Name: - L PRATHYUSHA

ANALYSIS OF THE WEATHER DATA

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.ar_model import AutoReg

!install pdarima
from pmdarima import auto_arima
#ignore harmless warnings
import warnings
warnings.filterwarnings("ignore")
!pip install textblob
from textblob import TextBlob
```

WEATHER DATASET Analysis Contents

1. loading and inspecting the data
2. data cleaning
3. framing Questions and solutions
4. Time series (plots, ADFULLER test for stationary, SARIMAX, partial and Autocorrelation, Auto Regression)
5. data analysis (analysis of every plot and graph is explained properly)
6. ARIMA model (installing pdarima, auto_arima and i did the analysis)
7. Sentimental Analysis
8. conclusion and learnings

Graphs included: - barplot, histogram, pairplot, displot, heatmap, boxplot, joint plot(hex,reg,kde), relplot, pointplot, countplot, stripplot

Loading the csv data

A CSV file (Comma Separated Values file) is a type of plain text file that uses specific structuring to arrange tabular data.

1. pandas recognized that the first line of the CSV contained column names, and used them automatically.
2. pandas is also using zero-based integer indices in the DataFrame. That’s because we didn’t tell it what our index should be.

PART 1: - Loading and inspecting the data

In [2]:

```
data=pd.read_csv('C:/Users/Prathyu Lachireddy/Desktop/weatherHistory.csv')
data.head(8)
```

Out[2]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)	Vis
0	2006-04-01 00:00:00.000 +0200	Partly Cloudy	rain	9.472222	7.388889	0.89	14.1197	251.0	15
1	2006-04-01 01:00:00.000 +0200	Partly Cloudy	rain	9.355556	7.227778	0.86	14.2646	259.0	15
2	2006-04-01 02:00:00.000 +0200	Mostly Cloudy	rain	9.377778	9.377778	0.89	3.9284	204.0	14
3	2006-04-01 03:00:00.000 +0200	Partly Cloudy	rain	8.288889	5.944444	0.83	14.1036	269.0	15
4	2006-04-01 04:00:00.000 +0200	Mostly Cloudy	rain	8.755556	6.977778	0.83	11.0446	259.0	15
5	2006-04-01 05:00:00.000 +0200	Partly Cloudy	rain	9.222222	7.111111	0.85	13.9587	258.0	14
6	2006-04-01 06:00:00.000 +0200	Partly Cloudy	rain	7.733333	5.522222	0.95	12.3648	259.0	9
7	2006-04-01 07:00:00.000 +0200	Partly Cloudy	rain	8.772222	6.527778	0.89	14.1519	260.0	9

In [12]:

```
# Loading the head and tail data

data.head()
```

Out[12]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)	Vis
0	2006-04-01 00:00:00.000 +0200	Partly Cloudy	rain	9.472222	7.388889	0.89	14.1197	251.0	15
1	2006-04-01 01:00:00.000 +0200	Partly Cloudy	rain	9.355556	7.227778	0.86	14.2646	259.0	15
2	2006-04-01 02:00:00.000 +0200	Mostly Cloudy	rain	9.377778	9.377778	0.89	3.9284	204.0	14
3	2006-04-01 03:00:00.000 +0200	Partly Cloudy	rain	8.288889	5.944444	0.83	14.1036	269.0	15
4	2006-04-01 04:00:00.000 +0200	Mostly Cloudy	rain	8.755556	6.977778	0.83	11.0446	259.0	15

In [6]:

```
data.tail()
```

Out[6]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)
96448	2016-09-09 19:00:00.000 +0200	Partly Cloudy	rain	26.016667	26.016667	0.43	10.9963	31.0
96449	2016-09-09 20:00:00.000 +0200	Partly Cloudy	rain	24.583333	24.583333	0.48	10.0947	20.0
96450	2016-09-09 21:00:00.000 +0200	Partly Cloudy	rain	22.038889	22.038889	0.56	8.9838	30.0
96451	2016-09-09 22:00:00.000 +0200	Partly Cloudy	rain	21.522222	21.522222	0.60	10.5294	20.0
96452	2016-09-09 23:00:00.000 +0200	Partly Cloudy	rain	20.438889	20.438889	0.61	5.8765	39.0

PART 2: - Data Cleaning

In [3]:

```
data.shape
```

Out[3]:

```
(96453, 12)
```

In [70]:

```
len(data)
```

Out[70]:

```
96453
```

In [4]:

```
data.dtypes
```

Out[4]:

```
Formatted Date               object
Summary                      object
Precip Type                  object
Temperature (C)             float64
Apparent Temperature (C)    float64
Humidity                    float64
Wind Speed (km/h)           float64
Wind Bearing (degrees)      float64
Visibility (km)             float64
Loud Cover                  float64
Pressure (millibars)        float64
Daily Summary                object
dtype: object
```

In [7]:

```
#This shows the all the titles of the data since this is a huge data to deal with, this cod
data.columns
```

Out[7]:

```
Index(['Formatted Date', 'Summary', 'Precip Type', 'Temperature (C)',
       'Apparent Temperature (C)', 'Humidity', 'Wind Speed (km/h)',
       'Wind Bearing (degrees)', 'Visibility (km)', 'Loud Cover',
       'Pressure (millibars)', 'Daily Summary'],
      dtype='object')
```

In [24]:

```
#isnull() function detect missing values in the given series object.
#It return a boolean same-sized object indicating if the values are NA.
#Missing values gets mapped to True and non-missing value gets mapped to False .

import numpy as np
data.isnull().sum()
```

Out[24]:

```
Formatted Date                0
Summary                       0
Precip Type                 517
Temperature (C)               0
Apparent Temperature (C)      0
Humidity                      0
Wind Speed (km/h)             0
Wind Bearing (degrees)        0
Visibility (km)               0
Loud Cover                    0
Pressure (millibars)          0
Daily Summary                 0
dtype: int64
```

In [25]:

```
#data.fillna(method='ffill')

null_values=data.fillna(np.mean(data))
null_values
```

Out[25]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)	Visibility (km)	L C
0	2006-04-01 00:00:00.000 +0200	Partly Cloudy	rain	9.472222	7.388889	0.89	14.1197	251.0	15.8263	
1	2006-04-01 01:00:00.000 +0200	Partly Cloudy	rain	9.355556	7.227778	0.86	14.2646	259.0	15.8263	
2	2006-04-01 02:00:00.000 +0200	Mostly Cloudy	rain	9.377778	9.377778	0.89	3.9284	204.0	14.9569	
	2006-04-01									

PART 3: - Solutions to few questions

1. Lowest temperature recorded in the given data?; mean values?

In [8]:

```
# i am trying to extract infomation from the weather data where it can show the lowest temp
# The result shows that the lowest temperature that is recorded in this particular part of
# -22 degrees is freezing cold, i did that by finding the lowest and the minimum value in t

data["Temperature (C)"].min()
```

Out[8]:

```
-21.822222222222226
```

In [9]:

```
# this shows the mean which is nothing but the average value of the  temperature data thoug
# the result is saying that the average temperature in this area is 11 degrees.

mean1 = data['Temperature (C)'].mean()
mean1
```

Out[9]:

```
11.932678437511868
```

In [10]:

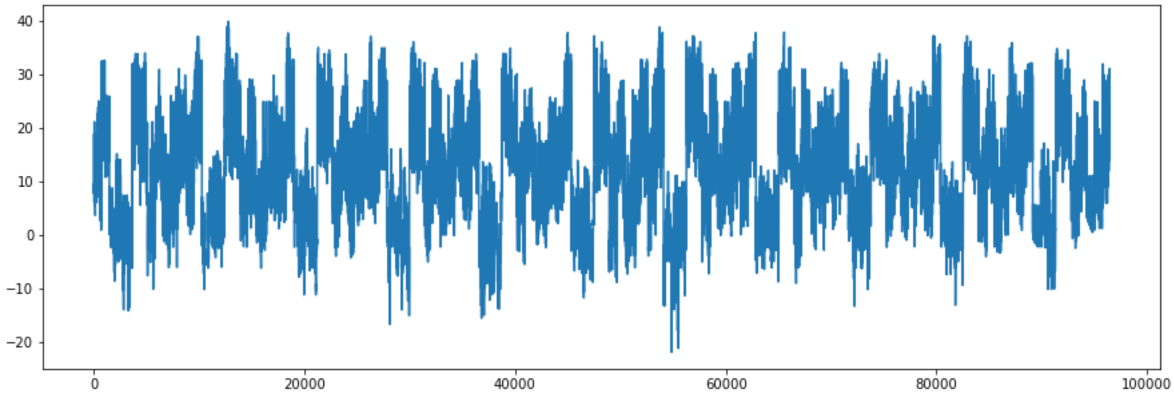
```
# the apparent temperature means the estimated temperature by analysing, but this is just a
# The result shows the mean for this is 10.85 degrees (11 degrees) which is close to the re
# then this data is relevant and trustable

mean2 = data['Apparent Temperature (C)'].mean()
mean2
```

Out[10]:

```
10.855028874166726
```

In [28]:

```
#the graph shows that variations in the temperature in the due course of time.
#it can be observed that in this particular part of the world where we are analysing the lo
#like there are many instances that the temperature is showing below 0 degrees which is col

import matplotlib.pyplot as plt
fig_dims = (15, 5)
fig, ax = plt.subplots(figsize=fig_dims)
data['Temperature (C)'].plot()
plt.show()
```



2. Unique Values

In [12]:

```
#nunique() function return number of unique elements in the object.
#It returns a scalar value which is the count of all the unique values in the Index.
data.nunique()
```

Out[12]:

```
Formatted Date              96429
Summary                        27
Precip Type                     2
Temperature (C)              7574
Apparent Temperature (C)     8984
Humidity                       90
Wind Speed (km/h)            2484
Wind Bearing (degrees)        360
Visibility (km)               949
Loud Cover                      1
Pressure (millibars)         4979
Daily Summary                 214
dtype: int64
```

In [13]:

