Estimation, Forecasting and Overbooking

Block 2

Zaenal Akbar (zaenal.akbar@sti2.at)
Topics:

1. Estimation and Forecasting
2. Overbooking

<table>
<thead>
<tr>
<th>Tuesday, 21.03.2017</th>
<th>146418</th>
<th>146419</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10:45 - 12:15</td>
<td>SR 4</td>
</tr>
<tr>
<td>2</td>
<td>12:45 - 14:15</td>
<td>SR 1</td>
</tr>
<tr>
<td>3</td>
<td>14:30 - 16:00</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>16:15 - 17:45</td>
<td>SR 4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Thursday, 23.03.2017</th>
<th>146420</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>09:00 - 10:30</td>
</tr>
<tr>
<td>2</td>
<td>10:45 - 12:15</td>
</tr>
<tr>
<td>3</td>
<td>12:45 - 14:15</td>
</tr>
</tbody>
</table>
Where we left of...

- Definition of Revenue Management
- The key questions it can answer
- History of Revenue Management
- Price building
- KPIs: RevPAR, GopPAR, RevPOST, ...
- Single Resource Capacity Control
  - Booking limits
  - Protection levels
  - Bid Price
  - Nesting
  - Static Models: 2-Class & n-Class
  - Heuristics
  - Dynamic and other models
- Customer Choice Behaviour
  - Buy Up Factors
  - Discrete Choice Models
1. Estimation and Forecasting
Introduction

You just got promoted to Manager of Hotel A.

Your employee just reported the cumulative booking from the last 8 days.

<table>
<thead>
<tr>
<th>Days prior</th>
<th>-8</th>
<th>-7</th>
<th>-6</th>
<th>-5</th>
<th>-4</th>
<th>-3</th>
<th>-2</th>
<th>-1</th>
<th>Today</th>
</tr>
</thead>
<tbody>
<tr>
<td># Booking</td>
<td>8</td>
<td>14</td>
<td>20</td>
<td>23</td>
<td>39</td>
<td>50</td>
<td>55</td>
<td>59</td>
<td>61</td>
</tr>
</tbody>
</table>

You might wonder:
- The average number of booking
- The dispersion of number of booking
- The number of incoming booking
Introduction

Estimation:
- Finding model parameters that best describe a given set of observed data
- **Descriptive** (characterizing what **has been** observed)
- Done relatively infrequently

Forecasting:
- Involves predicting future, unobserved values
- **Predictive** (characterizing what **will** be observed)
- Performed on an operational basis

Estimation → Forecasting
- An estimate of price sensitivity based on past sales data
- Use it in a forecast of future demand
Introduction

Quantity-based RM
- Use time-series methods, which use historical data to project the future
- Example:
  - Spill quantity -- the amount of demand that is lost by closing down a class
  - Recapture quantity -- the amount of spilled demand that is recaptured by substitute products

Price-based RM
- Forecasting demand as a function of marketing variables such as price or promotion
- Example:
  - the size of the potential customer population
  - stockout and low-inventory effects
  - switching behavior
Introduction

Data is the life-blood of a forecasting system
- Rely primarily on historical sales data
- Weakness -- products/programs change frequently -- little historical data

Data sources
- Sales-Transaction Data Sources -- transactional database
- Controls-Data Sources -- controlling process
  - When a class is closed for further bookings
  - Overbooking authorizations
  - Promotions activities
- Auxiliary Data Sources
  - Currency exchange-rate
  - Tax information
Partial-Bookings Data -- bookings occur over an extended period of time

<table>
<thead>
<tr>
<th>Number of Days Prior to the Usage of the Resource</th>
<th>Resource-Usage Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>-8</td>
<td>-7</td>
</tr>
<tr>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>8</td>
<td>14</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>11</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>12</td>
</tr>
</tbody>
</table>

Cumulative Bookings
Introduction

RM Forecasting
- Estimating a probability distribution of future demand
- Estimating demand as a function of prices variables or product attributes

Parametric Estimation
- Assume a specific functional form
- Estimate the parameters of this functional form

Non-Parametric Estimation
- Distribution or functions can be estimated directly based on observed historical data
Introduction

Forecasts can be made at different levels of aggregation
- How to aggregate data
- Airlines -- should the demand be forecast for each fare product or each booking class?

