Price Customization

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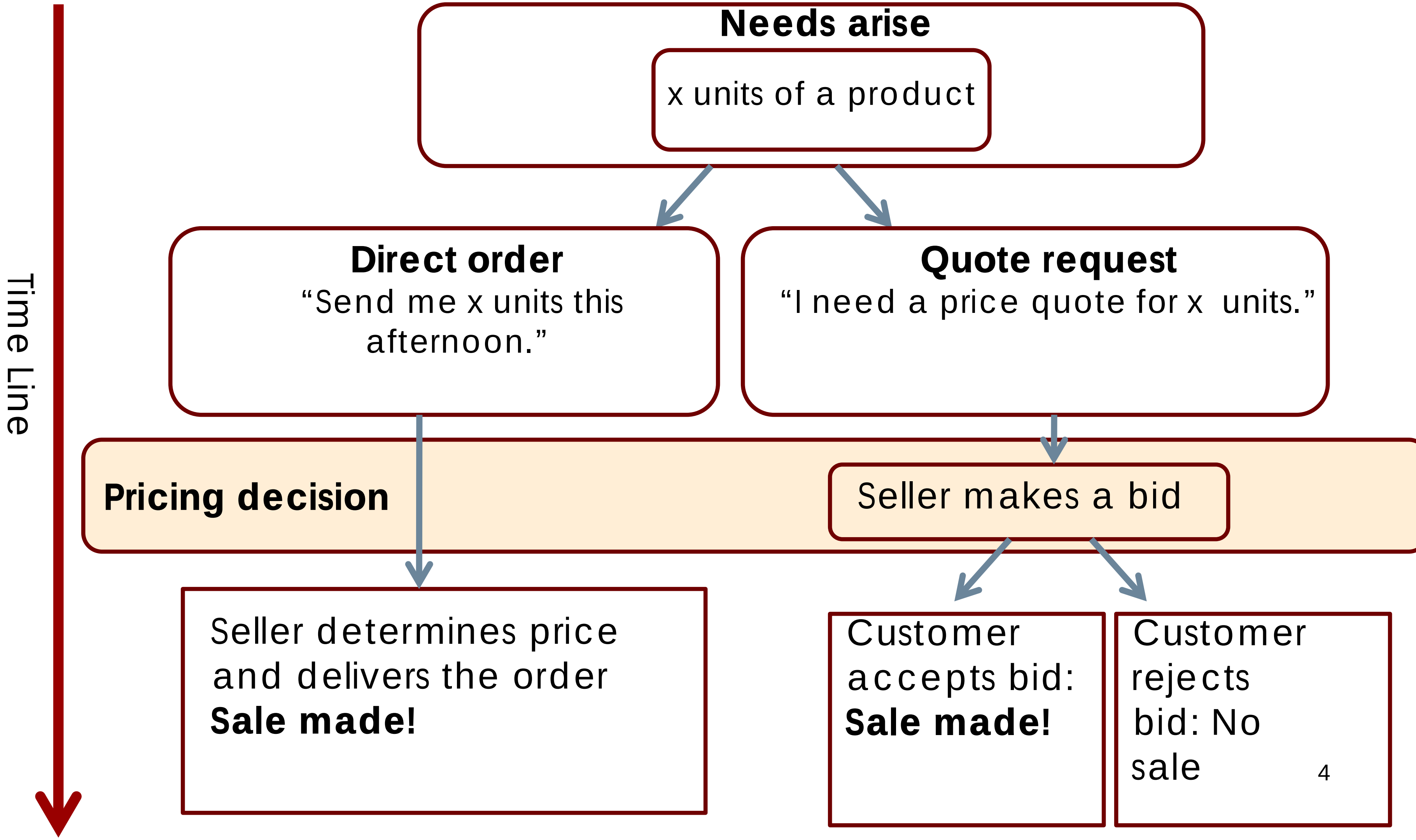
Agenda

