Homework 3

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Chapter 5: The Forecaster's Toolbox

```
# data wrangling
import pandas as pd
import numpy as np

# data visuals
import matplotlib.pyplot as plt
import seaborn as sns

# timeseries analysis
from darts import TimeSeries

# ts decomposition
from statsmodels.tsa.seasonal import STL
from statsmodels.tsa.seasonal import seasonal_decompose

# forecasting method
from darts.models import NaiveMean
from darts.models import NaiveSeasonal # K=1 for last value, K=4 for quarterly data
from darts.models import NaiveDrift
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsforecast\core.py:26:
  TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See
  https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from tqdm.autonotebook import tqdm
```

Resource:

- Darts Documentation

Exercise 1

Produce forecasts for the following series using whichever of NAIVE(y), SNAIVE(y) or RW(y ~ drift()) is more appropriate in each case:

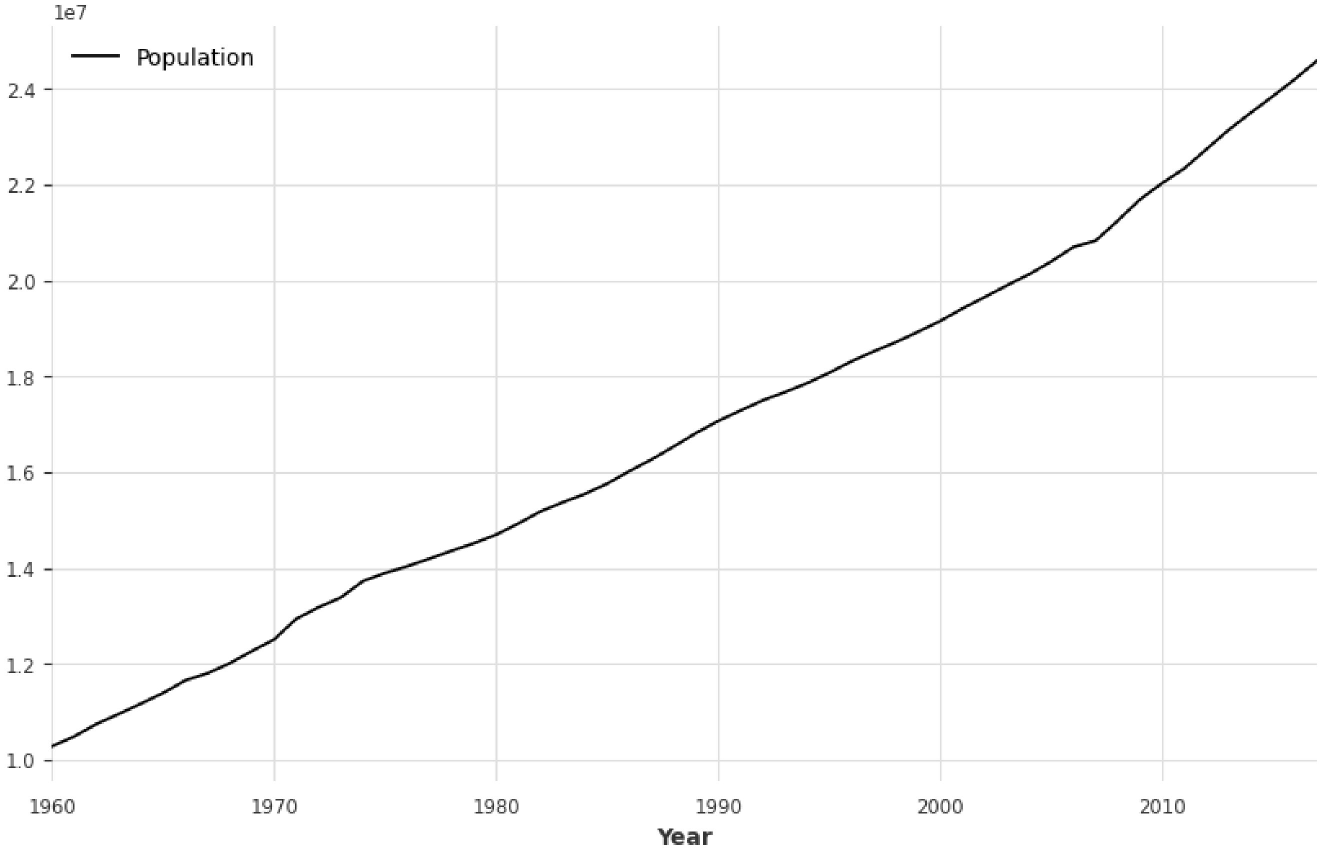
- Australian Population (global_economy)
- Bricks (aus_production)
- NSW Lambs (aus_livestock)
- Household wealth (hh_budget).
- Australian takeaway food turnover (aus_retail).

```
# reading in the data
df_global_economy = pd.read_csv("../rdata/global_economy.csv", parse_dates=['Year'])
df_production= pd.read_csv("../rdata/aus_production.csv", parse_dates=['Quarter'])
df_livestock = pd.read_csv("../rdata/aus_livestock.csv", parse_dates=['Month'])
df_budget = pd.read_csv("../rdata/hh_budget.csv", parse_dates=['Year'])
df_retail = pd.read_csv("../rdata/aus_retail.csv",parse_dates=['Month'])
```

Australian Population from `global_economy`

```
# filter australia
df_aus = df_global_economy.query('Country == "Australia"')
```

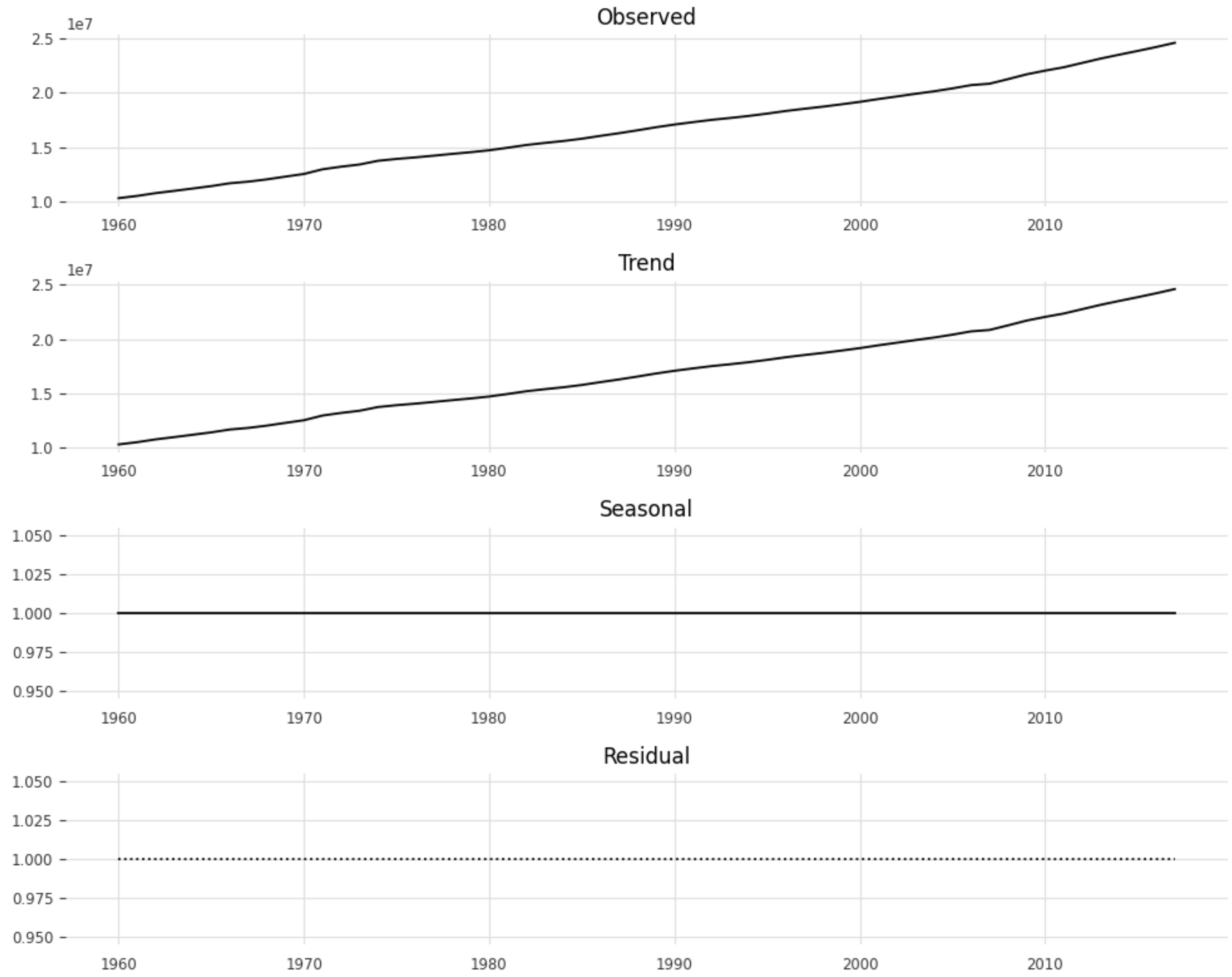
```
# plot australian timeseries pop
df_aus_pop = df_aus[['Year', 'Population']]
df_aus_pop.set_index('Year', inplace=True)
df_aus_pop.plot()
```



The Australian Populatiion has near perfect linear growth from the 1960 to 2020. Before, choosing which forecasting method to go with. I would like to see the decomposition of this time series just to make sure that my initial observation of no seasonality is correct.

```
# decompose this ts
decomposition = seasonal_decompose(df_aus_pop.Population, period = 1,
  model="multiplicative")

fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(10, 8))

ax1.plot(decomposition.observed)
ax1.set_title('Observed')

ax2.plot(decomposition.trend)
ax2.set_title('Trend')
```

```
ax3.plot(decomposition.seasonal)
ax3.set_title('Seasonal')

ax4.plot(decomposition.resid, linestyle = "dotted", markersize = 10)
ax4.set_title('Residual')

plt.tight_layout()
plt.show()
```

