Unbiased Learning to Rank from User Interactions

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Introduction

Learning to Rank in Information Retrieval

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- Key component for **search** and **recommendation**.
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Traditionally learning to rank uses **annotated datasets**:

- **Relevance annotations** for query-document pairs provided by **human judges**.

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- **stationary**, cannot capture **future changes in relevancy** (Lefortier et al., 2014).
- **not necessarily aligned with actual user preferences** (Sanderson, 2010),
  i.e. annotators and users often disagree.

Learning from User Interactions

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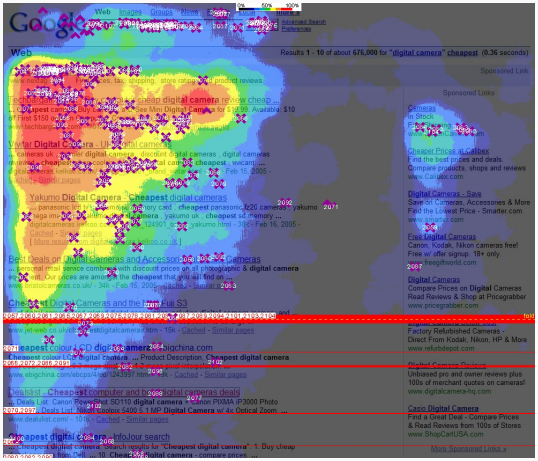
  - **Presentation bias:** Results that are **presented differently** will be **treated different**.
  - ...

The Golden Triangle



Source: http://www.mediative.com/

Learning from User Interactions: Goal

Goal of unbiased learning to rank:

- Optimize a ranker w.r.t. **relevance preferences** of users from their interactions.
- **Avoid** being **biased by other factors** that influence interactions.

Learning from User Interactions: Conclusion

Learning from Historical Interactions:

- Learn/estimate a **model of user behaviour** including their biases.
- Learn from historical data while **adjusting** for these **biases**.

Online Learning to Rank:

- Algorithms that can **intervene** during the learning process.
- Handle biases by having **control over displayed results**.

Learning from Historical Data

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By **modelling user biases** accurately, they can be **adjusted for effectively**.

Learning from Historical Data: History

History of this approach:

- **Click models**:
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  then correct for it in learning to rank for instant email-results (Wang et al., 2016).

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- **Unbiased learning**:
  Infer the effect of position bias on selection bias in click-data,
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- **Counter-factual learning**:
  Recast the approach with counter-factual learning theory,
  and broaden applicability to general ranking problems (Joachims et al., 2017).

IPS: Full Information Setting

Under assumption of **binary relevance**:

$$r(y) \in \{0, 1\}$$

The **loss** for a single query $\mathbf{q}$, a ranking $\mathbf{y}$, and the relevance r:

$$\Delta(\mathbf{y}|\mathbf{q}, r) = \sum_{y \in \mathbf{y}} \mathsf{rank}(y|\mathbf{y}) \cdot r(y). \tag{1}$$

Minimizing this loss is **trivial** if the relevances r are known (**full-information setting**).

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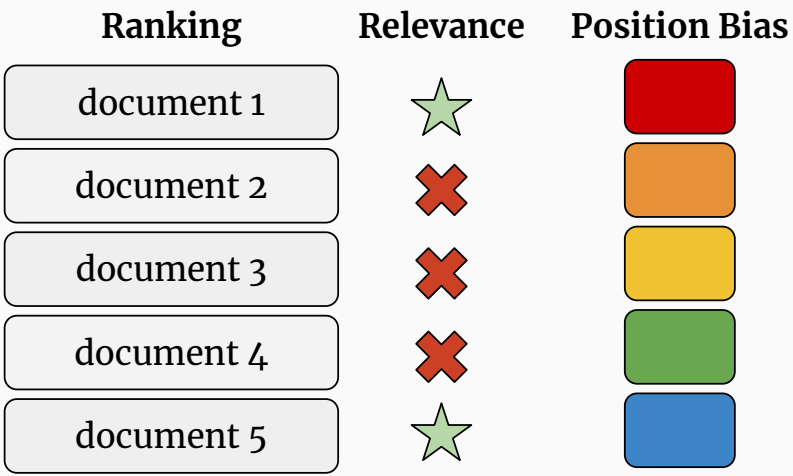