Bottom-up Forecasting Strategy
- Forecasting is performed at a detailed level to generate sub-forecasts
- Aggregate the detailed sub-forecasts
- Itinerary → Customers expected → Fare-class → Occupancy

Top-down Forecasting Strategy
- Forecasts are made at a high level of aggregation (super-forecasts)
- Disaggregate these super-forecasts down to the level of detail required
- Total number of guests/book/arrive/day/rate → fractions of guests/stay/a specific length of time → Guests/book/future-date/room-category & length-of-stay
Estimation

Estimator -- a formalized “guess” about the parameters of the underlying distribution from which a sample is assumed to be drawn

Can take on many forms and can be based on different criteria for a “best” guess

Non-Parametric Estimators
- Do not make any assumptions on the underlying distribution
- Simply computing the fraction of observations in the sample

Parametric Estimators
- Assume that there is an underlying distribution of the observed data
- Determine the unknown parameter using the sample and the characteristics of the observed data
Minimum Mean Square Error (MMSE)
- An estimation method which minimizes the Mean Square Error (MSE)

\[ \text{MSE}(\hat{\theta}) = E[(\hat{\theta} - \theta)^2] \]

\[ \bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \]

\[ \text{MSE}(\bar{X}) = E((\bar{X} - \mu)^2) \]

\[ \min_{\hat{\theta}} \text{MSE} \]
Estimation Methods

Maximum Likelihood Estimators
- Finding the parameters that maximize the “likelihood” of observing the sample data
- Likelihood is defined as the probability of the observations occurring

Method of Moments Estimators
- One equates moments of the theoretical distribution to their equivalent empirical averages in the observed data

Quantile Estimators
- Based on the empirical distribution
- One can compute a number of quantiles of a data set and equate these to the theoretical quantiles of the parametric distribution
Forecasting -- attempt to “predict” the future values of a sequence of data

Typically used for forecasting demand (demand to come)

Forecast quantities:
- Market prices
- Length of stay
- Cancellation and no-show rates

Forecastings effort in practice is directed at data-related tasks
- Collection
- Pre-processing
- Cleansing
I. Ad-Hoc Forecasting Methods

Referred to as structured forecasting methods
- Assuming a compositional structure on the data
- Breaking up and composing the series into hypothesized patterns

Three types of components:
1. **Level**
   -- the typical or “average” value of the data (not as statistical average)
2. **Trend**
   -- a predictable increase or decrease in the data values over time
3. **Seasonality**
   -- a periodic or repeating pattern in the data values over time
A common strategy -- try to “smooth” the data or average-out the noise components to estimate the level, trend, and seasonality components.
I.1 Same Day Last Year

Same-Day-Last-Year method uses the previous-year historical booking data to forecast the room booking this year.

<table>
<thead>
<tr>
<th>Date</th>
<th>Actual</th>
<th>Forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1/2014</td>
<td>Wed</td>
<td>69</td>
</tr>
<tr>
<td>2/1/2014</td>
<td>Thu</td>
<td>68</td>
</tr>
<tr>
<td>3/1/2014</td>
<td>Fri</td>
<td>64</td>
</tr>
<tr>
<td>4/1/2014</td>
<td>Sat</td>
<td>65</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>1/1/2015</td>
<td>Thu</td>
<td>68</td>
</tr>
<tr>
<td>2/1/2015</td>
<td>Fri</td>
<td>64</td>
</tr>
</tbody>
</table>
I.2 M-Period Moving Average

