42186 Model-based machine learning Project Description

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March 31, 2023



Project Description

Dataset and Research Question

This project set out to predict the delay time of domestic flights in the US and aims at answering the following questions:

- How can the delay of aircraft be predicted?
- How much does weather impact the delay time of the aircrafts?
- What limitations are there in the data and what strategies can be used to overcome them?

The dataset used is part of the Reporting Carrier On-Time Performance Dataset that contains information on domestic flights in the US reported to the United States Bureau of Transportation Statistics from January 2018 to July 2022. The dataset is available for download at Kaggle. Each flight is described in the dataset with basic information such as time, departure time, arrival time at the airport, the number of minutes the time was delayed, and some information about the reason the flight was delayed. In Table 1 the relevant features that will be used in the project are presented. The data will be enriched with weather features from Meteostat Developers API with information about wind speed, wind direction, temperature, precipitation, and visibility. Initially, the modeling will be limited to a specific airport, later results from different airports will be compared.

| Feature Name | Feature Description |
|---------------------------------|--|
| FlightDate | Departure date |
| Airline | Airline |
| Flight_Number_Marketing_Airline | Flight number |
| Origin | Origin of flight trip |
| Dest | Destination of flight trip |
| Cancelled | If the trip got cancelled |
| Diverted | If the flight was rescheduled to another destination |
| CRSDepTime | Time the flight is schedule to departure |
| DepTime | Actual departure time |
| DepDelayMinutes | Number of minutes the flight is delayed |
| OriginCityName | Origin city name |
| OriginStateName | Origin state name |
| DestCityName | Destination city name |
| DestStateName | Destination state name |
| TaxiOut | Time of the aircrafts movment on the ground at departure |
| TaxiIn | Time of the aricrafts movement on the ground at arrival |
| CRSArrTime | Time the flight is schedule to arrive |
| ArrTime | Actual arrival time |
| ArrDelayMinutes | Minutes the flight is delayed at arrival |

Table 1: Relevant features in the Reporting Carrier On-Time Performance Dataset for this project.

Drafts of Models

At least two different models will be tried out, a linear regression and a AR(1) model. For the linear regression model, all the timestamp related features are not included. The rest of the variables are treated as input variables and the target variable is as mentioned the arrival delay time. The generative process for this model is:

- 1. Draw coefficients $\beta \sim \mathcal{N}(\beta \mid \mathbf{0}, \lambda \mathbf{I})$
- 2. For each feature vector \mathbf{x}_n

(a) Draw target
$$y_n \sim \mathcal{N}\left(y_n \mid \boldsymbol{\beta}^{\top} \mathbf{x}_n, \sigma^2\right)$$

The PGM for this generative process is seen in Figure 1.

When implementing the AR(1)-model, the input variable is the arrival time timestamp and the target variable is the arrival delay times. The rest of the features including the weather features are treated as external features ($\mathbf{x_t}$). The generative process for this Ar(1) process is:

- 1. Draw transition coefficients β for the hidden states, $\beta \sim \mathcal{N}(\mathbf{0}, \lambda_1)$
- 2. Draw global variance for the observations, $\sigma^2 \sim \text{HalfCauchy}(\sigma^2 \mid \lambda_2)$
- 3. Draw global variance for the transitions, $\tau \sim \text{HalfCauchy}(\tau \mid \lambda_2)$
- 4. Draw first hidden state, $h_1 \sim \mathcal{N}(h_1 \mid \mu_0 + \mathbf{w}\mathbf{x}_1, \tau_0)$
- 5. Draw second hidden state, $h_2 \sim \mathcal{N} (h_2 \mid \beta_1 h_1 + \mathbf{w} \mathbf{x_2}, \tau)$
- 6. For each time $t \in (1)$:
 - (a) Draw observation noise, $\epsilon_t \sim \mathcal{N}\left(\epsilon_t \mid 0, \sigma^2\right)$
 - (b) Draw observation, $y_t \sim \mathcal{N}(y_t \mid h_t, \epsilon_t)$
- 7. for each time $t \in (2, ..., T)$:
 - (a) Draw transition noise, $r_t \sim \mathcal{N}(r_t \mid 0, \tau)$
 - (b) Draw transition, $h_t \sim \mathcal{N}(h_t \mid \beta_1 \cdot h_{t-1} + \mathbf{w}\mathbf{x_t}, r_t)$
 - (c) Draw observation noise, $\epsilon_t \sim \mathcal{N}\left(\epsilon_t \mid 0, \sigma^2\right)$
 - (d) Draw observation, $y_t \sim \mathcal{N}(y_t \mid h_t, \epsilon_t)$

The PGM for this generative process is also seen in Figure 1.