```
data['Wind Speed (km/h)'].nunique()
```

Out[13]:

```
2484
```

3. Finding the values that show when exactly 'the weather was clear'?

In [14]:

```
# this shows the the number of numerical data is there under each of the categories in the

#value_counts()
data.Summary.value_counts()
```

Out[14]:

```
Partly Cloudy                          31733
Mostly Cloudy                          28094
Overcast                               16597
Clear                                  10890
Foggy                                   7148
Breezy and Overcast                      528
Breezy and Mostly Cloudy                 516
Breezy and Partly Cloudy                 386
Dry and Partly Cloudy                     86
Windy and Partly Cloudy                   67
Light Rain                                63
Breezy                                    54
Windy and Overcast                        45
Humid and Mostly Cloudy                   40
Drizzle                                   39
Windy and Mostly Cloudy                   35
Breezy and Foggy                          35
Dry                                       34
```

In [87]:

```
#This code will display only the clear weather
#filtering
#data.head(2)
data[data.Summary == 'Clear']

#or

#groupby()
#data.head(2)
data.groupby('Summary').get_group('Clear')

#Here we are taking all the Clear weather data values from the summary in the weather data
# if there was clear weather for a person to go out.
```

Out[87]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)	Visibility (km)	Lo Co
223	2006-04-18 07:00:00.000 +0200	Clear	rain	8.688889	8.688889	0.93	1.4329	290.0	5.8443	
309	2006-04-20 21:00:00.000 +0200	Clear	rain	12.266667	12.266667	0.99	8.0500	320.0	6.1985	
337	2006-04-22 01:00:00.000 +0200	Clear	rain	9.355556	8.633333	0.96	6.4239	321.0	3.3649	

4. Rename the 'daily summary' column to 'Weather condition'.

In [92]:

```
#here i am displaying only the first five rows of the weather data.
#it could be observed that the last column is now renamed as 'Weather condition'
D=data.head(5)

D.rename(columns = {'Daily Summary': 'Weather condition'})
```

Out[92]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)	Vis
0	2006-04-01 00:00:00.000 +0200	Partly Cloudy	rain	9.472222	7.388889	0.89	14.1197	251.0	15
1	2006-04-01 01:00:00.000 +0200	Partly Cloudy	rain	9.355556	7.227778	0.86	14.2646	259.0	15
2	2006-04-01 02:00:00.000 +0200	Mostly Cloudy	rain	9.377778	9.377778	0.89	3.9284	204.0	14
3	2006-04-01 03:00:00.000 +0200	Partly Cloudy	rain	8.288889	5.944444	0.83	14.1036	269.0	15
4	2006-04-01 04:00:00.000 +0200	Mostly Cloudy	rain	8.755556	6.977778	0.83	11.0446	259.0	15

5. show that the weather is 'clear' and the humidity is greater than 0.95.

In [102]:

```
# we need to observe that in order to snow the temperature that is recorded should be negat
data[(data['Summary']=='Clear') & (data['Humidity'] > 0.95)]
```

Out[102]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Apparent Temperature (C)	Humidity	Wind Speed (km/h)	Wind Bearing (degrees)	Visibility (km)	Lo Co
309	2006-04-20 21:00:00.000 +0200	Clear	rain	12.266667	12.266667	0.99	8.0500	320.0	6.1985	
337	2006-04-22 01:00:00.000 +0200	Clear	rain	9.355556	8.633333	0.96	6.4239	321.0	3.3649	
	2006-04-22									

PART 4: - Time series

Time series analysis is a statistical technique that deals with time series data, or trend analysis. Time series data means that data is in a series of particular time periods or intervals.

In [14]:

```
from statsmodels.tsa.seasonal import seasonal_decompose

plt.plot(timeseries['Humidity'])
```

Out[14]:

```
[<matplotlib.lines.Line2D at 0x1b660ce45b0>]
```

In [18]:

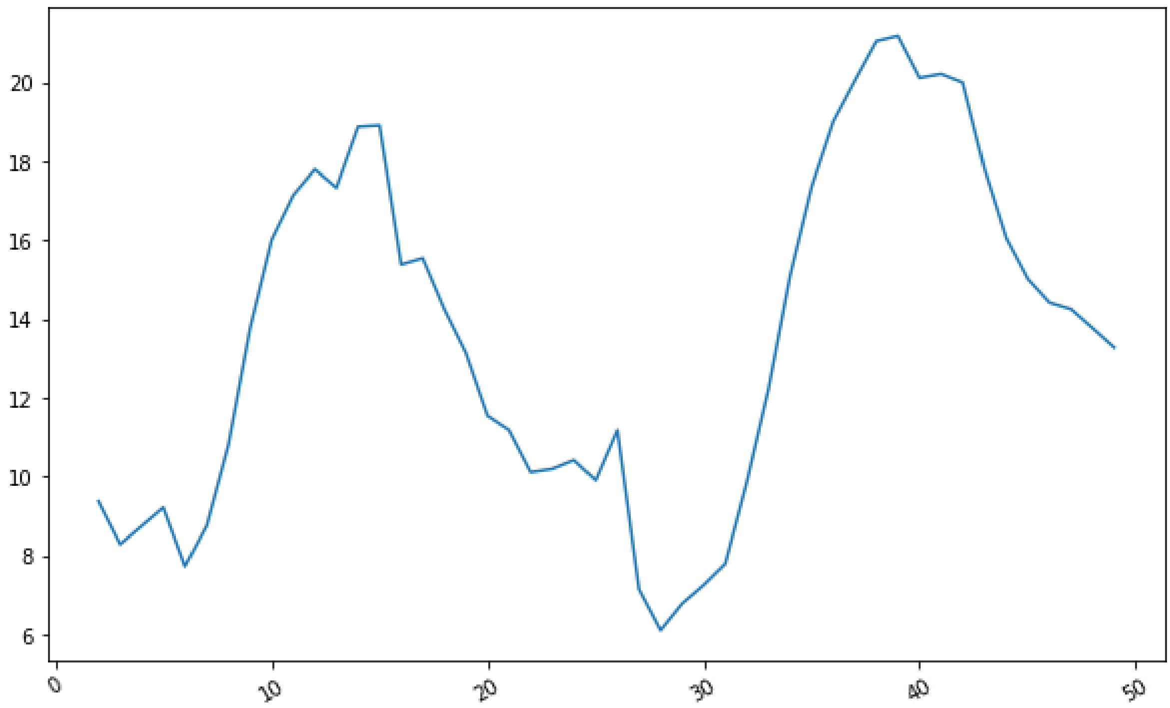
```
timeseries['Date']=pd.to_datetime(data['Formatted Date'])
```

In [26]:

```
#Moving average
#A simple moving average (SMA) is a calculation that takes the arithmetic mean,of a given s
# over the specific number of days in the past

plt.plot(data[1:50]['Temperature (C)'])
plt.xticks(rotation=30)
plt.show
```

Out[26]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [27]:

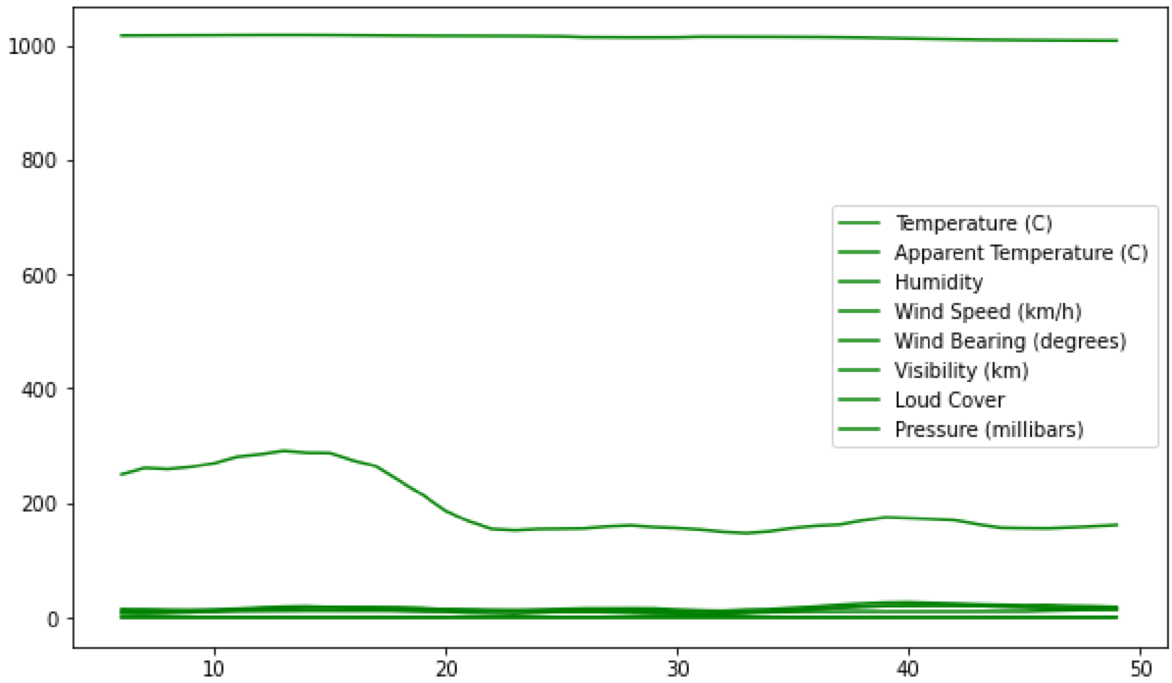
```
#rolling average transform
rollingseries=data[1:50].rolling(window=5)

rollingmean=rollingseries.mean()

print(rollingmean.head(10))
```

```
    Temperature (C)  Apparent Temperature (C)  Humidity  Wind Speed (km/h)
\
2               NaN                       NaN       NaN                NaN
3               NaN                       NaN       NaN                NaN
4               NaN                       NaN       NaN                NaN
5               NaN                       NaN       NaN                NaN
6          8.675556                  6.986667     0.870           11.08002
7          8.554444                  6.416667     0.870           13.12472
8          9.061111                  7.392222     0.868           12.56766
9         10.064444                  8.751111     0.846           12.86390
10        11.423333                 10.532222     0.810           13.58518
11        13.305556                 12.856667     0.728           15.06960

