Uber Freight: Assessment and Determination of Optimal Design Features for a Drop Trailer Service Offering and Network

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ABSTRACT

The trucking industry hauled 72.5% of all freight transported in the U.S. and served an essential function in transporting cargo nationwide from one place to another. Recently, the industry has suffered from significant disruption, such as a shortage of drivers and carriers. One of the leading causes of these issues is the lengthy detention time in most operational activities, such as loading and unloading time at the warehouse. Previous research recognized that the drop trailer offering serves as an effective solution for reducing the waiting time at warehouses and improving the on-time delivery rate. When it comes to our sponsoring company - Uber Freight, this type of service is still nascent, with several strategic questions unanswered. Specifically, two of the most crucial key research questions are 1) where it should expand its drop trailer service 2) what load requirement and network characteristics are best serviced with a drop trailer. Our capstone project first deployed the K-Means clustering method to address these questions to uncover the underlying pattern and key network characteristics of states that have successfully implemented the drop trailer service. The result showed that Illinois, Indiana, and Florida possess the highest feature similarity with those states and hence, are recommended for Uber Freight to introduce drop trailer service. Our project deployed a CART decision tree to decompose the critical features from our cluster results that provide a structured recommendation for drop trailer implementation to answer the second question above. The analysis indicated four features necessary for a Drop offering to be favourable compared to live loading dry-van offering. These four features lay out two sets of market conditions with their strategic consideration for Uber Freight to implement drop trailer in the future.

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We would also like to express our deep gratitude to Dr. Matthias Winkenbach, our research advisor, for his patient guidance, enthusiastic encouragement, and valuable critiques of this capstone project. He ensures that the project is always on the right track, implementing the correct methodology and academic rationale. Under his supervision, we were able to better understand the functional and technical requirements of the project. Along the journey, Ilya Jackson also plays a vital role in providing technical support for this project. We are grateful for his help during our data analysis and methodology development.

As both of us are not coming from an English-speaking country, writing a report in English fluently and efficiently is not a straightforward task. We want to extend our gratitude above to Pamela Siska for reviewing our reports numerous times and providing detailed feedback on areas of improvement.

Lastly, we both would like to provide a personal below.

Siqing: I would like to thank our capstone advisor, Dr. Matthias Winkenbach, for the technical guidance and our sponsoring company, Uber Freight, for sharing the industrial knowledge. I would also like to thank my families and friends for their support throughout the journey. Last but not least, I want to thank my capstone partner SK for the great 10-month time of working together.

SK: Nobody has been more important to me in the pursuit of this project than my family members. The successful completion of the project must be dedicated to my family, friends, and girlfriend – Shi Ting, whose love and guidance are with me in whatever I pursue. When I was down, you made sure to lift me up every chance you got, and you never failed to make me smile. Most importantly, I would like to express my great appreciation to my capstone partner. She sketched the big picture of this project and, at the same time, paid attention to details to ensure a flawless deliverable to the sponsoring company.

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GLOSSARY OF TERMS

Term	Description
Carrier	Refer to trucking company/third party logistic company or parcel/express company.
Container	Standard-sized rectangular box used to transport freight by highway, ship, or rail
Detention	The time carriers spend at shippers or receivers’ facility waiting for freight to be released.
Drop trailer	A carrier brings the tractor and trailer to the warehouse, unhooks the trailer from the tractor, and leaves the warehouse without waiting for loading/unloading operations.
Live loading	A carrier brings the tractor and trailer to the warehouse and waits for warehouse personnel to load/unload the goods in the trailer.
Rateview at booking	Market price of the shipment at the time of booking
Shipper	Cargo owner or a 3rd-party logistics firm that gives an order assignment to Uber Freight
Tractor	The head of the truck with the engine that provides power to haul the trailer
Trailer	The unpowered back part of the truck that is towed by the tractor

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1. INTRODUCTION

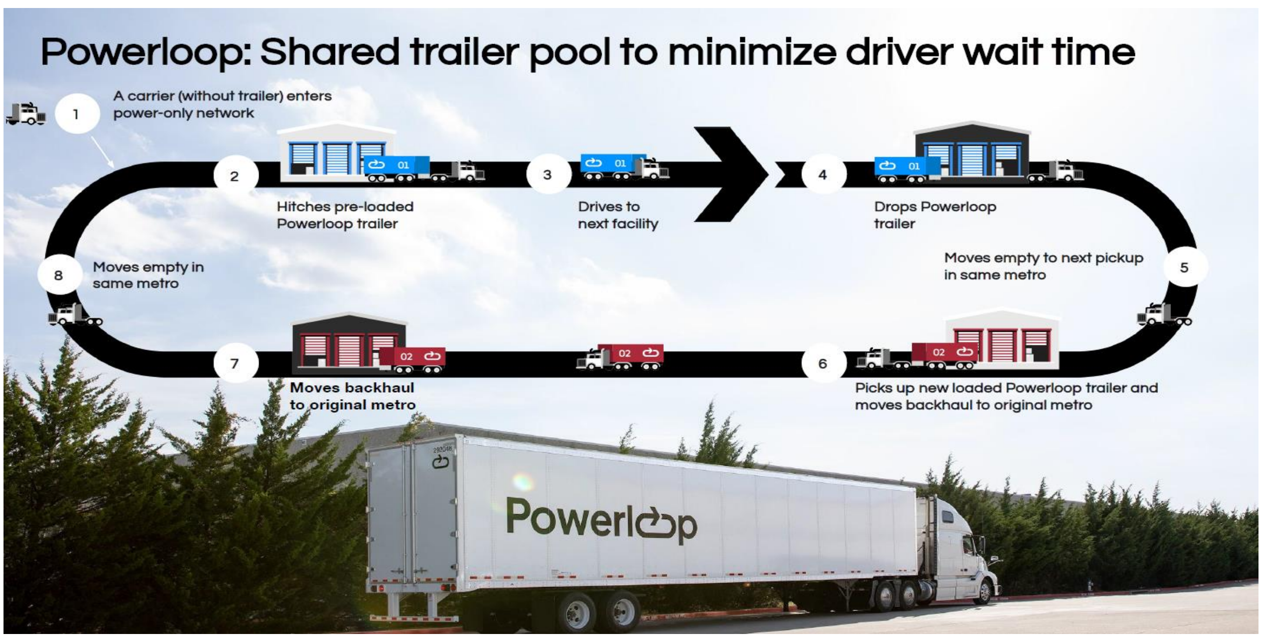
According to the American Trucking Associations (2020), the trucking industry in the U.S. hauled 72.5% of all freight transportation in 2019, with an industry value of nearly $800 billion. It acts as a vital function in facilitating and transporting cargoes nationwide from one place to another. The industry is considered to be highly fragmented, with 90% of the trucking companies (the industry usually refers to them as ‘carriers’) having fewer than six trucks in their fleet. Considering the harsh competition between the vast number of players in the market and the low-capital entry barrier for new players, carriers have always sought new service models to improve their business competitiveness.

In a conventional trucking service model via live loading mode, the driver typically spends a significant amount of time waiting at yards for the warehouse workers or the cargoes to be ready before the goods are loaded into and unloaded from trucks. The problems associated with live loading include a lengthy waiting time for drivers and an overall shortage of trucking cargo in the U.S..

Recently, drop trailer service came under the spotlight during the COVID-19 pandemic due to its nature of contactless delivery and the ability to relieve the driver shortage problem. As the name suggests, a drop trailer refers to the service provided by a carrier to ‘pick up’ a pre-loaded trailer and ‘drop’ the trailer at the destination warehouse. Generally, the drop trailer offers three main advantages compared to the traditional live loading. First, it reduces the turnaround time for carriers. Instead of waiting for the warehouse personnel to operate the trailer, carriers pick up and drop the trailer at their destination and leave. Second, it reduces congestion in warehouses for shippers. Third, it allows better planning for carriers with a predictable turnaround time in warehouses, eventually improving the utilization rate of trucks and drivers.

Considering the above advantages of the drop trailer service, our sponsoring company, Uber Freight, expanded its trucking business with its drop trailer service named ‘Powerloop’. This program allows carriers to arrive at and leave the shippers’ facilities at their convenience instead of waiting for loading and unloading activities (See Figure 1). What further differentiates the Powerloop program from the other drop trailer service is its own pool of trailers for leasing to carriers. By doing so, Powerloop extends its drop trailer service to smaller carriers who are unable to afford to buy trailers. The trailer-pooling system introduces more players into the drop trailer market, relieving the shortage of carriers for shippers and creating a win-win situation for shippers and carriers.

Figure 1: Uber Freight Powerloop Operational Model



While Uber Freight’s existing live loading offering is mature in the traditional trucking industry, with ample automation, market density, and liquidity, its newly drop trailer offering is still nascent, with several strategic questions unanswered. To expand the company’s geographic coverage for the drop trailer service in the future, Uber Freight must understand the key network characteristics and criteria for expanding its Powerloop service.

Although past work at MIT (e.g., Fankhauser and Li, 2019) has explored Powerloop in resource utilization (drivers, trailers), load requirements and network characteristics that are best serviced with a drop trailer remain unanswered. Given this uncertainty, this project aims to explore the potential network characteristics as a criterion and offer decision-makers a structured approach to understanding the condition of providing drop trailer instead of live loading. As part of the deliverables, we provide Uber Freight with recommendations to enable a successful drop trailer implementation in the future and a predictive model that help them to identify viable market pairs for future expansion.

2. LITERATURE REVIEW

To measure the success of drop trailer implementation, it is crucial to explore relevant trade-offs, metrics, and possible limitations associated with this type of freight service offering by first looking at the existing research. This chapter starts by examining the trade-off between drop trailer and live loading. We then focus on exploring relevant metrics to quantify this trade-off and possible limitations associated with drop trailer and live loading offering.

2.1 Drop Trailer vs. Live Loading

Previous study by Fankhauser and Li (2019) confirmed that drop trailer service can reduce carriers' detention time, which is the amount of time carriers spend at shipper facilities. Since shippers often pre-loaded trailers, the driver can pick up the unit and attach the trailer to the tractor. This advantage is particularly important in the midst of the current driver shortage as indicated by Correll (2019).

