Homework 5

Nick Climaco

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HA Chapter 8: Exponential Smoothing

#| message : false

#| output : false

import libraries

Exercise 8.1

Consider the the number of pigs slaughtered in Victoria, available in the aus_livestock dataset.

Month	Unnamed: 0	Animal	State	Count
1976-07-01	1	Bulls, bullocks and steers	Australian Capital Territory	2300.0
1976-08-01	2	Bulls, bullocks and steers	Australian Capital Territory	2100.0
1976-09-01	3	Bulls, bullocks and steers	Australian Capital Territory	2100.0
1976-10-01	4	Bulls, bullocks and steers	Australian Capital Territory	1900.0
1976-11-01	5	Bulls, bullocks and steers	Australian Capital Territory	2100.0
...	...	...	...	...
2018-08-01	29360	Sheep	Western Australia	160600.0
2018-09-01	29361	Sheep	Western Australia	121900.0
2018-10-01	29362	Sheep	Western Australia	134000.0
2018-11-01	29363	Sheep	Western Australia	153700.0
2018-12-01	29364	Sheep	Western Australia	127300.0

Part A

Use the ETS() function to estimate the equivalent model for simple exponential smoothing. Find the optimal values of and ℓ_0, and generate forecasts for the next four months.

```
# filter data
victorian_pigs = aus_livestock.query('Animal == "Pigs" & State ==
  "Victoria"')[['Count']]
```

```
from statsmodels.tsa.holtwinters import ExponentialSmoothing

model = ExponentialSmoothing(victorian_pigs, trend = 'additive', seasonal =
  None).fit()

predictions = model.forecast(steps=4) # predict the next 4 time steps
```

```
victorian_pigs.tail()
```

Month	Count
2018-08-01	102500.0
2018-09-01	82600.0
2018-10-01	100700.0
2018-11-01	98500.0
2018-12-01	92300.0

```
print(model.summary())
```

```
                       ExponentialSmoothing Model Results
================================================================================
Dep. Variable:                      Count   No. Observations:                558
Model:               ExponentialSmoothing   SSE                  49759385612.180
```

```
Optimized:                         True   AIC                      10222.807
Trend:                         Additive   BIC                      10240.105
Seasonal:                          None   AICC                     10222.960
Seasonal Periods:                  None   Date:             Sun, 03 Mar 2024
Box-Cox:                          False   Time:                     18:57:44
Box-Cox Coeff.:                    None
==============================================================================
                       coeff                 code              optimized
------------------------------------------------------------------------------
smoothing_level            0.3350000                alpha                True
smoothing_trend            0.0279167                 beta                True
initial_level              1.0843e+05                 l.0                True
initial_trend              -1924.8485                 b.0                True
------------------------------------------------------------------------------
```

The optimal $\alpha = 0.335$ and $l_0 = 1.0843e + 05$.

Having a lower alpha estimates means that the exponential decay is slower and we can expected that the next 4 forecasts will be close in value.

The forecasts for the next 4 time steps are below.

```python
print(predictions)
```

```
2019-01-01    95532.225056
2019-02-01    95637.681211
2019-03-01    95743.137366
2019-04-01    95848.593521
Freq: MS, dtype: float64
```

Part B

Compute a 95% prediction interval for the first forecast using $\hat{y} \pm 1.96s$ where s is the standard deviation of the residuals. Compare your interval with the interval produced by R

```python
# we need to calc only the first forecast
residuals_std = model.resid.std()

first_forecast = predictions.iloc[0]

margin_of_error = 1.96 * residuals_std

lower_limit = first_forecast - margin_of_error
upper_limit = first_forecast + margin_of_error

print(f'95% Prediction Interval: ({lower_limit:.2f}, {upper_limit:.2f})')
```

```
95% Prediction Interval: (77022.62, 114041.83)
```

Rcode :

````
```{r}
fc |>
  autoplot(tail(vic_pigs, 5)) +
  geom_line(aes(y = .fitted), col="#D55E00",
            data = augment(fit)) +
  labs(y="% of GDP", title="Victorian Pigs") +
  guides(colour = "none")
````

‘‘‘
````

Figure 1: image.png

My 95% confidence intervals is narrower compared to the confidence interval produced from the Rcode. We suspect that this may due to different smoothing and leveling estimates.

Exercise 8.5

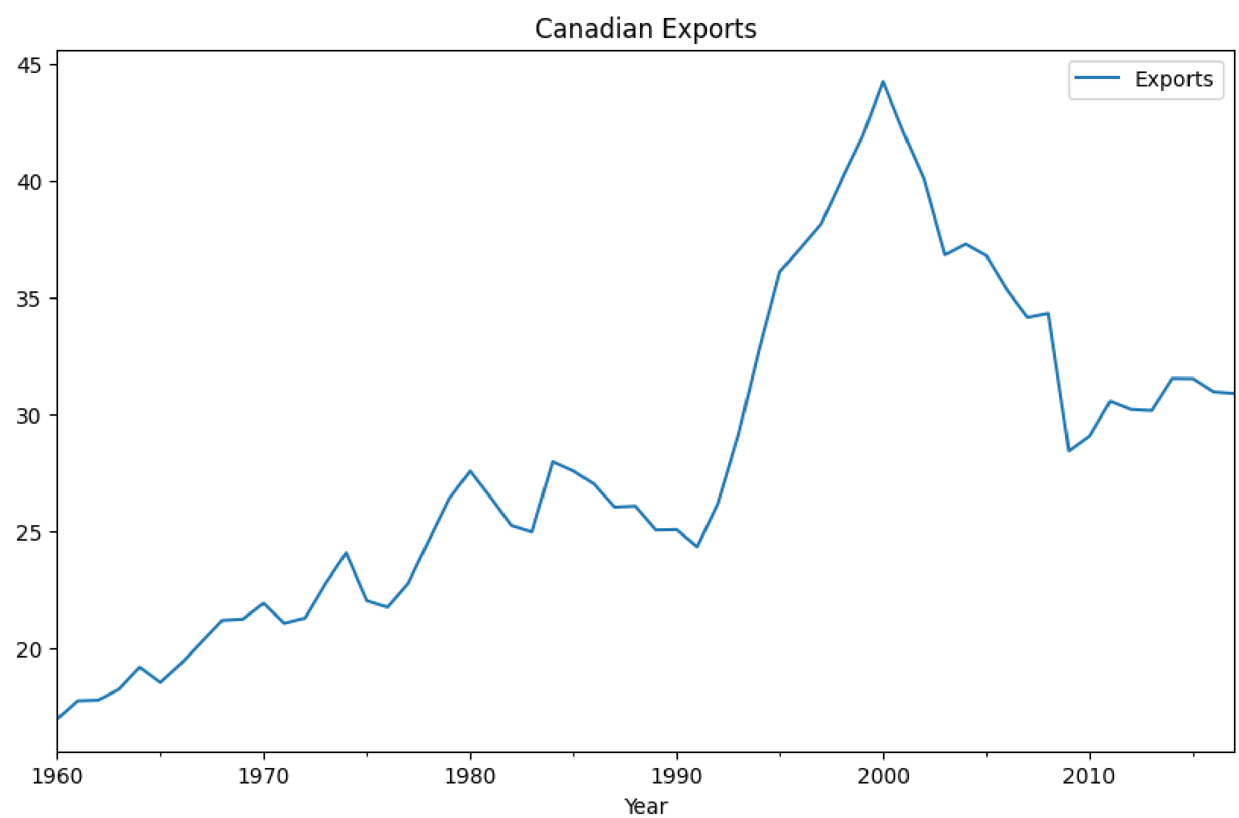
Data set `global_economy` contains the annual Exports from many countries. Select one country to analyse.

