Offline Evaluation of Ranking Policies with Click Models

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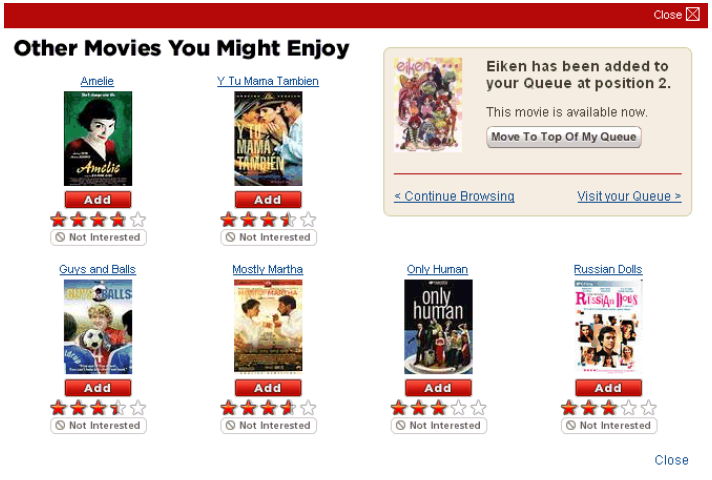
Motivation



Amazon, Facebook, Netflix

Motivation

Production Policy

Number of clicks: $\mathbb{R}(\ \ ) = 1$

Hypothetical Policy $\ddot{e}$

Number of clicks: $\mathbb{R}(\ddot{e}) = 2$

- How can we know $\mathbb{R}(\ddot{e}) = 2$?

Search “London” @ Adobe Stock

Directly Implementing New Policy $\ddot{e}$

Risks for directly implementing new policy $\ddot{e}$

- Expensive
- Uses a portion of live users and poor policy might harm user experience
- Not replicable

Can we know $\circledR(\ddot{e}) = 2$ without directly implementing it?

Offline Evaluation!

Setting

- Lists: $= (\ddot{A}_1; : : : ; \ddot{A}_U)$

- The value of list with the click realization $\acute{L}$:

$$\circledR(\ ; \acute{L}) = \sum_{\acute{y}=1}^{U} \acute{L}(\ddot{A}_{\acute{y}}; \acute{y})$$

- The value of a policy $\ddot{e}$:

$$\circledR(\ddot{e}) = \mathsf{E}_{\acute{l};\acute{L};\ \ \ddot{e}(\ j\acute{l})}[\circledR(\ ; \acute{L})]$$

Setting

- Suppose the clicks depend only on (item, position) pairs
- The CTR of putting item $\ddot{A}$ at $\acute{y}$-th position under context $\acute{l}$ is

$$\acute{L}(\ddot{A}; \acute{y}\ j\ \acute{l})$$

- The expected value of

$$\circledR(\quad) = \sum_{\acute{y}=1}^{\ddot{U}} \acute{L}(\ddot{A}_{\acute{y}}; \acute{y}\ j\ \acute{l})$$

Setting (Problem Definition)

Logged dataset $w = f(l'_{\tilde{I}};\ _{\tilde{I}}; \acute{L}_{\tilde{I}})g_{\tilde{I}=1}^{\acute{c}}$

- At each time $\tilde{I}$
  - The environment draws context $l'_{\tilde{I}}$ and click realizations $\acute{L}_{\tilde{I}}$
  - The learner observes $l'_{\tilde{I}}$ and selects $_{\tilde{I}}$ according to policy
  - The environment reveals $f\acute{L}_{\tilde{I}}(\ddot{A}_{\acute{y}}^{\tilde{I}}; \acute{y})g_{\acute{y}=1}^{U}$

Objective

- To design statistically efficient estimators based on logged dataset for any ranking policy

