Transforming eCommerce Product Segmentation with Machine Learning

by

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Bachelor of Technology in Engineering Physics

and

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Bachelor of Science in Mechanical Electric Engineering, Master of Business Administration

SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE IN SUPPLY CHAIN MANAGEMENT
AT THE
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ABSTRACT

Inventory management is one of the key elements of supply chain management for any organization to manage costs versus service level tradeoffs. Product segmentation for inventory is therefore a key lever for inventory management. Traditionally, this segmentation is done using only a single criterion. This paper presents a framework that uses a hybrid approach combining a multi-criteria decision-making technique, analytical hierarchy process, and machine learning algorithms, support vector machines and artificial neural networks, to improve product segmentation using multiple criteria as opposed to single criteria. Our results show an addition of 20-30% SKUs that should be in 'A' class that wouldn't have been classified as 'A' products using a univariable approach. The machine learning models show an accuracy of 92.3% for linear SVM and of 86.5% for ANN with 8 nodes, with linear SVM outperforming ANN. Hence, our work demonstrates that using a hybrid model with AHP and SVM results in a flexible and customizable segmentation model that is highly beneficial for any rapidly growing company with a heterogenous product portfolio and can serve to increase the service level as well as decrease inventory costs for companies.

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1 Introduction

This section outlines an overview of the business of our sponsor, discusses the problem statement and the challenges they currently face, and highlights the motivation behind this project. We then formulate these details into our key research question and define steps for the project.

1.1 Sponsor Overview

Our sponsoring company, Heyday, is an aggregator of brands that are native to digital marketplaces such as Amazon FBA and Shopify. It acquires and incubates small but successful deliver-to-consumer (D2C) brands and helps them grow organically by providing them with capabilities such as brand management, analytics, marketing, and operations. Figure 1 outlines the core capabilities deployed by Heyday to support the growth of brands and third-party sellers as a marketplace accelerator (Heyday, 2021). Leveraging these capabilities, Heyday supports brands in business processes such as demand planning, supply planning, global logistics, operations and procurement, transport management, and distribution. Heyday combines advanced analytics and forecasting to optimize Demand, Inventory and, Operations Planning (DIOP) processes (Heyday, 2021) for its acquired brands.

Figure 1

Heyday's advanced capabilities to support growth of brands (Heyday, 2021)

The company was founded in 2020 and has been rapidly growing since then by actively expanding its portfolio of brands. Heyday's current portfolio includes around 20 digital brands with over 3,000 stock keeping units (SKUs). So far, Heyday has raised approximately $1 billion from investors and henceforth continues to grow (Heyday, 2021).

1.2 Motivation and Problem Statement

Inventory management is one of the key elements of supply chain management for any organization. Controlling inventory helps integrate upstream processes such as manufacturing and purchasing with downstream activities such as demand and sales, thereby decreasing stock-out incidents and inevitably increasing customer satisfaction. In today's competitive market, companies are increasing their portfolio of SKUs to attract more customers, increase sales, and capture more market share, by offering buyers more choice. However, the large portfolio size also affects their inventory, since adding a greater number of items to the offering leads to companies holding obsolete or slow-moving inventory. This trend is especially relevant in the e-commerce industry, where most of the brands operate digitally. Therefore, there is a need to classify SKUs and segment them in order to efficiently manage the inventory.

Inventory segmentation or classification refers to classifying and segmenting inventory items (SKUs) into various categories, based on one or more characteristics of these items, to define optimum service level at a category level as opposed to a product level. Service level is defined as the probability of not stocking out. Even moderate-sized companies these days usually deal with hundreds to thousands of different items, and therefore it is inefficient and almost impossible to control inventory for each and every item.

At present, Heyday uses an undifferentiated policy that calls for a high service level across all SKUs. However, not all SKUs require the same service level, and few may require higher or lower service levels depending on a variety of factors. With its growing and heterogeneous portfolio of SKUs, Heyday needs a strong framework that can categorize the SKUs appropriately and enable them to define service level and control inventory for the most critical SKUs.

For inventory segmentation to work properly, the first step is to define the relevant characteristics (or attributes) that will determine the priority of each item in inventory (Kartal et al., 2016). These characteristics could include annual dollar value, lead time, unit cost, storage cost, demand, volatility, inventory level, inventory turnover and criticality. Potential methods for identifying and quantifying relevant characteristics include multi-criteria decision-making techniques such as simple additive weighting (SAW), and analytic hierarchy process (AHP). Once the relevant criteria are defined, the next step is to define a classification algorithm suitable for the product portfolio. This can be achieved by using machine learning algorithms such as Bayesian networks (BN), k-nearest neighbor (k-NN), support vector machines (SVM) and artificial neural networks (ANN) (Kartal et al., 2016).

In conclusion, Heyday is faced with two challenges: identifying attributes of SKUs that are most relevant for segmentation and building a segmentation model that is optimal for e-commerce marketplace brands and fast-moving consumer goods.

1.3 Key Research Question

The goal of our project is to define an inventory segmentation framework for the company's 3,000+ SKUs to define optimal service level for each segment.

Therefore, the key research questions for this project are:

1. What are the relevant criteria (attributes) for SKU segmentation for a digital marketplace accelerator?
2. What frameworks could be used to identify relevant criteria and attributes for the SKU segmentation in e-commerce, consumer packaged goods industry?
3. How could a model/framework be defined to classify SKUs and predict classes/segments for SKUs within a growing heterogeneous portfolio?

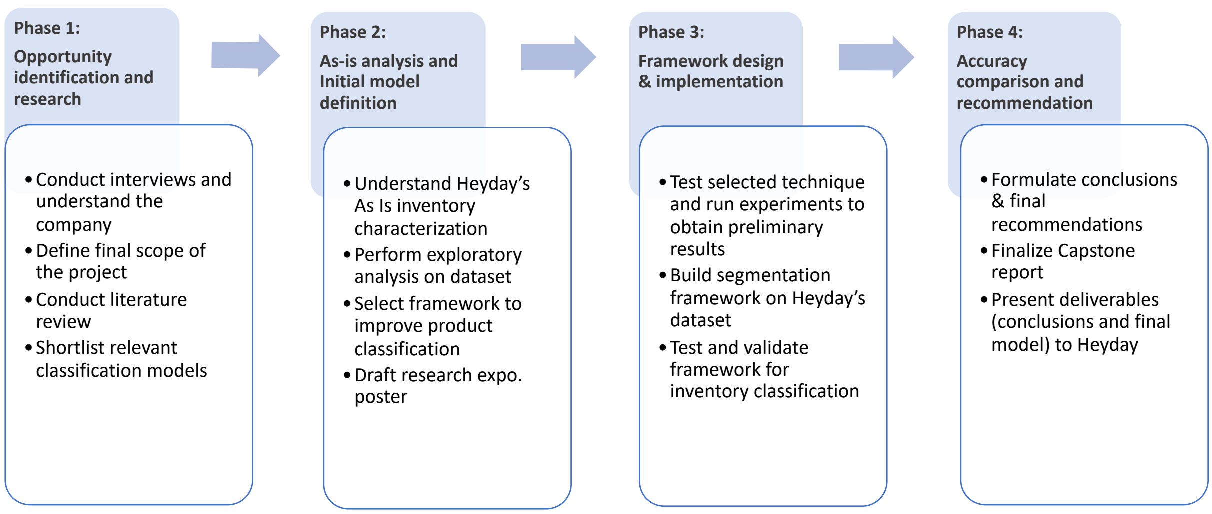
1.4 Project Steps

To efficiently manage the project, we developed a four-phase approach. The first phase is **opportunity identification and research**, focused on understanding the company, scoping the goal, and reviewing literature to identify and shortlist the different segmentation techniques. The second phase is **as-is analysis and initial model definition**, where we do the as-is mapping of the processes, perform exploratory analysis on Heyday's data sets. After initial analysis, we go into the third phase, **framework design and implementation**, where we test the selected techniques by running experiments on multiple samples and build the segmentation framework. Finally, in the fourth phase **accuracy comparison and**

final recommendation, we compare our segmentation with the current state, measure improvements and provide Heyday with our final recommendations. Figure 2 captures this approach in detail along with key tasks covered in each phase.

Figure 2

Flowchart depicting the Four Phase Approach towards the Project



2 Literature Review

The purpose of this section is to present the literature published on inventory classification techniques to identify the latest models and tools that have been developed. Once these models are identified, we select the most suitable technique to create an inventory classification framework that aligns with Heyday's business model and contributes to their business goals.

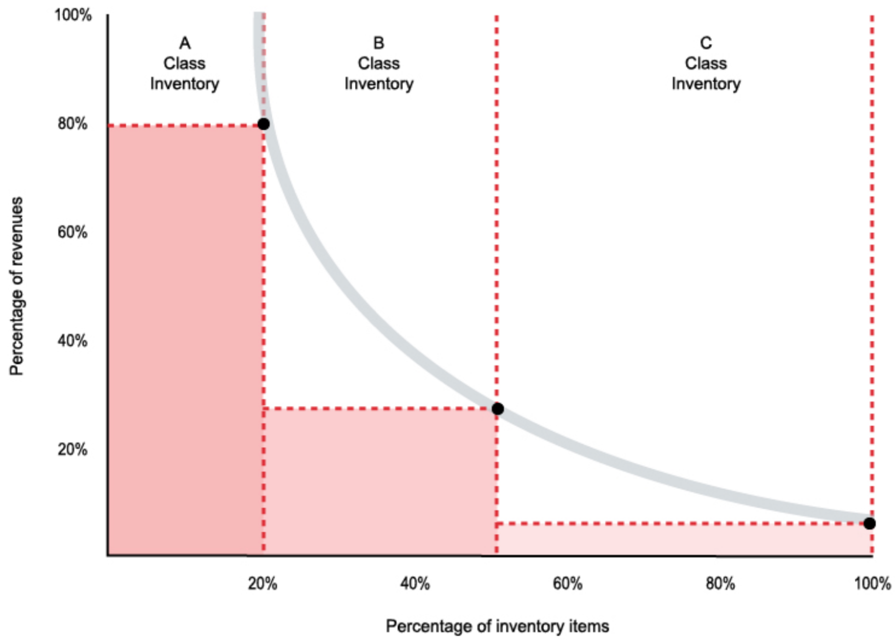
2.1 Traditional ABC Classification

The most commonly used classification technique for inventory uses the ABC analysis, which is based on Pareto's 80-20 principle. This method classifies inventory items into three categories based on the annual use value or revenue. Class A consists of 15–20% of items that contribute to a large amount of annual use value. Class C consists of 70–80% of items that contribute to a very small amount of annual use value. Class B consists of everything in between.

The key benefit of classifying inventory using the ABC method is that it leads to more efficient inventory counts and assures that inventory levels of highest-value items are consistently maintained when closely monitored. More details on inventory policies for these classes can be found in textbooks such as Silver et al. (1998). A typical classification structure looks like the one shown in Figure 3.

Figure 3

Traditional ABC Inventory Classification, based on Pareto's 80-20 principle (Rankin, 2020)



ABC classification is highly applicable in cases of homogeneous portfolios where the dominating differentiation between items is based on their dollar value. However, as noted earlier in section 1.2, most companies deal with a large and heterogeneous portfolio of SKUs; hence many other characteristics of SKUs such as lead time, criticality, demand, durability, unit price, etc. become increasingly important in deciding inventory position, and ABC analysis might not be sufficient.

2.2 Multi-Criteria Inventory Classification

Many studies emphasize that companies that deal with large number of SKUs need to consider multiple criteria for inventory classification, also known as Multi-Criteria Inventory Classification

(MCIC) (Ramanathan, 2006). Several complex techniques have been proposed for conducting MCIC analysis. These techniques broadly fall under the following categories:

1. Optimization
2. Multi-criteria decision making (MCDM)
3. Machine learning (ML)
4. Hybrid models using multi-criteria decision making and machine learning

2.2.1 Optimization of inventory classification

Over the years, several optimization models have been proposed for inventory classification including weighted linear optimization by Ramanathan (2006) and simple optimizer model by Ng (2007).

These models involve subjective assignment of weights to the different criteria done manually by a decision maker and then optimization is performed using those assigned weights. While these optimization methods are easily interpretable by inventory managers, they require a lot of effort from decision makers, especially in cases the number of criteria is large. Furthermore, these models fail to include categorical data points and therefore miss out on many of the characteristics relevant in inventory management.

