# Gulf Coast Area Rainfall Prediction

Jimmy Smart

# Project Outline

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  - Identify feature values
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  - Random Forest
- Comparing models
- Conclusion

# Introduction

Q:

Can we predict rainfall amounts for the Gulf Coast Area?

- Dataset contains historical weather data of five cities along the Gulf Coast shores.
- Our data is from https://ww.ncdc.noaa.gov/
- The original datasets for all 5 cities *New_Orleans.csv*, *Houston.csv, Pascagoula.csv, Mobile.csv* and *Tampa.csv* were loaded in and saved as 1 dataset into a Jupyter Notebook.
- The goal of this project is to use the features, from the datasets listed above, to predict daily rainfall amounts based on past rainfall

# Data Wrangling

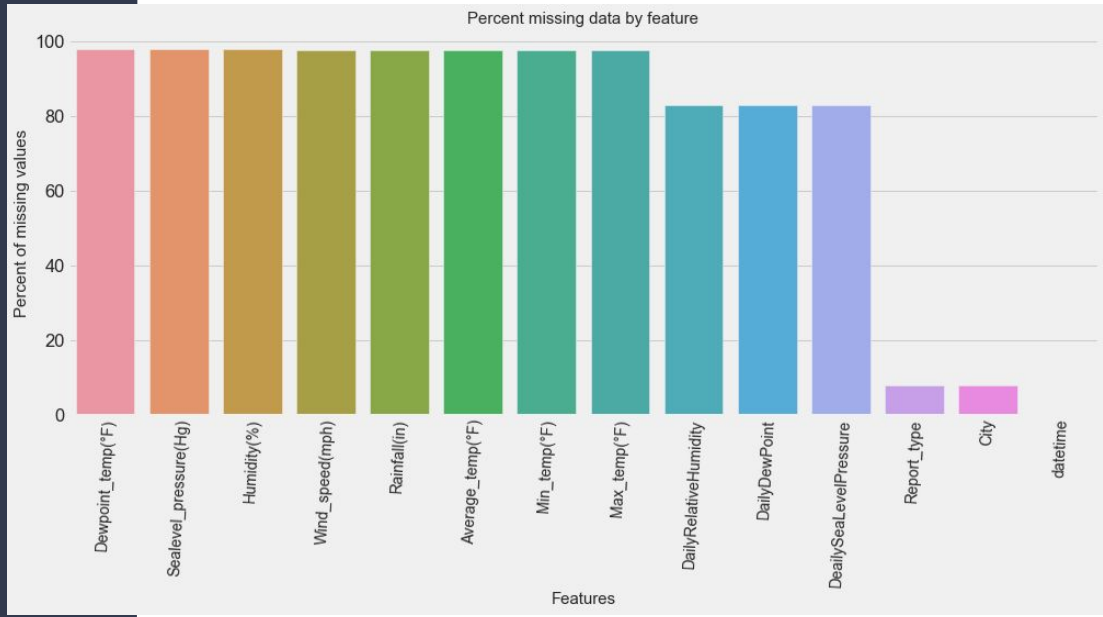
# Featured values from dataset

Our 5 datasets were given a quick cleaning within their original Excel format before being saved as CSV files and read into our notebook as one through glob. Concat was used to create one dataframe.

**Featured values:**

```
df = df[[
'STATION',
        'datetime',
        'REPORT_TYPE',
        'DailyDewPoint',
        'DailyRelativeHumidity',
        'DeailySeaLevelPressure',
        'DailyAverageDewPointTemperature',
        'DailyAverageRelativeHumidity',
        'DailyAverageSeaLevelPressure',
        'DailyMaximumDryBulbTemperature',
        'DailyMinimumDryBulbTemperature',
        'DailyAverageDryBulbTemperature',
        'DailyPeakWindSpeed',
        'DailyPrecipitation'
       ]]
```

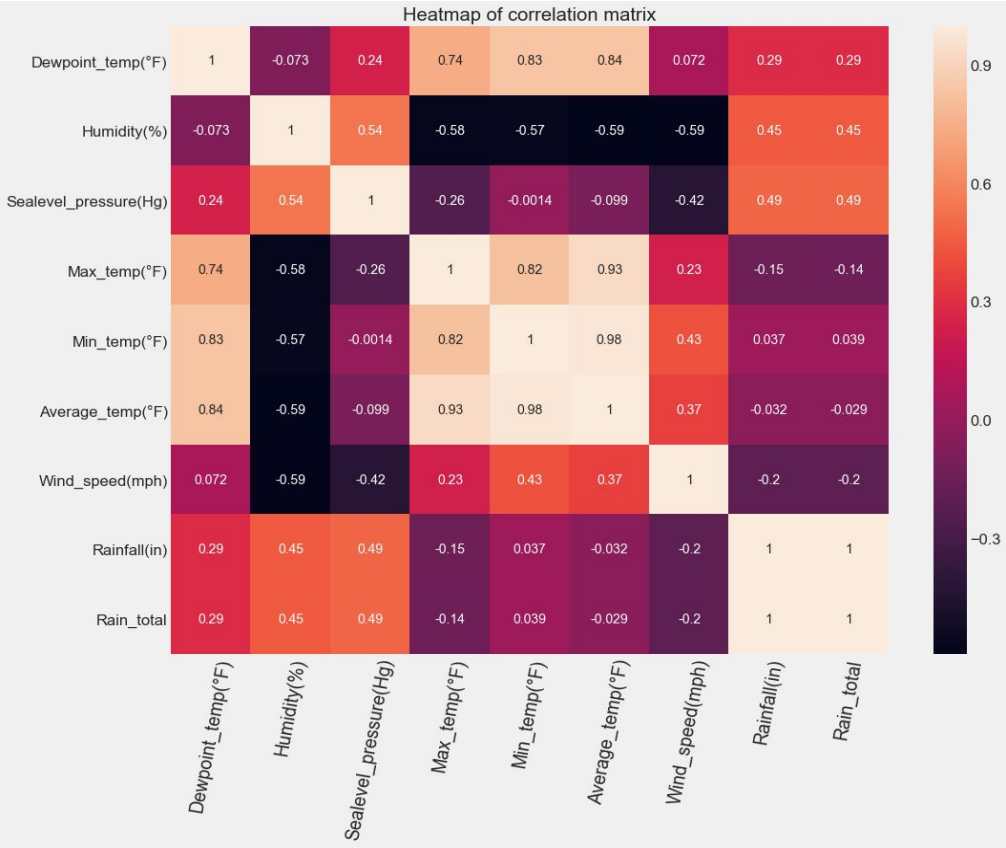
# Identifying missing data




- Our featured values had a large percentage of null values due to the structure of the dataset having hourly, daily, monthly data.
- Focus only on the daily data figures by using .loc to pull out rows that only consisted of daily data.

