D Lab: Supply Chains
Lectures 4 and 5

Class outline:

- What is Demand?
- Demand management
- Forecasting Demand
  - Bass Model
  - Causal Models
  - Exponential Smoothing

	ARTI	Air Liquide	Wecycler	Ghonsla	BPS	
Sinead Cheung		1				
Neha Doshi	1					
Emily Grandjean	1					
Shannon Kizilski	1					
Cherry Park		2				
Sanjana Puri			2			
Jessica Shi			1			
Spencer Wenck					1	
Chelsea Yeh		1				
Daniel			1			

Who is Alex Rogo?

If you don’t know, it means you are not reading “The Goal”…

Assignment: Next Monday

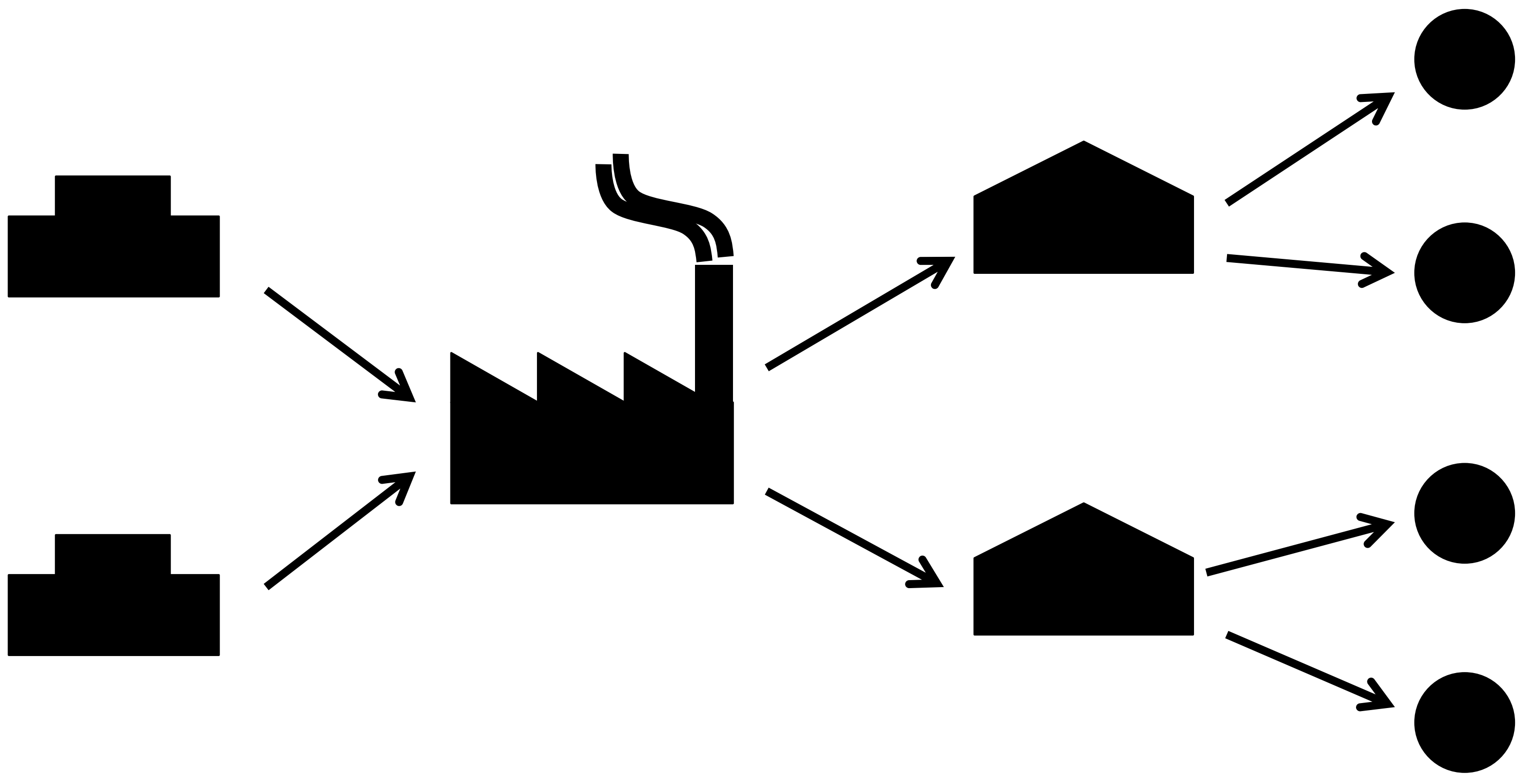
- *Book Review*

  This assignment is due at the beginning of class. Prepare a one page summary of *The Goal* formatted as follows:

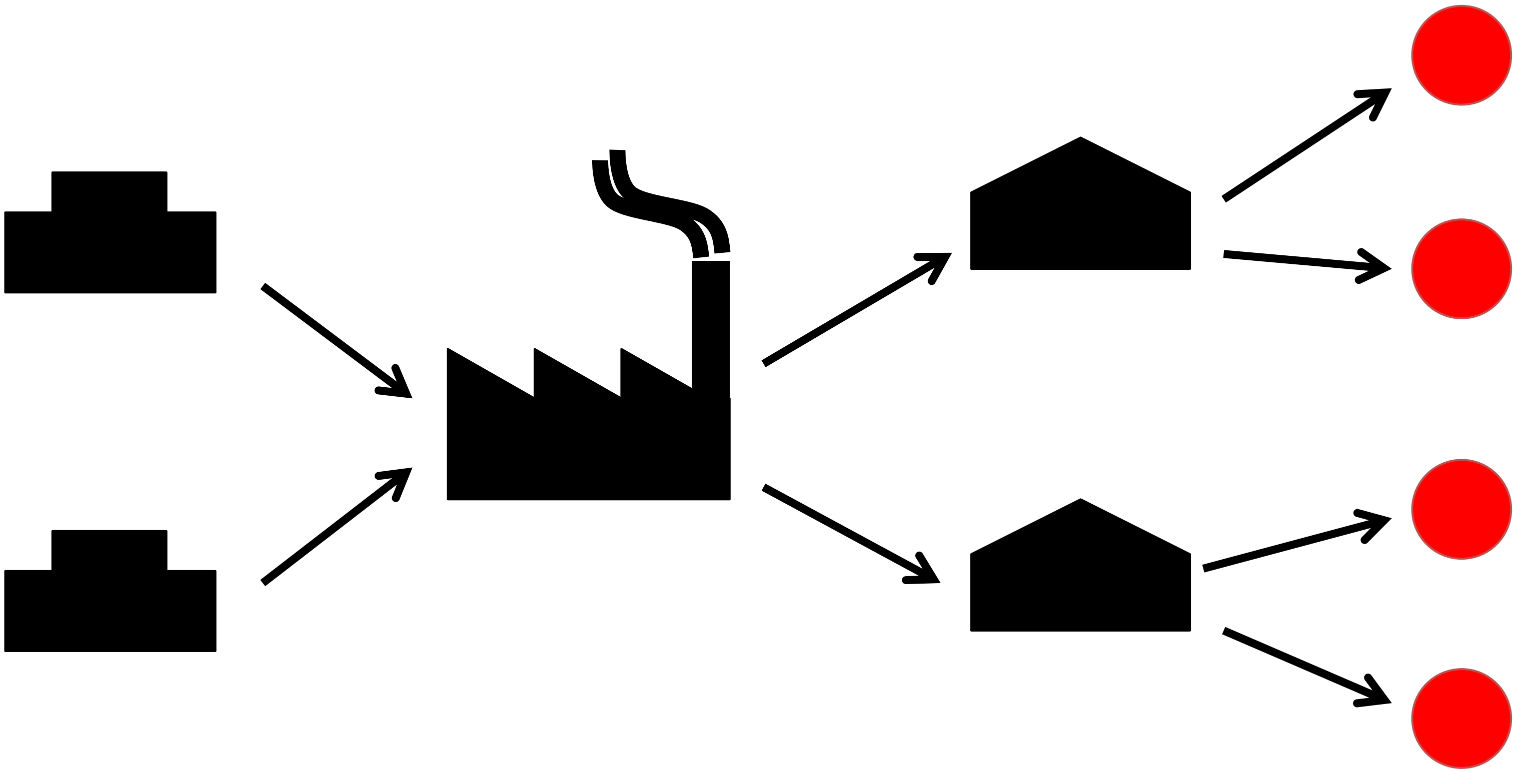
  1. List your (at most) 5 main take-aways from the book (at most 2-3 sentence each); and

  2. List the (at most) 3 main critiques (at most 2-3 sentence each) you would make about this book

Demand Management



Demand Management



What is demand?

From the Merriam-Webster dictionary,

Demand is the quantity of a commodity or service wanted at a specified price and time.

- How can we deal with demand from a SC point of view?
- Why is anticipating demand important?

Why forecast? - Two SC strategies

Two supply chain strategies for dealing with demand are

- **Make-to-order (MTO):** the company chooses to manufacture a product only after a request from a customer is received.

- **Make-to-stock (MTS):** based on **forecasts** production is done in anticipation of future demand.

Two SC strategies - Examples

Make-to-order (MTO)

- Construction Industry
- Customized products
- Services/Food

Make-to-stock (MTS)

- Vaccines and medicine
- Most consumer goods
- Agricultural Products

More examples?

