Project 6 - Time Series Analysis

Objective

The main objective of the analysis is to forecast the tempurature based on its historic behaviour.

Dataset

The data is referred from Kaggle which includes climate data of Delhi, India.

Dataset includes following variables:

date - Date of format YYYY-MM-DD.

meantemp - Mean temperature averaged out from multiple 3 hour intervals in a day.

humidity - Humidity value for the day (units are grams of water vapor per cubic meter volume of air).

wind_speed - Wind speed measured in kmph.

meanpressure - Pressure reading of weather (measure in atm).

Imports

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import rcParams
import seaborn as sns
import statsmodels.api as sm
```

In [2]:
```
data = pd.read_csv('DailyDelhiClimateTrain.csv', parse_dates=['date'], index_col='date')
data.head()
```

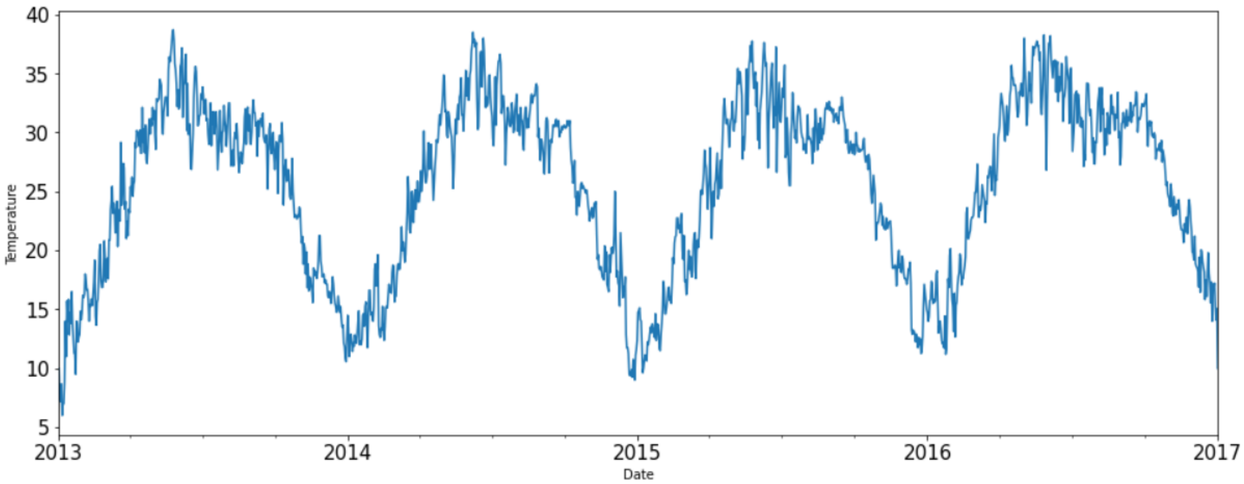
Out[2]:

date	meantemp	humidity	wind_speed	meanpressure
2013-01-01	10.000000	84.500000	0.000000	1015.666667
2013-01-02	7.400000	92.000000	2.980000	1017.800000
2013-01-03	7.166667	87.000000	4.633333	1018.666667
2013-01-04	8.666667	71.333333	1.233333	1017.166667
2013-01-05	6.000000	86.833333	3.700000	1016.500000

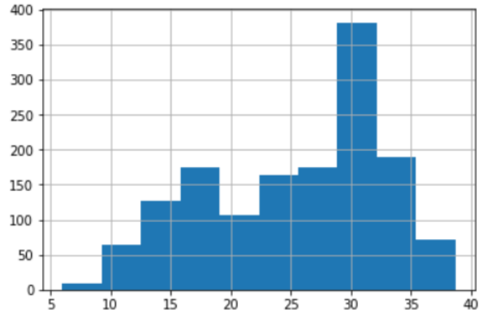
EDA

- Timeseries Decomposition (Trend, Seasonal, Noise).
- Data Smoothing.
- Conversion from non-stationary to stationary series.
- Plot Auto Correlation and Partial Auto Correlation.

In [3]:
```
data["meantemp"].plot(figsize=(16, 6), fontsize=15)
plt.xlabel("Date")
plt.ylabel("Temperature")
plt.show()
```



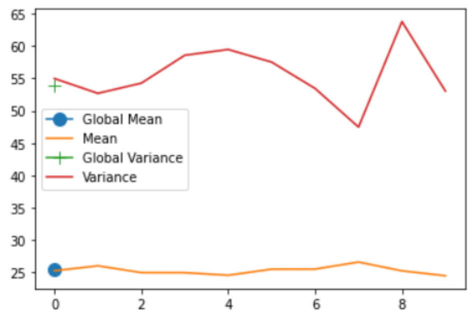
In [4]:
```python
data["meantemp"].hist()
plt.show()
```



In [5]:
```python
import random
import statistics

