Ανάκτηση Πληροφορίας

Relevance Feedback in Image Information Retrieval

Outline

- Motivation for Relevance Feedback (RF)
- Introduction to RF
- RF techniques in Image Databases
- Conclusions

Motivation

- Initial work on content-based retrieval focused on using low-level features like color and texture for image representation.
- After each image is associated with a feature vector, similarity between images is measured by computing distances between feature vectors in the feature space.
- It is generally assumed that the features are able to locate visually similar images close to each other in the feature space so that non-parametric approaches, like the *k*-nearest neighbor search, can be used for retrieval.

Motivation

- There are cases where the user is not satisfied by the answers returned.
- Several relevant objects may not be retrieved or in addition to the relevant objects there are a lot of non-relevant ones.
- Possible solutions:
  - Request more answers (e.g., next 10)
  - Rephrase and reexecute the query
  - Relevance feedback

A Possible Solution: RF

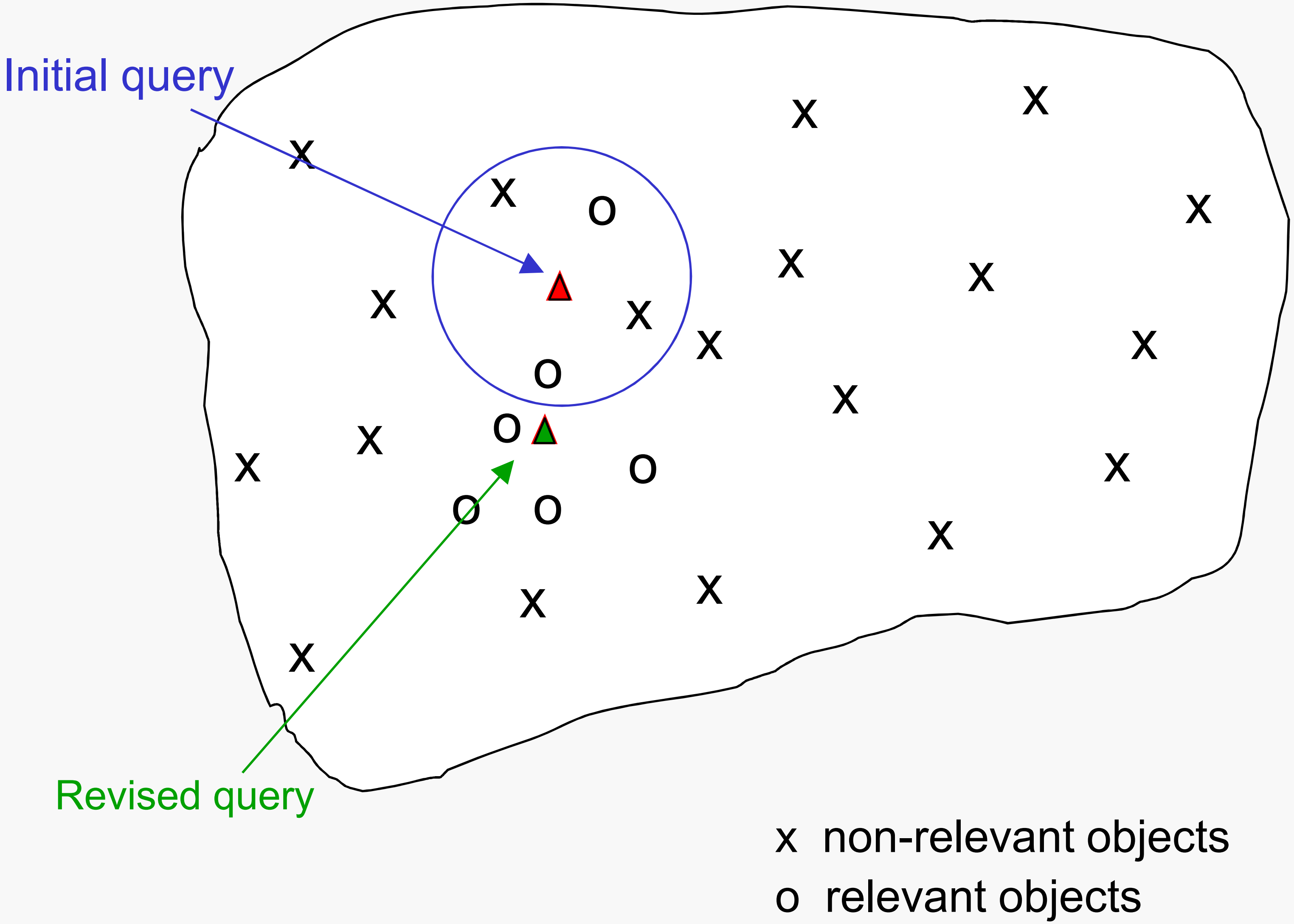
- Take advantage of user relevance judgments in the retrieval process:
  - User issues a query and gets back an initial hit list
  - User marks hits as relevant or non-relevant
  - The system computes a better representation of the information need based on this feedback
  - This process can be repeated more than once.

