Click modeling for display advertising

June 30, 2012

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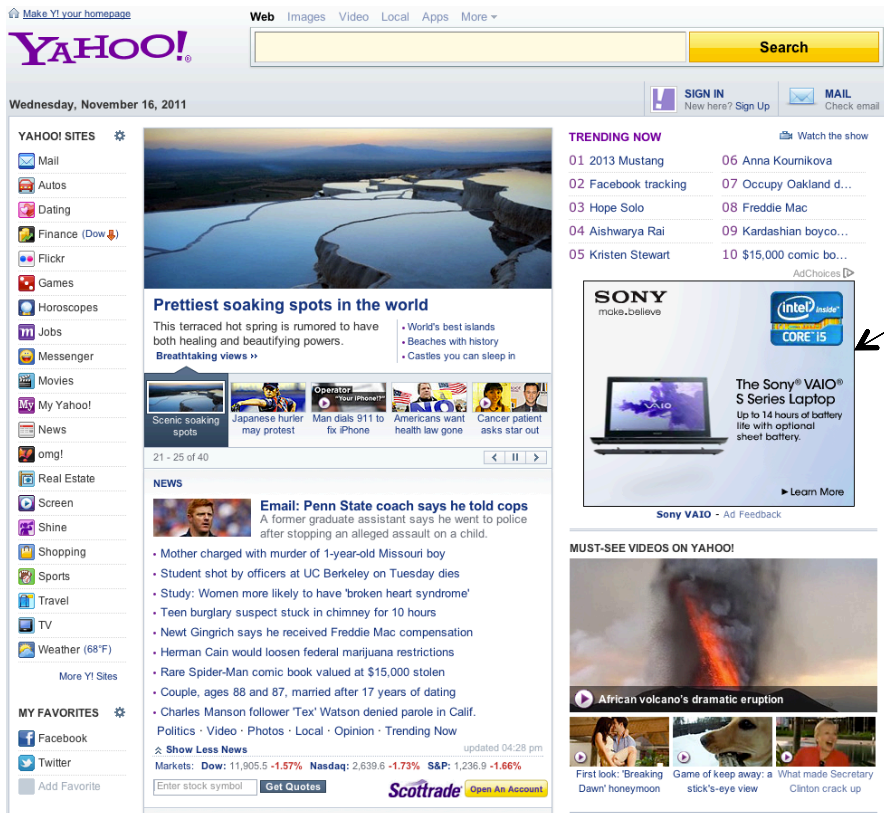
Outline

1. Display advertising
2. Modeling
3. Large scale learning
4. Explore / exploit

Display advertising



Display ad

Display advertising

- Rapidly growing multi-billion dollar business (38% of internet advertising revenue in 2010).
- Marketplace between:
  - Publishers: sell display opportunities
  - Advertisers: pay for showing their ad
- Two different modes:
  - Guaranteed delivery: opportunities are defined and sold in advance.
  - Non guaranteed delivery (this talk): real-time auction amongst advertisers is held at the moment when a user generates a display opportunity by visiting a publisher's web page.

Pricing type

- CPM (Cost Per Mille): advertiser pays per thousand impressions
- CPC (Cost Per Click): advertiser pays only when the user clicks
- CPA (Cost Per Action): advertiser pays only when the user performs a predefined action such as a purchase.

Generalized second price auction

$$\text{Winner}: \quad \arg\max_i \quad b_i p_i$$

$$b_i = \text{bid}$$

$$p_i = \text{probability (click or action)}$$

$$\text{Price charged:} \quad \frac{b_2 p_2}{p_1}$$

$$\text{with } b_1 p_1 > b_2 p_2 > \ldots$$

Click prediction

- Click prediction is a critical aspect of display advertising.
- Highly unbalanced problems (clickthrough rates < 1%).
- Related problem: action prediction for CPA (even more unbalanced).
- Very large amount of data: about 9B daily impressions.