meanVal, varianceVal = [], []
for i in range(10):
    sample = random.sample(list(data.meantemp), 100)
    meanVal.append(np.mean(sample))
    varianceVal.append(statistics.variance(sample))

plt.plot(np.mean(data.meantemp), marker="o", markersize=10, label='Global Mean')
plt.plot(meanVal, label='Mean')
plt.plot(statistics.variance(data.meantemp), marker="+", markersize=10, label='Global Variance')
plt.plot(varianceVal, label='Variance')
plt.legend()
plt.show()
```



In [6]:
```python
from statsmodels.tsa.stattools import adfuller

dfTest = adfuller(data.meantemp, autolag='AIC')

print('1. ADF: ' ,dfTest[0])
print('2. P-Value: ', dfTest[1])
print('3. Num Of Lags: ', dfTest[2])
print('4. Num Of Observations used For ADF Regression and Critical values Calculation: ', dfTest[3])
print('5. Critical Values:')
for key, val in dfTest[4].items():
    print('\t', key, ': ', val)
```

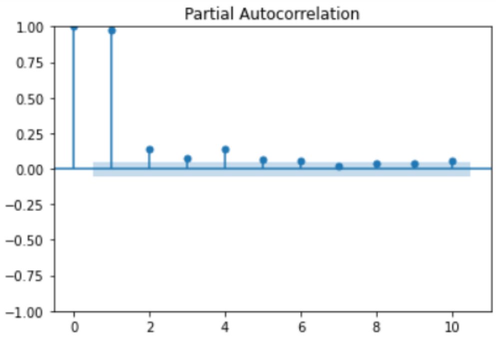
```
1. ADF:  -2.021069055920659
2. P-Value:  0.27741213723016633
3. Num Of Lags:  10
4. Num Of Observations used For ADF Regression and Critical values Calculation:  1451
5. Critical Values:
	 1% :  -3.4348647527922824
	 5% :  -2.863533960720434
	 10% :  -2.567831568508802
```

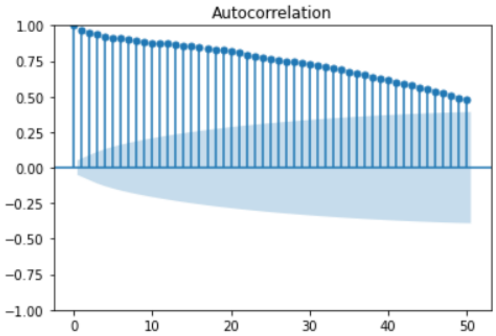
Observations:

- By **Visual Inspection**, we can see a seansonality in the line graph and histogram.
- Considering a reasonable mean, variance and existence of correlation, the series is not a white noise.
- Histogram is not normally distributed thus indicates non-stationarity.
- Next being **Global and Local Checks**, we can again confirm difference in variance while constant mean, resulting in non-stationarity.
- Based on **Dickey-Fuller Test** (Hypothesis testing), the p-value is less than 0.05, thus non-stationary.

In [7]:
```python
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
pacf = plot_pacf(data.meantemp, lags=10)
acf = plot_acf(data.meantemp, lags=50)
```

