

# **Temporal projection of natural atmospheric events in the United States Regions**

Haejeong Choi, Yanyu Long, Seung Ho Woo

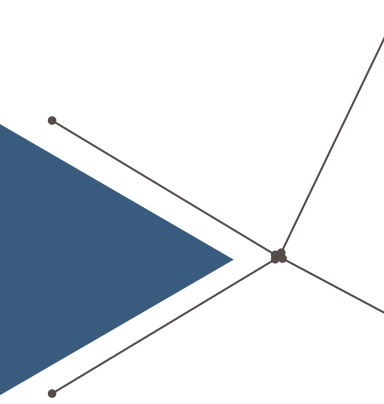
# 1 Introduction

The U.S. experiences a variety of extreme weather events, including hurricanes, floods, blizzards, droughts, and so on.

DISASTER TYPE	EVENTS	PERCENT FREQUENCY	EVENTS/YEAR	COST/YEAR	DEATHS/YEAR
Drought	28	9.6%	0.7	\$6.2B	93
Flooding	33	11.3%	0.8	\$3.6B	15
Freeze	9	3.1%	0.2	\$0.7B	4
Severe Storm	132	45.4%	3.1	\$7.0B	42
Tropical Cyclone	52	17.9%	1.2	\$24.1B	157
Wildfire	18	6.2%	0.4	\$2.5B	9
Winter Storm	19	6.5%	0.5	\$1.2B	28
All	291	100.0	6.9	\$45.4B	348

"Billion-dollar" events to affect the United States from 1980 to 2021. Data source: NOAA.

# 1 Introduction



Study the relationship between weather conditions and the occurrences of extreme weather events in the U.S.

Identify the most relevant indicators and the best-performing classification algorithms to predict natural disasters based on daily weather statistics.

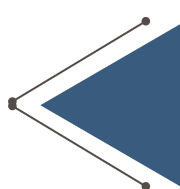
## Response

### NOAA Storm Event Database

- Extreme weather events such as drought, flood, wildfire, hurricane, etc. at the county level
- **ID: year-month, county**

## Predictors

### Historical weather data

- Hourly observations of temperature, humidity, pressure, wind direction, wind speed, etc.
  - **ID: year-month, city**
- 

## 2 Data preprocessing – storm event database

Compute the number of episodes observed in each county in each month from 2012 to 2017.

Original data

EVENT_ID	Date	STATE	COUNTY	EVENT_TYPE
678791	20170406	NEW JERSEY	GLOUCESTER	Thunderstorm Wind
679228	20170406	FLORIDA	LEE	Tornado
679268	20170405	OHIO	GREENE	Thunderstorm Wind
682042	20170416	OHIO	CLERMONT	Flood

Reshaped data

state	county	ym	num_episodes
ALABAMA	AUTAUGA	201202	1
		201203	1
		201204	1
		201205	1
		201207	3
		201212	1

Note: An episode may contain several different but related events.

## 2 Data preprocessing – hourly weather dataset

Convert hourly records to monthly summary statistics to match with the storm event dataset and deal with missing values.

### Hourly records

datetime	Portland
2012-10-01 13:00:00	81
2012-10-01 14:00:00	80
2012-10-01 15:00:00	80
2012-10-01 16:00:00	80
2012-10-01 17:00:00	79

### Daily average

date	city	humidity
2012-10-01	Portland	78.72727
2012-10-02	Portland	65.83333
2012-10-03	Portland	66.20833
2012-10-04	Portland	51.16667
2012-10-05	Portland	40.39130

### Monthly mean/sd

ym	city	humidity_avg
2012-10	Portland	72.68403
2012-11	Portland	83.52227
2012-12	Portland	86.07985
2013-01	Portland	81.90679
2013-02	Portland	81.29739

Example: humidity (%)

## 2 Data preprocessing – final dataset

We match the storm event records to the weather data in the previous month, and obtain a relatively balanced dataset.

ym	county	state	num _episodes	meantemp _avg	difftemp _avg	humidity _avg	...
2012-10	Bernalillo	New Mexico	0	287.0911	13.988084	29.01159	...
2012-10	Fulton	Georgia	0	289.5540	9.677601	71.63047	...
2012-10	Suffolk	Massachuse tts	1	286.0031	8.069497	73.28394	...
2012-10	Mecklenbur g	North Carolina	1	288.7042	10.650447	70.75719	...
2012-10	Cook	Illinois	1	284.6265	8.173461	62.01605	...
2012-10	Dallas	Texas	0	292.1314	10.156523	61.92640	...

