Delta Airlines Capstone Project

Shenglin Bai
Pamela Cheng
Foster Mosden
Guangming (Dola) Qiu
Benny Uhoranishema

EMORY | GOIZUETA BUSINESS SCHOOL

Agenda

- **Team Introduction**
- Business Understanding & Challenge
- Model Details
- Model Performance & Impact
- Risk
- How to Deploy the model?

Meet the Team - Delta Team 1

Client Contact
Foster Mosden

Faculty Contact
Guangming (Dola) Qiu

Tech Contact
Benny Uhoranishema

Project Manager
Shenglin Bai

Peer Facilitator
Pamela Cheng

- **Business Understanding & Challenge**
- Model Details
- Model Performance & Impact
- Risk
- How to Deploy the model?

The Challenge of Special Meal Provisioning

Current Practice

Manual Predictions

- Currently relies on manual predictions using past experiences and historical data

Over-Ordering

Conservative Estimates to Meet Needs

- Orders more meals than necessary to ensure no unmet needs

Impact of Over-Ordering

- Unconsumed meals lead to significant waste
- Requires additional resources for handling, storage, and disposal
- Increases operational expenditures

Need for Precision

Importance of Accurate Ordering

- Precision balances cost efficiency with customer satisfaction
- Accurate forecasting reduces waste and operational costs

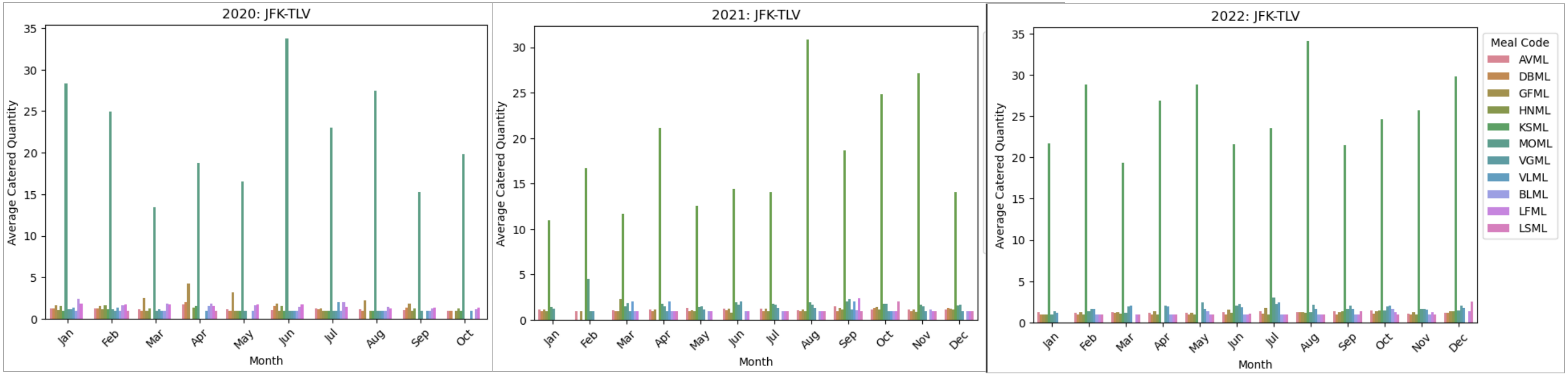
Strategic Imperative

- Refining forecasting practices boosts reputation
- Fosters passenger loyalty through improved service quality

Complexity of Forecasting Meal Demands

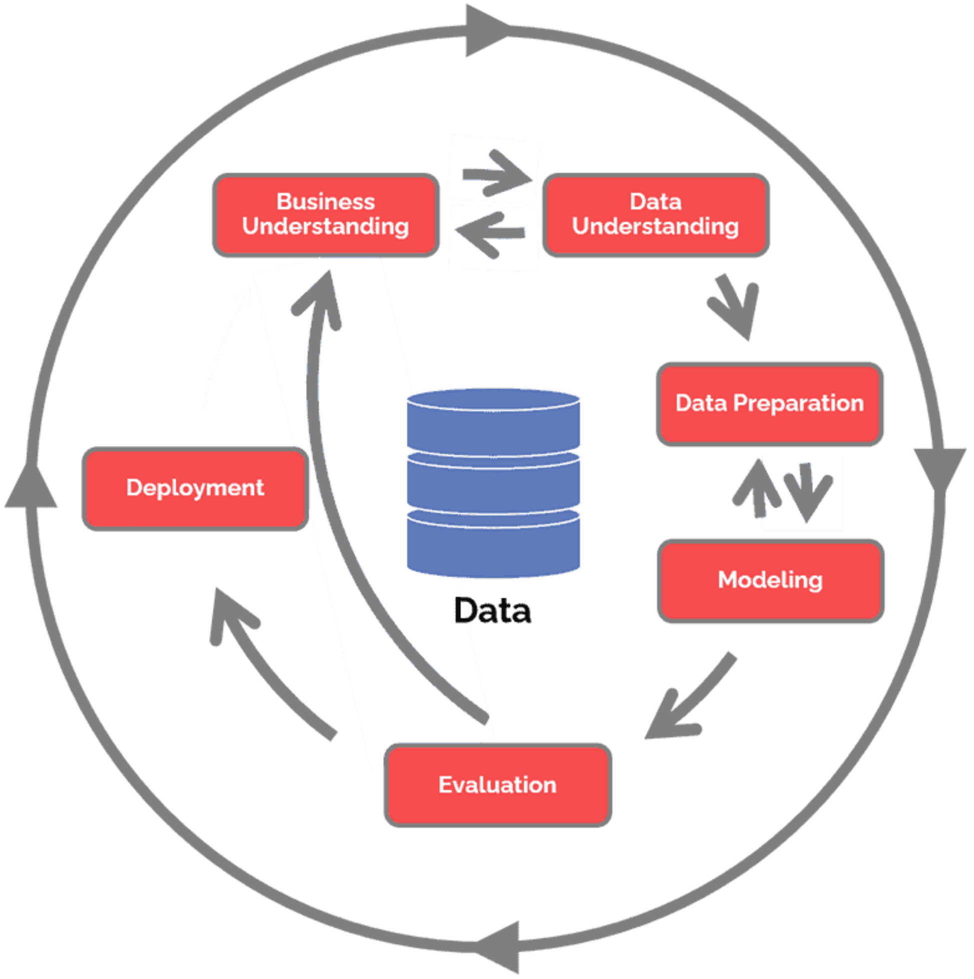
DELTA

- **Diverse Preferences:** the demand for different types of meals (e.g., vegetarian, gluten-free, kosher) varies significantly. Each type has its own pattern of demand.
- **Seasonal Demand Shifts:** meal requests fluctuate with seasons due to changes in passenger demographics and their preferences.
- **Cultural and Regional Preferences:** meal demands also vary depending on the flight's origin and destination. Flights to or from regions with specific dietary habits or restrictions



The Need for Advanced Predictive Solutions

Predictive models can integrate diverse factors such as meal type preferences, seasonal trends, regional dietary habits, and many other factors to enhance meal demand forecasting.



