Computational Advertising

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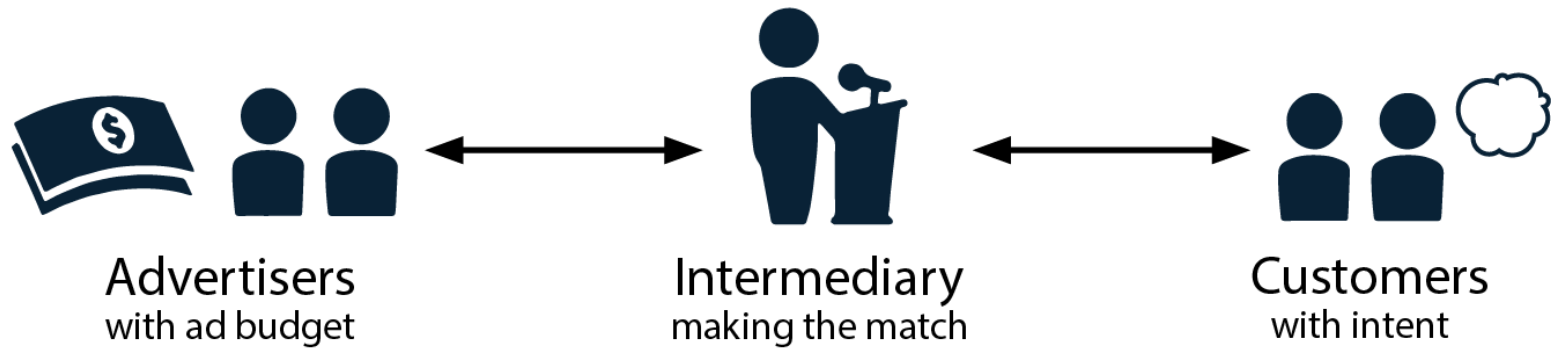
http://wnzhang.net

http://wnzhang.net/teaching/ee448/index.html

Content of This Course

- Introduction to computational advertising

- Auction for ad selection

- Sponsored search

- Contextual advertising

Advertising

Advertisers with ad budget ← → Intermediary making the match ← → Customers with intent

- Make the best match between advertisers and customers with economic constraints

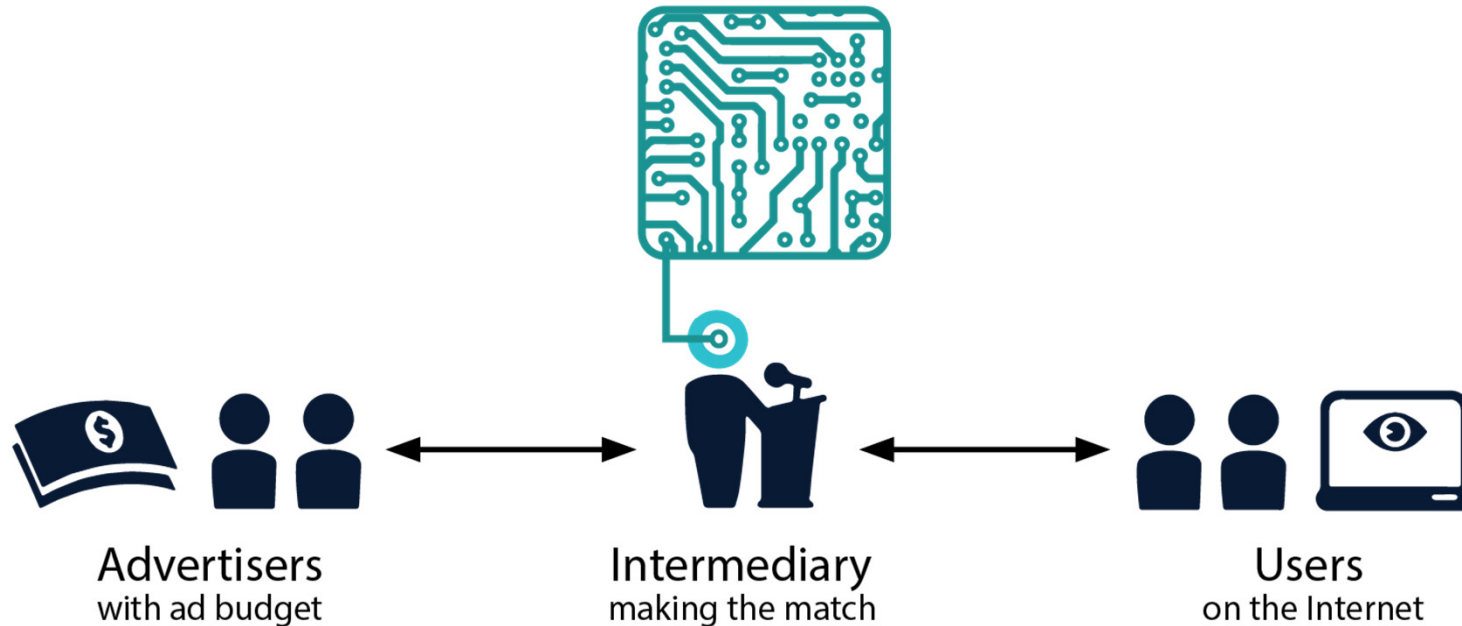*"Half the money I spend on advertising is wasted; the trouble is I don't know which half."*

- John Wanamaker

(1838-1922)

Father of modern advertising and a pioneer in marketing

Wasteful Traditional Advertising

Computational Advertising

- Design **algorithms** to make the best match between the advertisers and Internet users with economic constraints

Sponsored Search

Search: iphone 6s case

Sponsored Search
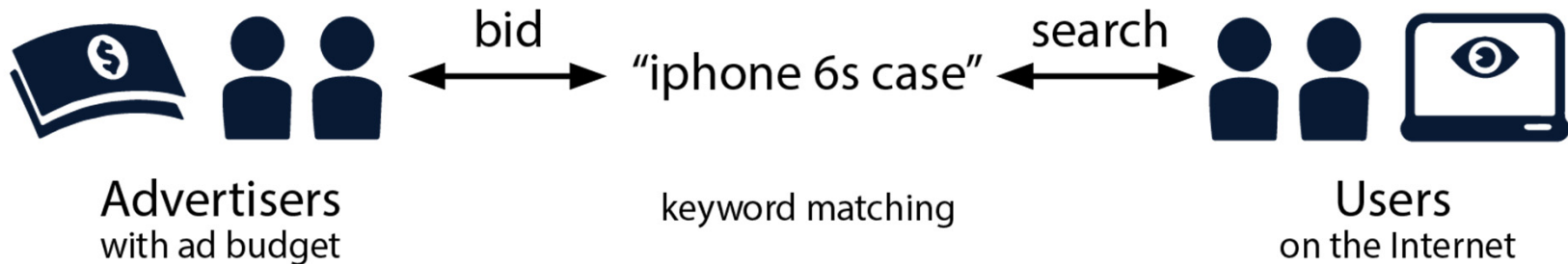
- Advertiser sets a bid price for the keyword
- User searches the keyword
  - This explicitly shows her information need
- Search engine hosts the auction to ranking the ads

Contextual Advertising

Contextual Advertising

- Advertiser sets a bid price for the keyword
- Search engine extracts topic keywords from webpages
  - Assuming the user's information need is the webpage content
- Search engine hosts the auction to ranking the ads

Display Advertising

http://www.nytimes.com/

Display Advertising

- Advertiser targets a segment of users
  - No matter what the user is searching or reading
- Intermediary matches users and ads by user information

