Decomposition in Time Series Data

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Published in Analytics Vidhya · 5 min read · Jan 14, 2020

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Decomposition in Time Series Data

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Decomposition is a statistical task in which the Time Series data is decomposed into several component or extracting seasonality, trend from a series data. These components are defined as follows:

- Level: The average value in the series.
- Trend: The increasing or decreasing value in the series.
- Seasonality: The repeating short-term cycle in the series.
- Noise: The random variation in the series.

Time series data are combination of these components. All the series have Level and noise. The trend and seasonality components are optional.

In time series data, these components are either additively or multiplicatively combined.

Additive Model:

Additive Model are the one where the variance of data doesn't change over different values of the time series. The systematic component is the arithmetic sum of the individual effects of the predictors.

Additive model is linear and the trend line here is a straight line and seasonality has same frequency and amplitude (height and width of the cycle respectively).

$\mathcal{Y}(t)=S\text{t} + T\text{ t} + \text{Rt}$

Where St = seasonal component,

Tt = trend-cycle component and

Rt = remainder component

Multiplicative Model:

Multiplicative Model are the one where as the data increases, so does the seasonal pattern or the variance increases. Here the trend and seasonal components are multiplied and then added to the error component.

Multiplicative model is non-linear, such as quadratic or exponential and the trend is a curved line and seasonality has an increasing or decreasing frequency and amplitude over time.

$\mathcal{Y}(t)=S\text{t} \times T\text{t} \times \text{Rt}$

Classical Decomposition

Decomposition is used for time series analysis. And the result can be used to inform forecasting model as per the problem. It gives us brief knowledge about the forecasting problem in terms of model complexity and how best to captures these components in the model.

The time series data may have multiplicative or additive components. There can be increase trend followed by decreasing or can be of non-repeating cycle with repeating seasonality components.

Decomposition helps us to better analyze the data and exploring different ways to solve the problem.

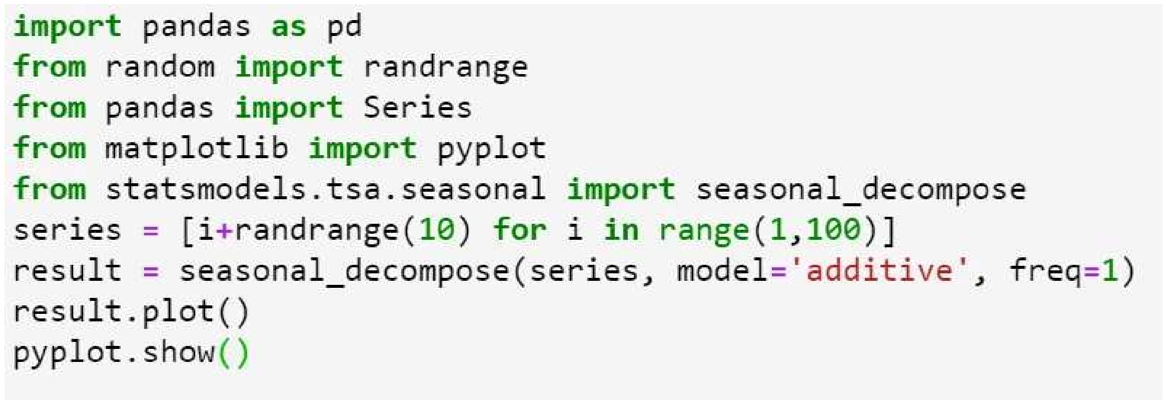
Python provide statsmodels library which helps to decompose a series data into its components. The function used is seasonal_decompose(). This function requires model to be specified as “Additive” or “Multiplicative”.

The output of the function is trend and seasonal series stored in an array. The residuals are the one when trend and seasonal components are removed from the data. Also, the original which is observed data is stored.

