DAT200 CA5 2022

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Imports

In [39]:
```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingRegressor
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKFold
from sklearn.metrics import r2_score, confusion_matrix, roc_curve, auc
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.pipeline import make_pipeline
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA
from scipy import stats
from mlxtend.plotting import scatterplotmatrix

import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import numpy as np
```

Reading data

In [2]:
```
raw_data = pd.read_pickle('train.pkl') # Naming the train data "raw_data"
test_data = pd.read_pickle('test.pkl') # Naming the test data "test_data"

# To inspect the data with excel
raw_data.to_csv("train_unpickled.csv")
test_data.to_csv("test_unpickled.csv")
```

Data exploration and visualisation

In [3]:
```
raw_data = raw_data.replace('missing', np.NaN)
test_data = test_data.replace('missing', np.NaN)
```

In [4]:
```
print(raw_data.isna().sum()) # Checking how many NaN values there are
```

```
Season                              39
Year                                37
Month                               31
Hour                                50
Holiday                             30
Weekday                             36
Working day                         34
Weather situation                   27
Temperature (normalized)            36
Feels-like temperature (normalized) 24
Humidity (normalized)               30
Windspeed                           34
Rental bikes count                   0
dtype: int64
```

In [5]:
```
print(f'\nThe shape of the training data is:{raw_data.shape}\n')
print(f'\nThe shape of the test data is:{test_data.shape}\n')
```

```
The shape of the training data is:(12165, 13)


The shape of the test data is:(5214, 12)
```

Data cleaning

In [6]:
```
dummies = pd.get_dummies(raw_data[['Season', 'Weather situation']], drop_first=True) # Converting 'season' and we
enc_data = pd.concat([raw_data, dummies], axis=1) # Merging / concatenating two dataframes
```

```
enc_data = enc_data._get_numeric_data()
enc_data
```

Out[6]:

	Year	Month	Hour	Holiday	Weekday	Working day	Temperature (normalized)	Feels-like temperature (normalized)	Humidity (normalized)	Windspeed	Rental bikes count	Season_Spring	Season_Su
0	1.0	6.0	18.0	0.0	1.0	1.0	0.76	0.6667	0.27	0.4478	791	0	
1	1.0	10.0	11.0	0.0	3.0	1.0	0.36	0.3485	0.66	0.2239	189	0	
2	0.0	6.0	22.0	0.0	6.0	0.0	0.64	0.6212	0.57	0.2239	190	1	
3	0.0	3.0	21.0	0.0	2.0	1.0	0.42	0.4242	0.54	0.2836	87	1	
4	1.0	11.0	5.0	0.0	2.0	1.0	0.34	0.3333	0.66	0.1343	34	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
12160	0.0	9.0	16.0	0.0	3.0	1.0	0.76	0.6970	0.52	0.2836	277	0	
12161	0.0	5.0	8.0	0.0	1.0	1.0	0.56	0.5303	0.73	0.2985	394	1	
12162	0.0	5.0	1.0	0.0	2.0	1.0	0.46	0.4545	0.59	0.0896	15	1	
12163	0.0	4.0	16.0	0.0	2.0	1.0	0.48	0.4697	0.77	0.3881	99	1	
12164	0.0	9.0	6.0	0.0	6.0	0.0	0.56	0.5303	0.94	0.1045	18	0	

12165 rows × 17 columns

In [7]:

```
# Encoding and imputing the test data aswell
dummies2 = pd.get_dummies(test_data[['Season', 'Weather situation']], drop_first=True) # Converting 'season' and

enc_test = pd.concat([test_data, dummies2], axis=1) # Merging / concatenating two dataframes
enc_test = enc_test._get_numeric_data()
enc_test
```

Out[7]:

