weather-prediction-fi

December 9, 2024

1 Requirements and Impots

[1]:
```
pip install -r requirements.txt
```

```
Requirement already satisfied: numpy in /opt/conda/lib/python3.11/site-packages
(from -r requirements.txt (line 1)) (1.24.4)
Requirement already satisfied: pandas in /opt/conda/lib/python3.11/site-packages
(from -r requirements.txt (line 2)) (2.0.3)
Requirement already satisfied: matplotlib in /opt/conda/lib/python3.11/site-
packages (from -r requirements.txt (line 3)) (3.8.0)
Requirement already satisfied: seaborn in /opt/conda/lib/python3.11/site-
packages (from -r requirements.txt (line 4)) (0.13.0)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.11/site-
packages (from -r requirements.txt (line 5)) (1.3.1)
Requirement already satisfied: scipy in /opt/conda/lib/python3.11/site-packages
(from -r requirements.txt (line 6)) (1.11.3)
Requirement already satisfied: umap-learn in /opt/conda/lib/python3.11/site-
packages (from -r requirements.txt (line 7)) (0.5.7)
Requirement already satisfied: umap in /opt/conda/lib/python3.11/site-packages
(from -r requirements.txt (line 8)) (0.1.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.11/site-packages (from pandas->-r requirements.txt (line
2)) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /opt/conda/lib/python3.11/site-
packages (from pandas->-r requirements.txt (line 2)) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in /opt/conda/lib/python3.11/site-
packages (from pandas->-r requirements.txt (line 2)) (2023.3)
Requirement already satisfied: contourpy>=1.0.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib->-r requirements.txt
(line 3)) (1.1.1)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.11/site-
packages (from matplotlib->-r requirements.txt (line 3)) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib->-r requirements.txt
(line 3)) (4.43.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib->-r requirements.txt
(line 3)) (1.4.5)
```

```
Requirement already satisfied: packaging>=20.0 in
/opt/conda/lib/python3.11/site-packages (from matplotlib->-r requirements.txt
(line 3)) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/python3.11/site-
packages (from matplotlib->-r requirements.txt (line 3)) (10.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/opt/conda/lib/python3.11/site-packages (from matplotlib->-r requirements.txt
(line 3)) (3.1.1)
Requirement already satisfied: joblib>=1.1.1 in /opt/conda/lib/python3.11/site-
packages (from scikit-learn->-r requirements.txt (line 5)) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/opt/conda/lib/python3.11/site-packages (from scikit-learn->-r requirements.txt
(line 5)) (3.2.0)
Requirement already satisfied: numba>=0.51.2 in /opt/conda/lib/python3.11/site-
packages (from umap-learn->-r requirements.txt (line 7)) (0.57.1)
Requirement already satisfied: pynndescent>=0.5 in
/opt/conda/lib/python3.11/site-packages (from umap-learn->-r requirements.txt
(line 7)) (0.5.13)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.11/site-packages
(from umap-learn->-r requirements.txt (line 7)) (4.66.1)
Requirement already satisfied: llvmlite<0.41,>=0.40.0dev0 in
/opt/conda/lib/python3.11/site-packages (from numba>=0.51.2->umap-learn->-r
requirements.txt (line 7)) (0.40.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.11/site-
packages (from python-dateutil>=2.8.2->pandas->-r requirements.txt (line 2))
(1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[2]:

```python
import pyspark
print(pyspark.__version__)
```

```
3.5.0
```

[3]:

```python
import numpy as np
import pandas as pd
from scipy import stats
from scipy.sparse import hstack
import matplotlib.pyplot as plt
import seaborn as sns

from pyspark.sql import SparkSession
from pyspark.ml.feature import VectorAssembler, StringIndexer

from pyspark.ml.classification import RandomForestClassifier


from pyspark.ml.evaluation import BinaryClassificationEvaluator
```

```
from pyspark.ml.classification import GBTClassifier
from pyspark.ml import Pipeline

from pyspark.ml.classification import LogisticRegression



from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans

import umap
from umap import UMAP


import warnings
```

2 Data Summary

[4]:
```
file_path = 'weatherAUS.csv'
try:
    df = pd.read_csv(file_path)
    print(f"File '{file_path}' loaded successfully.")
except FileNotFoundError:
    print(f"Error: The file '{file_path}' was not found. Please check the file␣
 ↪path and try again.")
    df = None

total_size = df.size
print("Total number of elements:", total_size)
```

```
File 'weatherAUS.csv' loaded successfully.
Total number of elements: 3345580
```

[5]:
```
print("Preview of the Dataset (Head):")
display(df.head())
```

```
Preview of the Dataset (Head):

         Date Location  MinTemp  MaxTemp  Rainfall  Evaporation  Sunshine  \
0  2008-12-01   Albury     13.4     22.9       0.6          NaN       NaN
1  2008-12-02   Albury      7.4     25.1       0.0          NaN       NaN
2  2008-12-03   Albury     12.9     25.7       0.0          NaN       NaN
3  2008-12-04   Albury      9.2     28.0       0.0          NaN       NaN
```

```
4  2008-12-05   Albury     17.5     32.3       1.0          NaN       NaN

  WindGustDir  WindGustSpeed WindDir9am  … Humidity9am  Humidity3pm  \
0           W           44.0          W  …        71.0         22.0
1         WNW           44.0        NNW  …        44.0         25.0
2         WSW           46.0          W  …        38.0         30.0
3          NE           24.0         SE  …        45.0         16.0
4           W           41.0        ENE  …        82.0         33.0

   Pressure9am  Pressure3pm  Cloud9am  Cloud3pm  Temp9am  Temp3pm  RainToday  \
0       1007.7       1007.1       8.0       NaN     16.9     21.8         No
1       1010.6       1007.8       NaN       NaN     17.2     24.3         No
2       1007.6       1008.7       NaN       2.0     21.0     23.2         No
3       1017.6       1012.8       NaN       NaN     18.1     26.5         No
4       1010.8       1006.0       7.0       8.0     17.8     29.7         No

   RainTomorrow
0            No
1            No
2            No
3            No
4            No

[5 rows x 23 columns]
```

[6]:
```python
print("\nSummary Statistics for Numerical Columns:")
numerical_summary = df.describe(include=[float, int])
display(numerical_summary)
```

```
Summary Statistics for Numerical Columns:

             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
```

[7]:
```
print("\nSummary Statistics for Categorical Columns:")
categorical_summary = df.describe(include=[object])
display(categorical_summary)
```

```
Summary Statistics for Categorical 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

       RainTomorrow
count        142193
unique            2
top              No
freq         110316
```

[8]:
```
print("\nNull Values in Each Column:")
null_values = df.isnull().sum()
display(null_values)
```

```
Null Values in Each Column:

Date                 0
Location             0
MinTemp           1485
MaxTemp           1261
Rainfall          3261
Evaporation      62790
Sunshine         69835
WindGustDir      10326
WindGustSpeed    10263
WindDir9am       10566
WindDir3pm        4228
WindSpeed9am      1767
WindSpeed3pm      3062
Humidity9am       2654
Humidity3pm       4507
Pressure9am      15065
Pressure3pm      15028
Cloud9am         55888
Cloud3pm         59358
Temp9am           1767
Temp3pm           3609
RainToday         3261
RainTomorrow      3267
dtype: int64
```

3 Missing Values

[9]:

