Descriptive Analytics

What is Descriptive Analytics?
- links the market to the firm through information
- information needed for actionable decisions
- principles for systematically collecting and interpreting data that can aid decision makers.

Types of Descriptive analytics
Exploratory research: (Ambiguous problem)
Descriptive research: (Aware of problem)
Causal research: (Problem clearly defined)

Exploratory research
- Develop initial hunches or insights
- Usually a first step in understanding a broader managerial problem
- Provides broad guidelines of what to test more rigorously

Focus groups:
- Rationale: in-depth probing, unstructured discussion, ability to observe dynamics
- Format: 8-10 individuals, 1 moderator, about 1-hr long, incentives for participants
- Common uses: Product concept, ad copy, survey design

Internet communities
- enhances engagement with customers: 6 months to 1 year long
- shorter deadlines are possible
- interesting patterns
- Caveat: ROI can be hard to determine

Descriptive Research:
- Generates data describing the composition and characteristics of relevant groups
- Typical managerial questions:

What are the characteristics of our customers
What is our share of wallet

This can be done via
- active data collection
- passively observing behavior

Active data collection:
Surveys
Self-reports of several types of consumer behavior

Surveys:
- Used by every Fortune 500 company
- Regularly used for gathering customer attitudes, satisfaction scores, purchase habits
- Data can be used to help segment customers

Mobile Surveys
- Allow you to capture customers' reactions in-situ rather than being retrospective
- The questionnaire can be tailored based on location and context
- Caveat: Marketers should be careful not to hasten customer fatigue

Net Promoter Score
promoters: Score of 9-10, passives: score of 7-8 and detractors: score of 0-6
NPS = Percentage of Promotors - Percentage of Detractors
Good indicator of stock prices, and brand value

self-reports:
store purchases: photo capture of receipts
word-of-mouth dynamics: diary of customers and network

Passive collection:
scanner data, media planning, web data and mobile data

Scanner data: grocery business plus health and beauty aids
the data chain, the data cube and aggregation

The value of sales data:
completeness, timeliness and accuracy

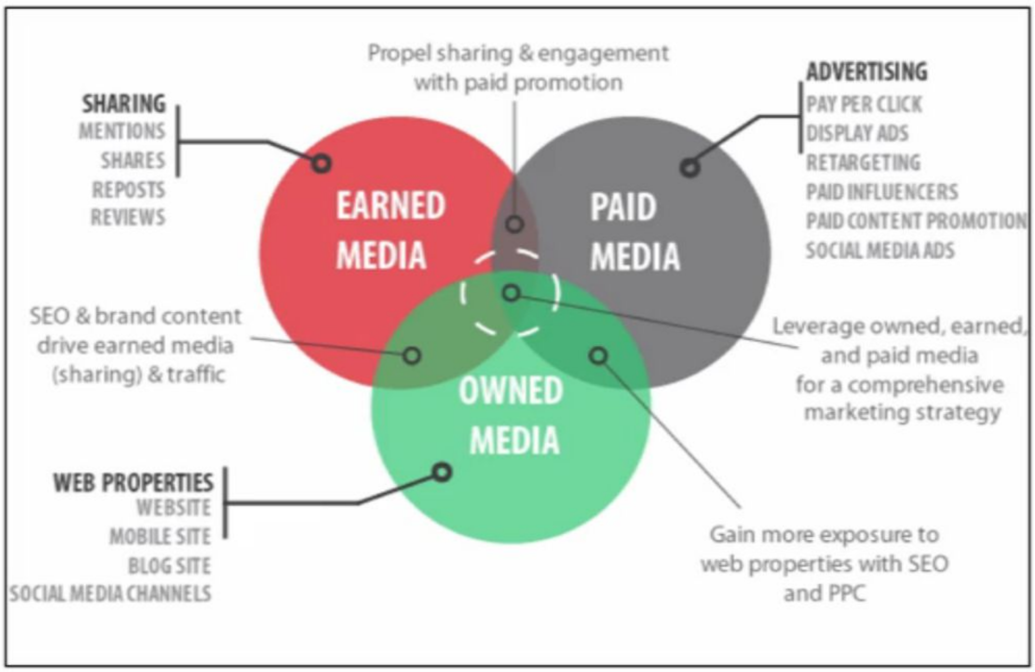
Managerial questions
impact of promotions, impact of displays and within and across category

