[Grupa 3] Praca Domowa nr3 Kacper Kurowski

April 13, 2021

1 [WUM] PD3

1.1 Kacper Kurowski

Wpierw wczytajmy dane

[3]:
```python
import os
os.getcwd()
```

[3]:
```
'/home/kurowskik'
```

[4]:
```python
import numpy as np
import pandas as pd

import seaborn as sns
sns.set_theme(style="darkgrid")

import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
import requests
```

[5]:
```python
aus_wheather = pd.read_csv( "/home/kurowskik/kaggle/weatherAUS.csv", sep = ",",␣
↪header=0)
```

[4]:
```python
aus_wheather
```

[4]:
```
              Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  \
0       2008-12-01   Albury     13.4     22.9       0.6          NaN
1       2008-12-02   Albury      7.4     25.1       0.0          NaN
2       2008-12-03   Albury     12.9     25.7       0.0          NaN
3       2008-12-04   Albury      9.2     28.0       0.0          NaN
4       2008-12-05   Albury     17.5     32.3       1.0          NaN
…              …      …     …      …        …         …
145455  2017-06-21    Uluru      2.8     23.4       0.0          NaN
145456  2017-06-22    Uluru      3.6     25.3       0.0          NaN
145457  2017-06-23    Uluru      5.4     26.9       0.0          NaN
```

```
145458  2017-06-24    Uluru      7.8     27.0       0.0          NaN
145459  2017-06-25    Uluru     14.9      NaN       0.0          NaN

        Sunshine WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  \
0            NaN           W           44.0          W  …        71.0
1            NaN         WNW           44.0        NNW  …        44.0
2            NaN         WSW           46.0          W  …        38.0
3            NaN          NE           24.0         SE  …        45.0
4            NaN           W           41.0        ENE  …        82.0
…          …         …            …        …  …         …
145455       NaN           E           31.0         SE  …        51.0
145456       NaN         NNW           22.0         SE  …        56.0
145457       NaN           N           37.0         SE  …        53.0
145458       NaN          SE           28.0        SSE  …        51.0
145459       NaN         NaN            NaN        ESE  …        62.0

        Humidity3pm  Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  \
0              22.0       1007.7       1007.1       8.0       NaN     16.9
1              25.0       1010.6       1007.8       NaN       NaN     17.2
2              30.0       1007.6       1008.7       NaN       2.0     21.0
3              16.0       1017.6       1012.8       NaN       NaN     18.1
4              33.0       1010.8       1006.0       7.0       8.0     17.8
…            …          …          …       …       …      …
145455         24.0       1024.6       1020.3       NaN       NaN     10.1
145456         21.0       1023.5       1019.1       NaN       NaN     10.9
145457         24.0       1021.0       1016.8       NaN       NaN     12.5
145458         24.0       1019.4       1016.5       3.0       2.0     15.1
145459         36.0       1020.2       1017.9       8.0       8.0     15.0

        Temp3pm  RainToday  RainTomorrow
0          21.8         No            No
1          24.3         No            No
2          23.2         No            No
3          26.5         No            No
4          29.7         No            No
…        …        …           …
145455     22.4         No            No
145456     24.5         No            No
145457     26.1         No            No
145458     26.0         No            No
145459     20.9         No           NaN

[145460 rows x 23 columns]
```

Możemy szybko zapoznać się z danymi

[7]:
```python
from pandas_profiling import ProfileReport
```

[33]:
```
profile = ProfileReport(aus_wheather, title="Pandas Profiling Report")
```

[37]:
```
profile.to_notebook_iframe()
```

```
<IPython.core.display.HTML object>
```

Możemy zauważyć, że zmienne Date, Location, WindGustDir, WindDir9am, WindDir3pm, RainToday i RainTomorrow mają wartości nieliczbowe. Dlatego postaramy się zakodować je przy pomocy liczb. Możemy również zauważyć, że jest dużo wierszy z Evaporation i Sunshine na NaN. Podobnie Cloud9am i Cloud3pm. Z tego powodu usuniemy te kolumny.

[6]:
```
del aus_wheather["Evaporation"]
del aus_wheather["Sunshine"]
del aus_wheather["Cloud9am"]
del aus_wheather["Cloud3pm"]
```

[7]:
```
direction_to_encoding = {
    "N" : [1.0,0.0,0.0,0.0],
    "NNW" : [0.75,0.25,0.0,0.0],
    "NW" : [0.5,0.5,0.0,0.0],
    "WNW" : [0.25,0.66,0.0,0.0],
    "W" : [0.0,1.0,0.0,0.0],
    "WSW" : [0.0,0.75,0.25,0.0],
    "SW" : [0.0,0.5,0.5,0.0],
    "SSW" : [0.0,0.75,0.66,0.0],
    "S" : [0.0,0.0,1.0,0.0],
    "SSE" : [0.0,0.0,0.75,0.25],
    "SE" : [0.0,0.0,0.5,0.5],
    "ESE" : [0.0,0.0,0.25,0.75],
    "E" : [0.0,0.0,0.0,1.0],
    "ENE" : [0.25,0.0,0.0,0.75],
    "NE" : [0.5,0.0,0.0,0.5],
    "NNE" : [0.75,0.66,0.0,0.25],
    "nan" : [0.0,0.0,0.0,0.0]
}
```

