# Research and Challenges for Online Advertising

***A Survey on Methods and Applications from a Machine Learning Perspective***

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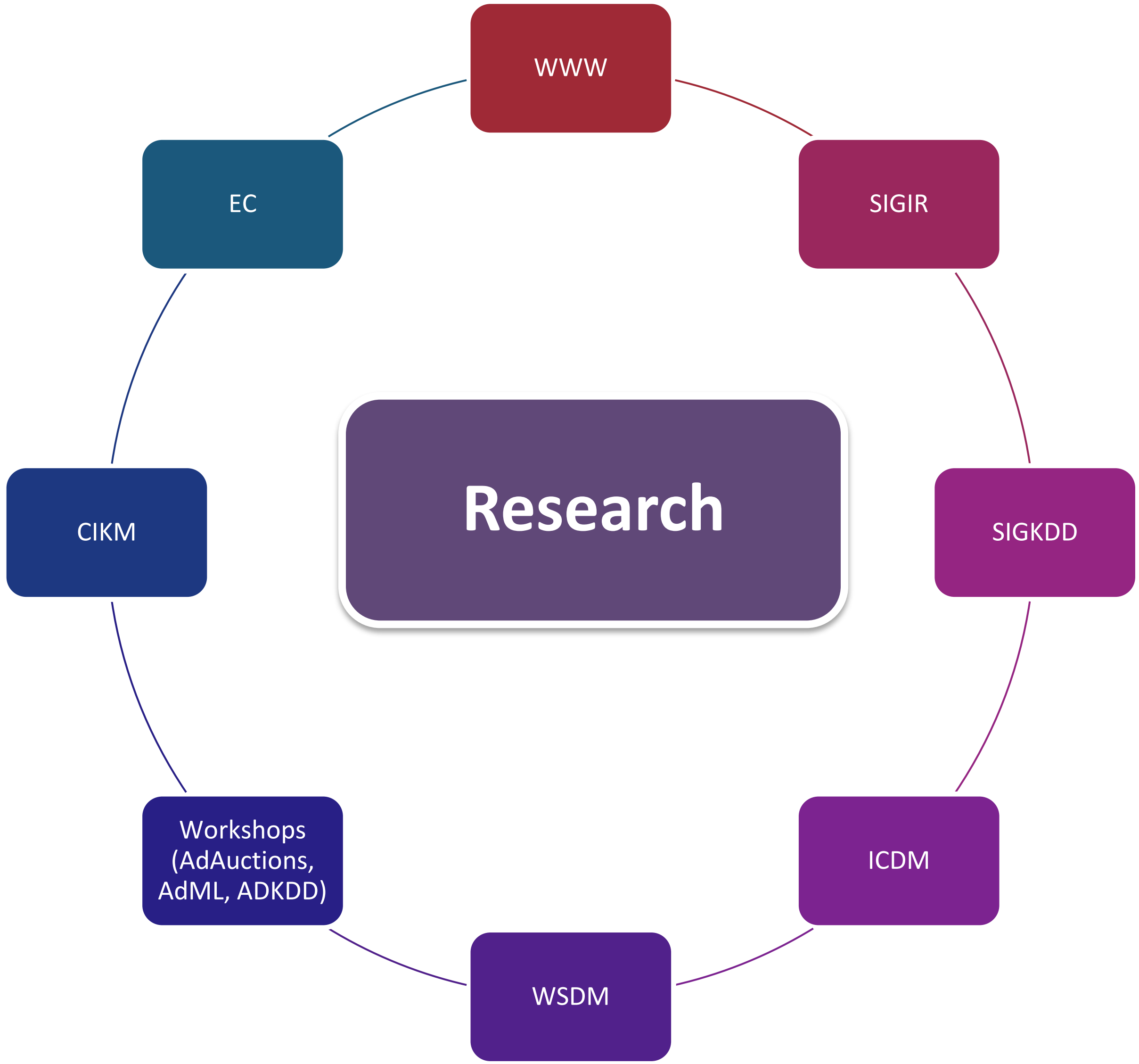
# Outline

**Research**

1. Introductory Concepts
2. Bidding Strategies of Advertisers
3. Predicting Clicks, CTR, or other metrics (for auctioneers)
4. Performance Evaluation of Advertiser's Strategies
5. Advertising on New Channels and Infrastructures

**Challenges**

1. Knowledge & Feature Management
2. Predicting Campaign Behavior
3. Optimization and Maximization of Campaign Objective Functions
4. ROI Evaluation

