



# **Abinbev's Travel Management Program**

**XN Project**

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**ALY6080 Experiential Learning Project – Goldspring Consulting**

**Date: December 1<sup>st</sup>, 2022**

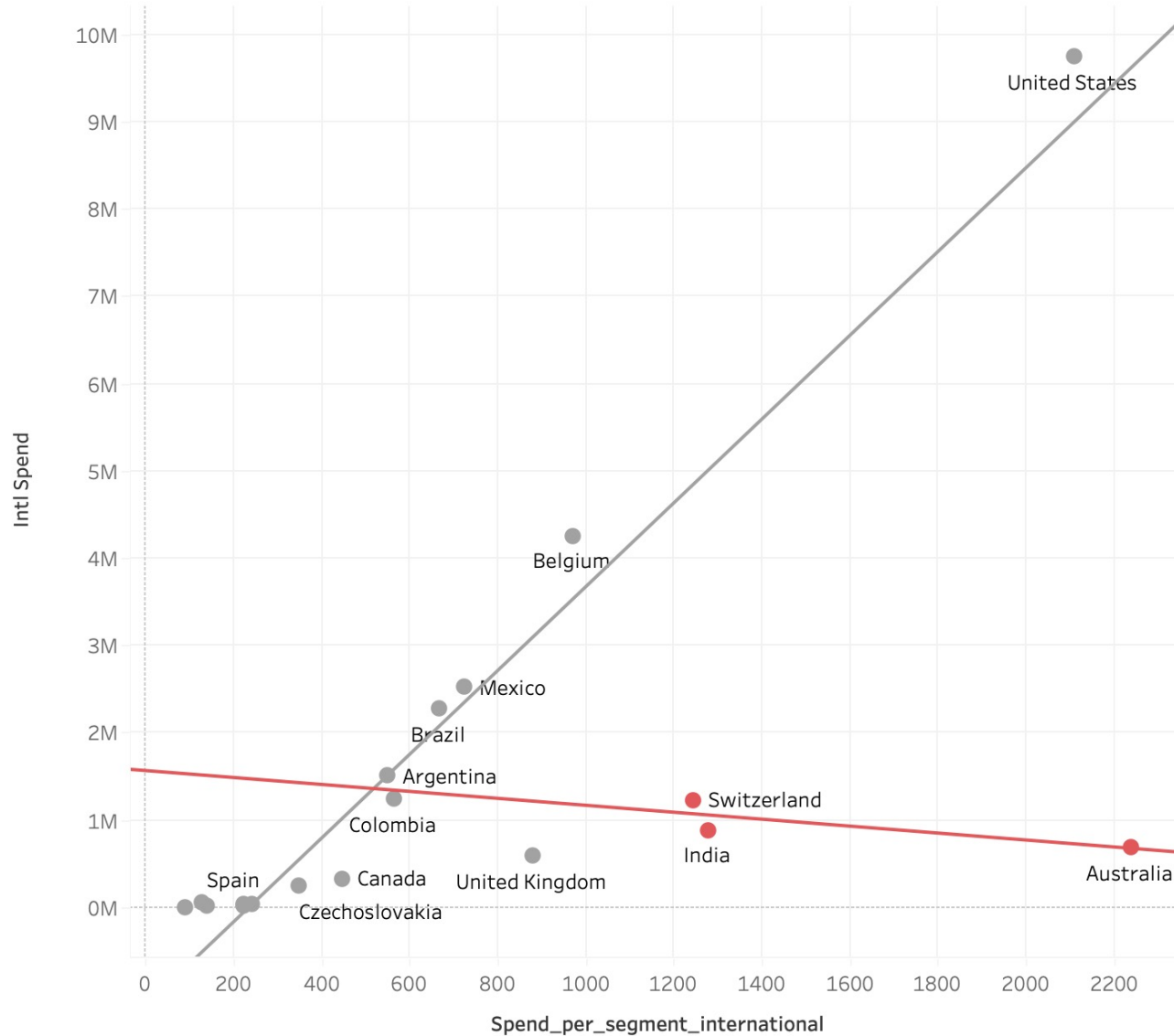
In the final phase of the XN project, we have focused our investigation on the development of optimization strategies to increase the savings incurred by ABInbev in their travel flight bookings.

Our strategy is based on our understandings of how TMCs both internal and external operate to minimize the risks involved in travel operations. To develop this strategy, we have based our empirical analysis on the estimations of savings that the client procurements should received based on their current savings margins. We use these predictions as a base line to identify pockets of sub-optimal purchasing which can be target for optimization.

- Optimize worldwide procurement  
Track 1: Spend Analysis
- Discover opportunities and re-orient travel management  
Track 2: Savings Analysis
- Data-driven identification of risk  
Track 3: Savings estimation and predictions

# Track 1: Expense Anomalies

Spend per segment vs Spend - International



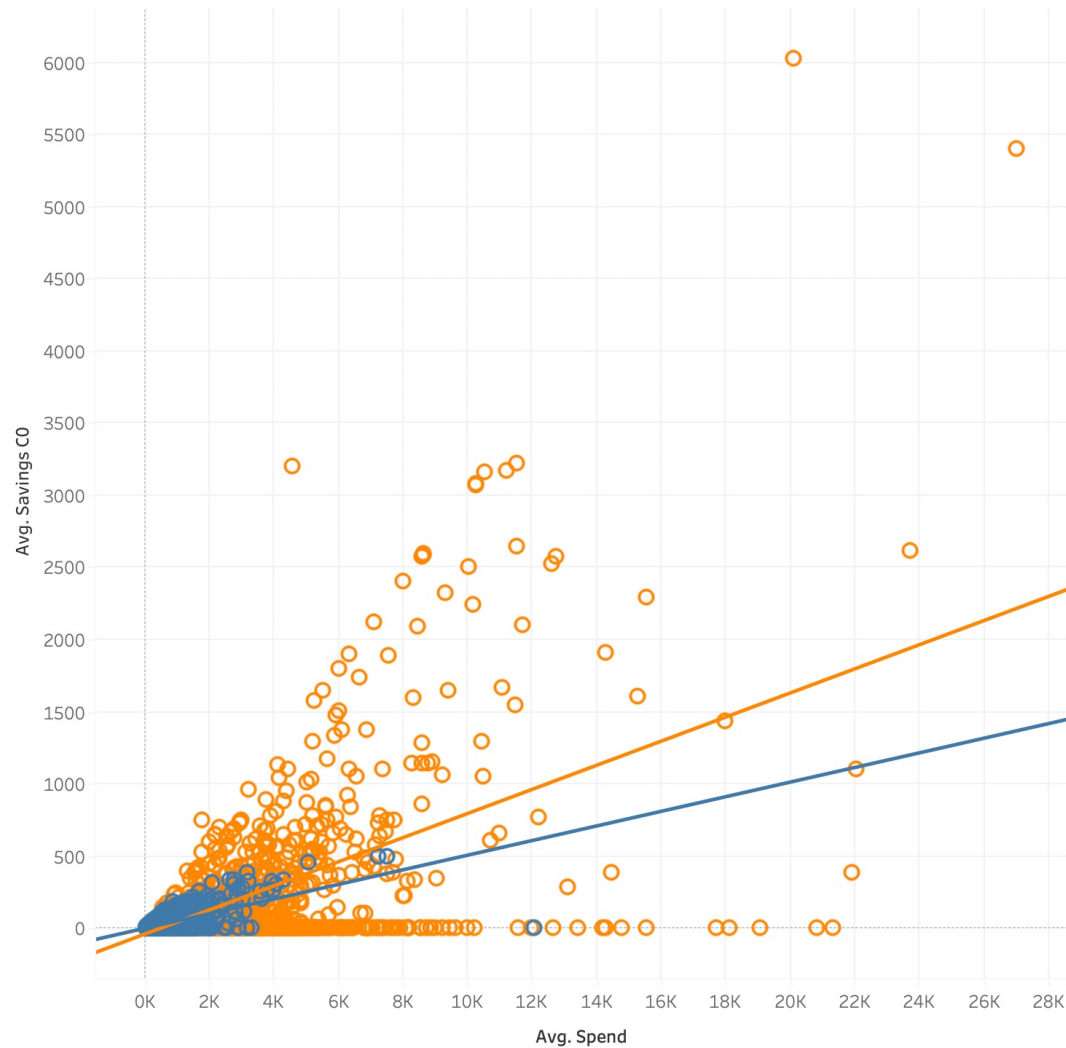
Most countries have spend\_per\_segment less than \$1000.