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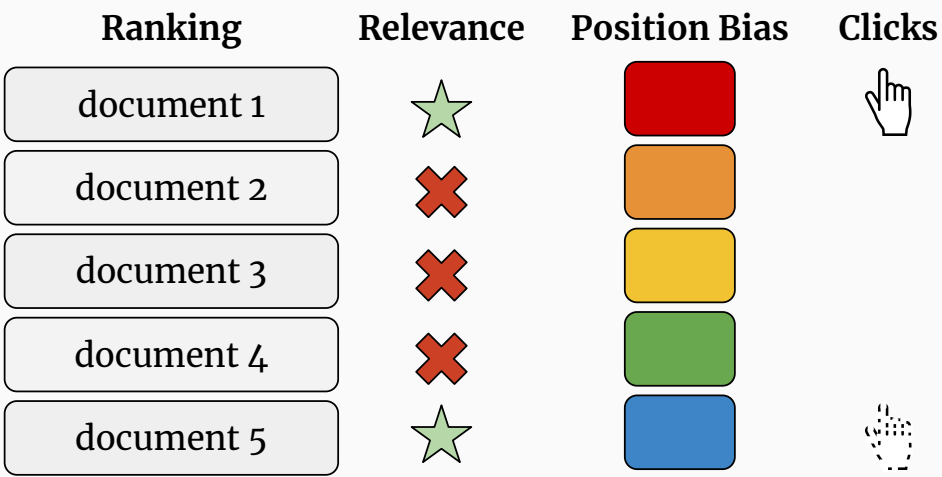

IPS: Bias in Naive Approach

Assume that every **relevant** document that is **observed** is **clicked** (no noise).

Due to **biases** the **probability** of a document y being **observed** in ranking $\bar{\mathbf{y}}$ is:

$$Q(o(y) = 1 | \mathbf{q}, \bar{\mathbf{y}}, r), \tag{2}$$

this is called the *propensity*.

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If we **naively estimate the loss** from clicks it is **biased**:

$$\begin{aligned} \mathbb{E}_o[\hat{\Delta}_{\text{naive}}(\mathbf{y}|\mathbf{q}, r)] &= \mathbb{E}_o[\sum_{y:o(y)=1 \wedge r(y)=1} \text{rank}(y|\mathbf{y}) \cdot r(y)] \\ &= \sum_{y \in \mathbf{y}} Q(o(y) = 1 | \mathbf{q}, \bar{\mathbf{y}}, r) \cdot \text{rank}(y|\mathbf{y}) \cdot r(y). \end{aligned} \tag{3}$$

IPS: Inverse Propensity Scoring

However, with **knowledge** of $Q(o(y) = 1|\mathbf{q}, \bar{\mathbf{y}}, r)$ it can be **corrected for** easily:

$$\hat{\Delta}_{IPS}(\mathbf{y}|\mathbf{q}, r) = \sum_{y:o(y)=1 \wedge r(y)=1} \frac{\mathsf{rank}(y|\mathbf{y}) \cdot r(y)}{Q(o(y) = 1|\mathbf{q}, \bar{\mathbf{y}}, r)}. \tag{4}$$

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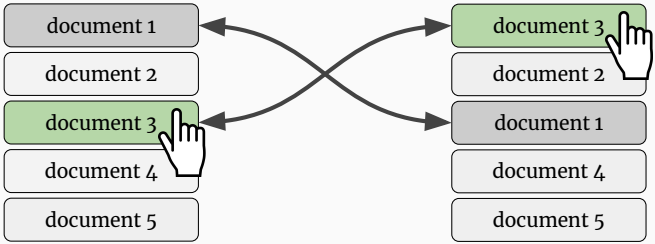
The **expected loss** now gives an **unbiased estimate**:

$$\begin{aligned}
\mathbb{E}_o[\hat{\Delta}_{\mathsf{IPS}}(\mathbf{y}|\mathbf{q}, r)] &= \mathbb{E}_o[\sum_{y:o(y)=1 \wedge r(y)=1} \frac{\mathsf{rank}(y|\mathbf{y}) \cdot r(y)}{Q(o(y) = 1|\mathbf{q}, \bar{\mathbf{y}}, r)})] \\
&= \sum_{y \in \mathbf{y}} \frac{Q(o(y) = 1|\mathbf{q}, \bar{\mathbf{y}}, r) \cdot \mathsf{rank}(y|\mathbf{y}) \cdot r(y)}{Q(o(y) = 1|\mathbf{q}, \bar{\mathbf{y}}, r)} \\
&= \sum_{y \in \mathbf{y}} \mathsf{rank}(y|\mathbf{y}) \cdot r(y) \\
&= \Delta(\mathbf{y}|\mathbf{q}, r).
\end{aligned}$$

IPS: Propensity Inference

However, the propensities $Q(o(y) = 1|\mathbf{q}, \bar{\mathbf{y}}, r)$ still have to be inferred.

