An Overview of Time Series Forecasting for Hotel Revenue Management

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Hotel Revenue Management

- The abundance of data in many applications and the opportunity to optimize operations based on the data has opened many opportunities.

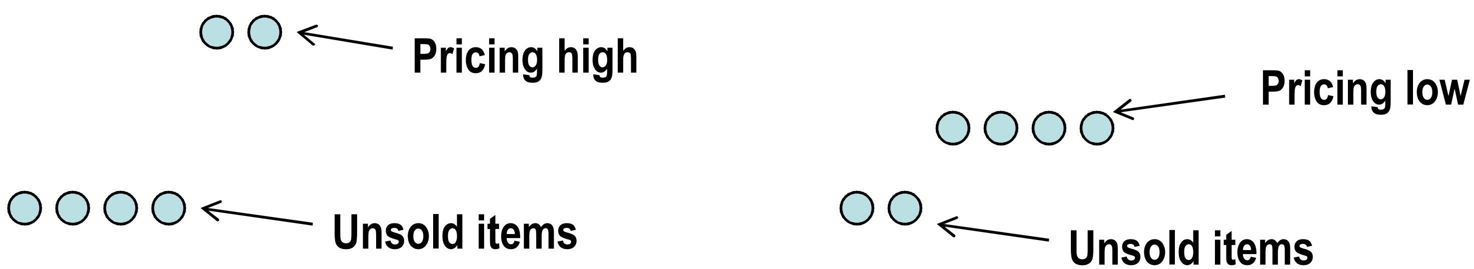
- One such application is revenue management for hotels.

Hotel Revenue Management

- Revenue management is the science of controlling price and/or inventory to maximize revenue.
- The hotel industry can potentially significantly increase their revenue through an optimized revenue management system.
- By dynamically setting a price and/or room allocation per category, one can optimize the revenue.

Hotel Revenue Management (Problem Description)

- Pricing rooms too cheaply can cause losing higher revenue from future higher-priced reservations (lost opportunity).
- Setting too high of a price could leave more rooms un-booked.



- This leads to a sophisticated optimization problem that takes into account future bookings and their probabilities.

Price Influencers

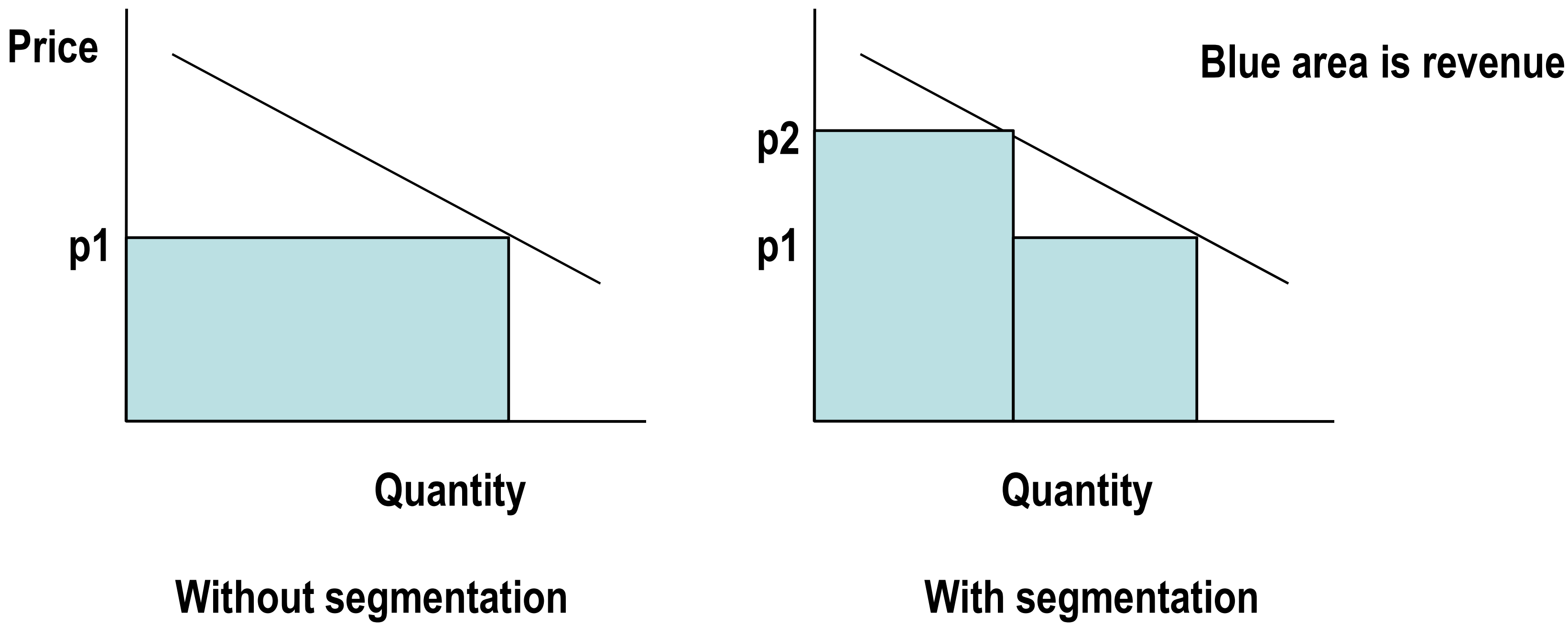
- Value for the customer.
- Price of competing products.
- Reference price.

