Forecasting PPI for U.S. Fuel Oil Using Classical and Hybrid Time Series Models

Data Bootcamp Final Project

Yutong Zhao

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Outlines

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Introduction

02
Data Description

03
Models and Methods

04
Results and Interpretation

05
Conclusion and Next Steps

01

Introduction

Predictive Task:
Producer Price Index of U.S. Fuel Oil

Objective:
Compare different predictive models and choose the most accurate one for our prediction

02

Data Description

Data Sources and Variables

Target

- Fuel Oil Producer Price Index (PPI)

Exogenous Variables

- CPI
- Crude Oil WTI spot price
- Industrial Production Index
- Unemployment Rate

Data Processing

01
Data cleaning

Missing values in exogenous data were resolved using linear interpolation and forward/backward filling

02
Feature selection

We choose exogenous variables that have an absolute value of correlation with PPI greater than 0.4

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Log transformation

To remove level-dependent volatility in the original PPI time series

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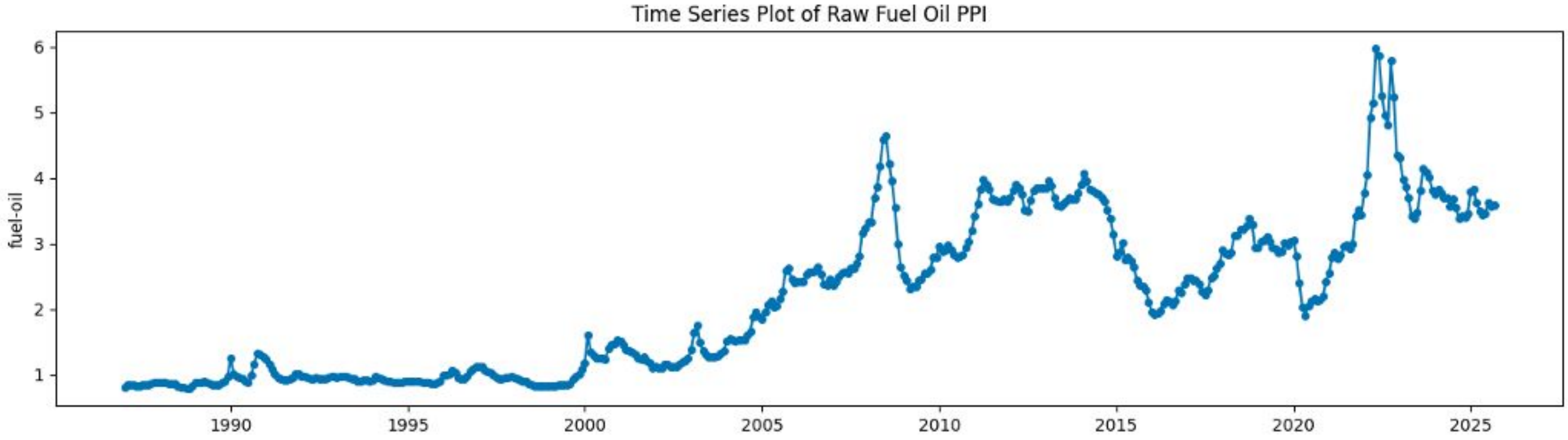
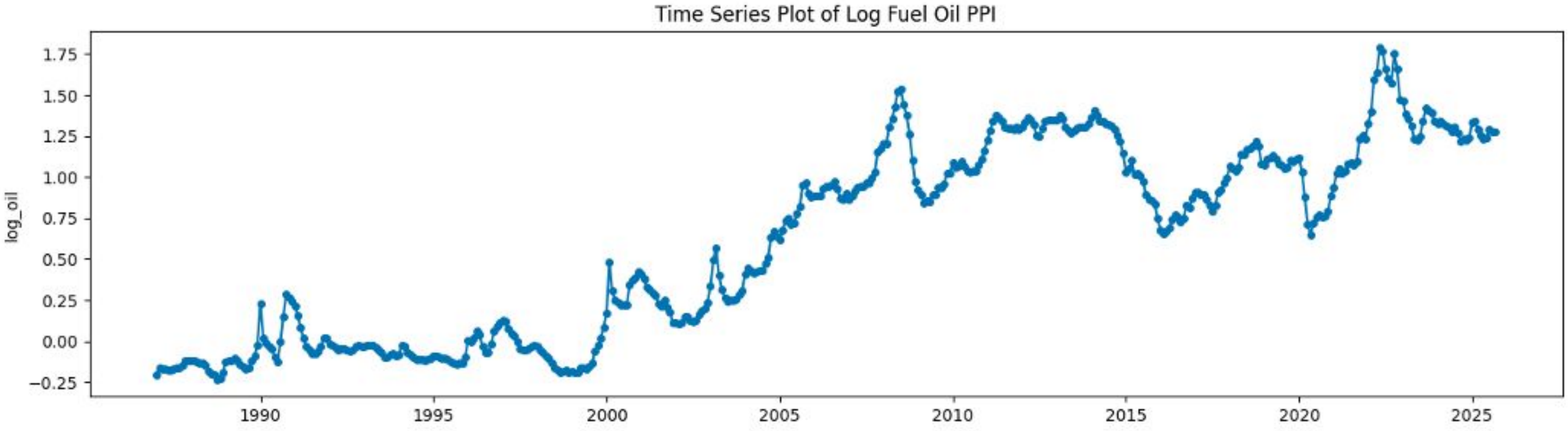
Feature Selection

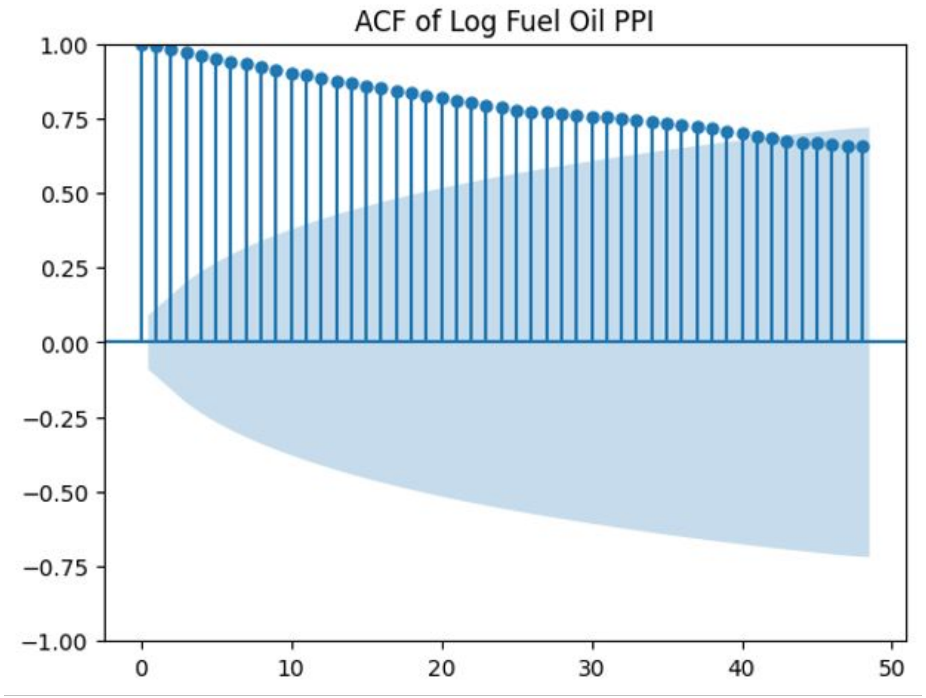
Correlation with PPI:

unemployment	0.003260
CPI	0.885557
Crude Oil (WTI) Price	0.938668
Industrial Production Index	0.826716

