Information Retrieval 1

Term-based Retrieval

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Document representation and matching

Evaluation	**Document representation & matching**	Conversational search
Learning to rank	IR—user interaction	Recommender systems

Outline

Outline

Documents as vectors

vocabulary of all documents

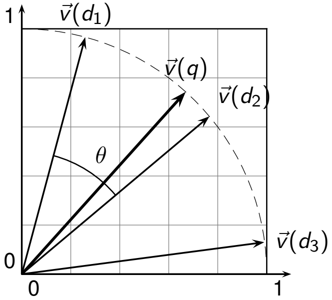
a document = a vector.
eg.doc1 =(1,1,1,0,1,1,1,..)

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Anthony	1	1	0	0	0	1	
Brutus	1	1	0	1	0	0	
Caesar	1	1	0	1	1	1	
Calpurnia	0	1	0	0	0	0	
Cleopatra	1	0	0	0	0	0	
mercy	1	0	1	1	1	1	
worser	1	0	1	1	1	0	
...							

1: this word occurs
0: this word does not occur

roduction to Information Retrieval”

Match using cosine similarity



similarity between a word in doc and a word in query

$$sim(d,q) = \cos(\vec{v}(d), \vec{v}(q)) = \frac{\vec{v}(d) \cdot \vec{v}(q)}{\|\vec{v}(d)\| \cdot \|\vec{v}(q)\|}$$

v的绝对值=size of vocab

$$= \frac{\sum_{i=1}^{|V|} d_i \cdot q_i}{\sqrt{\sum_{i=1}^{|V|} d_i^2} \cdot \sqrt{\sum_{i=1}^{|V|} q_i^2}}$$

Manning et al., "Introduction to Information Retrieval"

Term frequency

word anthony has occured 157 times in doc1

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth	...
Anthony	157	73	0	0	0	1	
Brutus	4	157	0	2	0	0	
Caesar	232	227	0	2	1	0	
Calpurnia	0	10	0	0	0	0	
Cleopatra	57	0	0	0	0	0	
mercy	2	0	3	8	5	8	
worser	2	0	1	1	1	5	
...							

Manning et al., "Introduction to Information Retrieval"

Term frequency

we can use either raw tf, or log tf. depends on the project

Raw term frequency	$tf(t,d)$
Log term frequency	$\begin{cases} 1 + \log tf(t,d) & \text{if } tf(t,d) > 0 \\ 0 & \text{otherwise} \end{cases}$

Inverse document frequency

分子分母互换位置

total nb of doc

the nb of doc that contain term (or word) t

$$idf(t) = \log \frac{N}{df(t)}$$

- $df(t)$ – document frequency of term t
- N – total number of documents in a collection

Inverse document frequency

the word with low tf has high idf.this is the effect of inverted df

10000 docs contain fly

Term	$df(t)$	$idf(t)$
calpurnia	1	6
animal	100	4
sunday	1000	3
fly	10,000	2
under	100,000	1
the	1,000,000	0

for $N = 1,000,000$ and $\log_{10}$

Manning et al., "Introduction to Information Retrieval"

TF-IDF

$$\text{TF-IDF}(t,d) = tf(t,d) \cdot idf(t)$$

- Term frequency
  - $tf(t,d)$
  - $\begin{cases} 1 + \log tf(t,d) & \text{if } tf(t,d) > 0 \\ 0 & \text{otherwise} \end{cases}$
- Inverse document frequency
  - $\log \frac{N}{df(t)}$
  - $\max\{0, \log \frac{N - df(t)}{df(t)}\}$

these two are standard tf and standard idf

Vector space model summary

- Documents and queries as vectors
- Match using cosine similarity
- Weights can be
  1. binary
  2. term frequency
  3. TF-IDF

Outline

1. Vector space model
2. Language modeling in IR
   - Method
   - Smoothing
3. BM25

Outline

2. Language modeling in IR
   - Method
   - Smoothing

Language model

A statistical language model is a probability distribution over sequences of words.