Part A

Plot the Exports series and discuss the main features of the data

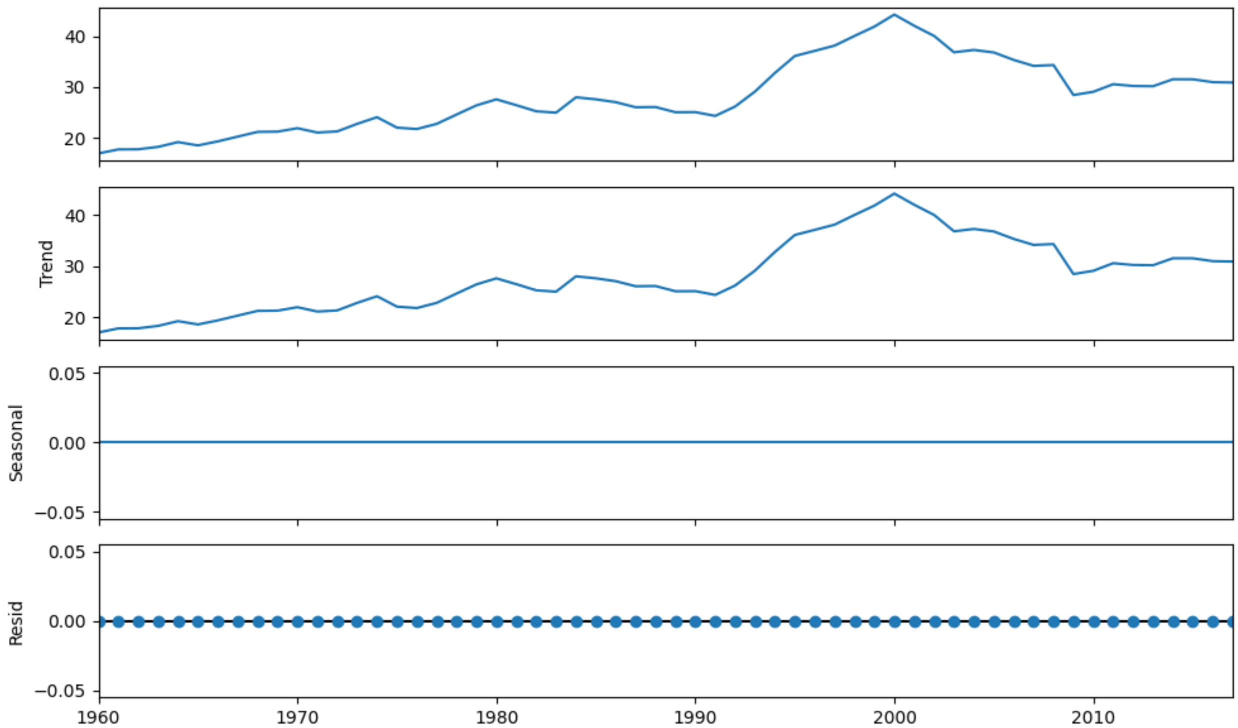
```
canada_exports = global_economy.query('Country == "Canada"')[['Exports']]
```

```
canada_exports.plot()
plt.title('Canadian Exports')
plt.show()
```




```
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(canada_exports, model='additive')
result.plot()
plt.show()
```



Canada's exports exhibits a overall upward trend from 1960 to 2017, with a notable growth during the 1990s. This trend peaked around the year 2000, followed by a decline until 2010 where it started to stabilize. The time series decomposition confirms the absence of seasonality, demosntrating a straight line seasonal component.

Part B

Use an ETS(A,N,N) model to forecast the series, and plot the forecasts.

```
# train test split
train_data, test_data = canada_exports[0:int(len(canada_exports)*0.8)],
  canada_exports[int(len(canada_exports)*0.8):]
```

```
# ETS(A,N,N) would be trend = 'add' and damped_trend = False
from statsmodels.tsa.exponential_smoothing.ets import ETSModel

ets_model = ETSModel(train_data['Exports'], trend = 'add', damped_trend = False,
  seasonal = None).fit()

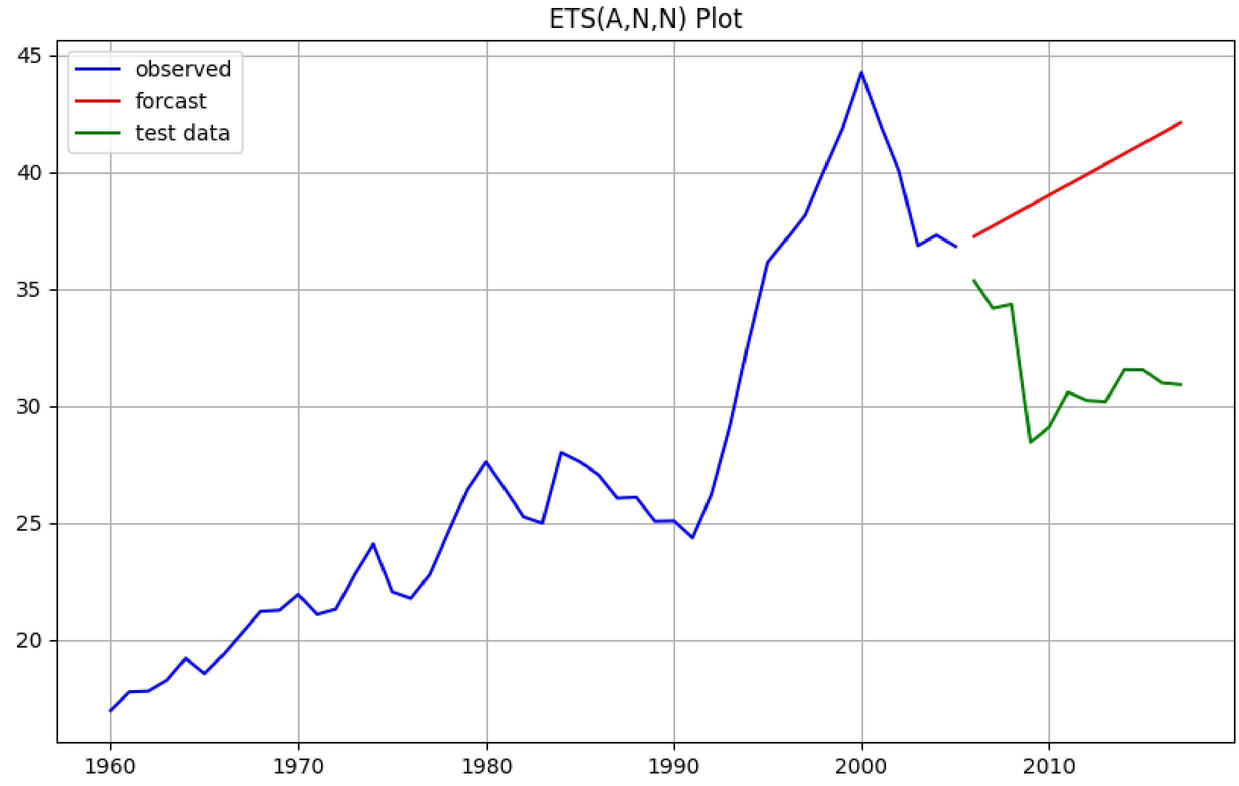
forecast = ets_model.forecast(steps=len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
plt.plot(train_data.index, train_data, color = 'blue', label='observed')
plt.plot(forecast.index, forecast, color = 'red', label='forcast')
```

```
plt.plot(test_data.index, test_data, color = 'green', label='test data')


plt.legend()
plt.title('ETS(A,N,N) Plot')
plt.grid(True)
plt.show()
```



Part C

Compute the RMSE values for the training data.

```
fitted_values = ets_model.fittedvalues
```

```
from sklearn.metrics import mean_squared_error
ann_rmse = mean_squared_error(train_data, fitted_values)

print(f'RMSE: {mean_squared_error(train_data, fitted_values)}')
```

```
RMSE: 2.1710919202650967
```

