Information Retrieval – Language models for IR

From Manning and Raghavan's course

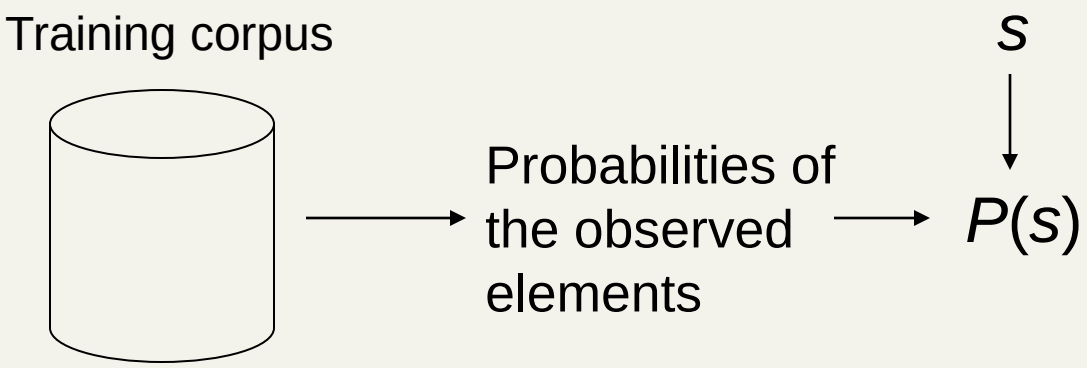
[Borrows slides from Viktor Lavrenko and Chengxiang Zhai]

Recap

- Traditional models
  - Boolean model
  - Vector space model
  - Probabilistic models
- Today
  - IR using statistical language models

Principle of statistical language modeling

- Goal: create a statistical model so that one can calculate the probability of a sequence of words $s = w_1, w_2, \ldots, w_n$ in a language.
- General approach:

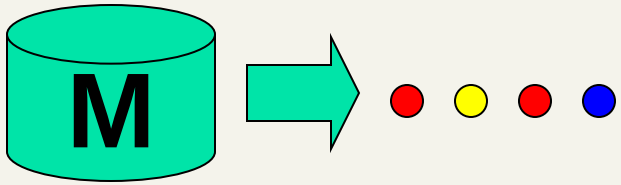


Examples of utilization

- Speech recognition
  - Training corpus = signals + words
  - probabilities: P(word|signal), P(word2|word1)
  - Utilization: signals ⟶ sequence of words
- Statistical tagging
  - Training corpus = words + tags (n, v)
  - Probabilities: P(word|tag), P(tag2|tag1)
  - Utilization: sentence ⟶ sequence of tags

Stochastic Language Models

- A statistical model for generating text
  - Probability distribution over strings in a given language



P(● ○ ● ● | M) = P(● | M)

P(○ | M, ●)

P(● | M, ● ○)

P(● | M, ● ○ ●)

Prob. of a sequence of words

$$P(s) = P(w_1, w_2, ...w_n)$$
$$= P(w_1)P(w_2 \mid w_1)...P(w_n \mid w_{1,n-1})$$
$$= \prod_{i=1}^{n} P(w_i \mid h_i)$$

Elements to be estimated:

$$P(w_i \mid h_i) = \frac{P(h_i w_i)}{P(h_i)}$$

- If h_i is too long, one cannot observe (h_i, w_i) in the training corpus, and (h_i, w_i) is hard generalize