Challenge

- The number of different lists is exponential in U

Existing Method - Direct Method

- Direct Method

$$\hat{R}(\pi) = \frac{1}{c} \sum_{i=1}^{n} \sum_{a \in A} \sum_{y=1}^{m} \pi(a; y, j, l_i) \hat{L}(a; y, j, l_i)$$

- Can be used to evaluate any policy
- Unstable when the number of observations for some item is small
- No theoretical guarantee for known computationally efficient method for some click models

Existing Method - Unstructured List Estimator [Strehl et al. 2010]

- Importance sampling (for list level)

$$\begin{aligned} \mathbb{R}(\ddot{e}) &= \mathsf{E}_{\ddot{e}}[\mathbb{R}(\ )] \\ &= \mathsf{E}_{\ddot{e}}\ \mathbb{R}(\ )\ \frac{(\ )}{(\ )} \\ &= \mathsf{E}\ \ \mathbb{R}(\ )\ \frac{\ddot{e}(\ )}{(\ )} \end{aligned}$$

- List estimator

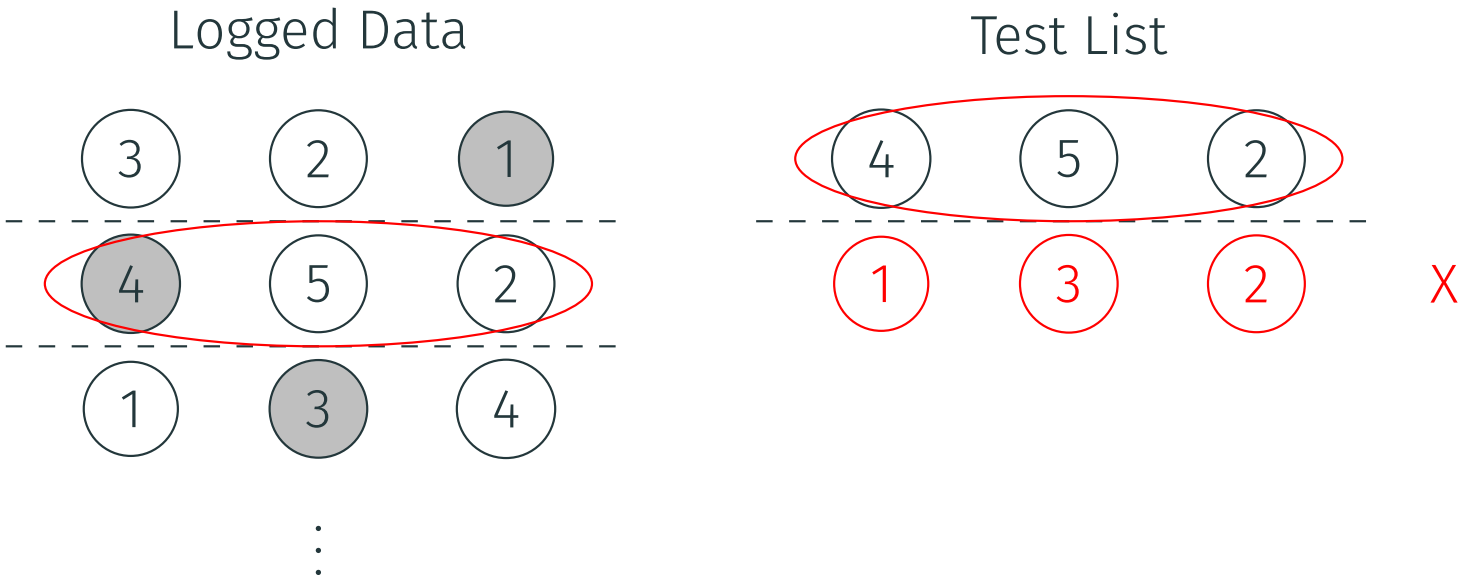
$$\hat{\mathbb{R}}_{\mathrm{L}}(\ddot{e}) = \frac{1}{jwj} \sum_{(\acute{l};\ ;\acute{L})\,2w} \mathbb{R}(\ ;\acute{L})\ \min\ \frac{\ddot{e}(\ \ j\ \acute{l})}{\wedge(\ \ j\ \acute{l})};\ ]$$

