Click Modeling in Search Advertising: Challenges & Solutions

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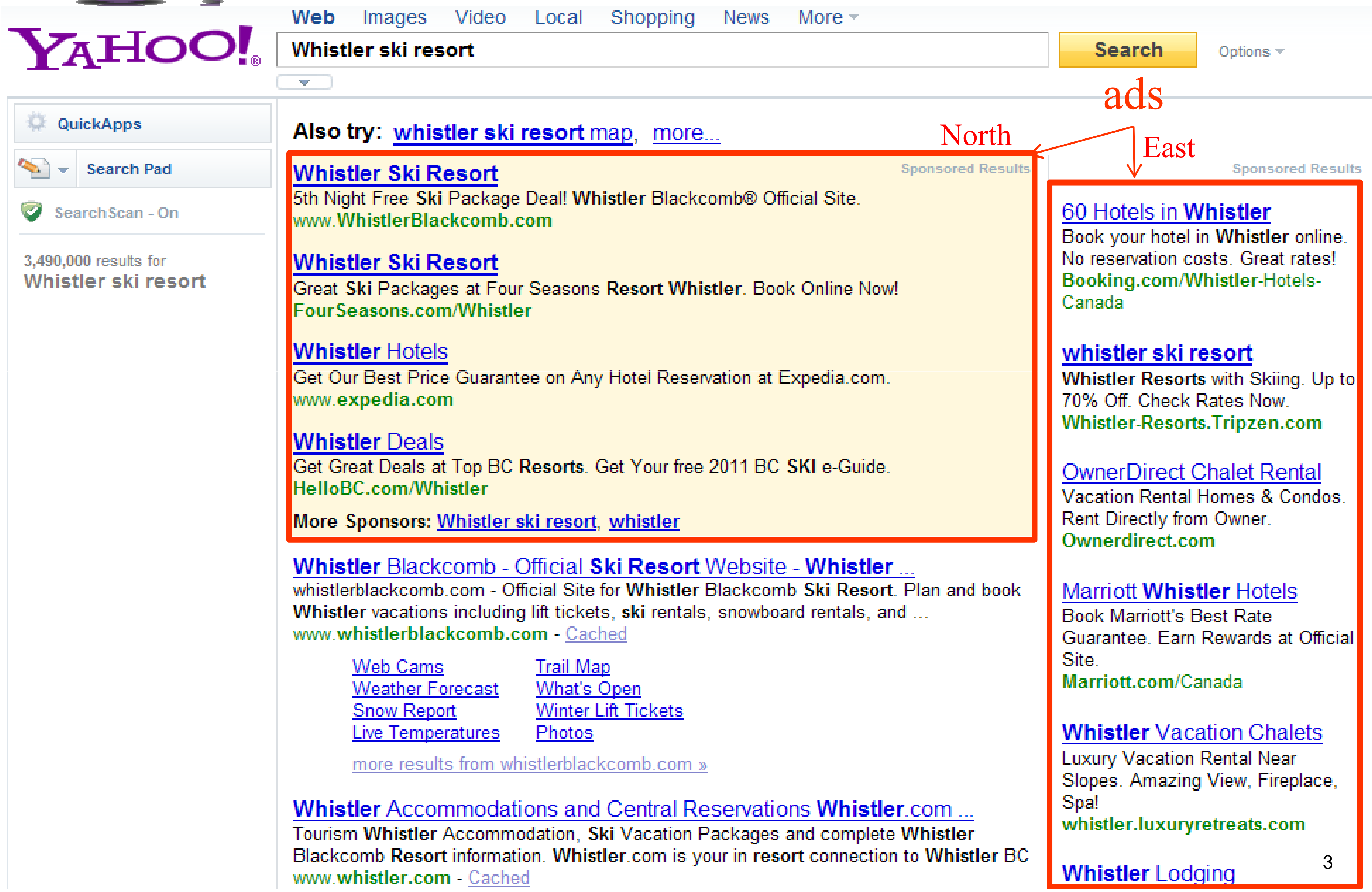
Sponsored Search Ads



Search Advertising - Problem

- General problem statement
  - Given a query by a user, select an optimal placement of eligible ads to maximize a total utility function that captures the expected revenue, user experience, and advertiser ROI
- Example utility: Expected Revenue

eCPM = Probability(good click | user, query, ad) * Bid

- Fundamental Problems
  1. **Estimate relevance of an ad to the user query**
  2. **Estimate probability of clicks**

Challenges in Click Modeling

- Biases
  - Position
  - Externality
  - Ad category
  - Selection
- Sparsity
- Missing data
- Dynamic and seasonal effects
- Noise, spam, etc.

