

TIME SERIES ANALYSIS: ARMA

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TIME SERIES ANALYSIS: ARMA

LEARNING OBJECTIVES

- Describe the difference between weakly and strongly stationary stochastic processes.
- · Understand, describe, and implement autoregressive models.
- · Understand, describe, and implement moving average models.
- Understand, describe, and implement ARMA models.

OPENING: TIME SERIES DATA

- A univariate time series is a sequence of measurements of the same variable collected over time.
 - Formally, we call this a <u>stochastic process</u> and might denote these measurements as random variables. $\{Y_t: t = 0, 1, ..., n\}$.
 - Most often (but not always) these measurements will be made at regular time intervals.

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STATIONARY PROCESSES

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- A stochastic process $\{Y_t: t = 0, 1, ...\}$ is <u>strongly stationary</u> if
 - $f(Y_{t_0}, Y_{t_1}, ..., Y_{t_n}) = f(Y_{t_0+k}, Y_{t_1+k}, ..., Y_{t_n+k})$ for all t_i and k.
 - More practically:
 - $\mu_{t_i} = \mu_{t_i+k}$
 - $Cov(Y_t, Y_{t+k}) = Var(Y_k)$
 - $\operatorname{Corr}(Y_t, Y_{t+k}) = \frac{\operatorname{Var}(Y_k)}{\operatorname{Var}(Y_0)}$

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- A stochastic process $\{Y_t: t = 0, 1, ...\}$ is <u>weakly stationary</u> if
 - $\mu_{t_i} = c$ for all t_i
 - $Cov(Y_t, Y_{t+k}) = Cov(Y_0, Y_k)$

STATIONARY PROCESSES

• Stationarity is often a convenient condition to have because it has lots of nice properties that allow results to "collapse down."

AUCREGRESIVE MODELS (AR)

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- We say this model is AR(p) because it includes the previous p values of Y.
 - The most common autoregressive model is AR(1).

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- A time series with high autocorrelation implies that the data is highly dependent on previous values therefore, an autoregressive model would perform well!
- Autoregressive models are useful for learning "falls" or "rises" in our series.
 - Typically this model type is useful for small-scale trends.

• Recall an AR(p) model:

$$Y_{t} = \beta_{0} + \beta_{1}Y_{t-1} + \beta_{2}Y_{t-2} + \dots + \beta_{p}Y_{t-p} + \varepsilon$$

• Note that we could instead write this as:

$$Y_t = \beta_0 + \sum_{i=1}^p \beta_i Y_{t-i} + \varepsilon$$

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 - By contrast: Autoregressive (AR) models use data from previous time points to predict the next time point.
- Moving average models predict the next value based on the overall average and how incorrect our previous predictions were.
 - This is useful for modeling a sudden occurrence like something going out of stock and thus sales are affected, or Donald Trump tweets about an organization and its stock price falls.

• As with AR models, we have an order term q and we call our moving average model MA(q).

$$Y_t = \mu + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \dots + \beta_q \varepsilon_{t-q}$$

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- MA models require a more complex fitting procedure:
 - Iteratively fit model.
 - Compute errors.
 - Refit.

• Note that MA models include the mean of the time series. Thus the behavior of an MA model is characterized by random jumps around the mean value.

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MOVING AVERAGE MODELS ≠ **MOVING AVERAGE**

- NOTE: Moving Average ≠ Moving Average <u>Models</u>!!!
- Moving average models take, as inputs, previous errors.
- Moving averages are not models and just average recent Y values!

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• ARMA models combine the autoregressive and moving average models.

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• This slowly incorporates changes in preferences, tastes, and patterns. We account for sudden changes based on random events as well as how we expect things to change over time given past events.