Ask the Expert

Tips and Tricks: Improve Forecast Accuracy Using Interactive Modeling in SAS® Visual Forecasting

Beth Ebersole, Principal Analytical Consultant

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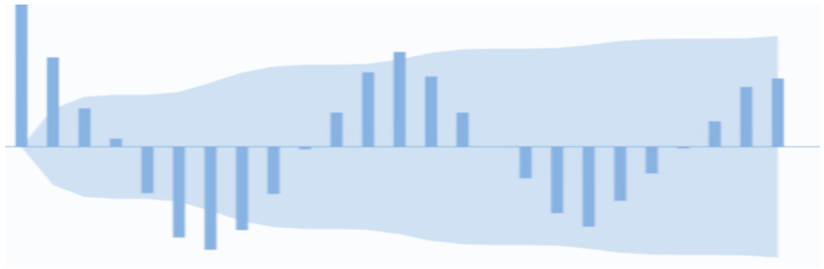
Beth Ebersole has 30 years of experience in analytics and estuarine science. She earned her master's degree in biostatistics at Johns Hopkins University. Ebersole develops enablement materials and conducts trainings on forecasting, machine learning, analytics, and AI trainings.

Ask the Expert

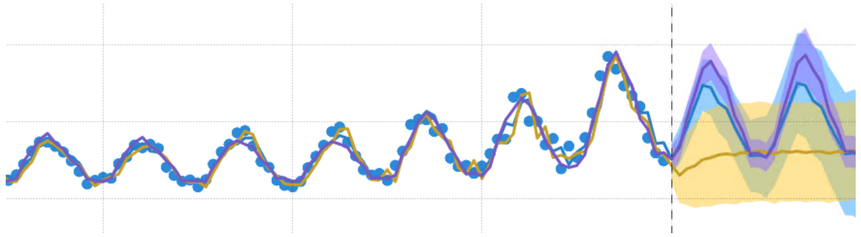
Visual Forecasting Interactive Node

Beth Ebersole, Principal Analytics Consultant

Overview: Interactive Modeling Node



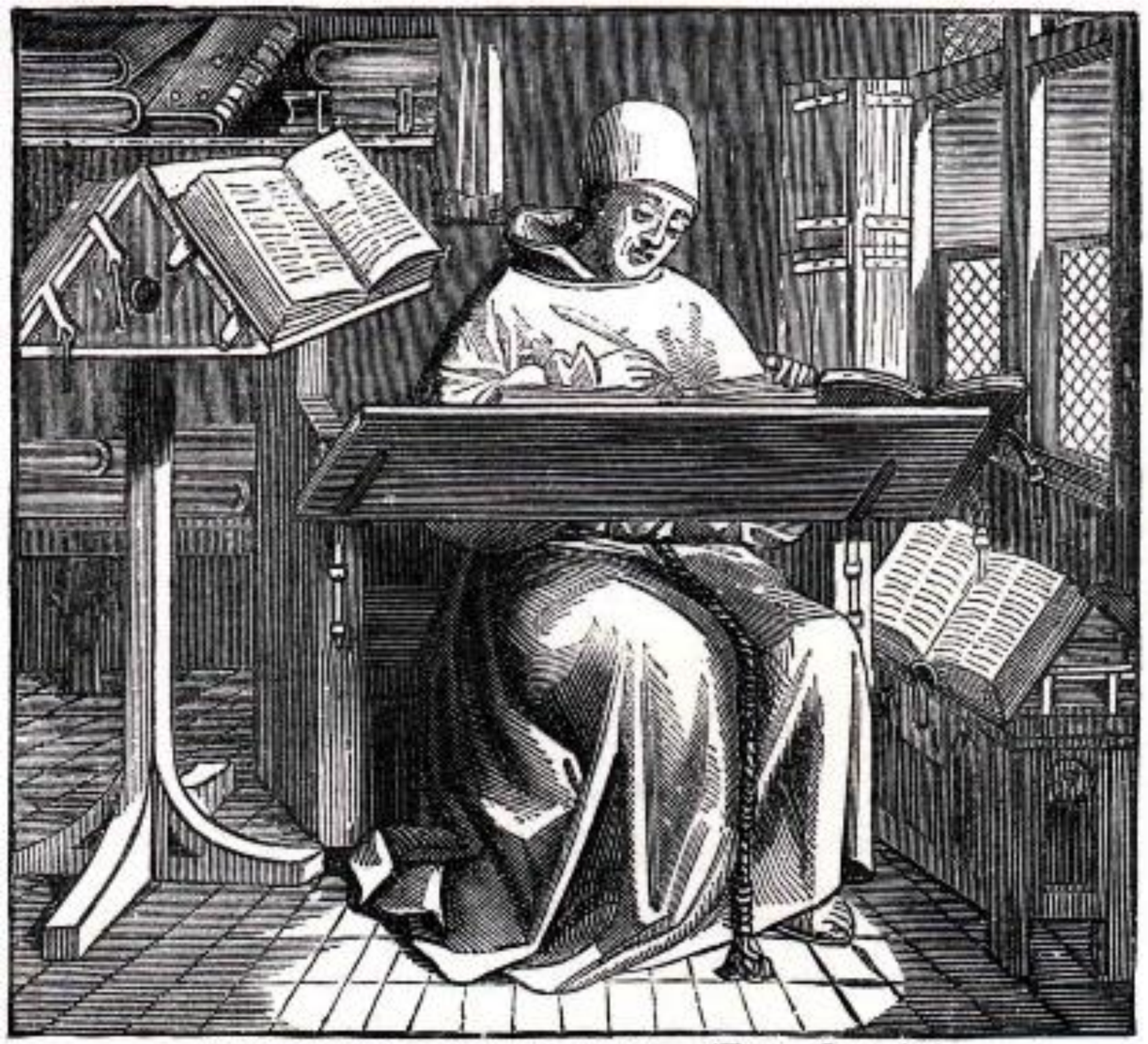
ARIMA: Sqrt(Y) ~ P = ((1)(1)s) D = (1) Q = ((1)(1)s) NOINT + INPUT1: Dif(1) CrudeOilProduction + INPUT2: Dif(1) CrudeOilImports



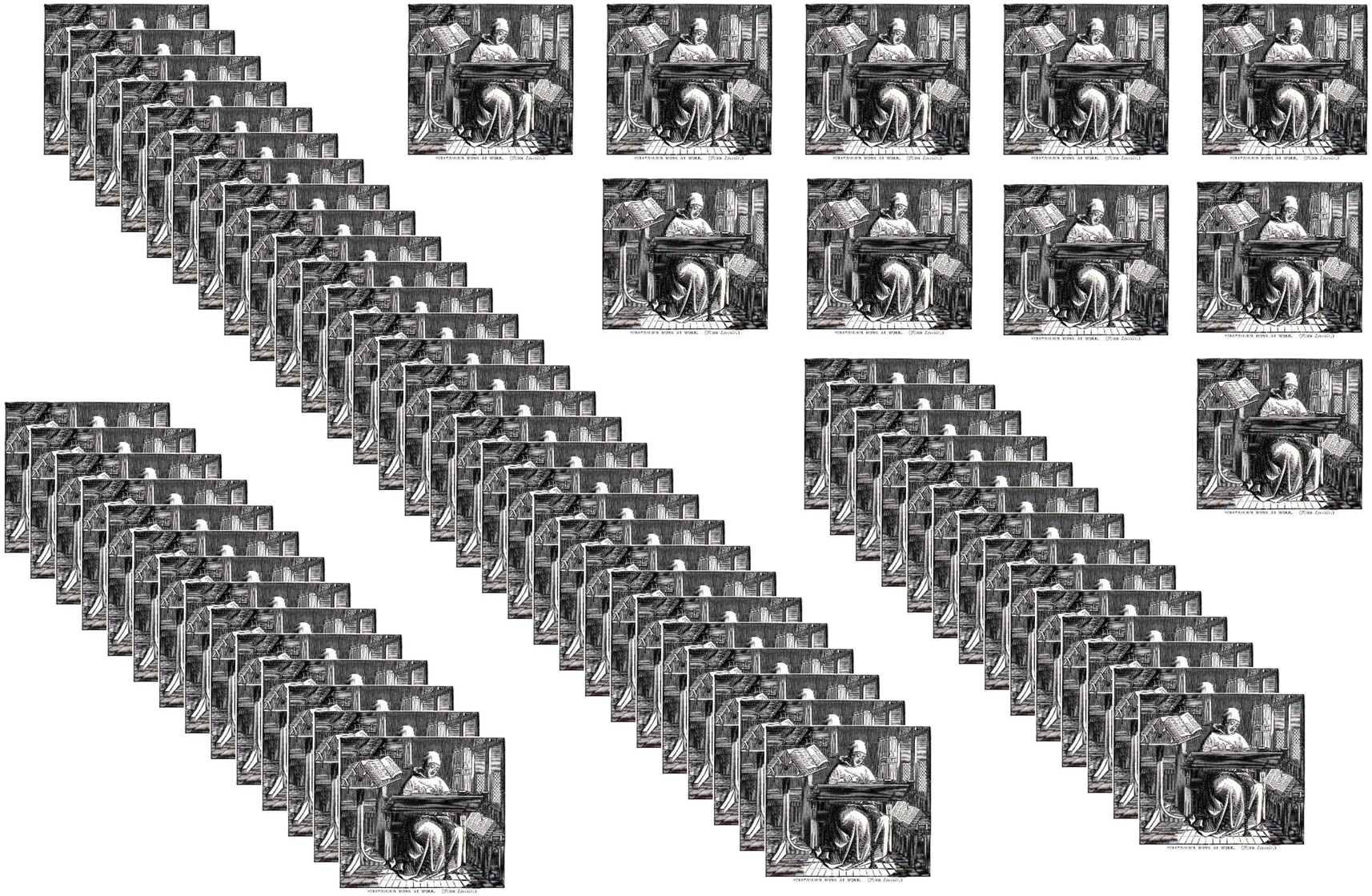
Model	Details
Beth_sqrt_ARIMAX1_1	ARIMA: Sqrt(Y) ~ P = ((1)(1)...
PREDECESSOR	Forecasts from Auto-forecas...

