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# Weather in Saudi Arabia

Data Miners Group
Raheed Albaloud (Leader)
Razan Albishri
Bashayer Alahmari
Suha Shafi
Ibrahim Alsufyani

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# Saudi Arabia Weather Dataset

**weather-sa-2017-2019-clean.csv** (18.81 MB)

Detail | Compact | Column

10 of 15 columns

| city | date | time | year | month | day | hour | minute | weather |
|---|---|---|---|---|---|---|---|---|
| Qassim | 1 January 2017 | 00:00 | 2017 | 1 | 1 | 24 | 0 | Clear |
| Qassim | 1 January 2017 | 01:00 | 2017 | 1 | 1 | 1 | 0 | Clear |
| Qassim | 1 January 2017 | 03:00 | 2017 | 1 | 1 | 3 | 0 | Clear |
| Qassim | 1 January 2017 | 04:00 | 2017 | 1 | 1 | 4 | 0 | Clear |
| Qassim | 1 January 2017 | 05:00 | 2017 | 1 | 1 | 5 | 0 | Clear |
| Qassim | 1 January 2017 | 06:00 | 2017 | 1 | 1 | 6 | 0 | Clear |
| Qassim | 1 January 2017 | 07:00 | 2017 | 1 | 1 | 7 | 0 | Sunny |
| Qassim | 1 January 2017 | 08:00 | 2017 | 1 | 1 | 8 | 0 | Sunny |
| Qassim | 1 January 2017 | 09:00 | 2017 | 1 | 1 | 9 | 0 | Sunny |
| Qassim | 1 January 2017 | 10:00 | 2017 | 1 | 1 | 10 | 0 | Sunny |
| Qassim | 1 January 2017 | 11:00 | 2017 | 1 | 1 | 11 | 0 | Sunny |
| Qassim | 1 January 2017 | 12:00 | 2017 | 1 | 1 | 12 | 0 | Sunny |
| Qassim | 1 January 2017 | 13:00 | 2017 | 1 | 1 | 13 | 0 | Sunny |
| Qassim | 1 January 2017 | 14:00 | 2017 | 1 | 1 | 14 | 0 | Sunny |
| Qassim | 1 January 2017 | 15:00 | 2017 | 1 | 1 | 15 | 0 | Sunny |
| Qassim | 1 January 2017 | 16:00 | 2017 | 1 | 1 | 16 | 0 | Sunny |
| Qassim | 1 January 2017 | 17:00 | 2017 | 1 | 1 | 17 | 0 | Sunny |
| Qassim | 1 January 2017 | 18:00 | 2017 | 1 | 1 | 18 | 0 | Clear |

# Load the dataset

In [2]:
```
weatherKSA = pd.read_csv('D:\Downloads\weather-sa-2017-2019-clean.csv')
weatherKSA.head()
```

Out[2]:

| | Unnamed: 0 | city | date | time | year | month | day | hour | minute | weather | temp | wind | humidity | barometer | visibility |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | Qassim | 1 January 2017 | 00:00 | 2017 | 1 | 1 | 24 | 0 | Clear | 17 | 11 | 64% | 1018.0 | 16 |
| **1** | 1 | Qassim | 1 January 2017 | 01:00 | 2017 | 1 | 1 | 1 | 0 | Clear | 17 | 6 | 64% | 1018.0 | 16 |
| **2** | 2 | Qassim | 1 January 2017 | 03:00 | 2017 | 1 | 1 | 3 | 0 | Clear | 15 | 11 | 72% | 1019.0 | 16 |
| **3** | 3 | Qassim | 1 January 2017 | 04:00 | 2017 | 1 | 1 | 4 | 0 | Clear | 15 | 11 | 72% | 1019.0 | 16 |
| **4** | 4 | Qassim | 1 January 2017 | 05:00 | 2017 | 1 | 1 | 5 | 0 | Clear | 15 | 9 | 72% | 1019.0 | 16 |

# Reshape and Clean The Dataset

# Shape of the Dataset

```
In [3]: print('Shape of the data is: ',weatherKSA.shape)

        Shape of the data is:  (249023, 15)
```

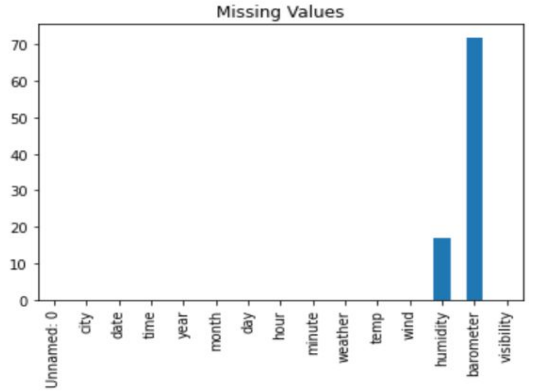
# Check if there are missing values

```
In [4]: weatherKSA.isnull().sum()
```

```
Out[4]: Unnamed: 0     0
        city           0
        date           0
        time           0
        year           0
        month          0
        day            0
        hour           0
        minute         0
        weather        0
        temp           0
        wind           0
        humidity      17
        barometer     72
        visibility     0
        dtype: int64
```

```
In [5]: weatherKSA.isnull().sum().plot(kind="bar", title="Missing Values")
```

```
Out[5]: <AxesSubplot:title={'center':'Missing Values'}>
```



# Drop and Replacement the NA values

```
In [6]: weatherKSA.drop('Unnamed: 0', axis=1, inplace = True)

In [8]: weatherKSA['humidity'].fillna(method='ffill',inplace=True)

In [9]: weatherKSA['barometer'].fillna(method='ffill',inplace=True)

In [7]: weatherKSA.columns

Out[7]: Index(['city', 'date', 'time', 'year', 'month', 'day', 'hour', 'minute',
               'weather', 'temp', 'wind', 'humidity', 'barometer', 'visibility'],
              dtype='object')
```

