



A Unified Framework of Recommending Diverse and Relevant Queries

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Outline

- Introduction
- Our Approach
- Experiments
- Summary

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Motivation

(1) Given query : 'abc'

'abc shows'
'abc television'
'abc tv'

Want queries is enough?

- Very short
- words are ambitious
- users lack of domain-specific knowledge

Relevance is enough?

abc

java

Advanced Search Language Tools

Google Search I'm Feeling Lucky

Search: the web pages from Hong Kong Custom

rank

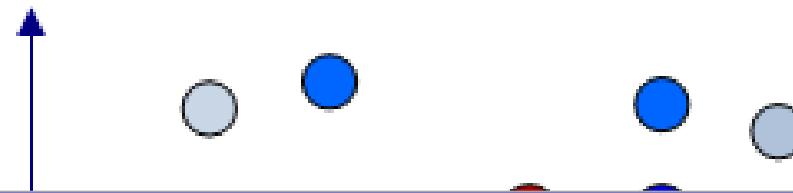
e.g.

alisa

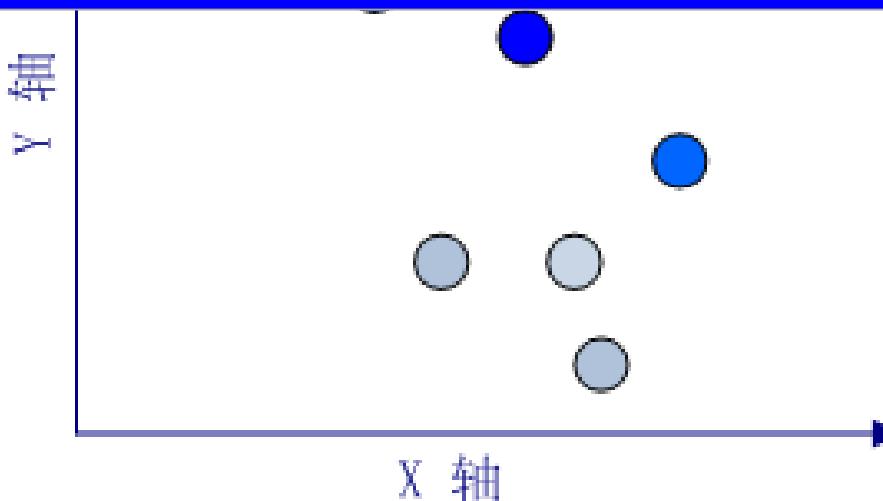
g kong

Motivation

Euclidean Space



(2) Is Euclidean space suitable?

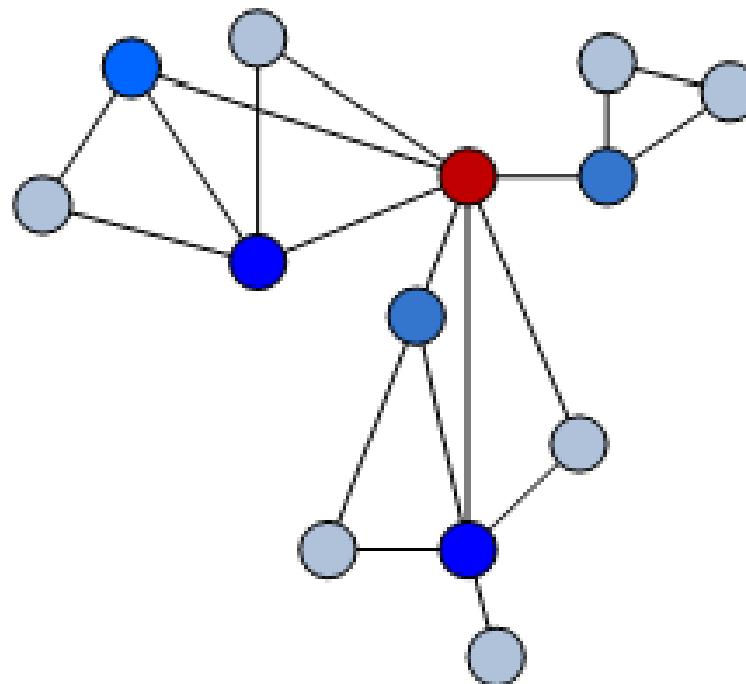


The **Red node** is the input query.