Several Aspects of Revenue Management

Market Segmentation

- Segment the market in order to apply differential pricing.
- Examples
  - Online versus in-store.
  - Airlines: advance purchase with penalties for changes, versus late purchase with unrestricted ability to change.
  - Outlets.

Market Segmentation

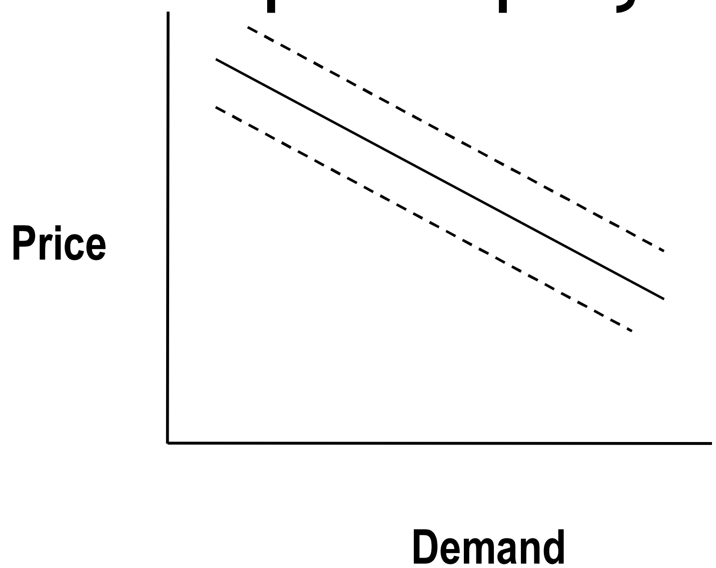


- Inventory control: Optimize the amount allocated to each segment.