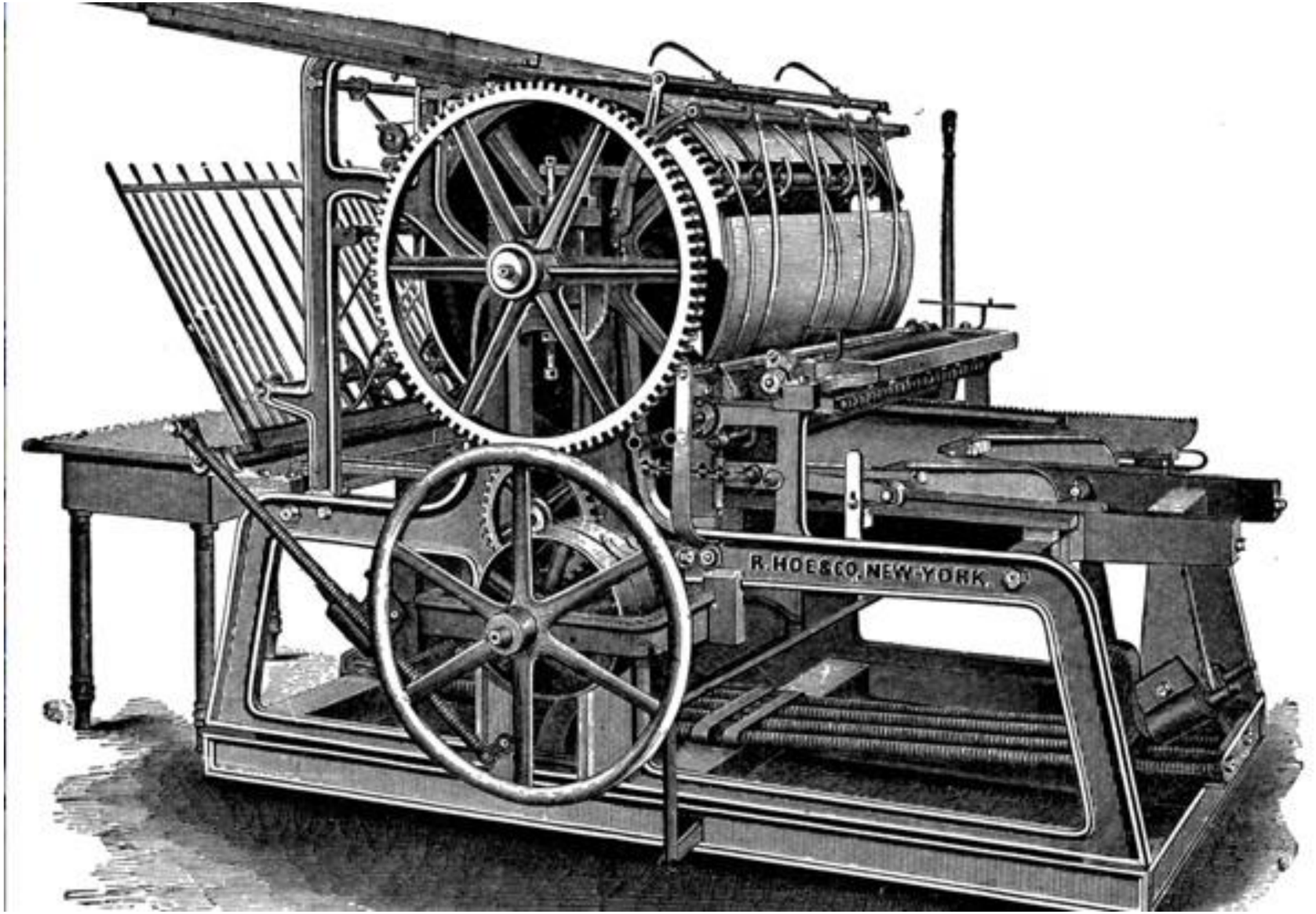
- Explore diagnostic plots
- Create your own models
- Visually compare multiple models
- Manually set a champion model

Automation

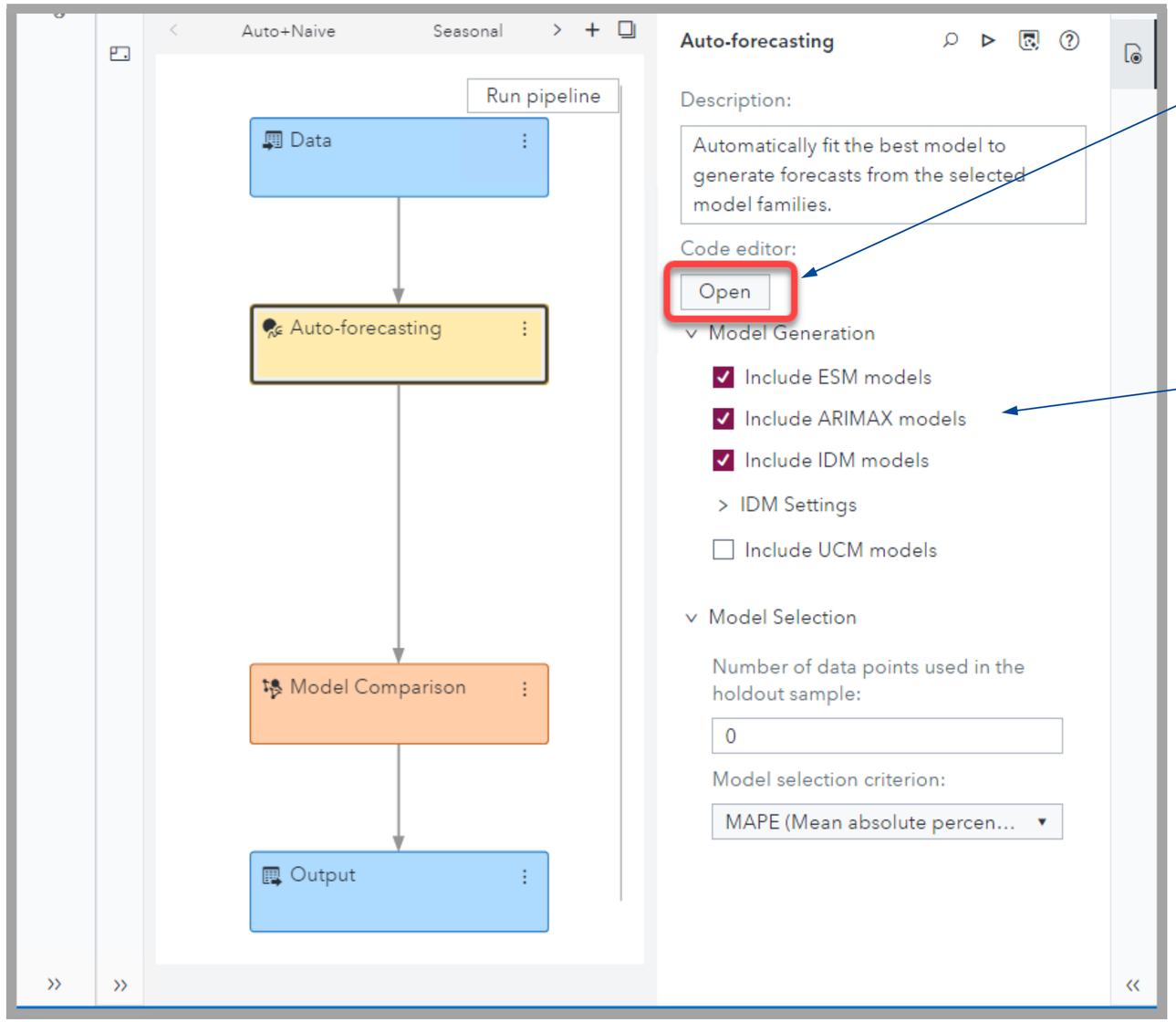


SCRIPTORIUM MONK AT WORK. (From *Lacroix.*)