| | null_sum | null_pct | dtypes | count | mean | median | std | min | max |
|---|---|---|---|---|---|---|---|---|---|
| **Average_temp** | 0 | 0.0 | float64 | 18243 | 70.944581 | 74.000000 | 12.746689 | 26 | 95 |
| **City** | 0 | 0.0 | object | 18243 | NaN | NaN | NaN | Houston | Tampa |
| **Dewpoint** | 0 | 0.0 | float64 | 18243 | 60.499926 | 64.500000 | 13.934829 | 4.70833 | 80 |
| **Humidity** | 0 | 0.0 | float64 | 18243 | 73.628929 | 75.000000 | 11.397478 | 21 | 100 |
| **Max_temp** | 0 | 0.0 | float64 | 18243 | 79.980266 | 82.000000 | 12.198700 | 31 | 109 |
| **Min_temp** | 0 | 0.0 | float64 | 18243 | 61.407170 | 65.000000 | 14.031359 | 16 | 85 |
| **Rainfall(in)** | 0 | 0.0 | object | 18243 | 0.159897 | 0.000000 | 0.523273 | 0 | 16.07 |
| **Sealevel_press** | 0 | 0.0 | float64 | 18243 | 30.049150 | 30.035833 | 0.140398 | 29.44 | 30.6954 |
| **Wind_speed** | 0 | 0.0 | object | 18243 | 23.381571 | 22.000000 | 37.303786 | 0 | 2237 |
| **datetime** | 0 | 0.0 | datetime64 | 18243 | NaN | NaN | NaN | 2010-01-01 | 2019-12-31 |

# EDA Analysis




- From this heatmap we can see that Dewpoint and our max, min, average daily temperatures have a positive correlation.
- While Humidity has a negative correlation with our temperature variables.
- Rainfall has decent correlations with Humidity(0.31) and Sealevel Pressure (0.49) which makes sense because as a storm rolls in humidity usually rises as does sealevel pressures.

# Data Visualization

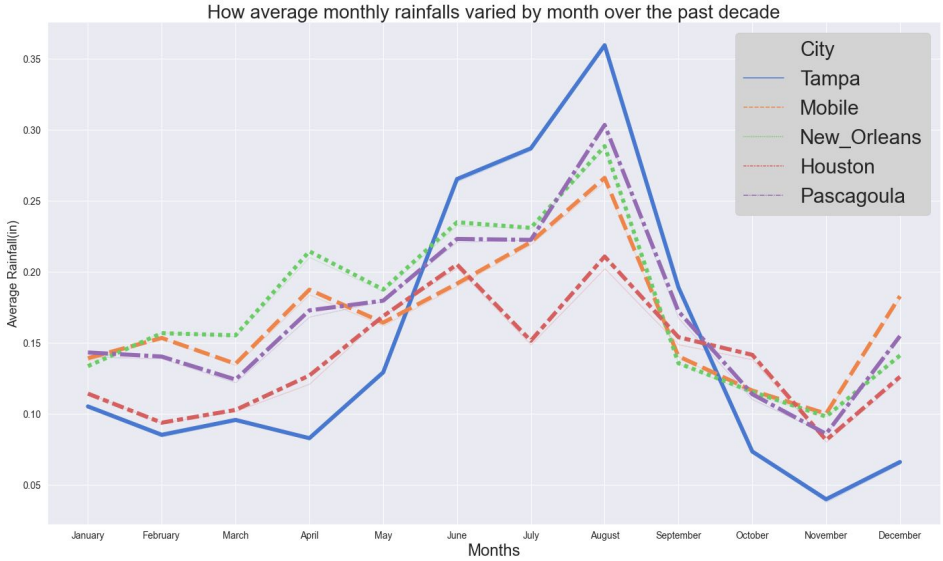
| City | Dewpoint(°F) | Humidity(%) | Sealevel_pressure(Hg) | Max_temp(°F) | Min_temp(°F) | Avg_temp(°F) | Wind_speed(mph) | Rainfall(in) | Rain_total |
|---|---|---|---|---|---|---|---|---|---|
| **Houston** | 59.784873 | 72.047958 | 30.021814 | 80.700192 | 60.899699 | 71.047136 | 24.181694 | 0.139984 | 510.80 |
| **Mobile** | 59.931493 | 77.123816 | 30.064963 | 78.147244 | 59.645736 | 69.145873 | 22.132712 | 0.166597 | 607.58 |
| **New Orleans** | 60.473006 | 71.836942 | 30.054149 | 79.387229 | 62.785969 | 71.346396 | 24.034804 | 0.174412 | 636.43 |
| **Pascagoula** | 59.076459 | 76.829816 | 30.054634 | 78.810907 | 56.954782 | 68.133461 | 20.773089 | 0.169819 | 619.67 |
| **Tampa** | 63.233489 | 70.308030 | 30.050197 | 82.854755 | 66.748698 | 75.049055 | 22.719649 | 0.148676 | 542.52 |