# Check if there are missing values

```
In [12]: weatherKSA.isnull().sum()

Out[12]: city          0
         date          0
         time          0
         year          0
         month         0
         day           0
         hour          0
         minute        0
         weather       0
         temp          0
         wind          0
         humidity      0
         barometer     0
         visibility    0
         dtype: int64
```

```
In [11]: weatherKSA.isnull().sum().plot(kind="bar", title="Missing Values")

Out[11]: <AxesSubplot:title={'center':'Missing Values'}>
```

# Description of Dataset

```
In [13]: weatherKSA.describe().T
```

Out[13]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **year** | 249023.0 | 2017.710007 | 0.706113 | 2017.0 | 2017.0 | 2018.0 | 2018.0 | 2019.0 |
| **month** | 249023.0 | 6.050694 | 3.521591 | 1.0 | 3.0 | 6.0 | 9.0 | 12.0 |
| **day** | 249023.0 | 15.691081 | 8.787958 | 1.0 | 8.0 | 16.0 | 23.0 | 31.0 |
| **hour** | 249023.0 | 12.536890 | 6.910254 | 1.0 | 7.0 | 13.0 | 19.0 | 24.0 |
| **minute** | 249023.0 | 0.131108 | 1.970710 | 0.0 | 0.0 | 0.0 | 0.0 | 59.0 |
| **temp** | 249023.0 | 24.722624 | 8.880913 | -4.0 | 18.0 | 24.0 | 31.0 | 50.0 |
| **wind** | 249023.0 | 12.957104 | 8.711619 | -1.0 | 7.0 | 11.0 | 19.0 | 163.0 |
| **barometer** | 249023.0 | 1015.452557 | 6.973451 | 904.0 | 1011.0 | 1016.0 | 1021.0 | 1101.0 |
| **visibility** | 249023.0 | 11.053453 | 7.053005 | -1.0 | 5.0 | 16.0 | 16.0 | 161.0 |

# Description of Dataset

```
In [14]: weatherKSA.describe(exclude = 'number').T
```

Out[14]:

| | count | unique | top | freq |
|---|---|---|---|---|
| **city** | 249023 | 13 | Jawf | 20352 |
| **date** | 249023 | 850 | 24 November 2018 | 321 |
| **time** | 249023 | 710 | 07:00 | 10415 |
| **weather** | 249023 | 81 | Clear | 98827 |
| **humidity** | 249023 | 92 | 13% | 6903 |

# Dataset Information

```
In [15]: weatherKSA.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 249023 entries, 0 to 249022
Data columns (total 14 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   city        249023 non-null  object
 1   date        249023 non-null  object
 2   time        249023 non-null  object
 3   year        249023 non-null  int64
 4   month       249023 non-null  int64
 5   day         249023 non-null  int64
 6   hour        249023 non-null  int64
 7   minute      249023 non-null  int64
 8   weather     249023 non-null  object
 9   temp        249023 non-null  int64
 10  wind        249023 non-null  int64
 11  humidity    249023 non-null  object
 12  barometer   249023 non-null  float64
 13  visibility  249023 non-null  int64
dtypes: float64(1), int64(8), object(5)
memory usage: 26.6+ MB
```

```
In [17]: weatherKSA["date"] = pd.to_datetime(weatherKSA["date"])
```

```
In [19]: weatherKSA.info()
```

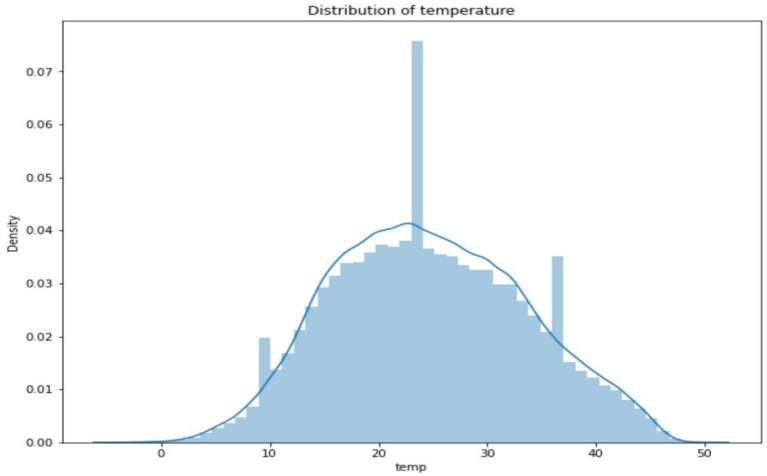
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 249023 entries, 0 to 249022
Data columns (total 14 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   city        249023 non-null  object
 1   date        249023 non-null  datetime64[ns]
 2   time        249023 non-null  object
 3   year        249023 non-null  int64
 4   month       249023 non-null  int64
 5   day         249023 non-null  int64
 6   hour        249023 non-null  int64
 7   minute      249023 non-null  int64
 8   weather     249023 non-null  object
 9   temp        249023 non-null  int64
 10  wind        249023 non-null  int64
 11  humidity    249023 non-null  object
 12  barometer   249023 non-null  float64
 13  visibility  249023 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(8), object(4)
memory usage: 26.6+ MB
```

# Performing EDA

# 1st Plot

In [20]:

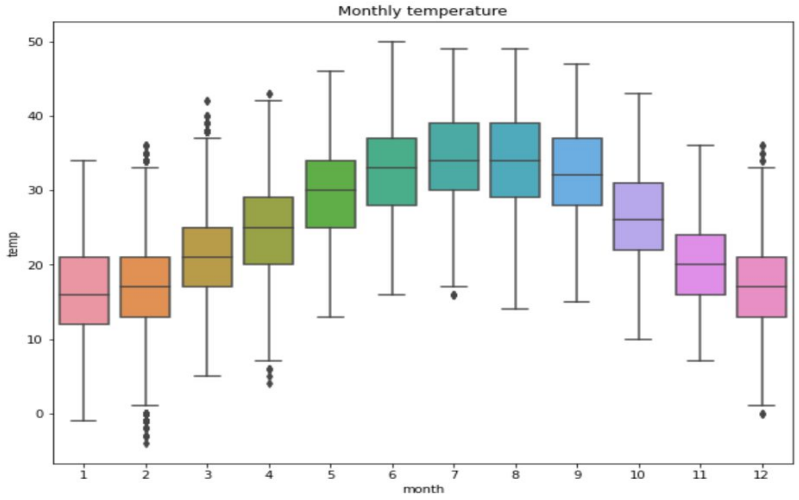
```
plt.figure(figsize=(10,8))
plt.title("Distribution of temperature")
sns.distplot(weatherKSA.temp);
```



# 2nd Plot

In [21]:

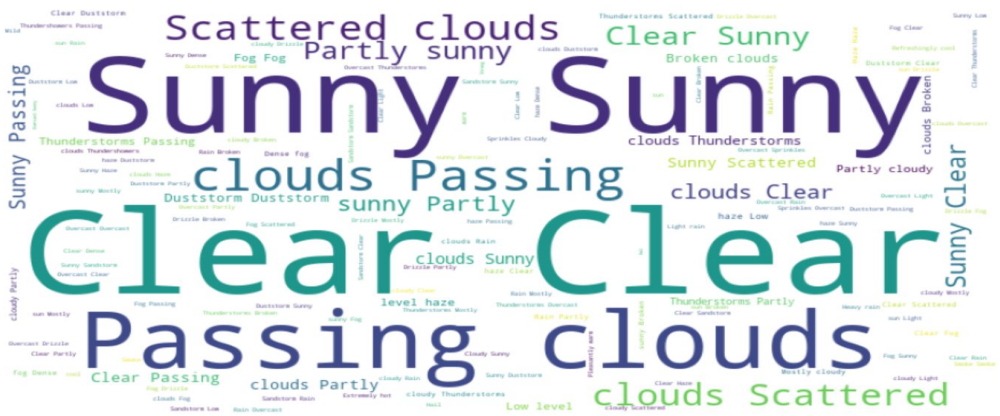
```
plt.figure(figsize=(10,8))
plt.title("Monthly temperature")
sns.boxplot(weatherKSA.month, weatherKSA.temp);
```



# 3rd Plot

In [22]:

```
words=' '.join((event for event in weatherKSA.weather.dropna() ))
wc=WordCloud(width=800,height=400,background_color='white').generate(words)
plt.figure(figsize=(16,8))
plt.axis("off")
plt.grid(False)
plt.imshow(wc);
```



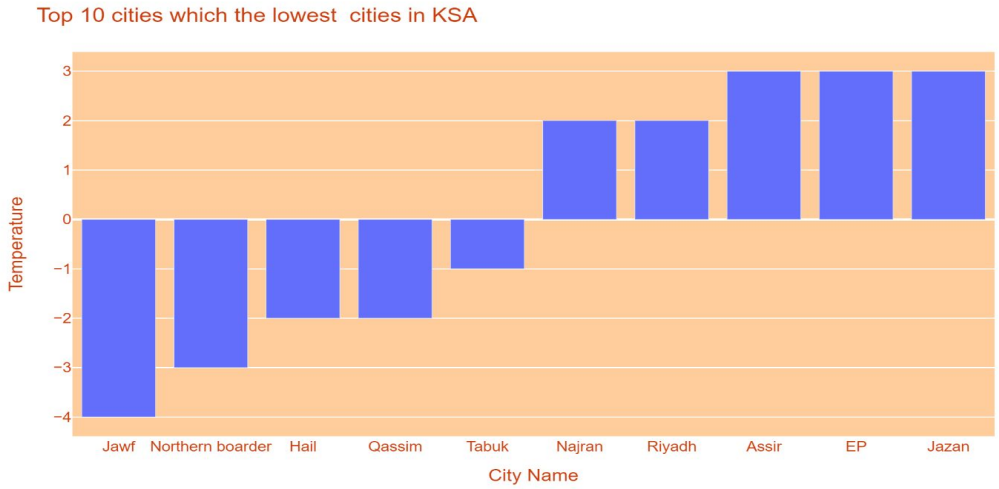
# 4th Plot

In [23]:
```
min_temp=weatherKSA.groupby('city')['temp'].min().sort_values()
min_temp.head(10).index
```

Out[23]:
```
Index(['Jawf', 'Northern boarder', 'Hail', 'Qassim', 'Tabuk', 'Najran',
       'Riyadh', 'Assir', 'EP', 'Jazan'],
      dtype='object', name='city')
```

In [24]:
```
fig=px.bar(y=min_temp.head(10),x=min_temp.head(10).index)
fig.update_layout(
    title="Top 10 cities which the lowest  cities in KSA",
    xaxis_title="City Name",
    yaxis_title="Temperature",
   #legend_title="",
    plot_bgcolor='#ffcc9c',
    font=dict(
        family="Arial",
        size=14,
        color="#cc3e0e"
    )
)
```

# 4th Plot


Top 10 cities which the lowest cities in KSA
Temperature
3
2
1
0
−1
−2
−3
−4
Jawf
Northern boarder
Hail
Qassim
Tabuk
Najran
Riyadh
Assir
EP
Jazan
City Name

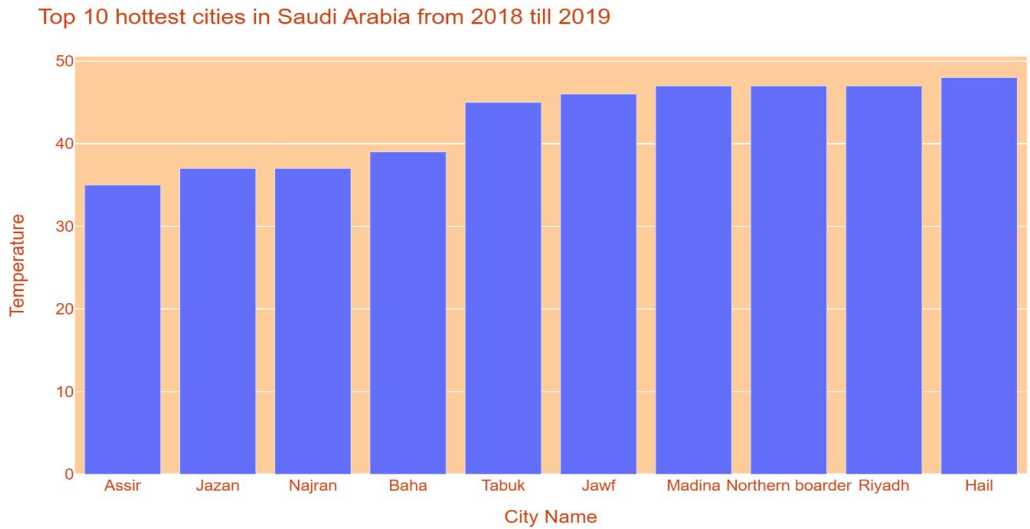
# 5th Plot

In [25]:
```
max_temp=weatherKSA.groupby('city')['temp'].max().sort_values()
max_temp.head(10).index
```

Out[25]:
```
Index(['Assir', 'Jazan', 'Najran', 'Baha', 'Tabuk', 'Jawf', 'Madina',
       'Northern boarder', 'Riyadh', 'Hail'],
      dtype='object', name='city')
```

In [26]:
```
fig=px.bar(y=max_temp.head(10),x=max_temp.head(10).index)
fig.update_layout(
    title="Top 10 hottest cities in Saudi Arabia from 2018 till 2019",
    xaxis_title="City Name",
    yaxis_title="Temperature",
    #legend_title="",
