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PRESENTATION COMPONENTS:

- PROJECT DESCRIPTION
- DATA SOURCES
- DATA RETRIEVAL AND CLEANING
- DATA VISUALIZATION AND ANALYSIS
- CONCLUSIONS



We looked at U.S. flight data from 2015-2018 and focused specifically on cancellations from weather. We looked at weather factors such as wind speed, precipitation, and temperature as well as time of year to make determinations around whether those factors had an effect on cancellation.

RESEARCH QUESTIONS



01

MONTH/YEAR

How does month of year impact flight cancellations in the U.S.?

02

WIND SPEED

How does wind speed affect U.S. flight cancellations by month of year?

03

TEMPERATURE

How does temperature affect U.S. flight cancellations by month of year?

04

PRECIPITATION

How does precipitation type affect U.S. flight cancellations by month of year?



OUR DATA

- LOCATION
- WIND SPEED
- TEMPERATURE
- PRECIPITATION
- TIME

DATA SOURCES

Airline Delay and Cancellation Data, 2009 - 2018 | Kaggle

Visual Crossing Weather | API

Geoapify | API

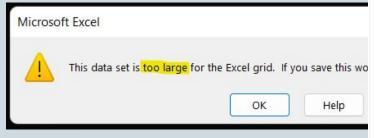
DATA EXPLORATION

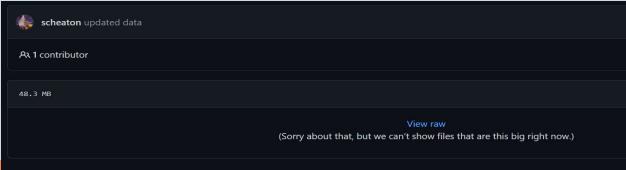
We compiled the following initial data for our exploration:



- Number of observations (raw dataset): Tens of millions
- Flight cancellation data included in our analysis:
 - Cancellations only due to weather
 - Cancelled flight data from 2009-2018
 - Narrowed data down to 2015 to 2018 to look at the most recent 4 years of data
 - Narrowed data to look at the top 5 airports by traffic
 - Airports: DFW, ATL, DEN, ORD, JFK
- Daily Weather Data from Historical Weather API for our selected date range and airport locations
- Longitude, Latitude information from Global Airport Database
- Airport details from the Geoapify API

DATA CLEANUP







Free

\$0/month

Get weather data using a free account without any need for a credit card.

Choose plan

1000 records/day

Single concurrency



```
# Search for null values that d
original_df.isna().sum()
FL_DATE
OP CARRIER
OP_CARRIER_FL_NUM
ORIGIN
DEST
CRS_DEP_TIME
DEP_TIME
                         86153
DEP DELAY
                         86153
TAXI OUT
                         89047
WHEELS_OFF
                         89047
WHEELS ON
                         92513
TAXI_IN
                         92513
CRS_ARR_TIME
ARR_TIME
                         92513
                        105071
ARR DELAY
CANCELLED
                             0
```