- Price Structures
- B2B Pricing Context
- Logistic Regression
- Application

Price Structure

- Architecture around which the firm's pricing mix is designed
- Used to leverage heterogeneity in price sensitivities arising from different dimensions
  - Preferences for product attributes
  - Timing of the purchase
  - Number of units bought

B2B Buying & Decision Process



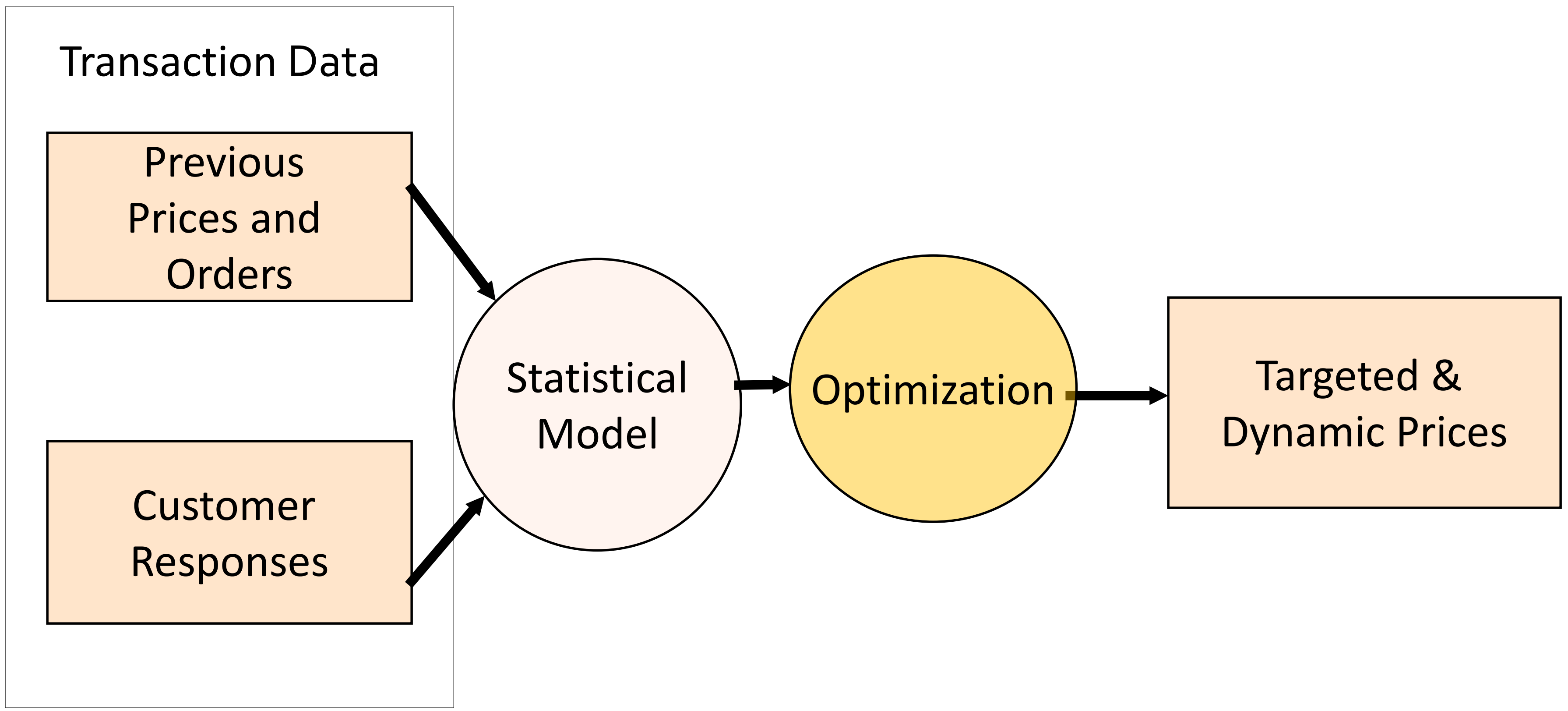
Data

- Many observations (purchase events) per customer
- We observe:
  - Time of purchase event
  - Quantity requested
  - Quote request or direct order
  - Quote acceptance/rejection
  - Price

Objective

- Determine what factors influence a customer to accept our bid
- How can we price our bid so that we have a higher chance of winning?