Two SC strategies - Tradeoffs

	MTS	MTO
Economies of Scale	✔	
More dependent on demand forecasts	✔	
Longer lead time for customers		✔
Easier to scale-up	✔	
Customizable products		✔

Forecasting is important for both models

Two SC strategies - Emerging Markets

In the context of emerging markets, think about the following question:

Can you give examples of products for which a MTO model "makes sense" in a developed economy but not in an emerging economy?

More reasons why forecasting is important

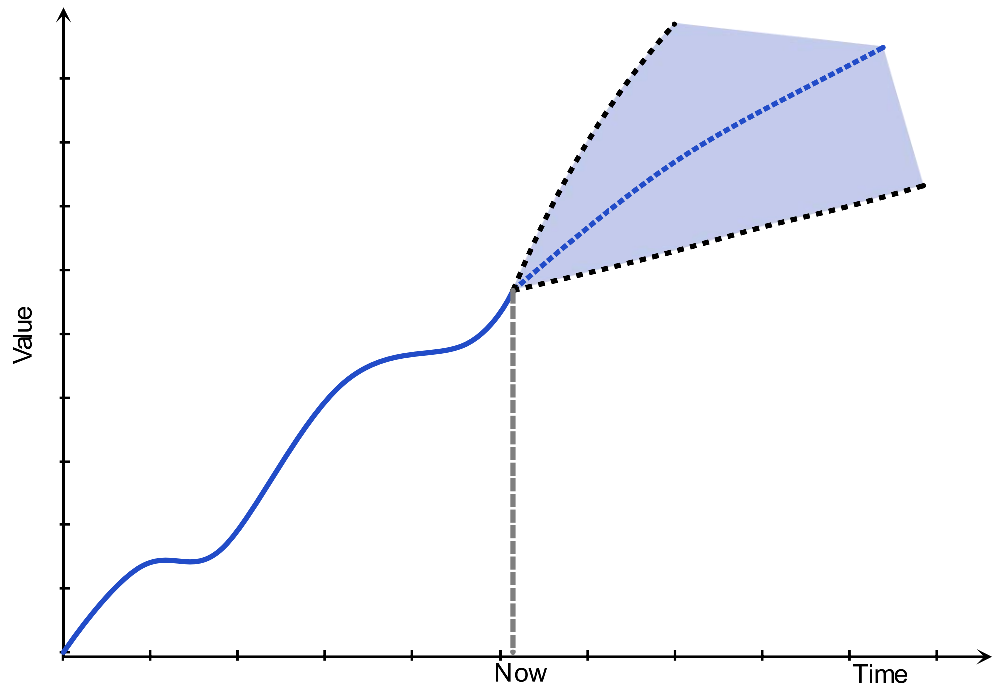
- Forecast used for inventory planning at retail store level and at DC level for products held in stock (ie, MTS)

- Forecast used to determine when to order more inventory

- Need for simple, robust methods applicable for wide range of contexts

Forecast principles

1. Forecasts are **always wrong** and should always include some measure of error
2. The longer the horizon, the larger the error
3. Method should be chosen based on need and context



Forecasting – formal definition

Previous observations of demand

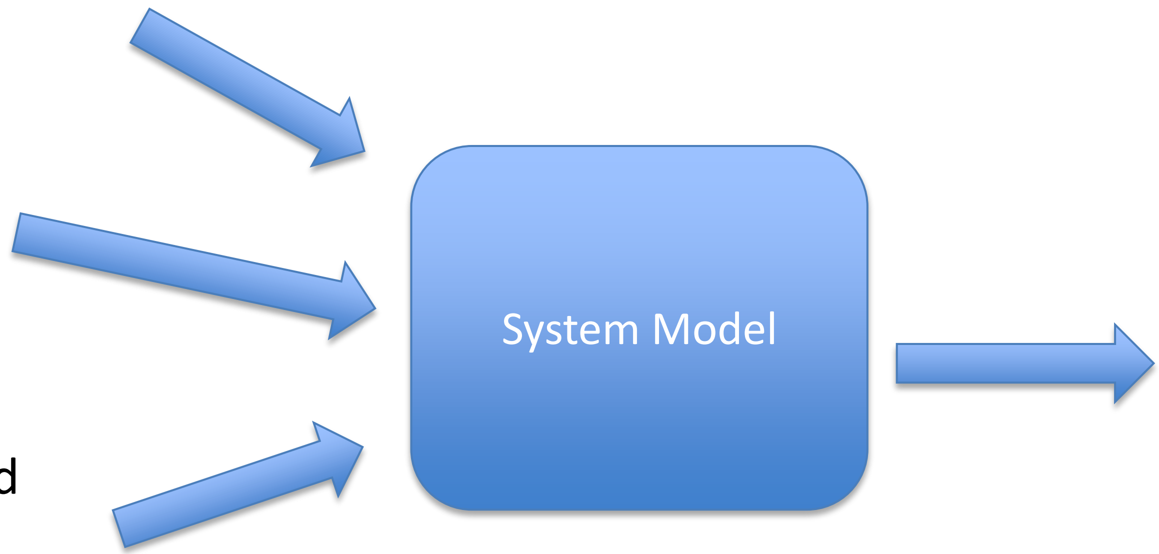
$$(D_1, D_2, \ldots, D_t)$$

Additional info:

$$\mathcal{I}$$

Forecast period

$$\tau$$



Forecast

$$F_{t+\tau}$$

Forecasting – formal definition

Previous observations of demand

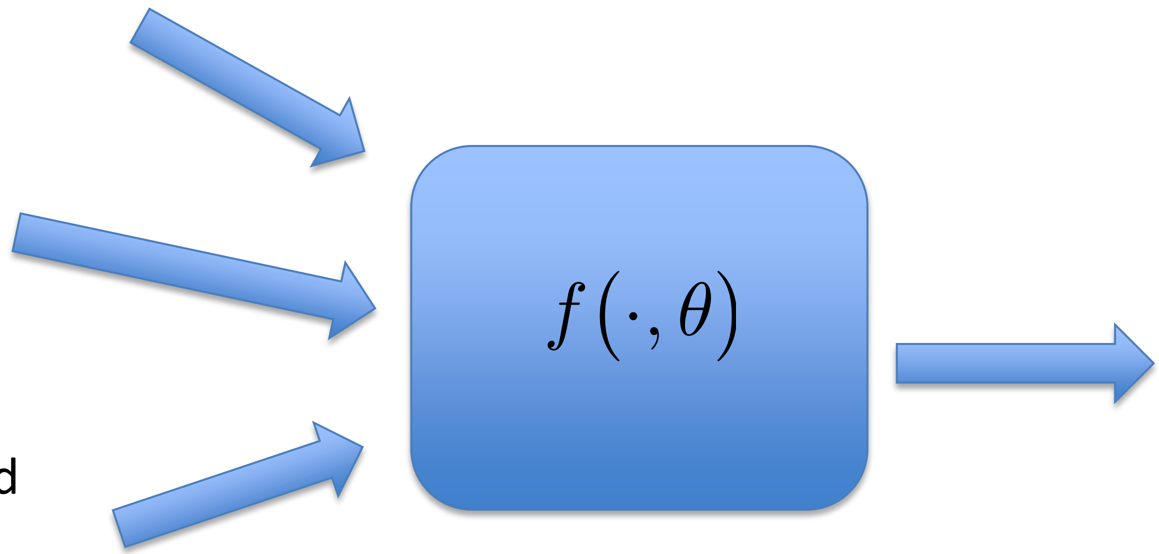
$$(D_1, D_2, \ldots, D_t)$$

Additional info:

$$\mathcal{I}$$

Forecast period

$$\tau$$



Forecast

$$F_{t+\tau}$$

How would you forecast seminar lunch boxes?