    plot_bgcolor='#ffcc9c',
    font=dict(
        family="Arial",
        size=14,
        color="#cc3e0e"
    )
)
```

# 5th Plot

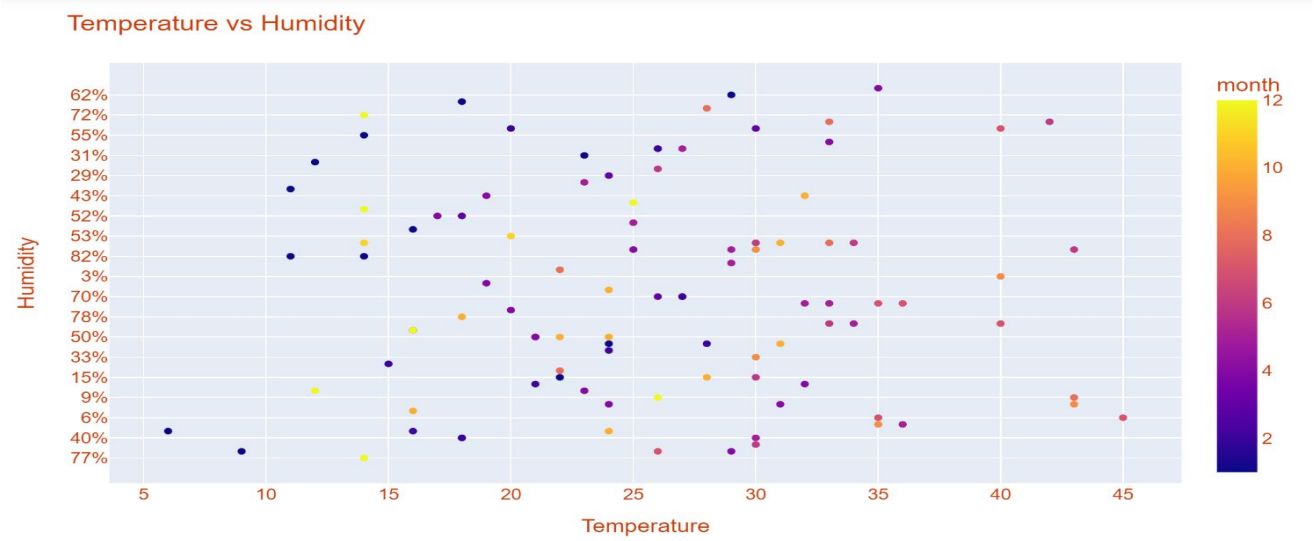

Top 10 hottest cities in Saudi Arabia from 2018 till 2019
Temperature
50
40
30
20
10
0
Assir
Jazan
Najran
Baha
Tabuk
Jawf
Madina
Northern boarder
Riyadh
Hail
City Name

# 6th Plot

In [27]:
```
sample_df=weatherKSA.sample(100)
```

In [28]:
```
fig=px.scatter(sample_df, x='temp',y='humidity',color='month',hover_name='city')
fig.update_layout(
    title="Temperature vs Humidity",
    xaxis_title="Temperature",
    yaxis_title="Humidity",
    legend_title="Month",
    font=dict(
        family="Arial",
        size=14,
        color="#cc3e0e"
    )
)
fig
```

# 6th Plot


Temperature vs Humidity
Humidity
62%
72%
55%
31%
29%
43%
52%
53%
82%
3%
70%
78%
50%
33%
15%
9%
6%
40%
77%
5
10
15
20
25
30
35
40
45
Temperature
month
12
10
8
6
4
2

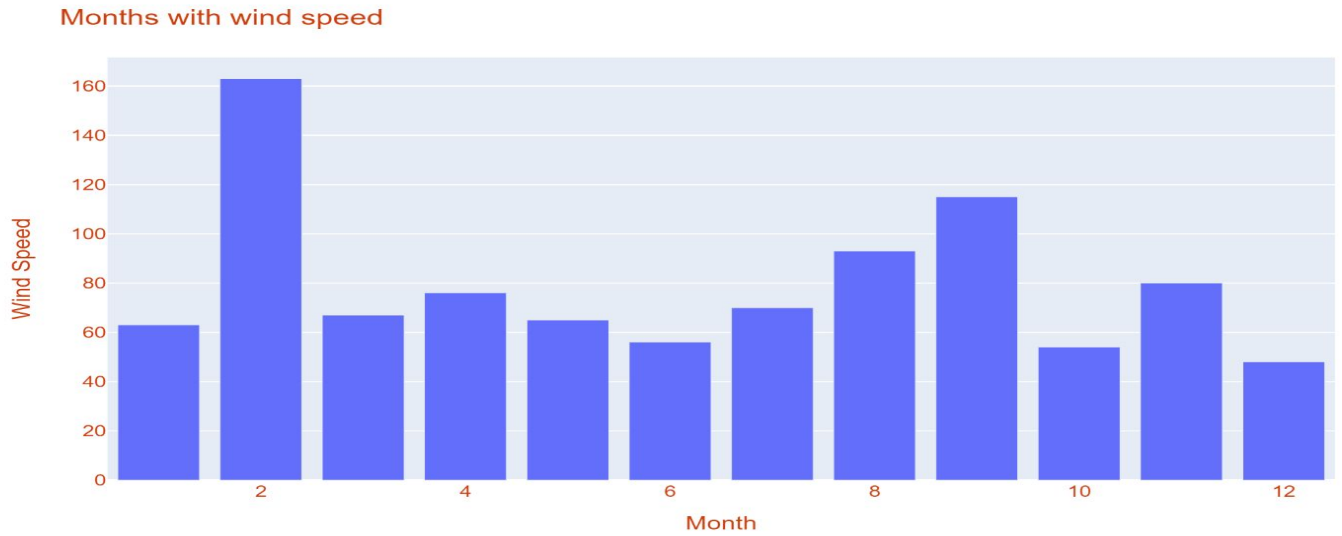
# 7th Plot

In [29]:
```
max_wind=weatherKSA.groupby('month')['wind'].max().sort_values(ascending=False)
max_wind.index
```

Out[29]:
```
Int64Index([2, 9, 8, 11, 4, 7, 3, 5, 1, 6, 10, 12], dtype='int64', name='month')
```

In [30]:
```
#plot the months with wind speed
fig=px.bar(y=max_wind,x=max_wind.index)
fig.update_layout(
    title="Months with wind speed",
    xaxis_title="Month",
    yaxis_title="Wind Speed",
        font=dict(
        family="Arial",
        size=14,
        color="#cc3e0e"
    )
)
fig
```

# 7th Plot


Months with wind speed
Wind Speed
160
140
120
100
80
60
40
20
0
2
4
6
8
10
12
Month

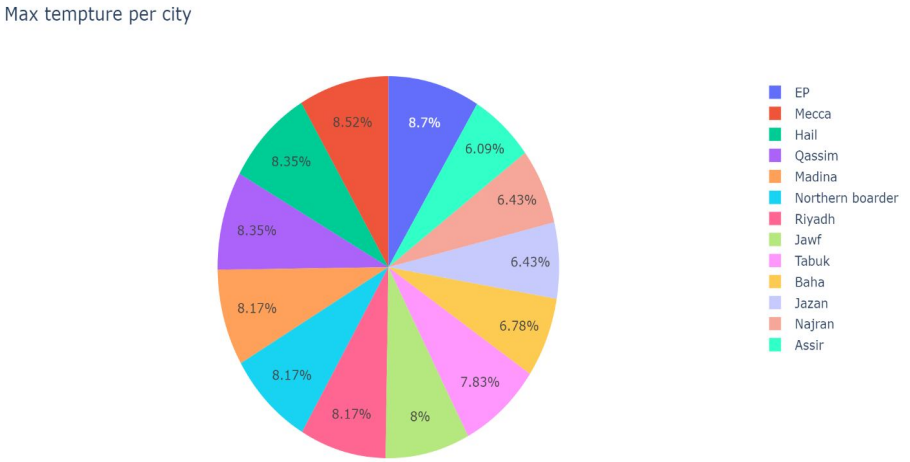
# 8th Plot

