Optimizing Ranking Models in an Online Setting

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Introduction

Learning to Rank in Information Retrieval

Learning to rank enables the optimization of ranking systems.

Traditionally learning to rank uses **annotated datasets**:

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

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There are **problems** with **annotated datasets**:

- **expensive** to make (Qin and Liu, 2013; Chapelle and Chang, 2011).
- **impossible** to create (Wang et al., 2016).
- **not necessarily aligned with actual user preferences** (Sanderson, 2010), i.e. annotators and users often disagree.

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Solves most of the problems of annotations:

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These methods have to handle:

- **Noise**: Users click for **unexpected reasons**.
- **Biases**: Interactions are affected by **position and selection bias**.

Dueling Bandit Gradient Descent

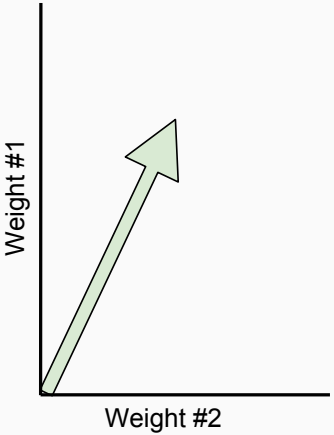
Dueling Bandit Gradient Descent: Introduction

Introduced by Yue and Joachims (2009) as the **first online learning to rank** method.

Intuition:

- **Interleaving** can compare rankers from **user interactions**.
- By **sampling model variants** and **comparing** them with **interleaving**, the *gradient* of a model w.r.t. user satisfaction can be **estimated**.

Dueling Bandit Gradient Descent: Visualization



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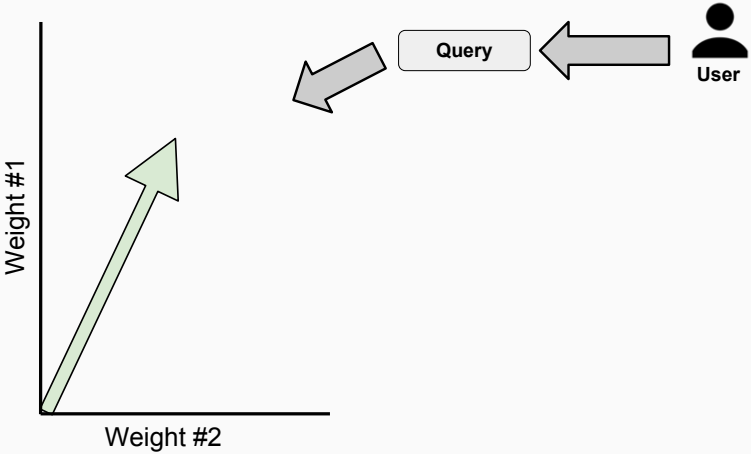

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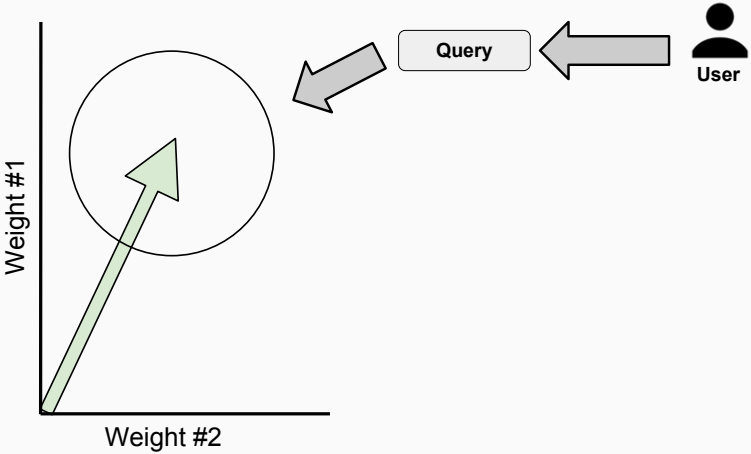