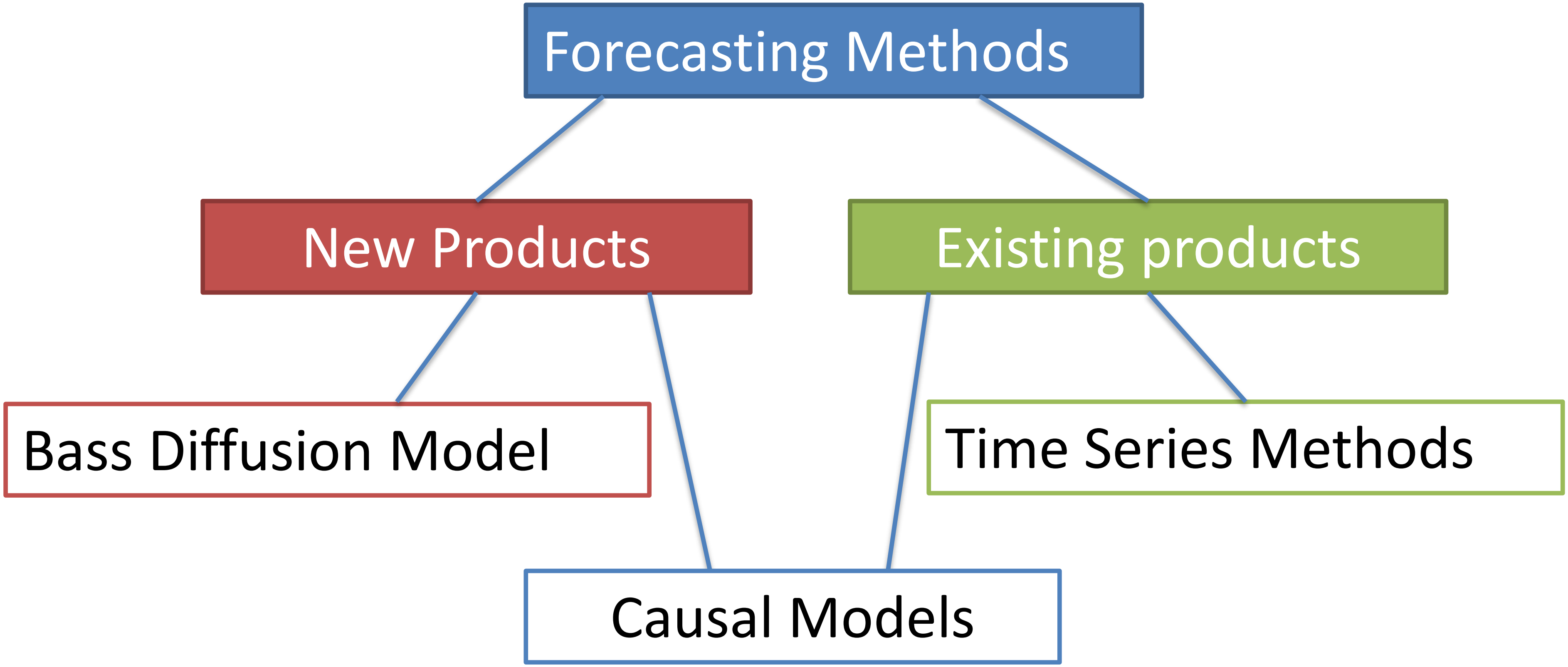
Factors for choosing forecast method

- How is forecast to be used? Need for accuracy? Units? Time period? Forecast horizon? Frequency of revision?
- Availability and accuracy of relevant data? censored?
- Computational complexity? Data requirements?
- How predictable is the entity? Are there independent factors that affect it or are correlated to it?
- Level of aggregation? Across geographies? Time? Product categories?
- Type of product? New or old?

Types of forecasts

- Qualitative; expert opinions
- Diffusion models
- Causal models, eg, regression
- Disaggregation of an aggregate forecast
- Aggregation of detailed forecasts
- Time series methods

Types of forecasts



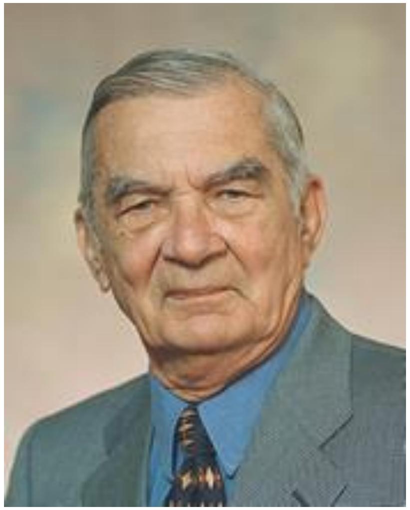
Forecasting the adoption of new products

Example: Water Purifier

Assume you are responsible for estimating a demand for a new cheap and efficient water purifier. How would you do it?

The Bass Diffusion Model

- Is a model for adoption of new products (consumer durables)
- One of the 10 most influential papers of "Management Science" in the last 50 years
- Widely used in marketing and strategy
- We will build the model from first principles



Frank Bass

The Bass Diffusion Model

Key idea: consumers are divided into 2 groups:

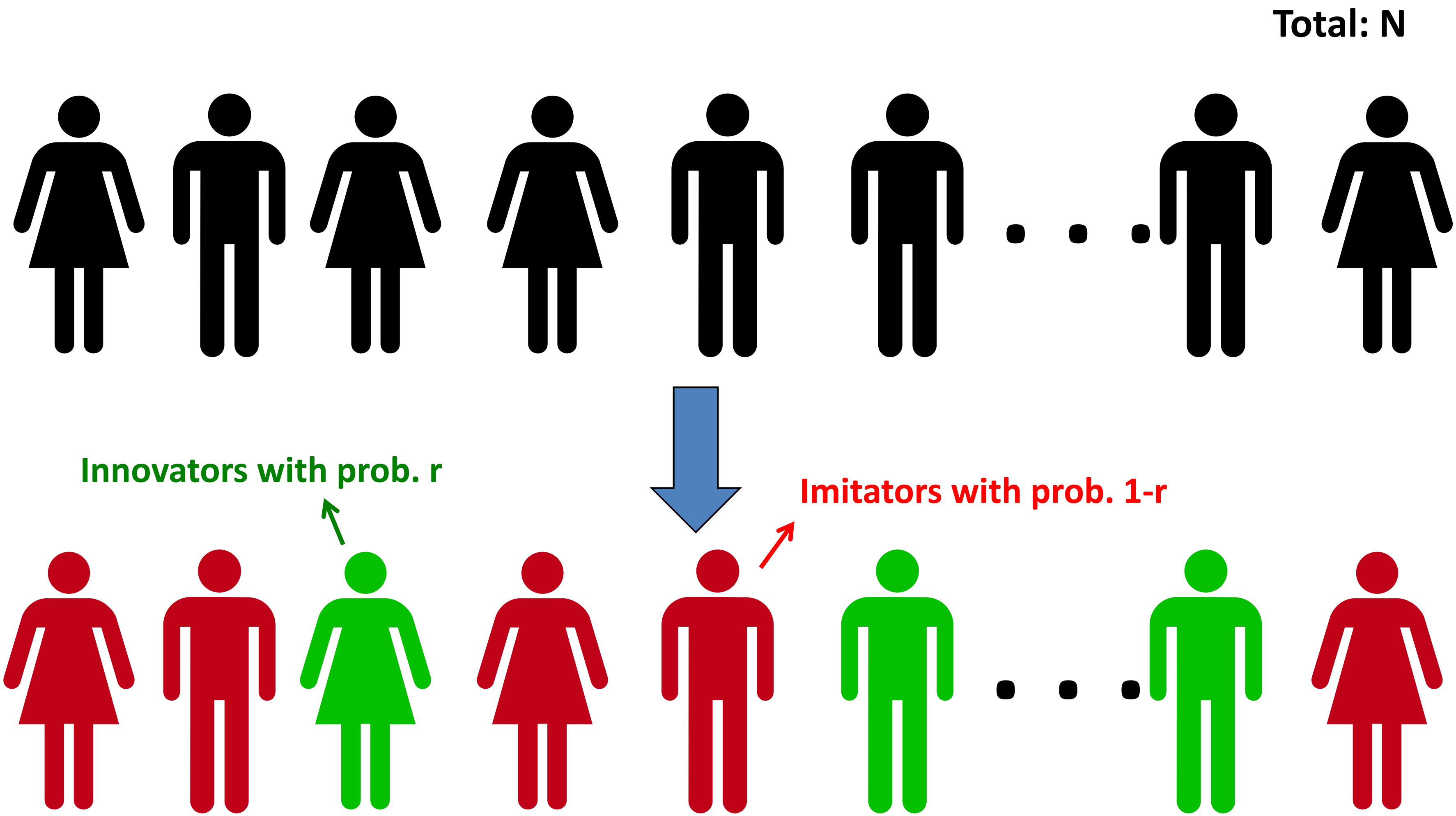
Innovators

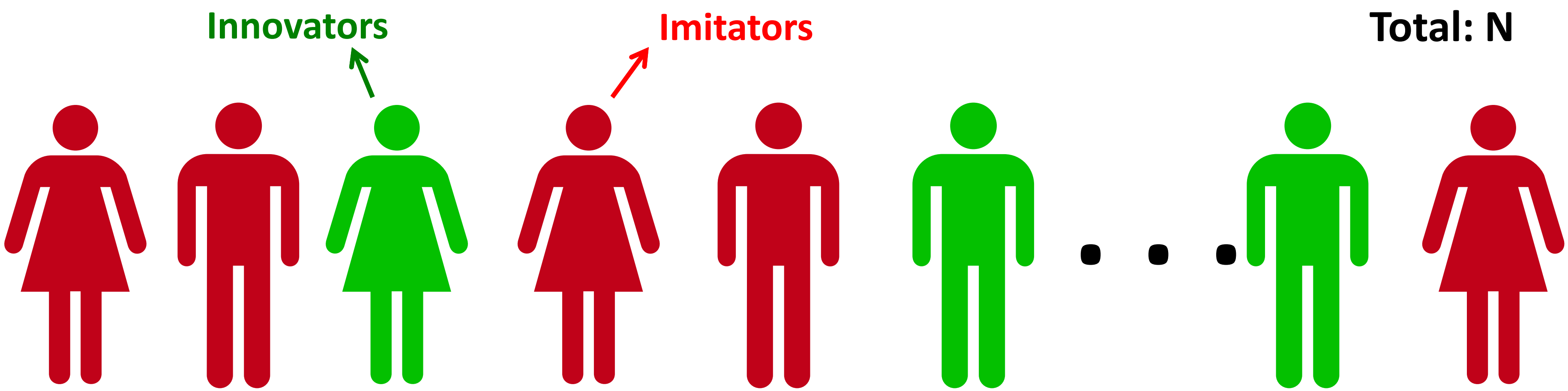
- Early adopters
- Not influenced by other individuals
- Driven by advertisement or some other external effect

