Weather in Australia - Team 7

This cell just loads all used moduls for running the notebook. Please install any package if you dont have it installed in your environment so far.

In [1]:
```
#disable some annoying warnings
import warnings
warnings.filterwarnings('ignore', category=FutureWarning)
#---------------------------#
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import pyplot
#plots the figures in place instead of a new window
%matplotlib inline

import statistics

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn import decomposition
from numpy import unique
from numpy import where
from sklearn.datasets import make_classification
from sklearn.cluster import KMeans
from matplotlib import pyplot
from sklearn.cluster import AffinityPropagation
from sklearn.cluster import AgglomerativeClustering
from IPython.display import display, clear_output

from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn import tree
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, recall_score, precision_sc
    explained_variance_score, mean_squared_error, r2_score, mean_absolute_error
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from xgboost import XGBClassifier, XGBRegressor

from abess import LinearRegression
import statsmodels.api as sm
```

Dataset Overview

We chose the rain in Australia dataset from Kaggle because we thought that it could be interesting to analyze a dataset with around 145000 rows. It is also interesting that data from about 10 years of daily observations from different locations throughout Australia has been collected.

Besides several numerical attributes, also several categorical attributes are provided. The attributes of the used dataset are explained below.

1. Date: The observation's date
2. Location: The location of the observation
3. MinTemp: The minimum temperature on that day (°C)
4. MaxTemp: The maximum temperature on that day (°C)
5. Rainfall: The rainfall amount measured in mm
6. Evaporation: The evaporation also measured in mm
7. Sunshine: The number of sunshine hours
8. WindGustDir: The strongest wind gust's direction
9. WindGustSpeed: The strongest wind gust's speed in km/h
10. WindDir9am: The wind's direction at 9 AM
11. WindDir3pm: The wind's direction at 3 PM
12. WindSpeed9am: The wind's speed (km/h) at 9 AM
13. WindSpeed3pm: The wind's speed (km/h) at 3 PM
14. Humidity9am: The humidity percentage at 9 AM
15. Humidity3pm: The humidity percentage at 3 PM
16. Pressure9am: The atmospheric pressure (hpa) at 9 AM
17. Pressure3pm: The atmospheric pressure (hpa) at 3 PM
18. Cloud9am: Fraction of obscured sky by clouds (in "oktas") at 9 AM
19. Cloud3pm: Same as above but at 3 PM
20. Temp9am: Temperature in °C at 9 AM
21. Temp3pm: Temperature in °C at 3 PM
22. RainToday: True, if it has been raining on that day, otherwise False
23. RainTomorrow: True, if it has been raining on the next day, otherwise False; target variable

In [2]:
```
# use the weather dataset of heterogenous data and plot first 5 lines
weather = pd.read_csv('data/weatherAUS.csv')
weather.head()
```

Out[2]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDi
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0	I
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0	

5 rows × 23 columns

In [3]:
```
# overview of the created datatypes
weather.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Date           145460 non-null  object
```

```
 1   Location       145460 non-null  object
 2   MinTemp        143975 non-null  float64
 3   MaxTemp        144199 non-null  float64
 4   Rainfall       142199 non-null  float64
 5   Evaporation    82670 non-null   float64
 6   Sunshine       75625 non-null   float64
 7   WindGustDir    135134 non-null  object
 8   WindGustSpeed  135197 non-null  float64
 9   WindDir9am     134894 non-null  object
 10  WindDir3pm     141232 non-null  object
 11  WindSpeed9am   143693 non-null  float64
 12  WindSpeed3pm   142398 non-null  float64
 13  Humidity9am    142806 non-null  float64
 14  Humidity3pm    140953 non-null  float64
 15  Pressure9am    130395 non-null  float64
 16  Pressure3pm    130432 non-null  float64
 17  Cloud9am       89572 non-null   float64
 18  Cloud3pm       86102 non-null   float64
 19  Temp9am        143693 non-null  float64
 20  Temp3pm        141851 non-null  float64
 21  RainToday      142199 non-null  object
 22  RainTomorrow   142193 non-null  object
dtypes: float64(16), object(7)
memory usage: 25.5+ MB
```

Data Preparation - Adjust Date Values

In this step, the data gets adjusted, in order to fit for our analysis. This adjustments go especially for the Date in the first place. Here the whole Date value gets split up into a new year month and day column, in order to better aggregate over the set.

In [4]:

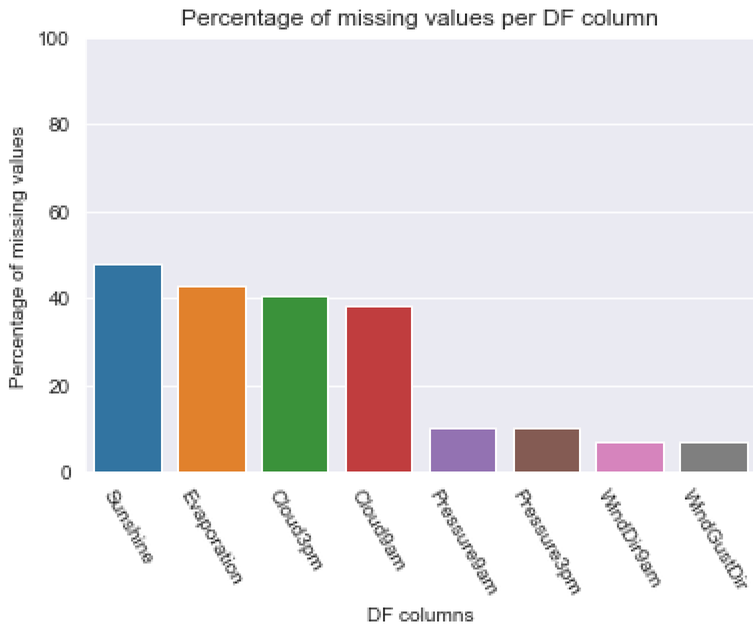
```
# Convert Date to a date type and create new columns
weather['Date_converted'] = pd.to_datetime(weather['Date'], format='%Y-%m-%d')
weather['Year'] = weather['Date_converted'].dt.year
weather['Month'] = weather['Date_converted'].dt.month
weather['Day'] = weather['Date_converted'].dt.day
```

Overview of missing values

In order to to a proper data cleaning and having a feeling, how many values are even missing, we analysed the amount of missing data per column. It can be seen that for some columns nearly half of the values (40 - 48%) are missing (shown in the table as well as the plot above).

In [5]:

```
# Calculate percentage of null values per attribute
missing_in_percentage = weather.isnull().sum() * 100 / len(weather)
missing = pd.DataFrame({'col': weather.columns, 'missing_percent': missing_in_percentage
missing.sort_values('missing_percent', inplace=True, ascending=False)

ax = sns.barplot(x="col", y="missing_percent", data=missing.head(8))
ax.set_ylim((0, 100))
ax.set_xticklabels(ax.get_xticklabels(), rotation=300)
ax.set_title('Percentage of missing values per DF column')
ax.set_xlabel('DF columns')
_ = ax.set_ylabel('Percentage of missing values')
```



Base for missing values

Missing values in different seasons

Now we further investigate this issue by looking at the columns sunshine, evaporation, cloud3pm and cloud9am by grouping the percentage of missing values first by season, to look whether we can see a seasonal affect. We also group the percentage of missing values by location to see if we can spot a locational affect. But as you can also see in the table below, there is no real trend, if the values tend to be not recorded in a specific season.

In [6]:

```
# Mapping the dates to seasons and calculate for each season and attribute the percentag
seasons = {
   1: 'Winter',
   2: 'Spring',
   3: 'Summer',
   4: 'Autumn'
}
df_values_season = weather[['Year', 'Month', 'Sunshine', 'Evaporation', 'Cloud3pm', 'Clo

df_values_season['Season'] = (df_values_season['Month'] % 12 + 3) // 3
df_values_season['Season_name'] = df_values_season['Season'].map(seasons)

df_season_count_null = df_values_season[['Sunshine', 'Evaporation', 'Cloud3pm', 'Cloud9a
df_season_count_all = df_values_season[['Sunshine', 'Evaporation', 'Cloud3pm', 'Cloud9am

df_missing_values_percent = (df_season_count_null / df_season_count_all) * 100
df_missing_values_percent['Season'] = df_missing_values_percent.index.tolist()
df_missing_values_percent.style.hide_index()
```

Out[6]:

Sunshine	Evaporation	Cloud3pm	Cloud9am	Season
47.395082	42.394657	40.996689	38.537510	Autumn
48.680222	43.780054	41.022894	38.830232	Spring
48.109535	42.861420	38.639519	36.793968	Summer
47.793406	43.593759	42.648482	39.562098	Winter

Missing values in different locations

As it can be seen, for 22 of the 49 locations no values are tracked which explains the large amount of missing data for the attributes 'Sunshine', 'Evaporation', 'Cloud3pm' and 'Cloud9am'. The reason for this is, however, unknown.

