AI BASED WEATHER PREDICTION SYSTEM

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DATE: 1/04/2024

Introduction:

The ability to accurately predict weather conditions is crucial for various applications, including agriculture, transportation, and disaster management. In this report, we present an AI-based weather prediction system that utilizes machine learning algorithms to forecast daily weather conditions.

Library Reference:

- **matplotlib.pyplot**: A plotting library used to generate visualizations such as histograms, box plots, and scatter plots.
- **seaborn**: A data visualization library based on matplotlib, providing high-level interfaces for drawing attractive statistical graphics.
- **scipy**: A scientific computing library that includes modules for statistics, optimization, interpolation, and more.
- **re**: The regular expression module in Python used for pattern matching and manipulation of strings.
- **missingno**: A library for visualizing missing data in datasets.
- **scipy.stats**: Submodule of scipy providing statistical functions and tests, such as t-tests and Pearson correlation.
- **sklearn.preprocessing**: Module from scikit-learn for data preprocessing tasks such as scaling and encoding.
- **sklearn.model_selection**: Submodule of scikit-learn for model selection and evaluation techniques like train-test splitting.
- **sklearn.neighbors.KNeighborsClassifier**: K-Nearest Neighbors classifier from scikit-learn for classification tasks.
- **sklearn.svm.SVC**: Support Vector Classifier from scikit-learn for classification tasks.
- **sklearn.ensemble.GradientBoostingClassifier**: Gradient Boosting classifier from scikit-learn for classification tasks.
- **xgboost.XGBClassifier**: Extreme Gradient Boosting classifier from XGBoost library for classification tasks.
- **sklearn.metrics**: Module from scikit-learn containing metrics for evaluating model performance.
- **numpy**: A library for numerical computing in Python, providing support for multidimensional arrays and mathematical functions.
- **pandas**: A data manipulation library in Python used for working with structured data, providing DataFrame objects for data analysis.

- **warnings**: A module in Python used to handle warnings.
- **LabelEncoder**: A class from scikit-learn for encoding categorical features as integers.

Methodology:

The machine learning models used here are 1. K-Nearest Neighbour(KNN), 2. Support Vector Machine(SVM), 3. Gradient Boost, 4. Extreme Gradient Boosting(XGBC).

#import required libraries

import matplotlib.pyplot as plt   #for creating plots and visualization

import seaborn as sns   #for data visualization

import scipy   #scientific computing library

import re   # Regular expression operations

import missingno as mso   # Missing data visualization

from scipy import stats   # Statistical functions

from scipy.stats import ttest_ind   # Statistical tests

from scipy.stats import pearsonr   # Statistical tests

from sklearn.preprocessing import StandardScaler,LabelEncoder # Data preprocessing

from sklearn.model_selection import train_test_split # Data splitting

from sklearn.neighbors import KNeighborsClassifier   # K-Nearest Neighbors classifier

from sklearn.svm import SVC   # Support Vector Machine classifier

from sklearn.ensemble import GradientBoostingClassifier   # Gradient Boosting classifier

from xgboost import XGBClassifier   # Extreme Gradient Boosting classifier

from sklearn.metrics import accuracy_score,confusion_matrix,classification_report # Evaluation metrics