[8]:
```
GustDir = pd.DataFrame(
    aus_wheather["WindGustDir"].fillna("nan").map(direction_to_encoding).
 ↪tolist(),
    columns=['WindGustDirN','WindGustDirW','WindGustDirS','WindGustDirE'],
    index = aus_wheather.index)
aus_wheather = aus_wheather.merge(GustDir, left_index=True, right_index=True)

GustDir9am = pd.DataFrame(
    aus_wheather["WindDir9am"].fillna("nan").map(direction_to_encoding).
 ↪tolist(),
    columns=['WindDir9amN','WindDir9amW','WindDir9amS','WindDir9amE'],
```

```
    index = aus_wheather.index)

aus_wheather = aus_wheather.merge(GustDir9am, left_index=True, right_index=True)
GustDir3pm = pd.DataFrame(
    aus_wheather["WindDir3pm"].fillna("nan").map(direction_to_encoding).
 ↪tolist(),
    columns=['WindDir3pmN','WindDir3pmW','WindDir3pmS','WindDir3pmE'],
    index = aus_wheather.index)
aus_wheather = aus_wheather.merge(GustDir3pm, left_index=True, right_index=True)
```

[9]:
```
def encode_dates(x):
    tmp = x.split("-")
    return [float( tmp[0]), float(tmp[1]), float(tmp[2]) ]
```

[10]:
```
dates = pd.DataFrame(
    aus_wheather['Date'].map( encode_dates).tolist(),
    columns=["Year", "Month", "Day"],
    index = aus_wheather.index)
aus_wheather = aus_wheather.merge(dates, left_index=True, right_index=True)
```

[11]:
```
def encodeRain(x):
    if x == "Yes":
        return 1
    elif x == "No":
        return 0
```

[12]:
```
aus_wheather['RainTomorrow'] = aus_wheather['RainTomorrow'].map( encodeRain)
aus_wheather['RainToday'] = aus_wheather['RainToday'].map( encodeRain)
```

[11]:
```
aus_wheather.columns
```

[11]:
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'WindGustDir',
       'WindGustSpeed', 'WindDir9am', 'WindDir3pm', 'WindSpeed9am',
       'WindSpeed3pm', 'Humidity9am', 'Humidity3pm', 'Pressure9am',
       'Pressure3pm', 'Temp9am', 'Temp3pm', 'RainToday', 'RainTomorrow',
       'WindGustDirN', 'WindGustDirW', 'WindGustDirS', 'WindGustDirE',
       'WindDir9amN', 'WindDir9amW', 'WindDir9amS', 'WindDir9amE',
       'WindDir3pmN', 'WindDir3pmW', 'WindDir3pmS', 'WindDir3pmE', 'Year',
       'Month', 'Day'],
      dtype='object')
```

[13]:
```
tmp = aus_wheather['Location'].map( lambda x: sum(bytearray(x, 'utf-8'))+len(x)␣
 ↪) # Kodujemy lokację, niestety nieróżnowartościowo
```

[14]:
```
print( len(pd.unique(aus_wheather['Location'])))
print( len(pd.unique(tmp))) # Niestety kodowanie nie jest różnowartościowe w␣
 ↪tym przypadku. Trudno.
```

```
49
46
```

[15]:
```
aus_wheather['Location'] = tmp
```

[15]:
```
aus_wheather.head()
```

[15]:
```
         Date  Location  MinTemp  MaxTemp  Rainfall WindGustDir  \
0  2008-12-01       629     13.4     22.9       0.6           W
1  2008-12-02       629      7.4     25.1       0.0         WNW
2  2008-12-03       629     12.9     25.7       0.0         WSW
3  2008-12-04       629      9.2     28.0       0.0          NE
4  2008-12-05       629     17.5     32.3       1.0           W

   WindGustSpeed WindDir9am WindDir3pm  WindSpeed9am  …  WindDir9amW  \
0           44.0          W        WNW          20.0  …         1.00
1           44.0        NNW        WSW           4.0  …         0.25
2           46.0          W        WSW          19.0  …         1.00
3           24.0         SE          E          11.0  …         0.00
4           41.0        ENE         NW           7.0  …         0.00

   WindDir9amS  WindDir9amE  WindDir3pmN  WindDir3pmW  WindDir3pmS  \
0          0.0         0.00         0.25         0.66         0.00
1          0.0         0.00         0.00         0.75         0.25
2          0.0         0.00         0.00         0.75         0.25
3          0.5         0.50         0.00         0.00         0.00
4          0.0         0.75         0.50         0.50         0.00

   WindDir3pmE    Year  Month  Day
0          0.0  2008.0   12.0  1.0
1          0.0  2008.0   12.0  2.0
2          0.0  2008.0   12.0  3.0
3          1.0  2008.0   12.0  4.0
4          0.0  2008.0   12.0  5.0