Idea: you may not know what you're looking for, but you'll know when you see it.

Forms of RF

- Explicit feedback: users explicitly mark relevant and irrelevant documents
- Implicit feedback: system attempts to infer user intentions based on observable behavior
- Blind feedback (also known as pseudofeedback): feedback in absence of any evidence, explicit or otherwise

The Goal of RF



RF in Text Retrieval

- RF was originally proposed for text-based information retrieval.
- The goal is to improve the quality of the returned documents.
- Fundamental work: Rocchio

Rocchio Method

- Used in practice:

$$\vec{q}_m = \alpha \vec{q}_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d}_j \in D_r} \vec{d}_j - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d}_j \in D_{nr}} \vec{d}_j$$

q_m = modified query vector;
q_0 = original query vector;
α, β, γ: weights (hand-chosen or set empirically);
D_r = set of known relevant doc vectors;
D_{nr} = set of known irrelevant doc vectors

- New query
  - Moves toward relevant objects
  - Away from irrelevant objects

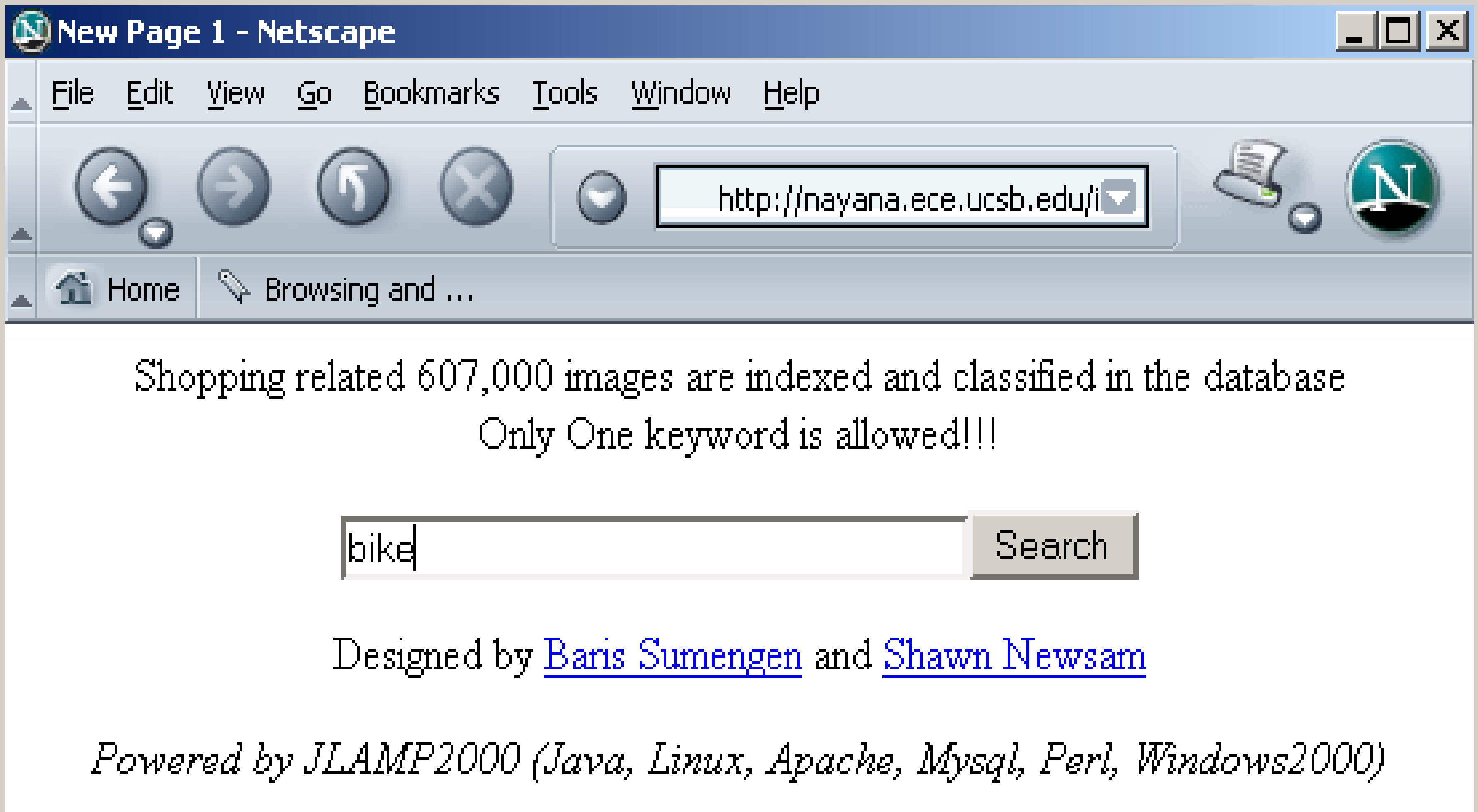
Rocchio Example

$$\text{query vector} = \alpha \cdot \text{original query vector} + \beta \cdot \text{positive feedback vector} - \gamma \cdot \text{negative feedback vector}$$

