Final Project: Classification with Python

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Instructions

In this notebook, you will practice all the classification algorithms that we have learned in this course.

Below, is where we are going to use the classification algorithms to create a model based on our training data and evaluate our testing data using evaluation metrics learned in the course.

We will use some of the algorithms taught in the course, specifically:

1. Linear Regression
2. KNN
3. Decision Trees
4. Logistic Regression
5. SVM

We will evaluate our models using:

1. Accuracy Score
2. Jaccard Index
3. F1-Score
4. LogLoss
5. Mean Absolute Error
6. Mean Squared Error
7. R2-Score

Finally, you will use your models to generate the report at the end.

==

About The Dataset

The original source of the data is Australian Government's Bureau of Meteorology and the latest data can be gathered from http://www.bom.gov.au/climate/dwo/.

The dataset to be used has extra columns like 'RainToday' and our target is 'RainTomorrow', which was gathered from the Rattle at https://bitbucket.org/kayontoga/rattle/src/master/data/weatherAUS.RData

Data Dictionary

This dataset contains observations of weather metrics for each day from 2008 to 2017. The **weatherAUS.csv** dataset includes the following fields:

Field	Description	Unit	Type
Date	Date of the Observation in YYYY-MM-DD	Date	object
Location	Location of the Observation	Location	object
MinTemp	Minimum temperature	Celsius	float
MaxTemp	Maximum temperature	Celsius	float
Rainfall	Amount of rainfall	Millimeters	float
Evaporation	Amount of evaporation	Millimeters	float
Sunshine	Amount of bright sunshine	hours	float
WindGustDir	Direction of the strongest gust	Compass Points	object
WindGustSpeed	Speed of the strongest gust	Kilometers/Hour	object
WindDir9am	Wind direction averaged of 10 minutes prior to 9am	Compass Points	object
WindDir3pm	Wind direction averaged of 10 minutes prior to 3pm	Compass Points	object
WindSpeed9am	Wind speed averaged of 10 minutes prior to 9am	Kilometers/Hour	float
WindSpeed3pm	Wind speed averaged of 10 minutes prior to 3pm	Kilometers/Hour	float
Humidity9am	Humidity at 9am	Percent	float
Humidity3pm	Humidity at 3pm	Percent	float
Pressure9am	Atmospheric pressure reduced to mean sea level at 9am	Hectopascal	float
Pressure3pm	Atmospheric pressure reduced to mean sea level at 3pm	Hectopascal	float
Cloud9am	Fraction of the sky obscured by cloud at 9am	Eights	float
Cloud3pm	Fraction of the sky obscured by cloud at 3pm	Eights	float
Temp9am	Temperature at 9am	Celsius	float
Temp3pm	Temperature at 3pm	Celsius	float
RainToday	If there was rain today	Yes/No	object
RainTomorrow	If there is rain tomorrow	Yes/No	float

Column definitions were gathered from
http://www.bom.gov.au/climate/dwo/IDCJDW0000.shtml

Data Tasks

1) Understand the shape of the data (Histograms, box plots, etc.)

2) Data Cleaning

3) Data Exploration

4) Feature Engineering

5) Data Preprocessing for Model

6) Basic Model Building

7) Model Tuning

8) Ensemble Model Building

9) Results

==

Import Libraries

In [1]:
```
import numpy as np
from numpy import count_nonzero, median, mean
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
#import squarify

import datetime
from datetime import datetime, timedelta, date

#import os
#import zipfile
import scipy
from scipy import stats
from scipy.stats.mstats import normaltest # D'Agostino K^2 Test
from scipy.stats import boxcox
from collections import Counter
```

```
import sklearn
from sklearn.impute import KNNImputer, MissingIndicator, SimpleImputer
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder, OneHo
from sklearn.preprocessing import PolynomialFeatures, RobustScaler, Binarizer, Ordi

from sklearn.compose import make_column_transformer, ColumnTransformer, make_column
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn import set_config

set_config(transform_output="pandas")


from sklearn.experimental import enable_halving_search_cv
from sklearn.model_selection import KFold, StratifiedKFold, GridSearchCV, Randomize
from sklearn.model_selection import train_test_split, cross_validate, cross_val_sco

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import precision_score, recall_score, ConfusionMatrixDisplay,
from sklearn.metrics import jaccard_score, log_loss, mean_squared_error, mean_absol

from sklearn.feature_selection import f_classif, chi2, RFE, RFECV
from sklearn.feature_selection import mutual_info_regression, mutual_info_classif
from sklearn.feature_selection import VarianceThreshold, GenericUnivariateSelect
from sklearn.feature_selection import SelectFromModel, SelectKBest, SelectPercentil

from sklearn.inspection import permutation_importance

from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC


import imblearn

from imblearn.under_sampling import RandomUnderSampler, CondensedNearestNeighbour
from imblearn.under_sampling import EditedNearestNeighbours, TomekLinks
from imblearn.over_sampling import RandomOverSampler, SMOTE, SMOTEN, SMOTENC
from imblearn.combine import SMOTEENN, SMOTETomek
from imblearn.ensemble import BalancedBaggingClassifier
from imblearn.metrics import classification_report_imbalanced
#from imblearn.pipeline import Pipeline

import feature_engine

from feature_engine.selection import DropConstantFeatures, DropDuplicateFeatures
from feature_engine.selection import DropCorrelatedFeatures, SmartCorrelatedSelecti
from feature_engine.selection import SelectBySingleFeaturePerformance



%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
```

```
sns.set(font_scale=1.2)

plt.rc('axes', titlesize=9)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)

import warnings
warnings.filterwarnings('ignore')

# This module lets us save our models once we fit them.
# import pickle

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows', None)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)

random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

Quick Data Glance

In [2]:
```
df = pd.read_csv("weather.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	date	mintemp	maxtemp	rainfall	evaporation	sunshine	windgustdir	windgustspeec
0	2008-02-01	19.50	22.40	15.60	6.20	0.00	W	41
1	2008-02-02	19.50	25.60	6.00	3.40	2.70	W	41
2	2008-02-03	21.60	24.50	6.60	2.40	0.10	W	41
3	2008-02-04	20.20	22.80	18.80	2.20	0.00	W	41
4	2008-02-05	19.70	25.70	77.40	4.80	0.00	W	41

