When Is Handcrafting Not a Curse?

by

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This position paper, with most ideas formed in 2016, has been shared within our lab since 06/2017:

https://github.com/qianli/papers

Abstract:

Recently, with the proliferation of deep learning, there is a strong trend of abandoning handcrafted systems/features in machine learning and AI by replacing them with “end-to-end” systems “learned from scratch”. These learning paradigms have achieved tremendous success. Researchers show that learning based algorithms are general — they can be applied to new domains and achieve good performance. In contrast, handcrafted systems are becoming the machine learning new “taboo” that is repeatedly criticized in recent papers. Merely motivated by the idea of critical thinking, we ask this question: are handcrafted systems really always a curse? is there any hidden merit of it?

In this short report, we discuss when handcrafted systems can in principle be used to solve tasks in new domains. We also discuss why sometimes handcrafted systems can be preferred.

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1Identical to the 06/2017 Github version with only a few typo/words corrected.
2We have two other similar papers to this, all shared internally at our Github since 06/2017. One of them was publicly released in 09/2017. These three position papers directly motivated our work on “object-oriented deep learning” and a few other handcrafted/symbolic projects in 2017.
1 Introduction: When Learning Becomes A Cult

Learning, the opposite of handcrafting, is one of the most powerful tools we discovered and it is still our favorite one. Recently, in the field of AI, there is a sweeping trend of applying learning to virtually everything with many cases of huge success. However, when people extremely like something, they tend to be against the opposite, resulting in a biased attitude towards handcrafting approaches. Here we argue that such an attitude is unnecessary. We discuss several scenarios that handcrafting approaches can be equally useful as learning or even preferred.

2 1 v.s. 0: Being Lazy Is Good; Being Too Lazy Is Not

The common deep learning doctrine is that they do not want to handcraft anything: even if they do, they are temporary — they want to learn them later if they can. This feature is heavily advertised as the advantage of deep learning: such systems can learn to solve everything instead of only improving the performance of one domain. On the other hand, handcrafted systems are heavily criticized since laborious handcrafting must be performed for every new task.

We totally agree with this strategy about being “lazy”: we do not encourage handcrafting any arbitrary AI systems, like what are used in your smart microwave/fridge. But in contrast to common deep learning view, we do encourage handcrafting one class of systems — “core AI systems”. A core AI system is defined to be something similar to Artificial General Intelligence (AGI) or anything that would conceivably lead to it. Handcrafting a smart microwave might not lead to much insight but handcrafting an AGI certainly does. In general, for something as crucial as AGI, it is unnecessary to have some partisan view against any approach — be it handcrafting or learning. As described in detail in Section 2.1 and in our “representations that learn” and “human-like learning” paper, a handcrafted AGI can still learn at a “meta” level and in principle can learn to solve any task — e.g., help you handcraft a smart microwave. This is why we focus on handcrafting core AI systems — we only need to handcraft one thing, and it can help you handcraft/learn everything else.

To summarize it, the comparison between the typical view of deep learning and our strategy is like comparing 0 and 1: instead of aiming at completely abandoning handcrafted representations (as pursued by most papers in recent years’ literature), we encourage handcrafting one thing but no more. Based on a reasonable assumption that a AGI system (either handcrafted or learned) would solve everything else for us, the total amount work we put to handcrafted systems is actually $O(1)$ instead of $O(n)$ (as commonly criticized by deep learning papers), where $n$ is the number of possible tasks we want to solve. From this perspective, handcrafting is not less efficient than learning.

2.1 Solving New Domains with Handcrafted Systems

It is commonly believed that a key advantage of systems “learned from scratch” over handcrafted ones is that they can be applied to new domains. However, as described in our “representations that learn” paper, it is possible to handcraft the system to some extent and then let it learn. Even the human brain is not completely learned from scratch. Many components are hardwired by evolution. This does not prevent humans to be universal problem solvers. In general, it should be safe to assume several priors in a general learning system: space, time, entities, properties, theory of mind, etc. These priors can be handcrafted into the system without affecting its generality. Also, from the “No free lunch theorems for optimization” [2], it is generally not possible to have an efficient learner for all possible problems. We should actively incorporate useful priors to build systems that adapt to our universe.