Problems of Scanner data
Misses out on convenience stores, and some big retailers
Cannot make causal statements
Don't know behaviors and psychographics
Don't know the exact set of choices faced by the consumer at the time of decision

Media planning
audio, TV, record the programme and the popularity of a TV show.
Who is watching what show?
How is the viewership pattern changing over time?
TV viewership -> Ad spend

Social media analytics
Audience engagement for a campaign
Brand mentions as compared to competitors
Sentiment analysis

Web data
Earned media, paid media and owned media



Mobile data
Is customer search on the mobile platform different from the desktop?
What information to show customers based on their location?
Location-based coupons

Causal analytics
Correlation = relation between two variables
Causation = one variable producing an effect in another variable

Causal inference: three requirements
- correlation: evidence of association between X and Y
- Temporal antecedence: X must occur before Y
- No third factor driving both
Control of other possible factors

A/B Testing
A/B testing is a form of statistical hypothesis testing with two variants leading to the technical term.
In online settings, such as web design (especially user experience design), the goal of A/B testing is to identify changes to web pages that increase or maximize an outcome of interest. Formally the current web page is associated with the null hypothesis. A/B testing is a way to compare two versions of a single variable typically by testing a subject's response to variable A against variable B, and determining which of the two variables is more effective.
- website optimization
- mobile app design
- customized design: one to one marketing

Predictive Analytics

Period 2
Predictive Analytics
Regression analysis
Quantify the relationship among two or more variables
- Explain a dependent variable, from a set of predictor variables called the independent variables
- Uses a linear additive relation between the dependent and independent variables

Demand curve
Demand prediction by following the regression

Optimal Pricing
As predictions can be done for different prices, we can also determine optimal price
The price is the one that maximizes overall profit
Intuition for each price, we predict demand
Demand -> revenue and profit

Period two
predict if the customer would stay with us and their economical value.
Old technique used starting from the late 1960
Excel can do that

limited data and computational resources
How many purchases the customers made? What was the dollar value of those customers?
Find the robust explanatory variables.

Recency

The last time the customer made a purchase with us, took a sales call or visited the product website
Frequency
How many purchases they made, economically beneficial activities they did over a set period of time
Monetary Value
What was the overall or the average monetary value of each and every one of them?

From RFM, we can determine the customer's worth in period two.

number of purchases, direct marketing

KPI: key performance indicators

Regression-type of data mining is sufficient in period two

Period 4:
When type questions or long-time questions such as the customer lifetime value cannot be answered in period 1-3. customer interestingness

An exemplar marketing dataset
We focus on all samples but not the single one. Though some samples may not contribute to the revenue over a period of time, collectively they still have an important value for the company in the future.

It matters for the customers that when they make or miss the donation.
Recency > Frequency > Monetary Value
Recency trumps Frequency

We use the data as an indication below the surface.

Based on our best guesses about the probability of "no donation" and propensity to donate, we can calculate expected frequency of future donations for each donor.

We care about recency and frequency but not the faraway past.

Probability Models
Compared with the regression models, probability models are used to predict the customer behavior over **a longer period of time**.

Heterogeneity: purchase probability
There is another probability about whether to continue the donation/purchase.
This is the so-called "buy till you die" model.

The insights about the data and model is the most critical thing.

Prescriptive analytic

Provide a recommendation on what actions to take to achieve some objective goal.

Defining a problem
A problem we would like to solve will typically have a set of goals we want to achieve, a set of actions we can take to achieve this goal and a model, which describes how the actions impact the goal.

The goal is to maximize the quantity to sell or the revenue.

There is a tradeoff between the price and quantity, which should be identified beforehand to help us understand the problem. Use graphs to find the max revenue.

The process of optimization ("finding the best price to maximize profit") tries to increase price until there is no additional gain in profit.
It follows the rule that the marginal revenue equals the marginal cost.
MR = MC

Market structure
The structure of the market is part of the model. It adds to the question of "how do my actions affect outcomes", also answers to questions such as "who else is also active in my market" and others.

We can use the same descriptive data from before to maximize profit in different cases.