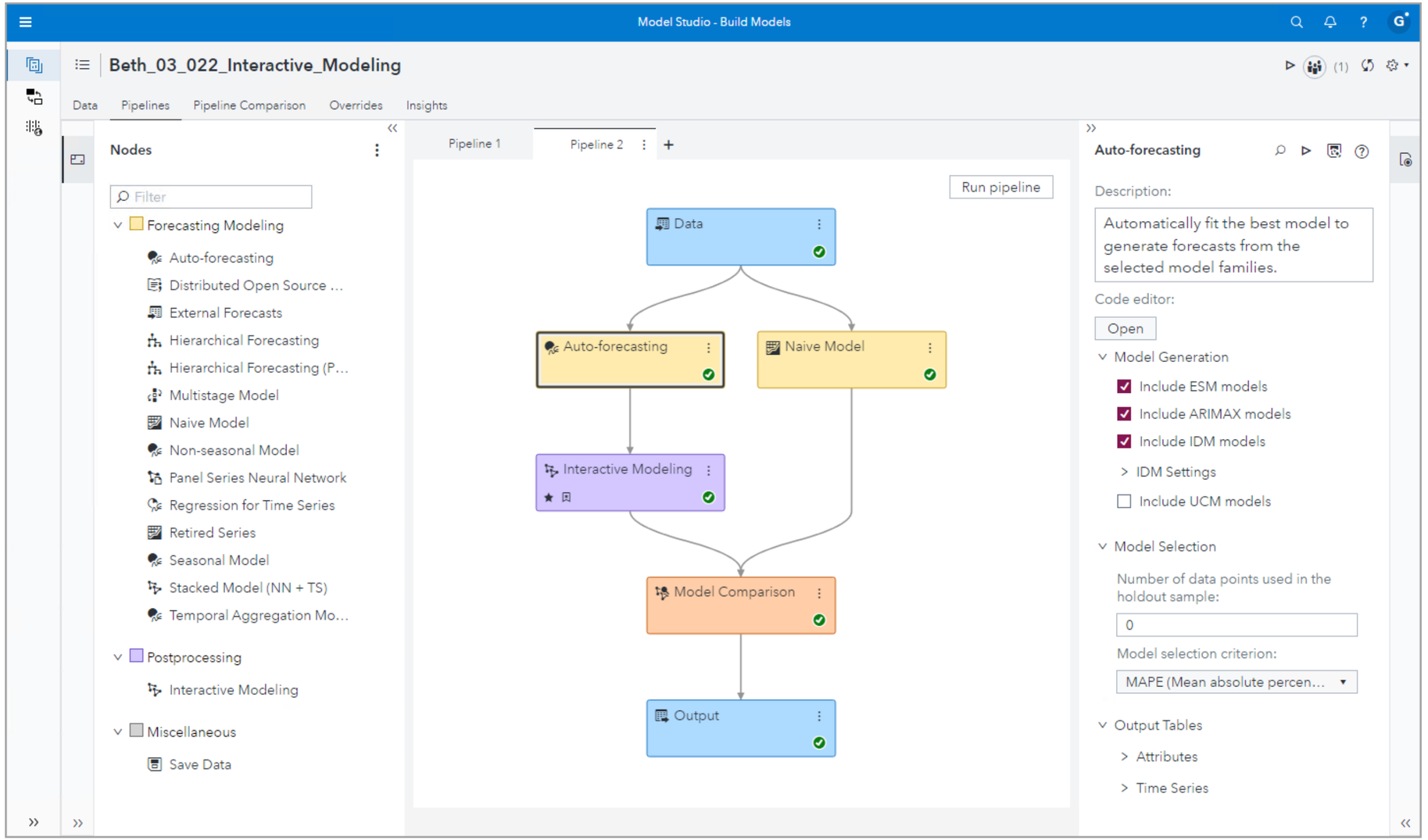
Automatic Forecasting



Open code editor to view code

By default Auto-forecasting node generates ESM, ARIMAX, and IDM models

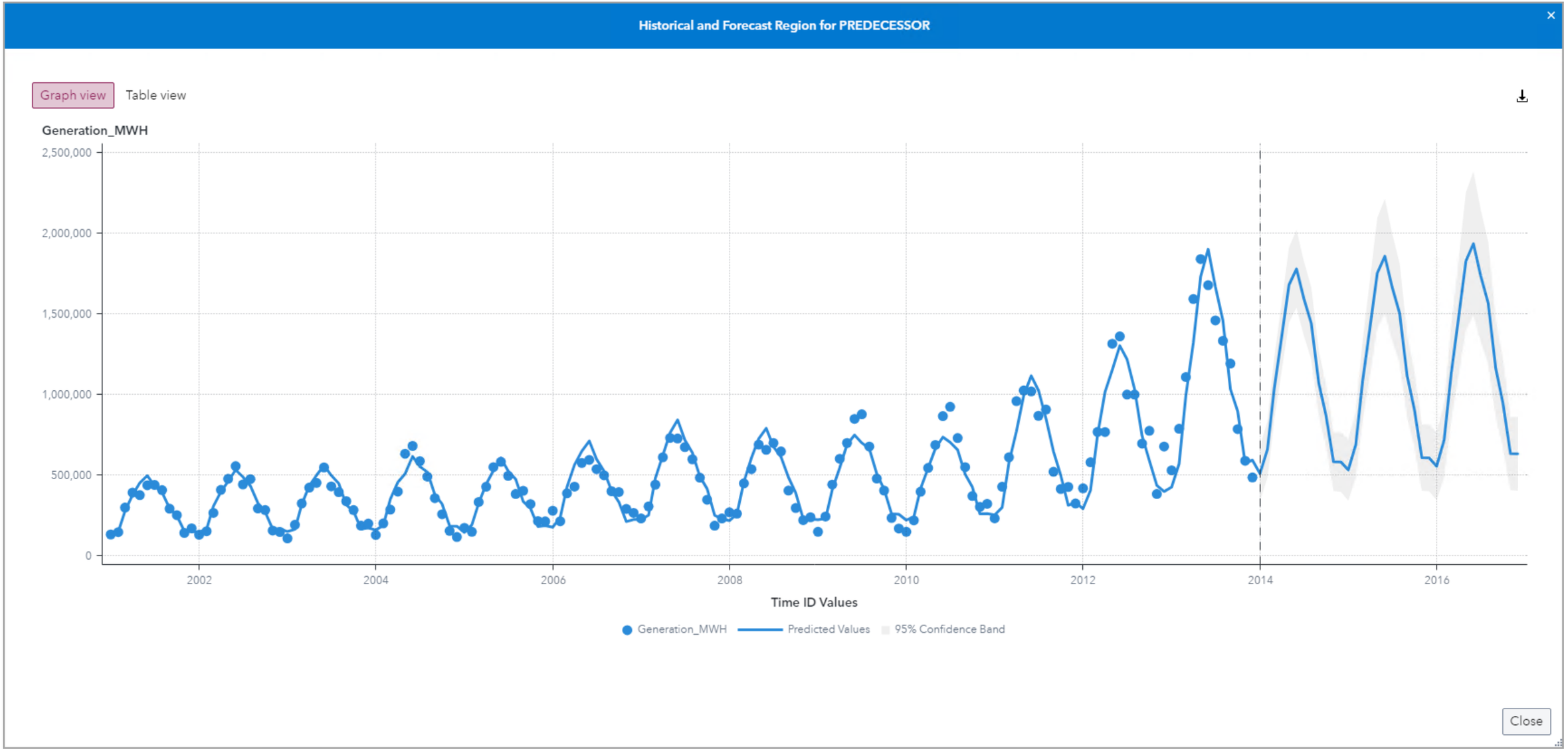
Visual Forecasting: Automation



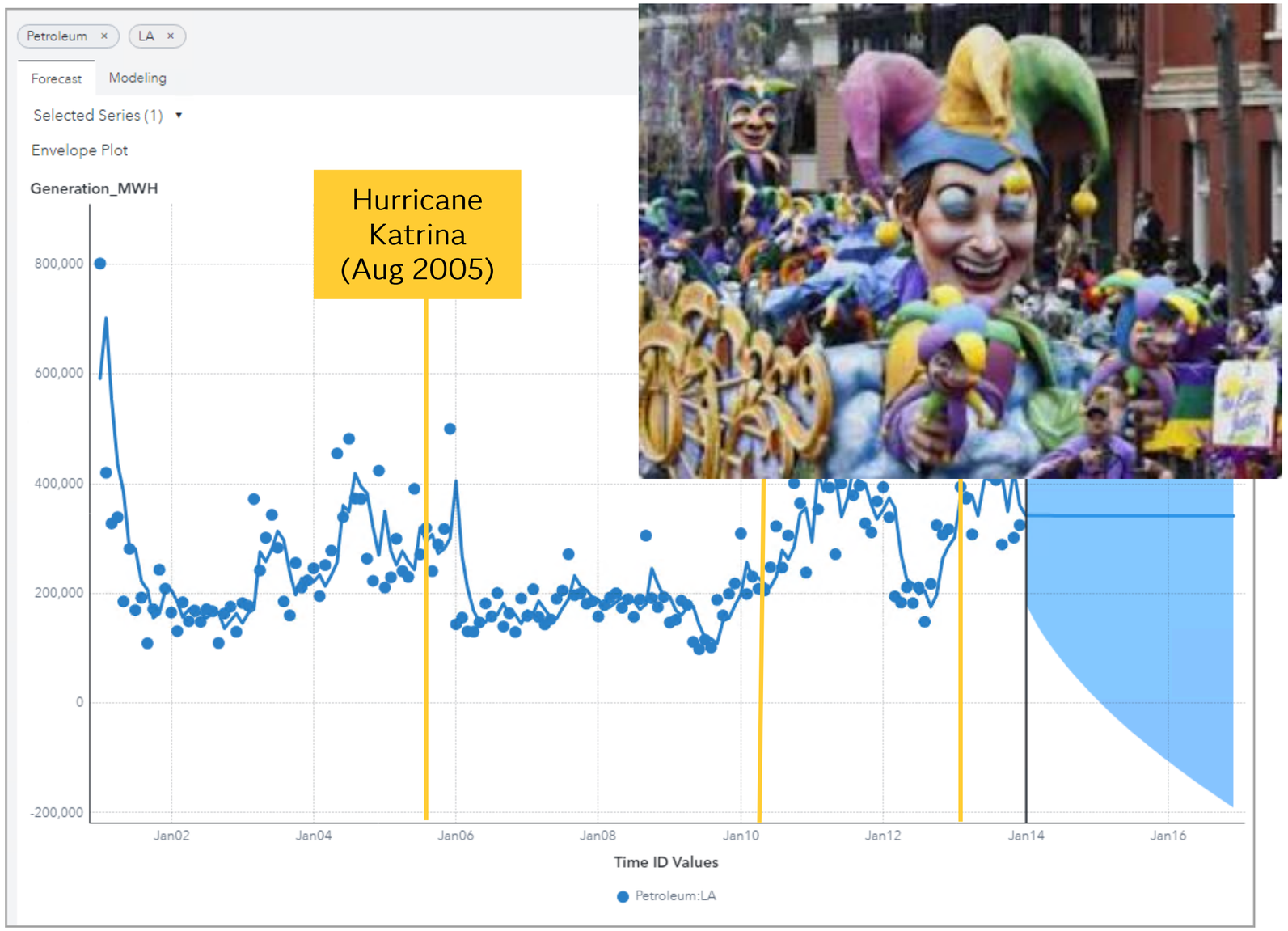
How Visual Forecasting Works

1. Diagnoses the time series using time series analysis techniques.
2. Creates a list of candidate model specifications based on the diagnostics.
3. Fits each candidate model specification to the time series.
4. Generates forecasts for each candidate fitted model.
5. Selects the most appropriate model specification based on either in-sample or holdout sample evaluation using a model selection criterion.
6. Refits the selected model specification to the entire historical range of the time series.
7. Generates forecasts from the fitted model.
8. Evaluates the forecast using in-sample analysis and provides for out-of-sample analysis of forecast performance.

