Time series forecasting Models

Time series forecasting involves predicting future values of a time-dependent variable based on historical data. It is widely used in various domains such as finance, economics, weather forecasting, sales, and more.

The various time series models serve different purposes and provide distinct capabilities in analyzing and forecasting time-dependent data.

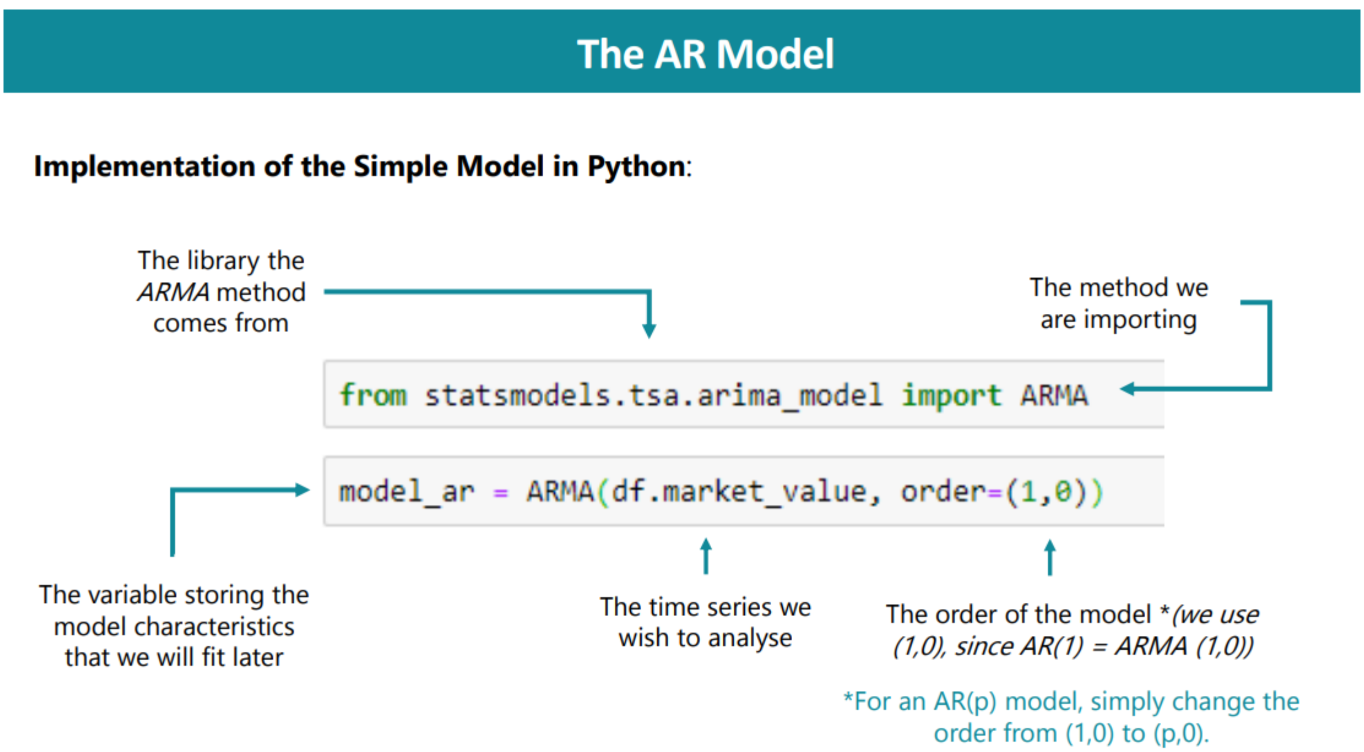
Here's a breakdown of what each model is used for and what they provide:

1. Autoregressive Model (AR):

- **Purpose:** The Autoregressive (AR) model represents a time series where the current value is a linear combination of its past values. It captures the serial correlation in the data.

- **Equation:** $Y_t = \phi_1 Y_{t-1} + \epsilon_t$
  Here, Y_t is the current observation, ϕ_1 is the autoregressive parameter, Y_{t-1} is the previous observation, and ϵ_t is the white noise error term.

- **Implementation:** The `AutoReg` function from `statsmodels` library is used for fitting an AR model.

