MaunaLoa

March 31, 2025

1 MaunaLoa Temperature Time Series

References: - ARIMA Model in Python Time Series Forecasting #6. Nachiketa Hebbar - ARIMA for Time Series Forecasting; A Complete Guide. Zaina Saadeddin - Time Series Forecasting with ARIMA: Everything You Need to Know!. Nayeem Islam

[ ]:
```
# Install pmdarima library
# pmdarima does not support Numpy 2.0

import pmdarima as pm
```

[ ]:
```
!python --version
```

```
Python 3.11.11
```

- python 3.11.11
- numpy 1.23.2
- pandas 2.2.2

[ ]:
```
!pip uninstall numpy
```

```
Found existing installation: numpy 1.26.4
Uninstalling numpy-1.26.4:
  Would remove:
    /usr/local/bin/f2py
    /usr/local/lib/python3.11/dist-packages/numpy-1.26.4.dist-info/*
    /usr/local/lib/python3.11/dist-
packages/numpy.libs/libgfortran-040039e1.so.5.0.0
    /usr/local/lib/python3.11/dist-
packages/numpy.libs/libopenblas64_p-r0-0cf96a72.3.23.dev.so
    /usr/local/lib/python3.11/dist-
packages/numpy.libs/libquadmath-96973f99.so.0.0.0
    /usr/local/lib/python3.11/dist-packages/numpy/*
Proceed (Y/n)? y
  Successfully uninstalled numpy-1.26.4
```

[ ]:
```
!pip install numpy==1.23.2
```

```
Collecting numpy==1.23.2
```

```
  Using cached
numpy-1.23.2-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata
(2.2 kB)
Using cached
numpy-1.23.2-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (17.0
MB)
Installing collected packages: numpy
```

```
ERROR: pip's dependency resolver does not currently take into account all
the packages that are installed. This behaviour is the source of the following
dependency conflicts.
scipy 1.15.2 requires numpy<2.5,>=1.23.5, but you have numpy 1.23.2 which is
incompatible.
jaxlib 0.5.1 requires numpy>=1.25, but you have numpy 1.23.2 which is
incompatible.
treescope 0.1.9 requires numpy>=1.25.2, but you have numpy 1.23.2 which is
incompatible.
plotnine 0.14.5 requires numpy>=1.23.5, but you have numpy 1.23.2 which is
incompatible.
albucore 0.0.23 requires numpy>=1.24.4, but you have numpy 1.23.2 which is
incompatible.
mizani 0.13.1 requires numpy>=1.23.5, but you have numpy 1.23.2 which is
incompatible.
blosc2 3.2.0 requires numpy>=1.26, but you have numpy 1.23.2 which is
incompatible.
pandas-stubs 2.2.2.240909 requires numpy>=1.23.5, but you have numpy 1.23.2
which is incompatible.
opencv-python-headless 4.11.0.86 requires numpy>=1.23.5; python_version >=
"3.11", but you have numpy 1.23.2 which is incompatible.
ml-dtypes 0.4.1 requires numpy>=1.23.3; python_version >= "3.11", but you have
numpy 1.23.2 which is incompatible.
chex 0.1.89 requires numpy>=1.24.1, but you have numpy 1.23.2 which is
incompatible.
opencv-contrib-python 4.11.0.86 requires numpy>=1.23.5; python_version >=
"3.11", but you have numpy 1.23.2 which is incompatible.
jax 0.5.2 requires numpy>=1.25, but you have numpy 1.23.2 which is incompatible.
bigframes 1.41.0 requires numpy>=1.24.0, but you have numpy 1.23.2 which is
incompatible.
imbalanced-learn 0.13.0 requires numpy<3,>=1.24.3, but you have numpy 1.23.2
which is incompatible.
xarray 2025.1.2 requires numpy>=1.24, but you have numpy 1.23.2 which is
incompatible.
albumentations 2.0.5 requires numpy>=1.24.4, but you have numpy 1.23.2 which is
incompatible.
```

[ ]:
```
!pip uninstall pandas
```

```
Found existing installation: pandas 2.2.3
Uninstalling pandas-2.2.3:
  Would remove:
    /usr/local/lib/python3.11/dist-packages/pandas-2.2.3.dist-info/*
    /usr/local/lib/python3.11/dist-packages/pandas/*
Proceed (Y/n)? y
  Successfully uninstalled pandas-2.2.3
```

