Business Data Analytics

Lecture 9:
Financial Forecasting

MTAT.03.319

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Call center scheduling (shift jobs)

• Consider a call center company
  • How many users will be calling at Call center?
  • What time most of the calls arrive?
  • Example: At 8 pm more calls .. And 4 pm less calls.
  • Predicting about future demands can help in making a proper job shift plans.

<table>
<thead>
<tr>
<th>Time (Hour)</th>
<th>#Calls</th>
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</thead>
<tbody>
<tr>
<td>16</td>
<td>10</td>
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<tr>
<td>17</td>
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<td>18</td>
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<td>19</td>
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<td>20</td>
<td>100</td>
</tr>
<tr>
<td>21</td>
<td>80</td>
</tr>
</tbody>
</table>
An investment firm wants to predict about the stock market.

History of stocks could be useful.

<table>
<thead>
<tr>
<th>Time (Date)</th>
<th>Closing price</th>
</tr>
</thead>
<tbody>
<tr>
<td>4/17/2017</td>
<td>139.92</td>
</tr>
<tr>
<td>4/18/2017</td>
<td>139.58</td>
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<tr>
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<td>4/24/2017</td>
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</tr>
</tbody>
</table>
Sales growth in a Company

- A company is expecting sales growth
  - Budget planning
  - Procurement of items
  - Hiring large sales team

<table>
<thead>
<tr>
<th>Time (Quarter)</th>
<th>Sales</th>
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<tbody>
<tr>
<td>Q1</td>
<td>10M</td>
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<tr>
<td>Q2</td>
<td>20M</td>
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<tr>
<td>Q3</td>
<td>22M</td>
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<tr>
<td>Q4</td>
<td>22M</td>
</tr>
<tr>
<td>Q1</td>
<td>25M</td>
</tr>
<tr>
<td>Q2</td>
<td>26M</td>
</tr>
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Commonality among three cases

**Time Series:** Time is one of the component
Would like to **predict** in next **time interval**

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</tr>
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</tr>
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<td>26M</td>
</tr>
<tr>
<td>Q3</td>
<td>?</td>
</tr>
</tbody>
</table>
Lecture 9: Financial Forecasting
What is (Financial) Forecasting?

- A **financial forecasting** is an estimate of future financial outcomes of an entity.

- Predicting about the future based on past and present data.

- Examples (Entity - Prediction):
  - Organization-Profit
  - Organization-Sales
  - Organization- Stock price
  - Country-GDP
  - Website-Traffic
Why Financial Forecasting is important?

• Tells you the **future environment** in which you may operate.
  • Forecasting is essential to making **marketing plans**
  • Forecasting helps in making a **financial plan** or for allocating budget for your business.
Difference between Predict and Forecast

• Predict
  • Cross-sectional data
  • Observe/record samples using some attributes/features in some snapshot of time
  • Not interested in trends
  • Example: Churn of customers

• Forecast
  • Time Series data
  • Observe/Record values only one variable at specific time intervals
  • Interested in trends.
  • Example: Stockprice
(Univariate) Time Series Data

• Notations
  • Time series $Y_1, Y_2, Y_3, \ldots, Y_{n-1}, Y_n$
  • $t = 1, 2, 3 \ldots$ (time period index)
  • $Y_t = \text{value of the series at time period } t$
  • $F_{t+k} = \text{Forecast for time period } k \text{ using data until time } k$
  • $e_{t+k} = Y_{t+k} - F_{t+k} = \text{Forecast error (residual) for the period } t+k$

• There is a natural order
  • $Y_n | Y_{n-1}, Y_{n-2} \ldots$ ()

<table>
<thead>
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<th>Date</th>
<th>t</th>
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</tr>
</thead>
<tbody>
<tr>
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</tr>
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<td>142.27</td>
</tr>
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<td>4/24/2017</td>
<td>6</td>
<td>143.80</td>
</tr>
<tr>
<td>4/25/2017</td>
<td>7</td>
<td>133.20</td>
</tr>
<tr>
<td>4/26/2017</td>
<td>8</td>
<td>140.21</td>
</tr>
<tr>
<td>4/27/2017</td>
<td>9</td>
<td>145.23</td>
</tr>
</tbody>
</table>
Components of Time Series

- **Systematic component**: Components of the time series that have consistency or recurrence and can be described and modeled.
  - Level: The value in the series.
  - General Trend: The increasing or decreasing value in the series.
  - Seasonal: The repeating short-term cycle in the series.
  - Cyclical Fluctuation: The repeating long-term cycle in the series.