    Wind Bearing (degrees)  Visibility (km)  Loud Cover  Pressure (milliba
rs)
2                      NaN              NaN         NaN
NaN
3                      NaN              NaN         NaN
NaN
```

A moving average (rolling average or running average) is a calculation to analyze data points by creating a series of averages of different subsets of the full data set. It is also called a moving mean (MM) or rolling mean and is a type of finite impulse response filter.

In [30]:

```
rollingmean.plot(color='green')
pyplot.show()
```



In [ ]:

```
#Additive model is used when the variance of the time series doesn't change over different
#On the other hand,
#if the variance is higher when the time series is higher then it often means we should use

mul_result=seasonal_decompose(timeseries['Wind Speed (km/h)'],model="multiplicative",freq=1

type(timeseries)
add_result=seasonal_decompose(timeseries['Wind Speed (km/h)'],model="additive",freq=1)

plt.rcParams.update({'figure.figsize':(10,10)})

mul_result.plot().suptitle('\nMultiplicative Decompose', fontsize=12)
```

ADFULLER test for stationary

In [20]:

```
from statsmodels.tsa.stattools import adfuller

data.head(2)

adfuller_result=adfuller(data.Humidity.values,autolag='AIC')

print(f'ADF Statistic: {adfuller_result[0]}')

print(f'p-value: {adfuller_result[1]}')


for key,Humidity in adfuller_result[4].items():

    print('Critical Values:')
    print(f' {key},{Humidity}')
```

```
ADF Statistic: -15.795917585436289
p-value: 1.0882942157158304e-28
Critical Values:
 1%,-3.430417847426096
Critical Values:
 5%,-2.8615699874869773
Critical Values:
 10%,-2.5667859612921466
```

SARIMAX: -

Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors, or SARIMAX, is an extension of the ARIMA class of models. Intuitively, ARIMA models compose 2 parts: the autoregressive term (AR) and the moving-average term (MA). The former views the value at one time just as a weighted sum of past values.

In [ ]:

```
D1=data.head(5)
D1
```

In [ ]:

```
sarimax_model= SARIMAX(D1['Temperature (C)'],order=(1,1,1),seasonal_order=(1,1,1,4),exog=D1
```

In [ ]:

```
res=sarimax_model.fit(disp=False)
```

In [17]:

```
res.summary()
```

Out[17]:

SARIMAX Results

Dep. Variable:	Temperature (C)	**No. Observations:**	5
Model:	SARIMAX(1, 1, 1)x(1, 1, 1, 4)	**Log Likelihood**	0.000
Date:	Mon, 26 Apr 2021	**AIC**	12.000
Time:	12:16:01	**BIC**	-inf
Sample:	0 - 5	**HQIC**	nan
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
Humidity	0	nan	nan	nan	nan	nan
ar.L1	0	nan	nan	nan	nan	nan
ma.L1	0	nan	nan	nan	nan	nan
ar.S.L4	0	nan	nan	nan	nan	nan
ma.S.L4	0	nan	nan	nan	nan	nan
sigma2	1.0000	nan	nan	nan	nan	nan

Ljung-Box (L1) (Q):	nan	**Jarque-Bera (JB):**	nan
Prob(Q):	nan	**Prob(JB):**	nan
Heteroskedasticity (H):	nan	**Skew:**	nan
Prob(H) (two-sided):	nan	**Kurtosis:**	nan

Warnings:
[1] Covariance matrix is singular or near-singular, with condition number nan. Standard errors may be unstable.

In [ ]:

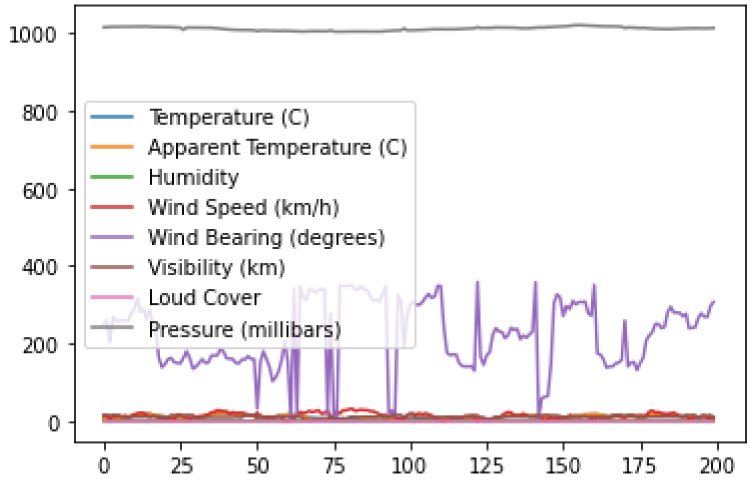
```
from statsmodels.graphics.tsaplots import plot_acf
plot_acf(heat)
```

In [44]:

```
data[:200].plot()
```

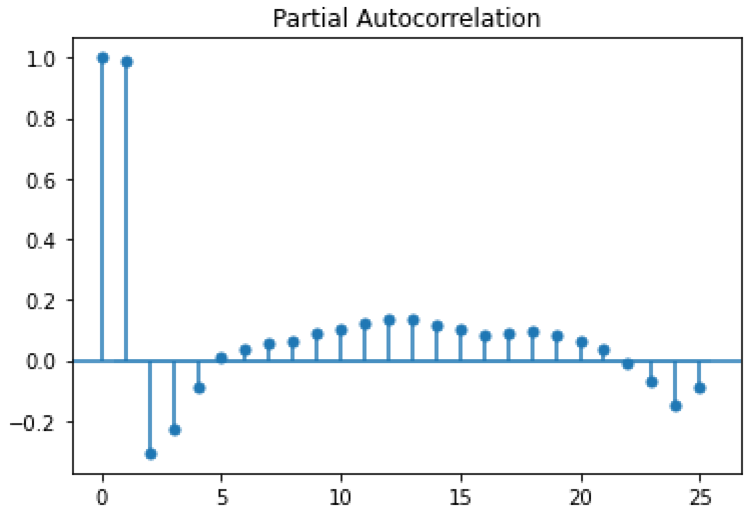
Out[44]:

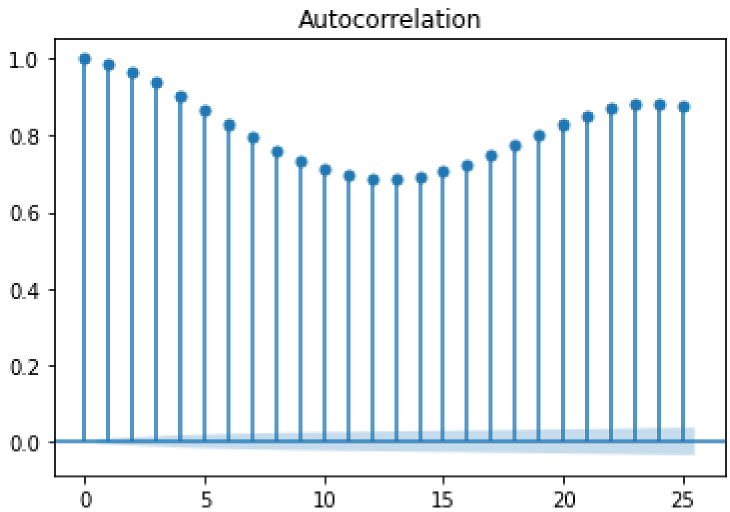
<AxesSubplot:>



In [49]:

```
from statsmodels.graphics.tsaplots import plot_pacf,plot_acf
pacf=plot_pacf(data['Temperature (C)'],lags=25)
acf=plot_acf(data['Temperature (C)'],lags=25)

#x- axis= time
#y- axis= Correlation
#higher the value the more the correlation in the data and the time.
#partial sees on the direct effect(previous and current time lag) and autocorrelation will
```





In [50]:

```
pred=model.predict(start=len(train),end=len(x)-1,dyamic=False)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-50-65fca40a8d7d> in <module>
----> 1 pred=model.predict(start=len(train),end=len(x)-1,dyamic=False)

NameError: name 'model' is not defined
```

In [64]:

```
from statsmodels.tsa.ar_model import AutoReg
X=data.Humidity
train=X[:len(X)-7]
test=X[len(X)-7:]

model=AutoReg(train,lags=10).fit()

print(model.summary())
```

```
                            AutoReg Model Results
==========================================================================
====
Dep. Variable:              Humidity   No. Observations:                9
6446
Model:                   AutoReg(10)   Log Likelihood               13369
5.186
Method:              Conditional MLE   S.D. of innovations
0.060
Date:               Mon, 26 Apr 2021   AIC                              -
5.610
Time:                       12:53:22   BIC                              -
5.609
Sample:                           10   HQIC                             -
5.610
                               96446
==========================================================================
======
                   coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------
------
intercept        0.0689      0.001     69.987      0.000       0.067
0.071
Humidity.L1      1.0223      0.003    317.696      0.000       1.016
1.029
Humidity.L2      0.0835      0.005     18.132      0.000       0.074
0.092
Humidity.L3     -0.0528      0.005    -11.456      0.000      -0.062
-0.044
Humidity.L4     -0.0886      0.005    -19.196      0.000      -0.098
-0.080
Humidity.L5     -0.0365      0.005     -7.897      0.000      -0.046
-0.027
Humidity.L6     -0.0078      0.005     -1.690      0.091      -0.017
0.001
Humidity.L7     -0.0159      0.005     -3.442      0.001      -0.025
-0.007
Humidity.L8     -0.0236      0.005     -5.119      0.000      -0.033
-0.015
Humidity.L9     -0.0132      0.005     -2.873      0.004      -0.022
-0.004
Humidity.L10     0.0389      0.003     12.101      0.000       0.033
0.045
                                    Roots
==========================================================================
====
                   Real          Imaginary           Modulus         Frequ
ency
```