In [7]:
```
df_values_location = weather[['Location', 'Sunshine', 'Evaporation', 'Cloud3pm', 'Cloud9
df_values_location_count_null = weather[['Sunshine', 'Evaporation', 'Cloud3pm', 'Cloud9a
# fillna is needed in order to get the
df_values_location_count_all = weather[['Sunshine', 'Evaporation', 'Cloud3pm', 'Cloud9am

df_missing_values_percent = (df_values_location_count_null / df_values_location_count_al
df_missing_values_percent['Location'] = df_missing_values_percent.index.tolist()
mask = (df_missing_values_percent == 100.).any(axis=1)
print(f'Untracked values based on location: {df_missing_values_percent[mask].shape[0]} o
```

```
Untracked values based on location: 22 of 49
```

Remove missing values

Since we can not clearly 'clean' missing values in any case, because we dont have information about the geo coordinates and also no mapping of close location, we simply drop these values. Still - 112925 samples are present

In [8]:
```
weather.drop(['Date','Sunshine', 'Evaporation', 'Cloud3pm', 'Cloud9am'],axis=1,inplace=T
```

Create artifical data for missing values in numeric attribute vectors when possible

For numeric data we set missing values for numeric attributes (given in the numerical_columns value) to the median based on the year, month and (location) when possible

For the categorical values we used the mode, imputation is based on location and current month, if we do not have data for a location than only the month was used.

In [9]:
```
numerical_columns = ["Pressure9am", "Pressure3pm", "Humidity3pm", "Humidity9am", "WindGu
                     "WindSpeed3pm", "WindSpeed9am", "Temp9am", "MinTemp", "MaxTemp", "R

for col in numerical_columns:
    weather[col] = weather[col].fillna(weather.groupby(['Year', 'Month', 'Location'])[co
    weather[col] = weather[col].fillna(weather.groupby(['Year', 'Month'])[col].transform

categorical_columns = ["WindDir9am", "WindGustDir", "WindDir3pm"]

for col in categorical_columns:
    weather[col] = weather[col].fillna(weather.groupby(['Year', 'Month', 'Location'])[co
    weather[col] = weather[col].fillna(weather.groupby(['Year', 'Month'])[col].transform
```

In [10]:
```
weather.dropna(inplace=True)
print(f'Amount of samples without missing values in any column: {weather.shape[0]}')
weather.head()
```

```
Amount of samples without missing values in any column: 140787
```

Out[10]:

	Location	MinTemp	MaxTemp	Rainfall	WindGustDir	WindGustSpeed	WindDir9am	WindDir3pm	WindSpeed
0	Albury	13.4	22.9	0.6	W	44.0	W	WNW	

1	Albury	7.4	25.1	0.0	WNW	44.0	NNW	WSW
2	Albury	12.9	25.7	0.0	WSW	46.0	W	WSW
3	Albury	9.2	28.0	0.0	NE	24.0	SE	E
4	Albury	17.5	32.3	1.0	W	41.0	ENE	NW

5 rows × 22 columns

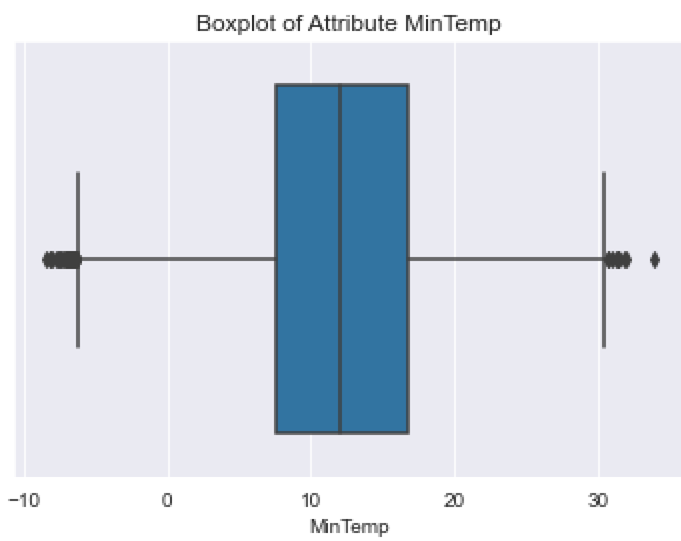
Check for valid values in all remaining (numeric) columns

In the next step, # check for minimum and maximum values in numeric attributes (in our case all attributes in the frame which have the datatype of float64. Here no out of range values could be detected.

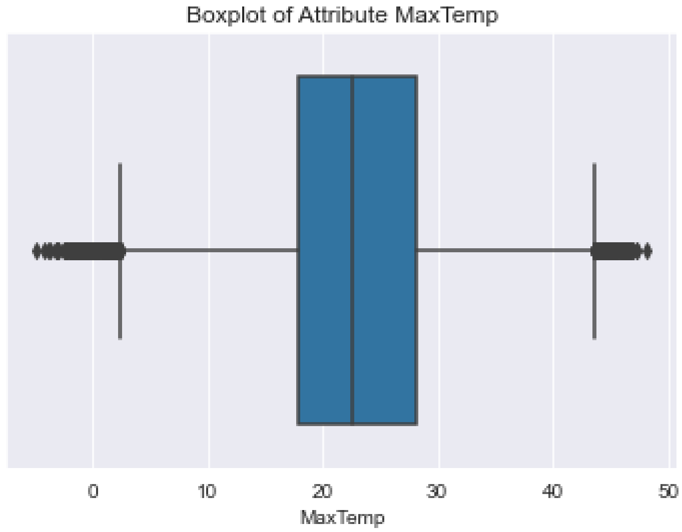
In [11]:

```
# check for minimum and maximum values in numeric attributes:
for col in weather.loc[:, weather.dtypes == 'float64']:
    print(f'Attribute {col}:')
    print("Min: {:.2f}, Q1: {:.2f}, Median {:.2f}, Q3: {:.2f}, Max: {:.2f}".format(weath
    sns.boxplot(x=weather[col])
    plt.title(f'Boxplot of Attribute {col}')
    plt.show()
```

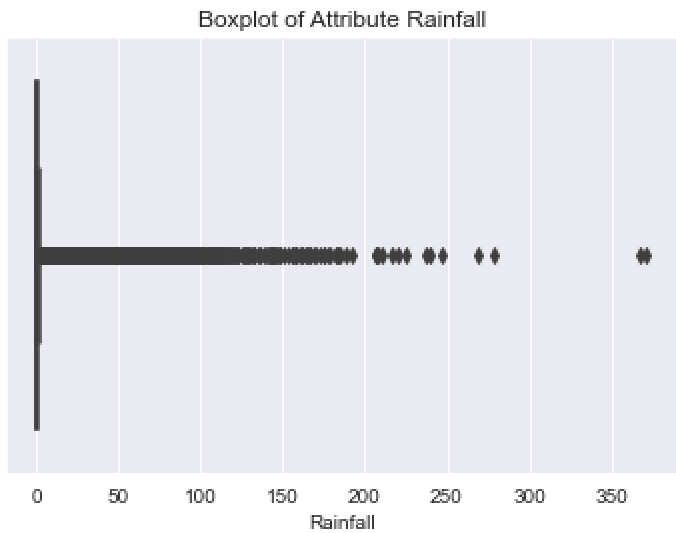
```
Attribute MinTemp:
Min: -8.50, Q1: 7.60, Median 12.00, Q3: 16.80, Max: 33.90
```



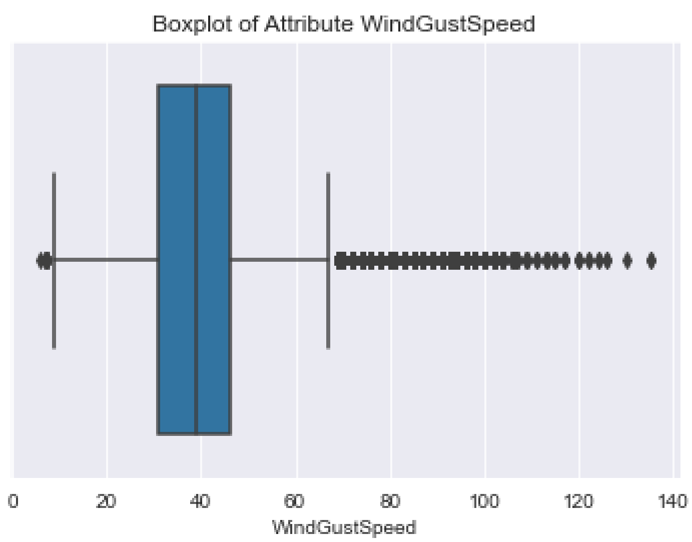

```
Attribute MaxTemp:
Min: -4.80, Q1: 17.90, Median 22.60, Q3: 28.20, Max: 48.10
```



