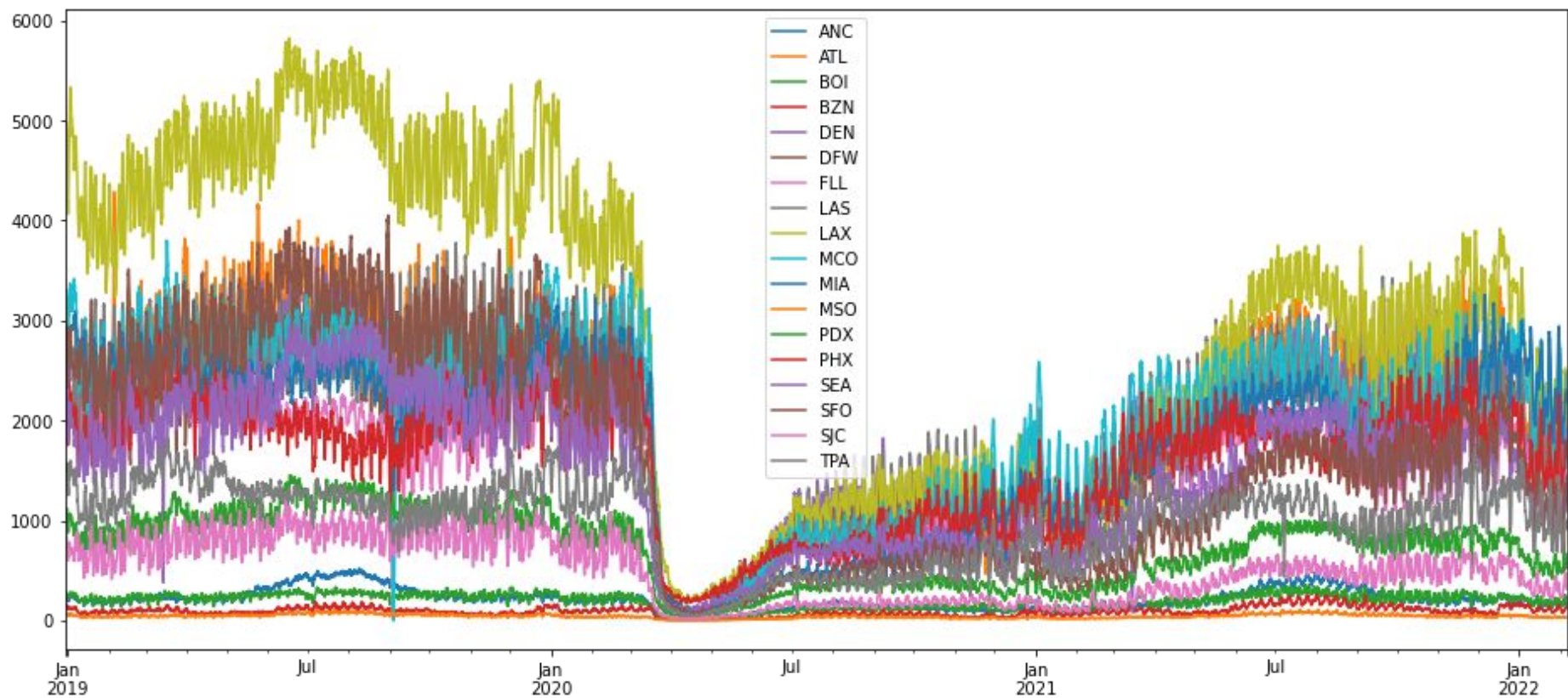


Predict TSA Throughput

A time series analysis

Problem Identification and Business Context



Predictive model - TSA Throughput

Purpose:

- Allow airports and airlines make better resource allocation and staffing decisions
- TSA efficiency and customer service
- Recovering from Covid-19 travel restrictions beginning in March 2020

Stakeholders:

- Airports
- Airlines
- Airport businesses

Challenges:

- Extreme weather
- War
- Pandemics

Data Collection

Data gathering: Github repository (source)

- Individual Csv files for each airport
- Columns for each gate
- Values: TSA throughput (number of people going through security)

Data Collection

Building final Dataframe:

- Aggregate all gates within an airport
- A column for each airport
- Datetime Index (hourly)