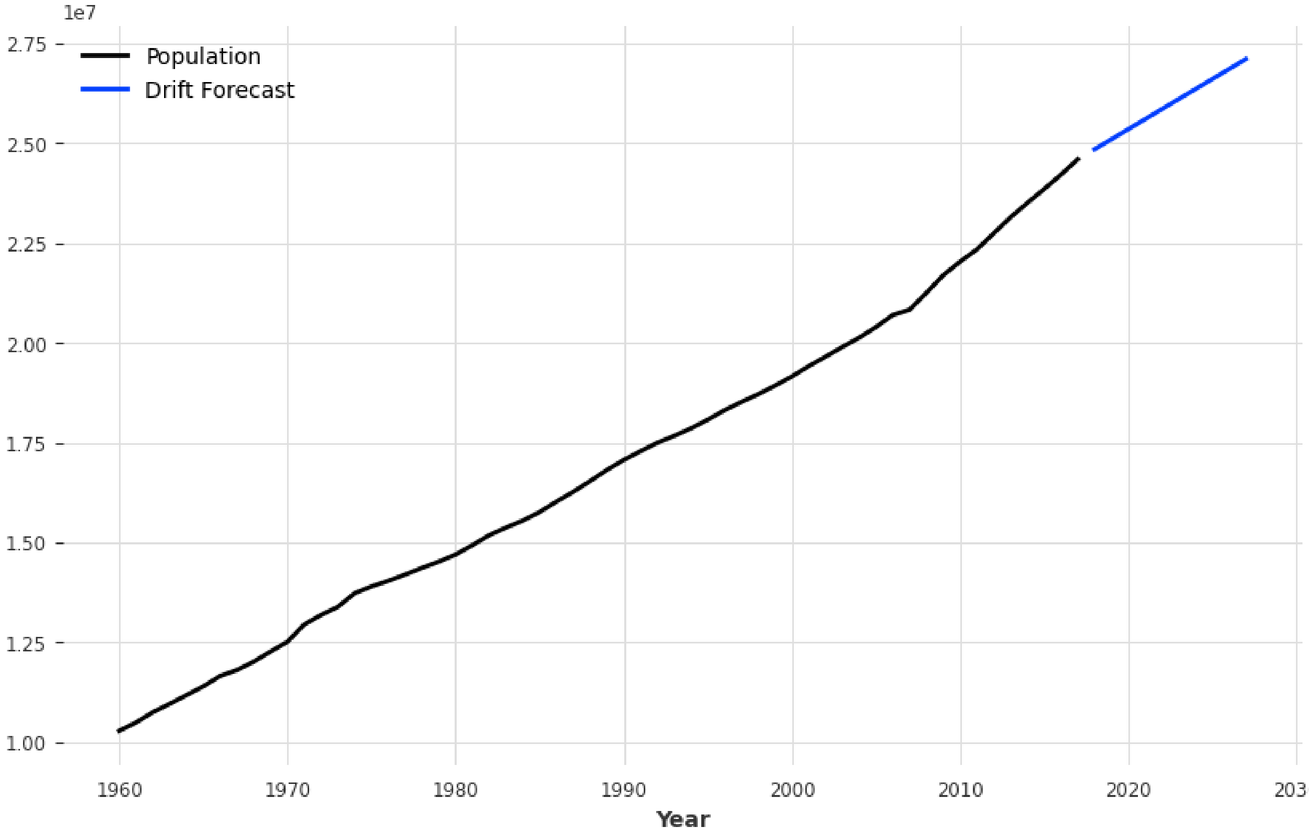


The trend line captures almost all of the observed data indicated that the seasonal component is constant at a value of 1. Thus, I believe that using the Drift method would be the most appropriate for this timeseries since it exhibits no seasonality and a overal upward trend. Wherein our forecast cast would be the average change seen in the data.

```
# convert df to ts
series = TimeSeries.from_dataframe(df_aus,'Year', 'Population')
```

```
drift = NaiveDrift()

drift.fit(series)
```

```
forecast = drift.predict(10) # 10 timesteps
series.plot()
forecast.plot(label='Drift Forecast', low_quantile = 0.05, high_quantile=0.95)
plt.legend()
```

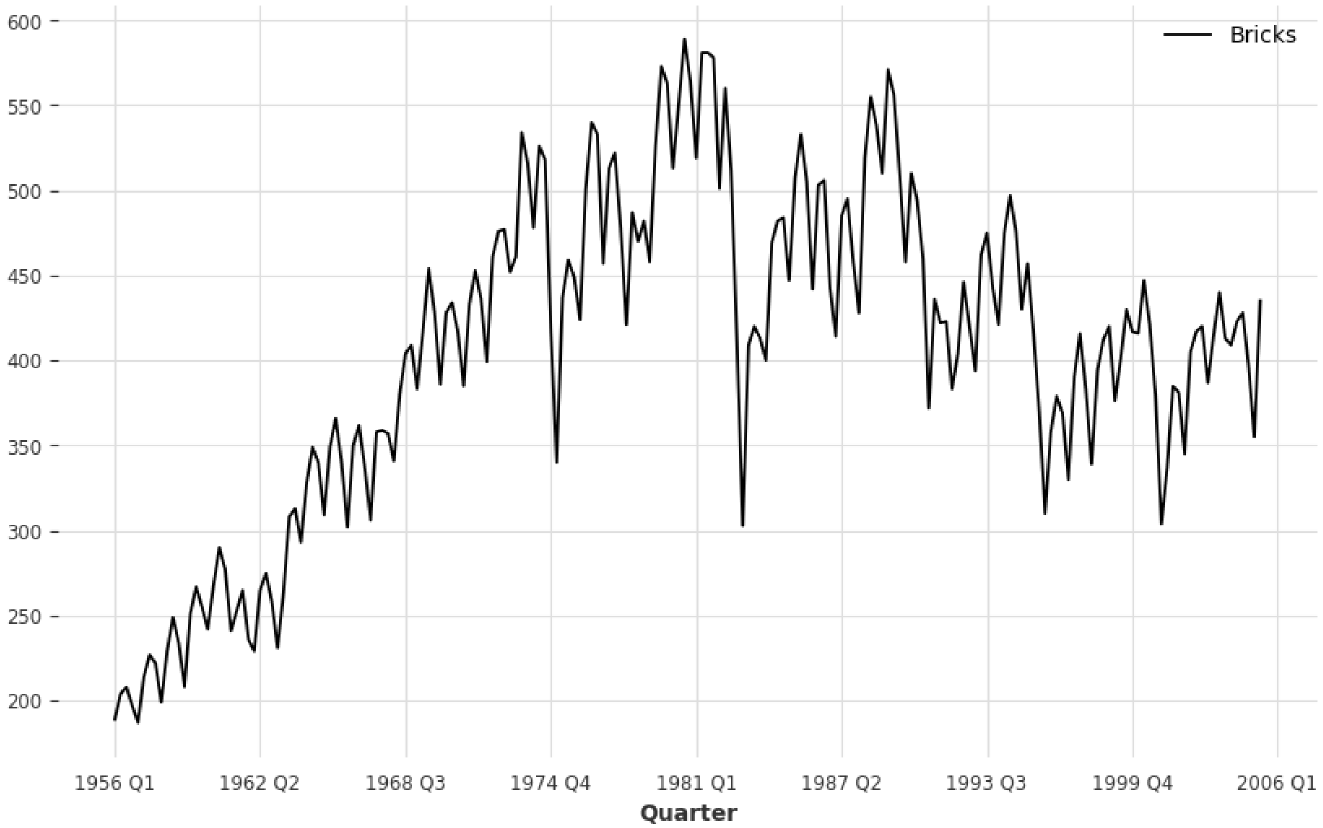


From the eye test, we observe that the Drift forecast is in-line with the data. It reasonable to agree with the forecast since the timeseries demonstrates an linear growth in population.

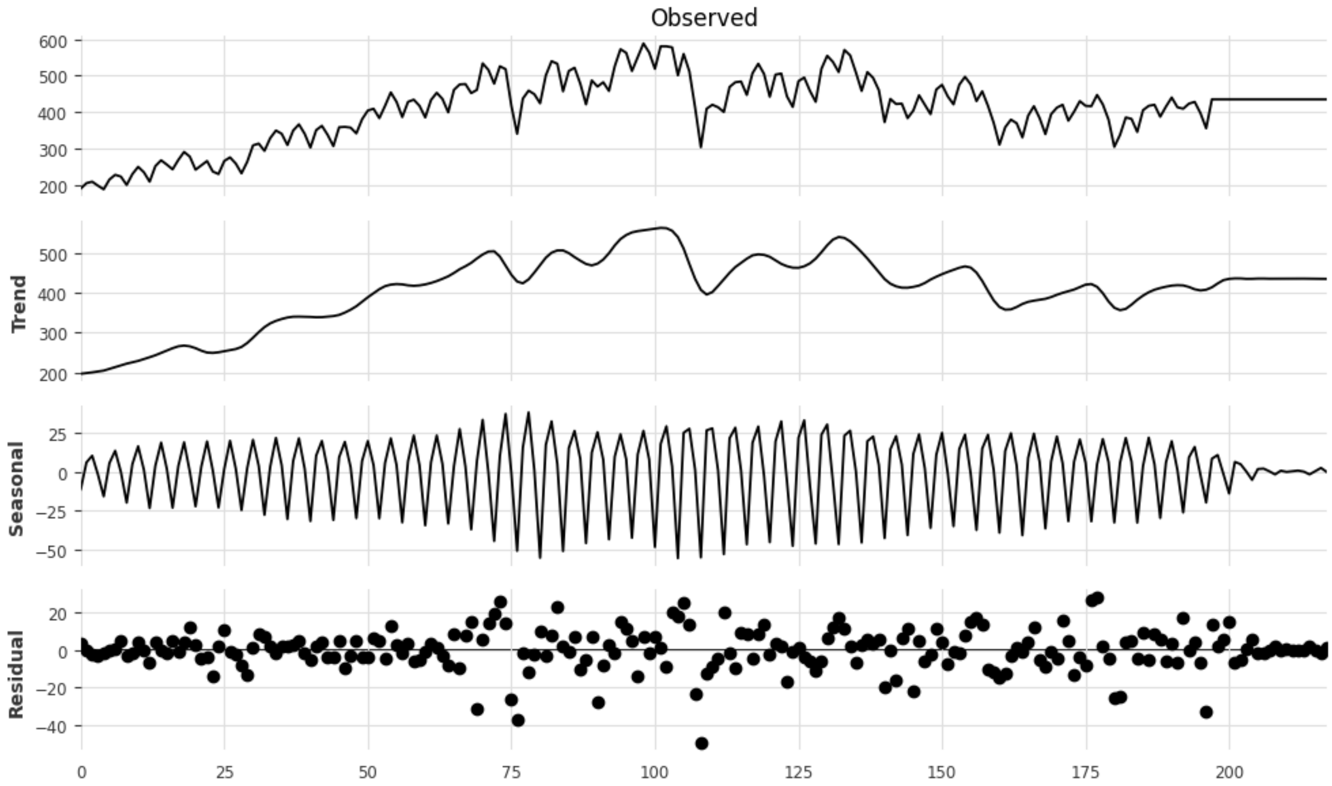
Bricks from `aus_production`

```
df_bricks = df_production[['Quarter', 'Bricks']]
```

```
df_bricks.set_index('Quarter').plot()
```



```
bricks_plot = df_bricks.set_index('Quarter')
bricks_plot['Bricks'] = bricks_plot['Bricks'].ffill()

decom = STL(bricks_plot['Bricks'].values, period = 4).fit()
decom.plot()
plt.show()
```