	Year	Month	Hour	Holiday	Weekday	Working day	Temperature (normalized)	Feels-like temperature (normalized)	Humidity (normalized)	Windspeed	Season_Spring	Season_Summer	S
0	1	6	19	0	5	1	0.70	0.6364	0.42	0.1642	1	0	
1	1	9	3	0	4	1	0.44	0.4394	0.77	0.0000	0	1	
2	0	4	14	0	1	1	0.58	0.5455	0.49	0.1940	1	0	
3	0	5	18	0	3	1	0.72	0.6667	0.58	0.2239	1	0	
4	0	4	3	0	3	1	0.40	0.4091	0.94	0.3284	1	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
5209	0	7	20	0	1	1	0.78	0.7424	0.59	0.2239	0	1	
5210	0	2	22	0	6	0	0.30	0.2576	0.28	0.4925	0	0	
5211	0	9	22	0	0	0	0.54	0.5152	0.68	0.0896	0	1	
5212	1	8	0	0	3	1	0.62	0.5758	0.83	0.1045	0	1	
5213	1	8	18	0	5	1	0.86	0.7576	0.36	0.2537	0	1	

5214 rows × 16 columns

Imputing data

In [8]:

```
imp = SimpleImputer(missing_values=np.NaN, strategy='median')
imp_data = imp.fit(enc_data.values)
imp_data = imp.transform(enc_data.values)
imp_df = pd.DataFrame(imp_data, columns=enc_data.columns)

imp_df.head() # Checking if the imputer worked
```

Out[8]:

	Year	Month	Hour	Holiday	Weekday	Working day	Temperature (normalized)	Feels-like temperature (normalized)	Humidity (normalized)	Windspeed	Rental bikes count	Season_Spring	Season_Summ
0	1.0	6.0	18.0	0.0	1.0	1.0	0.76	0.6667	0.27	0.4478	791.0	0.0	1
1	1.0	10.0	11.0	0.0	3.0	1.0	0.36	0.3485	0.66	0.2239	189.0	0.0	0

2	0.0	6.0	22.0	0.0	6.0	0.0	0.64	0.6212	0.57	0.2239	190.0	1.0	0
3	0.0	3.0	21.0	0.0	2.0	1.0	0.42	0.4242	0.54	0.2836	87.0	1.0	0
4	1.0	11.0	5.0	0.0	2.0	1.0	0.34	0.3333	0.66	0.1343	34.0	0.0	0

In [50]:

```
imp_df.info() # Checking the data types, should all be float numbers
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12165 entries, 0 to 12164
Data columns (total 17 columns):
 #   Column                                                Non-Null Count  Dtype  
---  ------                                                --------------  -----  
 0   Year                                                  12165 non-null  float64
 1   Month                                                 12165 non-null  float64
 2   Hour                                                  12165 non-null  float64
 3   Holiday                                               12165 non-null  float64
 4   Weekday                                               12165 non-null  float64
 5   Working day                                           12165 non-null  float64
 6   Temperature (normalized)                              12165 non-null  float64
 7   Feels-like temperature (normalized)                   12165 non-null  float64
 8   Humidity (normalized)                                 12165 non-null  float64
 9   Windspeed                                             12165 non-null  float64
 10  Rental bikes count                                    12165 non-null  float64
 11  Season_Spring                                         12165 non-null  float64
 12  Season_Summer                                         12165 non-null  float64
 13  Season_Winter                                         12165 non-null  float64
 14  Weather situation_Heavy rain, heavy snow or thunderstorm 12165 non-null  float64
 15  Weather situation_Light snow or light rain            12165 non-null  float64
 16  Weather situation_Misty and/or cloudy                 12165 non-null  float64
dtypes: float64(17)
memory usage: 1.6 MB
```

In [9]:

```
imp2 = SimpleImputer(missing_values=np.NaN, strategy='median')
imp_test = imp2.fit(enc_test.values)
imp_test = imp2.transform(enc_test.values)
imp_test_df = pd.DataFrame(imp_test, columns=enc_test.columns)

imp_test_df.head() # Checking if the imputer worked
```