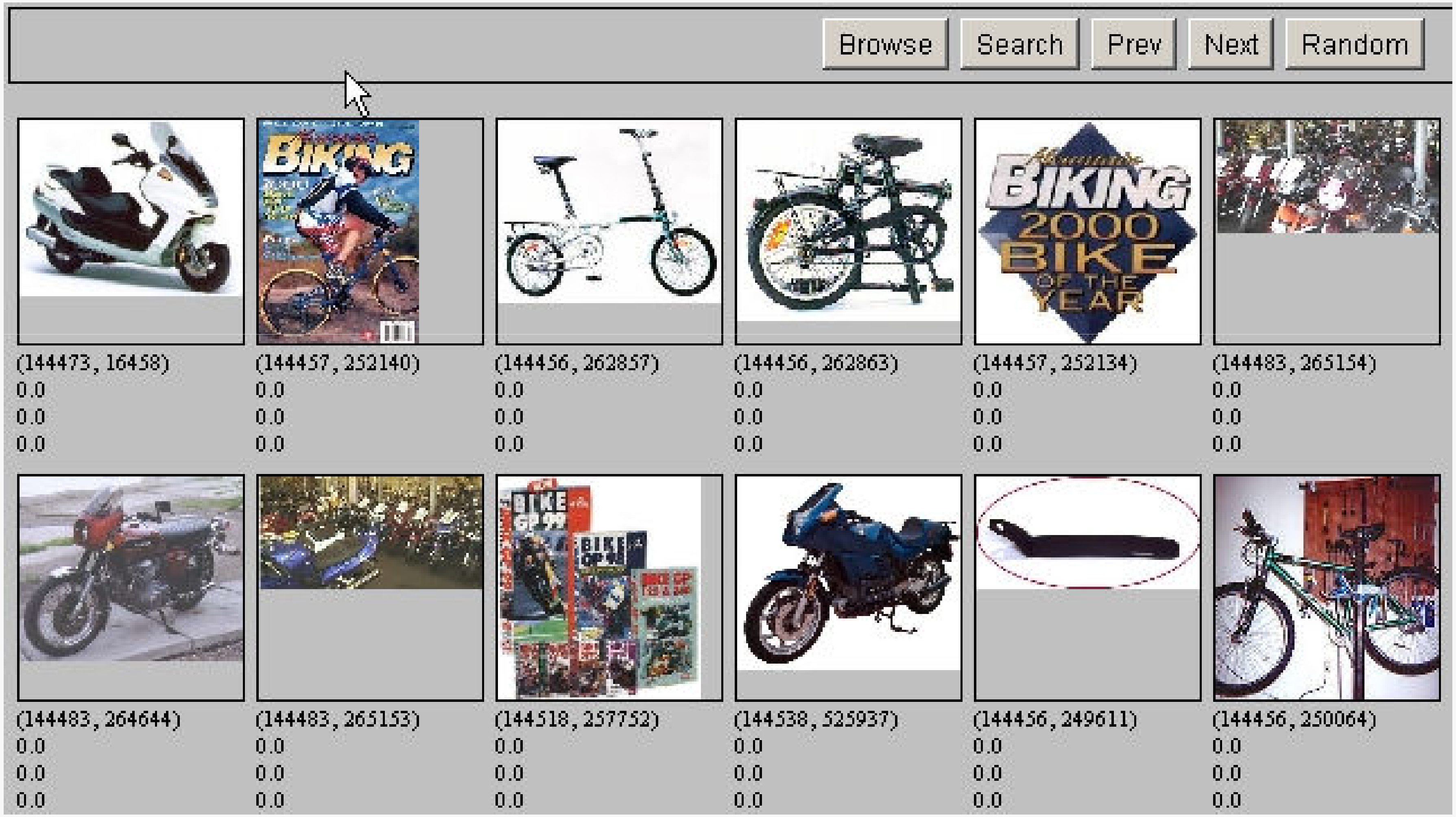
Typically, $\gamma < \beta$

Original query	0	4	0	8	0	0	$\alpha = 1.0$	0	4	0	8	0	0	
Positive Feedback	2	4	8	0	0	2	$\beta = 0.5$	1	2	4	0	0	1	(+)
Negative feedback	8	0	4	4	0	16	$\gamma = 0.25$	2	0	1	1	0	4	(-)
							New query	-1	6	3	7	0	-3	

