Homework 4

Question 1

```
# !pip install pycaret
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pycaret.time_series import *
import warnings
warnings.filterwarnings('ignore')
```

1. Read the csv file from the URL and set the first column in the data as the index column.

```
df = pd.read_csv('https://raw.githubusercontent.com/PJalgotrader/Deep_forecasting-USU/main/data/US_macro_Quarterly.csv')
df.set_index(df.columns[0], inplace=True)
df.index.name = 'date'
df.head()
```

date	realgdp	realcons	realinv	realgovt	realdpi	cpi	m1	tbilrate	unemp	pop	infl	realint
1959-03-31	2710.349	1707.4	286.898	470.045	1886.9	28.98	139.7	2.82	5.8	177.146	0.00	0.00
1959-06-30	2778.801	1733.7	310.859	481.301	1919.7	29.15	141.7	3.08	5.1	177.830	2.34	0.74
1959-09-30	2775.488	1751.8	289.226	491.260	1916.4	29.35	140.5	3.82	5.3	178.657	2.74	1.09
1959-12-31	2785.204	1753.7	299.356	484.052	1931.3	29.37	140.0	4.33	5.6	179.386	0.27	4.06
1960-03-31	2847.699	1770.5	331.722	462.199	1955.5	29.54	139.6	3.50	5.2	180.007	2.31	1.19

Next steps: Generate code with df View recommended plots New interactive sheet

2. Before moving forward, we first need to change the data frame index type into "PeriodIndex". Make sure you pick the right frequency for the data?

```
df.index = pd.to_datetime(df.index).to_period('Q')
df.head()
```

date	realgdp	realcons	realinv	realgovt	realdpi	cpi	m1	tbilrate	unemp	pop	infl	realint
1959Q1	2710.349	1707.4	286.898	470.045	1886.9	28.98	139.7	2.82	5.8	177.146	0.00	0.00
1959Q2	2778.801	1733.7	310.859	481.301	1919.7	29.15	141.7	3.08	5.1	177.830	2.34	0.74
1959Q3	2775.488	1751.8	289.226	491.260	1916.4	29.35	140.5	3.82	5.3	178.657	2.74	1.09
1959Q4	2785.204	1753.7	299.356	484.052	1931.3	29.37	140.0	4.33	5.6	179.386	0.27	4.06
1960Q1	2847.699	1770.5	331.722	462.199	1955.5	29.54	139.6	3.50	5.2	180.007	2.31	1.19

Next steps: Generate code with df View recommended plots New interactive sheet

3. Our variable of interest is "cpi" which stands for consumer price index. Keep this variable in the data and drop the rest.

