1.Task - ExplorationAnalysisAndClustering

January 18, 2024

1 1. Task - Exploration data analysis and clustering

The goal of this task is to explore (analyze) the dataset using explorative and statistical techniques to get more familiar with the dataset and its characteristics, specifically:

- Attribute value data types
- Attributes distribution
- Correlation beteen other attributes

1.1 Dataset - Weather in Australia

Link to dataset - https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package/

The goal of this dataset is to: **Predict next-day rain by training classification models on the target variable RainTomorrow**.

This dataset contains about 10 years of daily weather observations from numerous Australian weather stations.

1.2 Import packages

[ ]:
```
import pandas as pd # dataframes
import numpy as np # matrices and linear algebra
import matplotlib.pyplot as plt # plotting
import seaborn as sns # another matplotlib interface - styled and easier to use

pd.set_option('display.max_columns', None) # Show all columns
```

1.3 Load dataset

[ ]:
```
pathToDataset = "..\WeatherAUS_Data\weatherAUS.csv"
origDataframe = pd.read_csv(pathToDataset)
```

1.4 Examine our dataset

1.4.1 Quick Overview

- Firstly, quick overview of our dataset

[ ]:
```
origDataframe
```

[ ]:
```
             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 WindDir3pm  \
0            NaN           W           44.0          W        WNW
1            NaN         WNW           44.0        NNW        WSW
2            NaN         WSW           46.0          W        WSW
3            NaN          NE           24.0         SE          E
4            NaN           W           41.0        ENE         NW
…            …           …              …         …          …
145455       NaN           E           31.0         SE        ENE
145456       NaN         NNW           22.0         SE          N
145457       NaN           N           37.0         SE        WNW
145458       NaN          SE           28.0        SSE          N
145459       NaN         NaN            NaN        ESE        ESE

        WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  \
0               20.0          24.0         71.0         22.0       1007.7
1                4.0          22.0         44.0         25.0       1010.6
2               19.0          26.0         38.0         30.0       1007.6
3               11.0           9.0         45.0         16.0       1017.6
4                7.0          20.0         82.0         33.0       1010.8
…               …             …            …            …           …
145455          13.0          11.0         51.0         24.0       1024.6
145456          13.0           9.0         56.0         21.0       1023.5
145457           9.0           9.0         53.0         24.0       1021.0
145458          13.0           7.0         51.0         24.0       1019.4
145459          17.0          17.0         62.0         36.0       1020.2

        Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm RainToday  \
0            1007.1       8.0       NaN     16.9     21.8        No
1            1007.8       NaN       NaN     17.2     24.3        No
2            1008.7       NaN       2.0     21.0     23.2        No
3            1012.8       NaN       NaN     18.1     26.5        No
4            1006.0       7.0       8.0     17.8     29.7        No
```

```
…              …       …       …       …       …       …
145455       1020.3       NaN       NaN     10.1     22.4        No
145456       1019.1       NaN       NaN     10.9     24.5        No
145457       1016.8       NaN       NaN     12.5     26.1        No
145458       1016.5       3.0       2.0     15.1     26.0        No
145459       1017.9       8.0       8.0     15.0     20.9        No

       RainTomorrow
0                No
1                No
2                No
3                No
4                No
…               …
145455           No
145456           No
145457           No
145458           No
145459          NaN

[145460 rows x 23 columns]
```

We can se that our dataset has 145 460 rows and 23 columns (22 attributes + 1 target value). Some columns are categorical (WindGustDir, WindDir9am, RainToday, TrainTomorrow), others are represented by string (Date, Location) and also we have some real values (MinTemp, MaxTemp, Rainfall, …)

- Show some useful characteristics of real valued columns

[ ]:
```
origDataframe.describe()
```

[ ]:
```
             MinTemp        MaxTemp       Rainfall   Evaporation  \
count  143975.000000  144199.000000  142199.000000  82670.000000
mean       12.194034      23.221348       2.360918      5.468232
std         6.398495       7.119049       8.478060      4.193704
min        -8.500000      -4.800000       0.000000      0.000000
25%         7.600000      17.900000       0.000000      2.600000
50%        12.000000      22.600000       0.000000      4.800000
75%        16.900000      28.200000       0.800000      7.400000
max        33.900000      48.100000     371.000000    145.000000

            Sunshine  WindGustSpeed   WindSpeed9am   WindSpeed3pm  \
count  75625.000000  135197.000000  143693.000000  142398.000000
mean       7.611178      40.035230      14.043426      18.662657
std        3.785483      13.607062       8.915375       8.809800
min        0.000000       6.000000       0.000000       0.000000
25%        4.800000      31.000000       7.000000      13.000000
50%        8.400000      39.000000      13.000000      19.000000
```

```
75%       10.600000      48.000000      19.000000      24.000000
max       14.500000     135.000000     130.000000      87.000000

         Humidity9am    Humidity3pm   Pressure9am    Pressure3pm  \
count  142806.000000  140953.000000  130395.00000  130432.000000
mean       68.880831      51.539116    1017.64994    1015.255889
std        19.029164      20.795902       7.10653       7.037414
min         0.000000       0.000000     980.50000     977.100000
25%        57.000000      37.000000    1012.90000    1010.400000
50%        70.000000      52.000000    1017.60000    1015.200000
75%        83.000000      66.000000    1022.40000    1020.000000
max       100.000000     100.000000    1041.00000    1039.600000

          Cloud9am      Cloud3pm        Temp9am       Temp3pm
count  89572.000000  86102.000000  143693.000000  141851.00000
mean       4.447461      4.509930      16.990631      21.68339
std        2.887159      2.720357       6.488753       6.93665
min        0.000000      0.000000      -7.200000      -5.40000
25%        1.000000      2.000000      12.300000      16.60000
50%        5.000000      5.000000      16.700000      21.10000
75%        7.000000      7.000000      21.600000      26.40000
max        9.000000      9.000000      40.200000      46.70000
```

By looking at this table, we can see some useful characteristic about these attributes:

- The count of attributes does not correspond with the count of rows, so some rows does not have a value for that specific attribute
- Some attributes goes from 0 to 100 (Humidity attributes), others goes to negative values (Temp), others has small range such as from 0 to 9 (Cloud) and Pressures goes above 1000
- From previous examination, we get to the conclusion that these attributes has different scales, so we need them scale down/up so all attributes has the same scale

Now, let's take a look at the categorical attributes

[ ]:
```
origDataframe.describe(include='all').drop(columns=origDataframe.describe().
↪columns)
```

[ ]:
```
              Date  Location WindGustDir WindDir9am WindDir3pm RainToday  \
count       145460    145460      135134     134894     141232    142199
unique        3436        49          16         16         16         2
top     2013-11-12  Canberra           W          N         SE        No
freq            49      3436        9915      11758      10838    110319
mean           NaN       NaN         NaN        NaN        NaN       NaN
std            NaN       NaN         NaN        NaN        NaN       NaN
min            NaN       NaN         NaN        NaN        NaN       NaN
25%            NaN       NaN         NaN        NaN        NaN       NaN
50%            NaN       NaN         NaN        NaN        NaN       NaN
75%            NaN       NaN         NaN        NaN        NaN       NaN
```

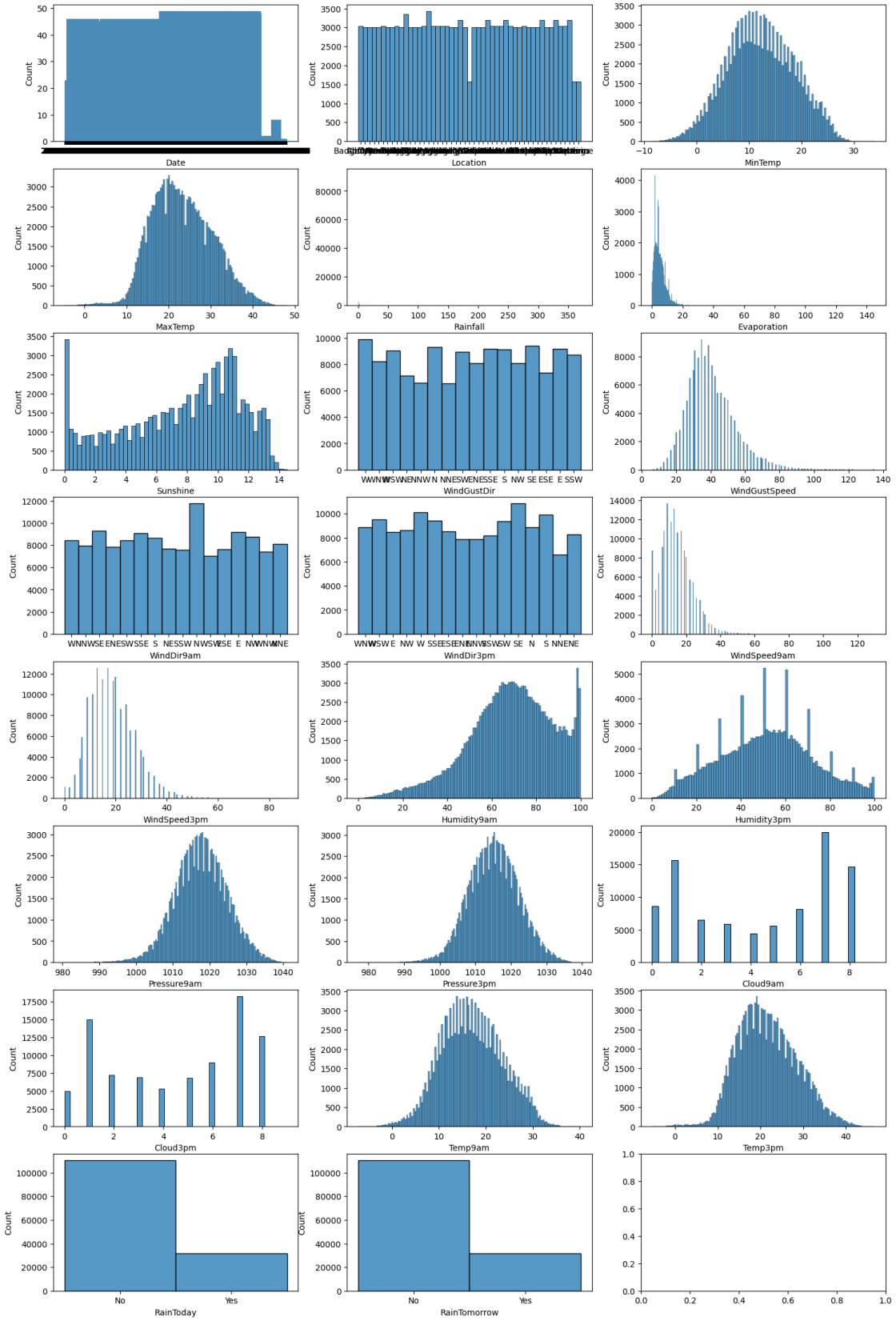
```
max             NaN       NaN          NaN        NaN        NaN       NaN

       RainTomorrow
count        142193
unique            2
top              No
freq         110316
mean            NaN
std             NaN
min             NaN
25%             NaN
50%             NaN
75%             NaN
max             NaN
```

We can see unique values, as well as the most occurring value with its frequency. For example, attribute WindDir9am has 16 unique categorical values with value 'N' (North) the most occurring one and its frequency is 11758 out of 134894.

