Ranking with Query-Dependent Loss for Web Search

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Outline

- ***Motivation***

- Incorporating Query Difference into Ranking
  - Position-sensitive query-dependent loss function
  - Learning methods
  - Example query-dependent loss functions
    - RankNet
    - ListMLE

- Experiments and Discussions

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Query Difference

Relational info needs

Navigational

Informational

Transactional

Queries

Subtopic retrieval

Topic distillation

Search intention

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Position-Sensitive Query Difference

Navigational

"WSDM 2010"

1. wsdm2010.org
2. …
3. …
4. …
5. …

…

n. …

The ranking model should aim to rank the exact web page on the top position of the result list

Informational

"New York City"

1. www.nyc.gov
2. en.wikipedia.org/wiki/New_York_City
3. www.nyctourist.com
4. www.nycgo.com
5. …

…

n. …

The ranking model should target at presenting a set of relevant web pages on the top-K positions of returned results.

Transactional

"winamp download"

1. www.winamp.com/media-player
2. …
3. …
4. …
5. …

…

n. …

This kind of position-sensitive query difference requires different objectives (loss function) for the ranking model

Incorporate Query Difference into Ranking

- We propose to incorporate query difference into ranking by introducing position-sensitive query-dependent loss functions in the learning process.

- Previous Work:
  - Key idea: employ different ranking functions for different classes/clusters of queries
  - Query type classification for web document retrieval (Kang et al. SIGIR2003)
  - Query-dependent ranking using k-nearest neighbor (Geng et al. SIGIR2008)
  - Incorporating query difference for learning retrieval functions in information retrieval (Zha et al. CIKM2006)

- We propose to learn one ranking function based on query-dependent loss function

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Incorporating Query Difference into Ranking: Query-Dependent Loss Function

$$L_f = \sum_{q \in Q} L(f)$$

❖Query level loss
❖Having same form among all queries

Diverse ranking objectives implied by different queries

$$L_f = \sum_{q \in Q} L(f; q)$$

❖Query level loss
❖Each query has its own form

Difficult and expensive in practice to define individual objective for each query

$$L_f = \sum_{q \in Q} \left(\sum_{i=1}^{m} \underbrace{P(C_i|q)}_{\textit{Query categorization}} \underbrace{L(f; q, C_i)}_{} \right)$$

Query categorization

❖Category level loss
❖Each query category has its own form

Query-Dependent Loss based on Query Taxonomy of Web Search

Navigational → C_N ← Transactional

The loss should focus on the exact relevant document

Informational → C_I

The loss should consider relevant documents which should be ranked in top-K positions

Query-dependent loss function:

$$L(f;q) = \alpha(q)L(f;q,C_I) + \beta(q)L(f;q,C_N).$$

$$\alpha(q) = P(C_I|q) \qquad \beta(q) = P(C_N|q)$$

$$L(f;q,C) = \sum_{x \in X_q} l(f(x), g(x), p(x); \Phi(q,C))$$

example-level loss
ranking scores
ground truth
true positions
important positions

The example-level loss l contribute to the whole loss if the true rank position $p(x)$ of the example x is included in $\Phi(q,C)$.
The actual value of example-level loss is defined by $f(x)$ and $g(x)$

Learning Methods

- Basic method:
  - To minimize the query-dependent loss function w.r.t. the ranking parameters, denoted as ω

$$L_f = \sum_{q \in Q} \underline{\alpha(q)} L(\underline{f_\omega}; q, C_I) + \underline{\beta(q)} L(\underline{f_\omega}; q, C_N)$$

  - First, obtain pre-defined categorization for each query
    - Navigational: $\alpha(q) = 0, \beta(q) = 1.$
    - Informational: $\alpha(q) = 1, \beta(q) = 0;$
  - Then, learn the parameters of ranking functions using traditional optimization methods
    - Gradient descent

Learning Methods

- Query categorization may not be available
- Even the existing query categorization may not be best for ranking

- Unified Method:
  - We propose to learn the ranking function jointly with query categorization
    - Consider query categorization is defined by a set of query features