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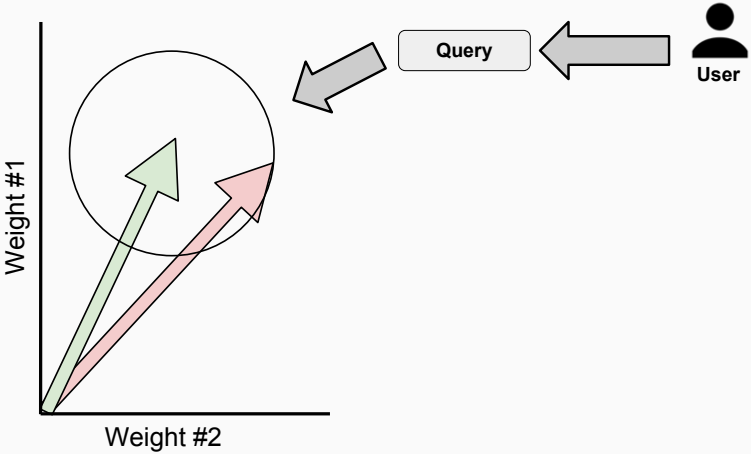

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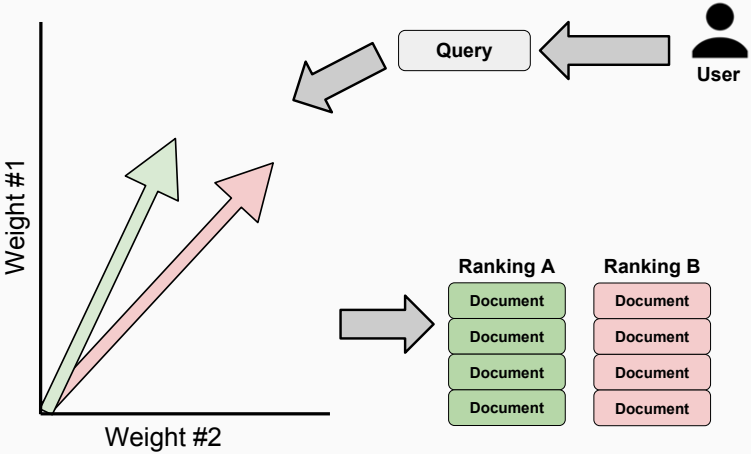

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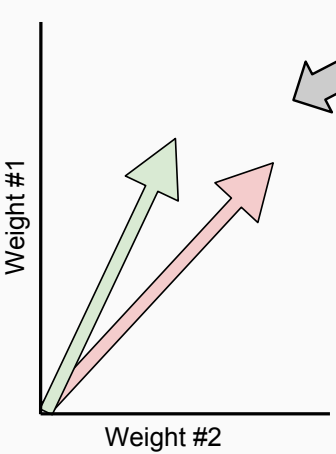

