TRENDCAST

Demand Forecast for Fashion Retailers

SFU BIG DATA

Team - Paranormal Distribution

Topics of Discussion

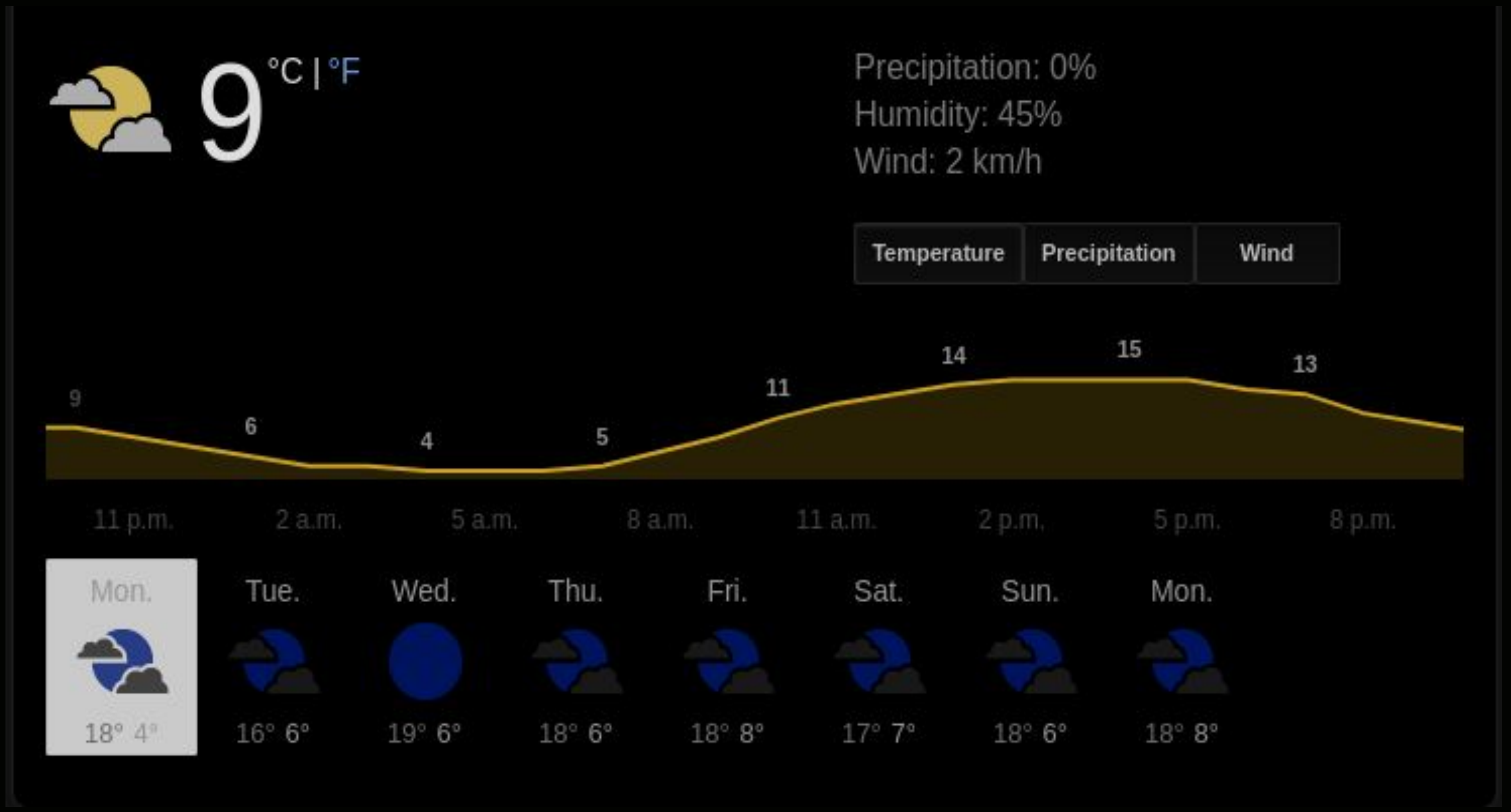
- Motivation
- Scope
- Workflow
- Results
- Challenges
- Future Work

Motivation

- Weather affects consumer behavior.
- Understanding consumer behavior is the key to boost sales and revenue.
- facilitate better stocking and shelving of products by retailers.

Scope

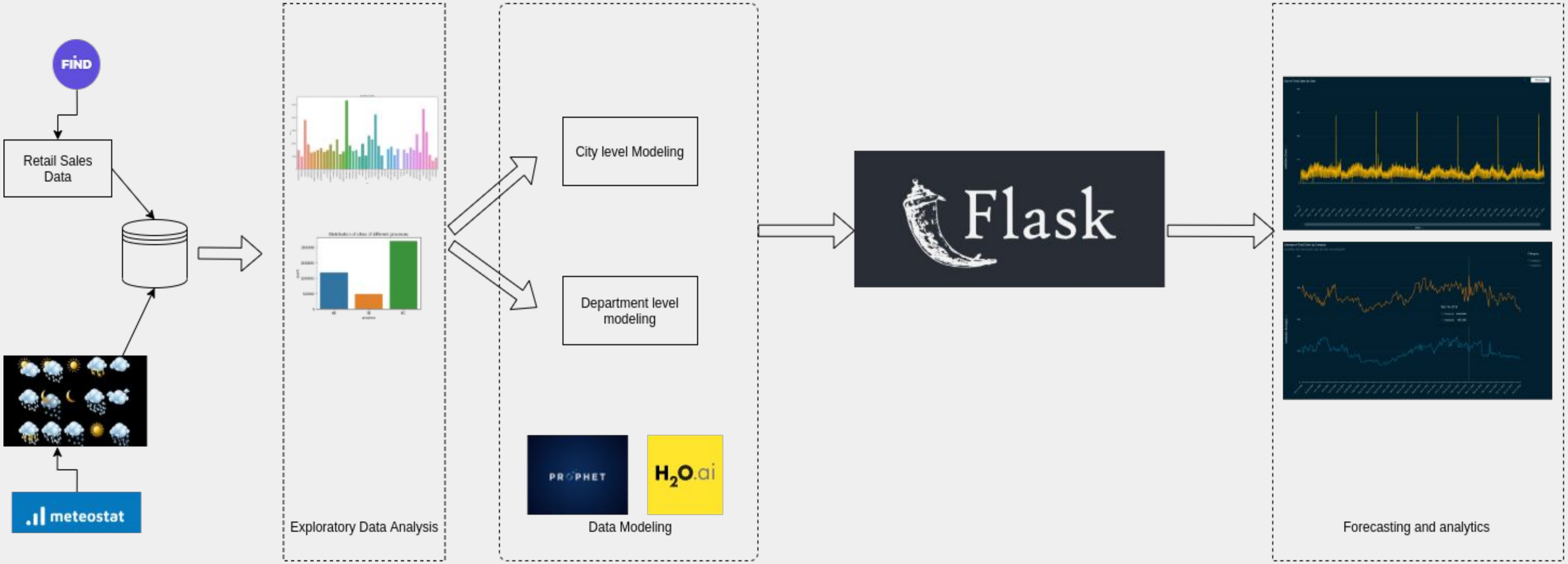
- How far can we predict?