Part D

Compare the results to those from an ETS(A,A,N) model. (Remember that the trended model is using one more parameter than the simpler model.) Discuss the merits of the two forecasting methods for this data set.

```
# for this it is trend ='add' and damped_trend = True

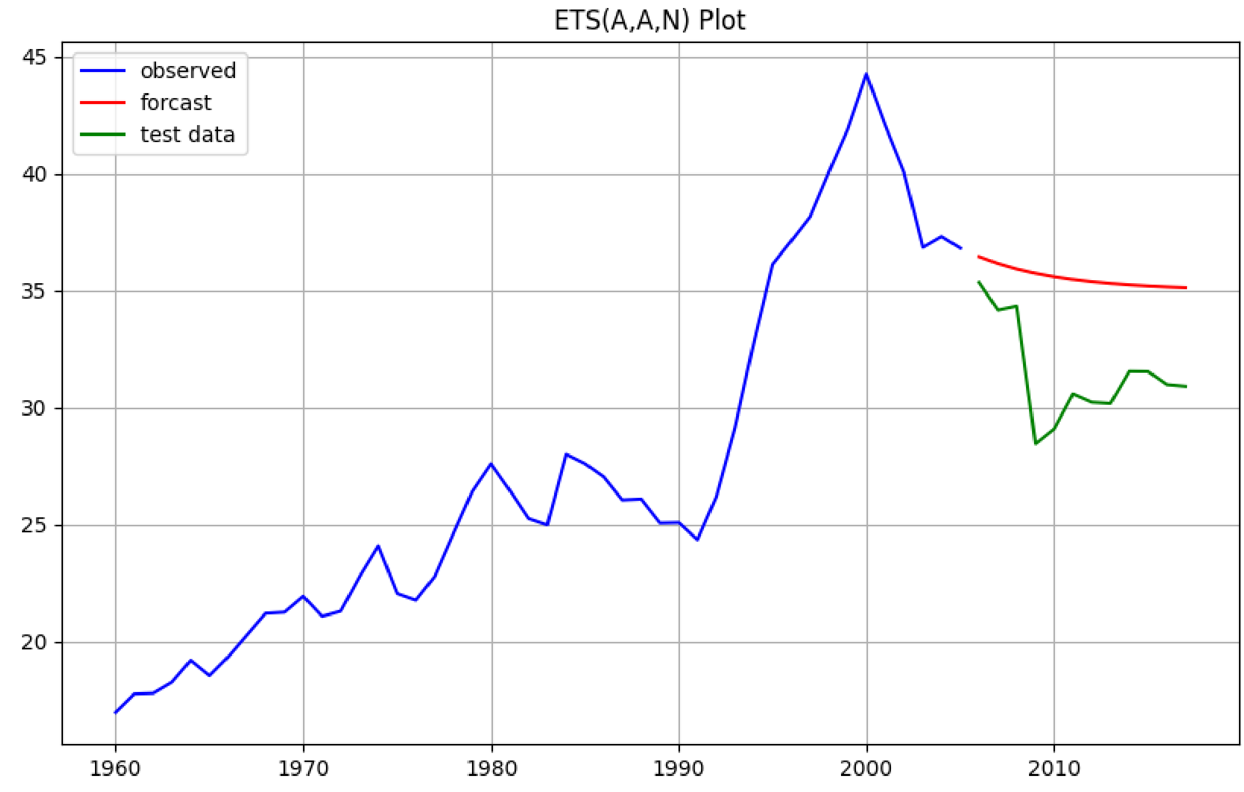
model = ETSModel(train_data['Exports'], trend = 'add', damped_trend=True,
  seasonal=None).fit()

aan_forecast = model.forecast(steps = len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
plt.plot(train_data.index, train_data, color = 'blue', label='observed')
plt.plot(aan_forecast.index, aan_forecast, color = 'red', label='forcast')
plt.plot(test_data.index, test_data, color = 'green', label='test data')

plt.legend(loc = 'upper left')
plt.title('ETS(A,A,N) Plot')
plt.grid(True)
plt.show()
```



```
fitted_values = model.fittedvalues
aan_rmse = mean_squared_error(train_data, fitted_values)
print(f'RMSE: {mean_squared_error(train_data, fitted_values)}')
```

```
RMSE: 1.9496787243825957
```

Part E

Compare the forecasts from both methods. Which do you think is best?

Based on the forecasts, we conclude that ETS(A,A,N) provides a better fit for out timeseries. Not only does its capture the observed downward trend of the test set, but this is also supported by its lower RMSE compared to the ETS(A,N,N) model's RMSE. The ETS(A,N,N) model's assumption of the constant trend leads to an incorrent forecast trajectory following the training set. highlinhting the importance of choosing a the correct model.

Part F

Calculate a 95% prediction interval for the first forecast for each model, using the RMSE values and assuming normal errors. Compare your intervals with those produced using R.

```
ann_forecast = forecast.iloc[0]
aan_forecast_val  = aan_forecast.iloc[0]

z_value = 1.96 # for 95 percent

prediction_interval = (ann_forecast - z_value * ann_rmse, ann_forecast + z_value
  * ann_rmse)
prediction_interval_2 = (aan_forecast_val - z_value * aan_rmse, aan_forecast_val
  + z_value * aan_rmse)
```

```

print('Confidence Interval of the first forecast of the ETS(A,N,N) model: ')
print(prediction_interval)
```

```
Confidence Interval of the first forecast of the ETS(A,N,N) model:
(32.980483846327374, 41.49116417376655)
```

```
print('Confidence Interval of the first forecast of the ETS(A,N,N) model: ')
print(prediction_interval_2)
```

```
Confidence Interval of the first forecast of the ETS(A,N,N) model:
(32.61034478739475, 40.25308538697453)
```

