The Adomaton Prototype: Automated Online Advertising Campaign Monitoring and Optimization

8th Ad Auctions Workshop, EC'12

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Basic Online Advertising Campaign Problems

Campaign Concepts

Products

- Products have landing pages

Keywords, Ad-Text

- Keywords needed for bidding, relevant to the landing page
- Ad-text

Campaign Management

- Campaigns need to be created and configured
- Keyword bidding needs to be optimized regularly

Objectives

Keywords and Ad Creatives

- Generate keywords & ads that best describe products

Campaign Creation and Optimization

- Select best keywords to optimize monetary profit or traffic
- Automatically repeat optimization in regular time intervals

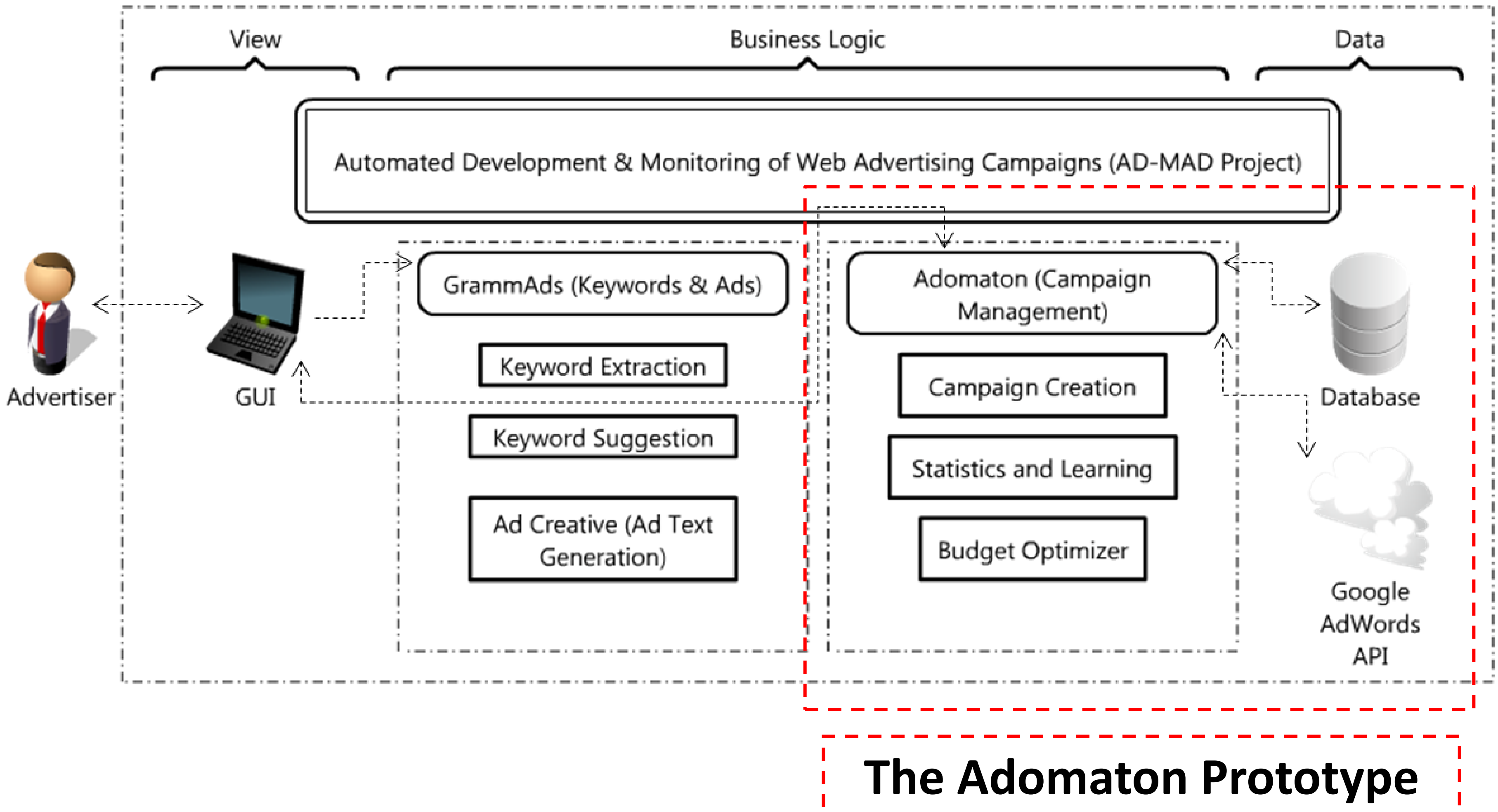
Budget Optimization for Multiple Keywords

