Two-step relevance feedback for semantic disambiguation in image retrieval

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Outline

- Content based image search
- Relevance Feedback
- The NN^k Idea
- Experiments and Results
- Conclusions

Content based image search

- Using an external image
  e.g. bigimbaz, retrievr
- Using an internal image
  e.g. pixsta
- Using keywords (and automated image annotation)
  e.g. behold

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- Of course, some features don't capture anything meaningful, and some facets are not captured by any features

Relevance feedback

Endow the retrieval system with some degree of freedom, e.g. a parametrised metric

1. Retrieve a first set of results with the system's default state.
2. Collect relevance feedback by letting users mark relevant and non-relevant images.
3. Change the system state, e.g. update parameters of the metric.
4. Retrieve again and go to 2 until user is satisfied.

Relevance feedback

- Many realisations of this basic template, e.g.
  - Rui *et al.* 98: $w_i \propto \frac{1}{\sigma_i}$
  - Ishikawa *et al.* 98: compute optimal query vector from positive and negative examples
  - Tong *et al.* 01: estimation of hyperplane between relevant and non-relevant images
  - Urban *et al.* 03: query weighted average over relevant images
  - Giacinto *et al.* 04: non-parametric instance-based relevance feedback
  - plus 400+ more

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- Limitations: default setting may not be suitable for the semantic facet of interest. In the worst case, no relevant images are retrieved in the first step

The NN^k idea

- The agnostic stance: assume we know nothing about which features may be important or which semantic facet a user is interested in.
- We extract the query's semantic facets by determining its neighbours under many different feature combinations.
- For each feature combination, we record only the nearest neighbour.
- There may not be many relevant nearest neighbours, but, if the features are any good, the semantic facet of interest should be represented by at least one neighbour.

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$$f_w(x, y) = \sum_{i=1}^{k} w_i d_i(x, y) \quad \text{(Why?)}$$

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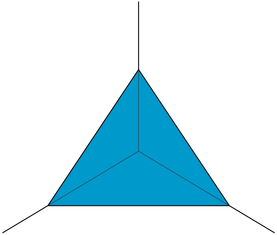
- We further assume that the w's add to 1 and are positive (Why?)

The NN^k idea with $k = 3$

- With $k = 3$, all weight vectors lie on a 2-dimensional simplex



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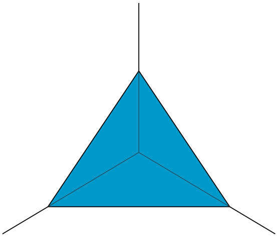
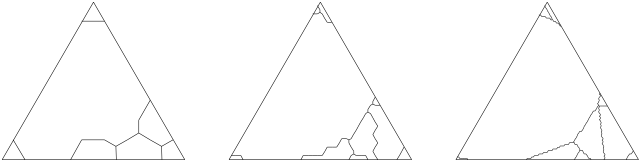


- For different positions on the simplex, we may get different nearest neighbour of an image query
- What is the simplex for $k = 2$?

The NN^k idea with $k = 3$

- Finding the NN^k by discretising the weight space.



- Each NN^k can be associated with a typical weight vector under which it is retrieved. We choose the mean weight vector.

The NN^k idea for relevance feedback

The proposed relevance feedback method

1. Retrieve the set of NN^k and determine supporting feature weights
2. Let users select relevant images from the set
3. Retrieve again with the selected weights

Experiments - Image data and visual features

- Two collections
  - Corel images: 32,000 images, 191 classes, 1.1 avg polysemy
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- Eight features ($\rightarrow NN^8$)
  - Tamura texture features
  - Gabor wavelets
  - HSV histograms
  - Colour Structure Descriptor
  - ...and others

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- Feature selection method by Rui et al. (2000)

1. Retrieve with uniform weights
2. Select and score relevant images
3. Update the weight of the jth feature according to

$$w_j \propto \left(\sum_{i=1}^{N} v_i d(p_{ij}, q_j) \right)^{-\frac{1}{2}}$$

where the sum is over the set of relevant images. This minimises the sum of the v_i-weighted distances between relevant images and the query.

Experimental details

- One ranked list for each relevant NN^k. How to merge these?
  - Round robin: ranks items according to their highest rank
  - CombSum: rank items according to average score
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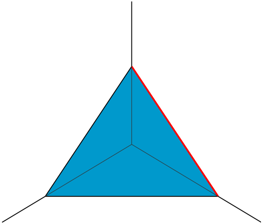
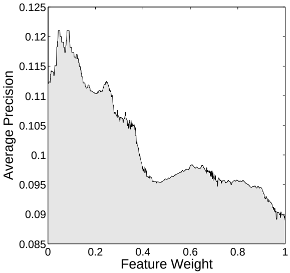
- Determining oracle performance





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NN^k (RR)	4.45	2.12	5.76	2.28

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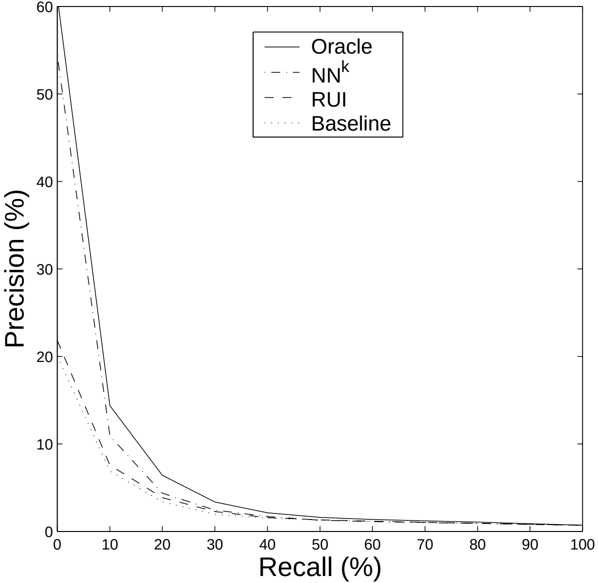

Oracle
NN^k
RUI
Baseline
Precision (%)
Recall (%)
0
10
20
30
40
50
60
70
80
90
100

Conclusions & Questions

- Simple framework for relevance feedback that shows good performance on fairly realistic datasets
- Individual distance functions and features can be more complex, e.g. EMD on keypoint representations (Jeong & Grauman, 2008)
- How can this two-step (one-shot) method be extended to several rounds of feedback?