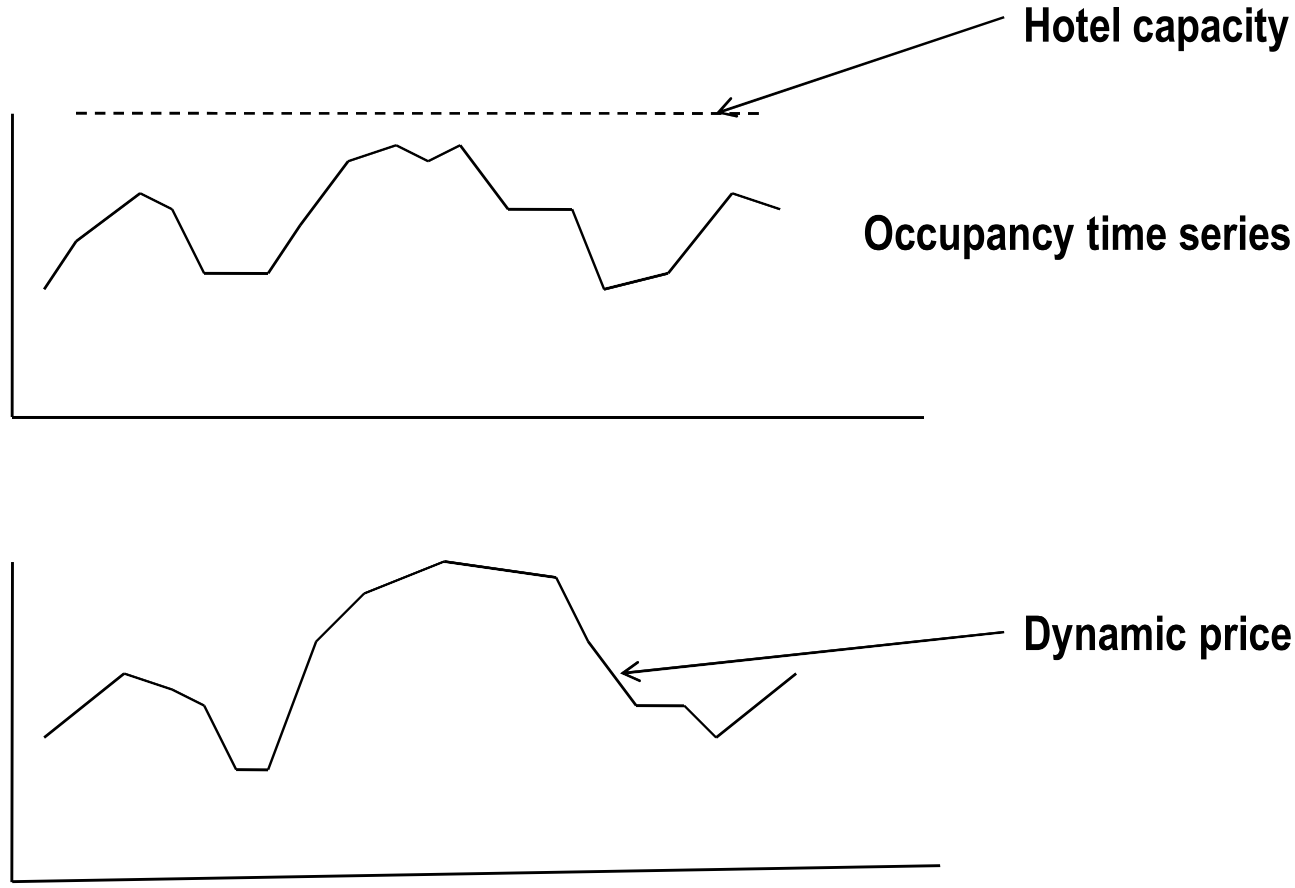
Other Aspect of Revenue Management

Dynamic Pricing

- Pricing is dynamic and changes day by day.
- It is influenced by day to day changes of demand.
- Seasonal aspects play a large role.



Dynamic Pricing



Dynamic Pricing

Hotel room arrivals and occupancy forecasting

- **In order to optimize price, we need to have an idea about future hotel traffic, and the demand for the rooms.**

Dynamic optimization of prices

- **Makes use of the forecasts obtained from previous step.**
- **Formulates a large scale optimization.**
- **Takes into account seasonal variations, demand-price relation, and some other necessary features.**

