Lab Assignment 5: Probability in Machine Learning

Aim: To understand the role of probability in machine learning by performing probability calculations and basic predictive modeling using the Weather Prediction dataset.

Task 1: Load and Explore the Dataset

1. Load the Weather Prediction dataset using pandas.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('seattle-weather.csv')
df.head()
```

	date	precipitation	temp_max	temp_min	wind	weather
0	2012-01-01	0.0	12.8	5.0	4.7	drizzle
1	2012-01-02	10.9	10.6	2.8	4.5	rain
2	2012-01-03	0.8	11.7	7.2	2.3	rain
3	2012-01-04	20.3	12.2	5.6	4.7	rain
4	2012-01-05	1.3	8.9	2.8	6.1	rain

2. Display dataset characteristics:

– Number of records and features

```
df.shape
```

```
(1461, 6)
```

– Data types of features (categorical, numerical)

```
df.dtypes
```

```
date             object
precipitation    float64
temp_max         float64
temp_min         float64
wind             float64
weather           object
dtype: object
```

– Summary statistics

```
df.describe()
```

```
       precipitation     temp_max     temp_min         wind
count    1461.000000  1461.000000  1461.000000  1461.000000
mean        3.029432    16.439083     8.234771     3.241136
std         6.680194     7.349758     5.023004     1.437825
min         0.000000    -1.600000    -7.100000     0.400000
25%         0.000000    10.600000     4.400000     2.200000
50%         0.000000    15.600000     8.300000     3.000000
75%         2.800000    22.200000    12.200000     4.000000
max        55.900000    35.600000    18.300000     9.500000
```

```
df.median(numeric_only=True)
```

```
precipitation     0.0
temp_max         15.6
temp_min          8.3
wind              3.0
dtype: float64
```

```
df.var(numeric_only=True)
```

```
precipitation    44.624996
temp_max         54.018944
temp_min         25.230571
wind              2.067341
dtype: float64
```

3. Identify missing values and handle them appropriately.

```
df.isnull().sum()
```

```
date             0
precipitation    0
temp_max         0
temp_min         0
wind             0
weather          0
dtype: int64
```

Task 2: Probability Calculations

1. Compute the probability of different weather conditions (rain, no rain, cloudy, etc.).

```
weather_counts = df['weather'].value_counts()
total = len(df)
weather_probability = weather_counts / total
print('Weather Probability:\n',weather_probability)
```

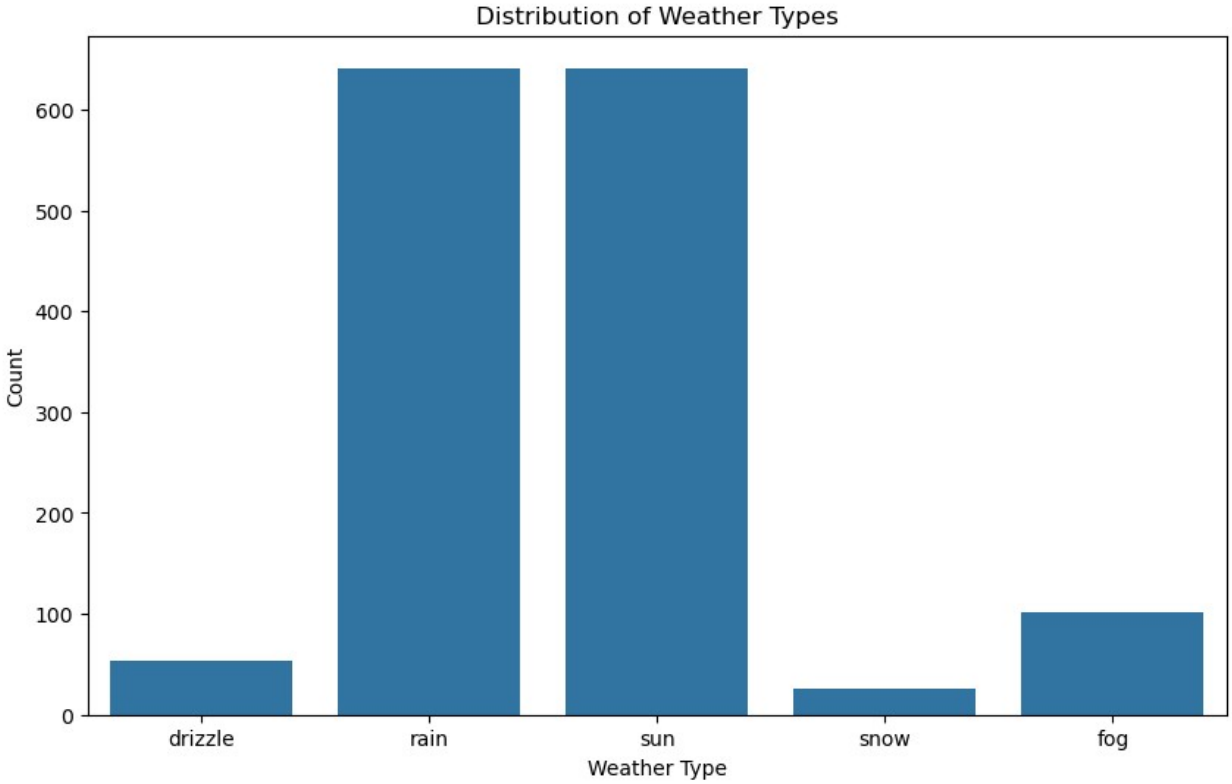
```
Weather Probability:
 weather
rain       0.438741
sun        0.438056
```

