

# Forecasting Process

IDS 552

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# Discussion Outline

- Forecasting setup
- Performance evaluation
- Communication and maintenance
- Neural networks for forecasting (video + notes)
  - <https://www.youtube.com/watch?v=aircAruvnKk&t=633s>

# Forecasting Setup

# What are we forecasting?

1. Number of orders (?)
  2. Number of shipments (?)
- Examples of issues:
    - An unfilled order may be rolled ahead to a future time bucket – orders overstate demand and shipments understate demand
    - If shortages are anticipated, customers may artificially inflate their orders to capture a larger share of an allocation – orders and shipments overstate demand
    - If shortages are anticipated, customers may withhold orders or direct their orders to substitute products or competitors – orders and shipments understate demand
    - Special Promotions typically increase customer orders and shipments during a particular season – orders and shipments understate demand if promotion is no longer in effect
  - Shipments have an advantage over orders because they are less likely to be manipulated

# Self-reported demand

Week	1	2	3	4	Month Total
Orders	50	50	60	60	220
Shipments	50	40	55	40	185
Shortages		10	5	20	35

1. Demand = (shipments + orders)/2 = (220 + 185)/2 = 202.5
  2. Demand = Shipments + latest shortages = 205
- Second definition avoids over-counting shortages
  - The best definition of self-reported demand depends on the specific situation
  - Since forecasting errors can be 20% or more, an operational definition of demand that is a few percent off is perfectly fine!

# Forecast horizon and updating

- Forecast horizon ( $k$ ): Number of periods ahead that we forecast
- $F_{t+k}$  is a  $k$ -step ahead forecast made at time  $t$
- Amtrak example: One month ahead forecast (i.e.  $F_{t+1}$ ) may suffice for revenue management but longer forecasts are likely needed for procurement and staffing decisions (e.g.  $F_{t+3}$ )
- Forecast updating: How recent is the data that you are using for prediction?
  - Suppose the goal is to predict next month ridership for Amtrak
  - Monthly updates of data implies that you are relying on 2-step ahead forecasts
  - Updating data every 3 months could mean that you are using 4-step ahead forecasts

- Data collection is not a one-time effort in business and typically requires multiple sources to reconcile quality
- Temporal frequency: At what time scale do you want to collect data?
  - Stock ticker data is available minute-by-minute and online purchases in a retail are recorded in real time
  - Is higher data frequency always better? Why or why not?
  - Suppose the goal is to forecast daily sales, then is minute-by-minute data appropriate?

- Top performer quote at NN5 time series competition:

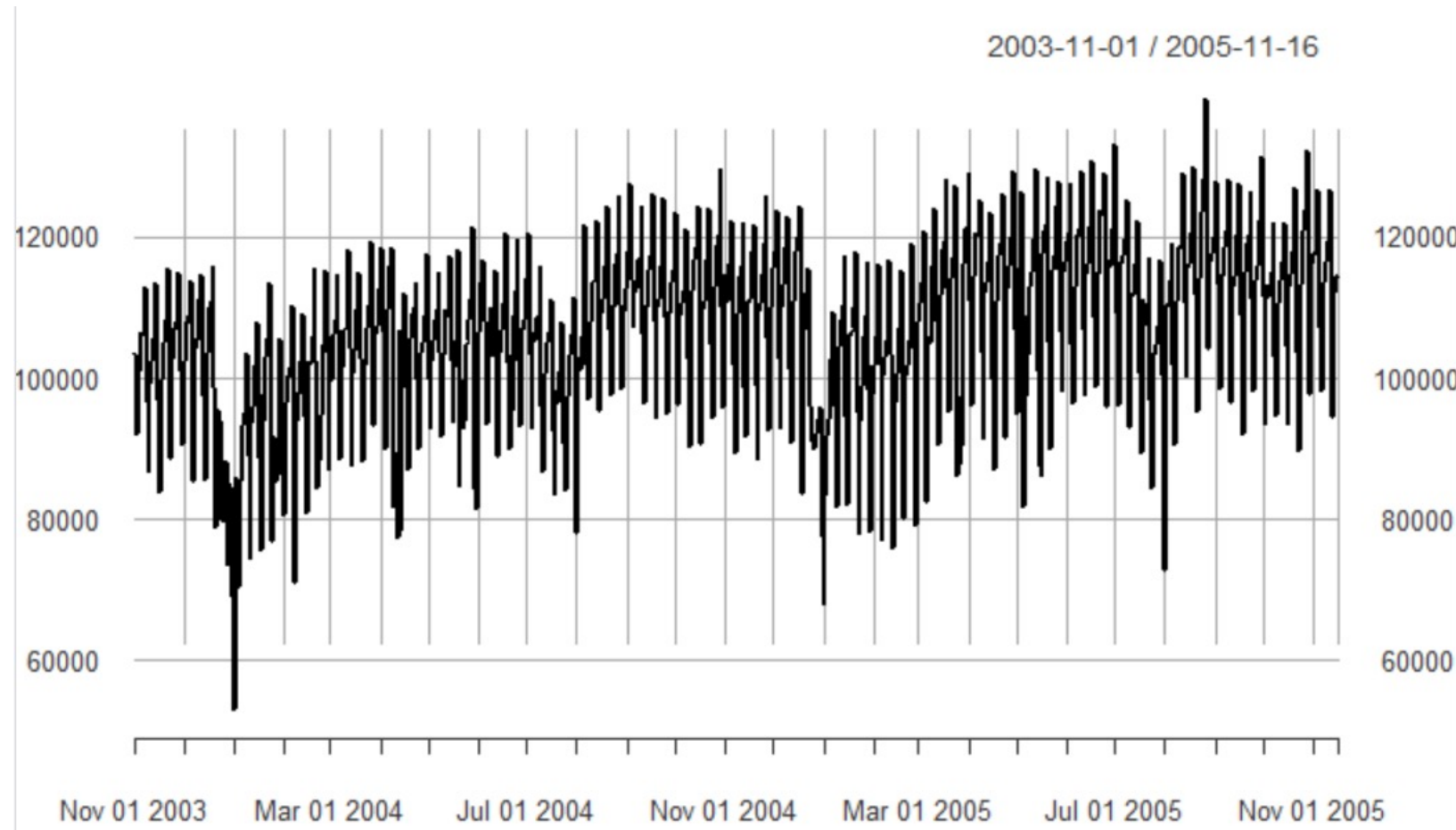
“To simplify the forecasting problem, we performed a time aggregation step to convert the time series from daily to weekly .... Once the forecast has been produced, we convert the weekly forecast to a daily one by a simple linear interpolation scheme”

