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Post Processing of Ranking in Search

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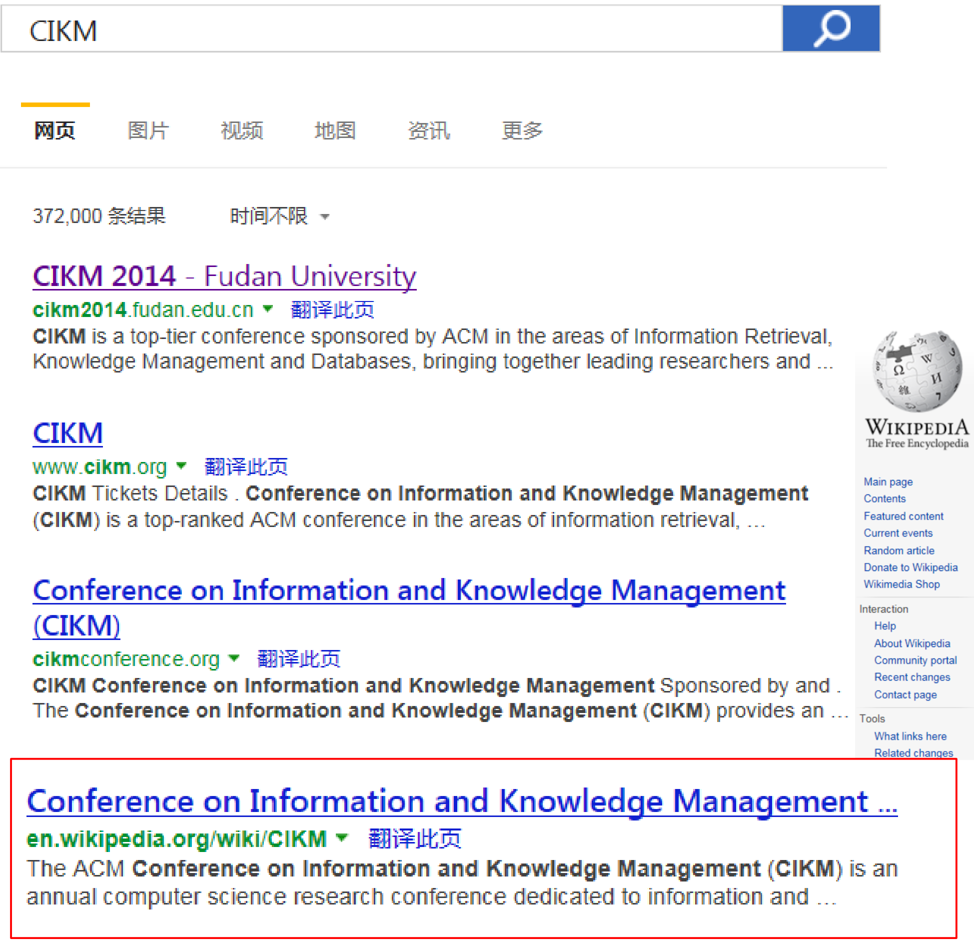
Joint work with Fangzhao Wu, Hang Li, and Xin Jiang