Trade-off between bias and variance

Empirical distribution over logged data

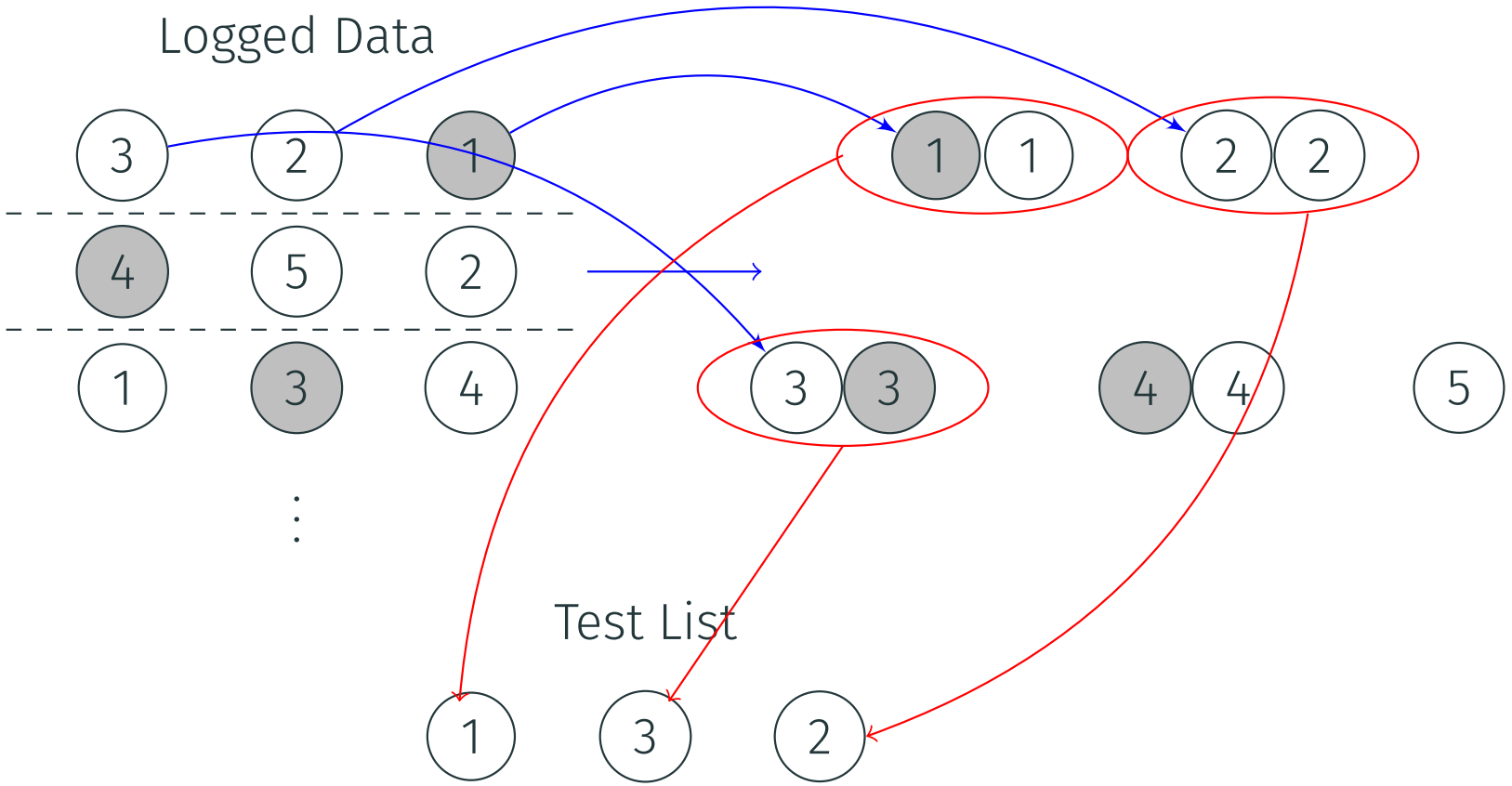
List Estimator - Disadvantages

- Disadvantages
  - Have to match the exact lists
  - The number of lists is exponential in U, thus ^(j l') is very small



