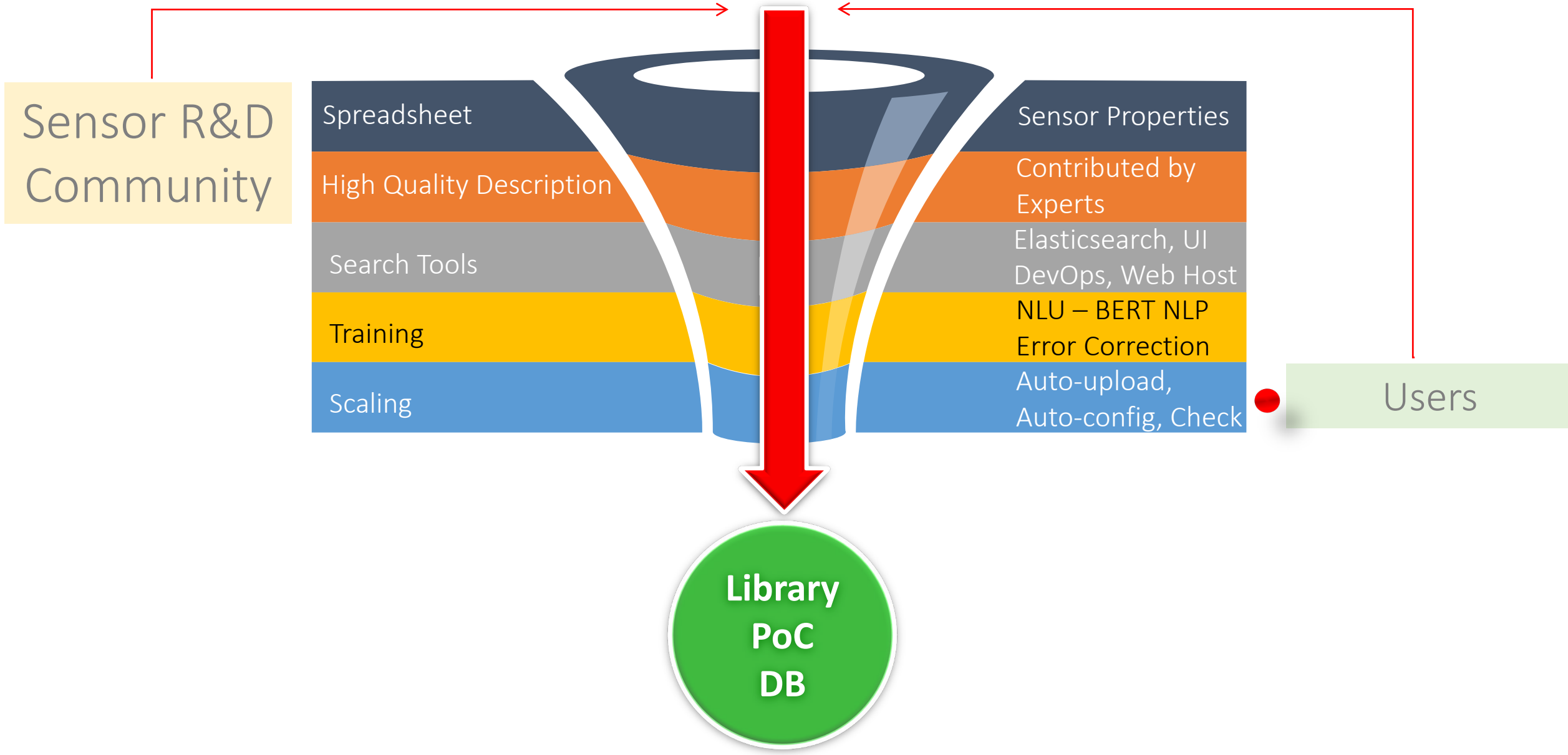
Auto-upload,
Auto-config, Check

Users

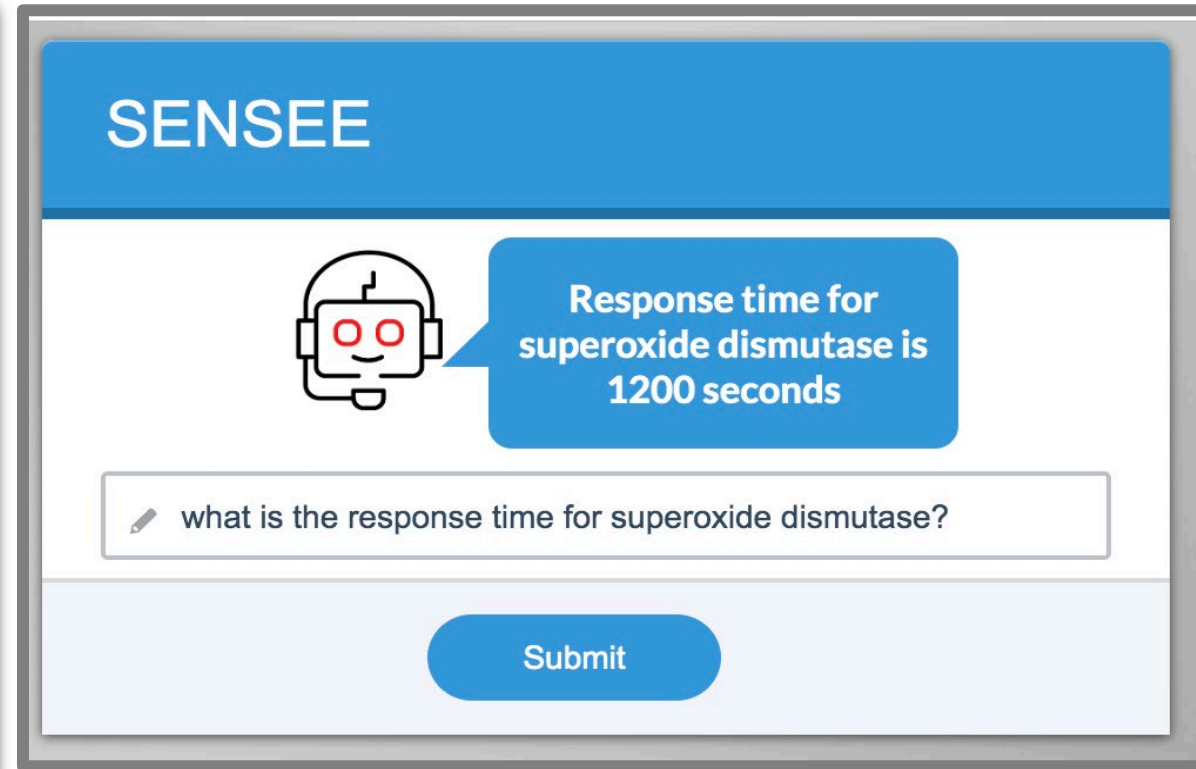
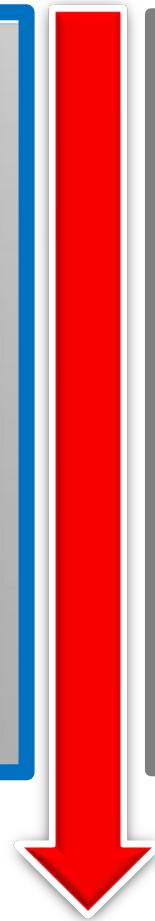
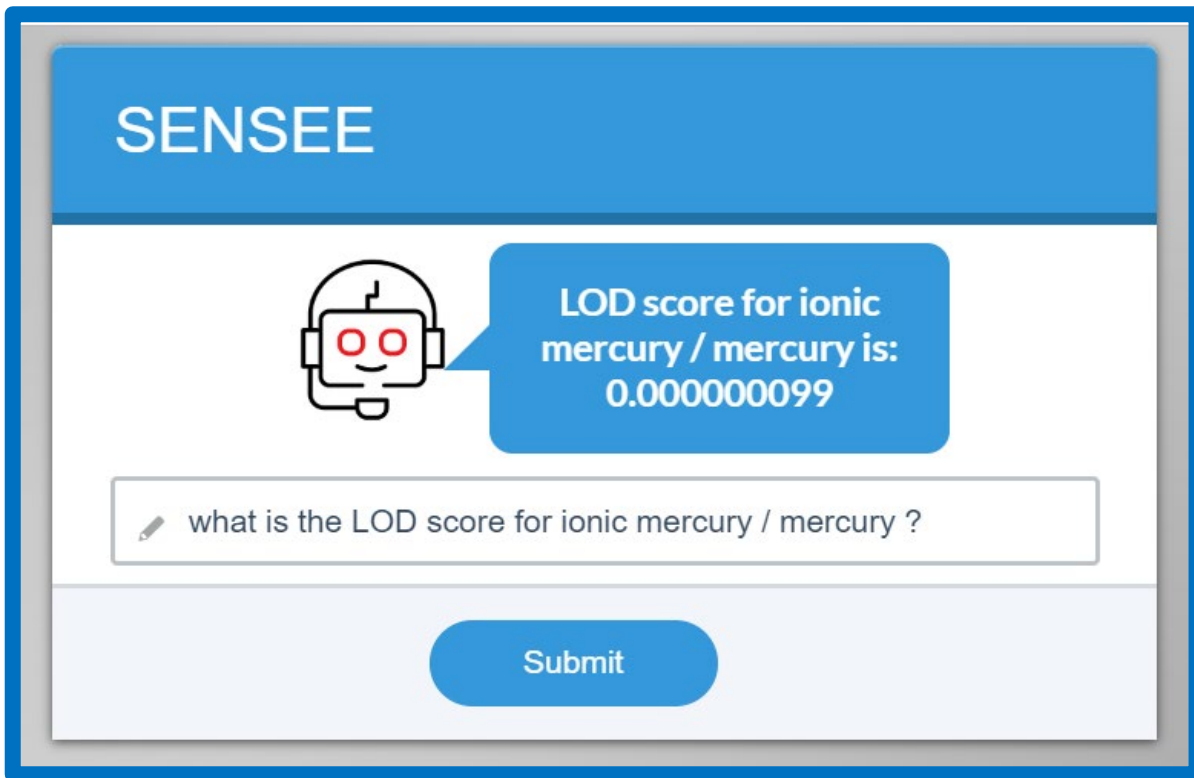
Library
PoC
DB



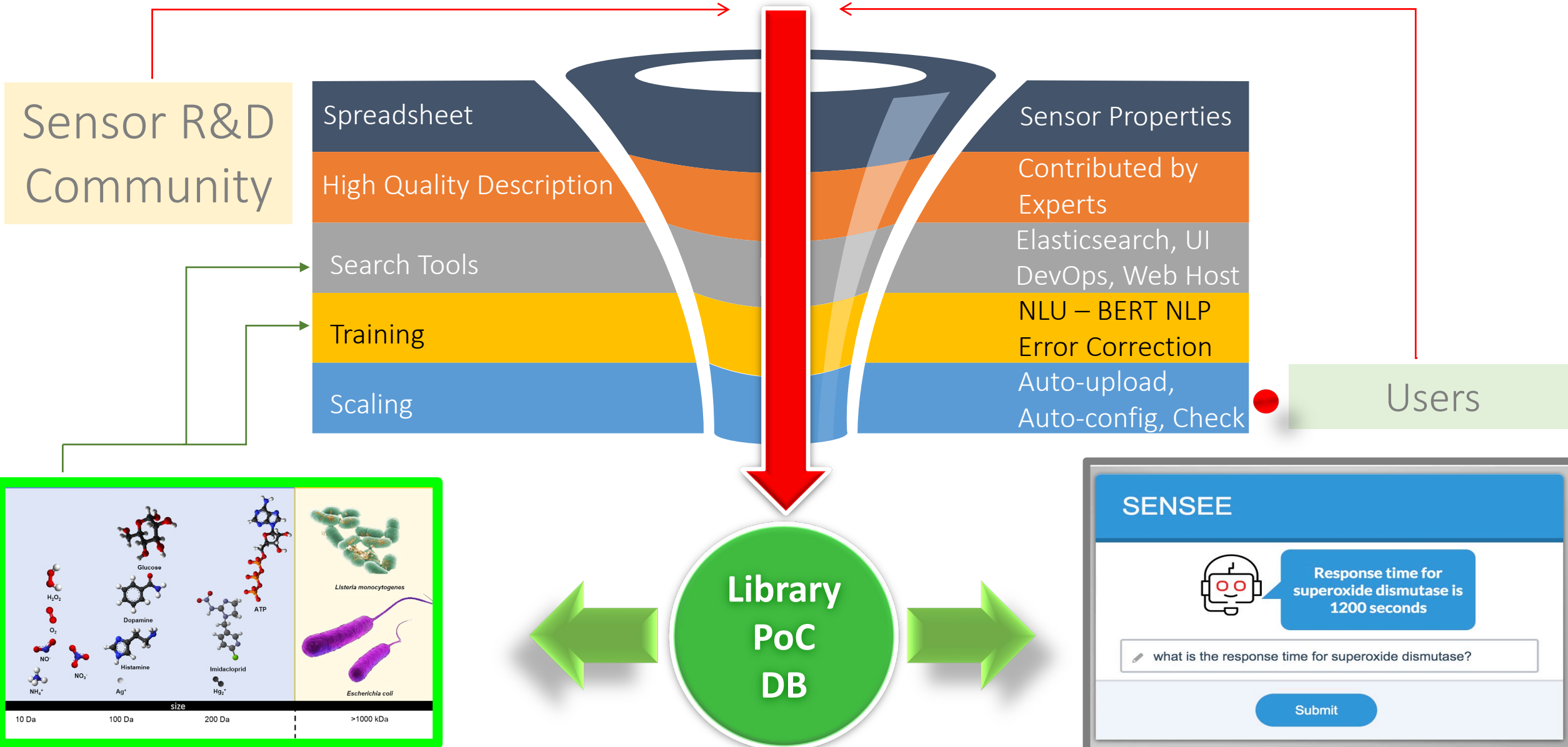
Development of SENSEE 1.0 (SENsor SEarch Engine)



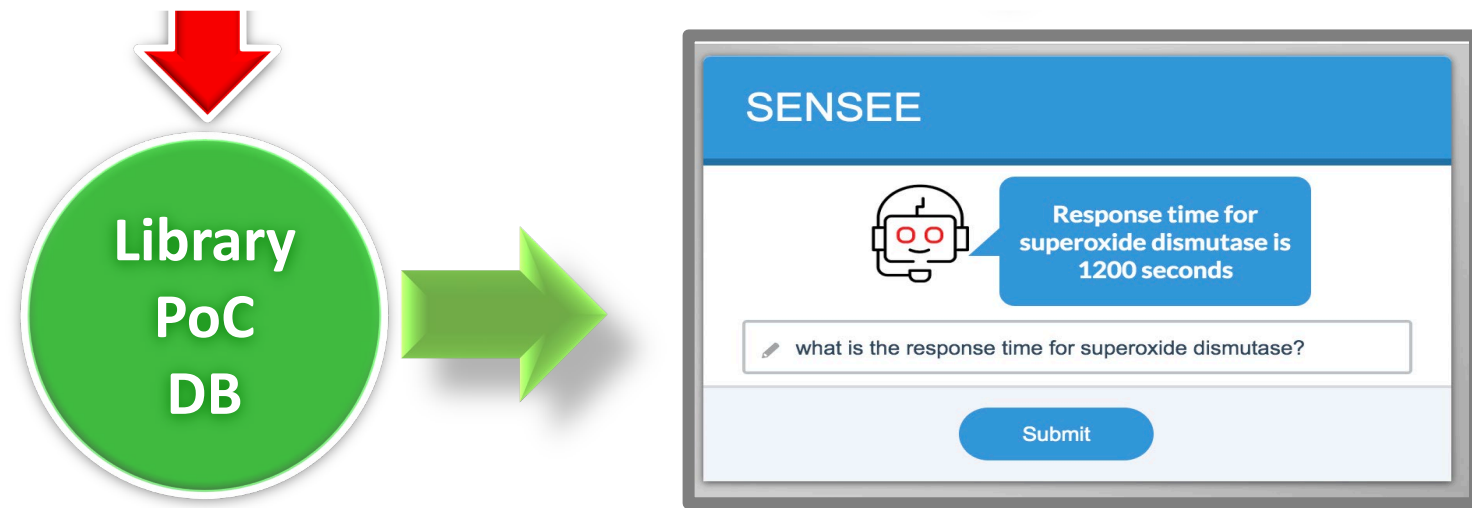
SENSEE 1.0 PROOF OF CONCEPT – DIALOG BOX APP



Development of SENSEE 1.0 (SENsor SEArch Engine)



This is where we are ...

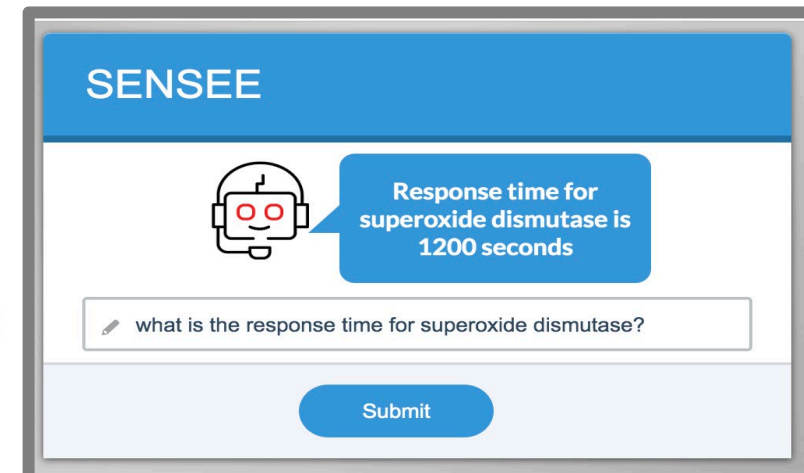
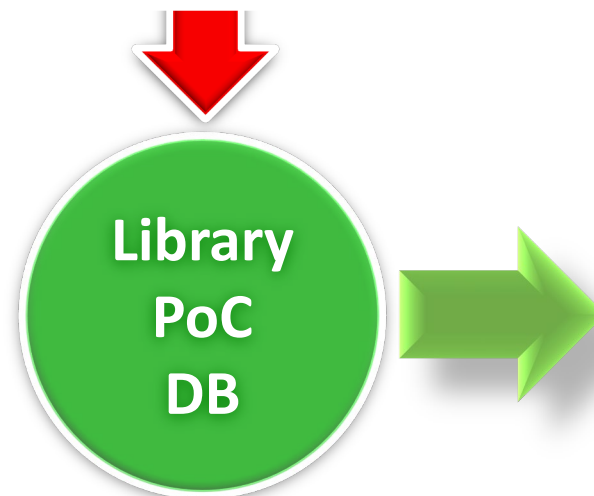


Development of SENSEE 1.0 – This is where we are



To move forward ...

<http://bit.ly/SUBSCRIBE-TO-SENSEE>



Research Community we need your help

Scaling

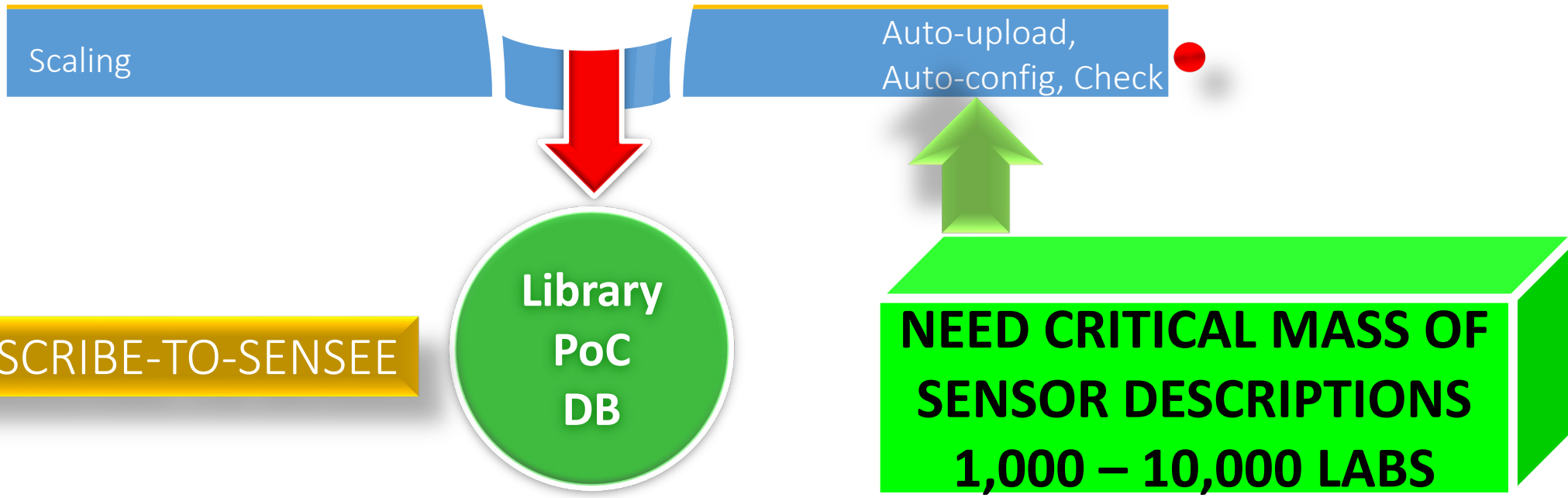
Auto-upload,
Auto-config, Check

Library
PoC
DB

**NEED CRITICAL MASS OF
SENSOR DESCRIPTIONS
1,000 – 10,000 LABS**

<http://bit.ly/SUBSCRIBE-TO-SENSEE>

It is useless without sensor descriptions



<http://bit.ly/SUBSCRIBE-TO-SENSEE>

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

NO sensor data until 2.0

Your sensor descriptions

Scaling

Auto-upload,
Auto-config, Check

Library
PoC
DB

**NEED CRITICAL MASS OF
SENSOR DESCRIPTIONS
1,000 – 10,000 LABS**

<http://bit.ly/SUBSCRIBE-TO-SENSEE>

XL auto-UPLOAD tool for your sensor descriptions

Scaling

Auto-upload,
Auto-config, Check

<http://bit.ly/SUBSCRIBE-TO-SENSEE>

Library
PoC
DB

**NEED CRITICAL MASS OF
SENSOR DESCRIPTIONS
1,000 – 10,000 LABS**

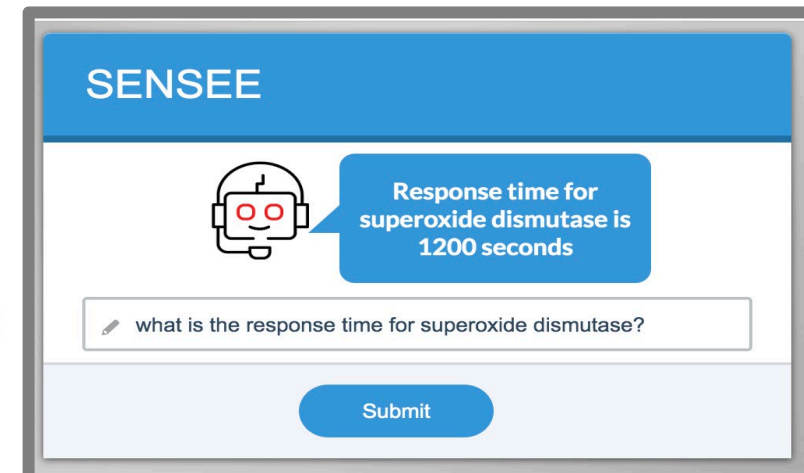
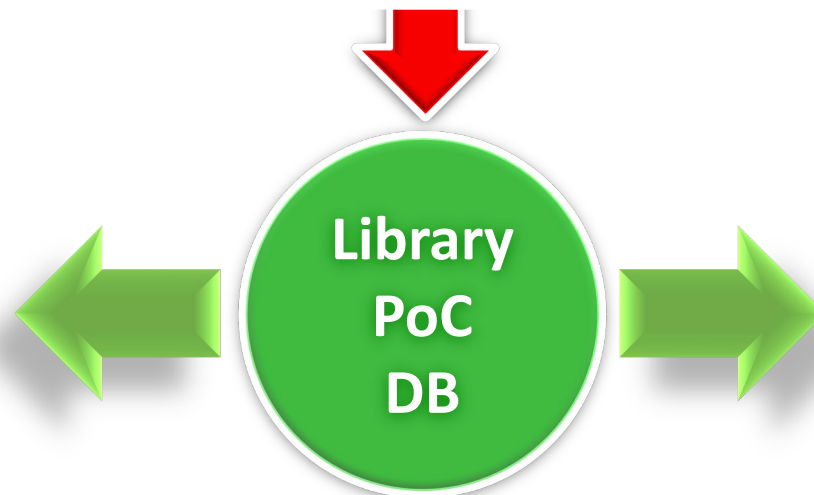
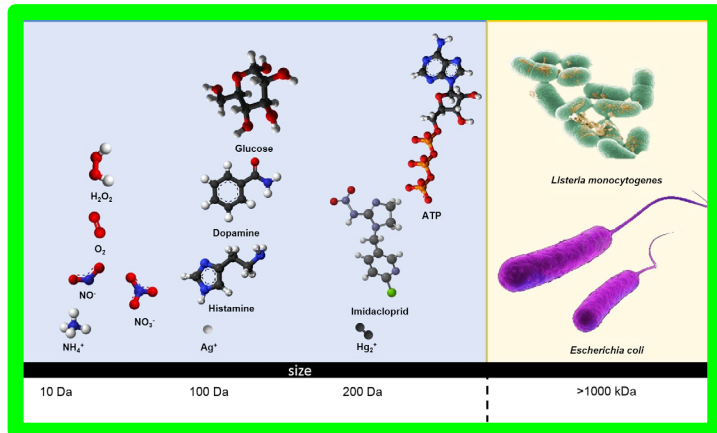
Your Spreadsheet

Sensor Properties

	A	B	C	D	E	F	G	H	I	J	K	L
1	MW [Da]	Category	Target	Recognition-transduction scheme	Platform	LOD [M]	Max range [M]	Selectivity (interferent species tested)	Response time [sec]	Durability	USECAT1	Link to paper(s)
2	1	small molecule	H+	H+ ionophore (liquid)	glass capillary	1.00E-13	1.00E-04	excellent (K+, Na+, Ca2+, Mg2+)	2	High	hydroponics	https://www.ncbi.nlm.nih.gov/pubmed/26088926
3	1	small molecule	H+	anthocyanin/nanocellulose	paper filter	1.00E-15	1.00E-02	excellent	2	high	irrigation water	https://www.ncbi.nlm.nih.gov/pubmed/28884510
4	18	small molecule	Ammonium	NH4+ ionophore (liquid)	glass capillary	5.00E-09	1.00E-01	excellent	5	medium	wastewater	http://www.allelopathyjournal.org/archives/?Year=2016&Vol=37&Issue=2&Month=3
5	18	small molecule	Ammonium	NH4+ ionophore (solid)	LSG	2.80E-05	5.00E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
6	30	small molecule	N/O radicals	nanoplatinum/nanoceria	Pt electrode	1.00E-08	3.00E-06	medium	1	medium	ocean water	https://pubs.rsc.org/en/Content/ArticleLanding/2017/AY/C7AY01964E#divAbstract
7	32	small molecule	DO	Pt porphyrin-nTiO2	fiber optic	1.00E-06	5.00E-06	excellent, temp sens	1	High	hydroponic media	https://www.sciencedirect.com/science/article/pii/S0925400514001117
8	32	small molecule	DO	Pt porphyrin	96 well	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	https://www.sciencedirect.com/science/article/pii/S016770121300331X
9	32	small molecule	DO	Pt porphyrin	glass vial	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	
10	34	small molecule	H2O2	fractal nPt	Pt electrode	5.00E-09	5.00E-05	excellent	1	high	ocean water	https://www.ncbi.nlm.nih.gov/pubmed/27121177
11	39	small molecule	K+	K+ ionophore (liquid)	glass capillary	1.00E-06	2.50E-01	excellent	2	low	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/24961073
12	41	small molecule	Ca2+	Ca2+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-01	excellent	1	low	Hoaglands media	https://onlinelibrary.wiley.com/doi/full/10.1002/jpln.201700319
13	58	small molecule	acetone	chemosensory proteins-nPt	Pt electrode	5.00E-06	1.00E-05	high	10	low	buffer	https://pubs.rsc.org/en/content/articlelanding/2018/an/c8an00065d#divAbstract
14	62	small molecule	Nitrate	NO3- ionophore (liquid)	glass capillary	1.00E-06	2.00E-01	excellent	2	medium	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/18985610
15	62	small molecule	Nitrate	NO3- ionophore (solid)	LSG	2.00E-05	1.50E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
16	108	small molecule	Ag+	Ag+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-02	excellent	2	high	wound dressing	https://link.springer.com/article/10.1007/s11356-014-3058-6
17	111	small molecule	histamine	diamine oxidase-nCu	LSG	6.30E-05	1.00E-03	excellent	2	medium	fermented fish	https://www.mdpi.com/2079-6374/8/2/42
18	147	small molecule	Glutamate	CNT/nPt/GlOx	Pt electrode	1.00E-06	1.00E-03	excellent	2	low	INS1 tissue culture	https://www.sciencedirect.com/science/article/pii/S0165027010001196
19	147	small molecule	Glutamate	CNT/nPt/GlOx	Si biochip	1.00E-06	5.00E-01	excellent	2	low	INS1 tissue culture	https://pubs.rsc.org/en/content/articlelanding/2011/im/c1im11561h#divAbstract
20	154	small molecule	catecholamines	nPt	LSG	5.00E-07	3.00E-03	excellent	2	high	ocean water	
21	154	small molecule	catecholamines	graphene anchored nCuO	LSG	3.00E-07	3.00E-03	high	2	medium	buffer	https://pubs.acs.org/doi/abs/10.1021/acssuschemeng.8b02510
22	176	small molecule	indole acetic acid	fractal nPt	Pt/Ir microwire	1.00E-06	1.00E-03	high	1	high	root growth media	https://link.springer.com/article/10.1007/s00344-017-9688-4
23	181	small molecule	Glucose	nPt/GOx	graphene paper	8.00E-08	1.00E-03	excellent	2	medium	buffer	https://www.ncbi.nlm.nih.gov/pubmed/27209574
24	181	small molecule	Glucose	nPt/GOx	Pt/Ir microwire	1.00E-07	5.00E-06	excellent	1	medium	blood	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166557
25	181	small molecule	Glucose	nPt/nCe/GOx	Pt electrode	1.00E-07	3.00E-06	excellent	1	medium	buffer	https://www.sciencedirect.com/science/article/pii/S0956566314000992

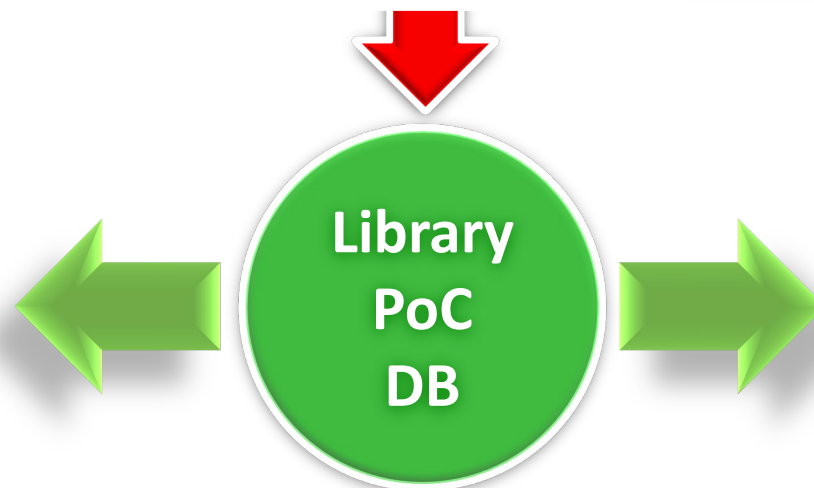
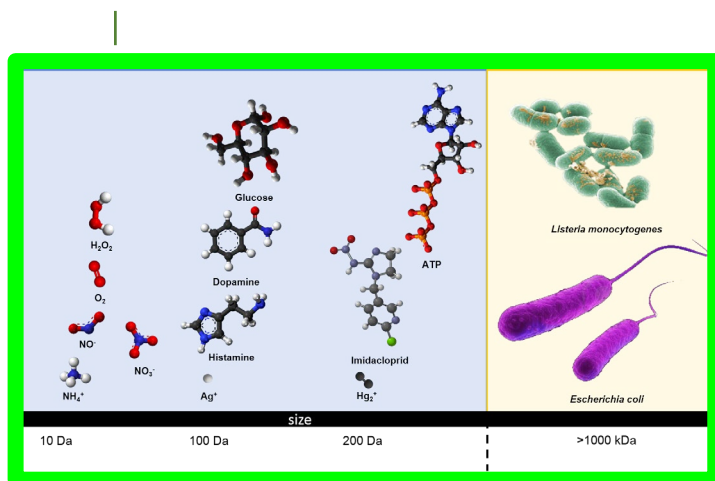
<http://bit.ly/SUBSCRIBE-TO-SENSEE>

We aim to improve visualization tool



What may follow

- ◆ Deploy SENSEE tool. Go live!
 - Automate Feature Engineering
 - Ingest Sensor-specific Data
 - Use cases for DIDA'S PoC
 - Knowledge Graph Algorithms
 - Semantic Data Catalogs
 - User directed search



SENSEE

Response time for superoxide dismutase is 1200 seconds

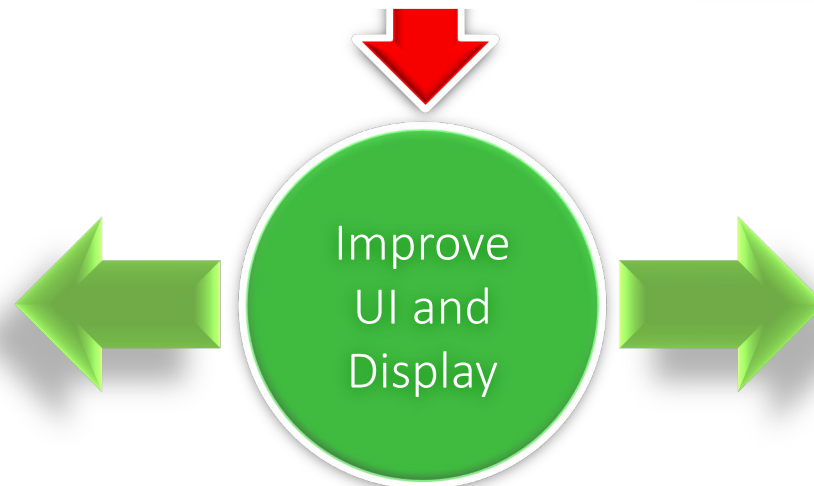
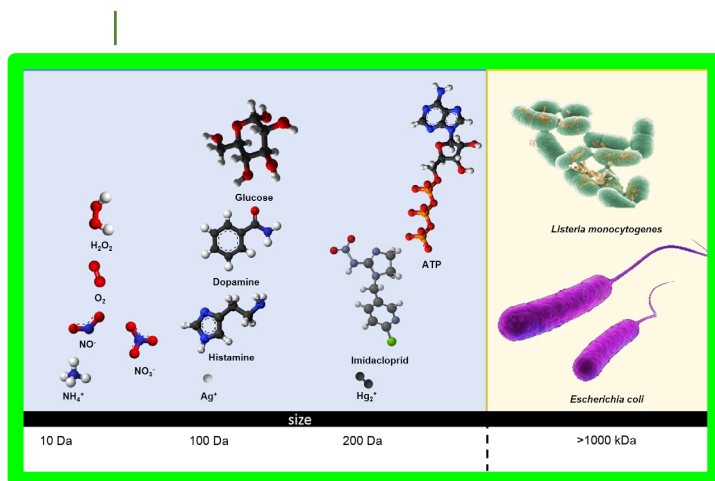
what is the response time for superoxide dismutase?

Submit

Development of SENSEE 1.0 (SENsor SEArch Engine)

Who will use SENSEE 1.0 tool? We anticipate that critical mass of sensor descriptions (categories, attributes) will improve the value of SENSEE 1.0 as a search tool for curated information. Users may be experts in academic and industrial labs. The task of sourcing, uploading, maintaining sensor descriptions may become cost-prohibitive unless a cooperative support structure is implemented to distribute and share the cost of professional services for SENSEE.

◆ Deploy SENSEE 1.0. Go live!



SENSEE

Response time for superoxide dismutase is 1200 seconds

what is the response time for superoxide dismutase?

Submit

THE
LONGEST
JOURNEY

SENSEE



DIDA'S



KIDS

SENSEE

2.0

THE
LONGEST
JOURNEY

SENSEE



DIDA'S



KIDS

SENSEE

2.0

- Ingest Sensor-specific Data

THE
LONGEST
JOURNEY

SENSEE



DIDA'S



KIDS

SENSEE 2.0 INGESTS SENSOR-SPECIFIC DATA BASED ON USE CASES

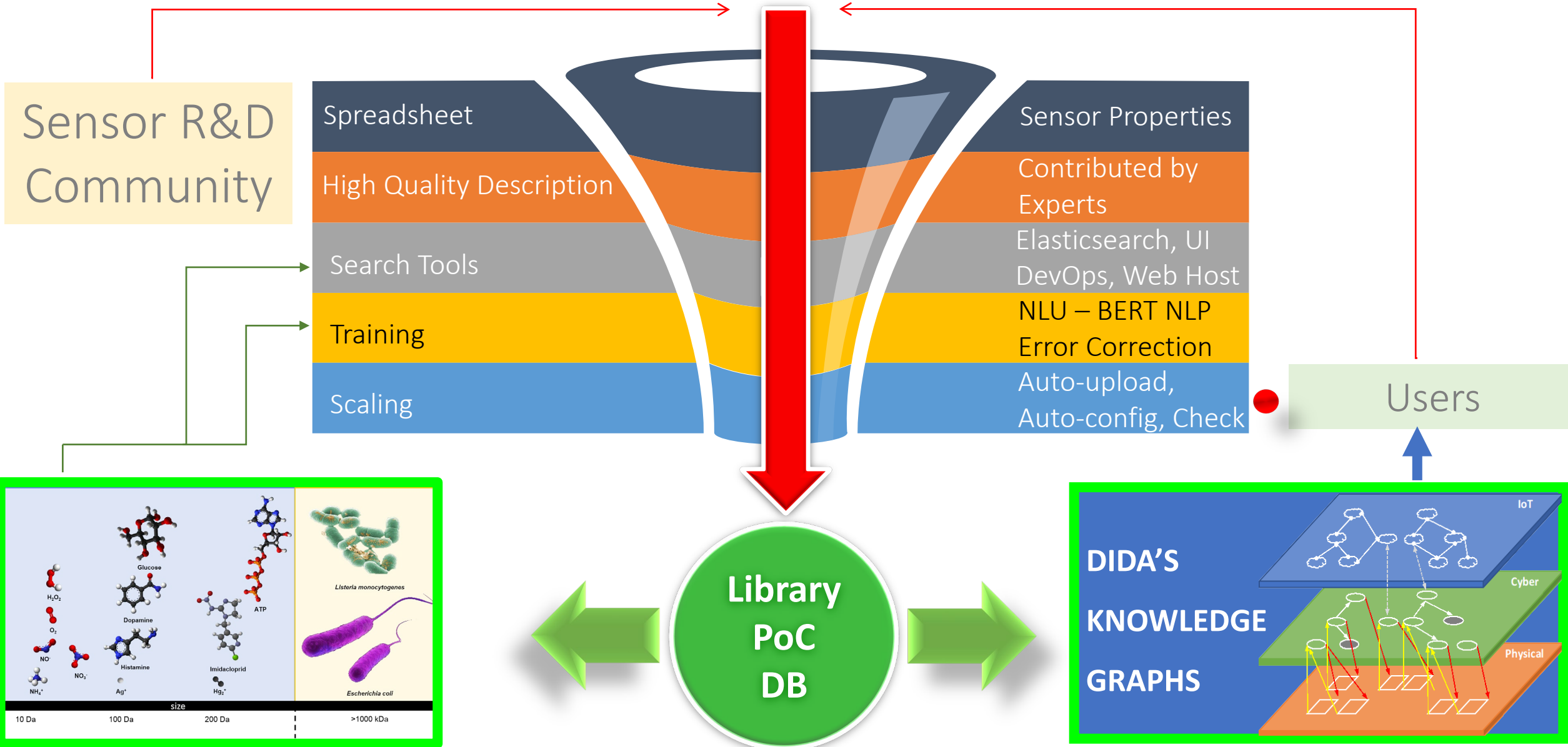
The key performance indicator (KPI) for SENSEE will be a measure of its quality of service (QoS metric) with respect to the delivery of precision responses and value of recommendations. Description of sensor types (categories, attributes) in SENSEE 1.0 may enable end-users to choose sensors relative to use cases. But, without sensor-specific data, *relative to the use case of the end-user*, the value of SENSEE diminishes. Acquisition of data from sensors in SENSEE 2.0 will be relative to use case. For example, if Comfrey Farms wishes to optimize quality of meat color in its pork product, the outcome (desired color of pork meat) may need to converge and combine data from ammonia sensors (amount of ammonia in the hog environment), homofermentative microbial species in feed (*Lactobacillus* sp) and colorimetric data from robotic arm involved in meat processing. SENSEE 2.0 aims to acquire end-user case-based sensor data to address problems and questions of pragmatic value. The feasibility of this approach may be challenged by sensor manufacturers (for example, ammonia gas sensor from C2Sense, microbial sensor from Thermo-Fisher and colorimetric sensor from Omron) who may want to aggregate their own data and encrypt data ports and data loggers to prevent data interoperability and distribution. Manufacturer's portals are focused on sensors specific to the manufacturer. SENSEE 2.0 is an open platform, catalyzing synergistic integration of data to synthesize information, with respect to the end-user's problem. The potential for profitability from data fusion followed by synthesis of actionable information, may be an economic incentive for end-users. It may encourage users to support the SENSEE-DIDA'S-KIDS platform approach by uploading sensor data to SENSEE 2.0 directly from their operations. DIDA'S, and in future DIDA'S KIDS, may evolve from data-informed DSS to synthesis of relevant information, followed by the knowledge-informed paradigm in decision science.

<http://bit.ly/PARTNER-WITH-PEAS>

SENSEE 2.0 and DIDA'S

Data-Informed Decision as a Service

Progress of Development – SENSEE 2.0 and DIDA'S

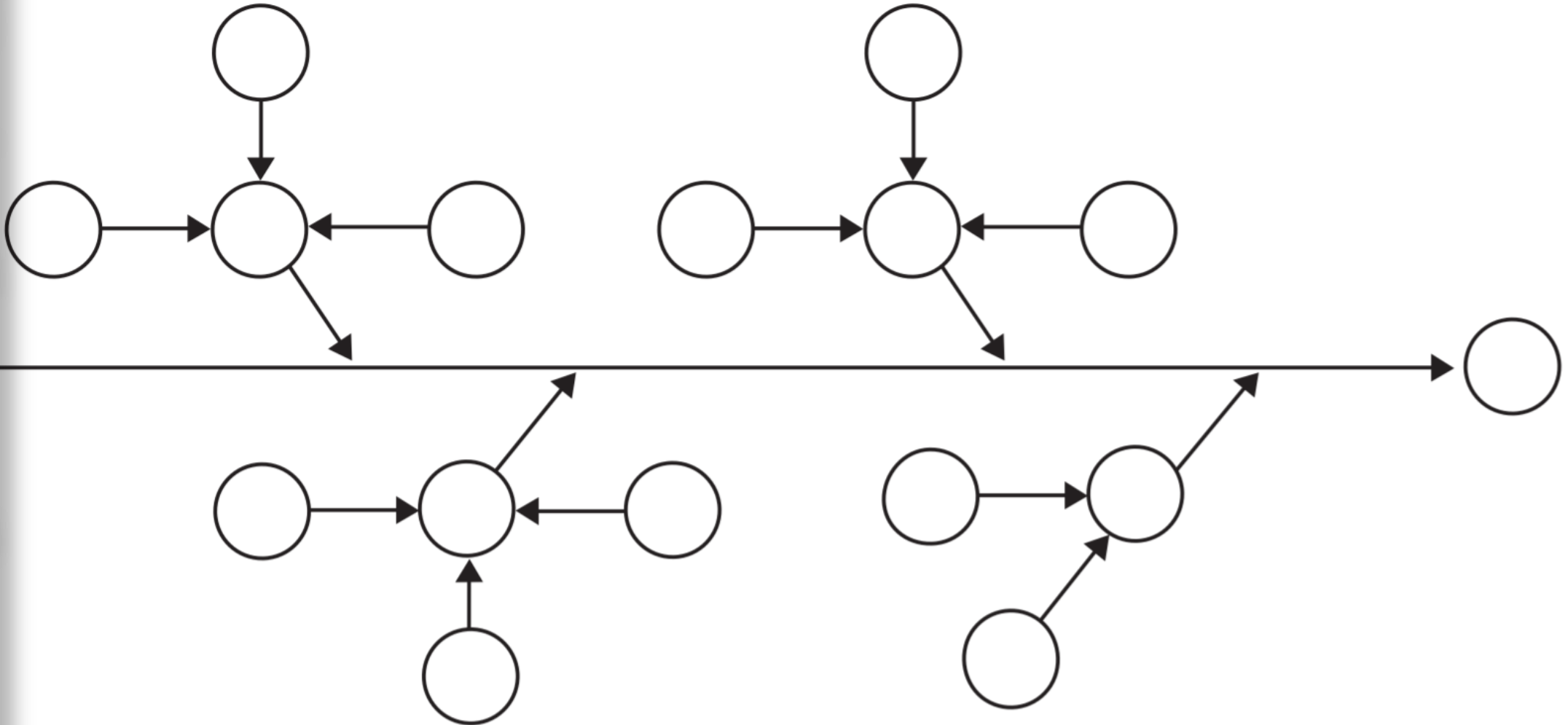


THE
LONGEST
JOURNEY

SENSEE

DIDA'S

KIDS

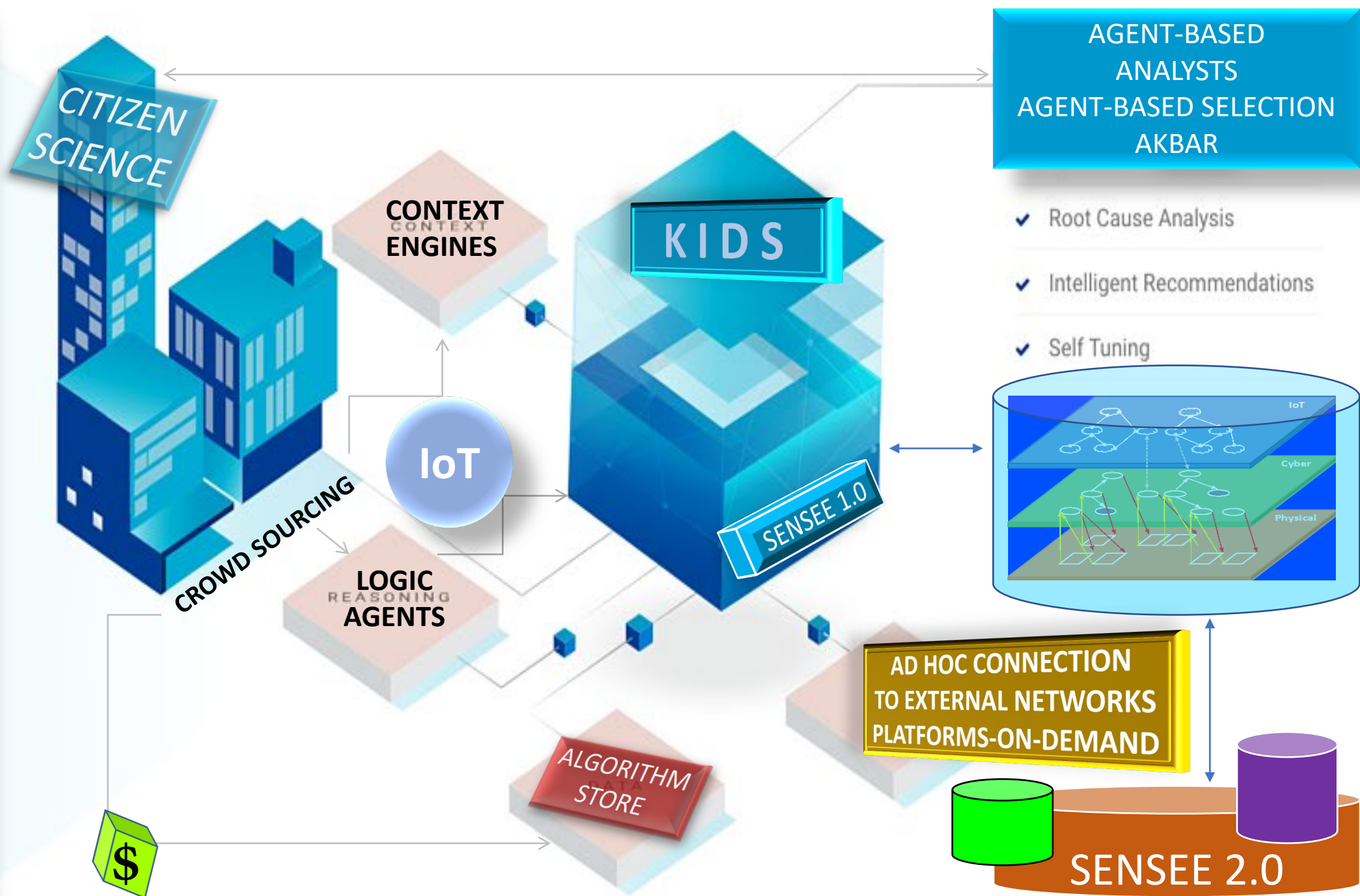


THE
LONGEST
JOURNEY

SENSEE

DIDA'S

KIDS



Anticipate challenges from manufacturers and users

SENSEE

2.0

Unless users allow access to raw data from sensors, the system may be unable to optimize outcomes or minimize risks, for questions which require specific case related data, from relevant sensors. With other general access data, for example, standard protocols for wastewater treatment, it may be possible to offer some degree of information or recommendation but then the value of convergence is limited in its scope.

Anticipated deliverables from SENSEE – Logic Tools?

SENSEE 1.0 (sensor descriptions) and SENSEE 2.0 (sensor-specific data) are tangible pursuits, which can deliver case based solutions, within the scope of [a] data-informed decision support for [b] limited interrelationships in a specific domain [c] restricted to information extraction and recommendation but [d] not approaching the extent of DIDA'S.

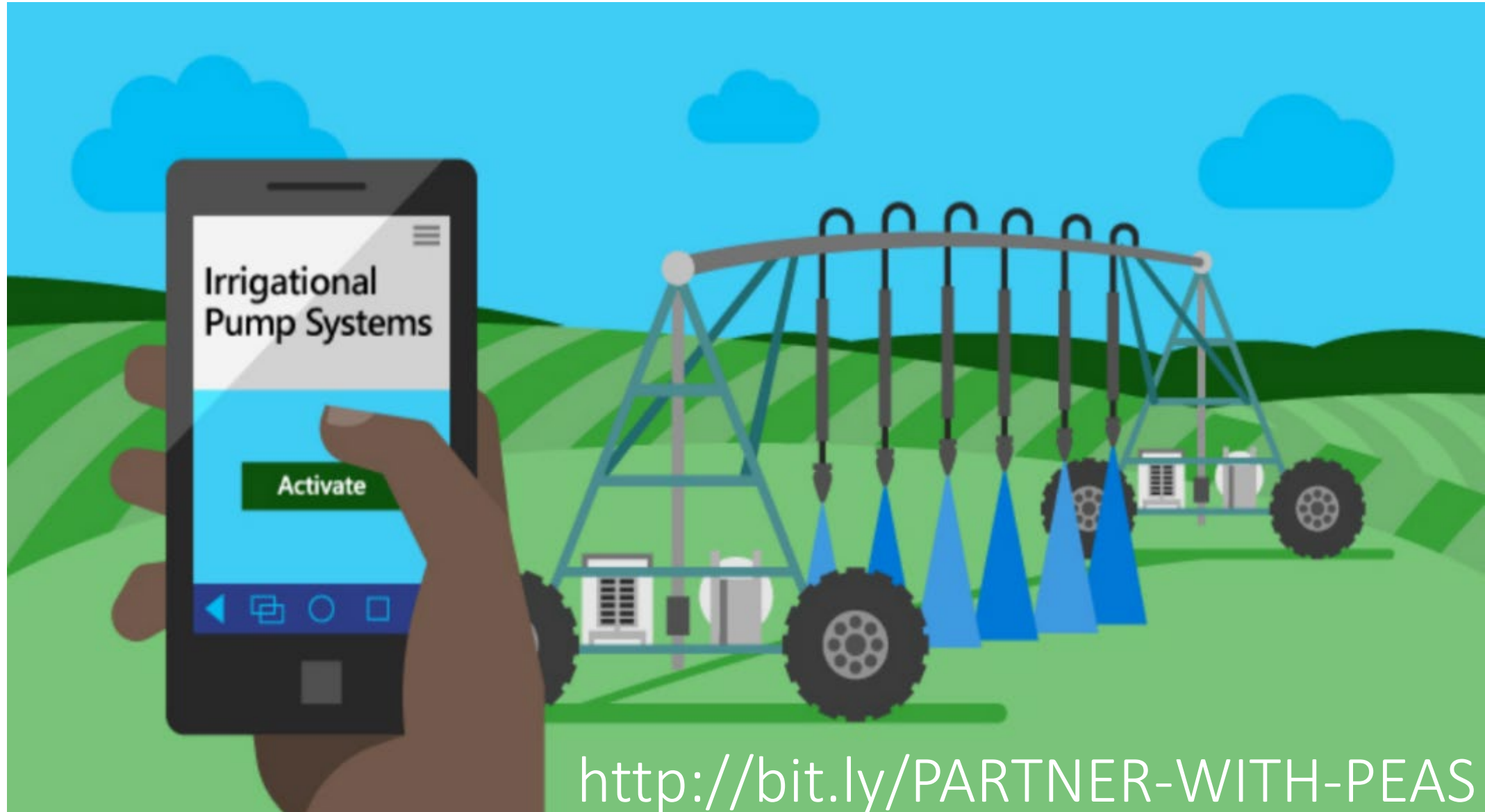
We can use data to create information (thrust of the current state of art with respect to so-called data science) and apply a set of rules and reasoning (logic, dependency, analytics, prior knowledge) to predict *known* unknowns, in the form of decision support for humans in the loop (recommendation without discovery or actuation) or venture to relinquish control for partial automation (risk-limited actuation) in an IFTTT (workflow) approach to basic service.