More **blue**, more relevant

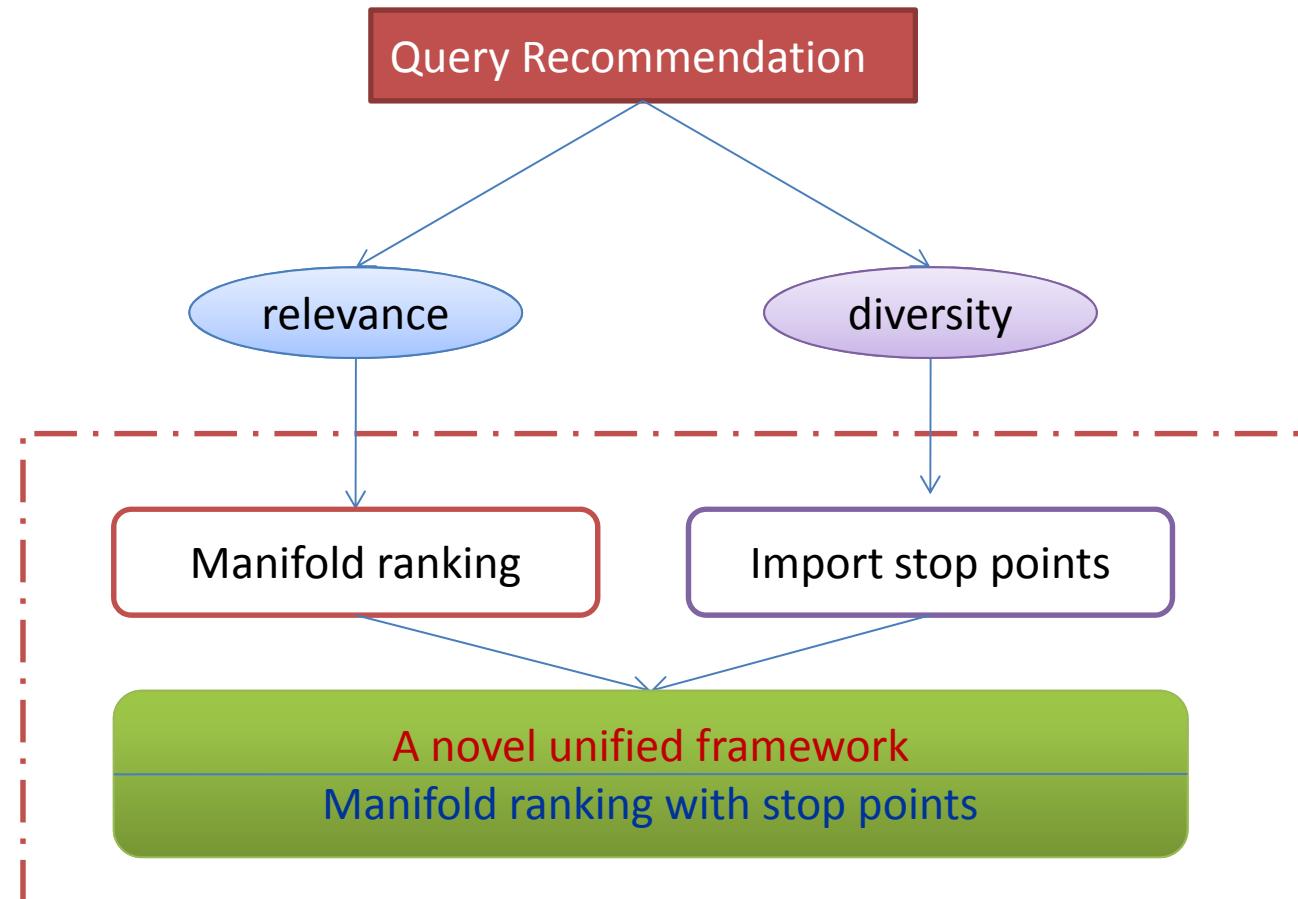
Motivation

Query Manifold



The **Red node** is the input query.
More **blue**, more relevant