```
In [32]: df = weatherKSA.groupby('city')[['temp']].max()
         df.reset_index(inplace=True)
         df
```

Out[32]:

| | city | temp |
|---|---|---|
| 0 | Assir | 35 |
| 1 | Baha | 39 |
| 2 | EP | 50 |
| 3 | Hail | 48 |
| 4 | Jawf | 46 |
| 5 | Jazan | 37 |
| 6 | Madina | 47 |
| 7 | Mecca | 49 |
| 8 | Najran | 37 |
| 9 | Northern boarder | 47 |
| 10 | Qassim | 48 |
| 11 | Riyadh | 47 |
| 12 | Tabuk | 45 |

```
In [33]: fig = px.pie(df, values='temp', names= 'city', title='Max tempture per city')
         fig.show()
```



# 9th Plot

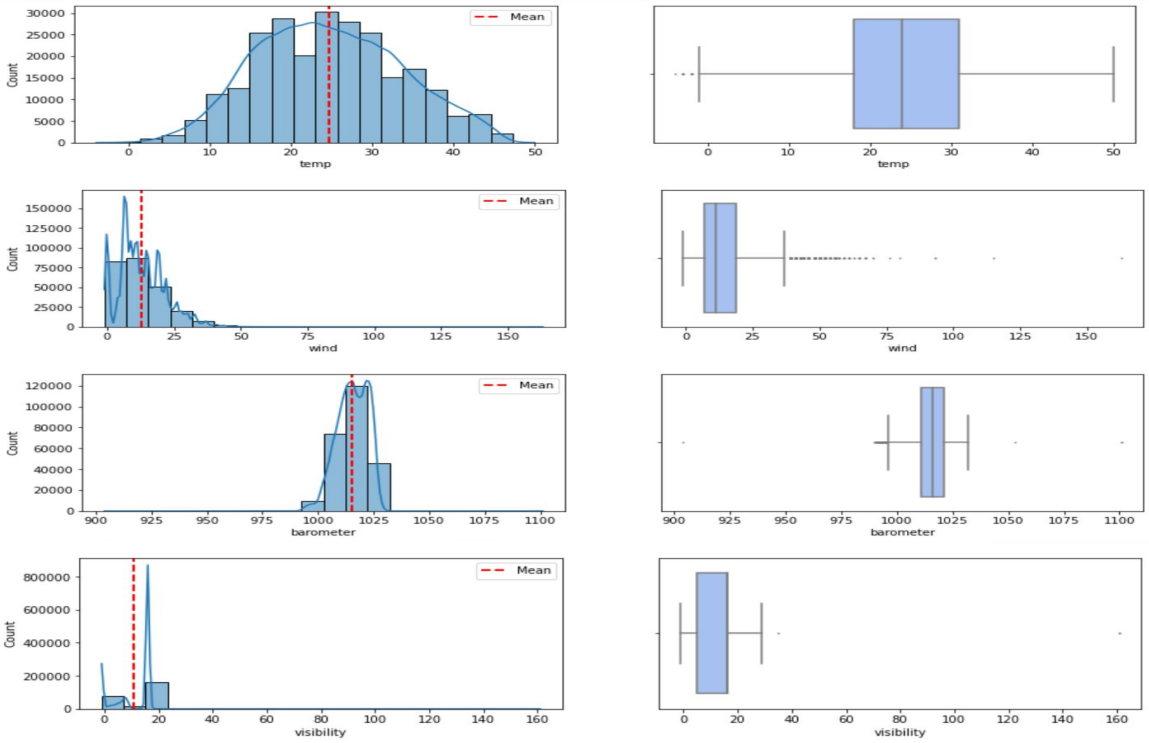
In [31]:

```
num_cols=weatherKSA.loc[:,'temp':'visibility'].select_dtypes(include=['int64','float64']).columns.tolist()
for i in num_cols:

    fig, axs = plt.subplots(1,2,figsize=(15, 3))

    sns.histplot(weatherKSA[i],bins=20, kde=True,ax=axs[0]);
    sns.boxplot(x= weatherKSA[i], ax = axs[1], color='#99befd', fliersize=1);

    axs[0].axvline(weatherKSA[i].mean(), color='r', linewidth=2, linestyle='--', label='Mean')
    axs[0].legend()
```


Mean
Count
temp
wind
barometer
visibility

# Machine Learning

**weather-sa-2017-2019-clean.csv** (18.81 MB)

Detail | Compact | Column

10 of 15 columns

| city | date | time | year | month | day | hour | minute | weather |
|---|---|---|---|---|---|---|---|---|
| Qassim | 1 January 2017 | 00:00 | 2017 | 1 | 1 | 24 | 0 | Clear |
| Qassim | 1 January 2017 | 01:00 | 2017 | 1 | 1 | 1 | 0 | Clear |
| Qassim | 1 January 2017 | 03:00 | 2017 | 1 | 1 | 3 | 0 | Clear |
| Qassim | 1 January 2017 | 04:00 | 2017 | 1 | 1 | 4 | 0 | Clear |
| Qassim | 1 January 2017 | 05:00 | 2017 | 1 | 1 | 5 | 0 | Clear |
| Qassim | 1 January 2017 | 06:00 | 2017 | 1 | 1 | 6 | 0 | Clear |
| Qassim | 1 January 2017 | 07:00 | 2017 | 1 | 1 | 7 | 0 | Sunny |
| Qassim | 1 January 2017 | 08:00 | 2017 | 1 | 1 | 8 | 0 | Sunny |
| Qassim | 1 January 2017 | 09:00 | 2017 | 1 | 1 | 9 | 0 | Sunny |
| Qassim | 1 January 2017 | 10:00 | 2017 | 1 | 1 | 10 | 0 | Sunny |
| Qassim | 1 January 2017 | 11:00 | 2017 | 1 | 1 | 11 | 0 | Sunny |
| Qassim | 1 January 2017 | 12:00 | 2017 | 1 | 1 | 12 | 0 | Sunny |
| Qassim | 1 January 2017 | 13:00 | 2017 | 1 | 1 | 13 | 0 | Sunny |
| Qassim | 1 January 2017 | 14:00 | 2017 | 1 | 1 | 14 | 0 | Sunny |
| Qassim | 1 January 2017 | 15:00 | 2017 | 1 | 1 | 15 | 0 | Sunny |
| Qassim | 1 January 2017 | 16:00 | 2017 | 1 | 1 | 16 | 0 | Sunny |
| Qassim | 1 January 2017 | 17:00 | 2017 | 1 | 1 | 17 | 0 | Sunny |
| Qassim | 1 January 2017 | 18:00 | 2017 | 1 | 1 | 18 | 0 | Clear |

# Transform all string values to integers

In [34]:
```
weatherKSA['weather']=weatherKSA['weather'].astype('category')
weatherKSA['weather']=weatherKSA['weather'].cat.codes
```

In [35]:
```
weatherKSA['city']=weatherKSA['city'].astype('category')
weatherKSA['city']=weatherKSA['city'].cat.codes
```

In [36]:
```
weatherKSA
```

Out[36]:

| | city | date | time | year | month | day | hour | minute | weather | temp | wind | humidity | barometer | visibility |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 10 | 2017-01-01 | 00:00 | 2017 | 1 | 1 | 24 | 0 | 1 | 17 | 11 | 64% | 1018.0 | 16 |
| **1** | 10 | 2017-01-01 | 01:00 | 2017 | 1 | 1 | 1 | 0 | 1 | 17 | 6 | 64% | 1018.0 | 16 |
| **2** | 10 | 2017-01-01 | 03:00 | 2017 | 1 | 1 | 3 | 0 | 1 | 15 | 11 | 72% | 1019.0 | 16 |
| **3** | 10 | 2017-01-01 | 04:00 | 2017 | 1 | 1 | 4 | 0 | 1 | 15 | 11 | 72% | 1019.0 | 16 |
| **4** | 10 | 2017-01-01 | 05:00 | 2017 | 1 | 1 | 5 | 0 | 1 | 15 | 9 | 72% | 1019.0 | 16 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **249018** | 4 | 2019-04-30 | 19:00 | 2019 | 4 | 30 | 19 | 0 | 40 | 32 | 19 | 14% | 1014.0 | -1 |
| **249019** | 4 | 2019-04-30 | 20:00 | 2019 | 4 | 30 | 20 | 0 | 40 | 29 | 9 | 22% | 1015.0 | -1 |
| **249020** | 4 | 2019-04-30 | 21:00 | 2019 | 4 | 30 | 21 | 0 | 40 | 27 | 7 | 24% | 1016.0 | -1 |
| **249021** | 4 | 2019-04-30 | 22:00 | 2019 | 4 | 30 | 22 | 0 | 1 | 26 | 0 | 26% | 1017.0 | 16 |
| **249022** | 4 | 2019-04-30 | 23:00 | 2019 | 4 | 30 | 23 | 0 | 1 | 24 | 7 | 29% | 1017.0 | 16 |

249023 rows × 14 columns

# Baseline Model