This is a form of data-driven, evidence-driven, ***reasoning*** solution with potential for partially automating workflow. The efficiency gains anticipated from “intelligent” decision support systems lies in our ability to integrate ***logic rules***. DIDA'S KIDS includes this format, as the foundation. Logic rules, if understood (semantics), integrated, optimized, and executed, may be the answer to 80% of the global problems, for a tiny fraction of the cost, which may accelerate market adoption and penetration of digital-agro services. Remaining 20% of issues may require DIDA'S KIDS to create dynamic knowledge composable tools embedded with statistical and mathematical modeling based machine learning solutions. These two approaches may be complimentary for 20% of the problems. But, knowledge tools may not be as critical for 80% of our everyday problems, eg, optimizing and actuating (partial automation) of irrigation water pump systems (control volume and distribution of water) based on soil moisture, salinity, ionic content and weather. Thus, we can focus on ***logic tools***.

Anticipated deliverables from SENSEE (SENSEE.ES)

SENSEE 1.0 (sensor descriptions) and SENSEE 2.0 (sensor-specific data) repositories, combined with analytics and artificial reasoning, harks back to “expert systems” which preceded the snake oil sales of AI (artificial intelligence) to the stage where hyped-up “AI systems” exploded to near-extinction (1990’s “winter of AI”). The recent re-invention of AI (2010’s) has catalyzed its re-entry into the den of vipers. SENSEE may stay clear of the foggy panache of AI and focus on delivering expert services, in near real-time, which are profitable for users. An expert service requires we create a framework for an expert system to partially mimic the decision-making ability of human experts, who can solve problems by using data and reasoning aided by prior knowledge. The SENSEE concept of expert service (ES) is not the 1980’s version of expert systems. In SENSEE.ES we will use advanced tools: elasticsearch, NLP, semantic catalogs, graph networks, machine learning, and digital-by-design concepts from the internet of things (IoT), using mobile, agile, standards-based tools to optimize data interoperability, semantic intertoperability, technical interoperability (open platform approach) and, ambitious of all, policy interoperability, to be globally adaptable. In the hands of the human analyst, SENSEE 2.0 is the data source to extract evidence and make informed decisions to act on the evidence (SENSEE 2.0 data). The human analyst supplements this decision making logic using domain expertise and experience in the organization (enterprise, farm, factory) to prescribe analytics and orchestrate any necessary course of action based on the data, processes and reasoning. An Agent-based system (ABS) emulating this “human” step (a part of the **logic tools portfolio** of SENSEE.ES) plus IFTTT (if this then that) type workflow based low level decision-driven partial automation, if combined, may suffice to solve many problems, eg, irrigation water flow.

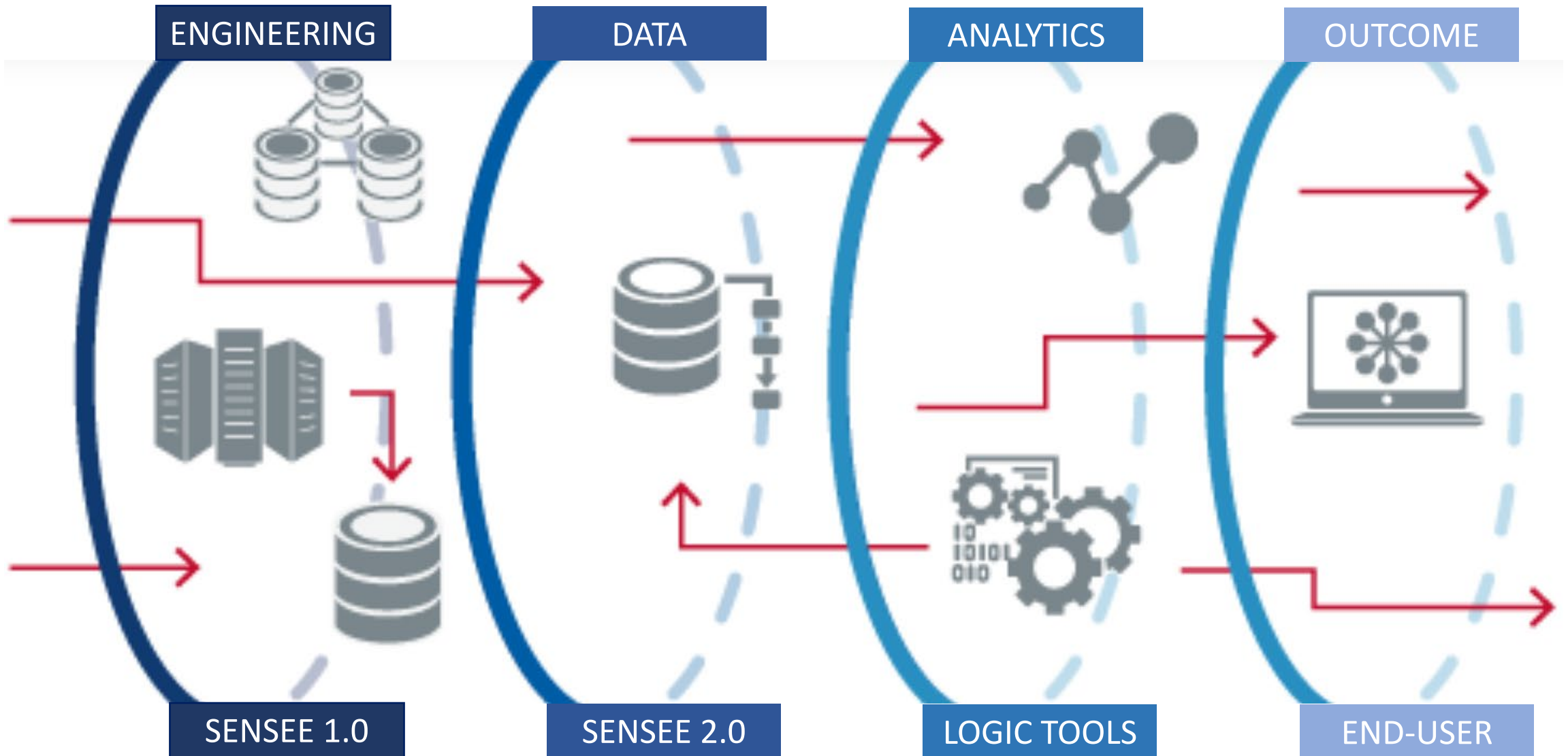
Deliverables from SENSEE – Logic Tools – call it ART ?



<http://bit.ly/PARTNER-WITH-PEAS>

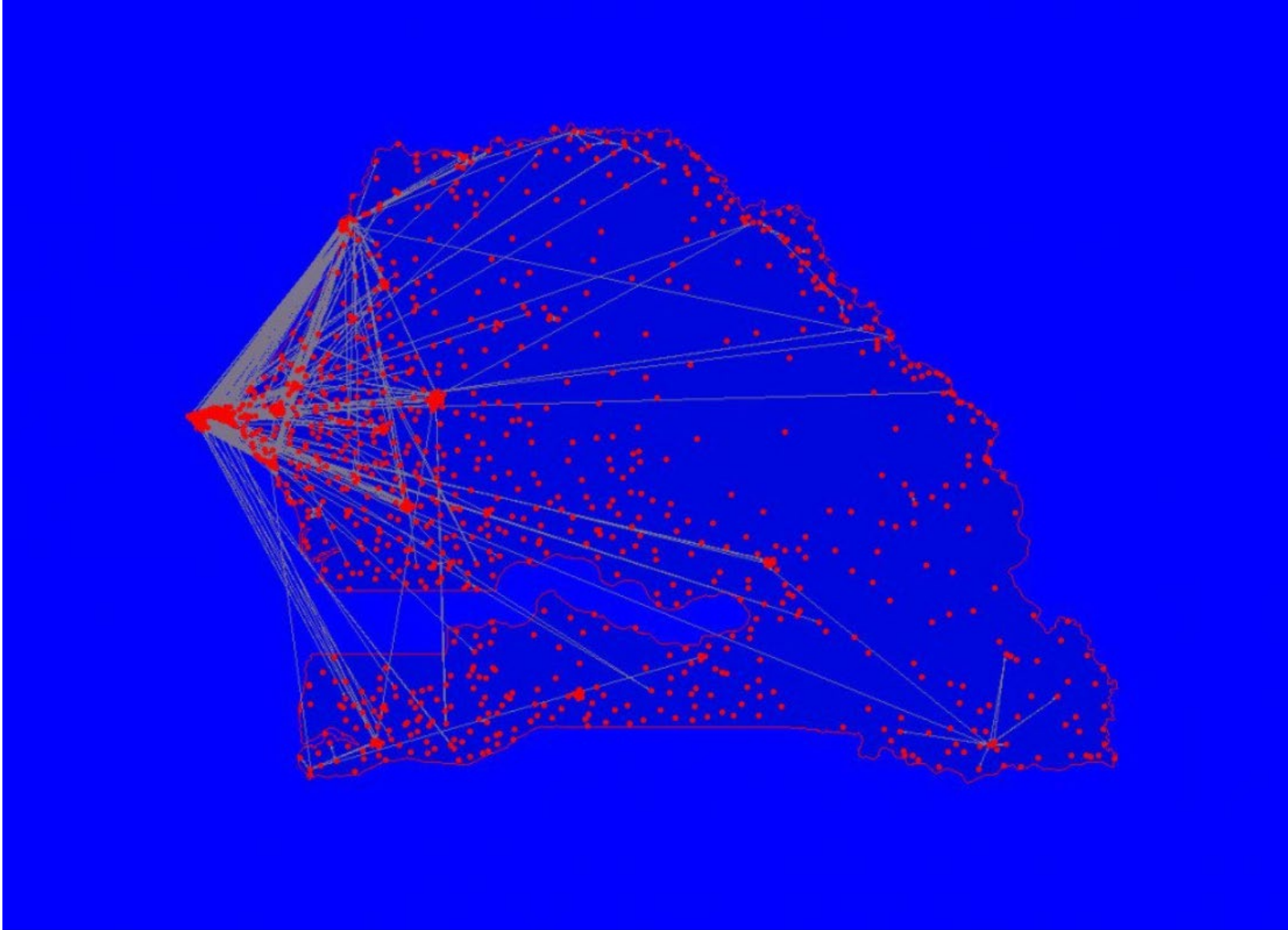
Short-term deliverable from SENSEE? ART of Simplicity

<http://bit.ly/PARTNER-WITH-PEAS>



The nexus of hardware and software lead to the “Plug-n-Play” paradigm. Extending that synergistic simplicity to data and data-informed decision support (DIDA’S) may evolve into DADA (“Drag and Drop Analytics”) and the subset SENSOR DADA.

Short-term deliverable from SENSEE? ART of Aggregation



Short-term deliverable from SENSEE? Use natural language

Machine Reading Comprehension (MRC)

uses neural network architecture, Reasoning Network (R-Net), to the mimic inferencing process (constrained by subject/predicate optimization/alignment).

<https://arxiv.org/pdf/1609.05284.pdf>

Another tool is BERT NLP which is also undergoing a series of tests.

<https://arxiv.org/pdf/1810.04805.pdf>

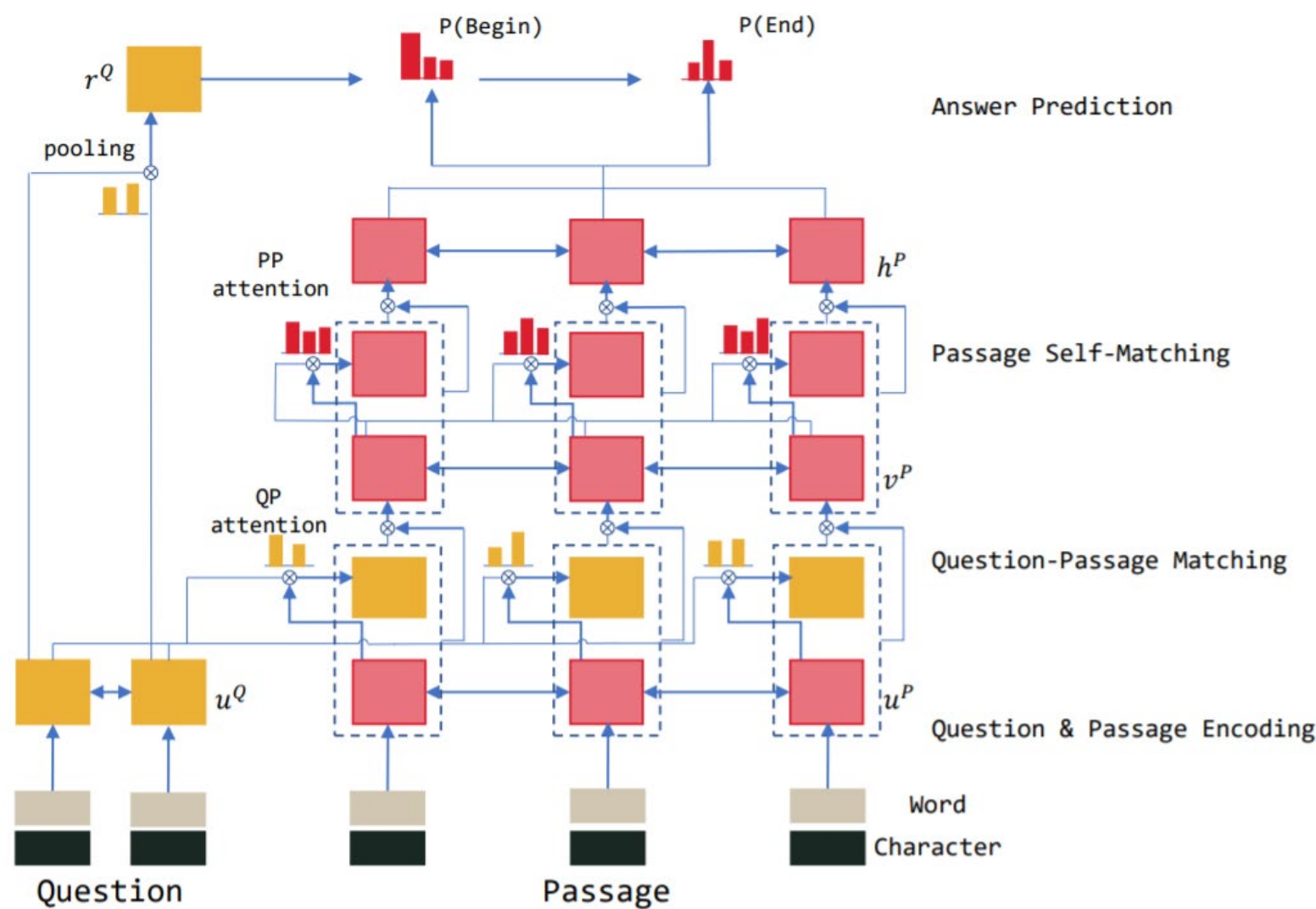
<https://rajpurkar.github.io/SQuAD-explorer/>

Convergence of MRC, R-Net, BERT, XLNet, HAN (hierarchical attention networks), etc, with KG (knowledge graphs) may help to mine contextual word embeddings. It may evolve as a tool not only for Q&A but for non-obvious relationship analysis (NORA) and extraction.

<https://arxiv.org/pdf/1906.08237.pdf>

<https://arxiv.org/pdf/1810.06033.pdf>

www.nature.com/articles/s41586-019-1335-8



https://blogs.microsoft.com/uploads/2018/02/The-Future-Computed_2.8.18.pdf

Deliverables from SENSEE – Logic Tools – call it ART ?

ART

Artificial Reasoning Tools

SENSEE leads us to ART, a logical middle ground that may deliver decision tools, as partial solutions for problems bounded by domains (not too expansive in scope) before DIDA'S KIDS.

PEAS PLATFORM
SIGN-POSTS ON THE ROAD AHEAD

Wisdom

HUMAN COGNITIVE TOOLS

Knowledge

KIDS

Information

DIDA'S

Data

SENSEE

< ART

ARTIFICIAL
REASONING
TOOLS (ART)

But, is knowledge still the key performance indicator?

– P

– E

– A

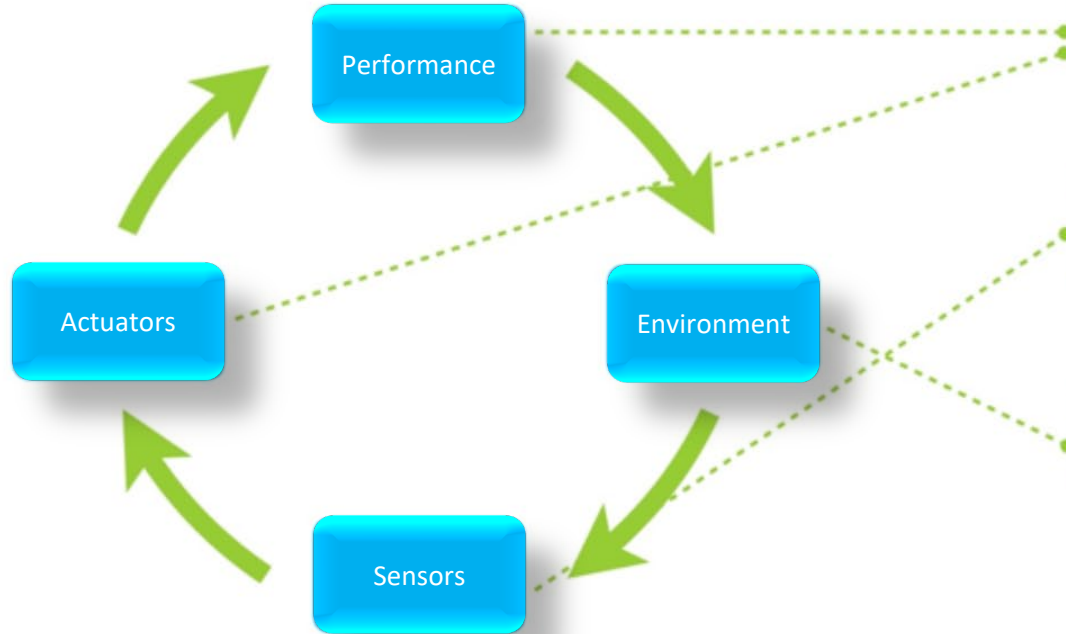
– S

– Performance



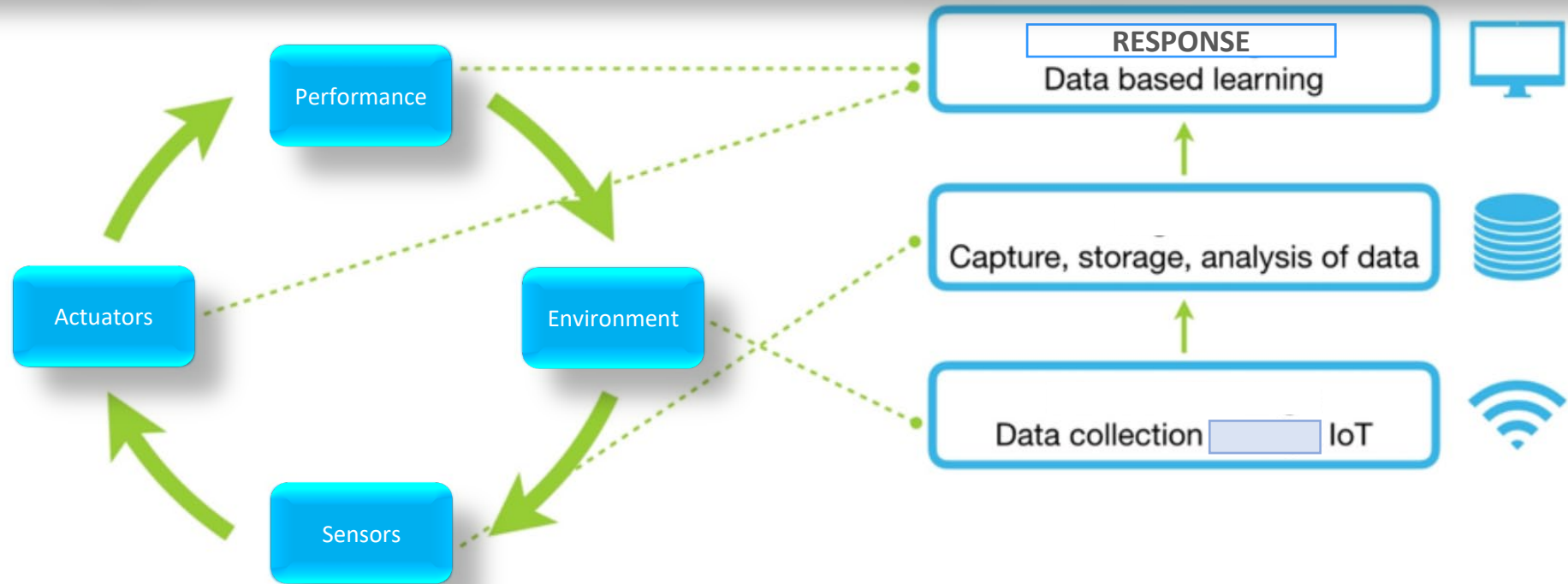
– Sensors

Knowledge is the ultimate key performance indicator



<http://bit.ly/PARTNER-WITH-PEAS>

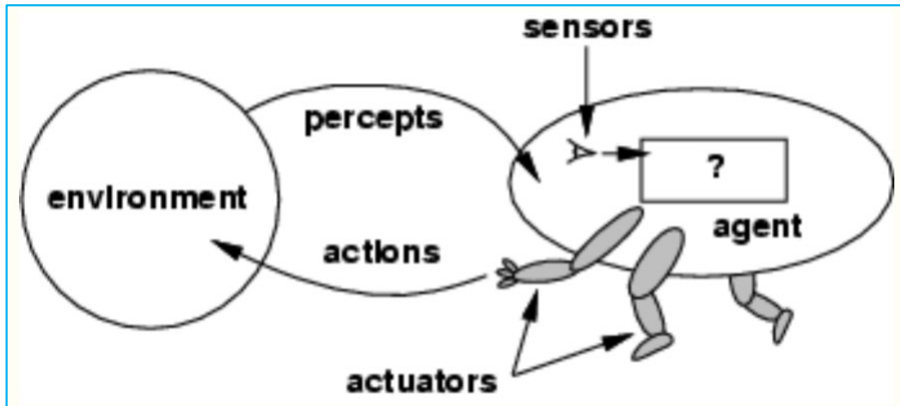
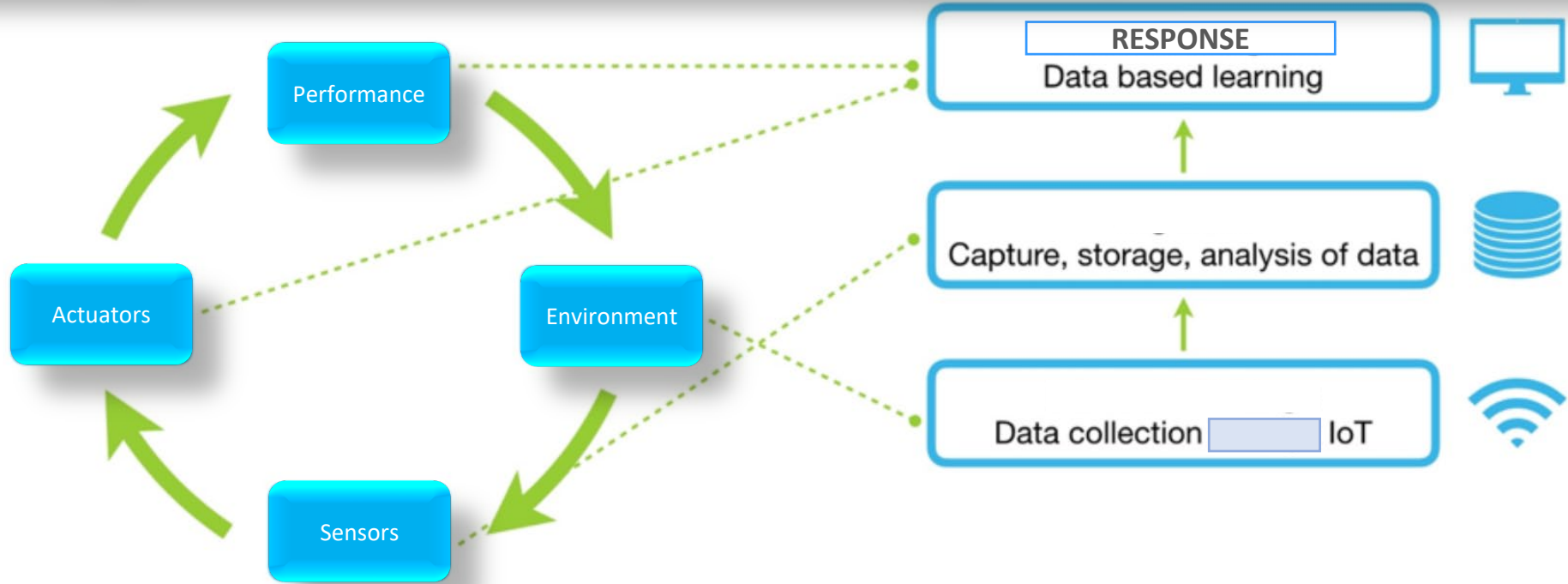
Knowledge is the ultimate key performance indicator



<http://bit.ly/PARTNER-WITH-PEAS>

Knowledge is the ultimate key performance indicator

<http://bit.ly/PARTNER-WITH-PEAS>



<https://www.ics.uci.edu/~welling/teaching/ICS171fall10/Agents171Fall10.pdf>

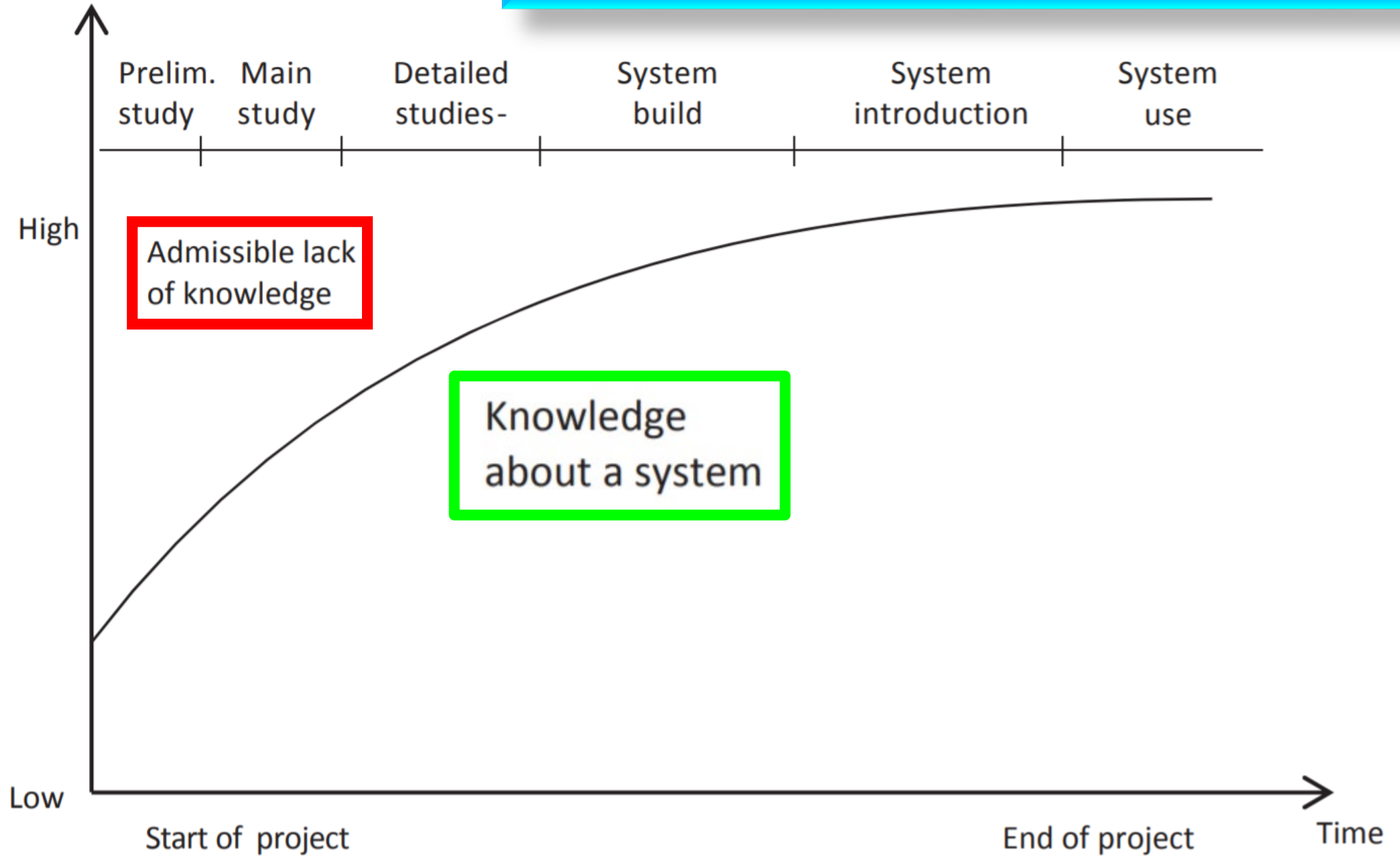
<https://courses.edx.org/asset-v1:ColumbiaX+CSMM.101x+1T2017+type@asset+block@AI+edx+intelligent+agents+new+1+.pdf>

Have we gained *knowledge* from data and decisions?

An open question, for the long run ...

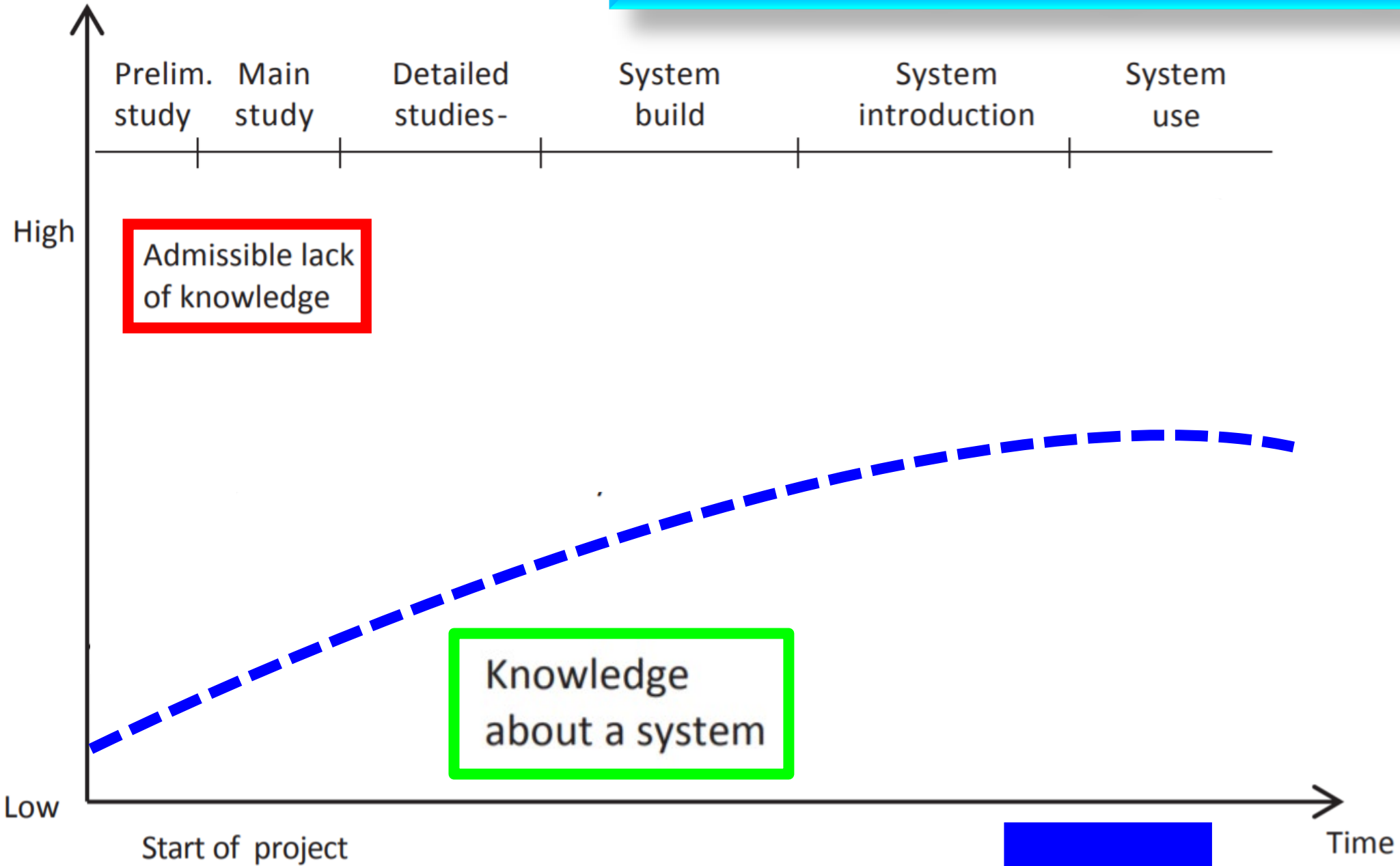
In a systems engineering approach, knowledge increases.

Knowledge

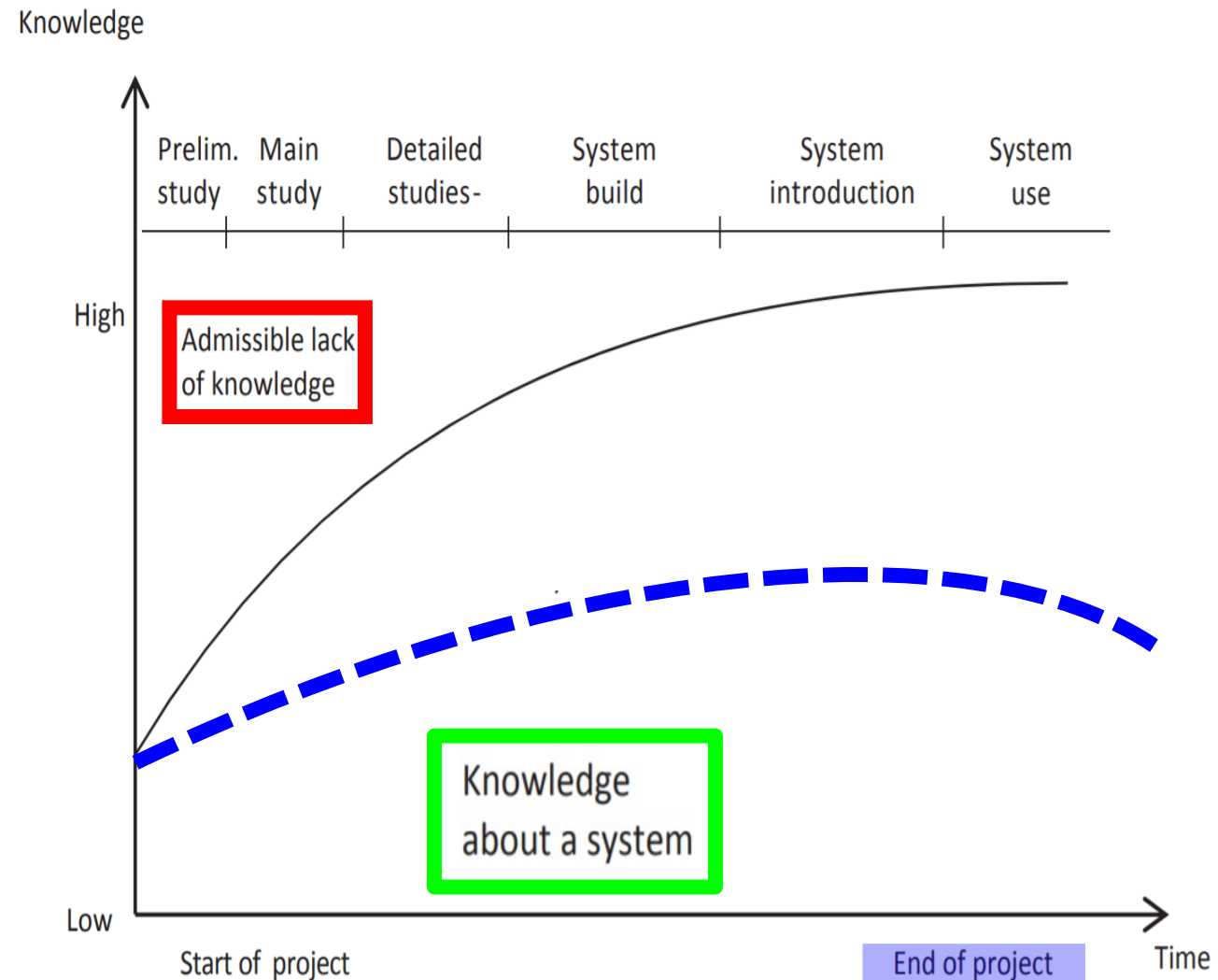
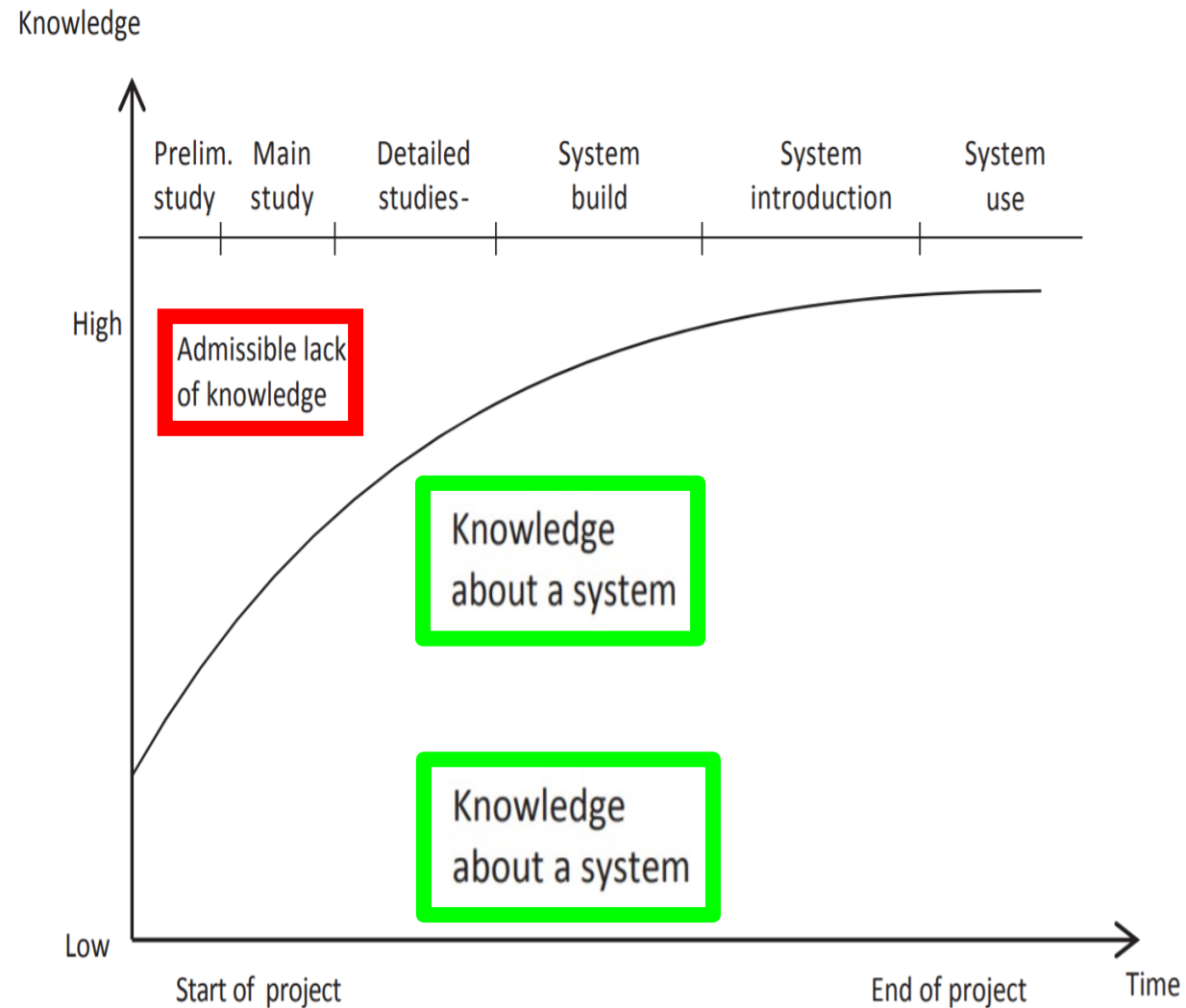


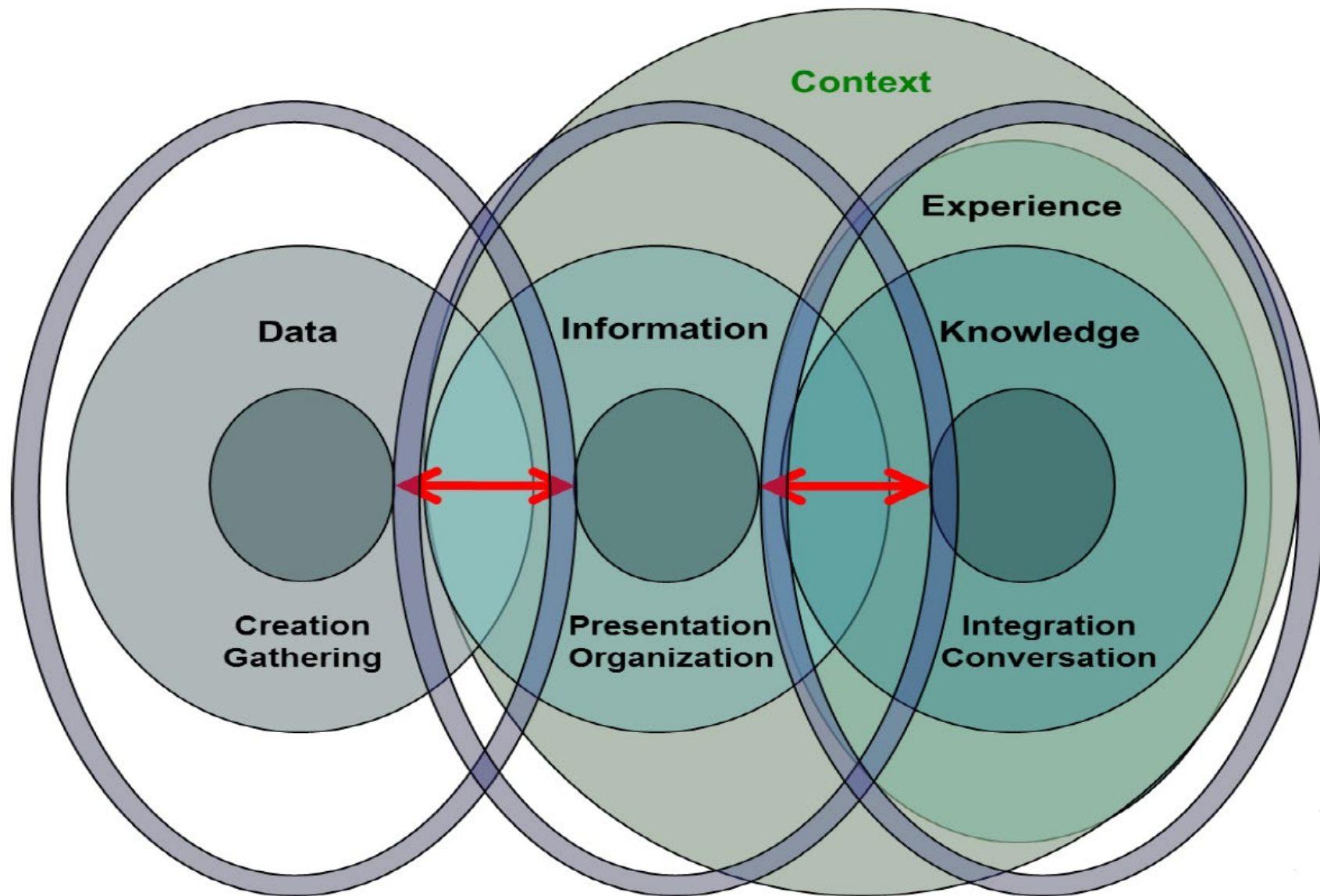
In the real world, knowledge increase may be bit sluggish.

Knowledge

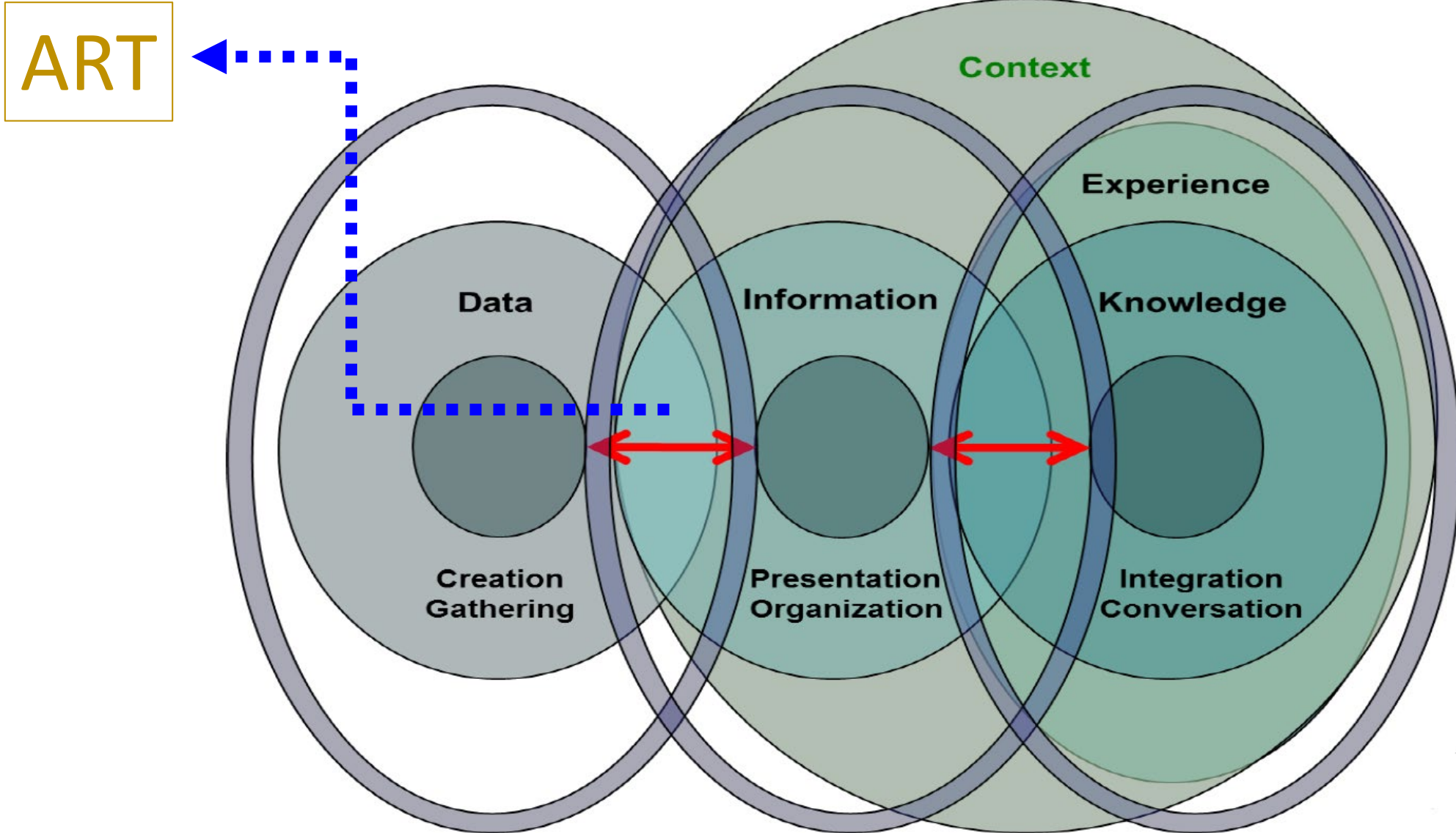


Have we gained knowledge from data and decisions?