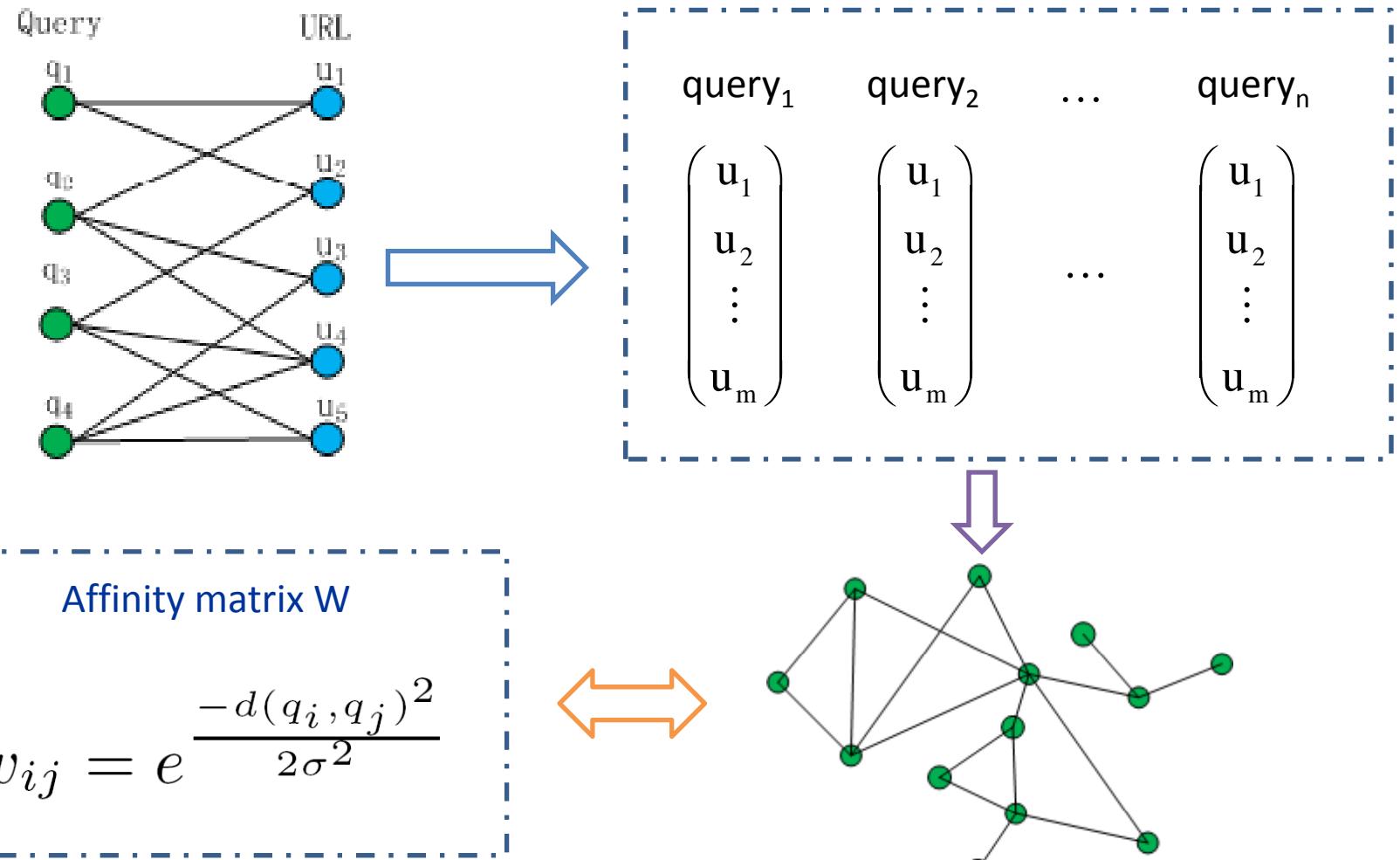
Contribution



Outline

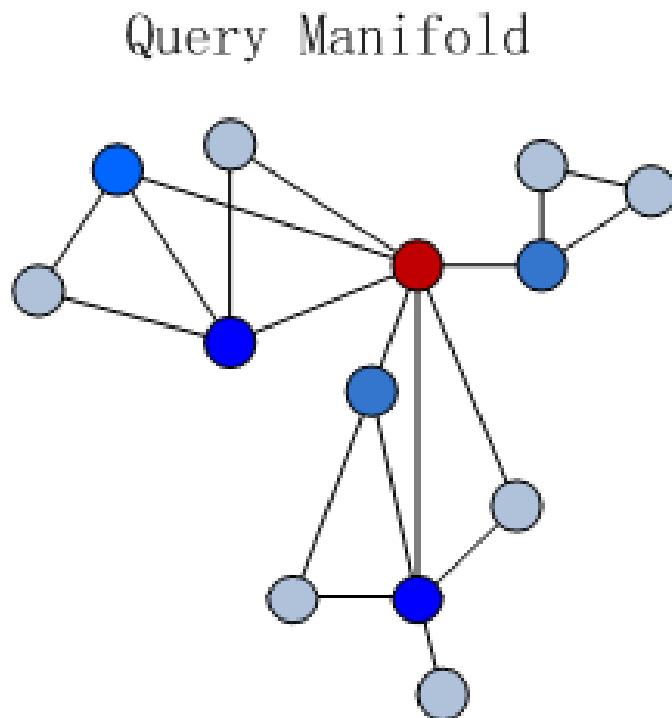
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Our Approach



