Selecting the Most Profitable Freight Offer

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Abstract

The freight industry has become a critical part of the economy ever since the outbreak of COVID-19 due to its significant impact on the supply chain and the delivery of essential goods. Flock Freight is a technology-enabled logistics company that aims to revolutionize the freight industry by providing cost-effective shipping methods. The company uses proprietary machine learning algorithms that take in the rich data which the company has gathered in previous years to combine less-than-truckload shipments into one truckload to improve efficiency and reduce potential costs. As a method of minimizing shipping costs, Flock Freight puts customers' orders to an auction so that freight companies compete with each other to ship orders at lower rates – the company needs to accept a good offer before the freight company withdraws the offer. The research team wants to develop a machine learning model that identifies offers with the best rate before it expires or the pickup deadline for the order approaches. The team suggests a two-part hybrid model that consists of a regression model that predicts minimum offer rates and a classification model that predicts the number of offers for each order. The hybrid model then decides whether to accept an offer or not. With the model, Flock Freight can make informed decisions and reduce the overall costs of shipments.

1. Introduction

Flock Freight is a logistics firm that endeavors to transform the freight industry by promoting shared truckloads, leading to decreased costs and carbon emissions in national freight shipping. The firm functions as an intermediary to connect customers with shipping companies, enabling a single truck to transport multiple deliveries from one region A to B in one trip. To pool multiple goods in a single truck, Flock Freight accepts offers from shipping companies such that a single offer can be made on multiple orders Flock Freight's customers seek to have delivered by a particular deadline. The firm selects the lowest offer rate for each order from the various offers it receives from different shipping companies. However, this process is complicated by the possibility of offers expiring abruptly, as truckers may divert their attention to other shipping platforms. Thus, the data science team at Flock Freight must develop a machine learning model that can swiftly identify the optimal offer as soon as it is made to tackle this challenge.

The secretary problem, a well-known optimal stopping problem in applied statistics, shares similarities with Flock Freight's challenge. In the secretary problem, the goal is to hire the best candidate from a pool of candidates without the ability to revisit previously rejected candidates. Upon extensive research, statisticians have proven that the probability of choosing the best candidate is maximized when you choose the first candidate to beat the first 37% of all candidates you interviewed. However, due to the fact that most orders at Flock Freight receive only a handful of offers, the secretary method performs worse than the algorithm already in place: the firm's machine learning model is better at choosing the best offer than the secretary method is. The firm does not know exactly how many offers each order will receive, and offer rates are subject to change based on delivery urgency. Moreover, the secretary method generalizes all cases of optimal stopping problems and fails to leverage the rich dataset available to Flock Freight. Thus, an algorithm as complex as Flock Freight's situation needs to be developed.

Flock Freight has access to two primary datasets that provide dense information: order and offer. The order dataset contains essential information about an order, including the shipping distance, time, location, freight size, and hazard level. The geographic data within this dataset plays a pivotal role in revealing the presence of traffic infrastructure that incentivizes trucking companies to pool multiple orders in a single truck. Furthermore, the time data helps Flock Freight understand how much time the firm has before it is desperate to take any offer. The offer dataset stores information on all offers made to Flock Freight, regardless of whether the offer was accepted or successfully delivered. Each offer instance includes a QUOTE_TYPE attribute that denotes the type of delivery a shipping company offers, namely a *pool* or a *quote*. The pooled truckload (PTL) aims to share a truck among multiple orders, while the full truckload (FTL) dedicates one truck to fulfill a single order.

One critical aspect to note about the data is that the Flock Freight dataset is not able to capture the entire nature of the bidding process. To serve its customers, Flock Freight cannot wait to receive all the offers an order could ever get because the company cannot wait until the pickup deadline approaches without choosing an offer. That is, the data lacks the true number of offers and the true lowest offer rates which freight companies are willing to provide.

As a solution to this problem, the team builds a hybrid model that consists of an XGB Regression model that predicts the minimum offer rate each order will receive and a Decision Tree model that predicts the number of offers each order will receive. Together, theXGB classifier hybrid model achieves a 0.79 accuracy is identifying best offers.