import numpy as np   # Numerical operations

import pandas as pd   # Data manipulation

```
# Reading the dataset from a CSV file named "seattle-weather.csv"
data=pd.read_csv("seattle-weather.csv")

# Displaying the first few rows of the dataset to understand its structure and contents
data.head()
# Getting the dimensions of the dataset
Data.shape
# Suppressing warnings to improve readability and Creating a count plot of the
'weather' variable using seaborn
import warnings
warnings.filterwarnings('ignore')
sns.countplot(x="weather",data=data,palette="hls")
# Counting occurrences of different weather conditions
countrain=len(data[data.weather=="rain"])
countsun=len(data[data.weather=="sun"])
countdrizzle=len(data[data.weather=="drizzle"])
countsnow=len(data[data.weather=="snow"])
countfog=len(data[data.weather=="fog"])
# Calculating and printing the percentage of occurrences for each weather condition
print("Percent of Rain:{:2f}%".format((countrain/(len(data.weather))*100)))
print("Percent of Sun:{:2f}%".format((countsun/(len(data.weather))*100)))
print("Percent of Drizzle:{:2f}%".format((countdrizzle/(len(data.weather))*100)))
print("Percent of Snow:{:2f}%".format((countsnow/(len(data.weather))*100)))
print("Percent of Fog:{:2f}%".format((countfog/(len(data.weather))*100)))
# Descriptive statistics for selected weather variables
data[["precipitation","temp_max","temp_min","wind"]].describe()
sns.set(style="darkgrid")
fig,axs=plt.subplots(2,2,figsize=(10,8))
# Creating violin plots for precipitation, temp_max, temp_min, and wind variables
sns.violinplot(data=data,x="precipitation",kde=True,ax=axs[0,0],color='green')
```

```
sns.violinplot(data=data,x="temp_max",kde=True,ax=axs[0,1],color='red')
sns.violinplot(data=data,x="temp_min",kde=True,ax=axs[1,0],color='skyblue')
sns.violinplot(data=data,x="wind",kde=True,ax=axs[1,1],color='yellow')

plt.figure(figsize=(12,6))
# Creating a boxplot of precipitation vs weather
sns.boxplot(x="precipitation",y="weather",data=data,palette="YlOrBr")

plt.figure(figsize=(12,6))
# Creating a boxplot of temp_max vs weather
sns.boxplot(x="temp_max",y="weather",data=data,palette="inferno")

plt.figure(figsize=(12,6))
# Creating a boxplot of temp_min vs weather
sns.boxplot(x="temp_min",y="weather",data=data,palette="YlOrBr")

import matplotlib.pyplot as plt
import seaborn as sns

# Convert non-numeric columns to numeric if possible
data_numeric = data.apply(pd.to_numeric, errors='ignore')

# Selecting only numeric columns
data_numeric = data_numeric.select_dtypes(include=['number'])

# Creating a heatmap to visualize correlation between numeric variables
plt.figure(figsize=(12, 7))
sns.heatmap(data_numeric.corr(), annot=True, cmap='coolwarm')
plt.show()
```

```
# Plotting a scatter plot between 'precipitation' and 'temp_max'
data.plot("precipitation","temp_max",style='o')
# Calculating Pearson correlation coefficient between 'precipitation' and 'temp_max'
print("Pearson correlation:",data["precipitation"].corr(data["temp_max"]))
# Performing a two-sample T-test between 'precipitation' and 'temp_max'
print("T Test and P value:",stats.ttest_ind(data["precipitation"],data["temp_max"]))

# Plotting a scatter plot between 'wind' and 'temp_max'
data.plot("wind","temp_max",style='o')
# Calculating Pearson correlation coefficient between 'wind' and 'temp_max'
print("Pearson correlation:",data["wind"].corr(data["temp_max"]))
# Performing a two-sample T-test between 'wind' and 'temp_max'
print("T Test and P value:",stats.ttest_ind(data["wind"],data["temp_max"]))

# Plotting a scatter plot between 'temp_max' and 'temp_min'
data.plot("temp_max","temp_min",style='o')

# Checking for missing values in the dataset and Printing the number of missing
values for each column
data.isna().sum()

plt.figure(figsize=(12,6))
# Creating a subplot with 1 row and 2 columns, and selecting the second subplot
axz=plt.subplot(1,2,2)
# Plotting missingness matrix using missingno's bar plot
mso.bar(data.drop(["date"],axis=1),ax=axz,fontsize=12);

# Creating a new DataFrame by dropping the "date" column from the original
DataFrame
df=data.drop(["date"],axis=1)
```

```
import pandas as pd
# Converting non-numeric columns to numeric, coercing errors to NaN
data_numeric = data.apply(pd.to_numeric, errors='coerce')

# Calculating the first quartile (Q1), third quartile (Q3), and interquartile range (IQR)
Q1 = data_numeric.quantile(0.25)
Q3 = data_numeric.quantile(0.75)
IQR = Q3 - Q1

# Determining the lower and upper bounds for outliers detection
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filtering outliers using IQR method
data_filtered = data_numeric[~((data_numeric < lower_bound) | (data_numeric > upper_bound)).any(axis=1)]

# Applying square root transformation to 'precipitation' and 'wind' columns in DataFrame df
df.precipitation=np.sqrt(df.precipitation)
df.wind=np.sqrt(df.wind)

sns.set(style="darkgrid")
# Creating a figure with 2 rows and 2 columns of subplots
fig,axs=plt.subplots(2,2,figsize=(10,8))

# Plotting histograms with kernel density estimates for 'precipitation', 'temp_max', 'temp_min', and 'wind'
sns.histplot(data=df,x="precipitation",kde=True,ax=axs[0,0],color='green')
sns.histplot(data=df,x="temp_max",kde=True,ax=axs[0,1],color='red')
```

```
sns.histplot(data=df,x="temp_min",kde=True,ax=axs[1,0],color='skyblue')
sns.histplot(data=df,x="wind",kde=True,ax=axs[1,1],color='orange')

df.head()

# Instantiating a LabelEncoder object
lc=LabelEncoder()
# Encoding the 'weather' column in DataFrame df
df["weather"]=lc.fit_transform(df["weather"])

df.head()

# Extracting feature variables (x) and target variable (y) from DataFrame df
# x contains all columns except "weather", converted to integer values
x=((df.loc[:,df.columns!="weather"]).astype(int)).values[:,0:]
# y contains the "weather" column values
y=df["weather"].values

# Printing the unique values of the 'weather' column in DataFrame df
df.weather.unique()
# Splitting the data into training and testing sets
# x_train: features for training, x_test: features for testing, y_train: target for training,
y_test: target for testing
# The test_size parameter specifies the proportion of the dataset to include in the
test split (here 10%)
# The random_state parameter ensures reproducibility of the split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=2)
# Instantiating the KNeighborsClassifier model
knn=KNeighborsClassifier()
# Fitting the model to the training data
```

```
knn.fit(x_train,y_train)
# Evaluating the model accuracy on the testing data
print("KNN Accuracy:{:.2f}%".format(knn.score(x_test,y_test)*100))

# Instantiating the Support Vector Machine (SVM) classifier
svm=SVC()
# Fitting the SVM model to the training data
svm.fit(x_train,y_train)
# Fitting the SVM model to the training data
print("SVM Accuracy:{:.2f}%".format(svm.score(x_test,y_test)*100))

# Instantiating the Gradient Boosting Classifier with specified hyperparameters
gbc=GradientBoostingClassifier(subsample=0.5,n_estimators=450,max_depth=5,max
_leaf_nodes=25)
# Fitting the model to the training data
gbc.fit(x_train,y_train)
# Evaluating the model accuracy on the testing data
print("Gradient Boosting Accuracy:{:.2f}%".format(gbc.score(x_test,y_test)*100))

import warnings
warnings.filterwarnings('ignore')
# Instantiating the Extreme Gradient Boosting (XGBoost) Classifier
xgb=XGBClassifier()
# Fitting the model to the training data
xgb.fit(x_train,y_train)
# Evaluating the model accuracy on the testing data
print("XGB Accuracy:{:.2f}%".format(xgb.score(x_test,y_test)*100))

# Providing input data for weather prediction
input=[[1.140175,8.9,2.8,2.469818]]
```

```python
# Predicting the weather using the trained XGBoost model
ot=xgb.predict(input)
print("The weather is:")
if(ot==0):
    print("Drizzle")
elif(ot==1):
    print("Fog")
elif(ot==2):
    print("Rain")
elif(ot==3):
    print("snow")
else:
    print("Sun")
```