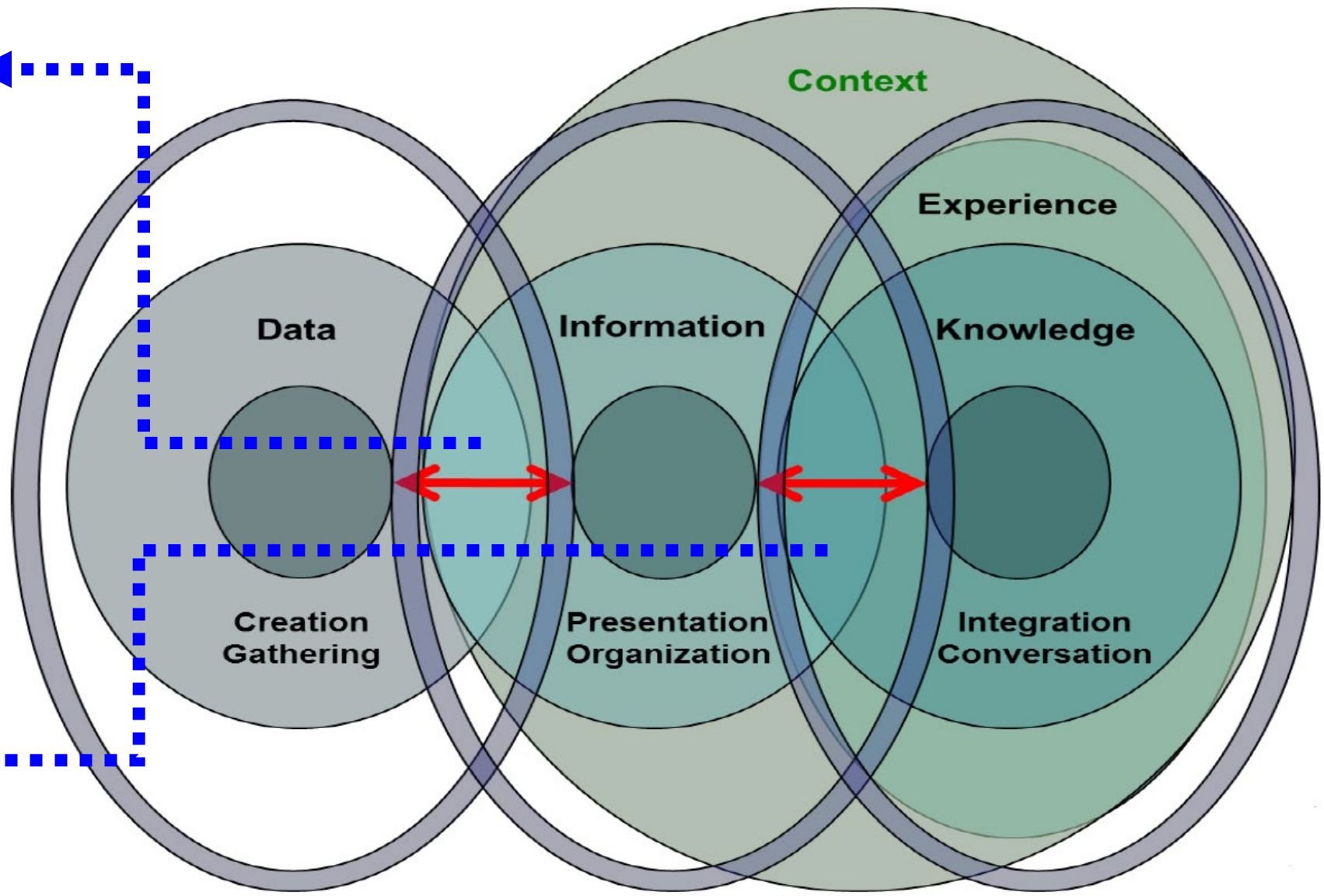




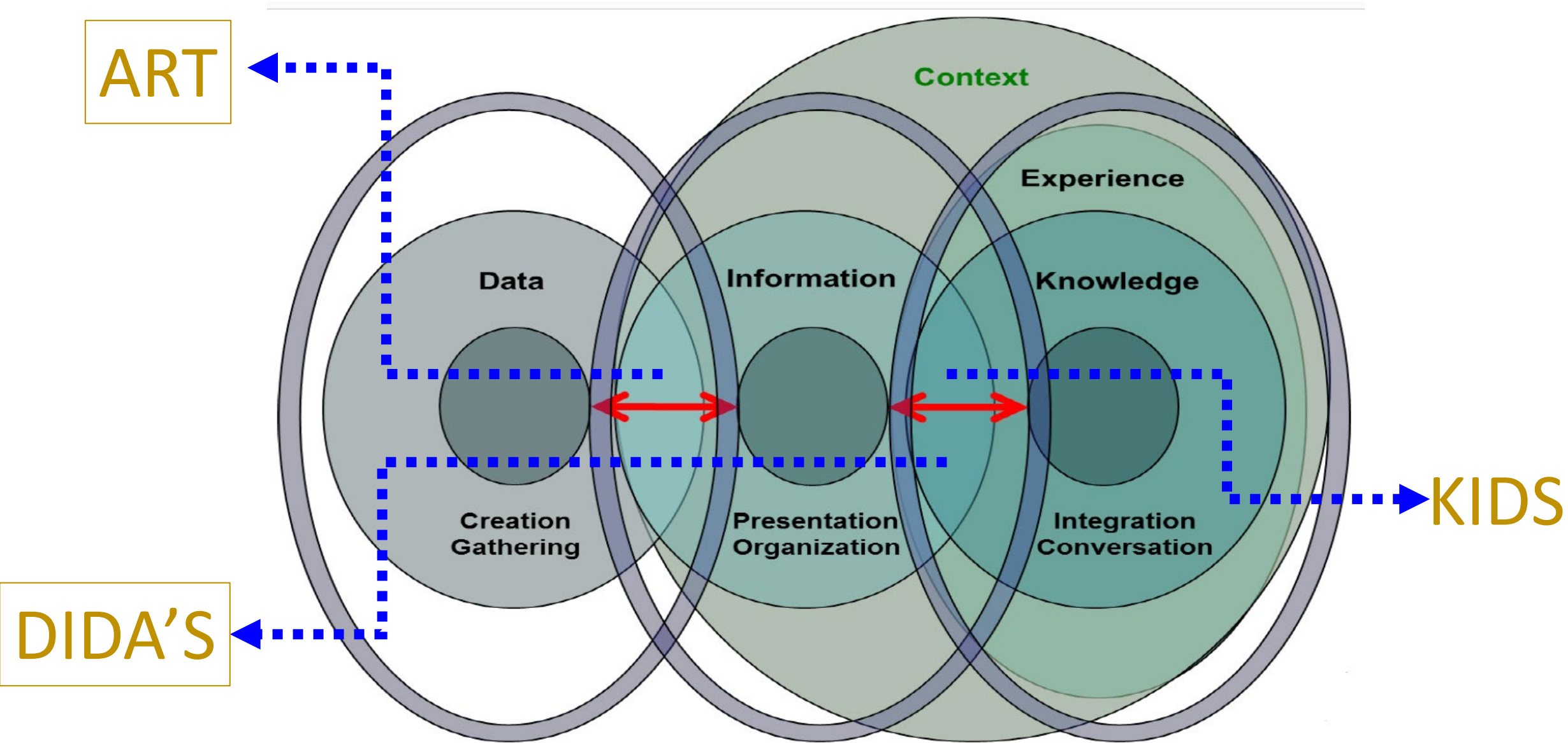
Artificial Reasoning Tools (ART)



ART



DIDA'S



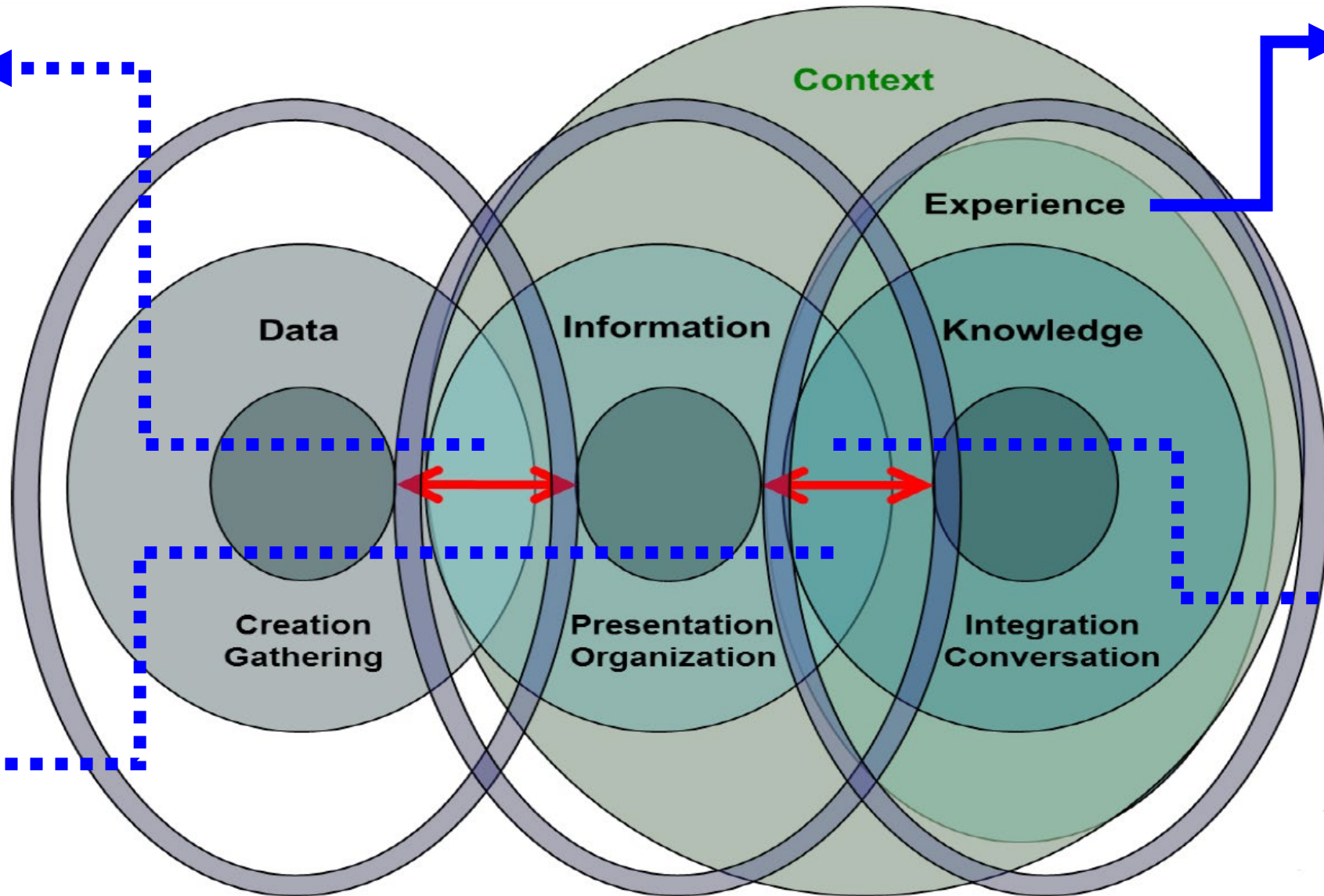
Data-Informed Decision as a Service

Knowledge-Informed Decision as a Service

Beyond knowledge, experience

ART

Realm
of
Experience



DIDA'S

KIDS

NEW YORK TIMES BESTSELLER

TRACY KIDDER

WINNER OF THE PULITZER PRIZE

MOUNTAINS BEYOND MOUNTAINS

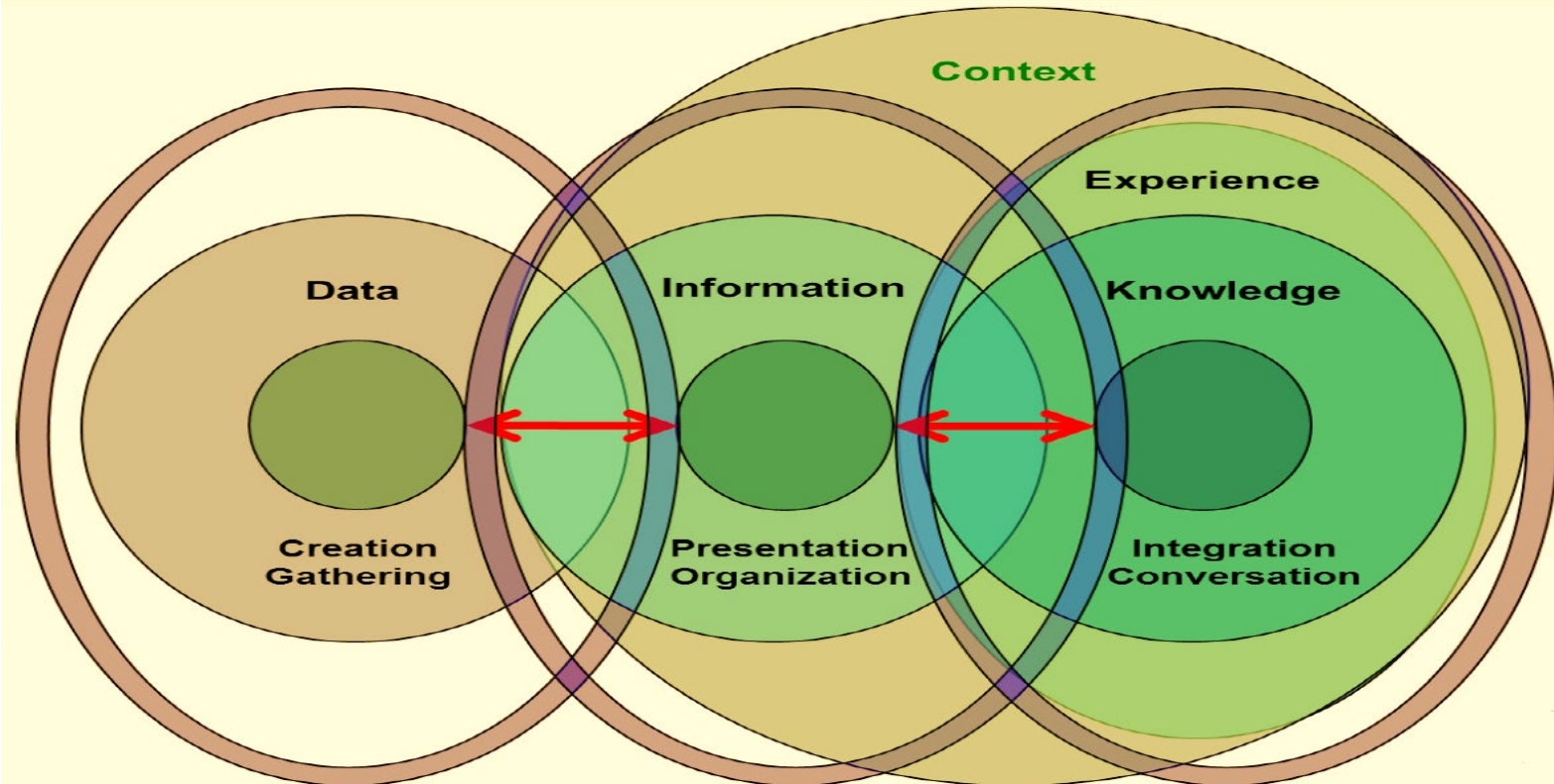
THE QUEST OF DR. PAUL FARMER,
A MAN WHO WOULD CURE
THE WORLD

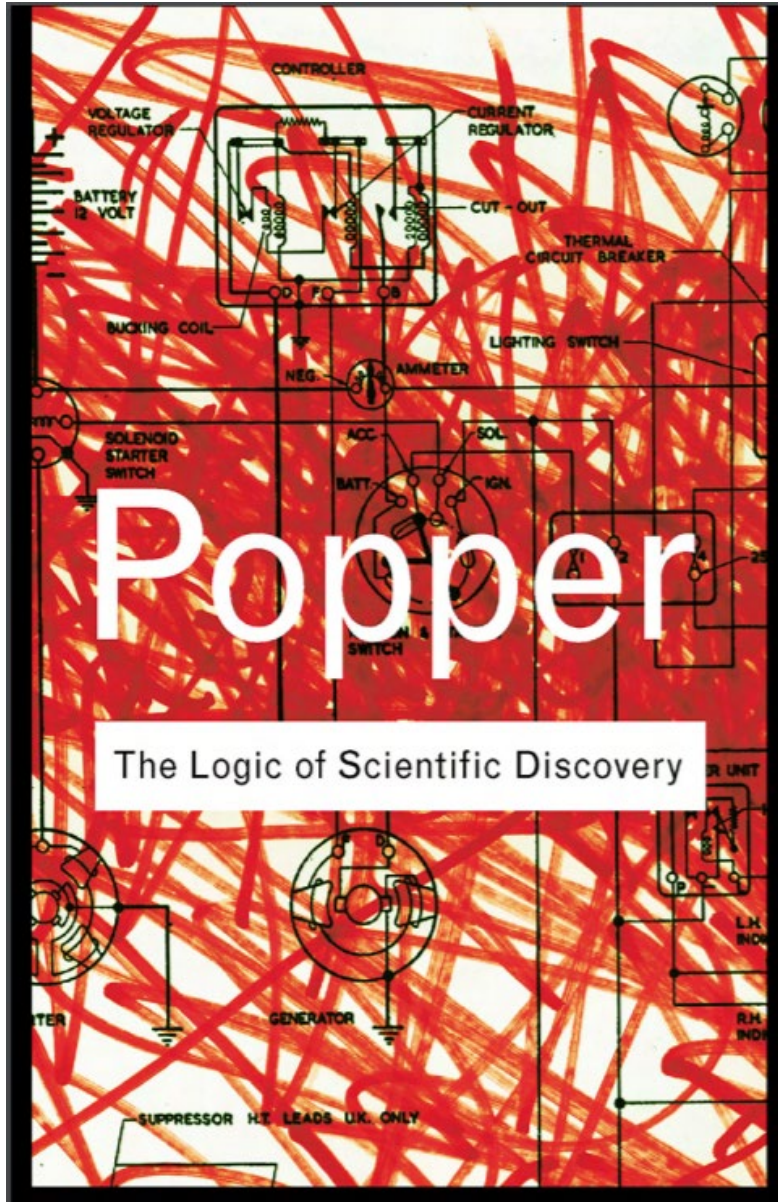


"INSPIRING, DISTURBING, DARING AND COMPLETELY ABSORBING."
—ABRAHAM VERGHESE, THE NEW YORK TIMES BOOK REVIEW

Beyond knowledge, experience

mountains beyond mountains





But how is the system that represents our world of experience to be distinguished? The answer is: by the fact that it has been submitted to tests, and has stood up to tests. This means that it is to be distinguished by applying to it that deductive method which it is my aim to analyse, and to describe.

‘Experience’, on this view, appears as a distinctive method whereby one theoretical system may be distinguished from others; so that empirical science seems to be characterized not only by its logical form but, in addition, by its distinctive method. (This, of course, is also the view of the inductivists, who try to characterize empirical science by its use of the inductive method.)

The theory of knowledge, whose task is the analysis of the method or procedure peculiar to empirical science, may accordingly be described as a theory of the empirical method—a theory of what is usually called ‘experience’.

Elusive Quest for Knowledge

Advanced integration of information, data, decisions

- KIDS may need TWINS

- KIDS may include SARA

KIDS need TWINS

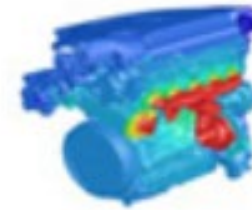
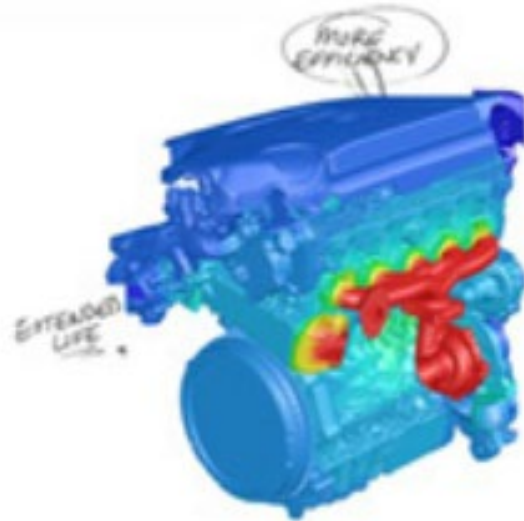
Adding PLM capacity in the form of Digital Twins to DIDA'S and KIDS

Digital Twin -- From Design to Operation

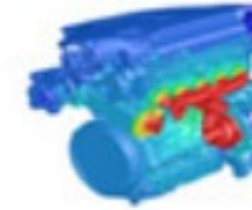
Physical Asset



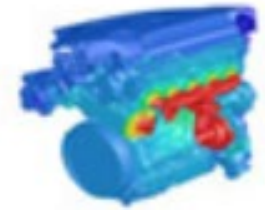
Virtual Prototype



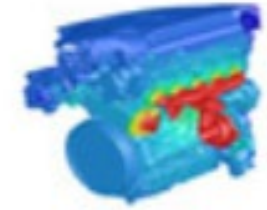
Digital Twin



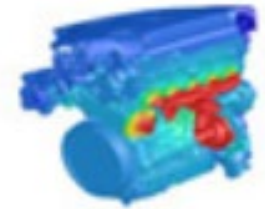
Digital Twin



Digital Twin



Digital Twin

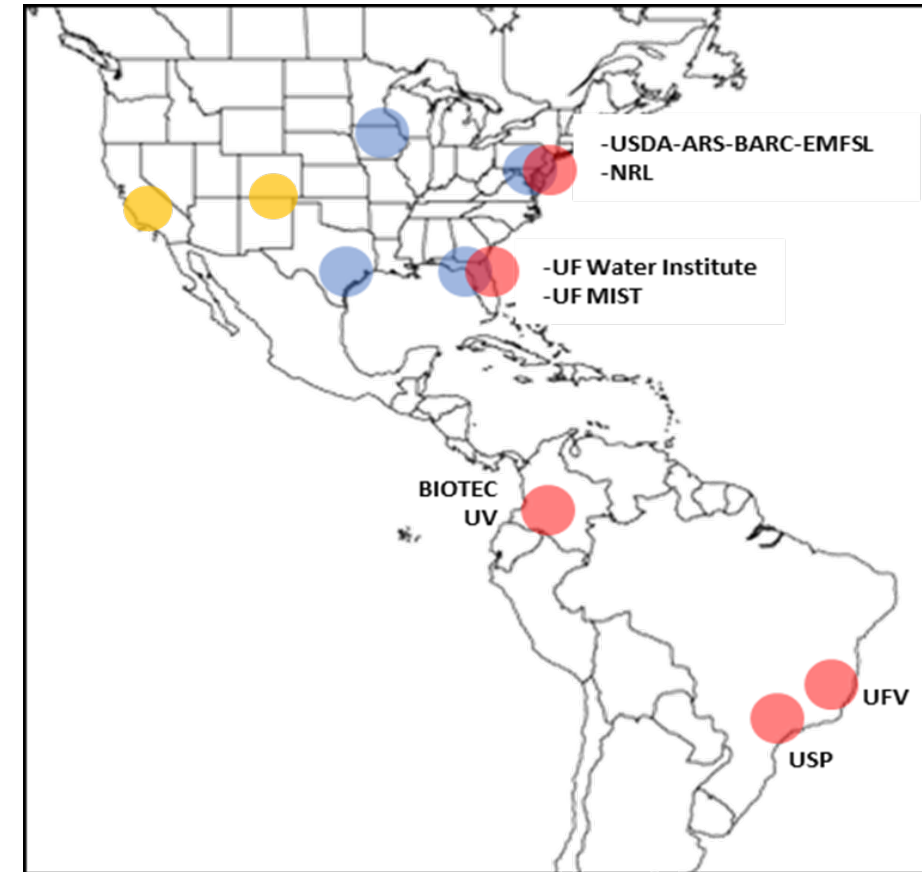
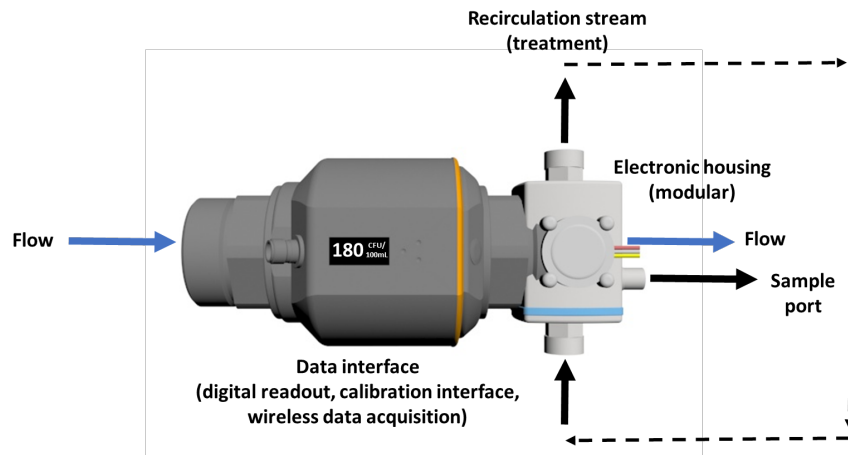
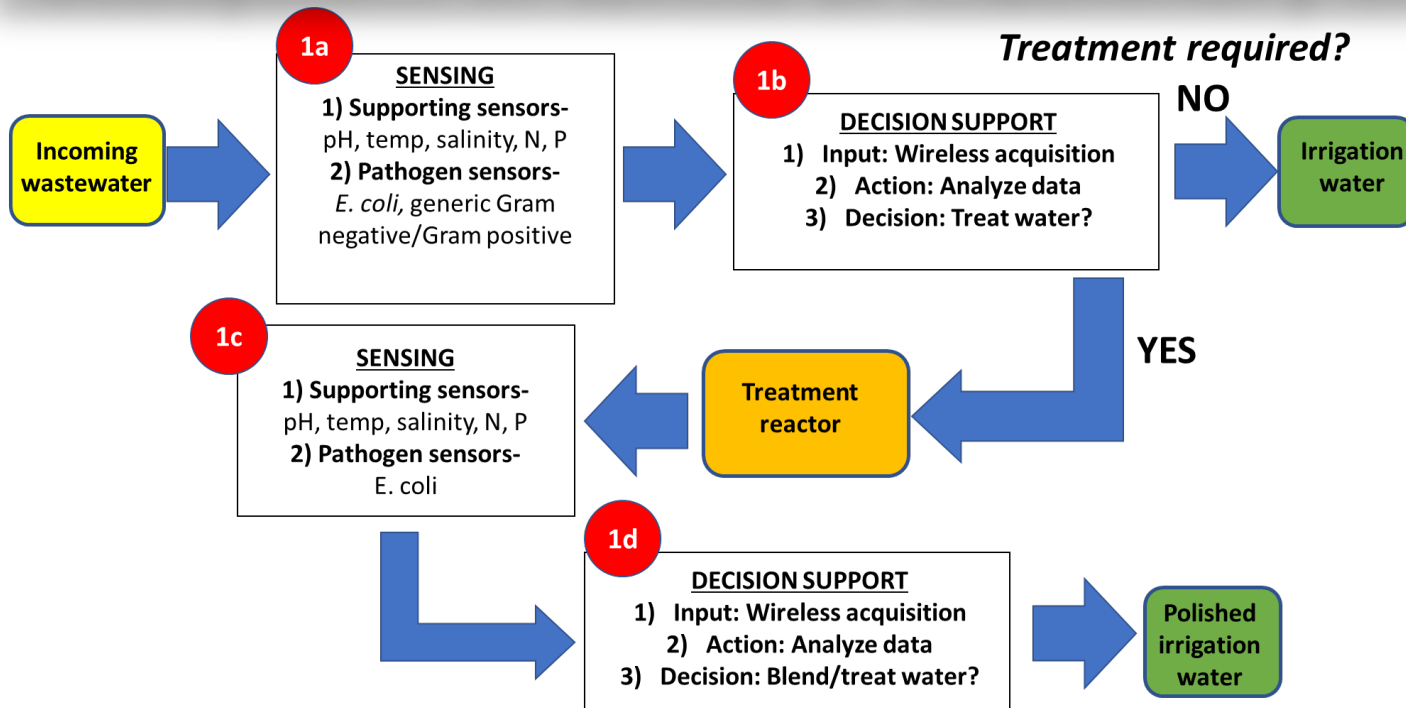


Digital Twin

Physics-based analytics to model the present state of every asset

CAD Courtesy of Volvo Cars

Use case: KIDS integrated with DIGITAL TWINS may improve the ecosystem in terms of machinery lifecycle in the agroecosystem



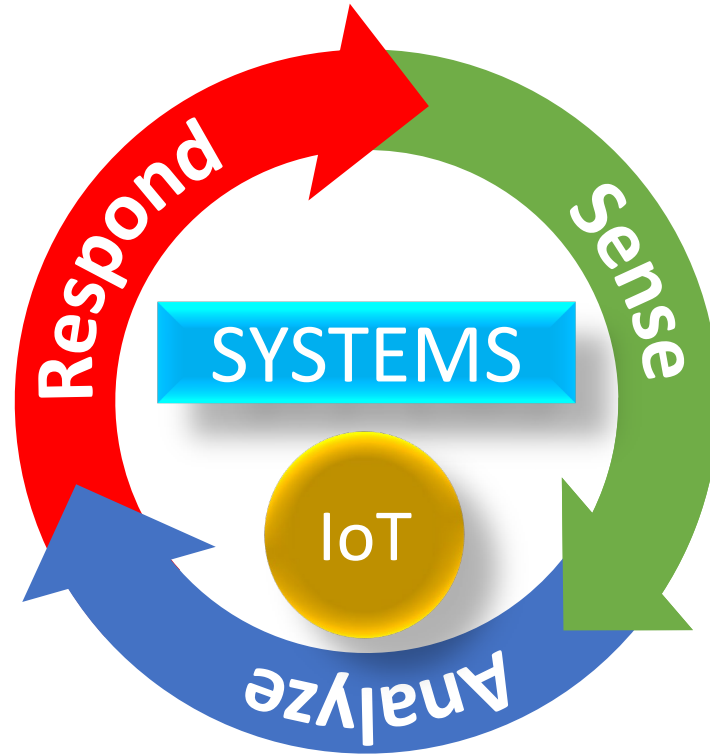
- SmartPath Institute
- Partner Institute
- Collaborator

KIDS to include SARA

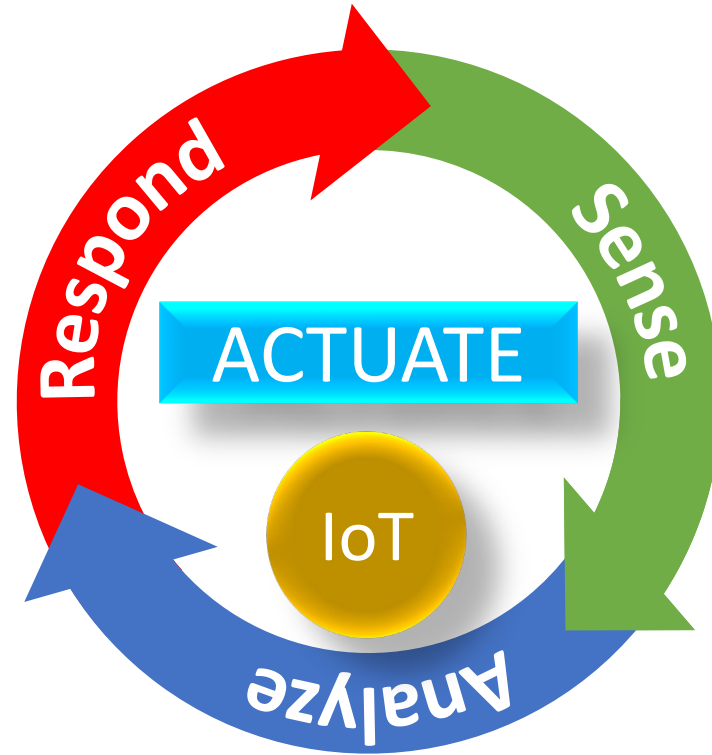
From sense, analyze, response, systems (SARS)

to sense, analyze, response, actuate (SARA)

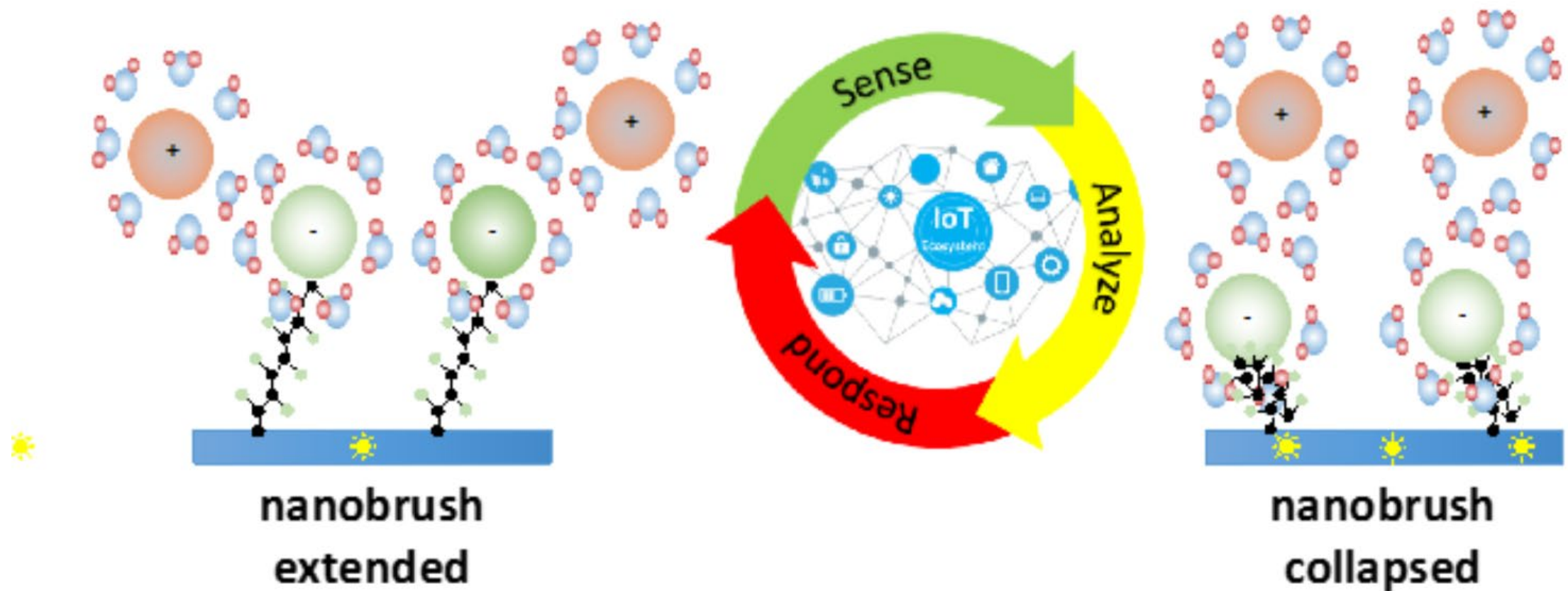
DIDA'S includes Sense, Analyze, Response, Systems (SARS)



KIDS to include Sense, Analyze, Response, Actuate (SARA)



Atoms to Bits - Sense, Analyze, Response, Actuate (SARA) Sensors using Smartphone



Nanomaterials can be monitored and controlled with smartphone

Future of digital transformation for the agro-ecosystem and emergence of digital products for traditional agri-businesses.

<https://emclamor.wixsite.com/mclamorelab>

Conventional Wisdom Questions Growth from Digital Transformation:

Conventional Wisdom Questions Growth from Digital Transformation:

BUSINESS
INSIDER

TECH FINANCE POLITICS STRATEGY LIFE ALL

BI PRIME INTELLIGENCE



NASA is opening the space station to \$35,000-a-night visits. A tourist who paid Russia \$30 million to get there a decade ago says it's a 'seismic shift.'

Dave Mosher 2h



NASA plans to open up the International Space Station to tourists and, to an even larger degree, commercial activity. NASA; Alyssa Powell/Business Insider

Conventional Wisdom ?

BUSINESS INSIDER

TECH FINANCE POLITICS STRATEGY LIFE ALL

BI PRIME INTELLIGENCE

NASA is opening the space station to \$35,000-a-night visits. A tourist who paid Russia \$30 million to get there a decade ago says it's a 'seismic shift.'

Dave Mosher 2h



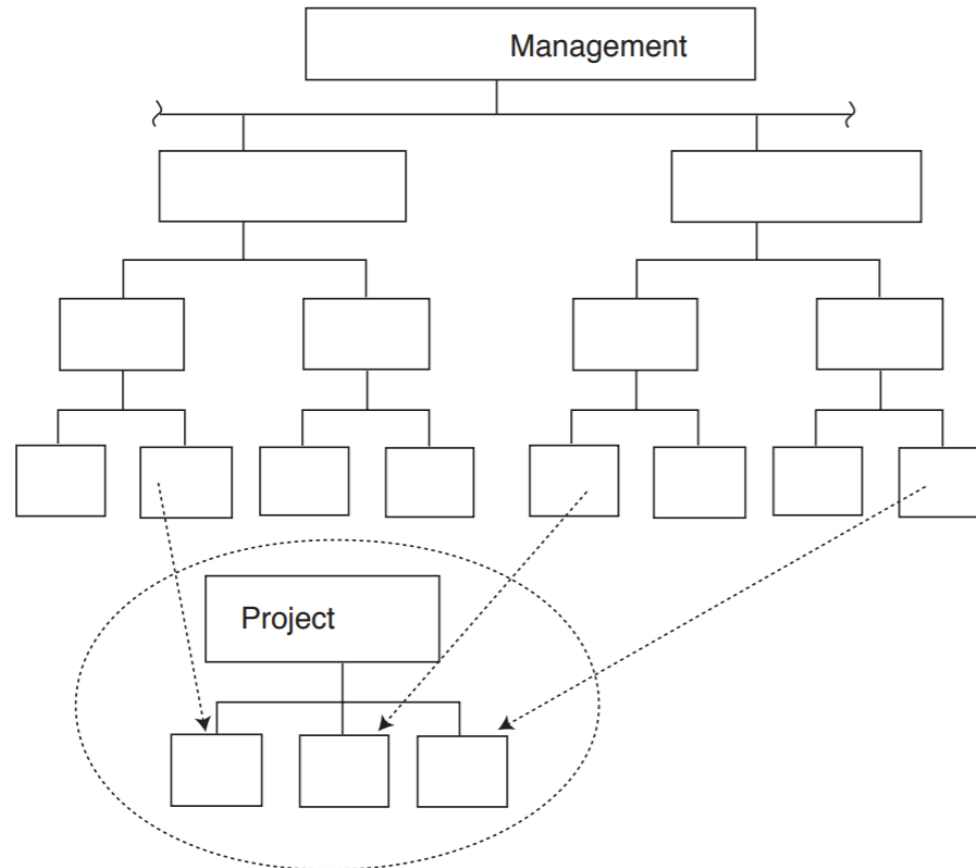
NASA plans to open up the International Space Station to tourists and, to an even larger degree, commercial activity. NASA; Alyssa Powell/Business Insider

Hadoop is sinking
because big data is
bullshit

MARTYN RICHARD JONES
goodstrat.com - THE GOOD STRATEGY COMPANY

martyn.jones@martyn.es

CONVENTIONAL WISDOM



Think different. Think non-linear. Think outside the box. Think beyond boundaries.

Exports from Latin America to India was US\$2 billion in 2000. In 2018, it exceeded US\$25 billion.

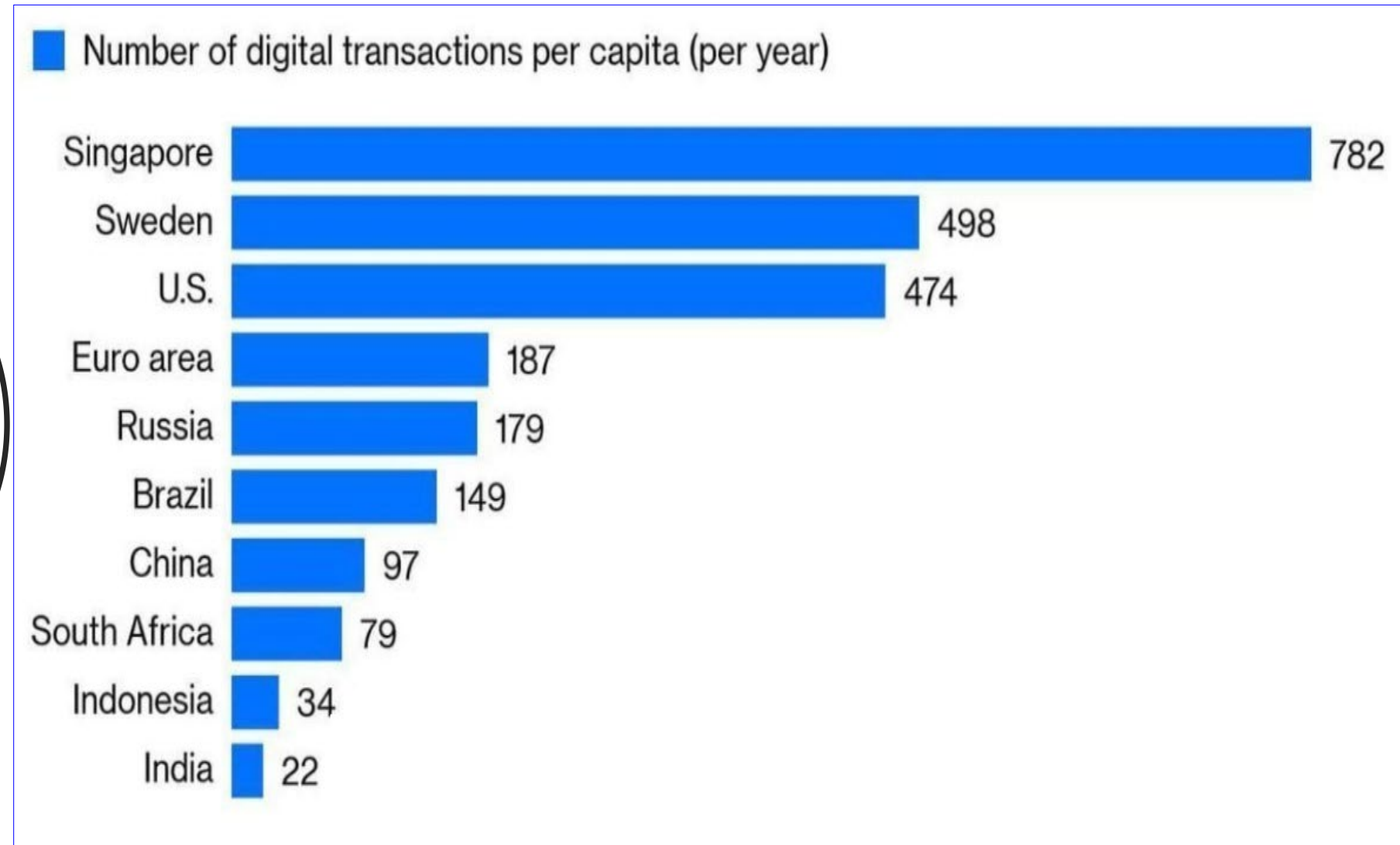
Mayores exportadores a la India

Venezuela, México y Brasil representaron dos tercios de los envíos de la región a la India



Is there a market for digital ART products in traditional agri-business?

To obtain the volume of potential digital transactions, multiply the number shown with the population of the country.





Ranveer Chandra
Chief Scientist, Azure Global at Microsoft



Tom Keane
Corporate Vice President of Azure Global - Microsoft Azure

Microsoft FarmBeats program uses Azure to connect agricultural devices and generate data intended to help farms transform business.

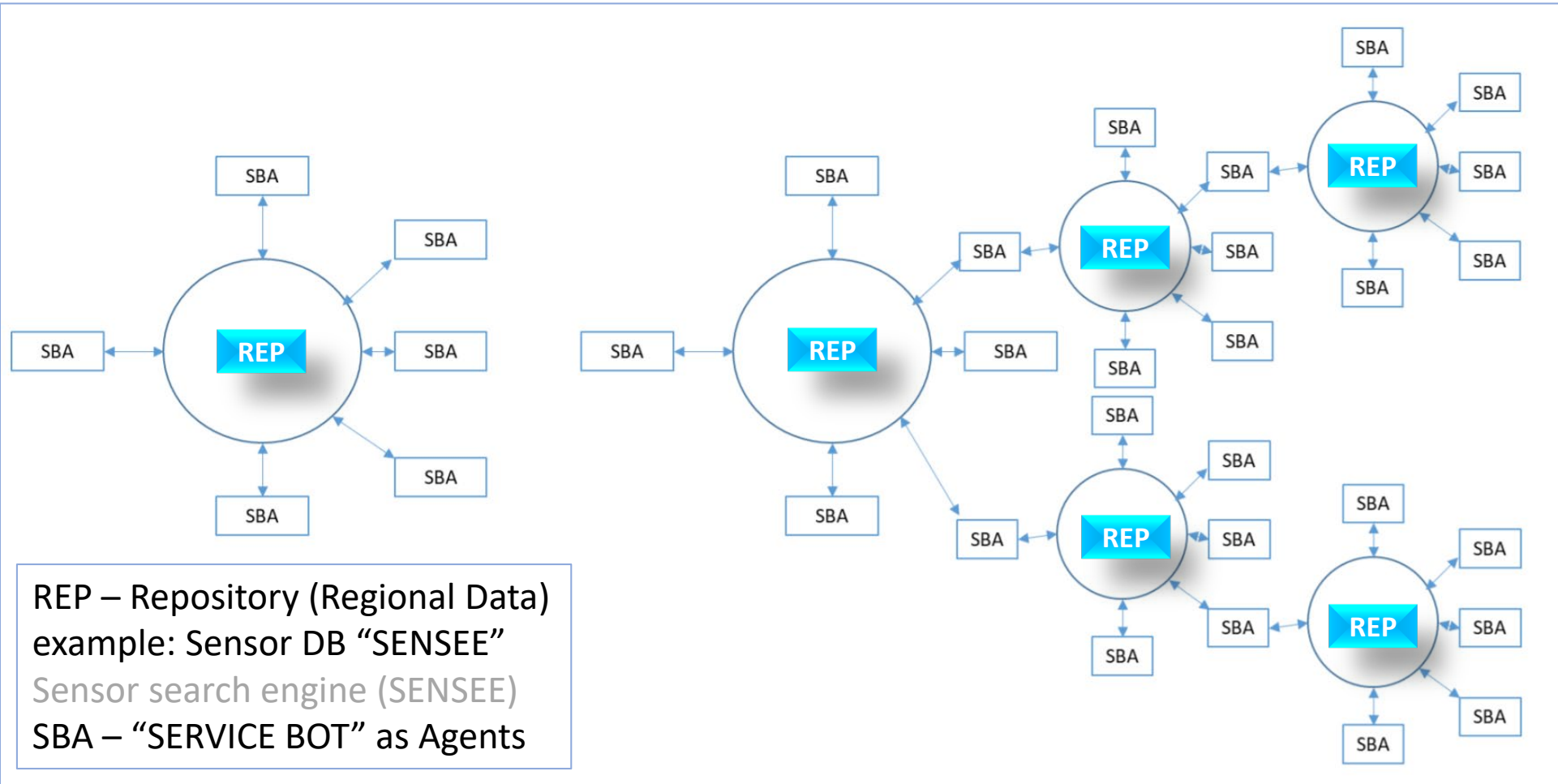




Low hanging fruits in digital-agro

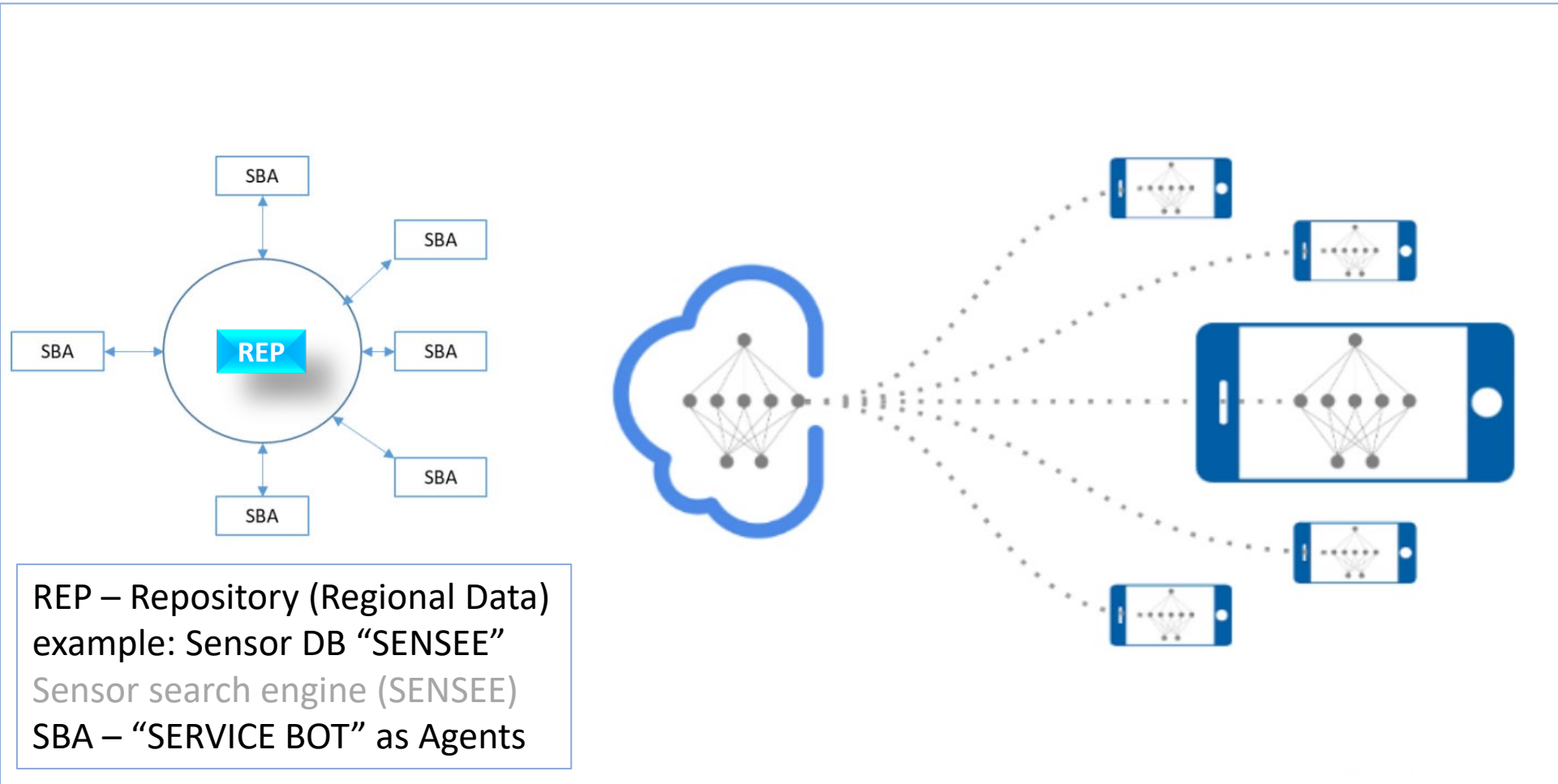
Prevention of food waste, global public health, water and food safety

Intelligent Information Arbitrage



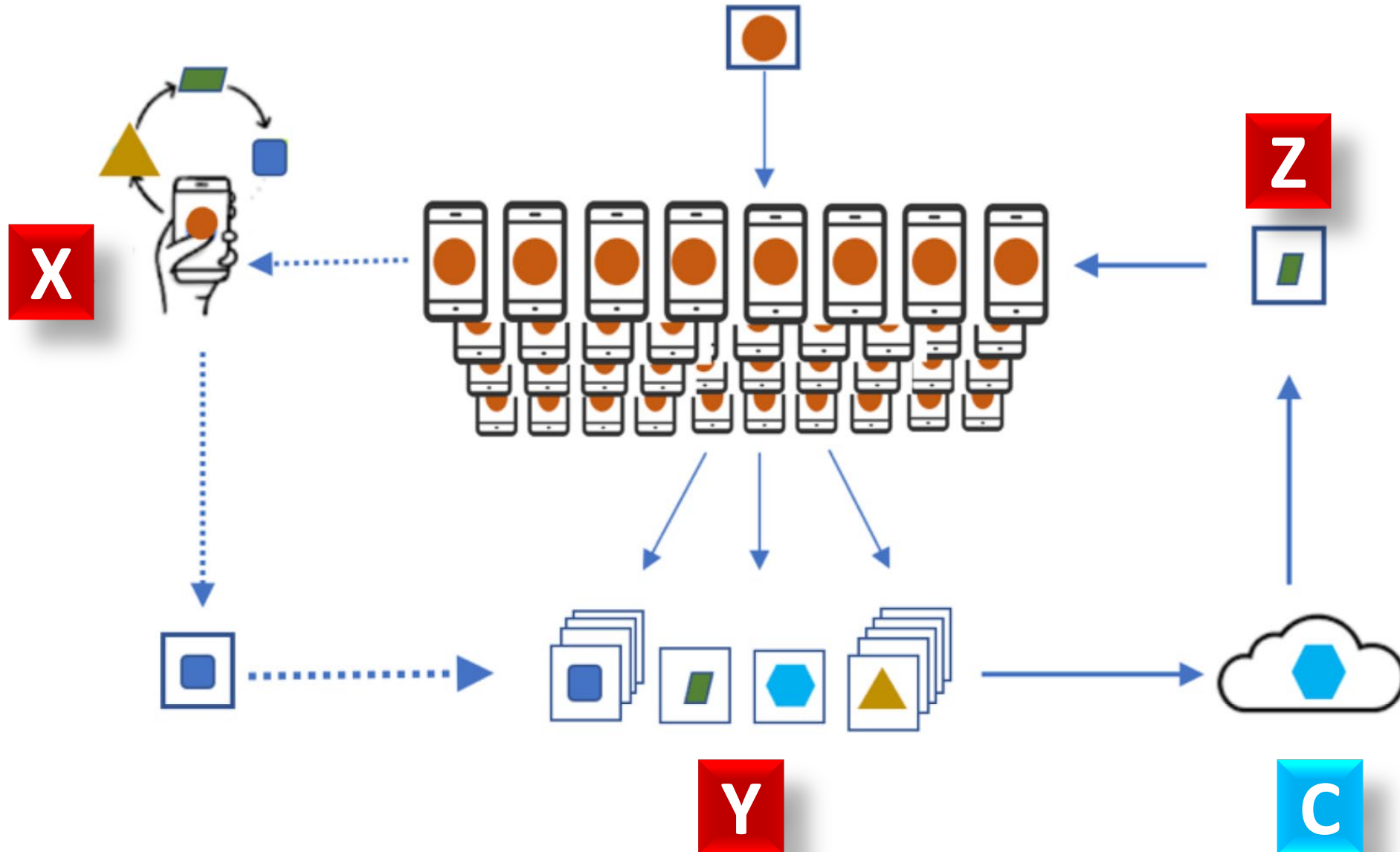
Locally distributed repositories [REP] containing data and questions (relevant to users and growers by crop or environment) can be globally connected using an Agent-based system

Intelligent Information Arbitrage



Locally distributed repositories [REP] containing data and questions (relevant to users and growers by crop or environment) can be globally connected and consumed by any system

Intelligent Information Arbitrage



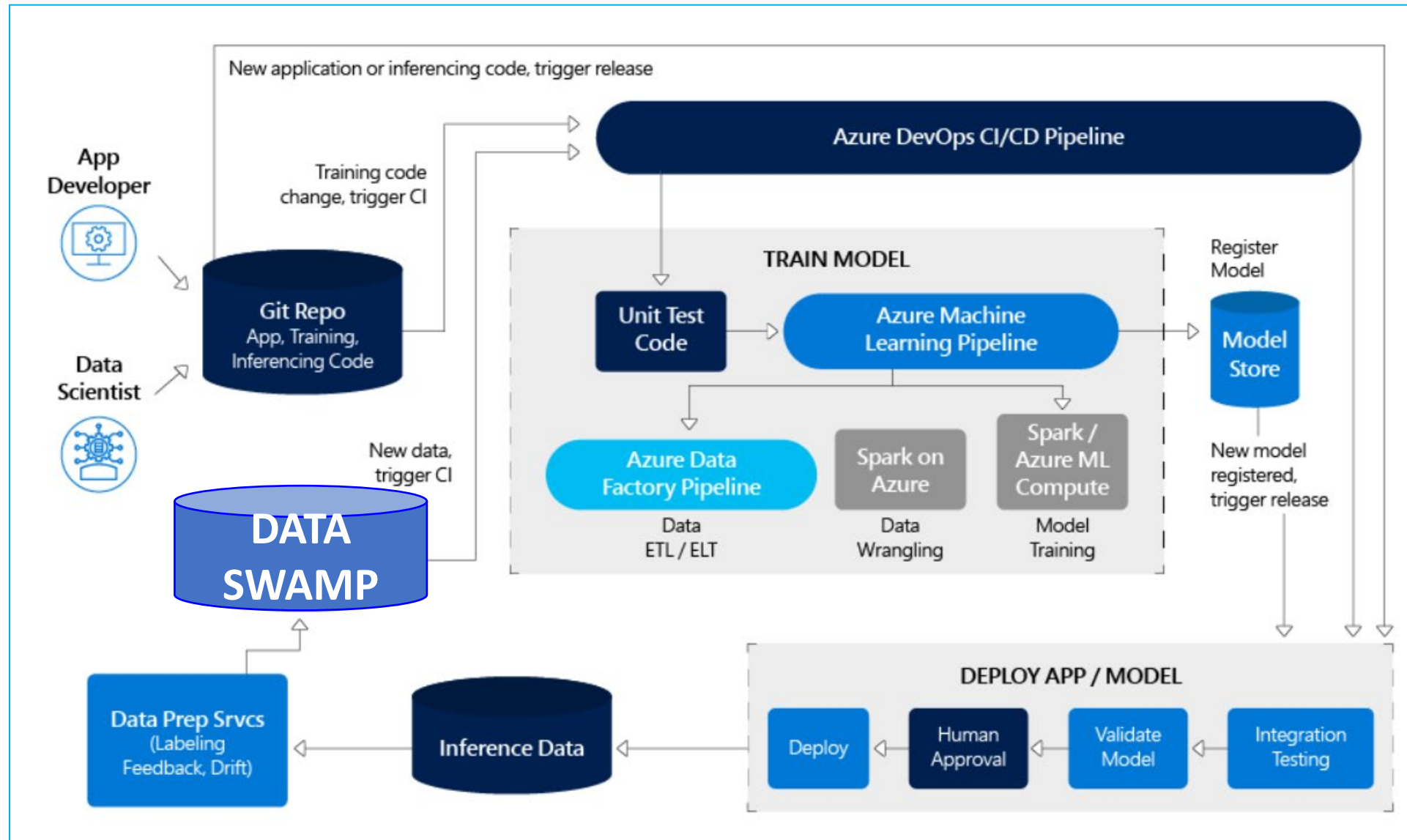
Intelligent Information Arbitrage



The value of the REP concept (SENSEE) may be enhanced by coupling publish-subscribe modes with crowd-sourced data adoption/dissemination. User “X” may update data, recommend tools or techniques or share outcomes/outputs (for example, growers can share photographs of infected produce or sinfully delicious tomatoes). Thus, local user personalization (point X, in the crowd) is sent/stored to the analytical platform (engine Y). An emerging consensus from contributed data (for example, improved technique or data with incorrect units or better use of a tool) is sent to cloud C for expert evaluation and critical analysis. Verified change Z is communicated to all subscribers, globally. This process repeats, to enhance open models and enrich common goals for public goods, using distributed data from crowdsourcing (users, farmers, growers, scientists, engineers, academics, politicians) but deploying a neutral/trusted analytical evaluator (cloud C) to deconstruct/reconstruct, aggregate/disaggregate data and models, to serve the best interest of the system. It may prevent data pollution, act to neutralize cyberthreats and stop, if possible, attacks perpetrated by GAN (general adversarial network) as infectious agents. This suggestion draws from “federated learning models” commonly used by financial institutions and banks to train fraud detection models without sharing their sensitive customer data. Popular frameworks now include TensorFlow Federated, an open source framework by Google for experimenting on decentralized data. PySyft is a open source library that is built on top of PyTorch for encrypted, privacy preserving deep learning. Federated AI Technology Enabler (FATE) is an open-source project initiated by WeBank’s AI group to provide a secure computing framework to support the Federated AI ecosystem. Despite the hype whipped up by the glib snake oil salesmen of AI, there is value in this approach, if and when rationally analyzed, for specific purposes, using bonafide tools, which may be customized for specific applications and are based on rigorous mathematics and statistics. It may be useful for SITS and its ecosystem to explore these advanced tools of the future and enterprise solutions around federated learning and other secure computation techniques across different verticals. At present, the primary deployment challenge may be the computational constraint of edge devices (smartphone, tablet) to perform local training, cloud consultations and inferencing. However, smartphones and IoT devices are increasingly equipped with GPUs or sufficient computing hardware to run CNN/RNN and other AI models at the edge to augment near-real time “intelligent” decision support systems, at the point of use. REP/SENSEE may be the SmartPath/SITS approach to harvest these ideas and convert them into actionable transactions that can help the ag industry in the pursuit of food.