Final selected exogenous features: CPI, Crude Oil (WTI) Price, Industrial Production Index

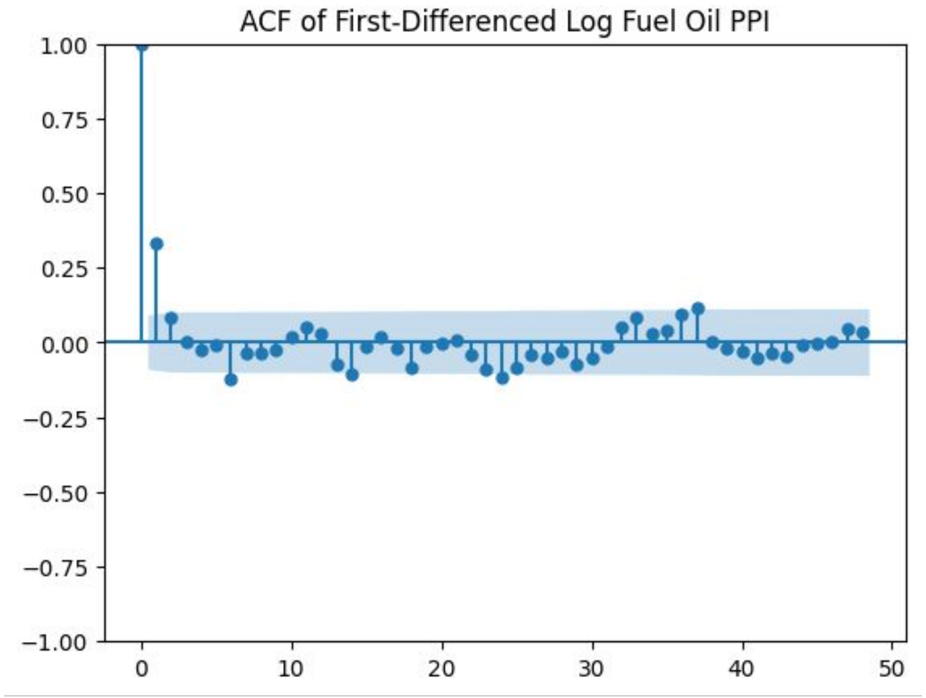

Time Series Plot of Raw Fuel Oil PPI
fuel-oil
1
2
3
4
5
6
1990
1995
2000
2005
2010
2015
2020
2025


Time Series Plot of Log Fuel Oil PPI
log_oil
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1990
1995
2000
2005
2010
2015
2020
2025



Original Series Stationarity Test:

ADF Statistic: -1.4299, p-value: 0.5679



Differenced Series Stationarity Tests:

ADF Statistic: -15.2333, p-value: 0.0000

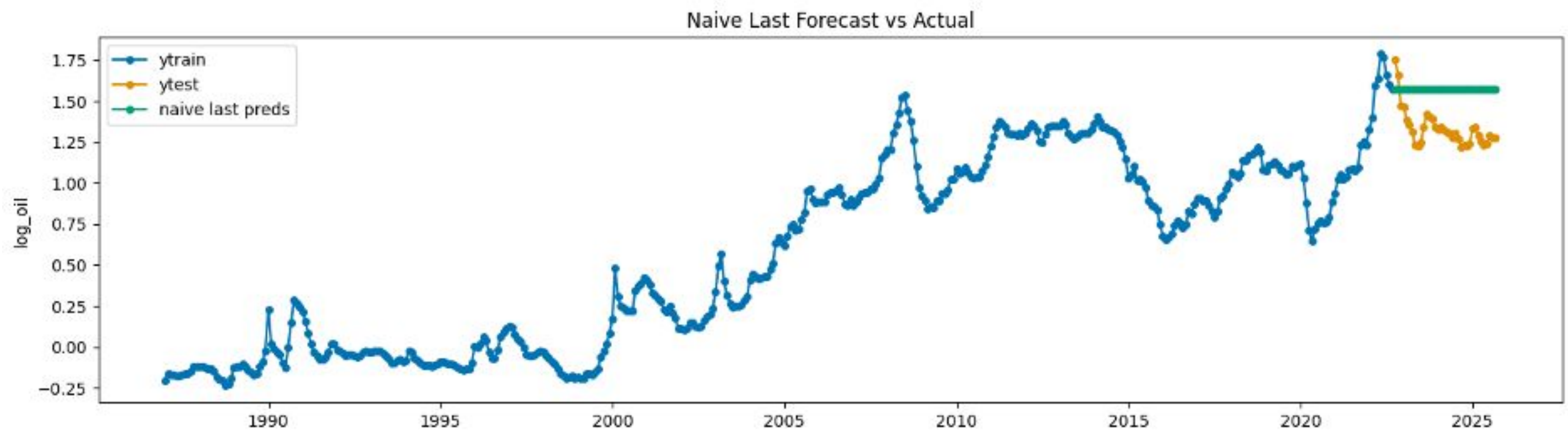
03

Models and Methods

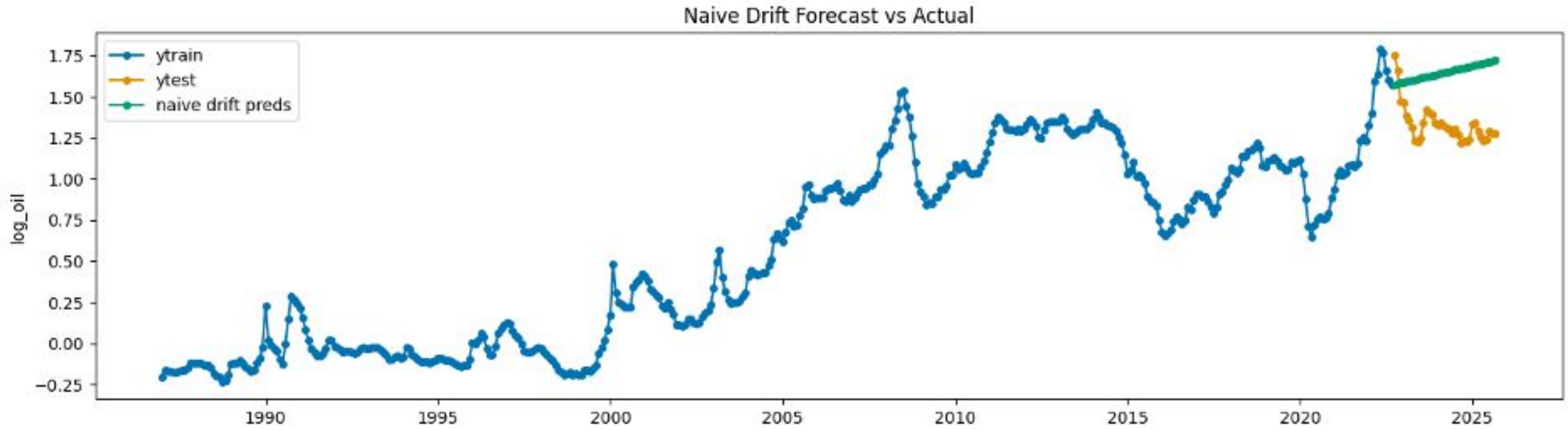
Benchmark Models

- Naive Last Value
- Naive Drift
- Naive Seasonal

Naive Last Value

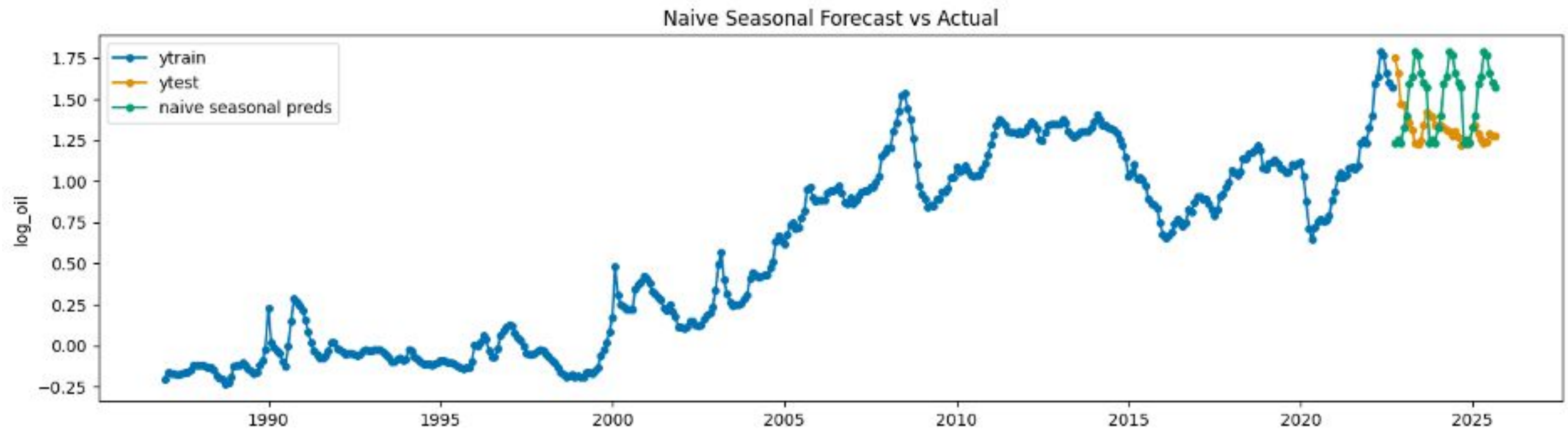


Naive Drift



Naive Drift Forecast vs Actual
ytrain
ytest
naive drift preds
log_oil
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
1990
1995
2000
2005
2010
2015
2020
2025

Naive Seasonal

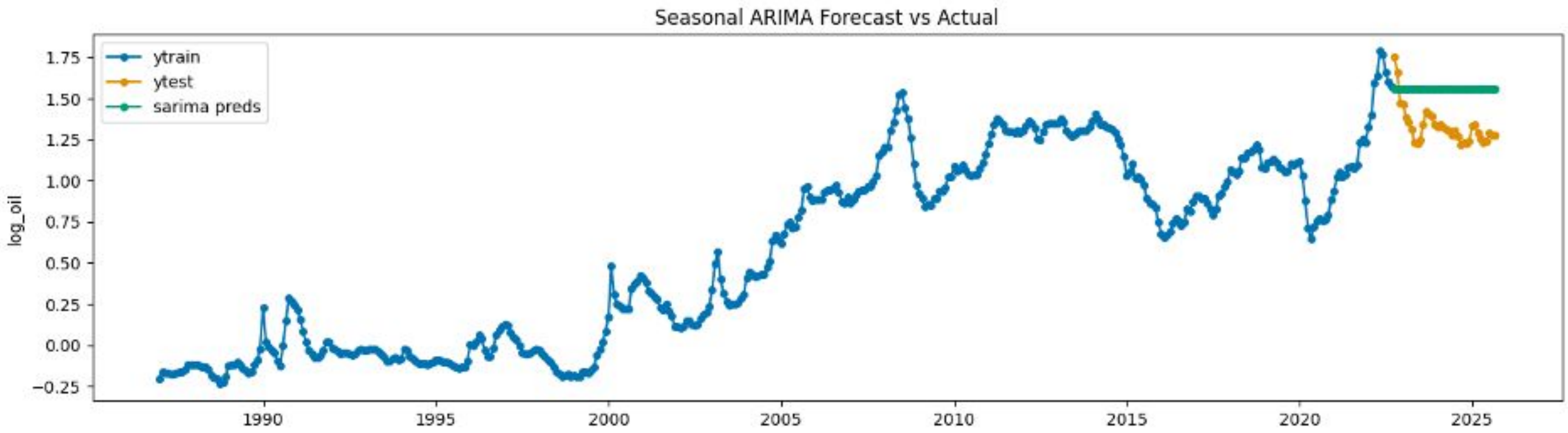


Classical Models

- **SARIMA**: Seasonal ARIMA models were fit using automated hyperparameter selection via AutoARIMA.

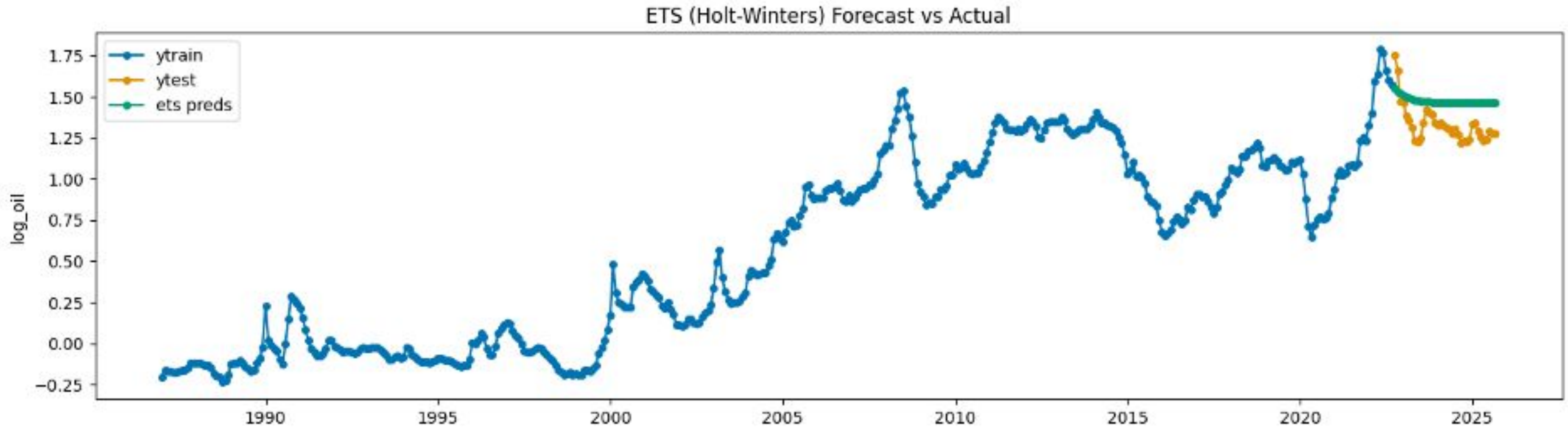
- **ETS**: Automatic Holt-Winters exponential smoothing using AutoETS