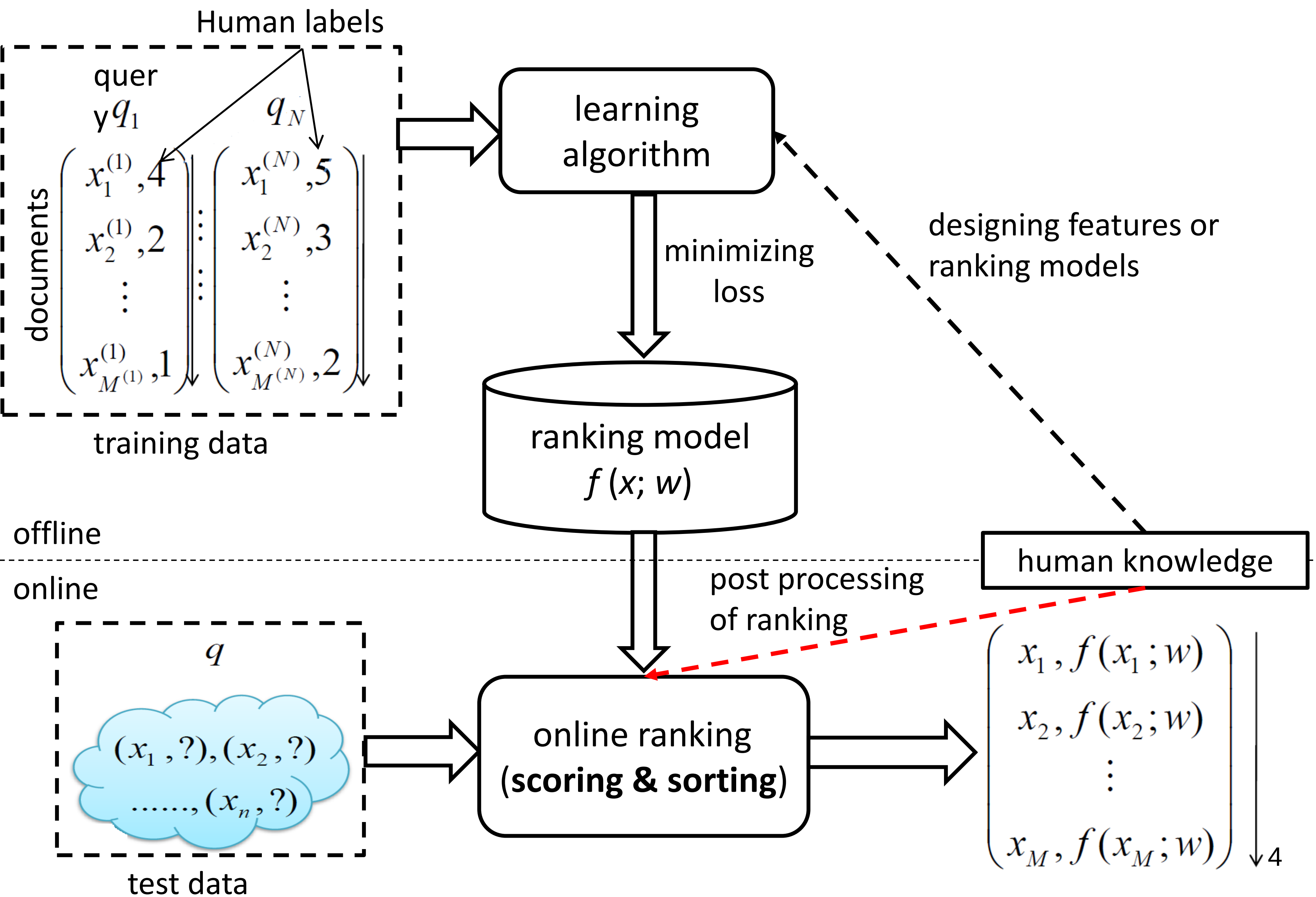
Outline

- Post processing of ranking
- Ranking optimization with constraints
- Summary

One may want to 'twist' relevance ranking



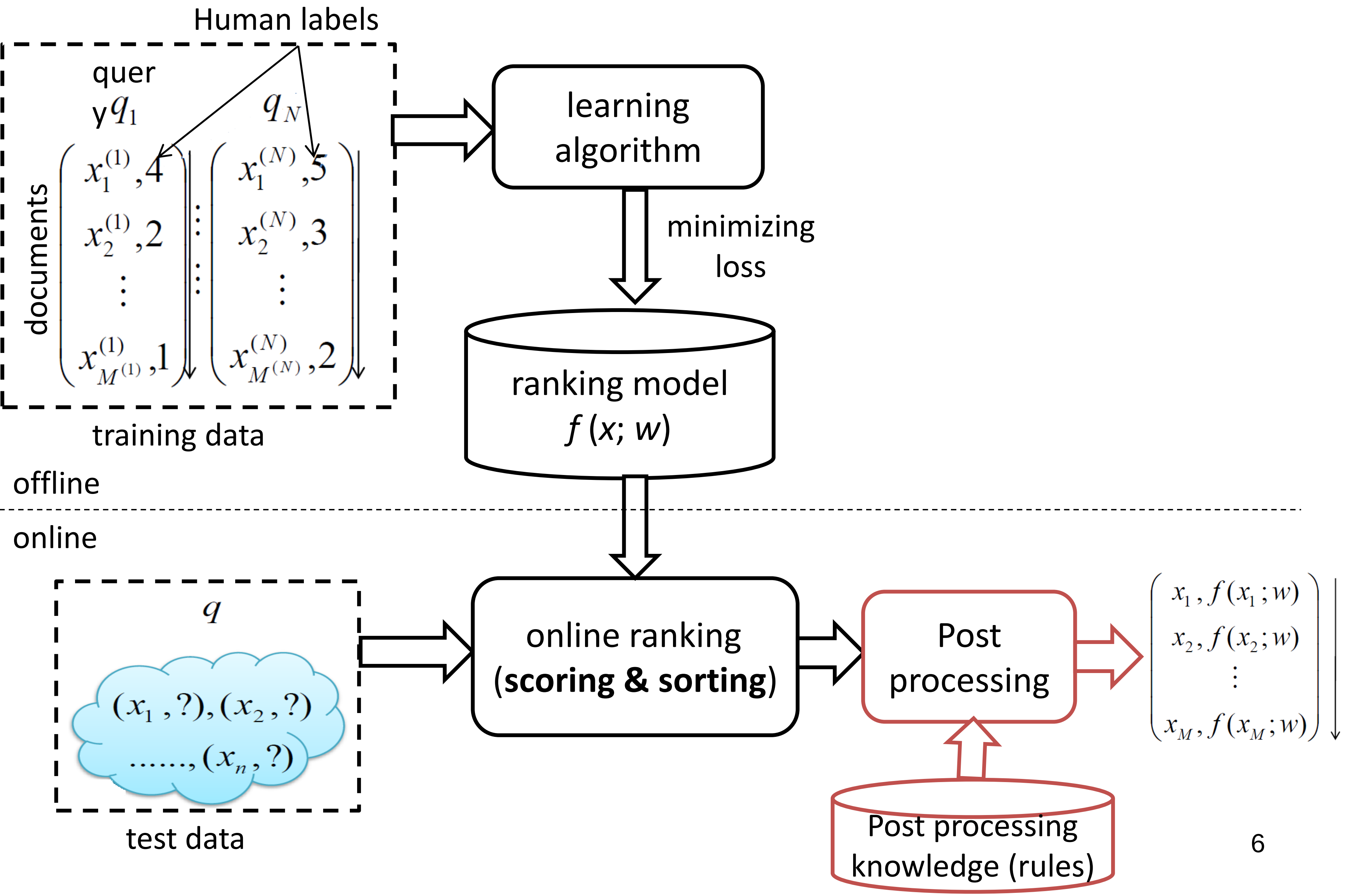
Learning Approach to Ranking



Incorporating Human Knowledge

- Designing features or ranking models
  - Indirect
  - Limited to cross-query knowledge, for generalizing to other queries; It is difficult, costly, or even impossible to implement in features and models to incorporate some types of knowledge
  - Modify both offline and online components
- Post processing of ranking
  - Direct (apply on test queries directly)
  - Can incorporate query/user/context dependent knowledge
  - Only modify online component

Post Processing of Ranking



Post Processing Knowledge (Rules)

- Query dependent
  - Specific query type: if the query is a name, promote the corresponding personal homepage
  - Specific query: if the query is “Microsoft”, promote http://www.microsoft.com/ to rank 1
- User dependent (personalization)
  - Query: “Michael Jordan”
    - For basketball fan: promote the Wikipedia entry of the basketball player
    - For CS researcher: promote the Wikipedia entry of the professor at the UC Berkeley

Post Processing Knowledge (cont')

- Context dependent (session-based)

	Query 1: "homes for rent in atlanta"		Query 2: "houses for rent in atlanta"
×	**Atlanta homes for rent - home rentals - houses for ren...** Rentlist is directory of Atlanta home rentals featuring links to... *http://www.rentlist.net*		**Atlanta homes for rent - home rentals - houses for ren...** Rentlist is directory of Atlanta home rentals featuring links to... *http://www.rentlist.net*
	Homes For Rent, lease in Atlanta suburbs. Can't sell ... Atlanta homes for rent, homes for lease in Gwinnett and north... *http://atlantahomesforrent.com*		**Homes for Rent in Atlanta, GA** Houses, Apartments and Homes for Rent in Atlanta, GA Find ... *http://www.usrentallistings.com/ga/atlanta*