Out[9]:

	Year	Month	Hour	Holiday	Weekday	Working day	Temperature (normalized)	Feels-like temperature (normalized)	Humidity (normalized)	Windspeed	Season_Spring	Season_Summer	Seas
0	1.0	6.0	19.0	0.0	5.0	1.0	0.70	0.6364	0.42	0.1642	1.0	0.0	
1	1.0	9.0	3.0	0.0	4.0	1.0	0.44	0.4394	0.77	0.0000	0.0	1.0	
2	0.0	4.0	14.0	0.0	1.0	1.0	0.58	0.5455	0.49	0.1940	1.0	0.0	
3	0.0	5.0	18.0	0.0	3.0	1.0	0.72	0.6667	0.58	0.2239	1.0	0.0	
4	0.0	4.0	3.0	0.0	3.0	1.0	0.40	0.4091	0.94	0.3284	1.0	0.0	

In [48]:

```
imp_test_df.info() # Checking the data types, should all be float numbers
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5214 entries, 0 to 5213
Data columns (total 16 columns):
 #   Column                                                Non-Null Count  Dtype  
---  ------                                                --------------  -----  
 0   Year                                                  5214 non-null   float64
 1   Month                                                 5214 non-null   float64
 2   Hour                                                  5214 non-null   float64
 3   Holiday                                               5214 non-null   float64
 4   Weekday                                               5214 non-null   float64
 5   Working day                                           5214 non-null   float64
 6   Temperature (normalized)                              5214 non-null   float64
 7   Feels-like temperature (normalized)                   5214 non-null   float64
 8   Humidity (normalized)                                 5214 non-null   float64
 9   Windspeed                                             5214 non-null   float64
 10  Season_Spring                                         5214 non-null   float64
 11  Season_Summer                                         5214 non-null   float64
 12  Season_Winter                                         5214 non-null   float64
 13  Weather situation_Heavy rain, heavy snow or thunderstorm 5214 non-null   float64
 14  Weather situation_Light snow or light rain            5214 non-null   float64
 15  Weather situation_Misty and/or cloudy                 5214 non-null   float64
dtypes: float64(16)
memory usage: 651.9 KB
```

Data exploration after cleaning

In [11]:
```python
print(imp_df.isna().sum()) # Checking if the NaN values are gone from the training data
print(f'\n{imp_test_df.isna().sum()}\n') # Checking if the NaN values are gone from the test data
print(f'\nThe shape of the imputed training data is: {imp_df.shape}\n')
print(f'\nThe shape of the imputed testing data is: {imp_test_df.shape}\n')
```

```
Year                                                   0
Month                                                  0
Hour                                                   0
Holiday                                                0
Weekday                                                0
Working day                                            0
Temperature (normalized)                               0
Feels-like temperature (normalized)                    0
Humidity (normalized)                                  0
Windspeed                                              0
Rental bikes count                                     0
Season_Spring                                          0
Season_Summer                                          0
Season_Winter                                          0
Weather situation_Heavy rain, heavy snow or thunderstorm    0
Weather situation_Light snow or light rain             0
Weather situation_Misty and/or cloudy                  0
dtype: int64

Year                                                   0
Month                                                  0
Hour                                                   0
Holiday                                                0
Weekday                                                0
Working day                                            0
Temperature (normalized)                               0
Feels-like temperature (normalized)                    0
Humidity (normalized)                                  0
Windspeed                                              0
Season_Spring                                          0
Season_Summer                                          0
Season_Winter                                          0
Weather situation_Heavy rain, heavy snow or thunderstorm    0
Weather situation_Light snow or light rain             0
Weather situation_Misty and/or cloudy                  0
dtype: int64


The shape of the imputed training data is: (12165, 17)


The shape of the imputed testing data is: (5214, 16)
```