- Given a sequence of length m
- A language model assigns probability $P(w_1, \dots, w_m)$ to this sequence
- Unigram language model

$$P(w_1, \dots, w_m) = P(w_1) \dots P(w_m)$$

- Bi-gram language model

$$P(w_1, \dots, w_m) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_2) \dots P(w_m \mid w_{m-1})$$

https://en.wikipedia.org/wiki/Language_model

Unigram language model example

Model M_1		Model M_2	
the	0.2	the	0.15
a	0.1	a	0.12
frog	0.01	frog	0.0002
toad	0.01	toad	0.0001
said	0.03	said	0.03
likes	0.02	likes	0.04
that	0.04	that	0.04
dog	0.005	dog	0.01
cat	0.003	cat	0.015
monkey	0.001	monkey	0.002
...	...	...	...

Manning et al., "Introduction to Information Retrieval"

Documents as distributions

- Unigram language model

$$P(t \mid M_d) = \frac{tf(t, d)}{dl(d)}$$

- A document is a multinomial distribution over words
- If some vocabulary terms do not appear in document d, then $P(t \mid M_d) = 0$
- This is addressed by smoothing

Match using query likelihood model (QLM)

- Likelihood of a document given a query

$$P(d \mid q) = \frac{P(q \mid d)P(d)}{P(q)}$$

- The prior distribution over queries $P(q)$ does not affect matching for a particular query

$$P(d \mid q) \stackrel{rank}{=} P(q \mid d)P(d)$$

- Usually, the prior distribution over documents $P(d)$ is assumed to be uniform

$$P(d \mid q) \stackrel{rank}{=} P(q \mid d) = P(q \mid M_d)$$

how many times the word t occurs in doc d

- "Bag of words" assumption: terms are independent

$$P(q \mid M_d) = \prod_{t \in q} P(t \mid M_d) = \prod_{t \in q} \frac{tf(t,d)}{dl(d)}$$

len of a doc

Match using KL-divergence

$$KL(M_d \| M_q) = \sum_{t \in V} P(t \mid M_q) \log \frac{P(t \mid M_q)}{P(t \mid M_d)}$$

Outline

2. Language modeling in IR
   - Method
   - Smoothing

Jelinek-Mercer smoothing

the probability estimate for a word present in the document

smoothing weight =1-lambda=0.1

how many times term t occurs in all documents

$$P_s(t \mid M_d) = \lambda P(t \mid M_d) + (1 - \lambda) P(t \mid M_c)$$
$$= \lambda \frac{tf(t, d)}{dl(d)} + (1 - \lambda) \frac{cf(t)}{cl}$$

vocabulary size

- $cf(t)$ – collection frequency of term t
- cl – collection length

Dirichlet smoothing

- A unigram language model can be seen as a multinomial distribution over words $\mathcal{L}_d(n_1, \ldots, n_k \mid p_1, \ldots, p_k)$
  - $n_i = tf(t_i, d)$
  - $p_i = P(t_i \mid M_d)$
- The conjugate prior for multinomial is the Dirichlet distribution $P_{prior}(p_1, \ldots, p_k; \alpha_1^{pr}, \ldots, \alpha_k^{pr})$
  - $\alpha_i^{pr} = \mu P(t_i \mid M_c)$
  - μ is a smoothing parameter ($\lambda = \frac{dl}{dl+\mu}$)
- The posterior is the Dirichlet distribution with parameters $\alpha_i^{po} = n_i + \alpha_i^{pr} = tf(t_i, d) + \mu P(t_i \mid M_c)$
- Dirichlet smoothing

$$P_s(t \mid M_d) = \frac{tf(t_i, d) + \mu P(t_i \mid M_c)}{dl(d) + \mu}$$

Language modeling for IR summary

- Documents and queries as distributions
- Match using QLM or KL-divergence
- Smoothing
  - Jelinek-Mercer smoothing
  - Dirichlet smoothing