	Rentals.com - Homes for Rent, Apartments, Houses ... Atlanta Home Rentals; Austin Home Rentals; Charlotte Home... *http://www.rentals.com*		**Atlanta Home Rentals, Homes for Rent in Atlanta ...** Atlanta Rentals - Homes for Rent in Atlanta, Apartments, Re... *http://www.rentals.com/Georgia/Atlanta*
×	**Atlanta Home Rentals, Homes for Rent in Atlanta ...** Atlanta Rentals - Homes for Rent in Atlanta, Apartments, Re... *http://www.rentals.com/Georgia/Atlanta*		**Homes For Rent, lease in Atlanta suburbs. Can't sell ...** Atlanta homes for rent, homes for lease in Gwinnett and north... *http://atlantahomesforrent.com*
	Homes for Rent in Atlanta, GA Houses, Apartments and Homes for Rent in Atlanta, GA Find ... *http://www.usrentallistings.com/ga/atlanta*	×	**Atlanta Homes for Rent, Rental Properties, Houses for ...** Search for Homes for Rent in Atlanta, Georgia for free. View li... *www.rentalhouses.com/find/GA/AtlantaArea/ATLANTA*

From Xiang et al., SIGIR' 10

Post Processing Knowledge (cont')

- Document (website) dependent
  - Example rule: if webpage from one site is ranked at top, webpages from the other site will be demoted

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编辑摘要

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中国科学院计算技术研究所 编辑

中科院计算所一般指中国科学院计算技术研究所

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http://baike.baidu.com/view/730187.htm

Heuristic Approaches

- Widely used in real search systems, however
  - Rules may be ambiguous, e.g., the document should be ranked at top three positions, no specific position is decided
  - Rules might be contradictory, e.g., two rules want to rank different documents to top 1
  - Different orders of applications of rules might yield different ranking results. The later one has higher priority
  - Hard to balance between application of rules and preservation of the original ranking list
  - Hard to manage the old/new rules
- Difficult to formalize in a theoretically sound, effective, and efficient way