[ ]:
```
!pip install pandas==2.2.2
```

```
Collecting pandas==2.2.2
  Using cached
pandas-2.2.2-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata
(19 kB)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-
packages (from pandas==2.2.2) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas==2.2.2) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas==2.2.2) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas==2.2.2) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas==2.2.2) (1.17.0)
Using cached
pandas-2.2.2-cp311-cp311-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (13.0
MB)
Installing collected packages: pandas
Successfully installed pandas-2.2.2
```

[ ]:
```
!pip install pmdarima
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.11/dist-
packages (2.0.4)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.4.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (3.0.12)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.26.4)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.2.2)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (1.6.1)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (1.15.2)
```

```
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (0.14.4)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.11/dist-
packages (from pmdarima) (2.3.0)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (78.1.0)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.11/dist-packages (from pmdarima) (24.2)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.11/dist-packages (from pandas>=0.19->pmdarima)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-
packages (from pandas>=0.19->pmdarima) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-
packages (from pandas>=0.19->pmdarima) (2025.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.6.0)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.11/dist-
packages (from statsmodels>=0.13.2->pmdarima) (1.0.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
packages (from python-dateutil>=2.8.2->pandas>=0.19->pmdarima) (1.17.0)
```

[ ]:
```python
# Load libraries
import pandas as pd
import numpy as np
```

1.1 Read Data: MaunaLoa Daily Temperatures

[ ]:
```python
# read csv file
df = pd.read_csv('/content/MaunaLoaDailyTemps-1.csv', index_col='DATE',␣
 ↪parse_dates=True)

# drop missing values
df = df.dropna()

# Show dataset
print('Shape of data', df.shape)
df.head()
```

```
Shape of data (1821, 5)
```

[ ]:

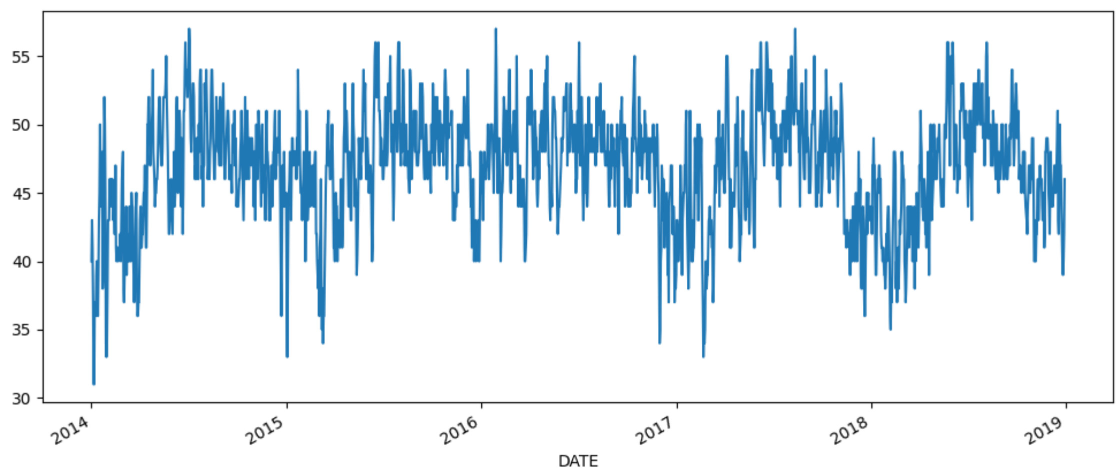
	MinTemp	MaxTemp	AvgTemp	Sunrise	Sunset
DATE					
2014-01-01	33.0	46.0	40.0	657	1756
2014-01-02	35.0	50.0	43.0	657	1756
2014-01-03	36.0	45.0	41.0	657	1757

2014-01-04	32.0	41.0	37.0	658	1757
2014-01-05	24.0	38.0	31.0	658	1758

The dataset has 1,821 rows and 5 columns.