(negative:positive = 948:726)

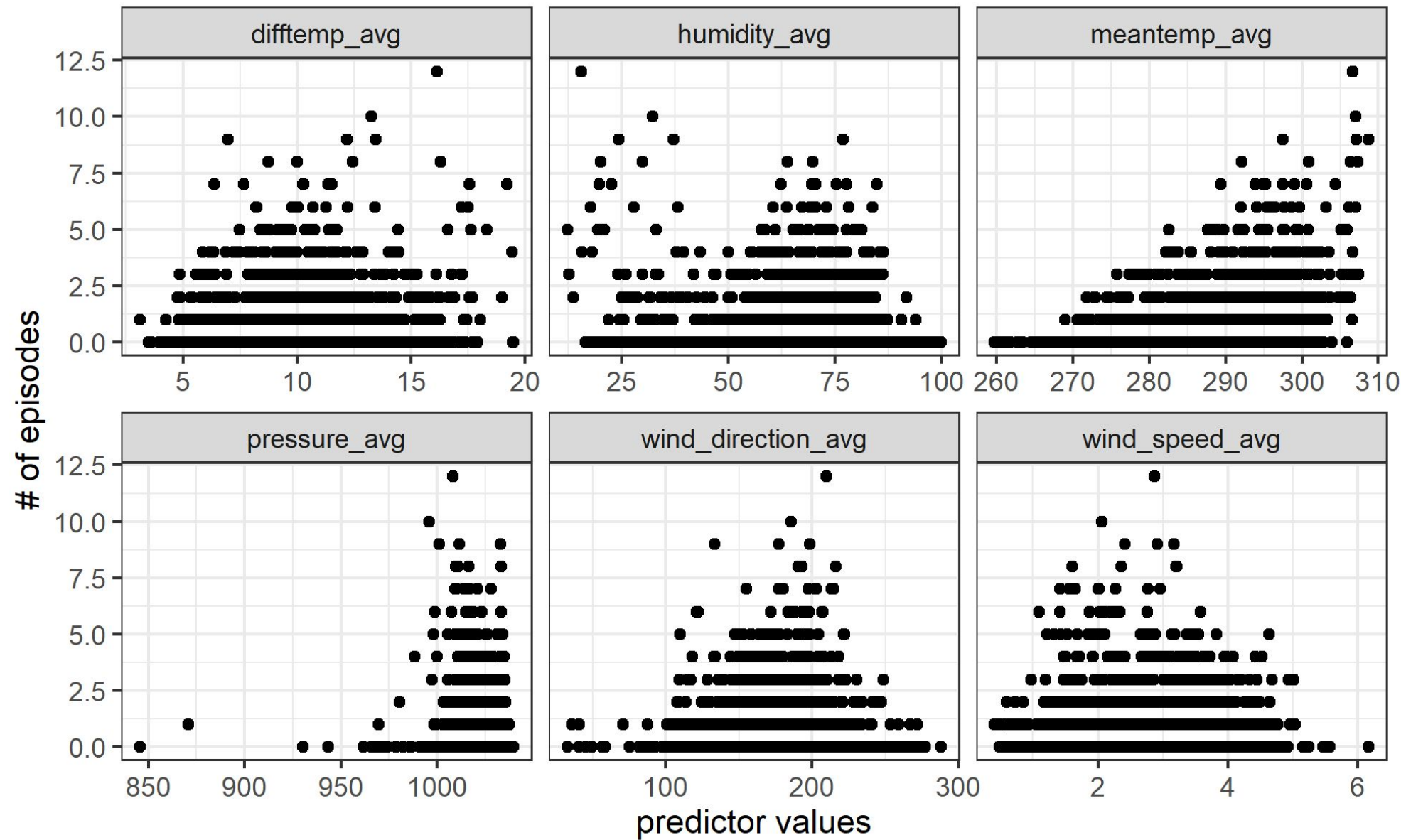
### Scale and Encode

- **Categorical Variable(State):** `LabelEncoder()`
- **Numerical Variable(Others):** `MinMaxScaler()`