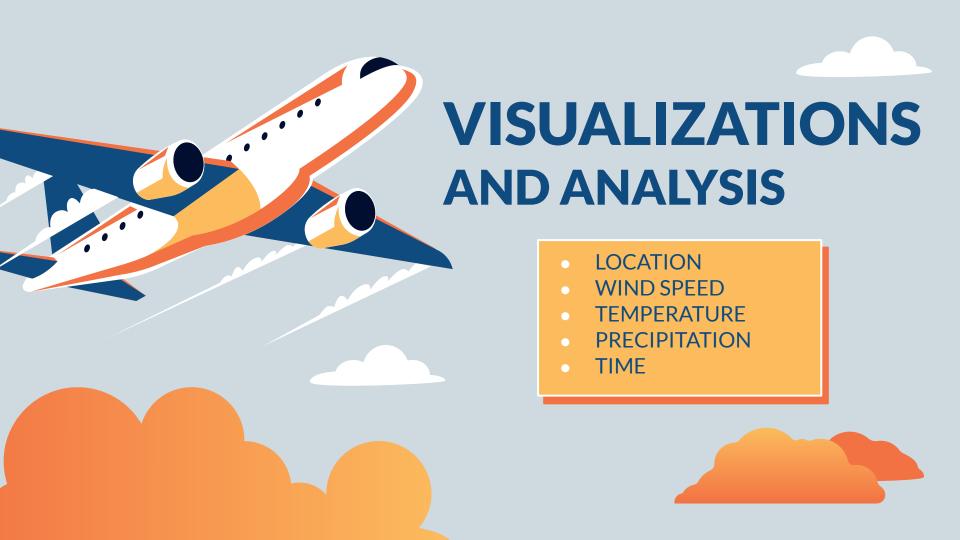


filtered df = filtered df[['Date', 'Origin', 'Destination', 'Expected Departure Time',\

```
def clean_flight_data(year):
   file = "raw data/" + str(year) + ".csv"
   original df = pd.read csv(file, sep=",", header=0, index col=False,
                             usecols=[0,3,4,5,6,7,12,13,14,16,21,23],
                             na filter = True)\
                            .reset index(drop=True)\
                            .fillna(0)
   filtered df = original df.loc[(original df['ORIGIN'].isin(focused airports) & \
                                ((original_df['CANCELLATION_CODE'] == 0 ) | \
                                 (original df['CANCELLATION CODE'] == 'B'))), :]
   filtered df.loc[filtered df['CANCELLATION CODE'] == 'B', 'WEATHER DELAY'] = 'CANCELLED'
   filtered df = filtered df.drop(columns = 'CANCELLATION CODE')
   filtered df = filtered df.rename(columns={'FL DATE' : 'Date',
                                                      'Origin'
                                        'ORIGIN'
                                       'DEST'
                                                       : 'Destination'
                                       'CRS_DEP_TIME' : 'Expected Departure Time',
                                                     : 'Actual Departure Time',
                                       'DEP_TIME'
                                       'DEP DELAY'
                                                     : 'Departure Delay',
                                       'CRS ARR TIME' : 'Expected Arrival Time',
                                       'ARR TIME'
                                                      : 'Arrival Time',
                                       'ARR DELAY'
                                                      : 'Arrival Delay',
                                       'DISTANCE'
                                                      : 'Distance'
                                       'WEATHER DELAY' : 'Weather Delay'})
   filtered_df = filtered_df[['Date', 'Origin', 'Destination', 'Expected Departure Time',\
                                      'Expected Arrival Time', 'Distance', 'Weather Delay']]
    return filtered df
for year in range(2015,2019):
                                    ## Takes about 7 minutes ##
   output path = 'clean data/focused airports ' + str(year) + '.csv'
   clean flight data(year).to csv(output path, index=False)
```