However, the drop trailer does occasionally pose limitations. For instance, one of the limitations is the nature of goods carried in the trailer. It has been suggested that perishable goods are not a suitable candidate for drop trailer since keeping the goods fresh under climate control may post further difficulty and cost for successful delivery (First Call Logistics, 2021). Even with investment in specific infrastructures such as refrigerated trailers, researchers have found that refrigerated cargo systems are still not designed to support the temperature homogeneity inside cargo trailers (Yildiz, 2019). Another limitation of drop trailer services lies in constrained warehouse or yard space. Idled trailers require yard space to store. The potential congestion issue here does not only add more effort to the relocation of the drop trailer's designated position but also inevitably increases the lead time and decreases the ability to adjust for urgent shipments (Wolhart, 2021).

The advantages and disadvantages of drop trailer helped us to understand the trade-off to lay out a structured approach to formulate metrics that measure drop trailer implementation success.

2.2 Drop Trailer Key Metrics

Next, we explored relevant literature to understand the quantitative impact of the drop vs. live trade-off. Overall, there are four core metrics or objectives in the field of transportation and logistics research that can be used to measure the performance of freight service offerings: 1) turnaround efficiency, 2) cost-effectiveness, 3) supply-demand balance, and 4) shipper/carrier density.

Starting with turnaround efficiency, most of the literature referred to this theme as the time spent on supply-chain processes or related operational activities (Sapry et al., 2016). For instance, the loading and unloading time is part of the formula that optimizes the trucking schedule for the forestry transport system in Acuna et al. (2011) research. In Zahid and Melan (2020), curbing the idling time at warehouses was also recognized as a recommended practice by most supply chain industry managers. From research in this area, we acknowledged that to quantify the successful deployment of drop trailers, this theme will be critical to be included for measurement.

In relation to cost-effectiveness, companies often seek cost as a key objective in their supply chain operation. Mura (2019), in his study, showed that transport costs, warehousing costs, and stock costs often represent the largest share of the logistics cost. Since one major advantage of the drop trailer service is the financial benefit to carriers and shippers due to a reduction in detention time (Wang and Liu, 2014), measuring the drop trailer's cost within the supply chain becomes critical (Feng and Cheng, 2019).

The third common metric dimension from literature is the supply-demand balance, measured by the absolute difference between the incoming and outgoing transactions in each period. For instance, in the field of ride-hailing service, it is believed that a mismatch between taxi supply and demand could lead to a decline in operational efficiency and customer satisfaction (Tang et al., 2019). Similarly, in the case of a drop trailer, it may be necessary for the decision-maker to balance the trailer to prevent any congestion issue that could result in potential loss of shipments.

The last metric we observed from the literature was the shipper /carrier density (Silver, Pyke, and Peterson, 1998). This dimension refers to the number of shippers and carriers in a particular geographical area to assess the coverage and freight lane design. Generally, the denser the network, the more freight transportation in a geographic area can flow and connect, which gives carriers and shippers more choices and opportunities to reach cost-saving and efficiencies (Grossardt, 2002). In addition, Friesz et al. (1986) found that shipper-carrier density as a design of nodes could influence routing and model choice of shippers and carriers. This finding was later affirmed by Peeta and Hernandez (2011), who show that a higher carrier density at the destination city enables better service to shippers.

Next, we explored several tools and techniques that could be adopted to methodologically address the network characteristic and requirements of drop trailer offering in line with the four key metrics described previously.

2.3 Methodology Selection

There are two main methodology branches in transportation and logistics study: 1) data science and 2) optimization. The data science approach is further split into unsupervised and supervised machine learning. In this section, we will review each approach.

We started by exploring a subset of the data science approach - unsupervised machine learning. Briefly explain, this type of algorithm learns patterns from untagged data and discovers hidden patterns or data groupings without human intervention. By far, there have been limited studies about the application of unsupervised machine learning related to drop trailer service. Yet, we were able to identify and learn from the study from Moskvichev et al. (2021) that used an unsupervised machine learning method, specifically the K-Means clustering, to determine the optimal locations for container storage. In their research, the cluster results allowed them to propose a better network design, providing better logistics services with a more organized transportation of goods within the supply chain. In our project, this type of method can also help identify the underlying pattern of all markets and group similar markets together.

Another data science approach is supervised machine learning. Contrary to unsupervised machine learning, this type of supervised algorithm works by using well "labeled" training data and based on that data, predicts the output. Some common examples of supervised machine learning algorithms are random forest and decision tree. For instance, van Riessen, Negenborn, and Dekker (2016) applied a decision tree to provide selection support for different intermodal transportation. This allows them to allocate incoming orders based on features such as booking lead time, transportation lead time, and regulatory impact. Similar to our project, we may also want to use the decision tree model to train models to yield a binary decision to implement drop trailer. Specifically, a decision tree is a non-parametric supervised machine learning method. Each branch node represents a choice between several different options, and each leaf node represents a classification decision (Maglogiannis, 2007). Generally, there are four popular types of decision tree algorithms: CART (Classification and Regression Trees), CHAID (Chi-squared Automatic Interaction Detection), ID3, and C4.5 (Gulati et al., 2016). The main differences between the four decision tree algorithms lie in how the data is split in the tree and what data categories can be deployed. For instance, CART and CHAID use statistical methods such as Gini Impurity and Chi-square independence tests (Gulati et al., 2016) to determine the best split at each step, respectively. In contrast, C4.5 and ID3 use a metric called Gain Ratio for their splitting process compared to Information Gain as deployed by ID3. Gain Ratio is a modification of the Information Gain concept that incorporates the number and size of the branches when choosing an attribute to remove the bias on decision trees with a massive number of branches.

Next, we moved to another branch of methodology widely used in transportation-related research - optimization. The core mechanism of optimization is to solve for a specific objective function under a set of constraints (Xu and Li, 2021). For instance, recent research from Xu et al. (2019) applied an optimization approach in the trucking industry to achieve cost minimization via route optimization. Furthermore, Xu et al. (2020) used optimization to recommend the number of tractors needed for different time-window.

From the research about data science and optimization methodology as explained above, we concluded that the former suit better toward the objective of our project due to its nature of learning and generalizing from historical data of Uber Freight's shipment transaction. In such an open-ended context, the optimization method may not apply to our project because it requires concrete numerical variables and constraints to solve a specific objective (Yan-Qiu and Hao, 2016). However, we foresee the need for an optimization method when Uber Freight plans to enhance its warehouse operational efficiency by relocating trailer to different regions.

3. DATA AND METHODOLOGY

To address our key research objectives of (1) providing Uber Freight with a recommendation on potential markets to implement drop trailer and (2) developing a predictive model to help Uber Freight identify viable drop trailer market pairs for future expansion, our team leveraged a three-step methodology: 1) feature selection, 2) K-Means clustering and 3) CART decision tree.

3.1 Feature Selection and Data Reprocessing

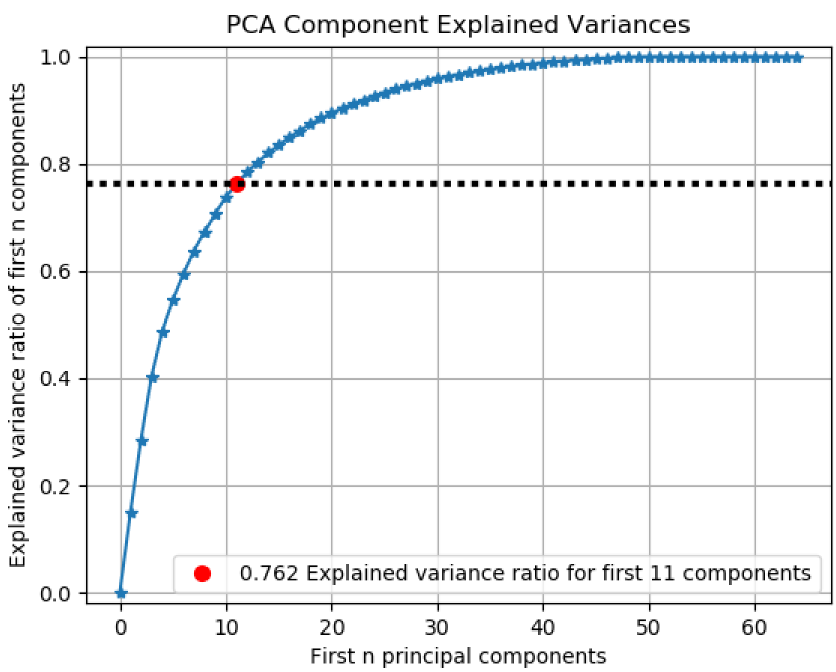
In the feature selection, we took a top-down approach from understanding the high-level project scope, decomposing the data fields into the technical and functional areas, to cleaning and processing the data.

Starting with the intention to establish a meaningful relationship between the data and the project objective, we walked through the project scope with the management team of Uber Freight to understand the key motivation and pain points in the current business in-depth. Next, we talked to the Uber Freight Expansion General Manager, who offered a detailed clarification of Uber Freight's drop trailer operation and services. Coupled with the insights obtained from the literature review, our team generated a list of preliminary features that could affect the implementation of the drop trailer service.

After defining the preliminary features, we then moved on to data processing. This step involves data manipulation, such as transposing the columns to rows into market pairs, applying formatting functions to standardize certain features' numerical values, and removing outliers to narrow the numerical range of data to a reasonable value threshold.

Along with our data processing step, we also consider using Principal Component Analysis (PCA) in the event when the feature dimensions are large. PCA is a statistical procedure that reduces the dimensionality of a dataset by 'summarizing' the essential features in the dataset (Lüthi et al., 2012). Mathematically, it works by projecting linear lines that minimize the mean squared error of the set of data. By setting a target percentage of cumulative variance, we could identify the optimal number of principal components from a plot of the number of principal components against the cumulative variance. The main benefit of applying PCA in our project is representing the data efficiently at a low dimensionality, ensuring no overlap of information.

Figure 2: A Sample of PCA component explained variance plot from Scikit-plot



The intended outcome of the above feature selection is to generate a business-centric dataset that applies to our sponsoring company. The data processing associated with this step produced a lean dataset so we could use it directly in our subsequent analysis to reduce the computational requirement.