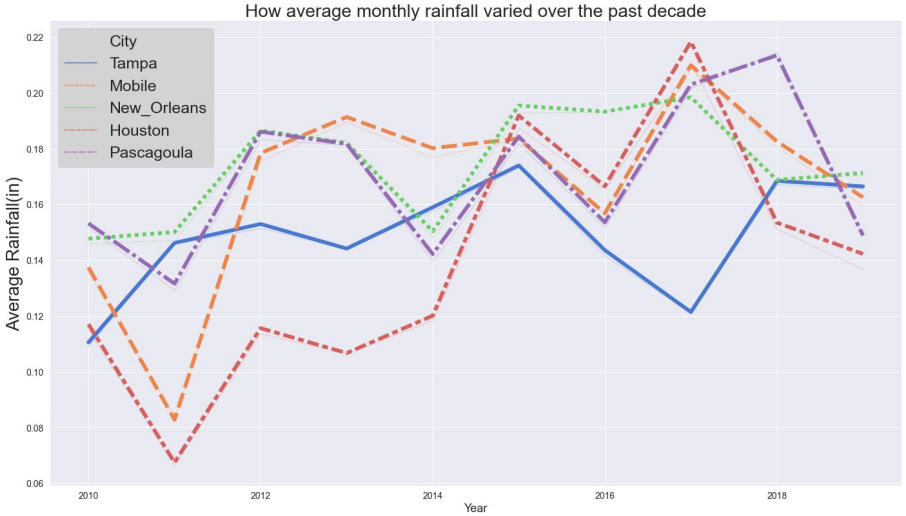
- Yearly averages of our features separated by our 5 cities
- Total rainfall amounts for the past decade

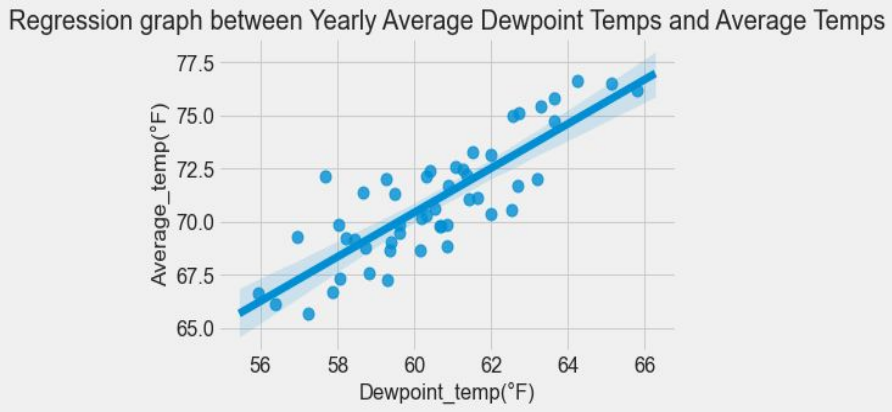
# Rainfall

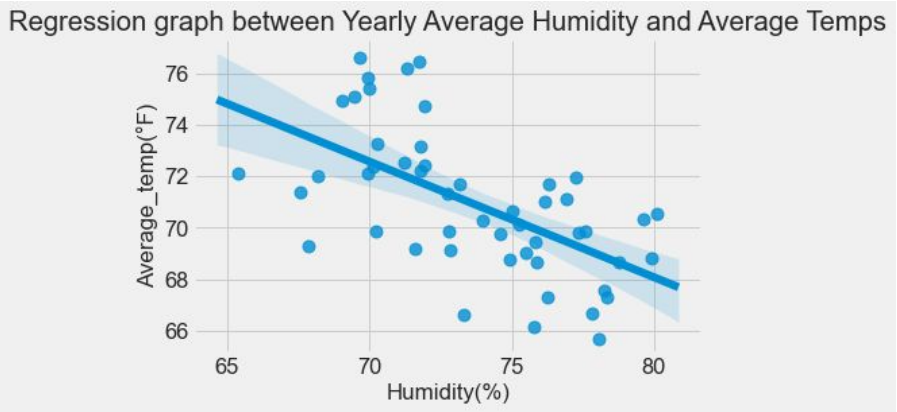
(left) Average monthly rainfalls varied by months for each of our cities. We can see that Tampa had the highest and lowest totals amongst our 5 cities.

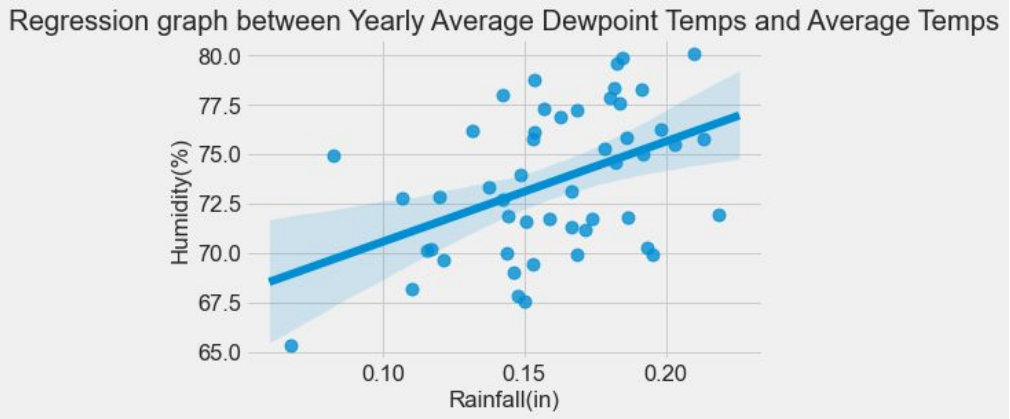
(right) yearly averages for rainfall amongst our cities tells a little bit of a different story than the monthly averages.