Document-Based Click Model (DCTR)

- $\acute{L}(\ddot{A}; \acute{y} \; j \; \acute{l})$ only depends on item $\ddot{A}$, for any context $\acute{l}$



Estimators for DCTR

- DCTR: $\acute{L}(\ddot{A}; \acute{y}\ j\ l')$ only depends on item $\ddot{A}$ for any context l'

$$\text{®}_{\text{I}}(\ddot{e}) = \frac{1}{jwj} \sum_{(l';\ ;\acute{L})\,2w} \sum_{\acute{y}=1}^{\text{Ü}} \acute{L}(\ddot{A}_{\acute{y}}; \acute{y})\ \min\ \left[\frac{\ddot{e}(\ddot{A}_{\acute{y}}\ j\ l')}{\wedge(\ddot{A}_{\acute{y}}\ j\ l')};\ 1 \right]$$

- List estimator

$$\text{®}_{\text{L}}(\ddot{e}) = \frac{1}{jwj} \sum_{(l';\ ;\acute{L})\,2w} \sum_{\acute{y}=1}^{\text{Ü}} \acute{L}(\ddot{A}_{\acute{y}}; \acute{y})\ \min\ \left[\frac{\ddot{e}(\quad j\ l')}{\wedge(\quad j\ l')};\ 1 \right]$$

Estimators for Click Models

Click Model	Assumption	Estimator
Random	$\acute{L}(\ddot{A};\acute{y}\,j\;)$ constant	$\hat{\mathbb{R}}_{\mathrm{R}}$
Rank-Based	$\acute{L}(\ddot{A};\acute{y}\,j\;)$ only depends on position $\acute{y}$	$\hat{\mathbb{R}}_{\mathrm{R}}$
Document-Based	$\acute{L}(\ddot{A};\acute{y}\,j\;)$ only depends on item $\ddot{A}$	$\hat{\mathbb{R}}_{\mathrm{I}}$
Position-Based	$\acute{L}(\ddot{A};\acute{y}\,j\;) = \;(\ddot{A}\,j\;)\,\check{E}(\acute{y}\,j\;)$	$\hat{\mathbb{R}}_{\mathrm{PBM}}$
Item-Position	$\acute{L}(\ddot{A};\acute{y}\,j\;)$	$\hat{\mathbb{R}}_{\mathrm{IP}}$

Analysis

Proposition (Unbiased in a larger class of policies)

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Proposition (Lower bias in estimating policy)

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Proposition (Better guarantee for policy optimization)

}ëÛ ÐÛġĨ ĚĎĀîÑĿ åĎıć× ÐĿ ġĨĝıÑĨıĝÛ× ÛġĨîĆÄĨĎĝġ ëÄĸÛ ÐÛĨĨÛĝ ĨëÛĎĝÛĨîÑÄĀ œıÄĝÄćĨÛÛġ ĨëÄć ĨëÄĨ ÐĿ ĀîġĨ ÛġĨîĆÄĨĎĝ

