Relevance Feedback

Tutorial Image Retrieval
Thomas Deselaers, Henning Müller
Outline

• What is relevance feedback
• Interfaces
• Instance-based relevance feedback
• Model-based relevance feedback
• Probabilistic relevance feedback
What is Relevance Feedback

• After an initial query, the user is presented with a set of results
• Then, the user gives feedback to the system
  – Marks images as relevant and/or
  – Marks images as irrelevant
• Relevance feedback can be given explicitly or implicitly
  – Explicit: marking of several images
  – Implicit: clicking on one image/stopping to search on
Positive and Negative Feedback

• Studies on strategies for relevance feedback
  – Positive feedback often a reordering of top results or one new query with a single image
    • Images have already much in common
  – Negative feedback is often the key to good results
    • Really new images are retrieved
    • Much more information is supplied
  – Problem with too much negative feedback!
    • Images with small number of features are returned
  – As much feedback as possible usually delivers best results
Problem with Negative Feedback

• Problem with too much negative feedback also in text retrieval

• Solution: Separately weighting positive and negative parts of feedback
  – Often positive=0.65, negative=0.35

• Compare Rocchio’s Method [later]
Interfaces

• Simple interface
Interfaces: Tree-based Query Interface

This is the IRMA (Image Retrieval in Medical Applications System from RWTH University Hospital)
Interfaces

• 3D Browsing and Searching Interface in MARS
Interfaces

• Video Search and Retrieval Interface

Nguyen et al. ACM Trans. MM 2008
Collection guide
Combination Schemes

• Given a set of positive and a set of negative examples (possibly empty)
• How can we use this information?

• In the following: different schemes to fuse these information cues

Joint work with R. Paredes, UPV
NotaBon

• $x$ image in the database
• $q$ query image
• $Q^+$ set of positively marked images
• $Q^-$ set of negatively marked images
• $p_x(r|q)$ probability that image $x$ is relevant given query $q$
• $p_x(\bar{r}|q)$ probability that image $x$ is irrelevant given query $q$
RF as Combination of Classifiers

- Consider relevance feedback images as training data for a kernel density classifier
- An image is relevant with probability
  \[ p_x(r|q) \propto \exp(-d(x, q_+)) \]
- Analog: irrelevant
  \[ p_x(\bar{r}|q_-) \propto \exp(-d(x, q_-)) \]
- Combine these classifiers by averaging (bagging)
  \[
p_x(r|(Q^+, Q^-)) = \frac{\alpha}{|Q^+|} \sum_{q_+ \in Q^+} p_x(r|q_+) + \frac{1 - \alpha}{|Q^-|} \sum_{q_- \in Q^-} (1 - p_x(\bar{r}|q_-))
\]

Default method in FIRE
Relevance Score

• Giacinto et al. propose an instance-based relevance feedback mechanism

• Relevance Score:

\[ RS(x, (Q^+, Q^-)) = \left(1 + \frac{\min_{q_+ \in Q^+} d(x, q_+)}{\min_{q_- \in Q^-} d(x, q_-)}\right)^{-1} \]

• Advantages: supports inhomogeneous sets \( Q^+ \) and \( Q^- \)
Rocchio’s Method

• Proposed for textual information retrieval by Rocchio in 1972
• Reformulate the query by going
  – Into the direction of the positive feedback $Q^+$
  – Away from the negative feedback $Q^-$
• Advantage: very fast, only one query has to be performed

$$\hat{q} = q + \beta \left( \sum_{q_+ \in Q^+} q_+ \right) - \gamma \left( \sum_{q_- \in Q^-} q_- \right)$$

Default method in GIFT
Quotient of Sums

• Try to define a sound probabilistic model for relevance feedback
• Determine probability for an image to be relevant (according to Bayes’ decision rule)

\[ p(r|x) = \frac{P(r)p(x|r)}{P(r)p(x|r) + P(\bar{r})p(x|\bar{r})} \]

• The different terms used here are defined in the following
• Inspired by RelevanceScore and FIRE’s method
Quotient of Sums

• Prior probabilities for images to be relevant or irrelevant:

\[ P(r) = \frac{|Q^+|}{|Q^+ \cup Q^-|} \quad P(\bar{r}) = \frac{|Q^-|}{|Q^+ \cup Q^-|} \]

• Emission probability for an image given relevant or irrelevant

\[ p(x | r) \propto \frac{1}{|Q^+|} \sum_{q \in Q^+} 1/d(x, q) \]

\[ p(x | \bar{r}) \propto \frac{1}{|Q^-|} \sum_{q \in Q^-} 1/d(x, q) \]
Quotient of Sums

• The likelihood for an image to be relevant then is

\[ S_{(Q^+, Q^-)}(x) = \frac{\sum_{q \in Q^+} 1/d(x, q)}{\sum_{q \in \{Q^+ \cup Q^-\}} 1/d(x, q)} \]

• This is used to rank images in retrieval
Tuning the system

• Apart from combining the queries, they can be used to tune parameters of the system
  – Compare to the learning of feature combinations

• Here:
  – Refine image comparison measures
Learning Weighted Distances

• Relevance feedback allows to use machine learning techniques to tune parameters of a system

• One possibility is to tune the distance function
  – Add weight for each component of the vectors which are compared

\[ d(x, q) = \sum_{i=1}^{D} w_i |x_i - q_i| \]

Joint work with R. Paredes, UPV
Learning Weighted Distances

• Optimisation:
  – Minimise the distances from each relevant (positive) image to all other relevant images
    \[
    \sum_{x \in Q^+} \sum_{q_+ \in Q^+ \setminus \{x\}} \sum_{q_- \in Q^- \setminus \{x\}} \frac{d(x, q_+)}{d(x, q_-)}
    \]
  – Analogously: Maximise the distances from each irrelevant (negative) image to all relevant images

Joint work with R. Paredes, UPV
Experimental Evaluation: WANG

WANG database: 1000 images, 10 classes, “easy task”
Evaluation on WANG Data

- $P(20)$
ImageCLEF Database

- 20,000 colour photographs
- Accompanied by semi-structured captions
  - English and Random
- Many images have similar visual content but varying
  - illumination
  - viewing angle
  - background
- Used in ImageCLEF in 2006 – 2008
- Publicly available from www.imageclef.org
Group photo with Machu Picchu and Huayna Picchu in the background.

Tourists are sitting on a grey gravel road in the foreground; a ruin with grey walls and many green terraces and a distinctive, rocky, steep mountain behind it; a wooden mountain range and white clouds in the background.
ImageCLEF Database: Query

- 39 topics with full information
  - Based on realistic topics (log-file analysis and interviews)
- Available in English only
- Augmented by a cluster tag
  - Defines how the rel. images should be clustered

Sample topic images:
Evaluation on ImageCLEF 2007 task

- $P(20)$
iCLEF: interactive multi-lingual image retrieval

• Simultaneous search in multiple languages
• User interaction
  – Have users participate
  – Competition
  – Researchers work on log-files
• Mainly text-based, visual extension would be interesting but difficult
iCLEF: user interface
Literature

Literature


Literature