Data Exploration and Cleaning

Data

18 columns: US International Airports

27216 rows: Hourly Data between

December 30th 2018 – February 5th 2022

Values: Number of people going through security

Airports

ANC - Anchorage

ATL - Atlanta

BOI - Boise

BZN - Bozeman

DEN - Denver

DFW - Dallas Fort Worth

FLL - Fort Lauderdale

LAS - Las Vegas

LAX - Los Angeles

MCO - Orlando

MIA - Miami

MSO - Missoula Montana

PDX - Portland

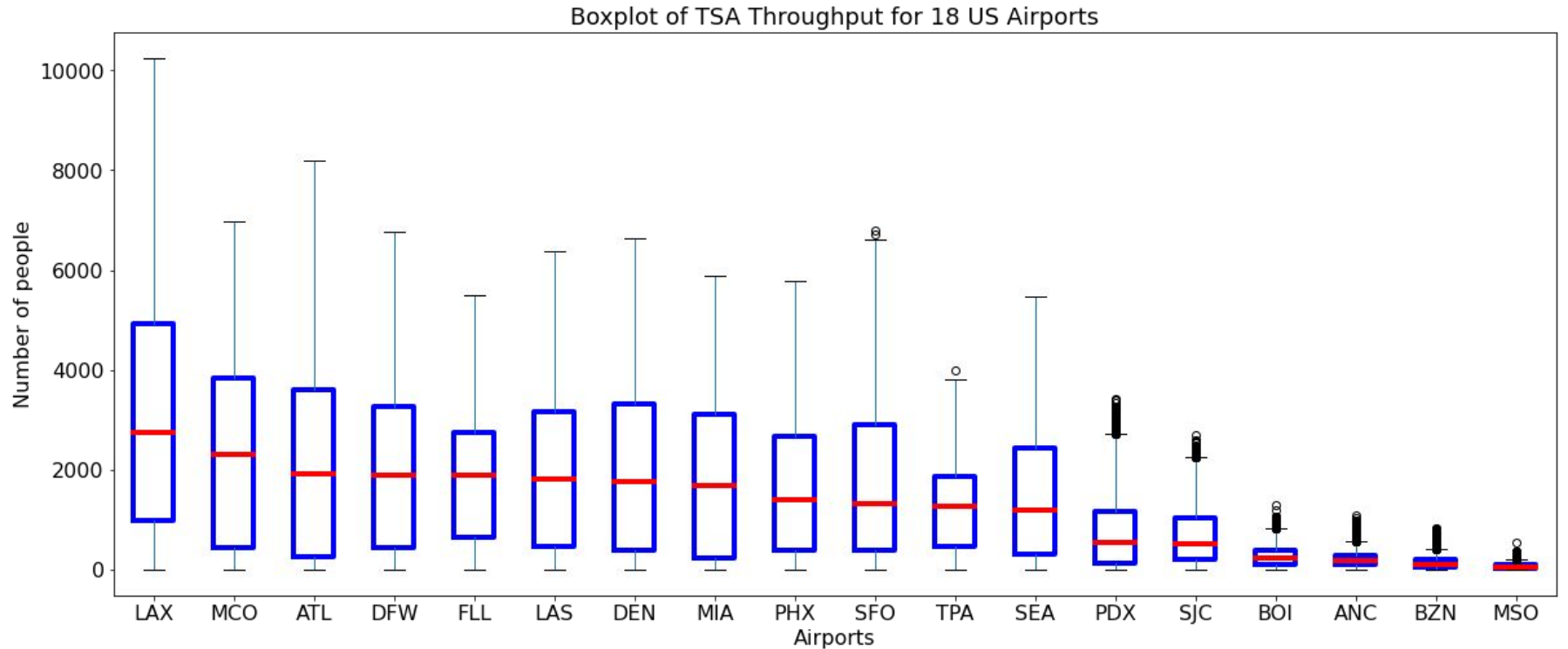
SEA - Seattle

SFO - San Francisco

SJC - San Jose

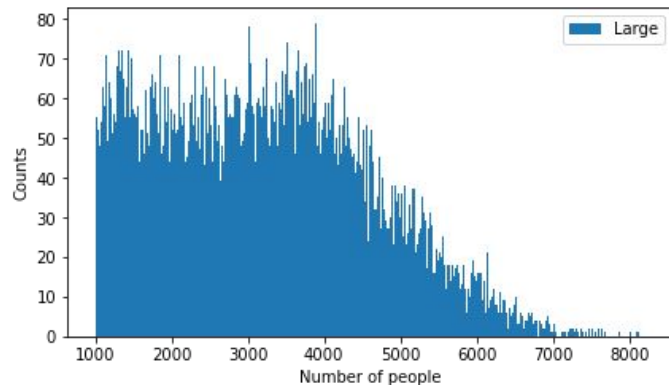
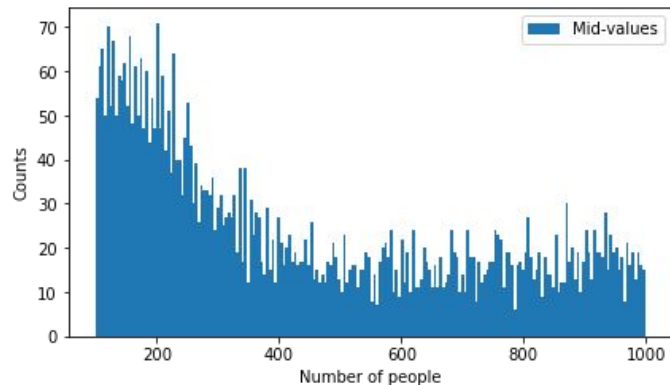
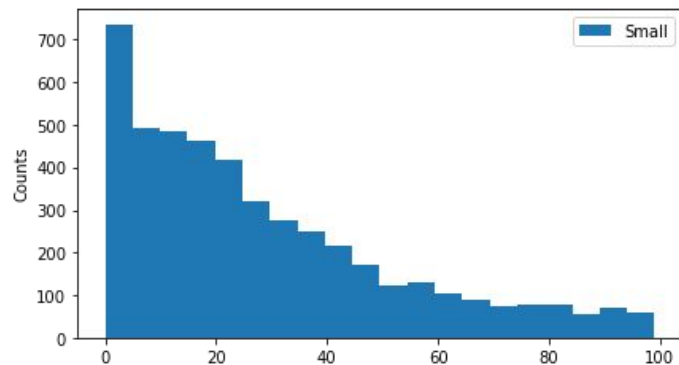
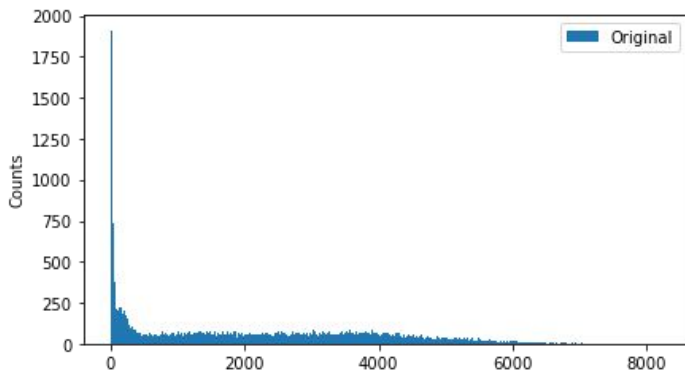
TPA - Tampa

Boxplots



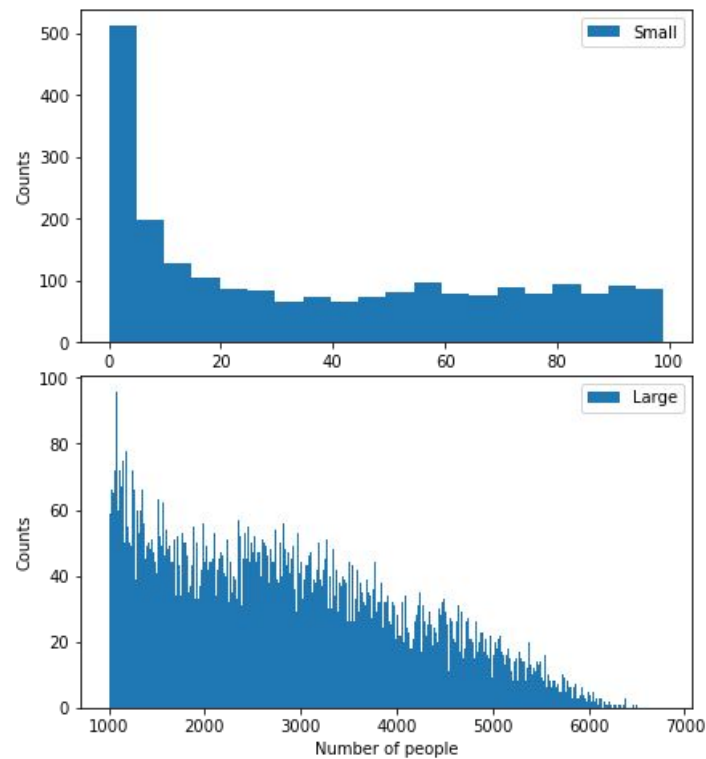
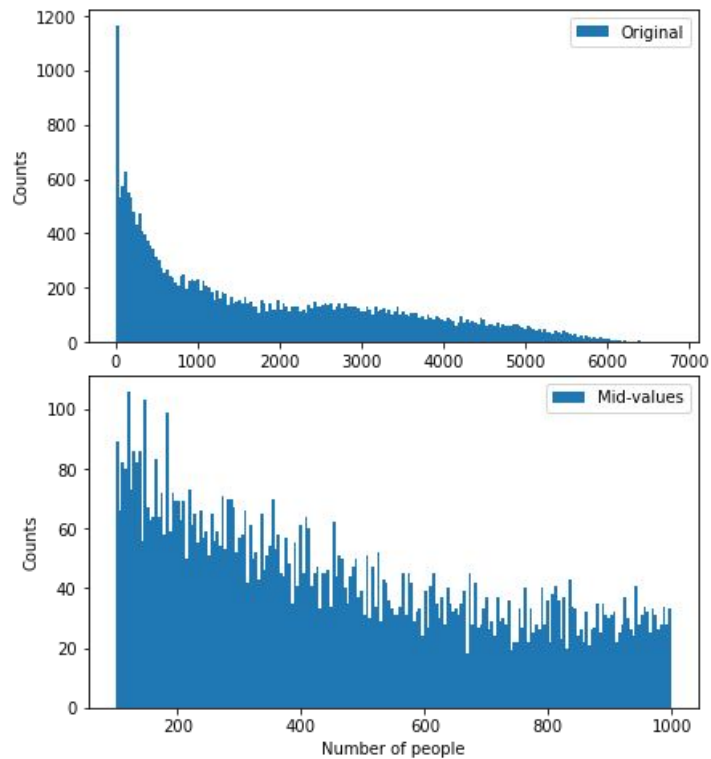
Histograms