Experiments

Personalized Web Search Challenge

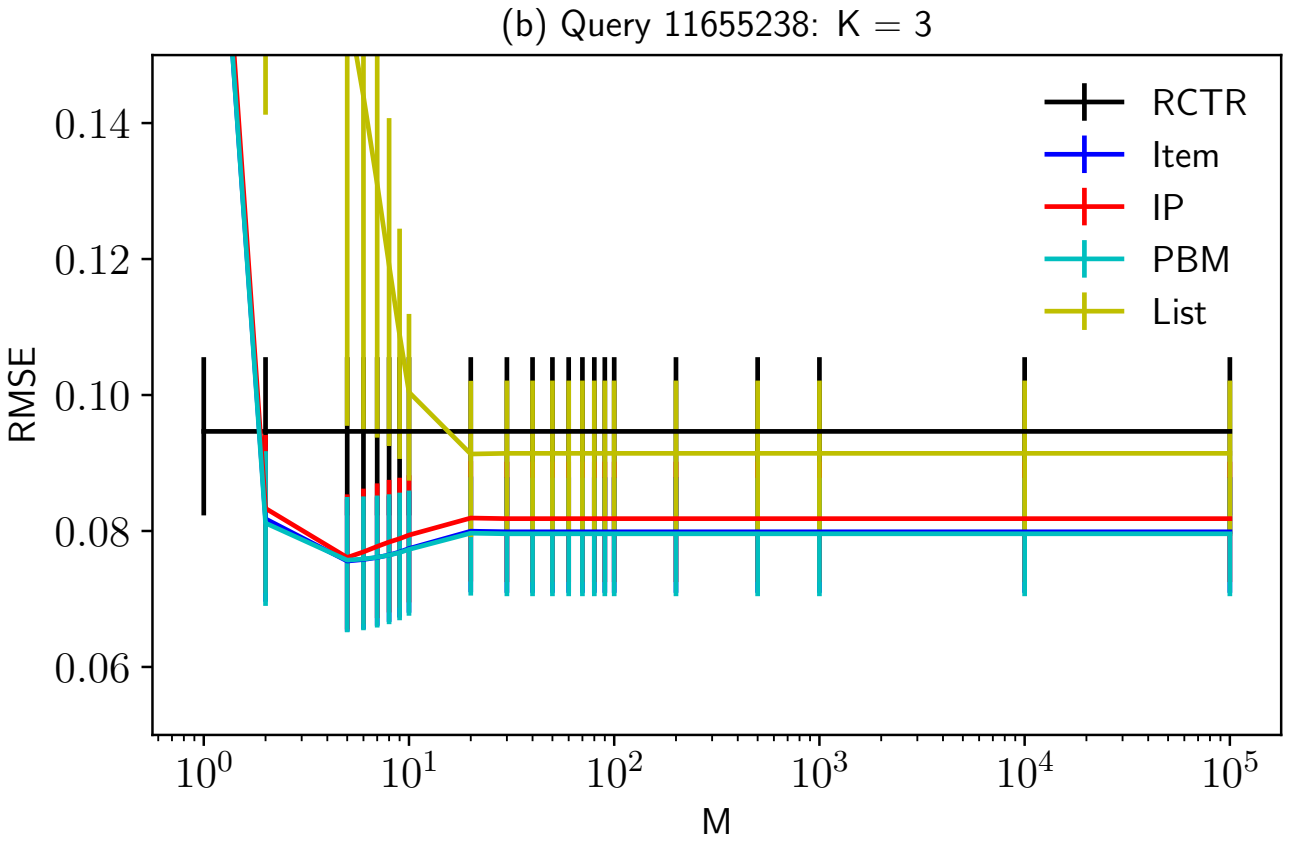
Re-rank web documents using personal preferences

$9,000 · 194 teams · 5 years ago

- Recorded over 27 days
- Each record contains
  - A query ID
  - The day when the query occurs
  - 10 displayed item as a response to the query
  - The corresponding click indicators of each displayed items