Willingness to Pay (WTP)
- It is how much (at most) would a consumer pay for an additional item s/he buys.
- We find it by calculating the area below the demand curve for each additional item
- Profit = WTP - Cost

Optimal bundle

In economics, **willingness to accept (WTA)** is the minimum amount of money that a person is willing to accept to abandon a good or to put up with something negative, such as pollution. It is equivalent to the minimum monetary amount required for sale of a good or acquisition of something undesirable to be accepted by an individual.
$u(w_0 + WTA, 1) = u(w_0, 0).$

Willingness to pay is the maximum amount an individual is willing to sacrifice to procure a good or avoid something undesirable.
$u(w_0 - WTP, 1) = u(w_0, 0).$

We can sell the consumer a bundle of items whose price is the sum of WTP.

The conclusion here is that if we know a little bit, whether it's a single consumer or a multiple consumer, and whether those consumers actually want one item or two items, we can choose whether to sell them in bundles, which will increase our profit. Or we need to price every item at the same price for every consumer, and then, we cannot make use of the willingness to pay to try and bundle those products together.

Competition and Online Advertising Models
Raising or lowering the price of products will yield strategic interaction between competitors in the market.

Online Advertising
Many advertisers count "click-through-rate" or "what percentage of the people exposed to an ad clicked on it" as a measure to determine the effectiveness of advertising.

We need to do multiple hypothesis test to validate the marketing model.

Customer analytics is a process by which data from customer behavior is used to help make key business decisions via market segmentation and predictive analytics. This information is used by businesses for direct marketing, site selection, and customer relationship management.
Marketing provides services in order to satisfy customers.
e.g. If you want to predict what each person's going to do, how many of them are going to see Ant Man, how many are going to see the previous Marvel films, how many are going to see the future Marvel films, that's a customer analytics problem.

Application to Analytics

"The future of marketing is business analytics. There's no firm today that should be thinking purely mass marketing, there should be no firm today that isn't thinking about individual level customers. There isn't any firm today that shouldn't be using technology to measure their customers better and the reason in parentheses science is now that you can measure stuff, marketing really has become a science. Meaning, we have data."

How to compute corporate profits?
Revenue - Cost per customer

Customer Analytics: Make profit one customer at a time

Customer Analytics refers to the collection, management, analysis and strategic leverage of an organization's granular data about the behavior of its customer.

Customer analytics can be characterized as:
Inherently granular: a focus on individual-level behavior ,not aggregate patterns
Behavioral: primary focus is on observed behavioral patterns, not demographics or attitudes, i.e. you can measure the customer behavior
Forward-looking: an orientation towards prediction, not just description
Multi-platform: desire to combine behaviors from multiple measurement systems. Data fusion.
Broadly applicable: the definition of a customer is industry agostic - it could be a user, reader, visitor, donor, client, etc.
Multidisciplinary: relevant fields include marketing, statistics, computer science, information science and operations research

The golden age of marketing
History of Marketing Science
In 1950s, business questions are
- How store-level prices relate to sales?
- What is the effectiveness of coupons?
- How much does regional advertising influence purchasing?
- What is the impact of in-store promotion on sales?

In 1960s and 1970s
- How do individual-level prices relate to catalog shopping behavior?
- What is the impact of frequency and timing of catalogs/mailers on purchase behavior?
- How does product assortment influence household purchase behavior?
- What types of advertising appeals/messages are more/less effective?

In 1980s the modern age of marketing
- Distribute individual-level discounts at checkout
- Trak customer over time to understand their long-term buying habits
- Measure person-level coupon and discount usage
- Greater knowledge of in-store experience

In 1990s and 2000s greater customer insight
- Track Page Browsing
- Track Products Considered
- Targeted Ads based on purchase history and context
- Link to past experience
Cookie Tracking
Loyalty Programs
If built properly, can link to offline

Internet allows not only to know what you bought, but also what you considered. This is where the targeting ads go for.

Application ROI:
How effective is display (long-term) versus SEM (short-term) digital advertising?
This is known as the advertising attribution problem.