- Modeling positional externalities*
  - Temporal Click Model
- Dealing with sparsity*
  - Ad hierarchy
  - Query-segment
- Dealing with missing data*
  - Mixture model

* Some of the recent work in Advertising Sciences, Y! Labs

Modeling User Click Behavior

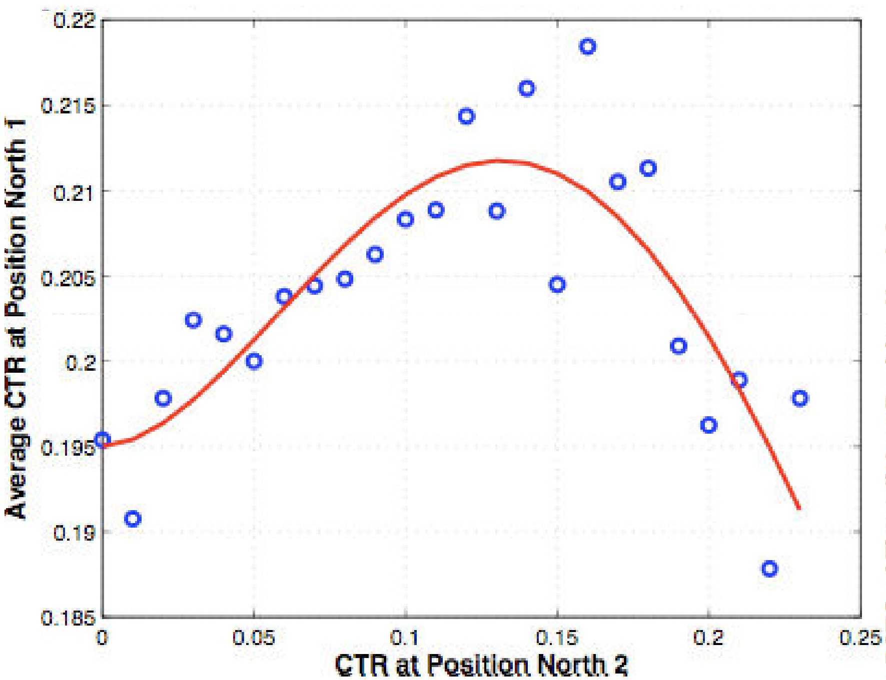
- **Models**
  - Cascade Model
  - Dependent Click Model
  - User Browsing Models
  - Click Chain Model
  - Session Utility Model
  - Bayesian Browsing Model
  - Dynamic Bayesian Browsing Model
  - Temporal Click Model*

- **Hypotheses**
  - Examination hypothesis
  - Cascade hypothesis
  - Rationality hypothesis
  - Positional rationality hypothesis*

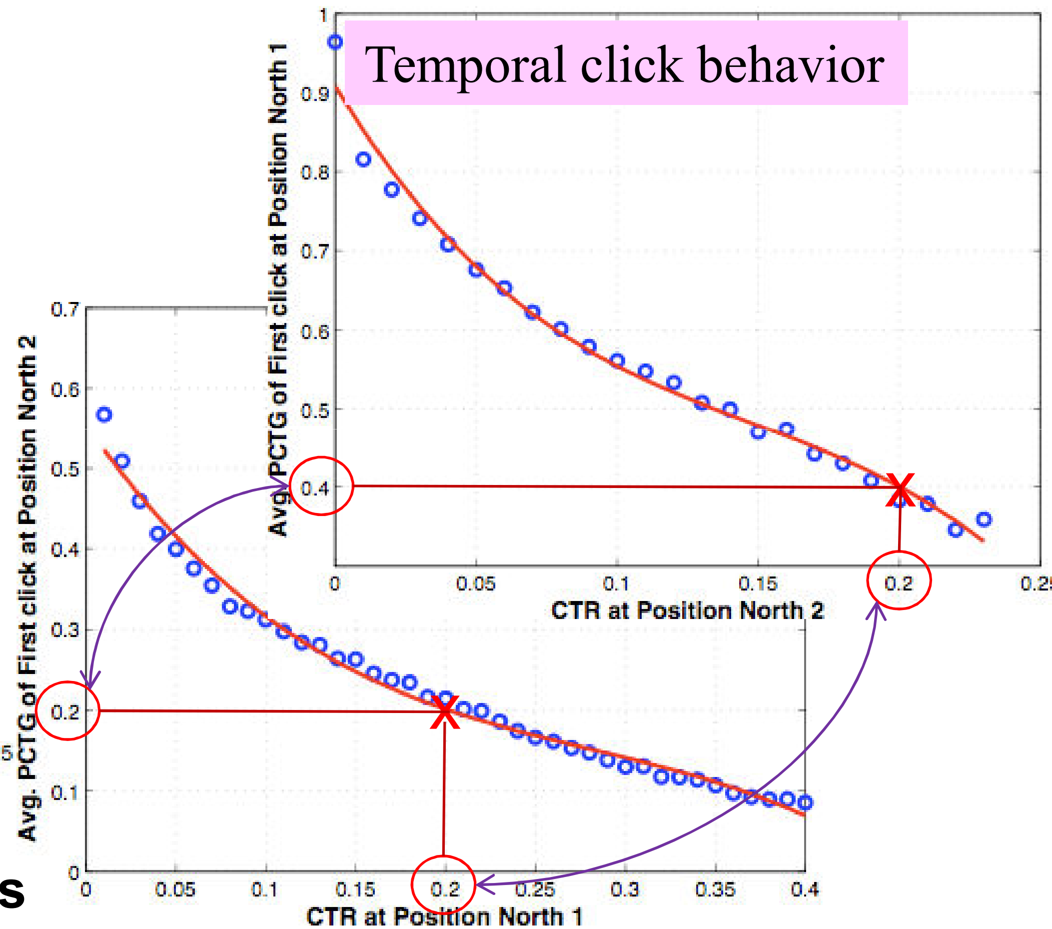
* Wanhong Xu, Eren Manavoglu and Erick Cantu-Paz. "Temporal Click Model for Sponsored Search", SIGIR 2010.

