Student: Duncan Ferguson
Student Id: 871641260
Class: Comp 4431-1
Assignment: Assignment 2
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Project was Completed by Individual, group is just listed below for reference to past code that might be reused from previous Excercises
Group: Name: Broken Toe
Group Members: Emma Bright, Mike Santoro

Assignment Description:

In this assignment you are to use Decision trees and Naive Bayes for classification. In addition, you are to explore your models to determine which feature vector attributes you can remove without "significantly hurting" classification importance. There is no single "right" answer for this question. Also, "significantly hurting" is a judgement call, please explain why you mean by that and provided numeric values. You should start with the full dataset and look at the decision tree features_importances_ and naive bayes permutation_importance to guid which attributes to remove. You will then want to iteratively remove attributes, possibly one at a time or several at a time. Again, there is no single "right way" to do this.

The goal is to predict whether it will rain tomorrow given the days weather statistics. The last column, "Rain Tomorrow" is the classification value for I have cleaned the data set for you. I removed a few attributes that were almost all zeros, and replaced missing values with the mean value for that column. Also, strings have been transformed into numeric values so the data set will work well for both decision trees and naive bayes.

What To Turn In:

1). A report that explains which attributes you have eliminated, why those, and what effect this has on the quality of predictions compared to using the full dataset. Feel free to include a table of feature_importances and permutation_importances that show how any why you reduced the set of attributes.

2). Your code for creating the decision tree and naive bayes models and getting the feature/permuttion importances. Your code does not need to cover your whole experimental space, but should provide enough information to show how you made at least one decision about which attribute (column) to eliminate

556
```
import numpy as np
import pandas as pd
```

```
from sklearn import tree
from sklearn.naive_bayes import *
from sklearn.model_selection import train_test_split
from sklearn.metrics import *
from sklearn.inspection import permutation_importance
import matplotlib.pyplot as plt
import seaborn as sns
```

To start of this project I have decided to look at the correlations first to get a bit more of a grasp on how the data is related.

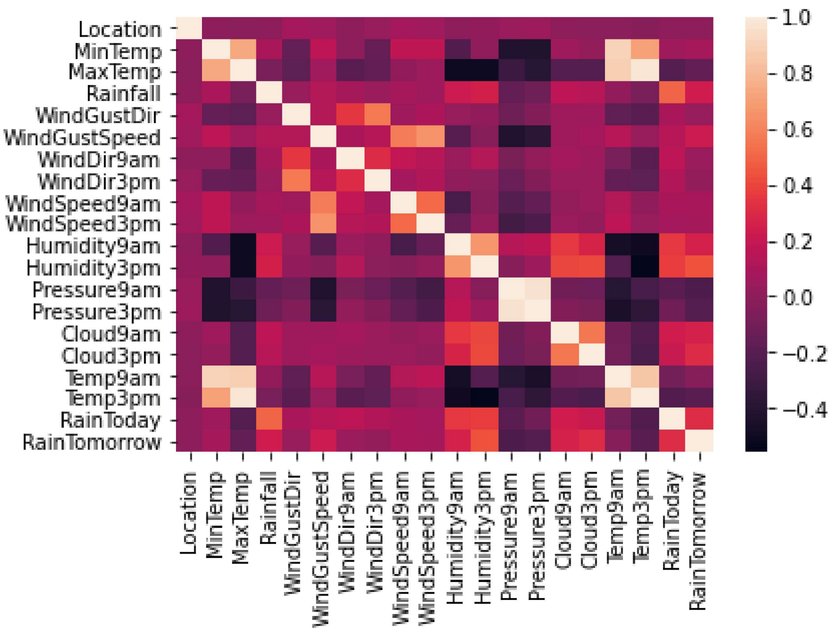
557
```
# Importing the Data

np.random.seed(0)
df = pd.read_csv("assignment2_cleanInfile.csv")
df.head()
df_did_rain = df[df["RainTomorrow"] != 0]
df_did_not_rain = df[df["RainTomorrow"] == 0]
print(df_did_rain["RainTomorrow"].unique())
print(df_did_not_rain["RainTomorrow"].unique())
```

```
[1]
[0]
```

558
```
sns.heatmap(df.corr())
```

558
```
<AxesSubplot:>
```



This Heat Map Correlation gives us some middle of the ground results. We can see that MinTemp and Temp9am are related, as well as with the max temp.