2.2.2 Multi-criteria decision making

Previous work in inventory management also includes multi-criteria decision-making techniques such as analytic hierarchy process (AHP) (Saaty, 1980), DEA-discriminant analysis

(Tavassoli et al., 2014), and fuzzy analytics (Baykasoğlu et al., 2016). AHP uses both qualitative and quantitative criteria for classification and requires subjective judgement to rank relative importance of elements into numeric value. These methods, while efficient, require management to spend a huge amount of time on developing information about each SKU.

2.2.3 Machine learning

With the rapid adoption of machine learning for large corpus of data, techniques such as k-nearest neighbor (k-NN), support vector machine (SVM) (Baykasoğlu et al., 2016), and artificial neural networks (ANN) (Yu, 2011) have been applied for inventory management. The k-nearest neighbor approach requires manually choosing appropriate distance metrics between data samples, which can be tedious for a dataset with large set of features. Both SVM and ANN can be employed to find a non-linear function approximation to estimate the class of the input inventory, which is significantly more powerful than heuristic or linear methods. Yu compares the performance of all three of these techniques on a dataset of 47 disposable SKUs (Yu, 2013). Artificial neural networks have also been previously used for inventory classification in the pharmaceutical industry (Partovi & Anandarajan, 2002).

2.2.4 Hybrid models using multi-criteria decision making and machine learning

Recently, a hybrid model that uses both multi-criteria decision making techniques and machine learning algorithms has been developed by Kartal et al. (2016) and demonstrates promising accuracy in multi criteria inventory classification. The authors initially conduct the ABC analysis using three different multi-criteria decision-making methods, simple additive weighting (SAW), Analytic Hierarchy Process (AHP), and VIKOR (Opricovic, 1998). The curated ABC classes using these methods are then used as the target labels for machine learning methods such as Naïve Bayes, Bayesian networks, support vector machine, and artificial neural networks (ANN). They show that support vector machines and ANN outperform all other techniques. Table 1 below lists a summary of all the models reviewed along with their advantages and limitations.

Table 1

Summary of Models assessed during Literature Review

Model	Advantages	Criteria used	Limitations	References
Classical ABC classification	Optimizes for max. revenue	Dollar usage	- Only successful when inventory is fairly homogenous and when the only difference between items is its annual use value (price*volume)	Silver et al (1998)
ABC with bi-criteria matrix approach	- Can classify the inventory based on more than one criteria and offers less complexity	Dollar usage with Criticality/Unit cost	- Becomes increasingly complicated for three or more criteria to classify inventory items - Equal weights of all criteria taken into account	Mitra, S., Pattanayak, S. K., & Bhowmik, P. (2013)
Multi-criteria ABC with Weighted Linear Optimization (Simple Additive Weighting SAW)	- Incorporates more than one criteria for heterogeneous portfolio - Simple model that can be easily understood by inventory managers.	Average unit cost, Annual dollar usage, Criticality & Lead time	- Can be outperformed by other methods	Ramanathan, R. (2006)
Multi-criteria inventory management using Analytic Hierarchy Process (AHP)	- Uses both qualitative & quantitative criteria for classification - Uses subjective judgement to rank relative importance of elements into numeric value	Annual demand, Unit price, Annual usage value, Unit weight of the component & Shape of the component	- Involvement of subjectivity can induce bias in the analysis - Subjective analysis is time consuming and costly	Flores, B. E., Olson, D. L., & Dorai, V. K. (1992)
Simulated annealing (integrating inventory classification & policy design)	- An integrated method to simultaneously classify inventory items and optimize an efficient control policy - Better than the initial ABC classification method	Annual dollar usage, Average unit cost & Lead time	- Joint optimization of classes and control policy may not be a desired solution - Optimization time can be fairly high as the sample size of the dataset increases	Mohammaditabar, D., Ghodsypour, S. H., & O'Brien, C. (2012)
Support Vector Machines for Multi-Attribute ABC Analysis	- Computational complexity does not depend on dimensionality of the input space - Less prone to over fitting when parameters are used effectively	Risk, Demand fluctuation, Average stock, Daily usage, Lead time, Consignment stock, unit cost, Unit size	- Decision is based on support vectors, and often does not represent all the input	Kartal, H.B., Oztekin, A., Gunasekaran, A., & Çebi, F. (2016)
Multiple Criteria Inventory Classification Based on Principal Components Analysis and Neural Network	- Uses interpretable dimensionality reduction approach, principal component analysis to generate features - Uses non-linear method (ANN) on top of generated features	Unit price, Ordering cost, Demand, Lead time	- PCA may not be useful for data with very few features - ANNs offer no interpretability of how the decision was made for predicting the class	Lei, Q. S., Chen, J., & Zhou, Q. (2005)
Multiple Criteria Inventory Classification Based on Bayesian networks	- Represent the probabilistic relationships between inputs and output - Low complexity, high scalability, linear computational time	Risk, Demand fluctuation, Average stock, Daily usage, Lead time, Consignment stock, unit cost, Unit size	- Independence assumptions between the features seldom satisfied in practice - Dependencies among variables cannot be evaluated	Kartal, H.B., Oztekin, A., Gunasekaran, A., & Çebi, F. (2016)
Multi Criteria decision making through integration of Fuzzy AHP and Artificial Neural Network	- Able to capture the vagueness of human thinking and to aid in solving the research problem through a structured manner and a simple process	Unit Price, Annual Demand, Criticality, Last Use Date & Durability	- Involvement of subjectivity can induce bias in the analysis - Subjective analysis is time consuming and costly	Kabir, G., & Akhtar Hasin, M. A. (2013)

2.3 Inventory Segmentation in eCommerce and CPG industries

In the case of B2C e-commerce companies, Patil and Divekar (2014) performed a study on various companies with the following findings. E-commerce has raised consumers' expectations and supply chains are becoming more reliant on effective inventory management strategies to avoid impacting customer satisfaction. Their study focused on late-delivered items and highlights the importance of balancing the tradeoff between inventory availability and consumer satisfaction in e-commerce businesses. In their recommendations, inventory classification is listed as one of the many strategies that B2C eCommerce companies can use against some of the problems that arise in the process of inventory management.

In the case of consumer-packaged goods (CPG), a study done by Jiang and Stevenson (2017) identified that the most comprehensive and viable method of segmenting inventory was through AHP using velocity, volatility, and profit margin factors to determine and improve customer service levels. While the dual matrix analysis and clustering showed similar results, AHP was deemed better as it allows for more flexibility in case the number of relevant factors to be considered were to increase or decrease as well as the ability to customize class size.

Pannu's (2021) research on segmentation of fast-moving consumer goods for a third-party provider stated dynamic ABC inventory classification using auto-regressive integrated moving-average (ARIMA) forecasting outperformed naïve classification using historical data. While the thesis was focused on dynamic storage for picking activities, which have the highest volatility in the warehouse, it is interesting to consider the possibility of using forecast data over historical data for typical inventory segmentation.

2.4 Conclusion from Literature Review

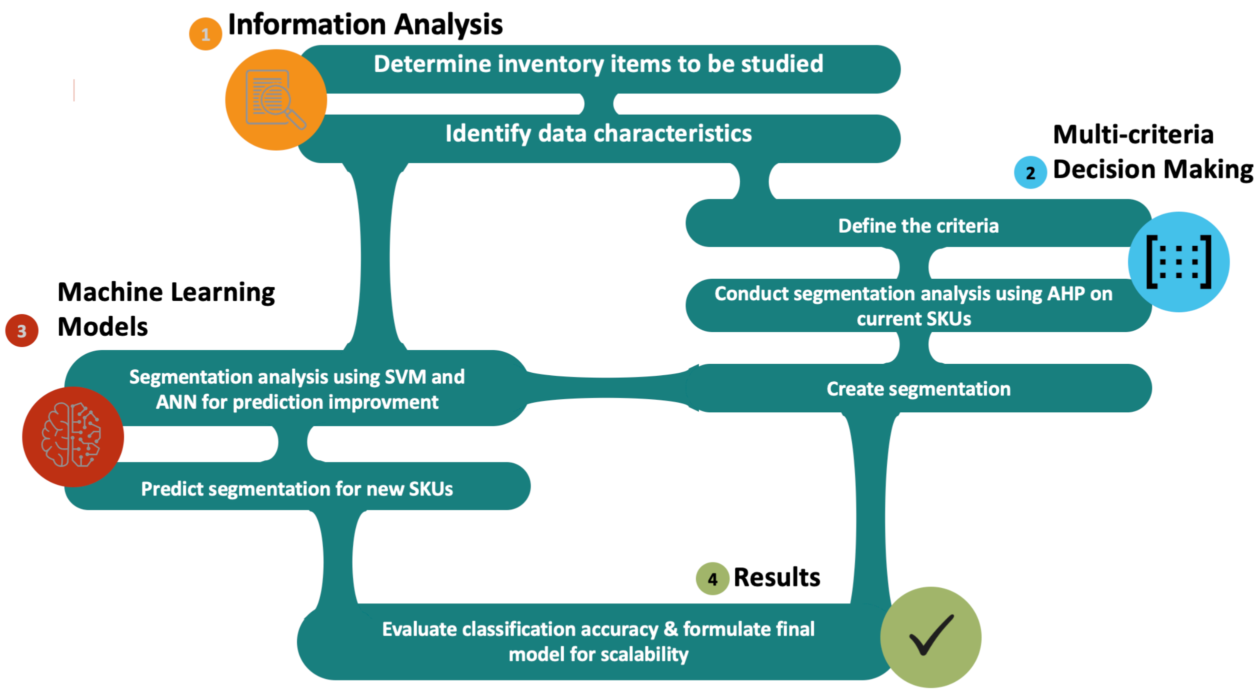
Our review of the existing literature on inventory classification strongly suggests the use of a multi-criteria decision-making techniques for identifying relevant attributes, possibly analytic hierarchy process in order to capture categorical characteristics of the SKUs. This would be combined with machine learning algorithms such as support vector machines or artificial neural network to predict classes. We believe that these methods would be successful for segmentation of fast-moving, highly volatile SKUs such as in the eCommerce or CPG industry.

3 Methodology

Heyday is looking for a way to segment their diverse portfolio to improve their service level as well as inventory management. To do the right segmentation, it is important to first understand Heyday's product portfolio and information to select the criteria that will be used to segment their inventory. After this, we use analytic hierarchy process (AHP) to create curated segmentation classes that will serve as the base of machine learning methods. We then test support vector machine (SVM), and artificial neural networks (ANN) for prediction accuracy on actual sales as well as forecasted sales data. Finally, we evaluate the classification accuracy and formulate the final segmentation. Figure 4 outlines the four-step methodology that we have curated for our segmentation analysis.

Figure 4

Four Step Segmentation Methodology for Inventory SKU Segmentation



3.1 Information Analysis

To begin creating the segmentation model, we began by understanding the current inventory management system deployed by Heyday and that their current segmentation was focused on having a very high service level target across all SKUs and brands. However, it is important to mention the diversity of their fast-growing portfolio and why segmentation was required. Heyday's portfolio includes over 15 digital brands and more than 3,000 distinct SKUs. While their inventory segmentation was a classic ABC analysis with almost equal service level targets, Heyday had assigned over 60 product categories and more than 100 subcategories that were combined into almost 150 unique product types. As we did not utilize all the categories and subcategories for our segmentation strategy, it brings to light the diversity and complexity of Heyday's portfolio. Heyday uses various third-party logistics vendors (3PLs) for storage and distribution, but to design the segmentation strategy we consolidated all the demand and didn't consider capacity constraints.

The analysis of their information helped us understand Heyday's model and choose the criteria to be used in the next step in accordance with the literature review, as well as Heyday's input. Finally, it is important to mention that since Heyday is an e-commerce business with a very fast-growing portfolio, we will try Pannu's 2021 approach of running the models both with actual sales as well as forecasted sales, to compare results. For actual sales we will be using forecast sales from 2021, since Heyday's demand forecast uses a rolling forecast of over 100 weeks; this will be our input for running the forecasted sales model when comparing results.

3.2 Multi-criteria decision making

As previously mentioned in Section 2.2.4, multi-criteria decision making, particularly AHP, give some of the best results for inventory segmentation, especially when used in consumer goods industries. As one of the main goals for segmentation is to improve customer service, we will be testing Jiang's & Stevenson's (2017) suggestion of velocity, volatility, and profit margin as well as testing some of the criteria by Flores et al. (1992), such as annual demand, unit price, and a criticality factor to mix qualitative and quantitative factors. This will allow us to leverage AHP's key advantage: taking into account subjective inputs from decision makers.