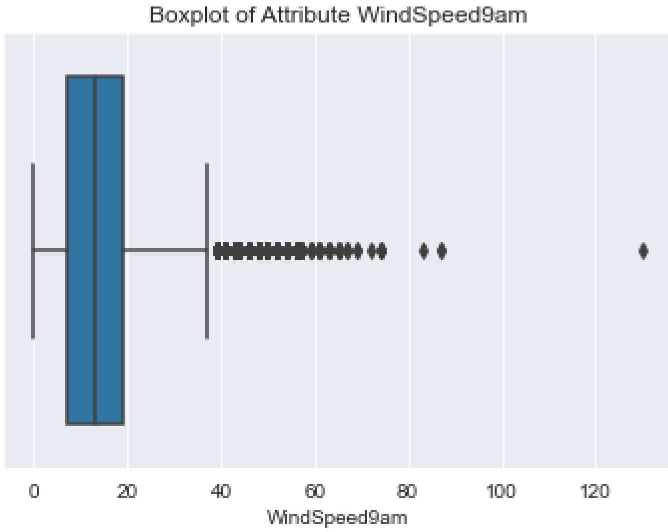

```
Attribute Rainfall:
Min: 0.00, Q1: 0.00, Median 0.00, Q3: 0.80, Max: 371.00
```



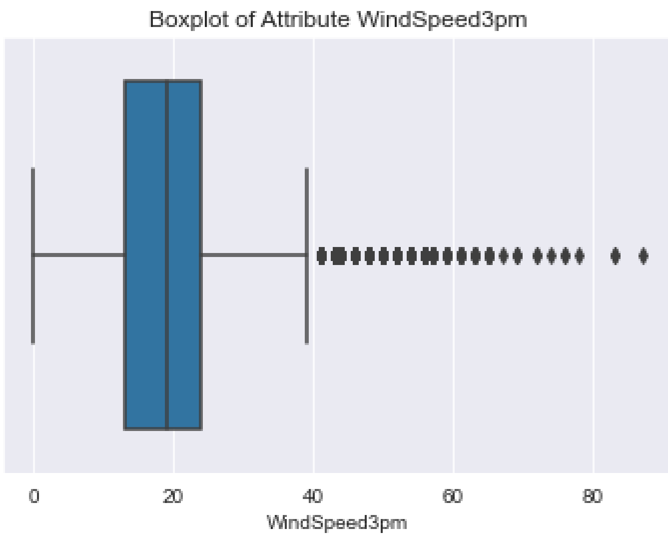

```
Attribute WindGustSpeed:
Min: 6.00, Q1: 31.00, Median 39.00, Q3: 46.00, Max: 135.00
```



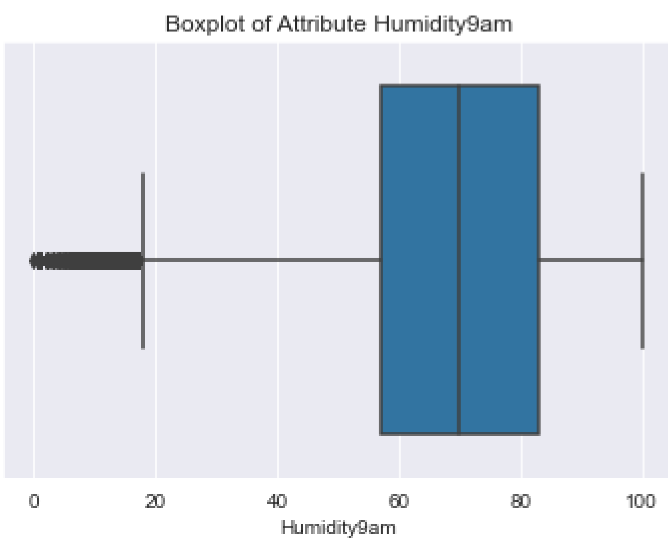

```
Attribute WindSpeed9am:
Min: 0.00, Q1: 7.00, Median 13.00, Q3: 19.00, Max: 130.00
```



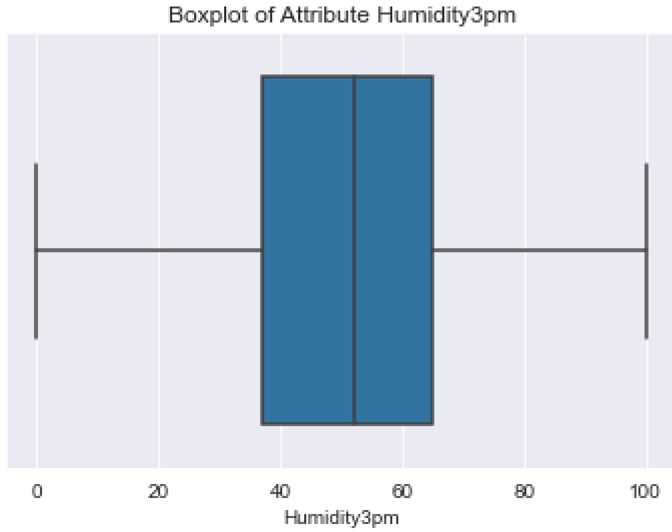

```
Attribute WindSpeed3pm:
Min: 0.00, Q1: 13.00, Median 19.00, Q3: 24.00, Max: 87.00
```



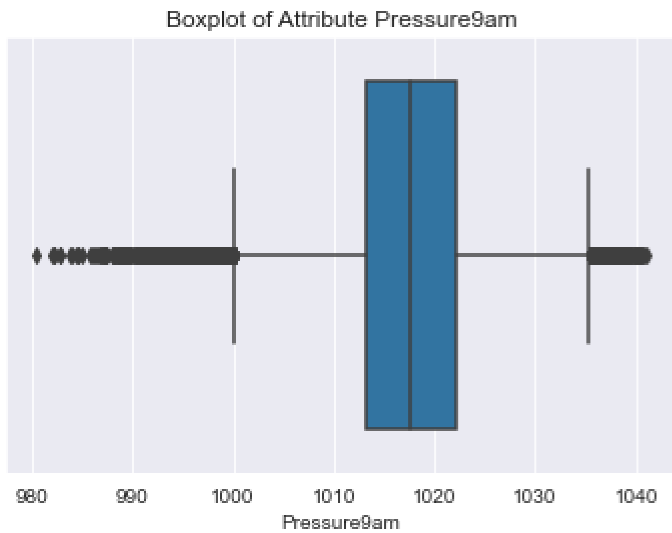

```
Attribute Humidity9am:
Min: 0.00, Q1: 57.00, Median 70.00, Q3: 83.00, Max: 100.00
```



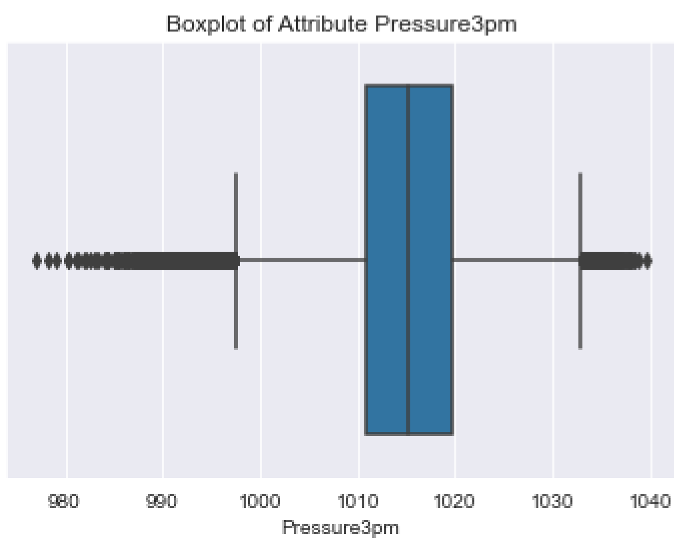

```
Attribute Humidity3pm:
Min: 0.00, Q1: 37.00, Median 52.00, Q3: 65.00, Max: 100.00
```



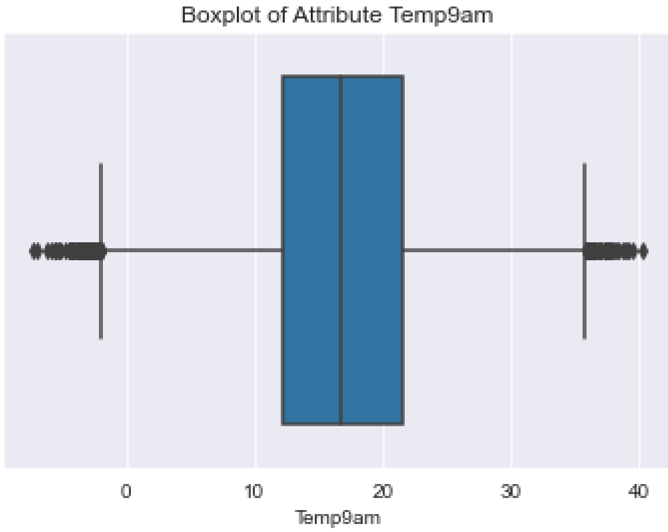

```
Attribute Pressure9am:
Min: 980.50, Q1: 1013.30, Median 1017.60, Q3: 1022.10, Max: 1041.00
```



