CBIR: Interaction & Evaluation

COMPSCI.708.S1.C

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Semantic vs. Feature Similarity

- The user seeks **semantic similarity**, but CBIR provides **similarity by data processing results**
- The challenge for a CBIR is to focus on a narrow information domain the user has in mind via specification, examples, and interaction
  - Early CBIR engines required from users to manually select low-level visual features and specify relative weights for each their possible representation

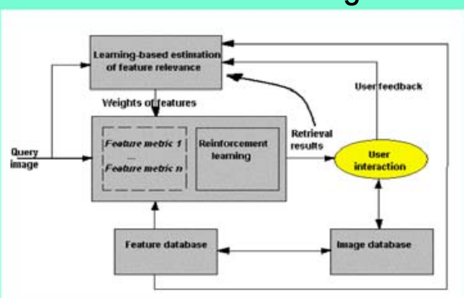
Early CBIR Engines

- Users had to know how the features are used
- Difficulties of representing semantic contents in terms of low-level features
  - Users need **semantics** (*"a sunset image", "penguins on icebergs"*), **rather than** general **low-level features** (*"a predominantly red/orange image", "predominantly oval black blobs on a white background"*)
  - There exist too many irrelevant images with similar dominant colours and regions (a "retrieval noise")
  - Difficulties by the highly subjective human perception

More Advanced CBIR Engines

- Low-level features are not adequate to contents
- ***Subjective perception***: different users and even the same user under different conditions may interpret the same image differently
- Visually similar images: due to their semantics, rather than their similar low-level features
  - Experimental CBIR engines (e.g. Photobook with FourEyes or PicHunter) use **relevance feedback** to adjust a query in such a way as to approach close to the user's expectations

Interactive CBIR Engine



Interactive CBIR Engine

- An interactive CBIR system contains:
  - an image database
  - a feature database
  - a selector of feature similarity metric
  - a block for evaluating feature relevance
- When a query arrives, the system has no prior knowledge about the query: all features have the same weight in computing the similarity measure

Interactive CBIR Engine

- After a fixed number of the top-rank (by the similarity to the query) images are retrieved, the user provides the *relevance feedback*
- The **feature relevance block** uses learning algorithms in order to re-evaluate the weights of each feature in line with the user's feedback
- The **metric selector** chooses the best similarity metric for the weighted features using reinforcement learning

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Interactive CBIR Engine

- By iteratively using the relevance feedback, the engine adjusts the query and brings the retrieved images closer to the user's expectations
  - The weight of each feature in the similarity computation is iteratively updated in accord with the high-level and subjective human perception
- The user need not map semantics onto features and specify weights and instead only informs the engine which images are relevant to the query

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Interactive QBE Retrieval

- Two-stage process of formulating a query:
  - an **initial formulation** when the user has no precise idea of what should be searched for
  - a **refined formulation** after the user took part in the iterative process of the relevance feedback
- First stage: the engine helps in formulating an "imprecise" query by providing sequential and feature-based browsing and sketching tools

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Interactive QBE Retrieval

- Second stage: the user gives **positive** and **negative feedback** to the system
- Feedback: (1) all currently retrieved images are labelled in accord with their relevance to user's expectations
  - E.g. image labelling into five groups: *highly relevant, relevant, neutral, irrelevant*, and *highly irrelevant* results of the retrieval

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Interactive QBE Retrieval

- Feedback: (2) The CBIR system processes both the query and the user-labelled retrieved images
  - The joint processing updates weights of features and chooses more adequate similarity metric
  - The **goal of processing**: to suppress the irrelevant outputs and enhance the relevant ones
    - If the range of feature values for the relevant images is similar to that for the irrelevant ones, then this feature cannot effectively separate these images and its weight should decrease
    - But if the "relevant" values vary in a relatively small range containing no or almost no "irrelevant" values, it is a crucial feature which weight should increase

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How To Evaluate Retrieval?

Items	*Relevant*	*Non-relevant*
Retrieved	***A*** : hits	***B***: Noise, or fallout
Not retrieved	***C***: misses	***D***: Correct rejection

Effectiveness of retrieval depend on the **filtering capacity** of the system, i.e. on proportions of relevant and non-relevant items among the retrieved data and with respect to the whole data base

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Evaluation of the QBE Retrieval

- Test-bed for the evaluation:
  - a collection of N images
  - a set of benchmark queries to the test bed data
  - the "ground-truth" quantitative assessment of the relevance of each image for each benchmark query
- Retrieval performance:
  - average *recall* / *precision*, i.e. average relative numbers of the relevant results returned to the user in all the benchmark queries

Evaluation of the QBE Retrieval

- Let $W_r \in [0,1]$ be a quantitative relevance of the item of rank r to the benchmark query
- For each cut-off value $n \in [1,N]$ of returns:
  - $A_n = W_1 + \ldots + W_n$ → returned relevant results
  - $B_n = n - A_n$ → returned irrelevant results
  - $C_n = W_{n+1} + \ldots + W_N$ → non-returned relevant results
  - $D_n = N - n - C_n$ → non-returned irrelevant results