Many excellent forecasts

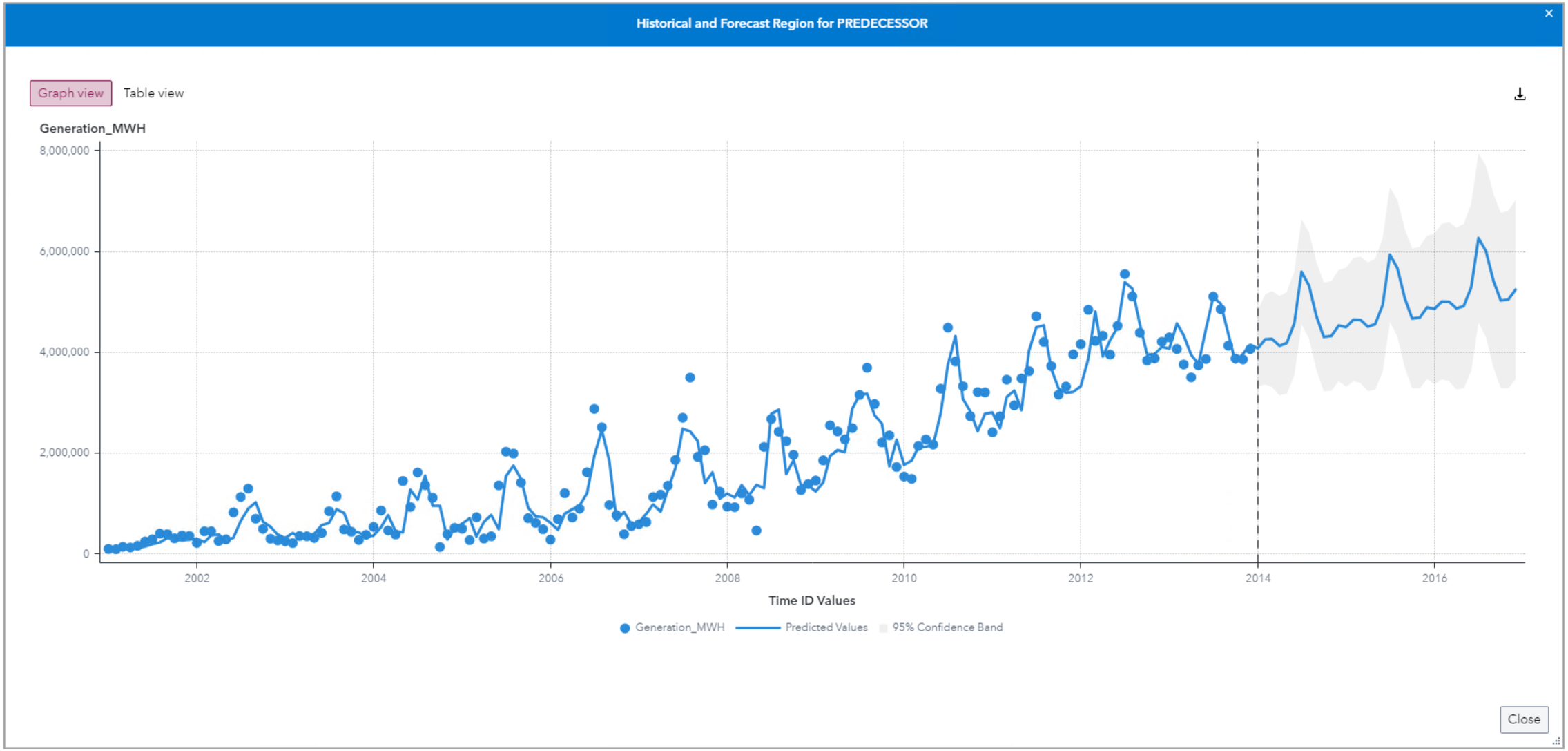


Some require an expert to review



Some may need truncating

Some may need modeling tweaks



Natural Gas × PA ×

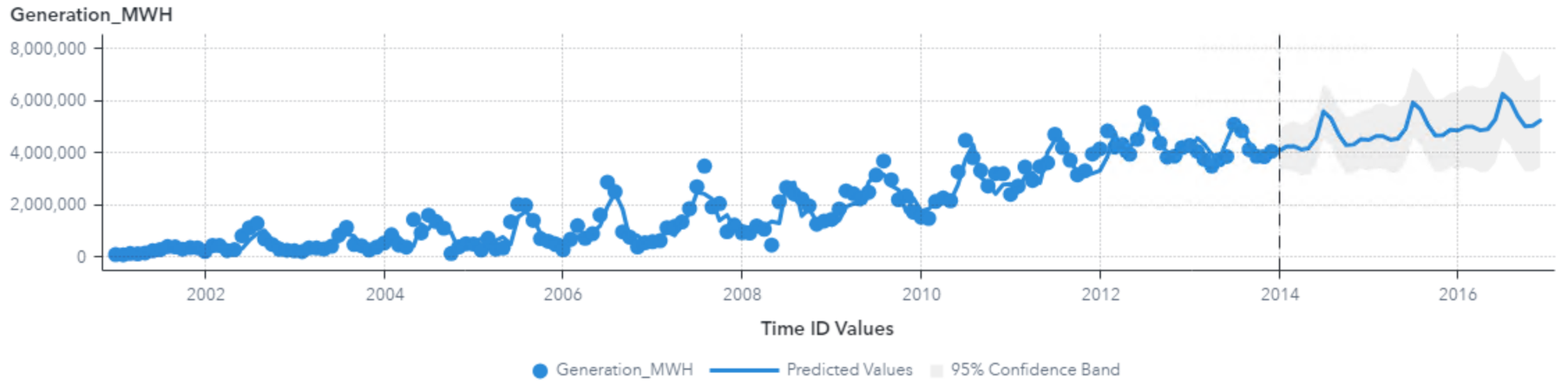
Forecast | Modeling | Series Analysis

Filter

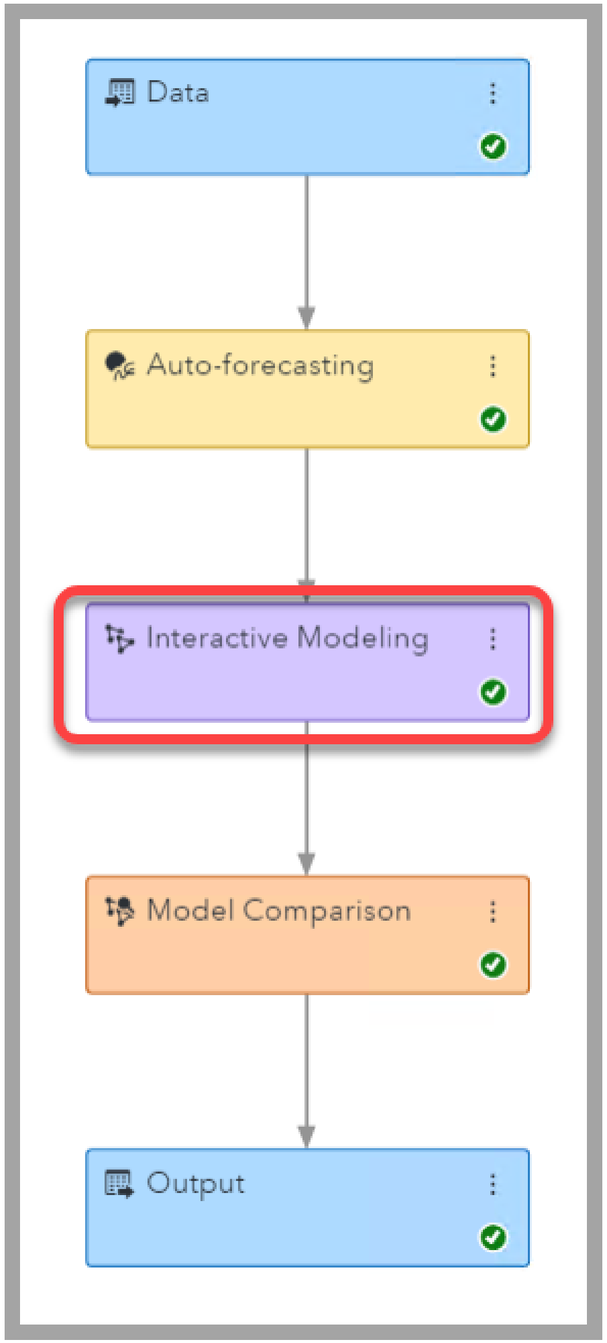
Model	Details	Compare	Type	In-sample MAPE
Beth_sqrt_ARIMAX1_1	ARIMA: Sqrt(Y) ~ P = ((1)(1)...	☐	Custom	27.948
PREDECESSOR	Forecasts from Auto-forecas...	☐	Inherited	28.770
DIAG1_ARIMAX1	ARIMA: Generation_MWH ...	☐	Generated	28.770
DIAG1_REGARIMA1	ARIMA: Generation_MWH ...	☐	Generated	30.253
DIAG1_ESM1	Winters Method (Additive)	☐	Generated	31.726

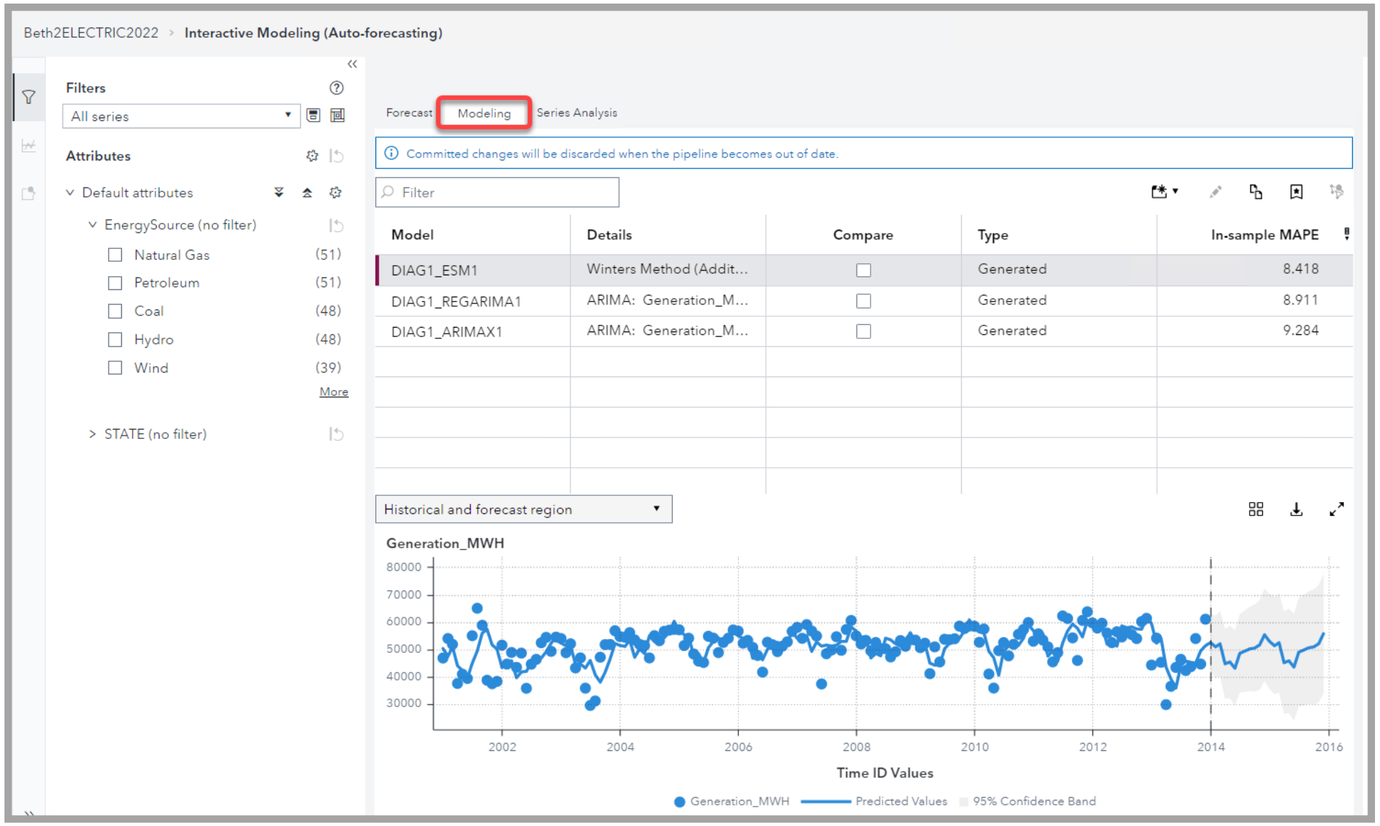
View diagnostic plot/table ▾

Historical and Forecast Region for PREDECESSOR



Interactive Modeling Node: Modeling Tab





The interactive modeling node lets you add **CUSTOMIZED**:

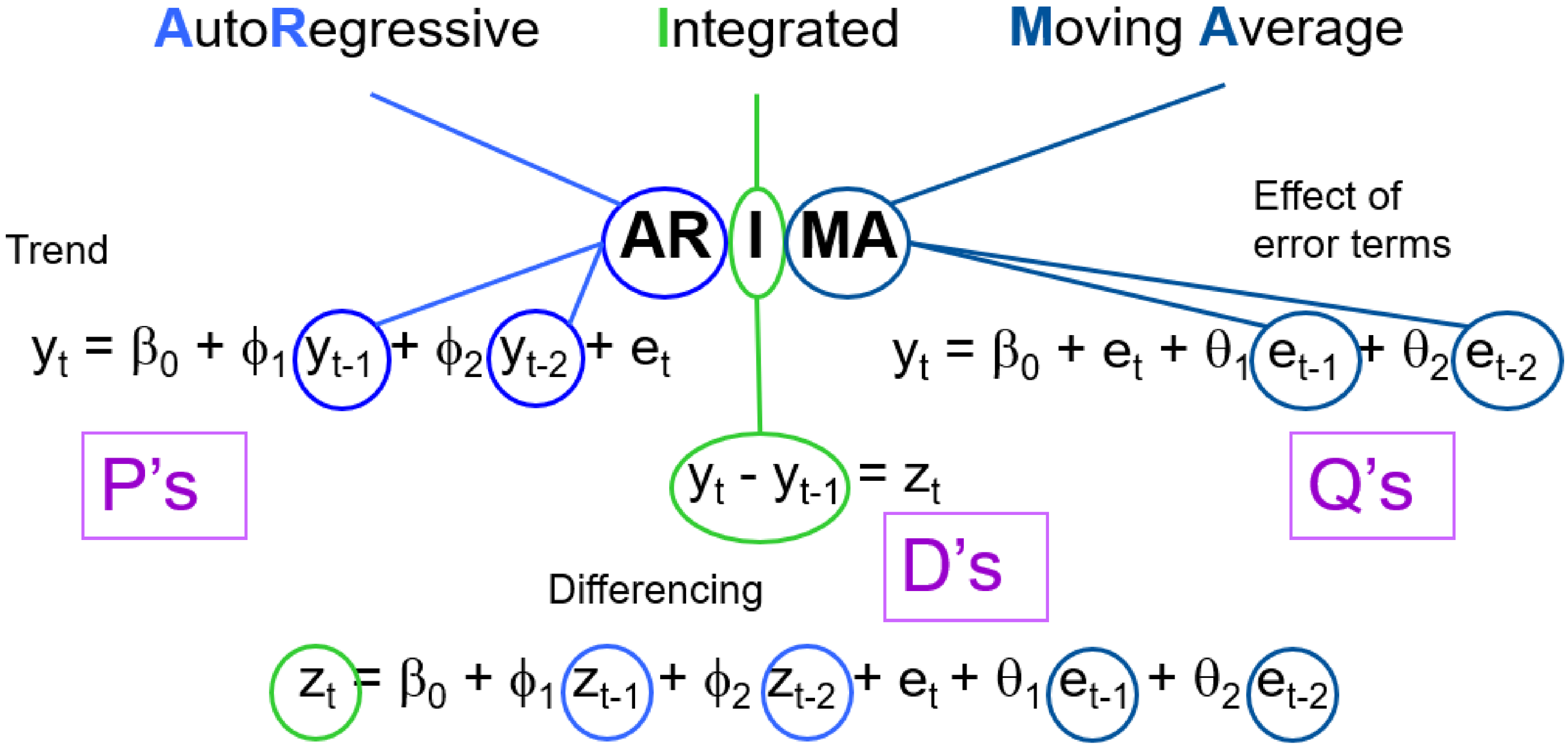
- exponential smoothing (ESM) models or
- ARIMA models

for any individual time series

Demonstration

SAS Visual Forecasting Interactive Modeling Node

LTS 2023.10



Box Jenkins Method

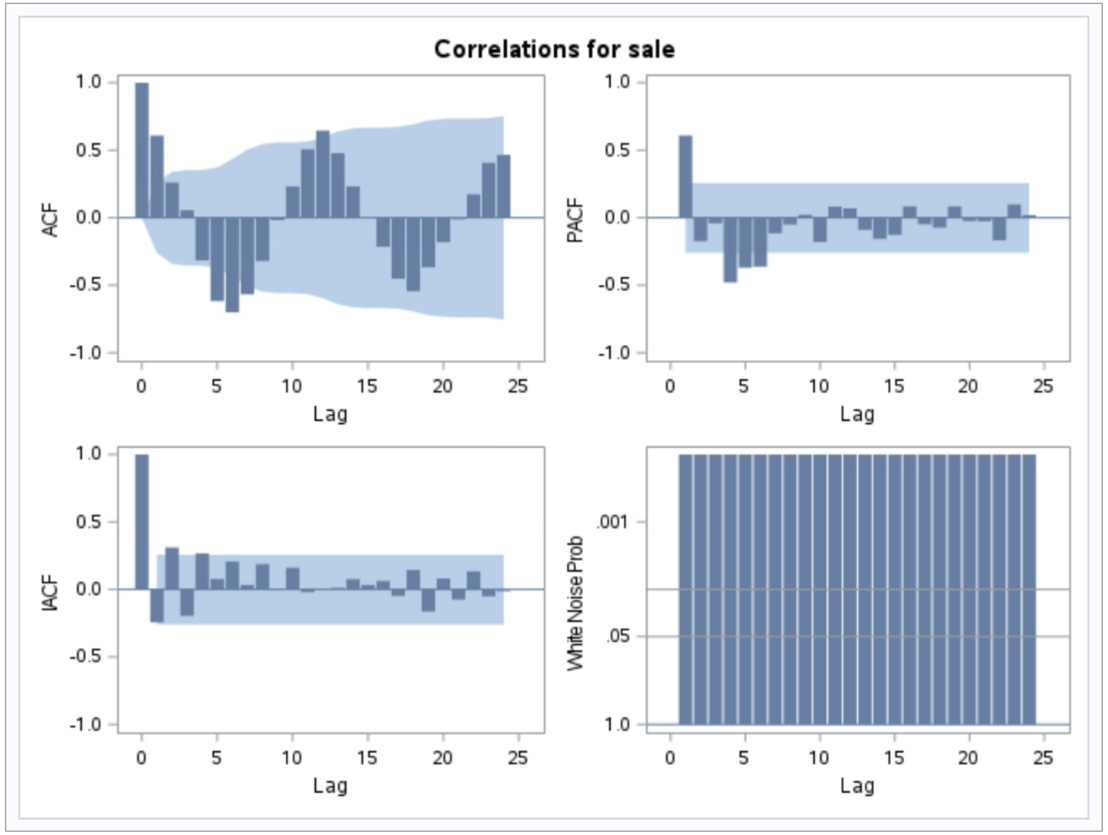
I. IDENTIFICATION STAGE – identify candidate ARIMA models
   A. Determine if time series is stationary
      1. If yes, move to next step
      2. If no, difference the time series, and then test the differences for stationarity
   B. Examine patterns in the ACF, PACF, and IACF plots and compare these to patterns expected from various ARMA models to determine AR and/or MA terms (p and q)

II. ESTIMATION AND DIAGNOSTIC CHECKING STAGE
   A. Estimate the parameters
   B. Review diagnostic plots to see if only white noise is left, meaning that your model is adequate