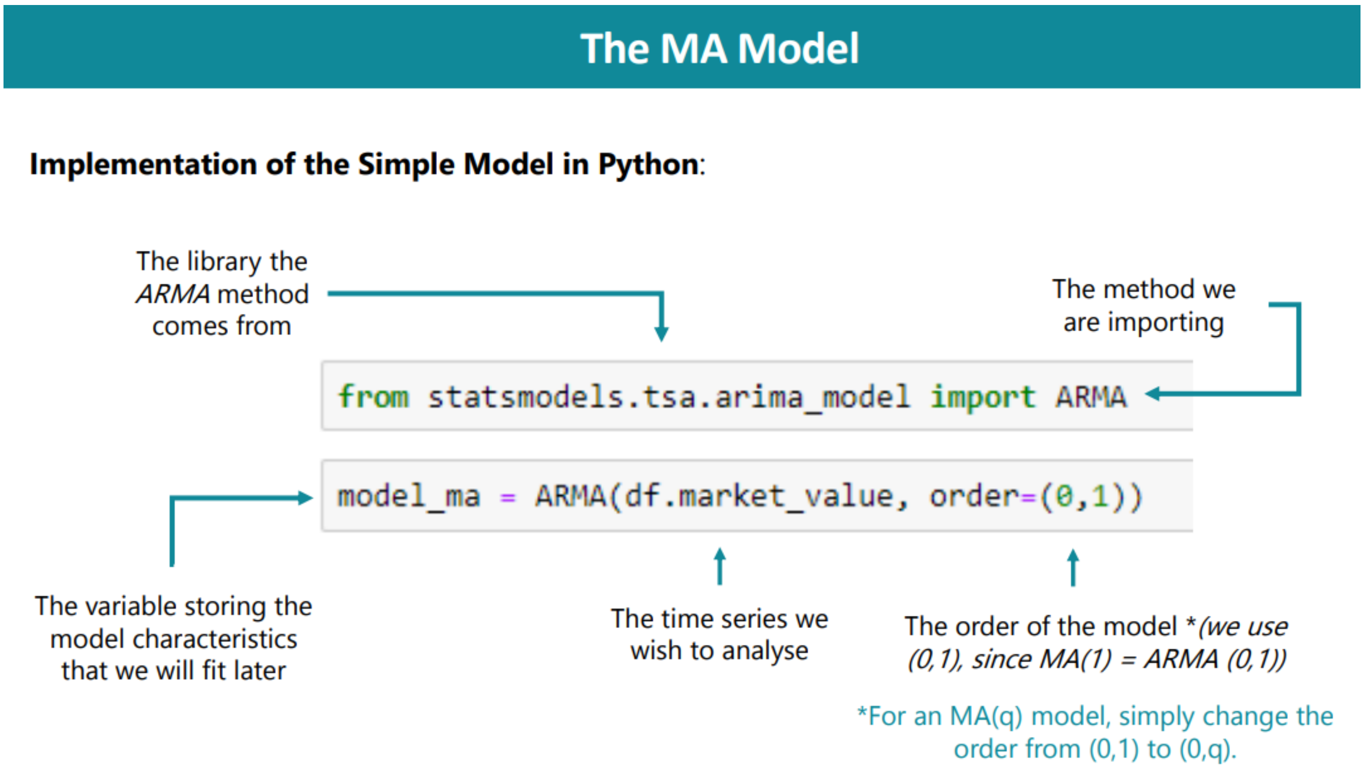


2. Moving Average Model (MA):

- **Purpose:** The Moving Average (MA) model represents a time series as a linear combination of past residual errors. It captures the short-term fluctuations in the data.

- **Equation:** $Y_t = \epsilon_t + \theta_1 \epsilon_{t-1}$
  Here, Y_t is the current observation, ϵ_t is the current white noise error term, θ_1 is the moving average parameter, and ϵ_{t-1} is the previous error term.

- **Implementation:** The `ARIMA` function from `statsmodels` library is used for fitting an MA model with order (0, 0, 1).