`StandardScaler()`: worst

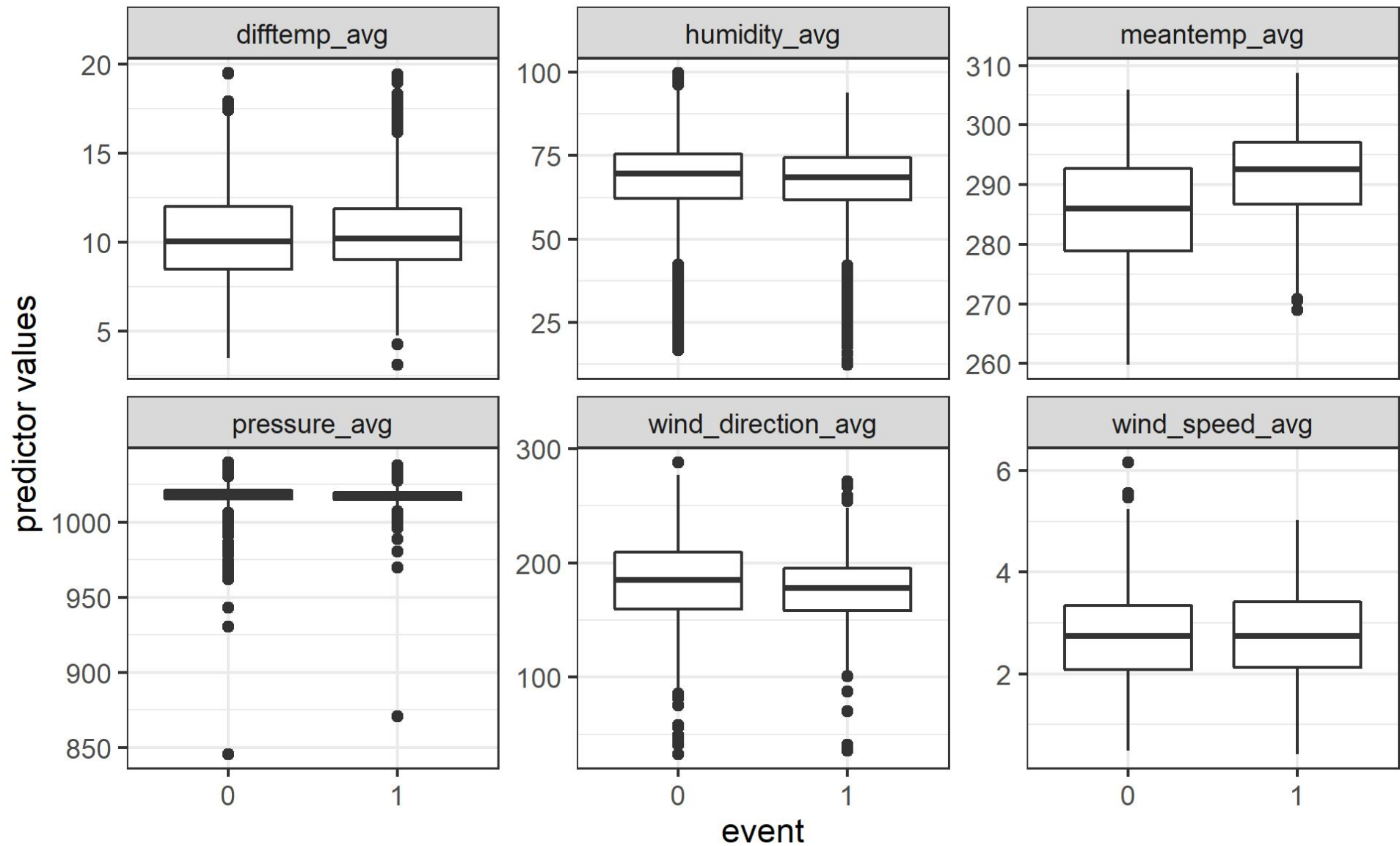
**Overall `RobustScaler()` was better than `MinMaxScaler()` for most of models, but for Gaussian Process Classifier, `MinMaxScaler()` performed better.