Imitators

- Influenced by other buyers
- Word of mouth
- **Network effects**

Motivation for the Bass model





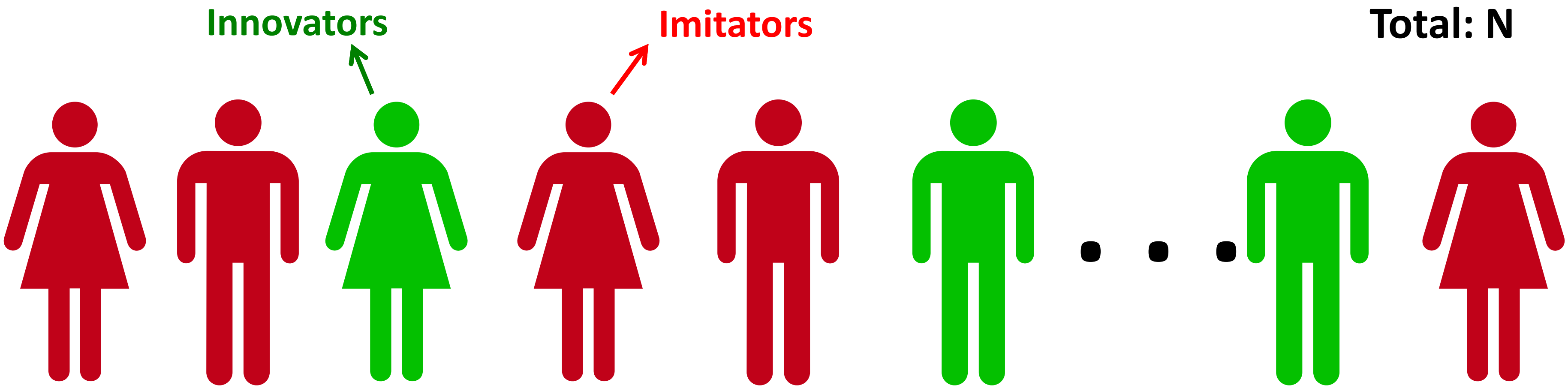
Innovators

Probability of adoption = p

Imitators

Probability of adoption = $q \frac{\# \text{ cons. adopted}}{N}$

t = 1



Innovators

Probability of adoption = p

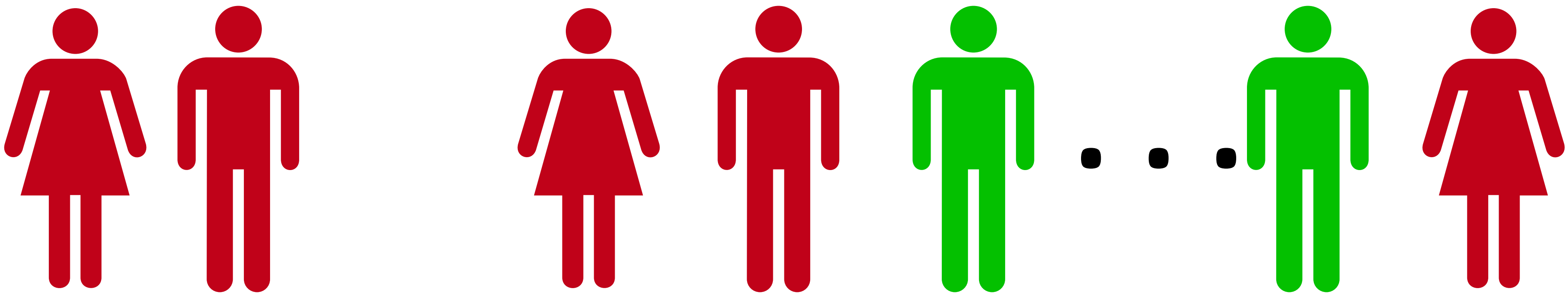
Imitators

Probability of adoption = $q \frac{\#\text{ cons. adopted}}{N}$

= 0

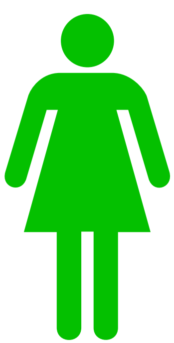
t = 2

Total: N



Innovators

Probability of adoption = p



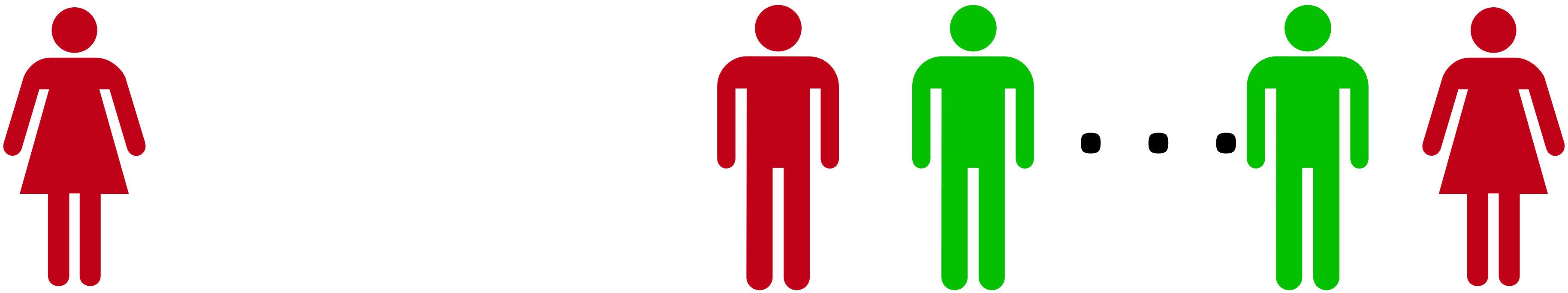
Imitators

Probability of adoption = $q \dfrac{\#\ \text{cons. adopted}}{N}$

= $\dfrac{q}{N}$

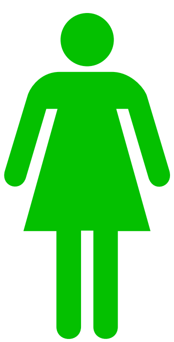
t = 3

Total: N



Innovators

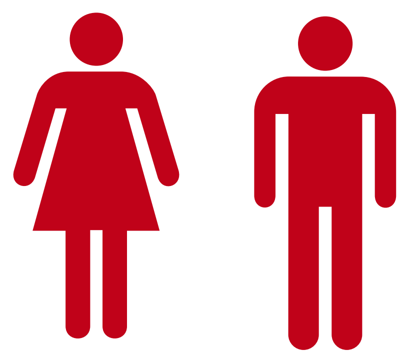
Probability of adoption = p



Imitators

Probability of adoption = $q\frac{\#\ \text{cons. adopted}}{N}$

$= \frac{3q}{N}$



Motivation (board)

- Market size: N
- Number of new adopters at time t: n_t
- Total number of adopters at time t: N_t
- Probability of being an innovator: r
- Probability of an innovator adopting at time t: p
- Probability of an imitator adopting at time t: $q\frac{N_{t-1}}{N}$

- Define $\tilde{p} = pr; \quad \tilde{q} = (1-r)q$

Bass Model

- We can approximate the model we just described by

$$\bar{n}_t = (N - N_{t-1})\left(\bar{p} + \bar{q}\frac{N_{t-1}}{N}\right), \quad N(0) = c$$

- The continuous differential equation becomes

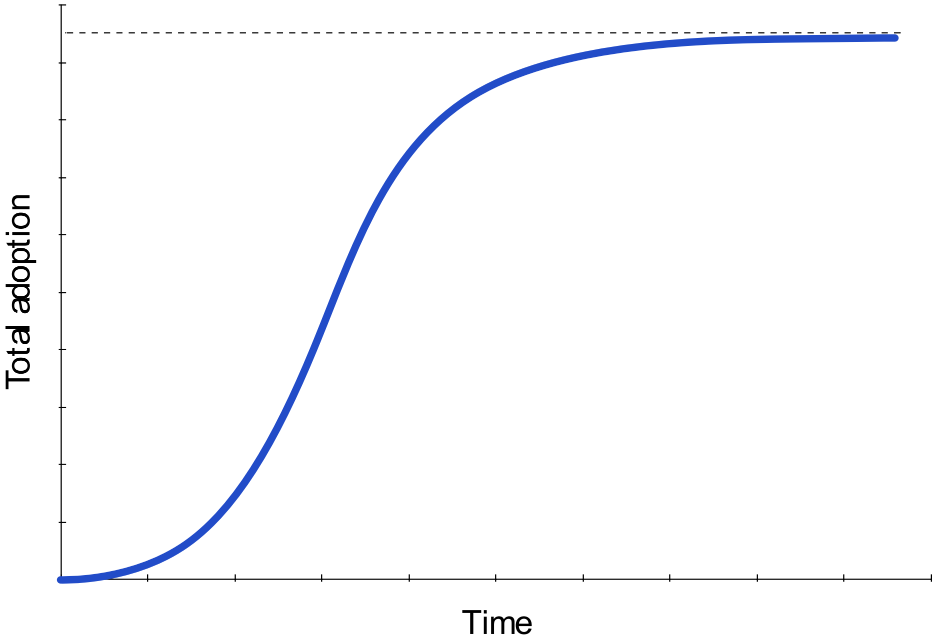
$$\frac{dN(t)}{dt} = (N - N(t))\left(\tilde{p} + \tilde{q}\frac{N(t)}{N}\right)$$