Reliable weather prediction for only the next one week.

- ➢ High confidence for one week
- ➢ Low confidence for weeks beyond.

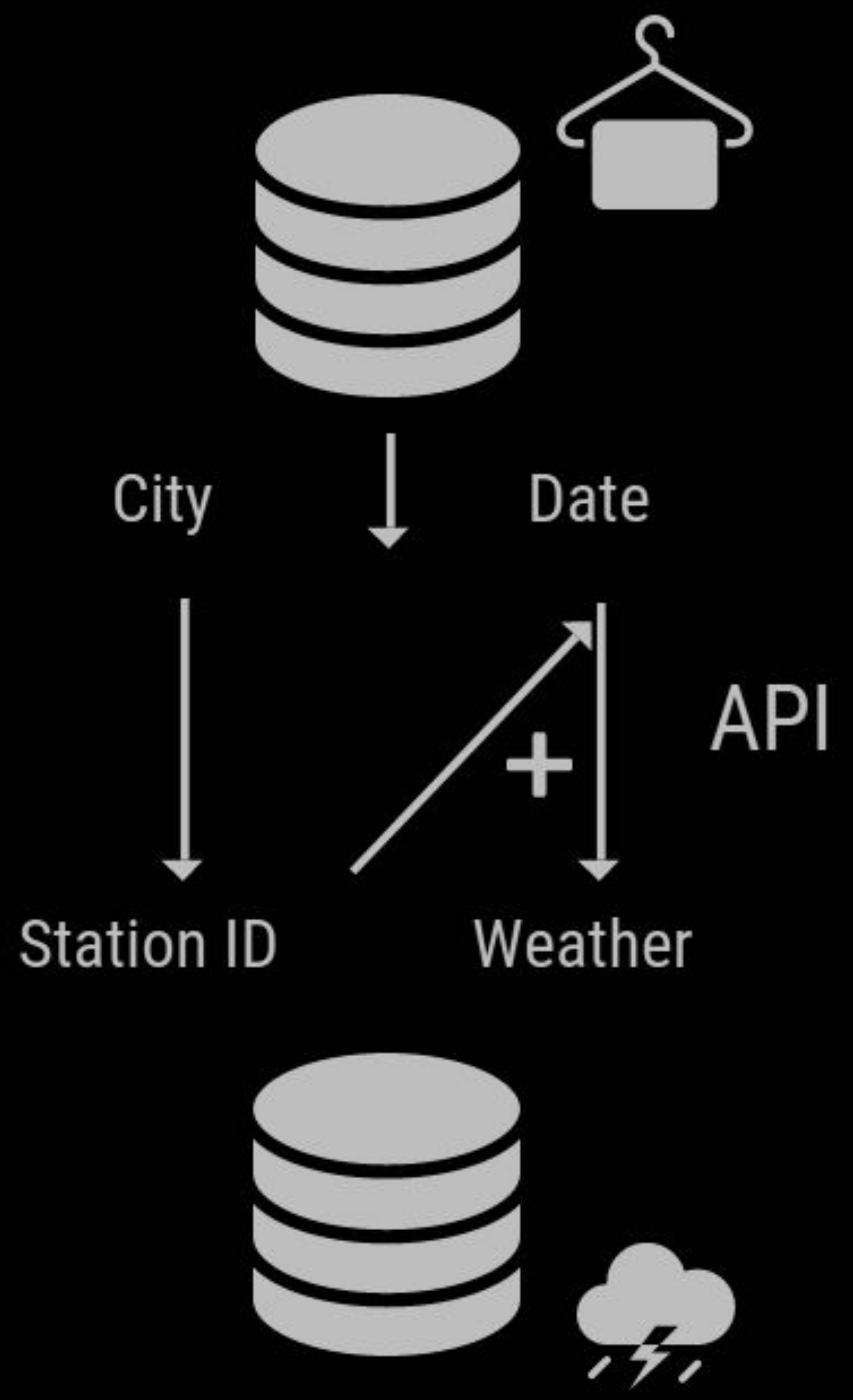
Workflow



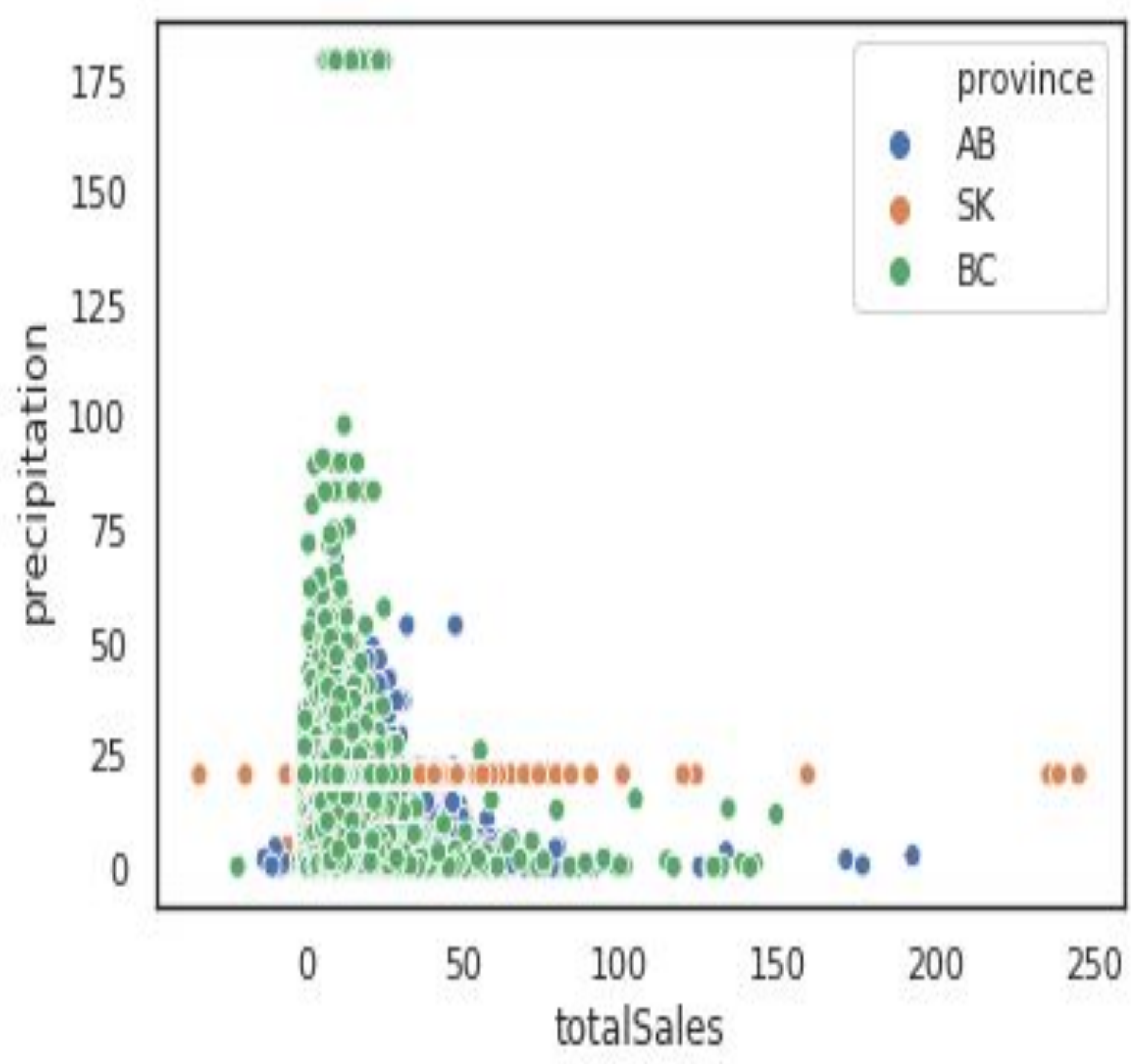
FIND
Retail Sales Data
meteostat
Exploratory Data Analysis
City level Modeling
Department level modeling
PROPHET
H2O.ai
Data Modeling
Flask
Forecasting and analytics

Data Collection

- API calls to Meteostat.
- Station IDs for each city.
- Weather for each station ID on each date of retail sales.
- Consolidate data for each city.
- Integrate Weather with Retail

