Offline Evaluation of Ranking Policies with Click Models

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Joint work with
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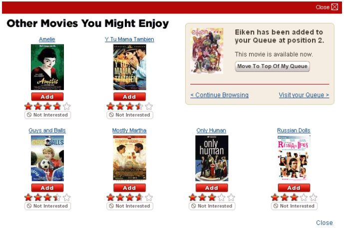
Vishwa Vinay (Adobe Research)
Zheng Wen (Adobe Research)

Motivation



Amazon, Facebook, Netflix

Motivation

Production Policy π

Number of clicks: $V(\pi) = 1$

Hypothetical Policy h

Number of clicks: $V(h) = 2$

Search “London” @ Adobe Stock

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Hypothetical Policy h

Number of clicks: $V(h) = 2$

- How can we know $V(h) = 2$?

Search “London” @ Adobe Stock

Directly Implementing New Policy h

Risks for directly implementing new policy h

- Expensive
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Offline Evaluation!

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$$V(A; w) = \sum_{k=1}^{K} w(a_k, k)$$

- The value of a policy h:

$$V(h) = \mathbb{E}_{x, w, A \sim h(\cdot|x)} \left[V(A; w) \right]$$

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- The expected value of A

$$V(A) = \sum_{k=1}^{K} \bar{w}(a_k, k \mid x)$$

Setting (Problem Definition)

Logged dataset $S = \{(x_t, A_t, w_t)\}_{t=1}^{n}$

- At each time t
  - The environment draws context x_t and click realizations w_t
  - The learner observes x_t and selects A_t according to policy π
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- To design statistically efficient estimators based on logged dataset for any ranking policy

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Challenge

- The number of different lists is exponential in K

Existing Method - Direct Method

- Direct Method

$$\hat{V}(h) = \frac{1}{n} \sum_{t=1}^{n} \sum_{a} \sum_{k=1}^{K} h(a, k \mid x_t) \, \hat{w}(a, k \mid x_t)$$

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- 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)

$$
\begin{aligned}
V(h) &= \mathbb{E}_{A \sim h}[V(A)] \\
&= \mathbb{E}_{A \sim h}\left[V(A) \cdot \frac{\pi(A)}{\pi(A)}\right] \\
&= \mathbb{E}_{A \sim \pi}\left[V(A) \cdot \frac{h(A)}{\pi(A)}\right]
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$$\hat{V}_{\mathrm{L}}(h) = \frac{1}{|S|} \sum_{(x,A,w) \in S} V(A; w) \ \min\left\{\frac{h(A \mid x)}{\hat{\pi}(A \mid x)},\ M\right\}$$

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Trade-off between bias and variance

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Empirical distribution over logged data

List Estimator - Disadvantages

- Disadvantages
  - Have to match the exact lists
  - The number of lists is exponential in K, thus $\hat{\pi}(A \mid x)$ is very small

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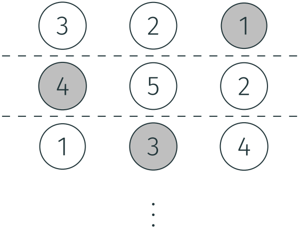
Logged Data



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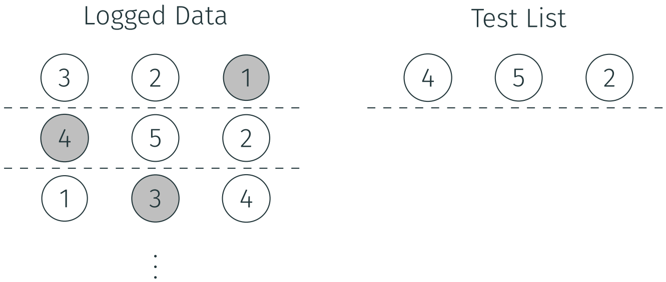