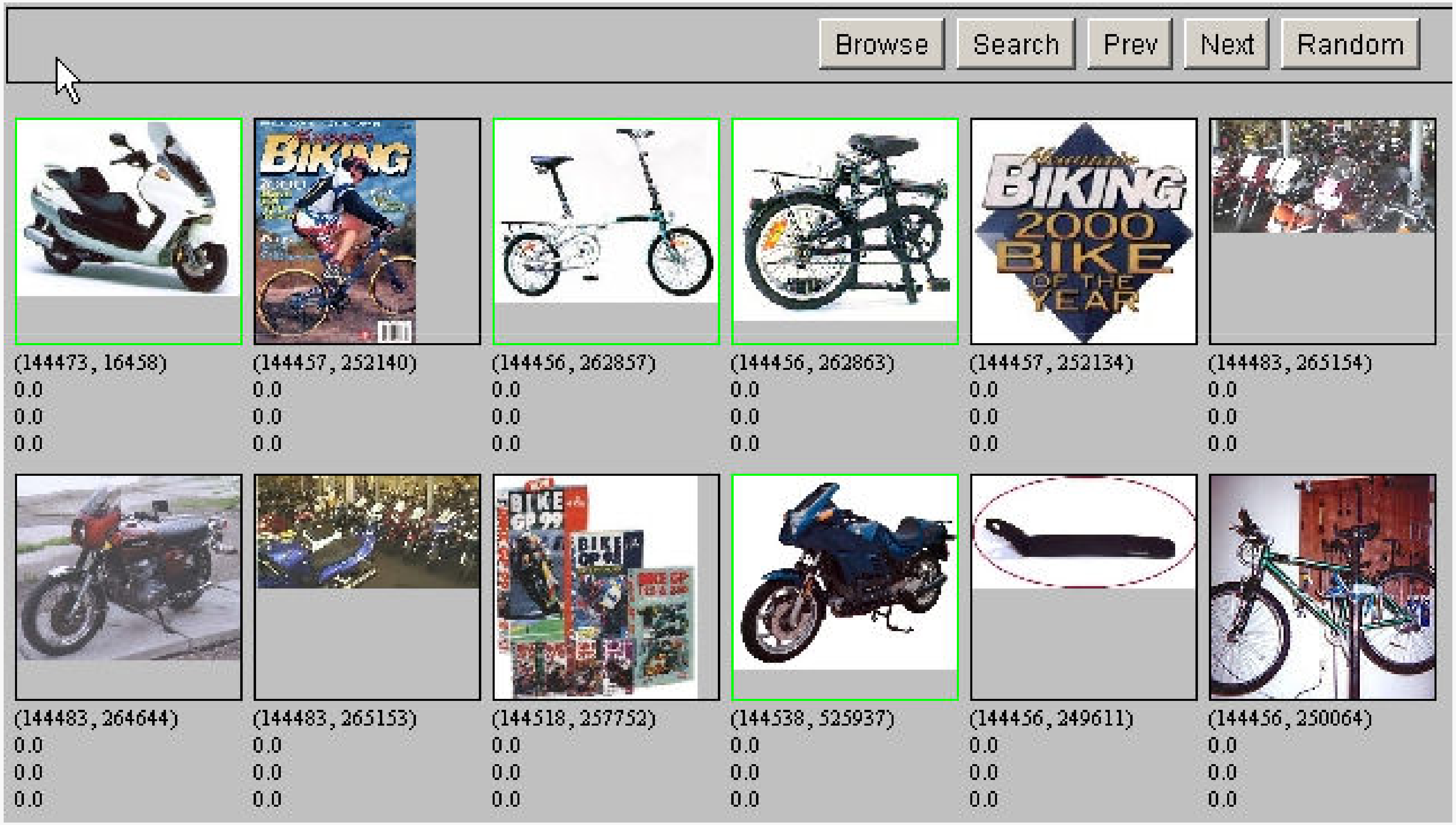
RF Example


New Page 1 - Netscape
File Edit View Go Bookmarks Tools Window Help
http://nayana.ece.ucsb.edu/i
Home
Browsing and ...
Shopping related 607,000 images are indexed and classified in the database
Only One keyword is allowed!!!
bike
Search
Designed by Baris Sumengen and Shawn Newsam
Powered by JLAMP2000 (Java, Linux, Apache, Mysql, Perl, Windows2000)

