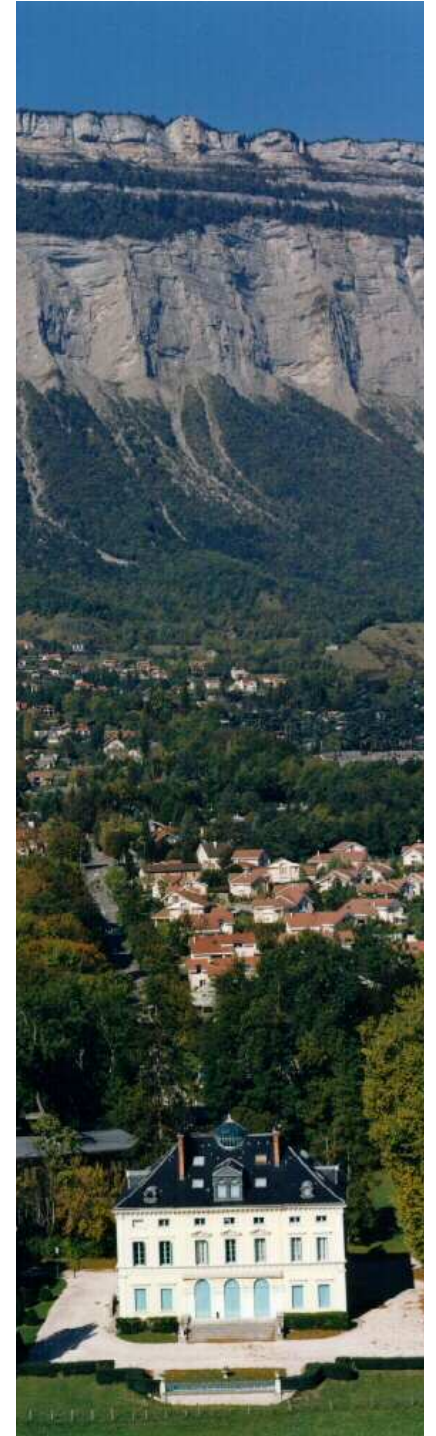


Learning optimally from self-interested data sources in on-line ad auctions

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* = large part of this work done while at
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Paid search and the GSP auction

The screenshot shows a search engine interface with the query "mortgage". The results are ranked by bid price p_i and cost-per-click c_i . Annotations include:

- Equations for bid and cost: $b_1 p_1 \geq$, $b_2 p_2 \geq$, $b_3 p_3 \geq$
- A box containing the equations: $c_1 p_1 = b_2 p_2$ and $c_1 = b_2 p_2 / p_1$
- A text box stating: "A higher estimate of p_i leads to"
 - A higher rank
 - A lower cost-per-click
- Other annotations: $b_4 p_4 \geq$ and $b_n p_n$

The search results include links to various mortgage-related websites such as Abbey, Ocean Re-Mortgage, and Money Supermarket.



Machine learning and the GSP auction

Bids b_i are observed, click probabilities p_i are not, and need to be **learned**.

Treating them as known or as point estimates leads to serious sub-optimality.



Single round approximation in GSP

When p_i are unknown optimal ad placement involves **exploring** new ads.

Example: current winner has $b_1=1, p_1=.06$.

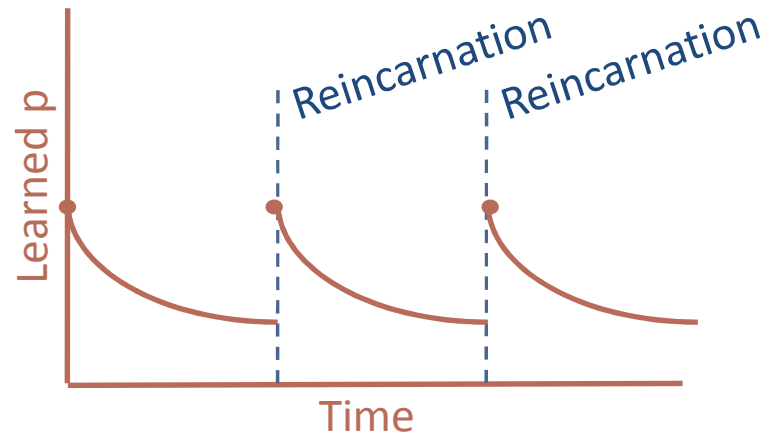
Shouldn't we try a new ad with $b_2=1, p_2=.05$?

Problem 1: GSP only cares for revenue in ***this*** round. It is **not optimal for multiple rounds.**



Advertiser cheating in GSP auctions

Problem 2: once estimate \hat{p}_i falls below initial estimate for a new ad, it is optimal for advertiser i to **reincarnate**.



For now this needs to be policed.



An alternative paid search auction

Question: is there an alternative paid search auction where reincarnating is not beneficial?
Where ads are optimally explored?