[5 rows x 34 columns]
```

Usuwamy kolumny zakodowane (przy pomocy innych kolumn)

[16]:
```
del aus_wheather["Date"]
del aus_wheather["WindGustDir"]
del aus_wheather["WindDir9am"]
del aus_wheather["WindDir3pm"]
```

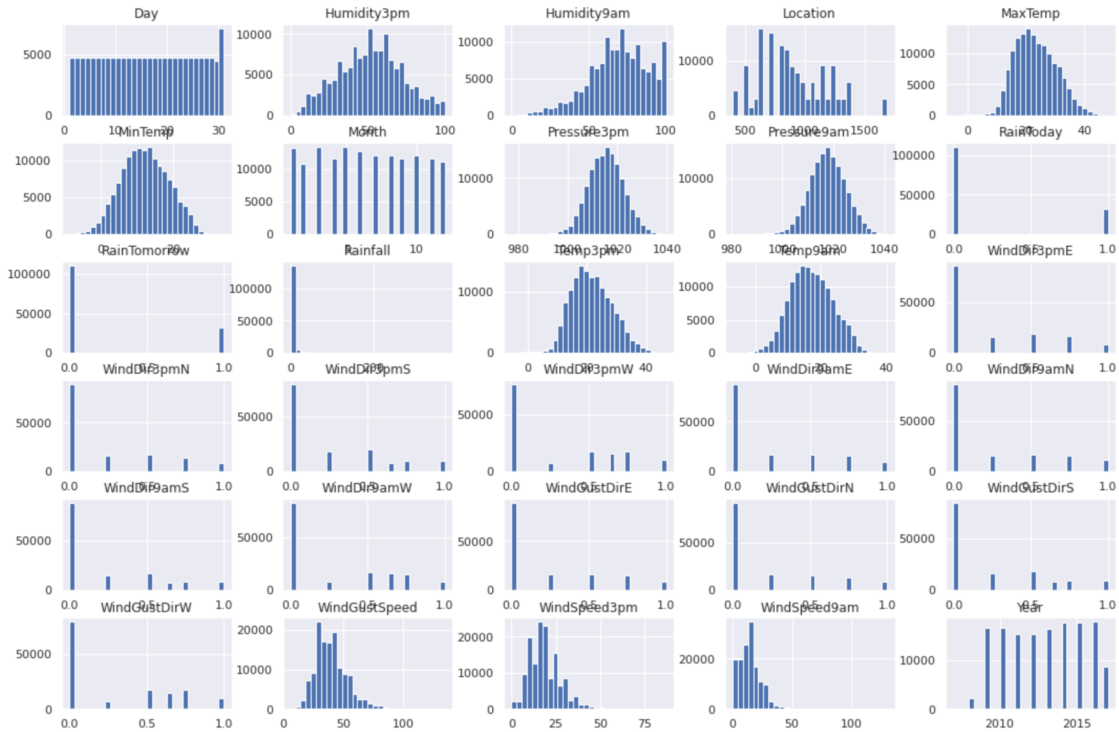
[24]:
```
aus_wheather.head()
```

[24]:
```
   Location  MinTemp  MaxTemp  Rainfall  WindGustSpeed  WindSpeed9am  \
0       629     13.4     22.9       0.6           44.0          20.0
```

```
1       629     7.4     25.1      0.0            44.0           4.0
2       629    12.9     25.7      0.0            46.0          19.0
3       629     9.2     28.0      0.0            24.0          11.0
4       629    17.5     32.3      1.0            41.0           7.0

   WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  …  WindDir9amW  \
0          24.0         71.0         22.0       1007.7  …         1.00
1          22.0         44.0         25.0       1010.6  …         0.25
2          26.0         38.0         30.0       1007.6  …         1.00
3           9.0         45.0         16.0       1017.6  …         0.00
4          20.0         82.0         33.0       1010.8  …         0.00

   WindDir9amS  WindDir9amE  WindDir3pmN  WindDir3pmW  WindDir3pmS  \
0          0.0         0.00         0.25         0.66         0.00
1          0.0         0.00         0.00         0.75         0.25
2          0.0         0.00         0.00         0.75         0.25
3          0.5         0.50         0.00         0.00         0.00
4          0.0         0.75         0.50         0.50         0.00

   WindDir3pmE    Year  Month  Day
0          0.0  2008.0   12.0  1.0
1          0.0  2008.0   12.0  2.0
2          0.0  2008.0   12.0  3.0
3          1.0  2008.0   12.0  4.0
4          0.0  2008.0   12.0  5.0