```python
binary_columns = ['RainToday', 'RainTomorrow']  # only for yes or no values
for col in binary_columns:
    if col in df.columns:
        mode_value = df[col].mode()[0]
        df[col].fillna(mode_value, inplace=True)
        print(f"Filled missing values in '{col}' with the mode: {mode_value}")
```

```
Filled missing values in 'RainToday' with the mode: No
Filled missing values in 'RainTomorrow' with the mode: No
```

[10]:

```python
# Fill missing values in numerical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
for col in numerical_columns:
    if df[col].isnull().sum() > 0:
        mean_value = df[col].mean()  #  can use median
        df[col].fillna(mean_value, inplace=True)
        print(f"Filled missing values in numerical column '{col}' with the mean:
 ↪ {mean_value}")
```

```
Filled missing values in numerical column 'MinTemp' with the mean:
12.19403438096892
Filled missing values in numerical column 'MaxTemp' with the mean:
23.22134827564685
Filled missing values in numerical column 'Rainfall' with the mean:
2.3609181499166656
Filled missing values in numerical column 'Evaporation' with the mean:
5.468231522922462
Filled missing values in numerical column 'Sunshine' with the mean:
7.6111775206611565
Filled missing values in numerical column 'WindGustSpeed' with the mean:
40.03523007167319
Filled missing values in numerical column 'WindSpeed9am' with the mean:
14.043425914971502
Filled missing values in numerical column 'WindSpeed3pm' with the mean:
18.662656778887342
Filled missing values in numerical column 'Humidity9am' with the mean:
68.88083133761887
Filled missing values in numerical column 'Humidity3pm' with the mean:
51.5391158755046
Filled missing values in numerical column 'Pressure9am' with the mean:
1017.6499397983052
Filled missing values in numerical column 'Pressure3pm' with the mean:
1015.2558888309618
Filled missing values in numerical column 'Cloud9am' with the mean:
4.4474612602152455
Filled missing values in numerical column 'Cloud3pm' with the mean:
4.509930082924903
Filled missing values in numerical column 'Temp9am' with the mean:
16.990631415587398
Filled missing values in numerical column 'Temp3pm' with the mean:
21.68339031800974
```

[11]:

```
categorical_columns = df.select_dtypes(include=['object']).columns
for col in categorical_columns:
    if col not in binary_columns and df[col].isnull().sum() > 0:  # Exclude Yes/
↪No columns already handled
        mode_value = df[col].mode()[0]
        df[col].fillna(mode_value, inplace=True)
        print(f"Filled missing values in categorical column '{col}' with the␣
↪mode: {mode_value}")
```

```
Filled missing values in categorical column 'WindGustDir' with the mode: W
Filled missing values in categorical column 'WindDir9am' with the mode: N
Filled missing values in categorical column 'WindDir3pm' with the mode: SE
```

[35]:
```
output_file_path = 'weatherAUS_updated.csv'

# Save the updated DF to a CSV file
df.to_csv(output_file_path, index=False)

print(f"\dataset saved successfully to '{output_file_path}'")
```

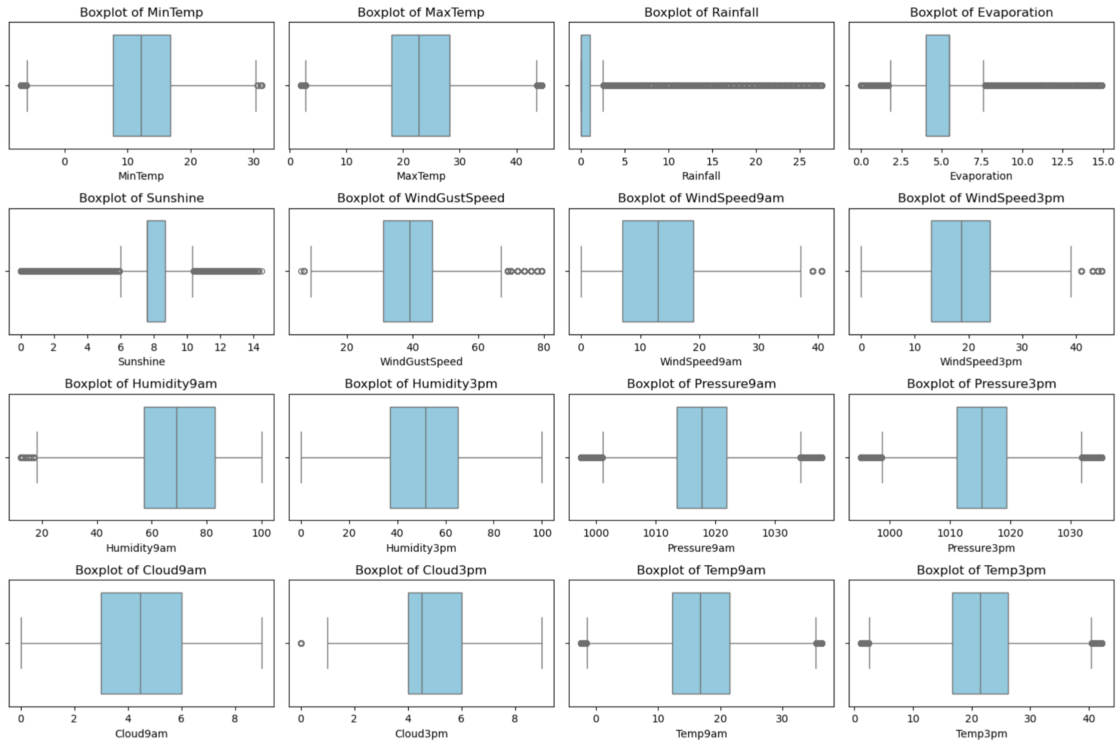
```
\dataset saved successfully to 'weatherAUS_updated.csv'
```

4 Outliers

[13]:
```
file_path = 'weatherAUS_updated.csv'
try:
    df = pd.read_csv(file_path)
    print(f"File '{file_path}' loaded successfully.")
except FileNotFoundError:
    print(f"Error: The file '{file_path}' was not found. Please check the file␣
 ↪path and try again.")
    df = None

total_size = df.size
print("Total number of elements:", total_size)
```

```
File 'weatherAUS_updated.csv' loaded successfully.
Total number of elements: 3345580
```

[33]:
```
# Only numerical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

plt.figure(figsize=(15, 10))

# Create boxplots for each numerical column
for i, col in enumerate(numerical_columns):
    plt.subplot(4, 4, i + 1)
    sns.boxplot(data=df, x=col, color='skyblue', fliersize=5)
    plt.title(f'Boxplot of {col}')
    plt.tight_layout()

# Show the plots
plt.show()
```



[14]:
```
from scipy.stats import zscore

# Select only numerical columns for Z-score calculation
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

# Initialize a dictionary to store outlier counts
outliers_info = {}
```

[15]:
```
for col in numerical_columns:
    # Calculate Z-scores for the column
    z_scores = zscore(df[col])