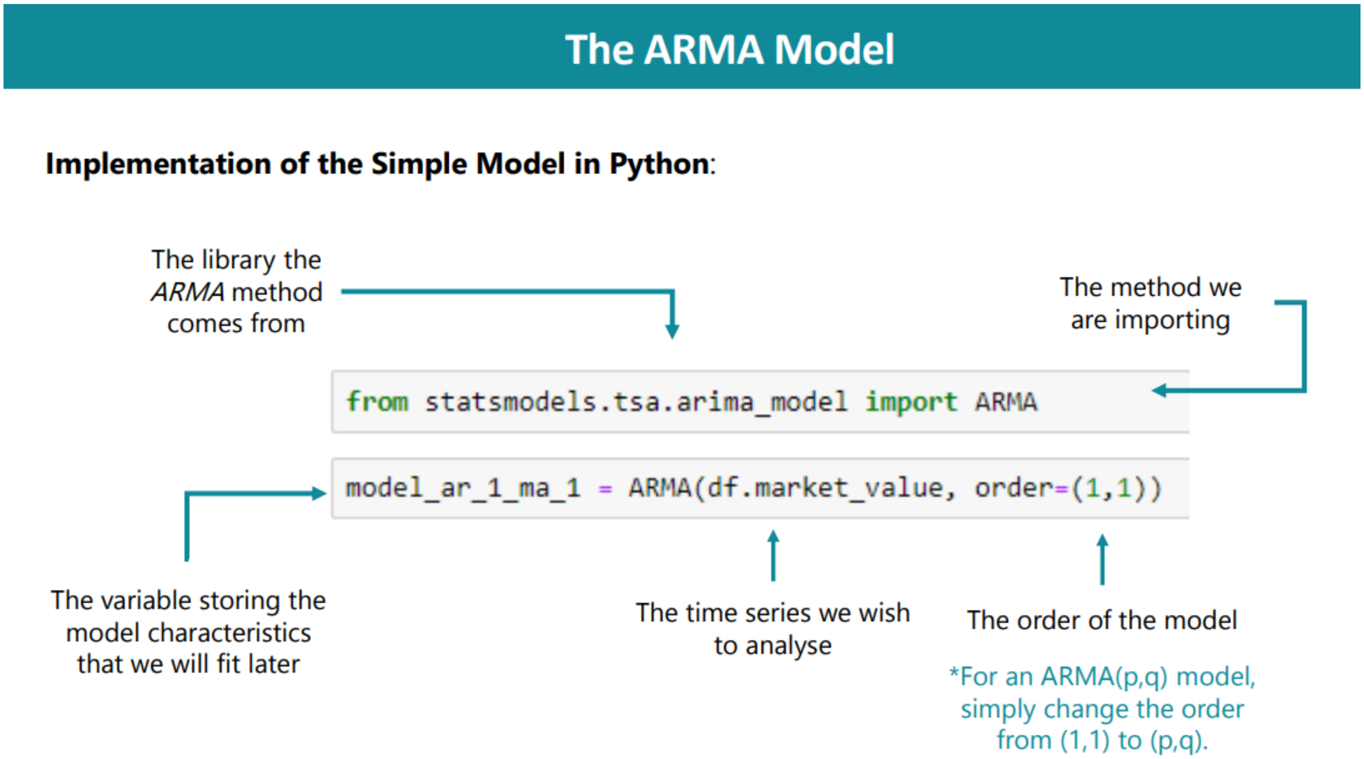


3. Autoregressive Moving Average Model (ARMA):

- **Purpose:** The Autoregressive Moving Average (ARMA) model combines both autoregressive and moving average components to capture both short-term and long-term dependencies.

- **Equation:** $Y_t = \phi_1 Y_{t-1} + \epsilon_t + \theta_1 \epsilon_{t-1}$
  Here, Y_t is the current observation, ϕ_1 is the autoregressive parameter, ϵ_t is the current white noise error term, θ_1 is the moving average parameter, and ϵ_{t-1} is the previous error term.

- **Implementation:** The `ARIMA` function from `statsmodels` library is used for fitting an ARMA model with order (1, 0, 1).



