TIME SERIES MODEL: VAR VS ARIMA

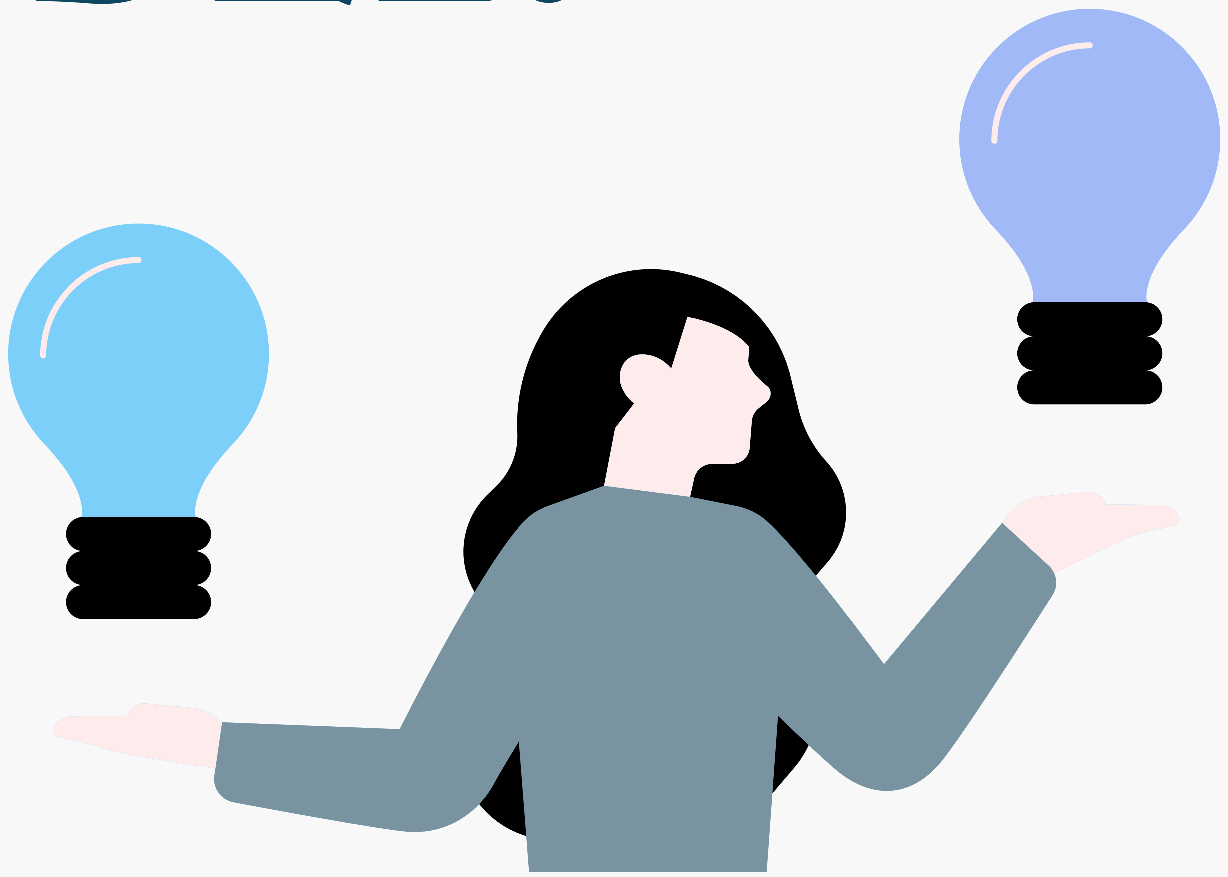

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Table of Contents

ARIMA(a univariate model)

Auto-Regressive Integrated Moving Average

- **AR: Autoregression.** A regression model that uses dependence relationship between an observation and a number of lagged observations.
- **I: Integration**. Calculating the differences between observations at different time points, **aiming to make the time series stationary**.
- **MA: Moving Average.** This approach considers the dependence that may exist between observations and the error terms created when a moving average model is used on observations that have a time lag.

Stationarity

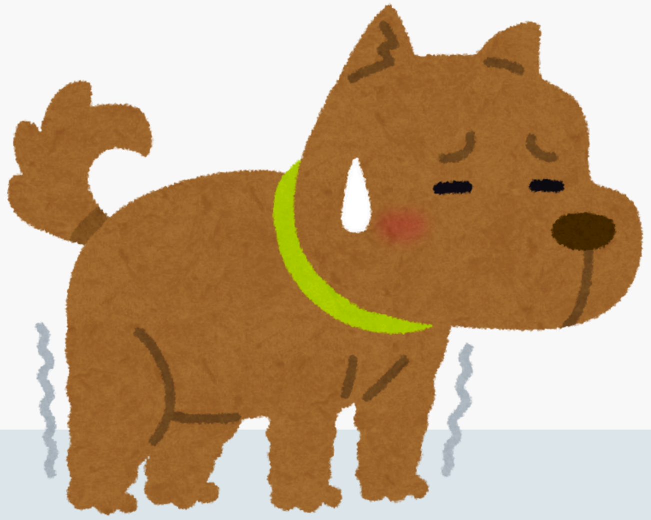
Stationary is essential for ARIMA to predict which includes:

- Mean value is constant
- Variance is constant
- Autocovariance depends on lag

Strengths

- The models are very **flexible**, successfully modeling an astonishing variety of irregular or quasi-periodic, smooth or choppy, constant or variable mean light curves
- **The dimensionality of the model is relatively low** with a moderate computational burden of the numerical optimization.
- **Error analysis** on the parameters naturally emerges through the **likelihood regression analysis.**
- They are **extensible to situations involving multivariate time series**, combinations of stochastic and deterministic behaviors, change points, and (moderately) irregular observation spacing

Weaknesses



- It is hard to model the nonlinear relationships between variables
- There is a constant standard deviation in errors in ARIMA model, which in practice it may not be satisfied