    # Identify outliers (where absolute Z-score > threshold)
    outliers = np.abs(z_scores) > 3

    # Get the count of outliers
    outlier_count = outliers.sum()  # Sum of True values gives the number of␣
 ↪outliers

    # Store the outlier count in the dictionary
    outliers_info[col] = outlier_count
```

[16]:
```
for col, outlier_count in outliers_info.items():
    print(f"Number of outliers in '{col}': {outlier_count}")
```

```
Number of outliers in 'MinTemp': 26
Number of outliers in 'MaxTemp': 346
Number of outliers in 'Rainfall': 2482
Number of outliers in 'Evaporation': 1867
Number of outliers in 'Sunshine': 0
Number of outliers in 'WindGustSpeed': 1717
Number of outliers in 'WindSpeed9am': 1362
Number of outliers in 'WindSpeed3pm': 958
Number of outliers in 'Humidity9am': 585
Number of outliers in 'Humidity3pm': 0
Number of outliers in 'Pressure9am': 772
Number of outliers in 'Pressure3pm': 666
Number of outliers in 'Cloud9am': 0
Number of outliers in 'Cloud3pm': 0
Number of outliers in 'Temp9am': 163
Number of outliers in 'Temp3pm': 460
```

[17]:
```
# Select only numerical columns for Z-score calculation
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

# Define the Z-score threshold
z_threshold = 3

# Loop through each numerical column
for col in numerical_columns:
    # Calculate Z-scores for the column
    z_scores = zscore(df[col])

    # Calculate the upper and lower bounds based on Z-threshold
    mean_value = df[col].mean()
    std_dev = df[col].std()
    lower_bound = mean_value - z_threshold * std_dev
    upper_bound = mean_value + z_threshold * std_dev

    # Identify an example outlier (if any exist)
    outlier_indices = df[(z_scores > z_threshold) | (z_scores < -z_threshold)].
↪index
    if len(outlier_indices) > 0:
        # Take the first outlier for display purposes
        example_index = outlier_indices[0]
        before_value = df.loc[example_index, col]

        # Cap the outlier
        capped_value = (
```

```
            upper_bound if before_value > upper_bound else lower_bound
        )
        # Display the before and after values
        print(f"Column: '{col}'")
        print(f" - Before Capping (Row {example_index}): {before_value}")
        print(f" - After Capping: {capped_value}\n")

        # Apply capping to the column
        df[col] = np.where(df[col] > upper_bound, upper_bound,
                           np.where(df[col] < lower_bound, lower_bound,␣
↪df[col]))
    else:
        print(f"Column: '{col}' has no outliers.\n")
```

```
Column: 'MinTemp'
 - Before Capping (Row 46923): -8.0
 - After Capping: -6.903215228998894

Column: 'MaxTemp'
 - Before Capping (Row 68): 44.8
 - After Capping: 44.48571958519393

Column: 'Rainfall'
 - Before Capping (Row 296): 28.8
 - After Capping: 27.508380832510234

Column: 'Evaporation'
 - Before Capping (Row 6063): 16.4
 - After Capping: 14.952854712019302

Column: 'Sunshine' has no outliers.

Column: 'WindGustSpeed'
 - Before Capping (Row 8): 80.0
 - After Capping: 79.38998835820152

Column: 'WindSpeed9am'
 - Before Capping (Row 3308): 48.0
 - After Capping: 40.62660283909846

Column: 'WindSpeed3pm'
 - Before Capping (Row 52): 48.0
 - After Capping: 44.81239984264633

Column: 'Humidity9am'
 - Before Capping (Row 6322): 9.0
 - After Capping: 12.316535883650047
```

```
Column: 'Humidity3pm' has no outliers.

Column: 'Pressure9am'
 - Before Capping (Row 12): 994.3
 - After Capping: 997.4645392714654

Column: 'Pressure3pm'
 - Before Capping (Row 12): 993.0
 - After Capping: 995.2639710641031

Column: 'Cloud9am' has no outliers.

Column: 'Cloud3pm' has no outliers.

Column: 'Temp9am'
 - Before Capping (Row 5890): 37.6
 - After Capping: 36.33829391075331

Column: 'Temp3pm'
 - Before Capping (Row 68): 43.4
 - After Capping: 42.23356116599605
```

[18]:
```python
print("\nUpdated Summary Statistics for Numerical Columns:")
numerical_summary = df.describe(include=[float, int])
display(numerical_summary)
```

```
Updated Summary Statistics for Numerical Columns:

             MinTemp        MaxTemp       Rainfall    Evaporation  \
count  145460.000000  145460.000000  145460.000000  145460.000000
mean       12.194085      23.224437       1.969541       5.387934
std         6.365420       7.074739       5.106232       2.594957
min        -6.903215       1.956977       0.000000       0.000000
25%         7.700000      18.000000       0.000000       4.000000
50%        12.100000      22.700000       0.000000       5.468232
75%        16.800000      28.200000       1.000000       5.468232
max        31.291284      44.485720      27.508381      14.952855

            Sunshine  WindGustSpeed   WindSpeed9am   WindSpeed3pm  \
count  145460.000000  145460.000000  145460.000000  145460.000000
mean        7.611178      39.942171      13.992645      18.624717
std         2.729486      12.774919       8.670736       8.577905
min         0.000000       6.000000       0.000000       0.000000
25%         7.611178      31.000000       7.000000      13.000000
50%         7.611178      39.000000      13.000000      18.662657
```

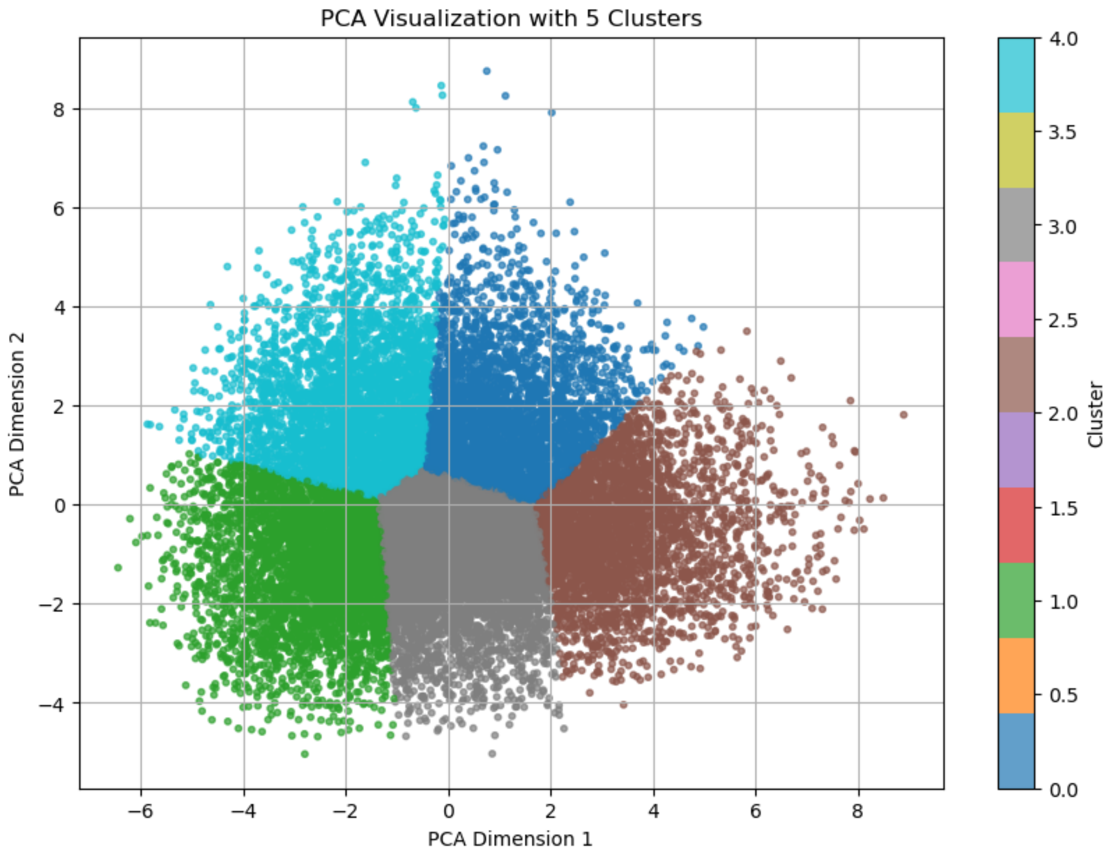
```
75%         8.700000       46.000000       19.000000       24.000000
max        14.500000       79.389988       40.626603       44.812400