Positional Rationality Hypothesis (based on randomized ranking study)

Existence of ad externalities



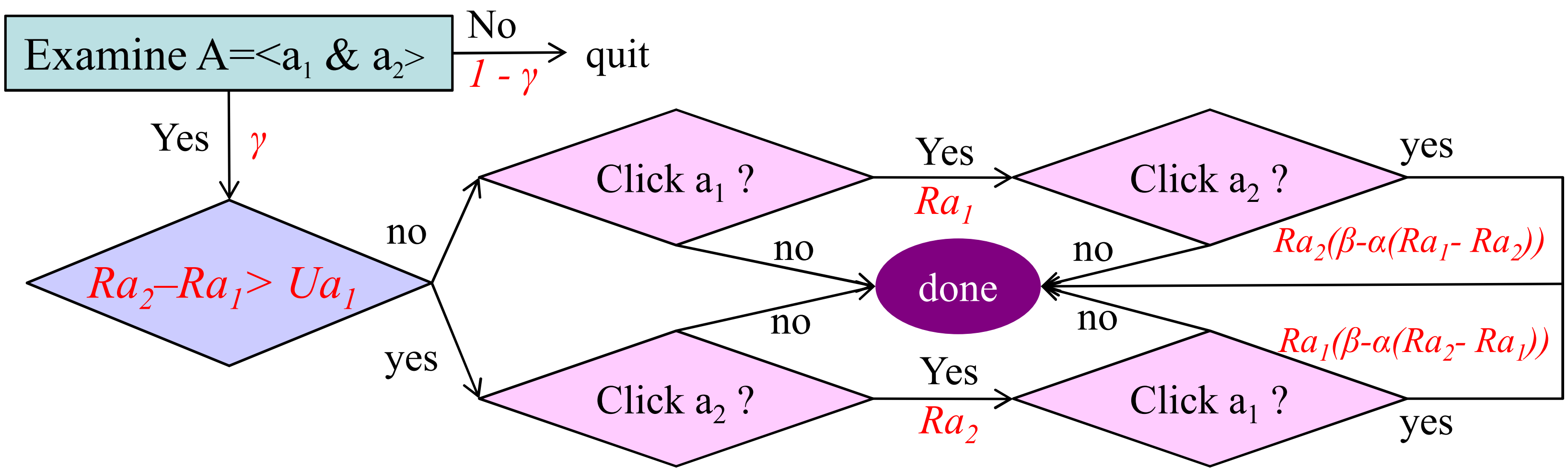
Temporal click behavior

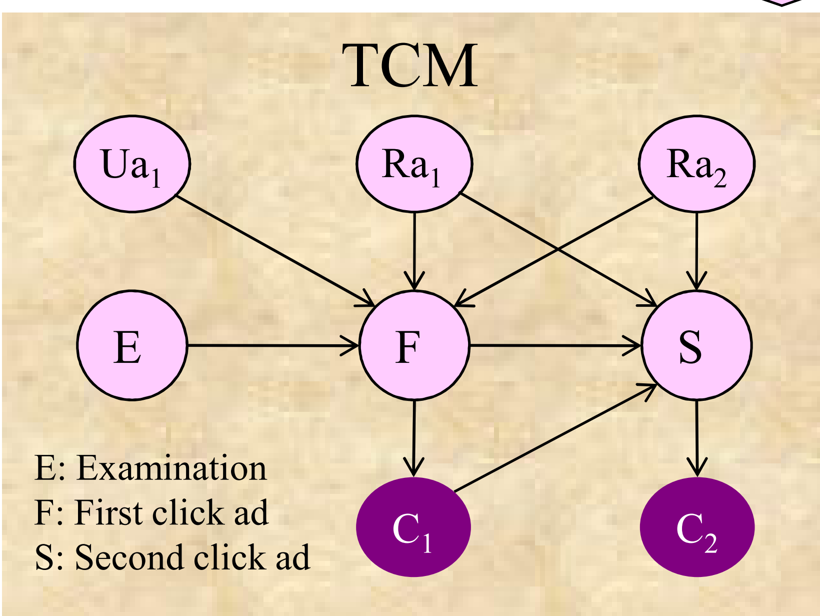


Positional Rationality Hypothesis

- Users examine both ads together to assess their qualities (Ra_1 & Ra_2)
- If the ad at position 2 is better than the ad at position 1 (by a positional preference threshold Ua_1), users would click the ad at position 2 first

