# Crossdocking vs. Traditional Warehousing: Small-Sample Data Augmentation to Assess Product Suitability

by

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## Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

## Abstract

This thesis tries to address supply chain strategy selection problem in logistics and transportation considering two main criteria pertaining to the decision: product characteristics and customer satisfaction. We tried to analyze the effect of product characteristics, lead time, and fill rate on the supply chain management strategy selection. The primary purpose of the thesis is to develop a tool with the capability of classifying products with different characteristics to their suitable supply chain strategy.

Due to data limitations, we first try to utilize the distribution-free bootstrap method to augment the data information and develop products with new characteristics. This is done with the help of bootstrap estimation of different fractiles of each data feature. After the data augmentation, we use a more comprehensive method to generate data based on learning of the underlying distribution of data in feature space by employing Wasserstein Generative Adversarial Network with gradient penalty (W-GAN). This method has emerged to tackle small sample size data for generative adversarial networks. The WGAN-GP used in the thesis is constructed from a three-layer generator and discriminator with dropout later and activation function of tan h (hyperbolic tangent).

Following that, we construct a multi-layer perceptron architecture network for classification of the new products with different characteristics. The sigmoid activation function of the constructed neural network transforms the network's binary label to a continuous label of between zero and one, enabling us to employ the result as an input of a utility function. After training the neural network, different utility functions, considering lead time, fill rate, and product characteristics, are defined. Linear, quadratic, square root and

logarithmic utility functions are described and compared.

In this thesis, we started with a sample data size of 20 and enriched the data by incorporating field knowledge such as extreme point analysis and including single feature impact. Following that, we applied the bootstrapping method to enlarge the sample size. Finally a W-GAN network was used to decode the underlying feature distribution and enables us to generate more samples for training the classifier. We could obtain 82% accuracy on training data and 80% on the test data which is quite a significant result given the coupling between the features.

## Acknowledgements

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Last but not least, thank you to my parents. You have always helped me, and this was no exception.

## Dedication

This thesis is dedicated to all of my loved ones.

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# Chapter 1

# Introduction

In today's business landscape pervasive with e-commerce and online shopping, the urge for an excellent logistics and transportation system is a necessity for competitive edge more than ever. Considering global warming and increased freight and passenger traffic, an optimized transportation system with less fuel consumption and shorter delivery lead time will benefit humans effectively. Therefore, the concept of innovation in supply chain and distribution centers in transportation is one of the essential efficiency issues in optimizing the chain of operations in Supply Chain Management (SCM).

Many techniques have been developed to optimize transportation between companies and customers in many years, one of which is the Crossdocking method. Crossdocking is a warehouse management concept in which items delivered to a Distribution Center (DC) by inbound trucks are immediately sorted out, reorganized based on customer demands, routed, and loaded onto outbound trucks for delivery to customers, without items being placed into inventory. If any item is held in storage, it is usually for a brief period that is generally less than 24 hours [41]. That is the distinction between a crossdock and a warehouse, where items are routinely stored for longer periods.

Many types of research have been conducted during the years regarding crossdocking. Nevertheless, implementing crossdock distribution centers is complicated and demands a high amount of coordination between suppliers, customers, and also distributors. Moreover, crossdock mathematical modelling could be one of the complex problems to solve as they have many specifications. According to Jan Van Belle's terminology [5], all these characteristics, like the shape of the cross-dock, door assignments and numbers, temporary storage, arrival pattern, departure time, and time frames, make the implementation of the model difficult.

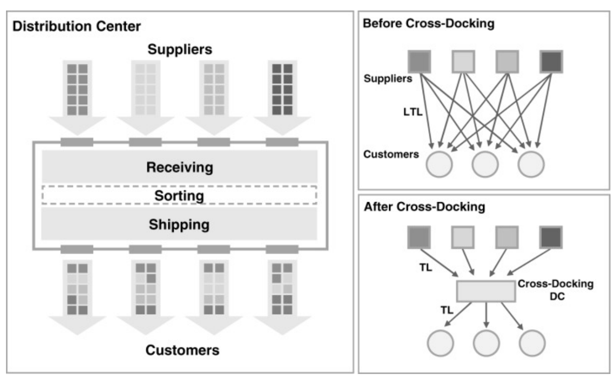



**Figure 1.1:** Crossdock system [39]

A huge part of the research in the field of crossdocking is dedicated to these mentioned specifications. For instance, Bartholdi and Gue [4] studied the best shape for a crossdock by analyzing the assignment of receiving and shipping doors. Furthermore, door assignment has been investigated in many studies [12, 30, 11]. An inside operations optimization, the temporary storage of products to avoid floor congestion and increase throughput has also been studied together with the effects of different combinations of the number of workers in receiving and shipping docks in different publications [1, 40].

Several articles focused on outside crossdocking operations, considering a limited number of characteristics, and tried to optimize the truck scheduling [35, 36, 37]. For example, Yu [41] does not consider the operations inside the warehouse or distribution center, such as scanning and sorting operations, and the focus of his study is on the outbound operations of a crossdock. Also, the arrival sequence the products at the shipping dock is the same as their unloading sequence at the receiving dock. Unlimited temporary storage and non-repeating truck holding are assumed by Yu throughout his study. Madani-Isfahani et al. studied crossdocking and optimized a crossdock case with repeating truck holding in his research [27]. Javanmard et al. considered the scheduling of a multi-product crossdock problem with time windows for deliveries and pickups [21]. Many other special cases for crossdocking have been proposed during decades of research.

Minimizing the cost of a crossdock in a specific situation, like minimizing the time a truck spends at a crossdock or minimizing the cost or time of operations, is another concept in crossdocking. A comprehensive review paper about crossdocking cost structures is represented in the work of Soleymani and Tolooie [38].

Regarding cost elements, the paper of Apte and Viswanathan [2] mentioned the costly elements of a crossdock, and Gümüs and Bookbinder [19] have studied crossdock transportation and facility costs, inventory costs, and in-transit inventory costs and calculated the minimum-total-cost locations.

It is evident that optimizing the inbound and outbound operations of a crossdock and understanding their cost structures and shapes would benefit different businesses. However, a more macroscopic view of the concept would raise this question: is crossdocking suitable for every industry? Much of the literature has been dedicated to optimizing crossdocking operations, and there are fewer papers casting light on the advisability of a crossdock for different industries with various products.

As crossdocking has been advertised during the past decades, it seems like a perfect opportunity for industries to cut off some unnecessary charges from their logistics operations with its help; however, crossdocking cannot fit every situation due to its specifications. Company goods and services must have specific characterization to be eligible to be delivered via a crossdock platform [23]. None of these strategies is suitable for all kinds of businesses. Hence, selecting the right system is one of the most challenging decisions new companies have to make according to their product characteristics.

Every industry might have a different logistics strategy decision because of varying factors, not solely their product characteristics. Elements like the company location, the budget for their logistics and operations, yearly sales, and considerations on their on-shelf availability and lead time can affect this decision. These are only a few factors affecting the decision-making for a proper logistics strategy. That is the reason why new investors are struggling with choosing the right logistics strategy for their businesses. In recent years, Some research has tackled this issue qualitatively [16] at the beginning of the research thread and quantitatively [7, 24] as the field grew.

Benrqya et al. [7] has done the research on crossdock Vs. traditional warehousing and we will highlight the differences in our work and his in **Section 2.4**. Quantitative modeling of crossdocking, as in Benrqya et al. [7], only works if all the company's detailed data are provided. The issue for most investors is that before launching the business, they do not have enough data to calculate the costs in detail. Various measures, such as how much it costs to hold and load the goods, the distance between customers, and the location of distribution centers can be considered in this regard. On the other hand, we have many businesses which have done their freight management using either CD or warehousing ideally. That is where the application of machine learning for classification comes to mind. This is the main difference of our work in comparison to Benrqya et al. [7] research. They have developed a purely mathematical cost and customer satisfaction modeling, while our focus is on the data driven decision making using the application of trained classifications.

Using real-world companies' information for product characteristics as our "features" and the choice of their strategy, CD or warehousing, as our "labels" for a two-category classification, could tackle this issue. However, the challenge is that that training of machine learning models usually requires large datasets. Unfortunately, the data are usually not easily accessible due to the big businesses' confidentiality issues. Alternatively, with the use of methods like bootstrapping [13] and GAN-based data augmentation [17], precisely the Wasserstein GAN data augmentation method proposed by Liu et al. [25], we can increase the sample size of the data sets, large enough to be able to achieve a generalizable data-driven decision-making model.

After using the bootstrapping method and GAN, classification using an MLP Neural Network is applied to classify the extended data. Although we might not have much data for this analysis, data augmentation methods allow us to see the extent to which applying machine learning techniques on the available businesses data would help us through optimization, especially for new industries. And finally, the impact of customer satisfaction on the overall logistics strategy selection decision has also been studied in this thesis.

The remainder of this work is organized as follows. **Chapter 2** provides an overview of literature on product characteristics and the selection of logistics strategies. After that, the research methodology and data augmentation methods are discussed in **Chapter 3**. Then, the empirical findings and analysis are described in **Chapter 4**. A utility function approach and its sensitivity analysis have been conducted to investigate the effect of customer satisfaction on the logistics strategy decision in **Chapter 5**. Lastly, the thesis conclusion and possible future research directions are discussed in **Chapter 6**.

# Chapter 2

# Literature Review

Over the years, several studies have tackled the challenge of logistics strategy selection. This was first done qualitatively, at the beginning of the research thread, and quantitatively as the field grew. For instance, Fisher [16], as a pioneer of this field, explored this question and tried to mention some suitable product characteristics for a CD or warehousing. Specifically, he proposed that if the product has a high demand, it has to go through a crossdock. Nonetheless, that analysis was too broad and insufficient, since a product may have several specifications that conflict with one another for strategy optimization. Later on, the literature became more quantitative using Key Performance Indicator (KPI) measurements like the work of Li et al. [23]. Ultimately Benrqya et al. [7] defined a cost model for a CD and a warehouse distribution center using real-world retail data. This approach, however, works only if all the detailed data of a company can be obtained, which is rarely the case in practice.

Different articles look at product suitability for crossdocking systems in various types and categories. In this thesis, I tried to merge all of their insights and develop the best categories and a solid timeline review. This approach covers almost every crucial factor to be considered in both qualitative studies and quantitative ones.

In this chapter, the product suitability of goods has been divided into two main categories: Product Specifications and Marketing Specifications. “Product specification” is considered the characteristic of a Stock Keeping unit (SKU), which describes the physical characteristic of a good, as carried in the company, or any attribute of products that describe the good itself. On the other hand, “marketing specification” is defined based on the sales or pricing factors that a product may have, which affect the process of decision-making for logistics strategy selection.