One possible way is by **swapping document pairs**:



Assuming the difference in click probabilities is **only affected** by the **observance probability**.

Learning from Historical Data: Conclusion

Unbiased learning to rank from historical data:

1. **Infer a user model** potentially from randomized rankings (e.g. swapped pairs).

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2. **Gather user-interaction logs** using the production ranker (**no randomization required**).
3. Learn an **unbiased ranking model** by applying **counter-factual learning**, using the user model and interaction logs.

Note that:

- Once an accurate user model is obtained, **randomization is no longer needed.**
- Also proven to be unbiased when **click noise is present**.

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Advantages:

- Can **learn unbiasedly** from **user interactions**.
- Learned ranking models **match user preferences** closer than annotations.
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Disadvantages:

- **Requires an accurate user model**, which may not always be feasible.
- **No comparison** with *online learning to rank* has been performed.

This is still a **very new and active** area of research.

Online Learning to Rank

Online Learning to Rank: Concept

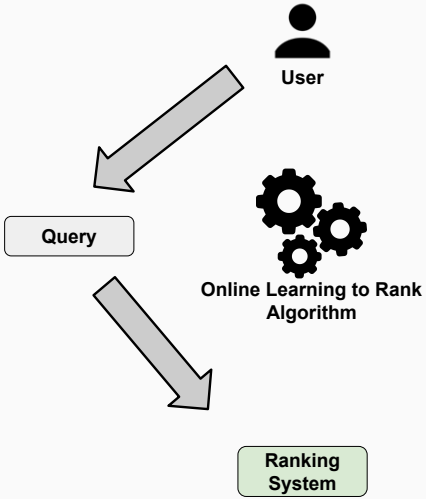
Online Learning to Rank methods have **control over what to display** to the user Yue and Joachims (2009).

Simultantiously they:

- **Decide** what **results to display** to the user.
- **Learn** from **user interactions** with chosen results.

These methods can be much **more efficient**,
because they have (more) **control over what data is gathered**.

Online Learning to Rank: Visualization



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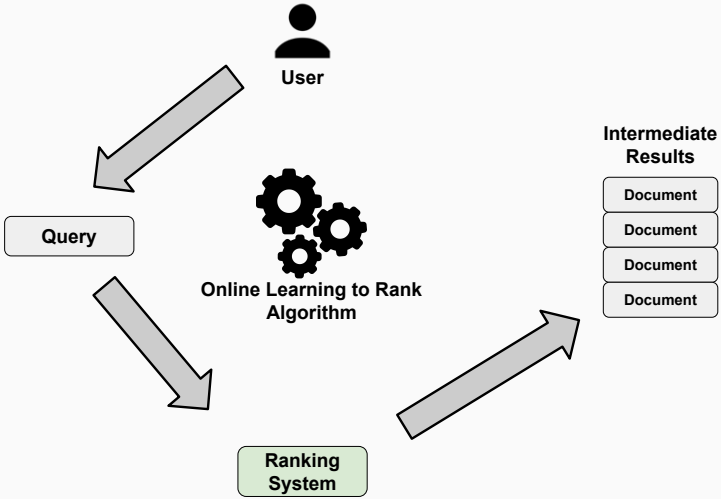

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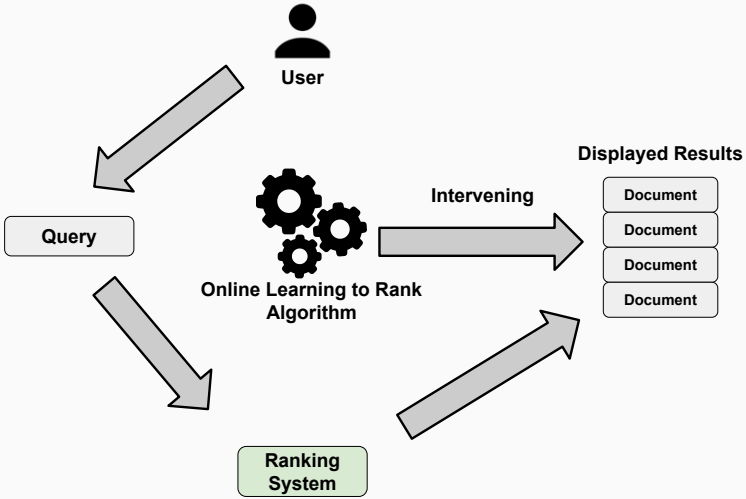