Dynamic Pricing

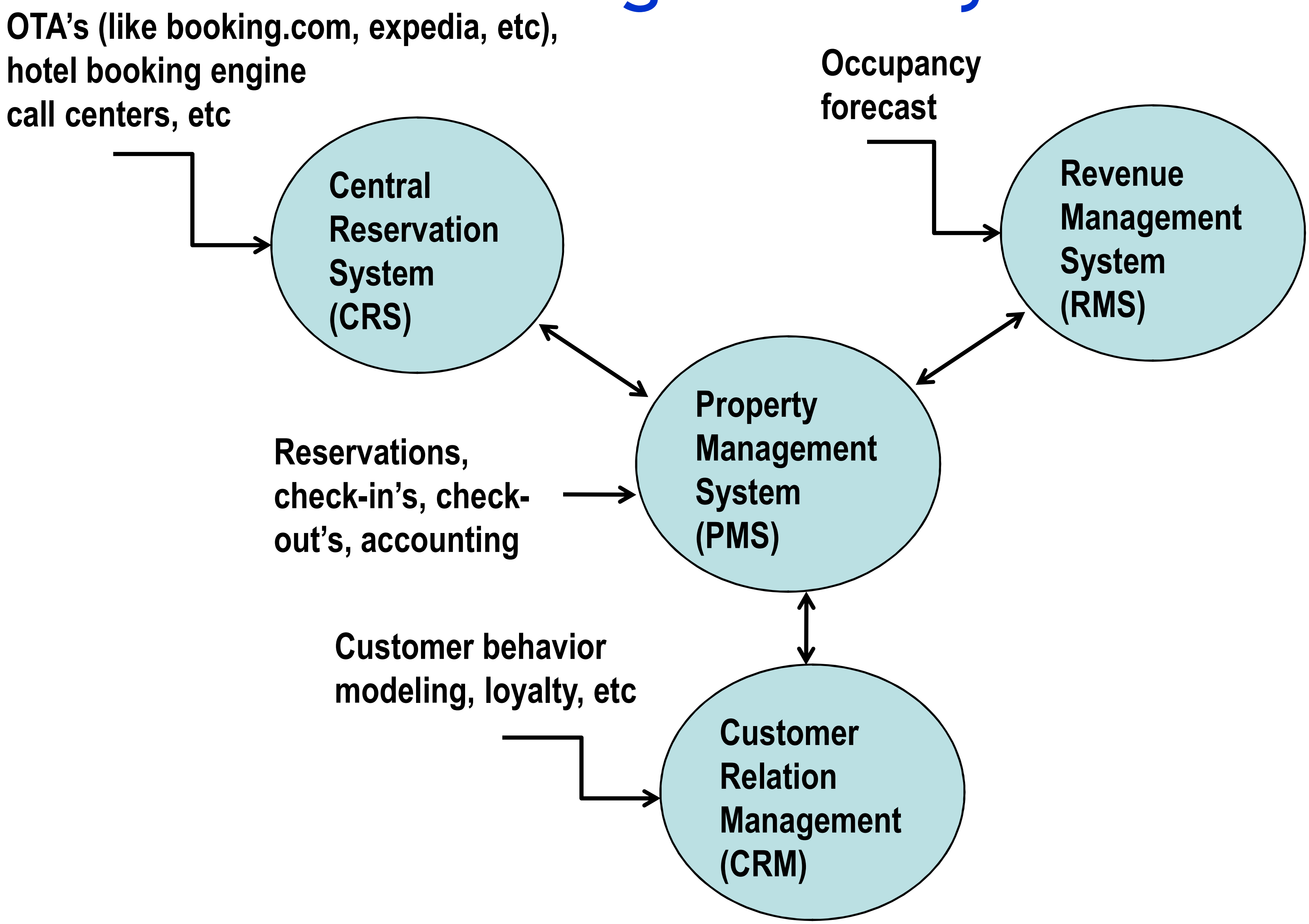
. There is a major trend for businesses to move from inventory-control pricing to dynamic pricing.

- Now we have a better infrastructure for adjusting prices quickly, due to prevalence of online sales, etc.

Dynamic Pricing

- Within a few years electronic price display will be cheap enough, that they will be deployed in standard brick and mortar stores.
- This simplifies price changes.

Hotel Management Systems



How Hotels Work?

- *Stay date:* the intended arrival day of the guest.
- *Reservations* arrive a few days or weeks before intended arrival day.
- *On the books (OTB)* reservations: Reservations that exist currently for a particular stay date.
- Any reservation books a certain number of days, or *length of stay (LOS).*
- Some reservations are booked as a block (group reservations).

How Hotels Work?

- *Cancellations:* A reservation can be cancelled prior to arrival.
- *No shows:* Guests who have a valid reservation, but do not show up on stay date.
- *Hotel capacity:* Total number of available rooms.
- *Overbooking:* When the hotel books more rooms than available capacity.
- *Denials:* Guests who are denied a reservation because hotel is fully booked.