In the following two subsections, we will look at both specifications and expand their applications in different real cases.

## 2.1 Qualitative Research: Product Specification

### 2.1.1 Product life cycle

Fisher [16] found that products with short life cycles have increased risk of obsolescence and unpredictability. Therefore, they need a responsive supply chain that reacts quickly to demand uncertainty and their short life cycle, which is mainly the goal of a crossdocking system. Fisher divided products into two main categories: innovative products (fashionable products) and functional ones.

Innovative products need a specific logistics system that can tackle all the uncertainties in their customer demand. In this case, the supply chain needs to focus on responsiveness, rather than efficiency and cost reduction. Therefore, for the innovative category of products with shorter life cycles, a logistic system including a crossdock is not recommended because innovative products have less predictable demand distributions.

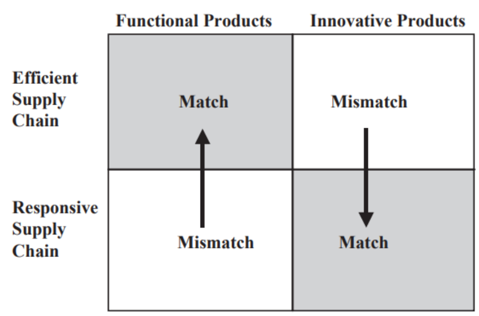



**Figure 2.1:** Matching supply chains with product life cycle [16].

On the other hand, when the demand for a product, such as a functional one, has a relatively predictable nature, using Fisher's own words, "now is a good time to focus on efficiency rather than responsiveness", and use fast and low safety stock logistics like a crossdock. However, those two product categories are at opposite ends of a spectrum, and there are many goods whose demand certainty lies somewhere in between those two extremes. Therefore, choosing the right logistics system is not as easy as it sounds.

According to Fisher, the certainty of demand for a specific product can also vary depending on its life cycle stage. For example, is the item in the introduction stage, in the decline stage or maturity step? In all these steps, a single product may need a different warehousing or distribution system. That is why many big corporations have logistics systems with a combination of crossdocking and traditional warehousing.

### 2.1.2 Product shelf life

Shelf life is another factor, since this dictates how long perishables can be kept before they cannot be sold, used, or consumed. Lovell et al. [26] suggest that networks holding low inventories and using faster transport methods are optimal for products with a short shelf life. Li et al. [23] consider that items with a short life become obsolete faster, and a CD distribution strategy is most appropriate for this type of product. An interesting approach, adopted by the Li et al. paper [23], is a measurement to assess product priorities. An essential element of this assessment is product shelf life. The priority indicator was introduced as follows:

$$\text{priority} = \text{value per unit/product life} \tag{2.1}$$

Li et al. [23] used distinct indicators to measure suitability of different products for a crossdocking system. Some of their work is mentioned in other parts of this thesis.

### 2.1.3 Product Value

Stock holding is a major unrecognized cost factor in an inventory system. A company's warehouse could end up piling costly materials, whose value is quite noticeable.

Payne and Peters [32] addressed the importance of product value in logistics strategy selection. They defined it as the "monetary density" that expresses the ratio between the dollar value of a product and its weight. They suggest that products with high monetary density are expensive to store because of their high value. Such items incur higher inventory costs in terms of working capital and insurance cost if they are held in warehouses, yet are relatively inexpensive to move because of their low weight. These types of products are more suitable for a full postponement strategy (Crossdocking), in which manufacturing and logistics operations are customer-order initiated. Products with low monetary density are more adapted to the full-speculation strategy (Warehousing), because they have a low value and then are relatively inexpensive to store.

### 2.1.4 Unit stock out

The unit stockout cost is another significant factor. Because crossdocking minimizes the level of inventory at the warehouse, the probability of stockout situations is higher [2]. On the other hand, if the unit stockout cost is low, the advantages of crossdocking can outweigh the increased penalty costs, making it the preferred strategy. Therefore, the crossdocking method is most effective for items with steady and consistent demand rates and low unit stockout costs.

On the other hand, for SKUs with unstable or fluctuating demand and high unit stockout costs, the traditional warehousing and distribution strategies are still preferable. When the demand rate is constant, but the unit stockout cost is high, crossdocking can still be implemented. With constant demand, if the DC management has proper planning, there would be a very low probability of stock out. This is why Apte and Viswanathan [2] mention that more precise planning systems are required to ensure that instances of stockouts/lost sales are kept to a minimum. The implemented planning systems could be reliable warehouse management systems (WMS) and product identifiers.

Similarly, when product demand fluctuates but the unit stockout cost is low, crossdocking can still be implemented with proper systems and planning tools to keep stockouts and the associated stockout cost reasonable. In these cases, the probability of stockout may become higher, but with lower stockout costs, the penalty of the mistakes becomes less significant.

| | | *Product demand rate* | |
| --- | --- | --- | --- |
| | | Stable and constant | Unstable or fluctuating |
| *Unit stock-out costs* | High | Cross-docking can be implemented with proper systems and planning tools | Traditional distribution preferred |
| | Low | Cross-docking preferred | Cross-docking can be implemented with proper systems and planning tools |

**Figure 2.2:** Matching supply chains with product demand and unit stock out [2].

### 2.1.5 Distance to suppliers and customers

According to the interpretation of Apte and Viswanathan [2], another factor that can influence the suitability of crossdocking includes the distance of the warehouse from other points in the distribution channel. In addition, the technology and systems used in crossdocking can be expensive. So, besides stable demand, the warehouse should manage a substantial volume of merchandise for the region, resulting in stability over time.

A further critical point is that if a warehouse is close to customers, the need for crossdocking is lessened, since the cost of building such an expensive DC would not be justified.

Therefore, the locations of DC, suppliers and customers are significantly important, and they should be considered.

A general overview of the literature on product specification is summarized in Table 2.1.

**Table 2.1:** Literature Overview on Product Specification

| Product Specifications | | | | Key References |
|---|---|---|---|---|
| Characteristic | Factors | Key performance for selection | logistics strategy | |
| Life cycle | short | - | CrossDock | Fisher et al.[16] |
| | long | | Warehouse | |
| shelf Life | short | priority | CrossDock | Lovell et al.[26] |
| | long | | Warehouse | |
| Product Value | low | priority | Warehouse | Pagh and Cooper [31] |
| | high | | CrossDock | |
| Unit Stock Out | low | - | CrossDock | Apte and Viswanathan [2] |
| | high | | Warehouse | |
| Distance to Customers | short | - | Warehouse | Apte and Viswanathan [2] |
| | long | | CrossDock | |

## 2.2 Qualitative Research: Marketing Specification

### 2.2.1 Popularity

Li et al. [23] define the "popularity", the number of times a product appears on orders from the customers.

$$\text{popularity} = \text{fraction of orders containing the product} \tag{2.2}$$

Increased product popularity leads to more frequent transits and larger volumes. Crossdocking works best for popular items because they do not require inventory storage and can be sent directly to their destinations. Therefore, it is reasonable to put a high priority on crossdocking of those SKUs with high popularity. For the computation of popularity, Li et al. [23] do not take account of the quantity sold. In their popularity calculation, quantity is not included since it has already been factored into the total cubic movement category, mentioned in the following section.

### 2.2.2 Total cubic movement

This factor refers to the total volume of an item moved through the facility. In a distribution center with limited space, assigning a high-cubic movement product to a crossdock could reduce inventory costs. That SKU no longer needs to take up storage space in the facility for a longer time, allowing the space to be utilized for other products. Li et al. [23] introduced a precise measure of cubic movement, which can be seen in Equation 2.3.

$$\text{Total cubic movement} = \text{demand} \times \text{product volume} \tag{2.3}$$

In this formulation, a combination of the demand and product volume has been considered. Two main factors relating to the cost of warehousing are the frequency of SKUs coming in and out of inventory, and also the volume they take up in the storage. The more frequently a product goes through the warehouse, and the larger that item's size, the greater the logistics's expense. The combination of these two factors can capture a good measurement of the logistics strategy selection.

### 2.2.3 Product demand rate

One way to look at the suitability of goods for a crossdocking system is to evaluate their demand rate. Apte and Viswanathan [2] experimented with the concept of *demand assessment*. Crossdocking is not suitable for every type of product. Items need to have a high demand rate, since the structure of the crossdocking system is based on the idea of high turnover in warehousing. This would not be possible with a low-demand-rate product. Products in crossdocks usually are shipped separately from suppliers and then during outbound process they get aggregated. The mentioned low-demand-rate product is referring to each of the products and they should have higher demand rate to go through crossdock.

As Apte and Viswanathan [2] explain, crossdocking works best when items coming into the warehouse are quickly pulled out by retailers or destination points. Therefore, in the daily planning of crossdocking, the demands of those items are an essential consideration. Therefore, crossdocking will not work if the incoming and outgoing loads are unbalanced. Hence, products that are more suitable for crossdocking are those whose demand rates are relatively stable and constant. Among these items are essential grocery items, as well as frequently-consumed perishable food items.

For perishable SKUs, demand tends to be stable. Since customers cannot buy and store large quantities, they must repurchase them regularly. The warehousing and transportation requirements for products with stable demand are more predictable, making planning and implementing crossdocking relatively straightforward. Retailers and distribution centers also require lower safety stocks for such products.

### 2.2.4 Product demand uncertainty

Pagh and Cooper [31] consider demand uncertainty to be a significant factor in selecting the right distribution strategy. Since the speculation risk is more significant for products with uncertain demand, the full postponement will be appropriate for such an item. Payne and Peters [32] assert that SKUs with low demand variability are more easily adapted to cross-docking methods. Product demand uncertainty has a close relationship with the product life cycle, and this aspect was discussed thoroughly in Section 1.1 (product specifications).

The indicator that Li et al. [23] introduced is the "Coefficient of Variation" measure, which is calculated as follows:

$$\text{Coefficient of Variation} = \text{standard deviation}/\mu \tag{2.4}$$

This measure can show the coefficient of variation of a product numerically.

A general overview of the literature on product specification is summarized in Table 2.2.

**Table 2.2:** Literature Overview on Marketing Specification

| Marketing Specifications | | | | Key References |
|---|---|---|---|---|
| Characteristic | Factors | Key performance for selection | logistics strategy | |
| Popularity | low | Fraction of orders containing this product | Warehouse | Li et al. [23] |
| | high | | CrossDock | |
| Cubic Movement | low | Demand and product volume | Warehouse | Li et al. [23] |
| | high | | CrossDock | |
| Demand Rate | low | - | Warehouse | Apte and Viswanathan [2] |
| | high | | CrossDock | |
| Demand Uncertainty | low | Coefficient of Variation | CrossDock | Apte and Viswanathan [2] |
| | high | | Warehouse | |

## 2.3 Quantitative Research

All those factors mentioned above should be part of the decision-making process for a proper logistics strategy selection. However, considering so many factors at once could be confusing and complicated to handle in the real world. One approach adopted by Li et al. [23] is to consider only a select set of the important factors. Popularity score, the cubic movement measure, coefficient of variation, and product life cycle scores all impact the final decision-making process.