1.4.2 Attribute distributions

Now let's take a look at distribution of attributes. We'll use different plots to visualize the distribution. Specifically, I'll use histograms, box plots, [add missing ones]

[ ]:
```
fig, axes = plt.subplots(8, 3, figsize=(18, 28))
#fig.suptitle('Attribute distributions')

rowIndex = 0
columnIndex = 0
for column in origDataframe.columns:
    sns.histplot(ax=axes[rowIndex, columnIndex], data=origDataframe[column])

    if columnIndex == 2:
        rowIndex += 1
        columnIndex = 0
    else:
        columnIndex += 1
```


Date
Location
MinTemp
MaxTemp
Rainfall
Evaporation
Sunshine
WindGustDir
WindGustSpeed
WindDir9am
WindDir3pm
WindSpeed9am
WindSpeed3pm
Humidity9am
Humidity3pm
Pressure9am
Pressure3pm
Cloud9am
Cloud3pm
Temp9am
Temp3pm
RainToday
RainTomorrow
No
Yes
Count

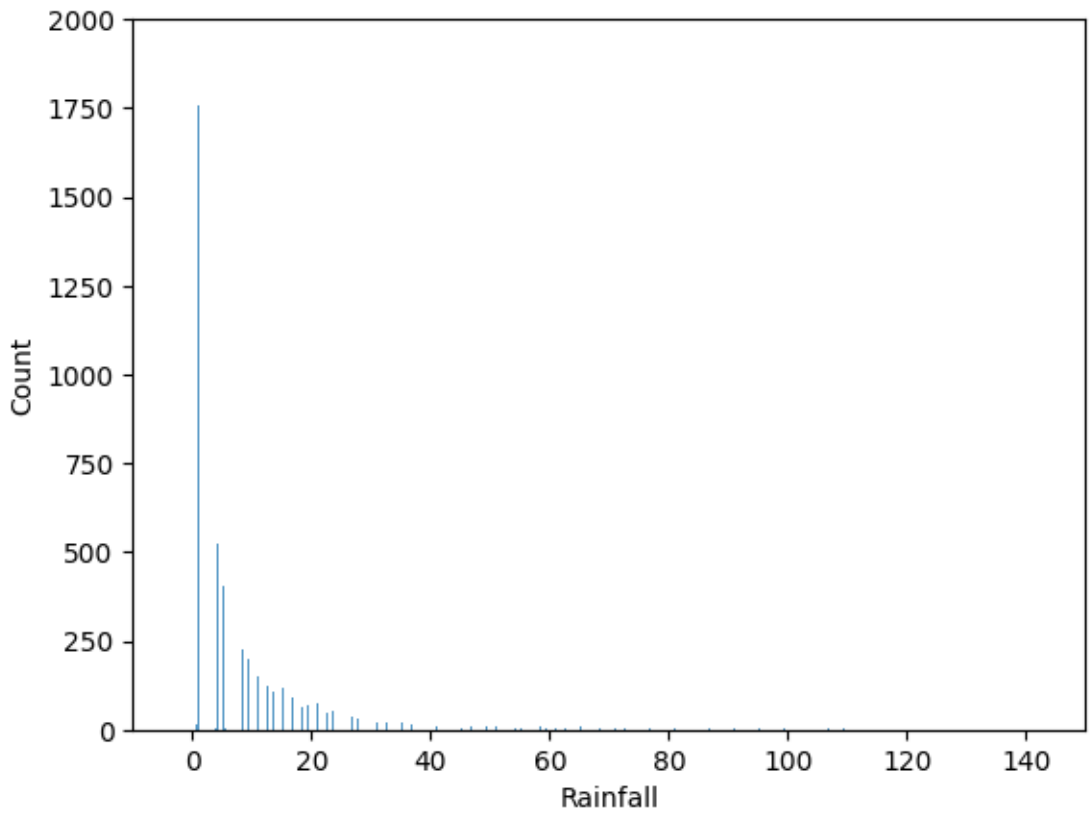
I've plotted histograms for all attributes.

- Attributes 'Date', 'Location' has uniform distribution with a few outliers
- Attributes 'WindGustDir', 'WindDir9am', 'WindDir3pm' has distribution close to uniform, 'WindDir9am' can also be considered as Gaussian (normal) distribution
- Other than mentioned attributes and 'RainToday', 'RainTomorrow', we notice that every attribute has Gaussian (normal) distribution, which is related to the fact that distributions gathered from environment tends to have Gaussian (normal) distribution.
- 'Cloud9am' and 'Cloud3pm' attributes have 2 peaks of Gaussian (normal) distribution
- Distribution for 'RainToday' and 'RainTomorrow' looks almost identical

Let's zoom a little bit to the 'Rainfall' column to see the distribution

[ ]:
```
sns.histplot(origDataframe['Rainfall'])
plt.ylim(0, 2000)
plt.xlim(-10, 150)
```

[ ]:
```
(-10.0, 150.0)
```



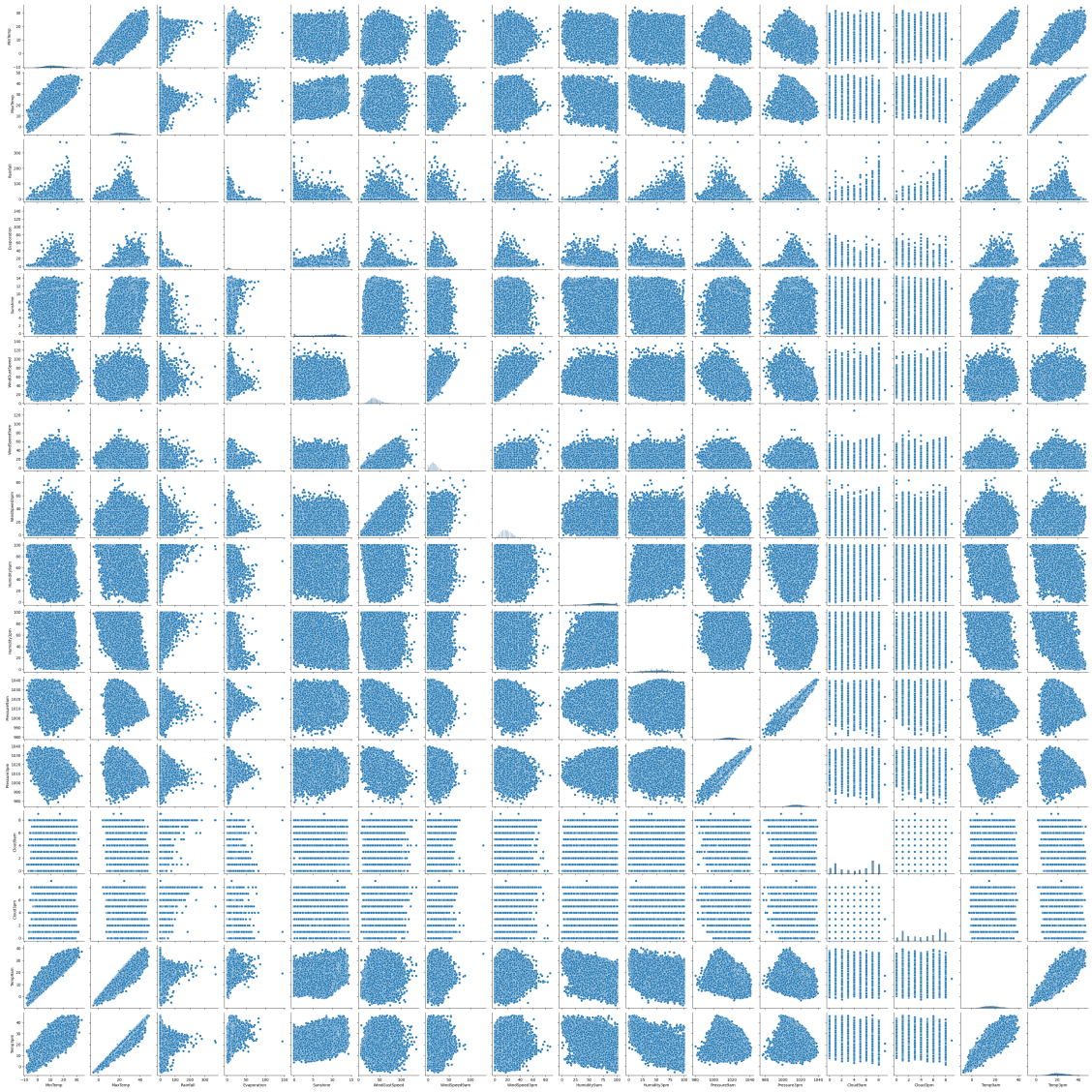
1.4.3 Attributes covariance

Recall that attributes has weak covariance between each other when their 'scatter' plot looks like a circle and has stronger covariance in case of ellipse.