ATL



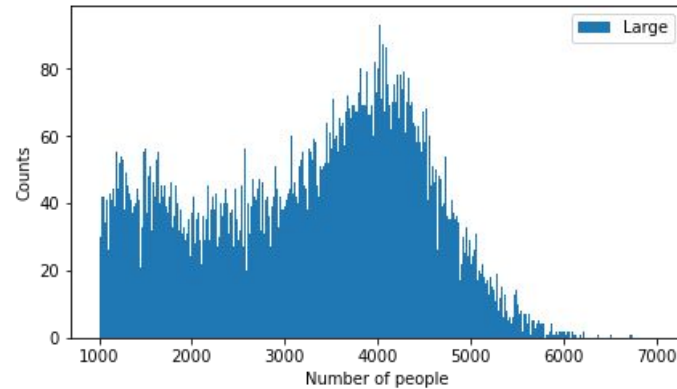
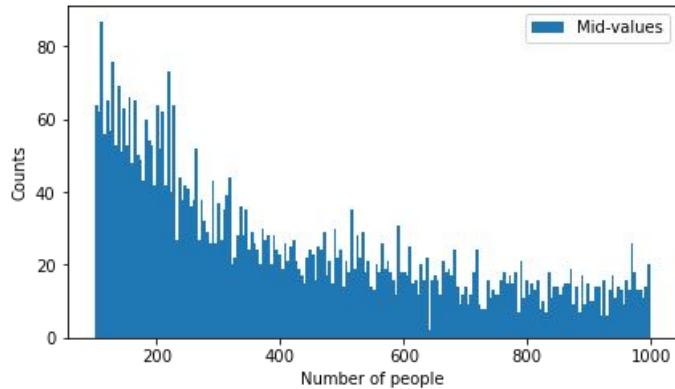
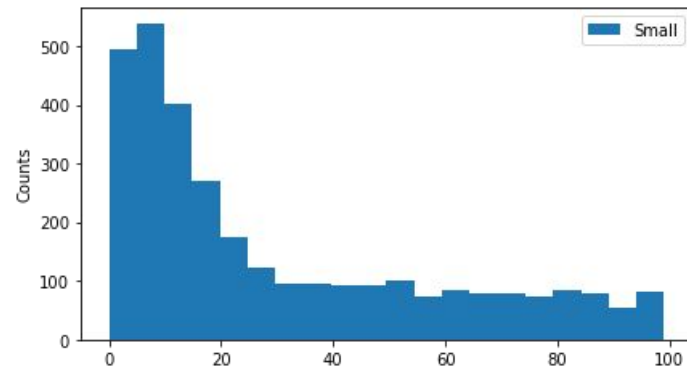
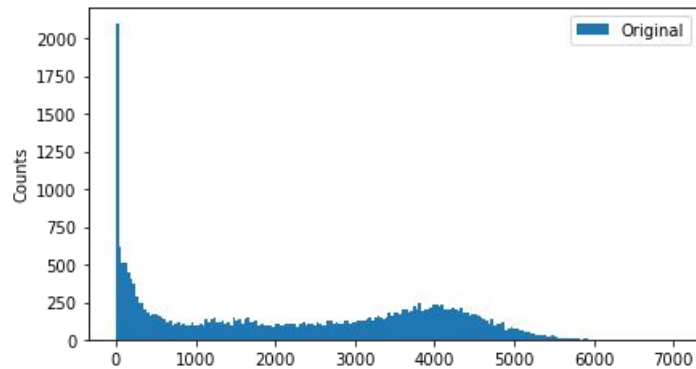
Histograms

SFO



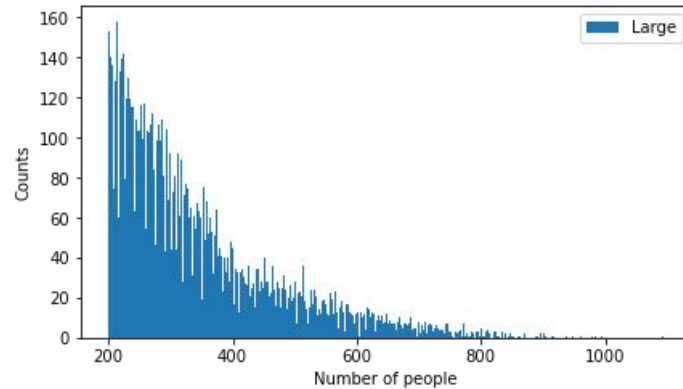
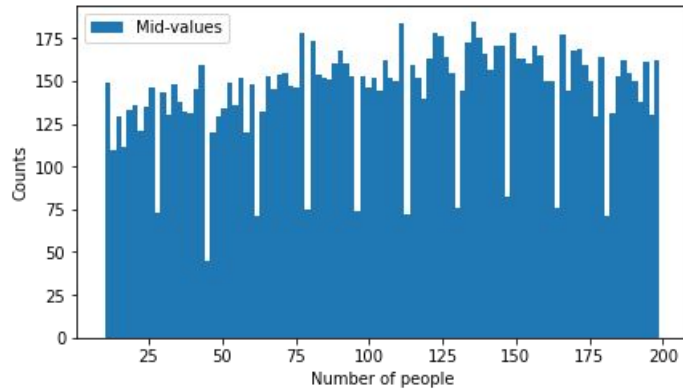
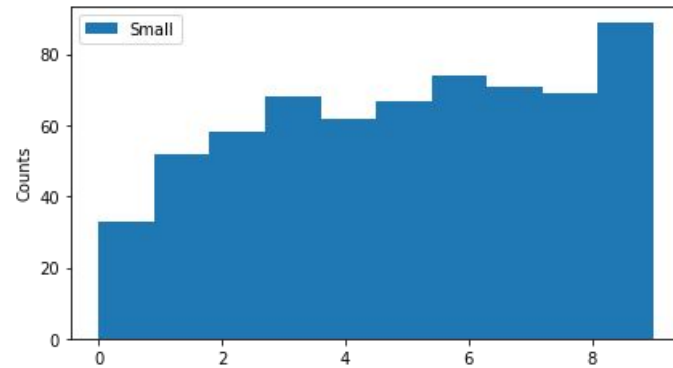
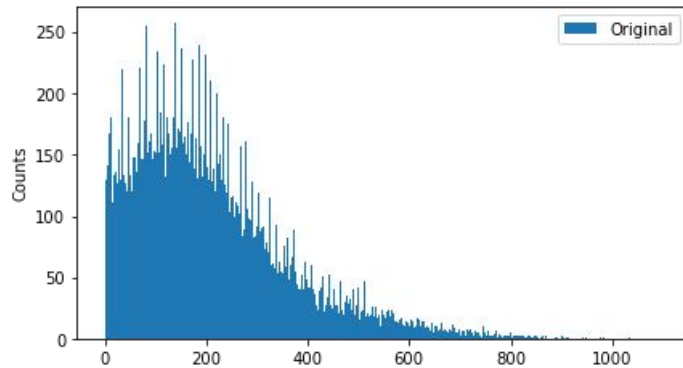
Histograms