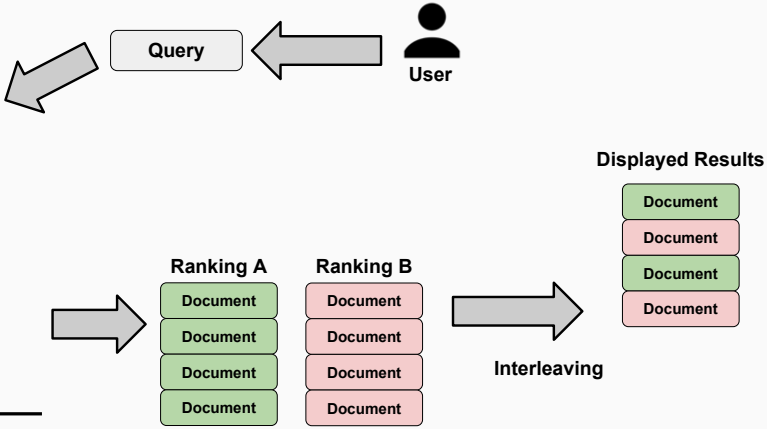

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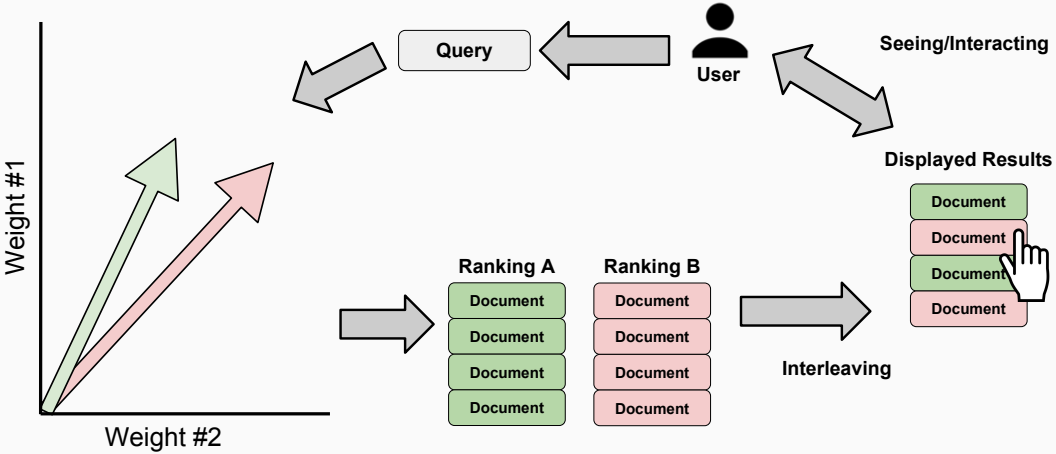

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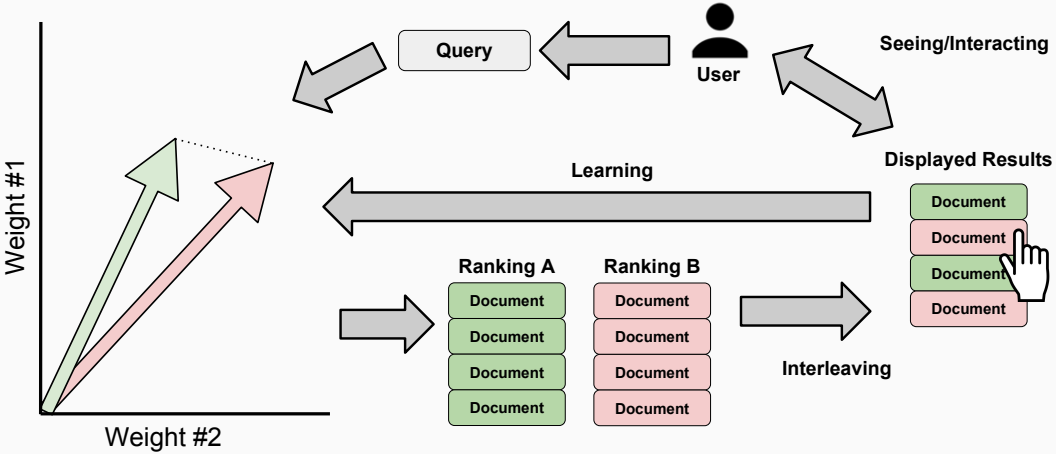

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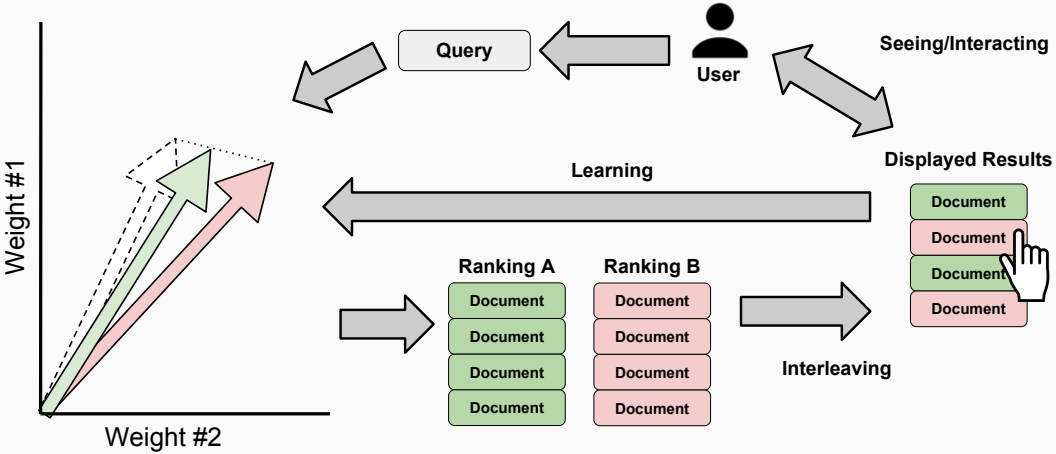

Dueling Bandit Gradient Descent: Properties

Basis of the online learning to rank **field**,
virtually all existing methods are **extensions** of this algorithm
(Schuth et al., 2016; Hofmann et al., 2013; Zhao and King, 2016; Wang et al., 2018a).