- **Non-Systematic component**: Components of the time series that cannot be directly modeled
  - Irregular Fluctuations or Residual Effect or Error or Noise: The random variation in the series.
Time Series Component 1&2: Level & Trend

- **Level**: Captures scale of the time series
- **Basically the value at each time interval** ($L_t$)

- **Trend**: is the increase or decrease in the series over a period of time.
- **Example**: population increase
- **Often** several years duration but for example, in stock markets we may be interested in shorter term trends.
Time Series Component 3: Seasonality

- **Seasonality** is the presence of variations (or fluctuation) that occur at specific regular intervals less than a year, such as daily, weekly, monthly, or quarterly.
- Seasonality may be caused by various factors, such as weather, vacation, and holidays.
- Seasonality consists of periodic, repetitive, and generally regular and predictable patterns in the levels of a time series.
- Examples:
  - Stock markets: Weekly seasonal variations.
  - Traffic to a website: Some hours of the day are typically busier than others, and this pattern recurs daily.

Source: https://en.wikipedia.org/wiki/Seasonality
Seasonality Example

Monthly Unadjusted Retail Sales

- Seasonality
- Upward Trend
Time Series Component 4: Cyclical Fluctuation

• It is the wavelike up and down fluctuations about the trend that is attributable to economic or business conditions.

• This fluctuation is also known as business cycle. During economic expansion, the cycle lies above the trend; during a downturn, beneath it. Repeating up and down movements.

• Usually 2-10 years duration.

• Exact duration of a cycle is not known beforehand -> difficult to consider when forecasting.
Cyclical Fluctuation Example
Time Series Component 5: Residual Effect or Irregular component or Error

- **Residual Effect** - is what remains, having removed the Trend, Cyclical and Seasonal components of a time series.
- Represents the random error effect of a time series, caused by events as widespread as wars, hurricanes, strikes and randomness of human actions or any unexplained causal factors.
- Short duration and non repeating
- Impossible to forecast
- **Residual Effect** is also called Irregular fluctuations or error
Residual Effect Example

Residual Effect
Time Series Components: Example
What is a Time Series?
A formal representation

• Each data point \((Y_t)\) at time \(t\) in a Time Series can be expressed as either a sum or a product of 3 components, namely, *Seasonality* \((S_t)\), *Trend* \((T_t)\) and *Error* \((\epsilon_t)\) a.k.a. White Noise.

• For Additive Time Series,
  • \(Y_t = S_t + T_t + \epsilon_t\)

• For Multiplicative Time Series,
  • \(Y_t = S_t \times T_t \times \epsilon_t\)
Additive Vs. Multiplicative

• Additive time series:
  • Even with an increasing trend, you still see roughly the same size peaks and troughs throughout the time series.
  • Absolute value is growing but changes stay relative.
  • Example: TV purchases every month (except seasonal), beer consumption

• Multiplicative time series:
  • With increasing trend, the amplitude of seasonal activity increases.
  • Example: Web traffic, airline passenger.