Temporal Click Model



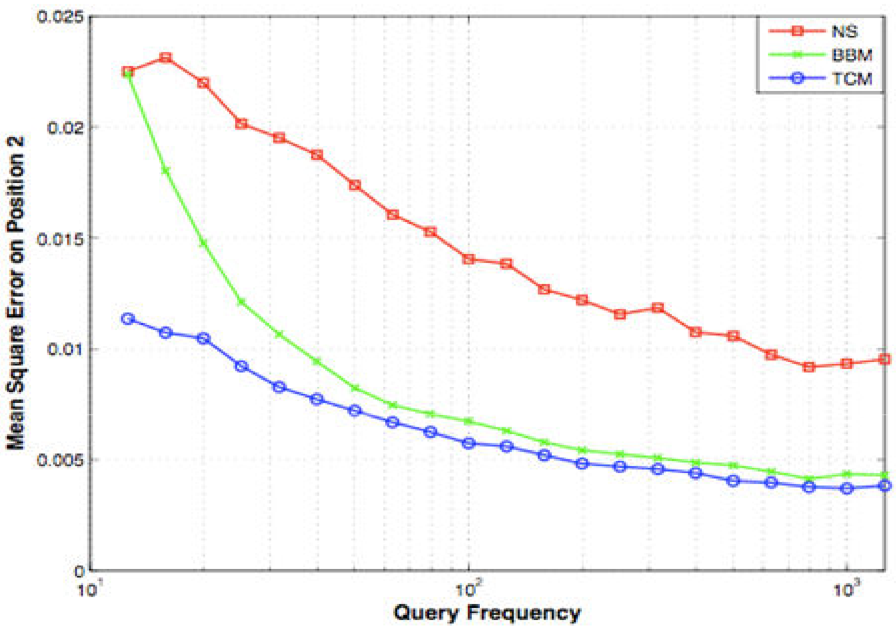


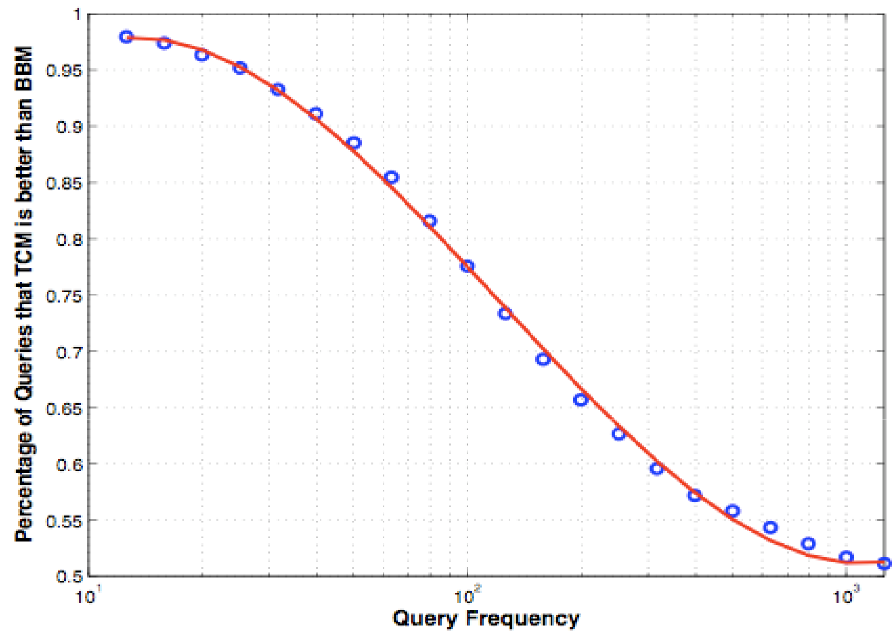
$$P(E=1|A)=\gamma.$$
$$P(F=a_2|E=1,A)=\mathbf{1}[R_{a_2}-R_{a_1}>U_{a_1}]$$
$$P(F=a_1|E=1,A)=\mathbf{1}[R_{a_2}-R_{a_1}\le U_{a_1}],$$
$$P(c_1=a_i|F=a_i)=R_{a_i}$$
$$P(c_1=\square|F=a_i)=1-R_{a_i}, i\in\{1,2\}.$$
$$P(S=\square|c_1=\square)=1$$
$$P(S=a_{3-i}|c_1=a_i,A)=\beta-\alpha(R_{a_i}-R_{a_{3-i}}), i\in\{1,2\}.$$
$$P(c_2=a_j|S=a_j)=R_{a_j}$$
$$P(c_2=\square|S=a_j)=1-R_{a_j}, j\in\{1,2\}$$
$$P(F=\square|E=0,A)=1$$
$$P(c_1=\square|F=\square)=1$$
$$P(c_2=\square|S=\square)=1$$

TCM Algorithms

- Posterior Distribution of user-perceived relevance (Ra_i) and ad position advantage (Ua_i) can be obtained in a closed form
- Parameters (α,β,γ) are estimated using maximum likelihood principle
  - γ in a closed form
  - α,β by a barrier method combined with Newton's method
- Click Through Rate (CTR) prediction in a closed form
  - CTR of a click sequence
  - CTR of an ad
- Map-Reduce implementation to process a large volume of search log

Experimental Results





Conclusions

- Temporal click sequences do provide implicit quality feedback
- TCM incorporates positional bias, externality, and user perceived relevance into a combined model
- TCM can be used to improve the CTR estimates. It outperforms BBM
- Positional Rationality Hypothesis may be too strong for higher frequency queries