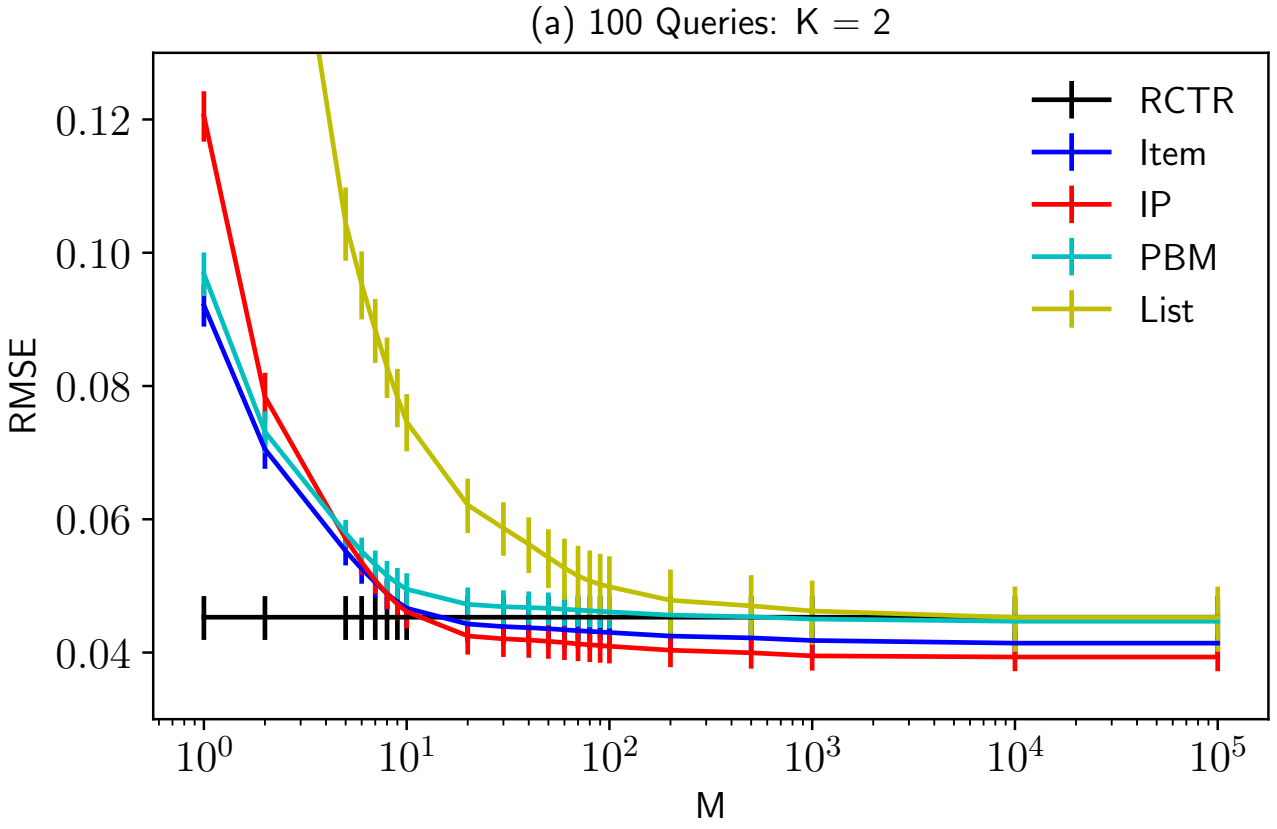
- Logged dataset w
  - Any record except day $\times$
  - $\wedge$ is the empirical distribution over w
- Evaluation policy $\ddot{e}$
  - Records of day $\times$
  - $\ddot{e}$ is the empirical distribution over these records
  - $\mathbb{R}(\ddot{e})$ is the average CTR for these records