MCO



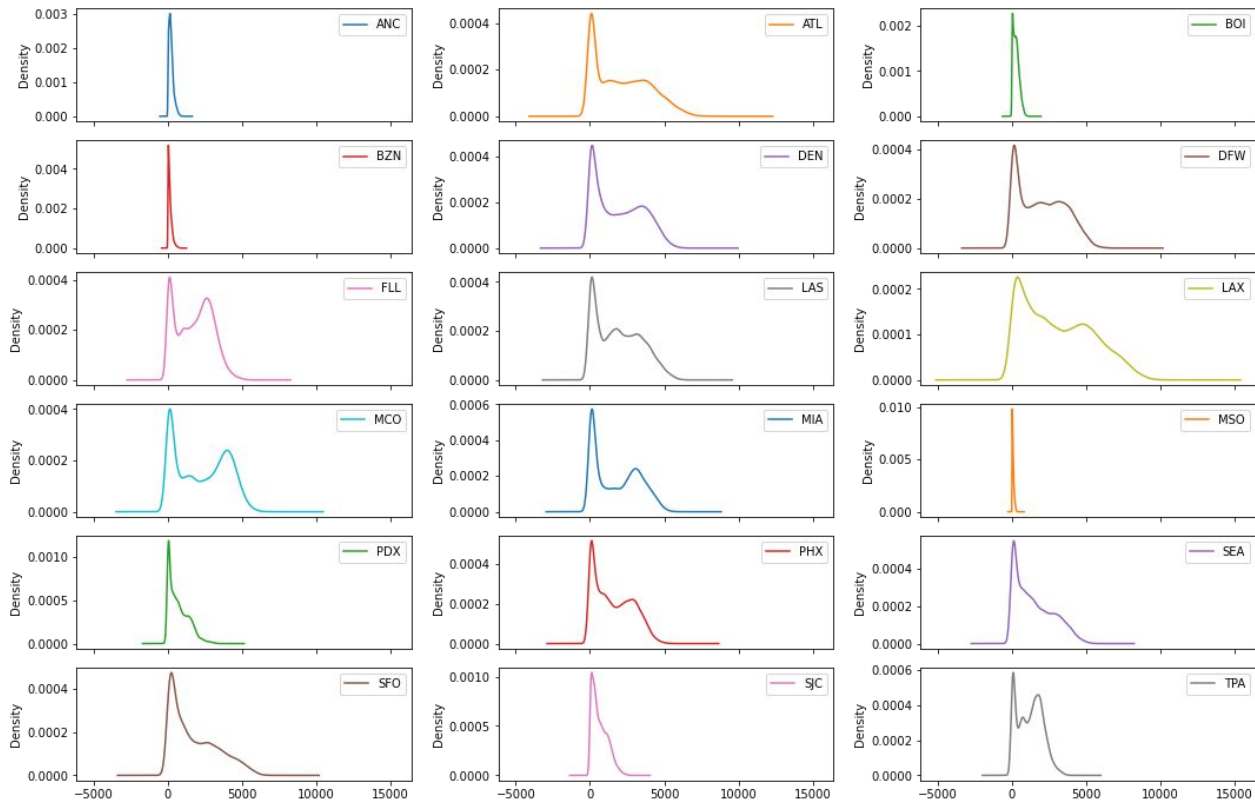
Histograms

ANC



Density Plots

Density plots for each airport

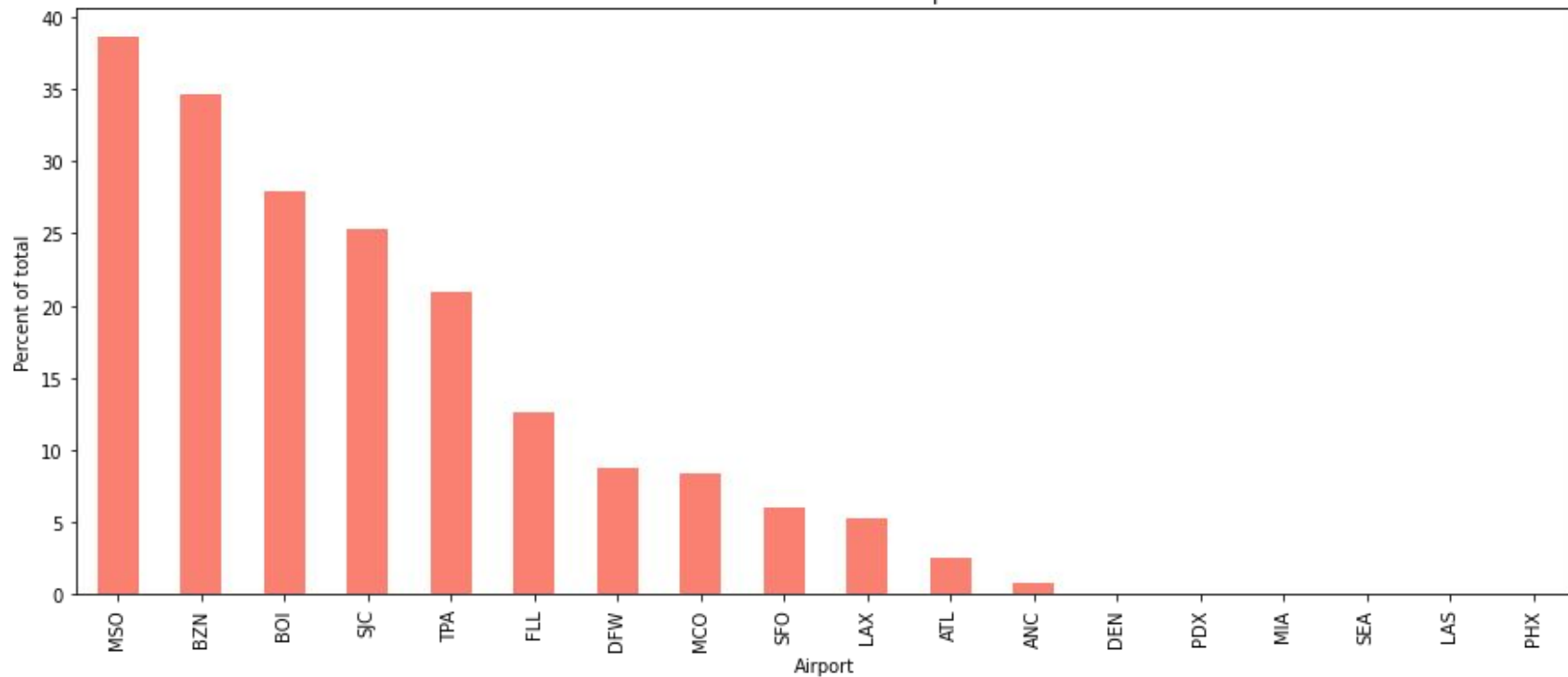


Data Distribution

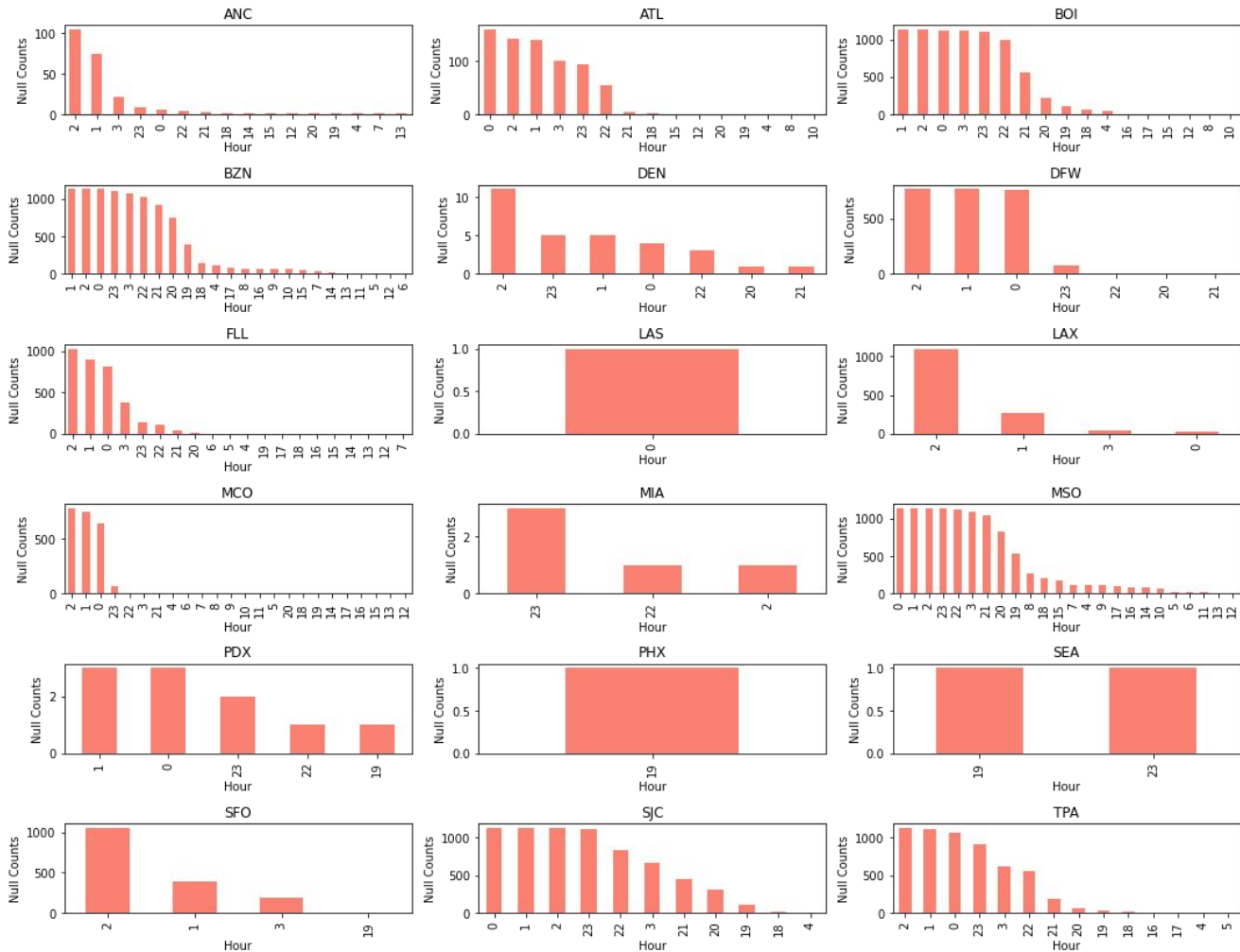
- First peak for relatively low counts
- Large airports have a second peak at higher counts
- Extremely busy times with relatively large throughput are much more rare