We will outline Zahedi's AHP methodology as cited by Subramanian and Ramanathan (2012):

- **STEP 1:** Structuring of the decision problem into a hierarchical model
  - The problem is decomposed to form a hierarchical model with a minimum of three levels (goal, criteria C_j, and alternatives L_n)
- **STEP 2:** Making pairwise comparisons and obtaining the judgmental matrix
  - Elements of a particular level are compared with each characteristic of the immediate upper level
  - Elements will be compared pairwise and assigned an attractiveness ranking in accordance with Heyday's priorities
  - Each entry a_{ij} of the judgmental matrix is governed by three rules:

$$a_{ij} > 0 \tag{1}$$

$$a_{ij} = 1/ a_{ji} \tag{2}$$

$$a_{ii} = 1$$

(3)

- **STEP 3:** Calculating local weights and consistency of comparisons
    - Local weights are calculated using the eigenvector method (EVM)
    - The normalized eigenvector corresponding to the principal eigen value of the judgmental matrix provides the local weights of the elements.
- **STEP 4:** Aggregating weights across various levels to obtain the final weights of alternatives
    - Once the local weights of elements of different levels they are aggregated to obtain the final weights of the decision alternatives through the following hierarchical aggregation rule.

$$L_1 = \sum_j [(Weight\ of\ L_1\ with\ respect\ to\ Criterion\ C_j) * (Importance\ of\ Criterion\ C_j)] \quad (4)$$

    - The weights of the alternatives and criteria are normalized

After completion, these aggregation weights will be used as the base for the next step of our machine learning models.

3.3 Machine Learning Models

Once we have the segmentation from AHP, we will use this to develop a supervised learning model using either support vector machines or artificial neural networks in order to predict classes for new datasets. The two techniques are further elaborated hereunder.

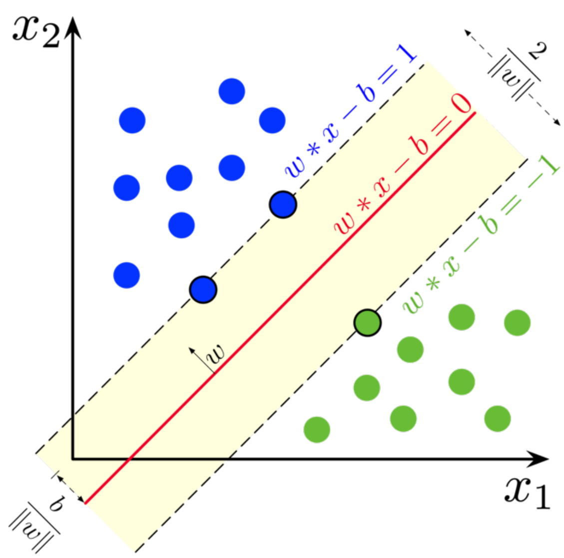
3.3.1 Support Vector Machines

One of the most widely used machine learning algorithms is support vector machines (SVM), which was developed by Vladimir Vapnik (1995). It has been applied to many problems in supply chain management and has consistently performed well.

SVM is a classification algorithm which uses previously defined classes or categories, y, and takes the attributes, x, as input to find the optimal hyperplane to divide the training data. This hyperplane is then used to determine the class for a new test datapoint. In the case of a binary classification problem, the hyperplane takes the form of a line, as illustrated in Figure 5. The line defined by the slope **ω** with an offset of b. The two classes can be identified on either side of this hyperplane.

Figure 5

Toy depiction of a binary classification problem using linear SVM (Rankin, Sebastien, 2020)



In this setup, the points belonging to both classes that are closest to the hyperplane are called the support vectors, and their distance to the hyperplane is known as the margin. Our objective with a SVM is to maximize our accuracy by maximizing the margin from the support vector to the hyperplane while minimizing the norm of weights $||w^2||$ (Kartal et al., 2013).

While linear SVM can be helpful in understanding the concept, it is often found to be limiting for real world datasets, as the classes may not be linearly separable. Kernel SVMs are the common solution to this problem, where the kernel ϕ is a function which transforms an input x_i to a transformed space x_i'. The points in this transformed space are linearly separable, resulting in the following optimization problem:

$$\min_{\omega,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i$$

$$y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i \tag{5}$$

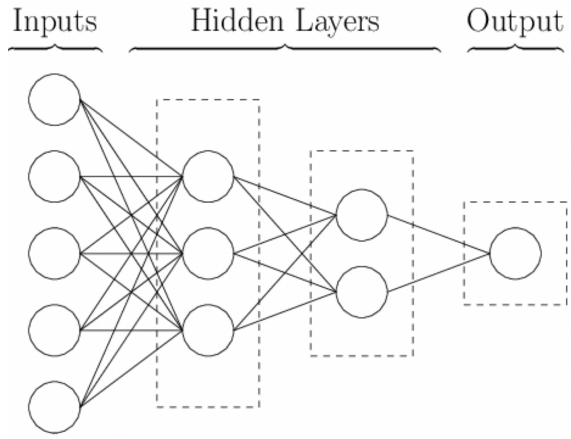
Where *C* is the regularizing term controlling the summation of the correct distance of all points to the hyperplane, denoted as ζ_i.

3.3.2 Artificial Neural Network

Artificial neural networks (ANNs) are loosely inspired by the human brain, in that a collection of neurons is arranged in a particular graph, with weights “learned” using the training data. Fully connected artificial neural networks (Partovi & Anandarajan, 2002) take as input a k-dimensional feature vector x_i and outputs a single score, which can then be used as a threshold to compute the resulting class. The network is composed of L hidden layers where each layer comprises of a set of neurons. Each neuron performs a linear function, $w^T x + b$, followed by an activation function such as Rectifying Linear Unit (ReLU) which is $\max(0, \text{input})$. Repeated application of a linear function followed by an activation function enables the model to perform a highly non-linear transformation of the input x_i, on which the final layer performs linear classification.

Figure 6

Graphical illustration of fully-connected neural network. (Cinelli et al., 2018)



In the case of a multi-class classification problem, the model outputs a per-class score, which then passes through a softmax function to get a per-class probability. The class with the highest probability is the predicted output**.** The model is trained using a stochastic gradient descent method that uses the gradients computed through Back Propagation (Rumelhart et al., 1986).

4 Results and Analysis

In this section, we discuss in detail the analysis we conducted on Heyday's dataset and the results obtained from analytic hierarchy process (AHP) and chosen machine learning algorithms: support vector machine (SVM) and artificial neural network (ANN). Finally we will address the limitations of our research.

4.1 Featurization of the Dataset

To answer our first research question about the relevant criteria (attributes) for SKU segmentation for a digital marketplace accelerator we needed to define these attributes. Based on the literature review as well as the company's targets and discussions with them we chose six determining attributes:

1. **Profit Margin:** Profit margin is one of the most important criteria for Heyday, as it helps them create brand strategies and understand which items to focus on. Items with high profit margin require more attention in inventory planning. It is defined as:

$$Profit\ Margin = \frac{(Unit\ Price - Landed\ Cost)}{Unit\ Price} * 100\% \tag{6}$$

2. **Unit Price:** Unit price of SKUs is helpful in determining direct inventory costs. It is the total landed cost of the items in dollars.
3. **Demand:** Total demand calculated in number of units is another important criterion in determining inventory requirements for a specific period. It allows visibility in terms of which items have the highest demand volumes. For our analysis, we use forecasted demand.
4. **Demand Fluctuation:** Demand Fluctuation, calculated as the coefficient of variation (CV) of demand, helps understand the demand volatility of different items and differentiate items with relatively stable and unstable demand during a determined period of time. This criterion is important because inventory management for unstable items is more difficult.

$$CV = \frac{Std. Deviation\ of\ Demand}{Avg. Demand} = \frac{\sigma}{\mu}$$

(7)

5. **Inventory Turnover:** It is used as a measure of inventory velocity to understand how quickly SKUs are moving in the inventory. It is especially important for fast-paced markets like e-commerce, where Heyday is positioned. It is defined as:

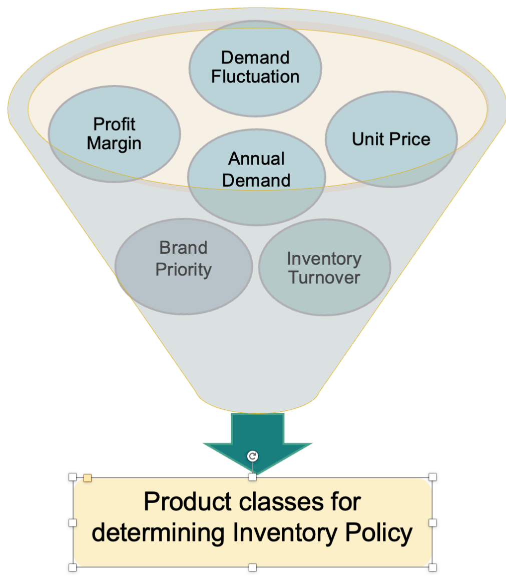
$$Inventory\ Turnover = \frac{Landed\ Cost}{Inventory\ on\ Hand\ + Inventory\ on\ Order}$$

(8)

6. **Priority:** The final attribute was a special request by Heyday, which we named Brand Priority. This is a subjective ranging from 1-5 that Heyday can use to elevate the priority of any SKU due to a management decision at any time. The idea was to avoid manual changes and have the lever embedded into the segmentation strategy.

Figure 7

Graphical Illustration of the Selected Attributes for Product Segmentation



4.2 AHP Results

4.2.1 AHP Attribute Comparison

The next step was to answer our second research question and determine the frameworks could be used to identify relevant criteria and attributes for the SKU segmentation in e-commerce, consumer packaged goods industry. While there are several techniques to compare the attributes we went with AHP comparison since as described in our literature review: "The main powerful feature of AHP is its ability to combine multiple criteria while effectively evaluating subjective opinions of decision-makers. This ability makes it applicable to combine it with other methodologies." – Kartal et al 2016. By choosing this technique we would have an extremely flexible and adaptable model as well as framework that could be adjusted at the speed that the segment was moving.

After selecting the attributes, we proceeded to conducting pairwise comparisons to determine Priority Vectors (also known as parameter weights) in multiple discussion meetings with Heyday. For this we used the scale comparison table as depicted in Table 2.

Table 2

Fundamental Scale for Pairwise Comparison of Attributes adapted from Saaty & Vargas (1991)

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one element over another
5	Strong importance	Experience and judgment strongly favor one element over another
7	Very strong importance	One element is favored very strongly over another, its dominance is demonstrated in practice
9	Extreme importance	The evidence favoring one element over another is of the highest possible order of affirmation.
2, 4, 6, 8 can be used to express intermediate values		

Using this scale, we went over each one of the attributes and compared the importance between each element with Heyday. At the beginning, of the workshop, Heyday considered all attributes to be extremely important however we explained that for AHP to work, it was important to consider the relative importance to the business and which attributes were more important to prioritize in line with their overall strategy. After a few iterations to ensure consistency, we came up with the pairwise comparison results illustrated in Table 3.

Table 3

Attribute Comparison Results based on Interviews with Heyday

A	B	Importance (A/B)	Intensity
Unit Price	Monthly Demand	B	3
	Demand Fluctuation	A	1
	Profit Margin	B	4
	Inv. Turnover	B	3
	Priority	B	3
Monthly Demand	Demand Fluctuation	A	4
	Profit Margin	B	2
	Inv. Turnover	A	3
	Priority	A	1
Demand Fluctuation	Profit Margin	B	4
	Inv. Turnover	B	2
	Priority	B	3
Profit Margin	Inv. Turnover	A	3
	Priority	A	2
Inv. Turnover	Priority	B	2

As previously mentioned, for the attribute comparison, we asked Heyday, whether the attribute from column A was more important than the attribute from column as well as the intensity of this difference on importance. For example, Monthly demand was moderately favored over unit price, while unit price and demand fluctuation have equal importance amongst them.

We can observe that there are no extreme values in this table, there are two reasons behind this. First off, the attributes were previously selected with Heyday and only the most relevant ones were selected. The second reason is that since we ran various iterations and wanted to make sure both consistent result as well as balanced weight of all attributes extreme values were avoided.

Once we had achieved a consistent comparison from all the attributes, the next step was to create the pairwise comparison matrix based on the intensity given to get the relative weights or priority vectors of each attribute.

To assign a value to each pairwise comparison we had to do it according to the following logic, if the base factor (row) is more important than the comparison factor being considered (column) we input the intensity factor given; otherwise, we use the reciprocal value. Flores et al 1992.

$$Reciprocal\ value = \frac{1}{intensity\ rating} \tag{9}$$

As an example of the filling of this table, we can see profit margin is moderately more important than inventory turnover with a value in the table of 0.33 (1/3) while the priority attribute is moderately more important than unit price with a value in the table of 3.