Problems with Dueling Bandit Gradient Descent:

- A **considerable gap** between DBGD and *best possible* performance.
- Ineffective at optimizing **non-linear models**.

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Advantage of Dueling Bandit Gradient Descent:

- Has a **theoretical foundation** based on proven **regret bounds**.

Pairwise Differentiable Gradient Descent

Pairwise Differentiable Gradient Descent

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

Intuition:

- A **pairwise** approach can be made **unbiased** while being **differentiable**.

Plackett Luce Model

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

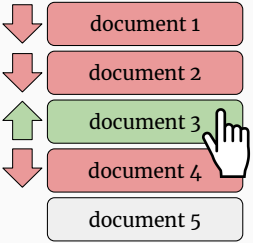
With the ranking scoring model $f(\mathbf{d})$ the distribution is:

$$P(d|f, D) = \frac{\exp^{f(\mathbf{d})}}{\sum_{d' \in D} \exp^{f(\mathbf{d}')}} \tag{1}$$

Unlike DBGD, **confidence is explicitly modelled**.

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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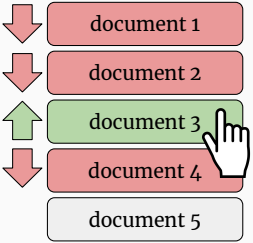

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PDGD weighs inferred preferences to account for **position/selection bias**.

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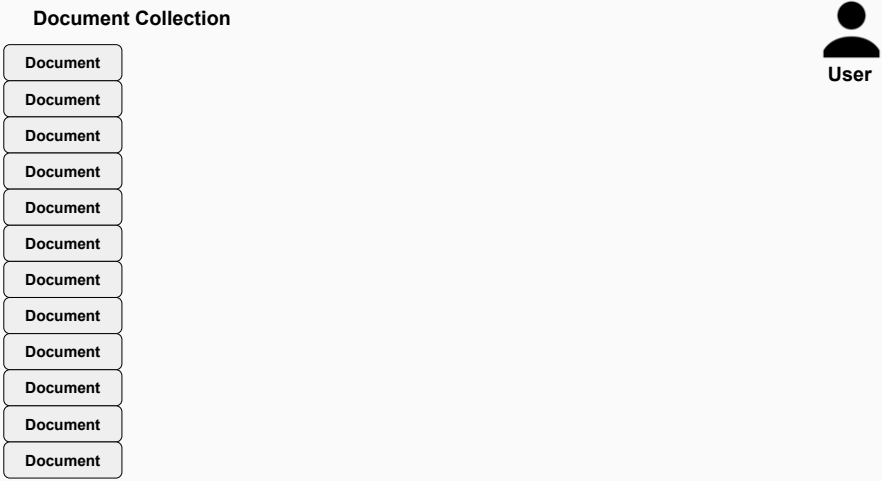

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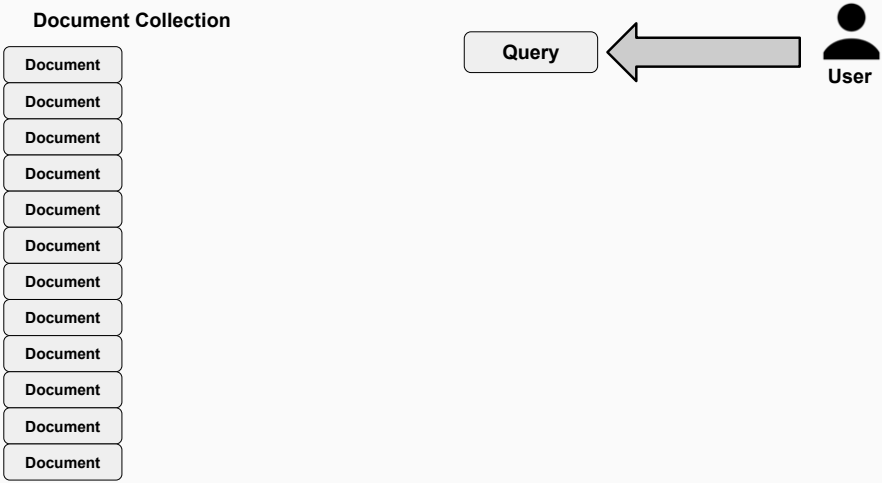