- Takeaway: Aggregation of the data may be useful even if the forecast is required at a more granular level (e.g. due to lack of data and/or excessive noise)

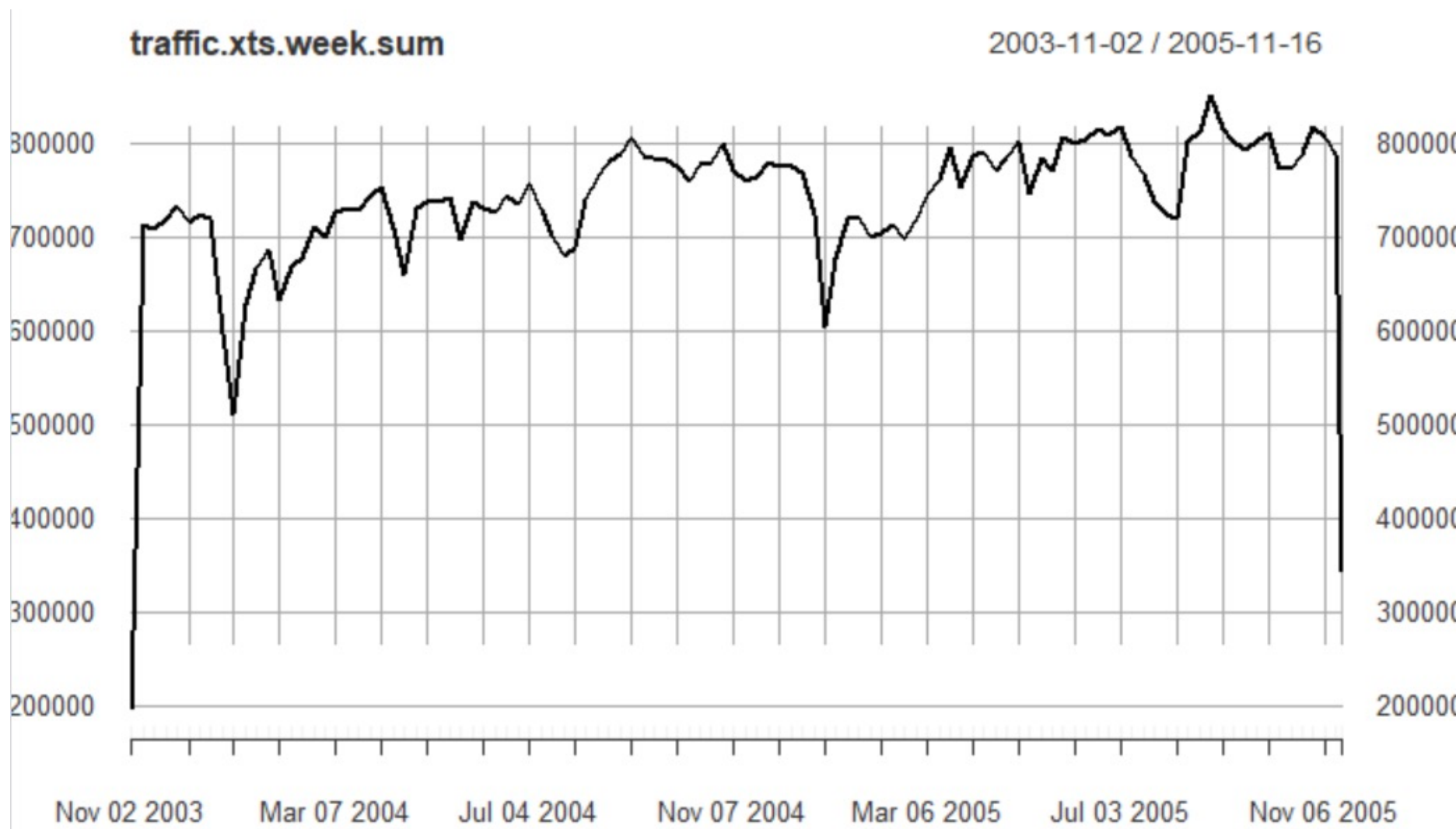


- Refers to the coverage of data (e.g. geographically)
- Amtrak ridership could be measured at the route-level, station-level, or state-level.
- Very fine granularity may lead to lack of observations
- Suppose track daily Amtrak ridership of senior citizens who require assistance on a specific route.
  - How might the series look?
  - Any issues?