Using the formulation introduced in the previous section (Equations 2.1 to 2.4), Li et al. [23] consider these four factors and normalize the results on each score. After dedicating a certain weight to each factor, based on the need of the supplier or retailer, those authors came up with a general score between 0 and 1 for the product. The closer the score to 1, the better for it to go through a crossdock based on the item's characteristics.

Another step, further removed from considering scores, is to develop complete mathematical modelling consisting of all the costs associated with different warehousing techniques. For example, the work of Bnrqya et al. [7] was the first to study a three-echelon supply chain model (supplier DC, retailer DC and stores) with three different distribution strategies (Traditional Warehousing, Crossdock Pick by Line, and Crossdock Pick by Store) and two performance measures (Total Cost and On-Shelf Availability). Moreover, their work [8] on the impact of shelf life on distribution strategies mathematically has been the first.

According to the definition of Benrqya [6] on crossdocking strategy, if the inventory is removed from the retailer DC and the allocation and sorting of the products are done at the crossdock platform (i.e., the retailer DC), this crossdocking strategy is referred to as the "crossdocking pick by line" (XDPL) strategy. If product allocation and sorting of the SKUs are done at the supplier DC level, this strategy is referred to as the "crossdocking pick by store" (XDPS) strategy.

Modelling aspects such as those above contribute to finding out under which conditions XDPL or XDPS can lead to an end-to-end supply chain reduction in costs compared to traditional warehousing. Although that approach is the most definite of all mentioned before, there is a downside to this in the real world. Such a methodology can only be considered if one has all the detailed information of a company.

## 2.4 Problem Statement

Upon reviewing the literature, a gap in the logistics strategy selection research can be observed. Imagine that a new corporation needs to plan for its logistics strategy. The decision-making team needs to know whether the supply channel of their products should be crossdock or traditional warehousing. They might need to inquire if a third-party logistics company should handle crossdocking; or if traditional warehousing alone would suffice.

Research in this area only comes up with vague recommendations basing on the item's characteristics. However, to make an accurate decision about the logistics strategy, more information about products, warehousing, hauling, and return costs are required. That is impossible for a new establishment in the industry to provide.

In this thesis, I tried to rely on the information provided by the same industries and their practices to find an answer. Using an ample amount of data from different industries with reasonably good variety in their products, we can assist a new company with a new product to decide whether to use traditional warehousing or crossdocking for their logistics strategy.

With an extensive data set of different products with their best practices of logistics strategy choice (traditional warehousing, crossdocking, or the combination), we can train a multi-layer perceptron neural network to predict the possibility of each new product logistics strategy.

This problem initially was solved with employing a famous civil engineering problem called modal split [20]. Modal Split is used to decide the probability that a person with a specific characteristic and financial situation will choose public transport or their car for a potential trip [15, 29, 22]. The modal split analysis is where trips between a given origin and destination pair ($T_{ij}$) are divided into trips using transit, trips by automobile drivers or trips by carpool. The main task of modal split analysis is to develop models that can be used to make such divisions.

This study tries to develop a tool (trained classification neural network) that fills this gap between an entirely qualitative approach only relying on several product specifications and a detailed mathematical modelling strategy selection approach.

# Chapter 3

# Research Methodology and Data

## 3.1 Data structure

I gathered the presented data from a paper published by Li et al. [23]. In that paper, using several formulas (Equations 2.1 to 2.4) from **Chapter 2**, the product characteristics were converted to four different KPIs which best describe the suitability of the selected logistics strategy. The original data contain five different features: Value per Stock keeping unit, Dimension, Weight, Life cycle, and demand. The KPI-based dataset contains the Popularity score, Cubic Movement score, Variation score, and PLC (Product Life Cycle) score varrying between 0 and 1, which play an important role in strategy selection (Table 3.1). With the help of the KPIs introduced, we were able to extract more beneficial information concerning the product marketing specifications like coefficient of variation and fraction of orders containing this product.

| Product Name | Popularity Score | Cubic Mvt Score | Variation Score | PLC Score | Label |
|---|---|---|---|---|---|
| Bread | 0.25 | 0.25 | 0.25 | 0.05 | Crossdock |
| T-Shirt | 0.04 | 0.08 | 0.09 | 0.1 | Warehouse |

**Table 3.1:** Sample of KPI measurements data.

| Product Name | Value (/SKU) | Dimension | Weight(KG) | Life Cycle (Weeks) | Demand | Fraction of Orders | Coefficient of Variation | Label |
|---|---|---|---|---|---|---|---|---|
| T-Shirt | 600 | 360000 | 25 | 12 | 41.67 | 0.52 | 0.68 | Warehouse |
| Bread | 100 | 490000 | 50 | 4 | 73.47 | 1 | 1 | Crossdock |

**Table 3.2:** Two samples of product characteristics data.

Now with a complete analysis of the original data, we have a product characteristic dataset with 7 features and their labels (Table 3.2).

As mentioned before, training an MLP requires an ample amount of data. Since the data extracted from the paper by Li et al. [23] was not enough, several data augmentation techniques were examined for generating more data based upon the on-hand data. An essential concept behind training neural networks is for the data to have "rich" information, since the generalizability of the trained model depends on the extensiveness of the presented train data. Otherwise, the network will over-fit the provided data, and will not perform adequately in the train condition. This is why data augmentation on the original dataset using field knowledge is critical. Without adding data augmentation and incorporating field knowledge to the data set, expanding the data only increases the quantity of the data, and no additional information is delivered to the model.

Therefore, for the neural network training and the field knowledge contribution to enriching the dataset on hand, two data augmentation techniques have been used. The knowledge of this field emanates from the impact on logistics strategy selection of literature on product characteristics. As mentioned in the literature review in **Chapter 2**, we can talk about the influence of each characteristic on logistics strategy, isolated from other characteristics. This means the a given product, with the same characteristics as a loaf of bread but with lower coefficient of variation, is definitely under the category of crossdock if the bread's label itself is "crossdock". This knowledge helps us to add several different abstract products with similar product characteristics but with minor modifications. This approach will give us more information about the data without losing any label on each category.

Another instance of using the field knowledge on the original data is that items at the extreme ends of the range of product characteristics could be assigned either to a crossdocking or warehousing classes, with high confidence. For example, a product with the highest demand, lowest coefficient of variation, and other specifications which assert that the product is better to go through a crossdock, should be labelled as a "crossdock" product. This situation applies to the analogous product on the other end of the spectrum.

After applying the data augmentation with field knowledge, now is the perfect place to expand the quantity of the available data, so that the training in an accurate manner would be possible.

## 3.2 Description of techniques chosen

Data augmentation methods such as Bootstrapping [42] and Generative Adversarial Networks [17] could be potentially beneficial in such problems where the data limitation is considered a hindrance. Bootstrapping is a distribution-free method for estimating data statistics, while GANs can be used to learn the underlying distribution of small-sample data, and generate new samples from the trained distribution to enrich the original data set. This data augmentation would help the classifier to perform more accurately.

Motivated by this, a new opportunity has opened up in the field of data-driven supply chain strategy analysis, as the issue of data sample size is less of a barrier. Therefore, in this thesis, we try to see the extent to which the application of machine learning techniques such as GAN or Bootstrapping, on a small-size business data set, would help with optimization and cost reduction, especially for new industries.

### 3.2.1 Bootstrapping

The bootstrap method is a statistical technique for estimating the parameters of a population by averaging estimates from multiple small data samples and generating more samples out of a given small sample. Importantly, samples are constructed by drawing observations from a large data sample, one at a time, and returning them to that sample after they have been chosen ("Sampling with replacement"). This allows a given observation to be included in a given small sample more than once. A bootstrapping approach is based on the principle that it may be better to interpret the characteristics of a population based on the sample available, rather than considering unrealistic assumptions about the population [9, 42].

The bootstrapping approach begins with a single sample of size $n$, $S = \{x_1, x_2, ..., x_n\}$. Using this sample, several bootstrap samples are then generated by sampling with replacement. With the help of this method, we then end up with a much better sample size. Bootstrapping resamples the original dataset with replacement several times to create simulated datasets. This process involves drawing random samples from the original dataset. Here's how it works:

The bootstrap method has an equal probability of randomly drawing each original data point for inclusion in the resampled datasets. The procedure can select a data point more than once for a resampled dataset, illustrating the "with replacement" aspect of the process. The procedure creates resampled datasets that are the same size as the original dataset. The process ends with the simulated datasets having many different combinations of the values that exist in the original dataset. Each simulated dataset has its own set of sample statistics, such as the mean, median, and standard deviation.

### 3.2.2 Bootstrapping Fractile Estimation

As we are lacking the real distribution of the small sample of products that we obtained from the work of Li et al. [23], the mean, standard deviation or other statistical metrics in bootstrapping do not suffice to draw a conclusion on the underlying distribution of the original data. Therefore, to estimate the original data distribution using the bootstapping technique, we use the population fractile statistical measure. The bootstrap estimate of population fractile can be calculated using the direct calculations proposed in the work of Efron and Tibshirani [13, 14]. A perfect implementation of this method on reorder level analysis has been done in the work of Bookbinder and Lordhal [9].

Calculation of different fractiles of the sample generated shows the approximate character of the original data. For instance, calculating nine different deciles of a population would give us an estimate of that probability density function of the population for the entire data range.

### 3.2.3 Wasserstein GAN

The use of Generative Adversarial Networks (GANs) [17] is an approach to generative modelling using deep learning methods, such as convolutional neural networks. Generative modelling is an unsupervised learning task in machine learning that involves automatically discovering and learning the distributions or patterns in input data, such that the model can be used to generate or output new examples that could have been drawn from the original dataset.

Supervised learning is a machine learning method in which models are trained using labelled data. When learning is supervised, models must find the mapping function relating the input variable (X) to the output variable (Y). Unsupervised learning is another machine learning method which recognizes the patterns from the unlabeled input data. The goal of unsupervised learning is to find the structure and patterns from the input data. Unsupervised learning requires no labels to be provided before hand. Rather, it finds patterns from the data on its own.

