# Baidu-ULTR: a large-scale dataset for Unbiased Learning to Rank

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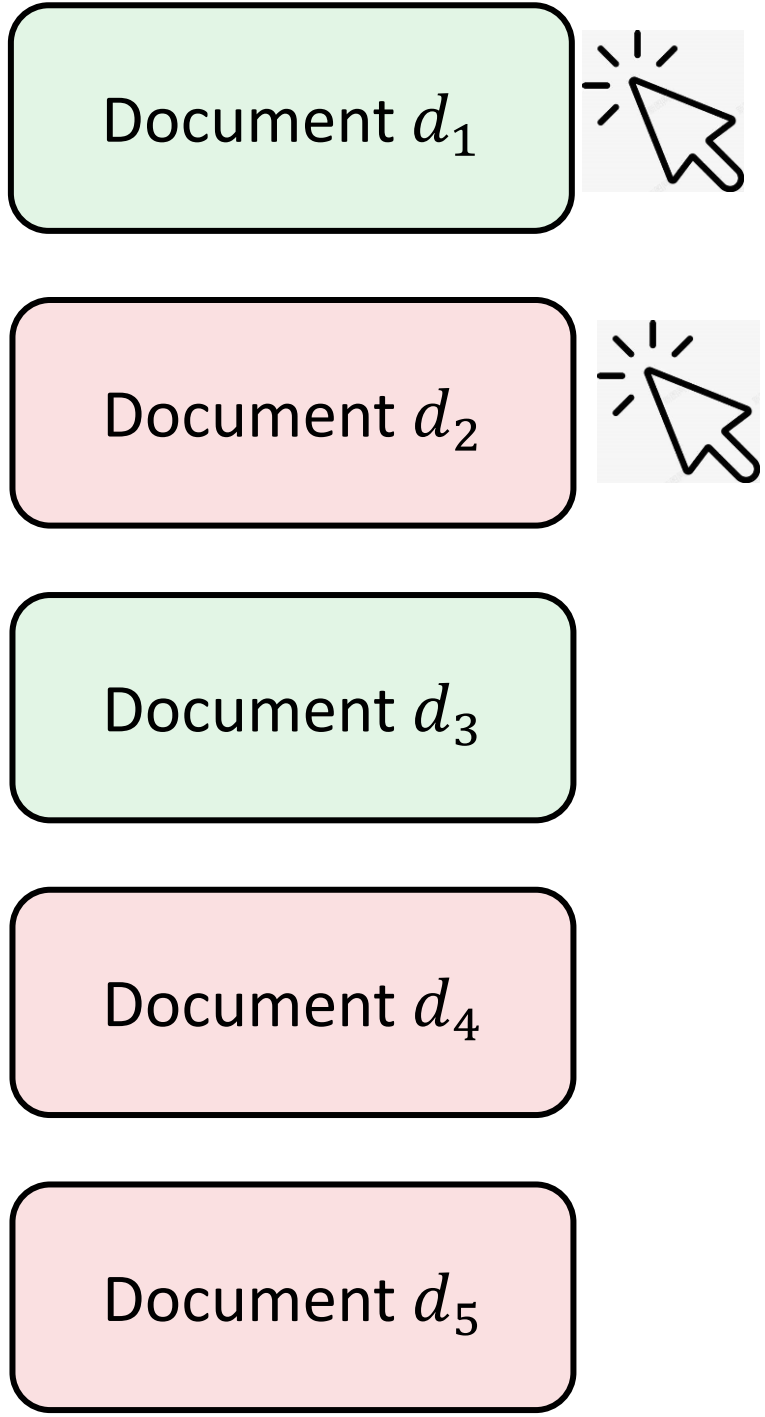
# Brief Introduction

- **Learning to Rank**
  rank the document with higher relevance to query higher position

- **Unbiased Learning to Rank**
  Learn an ideal relevance model with biased click model



# What we want toward an ideal dataset

- ☐ The dataset more like the real-world scenario
- ☐ The training and evaluation procedure similar with the real-world scenario
- ☐ The dataset can allow us utilize the advanced techniques