Challenges in Click Modeling

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Predictive Click Modeling

- Model probability of click per position

  $P(click|q, a, u, pos)$: q=query, a=ad, u=user, pos=position

  - Maximum Entropy model trained using regularized maximum likelihood estimation

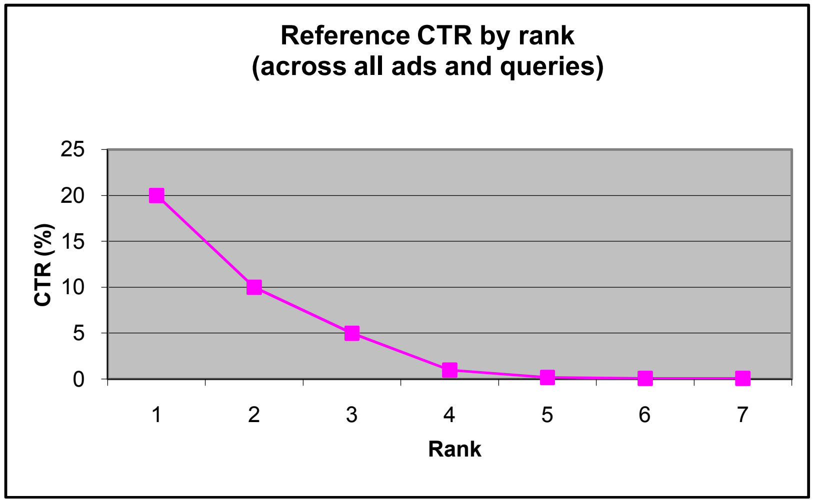
- Generate a position normalized click score

  $$P(click|q,a,u) = \Sigma_{pos} P(click|q,a,u,pos) * P(pos \mid q,a,u)$$

*Dustin Hillard, Eren Manavoglu, Hema Raghavan, Erick Cantu-Paz, Chris Leggetter, Rukmini Iyer. "The Sum of Its Parts: Reducing Sparsity in Click Estimation with Query Segments”. To appear in Journal of Information Retrieval, Special Topic Issue on Web Mining for Search

Click Prediction - Features

- Query features
- Query-Ad text matching features
- Time features
- Presentation features
- Click feedback features
  - Expected Clicks: $$EC = \sum_{r=1}^{n} refCTR_r * imps_r$$
  - Clicks over EC: $COEC = clicks / EC$
- Pair-wise conjunctions
- Continuous features are quantized
  - K-means clustering per feature
  - Special bin for the missing value
  - Allows non-linearity



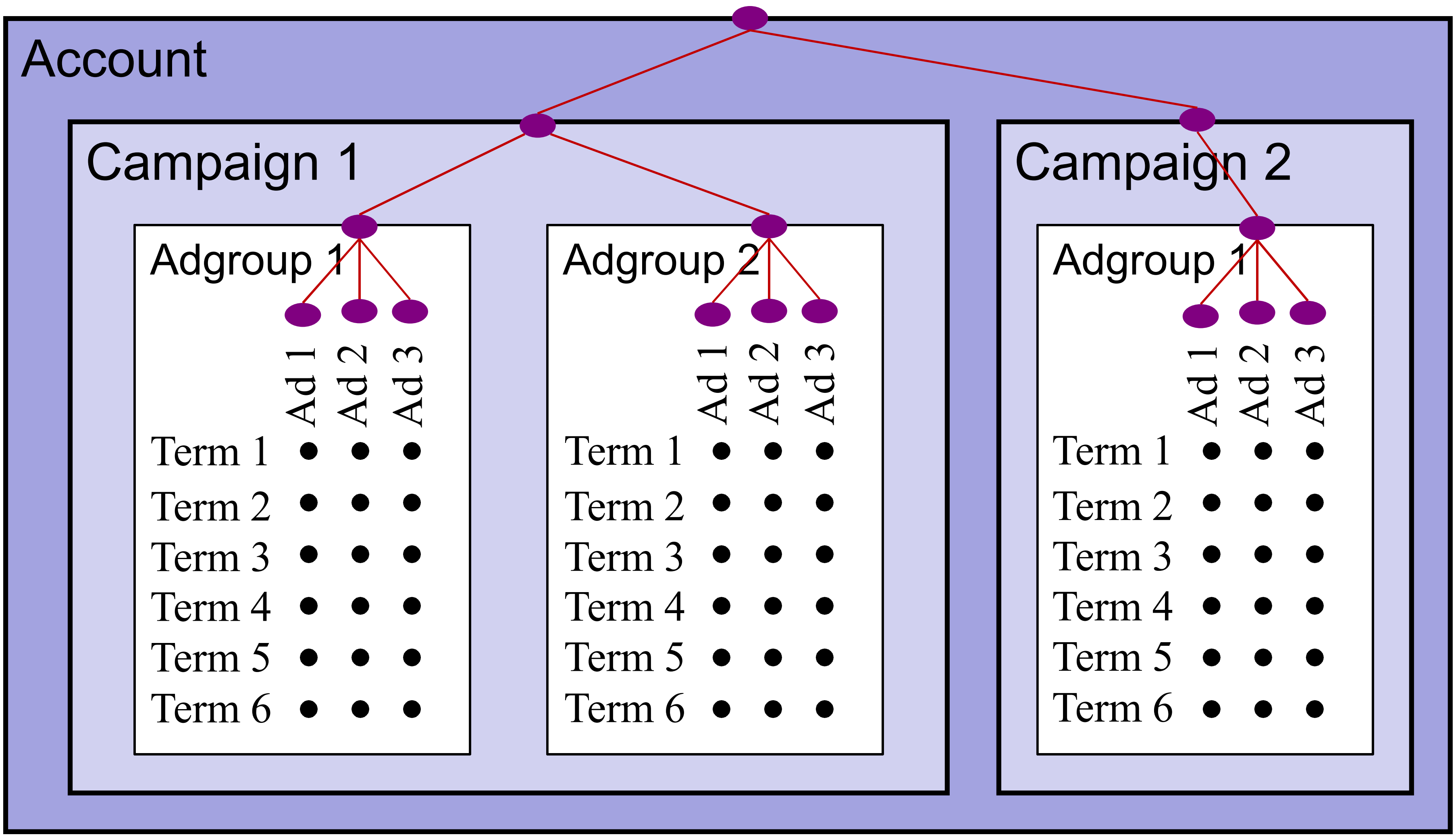
Deal with Sparsity - Leverage Data Hierarchy

- Past performance of ads for specific queries is a good predictor of future performance.