559
```
corr_matrix = df.corr().abs()
corr_matrix
```

559

	Location	MinTemp	MaxTemp	Rainfall	WindGustDir	WindGustSpeed	Win

	Location	MinTemp	MaxTemp	Rainfall	WindGustDir	WindGustSpeed	Win
Location	1.000000	0.006194	0.020490	0.003457	0.075197	0.069269	0.00
MinTemp	0.006194	1.000000	0.733919	0.103314	0.149557	0.173331	0.00
MaxTemp	0.020490	0.733919	1.000000	0.074202	0.176500	0.066329	0.18
Rainfall	0.003457	0.103314	0.074202	1.000000	0.033045	0.127250	0.08
WindGustDir	0.075197	0.149557	0.176500	0.033045	1.000000	0.129199	0.34
WindGustSpeed	0.069269	0.173331	0.066329	0.127250	0.129199	1.000000	0.10
WindDir9am	0.001938	0.002464	0.181369	0.083133	0.346856	0.105557	1.00
WindDir3pm	0.030553	0.145183	0.158061	0.042696	0.565715	0.142515	0.30
WindSpeed9am	0.077038	0.174946	0.014586	0.085977	0.063066	0.577864	0.18
WindSpeed3pm	0.064180	0.174187	0.050381	0.056762	0.111046	0.658377	0.14
Humidity9am	0.002065	0.232372	0.499777	0.221392	0.031133	0.209272	0.04
Humidity3pm	0.011066	0.005913	0.499725	0.249609	0.009683	0.025822	0.13
Pressure9am	0.036492	0.424357	0.309093	0.159676	0.120842	0.426600	0.06
Pressure3pm	0.046345	0.434034	0.397422	0.120366	0.042960	0.384642	0.01
Cloud9am	0.010908	0.061460	0.226776	0.171613	0.054864	0.052281	0.07
Cloud3pm	0.015860	0.015902	0.214469	0.145848	0.054884	0.080202	0.04
Temp9am	0.015596	0.897999	0.880087	0.011384	0.169948	0.146756	0.07
Temp3pm	0.022718	0.699828	0.969735	0.077553	0.188980	0.032274	0.19
RainToday	0.004146	0.055856	0.227421	0.500997	0.104836	0.148977	0.16
RainTomorrow	0.003579	0.083717	0.159087	0.236874	0.032470	0.225264	0.03

560

```
def train_data(df, drops=None):
    """This Function splits the data to train and test the data. It also an element for being able to
    drop certain rows."""
    # Y is the classification
    Y = df['RainTomorrow'].tolist()
    X = df.copy()
    X = X.drop(columns=["RainTomorrow"])
    if drops != None:
        X = X.drop(columns=drops)
    x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.25, random_state=42)
    return x_train, x_test, y_train, y_test, X
```

561

```
def decisionTree_Model(x_train, x_test, y_train, y_test, X, yes_print=False):
    """This Function goes through building a decision tree and creating a confusion matrix
    computing accuracy, and listing the decision tree features and their importance"""
    # Building out a decision tree
```

```
    dtree = tree.DecisionTreeClassifier(criterion="gini")
    dtree = dtree.fit(x_train, y_train)
    y_predicted = dtree.predict(x_test)
    accuracy = accuracy_score(y_test, y_predicted)
    important = dtree.feature_importances_
    df_importance_list = []
    for i, v in enumerate(important):
        df_importance_list.append([X.columns[i], v])
    df_importance = pd.DataFrame(df_importance_list, columns=["FName", "Score"])
    df_importance.sort_values(by=['Score'], ascending=False, inplace=True)
    decisionTree_Model_Features = df_importance["FName"].tolist()
    if yes_print:
        print("DecisionTree Accuracy: ", accuracy)
        print("DecisionTree Confusion Matrix:")
        print(confusion_matrix(y_test, y_predicted))
        print("decision tree dtree feature importance:")
        print(df_importance)
    return accuracy, decisionTree_Model_Features
```