A 3-Player Game
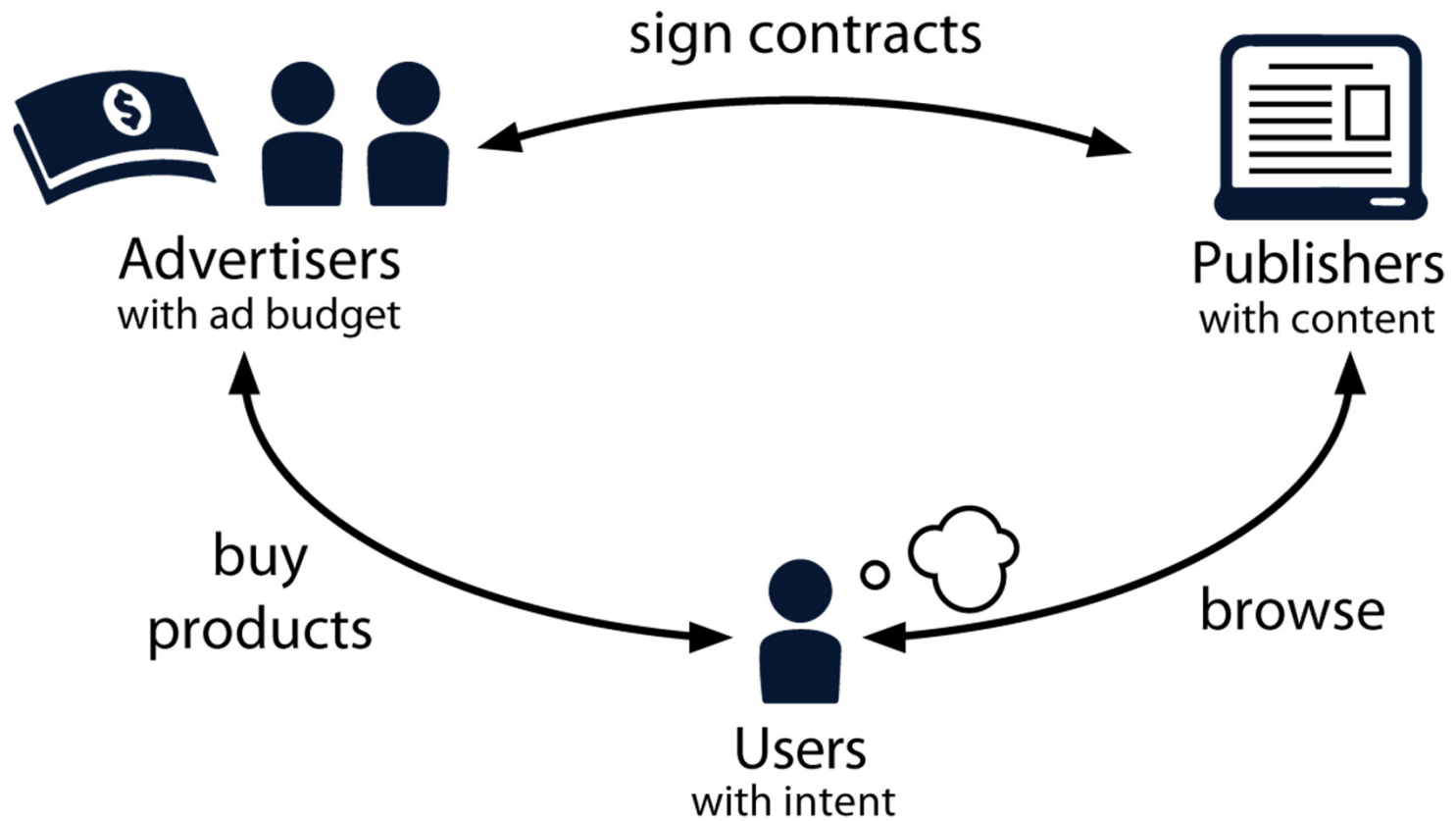
Computational Advertising Markets

- Statistics from IAB 2016 annual report

Legend: ■ Non-Mobile — — — → ■ Mobile — — — →

Shift from desktop to mobile

Mobile makes up more than 50% of internet advertising revenue for the first time

16% Overall CAGR

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Total	16.9	21.2	23.4	22.7	26.0	31.7	36.6	42.8	49.5	59.6	72.5
Mobile					0.6	1.6	3.4	7.1	12.5	20.7	36.6
Non-Mobile	16.9	21.2	23.4	22.7	25.4	30.1	33.2	35.7	37.0	38.9	35.9
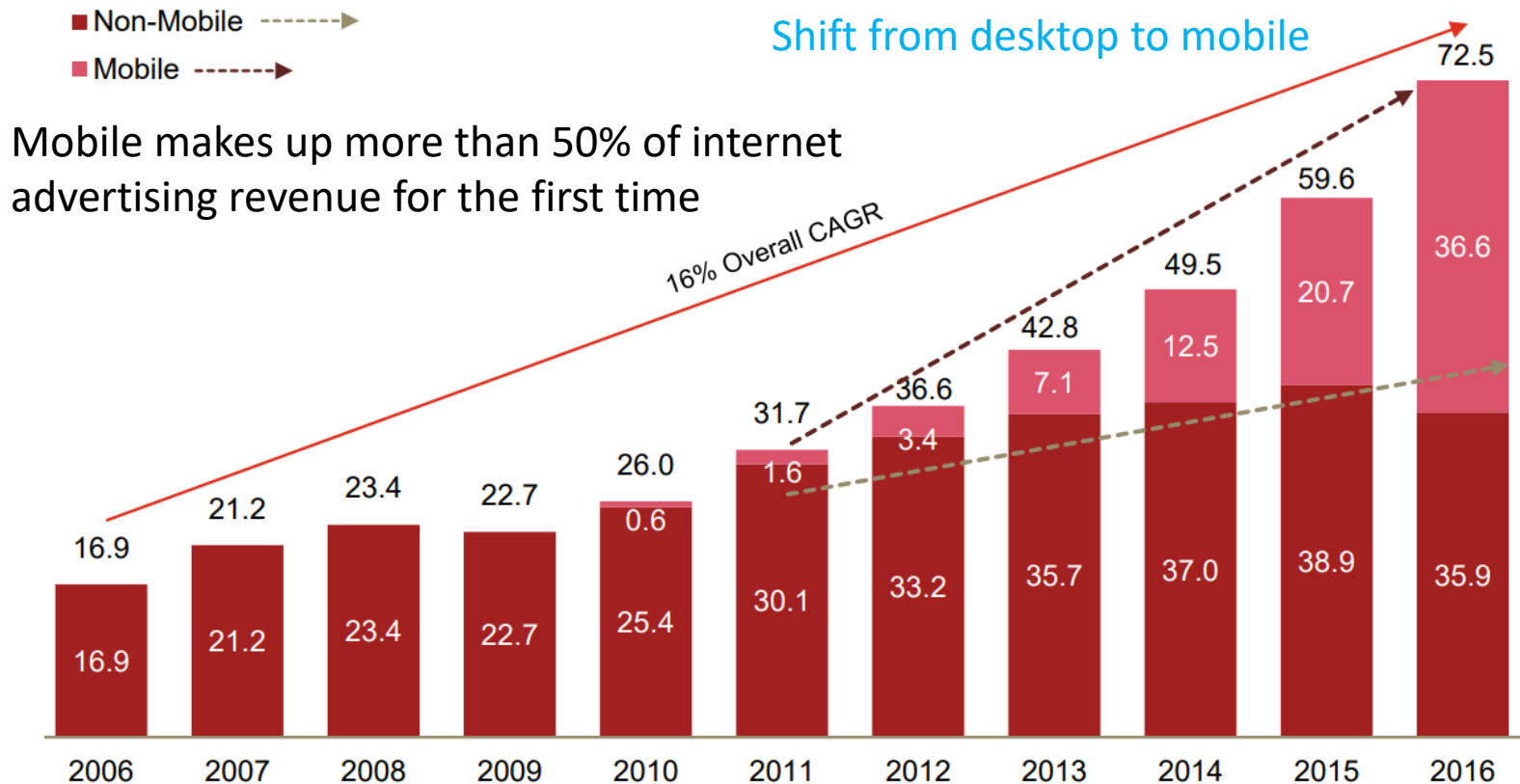
Computational Advertising Markets