```
c:\users\mahim\appdata\local\programs\python\python38\lib\site-packages\statsmodels\graphics\tsaplots.py:348: FutureWarning: Th
e default method 'yw' can produce PACF values outside of the [-1,1] interval. After 0.13, the default will change tounadjusted
Yule-Walker ('ywm'). You can use this method now by setting method='ywm'.
  warnings.warn(
```





Observations:

- From **PACF**, there is correlation with lag of upto 4 above the error band.
- In **ACF**, due to direct and indirect effects taken into consideration, the lag 50 is also correlated to current series.

Model Building

In [13]:
```
train = data.meantemp[:-30]
test = data.meantemp[-30:]
len(train)
```

Out[13]: 1432

In [14]:
```
from statsmodels.tsa.ar_model import AutoReg
autoRegModel = AutoReg(train, lags=4).fit()
autoRegModel.summary()
```

```
c:\users\mahim\appdata\local\programs\python\python38\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

Out[14]:

AutoReg Model Results

Dep. Variable:	meantemp	**No. Observations:**	1432
Model:	AutoReg(4)	**Log Likelihood**	-2704.218
Method:	Conditional MLE	**S.D. of innovations**	1.608
Date:	Sun, 01 Jan 2023	**AIC**	5420.437
Time:	23:09:20	**BIC**	5452.021
Sample:	01-05-2013	**HQIC**	5432.232
	- 12-02-2016		

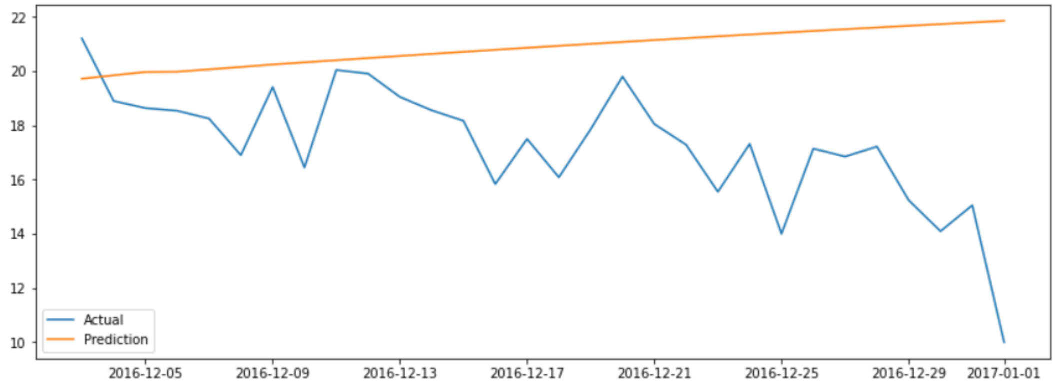
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	0.5163	0.158	3.270	0.001	0.207	0.826
meantemp.L1	0.8069	0.026	30.849	0.000	0.756	0.858
meantemp.L2	0.0484	0.034	1.433	0.152	-0.018	0.115
meantemp.L3	-0.0263	0.034	-0.781	0.435	-0.092	0.040
meantemp.L4	0.1514	0.026	5.803	0.000	0.100	0.203

Roots

	Real	**Imaginary**	**Modulus**	**Frequency**
AR.1	1.0136	-0.0000j	1.0136	-0.0000
AR.2	-1.9511	-0.0000j	1.9511	-0.5000
AR.3	0.5557	-1.7408j	1.8273	-0.2008
AR.4	0.5557	+1.7408j	1.8273	0.2008