562
```
def GausianNB_Model(x_train, x_test, y_train, y_test, X, yes_print=False):
    """This Function goes through the GausianNB model and calculates the accuracy, computes the confusion
    and then lists the Gaussian Model Features and their significance"""
    model2 = GaussianNB()
    model2.fit(x_train, y_train)
    gausianNB_predicted = model2.predict(x_test)
    accuracy = accuracy_score(y_test, gausianNB_predicted)
    imps = permutation_importance(model2, x_test, y_test)
    df_Gausian_Feature_Importance_List = []
    Gausian_Feature_Importance_List =  imps.importances_mean.tolist()
    for row in enumerate(Gausian_Feature_Importance_List):
        df_Gausian_Feature_Importance_List.append([X.columns[row[0]], row[1]])
    df_Gausian_Feature_Importance = pd.DataFrame(df_Gausian_Feature_Importance_List, columns=["Feature",
    df_Gausian_Feature_Importance.sort_values(by=["Significance"], ascending=False, inplace=True)
    GausianND_Features = df_Gausian_Feature_Importance["Feature"].tolist()
    if yes_print:
        print('\nconfusion_matrix from Gaussian naive bayes:')
        print(confusion_matrix(y_test, gausianNB_predicted))
        print('accuracy = ' + str(accuracy))
        print("gausianNB feature importance:")
        print(df_Gausian_Feature_Importance)
    return accuracy, GausianND_Features
```

563
```
df = pd.read_csv("assignment2_cleanInfile.csv")

x_train, x_test, y_train, y_test, X = train_data(df)
dt_a, dt_f = decisionTree_Model(x_train, x_test, y_train, y_test, X, True)

# train_data(df)
gm_a, gm_f = GausianNB_Model(x_train, x_test, y_train, y_test, X, True)
```

```
DecisionTree Accuracy:  0.7843258600804524
DecisionTree Confusion Matrix:
[[23618  4005]
 [ 3662  4264]]
decision tree dtree feature importance:
            FName     Score
11    Humidity3pm  0.268860
13    Pressure3pm  0.072560
3        Rainfall  0.063940
5   WindGustSpeed  0.060039
1         MinTemp  0.050088
```

```
10    Humidity9am  0.048687
12    Pressure9am  0.047536
16        Temp9am  0.045614
17        Temp3pm  0.045001
0        Location  0.040346
2         MaxTemp  0.039299
9    WindSpeed3pm  0.036592
8    WindSpeed9am  0.034055
7      WindDir3pm  0.031931
4     WindGustDir  0.031225
15       Cloud3pm  0.030189
6      WindDir9am  0.029780
14       Cloud9am  0.021221
18      RainToday  0.003038

confusion_matrix from Gaussian naive bayes:
[[24213  3410]
 [ 3488  4438]]
accuracy = 0.8059579735013643
gausianNB feature importance:
          Feature  Significance
11    Humidity3pm      0.013919
3        Rainfall      0.013587
13    Pressure3pm      0.005159
5   WindGustSpeed      0.004169
12    Pressure9am      0.003713
15       Cloud3pm      0.002729
1         MinTemp      0.001474
14       Cloud9am      0.000090
10    Humidity9am      0.000090
8    WindSpeed9am      0.000011
0        Location     -0.000096
9    WindSpeed3pm     -0.000191
7      WindDir3pm     -0.000326
4     WindGustDir     -0.000433
16        Temp9am     -0.000624
6      WindDir9am     -0.000805
17        Temp3pm     -0.001210
2         MaxTemp     -0.001536
18      RainToday     -0.002127
```

The Code above displays confusion matrix and accuracy of both the Decision Tree Model and the Gaussian Naive Bayes models with all of the features included. In this instance the Gaussian model was more accurate than the decision tree model. Both models show that rain today has the lowest score/signifcance in the models. One would assume that to make these models more accurate we would remove "RainToday" to improve the models.

I have set up the train_data function to drop features for retraining the data to be run back through the models.

564
```
# Dropping Rain Today
x_train, x_test, y_train, y_test, X = train_data(df, "RainToday")
# Decision Tree Model
dt_a, dt_f = decisionTree_Model(x_train, x_test, y_train, y_test, X, True)
```

```
DecisionTree Accuracy:  0.7815128414301387
DecisionTree Confusion Matrix:
[[23533  4090]
 [ 3677  4249]]
decision tree dtree feature importance:
```

```
           FName     Score
11    Humidity3pm  0.267915
13    Pressure3pm  0.073500
3        Rainfall  0.065227
5   WindGustSpeed  0.060248
1         MinTemp  0.053279
10    Humidity9am  0.049318
12    Pressure9am  0.047377
16        Temp9am  0.046591
17        Temp3pm  0.043340
0        Location  0.040075
2         MaxTemp  0.039315
9    WindSpeed3pm  0.037006
8    WindSpeed9am  0.034378
7      WindDir3pm  0.031334
4     WindGustDir  0.030908
15       Cloud3pm  0.030401
6      WindDir9am  0.029767
14       Cloud9am  0.020021
```