I've used seaborn's pairplot to plot all pairs of attributes, so we can take a look at those covariances.

[ ]:
```
sns.pairplot(origDataframe)
```

[ ]:
```
<seaborn.axisgrid.PairGrid at 0x225d2894280>
```

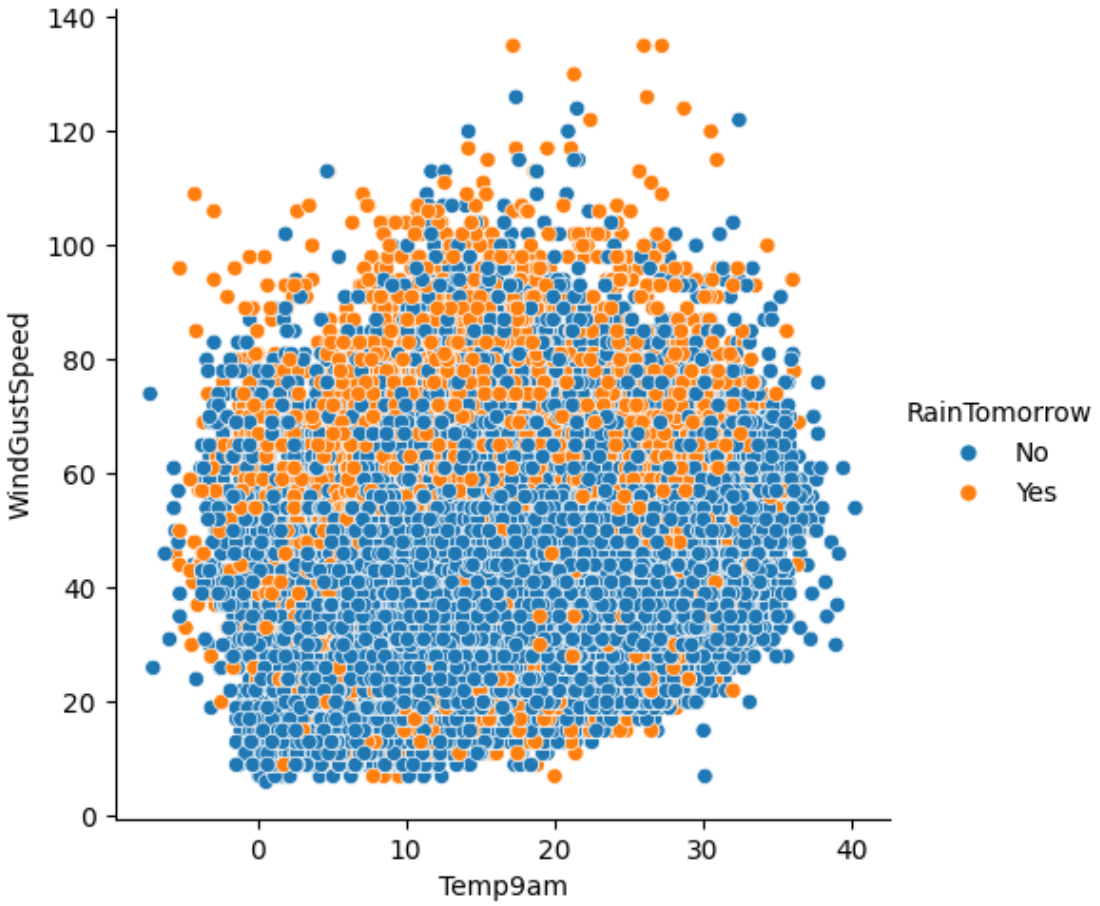


1.4.4 Closer look on the covariance

- Below I've plotted one of the most weak covariance in the dataset. The attributes 'Temp9am' and 'WindGustSpeed' does not relate between each other very much.

[ ]:
```
sns.relplot(origDataframe, x='Temp9am', y='WindGustSpeed', hue='RainTomorrow')
```

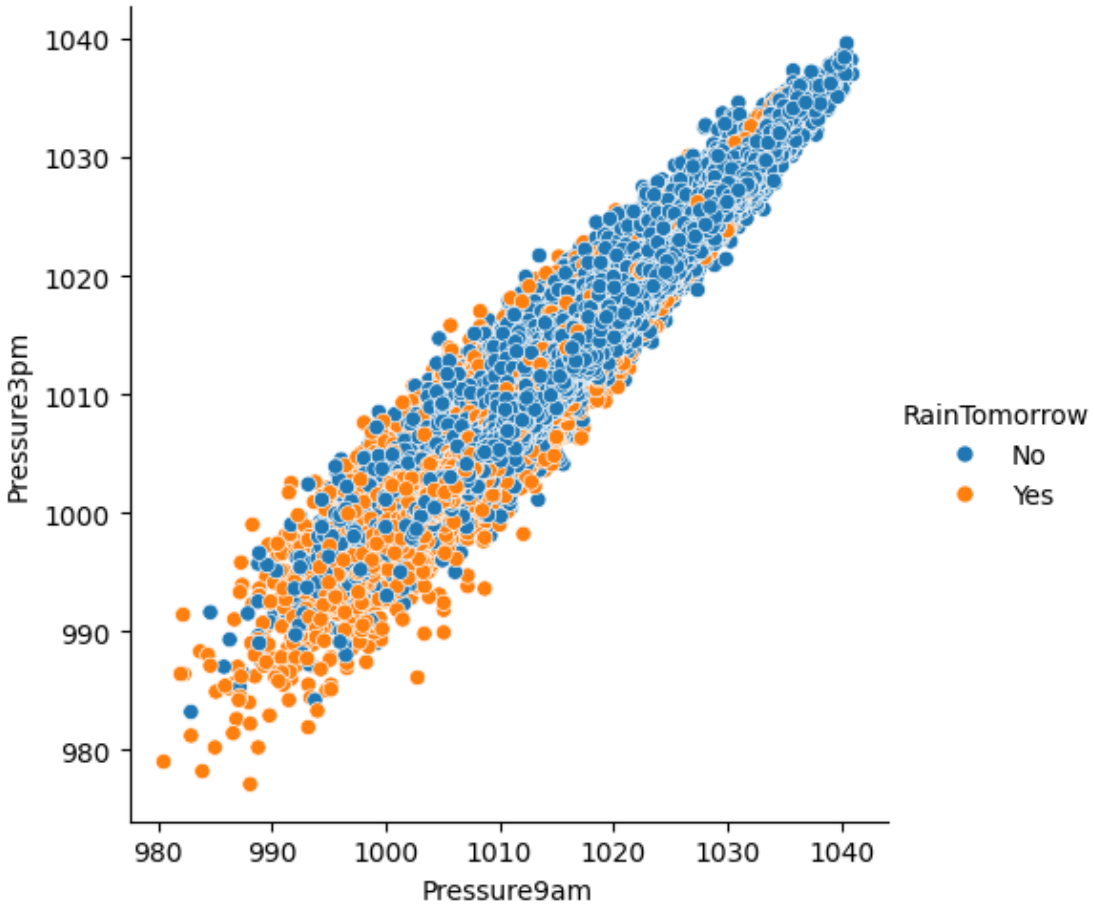
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x22609c39870>
```



- Now let's take a look at strong positive covariance

[ ]:
```
sns.relplot(origDataframe, x='Pressure9am', y='Pressure3pm', hue='RainTomorrow')
```

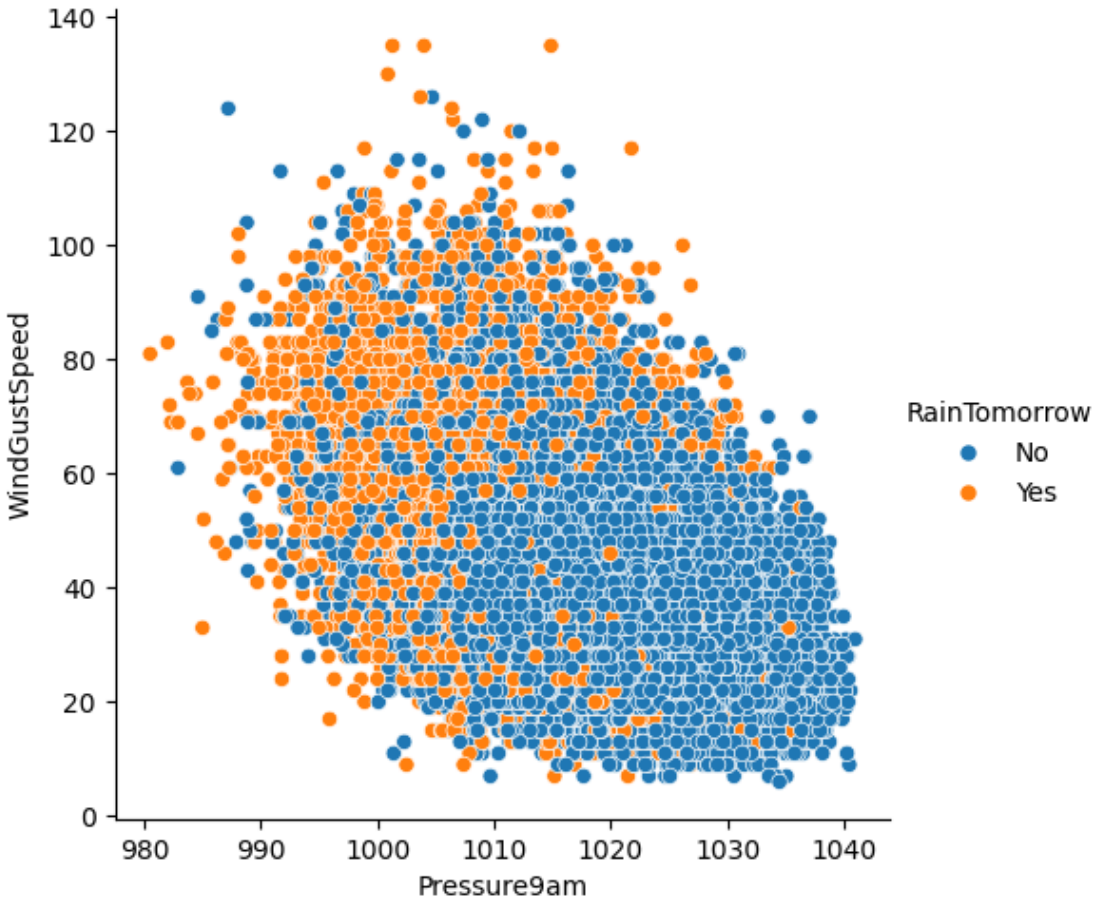
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x2262ba1fdc0>
```