[5 rows x 30 columns]
```

Możemy również popatrzeć na wykresy samodzielnie (może coś sie uda zauważyć)

[25]:
```
aus_wheather.hist(figsize=(18, 12), bins=30)
plt.show()
```



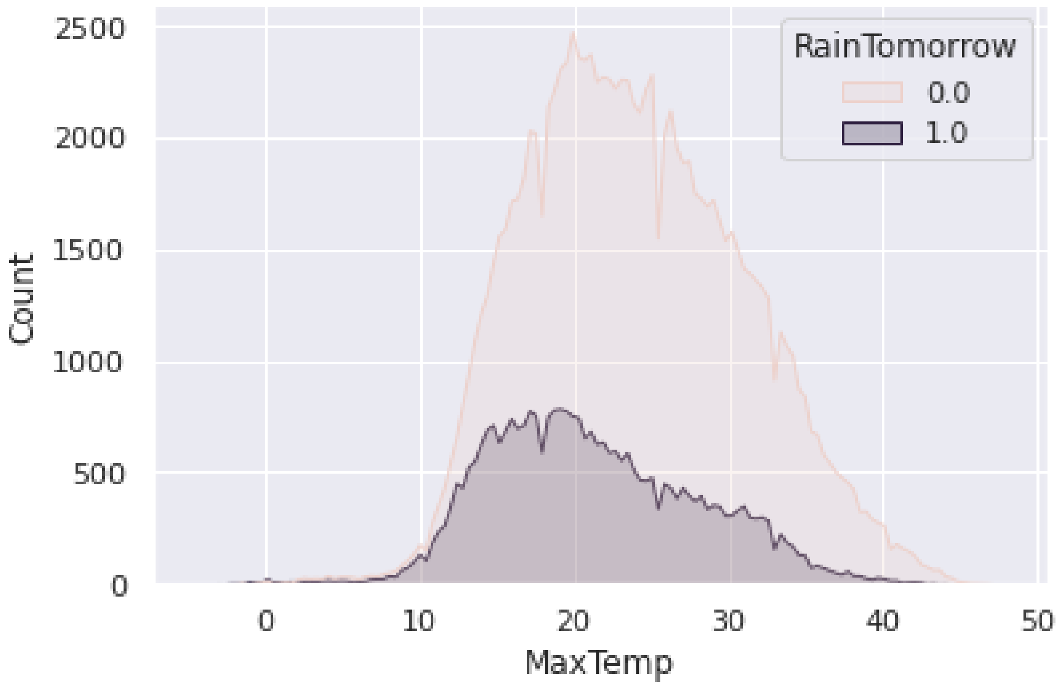
[26]:
```
import seaborn as sns
```

[16]:
```
aus_wheather.columns
```

[16]:
```
Index(['Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'WindGustSpeed',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Temp9am', 'Temp3pm', 'RainToday',
       'RainTomorrow', 'WindGustDirN', 'WindGustDirW', 'WindGustDirS',
       'WindGustDirE', 'WindDir9amN', 'WindDir9amW', 'WindDir9amS',
       'WindDir9amE', 'WindDir3pmN', 'WindDir3pmW', 'WindDir3pmS',
       'WindDir3pmE', 'Year', 'Month', 'Day'],
      dtype='object')
```

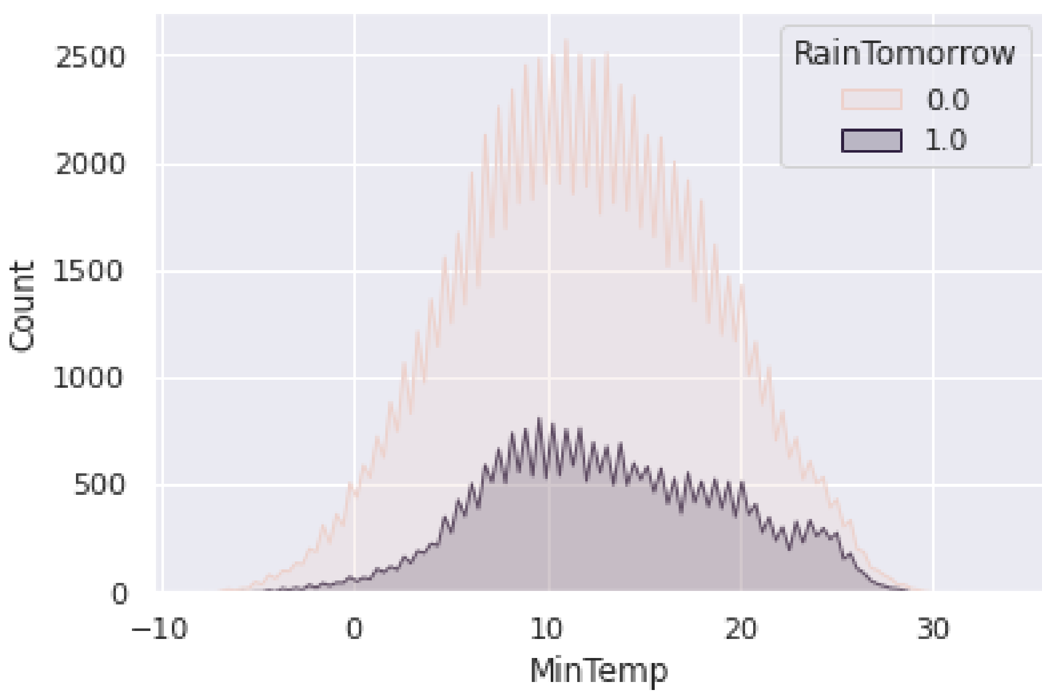
[18]:
```
sns.histplot(data=aus_wheather, x="MaxTemp", hue="RainTomorrow", element="poly")
```

[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8d22f0dca0>
```



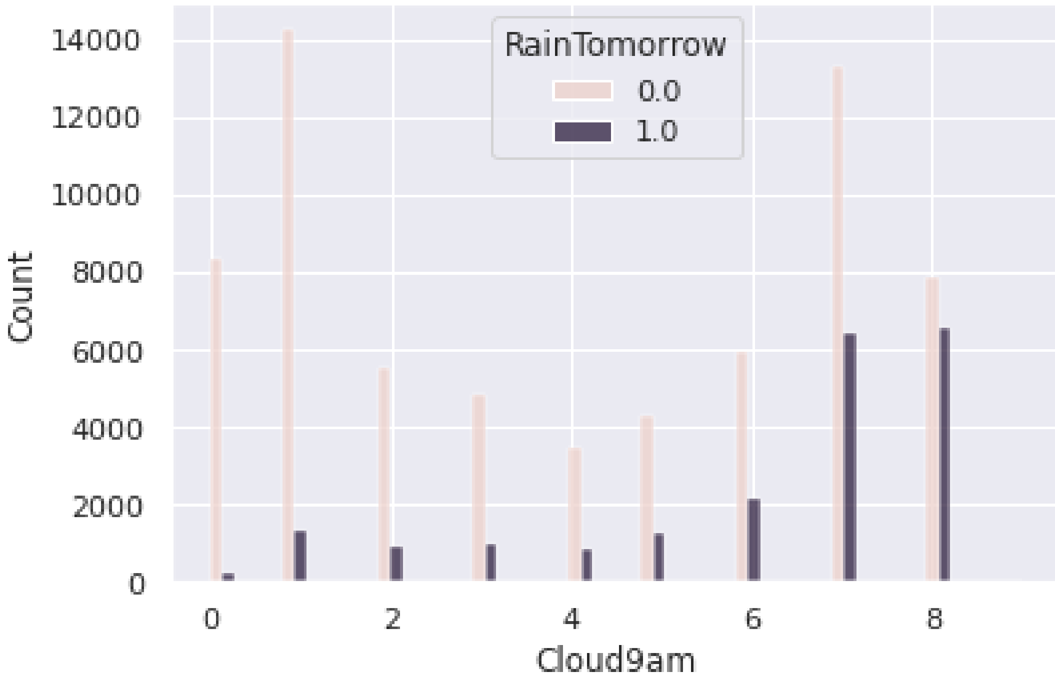
[133]:
```
sns.histplot(data=aus_wheather, x="MinTemp", hue="RainTomorrow", element="poly")
```