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3271 entries, 0 to 3270
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           3271 non-null   object 
 1   mintemp        3271 non-null   float64
 2   maxtemp        3271 non-null   float64
 3   rainfall       3271 non-null   float64
 4   evaporation    3271 non-null   float64
 5   sunshine       3271 non-null   float64
 6   windgustdir    3271 non-null   object 
 7   windgustspeed  3271 non-null   int64  
 8   winddir9am     3271 non-null   object 
 9   winddir3pm     3271 non-null   object 
 10  windspeed9am   3271 non-null   int64  
 11  windspeed3pm   3271 non-null   int64  
 12  humidity9am    3271 non-null   int64  
 13  humidity3pm    3271 non-null   int64  
 14  pressure9am    3271 non-null   float64
 15  pressure3pm    3271 non-null   float64
 16  cloud9am       3271 non-null   int64  
 17  cloud3pm       3271 non-null   int64  
 18  temp9am        3271 non-null   float64
 19  temp3pm        3271 non-null   float64
 20  raintoday      3271 non-null   object 
 21  raintomorrow   3271 non-null   int64  
dtypes: float64(9), int64(8), object(5)
memory usage: 562.3+ KB
```

In [5]:

```
df.dtypes.value_counts()
```

Out[5]:

```
float64    9
int64      8
object     5
dtype: int64
```

In [6]:

```
# Descriptive Statistical Analysis
df.describe(include="all")
```

Out[6]:

	date	mintemp	maxtemp	rainfall	evaporation	sunshine	windgustdir	windgus
count	3271	3271.00	3271.00	3271.00	3271.00	3271.00	3271	3
unique	3271	NaN	NaN	NaN	NaN	NaN	16	
top	2008-02-01	NaN	NaN	NaN	NaN	NaN	W	
freq	1	NaN	NaN	NaN	NaN	NaN	1425	
mean	NaN	14.88	23.01	3.34	5.18	7.17	NaN	
std	NaN	4.55	4.48	9.92	2.76	3.82	NaN	
min	NaN	4.30	11.70	0.00	0.00	0.00	NaN	
25%	NaN	11.00	19.60	0.00	3.20	4.25	NaN	
50%	NaN	14.90	22.80	0.00	4.80	8.30	NaN	
75%	NaN	18.80	26.00	1.40	7.00	10.20	NaN	
max	NaN	27.60	45.80	119.40	18.40	13.60	NaN	

In [7]:

```python
# Descriptive Statistical Analysis
df.describe(include=["int", "float"])
```

Out[7]:

	mintemp	maxtemp	rainfall	evaporation	sunshine	windgustspeed	windspeed9am
count	3271.00	3271.00	3271.00	3271.00	3271.00	3271.00	3271.0
mean	14.88	23.01	3.34	5.18	7.17	41.48	15.0
std	4.55	4.48	9.92	2.76	3.82	10.81	7.0
min	4.30	11.70	0.00	0.00	0.00	17.00	0.0
25%	11.00	19.60	0.00	3.20	4.25	35.00	11.0
50%	14.90	22.80	0.00	4.80	8.30	41.00	15.0
75%	18.80	26.00	1.40	7.00	10.20	44.00	20.0
max	27.60	45.80	119.40	18.40	13.60	96.00	54.0

In [8]:

```python
# Descriptive Statistical Analysis
df.describe(include="object")
```

Out[8]:

	date	windgustdir	winddir9am	winddir3pm	raintoday
count	3271	3271	3271	3271	3271
unique	3271	16	16	16	2
top	2008-02-01	W	W	E	No
freq	1	1425	1260	624	2422

In [9]:
```
df.raintomorrow.value_counts(normalize=True)
```

Out[9]:
```
0    0.74
1    0.26
Name: raintomorrow, dtype: float64
```

In [10]:
```
df.shape
```

Out[10]:
```
(3271, 22)
```

In [11]:
```
df.columns
```

Out[11]:
```
Index(['date', 'mintemp', 'maxtemp', 'rainfall', 'evaporation', 'sunshine', 'windg
ustdir', 'windgustspeed', 'winddir9am', 'winddir3pm', 'windspeed9am', 'windspeed3p
m', 'humidity9am', 'humidity3pm', 'pressure9am', 'pressure3pm', 'cloud9am', 'cloud
3pm', 'temp9am', 'temp3pm', 'raintoday', 'raintomorrow'], dtype='object')
```

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
date             0
mintemp          0
maxtemp          0
rainfall         0
evaporation      0
sunshine         0
windgustdir      0
windgustspeed    0
winddir9am       0
winddir3pm       0
windspeed9am     0
windspeed3pm     0
humidity9am      0
humidity3pm      0
pressure9am      0
pressure3pm      0
cloud9am         0
cloud3pm         0
temp9am          0
temp3pm          0
raintoday        0
raintomorrow     0
dtype: int64
```