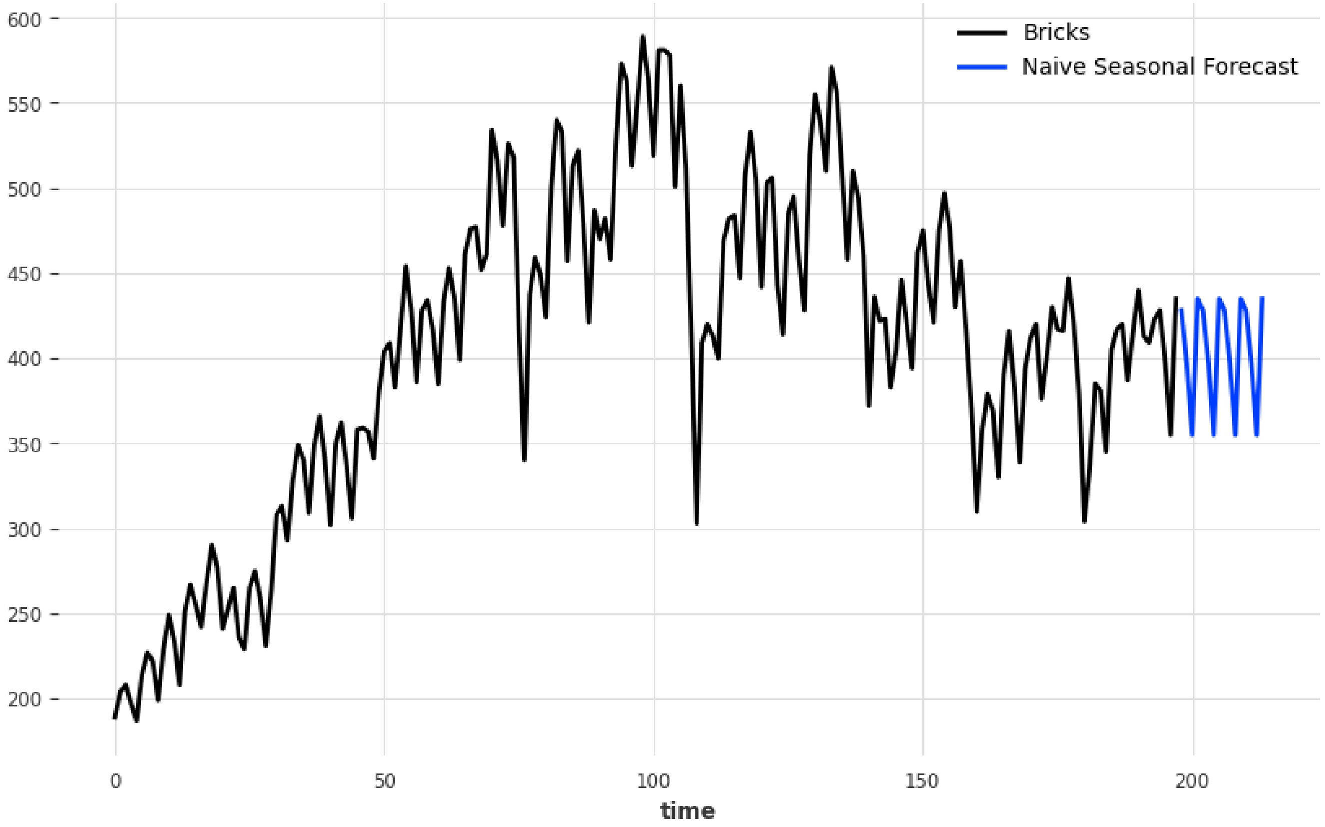


We see a high frequency of the seasonality component while it is unclear whether the trend line is increasing or decreasing. Thus, we believe that using the seasonal naive would be best for forecasting this particular time series.

```
df_bricks = df_bricks.dropna() # missing a data at the tail()

# format datetime to accomodate the input for darts library
df_bricks['Quarter'] = pd.to_datetime(df_bricks['Quarter'].astype(str), format='%Y Q%m')

df_bricks.set_index('Quarter')
```

	Bricks
Quarter	
1956-01-01	189.0
1956-02-01	204.0
1956-03-01	208.0
1956-04-01	197.0
1957-01-01	187.0
...	...
2004-02-01	423.0
2004-03-01	428.0
2004-04-01	397.0
2005-01-01	355.0
2005-02-01	435.0

```
# remove time col since it is set as the index
series = TimeSeries.from_dataframe(df_bricks, value_cols='Bricks',
  fill_missing_dates=True)

seasonal = NaiveSeasonal(K=4) # K=4 for quarterly data

seasonal.fit(series)

forecast = seasonal.predict(16)

series.plot()
forecast.plot(label='Naive Seasonal Forecast')
plt.legend()
```



NSW Lambs from aus_livestock

```
display(df_livestock.State.unique())
display(df_livestock.Animal.unique())
```

```
array(['Australian Capital Territory', 'New South Wales',
       'Northern Territory', 'Queensland', 'South Australia', 'Tasmania',
       'Victoria', 'Western Australia'], dtype=object)
```

```
array(['Bulls, bullocks and steers', 'Calves', 'Cattle (excl. calves)',
       'Cows and heifers', 'Lambs', 'Pigs', 'Sheep'], dtype=object)
```

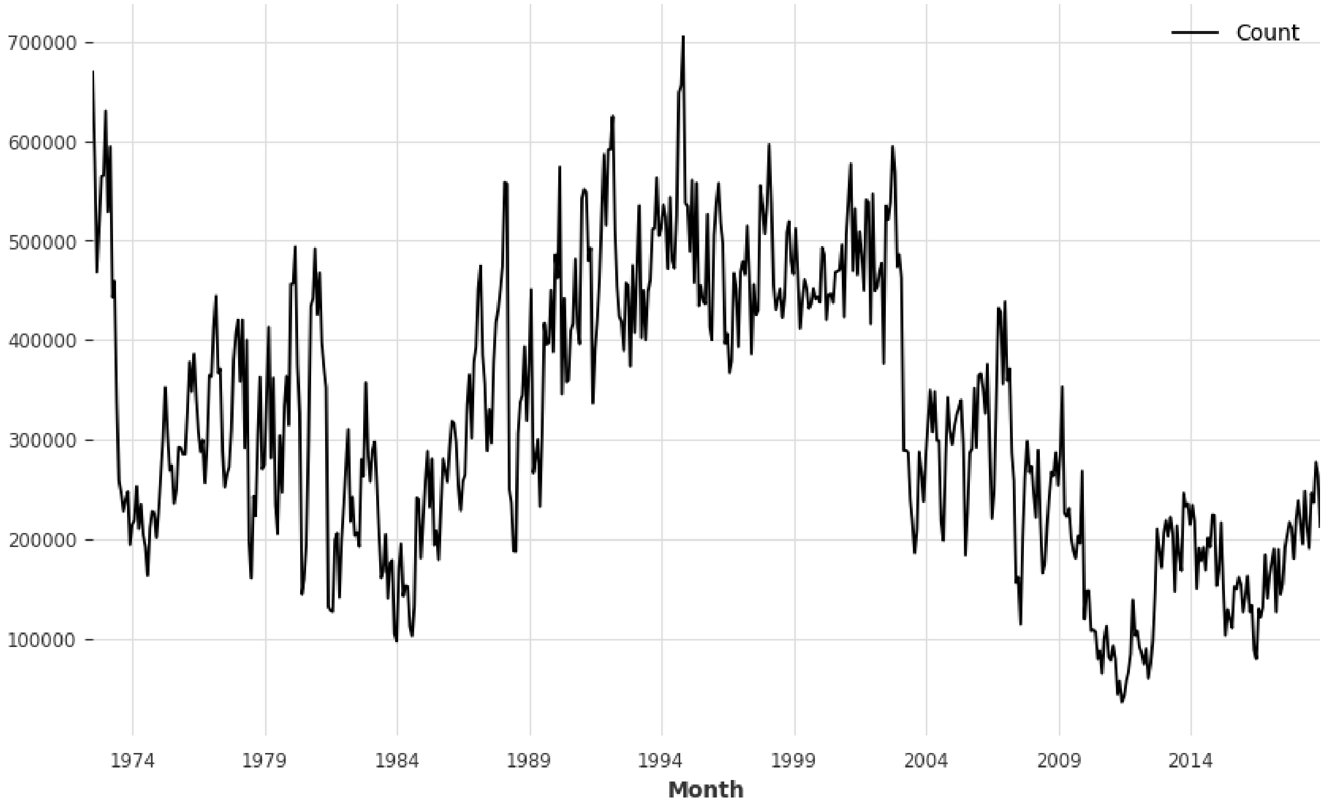
Assuming NSW means New South Wales. So, we need to filter `df_livestock` of sheep from New South Wales.

```
df_sheep = df_livestock.query('Animal == "Sheep" & State == "New South Wales"')
df_sheep
```