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Markdown JupyterLab Python 3 (ipykernel)

```
import seaborn as sns      #for data visualization
import scipy       #scientific computing library
import re      # Regular expression operations
import missingno as mso    # Missing data visualization
from scipy import stats   # Statistical functions
from scipy.stats import ttest_ind     # Statistical tests
from scipy.stats import pearsonr      # Statistical tests
from sklearn.preprocessing import StandardScaler,LabelEncoder # Data preprocessing
from sklearn.model_selection import train_test_split  # Data splitting
from sklearn.neighbors import KNeighborsClassifier    # K-Nearest Neighbors classifier
from sklearn.svm import SVC      # Support Vector Machine classifier
from sklearn.ensemble import GradientBoostingClassifier      # Gradient Boosting classifier
from xgboost import XGBClassifier        # Extreme Gradient Boosting classifier
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report      # Evaluation metrics
import numpy as np       # Numerical operations
import pandas as pd       # Data manipulation
```

[42]:

```
# Reading the dataset from a CSV file named "seattle-weather.csv"
data=pd.read_csv("seattle-weather.csv")

# Displaying the first few rows of the dataset to understand its structure and contents
data.head()
```

[42]:

	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

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Markdown JupyterLab Python 3 (ipykernel)

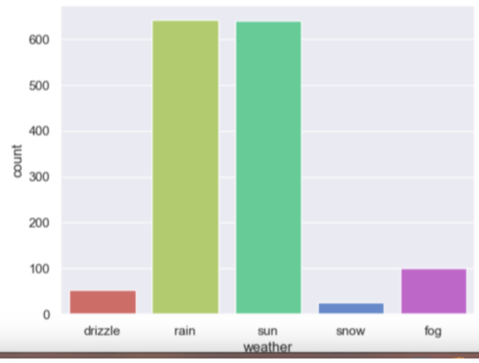
```
data.shape
```

[43]: (1461, 6)

[38]:

```
# Suppressing warnings to improve readability and Creating a count plot of the 'weather' variable using seaborn
import warnings
warnings.filterwarnings('ignore')
sns.countplot(x="weather",data=data,palette="hls")
```

[38]: <Axes: xlabel='weather', ylabel='count'>



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[44]:

```
# Counting occurrences of different weather conditions
countrain=len(data[data.weather=="rain"])
countsun=len(data[data.weather=="sun"])
countdrizzle=len(data[data.weather=="drizzle"])
countsnow=len(data[data.weather=="snow"])
countfog=len(data[data.weather=="fog"])
# Calculating and printing the percentage of occurrences for each weather condition
print("Percent of Rain:{:2f}%".format((countrain/(len(data.weather))*100)))
print("Percent of Sun:{:2f}%".format((countsun/(len(data.weather))*100)))
print("Percent of Drizzle:{:2f}%".format((countdrizzle/(len(data.weather))*100)))
print("Percent of Snow:{:2f}%".format((countsnow/(len(data.weather))*100)))
print("Percent of Fog:{:2f}%".format((countfog/(len(data.weather))*100)))
```

```
Percent of Rain:43.874059%
Percent of Sun:43.805613%
Percent of Drizzle:3.627652%
Percent of Snow:1.779603%
Percent of Fog:6.913073%
```