565
```
# Gaussian Naive Bayes Model
gm_a, gm_f = GausianNB_Model(x_train, x_test, y_train, y_test, X, True)
```

```
confusion_matrix from Gaussian naive bayes:
[[24720  2903]
 [ 3617  4309]]
accuracy = 0.8165911839995499
gausianNB feature importance:
          Feature  Significance
11    Humidity3pm      0.023117
3        Rainfall      0.017109
13    Pressure3pm      0.005840
5   WindGustSpeed      0.005592
12    Pressure9am      0.004923
15       Cloud3pm      0.003567
10    Humidity9am      0.003483
1         MinTemp      0.002627
14       Cloud9am      0.000647
0        Location     -0.000304
4     WindGustDir     -0.000636
16        Temp9am     -0.000647
7      WindDir3pm     -0.000720
6      WindDir9am     -0.000731
8    WindSpeed9am     -0.000793
9    WindSpeed3pm     -0.000866
17        Temp3pm     -0.001243
2         MaxTemp     -0.001542
```

Now looking at both the models with Raintoday removed we notice something interesting. The accuracy for the Gaussian model went up. While the Accuracy for the Decision Tree went slightly down.

The Next Step is to work with the Gaussian model removing features that have a negative significance. I have set up the code so that we can look at the accuracy, followed by the features that are included

566
```
x_train, x_test, y_train, y_test, X = train_data(df, ["RainToday", "MaxTemp"])
gm_a, gm_f = GausianNB_Model(x_train, x_test, y_train, y_test, X, True)
```

```
confusion_matrix from Gaussian naive bayes:
[[24901  2722]
 [ 3705  4221]]
accuracy = 0.8192072913443416
gausianNB feature importance:
          Feature  Significance
10    Humidity3pm      0.024124
2        Rainfall      0.018369
14       Cloud3pm      0.005272
9     Humidity9am      0.004912
4   WindGustSpeed      0.004518
12    Pressure3pm      0.003972
11    Pressure9am      0.002729
16        Temp3pm      0.001660
13       Cloud9am      0.001384
1         MinTemp      0.001170
15        Temp9am      0.000281
0        Location      0.000236
6      WindDir3pm     -0.000006
3     WindGustDir     -0.000051
5      WindDir9am     -0.000411
7    WindSpeed9am     -0.000850
8    WindSpeed3pm     -0.001176
```

The Gaussian Model continues to improve as we remove the features with the lowest significance until we start to remove features that have a positive significance. The Two following chunks of code show the reversal of accuracy improving.

567
```
x_train, x_test, y_train, y_test, X = train_data(df, ["RainToday",
                                                      "MaxTemp",
                                                      "WindSpeed3pm",
                                                      "WindGustDir",
                                                      "WindDir3pm",
                                                      "WindSpeed9am",
                                                      "WindDir9am",
                                                      "Temp9am",
                                                      "Location"])
gm_a, gm_f = GausianNB_Model(x_train, x_test, y_train, y_test, X, True)
```

```
confusion_matrix from Gaussian naive bayes:
[[25081  2542]
 [ 3683  4243]]
accuracy = 0.8248895890179752
gausianNB feature importance:
         Feature  Significance
4    Humidity3pm      0.026285
1       Rainfall      0.019106
2  WindGustSpeed      0.008945
8       Cloud3pm      0.005232
6    Pressure3pm      0.005137
5    Pressure9am      0.003994
3    Humidity9am      0.003668
9        Temp3pm      0.001890
7       Cloud9am      0.001885
0        MinTemp      0.001710
```