Modeling Framework



Modeling Bids

- Dependent Variable: Won or Not (0 /1)
- Possible Independent Variables (Continuous)
  - Price
  - Time since last contact
  - Quantity
  -

Modeling Bids

Customer	Bid Won	Time	Quantity	Price/lb	Cost/lb
1	0	9.000	3.500	2.126	1.585
1	0	0.071	1.150	3.247	1.780
1	0	6.286	0.205	2.400	1.534
1	0	10.000	1.025	2.100	1.750
1	1	0.286	0.232	2.603	1.920
1	0	0.714	1.058	2.948	2.130
2	0	0.429	0.536	2.593	1.731
2	0	9.714	1.371	2.540	1.846
2	1	19.429	0.126	2.532	1.699

Continuous Dependent Variable: Regression Analysis

- A simple regression equation is given by

$$y_i = \alpha + \beta x_i + e_i$$

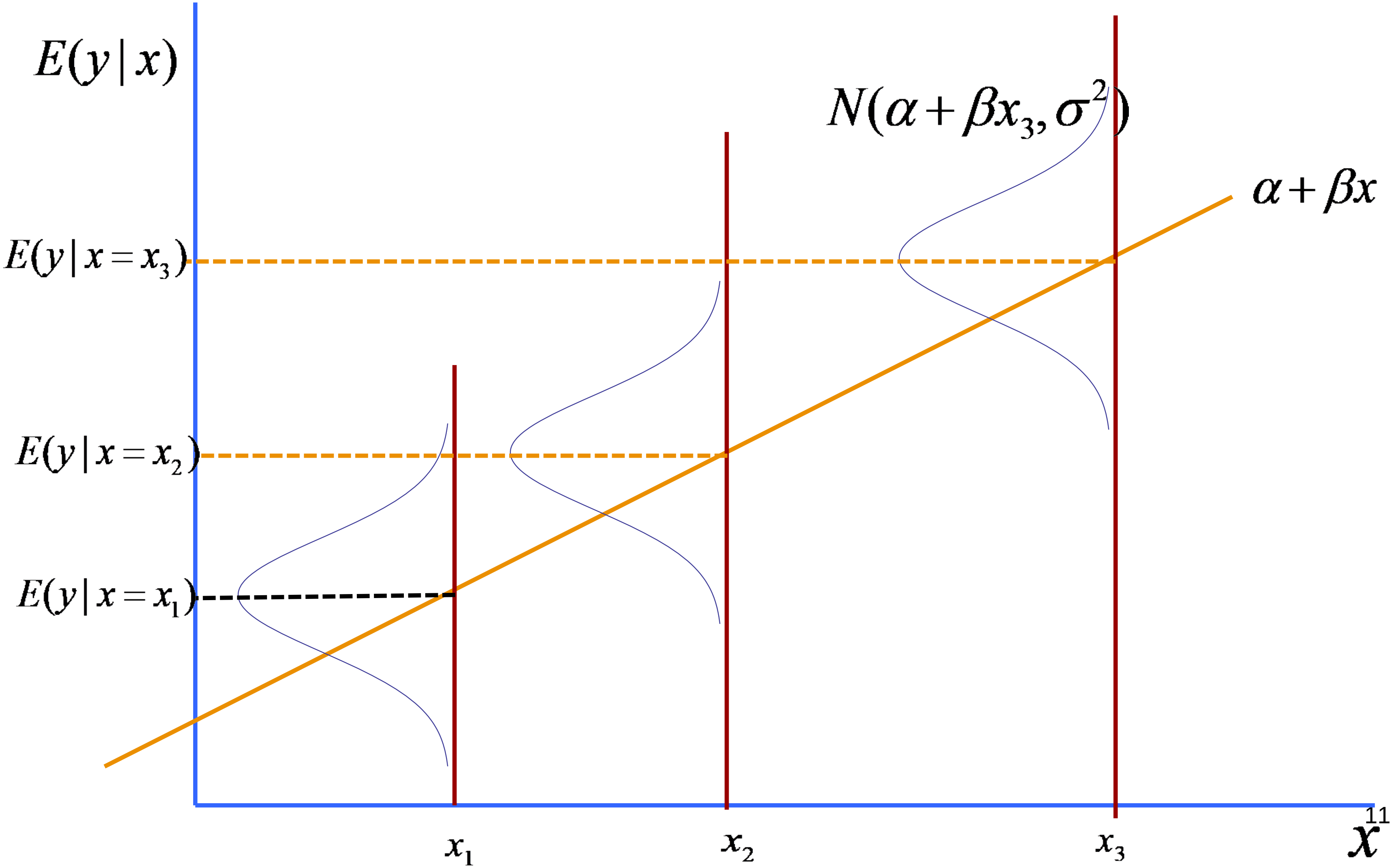
- This is the same as

$$y_i = E(y_i \mid x_i) + e_i$$

- The expectation (mean) is assumed to be linear. i.e.,

