

Machine Learning Fundamental – Final Project

Predictive Forecast Weather for Singapore
(Kind of rain)

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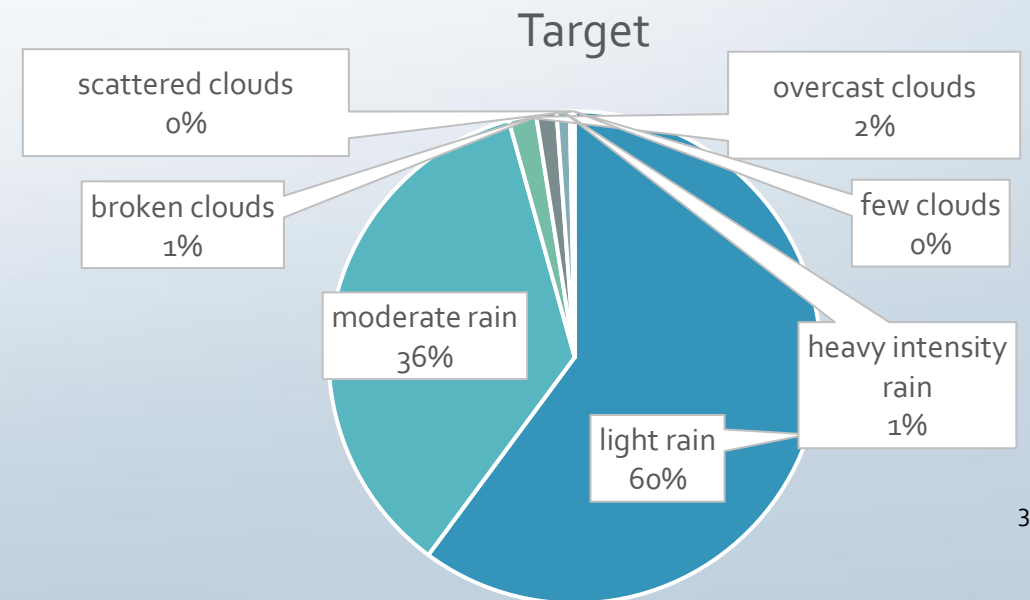
Introduction

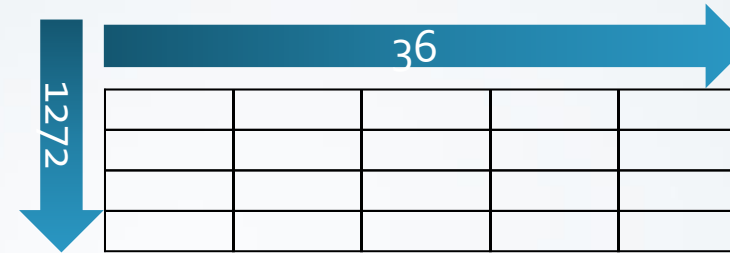
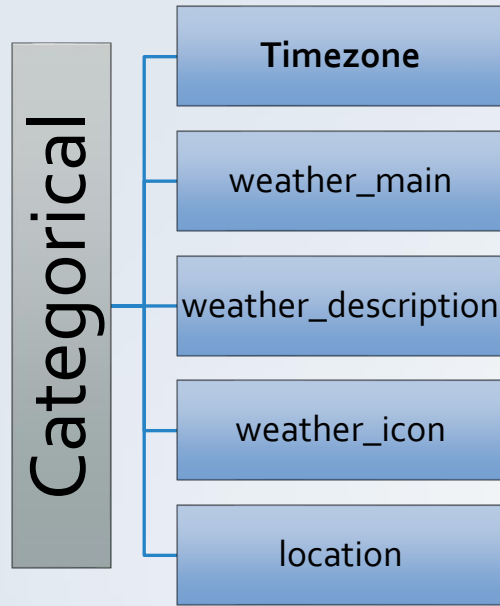
One of the main issues for people living in south-east Asia is the rainy weather, and sometimes the intensity of rain is bothering people, according to the dataset I use for this project, I have access to different measurements to predict a variety of specific situations of rainy and cloudy weather.

Introduction

The target value I face is unbalanced so I change the target to the prediction of the intensity of rain and focus on the light rain from other kinds of rain, to make the output balance.

By predicting the intensity of rain, I can help people in that area be ready for the intensity of rain, increase public transportation safety, and control traffic.





Numerical						
lat lon	dt	Pressure Humidity dew_point	wind_speed wind_deg wind_gust	Pop Rain Uvi	temp_day	feels_like_day
	Sunrise				temp_min	feels_like_nig
	Sunset				temp_max	ht
	Moonrise				temp_night	feels_like_eve
	Moonset				temp_eve	feels_like_mo
	moon_phase				temp_morn	rn

Data Cleaning

- Based on dataset we discussed, there are not a lot to do, just drop feature with unique values

```
[7] #drop feature with unique values
unique_val_cols = []
for cols in dataset.columns:
    if dataset[cols].nunique() == 1:
        unique_val_cols.append(cols)
dataset.drop(columns = unique_val_cols, inplace = True)
```



Data manipulation

- Fillna of rain feature with the constant value
- Creating two new features instead of 'sunrise', 'sunset', 'moonrise', & 'moonset'

,moonset,

Features contain Null values

- rain

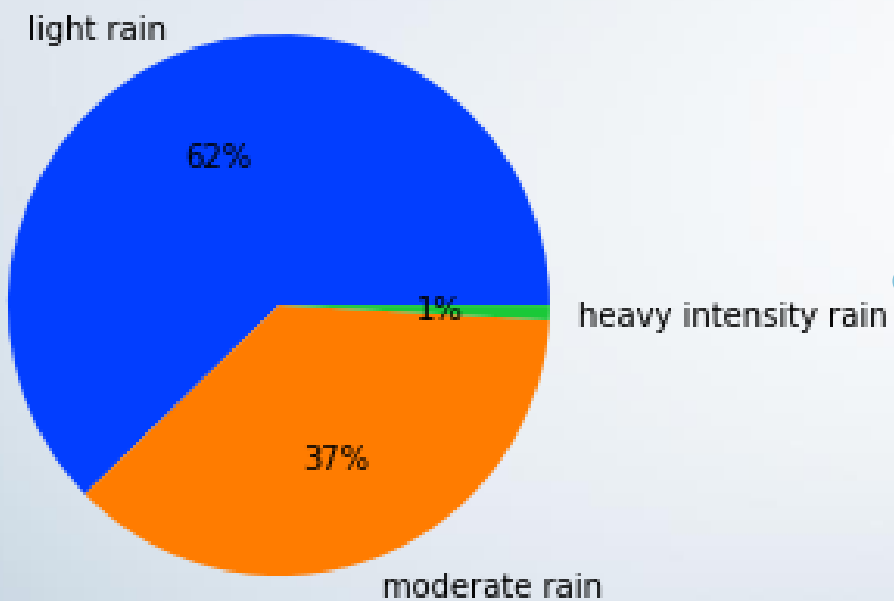
Creating two new features based on correct one

- `dataset['day_duration'] = dataset.apply(lambda x: dataset.sunset-dataset.sunrise).mean(axis=1)`
- `dataset['night_duration'] = dataset.apply(lambda x: dataset.moonrise-dataset.moonset).mean(axis=1)`

Data manipulation

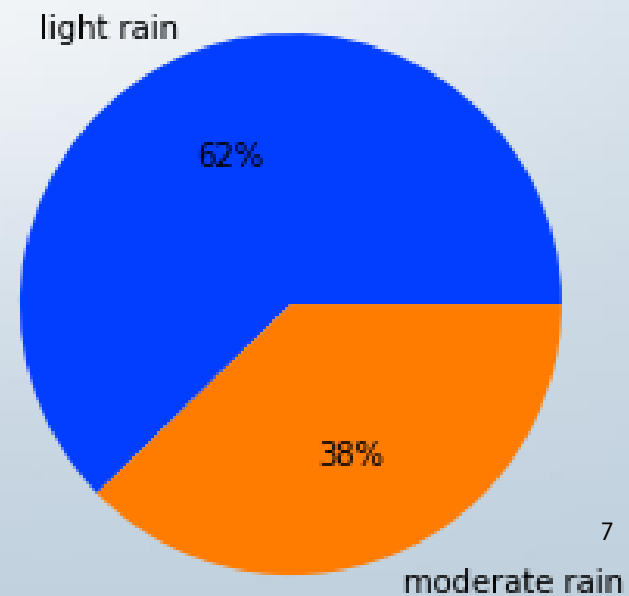
- Manipulation of target

Rain weather_description



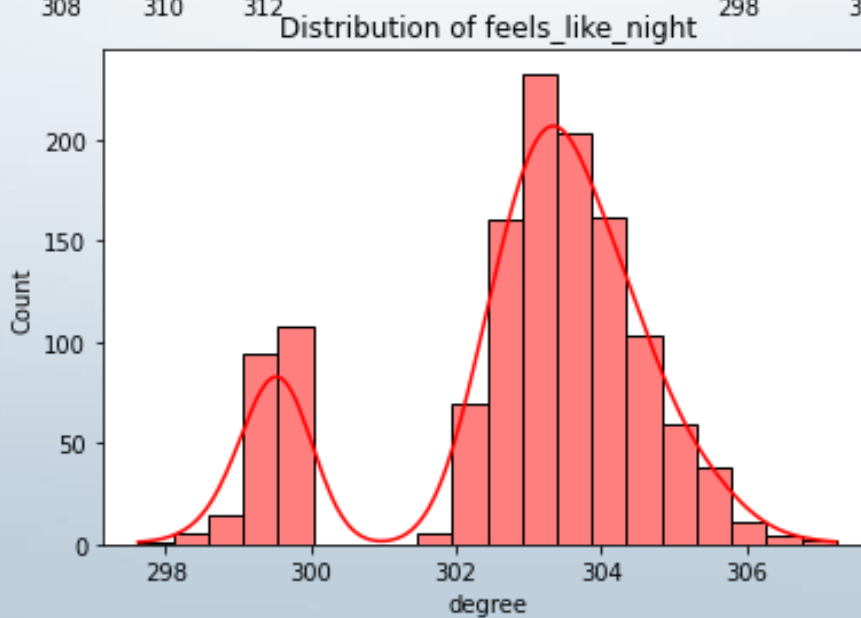
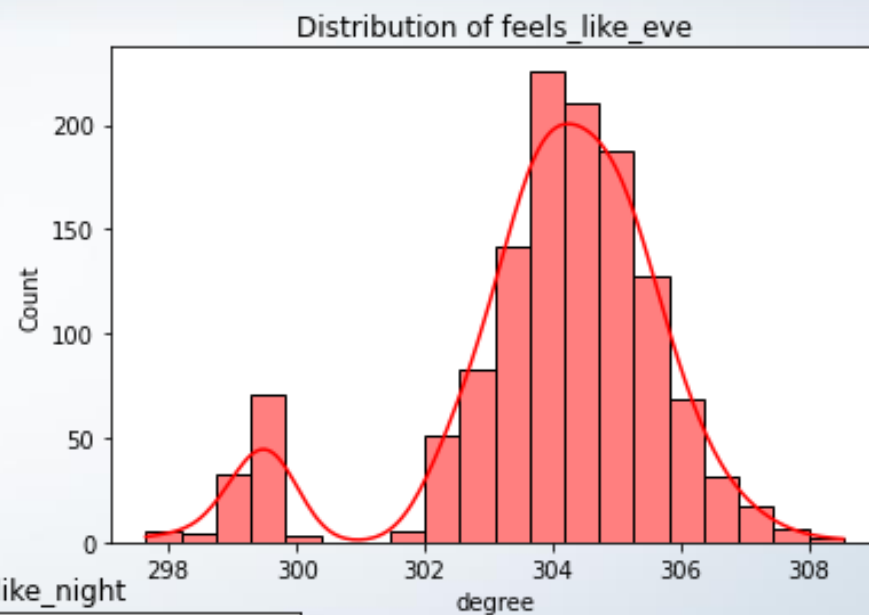
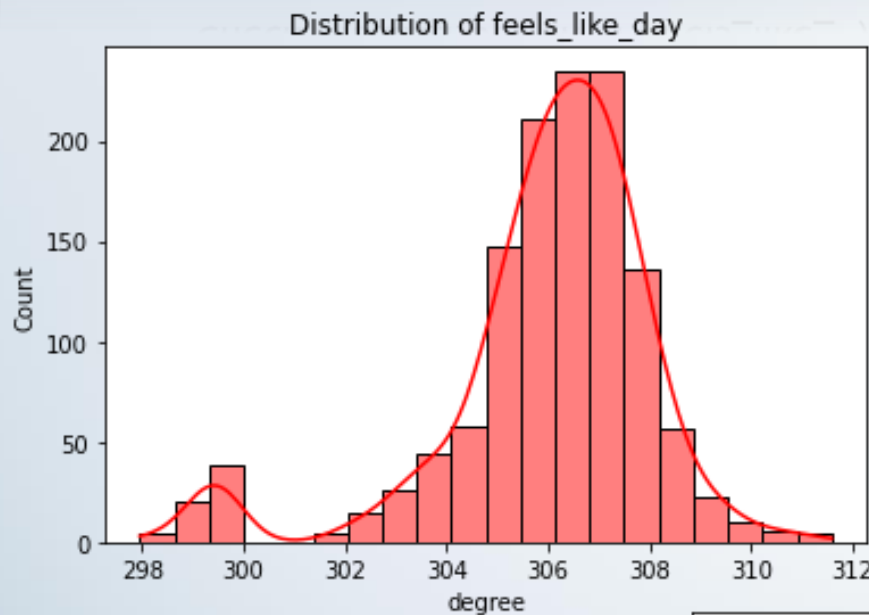
```
weather_description
light rain      500.0
moderate rain   501.0
Name: weather_id, dtype: float64
```

