Top-K Learning to Rank: Labeling, Ranking and Evaluation

Shuzi Niu, Jiafeng Guo, **Yanyan Lan**, Xueqi Cheng

Institute of Computing Technology,

Chinese Academy of Sciences

Outlines

- Motivation
- Top-K Learning to Rank Framework
  - Top-K Labeling Strategy
  - FocusedRank
  - Top-K Evaluation
- Experimental Results
- Conclusions & Future Work

Motivation

One great challenge for learning to rank: it is difficult to obtain reliable training data from human assessors!

Absolute Relevance Judgment $x \Rightarrow y$

Relevance Score

Drawbacks:

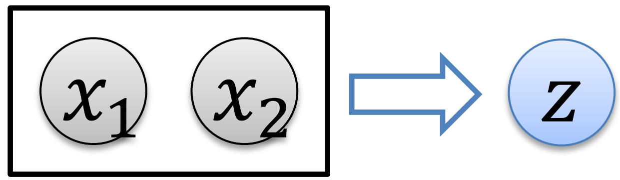
(1) Choice of the specific of the gradations.

(2) Increasing assessing burdens.

(3) High level of disagreement on judgments.

Motivation (cont')

Pairwise Preference Judgment



Preference Order

Pros:

(1) No need to determine the gradation specifications.
(2) Easier for an assessor to express a preference.
(3) Noise may be reduced.

Cons:

Complexity of judgment increases! (From O(n) to $O(n^2)$, O(n log n).)

How to reduce the complexity of pairwise preference judgment?

Motivation (cont’)

- Do we really need to get a total ordering for each query? ***NO!***
- Users mainly care about the top results in real web search application!

⇨ Take more effort to figure out the top results and judge the preference orders among them.

Top-K Ground-truth

$$\begin{pmatrix} \boxed{\begin{matrix} x_1 \\ x_3 \\ x_5 \end{matrix}} \\ x_2, x_4 \end{pmatrix}$$

Total ordering of top K results

Preferences between top K Documents and the other N-K documents

Motivation (cont')

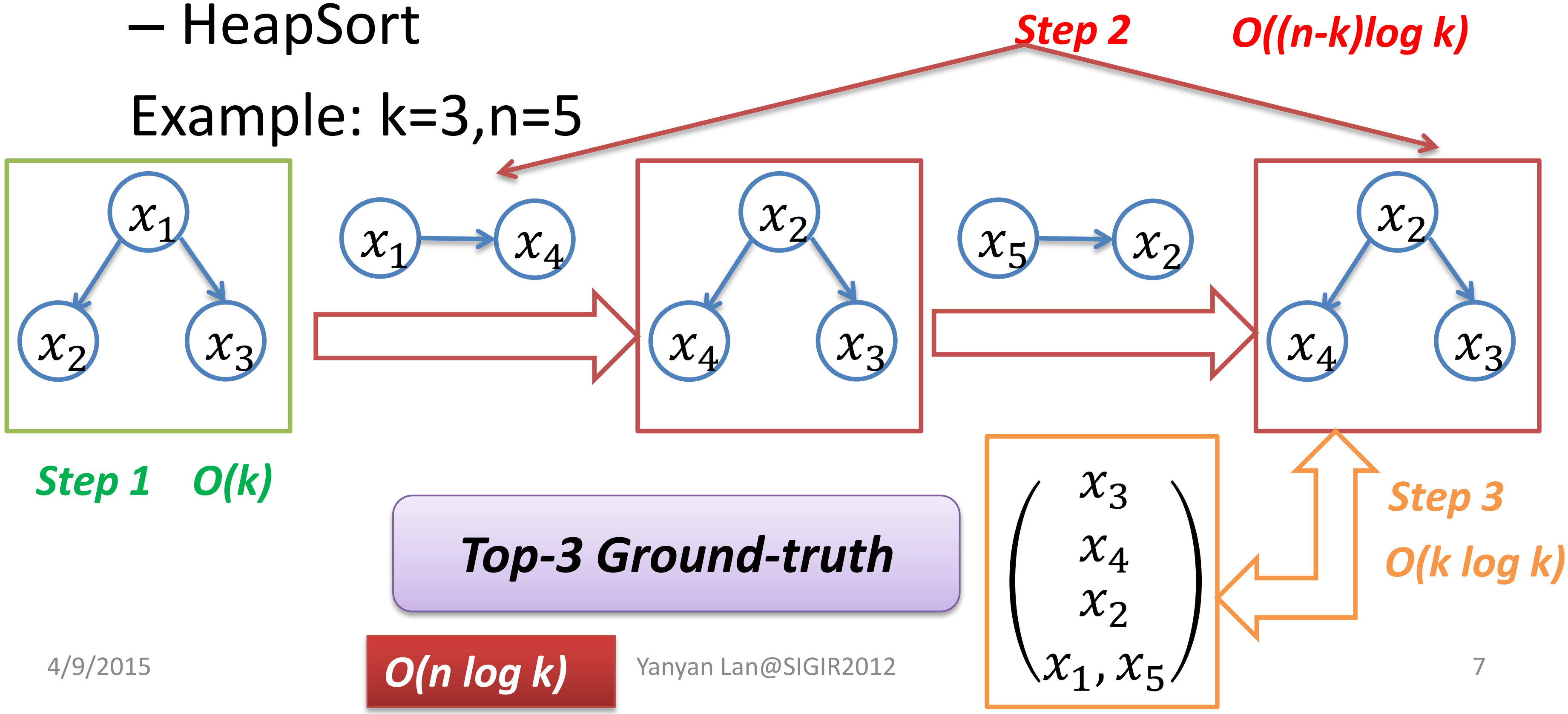
- Three Tasks:
  - How to design an efficient pairwise preference labeling strategy to get top-k ground-truth?
  - How to develop more powerful ranking algorithms in the new scenario?
  - How to define new evaluation measures for the new scenario?