- Current time $t$
- Values $t+k$ in the future - $k$-period ahead forecast
- Observed demand data: $Z_1, \ldots, Z_t$
- Forecast for period $t+1$:

$$\hat{Z}_{t+1} = \frac{Z_t + Z_{t-1} + \cdots + Z_{t-M+1}}{M}$$

- Simple M-period moving-average forecast
- $M$ - the span of the moving average

$$\hat{Z}_{t+k} = \hat{Z}_{t+1}, \quad k = 2, \ldots, K$$
I.2 M-Period Moving Average

Moving-Average Method

- Very simple and fast
- Its motivation is largely heuristic
- The most recent observations serve as better predictor for the future than do older data
- Instead of taking all the data, we average only the M most recent data
- Quick responds if the span M is small, but results in a more volatile forecast (more sensitive to noise in data)
- In practice, M may range from 3 to 15, depends on data characteristics and units used for the time intervals
- When the data exhibits an upward and downward trend, the moving average method will systematically under-forecast or over-forecast
I.3 Simple Exponential Smoothing

- Smoothing constant for the level, $0 < \alpha < 1$

$$\hat{Z}_{t+1} = A_t = \alpha z_t + (1 - \alpha) \hat{Z}_t$$
I.3 Simple Exponential Smoothing

- Simple and robust
- Generally have good forecast accuracy

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>71</td>
<td>70</td>
<td>69</td>
<td>68</td>
<td>64</td>
<td>65</td>
<td>72</td>
<td>78</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>70</td>
</tr>
<tr>
<td>α=0.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>α=0.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
I.3 Simple Exponential Smoothing
II. Time-Series Forecasting Methods

The forecasting procedure is specifically tailored to the underlying data-generation model.

We make a hypothesis about the specific type of process generating the time series of data:
- Use model-identification techniques
- Determine which models best fit the data

Apply the corresponding optimal forecasting method specific to that model.

They explicitly model the correlations between successive data points and exploit any dependence to make better forecasts.
III. Bayesian Forecasting Methods

Use the Bayes formula to merge a prior belief about forecast value with information obtained from observed data

- Forecasters may have some subjective beliefs about demand, based on human judgement or alternative data sources (test marketing and focus groups)

- Bayesian methods -- combine subjective knowledge with information obtained from data and observations

- Useful when there is no historical data -- introduce new products
  - An airline start flying on a new route -- no historical demand information
  - Fashion apparel products often change every season -- demand may be unrelated to the historical sales of past products
  - TV new series -- no historical demand information
Do not make a functional assumption a priori

Use interactions in a network-processing architecture to automatically identify the underlying function that best describes the demand process. Mimic the way the human brain learns from experience

An NN consists of underlying directed graph and a set of additional quantities defined on the graph

Feed-forward network = input - hidden - output layers

Defined quantities on the network: state variable, weight associated with arc, activation threshold, activation function
IV. Machine-Learning (Neural-Network) Methods

![Diagram of a neural network with layers and connections between input, hidden, and output nodes.](image-url)
IV. Machine-Learning (Neural-Network) Methods

Defining the Network
- Define a set of independent variables associated with each observation, represented by input nodes
- Define the activation functions, e.g. sum of the weights of incoming active nodes

Training
- A set of data is used to calibrate the weights and the values of the threshold functions

Forecasting
- We have a set of values for the parameters of the network: activation threshold, weights, and the parameters
Exploit some unique characteristics of reservation data -- period between repeated service is shorter than the period over which reservations are made.