This talk: yes! We discuss an application of the dynamic-VCG mechanism where advertisers have to **submit a bid and a belief.**



Optimal placements with uncertain p_i : multi-armed bandit problems

Optimal ad placement involves exploring new ads.

We can interpret it as a reinforcement learning problem.

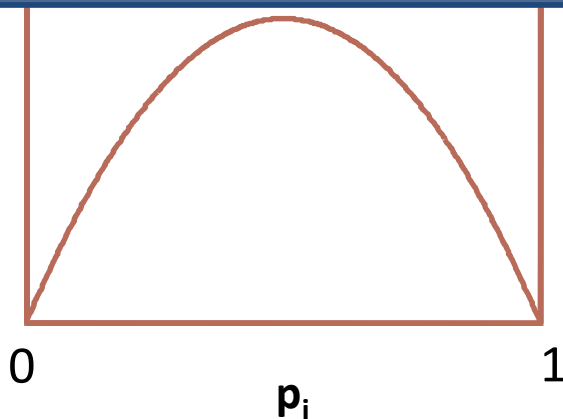
For a single slot, this is a classic **multi-armed bandit problem**.



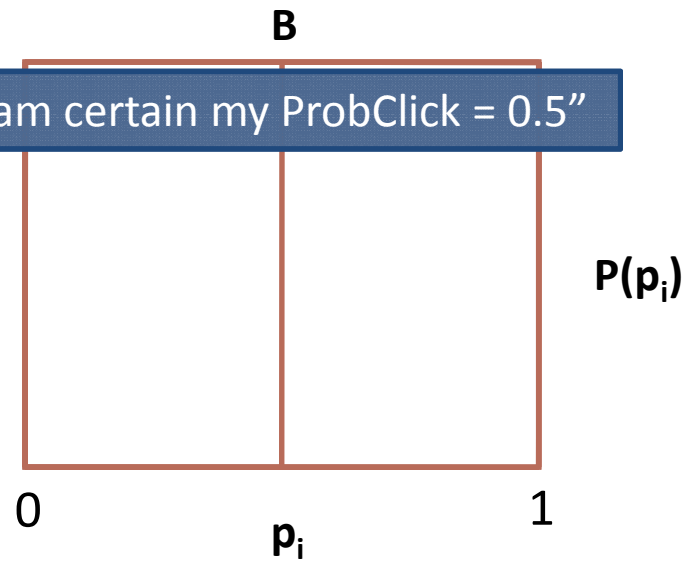
A multi-armed bandit example

Two ads, same $E[p_i]$, different $\text{Var}[p_i]$.

“My best guess is that my ProbClick = 0.5, but it could easily be 0.2 or 0.7”



“I am certain my ProbClick = 0.5”



Not only best guess for p_i matters. Need to
You get one round, do you place A or B?
maintain **belief**.



Bergemann and Välimäki's dynamic-VCG mechanism

At each round

1. Agents report their private state.
2. The centre acts optimally according to the reported state.
3. Agent a pays for this round the reduction in utility for the other agents that his report in this round implies (relative to the Vickrey-Clarke-Groves mechanism).

The multi-round extension of the Vickrey-Clarke-Groves mechanism



Properties of dynamic-VCG

Important properties of dynamic-VCG:

Efficiency: the assignment maximizes expected multi-round total utility.

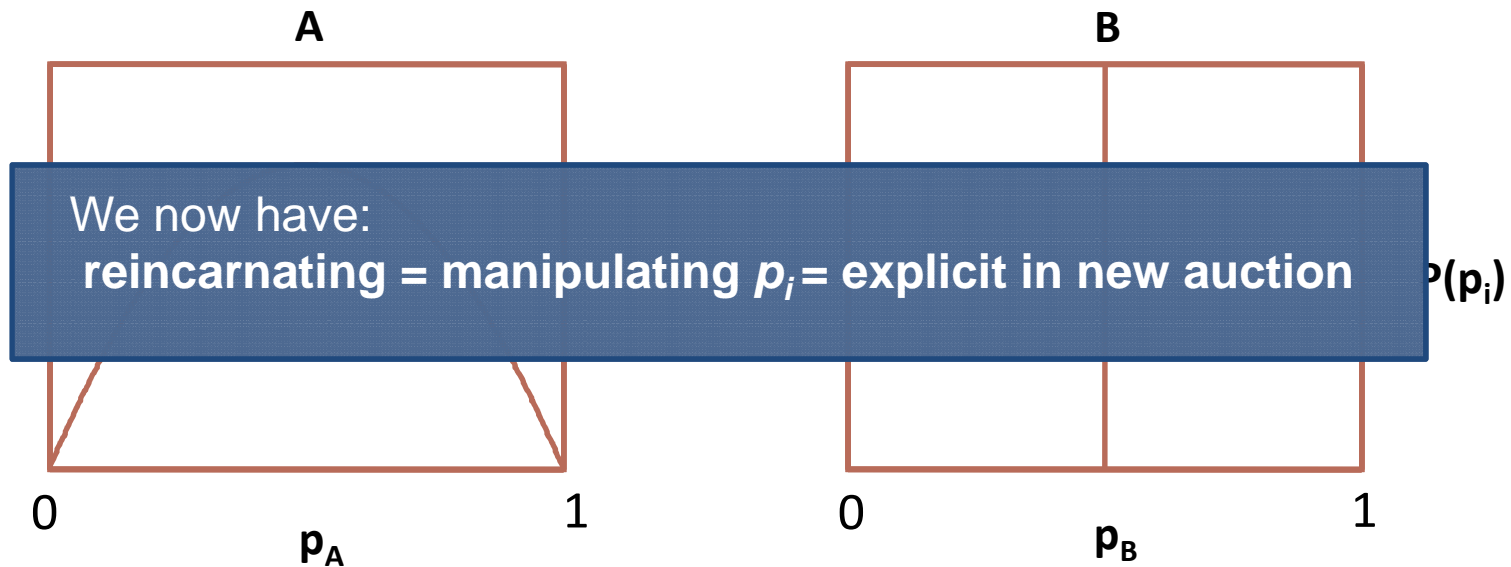
Truth-telling: the situation where all agents report true values for a click and true beliefs is an equilibrium



