Forecasting, Overbooking and Dynamic Pricing

Block 2
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Agenda

1. Estimation and Forecasting
2. Overbooking
3. Dynamic Pricing
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
Estimation and Forecasting
Introduction

Let start with the following data
- 8, 14, 20, 23, 39, 50, 55, 59, 61

Compute:
- The means
- The variances

Determine:
- What number comes next?
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
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>
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<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
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)

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

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

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

\[
\min_{\hat{\theta}} \text{MSE}
\]
Maximum-Likelihood (ML) Estimators

Finding the parameters that maximize the “likelihood” of observing the sample data

- Likelihood is defined as the probability of the observations occurring

\[ f(x_1, \cdots, x_n | \theta) = f(x_1 | \theta) \times \cdots \times f(x_n | \theta) \]

\[ \mathcal{L}(\theta; x_1, \cdots, x_n) = f(x_1, \cdots, x_n | \theta) = \prod_{i=1}^{n} f(x_i | \theta) \]

\[ \max_{\theta} \sum_{i=1}^{n} \ln f(x_i | \theta) \]
Other Estimation Methods

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
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.
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

$$\hat{Z}_{t+k} = \hat{Z}_{t+1}, \quad k = 2, \ldots, K$$
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
Simple Exponential Smoothing

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

\[ \hat{Z}_{t+1} = A_t = \alpha z_t + (1 - \alpha) \hat{Z}_t \]
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 exploits any dependence to make better forecasts.
Bayesian Forecasting Methods

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

- Useful when there is no historical data -- introduce new products -- no historical demand information
- Forecastsers 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
Bayesian Forecasting Methods

\[ P(A|B) = \frac{P(A \cap B)}{P(B)} \]

\[ P(\theta|x) = \frac{P(\theta \cap x)}{P(x)} = \frac{P(x \cap \theta) \times P(\theta)}{P(x)} \]

Posterior = Likelihood x Prior
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.
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
Pick-Up Forecasting Methods

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
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></td>
<td></td>
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<tr>
<td>-8  -7  -6  -5  -4  -3  -2  -1  0</td>
<td></td>
</tr>
<tr>
<td>6    3    11   4   9   8   13  3    13</td>
<td>10-Jun</td>
</tr>
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<td>8    6    6    3   16  11  5    4    2</td>
<td>11-Jun</td>
</tr>
<tr>
<td>1    2    0    0   3   6   2    6    8</td>
<td>12-Jun</td>
</tr>
<tr>
<td>6    0    4    1   2    6   3    2</td>
<td>13-Jun</td>
</tr>
<tr>
<td>3    8    8    6   5   1    2</td>
<td>14-Jun</td>
</tr>
<tr>
<td>1    0    2    7   6    4</td>
<td>15-Jun</td>
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<tr>
<td>0    1    1    6   5</td>
<td>16-Jun</td>
</tr>
<tr>
<td>1    11   12   6</td>
<td>17-Jun</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
Forecasting Errors and System Control

Measures of Forecast Errors
- Sum of forecast errors, mean error, MSE, ...

Bias Detection and Correction
- Tracking signal -- to see if the system is generating consistently biased forecasts

Outlier Detection and Correction
- Extreme values of data
- Caused by corrupted records or special non-recurring conditions in the demand process
- Pre-smooth the data to make them more robust to the presence of outliers -- moving-median smoothing

$$\tilde{z}_t = \text{Median}(z_{t-1}, z_t, z_{t+1})$$
No-Show and Cancellations Forecasting

Diagram:
- Start of bookings period
- Peak bookings period
- Peak bookings time
- Resource usage time

Key terms:
- Peak bookings
- Capacity
- Final bookings
- Net cancellations
- Net no-shows
- Final shows
Gas-Load Forecasting

Input layer

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

Hidden layer

$x_1$
$x_2$
$x_3$

Output layer

Load

$x_j$
● Estimation vs. Forecasting

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

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

● Estimation and Forecasting Errors
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
Introduction

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

Reservations

Overbooking limit

Reservations with overbooking

Show demand

Reservations without overbooking

C

0

T

Time
Overbooking Static: Averages

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>
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<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>n</th>
<th>probability(n)</th>
<th>0</th>
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<td>0</td>
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<td>€0.-</td>
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<td>€240.-</td>
<td>€360.-</td>
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<tr>
<td>1</td>
<td>40%</td>
<td>€50.-</td>
<td>€0.-</td>
<td>€120.-</td>
<td>€240.-</td>
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<tr>
<td>2</td>
<td>30%</td>
<td>€100.-</td>
<td>€50.-</td>
<td>€0.-</td>
<td>€120.-</td>
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<td>3</td>
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<td>€150.-</td>
<td>€100.-</td>
<td>€50.-</td>
<td>€0.-</td>
</tr>
<tr>
<td></td>
<td>Total Cost</td>
<td>€65.-</td>
<td>€49.-</td>
<td>€101.-</td>
<td>€204.-</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.
Customer Class Mix

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>
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<tr>
<th>Number in Party</th>
<th>Count of Passengers</th>
<th>Percentage</th>
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<td>45.1</td>
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<td>89.2</td>
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<td>90.3</td>
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<td>0.3</td>
<td>90.6</td>
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<tr>
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<td>4,960</td>
<td>1.1</td>
<td>91.7</td>
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<tr>
<td>&gt;10</td>
<td>36,375</td>
<td>8.3</td>
<td>100.0</td>
</tr>
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</table>

Total: 439,358 100.0

*Note: Data reported by Rothstein and Stone [446].
Overbooking Dynamic

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
Wrap-Up (2)

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
Dynamic Pricing
Introduction
Dynamic Pricing

Until now control via quantity, now control via price: personalized pricing, markdowns, display and trade promotions, coupons, discounts, clearance sales, auctions.