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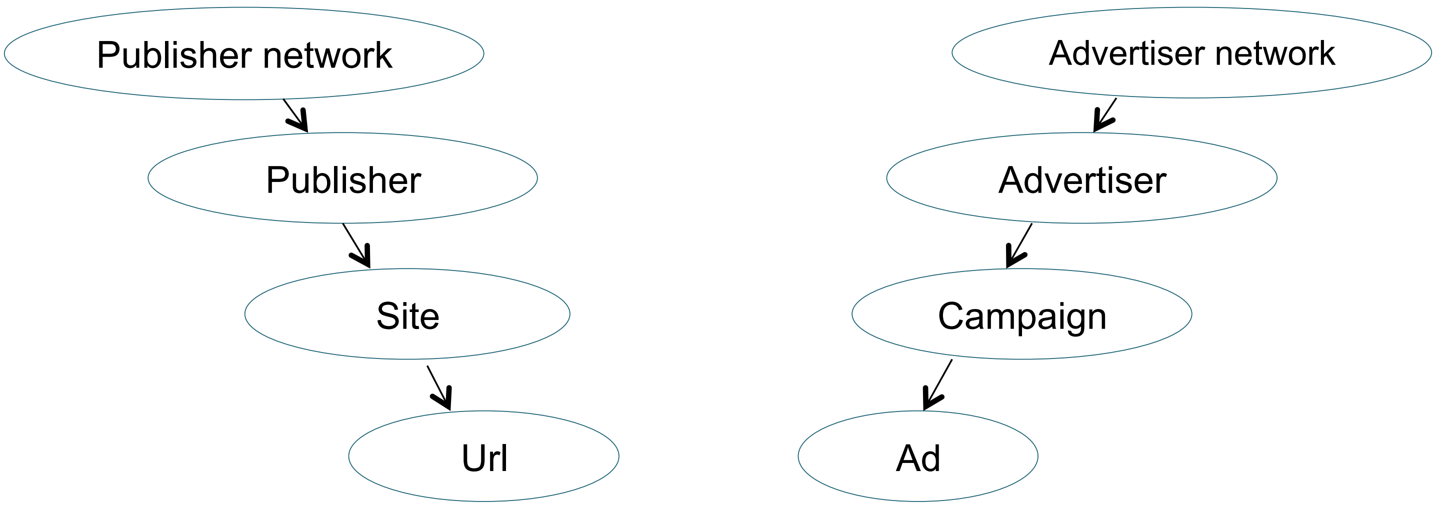
Features

- Three sources of features: user, ad, page
- In this talk: categorical features on ad and page.
- Two hierarchies of features:



Hashing trick

- Standard representation of categorical features: “one-hot” encoding

Site: (0 … 0 1 0 … 0)

cnn.com news.yahoo.com

- Dimensionality equal to the number of different values: can be very large
- Hashing to reduce dimensionality (made popular by John Langford in VW)