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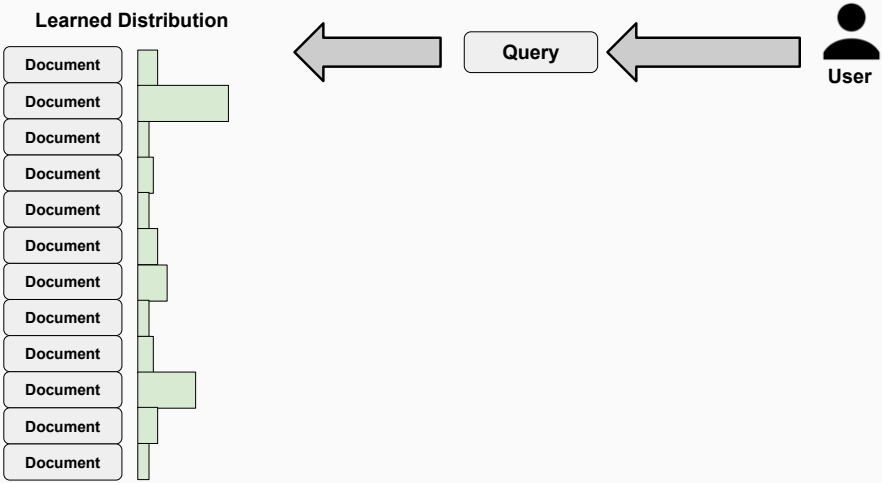

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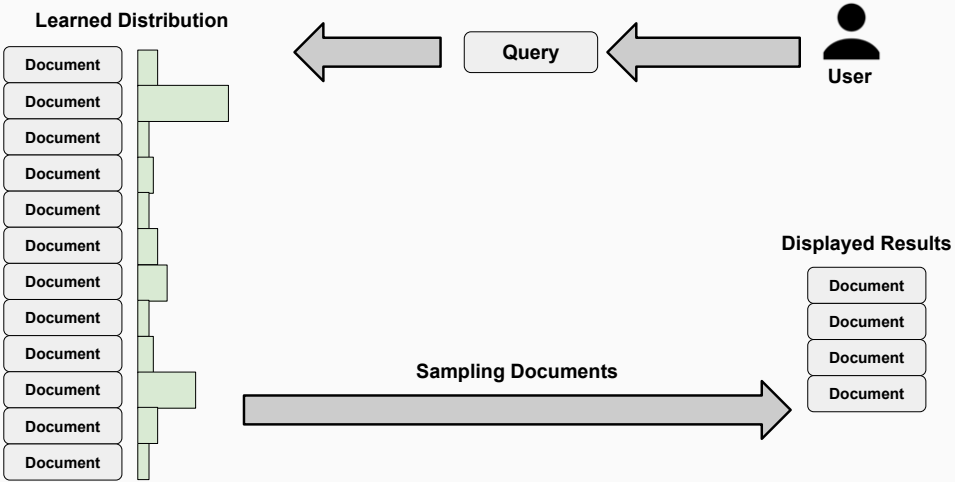

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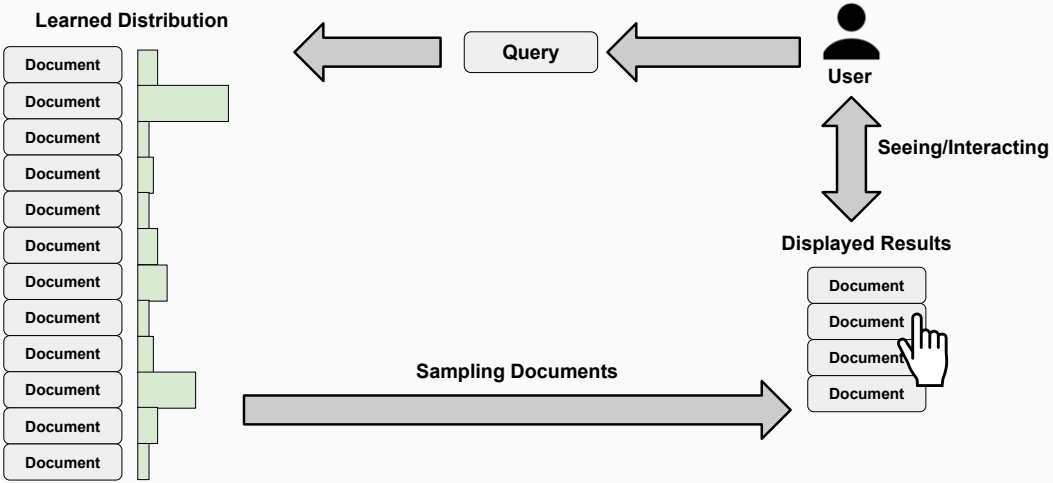