Rain weather_description



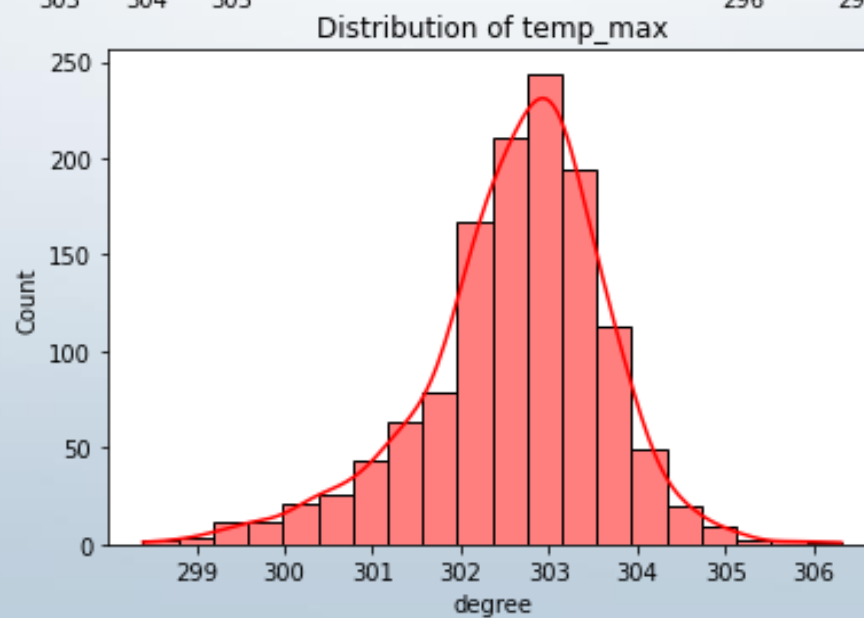
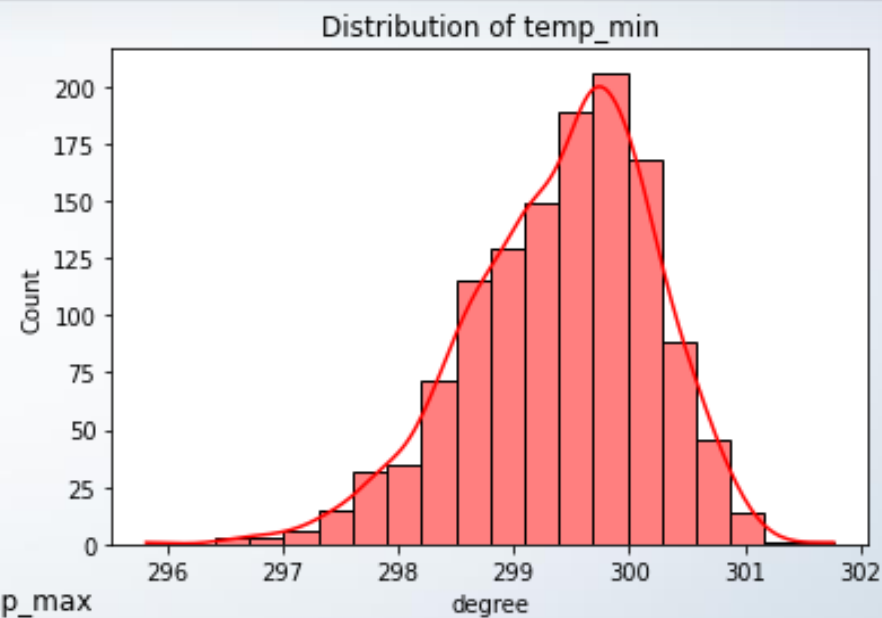
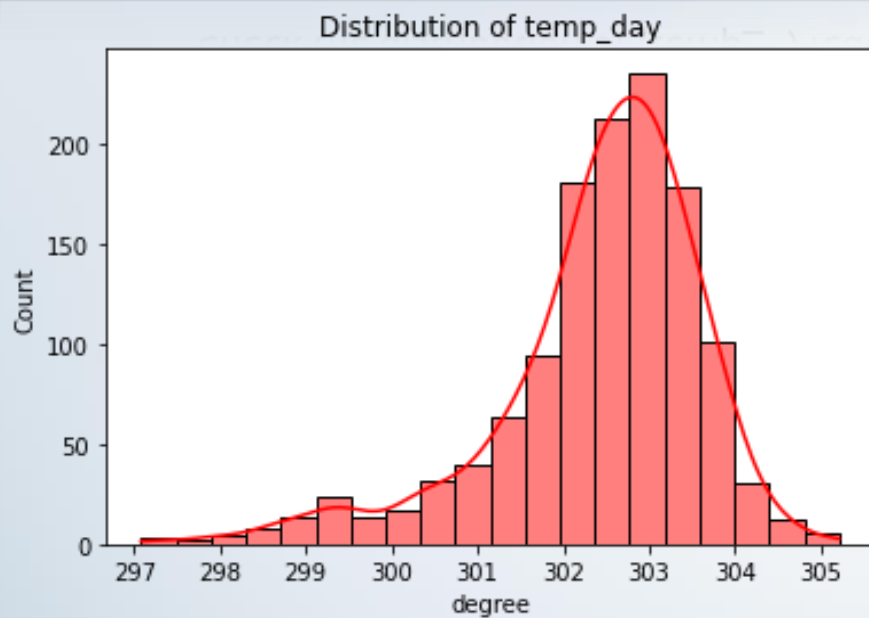
Data Analyze

- Check the distribution of (feels_like_*) features



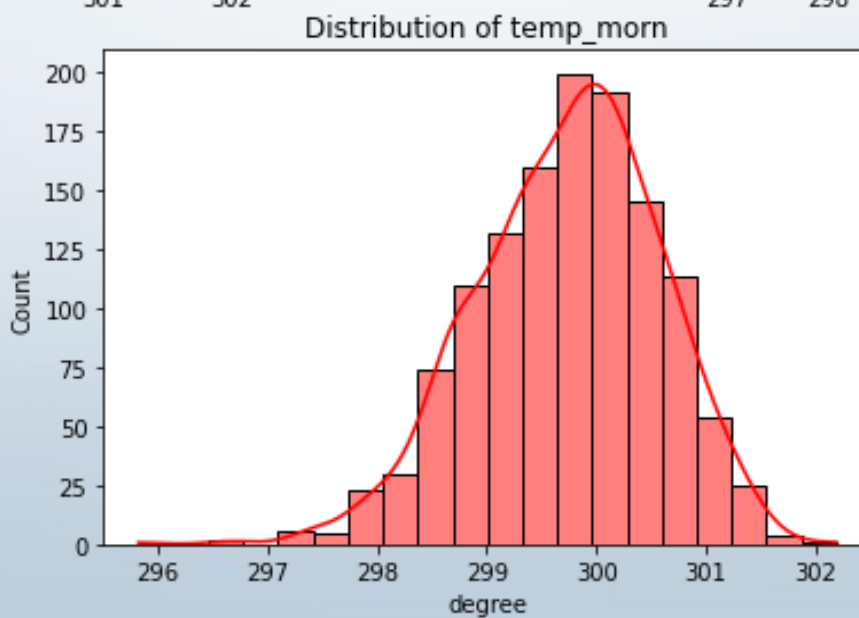
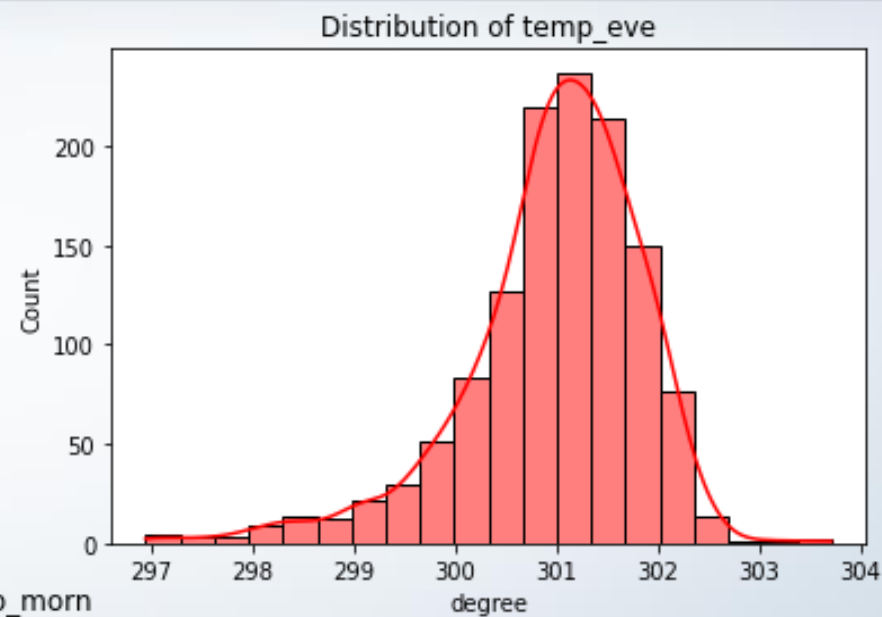
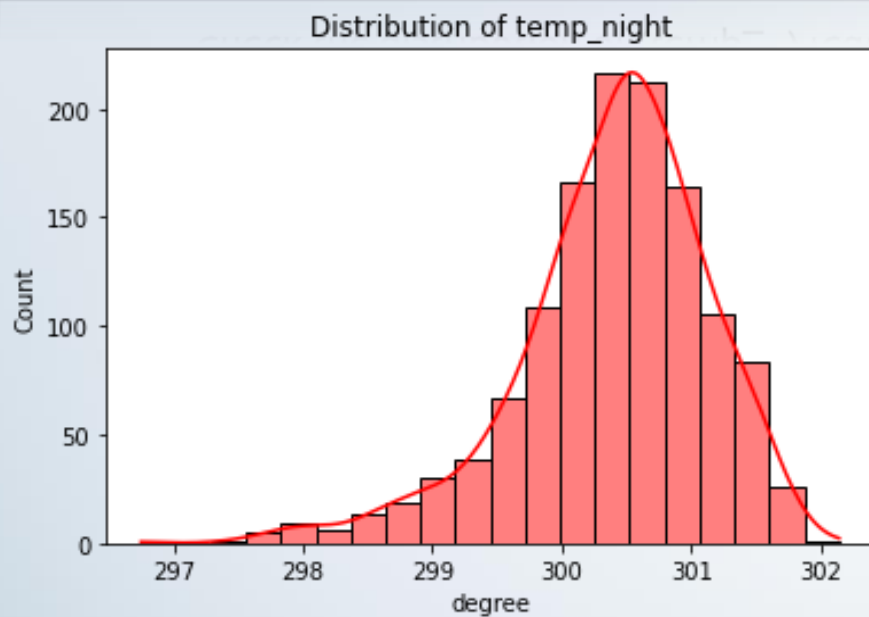
Data Analyze