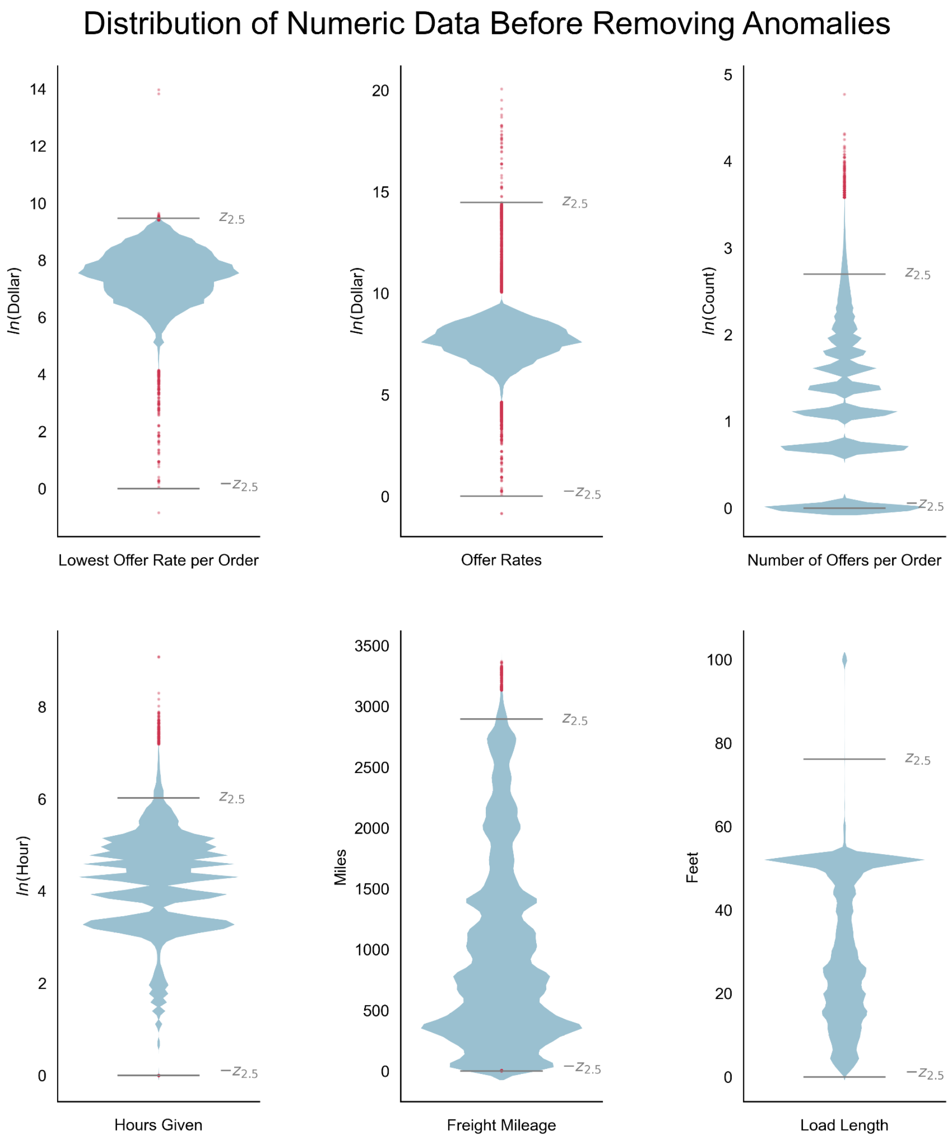
An XGB Regression model and Decision Tree model are used to estimate the minimum offer rate and the total number of offers an order will receive. Together, they power an XGB Classification model that identifies best offers.

2. Data Cleaning and EDA

These two datasets consist of 707,418 offers and 280,906 orders. The order dataset includes the order date, origin and destination zipcodes, route mileage, and shipping preferences. The order date is the date on which the shipper placed the order. The origin and destination zipcodes indicate the starting and ending points of the shipment. The route mileage is the distance between the origin and destination zipcodes. The shipping preferences may involve specific requirements such as temperature control or hazardous materials transportation. The offer dataset includes the offer date, rate, and type. The offer date is the date on which the carrier made the offer. The offer rate refers to the dollar amount the carrier is willing to be paid to ship an order. There are two types of offers: Full Truckload (FTL) and Partial Truckload (PTL). FTL shipping is a method in which a single order occupies an entire truck. FTL shipping is generally used for large and hazardous shipments. PTL is a method in which multiple orders share a truck. PTL shipping is typically less expensive since the customer only pays for the space used rather than the entire truck.