- Find a bidding strategy for the advertiser that maximizes his profit
- The budget of an advertiser needs to be split among several keywords
- Simple or Weighted Keyword Bidding Problem [1] similar to Conversions (Monetary Profit)
- Budget optimization is strongly NP-hard
  Approximate solution – Stochastic models
- Autonomous Bidding Agents
- Lack of experimentation in real-world campaign data

Our Approach

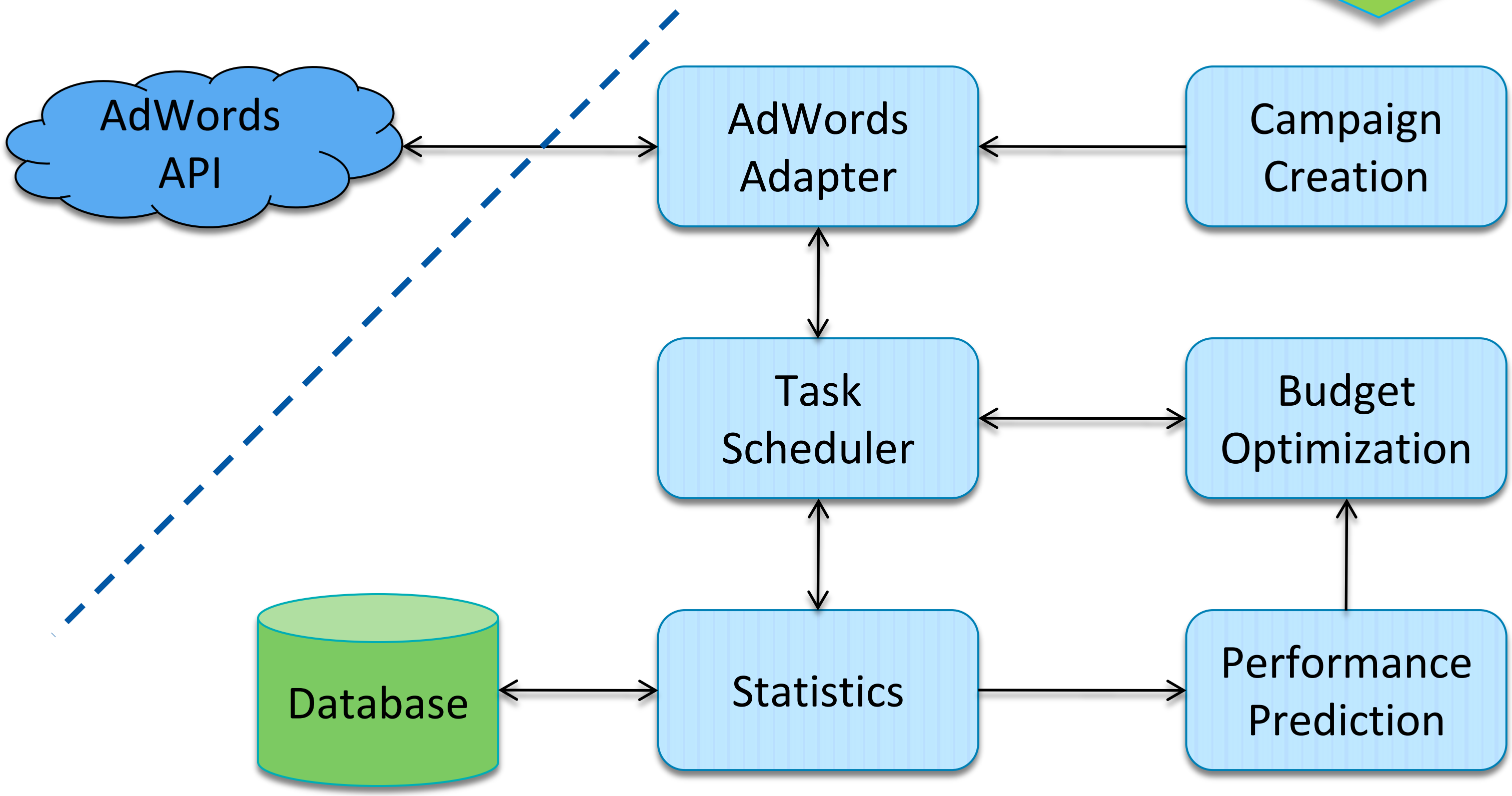
- **Automate** all the actions that need to be done for the campaign
- Bidding Strategy : Formulate the process as a *Multiple Choice Knapsack Problem* – Solve it with **Genetic Algorithm**
- Exploit *external information* from the ad auctions using **Impressions Prediction**
- Experiment in *real-world campaign data*: **Google AdWords** and its API