- Check the distribution of (temp_*) features – P1



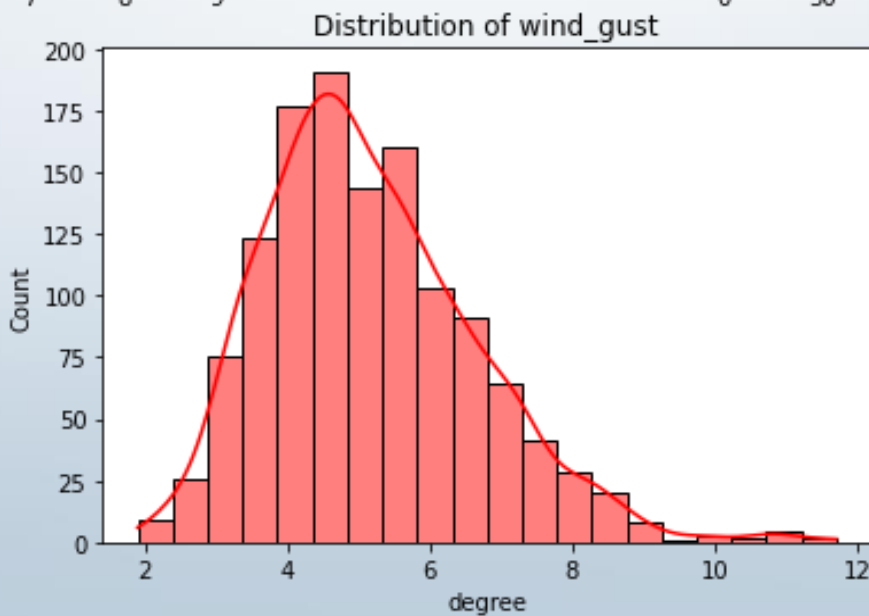
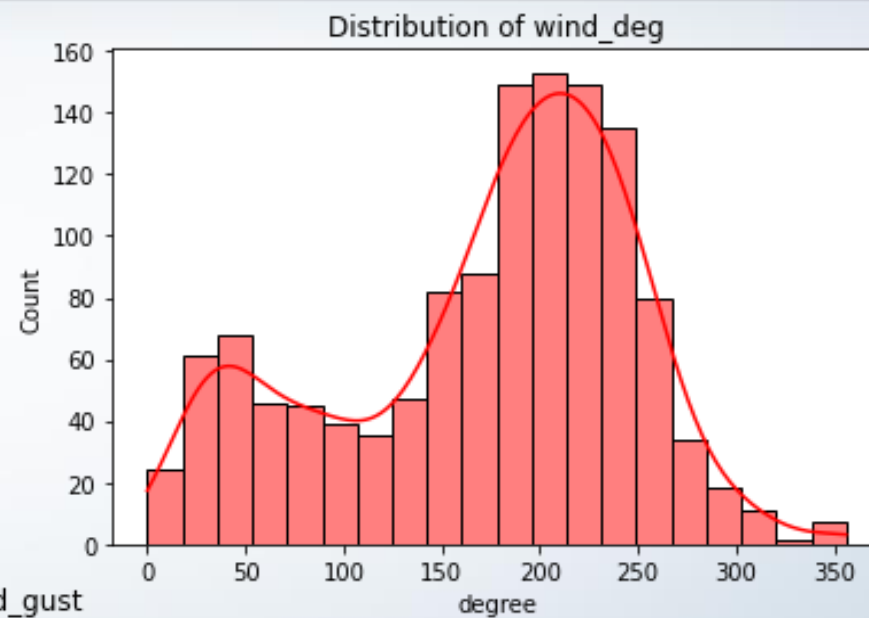
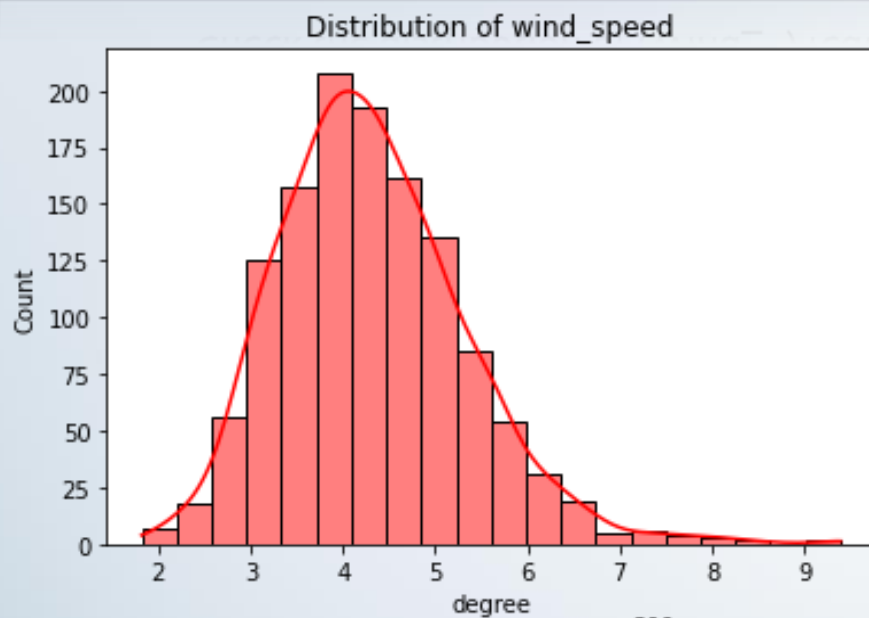
Data Analyze

- Check the distribution of (temp_*) features P2



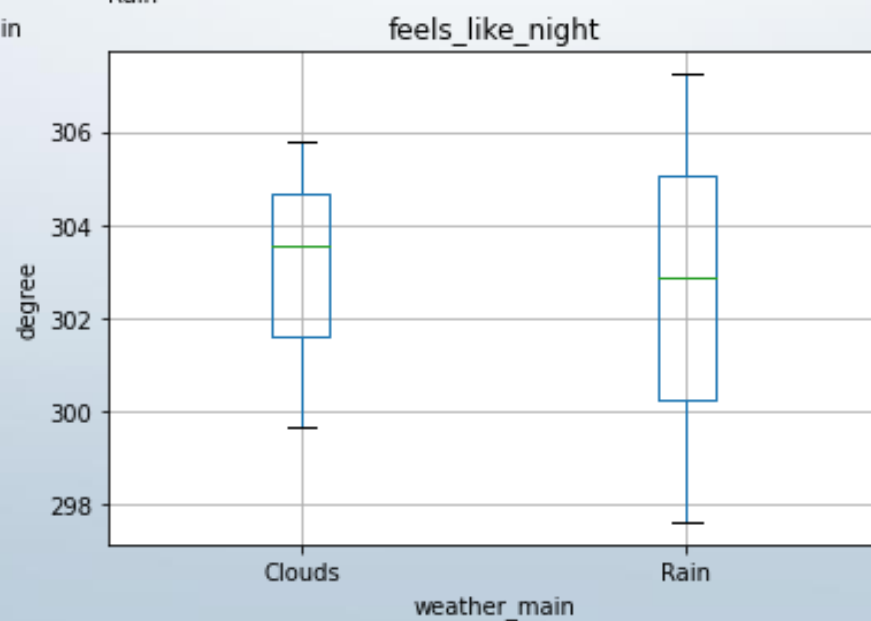
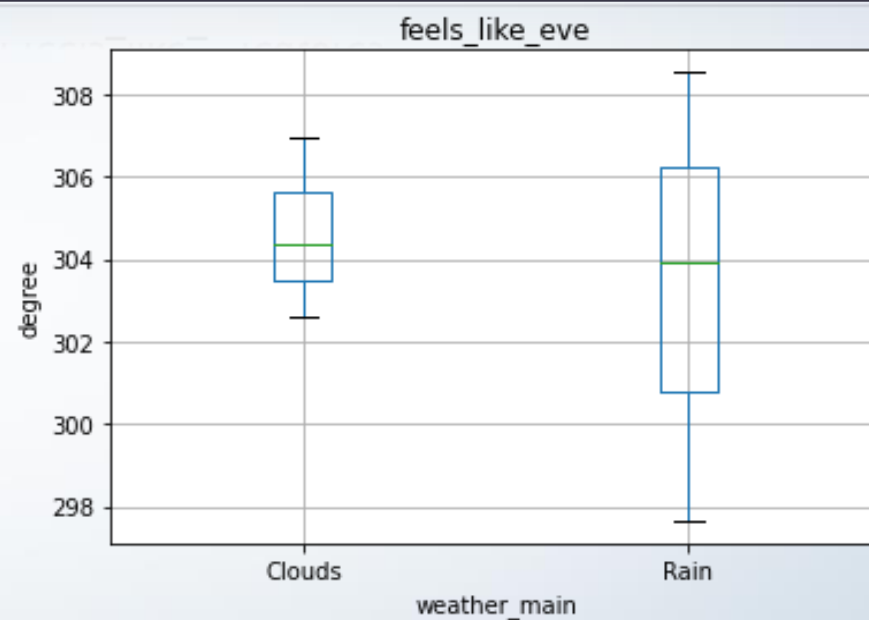
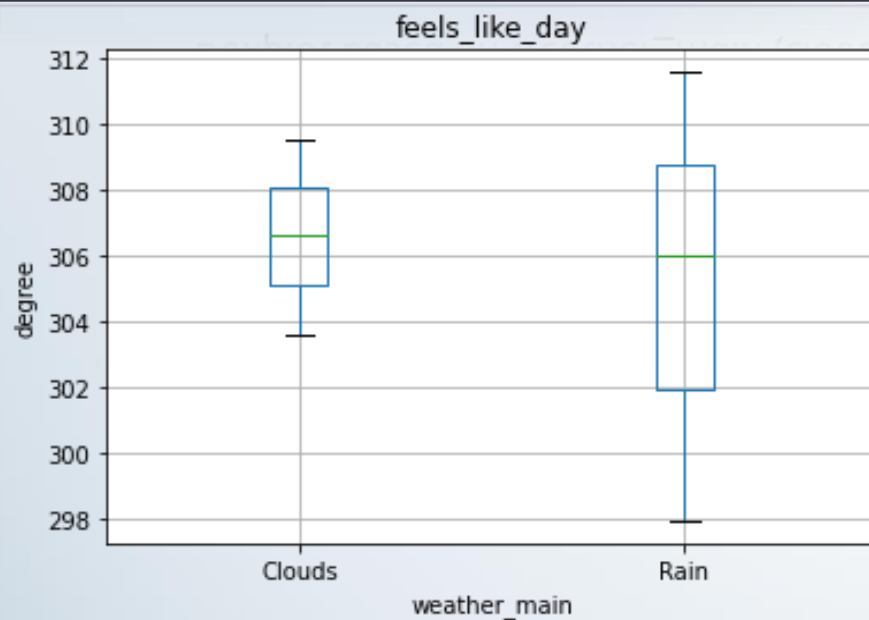
Data Analyze