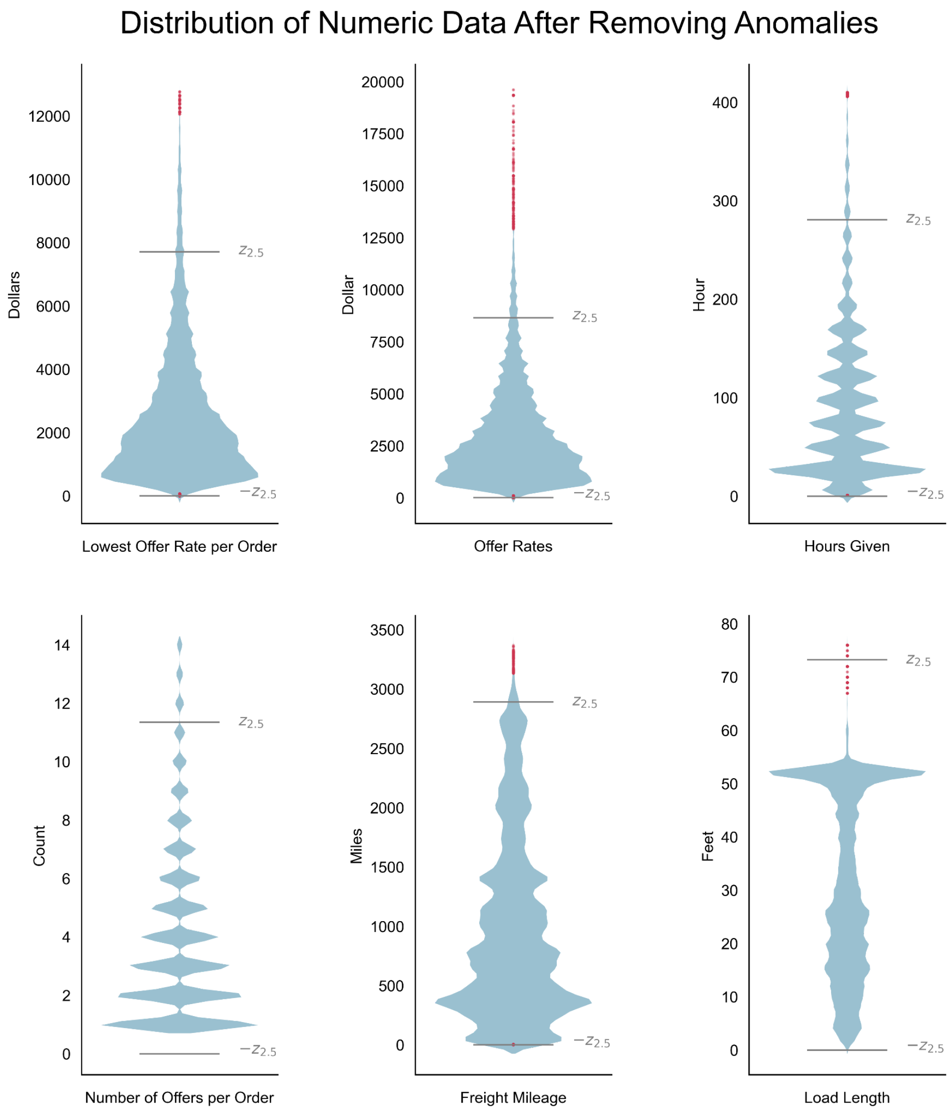
Despite the wealth of information contained within those datasets provided by Flock Freight, some limitations make analysis and modeling difficult due to data privacy concerns. One of the primary issues is that the origin and destination features only include 3-digit zipcodes because Flock Freight needs to anonymize its customer data, making it challenging to work with and limiting the accuracy of geographic analyses. Another limitation is the fact that Flock Freight cannot keep track of all offers that could have possibly been made on an order as doing so will risk the company to let offers expire. This means that the company is unable to collect accurate data on the actual number of offers and the lowest offer rate each order could have received. The lack of access to the true data makes our research team difficult to develop a model that accurately reflects the true nature of offers in the freight delivery industry.