Outline

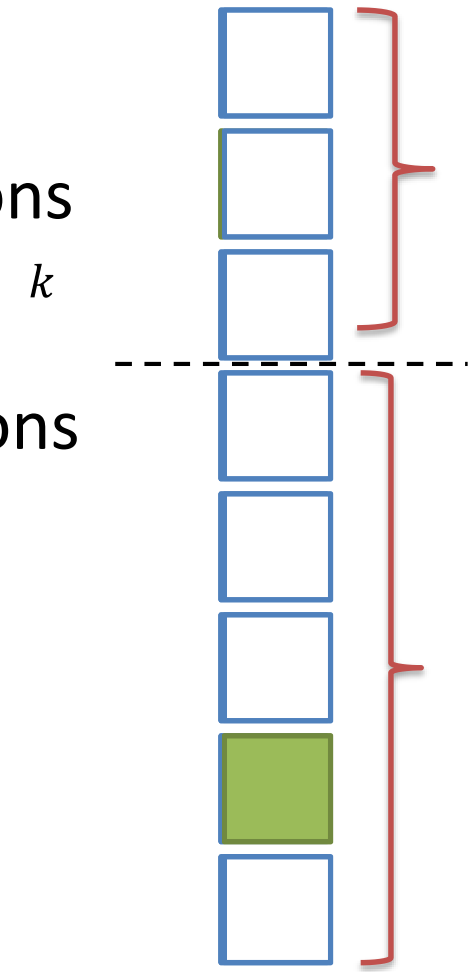
- Motivation of post processing of ranking
- Ranking optimization with constraints (Wu et al., CIKM 2014)
- Conclusion

Main Idea

- Traditional approaches
  - Mainly based on heuristic rules
  - No principled approach
- Our work
  - Formalizes as a constrained optimization problem
    - Constraints: post-processing rules
    - Object function: tradeoff between original ranking and rules
  - Implementation with Bradley-Terry model

Covered Constraints

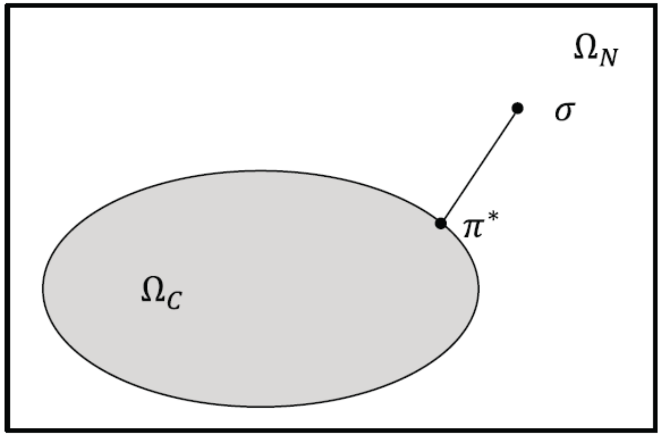
- Top-k constraint
  - A document should be at top k positions
- Not-top-k constraint
  - A document cannot be at top k positions



Related Work

- Post ranking with heuristics
  - **Result diversification**: re-ranking after a ranking list based on relevance is created [Dou et al., ‘11; Vee et al., ‘08]
  - **Personalized search**: client side re-ranking based on user interest [Radlinski & Dumais, ‘ 06; Sugiyama et al., ‘04; Teevan et al., ‘05]
  - **Context aware ranking**: demoting clicked URL in current search result, if it was clicked in the previous search in the same session [Xiang et al., ‘10]
- Probabilistic models for ranking
  - Plackett-Luce model: stage-wise generative model [Luce ‘75]
  - Mallows model: distance based [Mallows ‘57]
  - Bradely-Terry model: pairwise comparisons [Bradley & Terry, ‘52]

Ranking Optimization with Constraints



$$\min_{\pi \in \Omega_N} L(\sigma, \pi) + \lambda \cdot R(\mathcal{C}, \pi)$$

difference between σ and π

violation of constraints

- **Constraints:** rules for post ranking. $\mathcal{C} = \{c_i(\cdot)\}$, $c_i\colon \Omega_N \to \{0, 1\}$
- **Objective function:** trade-off between adherence to the *original ranking list* and satisfaction of the *constraints*

Probabilistic Approach

- Introducing probabilistic ranking model M and $\pi = \text{argmax}_{\tau} P(\tau|M)$

$$\min_M L(\sigma, M) + \lambda \cdot R(\mathcal{C}, M)$$

- Define
  - $L(\sigma, M) = -\log P(\sigma|M)$
  - $R(\mathcal{C}, M) = -\log P(\mathcal{C}|M)$
- Two steps
  - Estimating M

$$\min_M -\log P(\sigma|M) - \lambda \cdot \log P(\mathcal{C}|M)$$

  - Getting optimal ranking list

$$\pi^* = \text{argmax}_{\pi \in \Omega_N} P(\pi|M)$$

Using Bradley-Terry Model

- Represents distribution of permutation by making pairwise comparisons

$$p_{ij} = P\{(i,j)\} = \frac{\theta_i}{\theta_i + \theta_j}$$

- Probability of a permutation

$$P(\sigma|M) \propto \prod_{(i,j):\sigma(i)<\sigma(j)} p_{ij} = \prod_{(i,j):\sigma(i)<\sigma(j)} \frac{\theta_i}{\theta_i + \theta_j}$$

- Probability of a constraint set

$$P(\mathcal{C}|M) \propto \prod_{c\in\mathcal{C}} \prod_{(i,j)\in P^c} p_{ij} = \prod_{c\in\mathcal{C}} \prod_{(i,j)\in P^c} \frac{\theta_i}{\theta_i + \theta_j}$$