[133]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd005c48130>



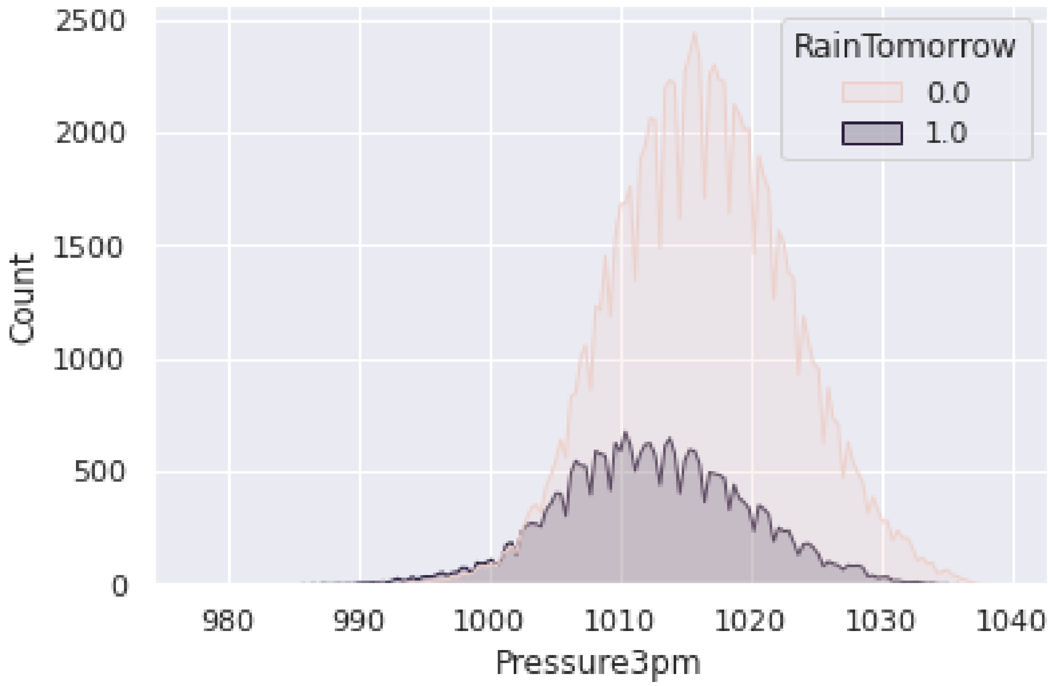
[134]:
```
sns.histplot(data=aus_wheather, x="Cloud9am", hue="RainTomorrow",␣
↪multiple='dodge')
```

[134]: <matplotlib.axes._subplots.AxesSubplot at 0x7fcff10c1730>



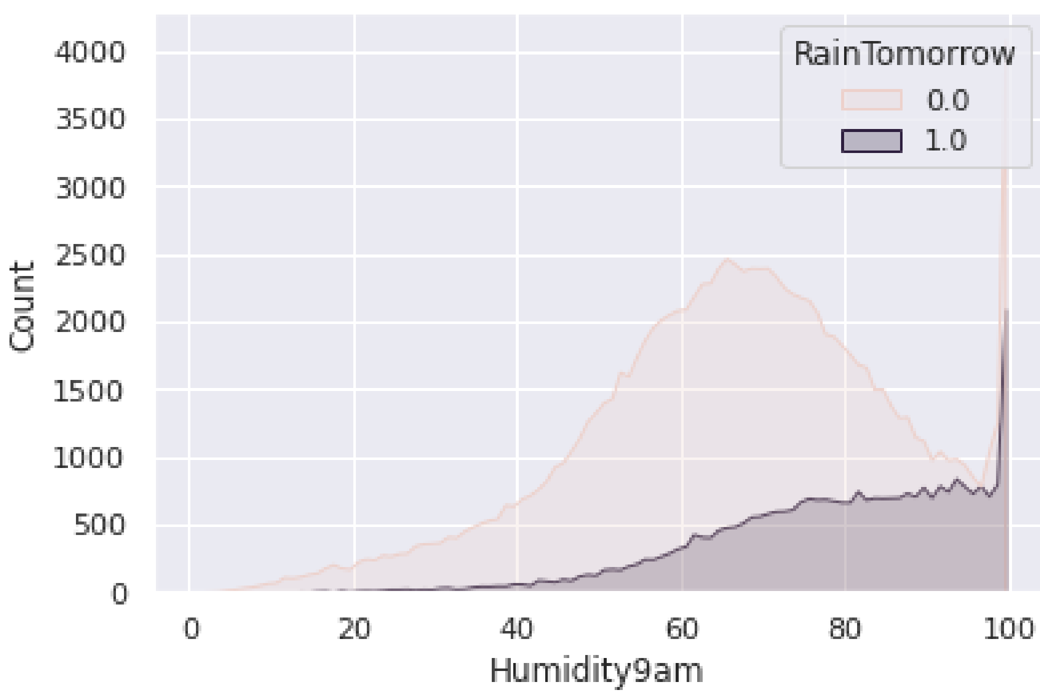
[137]:
```
sns.histplot(data=aus_wheather, x="Pressure3pm", hue="RainTomorrow",␣
↪element="poly")
```