Building a model that correctly identifies the best offer for each order requires the model to learn well from numeric data, including offer rates for orders and the number of offers each order receives. To ensure data quality, anomaly detection was executed to remove outliers.

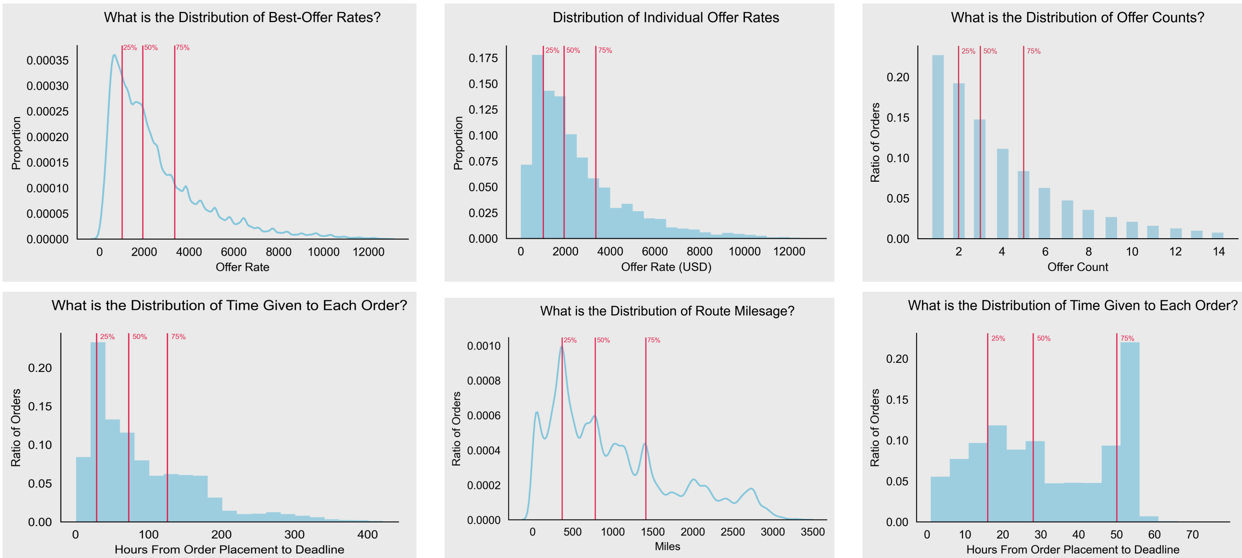


Distribution of major numeric data before removing anomalies.

The red dots in the figure above represent outliers outside the 0.01 and 99.9 percentiles, whereas the whiskers represent +/- 2.5 z-scores. As seen, there are a handful of offer rates that do not lie in the normal range. Moreover, multiple orders received an extremely large number of orders compared to others, so the scale had to be represented in terms of logs. As such, outliers beyond the +/- 2.5 z-score range were removed.

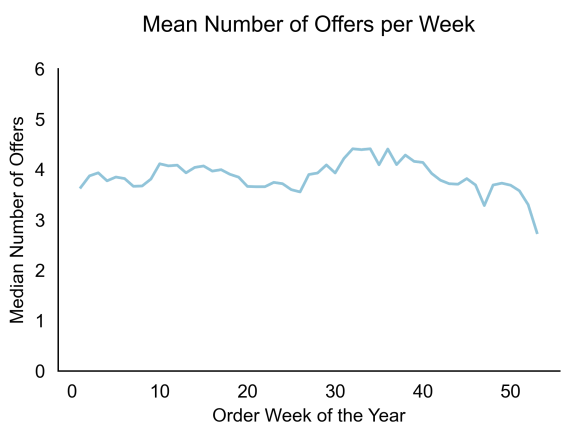


Distribution of major numeric data after removing anomalies.