Hotel Reservations

Occupancy

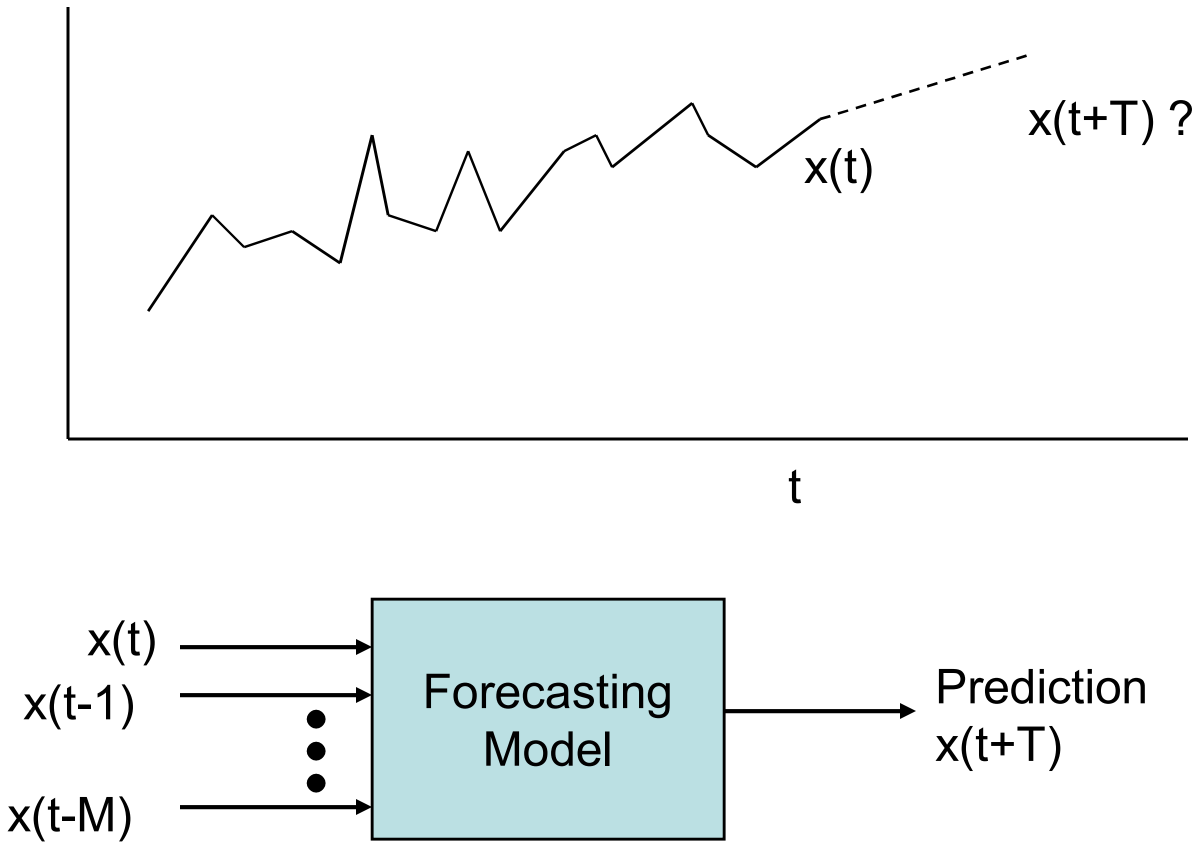
Number of days before stay date

Number of reservations on the books

Date	0	1	2	3	4	5	6	7	8
20170221	115	110	111	95	92	91	89	88	86
20170222	130	123	105	106	96	98	97	97	96
20170223	163	156	144	129	126	121	120	116	117
20170224	163	165	153	141	135	129	124	126	126
20170225	141	139	127	127	118	116	110	107	111
20170226	126	124	123	112	107	104	103	102	105
20170227	130	123	117	116	107	108	108	107	108
20170228	112	110	106	110	110	107	104	105	104
20170301	145	133	121	118	120	120	118	119	120
20170302	160	163	154	142	142	143	142	139	140
20170303	174	175	162	155	152	152	153	153	153
20170304	172	175	173	165	164	164	164	164	164
20170305	173	174	172	169	161	160	162	162	164
20170306	153	145	137	129	125	116	116	118	118
20170307	76	76	67	66	66	61	58	57	59
20170308	163	176	162	155	152	145	142	140	141
20170309	170	166	167	154	154	154	148	149	154
20170310	170	157	150	148	141	141	140	139	139

- The occupancy time series indicates demand.
- It has a major impact on the pricing.

Overview of Time Series Forecasting



Time Series Forecasting Approaches

- Reservations-based methods.
- Conventional: e.g. ARMA, exponential smoothing.
- Machine learning.
- Monte Carlo.

Reservations-Based Approach: The Pick-Up Method

- The reservations possess useful dynamics that help in forecasting the final arrivals or occupancy.

- The pick up computes the average number of reservations “picked up”, from now till stay date.