In [15]:
```python
pred0 = autoRegModel.predict(start=len(train), end=len(data.meantemp)-1)
plt.figure(figsize=(14, 5))
plt.plot(test, label='Actual')
plt.plot(pred0, label='Prediction')
plt.legend()
plt.show()
```

```
c:\users\mahim\appdata\local\programs\python\python38\lib\site-packages\statsmodels\tsa\deterministic.py:302: UserWarning: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index with a unit increment support extending. The inde
x is set will contain the position relative to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```



In [16]:
```python
from sklearn.metrics import mean_squared_error
rms = mean_squared_error(test, pred0, squared=False)
rms
```

Out[16]: 4.4577961380273665

Totally opposite to the trend 😅

Let's try experimenting with other features of the data, might provide some value to the regression calculations.

In [17]:
```python
from statsmodels.tsa.ar_model import AutoReg
autoRegModel = AutoReg(train, lags=4, trend='n', seasonal=True, exog=data.drop(columns=['meantemp'])[:-30]).fit()
autoRegModel.summary()
```

```
c:\users\mahim\appdata\local\programs\python\python38\lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No
frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

Out[17]:

AutoReg Model Results

Dep. Variable:	meantemp	**No. Observations:**	1432
Model:	Seas. AutoReg-X(4)	**Log Likelihood**	-2616.159
Method:	Conditional MLE	**S.D. of innovations**	1.512
Date:	Sun, 01 Jan 2023	**AIC**	5262.317
Time:	23:09:26	**BIC**	5341.278
Sample:	01-05-2013	**HQIC**	5291.805
	- 12-02-2016		

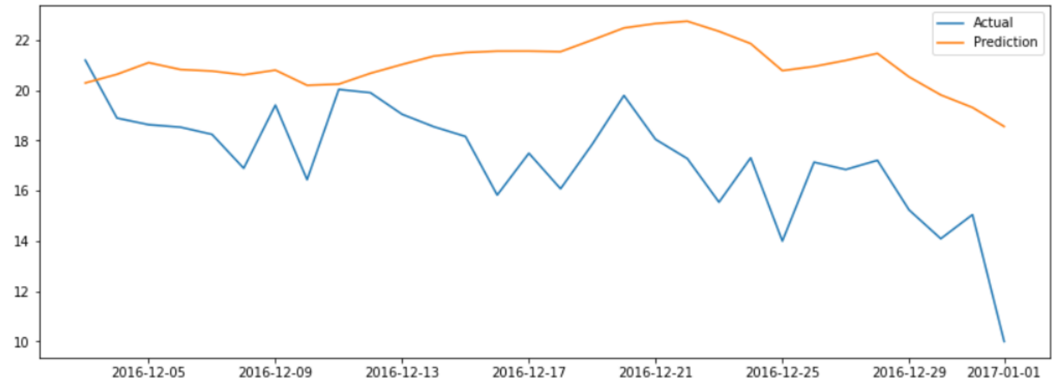
	coef	std err	z	P>|z|	[0.025	0.975]
s(1,7)	4.3167	0.398	10.840	0.000	3.536	5.097
s(2,7)	4.4042	0.398	11.060	0.000	3.624	5.185
s(3,7)	4.2396	0.398	10.659	0.000	3.460	5.019
s(4,7)	4.2531	0.399	10.653	0.000	3.471	5.036
s(5,7)	4.2117	0.401	10.492	0.000	3.425	4.998
s(6,7)	4.1733	0.399	10.448	0.000	3.390	4.956
s(7,7)	4.3778	0.402	10.877	0.000	3.589	5.167
meantemp.L1	0.7385	0.025	29.306	0.000	0.689	0.788
meantemp.L2	0.0516	0.032	1.617	0.106	-0.011	0.114
meantemp.L3	-0.0118	0.032	-0.371	0.711	-0.074	0.051
meantemp.L4	0.1599	0.025	6.485	0.000	0.112	0.208
humidity	-0.0390	0.003	-13.394	0.000	-0.045	-0.033
wind_speed	-0.0189	0.010	-1.972	0.049	-0.038	-0.000
meanpressure	-0.0002	0.000	-0.862	0.389	-0.001	0.000