**

### 3 Exploratory data analysis

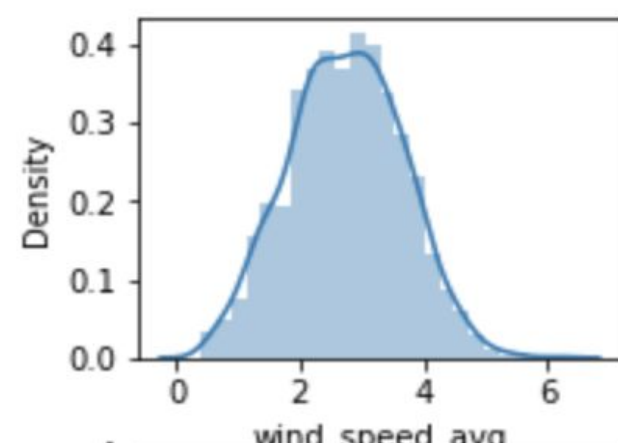
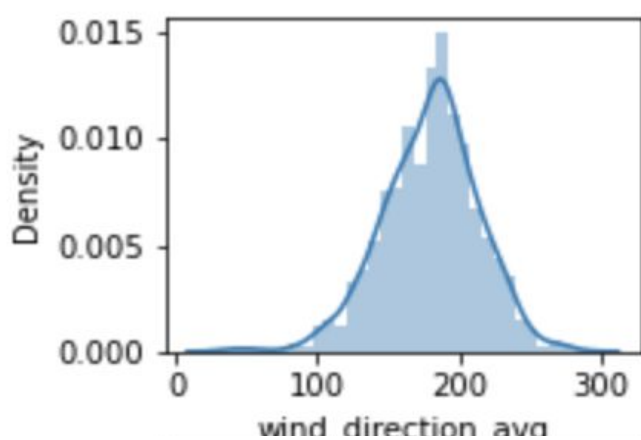
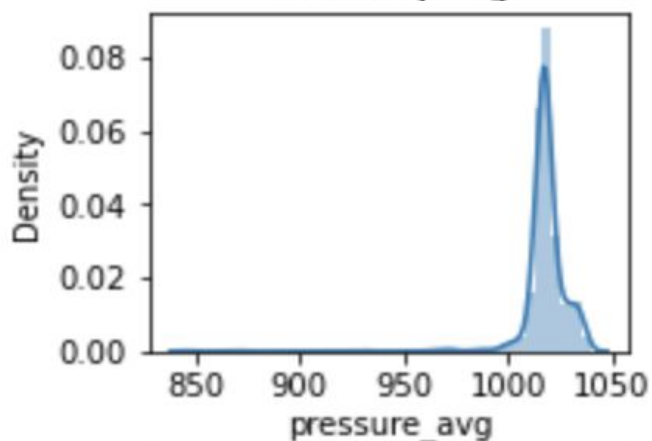
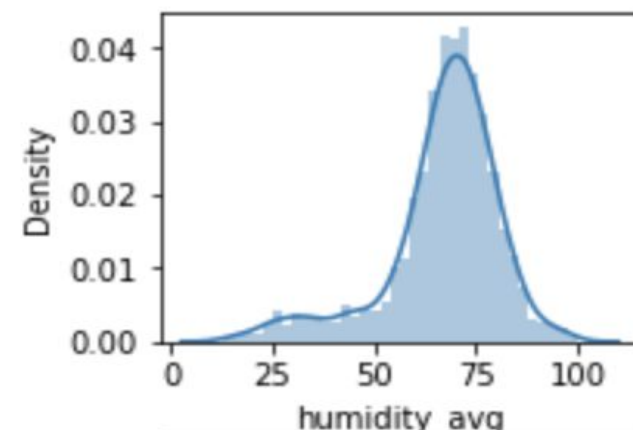
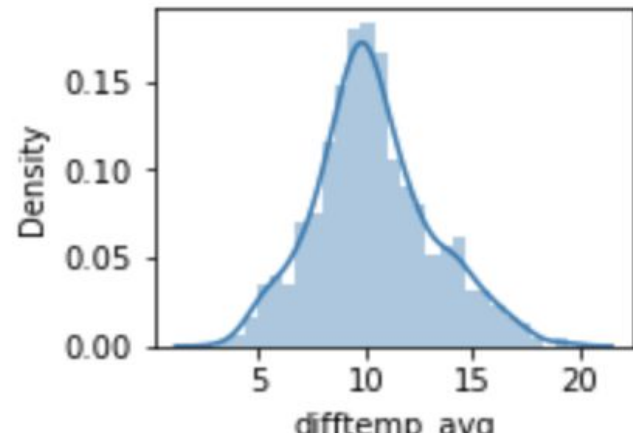
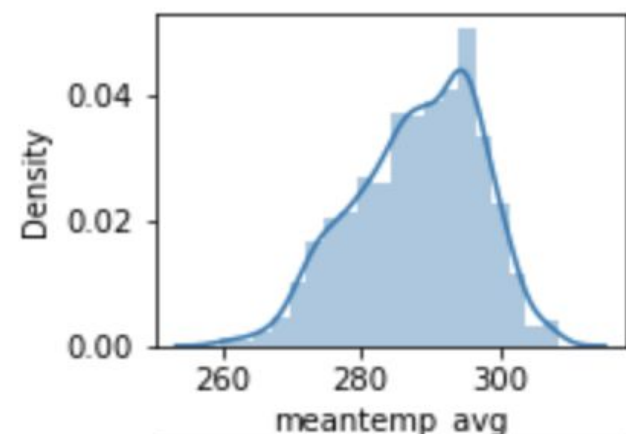