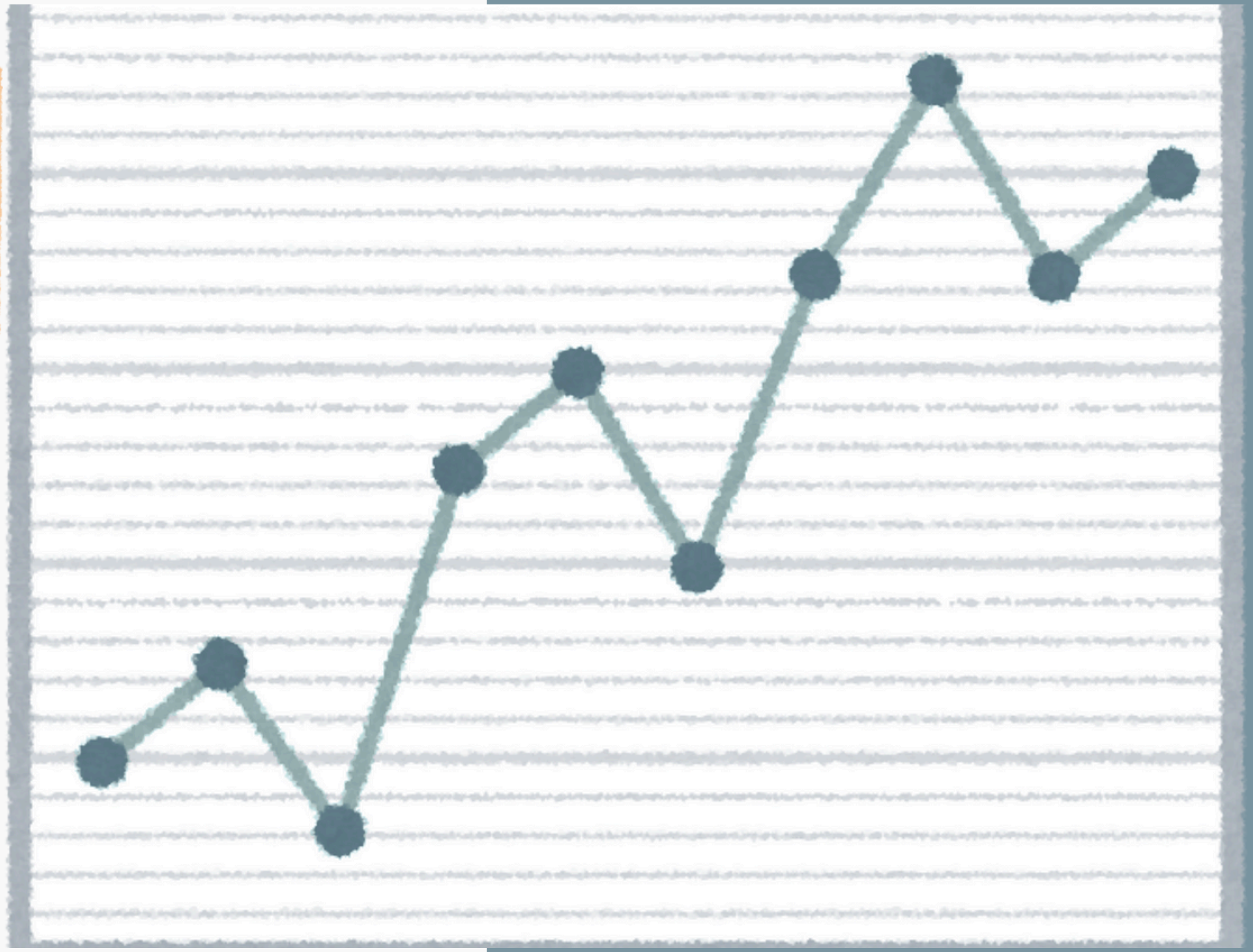
VAR (a multivariate model)