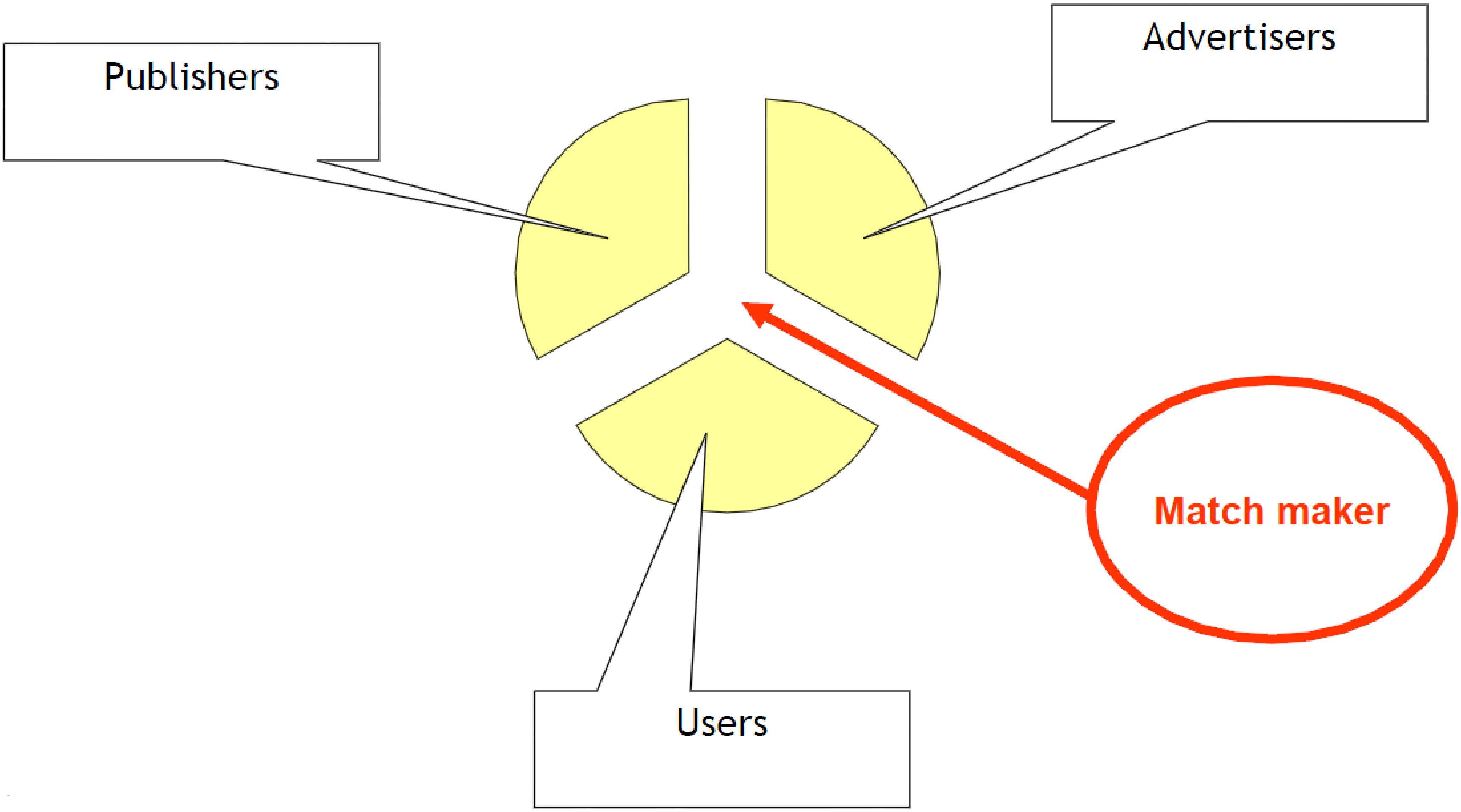

Research
WWW
SIGIR
SIGKDD
ICDM
WSDM
Workshops (AdAuctions, AdML, ADKDD)
CIKM
EC

# Introductory Concepts

1. Computational Advertising
2. Sponsored Search Ad Auctions

- Central problem of computational advertising
  - Find the "best match" between a given user in a given context and a suitable advertisement
    - Context: e.g. a user entering a query in a search engine ("sponsored search"), a user reading a web page ("content match" and "display ads"), a user watching a movie on a portable device, etc.
    - Constraints: e.g. limited budget of the advertiser on a specific period
    - Advertising is a form of information – IR problem
- Central Challenges
  1. Design markets and exchanges that help in this task, and maximize value for users, advertisers **(!)**, and publishers
  2. Build the infrastructure to support this process

# Participants: Publishers, Advertisers, Users, & "Matcher" (or Auctioneer)



# Business Models

1. CPM (Cost Per Thousand Impressions)
   - Advertisers pay for exposure of their message to a specific audience.
2. **CPC (Cost Per Click)** aka Pay per click (PPC)
   - Advertisers pay every time a user clicks on their listing and is redirected to their website.
3. CPA (Cost Per Action) or (Cost Per Acquisition)
   - The publisher takes all the risk of running the ad, and the advertiser pays only for the amount of users who complete a transaction, such as a purchase or sign-up.

# Generalized form of the game: The Sponsored Search Ad Auctions case (1)

- Sponsored Search
  - Sponsored Search Engine Results $\longrightarrow$ Textual Ads
  - Ads driven by search keywords = “sponsored search” (a.k.a. “keyword driven ads”, “paid search”, “adwords”, etc)
  - Advertiser chooses a “**bid phrase**” = query on which to display
  - Can also subscribe to “advanced match” = display me on related queries
- Generalized second-price auction (GSP) is a non-truthful auction mechanism for multiple items.

# Generalized form of the game: The Sponsored Search Ad Auctions case (2)

- Ad Auctions
  - Search Ad Management
    - A search engine receives bids from advertisers on certain search queries. Some ads are displayed with each search query and the search engine is paid the amount of the bid only if the user clicks on the ad. Each advertiser can give a budget, the total amount they are willing to pay for clicks in a month
  - The AdWords Problem
    - The data in this problem is a set of bids by advertisers on certain search queries, together with a total budget for each advertiser and information about the historical CTR for each ad/query.
    - The objective is to select on-line a fixed-size set of ads in response to each query that *will maximize the revenue to the search engine aka* ***the auctioneer***
    - Simplest version: the bids are on exactly the set of words in the search query (i.e. exact match option in AdWords)

# Optimization problem from the auctioneer's perspective

- Balance Algorithm for the Generalized AdWords Problem [Aranyak Mehta, Amin Saberi, Umesh Vazirani, and Vijay Vazirani. 2007. AdWords and generalized online matching. J. ACM 54, 5, Article 22]
  - When bidders can make differenting bids, have different budgets, and have different CTR for different queries, the Balance Algorithm awards an ad to the advertiser with the highest value of the function:

$$\Psi = x(1 - e^{-f})$$

  - $x$ : product of the bid and the CTR for that advertiser (…or/and Quality Score)
  - $f$: fraction of the advertiser's budget that remains unspent

- But…: the online advertising process *is also a profit maximization problem for the advertiser*
  - Bidding Strategies, ROI Maximization, Forecasting, Behavioral Targeting
    - Need to study it initially for the sake of simplicity as a "black box" returning clicks as a function of bid
    - Real advertising campaigns contain many different features. Even the goal of optimization has different aspects - Monetary profit or Clicks (Traffic) ?

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2. P. Maille, E. Markakis, M. Naldi, G. D. Stamoulis, B. Tuffin. *Sponsored Search Auctions: An Overview of Research with Emphasis on Game Theoretic Aspects.* To appear in the Electronic Commerce Research journal (ECR).