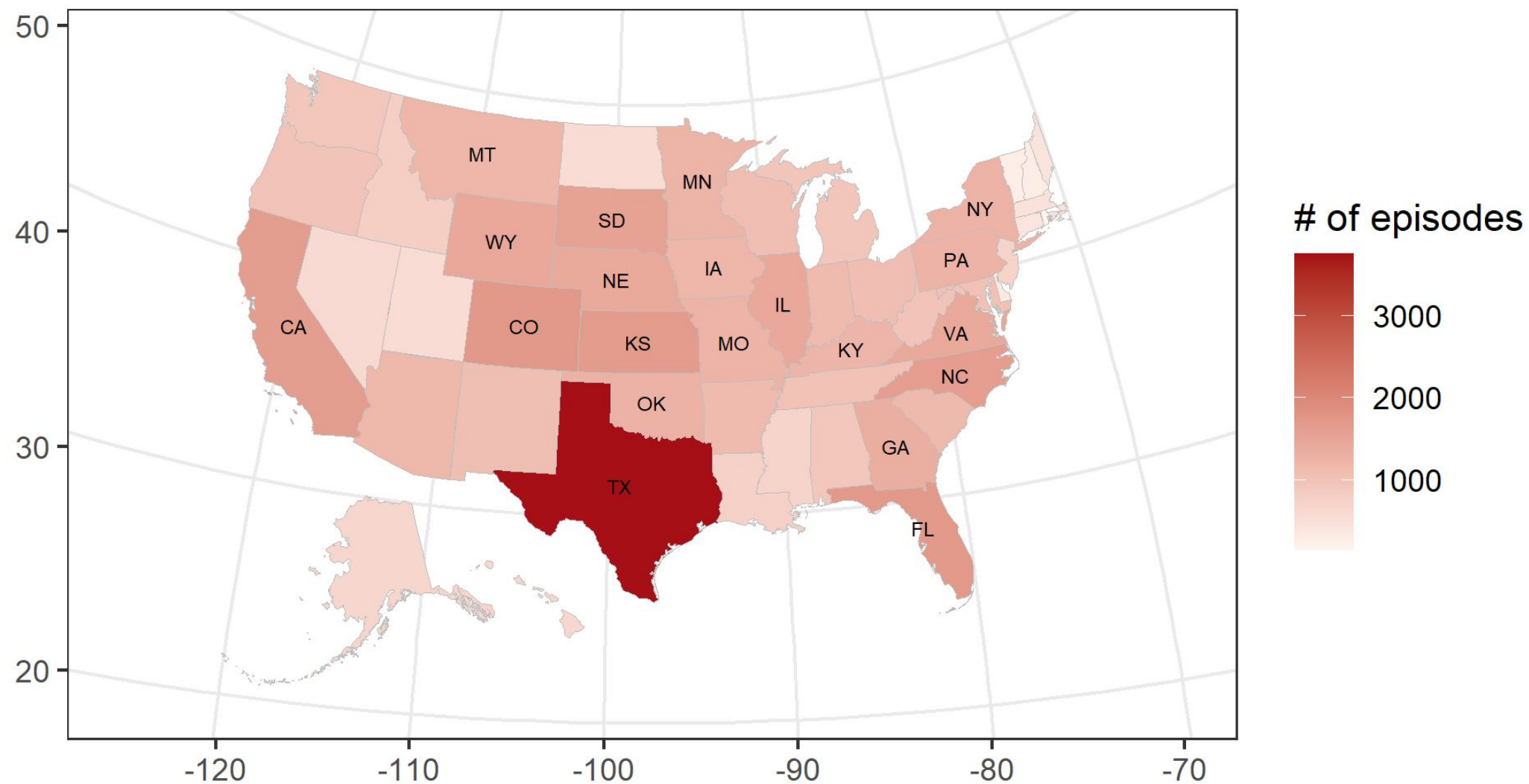
### 3 Exploratory data analysis



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### 3 Exploratory data analysis



Cumulative number of extreme weather events (episodes) in each state, 2012 - 2017

## 4 Train and Test

### Models with default parameters(Test Accuracy)

Classifier	Test Accuracy