SARIMA

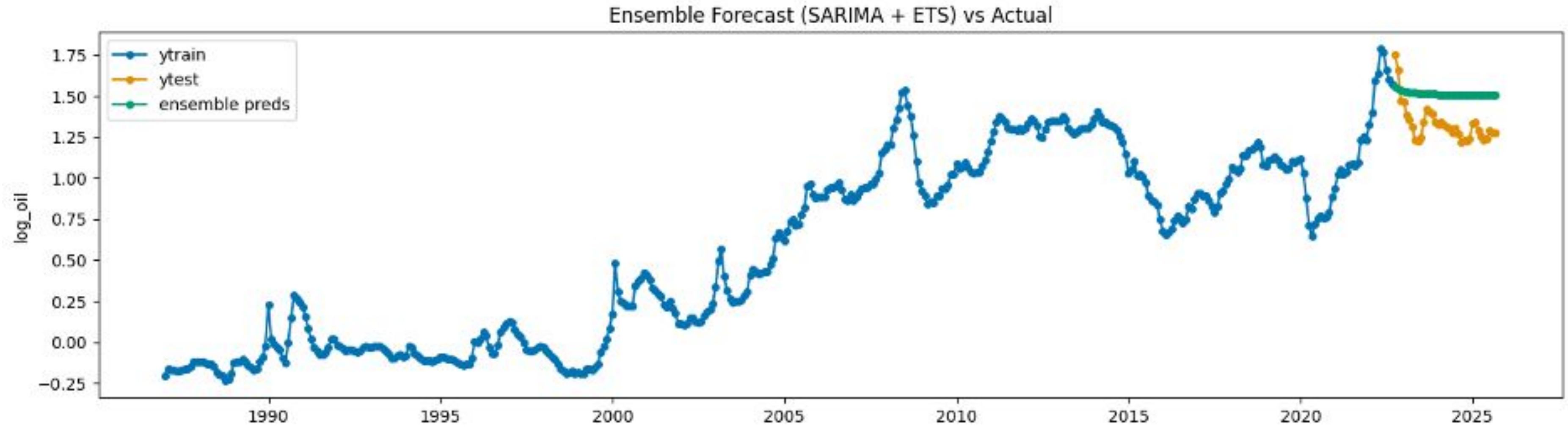


Seasonal ARIMA Forecast vs Actual
ytrain
ytest
sarima preds
log_oil
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
1990
1995
2000
2005
2010
2015
2020
2025

Exponential Smoothing (ETS)



Ensemble Model



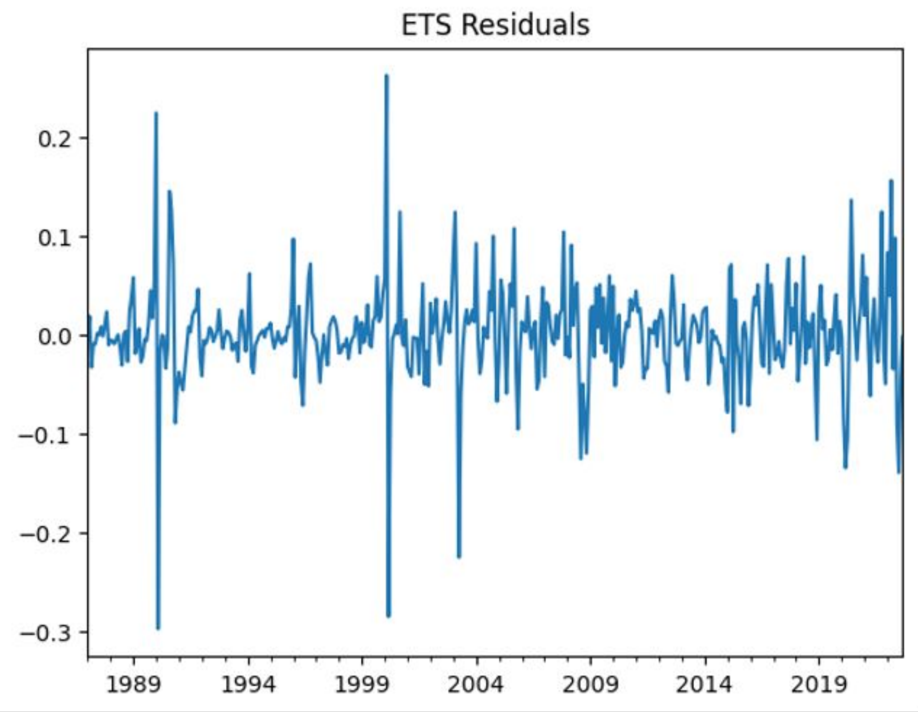
Hybrid ETS + XGBoost Model

Step 1 – Baseline Forecast Using ETS Model

	Model	MAPE
0	Naive Last	0.197224
1	Naive Drift	0.256290
2	Naive Seasonal	0.205604
3	SARIMA	0.186237
4	**ETS**	**0.124905**
5	Ensemble	0.155571

Step 2 - Residual Forecast

- Forecastability checking
- XGBoost Model


ETS Residuals
0.2
0.1
0.0
−0.1
−0.2
−0.3
1989
1994
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2014
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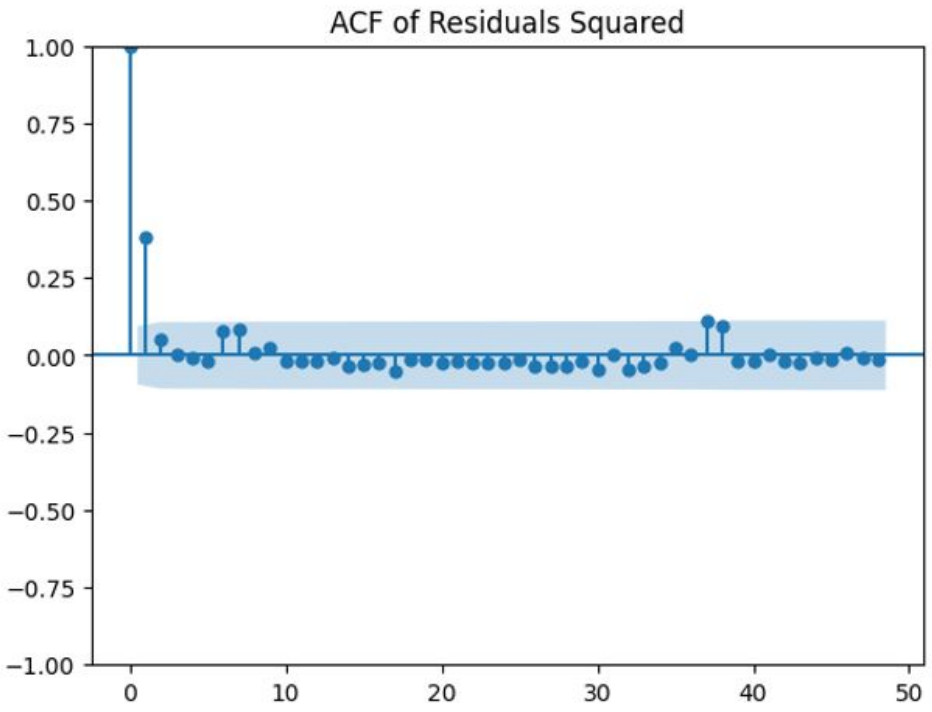
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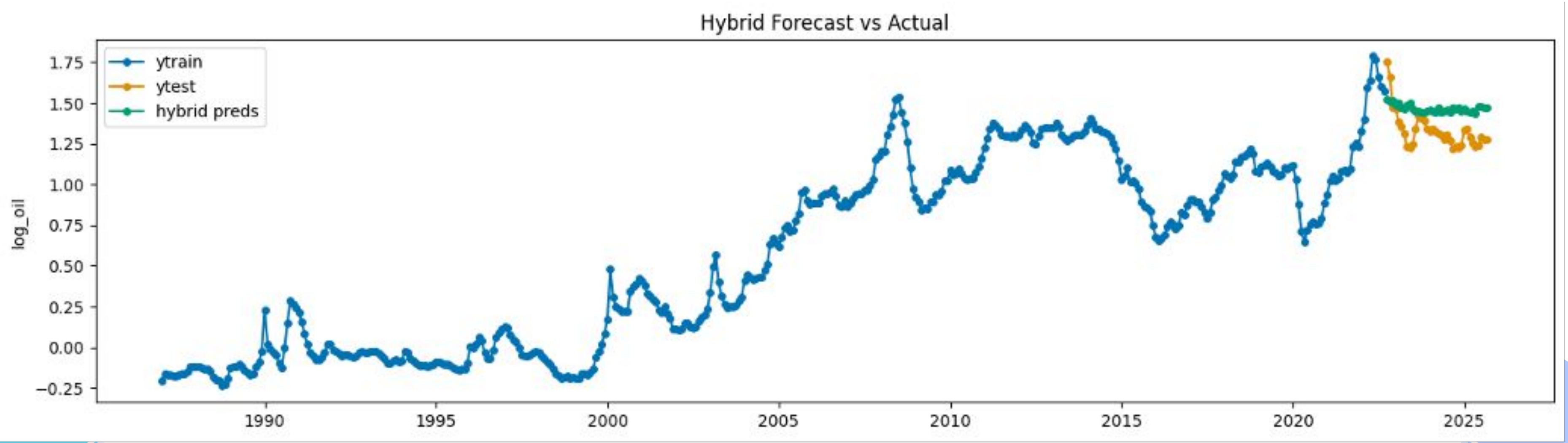
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
10
20
30
40
50