Vector Autoregression

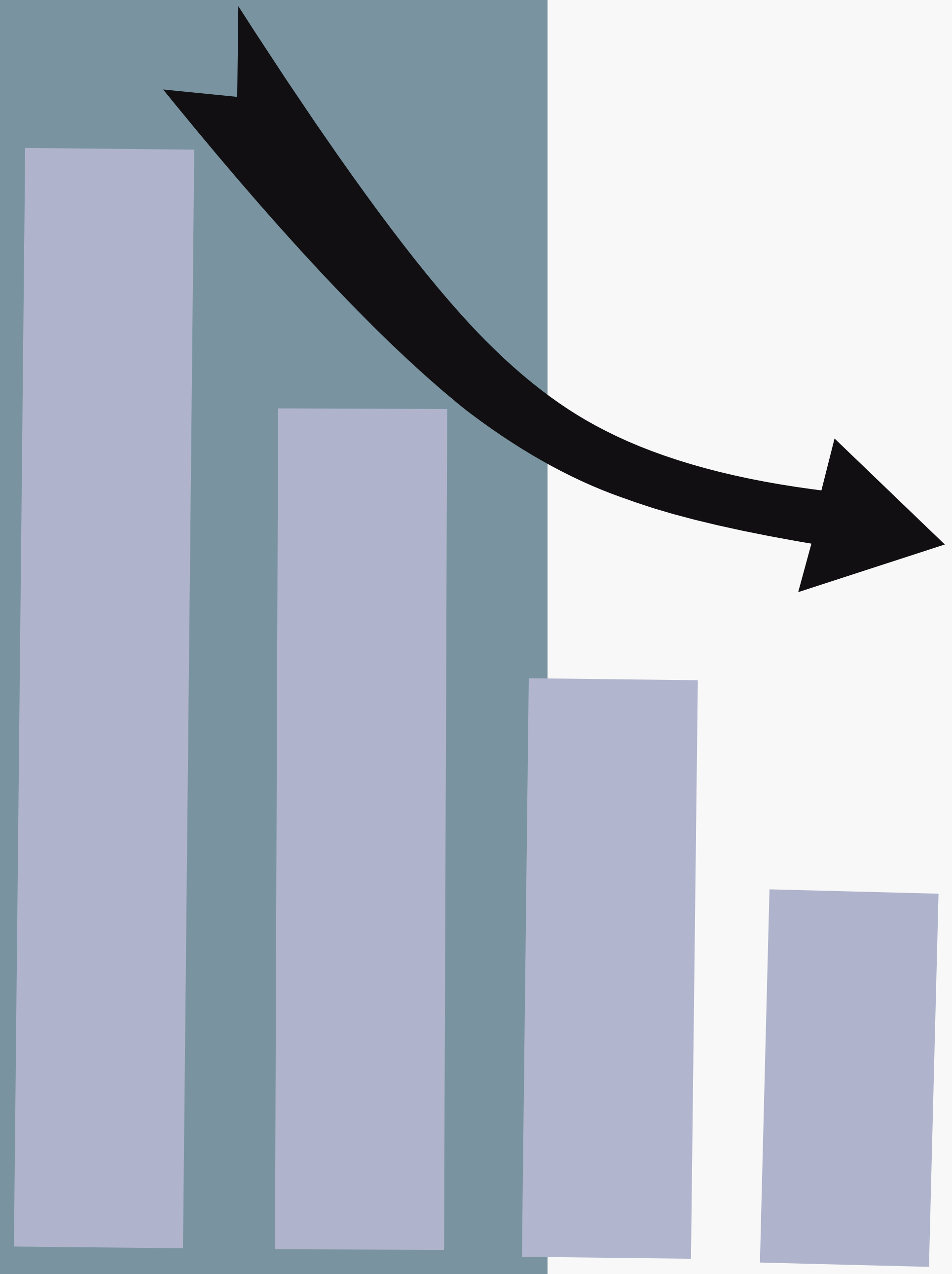
- **V: Vector.** The multivariate time series model involves two or more input variables, and leverages the interrelationship among the different time series variables.
- **AR: Autoregression.** A regression model that uses the dependence relationship between an observation and a number of lagged observations.

Strengths

- A vector autoregression model offers a **systematic** yet **flexible** way of capturing **complicated real-world behavior.**
- VAR models can provide **better forecasting performance** compared to simpler models

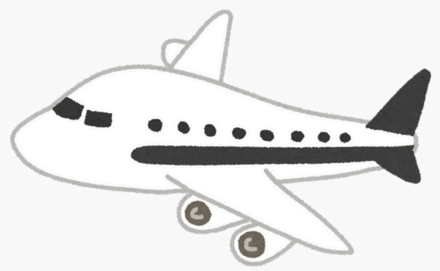


Weaknesses



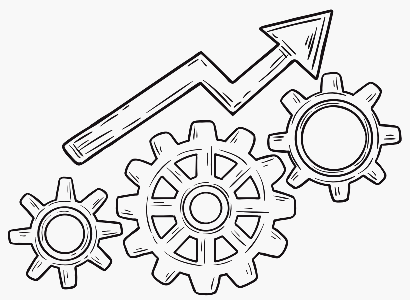
- VAR models require **a large amount of data** and it's important to carefully choose the number of lags for accurate forecasting.
- Because the **error terms across equations are related**, it's difficult to isolate the effect of a single shock or variable on the whole system
- VAR models are relatively flexible but still **require assumptions about stationarity and variable relationships.**

Application



Airplanes Forecast: In real-life airlines, ARIMA models can help airlines to make better decisions about their operations, such as scheduling flights, allocating resources, and adjusting prices

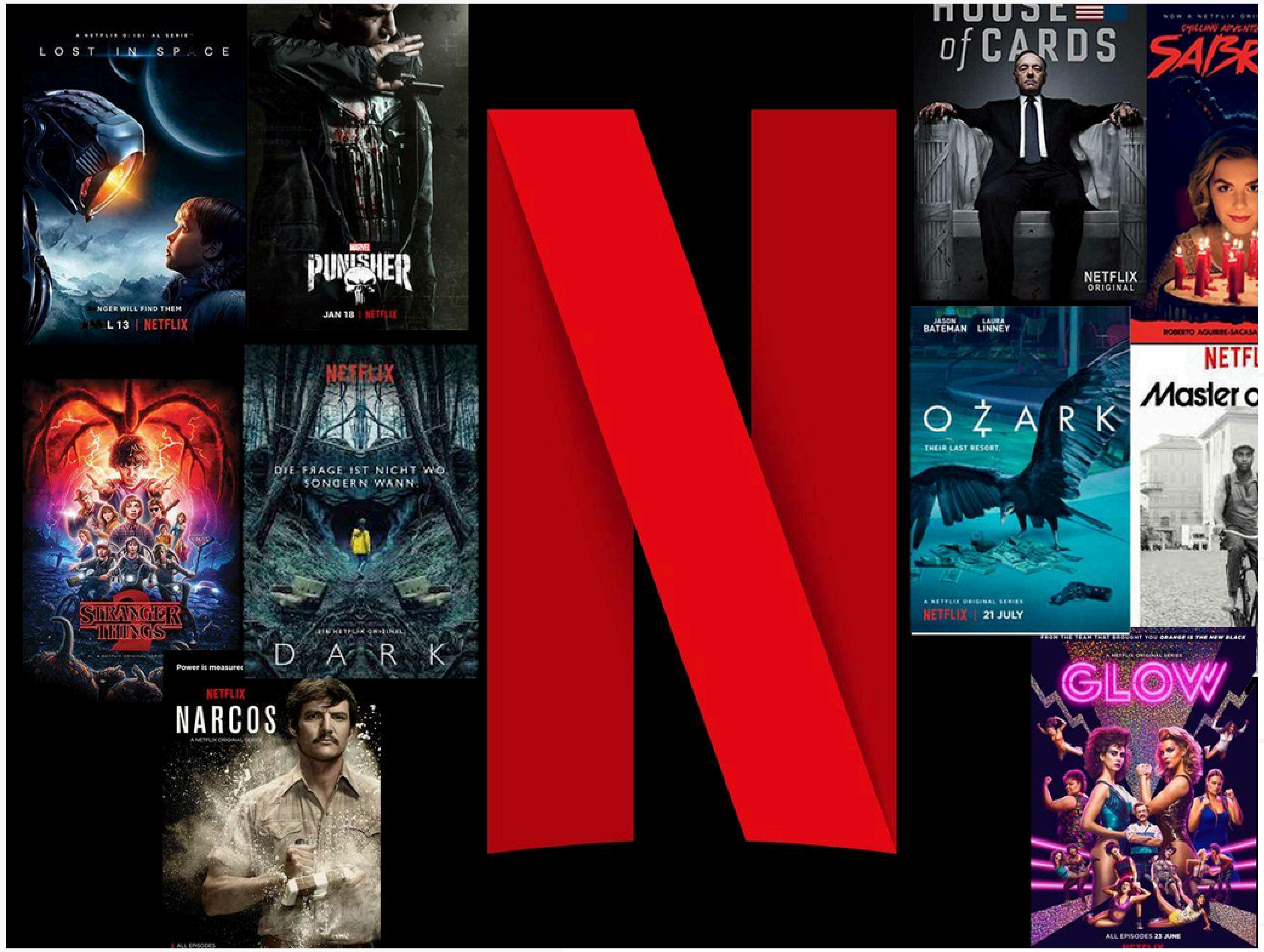
Stock Prices Prediction: VAR models estimate the relationships between different stocks, and ARIMA models can be used to predict the future values of a single stock