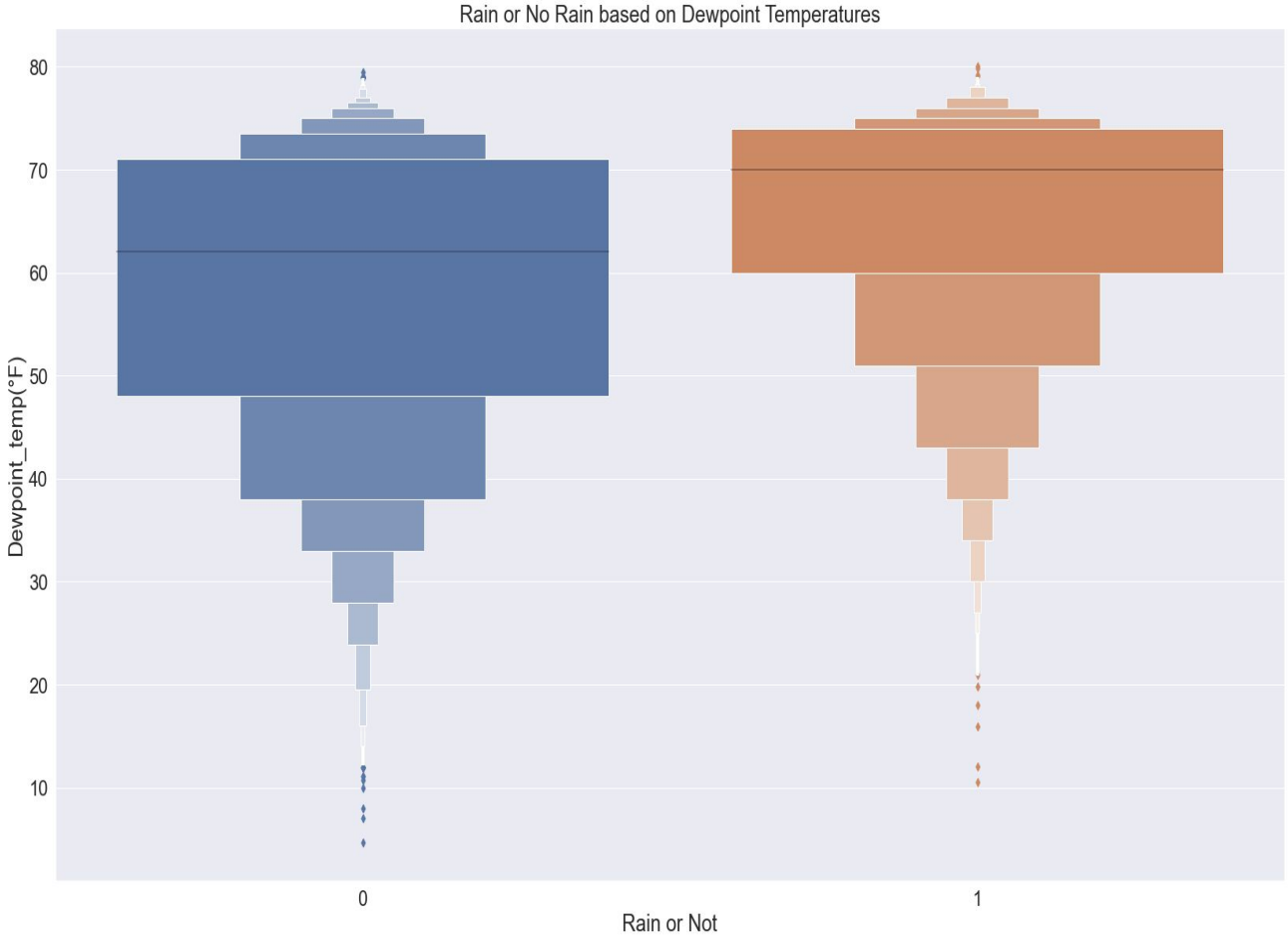





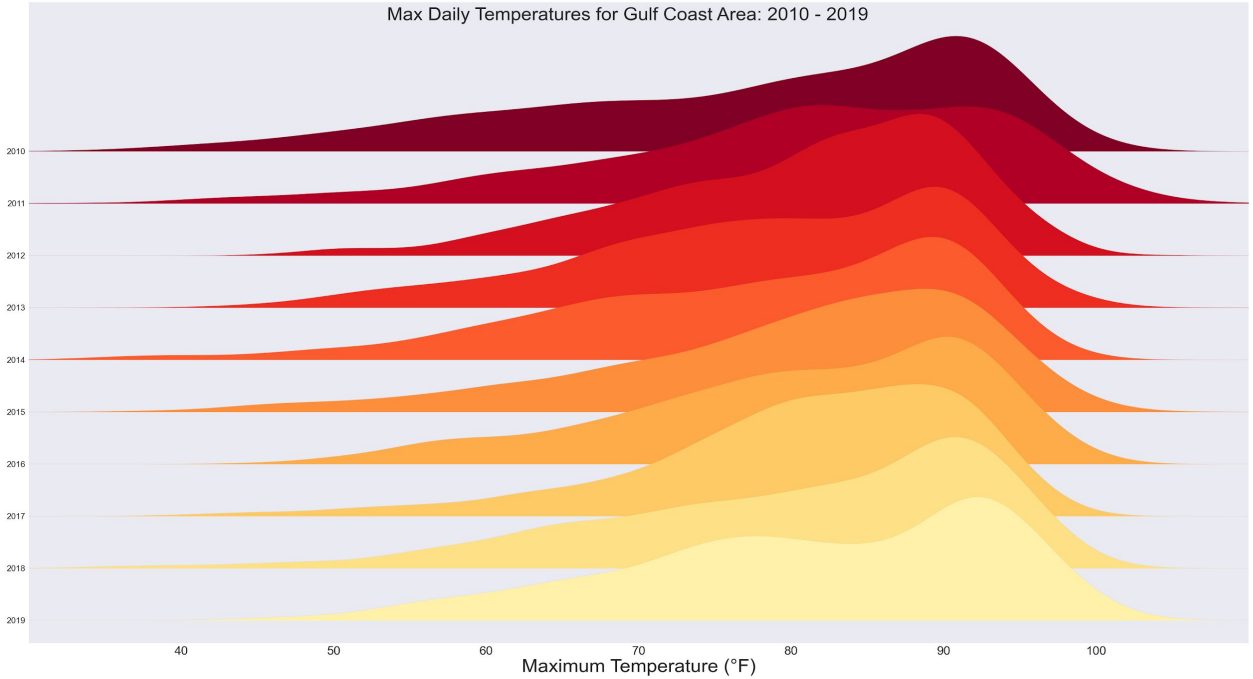




(top left) As our Dewpoint temperatures rose, so did our average temperatures. (top right) As our Humidity percentages rose our average temperatures decreased. (bottom center) As our rainfall increased so did our humidity percentages.