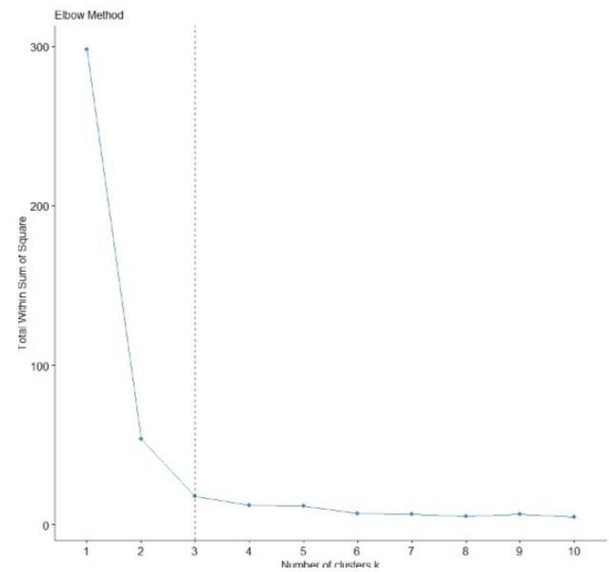
3.2 K-Means Clustering

K-Means clustering is an unsupervised machine learning method that partitions all data points into k clusters. The objective of using K-Means clustering as a part of our project methodology was to segment the live loading historical data into k clusters and identify which cluster exhibits the highest similarity to the current drop trailer market data, thereby identifying the most feasible state.

The procedure of K-Means clustering starts with the initialization of k random centroids. It then calculates the distance between all data points and centroids, subsequently assigning each data point to its nearest centroid (Zhang and Rudnicky, 2002). After this, the algorithm sums up all points in each cluster and divides them by the number of points in the cluster. The process will be repeated until the algorithm finds the ideal centroids, which is the assigning of data points to clusters that do not vary. Since the initialization of K-Means clustering is random, the clustering results will be different for every run. To mitigate the randomness, it is vital to run it multiple times and select the best iteration to minimize the Euclidean distance between the centroids and the data points.

Another question with our K-Means clustering is how to choose the optimal number of clusters. To identify the ideal value of k, we used the elbow method for a range of a different number of clusters of k. For each value of K, we calculate the Within-Cluster Sum of Square (WCSS). WCSS is the sum of the squared distance between each point and the centroid in a cluster. The WCSS value is largest when K = 1. On the other hand, as the number of clusters increases, the WCSS value will decrease (Cui, 2020). When we plot the WCSS against the number of clusters, the plot looks like an elbow and is named the 'Elbow Method'. By examining the x-axis on the plot, we take the k value where the elbow bends, and that k value is the optimal number of clusters. The elbow graph looks like Figure 3 (Saputra et al., 2020).

Figure 3: A sample of elbow graph from 'Effect of distance metrics in determining K-value in K-Means



By applying K-Means clustering, we could discover the similarity of states and compare those with states that have already implemented drop trailer (California, Georgia, Texas). Zooming into each cluster with the highest drop trailer implementation rate, we can then infer the most suitable market candidate for future drop trailer expansion based on the underlying hidden pattern of each market pair's characteristics.

3.3 CART Decision Tree

To decompose the clustering result into the importance of each feature from the previous step, we proceeded to construct a decision tree.

Before the actual construction of the decision tree, it is important first to streamline and select the impactful features to avoid the issue of over-fitting. Over-fitting will bias our decision tree to predict samples because it would have captured noise rather than important patterns in the class sample (Ying, 2019). To mitigate this risk, one way is to learn the feature distribution from a density plot. The objective was to identify which features have a strong impact in differentiating between drop trailer and live loading. Our hypothesis was that if for a given feature, the distribution plot for the various clusters is very similar, the feature does not really contain any information that would help a decision tree model decide whether a new observation is a drop trailer candidate or not. On the other hand, for a given feature, if we see that the distribution plot of one or multiple clusters differs significantly from the distribution plot of other clusters, this feature will help to explain the difference in drop trailer and live loading services. This means that we would keep that feature to build the decision tree.

For our decision tree, we chose the CART model from other types, such as CHAID, ID3, and C4.5, as explained in Chapter 2.3. CART is a specific algorithm that assists the tree in deciding on how and where to split a node into two or more sub-nodes. The process splits variables based on all possibilities of split criteria from many possible predictors with no requirement of each predictor's distribution (Lewis, 2000). In a detailed analysis of CART by Lewis (2000), it is further argued that CART has the advantage of reduced complexity as the algorithm can work well with little input or missing variables for a targeted class. When there are any outliers or inaccurate values after the aggregation of the dataset, CART is still able to adjust the predicted output by estimating the linear combinations of the true unmeasured or unmodelled factors of the missing variables. This is particularly useful as the features comprised transactions aggregated on a market level. In addition, CART deals with imbalanced data well without significantly considering the different underlying distribution of values and variable types of the features (Lewis, 2000). As a result, the CART decision tree handles outliers well. Other algorithms such as ID3 and C4.5 may not be able to handle outliers or bias well, as a skewed value could easily increase the information gain of ID3's splitting criteria easily (Yang et al., 2018).

In order to evaluate the accuracy and metrics of a classification problem like CART, most practitioners relied on the Precision-Recall (PR) curve and Receiver Operator Characteristic curve (ROC) (Zhou et al., 2021). First, PR is formed by precision and recall. Precision in statistic theory means the number of the correct positive prediction made ($Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$); whereas recall is a metric that allows us to measure the number of correct positive predictions made out of all positive predictions that could have been made ($Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$). These two combined elements as a PR curve will allow us to understand the algorithm's ability to classify possible samples or minority classes in the model (Hand, 2009). In our case, this can be used to measure the validity of our CART decision tree when predicting the suitability of the drop trailer implementation. On the other hand, ROC is similar to a PR curve. The difference is that ROC aims to plot the true positive rate (TPR) as a function of the false positive rate (FPR) at various threshold settings. Each point on the ROC curve conveys a sensitivity/specificity pair corresponding to a particular decision threshold. According to Zhou et al., 2021, both PR and ROC shall be considered concurrently to understand the strength of the binary classifier (i.e., drop trailer or live loading).

With the understanding of the importance of PR and ROC scores, we moved to identify the method that could increase the accuracy and robustness of our decision tree. Particularly, one way to do so is via the resampling of data. In our initial observation after the data preprocessing step, we noted a significant imbalance of data between market pairs that have implemented drop trailer services and those without. Hence, resampling may help to improve the classification ability of the CART decision tree in our case.

Typically, practitioners rely on two resampling mechanisms - random over-sampling and random under-sampling. In a typical programming package, the former method is conducted by simply adding datapoint from minority classes and vice versa for the case of random under-sampling. However, these two mechanisms may impose some bias. For instance, Batista et al. (2004) observed that simply over-sampling from minority class can over-fit the model, which has the negative consequences explained in Chapter 3.3. Similarly, random under-sampling can also unintentionally discard potential valid market pairs from our dataset that could be important to understand the importance of the feature (Japkowicz and Stephen, 2002). Knowing the risk, we acknowledged the need for a more optimal approach that allows us to mitigate the risk of the above heuristic approach.

Recently, an integrated sampling method Synthetic Minority Over-sampling Technique with Edited Nearest Neighbor (SMOTE-ENN), has gained interest in academic research as a more effective resampling approach (Japkowicz and Stephen, 2002). The SMOTE in the first part functions as an over-sampling mechanism to synthesize samples in the minority class by linearly interpolating the original data point. For instance, if the dataset is (1,2), it increases the number of samples by adding (2,4) in the minority class. On the other hand, the ENN in the second part serves as a data-cleaning tool to remove any noise from these newly generated minority samples. Moreover, it also serves as an under-sampling mechanism to delete the misclassified instance of the majority class (Xu et al., 2020).

Overall, the resampling process before building the CART decision tree allowed us to prevent the problem of over-fitting and effectively improve the classification ability of our decision tree. The intended outcome of the CART decision tree is a decision tree model incorporating the most impact features in drop trailer implementation. With the model, Uber Freight can identify suitable market pairs for drop trailer implementation based on future data.

4. RESULTS AND ANALYSIS

4.1 Feature Selection Result

This section entails how we applied the Uber Freight data to the methodology reviewed in Chapter 3. We demonstrate our analysis from feature selection, K-Mean clustering, CART decision tree, and their respective results.

Starting with the feature selection analysis, Uber Freight provided two datasets: 1) live loading transaction records from 2017 to 2021 nationwide and 2) drop trailer transaction records from 2017 to 2021, with the drop trailer service only available in California, Texas, and Georgia. There are 35 data fields in both datasets. The content (Appendix A: Uber Freight Original Data Fields) includes but is not limited to the date, time, price, and distance of each shipment.

The feature selection follows two main criteria: the relevance to the research objective and the availability of data summarized in Table 1. The relevance dimension here is defined as the impact and connection of the feature toward the research objective based on the discussions with Uber Freight and our literature review. On the other hand, data availability refers to the ease of data access either from the sponsoring company or external databases.

Table 1: Data Selection Criteria

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Data Availability</td></tr>
<tr><td>High</td><td>Low</td></tr>
<tr><td rowspan="2">Relevancy to the project objective</td><td>High</td><td>e.g., travel distance</td><td>e.g., population density</td></tr>
<tr><td>Low</td><td>e.g., booking channel</td><td>e.g., trailer size breakdown</td></tr>
</table>

To further explain the feature selection process, we can first look at the 'High Relevancy - High Data Availability' and 'Low Relevancy – Low Data Availability'.

On the 'High Relevancy - High Data Availability', the travel distance metric emerged because it directly impacts drop trailer implementation based on our literature review. Moreover, it also possesses high data availability because it can be computed from Uber Freight's dataset directly using data fields such as the route distance in miles within a market pair. On the other side of the spectrum, we included the breakdown of trailer size in a market as the Low Relevancy - Low Data Availability feature. Although the choice of a trailer size led to trade-offs such as inventory holding cost (Abate and De Jong, 2014) in the trucking industry, this feature is neither relevant nor obtainable because Uber Freight only uses a standard one-size trailer at the point of our research.

