CIS 678 Machine Learning

Time series data modeling

Outline

- How are the time series problems different than non time series problems?
- Stationary vs non-stationary signals
- AR(I)MA: Autoregressive Integrated Moving Average
    - From non no-stationary to stationary
    - Auto Regression
    - Moving Average

Let's look at some time-series data

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How are the time-series problems different?

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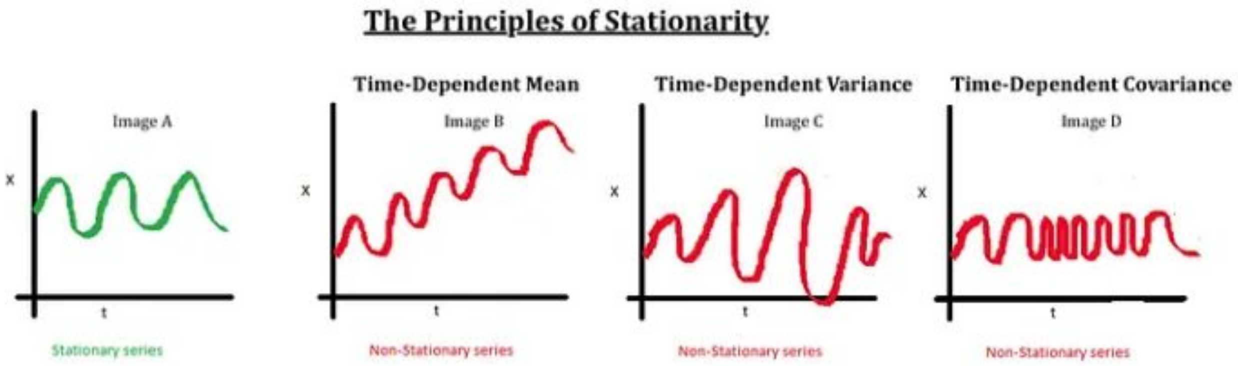
- For certain data, especially the time series, we can take advantage of the form:

  $f(y_t|X, y_{t-1}, y_{t-2, \ldots} y_0)$; essentially, here the input features are X plus the lagged instances of the target y.

Stationarity vs non-stationary signals

- A time-series is said to be stationary if it does not display any trends or seasonality.
- One more way of defining stationarity is that it is when data does not have any time-dependent mean, variance or covariance.



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Non stationary to stationary

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- or calculating percent of change

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Non stationary to stationary

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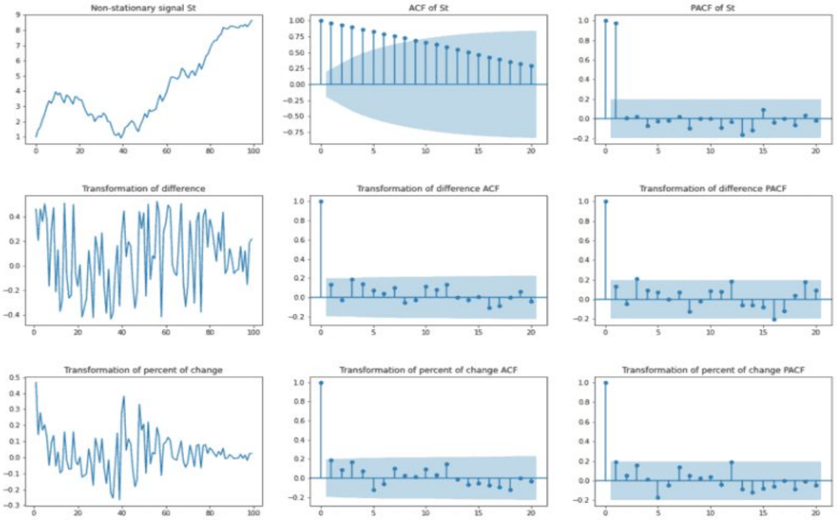

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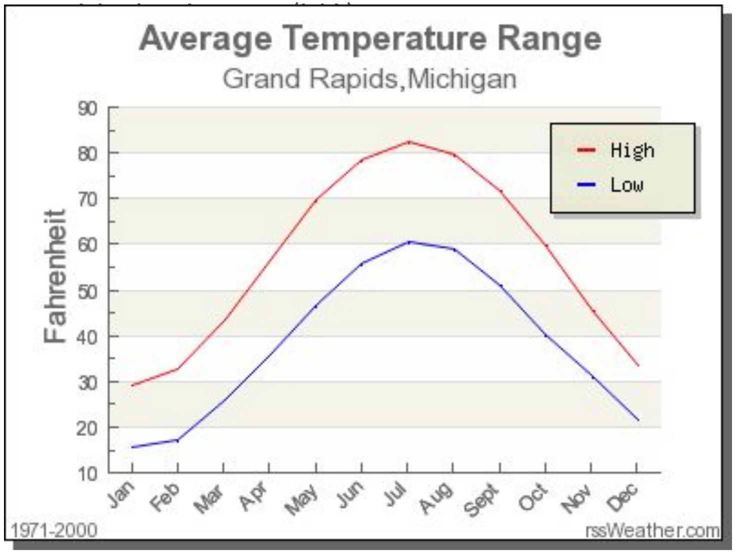
Statistical time series models

- Autoregressive Models (AR)
- Moving Average (MA)
- Autoregressive Moving Average (ARMA)
- Autoregressive Moving Integrated Average (ARIMA)

$$f(y_t | y_{t-1,}\, y_{t-2, \ldots.}\, y_0)$$

Statistical time series models

- Autoregressive Models (AR)