- We created a new feature (Rain-1 or Not-0)
- As we can see from the figure to the left, on days that we had rain, our average Dewpoint temperatures were higher than days without rain.
- Our non rainy days also showed lower falling outliers than on rainy days




| Year | Max_temp(°F): |
|---|---|
| 2010 | 78.081644 |
| 2011 | 80.559648 |
| 2012 | 80.828415 |
| 2013 | 78.713029 |
| 2014 | 78.003297 |
| 2015 | 80.202192 |
| 2016 | 80.704372 |
| 2017 | 80.885479 |
| 2018 | 80.456438 |
| 2019 | 81.356164 |

Here we can see how our average temperatures have fared over the months of our dataset. Summer months are typically known to be hot in this area with a bit of a break from the heat in the other months of the year.

# Data Visualization Summary

- We were able to see weather trends that can be useful to any clients looking to see how weather has been and may be in the future.
- Rainfall amounts fluctuate during parts of the season but look to be holding steady overall
- When looking at temperatures over the past decade we were able to see that there has been an upward trend towards average temperatures rising each year.

Statistical Analysis

# Bootstrapping

Bootstrap sampling to estimate a 95% confidence interval lower limit.

***Null Hypothesis:*** Can we predict rain patterns for years to come based on past data from the Gulf Coast Area.

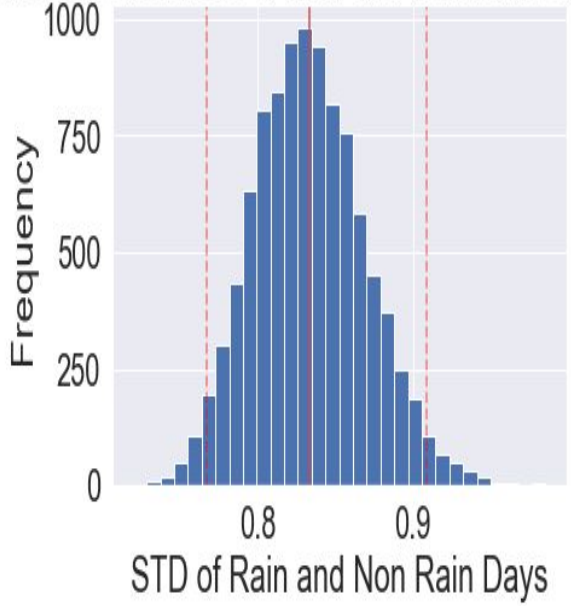
***Alternate Hypothesis:*** We will not be able to predict future rain patterns based off of past weather data for the Gulf Coast Area.

Difference of STD for rainfall and non rainfall days: *0.834636440830481*

Difference of STD for bootstrap samples: *0.8332447469738007*

The 95% confidence interval for the difference between the standard deviations of rainfall and non rainfall day is: *[0.76690786 & 0.90884574]*