- Example of negative covariance, although not as strong as the previous one

[ ]:
```
sns.relplot(origDataframe, x='Pressure9am', y='WindGustSpeed',␣
↪hue='RainTomorrow')
```

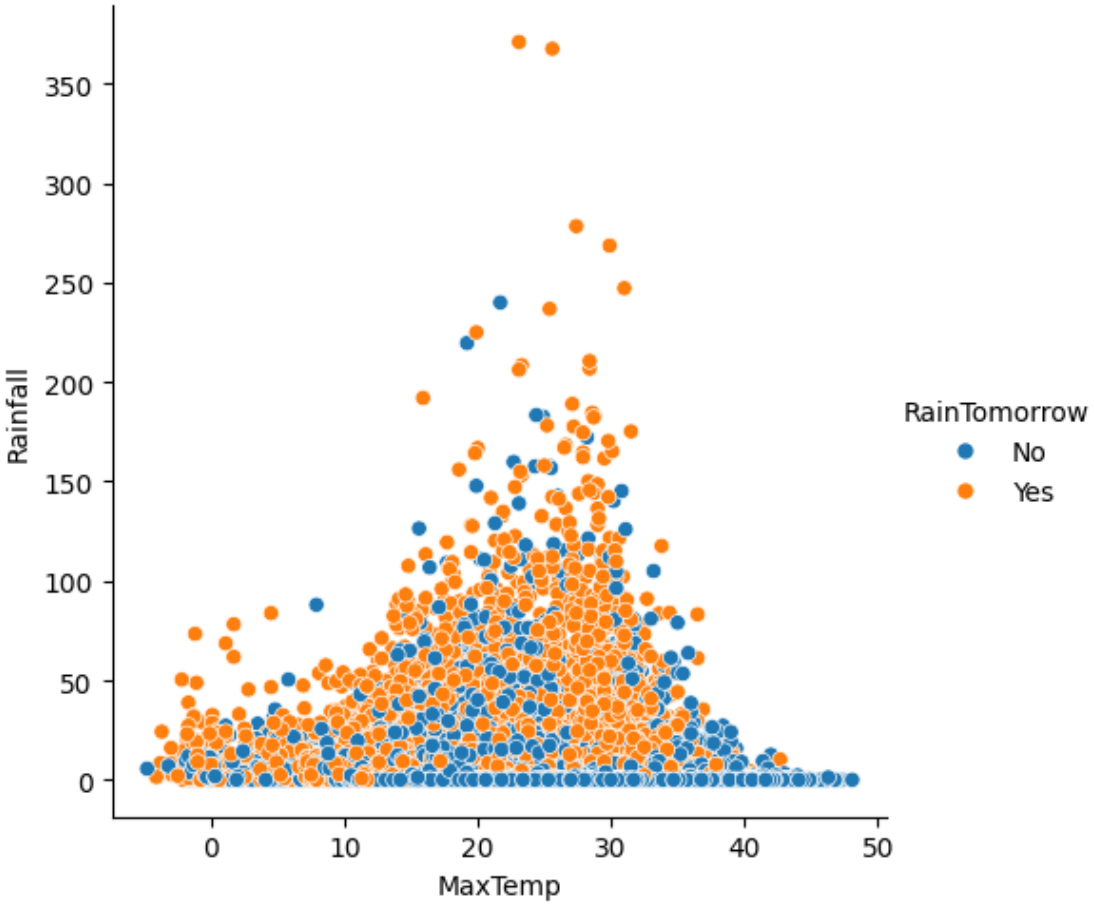
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x226376615d0>
```



- Some plots are interesting such this one. We can clearly observe that the higher rainfalls tends to have temperature between 15 to 30 degrees.

[ ]:
```
sns.relplot(origDataframe, x='MaxTemp', y='Rainfall', hue='RainTomorrow')
```

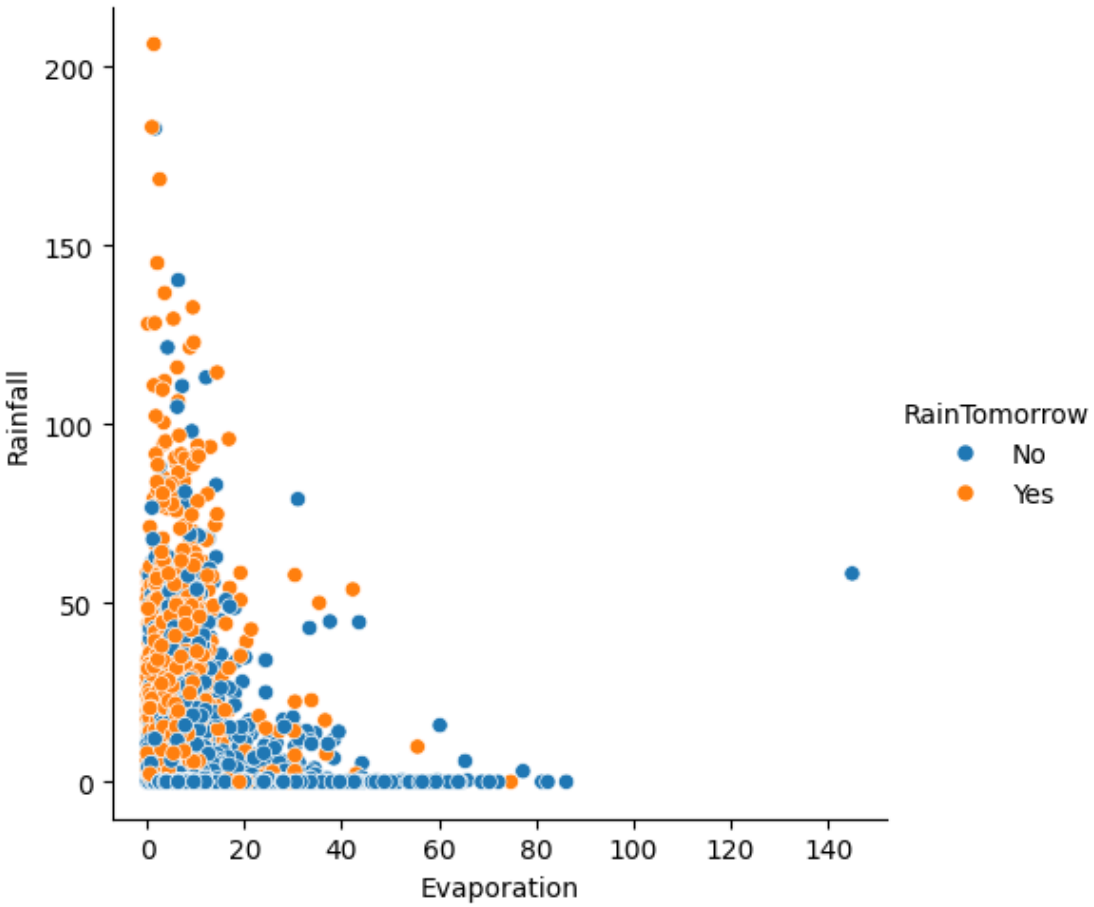
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x22637640940>
```



- Also during rainfall, there's less evaporation

[ ]:
```
sns.relplot(origDataframe, x='Evaporation', y='Rainfall', hue='RainTomorrow')
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x2263a53caf0>
```



1.4.5 Attribute correlation

Now let's take a look at the correlation. Correlation give us the measure of how strong or weak is the relation between attributes.

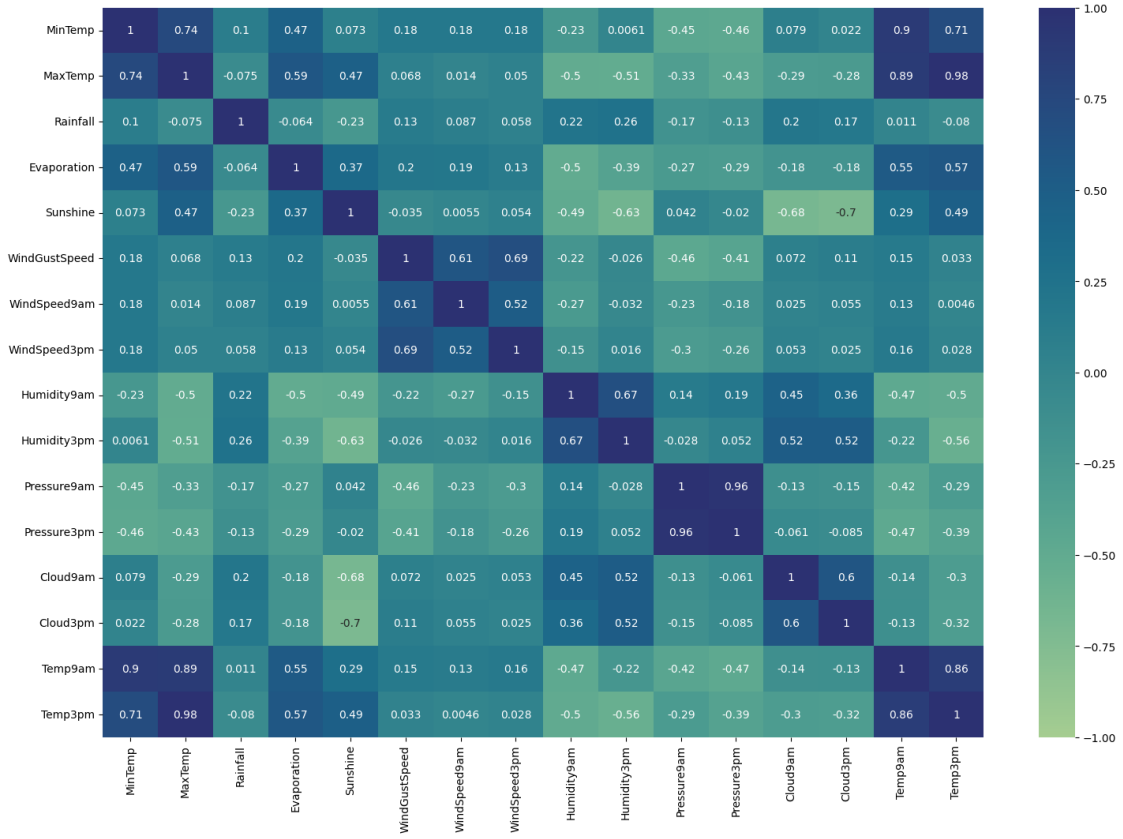
Select only attributes with numerical values