Making reincarnation a legitimate part of the auction

We require advertisers to submit

- A bid
- A **belief** over their probability p_i



A new single slot ad auction

- At $t=1$ centre provides default CTR beliefs
- At each round $t=1, \dots$
 1. Advertisers submit bid and optionally override CTR beliefs.
 2. Centre places ad that maximizes multi-round return to advertisers.
 3. Advertiser pays externality for this round (i.e. even if not clicked)
 4. Centre uses Bayes rule to update beliefs



Properties of the new ad auction

1. The p_i 's are learned at the optimal rate.
2. The placement is optimal over all rounds.
3. Reincarnation is not beneficial.
 - Advertiser can report belief in every round.
 - In particular belief associated with fresh ad.
 - But reporting truth is optimal.

This auction gives “loyalty benefits” at exactly the right rate



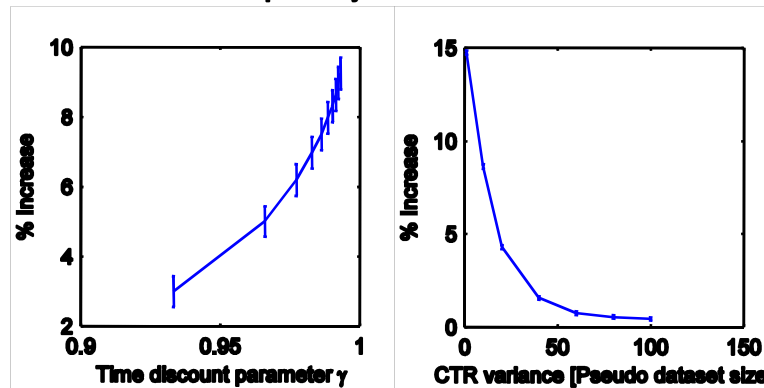
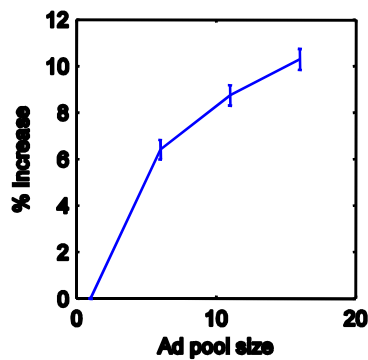
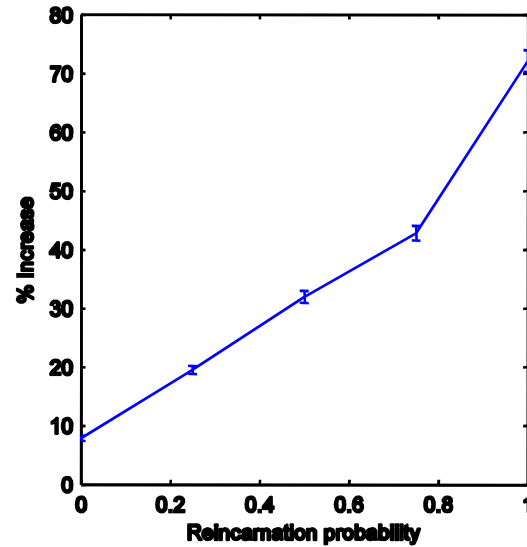
Truth-telling intuition

Externality pricing rule \rightarrow pay-per-impression

- Optimistic p_i : too many costs-per-impressions.
- Pessimistic p_i : lost opportunities.
- Similarly sub-optimal to be too confident/uncertain about beliefs.



Experiments



Machine Learning and Incentives

Learning a model in biology, medicine, etc.

≠

Learning a model of humans on the web.

Incentives form an important dimension often overlooked in Machine Learning.

Trick here is relatively widely applicable.



Questions?