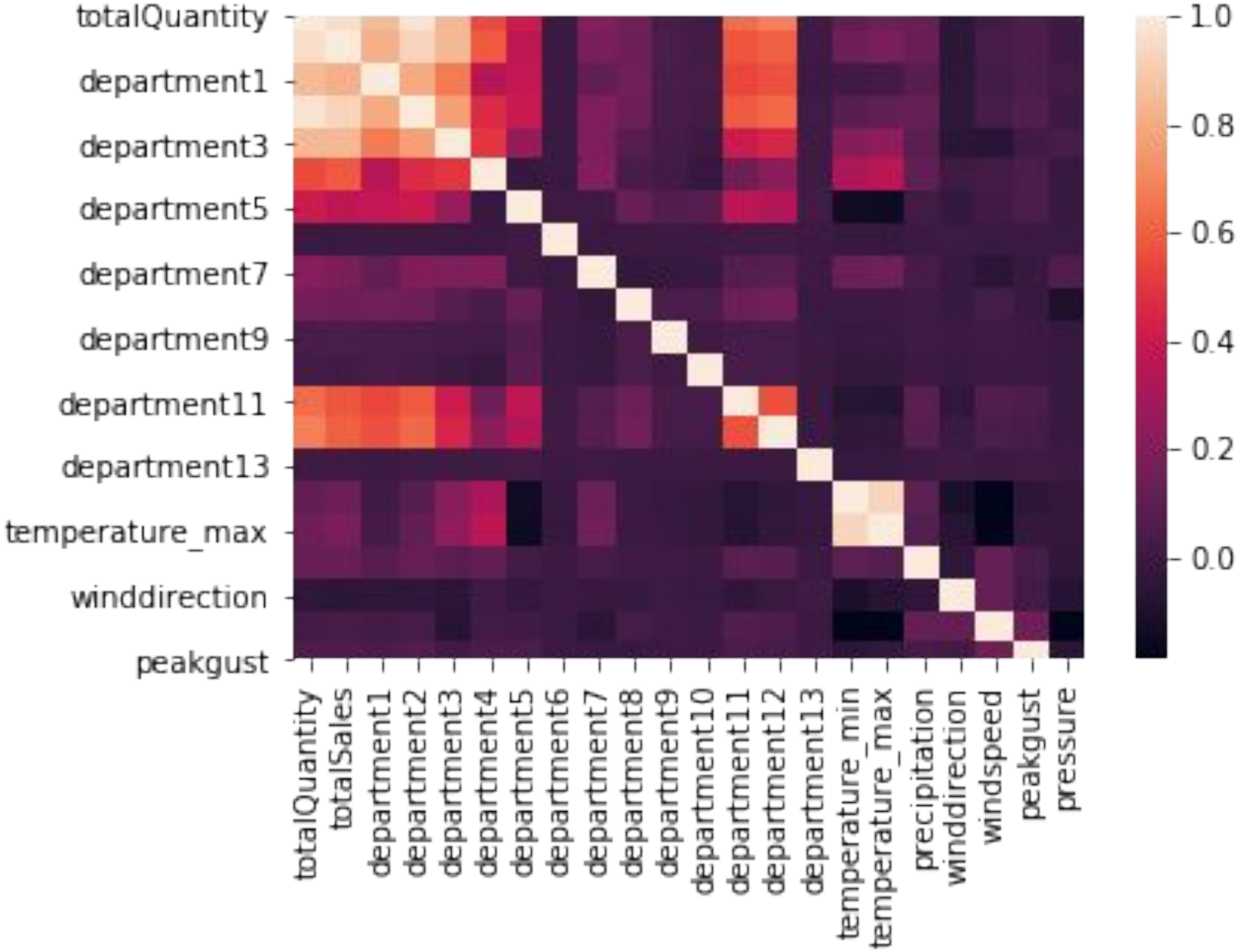


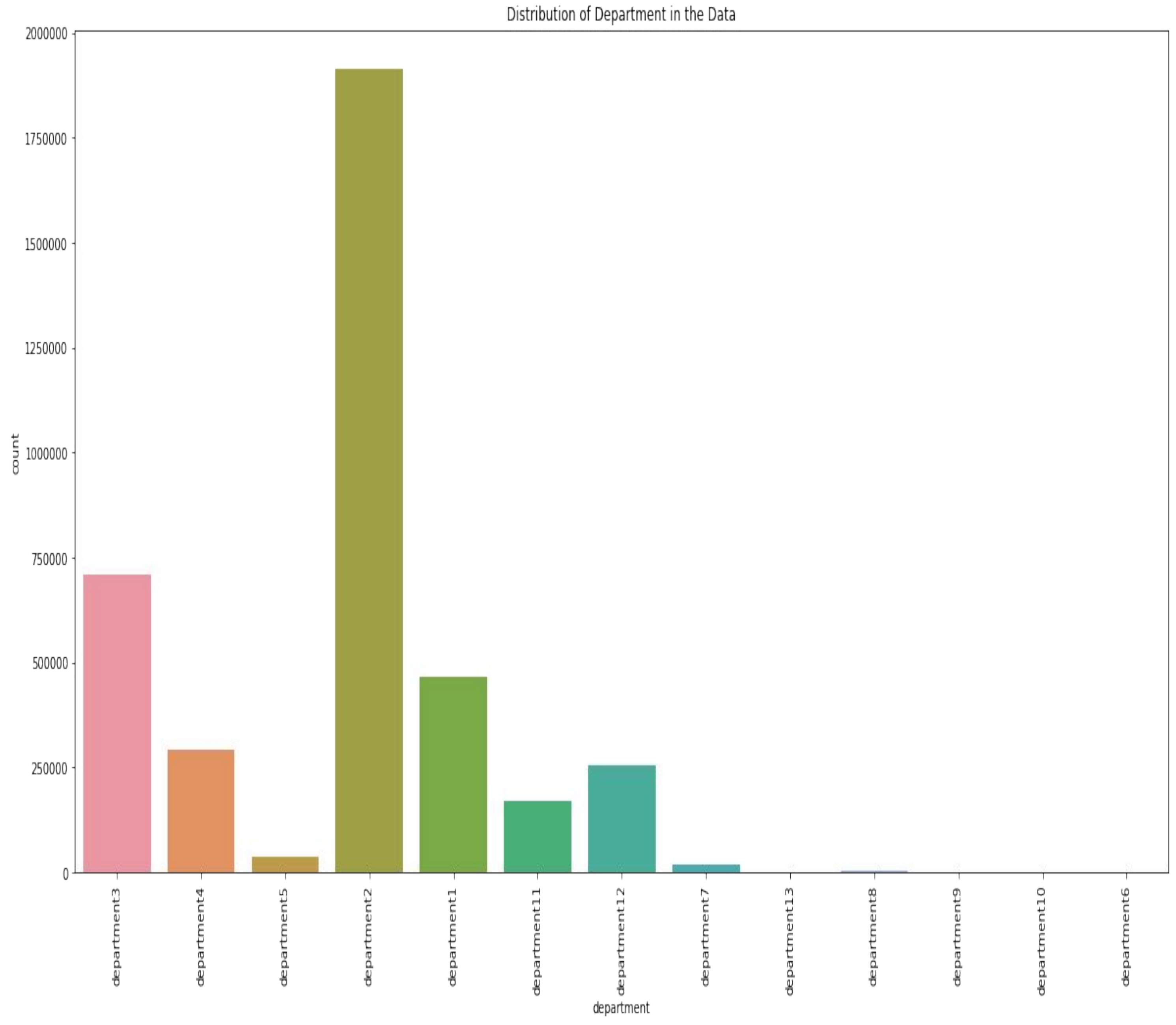
Exploratory Data Analysis



- Overall, Total Sales is weakly related to weather.
- Max and Min temperature influenced Department 4 the most.
- Max precipitation influenced Department 2 the most.
- Kelowna values were an outlier in precipitation.
- Precipitation and total sales have inverse relationship.