4. Autoregressive Integrated Moving Average Model (ARIMA):

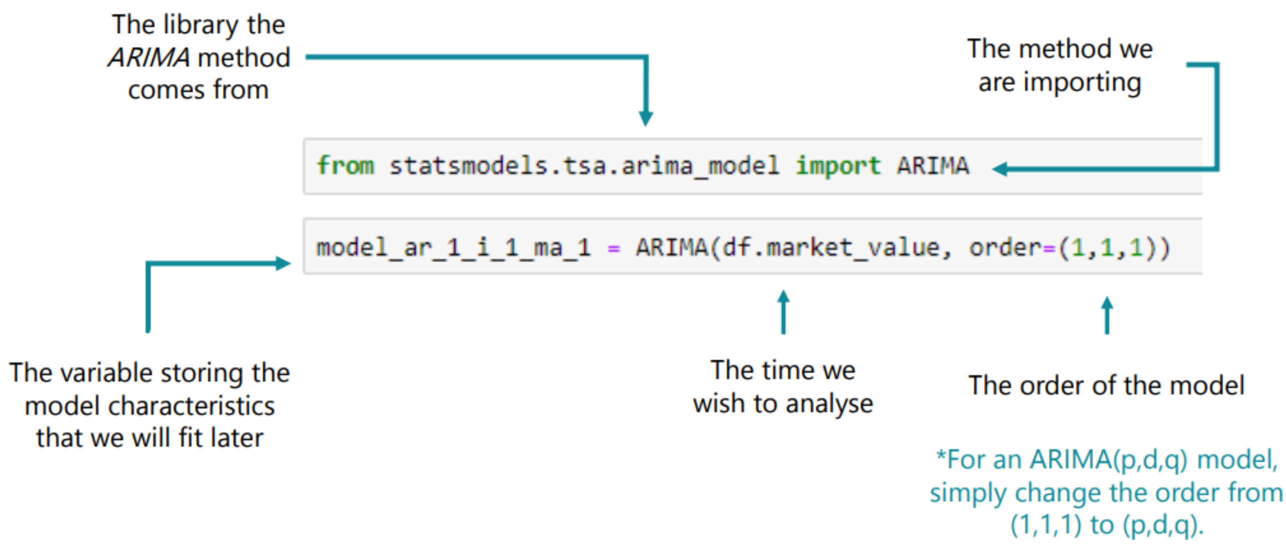
- **Purpose:** The Autoregressive Integrated Moving Average (ARIMA) model extends the ARMA model by incorporating differencing to make the time series stationary. It is suitable for non-stationary time series.

- **Equation:** $Y'_t = \phi_1 Y'_{t-1} + \epsilon_t + \theta_1 \epsilon_{t-1}$
  Here, Y'_t is the differenced series, ϕ_1 is the autoregressive parameter, ϵ_t is the current white noise error term, θ_1 is the moving average parameter, and ϵ_{t-1} is the previous error term.

- **Implementation:** The `ARIMA` function from `statsmodels` library is used for fitting an ARIMA model with order (1, 1, 1).