The pairwise comparison results are illustrated in Table 4.

Table 4

Pairwise Comparison based on Attribute Comparison Results
Base factor is read along the rows and comparison factor is read along the columns

	Unit Price	Monthly Demand	Demand Fluctuation	Profit Margin	Inv. Turnover	Priority
Unit Price	1.00	0.33	1.00	0.25	0.33	0.33
Monthly Demand	3.00	1.00	4.00	0.50	3.00	1.00
Demand Fluctuation	1.00	0.25	1.00	0.25	0.50	0.33
Profit Margin	4.00	2.00	4.00	1.00	3.00	2.00
Inv. Turnover	3.00	0.33	2.00	0.33	1.00	0.50
Priority	3.00	1.00	3.00	0.50	2.00	1.00
Total	15.00	4.92	15.00	2.83	9.83	5.17

Once we had the pairwise comparison, the next step to obtain the priority vector or weighted score was to calculate the eigen vector, or normalized form, of weights from the pairwise comparison. These values, which can be observed in Table 5 can be done with a variety of software's or using the following formulas:

$$EV\ Attribute = \frac{i_{base\ factor\ value}}{\sum base\ factor\ value} \tag{10}$$

Once we calculated the eigen vector of each individual attribute, we needed to calculate the priority vector or final weighted score, which indicates the relative importance to the company of each attribute for the segmentation. This can be done using the following formula, the results of this calculation can be found in table 5:

$$Priority\ vector = \frac{\sum comparison\ values}{n} \tag{11}$$

Table 5

Normalized pairwise comparison and consistency validations

	Unit Price	Monthly Demand	Demand Fluctuation	Profit Margin	Inv. Turnover	Priority	Total	Priority Vector
Unit Price	0.07	0.07	0.07	0.09	0.03	0.06	0.39	0.06
Monthly Demand	0.20	0.20	0.27	0.18	0.31	0.19	1.35	0.22
Demand Fluctuation	0.07	0.05	0.07	0.09	0.05	0.06	0.39	0.06
Profit Margin	0.27	0.41	0.27	0.35	0.31	0.39	1.99	0.33
Inv. Turnover	0.20	0.07	0.13	0.12	0.10	0.10	0.72	0.12
Brand Priority	0.20	0.20	0.20	0.18	0.20	0.19	1.18	0.20

The priority vector shows the relative importance of weights of the compared elements. Since we have normalized all the values the addition of all priority vectors equals to one.

In this paper one example of this calculations is: EV attribute of Unite Price = 1/15 = 0.07

The priority vector would be (0.07 unit price + 0.07 monthly demand + 0.07 demand fluctuation + 0.09 profit margin + 0.03 inventory turnover + 0.06 priority) / 6 = 0.06.

These weights or priority vectors indicate that for Heyday, unit price contributes about 6 %, monthly demand contributes about 22% demand fluctuation contributes about 6%, profit margin contributes about 33% inventory turnover contributes about 12% and priority contributes about 20% in their relative importance.

After having calculated the weights of each attribute as well as the final priority vector of each attribute it was important to ensure the comparisons were consistent. Consistency refers to the fact that the relative importance given between one attribute and the other is transitively maintained. In our case for example, Heyday established that monthly demand was more important than unit price and that profit margin was more important than monthly demand thus to be consistent unit price could not be assessed as more important than profit margin.

Saaty 1991 proved that for a consistent matrix, the largest eigen value or principal eigen value (λ_{max}) is almost equal to the size of the consistency matrix, or $\lambda_{max} \approx n$. The first step to verify consistency is to calculate the eigen values (λ) from each attribute. This is done obtained by performing the matrix product (MMult in Excel) between an attributes eigen vectors and the priority vectors divided over the attribute's eigen value. The values obtained can be found in Table 6.

Saaty 1991 gave a measure of consistency called the Consistency Index (CI). The CI approximation formula as well as the Consistency Ratio formulas can be found bellow. For our project we used Saaty's Random Index (RI) Value of 1.24 for 6 attributes, the results of these measures can be found in Table 6.

$$CI = \frac{\lambda \max - n}{n - 1} \tag{12}$$

$$CR = \frac{CI}{RI} \tag{13}$$

Table 6

Eigen Values and Consistency Index of Classification

	λ
Unit Price	6.06
Monthly Demand	6.23
Demand Fluctuation	6.08
Profit Margin	6.19
Inv. Turnover	6.07
Brand Priority	6.18
CI	0.05
RI	1.24
CRatio	0.04

As we can see, principal eigen value is 6.23 which is relatively close to n, Saaty determined that if the consistency ration was below 10%, then the inconsistency was acceptable. In our case our consistency ratio is 4% when comparing our six attributes which is acceptable so we could move on to the segmentation with these priority vectors we then moved on to the segmentation.

4.2.2 AHP Segmentation

Once we had our priority vectors weights, it was time for the next step in the AHP process which was multiplying the weights by the values of each attribute for all the SKUs. Since all attributes had different units, we transformed the data to a common scale using the following normalization equation:

$$N.Attribute = \frac{F_i - F_{min}}{F_{max} - F_{min}} \tag{14}$$

Where F_i is the i^{th} value of attribute under the transformation, while F_{min} and F_{max} are the minimum and maximum values of the attributes under the transformation (Flores et al., 1992). As a last step, we added the value of each transformed attribute to have a final AHP Value.

$$AHP\ Weight = \sum N.Attributes \tag{15}$$

For our segmentation we used Heyday's forecast following Pannu's 2021 recommendation. The first step was to determine into how many classes, we should segment the SKUs. For this we ran a K-Means Clustering Analysis in Alteryx and saw that the optimal number of buckets was three, as the cluster inertia decreased dramatically when increasing the number of clusters. After this validation was made, we determined we would segment the attributes following the AHP results into an ABC classification following Pareto's 80-20 distribution. used by several papers in the literature, such as Kartal and Cebi 2013, and the ABC intervals can be observed in Table 7.

Table 7

ABC Intervals

Segment	Cumulative RW%
A	0 – 20%
B	21% - 50%
C	51% - 100%

To determine the segment for each SKU we first calculated the Relative Weight (RW) percentage for each SKU using the following formula:

$$RW\ \% = \frac{AHP\ Weight_i}{\sum AHP\ Weights} * 100\%$$

(16)

Once established, we ranked the SKUs from largest to smallest AHP Weight Scores and calculated the cumulative RW %. Finally, we segmented the SKUs following the intervals in Table 7.

We decided to test different aggregation levels, such as, monthly, quarterly, bi-annually, and finally yearly, to later assess differences and determine if there was an optimal aggregation level to be used by the company. An extract of the results of one of these aggregations can be seen in Table 8.

Table 8

Extract from Q2 segmentation model (items hidden for confidentiality purposes)

Item	Weigthed Score	RW %	Cummulative RW	Weighted Score ABC
XX1	0.261	0.002	10%	A
XX2	0.253	0.002	11%	A
XX3	0.226	0.001	18%	A
XX4	0.220	0.001	20%	A
XX5	0.220	0.001	21%	B
XX6	0.205	0.001	33%	B
XX7	0.205	0.001	33%	B
XX8	0.204	0.001	34%	B
XX9	0.189	0.001	50%	B
XX10	0.189	0.001	51%	C
XX11	0.187	0.001	53%	C
XX12	0.173	0.001	70%	C
XX13	0.100	0.001	99%	C
XX14	0.088	0.001	100%	C

SUM of Weighted Score 151

We can observe from Table 8, how the relative weight is calculated, for example for item XX2, the RW is equal to .253 / 151 or .002. Also, we can discern the segmentation brakes which occur with the cumulative RW's following Pareto's distribution from Table 7.

Once we had the initial models of the different segmentations, we needed to compare them and determine whether the nature of the data suggested using one aggregation level over the other. We began by creating a histogram for each aggregation level by grouping the AHP weights into buckets and see if they behaved differently between aggregation levels (Figures 8 and 9)

Figure 8

Histogram of Quarterly SKU Distribution and Avg. Profit Margin across the obtained AHP scores with ABC classification

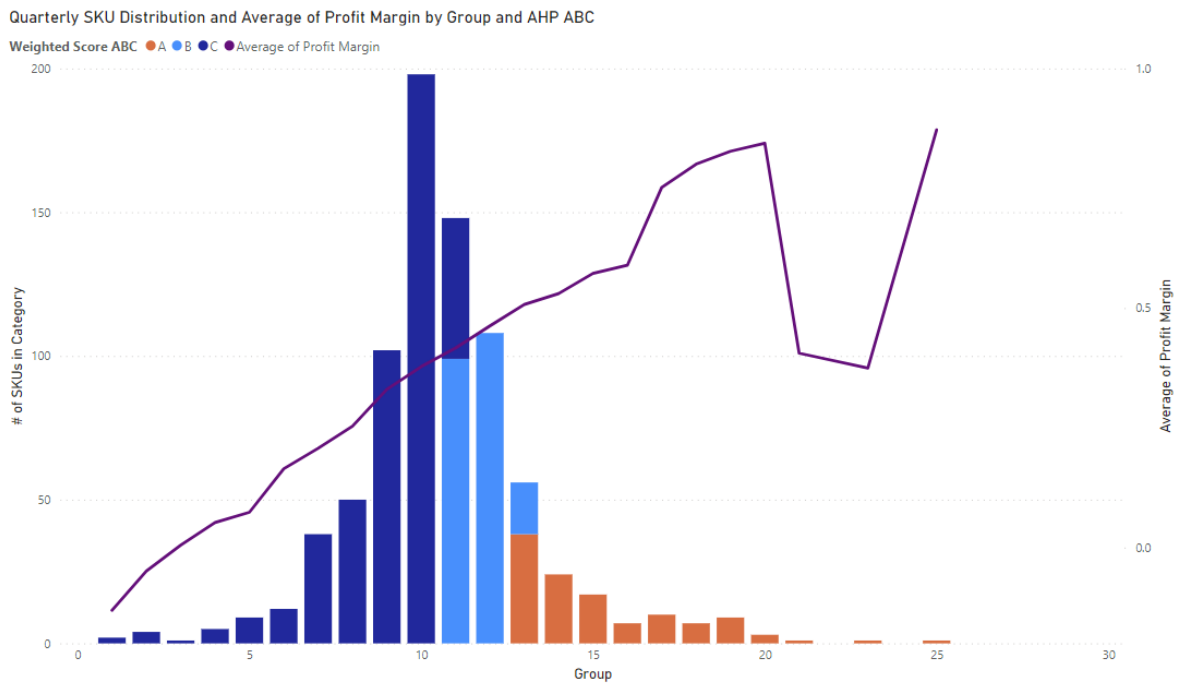
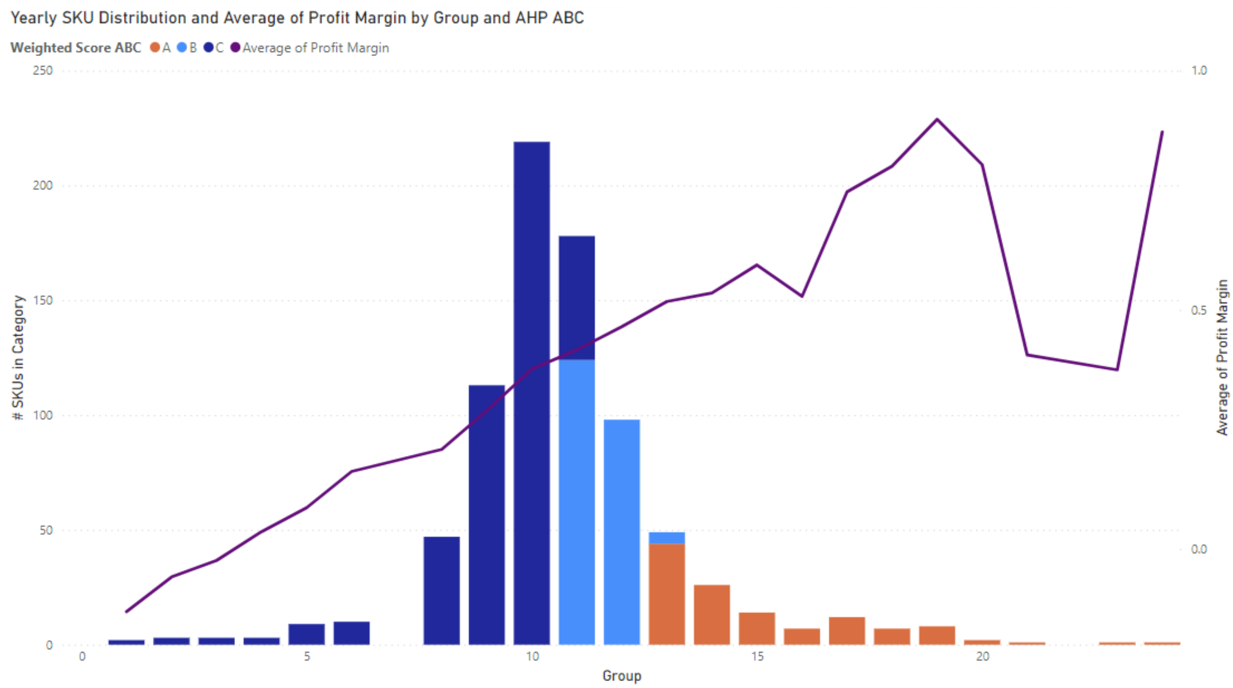


Figure 9

Histogram of Yearly SKU Distribution and Avg. Profit Margin across the obtained AHP scores with ABC classification



From these graphs, we can observe that in both cases, the data has what seems to be a normal distribution and that the average profit margin has an upward trend that follows the AHP Weight, this is explained due to its high relative priority vector weight. Another thing worth mentioning is that the cuts between ABC categories are very similar so there is no evidence that shows difference between one aggregation model and the next.