Parameters for query categorization

$$\alpha_\gamma(q) = \frac{\exp(\langle \gamma, \mathbf{z}_q \rangle)}{1 + \exp(\langle \gamma, \mathbf{z}_q \rangle)}, \quad \beta_\gamma(q) = \frac{1}{1 + \exp(\langle \gamma, \mathbf{z}_q \rangle)}$$

Features of query

    - …

Learning Methods

- Unified Method:
  - Alternates between minimizing the loss w.r.t. to ω and γ:

$$\textbf{while } (L_f(\omega_k, \gamma_k) - L_f(\omega_{k+1}, \gamma_{k+1})) > \epsilon \textbf{ do}$$

$$\omega_{k+1} \leftarrow \arg\min_{\omega} \sum_{q \in Q} \alpha_{\gamma_k}(q) L(f_{\omega_k}; q, \mathcal{C}_I) + \beta_{\gamma_k}(q) L(f_{\omega_k}; q, \mathcal{C}_N)$$

$$\gamma_{k+1} \leftarrow \arg\min_{\gamma} \sum_{q \in Q} \alpha_{\gamma_k}(q) L(f_{\omega_{k+1}}; q, \mathcal{C}_I) + \beta_{\gamma_k}(q) L(f_{\omega_{k+1}}; q, \mathcal{C}_N)$$

- We do not need query categorization during testing, thus γ will not be used for ranking during testing -- γ is considered as hidden information in learning

Example Query-Dependent Loss Functions

- RankNet: (pairwise)
  - Original loss function:

desired target values

$$L(o_{ij}) = -\bar{P}_{ij} \log P_{ij} - (1 - \bar{P}_{ij}) \log(1 - P_{ij})$$

  - Query-dependent loss function:

$$\underbrace{\boxed{L(o_{ij}, q)}}_{\text{q-d loss}} = \underbrace{\sum_{p(i)=1}^{n_q}}_{\text{sum over rank positions}} \underbrace{P(p(i)|x_i, g(x_i))}_{\text{Probability that } x_i \text{ with label } g(x_i) \text{ is ranked at position } p(i)} \Big(\underbrace{\alpha(q) \cdot \mathbf{1}_{\{p(i) \in \Phi(q, C_I)\}}}_{\text{informational}} + \underbrace{\beta(q) \cdot \mathbf{1}_{\{p(i) \in \Phi(q, C_N)\}}}_{\text{navigational}} \Big) \cdot L(o_{ij}),$$

q-d loss

sum over rank positions

navigational

informational

Probability that x_i with label $g(x_i)$ is ranked at position $p(i)$

Example Query-Dependent Loss Functions

- ListMLE: (listwise)
  - Original loss function:

$$L(f;q) = \phi(\Pi_f(\mathbf{x}), \mathbf{y}) = -\log \underline{P_{\mathbf{y}}^{k}(\Pi_f(\mathbf{x}))}$$

Plackeet-Luce model as top-k surrogate loss

    - $\mathbf{x}$: the list of documents
    - $\mathbf{y}$: the true permutation of document under q
    - $\Pi_f(\mathbf{x})$: the permutation ordered by ranking function f

  - Query-dependent loss function:

$$L(f;q) = \underline{-\alpha_q \log P_{\mathbf{y}}^{k_I}(\Pi_f(\mathbf{x}))} - \underline{\beta_q \log P_{\mathbf{y}}^{k_N}(\Pi_f(\mathbf{x}))}$$

Navigational: top-k_N surrogate likelihood loss
Informational: top-k_I surrogate likelihood loss

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- ***Experiments and Discussions***