$$h : \text{string} \rightarrow [0 \ldots 2^b - 1]$$

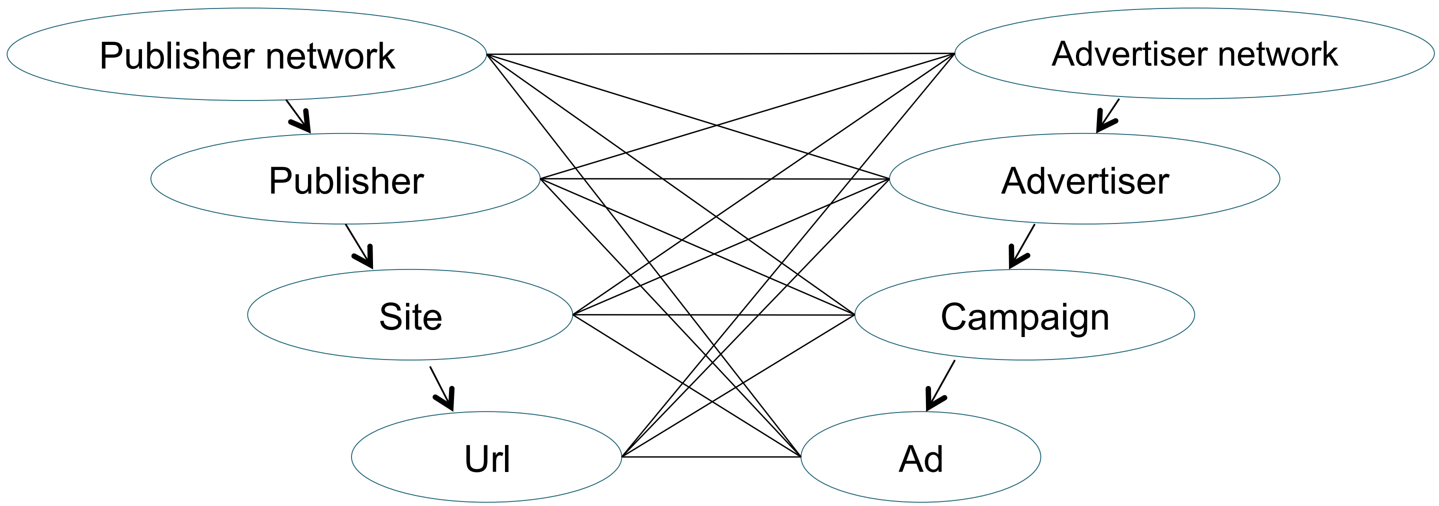
$$x_{h(v)} = 1$$

- Still one-hot encoding but dimensionality independent of number of values
- All features are hashed into the same space
- Risk of collision
- Collisions are form of regularization: infrequent feature values are washed away by the frequent ones.

Quadratic features

- Outer product between two features.
- Example: between *site* and *advertiser,*

  Feature = 1 $\Leftrightarrow$ site=finance.yahoo.com & advertiser=bank of america



- Similar to a polynomial kernel of degree 2
- Large number of values $\longrightarrow$ *hashing trick*

Advantages of hashing

- Statistical
  - Regularization
- Practical
  - Straightforward implement; no need to maintain dictionaries
- Most powerful when combined with quadratic features

Quote of John Langford about hashing:

At first it’s scary, then you love it

Learning

- Regularized logistic regression
  - Vowpal Wabbit open source package

- Regularization with hierarchical features $\approx$ backoff smoothing

$$w_{parent} \quad + \quad w_{child}$$

Well estimated

Small if rare value

- Negative data subsampled:
  - Statistical advantage (better balance)
  - Computational advantage

Evaluation

- Comparison with (Agarwal et al. ’10)
  - Probabilistic model for the same display advertising prediction problem
  - Leverages the hierarchical structures on the ad and publisher sides
  - Sparse prior for smoothing
- Model trained on three weeks of data, tested on the 3 following days
- Metrics: area under the ROC and PR curves, log likelihood

auROC	auPRC	Log likelihood
+ 3.1%	+ 10.0%	+ 7.1%

D. Agarwal et al., Estimating Rates of Rare Events with Multiple Hierarchies through Scalable Log-linear Models, KDD, 2010

Bayesian logistic regression

- Regularized logistic regression = MAP solution (Gaussian prior, logistic likelihood)
- Posterior is not Gaussian
- Diagonal Laplace approximation:

$$\Pr(w \mid D) \approx \mathcal{N}(\mu, \Sigma)$$

with:

$$\mu = \arg\min L(w)$$
$$\Sigma_{ii} = \frac{\partial^2 L}{\partial w_i^2}$$

and:

$$L(w) = -\log \Pr(w \mid D) = \sum_{j=1}^{n} \log(1 + \exp(-y_j w \cdot x_j)) + \lambda \|w\|^2$$

Model update

- Needed because ads / campaigns keep changing.
- The posterior distribution of a previously trained model can be used as the prior for training a new model with a new batch of data.