Ad formats – full year 2016

Total - $72.5 billion****

- Search
- Mobile
- Banner
- Video
- Other

24%
6%
7%
12%
51%

Mobile Formats

- Search
- Banner
- Video
- Other

47%
38%
11%
4%

Source: IAB/PwC Internet Ad Revenue Report, FY 2016
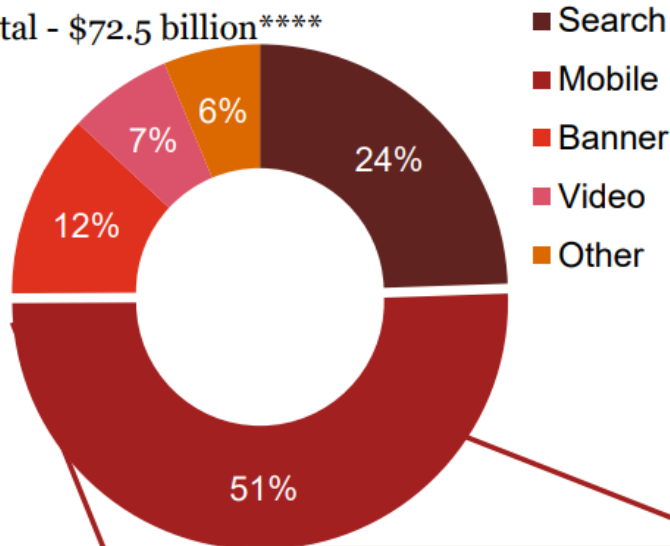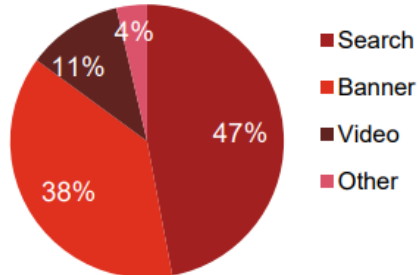
Ad formats – full year 2015

Total - $59.6 billion****

34%
8%
7%
16%
35%

Mobile Formats

- Search
- Banner
- Video
- Other

44%
45%
8%
4%

Computational Advertising Markets

Advertising format share, 2008 - 2016* (% of total revenue)
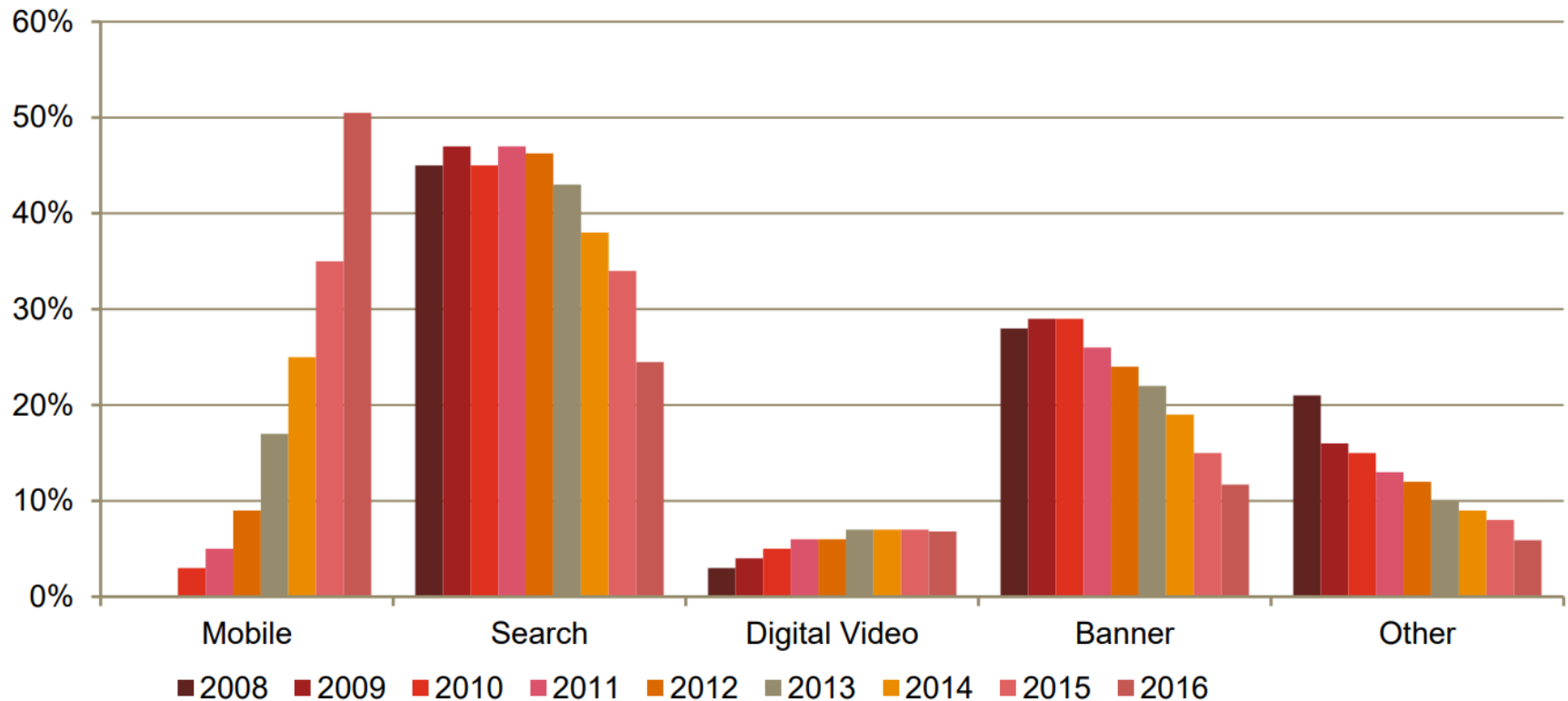
Computational Advertising Markets

Internet ad revenues by pricing model*
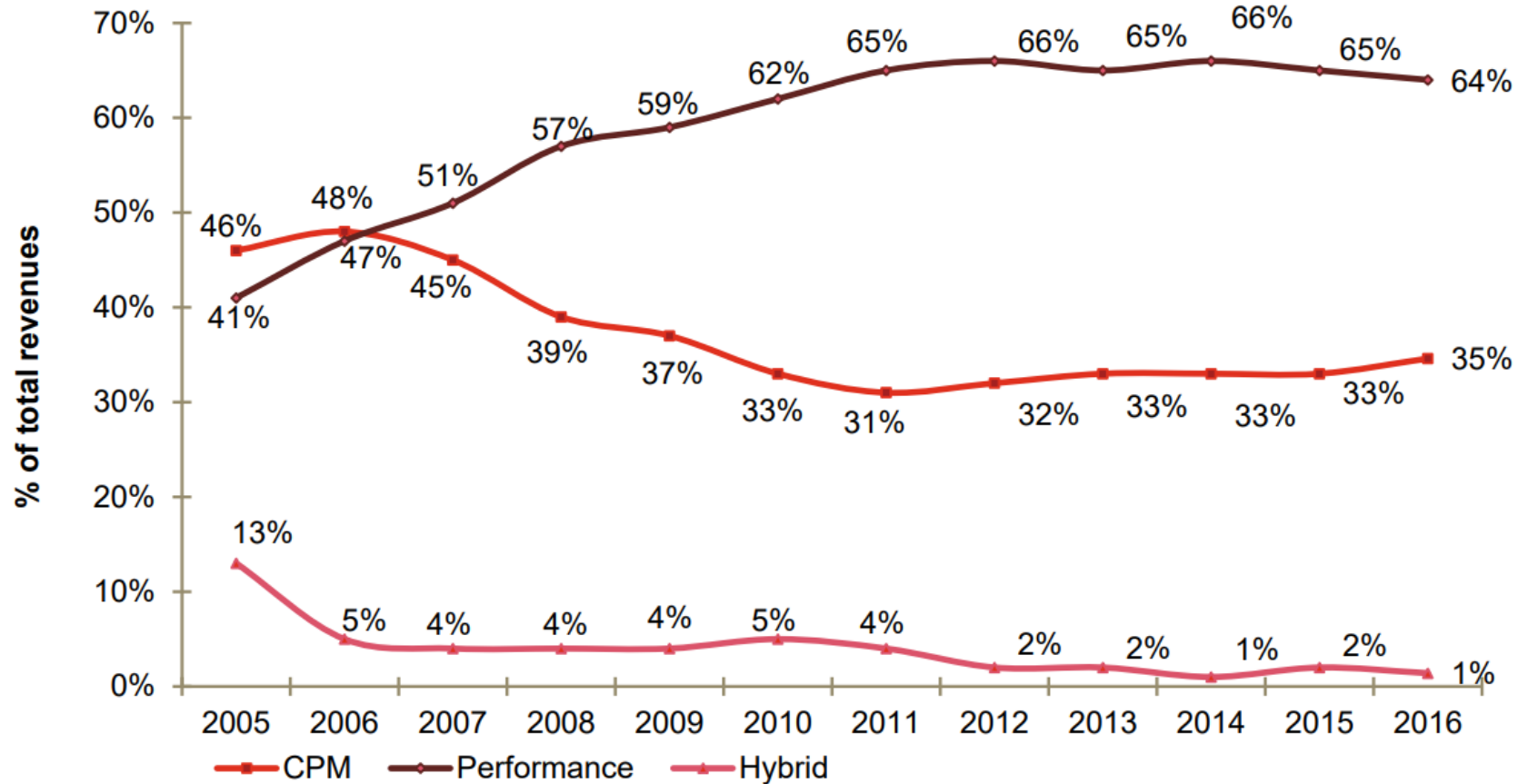
Advertisers care more and more about the ad performance, which drives a high motivation of data science for computational advertising optimization.