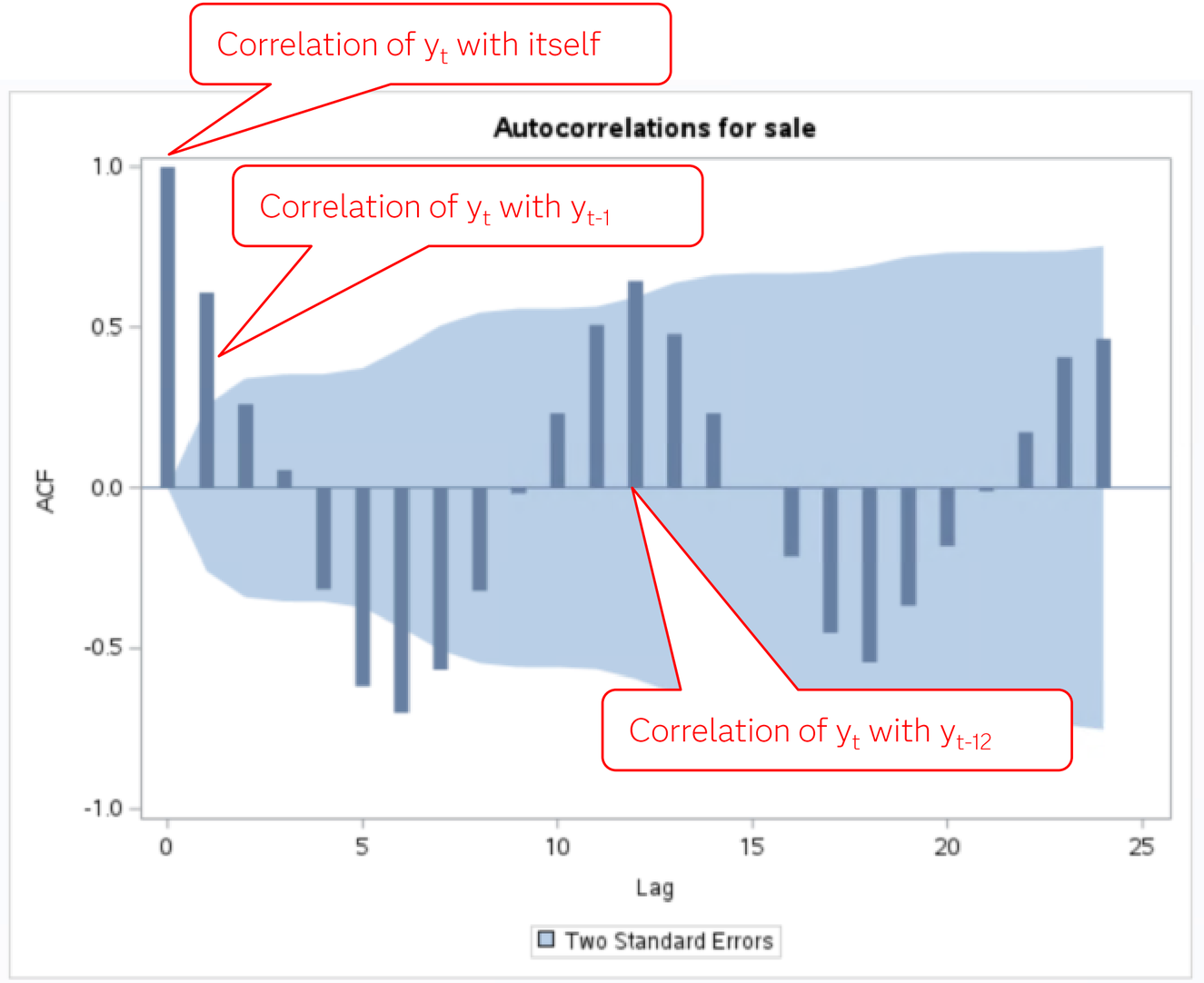
III. FORECASTING STAGE

Diagnostic Plots

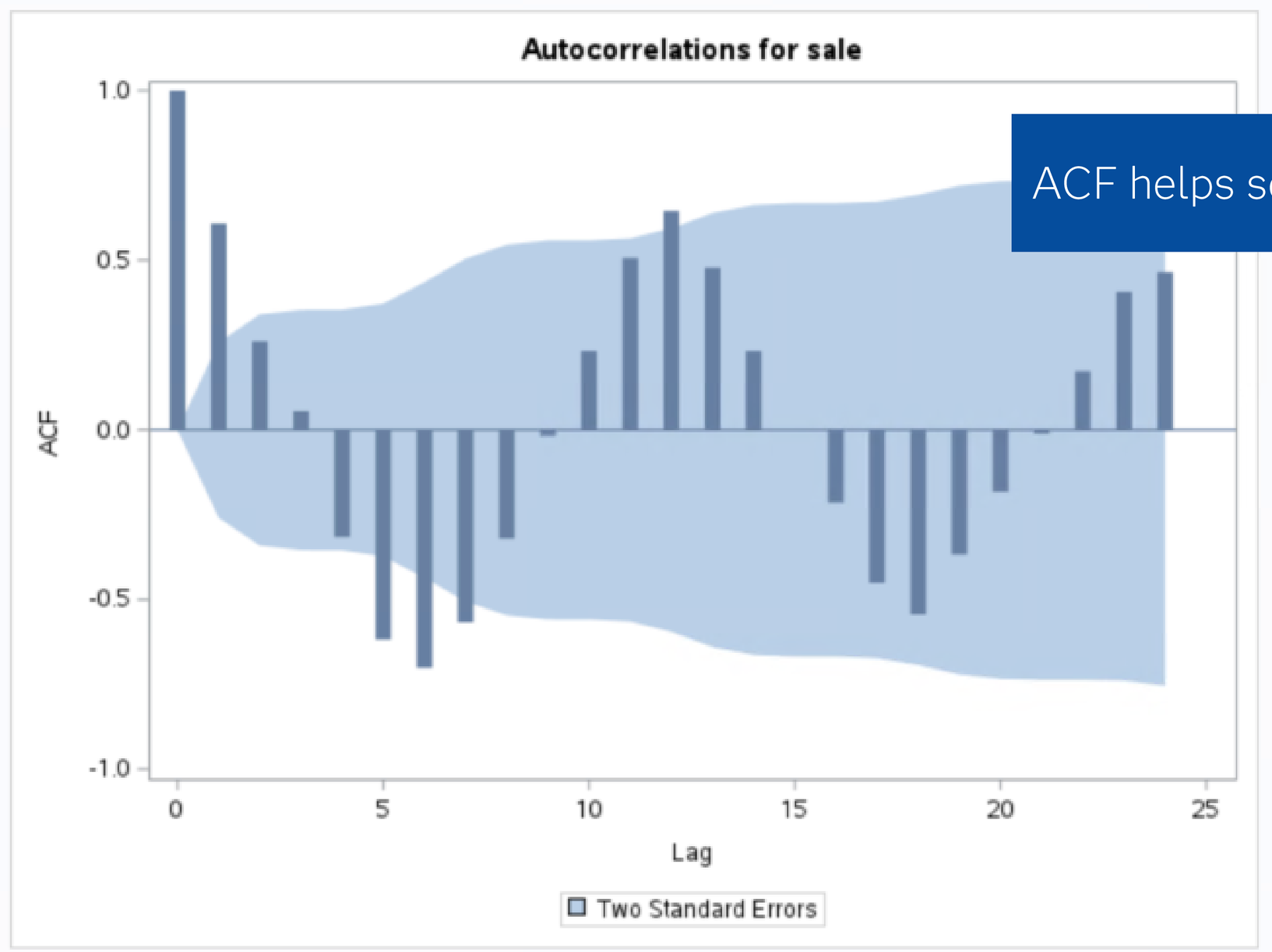
- Autocorrelation plots
  - Autocorrelation function plot (ACF)
  - Inverse autocorrelation function (IACF)
  - Partial autocorrelation function (PACF)
- White Noise plots