Project Objective

DELTA

Primary Objective

Replace Delta's current manual approach to meal planning with a data-driven predictive model using historical data, feature engineering, and machine learning techniques

Supporting Objectives

Improve the accuracy of meal quantity predictions to reduce the frequency and volume of meal surpluses and shortages.

Streamline the meal ordering and provisioning process, making it more responsive to actual passenger requirements.

Overview of the Process

DELTA

Business Problem	Develop an **8-week daily demand** forecast for **14 types** of **special meals** to minimize waste and improve operational efficiency
Predictive Modeling	The target outcome is to predict the **required quantity of each type of meal** for each cabin class on daily for per airport origin
Model Evaluation	Assume **equal weights** for over and under prediction. **MAE** and **MAPE** will be used to evaluate the model performance

Forecast Timeline

- The forecast horizon would be **8 weeks out** starting from the day of running the model

- Business Understanding & Challenge
- **Model Details**
- Model Performance & Impact
- Risk
- How to Deploy the model?

DELTA

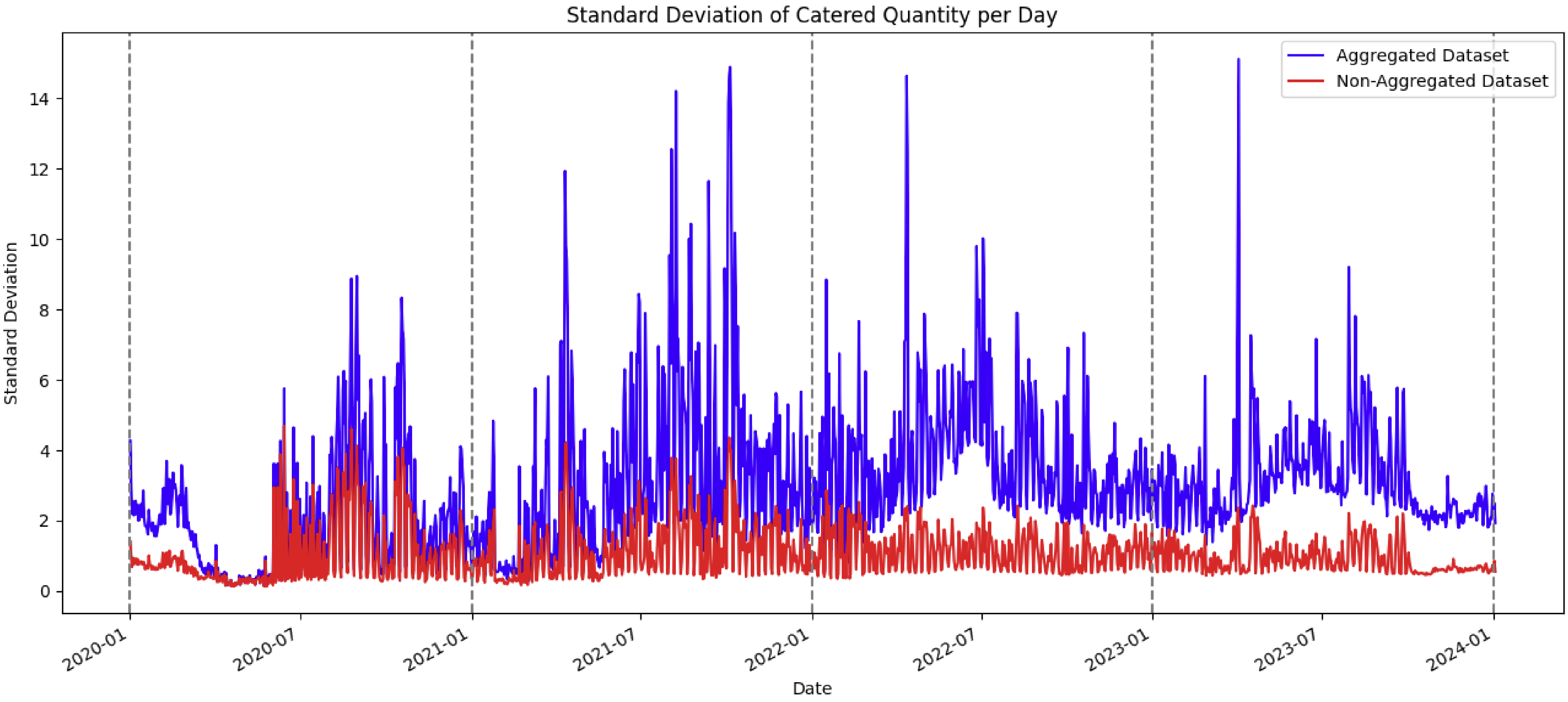
Aggregation Level & Feature Engineering

DELTA

FlightOrigin	Date (Day, Week, Month, Year)	MealCode	CabinCode	Time of Day (Breakfast, Lunch, Dinner, Brunch, Lunch/Dinner)

Location Based	- Origin Airport Coordinates - Indicator of whether airport is a Delta hub
Date Based	- Day of the week (Monday, Tuesday, etc.) to capture weekly trends - Number of days away from holidays which don't follow the Gregorian calendar (Passover, Chinese New Year) - Time series model prediction as a feature (SARIMAX model)
Flight Based	- Number of International or Domestic flights aggregated - Total distance traveled by aggregated flights - Total capacity of aggregated flights

Aggregation Increases Scale, Reveals Trends



- Business Understanding & Challenge
- Model Details
- **Model Performance & Impact**
- Risk
- How to Deploy the model?