         Humidity9am     Humidity3pm     Pressure9am     Pressure3pm  \
count  145460.000000   145460.000000   145460.000000   145460.000000
mean       68.894005       51.539116     1017.663747     1015.266767
std        18.813284       20.471189        6.674746        6.619300
min        12.316536        0.000000      997.464539      995.263971
25%        57.000000       37.000000     1013.500000     1011.100000
50%        69.000000       51.539116     1017.649940     1015.255889
75%        83.000000       65.000000     1021.800000     1019.400000
max       100.000000      100.000000     1037.835340     1035.247807

            Cloud9am        Cloud3pm         Temp9am         Temp3pm
count  145460.000000   145460.000000   145460.000000   145460.000000
mean        4.447461        4.509930       16.991338       21.686191
std         2.265604        2.092954        6.444951        6.833782
min         0.000000        0.000000       -2.357031        1.133219
25%         3.000000        4.000000       12.300000       16.700000
50%         4.447461        4.509930       16.800000       21.400000
75%         6.000000        6.000000       21.500000       26.200000
max         9.000000        9.000000       36.338294       42.233561
```

5 Visualization and EDA

[32]:
```python
max_samples = 20000  # Adjust based on memory constraints (Actually so we wont␣
 ↪take all day)
if len(df) > max_samples:
    df_sampled = df.sample(max_samples, random_state=42)
    print(f"Using a random sample of {max_samples} rows out of {len(df)}.")
else:
    df_sampled = df.copy()
    print(f"Using the full dataset of {len(df)} rows.")

# Separate numerical and categorical columns
numerical_columns = df_sampled.select_dtypes(include=['float64', 'int64']).
 ↪columns
categorical_columns = df_sampled.select_dtypes(include=['object']).columns

# Standardize numerical data
scaler = StandardScaler()
numerical_data_scaled = scaler.fit_transform(df_sampled[numerical_columns])

# Encode categorical data using sparse matrices
encoder = OneHotEncoder(sparse_output=True, handle_unknown='ignore')
categorical_data_encoded = encoder.
 ↪fit_transform(df_sampled[categorical_columns])
```

```python
# Combine numerical and categorical data
if len(categorical_columns) > 0:
    combined_data = hstack([numerical_data_scaled, categorical_data_encoded])
else:
    combined_data = numerical_data_scaled

# Apply PCA
pca = PCA(n_components=2)
pca_embedding = pca.fit_transform(combined_data.toarray())  # Convert sparse␣
 ↪matrix to dense if applicable

# K-Means clustering
n_clusters = 5  # Adjust based on your dataset
kmeans = KMeans(n_clusters=n_clusters, random_state=42, n_init=10)
cluster_labels = kmeans.fit_predict(pca_embedding)

plt.figure(figsize=(10, 7))
scatter = plt.scatter(
    pca_embedding[:, 0], pca_embedding[:, 1], c=cluster_labels, cmap='tab10',␣
 ↪alpha=0.7, s=10
)
plt.title(f'PCA Visualization with {n_clusters} Clusters')
plt.xlabel('PCA Dimension 1')
plt.ylabel('PCA Dimension 2')
plt.colorbar(scatter, label='Cluster')
plt.grid(True)
plt.show()
```

```
Using a random sample of 20000 rows out of 145460.
```




```
Explained variance by each component: [0.25609104 0.15842998]
Cumulative explained variance: [0.25609104 0.41452102]
```

[20]:
```python
max_samples = 20000  # Adjust based on memory constraints
if len(df) > max_samples:
    df_sampled = df.sample(max_samples, random_state=42)
    print(f"Using a random sample of {max_samples} rows out of {len(df)}.")
else:
    df_sampled = df.copy()
    print(f"Using the full dataset of {len(df)} rows.")
```

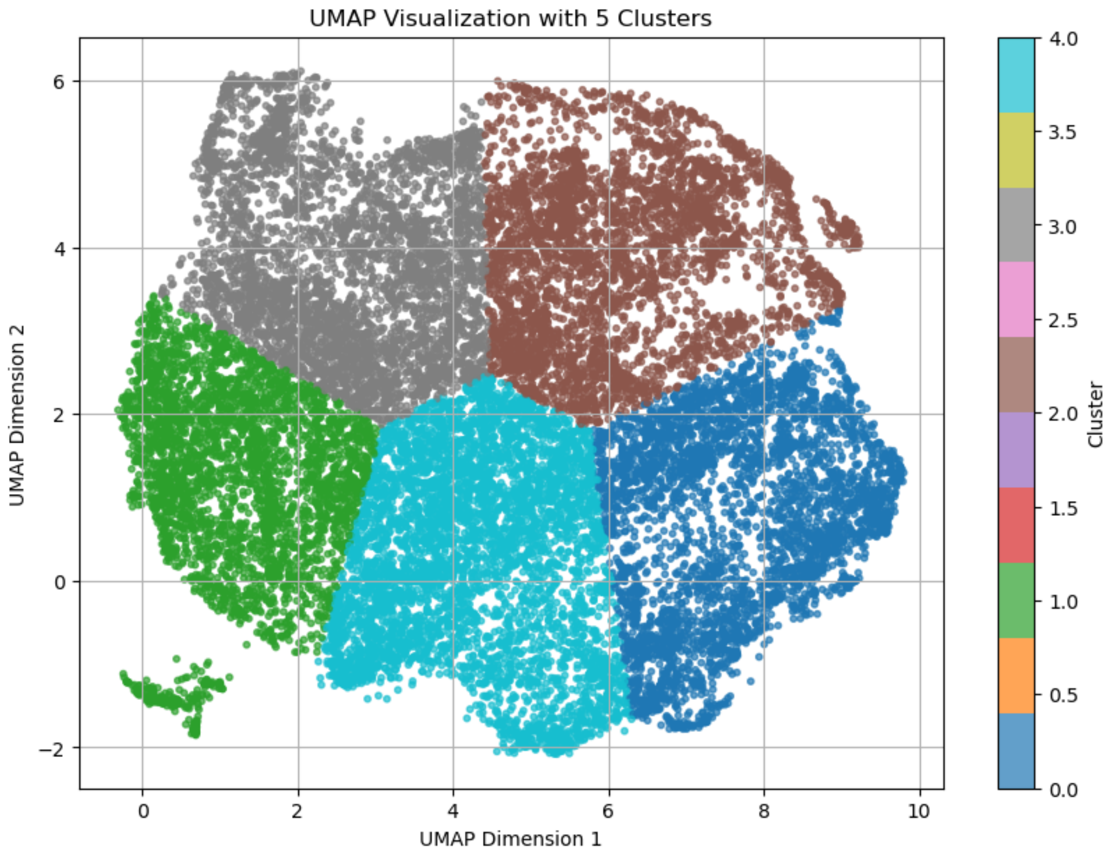
```
Using a random sample of 20000 rows out of 145460.
```

[21]:
```python
# Preprocess the data for UMAP
# Separate numerical and categorical columns
numerical_columns = df_sampled.select_dtypes(include=['float64', 'int64']).
 ↪columns
categorical_columns = df_sampled.select_dtypes(include=['object']).columns

