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.

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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, On
from sklearn.preprocessing import PolynomialFeatures, RobustScaler, Binarizer, O

from sklearn.compose import make_column_transformer, ColumnTransformer, make_col
from sklearn.pipeline import make_pipeline, Pipeline
```

```python
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, Random
from sklearn.model_selection import train_test_split, cross_validate, cross_val_

from sklearn.metrics import accuracy_score, classification_report, confusion_mat
from sklearn.metrics import precision_score, recall_score, ConfusionMatrixDispla
from sklearn.metrics import jaccard_score, log_loss, mean_squared_error, mean_ab

from sklearn.feature_selection import f_classif, chi2, RFE, RFECV
from sklearn.feature_selection import mutual_info_regression, mutual_info_classi
from sklearn.feature_selection import VarianceThreshold, GenericUnivariateSelect
from sklearn.feature_selection import SelectFromModel, SelectKBest, SelectPercen

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, CondensedNearestNeighbou
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, SmartCorrelatedSele
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	windg
0	2008-02-01	19.50	22.40	15.60	6.20	0.00	W	
1	2008-02-02	19.50	25.60	6.00	3.40	2.70	W	
2	2008-02-03	21.60	24.50	6.60	2.40	0.10	W	
3	2008-02-04	20.20	22.80	18.80	2.20	0.00	W	
4	2008-02-05	19.70	25.70	77.40	4.80	0.00	W	

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
count	3271	3271.00	3271.00	3271.00	3271.00	3271.00	3271
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]:

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

Out[7]:

	mintemp	maxtemp	rainfall	evaporation	sunshine	windgustspeed	windspeed
count	3271.00	3271.00	3271.00	3271.00	3271.00	3271.00	327
mean	14.88	23.01	3.34	5.18	7.17	41.48	1
std	4.55	4.48	9.92	2.76	3.82	10.81	
min	4.30	11.70	0.00	0.00	0.00	17.00	
25%	11.00	19.60	0.00	3.20	4.25	35.00	1
50%	14.90	22.80	0.00	4.80	8.30	41.00	1
75%	18.80	26.00	1.40	7.00	10.20	44.00	2
max	27.60	45.80	119.40	18.40	13.60	96.00	5

In [8]:

```
# 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', 'wi
ndgustdir', 'windgustspeed', 'winddir9am', 'winddir3pm', 'windspeed9am', 'winds
peed3pm', 'humidity9am', 'humidity3pm', 'pressure9am', 'pressure3pm', 'cloud9am
', 'cloud3pm', 'temp9am', 'temp3pm', 'raintoday', 'raintomorrow'], dtype='objec
t')
```