[137]: <matplotlib.axes._subplots.AxesSubplot at 0x7fcff6630fd0>



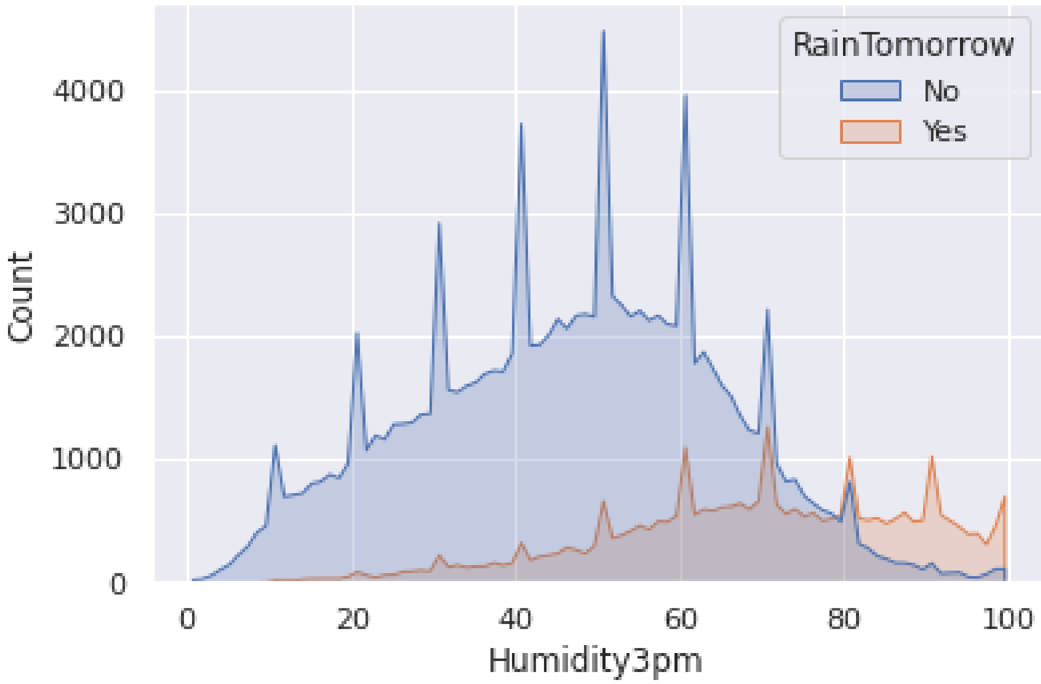
[138]:
```
sns.histplot(data=aus_wheather, x="Humidity9am", hue="RainTomorrow",␣
↪element="poly")
```

[138]: <matplotlib.axes._subplots.AxesSubplot at 0x7fcff64c6160>



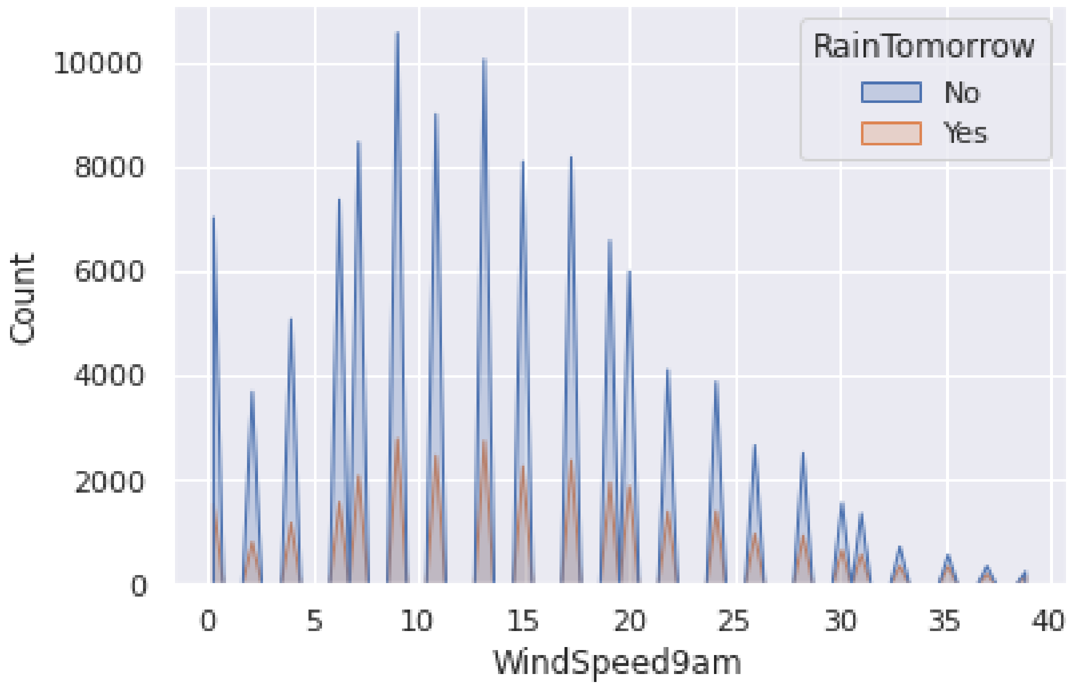
[33]:
```
sns.histplot(data=aus_wheather, x="Humidity3pm", hue="RainTomorrow",␣
↪element="poly")
```

[33]: <matplotlib.axes._subplots.AxesSubplot at 0x7f38115338e0>



[43]:
```
sns.histplot(data=aus_wheather[aus_wheather["WindSpeed9am"]<40],␣
↪x="WindSpeed9am", hue="RainTomorrow", element="poly")
```

[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3811c27c70>



1.2 Dzielenie zbiorów

Podział na zbiór treningowy (a ten na treningowy i walidacyjny) i na zbiór testowy

[30]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

[18]:
```
X = aus_wheather
```

[19]:
```
#imputer = KNNImputer(n_neighbors=10, weights="uniform") #imputacja powodowała␣
↪jakieś problemy, wiec po prostu uzupełnimy danie zerami
#imputer.fit_transform(X.sample(n=1000, random_state=1))
#X_tr = imputer.transform(X)
#from sklearn.experimental import enable_iterative_imputer
#from sklearn.impute import IterativeImputer
#imp = IterativeImputer(max_iter=10, random_state=0)
#imp.fit(X.sample(n=1000, random_state=1))
#X_tr = imp.transform(X)
X_fill = X.fillna(0)
```