$$E(y_i \mid x_i) = \alpha + \beta x_i$$

Regression Analysis



Modeling Bids: Discrete Choice Model

- The dependent variable Y is discrete, i.e., it is Bernoulli
- The variable Y is distributed Bernoulli means that
  - y_i =1 with probability p_i
  - y_i=0 with probability $1\text{-}p_i$
- The mean of the Bernoulli distribution is given by p, i.e.,

$$E(y_i \mid x_i) = p(x_i)$$

Modeling Bids

- Can we write

$$E(y_i \mid x_i) = p(x_i) = \alpha + \beta x_i$$

- The left side is a probability, i.e., it is restricted to be between 0 and 1.
- The right side, however, is unbounded
- A logistic regression can be useful in modeling this

Logistic Regression

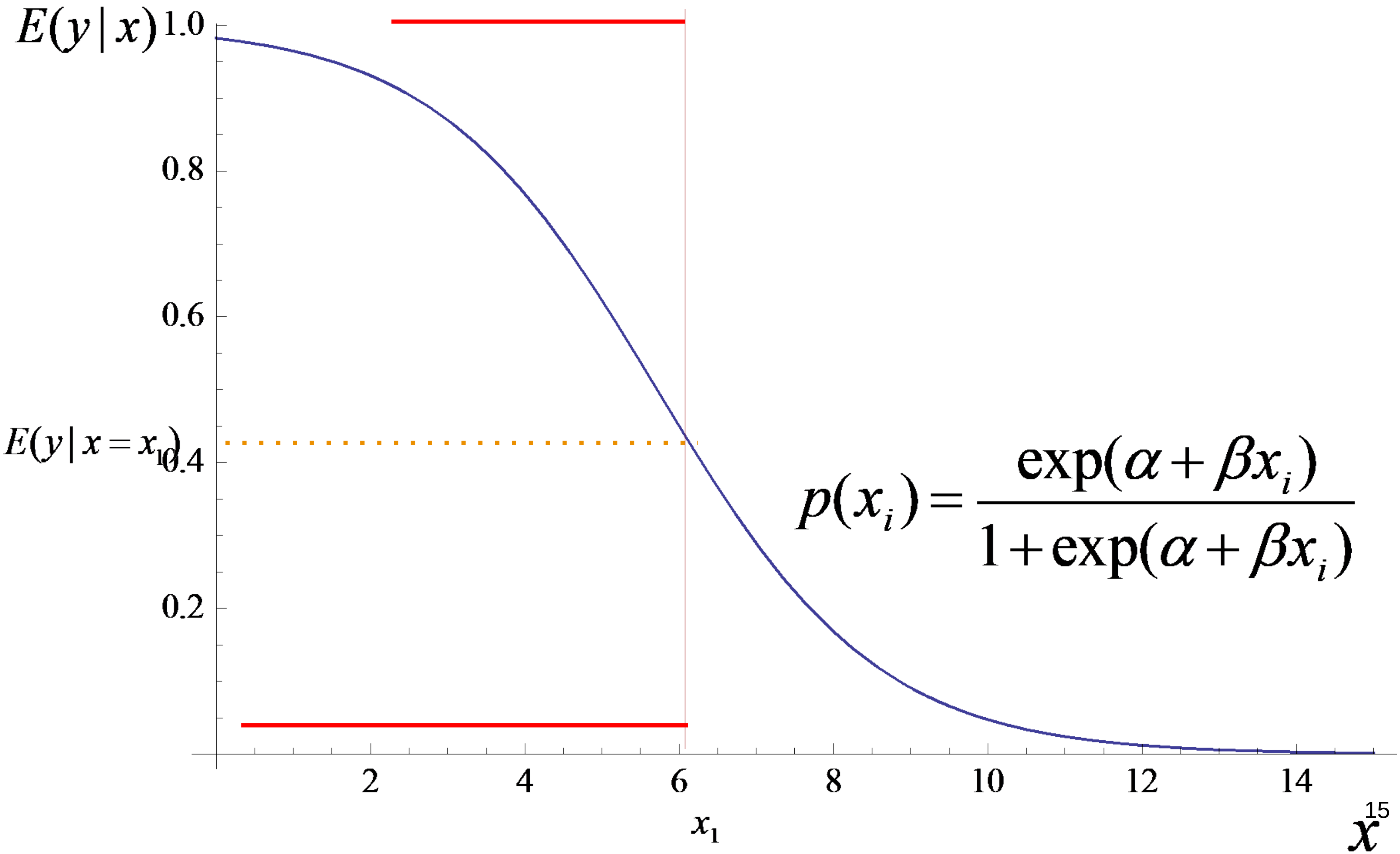
- We assume that the logit of the probability is linear, i.e.,