80%+ Reduction in Error over Benchmark Model

DELTA

Evaluation Level	Benchmark Naïve Bayes	Final LGBM	Error Reduction %
MAE at prediction level	2.47	0.49	80.08%
MAPE at prediction level	127.49%	16.64%	86.92%
MAE per airport per day	154.64	29.46	80.95%
MAPE per airport per day	11.43%	0.64%	94.39%
MAE per full day (across all airports)	5244.67	999.21	80.98%
MAPE per full day (across all airports)	171.57%	6.09%	96.45%

LGBM Saves Time & Money

Reducing the time to predict:

- The code takes under 10 minutes to train, predict, and output the entire 8 week prediction forecast

Cut costs by minimizing errors:

- Saving $3 ~ 4/per meal x Error Reduction/per day
  = $12k ~ 16k per day
  = **$4M ~ 6M per year**

10 Minutes to Retrieve Predictions

Reduce cost by 4 ~ 6 million USD <u>per year</u>

Reference: https://au.finance.yahoo.com/news/airline-meal-price-controversy-could-drive-up-costs-for-aussies-expert-warns-022832850.html

Error Analysis

- Provide a clear understanding of how overprediction and underprediction across each airport
  - When ordering the meal, easier to manual adjust based on error analysis and domain knowledge

Number of rows on the prediction level where there were more/less meals than demanded

Airport	MAPE	Overstock	Stockout
ANC	4.81%	4.05%	95.95%
ATL	28.55%	52.23%	47.77%
AUS	6.44%	20.81%	79.19%
BDL	4.02%	3.33%	96.67%
BNA	4.24%	0.88%	99.12%

- Business Understanding & Challenge
- Model Details
- Model Performance & Impact
- **Risk**
- How to Deploy the model?

Increased Risk of Stockouts From Rounding

The imbalance of over and under prediction stems from rounding errors. Without performing rounding, the error is balanced.

However, exclusively rounding up or down greatly increases the error of model. Rounding to the nearest integer reduces minimizes the error, but increases the frequency of stockouts

Results Without Rounding

Airport	MAPE	Overstock	Stockout
BNA	10.77%	84.95%	15.05%
IAD	11.5%	92.09%	7.91%
KOA	11.32%	84.07%	15.93%
MEM	11.11%	92.6%	7.4%
STL	10.83%	92.18%	7.82%

Overall prediction level MAPE: 24.0%

Results After Rounding to the Nearest Integer

Airport	MAPE	Overstock	Stockout
BNA	4.24%	0.88%	99.12%
IAD	4.01%	0.0%	100.0%
KOA	4.95%	0.0%	100.0%
MEM	3.78%	0.0%	100.0%
STL	4.01%	0.0%	100.0%

Overall prediction level MAPE: 16.85%

Overstock/Stockout % here is calculated as the number of rows on the prediction level where there were more/less meals than demanded

Reducing Stockout Risk with Adjustments

Airport	MAPE	Overstock	Stockout
BNA	4.24%	0.88%	99.12%
IAD	4.01%	0.0%	100.0%
KOA	4.95%	0.0%	100.0%
MEM	3.78%	0.0%	100.0%
STL	4.01%	0.0%	100.0%

If we add a small decimal (here 0.21) to the prediction result *before* we round them into whole numbers, we can achieve a greater balance of overstock and stockout

The adjustment value can be further tuned for a better balance of reducing MAPE while maintaining customer satisfaction.

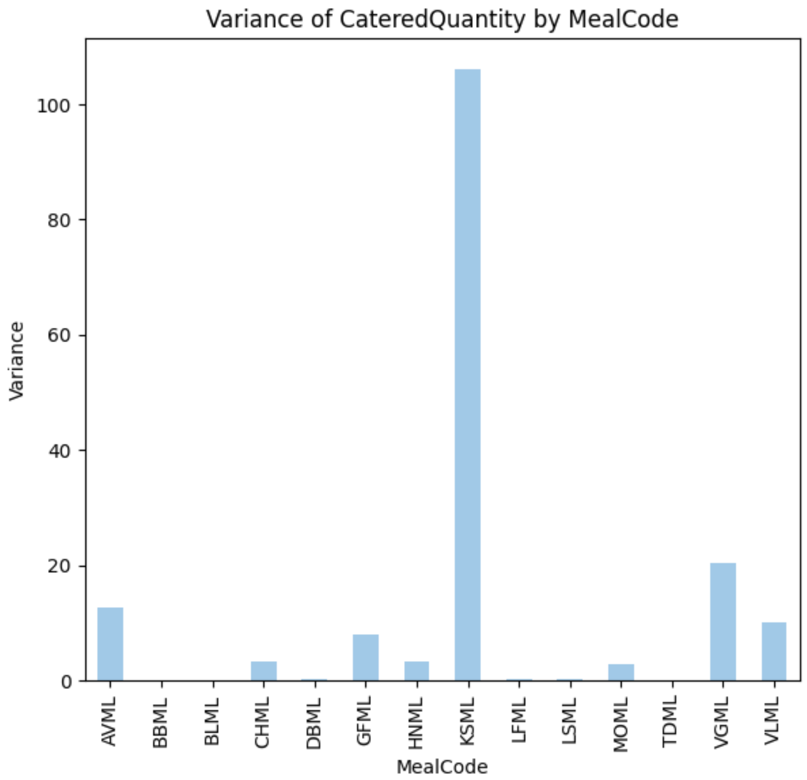
The adjustment here raised prediction-level MAPE from 16.85% to 24.53% across the test set