[40]:

```
# Descriptive statistics for selected weather variables
data[["precipitation","temp_max","temp_min","wind"]].describe()
```

[40]:

	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

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Markdown JupyterLab Python 3 (ipykernel)

```
print("Percent of Sun:{:2f}%".format((countsun/(len(data.weather))*100)))
print("Percent of Drizzle:{:2f}%".format((countdrizzle/(len(data.weather))*100)))
print("Percent of Snow:{:2f}%".format((countsnow/(len(data.weather))*100)))
print("Percent of Fog:{:2f}%".format((countfog/(len(data.weather))*100)))
```

```
Percent of Rain:43.874059%
Percent of Sun:43.805613%
Percent of Drizzle:3.627652%
Percent of Snow:1.779603%
Percent of Fog:6.913073%
```

[40]:
```
# Descriptive statistics for selected weather variables
data[["precipitation","temp_max","temp_min","wind"]].describe()
```

[40]:

	precipitation	temp_max	temp_min	wind
count	1461.000000	1461.000000	1461.000000	1461.000000
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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

Setting the seaborn style to "darkgrid"

sns.set(style="darkgrid")

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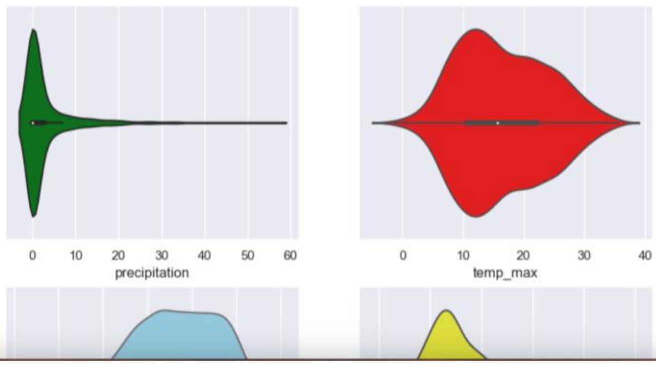
Markdown JupyterLab Python 3 (ipykernel)

[8]:
```
sns.set(style="darkgrid")
fig,axs=plt.subplots(2,2,figsize=(10,8))
# Creating violin plots for precipitation, temp_max, temp_min, and wind variables
sns.violinplot(data=data,x="precipitation",kde=True,ax=axs[0,0],color='green')
sns.violinplot(data=data,x="temp_max",kde=True,ax=axs[0,1],color='red')
sns.violinplot(data=data,x="temp_min",kde=True,ax=axs[1,0],color='skyblue')
sns.violinplot(data=data,x="wind",kde=True,ax=axs[1,1],color='yellow')
```

[8]: <Axes: xlabel='wind'>



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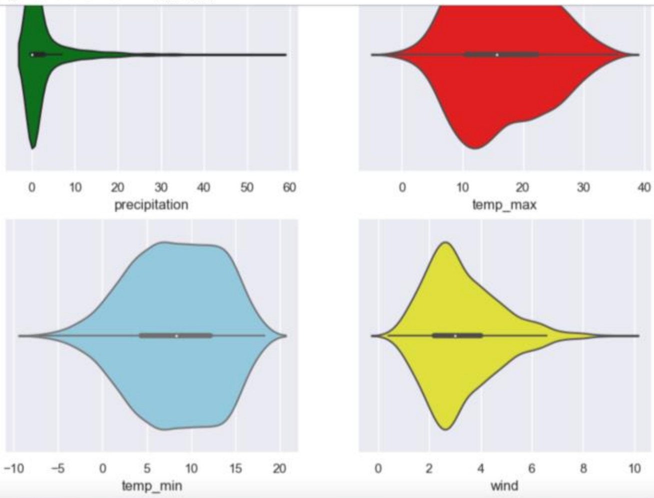

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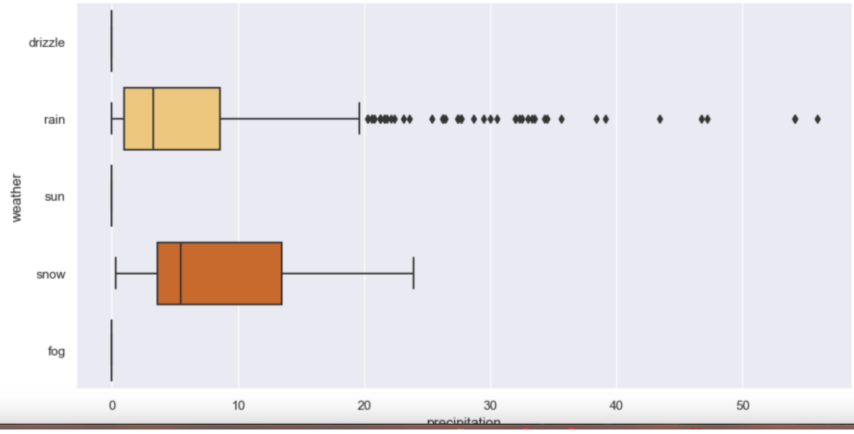
Markdown JupyterLab Python 3 (ipykernel)

```
[9]: plt.figure(figsize=(12,6))
     # Creating a boxplot of precipitation vs weather
     sns.boxplot(x="precipitation",y="weather",data=data,palette="YlOrBr")
```