Our Approach

- Traditional manifold ranking process



W - affinity matrix
D – diagonal matrix

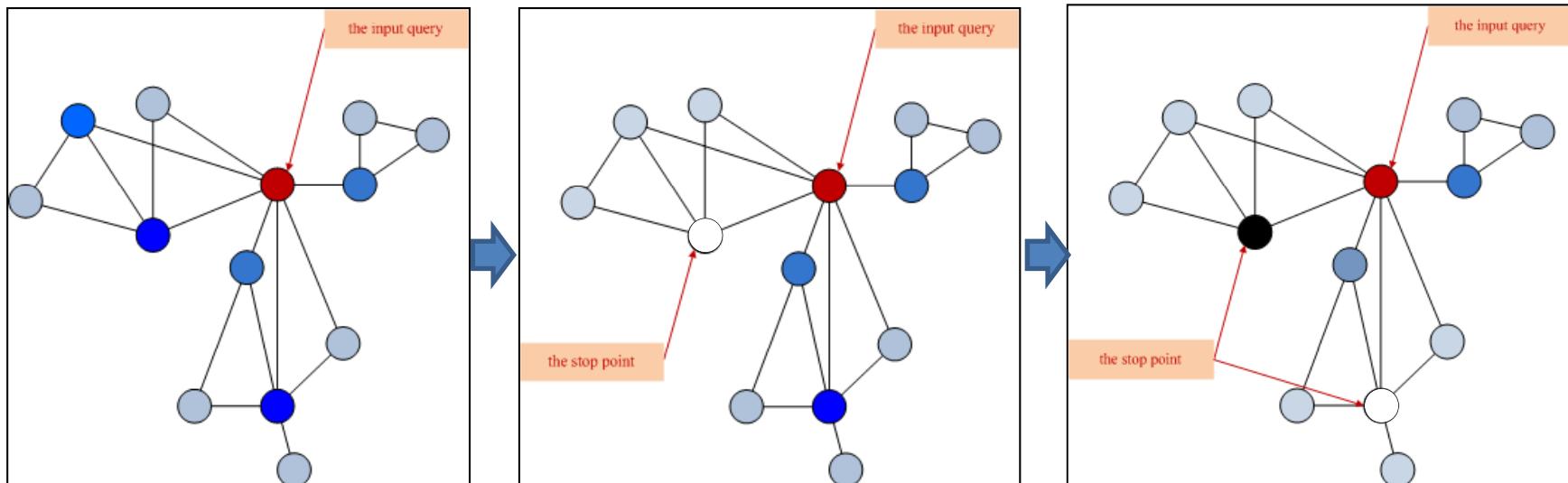
Step 1: $S = D^{-1/2}WD^{-1/2}$

Step 2: $f^{(t+1)} = \alpha S f^{(t)} + (1 - \alpha)y$

Step 3: ranking scores f_i^*

Our Approach

- Manifold ranking with stop points



Our Approach

$$f^{(t+1)} = \alpha S f^{(t)} + (1 - \alpha) y \quad (1)$$

T - set of stop points
 R - set of free points

$$\begin{pmatrix} f_R \\ f_T \end{pmatrix}^{(t+1)} = \alpha \begin{pmatrix} S_{RR} & S_{RT} \\ S_{TR} & S_{TT} \end{pmatrix} \begin{pmatrix} f_R \\ f_T \end{pmatrix}^{(t)} + (1 - \alpha) \begin{pmatrix} y_R \\ y_T \end{pmatrix} \quad (2)$$

$$\begin{pmatrix} f_R \\ f_T \end{pmatrix}^{(t+1)} = \alpha \begin{pmatrix} S_{RR} & 0 \\ S_{TR} & 0 \end{pmatrix} \begin{pmatrix} f_R \\ f_T \end{pmatrix}^{(t)} + (1 - \alpha) \begin{pmatrix} y_R \\ y_T \end{pmatrix} \quad (3)$$