USA, Canada, India, and Switzerland have spend\_per\_segment over 1000.

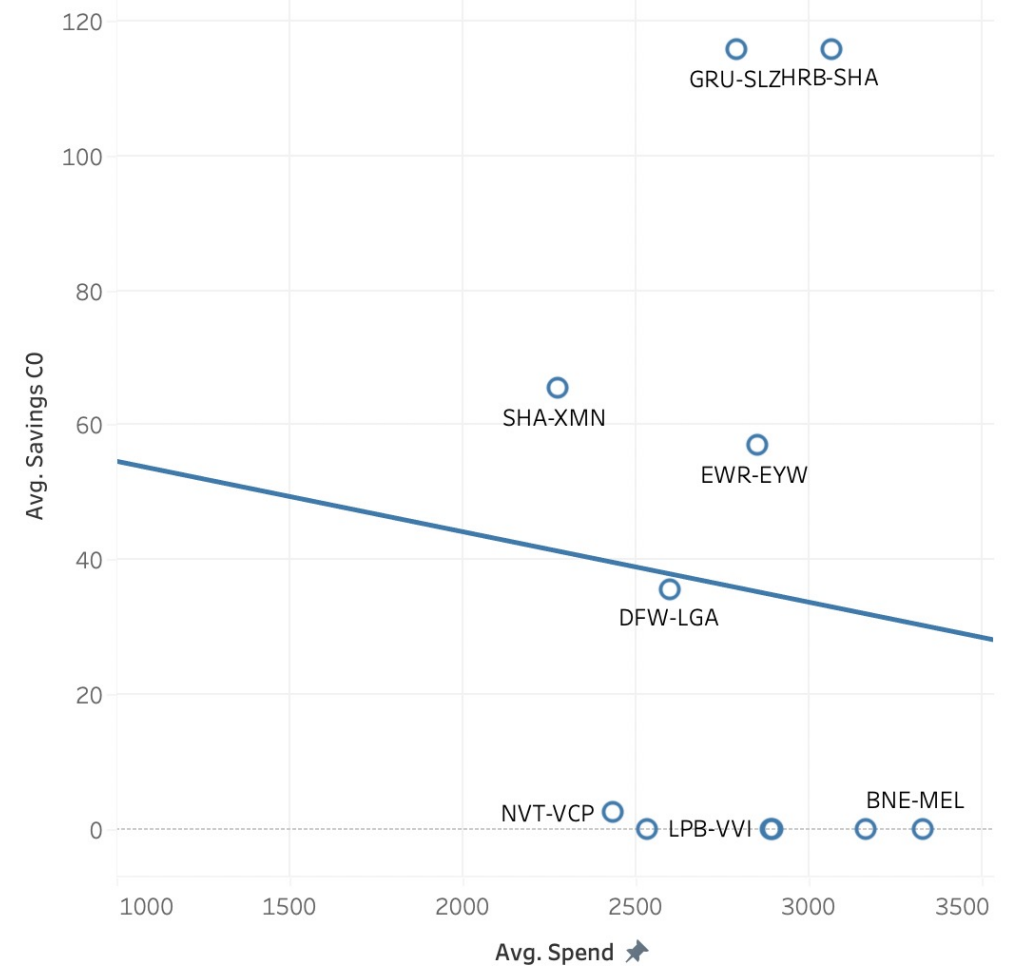
One of the causes for this variation is the volume of premium cabin bookings made in these markets.

## Track 2: Savings Analysis – Domestic Opportunities

Similar sub-optimal markets exist in domestic subsets as well. Visible upon distribution splitting.



Domestic market



## Track 3 - Procurement Data History

Market	Airline	Spend	Segments	Discount	Savings	Airport_1	Airport_2	Market_type	Market_Competition	predicted_savings	net_savings	market_status
BRU-JFK	Delta Air Lines	252241	38	0.15	37836	Belgium	United States	International	Highly Competitive	0	37836	general
GRU-JFK	American Air	193268	43	0.00	0	Brazil	United States	International	Competitive	3426	3426	sub_optimal
GRU-JFK	Delta Air Lines	167728	25	0.15	25159	Brazil	United States	International	Competitive	0	25159	general
GRU-JFK	Delta Air Lines	166527	28	0.10	16653	Brazil	United States	International	Competitive	0	16653	general
GRU-JFK	Delta Air Lines	143130	25	0.39	55821	Brazil	United States	International	Competitive	0	55821	general

**Developed a new data asset – master\_file\_markets\_data\_v2.0**

Bookings purchase data at market-airline-spend level.

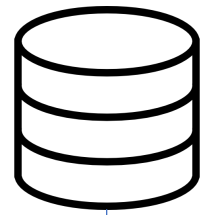
**Synthetic Variables –**

Airports, Market Type, Market Competition, Predicted Savings

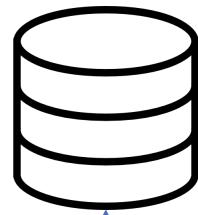
**Variable of Interest (Dependent variable) –**

predicted\_savings

## Track 3 – Savings Estimations



Purchases with savings



Purchases without savings (suboptimal)