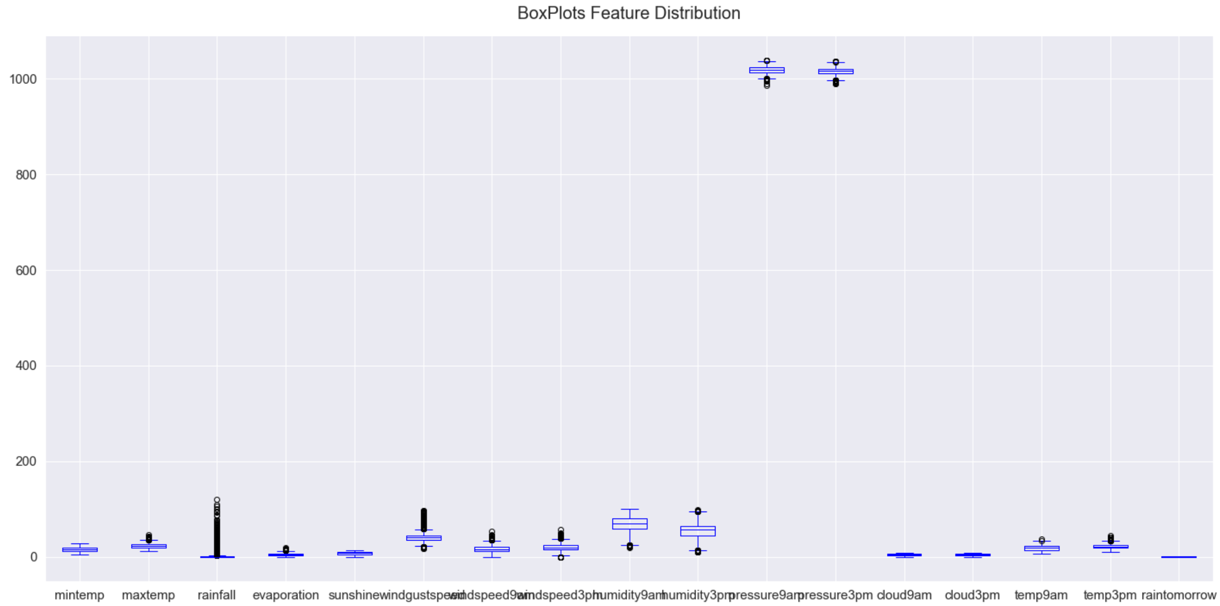
In [13]:
```
df.duplicated().sum()
```

Out[13]: 0

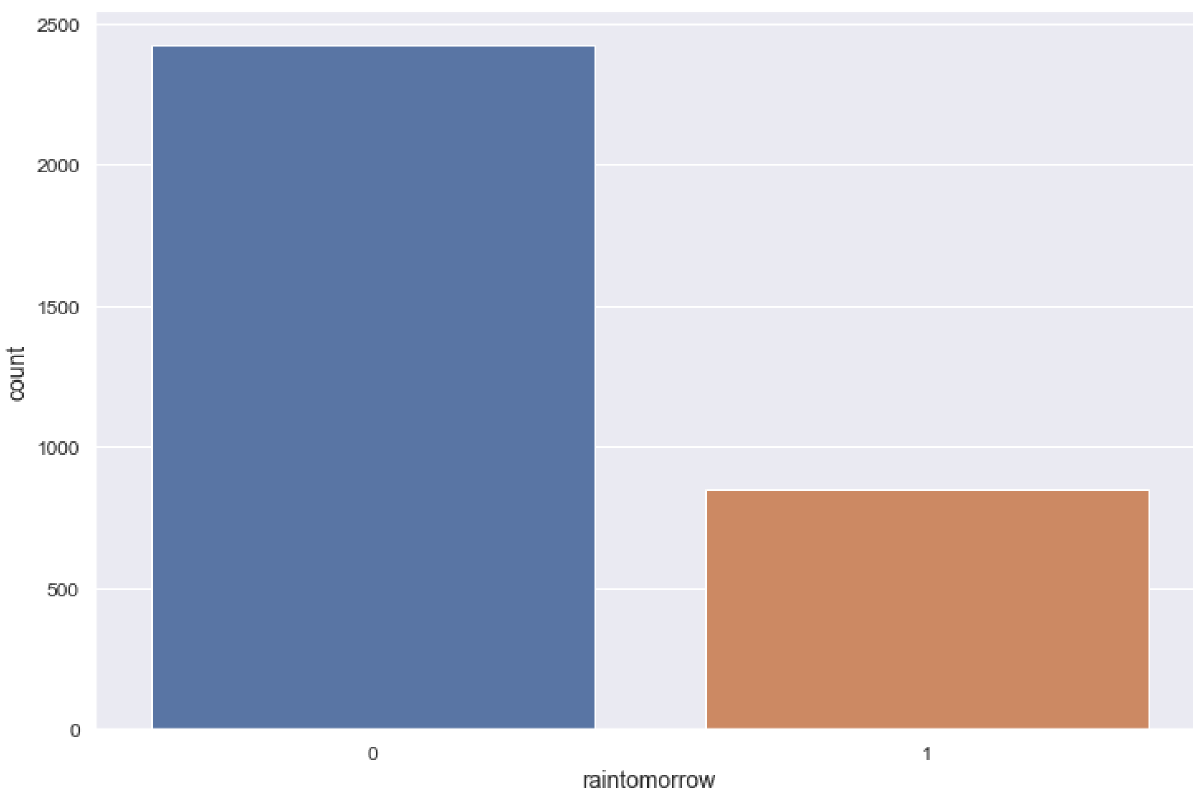
Data Visualization

In [14]:
```
df.hist(bins=50, figsize=(20,45), grid=False, layout=(len(df.columns),2), edgecolor
plt.suptitle('Histogram Feature Distribution', x=0.5, y=1.02, ha='center', fontsize
plt.tight_layout()
plt.show()
```

In [15]:
```
df.boxplot(figsize=(20,10), color="blue", fontsize = 15)
plt.title('BoxPlots Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20)
plt.tight_layout()
plt.show()
```



In [17]:
```
fig, ax = plt.subplots(figsize=(12,8))
sns.countplot(x=df.raintomorrow, data=df)
plt.show()
```



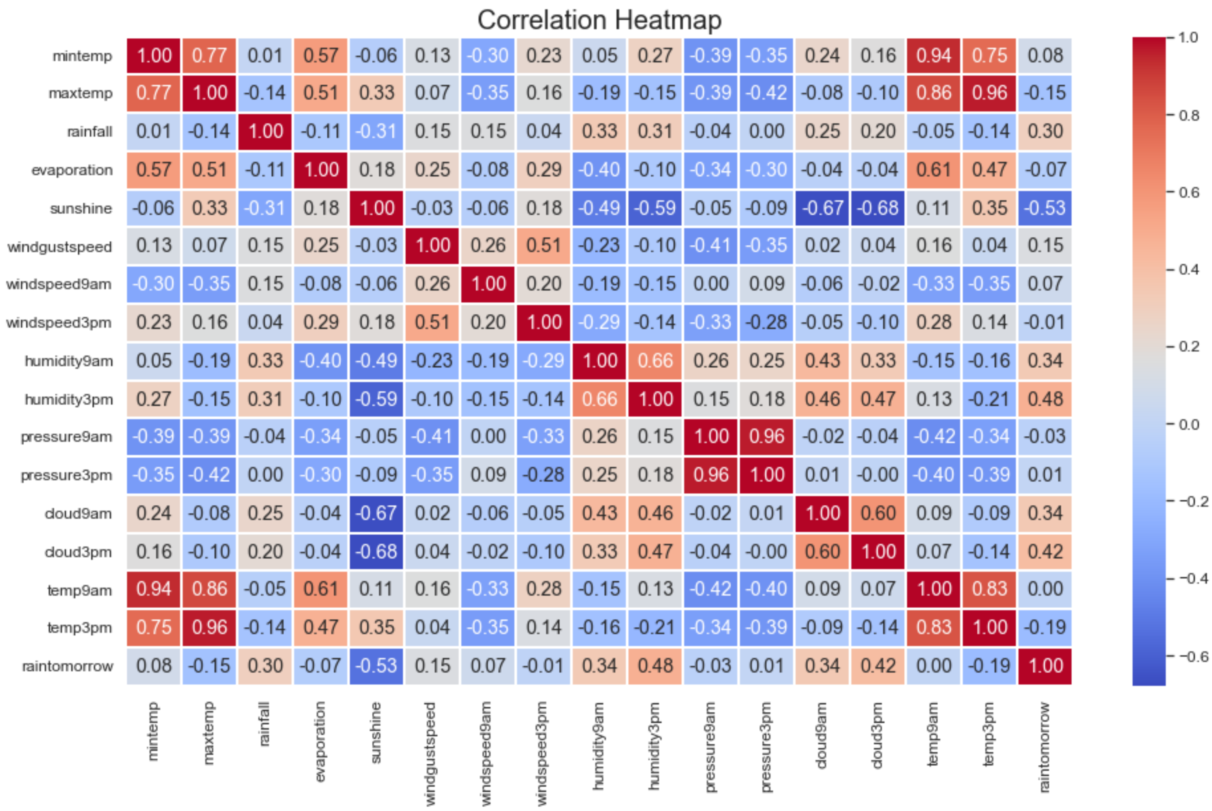
In [18]:
```
df.corr()
```

Out[18]:

	mintemp	maxtemp	rainfall	evaporation	sunshine	windgustspeed	wind
mintemp	1.00	0.77	0.01	0.57	-0.06	0.13	
maxtemp	0.77	1.00	-0.14	0.51	0.33	0.07	
rainfall	0.01	-0.14	1.00	-0.11	-0.31	0.15	
evaporation	0.57	0.51	-0.11	1.00	0.18	0.25	
sunshine	-0.06	0.33	-0.31	0.18	1.00	-0.03	
windgustspeed	0.13	0.07	0.15	0.25	-0.03	1.00	
windspeed9am	-0.30	-0.35	0.15	-0.08	-0.06	0.26	
windspeed3pm	0.23	0.16	0.04	0.29	0.18	0.51	
humidity9am	0.05	-0.19	0.33	-0.40	-0.49	-0.23	
humidity3pm	0.27	-0.15	0.31	-0.10	-0.59	-0.10	
pressure9am	-0.39	-0.39	-0.04	-0.34	-0.05	-0.41	
pressure3pm	-0.35	-0.42	0.00	-0.30	-0.09	-0.35	
cloud9am	0.24	-0.08	0.25	-0.04	-0.67	0.02	
cloud3pm	0.16	-0.10	0.20	-0.04	-0.68	0.04	
temp9am	0.94	0.86	-0.05	0.61	0.11	0.16	
temp3pm	0.75	0.96	-0.14	0.47	0.35	0.04	
raintomorrow	0.08	-0.15	0.30	-0.07	-0.53	0.15	

In [19]:

```
plt.figure(figsize=(16,9))
sns.heatmap(df.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2)
plt.title("Correlation Heatmap", fontsize=20)
plt.show()
```



==

Train Test Split

We've prepared our data and we're ready to model. There's one last step before we can begin. We must split the data into features and target variable, and into training data and test data. We do this using the `train_test_split()` function. We'll put 25% of the data into our test set, and use the remaining 75% to train the model.

Notice below that we include the argument `stratify=y`. If our master data has a class split of 80/20, stratifying ensures that this proportion is maintained in both the training and test data. `=y` tells the function that it should use the class ratio found in the `y` variable (our target).

The less data you have overall, and the greater your class imbalance, the more important it is to stratify when you split the data. If we didn't stratify, then the function would split the data randomly, and we could get an unlucky split that doesn't get any of the minority class in the test data, which means we wouldn't be able to effectively evaluate our model. Worst of all, we might not even realize what went wrong without doing some detective work.

Lastly, we set a random seed so we and others can reproduce our work.

No description has been provided for this image

In [20]:
```
df.shape
```

Out[20]: (3271, 22)

In [21]:
```
X = df.iloc[:,0:21]
y = df.iloc[:,21]
```

In [22]:
```
X.values, y.values
```

Out[22]:
```
(array([['2008-02-01', 19.5, 22.4, ..., 20.7, 20.9, 'Yes'],
        ['2008-02-02', 19.5, 25.6, ..., 22.4, 24.8, 'Yes'],
        ['2008-02-03', 21.6, 24.5, ..., 23.5, 23.0, 'Yes'],
        ...,
        ['2017-06-23', 9.4, 17.7, ..., 10.2, 17.3, 'No'],
        ['2017-06-24', 10.1, 19.3, ..., 12.4, 19.0, 'No'],
        ['2017-06-25', 7.6, 19.3, ..., 9.4, 18.8, 'No']], dtype=object),
 array([1, 1, 1, ..., 0, 0, 0], dtype=int64))
```

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [24]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[24]: ((2616, 21), (655, 21), (2616,), (655,))

In [25]:
```
Counter(y_train), Counter(y_test)
```

Out[25]: (Counter({0: 1937, 1: 679}), Counter({0: 485, 1: 170}))

==

In [26]:
```
y.value_counts()
```

Out[26]:
```
0    2422
1     849
Name: raintomorrow, dtype: int64
```

In [27]:
```
(y == 0).sum() / (y == 1).sum()
```

Out[27]: 2.852767962308598

==

Data Pipelines

Data Pipelines simplify the steps of processing the data. We use the module `Pipeline` to create a pipeline. `Pipeline` lets you chain together multiple operators on your data that both have a `fit` method.

Combine multiple processing steps into a `Pipeline`

A pipeline contains a series of steps, where a step is ("name of step", actual_model). The "name of step" string is only used to help you identify which step you are on, and to allow you to specify parameters at that step.

In [28]:
```
# Declare preprocessing functions

#imp = SimpleImputer(missing_values=np.nan, strategy='mean')
#ohe = OneHotEncoder()
#oe = OrdinalEncoder()
#ss = StandardScaler()
#mm = MinMaxScaler()
#skbest = SelectKBest()
```

In [29]:
```
list(df.select_dtypes(include=["int64","float64"]))
```

Out[29]:
```
['mintemp',
 'maxtemp',
 'rainfall',
 'evaporation',
 'sunshine',
 'windgustspeed',
 'windspeed9am',
 'windspeed3pm',
 'humidity9am',
 'humidity3pm',
 'pressure9am',
 'pressure3pm',
 'cloud9am',
 'cloud3pm',
 'temp9am',
 'temp3pm',
 'raintomorrow']
```

In [30]:
```
list(df.select_dtypes(include=["bool","object"]))
```

Out[30]:
```
['date', 'windgustdir', 'winddir9am', 'winddir3pm', 'raintoday']
```

In [31]:
```
dropcols = ['date']
```

In [32]:
```
numcols = ['mintemp', 'maxtemp', 'rainfall', 'evaporation', 'sunshine', 'windgustsp
 'humidity9am', 'humidity3pm', 'pressure9am', 'pressure3pm', 'cloud9am', 'cloud3pm'
```

In [33]:
```
catcols = ['windgustdir', 'winddir9am', 'winddir3pm', 'raintoday']
```