Null values

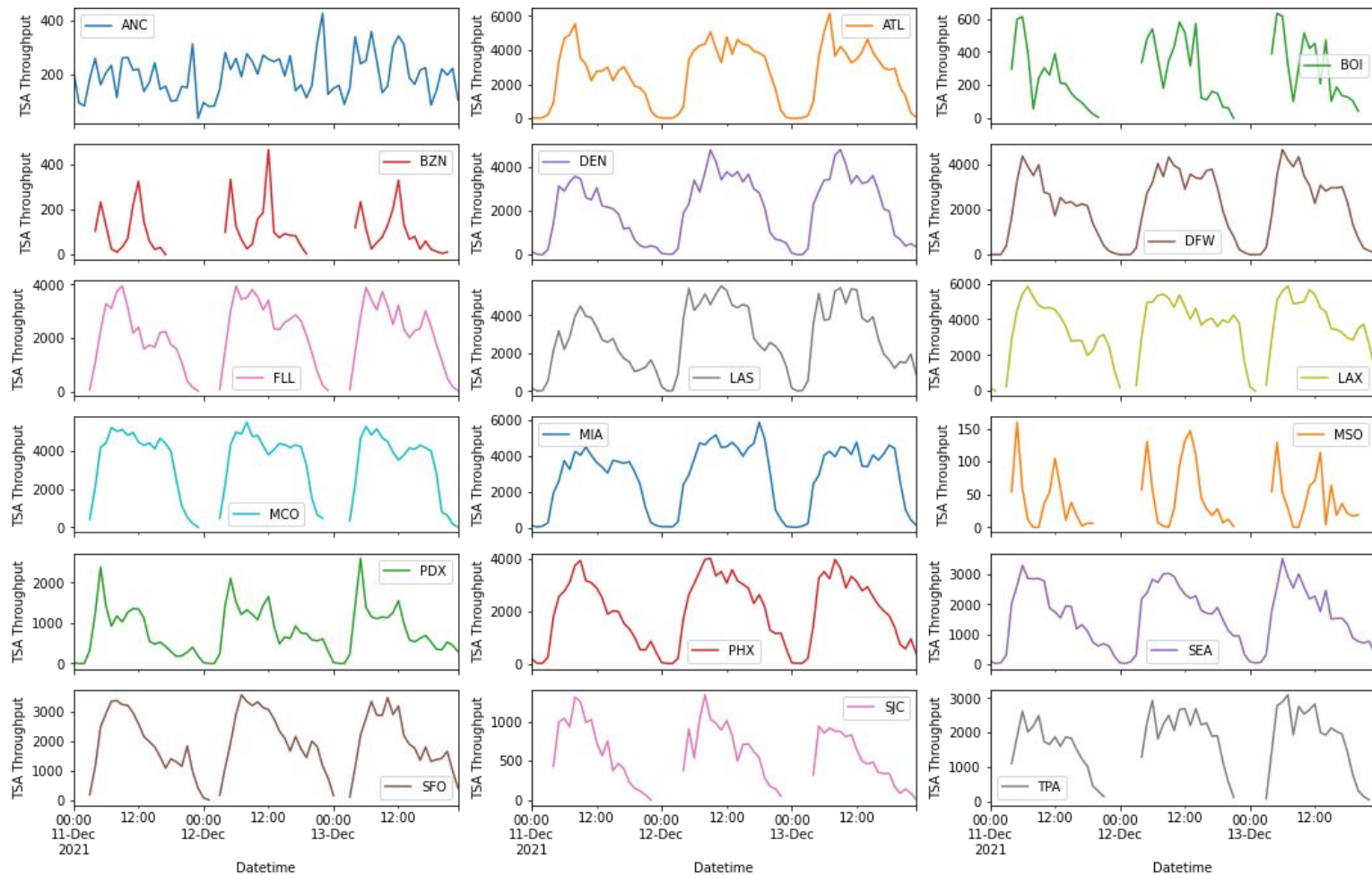
Percent null for each airport



Null value distribution per hour for each airport



TSA Throughput Timeseries (2-day slice)