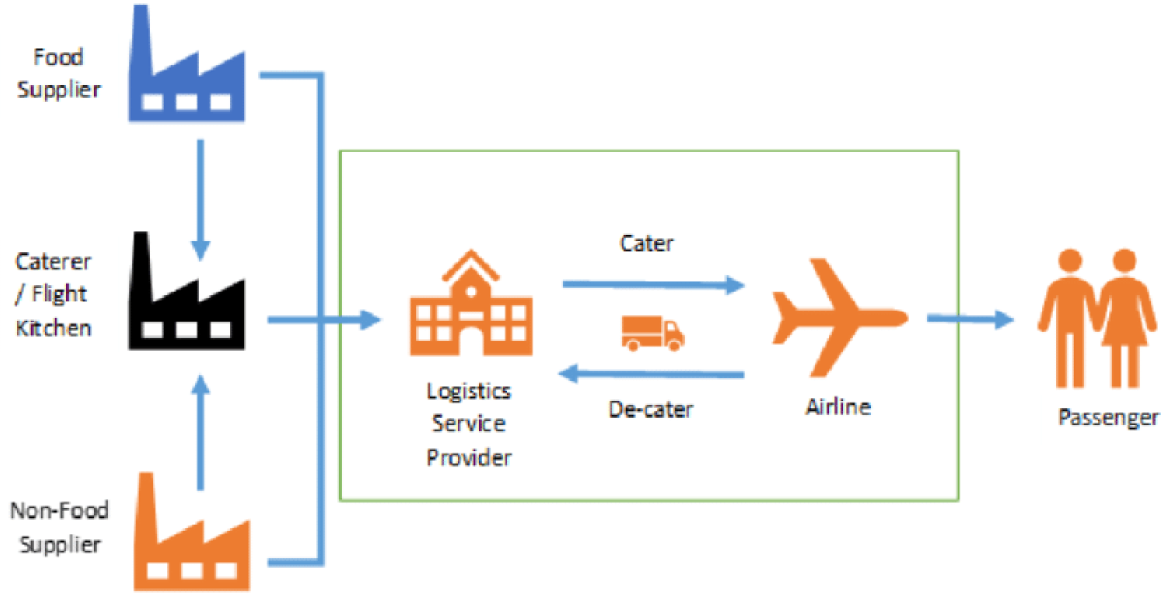
Airport	MAPE	Overstock	Stockout
BNA	10.63%	69.4%	30.6%
IAD	12.32%	70.99%	29.01%
KOA	12.91%	64.29%	35.71%
MEM	12.37%	74.55%	25.45%
STL	10.16%	73.91%	26.09%

Overstock/Stockout % here is calculated as the number of rows on the prediction level where there were more/less meals than demanded

Buffer Stocks for Highly Variable Meals

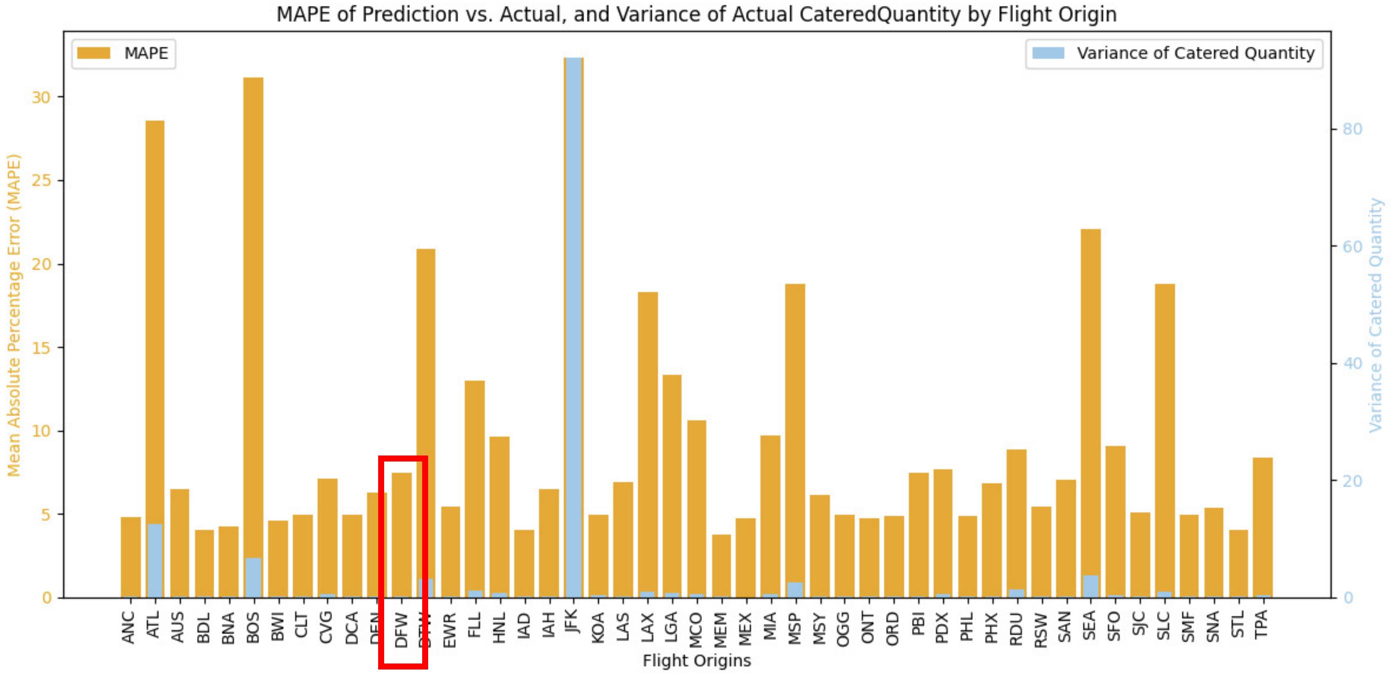
Implement a strategy of maintaining buffer stocks for meals with highly variable demand to mitigate potential stockouts.
This buffer allows for adjustments based on actual demand versus forecasted numbers.