[ ]:
```
dataframe = origDataframe.loc[:, origDataframe.describe().columns].copy()
```

Plot heatmap

[ ]:
```
plt.figure(figsize=(18,12))
sns.heatmap(dataframe.corr(), cmap='crest', vmin=-1, vmax=1, annot=True)
```

[ ]:
```
<Axes: >
```



By plotting heatmap, we'll get insights about correlation between attributes:

- Some attributes are highly correlated, such as 'MaxTemp' and 'MinTemp', 'Temp9am' and 'MinTemp', 'Humidity9am' and 'Humidity3pm' and others with positive correlation
- Other attributes has negative correlation, such as 'Cloud3pm' and 'Sunshine', 'Temp3pm' and 'Humidity3pm', and so on
- The biggest correlation has attributes 'Temp3pm' and MaxTemp with value 0.98 (and it is positive correlation), which is close to 1 (the maximum possible correlation)
- The smallest correlation has attributes 'WindSpeed9am' and 'Temp3pm' with value 0.0046

1.5 Clustering

- Algorithm that groups records into sub-groups based on their similarity between each other (meaning similarity in attributes)

1.5.1 K-means algorithm

- We define the number of groups "K" (clusters)

Brief algorithm overview:

- Create K random centroids (points)

- Do iteratively:
  - Assign all examples from training set to the closest centroid (using Euclidean distance)
  - Move centroids by their means (Mean is computed for every centroid from assigned examples to them)

Before we can use our Clustering algorithm, we need to drop not relevant attributes

[ ]:
```
origDataframe
```

[ ]:
```
             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 WindDir3pm  \
0            NaN           W           44.0          W        WNW
1            NaN         WNW           44.0        NNW        WSW
2            NaN         WSW           46.0          W        WSW
3            NaN          NE           24.0         SE          E
4            NaN           W           41.0        ENE         NW
…            …             …              …          …          …
145455       NaN           E           31.0         SE        ENE
145456       NaN         NNW           22.0         SE          N
145457       NaN           N           37.0         SE        WNW
145458       NaN          SE           28.0        SSE          N
145459       NaN         NaN            NaN        ESE        ESE

        WindSpeed9am  WindSpeed3pm  Humidity9am  Humidity3pm  Pressure9am  \
0               20.0          24.0         71.0         22.0       1007.7
1                4.0          22.0         44.0         25.0       1010.6
2               19.0          26.0         38.0         30.0       1007.6
3               11.0           9.0         45.0         16.0       1017.6
4                7.0          20.0         82.0         33.0       1010.8
…                …             …            …            …          …
145455          13.0          11.0         51.0         24.0       1024.6
145456          13.0           9.0         56.0         21.0       1023.5
145457           9.0           9.0         53.0         24.0       1021.0
145458          13.0           7.0         51.0         24.0       1019.4
145459          17.0          17.0         62.0         36.0       1020.2
```

```
        Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm RainToday  \
0            1007.1       8.0       NaN     16.9     21.8         No
1            1007.8       NaN       NaN     17.2     24.3         No
2            1008.7       NaN       2.0     21.0     23.2         No
3            1012.8       NaN       NaN     18.1     26.5         No
4            1006.0       7.0       8.0     17.8     29.7         No
…               …       …         …        …        …          …
145455       1020.3       NaN       NaN     10.1     22.4         No
145456       1019.1       NaN       NaN     10.9     24.5         No
145457       1016.8       NaN       NaN     12.5     26.1         No
145458       1016.5       3.0       2.0     15.1     26.0         No
145459       1017.9       8.0       8.0     15.0     20.9         No

       RainTomorrow
0                No
1                No
2                No
3                No
4                No
…               …
145455           No
145456           No
145457           No
145458           No
145459          NaN

[145460 rows x 23 columns]
```

By examining the available attributes in the training set, I concluded that every attribute is relevant in this scenario.

Date is a good candidate to be not relevant, but naturally there is less rain during summer than during the autumn, so thats the reason I take the attribute as well.

Location is relevant, some places have more rain than others (Tropical rainforest x desert)

We just **need** to drop the label (target value) and the categorical values, either by droping them or converting them to numerical values (e.g. by one-hot encoding or)

[ ]:
```
from sklearn.cluster import KMeans
```

Let's drop those rows with NaN values, but keep in mind that the clustering can be affected by this.

[ ]:
```
clusterDataframe = dataframe.dropna().copy()
clusterDataframeArray = clusterDataframe.values
print(clusterDataframeArray)
```

```
[[17.9 35.2  0.  …  5.  26.6 33.4]
```

```
[18.4 28.9  0.  …  1.  20.3 27. ]
[19.4 37.6  0.  …  6.  28.7 34.9]
…
[20.7 32.8  0.  …  0.  24.8 32.1]
[19.5 31.8  0.  …  1.  24.8 29.2]
[20.2 31.7  0.  …  5.  25.4 31. ]]
```

1.5.2 Use K-means clustering algorithm

We'll use the prepared dataframe for that called clusterDataframe

Prepare the kMean model

[ ]:
```
kMeans = KMeans(n_clusters=4, random_state=0, n_init='auto')
```

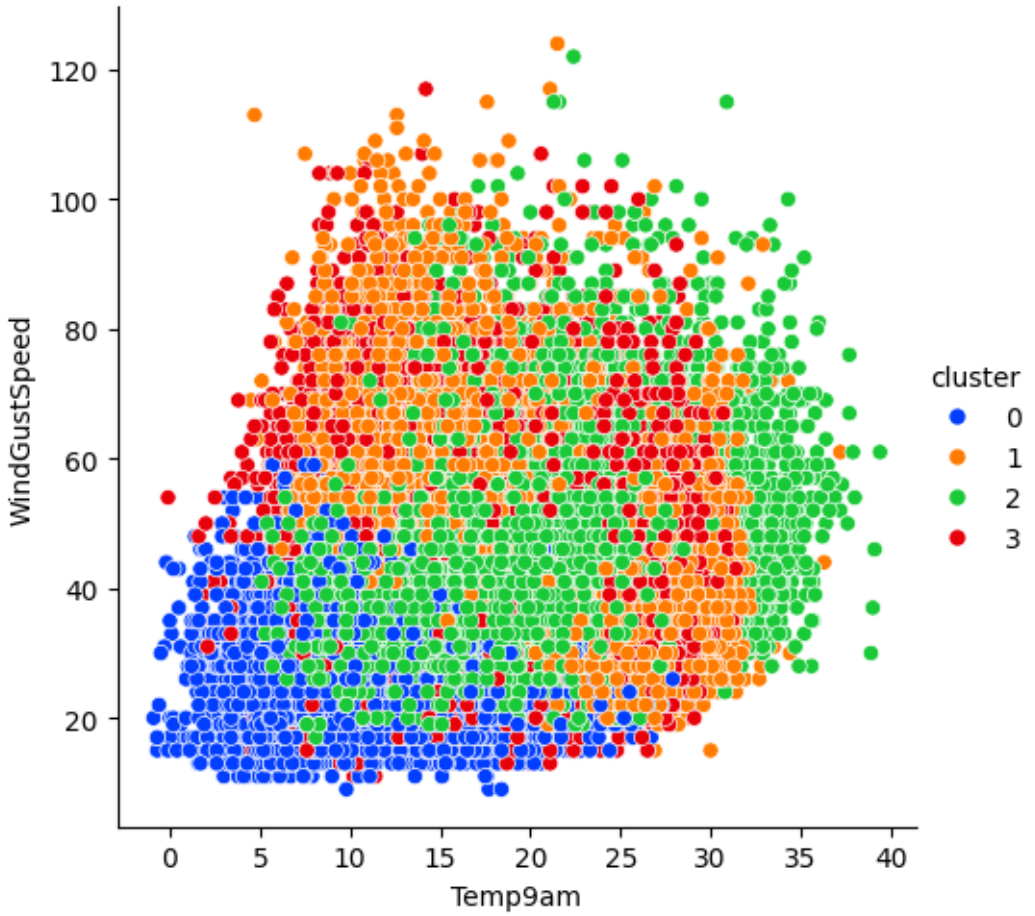
Fit the KMeans algorithm Then make predictions on the trained set and let's save cluster values to the dataframe

[ ]:
```
kMeans.fit(clusterDataframeArray)
predictedValues = kMeans.predict(clusterDataframeArray)

clusterDataframe['cluster'] = kMeans.labels_
```

Plot the clusters on some attributes

[ ]:
```
palette = sns.color_palette("bright", 4)
sns.relplot(clusterDataframe, x='Temp9am', y='WindGustSpeed', hue='cluster',␣
 ↪palette=palette)
```