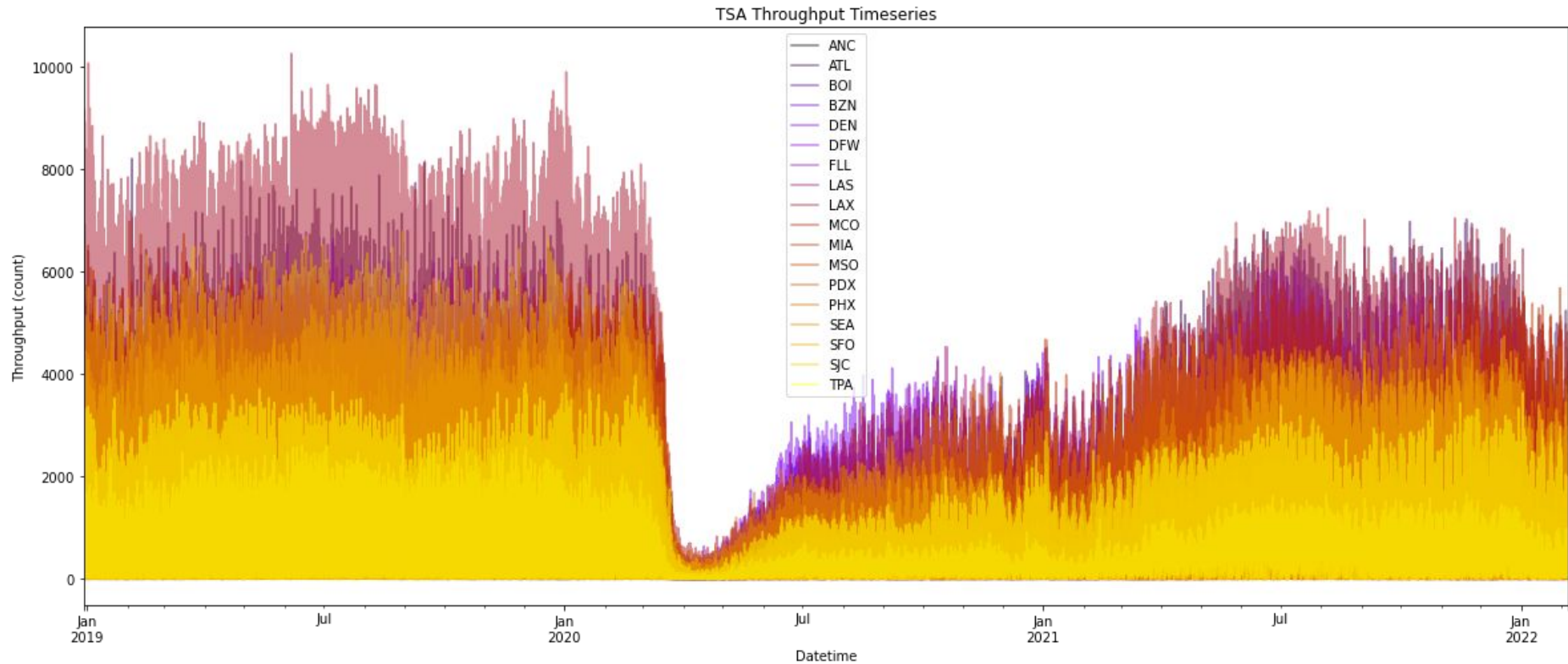


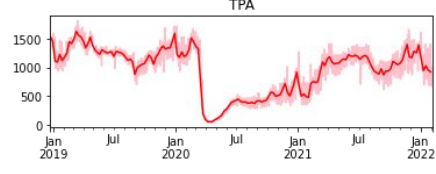
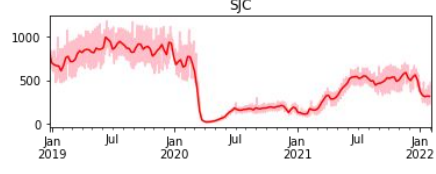
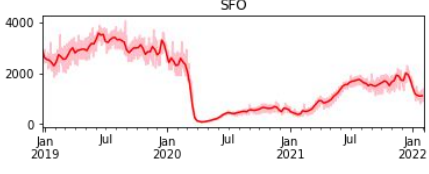
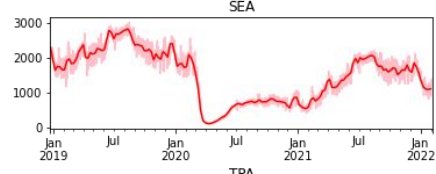
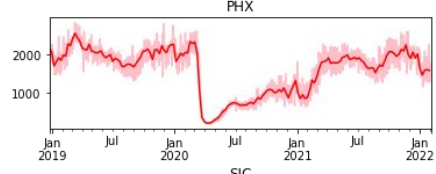
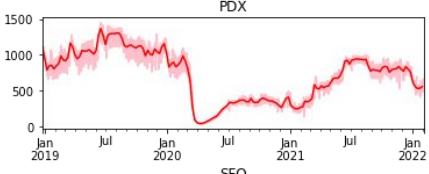
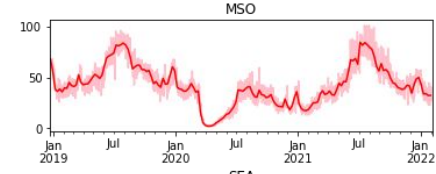
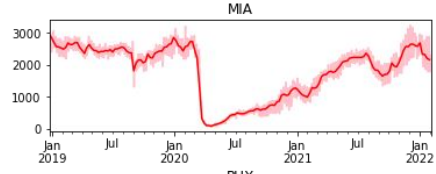
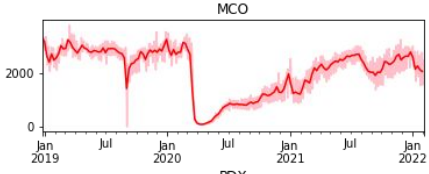
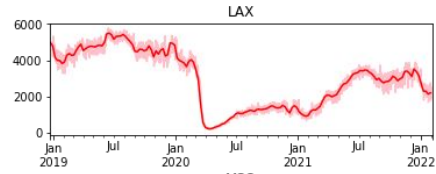
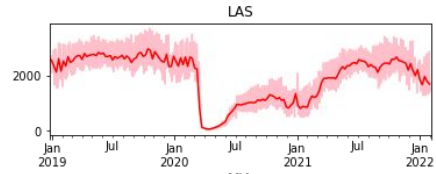
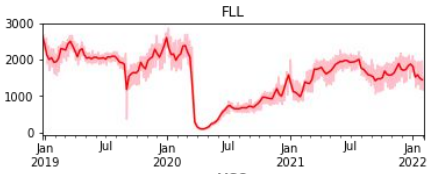
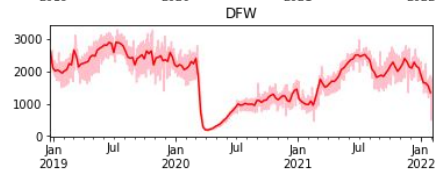
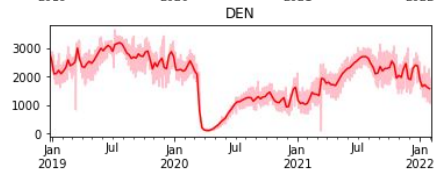
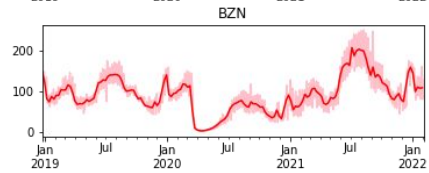
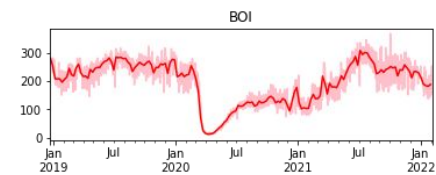
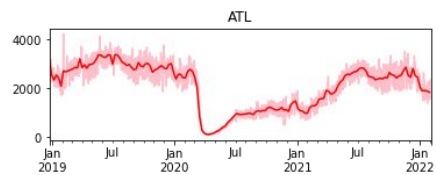
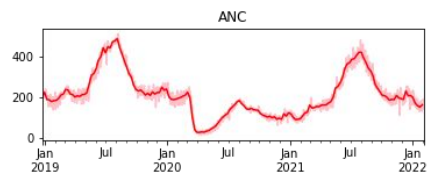
Null value treatment

- Small airports have a higher ratio of values missing than large airports
(Outgoing flight times for small vs large airports)
- Missing values are concentrated in late evening to early morning hours
(Least common times for outgoing flights for large airports)

