

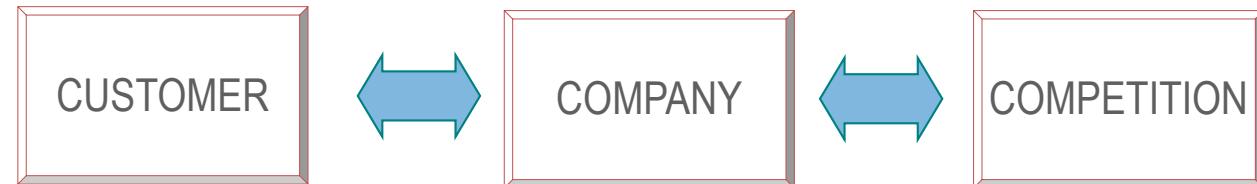
# Introduction to Marketing Analytics

## Session 4: Product

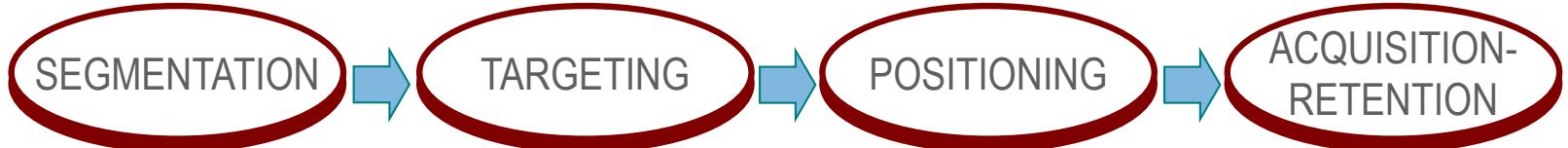
---

Professor Ricardo Montoya

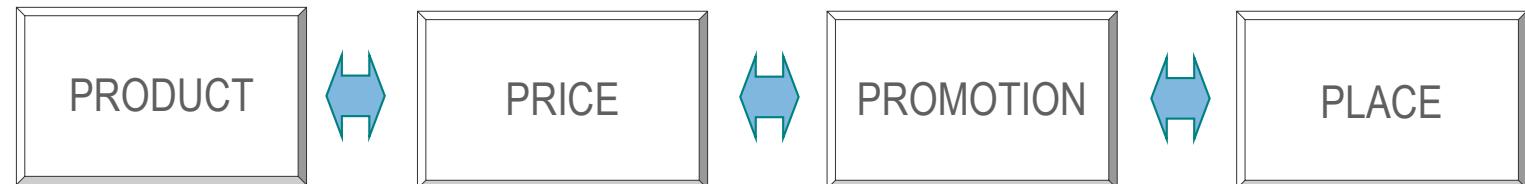
## Identify Market Opportunities



## Set Strategy



## Formulate Marketing Program



# Agenda

---

- New Product Development
  - Why do firms introduce new products?
  - Why do some good product ideas go bad?
  - What factors affect customers' adoption of new products?

# New Products

# New Products - Discussion

---

- Think of a new product. What is new about the product?



# Covid-19

## New restrictions...new behaviors

- New Starbucks Premium Instant Elevates Multi-Serve Instant Coffee (April 29, 2021)



# New to the World...



MODO



TiVo, TV your way.<sup>TM</sup>



# New To the World



# New Economy



Uber



# New to the World?

Total

Total Fresh Stripe

2 in 1 toothpaste & mouthwash

Sparkling White

Sensation Whitening

Sensitive Maximum Strength

Tartar Control

Tartar Control Plus Whitening

Baking Soda & Peroxide Whitening

Tartar Control with Baking Soda & Peroxide

Cavity Protection

Star Wars

Barbie toothpaste

Looney Tunes toothpaste

My First Colgate Toothpaste with Barney



**About 5 - 10% of new products are truly new**

# Types of New Products

		Market		
		L	M	H
Firm	L	Cost Reductions 11%		Repositionings 7%
	M		Product Line Extensions 26%	
	H	New Product Lines 20%		New to the World 10%



# New Products - Discussion

- Think of a new product. What is new about the product?
- **Why do you think the company introduced it?**



MODO



TiVo, TV your way.<sup>TM</sup>



# Support Additional Usage

---



Roomba (2002)

Braava (2013)