Gaussian Process Classifier	68.11%
RBF-Support Vector Machine	66.43%
Random Forest	65.95%
Neural Networks	64.75%
Nearest Neighbors	64.51%
Naive Bayes	63.55%
AdaBoost	63.31%
Decision Tree	62.35%
Linear Support Vector Machine	60.43%

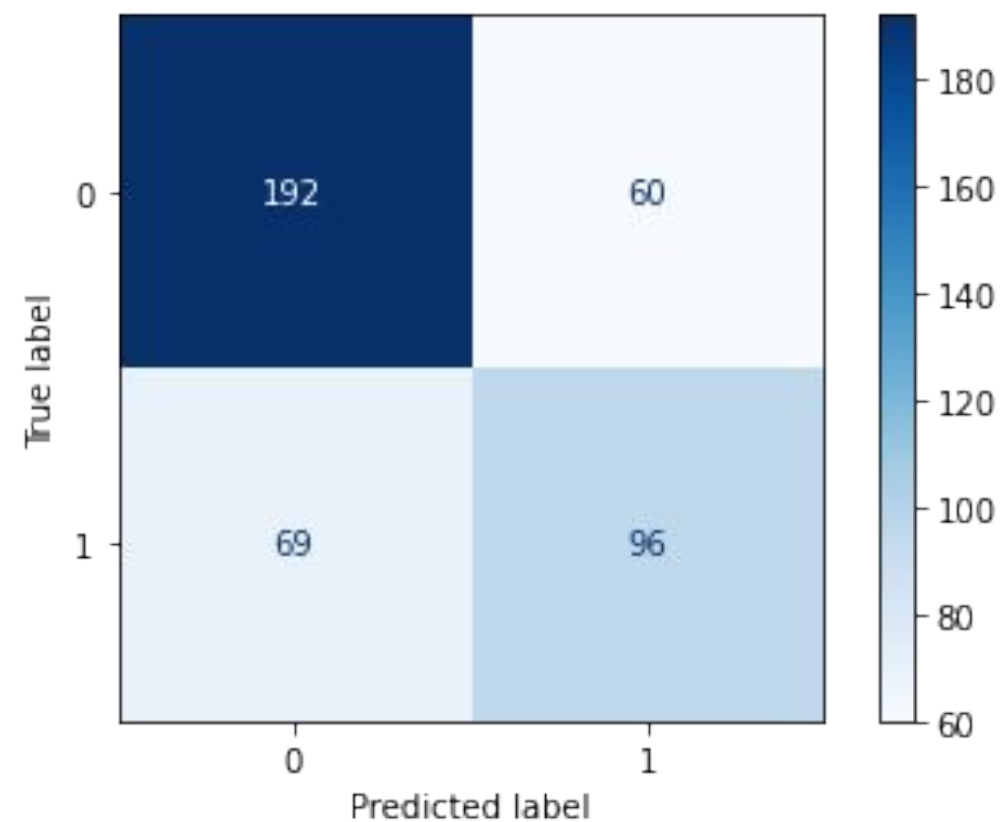
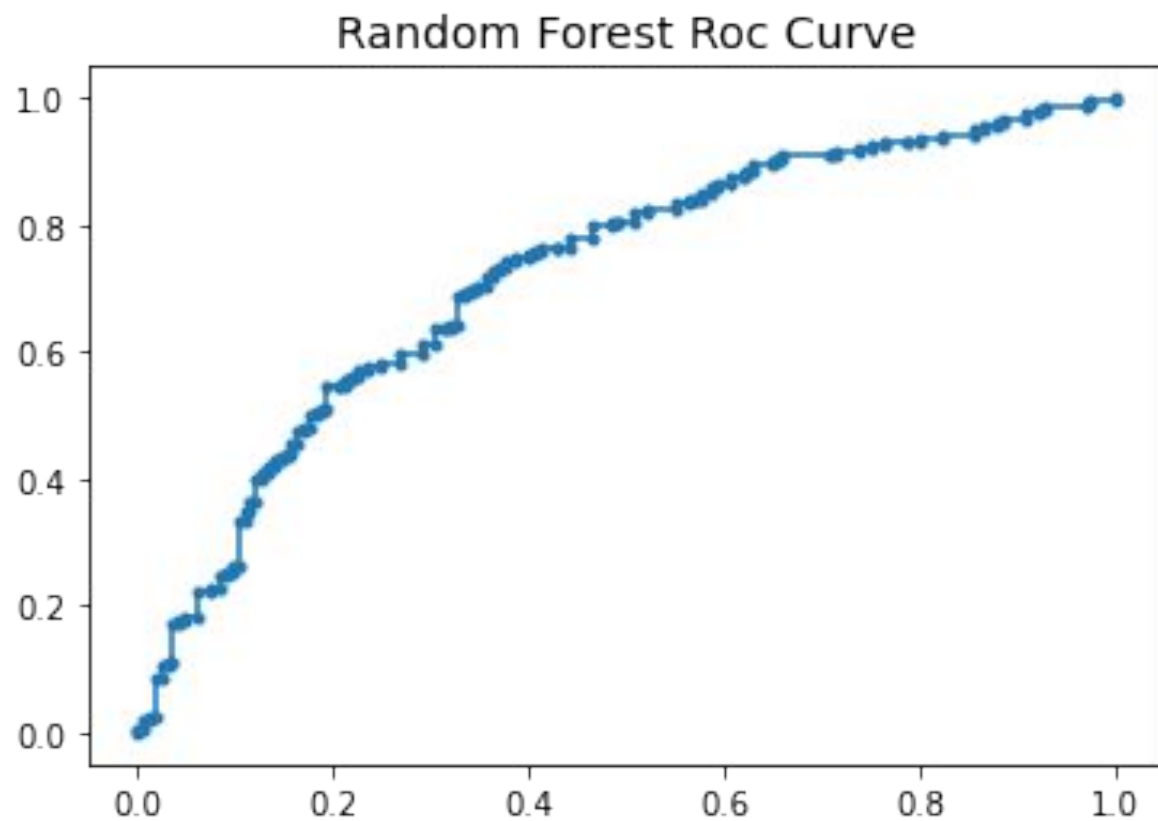
### Random Forest Parameter tuning