$$\ln\left(\frac{p(x_i)}{1-p(x_i)}\right)=\alpha+\beta x_i$$

- This means that the probability of success can be written as

$$p(x_i)=\frac{\exp(\alpha+\beta x_i)}{1+\exp(\alpha+\beta x_i)}$$

Logistic Regression



$$p(x_i) = \frac{\exp(\alpha + \beta x_i)}{1 + \exp(\alpha + \beta x_i)}$$

Multiple Logistic Regression

- We can do similarly when we have more than one independent variable

$$p_i = \frac{\exp(\alpha + \beta_1 Price_i + \beta_2 Feature_i)}{1 + \exp(\alpha + \beta_1 Price_i + \beta_2 Feature_i)}$$

- We need to find the values of the model parameters, i.e., α, β_1, β_2 which are most consistent with the data

Multiple Logistic Regression

- We can use Maximum Likelihood Estimation to obtain the values of the parameters
- Maximum Likelihood Estimates (MLE's) are those values of the parameters, that maximize the probability (Likelihood) of observing our dataset
- We can use the R software to compute the parameter Estimates

Logistic Regression of B2B Data

- Dependent variable (Bid Won)
- Independent Variables
  - Price /lb
  - Quantity sought
  - Time since last purchase event

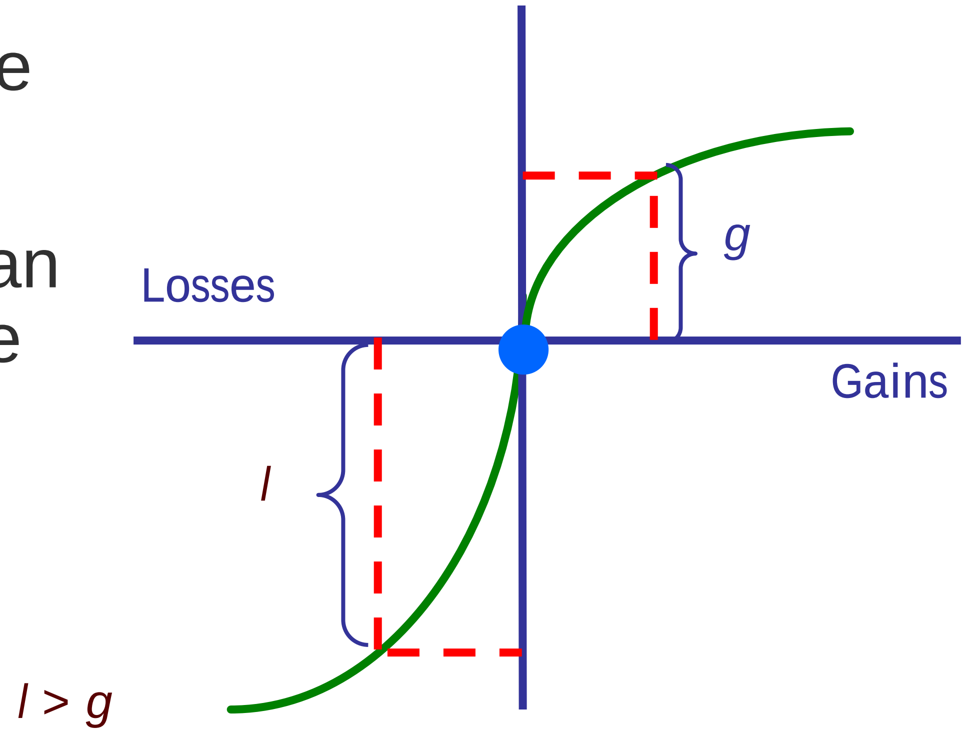
Logistic Regression Estimates

LogisticRegTrain (7,5)	Constant	Time	Quantity	PricePerLb
Coefficients	0.646	-0.031	-0.486	-0.194
Std error	0.055	0.003	0.025	0.015
p-value	8.56E-32	3.27E-33	1.23E-82	1.8238E-37
Log-likelihood	-10351.2			
Number valid obs	15887			
Total obs	15887			

Prospect Theory and Framing

Behavioral Approach: Prospect Theory

- Value is judged relative to a reference point
- Losses loom larger than gains (estimates range from 2.0x-2.5x)
- Diminishing sensitivity in both directions



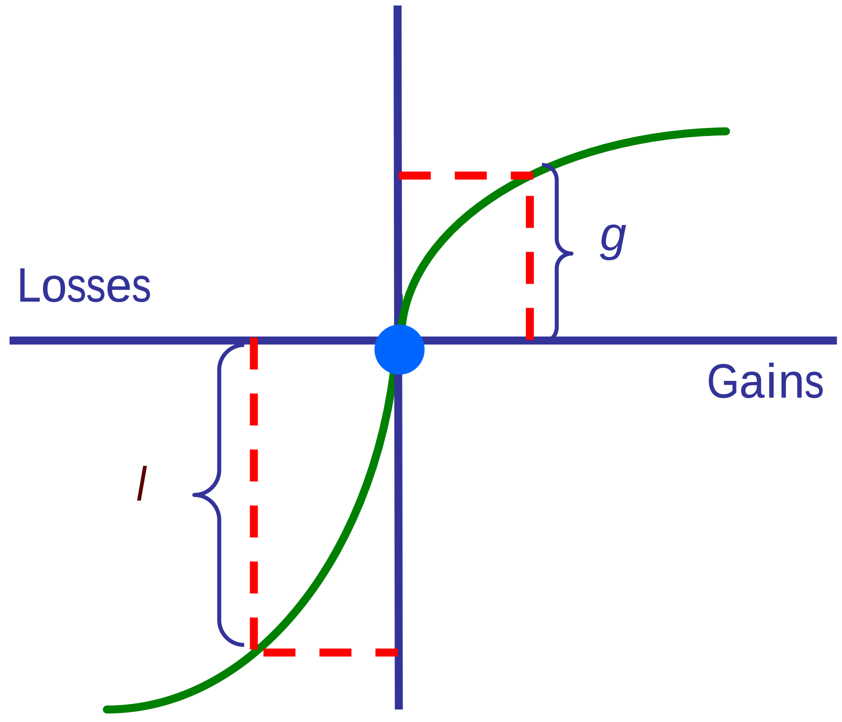
Source: D. Kahneman and A. Tversky (1979), “Prospect Theory: An Analysis of Decision under Risk,” *Econometrica, 47(2), 1124-31.*

Concepts from Prospect Theory

- **Loss aversion**
- Hedonic Framing
- Mental Accounting

How do these affect <u>pricing</u>?