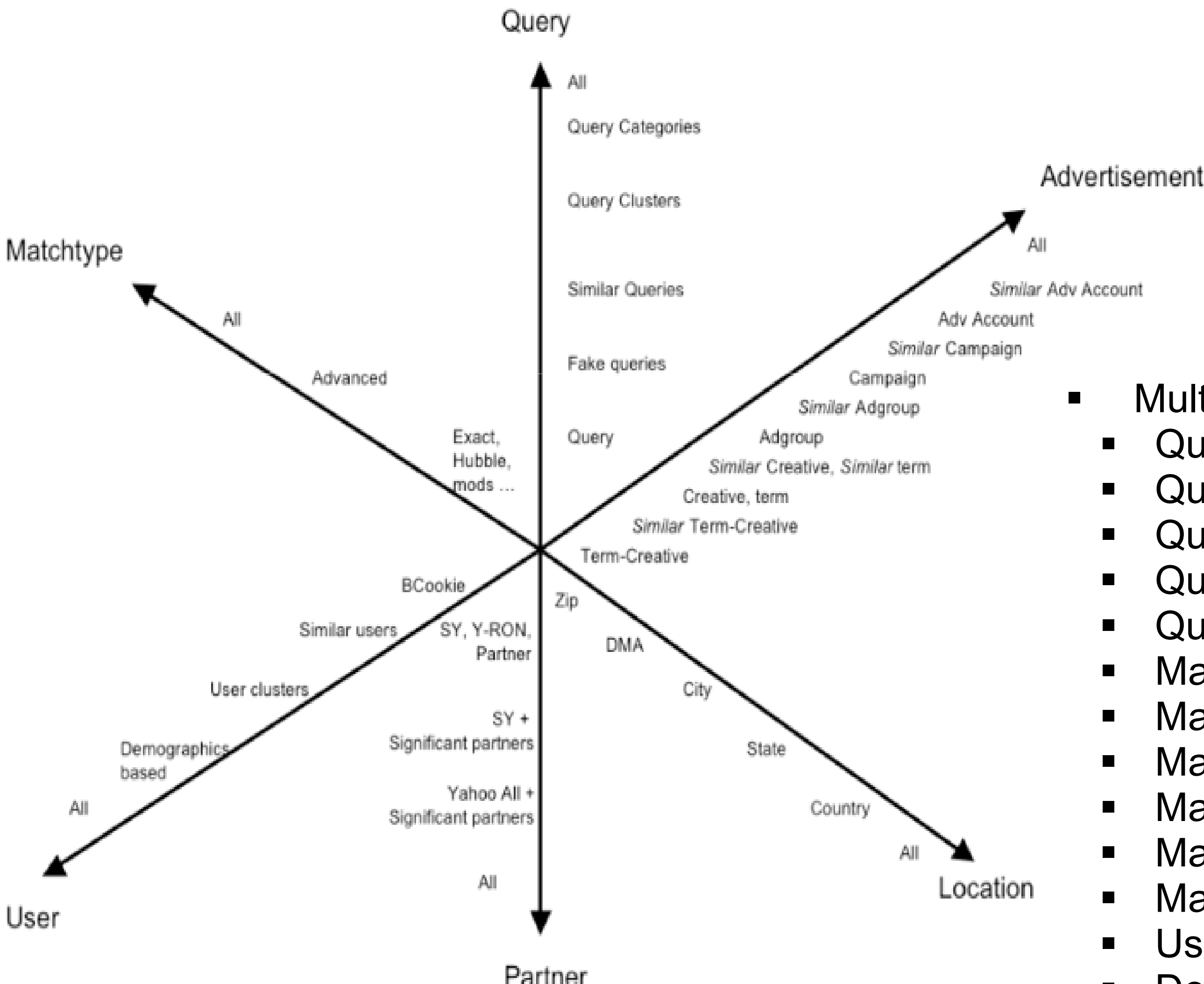
- But using only query-ad level history features is problematic
  - Data is sparse, tail is long
  - There are many new queries, and many new ads