- Check the distribution of (Wind_*) features



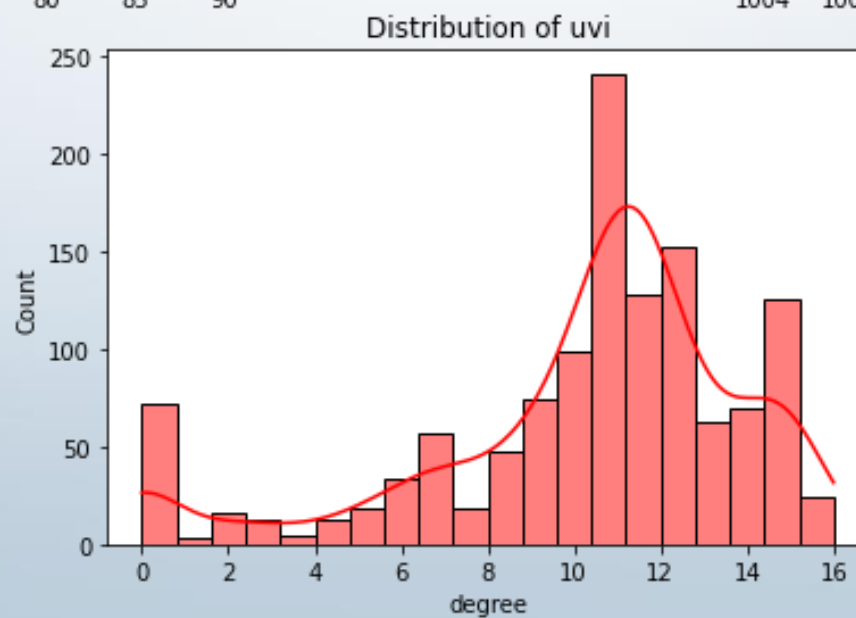
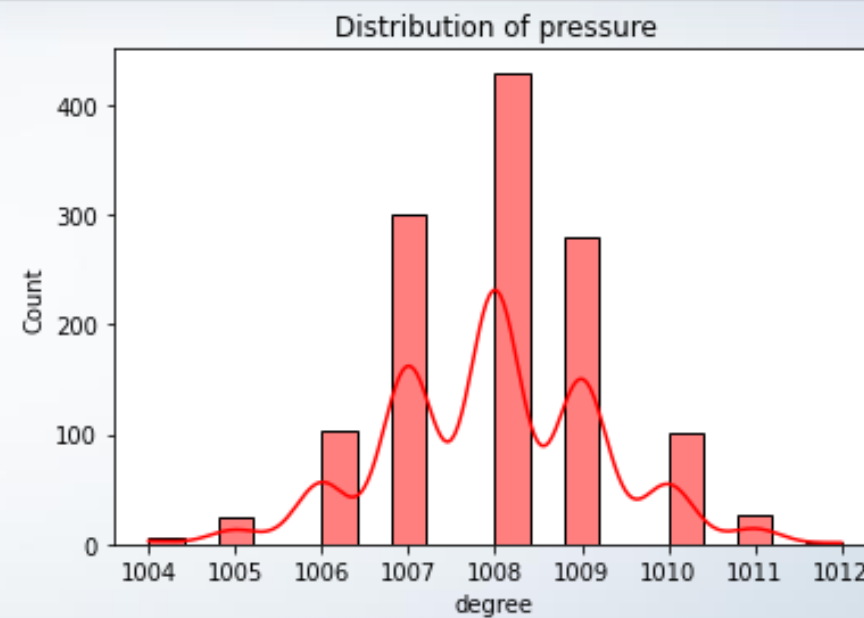
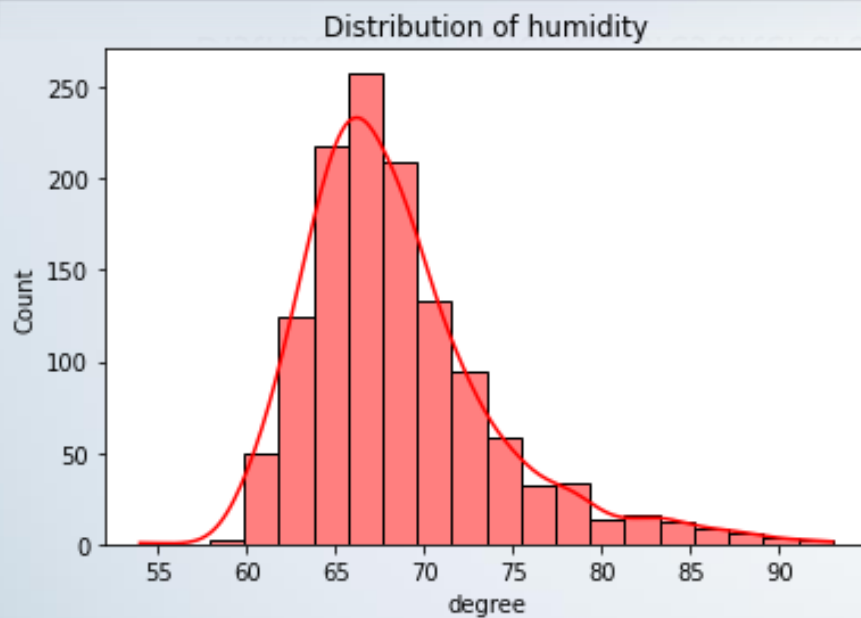
Data Analyze

- Boxplot based on weather_main (clouds, & rain) field for feels_like_* features



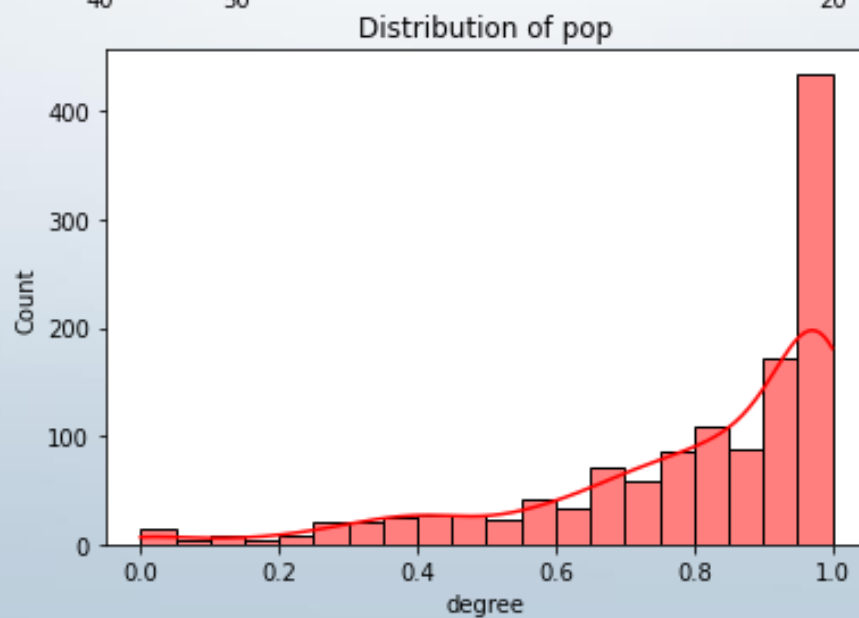
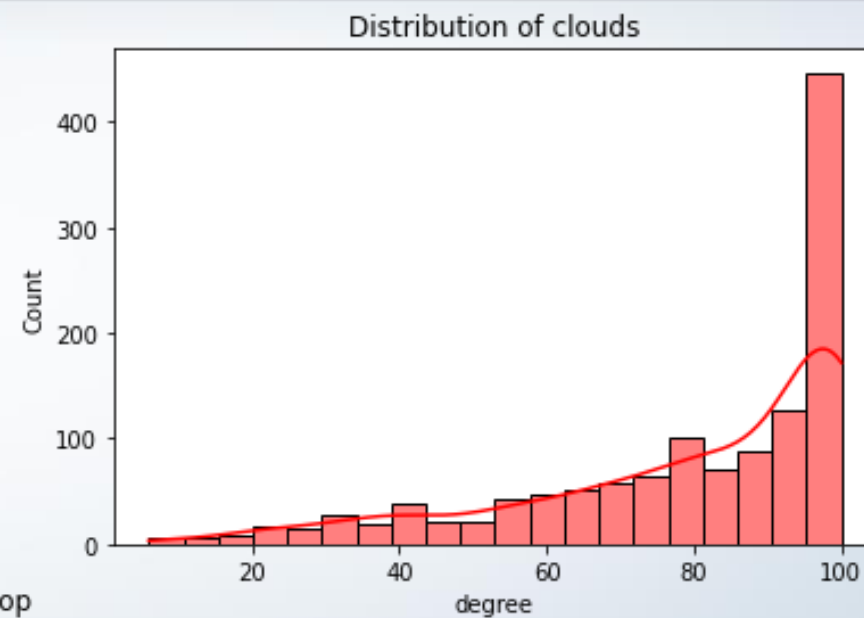
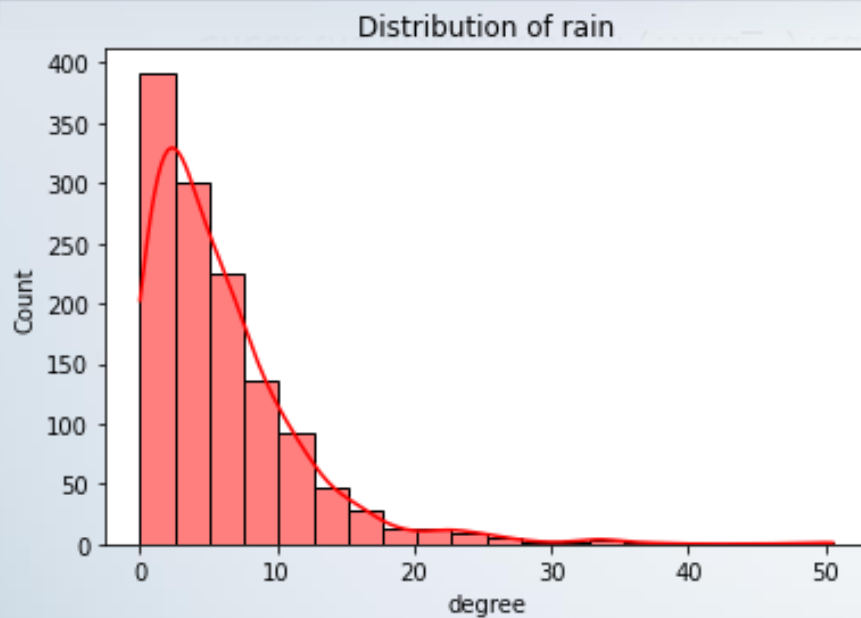
Data Analyze