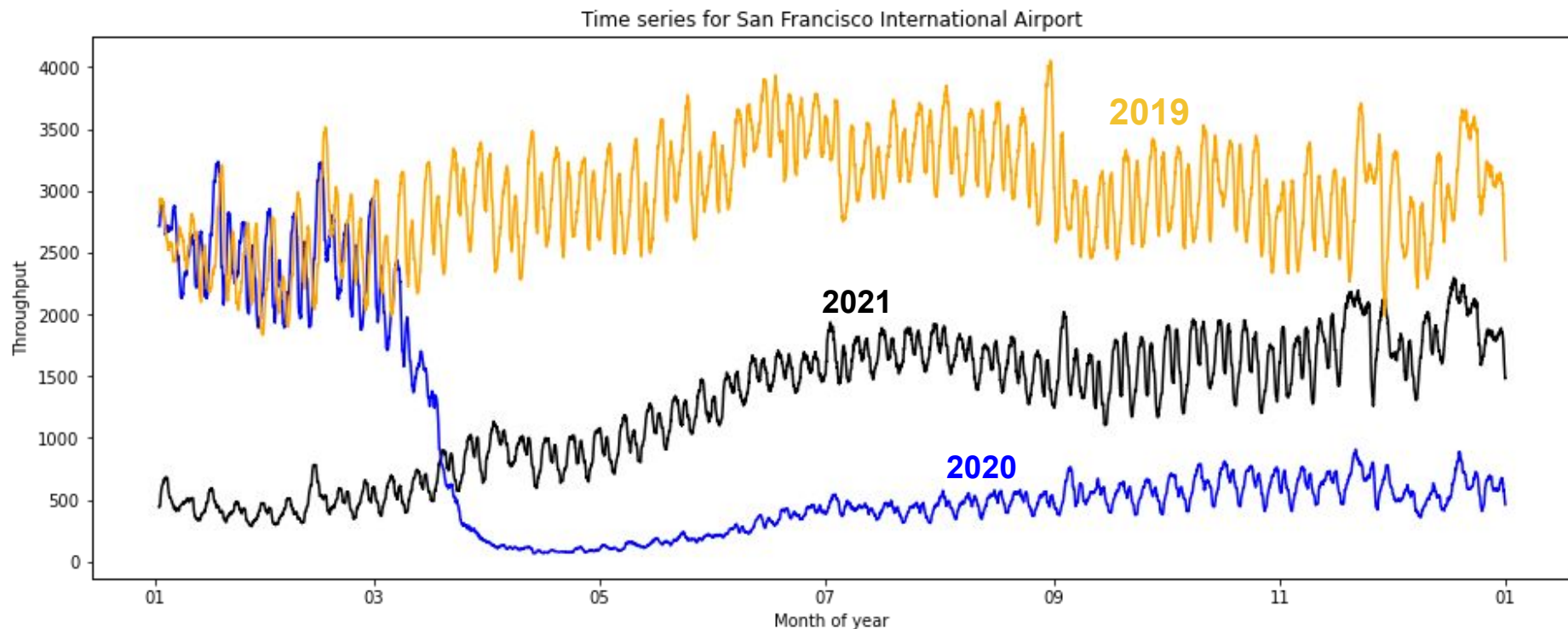
Impute null values with ZERO

Time Series Plot - All Airports

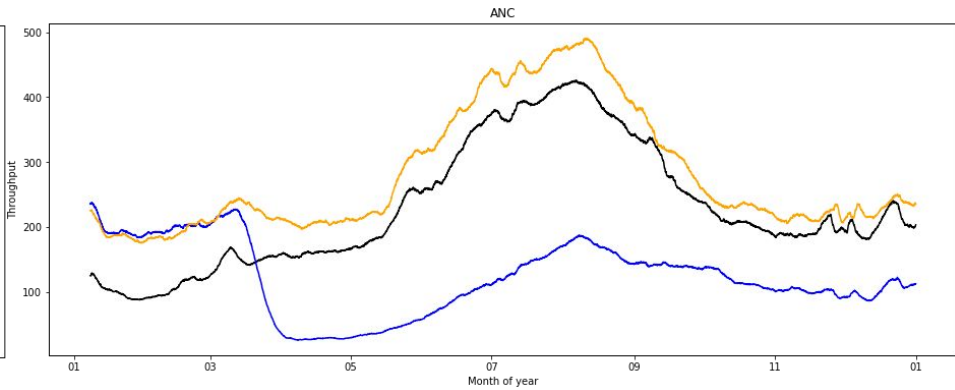
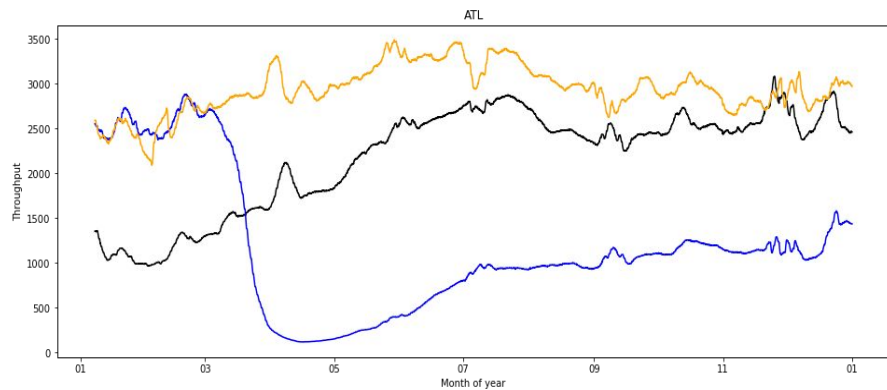
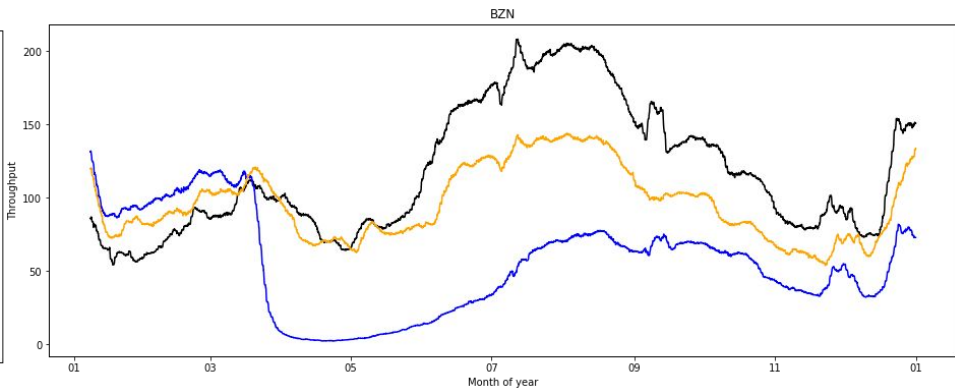
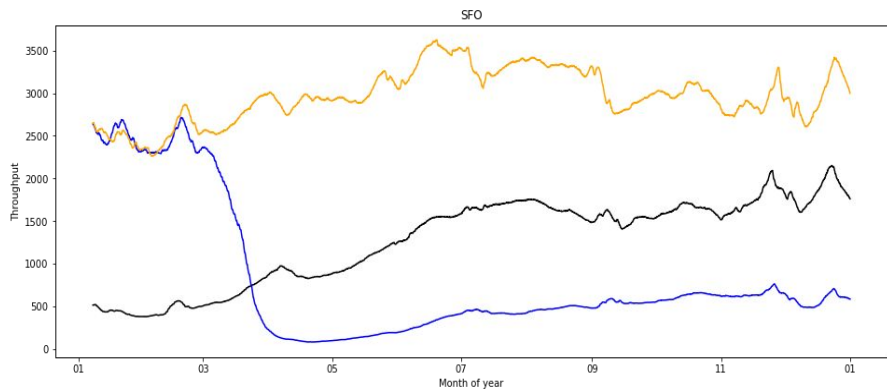




Yearly Trends - SFO

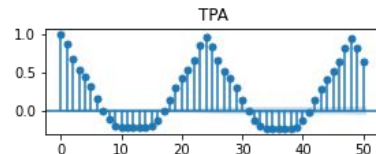
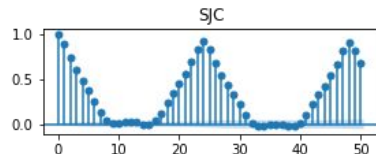
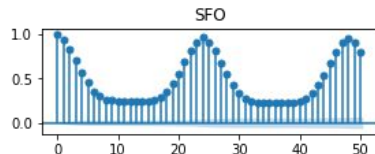
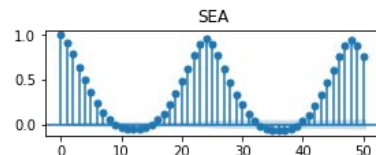
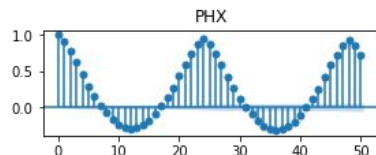
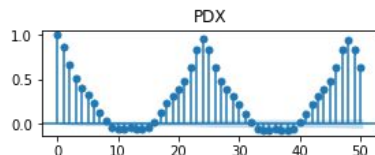
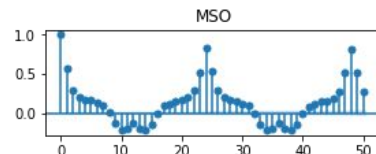
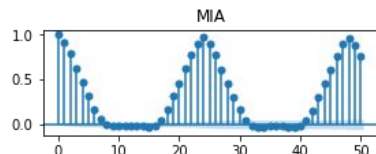
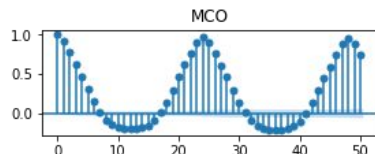
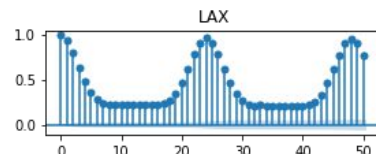
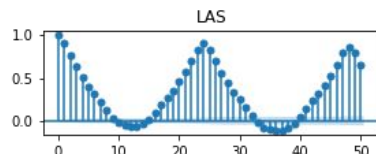
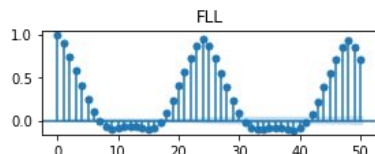
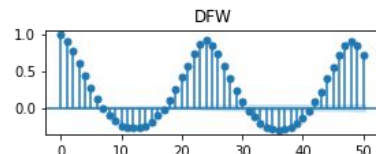
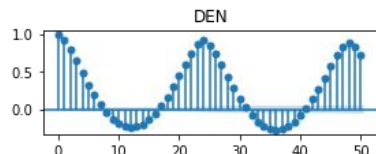
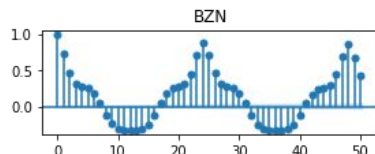
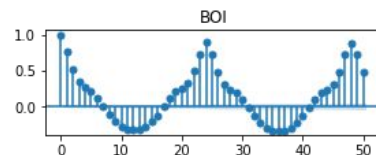
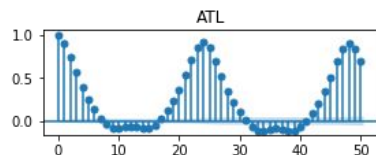
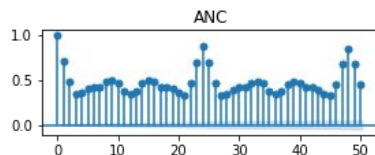