## Bootstrap Distribution of Differences of Rain and Non Rain Days in the Gulf Coast Area

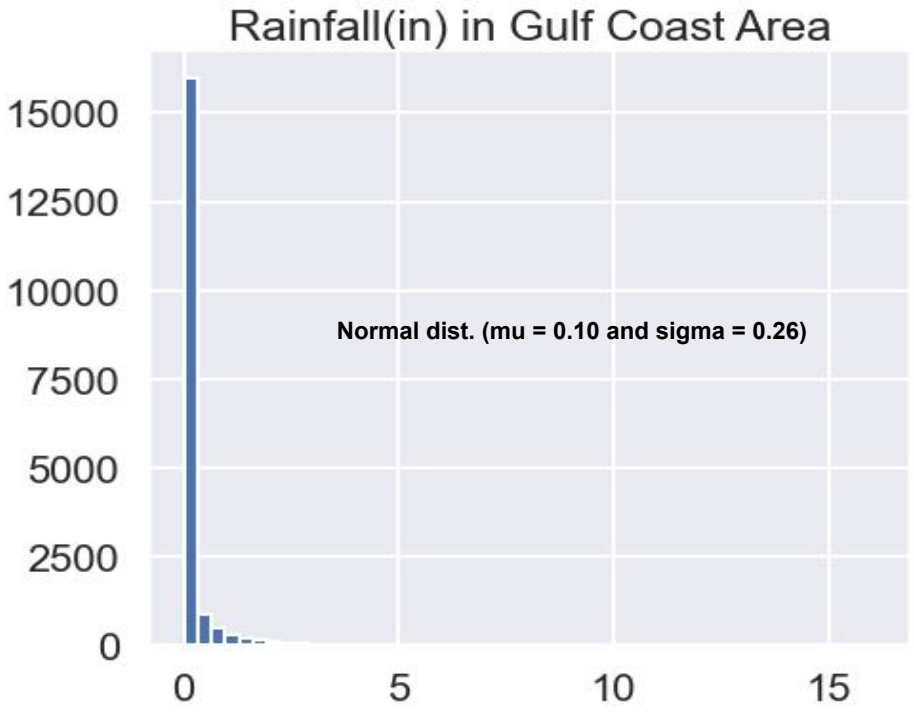


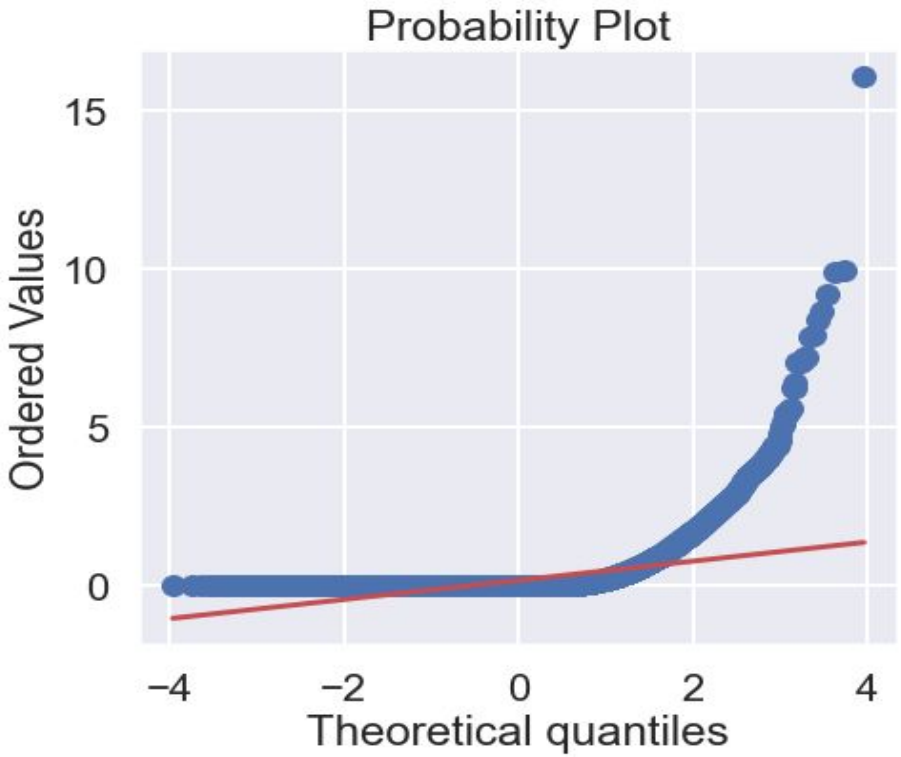

```
def diff_of_means(data_1, data_2):
    diff = np.mean(data_1) - np.mean(data_2)
    return diff

# Compute difference of mean rainfall and non rainfall:
empirical_diff_means
empirical_diff_means = diff_of_means(rainfall, no_rainfall)

# Draw 10,000 permutation replicates: perm_replicates
perm_replicates = draw_perm_reps(rainfall, no_rainfall,
diff_of_means, size=N_rep)

# Compute permutation p-value: perm_p
perm_p = np.sum(perm_replicates >= empirical_diff_means) /
len(perm_replicates)

#Compute p-value: p
p = np.sum(bs_perm_rep >= diff_means)/len(bs_perm_rep)
```

***P-value= 0.7383***

Performed our test at 5% significance level to calculate p-value between rainfall days and non rainfall days

**With a p-value of 0.7383, I can fail to reject the null hypothesis**




| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Rainfall(in)** | 18243.0 | 0.159897 | 0.5233 | 0.0 | 0.0 | 0.0 | 0.03 | 16.07 |

# Model Optimization

- FB Prophet
- Linear Regression
- XGBoost
- Random Forest

2 datasets:

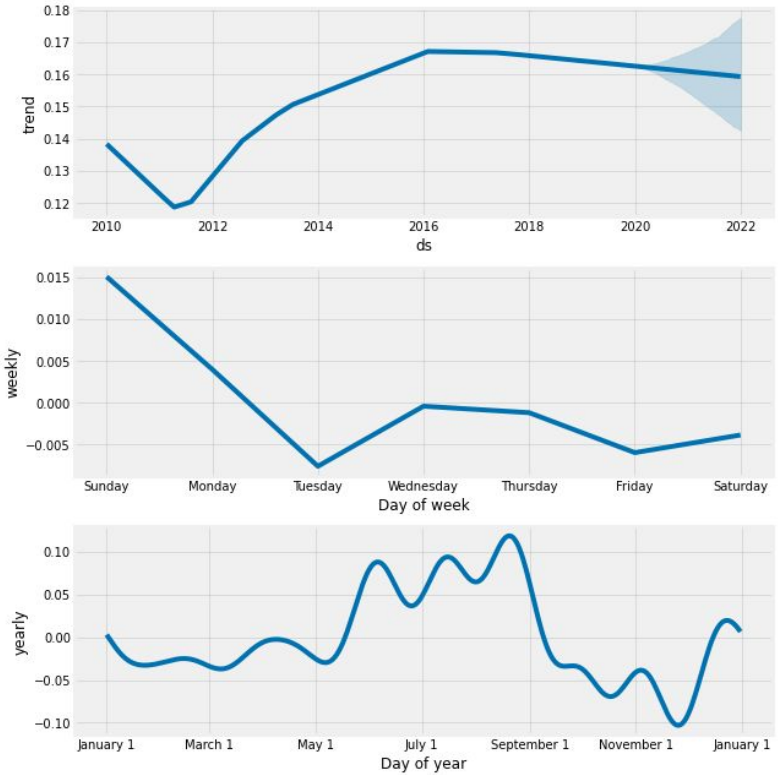
- without Rainfall outliers
- with Rainfall outliers

# Comparing Models

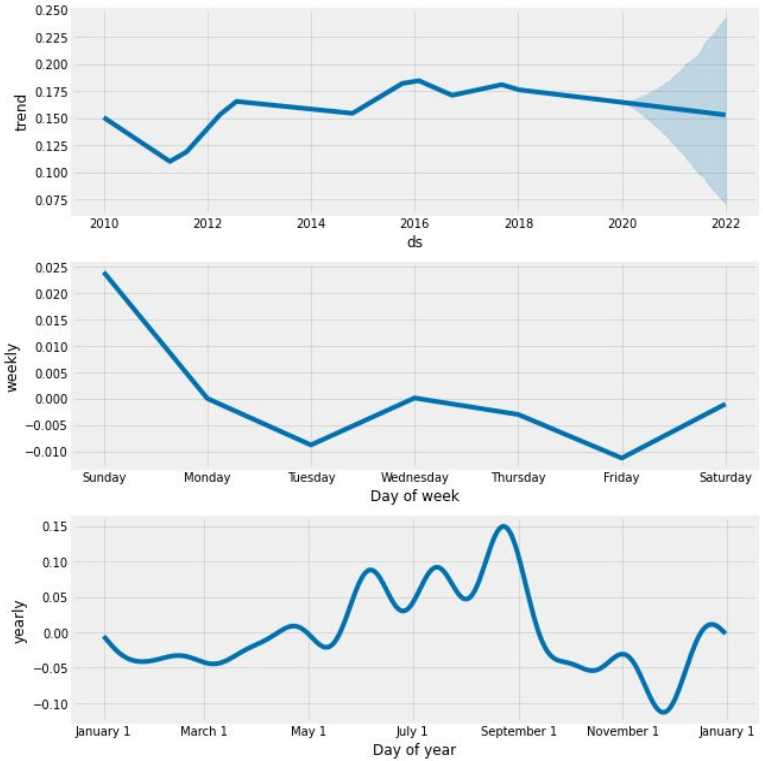
## without outliers

- Our r2 percentages fluctuate and showed an issue of overfitting with our Training set especially for XGBoost and RF
- Testing r2 relatively showed 20-30% relationship between your testing model and our dependent variable (Rainfall)
- MAE results are good as the values aren't too high which means we weren't "punished" too much for huge errors.
- RMSE results are good too considering they stayed fairly low as well