# Scale numerical data
```

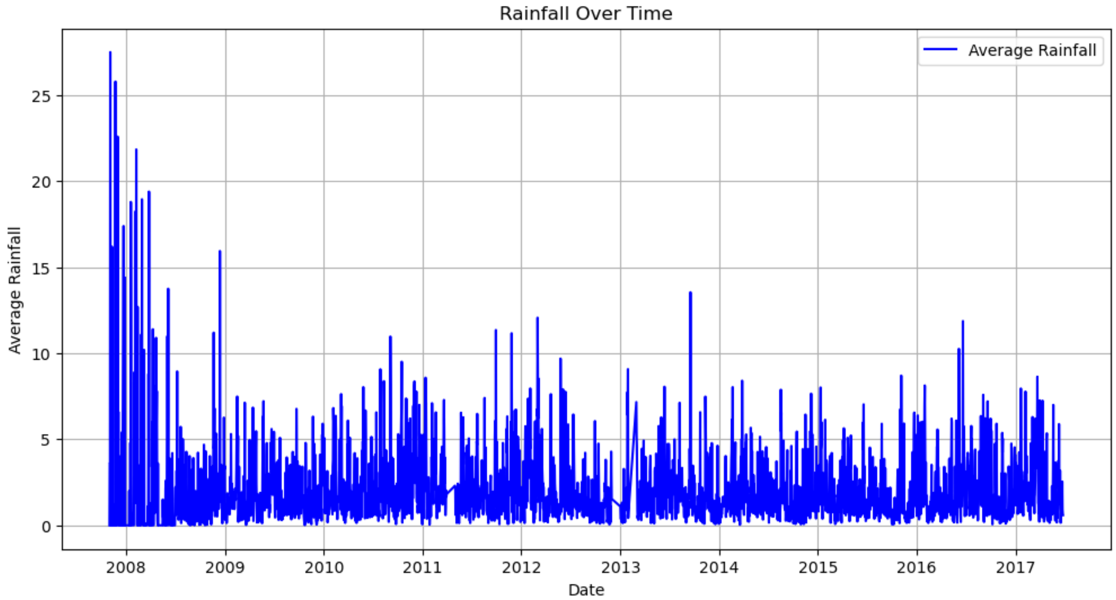
```
scaler = StandardScaler()
numerical_data_scaled = scaler.fit_transform(df_sampled[numerical_columns])

# Encode categorical data using sparse matrices
encoder = OneHotEncoder(sparse_output=True, handle_unknown='ignore')
categorical_data_encoded = encoder.
 ↪fit_transform(df_sampled[categorical_columns])
```

[22]:
```
# Combine numerical and encoded categorical data
if categorical_columns.any():
    combined_data = hstack([numerical_data_scaled, categorical_data_encoded])
else:
    combined_data = numerical_data_scaled

# Suppress the UMAP warning for n_jobs and use random_state for reproducibility
with warnings.catch_warnings():
    warnings.filterwarnings("ignore", category=UserWarning, module="umap")

    # Apply UMAP
    umap_reducer = umap.UMAP(n_neighbors=15, min_dist=0.1, random_state=42,␣
 ↪low_memory=True)
    embedding = umap_reducer.fit_transform(combined_data)

n_clusters = 5
kmeans = KMeans(n_clusters=n_clusters, random_state=42, n_init=10)
cluster_labels = kmeans.fit_predict(embedding)
```

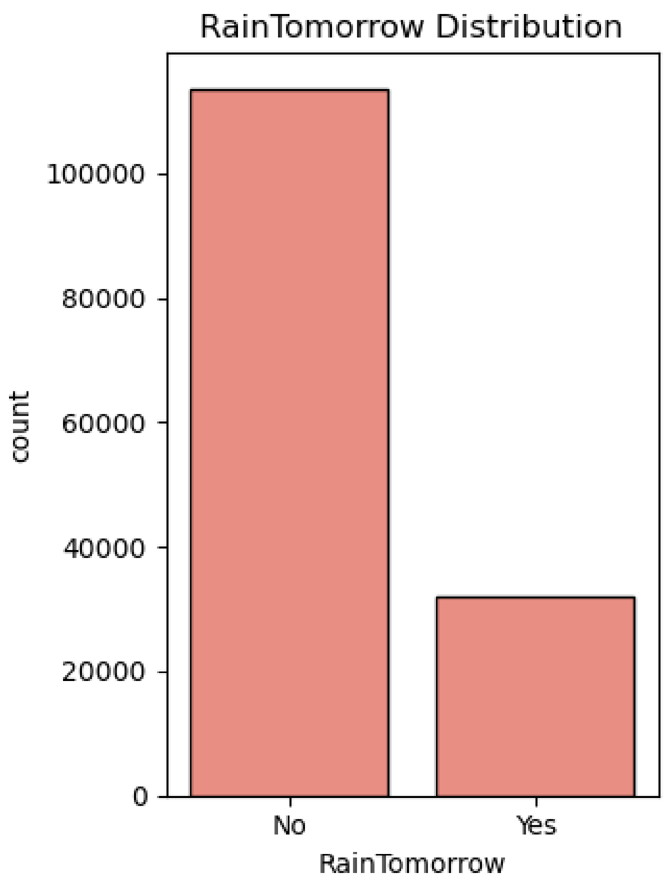
[23]:
```
plt.figure(figsize=(10, 7))
scatter = plt.scatter(embedding[:, 0], embedding[:, 1], c=cluster_labels,␣
 ↪cmap='tab10', alpha=0.7, s=10)
plt.title(f'UMAP Visualization with {n_clusters} Clusters')
plt.xlabel('UMAP Dimension 1')
plt.ylabel('UMAP Dimension 2')
plt.colorbar(scatter, label='Cluster')
plt.grid(True)
plt.show()
```



[24]:
```
# Plot average Rainfall over time
df['Date'] = pd.to_datetime(df['Date'])