Exploratory Data Analysis

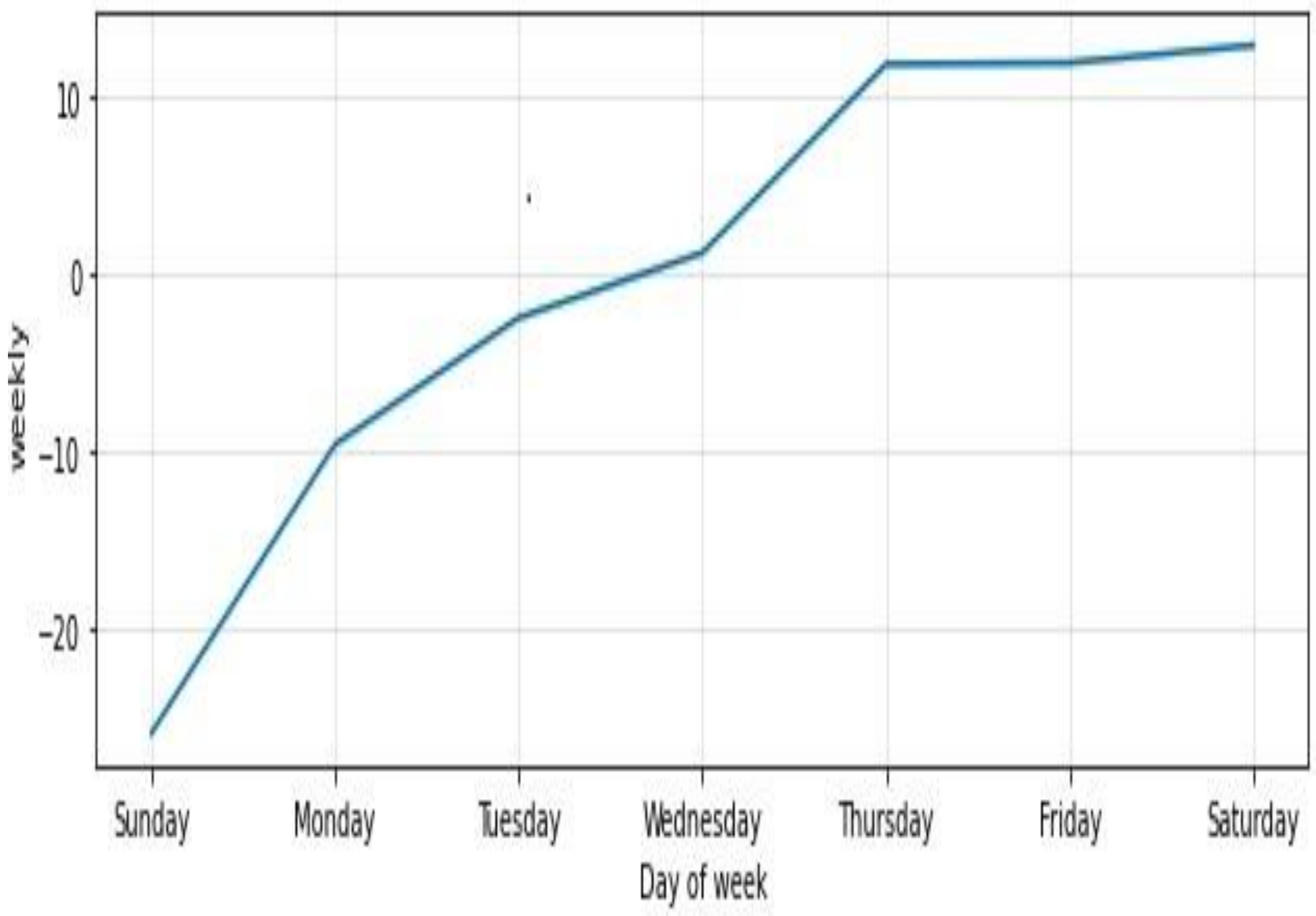




Feature Engineering

- Seasonality and patterns

- Greater sales on weekend - Feature for weekend or not.
- Features for Blackfriday, Cyber Monday and National holidays to enrich the data.