Top-K Learning to Rank

Top-k Learning to Rank： Labeling

- Top-k Labeling Strategy
  - Pairwise preference judgment
  - HeapSort

Example: k=3,n=5



Top-K Learning to Rank： Ranking

- New characteristics of top-k ground-truth

x_1 → Total ordering of top k items ⇒ *Listiwise ranking algorithms*

x_3

x_5

x_2, x_4 → Preferences between top k Items and the other n-k items ⇒ *Pairwise ranking algorithms*

$$L(f;q_i)=\beta\times L_{list}(f;T_i,\mathbf{y}_i)+(1-\beta)\times L_{pair}(f;P_i,\mathbf{y}_i)$$ ***FocusedRank***

Struct-SVM	RankSVM	FocusedSVM
AdaRank	RankBoost	FocusedBoost
ListNet	RankNet	FocusedNet

Top-K Learning to Rank: Evaluation

- Traditional evaluation measures, e.g. MAP, NDCG, ERR, are mainly defined on absolute relevance scores.
- In the scenario of top-k ground-truth, define a position-aware relevance score:

$$y_j^{(i)} = k + 1 - \pi_i(x_j^{(i)}), \text{ if } x_j^{(i)} \in T_i, \;\; y_j^{(i)} = 0, \text{ otherwise.}$$

  - *κ-NDCG*

$$\kappa - NDCG@l = \frac{1}{N_l'} \sum_{j=1}^{l} \frac{2^{y_j^{(i)}} - 1}{\log_2(1+j)},$$

  - *κ-ERR*

$$\kappa - ERR = \sum_{s=1}^{n} \frac{1}{n_i} R(y_s^{(i)}) \prod_{t=1}^{s-1} (1 - R(y_t^{(i)}), \; R(r) = \frac{2^r - 1}{2^{y_m^{(i)}}},$$

Experiments

- Effectiveness and efficiency of top-k labeling strategy
  - Data Sets: all the 50 queries from Topic Distillation task of TREC 2003, for each query, sample 50 documents.
  - Labeling Tools: top-10 labeling tool T1 and five-graded relevance judgment tool T2.
  - Assessors: Five graduate students who are familiar with web search.
  - Assignment: Divided into five folds Q1,…Q5, Ui judges Qi with T1 and Qi+1 with T2, for i=1,2,3,4, and U5 judges Q5 with T1 and Q1 with T2.

Experimental Results I

- Time Efficiency

Table 1: Comparison results of time efficiency

Method	Time per judgment(s)	Time per query(min)	Judgment complexity	#Judgments per query
Top-k labeling	5.51	13.13	$\mathcal{O}(n \log k)$	142.76
Five-grade judgment	13.87	11.78	$\mathcal{O}(n)$	50

- Agreement

	$A \succ B$	$A \sim B$	$A \prec B$
$A \succ B$	0.6749	0.2766	0.0485
$A \sim B$	0.1138	0.8198	0.0664
$A \prec B$	0.1047	0.3779	0.5174