(And how can you make use of them as a manager?)



Source: D. Kahneman and A. Tversky (1979), “Prospect Theory: An Analysis of Decision under Risk,” *Econometrica, 47(2), 1124-31.*

Loss Aversion

- Consider the following situation:
  - Station A sells gasoline for $3.60 per gallon but gives a *discount* of $0.10 per gallon if you pay cash
  - Station B sells gasoline for $3.50 per gallon but charges a *surcharge* of $0.10 per gallon if you pay by a credit card

- Which station would a buyer using a credit card be more likely to prefer?

Reference Prices

- Transaction utility measures perceived value of the ‘deal’, defined as the difference between price and the ‘reference price’
  - Have you ever bought a piece of clothing primarily because it was heavily discounted and then barely worn it?

Reference Prices

- How are reference prices formed?
  - Last price?
  - Quantity weighted or recency weighted past prices?
- How long does a given reference price last?
  - Depends upon the purchase cycle
  - Importance of the product category

Behavioral Effects

- Bid Acceptance could depend upon Reference prices
- The price last paid can be considered the Reference price
- Prospect theory suggests that reference price effects are asymmetric, i.e.,
  - Losses loom larger than gains

Asymmetric Reference Price Effects

- Gain

$$gain_i = \begin{cases} referencePrice_i - price_i \ , & \text{If } price_i < referencePrice_i, \\ 0 & , \quad \text{Otherwise.} \end{cases}$$

- Loss

$$loss_i = \begin{cases} price_i - referencePrice_i \ , & \text{If } price_i > referencePrice_i, \\ 0 & , \quad \text{Otherwise.} \end{cases}$$

Model with Reference Prices

LogisticRegTrain (7,8)	Constant	Time	Quantity	Gain	Loss	Qgain	Qloss
Coefficients	0.132	-0.032	-0.502	0.106	-0.324	0.055	-0.138
Std error	0.028	0.003	0.031	0.021	0.025	0.018	0.074
p-value	2E-06	2E-35	8E-60	5E-07	6E-38	2E-03	6E-02
Log-likelihood	-10237.3						

Model Selection

- How do we choose among different models?
- Need to balance goodness of fit against model complexity
- Bayesian Information Criterion (BIC) can be used to select models, where,
  - k is the number of model parameters
  - n is the number of observations
- The model with the lower BIC is preferred

$$BIC = -2\,MaxLogLike + k\ln(n)$$

Dynamic Targeted Optimal Pricing Policy

- Given the firm's cost structure, what should the optimal pricing be for each buyer at each purchase event?
- Given a potential order, and given the model parameters, one can use the profit function to set the price that maximizes expected profit

Optimization Based on Model 1

Optimization								
Imagine that you are facing a quote request which involves the following scenario, where you need to set the price per lb								
You need to select the price that maximizes the expected profit. We can use Solver to compute the optimal price								
Time	Quantity	PricePerLb	LagPrice	CostPerLb				
9.000	3.500	7.094	2.200	1.585				
Prob(Win)	Expected Profit							
0.062581441	1.206602976							

Optimization based on Model 2

- Model 2 gives lower optimal price

Time	Quantity	Loss	Gain	Qloss	Qgain	PricePerLb	LagPrice	CostPerLb
9.000	3.500	0.726	0.000	2.541	0.000	**2.926**	2.200	1.585
Prob(Win)	Expected Profit							
0.075591633	0.354782403							

Summary

- Discrete choice data can be modeled using
  - Logistic regression (binary choices)
  - Multinomial Logit model (choice among many brands)
- Customer-level choices are governed by behavioral effects such as Reference prices
- Statistical estimates can be used to maximize expected profits
- Quality of Optimal Prices depends upon the quality of your response model