[20]:
```
X_fill["RainTomorrow"] = X_fill["RainTomorrow"].astype( int)
X_fill["RainToday"] = X_fill["RainToday"].astype( int)
y_fill = X_fill["RainTomorrow"]
```

[21]:
```
X_train, X_test, y_train, y_test \
    = train_test_split(X_fill, y_fill, stratify = y_fill, test_size=0.2,␣
↪random_state=1)

X_train, X_val, y_train, y_val \
    = train_test_split(X_train, y_train, stratify = y_train, test_size=0.25,␣
↪random_state=1)
```

1.3 AdaBoostClassifier

[33]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
```

[26]:
```
alf = AdaBoostClassifier(n_estimators=100, random_state=0, learning_rate=0.9)
alf.fit(X_train, y_train)
```

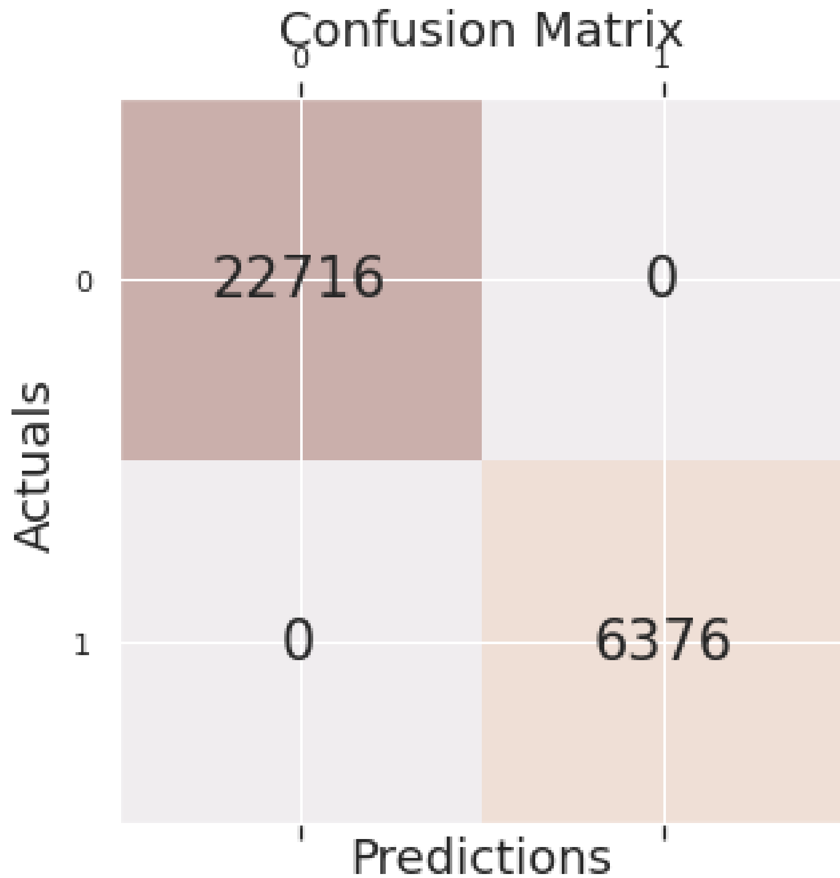
[26]:
```
AdaBoostClassifier(learning_rate=0.9, n_estimators=100, random_state=0)
```

[27]:
```
y_val_hat = alf.predict(X_val)
y_test_hat = alf.predict(X_test)
```

[28]:
```
alf.score(X_test, y_test)
```

[28]:
```
1.0
```

[31]:
```
conf_matrix = confusion_matrix(y_true=y_val, y_pred=y_val_hat.round())
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Oranges, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center',␣
↪size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```



[34]:
```
print('F1 Score: %.3f' % f1_score(y_test, y_test_hat))
```

```
F1 Score: 1.000
```

[35]:
```
print( accuracy_score(y_val, y_val_hat))
print( accuracy_score(y_test, y_test_hat))
```

```
1.0
1.0
```

Teoretycznie AdaBoostClassifer daje idealną predykcję zarówno na zbiorze testowym, jak i na zbiorze walidacyjnym.

1.4 GradientBoostingClassifier

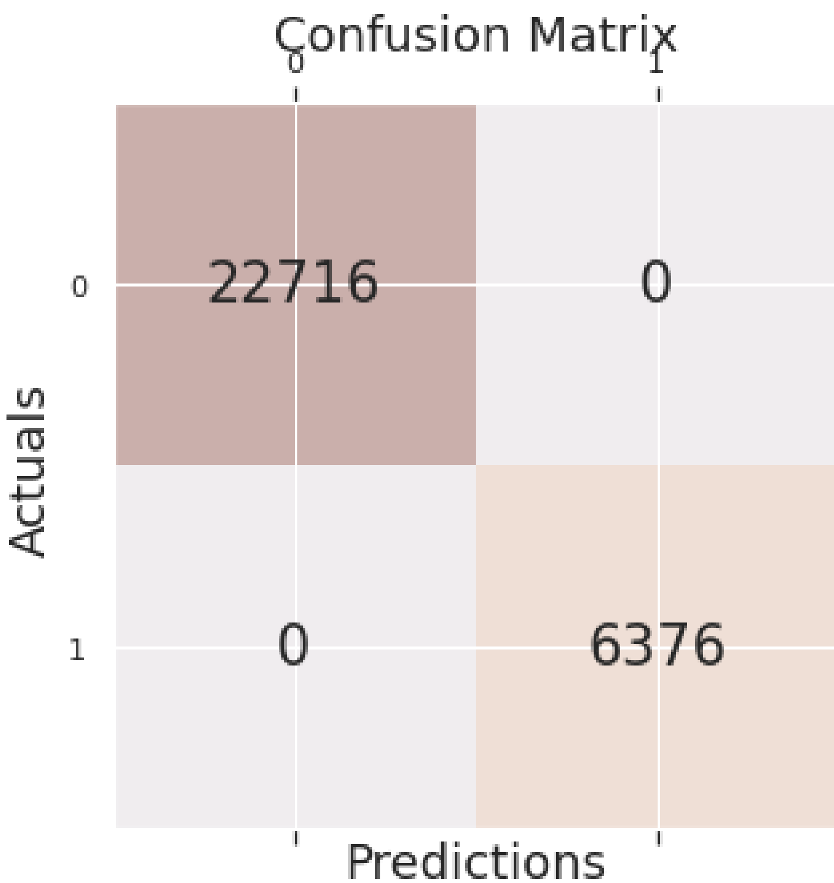
[38]:
```
from sklearn.ensemble import GradientBoostingClassifier
```