Computational Advertising Experts

Dr. Andrei Broder
Google

Dr. Vanja Josifovski
Pinterest
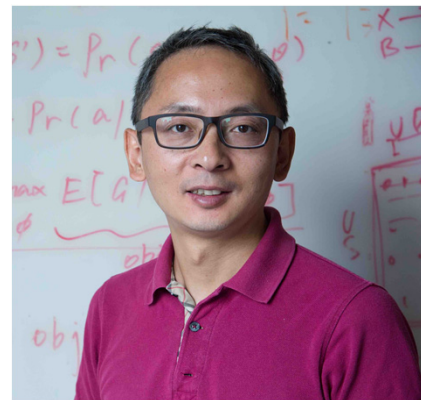
Prof. Jun Wang
University College London

- Stanford MS&E 239: Introduction to Computational Advertising
  - By Andrei Broder and Vanja Josifovski
  - https://web.stanford.edu/class/msande239/
- UCL COMPM041: Web Economics
  - By Emine Yilmaz and Jun Wang
  - http://www.cs.ucl.ac.uk/current_students/syllabus/compgw/compgw02_web_economics/
- Some material of this lecture is borrowed from these masters

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Online Auctions

- An auction is a process of buying and selling goods or services by offering them up for bid, taking bids, and then selling the item to the highest bidder

- Auctions are popular
  - Historical sale tool
    - Bonds, treasury bills, land leases, privatization, art, etc.
  - Internet marketplace
    - eBay changed the landscape as a gigantic auctioneer
    - Sponsored search (Google, Facebook, etc.)
    - Display ad exchange (Google AdX, Taobao's TANX, etc.)

Auction Settings

- Imagine we want to sell a single item
  - Later we'll extend this to multiple items
- We don't know what it's generally worth
  - Just what it's worth to us
- Each bidder (player) has her own intrinsic value of the item.
  - Willing to purchase it up to this price
  - Values are independent
- But we don't know these values
  - Differs from some previous game theory assumptions about knowledge of payoffs
- How should we proceed?

First Steps
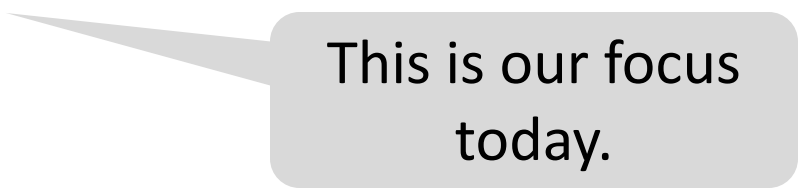
- We could just ask how much people are willing to pay
    - But would they lie?
    - Or manipulate the outcome?

- Problem:
    - How do we motivate buyers to reveal their true values?

- Auction theory: a sub-field of Mechanism Design
    - We design the market, "Economists as engineers"
    - Design an auction so that in equilibrium we get the results that we want

Goal of Auctions

A seller ("auctioneer") may have several goals.

Most common goals:

1. Maximize revenue (profit)

2. Maximize social welfare (efficiency)
   - Give the item to the buyer that wants it the most. (regardless of payments.)

3. Fairness
   for example, give items to the poor.

This is our focus today.

First Price Auction

- Each bidder writes his bid in a sealed envelope.
- The seller:
  - Collects bids
  - Open envelopes.
- Winner: the bidder with the highest bid.
- Payment: the winner pays her bid.
- Note: bidders do not see the bids of the other bidders.

at **$8**

$2 $8 $5 $3

First Price Auction is Unstable

- The constant price experimentation led to prices for all queries being updated essentially all the time (why?)

- This resulted in a highly turbulent market

Highest Price

Timestep
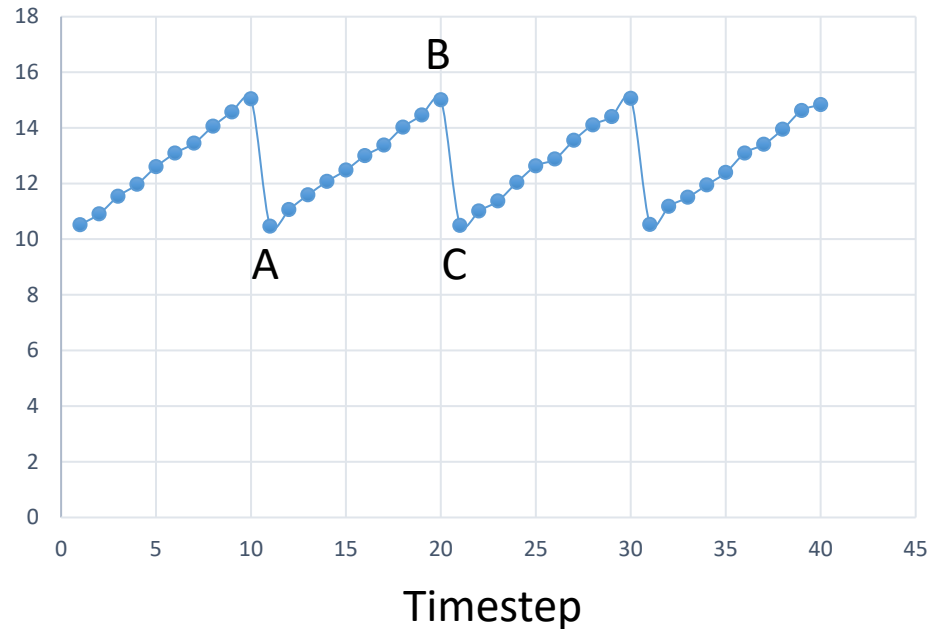
Lead to buyer's remorse and gaming
- A -> B: two bidders raise bid prices to get the first position
- B-> C: One of them reaches its maximum and then goes for the second position

Second Price Auction

- Each bidder writes his bid in a sealed envelope.
- The seller:
  - Collects bids
  - Open envelopes.
- Winner: the bidder with the highest bid.
- Payment: the winner pays the second highest bid.
- Note: bidders do not see the bids of the other bidders.

at **$5**

$2 $8 $5 $3

Second Price Auction is Truth-Telling

High Price

Market Price ● Case 1: non-profitable auction

Bid price

Market Price ● Case 2: negative profit

True value

Market Price ● Case 3: the same as bidding true value

0 Price

Market Price: the highest bid from all other competitors
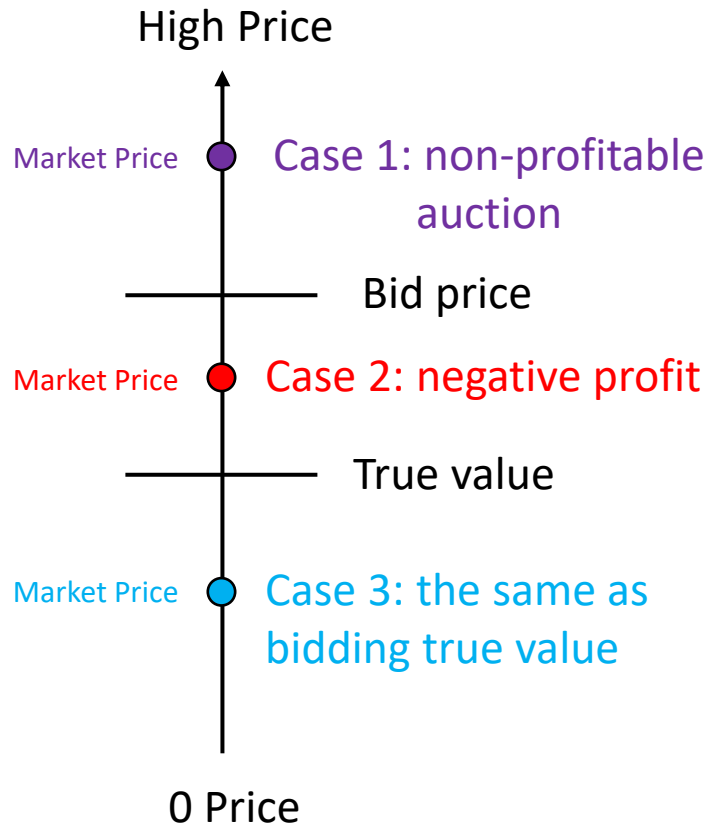
- If a bidder bids higher than her true value, then
  1. Market price > bid > true value: Not a profitable auction
  2. Bid > market price > true value: win a negative profit
  3. Bid > true value > market price: the same as bidding true value