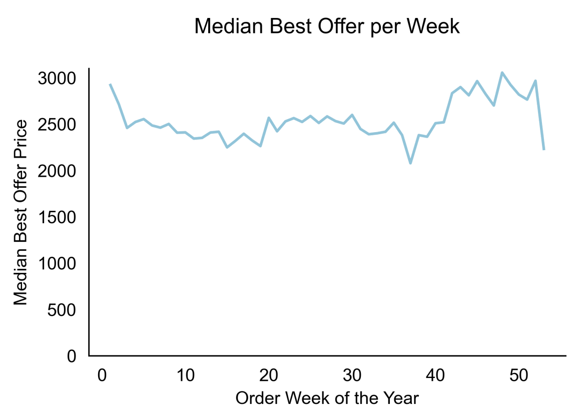


Distribution of major numeric data after removing anomalies.
Red lines represent percentiles.

The new dataset with outliers removed shows a more expected distribution of numeric data. A notable distribution is the number of offers each order receives – over 25% of all orders receive two or fewer orders. The small number of orders received from truckers may indicate that Flock Freight might accept offers too early from freight companies, disallowing the company to collect more data on the actual number of offers each order could have received. That is, before the company could count the true number of offers each order will receive until its pickup deadline, Flock Freight may be accepting early offers, preventing the accumulation of richer, accurate data.



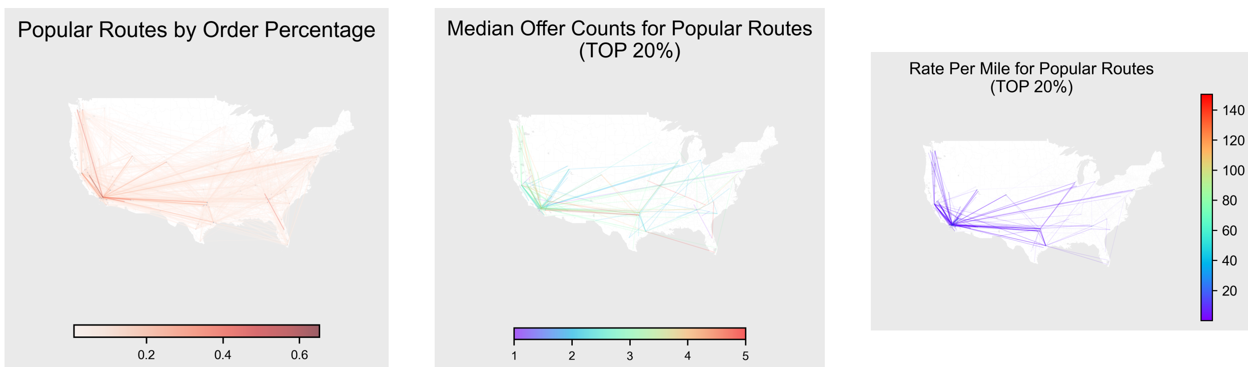
Change in "number of offers per order" by the week.



Change in median "lowest offer per order" by the week.

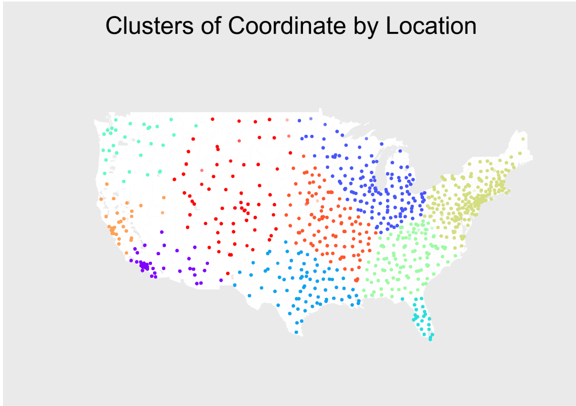
A simple time analysis was done to explore how offers change throughout the year. As expected, the number of offers dropped significantly in the last few weeks of the year. Surprisingly, however, the best offer values dropped in the final weeks, suggesting that the holiday season may not drive up freight delivery costs.

Another important feature the best-offer-identifier model must learn is categorical information about the origins and destinations of orders. Before analyzing the geolocation data, however, the team first had to convert the 3-digit categorical zipcodes to numerical coordinate data. Then, the team paired the origin coordinates with the destination coordinates to plot a map of where the most popular routes are.