```
fog        0.069131
drizzle    0.036277
snow       0.017796
Name: count, dtype: float64
```

```
mean = df.groupby('weather').mean(numeric_only = True)
print("Mean for each column by weather:")
print(mean)
```

```
Mean for each column by weather:
         precipitation   temp_max  temp_min      wind
weather
drizzle       0.000000  15.926415  7.111321  2.367925
fog           0.000000  16.757426  7.979208  2.481188
rain          6.557878  13.454602  7.588768  3.669891
snow          8.553846   5.573077  0.146154  4.411538
sun           0.000000  19.861875  9.343750  2.956406
```

```
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='weather')
plt.title('Distribution of Weather Types')
plt.xlabel('Weather Type')
plt.ylabel('Count')
plt.show()
```



2. Calculate conditional probabilities (e.g., probability of rain given high humidity).

```
high_precipitation = df['precipitation'].quantile(0.75)
high_precip_data = df[df['precipitation'] > high_precipitation]
rain_given_high_precip =
high_precip_data['weather'].value_counts(normalize=True).get('rain',
0)

print(f"P(rain | high precipitation) = {rain_given_high_precip:.4f}")
```

```
P(rain | high precipitation) = 0.9425
```

3. Apply Bayes' Theorem to predict weather conditions based on given evidence.

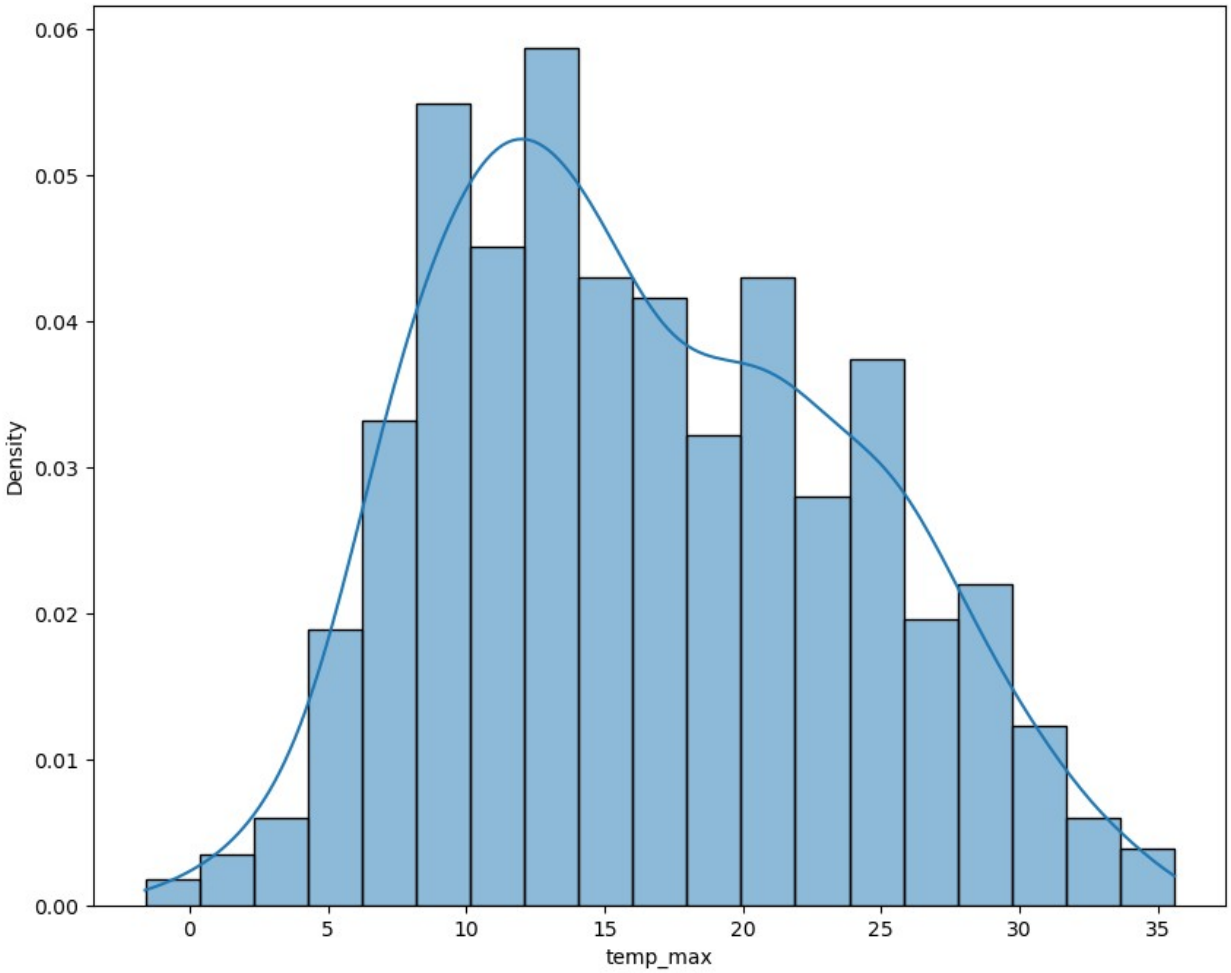
```
rain_data = df[df['weather'] == 'rain']
P_high_wind_given_rain = (rain_data['wind'] >
df['wind'].quantile(0.75)).mean()

P_high_wind = (df['wind'] > df['wind'].quantile(0.75)).mean()

P_rain = df['weather'].value_counts(normalize=True).get('rain', 0)

if P_high_wind > 0:
    P_rain_given_high_wind = (P_high_wind_given_rain * P_rain) /
P_high_wind
    print(f"P(rain | high wind) = {P_rain_given_high_wind:.4f}")
else:
    print("P(high wind) is zero; unable to calculate posterior
probability.")
```