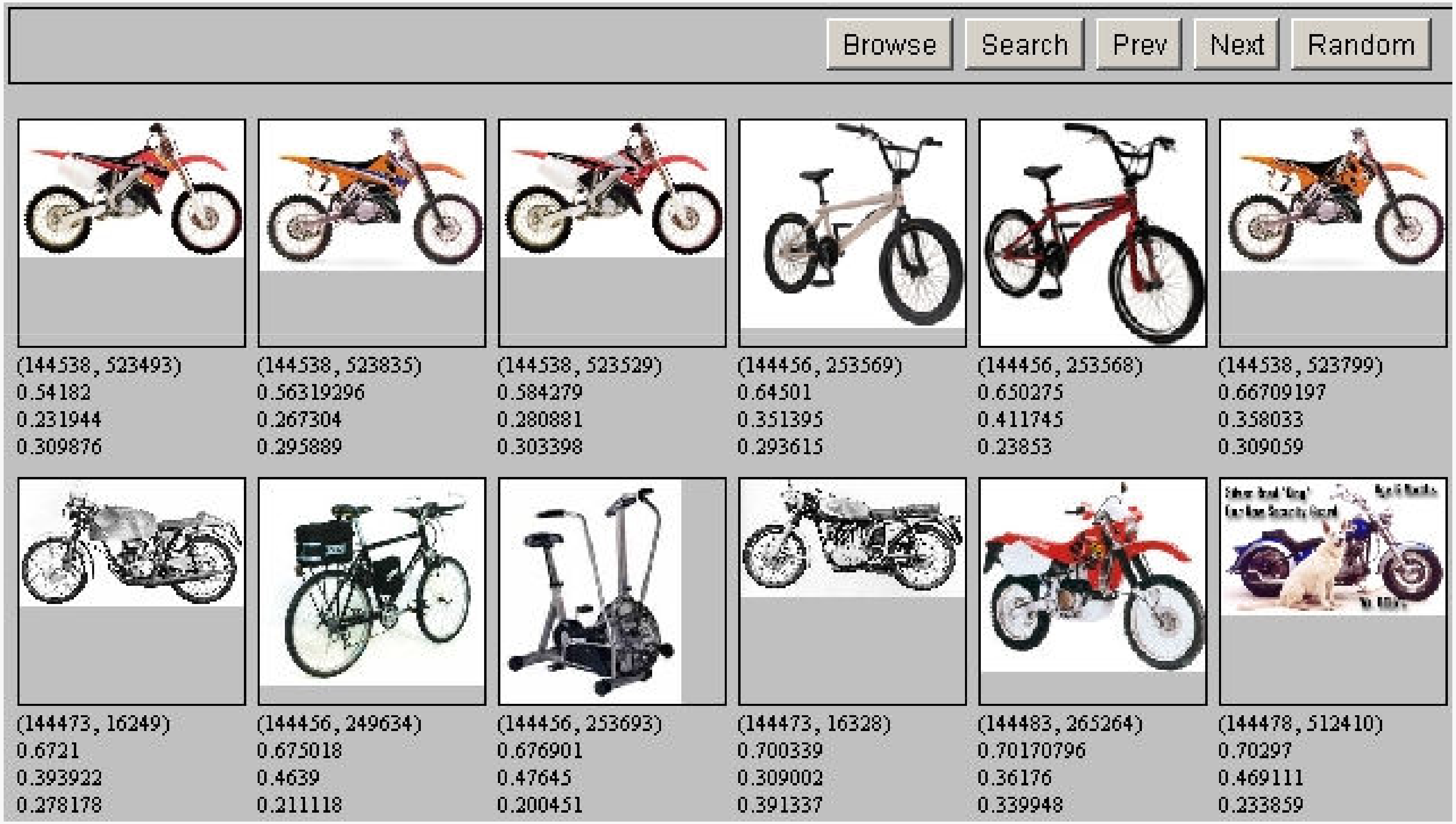
RF Example: initial results



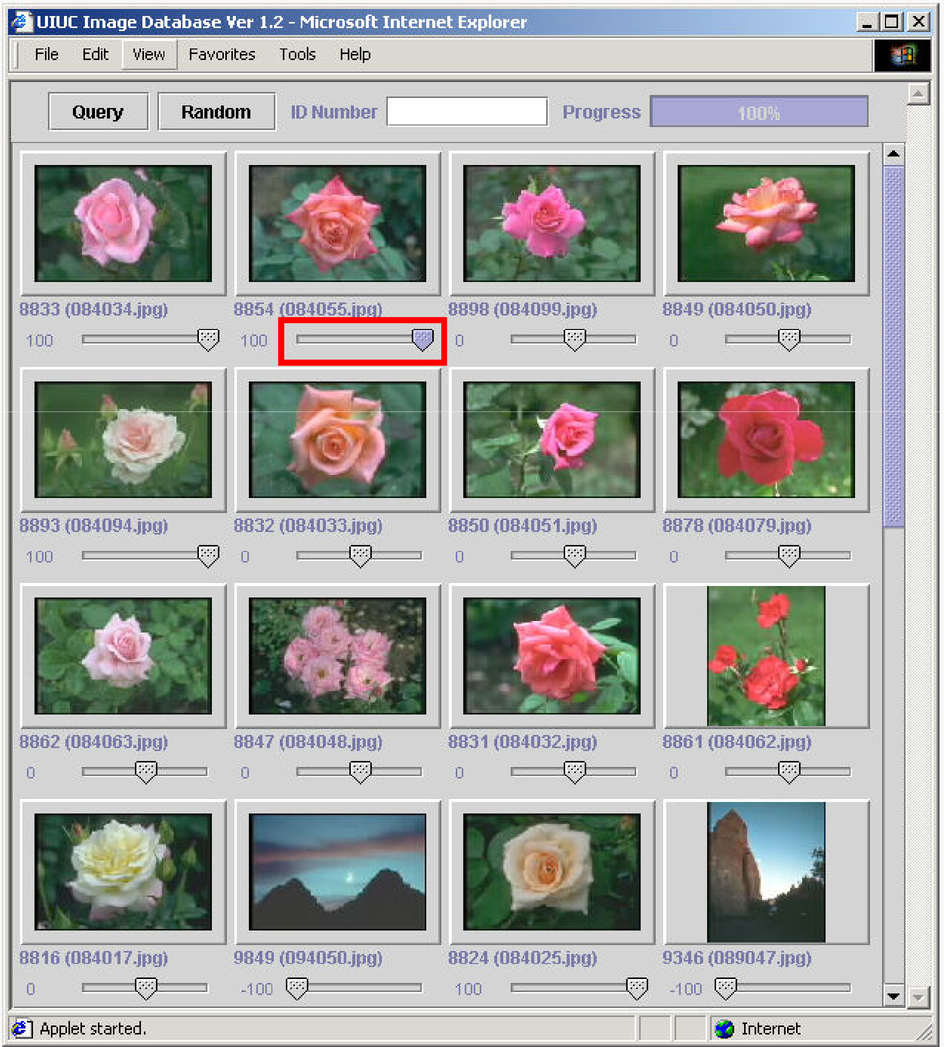
RF Example: user selection



RF Example: revised results



RF Example: alternative interface



Some RF Techniques

1. Yong Rui, Thomas S. Huang and Sharad Mehrotra. "Content-Based Image Retrieval with Relevance Feedback in MARS", *International Conference on Image Processing (ICIP)*, 1997.
2. Selim Aksoy, Robert M. Haralick, Faouzi A. Cheikh, Moncef Gabbouj. "A Weighted Distance Approach to Relevance Feedback", *International Conference on Pattern Recognition (ICPR)*, 2000.
3. Zhong Su, Hongjiang Zhang, Stan Li, and Shaoping Ma. "Relevance Feedback in Content-Based Image Retrieval: Bayesian Framework, Feature Subspaces, and Progressive Learning", *IEEE Transactions on Image Processing*, 2003.
4. DeokHwan Kim, ChinWan Chung. "Qcluster: Relevance Feedback Using Adaptive Clustering for ContentBased Image Retrieval", *SIGMOD*, 2003.
5. Junqi Zhang Xiangdong Zhou Wei Wang Baile Shi1 Jian Pei. "Using High Dimensional Indexes to Support Relevance Feedback Based Interactive Images Retrieval", *VLDB*, 2006.