Data Quality and Integration Risks

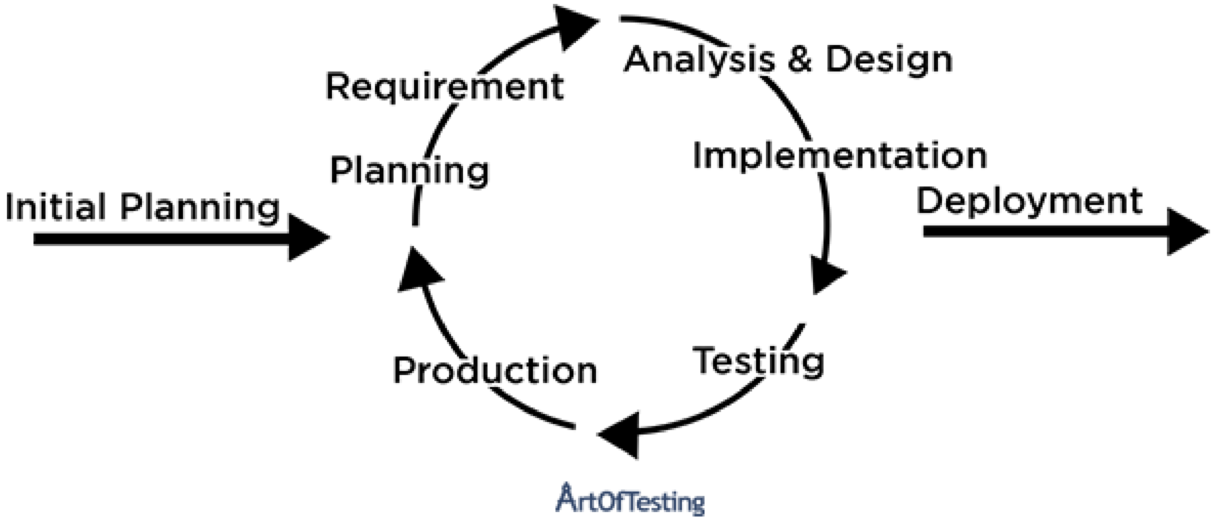
- Ensure high data quality and seamless integration with existing systems to prevent operational disruptions.
- Rigorous testing of data inputs and model integration is critical before full-scale implementation.



Iterative Process

Employ an adaptive risk management strategy that includes regular updates and evaluations of the model.

Engage continuously with stakeholders to refine the forecasting approach and align it more closely with actual needs.



- Business Understanding & Challenge
- Model Details
- Model Performance & Impact
- Risk
- **How to Deploy the model?**

DELTA

Model Deployment

Input File Structure:

- “**MM-DD-YYYY_pred**“ as input file format name.
- **Each row** in the input file represents **one flight** that needs a prediction.

Model Usage:

- The deployment can utilize an **existing model** or build a new one based on the **updated input data**.

Continue…

Data Pipeline:

- **Different pipelines** for processing historical **training data** and for **input data** used for predictions.

Output Structure:

- **The output** should follow a **predefined report** structure.
- **The output** are to be stored as separate files for **each airport,** organized in folders corresponding to **each day** from the prediction dataset.

CHALLENGES ARE FUEL FOR THE CLIMB

Thank you

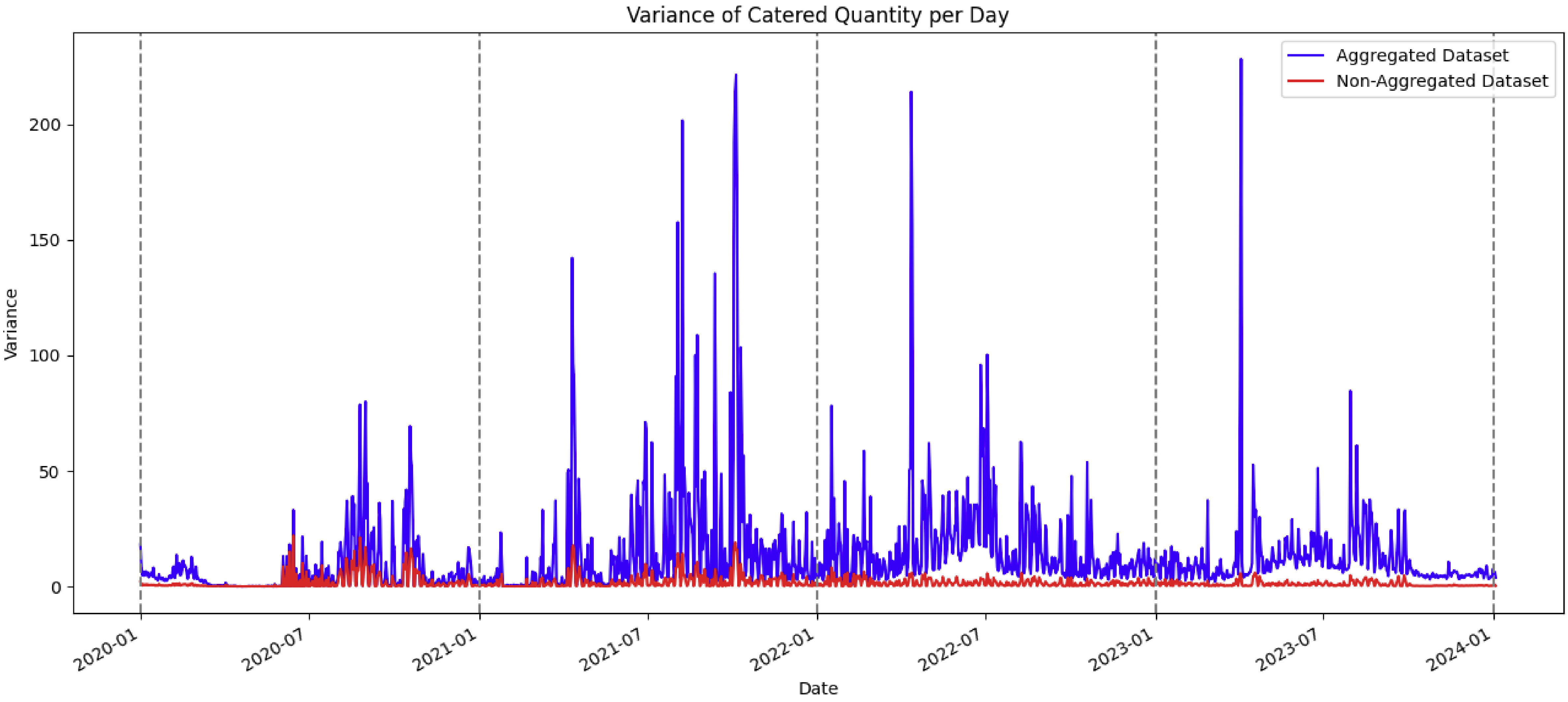
Any Questions?