Reservations-Based Approach: The Pick-Up Method

Number of days before stay date

Occupancy

Number of reservations on the books

Date	0	1	2	3	4	5	6	7	8		Number picked up
20170221	115	110	111	95	92	91	89	88	86		23
20170222	130	123	105	106	96	98	97	97	96		34
20170223	163	156	144	129	126	121	120	116	117		37
20170224	163	165	153	141	135	129	124	126	126		28
20170225	141	139	127	127	118	116	110	107	111		23
20170226	126	124	123	112	107	104	103	102	105		19
20170227	130	123	117	116	107	108	108	107	108		23
20170228	112	110	106	110	110	107	104	105	104		2
20170301	145	133	121	118	120	120	118	119	120		25
20170302	160	163	154	142	142	143	142	139	140		18
20170303	174	175	162	155	152	152	153	153	153		22
20170304	172	175	173	165	164	164	164	164	164		8
20170305	173	174	172	169	161	160	162	162	164		12
20170306	153	145	137	129	125	116	116	118	118		28
20170307	76	76	67	66	66	61	58	57	59		10
20170308	163	176	162	155	152	145	142	140	141		11
20170309	170	166	167	154	154	154	148	149	154		16
20170310	170	157	150	148	141	141	140	139	139		29
										Avg	20.4

- Number picked up is the extra amount of reservations that came from now till stay date.
- The average of this over all history is the average pick-up.
- Add that average to the on-the-books reservation, to obtain the forecast.

Reservations-Based Approach: The Pick-Up Method

Occupancy

Number of days before stay date

Number of reservations on the books

Date	0	1	2	3	4	5	6	7	8		picked up
20170221	115	110	111	95	92	91	89	88	86		23
20170222	130	123	105	106	96	98	97	97	96		34
20170223	163	156	144	129	126	121	120	116	117		37
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20170304	172	175	173	165	164	164	164	164	164		8
20170305	173	174	172	169	161	160	162	162	164		12
20170306	153	145	137	129	125	116	116	118	118		28
20170307	76	76	67	66	66	61	58	57	59		10
20170308	163	176	162	155	152	145	142	140	141		11
20170309	170	166	167	154	154	154	148	149	154		16
20170310	170	157	150	148	141	141	140	139	139		29
										Avg	20.4

- Example: We need to forecast occupancy for 20170310.
- Pick-up forecast = OTB + Avg pick-up = 141 + 20.4 = 161 approximately.
- Error in forecast = 170 – 161 = 9.

Reservations-Based Approach: The Pick-Up Method

- The pick-up method is very effective.
- It is simple to implement, and is widely used by practitioners.

Conventional Approaches

- Autoregressive (AR):

  $$x_t = a_1 x_{t-1} + a_2 x_{t-2} + \ldots + a_k x_{t-k} + \epsilon_t$$

  x_t = time series

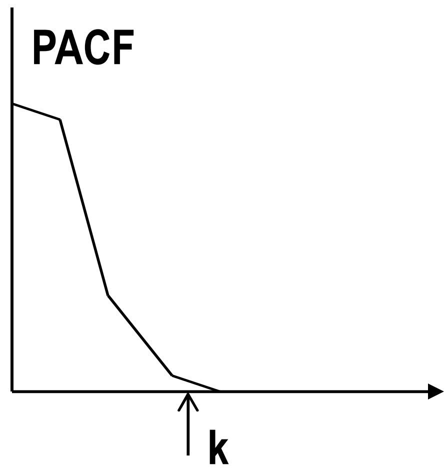
- Autoregressive moving average (ARMA(k,m)):

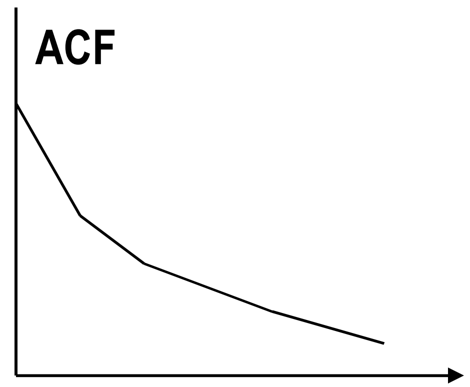
$$x_t = a_1 x_{t-1} + a_2 x_{t-2} + \ldots + a_k x_{t-k} + b_1 \epsilon_t$$
$$+ b_2 \epsilon_{t-1} + \ldots + + b_m \epsilon_{t-m+1}$$