```
P(rain | high wind) = 0.6264
```

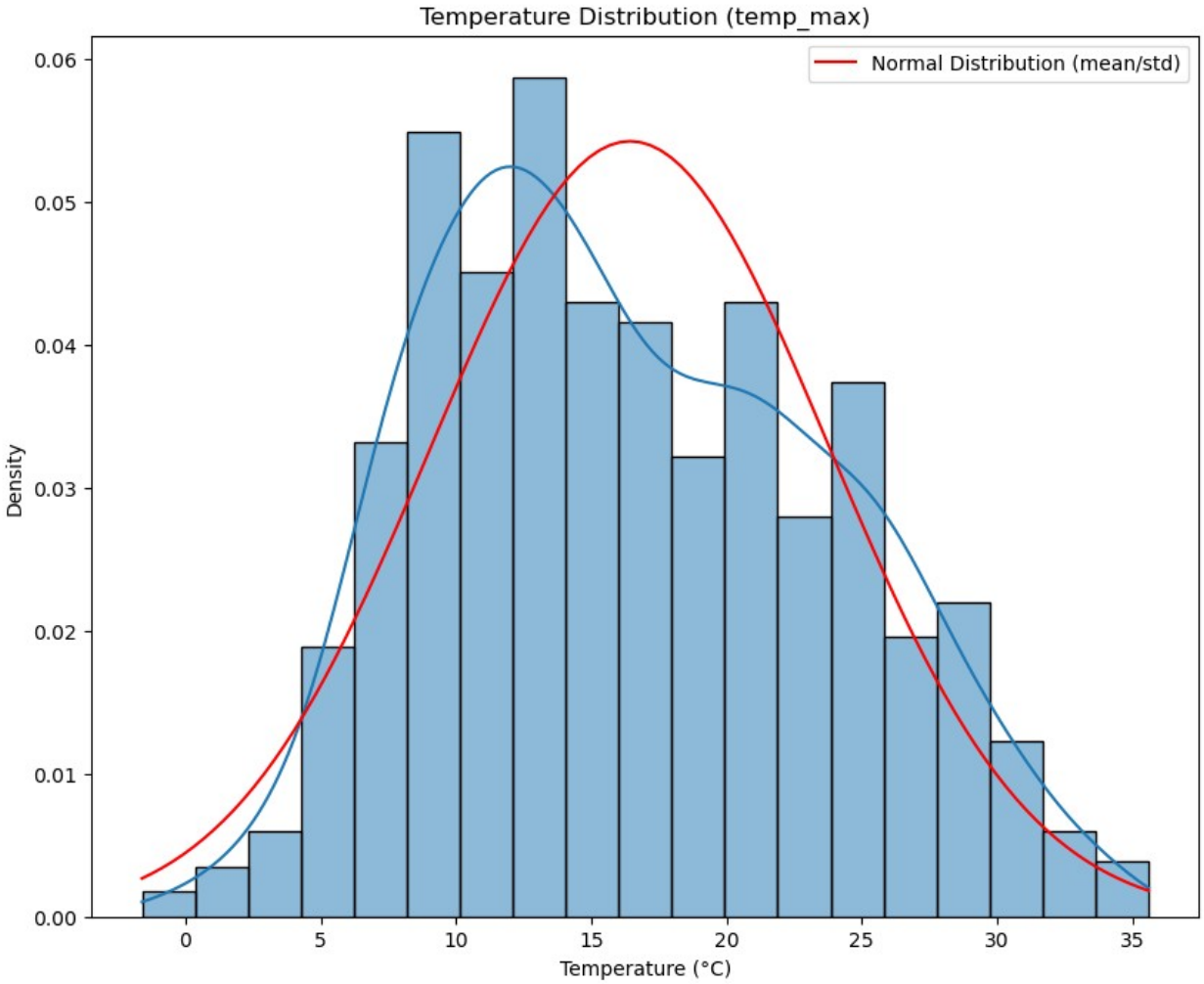
Task 3: Probability Distributions

1. Analyze normal distribution of temperature data.