P^c: set of preference pairs derived from constraint c
top-k constraint: $P^c = \{(i,j)|j: \sigma(j) > k\}$
not-top-k constraint: $P^c = \{(j,i)|j: \sigma(j) \leq k\}$

Objective Function

$$\min_{M} -\log P(\sigma|M) - \lambda \cdot \log P(\mathcal{C}|M)$$

$$P(\sigma|M) \propto \prod_{(i,j):\sigma(i)<\sigma(j)} \frac{\theta_i}{\theta_i+\theta_j},$$

$$P(\mathcal{C}|M) \propto \prod_{c\in\mathcal{C}} \prod_{(i,j)\in P^c} \frac{\theta_i}{\theta_i+\theta_j}$$

$$\min_{\Theta} f(\Theta) = -\sum_{(i,j):\sigma(i)<\sigma(j)} \log \frac{\theta_i}{\theta_i+\theta_j} - \sum_{c\in\mathcal{C}} \left(\rho^c \cdot \sum_{(i,j)\in\mathcal{P}^c} \log \frac{\theta_i}{\theta_i+\theta_j} \right)$$

$$\text{subject to } \forall i : \theta_i > 0, \sum_{i=1}^{N} \theta_i = 1,$$

$$\theta_i = \exp\{s_i\}, s_i \in R$$

$$\min_{\mathcal{S}} f(\mathcal{S}) = \sum_{(i,j):\sigma(i)<\sigma(j)} (\log(e^{s_i} + e^{s_j}) - s_i) + \sum_{c\in\mathcal{C}} \left(\rho^c \cdot \sum_{(i,j)\in\mathcal{P}^c} (\log(e^{s_i} + e^{s_j}) - s_i) \right)$$

THEOREM 4.1. *$f(\mathcal{S})$ is a convex function.*

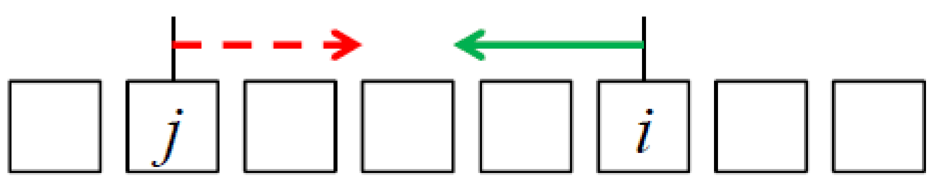
Optimizing with Gradient Descent

$$\frac{df}{ds_i} = \left(\sum_{j:\sigma(j)<\sigma(i)} \frac{e^{s_i}}{e^{s_i}+e^{s_j}} - \sum_{j:\sigma(i)<\sigma(j)} \frac{e^{s_j}}{e^{s_i}+e^{s_j}} \right) + \sum_{c\in\mathcal{C}} \rho^c \left(\sum_{j:(j,i)\in\mathcal{P}^c} \frac{e^{s_i}}{e^{s_i}+e^{s_j}} - \sum_{j:(i,j)\in\mathcal{P}^c} \frac{e^{s_j}}{e^{s_i}+e^{s_j}} \right)$$

Demote i Promote i

$$\mathcal{S}^{(t)} = \mathcal{S}^{(t-1)} - \gamma^{(t)} \left. \frac{\partial f}{\partial \mathcal{S}} \right|_{\mathcal{S}=\mathcal{S}_{t-1}}$$

- Intuitive explanation: given a pair (i, j), i be pushed upward and j be pushed downward with identical force strengths



Ranking Optimization Algorithm

Algorithm 1 Ranking Optimization Algorithm

Require: Initial ranking σ, constraints $\mathcal{C}$, and shrinkage rate $0 < \alpha < 1$

$\mathcal{S}^{(0)} \leftarrow$ random values
$t \leftarrow 1$
repeat
  $\nabla \mathcal{S} = \frac{\partial f}{\partial \mathcal{S}}\big|_{\mathcal{S}=\mathcal{S}^{(t-1)}}$ {Equation (6)}
  $\gamma \leftarrow 1$
  {search optimal step size using backtracking}
  while $f(\mathcal{S}^{(t-1)} - \gamma \nabla \mathcal{S}) > f(\mathcal{S}^{(t-1)}) - \frac{\gamma}{2} \| \nabla \mathcal{S} \|^2$ **do**
    $\gamma \leftarrow \alpha \gamma$
  end while
  $\mathcal{S}^{(t)} \leftarrow \mathcal{S}^{(t-1)} - \gamma \nabla \mathcal{S}$ {Equation (7)}
  $t \leftarrow t + 1$
until convergence
return $\Theta = \{\frac{e^{s_1}}{Z}, \cdots, \frac{e^{s_N}}{Z}\}$, where $Z = \sum_{n=1}^{N} e^{s_n}$

THEOREM 4.2. *Algorithm 1 converges in finite steps and the convergence rate is $O(\frac{1}{\epsilon})$, where $\epsilon > 0$ is the tolerance.*