rainfall_over_time = df.groupby('Date')['Rainfall'].mean()

plt.figure(figsize=(12, 6))
plt.plot(rainfall_over_time, label='Average Rainfall', color='blue')
plt.title('Rainfall Over Time')
plt.xlabel('Date')
plt.ylabel('Average Rainfall')
plt.legend()
plt.grid(True)
plt.show()
```

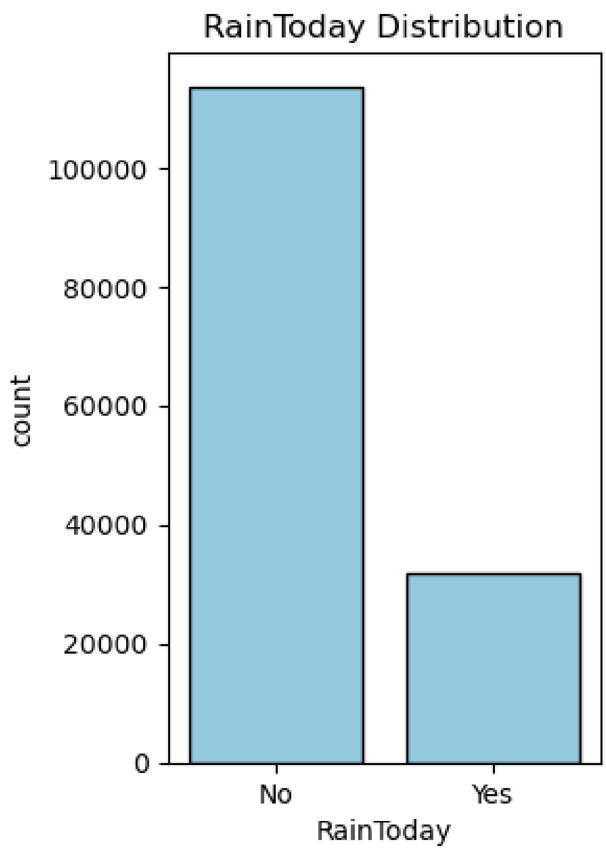


[25]:
```
# RainTomorrow Distribution
plt.subplot(1, 2, 2)
sns.countplot(data=df, x='RainTomorrow', color='salmon', edgecolor='black')  #␣
  ↪Simplified palette
plt.title('RainTomorrow Distribution')

plt.tight_layout()
plt.show()
```

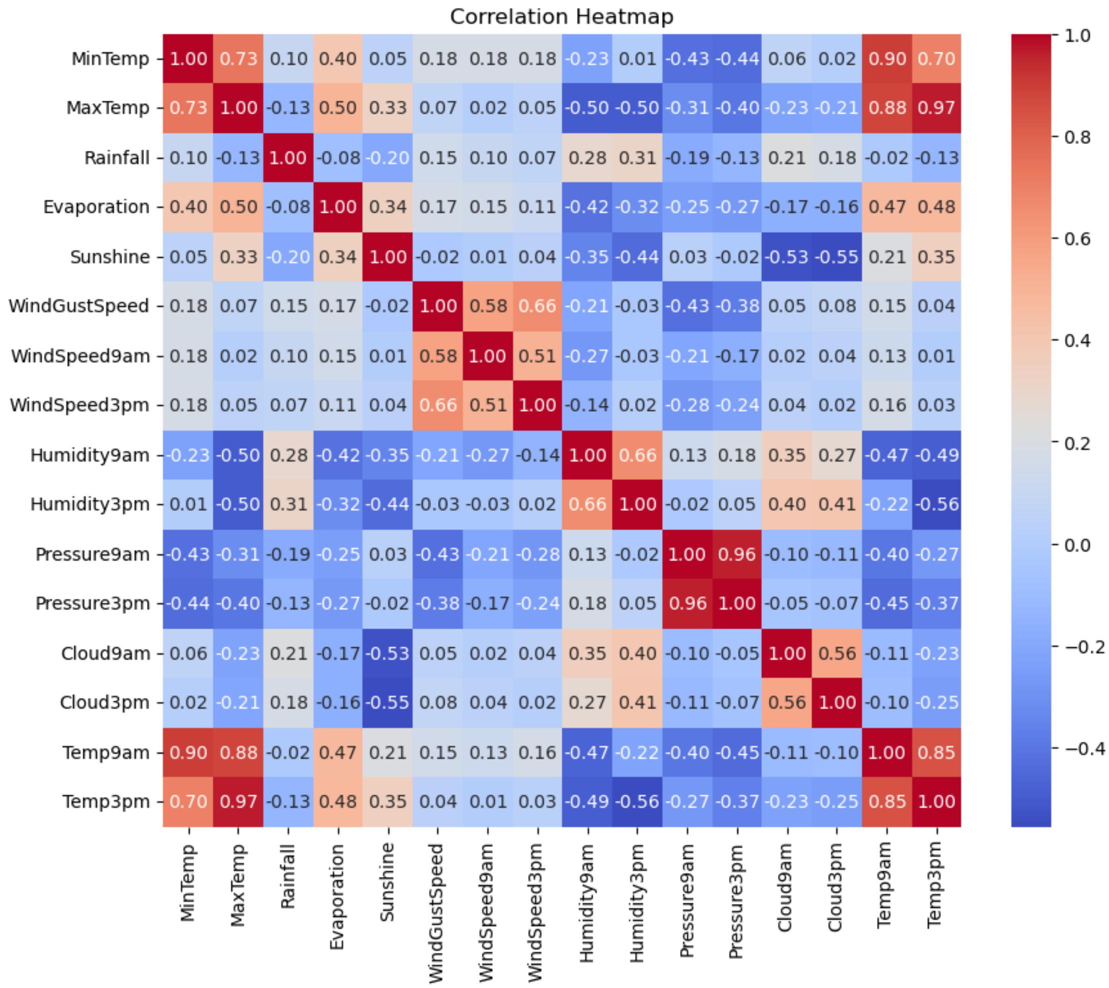


[26]:
```
# RainToday RainTomorrow
↪             Distributionplt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
sns.countplot(data=df, x='RainToday', color='skyblue', edgecolor='black')  #
↪Simplified palette
plt.title('RainToday Distribution')
```

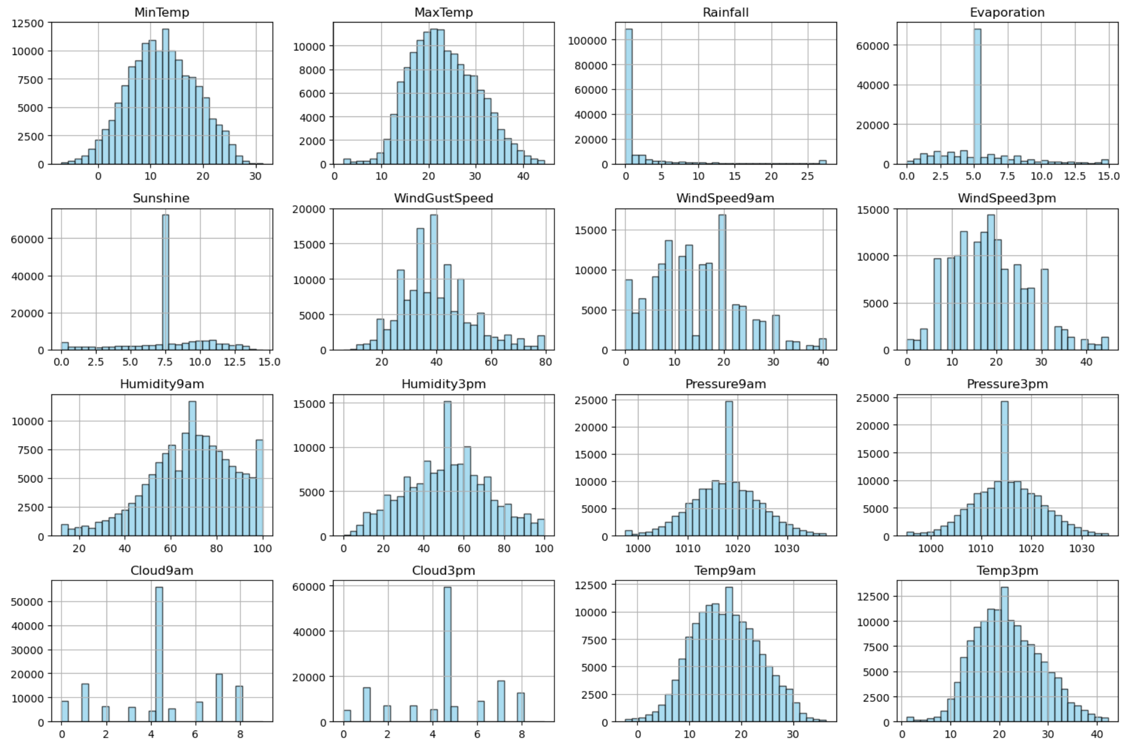
[26]:
```
Text(0.5, 1.0, 'RainToday Distribution')
```



[27]:
```
# Correlation heatmap
correlation_matrix = df[numerical_columns].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Heatmap")
plt.show()
```



[28]:
```
# Plot histograms for numerical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_columns):
    plt.subplot(4, 4, i+1)
    df[col].hist(bins=30, alpha=0.7, color='skyblue', edgecolor='black')
    plt.title(col)
    plt.tight_layout()
plt.show()
```



6 Machine Learning

[29]:
```
from pyspark.sql.functions import col, when