Intelligent Information Arbitrage



Intelligent Information Arbitrage

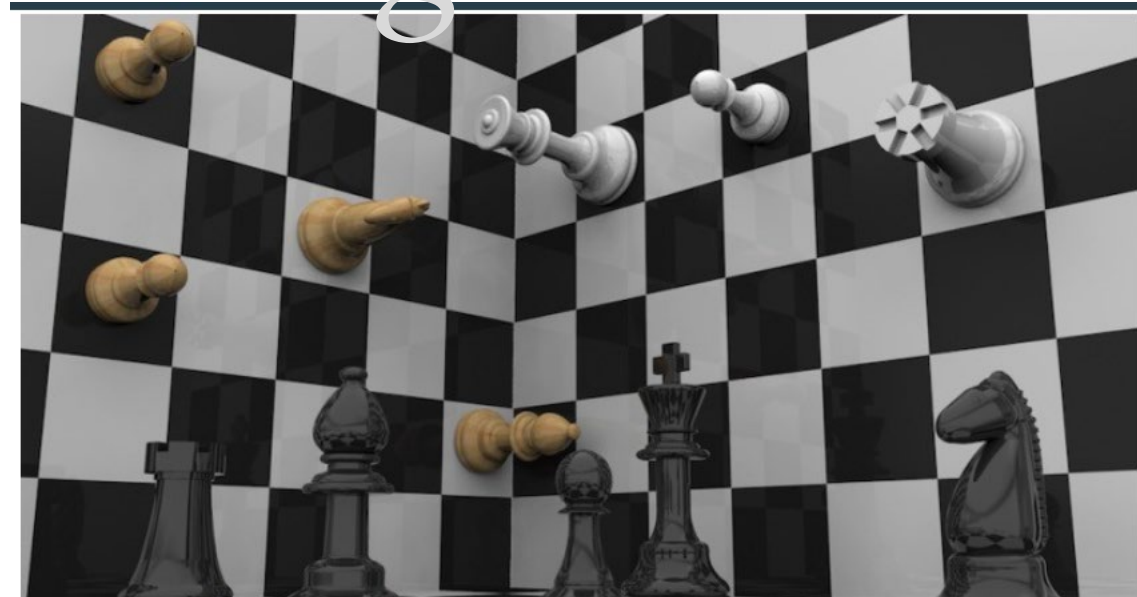


HARVEST and INVEST in UNSTRUCTURED DATA and (MERGE DATA IN CONTEXT FOR INTELLIGENT) DATA ANALYTICS

Intelligent Information Arbitrage

WATER v PEOPLE

Change the rules



1 in 3 people globally do not have access to safe drinking water – UNICEF, WHO

New report on inequalities in access to water, sanitation and hygiene also reveals more than half of the world does not have access to safe sanitation services.

18 June 2019 | News release | New York, Geneva

Billions of people around the world are continuing to suffer from poor access to water, sanitation and hygiene, according to a new report by UNICEF and the World Health Organization. Some 2.2 billion people around the world do not have safely managed* drinking water services, 4.2 billion people do not have safely managed sanitation services, and 3 billion lack basic** handwashing facilities.



Nada Osseiran
Communications Officer
WHO
Mobile: +41 79 445 1624







HHS Public Access

Author manuscript

J Public Health Manag Pract. Author manuscript; available in PMC 2019 January 01.

Published in final edited form as:

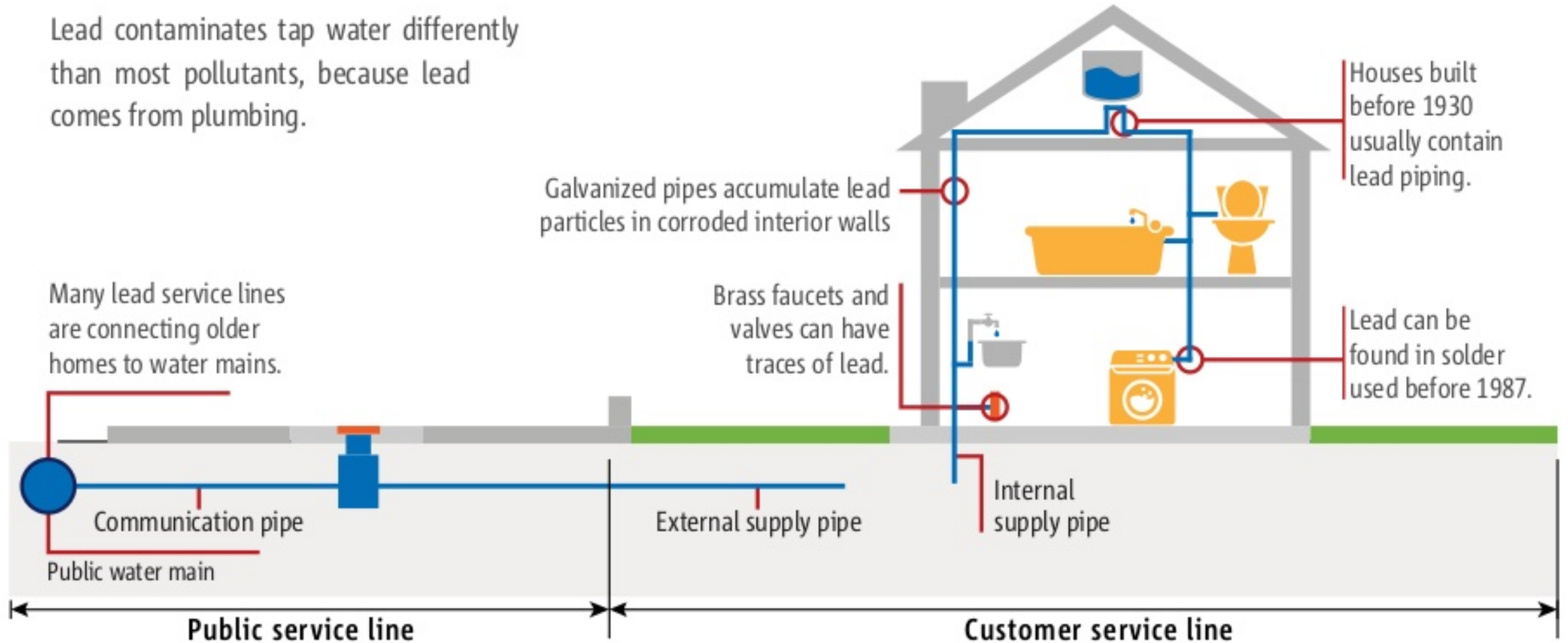
J Public Health Manag Pract. 2019 ; 25(Suppl 1 LEAD POISONING PREVENTION): S84–S90. doi:
10.1097/PHH.0000000000000871.

The Flint Water Crisis: A Coordinated Public Health Emergency Response and Recovery Initiative



THE PIPES

Lead contaminates tap water differently than most pollutants, because lead comes from plumbing.

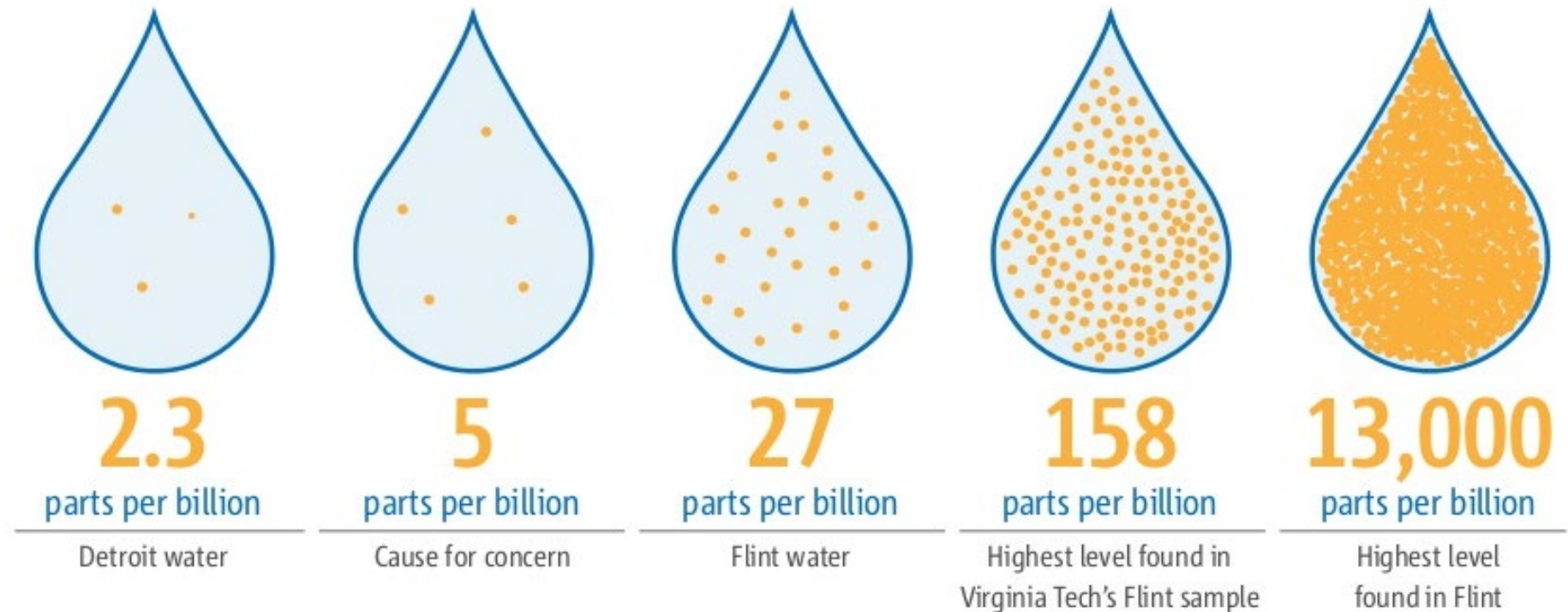


Summing up: water from Flint River moved through lead pipes, picking up the toxin as it went, and spread it throughout the population.

<https://www.slideshare.net/lbuckfire/the-flint-michigan-water-crisis-causes-effects>

THE KEY PROBLEM

Water from the Flint River is highly corrosive (its water has about 8 times more chloride (Cl⁻) in it than Detroit water) to iron and lead. Unfortunately, these pipe materials are widely used throughout Flint.

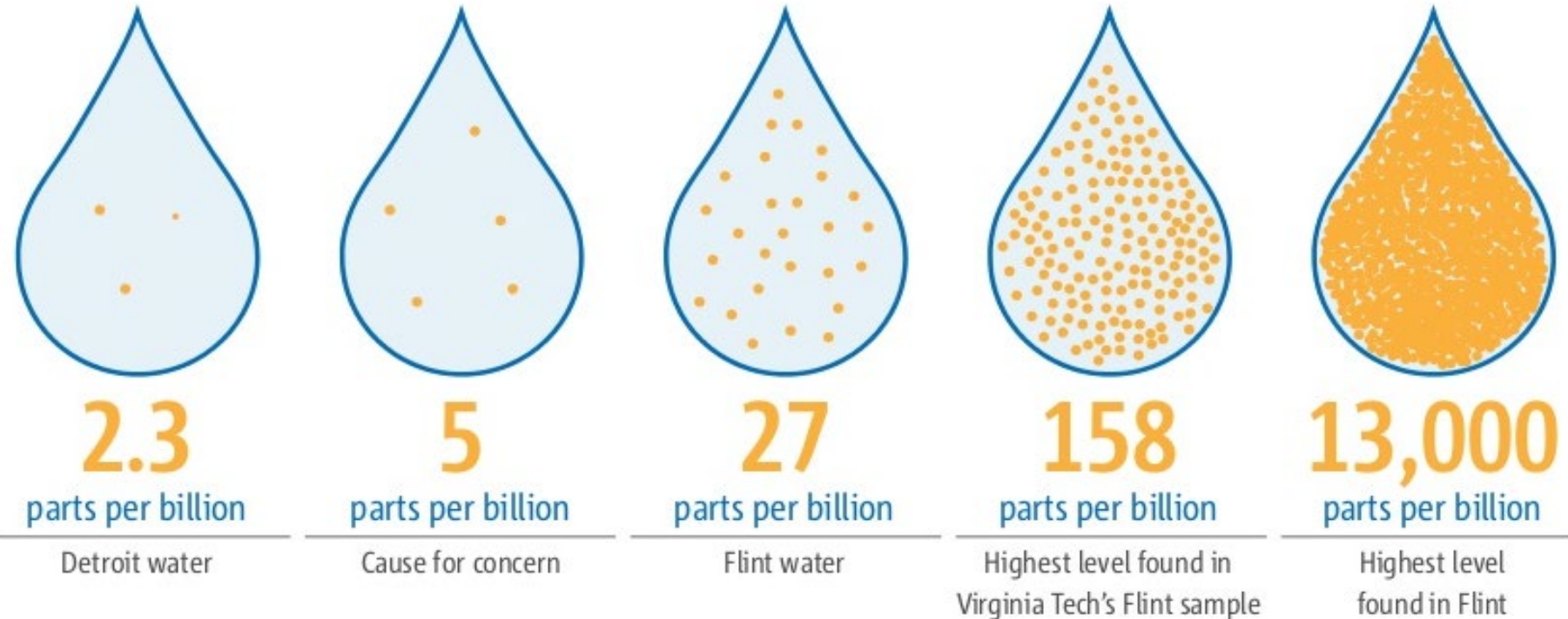


And, if these pipes are exposed to corrosive water, or if water sits too long inside them, the lead could be released and may end up coming out of the tap.

FLINT, MICHIGAN WATER CRISIS - LEAD POISONING FACTS AND FIGURES

THE KEY PROBLEM

Water from the Flint River is highly corrosive (its water has about 8 times more chloride (Cl^-) in it than Detroit water) to iron and lead. Unfortunately, these pipe materials are widely used throughout Flint.



And, if these pipes are exposed to corrosive water, or if water sits too long inside them, the lead could be released and may end up coming out of the tap.

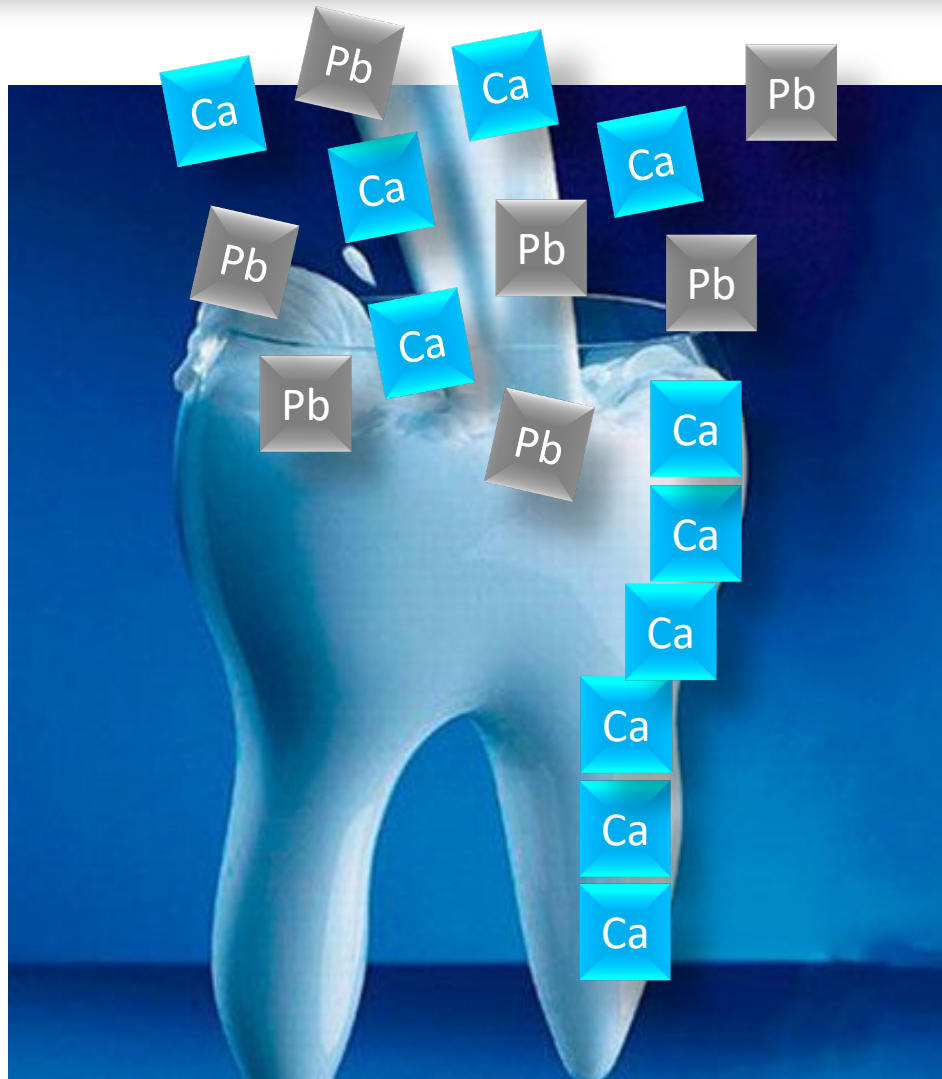
<https://www.slideshare.net/lbuckfire/the-flint-michigan-water-crisis-causes-effects>

THE FLINT'S WATER AND THE POISONED AMERICAN URBAN TRAGEDY CITY

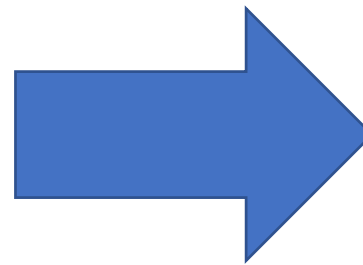
ANNA CLARK

Copyrighted Material

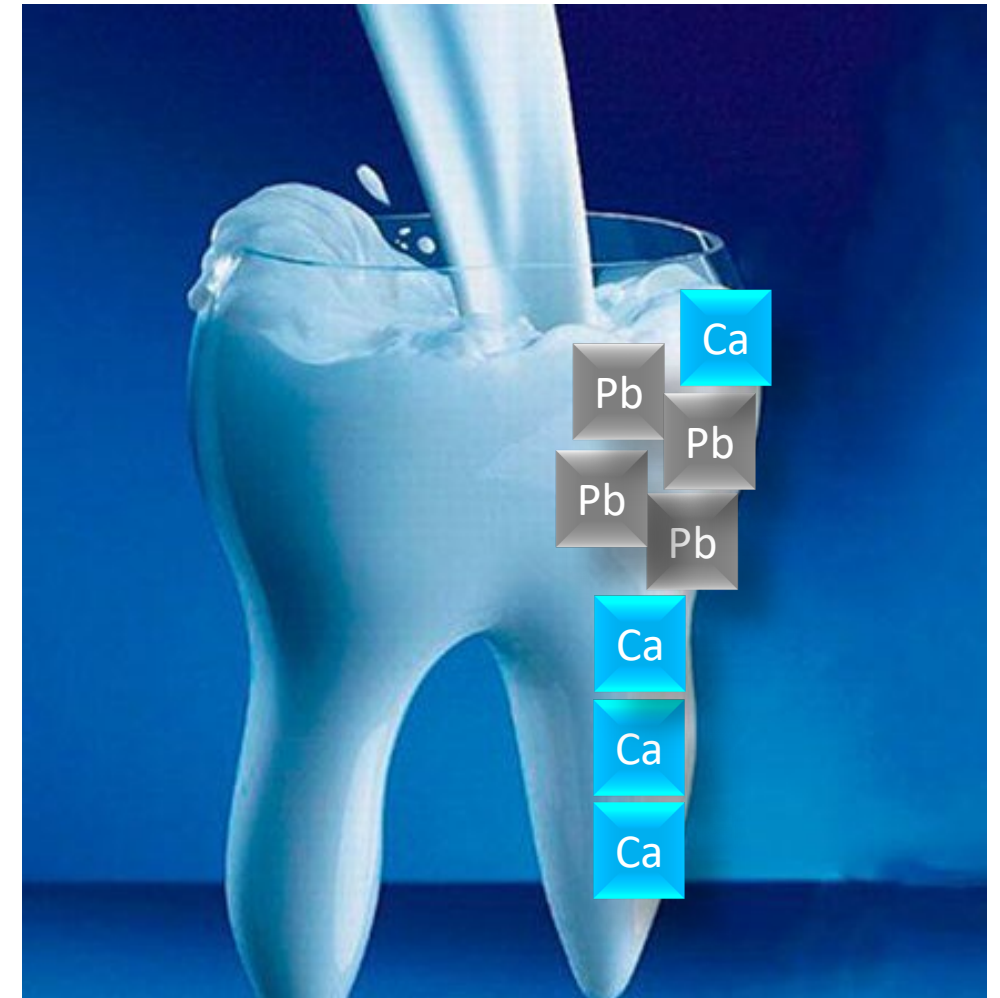
Lead (Pb) accumulates in teeth and bones



More lead exposure



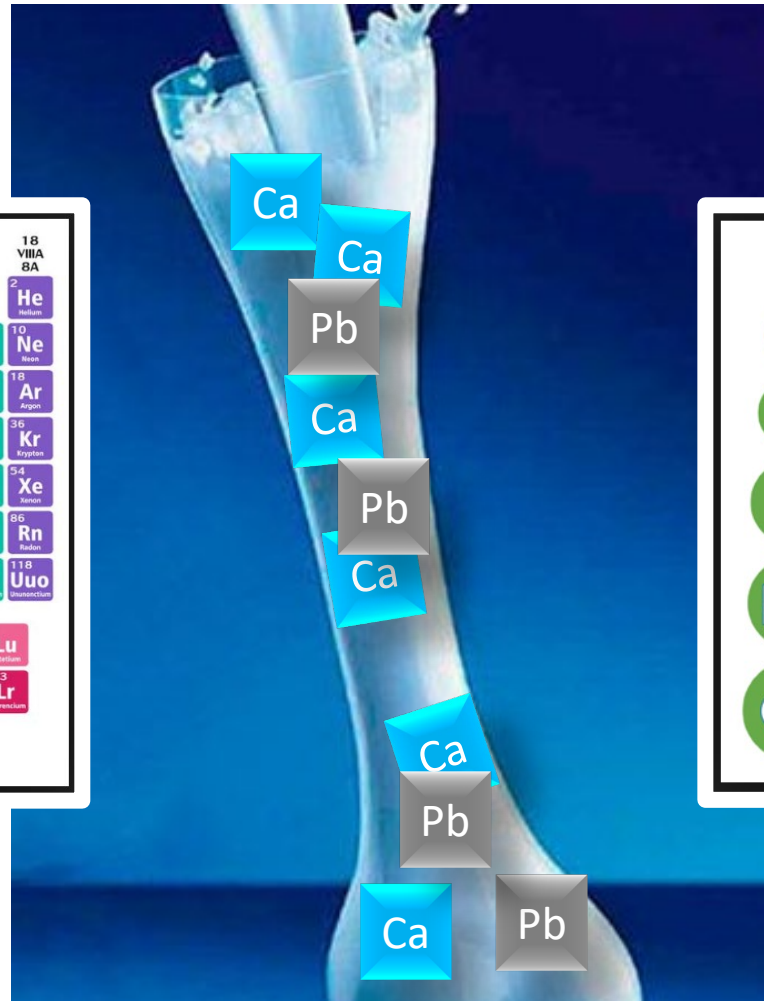
More lead is stored



Lead (Pb) accumulates in teeth and bones

Periodic Table of The Elements

The periodic table shows elements arranged by atomic number and grouped into categories: Alkali Metal, Alkaline Earth, Transition Metal, Basic Metal, Semimetal, Nonmetal, Halogen, Noble Gas, Lanthanide, and Actinide. The legend indicates that the symbol is the first letter (or first two) of the element's name.

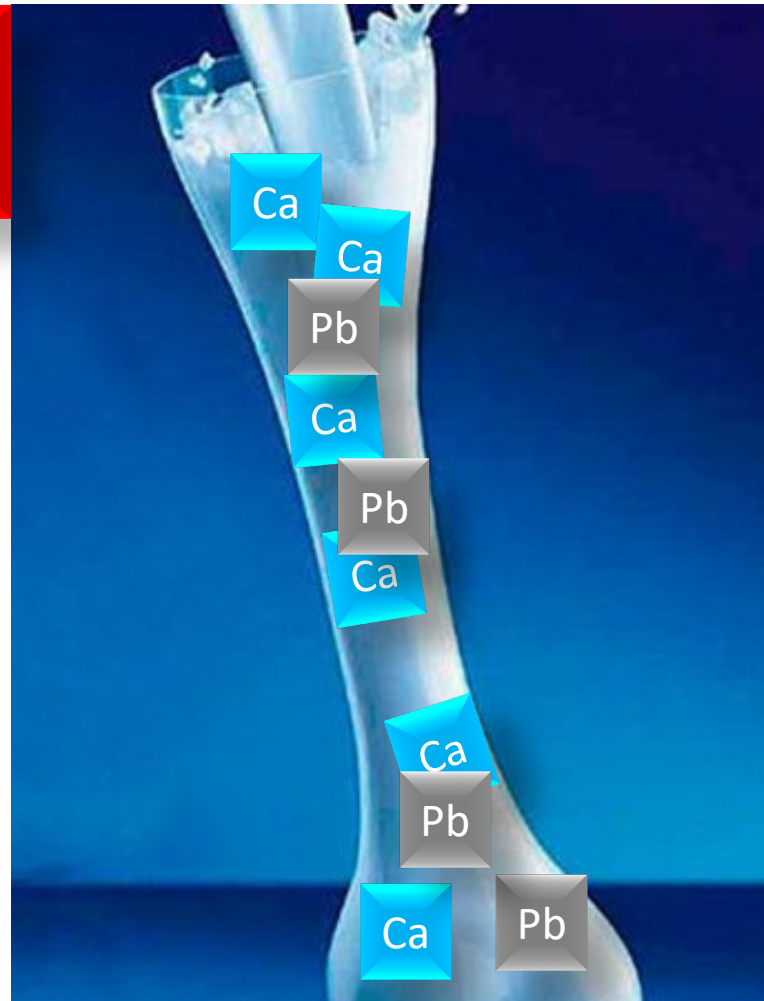


The diagram shows the relative sizes of atoms and ions for various elements. The elements are arranged in a grid, with the size of the circle representing the atomic or ionic radius. The elements shown are: H, Li, Na, K, Rb, Cs, He, Be, Mg, Ca, Sr, Ba, B, C, N, O, F, Ne, Al, Si, P, S, Cl, Ar, Ga, Ge, As, Se, Br, Kr, In, Sn, Sb, Te, I, Xe, Tl, Pb, Bi, Po, At, Rn. A vertical zigzag line labeled "Transition Metals" is shown between the main groups.

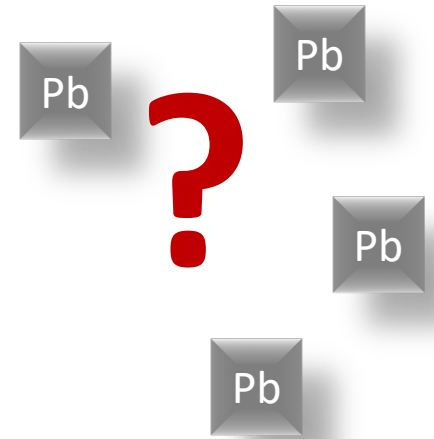
<https://chemistryonline.guru/ionic-radius/>

Lead (Pb) accumulates in teeth and bones

Osteoporosis

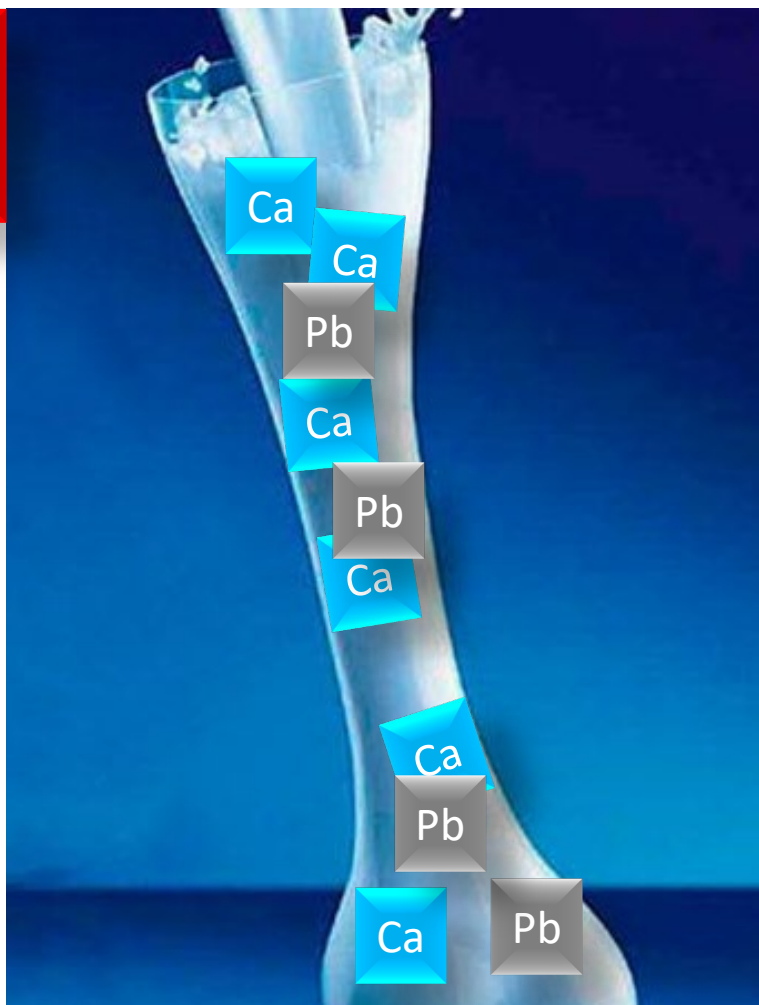


What happens to the **Pb** in the bones?

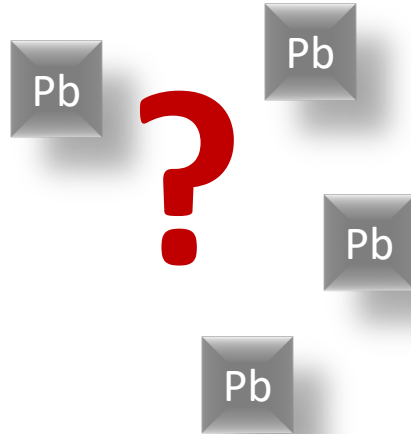


Lead (Pb) concentration increases in the blood

Osteoporosis



What happens to the **Pb** in the bones?



Childhood Lead Poisoning
causes dementia in adults





The Association between Blood Lead Levels and Osteoporosis Adults—Results from the Third National Health and Nutrition Examination Survey (NHANES III)

James R. Campbell and Peggy Auinger

Published: 1 July 2007 | <https://doi.org/10.1289/ehp.9716> | Cited by: 35

78% of the U.S. population (1970s) had blood lead levels $\geq 10 \mu\text{g}/\text{dL}$. Bone is a repository for 90–95% of the total body burden of lead and harbors it for years after initial exposure. Thus, a high proportion of adult Americans may currently have elevated bone lead levels. With this many who were exposed to lead when younger, and the morbidity associated with osteoporosis, it is important to investigate whether an association exists between lead exposure and osteoporosis in humans. Our objective was to conduct a secondary analysis to explore an association between lead exposure and osteoporosis in U.S. adults.

Pb from water accumulates in teeth and bones. When Pb leaches out of bones, it may contribute to osteoporosis in adult life. Increased amount of Pb in blood may also contribute to dementia, Alzheimer's and neurotoxicity.

www.ncbi.nlm.nih.gov/pmc/articles/PMC3567843/pdf/nihms367232.pdf

Published in final edited form as:
Curr Alzheimer Res. 2012 June ; 9(5): 563–573.

Alzheimer's Disease and Environmental Exposure to Lead: The Epidemiologic Evidence and Potential Role of Epigenetics

Kelly M. Bakulski¹, Laura S. Rozek^{1,2}, Dana C. Dolinoy¹, Henry L. Paulson³, and Howard Hu^{1,4,5,*}

¹University of Michigan, School of Public Health, Department of Environmental Health Sciences

²University of Michigan, Medical School, Department of Otolaryngology

³University of Michigan, Department of Neurology

⁴University of Michigan, Department of Epidemiology

⁵University of Michigan, Medical School, Department of Internal Medicine

Abstract

Several lines of evidence indicate that the etiology of late-onset Alzheimer's disease (LOAD) is complex, with significant contributions from both genes and environmental factors. Recent research suggests the importance of epigenetic mechanisms in defining the relationship between environmental exposures and LOAD. In epidemiologic studies of adults, cumulative lifetime lead (Pb) exposure has been associated with accelerated declines in cognition. In addition, research in animal models suggests a causal association between Pb exposure during early life, epigenetics, and LOAD. There are multiple challenges to human epidemiologic research evaluating the relationship between epigenetics, LOAD, and Pb exposure. Epidemiologic studies are not well-suited to accommodate the long latency period between exposures during early life and onset of Alzheimer's disease. There is also a lack of validated circulating epigenetics biomarkers and retrospective biomarkers of Pb exposure. Members of our research group have shown bone Pb is an accurate measurement of historical Pb exposure in adults, offering an avenue for future epidemiologic studies. However, this would not address the risk of LOAD attributable to early-life Pb exposures. Future studies that use a cohort design to measure both Pb exposure and validated epigenetic biomarkers of LOAD will be useful to clarify this important relationship.

Do you know what is in your drinking water?

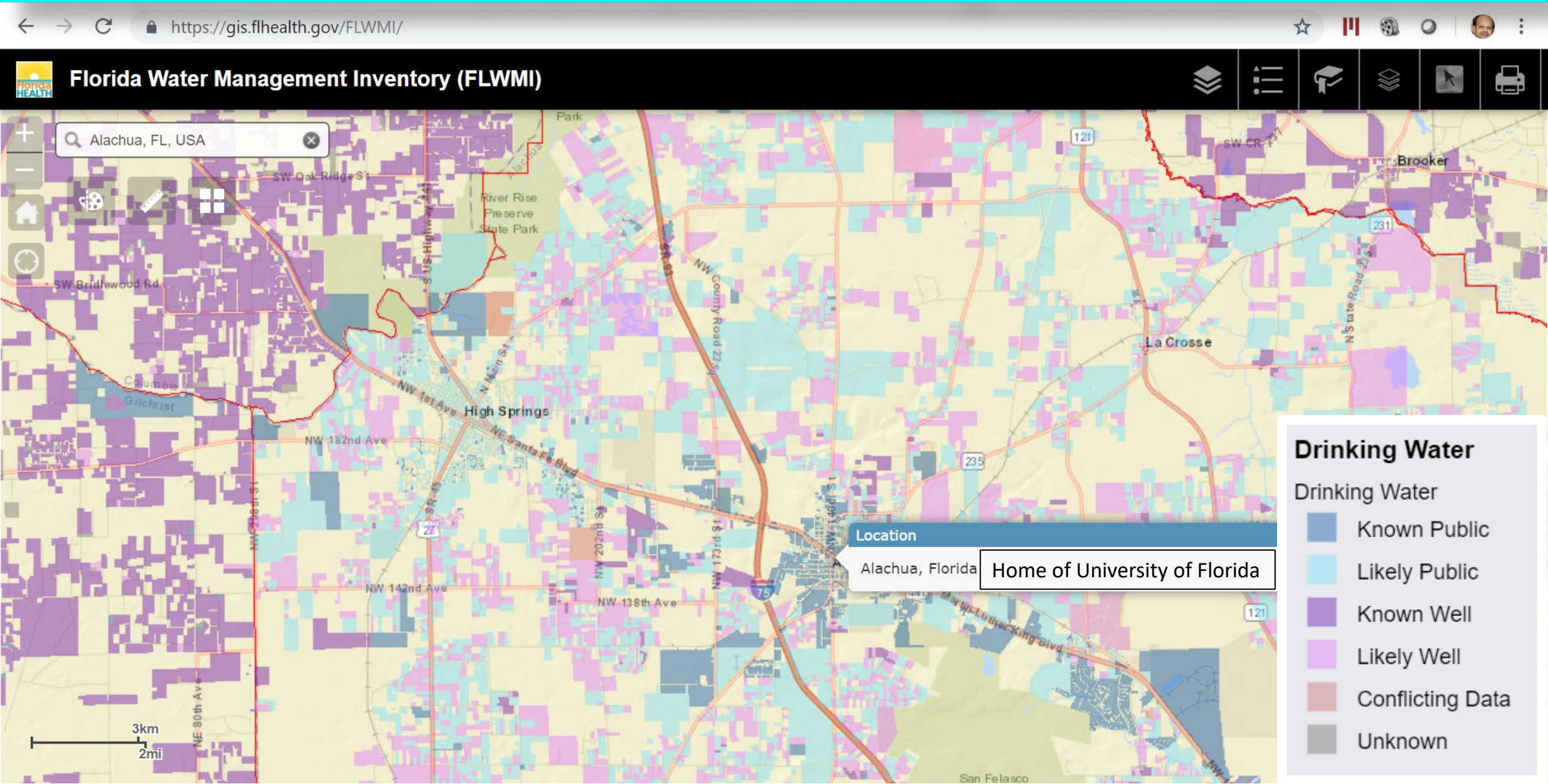
The Impact

535,000

U. S. children ages 1 to 5 years
have blood lead levels high
enough to damage their health.



Do you know what is in your drinking water from the well?



Drinking water from wells – schools near University of Florida

← → ↻ https://gis.flhealth.gov/FLWMI/

Florida Water Management Inventory (FLWMI)

Alachua, FL, USA

Parcel: 03127-010-004 (1 of 2)

Layer Name: Wastewater
Domestic Wastewater Disposal: LikelySeptic
Drinking Water Delivery: LikelyWell
Built Status: BLT
Land Use Category: RES
Physical Address: Null
Physical City: Null
Physical ZipCode: Null
County Parcel Number: 03127-010-004
County Alternate Key: 11982
GIS Acres: 6.246079
DOR County: 11
Wastewater Year Updated: 2014
Wastewater Data Source Type: DOH-HQ
Wastewater Source Name: Centrax 01-SA-06169
Tax Assessment Year: 2016

[Zoom to](#)

Legend

Drinking Water

- Known Public
- Likely Public
- Known Well
- Likely Well
- Conflicting Data
- Unknown

School Bd of Alachua Cty

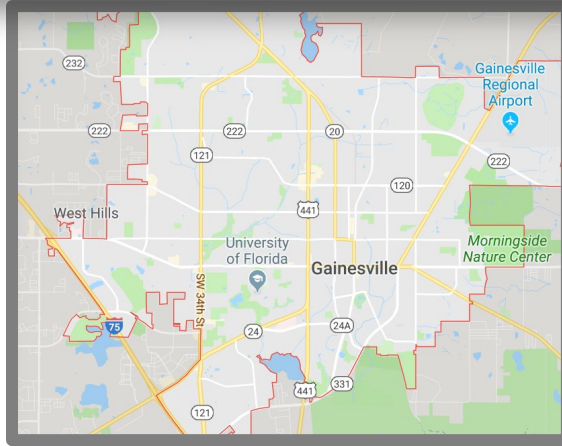
Mebane Middle School

NW 140th St

Drinking water from water treatment plant in Gainesville, FL

Gainesville Regional Utilities (GRU) - Murphree WTP

EWG's drinking water quality report shows results of tests conducted by the water utility and provided to the Environmental Working Group by the Florida Department of Environmental Protection, as well as information from the U.S. EPA Enforcement and Compliance History database (ECHO). For the latest quarter assessed by the EPA (July 2018 - September 2018), tap water provided by this water utility was in compliance with federal health-based drinking water standards.



WHAT ABOUT LEAD?

WANT TO FILTER THESE CONTAMINANTS OUT?

3

contaminants detected above health guidelines

5

other detected contaminants

Includes chemicals detected in 2015 for which annual utility averages exceeded an EWG-selected health guideline established by a federal or state public health authority; chemicals detected under the EPA's Unregulated Contaminant Monitoring Rule (UCMR 3) program in 2013 to 2015, for which annual utility averages exceeded a health guideline established by a federal or state public health authority; radiological contaminants detected between 2010 and 2015.

Chromium (hexavalent) <i>cancer</i>	+
Radiological contaminants <i>cancer</i>	+
Total trihalomethanes (TTHMs) <i>cancer</i>	+

WANT TO FILTER THESE CONTAMINANTS OUT?

Pollution sources

Click on each pollution source to see from which source contaminants come.



Agriculture



Industry



Treatment byproducts



Runoff & sprawl



Naturally occurring

Gainesville Regional Utilities (GRU) - Murphree WTP

EWG's drinking water quality report shows results of tests conducted by the water utility and provided to the Environmental Working Group by the Florida Department of Environmental Protection, as well as information from the U.S. EPA Enforcement and Compliance History database (ECHO). For the latest quarter assessed by the EPA (July 2018 - September 2018), tap water provided by this water utility was in compliance with federal health-based drinking water standards.

WHAT ABOUT LEAD?

WANT TO FILTER THESE CONTAMINANTS OUT?

3

contaminants detected above health guidelines

5

other detected contaminants

Includes chemicals detected in 2015 for which annual utility averages were lower than an EWG-selected health guideline established by a federal or state public health authority; chemicals detected under the EPA's Unregulated Contaminant Monitoring Rule (UCMR 3) program in 2013 to 2015, for which annual utility averages were lower than an EWG-selected health guideline established by a federal or state public health authority.

Chlorate	+
Chromium (total)	+
Haloacetic acids (HAA5)	+
Strontium	+
Vanadium	+

WANT TO FILTER THESE CONTAMINANTS OUT?

www.ewg.org/tapwater/system.php?pws=FL2010946

February 12, 2019

In an [agreement filed by the parties](#) of the 2017 settlement, the city of Flint committed to using a data-driven approach to locate the remaining lead pipes delivering drinking water to residents' homes. The city will use a statistical model—already proven effective in earlier efforts—to guide its selection of homes for service line excavations in 2019. This approach will increase efficiency and help ensure all remaining lead pipes are identified and removed.



OUR WORK OUR EXPERTS OUR STORIES GET INVOLVED ABOUT US

OUR STORIES › GUIDE

Flint Water Crisis: Everything You Need to Know

After officials repeatedly dismissed claims that Flint's water was making people sick, residents took action. Here's how the lead contamination crisis unfolded—and what we can learn from it.

November 08, 2018 | Melissa Denchak

Thursday, June 1, 2017

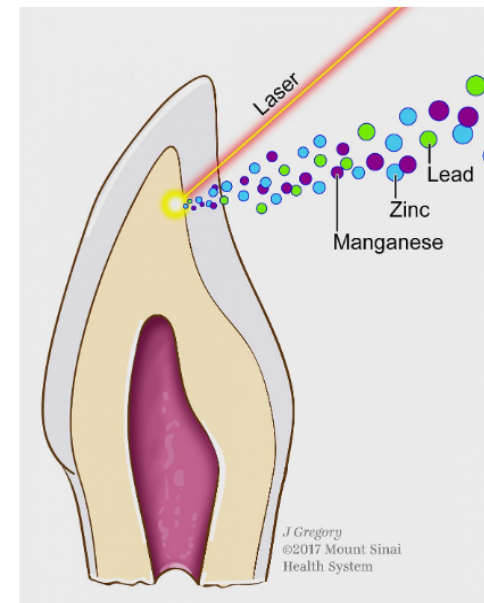
Baby teeth link autism and heavy metals, NIH study suggests



Baby teeth from children with autism contain more toxic lead and less of the essential nutrients zinc and manganese, compared to teeth from children without autism, according to an innovative study funded by the National Institute of Environmental Health Sciences (NIEHS), part of the National Institutes of Health. The researchers studied twins to control genetic influences and focus on possible environmental contributors to the disease. The findings, published June 1 in the journal *Nature Communications*, suggest that differences in early-life exposure to metals, or more importantly how a child's body processes them, may affect the risk of autism.

The differences in metal uptake between children with and without autism were especially notable during the months just before and after the children were born. The scientists determined this by using lasers to map the growth rings in baby teeth generated during different developmental periods.

The researchers observed higher levels of lead in children with autism throughout development, with the greatest disparity observed during the period following birth. They also observed lower uptake of manganese in children with autism, both before and after birth. The pattern was more complex for zinc. Children with autism had lower zinc levels earlier in the womb, but these levels then increased after birth, compared to children without autism.



Cross-section of tooth showing laser removal of the dentine layer, in tan, for analysis of metal content. Mount Sinai Health System



The Association between Blood Lead Levels and Osteoporosis Adults—Results from the Third National Health and Nutrition Examination Survey (NHANES III)

James R. Campbell and Peggy Auinger

Published: 1 July 2007 | <https://doi.org/10.1289/ehp.9716> | Cited by: 35

78% of the U.S. population (1970s) had blood lead levels $\geq 10 \mu\text{g}/\text{dL}$. Bone is a repository for 90–95% of the total body burden of lead and harbors it for years after initial exposure. Thus, a high proportion of adult Americans may currently have elevated bone lead levels. With this many who were exposed to lead when younger, and the morbidity associated with osteoporosis, it is important to investigate whether an association exists between lead exposure and osteoporosis in humans. Our objective was to conduct a secondary analysis to explore an association between lead exposure and osteoporosis in U.S. adults.

Pb from water accumulates in teeth and bones. When Pb leaches out of bones, it may contribute to osteoporosis in adult life. Increased amount of Pb in blood may also contribute to dementia, Alzheimer's and neurotoxicity.

www.ncbi.nlm.nih.gov/pmc/articles/PMC3567843/pdf/nihms367232.pdf

Published in final edited form as:
Curr Alzheimer Res. 2012 June ; 9(5): 563–573.

Alzheimer's Disease and Environmental Exposure to Lead: The Epidemiologic Evidence and Potential Role of Epigenetics

Kelly M. Bakulski¹, Laura S. Rozek^{1,2}, Dana C. Dolinoy¹, Henry L. Paulson³, and Howard Hu^{1,4,5,*}

¹University of Michigan, School of Public Health, Department of Environmental Health Sciences

²University of Michigan, Medical School, Department of Otolaryngology

³University of Michigan, Department of Neurology

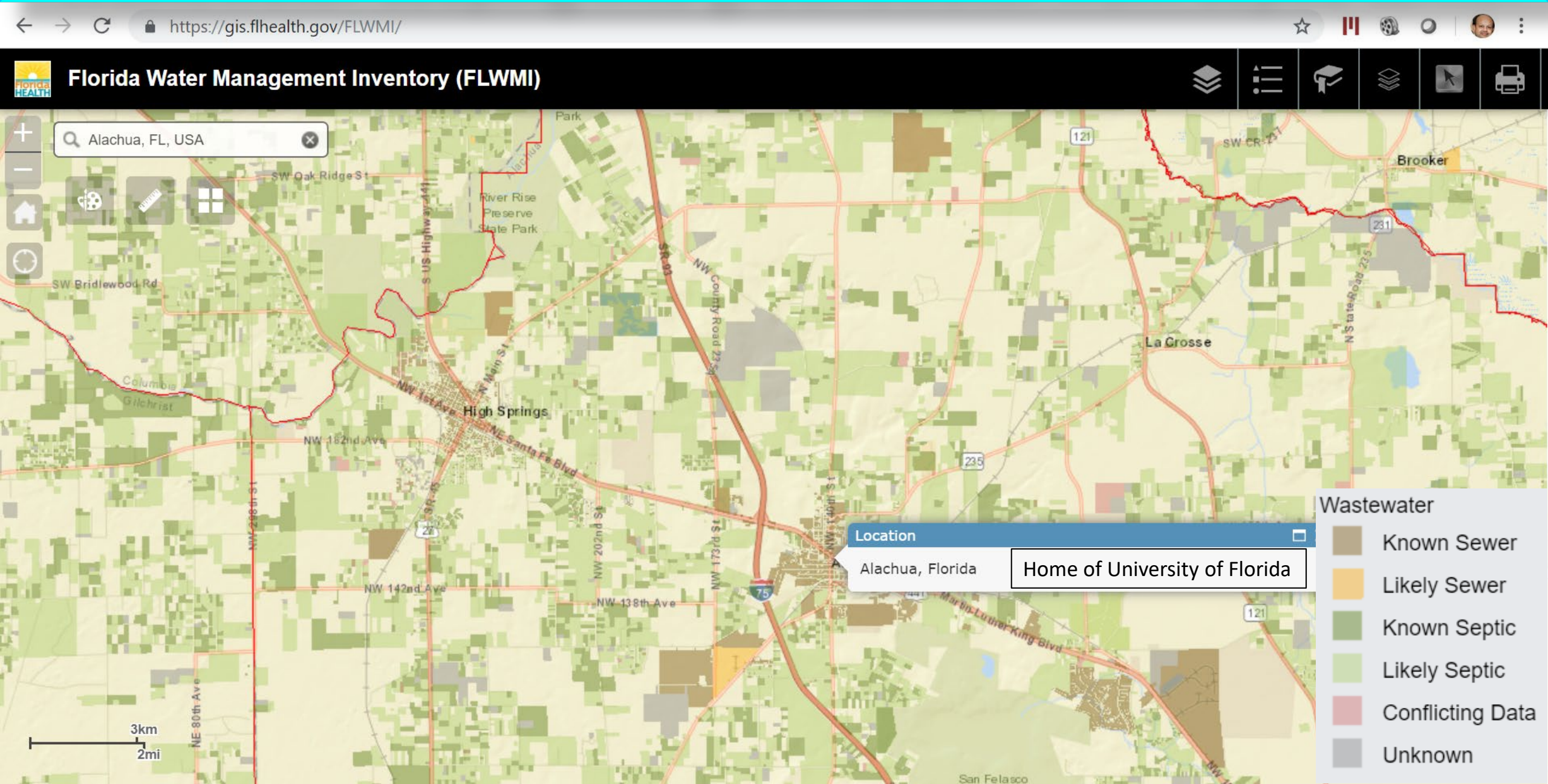
⁴University of Michigan, Department of Epidemiology

⁵University of Michigan, Medical School, Department of Internal Medicine

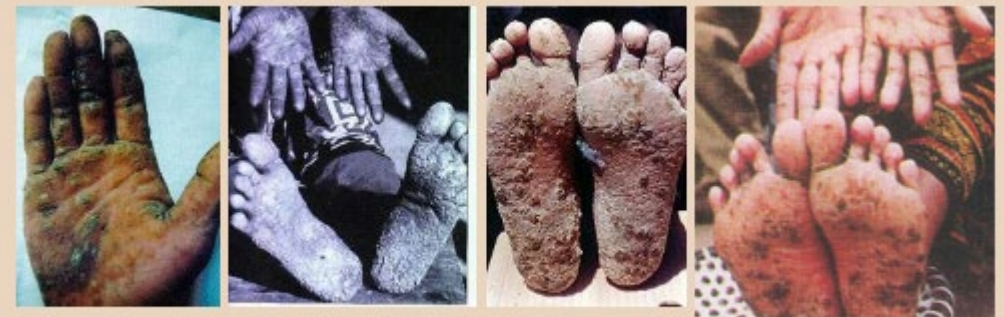
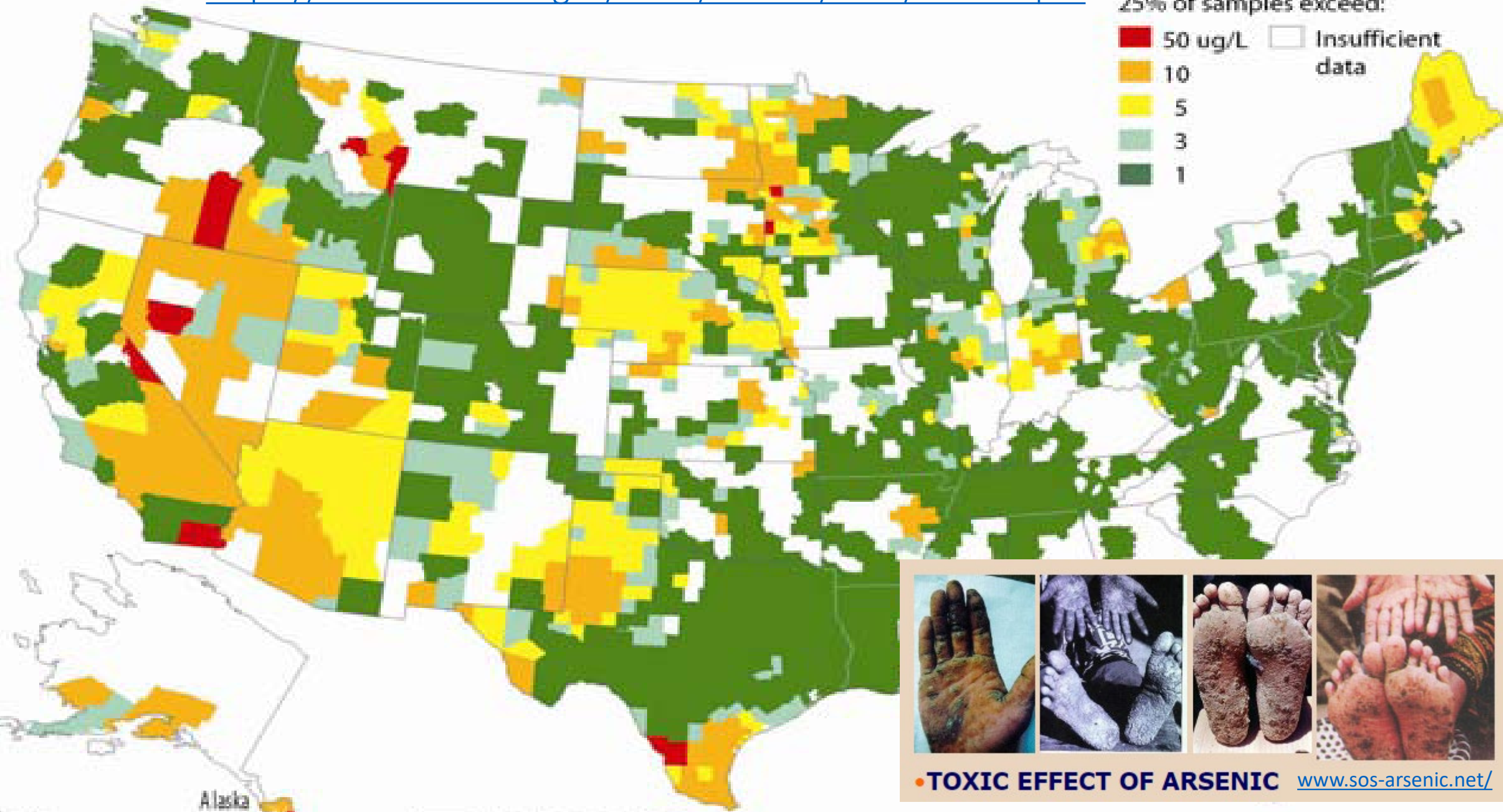
Abstract

Several lines of evidence indicate that the etiology of late-onset Alzheimer's disease (LOAD) is complex, with significant contributions from both genes and environmental factors. Recent research suggests the importance of epigenetic mechanisms in defining the relationship between environmental exposures and LOAD. In epidemiologic studies of adults, cumulative lifetime lead (Pb) exposure has been associated with accelerated declines in cognition. In addition, research in animal models suggests a causal association between Pb exposure during early life, epigenetics, and LOAD. There are multiple challenges to human epidemiologic research evaluating the relationship between epigenetics, LOAD, and Pb exposure. Epidemiologic studies are not well-suited to accommodate the long latency period between exposures during early life and onset of Alzheimer's disease. There is also a lack of validated circulating epigenetics biomarkers and retrospective biomarkers of Pb exposure. Members of our research group have shown bone Pb is an accurate measurement of historical Pb exposure in adults, offering an avenue for future epidemiologic studies. However, this would not address the risk of LOAD attributable to early-life Pb exposures. Future studies that use a cohort design to measure both Pb exposure and validated epigenetic biomarkers of LOAD will be useful to clarify this important relationship.