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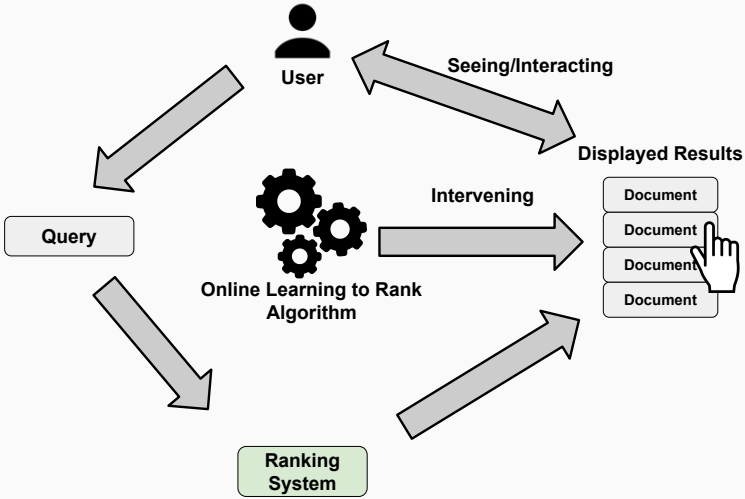

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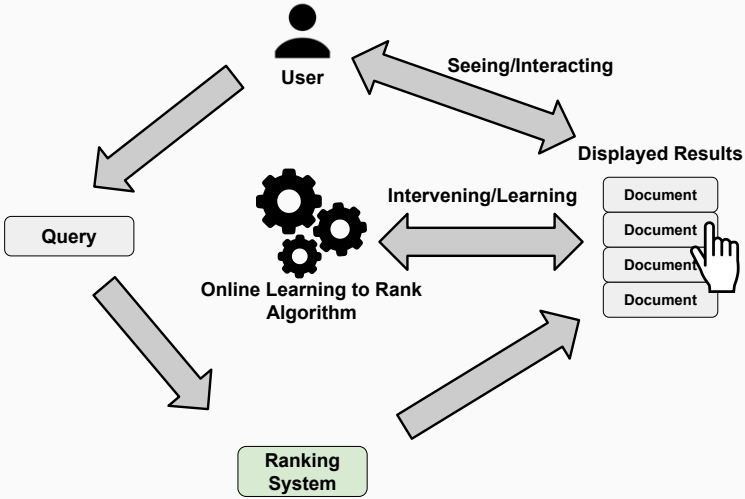

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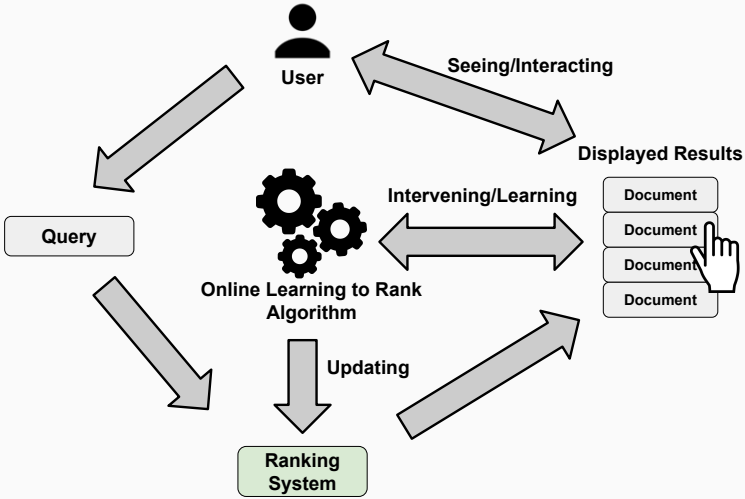

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Online methods also bring a **large risk**:

- **Unreliable** methods could **severely worsen the user experience immediately**.

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Advantages:

- Online methods learn **faster** by **intervening**, (than learning from historical data).
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- **No comparisons** performed with *learning from historical data*.

Pairwise Differentiable Gradient Descent

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We recently introduced **Pairwise Differentiable Gradient Descent** (Oosterhuis and de Rijke, 2018):

- Very different from previous Online Learning to Rank methods, that relied on sampling model variations similar to evolutionary approaches.

Intuition:

- A **pairwise** approach can be made **unbiased**, while being **differentiable**, without relying on online evaluation method or the sampling of models.

Plackett Luce Model

Pairwise Differentiable Gradient Descent optimizes a **Plackett Luce** ranking model, this models a **probabilistic distribution over documents**.