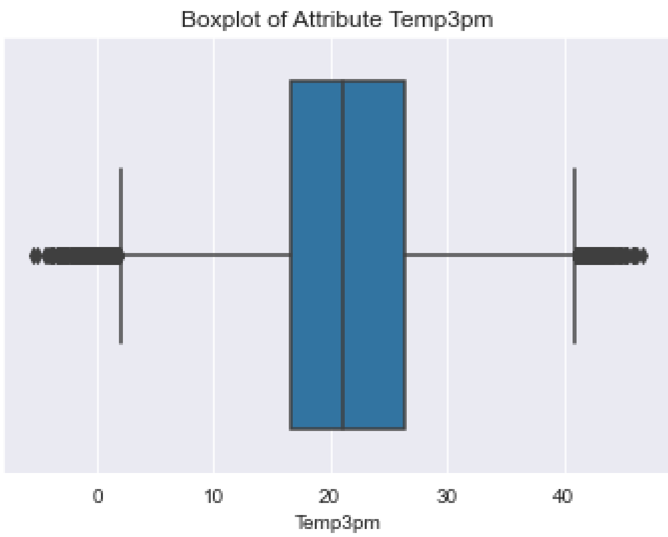

```
Attribute Pressure3pm:
Min: 977.10, Q1: 1010.80, Median 1015.20, Q3: 1019.68, Max: 1039.60
```




```
Attribute Temp9am:
Min: -7.20, Q1: 12.20, Median 16.70, Q3: 21.60, Max: 40.20
```



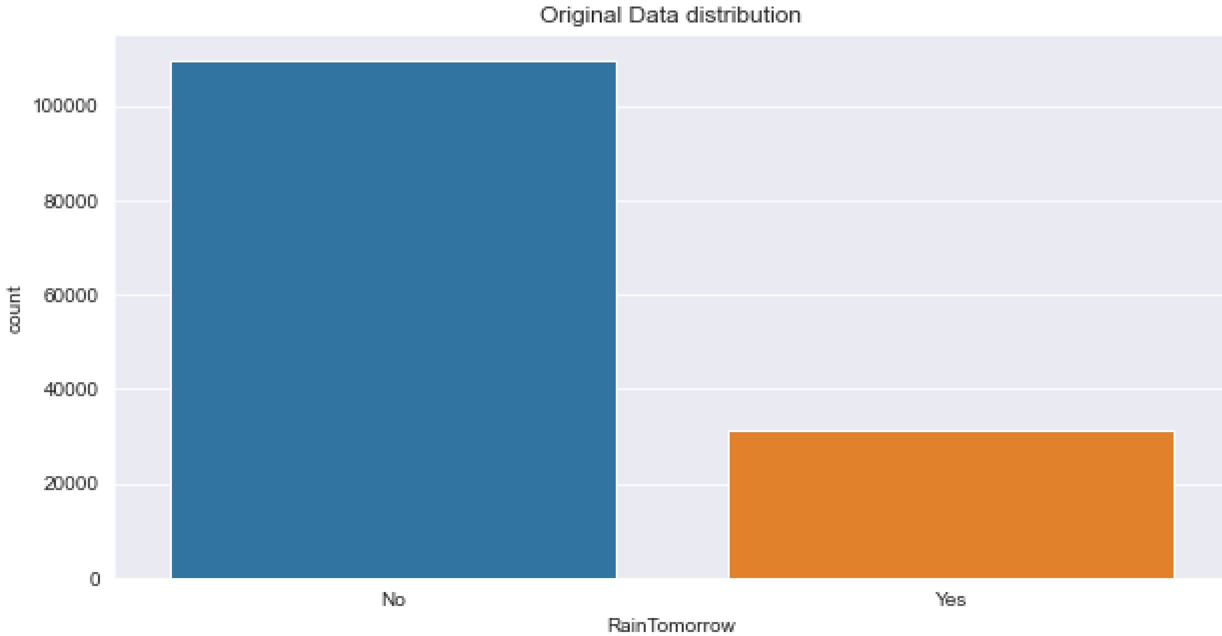

```
Attribute Temp3pm:
Min: -5.40, Q1: 16.60, Median 21.10, Q3: 26.40, Max: 46.70
```



Check the distribution of RainTomorrow samples

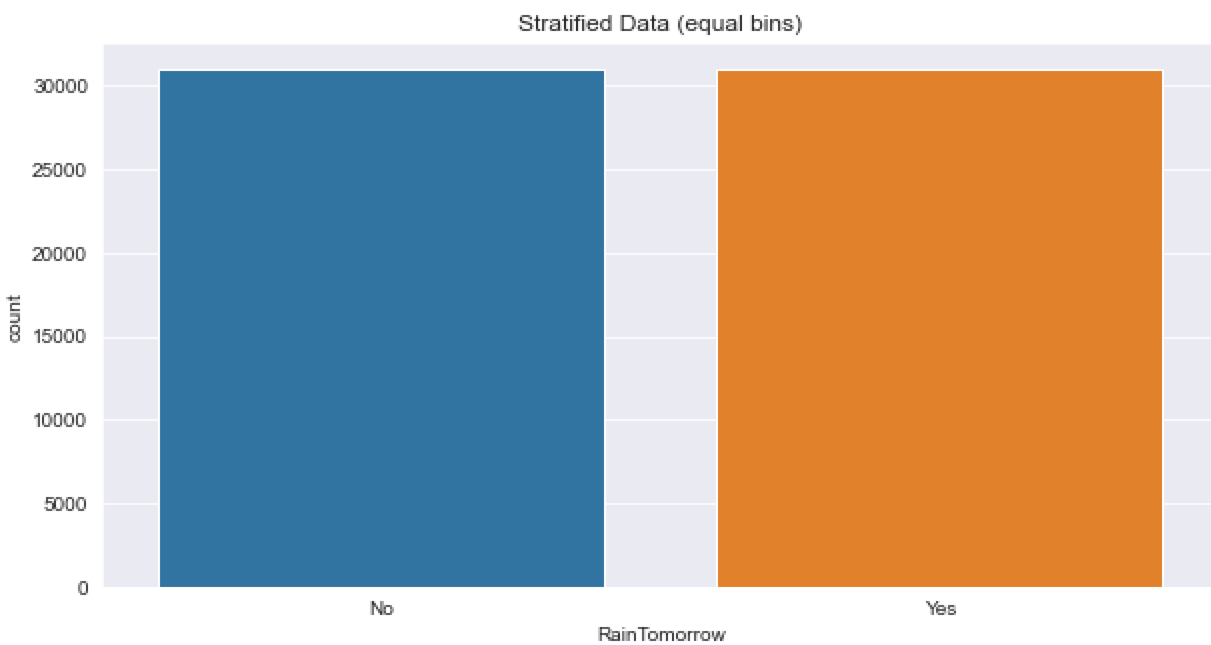
As we can clearly see in the next cell, there are a lot more samples of NOT-raining tomorrow, as samples WITH raining tomorrow

In [12]:
```
plt.figure(figsize=(10,5))
sns.countplot(x="RainTomorrow", data=weather);
plt.title('Original Data distribution')
plt.show()
```



In [13]:
```
# Disproportionate sampling:
# randomly select 4 samples from each stratum
stratified = weather.groupby('RainTomorrow', group_keys=False).apply(lambda x: x.sample(
```

In [14]:
```
plt.figure(figsize=(10,5))
sns.countplot(x="RainTomorrow", data=stratified)
plt.title("Stratified Data (equal bins)")
plt.show()
```



PCA to explore the underlying structure of the data

In [15]:
```
stratified.drop('Date_converted',axis=1,inplace=True)
for col in stratified.loc[:, stratified.dtypes == object]:
    # creating instance of labelencoder
    labelencoder = LabelEncoder()
    # Assigning numerical values and storing in another column
    stratified[f'{col}_num'] = labelencoder.fit_transform(stratified[col])
```

```
    # drop non-numeric column
    stratified.drop(col,axis=1,inplace=True)
```