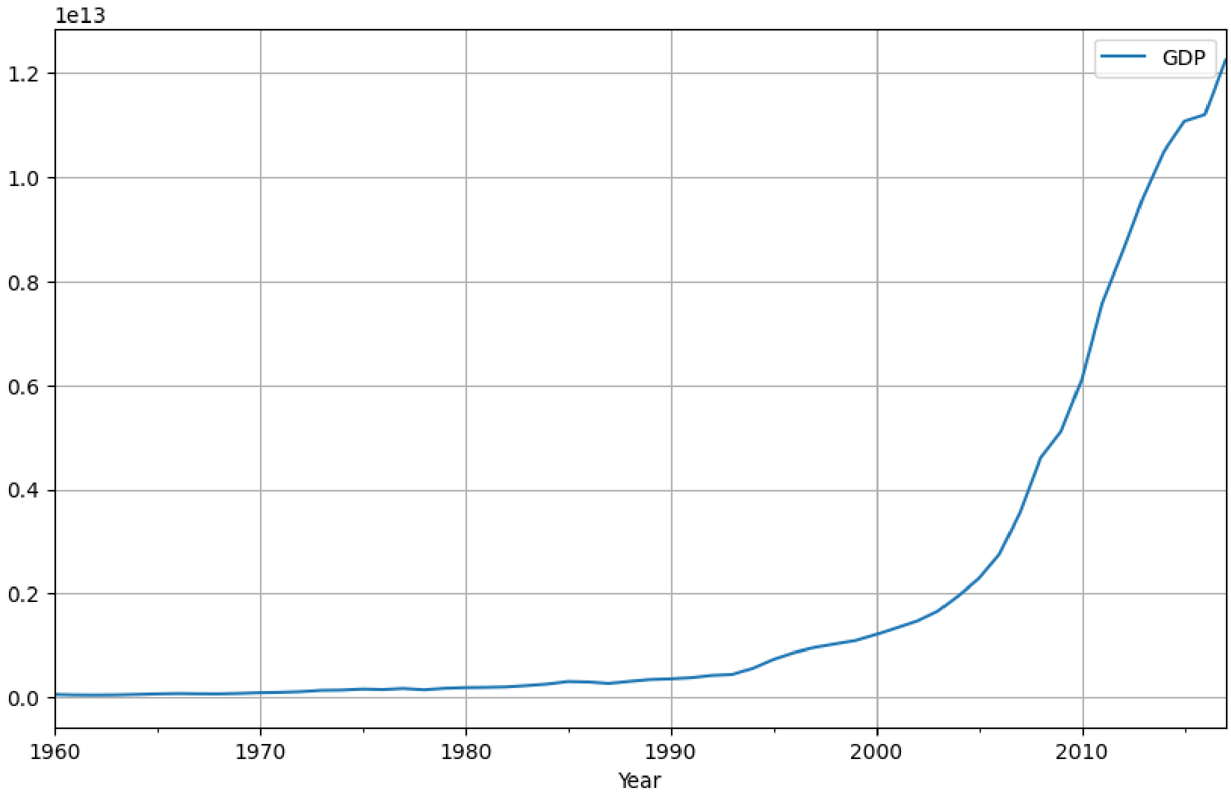
Exercise 8.6

Forecast the Chinese GDP from the `global_economy` data set using an ETS model. Experiment with the various options in the ETS() function to see how much the forecasts change with damped trend, or with a Box-Cox transformation. Try to develop an intuition of what each is doing to the forecasts.

[Hint: use a relatively large value of h when forecasting, so you can clearly see the differences between the various options when plotting the forecasts.]

```
china_gdp = global_economy.query('Country == "China"')[['GDP']]
```

```
china_gdp.plot()
plt.grid(True)
plt.show()
```




```
train_data, test_data = china_gdp[0:int(len(china_gdp)*0.8) +1],
  china_gdp[int(len(china_gdp)*0.8):]
```

```
# base model
model_1 = ETSModel(train_data['GDP'], trend='add', seasonal=None).fit()

forecast_1 = model_1.forecast(steps=len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
# with the damped trend

model_2 = ETSModel(train_data['GDP'], trend = 'add', damped_trend=True,
  seasonal=None).fit()
```

```
forecast_2 = model_2.forecast(steps = len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
# box-cox transformation
from scipy.stats import boxcox
from scipy.special import inv_boxcox1p

gdp_transformed, lmbda = boxcox(train_data['GDP']) #| type: ignore

train_data['gdp_boxcox'] = gdp_transformed

model_3 = ETSModel(train_data['gdp_boxcox'], trend = 'add', seasonal =
  None).fit()

forecast_3 = model_3.forecast(steps = len(test_data))
forecast_3 = inv_boxcox1p(forecast_3, lmbda) # undo the tranfromation
```

```
C:\Users\nickc\AppData\Local\Temp\ipykernel_28708\3408299051.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/i
  train_data['gdp_boxcox'] = gdp_transformed
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
# log transform with damped

train_data.loc[:, 'log_gdp'] = np.log(train_data['GDP']).copy()

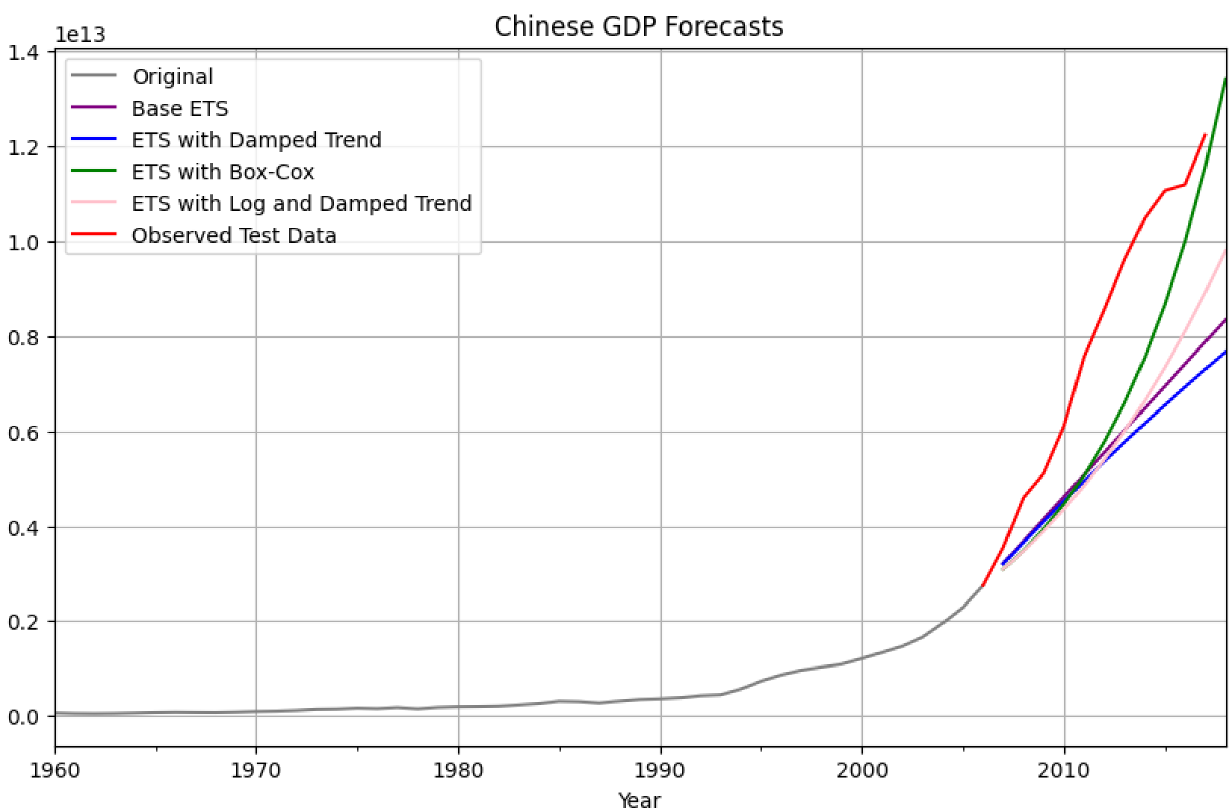
model_4 = ETSModel(train_data['log_gdp'], trend = 'add', damped_trend= True,
  seasonal = None).fit()

forecast_4 = model_4.forecast(steps= len(test_data))
forecast_4 = np.exp(forecast_4)
```

```
C:\Users\nickc\AppData\Local\Temp\ipykernel_28708\3159823729.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/i
  train_data.loc[:, 'log_gdp'] = np.log(train_data['GDP']).copy()
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```python
train_data['GDP'].plot(label='Original', color = 'grey')
forecast_1.plot(label='Base ETS', color = 'purple')
forecast_2.plot(label='ETS with Damped Trend', color ='blue')
forecast_3.plot(label='ETS with Box-Cox', color = 'green')
forecast_4.plot(label= 'ETS with Log and Damped Trend', color = 'pink')
test_data['GDP'].plot(label = 'Observed Test Data', color = 'red')
plt.legend()
plt.title('Chinese GDP Forecasts')
plt.grid(True)
plt.show()
```