GANs constitute a supervised learning problem with two sub-models: the generator model that we train to generate new examples from a multi-dimensional random input (which could be considered as "noise"), and the discriminator model that tries to classify examples as either "real" (belong to the provided dataset originally) or "fake" (using the generator). The two models are trained together in a game-like adversarial environment, until the generator becomes sufficiently expert in producing fake data samples, so that the discriminator model cannot distingush them from the original dataset, regardless of the amount of training.

The training of neural networks involves adjusting the weights to reduce errors or losses. In WGAN, on the other hand, the generator is not directly connected to the loss that we're trying to affect. The generator feeds the discriminator, and the discriminator produces the output we're trying to influence. As a result, the generator is penalized for generating a sample that the discriminator network classifies as fake. The "backpropagation" of this extra portion of the network is required. Backpropagation adjusts each weight in the right direction by calculating the weight's impact on the output. But the effect of a generator weight depends on the effect of the discriminator weights it feeds to. So backpropagation starts at the end and flows back through the discriminator into the generator.

There are several downsides to application of the GAN method. It has a reputation of being unstable and delicate in practice [3]. That is why many recent publications on the GAN subject has attempted to find novel ways of stabilizing the Vanilla GAN training [3, 28, 33, 34]. GANs are inherently unstable, since they include two networks, each of which has a different loss function. Moreover, training the GAN model could require a huge amount of data. This is often a significant barrier for several fields, as gathering data on a large scale might be time-consuming, expensive, or even impossible. These two reasons are the main motivation for the new GAN method called Wasserstein GAN, proposed by Arjovsky et al. [3].

The amazing point about the WGAN is that it has much of the original GAN structure. There are two main differences that arise in tackling the above issues of GAN. First, there is no discriminator in WGAN; it is called a "critic", as it scores the realness of the data generated instead of relying solely on labelling it fake (0) or real (1). That is why training the generator should seek a minimization of the distance between the distribution of the data observed in the training data set and the distribution observed in generated examples.

$$KL(\mathbb{P}_r \parallel \mathbb{P}_g) = \int \log(\frac{P_r(x)}{P_g(x)}) P_r(x) d\mu(x) \tag{3.1}$$

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\gamma \in \prod(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma} [\parallel x - y \parallel] \tag{3.2}$$

Another difference between GAN and WGAN is the way distance between distributions is calculated. While GAN uses the Kullback-Libler divergence formulation, in WGAN we use the Earth-Mover (EM) distance or Wasserstein-1 (Equations 3.1, and 3.2 before). Lastly, in the GAN, the generator and discriminator models must be updated in equal amounts. In WGAN, we train the critic more than the generator with the ratio of "n.critic", which is one of the hyperparameters of the WGAN. This hyperparameter represents the number of training of generator over the discriminator. The reason behind this is the fact that EM distance is now continuous and differentiable, and we should train the critic as much as possible for it to reach optimality.

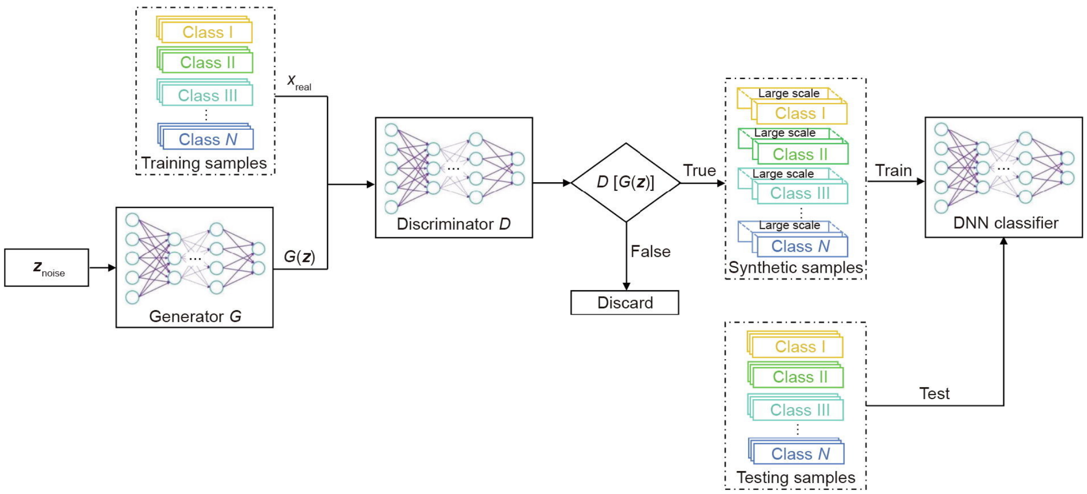



**Figure 3.1:** WGAN structure [25]

One good implementation of WGAN is the work of Liu et al. [25]. They have used the WGAN structure and a deep neural network to generate new data and classify those data into different stages of cancer. The structure used in this study is inspired by their work, (Figure 3.1), although with a different neural network architecture.

In this thesis, a special version of WGAN, with Gradient Penalty, is used. This method was introduced after the emergence of the WGAN method to address the convergence of WGAN on very small sample problems. This approach, proposed by Gulrajani et al. [18], was introduced to solve the problem of weight clipping in the original WGAN structure and make the model more stable. In their method, instead of the weight clipping approach, they have used the penalizing method of the norm of gradient of the critic with respect to its input.

$$L = \underset{\tilde{x}\sim P_g}{E}[D(\tilde{x}) - \underset{\tilde{x}\sim P_r}{E}[D(x)] + \lambda \underset{\hat{x}\sim P_{\hat{x}}}{E}[(\| \nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2] \tag{3.3}$$

An additional consideration, applied to the WGAN-GP code, was the implementation of GAN adaptive iteration. I have modified the process so that the number of n.critic would be calculated based on the loss values of both generators and discriminator. In every iteration, the code validates the loss functions. If the loss function value of the generator were smaller or larger than specific thresholds, then the number of training iterations on the discriminator would decrease or increase, respectively, in order to allow or prevent the generator from becoming too weak or too strong. This adaptive-iteration learning would help the structure be trained relatively evenly, and prevent the discriminator or generator from quickly becoming strong without competing with the discriminator for enough iterations. If that happens, the discriminator is left behind the generator, and the convergence would not happen. Therefore, training of generator and discriminator must happen almost synchronously, so that they can compete in the right environment and improve at each iteration logically.

### 3.2.4 Classification

In this thesis, I construct a multi-layer perceptron neural network to be trained and get the classification output of each specific product. A multi-layer perceptron (MLP) is a supervised learning algorithm that learns a function by training on a specific dataset. Given a set of features $X = \ x_1, x_2, ..., x_n$ and a label $Y = \ y_1, y_2, ..., y_n$, the MLP can learn a nonlinear function approximation for classification. An MLP can have one, or several, nonlinear layers called *hidden layers*. Figure 3.2 shows an overall structure of an MLP.

The leftmost layer, known as the input layer, consists of a set of neurons representing the input features. Each neuron in the hidden layer transforms the values from the previous layer with a weighted linear summation $w_1x_1 + w_2x_2 + ... + w_nx_n$, followed by a nonlinear activation function like the hyperbolic tan (tanh) function. Finally, the output layer receives the values from the last hidden layer and transforms them into output values (labels). This is done so that by adjusting the output of the test dataset, the backpropagation and customization of the weights would be possible.

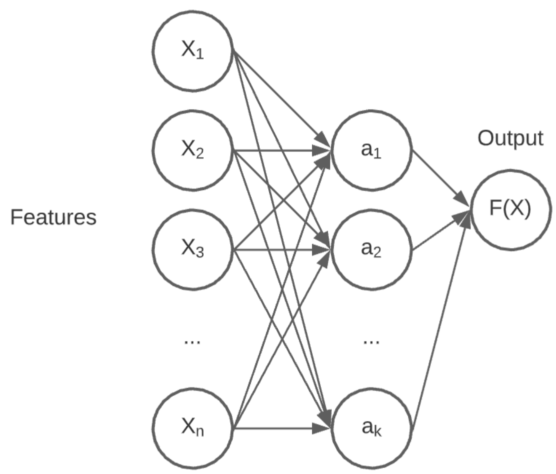



**Figure 3.2:** Multi-layer Perceptron

As mentioned before, the whole purpose of MLPs is to train multi-layer neural network weights so that the network, using nonlinear approximation, can predict the label or outcome of the input dataset. Looking at the concept of logistics strategy selection, we are facing the same situation. We have a product or even a business specification with a decision (label) to predict. This decision is an appropriate logistics strategy for that particular industry with specific production. Therefore, the idea of exploiting machine learning techniques, including MLP and logistic regression, came to mind.

As the decision of logistics strategy cannot be a definitive one, it is better not to consider the choice between warehousing and crossdocking options as a binary decision (look next paragraph). Therefore, treating the target of the MLP as binary values 0 or 1 (with 0 as pure traditional warehousing and 1 as a complete crossdocking strategy) is not a good idea; a continuous view of the issue could be more beneficial, as a result of providing a confidence margin of the decision as well. This perspective lets us choose an MLP with a sigmoid activation function that transfers the binary label to a probability-like measure. This insight into the outcome of the logistics strategy selection can help the decision-maker look at the product characteristic's output as a probability (decimal), not a definite label of 0 or 1. This approach was inspired by the modal split analysis in the field of civil engineering [29].

In this case, with an output of 0.23 as an example, the decision-maker can make an informed decision based on their product characteristics instead of getting only 0 as an output. The decimal output of 0.23 means the 0.23 of products with similar characteristics go through crossdock and the other 0.77 goes through warehouse. This probabilistic outcome means a product with a probability of 0.56 could be considered both for traditional warehousing and crossdocking. Even a mixed approach could be considered, instead of a pure crossdocking approach. This can happen with the help of logistic functions. Otherwise, a product with a probability outcome of 0.52 would only represent "one" as its value.

It would go under the category of crossdocking, and be treated the same way as a product with probability of 0.99 would have been treated.

This interpretation of the outcome could assist us in many ways. Many business developers are curious to know the confidence behind the outcome of the research done. A single label would raise so many questions and make us lose much helpful information on the subject. Proposing a probability based on product or business specifications can be helpful for both decision-makers and business owners. Moreover, a good sensitivity analysis of the result gives them how a simple change in their operations or even their marketing specifications could save a significant amount of money. For instance, a product with the probability of 0.52 could be modified to go through traditional warehousing instead of crossdocking, the latter is considered to be a more expensive strategy.

The continuous output of the neural network would be possible with use of the sigmoid activation function in the last layer of the constructed network. That is why in this thesis, I chose the logistic regression classifier.

### 3.2.5 Logistic Regression

Logistic regression is a classification algorithm like MLPs when the value of the labels is categorical in nature (warehousing or crossdocking). These categorical labels are the output of a special activation function called a "logistic function" or "sigmoid function".