3. Andrei Broder, Vanja Josifovski. Introduction to Computational Advertising Course, Stanford University, California

4. Anand Rajaraman and Jeffrey D. Ullman. Mining of massive datasets. Cambridge University Press, 2012, *Chapter 8 – Advertising on the Web*

5. James Shanahan. *Digital Advertising and Marketing: A review of three generations*. Tutorial on WWW 2012

6. Google AdWords Help http://support.google.com/adwords/?hl=en

7. IAB's Internet Advertising Revenue Report http://www.iab.net/AdRevenueReport

# Bidding Strategies of Advertisers

1. Theory of Computation
2. Autonomous Bidding Agents & Machine Learning
   - Adaptive Learning Trading Agents

# Budget optimization for multiple keywords

- The budget of an advertiser needs to be split among several keywords
- Find a bidding strategy for the advertiser that maximizes his profit
- In Feldman et al. 2007 [J. Feldman, S. Muthukrishnan, M. Pál, C. Stein: Budget optimization in search-based advertising auctions. ACM Conference on Electronic Commerce 2007: 40-49] the advertiser has some information about the other bidder's behavior in the form of some distributions for the cost of obtaining a certain slot
  - Stochastic model, randomized strategy, bid equally on all the keywords
  - Introduce Weighted Keyword Bidding Problem – similar to Conversions (Monetary Profit)
  - Budget optimization is strongly NP-hard
- Borgs et al. 2007 [C. Borgs, J. Chayes, N. Immorlica, K. Jain, O. Etesami, and M. Mahdian. 2007. Dynamics of bid optimization in online advertisement auctions. In *Proceedings of the 16th international conference on World Wide Web* (WWW '07). ACM, New York, NY, USA, 531-540.] assume for the optimality of bids the marginal ROI. For an optimal set of bids $\{b_{ij}^*\}$ the advertiser $i$ has the same marginal ROI at $b_{ij}^*$ across all keywords
  - They propose a bidding heuristic based on that fact, so they change each keyword bid based on the ROI performance of the previous day. Their system converges to its market equilibrium in the case of the first price mechanism with a single slot *when everybody adopts the proposed perturbed bid solution*

# Autonomous Bidding Agents

- Autonomous Trading Agents
  - Such agents must interact directly with other (human or automated) market participants, and so the behavior of these participants must be taken into account when designing *agent strategies*.
    1. Game-theoretic approach of finding an equilibrium
    2. Empirical approach of using *historical market data*
- The Trading Agent Competition - Ad Auctions (TAC/AA) game investigates complex strategic issues found in real sponsored search auctions through a simulation of the general auction process [Patrick R. Jordan and Michael P. Wellman. *Designing an Ad Auctions Game for the Trading Agent Competition*. 2010, In Agent-Mediated Electronic Commerce]

# Machine Learning Strategies

- Genetic Algorithms
- Artificial Neural Networks
- Particle Filters
- Mechanisms of Reinforcement Learning
  - Decision theory – Maximum Expected Utility
  - Find a proper utility function for the optimization
  - How an *agent* ought to take *actions* in an *environment* so as to maximize some notion of cumulative *reward*
  - Highly related to *dynamic programming* techniques

# Particle Filter [Tac Tex 09]

- Particle Filter or *sequential Monte Carlo method*
- They used it in order to *estimating the bids of other advertisers given periodic reports*
  - Search engines do not actually provide advertisers with periodic reports of the bid rankings of other advertisers (!)
- So they used also another approach: The problem they are trying to solve is a *conditional density estimation problem*
  - Learn a model that takes as input both a bid amount *b* and a set of features representing the current *state*, and outputs the probability that the advertiser's next bid is less than or equal to *b*. Thus by evaluating this model for different values of b, they build the cumulative distribution function for the advertiser's next bid for any given state

# Reinforcement learning

1. Q-Learning
   - Before learning has started, Q returns a fixed value, chosen by the designer. Then, each time the agent is given a reward (the state has changed) new values are calculated for each combination of a state s from S, and action a from A.
   - The core of the algorithm is a simple value iteration update. It assumes the old value and makes a correction based on the new information

$$Q(s_t,a_t) \leftarrow \underbrace{Q(s_t,a_t)}_{\text{old value}} + \underbrace{\alpha_t(s_t,a_t)}_{\text{learning rate}} \times \left[ \overbrace{\underbrace{R_{t+1}}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \underbrace{\max_{a_{t+1}} Q(s_{t+1},a_{t+1})}_{\text{max future value}}}^{\text{learned value}} - \underbrace{Q(s_t,a_t)}_{\text{old value}} \right]$$

   - Use an (adapted) artificial neural network as a function approximator
2. The Multi-armed bandit problem for a gambler is to decide which arm of a K-slot machine to pull to maximize his total reward in a series of trials
   - The objective is to maximize the sum of the collected rewards
   - The bandit problem is formally equivalent to a one-state Markov decision process

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1. R. Jordan and M. P. Wellman. Designing the Ad Auctions game for the Trading Agent Competition. In Agent-Mediated Electronic Commerce: Designing Trading Strategies and Mechanisms for Electronic Markets, Lecture Notes in Business Information Processing. Springer-Verlag, 2010.

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3. Stuart Russell and Peter Norvig. Artificial Intelligence: A Modern Approach (Third edition)

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7. D. Pardoe, D. Chakraborty, P. Stone, TacTex09: Champion of the First Trading Agent Competition on Ad Auctions

8. P. Stone, R.E. Schapire, J.A. Csirik, M.L. Littman, D. McAllester, ATTac-2001: A Learning, Autonomous Bidding Agent

9. Joannès Vermorel and Mehryar Mohri. 2005. Multi-armed bandit algorithms and empirical evaluation. In Proceedings of the 16th European conference on Machine Learning (ECML'05)

# Predicting Clicks, CTR, or other metrics (for auctioneers)

- KDD CUP 2012 - Track 2 - User Click Modeling based on Search Engine Log Data: CTR Prediction Task
  1. Bayesian & Probabilistic Approaches
  2. Neural Networks
  3. **Boosted Regression Trees**
- Evaluation: How to measure model accuracy in click prediction?
  1. Click Perplexity: it is computed for binary click events at each position of a query session independently
     - Smaller perplexity value indicates a better prediction
  2. Area Under Curve (AUC): probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one.