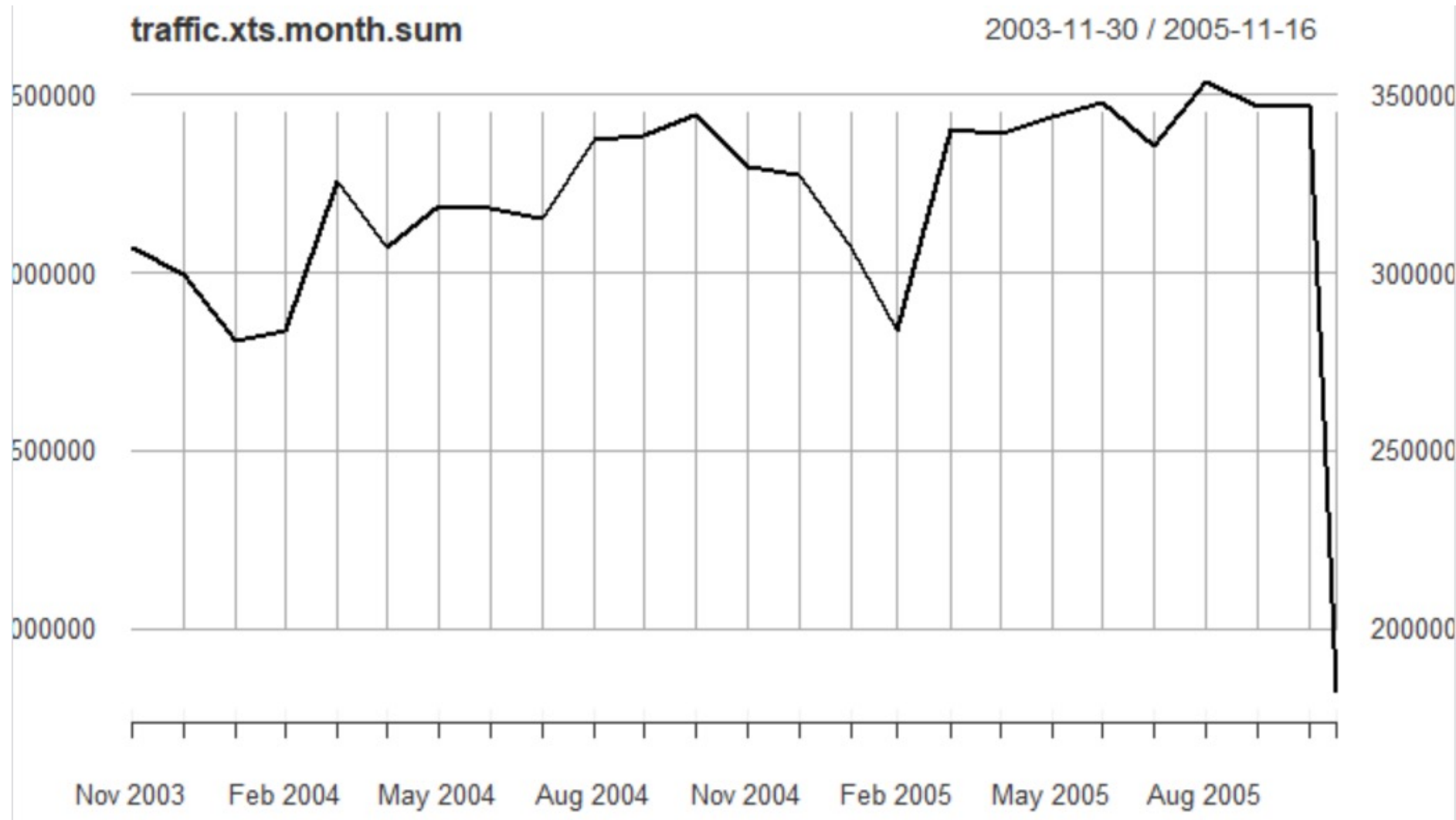
# Tunnel Traffic Data (by day)



# Tunnel Traffic Data (aggregate by week)



# Tunnel Traffic Data (aggregate by month)



# Visualizing time series: Initial step

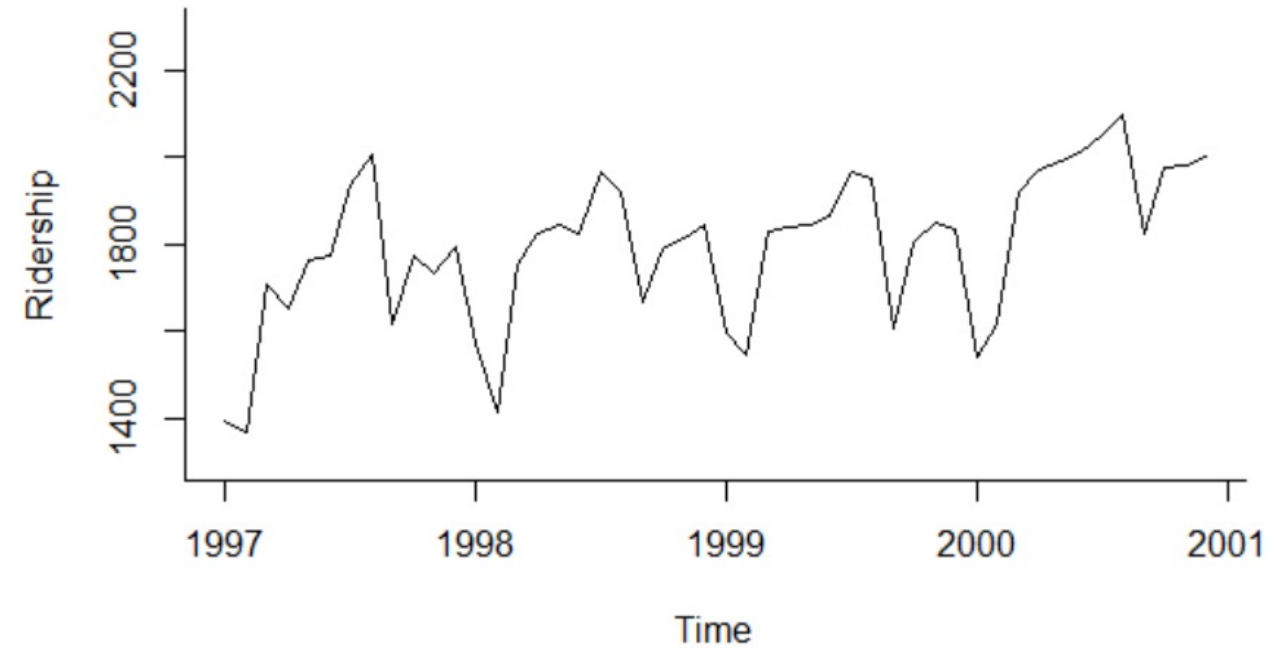
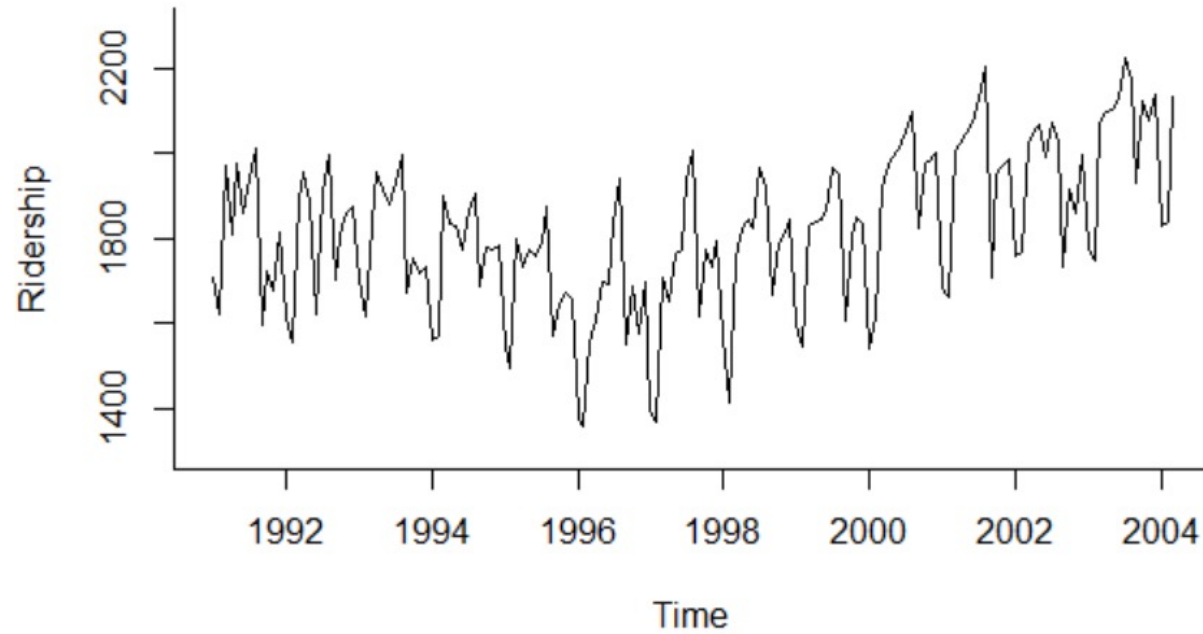
- Visualization helps detect initial patterns, inform models, and spot potential problems such as extreme values, unequal spacing, and missing values
- First step: Plot the time series
- Some additional operations to learn about the data:
  - Zooming in to shorter time periods
  - Adding trend lines
  - Suppressing seasonality via aggregation and averaging