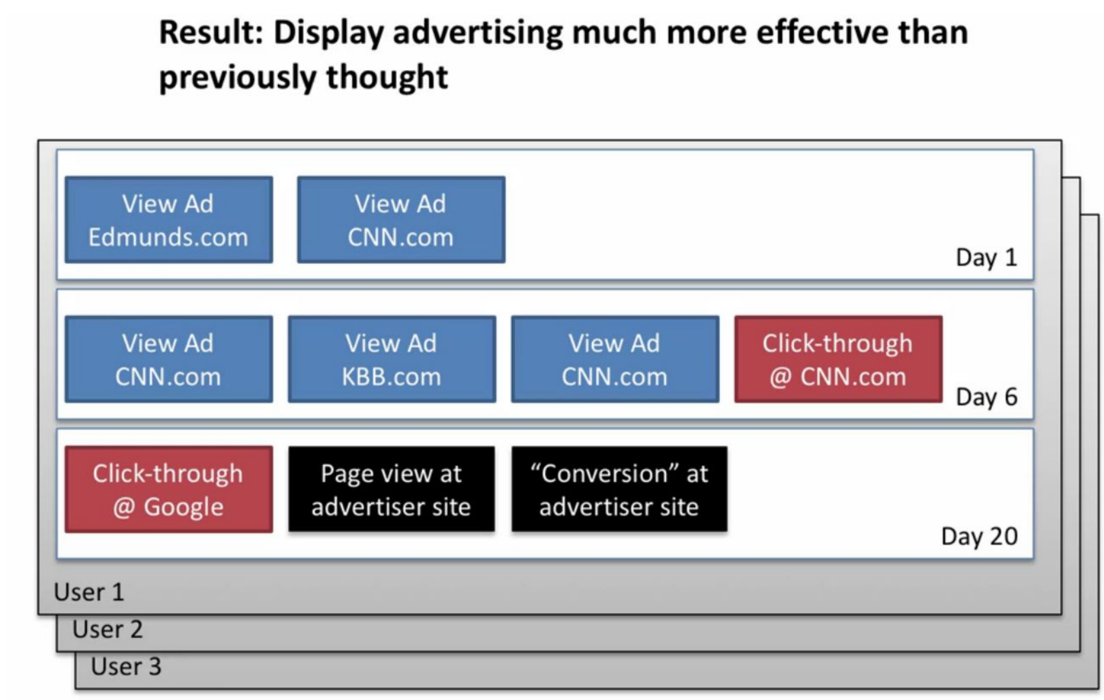
How do customers utilize multiple media platforms?
Known as the media optimization or channel cannibalization problem.

Reach and Frequency and its monetization counterpart
GRP = Reach * Frequency
Findings:
- Channels do NOT cannibalize each other in the long-term, heavy users are heavy users
- Channels do slightly cannibalize each other on a given day.

Number one, it's better for you to cannibalize your own sales than for someone else to cannibalize your sales. And secondly, what they found is, even though, and ESPN found this, and I have found this more generally true, through analytics, even if the mobile channel does partly cannibalize your other channels, the total volume actually goes up. And the way it worked for the ESPN World Cup is there was intraday cannibalization, meaning, if I spend more time on my mobile phone on a given day, I am gonna watch TV less on that day, but overall, I'm giving you an additional channel to engage with my firm. This is one of the really strong application areas of analytics today is the fact that you can measure people across multiple channels if you like. TV, mobile, web, streaming video means what matters is the total engagement. You don't worry as much about profit maximization for each channel, and imagine the same thing is true in sales. If you have online and offline sales, you shouldn't be worried about, well, if I launch online, is that gonna cannibalize my store? Well, maybe. But what you should care about is the total profitability, and it's the interplay between the two. And it's only through improved data and analytics can you assess that problem.

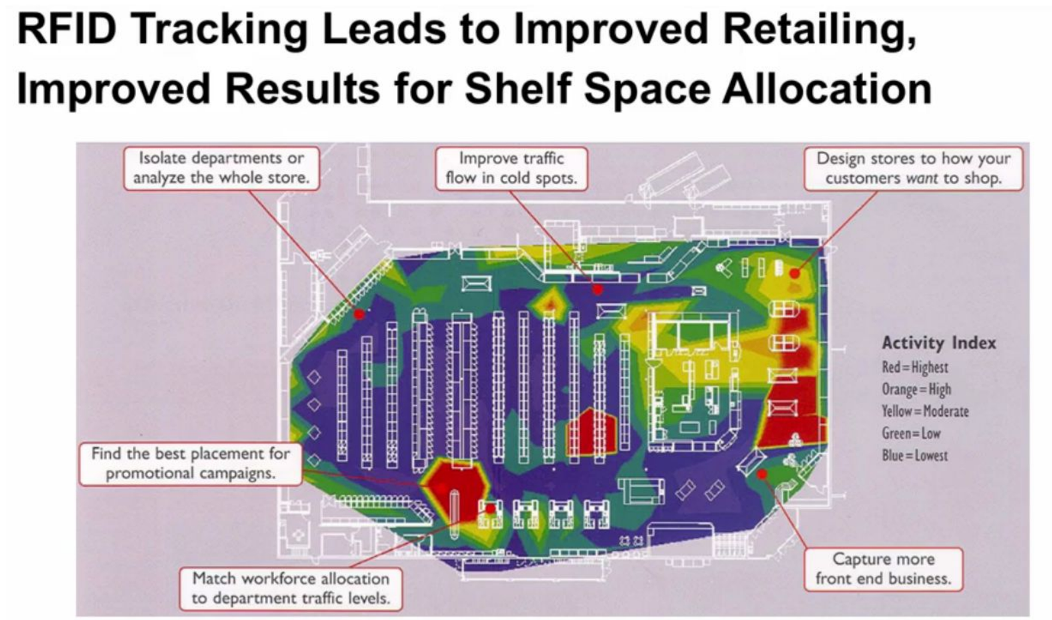
And this is a question, how valuable are price discounts?
Consider about the customer's Social network -- his word of mouth today