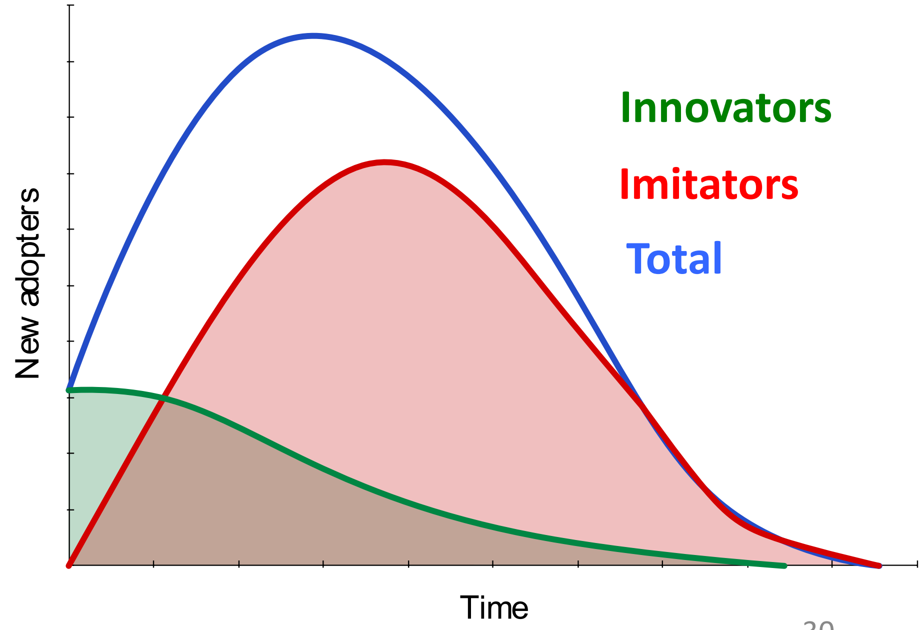
Innovators ($\tilde{p}$) Imitators ($\tilde{q}$)

Bass Model

- Thus, for the continuous approximation, we have, for $N(0) = 0$, the solution

$$N(t) = N \frac{1 - e^{-(\tilde{p}+\tilde{q})(t)}}{1 + \frac{\tilde{q}}{\tilde{p}} e^{-(\tilde{p}+\tilde{q})(t)}}$$





Estimation of parameters

- What parameters do we need to estimate?
  - Market Size N
  - Imitation $\tilde{q}$
  - Innovation $\tilde{p}$
- How do we estimate?
  - Early data + linear regression
  - Analogy (priors)
  - Focus groups
  - Macro Data
- **What is missing?**

Generalized Bass Model

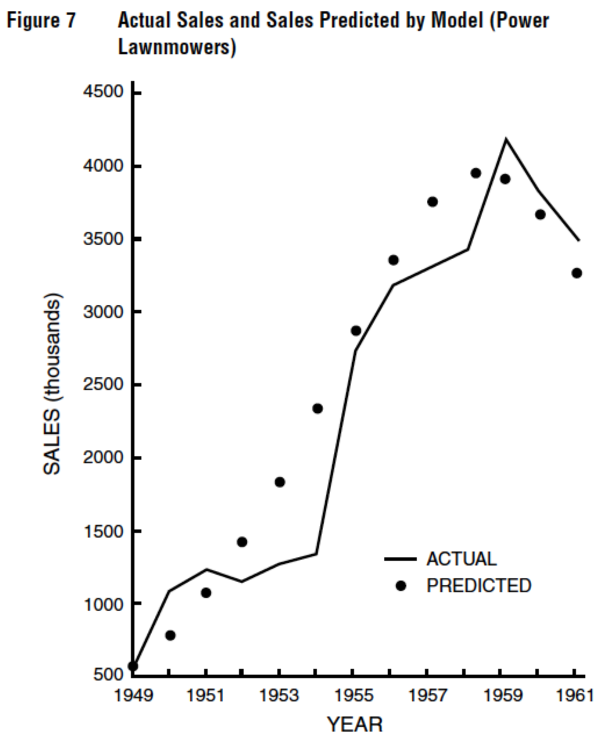
- Let "marketing effort" evolve as x(t). The new equation is:

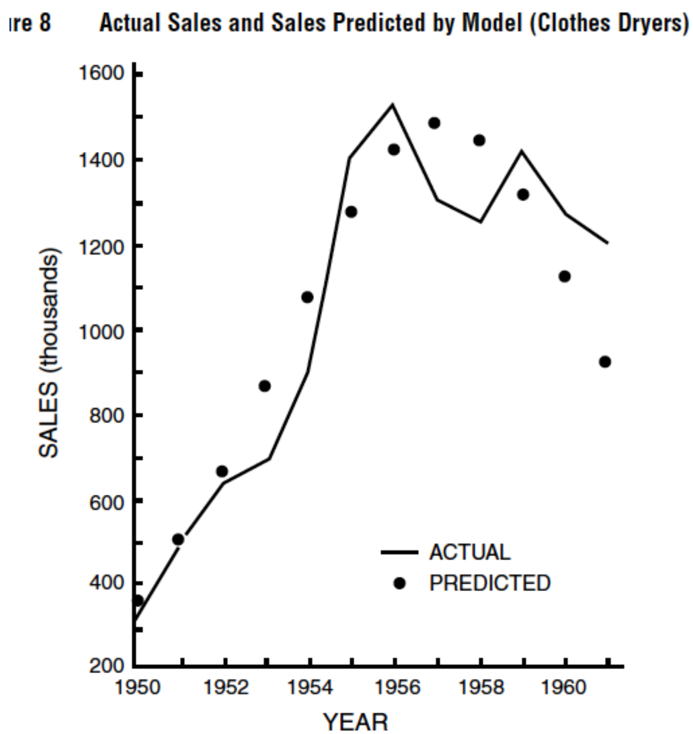
$$\frac{dN(t)}{dt} = (N - N(t))\left(\tilde{p} + \tilde{q}\frac{N(t)}{N}\right)x(t)$$

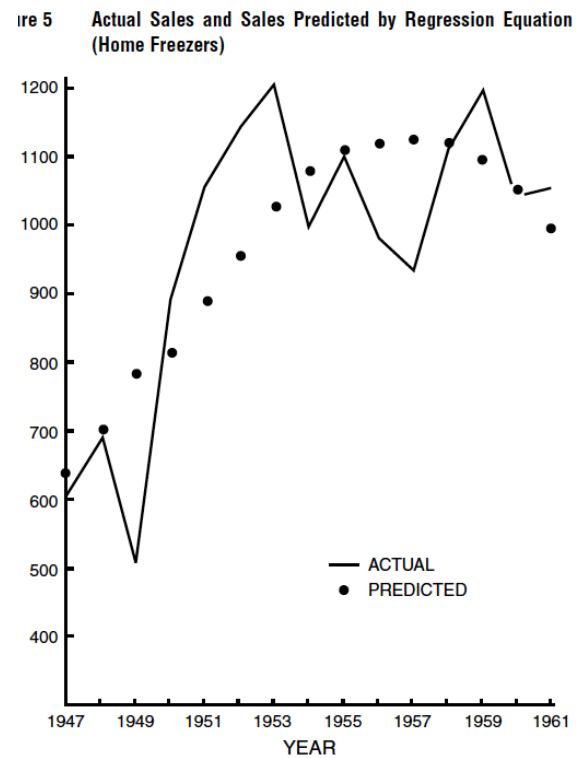
- When estimating or doing focus groups, try to map price vs. demand group

- Create a model for different prices

Bass Model Examples





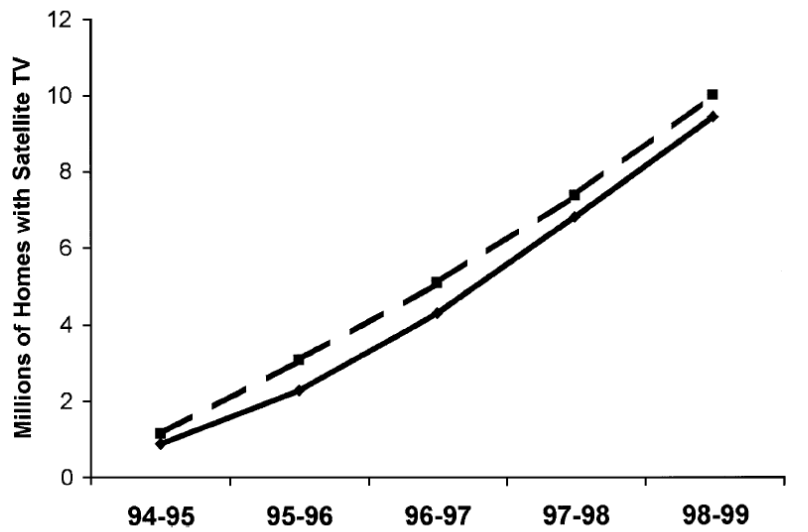


DIRECTV

- Launched in 1992
- How many people would subscribe to satellite TV and when?
- New technology
- p and q were estimated by analogy
- N was determined by market research and focus groups

DIRECTV

Year	1992 Forecast Number of TV Homes Acquiring DBS (Millions)	Actual Number of TV Homes Acquiring DBS (Millions)	1992 Forecast of Percent of TV Homes with DBS (Percentage)	Actual Yearly Percent of TV Homes with DBS (Percentage)
7/01/94–6/30/95	0.875	1.15	0.92	1.21
7/01/95–6/30/96	2.269	3.076	2.37	3.21
7/01/96–6/30/97	4.275	5.076	4.42	5.25
7/01/97–6/30/98	6.775	7.358	6.95	7.55
7/01/98–6/30/99	9.391	9.989	9.55	10.16