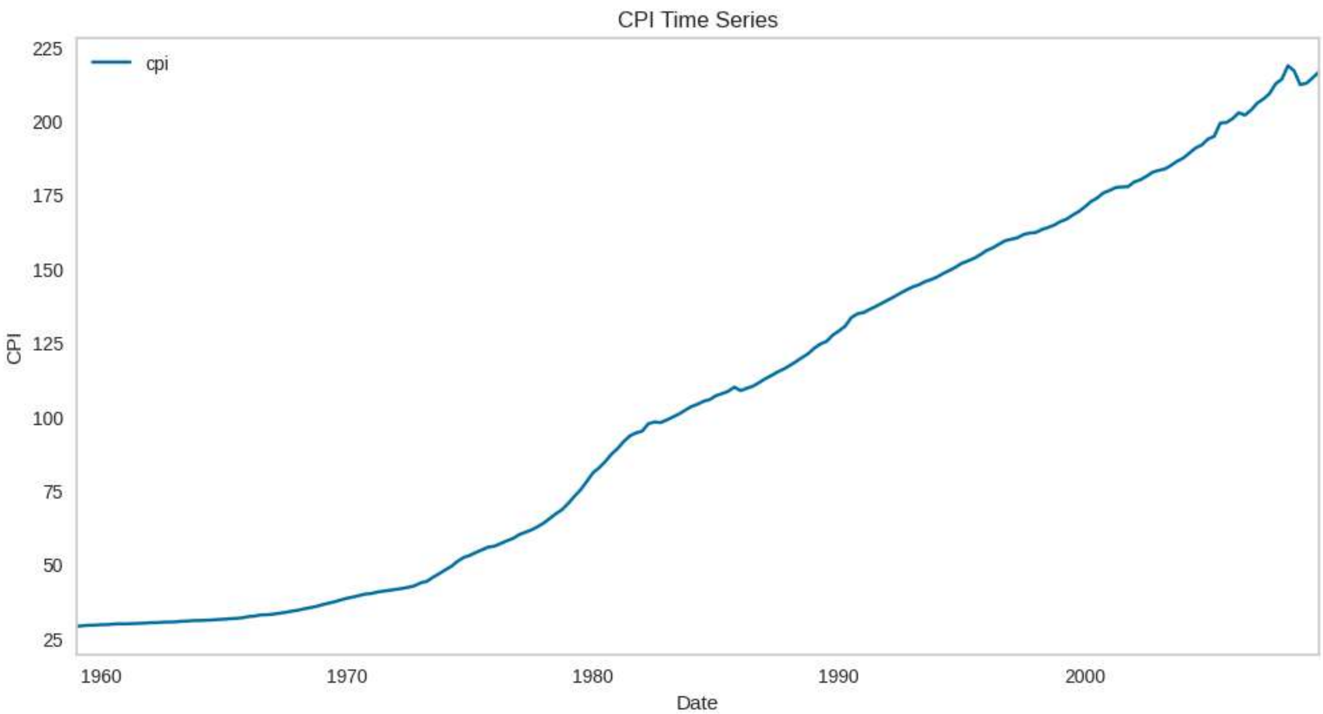
```
df = df[['cpi']]
df.head()
```

	cpi
date	
1959Q1	28.98
1959Q2	29.15
1959Q3	29.35
1959Q4	29.37
1960Q1	29.54

Next steps: Generate code with df | View recommended plots | New interactive sheet

4. Using Matplotlib, plot the time series for cpi. Before doing any further investigation, based on what you see, is this time series stationary? What does this imply? Do we need to use differencing here?

```
df.plot(figsize=(12,6))
plt.title('CPI Time Series')
plt.grid(visible=False)
plt.xlabel('Date')
plt.ylabel('CPI')
plt.show()
```



4. (Answer) - This series is not stationary, which means we will need to difference it (if not seasonal, then at least regular differencing).

5. Set up your PyCaret experiment with forecasting horizon = 24. How many in-sample observations do you have? How many hold out observations?

```
exp = TSForecastingExperiment()
exp.setup(data = df, target='cpi' ,  fh = 24, coverage=0.90)
```