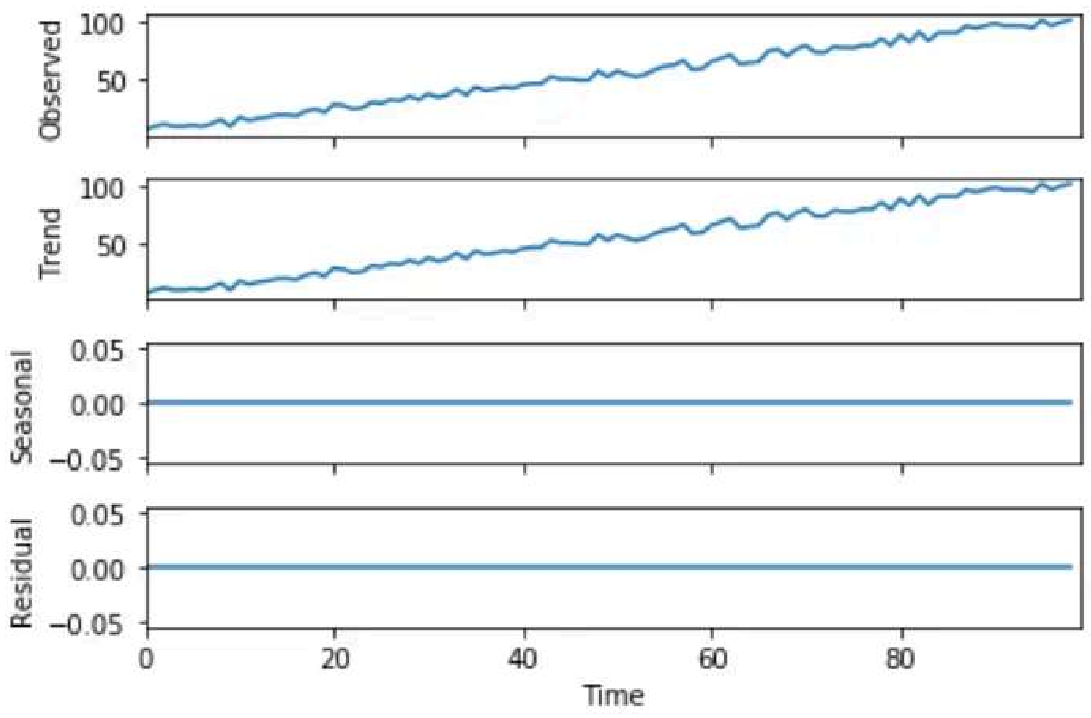
Additive Decomposition

Let’s see how Additive Decomposition works using the function seasonal_decompose().

Let’s generate number between 1 to 100 with some random noise. This series comprised of linearly increasing trend. The result obtained after applying additive decomposition is:



```
import pandas as pd
from random import randrange
from pandas import Series
from matplotlib import pyplot
from statsmodels.tsa.seasonal import seasonal_decompose
series = [i+randrange(10) for i in range(1,100)]
result = seasonal_decompose(series, model='additive', freq=1)
result.plot()
pyplot.show()
```



From the graph plotted we can see that the entire series is taken as series and there's no seasonality.

As we can see that there is no residual as well that means decomposition was not able to separate noise that we added to our series from the linear trend. It uses classical or Naïve method for decomposition.