Experimental Settings

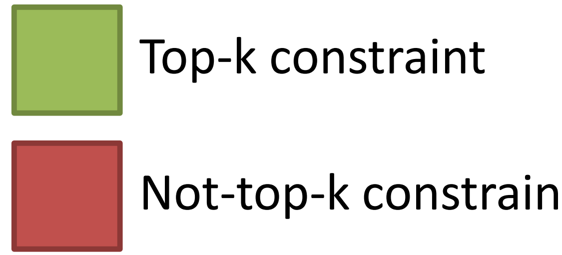
- Datasets

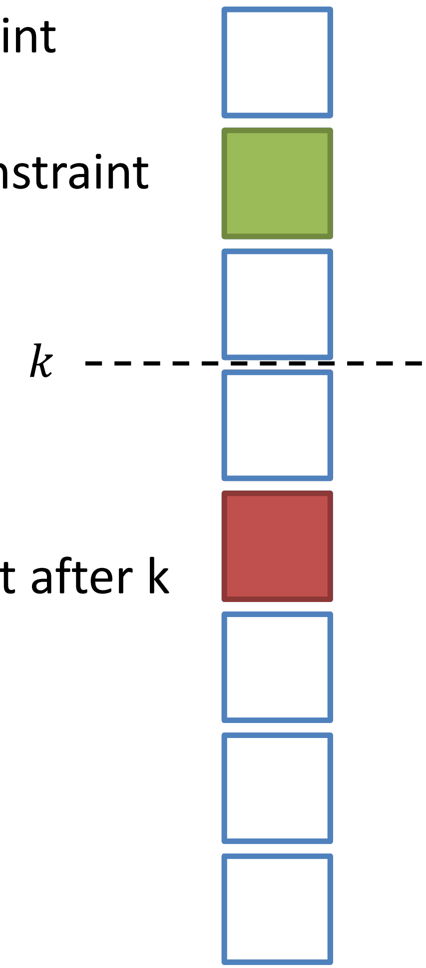
Table 1: Statistics of datasets.

dataset	# queries	#documents	#relevance levels
MQ2007	1692	69623	3
MQ2008	784	15211	3
OHSUMED	106	16140	3
.Gov	50	49058	2
Enterprise	183	5464	3

- Basic ranking model: LambdaMART
- Constraints construction
  - Top-k constraint (k = 1, 3, 5): for each query, sort documents according to labels and randomly select one document from top k positions
  - Not-top-k constraint (k = 5, 10): for each query, sort documents according to labels and randomly select one document from the positions after k positions

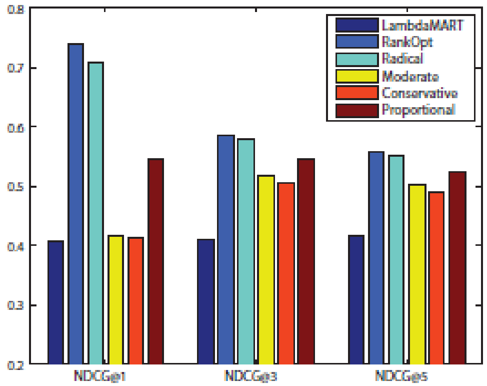
Experimental Settings



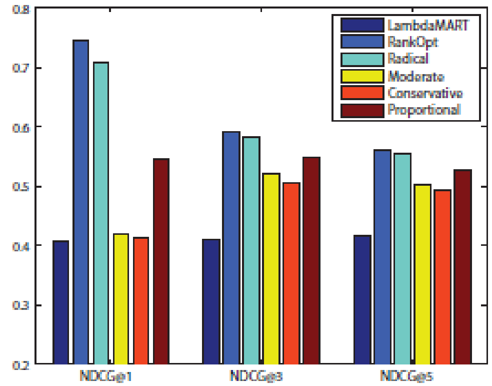


- Baselines
  - **Radical**
    - Top-k constraint → top one position
    - Not-top-k constraint → bottom position
  - **Moderate**
    - Top-k constraint → middle of the top *k* positions
    - Not-top-k constraint → middle of the remaining list after k
  - **Conservative**
    - Top-k constraint → the position of k
    - Not-top-k constraint → the position of k + 1.
  - **Proportional**
    - Top-k constraint → the position of $\left\lceil k \times \frac{pos}{N} \right\rceil$
    - Not-top-k constraint → the position of $\left\lceil k + pos\left(1 - \frac{k}{N}\right) \right\rceil$