[9]: <Axes: xlabel='precipitation', ylabel='weather'>



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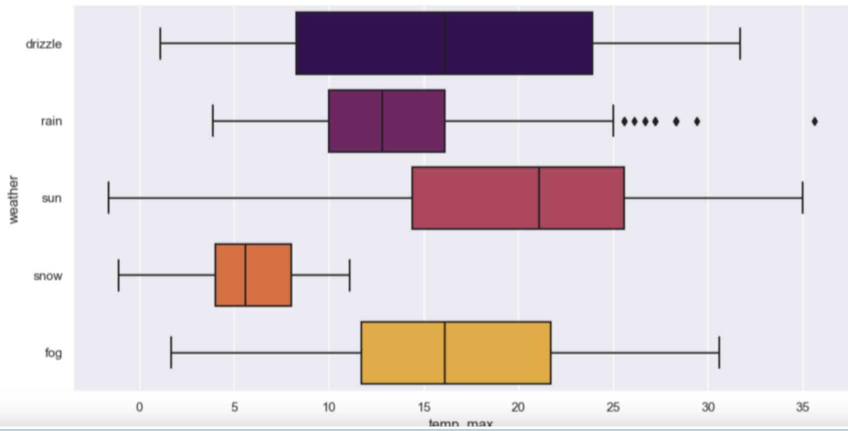
```
     # Creating a boxplot of temp_max vs weather
     sns.boxplot(x="temp_max",y="weather",data=data,palette="inferno")
```

[10]: <Axes: xlabel='temp_max', ylabel='weather'>



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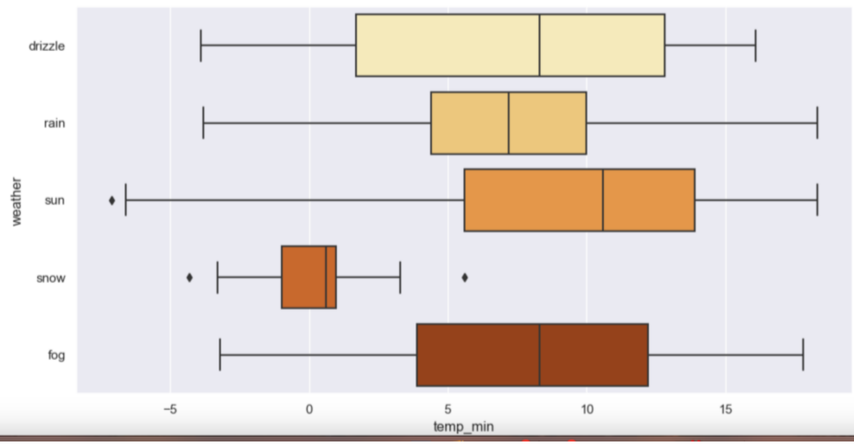
```
     # Creating a boxplot of temp_min vs weather
     sns.boxplot(x="temp_min",y="weather",data=data,palette="YlOrBr")
```

[11]: <Axes: xlabel='temp_min', ylabel='weather'>

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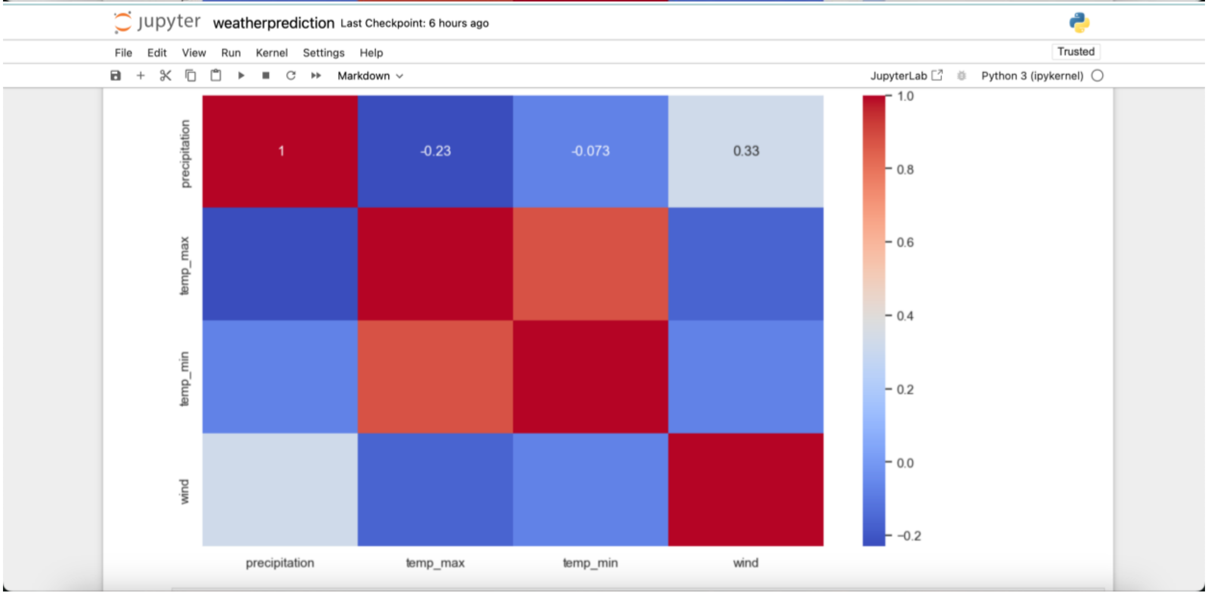
Python 3 (ipykernel)
[12]:
import matplotlib.pyplot as plt
import seaborn as sns
# Convert non-numeric columns to numeric if possible
data_numeric = data.apply(pd.to_numeric, errors='ignore')
# Selecting only numeric columns
data_numeric = data_numeric.select_dtypes(include=['number'])
# Creating a heatmap to visualize correlation between numeric variables
plt.figure(figsize=(12, 7))
sns.heatmap(data_numeric.corr(), annot=True, cmap='coolwarm')
plt.show()
precipitation
temp_max
1
-0.23
-0.073
0.33
1.0
0.8
0.6
0.4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precipitation
temp_max
temp_min
wind
1
-0.23
-0.073
0.33
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
precipitation
temp_max
temp_min
wind