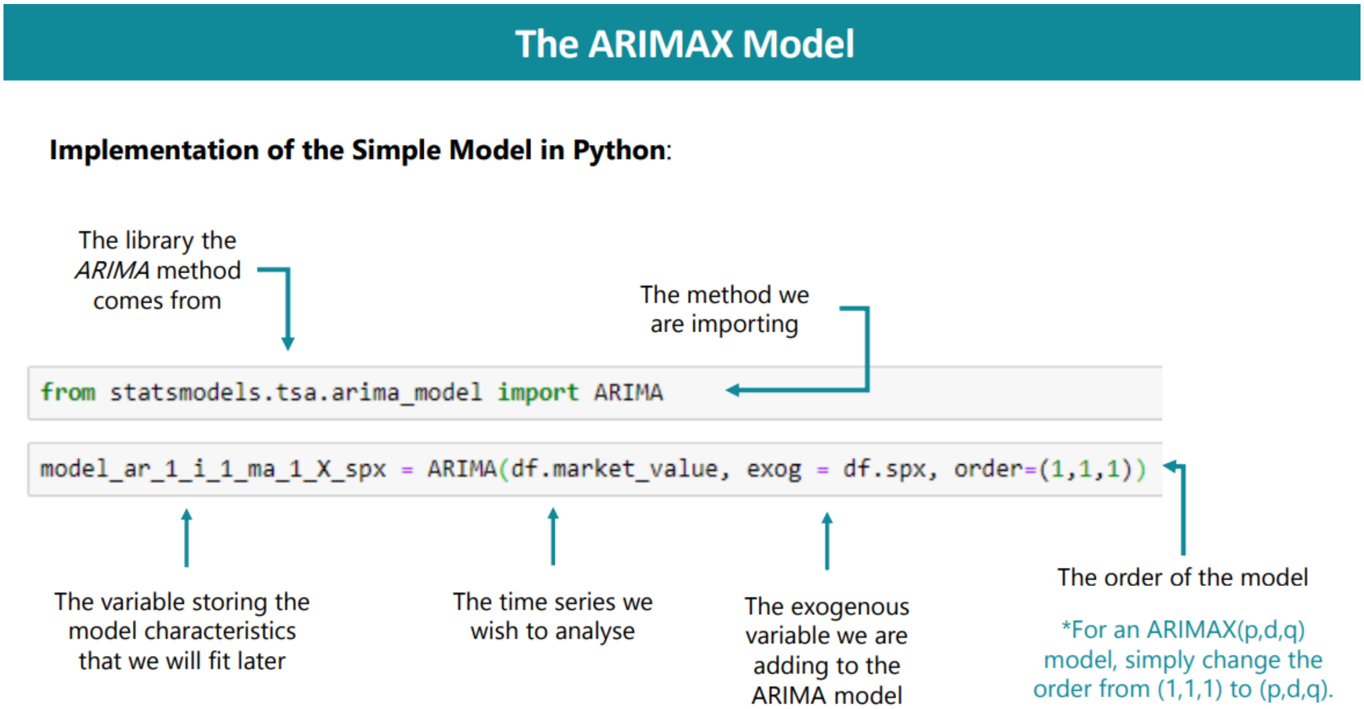
The ARIMA Model

Implementation of the Simple Model in Python:



5. Autoregressive Integrated Moving Average eXogenous Model (ARIMAX):

- **Purpose:** The ARIMAX model extends ARIMA by incorporating exogenous variables that may influence the time series.
- **Equation:** $Y'_t = \phi_1 Y'_{t-1} + \beta X_t + \epsilon_t + \theta_1 \epsilon_{t-1}$
  Here, Y'_t is the differenced series, ϕ_1 is the autoregressive parameter, X_t is the exogenous variable, β is the coefficient for the exogenous variable, ϵ_t is the current white noise error term, and θ_1 is the moving average parameter.
- **Implementation:** The `SARIMAX` function from `statsmodels` library is used for fitting an ARIMAX model.



6. Autoregressive Moving Average eXogenous Model (ARMAX):

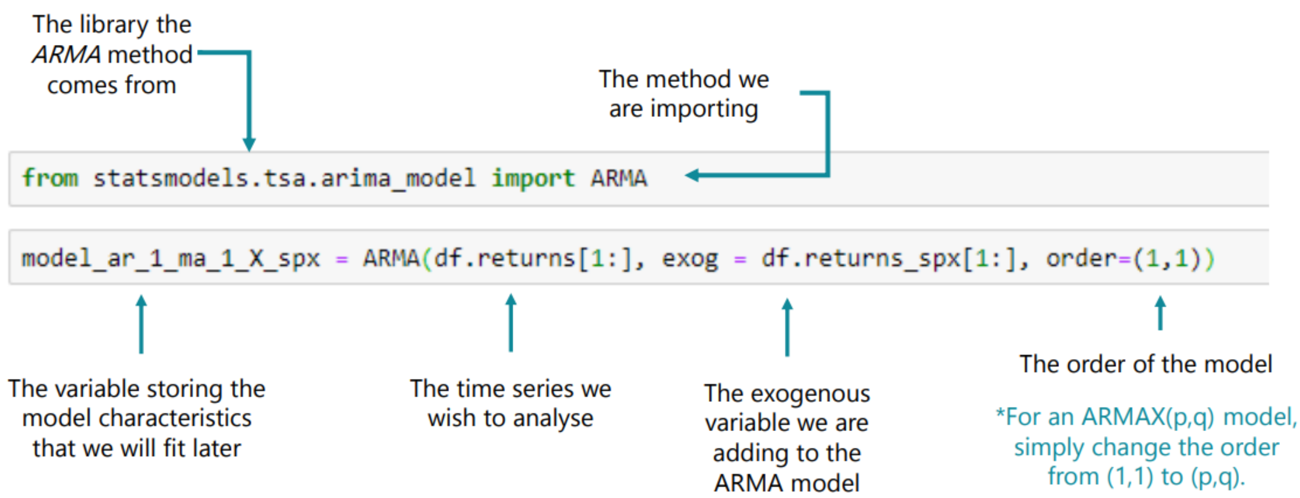
- **Purpose:** The ARMAX model incorporates exogenous variables into the ARMA model.
- **Equation:** $Y_t = \phi_1 Y_{t-1} + \beta X_t + \epsilon_t + \theta_1 \epsilon_{t-1}$

  Here, Y_t is the current observation, ϕ_1 is the autoregressive parameter, X_t is the exogenous variable, β is the coefficient for the exogenous variable, ϵ_t is the current white noise error term, and θ_1 is the moving average parameter.