**Robot**

# Line Extension for Segmentation



---

## CHOICE HOTELS INTERNATIONAL

# Better Meet Needs of Slightly Different Sub-segments Through Differentiation



Dannon - c.1947



# Address Needs of Potential Emerging Segments



# Address Needs of Potential Emerging Segments



UNIVERSIDAD  
TORCUATO DI TELLA

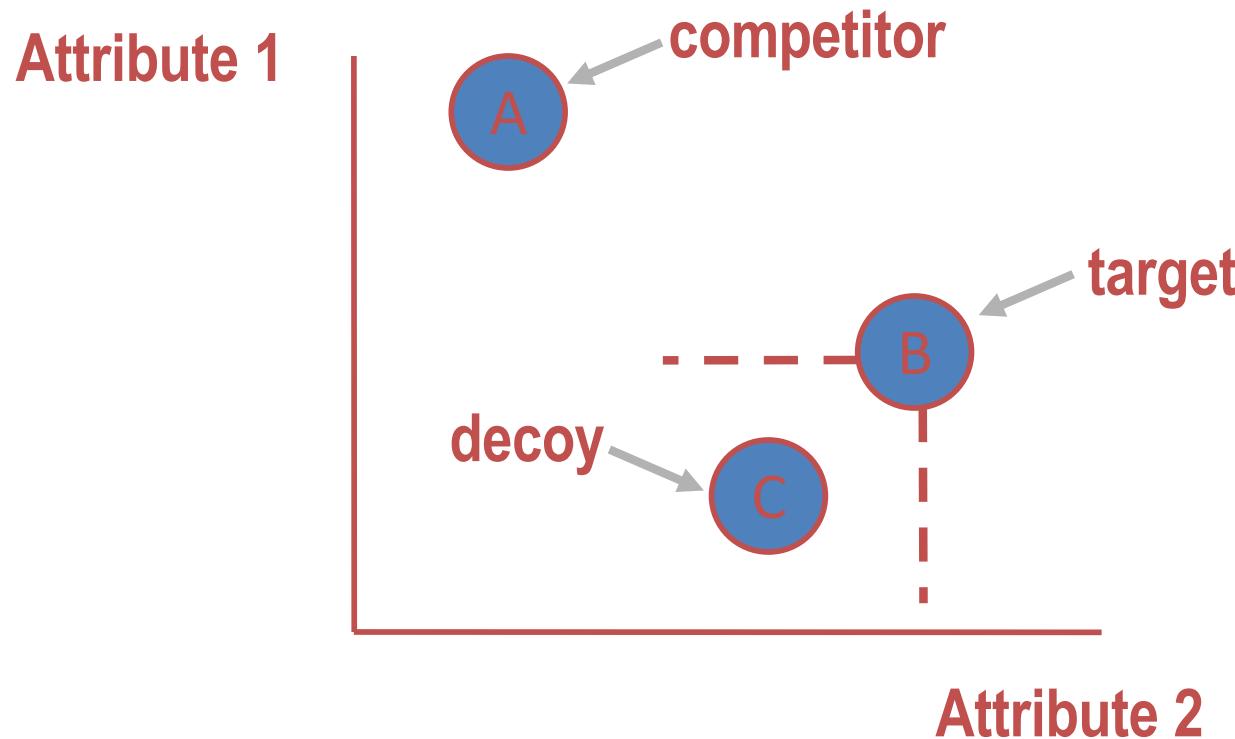
# Variety Seeking



UNIVERSIDAD  
TORCUATO DI TELLA

# Enhance Sales of Current Products

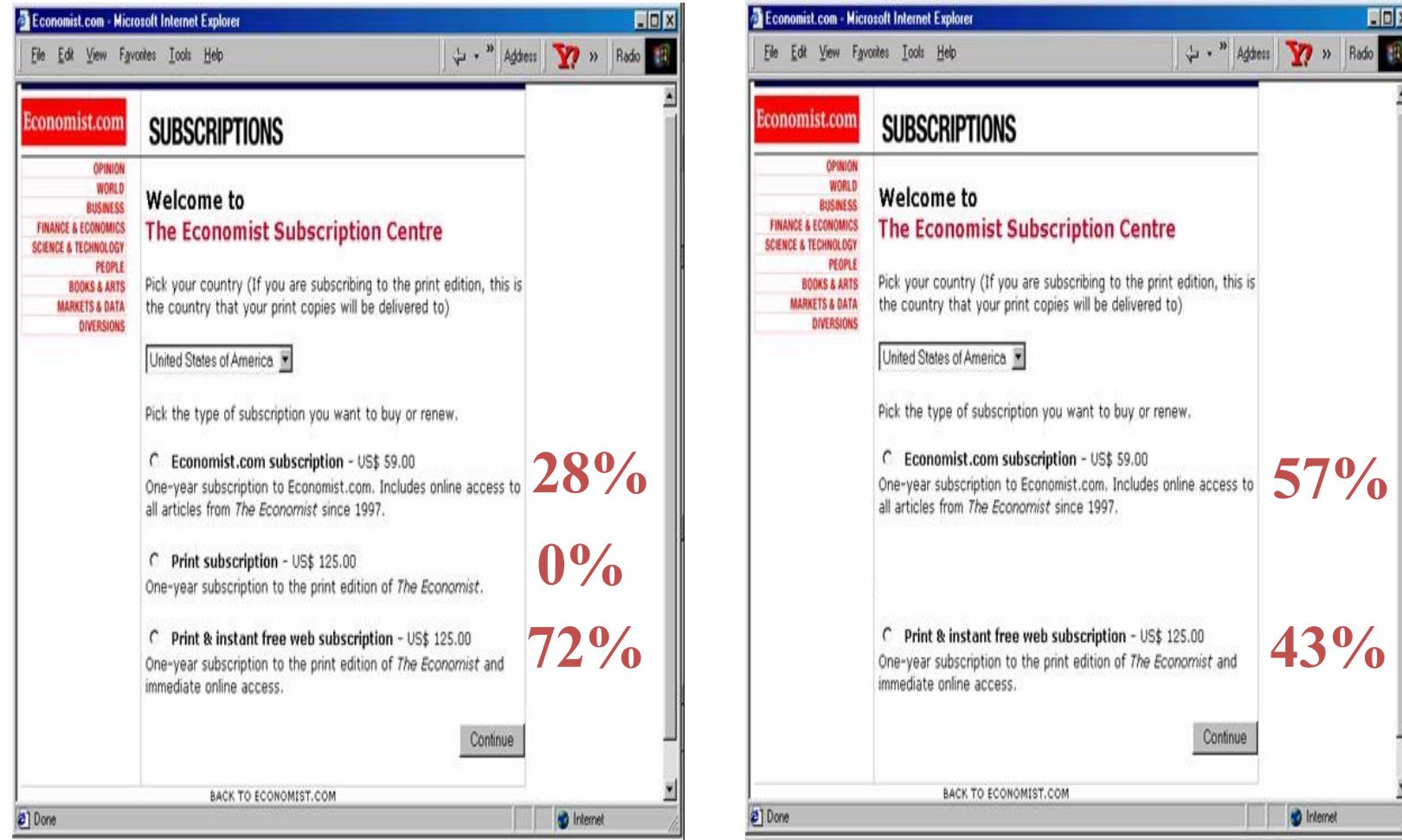
## Asymmetric Dominance Effect



# Enhance Sales of Current Products



# Asymmetric Dominance Effect



Source: Kivetz, Netzer, & Srinivasan 2004



UNIVERSIDAD  
TORCUATO DI TELLA

# Counter Encroachment by New Alternatives



# Control Shelf Space



# Alter Brand Image

---



# Why Do Firms Introduce New Products?

- Support additional usage
- Better meet needs of slightly different sub-segments through differentiation
- Address needs of **CUSTOMER** segments
- Encourage variety seeking
- Enhance sales of current products
- Counter encroachment by alternative products
- Control shelf space **COMPETITION**
- Alter brand image **COMPANY**

# New Products - Discussion

- What is new about the product?
- Why do you think the company introduced it?
- **Do you think it will be a success or a failure and why?**
- If you think the product will fail, what would you do differently?