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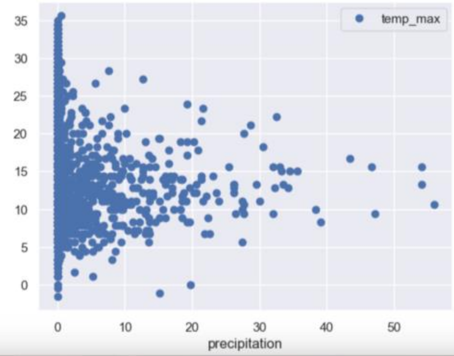
Markdown JupyterLab Python 3 (ipykernel)

[13]:
```python
# Plotting a scatter plot between 'precipitation' and 'temp_max'
data.plot("precipitation","temp_max",style='o')
# Calculating Pearson correlation coefficient between 'precipitation' and 'temp_max'
print("Pearson correlation:",data["precipitation"].corr(data["temp_max"]))
# Performing a two-sample T-test between 'precipitation' and 'temp_max'
print("T Test and P value:",stats.ttest_ind(data["precipitation"],data["temp_max"]))
```

```
Pearson correlation: -0.22855481643297046
T Test and P value: TtestResult(statistic=-51.60685279531918, pvalue=0.0, df=2920.0)
```



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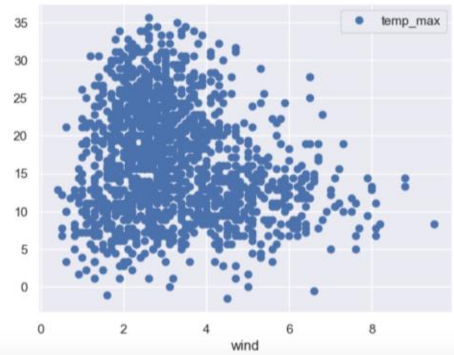
Markdown JupyterLab Python 3 (ipykernel)

[14]:
```python
# Plotting a scatter plot between 'wind' and 'temp_max'
data.plot("wind","temp_max",style='o')
# Calculating Pearson correlation coefficient between 'wind' and 'temp_max'
print("Pearson correlation:",data["wind"].corr(data["temp_max"]))
# Performing a two-sample T-test between 'wind' and 'temp_max'
print("T Test and P value:",stats.ttest_ind(data["wind"],data["temp_max"]))
```

```
Pearson correlation: -0.16485663487495486
T Test and P value: TtestResult(statistic=-67.3601643301846, pvalue=0.0, df=2920.0)
```



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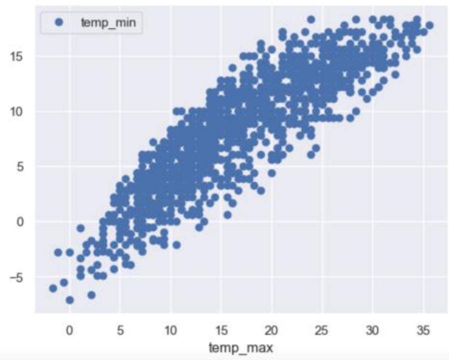
Markdown JupyterLab Python 3 (ipykernel)

[15]:
```python
# Plotting a scatter plot between 'temp_max' and 'temp_min'
data.plot("temp_max","temp_min",style='o')
```

[15]: <Axes: xlabel='temp_max'>



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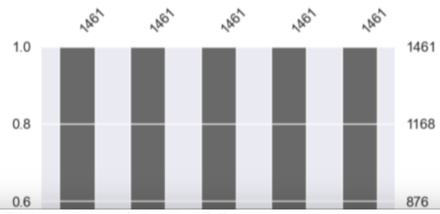
Markdown JupyterLab Python 3 (ipykernel)