$$S = \begin{pmatrix} S_{RR} & S_{RT} \\ S_{TR} & S_{TT} \end{pmatrix}$$

$$S_{RT} = S_{TT} = 0$$

$$f_R^{(t+1)} = \alpha S_{RR} f_R^{(t)} + (1 - \alpha) y_R \quad (4)$$

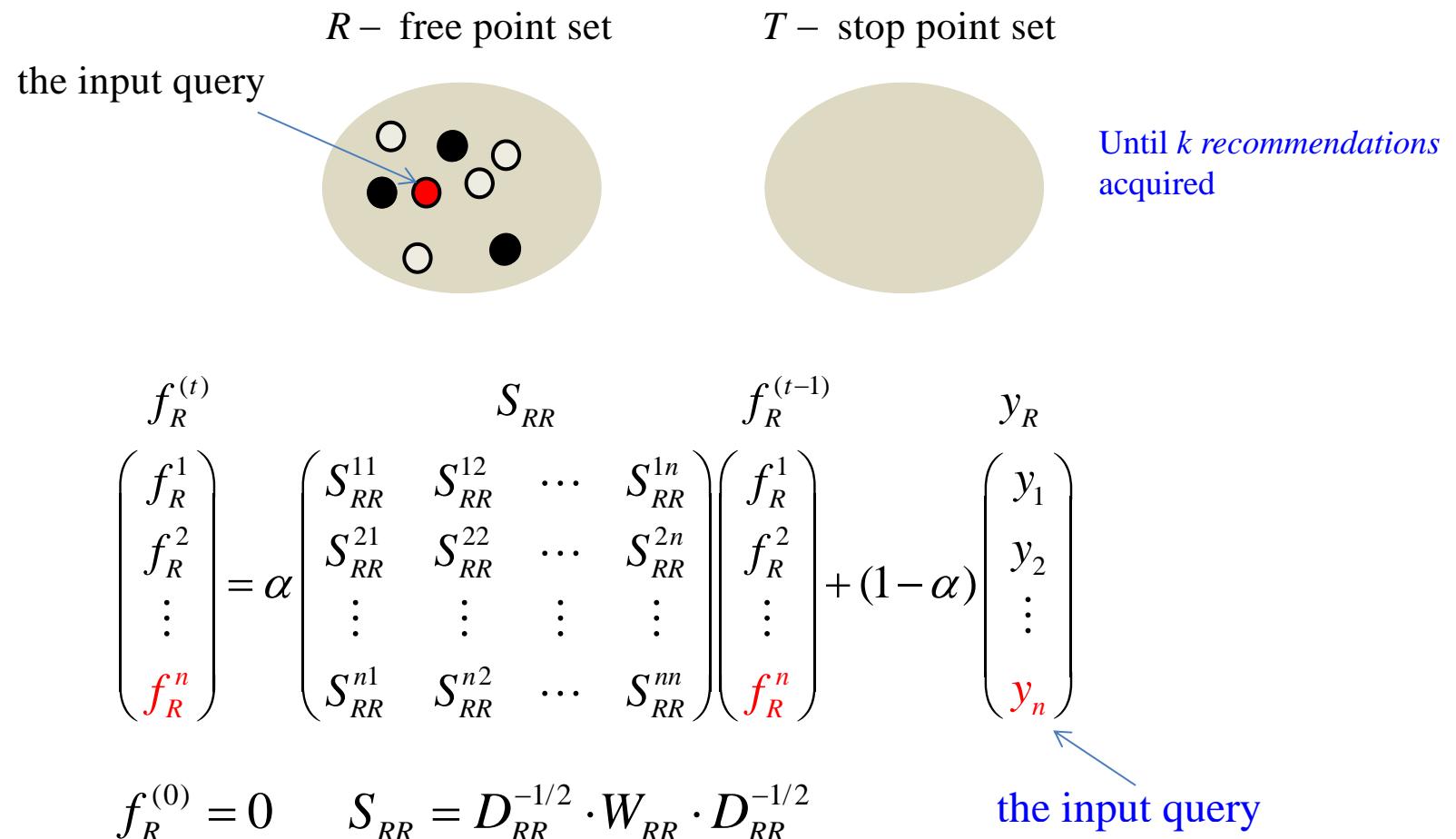
Our Approach

$$f_R^{(t+1)} = \alpha S_{RR} f_R^{(t)} + (1 - \alpha) y_R$$

THEOREM 1. *The sequence $\{f_R^{(t)}\}$ converges to*

$$f_R^* = (1 - \alpha)(I - \alpha S_{RR})^{-1} y_R.$$

Detailed Algorithm



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Experiments

- Data Set
 - 15 million queries (from US users) sampled over one month in May, 2006.
 - Clean the raw data
 - ignoring non-English queries
 - replacing all non-alphanumeric characters in each query with whitespace.
 - frequency less than 3 was removed
 - After cleaning
 - 191,585 queries, 251,427 URLs and 318,947 edges.
 - 1.66 distinct URLs, 1.27 distinct queries.

Experiments

- **Baselines**
 - **Pair-wise Based**
 - **Naïve** : only considers relevance
 - **MMR** (Maximal Marginal Relevance) : a linear combination of relevance and diversity
 - **Graph Based**
 - **Hitting time**: boost long tail queries
 - **Grasshopper**(Graph Random-walk with Absorbing States that HOPs among Peaks for Ranking) : absorbing random walk on the graph

Case Study

Table 1: Examples of query recommendations provided by different approaches (top 10 results)

query	Naive	Hitting_time	MMR	Grasshopper	Manisink
abc	abc shows abc television abc tv abc news abc breaking news	abc shows abc television associated builders and contractors abc tv news stories	abc shows abc breaking news associated builders and contractors abc nightline abc tv	abc tv abc news abc family abc shows abc breaking news	abc tv abc news abc nightline abc family associated builders and contractors abc shows abc daytime goodmorning america abc sports abc daytime national news
	abc family abc sports abc world news world news tonight abc soap operas	abc news abc world news tonight abc family channel espn sports abc nightline	abc television abc family abc sports abc daytime goodmorning america	nightline goodmorning america abc sports abc daytime national news	abc shows abc daytime goodmorning america abc sports abc soap operas
	yamaha america yamaha motor corp yamaha motor yamaha motor co yamaha motorcycle yamaha motors yamaha motorcycles yamaha quads yamaha snowmobiles yamaha scooters	yahama yamaha america yamaha motor corp yamaha motor co yamaha motor yamaha motorcycle yamaha snowmobiles yamaha quads yamaha outboard motors bluebook motorcycles	yamaha america yamaha atv parts yamaha boat motors yamaha motor corp yamaha snowmobiles yamaha motor yamaha drums yamaha guitars yamaha motorcycles yamaha atvs	yamaha motor yamaha america yamaha motor corp yamaha motor corp yamaha motorcycles motorcycles yamaha marine yamaha atv yamaha marine yamaha drums yamaha motorcycle parts yamaha snowmobiles yamaha quads	yamaha motor yamaha motor corp yamaha america yamaha america yamaha marine yamaha atv yamaha snowmobiles yamaha drums yamaha guitars yamaha quads yamaha boat motors