568
```
x_train, x_test, y_train, y_test, X = train_data(df, ["RainToday",
                                                      "MaxTemp",
                                                      "WindSpeed3pm",
```

```
                                                    "WindGustDir",
                                                    "WindDir3pm",
                                                    "WindSpeed9am",
                                                    "WindDir9am",
                                                    "Temp9am",
                                                    "Location",
                                                    "MinTemp"])
gm_a, gm_f = GausianNB_Model(x_train, x_test, y_train, y_test, X, True)
```

```
confusion_matrix from Gaussian naive bayes:
[[25075  2548]
 [ 3722  4204]]
accuracy = 0.823623730625334
gausianNB feature importance:
         Feature  Significance
3    Humidity3pm      0.024563
0       Rainfall      0.018673
1  WindGustSpeed      0.008996
5    Pressure3pm      0.005182
7       Cloud3pm      0.004670
4    Pressure9am      0.004563
2    Humidity9am      0.002678
8        Temp3pm      0.000675
6       Cloud9am      0.000624
```

Accuracy stops improving after we remove every feature that has a negative significance value. The two models above show the point at which the model no longer improves when removing variables.

These results show model manipulation using siginficance. Leaving us with the best model for the Gaussian Naive Bayes Model using backward selection as the model that includes:

Model: Gaussian Naive Bayes
Accuracy: 0.8248895890179752
Features: [Humidity3pm, RainFall, WindGustSpeed, Cloud3pm, Humidity9am, Preasure3pm, Preasure9am, Temp3pm, Cloud9am, Mintemp]

Now to take a look at manipulating the decision tree model. If we note from above that when we removed the lowest score feature, "RainToday", the model actually lost accuracy. Because of this I have decided to code in a backward selection by removing one variable at a time until the accuracy improves.

This process is then repeated with the newly improved model. Until Accuracy no longer improves. To save space in the print out. I have included the first step, followed all the way to the last two steps.

Below is the function that is used for removing a feature at a time. The selection input represents the variables that will be removed from the model.

569
```
def backward_selection(accuracy, features, selection, df, model):
    """This is a backward selection model that removes one feature at a time to see if we can improve the
```

```
    accuracy of the model. Once any improvement is reached the function returns which feature that was dr
    that improves the model. The features that were included and the accuracy of the new model"""
    features_loop = [word for word in features if word not in selection]
    accuracy_start = accuracy
    for feature in features_loop:
        x_train, x_test, y_train, y_test, X = train_data(df, [feature] + selection)  # Dropping selection
        if model == 1:  # 1 For decisionTree
            new_accuracy, new_features = decisionTree_Model(x_train, x_test, y_train, y_test, X, False)
        else:
            new_accuracy, new_features = GausianNB_Model(x_train, x_test, y_train, y_test, X, False)
        if new_accuracy >= accuracy_start:
            print("Accuracy:", new_accuracy, "\nFeatures:", new_features,"\nDropped Feature:", feature)
            return
    return "No Improvement"
```

570
```
# Starting the backward selection model with no drop features.
features = df.columns.tolist()
features.pop(-1)
accuracy = 0.7815128414301387
selection = []

backward_selection(accuracy, features, selection, df, 1)
```

```
Accuracy: 0.7832569129933331
Features: ['Humidity3pm', 'Pressure3pm', 'Rainfall', 'WindGustSpeed', 'MinTemp', 'Humidity9am', 'Pressure
Dropped Feature: Location
```

571
```
selection = ["Location"]
accuracy = 0.7832569129933331
backward_selection(accuracy, features, selection, df, 1)
```

```
Accuracy: 0.7865481448142001
Features: ['Humidity3pm', 'Pressure3pm', 'WindGustSpeed', 'Rainfall', 'MinTemp', 'Pressure9am', 'Humidity
Dropped Feature: Cloud3pm
```

589
```
selection = ["Location", "Cloud3pm"]
accuracy = 0.7865481448142001
backward_selection(accuracy, features, selection, df, 1)
```

589
```
'No Improvement'
```

This process shows us that removing the [Location, Cloud3pm] leaves us with the best accuracy on the model.