- ARIMA

Box Jenkins Approach

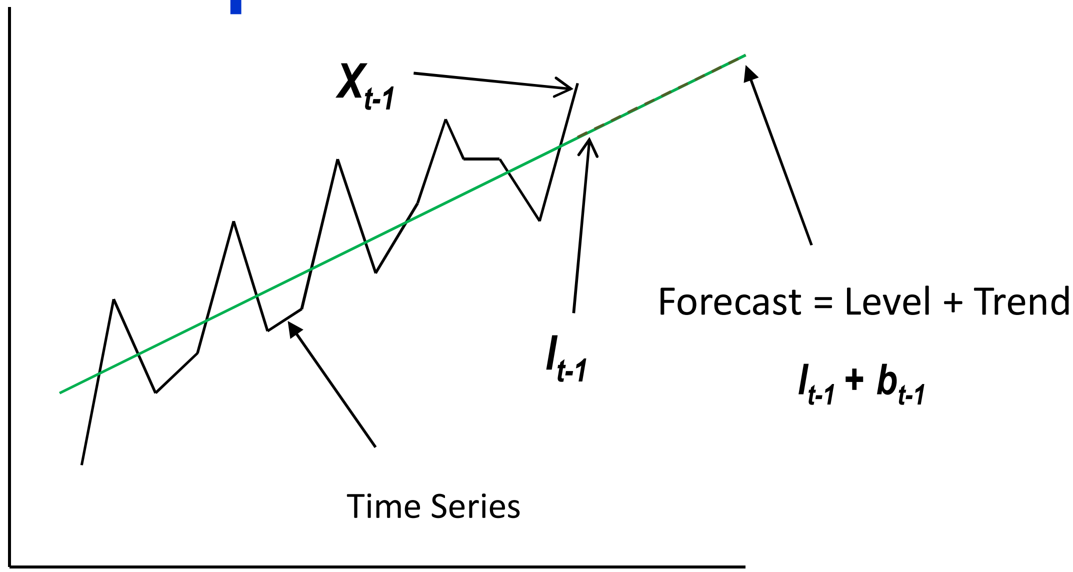
- It is an approach to design ARMA models.
- Check for nonstationarity. If nonstationary, use ARIMA.
- To obtain the orders *k*, *m* of ARMA(*k*,*m*), check autocorrelation plot and partial autocorrelation plot.





- Also can use Bayesian information criterion (BIC).

Exponential Smoothing



Holt's model:

$$l_t = a\, x_t + (1-a)(l_{t-1} + b_{t-1})$$

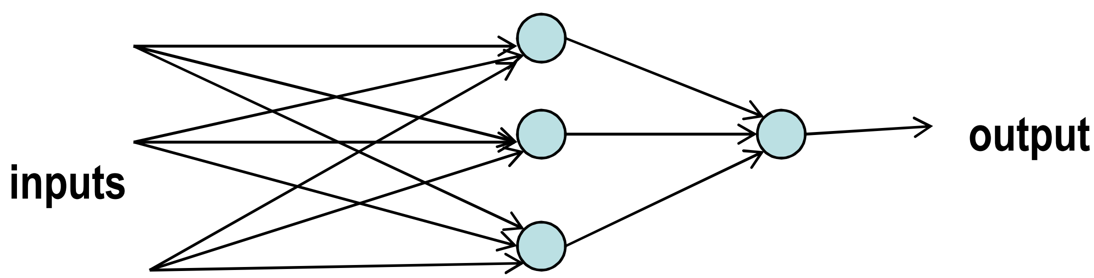
$$b_t = \beta\,(x_t - l_{t-1}) + (1-\beta)\,b_{t-1}$$

- where l_t is the estimated level and b_t is the estimated trend.
- m step ahead forecast: $x_{t+m} = l_t + m\, b_t$

Machine Learning Models

- Typically nonlinear models that learn relation between inputs and outputs, using data driven approaches, or certain probability models.

- Example: Neural networks:
- Networks of “neurons” inspired by the brain’s information processing ability:



Neural Network (Contd)

- NN output is given by

$$y = v_0 + \Sigma_j v_j f(\Sigma_i w_{ji} x_i + w_{i0})$$

- The weights w_{ji} and v_j are learned through minimizing the error function.
- The input variables are the past lags x_t, $x_{t-1}, \ldots, x_{t-k}$
- The output y is the value to be forecasted: x_{t+L}

Machine Learning (Contd)