Experiments - Example Query with $U = 3$



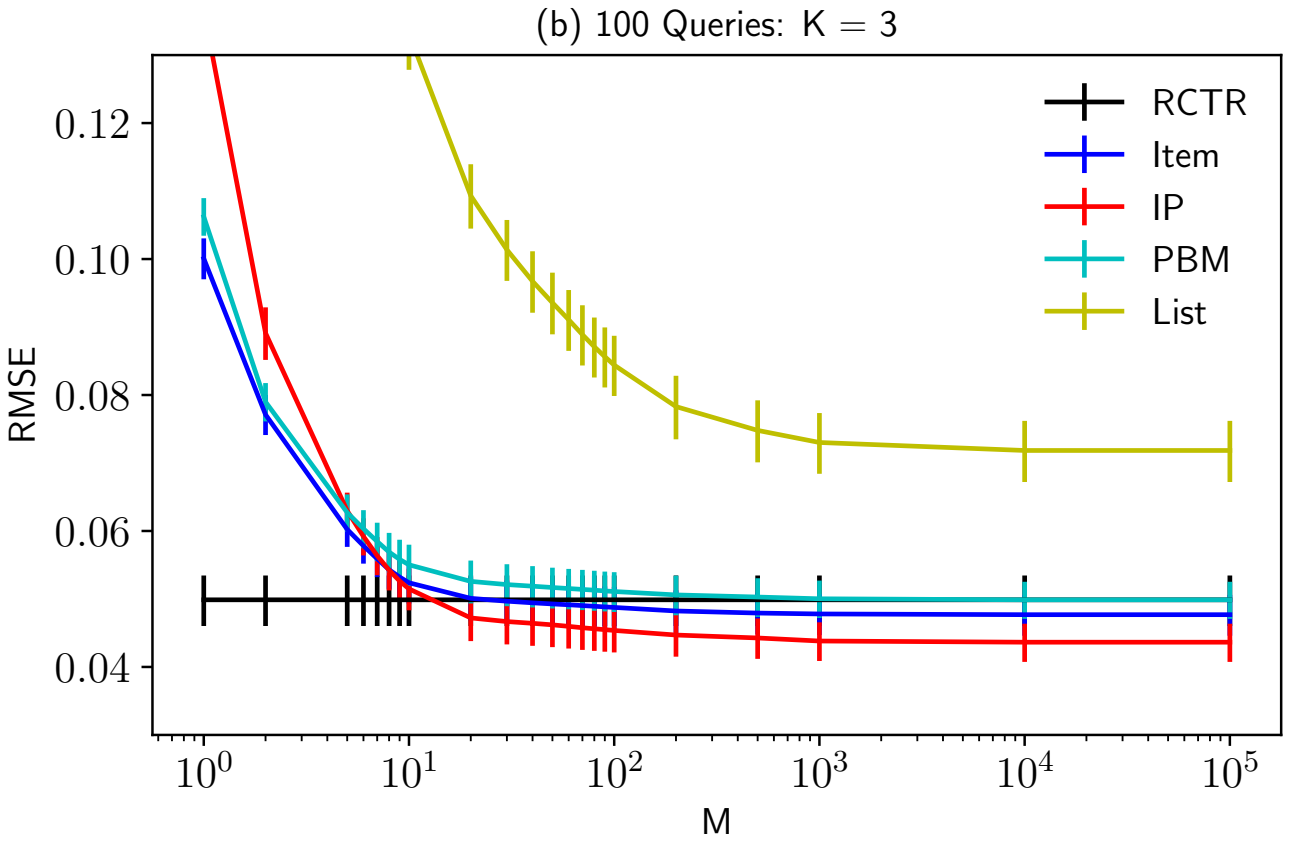
- Structured estimators better
- Tuning of J matters