[ ]:
```
# plot data
df['AvgTemp'].plot(figsize=(12,5))
```

[ ]:
```
<Axes: xlabel='DATE'>
```



1.2 Is Data Stationary?

If P-vlaue < 0.05, data is stationary

If P-value > 0.05, data is not stationary. Data has an increasing for decreasing trend/p>

[ ]:
```
# Function to check whether data is stationary or not
# Modeled time series data needs to be stationary
# The time series mean, variance, etc are constant over time

from statsmodels.tsa.stattools import adfuller

def ad_test(dataset):
  dftest = adfuller(dataset, 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)
```

```
    # Interpret the results
    if dftest[1] > 0.05:
        print("The data is not stationary.")
    else:
        print("The data is stationary.")
```

[ ]:
```
# P-value should be as low as possible. < 0.05

ad_test(df['AvgTemp'])
```

```
1. ADF:  -6.554680125068777
2. P-Value:  8.675937480199653e-09
3. Num of Lags:  12
4. Num of Observations Used for ADF Regression and Critical Values Calculation:
1808
5. Critical Values :
         1% :  -3.433972018026501
         5% :  -2.8631399192826676
         10% :  -2.5676217442756872
The data is stationary.
```

1.3 Find the Best ARIMA Model

[ ]:
```
# Load auto_arima
from pmdarima import auto_arima
# ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

[ ]:
```
# Find the best ARIMA model
stepwise_fit = auto_arima(df['AvgTemp'], trace=True, suppress_warnings=True)

stepwise_fit.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=8344.294, Time=4.38 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=10347.755, Time=0.07 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=8365.701, Time=0.29 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=9136.225, Time=0.37 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=19192.139, Time=0.04 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=8355.947, Time=2.16 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=8356.308, Time=5.38 sec
 ARIMA(3,0,2)(0,0,0)[0] intercept   : AIC=8347.324, Time=3.77 sec
 ARIMA(2,0,3)(0,0,0)[0] intercept   : AIC=8318.606, Time=3.82 sec
 ARIMA(1,0,3)(0,0,0)[0] intercept   : AIC=8330.189, Time=5.47 sec
 ARIMA(3,0,3)(0,0,0)[0] intercept   : AIC=8310.514, Time=4.54 sec
 ARIMA(4,0,3)(0,0,0)[0] intercept   : AIC=8332.054, Time=5.42 sec
```

```
ARIMA(3,0,4)(0,0,0)[0] intercept   : AIC=8317.479, Time=6.36 sec
ARIMA(2,0,4)(0,0,0)[0] intercept   : AIC=8305.268, Time=4.84 sec
ARIMA(1,0,4)(0,0,0)[0] intercept   : AIC=8296.961, Time=6.17 sec
ARIMA(0,0,4)(0,0,0)[0] intercept   : AIC=8455.435, Time=1.28 sec
ARIMA(1,0,5)(0,0,0)[0] intercept   : AIC=8295.814, Time=5.44 sec
ARIMA(0,0,5)(0,0,0)[0] intercept   : AIC=8419.091, Time=1.78 sec
ARIMA(2,0,5)(0,0,0)[0] intercept   : AIC=8302.138, Time=7.48 sec
ARIMA(1,0,5)(0,0,0)[0]             : AIC=8304.533, Time=0.62 sec

Best model:  ARIMA(1,0,5)(0,0,0)[0] intercept
Total fit time: 69.726 seconds
```

[ ]:

Dep. Variable:	y	**No. Observations:**	1821
Model:	SARIMAX(1, 0, 5)	**Log Likelihood**	-4139.907
Date:	Mon, 31 Mar 2025	**AIC**	8295.814
Time:	04:09:28	**BIC**	8339.871
Sample:	0 - 1821	**HQIC**	8312.068
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
intercept	1.3625	0.397	3.429	0.001	0.584	2.141
ar.L1	0.9707	0.009	113.365	0.000	0.954	0.987
ma.L1	-0.1219	0.024	-5.083	0.000	-0.169	-0.075
ma.L2	-0.2155	0.024	-8.836	0.000	-0.263	-0.168
ma.L3	-0.2028	0.024	-8.424	0.000	-0.250	-0.156
ma.L4	-0.1345	0.023	-5.885	0.000	-0.179	-0.090
ma.L5	-0.0459	0.024	-1.879	0.060	-0.094	0.002
sigma2	5.5010	0.172	31.927	0.000	5.163	5.839

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	21.33
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.81	**Skew:**	-0.18
Prob(H) (two-sided):	0.01	**Kurtosis:**	3.40

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

The best arima model is ARIMA(1,0,5). - p: The number of past values (lags) considered in the AR term. 1 - d: The degree of differencing applied to the data. 0 - q: The number of past forecast errors included in the MA term. 5

[ ]:

```
# Load ARIMA
from statsmodels.tsa.arima.model import ARIMA
```

1.4 Split Data into Train and Test

[ ]:
```
print(df.shape)
train = df.iloc[:-30]  # all values except the last 30 values
test = df.iloc[-30:] #last 30 values

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

```
(1821, 5)
(1791, 5) (30, 5)
```

1.5 Train the Model

[ ]:
```
model = ARIMA(train['AvgTemp'], order=(1,0,5))
model = model.fit()
model.summary()
```

[ ]:

Dep. Variable:	AvgTemp	**No. Observations:**	1791
Model:	ARIMA(1, 0, 5)	**Log Likelihood**	-4070.198
Date:	Mon, 31 Mar 2025	**AIC**	8156.395
Time:	02:17:28	**BIC**	8200.320
Sample:	0 - 1791	**HQIC**	8172.614
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	46.5856	0.758	61.454	0.000	45.100	48.071
ar.L1	0.9856	0.005	188.230	0.000	0.975	0.996
ma.L1	-0.1412	0.023	-6.124	0.000	-0.186	-0.096
ma.L2	-0.2268	0.024	-9.635	0.000	-0.273	-0.181
ma.L3	-0.2168	0.023	-9.251	0.000	-0.263	-0.171
ma.L4	-0.1479	0.023	-6.491	0.000	-0.193	-0.103
ma.L5	-0.0595	0.024	-2.438	0.015	-0.107	-0.012
sigma2	5.5093	0.174	31.624	0.000	5.168	5.851

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	14.88
Prob(Q):	0.97	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.82	**Skew:**	-0.15
Prob(H) (two-sided):	0.01	**Kurtosis:**	3.33

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[ ]:
```
# Make a prediction on the test data then compare to actual

start=len(train)
end=len(train)+len(test)-1
#pred=model.predict(start=start,end=end,typ='levels').rename('ARIMA␣
 ↪Predictions').rename('ARIMA Predictions')
```

```
pred=model.predict(start=start,end=end,typ='levels').rename('ARIMA Predictions')
pred.index = df.index[start:end+1]
print(pred)
```

```
DATE
2018-12-01    44.754109
2018-12-02    44.987795
2018-12-03    45.388741
2018-12-04    45.721545
2018-12-05    45.863733
2018-12-06    45.874126
2018-12-07    45.884370
2018-12-08    45.894466
2018-12-09    45.904417
2018-12-10    45.914225
2018-12-11    45.923891
2018-12-12    45.933418
2018-12-13    45.942808
2018-12-14    45.952063
2018-12-15    45.961185
2018-12-16    45.970175
2018-12-17    45.979036
2018-12-18    45.987769
2018-12-19    45.996377
2018-12-20    46.004861
2018-12-21    46.013222
2018-12-22    46.021463
2018-12-23    46.029586
2018-12-24    46.037591
2018-12-25    46.045481
2018-12-26    46.053258
2018-12-27    46.060923
2018-12-28    46.068477
2018-12-29    46.075922
2018-12-30    46.083261
Name: ARIMA Predictions, dtype: float64
```