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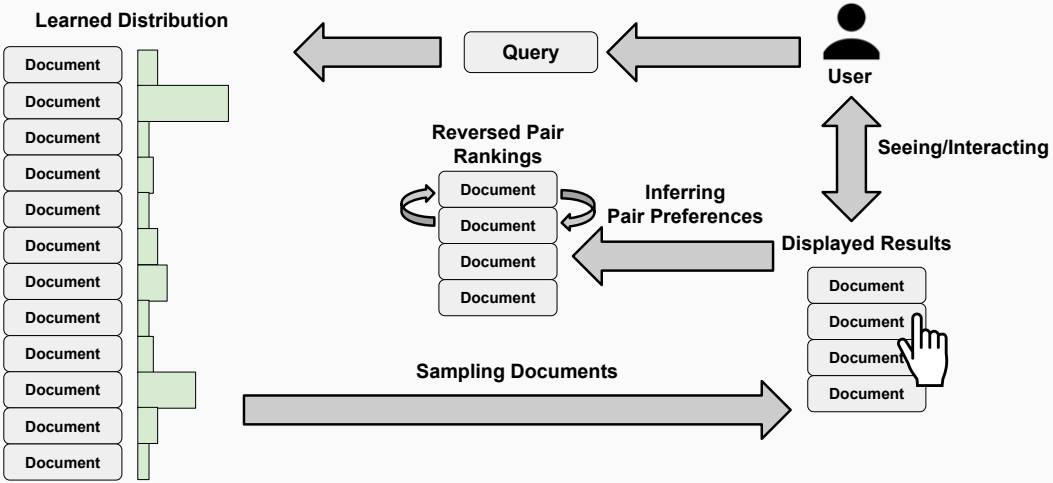

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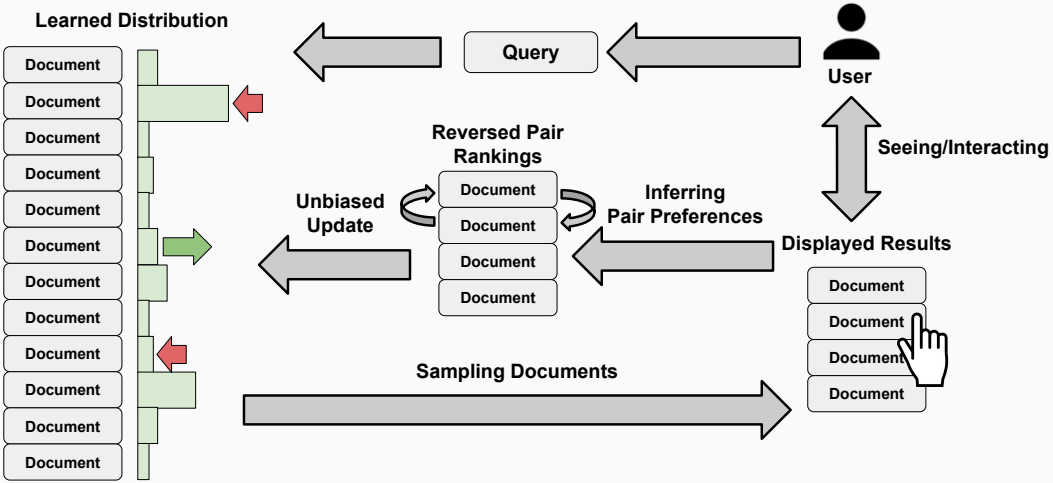

Pairwise Differentiable Gradient Descent: Properties

Pairwise Differentiable Gradient Descent does **not rely** on **online evaluation** or the **sampling** of models.

Advantages claimed by previous work (Oosterhuis and de Rijke, 2018):

- Much better point of convergence i.e. **long-term performance**.
- Much faster learning i.e. **short term performance**.
- Computationally much faster.