0 5 10 15 20 25 30 35
temp_max

[16]:
```python
# Checking for missing values in the dataset and Printing the number of missing values for each column
data.isna().sum()
```

[16]:
```
date             0
precipitation    0
temp_max         0
temp_min         0
wind             0
weather          0
dtype: int64
```

[17]:
```python
plt.figure(figsize=(12,6))
# Creating a subplot with 1 row and 2 columns, and selecting the second subplot
axz=plt.subplot(1,2,2)
# Plotting missingness matrix using missingno's bar plot
mso.bar(data.drop(["date"],axis=1),ax=axz,fontsize=12);
```



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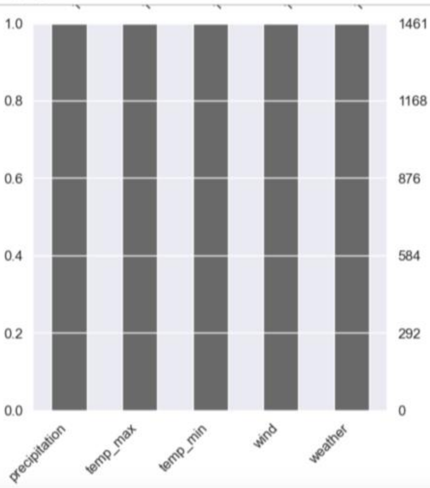

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Markdown JupyterLab Python 3 (ipykernel)

[18]:
```python
# Creating a new DataFrame by dropping the "date" column from the original DataFrame
df=data.drop(["date"],axis=1)
```

[19]:
```python
import pandas as pd
# Converting non-numeric columns to numeric, coercing errors to NaN
data_numeric = data.apply(pd.to_numeric, errors='coerce')

# Calculating the first quartile (Q1), third quartile (Q3), and interquartile range (IQR)
Q1 = data_numeric.quantile(0.25)
Q3 = data_numeric.quantile(0.75)
IQR = Q3 - Q1

# Determining the lower and upper bounds for outliers detection
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Filtering outliers using IQR method
data_filtered = data_numeric[~((data_numeric < lower_bound) | (data_numeric > upper_bound)).any(axis=1)]
```

[20]:
```python
# Applying square root transformation to 'precipitation' and 'wind' columns in DataFrame df
df.precipitation=np.sqrt(df.precipitation)
df.wind=np.sqrt(df.wind)
```

[21]:
```python
sns.set(style="darkgrid")
# Creating a figure with 2 rows and 2 columns of subplots
fig,axs=plt.subplots(2,2,figsize=(10,8))

# Plotting histograms with kernel density estimates for 'precipitation', 'temp_max', 'temp_min', and 'wind'
sns.histplot(data=df,x="precipitation",kde=True,ax=axs[0,0],color='green')
sns.histplot(data=df,x="temp_max",kde=True,ax=axs[0,1],color='red')
sns.histplot(data=df,x="temp_min",kde=True,ax=axs[1,0],color='skyblue')
sns.histplot(data=df,x="wind",kde=True,ax=axs[1,1],color='orange')
```

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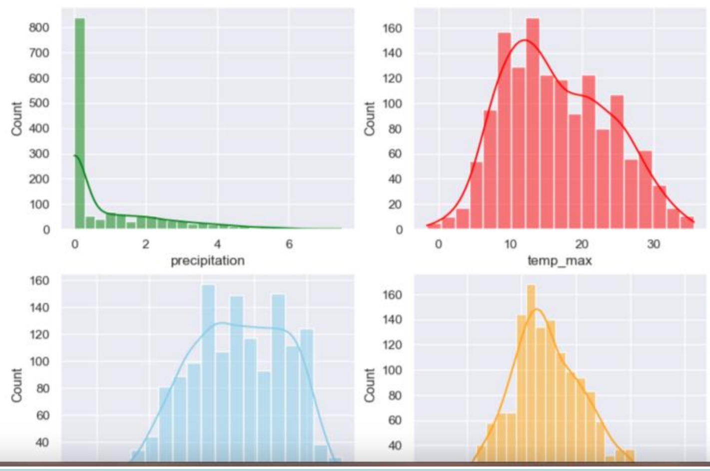
[21]: <Axes: xlabel='wind', ylabel='Count'>