[39]:
```
clf = GradientBoostingClassifier(n_estimators=90, learning_rate=0.8,
      max_depth=1, random_state=0).fit(X_train, y_train)
clf.score(X_test, y_test)
```

[39]: 1.0

[40]:
```
y_val_hat = clf.predict(X_val)
y_test_hat = clf.predict(X_test)
```

[41]:
```
conf_matrix = confusion_matrix(y_true=y_val, y_pred=y_val_hat)
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Oranges, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center',␣
 ↪size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```



[42]:
```
print('F1 Score: %.3f' % f1_score(y_test, y_test_hat))
```

```
F1 Score: 1.000
```

[43]:
```
print( accuracy_score(y_val, y_val_hat))
print( accuracy_score(y_test, y_test_hat))
```

```
1.0
1.0
```

Podobnie GradientBoostingClassifier otrzymuje idealne predykcje.

1.5 HistGradientBoostingRegressor

[45]:
```
from sklearn.experimental import enable_hist_gradient_boosting
from sklearn.ensemble import HistGradientBoostingRegressor
```

[46]:
```
est = HistGradientBoostingRegressor( l2_regularization= 2, learning_rate=0.7).
 ↪fit(X_train, y_train)
est.score(X_val, y_val)
```

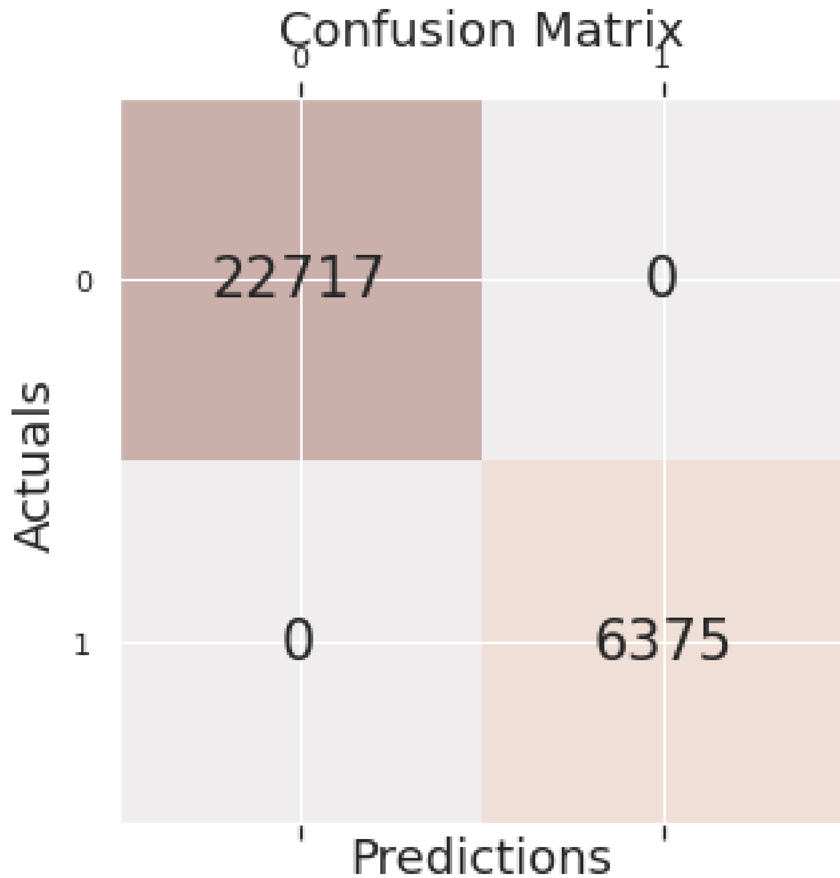
[46]:
```
1.0
```

[47]:
```
y_val_hat = est.predict(X_val).round()
y_test_hat = est.predict(X_test).round()
```

[48]:
```
from sklearn.metrics import precision_score, recall_score, f1_score,␣
 ↪accuracy_score
from sklearn.metrics import confusion_matrix
```

[49]:
```
conf_matrix = confusion_matrix(y_true=y_test, y_pred=y_test_hat)
```

[50]:
```
fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Oranges, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center',␣
 ↪size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```



[51]:
```
print('F1 Score: %.3f' % f1_score(y_test, y_test_hat))
```

```
F1 Score: 1.000
```

[52]:
```
print( accuracy_score(y_val, y_val_hat))
print( accuracy_score(y_test, y_test_hat))
```

```
1.0
1.0
```

Okazuje się zatem, że wszystkie Classifiery dają idealną predykcję danych.

1.6 Wnioski

Nie ma zbytnio jak wybrać w tym przypadku najlepszego klasyfikatora - zasadniczo wszystkie daję idealną predykcję. Jeżeli jednak byłoby to konieczne, w tym przypadku można unikać GradientBoostingClassifier, gdyż potrzeba najwięcej czasu by go uruchommić