In [34]:
```
# We create the preprocessing pipelines for both
# numerical and categorical data


drop_transformer = ColumnTransformer(transformers=
                                    ("dropcolumns", "drop", dropcols)
                                    )

numeric_transformer = Pipeline(steps=[
                              #("imputer", SimpleImputer(missing_values=np.nan, str
                              #("scalar", StandardScaler()),
                               ("minmax", MinMaxScaler()),
```

```
])

categorical_transformer = Pipeline(steps=[

                                  #("imputer", SimpleImputer(strategy="most_frequen
                                  #("onehot", OneHotEncoder(sparse_output=False, dr
                                   ("ordinal", OrdinalEncoder(categories='auto'))



])
```

In [35]:
```
preprocessor = ColumnTransformer(
               transformers=[
                            ("dropcolumns", "drop", dropcols),
                            ("numerical", numeric_transformer, numcols),
                            ("categorical", categorical_transformer, catcols),

                             ],
               remainder="passthrough",
               verbose_feature_names_out=False)
```

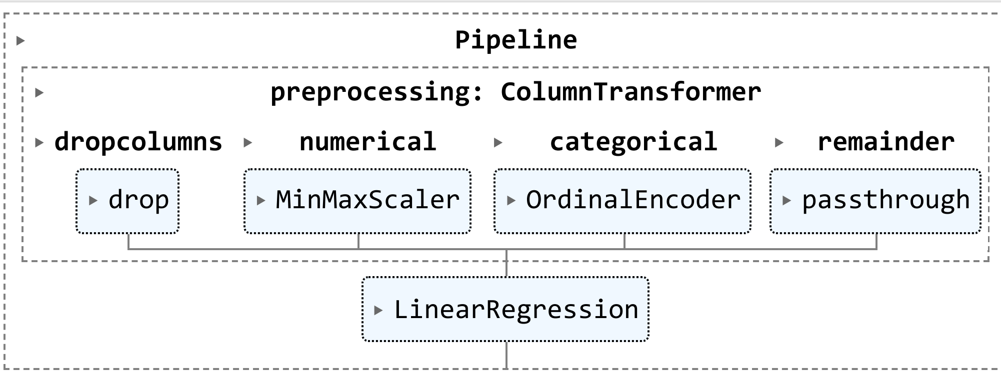
==

Linear Regression

In [36]:
```
lrpipeline = Pipeline(steps=
                      [
                       ("preprocessing", preprocessor),
                       ( "linreg",  LinearRegression())
                      ])
```

In [37]:
```
lrpipeline.fit(X_train,y_train)
```

Out[37]:



In [38]:
```
lrpipeline.predict(X_test)[0:5]
```

Out[38]:
```
array([ 0.06274677,  0.9693418 ,  0.77266864,  0.44409362, -0.01836328])
```

In [39]:
```
lr_pred = lrpipeline.predict(X_test)
```

In [40]:
```
print("MAE:", "%.3f" % mean_absolute_error(y_test, lr_pred))
print("MSE:", "%.3f" % mean_squared_error(y_test, lr_pred))
print("R2:", "%.3f" % r2_score(y_test, lr_pred))
```

```
MAE: 0.266
MSE: 0.126
R2: 0.345
```

In [41]:
```
lrtable = pd.DataFrame()
lrtable = lrtable.append({'Model': "Linear Regression",
                        'MAE':  mean_absolute_error(y_test, lr_pred),
                        'MSE': mean_squared_error(y_test, lr_pred),
                        'R2': r2_score(y_test, lr_pred),

                      },
                        ignore_index=True)

lrtable
```

Out[41]:

	Model	MAE	MSE	R2
0	Linear Regression	0.27	0.13	0.35

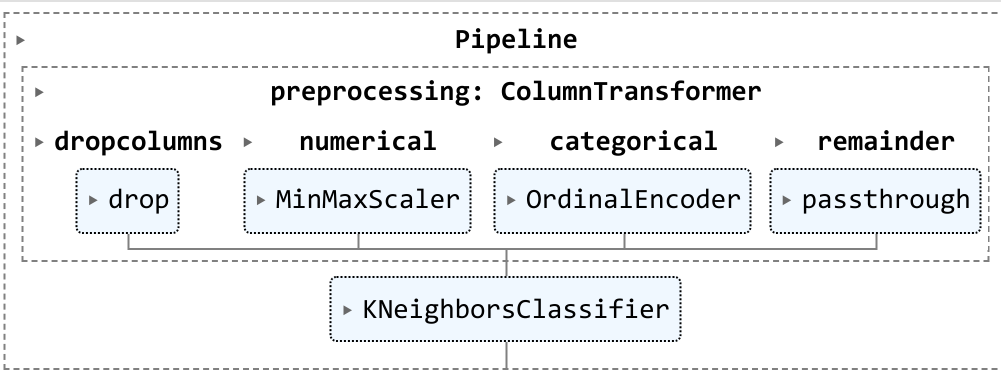
==

KNN

In [42]:
```
knnpipeline = Pipeline(steps=
                     [
                      ("preprocessing", preprocessor),
                      ( "knn",  KNeighborsClassifier(n_neighbors=4, n_jobs=-1))
                     ])
```

In [43]:
```
knnpipeline.fit(X_train,y_train)
```

Out[43]:



In [44]:
```
knnpipeline.predict(X_test)[0:5]
```

Out[44]:
```
array([0, 0, 1, 0, 0], dtype=int64)
```

In [45]:
```python
knn_pred = knnpipeline.predict(X_test)
```

In [46]:
```python
print("KNN Classifier\n")
print("Accuracy:", "%.3f" % accuracy_score(y_test, knn_pred))
print("Jaccard Score:", "%.3f" % jaccard_score(y_test, knn_pred))
print("F1 Score:", "%.3f" % f1_score(y_test, knn_pred))
```

```
KNN Classifier

Accuracy: 0.777
Jaccard Score: 0.247
F1 Score: 0.397
```

In [47]:
```python
knntable = pd.DataFrame()
knntable = knntable.append({'Model': "KNN Classification",
                        'F1':  f1_score(y_test, knn_pred),
                        'Jaccard Score': jaccard_score(y_test, knn_pred),
                        'Accuracy': accuracy_score(y_test, knn_pred)
                      },
                        ignore_index=True)

knntable
```

Out[47]:

	Model	F1	Jaccard Score	Accuracy
0	KNN Classification	0.40	0.25	0.78

Decision Tree

In [48]:
```python
dtpipeline = Pipeline(steps=[
                        ("preprocessor", preprocessor),
                        ("decisiontree", DecisionTreeClassifier(random_state=0, cla

])
```