Experiments - 100 Most Frequent Queries with $U = 2$



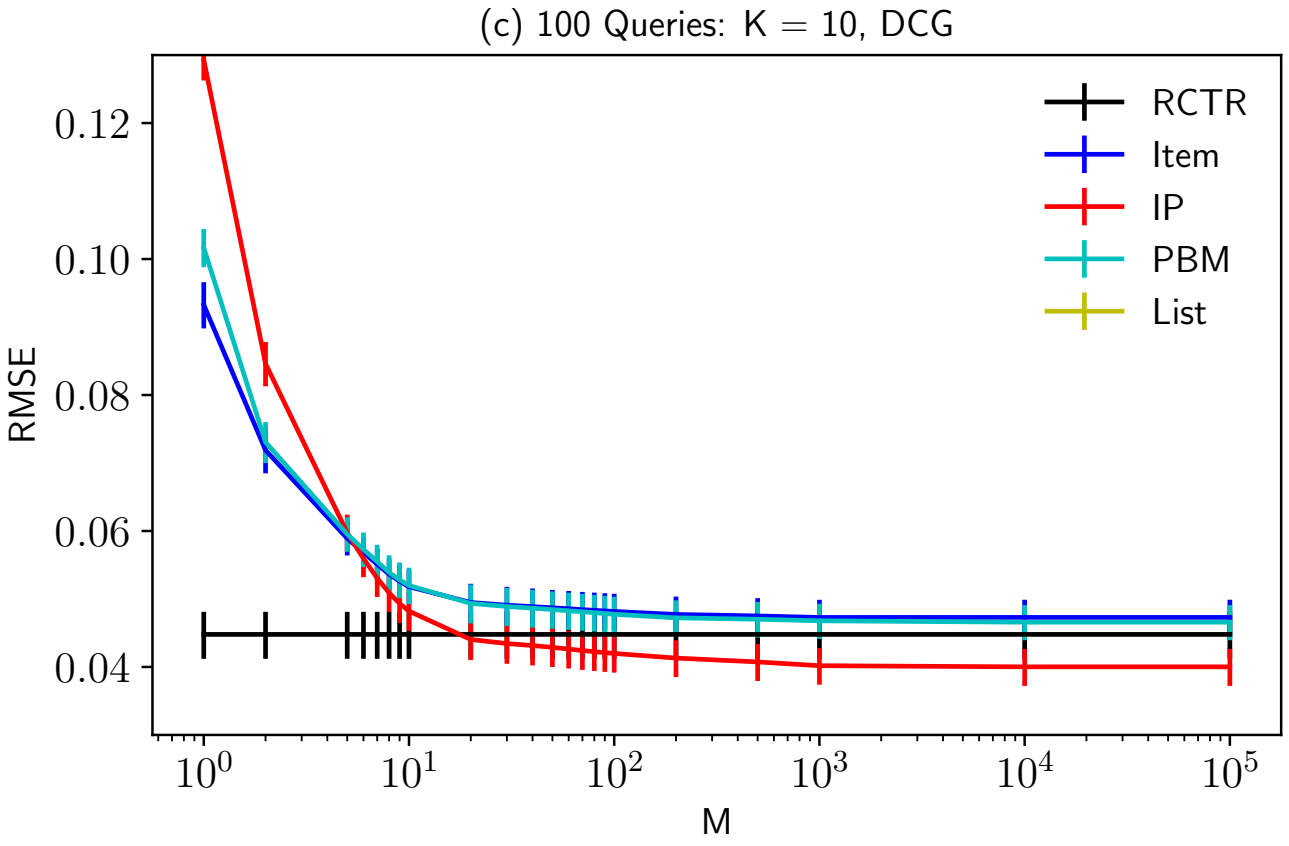
- IP estimator improves 18% over list estimator
- IP estimator improves 13% over RCTR estimator

Experiments - 100 Most Frequent Queries with $U = 3$



- IP estimator improves 46% over list estimator
- IP estimator improves 13% over RCTR estimator

Experiments - 100 Most Frequent Queries with $U = 10$, DCG



- IP estimator improves 82% over list estimator
- IP estimator improves 11% over RCTR estimator

Conclusions

- We propose various estimators for the expected number of clicks on lists generated by ranking policies that leverage the structure of click models
- We prove that our estimators are better than the unstructured list estimators
  - Less biased
  - Better guarantees for policy optimization
- Our estimators consistently outperform the list estimator in experiments

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