```
plt.figure(figsize =(10,8))
sns.histplot(df['temp_max'],kde = True,stat = 'density')
plt.show()
```

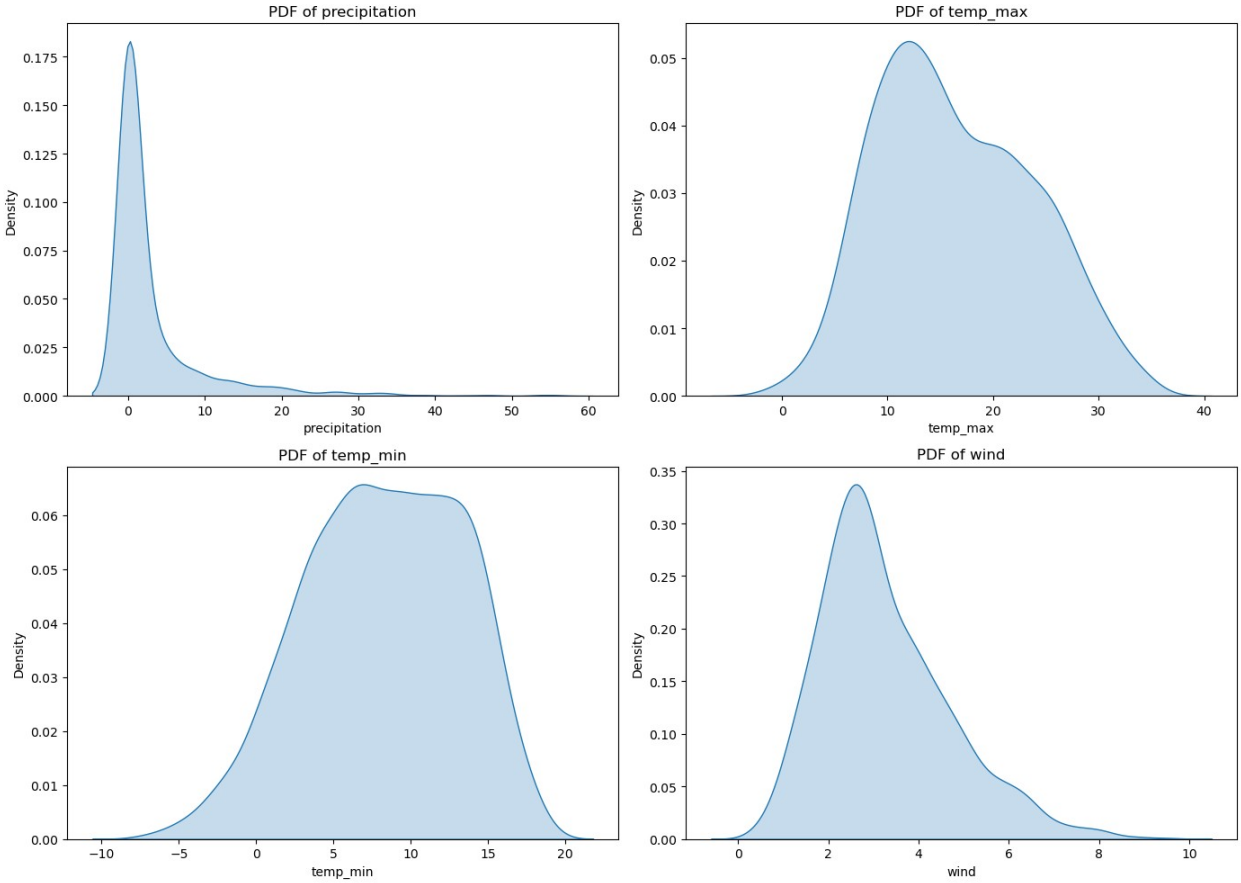



```
from scipy.stats import norm
mean_temp_max = df['temp_max'].mean()
std_temp_max = df['temp_max'].std()

x = np.linspace(df['temp_max'].min(), df['temp_max'].max(), 100)
pdf = norm.pdf(x, mean_temp_max, std_temp_max)
plt.plot(x, pdf, color='red', label="Normal Distribution (mean/std)")