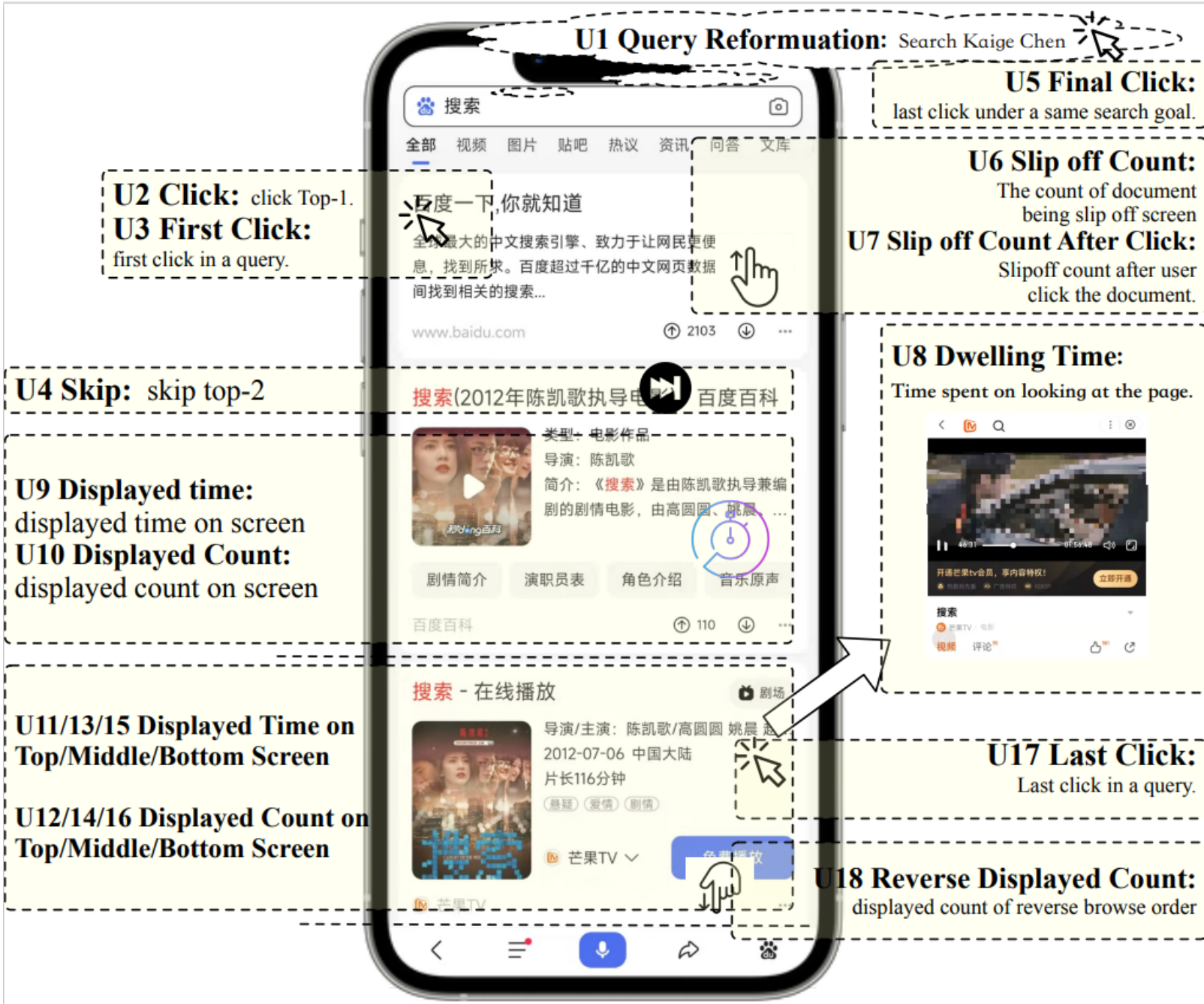
# Dataset more like real-world scenario

- Previous datasets only provides position, the only one page presentation feature.
- The new modern search engine can provide more page presentation features


(a) Rich Page Presentation Information in Baidu-ULTR

# Go beyond simple ULTR

**More user behavior:**
Click may not be the only signal for ULTR




(b) Rich User Behaviors in Baidu-ULTR

# Practical train and evaluation prototype

Table 1: Characteristics of publicly available datasets for unbiased learning to rank

| | Training Implicit Feedback Data | | | | | Validation & Test Data | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dataset | # Query | # Doc | # User Feedback | # Display-info | # Session | # Query | # Doc | # Label | # Feature | Pub-Year |
| Yahoo Set1 | 19,944 | 473,134 | 1 (Simulated click) | 1 (Position) | - | 9,976 | 236,743 | 5 | 519 | 2010 |
| Yahoo Set2 | 1,266 | 34,815 | 1 (Simulated click) | 1 (Position) | - | 5,064 | 138,005 | 5 | 596 | 2010 |
| Microsoft | ≈18,900 | ≈2,261,000 | 1 (Simulated click) | 1 (Position) | - | ≈12,600 | ≈1,509,000 | 5 | 136 | 2010 |
| Istella | 23,219 | 7,325,625 | 1 (Simulated click) | 1 (Position) | - | 1,559 | 550,337 | 5 | 220 | 2016 |
| Tiangong | 3,449 | 333,813 | 1 (Real Click) | 1 (Position) | 3,268,177 | 100 | 10,000 | 5 | 33 | 2018 |
| Baidu | 383,429,526 | 1,287,710,306 | 18 (Real Feedback) | 8 (Display Info) | 1,210,257,130 | 7,008 | 367,262 | 5 | ori-text | 2022 |