Require: Regularization parameter $\lambda > 0$.
$m_i = 0,\ q_i = \lambda.$ {Each weight w_i has an independent prior $\mathcal{N}(m_i, q_i^{-1})$}
for $t = 1, \ldots, T$ **do**
Get a new batch of training data $(\mathbf{x}_j, y_j),\quad j = 1, \ldots, n.$
Find $\mathbf{w}$ as the minimizer of: $\displaystyle \frac{1}{2}\sum_{i=1}^{d} q_i (w_i - m_i)^2 + \sum_{j=1}^{n} \log(1 + \exp(-y_j \mathbf{w}^\top \mathbf{x}_j)).$
$m_i = w_i$
$\displaystyle q_i = q_i + \sum_{j=1}^{n} x_{ij}^2 p_j (1 - p_j),\quad p_j = (1 + \exp(-\mathbf{w}^\top \mathbf{x}_j))^{-1}$ {Laplace approximation}
end for

- Influence of the update frequency (auPRC)

1 day	6 hours	2 hours
+3.7%	+5.1%	+5.8%

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Parallel learning

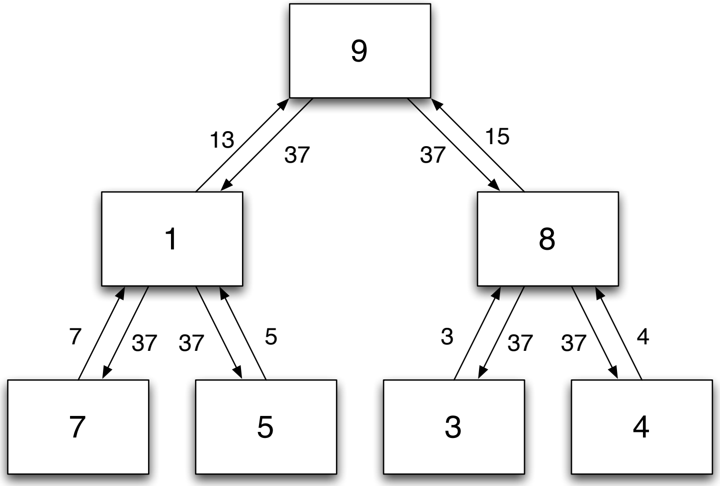
- 2B training samples
- 16M parameters
- Training set size = 400GB (compressed)
- Less than one hour with 500 machines

- Optimize: $$\min_{w \in \mathbb{R}^d} \sum_{i=1}^{n} \log(1 + \exp(-y_i w \cdot x_i)) + \lambda \|w\|^2$$

- Stochastic gradient descent (SGD) is fast on a single machine, but difficult to parallelize
- Batch (quasi-Newton) methods are straightforward to parallelize
  - L-BFGS with distributed gradient computation.

AllReduce

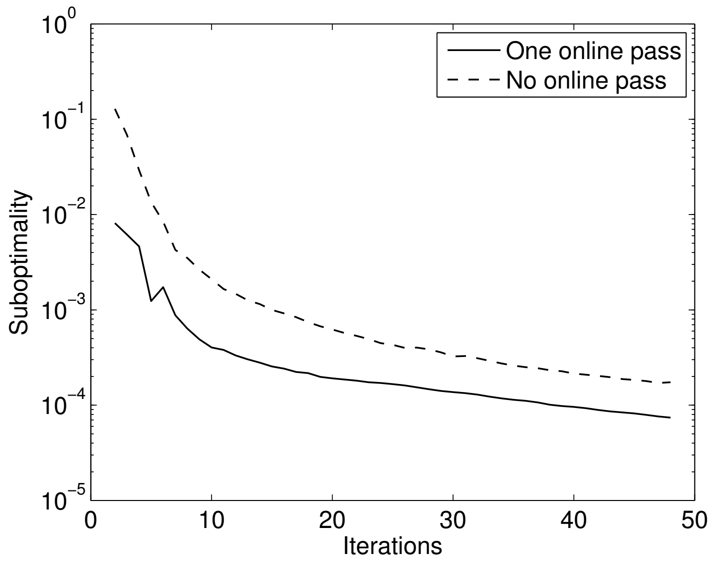
- Aggregate and broadcast across nodes



- Very little modification to existing code: just insert several AllReduce operations
- Compatible with Hadoop / MapReduce
  - Build a spanning tree on the gateway
  - Single MapReduce job
  - Leverage speculative execution to alleviate the slow node issue

Online initialization

- Hybrid approach:
  - One pass of online learning on each node
  - Average the weights from each node to get a warm start for batch optimization
- Best of both (online / batch) worlds.