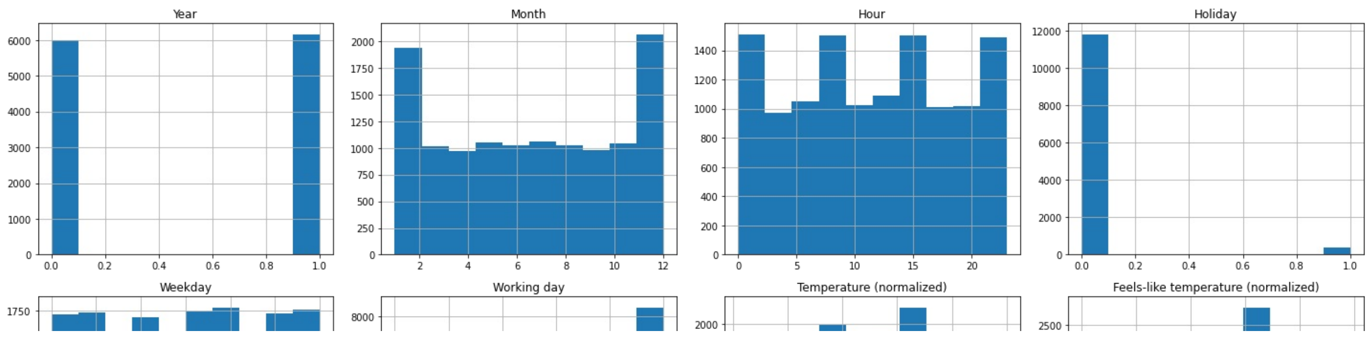
Preprocessing

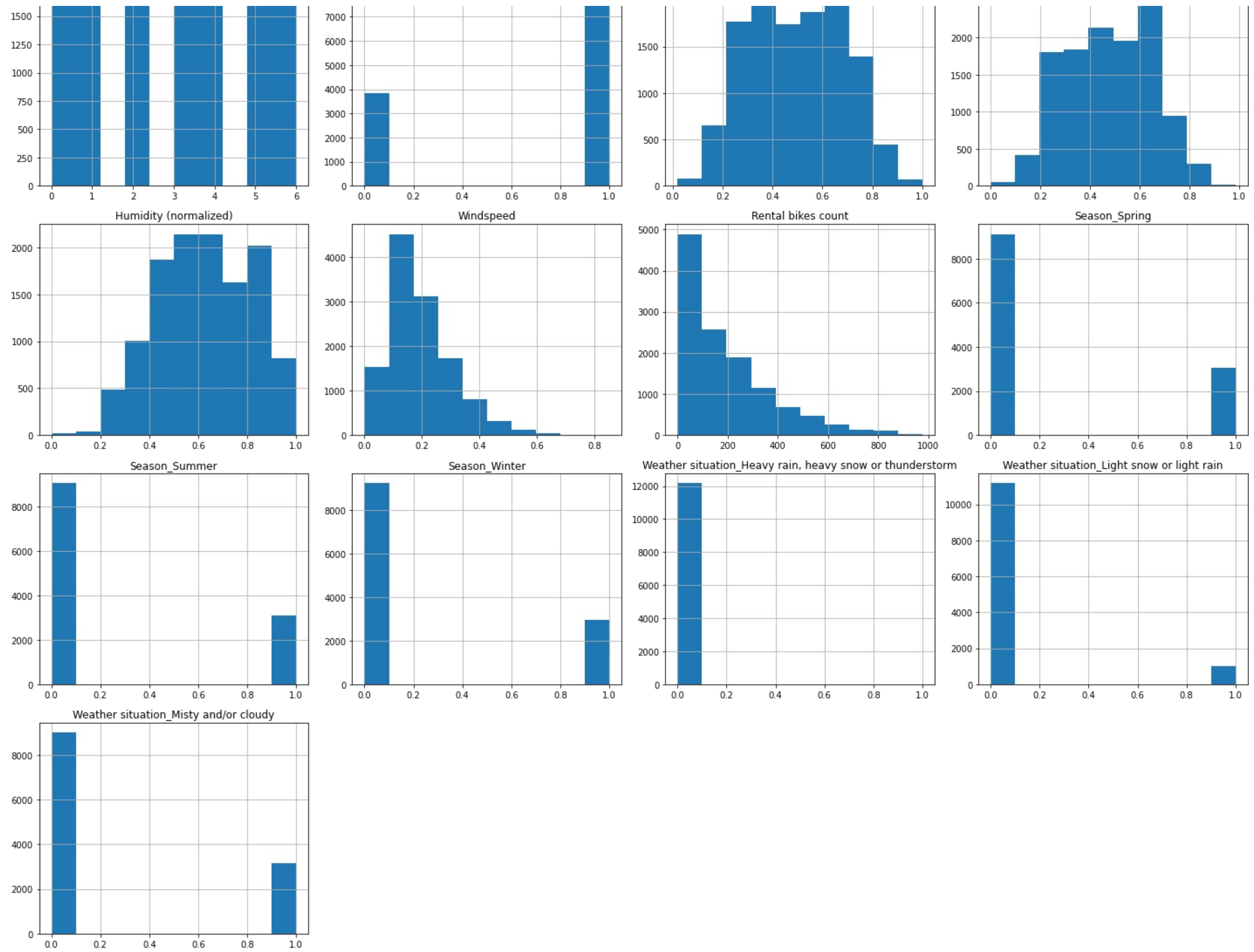
In [12]:
```python
X = imp_df.drop(['Rental bikes count'], axis=1)
y = imp_df['Rental bikes count']
```