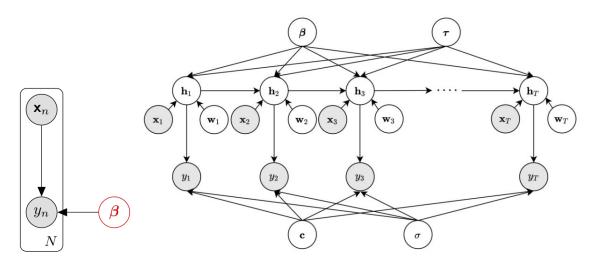


Figure 1: PGMs of the linear regression model and the AR(1) model.

notebook

March 31, 2023

1 MBML 2023

1.1 INIT

1.1.1 Load Packages

```
[]: import pandas as pd
import kaggle
import os
import shutil
import requests
import urllib
from urllib.request import urlopen, urlretrieve
from io import BytesIO
from zipfile import ZipFile
import matplotlib.pyplot as plt
import plotly.express as px
from IPython.display import Image
import numpy as np
from src.data import extract, load, transform
```

1.1.2 Set Flags

```
[]: pd.set_option('display.max_colwidth', None)
pd.set_option('display.max_columns', None)

DATA_DIR = "data/"
```

1.2 Data

1.2.1 Extract Data

```
[]: # Download Fligt Delay Dataset form Kaggle
kaggle.api.authenticate()
kaggle.api.dataset_download_files(
    "robikscube/flight-delay-dataset-20182022",
```

```
path=DATA_DIR,
  unzip=True,
)

for filename in os.listdir(DATA_DIR):
    f = os.path.join(DATA_DIR, filename)
    if f.endswith(".parquet") or filename == "Airlines.csv":
        pass
    else:
        if os.path.isfile(f):
            os.remove(f)
        else:
            shutil.rmtree(f)
```

```
[]: # Download Location of airports
urlretrieve(
    "https://raw.githubusercontent.com/lxndrblz/Airports/main/airports.csv",
    DATA_DIR + "airports.csv"
    )
```

1.2.2 Transform Data

1.2.3 Load Data

```
[]: main_df = extract.combine_parquet(data_path = "data/")
    main_df['count'] = 1
    airport_df = pd.read_csv('data/airports.csv')
    airline_df = pd.read_csv('data/Airlines.csv')
```

1.2.4 Define display options for later export to pdf

```
[]: pd.set_option('display.notebook_repr_html', True)

def _repr_latex_(self):
    return "\centering{%s}" % self.to_latex()

pd.DataFrame._repr_latex_ = _repr_latex_ # monkey patch pandas DataFrame
```

```
[]: # silence future warnings
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