Autocorrelation Function



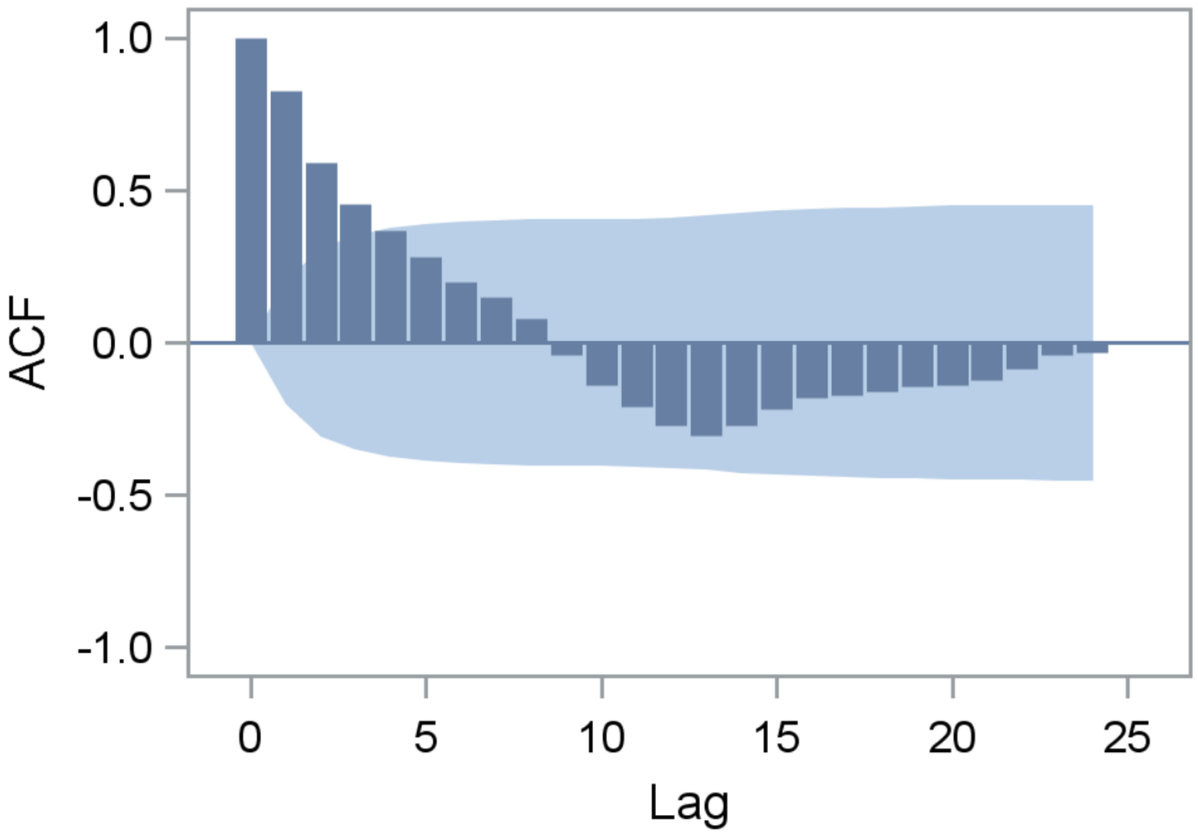
Autocorrelation Function



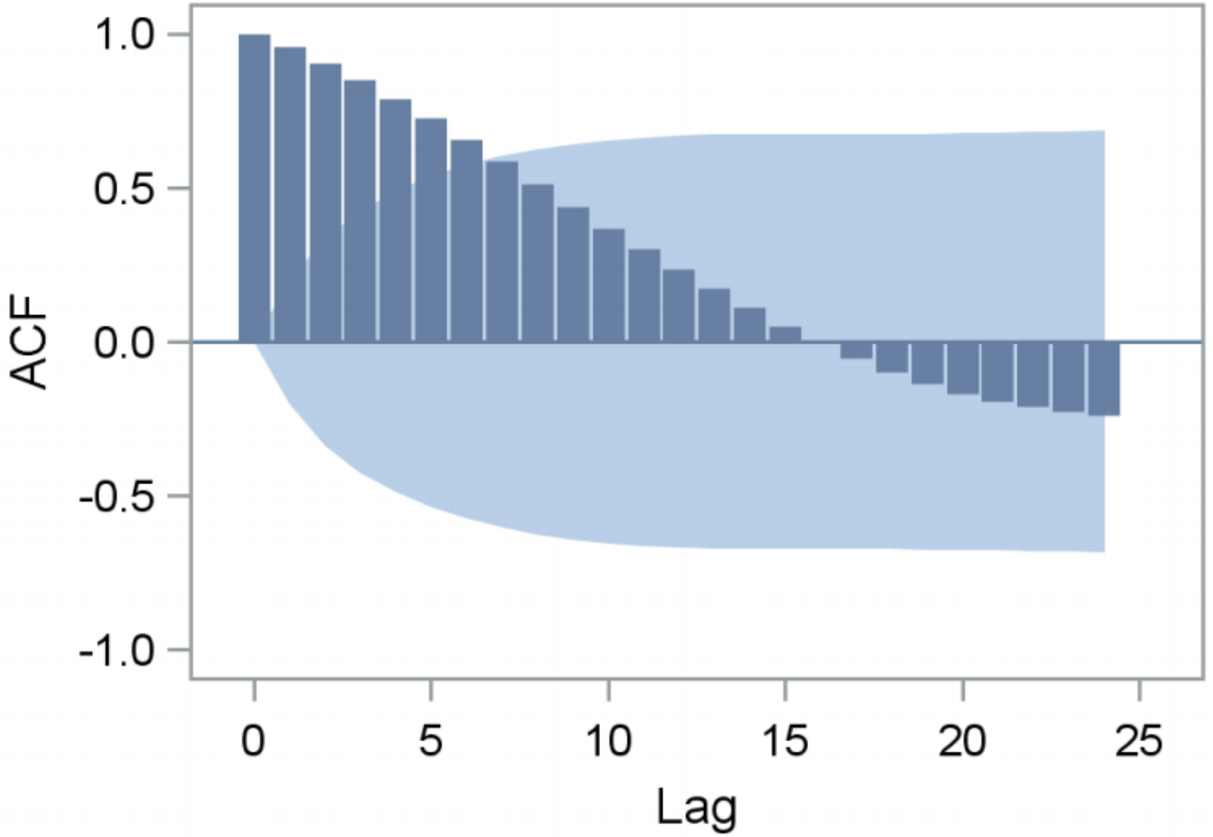
ACF helps select MA terms

gel

Determining Stationarity: Interpreting ACF Plots

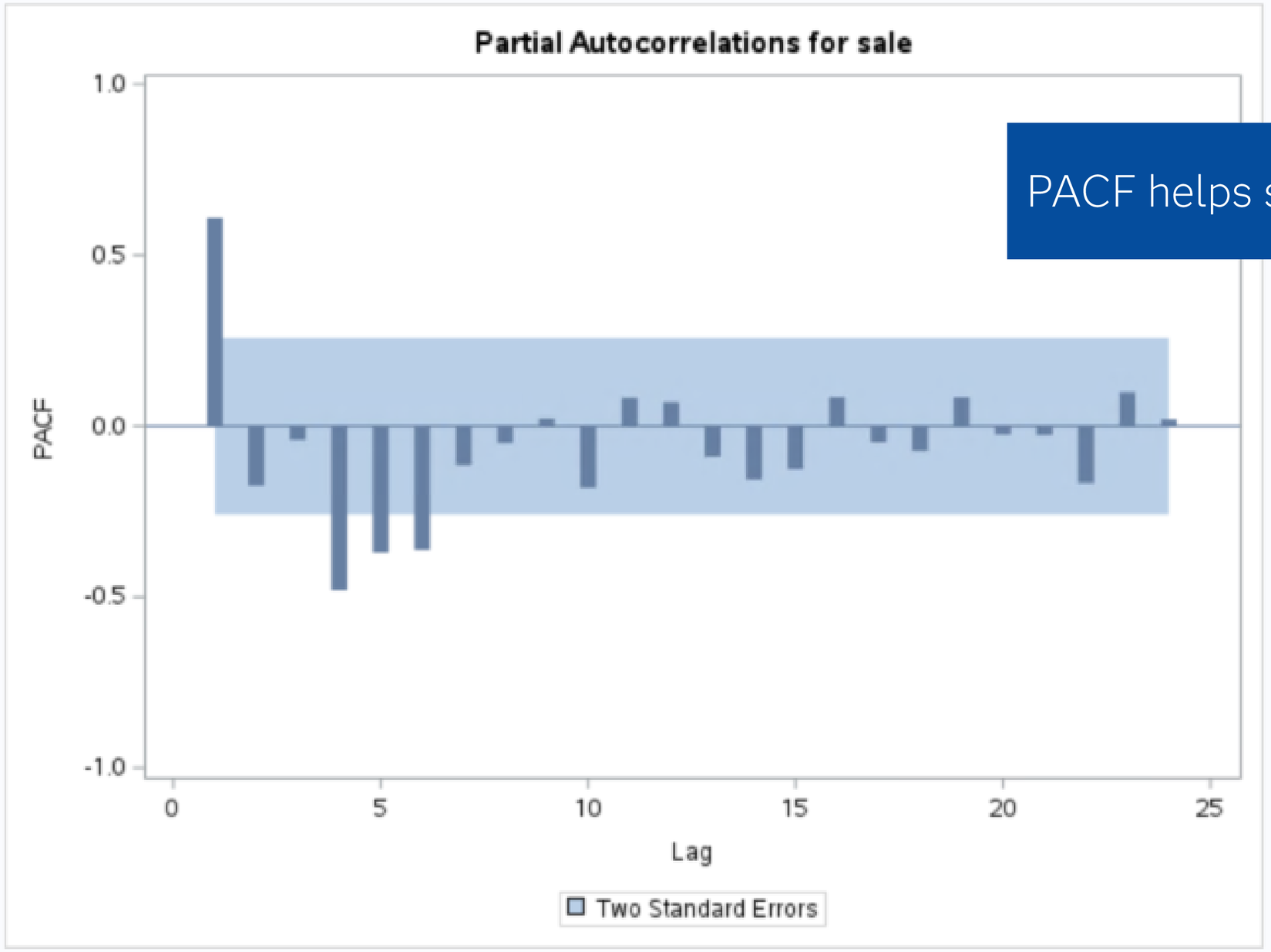


Rapid decay indicates stationarity



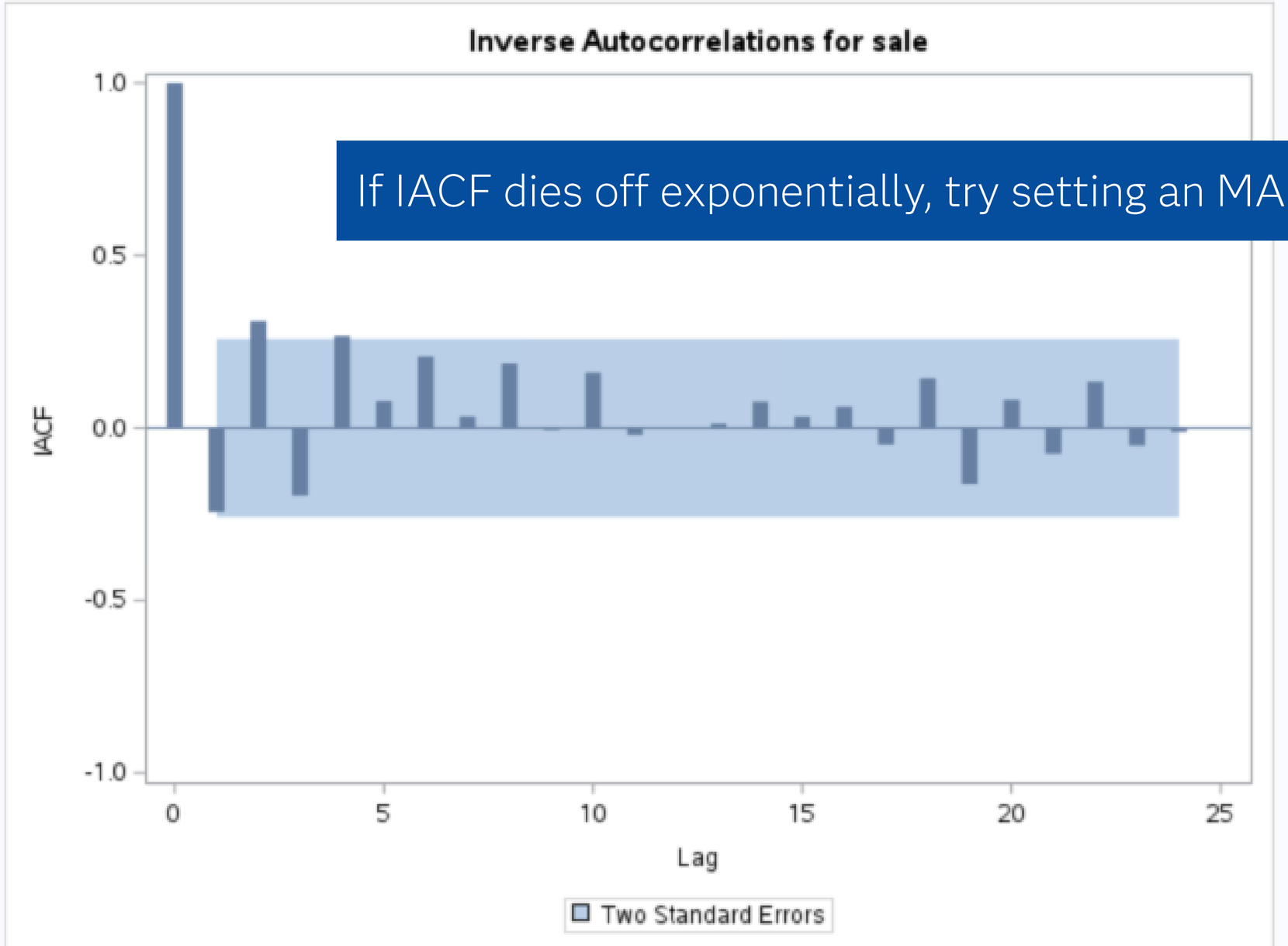
Slow decay indicates nonstationarity

Interpreting PACF

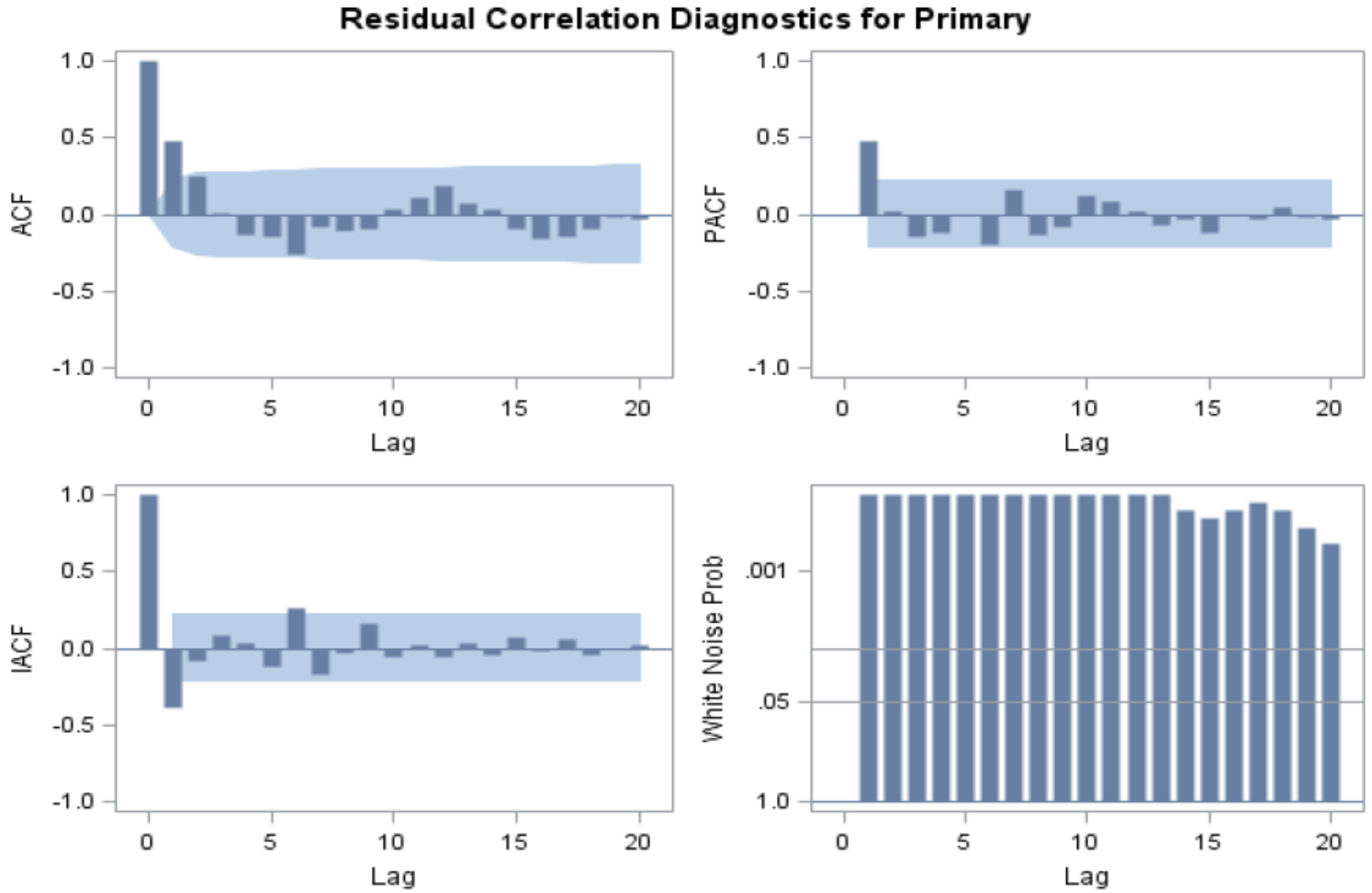


PACF helps select AR terms

Interpreting IACF

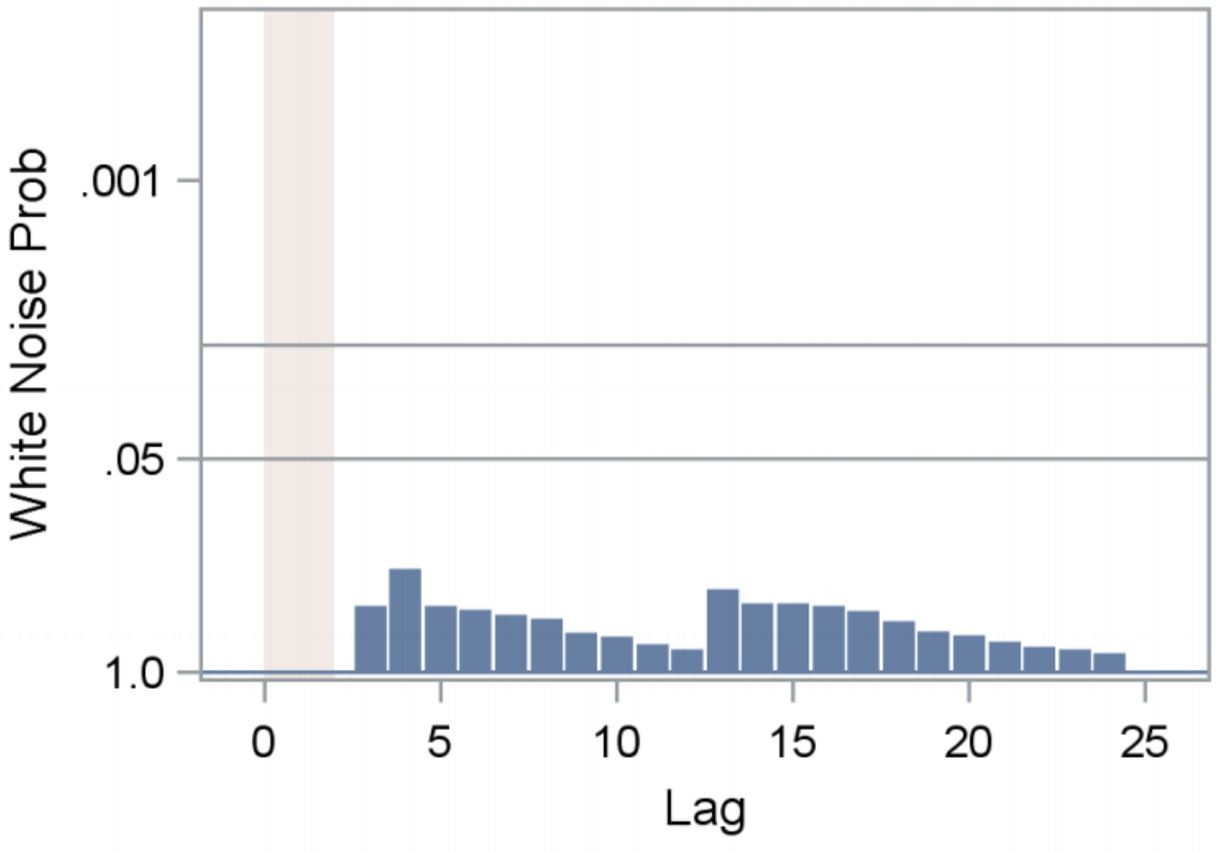


If IACF dies off exponentially, try setting an MA(1) term (q=1)

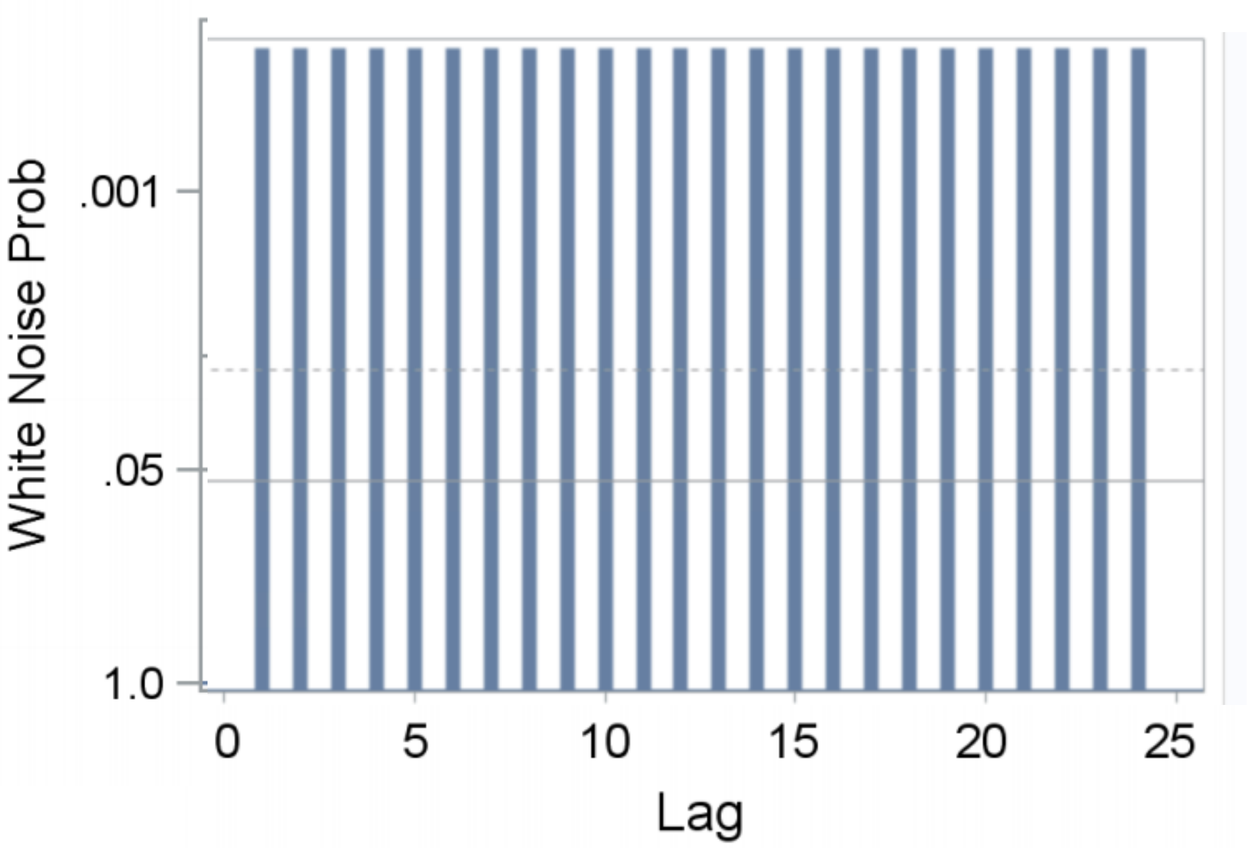


The spike at lag 1 on the PACF and the IACF plots suggest an AR(1), but the ACF plot does not have the decay you tend to expect to indicate an AR(1) model

Interpreting White Noise Plots



White Noise



Correlated (NOT White Noise)

Rules of Thumb

D

- If your time series is stationary, no differencing is needed.
- If your time series has a constant average trend, try one order of differencing.
- If your time series has a time-varying trend, try two orders of total differencing.

- Under-differenced: If the series has positive autocorrelations to a high number of lags, it likely needs a higher order of differencing.
- Appropriate or Over-differenced: If the Lag 1 autocorrelation is zero or negative, or the autocorrelations are all small and you see no pattern, then the series does not need a higher order of differencing.
- Over-differenced: If the lag-1 autocorrelation is -0.5 or lower, the series may be over-differenced.
- PRO TIP: Slightly too much or slightly too little differencing can also be corrected with AR or MA terms.

AR and MA terms:

- AR: If the partial autocorrelation function (PACF) of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is positive--i.e., if the series appears slightly "underdifferenced"--then consider adding one or more AR terms to the model. The lag beyond which the PACF cuts off is the indicated number of AR terms.
- MA: If the autocorrelation function (ACF) of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is negative--i.e., if the series appears slightly "overdifferenced"--then consider adding an MA term to the model. The lag beyond which the ACF cuts off is the indicated number of MA terms.
- AR & MA: If a mixed AR-MA model seems to fit the data, also try a model with one fewer AR term and one fewer MA term--particularly if the parameter estimates in the original model require more than 10 iterations to converge. BEWARE OF USING MULTIPLE AR TERMS AND MULTIPLE MA TERMS IN THE SAME MODEL.