Plots

In [13]:
```python
# Histograms

imp_df.hist(figsize=(20, 20)) # Making it big for easier inspection
plt.tight_layout()
plt.show()
```



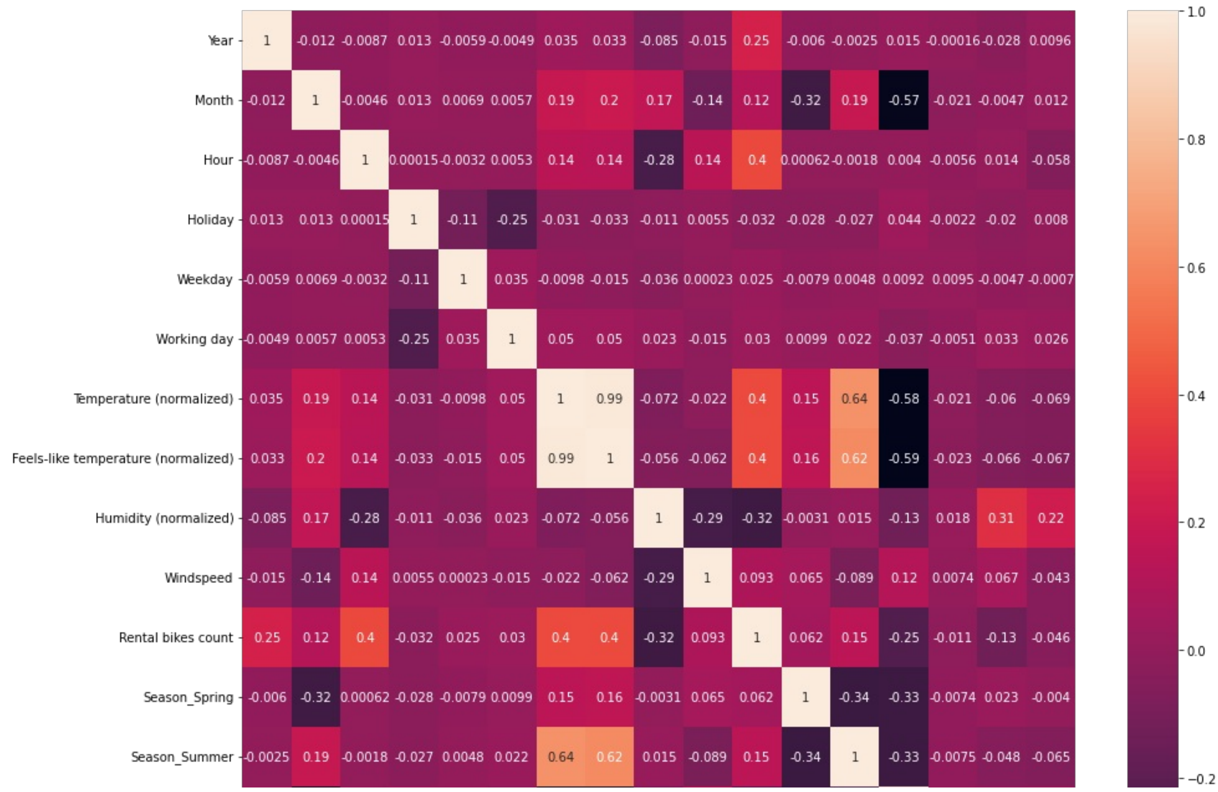


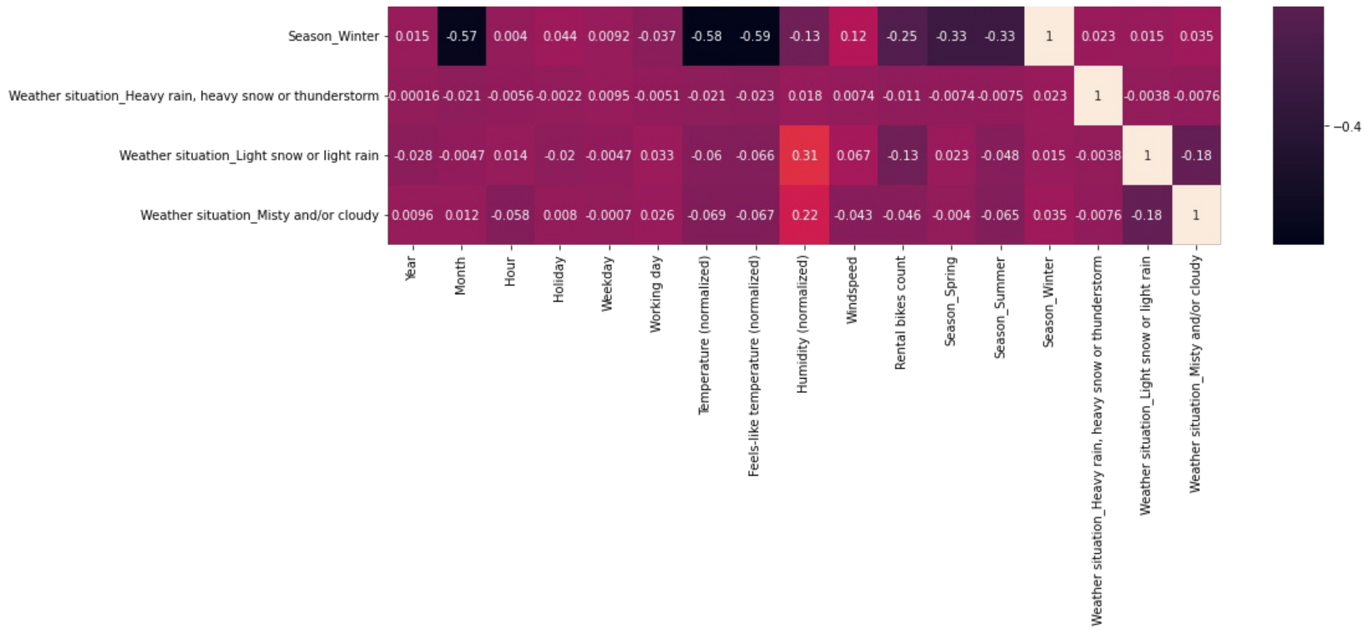
As one can see, the bikes are never used during heavy rain, but some times used when there is light snow or misty weather. Furthermore, one can see a trend where the bikes are mostly used during working days.