- **RandomizedSearchCV()**
- **Best Parameters: {'n\_estimators': 800, 'min\_samples\_split': 15, 'min\_samples\_leaf': 2, 'max\_features': 'sqrt', 'max\_depth': 40, 'criterion': 'gini', 'bootstrap': True}**

<b>Train Accuracy</b>	<b>91.87%</b>
<b>Test Accuracy</b>	<b>69.06%</b>
<b>AUC</b>	<b>0.7230</b>
<b>BER</b>	<b>0.3281</b>

## 4 Train and Test

### Random Forest - Result



### RBF SVM Parameter tuning

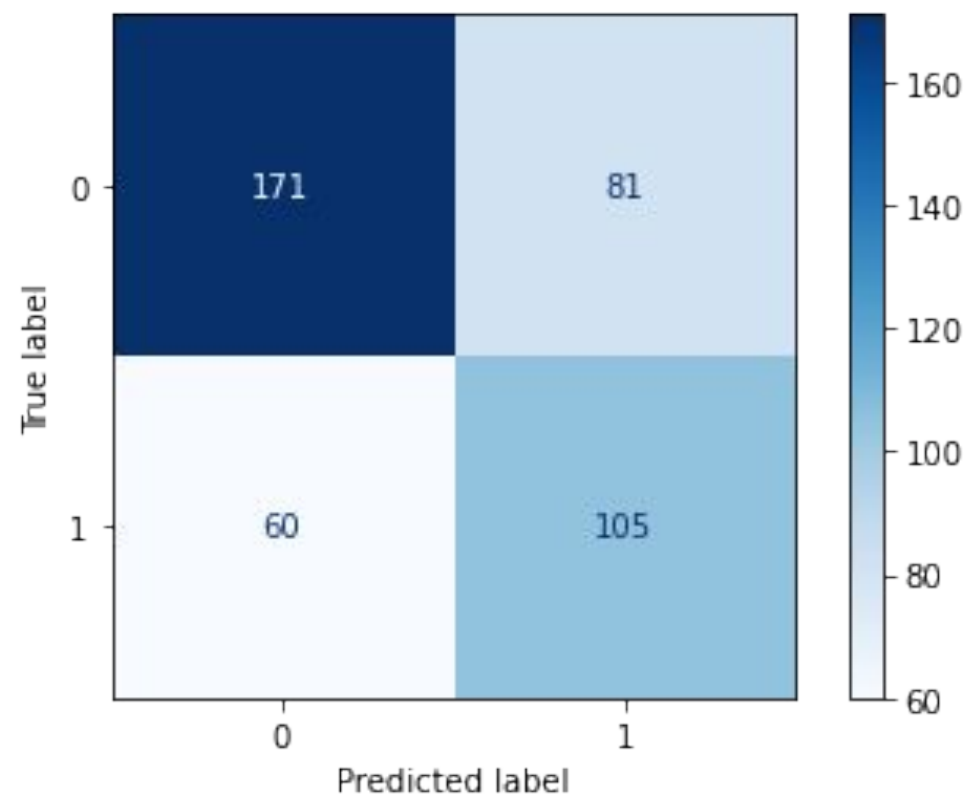
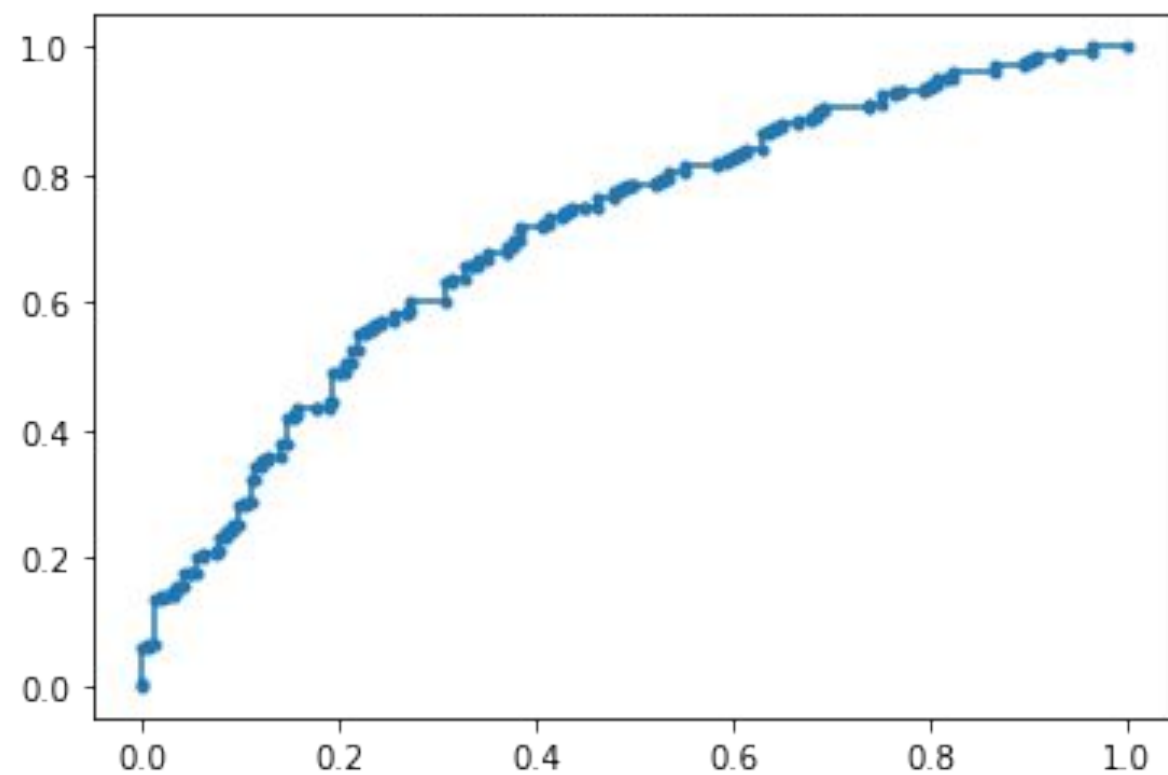
- **RandomizedSearchCV()**
- **Best Parameters: (gamma=1, C=5, kernel='rbf')**

<b>Train Accuracy</b>	<b>73.92%</b>
<b>Test Accuracy</b>	<b>66.19%</b>
<b>AUC</b>	<b>0.7102</b>
<b>BER</b>	<b>0.3425</b>