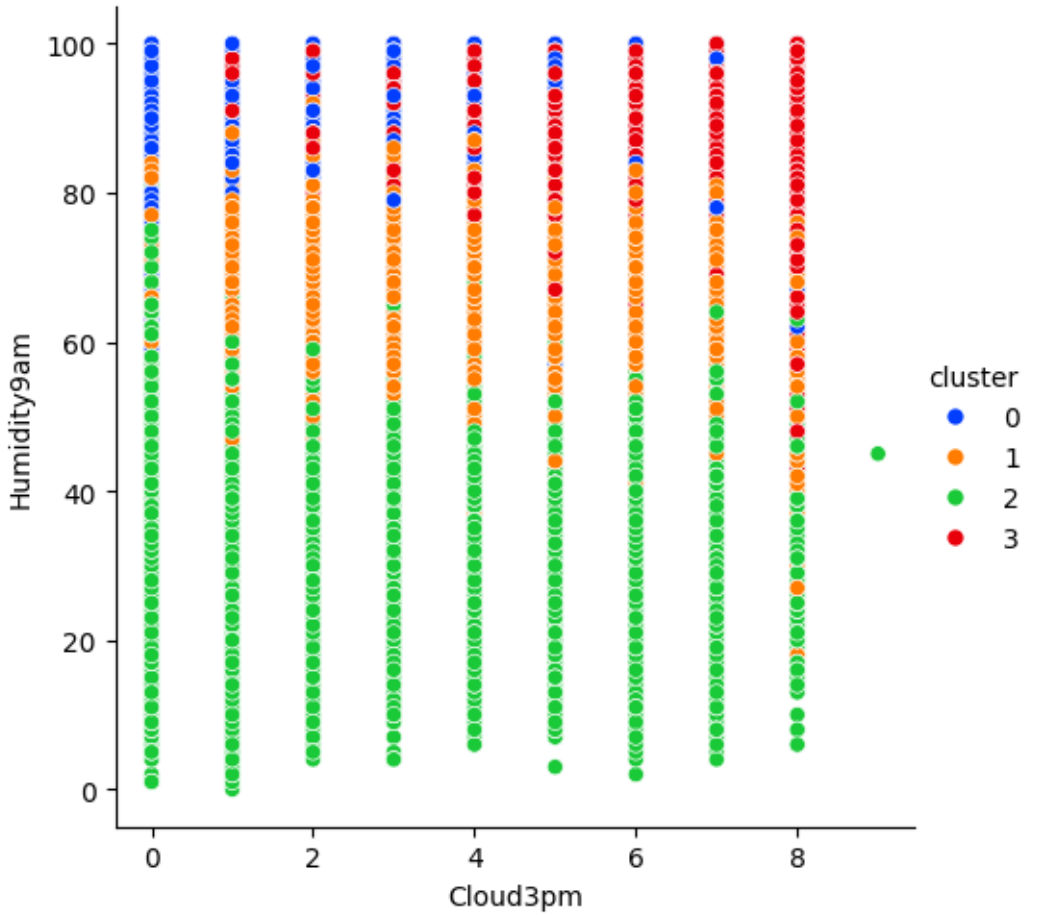
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x22639b15900>
```



- As we can see from the plot above, one group is located at the top of other (the blue one in this case) indicating that this group is different than the others on this attribute correlation

[ ]:
```
sns.relplot(clusterDataframe, x='Cloud3pm', y='Humidity9am', hue='cluster',␣
↪palette=palette)
```

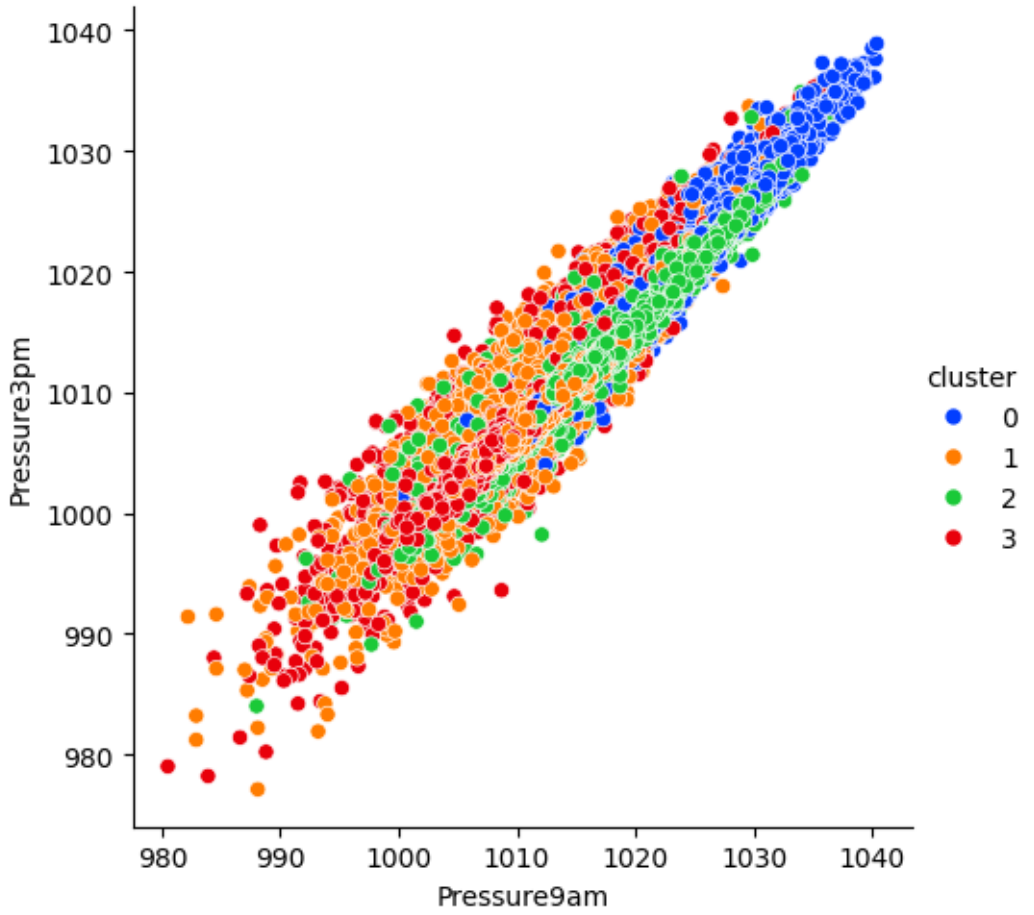
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x22639d47550>
```



- Using different attributes, we can see that the dominant group is green and it takes first half of the plot

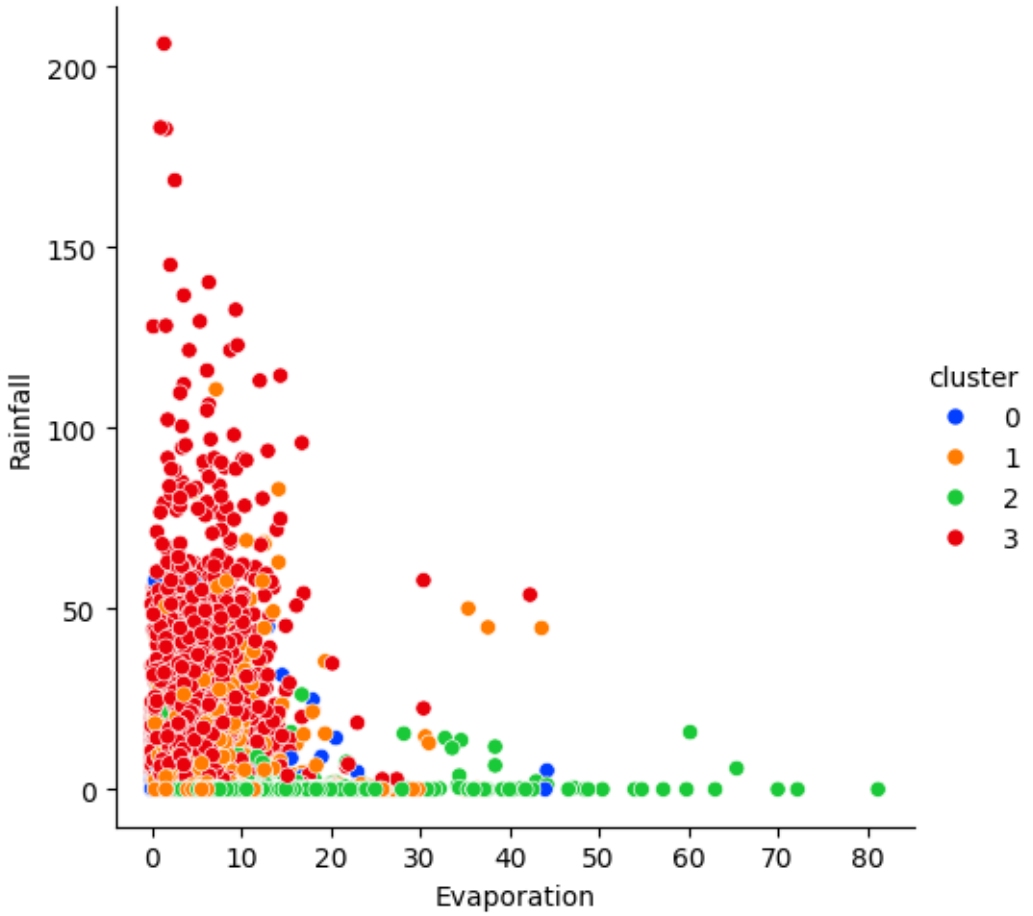
[ ]:
```
sns.relplot(clusterDataframe, x='Pressure9am', y='Pressure3pm', hue='cluster',␣
↪palette=palette)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x22639dcd8a0>
```