In the 'High Relevancy - Low Data Availability', we categorized features such as population density into this quadrant. Population density helps understand the shipment numbers that may drive the frequency of transactions from shippers, but it is not readily available from Uber Freight's dataset. Realizing the potential usefulness of this metric, we overcame the challenge and accessed external databases to obtain the population and land sizes of all states in the U.S. to compute the population density in each market. Lastly, we listed the booking channel as an example for the 'Low Relevancy - High Data Availability' quadrant. Upon discussion with Uber Freight's team, the booking channel is not a deciding factor for drop trailer freight service offering, although the metric is easily accessible from Uber Freight's data.

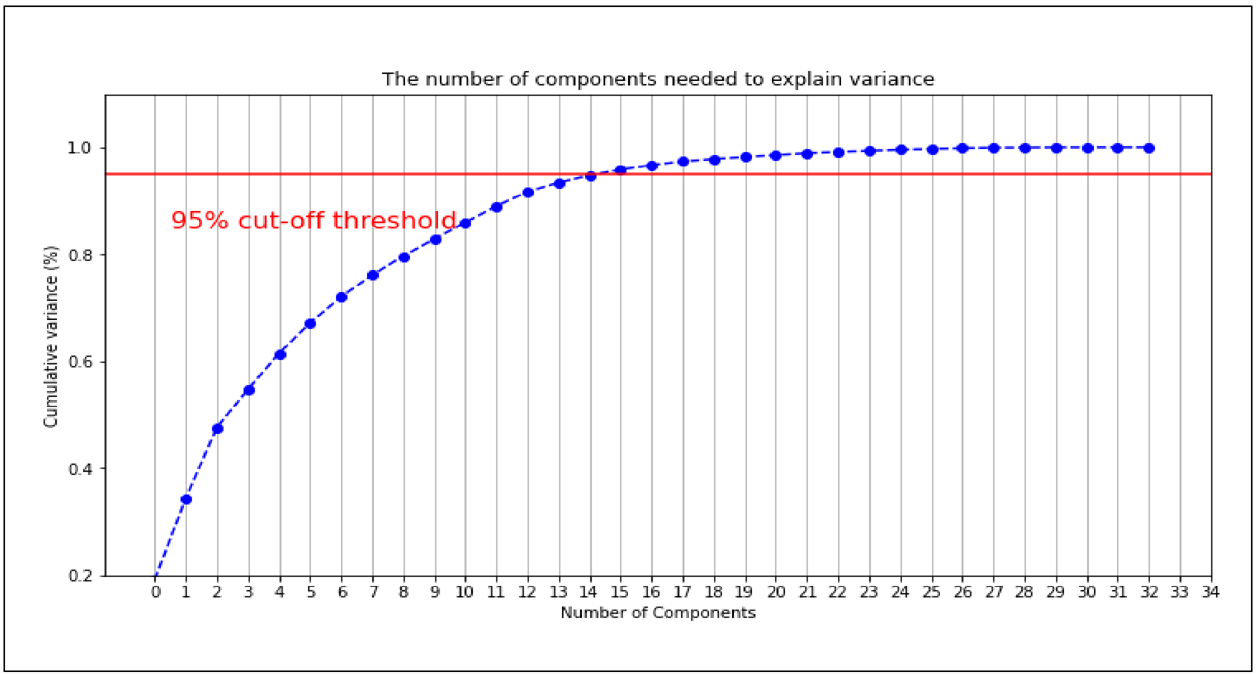
Based on the above thinking process, we selected 33 features and subsequently categorized them according to the four main metrics that we identified in Chapter 2.2:

1. Turnaround Efficiencies: This metric contains time-relevant features such as loading time, unloading time, and travel time. The metric aims to compare the idling time and traveling time.
2. Cost-Effectiveness: This metric contains price-relevant features such as market price and the price paid by Uber Freight to carriers per mile. The metric aims to capture the cost component of a shipment.
3. Supply-Demand Balance: This metric contains the number of shippers and carriers at origins and destinations. The metric captures the difference between the number of carriers and shippers.
4. Carrier/Shipper Density: This metric contains the density of shippers and carriers at origins and destinations. The metric aims to capture how the density of carriers or shippers will affect drop trailer implementation.

Detailed data fields by metrics are listed in Appendix B. There are six features under turnaround efficiencies, five features under cost-effectiveness, eight features under supply-demand balance, and 14 features under carrier/shipper density.

With 33 features categorized under four buckets, we moved on to conduct PCA. The objective of performing PCA is to convert a set of highly correlated features into a set of features with low correlations and dimensions. Based on a cumulative target variance of 95%, we obtained 14 principal components that summarized the 95% variance of 33 features (Figure 4). These 14 principal components served as inputs for the K-Means clustering.

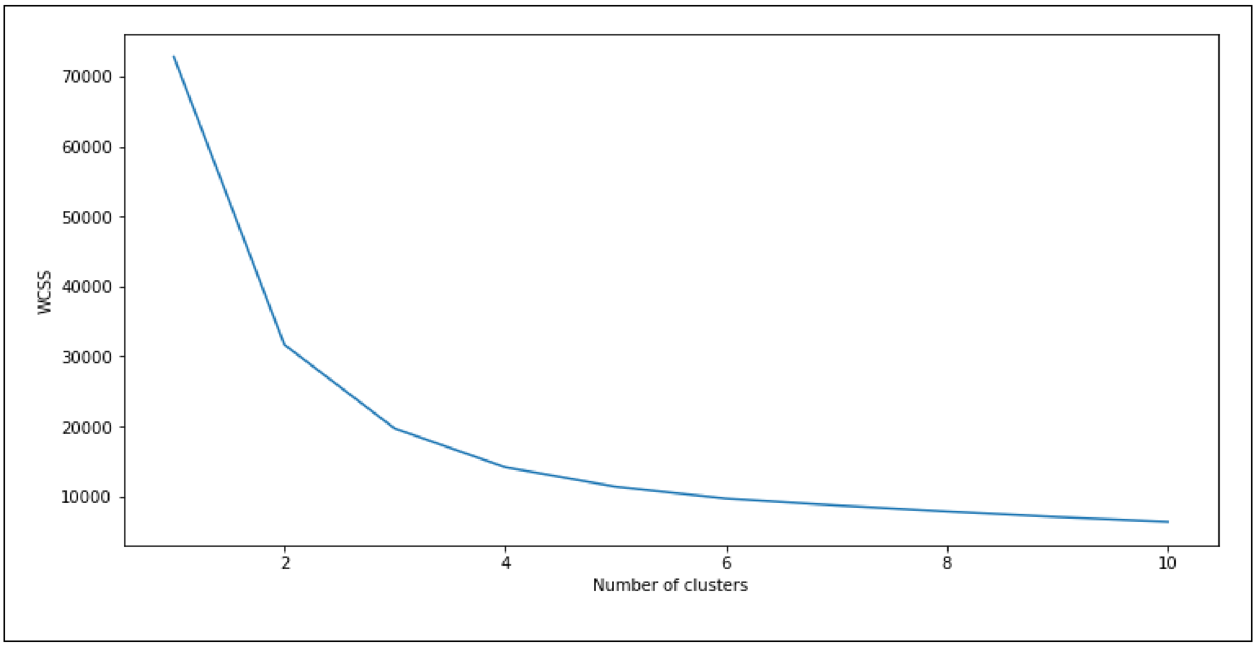
Figure 4: Principal Component Analysis (From 33 Features to 14 PCs)



4.2 K-Means Clustering Result

To select the optimal number of clusters, we measure the WCSS against various results of the number of clusters. In Figure 5, we saw the WCSS stagnated around k=4. Based on the optimal k value of 4, we conducted K-Means clustering with an open-source programming package built on Python scripting that allows data visualization and machine learning, named 'Orange'[1].

Figure 5: Elbow Plot for Optimal Clusters



The Orange software assigned each market pair a cluster number based on the K-Means clustering result. Extracting a summary of clustering results as an Excel sheet, we computed the percentage of drop trailer shipments in each cluster and obtained Table 1. The drop trailer percentage in each cluster was obtained

[1] Details of the Orange software can be found on the official website: https://orangedatamining.com/

by dividing the number of drop trailer market pairs by the total number of market pairs in the cluster. For instance, Cluster 1 (C1) has 17 market pairs with drop trailer service and 1365 market pairs in total; this means that the drop trailer percentage in this cluster is 1.25%. After comparing the drop trailer percentage in Table 2, we observed that cluster 3 (C3) has the highest drop trailer percentage among all clusters (Table 2). From here, we hypothesized that market pairs in this cluster possess a high similarity with market pairs that offer drop trailer service.

Given the drop trailer service is only offered intra-state, we used the total number of market pairs in cluster 3 minus the number of market pairs with the drop trailer service in cluster 3, which gave the number of 'non-drop trailer' market pairs in cluster 3. Among the 'non-drop trailer' market pairs in cluster 3, we filtered market pairs that are 'intra-state' market pairs only. By doing so, we shortlisted 29 intra-states 'non-drop trailer' market pairs from cluster 3 (Table 3). With these 29 intra-state market pairs, we calculated the number of intra-state market pairs for each state. The result showed that Illinois state tops the number of intra-state market pairs, followed by Indiana and Florida (Table 4). However, without further statistical analysis, it is insufficient to conclude that the three states are suitable candidates for drop trailer implementation. To affirm the robustness of our deduction, we re-conducted the K-Means clustering with k-value of 3 and 5. We chose the k-values because the WCSS became stagnated at these values. The results obtained from the additional K-Means clustering for three clusters (Table 5) and five clusters (Table 6) remain similar, as summarized in Table 7, consistently recommending Illinois, Indiana, and Florida as the top states for drop trailer implementation. This finding also aligned with Uber Freight's recent market expansion plan, as confirmed by our sponsoring company in a meeting.

The remaining question is, what network characteristics and key features that differentiate Florida, Illinois, and Indiana from other states? This was answered by our CART decision tree.