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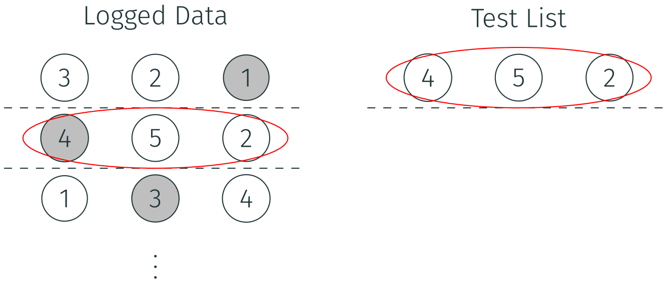

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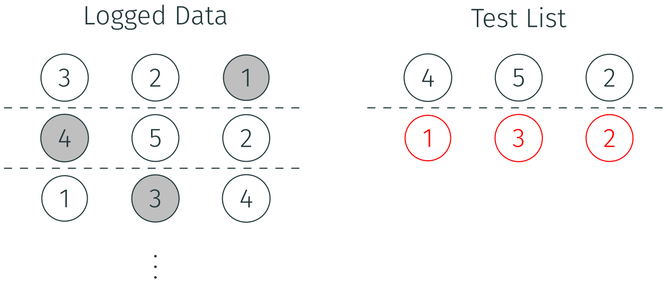

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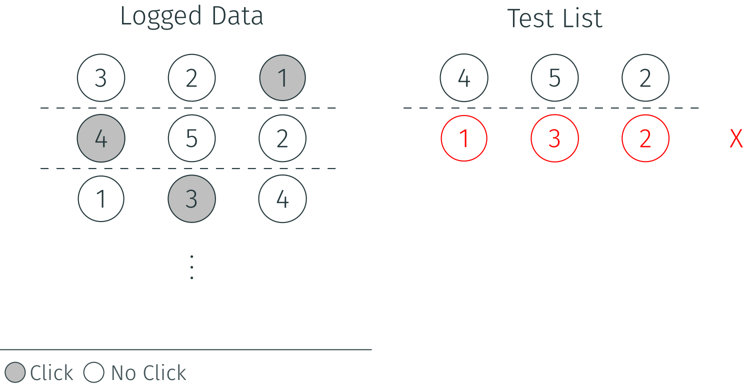

Document-Based Click Model (DCTR)

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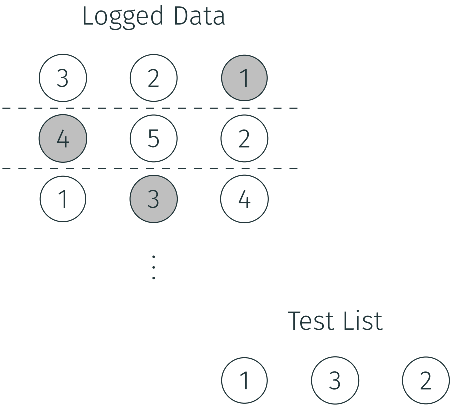

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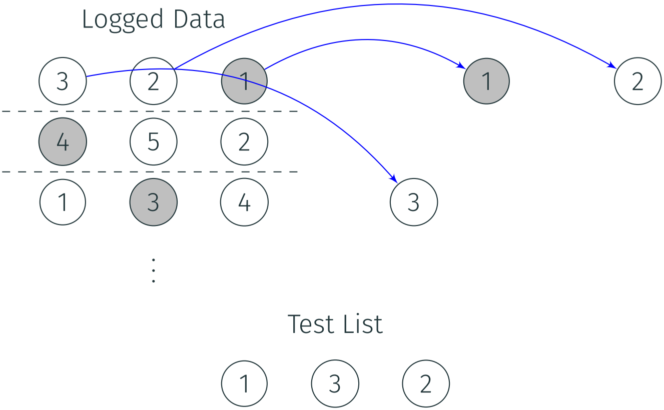