With the ranking scoring model $f(\mathbf{d}, \theta)$ the distribution is:

$$P(d|D,\theta) = \frac{\exp^{f(\mathbf{d},\theta)}}{\sum_{d' \in D} \exp^{f(\mathbf{d}',\theta)}} \tag{5}$$

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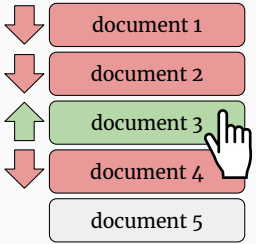
Confidence is explicitly modelled and **exploration** depends on the **available documents**, thus it **naturally varies per query** and even within the ranking,.

Bias in Pairwise Inference

Similar to existing pairwise methods (Oosterhuis and de Rijke, 2017; Joachims, 2002), Pairwise Differentiable Gradient Descent infers **pairwise document preferences from user clicks**:



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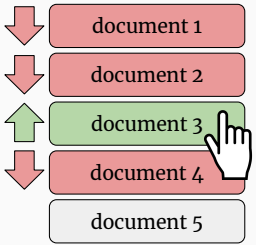
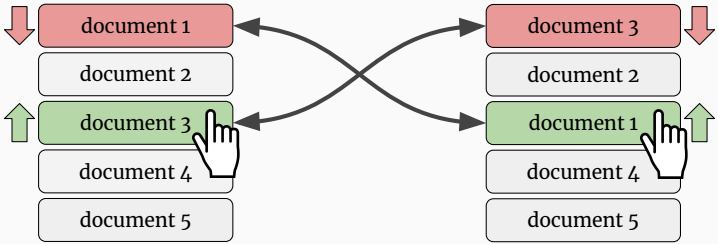


This approach is **biased**:

- Some preferences are **more likely to be inferred** due to **position/selection bias**.

Reversed Pair Rankings

Let $R^*(d_i, d_j, R)$ be R but with the **positions** of d_i and d_j **swapped**:



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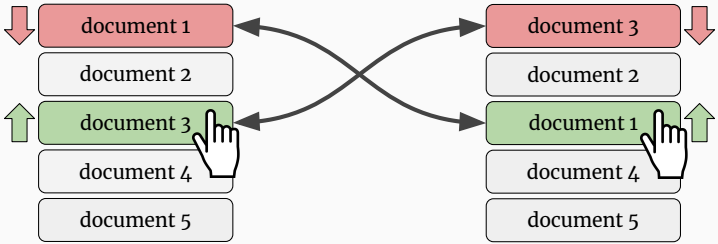

We assume:

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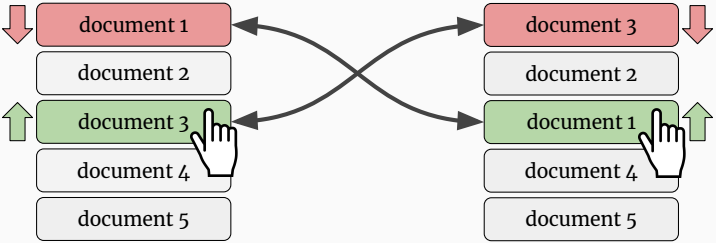

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Then scoring **as if** R and R^* are **equally likely to occur** makes the gradient **unbiased**.

Unbiasing the Pairwise Update

The **ratio** between the probability of the ranking and the reversed pair ranking indicates the **bias between the two directions**:

$$\rho(d_i, d_j, R) = \frac{P(R^*(d_i, d_j, R)|f, D)}{P(R|f, D) + P(R^*(d_i, d_j, R)|f, D)} \tag{6}$$

We use this ratio to **unbias the gradient estimation**:

$$\nabla f(\cdot, \theta) \approx \sum_{d_i >_{\mathbf{c}} d_j} \rho(d_i, d_j, R) \nabla P(d_i \succ d_j | D, \theta). \tag{7}$$

Unbiasedness of Pairwise Differentiable Gradient Descent

Under the reversed pair ranking assumption, we prove that **the expected estimated gradient** can be written as:

$$E[\nabla f(\cdot, \theta)] = \sum_{d_i, d_j} \alpha_{ij} (f'(\mathbf{d_i}, \theta) - f'(\mathbf{d_j}, \theta)). \tag{8}$$

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Where the weights α_{ij} will **match the user preferences** in expectation:

$$d_i =_{rel} d_j \Leftrightarrow \alpha_{ij} = 0, \tag{9}$$

$$d_i >_{rel} d_j \Leftrightarrow \alpha_{ij} > 0, \tag{10}$$

$$d_i <_{rel} d_j \Leftrightarrow \alpha_{ij} < 0. \tag{11}$$

Thus the estimated gradient is **unbiased w.r.t. document pair preferences**.

Pairwise Differentiable Gradient Descent: Method

Start with initial model θ_t.