Table 2: K-Means Clustering Result and Market Pair/Total Market Pairs Proportion (k=4)

4 clusters	**C1**	**C2**	**C3**	**C4**
Count of market pairs with drop trailer	17	25	36	61
Total count of market pairs	1,365	1,286	1,315	6,608
% With drop trailer	1.25%	1.94%	2.74%	0.92%

Table 3: Intra-State Market Pairs in Cluster 3

IL_CHI_IL_BLO	IN_IND_IN_EVA	NC_CHA_NC_GRE
IL_CHI_IL_QUI	IN_IND_IN_FTW	NC_CHA_NC_RAL
IL_CHI_IL_RFD	IN_IND_IN_GRY	NC_CHA_NC_WIL
IL_CHI_IL_ROC	IN_IND_IN_SBD	ND_BIS_ND_BIS
IL_CHI_IL_TAY	IN_IND_IN_TER	ND_BIS_ND_FAR
IL_JOL_IL_BLO	FL_LAK_FL_JAX	SD_RAP_SD_SXF
IL_JOL_IL_QUI	FL_LAK_FL_MIA	TN_MEM_TN_CHA
IL_JOL_IL_RFD	FL_LAK_FL_TAL	TN_MEM_TN_KNO
IL_JOL_IL_ROC	PA_PHI_PA_ERI	TN_MEM_TN_NAS
IL_JOL_IL_TAY	PA_PHI_PA_PIT	

Table 4: Recommended State for Drop Trailer (k = 4)

State	**Count of Market Pair**
IL	10
IN	5
FL, NC, TN	3

Table 5: K-Means Clustering Result and Market Pair/Total Market Pairs Proportion (k=5)

Five-Cluster	C1	C2	C3	C4	C5
Count of market pairs with drop trailer	16	34	33	51	5
Total count of market pairs	1,286	1,229	1,306	5,995	758
% With drop trailer	1.24%	2.77%	2.53%	0.85%	0.66%

Table 6: K-Means Clustering Result and Market Pair/Total Market Pairs Proportion (k=3)

Three-Cluster	C1	C2	C3
Count of market pairs with drop trailer	23	29	87
Total count of market pairs	1491	1364	7719
% With drop trailer	1.54%	2.13%	1.13%

Table 7: Summary of K-Means Clustering Result and Market Pair/Total Market Pairs Proportion

Best cluster result based on different no. of clusters			
K-value	3	4	5
Count of market pairs with drop trailer in the best cluster	29	36	34
Total count of market pairs in the best cluster	1364	1315	1229
% With drop trailer	2.13%	2.74%	2.77%
Top 3 recommended state	FL, IL, NY	IL, IN, FL	IL, IN, FL

4.3 CART Decision Tree Result

As a recap of Chapter 3.3, our construction of the CART decision was split into three steps: 1) trimming down features to avoid overfitting, 2) balancing the data, and 3) building the decision tree.

Starting from the first step, we first examined the feature importance by plotting two set of graphs for each feature from two perspectives: 1) four-cluster distribution and 2) drop trailer vs. live loading distribution.

Based on the plotting result (Figure 6), we segmented each feature into three categories: strong, moderate, and weak explanatory power. For instance, “market_price” has a stronger explanation power because the mean and variance of the distribution are distinct. Whereas for “population_density_at_source”, the distribution of four clusters appears to be mingled. This means that “population_density_at_source” does not provide a meaningful variable for the decision tree. Apart from the cluster’s distribution graph, we also cross-examined the difference of distribution from the perspective of the drop trailer vs. live loading distribution set of graphs for each feature, as shown in Figure 7. We confirmed that the distribution of each feature from two sets of the graph is almost the same. The homogeneity of the finding assured that we could apply the same set of features to our decision tree without the need to build a separate tree to compare performances for the different feature sets. In the end, we managed to trim down 33 features to 14 features, as listed in Appendix C.

Figure 6: Sample of Strong, Moderate and Weak Features Distribution (Four-Cluster)

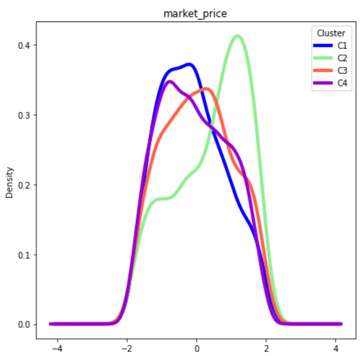
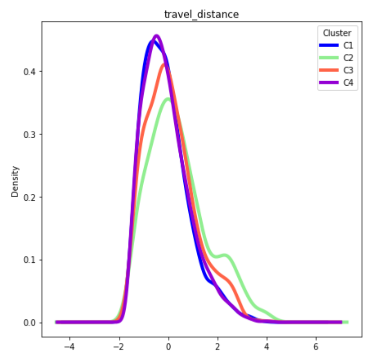
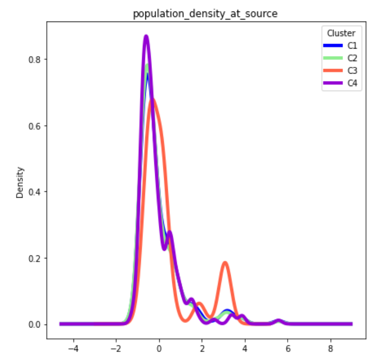
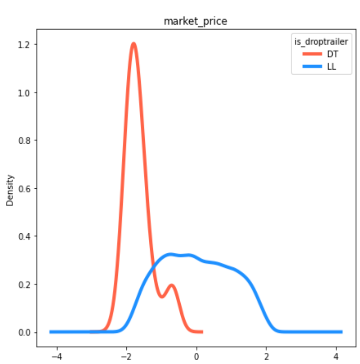
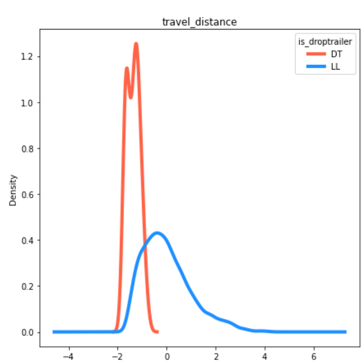
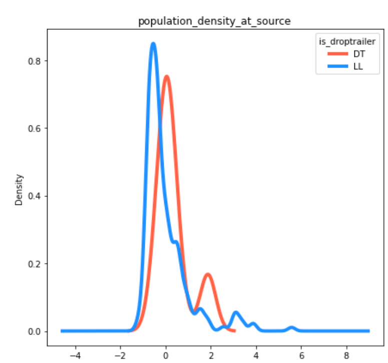
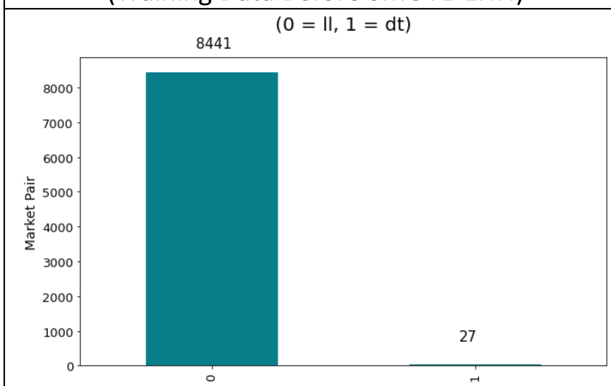
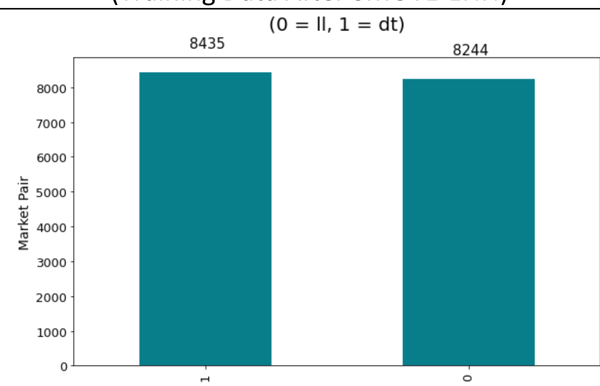
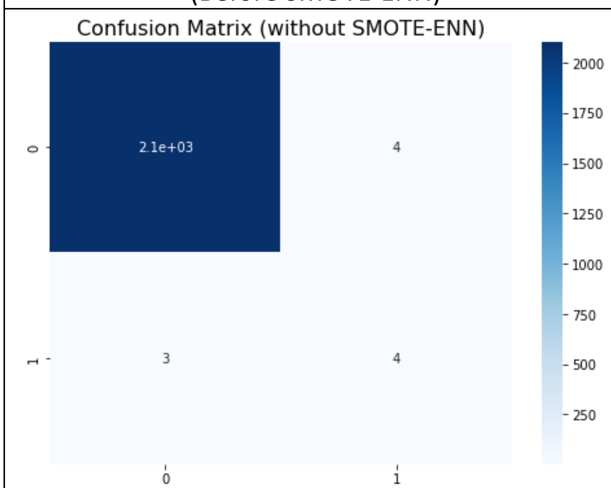
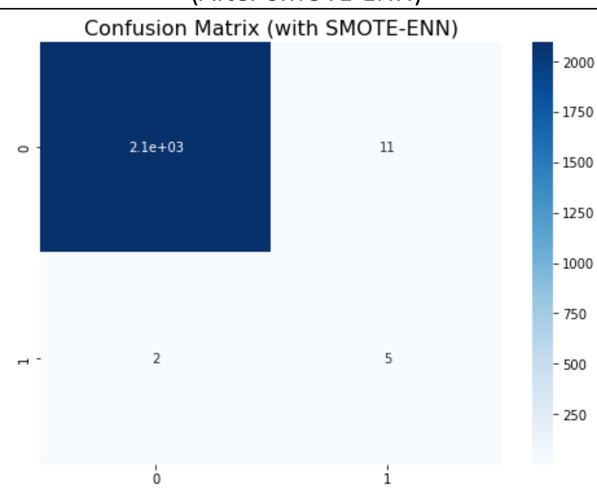
market_price	**travel_distance**	**population_density_at_source**
		
Strong Explanatory Power	**Moderate Explanatory Power**	**Weak Explanatory Power**
Each cluster is hugely differentiated	Most of the clusters are similar	All clusters are mingling together

Figure 7: Sample of Strong, Moderate and Weak Features Distribution (Drop vs. Live)

market_price	**travel_distance**	**population_density_at_source**
		
Strong Explanatory Power	**Moderate Explanatory Power**	**Weak Explanatory Power**
Each cluster is hugely differentiated	Most of the clusters are similar	All clusters are mingling together

The next step is the rebalancing of data. Our result shows that PR and ROC percentages increased after the SMOTE-ENN resampling, from 57.14% to 71.43%, and from 78.55% to 85.43%. This means that the classification ability has slightly improved compared to the previous imbalanced dataset. The confusion matrix also shows that the true positive and true negative sorting error has been slightly reduced (See Figure 8).