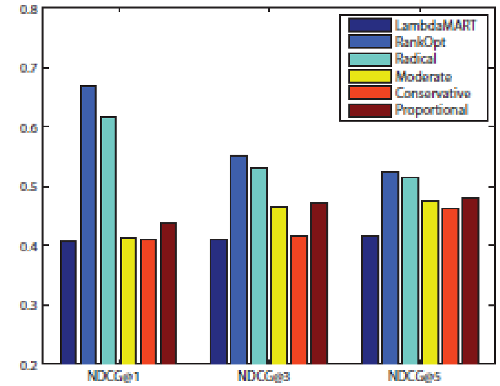
Experimental Results



(a) top-3, not-top-5, ρ^t=100, ρ^n=10

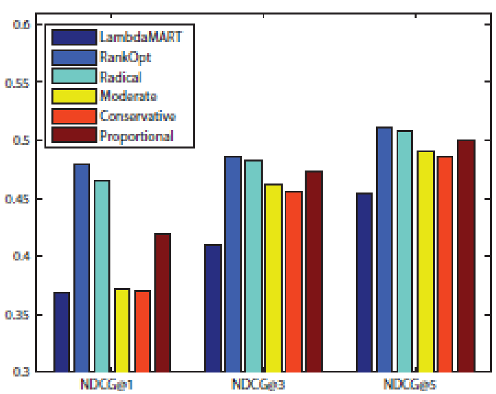


(b) top-3, not-top-10, ρ^t=100, ρ^n=10

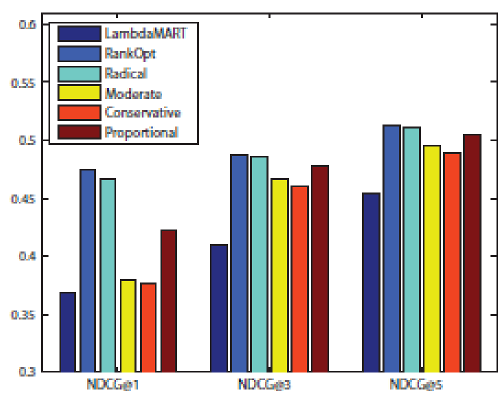


(c) top-5, not-top-10, ρ^t=100, ρ^n=10

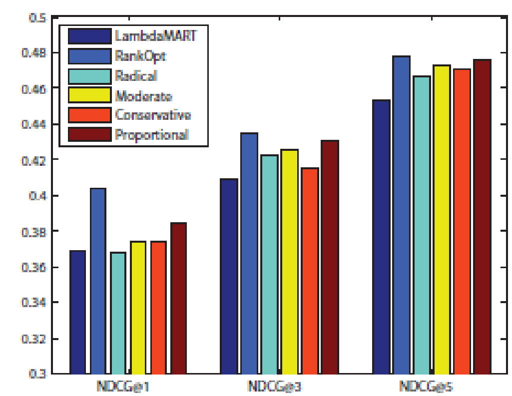
MQ2007



(a) top-3, not-top-5, ρ^t=10, ρ^n=0



(b) top-3, not-top-10, ρ^t=10, ρ^n=10



(c) top-5, not-top-10, ρ^t=10, ρ^n=10

MQ2008

Average Running Time per Query

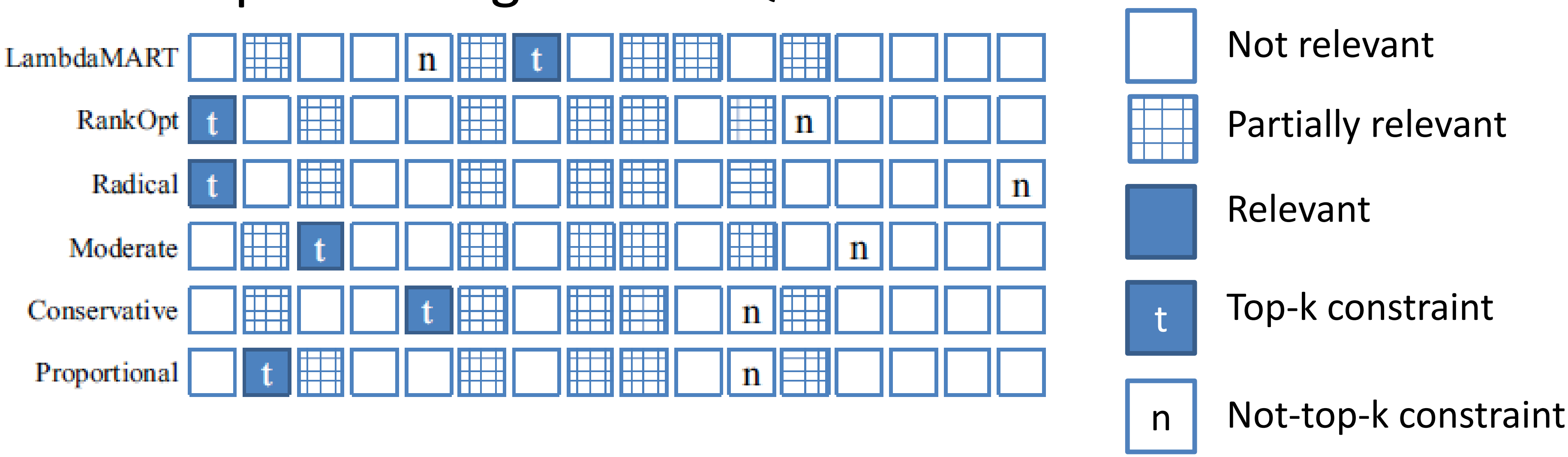
Table 2: Average time (in milliseconds) of ranking optimization in setting of (top-5, not-top-10).