```
In [37]: weatherKSA["weather"].value_counts(normalize=True)
```

```
Out[37]: 1     0.396859
         65    0.330066
         40    0.138060
         56    0.061456
         39    0.027809
                 ...
         19    0.000004
         63    0.000004
         15    0.000004
         62    0.000004
         43    0.000004
         Name: weather, Length: 81, dtype: float64
```

# Feature Selection

In [38]:
```
features = ['city','temp','wind','barometer','visibility']
x = weatherKSA.loc[:, features]
y = weatherKSA.loc[:, ['weather']]
```

In [39]:
```
x.shape
```

Out[39]: (249023, 5)

In [40]:
```
y.shape
```

Out[40]: (249023, 1)

In [41]:
```
le = LabelEncoder()

x.iloc[:,0] = le.fit_transform(x.iloc[:,0])
```

# Split the Data

In [42]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 0)
```

In [43]:
```
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

# Machine Learning

**1st model: DecisionTreeClassifier**

In [44]:
```
from sklearn.linear_model import LogisticRegression
```

In [45]:
```
classifier_log=LogisticRegression(random_state=0)
classifier_log.fit(x_train,y_train)
```

Out[45]:
```
LogisticRegression(random_state=0)
```

In [46]:
```
class_tree = DecisionTreeClassifier(criterion = 'gini', random_state = 45).fit(x_train, y_train)
preds_class = class_tree.predict(x_test)

val_train = round(class_tree.score(x_train, y_train),2)*100
val_test = round(class_tree.score(x_test, y_test),2)*100

print(f'Training Accuracy: {val_train}%')
print(f'Test Accuracy: {val_test}%')
```

```
Training Accuracy: 86.0%
Test Accuracy: 64.0%
```

# Machine Learning

**2nd model: Random Forest Classifier**

In [47]:

```
class_forest = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0)
class_forest.fit(x_train, y_train)
preds_class = class_forest.predict(x_test)

val_train = round(class_forest.score(x_train, y_train),2)*100
val_test = round(class_forest.score(x_test, y_test),2)*100

print(f'Training Accuracy: {val_train}%')
print(f'Test Accuracy: {val_test}%')
```

```
Training Accuracy: 85.0%
Test Accuracy: 65.0%
```

# Machine Learning

**3rd model: Decision Tree Classifier**

In [48]:

```
clf3 = DecisionTreeClassifier(criterion = 'gini', random_state = 0, max_depth=4)
clf3.fit(x_train, y_train)
preds_class = clf3.predict(x_test)

val_train = round(clf3.score(x_train, y_train),2)*100
val_test = round(clf3.score(x_test, y_test),2)*100

print(f'Training Accuracy: {val_train}%')
print(f'Test Accuracy: {val_test}%')
```

```
Training Accuracy: 59.0%
Test Accuracy: 59.0%
```

# Hyperparameter

In [49]:

```
n_estimators = [5,20,50,100]
max_features = ['auto', 'sqrt']
max_depth = [int(x) for x in np.linspace(10, 120, num = 12)]
min_samples_split = [2, 6, 10]
min_samples_leaf = [1, 3, 4]
bootstrap = [True, False]

random_grid = {'n_estimators': n_estimators,

'max_features': max_features,

'max_depth': max_depth,

'min_samples_split': min_samples_split,

'min_samples_leaf': min_samples_leaf,

'bootstrap': bootstrap}
```

# Hyperparameter

In [50]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(random_state = 50)
```

In [51]:
```
from sklearn.model_selection import RandomizedSearchCV
randomRF = RandomizedSearchCV(estimator = rf,param_distributions = random_grid,
               n_iter = 100, cv = 5, verbose=2, random_state=50, n_jobs = -1)
```

In [52]:
```
randomRF.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

Out[52]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(random_state=50),
                   n_iter=100, n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      120],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 3, 4],
                                        'min_samples_split': [2, 6, 10],
                                        'n_estimators': [5, 20, 50, 100]},
                   random_state=50, verbose=2)
```

# Hyperparameter

```
In [53]: y_pred = class_forest.predict(x_test)

In [54]: print(x_test)

[[ 0.51868193 -1.09482178 -1.48705256  1.22568844  0.70140464]
 [-1.12909595 -0.08102359  1.49509682 -0.35054133  0.70140464]
 [ 0.24405229  0.1442649  -0.68416619 -0.63712857 -1.71151938]
 ...
 [ 0.79331158  0.25690914 -1.02826035 -1.64018388  0.70140464]
 [ 0.24405229  0.70748612  0.00402213 -2.35665195 -1.71151938]
 [-0.8544663  -0.30631207 -0.22537398 -0.20724772  0.70140464]]

In [55]: y_pred = pd.DataFrame(y_pred)
```

# Hyperparameter

In [57]:
```
print ('Random grid: ', random_grid, '\n')
```

```
Random grid:  {'n_estimators': [5, 20, 50, 100], 'max_features': ['auto', 'sqrt'], 'max_depth': [10, 20, 30, 40, 5
0, 60, 70, 80, 90, 100, 110, 120], 'min_samples_split': [2, 6, 10], 'min_samples_leaf': [1, 3, 4], 'bootstrap': [Tr
ue, False]}
```