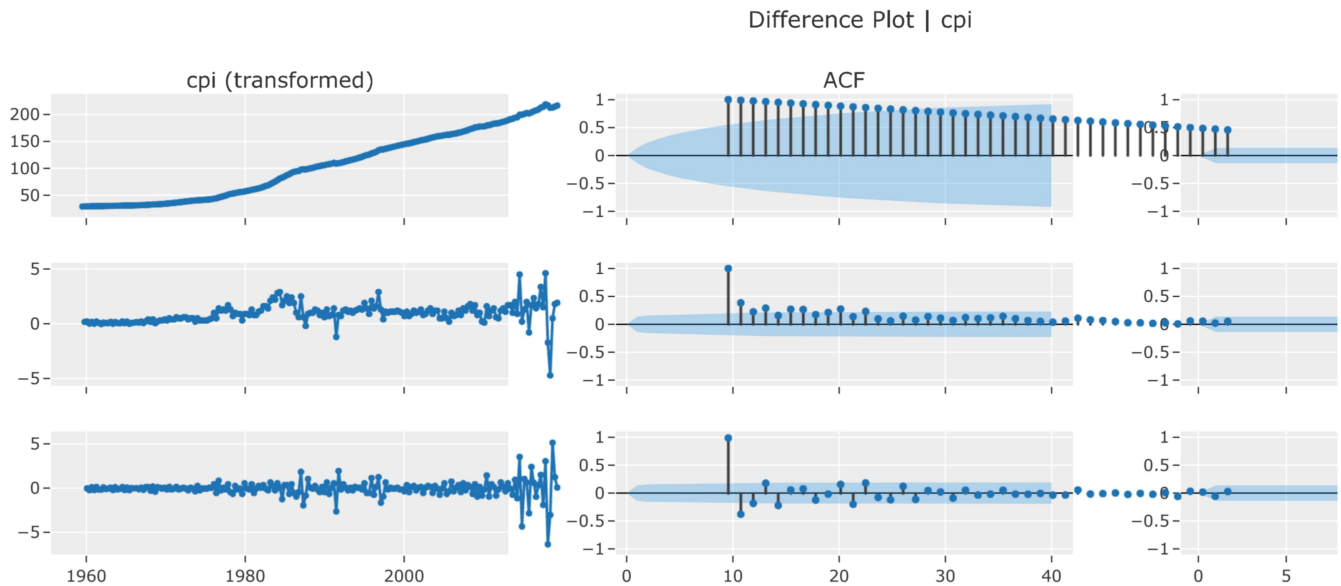
	Description	Value
0	session_id	5256
1	Target	cpi
2	Approach	Univariate
3	Exogenous Variables	Not Present
4	Original data shape	(203, 1)
5	Transformed data shape	(203, 1)
6	Transformed train set shape	(179, 1)
7	Transformed test set shape	(24, 1)
8	Rows with missing values	0.0%
9	Fold Generator	ExpandingWindowSplitter
10	Fold Number	3
11	Enforce Prediction Interval	False
12	Splits used for hyperparameters	all
13	User Defined Seasonal Period(s)	None
14	Ignore Seasonality Test	False
15	Seasonality Detection Algo	auto
16	Max Period to Consider	60
17	Seasonal Period(s) Tested	[3, 11]
18	Significant Seasonal Period(s)	[3, 11]
19	Significant Seasonal Period(s) without Harmonics	[3, 11]
20	Remove Harmonics	False
21	Harmonics Order Method	harmonic_max
22	Num Seasonalities to Use	1
23	All Seasonalities to Use	[3]
24	Primary Seasonality	3
25	Seasonality Present	True
26	Seasonality Type	mul
27	Target Strictly Positive	True
28	Target White Noise	No
29	Recommended d	2
30	Recommended Seasonal D	0
31	Preprocess	False
32	CPU Jobs	-1
33	Use GPU	False
34	Log Experiment	False
35	Experiment Name	ts-default-name
36	USI	318d

```
<pycaret.time_series.forecasting.oop.TSForecastingExperiment at 0x7ddbc5216c50>
```

5. (Answer) - There are 179 in-sample observations, and 24 hold-out observations.

6. Based on your analysis of the CPI data, which ARIMA model do you think would be the most appropriate? Justify your choice of parameters and explain if there's a need to consider a SARIMA model.

```
exp.plot_model(plot="diff", data_kwargs={"order_list": [1,2], "acf": True, "pacf": True})
```



6. (Answer) - I believe ARIMA(1,1,1) would be a good choice, since there appears to be no seasonality (from the original ACF chart), and the first difference is mostly stationary with only the first lag being important in both the ACF and PACF charts. The second difference doesn't appear to provide that much of an improvement over the first difference, so it's probably not worth it.