In [16]:
```
stratified.head()
```

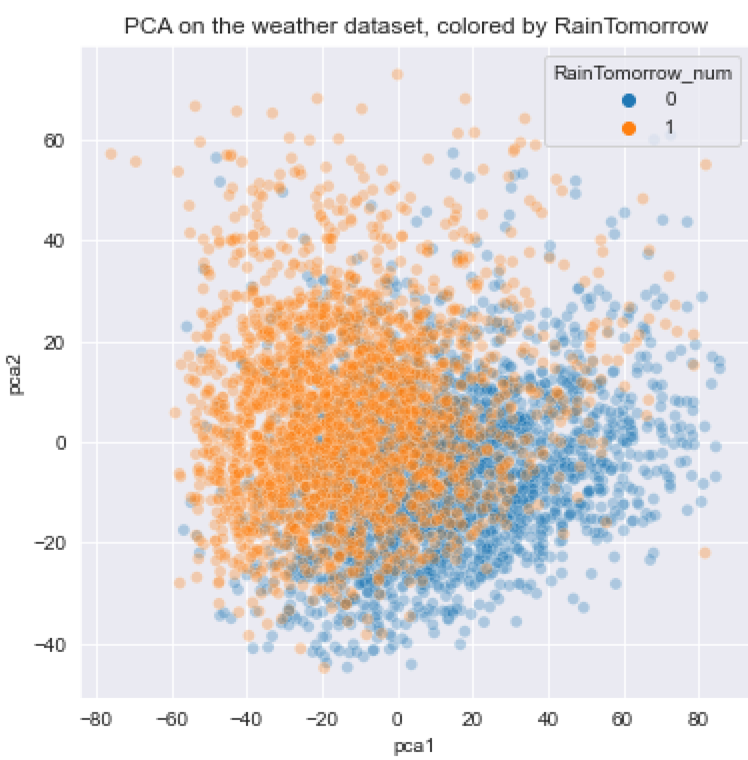
Out[16]:

	MinTemp	MaxTemp	Rainfall	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidit
16898	18.8	27.2	2.0	42.152514	0.0	19.0	87.0	59.0
77422	15.8	25.3	0.0	41.000000	20.0	17.0	82.0	67.0
57631	6.7	25.9	4.2	37.000000	9.0	15.0	100.0	37.0
50011	2.9	17.9	0.0	41.000000	7.0	22.0	63.0	33.0
143273	26.0	39.5	0.0	22.000000	0.0	0.0	57.0	43.3

5 rows × 21 columns

In [17]:
```
n_components = 7

pca = decomposition.PCA(n_components=n_components)
pca_pos = pca.fit_transform(stratified)

stratified['pca1']= pca_pos[:, 0]
stratified['pca2']= pca_pos[:, 1]
```

In [18]:
```
plt.figure(figsize=(6,6))
reducedPoints = stratified.groupby('RainTomorrow_num', group_keys=False).apply(lambda x:
sns.scatterplot(data=reducedPoints, x="pca1", y="pca2", hue="RainTomorrow_num",alpha=0.3
plt.title('PCA on the weather dataset, colored by RainTomorrow')
plt.show()
```



Decision Tree

In this section, we try to fit a Decision Tree classifier to our data. Therefore we do a GridSearch, where we try different criterions, maximum depths of the tree and splitting methods. The trained classifier also gets evaluated on 15% of the total data afterwards.

To keep the dataset clean, we removed all additional added attributes, we used in the previous section due to have more comfort. This does not change the actual data at all.

Note, that the data is also stratified like in the PCA above, so all classes are evenly distributed (standard would be to have a much higher amount of samples in the RainTomorrow=No comapred to RainTomorrow=Yes)

After creating the training and test sets, training and evaluating using a confusion matrix and accuracy as a score, we also provided an overview of the feature importance learned by the decision tree.

In [19]:
```
"""
Evaluates the model and returns accuracy as well as a confusion matrix. Also the time fo
@param model, sklearn model,trained model
@param x_test, np ndarray, data matrix
@param y_test, np ndarray, data vector
"""
def get_evaluation(model, x_test, y_test):
    y_pred = model.predict(x_test)
    accuracy = accuracy_score(y_test, y_pred)
    conf_mat = confusion_matrix(y_test, y_pred)
    rec_result = recall_score(y_test, y_pred, average=None, labels=[0,1])
    prec_result = precision_score(y_test, y_pred, average=None, labels=[0,1])


    print('\nAccuracy of Classifier on Test Image Data: ', accuracy)
    print()
    print('Recall (No Rain Tomorrow) of Classifier on Test Image Data: ', rec_result[0])
    print('Recall (Rain Tomorrow) of Classifier on Test Image Data: ', rec_result[1])
    print()
    print('Precision (No Rain Tomorrow) of Classifier on Test Image Data: ', prec_result
    print('Precision (Rain Tomorrow) of Classifier on Test Image Data: ', prec_result[1]
    print()
    print('\nConfusion Matrix: \n', conf_mat)

    plt.matshow(conf_mat)
    plt.title('Confusion Matrix')
    plt.colorbar()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    return None
```

In [20]:
```
def get_ROC(model, x_test, y_test):
    """
    Calculates AUC score and plots ROC curve
    @param model, sklearn model,trained model
    @param x_test, np ndarray, data matrix
    @param y_test, np ndarray, data vector
    """
    predictions = model.predict_proba(x_test)

    print('AUC score:')
    print(roc_auc_score(y_test, predictions[:,1]))

    fpr, tpr, _ = roc_curve(y_test, predictions[:,1])

    plt.clf()
    plt.plot(fpr, tpr)
    plt.xlabel('FPR')
    plt.ylabel('TPR')
```

```
    plt.title('ROC curve with AUC: {:.3f}'.format(roc_auc_score(y_test, predictions[:,1]
    plt.show()
```

In [21]:
```
param_grid = {
    'criterion': ['gini','entropy'],
    'max_depth': range(1,20),
    'splitter': ['random', 'best']
}

"""
Trains a decision tree using cross-validation and returns certain attributes of the rece
parameter combination.
@param x_train, np ndarray, data matrix
@param y_train, np ndarray, data vector
@param param_grid, dict, grid holding the paramaters for search
"""
def train_dec_tree(x_train,y_train,param_grid):
    tree = DecisionTreeClassifier(random_state=55)
    model = GridSearchCV(tree,param_grid=param_grid,n_jobs = -1)
    model.fit(x_train,y_train)
    return model.best_params_,model.best_estimator_
```

In [22]:
```
# remove target value and addtional added columns
X = stratified.drop(['RainTomorrow_num','pca1','pca2'], axis=1)
y = stratified['RainTomorrow_num']
print(f'shape of data matrix: {X.shape}')
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2)
print(f'shape of train matrix: {x_train.shape}')
print(f'shape of test matrix: {x_test.shape}')
X.head()
```

```
shape of data matrix: (62000, 20)
shape of train matrix: (49600, 20)
shape of test matrix: (12400, 20)
```

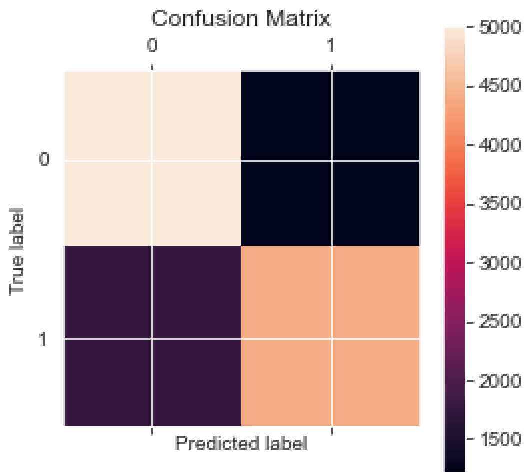
Out[22]:

	MinTemp	MaxTemp	Rainfall	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidit
16898	18.8	27.2	2.0	42.152514	0.0	19.0	87.0	59.0
77422	15.8	25.3	0.0	41.000000	20.0	17.0	82.0	67.0
57631	6.7	25.9	4.2	37.000000	9.0	15.0	100.0	37.0
50011	2.9	17.9	0.0	41.000000	7.0	22.0	63.0	33.0
143273	26.0	39.5	0.0	22.000000	0.0	0.0	57.0	43.3

In [23]:
```
# train decision tree with created training set and evaluate on created target set
params_dec_tree, model_dec_tree = train_dec_tree(x_train, y_train, param_grid)
_ = get_evaluation(model_dec_tree, x_test, y_test)
print("The best parameters are: {}".format(params_dec_tree))
```