Process: Backward Selection
Model: Decision Tree
Accuracy: 0.7865481448142001
Features:['Humidity3pm', 'Pressure3pm', 'WindGustSpeed', 'Rainfall', 'MinTemp', 'Pressure9am', 'Humidity9am', 'Temp9am', 'Temp3pm', 'MaxTemp', 'WindSpeed3pm', 'WindSpeed9am', 'WindDir9am', 'WindGustDir', 'WindDir3pm', 'Cloud9am', 'RainToday']

Using the same backward selection model methodology the next steps test the Gaussian Model to see if we can improve the model that we were left with by removing all the features with negative significance.

```
590 selection = ["RainToday", "MaxTemp", "WindSpeed3pm","WindGustDir", "WindDir3pm", "WindSpeed9am", "WindDir
                 "Temp9am", "Location"]
    accuracy = 0.8248895890179752
    backward_selection(accuracy, features, selection, df, 0)
```

```
Accuracy: 0.8256491040535598
Features: ['Humidity3pm', 'Rainfall', 'WindGustSpeed', 'Cloud3pm', 'Temp3pm', 'Cloud9am', 'Pressure3pm',
Dropped Feature: Humidity9am
```

```
591 Accuracy= 0.8256491040535598
    selection =  ['Humidity3pm', 'Rainfall', 'WindGustSpeed', 'Cloud3pm', 'Temp3pm', 'Cloud9am', 'Pressure3pm
                  'Pressure9am', 'MinTemp', "Humidity9am"]
    backward_selection(accuracy, features, selection, df, 0)
```

```
591 'No Improvement'
```

Looking at the results above. We can slighly improve the Gaussian model that we were given. By dropping Humidity9am from the model we were able to improve the Accuracy to 0.8256491040535598

Process: Remove negative significance features, then backward selection model
Model: Gaussian Naive Bayes
Accuracy: 0.8256491040535598
Features Included: ['Humidity3pm', 'Rainfall', 'WindGustSpeed', 'Cloud3pm', 'Temp3pm', 'Cloud9am', 'Pressure3pm', 'Pressure9am', 'MinTemp', "Humidity9am"]

The next steps are the Gaussian Naive Bayes model using only Backward Model Selection. As noted, I will remove the steps in the middle to save space.

```
592 selection = []
    accuracy = 0
    backward_selection(accuracy, features, selection, df, 0)
```

```
Accuracy: 0.8059861036878675
Features: ['Humidity3pm', 'Rainfall', 'Pressure3pm', 'WindGustSpeed', 'Pressure9am', 'Cloud3pm', 'MinTemp
Dropped Feature: Location
```

```
587 selection = ["Location", "MaxTemp", "WindGustDir", "WindDir9am", "WindSpeed9am", "MinTemp", "WindDir3pm",
                 "Humidity9am", "Temp9am", "RainToday", "Pressure9am"]
    accuracy = 0.8249177192044783
    backward_selection(accuracy, features, selection, df, 0)
```

```
Accuracy: 0.8276744774817857
Features: ['Humidity3pm', 'Rainfall', 'Cloud3pm', 'WindGustSpeed', 'Pressure3pm', 'Temp3pm']
Dropped Feature: Cloud9am
```

```
588 selection = ["Location", "MaxTemp", "WindGustDir", "WindDir9am", "WindSpeed9am", "MinTemp", "WindDir3pm",
                 "Humidity9am", "Temp9am", "RainToday", "Pressure9am", "Cloud9am"]
    accuracy = 0.8276744774817857
    backward_selection(accuracy, features, selection, df, 0)
```

588 'No Improvement'

After that Long selection Process we were able to come out with a accuracy of

Process: Backward Selection
Model: Gaussian Naive Bayes
Accuracy: 0.8276744774817857
Included Features: ['Humidity3pm', 'Rainfall', 'WindGustSpeed', 'Cloud3pm', 'Pressure3pm', 'Temp3pm']

This Produces a slight improvement from our last most accurate model. Listed below to show the difference.

Process: Remove negative significance features, then backward selection model
Model: Gaussian Naive Bayes
Accuracy: 0.8256491040535598
Features Included: ['Humidity3pm', 'Rainfall', 'WindGustSpeed', 'Cloud3pm', 'Temp3pm', 'Cloud9am', 'Pressure3pm', 'Pressure9am', 'MinTemp', "Humidity9am"]

The results from the backward model selection with the decision tree models left some room for improvement. It is beacuse of this reason that the next steps will test forward model selection.

Below is the function that is set up for forward model selection.