Fitting the Bass Model

The Bass difference equation is

$$\bar{n}_t = (N - N_{t-1})\left(\bar{p} + \bar{q}\frac{N_{t-1}}{N}\right)$$

$$\bar{n}_t = N\bar{p} + (\bar{q} - \bar{p})N_{t-1} + \bar{q}\frac{N_{t-1}^2}{N}$$

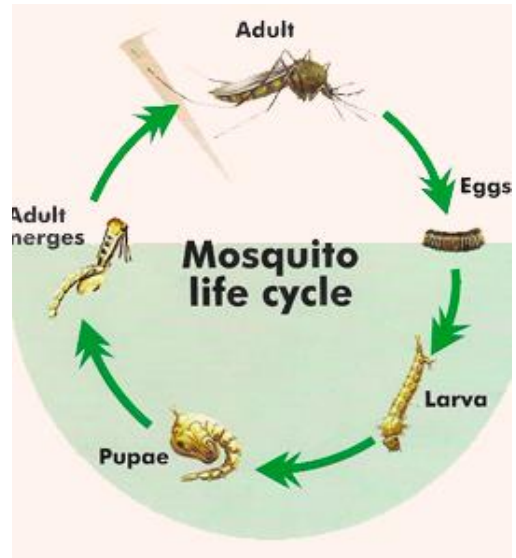
$$\bar{n}_t = a + bN_{t-1} + cN_{t-1}^2$$

We can fit this equation to the data!

Causal Models

Example – Dengue in India

- Dengue is transmitted by a mosquito, the *Ades Aegypti*



- During Summer monsoon, stagnant water accumulates
- This leads to a proliferation of mosquito reproduction
- A increase in mosquitos increases dengue transmission

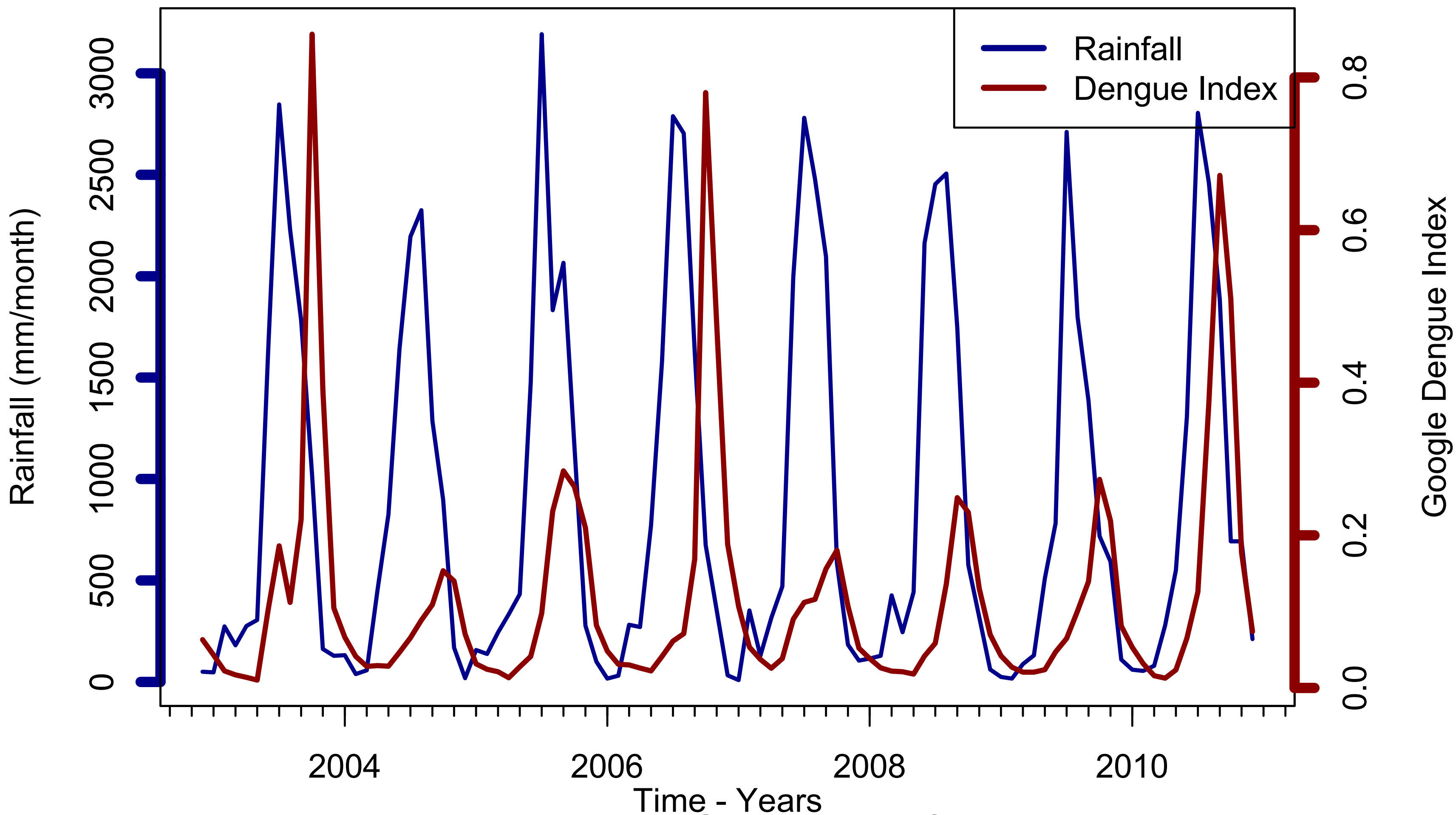
During rainy season there is a lot of stagnant water

Example – Dengue in India

- Causal models are very useful to estimate the occurrence of weather related diseases (and the demand for medicine/vaccines).

- Consider the relationship between monthly rainfall and the occurrence of Dengue Fever in India

Example – Dengue in India

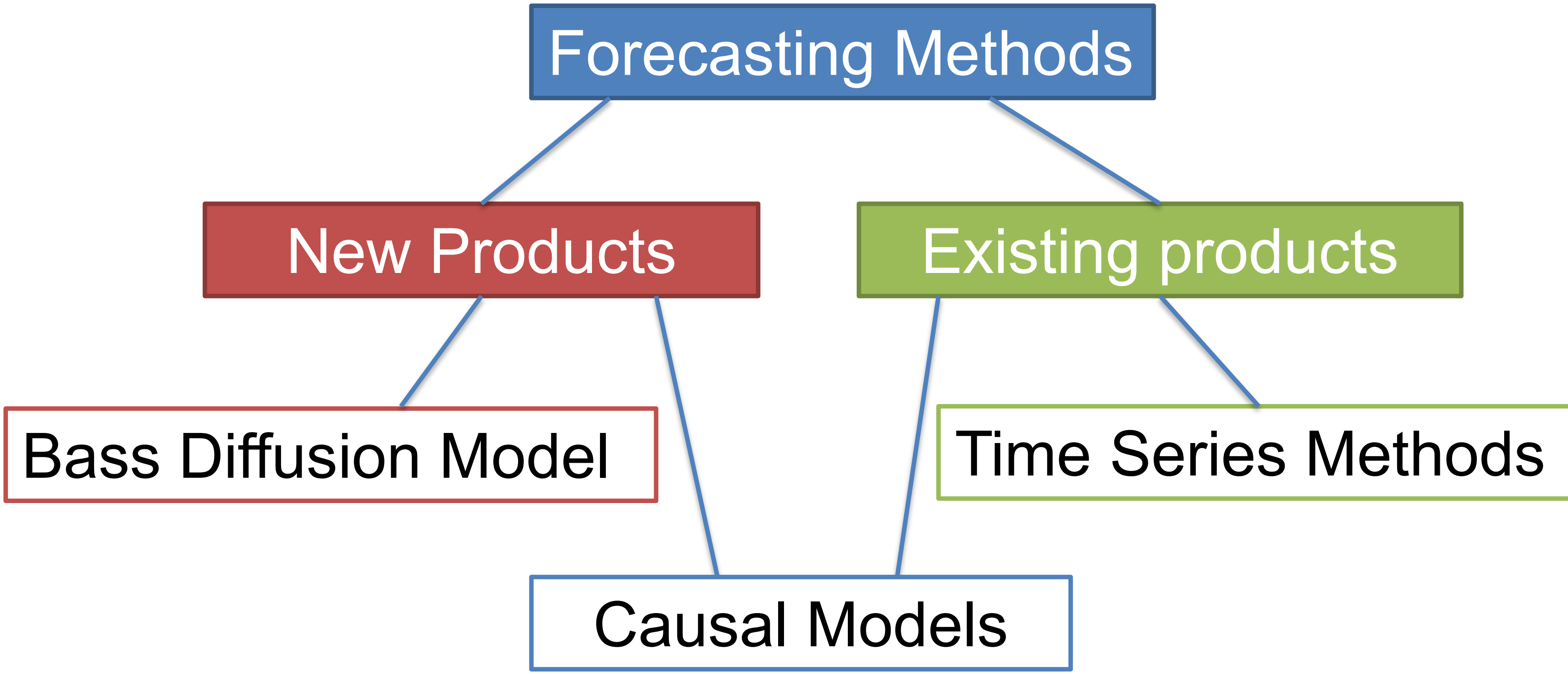


The index is an estimate by Google.org of Dengue Activity.