### Machine Learning

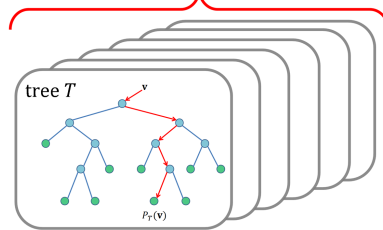
Train Data

Test Data

70%

30%

Decision Forest

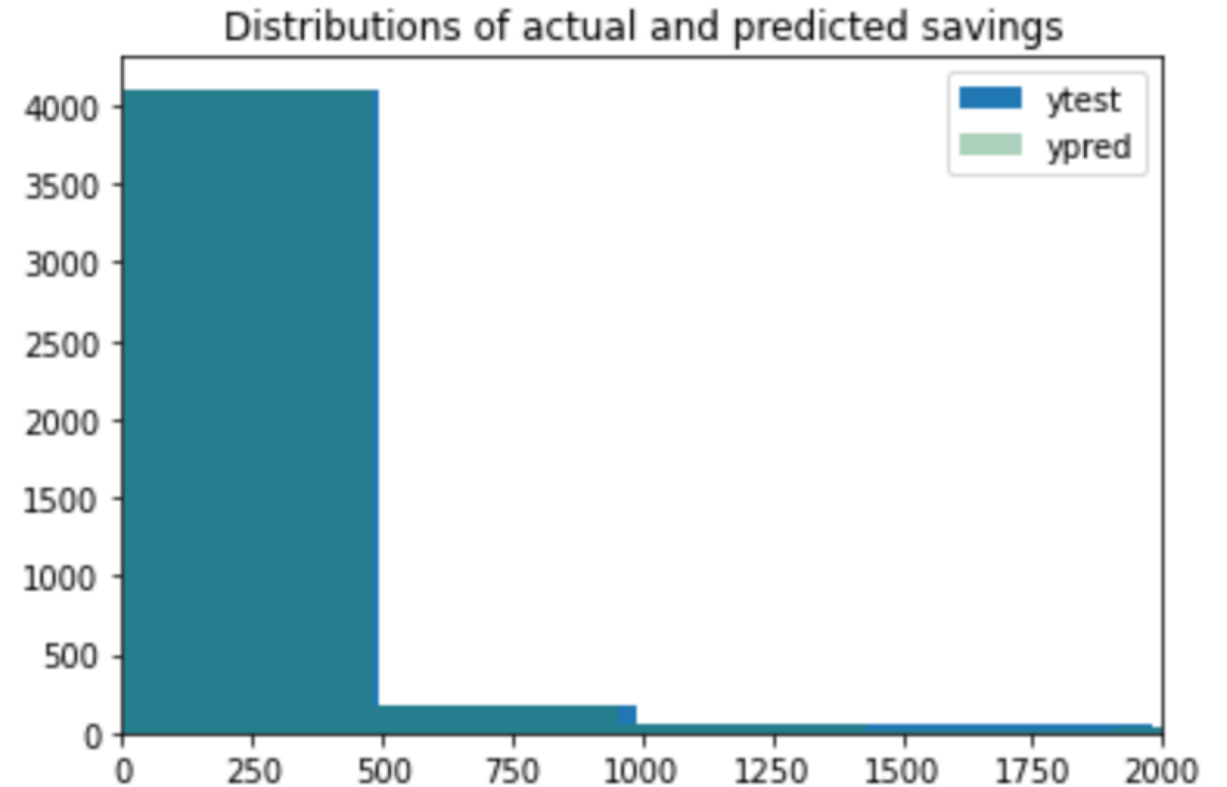


Predicted\_savings

Total 1640+ Unique Estimators Tested  
All estimators tested by sampling with replacement  
Final Model Selected – Random Forest Regressor  
Lowest error received based on simulation trial of 1K runs  
MAE: (76.94005627925893, 76.9413194483653) 95% CI

## Track 3 – Model Testing

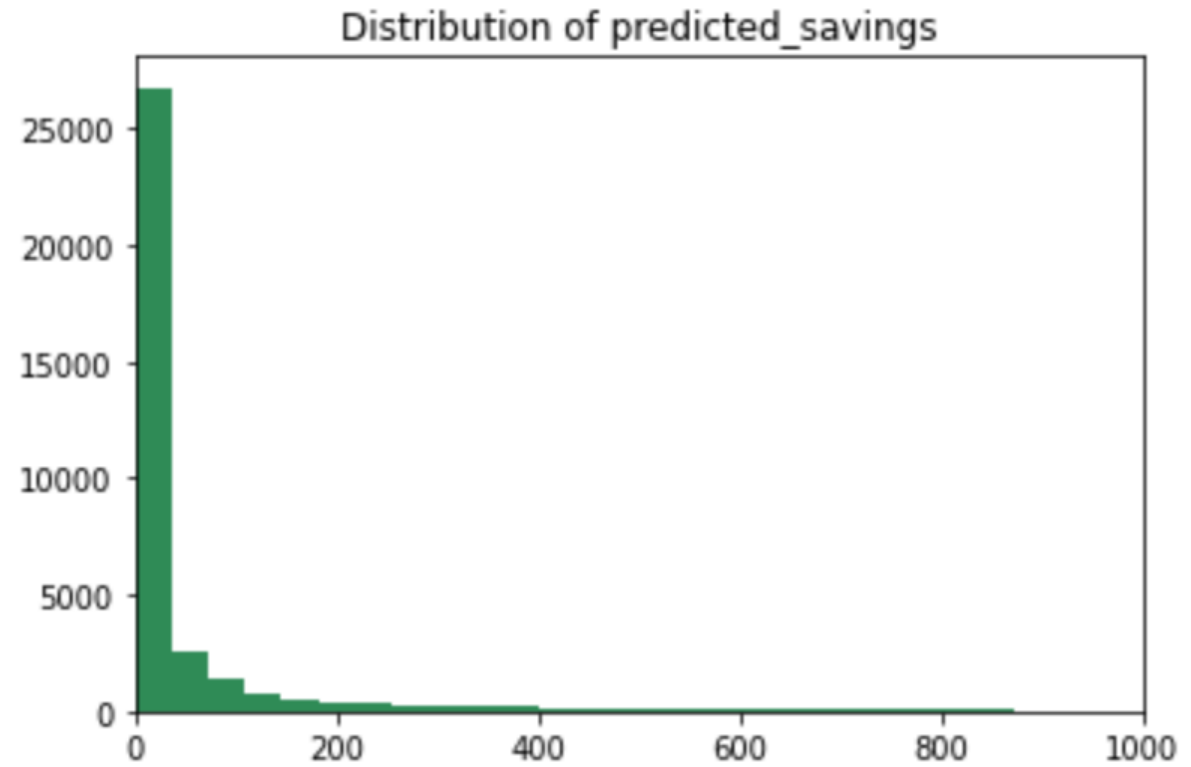
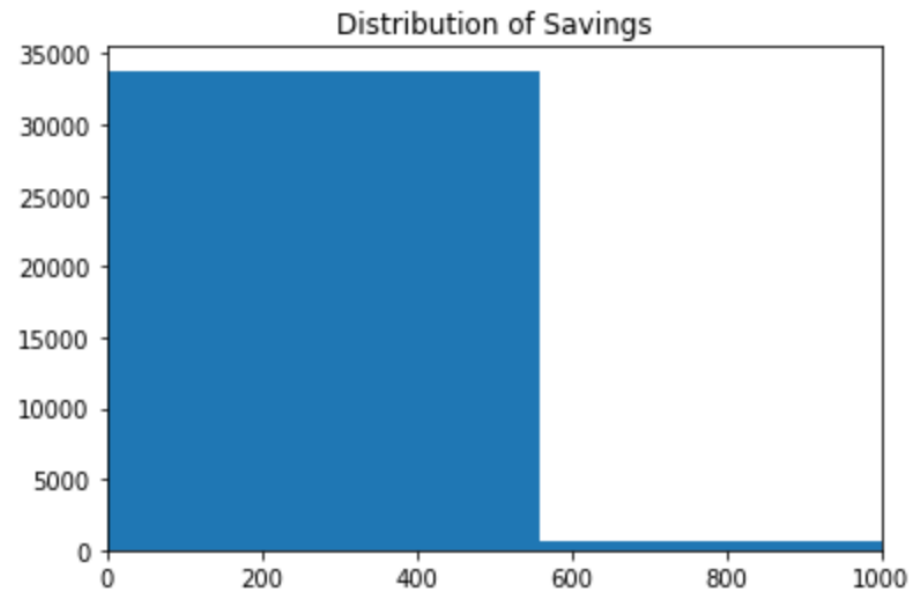
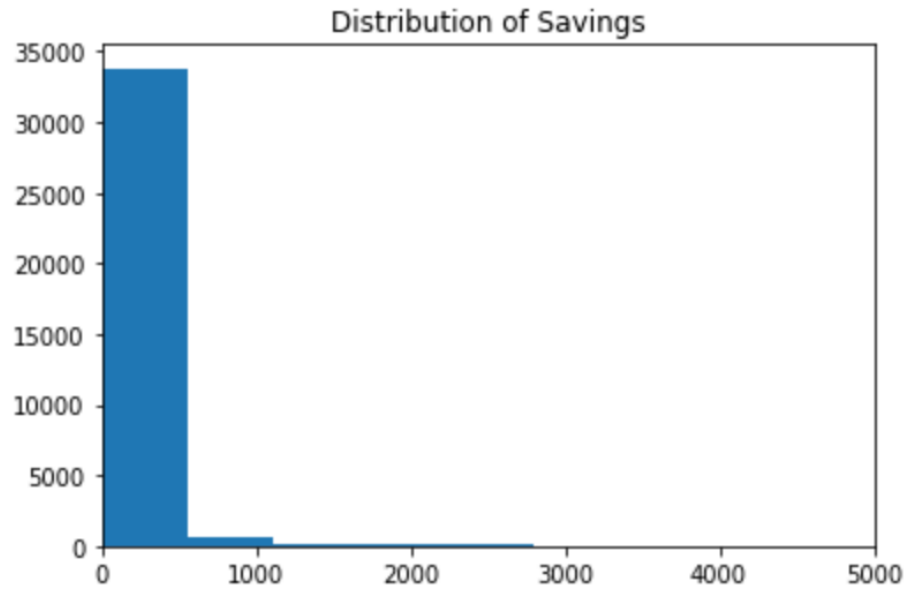
Savings		ypred	
count	4427.000	count	4427.000
mean	149.910	mean	155.838
std	396.965	std	402.266
min	1.000	min	3.429
25%	13.000	25%	17.503
50%	33.000	50%	36.896
75%	96.000	75%	110.181
max	4944.000	max	4764.000