Step 3 - Final Hybrid Forecast

ETS PPI forecast + XGBoost residual forecast



04

Results and Interpretation

Model Evaluation Method:
Mean Absolute Percentage Error (MAPE)

	Model	MAPE
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Conclusion

- Classical time-series models such as ETS and ARIMA for seasonal economic forecasting are effective
- Incorporating macroeconomic drivers through machine learning provides improvements in predictive accuracy

Further Analysis

- Expand the set of macroeconomic features
- Explore alternative machine learning techniques for residual forecasting, such as neural networks
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Thank you!

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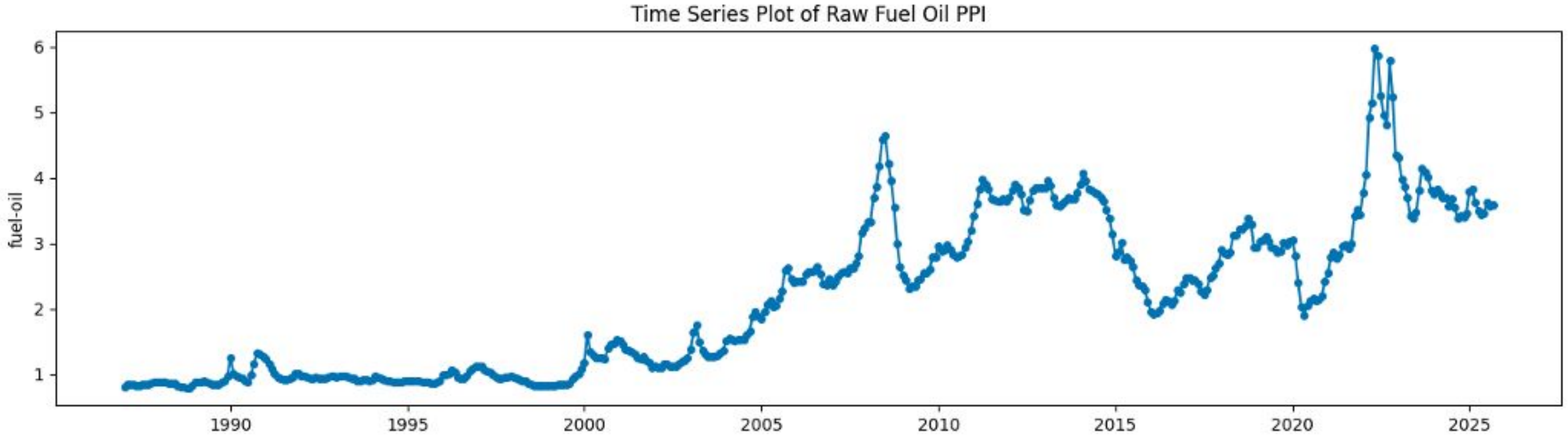
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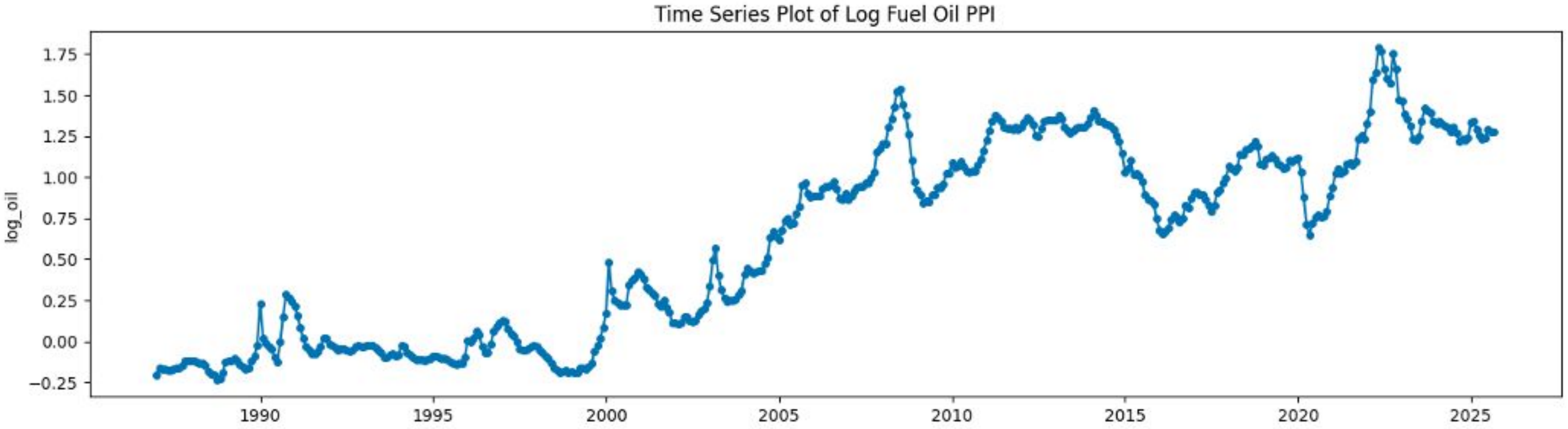
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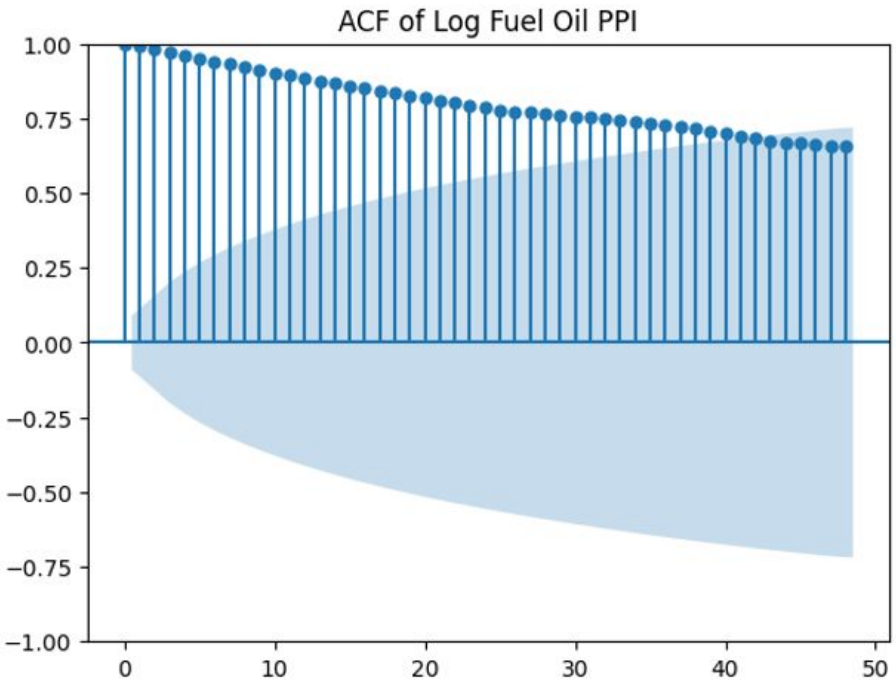