AD-MAD System Architecture



Adomaton Modules Communication

Communication with *GrammAds*- Settings:
Advertising Goal, Total Campaign Period & Budget, Location, Language, Network (Only Google Search and not Display Network due to lower CTRs – lower Quality Score)



Input Parameters for the Optimization Model

- The advertising agent has the role of an investor
- The capital is the total budget *B* for the period that the campaign is active
- The profit from the conversions or clicks for each investment is represented as *v*
  1. *Value for monetary profit*

     $$v(k,b) = Revenue(k) * CR(k,b) * Clicks(k,b) - w(k,b)$$

  2. *Value for traffic*

     $$v(k,b) = Clicks(k,b)$$

- The cost that the advertiser is finally charged for a specific investment is *w*
  - *Weight*

    $$w(k,b) = \overline{CPC}(k,b) * Clicks(k,b)$$

  where *k*: keyword , *b*: bid, *CR*: Conversion Rate, *CPC*: Cost-per-click

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Multiple-choice knapsack problem formulation

- Investment : Final item *x* which is a pair *(k, b)*
- The advertiser has *j* options of *(k,b)* candidate pairs
  - Only *one pair per investment* for his final proposal
- Total number *N* of the final chosen investments = *r* available keywords of the campaign
- Our objective:

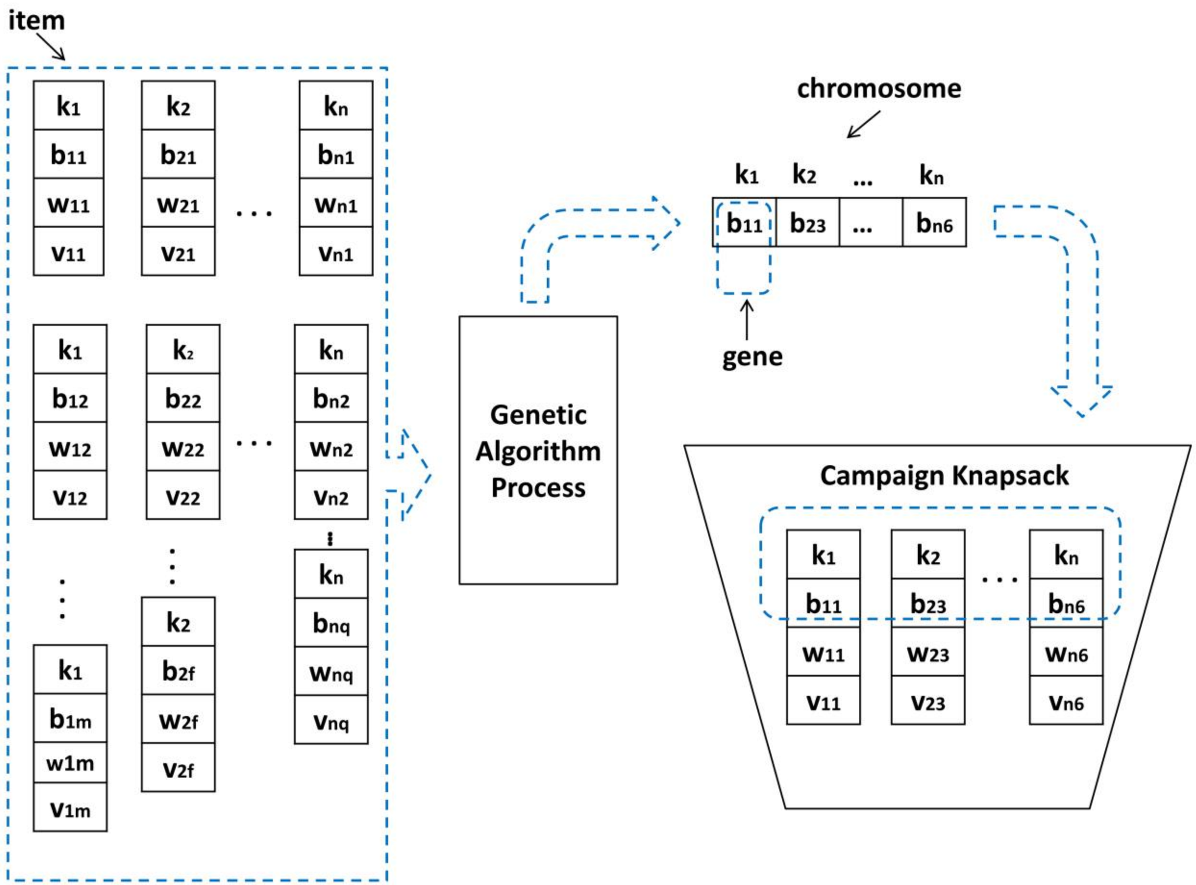
$$\text{maximize} \quad \sum_{i=1}^{r} \sum_{j \in N_i} v_{ij} x_{ij}$$