	Unnamed: 0	Month	Animal	State	Count
25458	25459	1972-07-01	Sheep	New South Wales	669400.0
25459	25460	1972-08-01	Sheep	New South Wales	581100.0
25460	25461	1972-09-01	Sheep	New South Wales	468100.0
25461	25462	1972-10-01	Sheep	New South Wales	515300.0
25462	25463	1972-11-01	Sheep	New South Wales	564500.0
...	...	...	...	...	...
26011	26012	2018-08-01	Sheep	New South Wales	245900.0
26012	26013	2018-09-01	Sheep	New South Wales	236800.0
26013	26014	2018-10-01	Sheep	New South Wales	277200.0
26014	26015	2018-11-01	Sheep	New South Wales	263600.0
26015	26016	2018-12-01	Sheep	New South Wales	212300.0

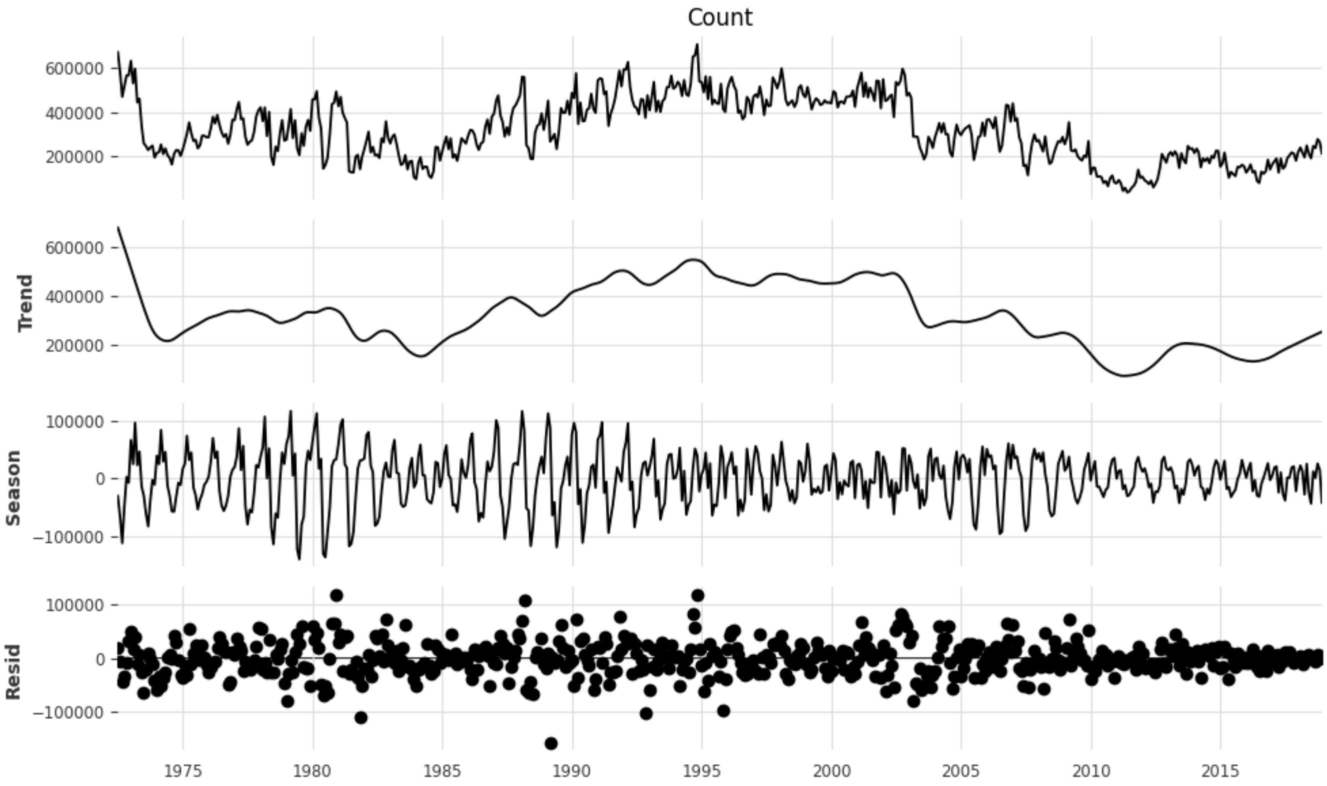
Next, we want to see the timeseries.

```
df_sheep[['Month', 'Count']].set_index(['Month']).plot()
```



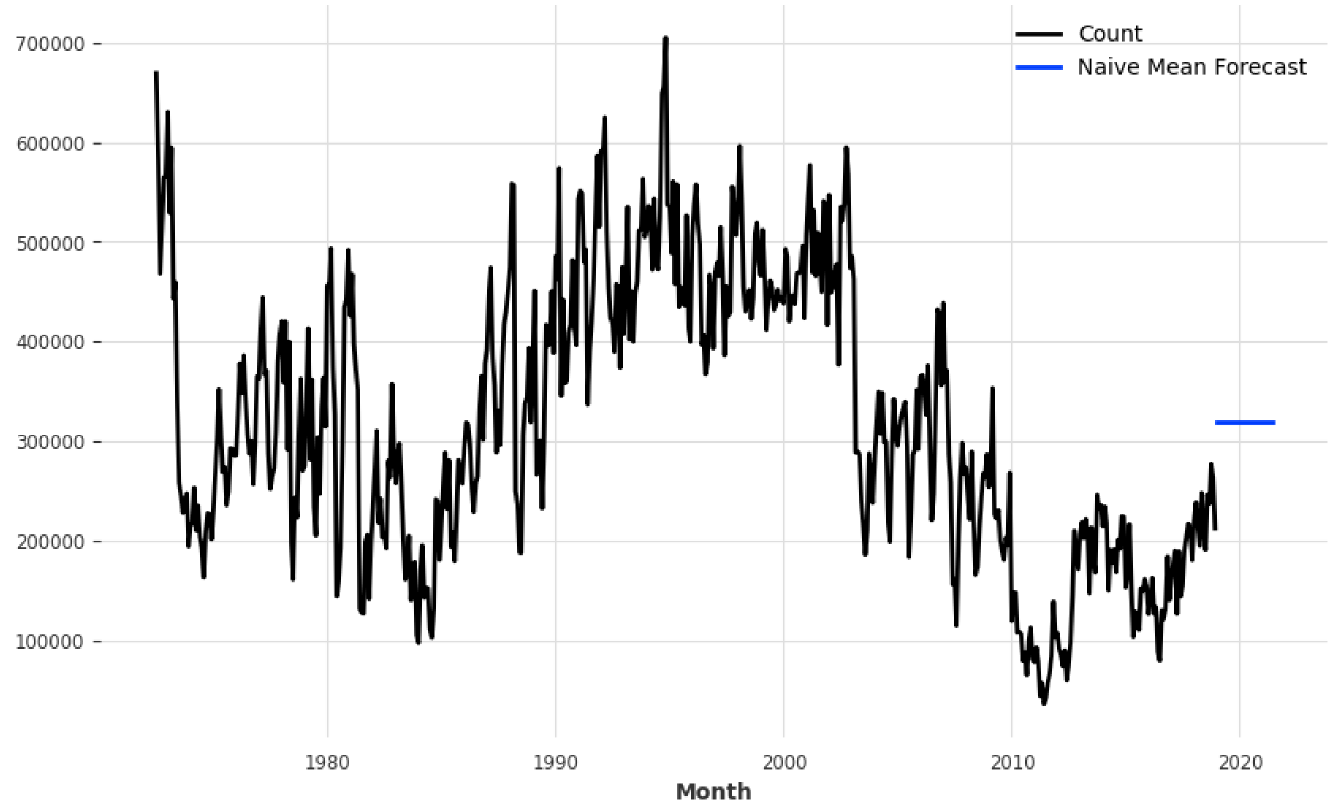
```
sheep = df_sheep.set_index('Month')
decomposition = STL(sheep['Count']).fit()
decomposition.plot()
```

```
plt.show()
```



We see that this time seres has no clear trend and inconsistent seasonality component which suggest that we use the Mean Naive method.

```
series = TimeSeries.from_dataframe(df_sheep, 'Month', 'Count')

model = NaiveMean()
model.fit(series)
forecast = model.predict(30) # 30 timesteps in the future in this case 30 months

series.plot()
forecast.plot(label = 'Naive Mean Forecast')
plt.legend()
```



Household Wealth from `hh_budget`

Let us see which columns and constrains we need to filter. We will need the `Year`, `Country` and `Wealth` columns.