Limitations of Existing Results

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Comparison based on **previous work**:

- Pairwise Differentiable Gradient Descent **outperforms** DBGD.
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- There is a **conflict** between the **proven regret bounds** of Dueling Bandit Gradient Descent and its **observed performance**.

Our contribution

First, we **critically look** at the regret bounds of Dueling Bandit Gradient Descent:

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Then we reproduce the comparison under different conditions:

- **Both cascading** and **non-cascading** click behaviour.
- Simulated conditions ranging from **ideal to extremely difficult**.
  We simulate *near-random* behaviour.

Experimental Results

Experimental Setup

Simulations based on **largest available industry datasets**:

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Simulated behaviour ranging from:

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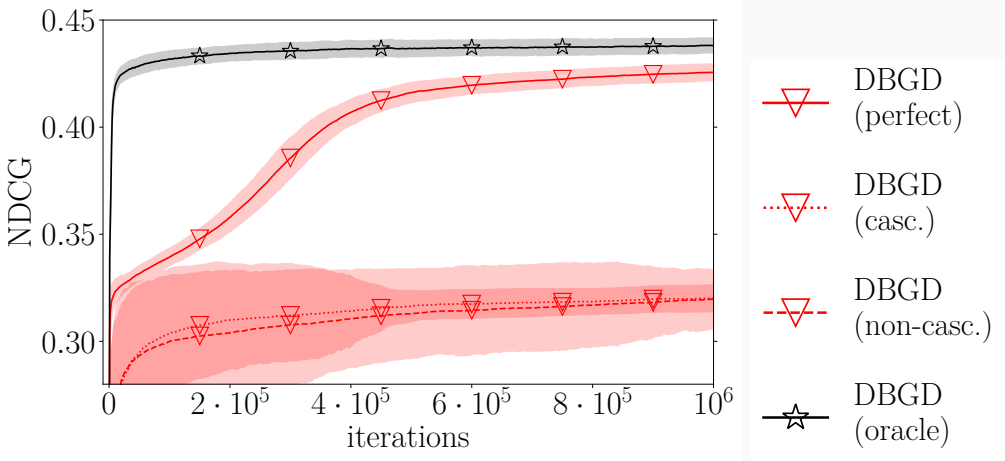
Dueling Bandit Gradient Descent with an **oracle instead of interleaving**, to see the **maximum potential** of better interleaving methods.

Comparison: Dueling Bandit Gradient Descent



Results from simulations on the MSLR-WEB10k dataset.

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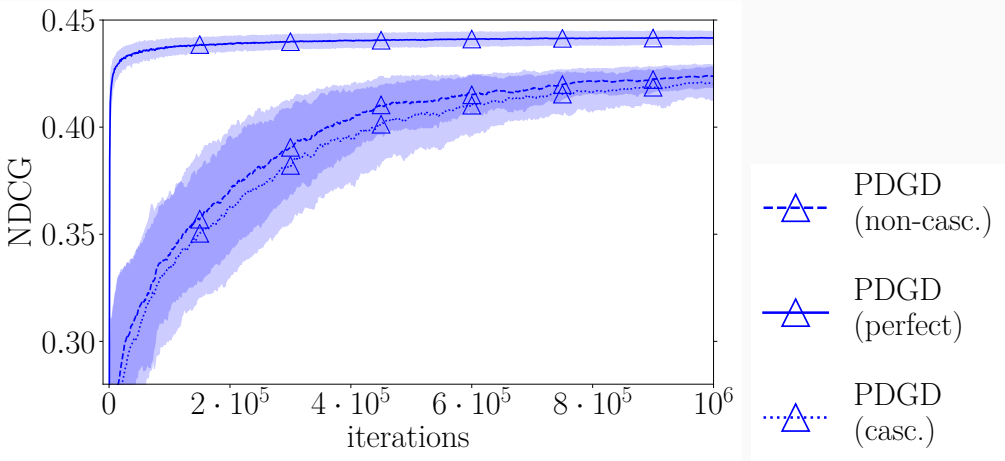