	MQ2008	MQ2007	OHSUMED	.Gov	Enterprise
time	4.24	6.85	134.53	70.06	6.45

- Tested on a Laptop PC with 2.4GHZ CPU and 4GB memory
- For most queries, the algorithm converges within 10 iterations
- Ranking optimization can be performed online

Case Study 1: How Ranking Optimization Works

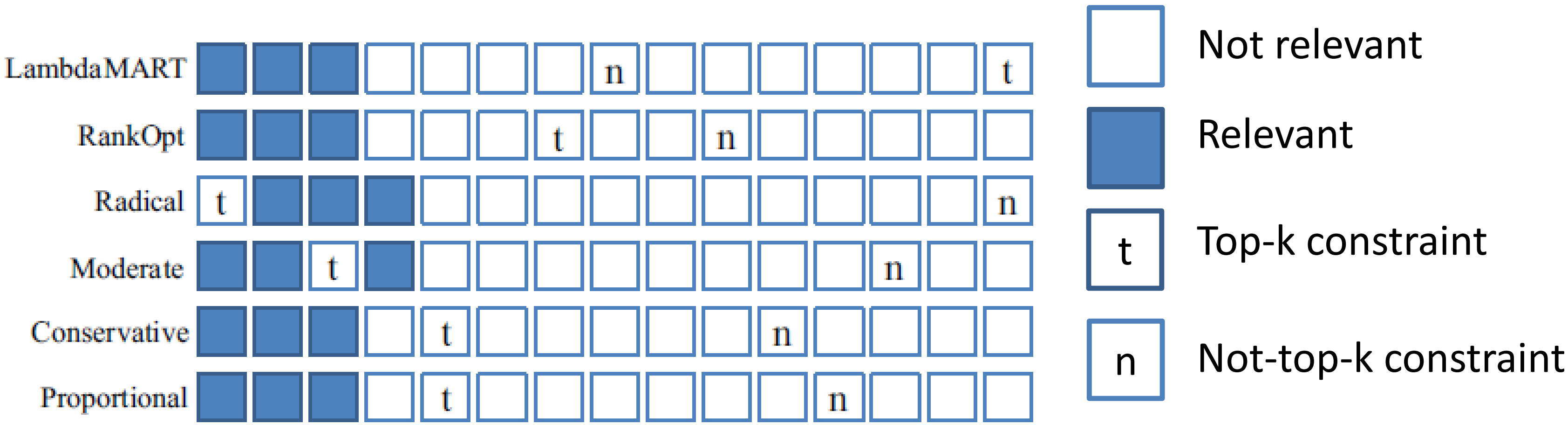
- Example ranking from MQ2008



  - RankOpt promoted the relevant document and demoted the not relevant documents
  - RankOpt outperformed baselines of Moderate, Conservative, and Proportional, when constraints are correct

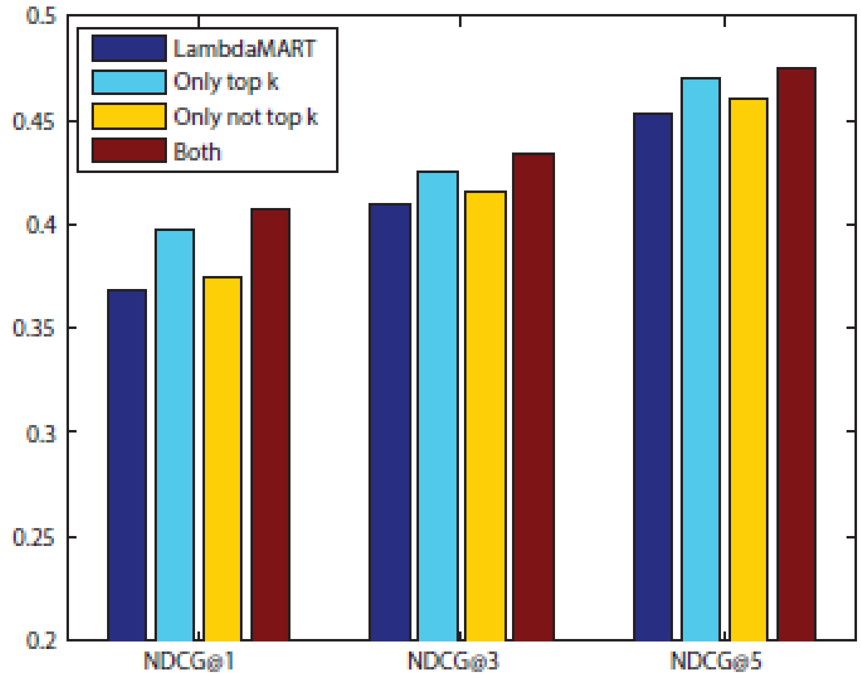
Case Study 2: How Ranking Optimization Works

- Example ranking from MQ2008



  - RankOpt outperformed Radical method, if constraints contain noise
  - RankOpt made good trade-off between constraints and original ranking

Discussion: Constraint Types



- Top-k and not-top-k constraints individually improved the ranking performances
- Performances be further improved when both are used
- RankOpt can leverage multiple types of constraints

Outline

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Summary

- Post-processing of ranking is important for search
- Heuristic approaches have limitations
- Our preliminary work makes use of Bradley-Terry model for handling the top-k and not-top-k rules
- Next step
  - Defining and incorporating other types of constraints into the framework, especially the constraints on search result diversification

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Thank you!