The next thing that we wanted to analyze was the distribution amongst SKU's and categories in the different models. To this end we created tree maps that combined our ABC classification with the total profit contribution from SKUs in each category which can be observed in Figures 10 and 11.

Figure 10

*Quarterly tree map comparing distribution of the SKUs across the obtained AHP scores with ABC classification comparing category and total profit contribution (Total Demand * Unit Price)*

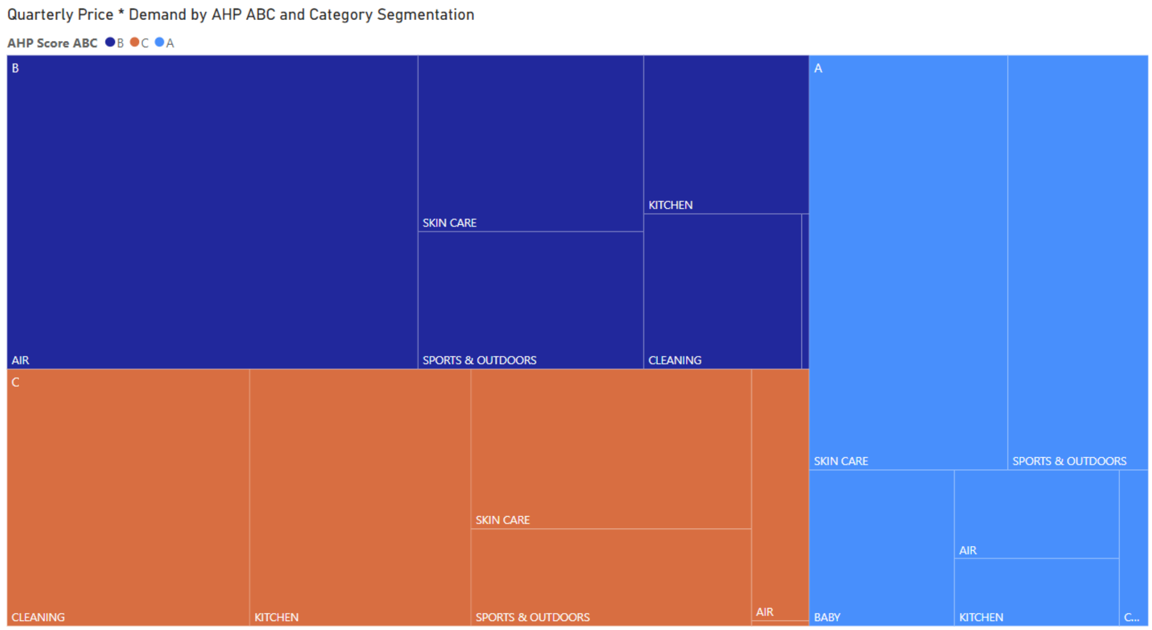
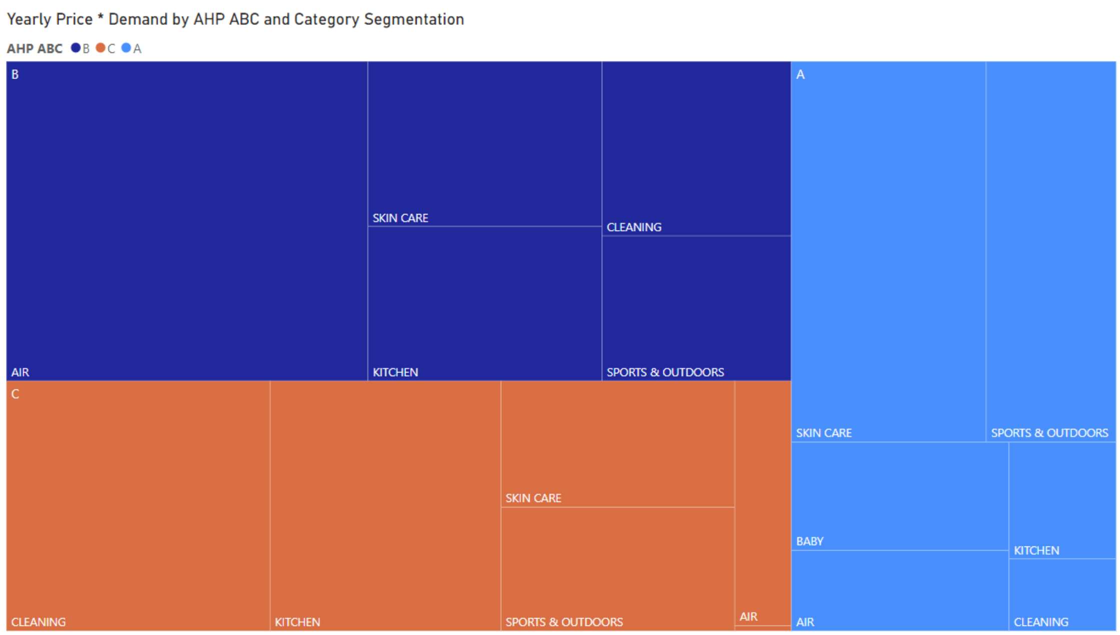


Figure 11

*Yearly tree map comparing distribution of the SKUs across the obtained AHP scores with ABC classification comparing category and total profit contribution (Total Demand * Unit Price)*



From the tree maps we observed that regardless of the aggregation model, SKUs behaved in a similar manner. There is no clear difference between contribution, brands, and ABC classification when we changed aggregation level. Thess two results, proved data followed the same trends regardless of the aggregation level and thus it would be a strategic decision from the company what the correct aggregate level would be.

Since the aggregation level did not really impact the behavior of the segmentation (Figures 8-11), and after discussing with Heyday, it was determined that we would build 5 different models. One model for each quarter as well as a yearly model so they could both be tested in their operation and determine which to keep. In table 9 we can see the comparison of the total number of SKUs in each of our models.

Table 9

ABC Comparison between the models

	Q1		Q2		Q3		Q4		Yearly	
	# SKUs	%	# SKUs	%	# SKUs	%	# SKUs	%	# SKUs	%
A	118	15%	118	15%	120	15%	119	15%	123	15%
B	225	28%	225	28%	226	28%	224	28%	227	28%
C	470	58%	470	58%	466	57%	470	58%	463	57%

Finally, once we had established quarterly and yearly models, we wanted to compare the overlap between our multi decision variable model and a traditional univariable approach. We compared our AHP models versus total contribution (Total Demand * Price) and Profit Margin, the results can be observed in Table 10.

Table 10

*Overlap comparison of univariable approach Total Demand * Unit Price and Profit Margin.*

Quarterly	Total Demand * Unit Price		Profit Margin	
Weighted AHP (A SKUs)	A	A-B	A	A-B
# SKUs	20	53	85	111
Overlap %	16%	43%	69%	90%

Yearly	Total Demand * Unit Price		Profit Margin	
Weighted AHP (A SKUs)	A	A-B	A	A-B
# SKUs	25	60	93	116
Overlap %	20%	49%	76%	94%

As expected, the main driver determining the ABC was profit margin however, as we used a multicriteria we found around 20-30% of new SKUs that would not have been classified as "A" if we had used a univariable approach

Using this information and having determined the segmentation for all SKUs we were ready to proceed with our machine learning models. An example of the final AHP segmentation by SKU, can be found under Appendix A.

4.3 Running Machine Learning Models

4.4 Running Machine Learning Models

This section discusses the steps followed to develop, run, validate, and test the two selected machine learning models for the project – support vector machines (SVM) and artificial neural networks (ANN).

For the purpose of the project, we chose to build the models using Alteryx, as suggested by our sponsor company. Alteryx is a commercial software package with an intelligence suite that offers data science tools for data preprocessing, feature selection, machine learning models, and analysis tools. Using this intelligence suite, we created a workflow which is easy to parse, investigate, alter, and iterate. All the steps in the pipeline are easy to relate to each other, and to adjust for different choices of hyperparameters for the models and data preprocessing. Alteryx will allow our sponsor, Heyday, to understand our work in a transparent manner, iterate on our work, and integrate it in their operations.

4.4.1 Preprocessing the Data

The first step of our analysis was data preprocessing. The dataset we had from the company was divided into two horizons: quarterly data and yearly data.
The quarterly data included four sets, one for each quarter, and the yearly data included one set. We ran all of the experiments on Q1 dataset which contained 813 samples (SKUs) in total.

We began our workflow by reading all these samples from the provided csv file and choosing the columns of interest. As developed previously during the AHP analysis, we have six features: profit margin, demand, demand fluctuation, inventory turnover, unit price, and brand priority. At this time, the sponsor company does not have 'brand priority' defined and so for preparing the machine learning pipeline, we omitted that feature and used the other five features. A sample dataset with these five features is shown in table 11.

Table 11

A random subset from the Q1 dataset containing 15 SKUs

SKU	Unit Price	Q Demand	Demand Fluctuation	Profit Margin	Inv. Turnover	Weighted Score ABC
1	9.94	1780.49	0.529	71%	0.000	A
2	24.99	98.06	0.521	32%	0.007	C
3	10.26	1058.44	0.508	2%	0.000	C
4	79.73	211.58	0.498	39%	0.012	C
5	13.92	732.56	0.497	32%	0.000	C
6	17.52	331.44	0.496	42%	0.001	B
7	43.68	202.05	0.488	38%	0.005	C
8	29.99	45.49	0.476	41%	0.052	B
9	17.88	883.34	0.474	43%	0.000	B
10	16.31	219.95	0.472	24%	0.019	C
11	34.93	448.43	0.472	29%	0.003	C
12	13.78	187.22	0.467	56%	0.004	A
13	408.53	143.51	0.452	46%	0.080	B
14	14.85	27639.99	0.437	29%	0.000	C
15	7.94	975.69	0.434	19%	0.000	C

Since the scale of these features don't match, we standardize these features between 0 and 1 using linear normalization function defined as:

$$f[i]_{normalized} = \frac{f[i] - \min(f)}{\max(f) - \min(f)} \tag{17}$$

where f is the feature column. This standardization is a common technique used in machine learning to regularize the relative impact of features on the predicted output. These normalized features were used as the X inputs for the machine learning algorithms.

The target variable or the Y input for classification is the final weighted score segmentation obtained as the output of AHP. We refer to this column as 'Weighted Score ABC'.

4.4.2 Developing the Workflows

The second step after preprocessing the data was to develop the workflows on Alteryx. This workflow consists of the following Alteryx tools:

1. **Input Data:** The Input Data tool is used to add data to the workflow by connecting it to a file or database.

2. **Data Cleansing:** The Data Cleansing tool is used to fix common data quality issues such as replacing null values, removing punctuation, removing trailing spaces, and modifying capitalization.

3. **Select:** The Select tool includes, excludes, and reorders the columns of data that pass through a workflow. Excluding columns can limit the data passing through a workflow and improve performance. It can also be used to modify the type and size of data, rename a column, or add a description.

4. **Create Samples:** The Create Samples tool is used to split the input records into 2 or 3 random samples. In the tool, we specify the percentage of records that are in the estimation and validation samples. If the total is less than 100%, the remaining records fall in the holdout sample.