In [49]:
```python
dtpipeline.fit(X_train, y_train)
```

Out[49]:

```
Pipeline
  preprocessor: ColumnTransformer
    dropcolumns    numerical       categorical       remainder
    drop           MinMaxScaler    OrdinalEncoder    passthrough
  DecisionTreeClassifier
```

In [50]:
```python
dtpred = dtpipeline.predict(X_test)
```

In [51]:
```python
dtpred[0:5]
```

Out[51]: array([0, 1, 1, 1, 0], dtype=int64)

In [52]:
```
print("Decision Tree Classifier\n")
print("Accuracy:", "%.3f" % accuracy_score(y_test, dtpred))
print("Jaccard Score:", "%.3f" % jaccard_score(y_test, dtpred))
print("F1 Score:", "%.3f" % f1_score(y_test, dtpred))
```

```
Decision Tree Classifier

Accuracy: 0.750
Jaccard Score: 0.352
F1 Score: 0.520
```

In [53]:
```
dttable = pd.DataFrame()
dttable = dttable.append({'Model': "Decision Tree Classifier",
                        'F1':  f1_score(y_test, dtpred),
                        'Jaccard Score': jaccard_score(y_test, dtpred),
                        'Accuracy': accuracy_score(y_test, dtpred)
                      },
                        ignore_index=True)

dttable
```

Out[53]:

	Model	F1	Jaccard Score	Accuracy
0	Decision Tree Classifier	0.52	0.35	0.75

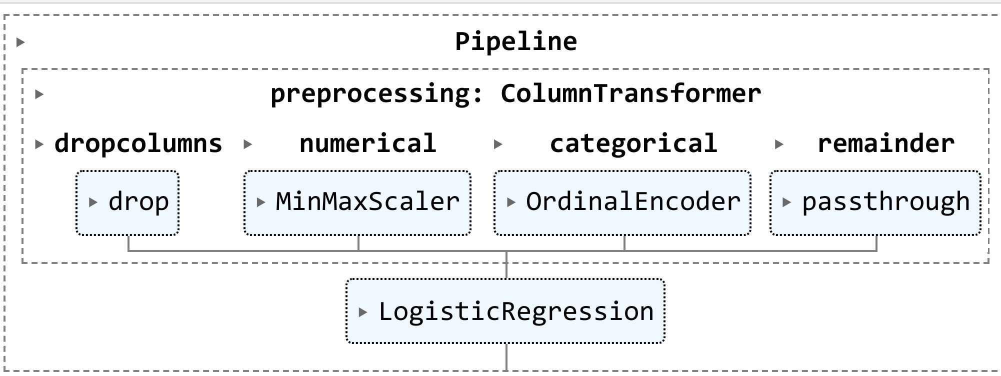
===

Logistic Regression

In [54]:
```
logrpipeline = Pipeline(steps=
                     [
                      ("preprocessing", preprocessor),
                      ( "logreg",  LogisticRegression(random_state=0, class_weight=
                     ])
```

In [55]:
```
logrpipeline.fit(X_train,y_train)
```

Out[55]:



In [56]:
```
logr_pred = logrpipeline.predict(X_test)
```

In [57]:
```
logr_proba = logrpipeline.predict_proba(X_test)
```

In [58]:
```
logr_pred[0:5]
```

Out[58]:
```
array([0, 1, 1, 1, 0], dtype=int64)
```

In [59]:
```
logr_proba[0:5]
```

Out[59]:
```
array([[0.88049369, 0.11950631],
       [0.02318631, 0.97681369],
       [0.10519224, 0.89480776],
       [0.29282371, 0.70717629],
       [0.92207827, 0.07792173]])
```

In [60]:
```
print("Logistic Classifier\n")
print("Accuracy:", "%.3f" % accuracy_score(y_test, logr_pred))
print("Jaccard Score:", "%.3f" % jaccard_score(y_test, logr_pred))
print("F1 Score:", "%.3f" % f1_score(y_test, logr_pred))
print("Log Loss Score:", "%.3f" % log_loss(y_test, logr_proba))
```

```
Logistic Classifier

Accuracy: 0.771
Jaccard Score: 0.462
F1 Score: 0.632
Log Loss Score: 0.476
```

In [61]:
```
logtable = pd.DataFrame()
logtable = logtable.append({'Model': "Logistic Classifier",
                        'F1':  f1_score(y_test, logr_pred),
                        'Jaccard Score': jaccard_score(y_test, logr_pred),
                        'Accuracy': accuracy_score(y_test, logr_pred),
                        'Log Loss' :  log_loss(y_test, logr_proba)
                      },
                        ignore_index=True)

logtable
```

Out[61]:

	Model	F1	Jaccard Score	Accuracy	Log Loss
0	Logistic Classifier	0.63	0.46	0.77	0.48

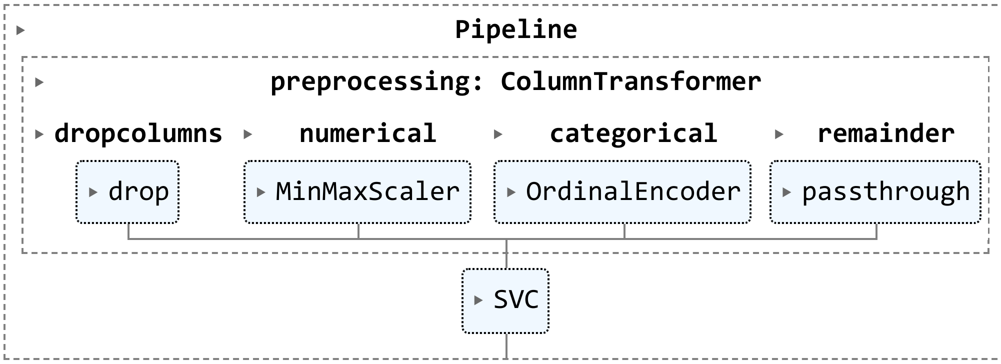
==

SVM

In [62]:
```
svmpipeline = Pipeline(steps=
                     [
                      ("preprocessing", preprocessor),
                      ( "svm",  SVC(kernel='sigmoid', random_state=0, class_weight=
                     ])
```

In [63]:
```
svmpipeline.fit(X_train,y_train)
```

Out[63]:



In [64]:
```
svm_pred = svmpipeline.predict(X_test)
```

In [65]:
```
print("Support Vector Classifier\n")
print("Accuracy:", "%.3f" % accuracy_score(y_test, svm_pred))
print("Jaccard Score:", "%.3f" % jaccard_score(y_test, svm_pred))
print("F1 Score:", "%.3f" % f1_score(y_test, svm_pred))
```

```
Support Vector Classifier

Accuracy: 0.456
Jaccard Score: 0.205
F1 Score: 0.341
```

In [66]:
```
svmtable = pd.DataFrame()
svmtable = svmtable.append({'Model': "SVM Classifier",
                        'F1':  f1_score(y_test, svm_pred),
                        'Jaccard Score': jaccard_score(y_test, svm_pred),
                        'Accuracy': accuracy_score(y_test, svm_pred),

                      },
                        ignore_index=True)


svmtable
```

Out[66]:

	Model	F1	Jaccard Score	Accuracy
0	SVM Classifier	0.34	0.21	0.46

==

Model Comparison Report

Create a table of results to compare model performance.