# Initialize Spark session
spark = SparkSession.builder.appName("Random Forest WeatherPrediction").
↪getOrCreate()

# Convert df to spark df
spark_df = spark.createDataFrame(df)

# Encode categorical variables into numeric
indexer = StringIndexer(inputCol="Location", outputCol="LocationIndex")
spark_df = indexer.fit(spark_df).transform(spark_df)

indexer_wind_dir = StringIndexer(inputCol="WindGustDir",␣
↪outputCol="WindGustDirIndex")
spark_df = indexer_wind_dir.fit(spark_df).transform(spark_df)

indexer_rain_today = StringIndexer(inputCol="RainToday",␣
↪outputCol="RainTodayIndex")
spark_df = indexer_rain_today.fit(spark_df).transform(spark_df)
```

```python
# Assemble feature columns into a single vector
assembler = VectorAssembler(
    inputCols=[
        'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
        'WindGustSpeed', 'Humidity9am', 'Humidity3pm', 'Pressure9am',␣
 ↪'Pressure3pm',
        'LocationIndex', 'WindGustDirIndex', 'RainTodayIndex'
    ],
    outputCol="features"
)
spark_df = assembler.transform(spark_df)

# Encode target variable as a numeric label
indexer_target = StringIndexer(inputCol="RainTomorrow", outputCol="label")
spark_df = indexer_target.fit(spark_df).transform(spark_df)

# Split data into training and testing sets
train_df, test_df = spark_df.randomSplit([0.8, 0.2], seed=1234)

# Train Random Forest
rf = RandomForestClassifier(labelCol="label", featuresCol="features",␣
 ↪numTrees=10, maxDepth=5, maxBins=100)
model = rf.fit(train_df)

# Generate predictions on test data
predictions = model.transform(test_df)

# Map numeric predictions back to 'Yes' or 'No'
predictions = predictions.withColumn(
    "predicted_outcome",
    when(col("prediction") == 0, "No").otherwise("Yes")
)

# Display a random sample of predictions
predictions.sample(withReplacement=False, fraction=0.1, seed=1234).
 ↪select("Date", "Location", "predicted_outcome").show(20)

# Evaluate the model using AUC
evaluator = BinaryClassificationEvaluator(labelCol="label",␣
 ↪rawPredictionCol="prediction")
auc = evaluator.evaluate(predictions)
print(f"Area Under ROC (AUC): {auc}")

# Stop Spark session
spark.stop()
```

```
+-------------------+-------------+-----------------+
|               Date|     Location|predicted_outcome|
+-------------------+-------------+-----------------+
|2009-01-28 00:00:00|BadgerysCreek|               No|
|2009-02-02 00:00:00|        Cobar|               No|
|2009-02-10 00:00:00|BadgerysCreek|              Yes|
|2009-02-19 00:00:00|BadgerysCreek|               No|
|2009-02-25 00:00:00|       Albury|               No|
|2009-02-28 00:00:00|BadgerysCreek|               No|
|2009-03-12 00:00:00|        Cobar|               No|
|2009-03-17 00:00:00|        Cobar|               No|
|2009-05-04 00:00:00|BadgerysCreek|               No|
|2009-05-04 00:00:00|        Cobar|               No|
|2009-05-10 00:00:00|       Albury|               No|
|2009-05-13 00:00:00|       Albury|               No|
|2009-07-01 00:00:00|        Cobar|               No|
|2009-07-19 00:00:00|BadgerysCreek|               No|
|2009-07-23 00:00:00|        Cobar|               No|
|2009-08-03 00:00:00|BadgerysCreek|               No|
|2009-08-04 00:00:00|        Cobar|               No|
|2009-09-01 00:00:00|       Albury|               No|
|2009-09-20 00:00:00|BadgerysCreek|               No|
|2009-10-04 00:00:00|        Cobar|               No|
+-------------------+-------------+-----------------+
only showing top 20 rows

Area Under ROC (AUC): 0.6605941347718546
```

[30]:

```
from pyspark.sql.functions import col, when

# Init Spark session
spark = SparkSession.builder.appName(" GBT WeatherPrediction").getOrCreate()

# Convert Pandas DataFrame to PySpark DataFrame
spark_df = spark.createDataFrame(df)

# SHandle categorical variables
indexer = StringIndexer(inputCol="Location", outputCol="LocationIndex")
spark_df = indexer.fit(spark_df).transform(spark_df)

indexer_wind_dir = StringIndexer(inputCol="WindGustDir",␣
↪outputCol="WindGustDirIndex")
spark_df = indexer_wind_dir.fit(spark_df).transform(spark_df)

indexer_rain_today = StringIndexer(inputCol="RainToday",␣
↪outputCol="RainTodayIndex")
spark_df = indexer_rain_today.fit(spark_df).transform(spark_df)
```