5. **Classification tools**

   i. **Support Vector Machines:** The Support Vector Machines tool finds the best equation of a line (1 predictor), a plane (2 predictors), or a hyperplane (3 or more predictors) that maximally separates the groups of rows, based on a measure of distance, into different categories, which depend on the target variable. The extent that groups are separated conditional on the kernel function used is known as the maximal margin. Finally, the separation of the groups may not be perfect, but a cost parameter (which is the cost of placing an estimation record into the "wrong" group) can also be specified. This tool uses the R tool.

   ii. **Neural Network:** The Neural Network tool creates a feedforward perceptron neural network model with a single hidden layer. The neurons in the hidden layer use a logistic (also known as a sigmoid) activation function, and the output activation function depends on the nature of the target field.

6. **Score:** The Score tool creates an estimate of a target variable by applying an R model to a set of supplied predictor variables. If the target variable is categorical, it provides probabilities that a record (based on the predictor variable) belongs to each category. If the target variable is continuous, it estimates the target variable’s value. Although it can be used to assess model performance, it does not do so on its own.

7. **Model Comparison:** The Model Comparison tool compares the performance of one or more different predictive models based on the use of a validation, or test dataset. It generates a report, a table of basic error measurements, and a table of prediction results of each model. The tool supports all binary classification, where the target variable has only two levels, such as "Yes" and "No", multinomial classification, where the target variable has more than two levels, such as "car", "bus", "train", and "airplane", and regression (continuous target variable) models.

The two pipelines are depicted in Figure 10 (for SVM) and Figure 11 (for ANN).

Figure 12

Alteryx workflow for SVM pipeline with dataset from a single quarter

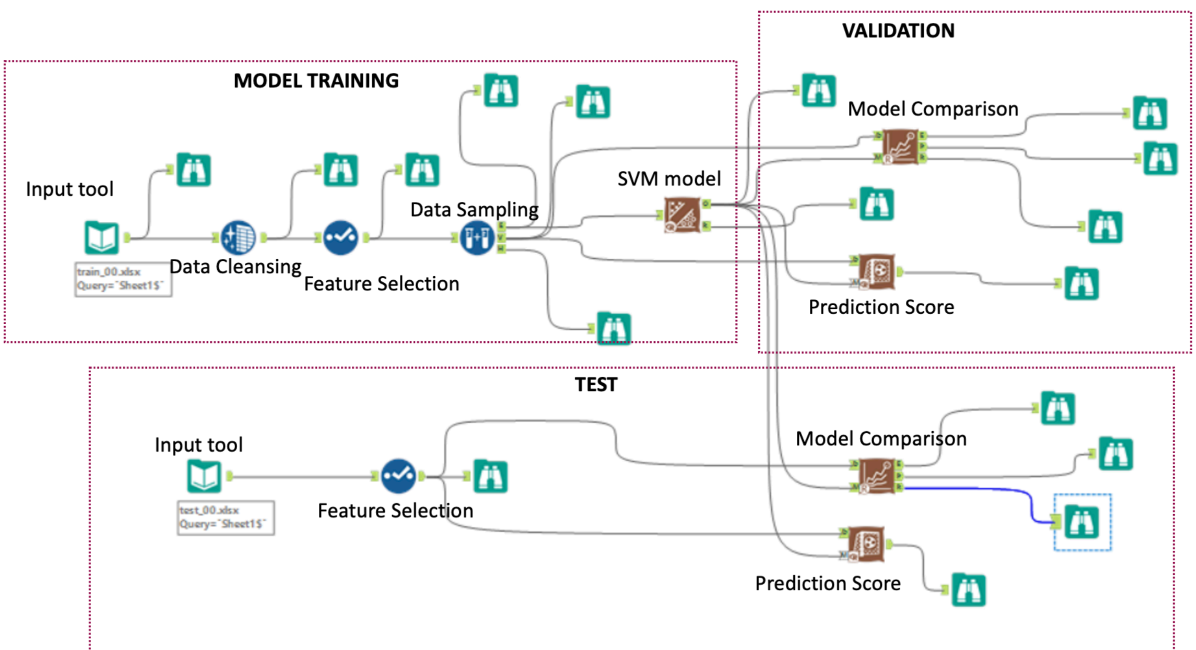
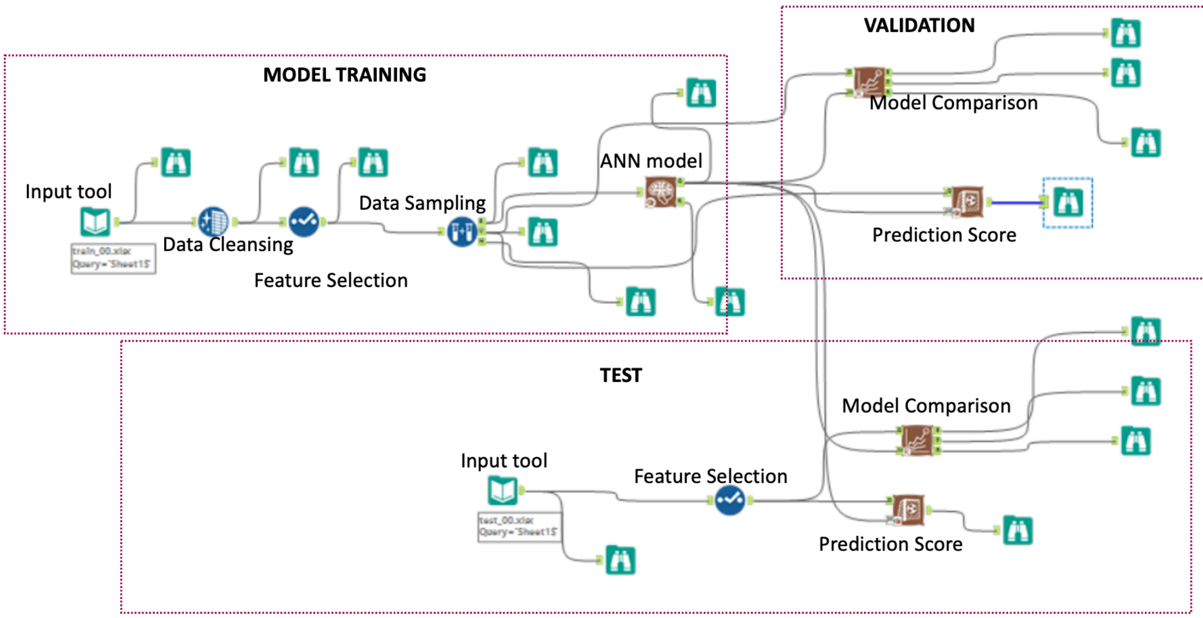


Figure 13

Alteryx workflow of ANN implemented on Q1 dataset performed on tain_00 and test_00



4.4.3 Training and Testing the Models

After developing the workflow in Alteryx, our next step was to split the dataset for training the models, validating it along with hyperparameter tuning, and testing it subsequently.

4.4.3.1 Cross Validation

To improve the statistical significance of our models, we decided to use the k-fold cross-validation approach. Cross-validation is primarily used in applied machine learning to estimate the ability of a machine learning model to generalize on unseen data and detect overfitting. Since our dataset is biased with more samples for class C, we balance our dataset by oversampling the minority classes (A and B) to match the number of samples from these classes to the number of samples with class label C. This resampled dataset is firstly divided into a train and test data, with exclusive SKUs in both datasets. The test set contains 150 SKUs that are not observed in any phase of the training pipeline. The features for the SKUs in the test are not used to compute statistics used for data pre-processing or any other part of the training pipeline. This test set with exclusive SKU information acts as a benchmarking dataset to measure the performance and generalization capability of our models.

Following the K-fold validation convention, we use k=10 and further split the train dataset into 10 different versions of the train and validation datasets with a 0.8:0.2 ratio. These 10 different splits of the original train dataset are then used to test the model accuracy with different hyperparameters.

4.4.3.2 Hyperparameter Tuning

Hyperparameters refer to the non-trainable parameters of a model and need to be defined prior to training. Hyperparameter tuning refers to tweaking the parameters of the model that cannot be learned.

Hyperparameter Tuning for SVM

For SVM, we chose to test both Linear SVM and SVM with Sigmoid kernel by tuning the hyperparameter C which is defined as the cost or the regularization parameter of the error term. The strength of the regularization is inversely proportional to C. The penalty is a squared l2 penalty.

For Sigmoid kernel SVM, the Gamma value is taken as the default value which is equal to 1 divided by the number of features. Therefore, for our analysis, gamma is 0.2.

For each of the kernel selections, we then inputted our 10 train and validation datasets obtained from the previous step and then tuned the C hyperparameter values as [0.5, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0]. For each of them, accuracy on train, validation, and test sets were recorded, and finally mean and standard deviation of accuracy obtained on the three datasets was calculated. Table 12 shows these values. The mean accuracy values of linear SVM over all 10-folds of the datasets are plotted for the different values of the hyperparameter C in Figure 14.

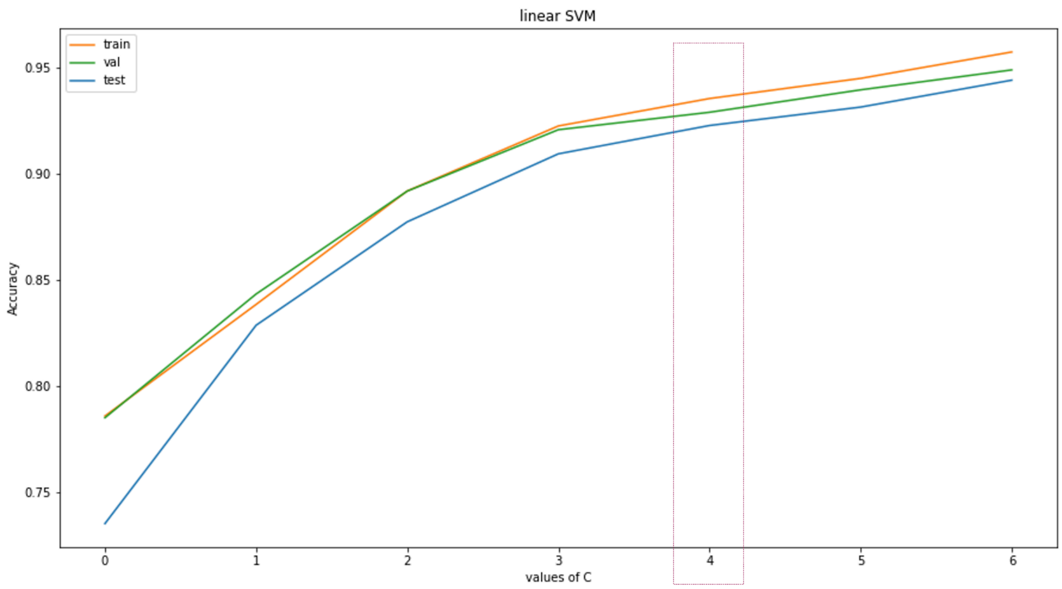
Table 12

Mean and standard deviation of accuracy for three-class classification using linear SVM and SVM with sigmoid kernel performed on 10-fold cross validation data and tuning the hyperparameter C

		Hyperparameter	Train		Validation		Test	
Model	**Kernel**	**C**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
SVM	Linear	0.5	0.786	0.017	0.785	0.020	0.735	0.030
		1.0	0.838	0.010	0.843	0.016	0.829	0.020
		2.0	0.892	0.011	0.892	0.023	0.877	0.016
		3.0	0.922	0.016	0.921	0.025	0.909	0.018
		4.0	**0.935**	**0.013**	**0.930**	**0.020**	**0.923**	**0.019**
		5.0	0.945	0.014	0.939	0.018	0.931	0.018
		6.0	0.957	0.007	0.949	0.014	0.944	0.010
	Kernel	**Hyperparameter**	**Train**		**Validation**		**Test**	
		C	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
	Sigmoid	0.5	0.545	0.015	0.536	0.022	0.489	0.050
		1.0	0.677	0.020	0.670	0.035	0.634	0.030
		2.0	0.761	0.013	0.760	0.019	0.706	0.030
		3.0	0.799	0.013	0.802	0.021	0.755	0.034
		4.0	0.820	0.020	0.823	0.023	0.792	0.029
		5.0	0.838	0.012	0.839	0.016	0.825	0.022
		6.0	0.846	0.005	0.850	0.019	0.839	0.022

Figure 14

Accuracy of Linear SVM over different values of regularization hyperparameter C



Hyperparameter Tuning for ANN

Similarly, for ANN, we chose a fully connected neural network and tuned the hyperparameter 'number of nodes in the hidden layer'. Since the Neural Network tool in Alteryx has only one hidden layer, we tuned the hyperparameter for the single hidden later. The model was randomly initialized with weights sampled between [-1.0, 1.0], and was trained using a weight decay of 0.1 for 100 iterations. We tested the neural network with different number of nodes in the hidden layers set to 6, 8, and 10. The choice of the number of hidden nodes is restricted to 10 as Alteryx does not support ANN model with hidden nodes greater than 10. Similar to SVM hyperparameter tuning, we performed the ANN hyperparameter tuning on the 10-fold train and validation datasets, and computed the mean and standard deviation of the accuracy over all runs. Table 13 shows these results.