7. Create the following models: (for all the models, set cross_validation=False)

- ARIMA(1,1,1). Why we are not motivated to try ARMA(p,q) model wit the cpi data? what does this have to do with the ADF test result?
- SARIMA(1,1,1)(0,1,0,4).
- Random walk with drift. Why do you think we don't need to try random walk with no drift for the cpi data?

```
arima = exp.create_model('arima', order = (1,1,1), seasonal_order=(0,0,0,4), cross_validation=False)
sarima = exp.create_model('arima', order = (1,1,1), seasonal_order=(0,1,0,4), cross_validation=False)
rand_walk = exp.create_model('arima', order = (0,1,0), seasonal_order=(0,0,0,4), cross_validation=False)
```

	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2
Test	2.7905	2.7050	7.3620	8.5104	0.0353	0.0361	0.2681

	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2
Test	2.4443	2.3811	6.4486	7.4914	0.0309	0.0316	0.4329

	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2
Test	2.8597	2.7581	7.5445	8.6773	0.0362	0.0371	0.2391

7. (Answer) - We don't need to try ARIMA(p,q) because there is obviously a trend in the data, or in other words, the ADF test shows the data is not stationary. And we don't need to try random walk without drift because there is very obviously drift in the data.

8. Compare the three models above and say which one has the highest hold-out set R-squared?

```
exp.compare_models([arima, sarima, rand_walk], cross_validation=False)
```

	Model	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2	TT (Sec)
1	ARIMA	2.4443	2.3811	6.4486	7.4914	0.0309	0.0316	0.4329	0.1800
0	ARIMA	2.7905	2.7050	7.3620	8.5104	0.0353	0.0361	0.2681	0.4200
2	ARIMA	2.8597	2.7581	7.5445	8.6773	0.0362	0.0371	0.2391	0.0600

```
ARIMA
ARIMA(order=(1, 1, 1), seasonal_order=(0, 1, 0, 4))
```

8. (Answer) - SARIMA had the best R-squared in the holdout set, I guess because it cant hurt to include seasonality, or maybe because the second differencing was, in fact, beneficial.

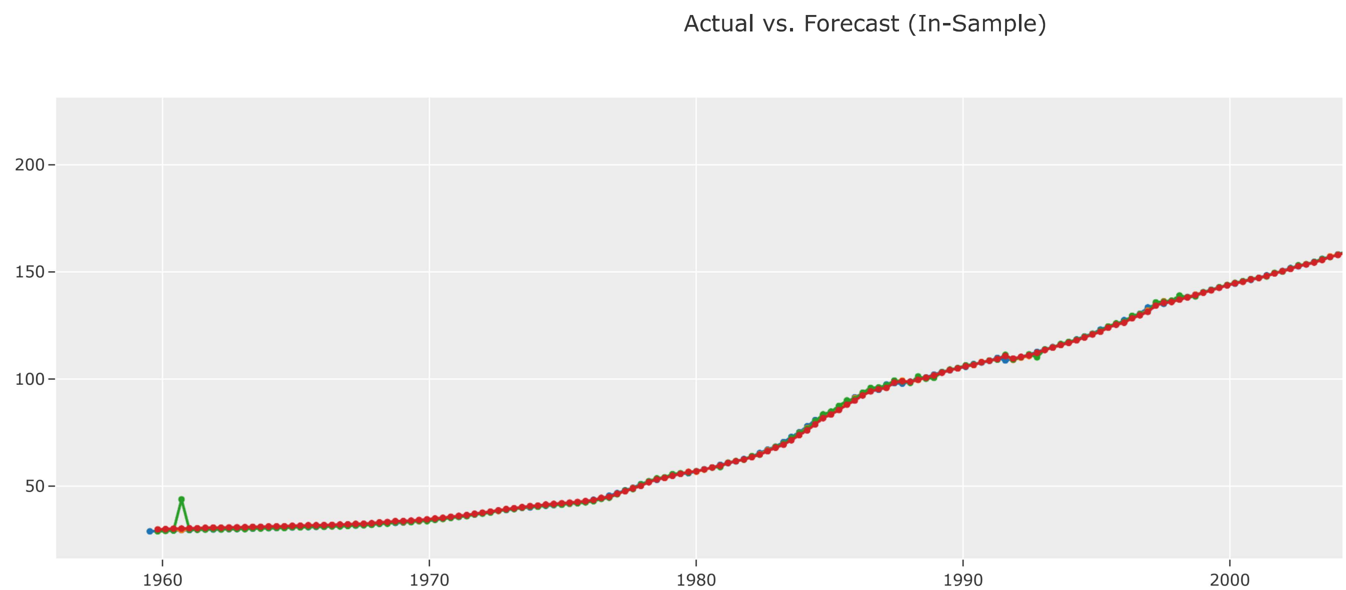
9. Write down the estimated formula for the ARIMA(1,1,1) model.