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	1.0416	-0.0000j	1.0416	-0.0000
AR.2	-1.9128	-0.0000j	1.9128	-0.5000
AR.3	0.4726	-1.7073j	1.7715	-0.2070
AR.4	0.4726	+1.7073j	1.7715	0.2070

In [18]:
```
pred1 = autoRegModel.predict( start=len(train), end=len(data.meantemp)-1, exog_oos=data.drop(columns=['meantemp'])[-30:])
plt.figure(figsize=(14, 5))
plt.plot(test, label='Actual')
plt.plot(pred1, label='Prediction')
plt.legend()
plt.show()
```

```
c:\users\mahim\appdata\local\programs\python\python38\lib\site-packages\statsmodels\tsa\deterministic.py:302: UserWarning: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index with a unit increment support extending. The index is set will contain the position relative to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
c:\users\mahim\appdata\local\programs\python\python38\lib\site-packages\statsmodels\tsa\deterministic.py:435: UserWarning: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index with a unit increment support extending. The index is set will contain the position relative to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```



In [19]:
```
rms = mean_squared_error(test, pred1, squared=False)
rms
```

Out[19]: 4.271293281591886

Following the trend with much ups and downs.

In [20]:
```
import pmdarima
sarimaModel = pmdarima.arima.auto_arima(train, d=1, m=4, stationary=False, test='adf')
```

In [21]:
```
sarimaModel.summary()
```

Out[21]:

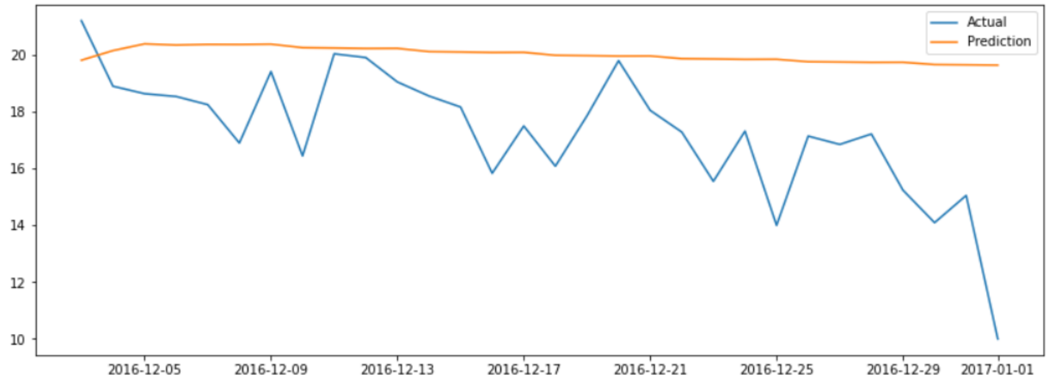
SARIMAX Results

Dep. Variable:	y	**No. Observations:**	1432
Model:	SARIMAX(1, 1, 3)x(1, 0, [1], 4)	**Log Likelihood**	-2698.464
Date:	Sun, 01 Jan 2023	**AIC**	5410.929
Time:	23:12:32	**BIC**	5447.792
Sample:	01-01-2013	**HQIC**	5424.694
	- 12-02-2016		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.4085	0.125	3.268	0.001	0.163	0.654
ma.L1	-0.6266	0.125	-5.006	0.000	-0.872	-0.381
ma.L2	-0.0428	0.039	-1.106	0.269	-0.119	0.033
ma.L3	-0.0930	0.040	-2.304	0.021	-0.172	-0.014
ar.S.L4	0.9139	0.057	15.903	0.000	0.801	1.026
ma.S.L4	-0.8758	0.069	-12.654	0.000	-1.011	-0.740
sigma2	2.5428	0.072	35.078	0.000	2.401	2.685

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	296.48
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.75	**Skew:**	-0.50
Prob(H) (two-sided):	0.00	**Kurtosis:**	5.00

In [22]:
```
pred2 = sarimaModel.predict(n_periods=30)
plt.figure(figsize=(14, 5))
plt.plot(test, label='Actual')
plt.plot(pred2, label='Prediction')
plt.legend()
plt.show()
```



In [23]:
```
mean_squared_error(test, pred2, squared=False)
```

Out[23]: 3.4199992717168044

Line is following the trend straightly and RMSE is also lowered.

In [24]:
```
trainAllVars = data[:-30]
testAllVars = data[-30:]
```

In [25]:
```
sarimaModelOnAllVars = pmdarima.arima.auto_arima(trainAllVars.meantemp,
                                                 X=trainAllVars.drop(columns=['meantemp']),
                                                 d=2, m=4, stationary=False, test='adf', trace=True)