plt.title("Temperature Distribution (temp_max)")
plt.xlabel("Temperature (°C)")
plt.ylabel("Density")
plt.legend()
plt.show()
```

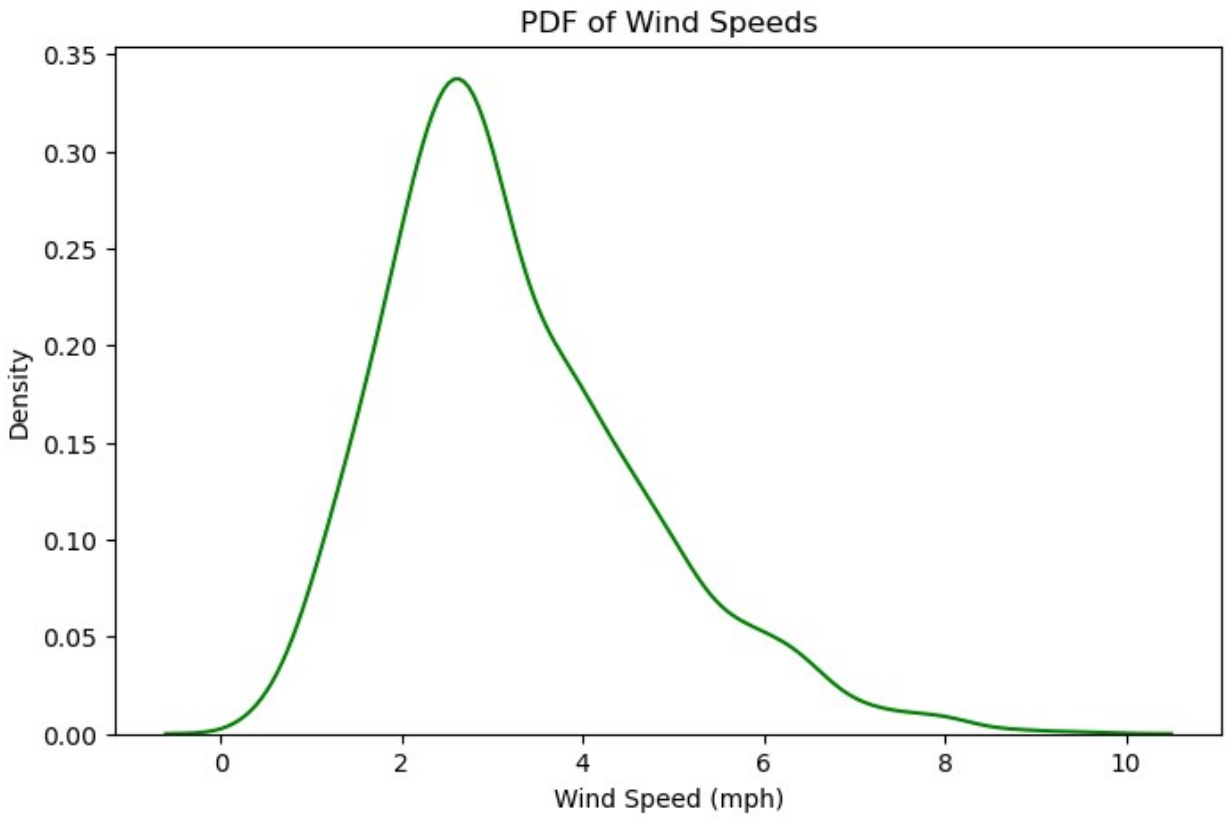


2. Compute and visualize probability density functions (PDFs) for different weather parameters.

```
numerical_features = ['precipitation', 'temp_max', 'temp_min', 'wind']

plt.figure(figsize=(14, 10))
for i, feature in enumerate(numerical_features, 1):