- Therefore, bidding higher than the true value is less optimal than bidding the true value

Second Price Auction is Truth-Telling

High Price

Market Price ● Case 1: non-profitable auction

——— True value

Market Price ● Case 2: loses a profitable auction

——— Bid price

Market Price ● Case 2: the same as bidding true value

0 Price

Market Price: the highest bid from all other competitors
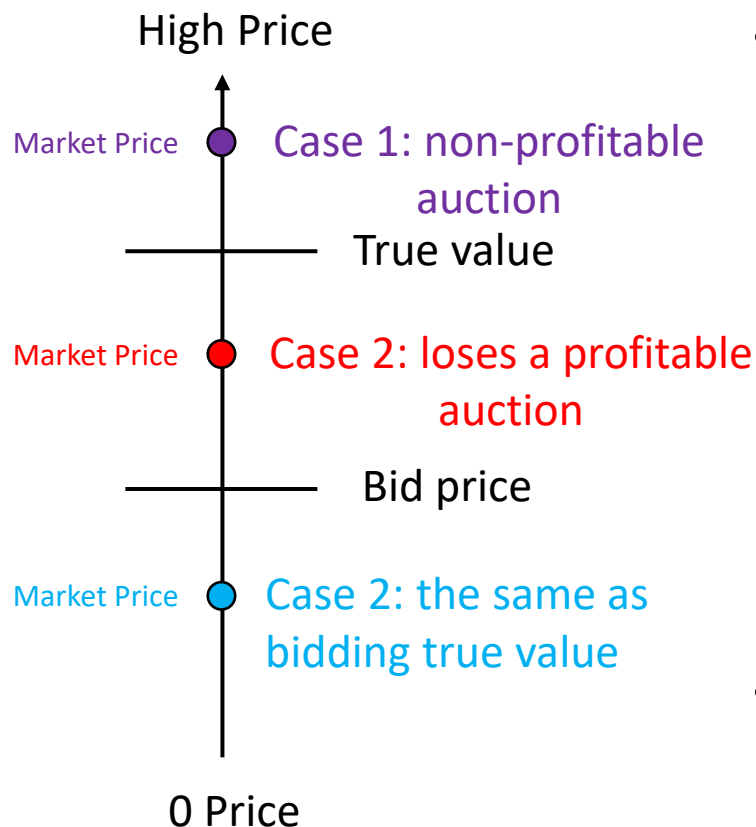
- If a bidder bids lower than her true value, then
    1. Market price > true value > bid: Not a profitable auction
    2. True value > Market price > bid: she loses a profitable auction
    3. True value > bid > market price: the same as bidding true value

- Therefore, bidding lower than the true value is less optimal than bidding the true value

A Mathematic Proof

- Notations
    - Market price as a random variable *z*
    - True value *r*

Profit given a bid *b*:
$$R(b) = \int_0^b (r - z)p(z)dz$$

Optimal bid:
$$b^* = \max_b R(b)$$

$$\frac{\partial R(b)}{\partial b} = (r - b)p(b)$$

$$\frac{\partial R(b)}{\partial b} = 0 \Rightarrow b^* = r$$
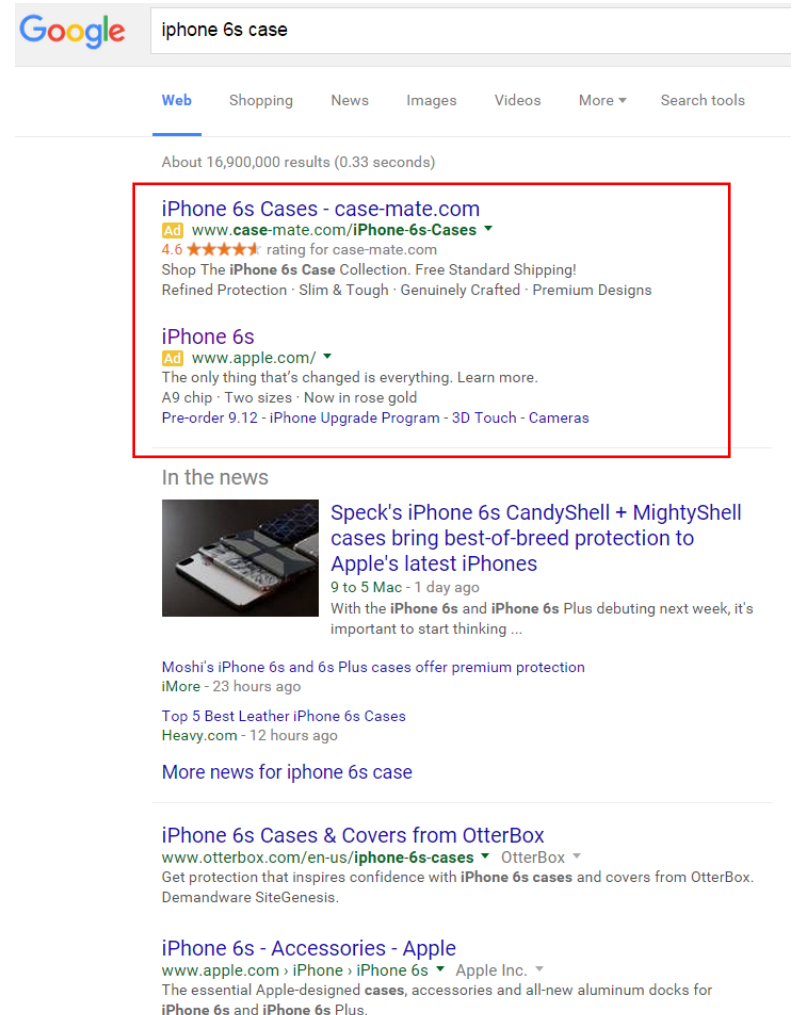
i.e., bid true value

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Sponsored Search

- Sponsored search, when a consumer searches for a term using a search engine, the advertisers' webpage appears as sponsored links next to the organic search results that would otherwise be returned using the neutral criteria employed by the search engine.

- Pricing scheme: cost-per-click (CPC), i.e., the advertiser pays the search engine a cost for each of the users' clicks on the ad link

Players in Sponsored Search

- Advertisers
  - Submit ads associated to certain bid keywords
  - Bid for positions
  - Pay CPC
- Users
  - Make queries to search engine, expressing some intent
- Search engine (a special case of publishers)
  - Executes query against web corpus and other data sources
  - Executes query against the ad corpus
  - Displays a search result page, i.e., organic results + ads

Player Utilities

- Each of the SE, Advertisers, and Users has its own utility
  - Advertisers: maximize the profit from advertising
    - Profit = product revenue – ad cost

  - Users: efficiently find the information they need
    - No matter the organic webpages or ad links

  - Search engine: maximize the profit by displaying ads
    - Profit = Probability of user click × CPC

- Whether is there are win-win-win solution?