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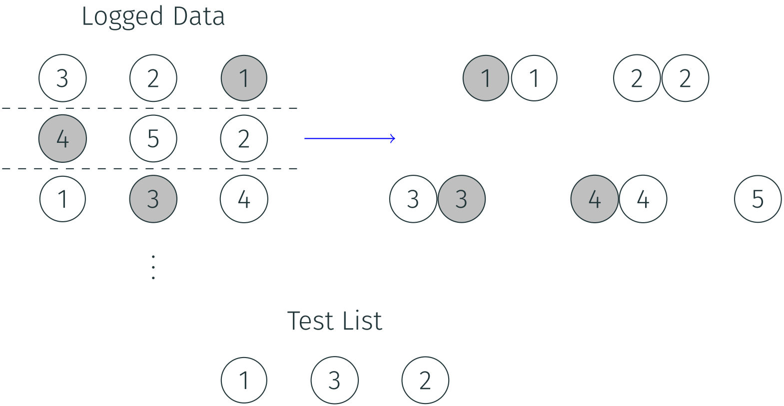

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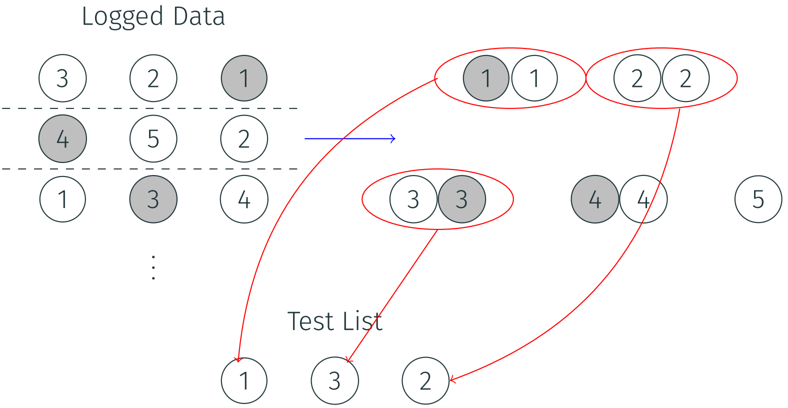

Estimators for DCTR

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Estimators for Click Models

Click Model	Assumption	Estimator
Random	$\bar{w}(a, k \mid \cdot)$ constant	$\hat{V}_{\mathrm{R}}$
Rank-Based	$\bar{w}(a, k \mid \cdot)$ only depends on position k	$\hat{V}_{\mathrm{R}}$
Document-Based	$\bar{w}(a, k \mid \cdot)$ only depends on item a	$\hat{V}_{\mathrm{I}}$
Position-Based	$\bar{w}(a, k \mid \cdot) = \mu(a \mid \cdot)\, p(k \mid \cdot)$	$\hat{V}_{\mathrm{PBM}}$
Item-Position	$\bar{w}(a, k \mid \cdot)$	$\hat{V}_{\mathrm{IP}}$

Analysis

Proposition (Unbiased in a larger class of policies)

The structured estimators are unbiased in a larger class of policies than list estimator.

Proposition (Lower bias in estimating policy)

The structured estimators have lower bias than list estimator.

Proposition (Better guarantee for policy optimization)

The best policy found by structured estimators have better theoretical guarantees than that by list estimator.

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

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Yandex

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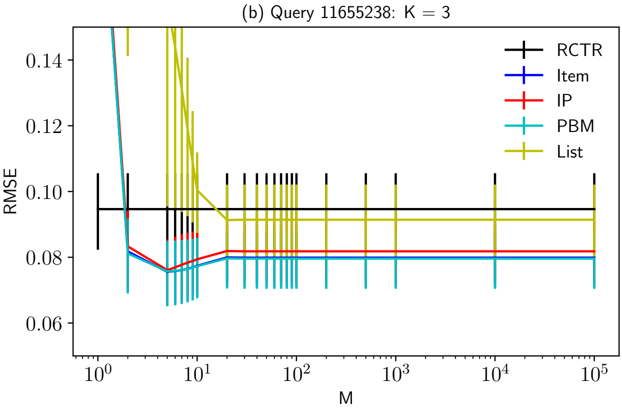
- Logged dataset S
  - Any record except day d
  - $\hat{\pi}$ is the empirical distribution over S
- Evaluation policy h
  - Records of day d
  - h is the empirical distribution over these records
  - $V(h)$ is the average CTR for these records