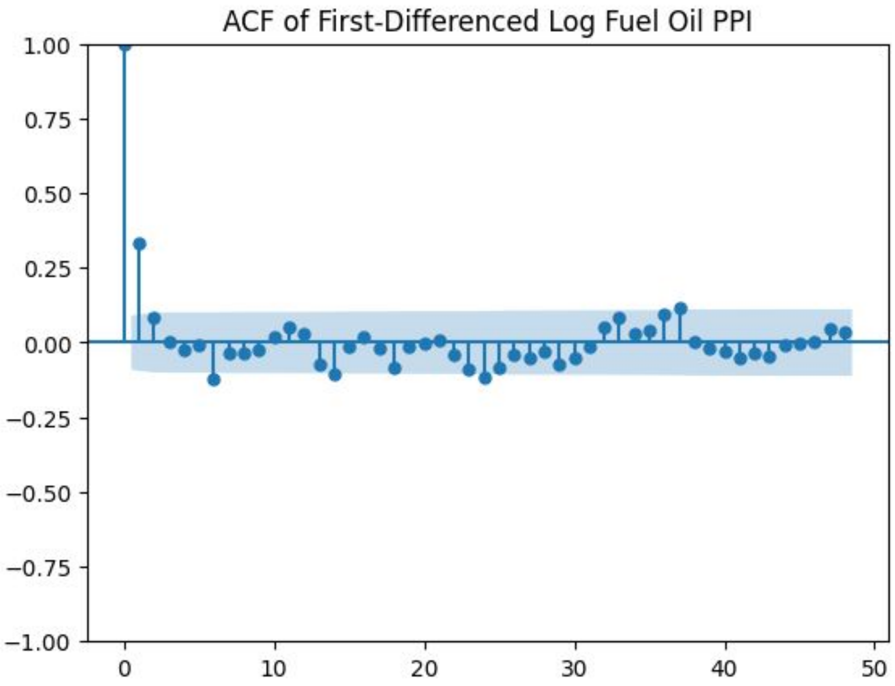

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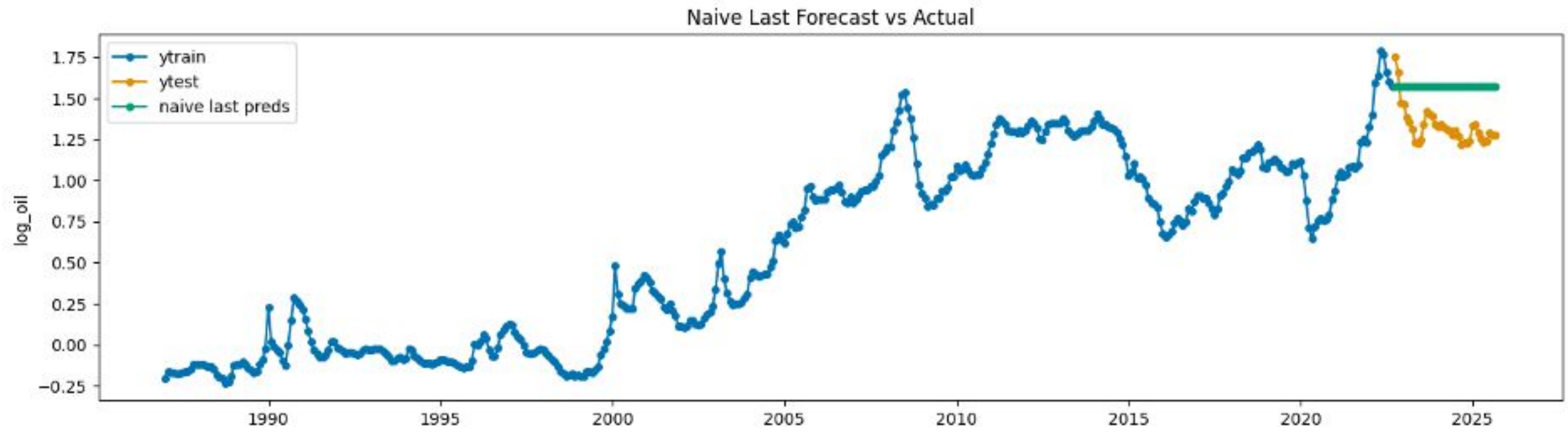

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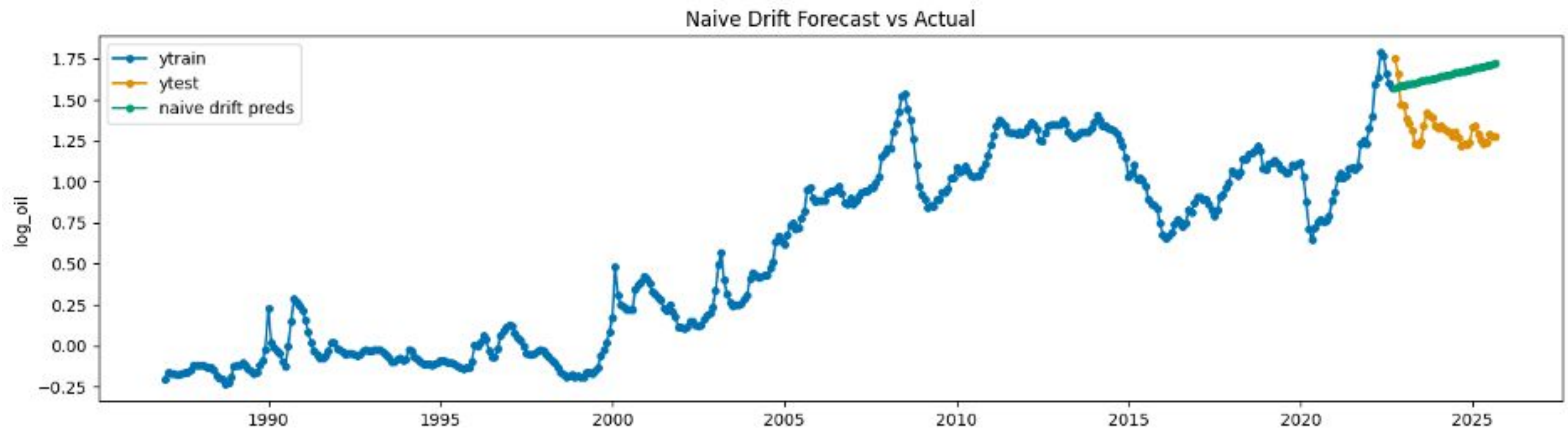