sarimaModelOnAllVars.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,2,2)(1,0,1)[4]             : AIC=4809.368, Time=7.00 sec
 ARIMA(0,2,0)(0,0,0)[4]             : AIC=5695.930, Time=2.66 sec
 ARIMA(1,2,0)(1,0,0)[4]             : AIC=5407.564, Time=1.75 sec
 ARIMA(0,2,1)(0,0,1)[4]             : AIC=inf, Time=4.16 sec
 ARIMA(2,2,2)(0,0,1)[4]             : AIC=4748.048, Time=6.54 sec
 ARIMA(2,2,2)(0,0,0)[4]             : AIC=4883.747, Time=4.00 sec
 ARIMA(2,2,2)(0,0,2)[4]             : AIC=4829.505, Time=9.56 sec
 ARIMA(2,2,2)(1,0,0)[4]             : AIC=4895.253, Time=5.54 sec
 ARIMA(2,2,2)(1,0,2)[4]             : AIC=4901.521, Time=11.48 sec
 ARIMA(1,2,2)(0,0,1)[4]             : AIC=inf, Time=6.33 sec
 ARIMA(2,2,1)(0,0,1)[4]             : AIC=4932.072, Time=5.30 sec
 ARIMA(3,2,2)(0,0,1)[4]             : AIC=4641.521, Time=8.00 sec
 ARIMA(3,2,2)(0,0,0)[4]             : AIC=inf, Time=5.87 sec
 ARIMA(3,2,2)(1,0,1)[4]             : AIC=4656.687, Time=8.03 sec
 ARIMA(3,2,2)(0,0,2)[4]             : AIC=4656.037, Time=11.00 sec
 ARIMA(3,2,2)(1,0,0)[4]             : AIC=4658.158, Time=7.86 sec
 ARIMA(3,2,2)(1,0,2)[4]             : AIC=4640.278, Time=11.86 sec
 ARIMA(3,2,2)(2,0,2)[4]             : AIC=4657.462, Time=12.22 sec
 ARIMA(3,2,2)(2,0,1)[4]             : AIC=4642.503, Time=11.88 sec
 ARIMA(3,2,1)(1,0,2)[4]             : AIC=4842.291, Time=10.25 sec
 ARIMA(3,2,3)(1,0,2)[4]             : AIC=4671.978, Time=11.96 sec
 ARIMA(2,2,1)(1,0,2)[4]             : AIC=5172.535, Time=8.64 sec
 ARIMA(2,2,3)(1,0,2)[4]             : AIC=4984.429, Time=10.78 sec
 ARIMA(3,2,2)(1,0,2)[4] intercept   : AIC=4662.571, Time=11.50 sec