Engineering: These models can be used in a variety of real-life applications, such as predicting equipment failures, optimizing production processes, and forecasting demand for products

We are using Netflix's stock market dataset

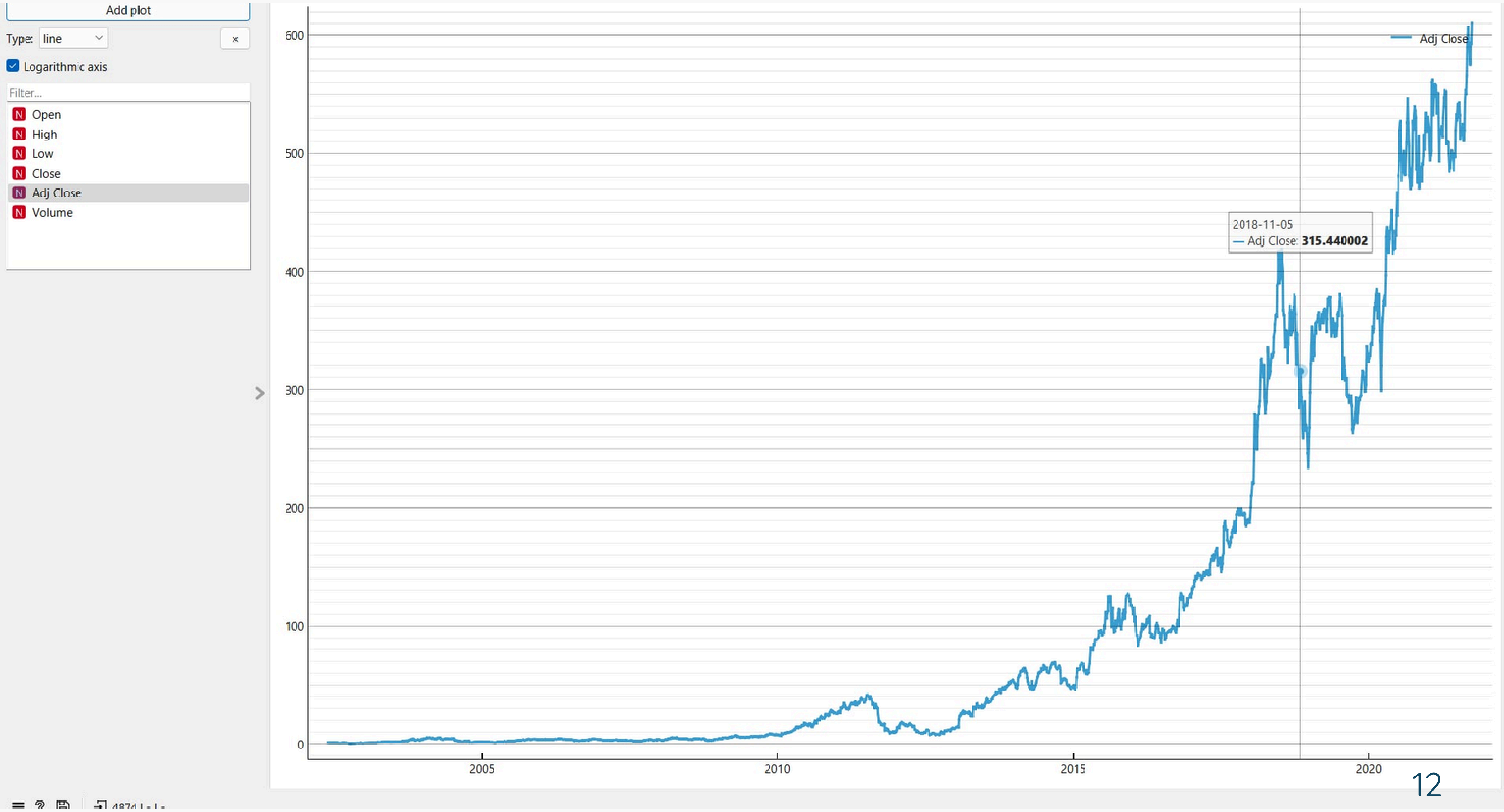