Experiments - Example Query with $K = 3$



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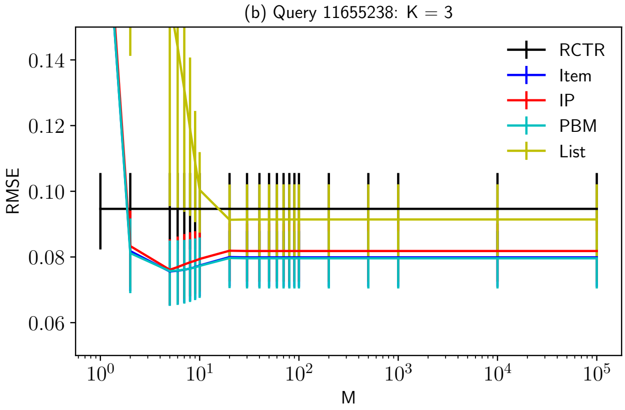

- Structured estimators better

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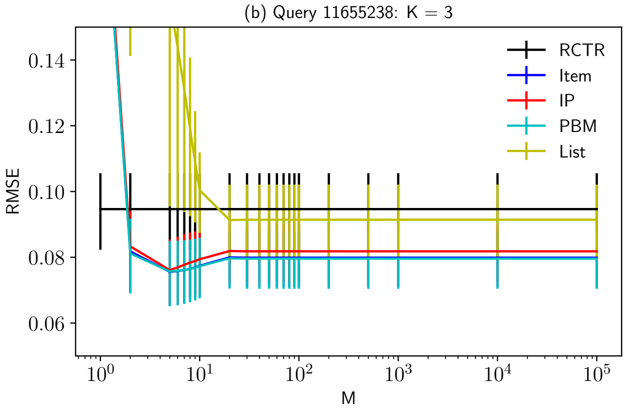
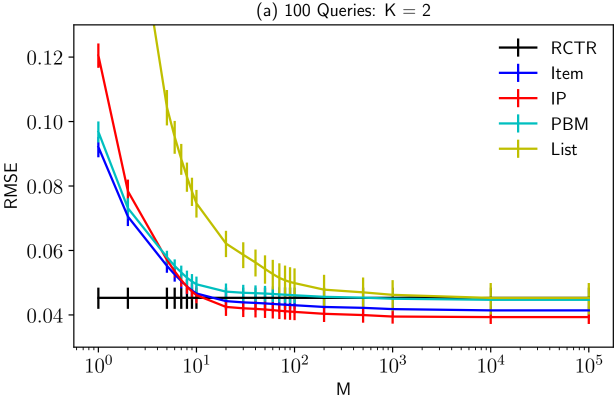


- Structured estimators better
- Tuning of M matters

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



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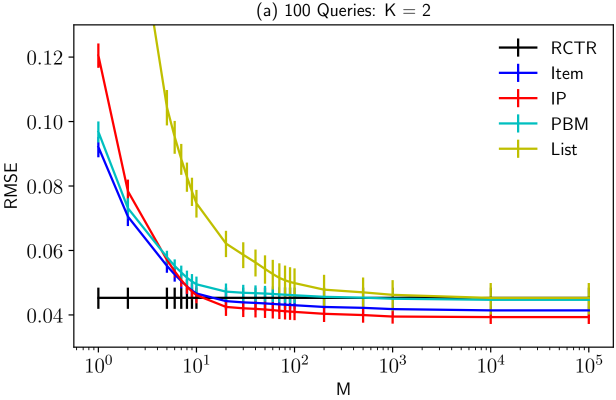

