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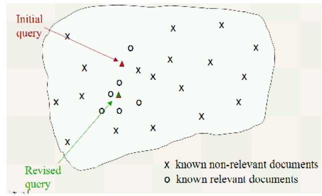
Relevance feedback + Text classification (Chapter 9+13)

Definition 1 (Rocchio relevance feedback)
Rocchio relevance feedback has the form

$$q_m = \alpha q_0 + \beta \frac{1}{|D_r|} \sum_{\vec{d_r} \in D_r} \vec{d_r} - \gamma \frac{1}{|D_{nr}|} \sum_{\vec{d_{nr}} \in D_{nr}} \vec{d_{nr}}$$

where q_0 is the original query vector, D_r is the set of relevant documents, D_{nr} is the set of non-relevant documents and the values α, β, γ depend on the system setting.



Exercise 9/1

What is the main purpose of Rocchio relevance feedback?

PSEUDO RELEVANCE FEEDBACK (top k docs as relevant)

IMPLICIT (INDIRECT) REL. FEEDBACK (e.g. click rate)

QUERY EXPANSION

Exercise 9/2

A user's primary query is *cheap CDs cheap DVDs extremely cheap CDs.* The user has a look on two documents: doc1 a doc2, marking doc1 *CDs cheap software cheap CDs* as relevant and doc2 *cheap thrills DVDs* as non-relevant. Assume that we use a simple *tf* scheme without vector length normalization. What would be the restructured query vector after considering the Rocchio relevance feedback with values $\alpha = 1$, $\beta = 0.75$, and $\gamma = 0.25$?

We rewrite the exercise to the table for an easier processing.

	relevant	non-relevant	
terms	doc1	doc2	query
CDs	2	0	2
cheap	2	1	3
software	1	0	0
thrills	0	1	0
DVDs	0	1	1
extremely	0	0	1

Table 1:

$$q_m = \overset{1}{\overset{\parallel}{\alpha}} \cdot \begin{pmatrix} 2 \\ 3 \\ 0 \\ 0 \\ 1 \\ 1 \end{pmatrix} + \overset{0.75}{\overset{\parallel}{\beta}} \cdot \frac{1}{1} \cdot \begin{pmatrix} 2 \\ 2 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} - \overset{0.25}{\overset{\parallel}{\gamma}} \cdot \frac{1}{1} \cdot \begin{pmatrix} 0 \\ 1 \\ 0 \\ 1 \\ 1 \\ 0 \end{pmatrix} = \dots = \begin{pmatrix} 3.5 \\ 4.25 \\ 0.75 \\ -0.25 \\ 0.75 \\ 1 \end{pmatrix}$$

Text classification and Naive Bayes (Chapter 13)

Definition 2 (Naive Bayes Classifier)
Naive Bayes (NB) Classifier assumes that the effect of the value of a predictor x on a given class c is class conditional independent. Bayes theorem provides a way of calculating the posterior probability $P(c|x)$ from class prior probability $P(c)$, predictor prior probability $P(x)$ and probability of the predictor given the class $P(x|c)$

$$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$$

and for a vector of predictors $X = (x_1, \dots, x_n)$

$$P(c|X) = \frac{P(x_1|c) \dots P(x_n|c)P(c)}{P(x_1) \dots P(x_n)}.$$

The class with the highest posterior probability is the outcome of prediction.