```
---------------------------------------------------------------------------
----
AR.1            1.1429           -0.2837j            1.1776           -0.
0387
AR.2            1.1429           +0.2837j            1.1776            0.
0387
AR.3            1.2578           -0.0000j            1.2578           -0.
0000
AR.4            0.6841           -1.2791j            1.4505           -0.
1718
AR.5            0.6841           +1.2791j            1.4505            0.
1718
AR.6           -0.3644           -1.4056j            1.4521           -0.
2904
AR.7           -0.3644           +1.4056j            1.4521            0.
2904
AR.8           -1.1714           -0.9163j            1.4872           -0.
3943
AR.9           -1.1714           +0.9163j            1.4872            0.
3943
AR.10          -1.5005           -0.0000j            1.5005           -0.
5000
---------------------------------------------------------------------------
----
```

PART 5: - DATA VISUALISATION

Bar plot

In [5]:

```
D2=data[0:1000]
```

here i am trying to show the bar graph while comparing the humidity and temperature in the environment and i have loaded the first 1000 rows of the data so that the graph is depicted properly with the sample size of 1000

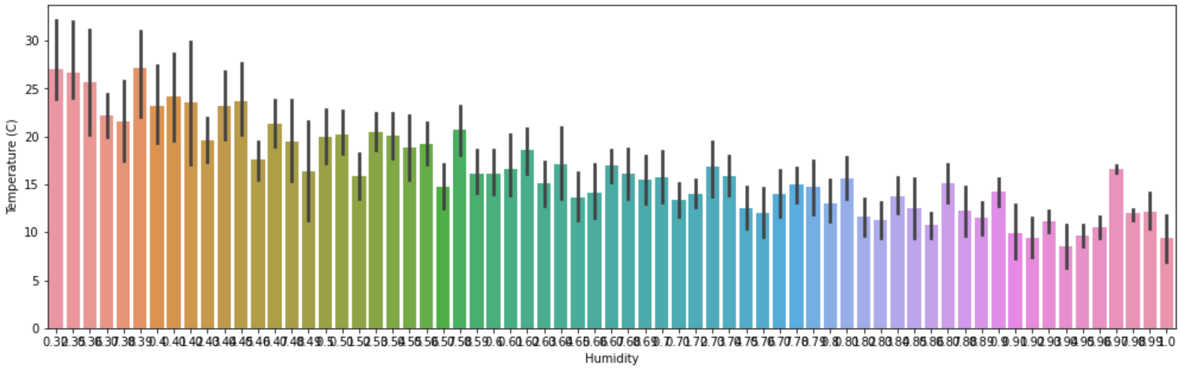
In [6]:

```
# from the result we can see that on the x-axis we have humdity and on the y-axis we have t
# when the humity level is at 0.3 then the temperature recorded is the highest where here i
# go anywhere between 25-30 degree celsius, also when the humity when is at its highest the
# like when it is at 0.9 then the temperature is between 10-15 degree celsius.

fig_dims = (17, 5)
fig, ax = plt.subplots(figsize=fig_dims)
sns.barplot(D2['Humidity'],D2['Temperature (C)'])
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[6]:

```
<AxesSubplot:xlabel='Humidity', ylabel='Temperature (C)'>
```



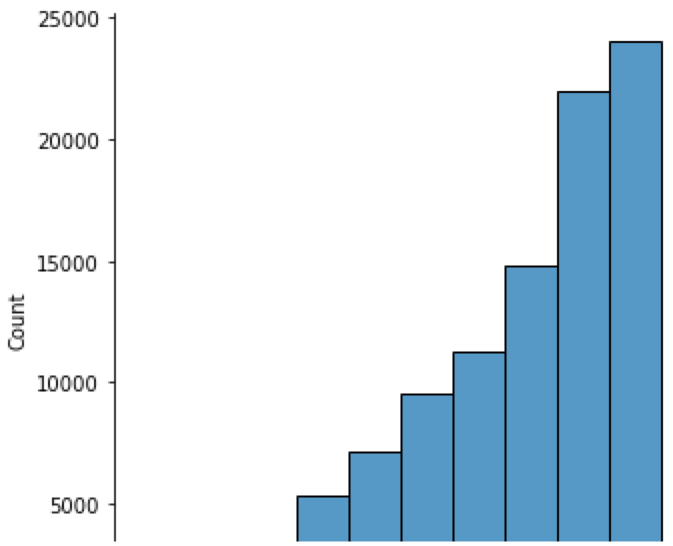
Histogram

In [59]:

```
#distplot lets you show a histogram with a line on it. This can be shown in all kinds of va
#distplot() function is used to plot the distplot. The distplot represents the univariate d
#i.e. data distribution of a variable against the density distribution.
#The seaborn. distplot() function accepts the data variable as an argument and returns the
#the bin size shows the number of bars that are being ploted

sns.displot(data['Humidity'],bins=10)
```

Out[59]:

<seaborn.axisgrid.FacetGrid at 0x20143ab7490>

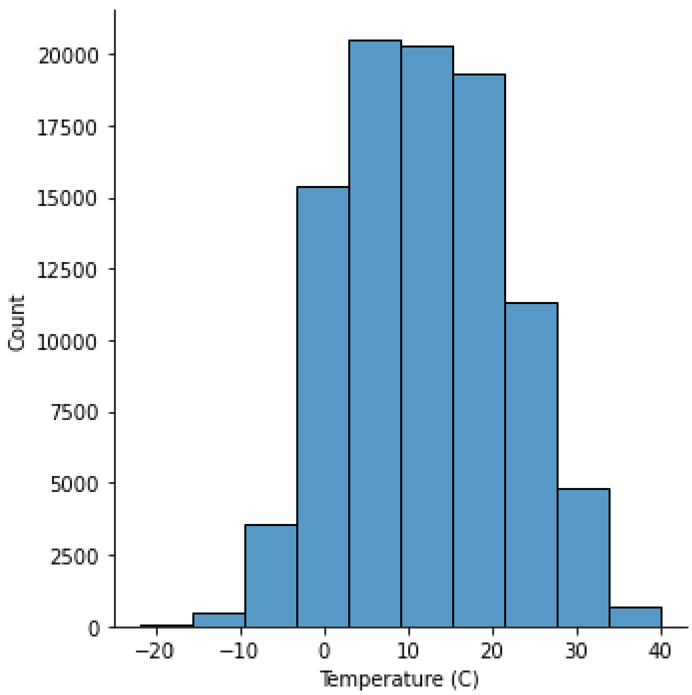


In [105]:

```
sns.displot(data['Temperature (C)'],bins=10)
```

Out[105]:

<seaborn.axisgrid.FacetGrid at 0x2015c284e50>



Heat Map

heatmap uses colored cells, typically in a single base color hue and extended using its shades, tones, and tints like shades of blue from light to dark. It shows a relative number of events for each day in a calendar view. Days are arranged into columns by week and grouped by month and years. That enables you to quickly recognize daily and weekly patterns.

In [ ]:

```
heat=data.drop(['Humidity','Loud Cover','Daily Summary','Pressure (millibars)'],axis=1)
heat
```

In [85]:

```
correlation=heat.corr()
correlation
```

Out[85]:

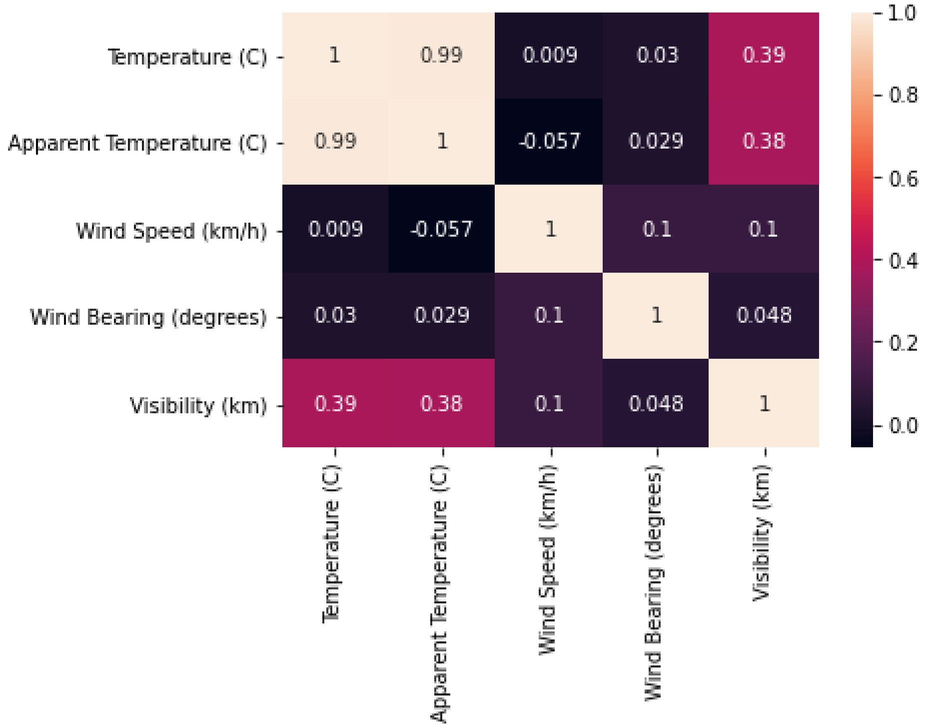
	Temperature (C)	Apparent Temperature (C)	Wind Speed (km/h)	Wind Bearing (degrees)	Visibility (km)
Temperature (C)	1.000000	0.992629	0.008957	0.029988	0.392847
Apparent Temperature (C)	0.992629	1.000000	-0.056650	0.029031	0.381718
Wind Speed (km/h)	0.008957	-0.056650	1.000000	0.103822	0.100749
Wind Bearing (degrees)	0.029988	0.029031	0.103822	1.000000	0.047594
Visibility (km)	0.392847	0.381718	0.100749	0.047594	1.000000