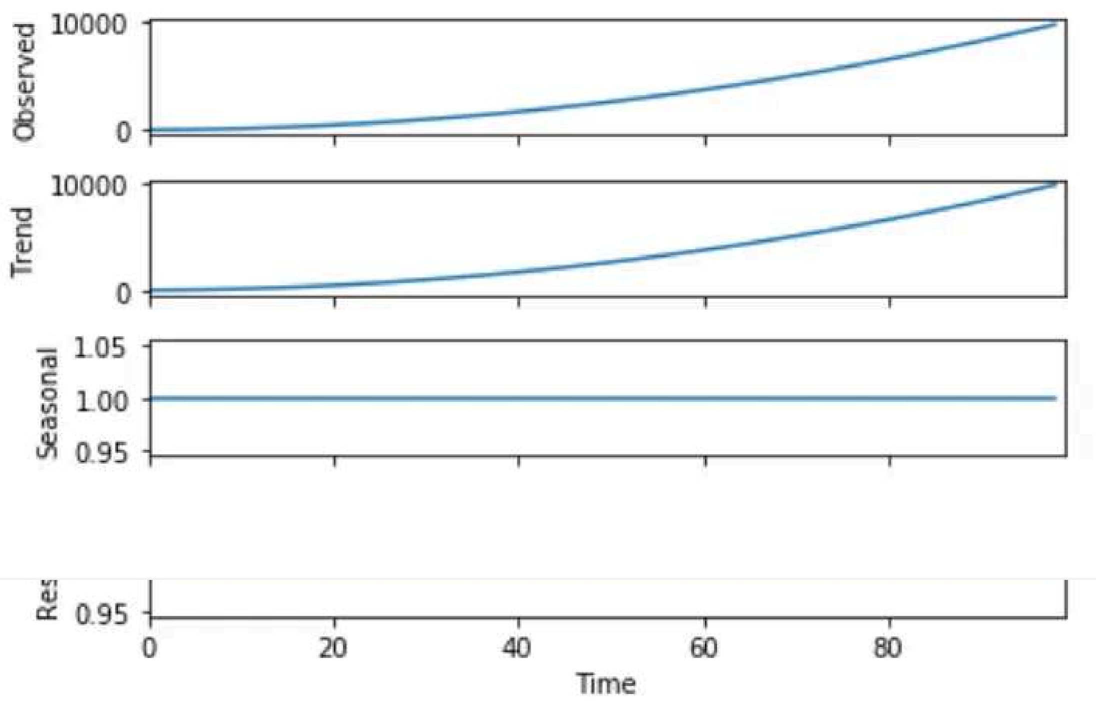
As Naïve Decomposition is a simple method, there are more advanced decompositions available such as Seasonal and Trend decomposition using Loess (STL) decomposition.

Multiplicative Decomposition

Let’s see how Multiplicative Decomposition works using the function seasonal_decompose ().

Let’s generate square of the time between 1 to 100 with some random noise. The result obtained after applying multiplicative decomposition is:

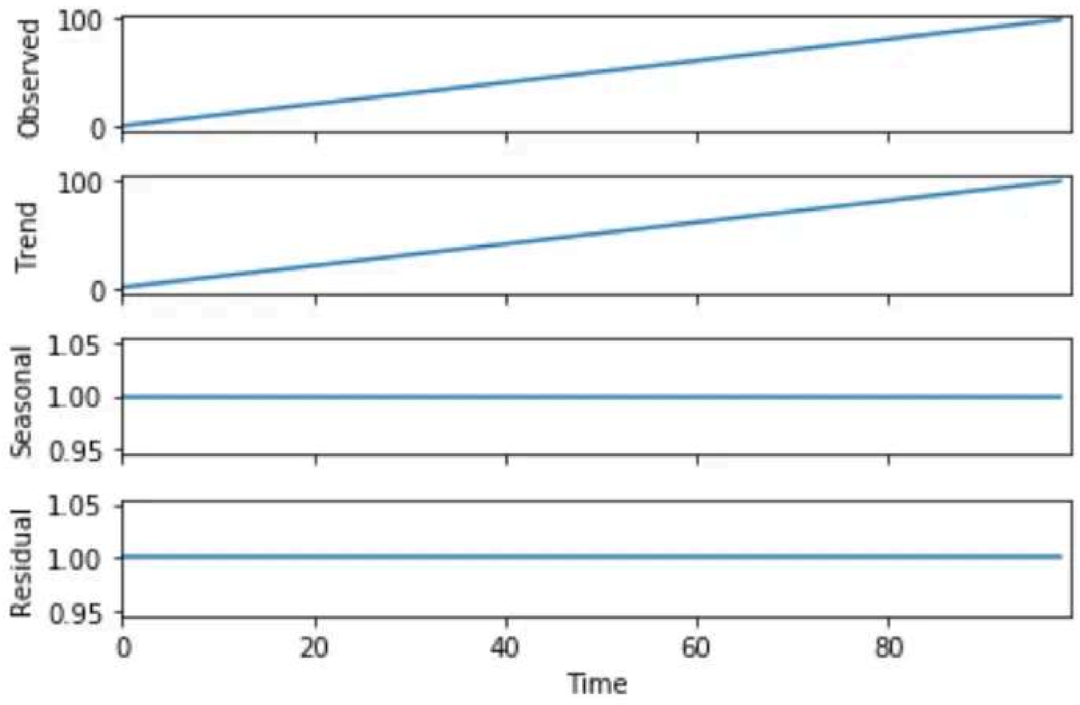
```
from pandas import Series
from matplotlib import pyplot
from statsmodels.tsa.seasonal import seasonal_decompose
series = [i**2.0 for i in range(1,100)]
result = seasonal_decompose(series, model='multiplicative', freq=1)
result.plot()
pyplot.show()
```



