Balancing Inbound and Outbound Flow of Trailers by Predicting Customer Compliance and Seasonality

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J.B. HUNT 360box

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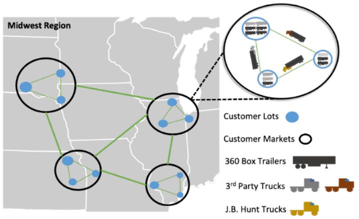
Headquartered in Lowell, Arkansas, J.B. Hunt is a transportation and logistics company that moves customer freight over both road and railway. Within J.B. Hunt is their 360 Box service, an adaptation of J.B. Hunt's standard truck transport model which utilizes a drop trailer format pairing third party carriers to move 360 Box trailers. We are focused on the balancing of trailer flow across 360 Box marketplaces. A balanced market has equal number of trailers entering and exiting during a specified time period.



$$Z_{m,t} = X_{m,t} - Y_{m,t}$$

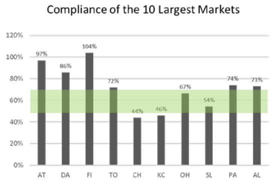
Number of trailers exiting market m during time t

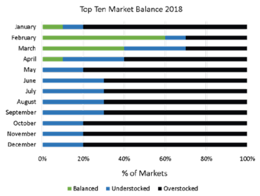
Number of trailers entering market m during time t

> 0 implies too many trailers, < 0 implies too few trailers, 0 is ideal

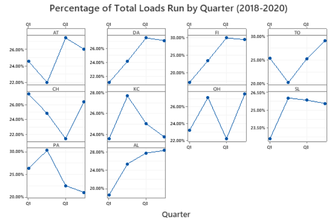
Customer Compliance and Seasonality

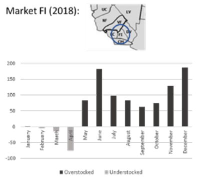
Customer compliance is the percentage of awarded volume that a customer ships. If the customer does not transport the full volume awarded to 360 Box, less containers leave an area than what was anticipated. This causes imbalances across all markets. Currently, 360 Box assumes compliance for all customers falls between 50-70%, but no data-driven predictive method is currently in place.

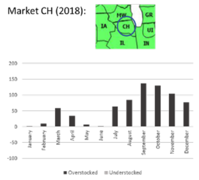




Seasonality of freight occurs when there are noticeable fluctuations in the amount of freight a customer ships throughout the year. 360 Box is used by a wide variety of customers, each with their own seasonality. Depending on the commodities being shipped by customers, and the associated demand for those commodities, shipping volume peaks and valleys seen across markets vary widely.

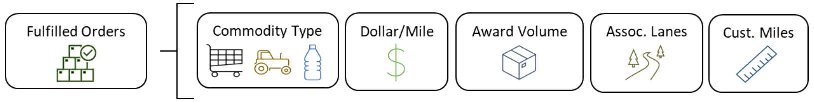




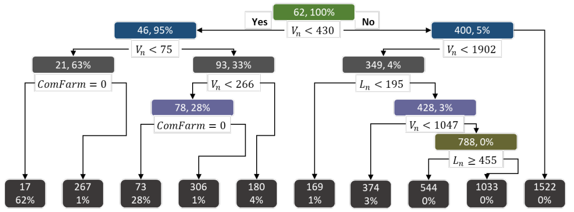


Predicting Customer Compliance

Our team tried to predict customer compliance as a function of significant information contained within customer award contracts. Our team first applied multiple linear regression to create a baseline model. We then applied random forest regression which showed much improvement over early multiple linear regression models.



Random forest regression is a machine learning technique that trains itself by constructing a series of decision tree models. The algorithm then selects the highest performing model to make predictions for newly presented datasets. Our model yielded an R^2 performance of 65%, which was an improvement over our multiple linear regression model ($R^2 = 57\%$). We found that our final random forest model resulted in a mean absolute percent error reduction of 27% compared to methods used by J.B. Hunt.



Model R^2 Performance:

65%

MAPE Improvement:

27%

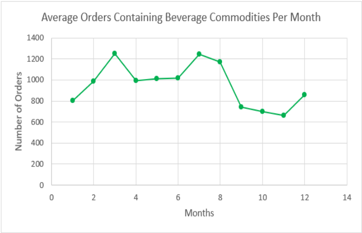
Seasonal Expectations Based on Historical Data

Conducting ANOVA on previous customer award/order data allowed us to provide suggestions on freight timing for various commodity types and origin-destination pairs. We found that the months of March and August see increases in shipments containing beverage commodity types. Additionally, orders moving from the Northeast to Southeast region are most often shipped in March, July, and August.

Grouping Information Using the Tukey Method and 95% Confidence

Factor	N	Mean	Grouping		
March	5	1251.2	A		
July	5	1245	A		
August	5	1171	A	B	
June	5	1017.8	A	B	C
May	5	1014	A	B	C
April	5	993.8	A	B	C
February	5	987	A	B	C
December	5	861	A	B	C
January	5	801.4	A	B	C
Septembe	5	743.8		B	C
October	5	700		B	C
November	5	662			C

Means that do not share a letter are significantly different.



Predicting Customer Seasonality

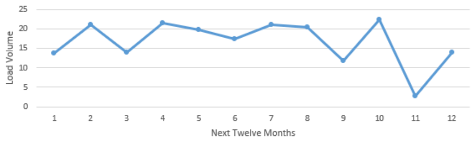
Our forecasting tool based on Holt-Winter's method creates a reliable 12-month volume forecast that accounts for observed trends and seasonality seen in a customer's past four years of data. Customer-lane keys are used to query and analyze historical customer data stored locally on the user's device. The tool configuration lends itself to easy integration with 360 Box data sources and future live-feed dashboard formats.

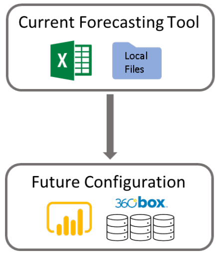
Customer Search Information

NATIONAL_ACCT_NBR	2508822
OZIP	66618
DZIP	17815

Lane Information

OCITY	TOPEKA
OSTATE	KS
DCITY	BLOOMSBURG
DSTATE	PA
EST. DISTANCE	1136





Anticipated Impact

By isolating specific customer markets and assigning real world costs to lanes utilized for rebalancing efforts, we were able to see both balance and cost implications. This was done through isolating specific customer markets and assigning real world costs to lanes utilized for rebalancing efforts. By factoring out rebalancing efforts taking place throughout the year, we can see raw imbalance for these markets in question and assess model accuracy and impact.

(2018-2019) Market: OH **Obs. Balance: -3671**

Prediction Method	Anticipated Balance	Percent Error
100% Assumed Compliance	-1764	51.95%
70% Assumed Compliance	-1235	66.36%
Random Forest Predicted	-2189	40.37%