| name | **R2 - Test** | **R2 - Train** | **MAE - Test** | **MAE - Train** | **RMSE - Test** | **RSME - Train** |
|---|---|---|---|---|---|---|
| FB Prophet | -0.001 | NaN | 0.248 | NaN | 0.468 | NaN |
| Linear Regression (multiple) | 0.223 | -2.600 | 0.214 | 0.220 | 0.396 | 0.406 |
| XGBoost | 0.255 | 0.650 | 0.161 | 0.220 | 0.373 | 0.217 |
| Random Forest | 0.292 | 0.847 | 0.167 | 0.065 | 0.382 | 0.142 |



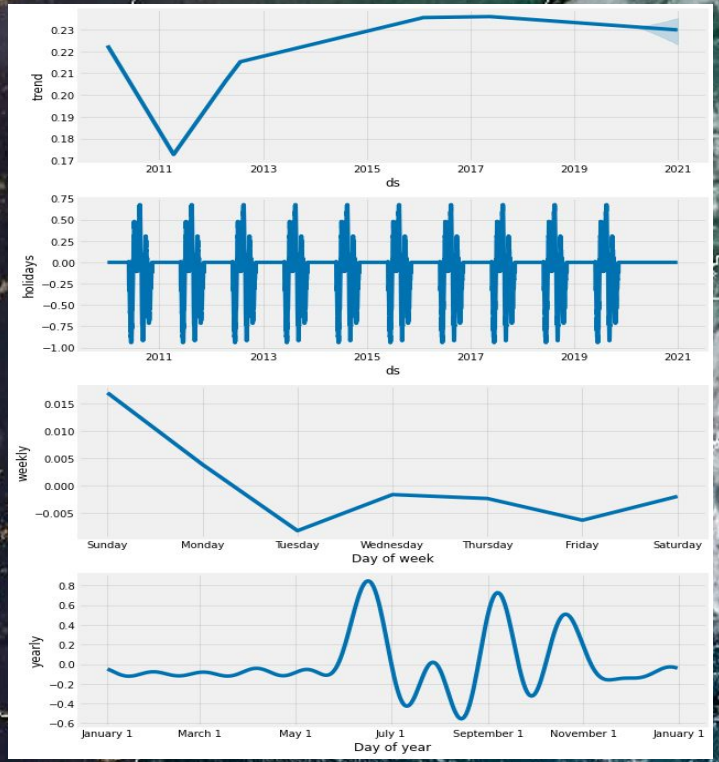

Model without outliers



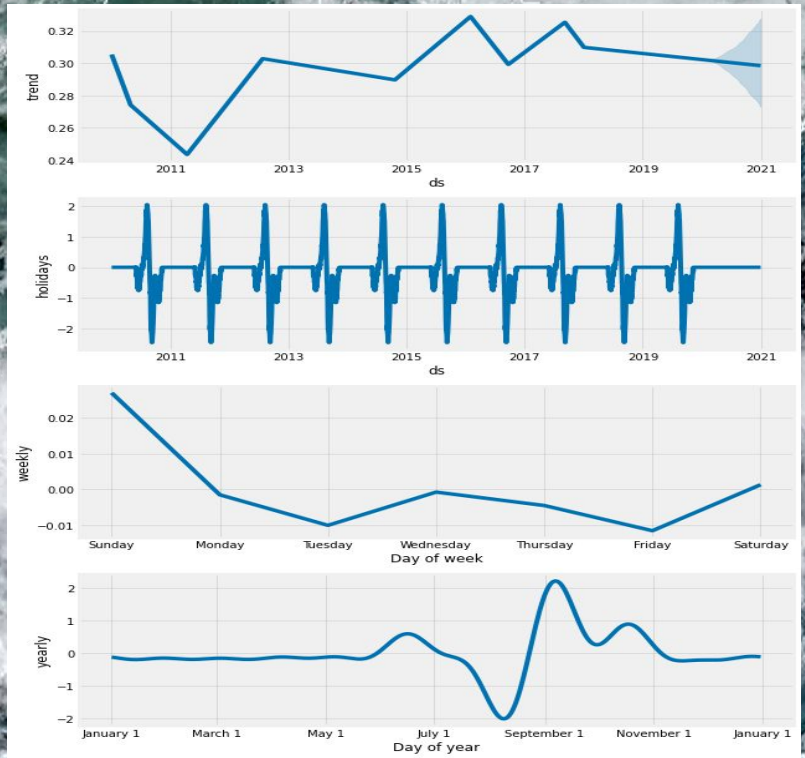

Model with outliers

# FB Prophet - trends

# Hurricane Season




Model without outliers




Model with outliers

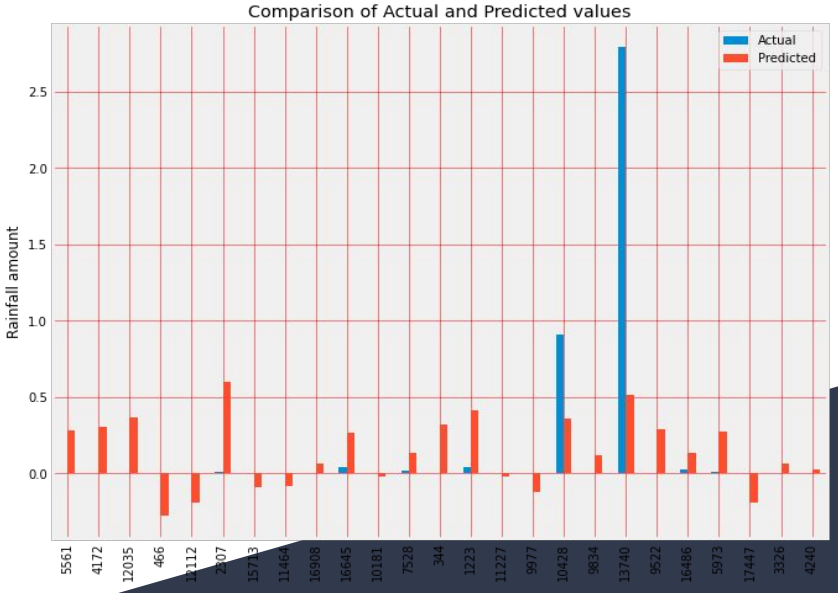
# Importance Features (without outliers)