DELTA SKYTEAM

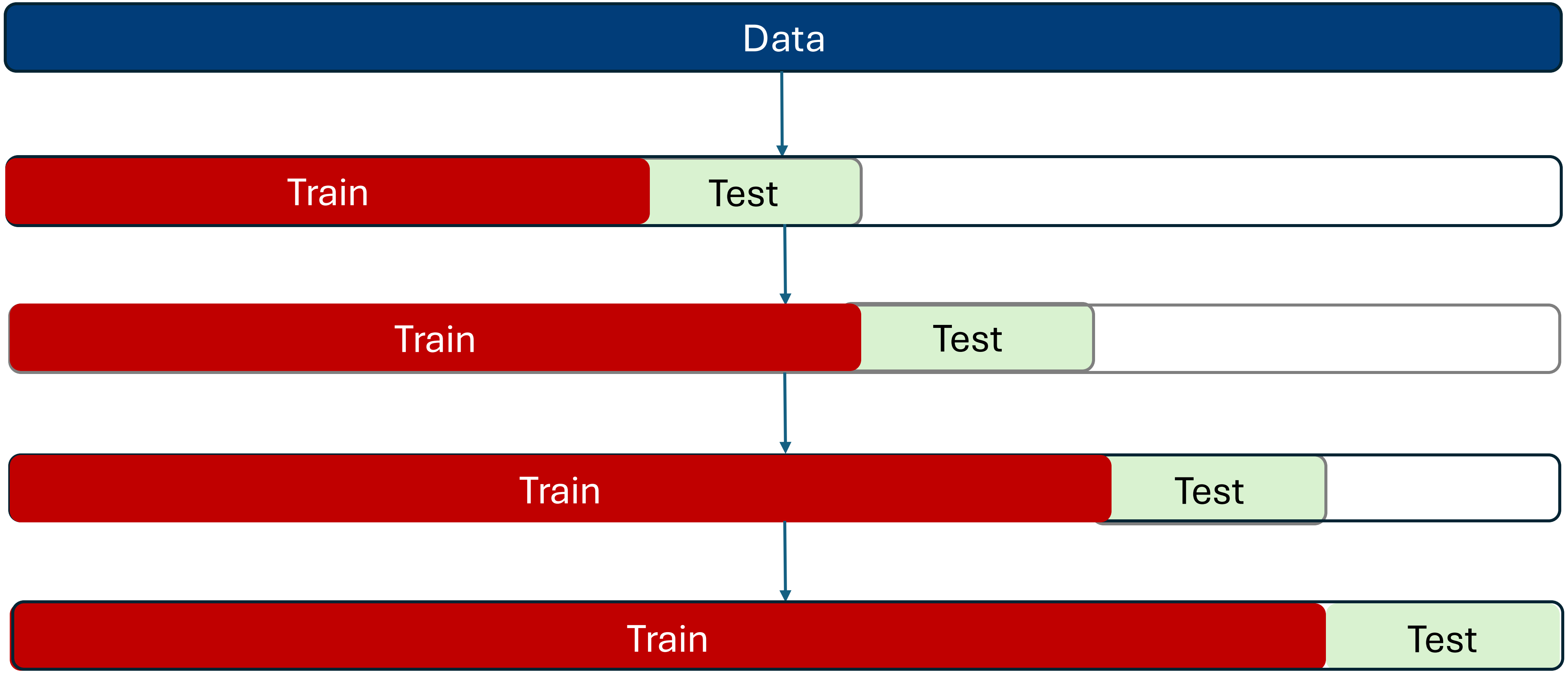
EMORY | GOIZUETA BUSINESS SCHOOL

- **Appendix**

Benefits of Aggregation before Modeling

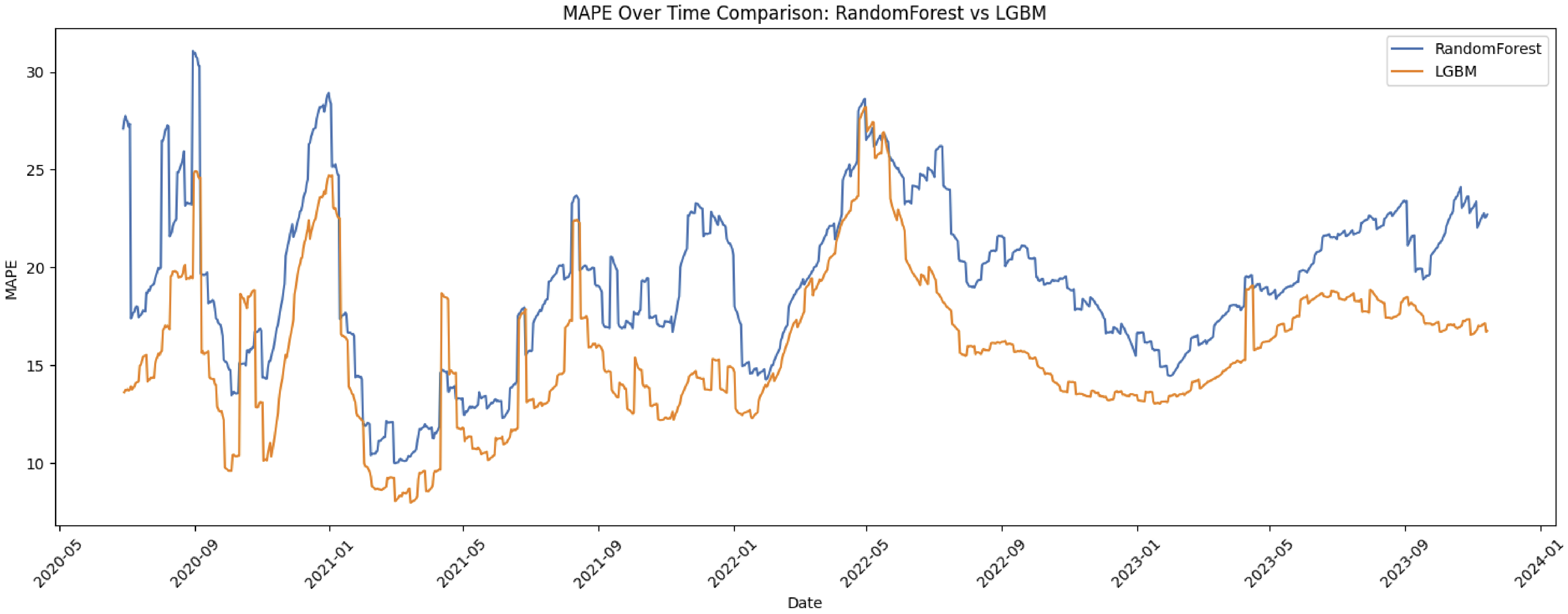


Experiment Design



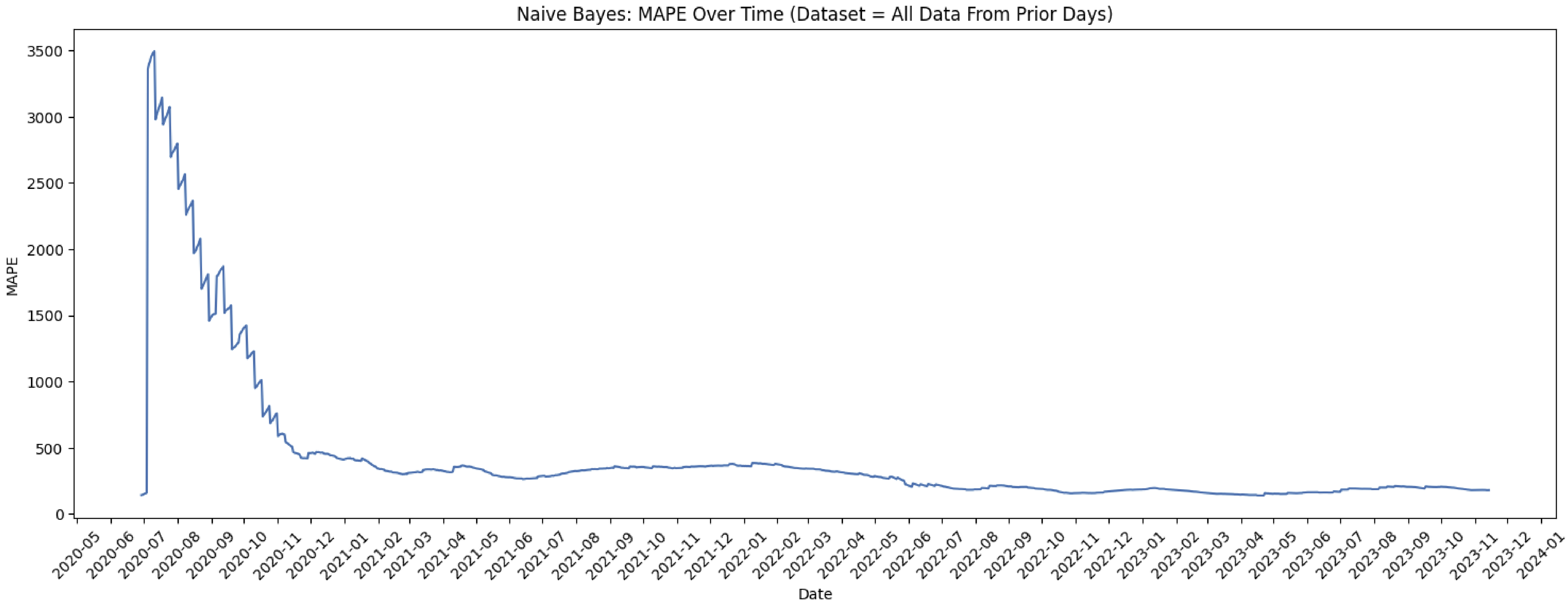
Experiment Performance Comparison

How this was generated: For each day in the dataset, all previous data was used as training data, and the following 8 weeks used for testing. So, for a given day, it displays the MAPE for all predictions in the following 8 weeks.