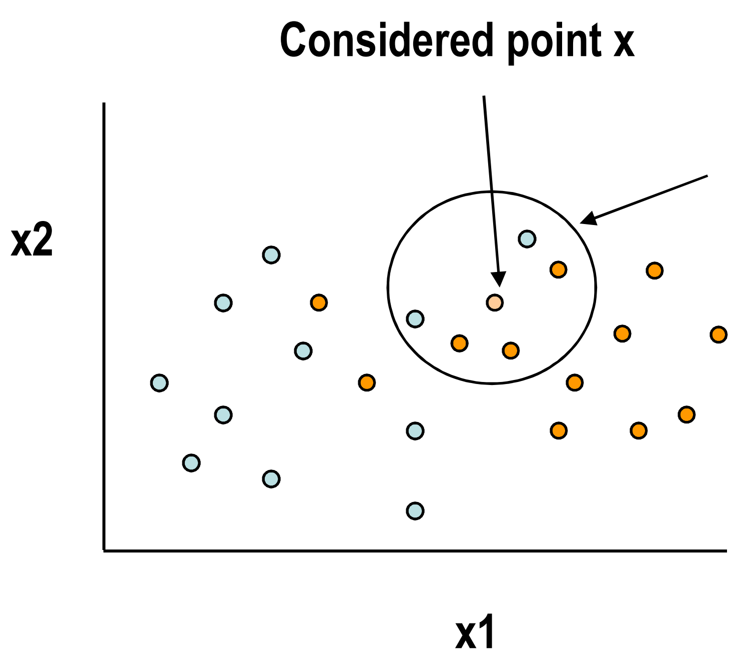
- Support vector regression (SVR)
- Forecast: $f\ (x) = \Sigma_i\, w_i\, x_i + b$
- Obtain w_i so as to minimize:

$$J = \Sigma_i\, w_i^2 + C\ \Sigma_m | y_m - f\ (x_m) |_{\epsilon}$$

- *where*
  - w_i is a weight parameter
  - x_m and y_m are respectively input and output training vectors.
  - $|\ \ |_{\epsilon}$ is the Є-sensitive error.

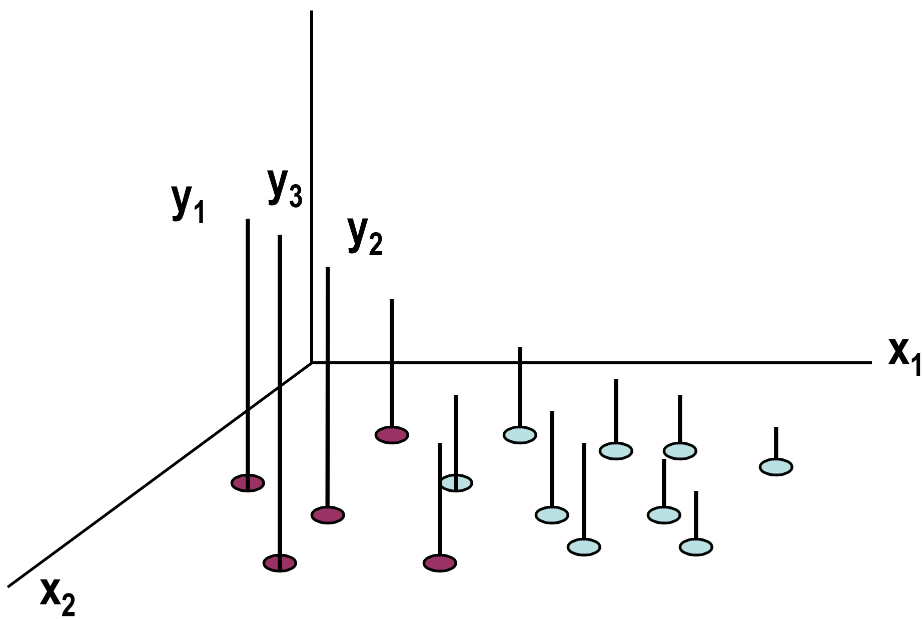
Machine Learning (Contd)

- K Nearest Neighbor:
- Consider the training set vectors $(x_t, x_{t-1}, \ldots, x_{t-k})^T$ with target output being the value to be forecasted: $y_t = x_{t+L}$



K-Nearest Neighbor (Contd)

- Forecast = $Avg(y_i)$ over the K neighbors



Monte Carlo Forecasting

- Obtain from first principles the physical model relating the quantity to be forecasted, and any internal variables.
- Model uncertainty using some probability densities.
- Simulate the model forward using Monte Carlo, and obtain the forecast.
- Examples of applications: weather forecasting.

Questions?

Please feel free to contact me any time during the year and further at amir@alumni.caltech.edu