$$\text{subject to} \quad \sum_{i=1}^{r} \sum_{j \in N_i} w_{ij} x_{ij} \leq B$$

$$\text{with} \sum_{j \in N_i} x_{ij} = 1, \text{ for all } 1 \leq i \leq r$$

$$\text{and } x_{ij} \in \{0, 1\}, \text{ for all } 1 \leq i \leq r \text{ and all } j \in N_i$$

Mapping of campaign system to the MCKP



- Items: options of keyword-bid pairs along with their profit *v* and cost *w*
- Chromosome ≡ Set of selected items

Why Genetic Algorithm?

- Deterministic methods will always find the same approximate solution in each run – choosing persistently certain keywords
  - Adapt much slower than a method with Exploration / Exploitation
- GA: Finds an approximately optimal solution
- Stochastic approach: Selection and mutation are based on probability and randomness
- Flexibility
  - Discover faster changes of keywords performance

Parameters Initialization

- Keywords and Bids
  - Define a default initial bid for all keywords that are going to be tested $b_{initial} \leftarrow maxEstimatedFirstPageBid$
  - For each landing page: AdGroup with Keywords, Ad-text
- Advertising goal
  - Optimization for monetary profit or traffic?
    1. Value = Actual Profit = Revenue from conversions – Cost or
    2. Value = Profit from traffic = Clicks

Tasks

First Testing Period

- Make a subset of the most relevant *n* keywords of each adgroup for testing (bid $b_{initial}$)
- Collect Statistics

Second Testing Period

- Make a new subset of the next most relevant *n* keywords of each adgroup for testing (bid again binitial)
- Make a random change in $m<<n$ keyword bids from the previous subset
  ($b_{new} = b_{previous} \pm b_{previous}$ x 50%)
- Collect Statistics
- *m, n* proportional to the total amount of keywords of a campaign

Perform Optimization

Next Testing Period

Genetic Algorithm Formulation (1/2)

- A possible solution is modeled as a **chromosome**

k1	k2	k3	…	kN
€0.60	€0.00	€0.45	…	€0.50

- Chromosome Fitness Function: Total profit expected for the bids selected in the genes

1. *Start*
   - Generate random population of *m* chromosomes
   - Chromosome representation: N genes, N being the number of available keywords

Genetic Algorithm Formulation (2/2)

2. *Fitness*
   - Evaluate the fitness f(x) of each chromosome x: $\sum \boldsymbol{v}(\boldsymbol{k}, \boldsymbol{b})$
   - Generated chromosome must pass the $\sum w(k, b) \leq B$ condition, otherwise randomly genes will be set to 0 until the condition is met
3. *New Population*
   - *Selection, Crossover, Mutation, Accepting*
4. *Replace*: Use new generated population for a further run
5. *Test*
   - *End condition:* Max Allowed Evolutions $\longleftarrow$ 3000
6. *Loop*

Optional Step: Impressions Prediction

- Google AdWords provides information such as
  - *Global Monthly Searches (GMS)*
  - *Competition* of a keyword
- Clicks, CTR, CR more dependent to inner factors (e.g. Relevance, Quality)
- Impressions more dependent to external factors
- Multiple Linear Regression: $y' = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$
  - Y: Impressions
  - X1: Clicks, X2: GMS, X3: Competition

Alternate evaluation of the fitness function of each chromosome in the population - Take into consideration *predicted values* instead of *actual past ones*

