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### \* Weighted Zone Scoring:

- Document is divided into zones
- For a query  $q$  and a document  $d$ , weighted zone scoring assigns to pair  $(q, d)$  a score in range  $[0, 1]$  by computing a linear combination of zone scores.
- For a set of documents, each document has  $L$  zones.
- Let  $g_1, \dots, g_L \in [0, 1]$  such that  $\sum_{i=1}^L g_i = 1$ .
- $\forall_{i=1}^L$ ,  $s_i$  be the boolean score denoting a match between  $q$  and  $i^{\text{th}}$  zone.  
 $s_i = 1$ , if all query term occur in that zone  
otherwise  $s_i = 0$ .
- Weighted zone score  $\Rightarrow \sum_{i=1}^L g_i \times s_i$ .

### \* Learning weights for zone scoring:

- How to determine weights  $g_i$  for weighted zone scoring?
- These weights are learned using training examples that have been judged editorially.
- There is a set of training examples each of which is a tuple of a query  $q$ , a document  $d$  and a relevance judgement for  $d$  on  $q$ .



## Scoring, Term Weighting

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## \* Vector Space Model.

## Ranked Retrieval

① System retrieves document wrt ranking order.

② Assign scores to each term for matching.

③ Supports free-text queries as well as boolean queries.

## Unranked Retrieval.

① System retrieves flat result with no ranking.

② Binary criterion for deciding relevance.

③ Info need has to be translated into boolean queries.

## \* Parametric Search :

→ Documents contain

- Data

- Meta data  $\Rightarrow$  specific form data associated with each document.

eg: author of book, date of publication etc

→ Provides search based on parameter.

→ Parametric search consists as usual of postings intersection and we can merge postings by standard inverted indexes as well as parametric indexes.



$S_T$	$S_B$	Score
0	0	0
0	1	$1-g$
1	0	$g$
1	1	1

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$$\text{score}(d, q) = g \cdot S_T(d, q) + (1-g) S_B(d, q)$$

$S_T \Rightarrow g_t$	title	$(g)$
$S_B \Rightarrow g_b$	body	$(1-g)$

error of scoring function with weight  $g$

$$\epsilon(g, \phi_j) = (r(d_j, q_j) - \text{score}(d_j, q_j))^2$$

where  $r$  = editorial relevance judgement quantized to 0, 1

$$\text{Total error} = \sum_j \epsilon(g, \phi_j)$$

eg Training examples  $n_{01}$  = relevant,  
 $n_{02}$  = irrelevant.  
 $S_T = 0$ ,  $S_B = 1$

$$\text{error} = (r(d, q) - s(d, q))^2$$

$$n_{01} \text{ error} = [1 - (1-g)]^2 n_{01}$$

$$n_{02} \text{ error} = [0 - (1-g)]^2 n_{02}$$

$$\text{Total error} = [1 - (1-g)]^2 n_{01} + [0 - (1-g)]^2 n_{02}$$



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Q When using weighted zone scoring, is it necessary for all zones to use same Boolean function?

Ans No,

Boolean score for title zone could be 1 when atleast half of the query terms occur in the zone and 0 otherwise.  
Boolean score for body zone could be 1 when all query terms occur in the body & 0 otherwise.

Q Author zone  $g_1 = 0.2$ , title zone  $g_2 = 0.31$ ,  
body zone  $g_3 = 0.49$ .  
Distinct scores?

Ans 1 if appears in all zones.

0.51 if appears in author & title zone

0.69 " " " & body zone

0.8 " " " title & " "

\* Term frequency:

- No. of occurrences of term  $t$  in document
- How many times term appear in a document?
- Denoted by  $tf_{t,d}$



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\* Document Frequency:

- No. of documents that contain term  $t$ .
- Denoted by  $df_t$ .

\* Collection Frequency:

- Total no. of occurrences of a term in the collection.

\* Bag of words model:

- A document is represented as a bag of words.
- Ordering of terms in a document is ignored.
- Contains no. of occurrences of each term.

eg "Mary is quicker than John" is identical to "John is quicker than Mary".

\* Inverse document frequency:

- Used to scale document frequency.

$$idf_t = \log \frac{N}{df_t}$$

where  $N$  = Total no. of documents in a collection.

- $idf$  of rare term will be high
- $idf$  of frequent term will be low.

nice



②

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### \* Weighting Scheme :

— Combination of term frequency & inverse document frequency to produce a composite weight for each term in each document.

$$tf-idf_{t,d} = tf_{t,d} * idf_t.$$

— Assigns a weight to a term  $t$  in document  $d$ .

① highest  $\rightarrow t$  occurs many times within a small no. of documents.

② lower  $\rightarrow t$  occurs fewer times in a document or occurs in many documents.

③ lowest  $\rightarrow t$  occurs virtually in all documents.

$$Score(q,d) = \sum_{t \in q} tf-idf_{t,d}.$$

NOTE : idf of term is always finite.

b/c  $df_{t,d} \geq 1$

$idf \leq \frac{\log N}{df_{t,d}} \rightarrow$  never becomes infinity.  
always greater than 1



## \* Vector Space Model.

— The representation of a set of documents as vectors in a common vector space is known as the vector space model.