Key Questions in Sponsored Search

- Key question 1: how to quantitatively estimate whether the user would like the displayed ad?
  - Solution: user click-through rate (CTR) estimation by machine learning

- Key question 2: how to rank and charge the ads given the bids and estimated CTRs?
  - Solution: generalized second price (GSP) auction

User Response Estimation Problem

- Problem definition

One instance data

- Date: 20160320
- Hour: 14
- Weekday: 7
- IP: 119.163.222.*
- Region: England
- City: London
- Country: UK
- Search Query: "iphone 6s case"
- OS: Windows
- Browser: Chrome
- Ad title: "iphone 6s case on sale!"
- Ad content: "Customize your case design"
- Bid keywords: "iphone case"
- User occupation: Student
- User tags: Sports

Corresponding label

➡ Click (1) or not (0)?

Predicted CTR (0.15)

One-Hot Binary Encoding

- A standard feature engineering paradigm

x=[Weekday=Friday, Gender=Male, City=Shanghai]

x=[0,0,0,0,1,0,0 0,1 0,0,1,0...0]

Sparse representation: x=[5:1 9:1 12:1]

- High dimensional sparse binary feature vector
  - Usually higher than 1M dimensions, even 1B dimensions
  - Extremely sparse
- More continuous features may be added
  - IR features, e.g., similarity between query and bid keywords, relevance between query and ad landing page

Training/Validation/Test Data

- Examples (in LibSVM format)

  1 5:1 9:1 12:1 45:1 154:1 509:1 4089:1 45314:1 988576:1
  0 2:1 7:1 18:1 34:1 176:1 510:1 3879:1 71310:1 818034:1
  …

- Training/Validation/Test data split
  - Sort data by time
  - Train:validation:test = 8:1:1
  - Shuffle training data

Training Logistic Regression

- Logistic regression is a binary classification model

$$p_\theta(y = 1|x) = \sigma(\theta^\top x) = \frac{1}{1 + e^{-\theta^\top x}}$$

- Cross entropy loss function with L2 regularization

$$\mathcal{L}(y, x, p_\theta) = -y \log \sigma(\theta^\top x) - (1 - y) \log(1 - \sigma(\theta^\top x)) + \frac{\lambda}{2} ||\theta||_2^2$$

- Parameter learning

$$\theta \leftarrow (1 - \lambda\eta)\theta + \eta(y - \sigma(\theta^\top x))x$$

  - Only update non-zero entries

Key Questions in Sponsored Search

- Key question 1: how to quantitatively estimate whether the user would like the displayed ad?
  - Solution: user click-through rate (CTR) estimation by machine learning

- Key question 2: how to rank and charge the ads given the bids and estimated CTRs?
  - Solution: generalized second price (GSP) auction

Advertiser Hierarchy
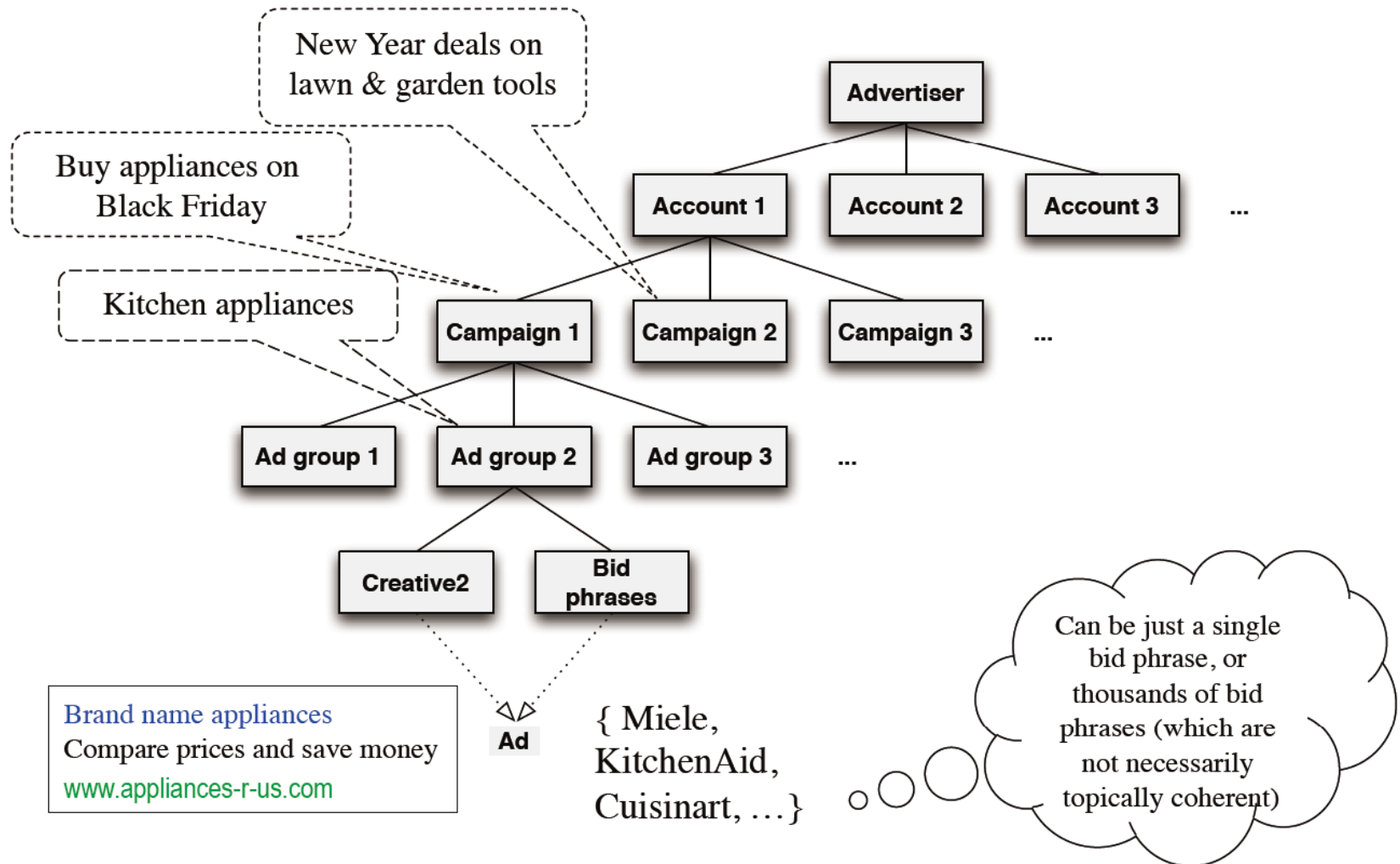
Advertiser-side Keyword Optimization

- Recommendation of new keywords to bid
  - Relevance r: the relevance between the keyword and the ad content. Can be measured using IR techniques
  - Volume v: how many search involves such a keyword daily? Can be obtained from search engine logs
  - Competitiveness c: how many advertisers are bidding for this keyword and how high is the market price?

- A straightforward solution: rank the candidate key words by $r \times v / c$
  - i.e., high relevance to the ad, high search volume, low competitiveness

Zhang, Ying, Weinan Zhang, Bin Gao, Xiaojie Yuan, and Tie-Yan Liu. "Bid keyword suggestion in sponsored search based on competitiveness and relevance." *Information Processing & Management* 50, no. 4 (2014): 508-523.