# Why Good Ideas Go Bad?



1986

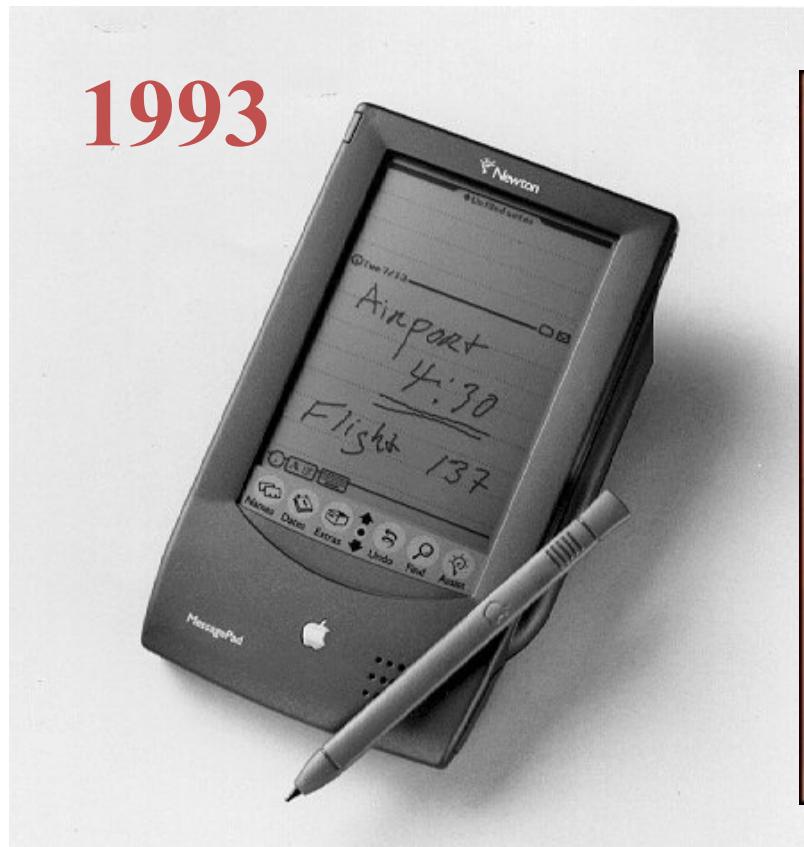


2013

Google Glass

# Problems with Product Quality or Product Attributes

1993



2004

# Problems with Product Quality or Product Attributes

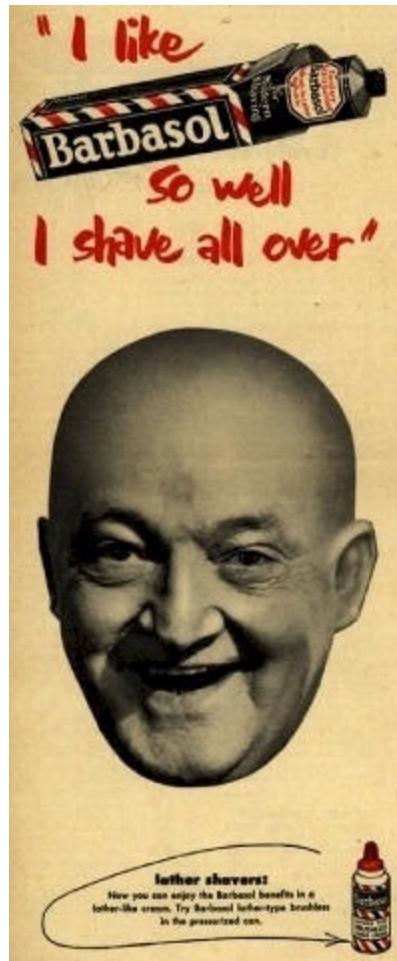


1974



2017

# Problems with Pricing



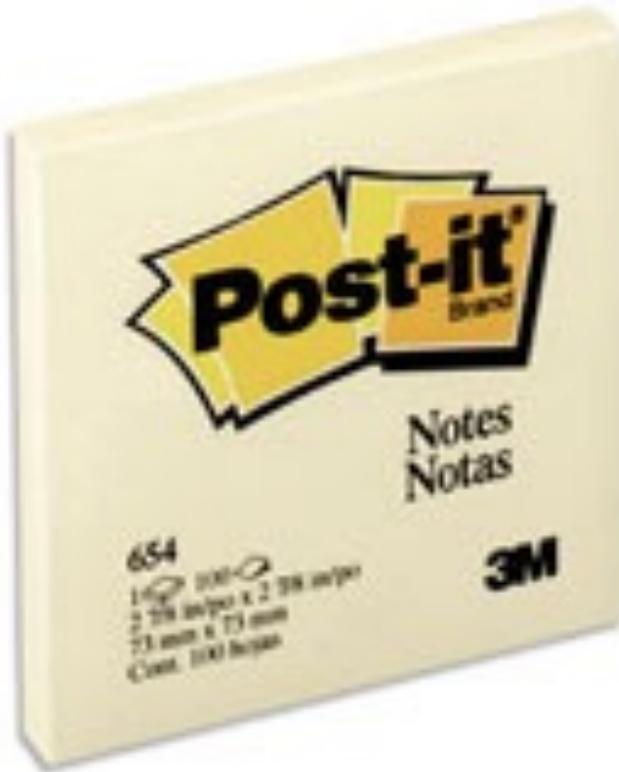
# Problems with Distribution (Place)

Holly Farms **1988**



Acquired by Tyson **1989**

# Problems with Promotion and Advertising



1977



2006

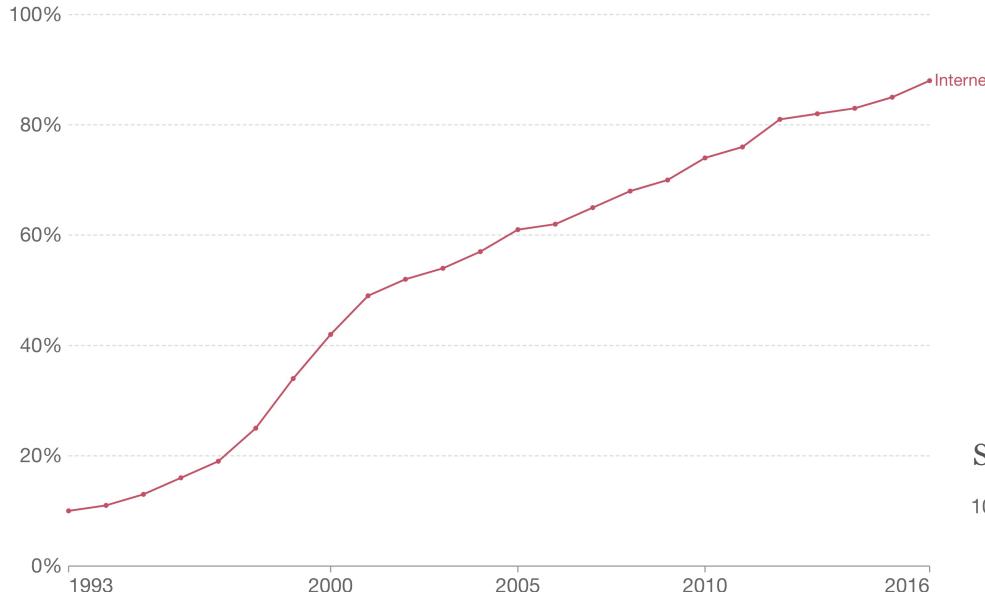
# Predict the Future?



# S-Shaped Diffusion Curve of New Products

Share of US households using specific technologies, 1993 to 2016

Our World  
in Data

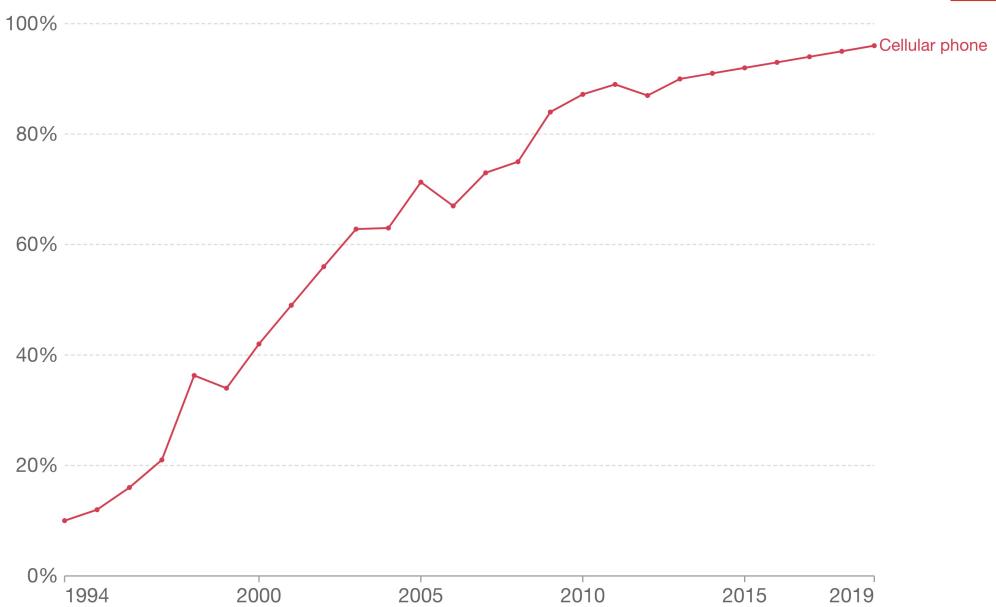


Source: Comin and Hobijn (2004) and others

Note: See the sources tab for definitions of adoption rates by technology.