The sigmoid function is an S shaped curve when plotted. The sigmoid function is shown in Equation 3.4 and in Figure 3.3.

$$\sigma(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}} \tag{3.4}$$

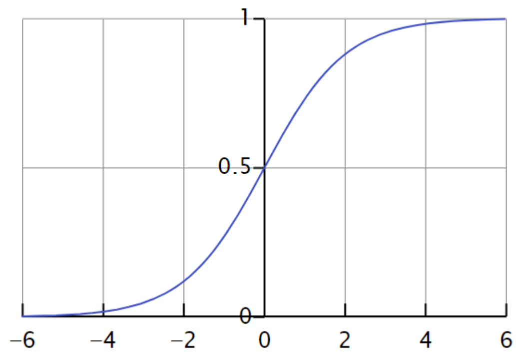



**Figure 3.3:** Logistic function (Sigmoid curve).

Many problems such as logistics strategy selection require a probability estimate as output. Logistic regression is an extremely efficient mechanism for calculating probabilities. Practically speaking, one can use the returned probability in either of the following ways: as the predicted probability or as a converted binary category.

The sigmoid function is a mathematical function utilized to map the predicted values to probabilities. That function maps any value into another value within a range of zero to one. The output value of a logistic function is between zero and one, and cannot go beyond this limit, so it forms an S shaped curve. This helps us to obtain not just the predicted classification, but also to obtain the probability of an event occurring. Use of logistic regression is encouraged in this application of classification. That is because, in this thesis I am looking more into the probability-like outcome of our products as the final decision, rather than their label being zero or one.

# Chapter 4

# Empirical Results and Analysis

## 4.1 Bootstrapping Synthesis Data

As mentioned in **Chapter 3**, the bootstrap fractile approximation assists us in estimating the distribution of each feature. To maintain the label of each class, the bootstrap method was applied to both classes separately. After writing the bootstrap resampling code in MATLAB, a synthesis data set of size 1000 as the training set for each class was available. Two generated dataset histograms for both the crossdock and warehouse classes are represented in Figure 4.1. This data enhancement is a significant improvement from the original data sample that was obtained from the paper of Li et al. [23].

As we review the data distribution across the seven product characteristics, we can see that each of these features may occur anywhere within the range, as illustrated in Figure 4.1. This is yet another indication that any product could be crossdocked or moved through the warehouse channel. Essentially, the effect of features combination determines whether a product is classified under the crossdocking class or warehousing. As Figure 4.1 shows, the distributions of each feature in the two classes are relatively close to each other. This data coupling makes the classification more difficult.

The histograms indicate that features 3, 5, and 6 (Weight, Demand, and Number of appearances on each order) have a more significant impact on classification than other features, since their data coupling is relatively low.

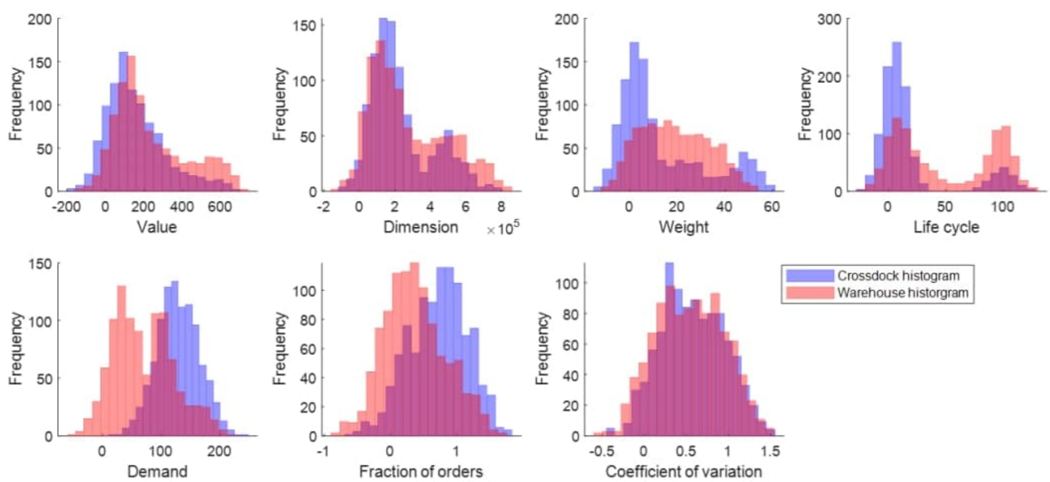



**Figure 4.1:** Histogram of bootstrapped data on both classes.

## 4.2 Wasserstein GAN synthesis Data

Now that the bootstrapped data have been augmented with the knowledge of the field, we need a solution that preserves the distribution of the generated data and does not change the labeling. A GAN method can be used in this situation. WGAN is then used on the augmented bootstrapped data, so that the network generator can learn the underlying distribution of the data for each class.

The reason of using the WGAN method is that after applying the bootstrappping it is evident from the results Figure 4.1 that the PDF estimation of all features are not smooth. The classifier inputs must not come from a rugged PDF estimation since it might result in over fitting of the classifier. Therefor, after applying the bootstrapping, the application of WGAN is required.

The WGAN-GP implemented in this thesis is composed of a three-layer generator and a three-layer discriminator, with dropout layer, and a hyperbolic tangent activation function. Each layer contains 30,20,10 neurons for the discriminator and the generator. The generator's input is a ten-dimensional noise, and its output is an abstract 7-dimensional product. The features are between -0.5 and 0.5 because of the normalization. Discriminator input is seven dimensions, each between -0.5 to 0.5, with a sigmoid activation function output. The discriminator output is a one dimension probability between 0 and 1.

By the time WGAN is fully trained, the network generator is thoroughly equipped to generate data similar to what is available from product characteristics with their labels. Suppose a good set of data becomes available to this research thread. In that case, this means that without even applying the bootstrap method, one can use the WGAN directly without losing any information from the original data.

Wasserstein GAN was applied on the data developed from bootstrapping. The results extracted from WGAN converged for both classes (Figures 4.2 and 4.3), allowing us to generate data.

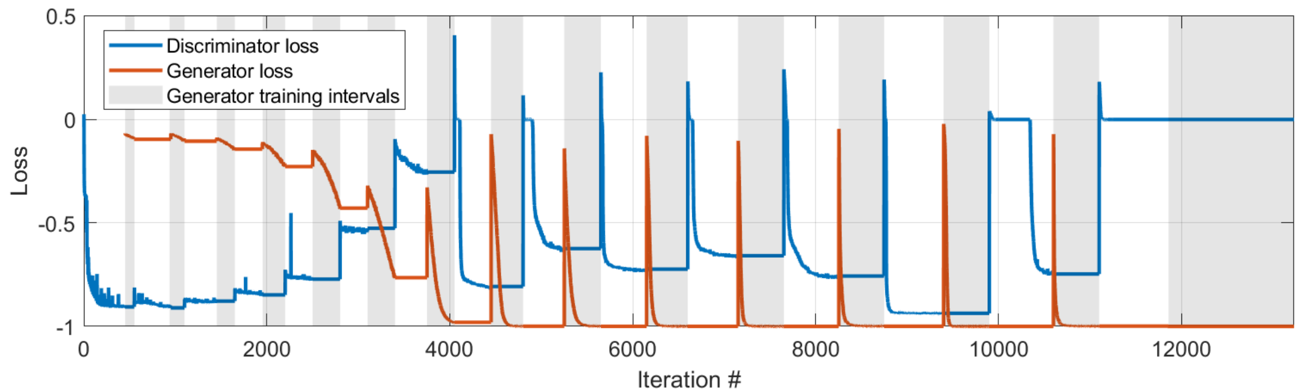



**Figure 4.2:** WGAN-GP convergence on warehouse data.

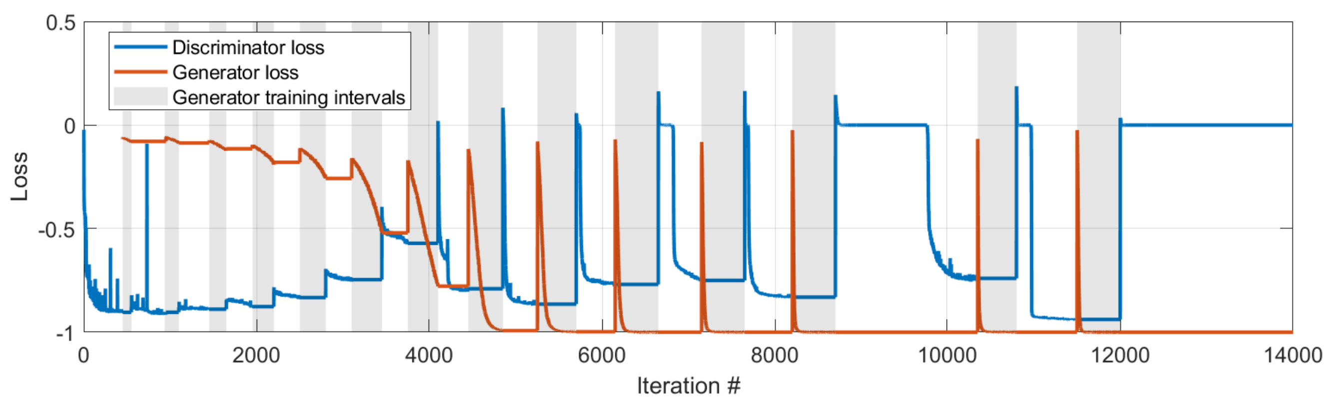



**Figure 4.3:** WGAN-GP convergence on crossdock data.

According to the GAN definition, the convergence of the GAN's generator and the discriminator is the most significant aspect of the training process. The WGAN convergence of each class is determined by the loss functions specified for the WGAN structure. In my code, the loss functions for generator and discriminator are defined as shown in Equations 4.1 and 4.2.

$$loss_D = \widetilde{Y} - Y + \lambda(\| \nabla_{\widehat{x}} \widehat{Y} \|_2 - 1)^2 \tag{4.1}$$

$$loss_G = -\widetilde{Y} \tag{4.2}$$

Based on the loss functions defined, the WGAN generator convergence happens when the generator can fool the discriminator. In other words, the loss function of the generator must eventually converge to -1. This is because the loss function is the minus of predicted label by discriminator. When the generator can full discriminator and discriminator assume all the generated data are real (1) then this means the generator has converged to the point that it can generate good data. That is why the convergence point of generator is -1 Equation 4.2. The exact process is applied to the discriminator loss function. At convergence, the generator must fool the discriminator, so the loss function value must converge to 0 (Figure 4.2). The discriminator is converged when it can differentiate between fake data and real data and based on the loss function defined Equation 4.1 this implies the convergence to zero. The same GAN structure was implemented for the crossdock class, and convergence can be seen in Figure 4.3.