- Distribution of other features after drop clouds samples



Data Analyze

- Check the distribution of (Wind_*) features

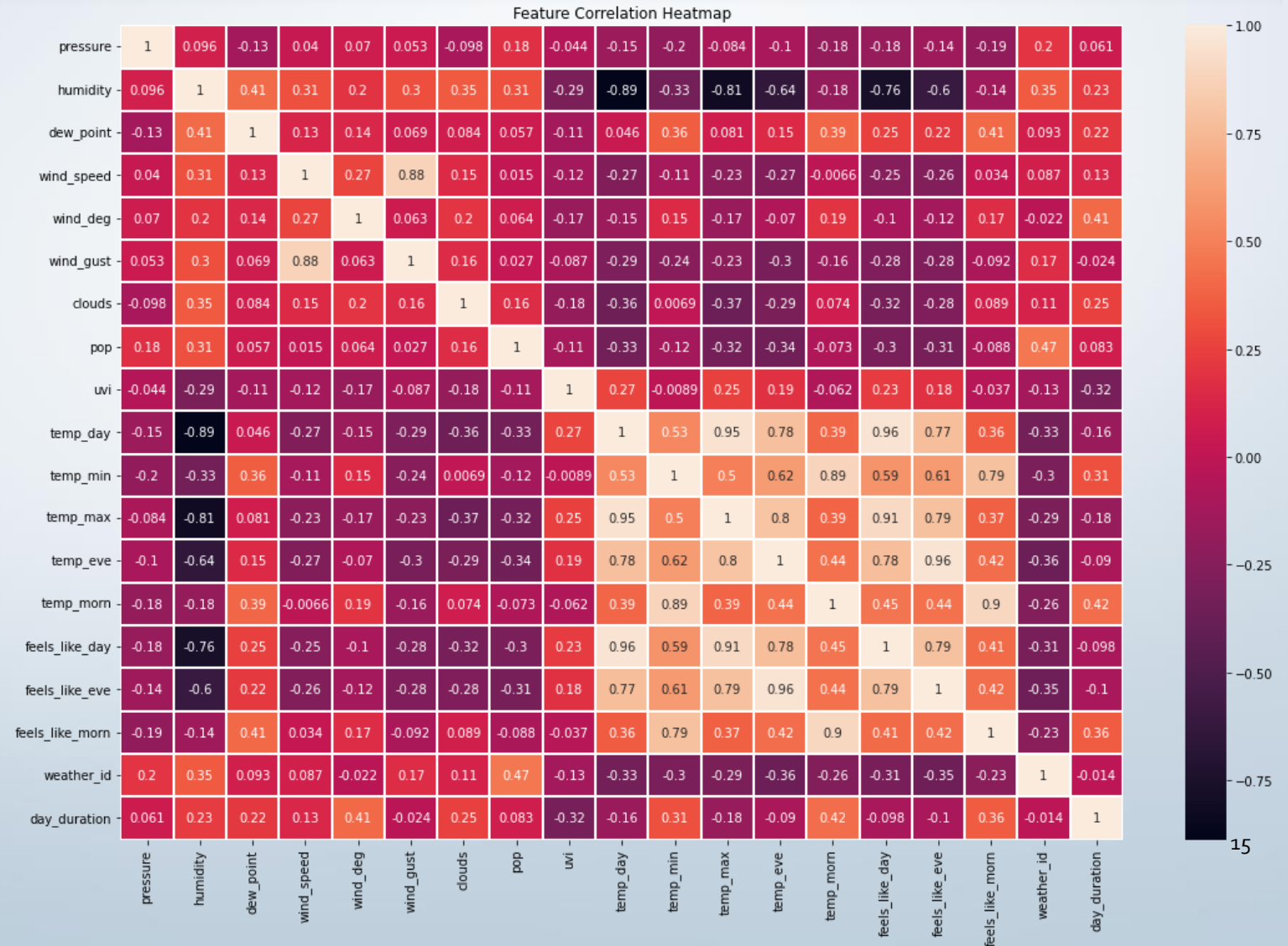


Data Analyze

- Heatmap graph



The amount of rain is related to after occurring so it is dropped. My assumption was the situation happened during the day so all information related to night are dropped.



Data Analyze

- Use Hypothesis test for checking the normal distribution

Features_name	p_value	Hypothesis_Description
pressure	0.442198	Normal Distribution
humidity	0.0	We can't reject Hypothesis test
dew_point	0.000001	We can't reject Hypothesis test
wind_speed	0.0	We can't reject Hypothesis test
wind_deg	0.0	We can't reject Hypothesis test
wind_gust	0.0	We can't reject Hypothesis test
clouds	0.0	We can't reject Hypothesis test
pop	0.0	We can't reject Hypothesis test
uvi	0.0	We can't reject Hypothesis test
temp_day	0.0	We can't reject Hypothesis test
temp_min	0.0	We can't reject Hypothesis test
temp_max	0.0	We can't reject Hypothesis test
temp_eve	0.0	We can't reject Hypothesis test
temp_morn	0.000001	We can't reject Hypothesis test
feels_like_day	0.0	We can't reject Hypothesis test
feels_like_eve	0.0	We can't reject Hypothesis test
feels_like_morn	0.0	We can't reject Hypothesis test
weather_id	0.0	We can't reject Hypothesis test
day_duration	0.0	We can't reject Hypothesis test

Feature selection

- Dependency with target

Hypothesis test for linear dependency

Features_name	p_value	linear_dependency_Description
pressure	0.0	Probably dependent
humidity	0.0	Probably dependent
dew_point	0.001095	Probably dependent
wind_speed	0.002269	Probably dependent
wind_deg	0.431777	Probably independent
wind_gust	0.0	Probably dependent
clouds	0.000085	Probably dependent
pop	0.0	Probably dependent
uvi	0.000008	Probably dependent
temp_day	0.0	Probably dependent
temp_min	0.0	Probably dependent
temp_max	0.0	Probably dependent
temp_eve	0.0	Probably dependent
temp_morn	0.0	Probably dependent
feels_like_day	0.0	Probably dependent
feels_like_eve	0.0	Probably dependent
feels_like_morn	0.0	Probably dependent
weather_id	0.0	Probably dependent
day_duration	0.613735	Probably independent

Hypothesis test for monotonic dependency

Features_name	p_value	monotonic_dependency_Description
pressure	0.0	Probably dependent
humidity	0.0	Probably dependent
dew_point	0.000778	Probably dependent
wind_speed	0.075576	Probably independent
wind_deg	0.946618	Probably independent
wind_gust	0.0	Probably dependent
clouds	0.000002	Probably dependent
pop	0.0	Probably dependent
uvi	0.000007	Probably dependent
temp_day	0.0	Probably dependent
temp_min	0.0	Probably dependent
temp_max	0.0	Probably dependent
temp_eve	0.0	Probably dependent
temp_morn	0.0	Probably dependent
feels_like_day	0.0	Probably dependent
feels_like_eve	0.0	Probably dependent
feels_like_morn	0.0	Probably dependent
weather_id	0.0	Probably dependent
day_duration	0.817769	Probably independent

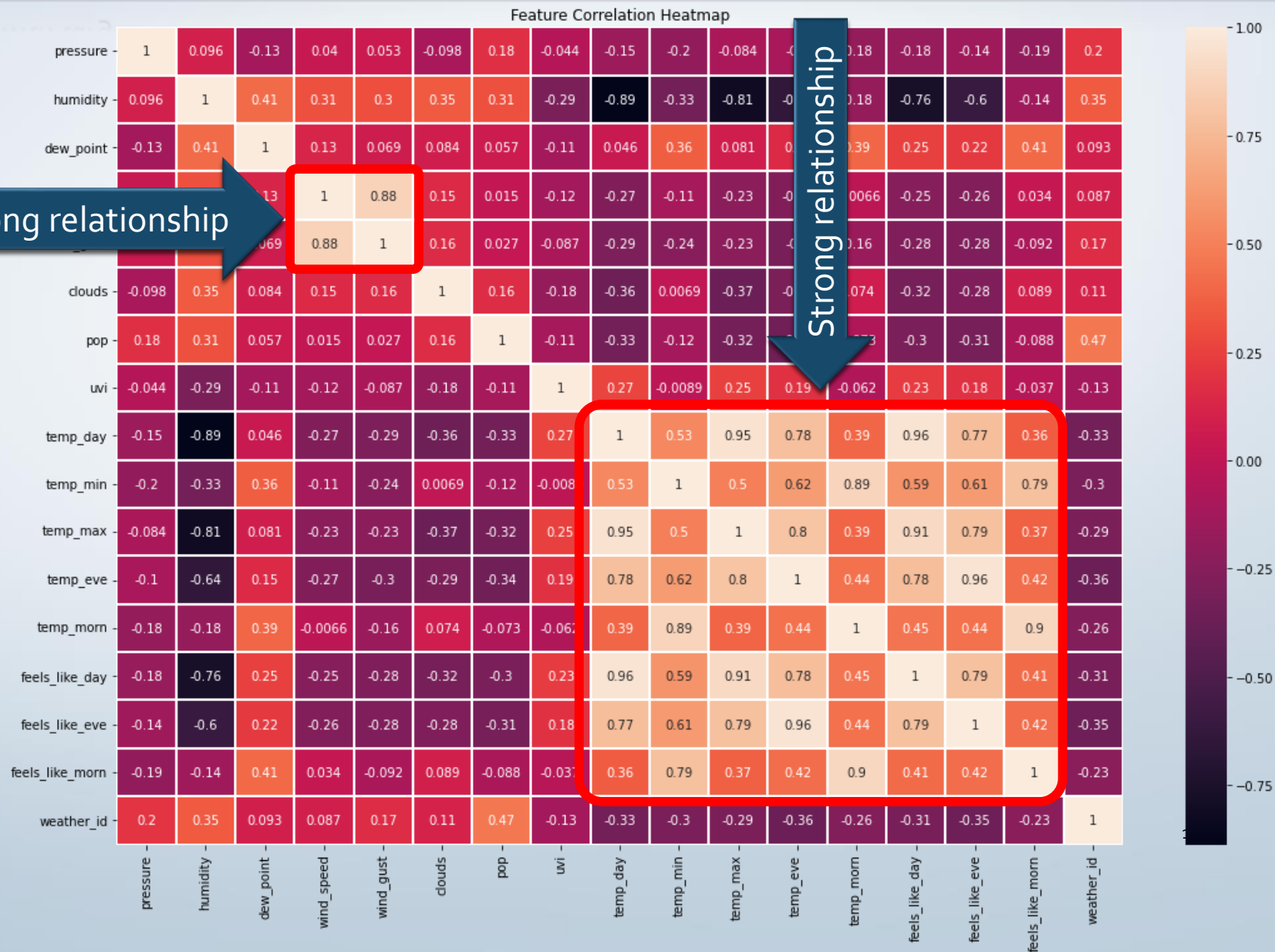
Feature selection

- Dependency with target

- four features: 'humidity'; 'feels_like_day'; 'temp_max'; 'temp_day'
 - two features: 'temp_morn'; 'feels_like_morn'
 - two features: 'wind_speed'; 'wind_gust'
- Has strong relation to each other and can bias learning algorithm

Strong relationship

Strong relationship



Feature selection

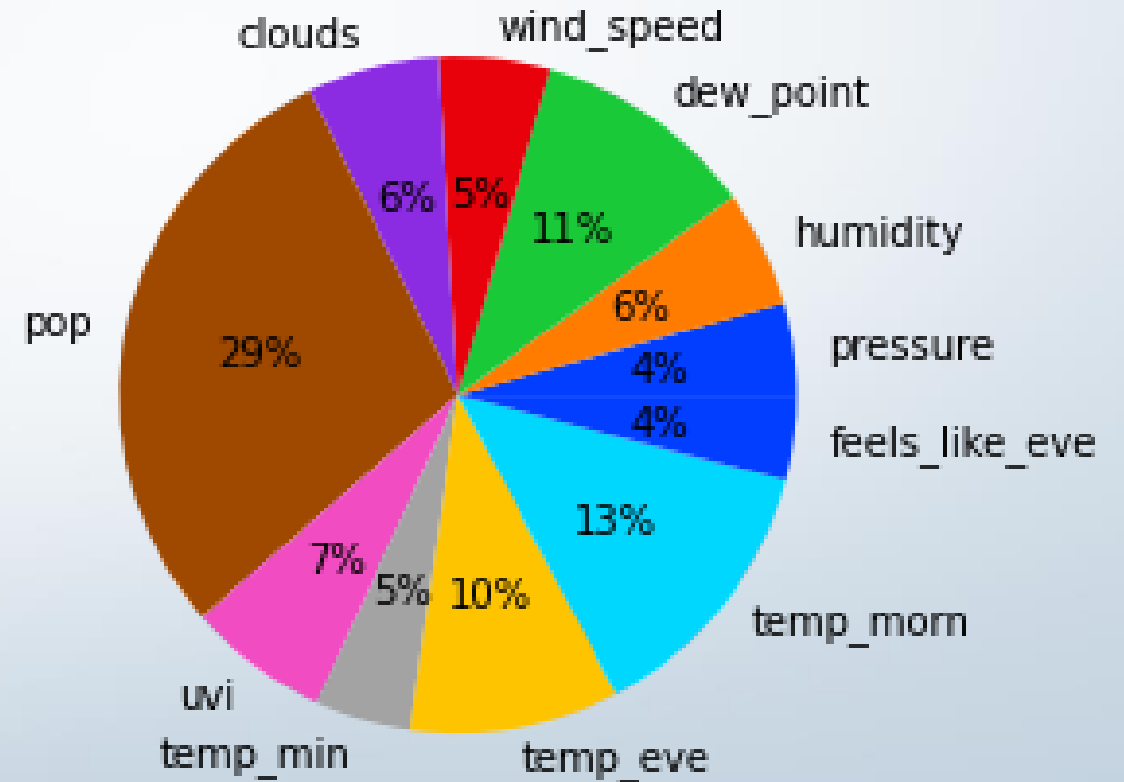
- Feature Importance with DecisionTree Algorithms