# Click Modeling Features

- Demographic/user features
- BM25
- WordsFoundUrl,Title,Body of Ad-text
- Ad Quality
- CurrentPosition
- Etc…

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2. Zeyuan Allen Zhu, Weizhu Chen, Tom Minka, Chenguang Zhu, and Zheng Chen. 2010. A novel click model and its applications to online advertising. In *Proceedings of the third ACM international conference on Web search and data mining* (WSDM '10). ACM, New York, NY, USA, 321-330.

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4. Thore Graepel, Joaquin Quiñonero Candela, Thomas Borchert, Ralf Herbrich: Web-Scale Bayesian Click-Through rate Prediction for Sponsored Search Advertising in Microsoft's Bing Search Engine. ICML 2010: 13-20

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7. Ying Zhang, Bernard J. Jansen, and Amanda Spink. 2009. Identification of factors predicting clickthrough in Web searching using neural network analysis. *J. Am. Soc. Inf. Sci. Technol.* 60, 3 (March 2009)

8. Stephen Tyree, Kilian Q. Weinberger, Kunal Agrawal, and Jennifer Paykin. 2011. Parallel boosted regression trees for web search ranking. In *Proceedings of the 20th international conference on World wide web* (WWW '11).

# Performance Evaluation of Advertiser's Strategies

- Evaluation Metrics? → ROI (Clicks/Monetary Profit?)

1. In [B. K. Szymanski and J. Lee. Impact of ROI on Bidding and Revenue in. Sponsored Search Advertisement Auctions.] considering minimum ROI, advertisers change their bidding and consequently the auctioneer's revenue

2. In [A. Ghose and S. Yang. 2008. An empirical analysis of sponsored search performance in search engine advertising. WSDM '08] empirically model the relationship between different metrics such as CTR, Conversion rates, bid prices and keyword ranks
   - The presence of retailer-specific information in the keyword increases CTR
   - The presence of brand-specific information in the keyword increases conversion rates

# Advertising on New Channels and Infrastructures

1. Location-based Advertising & Ads on Mobile Devices
2. Real time bidding for Ad Exchanges, Demand Side Platforms
3. Advertising on Social Networks
4. Trust in the channel

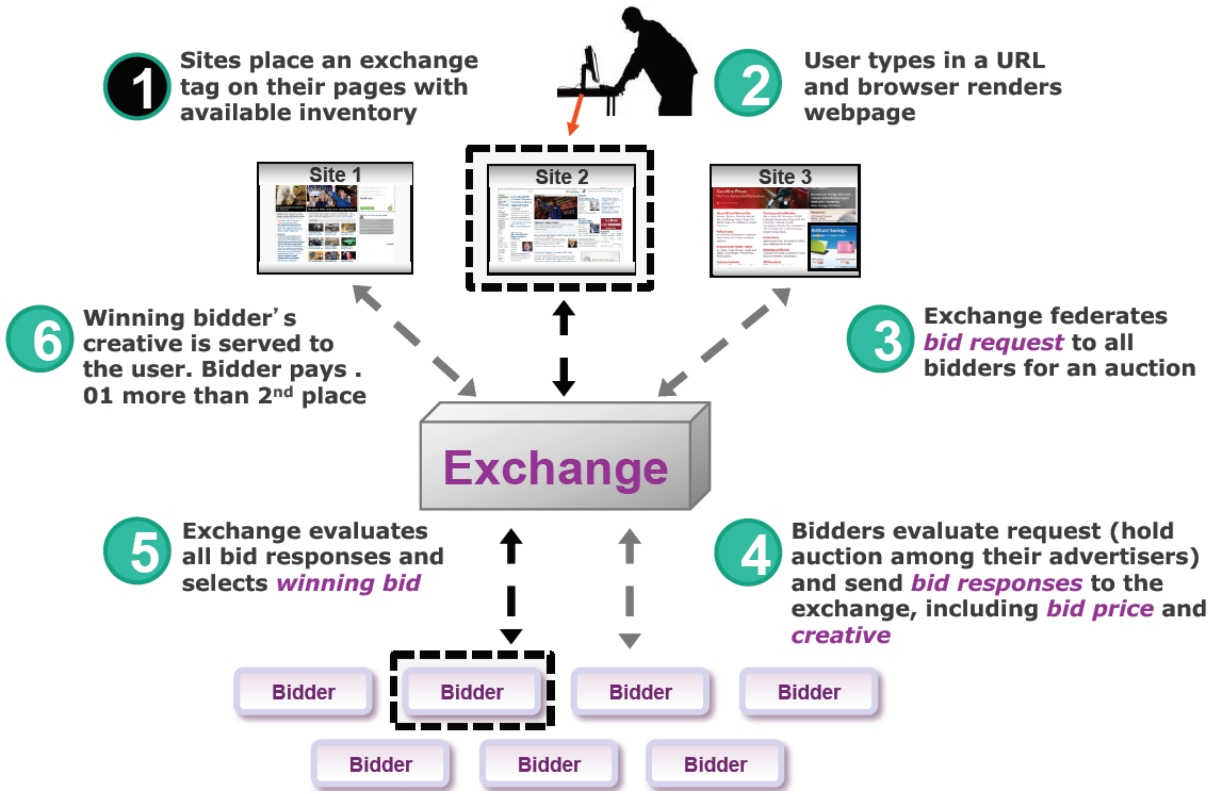
# Location-based Advertising & Ads on Mobile Devices

- Market Trends: Mobile phones and Tablet Market
  - Web Usage Mining/Analytics for Mobile Tracking & E-commerce reporting
- In [P. Zhao, D. Lymberopoulos, A. C. König, K. Berberich, J. Liu: Location-aware Click Prediction in Mobile Local Search, CIKM 2011] propose a set of location-aware features to efficiently capture the *variance* of mobile click behavior across locations in the click prediction model
  - Features: Country, state, zip code, traveling distance, business popularity
  - They used MART [Q. Wu, C. J.C. Burges, K. Svore, and J. G. October 2008. *Ranking, Boosting, and Model Adaptation*.], a learning tool based on Multiple Additive Regression Trees
  - Click prediction: proxy for ranking quality. Features that help improve click prediction will be useful in ranking as well.