Then indefinitely:

1. Wait for a user query.
2. **Sample** (without replacement) a **ranking** R from the document distribution:

$$P(d|D,\theta_t) = \frac{\exp^{f(\mathbf{d},\theta_t)}}{\sum_{d' \in D} \exp^{f(\mathbf{d}',\theta_t)}}. \tag{12}$$

3. **Display** the ranking R to the user.
4. **Infer document preferences** from the **user clicks**: $\mathbf{c}$.
5. **Update** model according to the **estimated (unbiased) gradient**:

$$\nabla f(\cdot,\theta) \approx \sum_{d_i >_{\mathbf{c}} d_j} \rho(d_i, d_j, R) \nabla P(d_i \succ d_j | D, \theta). \tag{13}$$

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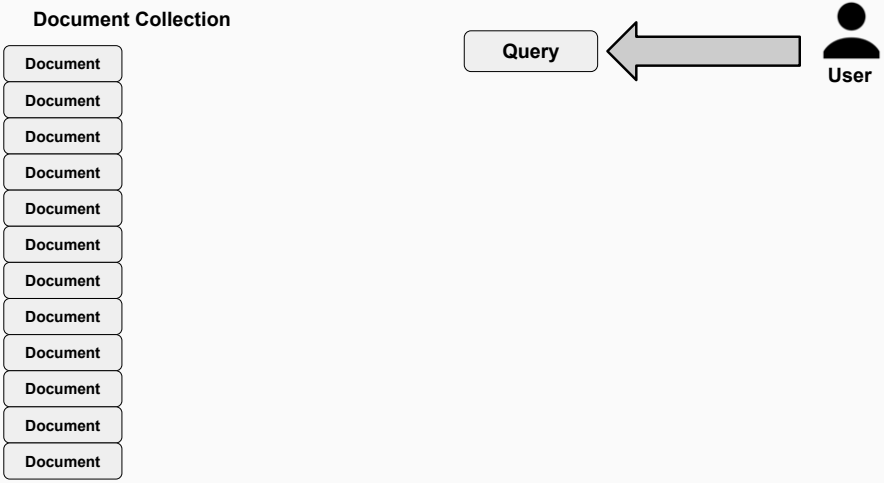
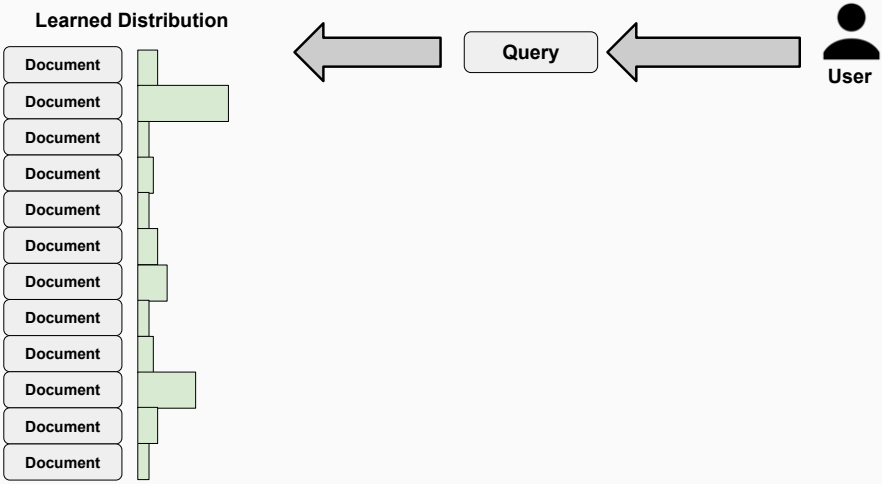


Pairwise Differentiable Gradient Descent: Visualization



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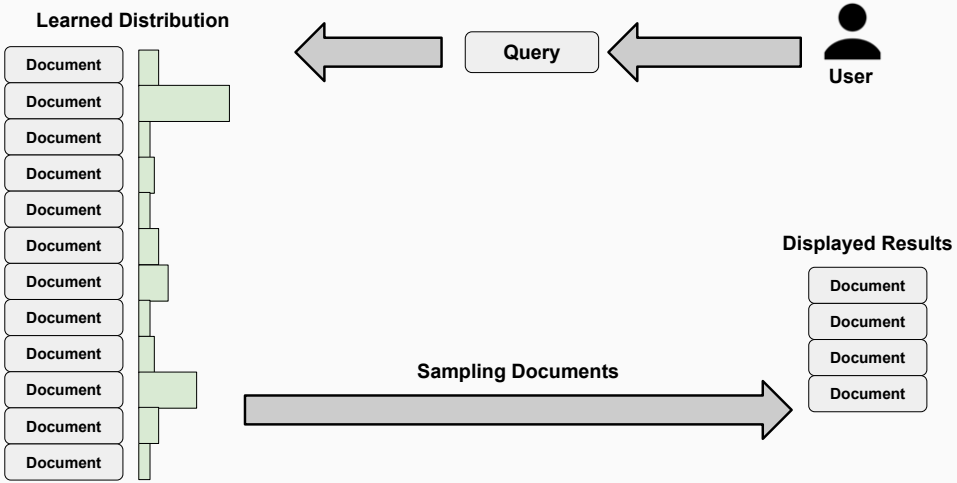