<table>
<thead>
<tr>
<th></th>
<th>No seasonality</th>
<th>Additive Seasonality</th>
<th>Multiplicative Seasonality</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No Trend</strong></td>
<td>Constant Trend Non-seasonal</td>
<td>Constant Trend with Additive Seasonality</td>
<td>Constant Trend with Multiplicative Seasonality</td>
</tr>
<tr>
<td><strong>Additive Trend</strong></td>
<td>Upward Linear Trend Non-seasonal</td>
<td>Upward Linear Trend with Additive Seasonality</td>
<td>Upward Linear Trend with Multiplicative Seasonality</td>
</tr>
<tr>
<td><strong>Multiplicative Trend</strong></td>
<td>Upward Exponential Trend Non-seasonal</td>
<td>Upward Exponential Trend with Additive Seasonality</td>
<td>Upward Exponential Trend with Multiplicative Seasonality</td>
</tr>
<tr>
<td><strong>Polynomial Trend</strong></td>
<td>3rd Order Polynomial Trend Non-seasonal</td>
<td>3rd Order Polynomial Trend with Additive Seasonality</td>
<td>3rd Order Polynomial Trend with Multiplicative Seasonality</td>
</tr>
</tbody>
</table>

Time Series Methods

• Time series forecasting relies on:
  • Sufficient past data being available
  • Data is of a high quality and truly representative.

• Time series methods are best suited to relatively stable situations

• Time series not suitable for:
  • Substantial fluctuations are common
  • Underlying conditions are subject to extreme change

Does not make sense to apply in every case!
Does not make sense?

• When the values are constant over time.
  • Example: Rent

constant value across different time units.
• When values can be represented using a known function.
  • Example: Such as sine function.

sine function can be used to predict values.
Forecasting Techniques

Qualitative ↔ Quantitative
Forecasting Techniques

Qualitative

1. Expertise
   • People with experience

2. Technical Knowledge
   • People with Technical know-how

3. Experience

4. Intuition

5. Delphi Method
   • Iterative approach: A set of questions are developed and shared with domain experts and depending upon what answers are received, adjustment are made

6. Executive opinion
   • Dominance of higher positioned people.

7. Salesforce opinion
   • Underestimate the demand, so that they are unable to meet the target

8. Consumer Survey
   • Consumer survey
Forecasting Techniques
Quantitative

- Linear Regression
- Multiple Linear Regression

Causal Models

Time-series Models

- Smoothing
  - Smooth the random parts of data to find sustainable and explicable patterns

- Trend
  - Find the broad sustainable trend, without Seasonal effects

- Trend & Seasonality
  - Find the trend as well as the seasonal effects

Source: [http://www.anallyz.com/timeseries](http://www.anallyz.com/timeseries)
Forecasting Techniques
Quantitative

- Linear Regression
- Multiple Linear Regression

Source: http://www.anallyz.com/timeseries
Smoothing Methods

• Smoothing techniques are used when there are no appreciable Trend, Cyclical or Seasonal patterns in the data.

• The prime objective is to average out the irregular components.

• Smoothing techniques rely on following Averaging Methods:
  • Simple, Weighted Moving Average
  • Single Exponential Moving Average
Moving Average

- A moving average is a technique to get an overall idea of the trends in a dataset; it is an average of any subset of numbers.

- **Simple Moving Average (SMA):** SMA uses average of past n values (called order or period of SMA) to predict a current value.

- The best n is obtained by trial-and-error, which results in least error.

- SMA is not very effective in case of Trend component and is not very useful as a forecasting tool.

- Their main use is in averaging sudden changes in data and finding the stable pattern in the data.

<table>
<thead>
<tr>
<th>Week</th>
<th>Sales</th>
<th>2 week moving average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>(8+10)/2 = 9</td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>(10+9)/2 = 9.5</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>(9+11)/2 = 10</td>
</tr>
<tr>
<td>6</td>
<td>13</td>
<td>10+11)/2 =10/5</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>(10+13)/2 = 11.5</td>
</tr>
</tbody>
</table>
**Weighted Moving Average (Example)**

<table>
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<th>Sales</th>
<th>2 week moving average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>0.2<em>8 + 0.8</em>10 = 9.6</td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>0.2<em>10 + 0.8</em>9 = 9.2</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>0.2<em>9 + 0.8</em>11 = 10.6</td>
</tr>
<tr>
<td>6</td>
<td>13</td>
<td>0.2<em>11 + 0.8</em>10 = 10.2</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>0.2<em>10 + 0.8</em>13 = 12.4</td>
</tr>
</tbody>
</table>