## 4 Train and Test

### RF SVM - Result

RF SVM Roc Curve





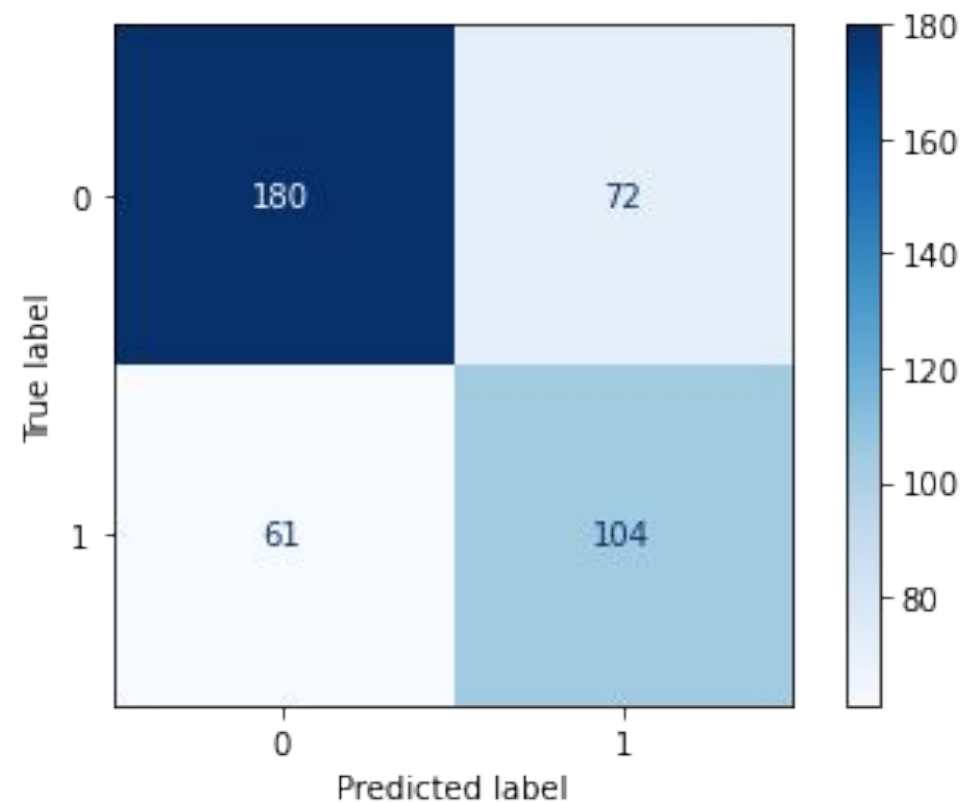
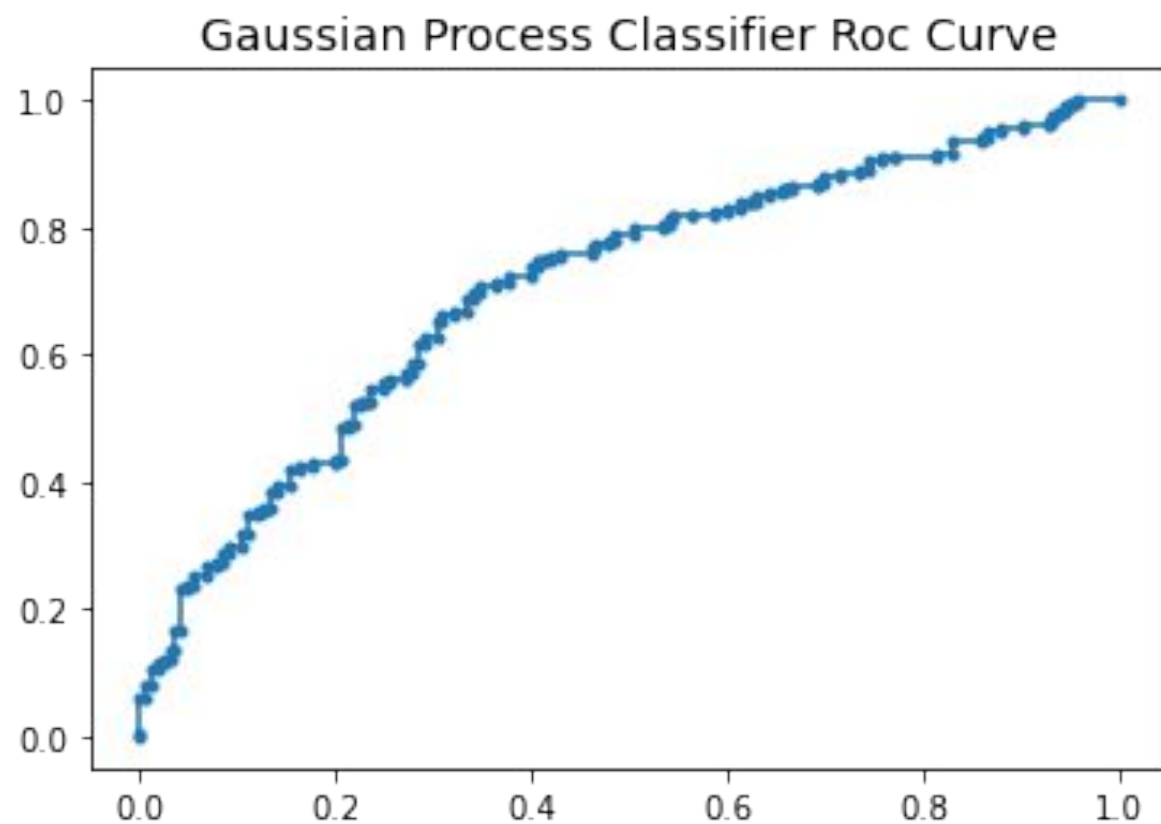
### Gaussian Process Classifier Parameter tuning

- **Best Parameters: kernel = 1.0 \* RBF(1.0)**
- **Radial Basis Function (RBF) kernel = Gaussian kernel**

<b>Train Accuracy</b>	<b>73.68%</b>
<b>Test Accuracy</b>	<b>68.11%</b>
<b>AUC</b>	<b>0.7078</b>
<b>BER</b>	<b>0.3277</b>

## 4 Train and Test

# Gaussian Process Classifier - Result





# Thank you

Haejeong Choi, Yanyu Long, Seung Ho Woo