Table 13

Mean and standard deviation of accuracy for three-class classification using ANN performed on 10-fold cross validation data and tuning hyperparameter 'number of nodes'

Model	Hyperparameter	Train		Validation		Test	
	Number of nodes	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Artificial Neural Network	6	0.844	0.033	0.853	0.033	0.828	0.045
	8	0.892	0.019	0.883	0.016	0.865	0.035
	10	0.084	0.023	0.849	0.041	0.0821	0.044

4.4.3.3 Error Metrics and Confusion Matrices

We present the test accuracy of SVM and ANN in Table 14 and Table 15, respectively, on one of the train, validation, and test sets obtained from 10-fold validation. Both models achieve high accuracy on the test set, with linear SVM (93.3%) outperforming ANN (86.5%) by a slight margin. For SVM, we choose the model trained with regularization parameter C=4 as the accuracy plateaus for values of C greater than 4 as seen in Figure 14. Based on accuracy of the ANN model for the different number of nodes in the hidden layer, we choose the model with 8 hidden nodes as it outperforms the ANN with 6 and 10 hidden nodes. We observe that SVM has consistent performance across the three classes, whereas the ANN model has biased performance with high performance on class C and relatively low accuracy on class A. This per-class performance for both models is presented as confusion matrices on the test data for both models in Table 16 and Table 17 respectively. In addition to the higher accuracy, the unbiased performance of the SVM on each class supports the choice of SVM over ANN for this classification task.

Table 14

Accuracy and error measures obtained on test_00 dataset using linear SVM with C = 4.0 (accuracy and error measures were obtained for all 10-fold cross validation datasets in a similar way)

Model	Accuracy	F1	Accuracy_A	Accuracy_B	Accuracy_C
Q1classes	0.9333	0.9333	0.9000	0.9000	1.0000

Table 15

Accuracy and error measures obtained on test_00 using the ANN and number of nodes = 8 (accuracy and error measures were obtained for all 10-fold cross validation datasets in a similar way)

Model	Accuracy	F1	Accuracy_A	Accuracy_B	Accuracy_C
	0.8400	0.8400	0.6600	0.8600	1.0000

We present the test accuracy of SVM and ANN in Table 9 and Table 10, respectively. Both models perform with high accuracy on the test set, with SVM (97.3%) outperforming ANN (96.3%) by a slight margin. In terms of accuracy, we can observe that SVM has consistent performance across the three classes, whereas the ANN model has biased performance profile with high performance on class C and relatively low accuracy on class A. This can be attributed to the class imbalance in the dataset caused due to application of ABC.

Furthermore, we analyze the models based on the F1 score. The F1 score I s defined as:

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{18}$$

Where,

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} = \frac{True\ Positive}{Total\ Predicted\ Positive} \tag{19}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} = \frac{True\ Positive}{Total\ Actual\ Positive} \tag{20}$$

A higher F1 score of SVM supports the efficiency of SVM model over the ANN model for the current dataset. By plotting the confusion matrix, presented in Table 11, we observe that the SVM sometimes misclassifies samples from Class A as Class B and Class C as Class B. A bias in the misclassification from ANN is revealed in the confusion matrix for ANN, presented in Table 12, which shows that the ANN misclassifies samples from Class A as Class B.

Table 16

Sample Confusion matrix of the test dataset using linear SVM algorithm run on Test_00 dataset

	Actual_A	Actual_B	Actual_C
Predicted_A	45	2	0
Predicted_B	5	45	0
Predicted_C	0	3	50

Table 17

Sample Confusion matrix of the test dataset using ANN algorithm run on Test_00 dataset

	Actual_A	Actual_B	Actual_C
Predicted_A	33	0	0
Predicted_B	17	43	0
Predicted_C	0	7	50

4.5 Limitations

Currently our scope was limited to a single company, but we are sure that if it were to be run in different industries the results would yield valuable insights about the correct frequencies, trends and weights used to segment inventories in an optimal way.

Another potential limitation can be in the ABC methodology. As AHP computes only a linear weighting over the features to compute a score that will be the base for the segmentation, this wouldn't work if the datasets contain a polynomial weighted score. For this project, we interviewed three subjects to get the AHP scores, which can be considered a statistically insignificant number. Interviewing a greater number Since Heyday did not have a baseline segmentation, since their model was that of an undifferentiated approach, the comparison we could do versus our segmentation was limited.

For this model we used the forecast data to segment and train our models since Heyday had a robust forecast in place and as established by Pannu's (2021) research this outperformed historical data in fast moving consumer goods segments. Since we currently didn't have a baseline to compare service level, we cannot establish a clear difference between our forecasted and the historical segmentation.

While both machine learning models achieve high accuracy on test set of the current dataset, several improvements can be made to make the models more efficient and robust. Some of these methods for improvement include: collecting more data, augmenting the data, and aggregating data temporally. We decided not to aggregate data temporally because the number of samples in our dataset were very low and computed classes for all SKUs that were not consistent across the quarters (temporally).

Finally, another limitation that can be observed from our model is the parametrization of our machine learning models. Since we used Alteryx due to its convenience and the existing usage of this tool by our sponsoring company, we were limited to the number of parametrizations we could do in our model. An example of this is in the hyper parameters, Alteryx's Neural Network creates a feed forward model with a single hidden layer this cannot be parametrized. Also, only their linear regression models allow for regularization. In summary, while Alteryx gave us good results, we were limited to the parametrization the software allowed us to perform.

5 Discussion

The purpose of this section is to discuss what we did during this Capstone, the advantages, and some key findings as well the assumptions we took for our project. During this discussion we will also refer to our key research questions. Finally, we will address the used model and possible modifications when replicating it.

Our first research question was based on the relevant criteria (attributes) for SKU segmentation for a digital marketplace accelerator. Our answer to this question was based mainly on the existing literature and discussing with our sponsor company of the importance of these attributes for them. As previously mentioned, we chose unit price, monthly demand, demand fluctuation, profit margin, inventory turnover and priority.

While these attributes gave us a good segmentation, they are not the only ones that we could've used. More so, we could do a different segmentation including more less or different attributes and compare service level and inventory cost results. Currently, literature doesn't have an answer of the "ideal" attributes to use as this is highly variable and depends on several factors which would result in constantly changing the segmentation model that in practice would be highly impractical and there is no evidence to support this would improve service level and result.

The second key question we addressed with our capstone was related to the frameworks that could be used to identify relevant criteria and attributes for the SKU segmentation in e-commerce, consumer packaged goods industry. Again, the basis to this answer and the subsequent creation of our model and framework was based on our literature review. The hybrid model that we implemented followed the research done by Kartal et al 2016 and we will discuss this in the following paragraphs.

With this Capstone, we were able to determine a framework to segment inventory in a rapidly changing market such as the e-commerce market in which Heyday operates. By utilizing analytic hierarchy process (AHP) we were able to integrate the company's priorities into the segmentation and thus come up with a much more robust segmentation than we could have obtained by using a univariate model.

Literature shows that AHP is not the only multicriteria segmentation technique that we could use, Jiang and Steverson 2017, compare dual matrix and clustering techniques, and while there is no definitive answer of which method was better, we chose AHP for the flexibility and adaptability it gave us.

The second part in our model used Artificial Neural Networks (ANN) and Support Vector Machines (SVM). We chose this Machine Learning models for two reasons. The first was their great results in the literature as discussed by Kartal et al 2016 that the models had for inventory segmentation. But the second and not less important was the compatibility with our sponsoring company's systems. Since Heyday already operated with Alteryx, using a solution that ran in this software was way of ensuring that the model would be useful. We feel confident with our current results as they are extensively backed in the literature. When we used K-means clustering the segmentation categories were very similar in densities, which increases our confidence in our model.

Our final research question was related on how a model/framework could be defined to classify SKUs and predict classes/segments for SKUs within a growing heterogeneous portfolio. We believe that while we have already addressed most of the assumptions for building our model/framework for inventory segmentation, as we mentioned in our results, the reason behind our 5 models had to do with a discussion with Heyday as there were no clear variations in the different time aggregations.

6 Conclusion

This section goes over the final conclusions that we got from our capstone research and the learnings from the project. In this section the results and finding will be summarized to outline the key takeaways that were obtained from our research. We will also go over the most relevant managerial insights and close the chapter with future research.

This paper describes a hybrid methodology of analytic hierarchy process, a multi-criteria decision-making model, integrated with machine learning methods for the analysis of multi-attribute inventory classification problem. Our capstone sponsor, Heyday, which is an aggressively growing company in terms of their product portfolio, seeks a robust automated methodology for product segmentation to improve their inventory processes.

In this paper, we started by identifying key research questions that arose specifically from understanding the company and its operations as well as from expanding it to the general issues of inventory management in similar industries as explained in the section 1.2. We then conducted literature review on inventory classification techniques to identify the latest models and tools that have been developed, which is covered in detail in section 2.

From literature, we saw that the classical single-criterion ABC inventory classification is simple, and straightforward, and therefore been used widely in industry applications. However, many studies have shown that there are many other criteria that influence inventory systems and therefore must be included in inventory decisions, as explained in detail in Section 2.2. For our sponsor company, factors such unit price, annual/quarterly demand, demand fluctuation, inventory turnover, profit margin, and brand priority influence their inventory movement and metrics, and are therefore deemed critical for effective inventory management. These factors were shortlisted based on many discussions with the company subjects as well as obtained from relevant studies done on similar topics, as highlighted in section 2. Further, according to many studies, as listed in Table 1, out of all the multi-criteria decision-making techniques applied in the field of inventory classification, analytic hierarchy process has shown best results. Therefore, we decided to deploy analytic hierarchy process for our project.

The six factors determined by the company as critical for their inventory based on their business and operational goals were used as attributes for product classification. These six attributes were then used for pair-wise classification to determine the relative importance of each attribute using Saaty’s (1991) Fundamental Scale for Pairwise Comparison depicted in Table 2. A comparison matrix was built (shown in Table 3) and then priority vectors were calculated for each attribute. This process is detailed in section 4.2.1 and the priority vectors obtained are listed in Table 5. The priority vectors were then normalized and multiplied with the normalized attribute values of each SKU to obtain the weighted score, which was then used for generating ABC classes.

Once inventory classes are determined using analytic hierarchy process, machine learning algorithms were deployed to predict the pre-identified classes to train the models. This allows the model to learn the relative importance of each attribute for the different classes and then enables us to use the model to predict classes for new products. We chose two machine learning models for our dataset – support vector machines and artificial neural networks – which were determined to show some of the best results in the studies done on inventory classification using machine learning. These studies and their suggestions are heighted in Sections 2.2.3 and 2.2.4. We tested both SVM and AMM on data from a single quarter and evaluated on a test set where the SKUs were different from the train set. To demonstrated statistically significant results, we conducted a k-fold validation with k=10, along with various values of hyperparameters both for SVM (linear, sigmoid kernel) and ANN. The hyperparameters tuned for SVM and ANN were 'cost function' and 'number of nodes in the hidden layer' respectively. These results are highlighted in Tables 12 and 13 in Section 4.3.3. Both models achieve high accuracy on the test set, with linear SVM (93.3%) outperforming ANN (86.5%) by a slight margin. In terms of accuracy, we observe that SVM has consistent performance across the three classes, whereas the ANN model has biased performance profile with high performance on class C and relatively low accuracy on class A.

Given that our test set had non-overlapping SKUs from the train and validation datasets, it is evident that our model does not overfit on the train set and indeed learns a trend over the selected features. Furthermore, it is important to note that AHP follows a linear approach to finding a threshold between the three classes. The choice of method for creating the initial classes is a relatively simple but effective one. In our work, the pipeline provided is modular, and in future, AHP can be replaced by a much more complex technique for determining initial classes. The results of our study indicate that machine learning methods can be very effectively applied to the multi-attribute inventory classification problem especially for growing portfolios and can be deployed to predict classes of new products. Our research findings also suggest that this methodology of combining machine learning algorithms with analytic hierarchy process can provide meaningful insights that can be used to support managerial decisions and overall improve inventory management strategies.