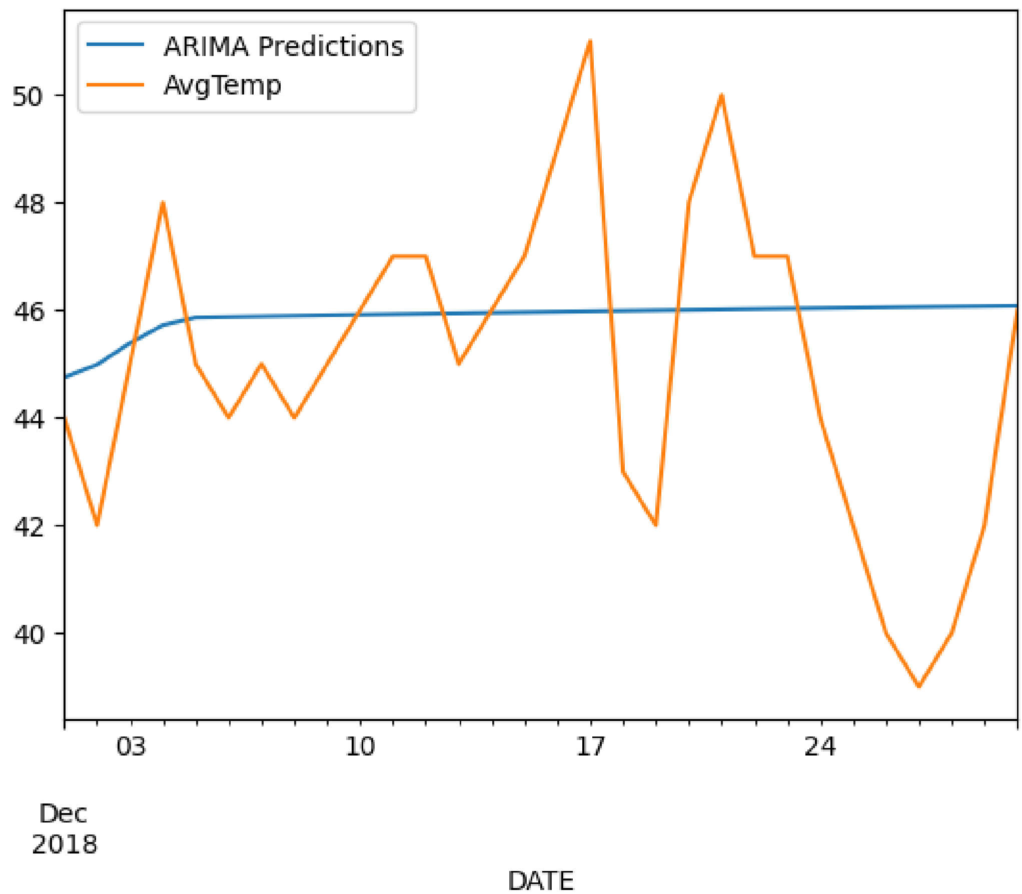
[ ]:
```
print(test['AvgTemp'])
```

```
DATE
2018-12-01    44.0
2018-12-02    42.0
2018-12-03    45.0
2018-12-04    48.0
2018-12-05    45.0
2018-12-06    44.0
2018-12-07    45.0
2018-12-08    44.0
```

```
2018-12-09    45.0
2018-12-10    46.0
2018-12-11    47.0
2018-12-12    47.0
2018-12-13    45.0
2018-12-14    46.0
2018-12-15    47.0
2018-12-16    49.0
2018-12-17    51.0
2018-12-18    43.0
2018-12-19    42.0
2018-12-20    48.0
2018-12-21    50.0
2018-12-22    47.0
2018-12-23    47.0
2018-12-24    44.0
2018-12-25    42.0
2018-12-26    40.0
2018-12-27    39.0
2018-12-28    40.0
2018-12-29    42.0
2018-12-30    46.0
Name: AvgTemp, dtype: float64
```