The main idea is to forecast incremental bookings and then aggregate these increments to obtain a forecast of total demand to come:

\[
\hat{Z}(t + k) = \sum_{i=0}^{k} \hat{Z}_{[i]}(t + k)
\]

- *k*-day ahead forecast
- *Z*[i](). -- the incremental booking forecast *i* days prior to the time of service
V. Pick-Up Forecasting Methods

Forecast for 13-June when we have one day remaining

<table>
<thead>
<tr>
<th>Number of Days Prior to the Usage of the Resource</th>
<th>Resource-Usage Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>-8</td>
<td>-7</td>
</tr>
<tr>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>8</td>
<td>6</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>11</td>
</tr>
</tbody>
</table>

Incremental bookings
Other Forecasting Methods

Delphi method
- Formal procedure for extracting analyst and managers’ opinion on expected demand
- Used primarily when no historical information or when there is unexpected demand shock or when RM is done manually

Fuzzy logic and Expert Systems
- Attempt to replicate the rules used by human analysis when monitoring and overriding a RM system

Based on fitting historical booking to a set of cumulative curves
- Current bookings on hand are extrapolated using these curves to give the forecast

Combining Forecast Methods
Estimation Errors

- Estimation Bias -- the lack of a good estimator, incomplete data, or nonconvergence of the estimation procedures

- Specification Errors -- arising from a model that does not reflect the underlying data-generating process

- Model Selection
  - To find a model that generalizes well and has good predictive power
  - For example, to rank the models according to some goodness-of-fit criterion and choose the highest-ranking one

- Overfitting
  - Keep a holdout sample and use the forecast errors on the holdout
Forecast Errors

- Forecast error: \( e_t = z_t - \hat{Z}_t \)

- Mean absolute deviation (MAD)

\[
MAD_N = \frac{\sum_{t=0}^{N} |e_t|}{N}
\]

- Mean squared error (MSE)

\[
MSE_N = \frac{\sum_{t=0}^{N} e_t^2}{N}
\]

- Mean absolute percentage error (MAPE)

\[
MAPE_N = \sum_{t=0}^{N} \left| \frac{e_t}{z_t} \right|
\]
Examples from Industry

Airline No-Show and Cancellations Forecasting
Examples from Industry

Gas-Load Forecasting

- Day of week
- Month of year
- Weekend
- Average dew point temperature
- Past temperature
- Past load

Input layer \( x_1 \)

Hidden layer \( x_2 \) and \( x_3 \)

Output layer \( x_J \)

Load
Wrap-Up (1)

● Estimation vs. Forecasting

● Estimation
  ○ Minimum Mean Square Error (MMSE) Estimators
  ○ Maximum-Likelihood (ML) Estimators and Other

● Forecasting
  ○ Ad-Hoc Forecasting Methods
  ○ Time-Series Forecasting Methods
  ○ Bayesian Forecasting Methods
  ○ Machine-Learning (Neural-Network) Methods
  ○ Pick-up Forecasting Methods
  ○ Other Methods

● Estimation and Forecasting Errors
● Examples from Industry
2. Overbooking
Introduction

Have you experienced any of the following situations:

- Cancel your booking
- Did not show up at the time of a service
- Change your booking with a penalty

Or any the following situations:

- Offered an upgrade
- Offered a compensation

Overbooking -- focus in increasing the total volume of sales in the presence of cancellations
General
How to optimize capacity utilization in a reservation-based system with significant cancellations.
RM in contrast is about how to create the best product mix.
One of the oldest and most successful tactics in RM.

General Outline
Controlling the level of reservations to balance the potential risks of denied service against the rewards of increased sales.

Biggest Challenge
How to handle negative effects of denying service and the resulting legal and regulatory issues.
Introduction

Business Context
Reservation basically a **forward contract** between customer and firm. Use service in the future at a fixed price usually cancellable (possibly penalty).

Reservations are valued if the cost of unavailability at the **desired consumption time** is higher than prior to the time of consumption. (e.g. “I **need** to take this flight to get to my meeting!”.)

Precommitment has own **risks** however. Possibly can’t consume product in future and need to handle incurred **penalty**.

Cancellation and no-show penalties allow customer and firm to **share risk**.

At least some penalty needs to be in place because of **high risk of abuse**.
Introduction

Overbooking
Firm usually gauges the risk of taking on more reservations than it can fulfill and balances it with the possibility of no-shows in order to optimize allocation.