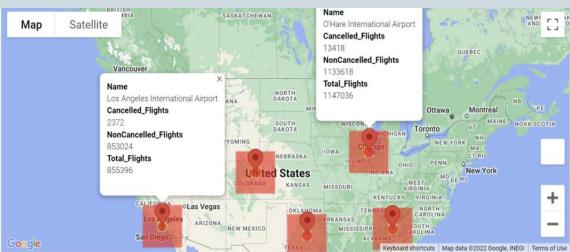
```
# Loop through the sample data rame
for index,row in source df.iterrows():
     #----Origin Latitude and Longitude
    lat=row["Latitude"]
    lng=row["Longitude"]
    datetime= row["Date"]
    # Build URL
    base url ="https://weather.visualcrossing.com/VisualCrossingWebServices/rest/services/timeline/"
    query_1 = (f"{lat},{lng}/{datetime}/?key={weather_api_key}")
    query 2 = "&include=obs%2Cfcst%2Cstats%2Calerts%2Ccurrent%2Chistfcst"
    query 3 = "&elements=tempmax,precip,preciptype,windspeed"
    new url= base url + query 1 + query 2 + query 3
     get the response
    # Use try and except to skip the missing data
     try:
        response = requests.get(new_url).json()
        source_df.loc[index,"Max Temp"]=response['days'][0]['tempmax']
        source df.loc[index, "Precip"]=response['days'][0]['precip']
        precip type list = response['days'][0]['preciptype']
        precip type str=""
        if precip_type_list != None :
            for precip_type in precip_type_list:
                precip_type_str += precip_type+","
         else:
             precip type str = "NA"
        source df.loc[index,"Precip Type"]=precip type str
        source df.loc[index,"Wind Speed"]=response['days'][0]['windspeed']
    except (KeyError, IndexError, JSONDecodeError):
        print("Data not found... skipping.")
    except requests. Timeout:
        print("Request Timeout...")
    except requests.ConnectionError:
        print("ConnectionError...")
```

```
\leftarrow \rightarrow G
              weather.visualcrossing.com/VisualCrossingWebServices/rest/services/timeline/32.896,-97.037/2015-01-01/3
     "queryCost": 1,
     "latitude": 32.896,
     "longitude": -97.037,
     "resolvedAddress": "32.896,-97.037",
     "address": "32.896,-97.037",
     "timezone": "America/Chicago",
     "tzoffset": -6,
   ▼ "days": [
      ₩ {
            "tempmax": 36,
            "precip": 0.58,
          ▼ "preciptype": [
                "rain",
                "snow"
             "windspeed": 8,
          ▼ "normal": {
              ▼ "tempmax": [
                    29.9,
                    55.1,
                    82.1
              ▼ "precip": [
                    0,
                    0,
                    0.6
              "windspeed": [
                    8.1,
                    18.8,
                    28.6
```