Figure 8: A Comparison of Training Dataset before and after SMOTE-ENN Sampling

Dataset Distribution (Training Data Before SMOTE-ENN)	Dataset Distribution (Training Data After SMOTE-ENN)
	
Confusion Matrix (Before SMOTE-ENN)	Confusion Matrix (After SMOTE-ENN)
	
Recall = 0.5714 ROC = 0.7855	Recall = 0.7143 ROC = 0.8543

Using the newly balanced data, we moved to the construction of the CART decision tree. The process of building the CART decision tree was also accompanied by a series of parameter tuning, or so-called "tree pruning", a term used in the machine learning field. In Python, we were able to adjust the model's parameters, including the tree depth, minimum number of leaf nodes, and the maximum sample leaf, to increase the robustness of our model. The best value of these parameters can be identified by evaluating the deviation between the accuracy score of training data and testing data to determine an optimal parameter for the model. To further explain, we want to ensure that the value of accuracy in the training and testing data is neither under-fitting nor over-fitting. If the training data is constant and close to 100%, while the testing score is lower, then it is a case of over-fitting on training data. On the other hand, if both the score of training and testing data is low, it is a sign of under-fitting on the training data.

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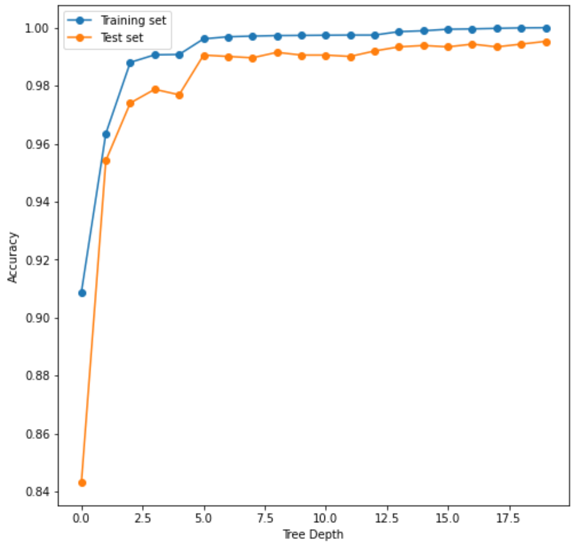
Figure 9 shows the accuracy score between training and testing data given a range of values for each parameter. For instance, in the simulation of the tree depth between 0 and 17.5, we observed that the difference between training and testing score accuracy is lowest when the depth is 5. We set the maximum depth accordingly to 5 to achieve the best maximum tree depth of our CART model. This selection process was followed similarly to identify the optimal value for other parameters, such as the minimum number of leaf nodes and the maximum sample leaf. Along with the model testing, we also tried a different combination of these parameter's values in multiple iterations to yield a model that mostly aligns with the business strategy and implication.

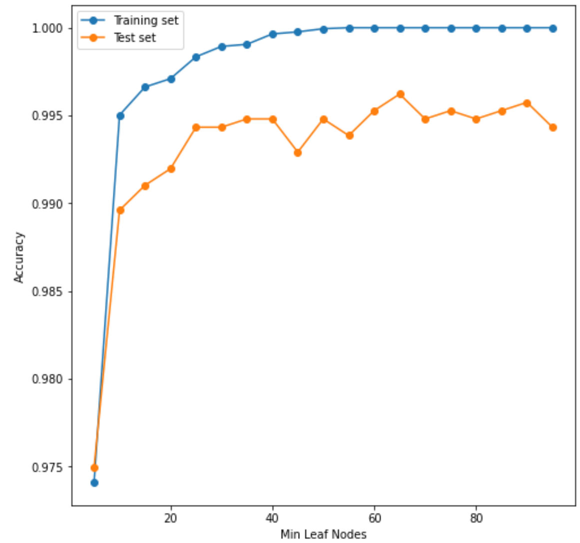
Other than parameter tuning, we also implemented a mechanism to impose a penalty cost to reduce the possibility of misclassification. This was done by setting the class weight in our CART decision tree as "balanced" in the "DecisionTreeClassfier" built-in function from scikit learn. This setting will allow the code to treat live loading and drop trailer class equally. Although our dataset has been rebalanced previously, this adjustment will further impose a cost of bias in mislabelling live loading and, at the same time, better predict the class we are interested in (Zheng et al., 2017), which in this case is the drop trailer.

With the above effort, we finally came out with the best version of our CART decision tree model (Figure 10). The decision tree consisted of 4 key features: (1) number of shipments at the source market, (2) travel distance, (3) market price, and (4) carrier to shipment ratio at the destination market. Figure 11 is the same CART decision tree but with an extra layer that allows us to understand the distribution of data and its split point. Each of the four features represents one of the four themes we defined during our feature selection process.

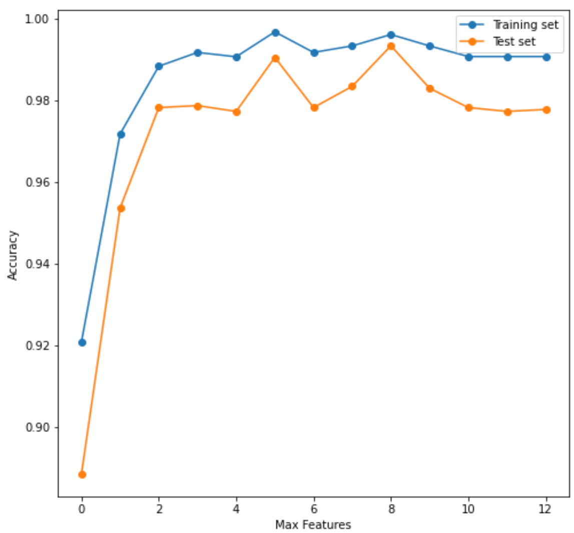
Figure 9: Training vs. Test Data Evaluation in CART Decision Tree Post-Pruning Process



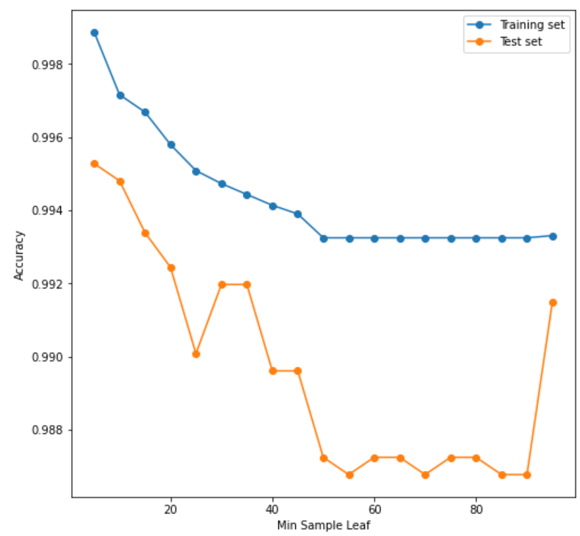
Optimal Tree Depth: 4-6



Optimal Minimum Sample Leaf: 20-40



Optimal Maximum Features: 4-6



Optimal Minimum Sample Leaf: 5-10

Figure 10: CART Decision Tree for Uber Freight's Drop Trailer Implementation

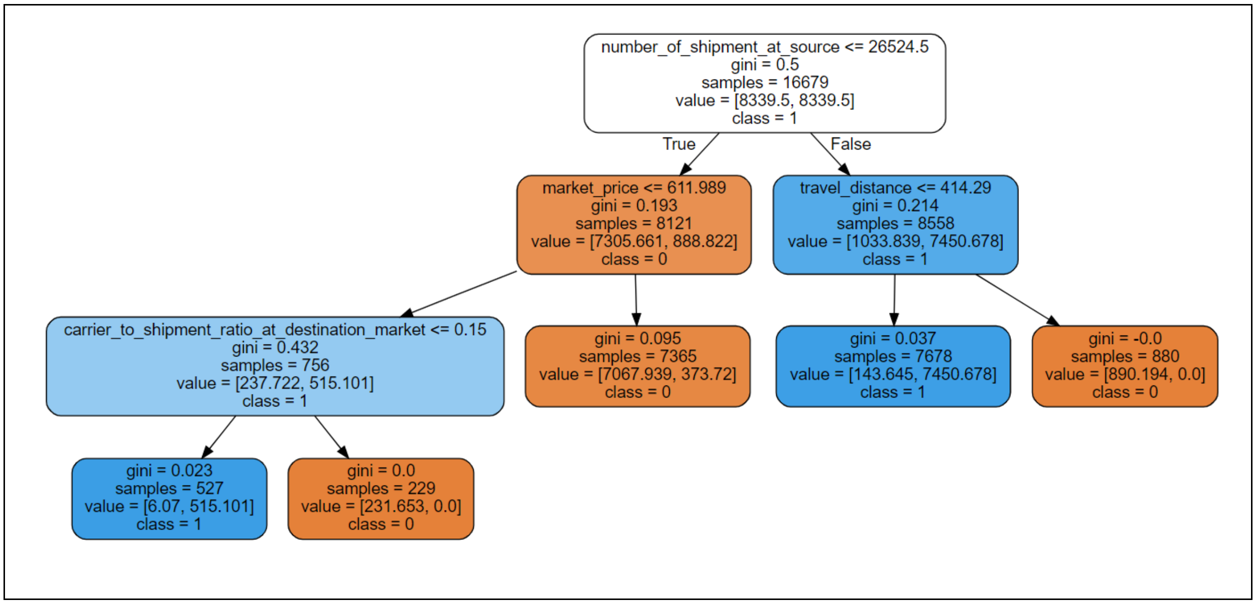
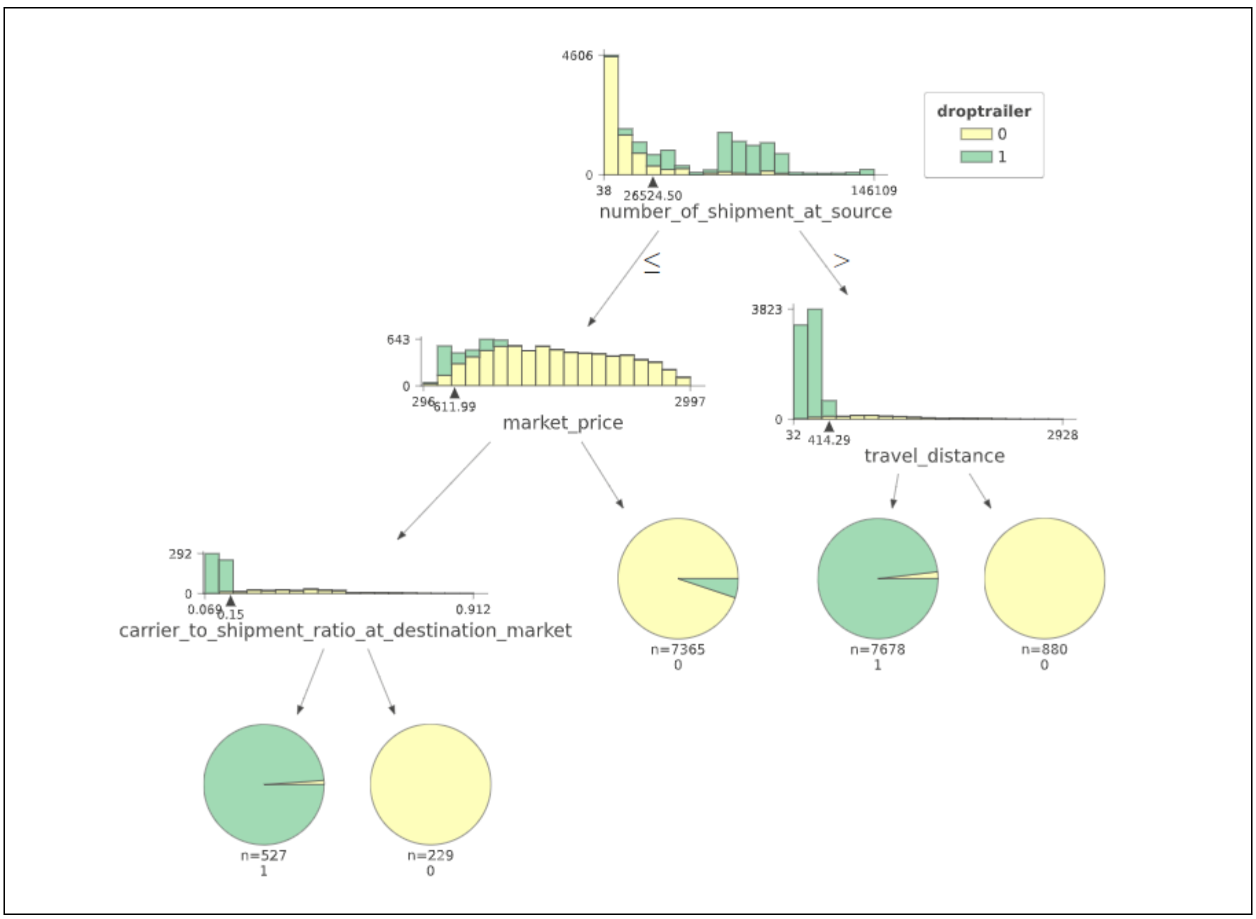