In [86]:

```
sns.heatmap(correlation,xticklabels=correlation.columns,yticklabels=correlation.columns,ann
```

Out[86]:

```
<AxesSubplot:>
```



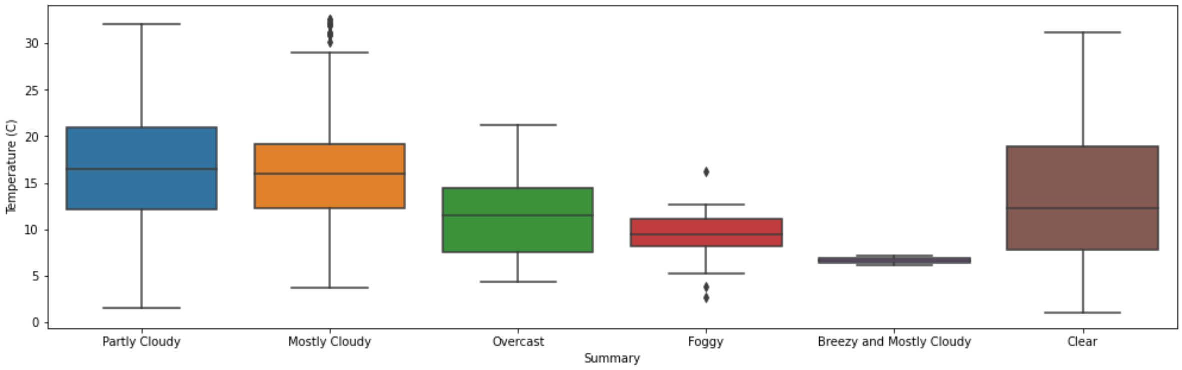
In [ ]:

```
x=data['Wind Speed (km/h)']
y=data['Wind Bearing (degrees)']

plt.pie(y,
        labels=x,
        radius=2,
       autopct='%0.2f%%',
       shadow=True,
       explode=[0.5,0.1,0.2,0.9,0])
```

Seaborn plot

In [8]:

```
P=data.head(1000)
fig_dims = (17, 5)
fig, ax = plt.subplots(figsize=fig_dims)
fig=sns.boxplot(data=P, x='Summary',y='Temperature (C)')
plt.show()
```

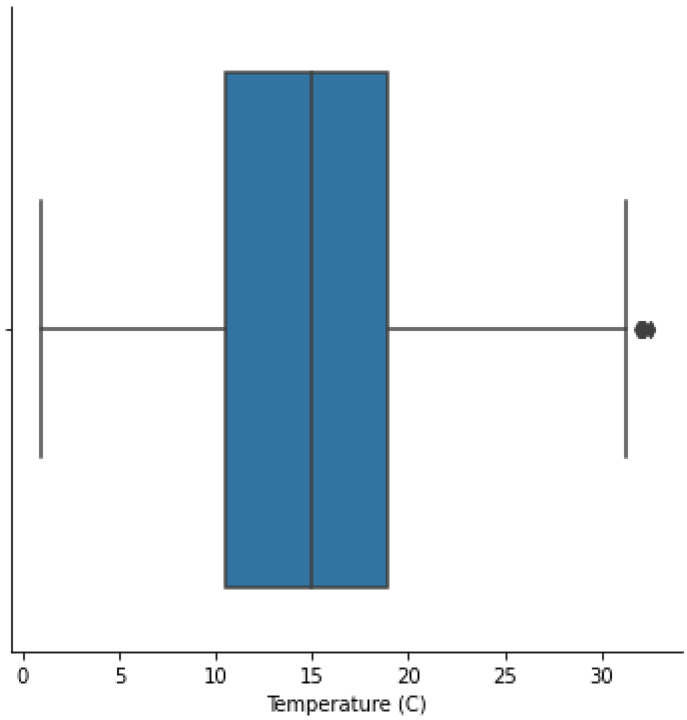


In [65]:

```
sns.catplot(x='Temperature (C)', kind='box',data=D2)
```

Out[65]:

```
<seaborn.axisgrid.FacetGrid at 0x201515b6700>
```



ANALYSIS for boxplot: - A boxplot is a standardized way of displaying the distribution of data based on a five number summary (“minimum”, first quartile (Q1) divided 25%, median, third quartile (Q3) upper 25% , and “maximum”). the box plot which is shown above depicts the temperature in the weather data and it is observed that the left line(wisker) shows the lower point which is between 0-5 and the median here is 15 degrees in temperature. Boxplots do really help us to understand the quartiles part of the data. the right wisker shows the highest temperature recorded which is 30 degrees. but the points which are places ouside the line are known as the outliers of the data where in this case the rare recorded temperatures in a particular geographic area.

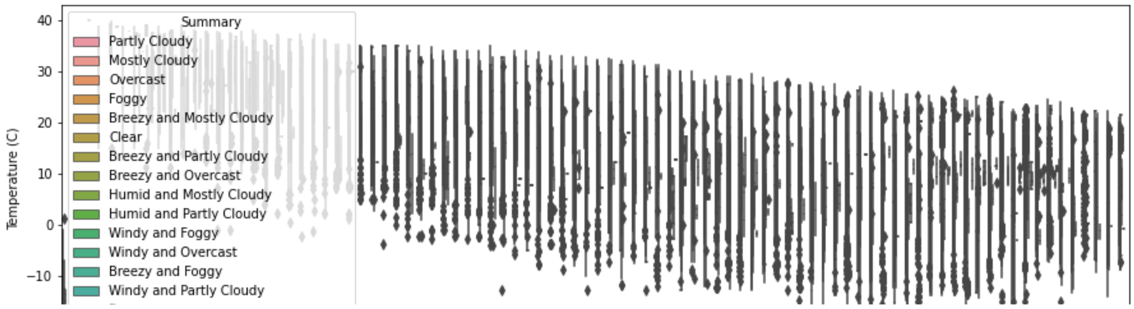
In [22]:

```
fig_dims = (15, 5)
fig, ax = plt.subplots(figsize=fig_dims)
sns.boxplot(data['Humidity'],data['Temperature (C)'],hue=data['Summary'],ax=ax)
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorator
s.py:36: FutureWarning: Pass the following variables as keyword args: x,
y. From version 0.12, the only valid positional argument will be `data`, a
nd passing other arguments without an explicit keyword will result in an e
rror or misinterpretation.
  warnings.warn(
```

Out[22]:

```
<AxesSubplot:xlabel='Humidity', ylabel='Temperature (C)'>
```



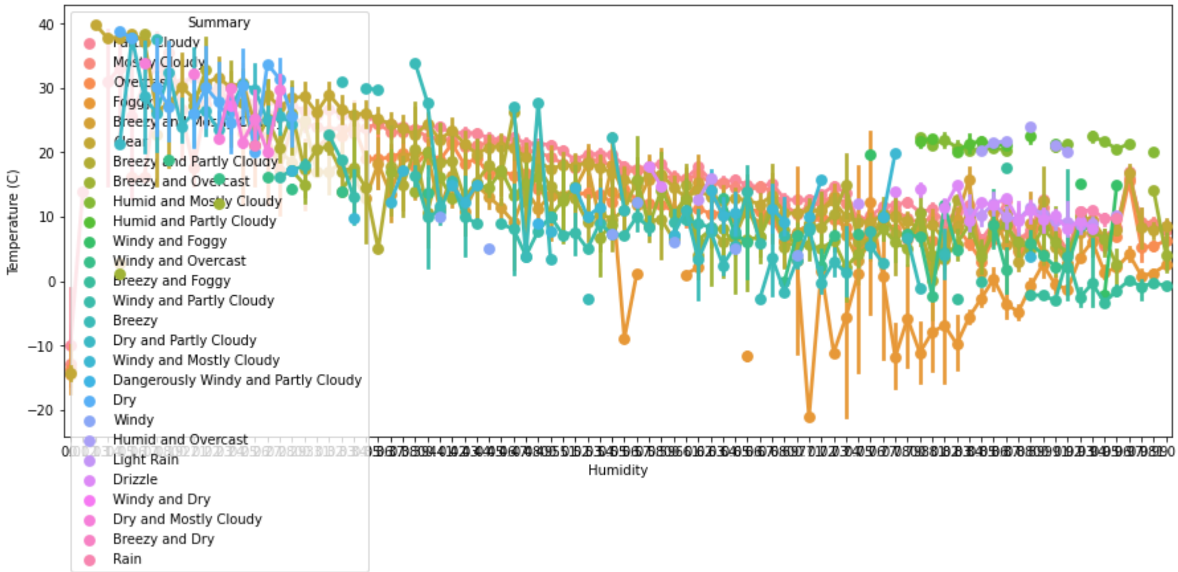
In [19]:

```
#point plot represents an estimate of central tendency for a numeric variable by the positi
#provides some indication of the uncertainty around that estimate using error bars.

# ANALYSIS: - Variable 1: - humidity and variable 2: - temperature
# this graph shows the points of the two variables that are being chosen in different vario

fig_dims = (15, 6)
fig, ax = plt.subplots(figsize=fig_dims)
sns.pointplot(data['Humidity'],data['Temperature (C)'],hue=data['Summary'],ax=ax)
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[19]:

```
<AxesSubplot:xlabel='Humidity', ylabel='Temperature (C)'>
```



In [32]:

```
# by using the .drop function we can eliminate few columns from the data and then we can an