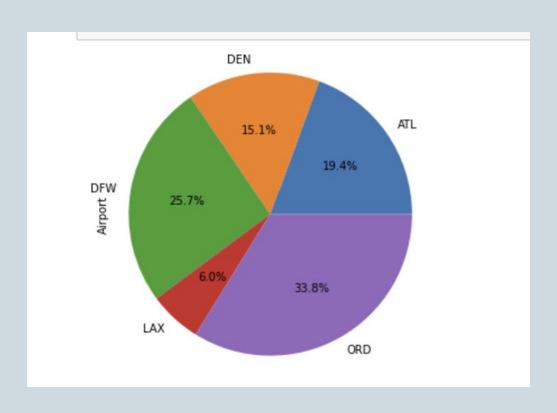


LOCATION

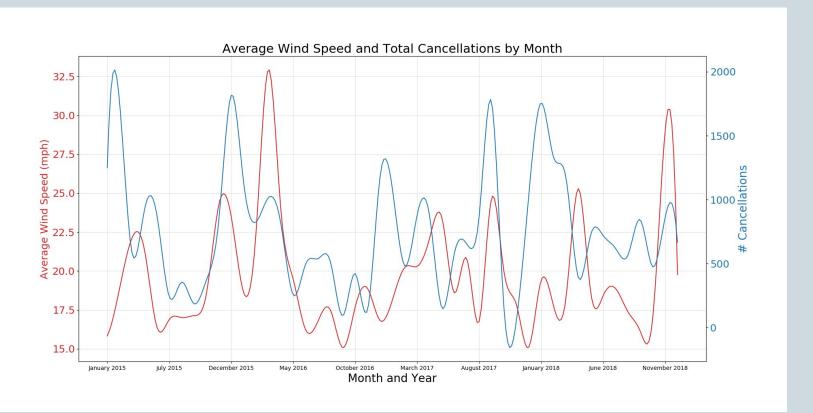




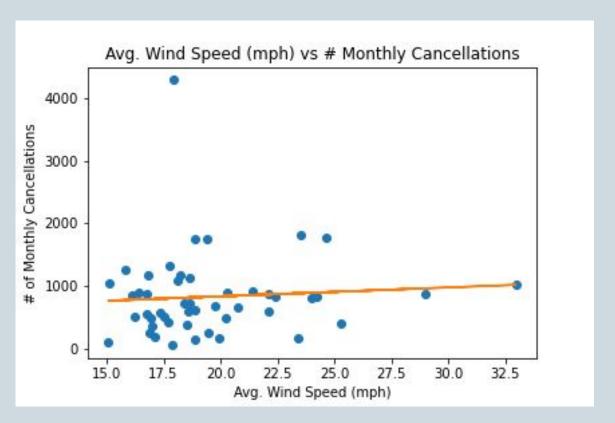
LOCATION



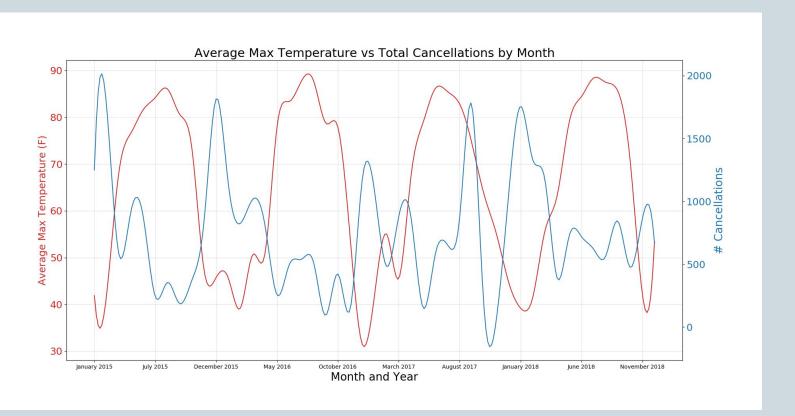
WIND SPEED



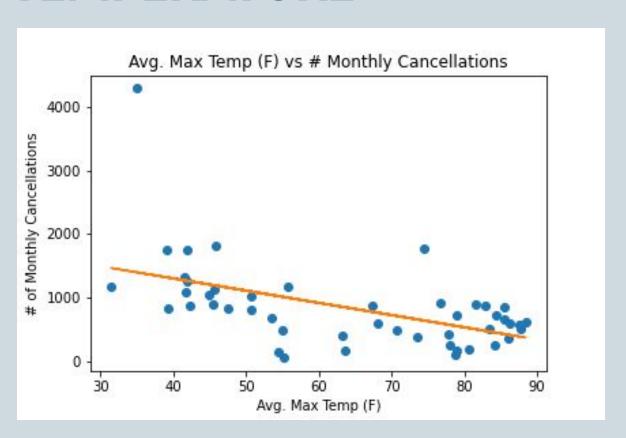
WIND SPEED



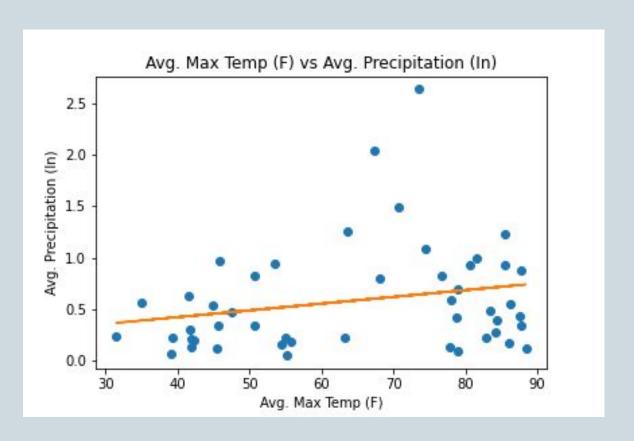
TEMPERATURE



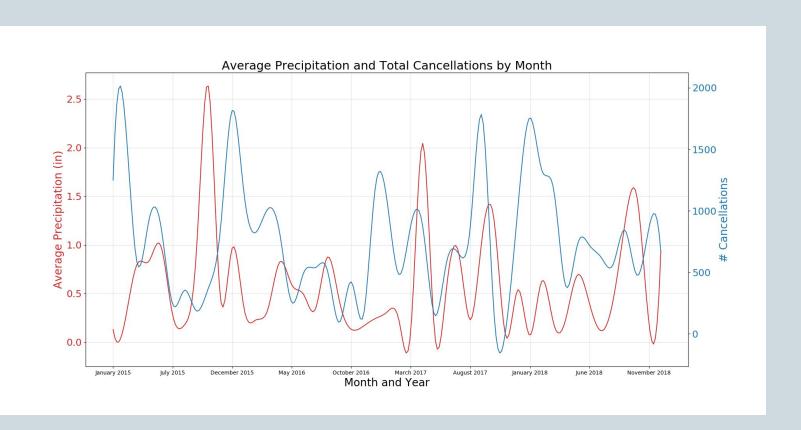
TEMPERATURE



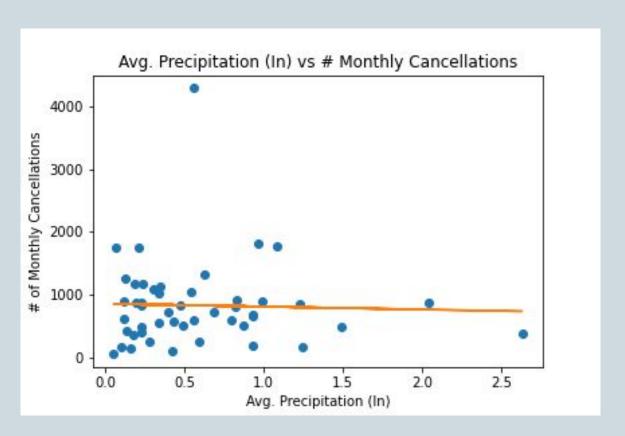
TEMPERATURE



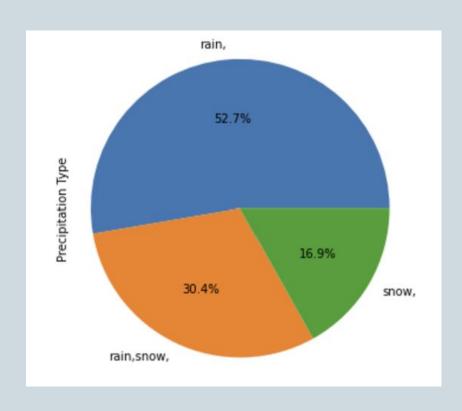
PRECIPITATION

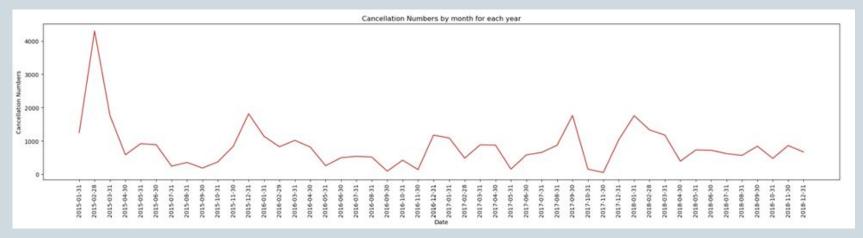


PRECIPITATION



PRECIPITATION







```
22.138 25.999 49.456
                                                                                                                            54.090 | 58.124 | 61.777 | 62.892 | 66.206
                                                                                                                                                                          73.254 76.084
                                                                                                                                                                  69.336
                                                                                                      22.859
                                                                                                             26.785 50.548
                                                                                                                             55.230 | 59.304 | 62.990 | 64.116 | 67.459 | 70.616 | 74.566 | 77.419
                                                                                                                            56.369 | 60.481 | 64.201 | 65.337 | 68.710 | 71.893
                                                                                                      23.584 27.575 51.639
                                                                                                                                                                          75.874 78.750
52.729 | 57.505 | 61.656 | 65.410 | 66.555 | 69.957
                                                                                                      24.311
                                                                                                             28.366
                                                                                                                                                                  73.166 77.179 80.077
               df.columns = ["observed", "expected"]
                                                                                                                     53.818 | 58.641 | 62.830 | 66.617 | 67.771 | 71.201 | 74.437
                                                                                                                                                                          78.481 81.400
                                                                                                      25.041
                                                                                                             29.160
               df.head()
                                                                                                      25.775 29.956
                                                                                                                            59.774 64.001 67.821 68.985 72.443
                                                                                                                     54.906
                                                                                                                                                                  75.704
                                                                                                                                                                          79.780 82.720
    Out[21]:
                                                                                                                            60.907 | 65.171 | 69.023 | 70.197 | 73.683 | 76.969 | 81.075 | 84.037
                                                                                                      26.511
                                                                                                             30.755 55.993
                            observed expected
                                                                                                      27.249 31.555 57.079
                                                                                                                            62.038 | 66.339 | 70.222 | 71.406 | 74.919 | 78.231
                                                                                                                                                                          82.367 85.351
               January 2015
                                1250
                                          752
                                                                                                      27.991
                                                                                                             32.357
                                                                                                                     58.164
                                                                                                                             63.167 | 67.505 | 71.420 | 72.613 | 76.154
                                                                                                                                                                  79.490
                                                                                                                                                                          83.657
                                                                                                                                                                                  86.661
                 March 2015
                                1759
                                          752
                                                                                                51
                                                                                                      28.735 33.162
                                                                                                                     59.248
                                                                                                                            64.295 68.669
                                                                                                                                           72.616 73.818 77.386
                                                                                                                                                                  80.747
                                                                                                                                                                          84.943 87.968
                  April 2015
                                 585
                                          752
                                                                                                      29.481
                                                                                                             33.968
                                                                                                                     60.332
                                                                                                                            65.422 | 69.832 | 73.810 | 75.021 | 78.616 | 82.001
                                                                                                                                                                          86.227 89.272