Important Features Selection
without scaler

DecisionTreeClassifier()

	feature	importance
5	pop	0.296312
9	temp_morn	0.129936
2	dew_point	0.113511
8	temp_eve	0.106330
4	clouds	0.066606
7	temp_min	0.056014
6	uvi	0.052007
3	wind_speed	0.050781
10	feels_like_eve	0.049048
1	humidity	0.046357
0	pressure	0.033098

Rain weather_description



Feature selection

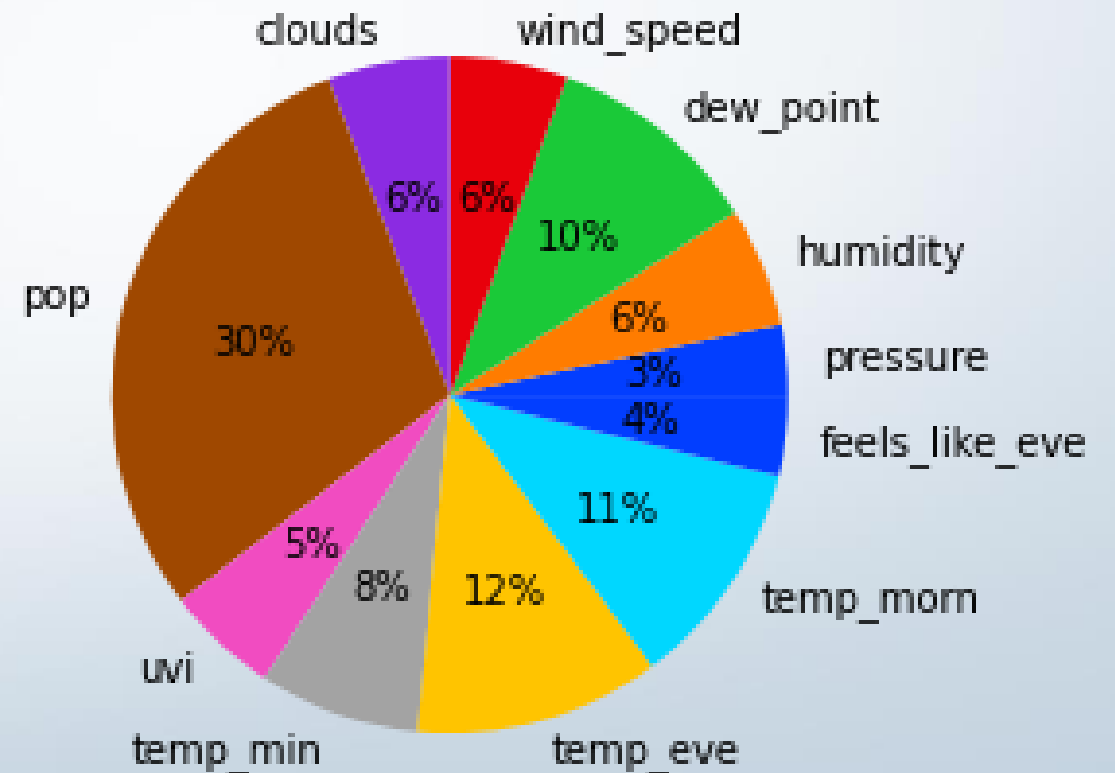
- Feature Importance with DecisionTree Algorithms

```
DecisionTreeClassifier()
```

	feature	importance
5	pop	0.302230
9	temp_morn	0.112852
2	dew_point	0.098716
8	temp_eve	0.098160
7	temp_min	0.074012
6	uvi	0.068048
1	humidity	0.060233
3	wind_speed	0.055582
4	clouds	0.051992
10	feels_like_eve	0.039181
0	pressure	0.038995

Important Features Selection with scaler

Rain weather_description

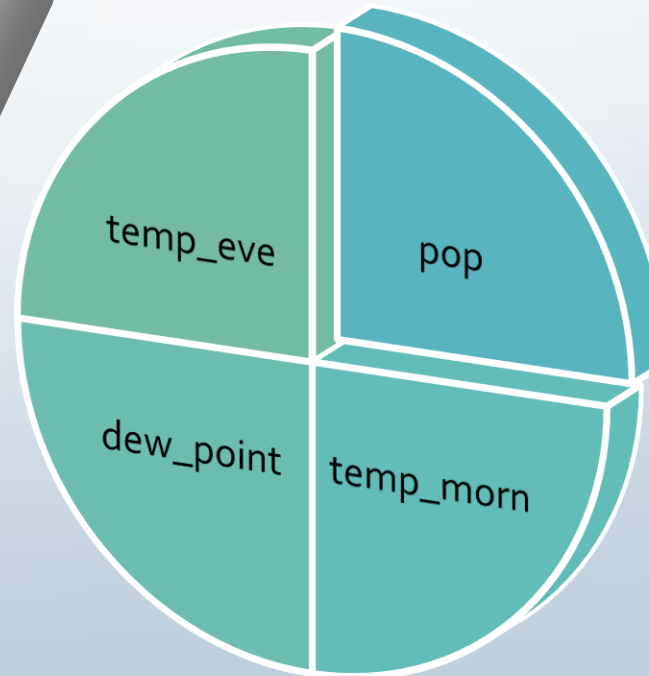


Feature selection

- Final Dataset for Machine Learning Algorithms

	pressure	humidity	dew_point	wind_speed	clouds	pop	uvi	temp_min	temp_eve	temp_morn	feels_like_eve	weather_id
0	1009	73	296.42	5.13	100	0.98	13.39	297.92	300.72	298.03	303.70	501
1	1008	60	294.75	5.13	67	0.41	14.43	297.90	301.17	297.90	304.27	500
2	1007	60	294.06	4.51	77	0.38	15.20	297.40	300.91	297.40	303.73	500
3	1007	66	295.27	4.27	99	0.30	14.38	297.77	300.94	297.79	304.05	500
4	1007	69	296.01	3.06	86	0.97	14.31	298.87	300.56	299.19	303.71	500

4 Important Features



Modeling and Hyperparameter Optimization

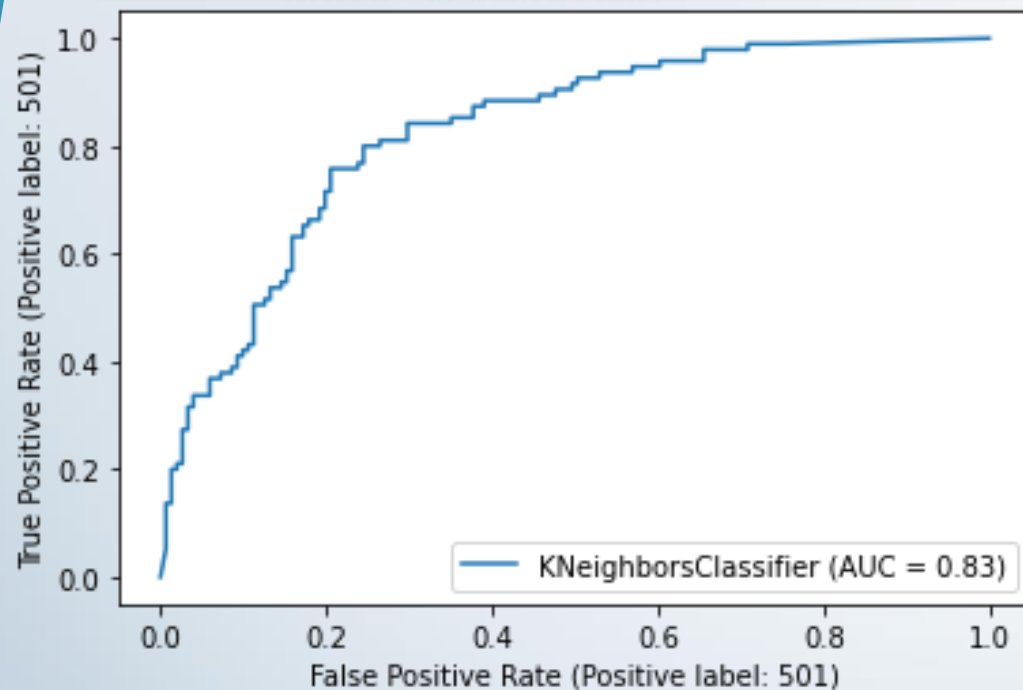
- Default & Tunned Result with whole data

	Training_time	test_Accuracy	preci_score_500	recall_score_500	preci_score_501	recall_score_501	f1_score
Default Model							
DecisionTree	0.012645	0.711382	0.768212	0.763158	0.621053	0.627660	0.711669
KNN	0.006194	0.752033	0.847682	0.771084	0.600000	0.712500	0.756793
LogesticRegression	0.038268	0.760163	0.841060	0.783951	0.631579	0.714286	0.763318
RandomForest	0.265652	0.743902	0.841060	0.765060	0.589474	0.700000	0.748819
SVM	0.036104	0.739837	0.841060	0.760479	0.578947	0.696203	0.745254

	Training_time	test_Accuracy	preci_score_500	recall_score_500	preci_score_501	recall_score_501	f1_score
Tunned Model							
DecisionTree	0.009862	0.731707	0.754967	0.797203	0.694737	0.640777	0.729938
KNN	0.005131	0.735772	0.867550	0.744318	0.526316	0.714286	0.745689
LogisticRegression	0.039320	0.739837	0.814570	0.773585	0.621053	0.678161	0.742198
RandomForest	0.134123	0.784553	0.854305	0.806250	0.673684	0.744186	0.786792
SVC	0.041927	0.764228	0.834437	0.792453	0.652632	0.712644	0.766367

Modeling and Hyperparameter Optimization

• KNN evaluation Details



Classification report:

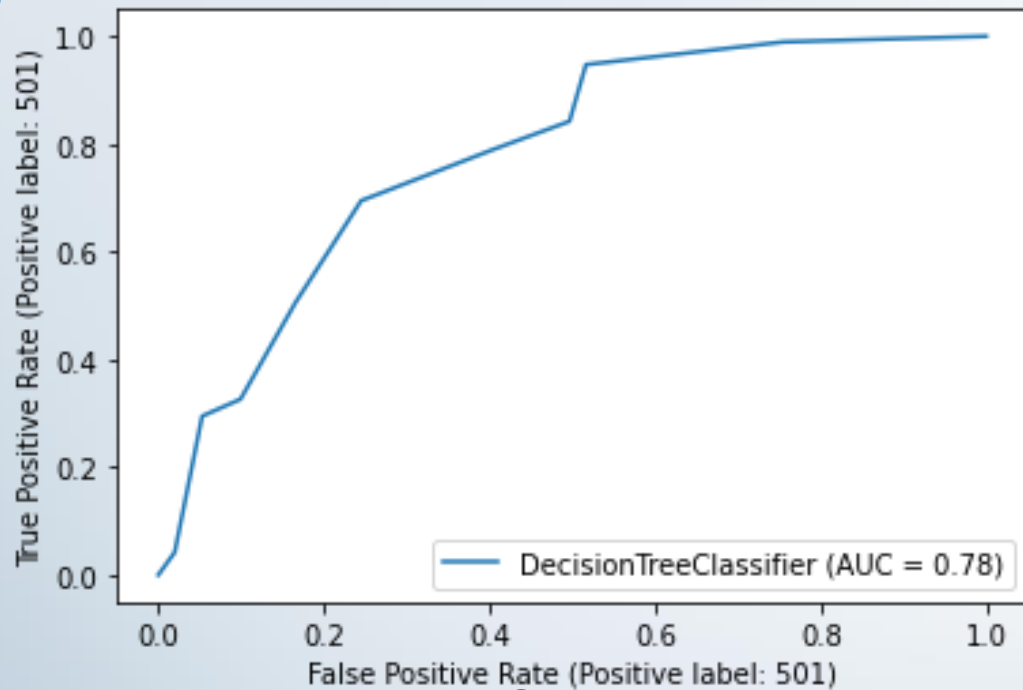
	precision	recall	f1-score	support
500	0.74	0.87	0.80	151
501	0.71	0.53	0.61	95
accuracy			0.74	246
macro avg	0.73	0.70	0.70	246
weighted avg	0.73	0.74	0.73	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	131	20
1	45	50