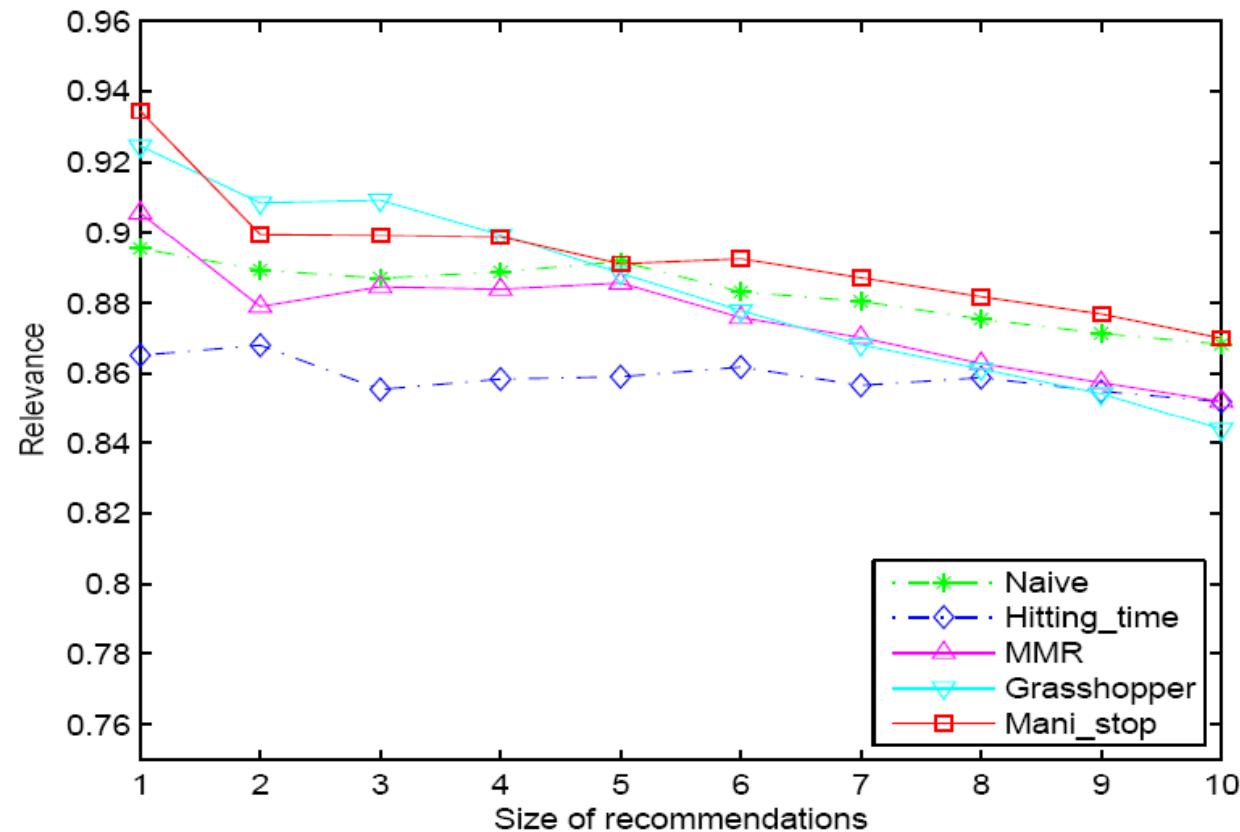
Experiments

- **Automatic Evaluation**
 - Open Directory Project(ODP) <-> Relevance
 - Commercial search engine (i.e., Google) <-> Diversity
- **Evaluation metrics**
 - Relevance
 - Diversity
 - Q-measure

$$\begin{aligned} \text{div rel}(q) &= \overline{\left(\frac{1}{|U|} \sum_{q' \in U} r(q, q') \right)} \\ &= \frac{(1 + \beta)}{\text{div}(q) + \frac{1}{\text{rel}(q)}}, \end{aligned}$$