                   May 2015
                                 919
                                          752
                                                                                                      30.230 34.776 61.414
                                                                                                                             66.548 | 70.993 | 75.002 | 76.223 | 79.843 | 83.253 | 87.507 | 90.573
                  June 2015
                                 886
                                          752
                                                                                                      30.981
                                                                                                             35.586
                                                                                                                     62.496
                                                                                                                             67.673 | 72.153 | 76.192 | 77.422 | 81.069 | 84.502
                                                                                                                                                                          88.786 91.872
                                                                                                55
                                                                                                      31.735 36.398
                                                                                                                     63.577
                                                                                                                            68.796 73.311 77.380 78.619 82.292 85.749 90.061 93.168
           # With four rows, the degree of freedom is 47-1 = 46
                                                                                                                            69.919 74.468 78.567 79.815 83.513 86.994
                                                                                                      32.490 37.212
                                                                                                                     64.658
                                                                                                                                                                          91.335 94.461
               # With a p-value of 0.05, the confidence level is 1.00-0.05 = 0.95.
                                                                                                                    65.737 71.040 75.624 79.752 81.009 84.733 88.236
                                                                                                57
                                                                                                      33.248 38.027
                                                                                                                                                                          92.605 95.751
              critical value = st.chi2.ppf(q = 0.95, df = 46)
                                                                                                      34.008 | 38.844 | 66.816 | 72.160 | 76.778 | 80.936 | 82.201 | 85.950 | 89.477 | 93.874 | 97.039
               critical value
                                                                                                      34,770 | 39,662 | 67,894 | 73,279 | 77,931 | 82,117 | 83,391 | 87,166 | 90,715 | 95,140 | 98,324
    Out[19]: 62.829620411408165
                                                                                                      35.534 | 40.482 | 68.972 | 74.397 | 79.082 | 83.298 | 84.580 | 88.379 | 91.952 | 96.404 | 99.607
In [22]: 

# Run the chi square test
               st.chisquare(df['observed'], df['expected'])
```