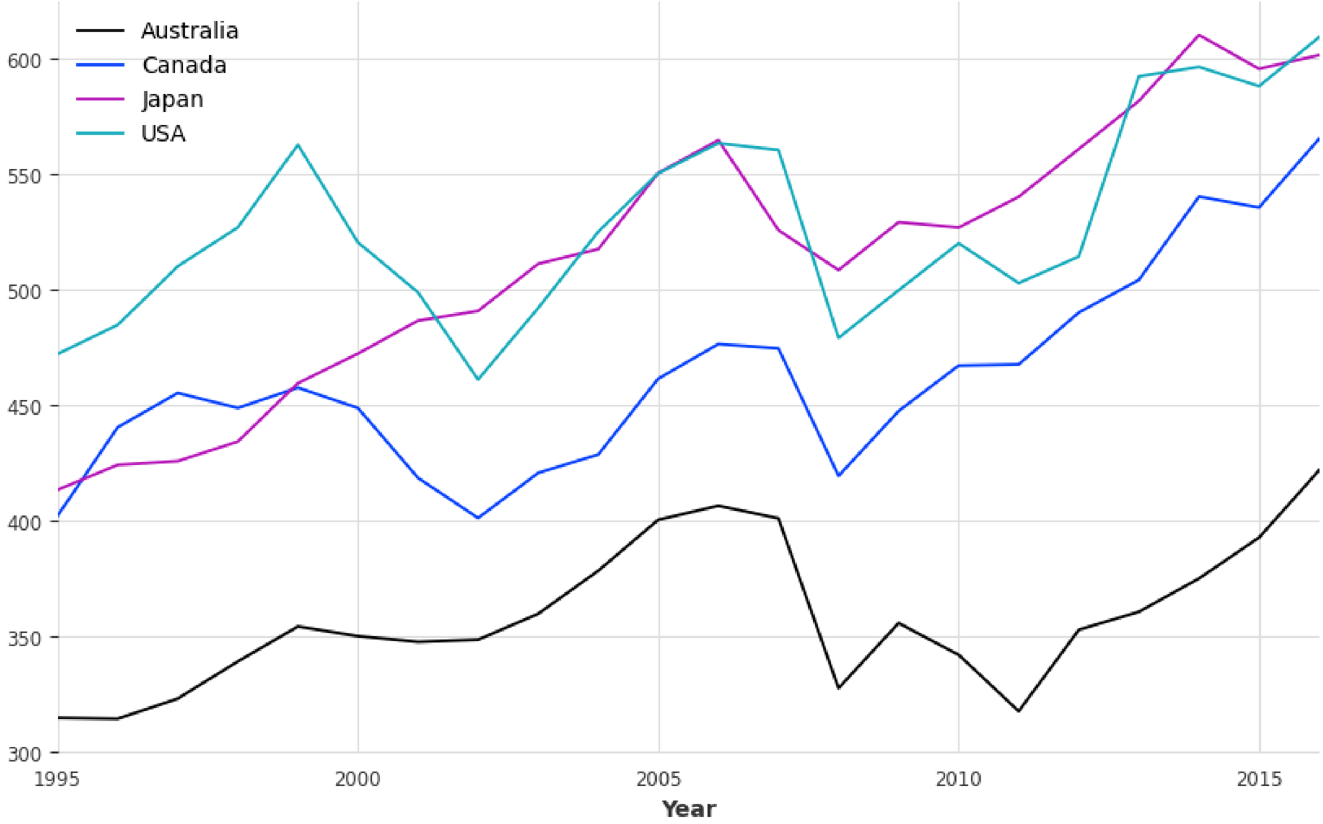
```
df_wealth = df_budget[['Year', 'Country', 'Wealth']]
df_wealth
```

	Year	Country	Wealth
0	1995-01-01	Australia	314.9344
1	1996-01-01	Australia	314.5559
2	1997-01-01	Australia	323.2357
3	1998-01-01	Australia	339.3139
4	1999-01-01	Australia	354.4382
…	…	…	…
83	2012-01-01	USA	514.4276
84	2013-01-01	USA	592.3568
85	2014-01-01	USA	596.4713
86	2015-01-01	USA	588.1454
87	2016-01-01	USA	609.2657

So, we have annual data for wealth of four different countries. Based on the prior exercise, we can assume that we want the Australian data.

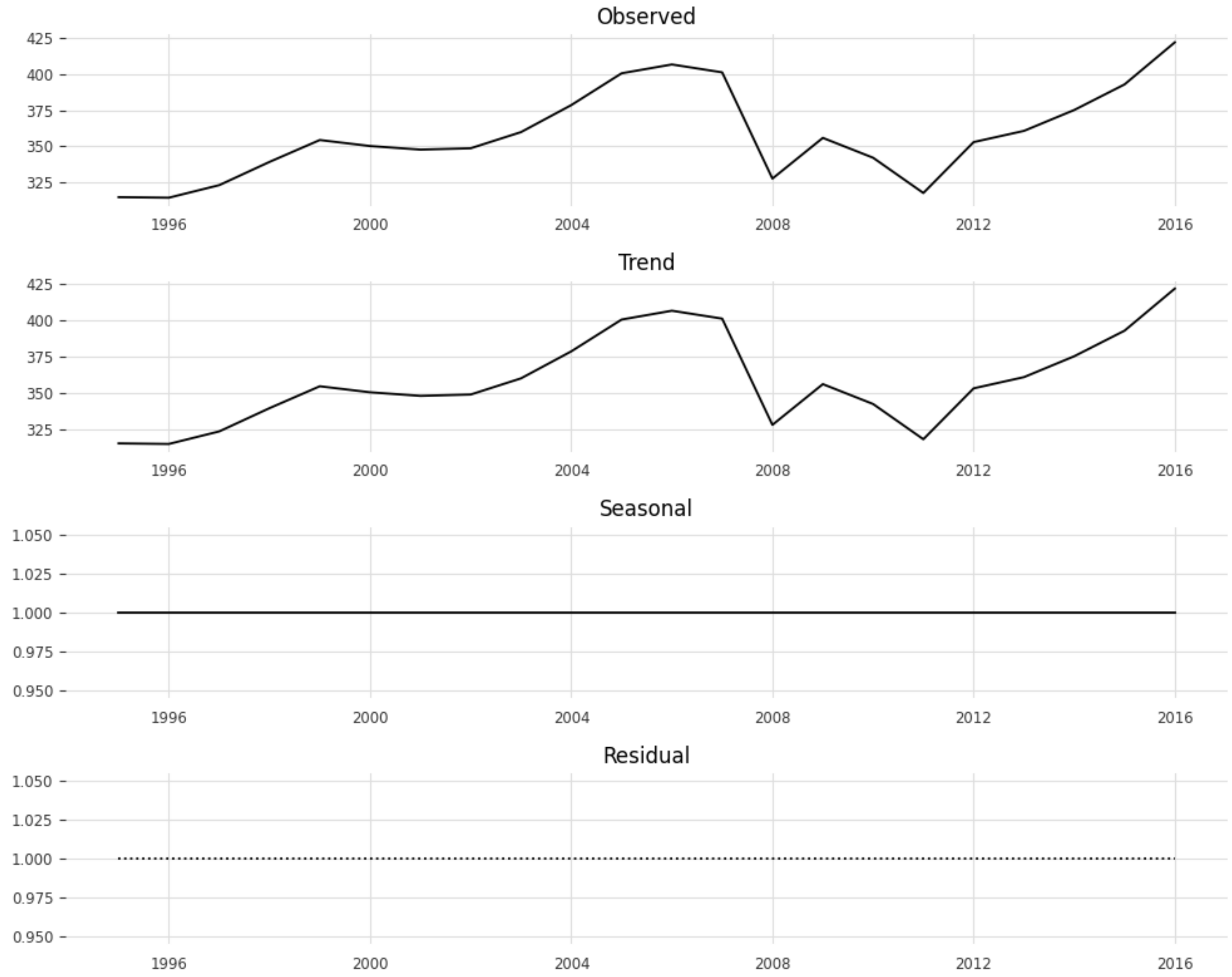
```
wealth = df_wealth
wealth = wealth.set_index(['Year'])
```

```
wealth.groupby('Country')['Wealth'].plot()
plt.legend()
```



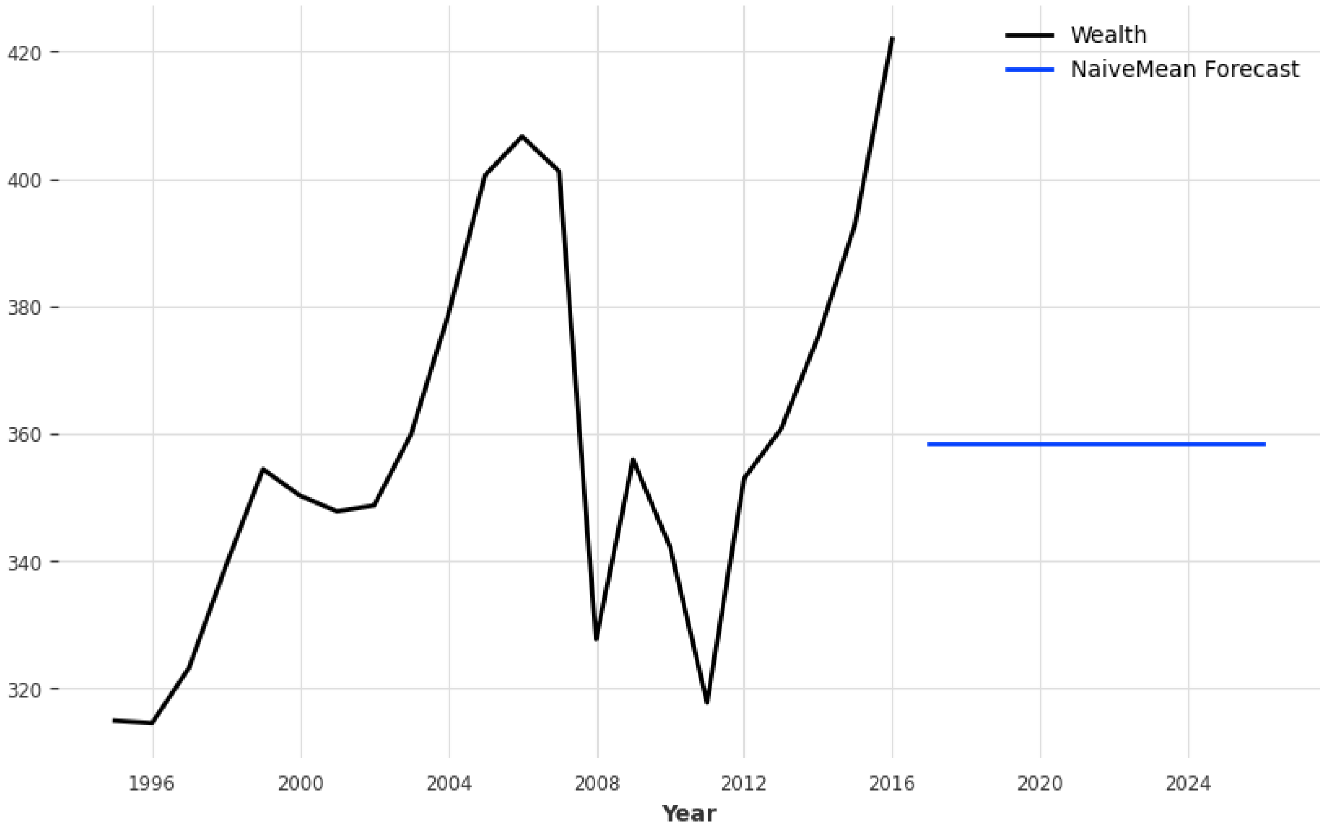
```
aus_wealth = wealth.query('Country == "Australia"')
```

```
decomposition=seasonal_decompose(aus_wealth.Wealth, period=1,model="multiplicative")

fig, (ax1, ax2, ax3, ax4) = plt.subplots(4, 1, figsize=(10, 8))

ax1.plot(decomposition.observed)
ax1.set_title('Observed')

ax2.plot(decomposition.trend)
ax2.set_title('Trend')

ax3.plot(decomposition.seasonal)
ax3.set_title('Seasonal')

ax4.plot(decomposition.resid, linestyle = "dotted", markersize = 10)
ax4.set_title('Residual')

plt.tight_layout()
plt.show()
```