[ ]:
```
pred.plot(legend=True)
test['AvgTemp'].plot(legend=True)
```

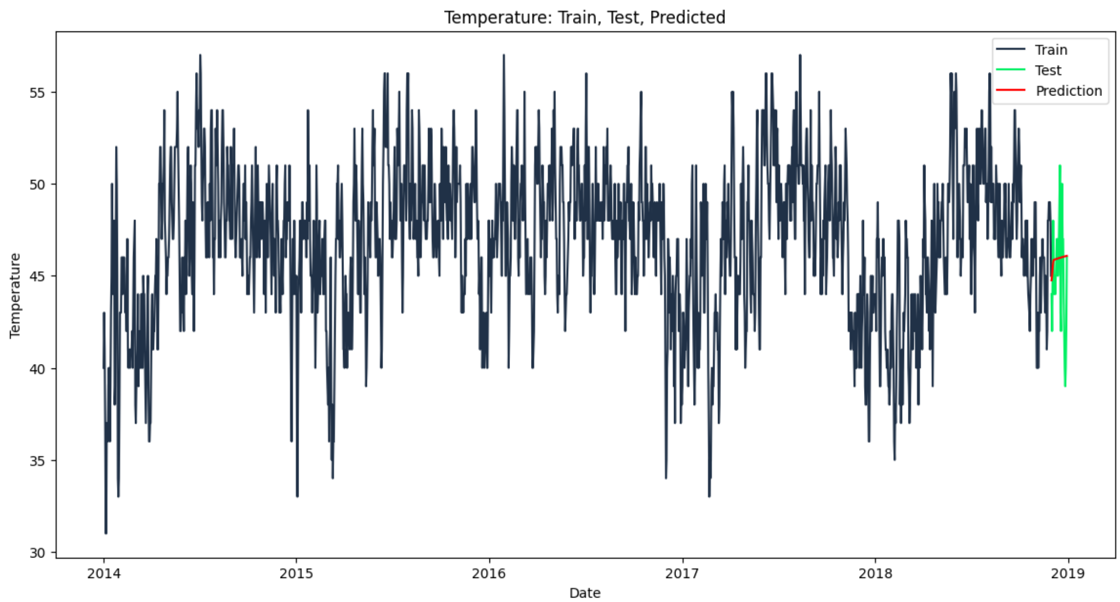
[ ]:
```
<Axes: xlabel='DATE'>
```



1.6 Plot Train, Test, & Predicted Data

```
[ ]: # Load matplotlib
import matplotlib.pyplot as plt

# Define plot
plt.figure(figsize=(14,7))
plt.plot(train.index, train["AvgTemp"], label='Train', color='#203147') # train␣
 ↪data
plt.plot(test.index, test["AvgTemp"], label='Test', color='#01ef63')    # test␣
 ↪data
plt.plot(test.index, pred, label='Prediction', color='red')           #␣
 ↪forecasted data
plt.title('Temperature: Train, Test, Predicted')
plt.xlabel('Date')
plt.ylabel('Temperature')
plt.legend()
plt.show()
```



[ ]:
```
test['AvgTemp'].mean()
```

[ ]: 45.0

The average for the test data is 45.

[ ]:
```
pred = pred[:len(test)]
test_temp = test['AvgTemp'][:len(forecast)]

# Calculate RMSE

from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mean_squared_error(test_temp,pred))
print(f"RMSE: {rmse: .4f}")
```

```
RMSE:  3.0005
```

On average predictions are off by +/- 3 degrees.

1.7 Forecast Past the End of the Original Data

Forecast: 2018-12-31 to 2109-04-09

[ ]:
```
# Forecast future value
forecast = model_fit.forecast(steps = 100)

print(forecast)
```

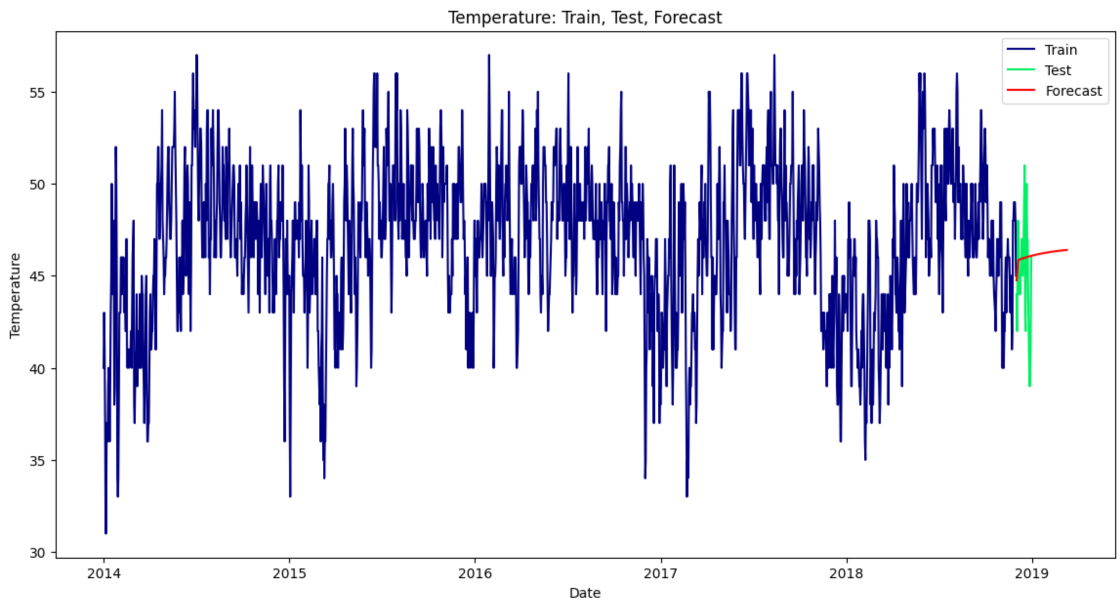
```
1791    44.754109
1792    44.987795
1793    45.388741
1794    45.721545
1795    45.863733
          …
1886    46.392716
1887    46.395493
1888    46.398231
1889    46.400928
1890    46.403587
Name: predicted_mean, Length: 100, dtype: float64
```