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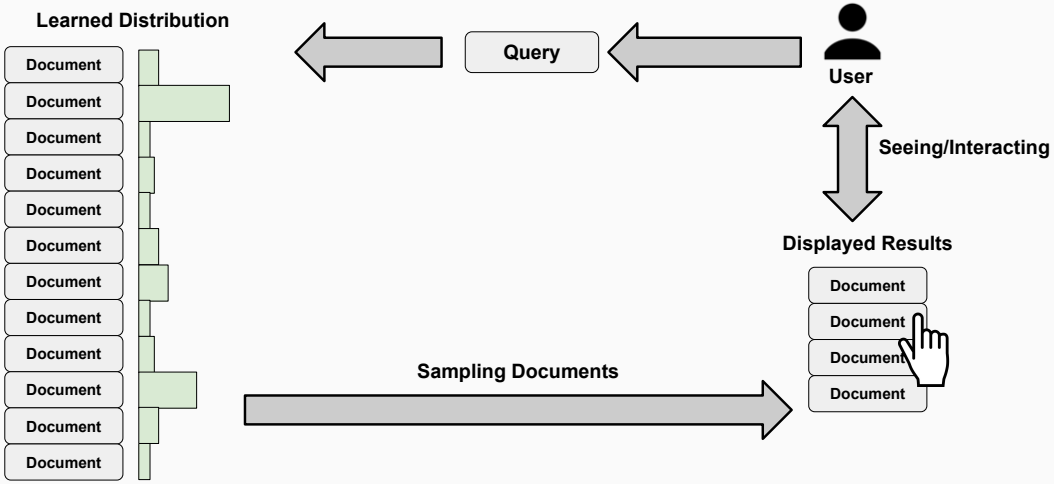

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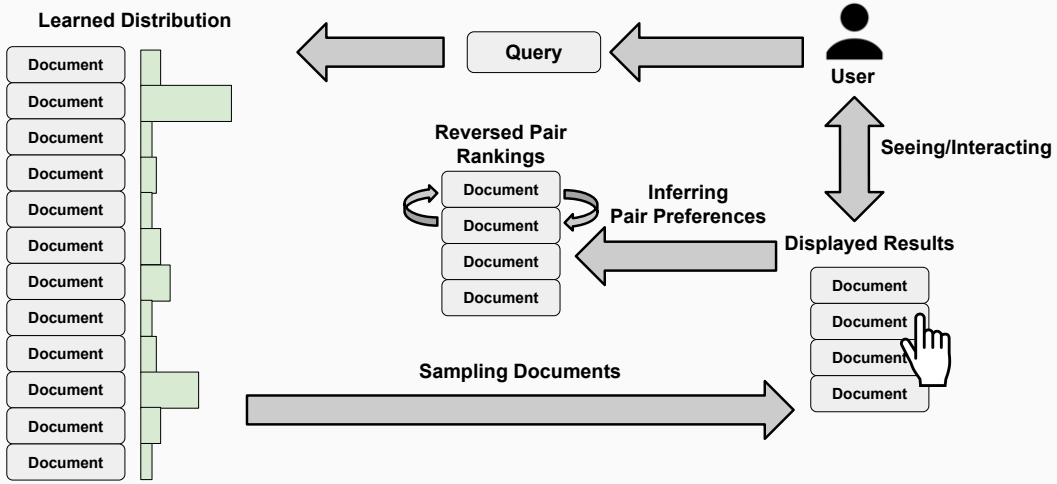