Causal Models

Can you think of other examples?

Types of forecasts

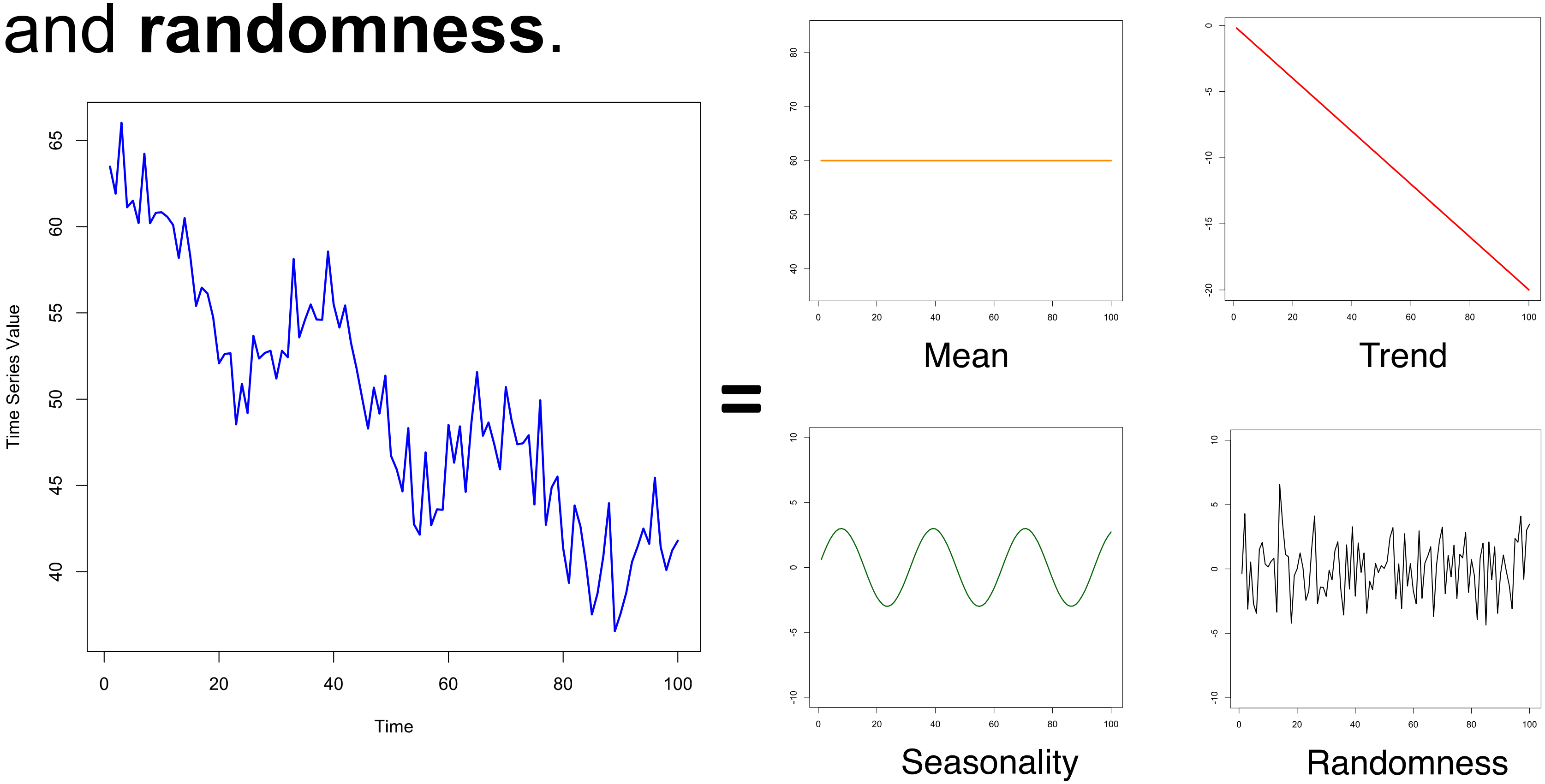


Time Series Methods

- Used when there is limited information available about exogenous factors that influence demand
- Short horizon forecast (usually < 1 year)
- We will discuss methods that are easy to implement

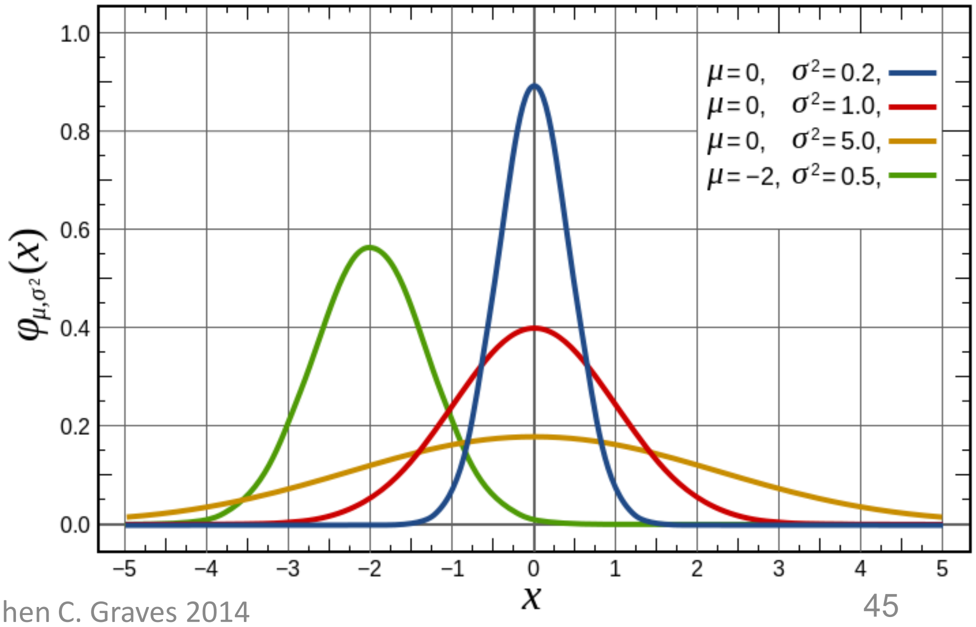
Time Series – Components of Demand

In practice, it is useful to understand and estimate 4 components of demand: **mean, trend, seasonality** and **randomness**.



Randomness

- Usually modeled using probability distributions
- Two components: mean and variance
  - Mean: Average Value
  - Variance: "spread"



Time Series Methods

Assume demand has the form

$$D_t = \mu_t + \epsilon_t$$

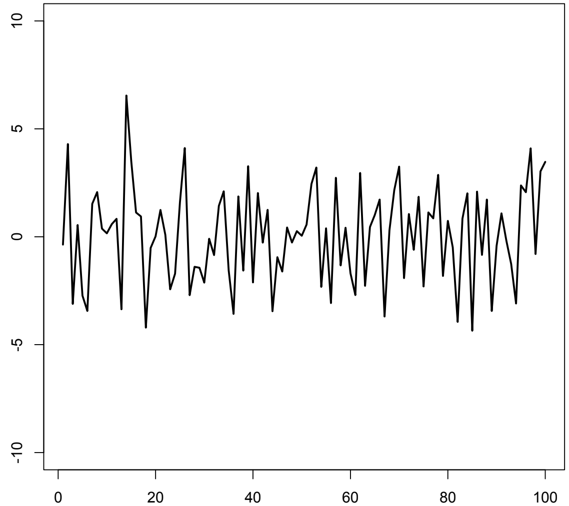
Permanent component: Mean, trend, seasonality

Randomness

In addition, assume that

Mean: $E[\epsilon_t] = 0$

Variance: $\mathrm{var}(\epsilon_t) = \sigma^2$



Randomness

Time Series Methods

Assume demand has the form

$$D_t = \mu_t + \epsilon_t$$

In addition, assume that $E[\epsilon_t] = 0 \;\; \text{var}(\epsilon_t) = \sigma^2$

Forecast method determines

S_t : Expost estimate of the permanent component

$F_{t+\tau}$: forecast at time τ

Time Series Methods

- What is permanent component and expost estimate?