Outline

BM25

$$BM25 = \sum_{t \in q} \log \left[\frac{N}{df(t)} \right] \cdot \frac{(k_1 + 1) \cdot tf(t,d)}{k_1 \cdot \left[(1 - b) + b \cdot \frac{dl(d)}{dl_{avg}} \right] + tf(t,d)}$$

k1 controls tf
b controls doc len

- k_1, b – parameters
- $dl(d)$ – length of document d
- dl_{avg} – average document length

if 10 doc in total.
then dlavg = (dl
(doc1)+...+dl
(doc10))/10

BM25

BM25 is a weighting scheme in inverted index

IDF =inverse doc frequency

$$BM25 = \sum_{t \in q} \log\left[\frac{N}{df(t)}\right] \cdot \frac{(k_1 + 1) \cdot tf(t,d)}{k_1 \cdot \left[(1-b) + b \cdot \frac{dl(d)}{dl_{avg}}\right] + tf(t,d)}$$

BM25 = sum of IDF

- What if $k_1 \in \{0, \infty\}$?
- What of $b \in \{0, 1\}$?
- What if $tf(t,d)$ is small/large? $k_1 \in [1.2, 2], b = 0.75$

BM25 for long queries

$$BM25 = \sum_{t \in q} \log \left[\frac{N}{df(t)} \right] \cdot \frac{(k_1 + 1) \cdot tf(t,d)}{k_1 \cdot \left[(1-b) + b \cdot \frac{dl(d)}{dl_{ave}} \right] + tf(t,d)} \cdot \frac{(k_3 + 1) tf(t,q)}{k_3 + tf(t,q)}$$

Experimental comparison

Collection	Method	Parameter	MAP	R-Prec.	Prec@10
Trec8 T	Okapi BM25	Okapi	0.2292	0.2820	0.4380
	JM	$\lambda = 0.7$	0.2310 (p=0.8181)	0.2889 (p=0.3495)	0.4220 (p=0.3824)
	Dir	$\mu = 2,000$	**0.2470** (p=0.0757)	0.2911 (p=0.3739)	**0.4560** (p=0.3710)
	Dis	$\delta = 0.7$	0.2384 (p=0.0686)	0.2935 (p=0.0776)	0.4440 (p=0.6727)
	Two-Stage	auto	0.2406 (p=0.0650)	**0.2953** (p=0.0369)	0.4260 (p=0.4282)

Figure: TREC-8 Newswire, ad-hoc track, queries 401–450, title-only

G. Bennett, "A Comparative Study of Probabilistic and Language Models for Information Retrieval"

Experimental comparison

Collection	Method	Parameter	MAP	R-Prec.	Prec@10
TREC-2001 T	Okapi BM25	Okapi	0.1522	0.2056	0.2918
	JM	$\lambda = 0.7$	0.1113 (p=0.0003)	0.1505 (p=0.0037)	0.2122 (p=0.0003)
	Dir	$\mu = 2,000$	**0.1774** (p=0.0307)	**0.2238** (p=0.3236)	**0.3184** (p=0.3165)
	Dis	$\delta = 0.7$	0.1370 (p=0.0511)	0.1906 (p=0.053)	0.2653 (p=0.1348)
	Two-Stage	auto	0.1441 (p=0.2963)	0.1934 (p=0.3992)	0.2898 (p=0.8962)

Figure: TREC-2001 Web data, ad-hoc track, queries 501–550, title-only

G. Bennett, "A Comparative Study of Probabilistic and Language Models for Information Retrieval"

Content-based retrieval summary

- Vector space model
  - Documents and queries as vectors
  - Match using cosine similarity
- Language modeling in IR
  - Documents and queries as discrtibutions
  - Match using QLM or KL-divergence
- BM25

Materials

Query likelihood

- Manning et al., Chapters 6, 9, 11, 12
- Croft et al., Chapter 7