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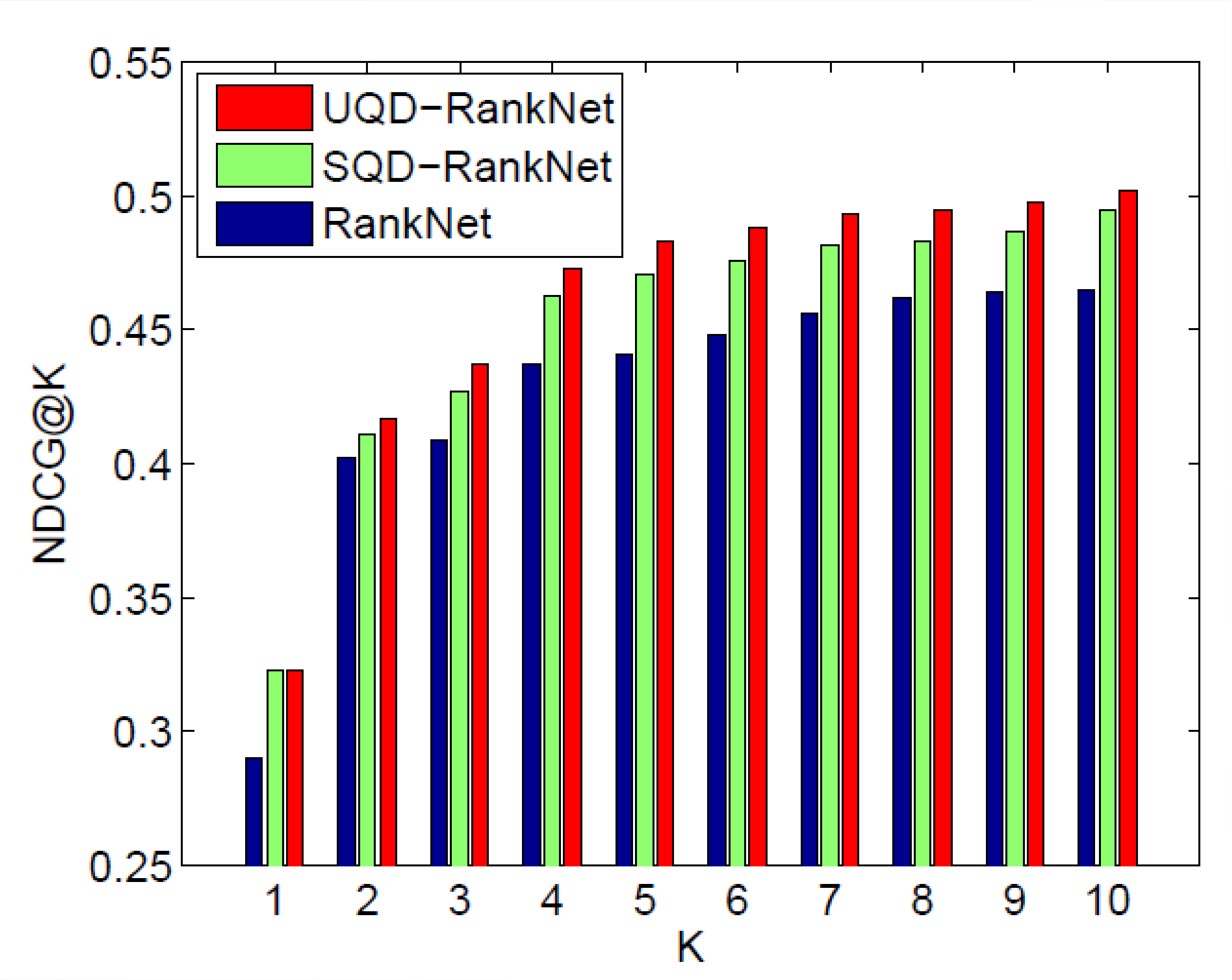
Experimental Setup