616
```
def forward_selection(accuracy, features, selection, df, model):
    """This is a backward selection model that removes one feature at a time to see if we can improve the
    accuracy of the model. Once any improvement is reached the function returns which feature that was dr
    that improves the model. The features that were included and the accuracy of the new model"""
    features_loop = [word for word in features if word not in selection]
    best_accuracy = accuracy
    for feature in features_loop:
        drop_features = [word for word in features if word not in [feature] + selection]
        x_train, x_test, y_train, y_test, X = train_data(df, drop_features)  # Dropping selection and fea
        if model == 1:  # 1 For decisionTree
            new_accuracy, new_features = decisionTree_Model(x_train, x_test, y_train, y_test, X, False)
        else:
            new_accuracy, new_features = GausianNB_Model(x_train, x_test, y_train, y_test, X, False)
        if new_accuracy >= best_accuracy:
            best_accuracy = new_accuracy
            add_feature = feature
    if best_accuracy > accuracy:
            print("Accuracy:", best_accuracy, "\nAdd Feature:", add_feature, "\nModel Features", [add_fea
    else:
        return "No Improvement"
```

617
```
features = df.columns.tolist()
features.pop(-1)
accuracy = 0
selection = []
```

```
forward_selection(accuracy, features, selection, df, 1)
```

```
Accuracy: 0.8219921798081521
Add Feature: Humidity3pm
Model Features ['Humidity3pm']
```

618
```
selection = ['Humidity3pm']
accuracy = 0.8219921798081521
forward_selection(accuracy, features, selection, df, 1)
```

```
Accuracy: 0.8268868322596978
Add Feature: Location
Model Features ['Location', 'Humidity3pm']
```

619
```
selection = ['Location', 'Humidity3pm']
accuracy = 0.8268868322596978
forward_selection(accuracy, features, selection, df, 1)
```

619
```
'No Improvement'
```

The Forward Selection with the decision tree has vastly improved our model. We only have two features that are being used, but the accuracy is much better. There are a lot of reasons for this. This appears to show that location and Humidity are the best predictors for rain tomorrow.

Process: Forward Model Selection
Model: Decision tree
Accuracy: 0.8268868322596978
Features: ['Location', 'Humidity3pm']

Next Process is to test the Gaussian Model using forward selection

621
```
accuracy = 0
selection = []
forward_selection(accuracy, features, selection, df, 0)
```

```
Accuracy: 0.8205012799234859
Add Feature: Humidity3pm
Model Features ['Humidity3pm']
```

624
```
accuracy = 0.8291372471799489
selection = ['Pressure3pm', 'WindGustSpeed', 'Humidity3pm']
forward_selection(accuracy, features, selection, df, 0)
```

```
Accuracy: 0.8298967622155334
Add Feature: Cloud3pm
Model Features ['Cloud3pm', 'Pressure3pm', 'WindGustSpeed', 'Humidity3pm']
```

625
```
accuracy = 0.8298967622155334
selection = ['Cloud3pm', 'Pressure3pm', 'WindGustSpeed', 'Humidity3pm']
forward_selection(accuracy, features, selection, df, 0)
```

625
```
'No Improvement'
```

Process: Forward Model Selection
Model: Gaussian Naive Bayes
Accuracy = 0.8298967622155334
Features: ['Cloud3pm', 'Pressure3pm', 'WindGustSpeed', 'Humidity3pm']

Final Conclusion

The best results that we found for both

Process: Full Model Gaussian Naive Bayes Model: Gaussian Naive Bayes Accuracy: 0.8059579735013643 Features: All

Improved to:

Process: Forward Model Selection
Model: Gaussian Naive Bayes
Accuracy = 0.8298967622155334
Features: ['Cloud3pm', 'Pressure3pm', 'WindGustSpeed', 'Humidity3pm']

Process: Full Model Decision Tree Model: Decision Tree Accuracy: 0.7843258600804524 Features: All

Improved to:

Process: Forward Model Selection
Model: Decision tree
Accuracy: 0.8268868322596978
Features: ['Location', 'Humidity3pm']

First we looked at the Significance and the score values for the Gaussian and the Decision Tree. The Significance Values that were negative for the Gaussian model did have significant impact on decreasing the model accuracy. By removing them we were able to improve the accuracy score. When looking at the decision tree feature scores removing the lowest one did not necessarily improve the model.

To expand on these models we used both backward and forward model selection. Backward model selection process removed one features at a time until the accuracy was improved. It then proceeded by removing that feature and then looping all the other features until a greater accuracy was achieved.

The forward model selection added one feature at a time and took the feature that improved the accuracy the most, until adding features no longer improved the model.

The forward model selection produced the greatest improvements in accuracy on both the Decision tree and the Gaussian full models.