Modeling and Hyperparameter Optimization

• DecisionTree evaluation Details



Classification report:

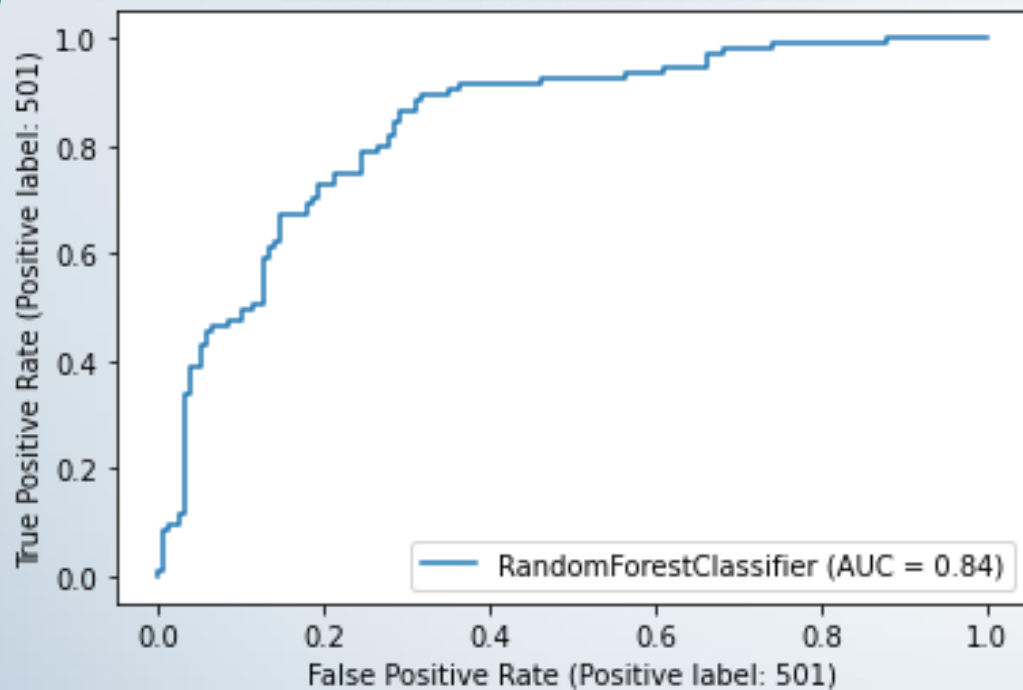
	precision	recall	f1-score	support
500	0.80	0.75	0.78	151
501	0.64	0.69	0.67	95
accuracy			0.73	246
macro avg	0.72	0.72	0.72	246
weighted avg	0.74	0.73	0.73	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	114	37
1	29	66

Modeling and Hyperparameter Optimization

• RandomForest evaluation Details



Classification report:

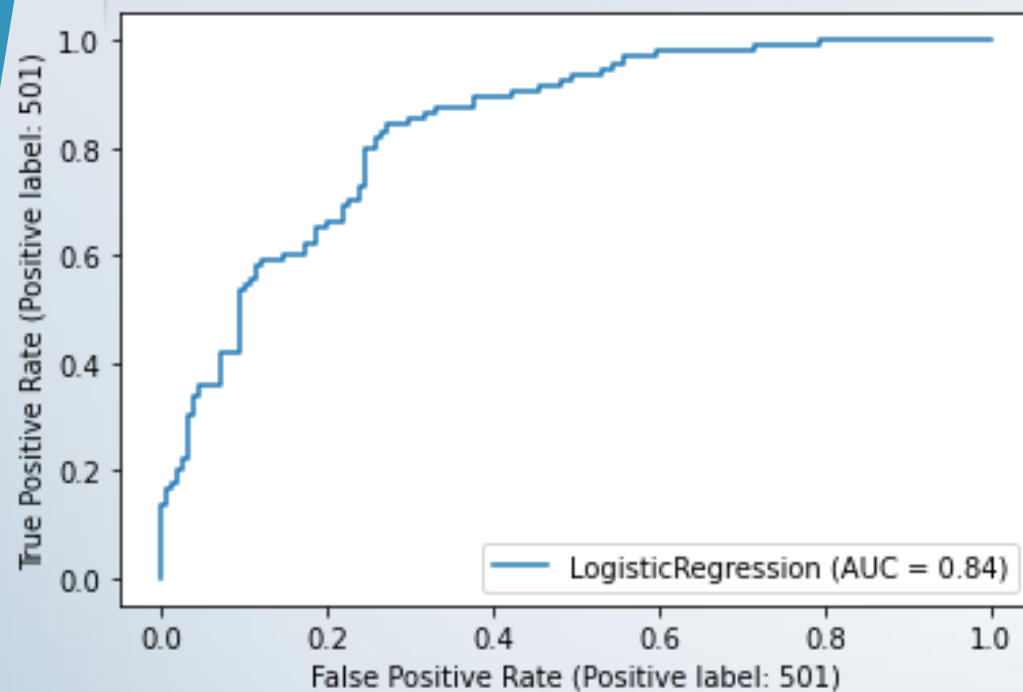
	precision	recall	f1-score	support
500	0.81	0.85	0.83	151
501	0.74	0.67	0.71	95
accuracy			0.78	246
macro avg	0.78	0.76	0.77	246
weighted avg	0.78	0.78	0.78	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	129	22
1	31	64

Modeling and Hyperparameter Optimization

• LogisticRegression evaluation Details



Classification report:

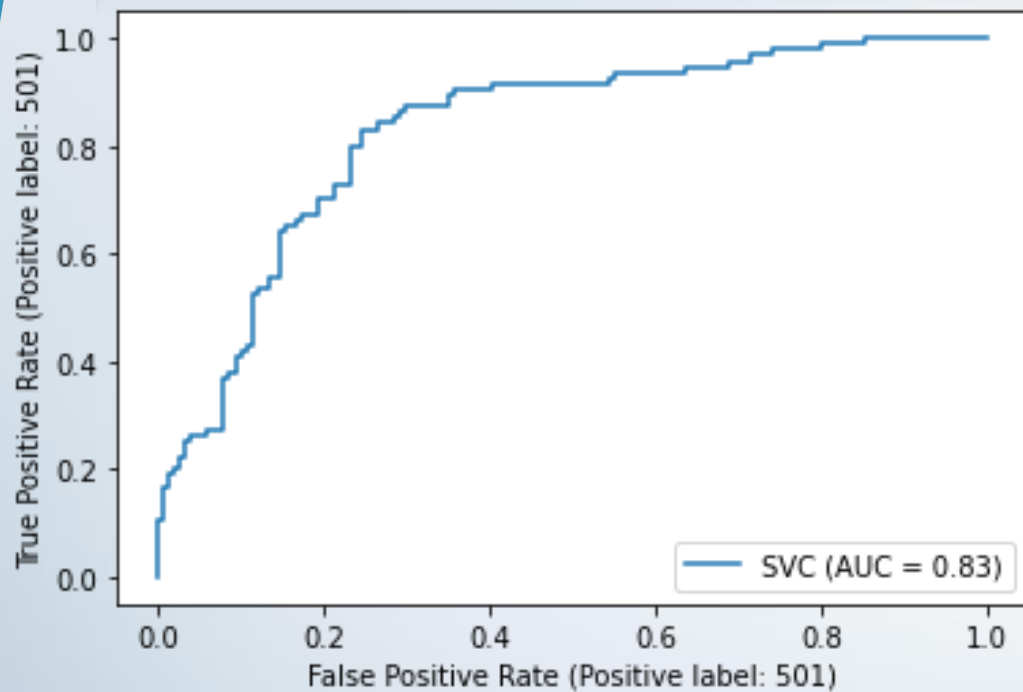
	precision	recall	f1-score	support
500	0.77	0.81	0.79	151
501	0.68	0.62	0.65	95
accuracy			0.74	246
macro avg	0.73	0.72	0.72	246
weighted avg	0.74	0.74	0.74	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	123	28
1	36	59

Modeling and Hyperparameter Optimization

• SVM evaluation Details



Classification report:

	precision	recall	f1-score	support
500	0.79	0.83	0.81	151
501	0.71	0.65	0.68	95
accuracy			0.76	246
macro avg	0.75	0.74	0.75	246
weighted avg	0.76	0.76	0.76	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	126	25
1	33	62

Modeling and Hyperparameter Optimization

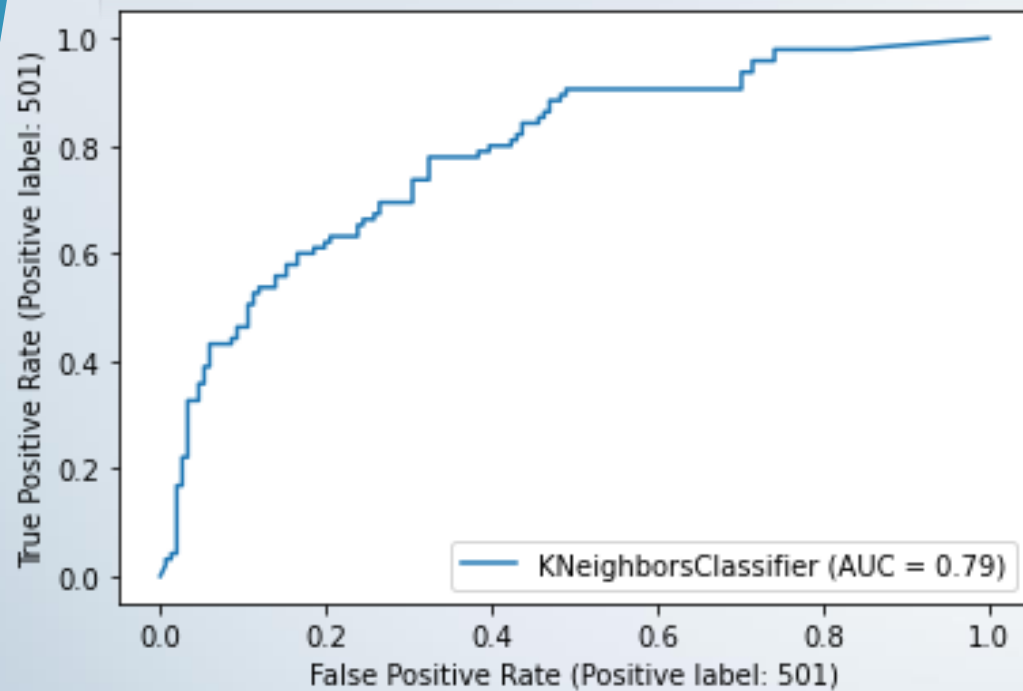
- Default & Tunned Result with 4 important features