Share of US households using specific technologies, 1994 to 2019

Our World  
in Data



Source: Comin and Hobijn (2004) and others

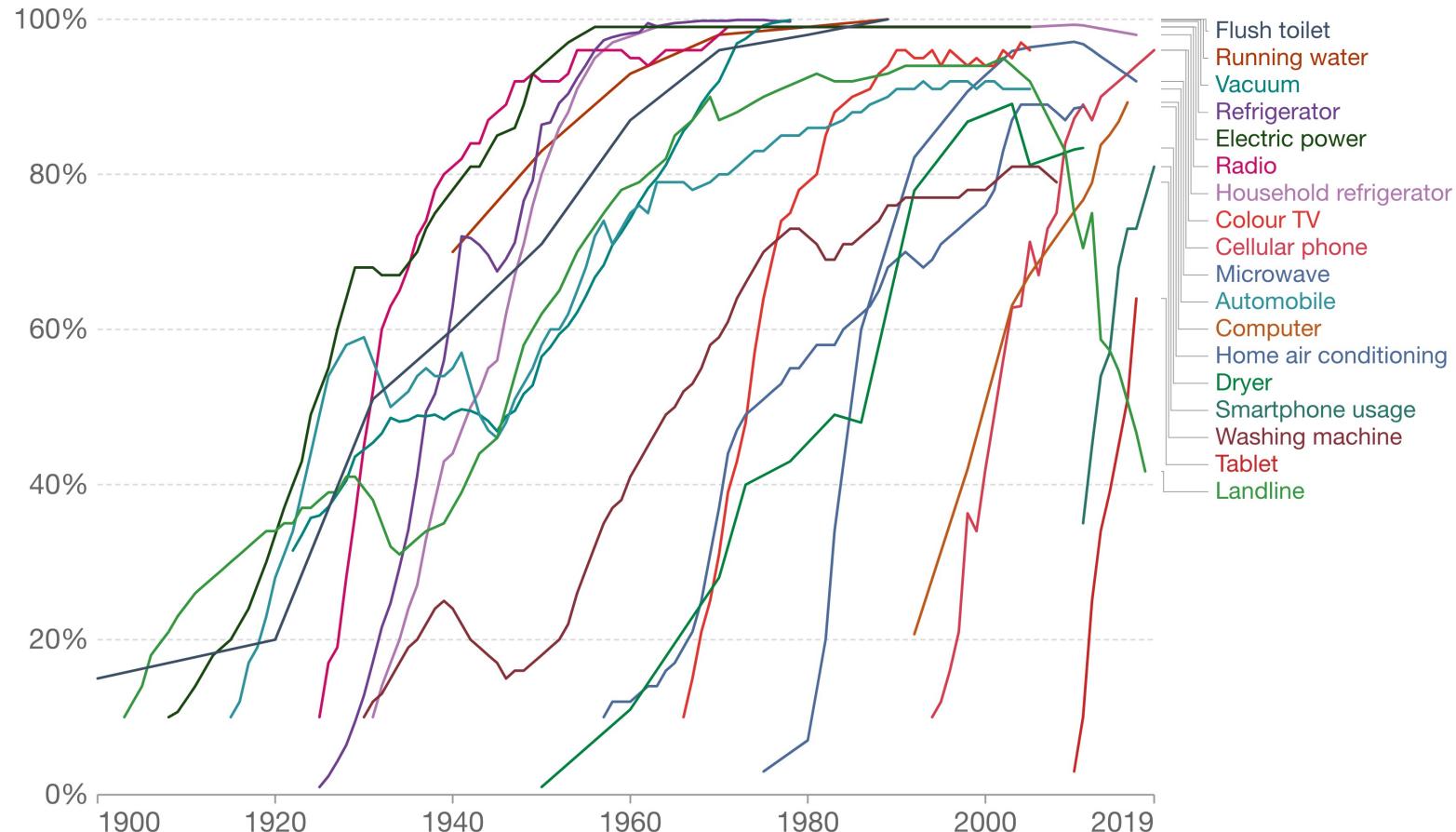
Note: See the sources tab for definitions of adoption rates by technology.

OurWorldInData.org/technology-adoption/ • CC BY

# Diffusion Curve of Technology Adoption

Share of US households using specific technologies, 1900 to 2019

Our World  
in Data



Source: Comin and Hobijn (2004) and others

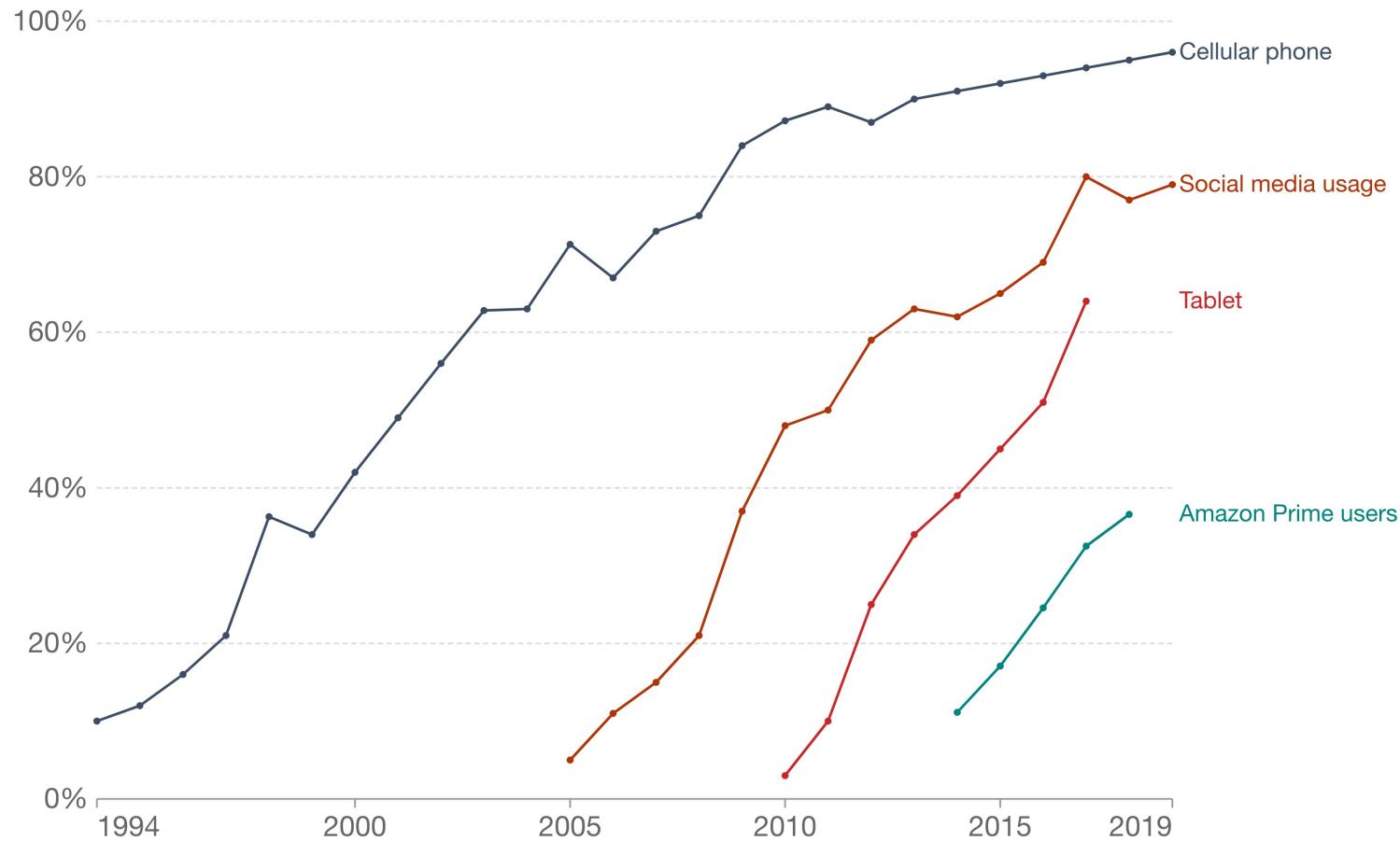
Note: See the sources tab for definitions of adoption rates by technology.