```
[]: # set max number of rows of dataframe pd.set_option('display.max_rows', 80)
```

1.2.5 Describe Data

Display two first rows of data

pd.DataFrame(main_df.iloc[:2,:30].T)

| | 0 | 1 |
|---|----------------------|--------------------|
| FlightDate | 2018-01-23 00:00:00 | 2018-01-24 00:00:0 |
| Airline | Endeavor Air Inc. | Endeavor Air Inc. |
| Origin | ABY | ABY |
| Dest | ATL | ATL |
| Cancelled | False | False |
| Diverted | False | False |
| CRSDepTime | 1202 | 1202 |
| DepTime | 1157.0 | 1157.0 |
| DepDelayMinutes | 0.0 | 0.0 |
| DepDelay | -5.0 | -5.0 |
| ArrTime | 1256.0 | 1258.0 |
| ArrDelayMinutes | 0.0 | 0.0 |
| AirTime | 38.0 | 36.0 |
| CRSElapsedTime | 62.0 | 62.0 |
| ActualElapsedTime | 59.0 | 61.0 |
| Distance | 145.0 | 145.0 |
| Year | 2018 | 2018 |
| Quarter | 1 | 1 |
| Month | 1 | 1 |
| DayofMonth | 23 | 24 |
| DayOfWeek | 2 | 3 |
| Marketing_Airline_Network | DL | DL |
| Operated_or_Branded_Code_Share_Partners | DL_CODESHARE | DL_CODESHAR |
| DOT_ID_Marketing_Airline | 19790 | 19790 |
| IATA_Code_Marketing_Airline | DL | DL |
| Flight_Number_Marketing_Airline | 3298 | 3298 |
| Operating_Airline | 9E | 9E |
| DOT_ID_Operating_Airline | 20363 | 20363 |
| IATA_Code_Operating_Airline | 9E | 9E |
| Tail_Number | N8928A | N800AY |

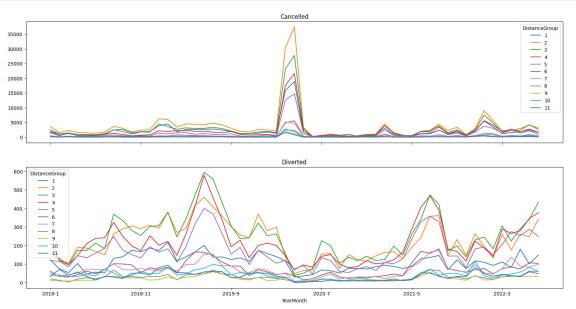
[]: pd.DataFrame(main_df.iloc[:2,30:].T)

[]:

| | 0 | 1 |
|---------------------------------|-------------|-------------|
| Flight_Number_Operating_Airline | 3298 | 3298 |
| OriginAirportID | 10146 | 10146 |
| OriginAirportSeqID | 1014602 | 1014602 |
| OriginCityMarketID | 30146 | 30146 |
| OriginCityName | Albany, GA | Albany, GA |
| OriginState | GA | GA |
| OriginStateFips | 13 | 13 |
| OriginStateName | Georgia | Georgia |
| OriginWac | 34 | 34 |
| DestAirportID | 10397 | 10397 |
| DestAirportSeqID | 1039707 | 1039707 |
| DestCityMarketID | 30397 | 30397 |
| DestCityName | Atlanta, GA | Atlanta, GA |
| DestState | GA | GA |
| DestStateFips | 13 | 13 |
| DestStateName | Georgia | Georgia |
| DestWac | 34 | 34 |
| DepDel15 | 0.0 | 0.0 |
| DepartureDelayGroups | -1.0 | -1.0 |
| DepTimeBlk | 1200 - 1259 | 1200 - 1259 |
| TaxiOut | 14.0 | 13.0 |
| WheelsOff | 1211.0 | 1210.0 |
| WheelsOn | 1249.0 | 1246.0 |
| TaxiIn | 7.0 | 12.0 |
| CRSArrTime | 1304 | 1304 |
| ArrDelay | -8.0 | -6.0 |
| ArrDel15 | 0.0 | 0.0 |
| ArrivalDelayGroups | -1.0 | -1.0 |
| ArrTimeBlk | 1300-1359 | 1300-1359 |
| DistanceGroup | 1 | 1 |
| DivAirportLandings | 0.0 | 0.0 |
| count | 1 | 1 |

```
g_main_df[[prediction_cols[i],"YearMonth"]].

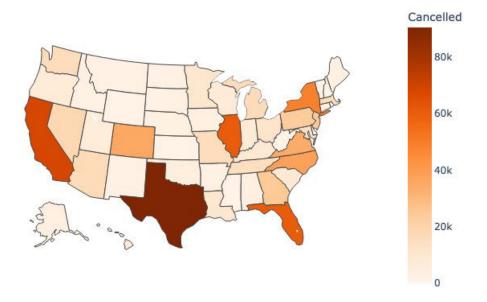
plot(x="YearMonth",y=prediction_cols[i],kind = "line", legend = True,ax = ax[i],sharex = True,title = prediction_cols[i])
```



```
[]: g_main_df = main_df.groupby(["OriginState"]).sum()
```

[]:

Count of Cancelled flights by origin state



```
[]: state_df = g_main_df[['Cancelled', 'count']].reset_index()
     state_df["ratio"] = state_df['Cancelled']/state_df['count']
     # plot a choropleth with color range by count per state
     fig = px.choropleth(state_df,
                         locations='OriginState',
                         locationmode="USA-states",
                         scope="usa",
                         color="ratio",
                         color_continuous_scale="Oranges",
     # center the title
     fig.update_layout(title_text='Ratio of Cancelled flights by origin state', u
      \rightarrowtitle_x=0.5)
     # export plot to image to compatability with pdf conversion
     #fig.show()
     im = fig.to_image("jpeg")
     Image(im)
```

[]:

Ratio of Cancelled flights by origin state