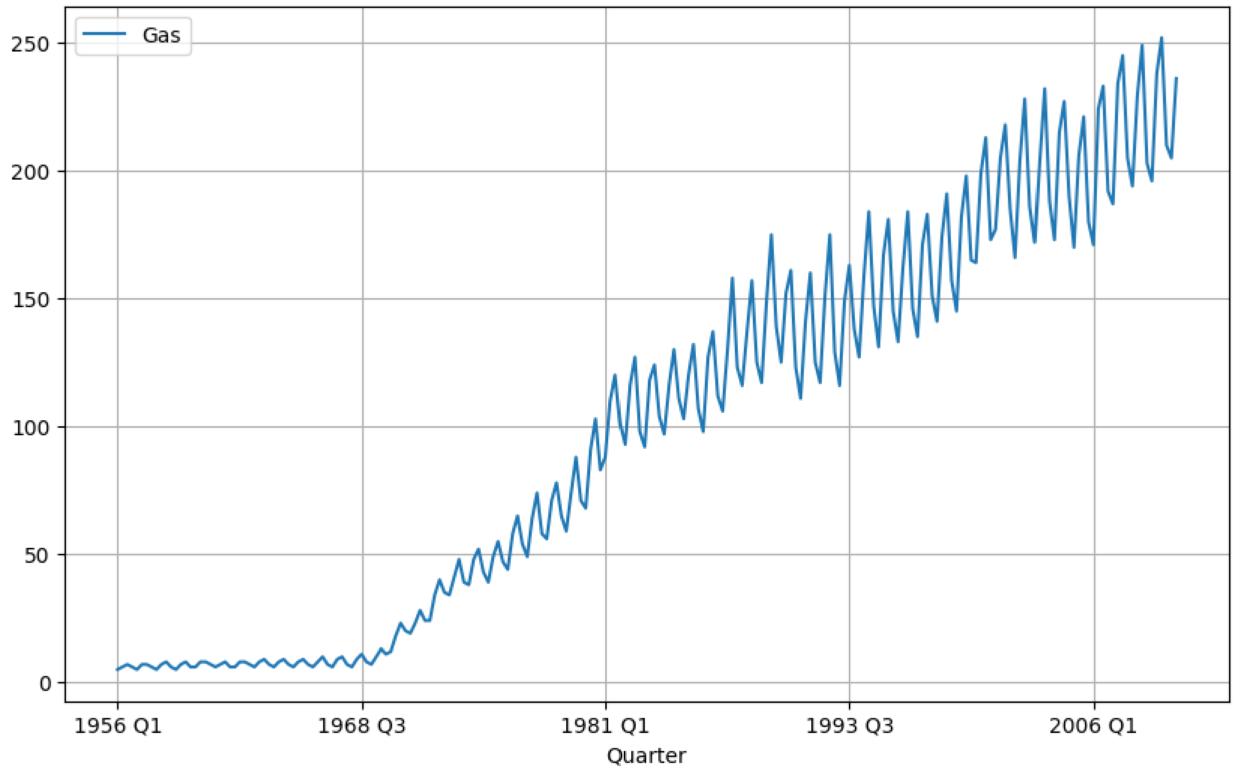
The base model with simple exponential smoothing captures the general upward trend of China's GDP. However, as the base model it might not capture the growth rate of the data since the appears to be linear. The dampening factor smooths out the trend. This introduces the intuition that the explosive growth rate observed in the past might slow down in the future. The forecast reflects a less steep trajectory. The Box-Cox transformation often helps when the pattern of increase in a time series changes over time. In this case, since it fits the test data closely, the intuition is that Chinese GDP might have a pattern of increasingly rapid growth that the standard ETS model wasn't fully capturing. The log transformation tends to scale down large values. In combination with dampening, this model intuitively suggests a very conservative forecast but knows that growth exists, but will progress much slower than any of the other models project.

Exercise 8.7

Find an ETS model for the Gas data from `aus_production` and forecast the next few years. Why is multiplicative seasonality necessary here? Experiment with making the trend damped. Does it improve the forecasts?

```
aus_gas = aus_production[['Gas']]
```

```
aus_gas.plot()
plt.grid(True)
plt.show()
```



The Gas production data displays an increasing variance pattern over time. This means that the magnitude of the fluctuations and the impact of the trend component likely scale with the underlying production level. Therefore, a multiplicative ETS model is expected to better capture this behavior and generate more reliable forecasts.

```
train_data, test_data = aus_gas[0:int(len(aus_gas)*0.8) +1],
  aus_gas[int(len(aus_gas)*0.8):]
```

```
# base model
model = ETSModel(train_data['Gas'], trend = 'add').fit()

forecast_base = model.forecast(steps = len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:559: Use
  _index = to_datetime(index)
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: Valu
  return get_prediction_index(
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: Futu
  return get_prediction_index(
```

```
#  change seasonal to multiplicative
model_mul = ETSModel(train_data['Gas'], trend = 'add', seasonal = 'mul',
  seasonal_periods = 4).fit()

forecast_mul = model_mul.forecast(steps = len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:559: User
  _index = to_datetime(index)
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: Valu
  return get_prediction_index(
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: Futu
  return get_prediction_index(
```

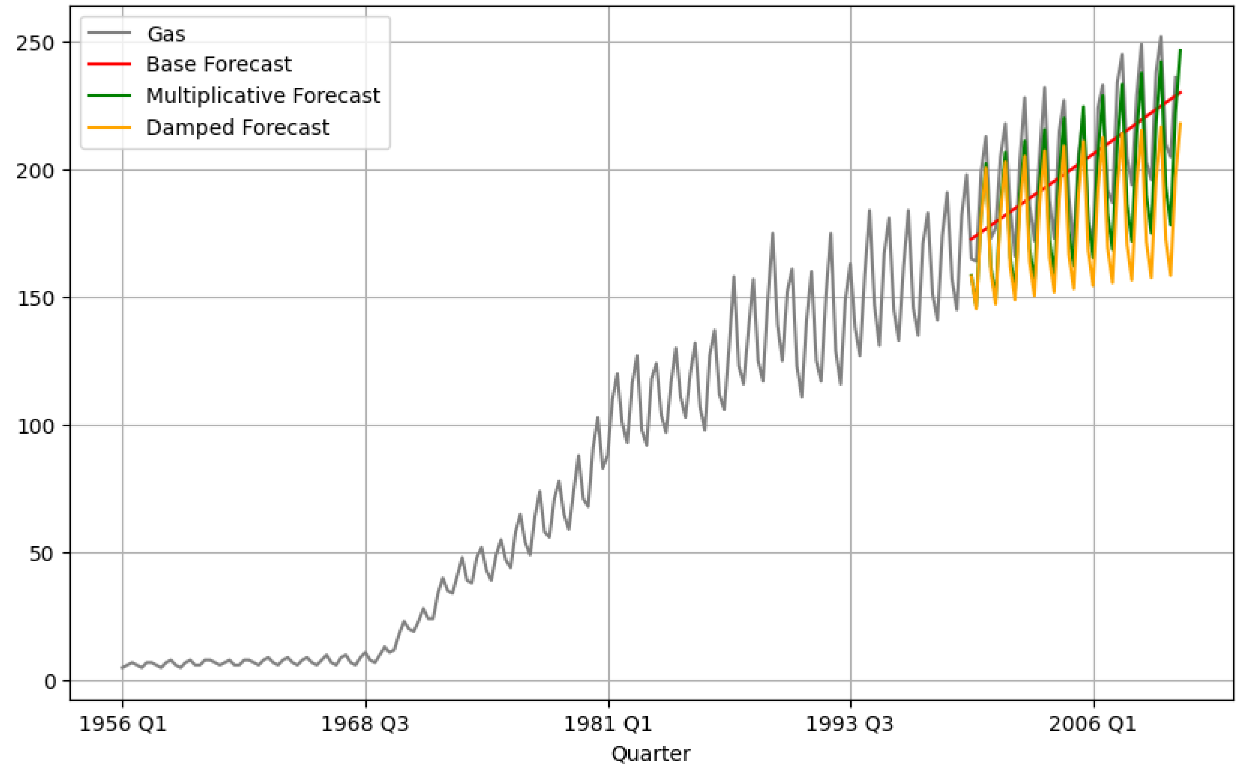
```
model_damped = ETSModel(train_data['Gas'], trend = 'add', damped_trend=True,
  seasonal = 'mul', seasonal_periods = 4).fit()

forecast_damped = model_damped.forecast(steps = len(test_data))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:559: User
  _index = to_datetime(index)
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: Valu
  return get_prediction_index(
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:836: Futu
  return get_prediction_index(
```

```
aus_gas.plot(label='Observed Data', color = 'grey')
forecast_base.plot(label = 'Base Forecast', color = 'red')
forecast_mul.plot(label = 'Multiplicative Forecast', color = 'green')
forecast_damped.plot(label = 'Damped Forecast', color = 'orange')

plt.legend()
plt.grid(True)
plt.show()
```



The damped trend into the ETS model results in a more conservative trend forecast, suggesting a potential slowdown in the growth rate compared to the basic ETS model. While the multiplicative seasonal ETS model appears to align more closely with the observed data patterns than the damped forecast.Thus, indicates that the variance in the time series might increase along with the overall level, making the multiplicative seasonality model a better fit.