The adversarial behaviour of the network can be seen in each generator and discriminator training intervals in Figures 4.2 and 4.3. In training, the GAN structure is designed so that the discriminator gets trained and tries to have a better performance and distinguish fake from real data. Then, after training for a specific number of iterations, the generator tries to better its performance. As the training goes forward, the generator gets stronger and gets closer to -1, while the discriminator performance worsens and moves closer to 0.

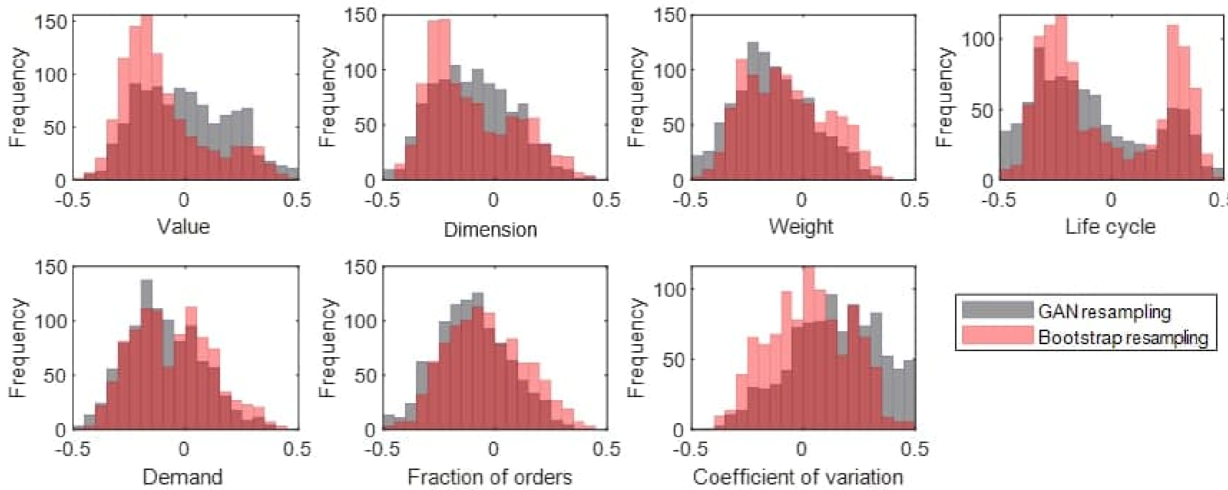



**Figure 4.4:** WGAN-GP generated data for warehouse class.

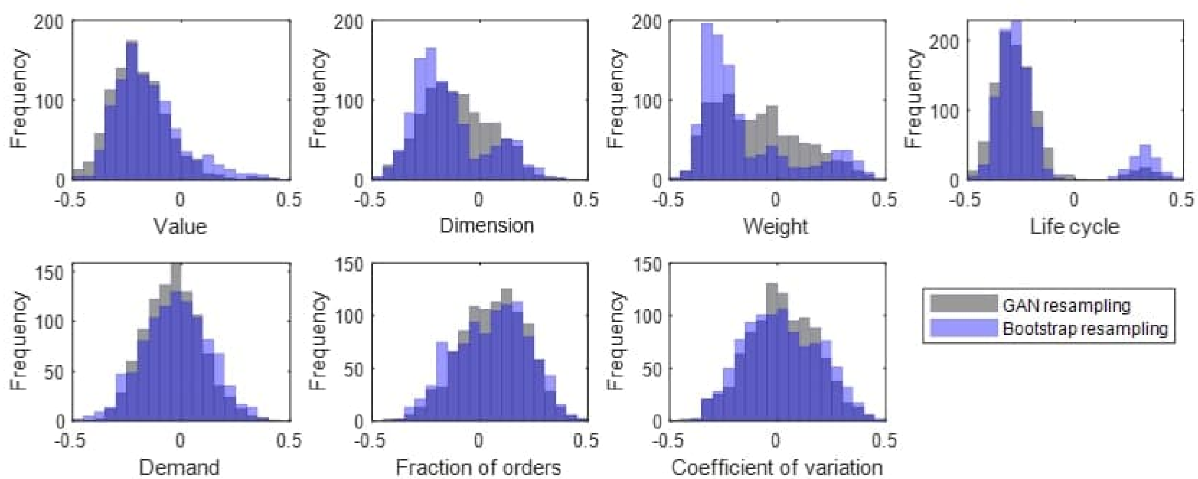



**Figure 4.5:** WGAN-GP generated data for crossdock class.

The results of generated data from WGAN are shown in Figures 4.4 and 4.5. These results indicate an acceptable performance of the Wasserstein GAN network that was built. The WGAN structure was tailored to the data that we already have on hand with a generator and discriminator network of three layers. The loss functions of generator and discriminator have been defined as Equations 4.1 and 4.2. The near-perfect convergence of the discriminator and generator loss can be seen in Figures 4.2 and 4.3.

## 4.3 Classification Results

The purpose of the data augmentation in **Chapters 2** to **4** was to obtain an expressive data set. Using the bootstrapping method and data augmentation with field knowledge and finally WGAN, we have reached that goal. An expressive data set with its labels is available for training the MLP network. Use of the obtained data set as an input to the constructed multi-layer perceptron neural network can train a model. The trained network can anticipate the new product's label, with the different product characteristics, as its probability of choosing its logistics strategy to be crossdocking or traditional warehousing.

We have separated a dataset of size 40 from the original on hand at the beginning, and then applied the bootstrapping and WGAN methods on the generated dataset, so that the test and train accuracy of the classifier would be accurate.

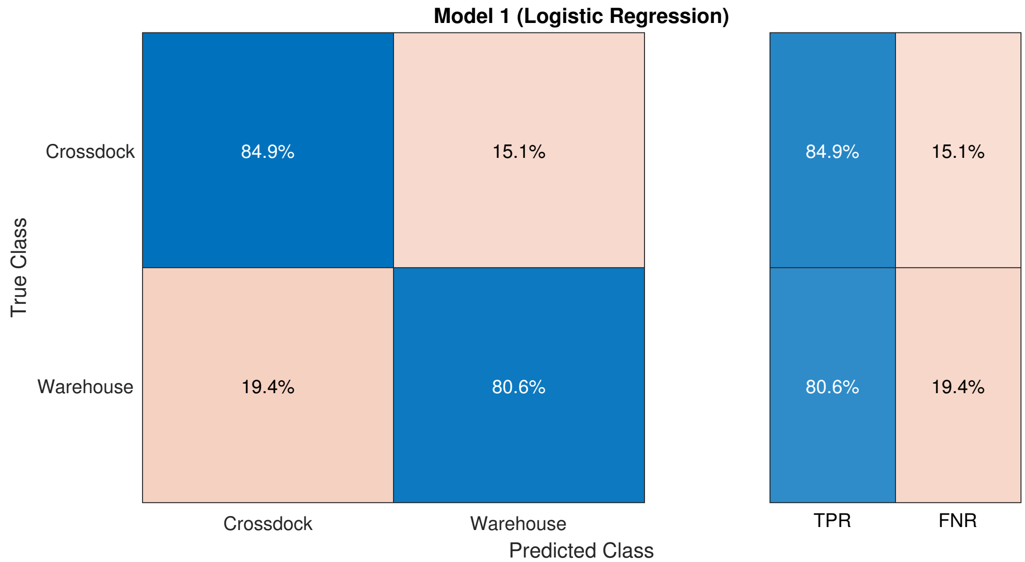



**Figure 4.6:** Confusion matrix of logistic regression.

Figure 4.6 shows the confusion matrix on the classification applied on the concatenated dataset. This matrix design, known as a confusion matrix, allows the user to visualize the results of supervised learning algorithms in a specific table format. Rows of the matrix represent instances in actual classes, and columns represent instances in predicted classes and vice versa. Its name has derived from the fact that it quickly shows when the system is confusing two classes.

It can be seen how the 82% accuracy of the classification is divided between the two classes of crossdock and warehouse. 84.9% of crossdock data has been classified under the right category, and the corresponding number for warehouse data is 80.6%. In the categories of crossdock and warehouse, 15.1% and 19.4% of classification data was not right, respectively. The results of the confusion matrix indicate a lower accuracy in the warehousing category than for crossdocking.

Figure 4.7 shows all the predicted labels including correct and incorrect labels of two classes. This shows how much the data of the two classes are entangled, and the complexity of a dataset in all dimensions are represented.

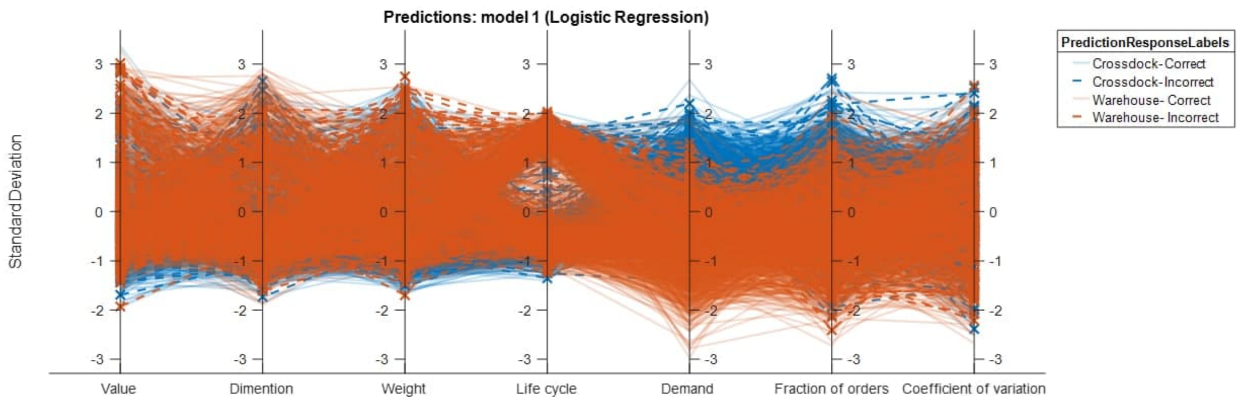



**Figure 4.7:** Prediction responese labels on both crossdock and warehouse classes.

One of the most important evaluation metrics for checking any classification's performance is the AUC (Area Under the Curve)-ROC (Receiver Operating Characteristics) curve, which is shown in Figure 4.8.