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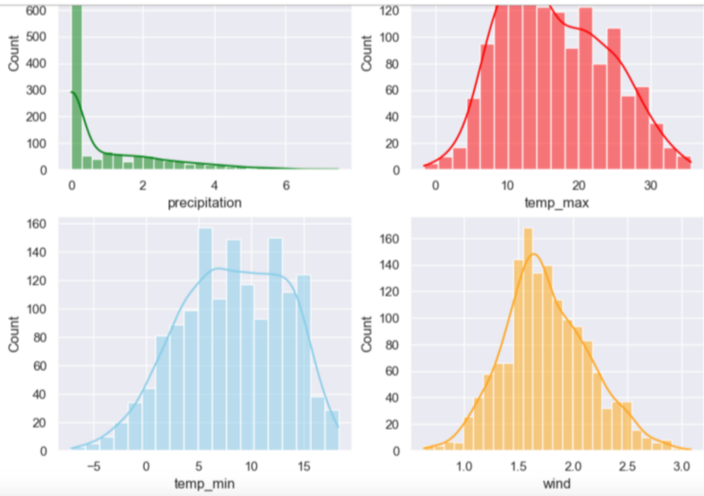

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Markdown JupyterLab Python 3 (ipykernel)

[22]:
```python
df.head()
```

[22]:

	precipitation	temp_max	temp_min	wind	weather
0	0.000000	12.8	5.0	2.167948	drizzle
1	3.301515	10.6	2.8	2.121320	rain
2	0.894427	11.7	7.2	1.516575	rain
3	4.505552	12.2	5.6	2.167948	rain
4	1.140175	8.9	2.8	2.469818	rain

[23]:
```python
# Instantiating a LabelEncoder object
lc=LabelEncoder()
# Encoding the 'weather' column in DataFrame df
df["weather"]=lc.fit_transform(df["weather"])
```

[24]:
```python
df.head()
```

[24]:

	precipitation	temp_max	temp_min	wind	weather
0	0.000000	12.8	5.0	2.167948	0
1	3.301515	10.6	2.8	2.121320	2
2	0.894427	11.7	7.2	1.516575	2
3	4.505552	12.2	5.6	2.167948	2
4	1.140175	8.9	2.8	2.469818	2

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Markdown JupyterLab Python 3 (ipykernel)

[25]:
```python
# Extracting feature variables (x) and target variable (y) from DataFrame df
# x contains all columns except "weather", converted to integer values
x=((df.loc[:,df.columns!="weather"]).astype(int)).values[:,0:]
# y contains the "weather" column values
y=df["weather"].values
```

[26]:
```python
# Printing the unique values of the 'weather' column in DataFrame df
df.weather.unique()
```

[26]: array([0, 2, 4, 3, 1])

[27]:
```python
# Splitting the data into training and testing sets
# x_train: features for training, x_test: features for testing, y_train: target for training, y_test: target for testing
# The test_size parameter specifies the proportion of the dataset to include in the test split (here 10%)
# The random_state parameter ensures reproducibility of the split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=2)
```

[28]:
```python
# Instantiating the KNeighborsClassifier model
knn=KNeighborsClassifier()
# Fitting the model to the training data
knn.fit(x_train,y_train)
# Evaluating the model accuracy on the testing data
print("KNN Accuracy:{:.2f}%".format(knn.score(x_test,y_test)*100))
```

KNN Accuracy:74.15%

[29]:
```python
# Instantiating the Support Vector Machine (SVM) classifier
svm=SVC()
# Fitting the SVM model to the training data
svm.fit(x_train,y_train)
# Fitting the SVM model to the training data
print("SVM Accuracy:{:.2f}%".format(svm.score(x_test,y_test)*100))
```

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Code JupyterLab Python 3 (ipykernel)

```python
gbc=GradientBoostingClassifier(subsample=0.5,n_estimators=450,max_depth=5,max_leaf_nodes=25)
# Fitting the model to the training data
gbc.fit(x_train,y_train)
# Evaluating the model accuracy on the testing data
print("Gradient Boosting Accuracy:{:.2f}%".format(gbc.score(x_test,y_test)*100))
```

Gradient Boosting Accuracy:78.91%

[31]:
```python
import warnings
warnings.filterwarnings('ignore')
# Instantiating the Extreme Gradient Boosting (XGBoost) Classifier
xgb=XGBClassifier()
# Fitting the model to the training data
xgb.fit(x_train,y_train)
# Evaluating the model accuracy on the testing data
print("XGB Accuracy:{:.2f}%".format(xgb.score(x_test,y_test)*100))
```

XGB Accuracy:80.27%

[32]:
```python
# Providing input data for weather prediction
input=[[1.140175,8.9,2.8,2.469818]]
# Predicting the weather using the trained XGBoost model
ot=xgb.predict(input)
print("The weather is:")
if(ot==0):
    print("Drizzle")
elif(ot==1):
    print("Fog")
elif(ot==2):
    print("Rain")
elif(ot==3):
    print("snow")
else:
    print("Sun")
```

Results:

- **K-Nearest Neighbors (KNN) Classifier:**
  - Accuracy: 74.15%
- **Support Vector Machine (SVM) Classifier:**
  - Accuracy: 79.59%
- **Gradient Boosting Classifier:**
  - Accuracy: 78.91%
- **Extreme Gradient Boosting (XGB) Classifier:**
  - Accuracy: 80.27%
- These results indicate the performance of each machine learning model in predicting weather conditions based on the input features. Among the models tested, the XGB classifier achieved the highest accuracy, suggesting it may be the most effective for weather prediction tasks in this context.