From the decomposition, it clear that there is minimal seasonality and the trend line is unclear without further analysis. Thus, we believe using Naive Mean forecast would be the best for this time series.

```
series = TimeSeries.from_dataframe(aus_wealth, value_cols='Wealth')

model = NaiveMean()

model.fit(series)

forecast = model.predict(10)

series.plot()
forecast.plot(label='NaiveMean Forecast')
plt.legend()
```

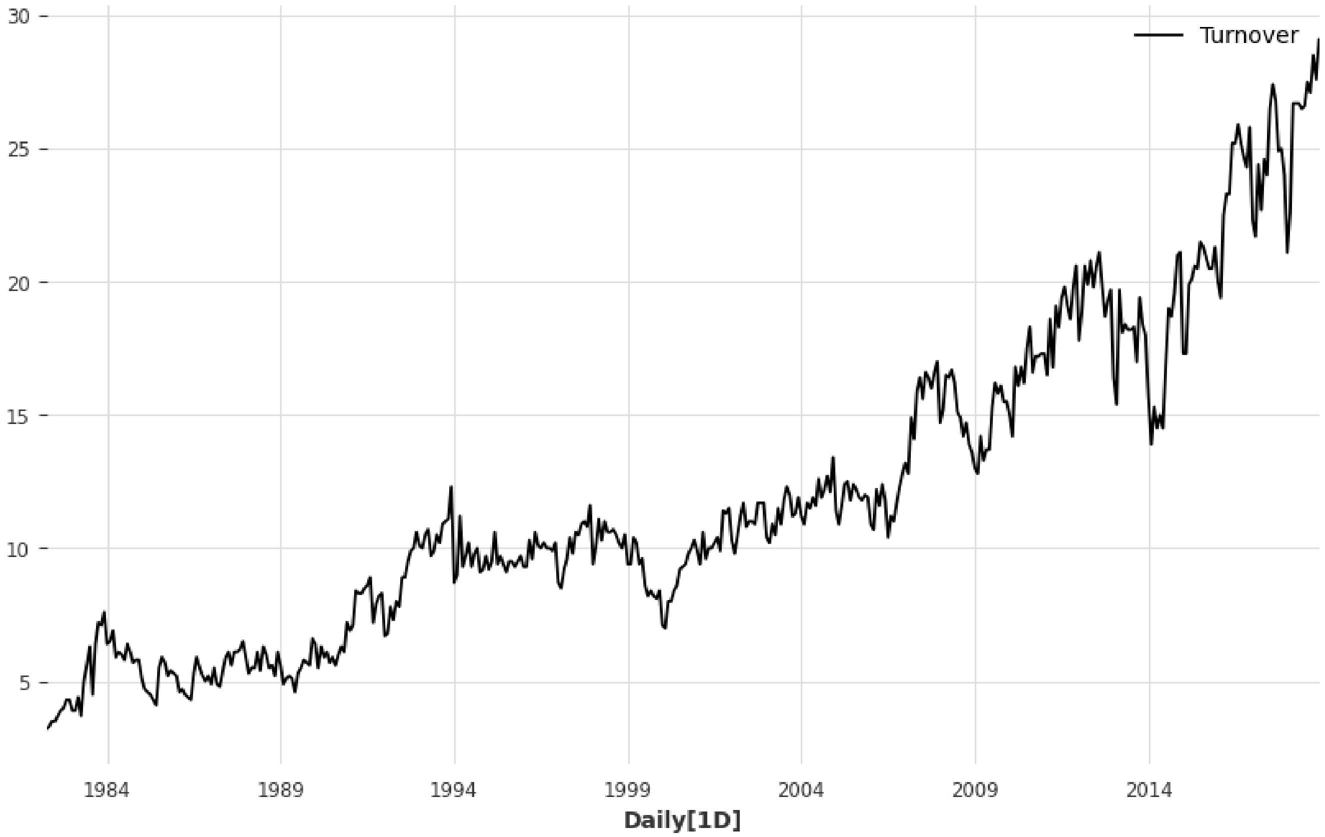


Australian takeaway food turnover from `aus_retail`

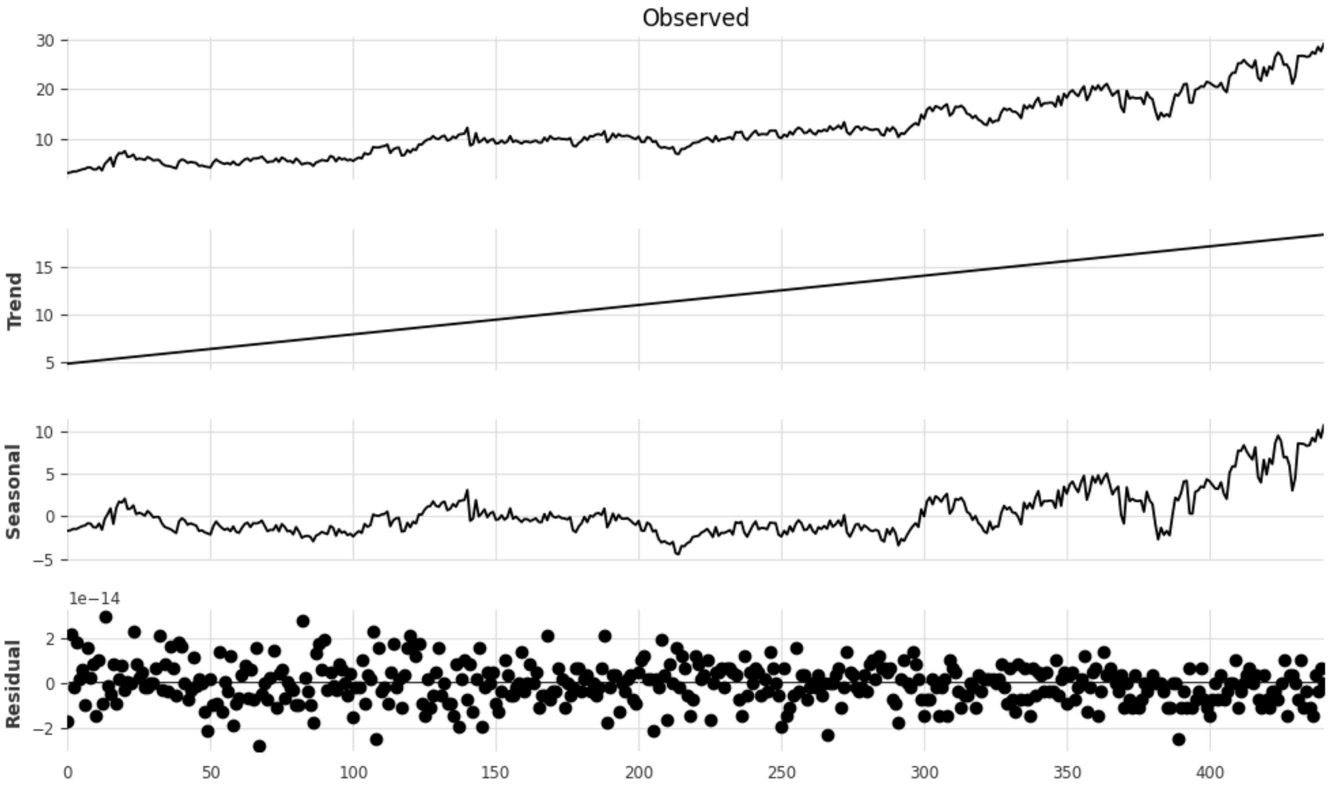
We are going to filter take away food services in the Australian Capital Territory because we tried plotting all of the territories in one plot which leds to a overcrowded plot. Therefore, we will focus on the Australian Capital Regions.

```
df_takeaway = df_retail.query('Industry == "Takeaway food services" & State ==
  "Australian Capital Territory"')
df_takeaway = df_takeaway[['Month', 'Turnover']]
df_takeaway.set_index('Month', inplace=True)
```