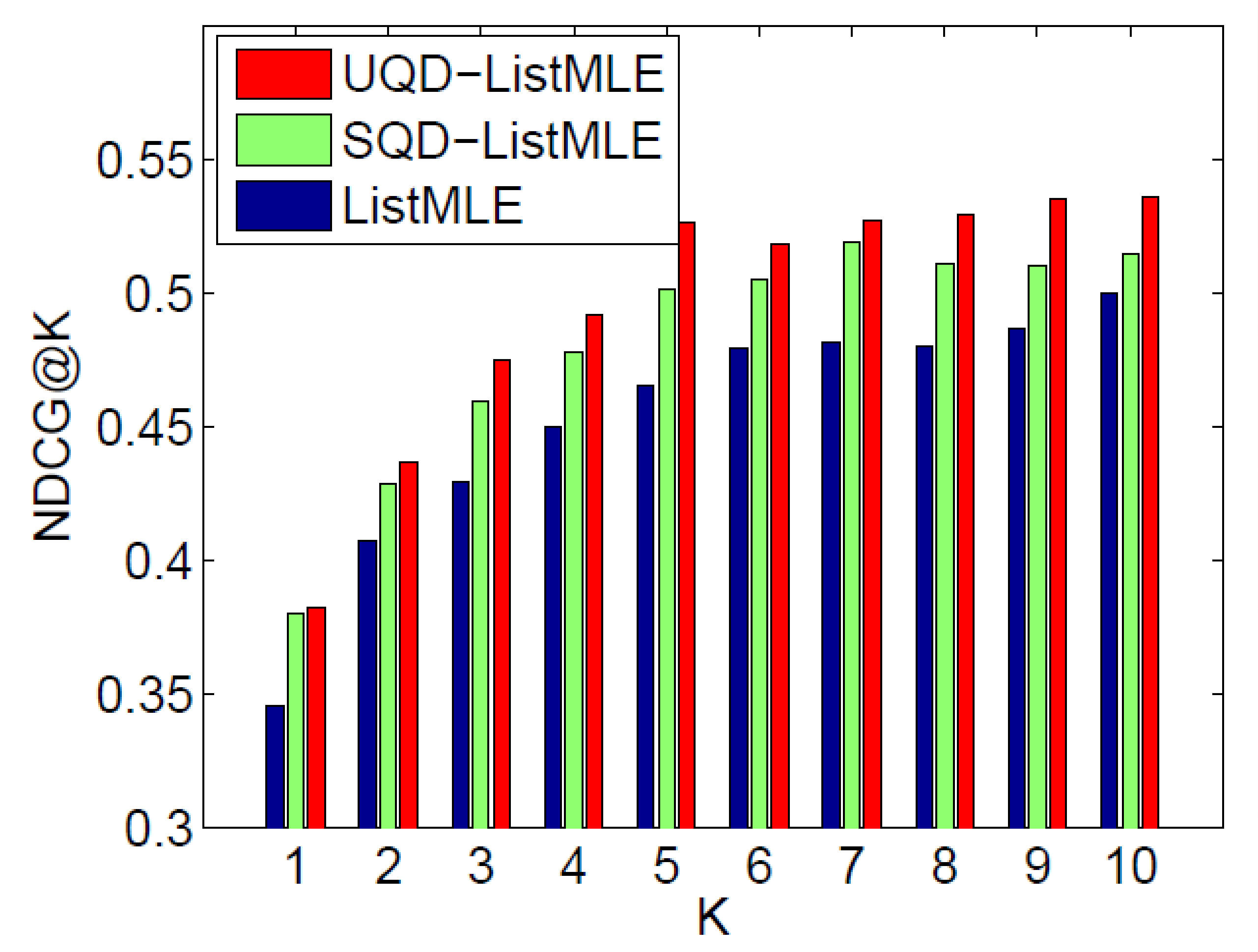
- Dataset: LETOR 3.0:
  - TREC2003
    - 300 navigational queries, 50 informational queries
  - TREC2004
    - 150 navigational queries, 75 informational queries
  - 64 features for ranking
  - To define query features:
    - Use a reference model (BM25) to find top-50 ranked documents, and take the mean of the features values of the 50 documents as the features of the query
- Compared methods:
  - Ranking algorithms using original loss function (*RankNet, ListMLE*)
  - Ranking algorithms using query-dependent loss function with pre-defined query categorization (*SQD-RankNet, SQD-ListMLE*)
  - Ranking algorithms using query-dependent loss function without pre-defined query categorization (*UQD-RankNet, UQD-ListMLE*)
- 5-fold cross validation