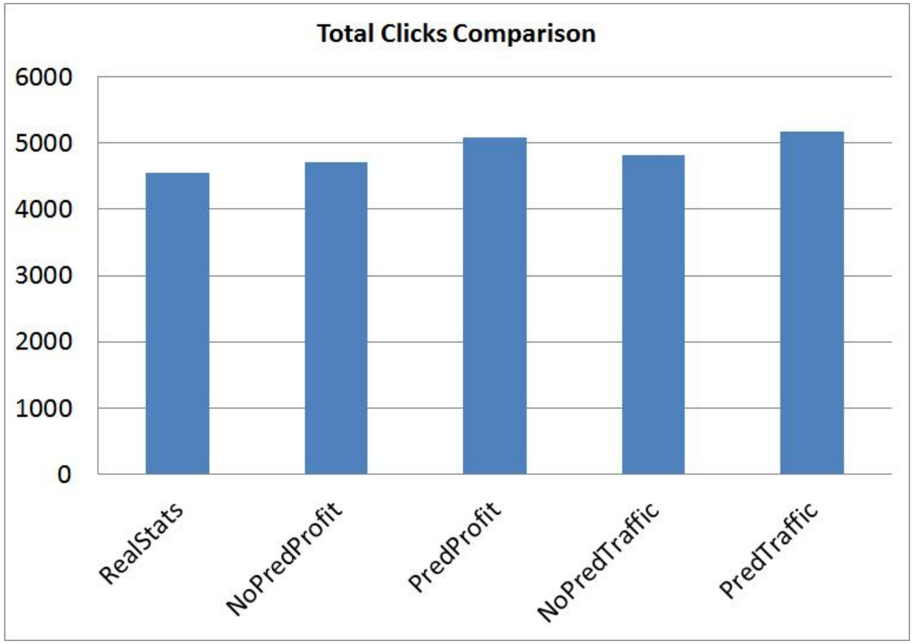
Performance Evaluation on Historical Data

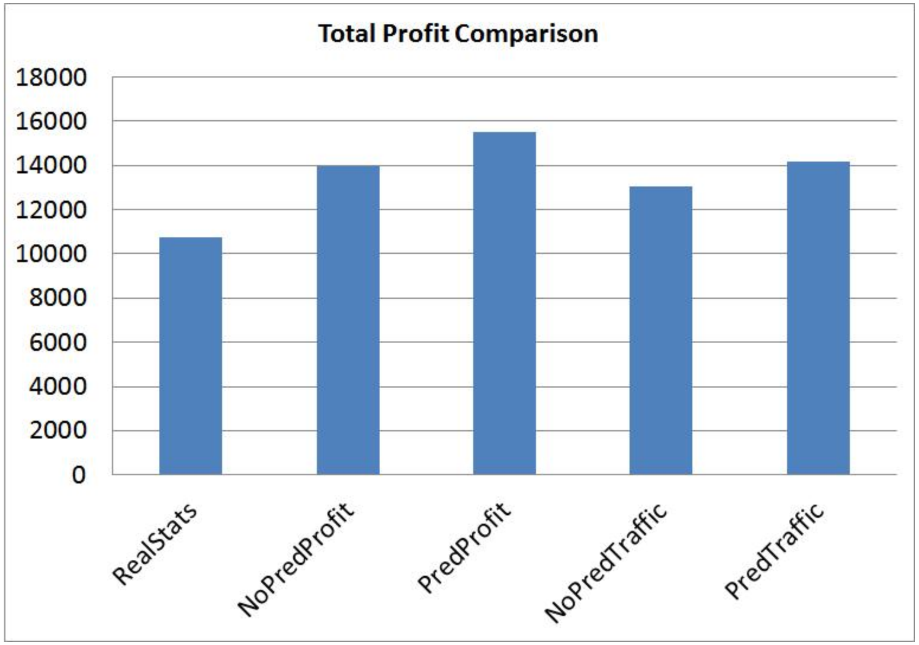
- Large scale AdWords Campaign of a web site in the area of car rental – Statistics for 39 weeks

- Four basic testing scenarios:
  1. Budget Optimization for Profit with No Prediction(NoPredProfit)
  2. Budget Optimization for Traffic with No Prediction(NoPredTraffic)
  3. Budget Optimization for Profit With Prediction (Pred-Profit)
  4. Budget Optimization for Traffic With Prediction (Pred-Traffic)