[OurWorldInData.org/technology-adoption/](http://OurWorldInData.org/technology-adoption/) • CC BY

# Diffusion Curve of Technology Adoption

Share of US households using specific technologies, 1994 to 2019

Our World  
in Data



Source: Comin and Hobijn (2004) and others

Note: See the sources tab for definitions of adoption rates by technology.

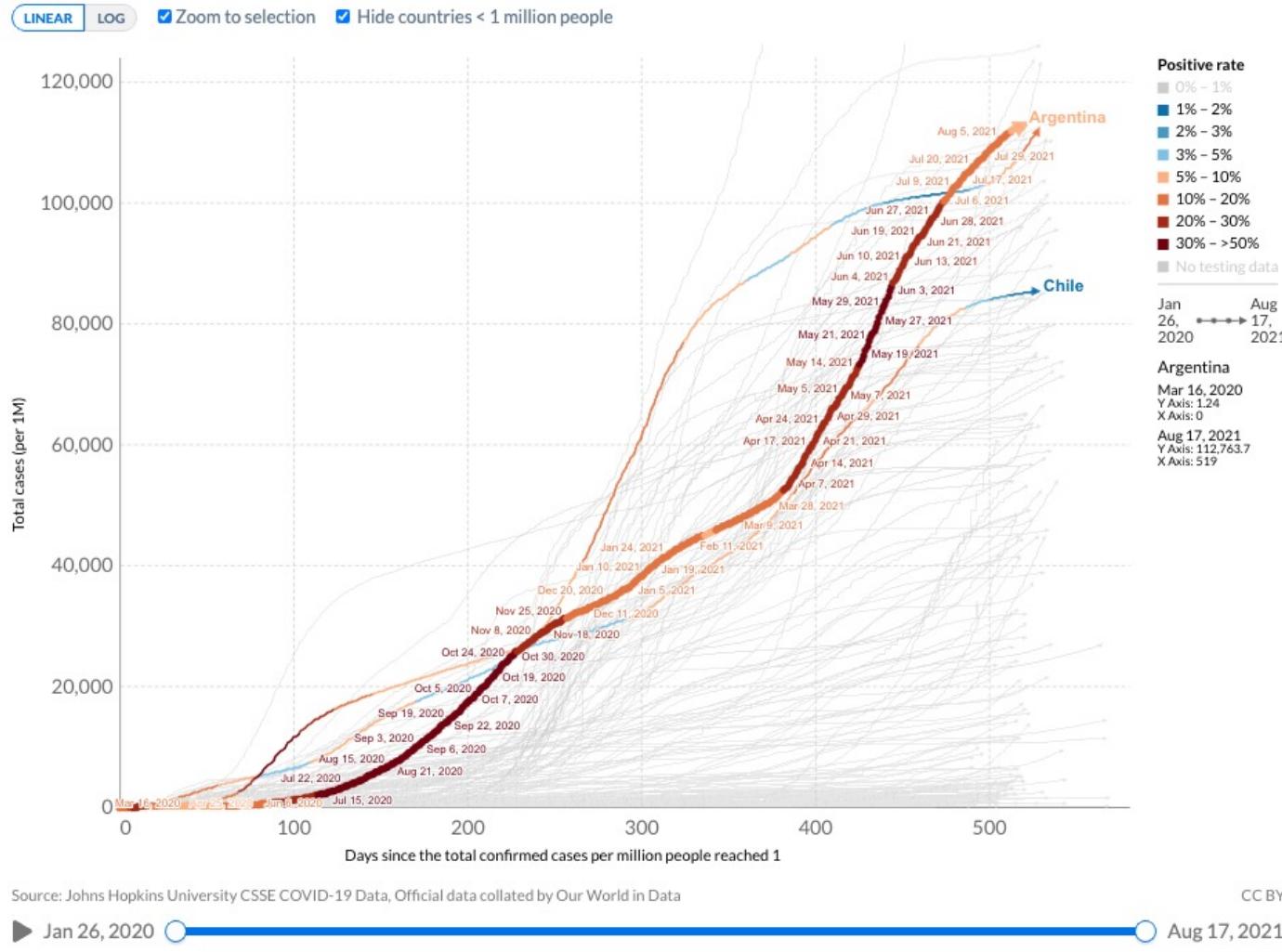
[OurWorldInData.org/technology-adoption/](http://OurWorldInData.org/technology-adoption/) • CC BY

# Diffusion Curve Covid-19

## Cumulative confirmed COVID-19 cases per million people

The number of confirmed cases is lower than the number of actual cases; the main reason for that is limited testing.

Our World  
in Data



# Factors Affecting Customer Adoption

---

- Advantage
- Compatibility
- Complexity
- Observability
- Risk
- Divisibility

# Main Takeaways (New Products)

---

- Why do firms introduce new products?
  - Think of the 3Cs...
- Why do some good product ideas go bad?
  - Think of the 4Ps...
- What factors affect customers' adoption of new products?
  - Think of ACCORD!

# **Modeling Choice Decisions**

# Modeling Choice Decisions

---

- Imagine the following decisions
  - Buying a house
  - A company deciding whether to enter a market
  - A student deciding a career to study
- We need a structure to model this kind of behavior

# Examples of Some Applications

---

- Problems that require the use of choice models in marketing
  - Purchases in supermarkets
  - Use of promotions
  - Search and purchases in multichannel environments
  - Answers to preference surveys (conjoint analysis)
  - Redemptions in loyalty programs
  - Movies to see on VOD systems (video-on-demand)
  - And many, many others...

# **Discrete Choice Models**

# Utility Maximization

- We want to describe  $P_{ni}$ , the probability that an agent  $n$  ( $n = 1, \dots, N$ ) chooses alternative  $i$  ( $i=1,\dots,I$ )
- We assume that the consumer (the firm) decides among the available alternatives by maximizing an underlying utility  $u_{ni}$  (profit  $\pi_{ni}$ )
  - Choosing the alternative that yields the highest utility within the choice set
- The utility  $u_{ni}$  is known by the decision maker, but not for the analyst and therefore we decompose it in deterministic component ( $v_{ni}$ ) and a stochastic component ( $\epsilon_{ni}$ )
  - Only the deterministic component is observable to the analyst

$$u_{ni} = v_{ni} + \epsilon_{ni}$$

# Properties of Choice Models

- Finite number of alternatives
  - The decision maker chooses among a finite number of alternatives (choice set)
- Mutually exclusive
  - If not originally in the data, exclusive alternatives must be constructed
    - If alternatives A and B are not exclusive, create alternatives: A only, B only, both A & B
  - Exhaustives
    - All possible alternatives must be included (include none of the other alternatives)

# Derivation of Choice Probabilities

- Utility of alternative  $i$ 
  - $u_{ni} = v_{ni} + \epsilon_{ni}$
- Consumer chooses alternative  $i$ 
  - If and only if  $u_{ni} > u_{nj} \forall j \neq i$

$$\begin{aligned} P_{ni} &= \Pr(u_{ni} > u_{nj}, \forall j \neq i) \\ &= \Pr(v_{ni} + \epsilon_{ni} > v_{nj} + \epsilon_{nj}, \forall j \neq i) \\ &= \Pr(\epsilon_{nj} - \epsilon_{ni} < v_{ni} - v_{nj}, \forall j \neq i) \\ &= \int_{\epsilon} I(\epsilon_{nj} - \epsilon_{ni} < v_{ni} - v_{nj}, \forall j \neq i) f(\epsilon_n) d\epsilon_n \end{aligned}$$

# Some cases

- Different assumptions about the distribution of error would imply different models
  - Logit, probit, mixed logit, etc
- The integral has closed-form solution for some cases
  - Logit, nested logit, hierarchical logit
  - iid extreme value distribution assumption
  - In these cases Maximum Likelihood Estimation (MLE) is useful to estimate the model's parameters
- In cases without closed-form solution, the integral must be evaluated numerically through simulation

# Example

- Supermarket purchases of soda (coca-cola, pepsi, others)
  - Consumer  $i$
  - Purchase occasion  $t$
  - Product  $j$
- Let  $u_{ijt}$  utility that product  $j$  gives to customer  $i$  at purchase occasion  $t$ 
  - $u_{ijt} = v_{ijt} + \varepsilon_{ijt}$
- What can we include in  $v_{ijt}$ ?