In [14]:

```
# Correlation matrix

plt.figure(figsize=(15, 15)) # Making it big for easier inspection
corr_matrix = imp_df.corr()
sns.heatmap(corr_matrix, annot=True)
plt.show()
```





As seen above, Temperature (normalized) correlates with Feels-like temperature (normalized). However, both Temperature (normalized) and Feels-like temperature (normalized) inversely correlate with Season_Winter. One can also see a trend where there are more bikes used during the summer and less used during the winter.

Train test split

In [15]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=1)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(8515, 16) (3650, 16) (8515,) (3650,)
```

Scaling

In [ ]:
```

```

Modelling

Data pipeline with regression model

In [16]:
```
gbr_pipe = make_pipeline(StandardScaler(), GradientBoostingRegressor(random_state=21))

param_dist = [{'gradientboostingregressor__learning_rate': [0.01, 0.02, 0.05, 0.1],
'gradientboostingregressor__n_estimators':[500],
'gradientboostingregressor__min_samples_leaf': [1, 3, 9],
'gradientboostingregressor__max_depth':[5, 6, 7],
'gradientboostingregressor__max_features':[0.3,0.6,1.0]}]

g_search_gbr = GridSearchCV(estimator=gbr_pipe,
                            param_grid=param_dist,
                            scoring='r2',
                            cv=10,
                            n_jobs=-1)
```

In [17]:
```
g_search_gbr.fit(X_train, y_train) # Finding the best parameters for GBR
```

Out[17]:
```
GridSearchCV(cv=10,
             estimator=Pipeline(steps=[('standardscaler', StandardScaler()),
                                       ('gradientboostingregressor',
                                        GradientBoostingRegressor(random_state=21))]),
             n_jobs=-1,
             param_grid=[{'gradientboostingregressor__learning_rate': [0.01,
                                                                       0.02,
                                                                       0.05,
                                                                       0.1],
                          'gradientboostingregressor__max_depth': [5, 6, 7],
                          'gradientboostingregressor__max_features': [0.3, 0.6,
```

```
                                                            1.0],
                              'gradientboostingregressor__min_samples_leaf': [1, 3,
                                                                              9],
                              'gradientboostingregressor__n_estimators': [500]}],
             scoring='r2')
```

In [18]:

```
best_params = g_search_gbr.best_params_
print('The best parameters achieved from the grid search are: ', best_params)
```

```
The best parameters achieved from the grid search are:  {'gradientboostingregressor__learning_rate': 0.05, 'gradi
entboostingregressor__max_depth': 7, 'gradientboostingregressor__max_features': 0.6, 'gradientboostingregressor__
min_samples_leaf': 3, 'gradientboostingregressor__n_estimators': 500}
```

In [19]:

```
gbr_best =  g_search_gbr.best_estimator_
gbr_best.fit(X, y) # Fitting the best parameters into the model
```

Out[19]:

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('gradientboostingregressor',
                 GradientBoostingRegressor(learning_rate=0.05, max_depth=7,
                                           max_features=0.6, min_samples_leaf=3,
                                           n_estimators=500,
                                           random_state=21))])
```

In [20]:

```
y_pred = gbr_best.predict(imp_test_df)

print('Gradient boosting regressor training data accuracy: {0:.2f}'.format(gbr_best.score(X_train, y_train)))

print('Gradient boosting regressor test data accuracy: {0:.2f}'.format(gbr_best.score(X_test, y_test)))
```

```
Gradient boosting regressor training data accuracy: 0.98
Gradient boosting regressor test data accuracy: 0.98
```