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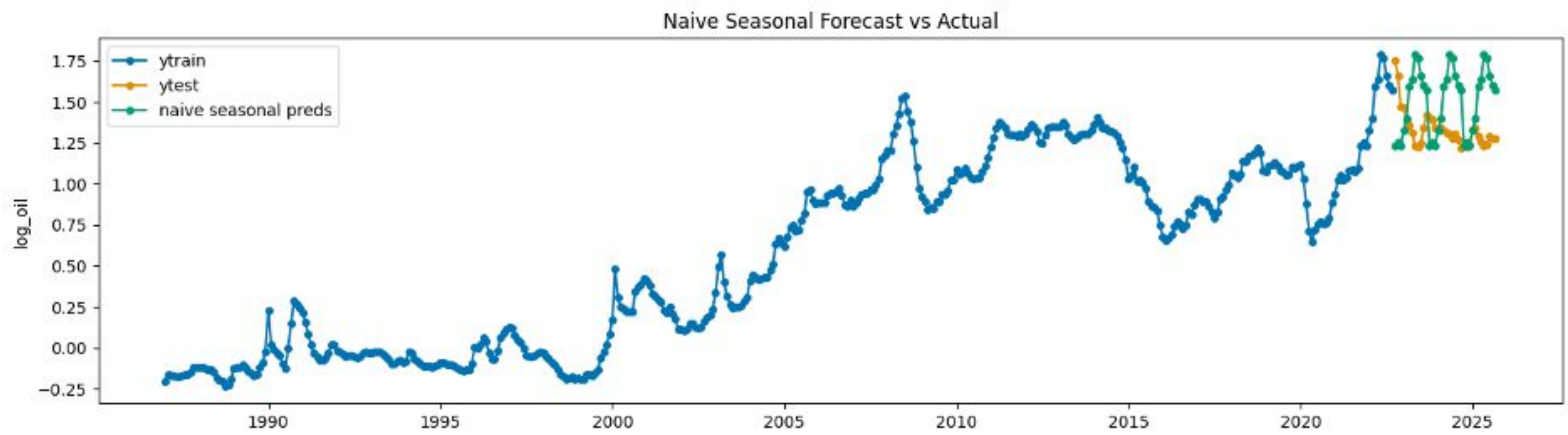

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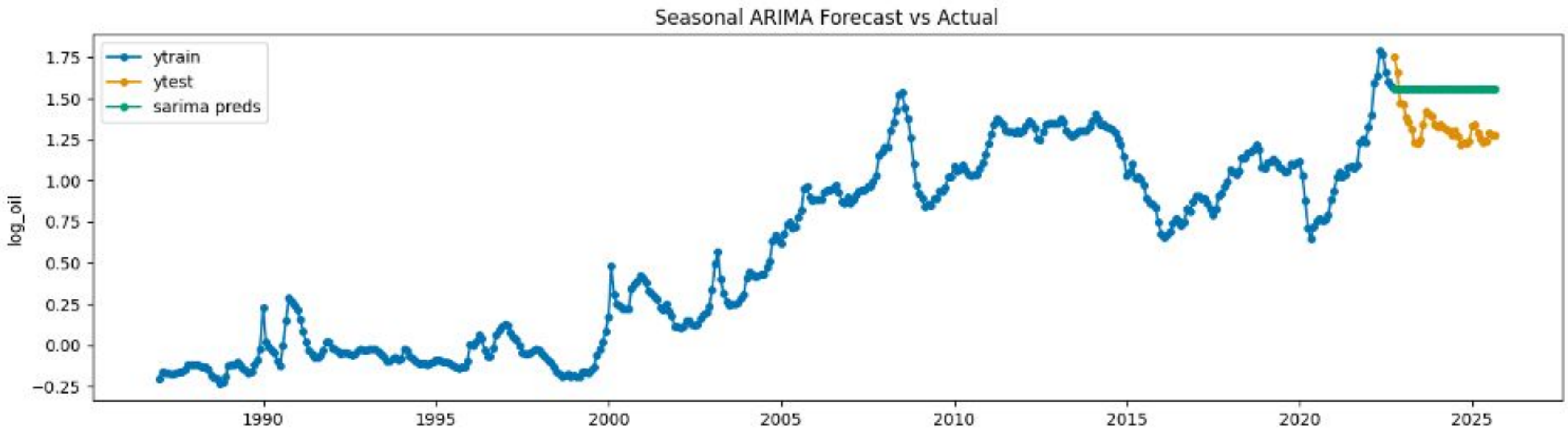

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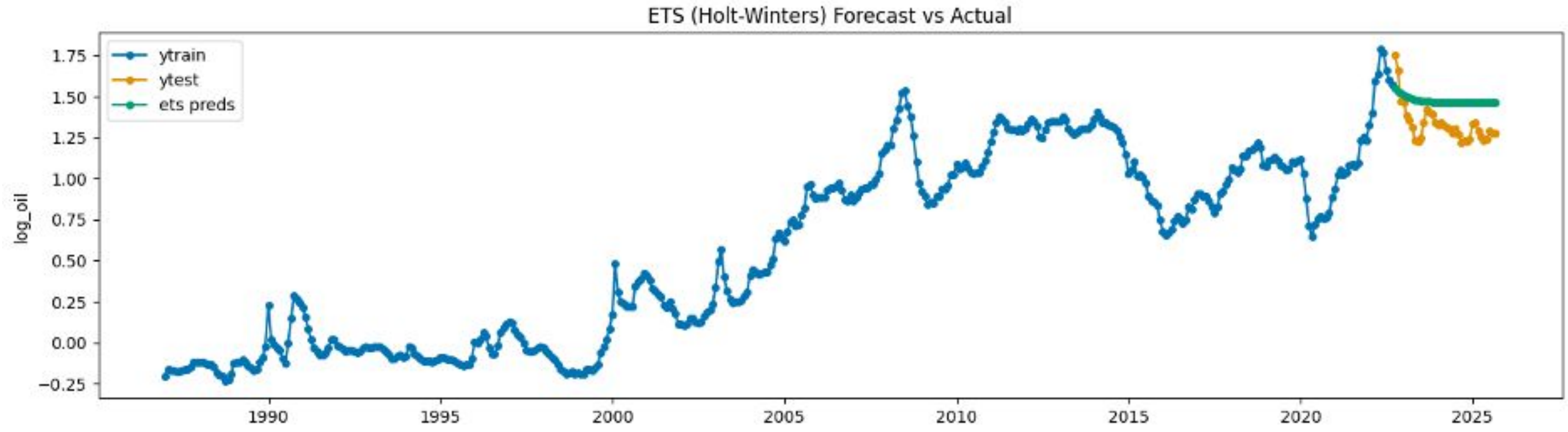

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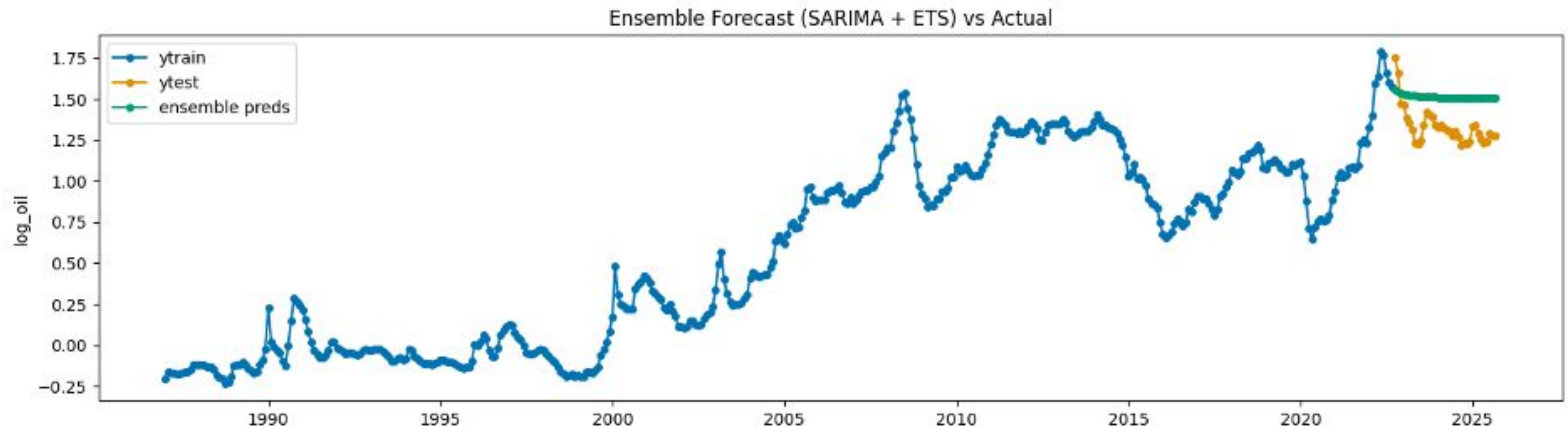