What is the ROI of Facebook?
Is more "likes"/mentions valuable?
FB and Online have greater short-term effects
TV has a longer carry-over effect
When compared to cost, the markets are fairly efficient, i.e. total integrated impact over time is proportional to cost.
If I know how much you do online, even if I know how much television ads you see, knowing how many likes you saw on Facebook for a given product helps me predict purchase data more so than just traditional online or television advertising. That's the magic of customer attribution and customer level data.



Radically new datasets in marketing
A series of measurement devices to track shoppers:
- Shopping plan (intentions survey)
- Shopping path (RFID)
- Field of vision (Eye-cam)
- Purchase (scanner data)

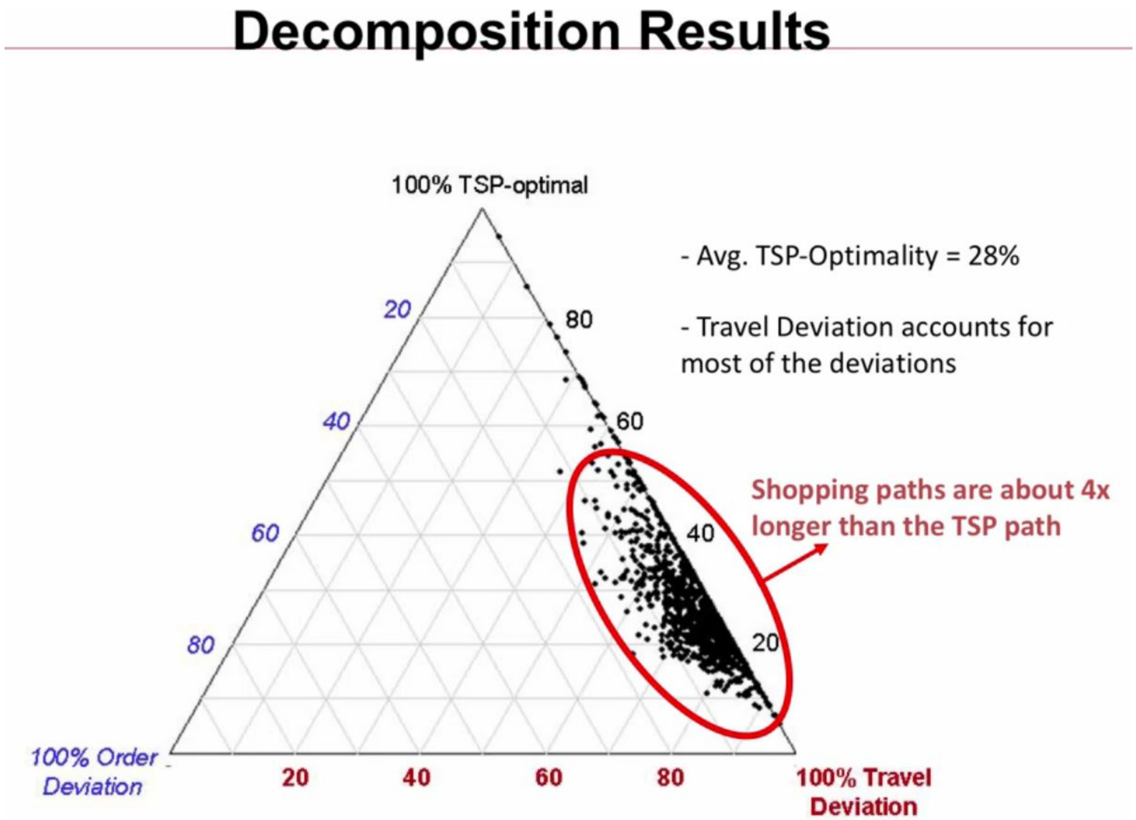
Eyetracker from the stores, now the mobile devices have the geospatial information. It solves the problem of how shoppers move.
On average, a shopper only covers ~25% of a store physically.