- IP estimator improves 18% over list estimator
- IP estimator improves 13% over RCTR estimator

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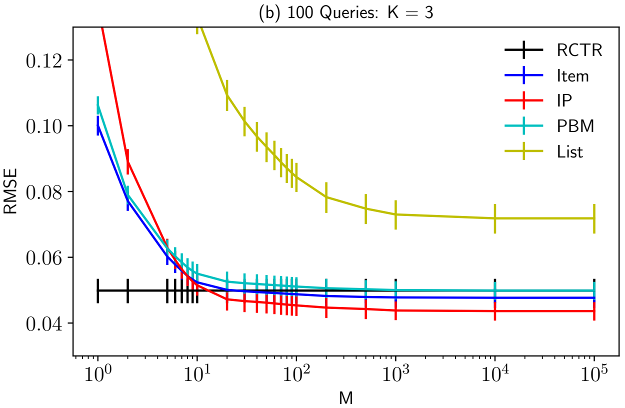

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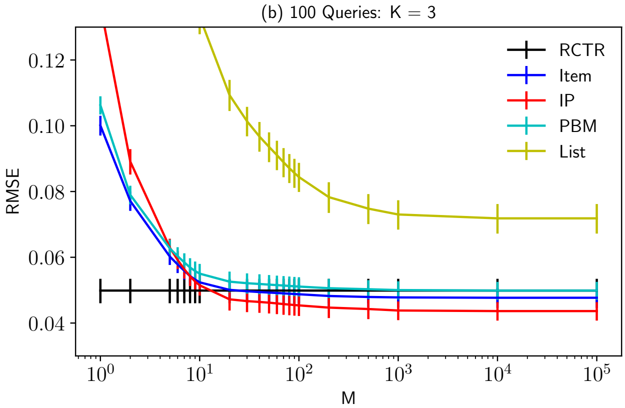
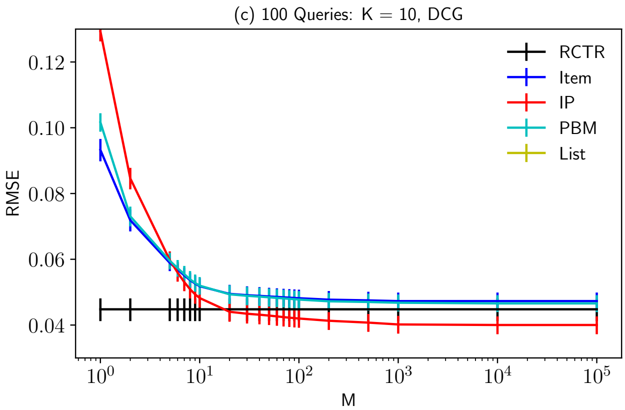


- IP estimator improves 46% over list estimator
- IP estimator improves 13% over RCTR estimator

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



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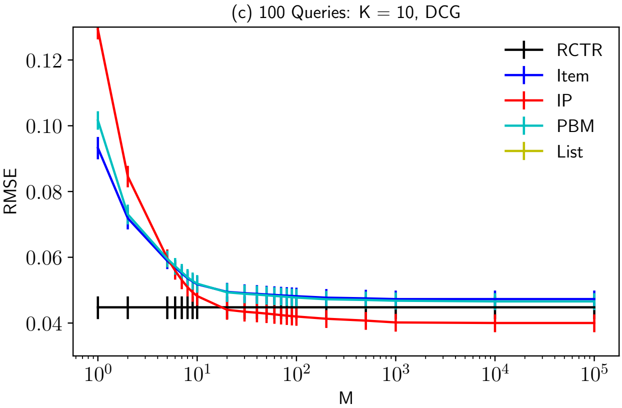

- IP estimator improves 82% over list estimator
- IP estimator improves 11% over RCTR estimator

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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