# Specific features (and targeting dimensions) for mobile advertising [Introduction to Computational Advertising, Course Slides 2011, Stanford ]

- High precision demographics
  - Billing address, subscription plan, monthly charges, credit history, SMS habits, etc.
- Location
  - Geo (GPS or tower triangulation)
  - Location functionality: Shopping mall, at home, airport, etc
  - Personal context: working, on vacation, etc
- Social context
  - Alone, with colleagues, with family, with friends, travelling, …
- Language
- Device model, capabilities, OS, installed apps (?)
- Time of day
- Speed (walking vs. driving)
- Recent history
- Page orientation, number of scrolls, etc.
- Specific application data (e.g. music tastes)

# Real time bidding for Ad Exchanges, Demand Side Platforms [James Shanahan. *Digital Advertising and Marketing: A review of three generations*. Tutorial on WWW 2012]

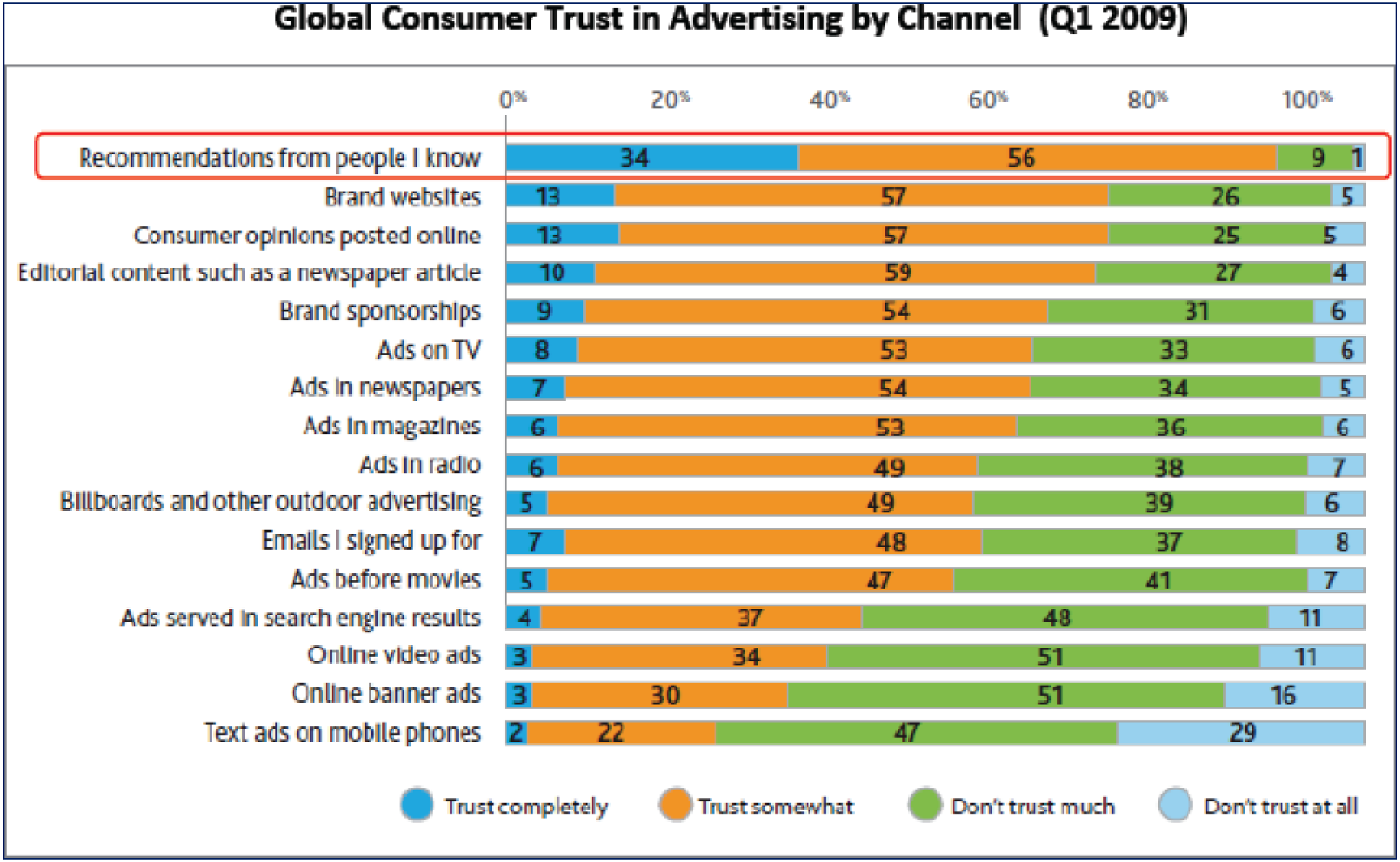



- A demand-side platform (DSP) is a system that allows digital advertisers to manage multiple ad exchange and data exchange accounts through one interface.
- Real time bidding for displaying online ads takes place within the ad exchanges, and by utilizing a DSP, marketers can manage their bids for the banners and the pricing for the data that they are layering on to target their audiences. Much like Paid Search, using DSPs allows users to optimize based on set Key Performance Indicators such as Cost-per-clicks, and Cost-per-action.