Expost estimate is where we "think" that the permanent component is in the time period

- We are ready to discuss forecasting methods

Moving Average

- Recent observations are more "informative" than old observations
- Uses *n* previous observations
- Expost estimate of the permanent component μ_t is

$$S_t = \frac{D_{t-n+1} + \ldots + D_{t-1} + D_t}{n}$$

- Forecast is $F_{t+\tau} = S_t, \ \forall \tau > 0$

Moving Average

- Advantages: Simple, only one “knob” (n)

- Disadvantages: weighs all previous demand equally

- Example

Weighted Moving Average

- Weighs previous observations using weights $w_1, \ldots, w_n$ where

$$\sum_{i=1}^{n} w_i = 1$$

- We have the expost estimate

$$S_t = w_1 D_t + w_2 D_{t-1} + \ldots + w_n D_{t-n+1}$$

and the forecast (again) is

$$F_{t+\tau} = S_t,\ \forall \tau > 0$$

Weighted Moving Average

- Advantages: Flexibility
- Disadvantages: too many “knobs”
- Solution: Exponential Smoothing

Exponential Smoothing

- Weighs previous observations using a geometric time series such that

$$w_i = \alpha(1-\alpha)^{i-1}$$

Note that

$$\sum_{i=1}^{\infty} w_i = 1$$

Thus,

$$S_t = \alpha D_t + \alpha(1-\alpha)D_{t-1} + \alpha(1-\alpha)^{i-2}D_{t-2} + \ldots$$

$$S_t = \alpha D_t + (1-\alpha)S_{t\_1}$$

Exponential Smoothing

- Only one parameter to adjust - α
- Doesn't weigh previous forecasts equally
- Very simple update equation
- Examples

Exponential Smoothing vs. Moving Average

- Assume permanent component is constant

$$\mu_t = \mu$$

- For exponential smoothing:

$$E[S_t] = \mu \quad , \quad \mathrm{var}(S_t) = \frac{\alpha}{2-\alpha}\sigma^2$$

- For moving average

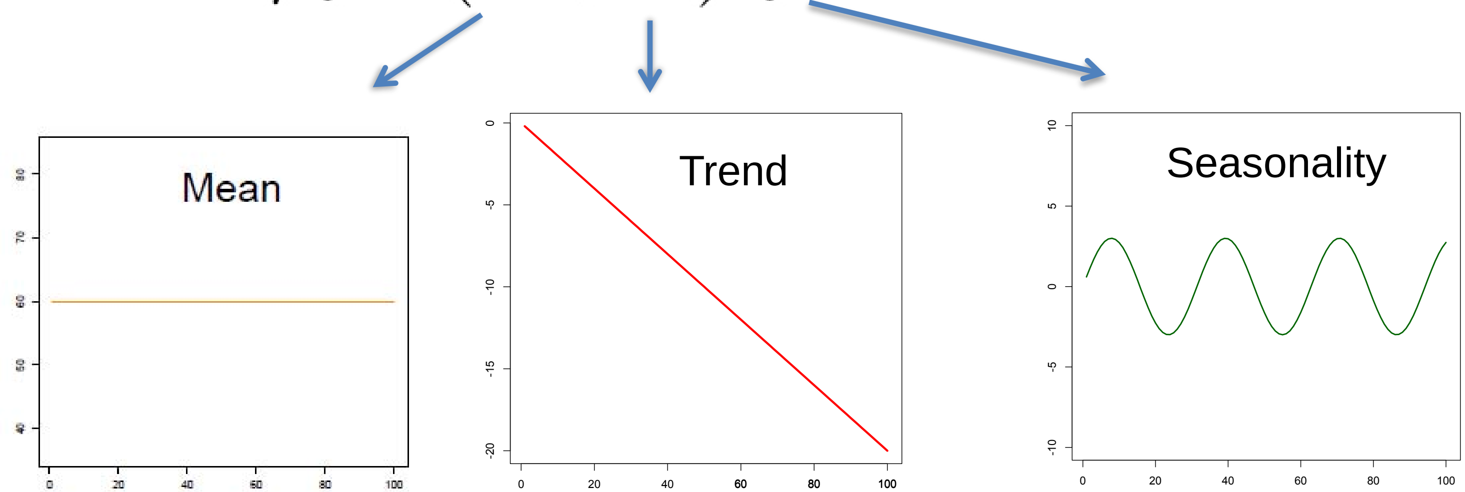
$$E[S_t] = \mu \quad , \quad \mathrm{var}(S_t) = \frac{\sigma^2}{n}$$

Holt-Winters Method

- So far, we did not explicitly estimate seasonality or trend

- Assume that the permanent component is

$$\mu_t = (m + bt)c_t$$



Holt-Winters Method

- So far, we did not explicitly estimate seasonality or trend

- Assume that the permanent component is

$$\mu_t = (m + bt)c_t$$

- Demand is

$$D_t = (m + bt)c_t + \epsilon_t$$

Holt-Winters Method

- Assume we know that the length of a season is L
- Let $x_t = m + bt$ be the *deseasonalized* permanent component
- We now need to estimate, m, b, c_t

Idea: Exponential smoothing on all the parameters!

Expost Estimates

- Deseasonalized demand

$$x_t = m + bt \longrightarrow X_t$$

- Trend

$$b_t \longrightarrow B_t$$

- Seasonal factor

$$c_t \longrightarrow C_t$$

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Where we think the deaseason. permanent component will be

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

↓

Deaseasonalized demand

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Smoothing coefficient

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Estimate of slope

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Seasonality

$$C_t = \gamma \frac{D_t}{X_t} + (1-\gamma)C_{t-L}$$

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Seasonality

Another smoothing coef.

$$C_t = \gamma \frac{D_t}{X_t} + (1-\gamma)C_{t-L}$$

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Seasonality

Another smoothing coef. (γ)

$$C_t = \gamma \frac{D_t}{X_t} + (1-\gamma)C_{t-L}$$

Expost Estimates

Deseasonalized demand

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

Trend

$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

Seasonality

Seasonality factor

$$C_t = \gamma \frac{D_t}{X_t} + (1-\gamma)C_{t-L}$$

Forecast

- Given

$$X_t = \alpha \frac{D_t}{C_{t-L}} + (1-\alpha)(X_{t-1} + B_{t-1})$$

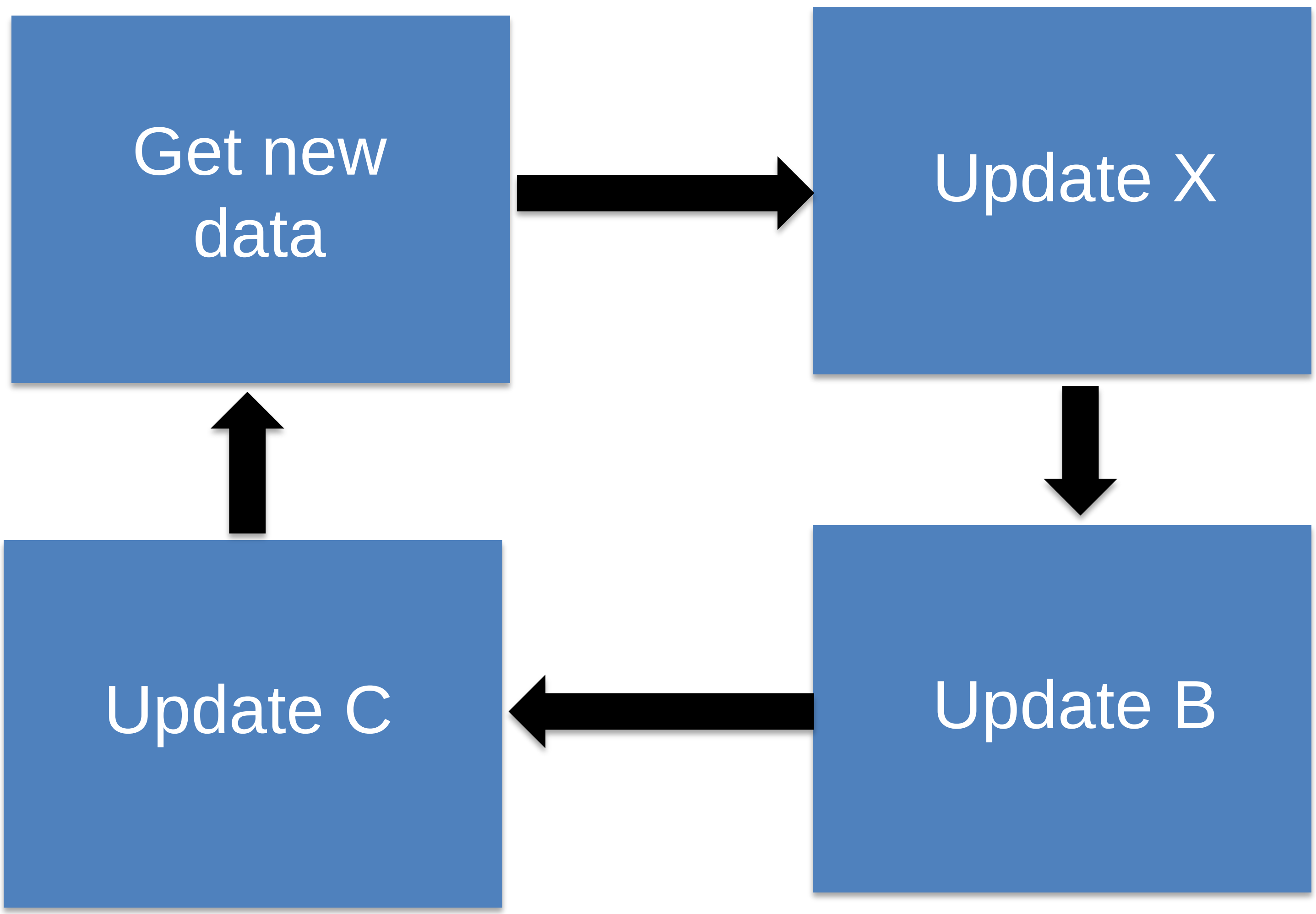
$$B_t = \beta(X_t - X_{t-1}) + (1-\beta)B_{t-1}$$

$$C_t = \gamma \frac{D_t}{X_t} + (1-\gamma)C_{t-L}$$

- The forecast is

$$F_{t+\tau} = (X_t + \beta_t \cdot \tau)C_{t+\tau}$$

Holt-Winters Method



Wrap-up

	Variables	Info
Moving Average	n	none
Weighted moving Average	$(w_1, \ldots, w_n)$	none
Exponential Smoothing	α	none
Holt-Winters	α, β, γ	L

15.772J / EC.733J D-Lab: Supply Chains
Fall 2014