Wastewater seeping into groundwater from septic tanks?



Arsenic concentrations in at least 25% of samples exceed:



• **TOXIC EFFECT OF ARSENIC** www.sos-arsenic.net/

Alaska

Rebecca Jane Austin Datta, BSc, MS, MPH, MRSC and Doctoral (PhD) student at the Department of Epidemiology, College of Public Health & Health Professions and College of Medicine, University of Florida, Gainesville, FL 32611



WATER

Wastewater assay for Public Health

Enantiomeric Profiling of
Chemical Contrabands

Oleamide	natural product
6β-Hydroxytestosterone	natural product
Tiglic acid	natural product
6-Aminocaproic acid	natural product
(±)-Abscisic acid	natural products
(±)-Abscisic acid	natural products
α-Pinene-2-oxide	natural products
L-Phenylalanine	amino acid
Triphenylphosphine oxide	Industrial
PEG n8	Industrial
PEG n7	Industrial
PEG n5	Industrial
PEG Monolaurate n6	Industrial
Diisooctyl phthalate	Industrial
Diethyl phthalate	Industrial
Dibutyl phthalate	Industrial
PEG n6	Industrial - surfactant
C10_OE4	industrial surfactant
8-Hydroxyquinoline	industrial transformation product
3,5-di-tert-Butyl-4-hydroxybenz	industrial transformation product
N,N'-Dicyclohexylurea	pesticide
Metalaxyl	pesticide
DEET	pesticide
Paracetamol	pharm
Carbamazepine	pharm
Iminostilbene	pharm - metabolite of carbamazepine
Caffeine	pharm
Griseofulvin	pharm - antifungal
1,3-Benzodioxolyl-N-methylbut	Pharm methamphetamine illicit drug
Adenosine	Pharm?
Oxybenzone	consumer product: sunscreen
Galaxolidone	consumer product: synthetic musk

Chemicals Identified

←..... 35 features identified out of total of 3,338 features

Pharmaceuticals

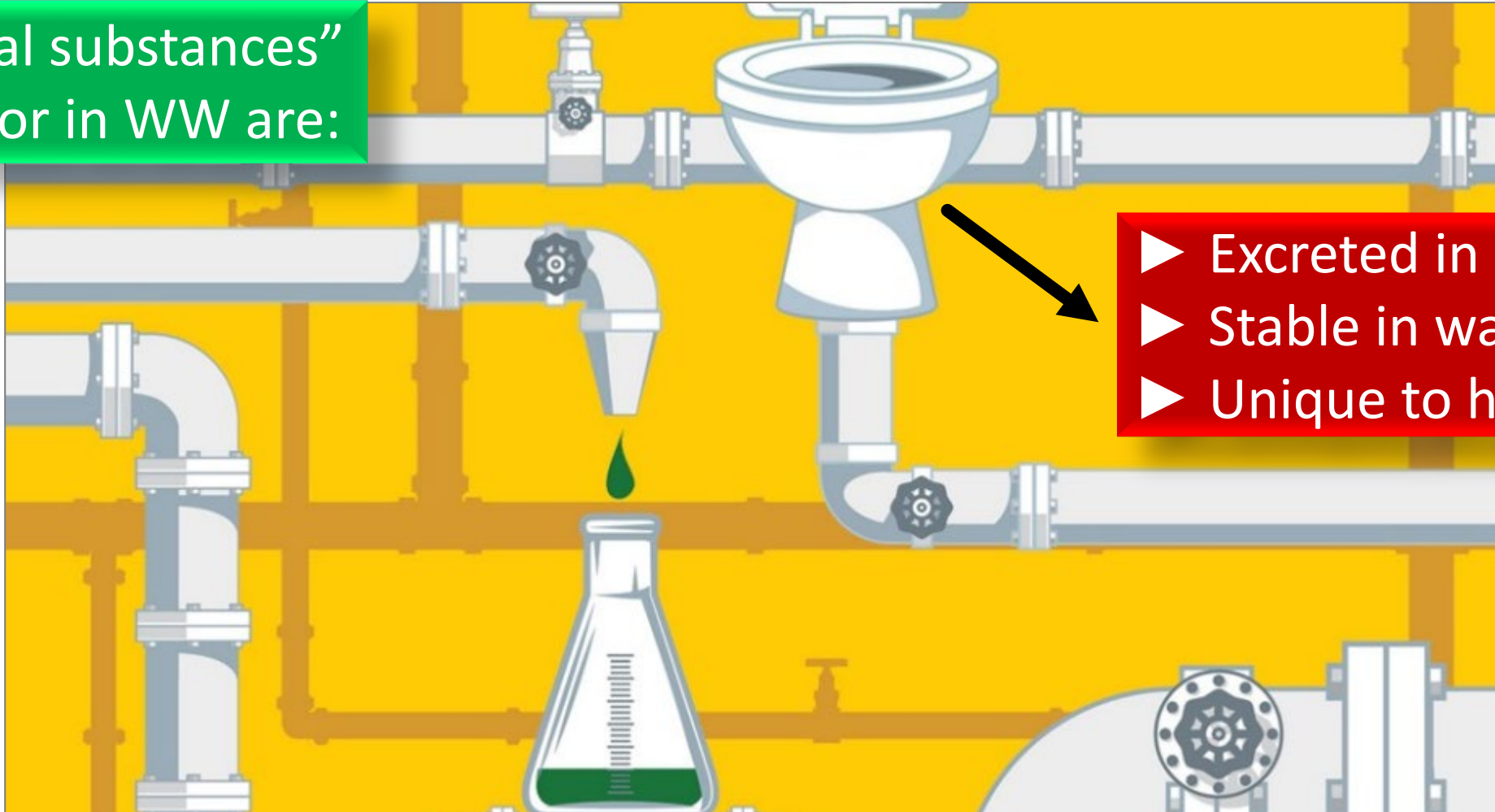


Paracetamol	pharm
Carbamazepine	pharm
Iminostilbene	pharm - metabolite of carbamazepine
Caffeine	pharm
Griseofulvin	pharm - antifungal
1,3-Benzodioxolyl-N-methylbut	Pharm methamphetamine illicit drug
Adenosine	Pharm?



Wastewater based Epidemiology (WWE)

The “ideal substances”
to monitor in WW are:

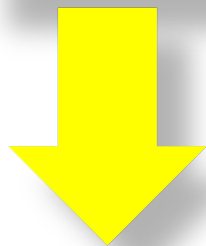


- ▶ Excreted in urine/feces
- ▶ Stable in waste water
- ▶ Unique to human

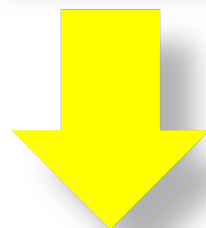
Arnaud, Celia (2018) To monitor the health of cities' residents, look no further than their sewers. *Chemical & Engineering News* **96** (18) 30-38 ▶ URL ◆ <https://cen.acs.org/environment/water/monitor-health-citiesresidents-look-further/96/i18>

Wastewater based Epidemiology (WWE)

Pooled urine and stool samples



Population-level de-identified data



Early warnings of epidemics

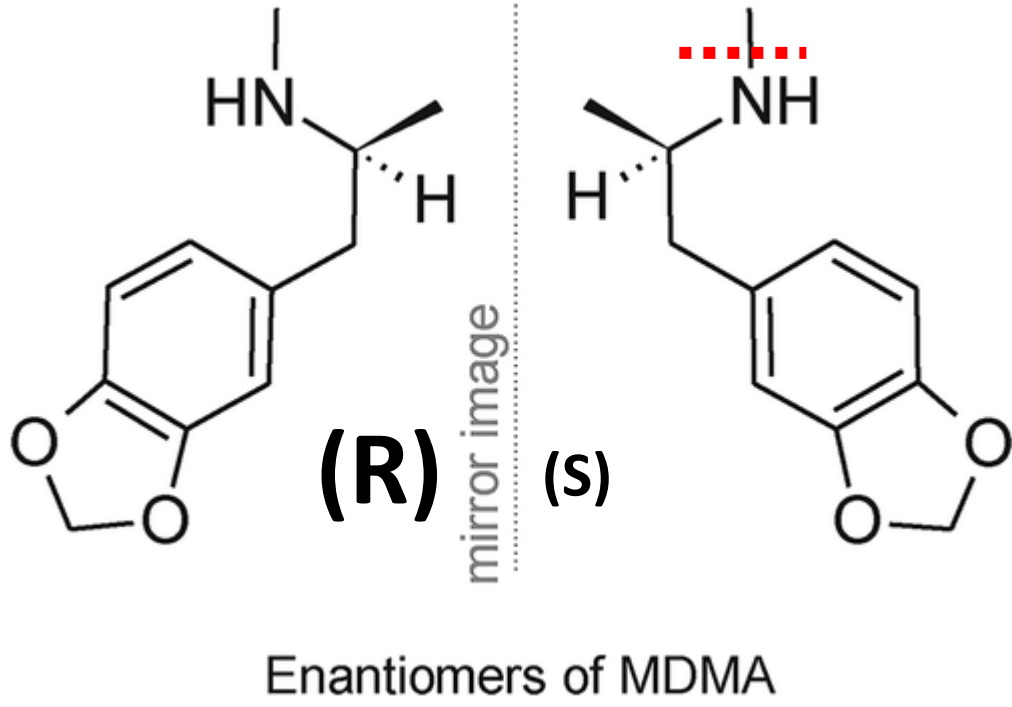
Current Monitoring

- Nicotine, alcohol
- Pharmaceuticals
- Illicit drugs

+ Future Monitoring

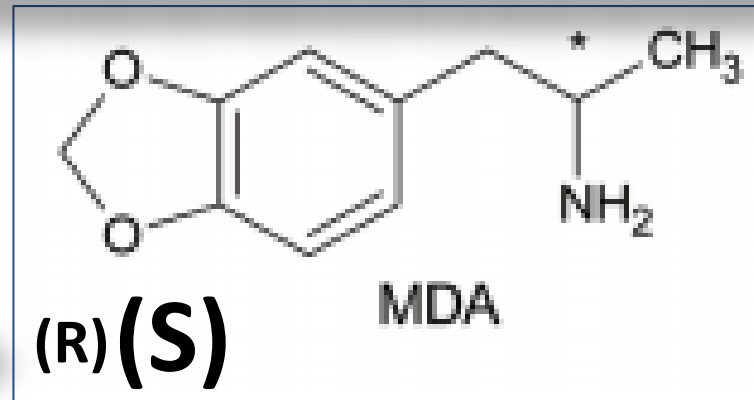
- ▶ Disease Bio-Markers?

Enantiomeric Profiling



Technique to determine if drug or metabolite composition in a sample originated from disposal vs consumption of drug. Chiral molecules (if one chiral center is present) exist as two enantiomers (opposite forms) which are non-superimposable mirror images (LEFT panel). The drugs generally exist as a 1:1 racemic mixture. The enantiomeric ratio changes if the drug is consumed. The post-metabolic enantiomeric signature in the waste water will depend on amounts ingested versus production waste or if the drug was just flushed down the toilet.

CYP3A4



3,4-MethyleneDioxyMethamphetamine (MDMA) aka ecstasy

3,4-methylenedioxy-amphetamine (MDA) metabolite

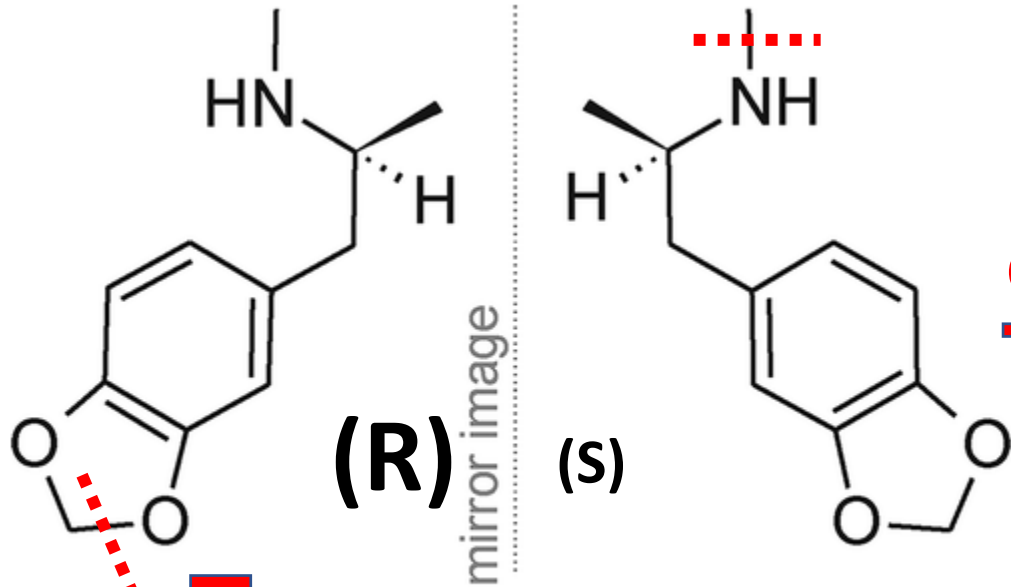
S-MDMA enantiomer preferentially metabolized
→ increases concentration of R-MDMA
R-MDMA Enantiomeric Fraction (EF) = 0.57

S-MDA enantiomer preferentially formed
→ increased concentration of S-MDA (EF = 0.63)
<https://pubs.acs.org/doi/abs/10.1021/es203113y>

Cytochrome P450 3A4 (**CYP3A4**) (EC 1.14.13.97) is an enzyme found in the liver (and intestine). It oxidizes small foreign organic molecules (xenobiotics), such as toxins or drugs, to aid in the excretion (remove from body) of the metabolites via urine / feces.

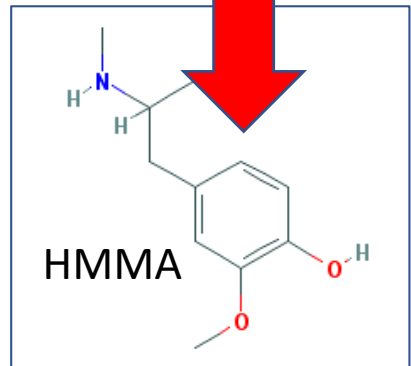
Enantiomeric Profiling

3,4-Methylenedioxyamphetamine



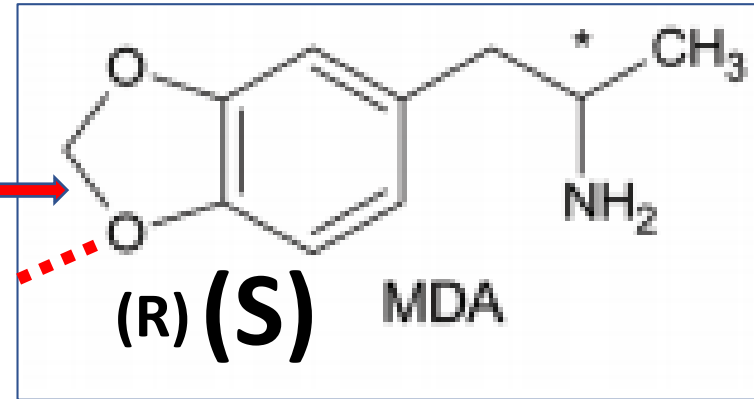
Enantiomers of MDMA

CYP1A2, COMT



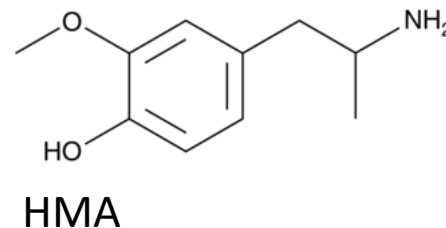
CYP2D6
4-hydroxy-3-methoxymethamphetamine
(HMMA) metabolite

CYP3A4



3,4-methylenedioxyamphetamine
(MDA)
metabolite

**CYP2D6,
COMT**



4-hydroxy-3-methoxyamphetamine
(HMA) metabolite

Metabolism of MDMA, MDA

- Following oral administration, MDMA is absorbed rapidly into the bloodstream. Two metabolic pathways for MDMA in humans have been described. In the major pathway, MDMA is demethylated by CYP2D6 to form 3,4-dihydroxymethamphetamine (HHMA). HHMA, an unstable intermediate, is subsequently converted to 4-hydroxy-3-methoxymethamphetamine (HMMA) by catechol-*O*-methyltransferase (COMT) and further metabolized to 4-hydroxy-3-methoxyamphetamine (HMA) by CYP1A2. In the minor pathway, MDMA is *N*-demethylated by CYP3A4 to 3,4-methylenedioxyamphetamine (MDA) with further demethylation by CYP2D6 to form 3,4-dihydroxyamphetamine (HHA). This compound is *O*-methylated by COMT to form HMA. These four metabolites, particularly HMMA and HMA, are known to be excreted in the urine as conjugated glucuronide and sulfate metabolites. www.ncbi.nlm.nih.gov/pmc/articles/PMC3159864/

Underestimating Cocaine Usage ?

Estimated actual cocaine use >3X per official government statistics

Cocaine in surface waters: a new evidence-based tool to monitor community drug abuse

Ettore Zuccato , Chiara Chiabrando, Sara Castiglioni, Davide Calamari, Renzo Bagnati, Silvia Schiarea and Roberto Fanelli

Environmental Health 2005 4:14

<https://doi.org/10.1186/1476-069X-4-14> | © Zuccato et al; licensee BioMed Central Ltd. 2005

2700 mg of cocaine consumed daily per 1000 adults (15-34 years). If a “dose” is 100 mg, it is 27 doses per 1000 adults, daily. Use of whole population data (all age groups) is an erroneous exposure measurement. Cocaine metabolite levels were similar in raw versus treated sewage water. The latter suggests that water remediation methods failed to remove the cocaine metabolites from waste water. Polluted water was discharged into the river.



<https://ehjournal.biomedcentral.com/articles/10.1186/1476-069X-4-14>

Method for determining “doses/day/1,000 inhabitants”

1. Sample collection
(composite 24-h samples)

2. Sample analysis to obtain the
concentrations of the target residues

Flow rate (m³/day)

3. Amount of target residues entering
the treatment plant (g/day)

Human metabolism
correction factors

4. Amount of a substance consumed by the
population served by the treatment plant

Population estimates

5. Normalisation of the amount of substance
to a defined population (g or mg/day/1 000 inhabitants)

Mean dose

6. Amount of substance as doses/day/1 000 inhabitants

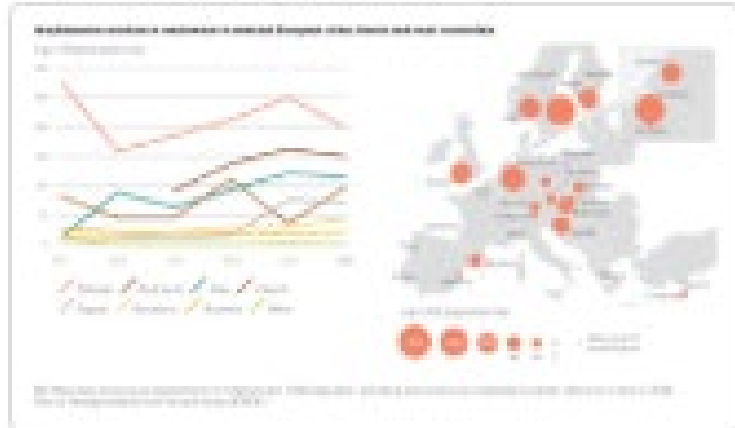
score

Sewage Analysis CORe
group Europe (SCORE)

<http://score-cost.eu/>

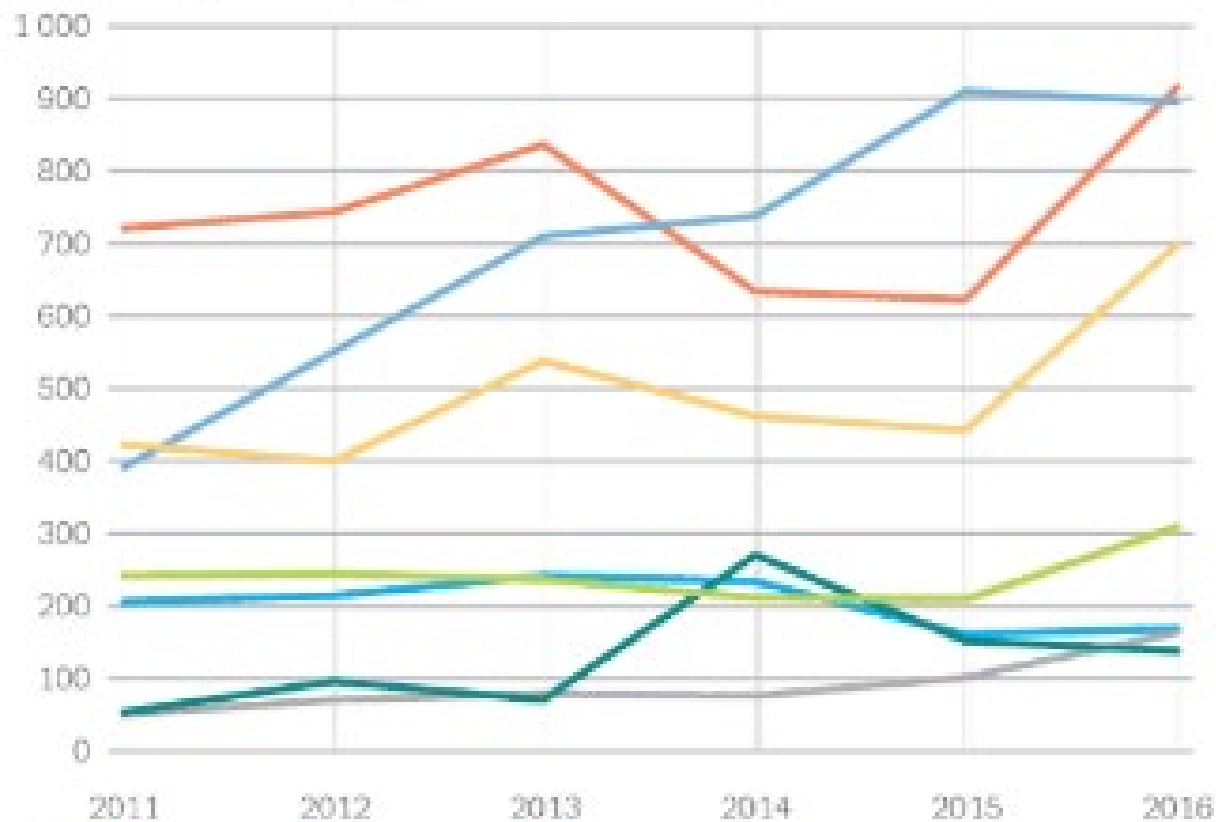


Wastewater testing in European cities

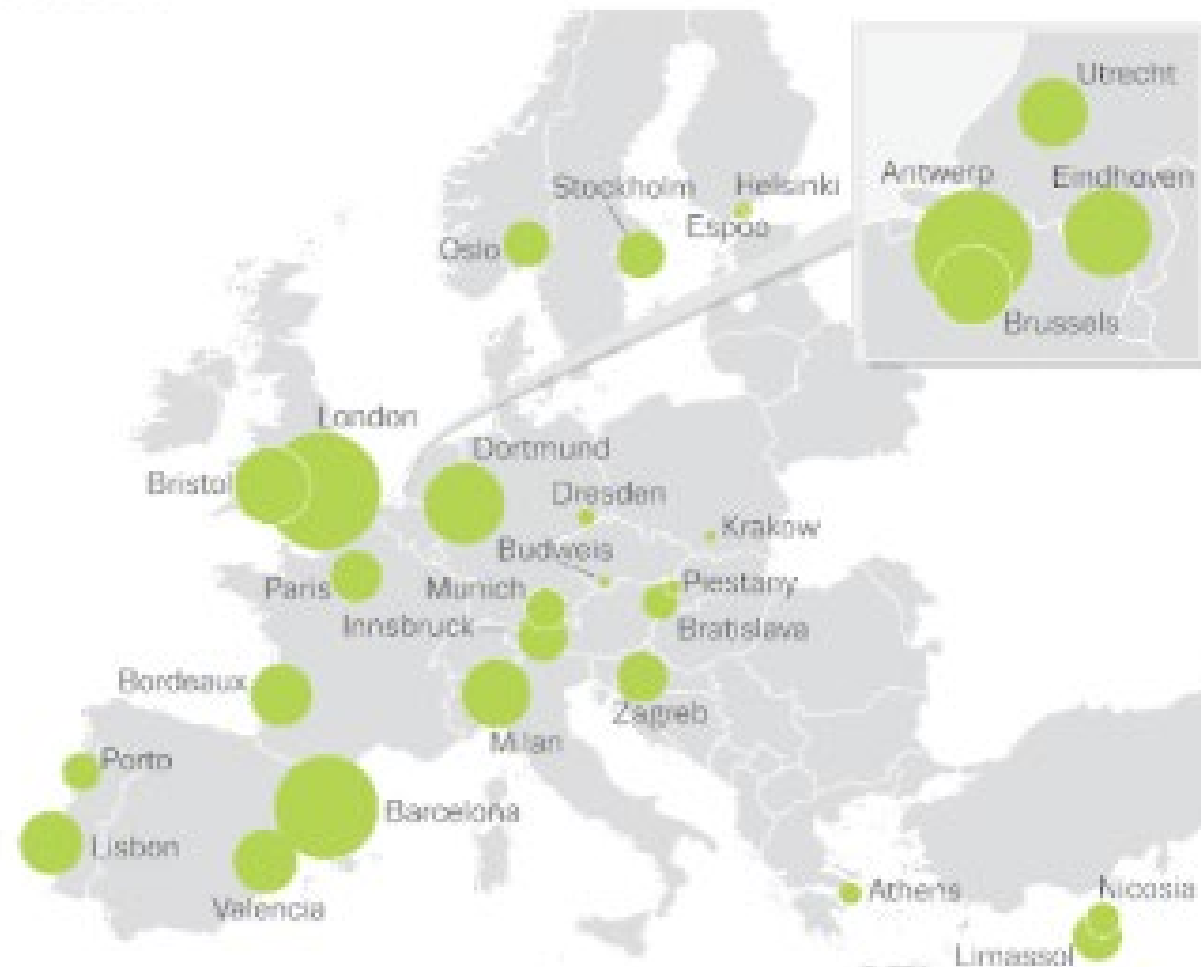


Cocaine residues in wastewater in selected European cities: trends and most recent data

mg/1 000 population/day



Antwerp London Barcelona Milan
Paris Zagreb Oslo



mg/1 000 population/day



NB: Mean daily amounts of benzoylcegonine in milligrams per 1 000 population. Sampling was carried out in selected European cities over a week in 2016.

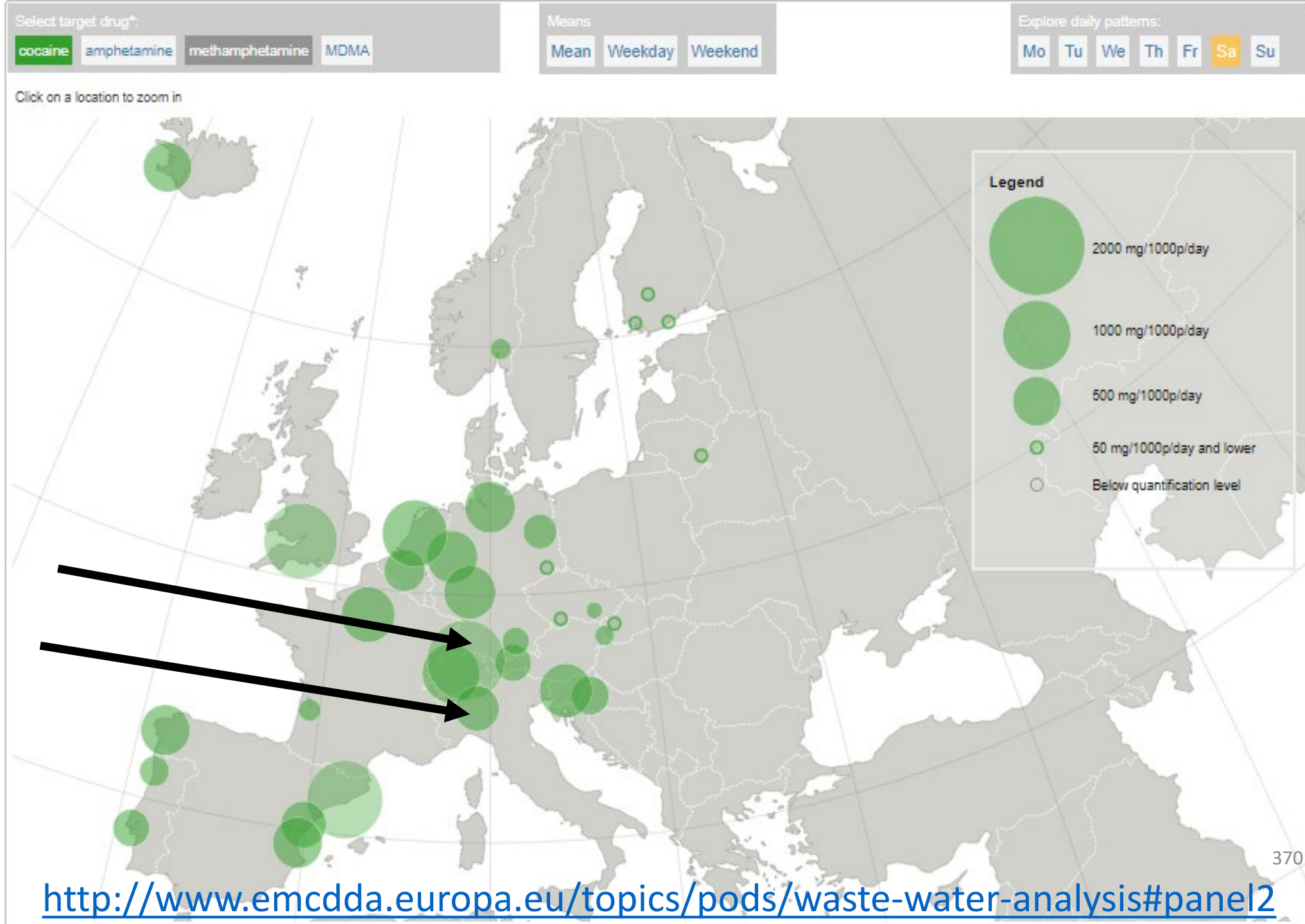
Source: Sewage Analysis Core Group Europe (SCORE). www.emcdda.europa.eu/system/files/publications/2757/POD_Wastewater%20analysis.pdf 369

Wastewater analysis & drugs (multi-city study)

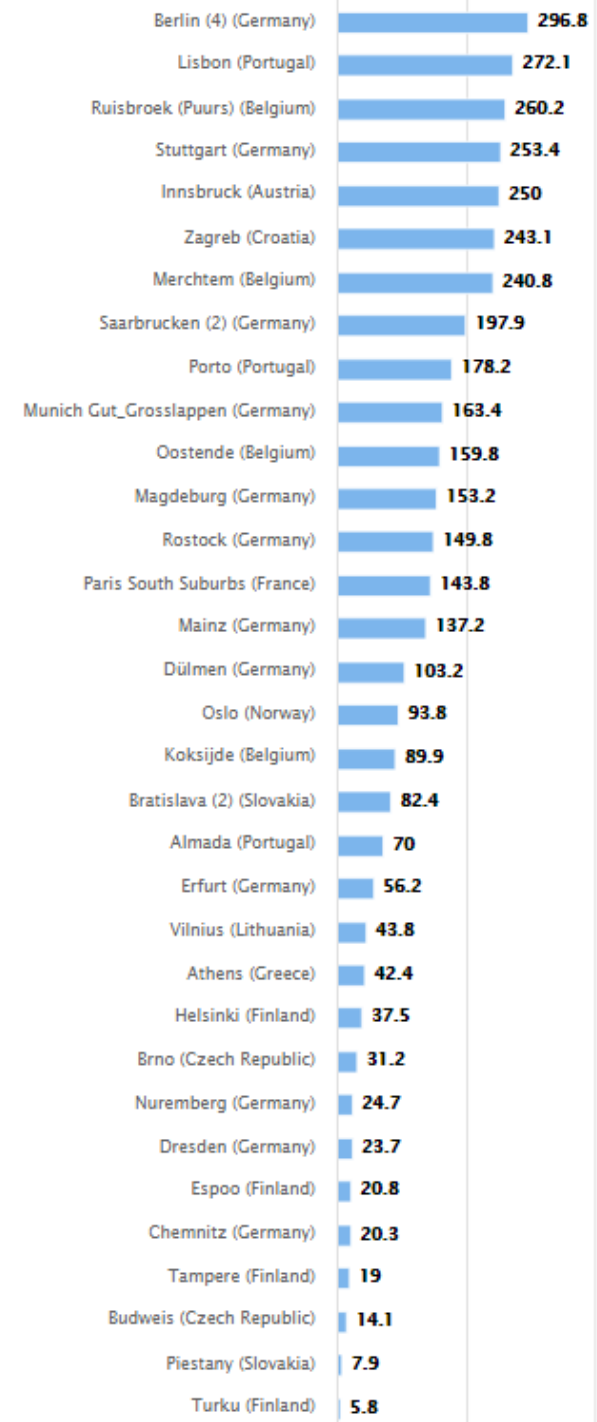
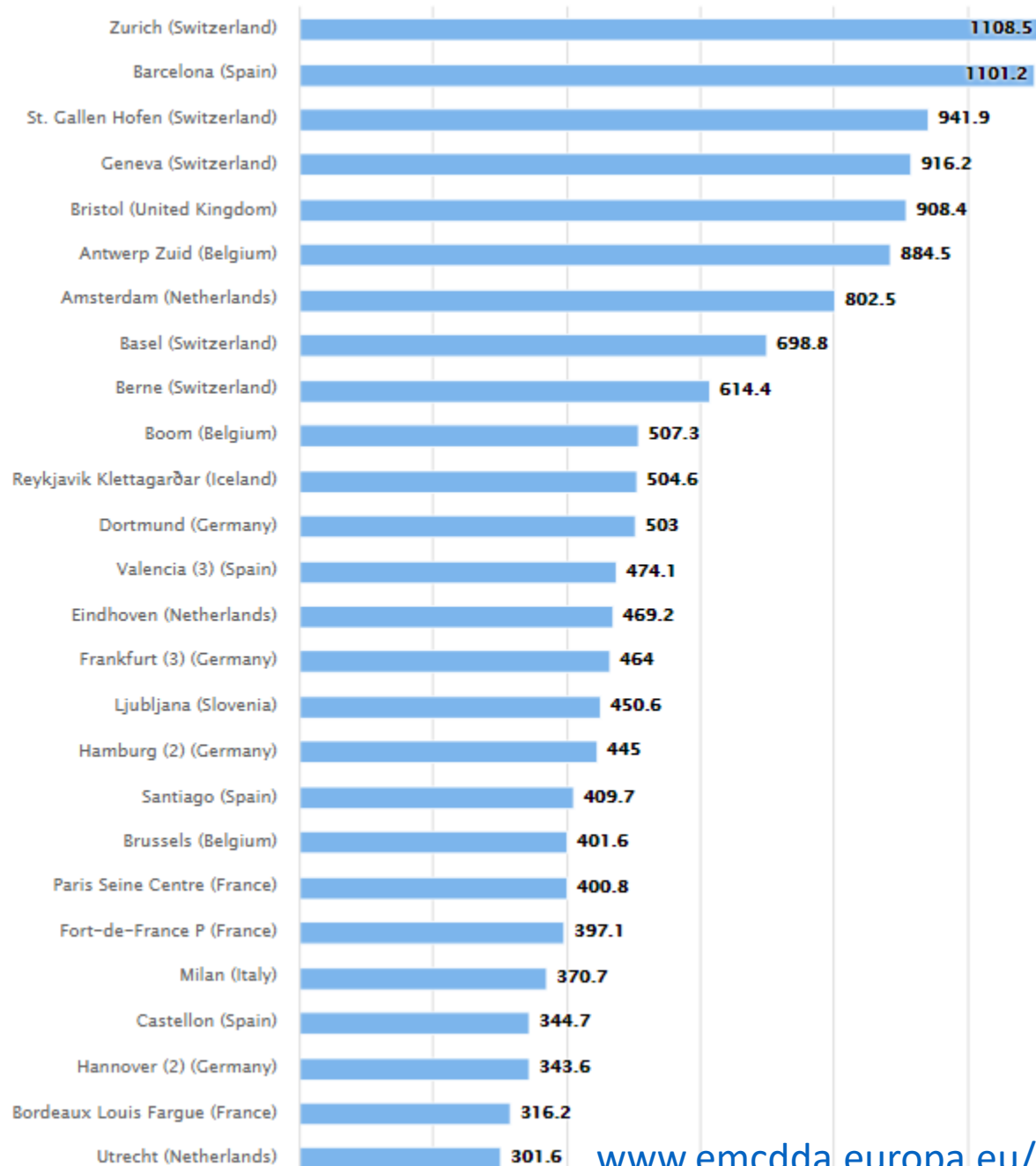
Cocaine (2017) "Saturday"

Zurich = 1320 mg per
1,000 persons

Milan = 420 mg per
1,000 persons



COCAINE WEEKEND MEAN 2017 (mg/1000 people/day)

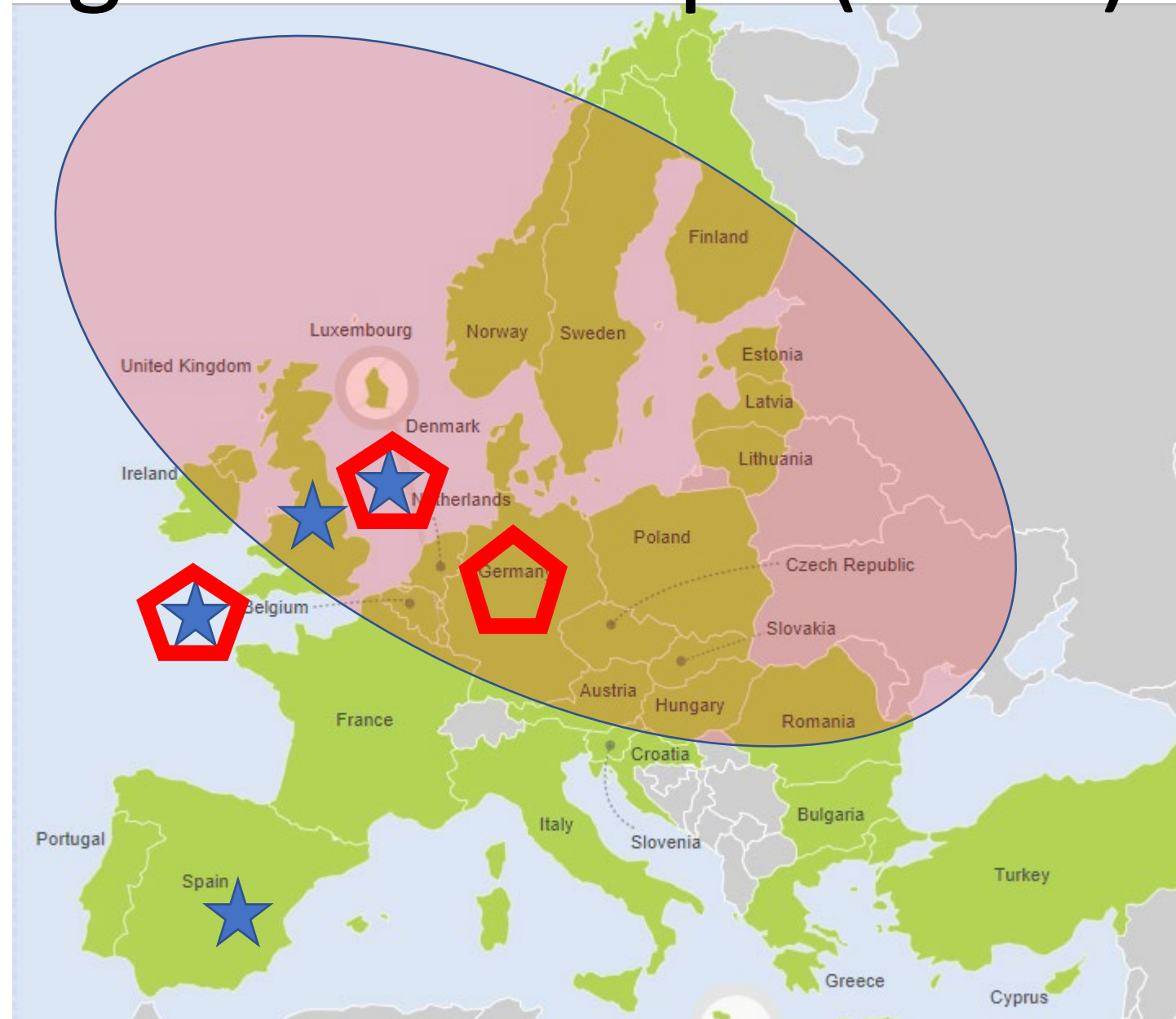


Patterns of illicit drug use in Europe (2017)

★ Cocaine

Amphetamine,
Methamphetamine

MDMA (ecstasy)



Wastewater-based Molecular Epidemiology

Sensors differentiate between Enantiomers



AUSTRALIAN
**CRIMINAL
INTELLIGENCE
COMMISSION**



THE UNIVERSITY
OF QUEENSLAND
AUSTRALIA



University of
South Australia

NATIONAL WASTEWATER DRUG MONITORING PROGRAM

<https://acic.govcms.gov.au/sites/g/files/net3726/f/nwdmp4.pdf?v=1522809564>



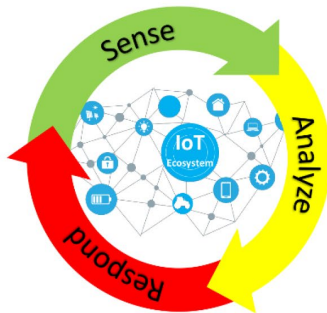
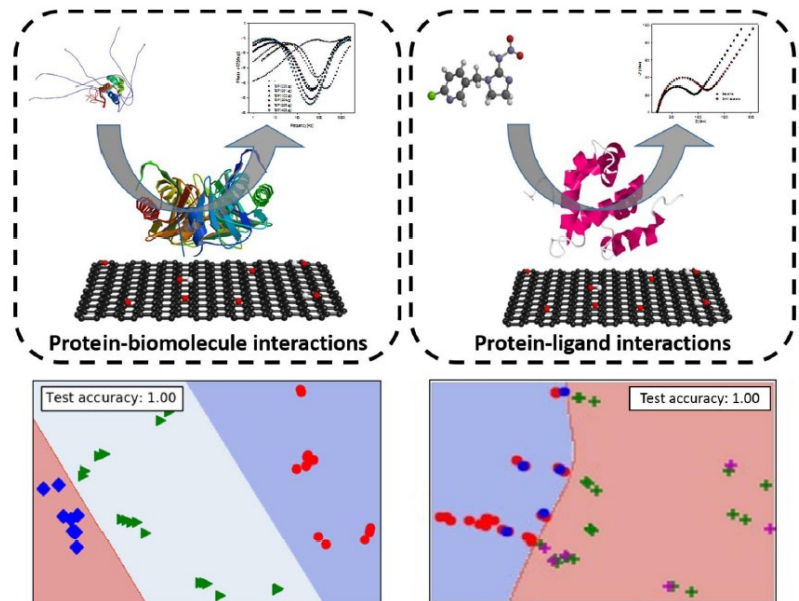
Capital city **cocaine**
and **heroin** average
consumption
exceeded regional
consumption.



Regional **nicotine, methylamphetamine, MDA,**
oxycodone and **fentanyl** average consumption
exceeded capital city consumption.

Rebecca Jane Austin Datta, BSc, MS, MPH, MRSC and Doctoral (PhD) student at the Department of Epidemiology, College of Public Health & Health Professions and College of Medicine, University of Florida, Gainesville, FL 32611

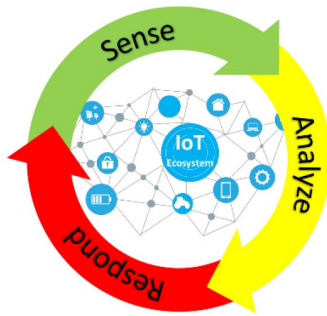
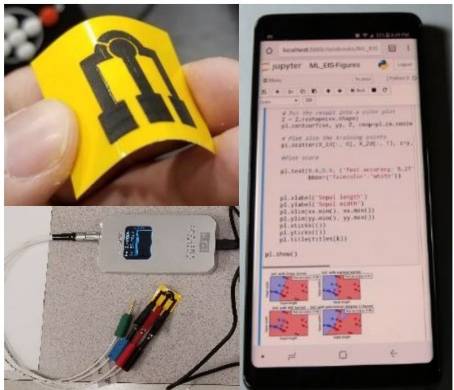
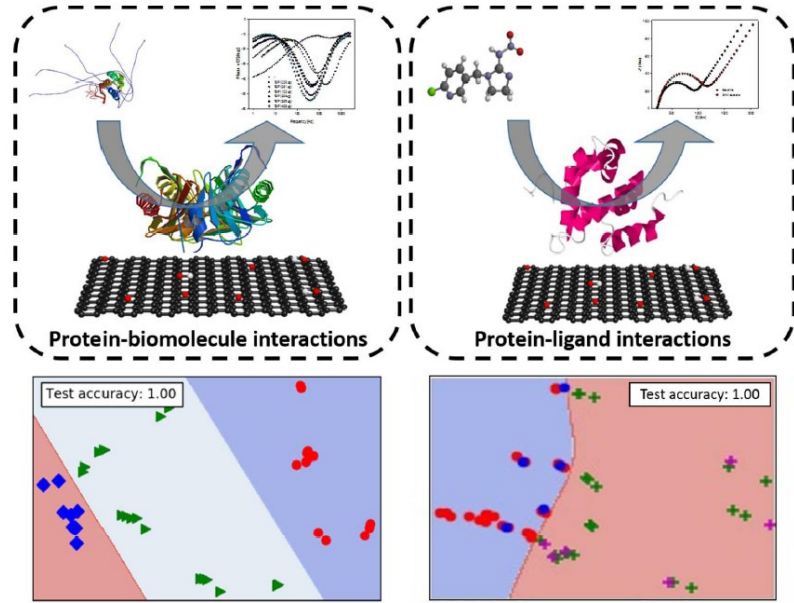
Water ART – IoT Data Analytics of Value to End-User



VALUE



Water ART – A Global Need for this Social Business ?



Flint, Michigan

Fes, Morocco

What can the user do with this data ??

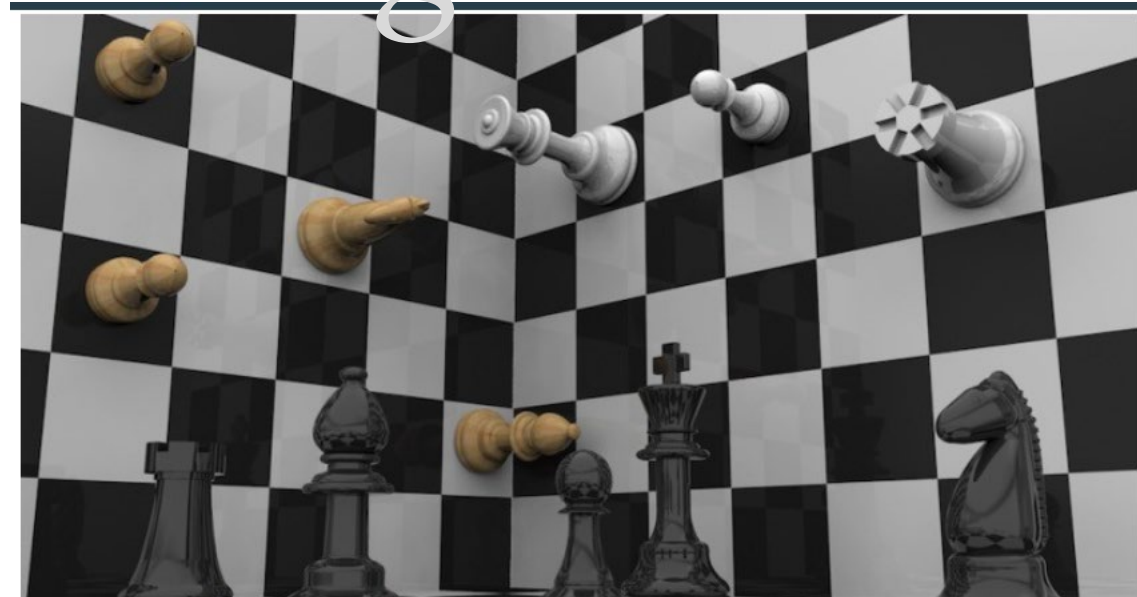
Fatehpur, India

Fuzhou, China

Intelligent Information Arbitrage

WATER: Social Businesses need PAPPU

Change the rules



SENSEE is not enough

SENSEM
SENSYN
SENSICS



Intelligent Information Arbitrage isn't enough

FOOD – Social Businesses need PAPPU

FOOD v PEOPLE

Prevent food wastage by detecting food health

Estimated 11 billion people to feed at the dawn of the 22nd Century

Pounds of dry feed needed to grow a body mass

Salmon



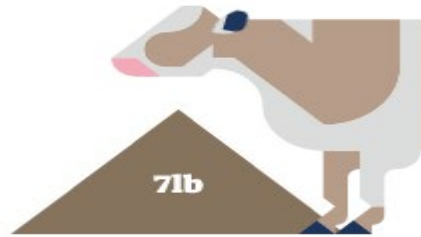
Chicken



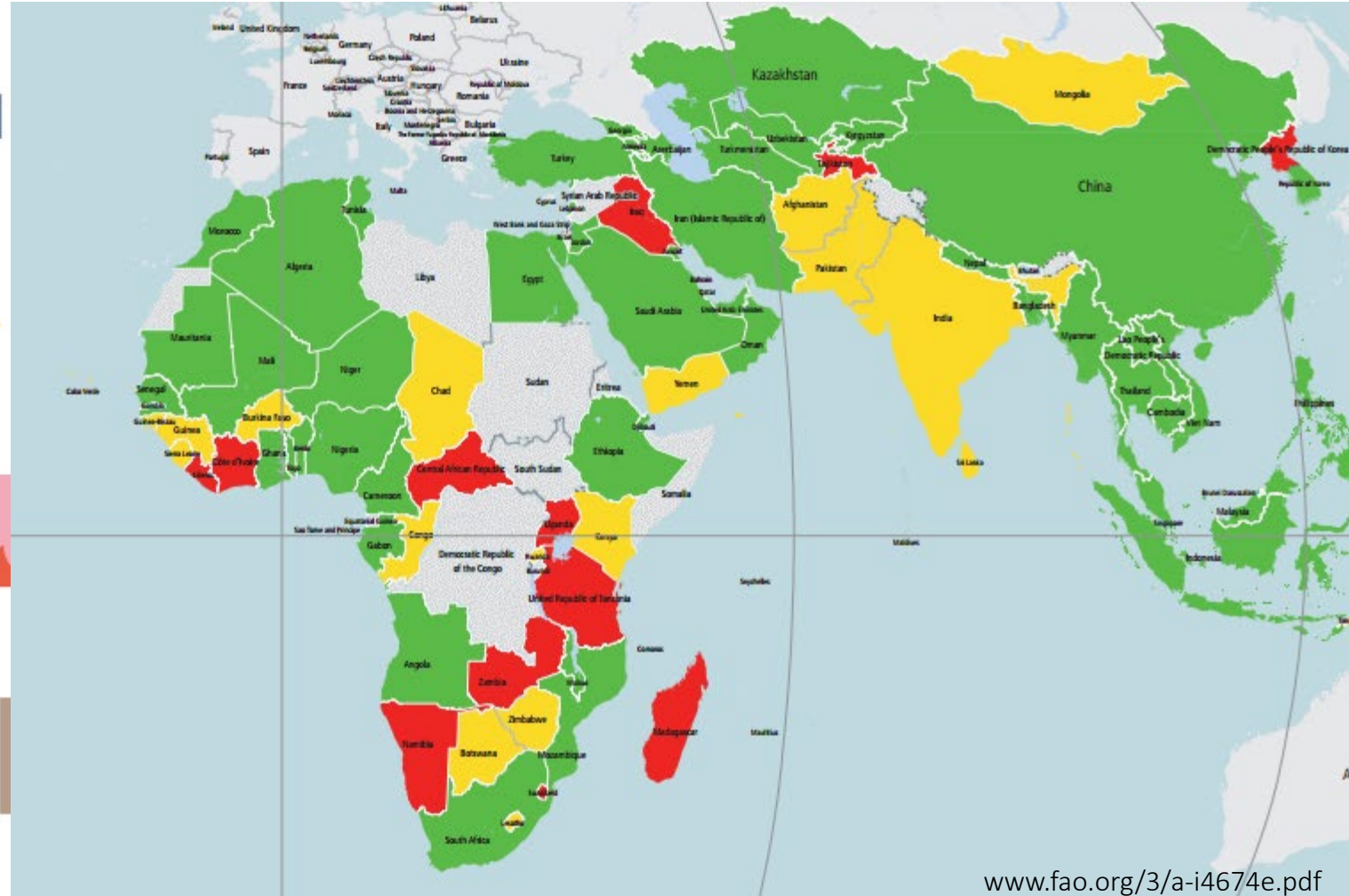
Pork



Beef



The End of Plenty
by Joel K Bourne



www.fao.org/3/a-i4674e.pdf

www.un.org/sustainabledevelopment/blog/2015/07/what-progress-has-been-made-in-ending-global-poverty/
[http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How to Feed the World in 2050.pdf](http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf)

Do we really waste about 68% of the food in the US ?