Error terms are IID extreme value

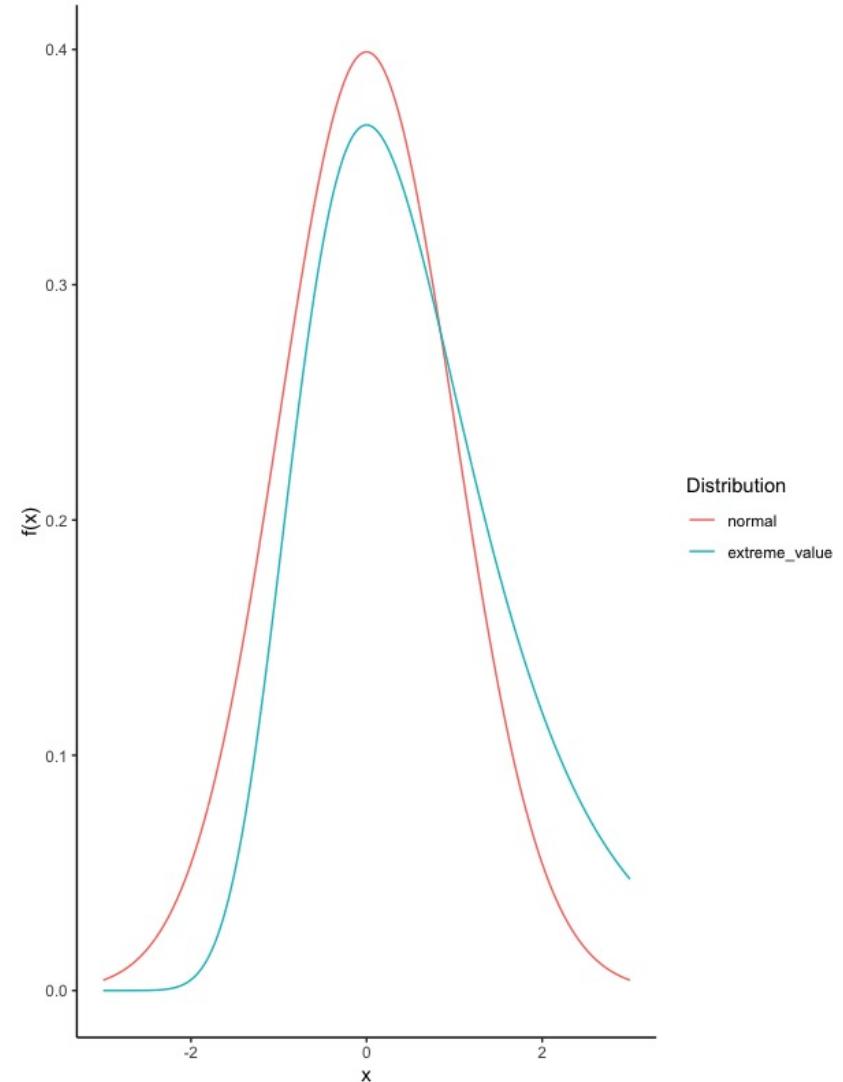
# Logit

# Logit: Definition

- The logit model results from assuming that each  $\varepsilon_{ni}$  is independently distributed Extreme Value:

$$F(\varepsilon_{ni}) = e^{-e^{-\varepsilon_{ni}}}$$
$$f(\varepsilon_{ni}) = e^{-\varepsilon_{ni}} e^{-e^{-\varepsilon_{ni}}}$$

- This distribution is also known as Gumbel or Extreme Value type I



# Logit: Choice Probability

$$P_{ni} = \Pr(v_{ni} + \varepsilon_{ni} > v_{nj} + \varepsilon_{nj}, \forall j \neq i)$$

$$= \Pr(\varepsilon_{nj} < \varepsilon_{ni} + v_{ni} - v_{nj}, \forall j \neq i)$$

$$P_{ni} = \int_{\varepsilon_{ni}} \left( \prod_{j \neq i} e^{-e^{-(\varepsilon_{ni} + v_{ni} - v_{nj})}} \right) e^{-\varepsilon_{ni}} e^{-e^{-\varepsilon_{ni}}} d\varepsilon_{ni}$$


$$P_{nj} | \varepsilon_{ni} \quad f(\varepsilon_{ni})$$

$$t = \exp(-\varepsilon_{ni})$$

$$dt = -\exp(-\varepsilon_{ni})d\varepsilon_{ni}$$

$$P_{ni} = \int_{-\infty}^0 -\exp\left(-t \sum_j e^{-(v_{ni} - v_{nj})}\right) dt = \frac{\exp\left(-t \sum_j e^{-(v_{ni} - v_{nj})}\right)}{-\sum_j e^{-(v_{ni} - v_{nj})}} \Big|_0^\infty \rightarrow$$

$$P_{ni} = \frac{e^{v_{ni}}}{\sum_j e^{v_{nj}}}$$

# **Choice-based Conjoint**

# Type of Conjoint Analysis

- State of the art
  - Choice-based conjoint
  - Adaptive
  - Sawtooth software



Know Your Market.

Conjoint Consulting Services      Conjoint Programming Services      Our Methodologies      About Us      Contact Us



## Understanding Conjoint in 15 Minutes by Joseph Curry

**Conjoint analysis has become popular because it is far less expensive and time consuming than concept testing.**

**Conjoint analysis** is a popular marketing research technique that marketers use to determine what features a new product should have and how it should be priced. Conjoint analysis became popular because it was a far less expensive and more flexible way to address these issues than concept testing.

The basics of conjoint analysis are not hard to understand. I'll attempt to acquaint you with these basics in the next 15 minutes so that you can appreciate what conjoint analysis has to offer. A simple example is all that's required.

Suppose we want to market a new golf ball. We know from experience and from talking with golfers that there are three important product features:

- Average Driving Distance
- Average Ball Life
- Price

We further know that there is a range of feasible alternatives for each of these features, for instance:

Average Driving Distance	Average Ball Life	Price
275 Yards	54 Holes	\$1.25
250 Yards	36 Holes	\$1.50
225 Yards	18 Holes	\$1.75

Obviously, the market's "ideal" ball would be:

Average Driving Distance	Average Ball Life	Price
275 Yards	54 Holes	\$1.25

And the "ideal" ball from a cost of manufacturing perspective would be:

# Example Choice-based Conjoint

---

- Digital Cameras
  - 125 subjects
  - 5 attributes, 4 levels each
  - 20 questions (16 for training/calibration, 4 for testing)
- Attributes
  - Price: 200, 300, 400, 500 (US\$)
  - Resolution: 2, 3, 4, 5 (Megapixels)
  - Battery Life: 150, 300, 450, 600 (pictures)
  - Optical Zoom: 2, 3, 4, 5 x
  - Camera size: SLR, Medium, Pocket, ultra compact

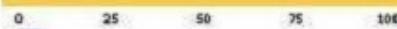
# Design

## Choose a Camera

From the choices presented here, please select your most preferred camera choice.