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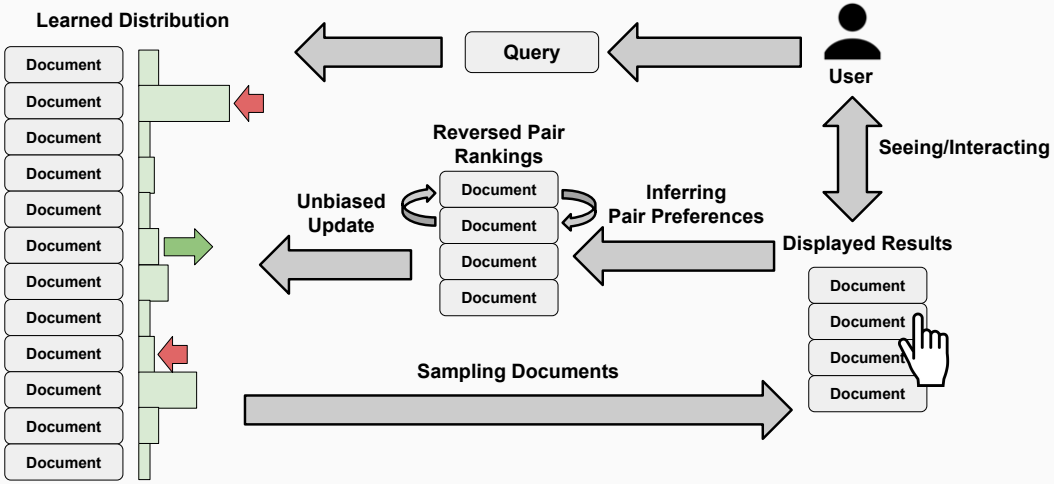


Experimental Results

Experimental Setup

Comparison of Pairwise Differentiable Gradient Descent with **previous Online Learning to Rank methods**.

Simulations based on the annotated learning-to-rank datasets.

- **Largest available industry datasets**: MSLR-Web10k, Yahoo Webscope, Istella.

User behaviour simulated using **cascading click models**.

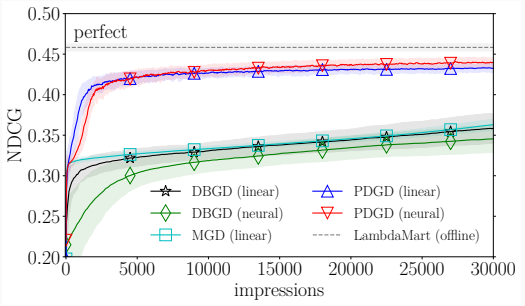
Experiments **repeated** under **varying levels** of noise and bias.

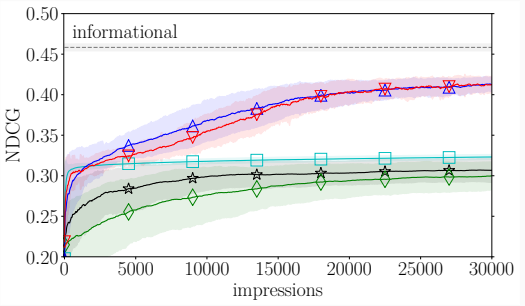
Pairwise Differentiable Gradient Descent: Results

Results **across all datasets** (MSLR-Web10k, Yahoo Webscope, Istella) we observe:

- **Large improvements** in performance of **convergence** under all levels of noise.
- Much **faster learning (better user experience)** under all levels of noise.

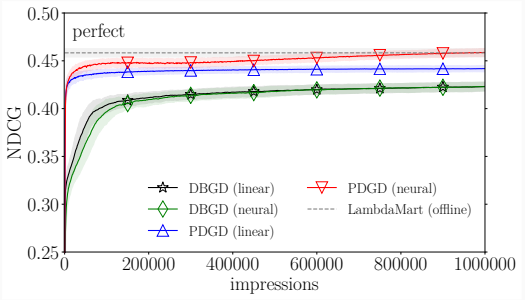
Pairwise Differentiable Gradient Descent: Results Short Term

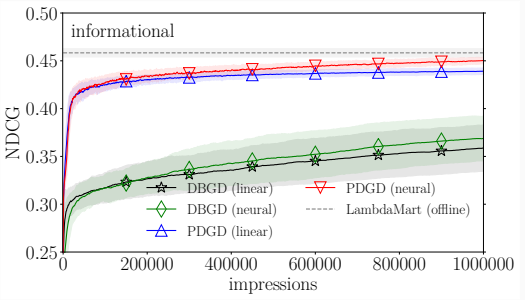




Results of simulations on the MSLR-WEB10k dataset, a perfect user (left) and an informational user (right).

Pairwise Differentiable Gradient Descent: Results Long Term





Results of simulations on the MSLR-WEB10k dataset, a perfect user (left) and an informational user (right).

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- **Supervised approaches** to learning to rank are **limited**.
  - **Annotations often disagree** with user preferences.

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- Clear, that different situations suit different approaches.
- Unclear, when which approach is preferred (still missing a direct comparison).

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