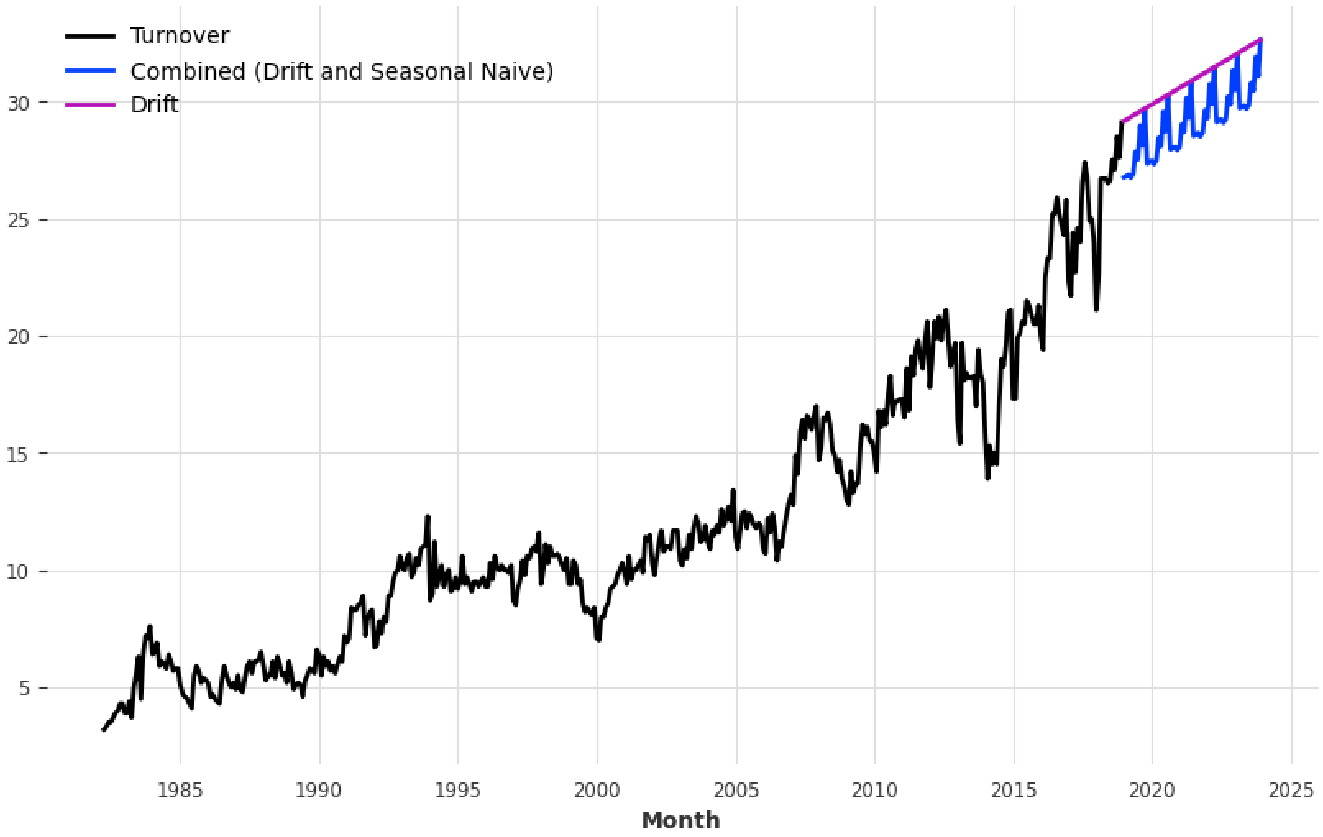
```
df_takeaway.plot()
plt.xlabel("Daily[1D]")
plt.show()
```



```
decomp = STL(df_takeaway['Turnover'].values, period=365).fit()
decomp.plot()
plt.show()
```



```
series = TimeSeries.from_dataframe(df_takeaway)

season_model = NaiveSeasonal(K=10) # captures the pattern for 14 days (bi-weekly
  pattern)
drift_model = NaiveDrift()

season_model.fit(series)
drift_model.fit(series)

seasonal_forecast = season_model.predict(60)
drift_forecast = drift_model.predict(60)

combined_forecast = seasonal_forecast + drift_forecast - series.last_value()

series.plot()
combined_forecast.plot(label='Combined (Drift and Seasonal Naive)')
drift_forecast.plot(label='Drift')
plt.legend()
plt.show()
```



After decomposing the timeseries and observing that its overall trend is increasing, we wanted to imploy a combination of the simple forecasting methods. There is some seasonality but it was unclear the whether the pattern was weeky or monthly. So, we decide to use bi-weekly to forcast this timeseries.

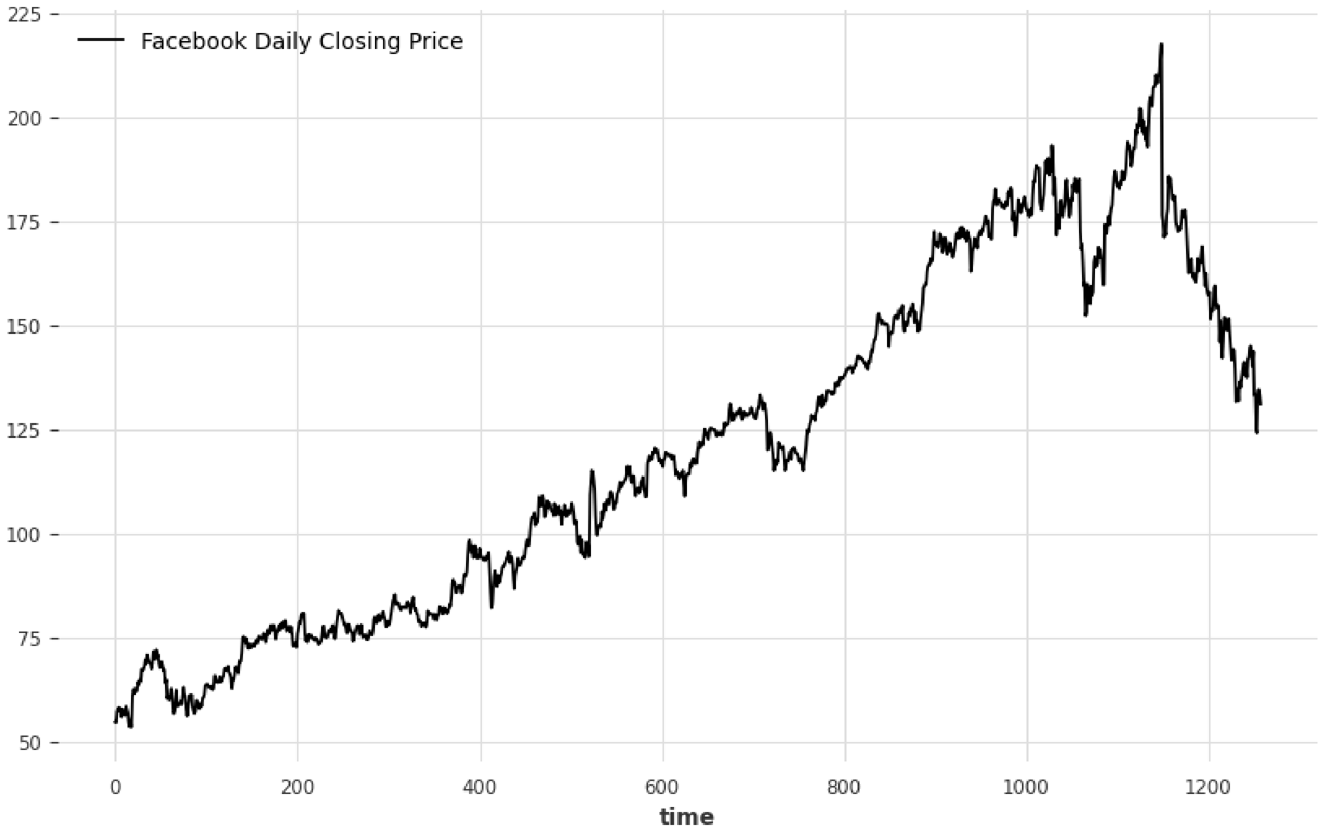
Exercise 2

Use the Facebook stock price (data set gafa_stock) to do the following:

```
df_gafa_stock = pd.read_csv("../rdata/gafa_stock.csv", parse_dates = ['Date'], index_col
  = ['Date'])

fb_stock = df_gafa_stock.query('Symbol == "FB"')

fb_stock_close = fb_stock['Close']

fb_stock_close = fb_stock_close.rename_axis('Date').reset_index()
```

- Produce a time plot of the series.

```
fb_stock_close['Close'].plot(label='Facebook Daily Closing Price')
plt.legend()
plt.show()
```