Best model:  ARIMA(3,2,2)(1,0,2)[4]
Total fit time: 194.227 seconds
```

Out[25]:

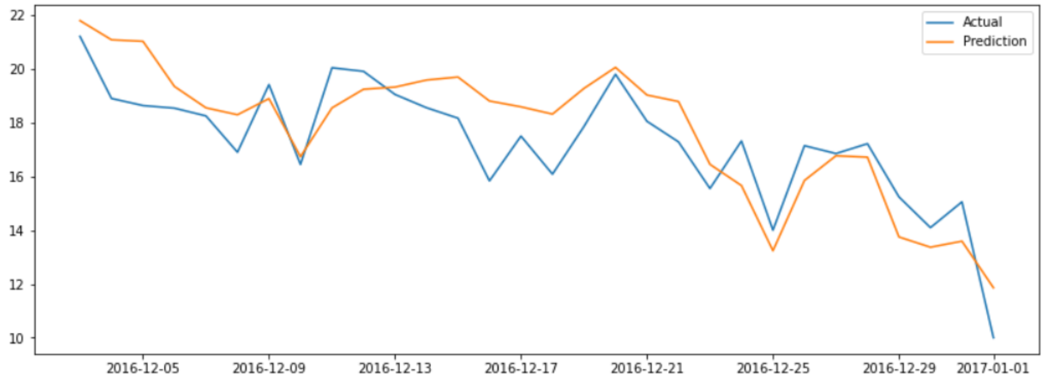
SARIMAX Results

Dep. Variable:	y	**No. Observations:**	1432
Model:	SARIMAX(3, 2, 2)x(1, 0, 2, 4)	**Log Likelihood**	-2308.139
Date:	Sun, 01 Jan 2023	**AIC**	4640.278
Time:	23:15:47	**BIC**	4703.464
Sample:	01-01-2013	**HQIC**	4663.873
	- 12-02-2016		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
humidity	-0.1402	0.003	-43.014	0.000	-0.147	-0.134
wind_speed	-0.0286	0.006	-4.758	0.000	-0.040	-0.017
meanpressure	-3.924e-05	0.000	-0.128	0.898	-0.001	0.001
ar.L1	-0.7070	0.056	-12.600	0.000	-0.817	-0.597
ar.L2	-0.2886	0.034	-8.463	0.000	-0.355	-0.222
ar.L3	-0.3550	0.034	-10.484	0.000	-0.421	-0.289
ma.L1	-0.3403	0.057	-6.004	0.000	-0.451	-0.229
ma.L2	-0.6049	0.054	-11.295	0.000	-0.710	-0.500
ar.S.L4	-0.2485	0.334	-0.744	0.457	-0.903	0.406
ma.S.L4	-0.0253	0.339	-0.075	0.941	-0.690	0.640
ma.S.L8	-0.1326	0.094	-1.410	0.159	-0.317	0.052
sigma2	1.4043	0.036	39.427	0.000	1.334	1.474

Ljung-Box (L1) (Q):	0.38	**Jarque-Bera (JB):**	688.40
Prob(Q):	0.54	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.82	**Skew:**	-0.22
Prob(H) (two-sided):	0.03	**Kurtosis:**	6.37

In [26]:
```
pred3 = sarimaModelOnAllVars.predict(n_periods=30, X=testAllVars.drop(columns=['meantemp']))
plt.figure(figsize=(14, 5))
plt.plot(test, label='Actual')
plt.plot(pred3, label='Prediction')
plt.legend()
plt.show()
```



In [27]:
```
mean_squared_error(test, pred3, squared=False)
```

Out[27]: 1.3504414642350195

Ahh!! Looks quite similar to the actual values.

Best Model to Choose

Models	Root Mean Square Error
Auto Regressive Model	4.4578
AR Model with supporting features	4.2713
SARIMA Model	3.4199
SARIMA with supporting features	**1.3504**

Based on the Root Mean square error of each of the models created, **SARIMA** outperformed other models with RMSE of 1.3504.

Future Scope

Will try to use some deep learning models to reduce the errors and provide more accurate results. Also can add multiple datasets to build robust model.

Thank You,

Aditya Mahimkar.

Connect with me on GitHub and Kaggle.