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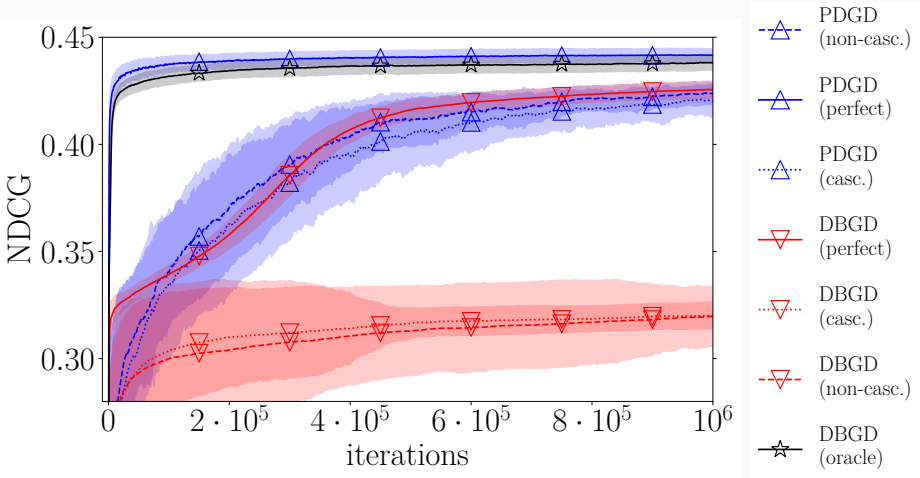

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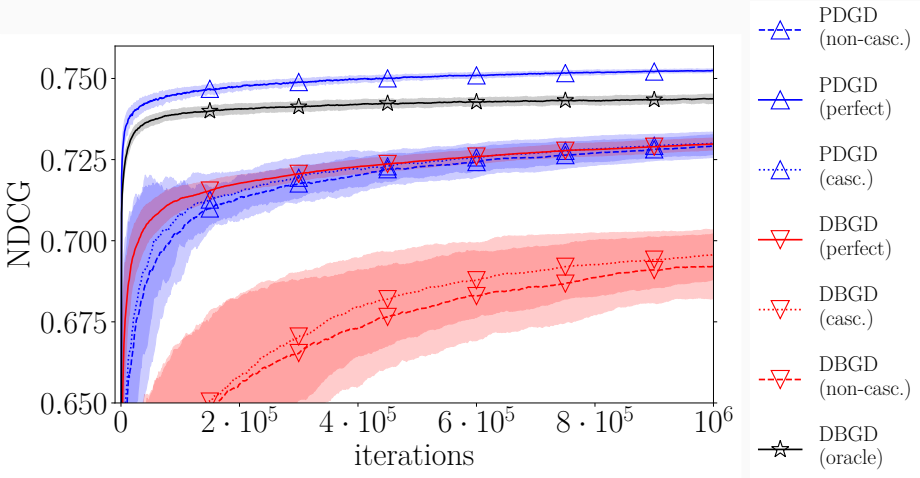

Results from simulations on the Yahoo Webscope dataset.

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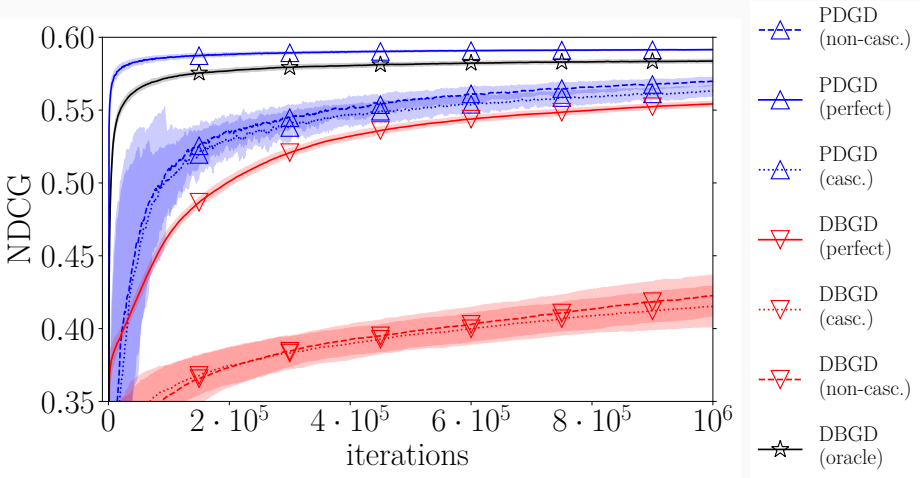

Results from simulations on the Istella dataset.

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Please continue our work: `https://github.com/HarrieO/OnlineLearningToRank`

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