- We can aggregate click history at coarser granularity in data hierarchies

Natural Ad Data Hierarchy



Hierarchies Exist in other Dimensions

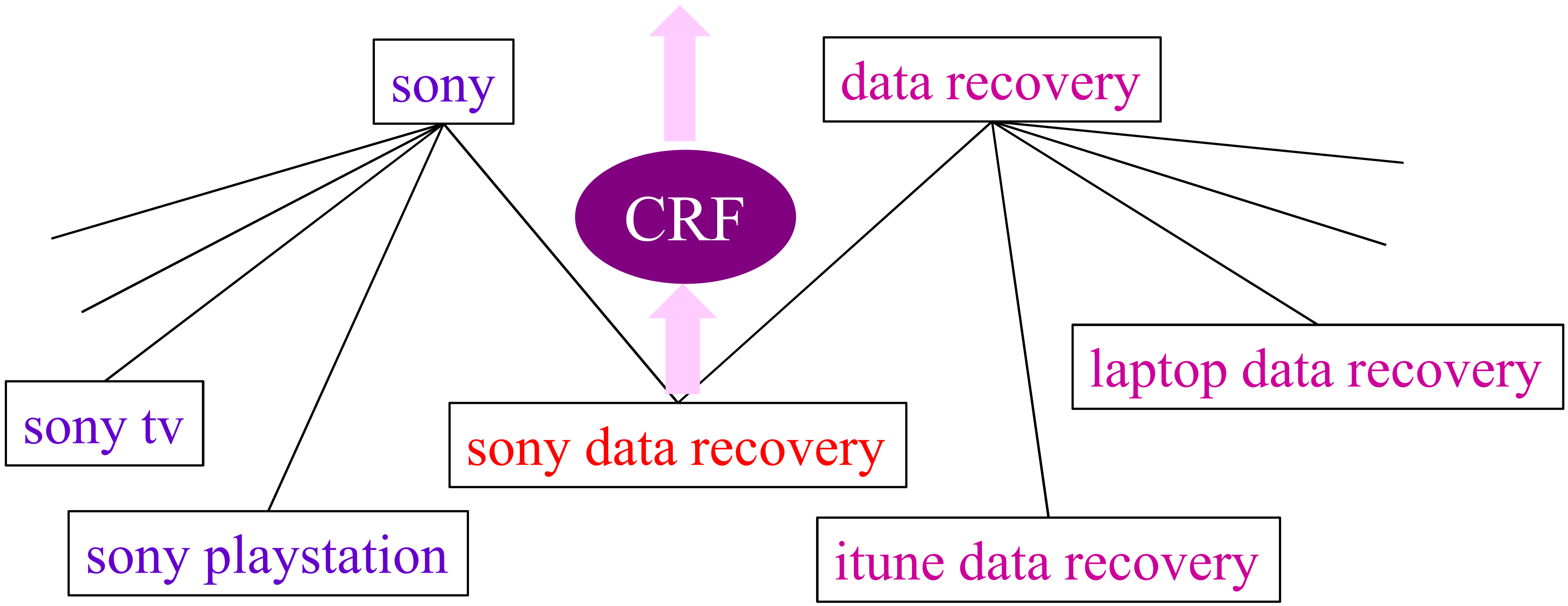


- Multiple levels
  - Query X Term X Creative
  - Query X Ad Group
  - Query X User Location
  - Query X Domain
  - Query X Bidded Term
  - Matchtype X Term X Creative
  - Matchtype X Term
  - Matchtype X Creative
  - Matchtype X Ad Group
  - Matchtype X Campaign
  - Matchtype X Account
  - User Location X Domain
  - Domain

Creating Query Segment Hierarchy

Segments	Probability
| sony | data recovery |	0.742
| sony data recovery |	0.208
| sony | data | recovery|	0.038

- CRF Segmentation
  - Trained on human labeled query phrases
  - Better than HMM and other methods in P/R & Phrase-WER



Segment-level Aggregates

- New click feedback features
  - QuerySegment
  - QuerySegment X Ad Id
  - QuerySegment X Domain

- Query: super mario bros 3 game online

Click feedback

for segments

conf	Query Segment	Clicks	EC
0.31	online	200k	160k
0.24	super mario bros 3	30	38
0.20	game	171k	142k
0.11	super mario bros 3 game	10	7
0.04	game online	821	711

for segments X domain

Query Segment	Domain	Clicks	EC
online	gamenet	none	none
super mario bros 3	gamenet	4.4	5
game	gamenet	520	370
super mario bros 3 game	gamenet	none	none
game online	gamenet	2	2.5

Click Model w/ Segment-level Aggregates

- Approach:
  - Provide query segment click history as features
  - Combine query segments, weighted by confidence
  - For missing ad, back-off to query segment level
- Test on two weeks of search traffic
  - Neutral impact on traffic with sufficient history
  - Significant gains across multiple low history slices

Traffic Slice	Slice Coverage	Precision/Recall AUC
No North Ads	29%	+15%
South Ads	25%	+12%
No Account History	0.3%	+9%
No Query History	25%	+9%
No Query/Domain History	49%	+6%
All Advanced Ads	49%	+5%
Query >= 4 words	20%	+3%

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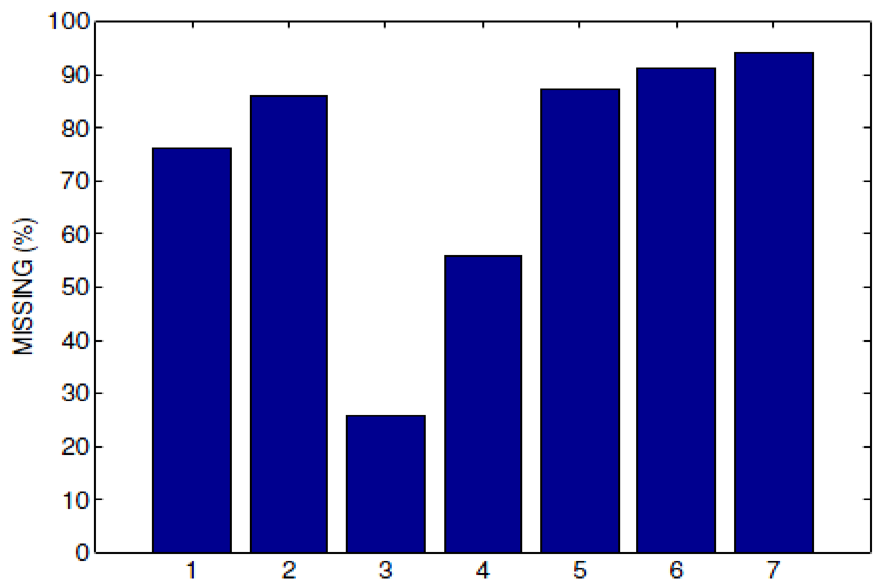
Missing Click Data