Evaluation of the QBE Retrieval

- Recall $R_n = A_n / (A_n + C_n)$ is a relative amount of the relevant results returned among the n top-rank matches after a query
  - Recall by itself is not a good quality measure (as $R_N = 1.0$)
  - *Example*: N=10 database images; n = 3 images returned; W_1=0.9; W_2=0.8; W_3=0.7; $W_4 \ldots W_6$=0.4, $W_7 \ldots W_{10}$=0.2 – the relevance of the images ranked w.r.t. a query:
    - $A_3 = W_1 + W_2 + W_3 = 0.9 + 0.8 + 0.7 = 2.4$
    - $C_3 = W_4 + \ldots + W_{10} = 0.4 \times 3 + 0.2 \times 4 = 2.0$ →
    - $\mathbf{R_3} = 2.4 / (2.4 + 2.0) = 2.4 / 4.4 = \mathbf{0.545}$

Evaluation of the QBE Retrieval

- Precision $P_n = A_n / n$ is a proportion of relevant results returned among the n top-rank matches after a query
  - Precision is the average relevance of the returned results
  - *Example*: N=10 database images; n = 3 images returned; W_1=0.9; W_2=0.8; W_3=0.7; $W_4 \ldots W_6$=0.4, $W_7 \ldots W_{10}$=0.2 – the relevance of the images ranked w.r.t. a query:
    - $A_3 = W_1 + W_2 + W_3 = 0.9 + 0.8 + 0.7 = 2.4$ →
    - $\mathbf{P_3} = 2.4 / 3 = \mathbf{0.8}$
  - **Precision–recall graph** depicts the degradation of precision at n as one traverses the output list

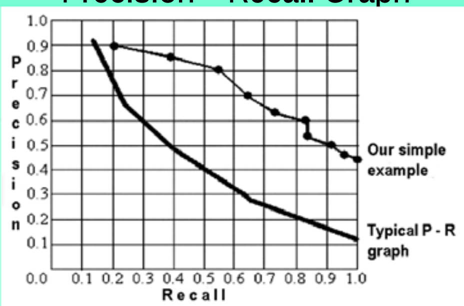
Evaluation of the QBE Retrieval

- Fallout $F_n = B_n/(B_n+D_n) = (n-A_n)/(N-A_n-C_n)$ is the relative amount of retrieved irrelevant items
  - It measures how quickly precision drops as recall increases
  - *Example*: N=10 database images; n = 3 images returned; W_1=0.9; W_2=0.8; W_3=0.7; $W_4 \ldots W_6$=0.4, $W_7 \ldots W_{10}$=0.2 – the relevance of the images ranked w.r.t. a query:
    - $A_3 = W_1 + W_2 + W_3 = 0.9 + 0.8 + 0.7 = 2.4$
    - $C_3 = W_4 + \ldots + W_{10} = 0.4 \times 3 + 0.2 \times 4 = 2.0$ →
    - $B_3 = 3 - 2.4 = 0.6$; $D_3 = 10 - 3 - 2.0 = 5.0$ →
    - $\mathbf{F_3} = 0.6 / (0.6 + 5.0) = 0.6 / 5.6 = \mathbf{0.107}$

Evaluation for n Top-rank Items

n	1	2	3	4	5	6	7	8	9	10
W_n	0.90	0.80	0.70	0.40	0.40	0.40	0.20	0.20	0.20	0.20
A_n	0.90	1.70	2.40	2.80	3.20	3.60	3.80	4.00	4.20	4.40
C_n	3.50	2.70	2.00	1.60	1.20	0.80	0.60	0.40	0.20	0.00
$\mathbf{R_n}$	**0.20**	**0.39**	**0.55**	**0.64**	**0.73**	**0.82**	**0.83**	**0.91**	**0.96**	**1.00**
$\mathbf{P_n}$	**0.90**	**0.85**	**0.80**	**0.70**	**0.64**	**0.60**	**0.54**	**0.50**	**0.47**	**0.44**
B_n	0.10	0.30	0.60	1.20	1.80	2.40	3.20	4.00	4.80	5.60
D_n	5.50	5.30	5.00	4.40	3.80	4.20	2.40	1.60	0.80	0.00
$\mathbf{F_n}$	**0.02**	**0.05**	**0.11**	**0.21**	**0.32**	**0.43**	**0.57**	**0.71**	**0.86**	**1.00**

Precision – Recall Graph



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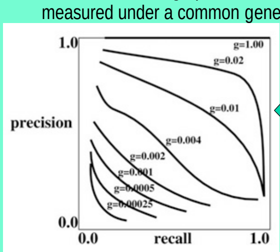
Generality Vs. Performance

- Precision - Recall graphs are meaningful only if their points are measured under a common generality: $G=(A_n + C_n)/N$

G is the common average expected performance



Typical P-R curves for retrieving a constant-size group of totally relevant items embedded in a growing number of irrelevant items

In practice, no complete ground truth to evaluate recall and generality is known; only their lower bounds $A_n/(N-n-A_n)$ and A_n/N can be used to analyse a CBIR system

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