$y'_t = c + \phi y'_{t-1} + \theta \epsilon_{t-1} + \epsilon_t$

where $y'_t = y_t - y_{t-1}$

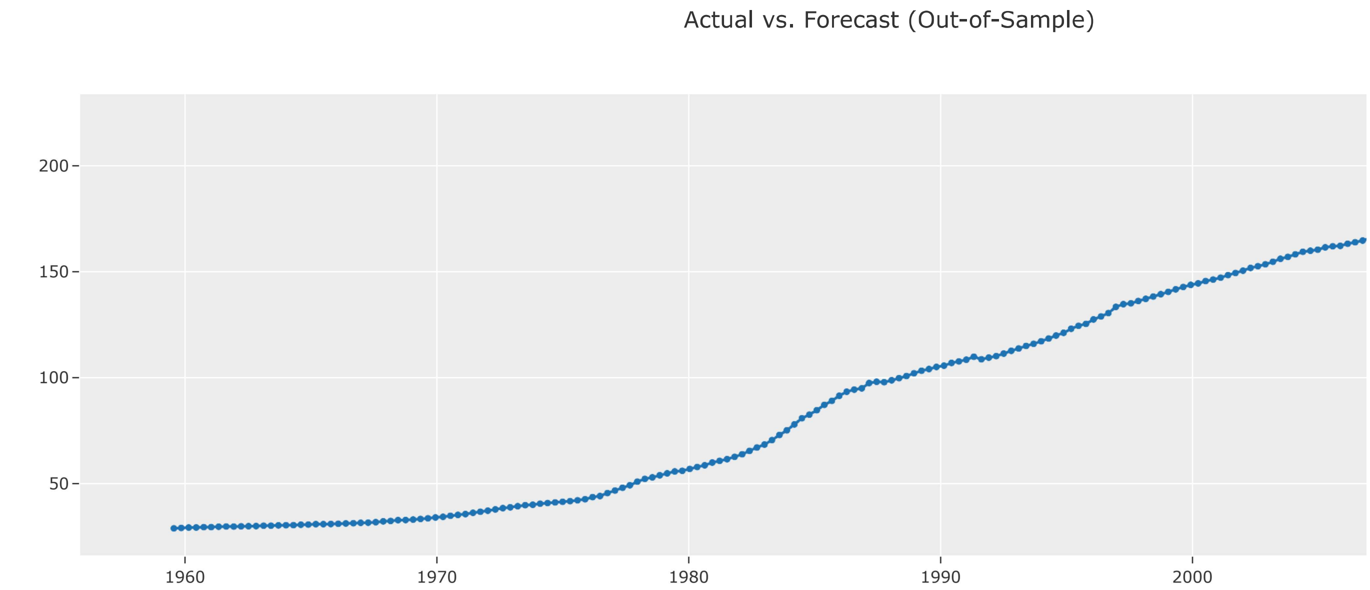
10. Plot the in-sample predictions for all the three methods above. Do it in one plot.

```
exp.plot_model([arima, sarima, rand_walk], plot='insample', data_kwargs={'labels':["ARIMA", "SARIMA", "Random Walk"]})
```