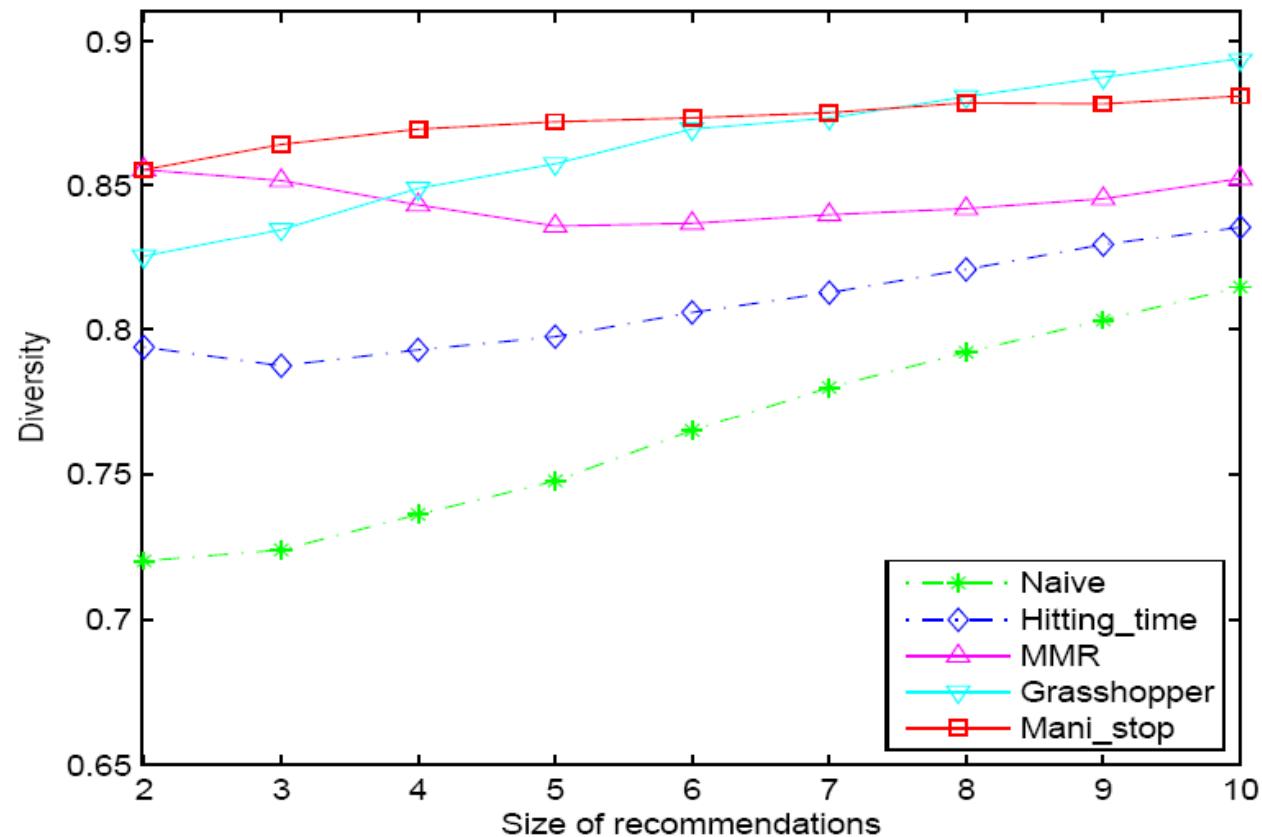
Experiments

Figure 1: Average Relevance of Query Recommendation over Different Recommendation Size under Five Approaches.



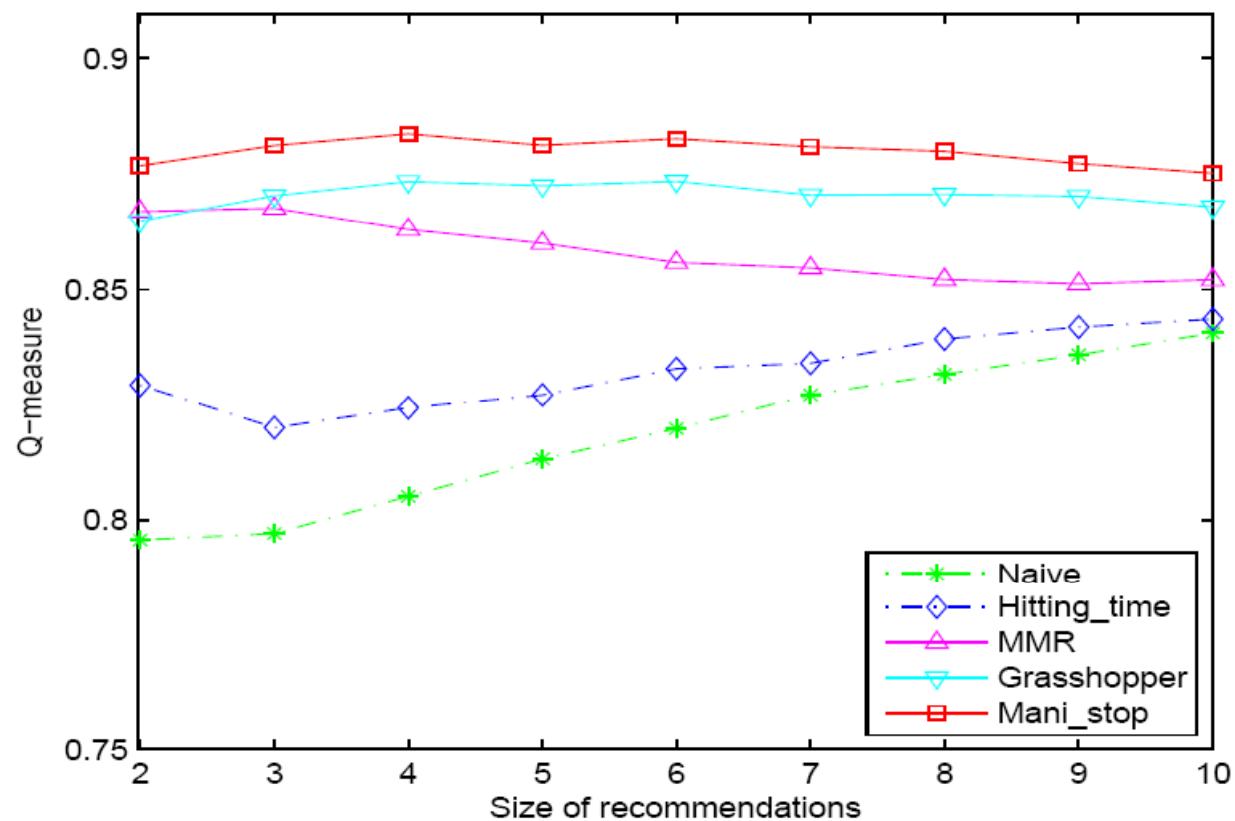
Experiments

Figure 2: Average Diversity of Query Recommendation over Different Recommendation Size under Five Approaches.