- Pipeline: (1) click data for training (2) annotation data for evaluation
- Existing datasets utilize synthetic data for training, and small annotation set
- Provide real-world click data and a fairly large testset

# Utilize more advanced techniques

- Large-scale pretrain model, e.g., BERT, ERNIE,  are common utilized in Natural Language Processing.
- Existing datasets provide only provide preprocess features, e.g., tf-idf, BM25
- Baidu-ULTR provides raw tokens after desensitization.
- The dataset size is 20 times larger than existing datasets.

# Primary Experiments

Table 4: Comparison of unbiased learning to rank (ULTR) algorithms with different learning paradigms on Baidu-ULTR using cross-encoder as ranking models. The best performance is highlighted in bold

| | DCG@1 | ERR@1 | DCG@3 | ERR@3 | DCG@5 | ERR@5 | DCG@10 | ERR@10 |
|---|---|---|---|---|---|---|---|---|
| Naive | 1.235±0.029 | 0.077±0.002 | 2.743±0.072 | 0.133±0.003 | 3.889±0.087 | 0.156±0.003 | 6.170±0.124 | 0.178±0.003 |
| IPW | 1.239±0.038 | 0.077±0.002 | 2.742±0.076 | 0.133±0.003 | 3.896±0.100 | 0.156±0.004 | 6.194±0.115 | 0.178±0.003 |
| REM | 1.230±0.042 | 0.077±0.003 | 2.740±0.079 | 0.132±0.003 | 3.891±0.099 | 0.156±0.004 | 6.177±0.126 | 0.178±0.004 |
| PairD | 1.243±0.037 | 0.078±0.002 | 2.760±0.078 | 0.133±0.003 | 3.910±0.092 | 0.156±0.003 | 6.214±0.114 | 0.179±0.003 |
| DLA | **1.293**±0.015 | **0.081**±0.001 | **2.839**±0.011 | **0.137**±0.001 | **3.976**±0.007 | **0.160**±0.001 | **6.236**±0.017 | **0.181**±0.001 |

- No algorithm shows much better result than the naïve algorithm
- DLA perform best across all methods

# Performance on query with different frequency

Table 5: Performance comparison of evaluation ULTR algorithms versus different search frequencies. The best performance is highlighted in boldface.

| Model | DCG@3 | | | DCG@5 | | | DCG@10 | | |
|---|---|---|---|---|---|---|---|---|---|
| | High | Mid | Tail | High | Mid | Tail | High | Mid | Tail |
| Naive | 3.960±0.058 | 2.992±0.119 | 1.742±0.079 | 5.596±0.098 | 4.254±0.142 | **2.474**±0.092 | 8.812±0.140 | **6.777**±0.173 | 3.942±0.121 |
| IPW | 4.017±0.132 | 2.976±0.111 | 1.722±0.061 | 5.699±0.145 | 4.235±0.140 | 2.447±0.090 | 8.969±0.146 | 6.762±0.163 | 3.925±0.109 |
| REM | 3.994±0.114 | 2.982±0.124 | 1.723±0.067 | 5.665±0.128 | 4.237±0.158 | 2.454±0.074 | 8.904±0.147 | 6.755±0.183 | 3.927±0.104 |
| PairD | 4.018±0.102 | 2.993±0.110 | **1.750**±0.079 | 5.662±0.120 | 4.267±0.129 | 2.474±0.088 | 8.924±0.145 | 6.804±0.153 | **3.961**±0.119 |
| DLA | **4.226**±0.042 | **3.073**±0.022 | **1.750**±0.016 | **5.894**±0.030 | **4.300**±0.020 | 2.472±0.009 | **9.147**±0.044 | 6.767±0.027 | 3.920±0.009 |

- All algorithms performance drop from high to tail
- Naïve algorithm shows good performance in Tail query

# Discussion

-- Challenge & Opportunity

# Challenge

- Biases in Real-World User feedback
- Long-tail Phenomenon
- Mismatch between Training and Test
  - In training stage, only top-10 documents recorded.
  - In test stage,  top-30 documents and further documents samples

# Opportunity

- ☐ Pretraining models for Ranking
- ☐ Causal Discovery
- ☐ Multi-task Learning

# Thanks!