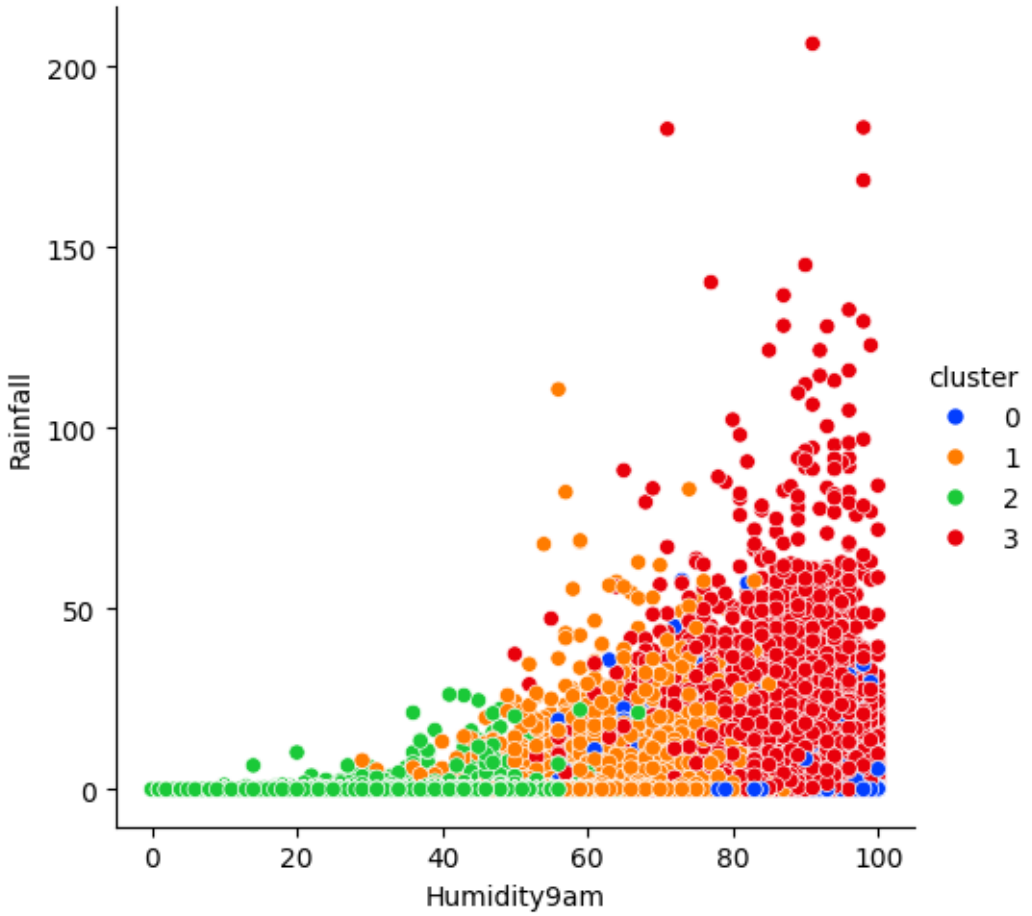
[ ]:
```
sns.relplot(clusterDataframe, x='Evaporation', y='Rainfall', hue='cluster',␣
↪palette=palette)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x22639ebd660>



[ ]:
```
sns.relplot(clusterDataframe, x='Humidity9am', y='Rainfall', hue='cluster',␣
↪palette=palette)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x2263adb5540>



1.5.3 Let's now use different value for K

When working with clustering, use different value for K variable. Some of the clustering may be better than others.

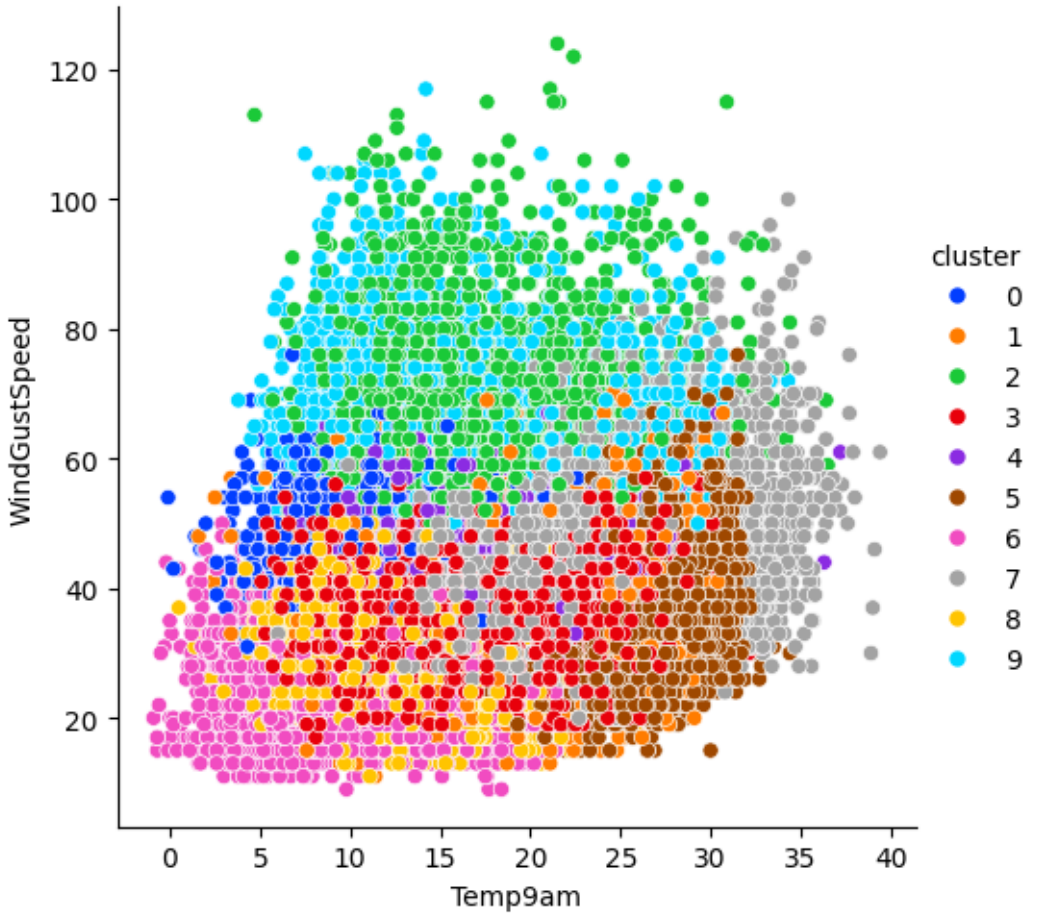
Also we can use different clustering algorithm called Hierarchical clustering, but I worked in the next section again with KMeans, but this time with 10 clusters and visualized them.

[ ]:
```
clusterDataframe = clusterDataframe.drop('cluster', axis=1)
clusterDataframeArray = clusterDataframe.values
print(clusterDataframeArray)

kMeans = KMeans(n_clusters=10, random_state=0, n_init='auto')

kMeans.fit(clusterDataframeArray)
predictedValues = kMeans.predict(clusterDataframeArray)

clusterDataframe['cluster'] = kMeans.labels_
```

```
[[17.9 35.2  0.  …  5.  26.6 33.4]
 [18.4 28.9  0.  …  1.  20.3 27. ]
 [19.4 37.6  0.  …  6.  28.7 34.9]
 …
 [20.7 32.8  0.  …  0.  24.8 32.1]
 [19.5 31.8  0.  …  1.  24.8 29.2]
 [20.2 31.7  0.  …  5.  25.4 31. ]]
```

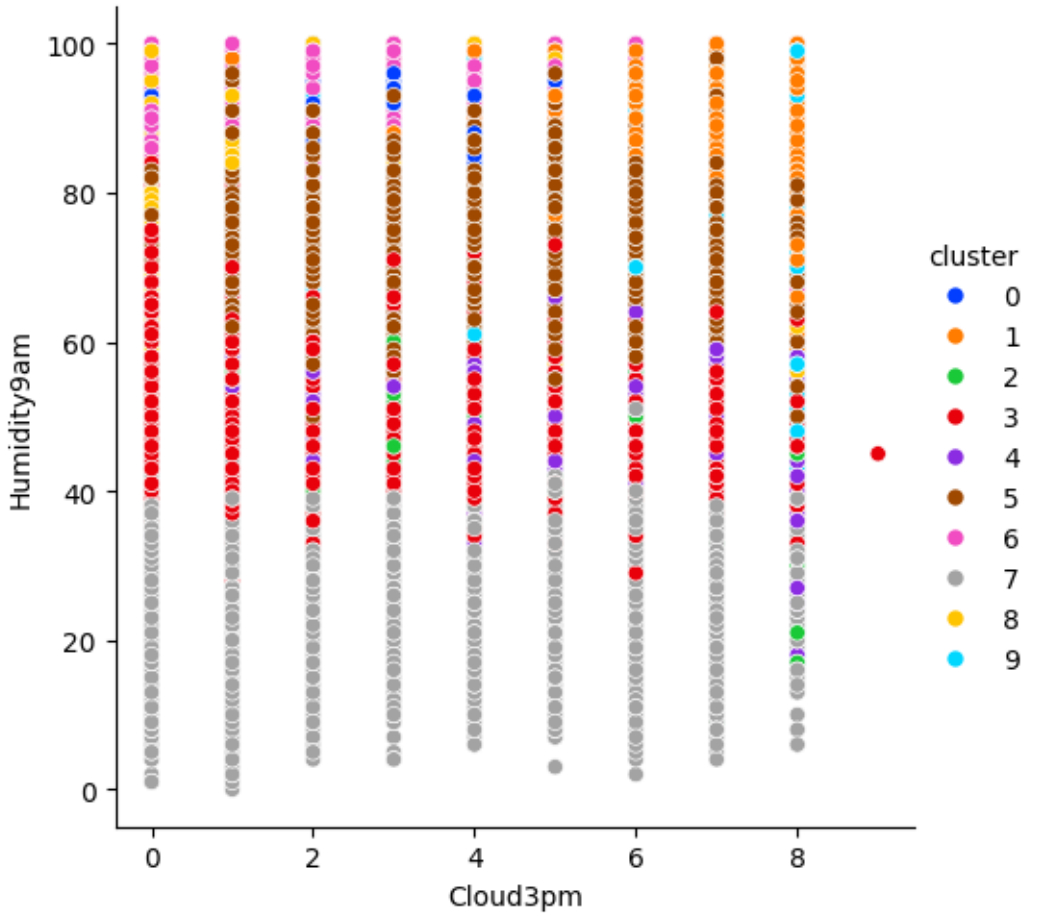
[ ]:
```
palette = sns.color_palette("bright", 10)
sns.relplot(clusterDataframe, x='Temp9am', y='WindGustSpeed', hue='cluster',␣
 ↪palette=palette)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x22639ad3fa0>
```