# Amtrak Ridership Data

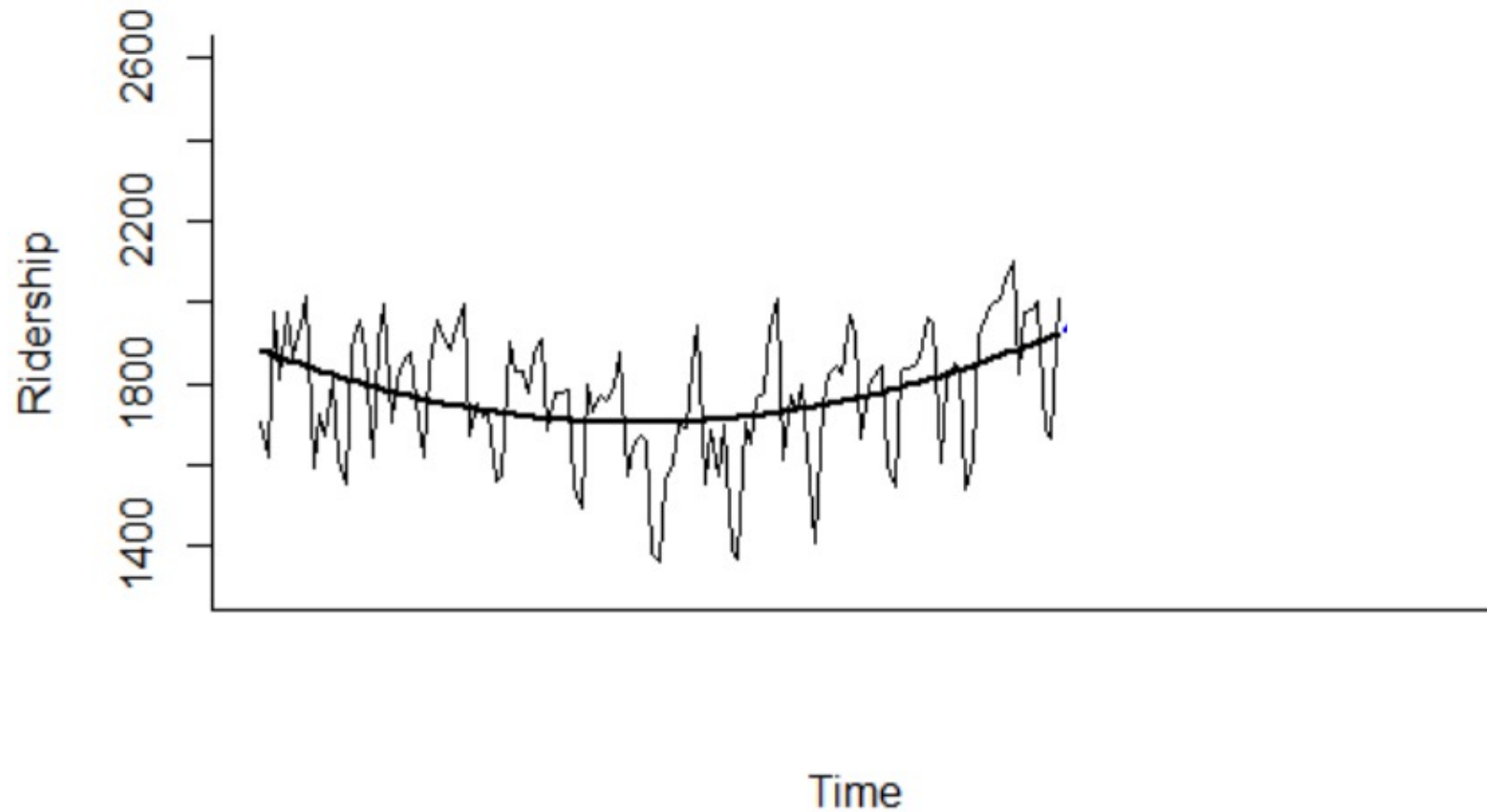
Month	Ridership
Jan-91	1708.917
Feb-91	1620.586
Mar-91	1972.715
Apr-91	1811.665
May-91	1974.964
Jun-91	1862.356
Jul-91	1939.86
Aug-91	2013.264
Sep-91	1595.657
Oct-91	1724.924
Nov-91	1675.667
Dec-91	1813.863
Jan-92	1614.827
Feb-92	1557.088
Mar-92	1891.223
Apr-92	1955.981
May-92	1884.714
Jun-92	1623.042
Jul-92	1903.309