- Weights are attached to each previous data points.
- Depending on whether recent historical points are more or less important, a high or low weights can be attached respectively.
- Weighted MA is used when there is a clear indication of Trend component in Time series data.
Single Exponential Moving Average

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<td>1</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>0.5<em>10 + 0.5</em>8 = 9</td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>0.5<em>9 + 0.5</em>10 = 9.5</td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>?</td>
</tr>
<tr>
<td>5</td>
<td>10</td>
<td>?</td>
</tr>
<tr>
<td>6</td>
<td>13</td>
<td>?</td>
</tr>
<tr>
<td>7</td>
<td></td>
<td>?</td>
</tr>
</tbody>
</table>

Exponential smoothing is usually used to make short term forecasts. Used when there is no trend and seasonality

\[ L_t = \alpha Y_t + (1 - \alpha) L_{t-1} \]

\( L_t \) = Future value to be predicted
\( L_{t-1} \) = Previous predicted Future value
\( Y_t \) = Previous actual value
\( \alpha \) = smoothing constant. Between 0 to 1.
\( \alpha = 1 \), past values have no influence over forecasts (under-smoothing)
\( \alpha = 0 \), past values have equal influence on forecasts (over-smoothing)

Possible Initialization: \( L_1 = Y_1 = F_1 \)

\( \alpha = 0.5 \)

Selecting \( \alpha \)
Typical values: 0.1, 0.2
Trial and Error
Minimize RMSE or MAPE of training
Why it is called Exponential

\[ L_t = \alpha Y_t + (\alpha - 1) L_{t-1} \]

\[ L_t = \alpha Y_t + (1-\alpha)[\alpha Y_{t-1} + (1-\alpha) L_{t-2}] = \]
\[ = \alpha Y_t + \alpha (1-\alpha)Y_{t-1} + (1-\alpha)^2 L_{t-2} = ... \]
\[ = \alpha Y_t + \alpha (1-\alpha)Y_{t-1} + \alpha (1-\alpha)^2 Y_{t-2} + ... \]

ARMA and ARIMA for Forecasting

• Models:
  • MA: Moving Average
  • AR: Autoregressive
  • ARMA: Autoregressive Moving Average
  • ARIMA: Autoregressive Integrated Moving Average

• ARMA/ARIMA
  • is usually more accurate and general purpose.
  • Needs more data points as compared to Smoothing
  • Suitable when data is relatively stable and not very volatile.
ARMA and ARIMA

• Underlying Assumptions

• Stationary (for AR models)
  • What we mean by stationary?
    • Mean should be constant according to the time.
    • Variance should be equal from the mean at different time interval.
    • Covariance should equal.

• Invertibility (for MA models)
  • Series can be represented by a finite order MA or convergent AR process.
  • Uses the autocorrelation function (ACF) and partial ACF (PACF) for identification (we will discuss ACF/PACF in coming slides)
Stationary Series: Mean

• Mean of the series should not be a function of time rather should be a constant.

• Green graph satisfying the condition whereas the graph in red has a time dependent mean.

Source: https://www.analyticsvidhya.com/blog/2015/12/complete-tutorial-time-series-modeling/
Stationary Series: Variance

- Variance of the series should not be a function of time.
  - This property is known as homoscedasticity.
- Notice the varying spread of distribution in the right hand graph.

Source: https://www.analyticsvidhya.com/blog/2015/12/complete-tutorial-time-series-modeling/
Stationary Series: Covariance

• Covariance of the $i^{th}$ term and the $(i+m)^{th}$ term should not be a function of time.

• Right hand side: spread becomes closer as the time increases. Hence, the covariance is not constant with time for the ‘red series’.

Source: https://www.analyticsvidhya.com/blog/2015/12/complete-tutorial-time-series-modeling/
ARIMA
Autoregressive time-series models

Regression
\[ y = b_0 + b_1 x + \varepsilon_t \]

AutoRegression: Self regression
\[ x_t = b_0 + b_1 x_{t-1} + b_2 x_{t-2} + \varepsilon_t \]

Abbreviated as AR(\(p\)) models, the \(p\) indicates how many lagged values of the dependent variable are used and is known as the “order” of the model.