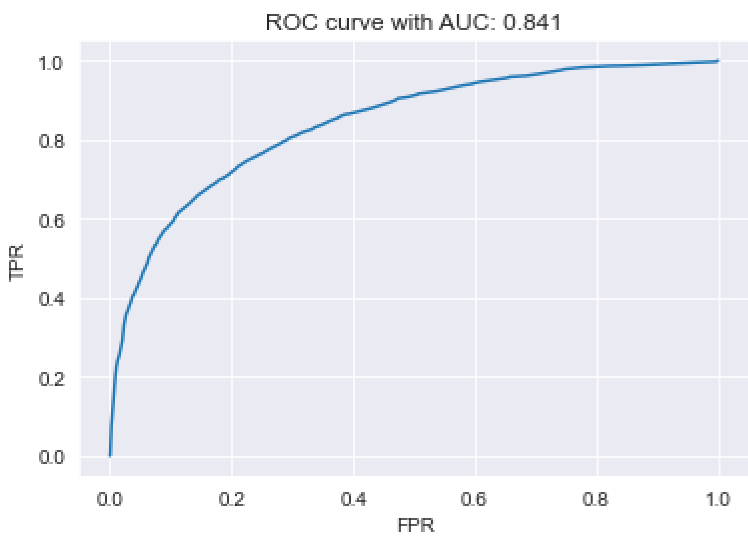
```
Accuracy of Classifier on Test Image Data:  0.7587096774193548

Recall (No Rain Tomorrow) of Classifier on Test Image Data:  0.8038177735001604
Recall (Rain Tomorrow) of Classifier on Test Image Data:  0.7131041193642556

Precision (No Rain Tomorrow) of Classifier on Test Image Data:  0.7390855457227139
Precision (Rain Tomorrow) of Classifier on Test Image Data:  0.7823843416370106


Confusion Matrix:
 [[5011 1223]
 [1769 4397]]
The best parameters are: {'criterion': 'gini', 'max_depth': 8, 'splitter': 'best'}
C:\Users\fnern\AppData\Local\Temp\ipykernel_13500\1287647186.py:27: MatplotlibDeprecatio
```

```
nWarning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since 3.5 and
will be removed two minor releases later; please call grid(False) first.
  plt.colorbar()
```

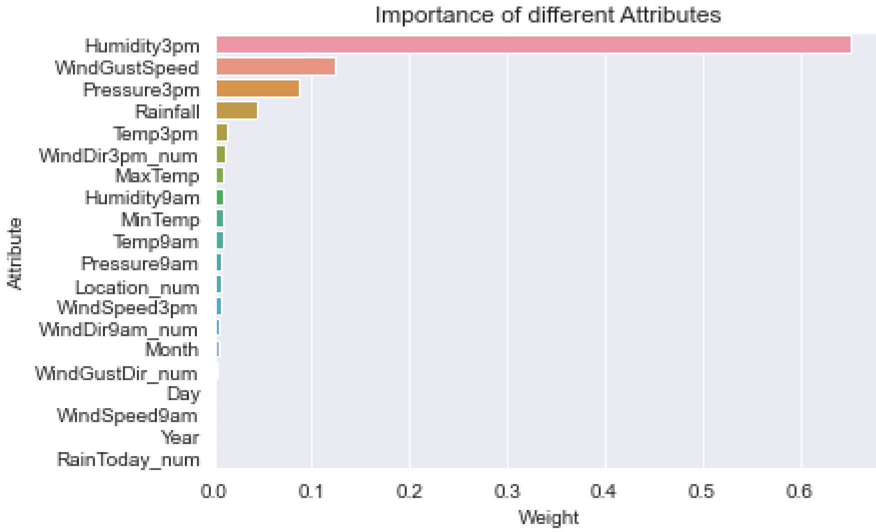


In [24]:
```
# print AUC score and ROC curve
get_ROC(model_dec_tree, x_test, y_test)
```

```
AUC score:
0.8412330766242606
```



In [25]:
```
# create overview of feature importance, of learned decision tree
attribute_weights = pd.DataFrame({
    'Attribute' : x_train.columns,
    'Weight' : model_dec_tree.feature_importances_
}).sort_values(by='Weight', ascending=False)
plt.title('Importance of different Attributes')
sns.barplot(data = attribute_weights, x='Weight', y='Attribute');
```



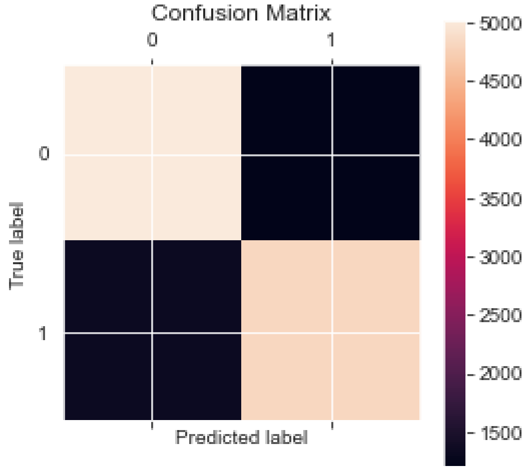
Random Forest

In [26]:
```
param_grid_forest = {
    'criterion': ['gini','entropy'],
    'max_depth': range(5,25)
}

"""
Trains a random forest using cross-validation and returns certain attributes of the rece
parameter combination.
@param x_train, np ndarray, data matrix
@param y_train, np ndarray, data vector
@param param_grid, dict, grid holding the paramaters for search
"""
def train_random_forest(x_train,y_train,param_grid):
    ensemble = RandomForestClassifier(random_state=55)
    model = GridSearchCV(ensemble,param_grid=param_grid, n_jobs = -1)
    model.fit(x_train,y_train)
    return model.best_params_,model.best_estimator_
```

In [27]:
```
# train decision tree with created training set and evaluate on created target set
params_random_forest, model_random_forest = train_random_forest(x_train, y_train, param_
_ = get_evaluation(model_random_forest, x_test, y_test)
print("The best parameters are: {}".format(params_random_forest))
```

```
Accuracy of Classifier on Test Image Data:  0.7940322580645162

Recall (No Rain Tomorrow) of Classifier on Test Image Data:  0.8055822906641001
Recall (Rain Tomorrow) of Classifier on Test Image Data:  0.7823548491728836

Precision (No Rain Tomorrow) of Classifier on Test Image Data:  0.7891263356379635
Precision (Rain Tomorrow) of Classifier on Test Image Data:  0.7992047713717694


Confusion Matrix:
 [[5022 1212]
 [1342 4824]]
The best parameters are: {'criterion': 'entropy', 'max_depth': 24}
```

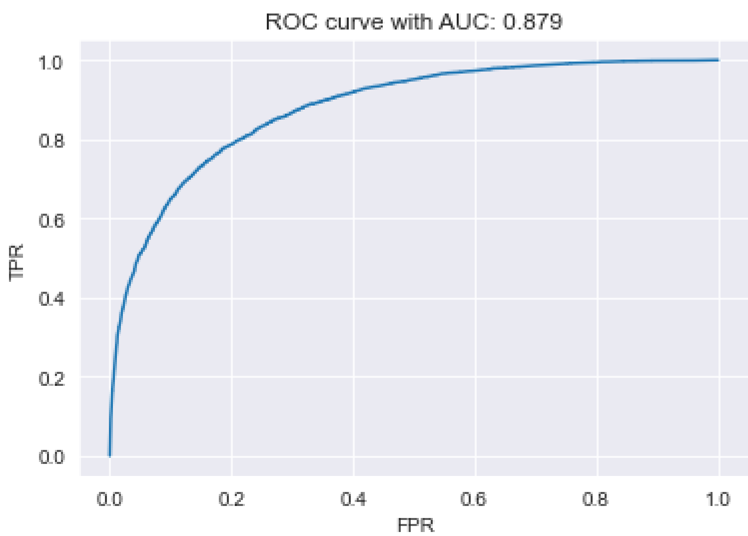
```
C:\Users\fnern\AppData\Local\Temp\ipykernel_13500\1287647186.py:27: MatplotlibDeprecatio
nWarning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since 3.5 and
will be removed two minor releases later; please call grid(False) first.
  plt.colorbar()
```



In [28]:

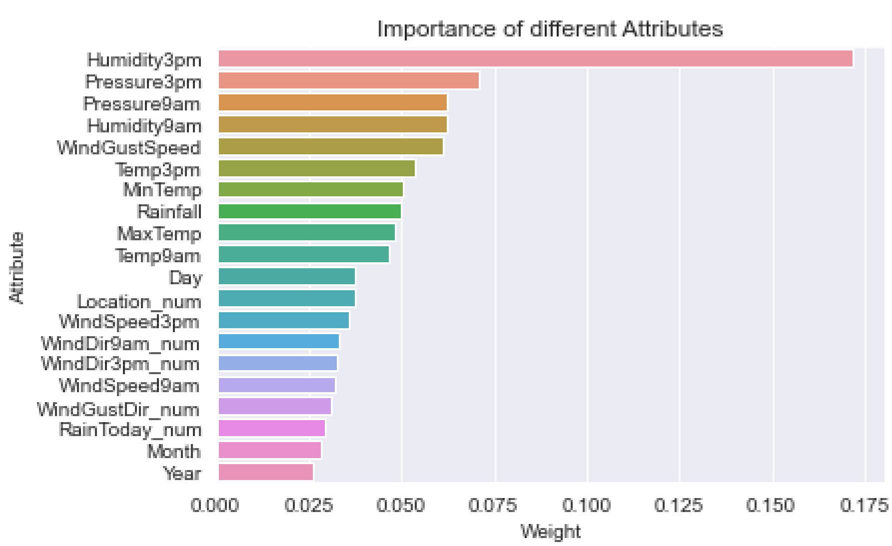
```
# print AUC score and ROC curve
get_ROC(model_random_forest, x_test, y_test)
```

```
AUC score:
0.8792509733123088
```