We can see from the graph that the trend line is quadratic. Exponential changes can be transformed to linear by data transformation.

Let's see the how the graph changes when the data is transformed:

```
from pandas import Series
from matplotlib import pyplot
import math
from statsmodels.tsa.seasonal import seasonal_decompose
series = [math.sqrt(i**2.0) for i in range(1,100)]
result = seasonal_decompose(series, model='multiplicative',freq=1)
result.plot()
pyplot.show()
```



From the above graph, we can see how the graph changes from quadratic to linear by taking square root of the data.

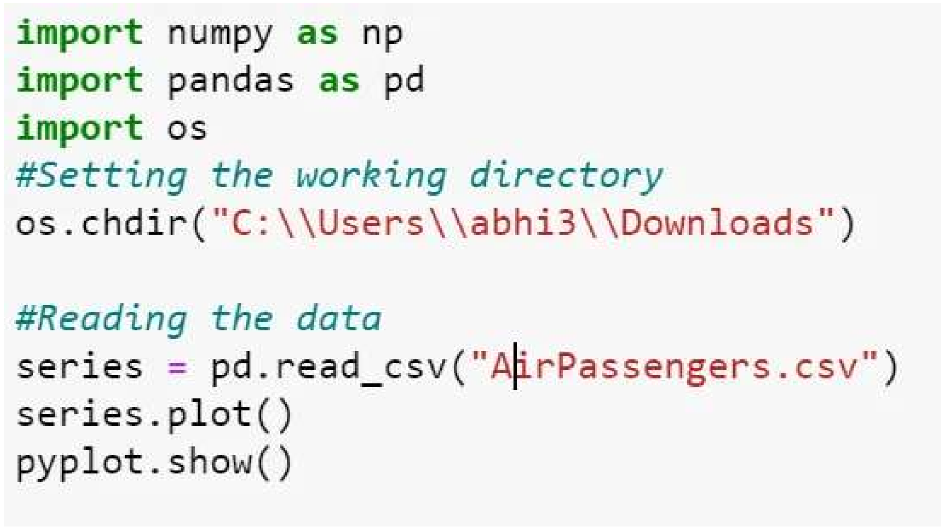
Decomposition on Time Series dataset

Data set Description:

Dataset: Airline Passenger Dataset

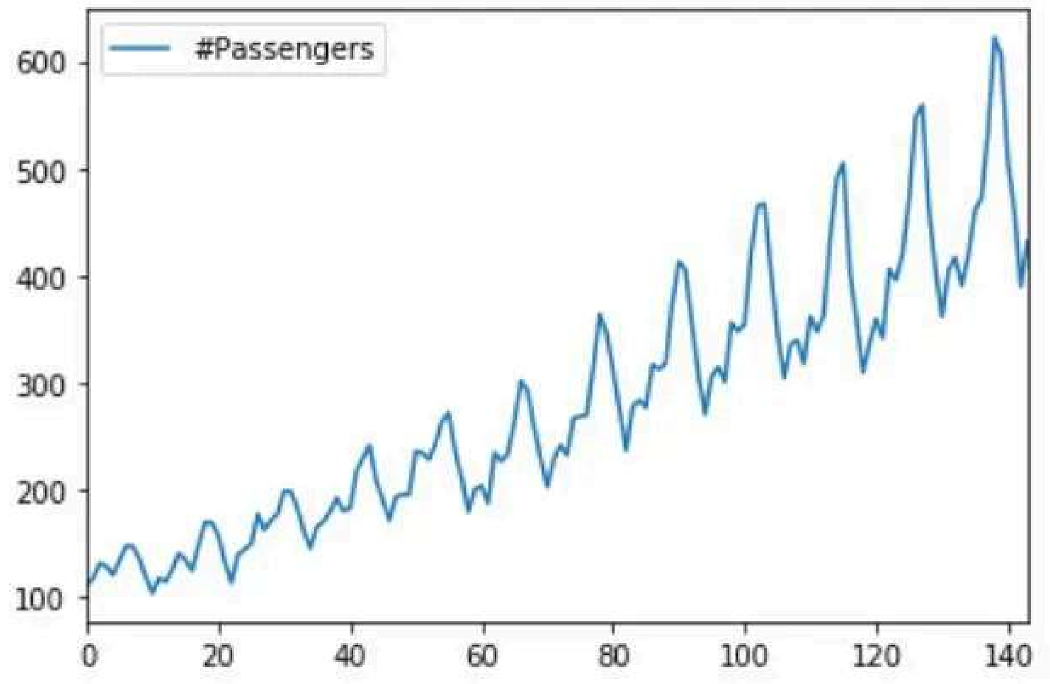
Rows X Columns = 144 X 2

Columns : Month, #Passengers



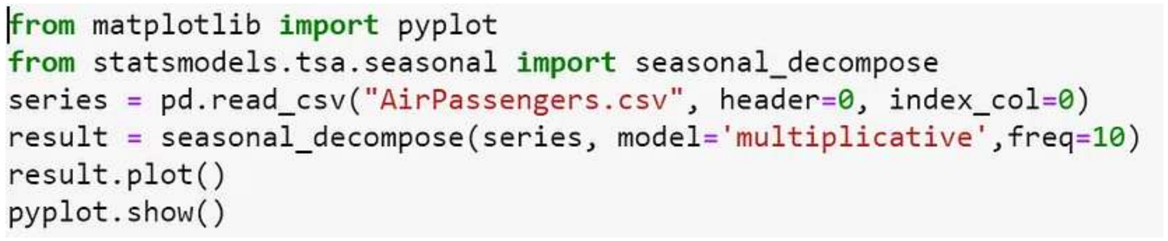
```
import numpy as np
import pandas as pd
import os
#Setting the working directory
os.chdir("C:\\Users\\abhi3\\Downloads")

#Reading the data
series = pd.read_csv("AirPassengers.csv")
series.plot()
pyplot.show()
```