More than two-thirds of total food
wasted – which is ~ 63 million tons

Value wasted ~ \$150 Billion (total
food wasted value US\$218 Billion)

43

million tons

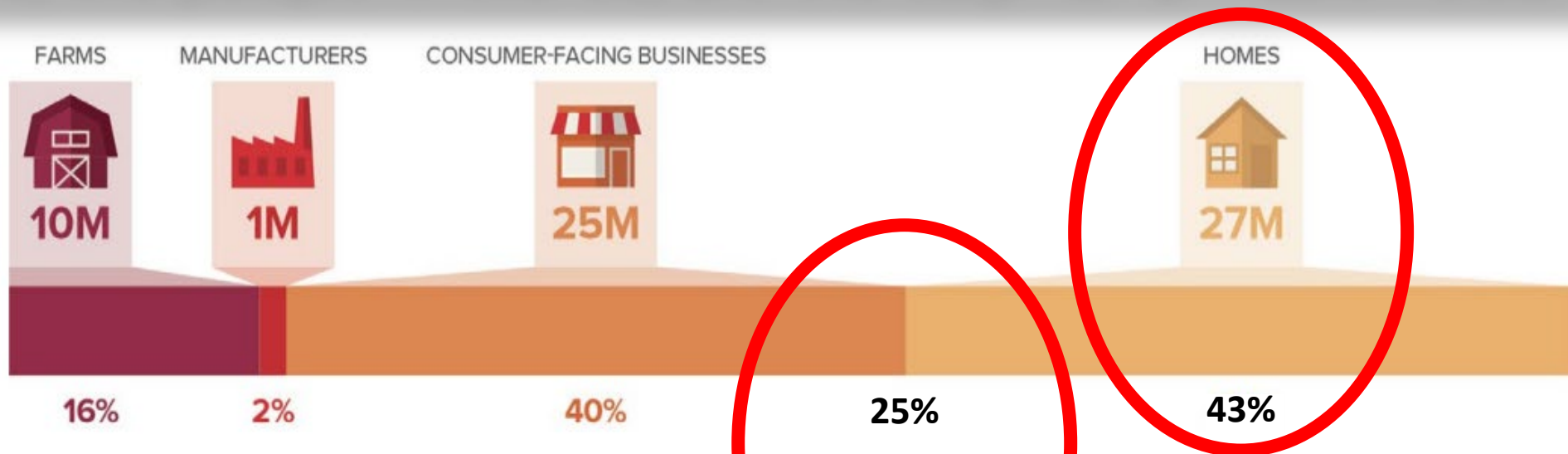
\$150

Billion

US Report • http://www.refed.com/downloads/ReFED_Report_2016.pdf

EU Report • <http://data.consilium.europa.eu/doc/document/ST-10730-2016-INIT/en/pdf> from www.eu-fusions.org/

Yes. We, the people in the US, are the culprits → ~68% FOOD WASTED

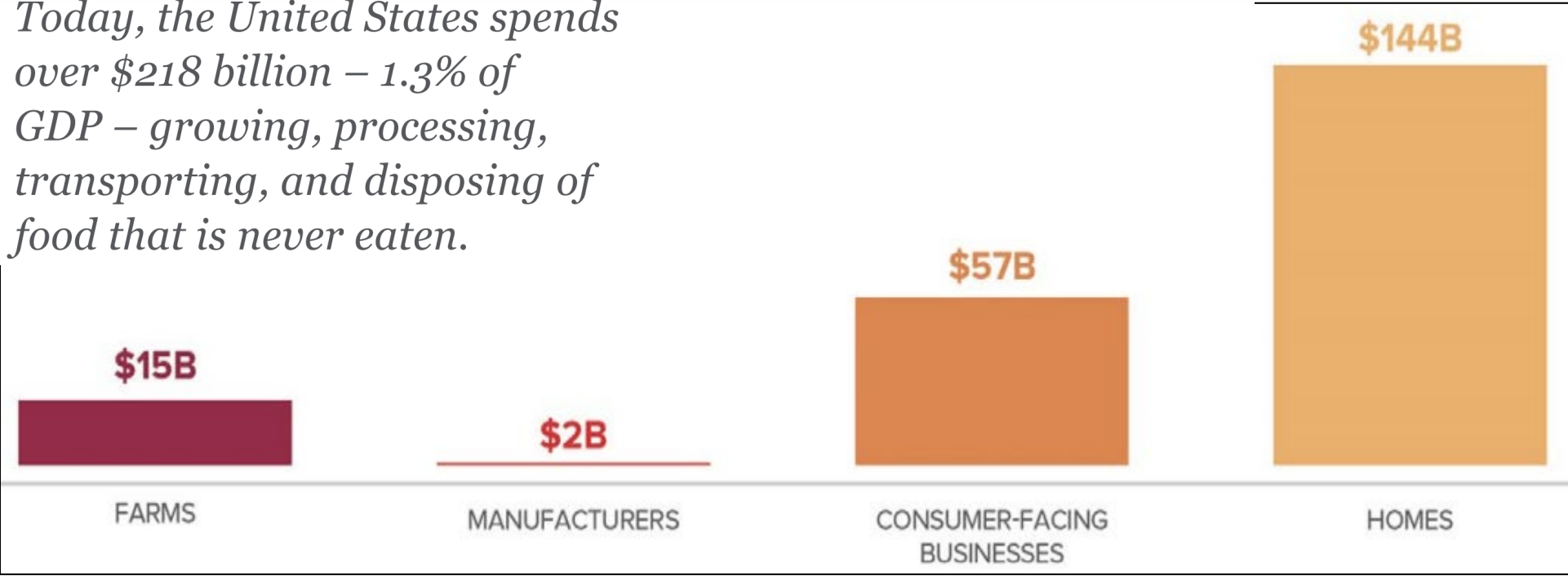


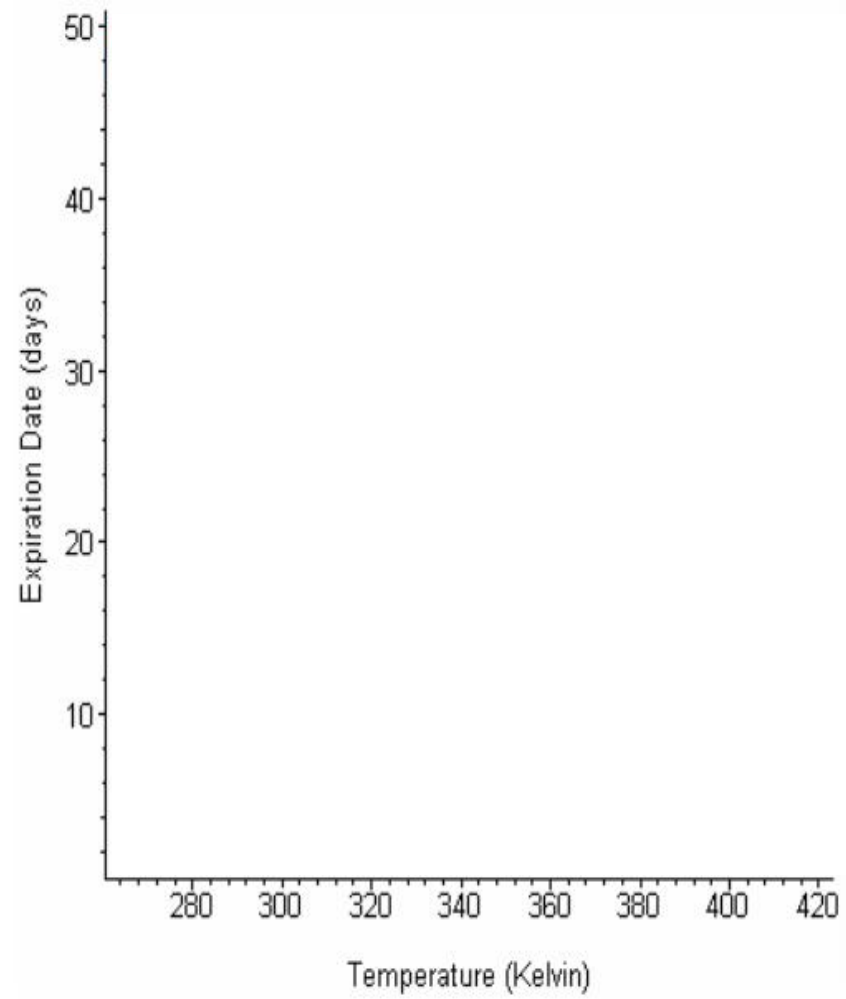
CONSUMER-FACING BUSINESSES INCLUDE



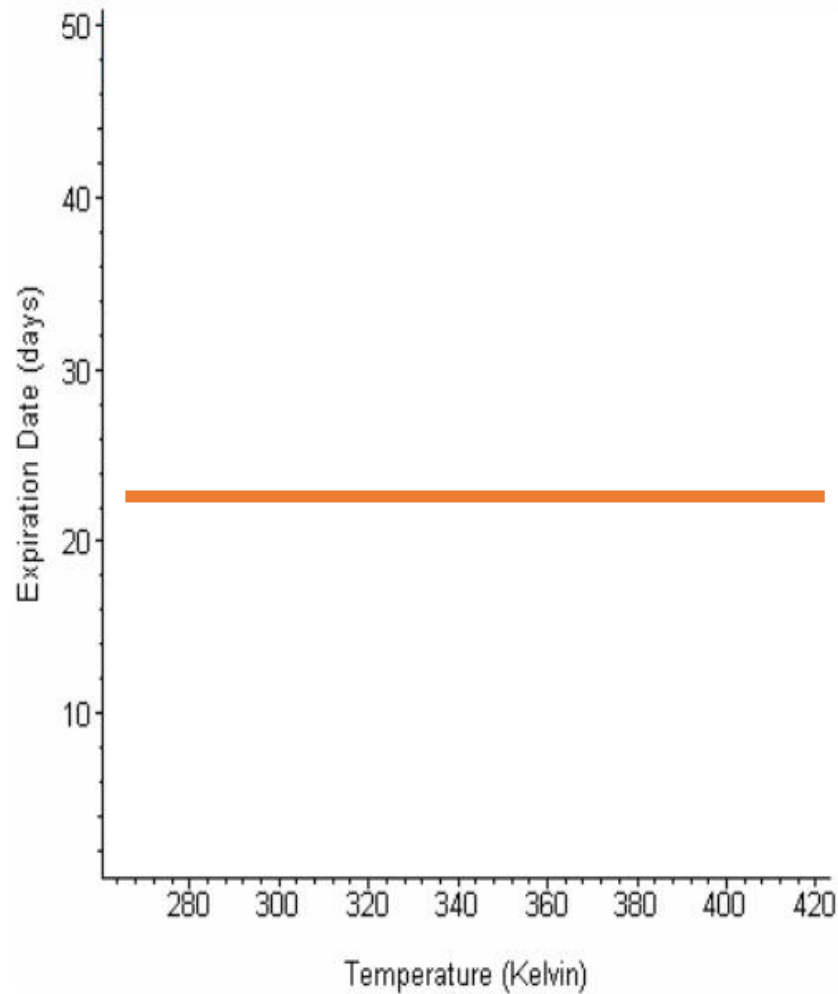
FOOD WASTE in the US: approx. 63 million tons, \$218 billion, 1.3% GDP

Today, the United States spends over \$218 billion – 1.3% of GDP – growing, processing, transporting, and disposing of food that is never eaten.





Storage

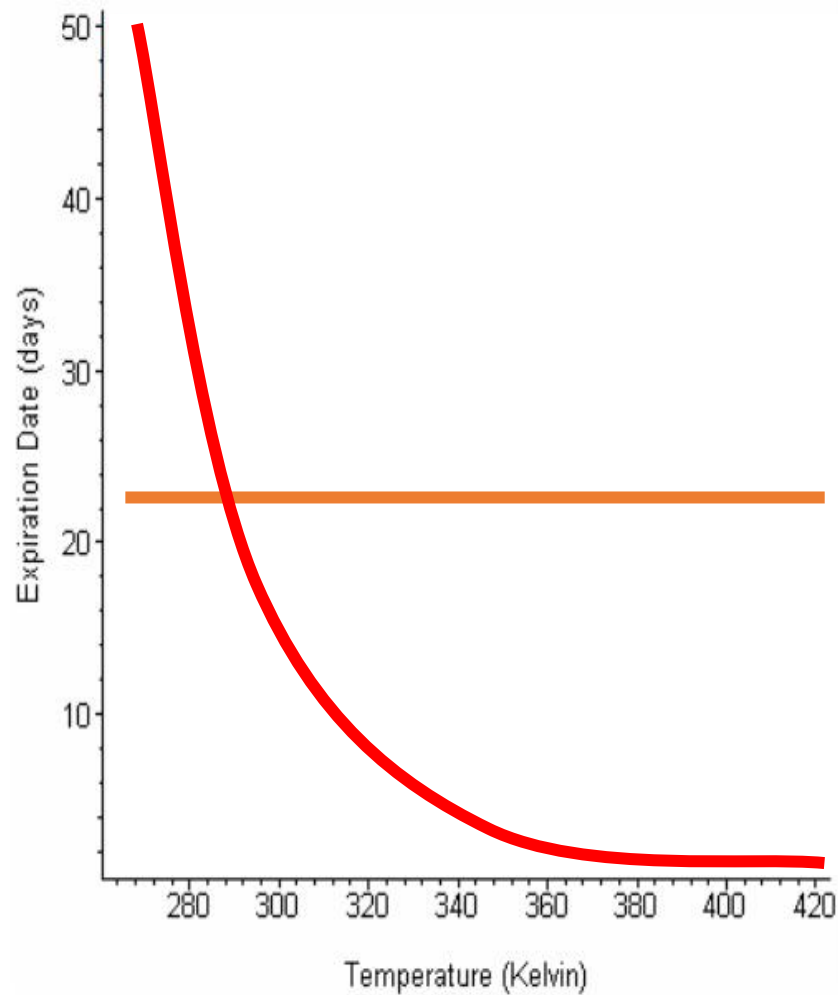


$$\frac{\partial Q}{\partial t} = -k_1 e^{\left[-\frac{E_a}{R_g T(t)} \right]} Q^n$$

Variables

- E_a Activation energy
- k_1 Arrhenius constant
- n Order of the reaction
- T Temperature
- Q Quality
- t Time

Storage


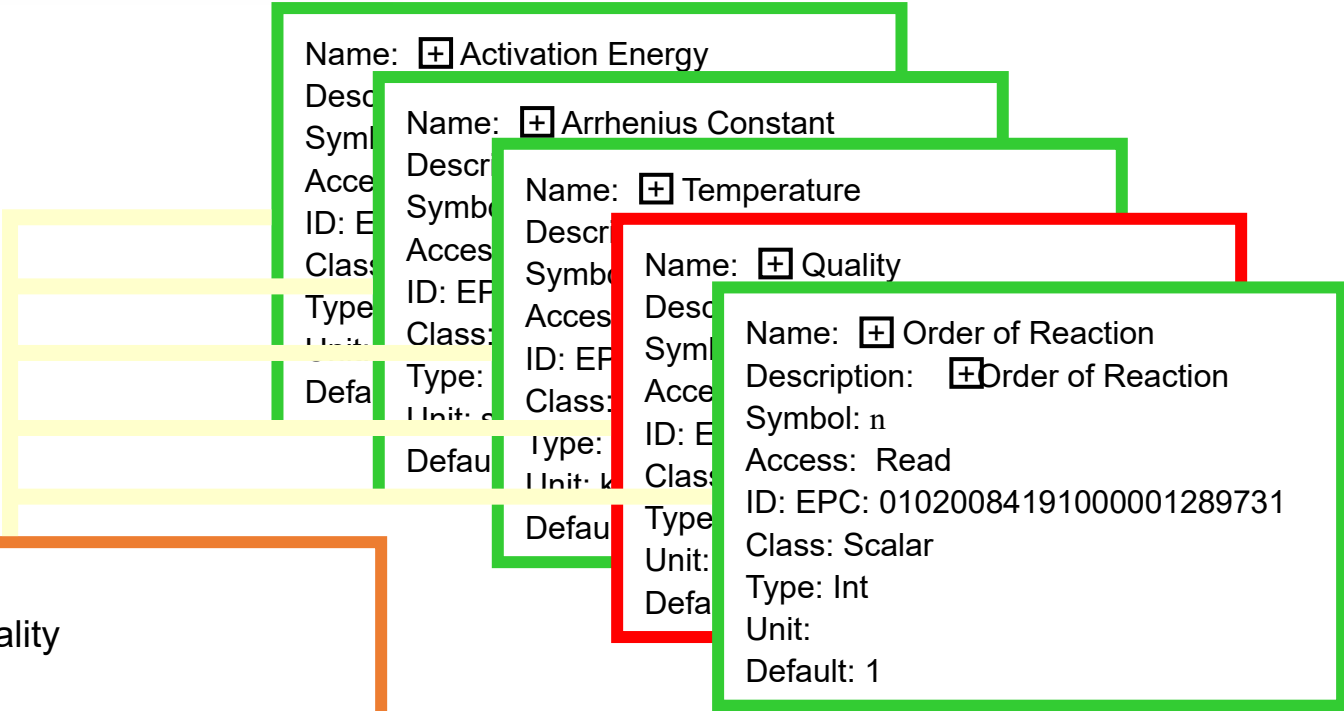


$$\frac{\partial Q}{\partial t} = -k_1 e^{\left[-\frac{E_a}{R_g T(t)} \right]} Q^n$$

Variables

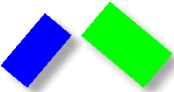
- E_a Activation energy
- k_1 Arrhenius constant
- n Order of the reaction
- T Temperature
- Q Quality
- t Time

Shelf Life

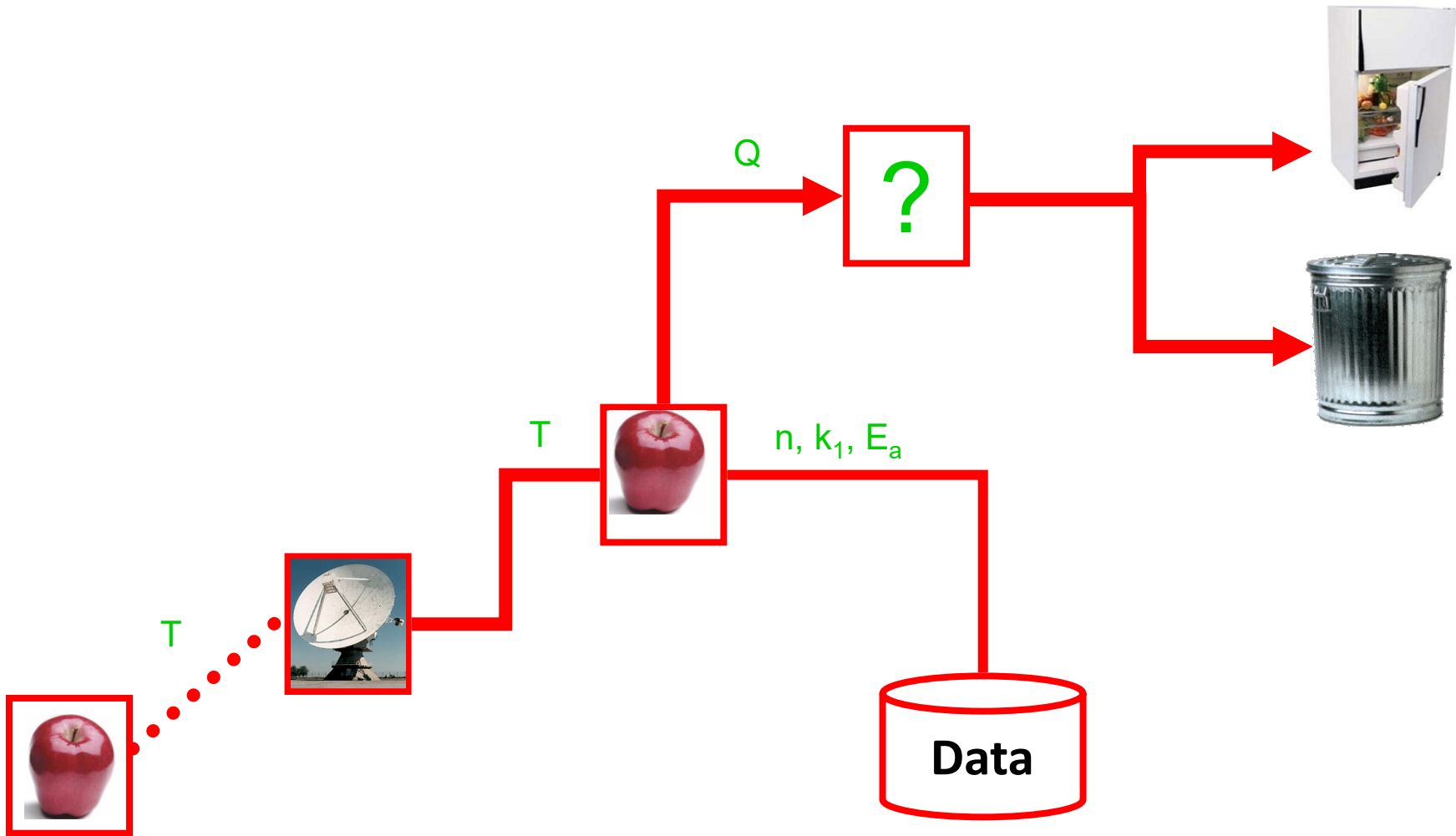


Food Quality

Name: Food Quality
Description: Food Quality based Arrhenius
Developer: Natick Army Laboratories
ID: EPC: 010300908808BF60000000AA
Comp: \$0.25 per month
Type: Analytic
Rate: 1 to 10,000 sec
Algorithm:

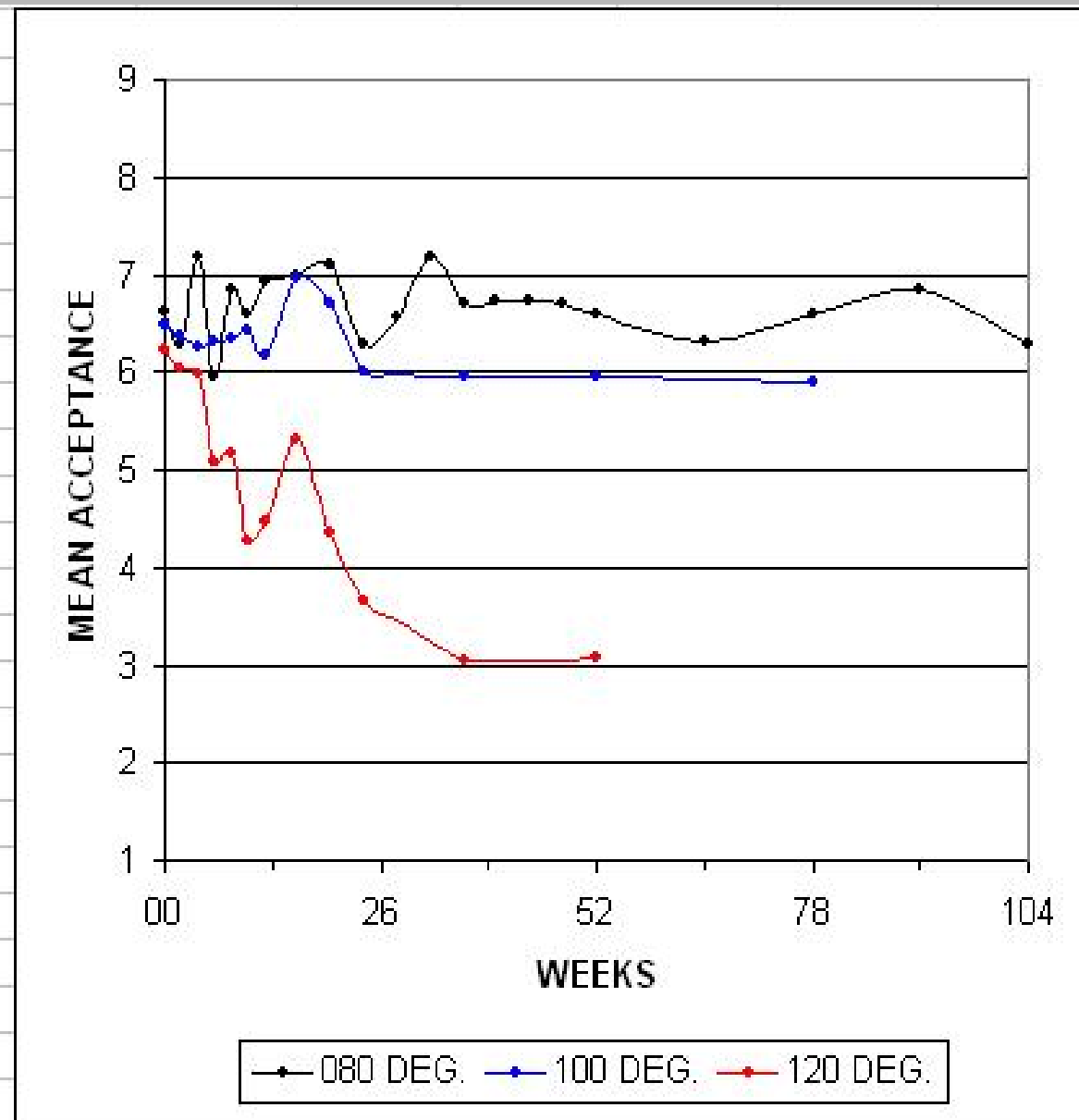


Shelf Life \rightleftharpoons Answers (not numbers)



Monitoring Perishables (MRE Simulation)

WKS	080 DEG.	100 DEG.	120 DEG.
00	6.622	6.486	6.243
02	6.282	6.359	6.026
04	7.194	6.250	5.972
06	5.949	6.308	5.077
08	6.850	6.350	5.175
10	6.600	6.429	4.286
12	6.944	6.167	4.472
16	7.000	6.947	5.316
20	7.111	6.694	4.361
24	6.300	6.000	3.667
28	6.579		
32	7.189		
36	6.694	5.944	3.028
40	6.730		
44	6.730		
48	6.703		
52	6.583	5.944	3.056
65	6.316		
78	6.583	5.889	
91	6.842		
104	6.300		
130			
156			



Please Select an MRE:

01.0000489.00016F.000169DC1

Start Temperature Sensor

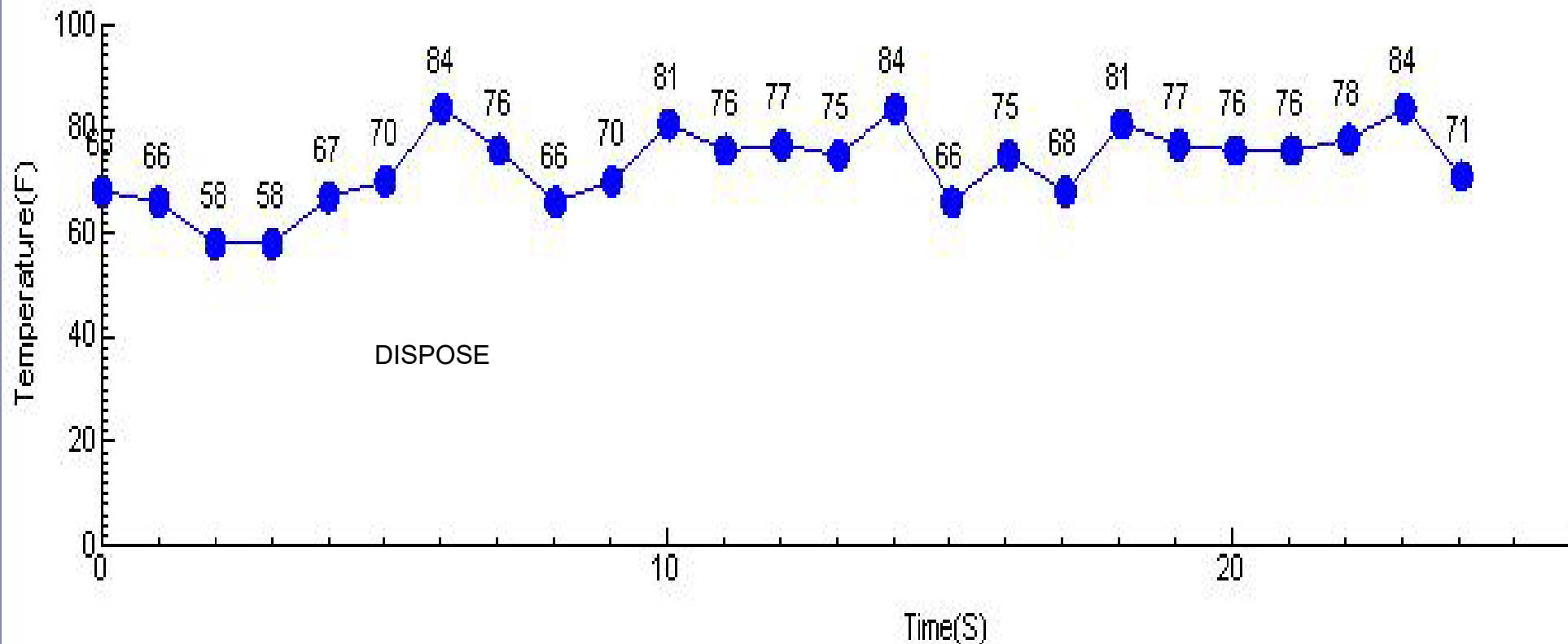
Stop Temperature Sensor

Day: Friday, May 23, 2003

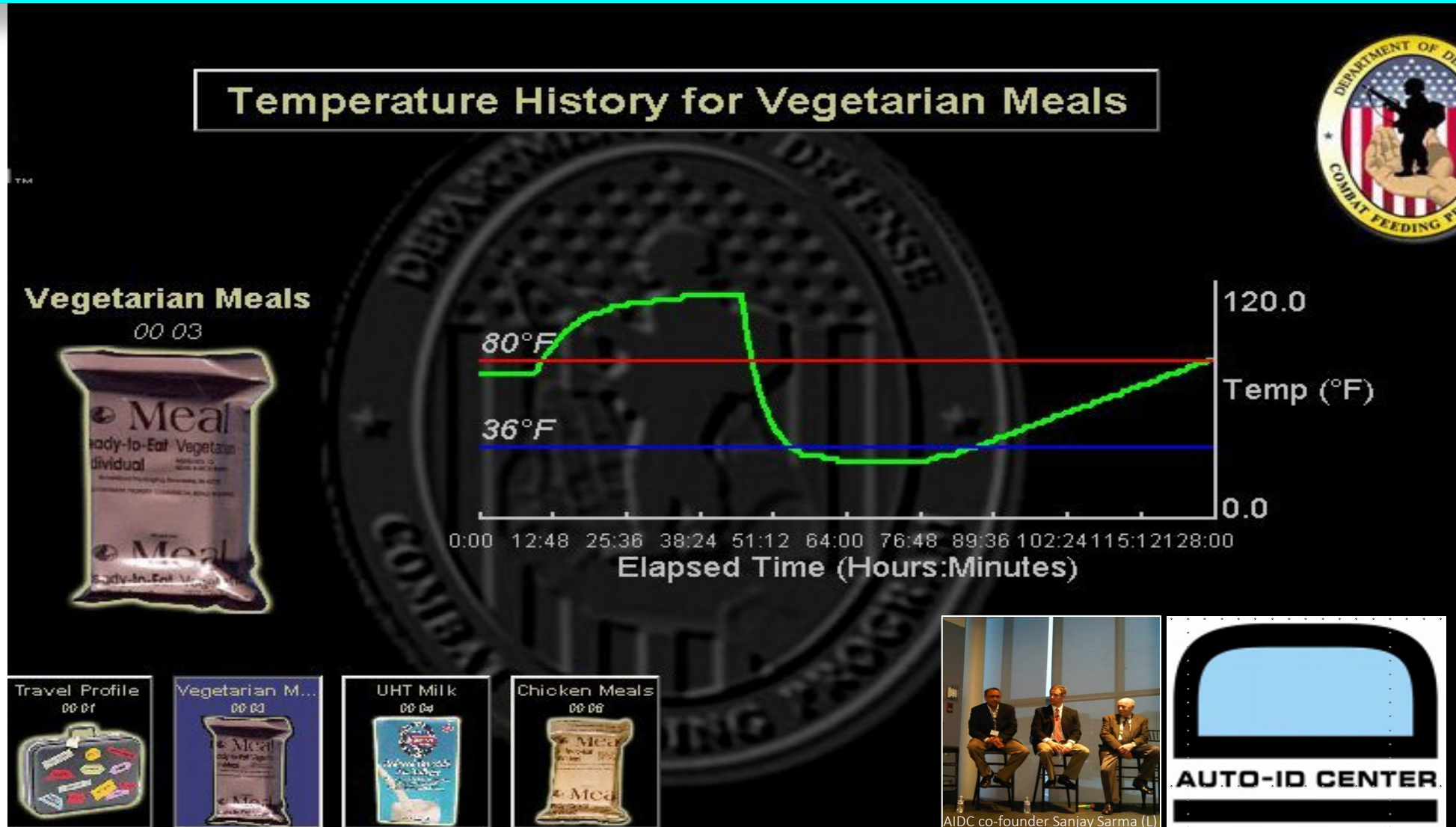
Time: 11:23:07 AM

Temperature: 71

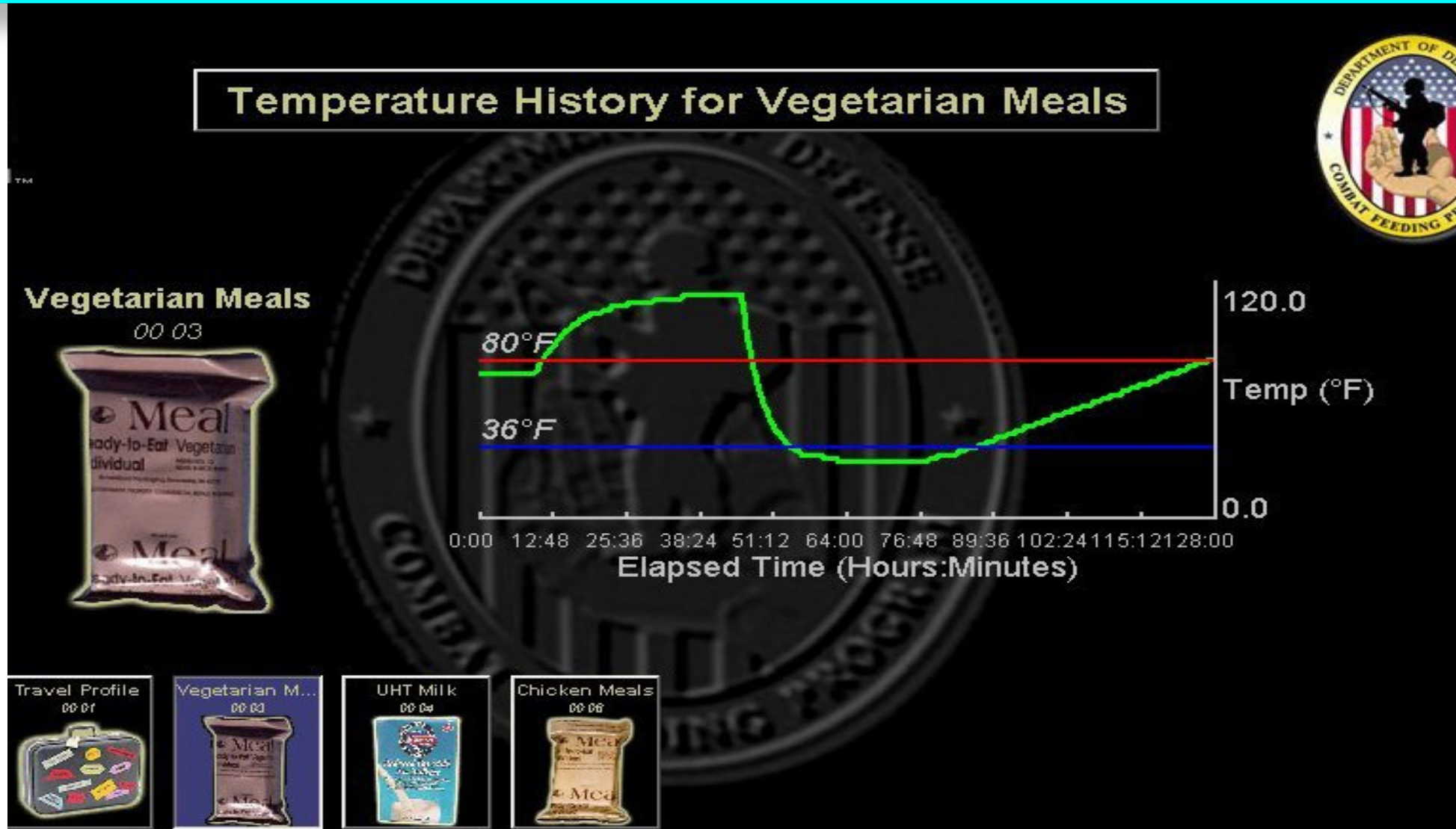
Time Temperature Chart



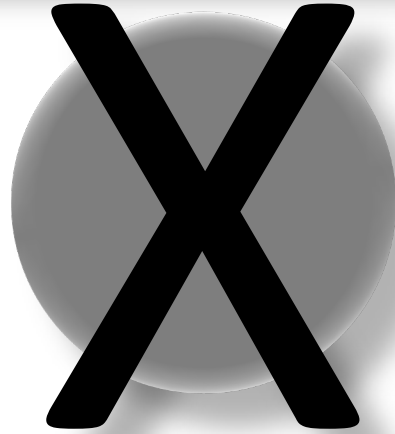
SENSEE can hold RFID + Temperature Sensor Data • Convergence of Systems



Is this data analytics of value to the end-user on the front lines of a war zone?



NOT GOOD



Knowledge Tools

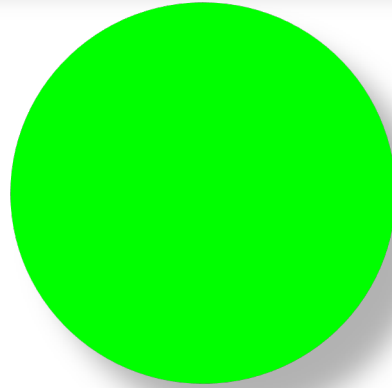
- Agent-based model
- Data-informed models
- Data visualization
- Network models
- Data & database modeling
- Document Modeling
- Metamodeling
- Ontological Modeling
- Business Process Modeling
- Natural language processing
- Machine Learning, ANN, DL

Statistical Tools

- Stochastic
- Bayesian & Adaptive
- Dynamic models
- Hierarchical models
- Factor analysis
- Monte Carlo models
- Population Modeling
- Dynamical system
- Stochastic system eqn
- Social network analysis
- Topic modeling

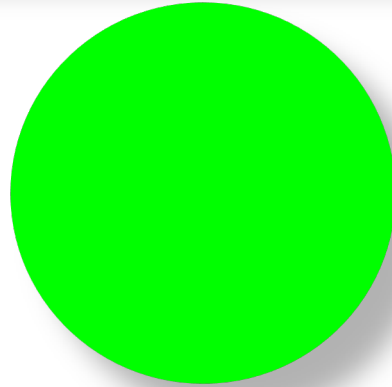
SIMPLICITY – THE TRAFFIC LIGHT OUTCOME – ANSWERS, not numbers

GOOD

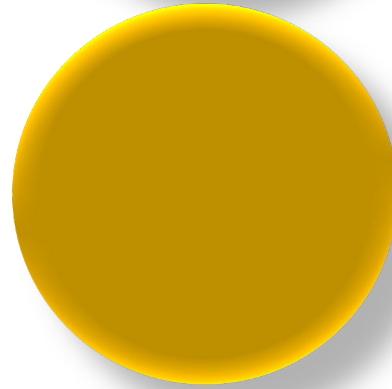


SIMPLICITY – THE TRAFFIC LIGHT OUTCOME – ANSWERS, not numbers

GOOD

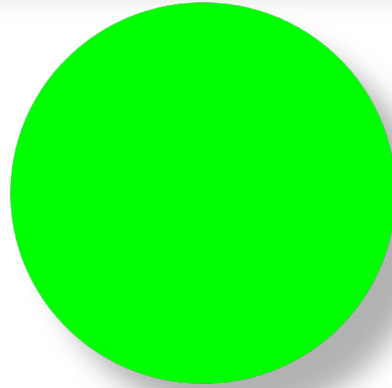


INSPECT

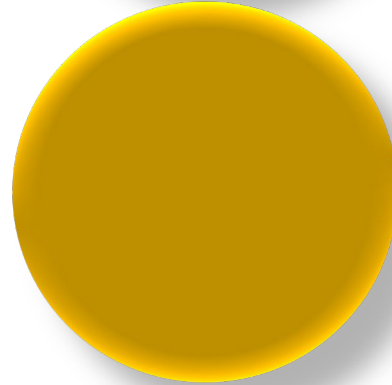


SIMPLICITY – THE TRAFFIC LIGHT OUTCOME – ANSWERS, not numbers

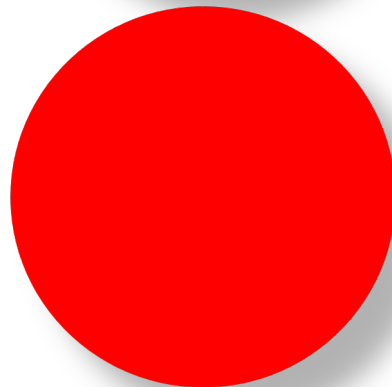
GOOD



INSPECT



REJECT





MRE Quality Application

Please Select an MRE:

01.0000A89.00016F.000169DC1

Quality: 50 -100 Issue, 20 - 49 Inspect, 0 - 19 Discard

ISSUE

INSPECT

DISPOSE

DISPOSE

Discard

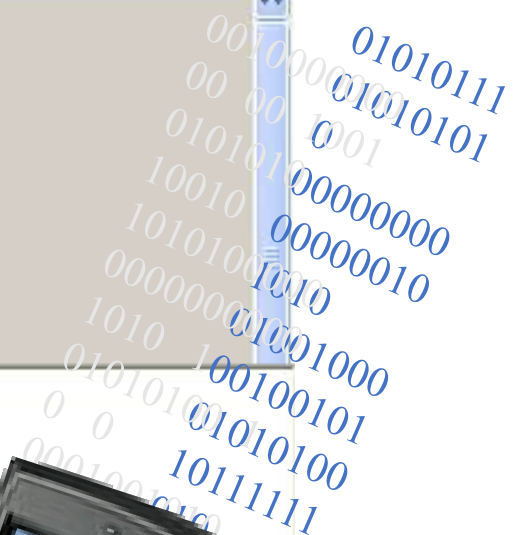
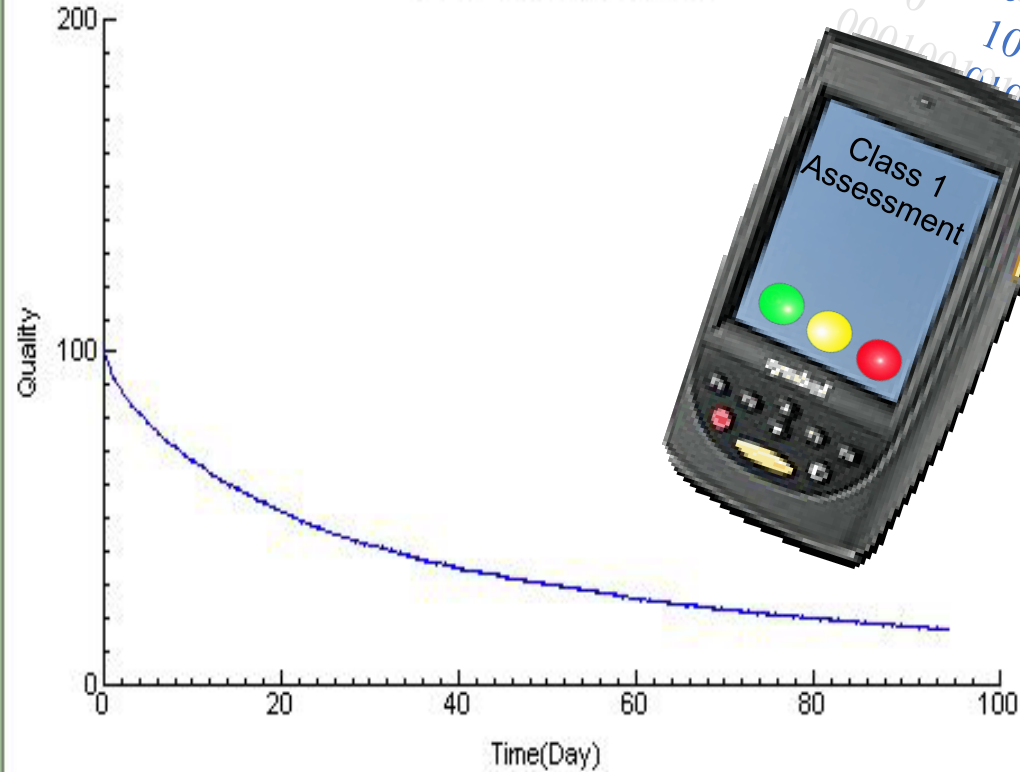
Time and Temperature Data:

```

--1Monday, April 28, 200312:17:32 PM81
Monday, April 28, 20039:44:10 PM64
Friday, May 23, 200311:18:54 AM59
Friday, May 23, 200311:18:55 AM49
Friday, May 23, 200311:18:56 AM53
Friday, May 23, 200311:18:57 AM54
Friday, May 23, 200311:18:58 AM56
Friday, May 23, 200311:18:59 AM42
Friday, May 23, 200311:19:00 AM54
Friday, May 23, 200311:19:01 AM54
Friday, May 23, 200311:19:02 AM42

```

Time Quality Chart



FOOD ART – A Global Need for this Social Business ?

Grocery Store Perishability

Is the spinach fresh? Is the fish smelling fishy? Is the chicken safe to eat?



YOU WANT TO KNOW IF THE CHICKEN IS STILL GOOD TO EAT. YOU DON'T TRUST THE "SELL BY" DATE ON THE LABEL

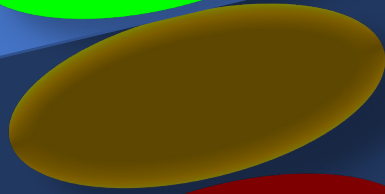
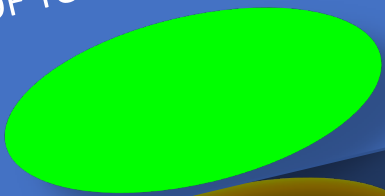
ALWAYS BUY QUALITY



WHAT IF THE PACK OF “CHICKEN” CAN TALK TO YOU AND OFFER YOU A REAL-TIME UPDATE ABOUT ITS QUALITY AND FOOD SAFETY?



THIS IS A NON-TOXIC
BIOGENIC AMINE SENSOR
TO MONITOR THE SAFETY
OF YOUR FRESH FOOD

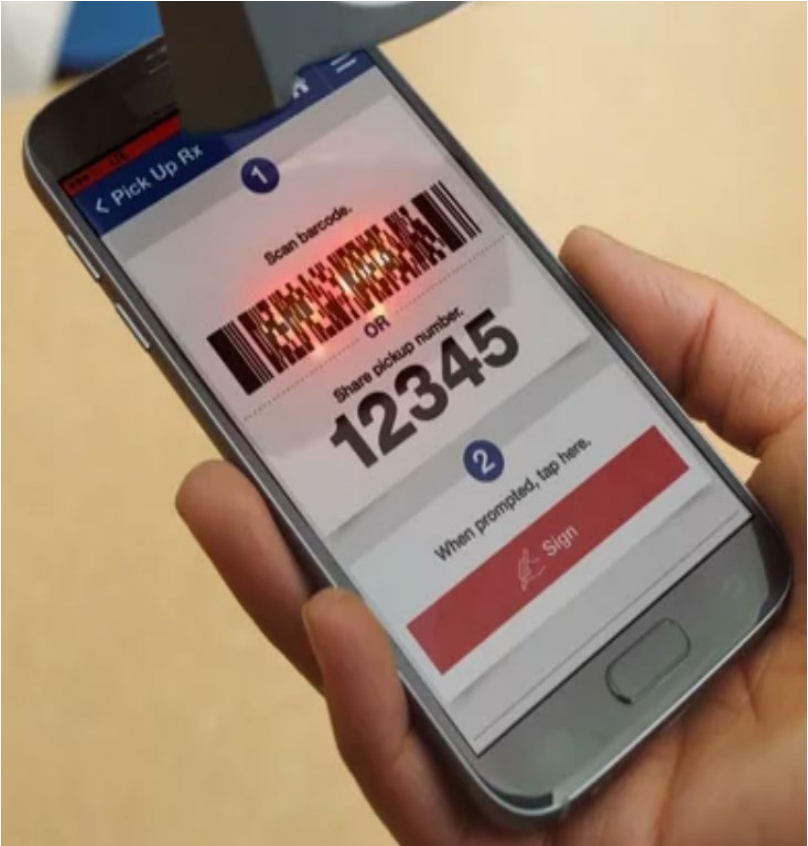


Yes We Can!