# Advertising on Social Networks

- Social Network Campaigns
  - Same basic structure for Facebook advertising campaigns
  - Generated text as a promotion tweet for Twitter
- Corporate Reputation Mining for the advertised products/services/brand names
  - Opinion Mining from web pages with *reviews*

# Trust in the channel

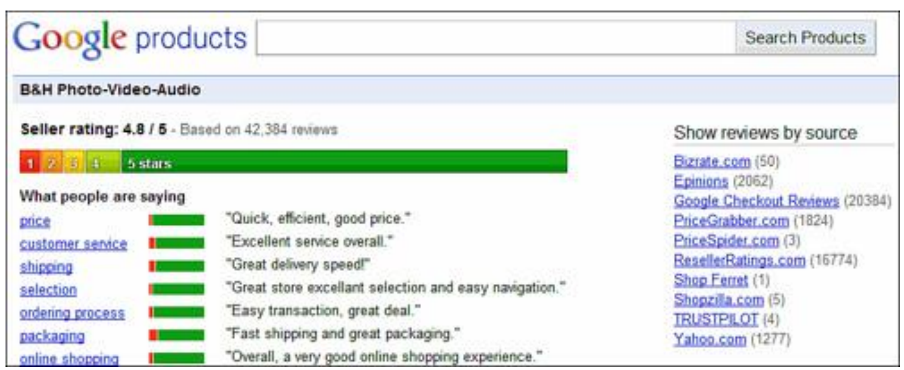



Source: The Nielsen Company: Social Media Insights: October 2009

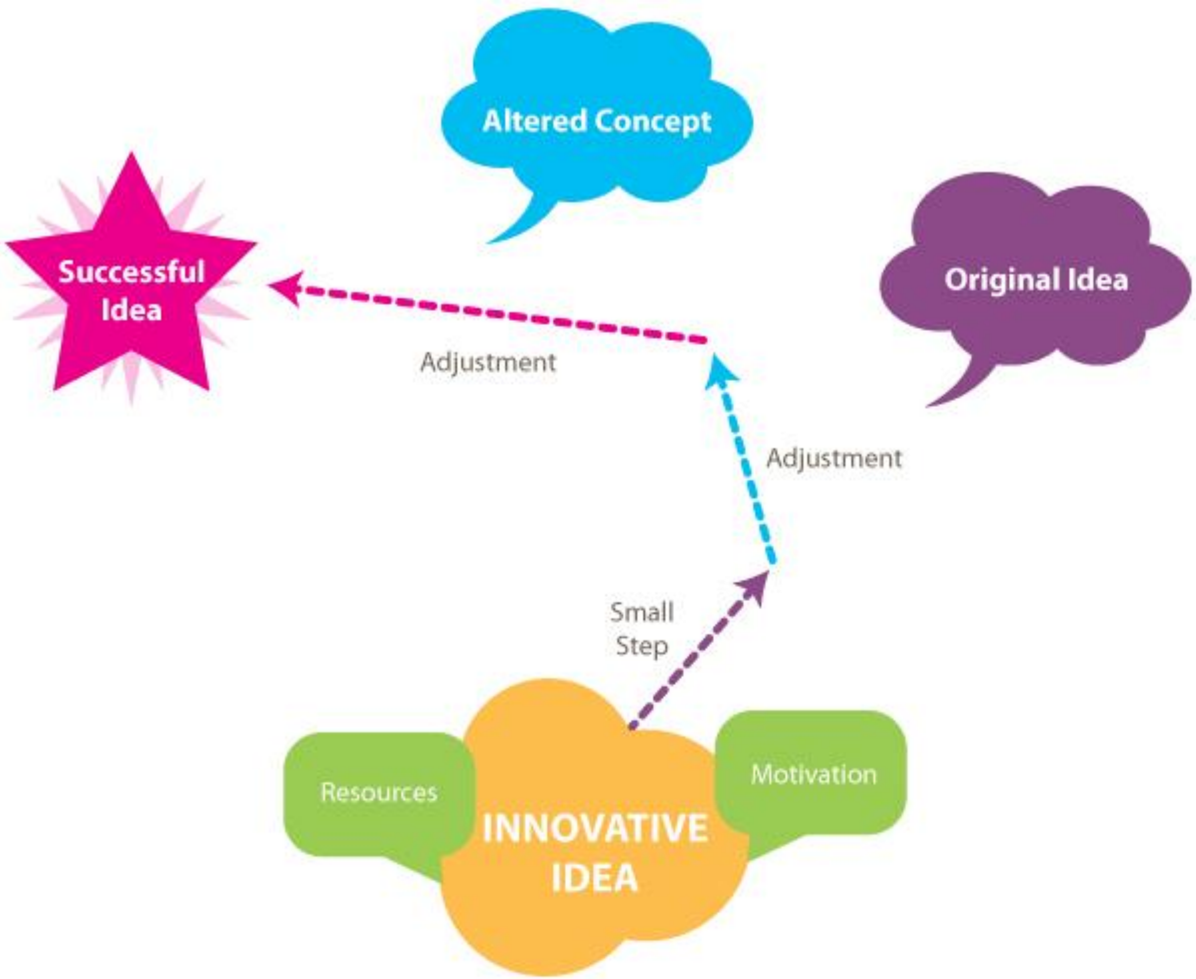
# How Reviews Impact AdWords

- Social signals outside of CTR in AdWords SERPs are contained within rich snippets, and specifically product reviews


Note the confidence-inspiring five stars: good stuff for the advertiser. If we click through the rated button we see more information about the advertiser…



# Challenges



Altered Concept
Successful Idea
Original Idea
Adjustment
Adjustment
Small Step
Resources
INNOVATIVE IDEA
Motivation

# Knowledge & Feature Management

1. Automated Feature Generation for Campaigns
   - “GrammAds”: Keyword and Ad Creative Generator for Online Advertising Campaigns – a brief summary of our system
2. Integrated dataset of features of advertising campaigns – Feature Selection
   - Initial setting of campaign parameters

# "GrammAds": Keyword and Ad Creative Generator for Online Advertising Campaigns

- (1) Proposes valid and representative keywords for a landing page through keyword extraction, co-occurrence between terms, and keyword suggestion from search result snippets [S. Thomaidou, M. Vazirgiannis. Multiword Keyword Recommendation System for Online Advertising. In *Proceedings of the 2011 International Conference on Advances in Social Network Analysis and Mining* (ASONAM '11), Kaohsiung, Taiwan. IEEE Computer Society] (Demo Link: GrammAds)