| Features | FB Prophet | LR (multiple) | XGBoost | Random Forest |
|---|---|---|---|---|
| **Sealevel_pressure(Hg)** | -0.194383 | -0.212812 | 0.104949 | 0.149999 |
| **Max_temp(°F)** | 0.007984 | -0.002402 | 0.102125 | 0.096114 |
| **Average_temp(°F)** | 0.064095 | 0.009596 | 0.102010 | 0.062910 |
| **Min_temp(°F)** | 0.109440 | 0.007863 | 0.138275 | 0.088046 |
| **Dewpoint_temp(°F)** | 0.159427 | -0.017660 | 0.071421 | 0.103797 |
| **Wind_speed(mph)** | 0.326622 | 0.019038 | 0.241180 | 0.212961 |
| **Humidity(%)** | 0.331100 | 0.018864 | 0.240040 | 0.286172 |

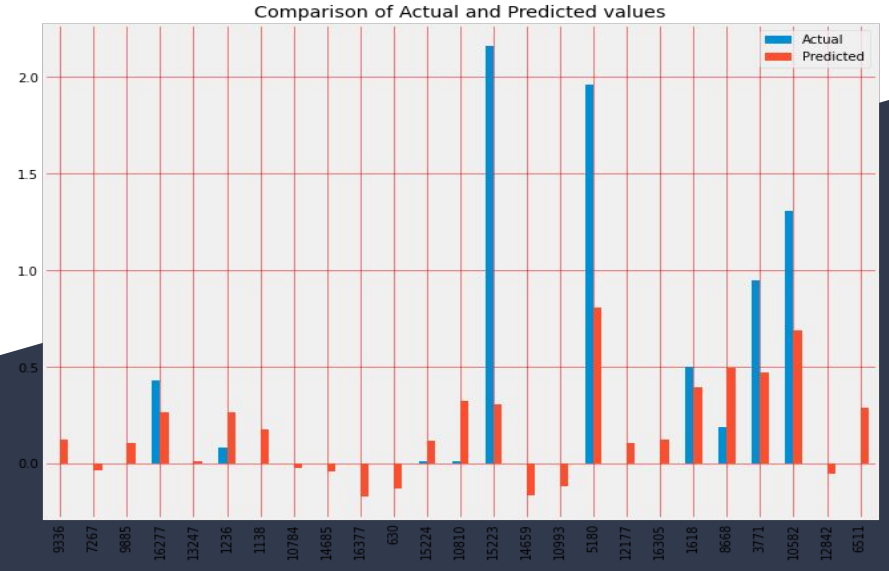
# Importance Features (with outliers)

| Features | FB Prophet | LR (multiple) | XGBoost | Random Forest |
|---|---|---|---|---|
| **Sealevel_pressure(Hg)** | -0.194946 | -0.228957 | 0.106688 | 0.150871 |
| **Max_temp(°F)** | 0.005526 | 0.006074 | 0.130203 | 0.098977 |
| **Average_temp(°F)** | 0.060142 | -0.006568 | 0.135132 | 0.061892 |
| **Min_temp(°F)** | 0.104485 | 0.017008 | 0.122700 | 0.099537 |
| **Dewpoint_temp(°F)** | 0.150118 | -0.019476 | 0.096356 | 0.104089 |
| **Wind_speed(mph)** | 0.311427 | 0.022094 | 0.192597 | 0.212199 |
| **Humidity(%)** | 0.321254 | 0.020152 | 0.216324 | 0.272435 |

# Linear Regression Prediction




Without outliers




With outliers

# Comparing Models
## with outliers

- R2 scores stayed relatively near our models without outliers. XGBoost's overfitting is still high but was able to come down some.
- Again r2 relatively showed 20-30% relationship between your testing models and our dependent variable (Rainfall)
- MAE results are good as the values aren't too high which means we weren't "punished" too much for huge errors.
- RF RMSE results are good considering they are fairly low

| name | **R2 - Test** | **R2 - Train** | **MAE - Test** | **MAE - Train** | **RMSE - Test** | **RSME - Train** |
|---|---|---|---|---|---|---|
| FB Prophet | -0.003 | NaN | 0.261 | NaN | 0.544 | NaN |
| Linear Regression (multiple) | 0.174 | -2.726 | 0.235 | 0.233 | 0.511 | 0.456 |
| XGBoost | 0.346 | 0.277 | 0.167 | 0.233 | 0.409 | 0.318 |
| Random Forest | 0.311 | 0.851 | 0.170 | 0.065 | 0.196 | 0.026 |

# Conclusion Results

**Results:**

- XGBoost and RF model with outliers included  looks to be the models worth focusing on and trying to achieve better results with. Their respective MAE and RMSE metrics were in good ranges
- Our models did not score as high as we would have liked in regards to r2 but we were able to see benefits from them
- We were able to find which features offered more importance. Coupled with more features could help increase our predictions
- Prophet and LR models offered useful historical and future trends as well as offer insight of important features

**Next Steps:**

- Predicting weather can be tricky as we've seen. To build a better model we might need to look at historical weather data from other parts of the country and world.
- The features we used didn't have as big of an impact as we would have like. For future modeling we could bring in more features and find a better mixture of features that show more importance to our Rainfall variable