Robustness and Scaling

- Slowest node is the bottleneck
- Speculative execution: when a node appears to be slow, start a duplicate job

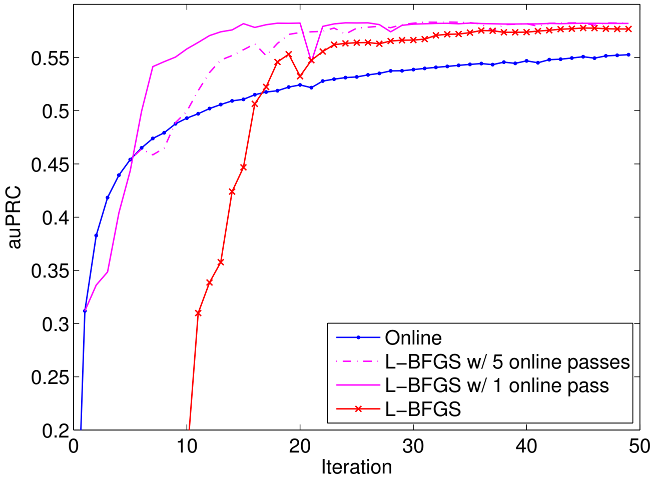
Distribution of computing time over 1000 nodes, with and without speculative execution

	5%	50%	95%	Max	Comm. time
Without	29	34	60	758	26
With	29	33	49	63	10

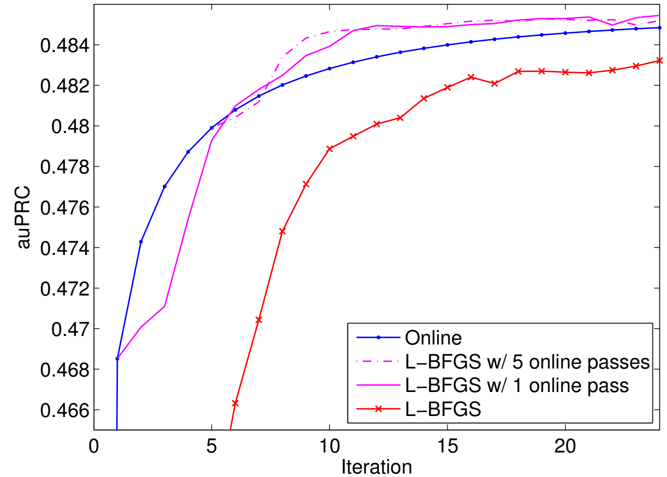
- Can scale up to 1000 nodes

Nodes	100	200	500	1000
Comm time / pass	5	12	9	16
Median comp time / pass	167	105	43	34
Max comp time / pass	462	271	172	95
Wall clock time	3677	2120	938	813

Test accuracy



Splice site prediction (Sonnenburg et al. '10)