Р

DF

0.995

0.975

21.421 | 25.215 | 48.363

0.20

0.05

0.10

0.025

0.02

52.949 | 56.942 | 60.561 | 61.665 | 64.950 | 68.053 | 71.938 | 74.745

0.01

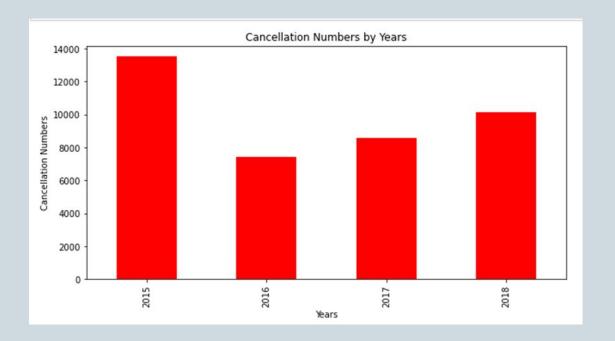
0.005

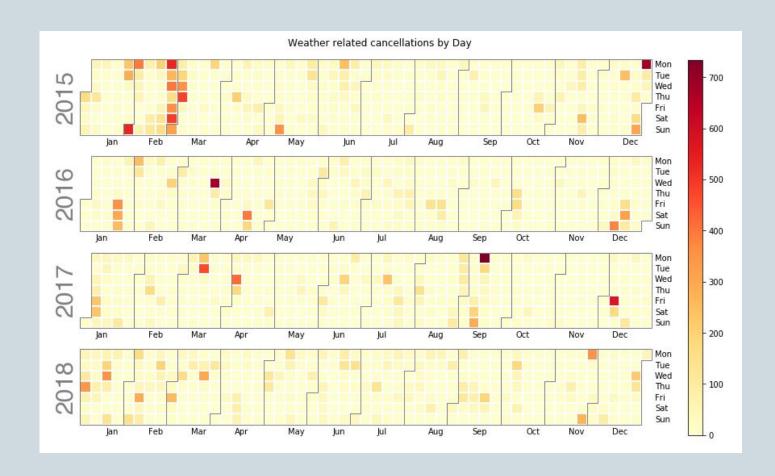
0.002

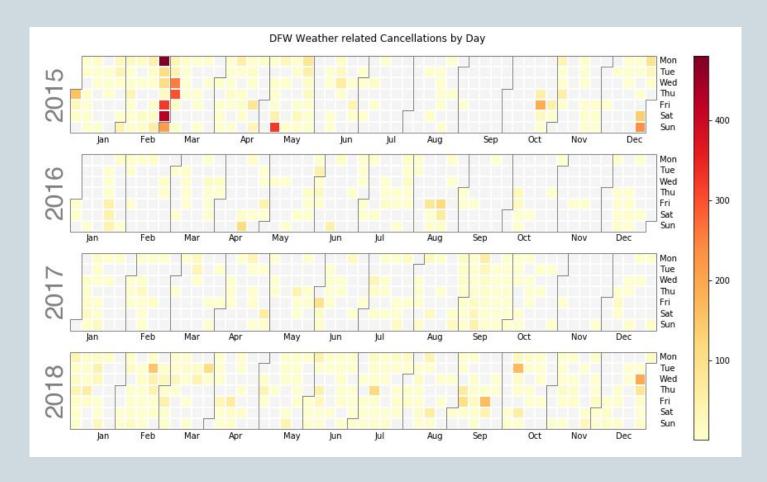
0.001

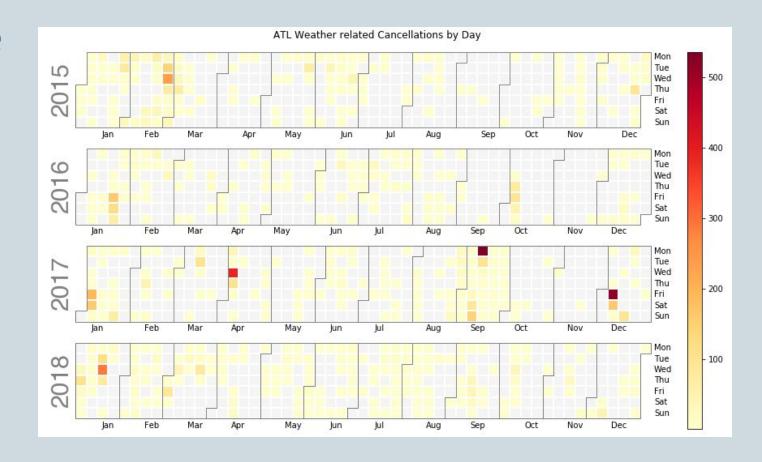
Since the chi-square value of 12603.59 at a confidence level of 95% exceeds the critical value of 62.83, we conclude that the differences seen in the number of cancellations by months of year are statistically significant.

Out[22]: Power divergenceResult(statistic=12603.594414893618, pvalue=0.0)



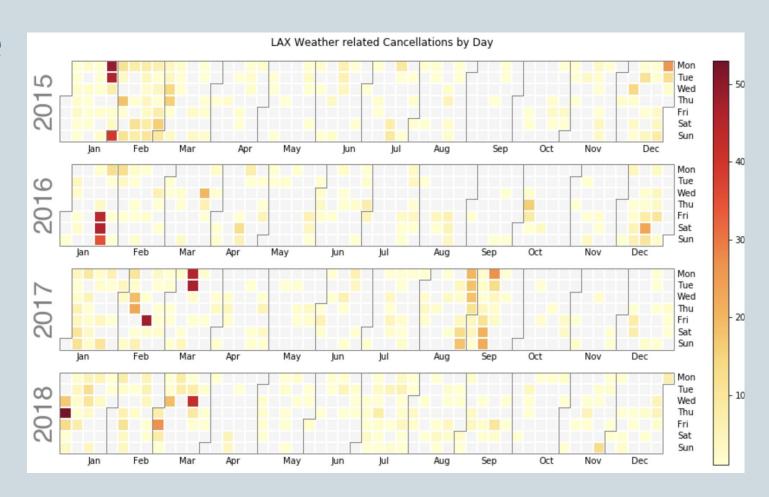














CONCLUSIONS



Our target variable was flight cancellations caused by weather. Our predictor variables are average temperature, wind speed, and precipitation. Our findings:

- How does month of year impact flight cancellations in the U.S.?
 - We reject the null hypothesis, weather factors impact flight cancellations by month of year
- How does wind speed affect U.S. flight cancellations by month of year?
 - We fail to reject the null hypothesis, wind speed will result in no impact on flight cancellations
- How does temperature affect U.S. flight cancellations by month of year?
 - We reject the null hypothesis, temperature impacts flight cancellations by month of year
- How does precipitation type affect U.S. flight cancellations by month of year?
 - We fail to reject the null hypothesis, precipitation will result in no impact on flight cancellations

IMPLICATIONS

- Weather cancellation factors are not mutually exclusive, there can be many weather factors impacting a single cancelled flight. Therefore, we are not able to draw strong correlations to across all observations to a single weather factor, however we did see a significant relationship of weather related cancellations to month and temperature.
- Our observations lead us to fail to reject the null hypothesis specific to wind speed and precipitation factors as they relate to the sample data for canceled flights by weather from top 5 U.S. airports during 2015 2018.
- These observations lead us to reject the null hypothesis for weather impact flight cancellations by month of year and average temperature based on our statistical analysis of data from the sample airports for the years 2015-2018.
- Based on these takeaways we uncovered while analyzing the data, considerations to continue this investigation would include an analysis of seasonality specific to weather related flight cancellations as well as a broader scope of locations such as regions or climates.