- **Implementation:** The `ARIMA` function from `statsmodels` library is used for fitting an ARMAX model with exogenous variables.

The ARMAX Model

Implementation of the Simple Model in Python:

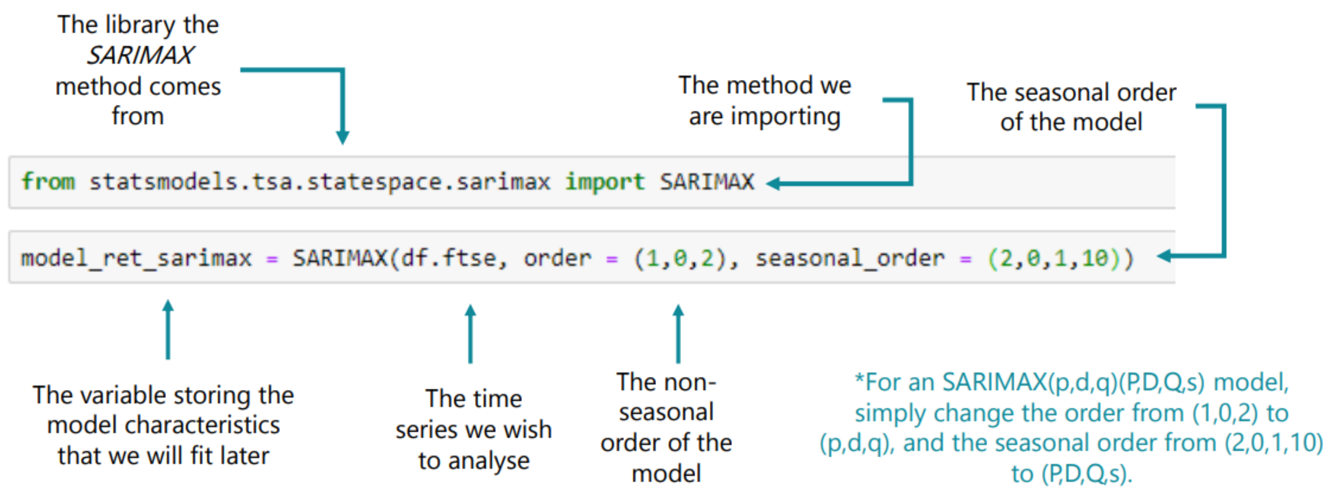


7. Seasonal Autoregressive Integrated Moving Average eXogenous Model (SARIMAX):

- **Purpose:** The SARIMAX model extends ARIMAX to handle seasonality in the time series.
- **Equation:** Similar to ARIMAX, but with additional terms for seasonal components.
- **Implementation:** The `SARIMAX` function from `statsmodels` library is used for fitting a SARIMAX model with seasonal order.

The SARIMAX Model

Implementation of the Model in Python:



8. Autoregressive Conditional Heteroskedasticity Model (ARCH):

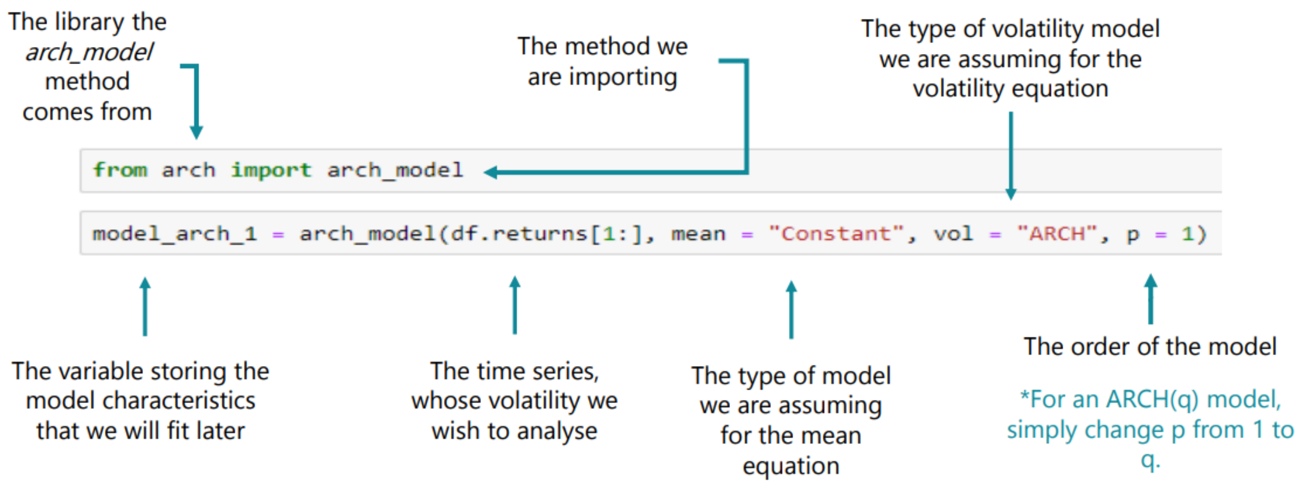
- **Purpose:** The ARCH model models time-varying volatility in a time series, allowing for changing variances over time.

- **Equation:** $Y_t = \epsilon_t \sqrt{h_t}$
  Here, Y_t is the current observation, ϵ_t is the white noise error term, and h_t is the conditional variance.

- **Implementation:** The `arch_model` function from the `arch` library is used for fitting an ARCH model.

The ARCH Model

Implementation of the Simple Model in Python:



9. Generalized Autoregressive Conditional Heteroskedasticity Model (GARCH):

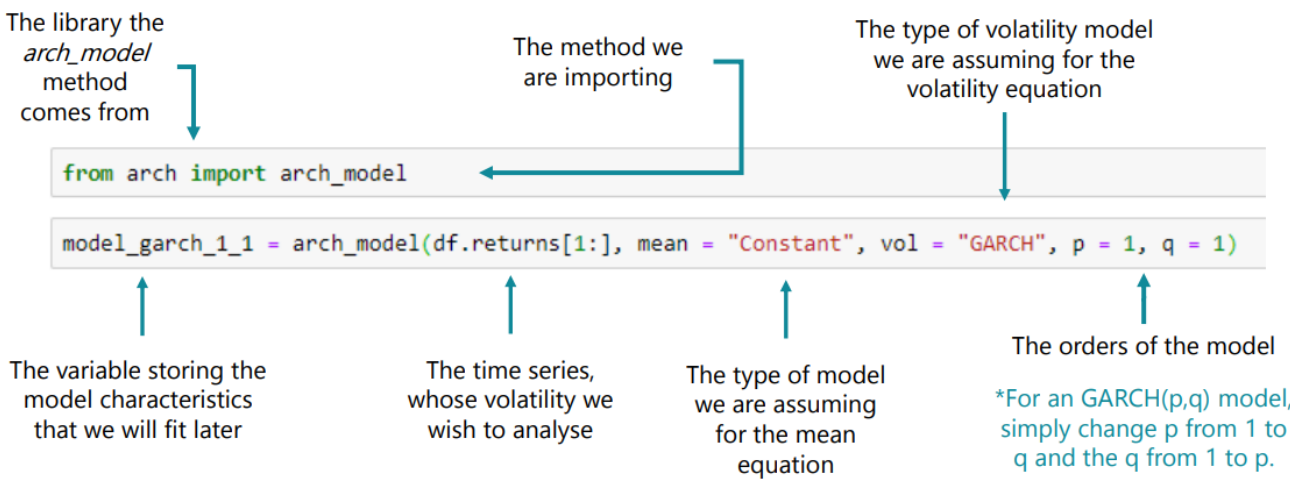
- **Purpose:** The GARCH model extends ARCH by incorporating lagged conditional variances in addition to lagged squared residuals.

- **Equation:** Similar to ARCH, but with additional terms for lagged conditional variances.

- **Implementation:** The `arch_model` function from the `arch` library is used for fitting a GARCH model.

The GARCH Model

Implementation of the Simple Model in Python:



These models offer a diverse set of tools for analyzing and forecasting time series data, each catering to different aspects of the data's structure and characteristics. The choice of model depends on the specific nature of the time series and the goals of the analysis.