Results on RankNet



TREC2003

Results on ListMLE



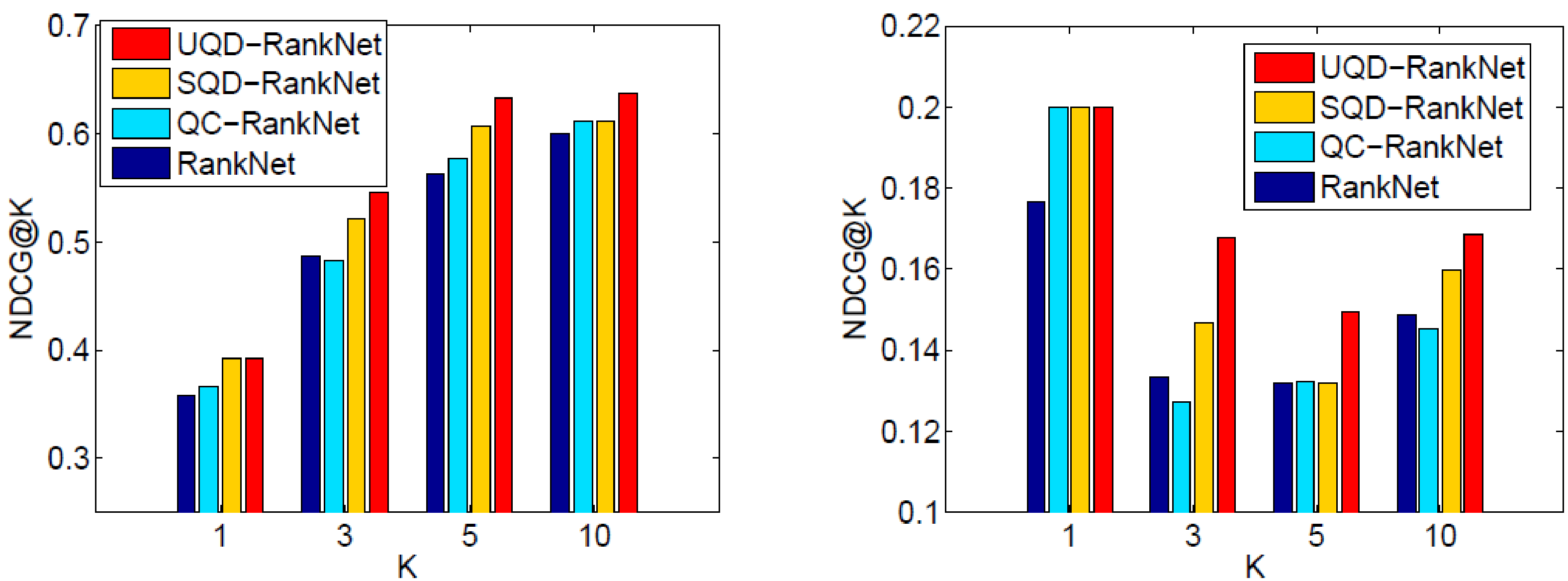
TREC2004

Discussions (1)

- Query-specific categories (features) is not available at testing time:
  - They can be viewed as extra tasks for the learner
  - Query-specific categories (features) of training data are transferred into other common features as training signals
  - The extra training signals serve as a query-specific inductive bias for ranking

Discussions (2)

- Query-dependent loss function vs. query-dependent ranking function
  - Query-dependent loss function contains more information for



(a) Navigational queries (b) Informational queries

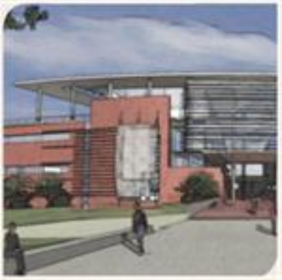
approach

Summary

- Proposed to incorporate query difference into ranking by introducing query-dependent loss functions

- Introduced a new methods for learning the ranking function jointly with learning query categorization

- Exploited the position-sensitive query-dependent loss function on a popular query categorization scheme of Web search and applied it to two specific ranking algorithms, RankNet and ListMLE



Thanks!

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