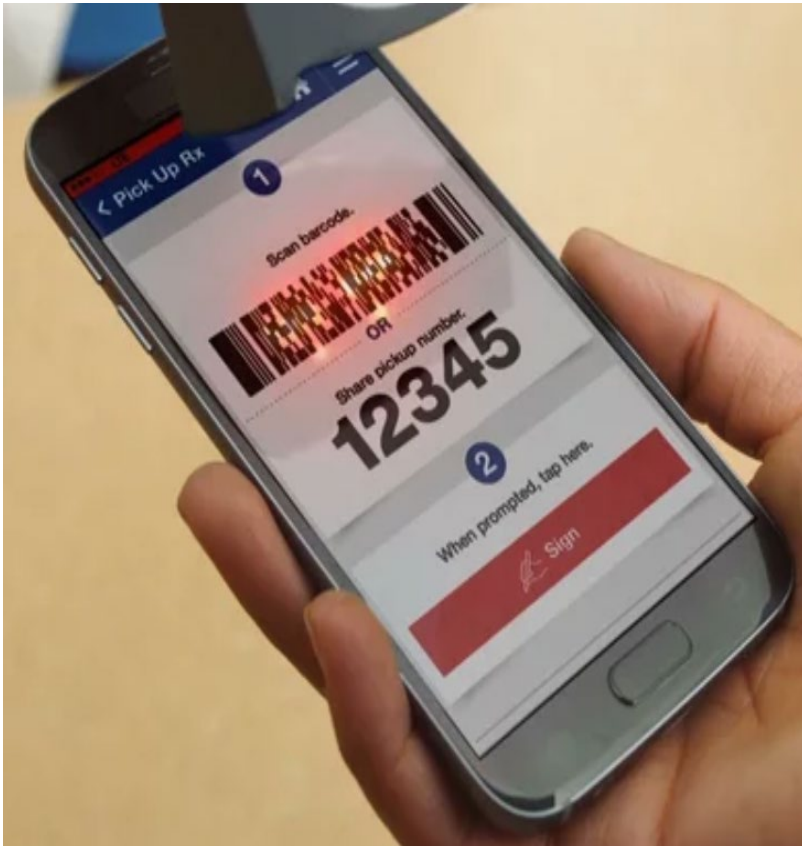




THE SKU (PRODUCT NUMBER) SHOWS ON THE MOBILE APP

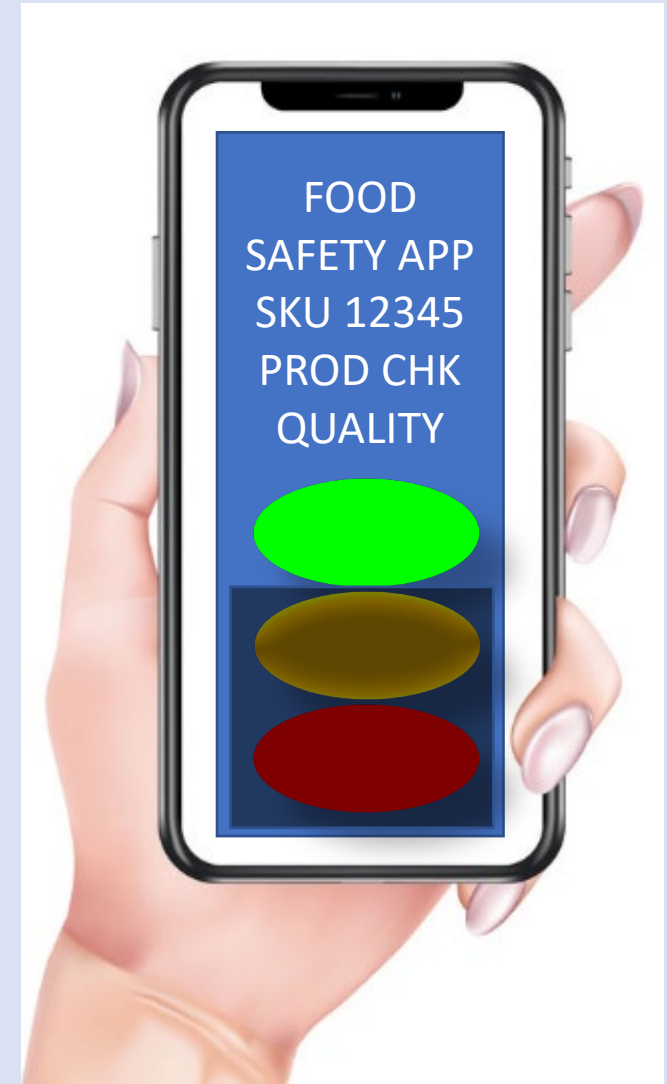


THE SKU (PRODUCT NUMBER) SHOWS ON THE MOBILE APP

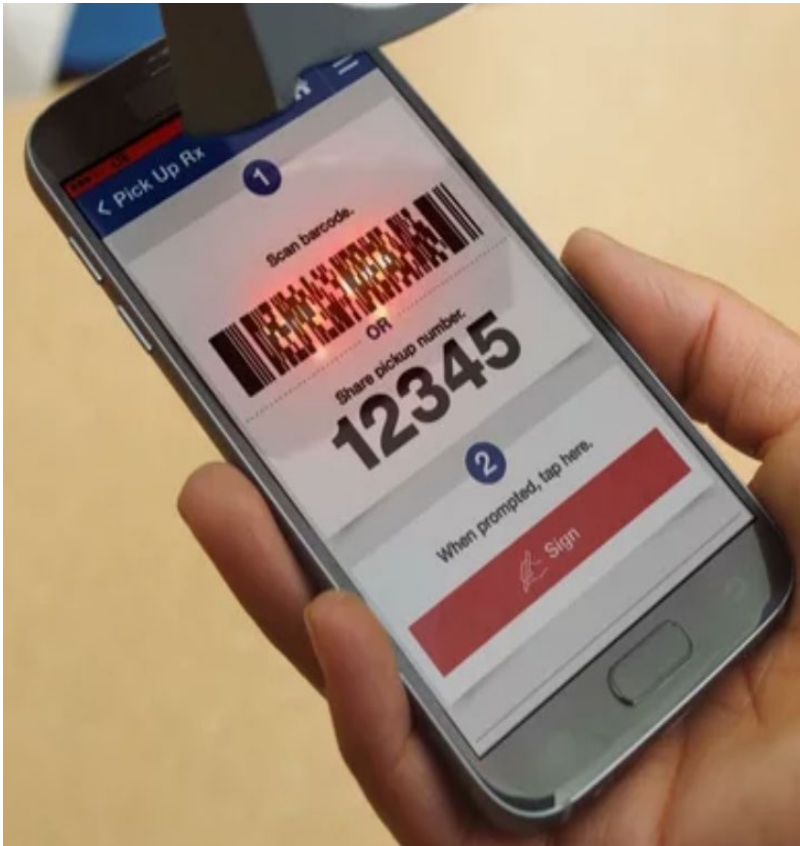


**WOULD YOU PAY 1 CENT TO USE THIS
FOOD APP HEALTH SAFETY SERVICE ?**

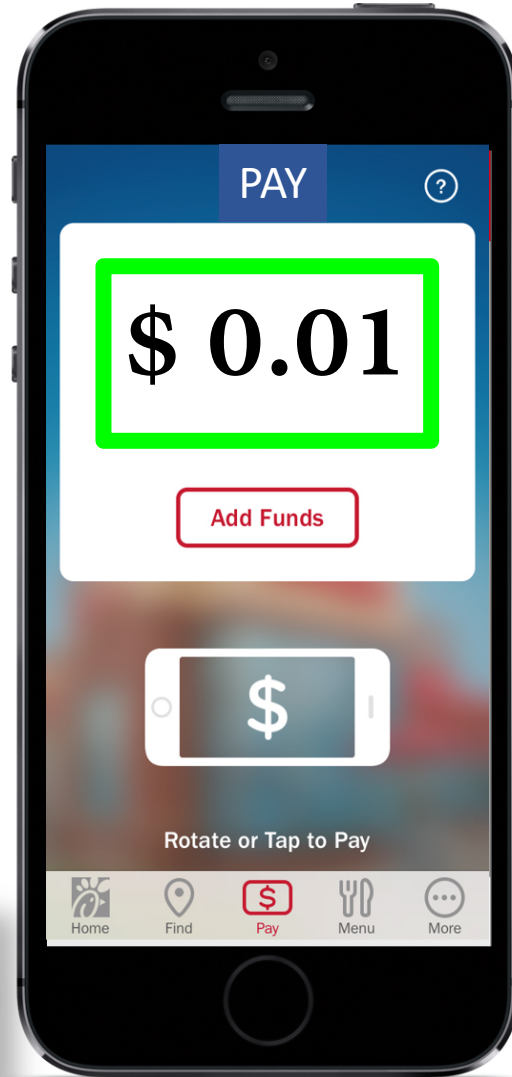
IT IS YOUR HEALTH



THE SKU (PRODUCT NUMBER) SHOWS ON THE MOBILE APP

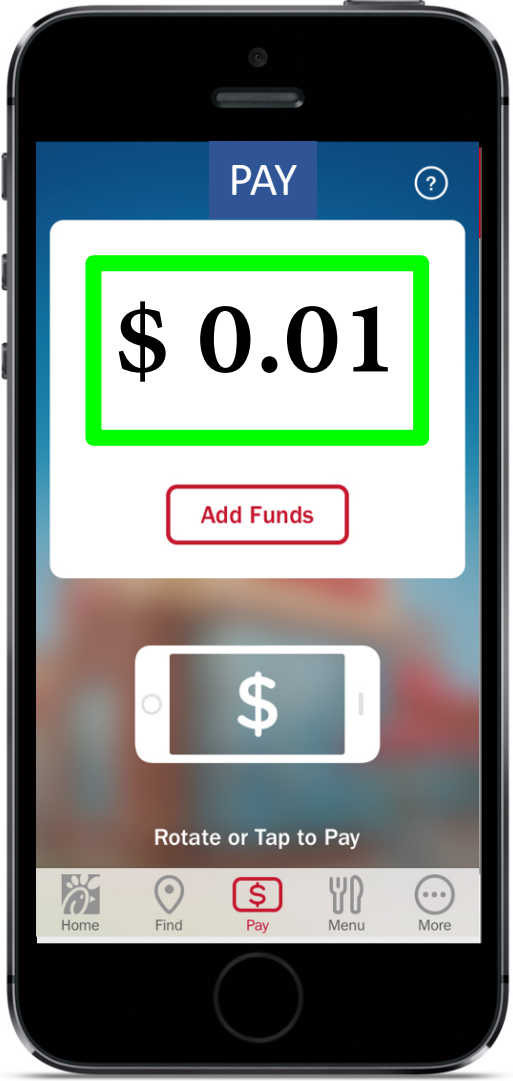


WOULD YOU PAY 1 CENT TO USE THIS FOOD APP HEALTH SAFETY SERVICE ?



IT IS YOUR HEALTH

PEAS OF YOUR MIND



PAY



\$ 0.01

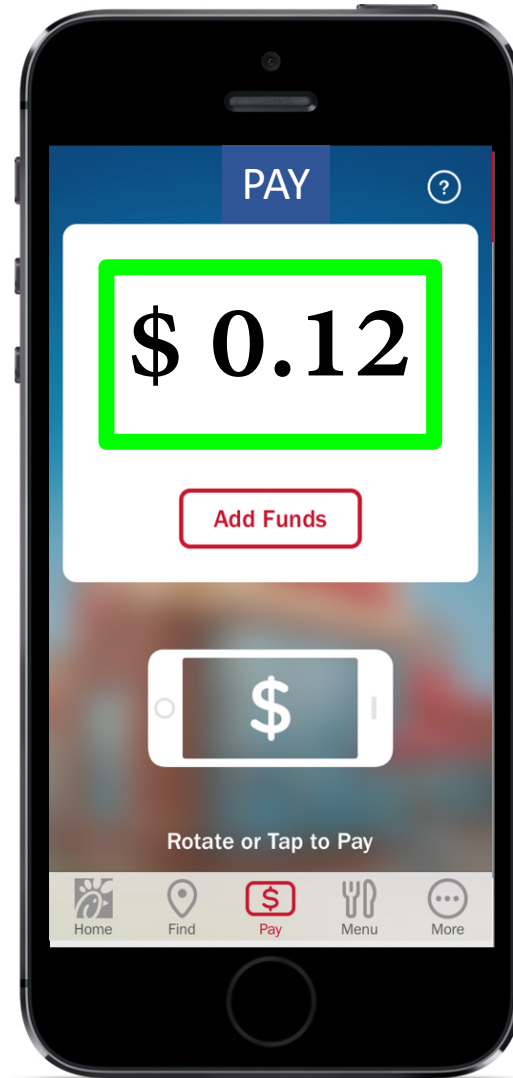
Add Funds



Rotate or Tap to Pay

- Home
- Find
- Pay
- Menu
- More

REMEMBER IoT ? HOW NANO-FEES MAY GENERATE MEGA-MILLIONS



0.12
cents

REMEMBER IoT ? HOW NANO-FEES MAY GENERATE MEGA-MILLIONS

The user will also need access to the cattle tracking and monitoring web application. For example, the cost of an annual subscription to the Cattle Tags Technologies app will be \$5 per animal.



0.12
cents

Software subscription cost \$0.0137 per cow per day



LoRaWAN ear tag from Cattle Tags Technologies starts from \$39. Tags have embedded GPS receiver, accelerometer, temperature sensor and replaceable battery. Operator reads RFID-tag with Bluetooth reader (ID sent to ERP system). Installation of activated LoRaWAN ear tag follows. alex.trubitcin@gmail.com

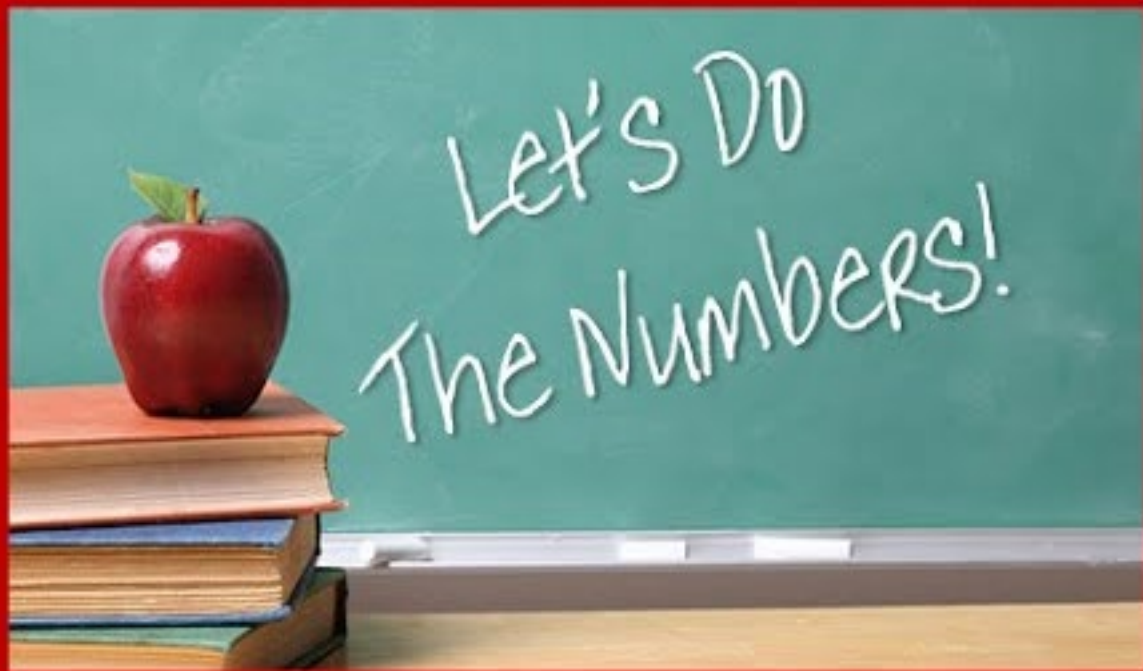
Digital Transformation (Connectivity+App+Tag) Cost \$0.12 per cow per day

Proposal generates following remark from a VC
(Mr Vinod Vaticinator, Venture Capitalist)

A joke? 1 cent ?

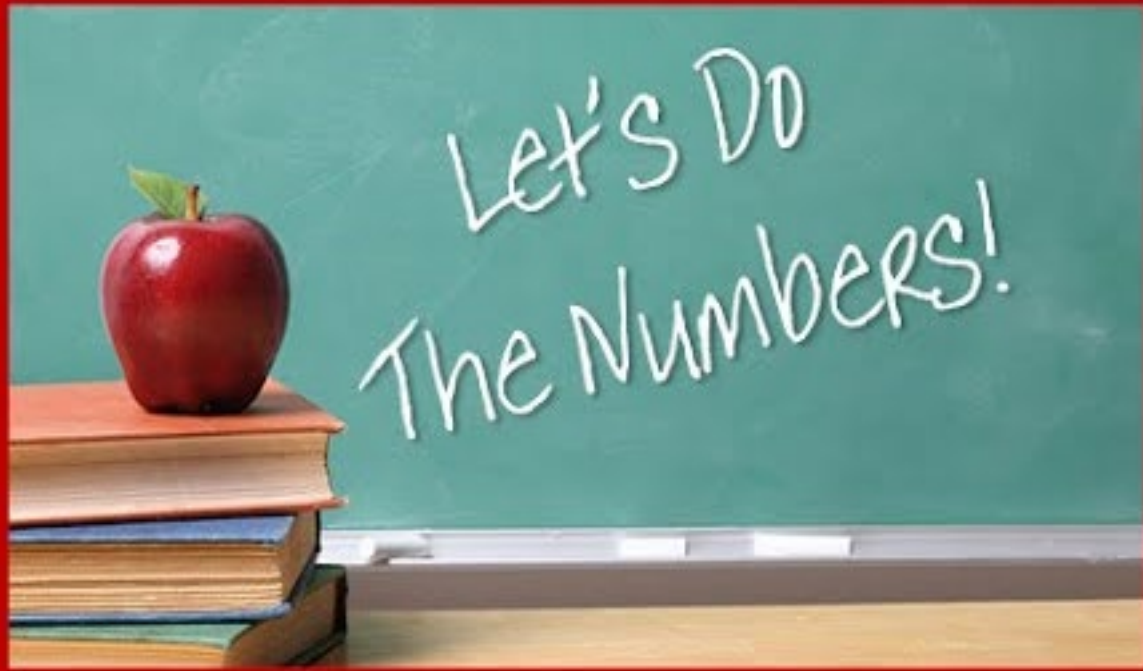
Bad business !!

You are fired !

A man with short, graying hair, wearing a dark suit, light blue shirt, and patterned tie, is speaking into a microphone. He is pointing his right index finger towards the camera. The background is a dark green wall with a faint, larger image of the same man.

KAI RYSSDAL
MARKETPLACE | NOV. 9, 2018

<https://www.marketplace.org/shows/marketplace/07092018/>



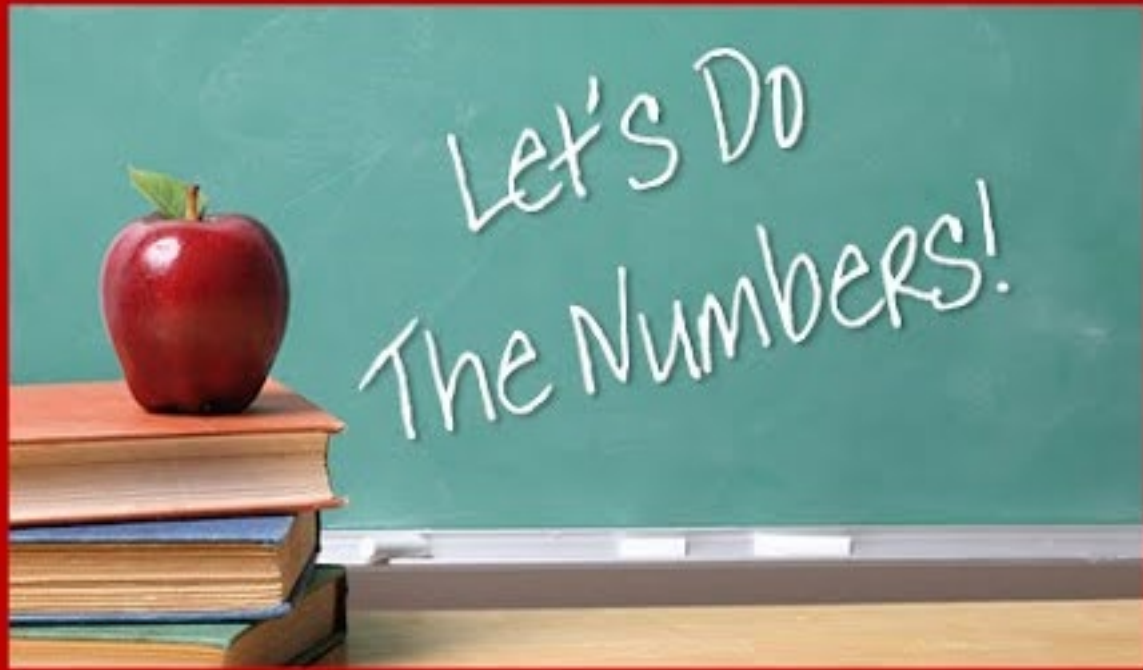
Number of Supermarkets - 2018

*2 million or more in annual sales

Source: [Progressive Grocer Magazine](#)

38,307

Transaction count is the metric you seek. Also known as customer count. It is the number of transactions per period. The most accessible of these is transactions per day. Even a smaller successful grocery store will approach 2000 transactions per a day. You can assume the actual foot traffic is higher as people shop together, but this number is not usually kept track of.



28 BILLION

ANNUAL GROCERY TRANSACTIONS IN US

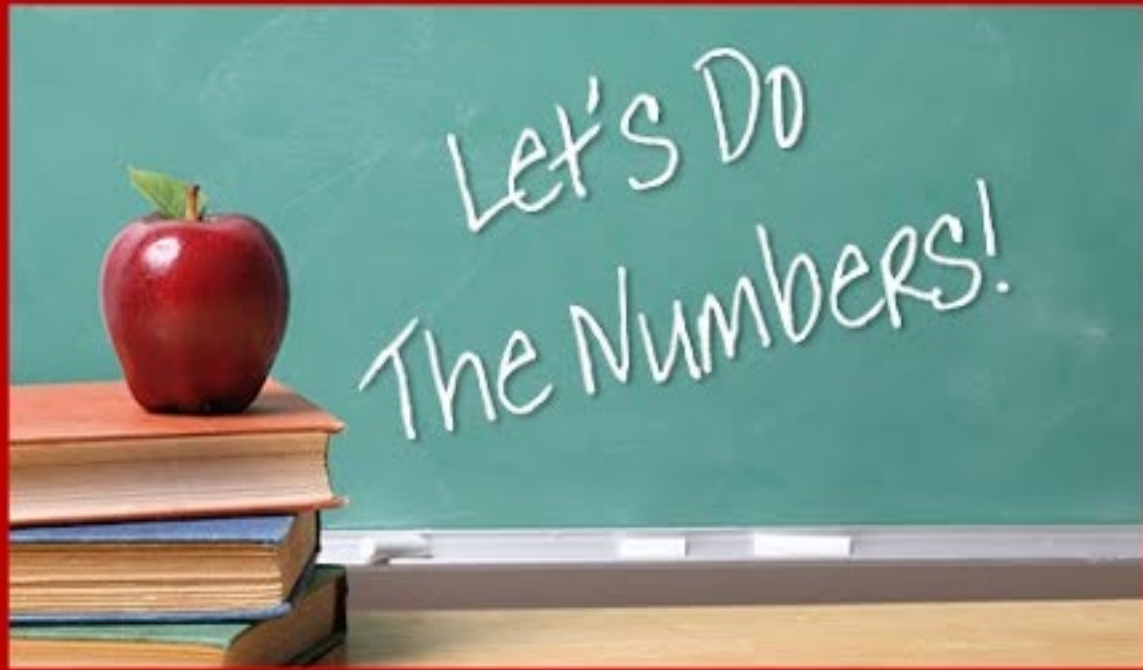
Number of Supermarkets - 2018

*2 million or more in annual sales

Source: [Progressive Grocer Magazine](#)

38,307

Transaction count is the metric you seek. Also known as customer count. It is the number of transactions per period. The most accessible of these is transactions per day. Even a smaller successful grocery store will approach 2000 transactions per a day. You can assume the actual foot traffic is higher as people shop together, but this number is not usually kept track of.



0.28 BILLION

ONLY 1% TRANSACTIONS BOUGHT CHKN
AND CUSTOMER WILLING TO PAY 1 CENT

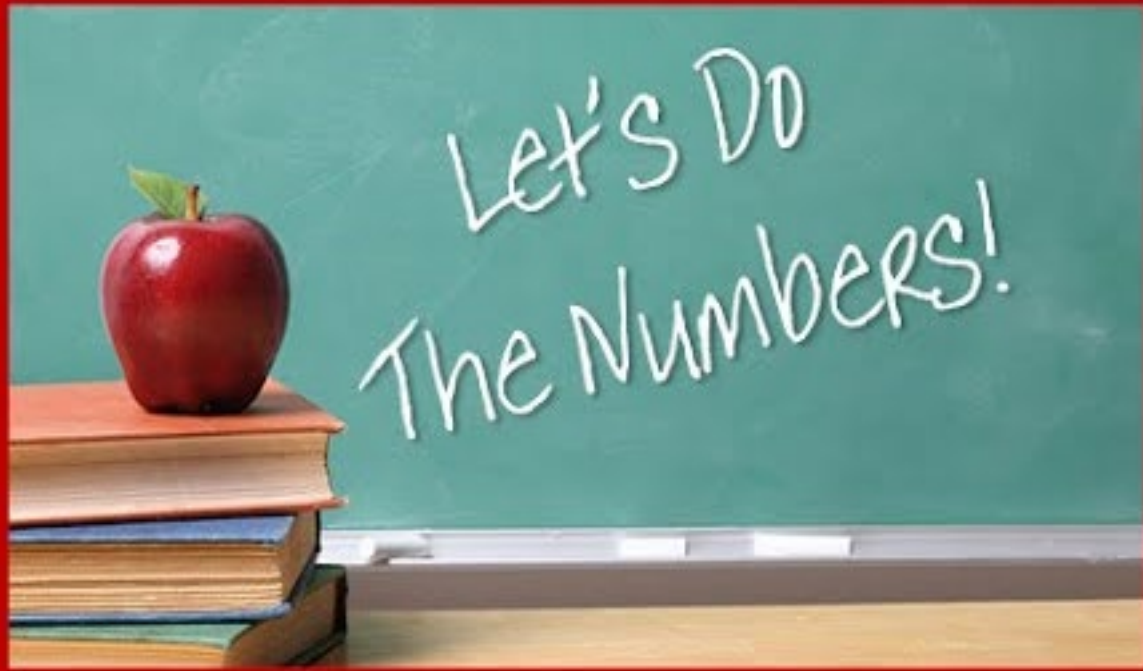
Number of Supermarkets - 2018

*2 million or more in annual sales

Source: [Progressive Grocer Magazine](#)

38,307

Transaction count is the metric you seek. Also known as customer count. It is the number of transactions per period. The most accessible of these is transactions per day. Even a smaller successful grocery store will approach 2000 transactions per a day. You can assume the actual foot traffic is higher as people shop together, but this number is not usually kept track of.



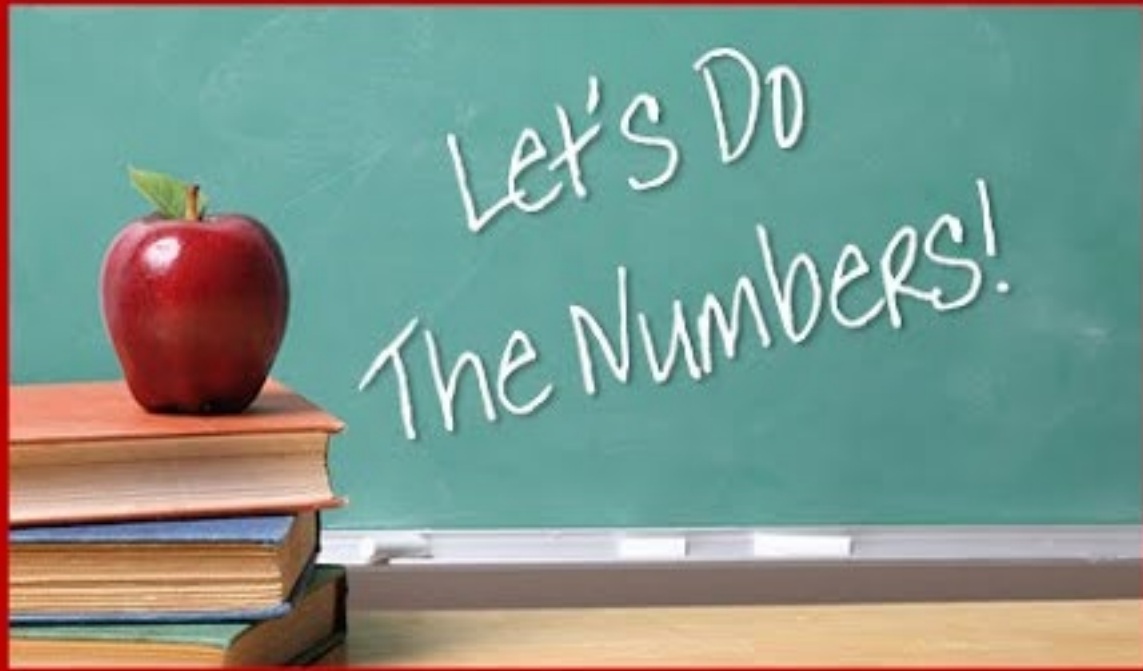
0.28 BILLION

ONLY 1% TRANSACTIONS BOUGHT CHKN
AND CUSTOMER WILLING TO PAY 1 CENT

FROM 1 USE - PAY A PENNY PER USE (PAPPU) - FOR ONLY 1 ITEM

\$2.8 million

ANNUAL REVENUE ONLY IN USA



Average number items carried in
a supermarket in 2017

Source: Food Marketing Institute

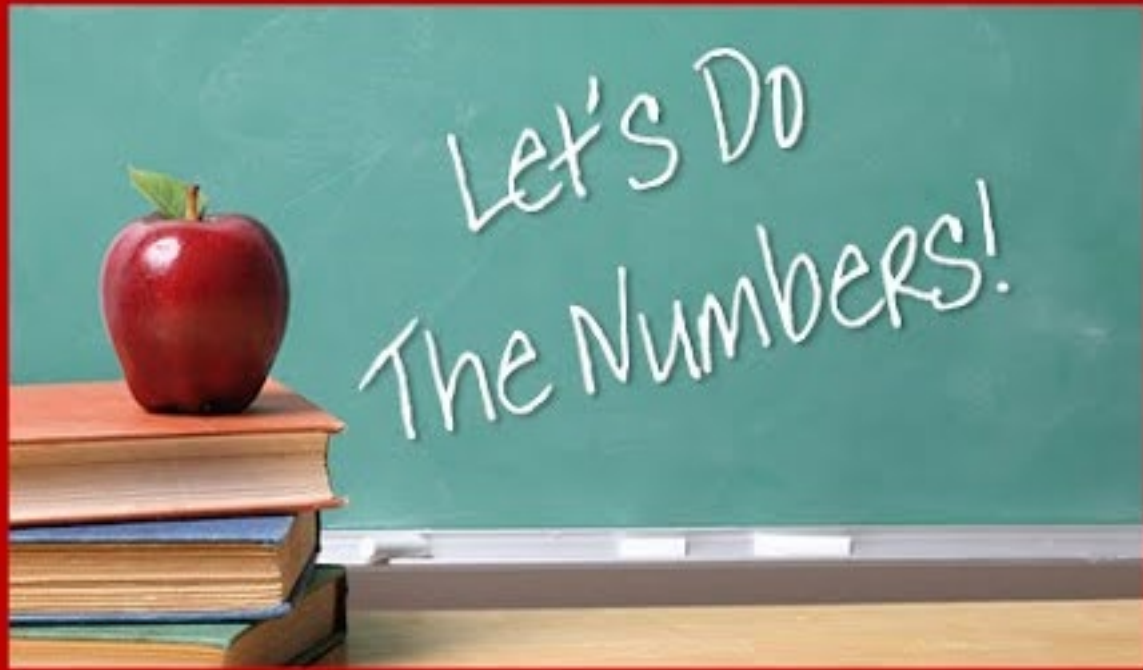
30,098

1% OF ITEMS USE FOOD SAFETY SENSOR
CUSTOMERS PAY 10 CENT/TRANSACTION

FOOD SAFETY - PAY A PENNY PER USE (PAPPU) - 10% TRANSACTIONS

\$280 million

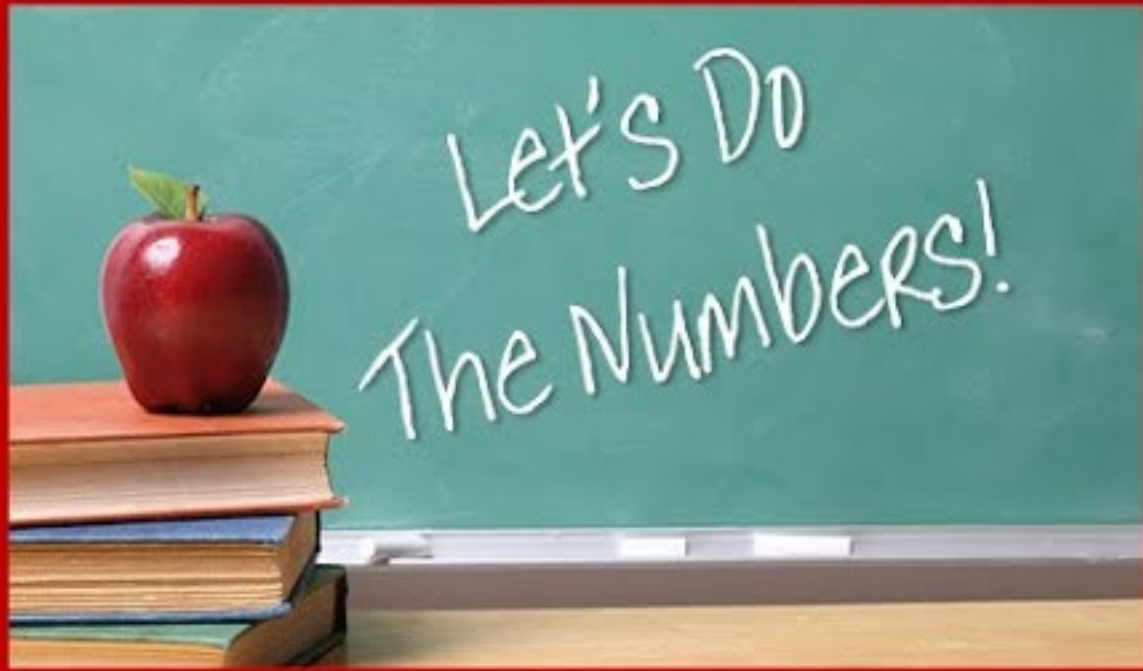
10% of 28 billion transactions pays \$0.10 per transaction = \$280 million revenue p.a.



FOOD SAFETY – PAY A PENNY PER USE (PAPPU) – GLOBAL POTENTIAL

Billion Dollar Industry?

ANNUAL GROSS REVENUE

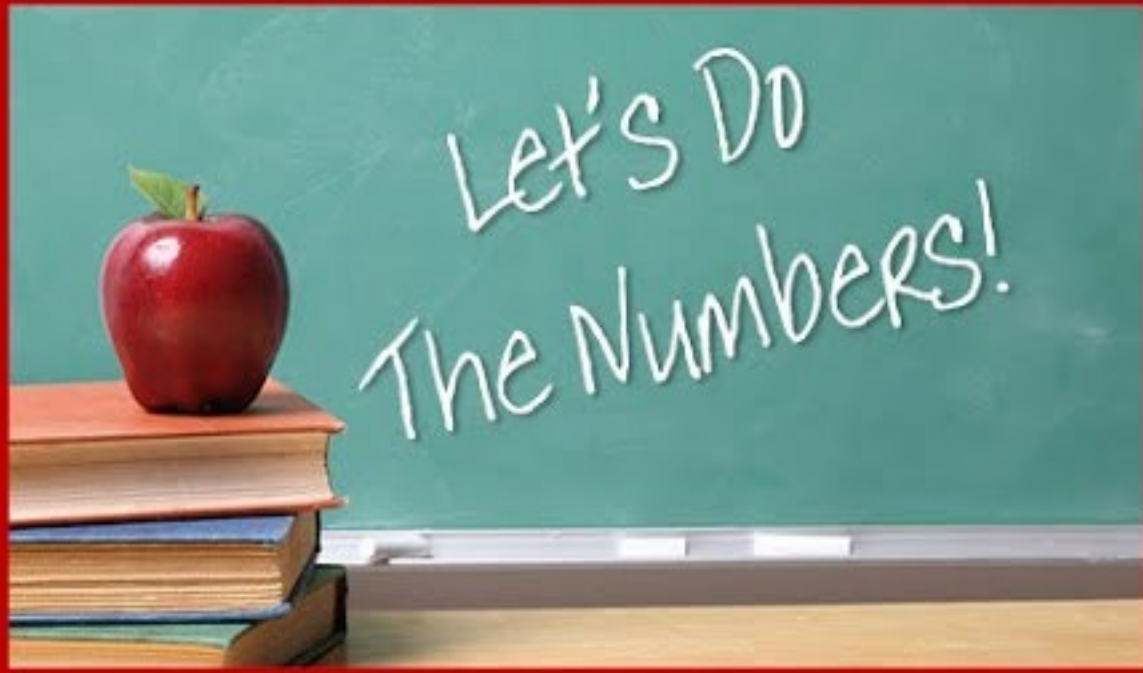


JUST
1 cent
PAPPU

FOOD SAFETY – PAY A PENNY PER USE (PAPPU) – GLOBAL POTENTIAL

Billion Dollar Industry

<http://bit.ly/Economics-of-Technology>
<https://www.law.uchicago.edu/files/file/coase-nature.pdf>
<http://web.pdx.edu/~nwallace/EHP/TCEProgression.pdf>
<https://pdfs.semanticscholar.org/e4e8/a0486808360d056dbe212f7424273558538c.pdf>
http://www.economics-ejournal.org/economics/discussionpapers/2007-3/at_download/file



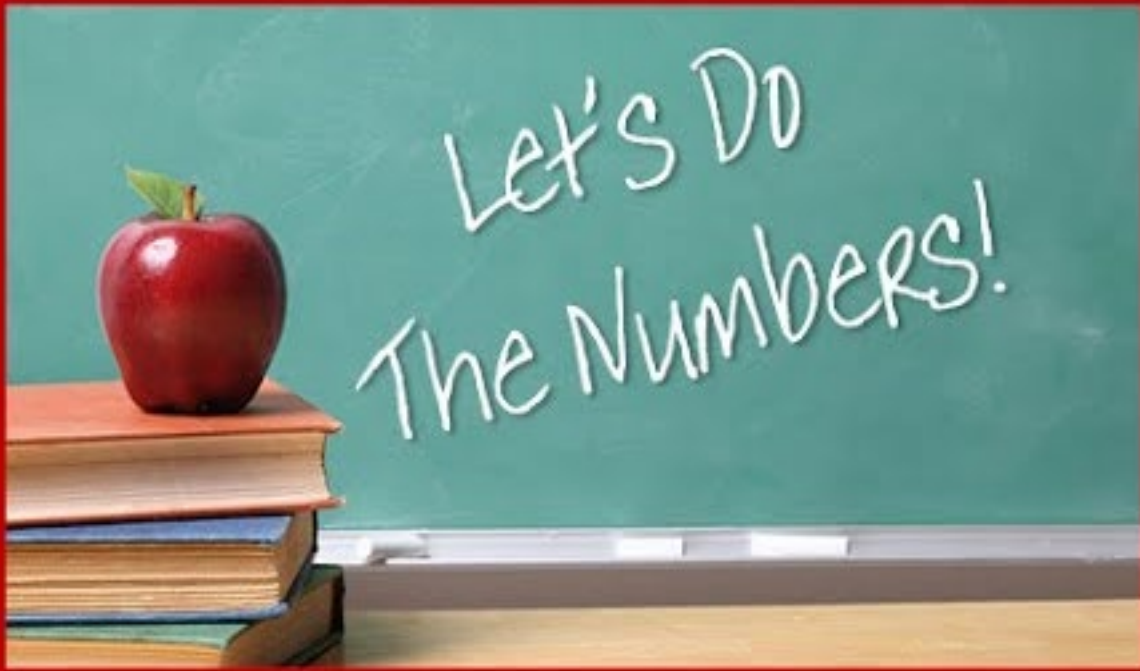
REALITY CHECK

Economies of scale may take several years to reach market penetration to generate mega revenues from nano payments, for example, the PAPPU model.

FOOD SAFETY – PAY A PENNY PER USE (PAPPU) – GLOBAL POTENTIAL

Billion Dollar Industry

THINK FOOD SAFETY AS PAY PER USE PERSONALIZED SERVICE



PAY A PENNY PER USE GLOBAL SERVICES

HPE CEO Pledges to Sell 'Everything as a Service' by 2022

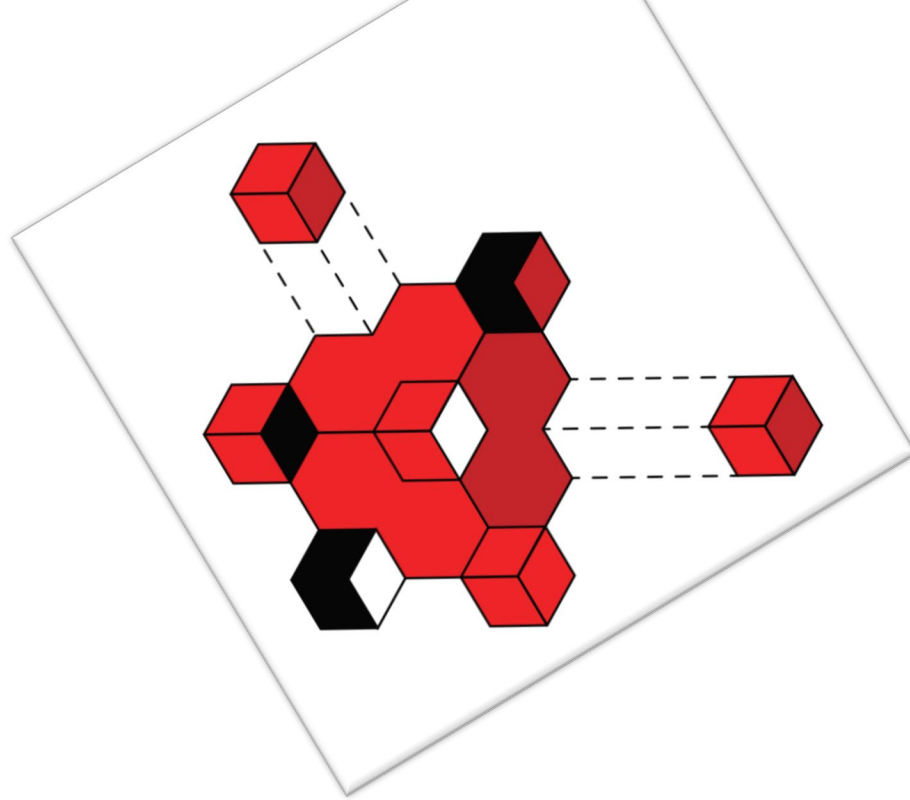
In its boldest move yet to make on-prem IT more like public cloud, the company says GreenLake is its future.

Yevgeniy Sverdlik | Jun 19, 2019

Three years from now, every product Hewlett Packard Enterprise sells will be available as a service. That's the pledge CEO Antonio Neri made from stage Tuesday afternoon during his keynote at the company's Discover conference in Las Vegas. The pledge covers both hardware and software in the enterprise tech giant's sprawling portfolio.

THINK FOOD SAFETY AS PAY PER USE PERSONALIZED SERVICE

<https://www.datacenterknowledge.com/hewlett-packard-enterprise/hpe-ceo-pledges-sell-everything-service-2022>

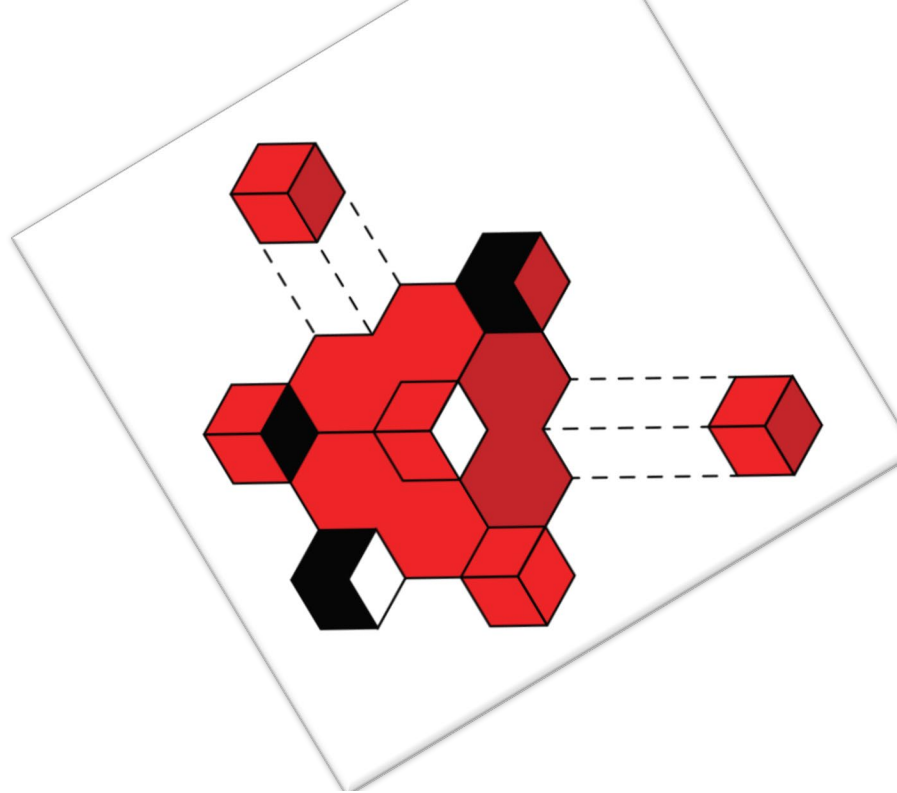


WORLD
ECONOMIC
FORUM

COMMITTED TO
IMPROVING THE STATE
OF THE WORLD

Insight Report

Top 10 Emerging Technologies 2019



WORLD
ECONOMIC
FORUM

COMMITTED TO
IMPROVING THE STATE
OF THE WORLD

Insight Report

Top 10 Emerging Technologies 2019

http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2019_Report.pdf



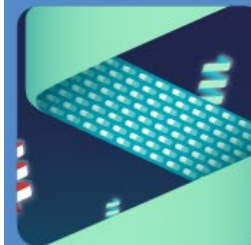
1. Bioplastics for a Circular Economy



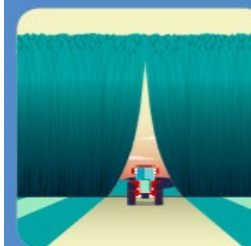
2. Social Robots



3. Tiny Lenses for Miniature Devices



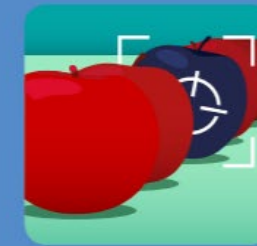
4. Disordered Proteins as Drug Targets



5. Smarter Fertilizers Can Reduce Environmental Contamination



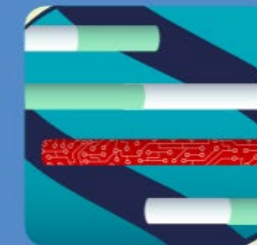
6. Collaborative Telepresence



7. Advanced Food Tracking and Packaging



8. Safer Nuclear Reactors

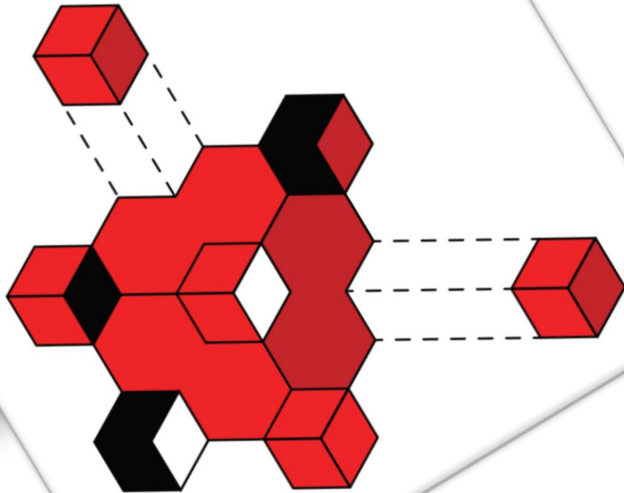


9. DNA Data Storage



10. Utility-Scale Storage of Renewable Energy

THINK FOOD SAFETY
AS A PAY PER USE
PERSONALIZED SERVICE



COMMITTED TO
IMPROVING THE STATE
OF THE WORLD

Insight Report

Top 10 Emerging Technologies 2019

http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2019_Report.pdf



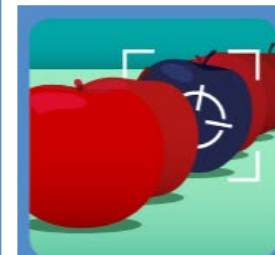
1. Bioplastics for a Circular Economy



6. Collaborative Telepresence



2. Social Robots



7. Advanced Food Tracking and Packaging



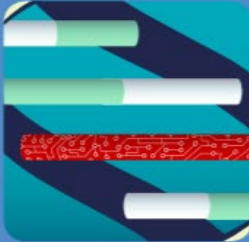
3. Tiny Lenses for Miniature Devices



8. Safer Nuclear Reactors



4. Disordered Proteins as Drug Targets



9. DNA Data Storage



5. Smarter Fertilizers Can Reduce Environmental Contamination



10. Utility-Scale Storage of Renewable Energy

HPE CEO Pledges to Sell 'Everything as a Service' by 2022

In its boldest move yet to make on-prem IT more like public cloud, the company says GreenLake is its future.

Yevgeniy Sverdlik | Jun 19, 2019

Three years from now, every product Hewlett Packard Enterprise sells will be available as a service. That's the pledge CEO Antonio Neri made from stage Tuesday afternoon during his keynote at the company's Discover conference in Las Vegas. The pledge covers both hardware and software in the enterprise tech giant's sprawling portfolio.



Insight Report

Top 10 Emerging Technologies 2019



1. Bioplastics for a Circular Economy



6. Collaborative Telepresence

THINK FOOD SAFETY AS A PAY PER USE PERSONALIZED SERVICE



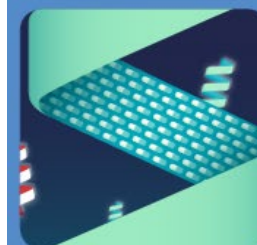
7. Advanced Food Tracking and Packaging



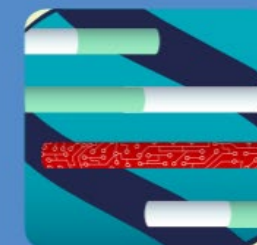
3. Tiny Lenses for Miniature Devices



8. Safer Nuclear Reactors



4. Disordered Proteins as Drug Targets



9. DNA Data Storage



5. Smarter Fertilizers Can Reduce Environmental Contamination

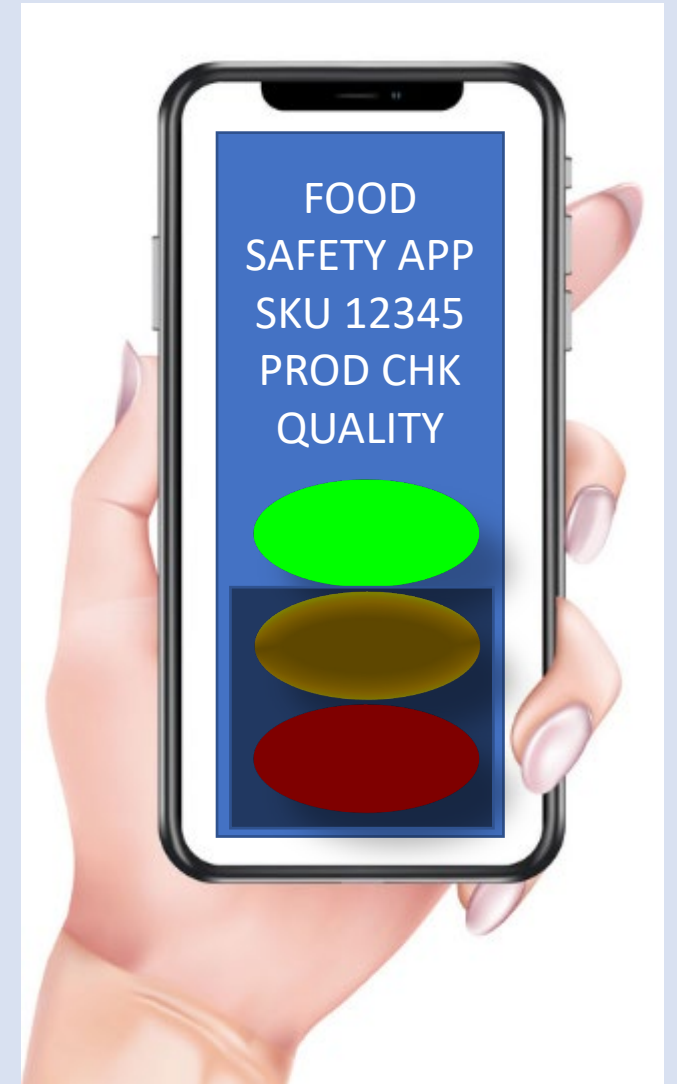


10. Utility-Scale Storage of Renewable Energy

FOOD ART ?