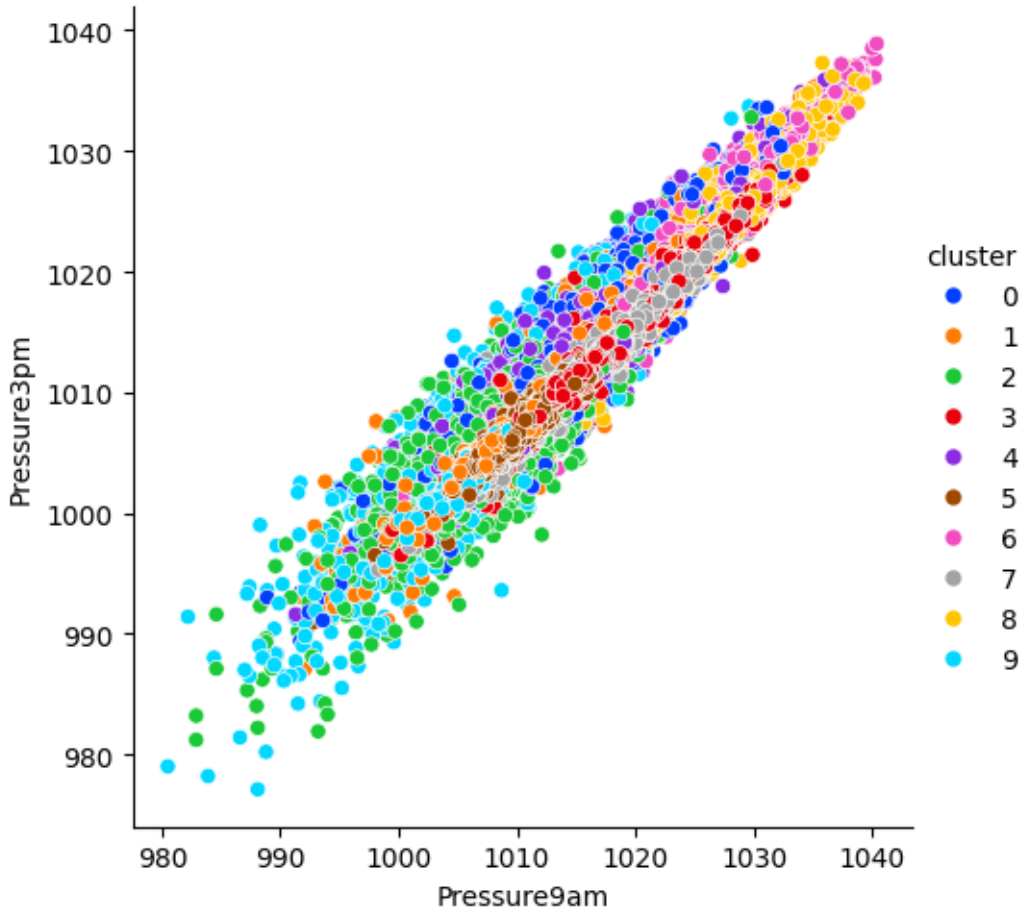
[ ]:
```
sns.relplot(clusterDataframe, x='Cloud3pm', y='Humidity9am', hue='cluster',␣
 ↪palette=palette)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x2263b877880>
```



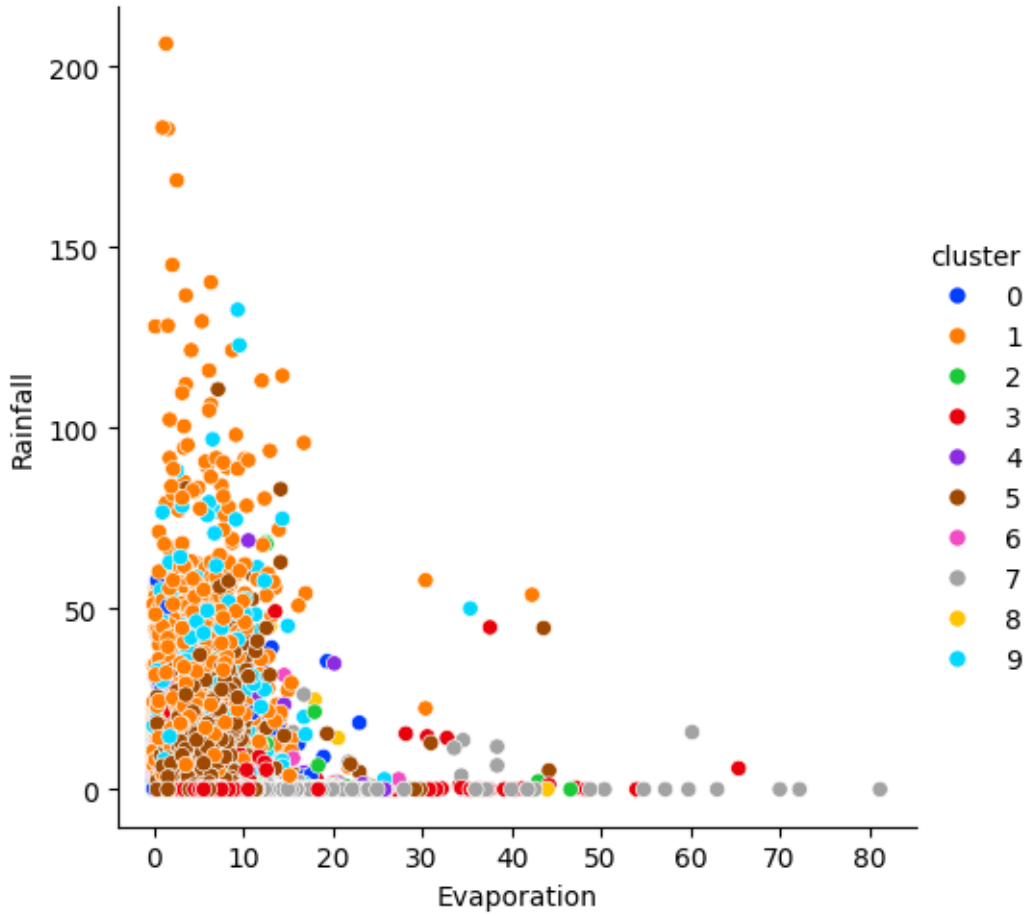
[ ]:
```
sns.relplot(clusterDataframe, x='Pressure9am', y='Pressure3pm', hue='cluster',␣
↪palette=palette)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x22644247f10>



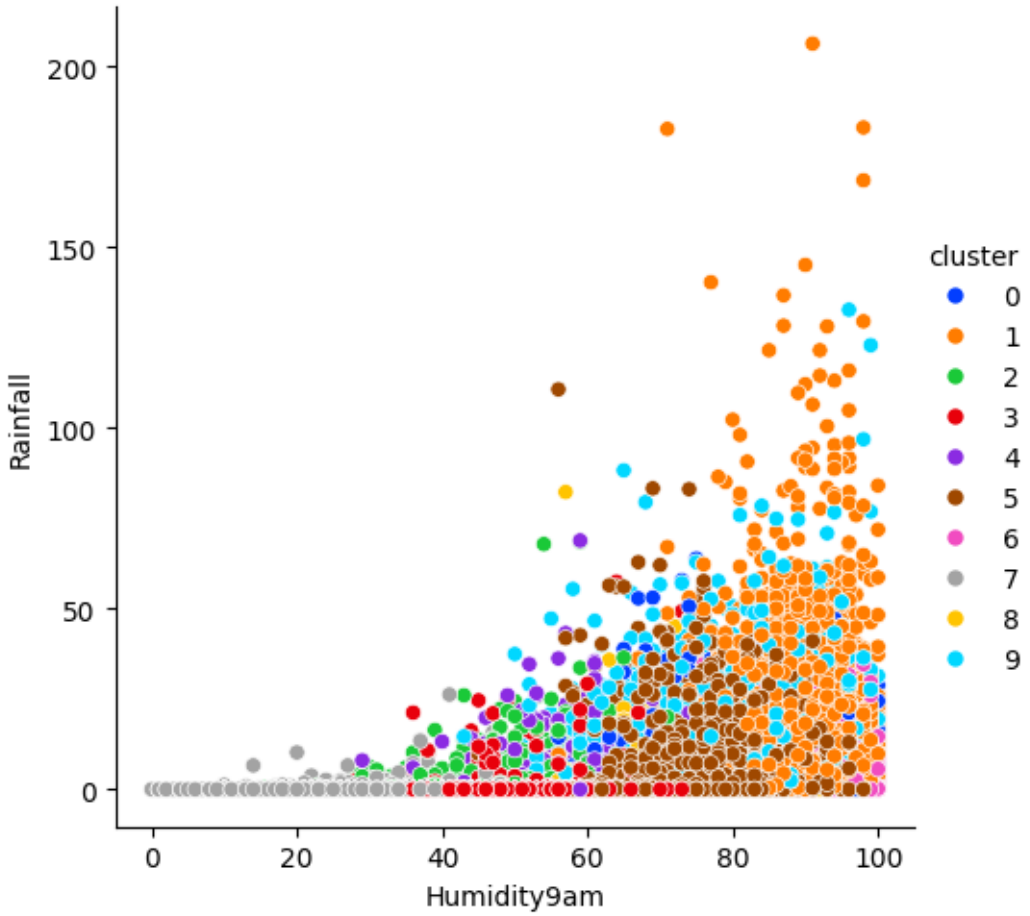
[ ]:
```
sns.relplot(clusterDataframe, x='Evaporation', y='Rainfall', hue='cluster',␣
↪palette=palette)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x226441d5d50>
```



[ ]:
```
sns.relplot(clusterDataframe, x='Humidity9am', y='Rainfall', hue='cluster',␣
↪palette=palette)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x226448e38b0>
```



2 Summary

In this notebook, we took a look at the Australia weather dataset. Specifically, we examined the dataset by:

- By **looking at the attributes** (Whether or not they are numerical/categorical, what type of data they consist of)
- By **Attribute distribution** (What is the distribution of each attribute)
- By **Attribute covariance** (How one attribute depends on the others)
- By **Attribute correlation** (How strong is the relation between attributes)

Also we used K-Means algorithm to perform Clustering on the dataset (Firstly, with K = 4 and then with K = 10). The clustering algorithm tried to group examples that are similar with each others and gave us results as we saw in the susbequent plots.