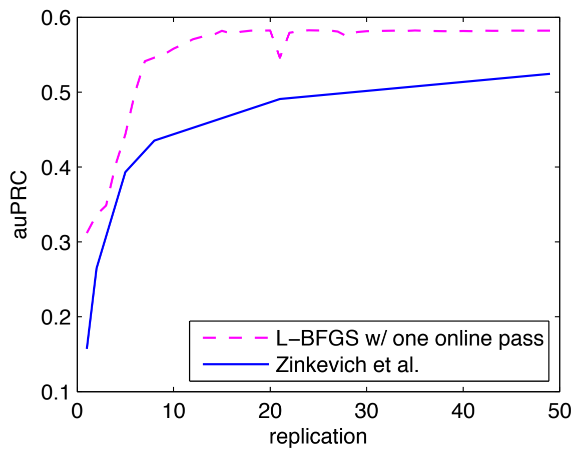


Display advertising

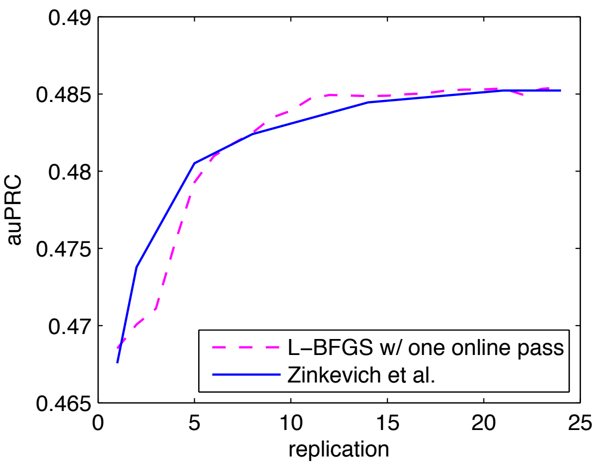
One online pass followed by L-BFGS is the best combination

S. Sonnenburg and V. Franc, COFFIN: A Computational Framework for Linear SVMs, ICML 2010

- Comparison with (Zinkevich et al. ‘10):
  - Replicate the data, do one pass of online learning on each node, average the solution
  - Potential drawbacks:
    - Single pass over the data might hurt accuracy
    - More data to communicate over the network



Splice site prediction



Display advertising

M. Zinkevich et al., Parallelized stochastic gradient descent, NIPS 2010

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Thompson sampling

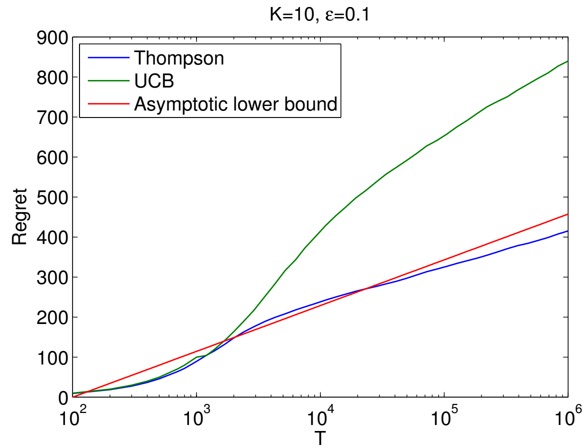
- Heuristic to address the Explore / Exploit problem, dating back to Thompson (1933)
- Simple to implement
- Good performance in practice (Graepel et al. '10, Chapelle and Li '11)
- Rarely used, maybe because of lack of theoretical guarantee.

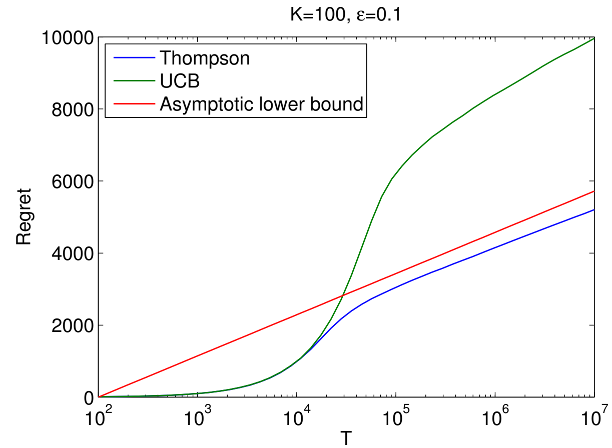
$D = \emptyset$
for $t = 1, \ldots, T$ **do**
  Receive context x_t
  Draw θ^t according to $P(\theta|D)$
  Select $a_t = \arg\max_a \mathbb{E}_r(r|x_t, a, \theta^t)$
  Observe reward r_t
  $D = D \cup (x_t, a_t, r_t)$
end for