```python
# feature vector
assembler = VectorAssembler(
    inputCols=[
        'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
        'WindGustSpeed', 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm',
        'LocationIndex', 'WindGustDirIndex', 'RainTodayIndex'
    ],
    outputCol="features"
)
spark_df = assembler.transform(spark_df)

# Encode the target variable 'RainTomorrow'
indexer_target = StringIndexer(inputCol="RainTomorrow", outputCol="label")
spark_df = indexer_target.fit(spark_df).transform(spark_df)

# Split the data into training and testing sets
train_df, test_df = spark_df.randomSplit([0.8, 0.2], seed=1234)

# GBT
gbt = GBTClassifier(labelCol="label", featuresCol="features", maxIter=10, maxBins=100)

# Fit the model
model = gbt.fit(train_df)

#  Make predictions
predictions = model.transform(test_df)

# Map the numeric predictions back to string labels ('Yes' or 'No')
predictions = predictions.withColumn(
    "predicted_outcome",
    when(col("prediction") == 0, "No").otherwise("Yes")
)

# Show predictions
predictions.select("Date", "Location", "predicted_outcome").show()

# Evaluate the model using AUC
evaluator = BinaryClassificationEvaluator(labelCol="label", rawPredictionCol="prediction")
auc = evaluator.evaluate(predictions)
print(f"Area under ROC (AUC): {auc}")

# Stop session
spark.stop()
```

```
+-------------------+-------------+-----------------+
|               Date|     Location|predicted_outcome|
+-------------------+-------------+-----------------+
|2008-12-02 00:00:00|       Albury|               No|
|2008-12-05 00:00:00|       Albury|               No|
|2008-12-22 00:00:00|       Albury|               No|
|2008-12-25 00:00:00|       Albury|               No|
|2008-12-26 00:00:00|       Albury|               No|
|2008-12-27 00:00:00|       Albury|               No|
|2008-12-28 00:00:00|       Albury|               No|
|2009-01-02 00:00:00|        Cobar|               No|
|2009-01-05 00:00:00|        Cobar|               No|
|2009-01-06 00:00:00|BadgerysCreek|               No|
|2009-01-08 00:00:00|       Albury|               No|
|2009-01-09 00:00:00|BadgerysCreek|               No|
|2009-01-09 00:00:00|        Cobar|               No|
|2009-01-10 00:00:00|       Albury|               No|
|2009-01-11 00:00:00|        Cobar|               No|
|2009-01-12 00:00:00|        Cobar|               No|
|2009-01-14 00:00:00|BadgerysCreek|               No|
|2009-01-14 00:00:00|        Cobar|               No|
|2009-01-16 00:00:00|       Albury|               No|
|2009-01-18 00:00:00|        Cobar|               No|
+-------------------+-------------+-----------------+
only showing top 20 rows

Area under ROC (AUC): 0.7034931086786104
```

[31]:
```python
from pyspark.sql.functions import col, when



# Initialize Spark session
spark = SparkSession.builder.appName("Logistic Regression WeatherPrediction").
 ↪getOrCreate()

# Convert Pandas DataFrame to PySpark DataFrame
spark_df = spark.createDataFrame(df)

#  Handle categorical variables by encoding them into numeric indices
indexer_location = StringIndexer(inputCol="Location", outputCol="LocationIndex")
spark_df = indexer_location.fit(spark_df).transform(spark_df)

indexer_wind_dir = StringIndexer(inputCol="WindGustDir",␣
 ↪outputCol="WindGustDirIndex")
spark_df = indexer_wind_dir.fit(spark_df).transform(spark_df)
```

```python
indexer_rain_today = StringIndexer(inputCol="RainToday",␣
↪outputCol="RainTodayIndex")
spark_df = indexer_rain_today.fit(spark_df).transform(spark_df)

#  Assemble feature columns into a single vector
assembler = VectorAssembler(
    inputCols=[
        'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
        'WindGustSpeed', 'Humidity9am', 'Humidity3pm', 'Pressure9am',␣
↪'Pressure3pm',
        'LocationIndex', 'WindGustDirIndex', 'RainTodayIndex'
    ],
    outputCol="features"
)
spark_df = assembler.transform(spark_df)

# Encode the target variable 'RainTomorrow' as a numeric label
indexer_target = StringIndexer(inputCol="RainTomorrow", outputCol="label")
spark_df = indexer_target.fit(spark_df).transform(spark_df)

# Split the data into training and testing sets
train_df, test_df = spark_df.randomSplit([0.8, 0.2], seed=1234)

# Train the Logistic Regression model
logistic_reg = LogisticRegression(labelCol="label", featuresCol="features",␣
↪maxIter=10, regParam=0.01, elasticNetParam=0.0)
logistic_model = logistic_reg.fit(train_df)

# Make predictions on the test data
predictions = logistic_model.transform(test_df)

#  Map the numeric predictions back to string labels ('Yes' or 'No')
predictions = predictions.withColumn(
    "predicted_outcome",
    when(col("prediction") == 0, "No").otherwise("Yes")
)

# Display predictions
predictions.select("Date", "Location", "predicted_outcome").show(20)

#  Evaluate the model using AUC
evaluator = BinaryClassificationEvaluator(labelCol="label",␣
↪rawPredictionCol="rawPrediction")
auc = evaluator.evaluate(predictions)
print(f"Area Under ROC (AUC) for Logistic Regression: {auc}")

# Stop Spark session
```

```
spark.stop()
```

```
+-------------------+-------------+-----------------+
|               Date|     Location|predicted_outcome|
+-------------------+-------------+-----------------+
|2008-12-02 00:00:00|       Albury|               No|
|2008-12-05 00:00:00|       Albury|               No|
|2008-12-22 00:00:00|       Albury|               No|
|2008-12-25 00:00:00|       Albury|               No|
|2008-12-26 00:00:00|       Albury|               No|
|2008-12-27 00:00:00|       Albury|               No|
|2008-12-28 00:00:00|       Albury|               No|
|2009-01-02 00:00:00|        Cobar|               No|
|2009-01-05 00:00:00|        Cobar|               No|
|2009-01-06 00:00:00|BadgerysCreek|               No|
|2009-01-08 00:00:00|       Albury|               No|
|2009-01-09 00:00:00|BadgerysCreek|               No|
|2009-01-09 00:00:00|        Cobar|               No|
|2009-01-10 00:00:00|       Albury|               No|
|2009-01-11 00:00:00|        Cobar|               No|
|2009-01-12 00:00:00|        Cobar|               No|
|2009-01-14 00:00:00|BadgerysCreek|               No|
|2009-01-14 00:00:00|        Cobar|               No|
|2009-01-16 00:00:00|       Albury|               No|
|2009-01-18 00:00:00|        Cobar|               No|
+-------------------+-------------+-----------------+
only showing top 20 rows

Area Under ROC (AUC) for Logistic Regression: 0.8511685455881767
```

[ ]:

```

```