2002-2021



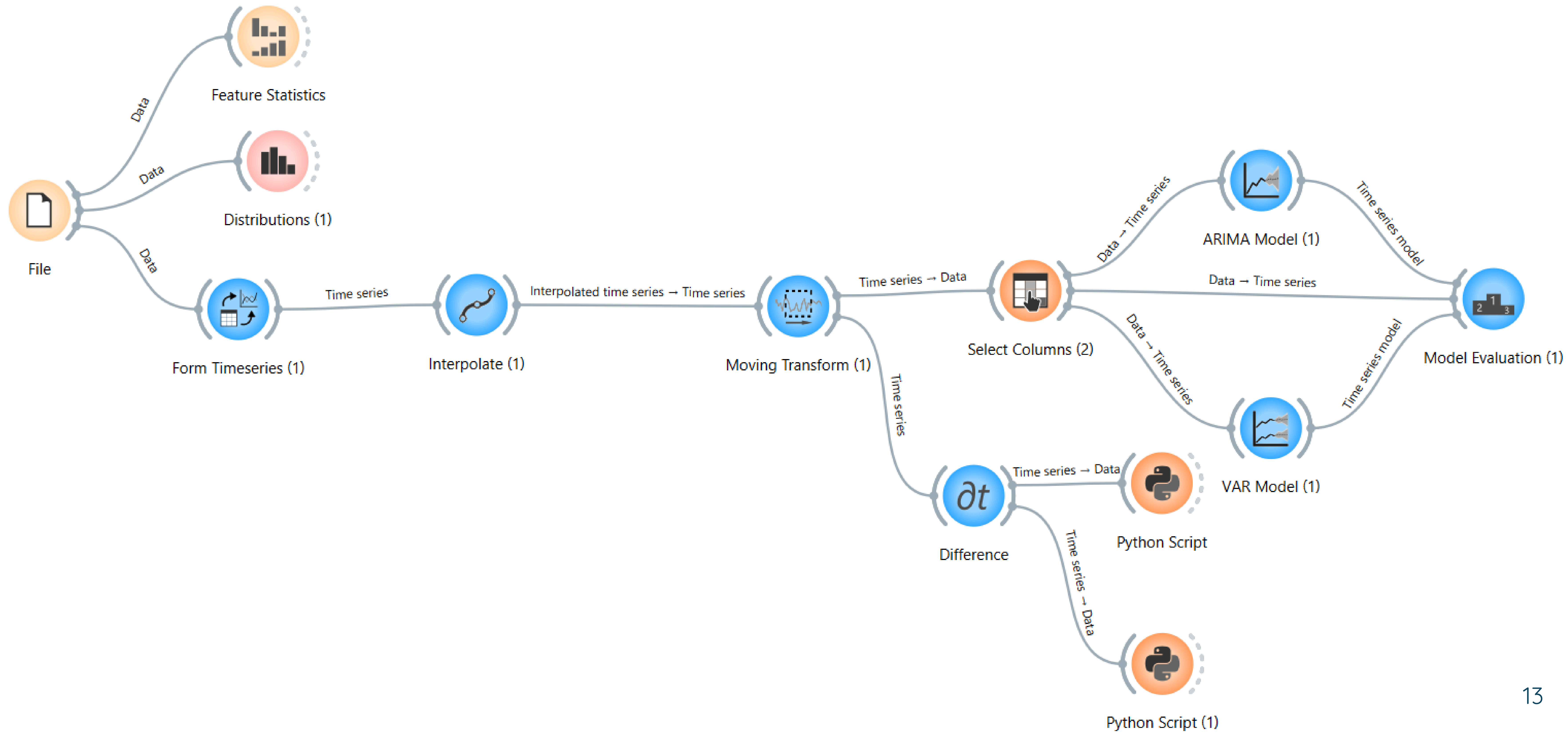
Research Object:

+To model and forecast Netflix stock price using an ARIMA and Var model on adjusted closing prices.

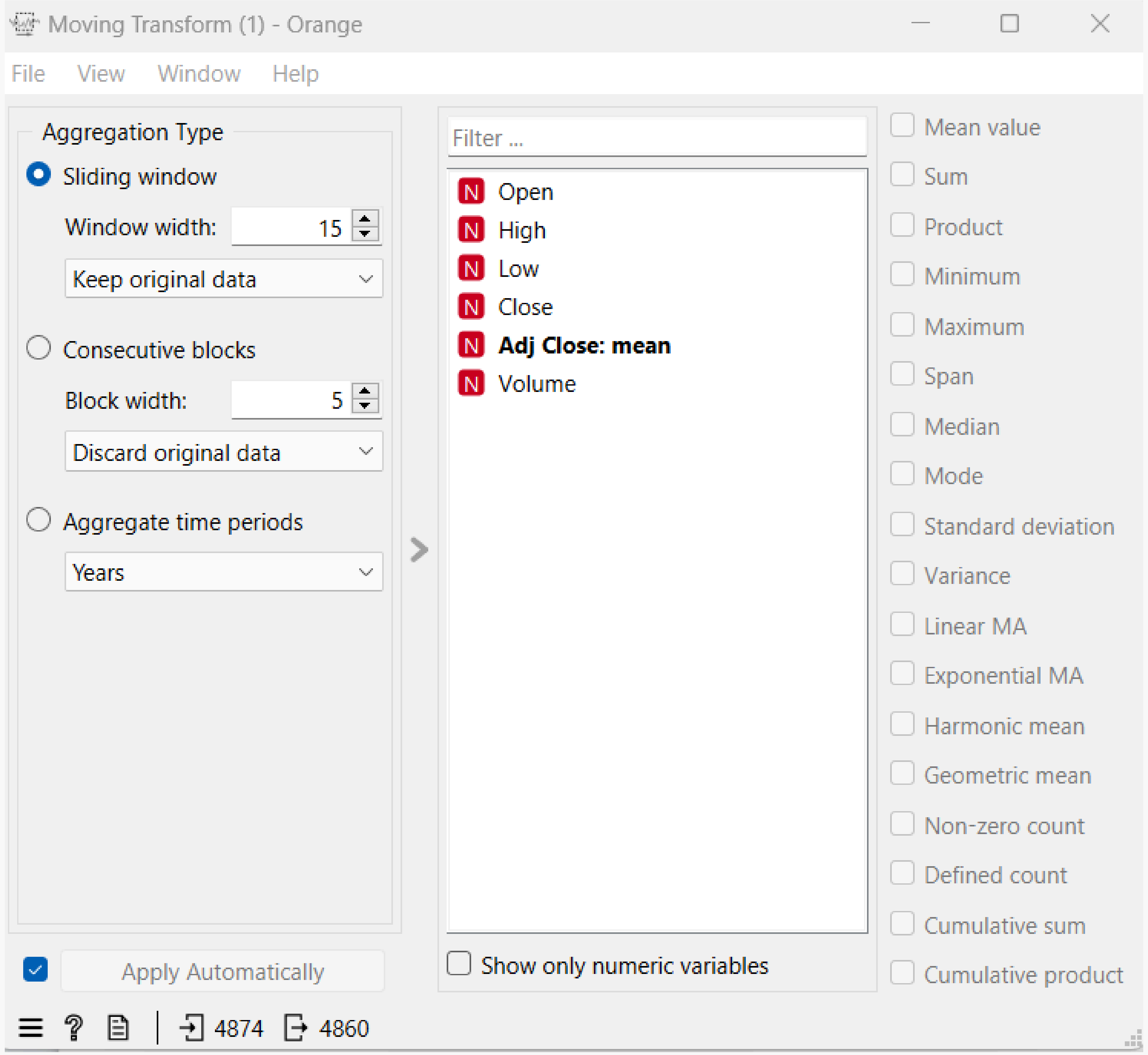
+ Optimize Arima Model.