**ALGORITHM 1:** Ad-text automatic creation

**Input**: Landing Page HTLM Document $d$, $t$ the target of the advertisement
**Output**: An ad-text
Let $\lambda$ be the length of a sentence in characters
Let $\phi$ be the set of the action phrases
$limit_1 = 25, limit_2 = 35$
$\triangleright$ Choose a proper action phrase $p_{action} \in \phi$ with respect to $t$
$p_{action} \mapsto t$
$bidPhrase \leftarrow keywordGenModule(url_{destination})$
$\triangleright$ Retrieve the first phrase of the title until the first punctuation
$title = < p_1, p_2, \ldots, p_n >$
**if** $\lambda_{p_1} < limit_1$ **then**
    $head \leftarrow p_1 \cap bidPhrase$
**else**
    $head \leftarrow bidPhrase$
$head \leftarrow capitalizeFirstLetterOfGrams(head)$
$\triangleright$ Summarise $d$ in 1 sentence using Bayesian classifier
$d_{summary} \leftarrow summariser(d, 1)$
$d_{summary} = < s_1, s_2, \ldots, s_N >$
**while** $\lambda_{\bigcap_{i \in N} s_i} \leq limit_2$ **do**
    $dl_1 \leftarrow \bigcap_{i \in N} s_i$
**end**
**while** $\lambda_{(\bigcap_{k \in N} s_k) \cap p_{action}} \leq limit_2$ **do**
    $dl_2 \leftarrow \bigcap_{k \in N} s_k$
**end**
**if** $s_{final}$ *is a stopword* **then**
    remove $s_{final}$ from $dl_2$
$dl_2 \leftarrow (dl_2 \cap p_{action})$
$url_{display} \leftarrow "www." \cap p_1 \cap ".com"$
$adText \leftarrow (head \cap dl_1 \cap dl_2 \cap url_{display})$
**return** $adText$

(2) Automatically generates ad-texts through a *generic summary* approach

# Automated Ad-text Generator Ideas

1. Paraphrasing methods, sentence extraction and compression, sentence and surface realizers, text summarization [Ion Androutsopoulos and Prodromos Malakasiotis. 2010. *A survey of paraphrasing and textual entailment methods*. J. Artif. Int. Res. 38, 1 (May 2010), 135-187. ] [Dimitrios Galanis and Ion Androutsopoulos. 2010. *An extractive supervised two-stage method for sentence compression*. In Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics (HLT '10).]

or / and

2. Combination with category specific *templates* which will be filled with the product characteristics, such as name, price, location, etc. The above features will be extracted from customer's web page primarily

# Campaign Settings & Features

- Expansion for the Keyword Generator
  - Automatic setting of the proper *matching option* for each generated keyword - *Clustering* of keywords
    - Broad Match
    - Phrase Match
    - Exact Match
    - Negative Keyword

# Initial Setting of Campaign Parameters

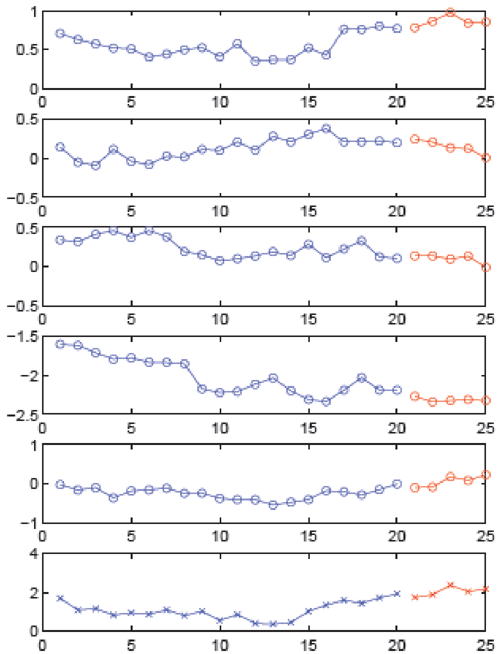
- Until now ⟶ Settings for Textual Ads & Sponsored Search only
- Should we considered more input features for initialization of campaign parameters? – *more targeting*
- AdWords Campaign Settings
  - Location, Language
  - Networks, Devices
  - Ad scheduling (e.g. only show ads at selected times)
  - Demographic options for Display Network

# Predicting Campaign Behavior (1)

- Preliminary experiments
  - Multiple Linear Regression
    - Depended variable: Impressions
    - Predictors: Clicks, GMS, Competition
- M5P (decision tree algorithm ) [Quinlan J. R. (1992). Learning with continuous classes. Proceedings of the Australian Joint Conference on Artificial Intelligence. 343--348. World Scientific, Singapore] [Wang, Y and Witten, I. H. (1997). Induction of model trees for predicting continuous classes. European Conference on Machine Learning, Prague]
  - Prediction of Clicks given as attributes
    - Maxcpc (Bid), Cost (!) , Quality Score, GMS, Competition
- Should we focus on predicting the proper bid given desired Clicks or Monetary Profit/Conversions?
  - Or simulating/forecasting Clicks or CTR given bid?
    - Knowing values of state *t-1* can we predict values of state *t*?

# Predicting Campaign Behavior (2)

- Predicting return – Linear Parameter Models for Regression



Predicting stock return using a linear LPM. The top five panels present the inputs $x_1, \ldots, x_5$ for 20 train days (blue) and 5 test days (red). The corresponding train output (stock return) $y$ for each day is given in the bottom panel. The predictions $y_{21}, \ldots, y_{25}$ are the predictions based on $y_t = \sum_i w_i x_{it}$ with $\mathbf{w}$ trained using ordinary least squares. With a regularisation term $0.01\mathbf{w}^\mathsf{T}\mathbf{w}$, the OLS learned $\mathbf{w}$ is $[1.42, 0.62, 0.27, -0.26, 1.54]$. Despite the simplicity of these models, their application in the finance industry is widespread, with significant investment made on finding factors $\mathbf{x}$ that may be indicative of future return.