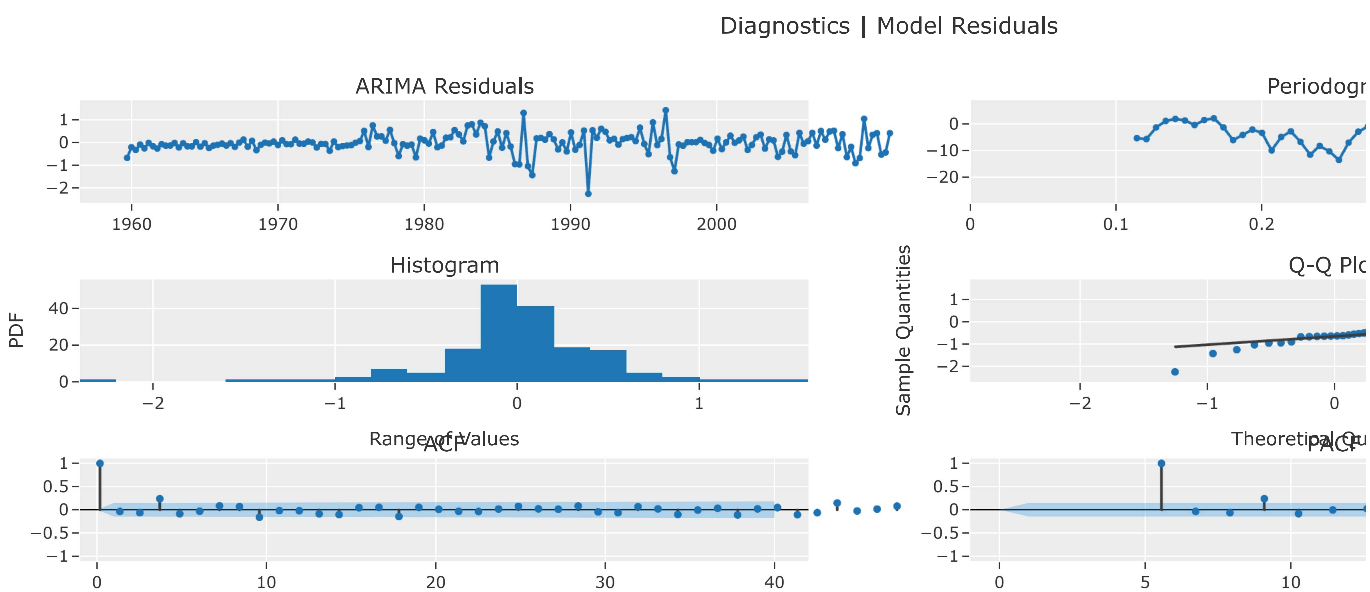
11. Plot the 36-period forecasts for all the three methods above. Do it in one plot.

```
exp.plot_model([arima, sarima, rand_walk], plot='forecast', data_kwargs={'labels':["ARIMA", "SARIMA", "Random Walk"], 'fh':36})
```



12. Plot the "diagnostics" plot for the ARIMA(1,1,1) model? are the residuals stationary? confirm your answer by reporting the pvalue for the ADF test?

```
exp.plot_model(arima, plot='diagnostics')
```




```
exp.check_stats(arima, test = 'adf')
```

	Test	Test Name	Data	Property	Setting	Value
0	Stationarity	ADF	Residual	Stationarity	{'alpha': 0.05}	True
1	Stationarity	ADF	Residual	p-value	{'alpha': 0.05}	0.0
2	Stationarity	ADF	Residual	Test Statistic	{'alpha': 0.05}	-6.338817
3	Stationarity	ADF	Residual	Critical Value 1%	{'alpha': 0.05}	-3.46828
4	Stationarity	ADF	Residual	Critical Value 5%	{'alpha': 0.05}	-2.878202
5	Stationarity	ADF	Residual	Critical Value 10%	{'alpha': 0.05}	-2.575653

12. (Answer) - The redisuals do appear to be at least weakly stationary, and the p-value of the ADF test confirms this, since it is reported as 0.0 (which means it is less than 0.0000005, based on the number of digits present in the other reported statistics)