- Simulation: Metrics are computed as if CTR, clicks, costs, impressions were maintained the same for each *(k,b)* choice in the future

Weekly performance Evaluation compared to RealStats

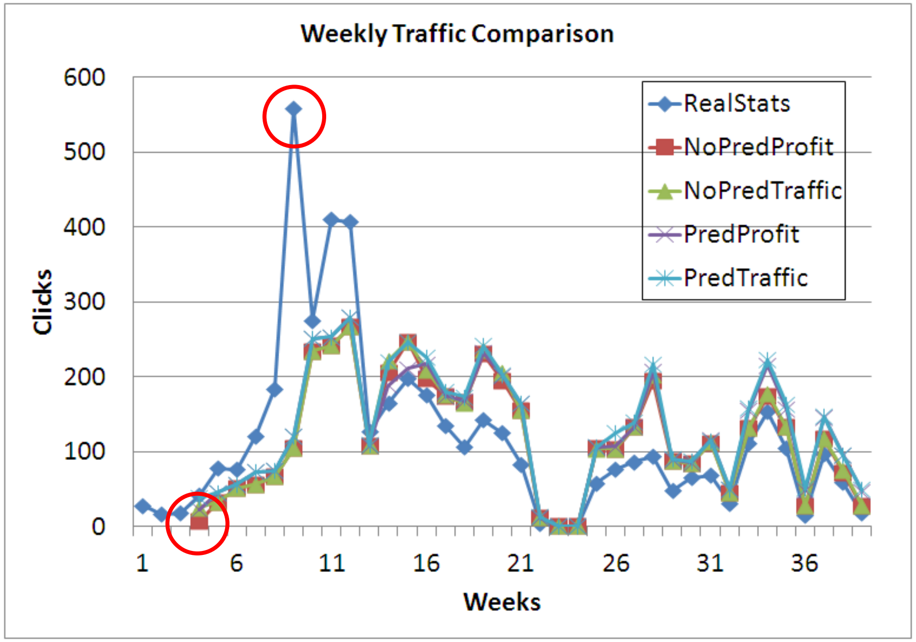


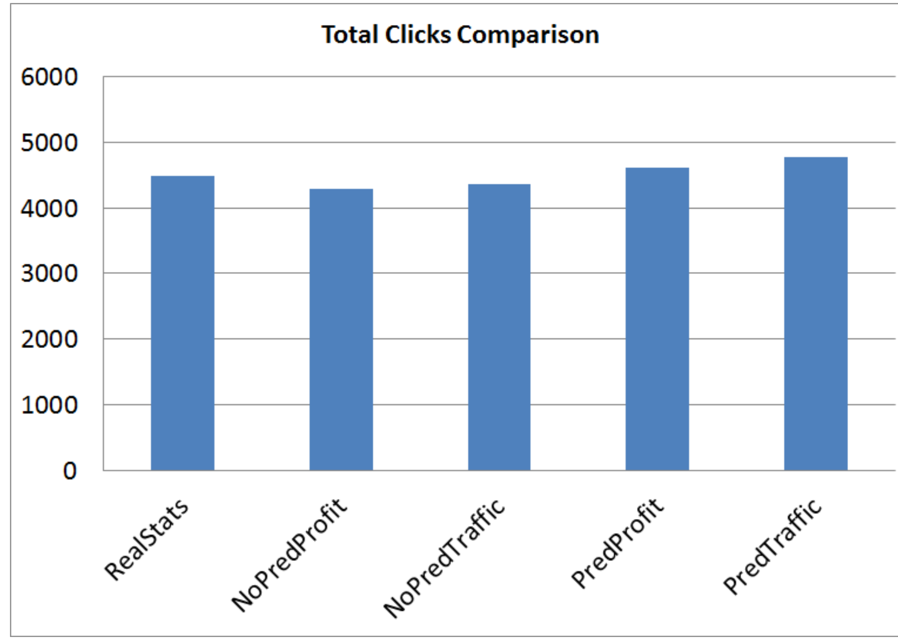


- We apply GA to evaluate the hypothesis of choosing the optimal keyword-bid combination of each week – **taking into consideration only the real used keywords and bids of the week**

- Our methods outperform the real manual bidding strategy

GA on optimizing next week's performance





- Take into consideration *(k,b)* from weeks 1 to i-1
- The advertiser until the 3rd week had been testing very few keyword options (3-4) and the GA needed more testing data to perform a valid optimization
- Using **outdated** data does not correspond to valid calculation of receiving impressions & clicks
- Our two methods **which use prediction**, surpass the real results → capture **current external factors** and conditions of the ad auction