Kaggle submission GBR

In [21]:

```
pred2_df = pd.DataFrame(data=y_pred)
pred2_df.reset_index(level=0, inplace=True)
pred2_df.columns = ['idx', 'Rental bikes count']
pred2_df['Rental bikes count'] = pred2_df['Rental bikes count'].apply(np.int64) # Converting the float values to

pred2_df.to_csv('Pred2_gbr.csv', index=False, sep=',')
```

Data pipeline with classification model

Binning train target values

Can be performed with ex. pandas.qcut or pandas.cut

```
n_bins = 10
y_train_binned = pd.cut(y_train, n_bins, labels=False) # or
y_train_binned = pd.qcut(y_train, n_bins, labels=False)
```

In [37]:

```
# I found out that the accuracy decreased when I used more than 5 bins

n_bins = 5
y_train_binned = pd.cut(y_train, n_bins, labels=False)
y_test_binned = pd.cut(y_test, n_bins, labels=False)
```

Binned Random Forest Pipeline

In [28]:

```
forest = make_pipeline(StandardScaler(), RandomForestClassifier(random_state=21))

param_dist = {
    'randomforestclassifier__n_estimators': [50, 100, 200, 300],
    'randomforestclassifier__max_depth': [2, 4, 6, 8, 10],
    'randomforestclassifier__min_samples_leaf': [1, 5, 10],
    'randomforestclassifier__max_features': ['auto', 'sqrt'],
    'randomforestclassifier__bootstrap': [True, False]
}
```

```
forest_gs = GridSearchCV(estimator=forest, param_grid=param_dist, scoring='r2', cv=5, n_jobs=-1)
```

In [29]:

```
forest_gs.fit(X_train, y_train_binned)
```

Out[29]:

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('standardscaler', StandardScaler()),
                                       ('randomforestclassifier',
                                        RandomForestClassifier(random_state=21))]),
             n_jobs=-1,
             param_grid={'randomforestclassifier__bootstrap': [True, False],
                         'randomforestclassifier__max_depth': [2, 4, 6, 8, 10],
                         'randomforestclassifier__max_features': ['auto',
                                                                  'sqrt'],
                         'randomforestclassifier__min_samples_leaf': [1, 5, 10],
                         'randomforestclassifier__n_estimators': [50, 100, 200,
                                                                  300]},
             scoring='r2')
```

In [30]:

```
best_params = forest_gs.best_params_

print('The best parameters achieved from the grid search are: ', best_params)
```

```
The best parameters achieved from the grid search are:  {'randomforestclassifier__bootstrap': False, 'randomfores
tclassifier__max_depth': 10, 'randomforestclassifier__max_features': 'auto', 'randomforestclassifier__min_samples
_leaf': 1, 'randomforestclassifier__n_estimators': 50}
```

In [33]:

```
forest_best =  forest_gs.best_estimator_
forest_best.fit(X_train, y_train_binned)
```

Out[33]:

```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('randomforestclassifier',
                 RandomForestClassifier(bootstrap=False, max_depth=10,
                                        n_estimators=50, random_state=21))])
```

In [34]:

```
y_pred = forest_best.predict(imp_test_df)

print('Forest training data accuracy: {0:.2f}'.format(forest_best.score(X_train, y_train_binned)))

print('Forest test data accuracy: {0:.2f}'.format(forest_best.score(X_test, y_test_binned)))
```

```
Forest training data accuracy: 0.86
Forest test data accuracy: 0.80
```

Kaggle submission Binned random forest pipeline

In [35]:

```
pred3_df = pd.DataFrame(data=y_pred)
pred3_df.reset_index(level=0, inplace=True)
pred3_df.columns = ['idx', 'Rental bikes count']
pred3_df['Rental bikes count'] = pred3_df['Rental bikes count'].apply(np.int64) # Converting the float values to

pred3_df.to_csv('Pred_forest.csv', index=False, sep=',')
```

I got the best results from using the Gradient Boosting Regressor model. It performed much better than the binned random forest pipeline.