    plt.subplot(2, 2, i)
    sns.kdeplot(data=df, x=feature, fill=True)
    plt.title(f'PDF of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Density')

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

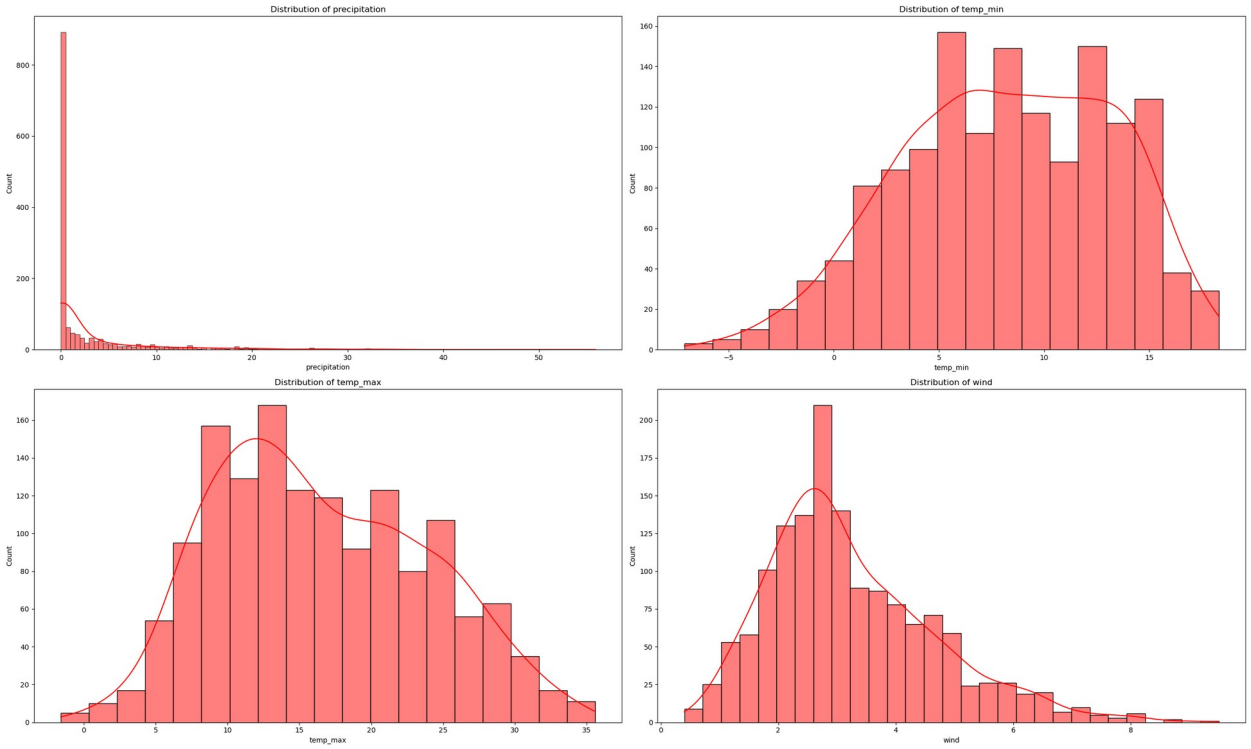



```
plt.figure(figsize=(8, 5))
sns.kdeplot(df['wind'], color='green')
plt.title("PDF of Wind Speeds")
plt.xlabel("Wind Speed (mph)")
plt.show()
```