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Statistical time series models

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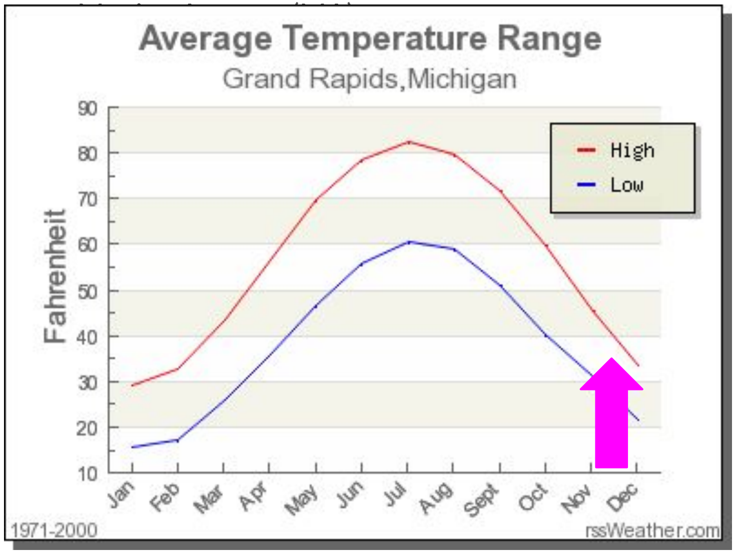

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Statistical time series models

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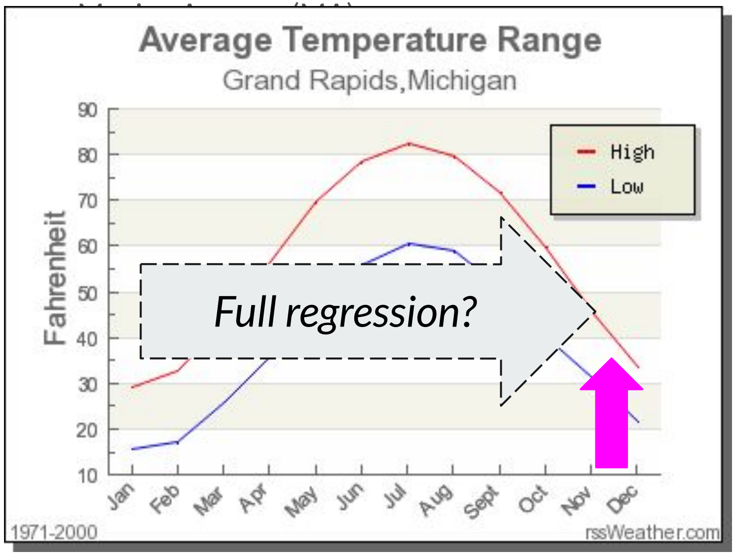

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Statistical time series models

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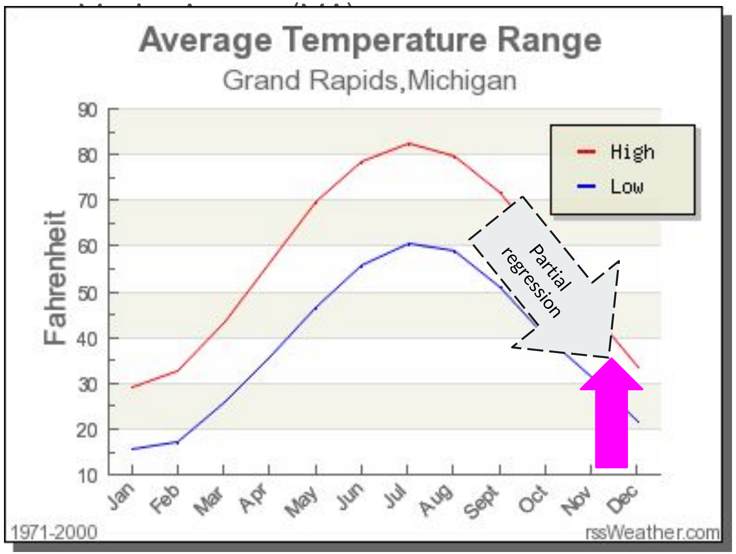

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Statistical time series models

- Autoregressive Models (AR)

The **AR(*p*)** model is defined as,

$$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

where p is the order of the model

Statistical time series models

- Moving Average (MA)

*MA(q): moving average model of **order q**:*

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

$$X_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$$

Statistical time series models

- Autoregressive Moving Average (ARMA)

ARMA(p, q) model

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

with p autoregressive terms and q moving-average terms.

AR(I)MA

- AutoRegressive Integrated Moving Average (ARIMA) is a statistical model for forecasting time series data.

A combined model with **AR**, **MA**, but first transforming the signal to stationary.

- **AR (Autoregression):** This emphasizes the dependent relationship between an observation and its preceding or 'lagged' observations.
- **I (Integrated):** To achieve a stationary time series, one that doesn't exhibit trend or seasonality, differencing is applied. It typically involves subtracting an observation from its preceding observation.
- **MA (Moving Average):** This component zeroes in on the relationship between an observation and the residual error from a moving average model based on lagged observations.

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AR(I)MA

The parameters of the ARIMA(p,d,q) model are defined as follows:

- **p**: The lag order, representing the number of lag observations incorporated in the model.
- **d**: Degree of differencing, denoting the number of times raw observations undergo differencing.
- **q**: Order of moving average, indicating the size of the moving average window.

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Notebook presentation

Notebook

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