In a Grocery Store Near You

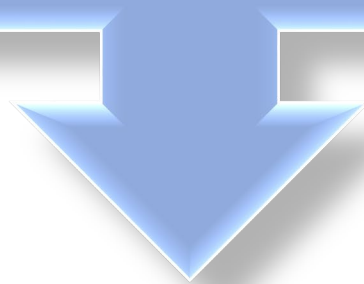
IT IS YOUR HEALTH



PEAS OF YOUR MIND

FRESH SENSE™

CHECK WITH YOUR
FOOD SAFETY APP



FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE™

CHECK WITH YOUR
FOOD SAFETY APP

SENSEE

SMALL PART
BUT USEFUL

FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE™



FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE™



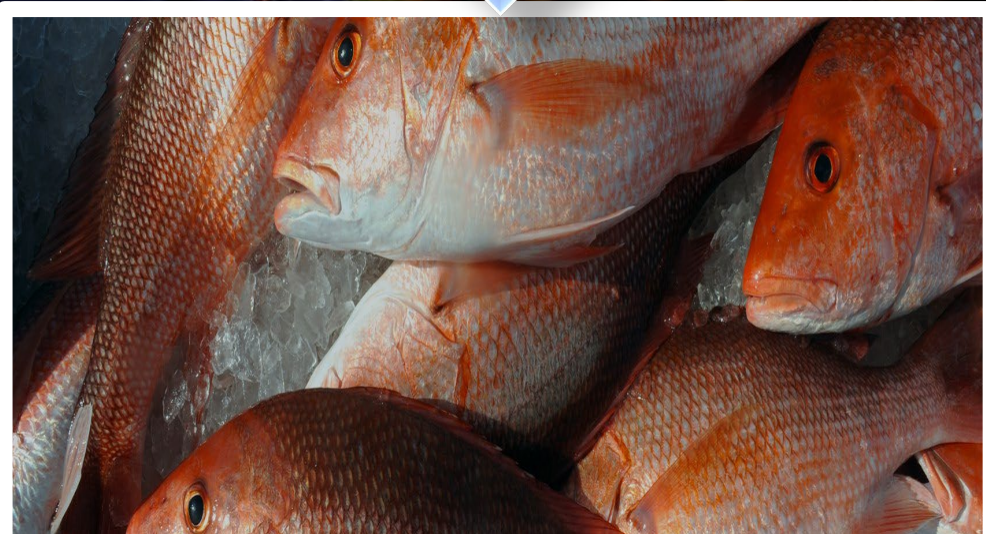
SENSEE
SMALL PART
BUT USEFUL

KIDS

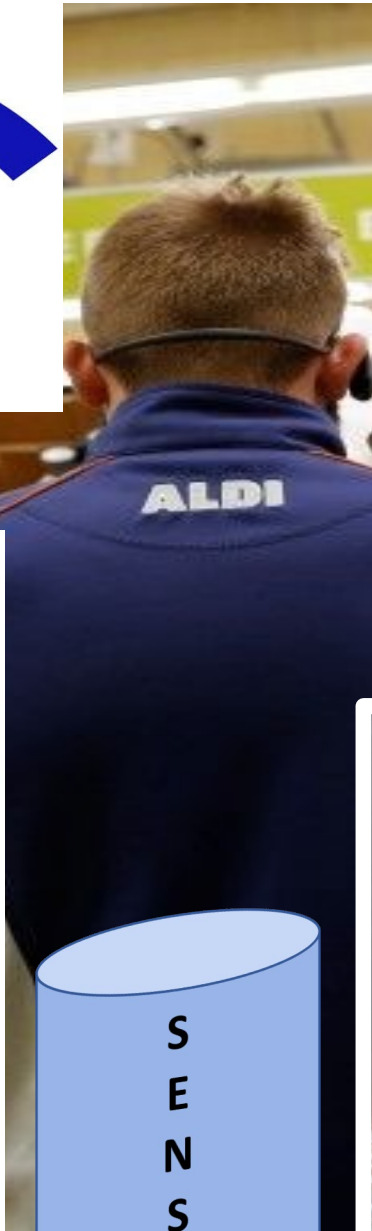
FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE



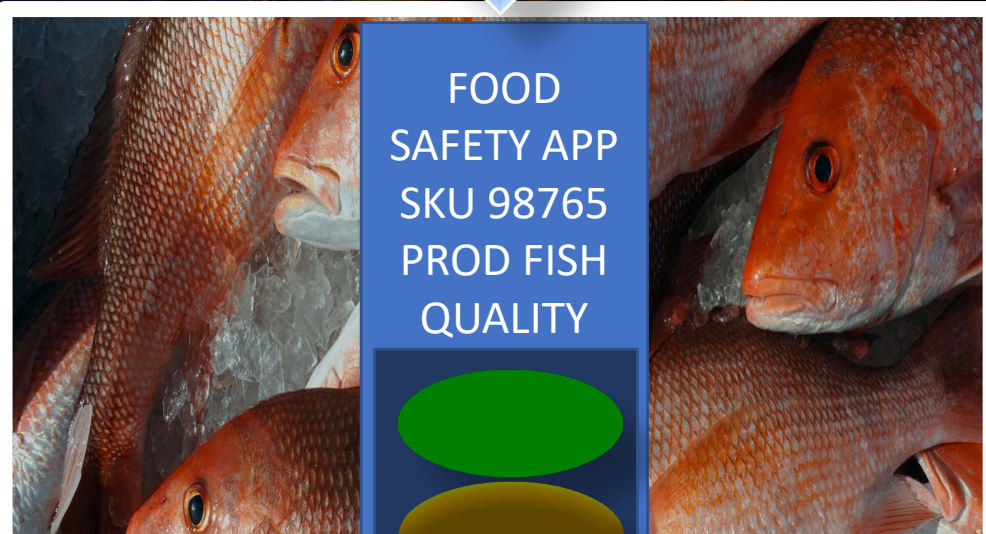
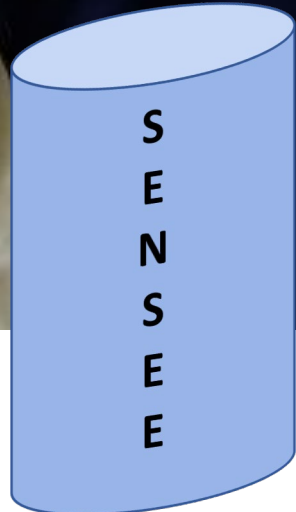
FRESH SENSE™
CHECK WITH YOUR
FOOD SAFETY APP



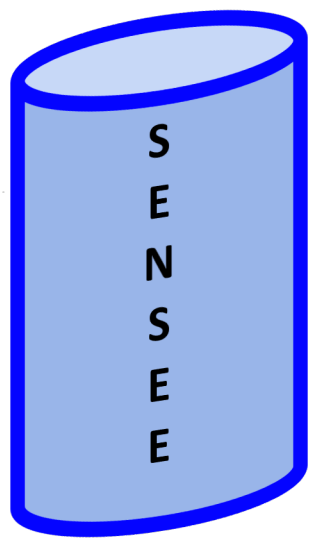
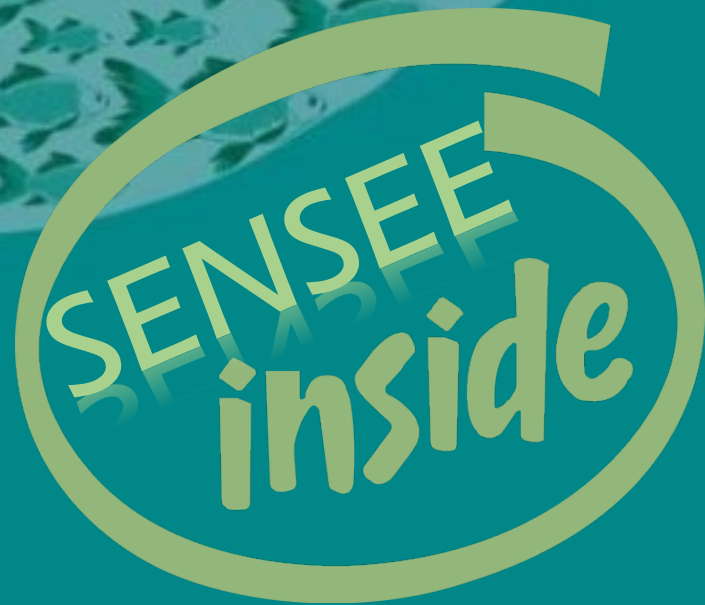
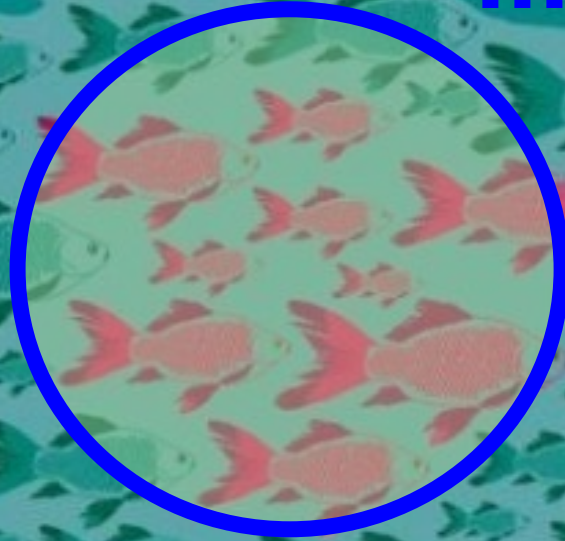
FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE



FRESH SENSE™
CHECK WITH YOUR
FOOD SAFETY APP



FOOD ART



THINK FOOD SAFETY
AS A PAY PER USE
PERSONALIZED SERVICE

Summary – A Sense of the Future



SENSEE, SNAPS, ART, DIDA'S, KIDS

Are these ingredients for a Google of Ag and/or fuel for future scientific research ?

PEAS

Platform for the Agro-Ecosystem

A few lofty goals, perhaps best attempted in stages, from data to data-informed, with knowledge-informed as a future performance index (KPI). Granularity of data from sensors feed decisions with information and knowledge. In the short term, offer logic tools (ART) for users, reduce food waste and contribute to food safety.

Being KIDS – Is “knowledge-informed” a challenging goal?

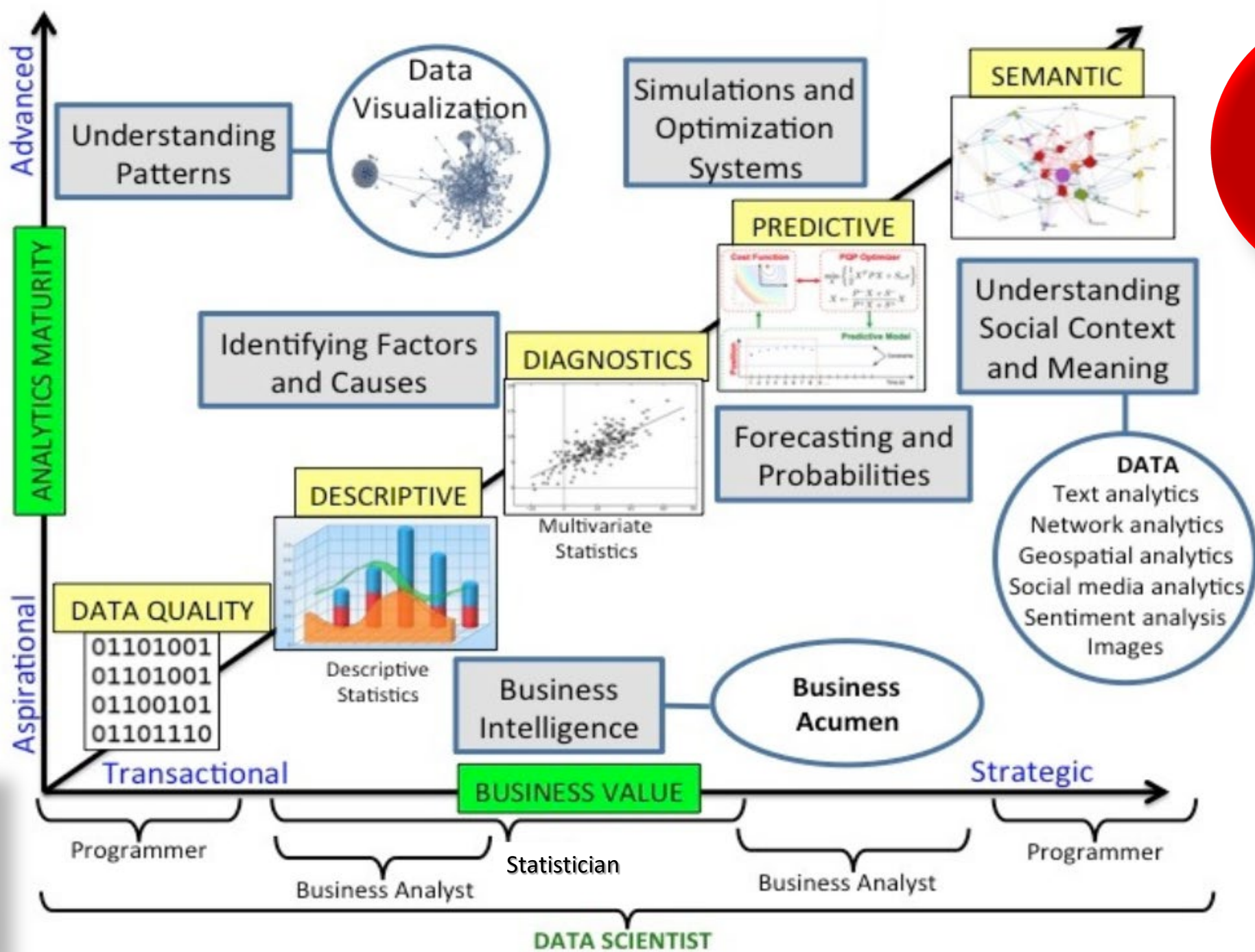
Knowledge combination/integration beyond (heterogenous) rules and ontologies are not only difficult, but calls for **new thinking**. The semantics of knowledge bases other than rules (for example, descriptions of temporal processes like workflows which could logically decide when the irrigation system must turn on/off the water pumps, or protocols in spatio-temporal logic) must be integrated. We may need some form of logic framework in which knowledge modules, having different native semantics, can be overlaid with meaningful semantics, preferably agnostic of linguistic bias, ideally as a “plug and play” operation, graph-friendly for non-expert end-users to decompose and/or re-compose the choice of logic and logic tools, based on experience from expert humans in the loop. Chaperoning convergence between distributed domain(s) knowledge, operational rules, data, information, and systems science, is a daunting and challenging goal.

Being KIDS – the path to “knowledge-informed”

KIDS

SENSEE
1.0, 2.0

KIDS



**SENSEE
1.0, 2.0**



KIDS

USER

In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.



KIDS

Business
need

In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.



KIDS

Business
need

Idea

In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.



KIDS

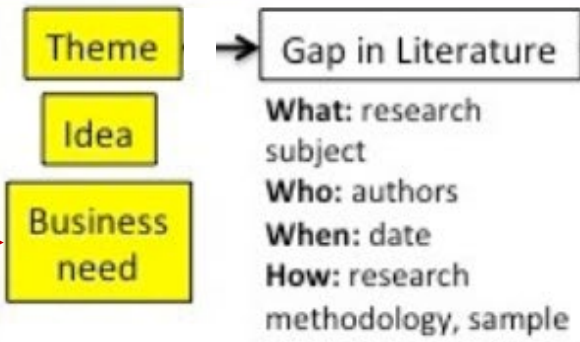
Theme

Idea

Business
need

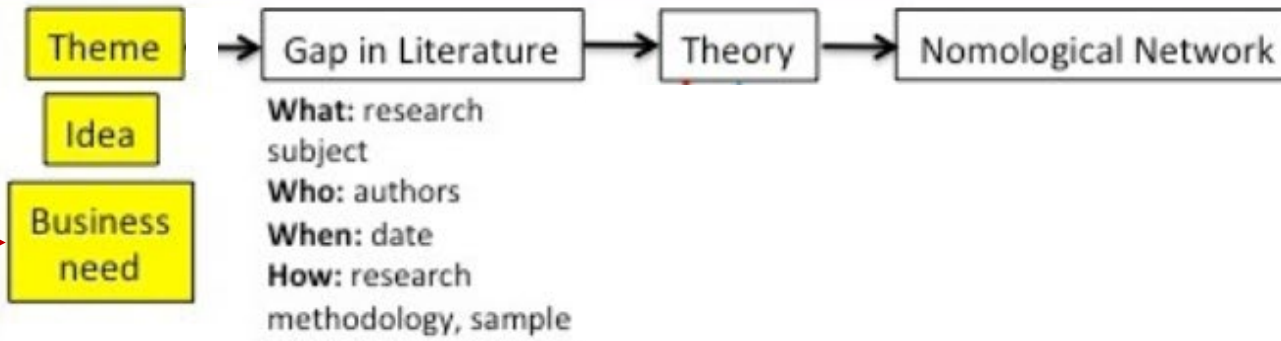
In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.

KIDS



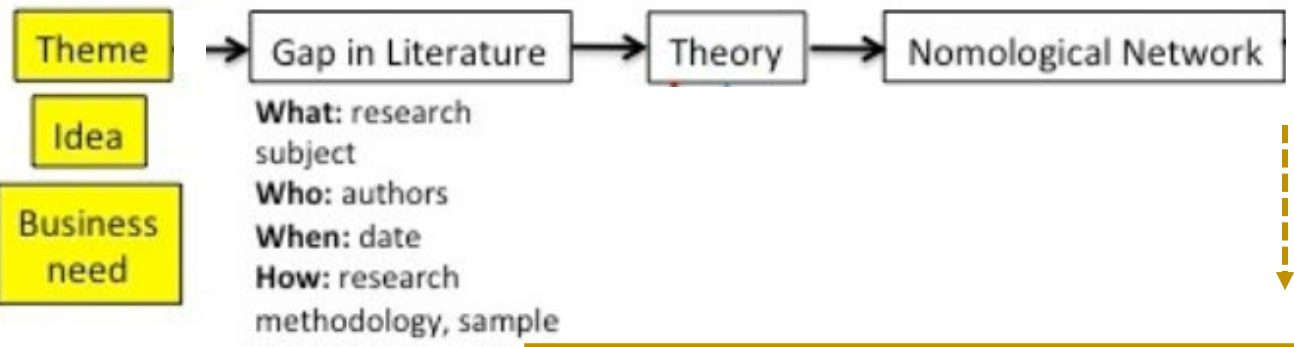
In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.

KIDS

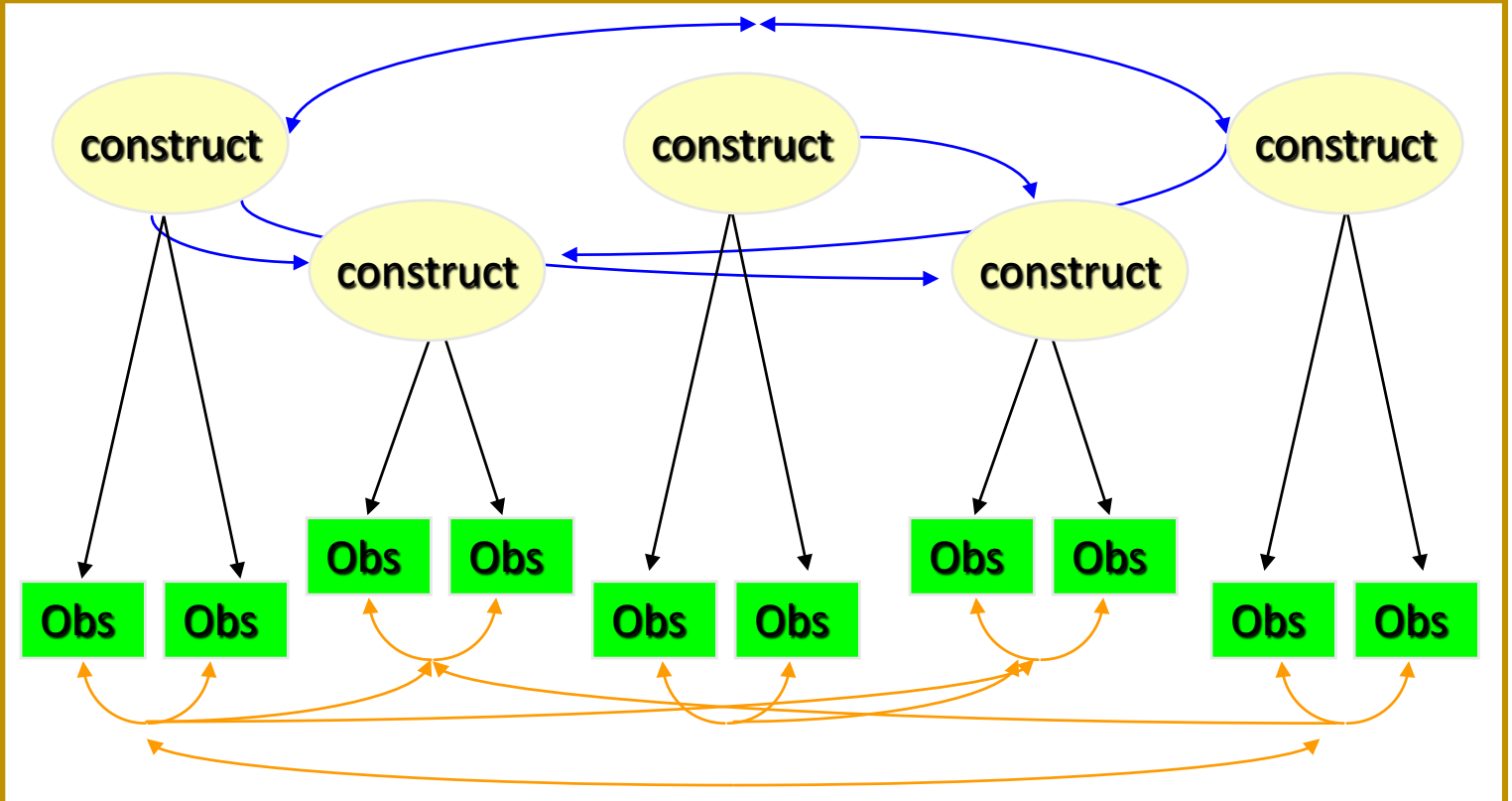


In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.

KIDS

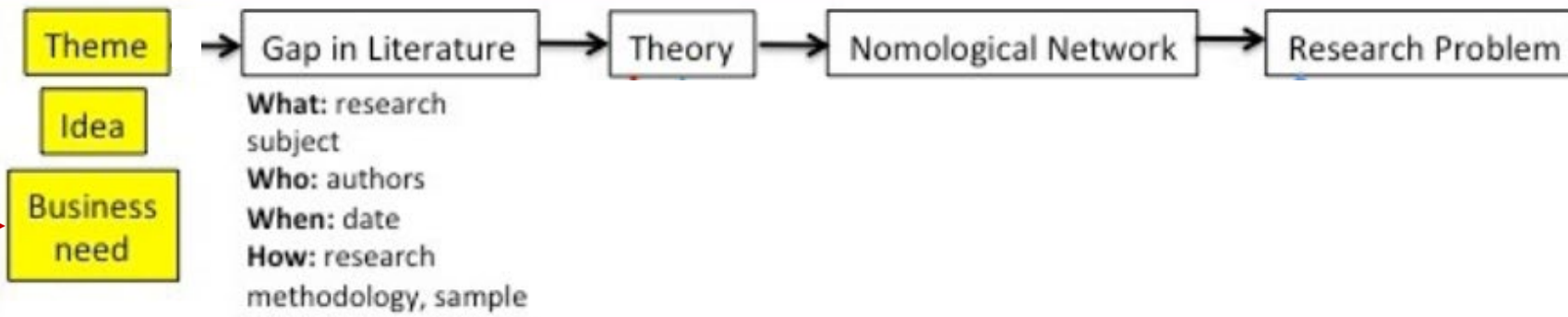


In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.

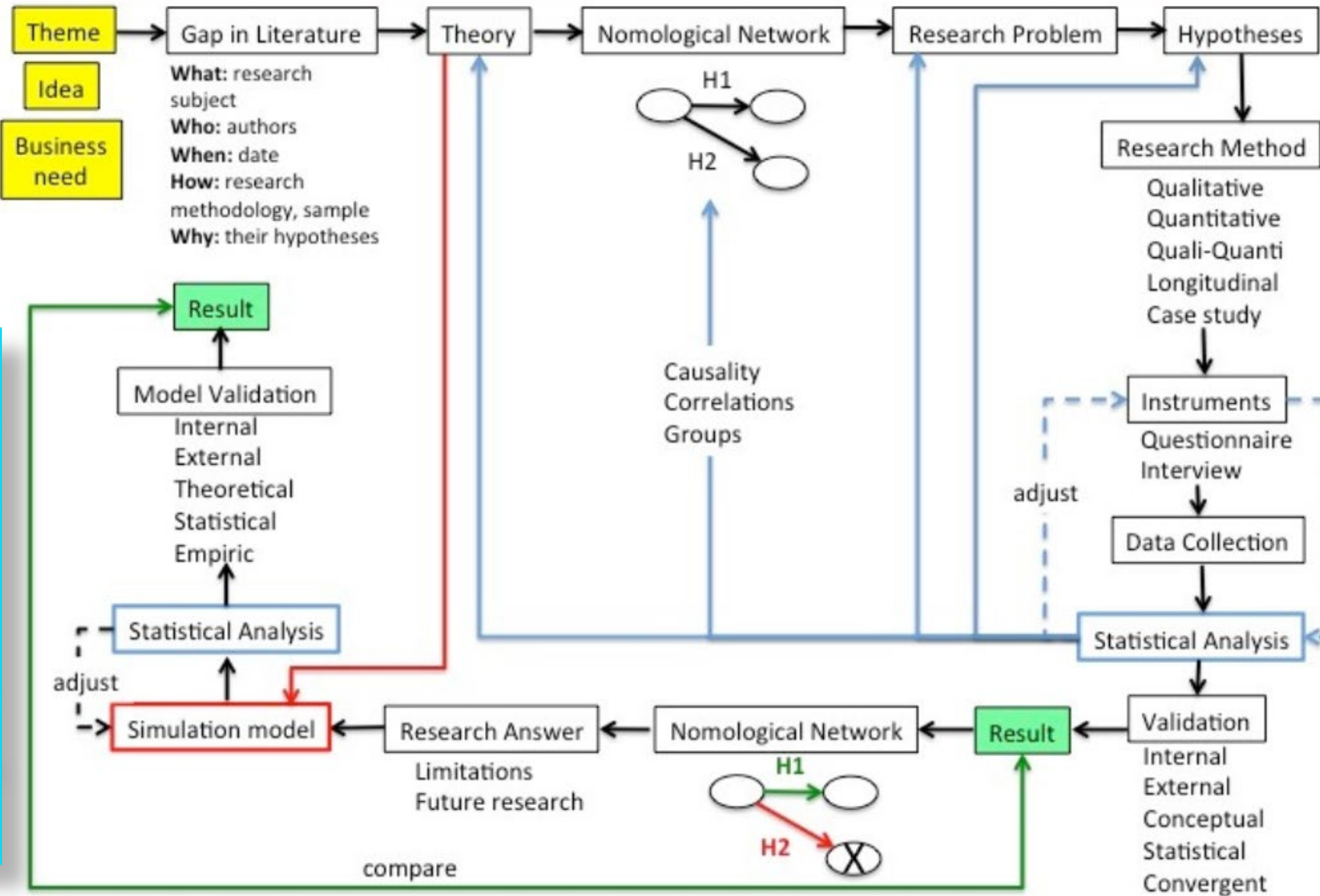
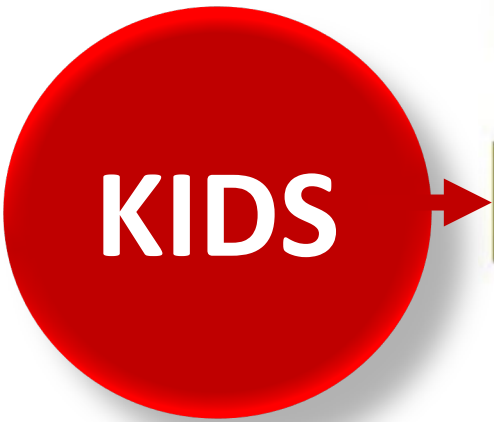


An idea circa 1955, the nomological net represents concepts (constructs) of interest, their observable manifestations and interrelationships. It appears to share common grounds with system dynamics and **knowledge graphs**.

KIDS



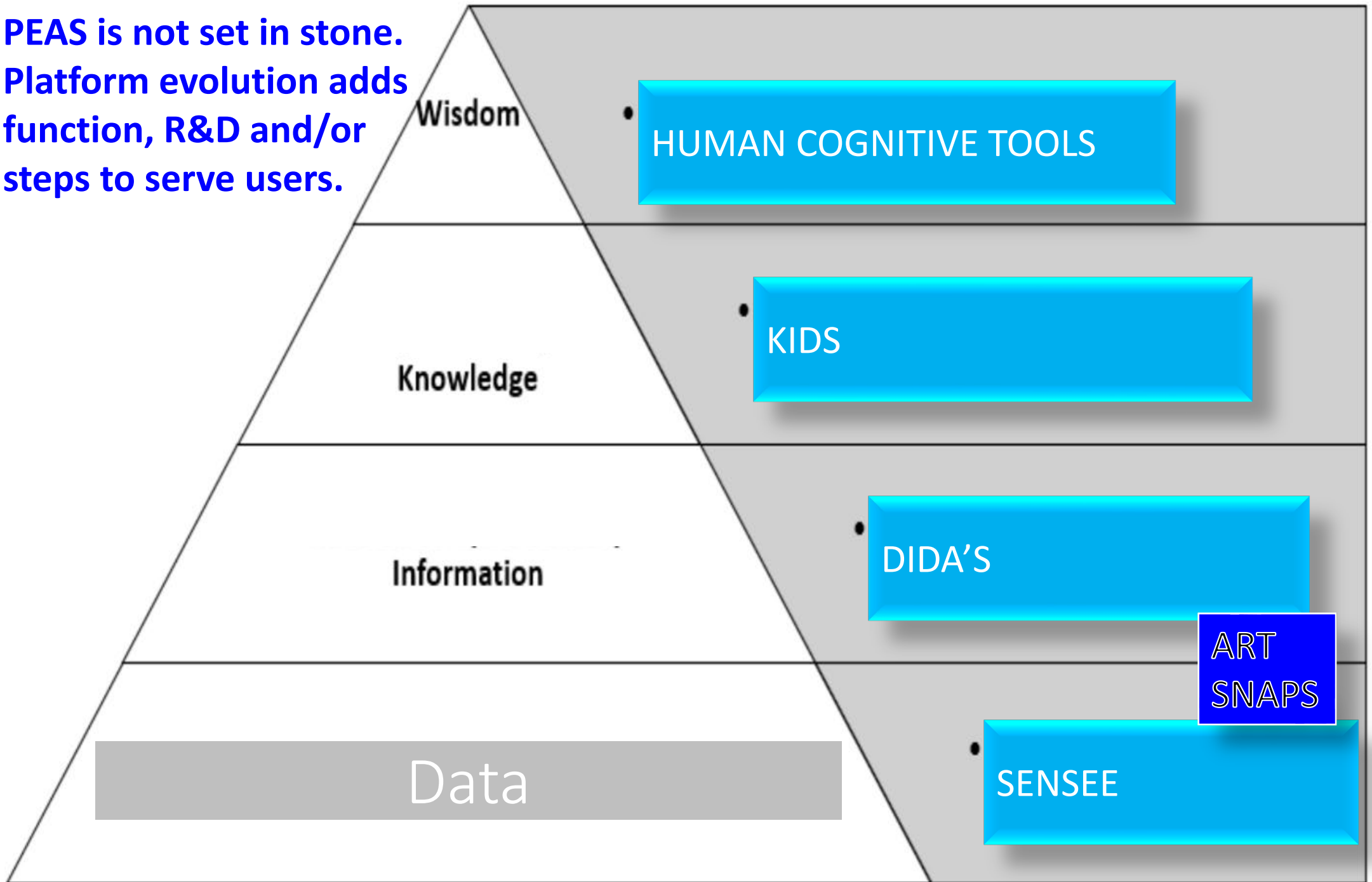
In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.

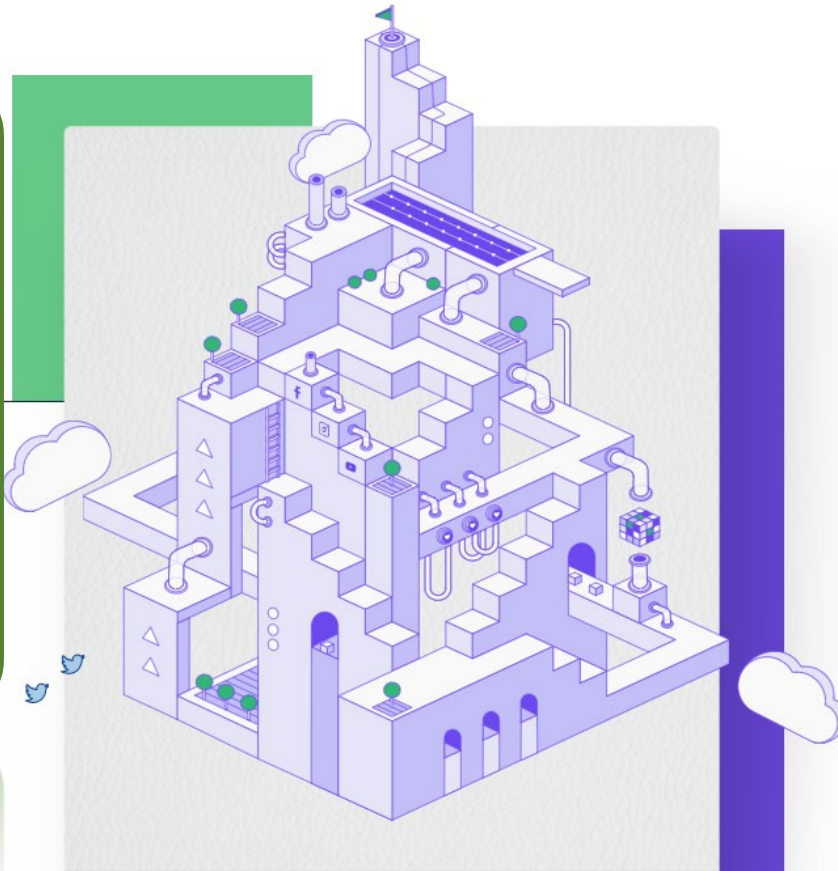
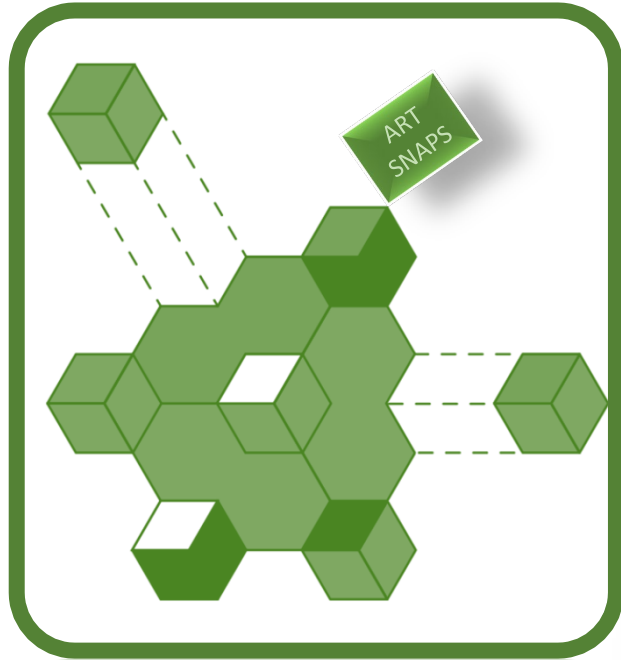


In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.

PEAS PLATFORM

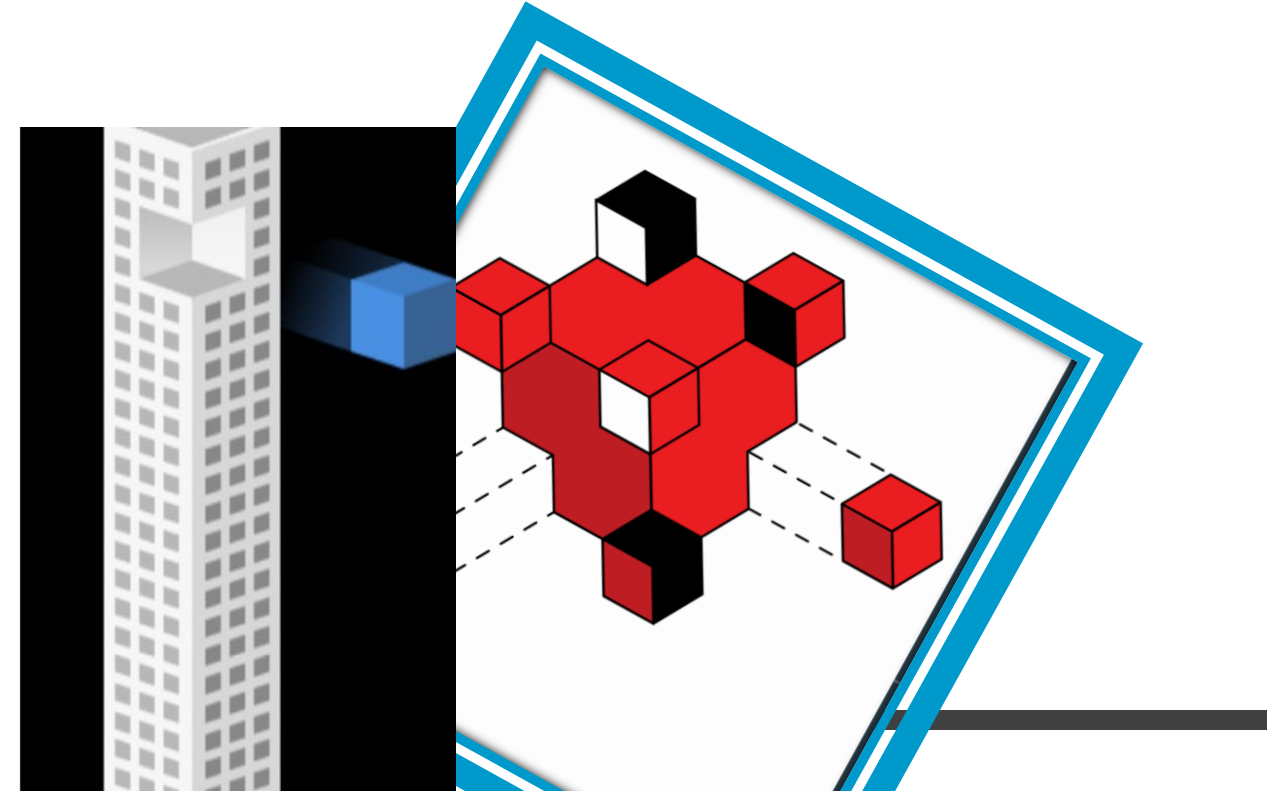
PEAS is not set in stone.
Platform evolution adds
function, R&D and/or
steps to serve users.





KNOWLEDGE SYSTEMS SOLUTIONS
ARE OFTEN MULTI-LAYERED IDEAS





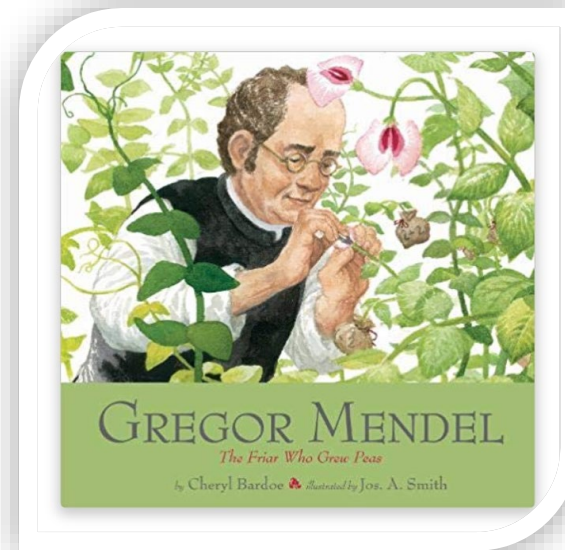
WORLD
ECONOMIC
FORUM

COMMITTED TO
IMPROVING THE STATE
OF THE WORLD

Insight Report

Top 10 Emerging Technologies 2019

http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2019_Report.pdf

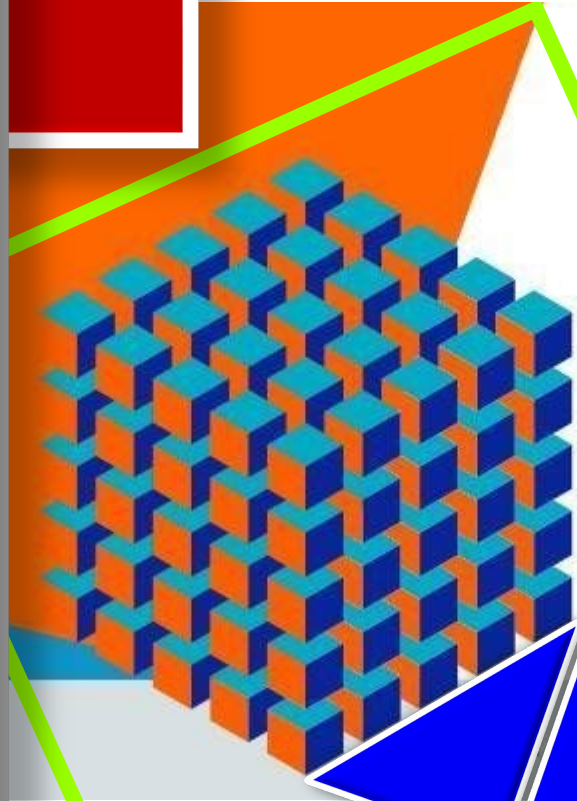


7. Advanced Food Tracking and Packaging

5. Smarter Fertilizers Can Reduce Environmental Contamination

SUMMARY

- 1) Social business entrepreneurs must recognize: Data \neq Information \neq Knowledge
- 2) Develop portfolio of ART (pareto solutions - logic tools - for the next ***billion*** users)
- 3) Context determines the perishability phase of data > information > decision > knowledge
- 4) Relationships must be relative to context before connecting relevant contextual data (R2C2)



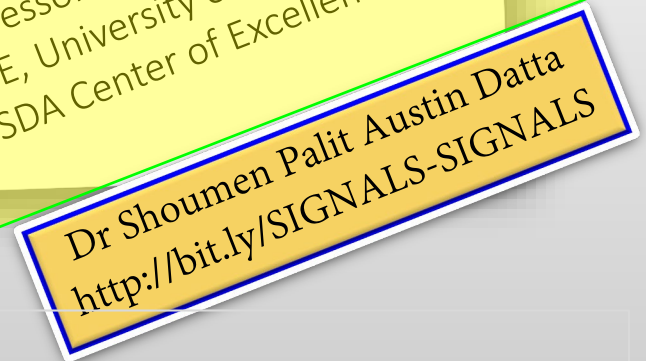
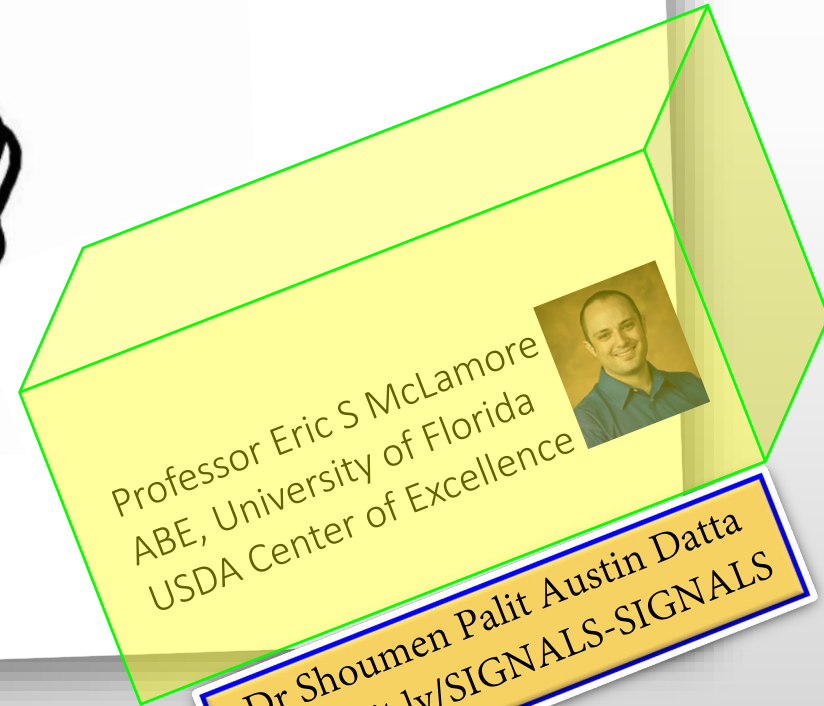
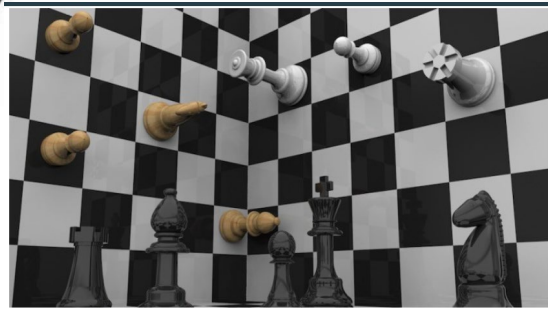
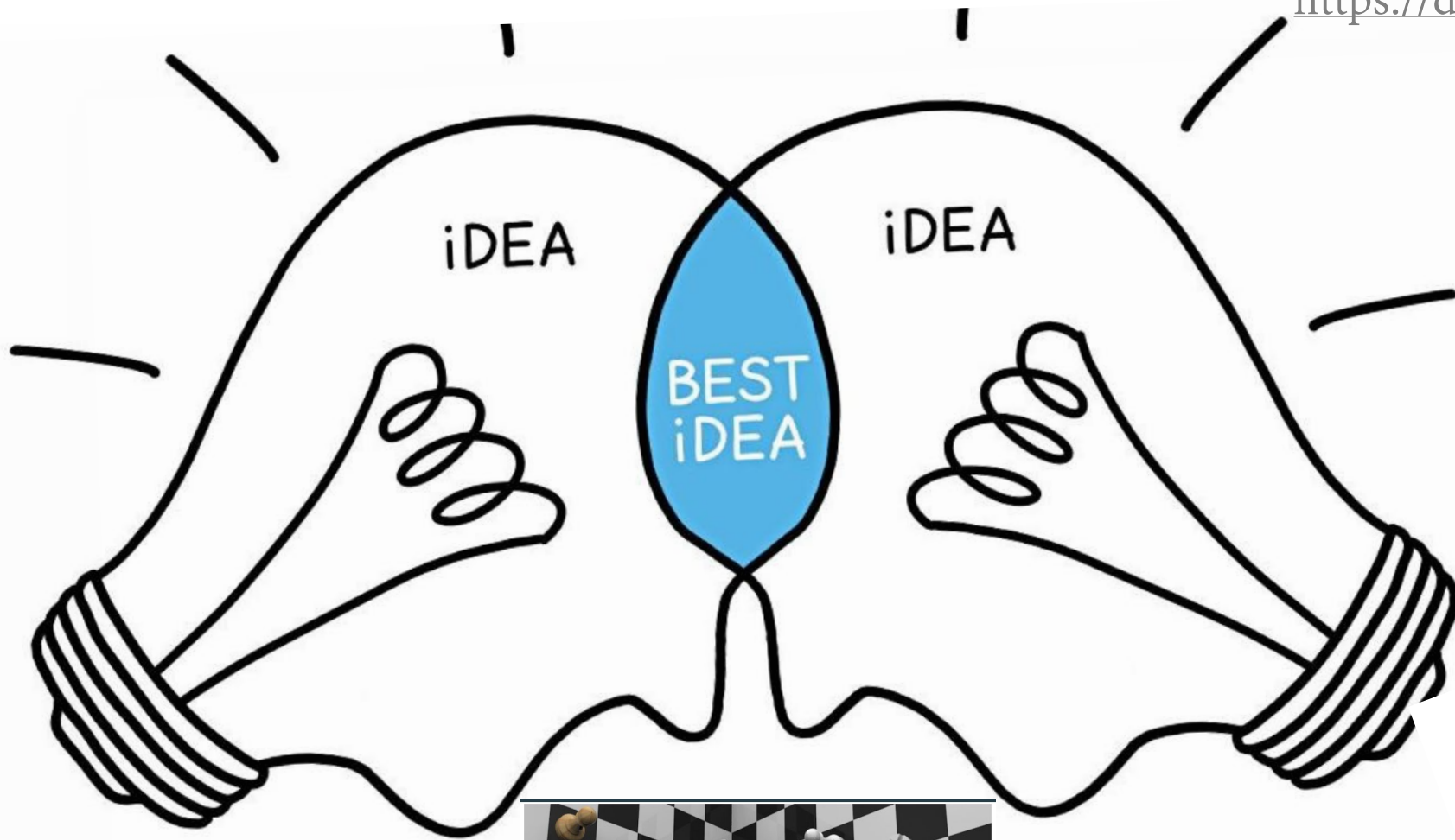
Professor Eric S McLamore
ABE, University of Florida
USDA Center of Excellence



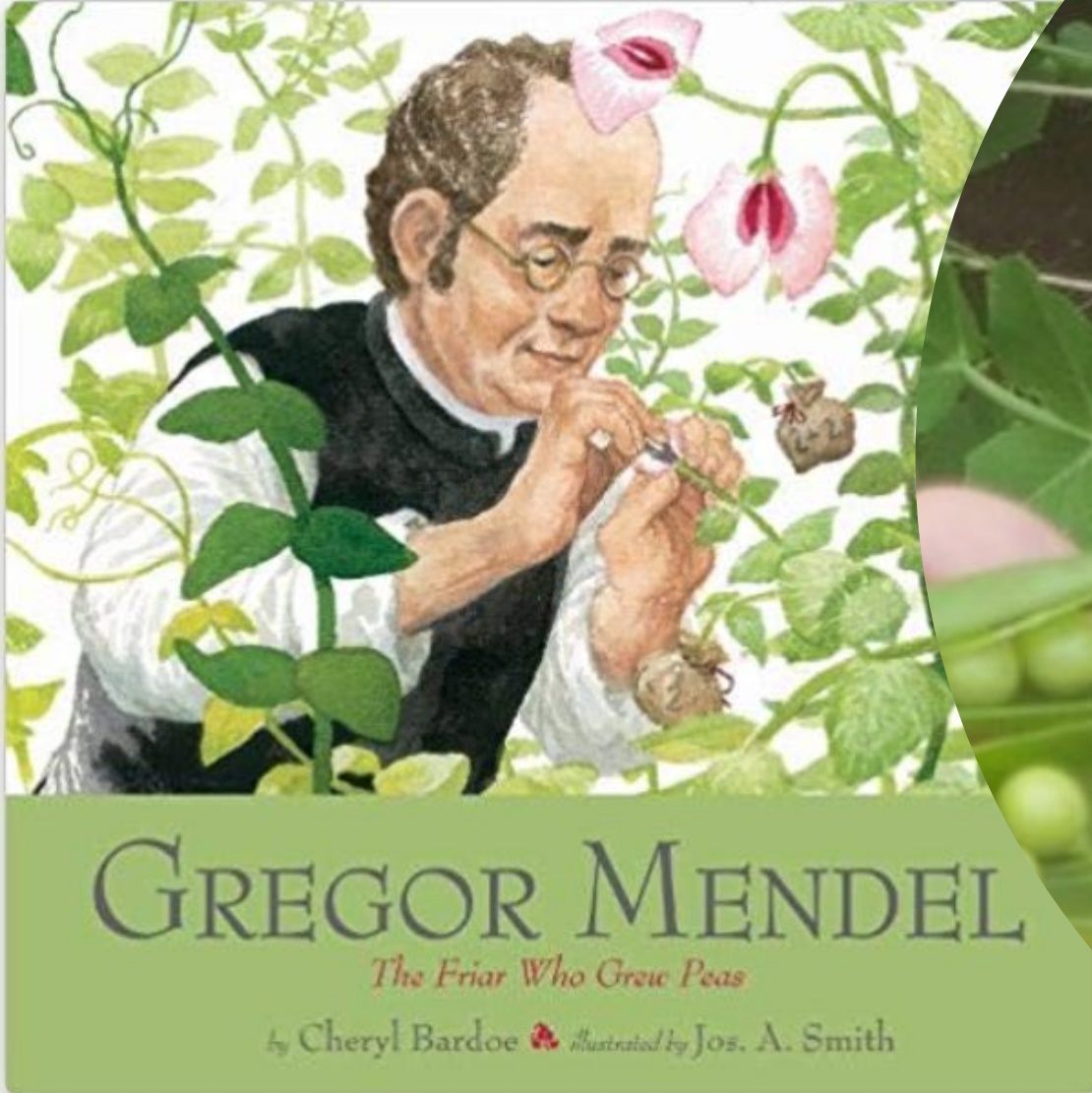
Dr Shoumen Palit Austin Datta
<http://bit.ly/SIGNALS-SIGNALS>

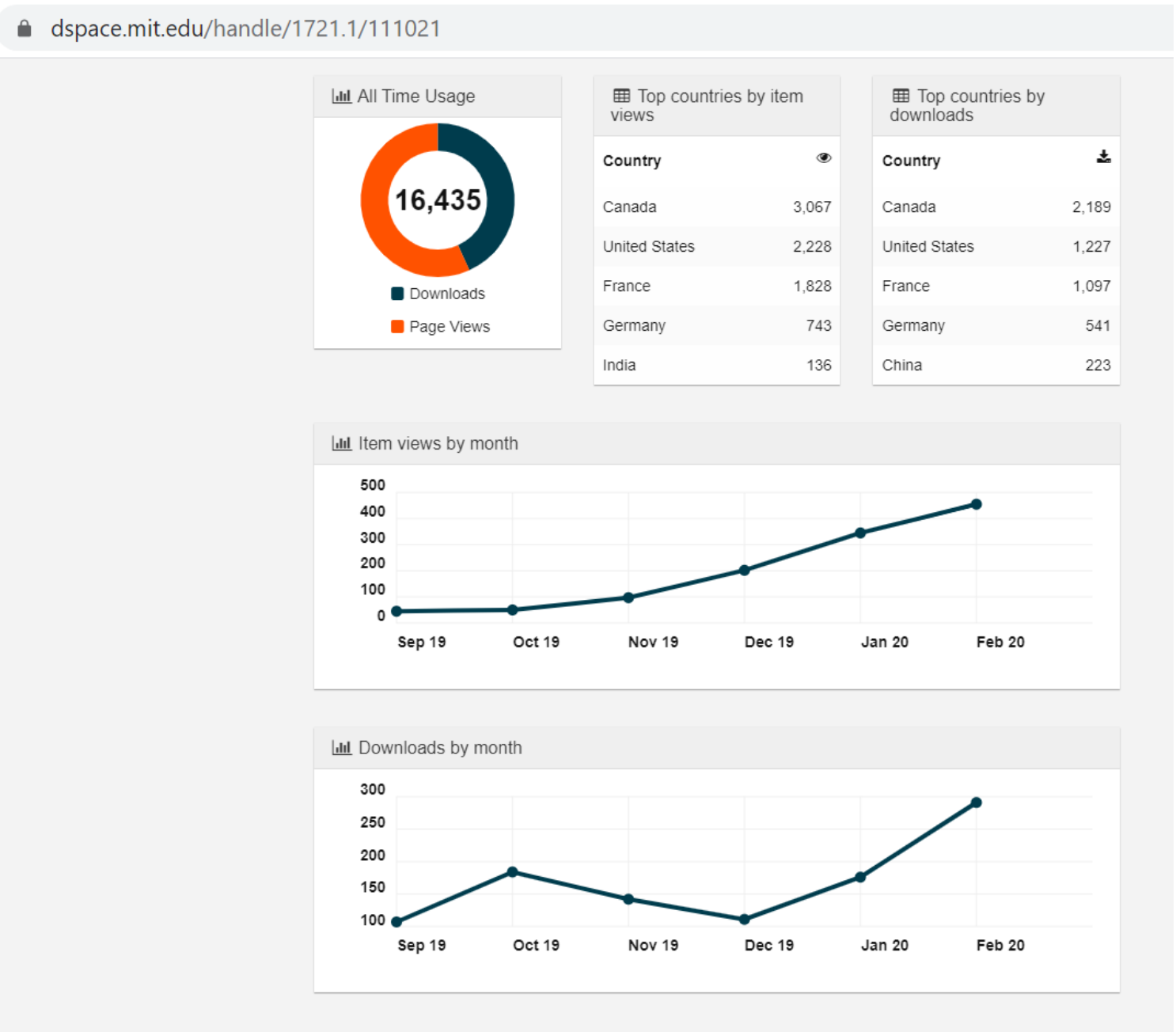
“If your actions inspire others to dream more, learn more, do more and become more, then you are an enabler.” JQA

Suggested topics for in-depth exploration:
[0] <https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-441-information-theory-spring-2010/>
[1] <https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-002-introduction-to-computational-thinking-and-data-science-fall-2016/lecture-videos/index.htm>
[2] <https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-spring-2005/>
[3] <https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-fall-2010/lecture-videos/>
[4] <https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-825-techniques-in-artificial-intelligence-sma-5504-fall-2002/>
[5] <https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-868j-the-society-of-mind-fall-2011/video-lectures/>



PEAS





Thank you for visiting the MIT Library <https://dspace.mit.edu/handle/1721.1/111021>