- Both the test distribution and predicted distributions are almost identical.
- Models exhibits the capability to have be in close range of actual observations.
- Model has excellent error reductio for the current variance fit.



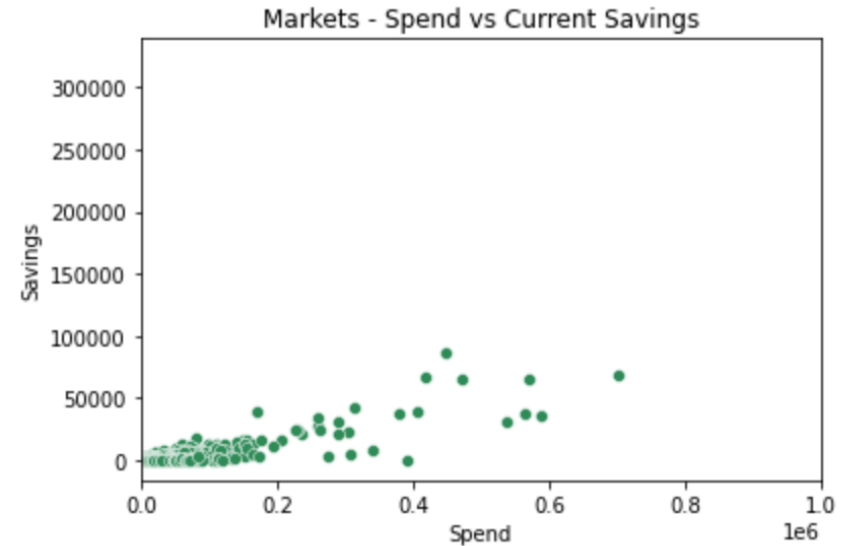
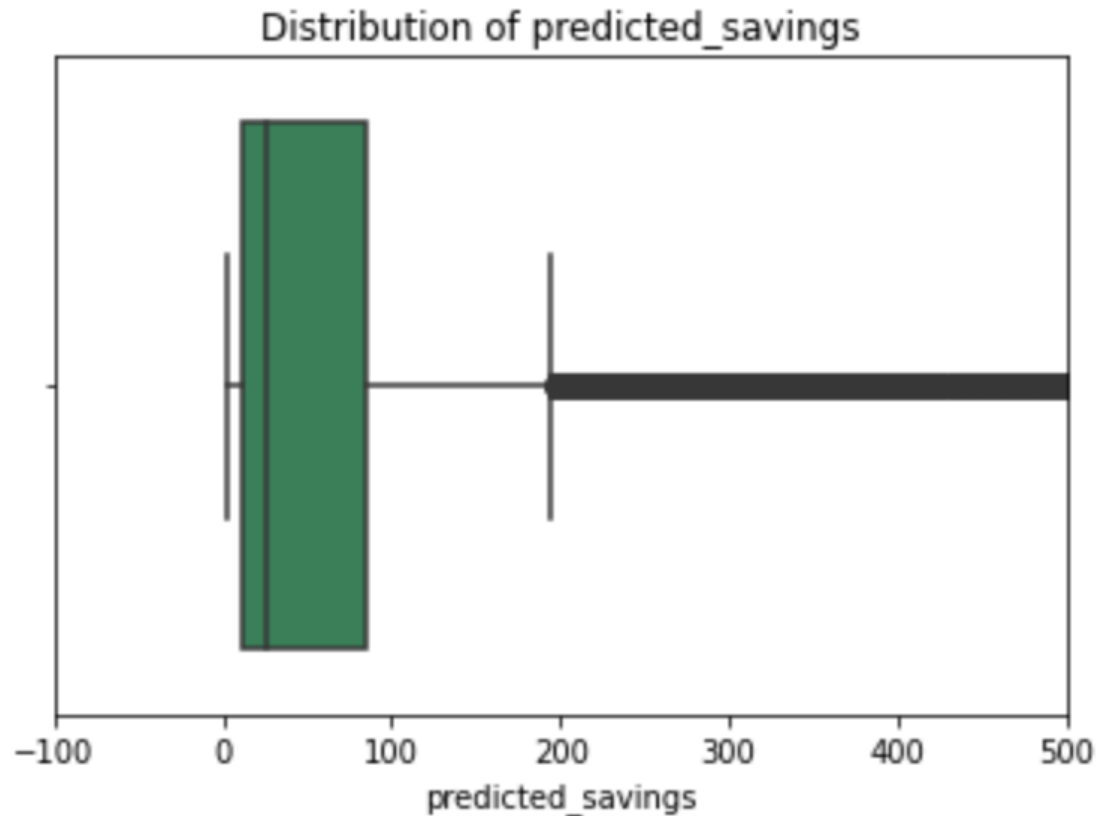
## Track 3 – Analysis of Predicted Savings



## Track 3 – Analysis of predicted savings (Macro)

Total Transactions: 20031  
Total Sum: \$2,299,665  
Average per purchase: \$114.8

### Quick Facts on predicted\_savings



# Track 3 – Markets with zero current savings.

Many markets have not received any savings for purchases. But have significant spend.  
Table of markets with measures

Market	Predicted Savings	Savings	Spend
BLR-GRU	43,524	0	390,520
GRU-JFK	38,316	0	569,434
BOG-MEX	34,467	0	316,597
BRU-GRU	34,395	0	264,726
EZE-GRU	34,217	0	294,327
BLR-BRU	31,891	0	253,276
GRU-MEX	21,864	0	202,558
BLR-JFK	18,637	0	142,752
JFK-JNB	17,434	0	264,951
GRU-SCL	17,281	0	146,824
BRU-JFK	16,772	0	240,057
EZE-JFK	16,357	0	137,794
MEX-SDQ	16,112	0	128,747
BRU-MEX	15,670	0	138,765
CGH-SDU	15,497	0	128,101

Top 5 markets with zero current savings account for 1.8 M USD in spend and approx. 180,000 in savings.