**Stock out** = customers have a reservation and there are no rooms left
**Overage** = customers denied reservation and rooms are unoccupied
Static Overbooking Models

![Graph showing reservations and overbooking models over time.](image)

- Reservations with overbooking
- Reservations without overbooking
- Overbooking limit
- Show demand
- Time (T)
- Reservations (C)

www.sti-innsbruck.at
Easy and quick solution, calculate the **average** of the number of **no-shows** \( n \) and their respective **probability**.

**Simple Formula**

\[
\sum n \times \text{probability}(n)
\]

<table>
<thead>
<tr>
<th>( n )</th>
<th>probability((n))</th>
<th>( n \times \text{probability}(n))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>20%</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>40%</td>
<td>0.4</td>
</tr>
<tr>
<td>2</td>
<td>30%</td>
<td>0.6</td>
</tr>
<tr>
<td>3</td>
<td>10%</td>
<td>0.3</td>
</tr>
</tbody>
</table>

**Overbook # rooms:** \( \text{SUM} = 1.3 \)
Overbooking
Static: Spreadsheets

Based on **Overage** and **Stock-out** build up a spreadsheet detailing the costs of overbooking taking the probabilities into account, select lowest total cost.

For example with an Overage of **€50.-** and a Stock-out of **€120.-**

<table>
<thead>
<tr>
<th>Number of Reservations Overbooked</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n$</td>
<td>$\text{probability}(n)$</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>20%</td>
<td>€0.-</td>
<td><strong>€120.-</strong></td>
<td>€240.-</td>
</tr>
<tr>
<td>1</td>
<td>40%</td>
<td><strong>€50.-</strong></td>
<td>€0.-</td>
<td>€120.-</td>
</tr>
<tr>
<td>2</td>
<td>30%</td>
<td>€100.-</td>
<td>€50.-</td>
<td>€0.-</td>
</tr>
<tr>
<td>3</td>
<td>10%</td>
<td>€150.-</td>
<td>€100.-</td>
<td>€50.-</td>
</tr>
<tr>
<td><strong>Total Cost</strong></td>
<td><strong>€65.-</strong></td>
<td><strong>€49.-</strong></td>
<td>€101.-</td>
<td><strong>€204.-</strong></td>
</tr>
</tbody>
</table>
The **Marginal Cost** approach (also called **Newsvendor model**) is again based on **Overage and Stock-out**.

We will book guests until the cost of a **dissatisfied customer** is in **balance** with the cost of an **empty room**.

This is expressed in the following heuristic:

\[
\frac{\text{Overage}}{\text{Stock-out} + \text{Overage}} = P(\text{Overbook} \geq \text{No Shows})
\]

For our example from before this equals 29% meaning we’ll overbook 1 room since this number is first exceeded by the **cumulative percent of no-shows** in this configuration.
Different classes may have quite different cancellation rates:
- Full-coach customers often have no cancellation penalty
- Discount-class customers incur a significant fee for cancelling a reservation

Exact methods:
- Keeping track of the inventory of each class as a separate state variable
- Making overbooking decisions based on this complete vector of state variables

Estimation methods:
- Estimate the cancellation probability for each resource separately
- Capture at least the historical mix of customer segments booked on each resource
The presence of groups is important
- If a group decides to cancel, then all reservations are cancelled simultaneously