In [29]:

```
# create overview of feature importance, of learned decision tree
attribute_weights = pd.DataFrame({
    'Attribute' : x_train.columns,
    'Weight' : model_random_forest.feature_importances_
}).sort_values(by='Weight', ascending=False)
plt.title('Importance of different Attributes')
sns.barplot(data = attribute_weights, x='Weight', y='Attribute');
```



Extreme Gradient Boosting

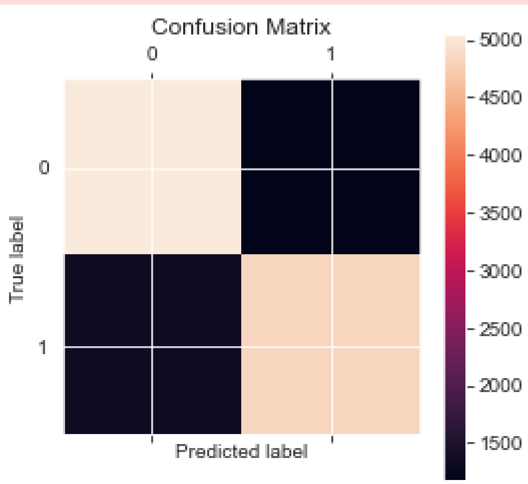
In [30]:
```
xgb = XGBClassifier()
xgb.fit(x_train, y_train)
```

```
C:\Users\fnern\miniforge3\envs\stat\lib\site-packages\xgboost\sklearn.py:1224: UserWarni
ng: The use of label encoder in XGBClassifier is deprecated and will be removed in a fut
ure release. To remove this warning, do the following: 1) Pass option use_label_encoder=
False when constructing XGBClassifier object; and 2) Encode your labels (y) as integers
starting with 0, i.e. 0, 1, 2, ..., [num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[13:17:02] WARNING: D:\bld\xgboost-split_1645118015404\work\src\learner.cc:1115: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logist
ic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to r
estore the old behavior.
```

Out[30]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=12,
              num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

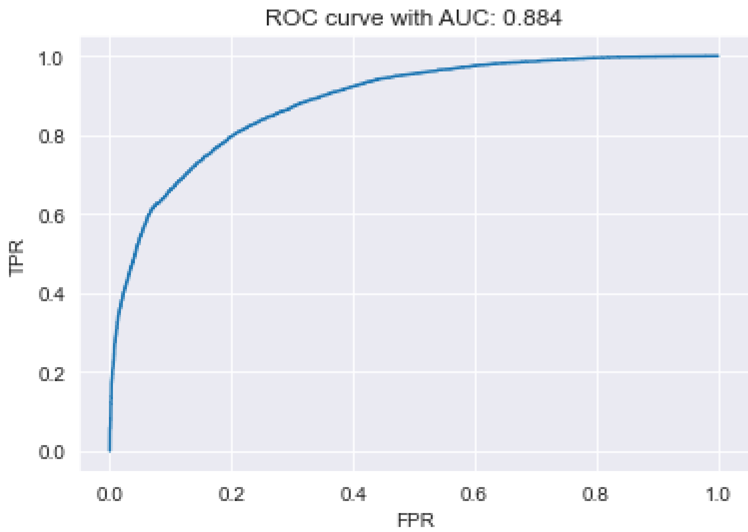
In [31]:
```
_ = get_evaluation(xgb, x_test, y_test)
```

```
Accuracy of Classifier on Test Image Data:  0.7970967741935484

Recall (No Rain Tomorrow) of Classifier on Test Image Data:  0.8103946102021174
Recall (Rain Tomorrow) of Classifier on Test Image Data:  0.7836522867337009

Precision (No Rain Tomorrow) of Classifier on Test Image Data:  0.7911055433761353
Precision (Rain Tomorrow) of Classifier on Test Image Data:  0.8034585966079149


Confusion Matrix:
 [[5052 1182]
 [1334 4832]]
C:\Users\fnern\AppData\Local\Temp\ipykernel_13500\1287647186.py:27: MatplotlibDeprecatio
nWarning: Auto-removal of grids by pcolor() and pcolormesh() is deprecated since 3.5 and
will be removed two minor releases later; please call grid(False) first.
  plt.colorbar()
```

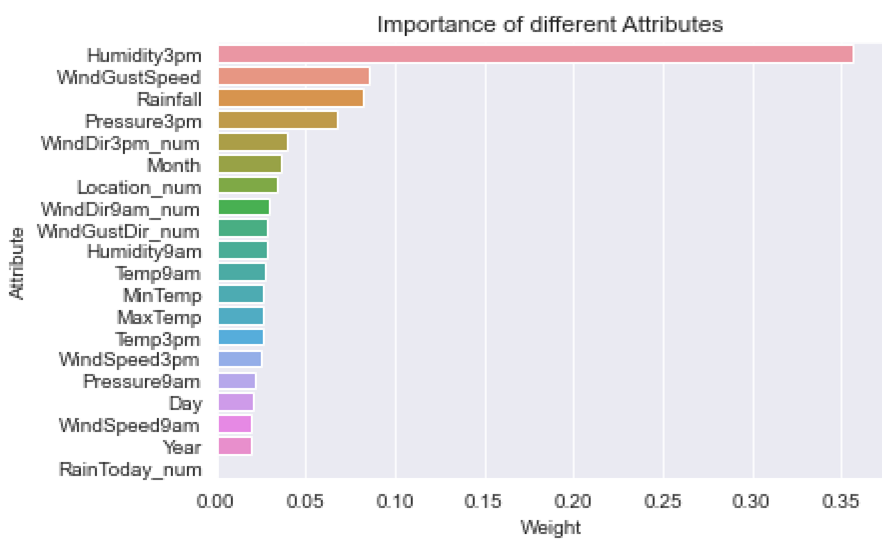


In [32]:
```
# print AUC score and ROC curve
get_ROC(xgb, x_test, y_test)
```

```
AUC score:
0.8843915285277569
```



In [33]:
```
# create overview of feature importance, of learned decision tree
attribute_weights = pd.DataFrame({
    'Attribute' : x_train.columns,
    'Weight' : xgb.feature_importances_
}).sort_values(by='Weight', ascending=False)
plt.title('Importance of different Attributes')
sns.barplot(data = attribute_weights, x='Weight', y='Attribute');
```



Regression

In this part, are going to develop an estimator for the rainfall. Since, rainfall is a continuous variable, this is obviously a regression task.

Since, this is going to be a multiple regression task, and therefore, not all variables might have a significant impact, we chose the best subset selection method for identifying the required variables.

Data preparation for the regression part

In [34]:
```
x_train_reg = x_train.loc[x_train['Rainfall'] > 0, x_train.columns != 'Rainfall'].copy()
x_test_reg = x_test.loc[x_test['Rainfall'] > 0, x_test.columns != 'Rainfall'].copy()

y_train_reg = x_train[x_train['Rainfall'] > 0]['Rainfall'].copy()
y_test_reg = x_test[x_test['Rainfall'] > 0]['Rainfall'].copy()
```

Now, after the data is prepared for the regression part, we can now start to fit some regression models. We decided to use the regression version of our classifiers.

Our first model is the regression tree.