2-Nov	1858.345
2-Dec	1996.352
3-Jan	1778.033
3-Feb	1749.489
3-Mar	2066.466
3-Apr	2098.899
3-May	2104.911
3-Jun	2129.671
3-Jul	2223.349
3-Aug	2174.36
3-Sep	1931.406
3-Oct	2121.47
3-Nov	2076.054
3-Dec	2140.677
4-Jan	1831.508
4-Feb	1838.006
4-Mar	2132.446

# Data Plots



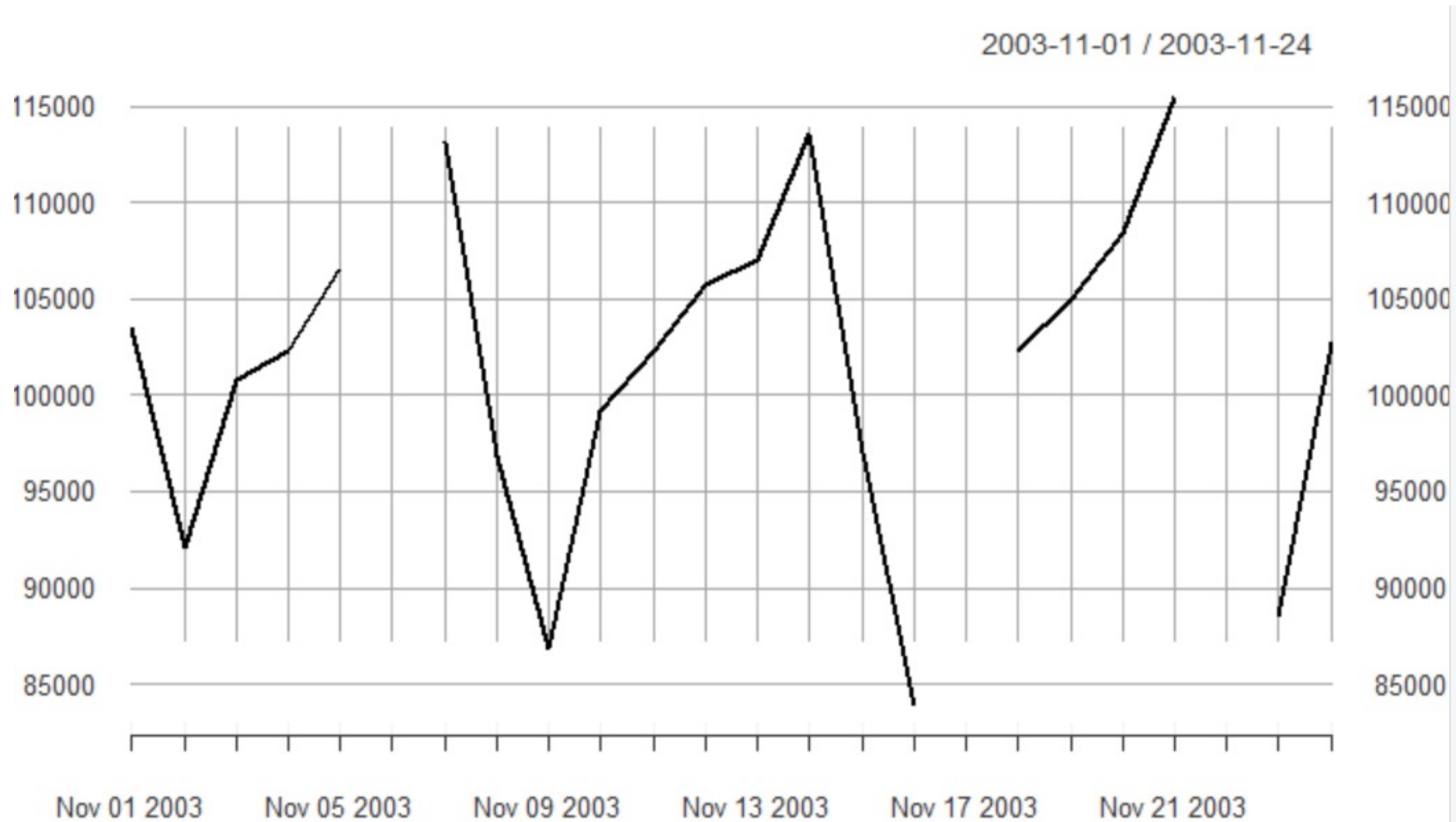
# Quadratic Regression





- Missing values: Holes in the series
- Is this an issue?
  - Yes, for linear regression
  - Not necessarily for methods such as neural networks
- Possible methods for filling in missing values
  - Average neighboring values
  - Create a forecast of missing values using past data