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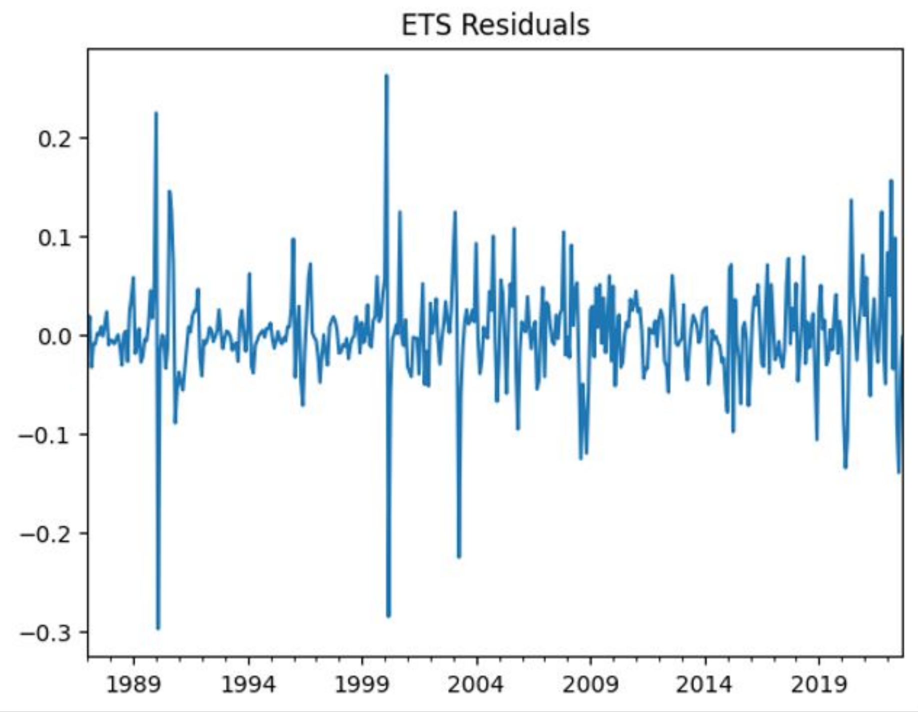
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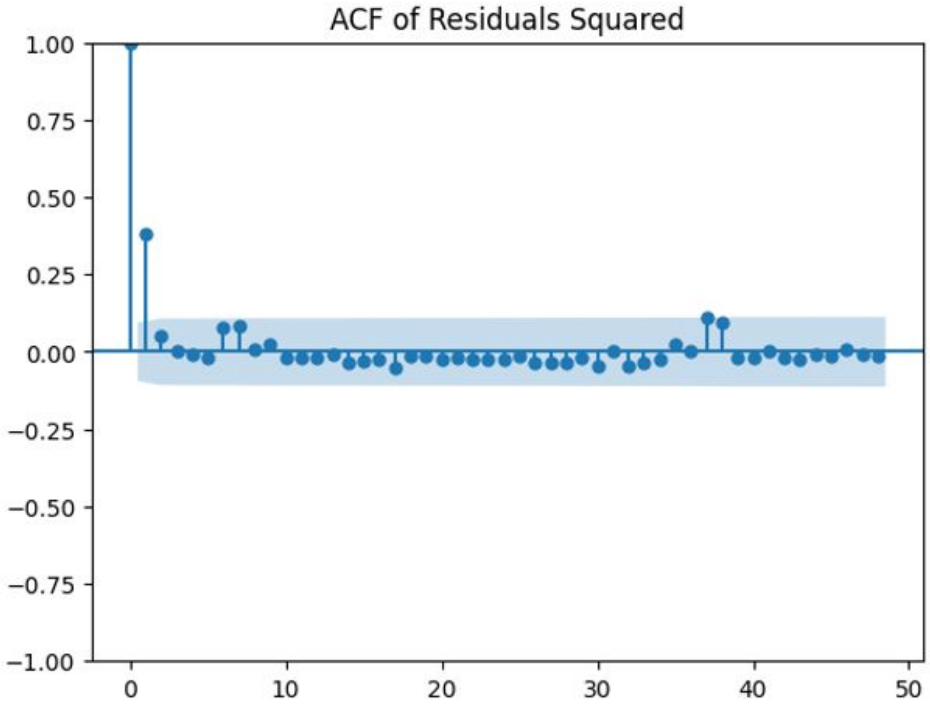
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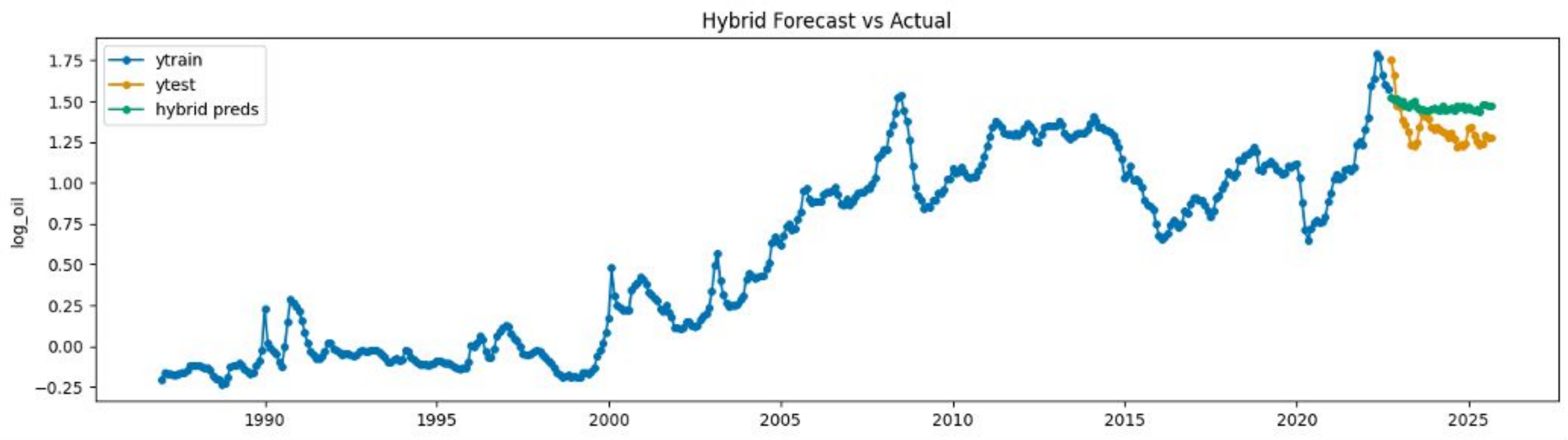

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