CBIR with RF in MARS

- There is an urgent need to develop integration mechanisms to link the image retrieval model to text retrieval model, such that the well established text retrieval techniques can be utilized.
- This paper studies approaches of converting image feature vectors (Image Processing domain) to weighted-term vectors (IR domain).
- Furthermore, the relevance feedback technique from the IR domain is used in content-based image retrieval to demonstrate the effectiveness of this conversion.
- Experimental results show that the image retrieval precision increases considerably by using the proposed integration approach.
- The method has been implemented in the MARS prototype system developed at the University of Illinois @ Urbana Campaign.

Weighted Distance Approach

Selim Aksoy, Robert M. Haralick, Faouzi A. Cheikh, Moncef Gabbouj. A Weighted Distance Approach to Relevance Feedback, *Proceedings of International Conference on Pattern Recognition (ICPR)*, 2000.

Weighted Distance Approach

K number of iterations

Q number of features in feature vector

R^k retrieval set after the k-th iteration

R^k_{rel} set of objects in R^k marked as relevant

F^k_j values of the j-th feature component of images in R^k

$F^k_{rel,j}$ values of the j-th feature component of images in R^k_{rel}

Weighted Distance Approach

- The similarity between images is measured by computing distances between feature vectors in the feature space.
- Given two feature vectors x and y and the weight vector w, we use the weighted distances L_1 or L_2:

$$L_1(x, y; w) = \sum_{j=1}^{Q} | w_j \cdot (x_j - y_j) |$$

$$L_2(x, y; w) = \left(\sum_{j=1}^{Q} | w_j \cdot (x_j - y_j) |^2 \right)^{1/2}$$

Weighted Distance Approach

- From the pattern recognition point of view, for a feature to be good, its variance among all the images in the database should be large but its variance among the relevant images should be small.
- Any one of these is not enough alone but characterizes a good feature when combined with the other.

Weighted Distance Approach

Let w_j^k denote the weight of the *j*-th feature component in the *k*+1 iteration.

This weight is given by the following equation:

$$w_j^k = \frac{\sigma_j^0}{\sigma_{rel,j}^k}$$

where:

$$\sigma_j^0 = std(F_j^0) \qquad \sigma_{rel,j}^k = std(F_{rel,j}^k)$$

Weighted Distance Approach

According to the values of σ_j^0 and $\sigma_{rel,j}^k$ there are four different cases:

	σ_j^0	$\sigma_{\mathrm{rel},j}^k$	$w_j^k = \sigma_j^0 / \sigma_{\mathrm{rel},j}^k$
best case	large	small	large
	large	large	~ 1
	small	small	~ 1
worst case	small	large	small

Weighted Distance Approach

Case 1

- When σ_j^0 is large and $\sigma_{rel,j}^k$ is small, w_j^k becomes large.
- This means that the feature has a diverse set of values in the database but its values for relevant images are similar.
- This is a desired situation and shows that this feature is very effective in distinguishing this specific relevant image set, so a large weight assigns more importance to this feature.

Weighted Distance Approach

Case 2

- When both σ_j^0 and $\sigma_{rel,j}^k$ are large, w_j^k is close to 1.
- This means that the feature may have good discrimination characteristics in the database but is not effective for this specific relevant image group.
- The resulting weight does not give any particular importance to this feature.

Weighted Distance Approach

<u>Case 3</u>

- When both σ_j^0 and $\sigma_{rel,j}^k$ are small, w_j^k is again close to 1.
- This is a similar but slightly worse situation than the previous one.
- The feature is not generally effective in the database and is not effective for this relevant set either.
- No importance is given to this feature.

Weighted Distance Approach

Case 4

- When σ_j^0 is small and $\sigma_{rel,j}^k$ is large, w_j^k becomes small.
- This is the worst case among all the possibilities.
- The feature is not generally effective and even causes the distance between relevant images to increase.
- A small weight forces the distance measure to ignore the effect of this feature.