Seasonal Terms

If your series has a strong and consistent seasonal pattern.

- Seasonal AR: If the autocorrelation of the appropriately differenced series is positive at lag s, where s is the number of periods in a season, then consider adding seasonal AR term to the model.
- Seasonal MA: If the autocorrelation of the differenced series is negative at lag s, consider adding a seasonal MA term to the model.
- AVOID using more than one or two seasonal parameters in the same model, because:
  - Overfitting
  - Estimation problems
- PRO TIP: Never use more than one order of seasonal differencing or more than 2 orders of total differencing (seasonal+nonseasonal)

INT or NOINT?

- A model with no orders of differencing commonly includes a constant term (allows for a non-zero mean value).
- In a model with one order of total differencing, a constant term should be included if the series has a non-zero average trend.
- A model with two orders of total differencing normally does not include a constant term.

Unit Root Tests

Unit Root Test:

- If there is a unit root in the AR part of the model--i.e., if the sum of the AR coefficients is almost exactly 1--you should reduce the number of AR terms by one and increase the order of differencing by one.
- If there is a unit root in the MA part of the model--i.e., if the sum of the MA coefficients is almost exactly 1--you should reduce the number of MA terms by one and reduce the order of differencing by one.

For More Information

- Joe Katz's video on Interactive Modeling in SAS Visual Forecasting from May 2021 https://www.youtube.com/watch?v=BsSyQ9WNmTg
- Documentation Overview of Interactive Modeling https://go.documentation.sas.com/doc/en/vfcdc/v_011/vfug/p1i2p822aeeo75n1sw7yn29zos68.htm?homeOnFail
- Picking the p d q's: Identifying, autoregressive, differencing, and moving average terms for ARIMA models https://people.duke.edu/~rnau/arimrule.htm
- Pancratz, Alan. 1983. *Forecasting with Univariate Box-Jenkins Methods: Concepts and Cases*.

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- 29 years of experience in machine learning, AI, analytics and estuarine science
- M.S. from the Johns Hopkins University in Biostats
- Enables SAS users to get the most out of their advanced analytics software
- Lives in Annapolis, Maryland, USA and enjoys swimming, boating, crabbing and all things water-related
- Huge Baltimore Ravens (American football) fan