Exercise 8.8

Recall your retail time series data (from Exercise 7 in Section 2.10).

```
C:\Users\nickc\AppData\Local\Temp\ipykernel_28708\3632377730.py:2: UserWarning: Could not infe
  aus_retail = pd.read_csv('c:/Users/nickc/DataScience/NickAMC.github.io/DATA_624_S24/rdata/aus
```

```
aus_retail.State.unique()
```

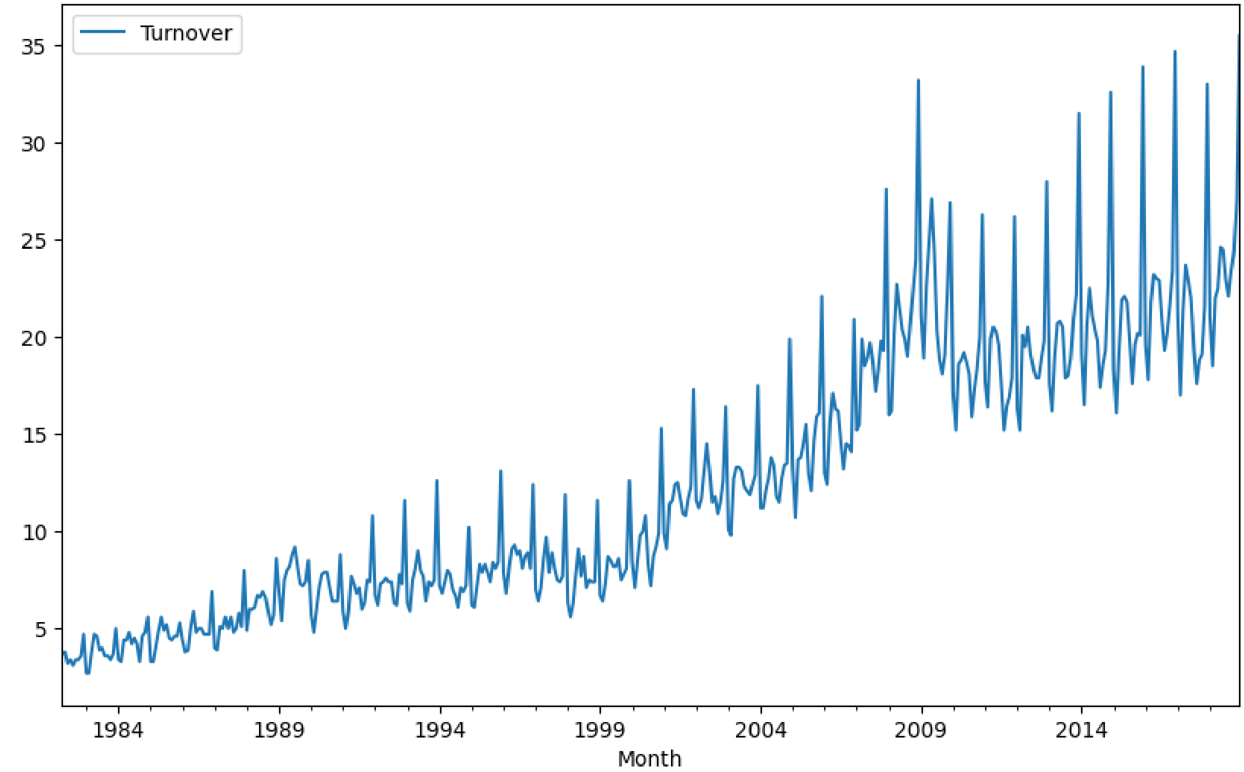
```
array(['Australian Capital Territory', 'New South Wales',
       'Northern Territory', 'Queensland', 'South Australia', 'Tasmania',
       'Victoria', 'Western Australia'], dtype=object)
```

```
clothing_retail = aus_retail.query('Industry == "Clothing retailing" & State ==
  "Australian Capital Territory"')[['Turnover']]
```

Part A

Why is multiplicative seasonality necessary for this series?

```
clothing_retail.plot()
plt.show()
```




```
train, test= clothing_retail[0:int(len(clothing_retail)*0.8) +1],
  clothing_retail[int(len(clothing_retail)*0.8):]
```

Part B

Apply Holt-Winters' multiplicative method to the data. Experiment with making the trend damped.

```
model= ETSModel(train['Turnover'], trend='add', seasonal='mul',
  damped_trend=False).fit()

forecast= model.forecast(steps = len(test))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
model_damp = ETSModel(train['Turnover'], trend='add', seasonal='mul',
  damped_trend=True).fit()

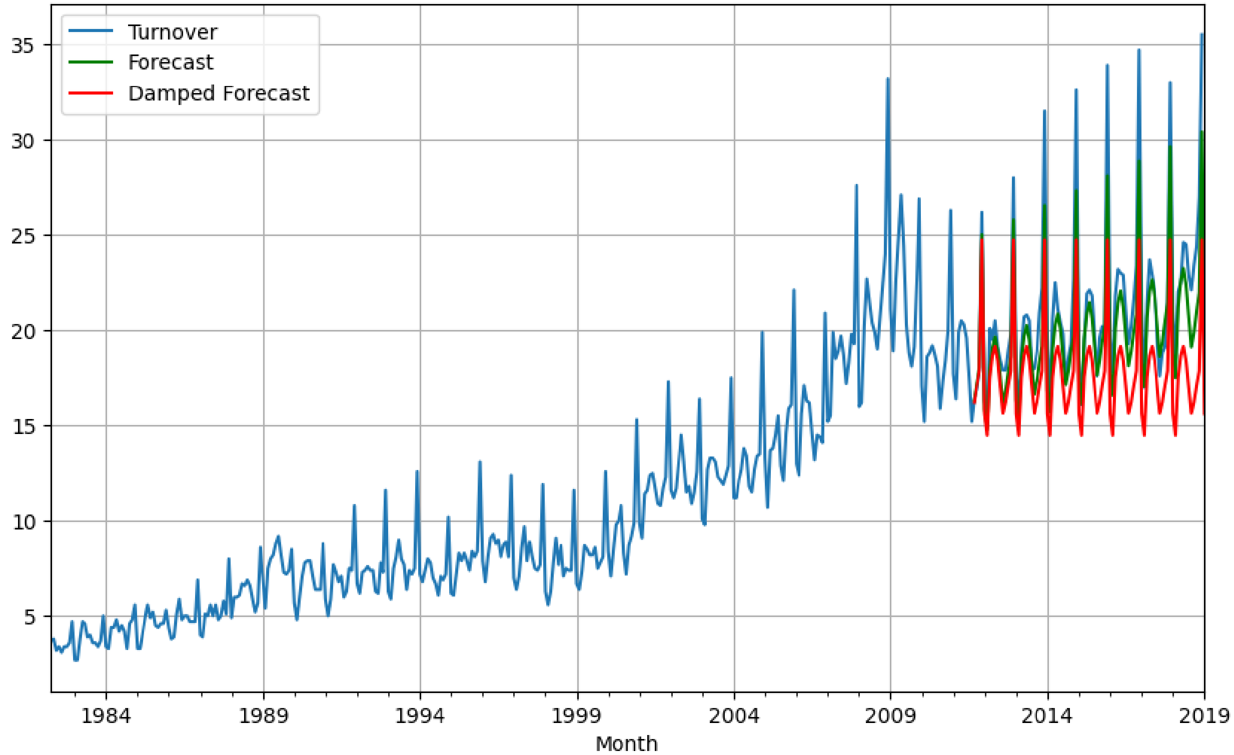
forecast_damp = model_damp.forecast(steps = len(test))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
```

```
  self._init_dates(dates, freq)
```

```
clothing_retail.plot(label = 'Observed')
forecast.plot(label = 'Forecast', color = 'green')
forecast_damp.plot(label = 'Damped Forecast', color = 'red')

plt.legend()
plt.grid(True)
plt.show()
```