Yearly Trends



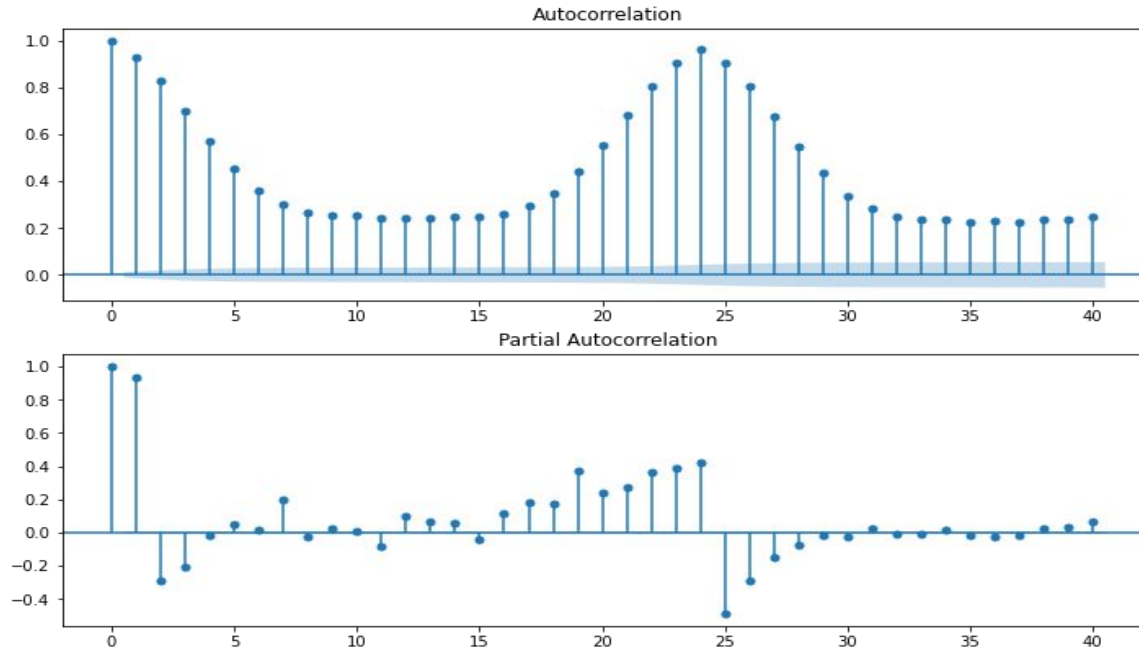
Preprocessing and Training

Autocorrelation



Seasonality - SFO

Strong seasonality with period of 24 (hours)

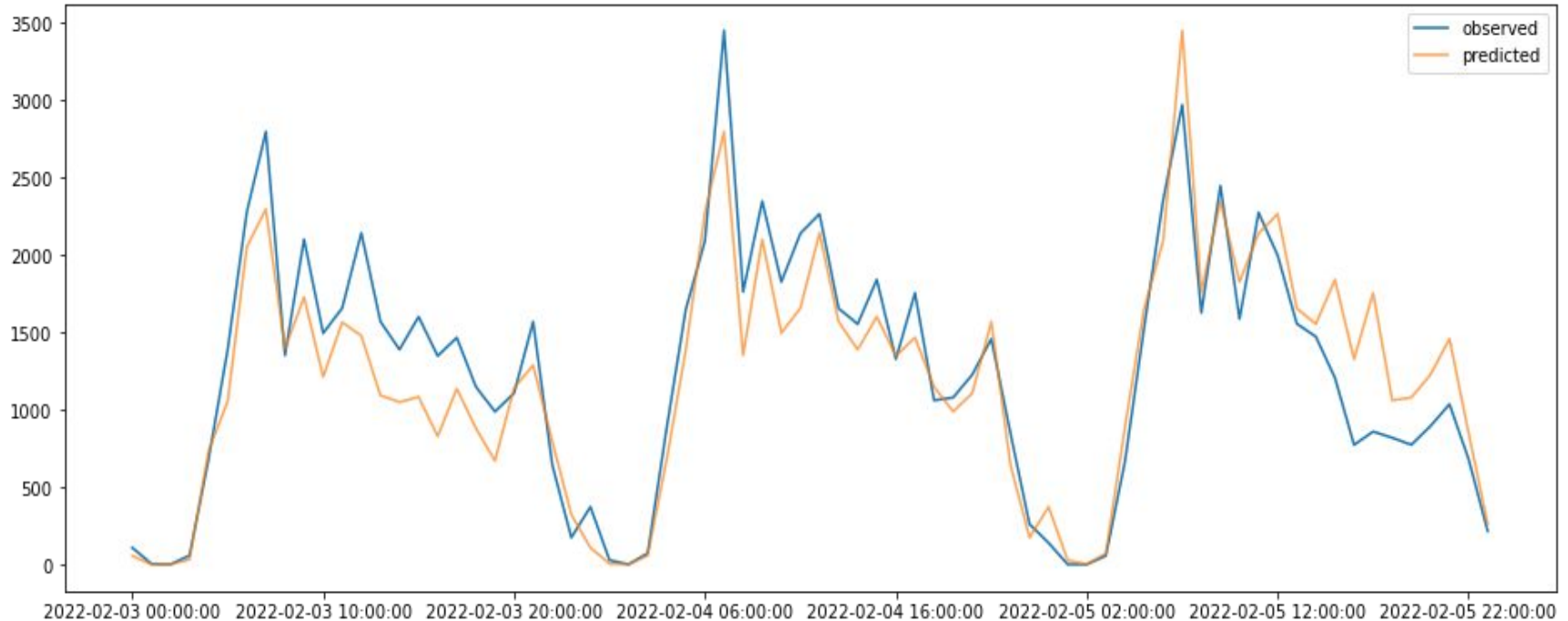


Augmented Dicky-Fuller Test

- Null hypothesis - time series is non-stationary
- Only tests for trend
- Reject null if p-value is small (less than 5%)

Baseline Model - Yesterday's values

Mean Error = 276 people



Modeling

ARIMA Model

Grid search

$(p, d, q) \times (P, D, Q, S)$

Evaluate Model

Prediction

Future work: