Faculty Development Program-2015, (CSE: Information Retrieval)

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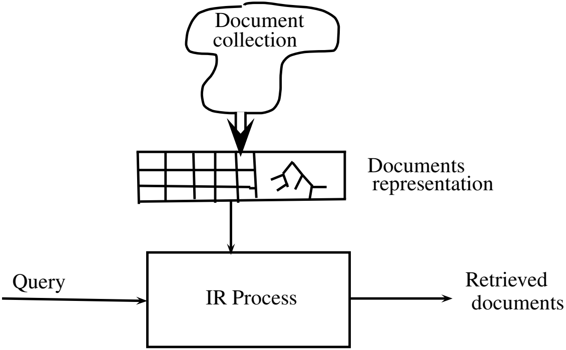
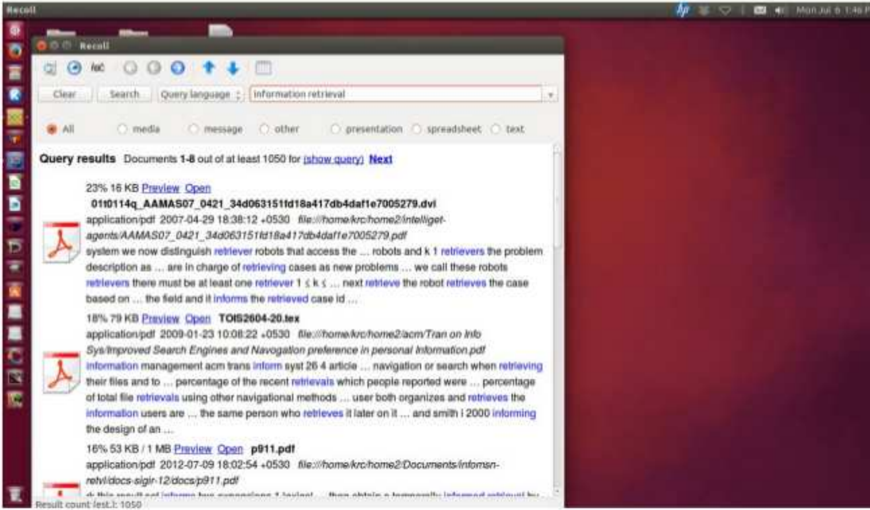
Basic Model of IR



Search Engine



Taxonomy of IR Models

Three classic models in IR are:

- Boolean: Document and query are sets of Index terms.
- Vector Space: Query and documents are vectors in t-dimensional space.
- Probabilistic: representation are based on probability theory.

Formal Charaterization of models

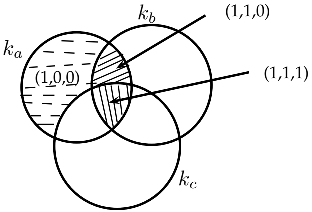
- IR Model : $[\mathbf{D}, \mathbf{Q}, \mathscr{F}, R(q_i, d_j)]$
- **D**: logical view/representation of documents
- **Q**: logical view/representation of query
- $\mathscr{F}$: framework for representation of queries, documents, and their relationship
- $R(q_i, d_j)$: a ranking function (a real number), $q_i \in \mathbf{Q}$, $d_j \in \mathbf{D}$

Concepts

- Document is transformed to index terms
- Nouns are index terms (others less useful)
- More frequent keywords as index terms
- Index terms are assigned weights
- k_i (index term), d_j is document, then $w_{i,j} \geq 0$ is weight for pair (k_i, d_j).
- Let $K = \{k_1, k_2, \dots k_t\}$ is set of index terms. Weight $w_{i,j} \geq 0$ associated with each term k_i and document d_j. For $k_i \notin d_j$, $w_{i,j} = 0$.
- d_j has associated index term Vector $\overrightarrow{d_j} = (w_{i,j}, \dots w_{t,j})$
- Let $g_i(\bar{d_j}) = w_{i,j}$, is a function that returns weight associated with each term. For the sake of simplicity, we assume that term weights in a sentence are independent. However, in a true sense they are not, say in *computer network*, the term "computer attracts the existence of "network", and vice-versa.

Boolean Model

- It is based on theory of Boolean algebra, simple, intuitive.
- Consider that index terms are present/absence. $w_{i,j} \in \{0, 1\}$.
- Query q's terms are linked by *and*, *or*, *not*. q is either *CNF* or *DNF*.
- $q = k_a \wedge (k_b \vee \neg k_c)$ can be written in DNF as $\overrightarrow{q}_{dnf} = (1,0,0) \vee (1,1,0) \vee (1,1,1)]$. Each component (e.g., $(1,1,0)$) is binary weighted vector associated with tuple (k_a, k_b, k_c).



- drawback: retrieval strategy is binary decision

Boolean Model

- For $w_{i,j} \in \{0, 1\}$, $\overrightarrow{q}_{dnf}$ as query vector, let $\overrightarrow{q}_{cc}$ be any of disjunctive components of $\overrightarrow{q}_{dnf}$.
- Similarity of d_j to q is:

$$sim(d_j, q) = \begin{cases} 1 & \text{if } \exists \overrightarrow{q}_{cc} | (\overrightarrow{q}_{cc} \in \overrightarrow{q}_{dnf}) \wedge (\forall k_i, g_i(\overrightarrow{d}_j) = g_i(\overrightarrow{q}_{cc})) \\ 0 & \text{otherwise.} \end{cases}$$

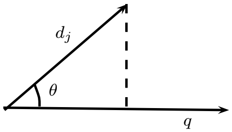
- if $sim(d_j, q) = 1$ then d_j is relevant to q, else not.
- no notion of *partial match*
- e.g., $\overrightarrow{d}_j = (0, 1, 0)$, so d_j includes index term k_b, but not relevant to query $q = k_a \wedge (k_b \vee \neg k_c)$.
- Index term weighting brings *vector model*.

Vector Model

- Considers the documents that match partially
- Non-binary weights to index terms in queries and documents
- Documents' Similarity is ordered in descending order
- $w_{i,j}$ for (k_i, d_j) is positive and non-binary.
- Let $w_{i,j}$ is weight for pair (k_i, q). $\overrightarrow{q} = (w_{1,q}, \ldots, w_{t,q})$, and t is index term count. Vector $\overrightarrow{d}_j = (w_{i,j}, \ldots, w_{t,j})$.
- Cosine of θ adopted as $sim(d_j, q)$
- Vector model evaluates degree of similarity between document d_j and query q as a correlation between $\overrightarrow{d}_j$ and $\overrightarrow{q}$.
- This correlation is θ, angle between vectors.

Vector Model

Vectors: $\overrightarrow{d}_j$, $\overrightarrow{q}$.



$$sim(d_j, q) = \frac{\overrightarrow{d}_j \cdot \overrightarrow{q}}{|\overrightarrow{d}_j| \times |\overrightarrow{q}|}$$
$$= \frac{\sum_{i=1}^{t} w_{i,j} \times w_{i,q}}{\sqrt{\sum_{i=1}^{t} w_{i,j}^2} \times \sqrt{\sum_{j=1}^{t} w_{i,q}^2}}$$

- where, $|\overrightarrow{d}_j|$ and $|\overrightarrow{q}|$ are the norms of document and query vectors. The $|\overrightarrow{q}|$ does not effect ranking as it is same for all docs.
- The factor $|\overrightarrow{d}_j|$ provides normalization.
- vector model ranks the docs in order of their similarity to query, i.e., as per $sim(d_j, q)$.
- A threshold is used to reject those below that.

clustering

- Given collection set C of objects, and description of set A, classify $x \in C$ to $R(x, A)$, and $\neg R(x, A)$, here R is relation. (This is clustering) (vague !).
- Example: C is all cars, and A is Maruti-Alto.
- Example: C is all cancer patients, and $A = \{$terminal, advanced, metastatis, diagnosed, healthy$\}$. Then A divides C into five clusters.
- For $C =$ all docs, and $A =$ features of some docs, what $x \in C$ is $x \in A_i$ (for $i = 1, n$) is clustering.
- A is documents features.
- Term weights? it is based on two factors: 1) intra-clustering similarity, is based on term frequency (*tf*) of term k_i, in d_j (how well the term describes the doc.), 2) inter-cluster similarity, inverse of the freq. of k_i among documents (*idf*).

Vector model

- Let Docs $= N$, the k_i term exists in n_i numbers. $freq_{i,j}$ is freq (counts) of k_i in the d_j, the normalized freq of k_i in d_j,

$$f_{i,j} = \log \frac{freq_{i,j}}{max_l \ freq_{l,j}}$$

,

where, maximum is computed over all terms in doc d_j. If $k_i \notin d_j$, then $f_{i,j} = 0$.

- Let *idf* is *inverse document frequency* for k_i,

$$idf_i = \log \frac{N}{n_i}$$

- Best known weighted scheme is: $tf \times idf$

Adv: of vector:

- term weighting improves retrieval performance
- partial matching of q and d_j, allows retrieval of those not matching fully
- disadv: index terms are assumed mutually independent

Probabilistic model

- Given d_j and q, model will find probability that d_j is relevant to q.
- Certainly, $R \subseteq D$ is relevant to q; the R is ideal answer set
- Here, $w_{i,j} \in \{0,1\}$, $q \subseteq \bigcup\{k_i\}$
- $R \subseteq D$ is set of relevant docs and $\bar{R}$ is non-relevant.
- Let $P(R|\vec{d}_j)$ is prob. that d_j is relevant to q, and Let $P(\bar{R}|\vec{d}_j)$ is prob. that d_j is non-relevant to q
- Similarity of d_j to q,

$$sim(d_j, q) = \frac{P(R|\vec{d}_j)}{P(\bar{R}|\vec{d}_j})$$

- Using Bayes rule: $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$,

$$sim(d_j, q) = \frac{P(\vec{d_j}|R)P(R)}{P(\vec{d}_j|\bar{R})P(\bar{R})}$$

where, $P(\vec{d_j}|R$ is probability randomly selecting doc. given that it is relevant. $P(R)$ is prob. that selected doc is relevant.

- Since $P(R)$ and $P(\bar{R})$ are same for all docs.

$$sim(d_j, q) \sim \frac{P(\vec{d_j}|R)}{P(\vec{d}_j|\bar{R})}$$

Probabilistic model

- Assuming independence of index terms:

$$sim(d_j, q) \sim \frac{(\prod_{g_i(\vec{d}_j)=1} P(k_i|R)) \times (\prod_{g_i(\vec{d}_j)=0} P(\bar{k}_i|R))}{(\prod_{g_i(\vec{d}_j)=1} P(k_i|\bar{R})) \times (\prod_{g_i(\vec{d}_j)=0} P(\bar{k}_i|\bar{R}))}$$

- where $P(k_i|R)$ is prob. that k_i exists in a doc randomly selected from R, and $\vec{k}_i$ means does not exist.