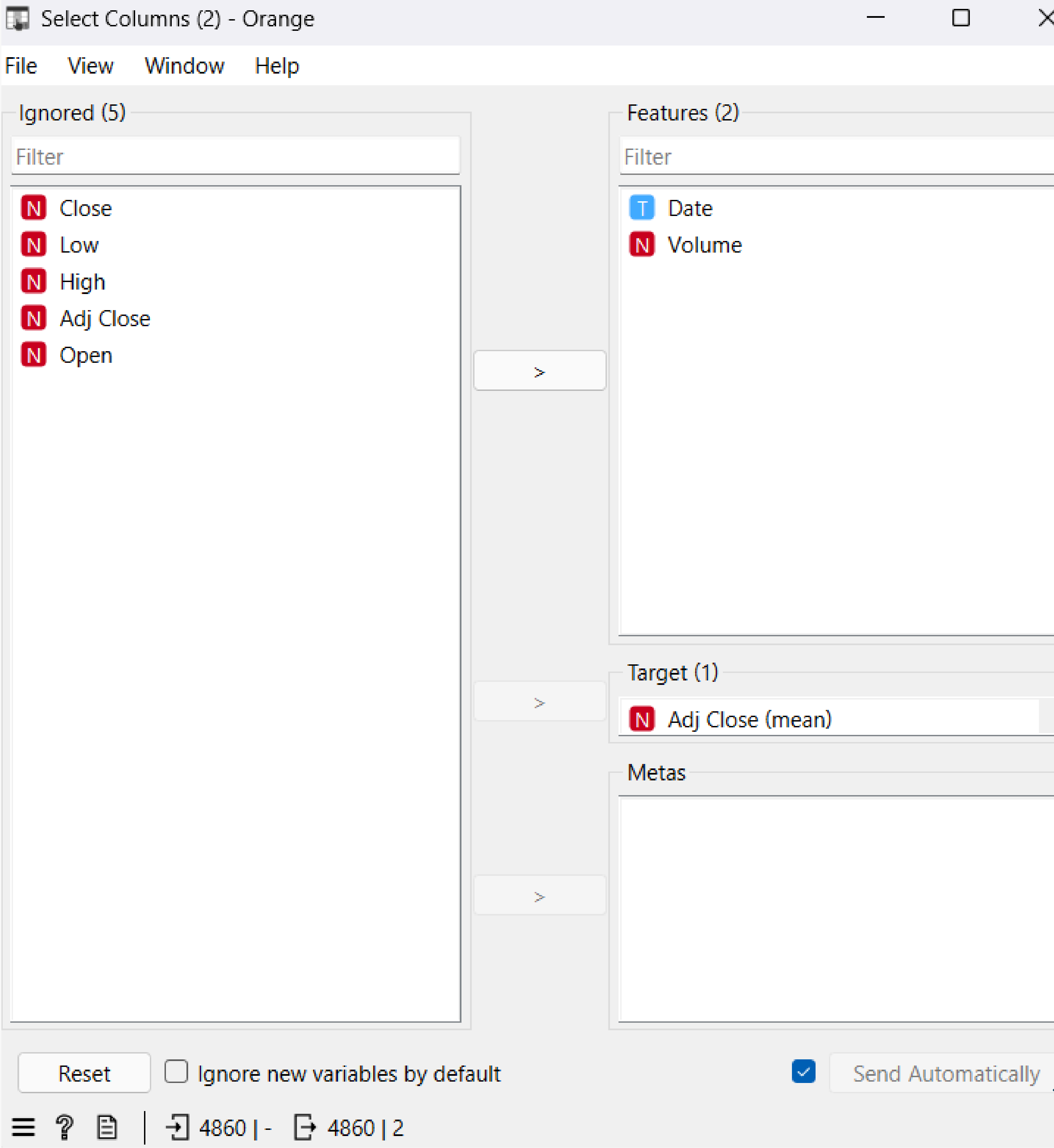


Orange workflow



Orange workflow





Model Evaluation (1) - Orange

View Window Help

Evaluation Parameters

Number of folds: 20

Forecast steps: 5

	RMSE	MAE	MAPE	POCID	$\hat{R}^2$	AIC	BIC
ARMA(1,0,0)	6.637	3.037	0.009	47.5	0.952	13382	13401
VAR(1,n)	6.188	3.277	0.009	65.7	0.958	55.4	55.4
ARMA(1,0,0) (in-sample)	1.823	0.094	0.005	89.7	1.000	13998	14018