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()
```

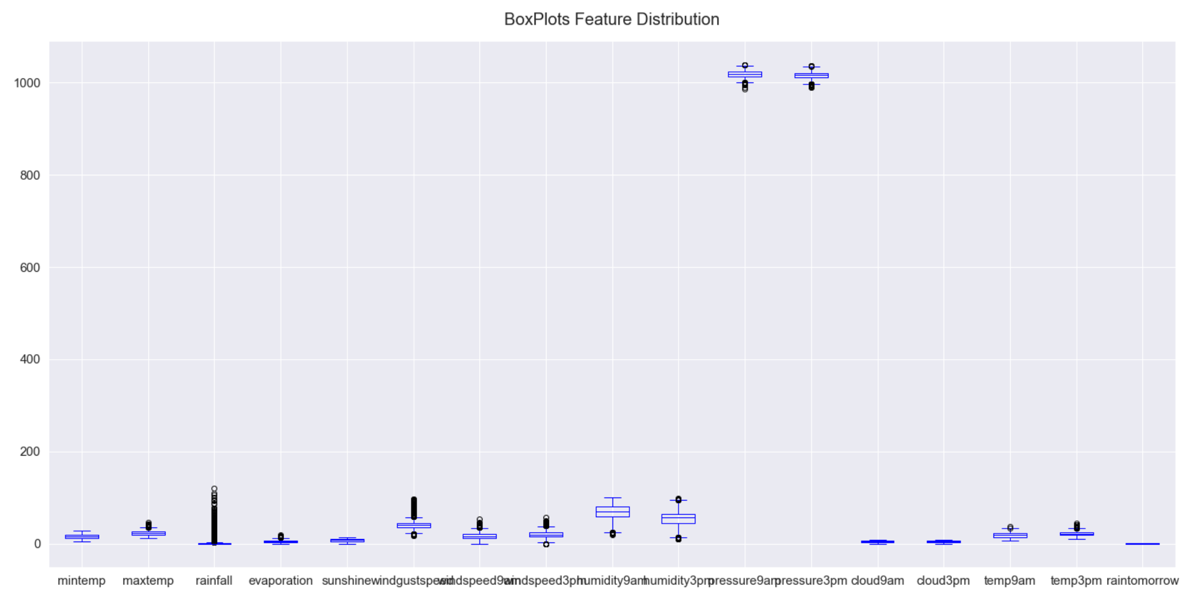
Out[13]:
```
0
```

Data Visualization

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

In [15]:

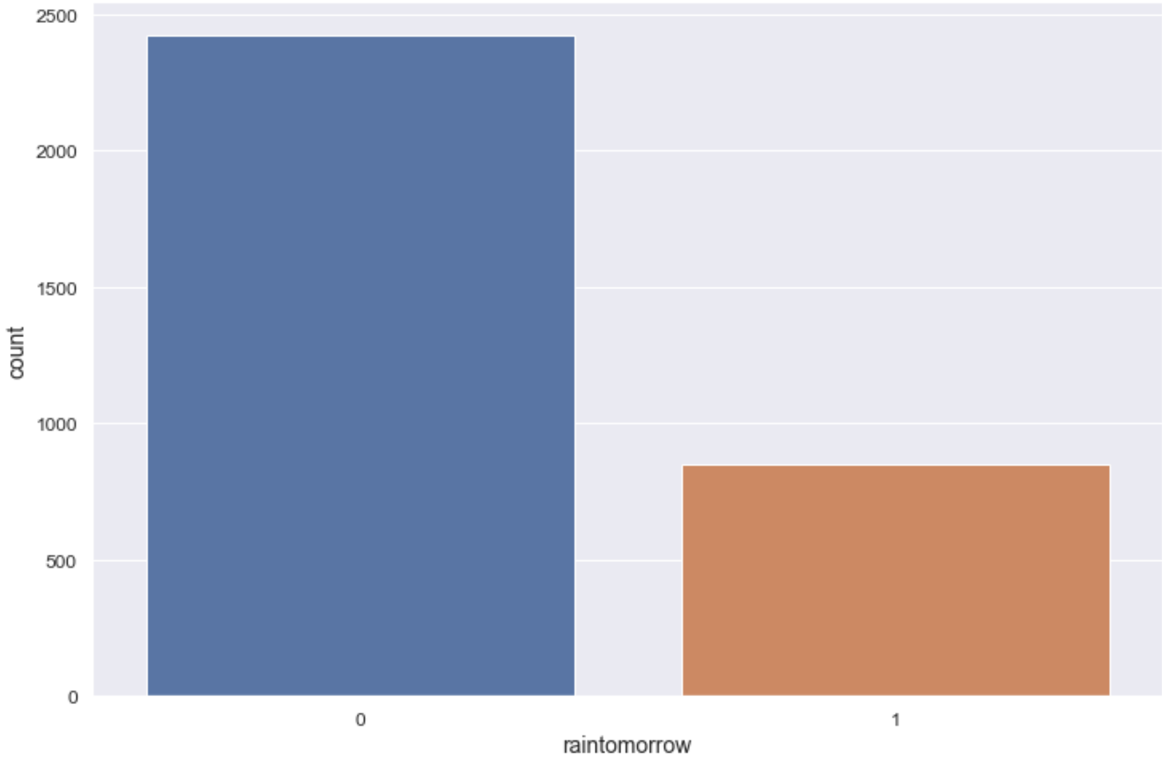
```python
df.boxplot(figsize=(20,10), color="blue", fontsize = 15)
plt.title('BoxPlots Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=
plt.tight_layout()
plt.show()
```



In [17]:

```python
fig, ax = plt.subplots(figsize=(12,8))
```

```
sns.countplot(x=df.raintomorrow, data=df)
plt.show()
```

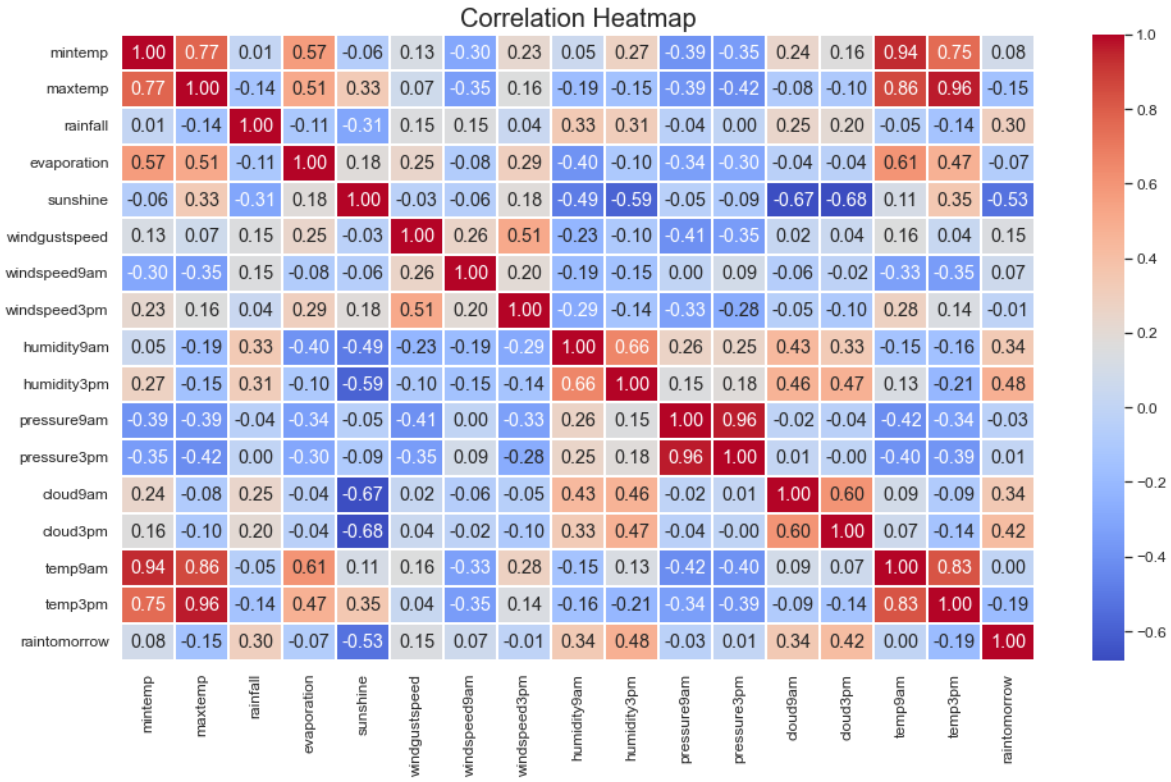


In [18]:
```
df.corr()
```

Out[18]:

	mintemp	maxtemp	rainfall	evaporation	sunshine	windgustspeed	w
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.

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_
```

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', 'windgus
 'humidity9am', 'humidity3pm', 'pressure9am', 'pressure3pm', 'cloud9am', 'cloud3
```

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,
                              #("scalar", StandardScaler()),
                               ("minmax", MinMaxScaler()),
])

categorical_transformer = Pipeline(steps=[

                                  #("imputer", SimpleImputer(strategy="most_freq
                                  #("onehot", OneHotEncoder(sparse_output=False,
                                   ("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)
```

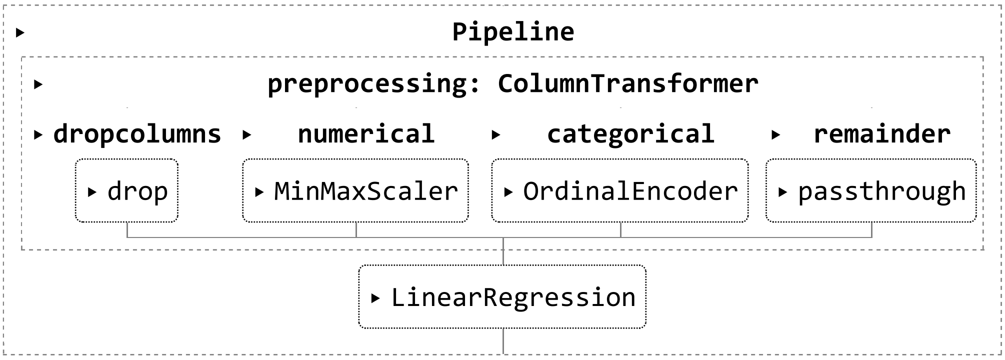
==

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]:

```
▸ Pipeline
  ▸ preprocessing: ColumnTransformer
    ▸ dropcolumns   ▸ numerical      ▸ categorical      ▸ remainder
      ▸ drop        ▸ MinMaxScaler   ▸ OrdinalEncoder   ▸ passthrough
  ▸ KNeighborsClassifier
```

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

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

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

In [46]:
```
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]:
```
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]:
```
dtpipeline = Pipeline(steps=[
                             ("preprocessor", preprocessor),
                             ("decisiontree", DecisionTreeClassifier(random_state=0,

])
```

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

Out[49]:

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

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

In [51]:
```
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_weig
                        ])
```

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

Out[55]:

▸ **Pipeline**

▸ **preprocessing: ColumnTransformer**

▸ **dropcolumns** ▸ **numerical** ▸ **categorical** ▸ **remainder**

▸ drop ▸ MinMaxScaler ▸ OrdinalEncoder ▸ passthrough

▸ LogisticRegression

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

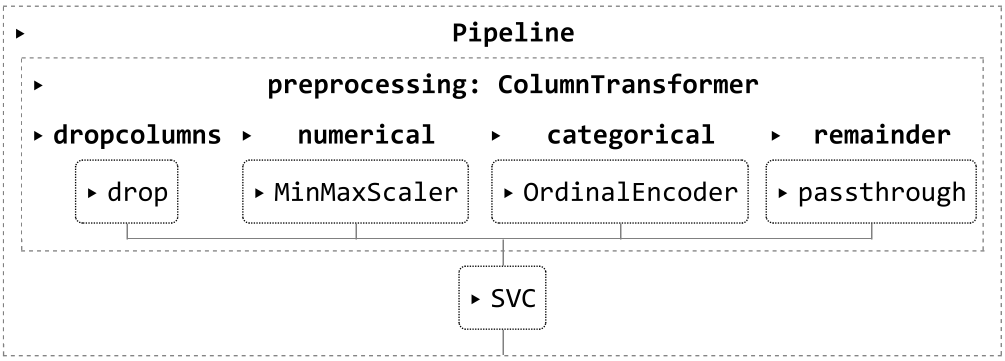
==

SVM

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

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

===

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))
```

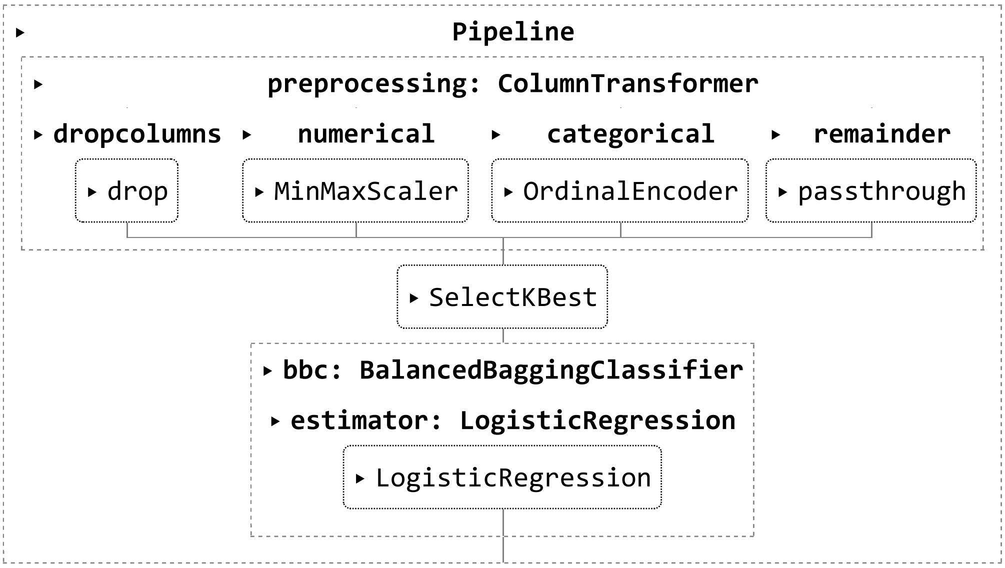
==

Balanced Bagging Classifer

In [69]:
```
bbclogpipeline = Pipeline(steps=
                          [
                           ("preprocessing", preprocessor),
                           ("skbest", SelectKBest(f_classif, k=10)),
                           ("bbc",   BalancedBaggingClassifier(estimator=Logi
                                                               n_estimators=1
                                                               max_samples=1.
                                                               sampling_strat
                                                               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, 0.4978728
3]),
 '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, 0.5762711
9]),
 'train_f1': array([0.58396723, 0.59018332, 0.57827103, 0.59440143, 0.5896226
4]),
 'test_precision': array([0.44565217, 0.43884892, 0.42394822, 0.4012945 , 0.429
60289]),
 'train_precision': array([0.42795883, 0.43504795, 0.42343884, 0.43926056, 0.43
365134]),
 'test_accuracy': array([0.68320611, 0.67686424, 0.6500956 , 0.62332696, 0.6653
9197]),
 'train_accuracy': array([0.66013384, 0.66889632, 0.65504061, 0.67462972, 0.667
46297]),
 'test_roc_auc': array([0.87844906, 0.86002291, 0.89025688, 0.86394209, 0.85672
215]),
 'train_roc_auc': array([0.87210307, 0.8762876 , 0.86850591, 0.87506208, 0.8764
3914]),
 'test_recall': array([0.90441176, 0.9037037 , 0.96323529, 0.91176471, 0.875
]),
 'train_recall': array([0.91896869, 0.91727941, 0.91160221, 0.91896869, 0.92081
031])}
```

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

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

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

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

==

Python code done by Dennis Lam