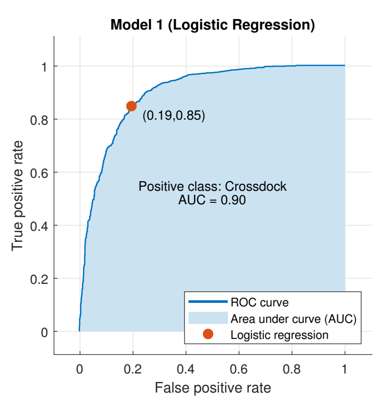



**Figure 4.8:** WGAN-GP generated data for crossdock class.

The scatter plot, shown in Figure 4.9, depicts the dataset in only two dimension, Number of appearance on each order and the demand. Moreover, the correct label predictions and the incorrect ones can be seen. This graph may be a good explanation of the performance of the classification.


**Figure 4.9:** WGAN-GP generated data in to examplary features for crossdock class.

Now for the results on classification, we have concatenated two data categories data with their labels. The classification was applied to the new data and an 82% accuracy from the logistic regression classifier in MATLAB was achieved. Result are represented in Figure 4.8 .

As shown in Figure 4.9, it is obvious that the distributions of data from two classes are very similar, and they have high decoupling in most of the features. This shows the significant performance of the training with the data on hand. An important takeaway from this study is the fact that with a rich set of data from different product characteristics, the classification of logistics strategy selection would be an excellent way to categorize different SKUs of a company, because a very good accuracy was achieved. This would be helpful to industry novices who are at the beginning of their business investment.

# Chapter 5

# Utility and Customer Satisfaction

## 5.1 Background/Reasoning

The results of the classification and labeling of the SKUs' characteristics assisted me in seeing the issue from another perspective. As shown in **Chapter 4**, the outcome of the constructed neural network could be interpreted as a probability that is between zero and one.

One cannot talk about the possibility of choosing the best logistics strategy without considering the two important criteria of fill rate and lead time in the process of delivering goods. These two factors concern customer satisfaction. A fill rate of a product is the percentage of demands that a retailer or supplier would be able to meet. As an example, a 90% fill rate means that for the particular good, the seller would be capable of satisfying 90% of the number of units demanded, when there is a demand for that SKU without backordering or losing the sale. When referring to lead time, it determines the number of days it takes for a retailer to receive the products after an order has been placed.

It is vital for businesses to deliver the products to their customers and fulfill their needs properly. The more a business spends on their fill rate, the happier their customers become. The faster an order is delivered, the better the customer's experience.

During years of adjusting these two factors in the field of logistics strategy selection, the studies show there is no magic number for fill rate and lead time for the businesses around the world. These two parameters are completely dependent on the situation of the business expenses, and also on how much customer satisfaction they are seeking to acquire. These are the factors that should be tailored to every company's situation.

Business owners, especially those starting out, would find it very expensive to achieve a good fill rate and lead time. Hypothetically, if a company wanted to have a 100% fill rate, so much of its resources would go into fulfilling its products' demands all the time. This is not the case for most scenarios, since there is an optimum point beyond which there are diminishing ... in demand fulfillment. The expenses neet to be reasonable for the supplier or retailer.

Now with the necessary insight into the two key parameters in logistics strategy selection, I have decided to factor in these two criteria in my decision-making calculations. This would help the reader to understand the impact of these two elements on the results. Therefore, besides considering the product characteristic of an SKU, the ideal fill rate and lead time of the company must be considered. With the help of the introduced neural network, I have a probability solely based on product characteristics. Now by considering this probability as a *utility*, I may add the fill rate and lead time factors to the output of the proposed utility function and calculate a more accurate utility or probability of that good or item going through crossdocking or warehousing.

## 5.2 Approach

If we view the probability outcome of the logit model as a utility based on the product characteristics, we can calculate a utility in terms of the fill rate and lead time of the SKUs. Let us call the utility as a function of fill rate and lead time the "customer satisfaction utility". By combining the customer satisfaction utility and the characteristic utility, now we have a more expressive result as a utility.

Inspired by the work of Bookbinder and Lynch [10], I made a synthesis addition of fill rate and lead time to the original data set with 20,000 data. The lead time is a number between 2 to 10 days, and the fill rate is between 60% to 100%, assigned randomly. For instance, information on two SKUs, Bread and T-Shirts, can be seen in Table 5.1. The lead time of the Bread was considered as 7 days and its fill rate is assumed to be 83%.

| Product Name | Value (/SKU) | Dimension | Weight(KG) | Life Cycle (Weeks) | Lead Time | Fill Rate |
|---|---|---|---|---|---|---|
| Bread | 100 | 490000 | 50 | 4 | 7 | 83 |
| T-Shirt | 600 | 360000 | 25 | 12 | 3 | 97 |

**Table 5.1:** Sample of data with lead time and fill rate.

### 5.2.1 Effect of Utility Function Definition

We already calculated the Bread outcome from our logistic regression calculations. Now is the time for calculating the utility of customer satisfaction. As presented in the literature of the field, the calculation of a utility function may vary, depending on the functional form that you choose [10]. There are several variations and I have decided to calculate the customer satisfaction utility function with Linear, Quadratic, Square Root, and Logarithmic Utility Functions.

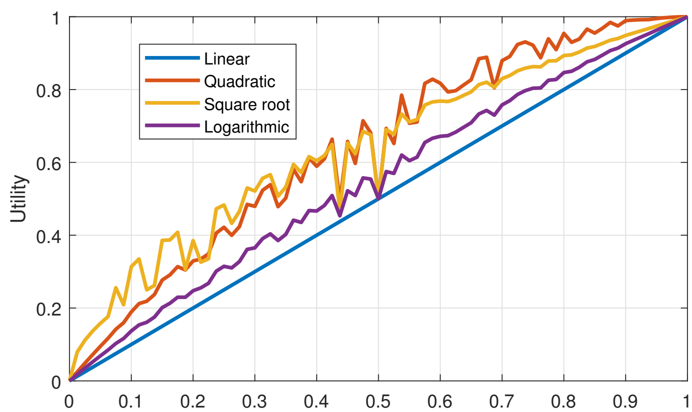



**Figure 5.1:** Different utility function definitions.

Figure 5.1 depicts the difference between utility functions' definition. The linear utility considers the utility of customer satisfaction and product characteristics equally. The logarithmic utility is the closest to the linear utility. On the other hand, quadratic utility and square root utility affect the overall utility more. The utility function is dependent on the corporate needs and specifications.

### 5.2.2 Results

| Product | Label | General | Lead Time | Fill Rate | U(V1) | U(V2) | Utility Linear | Score |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.45 | 7 | 83 | 0.37 | 0.57 | 0.47 | 0.46 |
| 2 | 0 | 0.21 | 3 | 97 | 0.87 | 0.92 | 0.9 | 0.55 |

**Table 5.2:** Sample of data with linear utility function.

The linear utility function is calculated using the formulation of $U(V) = V$. After normalizing the lead time and fill rate values, the utility for each of them would be $U(V_1) = V_1$ and $U(V_2) = V_2$. The combination utility of two functions $U(V_1)$ and $U(V_2)$ were calculated by linearity assumption of $U(V) = \frac{1}{2}U(V_1) + \frac{1}{2}U(V_2)$. This assumption could be different which will be discussed in the following section.

Table 5.6 shows that the calculation of utility by factoring in the customer satisfaction could be beneficial. There is not much impact of customer satisfaction on utility for product 1, since there is a pretty large lead time for delivery. For the second product, on the other hand, the effect is quite significant, since both fill rate and lead time are harder to satisfy, and one would need a proper logistics strategy that can have a greater frequency of deliveries.

A higher probability of the outcome score shows us that the product is better to go through a faster channel such as crossdocking. In crossdocking, there could be a greater number of deliveries of goods, and this could lead to better fulfillment, thus, better fill rate and lead time. This is mainly because in traditional warehousing, it is most economical for trucks to wait until they can be filled with products and then deliver the SKUs to the customers. This means longer lead time, and perhaps shelves that are not as full.

| Product | Label | General | Lead Time | Fill Rate | U(V1) | U(V2) | Utility Quadratic | Score |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.45 | 7 | 83 | 0.60 | 0.81 | 0.71 | 0.58 |
| 2 | 0 | 0.21 | 3 | 97 | 0.98 | 0.92 | 0.98 | 0.60 |

**Table 5.3:** Sample of data with quadratic utility function.

The Quadratic utility function is calculated using the formulation of $U(V) = 2V - V^2$. The utility for each of them would be $U(V_1) = 2V_1 - {V_1}^2$ and $U(V_2) = 2V_2 - {V_2}^2$. The combination utility of two functions $U(V_1)$ and $U(V_2)$ were calculated by assuming equal weight to the two alternatives $U(V) = \frac{1}{2}U(V_1) + \frac{1}{2}U(V_2)$.

Table 5.3 shows how important the role of Lead time and fill rate could be in calculating the label of an SKU. The score generated from the logistic regression for product 1 was calculated as 0.45. After consideration of the lead time and fill rate, that score is modified to 0.69. This stems from the fact that the fill rate considered for this product (83%) is rather high, increasing the probability of going through crossdocking.

| Product | Label | General | Lead Time | Fill Rate | U(V1) | U(V2) | Utility Square Root | Score |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.45 | 7 | 83 | 0.61 | 0.75 | 0.68 | 0.57 |
| 2 | 0 | 0.21 | 3 | 97 | 0.93 | 0.96 | 0.94 | 0.58 |

**Table 5.4:** Sample of data with square root utility function.

The Square Root utility function is calculated using the formulation of $U(V) = \sqrt{V}$.

The utility for each of them would be $U(V_1) = \sqrt{V_1}$ and $U(V_2) = \sqrt{V_2}$. The combination utility of two functions $U(V_1)$ and $U(V_2)$ were calculated by linearity assumption of $U(V) = \frac{1}{2}U(V_1) + \frac{1}{2}U(V_2)$.

Table 5.4 seems to be an assumption in the middle. The utility impact on the outcome results lies between the linear and quadratic utility calculations.

| Product | Label | General | Lead Time | Fill Rate | U(V1) | U(V2) | Utility Logarithmic | Score |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.45 | 7 | 83 | 0.45 | 0.65 | 0.55 | 0.50 |
| 2 | 0 | 0.21 | 3 | 97 | 0.90 | 0.94 | 0.92 | 0.56 |

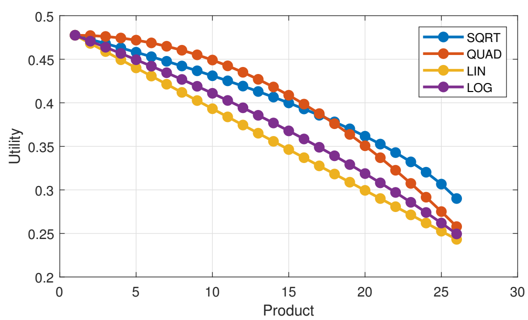
**Table 5.5:** Sample of data with logarithmic utility function.