View Window Help

Evaluation Parameters

Number of folds: 20

Forecast steps: 10

Apply

	RMSE	MAE	MAPE	POCID	$\hat{R}^2$	AIC	BIC
ARMA(1,0,0)	12.0	6.597	0.017	44.7	0.739	12682	12701
VAR(1,n)	11.6	6.147	0.016	58.8	0.755	55.3	55.3
ARMA(1,0,0) (in-sample)	1.823	0.094	0.005	89.7	1.000	13998	14018
VAR(1,n) (in-sample)	1.002	0.092	0.005	88.3	1.000	55.4	55.4

View Window Help

Evaluation Parameters

Number of folds: 20

Forecast steps: 15

Apply

	RMSE	MAE	MAPE	POCID	$\hat{R}^2$	AIC	BIC
VAR(1,n)	14.2	6.612	0.020	53.5	0.658	55.1	55.2
ARMA(1,0,0)	13.8	8.566	0.020	47.8	0.676	11807	11826
ARMA(1,0,0) (in-sample)	1.823	0.094	0.005	89.7	1.000	13998	14018
VAR(1,n) (in-sample)	1.002	0.092	0.005	88.3	1.000	55.4	55.4

We try to improve the result

- We set d= 1

$$\Delta X_t = X_t - X_{t-1}$$

where:

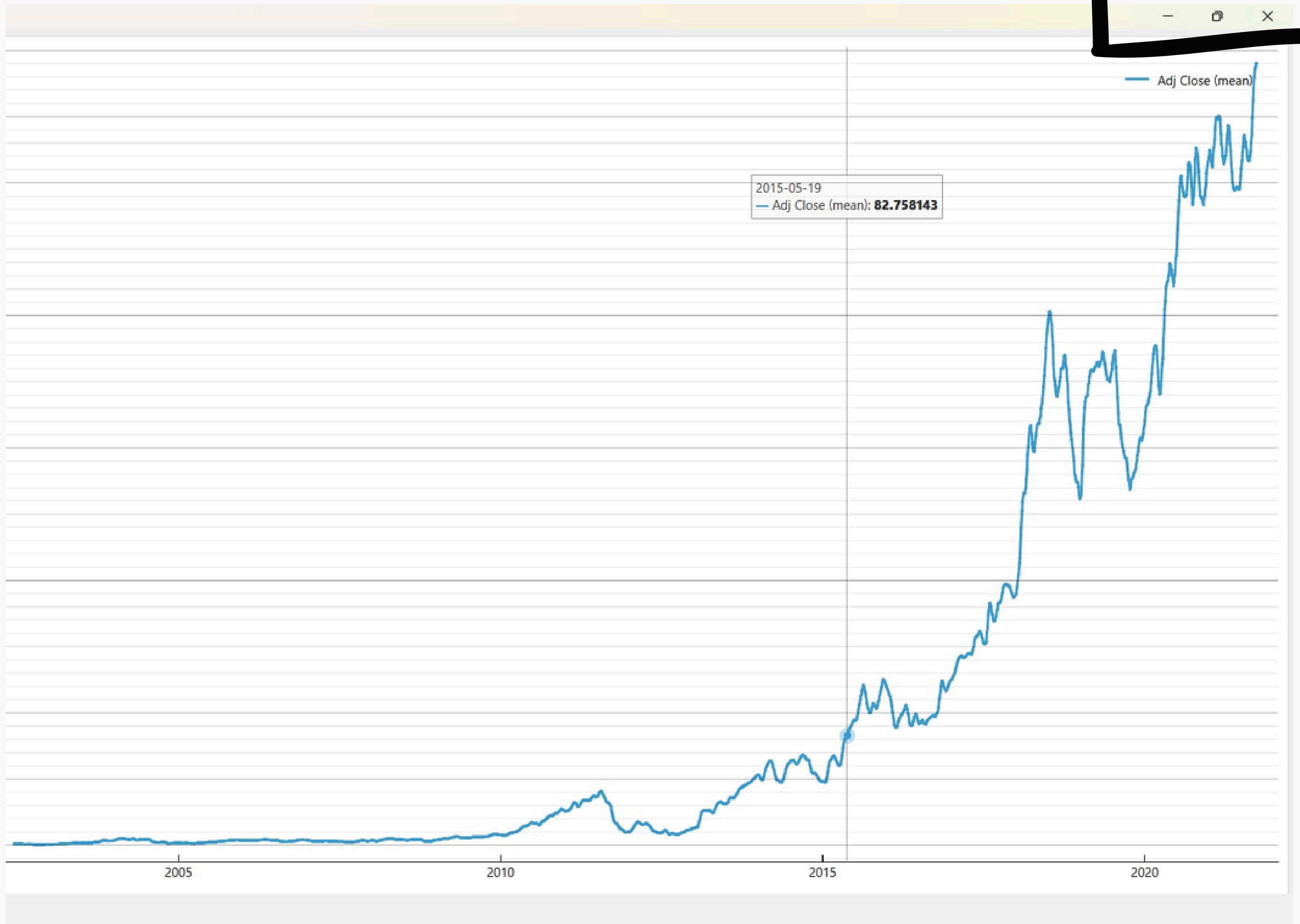
- ΔX_t is the differenced series,
- X_t is the value of the series at time t,
- X_{t-1} is the value of the series at time $t-1$.