Sponsored Search Ad Pricing Scheme
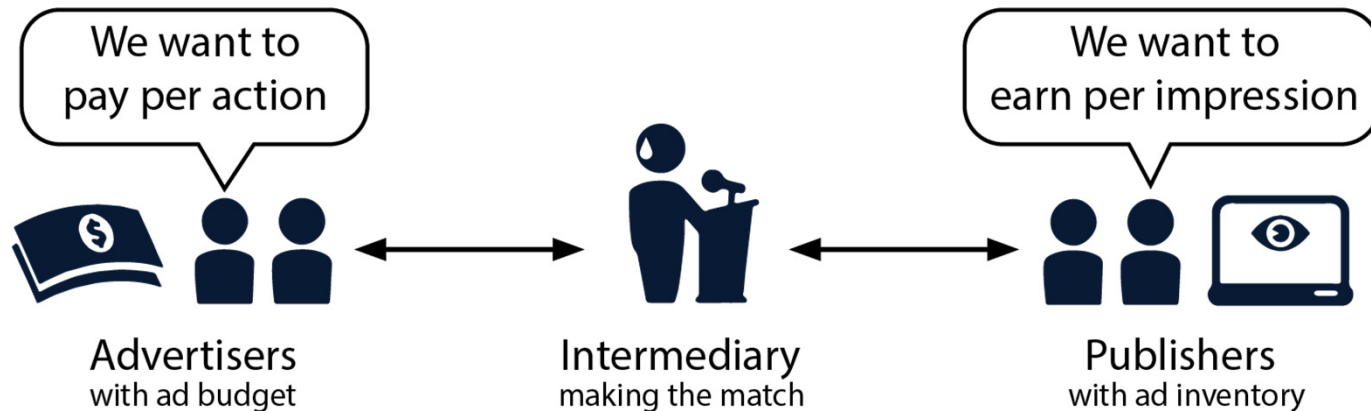
- Different pricing schemes
  - CPM: cost per mille impression [favored by publisher]
    - charge the advertiser for each ad display
  - CPA: cost per action [favored by advertiser]
    - Charge the advertiser for each conversion (i.e., user execute a particular action, e.g., product purchase, registration etc.)
  - CPC: cost per click [practically used for sponsored search]
    - A trade-off between CPM and CPA

Sponsored Search Ad Ranking
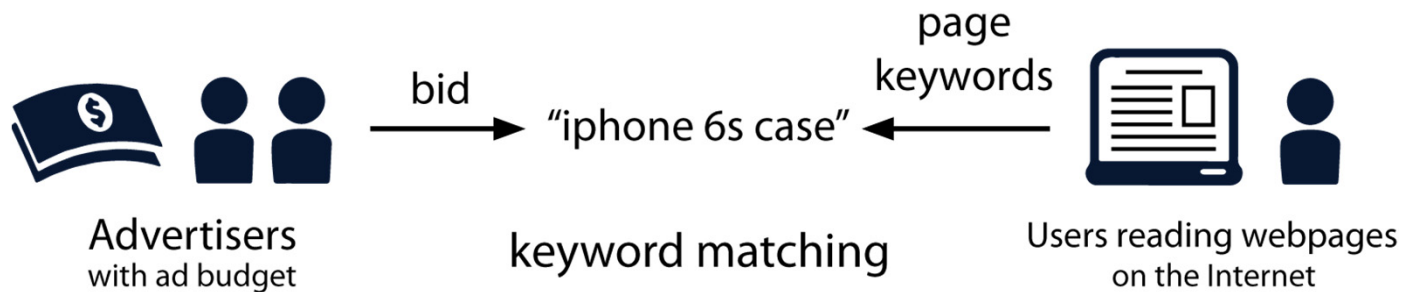
- A straightforward ad ranking scheme: rank the ad by expected cost, i.e., predicted CTR × bid

- An example candidate ad list

Ad ID	pCTR (%)	Bid ($)	Expected Cost ($)	Rank
1	0.3	0.1	0.0003	4
2	0.2	0.8	0.0016	1
3	0.1	0.5	0.0005	3
4	0.3	0.05	0.00015	5
5	0.2	0.4	0.0008	2

Generalized Second Price (GSP) Auction

- Classic second price auction (ranking by bid): the winner pays the second highest bid price
  - i.e., pay the lowest price to maintain her winning situation
- Generalized second price auction
  - ranking by CTR × bid
  - There are multiple ad slots
  - the winner of each ad slot pays the lowest price to maintain her winning situation

$$\text{cost}_i = \frac{\text{CTR}_{i+1} \times \text{bid}_{i+1}}{\text{CTR}_i}$$

- GSP (non-truth-telling) is a simplified version of Vickrey-Clarke-Groves (VCG) auctions (truth-telling)

Edelman, Benjamin, Michael Ostrovsky, and Michael Schwarz. "Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords." *American economic review* 97.1 (2007): 242-259.

An Example of GSP

Ad ID	Rank	pCTR (%)	Bid ($)	Expected Cost ($)	Cost ($)
2	1	0.2	0.8	0.0016	0.4
5	2	0.2	0.4	0.0008	0.25
3	3	0.1	0.5	0.0005	0.3
1	4	0.3	0.1	0.0003	0.05
4	5	0.3	0.05	0.00015	entry price

- To rank higher: the advertiser needs to
  1. design ad content, seek bid keywords to higher the CTR
  2. higher the bid price
- To pay less: the advertiser needs to make efforts to higher the ad CTR

$$\text{cost}_i = \frac{\text{CTR}_{i+1} \times \text{bid}_{i+1}}{\text{CTR}_i}$$

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Contextual Advertising

- Textual advertising on third party web pages

- Complement the content of the web page with paid content

- Ubiquitous on the web

- Supports the diversity of the web
  - Sites small and big rely on CM revenue to cover for the cost of existence

- Players
  - Google AdSense
  - Microsoft ContentAds
  - Baidu Display Network

How Does it All Work: the Front End

- Two main approaches
  1. Page fully built by publisher using ads supplied by the ad network.
     - E.g.: XML feed (Usually done with large partners.)
  2. Dynamic loading of ads
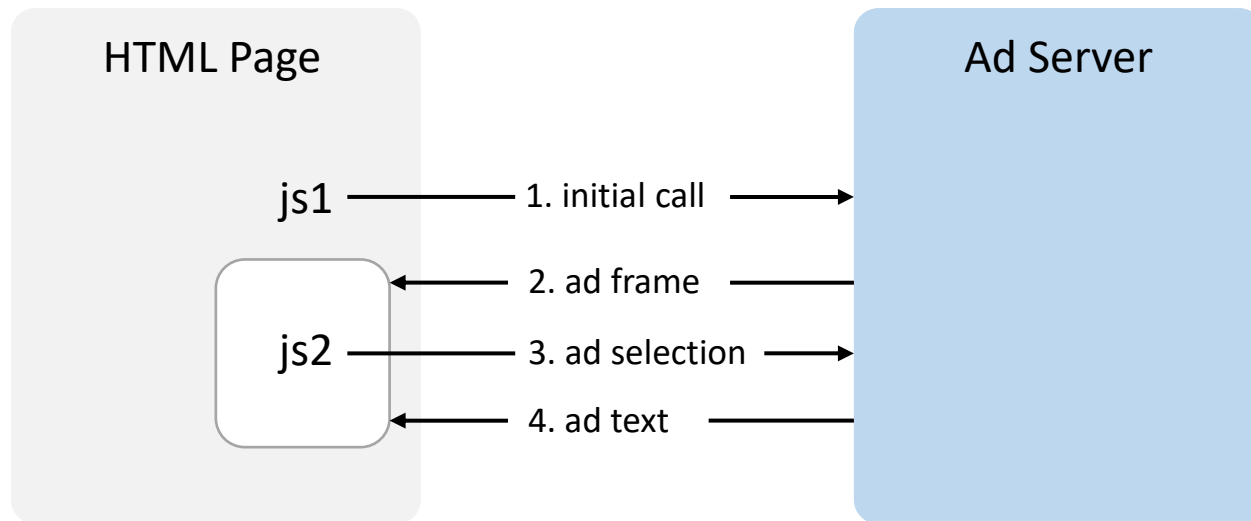
js: javascript s a high-level, dynamic, weakly typed, prototype-based, multi-paradigm, and interpreted programming language.