[ ]:
```
forecast.index = pd.date_range(start=df.index[-1], periods=101,␣
 ↪inclusive="right")
print(forecast)
```

```
2018-12-31    44.754109
2019-01-01    44.987795
2019-01-02    45.388741
2019-01-03    45.721545
2019-01-04    45.863733
                ...
2019-04-05    46.392716
2019-04-06    46.395493
2019-04-07    46.398231
2019-04-08    46.400928
2019-04-09    46.403587
Freq: D, Name: predicted_mean, Length: 100, dtype: float64
```

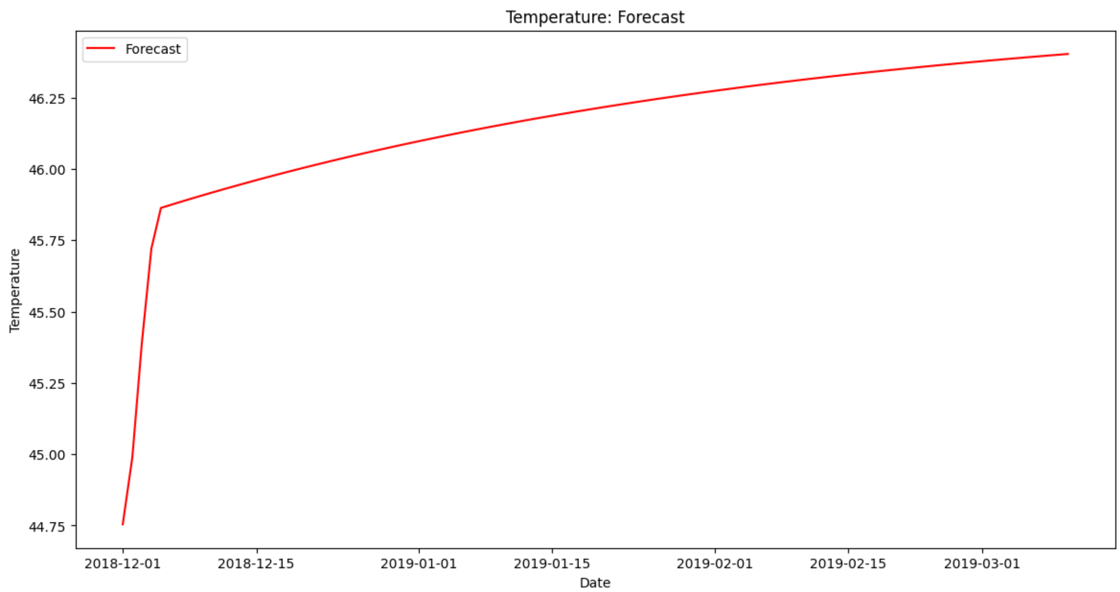
[ ]:
```
last_date = train.index[-1]
forecast_index = pd.date_range(last_date,periods=101, inclusive="right")

# Define plot
plt.figure(figsize=(14,7))
plt.plot(train.index, train["AvgTemp"], label='Train', color="navy") # train␣
 ↪data
plt.plot(test.index, test["AvgTemp"], label='Test', color='#01ef63') # test data
plt.plot(forecast_index,forecast, label='Forecast', color='red')    #␣
 ↪forecasted data
plt.title('Temperature: Train, Test, Forecast')
plt.xlabel('Date')
plt.ylabel('Temperature')
plt.legend()
plt.show()
```



[ ]:
```
last_date = train.index[-1]
forecast_index = pd.date_range(last_date,periods=101, inclusive="right")

# Define plot
plt.figure(figsize=(14,7))
#plt.plot(train.index, train["AvgTemp"], label='Train', color="navy") # train data
#plt.plot(test.index, test["AvgTemp"], label='Test', color='#01ef63') # test data
plt.plot(forecast_index,forecast2, label='Forecast', color='red')     # forecasted data
plt.title('Temperature: Forecast')
plt.xlabel('Date')
plt.ylabel('Temperature')
plt.legend()
plt.show()
```


Temperature: Forecast
Forecast
46.25
46.00
45.75
45.50
45.25
45.00
44.75
Temperature
2018-12-01
2018-12-15
2019-01-01
2019-01-15
2019-02-01
2019-02-15
2019-03-01
Date