# Tunnel Traffic Missing Data

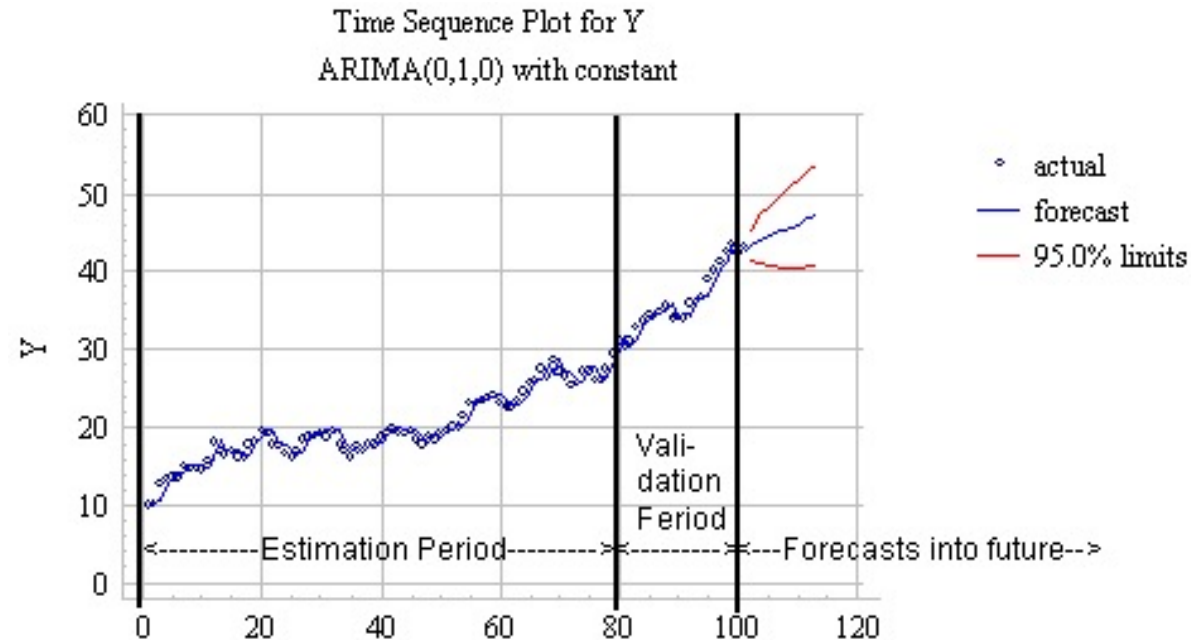


- Extreme values: What makes them extreme?
  - Difficult to justify removal without knowing the source (e.g. data entry error or rare event?)
  - Practical solution: Create forecasts with and without extreme values and understand its impact

# Performance Evaluation

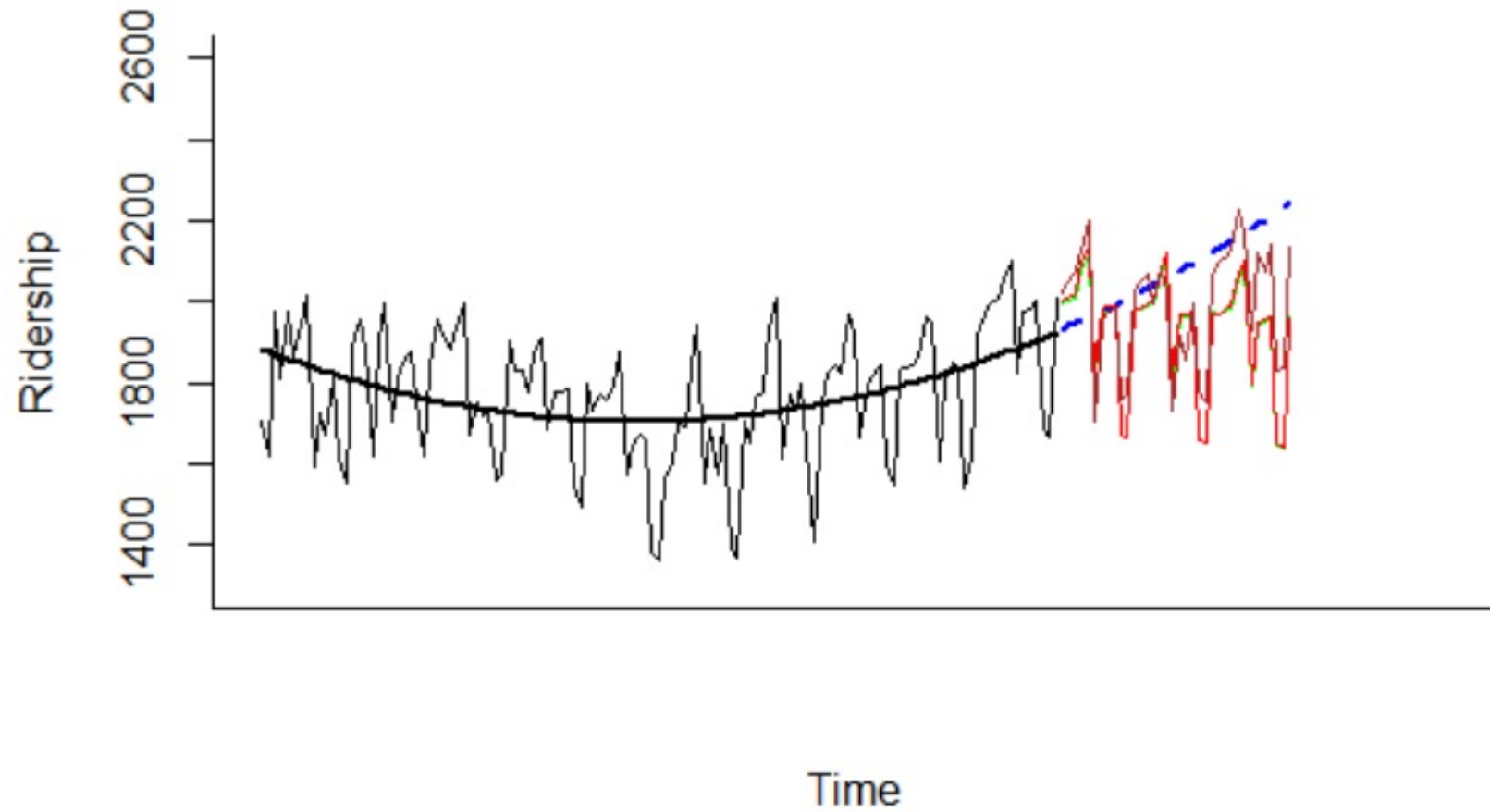
# Revisit data partitioning: Model calibration and choice

- Partition data into training and validation sets



- We calibrate models on the training set and test it on the validation set
- Validation period is typically chosen to mimic the forecast horizon