6.1 Managerial Insights

After concluding our research in inventory management, the first conclusion we need to bring up to our sponsor company is the need to segment inventory. While their current strategy of a high undifferentiated service level across all their SKUs has worked, literature and experience has shown this is not sustainable particularly with a growing portfolio as they will quickly become highly inventory leveraged which can not only hinder their growth but may also put their financial health at risk.

Our proposed framework and model showed that only 15% of SKUs should be held with the maximum service level while almost 60% can have a lower service level (See table 9) without putting customer satisfaction at risk. Jiang and Steverson 2017, proposed that A class SKU have an agreed service level of 95%, B a service level of 91% and C items 84%. While the number to be used by Heyday when calculating their actual inventory policy need to be agreed by management, these numbers show how using our segmentation they can reduce their inventory costs.

While we will not mention Heydays current service level target, if we were to assume that Heyday currently used 95% service level across all their SKUs, and they followed Jiang and Steverson 2017 targets, this would mean reducing by more than 10% this service level in 60% of the portfolio could represent significant savings.

By utilizing AHP as the base of our model, Heyday can very quickly modify and change the importance of attributes to reflect management objectives and simulate different scenarios that will help them take decisions. Also, since AHP ultimately transforms management subjective opinions into linear and comparable measures, these are very easy to be understood by machine learning models.

Heyday only needs to retrain the artificial neural network model (as it had the best results) whenever the importance of attributes has changed. In other cases, when the values of the attributes change, they can simply be inputted into the model and the model will be able to categorize automatically and precisely all SKUs based on the new values.

Finally, since our machine learning models are creating the segmentation based on the total AHP weights, SKUs that change their characteristics will automatically be re-categorized into the corresponding segment. This is especially important when deciding upcoming purchases or future inventory level as a type “C” SKU can be reclassified as type “A” if it over performs and increase its inventory level or vice versa an underperforming SKU will need to reduce its inventory and prevent the company from unnecessary inventory spending.

6.2 Future Research

One of the goals of inventory segmentation is service level, as future research we could perform a comparison of the different models and establish a baseline to determine what would the best combination of inventory be to maximize profit.

The exercise provided 5 different models (A yearly model and a model per each quarter), these models and time aggregations however, most likely hold true only for Heyday, as their product portfolio and trends are unique. To validate this hypothesis further research would have to be performed, across different companies in the same realm to establish if there's evidence to support creating models on a certain aggregation.

As future research other multi-criteria decision-making techniques could be assessed however, we believe that AHP is a great tool for building a model that needs to be adaptable as well as proficient in a rapidly changing environment.

As a next step it will be important to determine the correct frequency to recalibrate the models, from re-defining the AHP weights or inputting new data to re-run the training models. It will be important to follow up and review the difference between models with each update to establish the best cycle to update both the training data as well as the ML models.

As an additional next step in for future research, service level categories need to be agreed with Heyday and ultimately compare inventory levels with the actual unique service level across all SKUs. The importance would be not only to compere these inventory levels but also compare with Service Level, which now we didn't have enough information to perform this analysis.

For the Machine Learning component, future research should be performed using other software that allows for a more in-depth customization of the hyper parameters. This research can be performed in Python for example where the number of neurons and activation functions can be configured for an artificial neural network model.

As we mentioned, we used Support Vector Machines (SVM) and Artificial Neural Networks (ANN) as they were highly regarded by the literature and compatible with Alteryx, future research could be performed using other machine learning models such as Bayes Classifiers which are also mentioned by Kartal et al 2016.

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8 Appendix

Appendix A – Segmentation Model Samples

Item	N Avg Unit Price	N Avg. Month Demand	N. Demand Fluctuation	N.Profit Margin	N.Inv. Turnover	N. Brand Priority	Weigthed Score	Weighted Score ABC	Cummulative Score	%contribution *1000
1	0.23	0.00	-	0.95	0.93	0.00	0.44	A	0%	2.58
2	0.01	1.00	0.37	0.50	0.00	0.00	0.41	A	0%	2.42
3	0.03	0.86	0.37	0.52	0.00	0.00	0.39	A	1%	2.29
4	1.00	0.01	0.54	0.78	0.04	0.00	0.37	A	1%	2.14
5	0.02	0.00	0.43	1.00	0.00	0.00	0.36	A	1%	2.11
6	0.02	0.00	0.43	1.00	0.00	0.00	0.36	A	1%	2.10
7	0.01	0.01	0.39	1.00	0.00	0.00	0.36	A	2%	2.10
8	0.04	0.00	0.44	0.99	0.00	0.00	0.36	A	2%	2.10
9	-	0.00	0.40	1.00	0.00	0.00	0.36	A	2%	2.09
10	0.03	0.00	0.47	0.98	-	0.00	0.36	A	2%	2.08
11	0.01	0.02	0.57	0.93	-	0.00	0.35	A	2%	2.05
12	0.01	0.02	0.57	0.93	-	0.00	0.35	A	3%	2.05
13	0.02	0.00	0.39	0.98	0.00	0.00	0.35	A	3%	2.05
14	0.01	0.00	0.55	0.91	0.01	0.00	0.34	A	3%	1.99
15	0.01	0.09	0.47	0.87	0.00	0.00	0.34	A	3%	1.98
16	0.01	0.00	0.52	0.91	0.01	0.00	0.34	A	3%	1.97
17	0.01	0.07	0.45	0.88	0.00	0.00	0.34	A	4%	1.96
18	0.02	0.00	0.64	0.87	-	0.00	0.33	A	4%	1.94
19	0.01	0.01	0.44	0.91	-	0.00	0.33	A	4%	1.93
20	0.01	0.06	0.47	0.85	0.00	0.00	0.33	A	4%	1.91
21	0.01	0.01	0.64	0.84	0.00	0.00	0.32	A	4%	1.89
22	0.01	0.01	0.64	0.84	0.00	0.00	0.32	A	5%	1.89
23	0.01	0.03	0.72	0.81	0.00	0.00	0.32	A	5%	1.87
24	0.10	0.00	0.41	0.86	0.00	0.00	0.32	A	5%	1.86
25	0.01	0.01	0.39	0.87	0.00	0.00	0.32	A	5%	1.85
26	0.02	0.00	0.42	0.86	0.00	0.00	0.32	A	5%	1.84
176	0.02	0.00	0.58	0.59	0.00	0.00	0.23	B	28%	1.37
177	0.01	0.01	0.58	0.58	0.01	0.00	0.23	B	28%	1.36
178	0.03	0.02	0.38	0.61	0.01	0.00	0.23	B	28%	1.36
179	0.02	0.00	0.50	0.60	0.02	0.00	0.23	B	28%	1.36
180	0.02	0.00	0.46	0.61	0.00	0.00	0.23	B	28%	1.36
181	0.01	0.02	0.40	0.61	0.00	0.00	0.23	B	29%	1.36
182	0.02	0.00	0.62	0.57	0.00	0.00	0.23	B	29%	1.36
183	0.15	0.00	0.46	0.55	0.08	0.00	0.23	B	29%	1.36
184	0.14	0.00	0.42	0.55	0.11	0.00	0.23	B	29%	1.36
185	0.01	0.03	0.72	0.54	0.00	0.00	0.23	B	29%	1.36
186	0.02	0.01	0.58	0.58	0.00	0.00	0.23	B	29%	1.36
187	0.10	0.01	0.35	0.61	0.00	0.00	0.23	B	29%	1.36
188	0.02	0.01	0.50	0.59	0.01	0.00	0.23	B	29%	1.36
189	0.01	0.00	0.54	0.59	0.01	0.00	0.23	B	30%	1.35
190	0.02	0.01	0.79	0.54	0.00	0.00	0.23	B	30%	1.35
191	0.24	0.17	0.36	0.47	0.00	0.00	0.23	B	30%	1.35
192	0.02	0.23	0.38	0.46	0.00	0.00	0.23	B	30%	1.35
193	0.14	0.00	0.44	0.56	0.05	0.00	0.23	B	30%	1.35
194	0.01	0.13	0.32	0.54	0.00	0.00	0.23	B	30%	1.35
195	0.06	0.08	0.68	0.50	-	0.00	0.23	B	30%	1.35
196	0.02	0.00	0.39	0.61	0.01	0.00	0.23	B	31%	1.35
197	0.27	0.00	0.45	0.51	0.12	0.00	0.23	B	31%	1.35
198	0.01	0.00	0.45	0.60	0.01	0.00	0.23	B	31%	1.35
199	0.11	0.01	0.78	0.51	0.01	0.00	0.23	B	31%	1.34
200	0.01	0.18	0.36	0.50	0.00	0.00	0.23	B	31%	1.34
201	0.07	0.01	0.76	0.52	0.01	0.00	0.23	B	31%	1.34
202	0.02	0.08	0.40	0.56	0.00	0.00	0.23	B	31%	1.34
203	0.01	0.02	0.36	0.60	0.00	0.00	0.23	B	31%	1.34
204	0.02	0.01	0.50	0.59	0.00	0.00	0.23	B	32%	1.34
205	0.01	0.02	0.37	0.60	0.00	0.00	0.23	B	32%	1.34
206	0.14	0.00	0.45	0.56	0.05	0.00	0.23	B	32%	1.34
207	0.12	0.00	0.43	0.58	0.01	0.00	0.23	B	32%	1.33
220	0.09	0.01	0.57	0.54	0.00	0.00	0.23	B	34%	1.32
221	0.04	0.00	0.67	0.53	0.04	0.00	0.23	B	34%	1.32
222	0.01	0.01	0.40	0.59	0.00	0.00	0.23	B	34%	1.32
223	0.18	0.00	0.54	0.52	0.06	0.00	0.23	B	34%	1.32
389	0.13	0.00	0.48	0.50	0.01	0.00	0.21	C	55%	1.22
390	0.06	0.00	0.63	0.50	-	0.00	0.21	C	55%	1.22
391	0.02	0.00	0.41	0.50	0.14	0.00	0.21	C	55%	1.22
392	0.01	0.00	0.52	0.52	0.02	0.00	0.21	C	56%	1.22
393	0.05	0.02	0.56	0.50	0.00	0.00	0.21	C	56%	1.22
394	0.07	0.01	0.70	0.47	0.01	0.00	0.21	C	56%	1.22
395	0.01	0.01	0.59	0.51	0.01	0.00	0.21	C	56%	1.22
396	0.01	0.00	0.45	0.54	0.01	0.00	0.21	C	56%	1.22
397	0.01	0.01	0.52	0.52	0.00	0.00	0.21	C	56%	1.22
398	0.02	0.01	0.51	0.52	0.01	0.00	0.21	C	56%	1.22
399	0.01	0.00	0.54	0.52	0.00	0.00	0.21	C	56%	1.22
400	0.01	0.01	0.63	0.50	0.00	0.00	0.21	C	57%	1.22
401	0.18	0.01	0.50	0.49	0.01	0.00	0.21	C	57%	1.22
402	0.02	0.02	0.35	0.54	0.00	0.00	0.21	C	57%	1.22
403	0.02	0.01	0.40	0.54	0.00	0.00	0.21	C	57%	1.22
404	0.08	0.01	0.43	0.52	0.00	0.00	0.21	C	57%	1.21
405	0.02	0.04	0.31	0.54	0.00	0.00	0.21	C	57%	1.21
406	0.01	0.01	0.50	0.52	0.01	0.00	0.21	C	57%	1.21
407	0.01	0.00	0.45	0.53	0.00	0.00	0.21	C	57%	1.21
408	0.12	0.03	0.45	0.49	0.01	0.00	0.21	C	58%	1.21
409	0.03	0.04	0.33	0.53	0.00	0.00	0.21	C	58%	1.21
410	0.01	0.01	0.34	0.55	0.00	0.00	0.21	C	58%	1.21
411	0.01	0.03	0.54	0.50	0.00	0.00	0.21	C	58%	1.21
412	0.08	0.01	0.86	0.43	0.00	0.00	0.21	C	58%	1.21
413	0.01	0.05	0.38	0.51	0.00	0.00	0.21	C	58%	1.21
414	0.02	0.01	0.63	0.50	0.00	0.00	0.21	C	58%	1.21
415	0.02	0.01	0.44	0.52	0.00	0.00	0.21	C	58%	1.21