	Training_time	test_Accuracy	preci_score_500	recall_score_500	preci_score_501	recall_score_501	f1_score
Default Model							
DecisionTree	0.008922	0.727642	0.768212	0.783784	0.663158	0.642857	0.726892
KNN	0.006016	0.727642	0.807947	0.762500	0.600000	0.662791	0.730473
LogisticRegression	0.029366	0.747967	0.801325	0.790850	0.663158	0.677419	0.748479
RandomForest	0.243966	0.743902	0.788079	0.793333	0.673684	0.666667	0.743657
SVC	0.039934	0.613821	1.000000	0.613821	0.000000	0.000000	0.760705

	Training_time	test_Accuracy	preci_score_500	recall_score_500	preci_score_501	recall_score_501	f1_score
Tunned Model							
DecisionTree	0.009302	0.735772	0.761589	0.798611	0.694737	0.647059	0.734213
KNN	0.007191	0.743902	0.834437	0.768293	0.600000	0.695122	0.748023
LogisticRegression	0.018005	0.711382	0.834437	0.732558	0.515789	0.662162	0.719932
RandomForest	0.118569	0.772358	0.827815	0.806452	0.684211	0.714286	0.773318
SVC	0.042829	0.727642	0.788079	0.772727	0.631579	0.652174	0.728487

Modeling and Hyperparameter Optimization

• KNN evaluation Details



Classification report:

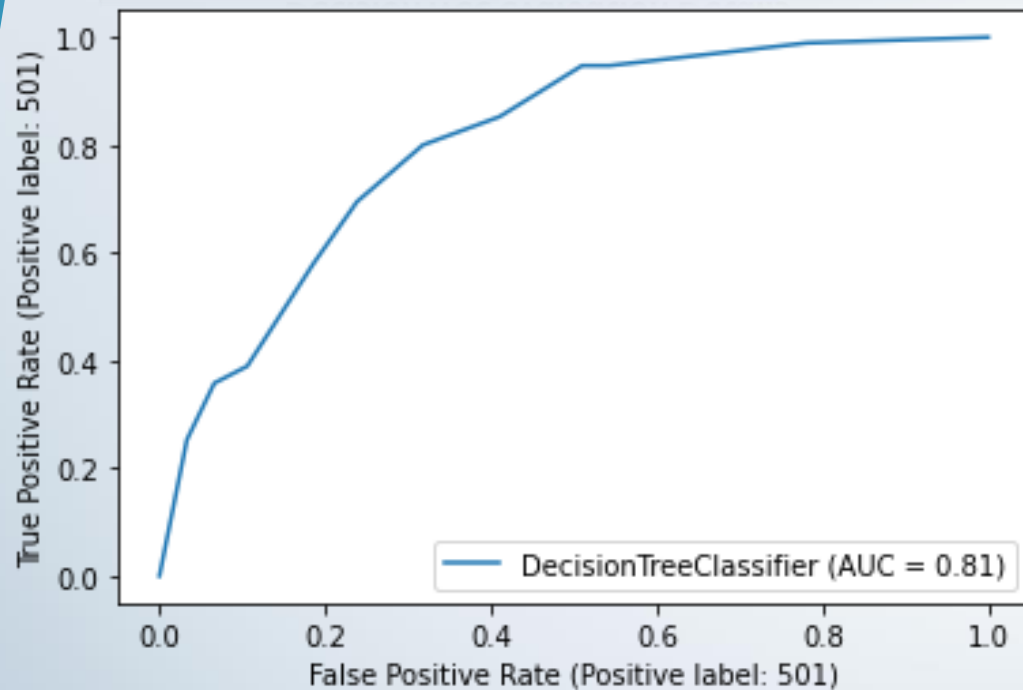
	precision	recall	f1-score	support
500	0.77	0.83	0.80	151
501	0.70	0.60	0.64	95
accuracy			0.74	246
macro avg	0.73	0.72	0.72	246
weighted avg	0.74	0.74	0.74	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	126	25
1	38	57

Modeling and Hyperparameter Optimization

• DecisionTree evaluation Details



Classification report:

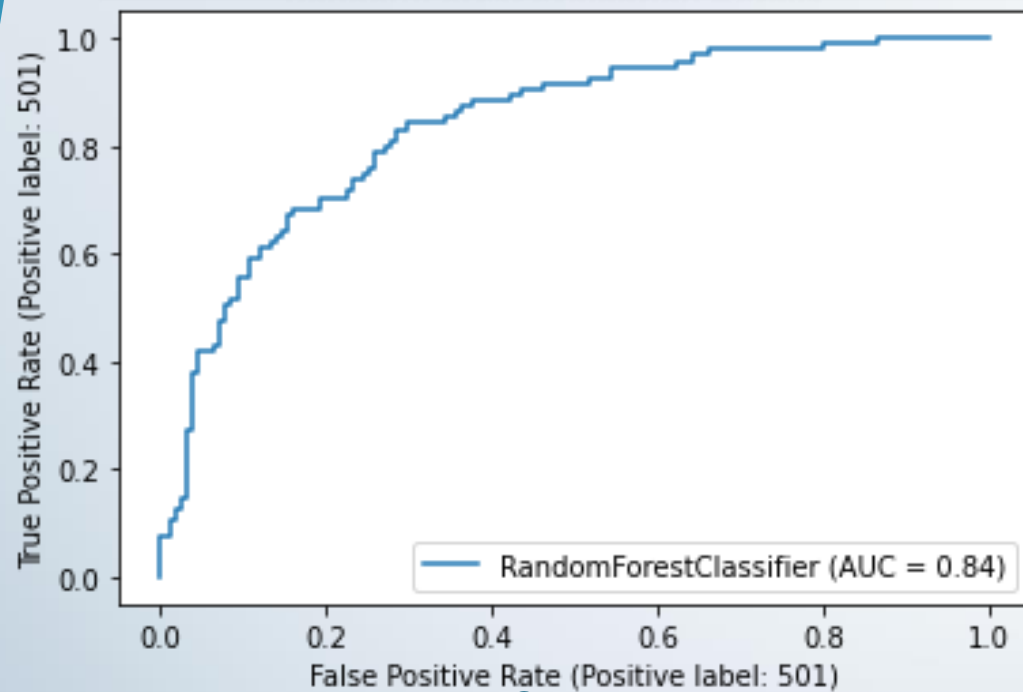
	precision	recall	f1-score	support
500	0.80	0.76	0.78	151
501	0.65	0.69	0.67	95
accuracy			0.74	246
macro avg	0.72	0.73	0.72	246
weighted avg	0.74	0.74	0.74	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	115	36
1	29	66

Modeling and Hyperparameter Optimization

• RandomForest evaluation Details



Classification report:

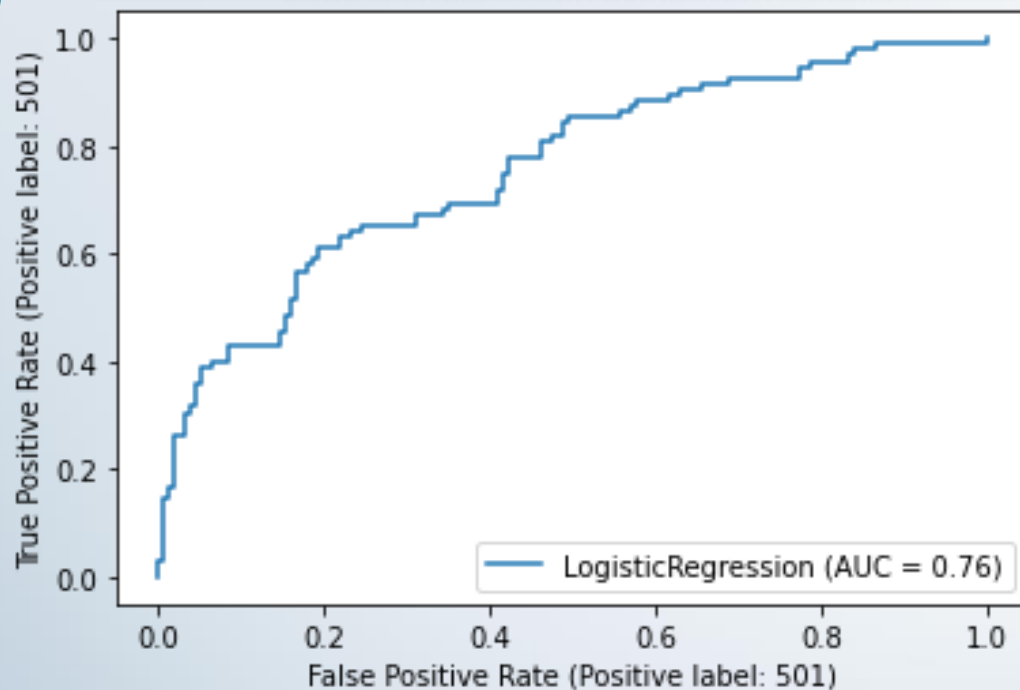
	precision	recall	f1-score	support
500	0.81	0.83	0.82	151
501	0.71	0.68	0.70	95
accuracy			0.77	246
macro avg	0.76	0.76	0.76	246
weighted avg	0.77	0.77	0.77	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	125	26
1	30	65

Modeling and Hyperparameter Optimization

• LogisticRegression evaluation Details



Classification report:

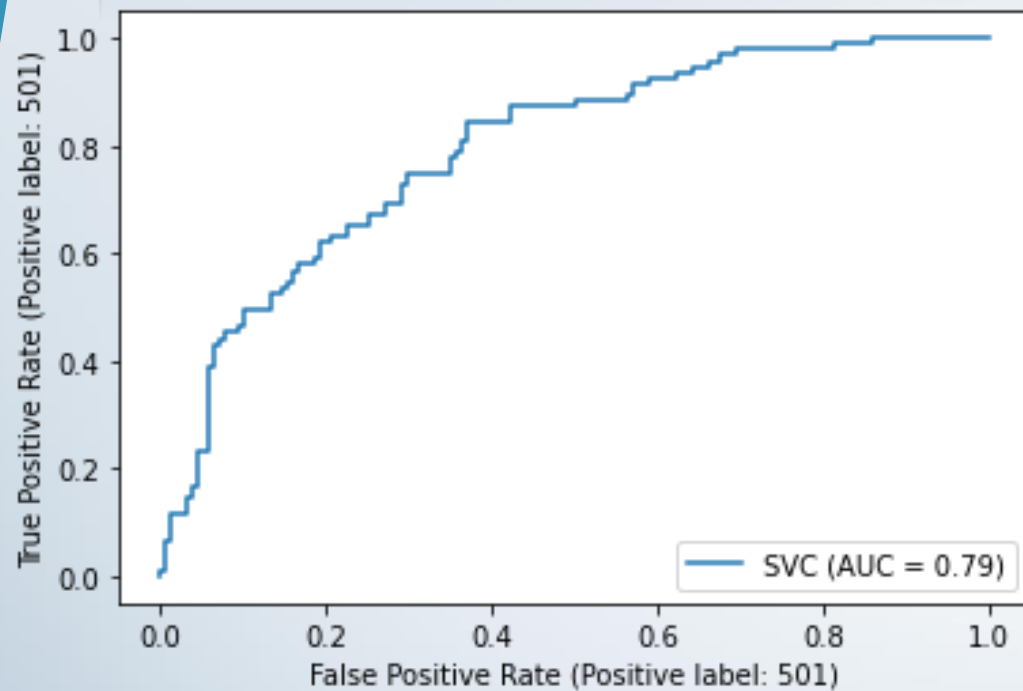
	precision	recall	f1-score	support
500	0.73	0.83	0.78	151
501	0.66	0.52	0.58	95
accuracy			0.71	246
macro avg	0.70	0.68	0.68	246
weighted avg	0.71	0.71	0.70	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	126	25
1	46	49

Modeling and Hyperparameter Optimization

• SVM evaluation Details



Classification report:

	precision	recall	f1-score	support
500	0.77	0.79	0.78	151
501	0.65	0.63	0.64	95
accuracy			0.73	246
macro avg	0.71	0.71	0.71	246
weighted avg	0.73	0.73	0.73	246

Confusion matrix (Rows actual, Columns predicted):

	0	1
0	119	32
1	35	60