Weighted Distance Approach

<u>Retrieval Algorithm</u>

[1] initialize all weights uniformly. $w_j^0 = 1/Q \quad j = 1, 2, ..., Q$

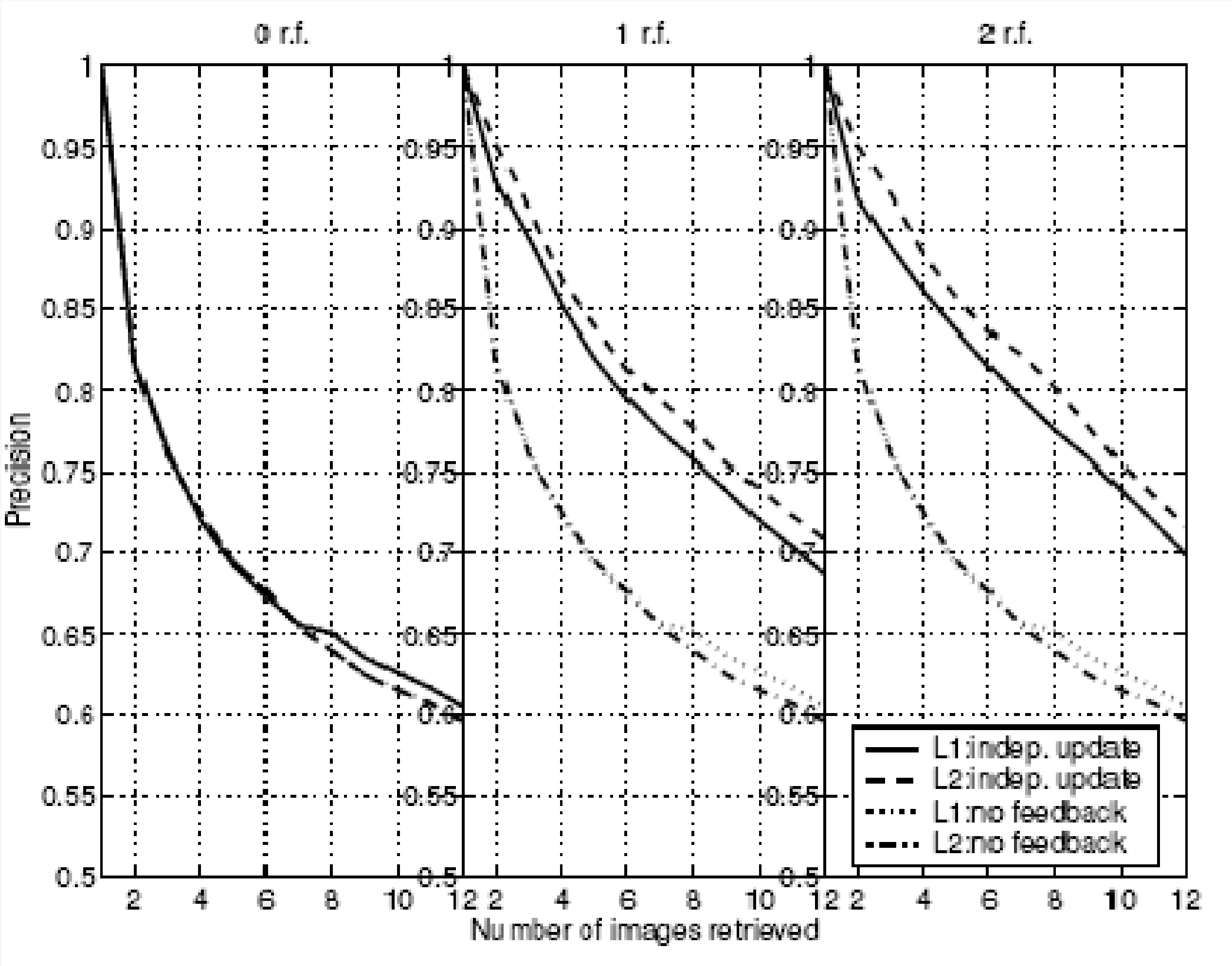
[2] compute $\sigma_j^0 \quad j = 1, 2, \ldots, Q$.

[3] for $k = 1$, $k <= K$, k++

- search the DB using w_j^{k-1} and retrieve R^k
- get feedback from user and populate R_{rel}^k
- compute $\sigma_{rel,j}^k \quad j = 1, 2, \ldots, Q$
- compute $$w_j^k = \frac{\sigma_j^0}{\sigma_{rel,j}^k} \qquad j = 1, 2, \ldots, Q$$
- normalize $$w_j^k = \frac{w_j^k}{\sum_{j=1}^{Q} w_j^k}$$

Weighted Distance Approach

Precision results



Weighted Distance Approach

Precision results

Distance	0 rf	1 rf	2 rf
L_1	0.60	0.69 (13.53%)	0.70 (1.71%)
L_2	0.60	0.71 (19.03%)	0.72 (1.06%)