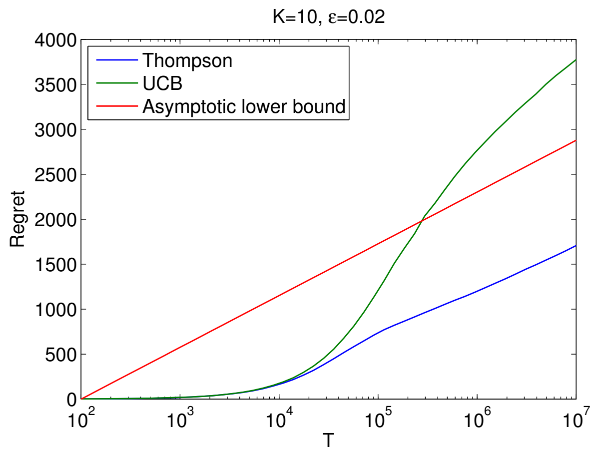
T. Graepel et al., Web-scale Bayesian click-through rate prediction for sponsored search advertising in Microsoft's Bing search engine, ICML 2010
O. Chapelle and L. Li, An Empirical Evaluation of Thompson Sampling, NIPS 2011

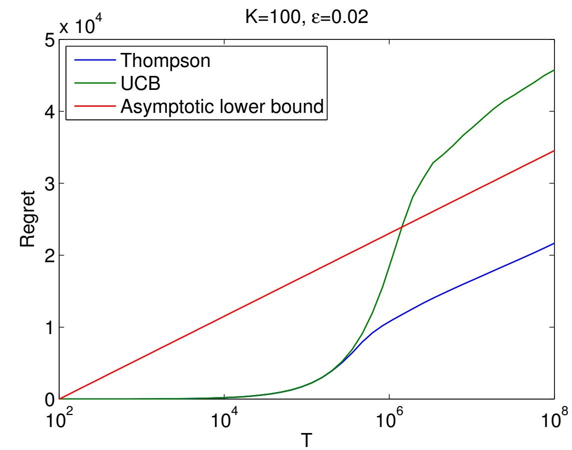
E/E simulations

- MAB with K arms
- Best arm has mean reward = 0.5, others have 0.5 − ε.