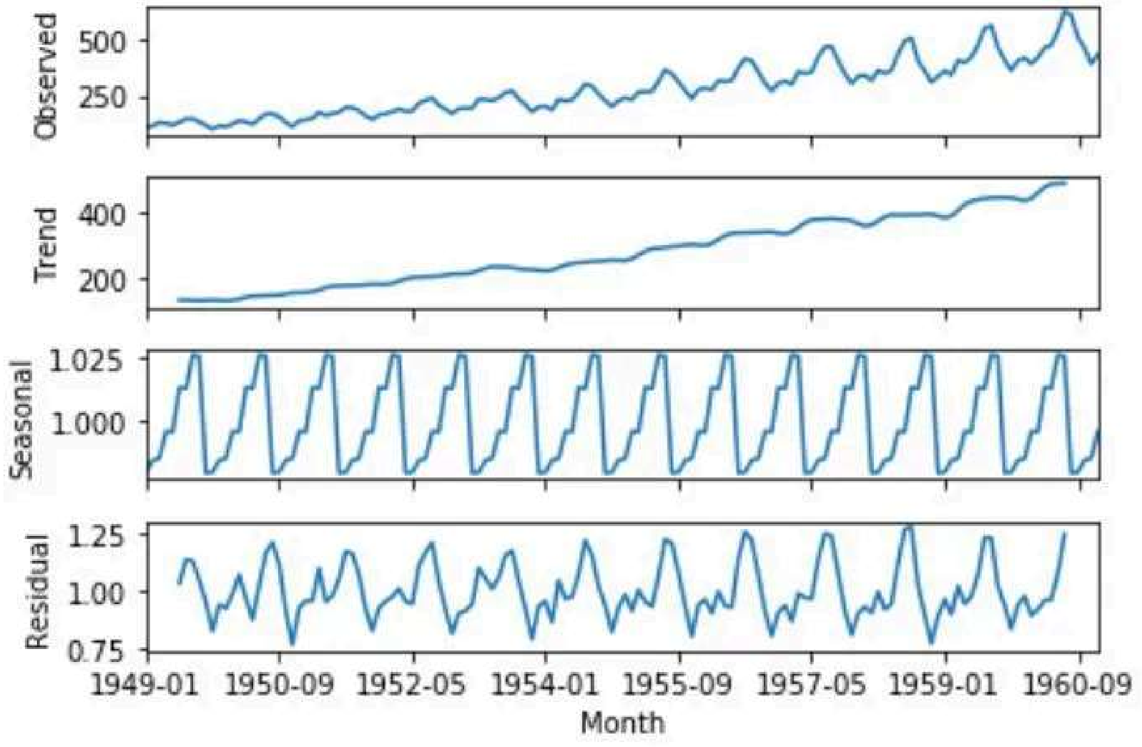


We can see the graph have seasonal and trend as well. Decomposing this gives us clear picture of all the component in the series.

Let's use Multiplicative Decomposition and look at the resultant graphs.



```
from matplotlib import pyplot
from statsmodels.tsa.seasonal import seasonal_decompose
series = pd.read_csv("AirPassengers.csv", header=0, index_col=0)
result = seasonal_decompose(series, model='multiplicative',freq=10)
result.plot()
pyplot.show()
```



We can clearly see from the graph that the trend and seasonality from the series have some pattern even the residual shows high variance in the early and late years.

SEATS Decomposition

Here “SEATS” stand for “Seasonal Extraction in ARIMA Time Series”. Here the series data is either quarterly or monthly.

Advantage of SEATS

- Model-based
- Smooth trend estimate
- Allows estimates at end points
- Allows changing seasonality
- Developed for economic data

STL Decomposition

Here “STL” stands for “Seasonal and Trend decomposition using Loess”. It is more robust and versatile method used for decomposition. Loess is a method for estimating Non-Linear relationship.

Advantage of STL

- Can handle any type of seasonality
- Seasonal component allowed to change over time, and rate of change controlled by user.
- Smoothness of trend-cycle also controlled by user.
- Robust to outliers Not trading day or calendar adjustments.
- Only additive.
- Take logs to get multiplicative decomposition.
- Use Box-Cox transformations to get other decompositions.

Forecasting with Decomposition

We forecast seasonal component and seasonally adjusted component (trend and residual together) separately to forecast a decomposed series data.

It is assumed that seasonal component changes very slowly over time or is unchanging, so the forecast can be done by taking last year data of the estimated component.

In simple words we use Naïve method for seasonal component.

Any non-seasonal forecasting methods like random walk with drift model or Holt's method or non-seasonal ARIMA method can be used for forecasting seasonally adjusted component.

Summary

From the above, we learned:

- Why Decomposition of Time series data is important.
- Various methods of decomposing time series data.
- How can we forecast a time series data with decomposition.

*academic work at Praxis Business School,Bangalore.