Figure 11: CART Decision Tree for Uber Freight's Drop Trailer Implementation (by distribution)



5. DISCUSSION

This chapter explains the real-life implications and recommendations based on our analysis and results in Chapter 4.

Per Chapter 4.3, the CART decision tree shows two sets of market conditions that can make drop trailer service attractive for implementation. These sets of conditions are summarized in Table 8.

Table 8: Network Condition and Strategy Consideration for drop trailer Offering

	Low Shipment Volume Market Condition	**High shipment Volume Market Condition**
Condition	• Number of shipments at source ≤ 26,525, market price ≤ 612, carrier to shipment ratio at destination market ≤ 0.197	• Number of shipments at source ≥ 26,525, travel distance ≤ 413
Strategic Consideration	• Work on pricing strategy to drive drop trailer adoption. • Incentivize stronger carrier to participate in the drop trailer program	• Focus on shorter and compact market pair

As we can see from the decision tree, the most significant feature in drop trailer implementation is the number of shipments at the source. This feature refers to the total number of shipments at source market from 2017 to early 2021, yielding an average annualized shipment number of about 6,630.

5.1 Low Shipment Volume Market Condition

When the annual shipment number at a source market is less than 6,630, two features determine the attractiveness of the drop trailer service: (1) market price and (2) the carrier to shipment ratio at the destination.

Starting with the market price, our exploratory analysis shows that Uber Freight pays an average price of $520 for a drop trailer shipment and an average price of $1,723 for a live loading shipment. Hence, when the market price is less than $612, Uber Freight yields a better margin from implementing drop trailer service.

Another important consideration after the market price is the carrier to shipment ratio at the destination market. For a viable network, the carrier to shipment ratio is preferred to be as low as possible at the destination market. The decision tree indicates that the carrier to shipment ratio at the destination market should be less than 0.15, equivalent to at least six shipments to one carrier. On the other hand, if the ratio is more than 0.15, the market may be too saturated to offer drop trailer service. This is because an increase in the density of carriers hinders them from achieving their maximum capacity utilization (American Trucking Association, 2020).

Overall, under this low shipment volume market condition, Uber Freight should pay attention to its pricing and competitiveness in the market.

Firstly, the market price threshold dictated the pricing strategy to carriers from Uber Freight. Since the price paid by Uber Freight determines the drop trailer take-up rate by carriers, it is imperative for the company to decide the approximate price of each transaction or what the “average” shipment will cost as compared with the market price. Our initial exploratory analysis found out that the average price for a drop trailer shipment is $520, which is significantly lower than the live loading price of $1,723. Hence, when the drop trailer rate is close to that of live loading, there is little incentive for shippers and carriers to use drop trailer.

Currently, Uber Freight’s pricing is generated by its proprietary algorithm, which is based on real-time market data which sets the most competitive prices at the time as well as internal expert judgment (personal communication, 2022). As such, the company has limited levers to control or implement more sophisticated pricing. Nevertheless, one additional feature that can be implemented to maximize the profit is to allow for an auction model for drivers or carriers to submit bids, given the “perishable,” time-sensitive nature of the service (Einav et al., 2018). Furthermore, Uber Freight can also introduce better forecasting and analytic ability to predict appropriate pricing strategy (either over or under-price) to drive adoption.

Other than market price under this market condition, the carrier to shipment ratio has significant theoretical value and practical significance for the application and development of drop trailer platform design. In order to have a successful platform that matches supply and demand, a company must have a matching strategy within the value chain to match both the supply and demand sides simultaneously without any discrimination (Arthur, 1996; Cusumano and Gawer, 2002). It is usually agreed that the matching strategy between consumers and producers should align with the platform development since the demand patterns often require different resource allocation and operations at different times (Edelman, 2020).

Since the establishment of Uber Freight, the company has attracted sufficient shippers to use the platforms. However, to have viable drop trailer services in a market, the company should focus on getting shipments and securing a reliable supply side (i.e., carriers). In particular, they should maintain a healthy carrier to shipment ratio to avoid over-competition (Kim, 2015). For instance, Uber Freight could work with carriers, third-party logistic companies, and trucking carriers that can serve multiple shipments simultaneously.

When the carriers have a limited infrastructure to support shipper requests, the platform can encourage load and resource sharing among more prominent carriers (Feng and Cheng, 2021). The premise of load-sharing is that the carriers are compensated for lending out their extra resources, increasing their revenues (Figliozzi, 2006). Using an optimization method, Figliozzi (2006) proved that bundling of load within carriers in an incentive framework could increase the space for profit from a system perspective. For Uber Freight to implement this, a framework for clear collaboration rules and policies must be established to ensure service fulfillment and control. Furthermore, to induce more handling capability, they should also work with carriers to increase systematic management of warehouse operational improvements such as facility and schedule optimization so that they can handle more incoming shipments without the need to add new carriers.

We have so far considered the implication on the supply side of Uber Freight's platform for drop trailer services. From the demand side, Uber Freight should also design an attractive paid-out contract and intensive marketing to get more shippers so that a certain volume of shipments can be reached when there is an over-supplied situation. In summary, for future expansion under this market condition, Uber Freight's campaign must be broad-based, acknowledging the carrier and shipment ratio and emphasizing more local coordination among diverse types of carriers.

5.2 High Shipment Volume Market Condition

When the number of shipments at a source is more than 6,631 per year, we consider the market to be a high shipment volume market.

Under this scenario, travel distance becomes more critical to determine whether a drop trailer service should be offered or not. From the tree, it is observed that when the travel distance between source and destination is less than the threshold of 414 miles, it is more favorable to offer the drop trailer service. This finding also aligns with Uber Freight's hypothesis that there is a length of haul (i.e., travel distance) at which turnaround efficiencies gained from Drop solutions are less relevant.

To further explain the phenomenon, we can revisit the turnaround efficiency, linking to the underlying model of drop trailer offering. In a market pair with a shorter traveling distance, the fraction of loading and unloading time is higher, although the actual loading and unloading time is the same. This amplifies the impact of loading and unloading time consumption. Hence, in a shorter travel distance, the drop trailer service is preferred due to its time-saving nature during loading and unloading. This means that Uber Freight would need to be careful to select the shortest and most compact market pair that yields the travel distance within the 414-mile threshold for the drop trailer service to be attractive. To understand this relationship, we exemplify it with two examples of market pairs in Table 9.

Table 9: Market pairs with Similar Loading and Unloading Time but Different Travel Distance

	Travel distance	**Fraction of Sum of Loading and Unloading Time over Cycle Time**	**Loading time in seconds**	**Unloading time in seconds**
Market Pair A: TX_MCA_UT_SLC	1,556	0.045	11,800	11,269
Market Pair B: MO_JOP_IL_BLO	398	0.29	11,558	11,778

Although market pairs A and B have similar loading and unloading times, due to the difference in travel distance, the fraction of the total loading and unloading time over cycle time for B is much higher than A. Hence, it is more tempting to implement the drop trailer service in B due to the fraction of loading and unloading time the drop trailer service can save.

This conclusion is helpful if Uber Freight considers incorporating shipper-agnostic drop yards. For instance, if the distance between source and destination is more than 414 miles, adding a drop yard in the middle point may enable a more efficient first- and last-mile delivery in congested urban areas, handled by Uber Freight's network of contracted local fleets (Boysen, N. et, 2020). However, to implement this approach, Uber Freight must provide clear communication and visibility to meet pick-up schedules to avoid any consequent delays (Wu and Zheng, 2021).