Question 2

1. Create the auto_ets and auto_arima model as two separate models. Again, set the cross_validation = False

```
auto_ets = exp.create_model('ets', cross_validation=False)
auto_arima = exp.create_model('auto_arima', start_p=0, start_q=0, max_p=5, max_q=5, sp=4, cross_validation=False)
```

	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2
Test	2.8143	2.7095	7.4246	8.5244	0.0356	0.0365	0.2657

	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2
Test	2.5156	2.4395	6.6367	7.6752	0.0318	0.0325	0.4047

2. Between the three models (auto_arima, auto_ets, ARIMA(1,1,1)) which one is the winner, based on hold-out R-squared? Plot its forecasts for 36 periods ahead.

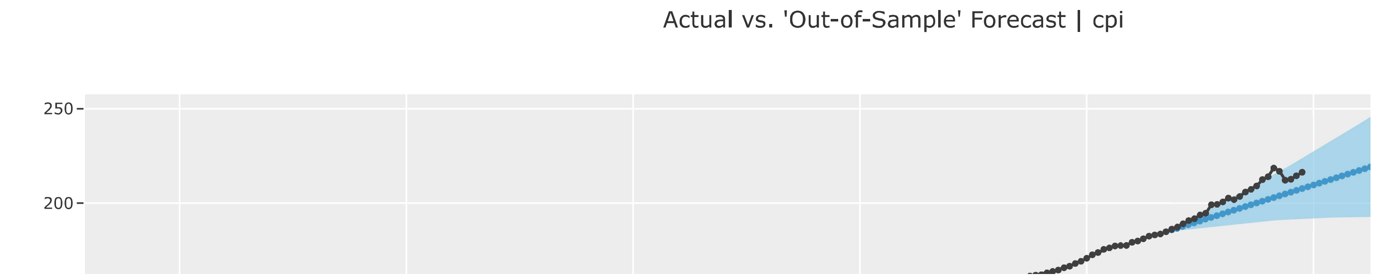
```
exp.compare_models([arima, auto_ets, auto_arima], cross_validation=False)
```

	Model	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2	TT (Sec)
2	Auto ARIMA	2.5156	2.4395	6.6367	7.6752	0.0318	0.0325	0.4047	10.4200
0	ARIMA	2.7905	2.7050	7.3620	8.5104	0.0353	0.0361	0.2681	0.5100
1	ETS	2.8143	2.7095	7.4246	8.5244	0.0356	0.0365	0.2657	0.1300

```
▾ AutoARIMA
AutoARIMA(random_state=5256, sp=4, start_p=0, start_q=0, suppress_warnings=True)
```

2. (Answer) - The Auto ARIMA model boasts the best R-squared in the hold-out set.

```
exp.plot_model(auto_arima, plot='forecast', data_kwargs={'fh':36})
```



3. Finalize your auto_arima model (train it with the entire data set) and save it as my_best_model.

```
final_model = exp.finalize_model(auto_arima)
exp.save_model(final_model, 'my_best_model')
```

```
Transformation Pipeline and Model Successfully Saved
(ForecastingPipeline(steps=[('forecaster',
                             TransformedTargetForecaster(steps=[('model',
                                                                 ForecastingPipeline(steps=[('forecaster',
                                                                                             TransformedTargetForecaster(steps=
[('model',

AutoARIMA(random_state=5256,

sp=4,

start_p=0,

start_q=0,

suppress_warnings=True))]))]))]))]),
 'my_best_model.pkl')
```

4. What is the forecast value for 2025Q1 (this is unseen data) if you use my_best_model?

```
unseen_predictions = exp.predict_model(final_model, fh=64)
print(f"The predicted value for 2025Q1 is {unseen_predictions.loc['2025Q1','y_pred']:.1f}")
```

```
The predicted value for 2025Q1 is 282.9
```

```
exp.plot_model(final_model, plot='forecast', data_kwargs={'fh':64})
```