Part C

Compare the RMSE of the one-step forecasts from the two methods. Which do you prefer?

```
from sklearn.metrics import mean_squared_error


rmse = np.sqrt(mean_squared_error(test['Turnover'], forecast))
rmse_damp = np.sqrt(mean_squared_error(test['Turnover'], forecast_damp))

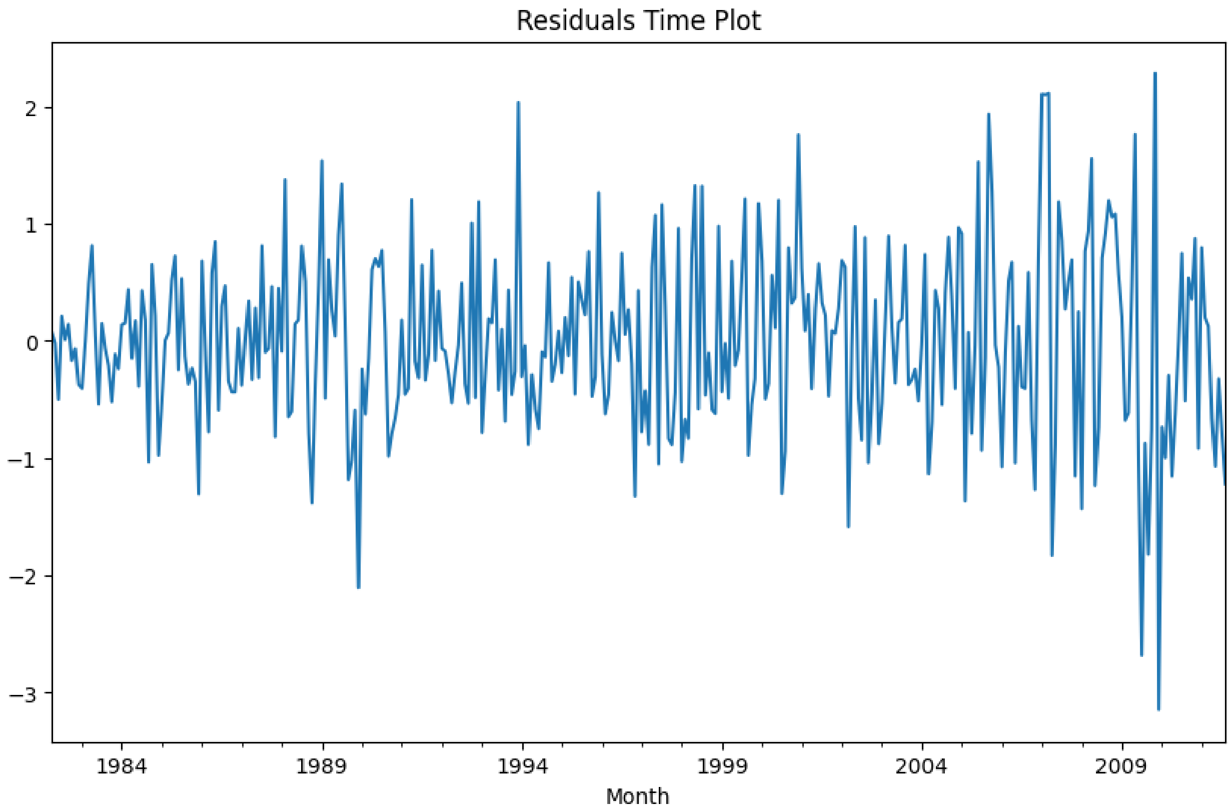
print("RMSE (Multiplicative ETS):", rmse)
print("RMSE (Damped Multiplicative ETS):", rmse_damp)
```

```
RMSE (Multiplicative ETS): 5.032452417615934
RMSE (Damped Multiplicative ETS): 6.015841153098568
```

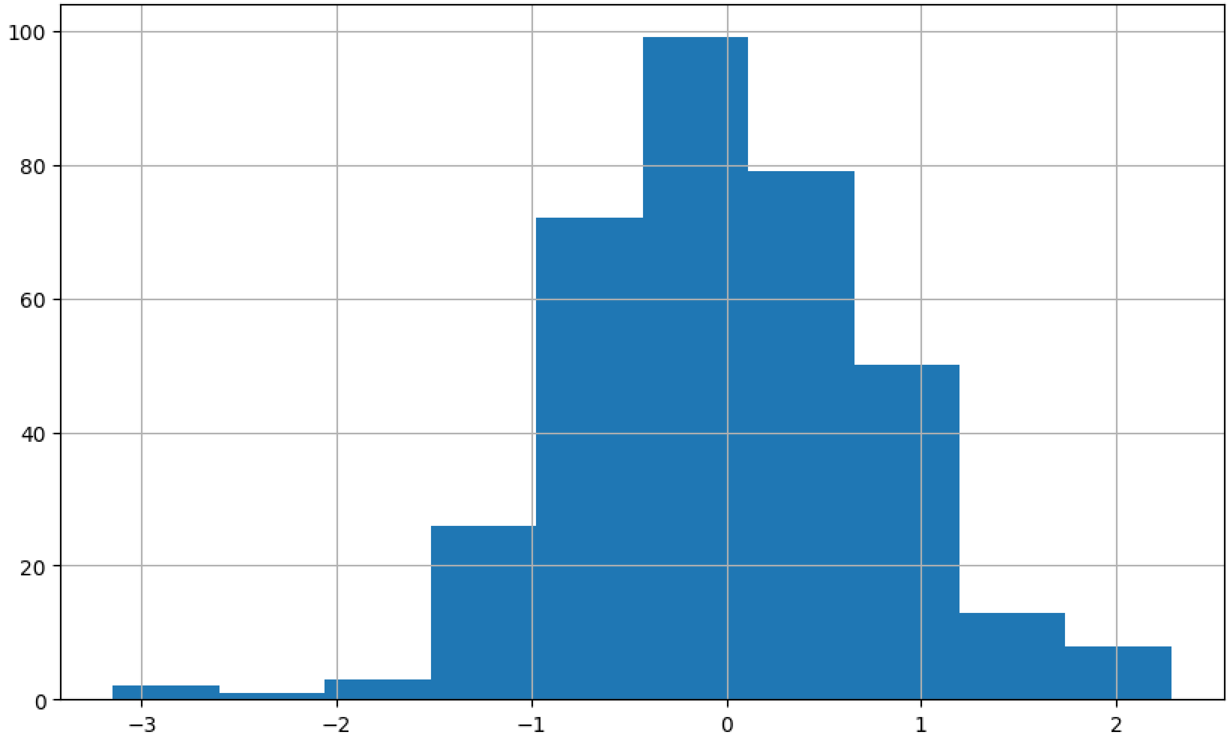
Part D

Check that the residuals from the best method look like white noise.

```
residuals = model.resid
residuals.plot()
plt.title('Residuals Time Plot')
plt.show()
```




```
residuals.hist()
plt.show
```