Top 10 Labeling

	$A \succ B$	$A \sim B$	$A \prec B$
$A \succ B$	0.6272	0.2913	0.0815
$A \sim B$	0.2825	0.5232	0.1944
$A \prec B$	0.1534	0.3826	0.4640

5 Graded Labeling

Experiments (cont')

- Performance of FocusedRank
  - Baselines:

  (1) Pairwise: RankSVM, RankBoost, RankNet,

  (2) Listwise: SVMMAP, AdaRank, ListNet,

  (3) Top-k: Top-k ListMLE

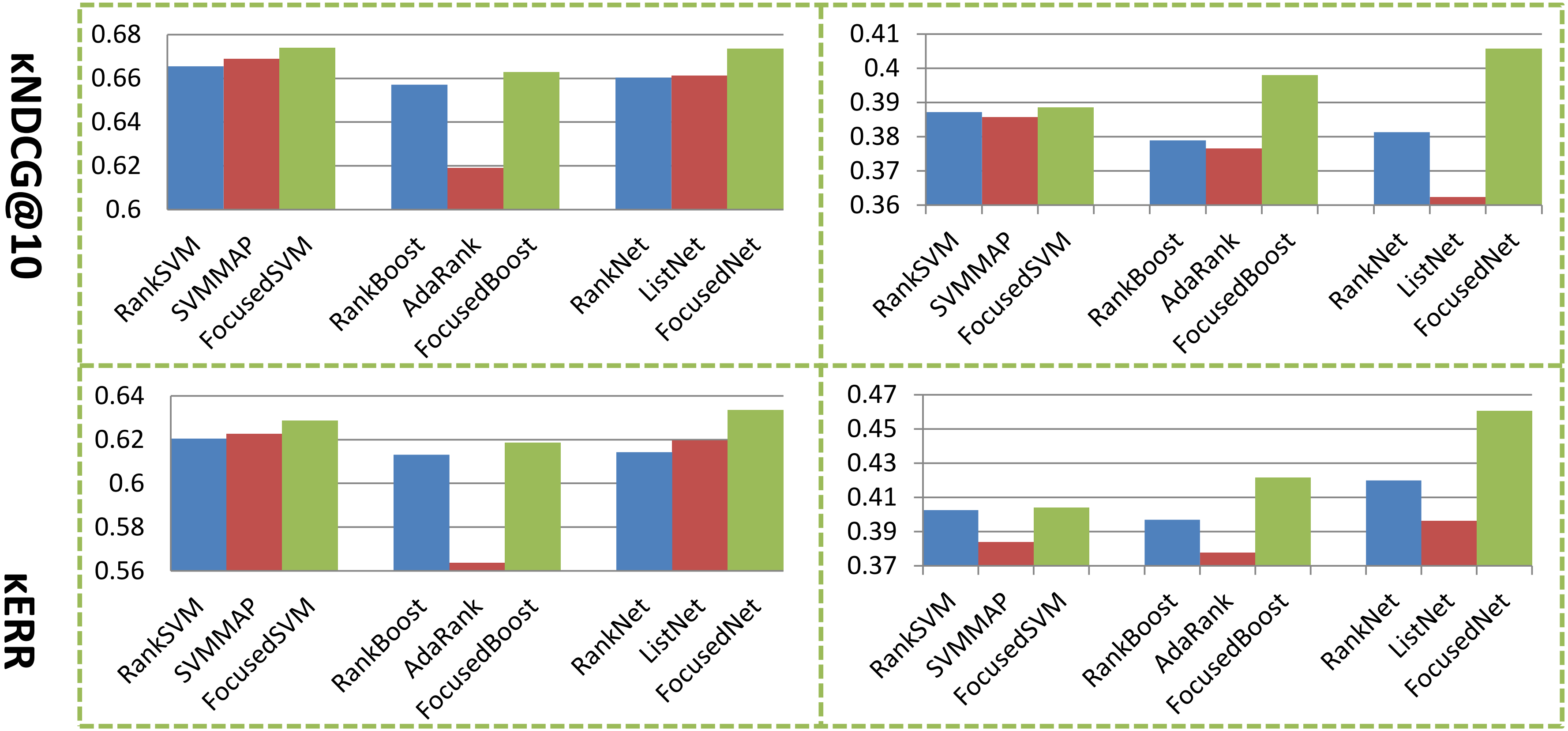
  - Data Sets:

  (1) MQ2007 (From LETOR): Graded MQ2007 and Top-k MQ2007

  (2) TD2003 (Previous constructed data): Graded TD2003 and Top-k TD2003

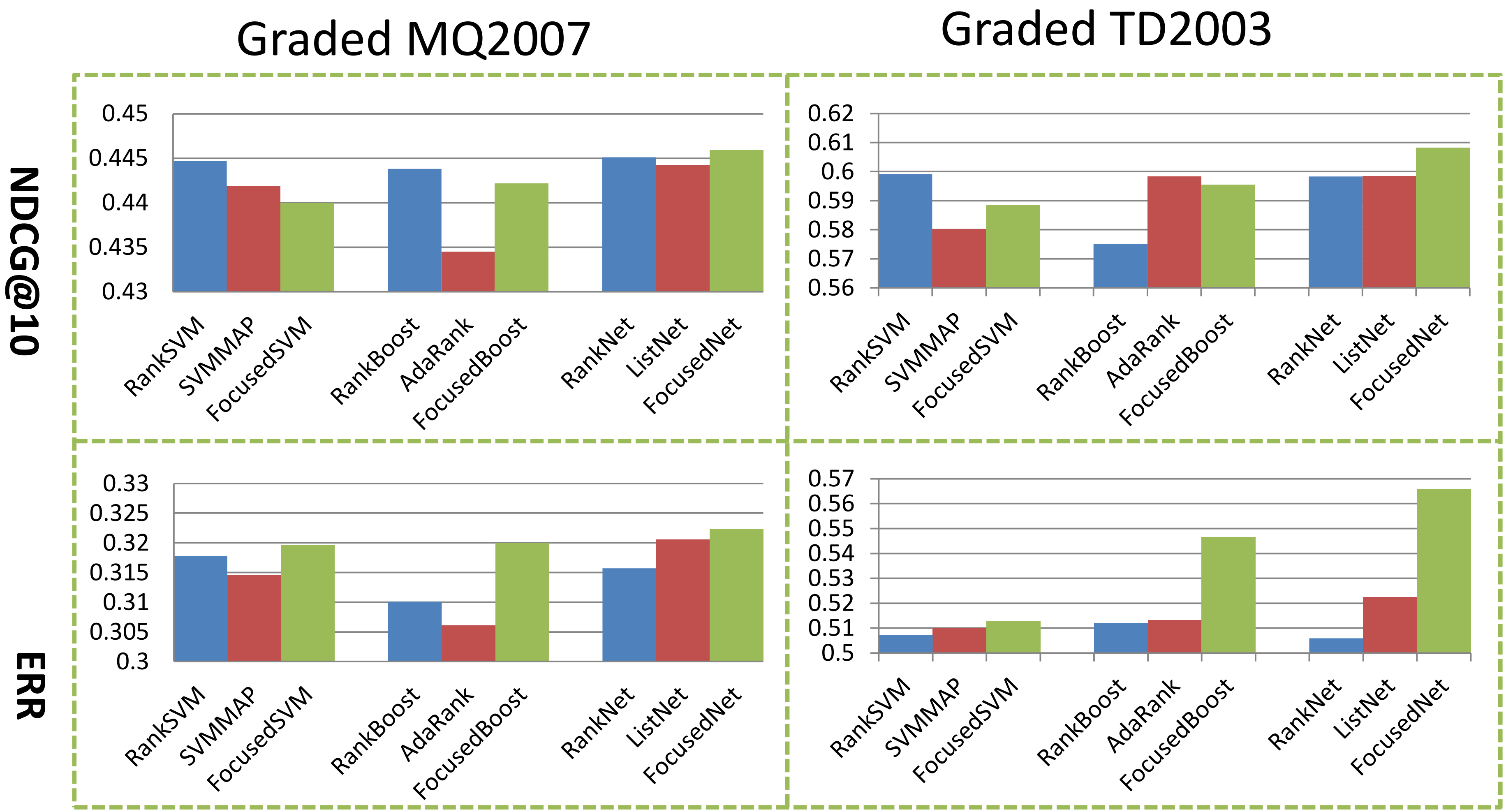
Experimental Results II

Top-10 MQ2007 | Top-10 TD2003



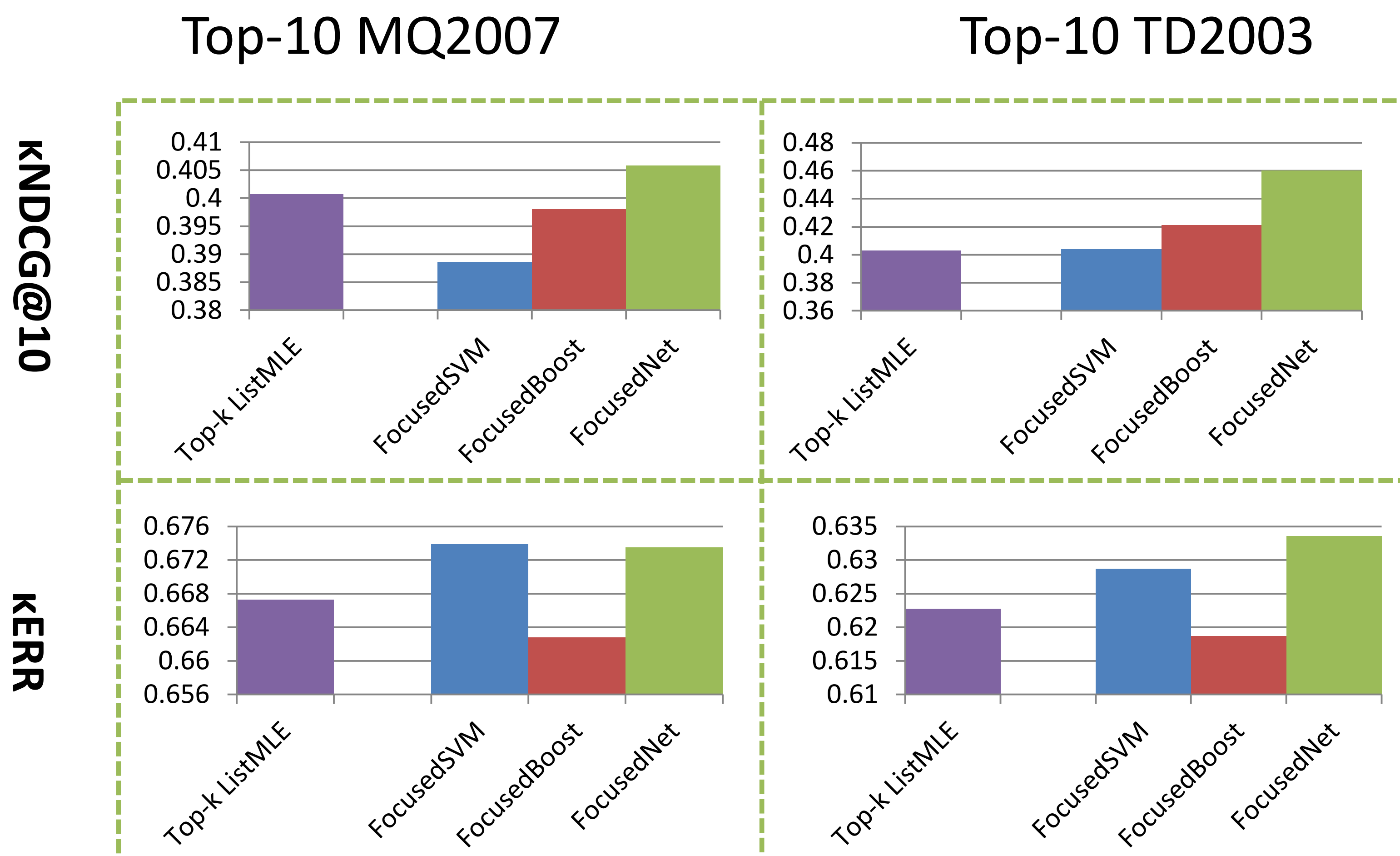
Performance comparison among
FocusedRank, pairwise and listwise algorithms on Top-k datasets.

Experimental Results II (cont')



Performance comparison among FocusedRank, pairwise and listwise algorithms on Graded datasets.

Experimental Results II (cont')



Performance comparison between
FocusedRank and Top-k ListMLE on Top-k datasets.

Conclusions

- Top-K Learning to Rank Framework
  - Top-k labeling strategy: obtain reliable relevance judgments via pairwise preference judgment. Complexity is reduced to O(n log k).
  - FocusedRank: capture the characteristics of the top-k ground-truth.
  - Top-k evaluation measures
- Empirical studies show the efficiency and reliability of top-k labeling strategy, and demonstrate the effectiveness of FocusedRank.

Future Work

- Further reduce the complexity of top-k labeling strategy.
- Design new ranking models for top-k ranking.
- Rank aggregations of top-k ground-truth.
- Active learning in top-k labeling strategy.

Thanks for your Attention!

Thank SIGIR 2012 for providing Shuzi Niu
the student travel grants!
Thank the committee for granting us the best student paper award!

lanyanyan@ict.ac.cn