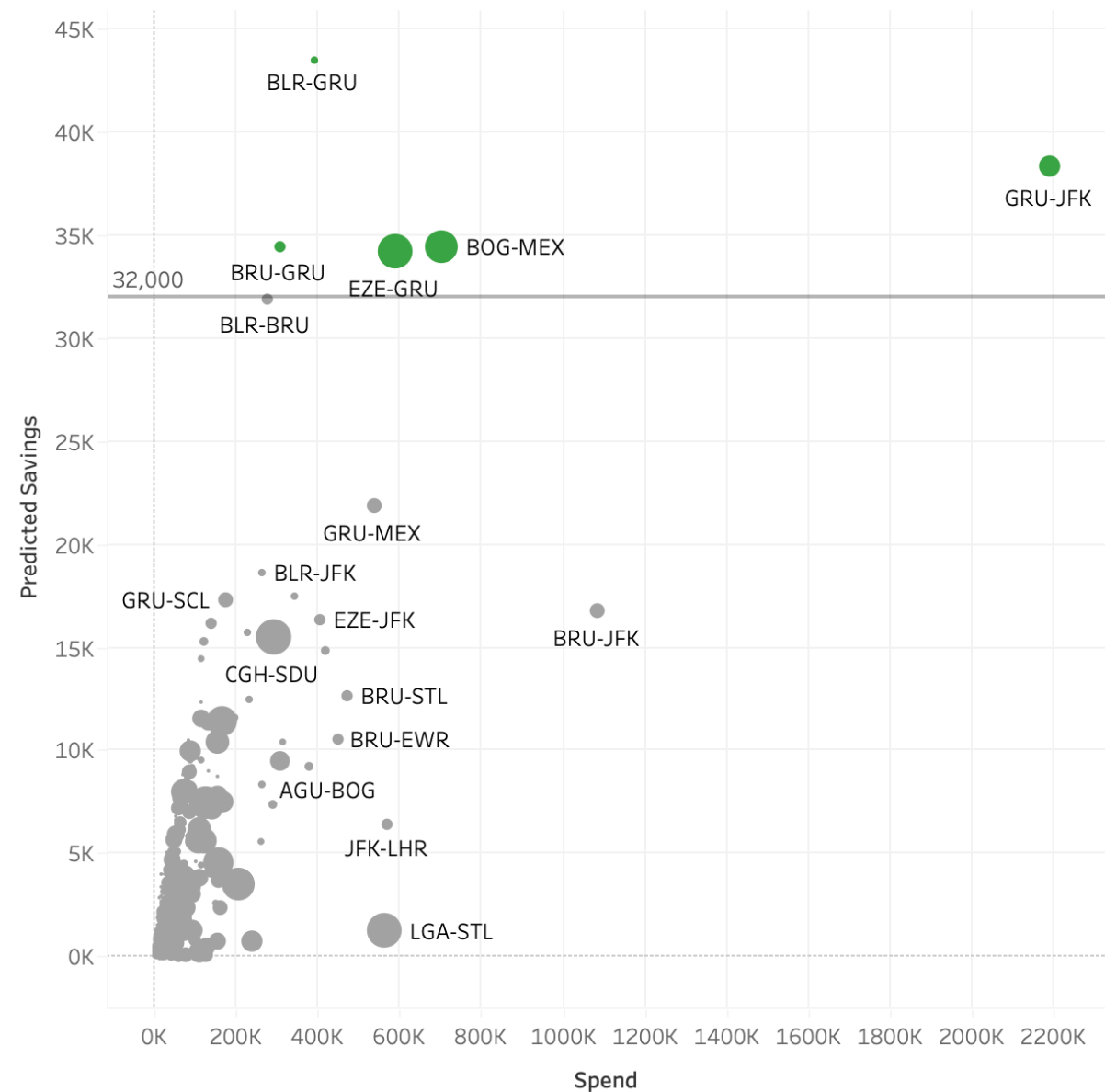
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# Track 3 – Markets with zero current savings.