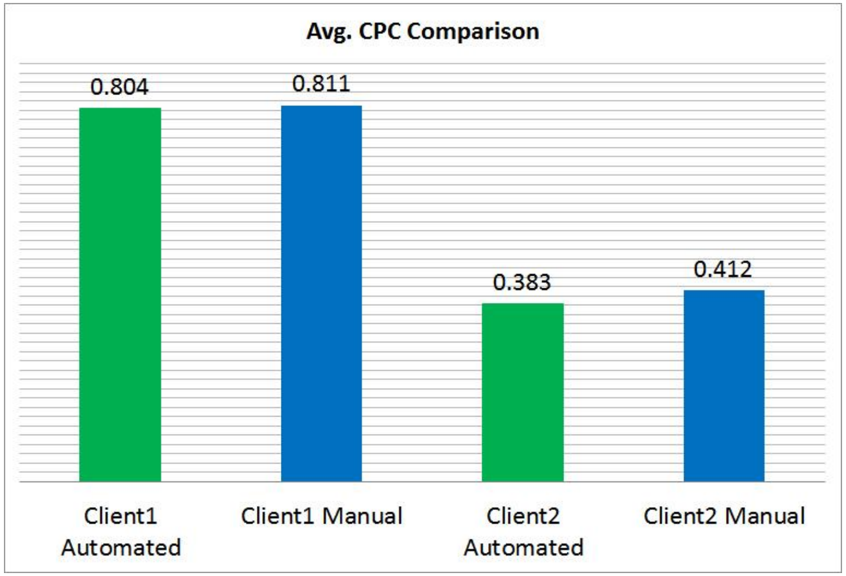
Scenario Comparison for 40th week Optimization

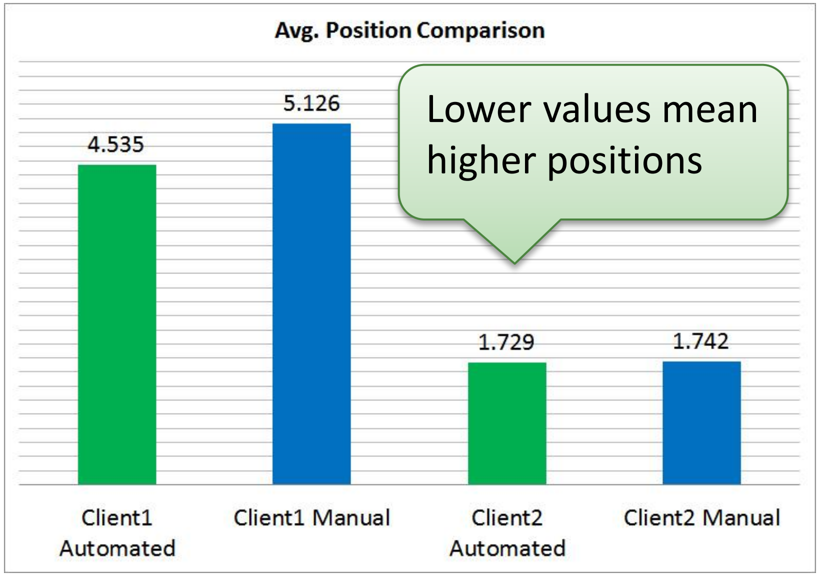
Budget = 50	Clicks	Cost	Profit	#Keywords Used	AverageBid
NoPredProfit	60	49.94	219.51	24	1.49
NoPredTraffic	61	49.93	206.22	23	1.43
PredProfit	82.36	49.90	317.1	16	1.37
PredTraffic	86.51	49.88	274.81	18	1.42
Budget = 100	**Clicks**	**Cost**	**Profit**	**#Keywords Used**	**AverageBid**
NoPredProfit	108	99.93	374.98	25	1.48
NoPredTraffic	109	99.92	356.44	26	1.44
PredProfit	130.80	99.87	467.86	20	1.41
PredTraffic	134.21	99.92	364.53	19	1.46
Budget = 200	**Clicks**	**Cost**	**Profit**	**#Keywords Used**	**AverageBid**
NoPredProfit	197	199.87	621.32	56	1.55
NoPredTraffic	200	199.90	582.21	54	1.50
PredProfit	236.94	199.86	787.63	31	1.42
PredTraffic	248.60	199.85	638.13	32	1.43
Budget = 400	**Clicks**	**Cost**	**Profit**	**#Keywords Used**	**AverageBid**
NoPredProfit	333	389.61	798.90	98	1.61
NoPredTraffic	340	399.92	791.93	102	1.63
PredProfit	425.74	399.82	1313.99	54	1.51
PredTraffic	447.42	399.90	1191.51	45	1.45
Budget = 600	**Clicks**	**Cost**	**Profit**	**#Keywords Used**	**AverageBid**
NoPredProfit	333	389.60	798.90	97	1.61
NoPredTraffic	343	405.16	795.28	107	1.63
PredProfit	607.74	599.84	1645.60	70	1.56
PredTraffic	622.69	599.82	1569.21	68	1.52