# Products Bought

\[ \text{CLV} \]

2M 3M 4M 5M

\[ \text{# Products Bought} \]

2 3 4 5 6
Autoregressive time-series models

Abbreviated as AR($p$) models, the $p$ indicates how many lagged values of the dependent variable are used and is known as the “order” of the model.

• Current values are a function of prior values.
• The “order” of the AR($p$) models is the number of prior values used in the model.
  • $\text{AR}(1) \Rightarrow x_t = b_0 + b_1 x_{t-1} + \varepsilon_t$
  • $\text{AR}(2) \Rightarrow x_t = b_0 + b_1 x_{t-1} + b_2 x_{t-2} + \varepsilon_t$

Generic AR($p$) model

\[ AR(p) = x_t = b_0 + \sum_{i=1}^{p} b_i x_{t-i} + \varepsilon_t \]

Source: https://www.cfainstitute.org
ARIMA

Integrated: Degree of Differencing

Differencing: Subtracting prior values from the current values.

Example of 1\textsuperscript{st} order differencing.

<table>
<thead>
<tr>
<th>Values</th>
<th>1\textsuperscript{st} order Differencing</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>4</td>
<td>4-5</td>
<td>-1</td>
</tr>
<tr>
<td>6</td>
<td>6-4</td>
<td>2</td>
</tr>
<tr>
<td>7</td>
<td>7-6</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>9-7</td>
<td>2</td>
</tr>
<tr>
<td>12</td>
<td>12-9</td>
<td>3</td>
</tr>
<tr>
<td>12</td>
<td>12-12</td>
<td>0</td>
</tr>
</tbody>
</table>
A moving average is a technique to get an overall idea of the trends in a dataset; it is an average of any subset of numbers.

It represents the error of the model as a combination of previous error terms $e$ with lags $q$

$$x_t = b_0 + d_0 e_t + d_1 e_{t-1} + d_2 e_{t-2}$$

Generic MA($q$) model  $MA(q) = x_t = b_0 + \sum_{j=0}^{q} d_j e_{t-j}$
ARMA model

• ARMA \((p,q)\)

• For AR\((p)\) and MA\((q)\) model, the pattern explains the variable to be predicted (GDP) is explained by its own past values and the current and past values of the error term

\[
x_t = b_0 + \sum_{i=1}^{p} b_i x_{t-i} + \varepsilon_t + \sum_{j=0}^{q} d_j e_{t-j}
\]
ARIMA

• Autoregressive Integrated Moving Average.
  • Autoregressive (AR)
  • Integrated (I)
  • Moving Average (MA)

• ARIMA is specified by three order parameters p, d, q
  • p: number of Autoregressive terms (AR)
  • d: how many non-seasonal differences are needed to achieve stationarity (I)
  • q: number of lagged forecast errors in the prediction equation (MA)

• ARIMA works on the assumption that the data is stationary
  • Trend and Seasonality of the data has been removed.

• ARIMA (1, 1, 2) indicates the model has: one lag of the dependent variable (1),
  the variable being used is of first-difference stationary and two lags of the
  error term (2)
How to make sure a series is Stationary

• By handling Trend and Variances
  • To remove unequal variances
    • By using log of the series.
  • To address the trend component.
    • By taking difference of the series.

• How to test your series is Stationary?
  • Dickey-Fuller test
    • adf.test()
  • If p value is < 0.05, series is stationary.
Is it stationary?

Mean: If mean is constant?

Variance: If variance is constant?

Co-variance: What about co-variance?
Is it stationary?

Mean: Increasing

Variance: not constant

Co-variance: Varying
Understanding Stationary Series

Is it Stationary?
- Mean?
- Variance?
- Covariance?

Is it Stationary?
- Mean?
- Variance?
- Covariance?
How to remove trend?

**Detect:** A simple Run Plot (Line chart) may show Trend.

**Remove:** In order to make the data stationary, current data point is subtracted from the previous one for the entire series (differencing).