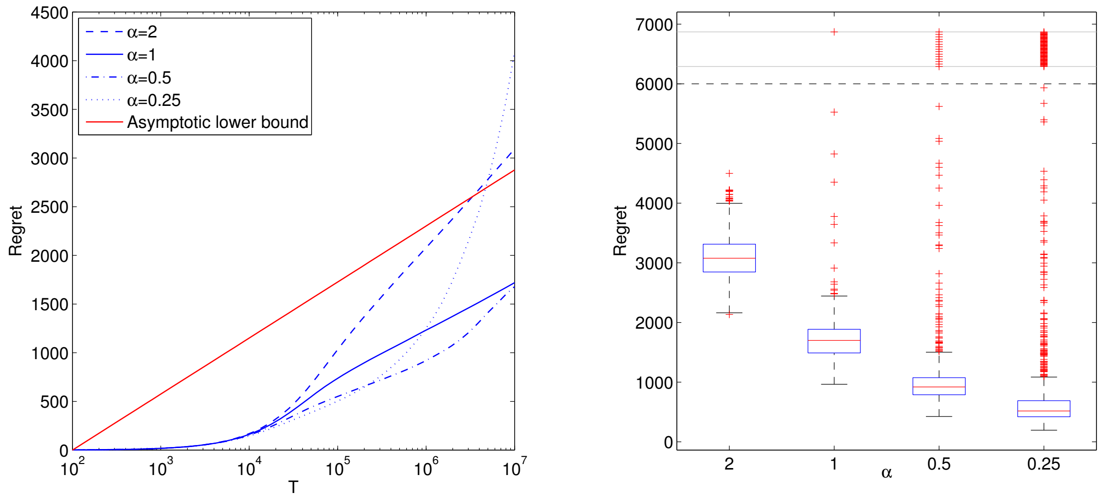






Posterior reshaping

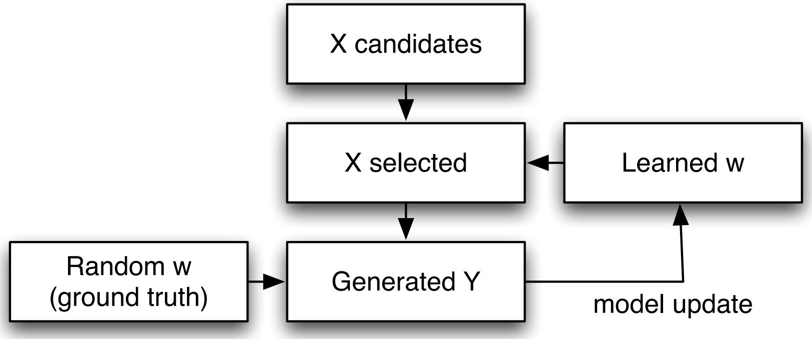
- Add a knob to control the exploration / exploitation trade-off.
- Multiply the variance by α
  - $\alpha > 1$: wider posterior $\longrightarrow$ more exploration
  - $\alpha < 1$: narrower posterior $\longrightarrow$ more exploitation



- $\alpha < 1$ tends to achieve smaller regrets, but is riskier in the long run.

Evaluation

- 13,000 hourly opportunities
- Set of eligible ads varies from 1 to 5,910 (mean 1,364). Total ads = 66,373
- Semi-simulated environment: real input features, but labels generated.
- Comparison of E/E algorithms:
  - 4 days of data
  - Cold start
- Algorithms:
  - UCB: mean + α std. dev.
  - ε-greedy
  - Thompson sampling

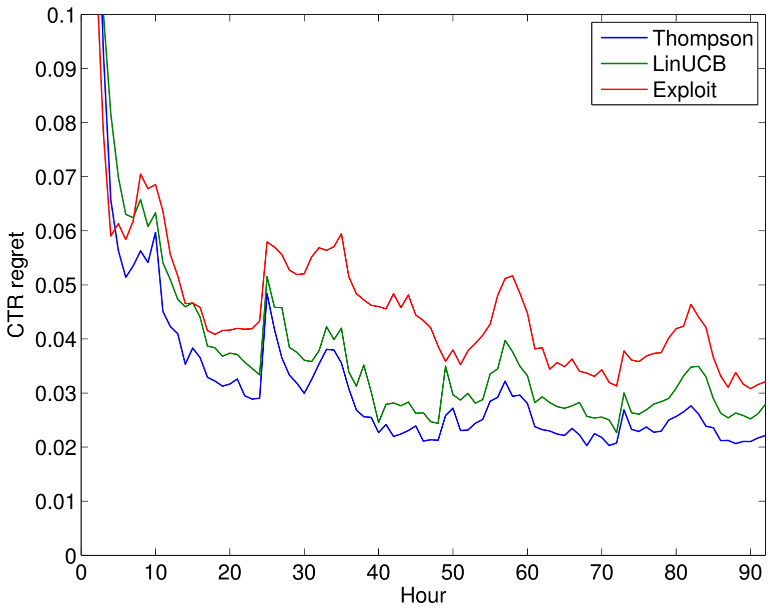


- CTR regret (in percentage):

Thompson (0.5)	UCB (2)	ε-greedy (0.005)	Exploit-only	Random
3.72	4.14	4.98	5.00	31.95

Best parameter value in parenthesis

- Regret over time:



Open questions

- Hashing
  - Theoretical performance guarantees
- Sample selection bias
  - System is trained only on selected ads, but all ads are scored.
  - Possible solution: inverse propensity scoring
  - But we still need to bias the training data toward good ads.
- Explore / exploit
  - Evaluation framework
  - Regret analysis of Thompson's sampling
  - E/E with a budget; with multiple slots
  - Delayed feedback → automatic throttling

Conclusion

- Simple yet efficient techniques for click prediction

- Main difficulty in applied machine learning: avoid the bias (because of academic papers) toward complex systems
  - It's *easy* to get lured into building a *complex* system
  - It's *difficult* to keep it *simple*