Weather=data.drop(['Loud Cover','Daily Summary','Apparent Temperature (C)','Pressure (milli
Weather
```

Out[32]:

	Formatted Date	Summary	Precip Type	Temperature (C)	Humidity	Wind Speed (km/h)
0	2006-04-01 00:00:00.000 +0200	Partly Cloudy	rain	9.472222	0.89	14.1197
1	2006-04-01 01:00:00.000 +0200	Partly Cloudy	rain	9.355556	0.86	14.2646
2	2006-04-01 02:00:00.000 +0200	Mostly Cloudy	rain	9.377778	0.89	3.9284
3	2006-04-01 03:00:00.000 +0200	Partly Cloudy	rain	8.288889	0.83	14.1036
4	2006-04-01 04:00:00.000 +0200	Mostly Cloudy	rain	8.755556	0.83	11.0446
...	...	...	...	...	...	...
96448	2016-09-09 19:00:00.000 +0200	Partly Cloudy	rain	26.016667	0.43	10.9963
96449	2016-09-09 20:00:00.000 +0200	Partly Cloudy	rain	24.583333	0.48	10.0947
96450	2016-09-09 21:00:00.000 +0200	Partly Cloudy	rain	22.038889	0.56	8.9838
96451	2016-09-09 22:00:00.000 +0200	Partly Cloudy	rain	21.522222	0.60	10.5294
96452	2016-09-09 23:00:00.000 +0200	Partly Cloudy	rain	20.438889	0.61	5.8765

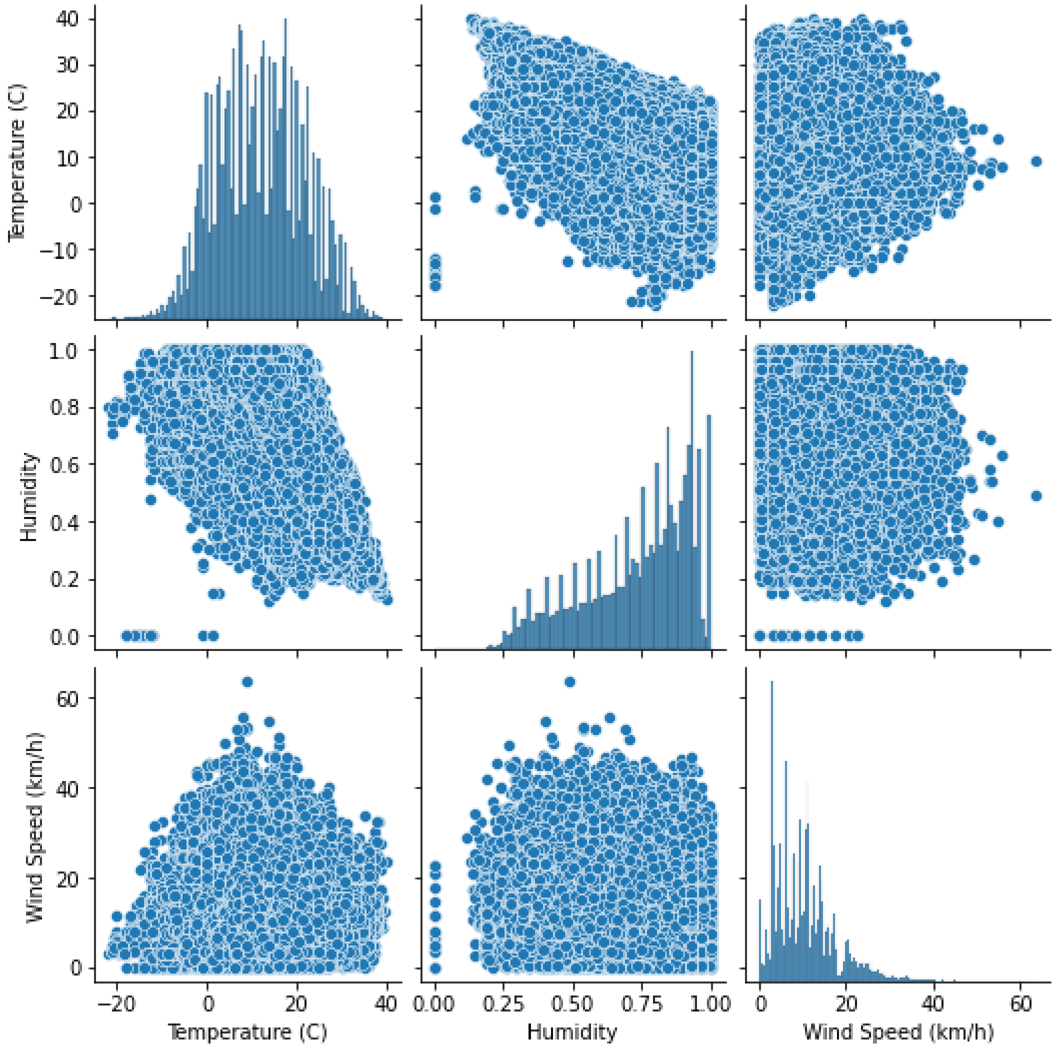
96453 rows × 6 columns

In [47]:

```
import seaborn as sns

sns.pairplot(Weather)
```

Out[47]:

<seaborn.axisgrid.PairGrid at 0x201378f6520>



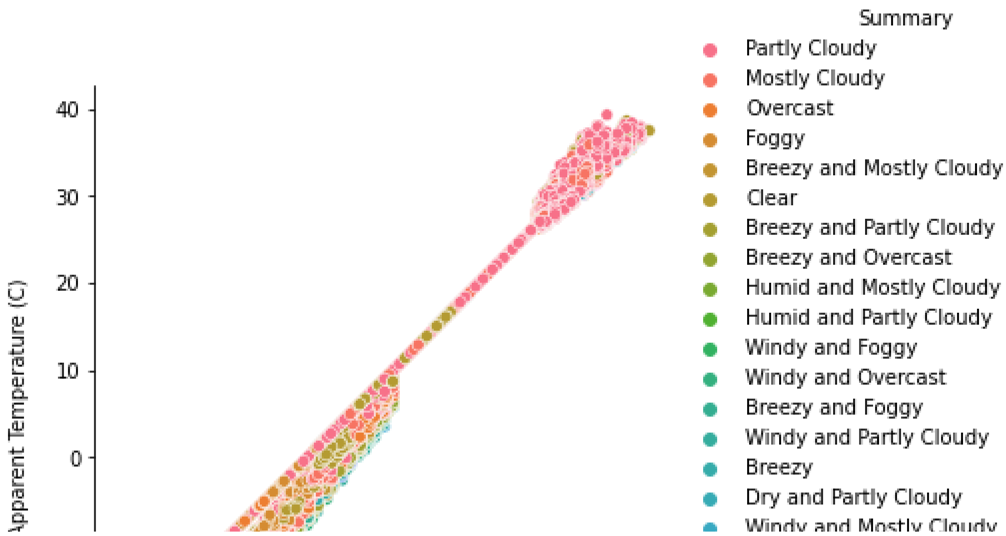
ANALYSIS (Pairplot) : -

In [36]:

```
# the pairplot that i have displayed here shows that on the x-axis we have temperature(C) a
# it could be observed that when the temperature is low then the initial summary values met
# like when the temperature is at -10 and the apparent temp is at -20 then there is a lot o
# values like partly cloudy, windly, breezy etc could be observed in the lowest and highest
# the same could be observed that lowest and highest recorded temperature (lowest=-10 to 0
# highest=(30 to 40 degrees(c)))
# as at normal temperature like 20 degrees(c), then there are not much conditions.
# where we can conclude then there will be many weather conditons that will be observed at


sns.relplot(x='Temperature (C)',y='Apparent Temperature (C)',hue='Summary',data=Weather)
```

Out[36]:

```
<seaborn.axisgrid.FacetGrid at 0x1d58ba95520>
```



ANALYSIS: -the graphs depicts the graphical representation between aparent and temperature. This is a figure-level function for visualizing statistical relationships using two common approaches. Scatter Plots- Each plot point is an independent observation, every colour depicts a differernt weather condition in the Summary data

so, it could be observed that partly cloudy, mostly cloudy, overcast all of these are the occuring when the temperature is low. if the temperature is low as 10 to -20 then these type of weather conditions are occuring. on contray. it either rains, breezy, cloudy, dry and windy type of weather occurs when the temperature is comparitively high that is between 30 to 40 or more degrees of temperature.

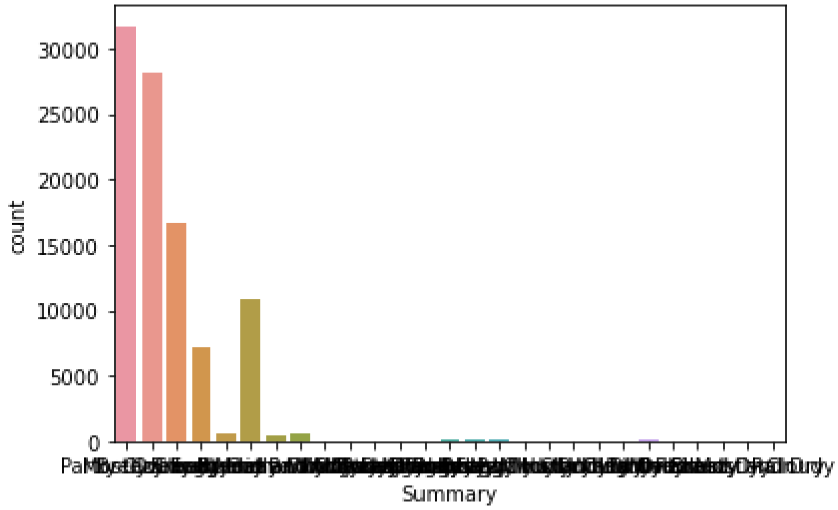
In [30]:

```
sns.countplot(data['Summary'])
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variable as a keyword arg: x. From
version 0.12, the only valid positional argument will be `data`, and passing
other arguments without an explicit keyword will result in an error or misin
terpretation.
  warnings.warn(
```

Out[30]:

```
<AxesSubplot:xlabel='Summary', ylabel='count'>
```



it Shows the counts of observations in each categorical bin using bars. A count plot can be thought of as a histogram across a categorical, instead of quantitative, variable.

JOINT PLOTS

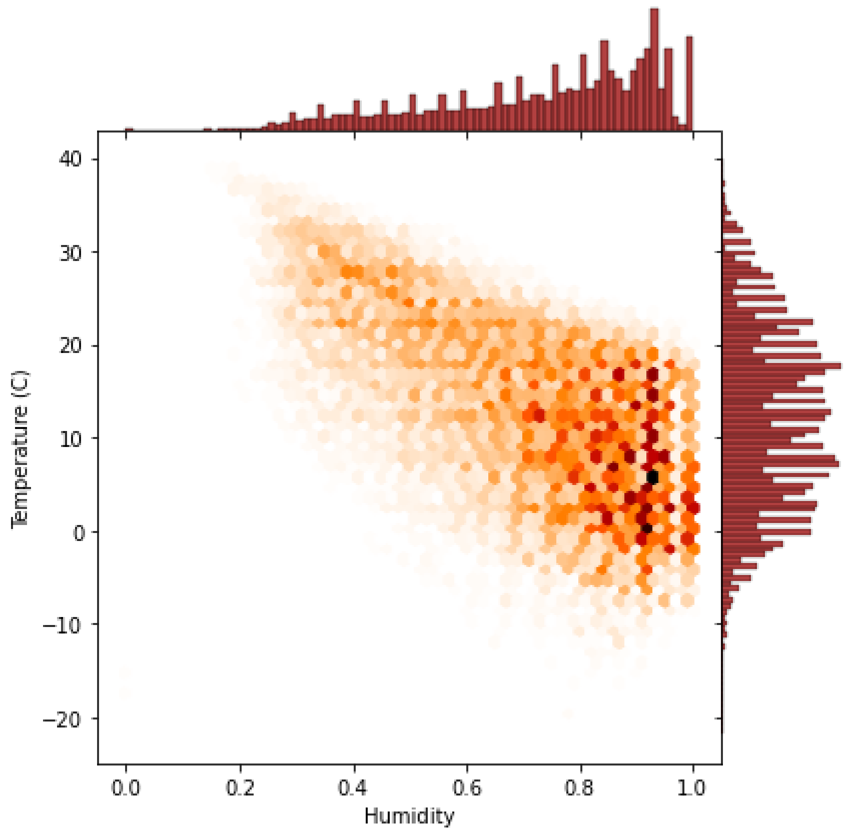
In [83]:

```
cmap=plt.cm.gist_heat_r
sns.jointplot(data['Humidity'],data['Temperature (C)'],kind="hex",space=0, color=cmap(.6),
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[83]:

```
<seaborn.axisgrid.JointGrid at 0x2015c160580>
```



kind="hex" will use matplotlib.axes.Axes.hexbin() to compute a bivariate histogram using hexagonal bins. Along with which we can observe that there is histogram that is being depicted on the top and the right sides of the graph. we have chosen 2 variables which are temperature and humidity. the default colour was blue and by adding "space=0, color=cmap(.6), cmap=cmap", this code we can change the colour according to the hex code of the colour.The histogram on the top shows the distribution of the variable at the x-axis (humidity) and the histogram to the right shows the distribution of the variable at the y-axis(temperature).

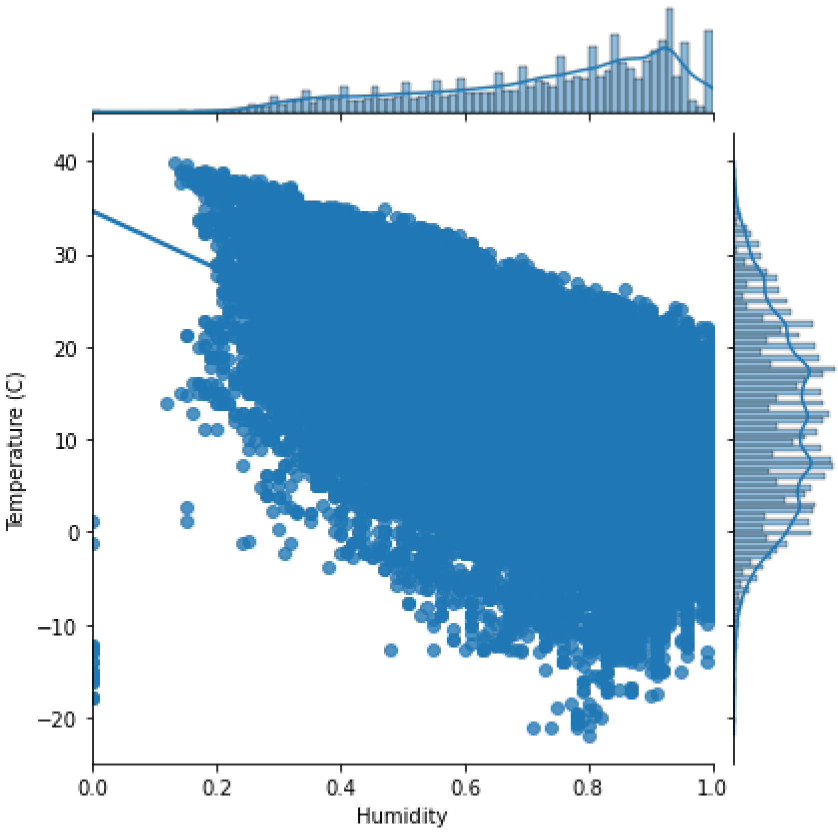
In [26]:

```
#in this jointplot we can see that the kind is regression and the line shows the line of be
#It is very helpful to have univariate and bivariate plots together in one figure.

sns.jointplot(data['Humidity'],data['Temperature (C)'],kind="reg")
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[26]:

```
<seaborn.axisgrid.JointGrid at 0x1d5905bef40>
```



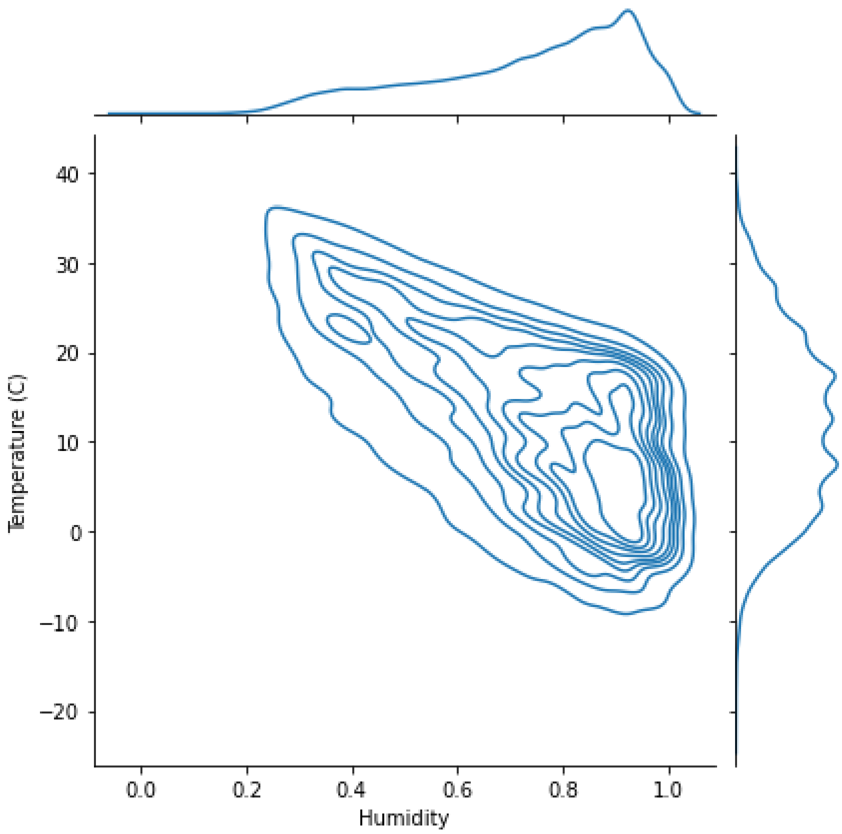
In [42]:

```
sns.jointplot(data['Humidity'],data['Temperature (C)'],kind="kde")
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[42]:

```
<seaborn.axisgrid.JointGrid at 0x201378eafd0>
```



STRIP PLOT

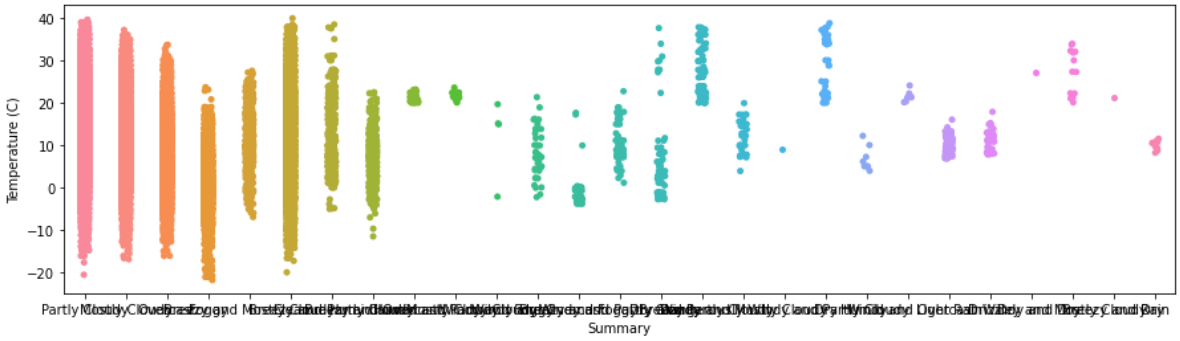
In [37]:

```
# this shows the clustering of the most repeated weather conditons in the weather data.
# the most crowded one with most of the values is partly cloudly and mostly cloudy.
# where we can conclude that these are the two weather conditions that were observed when t
# these two conditons are crowded especially near 10 -15 degrees celsius.
# and the foggy condition is found when the temperature drops below to 10 degrees.

fig_dims = (15, 4)
fig, ax = plt.subplots(figsize=fig_dims)
sns.stripplot(data['Summary'],data['Temperature (C)'])
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[37]:

```
<AxesSubplot:xlabel='Summary', ylabel='Temperature (C)'>
```



Analysis: -the graph shows the data where it is placed according to the category which is given in the 'SUMMARY' of the csv data that i have loaded. it yet shows that these are the number of values in a particular category like 'partly cloudly' according to the temperature. it shows how crowded that one particular category is.

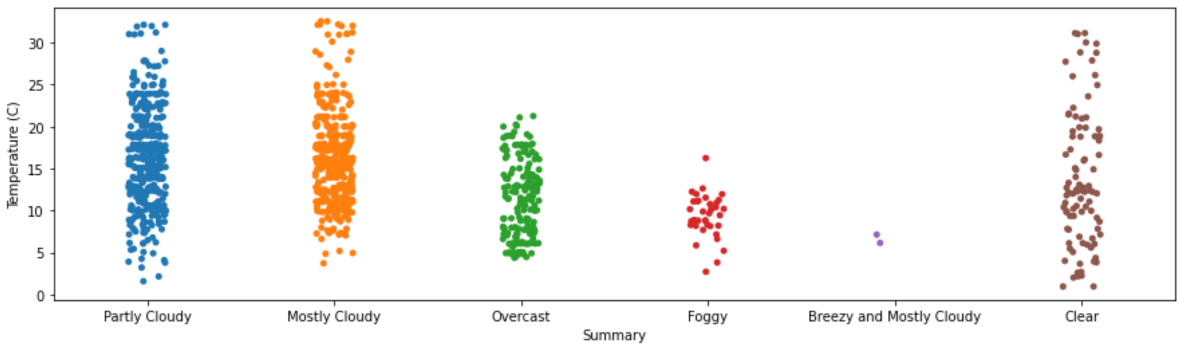
In [23]:

```
# with the first 1000 rows of the data.
# this shows the clustering of the most repeated weather conditons in the weather data.
# the most crowded one with most of the values is partly cloudly and mostly cloudy.
# where we can conclude that these are the two weather conditions that were observed when t
# these two conditons are crowded especially near 10 -15 degrees celsius.
# and the foggy condition is found when the temperature drops below to 10 degrees.

fig_dims = (15, 4)
fig, ax = plt.subplots(figsize=fig_dims)
sns.stripplot(D2['Summary'],D2['Temperature (C)'])
```

```
C:\Users\Prathyu Lachireddy\anaconda3\lib\site-packages\seaborn\_decorators.
py:36: FutureWarning: Pass the following variables as keyword args: x, y. Fr
om version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or m
isinterpretation.
  warnings.warn(
```

Out[23]:

```
<AxesSubplot:xlabel='Summary', ylabel='Temperature (C)'>
```



PART 6: - ARIMA Model

Autoregressive Integrated Moving Average Model. An ARIMA model is a class of statistical models for analyzing and forecasting time series data. It explicitly caters to a suite of standard structures in time series data, and as such provides a simple yet powerful method for making skillful time series forecasts.

In [24]:

```
!pip install pmdarima
from pmdarima import auto_arima
import warnings
warnings.filterwarnings("ignore")
from statsmodels.tsa.arima_model import ARIMA
```

In [49]:

```
stepwise_fit= auto_arima(data['Temperature (C)'],trace=True,
                        suppress_warnings=True)

stepwise_fit
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=161.944, Time=0.29 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=276.186, Time=0.01 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=178.223, Time=0.03 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=225.804, Time=0.06 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=385.767, Time=0.01 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=171.274, Time=0.07 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=160.173, Time=0.34 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=171.279, Time=0.06 sec
 ARIMA(2,0,0)(0,0,0)[0] intercept   : AIC=166.392, Time=0.05 sec
 ARIMA(3,0,1)(0,0,0)[0] intercept   : AIC=161.820, Time=0.37 sec
 ARIMA(3,0,0)(0,0,0)[0] intercept   : AIC=165.170, Time=0.06 sec
 ARIMA(3,0,2)(0,0,0)[0] intercept   : AIC=inf, Time=0.35 sec
 ARIMA(2,0,1)(0,0,0)[0]             : AIC=170.511, Time=0.08 sec

Best model:  ARIMA(2,0,1)(0,0,0)[0] intercept
Total fit time: 1.806 seconds
```

Out[49]:

```
ARIMA(order=(2, 0, 1), scoring_args={}, suppress_warnings=True)
```

Analysis of Auto Arima: - It takes into account the AIC and BIC values generated (as you can see in the code) to determine the best combination of parameters. AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values are estimators to compare models. The lower these values, the better is the model.

In [36]:

```
print(data.shape)
train=data.loc[:-10]
test=data.loc[-20:]

print(train.shape,test.shape)
```

```
(96453, 12)
(0, 12) (96453, 12)
```

In [ ]:

```
model=ARIMA(train['Temperature (C)'],order=(2,0,12))
model=model.fit()
model.Summary
```

PART 8: - Sentimental Analysis: -

Sentiment analysis is the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information.

In [22]:

```
from textblob import TextBlob
type1="Summary"
type2="Wind Speed (km/h)"
blob1= TextBlob(type1)
blob2=TextBlob(type2)
print(blob1.sentiment)
print(blob2.sentiment)
```

```
Sentiment(polarity=0.0, subjectivity=0.0)
Sentiment(polarity=0.0, subjectivity=0.0)
```

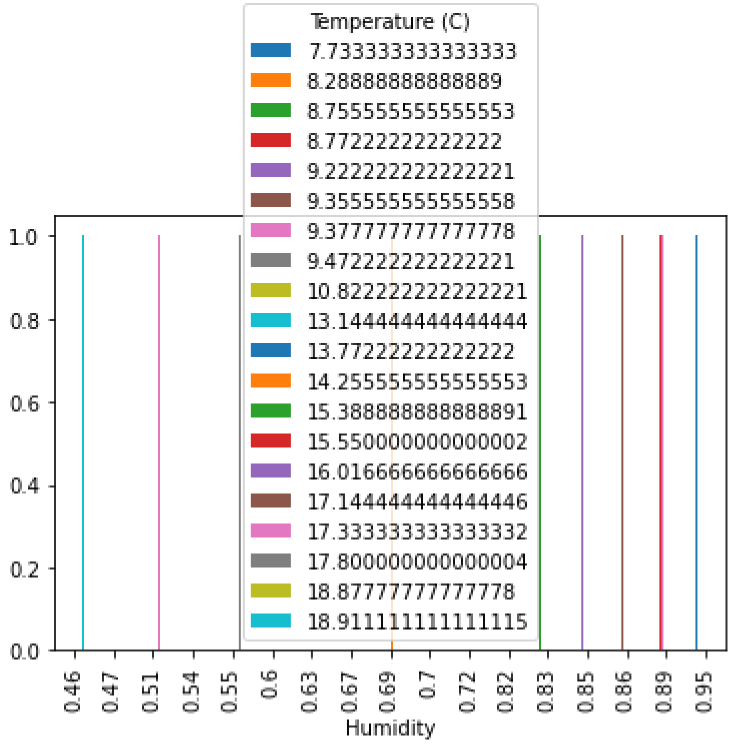
Analysis: -The TextBlob package for Python is a convenient way to do a lot of Natural Language Processing (NLP) tasks.Recognizing “very” as a modifier word, TextBlob will ignore polarity and subjectivity and just use intensity to modify. The polarity score is a float within the range [-1.0, 1.0]. The subjectivity is a float within the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective. Let’s use this now to get the sentiment polarity and labels for each news article and aggregate the summary statistics per news category.

In [7]:

```
P=data.head(20)
airline_sentiment = P.groupby(['Humidity', 'Temperature (C)']).Summary.count().unstack()
airline_sentiment.plot(kind='bar')
```

Out[7]:

```
<AxesSubplot:xlabel='Humidity'>
```



PART 8: - Conclusion

Here, in this assignment i have included all the concepts of cleaning, panfas, using all the plots and with some research i have understood additional plots like jointplots and different categories among them. like: -

1. basic operations like loading the csv data in the form of the dataframe in Jupyter notebook
2. dataframe and cleaning the data
3. Basic data inspections(head, tail,dtypes,nunique ,accessing columns and rows, sorting, filtering)
4. Groupby funtions (count, groupby, nunique)
5. Plots(barplot, histogram, pairplot, displot, heatmap, boxplot, joint plot(hex,reg,kde), relplot, pointplot, countplot, stripplot)

To conclude i would like to say that this assignment has helped me analyse and interpret the real time data set and i have learnt on how does a real data is interpreted. i would like to talk about the importance of analytics, Analytics allow you to quantify the effects of making a change to your marketing strategy, and that's invaluable to the process of improving and optimizing online marketing campaigns. The biggest benefit of utilizing proper analytics is being able to identify strengths and weaknesses. For example, let’s say you run a blog for your car detailing business. You’re just starting out, and aren’t sure what kinds of posts will bring you the most traffic, or provide the most value to your readers. If you’re using analytics, you’ll be able to measure which blog posts attract the most traffic, which get the least traffic, which have a high bounce rate, a low bounce rate, and so on. It will be easy to tell which blog posts are performing better or worse than others. since i had to develop everything from the base data it was very insightful as it totally was interpretation based. this kind of interpretation would be used even in the real organisation the key idea is to collect data about the organization and use them to improve operations. Raw form of data is not of any use.If you are trying to bring any significant improvement in your business, then analytics is your best bet to bring about an informed transformation.

THANK YOU