Distinction not always obvious, e.g. closing discount class availability is similar to raising a product’s price.

Probably oldest technique for revenue management.

Main question
How to make price adjustments to maximize revenue?
Introduction
Price- vs. Quantity-Based RM

Quantity-Based RM
- Operates by rationing the quantity sold to different products or to different segments of customers
- Involves reducing sales by limiting supply

Price-Based RM
- Operates by “rationing” the price
- Involves reducing sales by increasing price
Role in Industry

Retailing
Especially in apparel and other seasonal-goods sectors, on the forefront in deploying science-based software for pricing.

Manufacturing
In 1998, Ford reported that the first five U.S. sales regions using this new pricing approach collectively beat their profit targets by $1 billion, while the 13 that used their old methods fell short of their targets by about $250 million.

E-Business
E-tailers can discount and markdown on the fly based on customer loyalty and click-stream behaviour.
Examples

**Style-Goods Markdown Pricing**
Use markdown pricing to clear excess inventory before the end of the season.
Use markdown as a form of demand learning, a segmentation mechanism to separate price-insensitive/sensitive customers.

**Discount Airline Pricing**
Offer tickets at different prices for different flights, and moreover, during the booking period for each flight, vary prices dynamically based on capacity and demand for that specific departure.

**Consumer Packaged-Goods Promotion**
Promotions are short-run, temporary price reductions.
Modeling Dynamic Pricing
Myopic- vs. Strategic-Customer Models

Consumer choice and resulting market response models are used in dynamic pricing. Additional factors apply however:

1. how individual customers **behave over time**
2. the state of **market conditions**, specifically the level of competition and the size of the customer population.

**Myopic Customer Model**
Buy as soon as the offered price is less than their willingness to pay. Do not adopt complex buying strategies, e.g. refusing to buy in the hope of lower prices in the future.

**Strategic Customer Model**
Allow for the fact that customers will optimize their own purchase behavior in response to the pricing strategies of the firms.

**Myopic** appropriate for less expensive and less durable purchases. As these factors increase **strategic** becomes more important.
In an infinite population model, we assume that we are sampling with replacement when observing customers. Past history of observed demand has no effect. Often termed the nondurable-goods assumption in economics (e.g., a can of Coke).

The finite population model assumes a random process without replacement. If one of the customers in the population purchases, the customer is removed from the population of potential customers. This is termed the durable-goods assumption in economics (e.g., an automobile).
Finite population models typically lead to price skimming as an optimal strategy.

Infinite population models however assume that same price that yields a high revenue in one period will yield a high revenue in later periods.

When to use?
Infinite: relatively small fraction of large population of potential customers, or consumable goods.

Finite: large fraction of the potential pool of customers or if the product is a durable good.
Monopoly
Demand only depends on firm’s own price. Does not consider competitive reaction to a price change. Easy but dangerous. The price-sensitivity estimates may prove wrong if the optimize strategy deviates significantly from past strategies because then the resulting competitive response may be quite different from the historical response.

Oligopoly
Equilibrium-price response of competitors is explicitly modeled and computed. Assumes competition behaves rationally, which is dangerous! Also more complex and needs access to competition data.

Perfect Competition
Many competing firms supply an identical commodity. The output of each firm is assumed to be small relative to the market size. Each firm is essentially a price taker, i.e. able to sell as much as it wants at the prevailing market price, but unable to sell anything at higher prices.
Promotions Optimization

Promotions are short-run, temporary price changes
- Frequently applied to replenishable and consumable goods
- Run either by the manufacturer or by retailers

Promotions in the framework of RM
1. A manufacturer using price to dispose excess inventory
2. A manufacturer trying to gain market share to induce customers to try out its products
3. Retailers experimenting with price to find optimal price points
4. Separating price-sensitive customers, who are willing to use coupons or who wait for deals
5. Retailers trying to increase store traffic, once inside customers likely to purchase non-promotional items
6. A tactic for store brands or small firms to compete against the large advertising budgets
Wrap-Up (3)

Price-Based vs. Quantity-Based RM

Role in Industry

Modeling Dynamic Pricing
- Myopic- vs. Strategic-Customer Models
- Infinite- vs. Finite-Population Models
- Monopoly, Oligopoly, and Perfect-Competition

Promotions Optimization
Forecasting, Overbooking and Dynamic Pricing

Hands on Exercises
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 can volunteer to present their results.

Volunteering will positively influence your grade!
TODO see lecture slides

Download the worksheets from the course website (Forecasting.xlsx)
Select “Pick-Up Forecasting” worksheet

Fill all missing values randomly (min value - max value of existing values)

Solve the problem by using Pick-up Forecasting Method

2 or 3 volunteer groups present
Forecasting Models

TODO see lecture slides

Excel file with data from the previous exercise
a. Select “M-Moving Average” worksheet
b. Copy the first row of your data in “Pick-Up Forecasting” worksheet
c. Use a simple M-period moving average method to forecasts one period ahead with M = 5
d. Repeat step c to predict 5 periods ahead
e. Repeat step d with M = 10

2 or 3 volunteer groups present

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

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

1 volunteer group will present their 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.