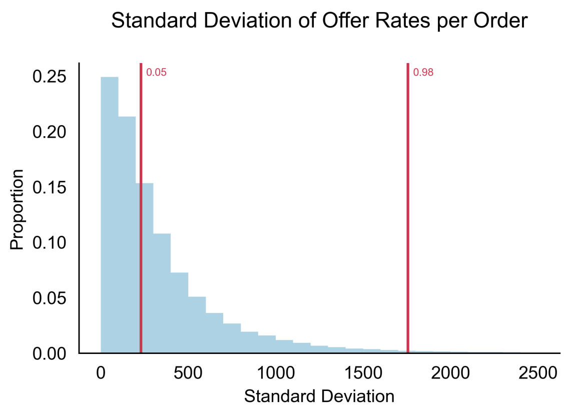
Map data show dubious trends in orders that could help train models.

The first map shows the popular routes by their percentage share of all the orders placed to Flock Freight. The second map shows how many orders each of the top 20% popular routes receive. The third map shows that there is no difference in rate dollar per route mileage – no popular routes seem to be less desirable by truckers. Although the team believes that the coordinate data can reveal important information about which routes receive more offers and better offers, the team was concerned that working with numerical coordinate data may not be the best option when it comes to training a model. Thus, the team ran a clustering algorithm to cluster each of the origin and destination coordinates into groups.



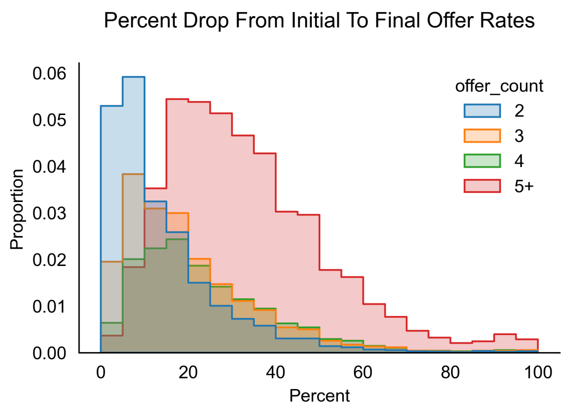
The origin and destination coordinates are grouped into 10 regions.

Each order can receive an unlimited number of offers, meaning that carriers can initially ask for an extremely high price and then settle for a more reasonable price. The team was curious to know what the distribution of offers for each order looks like.



The first red line represents the 50th percentile, the second line the 98th percentile.

As expected, more than 50 percent of the orders have standard deviation values of over 200, suggesting that the gap between the initial and final offers is extreme. The following plot was created to investigate further how these price drops look against the number of offers each order receives.



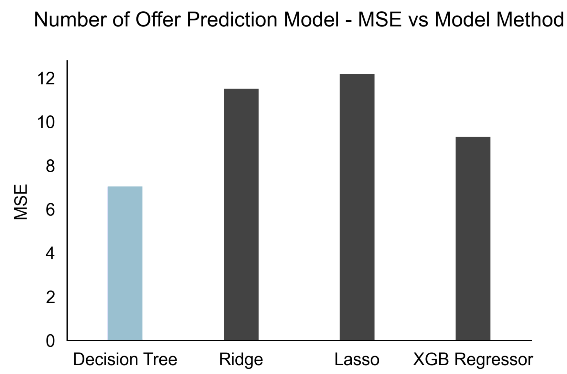
Orders that receive more offers have wider gaps between initial and final offer amounts.

As expected, orders that receive more offers have greater price drops since the initial offer. This analysis suggests that, to accurately predict the final offer rate, it is important to know how many offers an order will receive. That is, before building a model that identifies the best offer for each order, it is important to build a model that guesses the number of offers an order will receive.

3. Methods

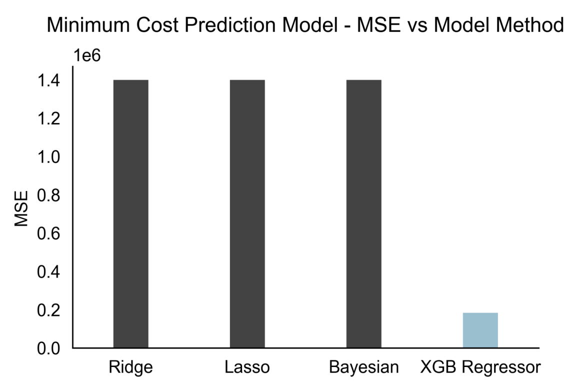
By recognizing that the secretary method is not a viable solution for selecting the optimal shipping offer, Flock Freight embarked on developing a machine learning model specifically tailored to their unique problem. The model is designed to identify the optimized offer for each order based on two key components: the number of offers and the expected minimum offer rates. To achieve this goal, the research team developed a hybrid classification model that combines predictions from the two models to select the offer with the lowest cost.