## Zero Savings Market Potential

Segment Volume indicated by Size



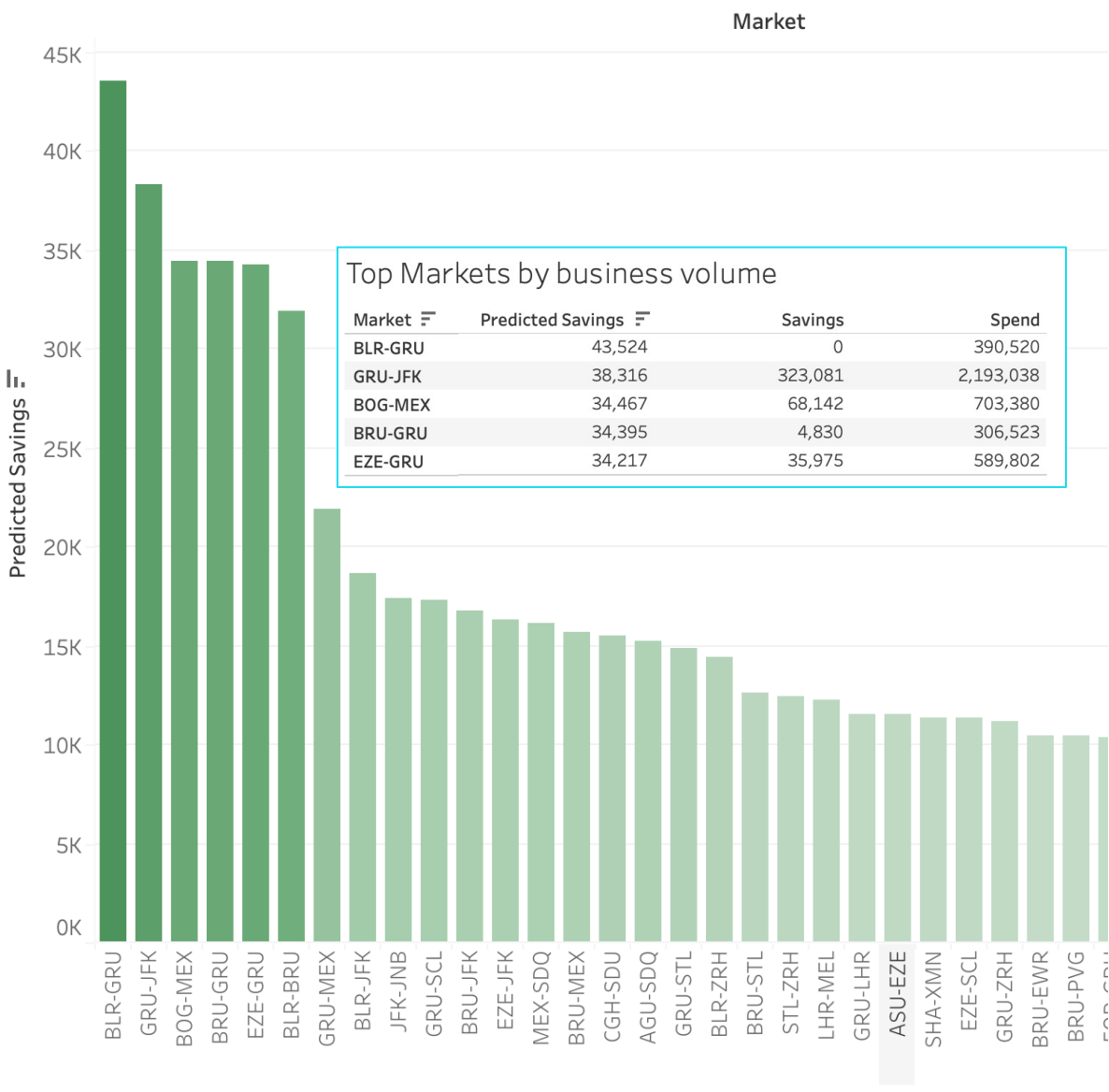
## Zero Savings Markets vs Others

### Purchase Level Metrics

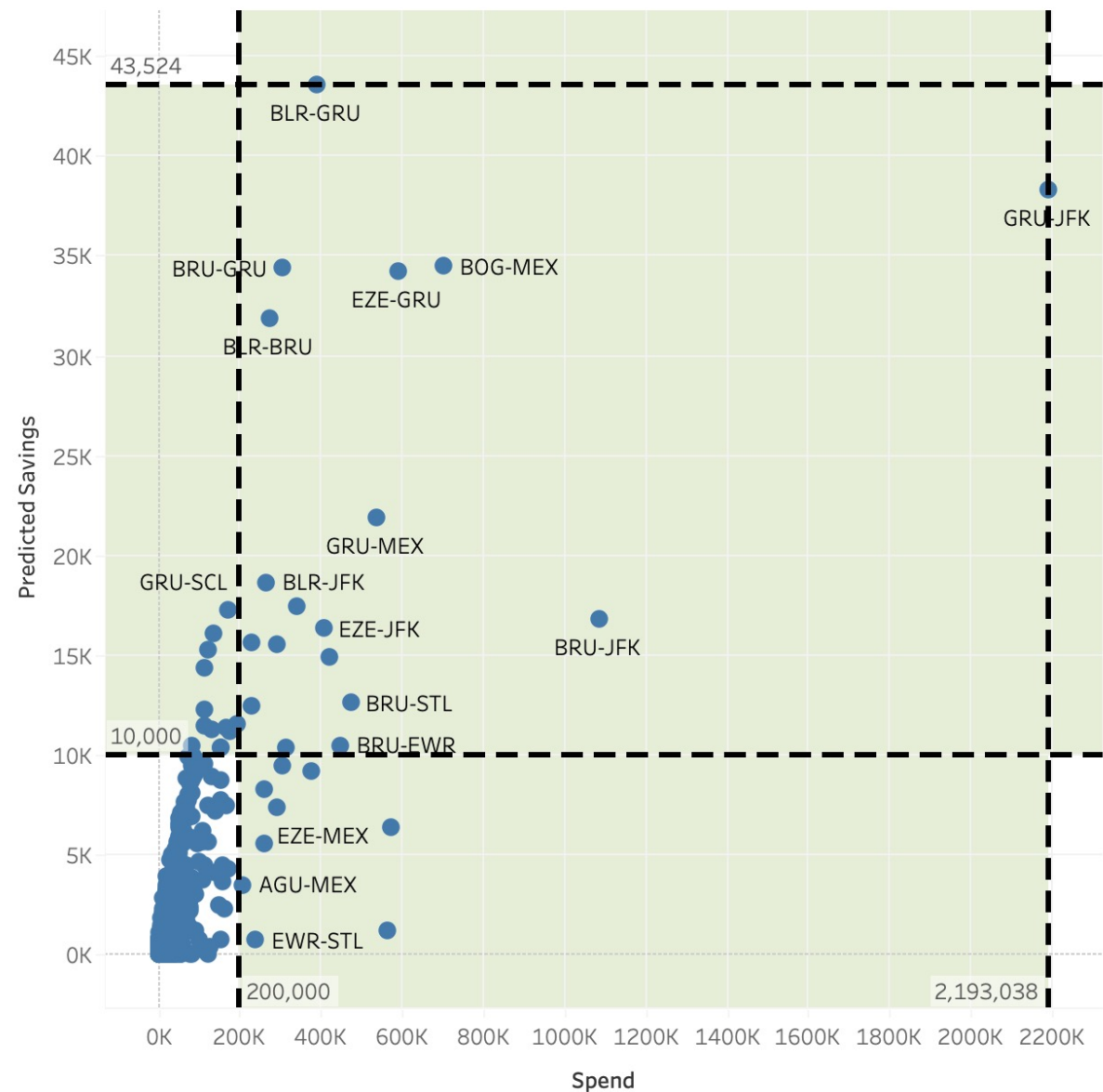
In / Out of Market - Zero Savings	Predicted Savings	Savings	Spend
In	2,299,665	2,682,984	41,706,922
Out	0	363,145	3,609,517

# Track 3 – Top markets by volume

Markets by volume - Predicted Savings



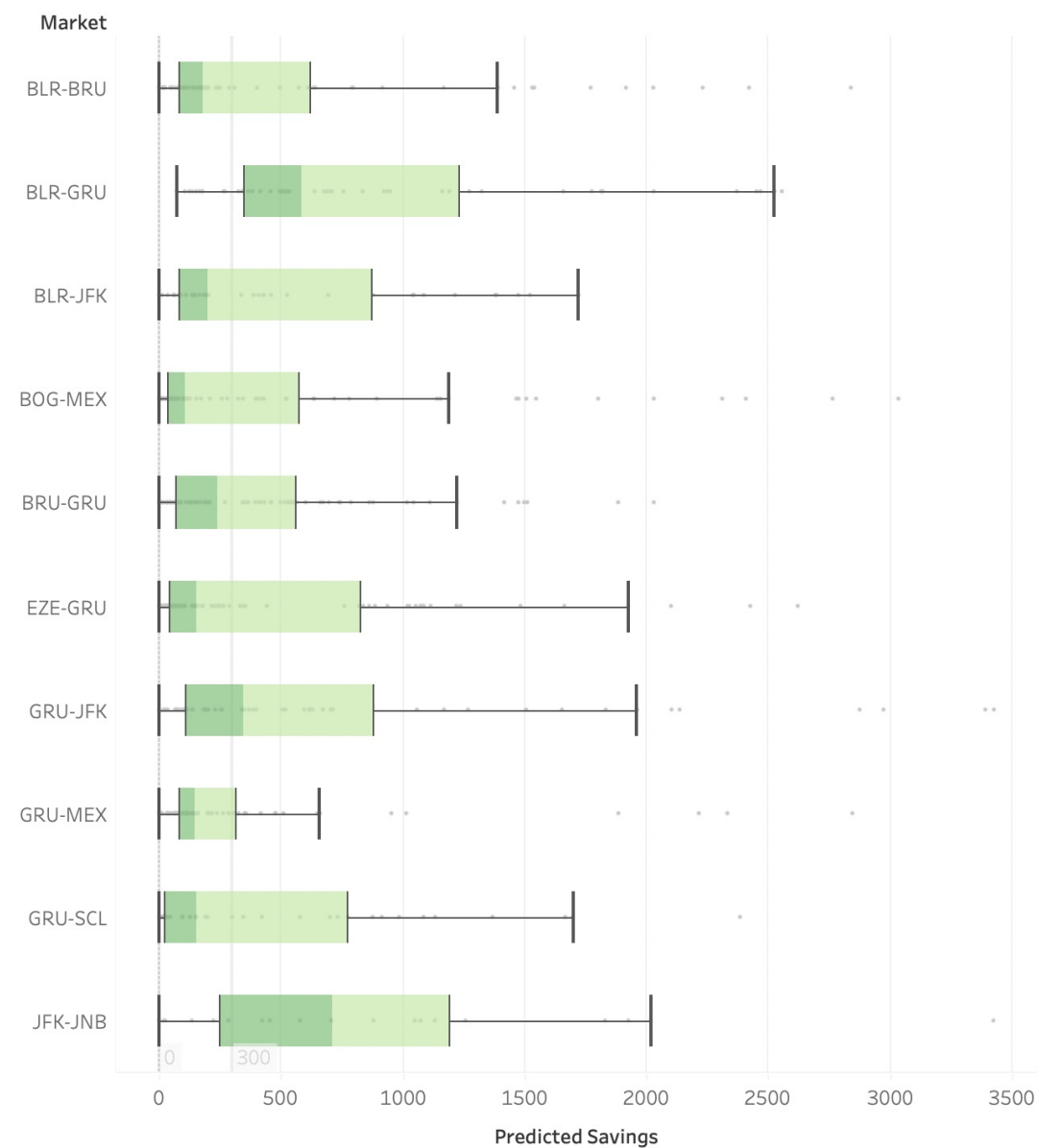
Markets by Volume Bi-variate  
Spend vs Predicted Savings



# Track 3 – Optimization by Markets

1/4th sub-optimal purchases with top 10 market

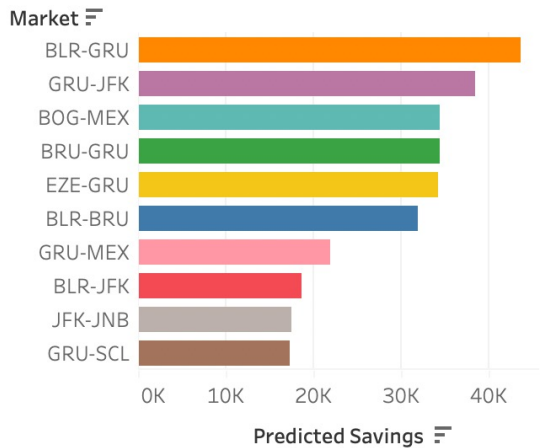
Distribution of sub-optimal purchases across Market and their predicted savings.