Experiments

Figure 3: Average Q-measure of Query Recommendation over Different Recommendation Size under Five Approaches.



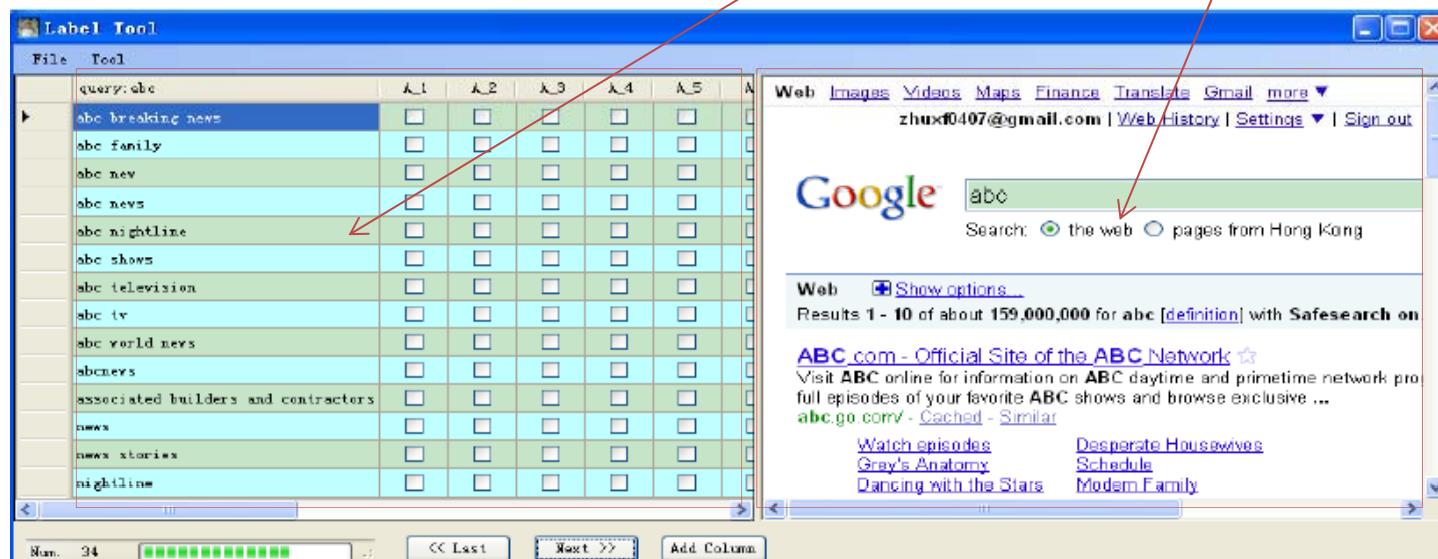
Experiments

- **Manual Evaluation**

- Recommendation pool
- 3 human judges
- Label tool

Recommendation pool

search results



Experiments

- **Evaluation Metrics**

- α -nDCG (α -normalized Discounted Cumulative Gain)

$$G(k) = \sum_{i=1}^I J_i(k) (1 - \alpha)^{C_i(k-1)}$$

- Intent-Coverage

$$\text{Intent-Coverage}(k) = \frac{1}{I} \sum_i^I B_i(k),$$

Experiments

Table 2: Performance of recommendation results over a sample of queries under five different approaches.

	α -nDCG@5	α -nDCG@10	Intent-Coverage@5	Intent-Coverage@10
Naive	0.717	0.689	0.300	0.536
Hitting_time	0.770 (7.4 \ddagger /*/*/*)	0.738 (7.1 \ddagger /*/*/*)	0.348 (16 \ddagger /*/*/*)	0.585 (9.3 \ddagger /*/*/*)
MMR	0.799 (11.4 \ddagger /3.8/*/*)	0.742 (7.7 \ddagger /0.5/*/*)	0.384 (28 \ddagger /10.3 \ddagger /*/*)	0.585 (9.1 \ddagger /0/*/*)
Grasshopper	0.794 (10.7 \ddagger /3.1/-0.6/*)	0.768 (11.5 \ddagger /4.1/3.5 \ddagger /*)	0.373 (24.3 \ddagger /7.2/-2.9/*)	0.616 (14.9 \ddagger /5.1/5.3/*)
Mani_stop	0.838 (16.9 \ddagger /8.8 \ddagger /4.9 \ddagger /5.5 \ddagger)	0.806 (17 \ddagger /9.2 \ddagger /8.6 \ddagger /4.9 \ddagger)	0.436 (45.3 \ddagger /25.3 \ddagger /13.5 \ddagger /16.9 \ddagger)	0.665 (24.1 \ddagger /13.5 \ddagger /13.7 \ddagger /8 \ddagger)

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Summary

- A Novel Unified Model
 - Relevant and salient queries
 - Diverse
- Experimental results
 - Automatic evaluation
 - Manual evaluation



Thank you!

Q&A

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