The first component of the model involved predicting the number of offers each order would receive, accomplished through a classification model. This model generated a column labeled PREDICTED_OFFER_COUNT. After conducting a thorough model selection process, which included Ridge, Lasso, XGBoost, and Decision Tree models, the team found that the Decision Tree Classifier outperformed the other models – while the Decision Tree has an MSE score of 7.05, Ridge Regression is at 11.51, Lasso Regression at 12.18, and XGBoost Regressor at 9.32. Hyper parameter tuning reveals that the Decision Tree's MSE can go down to 5.49 with the following values: max_depth = 40; min_samples_leaf = 2; min_samples_split = 2.



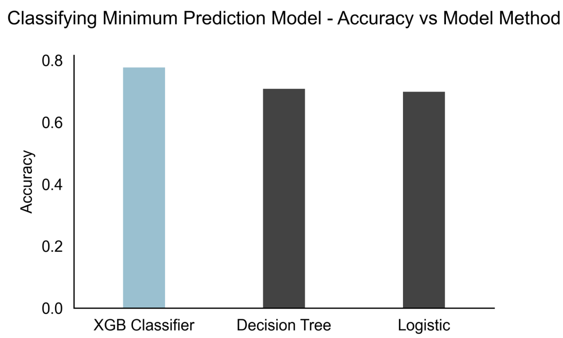
Decision Tree performs best at estimating the number of offers an order will receive.

For the second part of the model, the team developed a regression model to predict the lowest offer rate each order will receive. This model generated a column labeled PREDICTED_MIN_RATE. The team conducted a similar model selection process, which included Ridge, Lasso, Bayesian, and XGBoost models, and ultimately found that the XGBoost Regressor takes a significant lead with its MSE score at 183895.2, compared to Ridge Regression's 1400435.74, Lasso Regression's 1400173.5295965234, and Bayesian Regression's 1400432.6838781652. Upon tuning the XGBoost Regressor (max_depth = 10, n_estimators = 500, reg_alpha = 1, reg_lambda = 1), the team lowered the MSE score to 87619.44.



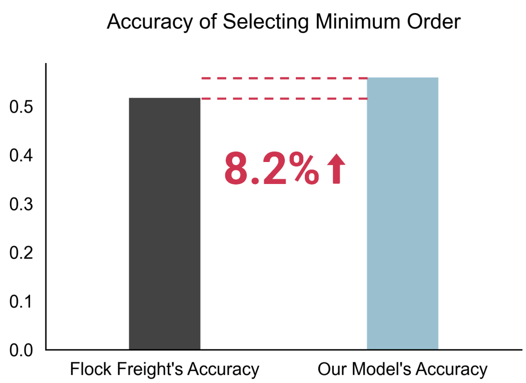
XGBoost Regressor significantly outperforms other models.

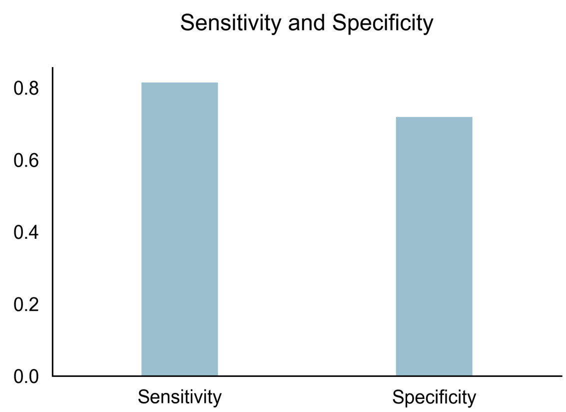
Finally, the team leveraged the two previous models' PREDICTED_MIN_RATE and PREDICTED_OFFER_COUNT outputs to create the hybrid classification model for identifying the best offer. This model underwent a similar selection process that included Logistic Regression (0.70 accuracy), Decision Tree (0.71 accuracy), and XGBoost (0.78 accuracy). With a maximum depth of 10, 500 estimators, and regularization parameters (reg_alpha = 1 and reg_lambda = 1), the accuracy score rises to 0.79.