3By one thing we actually mean $O(1)$. There could be multiple important things that all require some hand-engineering. But we expect the total number to be a constant instead of $O(n)$. 

2
3 Handcrafted Representations As Shortcuts For Grounding and Understanding

One weakness of old school AI is that symbols are not grounded on “sensory reality”. Recently, due to the rising popularity of Visual Question Answering (VQA), there is a renewed interest in grounding language on visual representations.

However, we argue that grounding problem might be a tip of the iceberg of a much profound problem — what we call “the understanding problem”. In addition to understanding sensory entities, there are abstract concepts that do not have clear sensory correspondence: time, intention, likelihood, theory of mind, etc. Understanding these concepts does not fall into the classic realm of “grounding problem”. But the challenge is equally profound: how do we understand these concepts beyond a superficial pattern-recognition manner. Machine learning or deep learning typically adopts the hypothesis that humans “learn” to understand these concepts. But it is still a mystery how every human can understand perfectly all of these concepts given only limited sensory experience. We argue that there exists a possibility that special mechanisms are provided by evolution to facilitate understanding these concepts, in extreme scenarios evolution could just “handcraft” these representations.

From a pragmatic point of view, before we figure out the biological trick provided by evolution or how to naturally learn these concepts, we should not abandon “handcrafted” approaches — we can use them as temporary replacements to first build a full-fledged system. Such “handcrafted” representations can gradually be replaced by more natural solutions when they are discovered.

4 Neural V.S. Handcrafted Representations: Some Conjectures

It is clear that connectionism/neural systems are hard to beat in the realm of sensory and perception. However, we conjecture that: (1) pure connectionism system (i.e., all neural, no computer science concepts at all) cannot succeed soon enough in high-level tasks like reasoning, logic/math understanding, intelligent planning, etc. (2) Although it might sound glooming, neural approaches might be fundamentally inferior to symbolic approaches on above problems. In general, even humans are not very good at abstract reasoning (e.g., math) even if we try very hard to learn them. There may be a fundamental limit of how far we can get with pure neural approaches. (3) The first systems that achieve human-level general intelligence will be hybrid systems. To make this conjecture not vacuously true: “handcrafted” representations will play at least as significant roles as the neural parts in such systems.

5 When Could Handcrafted Systems Ever Be Preferred?

We note that most criticisms on handcrafted systems focus on its inferior performance. But the reality is that performance is not the only thing we care about. We argue that: (1) there is an endless pursuit of white-box understanding of intelligence. Just like Richard Feynman said: “What I cannot create, I do not understand”. Being able to explicitly handcraft every minute aspect of an AI system implies more white-box understanding of intelligence. This knowledge cannot be acquired by merely learning opaque behaviourism agents.

(2) Many difficult problems in neural approaches just vanish when it comes to handcraft/symbolic systems: e.g., catastrophic forgetting — there is no reason a handcrafted memory will forget any previous skills or experiences.

4Of course, eventually we will figure out a pure neural approach just like our brain. But it is a arguably more difficult than achieving human-level intelligence.

5Maybe people will say it is too laborious. But we can still aim at that instead of going to the “all-learning” extreme.

6The core AI system mentioned in Section 2 not any arbitrary AI systems.
Last but not least, I believe our strongest reason to choose handcrafted systems is based on a non-technical concern: AI Safety. Handcrafting might be better suited creating safe AI. In general, the more self-organized or learned components there are in a system, the less we know about how it works. Even if one day we got a black-box human-level AI, the research of AI would not end. We would work on building a more and more transparent AIs by increasingly handcrafting it until we fully understand every aspect of this system. In other words, there might be a “post-AGI” research stage that learned components in AGI are eventually replaced by handcrafted representations to ensure complete understanding and control. Regardless of our research interest, the safest outcome for humanity is that white-box handcrafted AGI are created first. In this light, handcrafted systems are generally preferred over a equally well performing learned system.

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References