# Validation




# Let's forecast?

- Suppose we have chosen the “best” model based on the training and validation partition
- Do we start forecasting?
- No!! We need to recalibrate on the complete data set, that is, without partitioning
- Why?
  - You have more data to calibrate the model parameters
  - Throwing away the validation period amounts to removing the most recent data
  - If a model is calibrated using only the training set, then it must forecast further than the validation period to be useful

# Naïve forecast benchmarks

- k-step ahead naïve forecast at time  $t$ :

$$F_{t+k} = D_t$$



Current  
demand value

- k-step seasonal naïve forecast [assume we have  $M$  ( $> k$ ) seasons]:

$$F_{t+1} = D_{t-M+1}$$

$$F_{t+2} = D_{t-M+2}$$

$$F_{t+k} = D_{t-M+k}$$



- We discussed error measures in the last class (e.g. MAPE)
- Forecast error:  $E_t = F_t - D_t$
- Mean absolute deviation:  $MAD = \frac{1}{n} \sum_{t=1}^n |E_t|$
- MAD is also known as mean absolute error (MAE)
- R has an “accuracy” function to automatically compute prediction accuracy measures, including average error, MAD, and MAPE

- Mean absolute scaled error (MASE) compares a forecasting method relative to a naïve forecast
- Assume an  $n$  period training set and a  $v$  period validation set

$$MASE = \frac{\text{validation MAD } (v \text{ periods})}{\text{training MAD of naive forecasts } (n \text{ periods})} = \frac{\frac{1}{v} \sum_{t=n+1}^{n+v} |E_t|}{\frac{1}{n} \sum_{t=1}^n |D_{t-1} - D_t|}$$

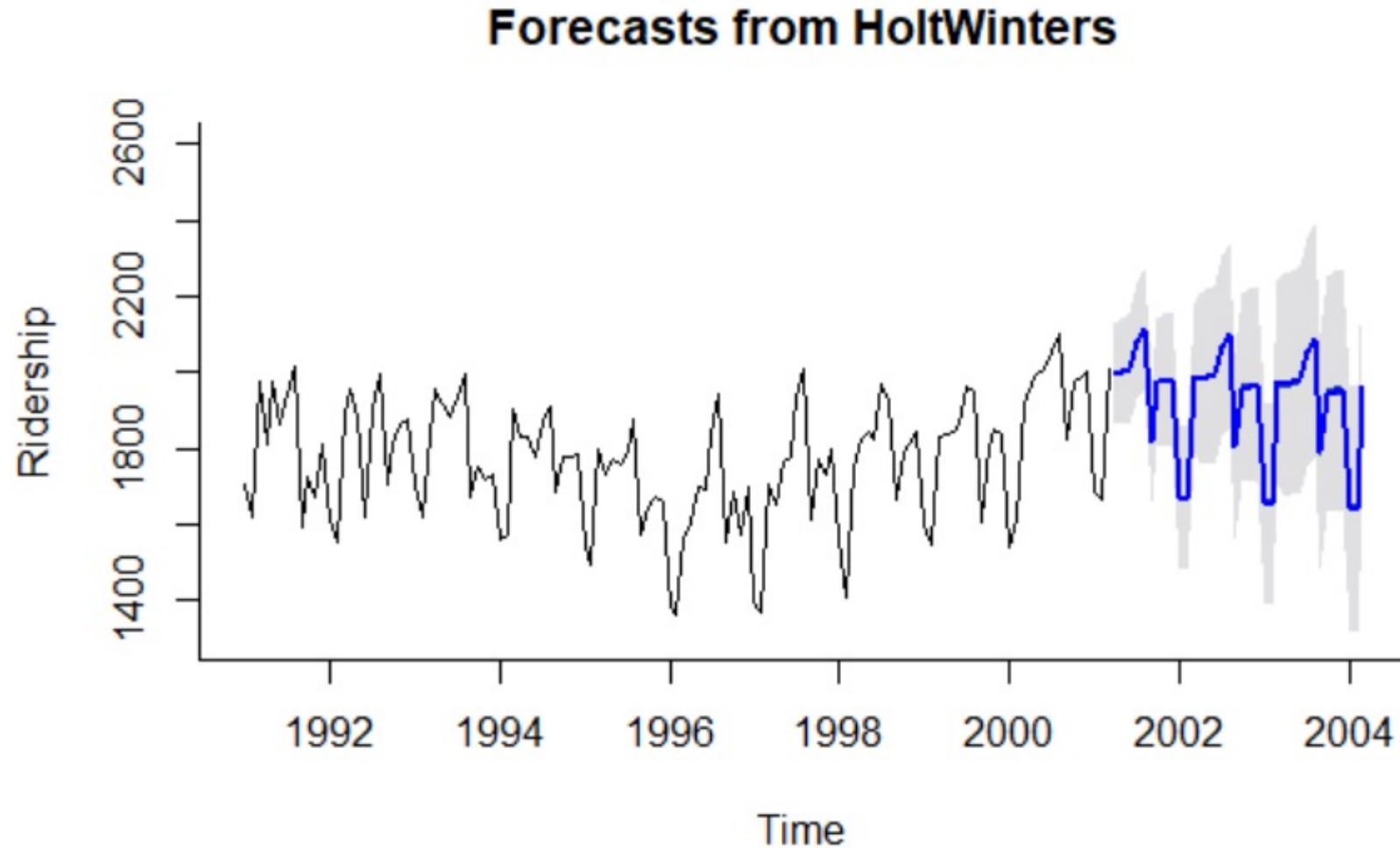
- MASE greater than 1 indicates worse performance than naïve forecast, while a value less than 1 indicates an improvement over the naïve forecast

# Forecast accuracy vs profitability

- When using error measures (e.g.  $MSE$ ), large errors typically carry more weight than small errors
- Is this always true?
- No, underage and overage costs resulting from errors may differ
- Example: inventory systems

- Compare methods based on prediction intervals
- Don't just display a point forecast but intervals around this number indicating the level of uncertainty
- Common choice is to construct a 95% confidence interval