XGB Classifier marginally performs better than Decision Tree and Logistic Regression.

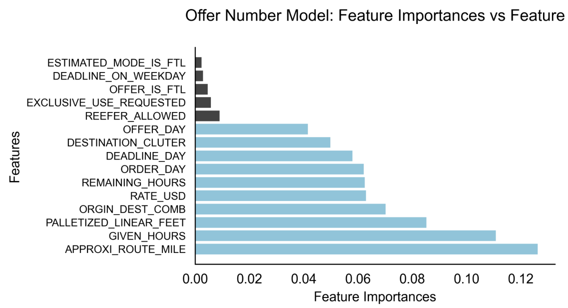
4. Results



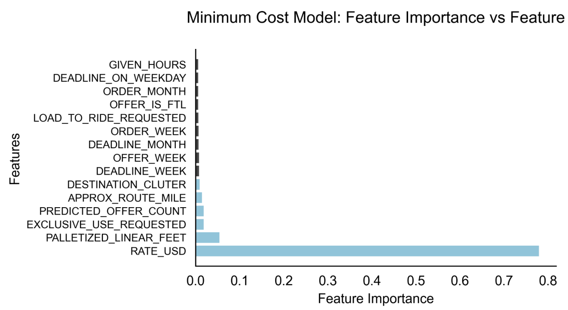


Performance metrics show that the hybrid model is an improvement from the existing Flock Freight model and that the hybrid model is free from bias according to Sensitivity and Specificity.

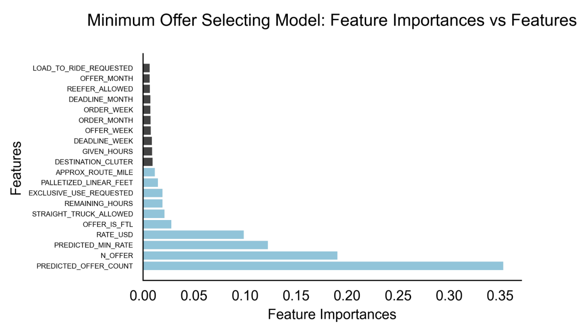
The evaluation of the hybrid model entailed determining its ability to identify the best offer accurately. The model's accuracy, quantified by the proportion of correctly identified minimum offer rates, was found to be 0.559, which surpassed the performance of Flock Freight's previous model, which had an accuracy of 0.517. Furthermore, the sensitivity, which is the proportion of actual minimum offer rates our model correctly identified, was about 81.4%. The specificity, which is the proportion of actual non-minimum offer rates that the model correctly identified, was approximately 71.8%.



The shipping distance, number of hours between order placement and pickup deadline, and the length of the freight are the three most important factors when predicting the number of offers an order will receive.



The current offer rate is the most important feature for estimating the minimum offer rate for orders.



The number of offers an order is expected to receive, the number of offers the order has received so far, and the minimum offer rate the order is expected to receive are the most important features when identifying offers with best rates.

The hybrid model outperformed the previous model used by Flock Freight in terms of accuracy. Additionally, the sensitivity and specificity metrics suggest that our model can correctly identify both minimum and non-minimum offer rates, proving the model's effectiveness in real-world scenarios.

5. Discussion

In conclusion, the research team's development of a machine learning model has proven to be successful. The hybrid classification model, which incorporates predictions from two separate models to identify the optimized offer for each order based on the number of offers and the minimum offer rates, has demonstrated its ability to determine the best offer accurately. This model could assist Flock Freight in making informed decisions and reducing overall shipping costs. However, it is essential to note that the model still contains a limitation. The datasets used for model training and evaluation are based on Flock Freight's previous historical data. Therefore, the model's ability to generalize to new and unfamiliar conditions outside the historical data is uncertain. A potential approach for further research is to conduct a longitudinal study, collecting data over the years. It would provide a more comprehensive understanding of the model's performance under various conditions. Moreover, a Reinforcement Learning Model could guide the computer to learn when to accept and decline offers, although defining the reward function still remains a mystery.