3. Generate histograms and kernel density plots to understand feature distributions.

```
weather_features = ['precipitation', 'temp_min', 'temp_max', 'wind']
plt.figure(figsize=(25, 15))

for i, feature in enumerate(weather_features, 1):
    plt.subplot(2, 2, i)
    sns.histplot(df[feature], kde=True, color='red')
    plt.title(f"Distribution of {feature}")

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



Task 4: Basic Predictive Modeling

1. Implement a Naïve Bayes classifier to predict whether it will rain or not based on weather conditions.

```
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import
accuracy_score,precision_score,recall_score,f1_score,confusion_matrix,
classification_report

df['rain_label'] = (df['weather'] == 'rain').astype(int)
df.head()
```

```
         date  precipitation  temp_max  temp_min  wind  weather
rain_label
0  2012-01-01            0.0      12.8       5.0   4.7  drizzle
0
1  2012-01-02           10.9      10.6       2.8   4.5     rain
1
2  2012-01-03            0.8      11.7       7.2   2.3     rain
1
3  2012-01-04           20.3      12.2       5.6   4.7     rain
1
4  2012-01-05            1.3       8.9       2.8   6.1     rain
1
```

```
features = ['precipitation','temp_max','temp_min','wind']
X = df[features]
y = df['rain_label']

X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.3,random_state=42)

model = GaussianNB()
model.fit(X_train,y_train)

GaussianNB()

y_pred = model.predict(X_test)
```

2. Evaluate the model using:

– Accuracy

```
acc = accuracy_score(y_test,y_pred)
print("Accuracy: " + str(round(acc, 4)))

Accuracy: 0.7859
```

– Precision, Recall, and F1-score

```
pre = precision_score(y_test,y_pred)
print("Precision: " + str(round(pre,4)))

Precision: 0.8952

recall = recall_score(y_test,y_pred)
print("recall: " + str(round(recall,4)))

recall: 0.5781

f1 = f1_score(y_test, y_pred)
print("f1_score: " + str(round(f1,4)))

f1_score: 0.7025
```

– Confusion matrix

```
cm = confusion_matrix(y_test, y_pred)
print(cm)

[[234  13]
 [ 81 111]]

print("\nClassification Report:")
print(classification_report(y_test, y_pred))


Classification Report:
              precision    recall  f1-score   support
```

```
              precision    recall  f1-score   support

           0       0.74      0.95      0.83       247
           1       0.90      0.58      0.70       192

    accuracy                           0.79       439
   macro avg       0.82      0.76      0.77       439
weighted avg       0.81      0.79      0.78       439
```