In [67]:
```
all_tables = pd.concat([lrtable,knntable,dttable,logtable,svmtable], axis=0)
```

In [68]:
```
all_tables
```

Out[68]:

	Model	MAE	MSE	R2	F1	Jaccard Score	Accuracy	Log Loss
0	Linear Regression	0.27	0.13	0.35	NaN	NaN	NaN	NaN
0	KNN Classification	NaN	NaN	NaN	0.40	0.25	0.78	NaN
0	Decision Tree Classifier	NaN	NaN	NaN	0.52	0.35	0.75	NaN
0	Logistic Classifier	NaN	NaN	NaN	0.63	0.46	0.77	0.48
0	SVM Classifier	NaN	NaN	NaN	0.34	0.21	0.46	NaN

==

Methods treating imbalance dataset overview

Different techniques used:

- Random Undersampling: RandomUnderSampler(sampling_strategy='auto', random_state=None, replacement=False)
- Condensed Nearest Neighbours (CNN): CondensedNearestNeighbour(sampling_strategy='auto', random_state=None, n_neighbors=None, n_seeds_S=1, n_jobs=None)
- Tomek Links
- One Sided Selection
- Edited Nearest Neighbours
- Repeated Edited Nearest Neighbours
- All KNN
- Neighbourhood Cleaning Rule
- NearMiss
- Instance Hardness Threshold

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Imblearn Methods

Random Under-Sampling

Undersampling can be defined as removing some observations of the majority class. This is done until the majority and minority class is balanced out.

Undersampling can be a good choice when you have a ton of data -think millions of rows. But a drawback to undersampling is that we are removing information that may be valuable.

Random Over-Sampling

Oversampling can be defined as adding more copies to the minority class. Oversampling can be a good choice when you don’t have a ton of data to work with.

A con to consider when undersampling is that it can cause overfitting and poor generalization to your test set.

Under-Sampling: Tomek Links

Tomek links are pairs of very close instances but of opposite classes. Removing the instances of the majority class of each pair increases the space between the two classes, facilitating the classification process.

Synthetic Minority Oversampling Technique (SMOTE)

This technique generates synthetic data for the minority class.

SMOTE (Synthetic Minority Oversampling Technique) works by randomly picking a point from the minority class and computing the k-nearest neighbors for this point. The synthetic points are added between the chosen point and its neighbors.

SMOTE + ENN and SMOTE + Tomek Links

Combined used of SMOTE and ENN or Tomek Links to amplify the minority class and remove noisy observations that might be created.

```
# Define oversampling strategy.

SMOTE = SMOTE()
```

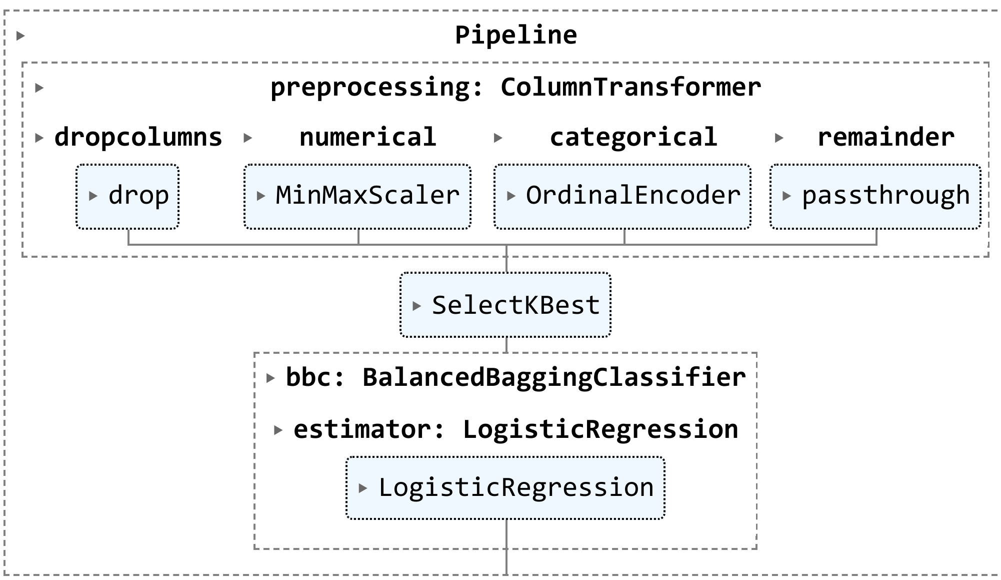
```
    # Fit and apply the transform.

    X_train_SMOTE, y_train_SMOTE = SMOTE.fit_resample(X_train, y_train)
    X_train_SMOTE = pd.DataFrame(X_train_SMOTE,
                                 columns = X_train.columns)

    print('After oversampling: ', Counter(y_train_SMOTE))

==============================================================
```

Balanced Bagging Classifer

In [69]:
```
bbclogpipeline = Pipeline(steps=
                          [
                           ("preprocessing", preprocessor),
                           ("skbest", SelectKBest(f_classif, k=10)),
                           ("bbc",   BalancedBaggingClassifier(estimator=Logisti
                                                               n_estimators=100,
                                                               max_samples=1.0,
                                                               sampling_strategy
                                                               random_state=0
                                                               ))
                          ])
```

In [70]:
```
bbclogpipeline.fit(X_train,y_train)
```

Out[70]:



In [71]:
```
bbclog_pred = bbclogpipeline.predict(X_test)
```

In [72]:
```
print("Accuracy:", "%.3f" % accuracy_score(y_test, bbclog_pred))
print("Precision:", "%.3f" % precision_score(y_test, bbclog_pred))
print("Recall:", "%.3f" % recall_score(y_test, bbclog_pred))
print("F1 Score:", "%.3f" % f1_score(y_test, bbclog_pred))
print("ROC-AUC Score:", "%.3f" % roc_auc_score(y_test, bbclog_pred))
```

```
Accuracy: 0.638
Precision: 0.411
Recall: 0.912
F1 Score: 0.567
ROC-AUC Score: 0.727
```