- Missing click feedback for new ads, tail queries, etc.
- One analysis
  - 1.6 Billion random samples in a 3-week period
  - Missing click data when EC < 200 (std dev of CTR estimate < 0.1)
  - Only about 5.7% of samples have all the 7 aggregated clicks available



*Ozgur Cetin, Kannan Achan, Erick Cantu-Paz, and Rukmini Iyer. "Missing Click History in Sponsored Search: A Generative Modeling Solution“. AdKDD 2010.

Handling Missing Click Data

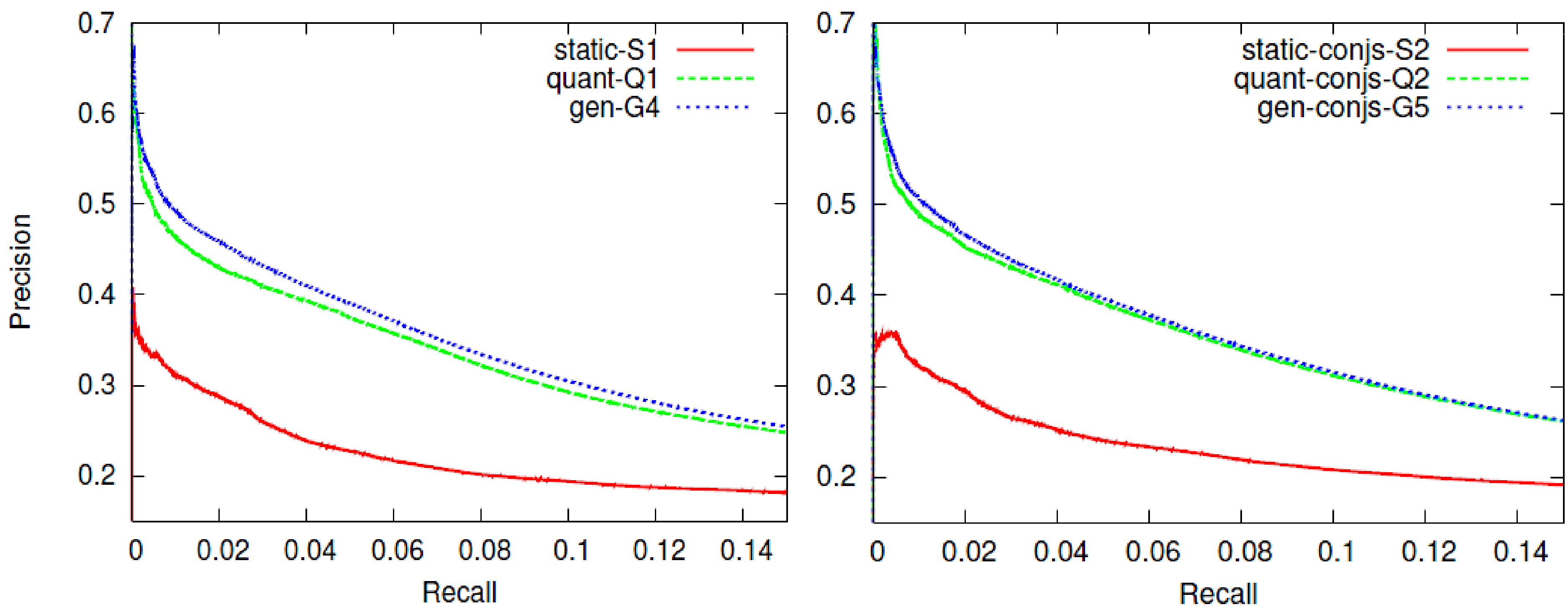
- Mixture of Gaussians model for click feedback features
- Parameter estimation
  - Use EM algorithm
- Probabilistic inference
  - Posterior distribution of the missing data conditioned on the observed ones
- Derive features from latent structure in the mixture model
  - Posterior probability vector

- Handle missing data in Maximum Entropy Model
  - Add a special bin for indication of a missing feature
  - Use imputed feature mean and variance when missing
  - Add posterior probability vector as additional features

Precision-Recall Curves

	Features	Params
S1	static	147
Q1	static + quant (click feats)	294
G4	static + click feats + imputed	338

	Features	Params
S2	static + conj's	3583
Q2	static + quant (click feets) + conj's	14944
G5	static + click feats+imputed+conj's	4896



Concluding Remarks

- Click prediction is a central problem in Search Advertising
- Click modeling is challenging because of various biases, sparsity, missing data, and the dynamic nature of clicks and marketplace
- Machine learning techniques can be employed to deal with some of those challenging problems
- Computational Advertising is a rich interdisciplinary field for applying machine learning techniques

Thank you!

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