Modeling

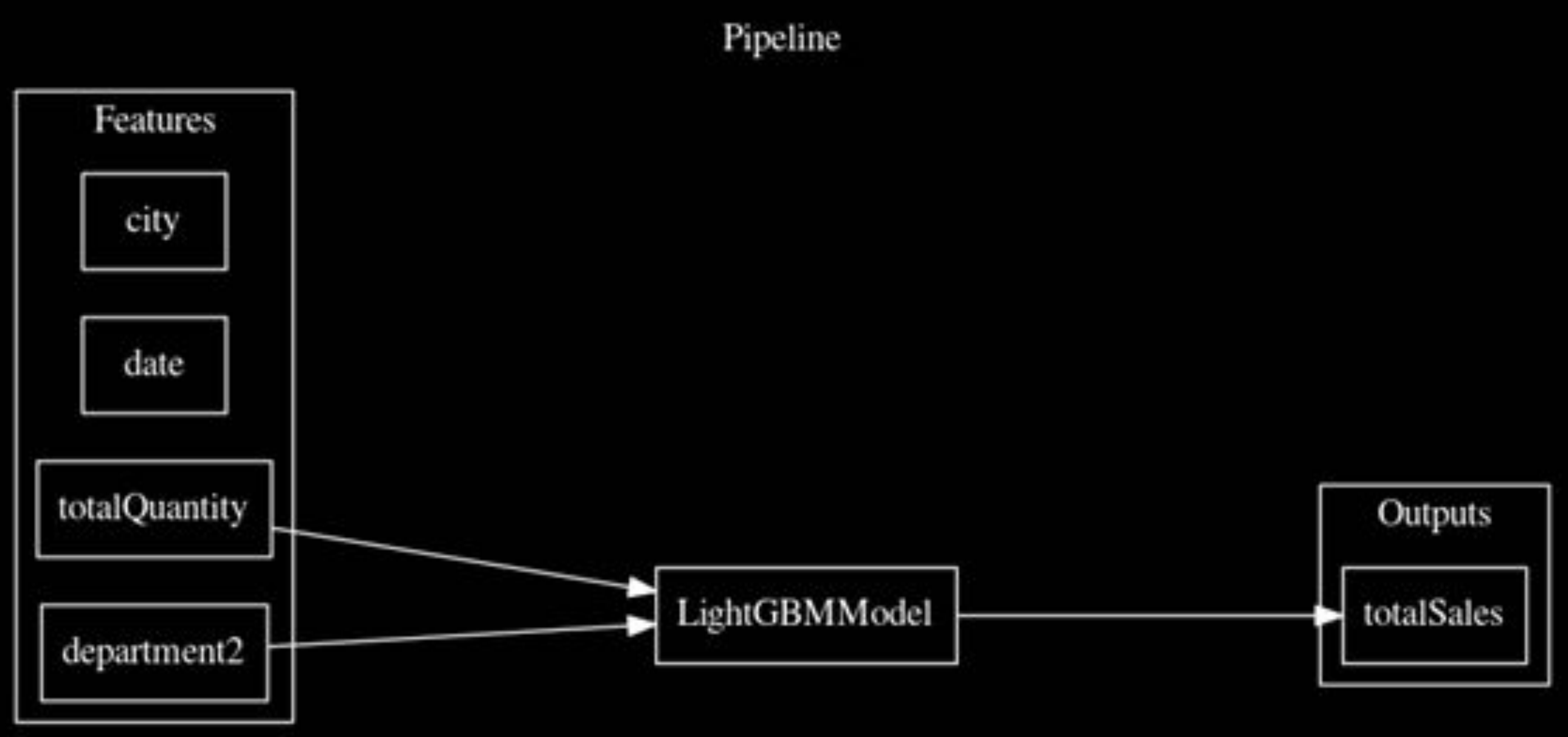
- Challenges

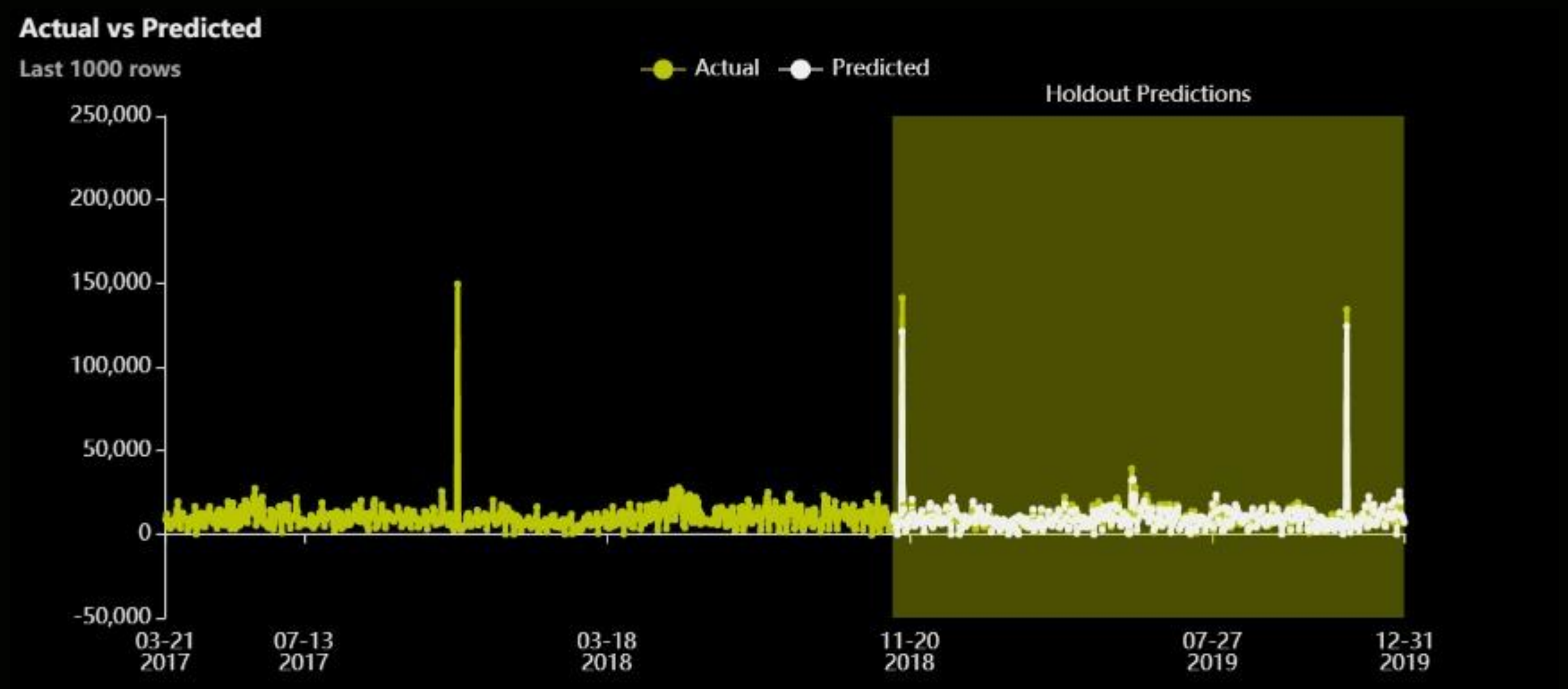
- Generalized model trained on all the cities together performed poorly based on metrics such as R2 and MSE.
- Seeing the trend in each city, we decided to model sales based on each city separately.
- Achieved better evaluation score for sales forecast for each city for the upcoming week.

Modeling

- H20.ai

- H20.ai as comparison model for benchmark purposes
- H20.ai developed various features to compare the performance across different models.
- It settled on:
    - LightGBM model
    - evaluation metrics: R2 and MSE





Modeling

- FbProphet, City-level modeling

- Models were trained with and without weather features to evaluate the effect of weather

- Equation:

  $y(t) = g(t) + s(t) + h(t) + \epsilon$

- Prophet models on trend, seasonality and holidays. Error term ϵ is assumed to be normally distributed

- For predicting sales on the city-level, we aggregated data to the city-level

Modeling

- FbProphet, Department-level modeling

- Our goal is to help retailers better forecast their supplies, for which we need to forecast the quantity required in each department.