(Example from David Barber, 2012. Bayesian Reasoning and Machine Learning)

- States
  - Markov Property *state t-1* $\rightarrow$ *state t*
  - Hidden Markov Models – predict transitions in keyword state

# Optimization and Maximization of Campaign Objective Functions

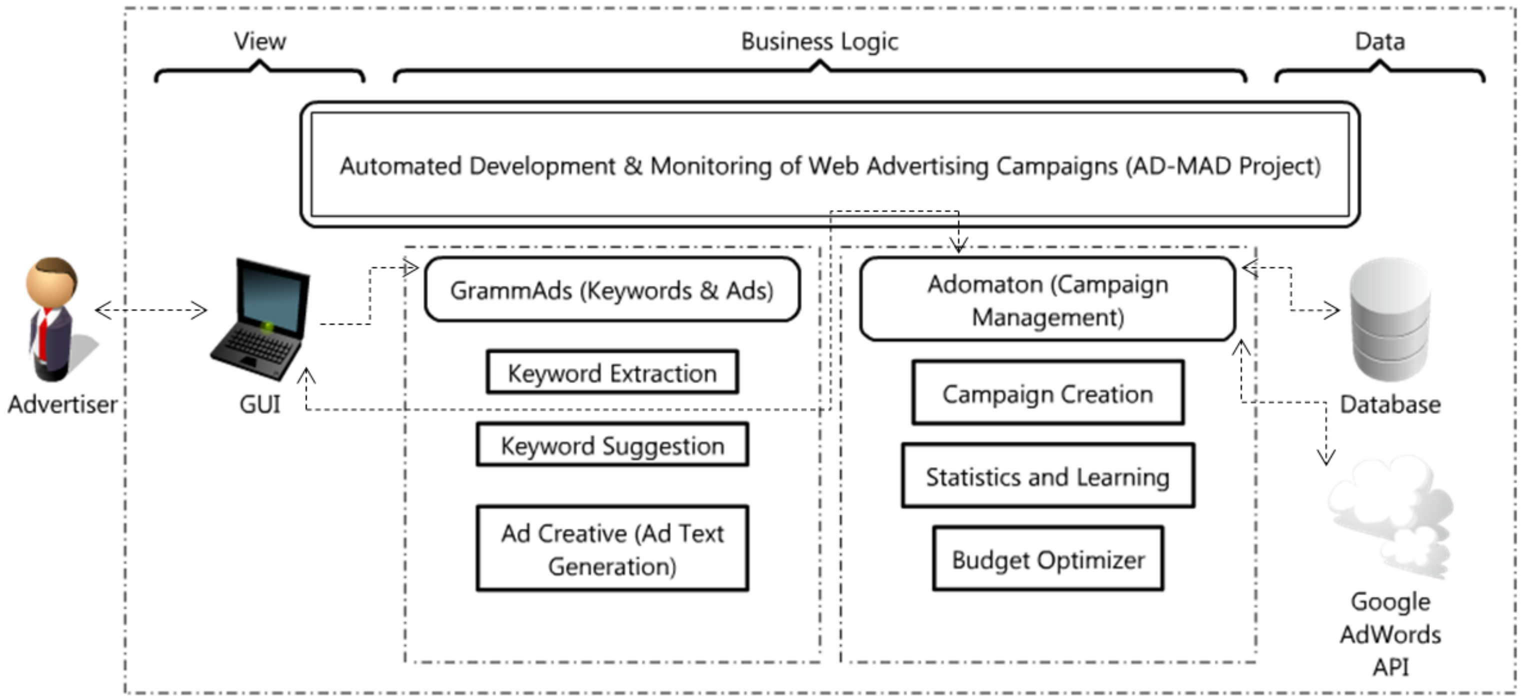
- *Adomaton*: Initializing, monitoring, and managing the advertising campaigns in the course of time, based on keyword statistics maintained by the system, in the view of *optimizing* available budget. [K. Liakopoulos, S. Thomaidou, M. Vazirgiannis.The Adomaton Prototype: Automated Online Advertising Campaign Monitoring and Optimization, In Ad Auctions Workshop, 13th ACM Conference on Electronic Commerce 2012]
  - Goal: Maximizing Traffic (Clicks) or Monetary Profit (given a profit per sale/conversion)
  - Bidding Strategy: Genetic Algorithm
    - A final list of keyword-bid pairs *(k,b)* is produced from the fittest chromosome.
  - Impressions Prediction through Multiple Linear Regression

$$[Clicks(k_i, b_i), GMS(k_i), Competition(k_i)] \quad ? \rightarrow Impressions(k_i, b_i)$$

# Some issues regarding GA strategy

- We evaluate the fitness of one strategy per time period using the described algorithm. So, the exploration vs exploitation process is over the modeled space of keyword-bid pairs, not actually evaluating *multiple strategies per period* in the real market
  - Classic approach: Linear programming: Mixed Integer Programming (MIP) problem
- Need to apply multiple alternative algorithms, articulate the tradeoffs, and illustrate them in the application

# AD-MAD System Architecture



# More aspects of Campaign Optimization

- Not a static process (specific bidding strategies) but constant change of settings and parameters – Dynamic models need to follow certain *trends*
- Finding trending topics for bidding on new queries
  - Query/keyword expansion, synonyms and relevant keywords with the content of the campaign and how we can bid on seasonal searches, trending queries, etc.
- Scheduling ads for special promotions or events
  - *Automated rules*: new option on AdWords

# ROI Evaluation

- Capital Allocation: Did our investment achieve the desired results in respect to the given goals?
  - Proper evaluation metrics
- Google Analytics
  - Comparison with traffic from organic results or direct traffic
  - More features for Behavioral Targeting

# Summary

- There is space for further research from a machine learning approach due to system complexity
- Discover the proper features and exploit them to adjust the bid value
- Need for a good, organized dataset for our purposes
- Simulations as an initial evaluation of a bidding strategy or prediction task and then apply it to real world conditions and environment
- Online learning problems – Difficult to find a precise evaluation function for continuous involving/dynamic models

# Ongoing Work

1. Find an alternate bidding strategy
   - e.g. a Reinforcement Learning method such as Contextual Bandit Learning [Lihong Li et al. *A contextual-bandit approach to personalized news article recommendation.* WWW 2010] or Q-learning
   - Simulation using for example the server infrastructure of the Trading Agent Competition Ad Auction game (TAC/AA)
2. Click or *bid* prediction using advertiser's campaign statistical data and external factors
   - Dataset: Past campaigns from Google Online Marketing Challenge DB-NET team participation (semi-finalists), 39 weeks car rental company campaign, etc.
     - Could be A3 Yahoo! Dataset from Webscope any useful?

# Thank you! ☺

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