If Data is changing at a constant rate.
   One Diff enough generally (1st Order differencing)
If not
   Differencing process may be needed one more time (2nd Order Differencing)

Source: http://www.anallyz.com/timeseries
In order to test whether or not the series is stationary or not and their error term is auto correlated, we usually use

- **Auto-correlation Function Plot (ACF)**
- **Partial Auto-correlation function (PACF)**

A gradual decay in ACF plot is also a sign of “Nonstationarity” in the data.
Autocorrelation & Partial Autocorrelation

**Autocorrelation Function**

- Auto-correlation is the similarity between values of a same variable across observations.
- Auto-correlation Function tells you how correlated points are with each other.
- It is used to determine how past and future data points are related in a time series. It’s value can range from -1 to 1.

**Partial Autocorrelation Function**

- Partial Autocorrelation measure the degree of association between $Y_t$ and $Y_{t-p}$ when the effects at other time lags 1, 2, 3, ..., (p-1) are removed.

<table>
<thead>
<tr>
<th>MODEL</th>
<th>ACF</th>
<th>PACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(p)</td>
<td>Spikes decay towards zero</td>
<td>Spikes cutoff to zero</td>
</tr>
<tr>
<td>MA(q)</td>
<td>Spikes cutoff to zero</td>
<td>Spikes decay towards zero</td>
</tr>
<tr>
<td>ARMA(p,q)</td>
<td>Spikes decay towards zero</td>
<td>Spikes decay towards zero</td>
</tr>
</tbody>
</table>
For Auto-regressive

\[ > \text{acf}(\text{AirPassengers}) \]  
\[ > \text{acf}((\text{diff}(\log(\text{AirPassengers})))) \]

Value of q is 1
Moving Average and Integrated

Moving Average

Integrated

> diff(log(AirPassengers))

Value of d is 0

Value of p is 0
Framework of ARIMA Time Series Modeling

1. Explore the data (Visualization)
   Essential to analyze the trends prior to building any kind of time series model

2. Stationarize the series
   Dickey – Fuller is one of the popular test to check

3. Find optimal value (Using auto.arima from forecasting package, or ACF /PACF)
   Find optimal parameters (p, q, d)

4. Build the ARIMA model

5. Make Predictions
Evaluation

• Data Partitioning (Temporal Partitioning)
  • Fixed Partitioning
  • Roll-Forward Partitioning
Data Partitioning (Temporal Partitioning)

Fixed Partitioning
Data Partitioning (Temporal Partitioning)

Roll-Forward Partitioning
Data Partitioning (Temporal Partitioning)

Roll-Forward Partitioning

Or do not drop the old data

Use: Deployment scenario is roll-forward.
Forecasting Techniques

**Qualitative**

- Expertise
- Technical Knowledge
- Experience
- Intuition
- Delphi Method
- Executive opinion
  - Dominance of higher positioned people.
- Salesforce opinion
  - Underestimate the demand, so that they are unable to meet the target
- Consumer Survey

**Quantitative**

- Time Series Methods
  - Moving Average
  - ARIMA
  - Exponential smoothing
  - Trend Projection
  - Decomposition
- Causal Methods
  - Linear regression
  - Multiple linear regression.
Summary
Steps of Forecasting Tasks

1. Define Goal: What would you like to forecast?

2. Get Data: Online or specific organizations can provide data?

3. Explore and Visualize Series: Graphs -- Trend and Seasonality

4. Partition Series: Strict or roll-forward

5. Apply Forecasting Method/s: AR, MA, ARIMA etc

6. Evaluate and Compare Performance: RMSE, MAE etc
References

• Forecasting: Principles and Practice
  • By George Athanasopoulos and Rob J. Hyndman

• Practical Time Series Forecasting with R: A Hands-On Guide
  • By Galit Shmueli and Kenneth C. Lichtendahl

• A Little Book of R For Time Series Release 0.2
  • By Avril Coghlan

• Top Books on Time Series Forecasting With R
  • https://machinelearningmastery.com/books-on-time-series-forecasting-with-r/
Demo time!

https://courses.cs.ut.ee/2019/bda/spring/Main/Practice