- Built time-series model for each department in each city to forecast quantity sold in each department

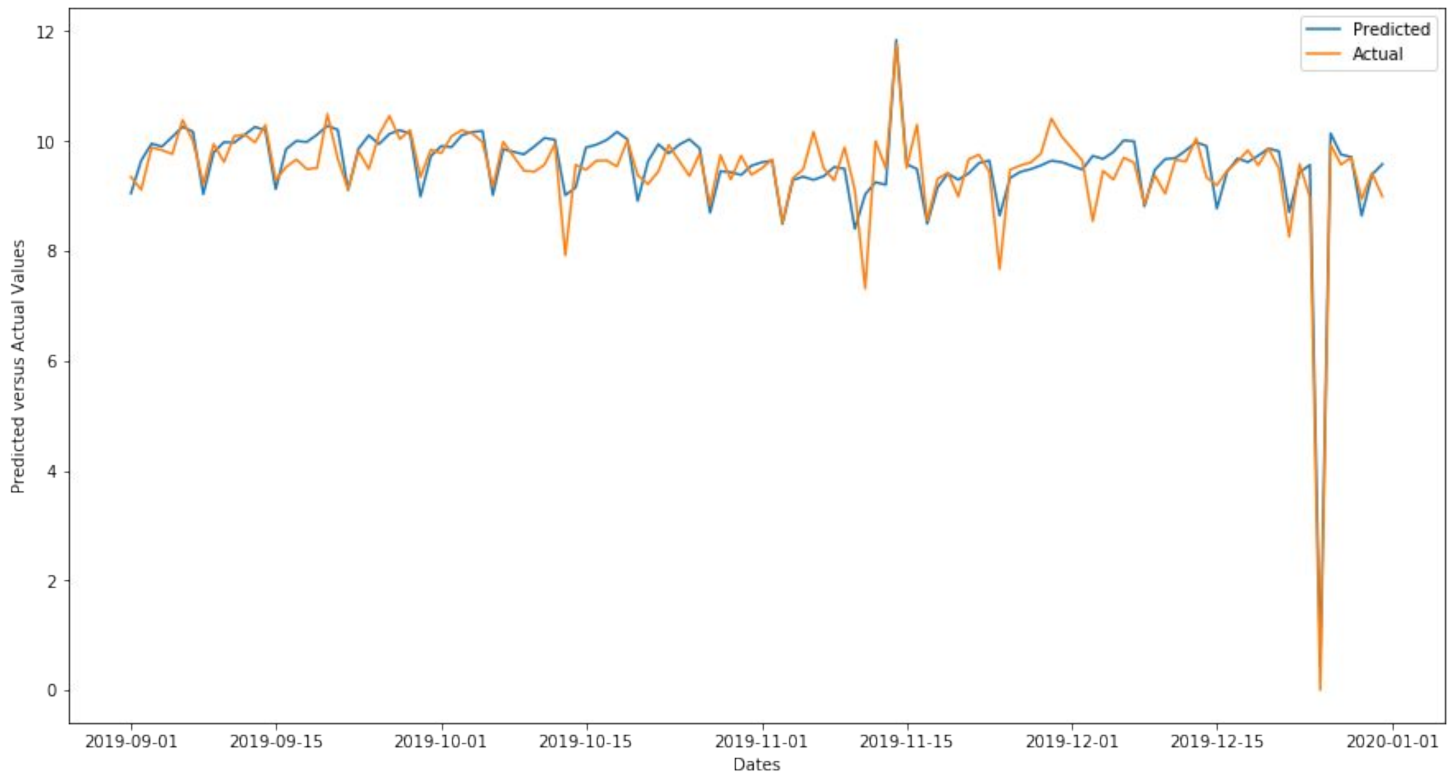
Results

City-level Model:

Average total loss (RMSE):