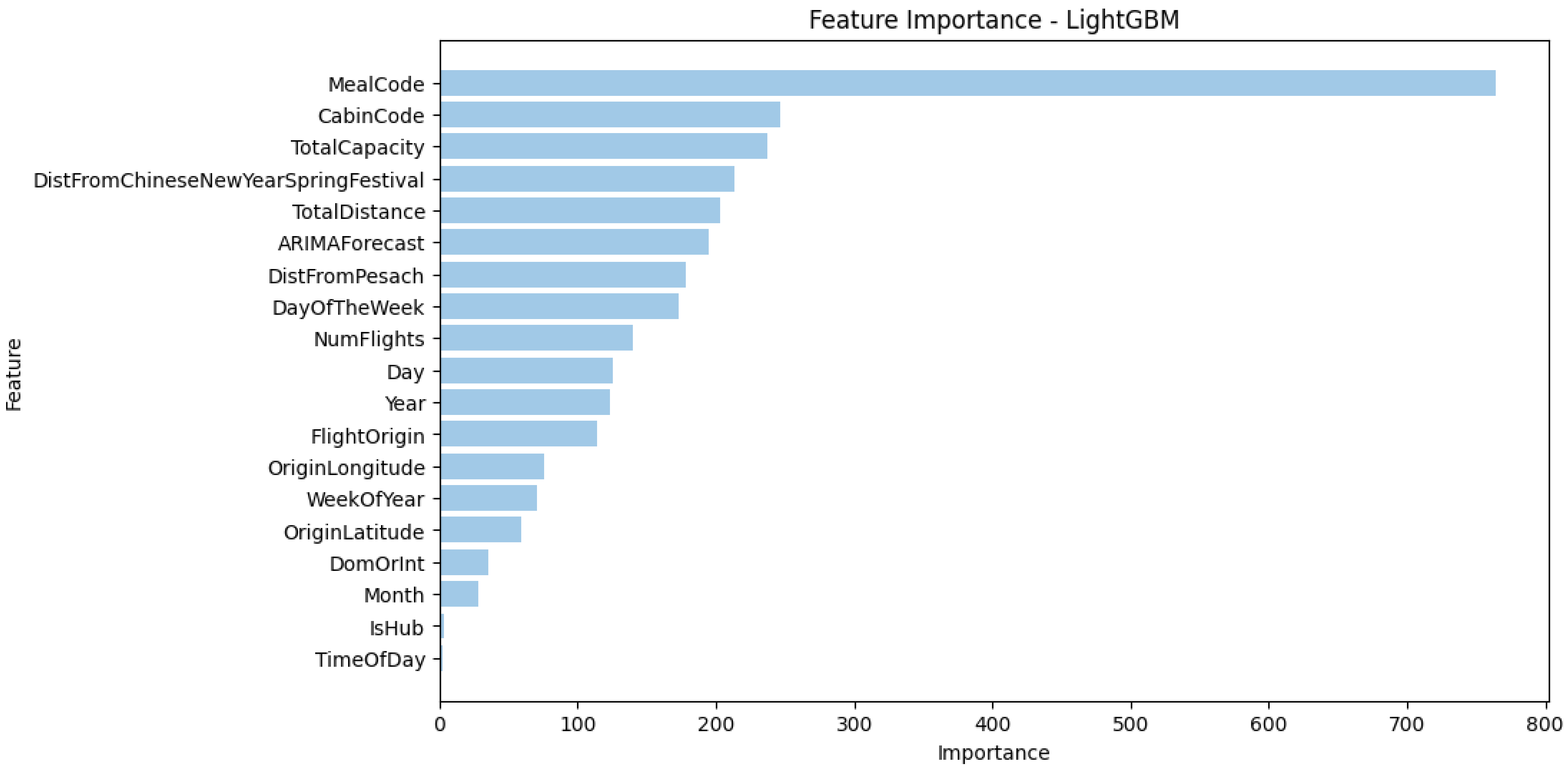


Baseline Experiment Performance Comparison

Note that the scale of the y-axis here is much different than that seen in the previous graph

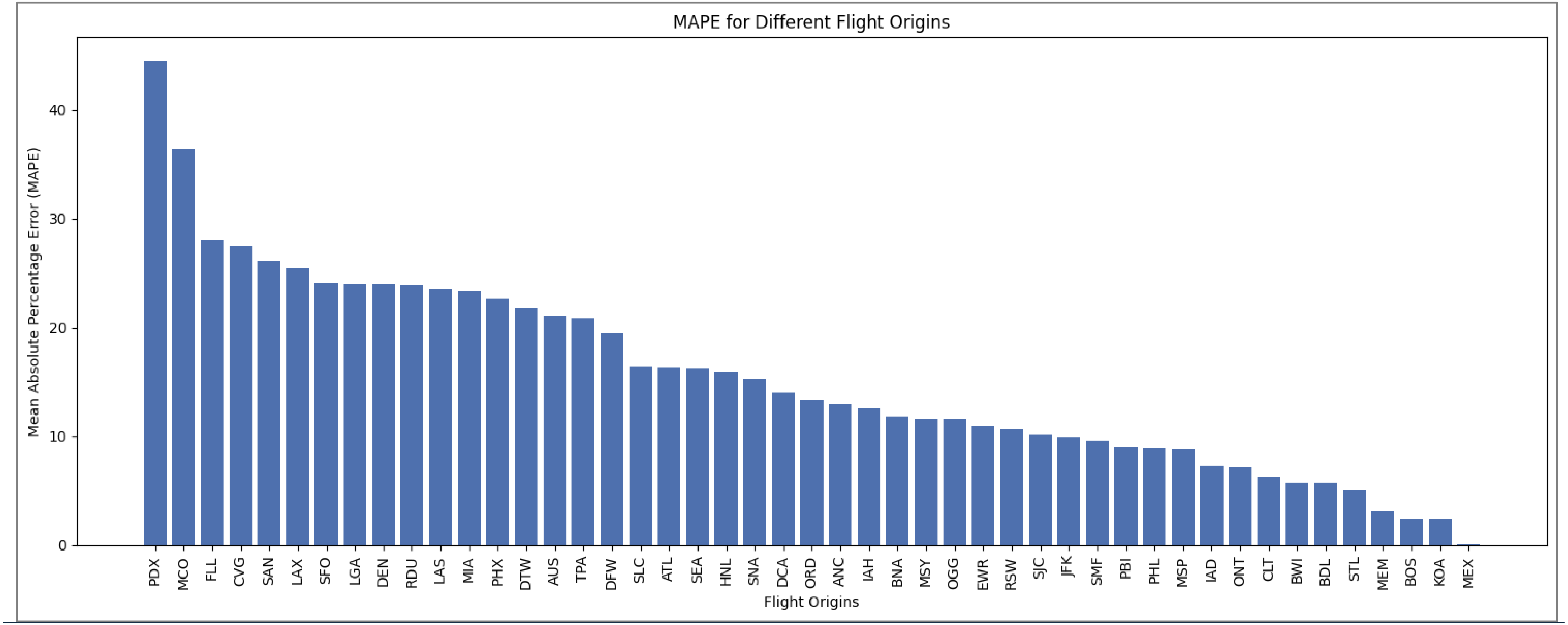


Most Important Factors During Meal Prediction



Error Analysis

Using the first 70% of the dataset for training and the final 20% for test, we got predictions, rounded to the nearest integer, grouped by FlightOrigin, and computed the MAPE



The Features that explain Meal Selection

We maintain the following features from the initial dataset:

- FlightOrigin, CabinCode, MealCode, Year, Month, Day

After feature engineering and aggregation, we have added:

- Location based features:
  - Latitude, Longitude – capture location-based trends of meal demand
  - Hub – whether the origin airport is in a Delta hub city
- Date based features:
  - Distance from CNY, Passover – capture the number of days away from holidays on non-Gregorian calendars within the current year
  - Day of the week – Monday through Sunday, capturing weekly trends
  - Week of the year – out of 52, to capture week-specific ordering trends
- Flight based features:
  - DomOrInt – whether the flights are domestic or international
  - Number of flights – total number of flights aggregated
  - Total distance – total distance, in miles, traveled by all flights aggregated
  - Total capacity – the total capacity of all cabins aggregated
  - Time of day – Breakfast, Lunch, Dinner, Brunch, Lunch/Dinner

Experiment Design

- Our plan is to evaluate our model using a rolling window system
  - This will allow us to observe how predictions change over time as additional data is collected
  - Additionally, it will enable us to gain an idea of real-world performance by continuously modeling and avoiding data leakage
- Data
  - Split data into 80% training, 10% validation, and 10% testing.
  - Preserve COVID-period data; the model is expected to identify trends.