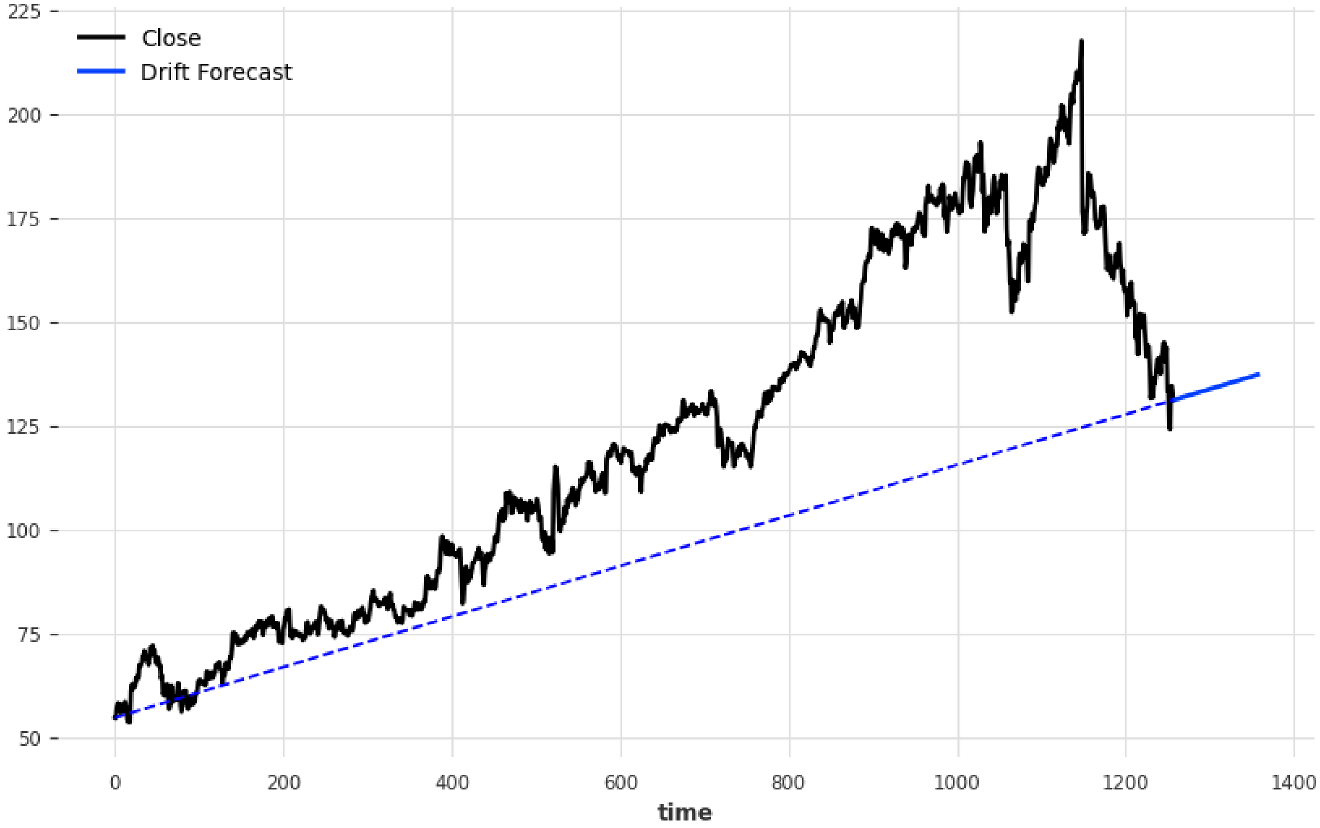


- Produce forecasts using the drift method and plot them.
- Show that the forecasts are identical to extending the line drawn between the first and last observations.

For the next two bullet points, we will create a drift forecast of the fb closing price data and then draw a dash line between the first and last values to determine whether the drift forecast is identical to the dash line.

```
series = TimeSeries.from_dataframe(fb_stock_close, value_cols='Close')

drift = NaiveDrift()
drift.fit(series)

forecast = drift.predict(100) # predict the next 100 days since it is daily data

series.plot()
forecast.plot(label='Drift Forecast')

first_value = series.first_value()
last_value = series.last_value()

# superimpose dash line on plot
plt.plot([series.time_index[0], series.time_index[-1]], [first_value, last_value], '--',
  color = 'blue')
```

```
plt.legend()
plt.show()
```

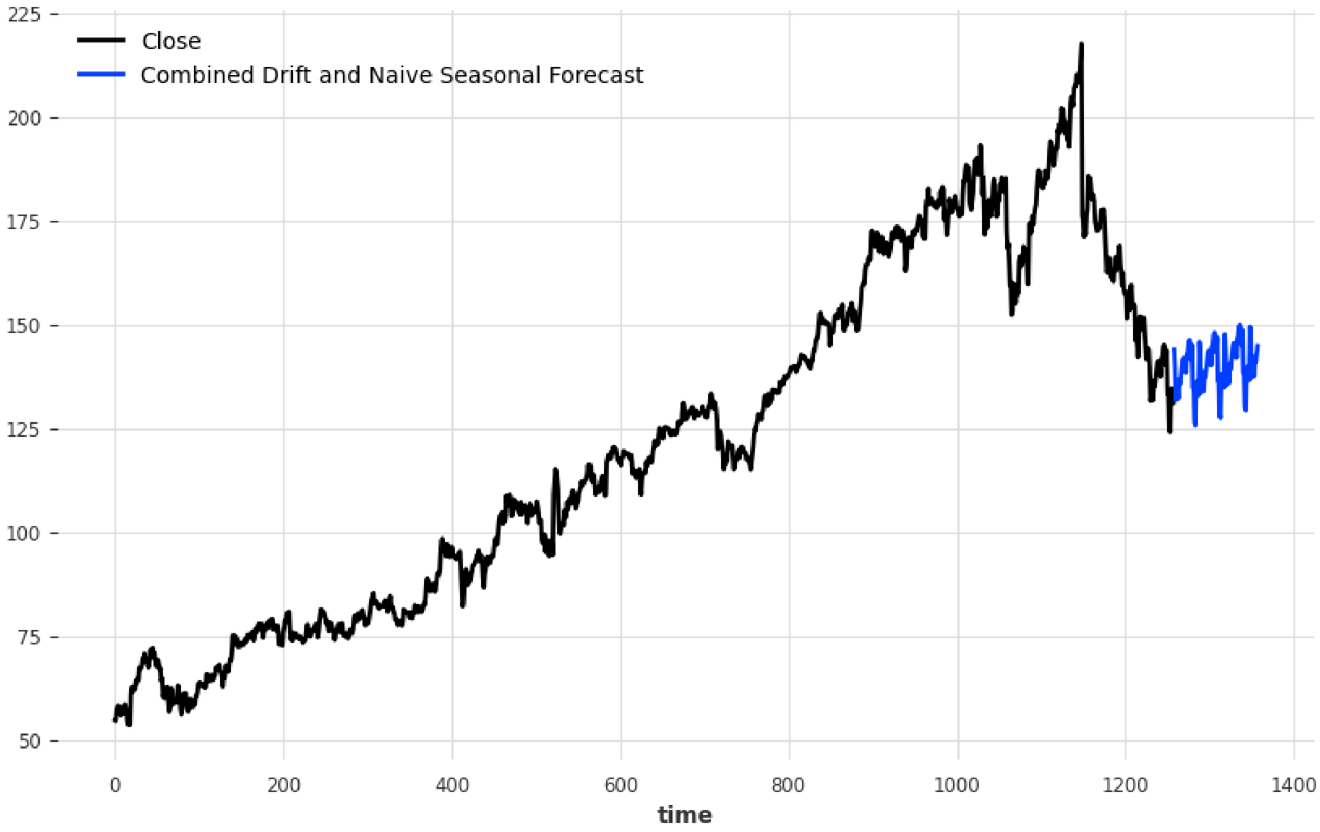


The drift forecast is identical to the superimposed dashed line on the plot.

- Try using some of the other benchmark functions to forecast the same data set. Which do you think is best? Why?

We can observe that the drift method does not capture the seasonal component of the data. So, we propose that a combination of NaiveSeaonal and the drift method might be a better bencamrk function to forecast.

```
seasonal = NaiveSeasonal(K=30)
seasonal.fit(series)
seasonal_forecast = seasonal.predict(100)
combination = seasonal_forecast + forecast - series.last_value()

series.plot()
combination.plot(label="Combined Drift and Naive Seasonal Forecast")
plt.legend()
plt.show()
```



Exercise 3

Apply a seasonal naïve method to the quarterly Australian beer production data from 1992. Check if the residuals look like white noise, and plot the forecasts. The following code will help.

```
# Extract data of interest
recent_production <- aus_production |>
  filter(year(Quarter) >= 1992)

# Define and estimate a model
fit <- recent_production |> model(SNAIVE(Beer))
#Look at the residuals

fit |> gg_tsresiduals()

# Look a some forecasts
fit |> forecast() |> autoplot(recent_production)
```

What do you conclude?

```
aus_beer = df_production[['Quarter', 'Beer']]
aus_beer = aus_beer.query('Quarter >= "1992 Q1"')
```

```

aus_beer['Quarter'] = pd.to_datetime(aus_beer['Quarter'].astype(str), format = "%Y Q%m")
aus_beer
```

	Quarter	Beer
144	1992-01-01	443
145	1992-02-01	410
146	1992-03-01	420
147	1992-04-01	532
148	1993-01-01	433
...	...	...
213	2009-02-01	398
214	2009-03-01	419
215	2009-04-01	488
216	2010-01-01	414
217	2010-02-01	374

```python
aus_beer.set_index('Quarter', inplace=True)
```

```
KeyError: "None of ['Quarter'] are in the columns"
```

```python

aus_beer
```

	Beer
Quarter	
1992Q1	443
1992Q1	410
1992Q1	420
1992Q2	532
1993Q1	433
...	...
2009Q1	398
2009Q1	419
2009Q2	488
2010Q1	414
2010Q1	374

```python
aus_beer.reset_index(inplace=True)
series = TimeSeries.from_dataframe(aus_beer, 'Quarter', 'Beer')

model = NaiveSeasonal(K=4)

model.fit(series)

forecast = model.predict(4)

series.plot()
forecast.plot(label='Naive Seasonal Forecast')
plt.legend()
plt.show()
```

```
TypeError: Cannot interpret 'period[Q-DEC]' as a data type
```

Exercise 4

Repeat the previous exercise using the Australian Exports series from global_economy and the Bricks series from aus_production. Use whichever of NAIVE() or SNAIVE() is more appropriate in each case

Exercise 7

For your retail time series (from Exercise 7 in Section 2.10):

a. Create a training dataset consisting of observations before 2011 using

```r
myseries_train <- myseries |>
  filter(year(Month) < 2011)
```

b. Check that your data have been split appropriately by producing the following plot.

```r
autoplot(myseries, Turnover) +
  autolayer(myseries_train, Turnover, colour = "red")
```

c. Fit a seasonal naïve model using SNAIVE() applied to your training data (myseries_train).

```r
fit <- myseries_train |>
  model(SNAIVE())
```

d. Check the residuals.

```r
fit |> gg_tsresiduals()
```

Do the residuals appear to be uncorrelated and normally distributed?

e.Produce forecasts for the test data

```r
fc <- fit |>
  forecast(new_data = anti_join(myseries, myseries_train))
fc |> autoplot(myseries)
```

f. Compare the accuracy of your forecasts against the actual values.

```r
fit |> accuracy()
fc |> accuracy(myseries)
```

g.How sensitive are the accuracy measures to the amount of training data used?