<table>
<thead>
<tr>
<th>Number in Party</th>
<th>Count of Passengers</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>198,056</td>
<td>45.1</td>
<td>45.1</td>
</tr>
<tr>
<td>2</td>
<td>114,418</td>
<td>26.0</td>
<td>71.1</td>
</tr>
<tr>
<td>3</td>
<td>28,641</td>
<td>6.5</td>
<td>77.6</td>
</tr>
<tr>
<td>4</td>
<td>25,688</td>
<td>5.8</td>
<td>83.5</td>
</tr>
<tr>
<td>5</td>
<td>17,930</td>
<td>4.1</td>
<td>87.6</td>
</tr>
<tr>
<td>6</td>
<td>7,134</td>
<td>1.6</td>
<td>89.2</td>
</tr>
<tr>
<td>7</td>
<td>2,135</td>
<td>0.5</td>
<td>89.7</td>
</tr>
<tr>
<td>8</td>
<td>2,896</td>
<td>0.7</td>
<td>90.3</td>
</tr>
<tr>
<td>9</td>
<td>1,125</td>
<td>0.3</td>
<td>90.6</td>
</tr>
<tr>
<td>10</td>
<td>4,960</td>
<td>1.1</td>
<td>91.7</td>
</tr>
<tr>
<td>&gt;10</td>
<td>36,375</td>
<td>8.3</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Total 439,358 100.0

*Note: Data reported by Rothstein and Stone [446].*
Static models do not explicitly account for the dynamics of arrivals, cancellations, and decision making over time

Exact Approaches
- As demand to come increases (stochastically), it is better to be less aggressive at any given point in time
- We have more opportunities to book seats in the future, we do not need to take as great an overbooking risk in the current period

Heuristic Approaches Based on Net Bookings
- The change in bookings on hand depends on both the number of cancellations and new reservations that are accepted
- Can be used to provide an alternative estimate of the cancellation rate
Combining Capacity Control and Overbooking

So far we ignored the interaction of overbooking decisions with capacity controls. However there are exist exact and approximate methods to model cancellations and no-shows together with the class allocations of quantity-based RM.

Assumptions, cancellations and no-shows are...
1. equally probable for all customers
2. independent across customers
3. in any period are independent of the time the reservations were accepted
4. Additionally: refunds and denied-service costs same for all customers

The assumptions imply that the number of no-shows and the costs incurred are only a function of the total number of reservations on hand.
Combining Capacity Control and Overbooking

(1) and (4)
- Cancellation options and penalties are often linked directly to a class
- Cancellation and no-show rates and costs can vary significantly from one class to the next (complicates the model significantly)

(2) is unrealistic since reservations from people in groups typically cancel at the same time

(3) is less of a problem in practice and has some empirical support

In most implementations, the overbooking problem is separated from the capacity/allocation problem
Static Overbooking Models
- Static - Averages
- Static - Marginal Costs
- Customer Class Mix
- Group Cancellation

Dynamic Overbooking Models
- Exact Approaches
- Heuristic Approaches Based on Net Bookings

Combining Capacity Control and Overbooking Models
Forecasting, Overbooking and Dynamic Pricing

Hands on Exercises
Preliminaries

You will use Excel to solve the following examples. (LibreOffice, or Google Sheets works fine as well)

Please build groups of three or four

Each group will solve the problem and present their results.
Forecasting Models

TODO see lecture slides

Use the prepared worksheets (Forecasting.xlsx), and solve defined problem from each worksheet.

M-Moving Average
- Use M=3,5,...,15

Simple Exponential Smoothing
- Use smoothing constant=0.1,0.3,0.5,0.7
- Compare the data and your results in a chart
Forecasting Models

Pick-Up Forecasting Method
- Forecast 1, 3, 7 days ahead
- Compute errors of your results
- Compare the actual booking and your forecast results in a chart

Present your results in front of the class.

Send your Excel file to zaenal.akbar@sti2.at by the end of the seminar
Remember to put your names in the email
This exercise is about implementing overbooking strategies
You’ll find some toy data for an example hotel. In the worksheet “Hotel Data” you’ll find information on expected no-shows and their probabilities as well as stock-out and overage fees.

1. Open the “Overbooking” excel file and change to the “Overbooking” worksheet.
2. Create overbooking schemes using
   a. Averages
   b. Spreadsheet method
   c. Marginal Cost approach

Present your findings to the rest of the group

Send your Excel file to zaenal.akbar@sti2.at by the end of the seminar
Remember to put your names in the email