The Logarithmic utility function is calculated using the formulation of $U(V) = ln(1 + V)]/ln(2)$. The utility for each of them would be $U(V_1) = ln(1 + V_1)]/ln(2)$ and $U(V_2) = ln(1+V_2)]/ln(2)$. The combination utility of two functions $U(V_1)$ and $U(V_2)$ were calculated by assuming equal weight to the two alternatives $U(V) = \frac{1}{2}U(V_1) + \frac{1}{2}U(V_2)$.

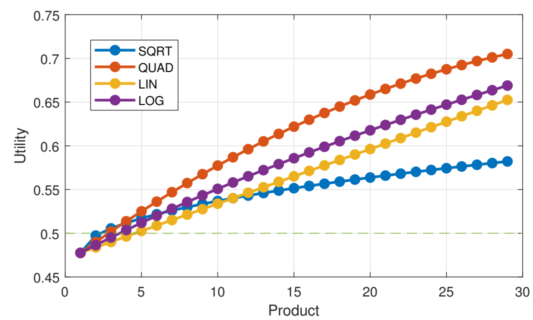
Table 5.5 shows that, in comparison to other utility functions, the function of logarithmic utility is the closest to the linear utility.

### 5.2.3 Sensitivity Analysis of Fill Rate/Lead Time

The effect of lead time and fill rate on the utility function is pretty significant, as can be seen in Figure 5.2. This sensitivity analysis depicts how much a corporation needs to be aware of its speculations about the lead time and demand. As it is shown, the change of lead time between 2 to 10 days can change the decision of logistics strategy planing from a case close to 50-50 percent, which is suitable for a mixed strategy, to a 0.29 score, which is definitely in the spectrum of traditional warehousing. This analysis again reveals that any product can go through a crossdock or warehouse, depending on its lead time and fill rate specifications.




(a) Sensitivity analysis on lead time.




(b) Sensitivity analysis on fill rate.

**Figure 5.2:** Impact of fill rate and demand on utility.

This case happens in the sensitivity of the fill rate, as well. As can be seen in Figure 5.2, the same product with 30 different fill rate values was examined. Utility functions for all four different forms have been calculated, and changes in the fill rate from 60% to 100% were considered. Figure 5.2 depicts how the increase in fill rate influences the utility output, changing the value from 47% to 66%, a significant increase.

### 5.2.4 Effect of the Utility Function

According to Tables 5.2 to 5.5, the outcome of the linear summation of the two utilities could be one approach. As customer satisfaction utility and product characteristic utility are both considered as "utilities", they could be examined as two parts of an overall utility function with a specified correlation. The combination of these two utility outcomes could be linear, but it could also be quadratic, square root, logarithmic and so many other relations, as well. This relationship could be defined from the nature of the business and other factors.

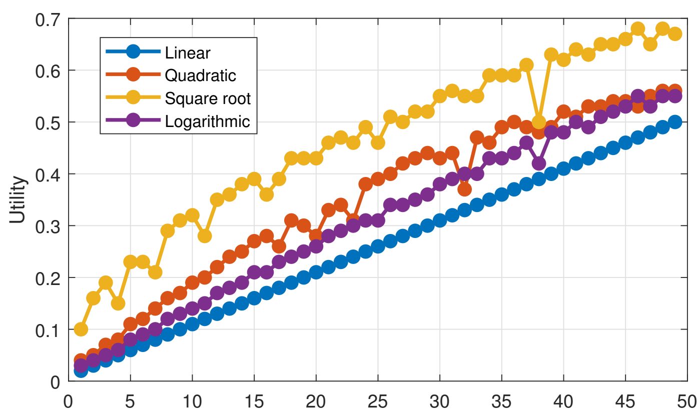



**Figure 5.3:** Sensitivity analysis on utility function.

We would compare several cases of overall utilities with different functional forms to see the performance differences between them. The utility functions employed were defined in Equations 5.1 to 5.4.

$$U(V) = \frac{1}{2}(U(V_{\text{Product}}) + \frac{1}{2}(U(V_{\text{Customer}}) \tag{5.1}$$

$$U(V) = \frac{1}{2}\frac{(ln(1 + U(V_{Product}))}{ln(2)} + \frac{1}{2}\frac{(ln(1 + U(V_{Customer}))}{ln(2)} \tag{5.2}$$

$$U(V) = \frac{1}{2}\sqrt{U(V_{\text{Product}})} + \frac{1}{2}\sqrt{U(V_{\text{Customer}})} \tag{5.3}$$

$$U(V) = \frac{1}{2}(2 \times U(V_{\text{Product}}) - U(V_{\text{Product}})^2) + \frac{1}{2}(2 \times U(V_{\text{Customer}}) - U(V_{\text{Customer}})^2) \tag{5.4}$$

Figure 5.3 shows the differences between all four defined utility functions.

### 5.2.5 Use of Utility Function as Field Knowledge

All the mathematical formulations proposed in this chapter assist us again in applying the field knowledge to the original data. The outcome utility of the sigmoid function and customer satisfaction utility effect could enable us to incorporate each product's lead time and fill rate data into the original data set as features. After applying customer satisfaction data, the difference in overall utility might change the label of a crossdock-product to a warehouse-product, and vice versa. This is field knowledge applied to the data on hand. Therefore, by applying the calculations to all the generated data and calculating the new labels, we have a new set of data containing product characteristics and lead time and fill rate, incorporating their label. This new data set could be another entry to the neural network; the training process would then happen more comprehensively, including product specifications.

| Product | Label | General | Lead Time | Fill Rate | U(V1) | U(V2) | Utility | Score | New Label |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.45 | 7 | 83 | 0.37 | 0.57 | 0.71 | 0.47 | 0 |
| 2 | 0 | 0.21 | 3 | 97 | 0.98 | 0.92 | 0.98 | 0.60 | 1 |

**Table 5.6:** Customer satisfaction label change.

# Chapter 6

# Conclusion and Future Research

Examination of the literature on logistics strategy selection reveals that scholars have devoted most field studies to the industries' internal logistics operations. For example, researchers have mainly concentrated in dedicating the literature on crossdocking or traditional warehousing specifications, as well as truck scheduling optimization, crossdock design, and distribution center operation planning. Few studies have been done regarding the choice of a proper logistics strategy for products in different industries. Therefore, a more macroscopic view of the logistics strategy selection issue, represented in this thesis, may fill this gap and complete our picture of the research thread of logistics strategy selection.

The present study has divided the logistics strategy selection studies into two main categories: qualitative studies and purely quantitative ones. In the qualitative approaches, writers have considered only overall product characteristics to decide the optimized logistics strategy for businesses. On the other hand, quantitative researchers have defined a detailed mathematical cost modelling approach to logistics operation, to determine the least expensive approach. Although cost minimization plays a vital role in the logistics selection, companies must also consider the satisfaction of their customers and product characteristics. This thesis presents an approach that incorporates product characteristics and customer satisfaction into logistics strategy selection decisions.

If more data were on hand in different industries' logistics, the possibility of data-driven decision-making emerges in the field. Many successful businesses could be considered as best practices for new businesses and startups. These best-practice datasets have been utilized for training a neural network for logistics strategy classification in this thesis. The richer the data set is in training multi-layered perceptron neural networks, the better the results. However, because of the enormous data set requirement of classification models, the data availability issue still exists in the logistics field.

A small data sample was available in this study. That was expanded using Bootstrapping and Generative Adversarial Networks methods. The use of bootstrapping has assisted me in reaching a new data set of 20,000 unique products. Following that, I used the Wasserstein GAN method to find the underlying distribution of the data on hand, and generated new samples based on the distribution found.

With enough data on hand, the original purpose of the thesis, i.e. training a classifier, was achieved with a 82% accuracy. Inspired by the modal split and logistic function concept and obtaining a large enough dataset, a multi-layered perceptron neural network with the sigmoid activation function (Logistic regression) has been trained. The outcome of each product in the trained network is a probability between zero and one, which could be interpreted as the possibility of choosing the most suitable logistics strategy for each product. That could be considered a novel idea in this field, since any business, even a new one, could provide the characteristics of their goods. A score between zero and one could help them realize the best logistics strategy for their product, based on its characteristics.

After the product characteristic consideration, the impact of customer satisfaction has been considered using the utility function. By viewing the output of the trained model as a utility, a well-defined utility function considering customer satisfaction is presented. Customer satisfaction parameters such as lead time and fill rate, and the budget on hand for every industry might differ. The proposed utility could emphasize the importance of these factors all together in the logistics strategy-selection decision. Each business could define the utility function differently based on characteristics of the firm, so different definitions have been applied throughout this thesis. The sensitivity analysis on the final utility functions could be helpful in deciding the utility function that suits the businesses the best.

In conclusion, the purpose of this thesis was to tackle the logistics strategy selection problem more comprehensively. In this field, some research has been done solely on the product characteristics and their nature in choosing logistics strategy. Other studies have done some mathematical modelling based on costs or customer service. However, no research has been done considering all these criteria together in choosing the best logistics strategy for a industry.

Although well-established industries with all the necessary data could benefit from the studies of deterministic mathematical modelling like Bnrqya's [7], new companies and startups (which do not usually have enough data on hand) could be assisted by this thesis. No product can be categorized under crossdocking or warehousing solely based on its specification. As was concluded from **Chapter 5**, for instance, different lead times and fill rates of the same SKU would alter the decision of logistics strategy selection completely. Building a vast warehouse or a crossdock, or even contracting with some third-party logistics provider for LTL (less than truckload) deliveries or crossdocking before one knows what is best for the future of their product, could be very expensive for the company. That is why all the factors, including a budget, customer satisfaction, and product characteristics, should be considered in the process of decision-making. This is where the presented thesis would come to assist businesses. This study aims to develop a data-driven tool to predict the probability of a product being classified under a proper logistics strategy. Therefore, even with small data and augmentation techniques, the tool is adequately developed, which could only improve with the help of a more extensive data set.

For future research, any line of research that could enhance the logistics strategy selection with a good set of data would strengthen the result of this thesis. With additional real-world data from varied corporations, the ability of the trained neural network would be closer to reality. Since this thesis is data-based, and the trained neural network results from the data structure that we feed into it, a richer data set could improve the results, especially in the WGAN domain. With a more extensive data set, there is a possibility that using the GAN would be enough, and the application of WGAN could be eliminated.

Another avenue for further research is to consider budget and customer satisfaction criteria as input features of the neural network. Considering the impact of customer satisfaction variables, or even a budget constraint, on the data is a proper way of enforcing additional knowledge of the field. That would make the data on-hand even more expressive. This approach would make the model's training more complicated; however, this technique would eliminate the requirement to define a utility function.

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