Arima(1,0,0) **Arima(1,1,0)**

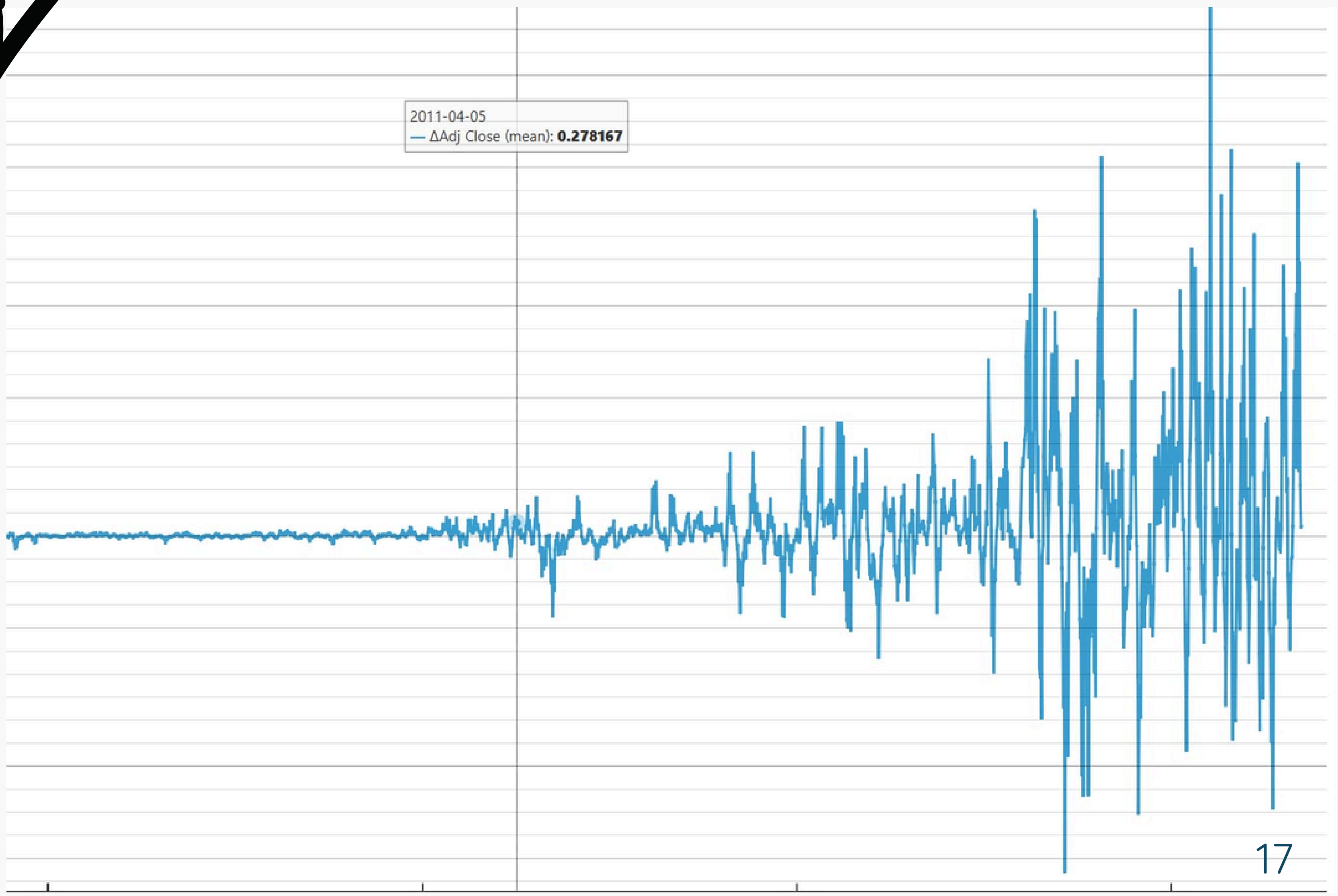
Stationary

We try to improve the result

Arima(1,0,0)



Arima(1,1,0)



Augmented Dickey-Fuller test (ADF test)

Result	Interpretation
p-value < 0.05	Reject H_0 ⇒ Series is stationary
p-value ≥ 0.05	Fail to reject H_0 ⇒ Series is non-stationary

Console

```
  File "C:\Users\lemin\AppData\Local\Programs\Orange\Lib\site-packa
    domain = tab.domain
             ^^^^^^^^^^
AttributeError: 'NoneType' object has no attribute 'domain'
>>>
Running script:
ADF Statistic: -9.589463872315827
p-value: 2.0545699889893552e-16
>>>
Running script:
```

The ADF test helps you decide:

Null hypothesis (H_0): The series has a unit root (i.e., non-stationary)

Alternative hypothesis (H_1): The series is stationary

Conclusion from new model

After performing model optimization and comparing evaluation metrics, ARIMA(1,1,0) outperformed the VAR(1,n) model. Specifically, ARIMA demonstrated a higher R^2 (indicating better explanatory power) and a lower RMSE (indicating better prediction accuracy).

rameters
ds: 20
5

	RMSE	MAE	MAPE	POCID	$\hat{R}^2$
VAR(1,n)	6.188	3.277	0.009	65.7	0.958
ARIMA(1,1,0)	3.377	1.542	0.004	83.8	0.988
VAR(1,n) (in-sample)	1.002	0.092	0.005	88.3	1.000

arameters
ds: 20
: 10

	RMSE	MAE	MAPE	POCID	$\hat{R}^2$
VAR(1,n)	11.6	6.147	0.016	58.8	0.755
ARIMA(1,1,0)	7.849	4.192	0.011	68.3	0.888
VAR(1,n) (in-sample)	1.002	0.092	0.005	88.3	1.000

Conclusion

- **Strengths & Weaknesses:**
  - **ARIMA**: Effective for stationary data with strong autocorrelations but struggles with complex relationships among multiple variables.
  - **VAR**: Handles multiple time series with interdependencies but requires a larger dataset and assumes variable stationarity.

- **Choosing ARIMA vs. VAR:**
  - ARIMA when analyzing a single time series with clear patterns.
  - VAR when multiple time series influence one another and relationships need to be modeled.

References

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Thank you