— Used for IR operations including scoring documents on a query, document classification and document clustering.

→ Dot product :-

—  $\vec{v}(d) \Rightarrow$  It is a vector derived from document  $d$ , with one component for each dictionary term.

— Set of documents in a collection then viewed as a set of vectors in vector space, having one axis for each term.

— It loses the relative ordering of terms in each document.

— Similarity between two documents is calculated using Cosine Similarity of the vector.

$$\text{sim}(d_1, d_2) = \frac{\vec{v}(d_1) \cdot \vec{v}(d_2)}{\|\vec{v}(d_1)\| \|\vec{v}(d_2)\|}$$

euclidean lengths.      ← dot product

nice



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Dot product of two vector  $\vec{x}$  and  $\vec{y}$   
 $\sum_{i=1}^m x_i y_i$

// For concept building only.

Let  $\vec{v}(d)$  = document vector for  $d$ .

$m$  = components for  $d$

$\vec{v}_1(d) \dots \vec{v}_m(d)$

Euclidean length =  $\sqrt{\sum_{i=1}^m \vec{v}_i^2(d)}$

$\text{sim}(d_1, d_2) = \hat{v}(d_1) \cdot \hat{v}(d_2)$

$\therefore \hat{v}(d_i) = \frac{\vec{v}(d_i)}{|\vec{v}(d_i)|}$  unit vector

example:

	Doc 1	Doc 2	Doc 3
car	27	4	24
auto	3	33	0
insurance	0	33	29
best	14	0	17

Euclidean length for  $d_1$   $\sqrt{\sum_{i=1}^4 \vec{v}_i^2(d)}$

$$d_1 = \sqrt{(27)^2 + (3)^2 + (14)^2} = 30.56$$

$$d_2 = 46.84$$

$$d_3 = 41.30$$



## Query as a vector:

- Query can also be represented as a ~~document~~ vector similar to document
- Only -terms present in a query are non-zero vector for the query.

$$\text{score}(q, d) = \frac{\vec{V}(q) \cdot \vec{V}(d)}{|\vec{V}(q)| |\vec{V}(d)|}$$

## \* Advantages of VSM

- ① Simple model based on Linear algebra
- ② Term weights not binary
- ③ Allows partial matching
- ④ Rank documents according to their relevance.

## \* Disadvantages of VSM

- ① Loses ordering of terms.
- ② Assumes -terms are statistically 'independent'.
- ③ Substrings might results in false positive match.
- ④ We cannot search phrases.



(Food for thoughts) Chap # 06.

① Answer pg # 7, 8

② Terms: dil, Pakistan, jan, hum, sub, ki, aur

	$d_1$	$d_2$	$d_3$	$df$	$idf$	$tf_1 \times idf$	$tf_2 \times idf$	$tf_3 \times idf$
aur	0	0	1	1	0.477	0	0	0.477
dil	2	0	1	2	0.176	0.352	0	0.176
hum	0	1	0	1	0.477	0	0.477	0
jan	2	1	1	3	0	0	0	0
ki	0	1	0	1	0.477	0	0.477	0
Pakistan	2	1	2	3	0	0	0	0
sub	0	1	0	1	0.477	0	0.477	0

Query: dil jan Pakistan.

	$tf$	$idf$	$tf \times idf$
aur	0	1	0
dil	1	2	0.176
hum	0	1	0
jan	1	3	0
ki	0	1	0
Pakistan	1	3	0
sub	0	1	0



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Cosine similarity of query with document 1

$$\text{sim}(\vec{v}(q), \vec{v}(d_1)) = \frac{\vec{v}(q) \cdot \vec{v}(d_1)}{|\vec{v}(q)| |\vec{v}(d_1)|}$$

$$= \frac{i + j + k}{\sqrt{1^2 + 1^2 + 1^2}} \cdot \frac{2i + 2j + 2k}{\sqrt{2^2 + 2^2 + 2^2}}$$

$$= \left( \frac{i}{\sqrt{3}} + \frac{j}{\sqrt{3}} + \frac{k}{\sqrt{3}} \right) \left( \frac{i}{\sqrt{3}} + \frac{j}{\sqrt{3}} + \frac{k}{\sqrt{3}} \right)$$

$$= 1.$$

③  $q_1 = 0.2, q_2 = 0.31, q_3 = 0.49$

if term appear in  $q_1 = 0.21$

" " "  $q_2 = 0.31$

" " "  $q_3 = 0.49$

" " "  $q_1 \& q_2 = 0.51$

" " "  $q_1 \& q_3 = 0.69$

" " "  $q_2 \& q_3 = 0.8$



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(4)  $Idf = \log \left( \frac{N}{df} \right)$

$$Idf = \log \left( \frac{1}{1} \right)$$

$$Idf = 0$$

Idf will be 0 if term appears in all documents.

(5) Because  $df_{t,d} \geq 1$

$$idf \leq \log \frac{N}{df_{t,d}}$$

$df_{t,d}$

→ Yeh kbhi 0 zero nhi hoga islye finite.