In [73]:
```
scoring = {'accuracy', 'precision', 'recall', 'f1', 'roc_auc'}
```

In [74]:
```
# K-Fold Cross-Validation
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=0)
```

In [75]:
```
# estimate generalization error
bbclogcv = cross_validate(estimator=bbclogpipeline,
                    X=X_train,
                    y=y_train,
                    scoring=scoring,
                    return_train_score=True,
                    cv=skf)
```

In [76]:
```
bbclogcv
```

Out[76]:
```
{'fit_time': array([0.52892494, 0.51568007, 0.55699372, 0.50258517, 0.49787283]),
 'score_time': array([0.07506871, 0.10375261, 0.09617186, 0.09059668, 0.0806238
7]),
 'test_f1': array([0.59708738, 0.59079903, 0.58876404, 0.55730337, 0.57627119]),
 'train_f1': array([0.58396723, 0.59018332, 0.57827103, 0.59440143, 0.58962264]),
 'test_precision': array([0.44565217, 0.43884892, 0.42394822, 0.4012945 , 0.429602
89]),
 'train_precision': array([0.42795883, 0.43504795, 0.42343884, 0.43926056, 0.43365
134]),
 'test_accuracy': array([0.68320611, 0.67686424, 0.6500956 , 0.62332696, 0.6653919
7]),
 'train_accuracy': array([0.66013384, 0.66889632, 0.65504061, 0.67462972, 0.667462
97]),
 'test_roc_auc': array([0.87844906, 0.86002291, 0.89025688, 0.86394209, 0.8567221
5]),
 'train_roc_auc': array([0.87210307, 0.8762876 , 0.86850591, 0.87506208, 0.8764391
4]),
 'test_recall': array([0.90441176, 0.9037037 , 0.96323529, 0.91176471, 0.875
]),
 'train_recall': array([0.91896869, 0.91727941, 0.91160221, 0.91896869, 0.9208103
1])}
```

In [77]:
```
# mean train set roc-auc
bbclogcv["train_roc_auc"].mean()
```

Out[77]:
```
0.8736795595908102
```

In [78]:
```
# mean test set roc-auc
bbclogcv["test_roc_auc"].mean()
```

Out[78]:
```
0.8698786164349862
```

In [80]:
```
!jupyter nbconvert --to webpdf --allow-chromium-download FinalProjectClassification
```

```
[NbConvertApp] Converting notebook FinalProjectClassificationwithPython.ipynb to web
pdf
[NbConvertApp] WARNING | Alternative text is missing on 8 image(s).
[NbConvertApp] Building PDF
Traceback (most recent call last):
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\webpdf.py", l
ine 78, in main
    from playwright.async_api import async_playwright  # type: ignore[import]
  File "C:\ProgramData\Anaconda3\lib\site-packages\playwright\async_api\__init__.p
y", line 25, in <module>
    import playwright.async_api._generated
  File "C:\ProgramData\Anaconda3\lib\site-packages\playwright\async_api\_generated.p
y", line 25, in <module>
    from playwright._impl._accessibility import Accessibility as AccessibilityImpl
  File "C:\ProgramData\Anaconda3\lib\site-packages\playwright\_impl\_accessibility.p
y", line 17, in <module>
    from playwright._impl._connection import Channel
  File "C:\ProgramData\Anaconda3\lib\site-packages\playwright\_impl\_connection.py",
line 36, in <module>
    from pyee.asyncio import AsyncIOEventEmitter
ModuleNotFoundError: No module named 'pyee.asyncio'

The above exception was the direct cause of the following exception:

Traceback (most recent call last):
  File "C:\ProgramData\Anaconda3\lib\runpy.py", line 197, in _run_module_as_main
    return _run_code(code, main_globals, None,
  File "C:\ProgramData\Anaconda3\lib\runpy.py", line 87, in _run_code
    exec(code, run_globals)
  File "C:\ProgramData\Anaconda3\Scripts\jupyter-nbconvert.EXE\__main__.py", line 7,
in <module>
  File "C:\ProgramData\Anaconda3\lib\site-packages\jupyter_core\application.py", lin
e 285, in launch_instance
    return super().launch_instance(argv=argv, **kwargs)
  File "C:\ProgramData\Anaconda3\lib\site-packages\traitlets\config\application.py",
line 1043, in launch_instance
    app.start()
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\nbconvertapp.py", line
414, in start
    self.convert_notebooks()
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\nbconvertapp.py", line
589, in convert_notebooks
    self.convert_single_notebook(notebook_filename)
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\nbconvertapp.py", line
555, in convert_single_notebook
    output, resources = self.export_single_notebook(
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\nbconvertapp.py", line
481, in export_single_notebook
    output, resources = self.exporter.from_filename(
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\templateexpor
ter.py", line 389, in from_filename
    return super().from_filename(filename, resources, **kw)  # type:ignore
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\exporter.py",
line 201, in from_filename
    return self.from_file(f, resources=resources, **kw)
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\templateexpor
```

```
ter.py", line 395, in from_file
    return super().from_file(file_stream, resources, **kw)  # type:ignore
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\exporter.py",
line 220, in from_file
    return self.from_notebook_node(
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\webpdf.py", l
ine 172, in from_notebook_node
    pdf_data = self.run_playwright(html)
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\webpdf.py", l
ine 161, in run_playwright
    pdf_data = pool.submit(run_coroutine, main(temp_file)).result()
  File "C:\ProgramData\Anaconda3\lib\concurrent\futures\_base.py", line 446, in resu
lt
    return self.__get_result()
  File "C:\ProgramData\Anaconda3\lib\concurrent\futures\_base.py", line 391, in __ge
t_result
    raise self._exception
  File "C:\ProgramData\Anaconda3\lib\concurrent\futures\thread.py", line 58, in run
    result = self.fn(*self.args, **self.kwargs)
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\webpdf.py", l
ine 159, in run_coroutine
    return loop.run_until_complete(coro)
  File "C:\ProgramData\Anaconda3\lib\asyncio\base_events.py", line 647, in run_until
_complete
    return future.result()
  File "C:\ProgramData\Anaconda3\lib\site-packages\nbconvert\exporters\webpdf.py", l
ine 84, in main
    raise RuntimeError(msg) from e
RuntimeError: Playwright is not installed to support Web PDF conversion. Please inst
all `nbconvert[webpdf]` to enable.
```

```
=================================================================
```

Python code done by Dennis Lam