What about the online store?
We should know about the customer's excursion behavior.

1. Do you want efficient shoppers, or do you want people that wander more?
2. Create heat map to explore what fraction of data the store is being covered.
3. Now we're gonna analyze the data under the framework of a traveling salesman problem.
people that are more efficient, in and out shoppers, are they more valuable to the firm or less valuable to the firm?
4. Who you should be targeting.
5. Show you about decision making of the firm.

Order deviation describes the order of products the consumer purchase.
Travel deviation is related to the wiggliness.

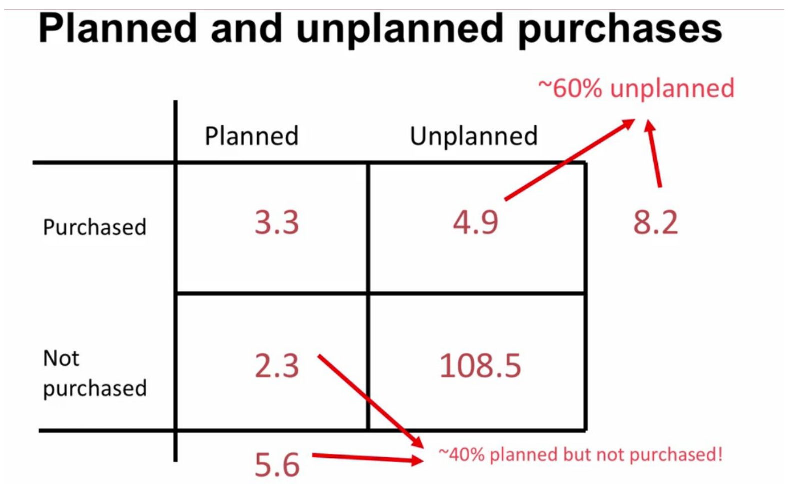


Group 4 are people that go in the wrong order. And they have the most jiggliness. And notice those people buy on average about ten items every time they go to a store where the people that are most efficient, which is group 1, only buy about half as much. So notice how I've turned new data, which is where people go in the store.

Clustering Consumers Based on Deviations

Paths with high order deviation tend to be associated with more purchases (no effect for travel deviation)

	Group 1	Group 2	Group 3	Group 4
Order Deviation (H/L) Travel Deviation (H/L)	L L	H L	L H	H H
Number of shoppers	203	294	294	202
Mean % order deviation	0.4%	6.3%	0.6%	4.8%
Mean % travel deviation	59.5%	62.5%	78.6%	76.1%
Mean unique number of zones visited	38.2	52.1	48.9	59.7
Mean basket size (number of categories)	4.5	8.7	5.6	9.6
Mean unique number of aisles entered	4.7	7.7	7.1	9.6
Mean unique number of aisles traversed	1.4	2.8	2.5	3.7



Indoor marketing
Shopping in the grocery store.
The products placed at the height of 5'6" are most purchased. People scan from left to right.

Uses of advanced management science by leading firms
Kolh: geospatial from wifi with unique IP address, real-time coupon,
Netflix: Designing content, meta-tagging data, based on the taste of the consumers, the director can create movies to match the topic.
American express: social network=based churn model, NLP to analyze the consumer's behavior on the social network.
Health-care providers: patient health, medical record, predictive analytics, reactive -> proactive
Google free taxi: partner with retailers to customize their service with free rides. CLV (customer lifelong value)
Starbucks: customer loyalty = no deal. reward the infrequent customer
Call centers: call ordering, intonation, NLP, different people handle different people
Amazon: ship before you buy, distribute the product beforehand so that the customer can get earlier. predict forward.

Takeaways
Technology meets management science
It is never the golden age, and better data leads to better science
It is real monetization

5 major points to remember
Start with Data: build the infrastructure according to data. Better data
Data exploration. What you are looking for
Predictive models. Churn model. Dollar value.
Optimization. Price. Target advertising. Email.
Decision. Predict forward.