➢ without weather = 0.728

➢ with weather = 0.723

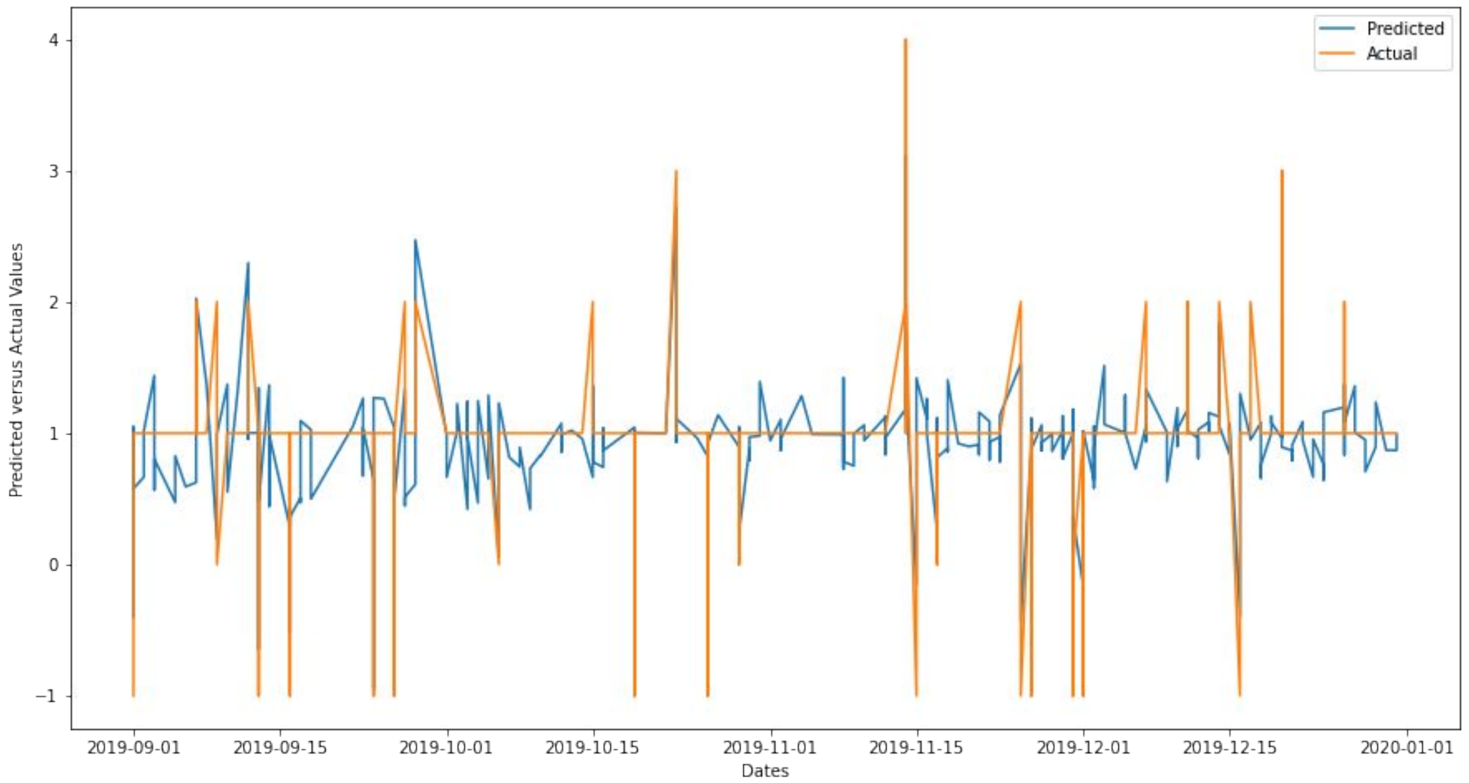


Department-level Model:

Average total loss (RMSE):

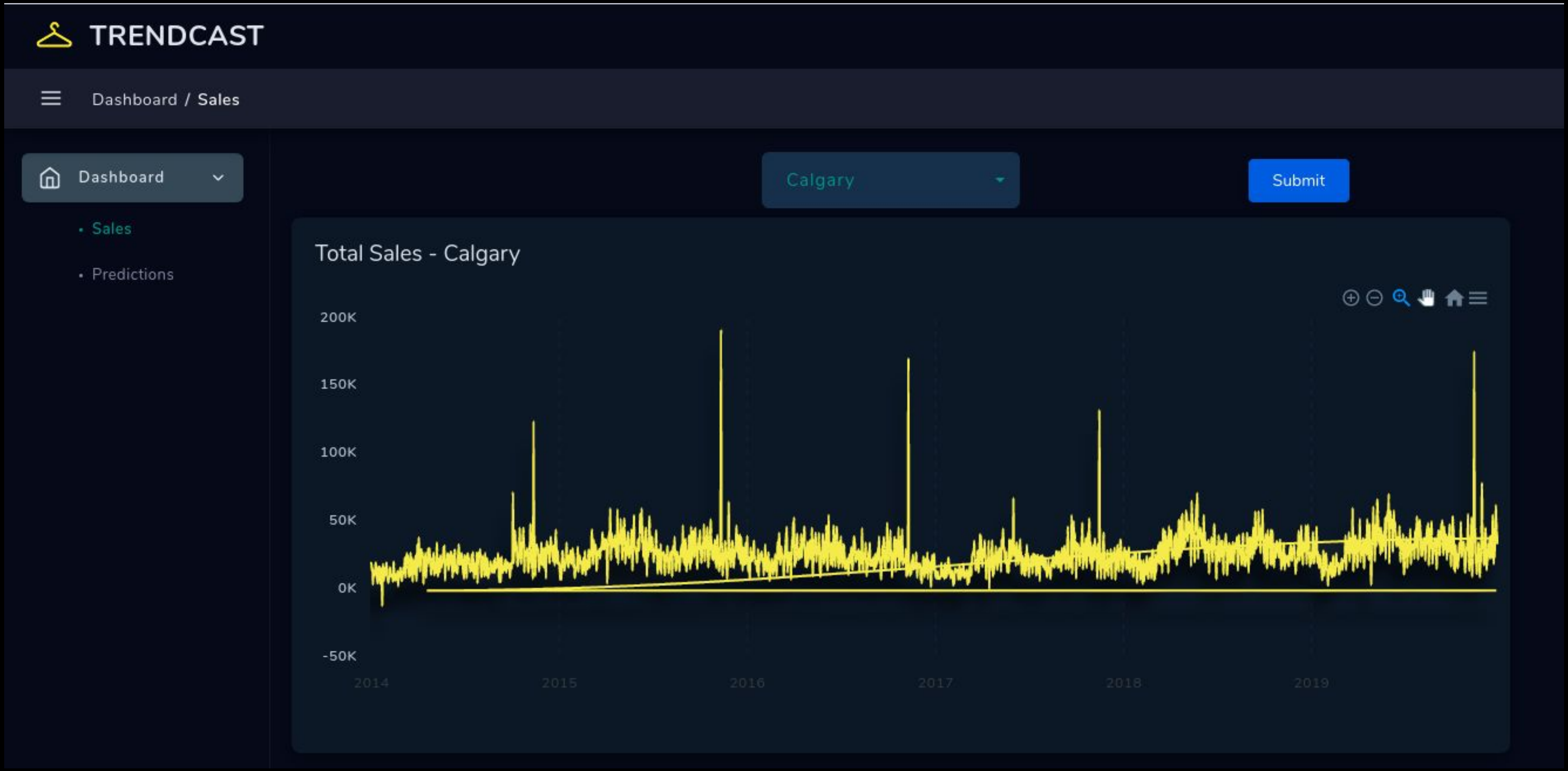
➢ without weather = 0.426

➢ with weather = 0.483



Flask Web Application

- Sales Data



Flask Web Application

- Predictions

Challenges

- ➢ Sparse sales records in Retail Sales data
- ➢ More than 60% missing records in some parts of weather data
- ➢ Imbalanced data and high cardinality
- ➢ High anonymity of data made it hard to apply domain knowledge.

Future Work

- Improve prediction confidence for beyond a week’s time.
- Improve performance for cities with less data and high bias.

Meet The Team

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