Predicted Savings

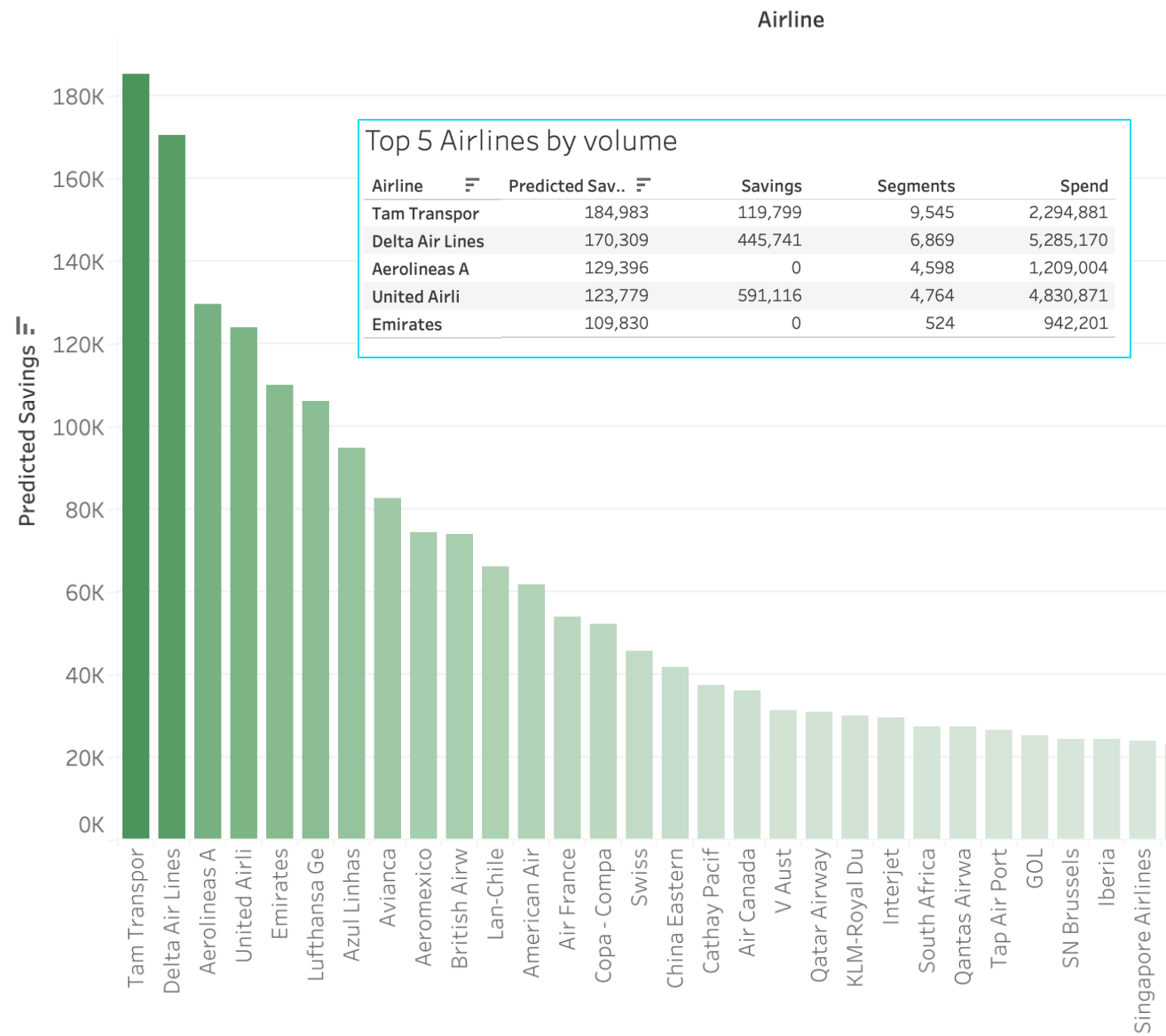
0 3426

Predicted saving by Market

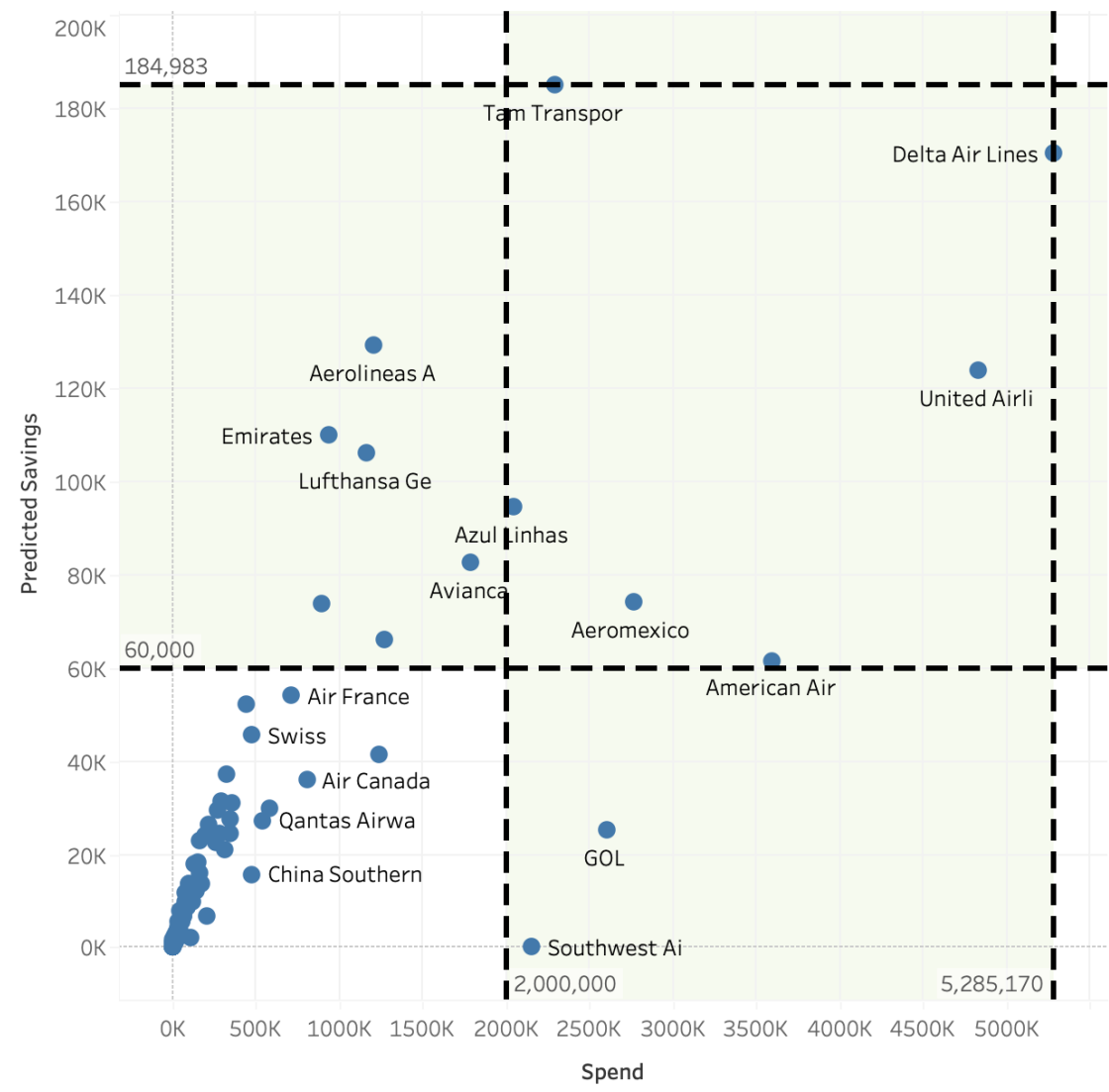


# Track 3: Airline by business volume

Airlines by Volume - Predicted Savings



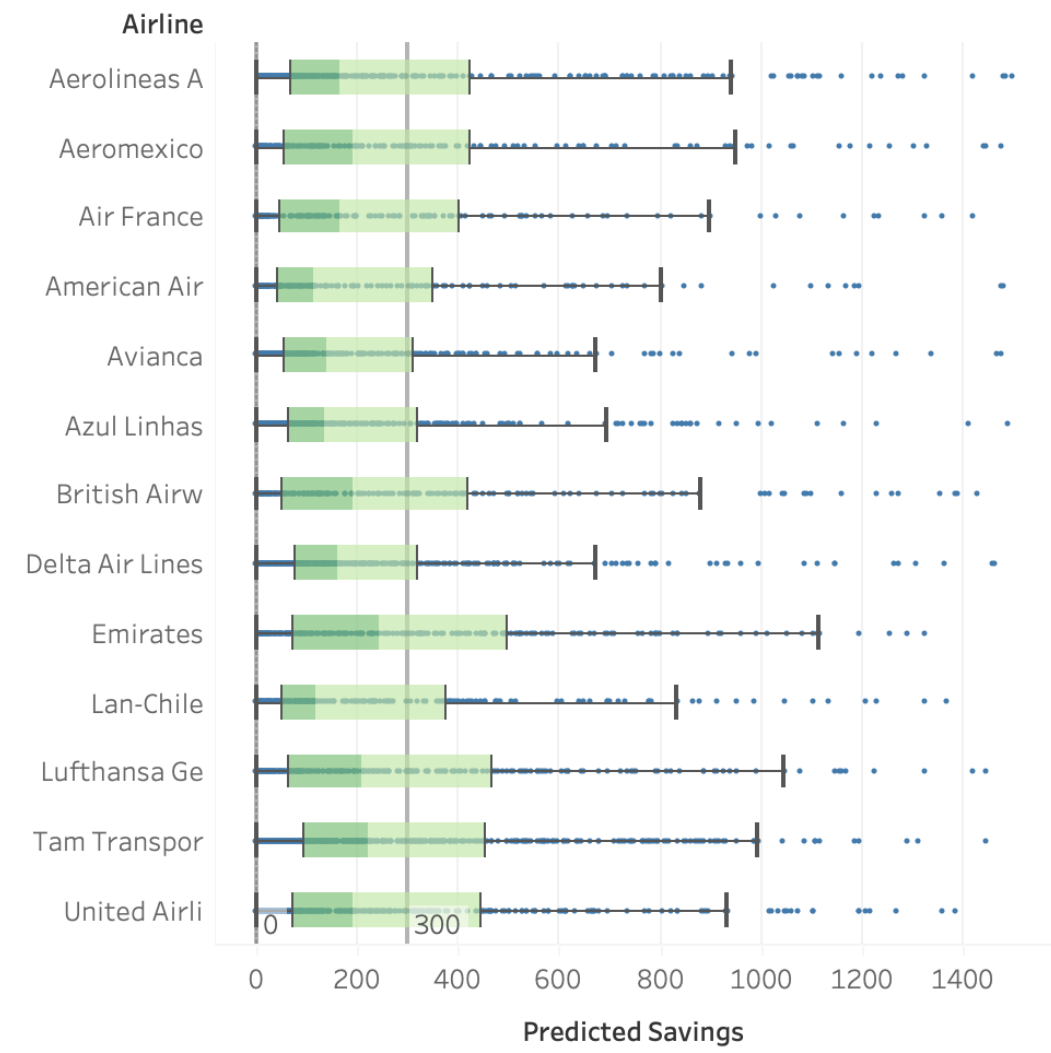
Airlines by Volume Bi-variate  
Spend vs Predicted Savings



# Track 3: Optimization by Airline

1/4th sub-optimal purchases with top airlines are estimated to get at least \$300 in savings

Distribution of sub-optimal purchases across airlines and their predicted savings.





# Track 3: Zero Savings Airlines

Certain Airlines have a significant volume of spend which is not covered.

Airline	Market Status	
Aegean Airli	sub_optimal	100.00%
Aer Lingus	sub_optimal	100.00%
Aero Calif	sub_optimal	100.00%
Aeroflot	sub_optimal	100.00%
Aeroleasing	sub_optimal	100.00%
Aerolineas A	sub_optimal	100.00%
Aeromexico	general	78.06%
	sub_optimal	21.94%
Aerorepublic	sub_optimal	100.00%
Air Alm	sub_optimal	100.00%
Air Alps Avi	sub_optimal	100.00%
Air Baltic C	sub_optimal	100.00%
Air Canada	general	58.63%
	sub_optimal	41.37%
Air China	general	14.94%
	sub_optimal	85.06%
Air Dolomiti	sub_optimal	100.00%
Air Enterpri	sub_optimal	100.00%
Air Europa	sub_optimal	100.00%
Air Fiji	sub_optimal	100.00%
Air France	general	36.14%
	sub_optimal	63.86%
Air Georgia	sub_optimal	100.00%

Certain Airlines have a significant volume of spend which is not covered.

Airline	Market Status	% of Total Spend along Market Status	Predicted Savings
Aeromexico	general	78.06%	0
	sub_optimal	21.94%	74,275
Air China	general	14.94%	0
	sub_optimal	85.06%	22,400
Air France	general	36.14%	