5.3 Future Research

Although the project addressed the key research objectives and provided recommendations on drop trailer implementation for Uber Freight, three areas can be further explored to expand the explanatory power of our model.

5.3.1 An Expansion of Transaction Data Nationwide

As the Powerloop service is relatively new, with only five years' history across three states, there was a limitation to obtain a comprehensive amount of drop trailer transaction data nationwide. Although the initial dataset consists of over 2 million transaction entries, spanning between 2017 and 2021, the actual market pairs that are aggregated by average significantly reduce the portion of data on the states that have implemented drop trailer (i.e., California, Georgia, and Texas). It is recommended that as Uber Freight expands its services to other states, future research should gather more Uber Freight transactional data to improve our model accuracy.

5.3.2 An Expansion of Industrial Data

In terms of industrial data, the project acknowledged the need for other industrial data, such as warehouse size. As shown in Chapter 2.1, it is agreed that the warehouse size is a significant factor to be considered when deciding whether to implement drop trailer. In a state where there is a big difference between supply and demand, bigger warehouse space is preferred to implement drop trailer. Communication with industry and academic experts confirmed that warehouse sizes should be considered when building the machine learning model. However, we cannot obtain this metric due to the time constraints and limitations in accessing reliable databases.

For future research, it is recommended to find out such as 'High Relevancy - Low Data Availability' dataset and incorporate them into the model.

5.3.3 An Expansion of Methodology for Verification

While we have conducted repetitive tests and verification of the unsupervised machine learning model (K-Means) and supervised machine learning model (CART decision tree), exploration of other machine learning models could be used to diversify the methodology. On top of the unsupervised machine learning model (K-Means), future research could investigate K-Medians clustering algorithm to mitigate the impact of outliers, although the time required to run the model can be longer. In addition, mean-shifting clustering is also an alternative with the benefit of discarding a pre-set number of clusters, but it comes with the disadvantage of requiring a selection of radius.

6. CONCLUSION

With the rising need to improve the driver and truck utilization rate to relieve the shortage of drivers, determining where and under what conditions to implement drop trailer for our sponsoring company, Uber Freight, is a critical strategic and tactical issue.

Our K-Means clustering result showed that Illinois, Indiana, and Florida possess the highest feature similarity with states that have already successfully deployed drop trailers. To understand the critical features, our study further scaled to a predictive decision tree model that enables Uber Freight to identify market pairs suitable for drop trailer implementation in the future. The decision tree recognized the four most impactful features in drop trailer implementation: 1) number of shipments at source market, 2) travel distance, 3) market price, 4) carrier to shipment ratio at destination market. The four features also aligned with the four drop trailer metrics discovered from the literature review: 1) turnaround efficiencies, 2) cost-effectiveness, 3) supply-demand balance and 4) carrier/shipper density. The four features illustrated essentially lays out two sets of favorable market conditions to implement drop trailer service along with their strategic implication.

In the first set of market conditions (low shipment volume market condition), the market demand is forecast to be low. Uber Freight needs to develop a pricing strategy to drive up the adoption of drop trailer service. The significant impact of a carrier to shipment ratio also translates to a market strategy for Uber Freight to secure more reliable carriers. For the second set of market conditions (high shipment volume market condition), Uber Freight should carefully select routes with the distance within a threshold for drop trailer implementation, focusing on the turnaround efficiency metric of the drop trailer service.

In conclusion, our research provided a foundation of factors for Uber Freight and other drop trailer carriers to consider when expanding the drop trailer service. To ensure a successful market expansion, further research could be done by obtaining more transactional and industrial data nationwide to develop more features, such as the average warehouse size of the carriers. Another exploration area is to further disaggregate the population density on a market pair level, investigating whether the impact of population density is more potent at a market pair level than at a state level. Future research could cover other areas such as a hybrid model of drop trailer and live loading or a yard operation to increase network efficiency with more comprehensive features.

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APPENDIX

Appendix A: Uber Freight Original Data Fields

In Table 10, we list all fields from the original data provided by Uber Freight.

Table 10: Original Data Fields from Uber Freight

Column Number	Data Field	Data Type
1	external_load_id	String
2	shipper_uuid	String
3	carrier_uuid	String
4	booking_channel	Categorical
5	comparable_carrier_price	Numeric
6	destination_actual_arrival_utc_time	DateTime
7	destination_actual_departure_utc_time	DateTime
8	destination_city	Categorical
9	destination_state	Categorical
10	destination_country_iso2	Categorical
11	destination_start_utc_time	DateTime
12	destination_end_utc_time	DateTime
13	destination_market_id	String
14	destination_market_name	String
15	destination_region	Categorical
16	destination_timezone	DateTime
17	equip_type	Categorical
18	is_utp	Boolean
19	load_status	Categorical
20	load_status_category	Categorical
21	max_available_to_max_book_hrs	Numeric
22	rateview_at_booking	Numeric
23	route_distance_in_miles	Numeric
24	source_actual_arrival_utc_time	DateTime
25	source_actual_departure_utc_time	DateTime
26	source_city	Categorical
27	source_state	Categorical
28	source_country_iso2	Categorical
29	source_start_utc_time	DateTime
30	source_end_utc_time	DateTime
31	source_market_id	String
32	source_market_name	String
33	source_region	Categorical
34	source_timezone	Categorical
35	total_carrier_price	Numeric

Appendix B: Data Fields by Metrics

This appendix consists of four tables, each representing a theme developed from the literature review.

In each table, there are the features under the theme, with the unit and datatype of each feature.

Table 11: Turnaround Efficiencies Theme and its Features

Turnaround Efficiencies		
	Features for a Market Pair	**Unit and Datatype**
1	Unloading time at Destination Market	In seconds
2	Loading time at Source Market	In seconds
3	Fraction of Travel time of the cycle Time	Travel Time / Cycle Time, fraction number
4	Fraction of Loading time of the cycle Time	Loading Time / Cycle Time, fraction number
5	Fraction of Unloading time of the cycle Time	Unloading Time / Cycle Time
6	Travel Distance	Route_distance_in_miles, number

Table 12: Cost-Effectiveness Theme and its Features

Cost-Effectiveness		
	Features for a Market Pair	**Unit and Datatype**
7	Market price	Rateview_at_booking, number
8	Carrier price paid by Uber	Comparable_carrier_price, number
9	Cost Differences	Rateview_at_booking - Comparable_carrier_price, number
10	Market price per mile	Rateview_at_booking / route_distance_in_miles, number
11	Carrier price paid by Uber per mile	Comparable_carrier_price / route_distance_in_miles, number

Table 13: Supply Demand Balance Theme and its Features

Supply-Demand Balance		
	Features for a Market Pair	**Unit and Datatype**
12	No. of Shippers at Destination	No. of distinct shipper_uuid
13	No. of Carriers at Destination	No. of distinct carrier_uuid
14	No. of Shipment at Destination	No. of distinct external_load_id
15	No. of Shippers at Source	Same value as 12
16	No. of Carriers at Source	Same value as 13
17	No. of Shipment at Source	Same value as 14

18	average_monthly_source_ supply_demand_balance	At source, average monthly supply - average monthly demand
19	average_monthly_destination_ supply_demand_balance	At destination, average monthly supply - average monthly demand

Table 14: Carrier/Shipper Density Theme and its Features

Carrier/Shipper Density		
	Features for a Market Pair	**Unit and Datatype**
20	Shipper to Shipment Ratio at Destination Market	No. of distinct unique shipper_uuid / No. of distinct external_load_id, fraction
21	Carrier to Shipment Ratio at Destination Market	No. of distinct carrier_uuid / No. of distinct external_load_id, fraction
22	Shipper to Carrier Ratio at Destination Market	No. of distinct shipper_uuid / No. of distinct carrier_uuid, fraction
23	Shipper to Shipment Ratio at Source Market	Same value as 20
24	Carrier to Shipment Ratio at Source Market	Same value as 21
25	Shipper to Carrier Ratio at Source Market	Same value as 22
26	Shipper Density at Destination	No. of distinct shipper_uuid / destination_market_land_area
27	Carrier Density at Destination	No. of distinct carrier_uuid / destination_market_land_area
28	Shipment Density at Destination	No. of distinct external_load_id / destination_market_land_area
29	Population Density at Destination	destination_market_population_density
30	Shipper Density at Source	fraction number
31	Carrier Density at Source	fraction number
32	Shipment Density at Source	fraction number
33	Population Density at Source	fraction number

Appendix C: Feature Selection for CART Decision Tree

This appendix consists of four tables, each representing a theme and the features under the theme which are used for constructing the CART decision tree.

Table 15: Features under Turnaround Efficiencies used for CART decision tree

Turnaround Efficiencies		
	features for a Market Pair	**Unit and Datatype**
1	Unloading time at Destination Market	In seconds
2	Loading time at Source Market	In seconds

Table 16: Features under Cost-Effectiveness used for CART decision tree

Cost-Effectiveness		
	features for a Market Pair	**Unit and Datatype**
3	Market price	Rateview_at_booking, number
4	Carrier price paid by Uber	Comparable_carrier_price, number
5	Cost Differences	Rateview_at_booking - Comparable_carrier_price, number

Table 17: Features under Supply-Demand Balance used for CART decision tree

Supply-Demand Balance		
	features for a Market Pair	**Unit and Datatype**
6	No. of Shippers at Destination	No. of distinct shipper_uuid
7	No. of Shipment at Destination	No. of distinct external_load_id
8	No. of Carriers at Source	Same value as 13
9	average_monthly_source_ supply_demand_balance	At source, average monthly supply - average monthly demand
10	average_monthly_destination_ supply_demand_balance	At destination, average monthly supply - average monthly demand

Table 18: Features under Carrier/Shipper Density used for CART decision tree

Carrier/Shipper Density		
	features for a Market Pair	**Unit and Datatype**
11	Carrier to Shipment Ratio at Destination Market	No. of distinct carrier_uuid / No. of distinct external_load_id, fraction
12	Shipper Density at Source	fraction number
13	Carrier Density at Source	fraction number
14	Shipment Density at Source	fraction number
15	Population Density at Source	fraction number

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