In [58]:
```
print ('Best Parameters: ', randomRF.best_params_, ' \n')
```

```
Best Parameters:  {'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 3, 'max_features': 'sqrt', 'max
_depth': 20, 'bootstrap': True}
```

In [59]:
```
bestRand = RandomForestRegressor(n_estimators = 100, min_samples_split = 6, min_samples_leaf= 4,
                                 max_features = 'sqrt', max_depth= 120, bootstrap=False)
bestRand.fit( x_train, y_train)
```

Out[59]:
```
RandomForestRegressor(bootstrap=False, max_depth=120, max_features='sqrt',
                      min_samples_leaf=4, min_samples_split=6)
```

# Model Evaluation

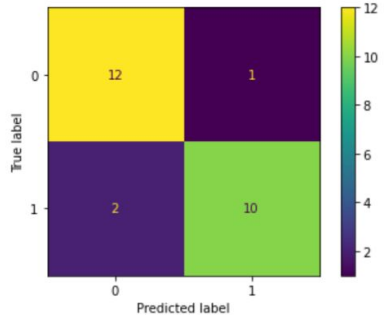
In [64]:
```
from sklearn.datasets import make_classification
x, y = make_classification(random_state=0)
x_train, x_test, y_train, y_test = train_test_split( x,y , random_state=0)
```

In [65]:
```
from sklearn.svm import SVC
clf = SVC(random_state=0)
```

In [66]:
```
clf.fit(x_train, y_train)
```

Out[66]:
```
SVC(random_state=0)
```

In [67]:
```
plot_confusion_matrix(clf, x_test, y_test)
plt.show()
```



# Model Evaluation

In [35]:
```
from sklearn.metrics import precision_score, recall_score, accuracy_score
```

In [36]:
```
print("Precision Score : ",precision_score(y_test, y_pred,
                                           pos_label='positive',
                                           average='micro'))
print("Recall Score : ",recall_score(y_test, y_pred,
                                     pos_label='positive',
                                     average='micro'))
```

```
Precision Score :  0.6494127095673126
Recall Score :  0.6494127095673126
```

In [37]:
```
print('Accuracy Score: %.3f' % accuracy_score(y_test, y_pred))
```

```
Accuracy Score: 0.649
```

# Pipeline

In [70]:
```
x_test= pd.DataFrame(x_test)
```

In [71]:
```
x_train= pd.DataFrame(x_train)
```

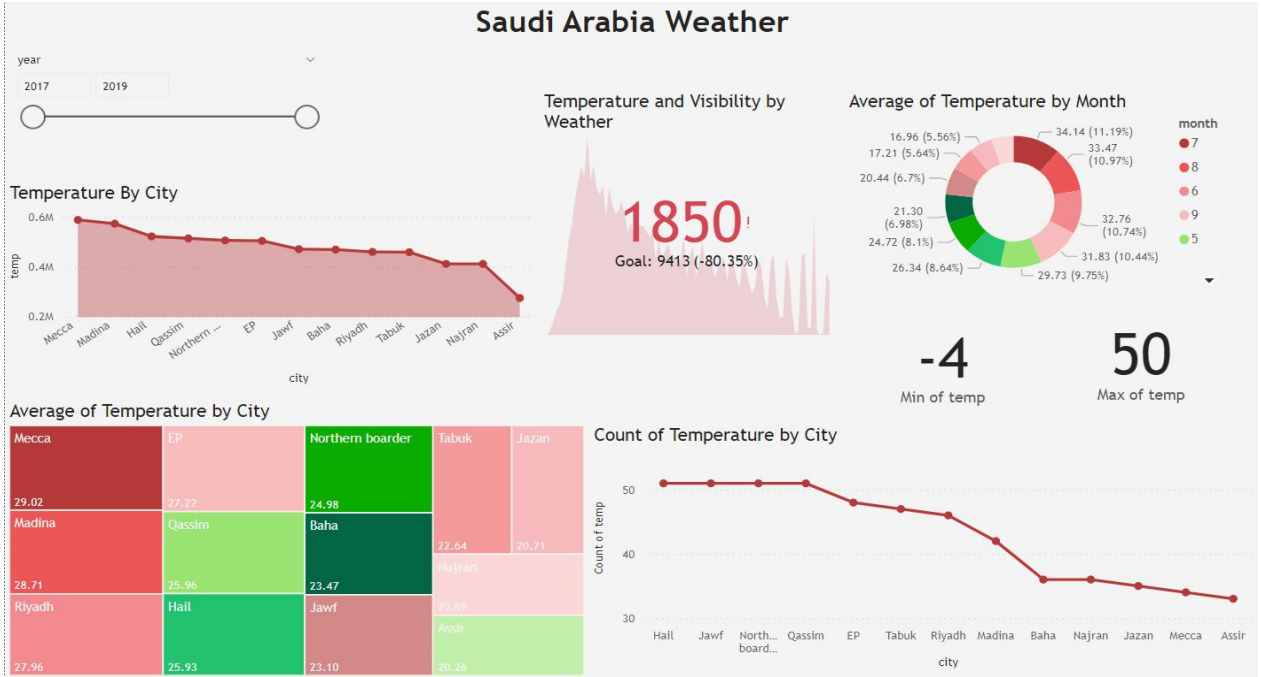
In [72]:
```
x_train_n = x_train.select_dtypes(exclude=["category", "object"])
x_test_n = x_test.select_dtypes(exclude=["category", "object"])

pipe = make_pipeline(
    SimpleImputer(),
    StandardScaler(),
    LogisticRegression()
)

pipe.fit(x_train_n,y_train)
pipe.score(x_test_n, y_test)
print(f'Pipeline Accuracy: {pipe.score(x_test_n, y_test)}')
```

```
Pipeline Accuracy: 0.92
```

# PowerBi Dashboard



# Thanks

# Resources

- weather-sa dataset
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