Question 1 of 20

Features	Choice A	Choice B	Choice C	Choice D
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
 Price	\$300	\$300	\$400	\$400
 Resolution	2 Megapixels	3 Megapixels	2 Megapixels	2 Megapixels
 Battery Life	300 pictures	600 pictures	150 pictures	600 pictures
 Optical Zoom	4x	2x	5x	2x
 Camera Size	SLR sized	SLR sized	Medium sized	SLR sized



# Choice Model

- We assume a Multinomial logit choice model
- Individual  $n$ , alternative  $j$ , question  $t$
- 5 attributes with 4 levels each implies 15 dummies
  - base level = Price 500, Resolution 2MP, Battery Life 150p, Optical Zoom 2x, Camera Size SLR

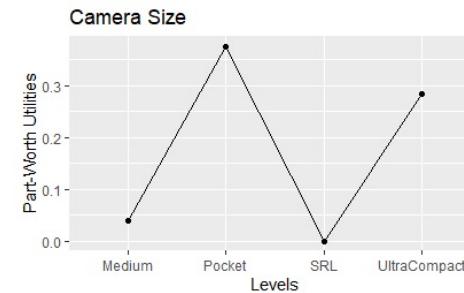
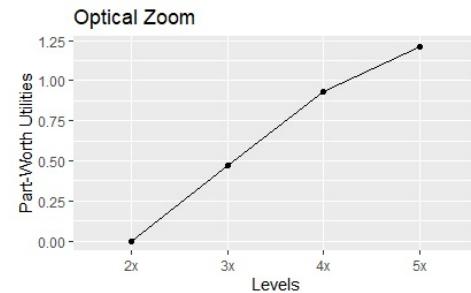
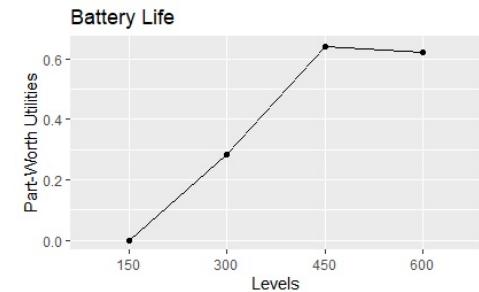
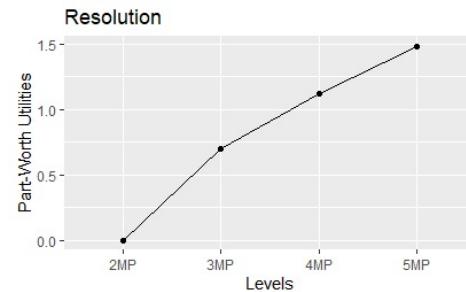
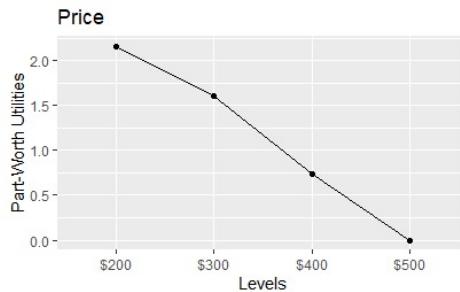
$$\nu_{njt} = \beta_1 Price_{njt}^{400} + \dots + \beta_{15} CS_{njt}^{UltraCompact}$$

$$P_{njt} = \frac{\exp(\nu_{njt})}{\sum_k \exp(\nu_{nkt})}$$

# Model and Results

- Modeling in R

```
plainlogit <- mlogit(chosen_alt ~ 0 + Price400 + Price300 + Price200 + Resolution3MP + Resolution4MP + Resolution5MP  
+ BL300 + BL450 + BL600 + OZ3X + OZ4X + OZ5X + CSMedium + CSPocket + CSUltraCompact,  
data = data.logit)
```

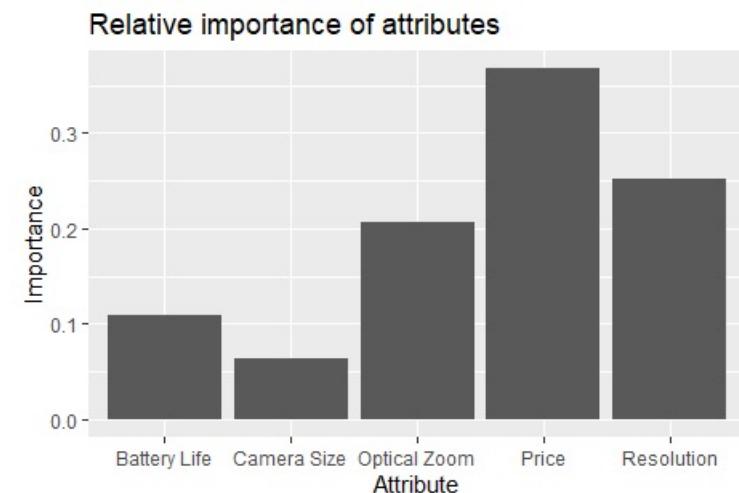


# Results

```
## Coefficients :  
## Estimate Std. Error t-value Pr(>|t|)  
## Price.400 0.7343 0.1074 6.84 8.1e-12 ***  
## Price.300 1.6010 0.1008 15.89 < 2e-16 ***  
## Price.200 2.1627 0.0940 23.01 < 2e-16 ***  
## Resolution.3MP 0.7020 0.0937 7.49 6.8e-14 ***  
## Resolution.4MP 1.1202 0.0922 12.15 < 2e-16 ***  
## Resolution.5MP 1.4850 0.0857 17.32 < 2e-16 ***  
## BL.300 0.2847 0.0885 3.22 0.0013 **  
## BL.450 0.6426 0.0820 7.83 4.7e-15 ***  
## BL.600 0.6221 0.0874 7.12 1.1e-12 ***  
## OZ.3x 0.4692 0.0992 4.73 2.2e-06 ***  
## OZ.4x 0.9302 0.0893 10.41 < 2e-16 ***  
## OZ.5x 1.2147 0.0874 13.90 < 2e-16 ***  
## CS.Medium 0.0384 0.0812 0.47 0.6366  
## CS.Pocket 0.3758 0.0791 4.75 2.0e-06 ***  
## CS.UltraCompact 0.2846 0.0787 3.61 0.0003 ***  
## ---  
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Log-Likelihood: -2030
```

# Model Results

- Ideal digital camera:
  - Low price (200 US\$)
  - 5 megapixels
  - Battery life of 450 pictures
  - 5x optical zoom
  - Pocket size



# Model Results

- The utility of getting a camera with 5 megapixels relative to getting one of 2 megapixels is:  
$$u(\text{Resolution. } 5MP) - u(\text{Resolution. } 2MP) = 1.4850$$
- The utility of paying a low price relative to paying a high price is:  
$$u(\text{Price. } 200) - u(\text{Price. } 500) = 2.1627$$
- The price range is:  
$$\text{US\$}500 - \text{US\$}200 = \text{US\$}300$$
- Hence, the willingness to pay for a 3 extra MP is:

$$\frac{\text{US\$}300}{2.1627} * 1.485 = \text{US\$}205.99$$

# Model Results

- Including the heterogeneity across respondents
- Mixed logit

```
mixedlogit2 <- mlogit(chosen_alt ~ 0 + Price400 + Price300 + Price200 + Resolution3MP  
+ Resolution4MP + Resolution5MP + BL300 + BL450 + BL600 + OZ3X  
+ OZ4X + OZ5X + CSMedium + CSPocket + CSUltraCompact,  
rpar = c(Price400 ="n", Price300 ="n", Price200 ="n",  
Resolution3MP ="n", Resolution4MP ="n", Resolution5MP ="n",  
BL300 ="n", BL450 ="n", BL600 ="n", OZ3X ="n", OZ4X ="n",  
OZ5X ="n", CSMedium ="n", CSPocket ="n", CSUltraCompact ="n"),  
correlation = TRUE, data = data.logit, panel = TRUE)
```