	sub_optimal	63.86%	54,026

☒ Keep Only ☐ Exclude ☐ ☐ ☐

3 items selected · SUM of Measure Values: 150,701

Airline: Air France  
Market Status: sub\_optimal  
Predicted Savings: 54,026

# Future Research & Recommendations

## Data

- Explore **more variables** that are better explainers of sub-optimal purchasing.
- Roll-up high cardinality data point into lesser categories.
- Join data points that record **metrics** on markets, airlines, value add. services, etc.

## Analysis

- Explore additional market and purchase **prioritization strategies**.
- Build a **simulation model** that optimizes prioritization for max savings vs min deltas.
- Validate optimization model with real re-contracting observations to test.
- Deploy as a BI solution and conduct **User Acceptance** tests.

## References

1. API Reference scikit learn. Retrieved on November 29<sup>th</sup> 2022 (<https://scikit-learn.org/stable/modules/classes.html>)
2. Hyper-parameter tuning the Random Forest by Towards Data Science. Retrieved on November 29<sup>th</sup> 2022 (<https://towardsdatascience.com/hyperparameter-tuning-the-random-forest-in-python-using-scikit-learn-28d2aa77dd74>)
3. Regression Metrics for Machine Learning by Machine Learning Mastery. Retrieved on November 29<sup>th</sup> 2022 (<https://machinelearningmastery.com/regression-metrics-for-machine-learning/>)
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6. Model selection and evaluation scikit learn. Retrieved on November 29<sup>th</sup> 2022 ([https://scikit-learn.org/stable/model\\_selection.html](https://scikit-learn.org/stable/model_selection.html))

Thank you!