# Holt Winters



# Forecasting Communication and Maintenance

# Presenting forecasts

- Typically involves an oral presentation accompanied by slides
- What kind of audience might the presentation target in a business?
  - Managerial
  - Technical
- Goal of the presentation?
  - Make recommendations or observations (you have a clear desired outcome)
  - Promote discussion on an issue (unclear outcome but presentation is still geared towards highlighting specific issues)

- Identify a few key points you would like to highlight in the concluding slide
- Each slide of your presentation should play a role towards making these key points in a convincing and appealing manner
- Set the stage for what's coming
  - Outline and provide general context for the presentation (e.g. Is your presentation addressing a specific action item raised in the last meeting?)
  - Need to establish why the remaining material is important
- Managerial audience: Avoid too much technical detail and keep the focus on the forecasts
- Technical audience: Include a high-level description of the forecasting method, the data used for generating forecasts, and the performance evaluation and results



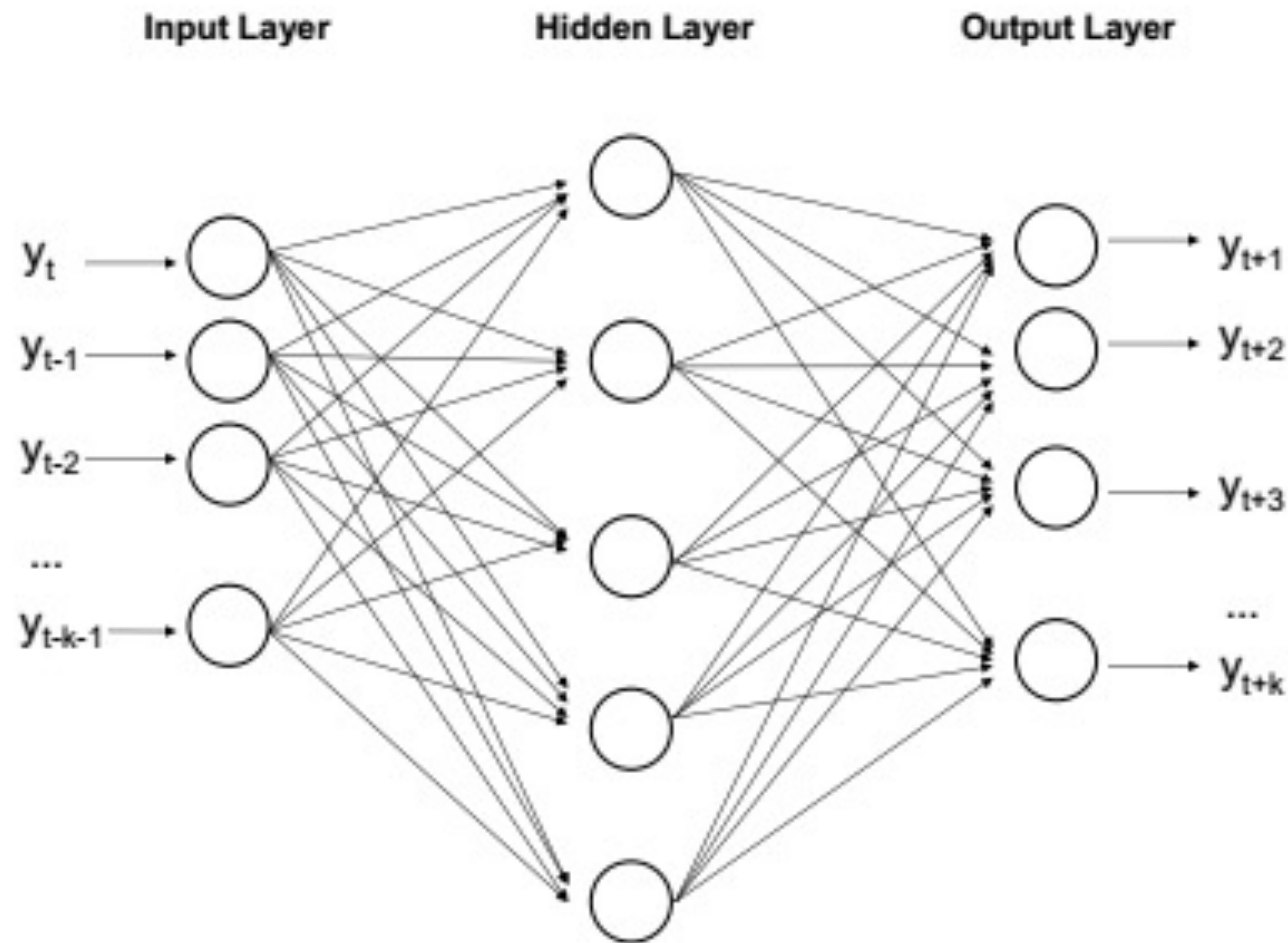
- Use charts as opposed to tables when possible
- Dynamic plots are quite useful to drill down and make the presentation interactive
- When showing forecasts, choose the scale of each chart carefully to highlight the main trend that you want to talk about, and avoid showing meaningless details
- If you want to highlight uncertainty, use prediction intervals

- It is imperative that you periodically reassess the performance of the forecast being generated
- Useful to create two graphs:
  1. Plot of the actual and forecast values
  2. Plot of forecast errors
- The first graph is useful to detect deterioration of forecast precision, while the second directly indicates the direction of deviation and their magnitude

- There needs to be clear documentation of the forecasting process used in your firm or department
- This document should include the steps used in either creating or modifying a forecast
- Create a repository of past forecasts as it will allow you to evaluate how your firm's forecasting performance changes over time

# Neural Network for forecasting

- Time series neural network



- Time series neural network can be extended to include external information by specifying additional input nodes.
- For instance, to better forecast the annual Japanese tourist arrivals in Hong Kong, a neural network structure can be constructed including six nodes:
  - service price
  - average Hotel rate
  - foreign exchange rate
  - population
  - marketing expenses
  - gross domestic expenditure

(R. Law and N. Au. A neural network model to forecast Japanese demand for travel to Hong Kong.)