- Assume random coefficients are normally distributed across the respondents

# Model Results

- The output should look like this:

Coefficients :	Estimate	Std. Error	z-value	Pr(> z )	
Price400	1.2373871	0.1659053	7.4584	8.749e-14	***
Price300	2.9098800	0.1781798	16.3311	< 2.2e-16	***
Price200	3.4565085	0.1770709	19.5205	< 2.2e-16	***
Resolution3MP	1.0979361	0.1504207	7.2991	2.898e-13	***
Resolution4MP	1.8817822	0.1573867	11.9564	< 2.2e-16	***
Resolution5MP	2.3610692	0.1472248	16.0372	< 2.2e-16	***
BL300	0.7213590	0.1601211	4.5051	6.635e-06	***
BL450	1.3231613	0.1622235	8.1564	4.441e-16	***
BL600	1.2292077	0.1550604	7.9273	2.220e-15	***
OZ3X	1.1060940	0.1829590	6.0456	1.489e-09	***
OZ4X	1.8726725	0.1698338	11.0265	< 2.2e-16	***
OZ5X	2.2814167	0.1649571	13.8304	< 2.2e-16	***
CSMedium	0.4926950	0.1500134	3.2843	0.0010222	**
CSPocket	0.9660882	0.1505700	6.4162	1.397e-10	***
CSUltraCompact	1.1912076	0.1469165	8.1081	4.441e-16	***
chol.Price400:Price400	1.2508851	0.1760448	7.1055	1.199e-12	***
chol.Price400:Price300	1.8546057	0.1679862	11.0402	< 2.2e-16	***
chol.Price300:Price300	1.7911545	0.1628669	10.9977	< 2.2e-16	***

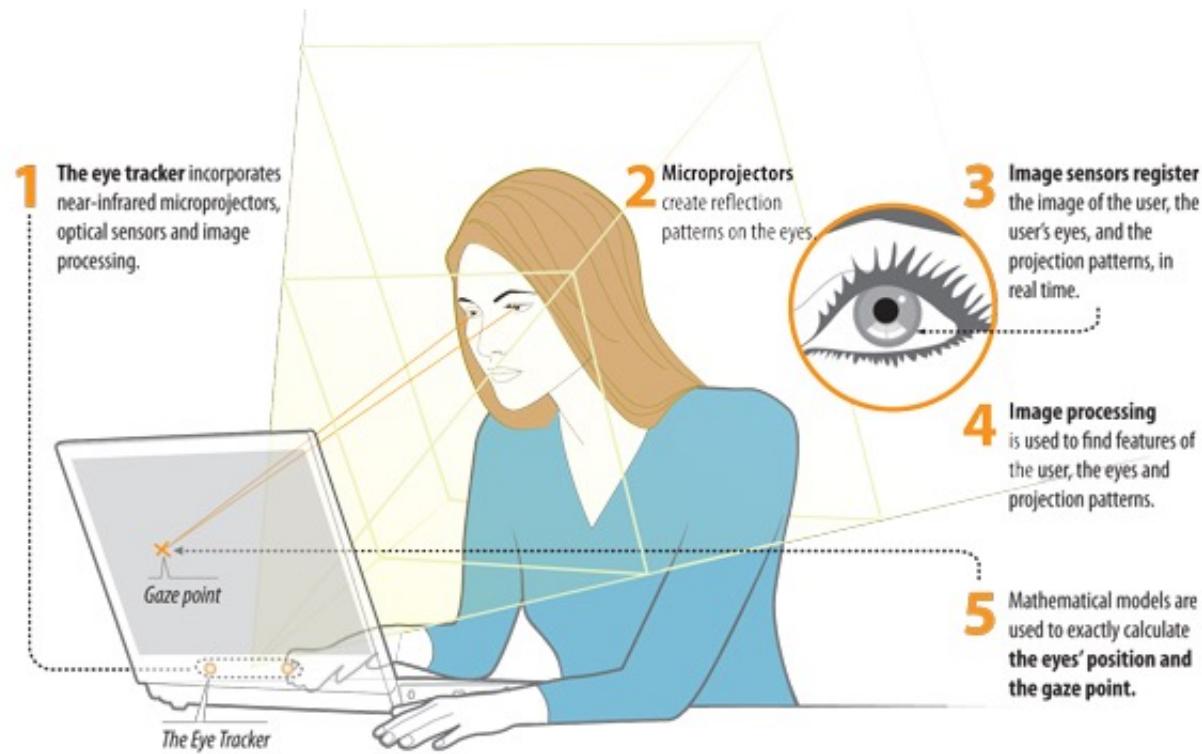
# Model Results

- Random Coefficients:

random coefficients	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Price400	-Inf	0.39367790	1.2373871	1.2373871	2.081096	Inf
Price300	-Inf	1.17082143	2.9098800	2.9098800	4.648939	Inf
Price200	-Inf	1.36817665	3.4565085	3.4565085	5.544840	Inf
Resolution3MP	-Inf	0.69695940	1.0979361	1.0979361	1.498913	Inf
Resolution4MP	-Inf	0.85078283	1.8817822	1.8817822	2.912782	Inf
Resolution5MP	-Inf	0.80862412	2.3610692	2.3610692	3.913514	Inf
BL300	-Inf	0.25143253	0.7213590	0.7213590	1.191285	Inf
BL450	-Inf	0.60974875	1.3231613	1.3231613	2.036574	Inf
BL600	-Inf	0.46584469	1.2292077	1.2292077	1.992571	Inf
OZ3X	-Inf	-0.50378660	1.1060940	1.1060940	2.715975	Inf
OZ4X	-Inf	0.09357707	1.8726725	1.8726725	3.651768	Inf
OZ5X	-Inf	0.46431406	2.2814167	2.2814167	4.098519	Inf
CSMedium	-Inf	-0.31274604	0.4926950	0.4926950	1.298136	Inf
CSPocket	-Inf	0.04656451	0.9660882	0.9660882	1.885612	Inf
CSUltraCompact	-Inf	0.06969789	1.1912076	1.1912076	2.312717	Inf

# Cutting-edge Research

- Eye-tracking



# Eye-tracking

Su amigo le ha dado el siguiente ranking de importancia:

- 1 Precio
- 2 Calidad de la comida
- 3 Categoría de la habitación
- 4 Vista al mar
- 5 Recomendación de clientes
- 6 Distancia al centro

Por favor considere primero el ranking , luego seleccione las mejores vacaciones para su amigo aplicando la regla de elección que se ha explicado arriba.

	Paquete A	Paquete B	Paquete C	Paquete D
Calidad de la comida	excelente (+)	bueno (o)	deficiente (-)	excelente (+)
Recomendaciones de clientes	90% (+)	90% (+)	70% (o)	90% (+)
Distancia al Centro	3km (-)	1km (+)	3km (-)	2km (o)
Vista al mar	Sin vista al mar (-)	Vista completa al mar (+)	Vista completa al mar (+)	Sin vista al mar (-)
Precio	\$599 mil (o)	\$599 mil (o)	\$650 mil (-)	12 mil (o)
Categoría de la habitación	Deluxe (+)	Superior (o)	Estándar (-)	Deluxe (+)
	○	○	○	○
	13	4	10	8
	11	12	9	10
	continuar			

# Introduction to Marketing Analytics

## Session 4: Product

---

Professor Ricardo Montoya