Contextual Ads and Sponsored Search
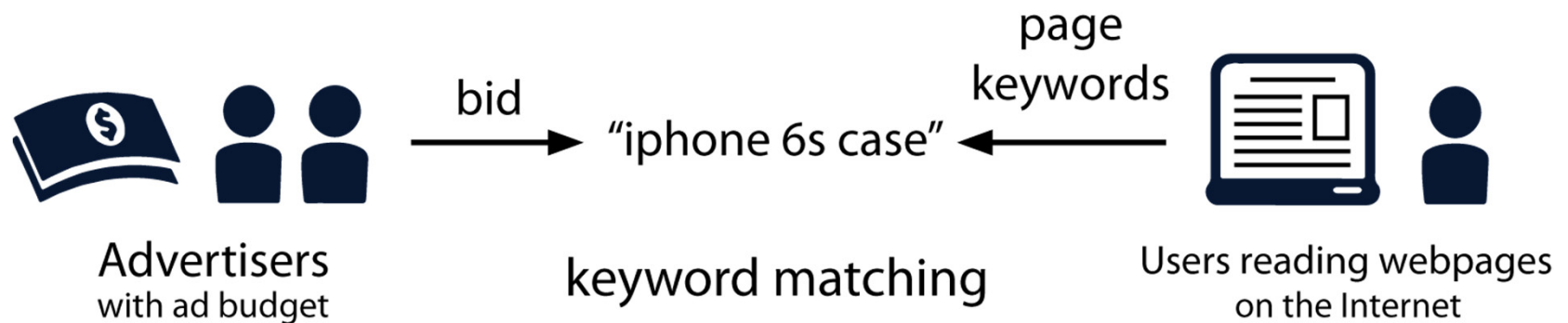
- Contextual ads is a natural way to expand the volume of textual ad campaigns in sponsored search
- No significant difference from advertisers' perspective
  - Same type of ads
  - Still bid keywords and participate keyword auctions
  - Can opt into contextual advertising for each ad group

Keywords Extraction for Contextual Ads
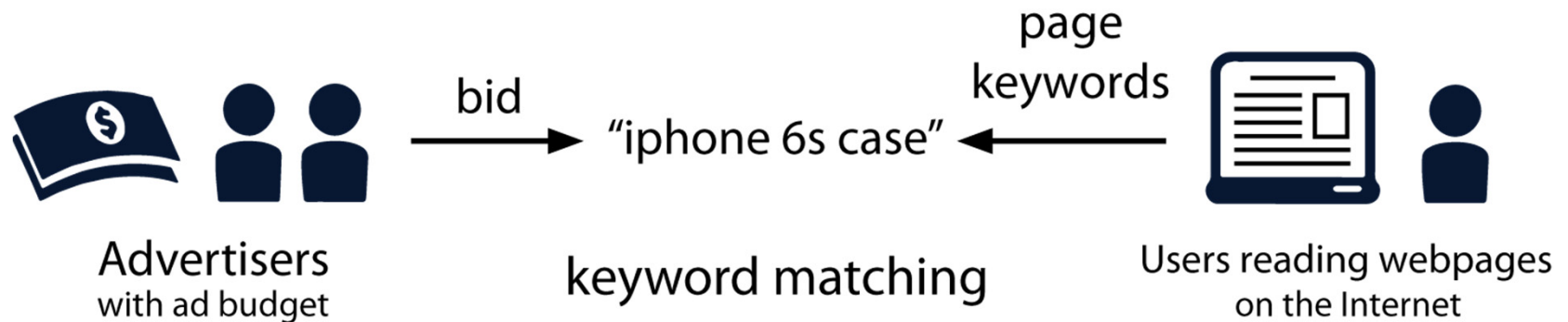
- Key technique in contextual ads is to extract good keywords from the page to raise the auction
  - The keywords still reveal the page topic (i.e., the user's intent)
  - The keywords might not necessarily occur in the page content

Techniques of Webpage Keyword Extraction (I)

- A machine learning approach
  - Finding Advertising Keywords on Web Pages. Wen-tau Yih et al. WWW 2006.
 - Human labels whether each candidate keyword in the page content is an appropriate keyword for this web page
  - Extract features for each candidate keyword in the page content
  - Train a machine learning model (e.g., logistic regression or SVM) with the data
  - Given a test web page, use the model to score the keywords and return the top-N results

features	
A	all
-C	capitalization
-H	hypertext
-IR	IR
-Len	length
-Lin	linguistic
-Loc	location
-M	meta
-Ms	meta section
-Q	query log
-T	title
-U	URL

- Cons: (i) can only extract keywords in the web page;
  (ii) cannot disambiguate the semantics of a keyword, e.g., apple

# Techniques of Webpage Keyword Extraction (II)

- Two semantic approaches
  - A Semantic Approach to Contextual Advertising. Andrei Broder et al. SIGIR 2007.
  - Advertising Keywords Recommendation for Short-text Web Pages using Wikipedia. Weinan Zhang et al. TIST 2012.
  - Leverage taxonomies or knowledge graphs to calculate semantic similarity between a keyword to a web page
  - Node distance and PageRank algorithms to calculate the consensus of semantic topic of a keyword
    - E.g., apple for fruit or a company
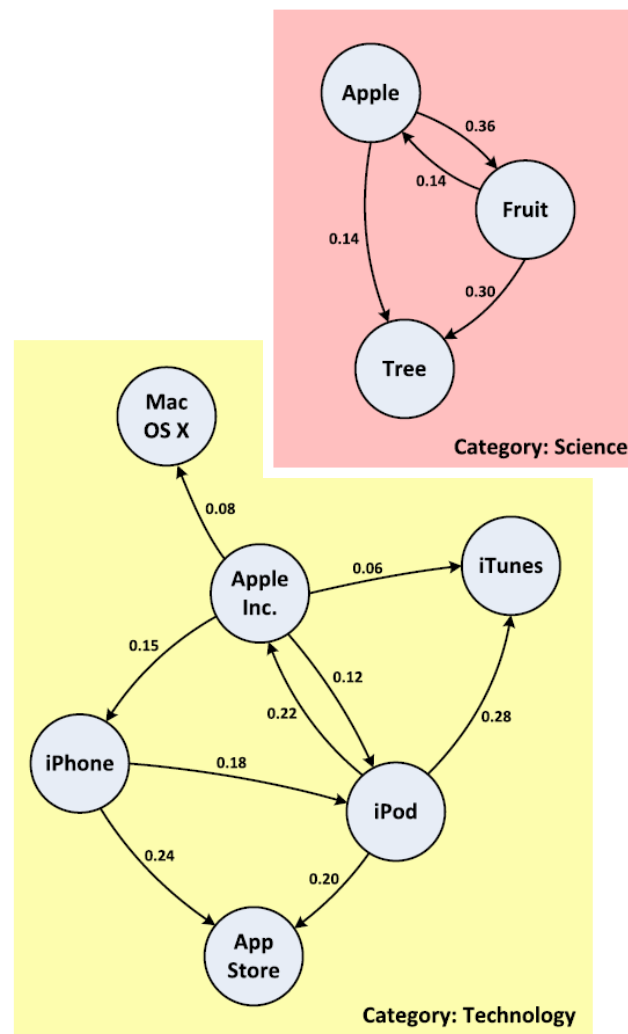
Summary
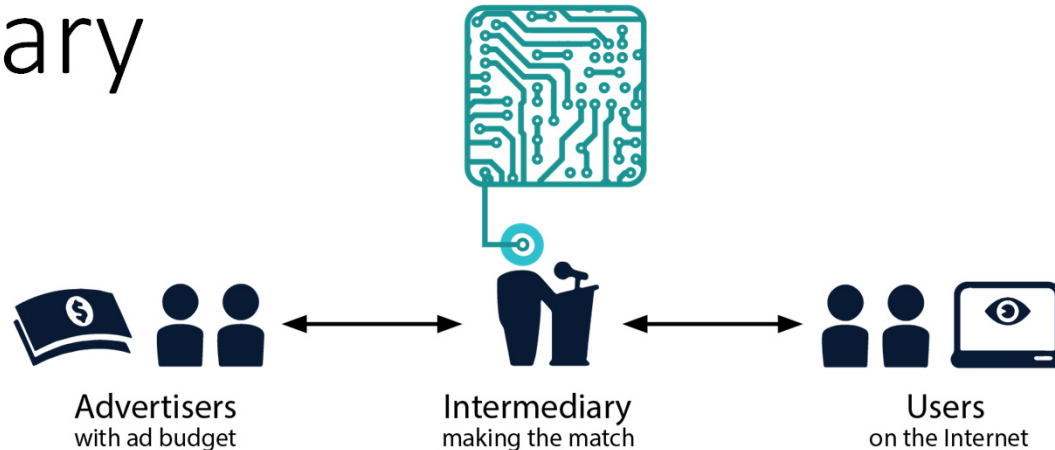
- Computational advertising: design algorithms to make the best match between the advertisers and Internet users with economic constraints

- (Generalized) second price auction is the main type of trading ad display opportunities

- Search engine based sponsored search and contextual ads are the main types of CA before 2010

- Intelligent display advertising by real-time bidding and behavioral targeting emerges in 2011, which is focus of our next lecture