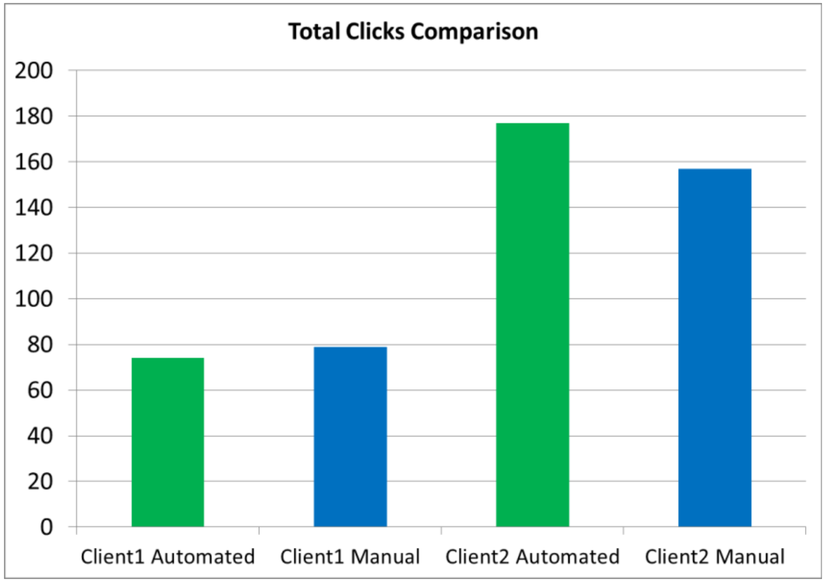
Real-time parallel competing campaigns

- Google AdWords campaigns for two companies
    1. Client1 is a company that offers web developing solutions (a highly competitive field for online advertising)
    2. Client2 is a company that offers aluminum railing and fencing products
- For each company: one manual and one automated campaign
    - Advertising Goal: Optimization for Traffic
    - Same keywords & budget in order to test only the monitoring and optimization process

Automated Campaigns VS Manual







Ongoing & Future Work

- Good basis for a larger system
- Machine Learning: Discover more external factors and proper features. Exploit them to adjust the bid value
- Compare with a deterministic method
- Test a Reinforcement Learning Bidding Strategy
  - Markov property
  - Handle properly the exploration/exploitation trade-off of keyword-bid pair tests
- Click prediction

Thank You

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Genetic Algorithm Formulation (2/2) [details]

- [Fitness] : Total profit expected for the bids selected in the chromosome genes
  - Evaluate the fitness f (x) of each chromosome x: $\sum \boldsymbol{v}\ (\boldsymbol{k}, \boldsymbol{b}\ )$
  - When a chromosome is generated it has to pass the $\sum w\ (k, b\ ) \leq B$ condition, otherwise randomly selected genes of the chromosome will be set to 0 until the condition is met
- [New Population] : Create a new population by repeating following steps until the new population is complete
  - [Selection] Select two parent chromosomes from a population according to their fitness (Weighted RWS)
  - [Crossover] With a crossover probability cross over the parents to form a new offspring
  - [Mutation] With a mutation probability mutate new offspring at each locus (position in chromosome)
  - [Accepting] Place new offspring in a new population
- [Replace] Use new generated population for a further run of algorithm
- [Test]
  - [End Condition]: Since we don't know what the best answer is going to be, we just evolve the max number of times (max allowed evolutions = 3000)
  - If the end condition is satisfied, stop, and return the best solution in current population
- [Loop] Go to Fitness Evaluation Step