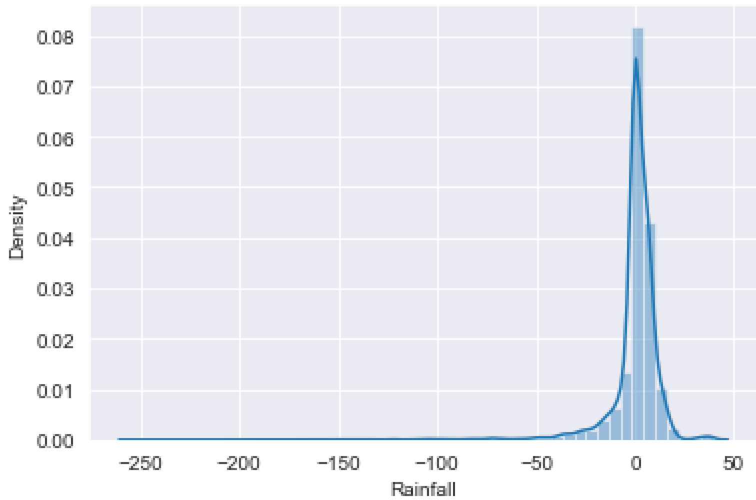
Regression tree

In [35]:
```
"""
Evaluates the regression model.
@param model, sklearn model,trained model
@param x_test, np ndarray, data matrix
@param y_test, np ndarray, data vector
"""
def get_regression_evaluation(model, x_test, y_test):
    y_pred = model.predict(x_test)

    explained_variance = explained_variance_score(y_test, y_pred)
    m_squared = mean_squared_error(y_test, y_pred)
    absolute = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    print(f"Explained variance: {explained_variance:.4f}")
    print(f"Mean squared error: {m_squared:.4f}")
    print(f"RMSE: {np.sqrt(m_squared):.4f}")
    print(f"Mean absolute error: {absolute:.4f}")
    print(f"R2 score: {r2:.4f}")

    sns.distplot(y_pred - y_test)

    return None
```

In [36]:
```
dec_tree_grid = {
    'criterion': ['squared_error','absolute_error'],
    'max_depth': range(1,10),
    'splitter': ['random', 'best'],
    "max_features":["auto", "sqrt", None],
}

"""
Trains a decision tree regressor using cross-validation and returns attributes of the re
parameter combination.
@param x_train, np ndarray, data matrix
@param y_train, np ndarray, data vector
@param param_grid, dict, grid holding the paramaters for search
@param use_pref_defined_model, bool, indicates whether the predefined model version shou
"""
def train_dec_tree_regressor(x_train, y_train, param_grid, use_pref_defined_model: bool)
    if use_pref_defined_model:
        best_params =  {'criterion': 'squared_error', 'max_depth': 4, 'max_features': 'a
        tree = DecisionTreeRegressor(random_state=55, **best_params)
        tree.fit(x_train, y_train)
        return best_params, tree

    tree = DecisionTreeRegressor(random_state=55)
    model = GridSearchCV(tree, param_grid=param_grid, scoring="neg_mean_squared_error",
    model.fit(x_train, y_train)
    return model.best_params_, model.best_estimator_
```

In [37]:
```
params_dec_tree_regressor, model_dec_tree_regressor = train_dec_tree_regressor(x_train_r
_ = get_regression_evaluation(model_dec_tree_regressor, x_test_reg, y_test_reg)
#print("The best parameters are: {}".format(params_random_forest))
```

```
Explained variance: 0.1821
Mean squared error: 194.2738
RMSE: 13.9382
Mean absolute error: 6.5251
R2 score: 0.1821
```



In [38]:

```
print("The best parameters are: {}".format(params_dec_tree_regressor))
```

```
The best parameters are: {'criterion': 'squared_error', 'max_depth': 4, 'max_features':
'auto', 'splitter': 'best'}
```

Random Forest Regressor

In [39]:

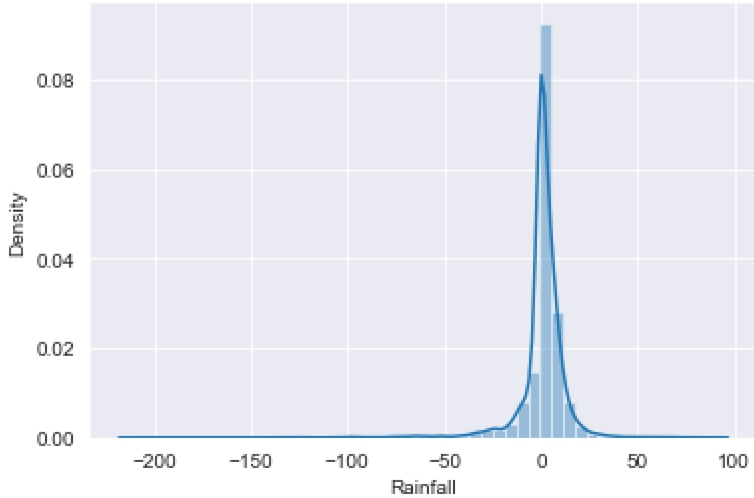
```
rand_forest_reg_grid = {
    'n_estimators': [50, 100, 150, 200],
    'criterion': ['squared_error','absolute_error'],
    "max_features":["auto", "sqrt"],
}

"""
Trains a random forest regressor using cross-validation and returns attributes of the re
parameter combination.
@param x_train, np ndarray, data matrix
@param y_train, np ndarray, data vector
@param param_grid, dict, grid holding the paramaters for search
@param use_pref_defined_model, bool, indicates whether the predefined model version shou
"""
def train_random_forest_regressor(x_train, y_train, param_grid, use_pref_defined_model:
    if use_pref_defined_model:
        best_params = {'criterion': 'squared_error', 'max_features': 'sqrt', 'n_estimato
        forest = RandomForestRegressor(random_state=55)
        forest.fit(x_train, y_train)
        return best_params, forest

    forest = RandomForestRegressor(random_state=55)
    model = GridSearchCV(forest, param_grid=param_grid, scoring="neg_mean_squared_error"
    model.fit(x_train, y_train)
    return model.best_params_, model.best_estimator_
```

In [40]:

```
params_random_forest_regressor, model_random_forest_regressor = train_random_forest_regr
_ = get_regression_evaluation(model_random_forest_regressor, x_test_reg, y_test_reg)
print("The best parameters are: {}".format(params_random_forest))
```

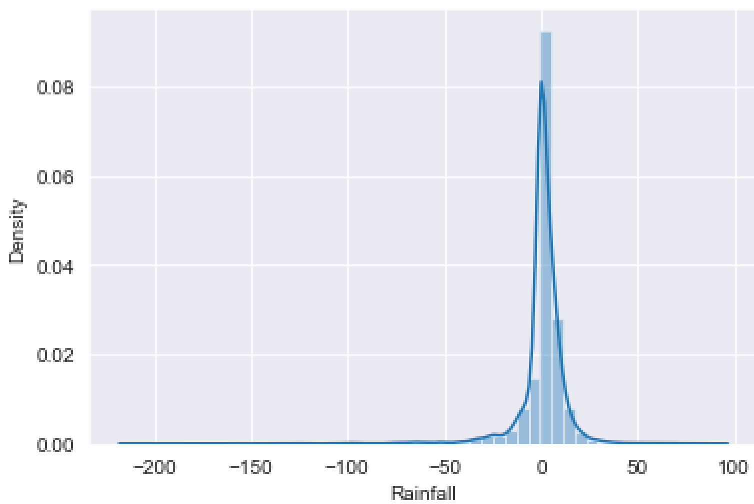
```
Explained variance: 0.2415
Mean squared error: 180.6168
RMSE: 13.4394
Mean absolute error: 6.4144
```

```
R2 score: 0.2396
The best parameters are: {'criterion': 'entropy', 'max_depth': 24}
```



In [41]:
```
_ = get_regression_evaluation(model_random_forest_regressor, x_test_reg, y_test_reg)
print("The best parameters are: {}".format(params_random_forest_regressor))
```

```
Explained variance: 0.2415
Mean squared error: 180.6168
RMSE: 13.4394
Mean absolute error: 6.4144
R2 score: 0.2396
The best parameters are: {'criterion': 'squared_error', 'max_features': 'sqrt', 'n_estim
ators': 200}
```



Extreme Gradient Boosting Regression

In [42]:
```
xgb_grid = {
    'max_depth': [3,6,10],
    'learning_rate': [0.01, 0.05, 0.1],
    'n_estimators': [100, 500, 1000],
    'colsample_bytree': [0.3, 0.7]
}

"""
Trains an XGB regressor using cross-validation and returns attributes of the received mo
parameter combination.
@param x_train, np ndarray, data matrix
@param y_train, np ndarray, data vector
@param param_grid, dict, grid holding the paramaters for search
@param use_pref_defined_model, bool, indicates whether the predefined model version shou
"""
```

```
def train_xgb_regressor(x_train, y_train, param_grid, use_pref_defined_model: bool):
    if use_pref_defined_model:
        best_params = {'colsample_bytree': 0.3, 'learning_rate': 0.05, 'max_depth': 6, '
        xgb = XGBRegressor(seed = 55, **best_params)
        xgb.fit(x_train, y_train)
        return best_params, xgb
    xgb = XGBRegressor(seed = 55)
    model = GridSearchCV(xgb, param_grid=param_grid, scoring="neg_mean_squared_error", v
    model.fit(x_train, y_train)
    return model.best_params_, model.best_estimator_
```

In [43]:
```
xgb_params, xgb_regressor = train_xgb_regressor(x_train_reg, y_train_reg, xgb_grid, True
_ = get_regression_evaluation(xgb_regressor, x_test_reg, y_test_reg)
print(f"The best parameters are: {xgb_params}")
```

```
Explained variance: 0.2652
Mean squared error: 174.5347
RMSE: 13.2112
Mean absolute error: 6.4548
R2 score: 0.2652
The best parameters are: {'colsample_bytree': 0.3, 'learning_rate': 0.05, 'max_depth':
6, 'n_estimators': 500}
```