Residuals exhibits no clear patterns and appears to be randomly scatterred around zero.

```
print(model.summary())
```

```
                                 ETS Results
==============================================================================
Dep. Variable:                Turnover   No. Observations:                  353
Model:                        ETS(AAM)   Log Likelihood                -406.420
Date:                 Sun, 03 Mar 2024   AIC                            848.840
Time:                         18:57:51   BIC                            918.437
Sample:                     04-01-1982   HQIC                           876.533
                          - 08-01-2011   Scale                            0.586
Covariance Type:                approx
=======================================================================================
                          coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------------
smoothing_level         0.6078      0.069      8.747      0.000       0.472       0.744
smoothing_trend      6.078e-05        nan        nan        nan         nan         nan
smoothing_seasonal   3.922e-05      0.085      0.000      1.000      -0.166       0.166
initial_level           3.5788    154.259      0.023      0.981    -298.763     305.921
initial_trend           0.0488      2.105      0.023      0.981      -4.078       4.175
initial_seasonal.0      0.9403     40.529      0.023      0.981     -78.496      80.376
initial_seasonal.1      0.7779     33.530      0.023      0.981     -64.940      66.495
initial_seasonal.2      0.8369     36.073      0.023      0.981     -69.866      71.539
initial_seasonal.3      1.3232     57.037      0.023      0.981    -110.468     113.114
initial_seasonal.4      0.9580     41.294      0.023      0.981     -79.976      81.892
```

```
initial_seasonal.5      0.9168     39.517      0.023      0.981     -76.536      78.370
initial_seasonal.6      0.8706     37.526      0.023      0.981     -72.679      74.420
initial_seasonal.7      0.8383     36.134      0.023      0.981     -69.983      71.660
initial_seasonal.8      0.9117     39.296      0.023      0.981     -76.108      77.931
initial_seasonal.9      0.9851     42.463      0.023      0.981     -82.242      84.212
initial_seasonal.10     1.0269     44.265      0.023      0.981     -85.730      87.784
initial_seasonal.11     1.0000     43.103      0.023      0.981     -83.481      85.481
===================================================================================
Ljung-Box (Q):                       21.06   Jarque-Bera (JB):                 13.38
Prob(Q):                              0.64   Prob(JB):                          0.00
Heteroskedasticity (H):               2.67   Skew:                             -0.00
Prob(H) (two-sided):                  0.00   Kurtosis:                          3.95
===================================================================================

Warnings:
[1] Covariance matrix calculated using numerical (complex-step) differentiation.
```

The Ljung-Box indicates that the residuals are uncorrelated and Jarque-Bera test rejects the null where the residuals are normality distributed.

Part E

Now find the test set RMSE, while training the model to the end of 2010. Can you beat the seasonal naïve approach from Exercise 7 in Section 5.11?

```
train_2010 = clothing_retail.loc[:'2010']
model_2010 = ETSModel(train_2010['Turnover'], trend='add', seasonal='mul',
  damped_trend=True).fit()

forecast_2010 = model_2010.forecast(steps=len(test))
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
test_rmse = np.sqrt(mean_squared_error(test['Turnover'], forecast_2010))
print("Test Set RMSE (ETS Model):", test_rmse)
```

```
Test Set RMSE (ETS Model): 5.003789852798558
```

Exercise 8.9

For the same retail data, try an STL decomposition applied to the Box-Cox transformed series, followed by ETS on the seasonally adjusted data. How does that compare with your best previous forecasts on the test set?

```
turnover_boxcox, lmbda = boxcox(train['Turnover'])

train['Turnover_boxcox'] = turnover_boxcox
```

```
C:\Users\nickc\AppData\Local\Temp\ipykernel_28708\381446324.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

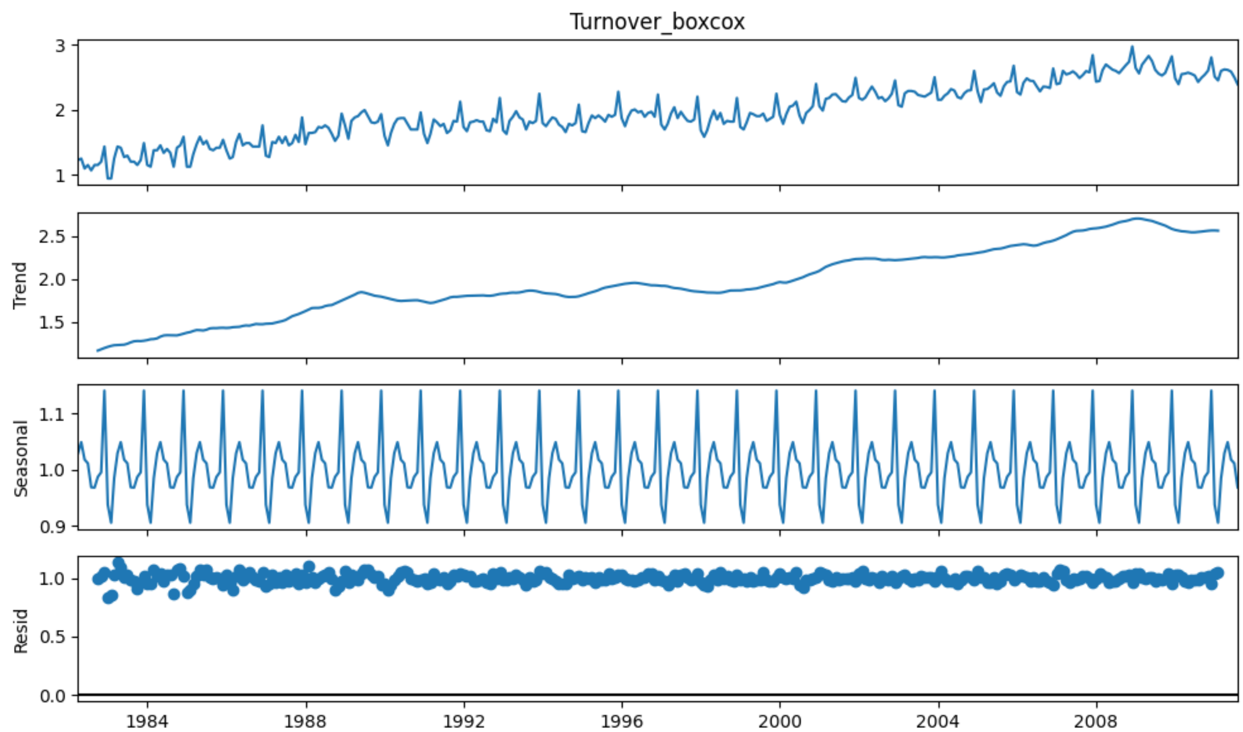
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/i
  train['Turnover_boxcox'] = turnover_boxcox
```

```python
stl = seasonal_decompose(train['Turnover_boxcox'], model='mupltiplicative',
  period=12)
```

```python
stl.resid.isna().sum()
```

```
12
```

```python
stl.plot()
plt.show()
```




```python
test_decomposed = seasonal_decompose(train['Turnover_boxcox'], model='additive',
  period=12)
test_resid = test_decomposed.resid.dropna()
```

```python
model_ets = ExponentialSmoothing(stl.resid.dropna() + 0.001, trend='add',
  seasonal='mul', seasonal_periods=12).fit()

forecast= model_ets.forecast(steps=len(test_resid))

forecast = inv_boxcox1p(forecast, lmbda)
```

```
c:\Users\nickc\DataScience\ds_env\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: Valu
  self._init_dates(dates, freq)
```

```
test_rmse = np.sqrt(mean_squared_error(test_resid, forecast))
print("Test Set RMSE (ETS Model):", test_rmse)
```

```
Test Set RMSE (ETS Model): 1.8695669650523843
```