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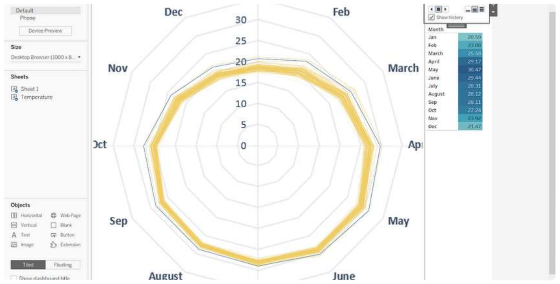

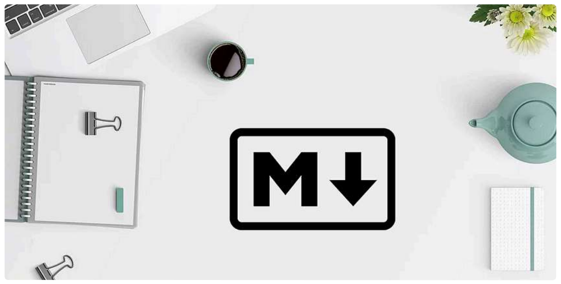

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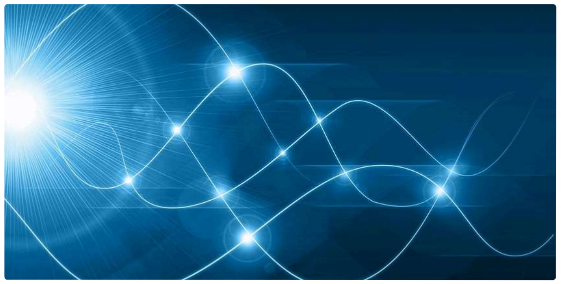

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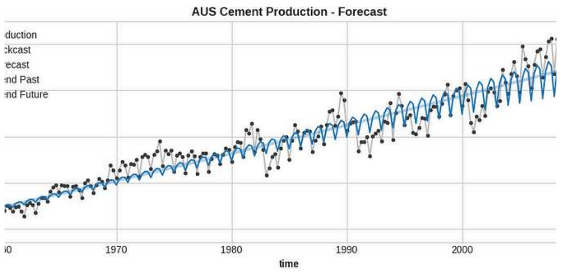

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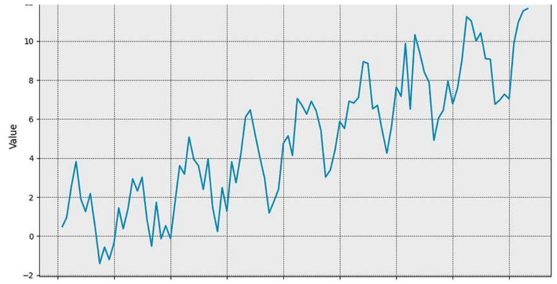

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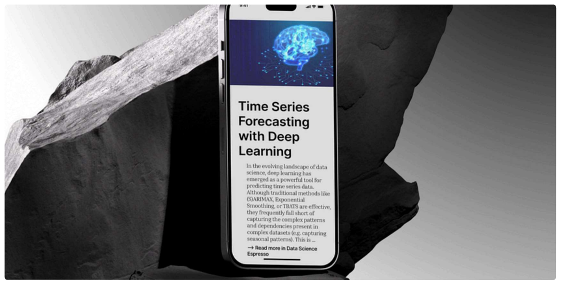

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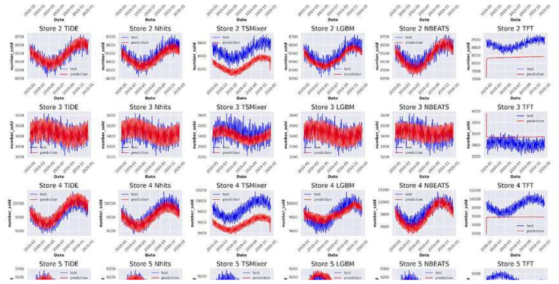

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