- Solution: limit the length of h_i

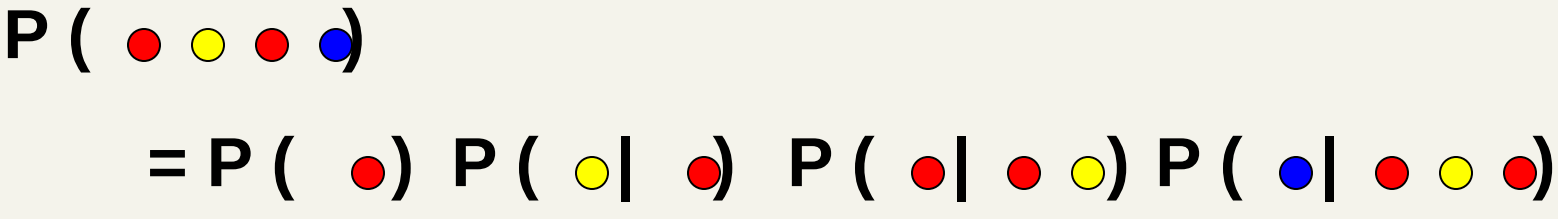
n-grams

- Limit h_i to n-1 preceding words

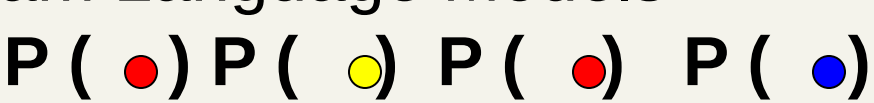
  Most used cases

  - Uni-gram: $$P(s) = \prod_{i=1}^{n} P(w_i)$$
  - Bi-gram: $$P(s) = \prod_{i=1}^{n} P(w_i \mid w_{i-1})$$
  - Tri-gram: $$P(s) = \prod_{i=1}^{n} P(w_i \mid w_{i-2} w_{i-1})$$

Unigram and higher-order models



- Unigram Language Models



Easy.
Effective!

- Bigram (generally, *n*-gram) Language Models

Estimation

- History: short long

  modeling: coarse refined

  Estimation: easy difficult

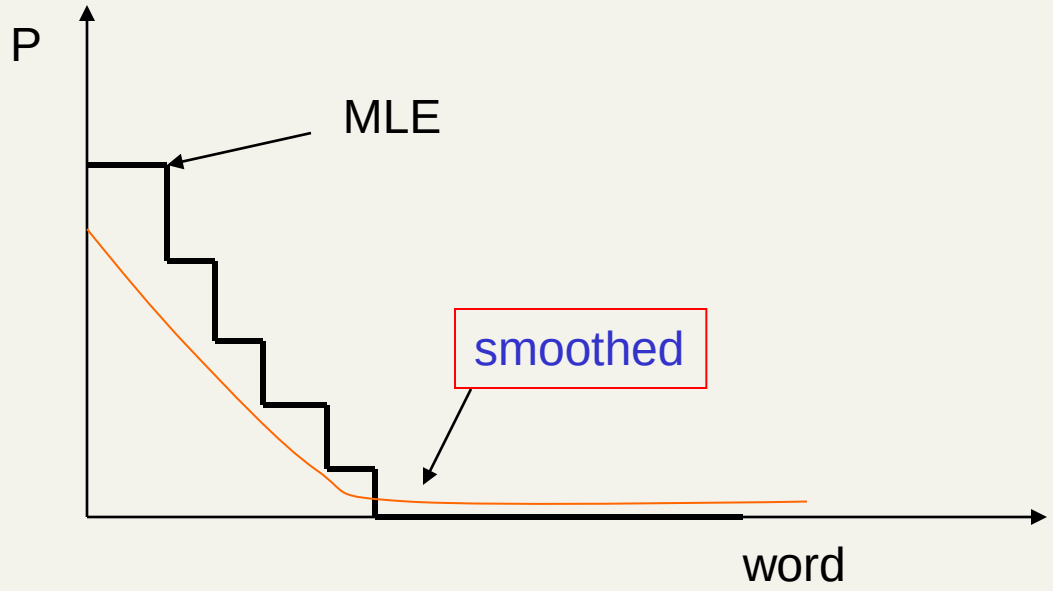
- Maximum likelihood estimation MLE

$$P(w_i) = \frac{\#(w_i)}{|C_{uni}|} \quad P(h_i w_i) = \frac{\#(h_i w_i)}{|C_{n-gram}|}$$

  - If (h_i m_i) is not observed in training corpus, $P(w_i|h_i)=0$ → (h_i m_i) coud still be possible in the language
  - Solution: smoothing

Smoothing

- Goal: assign a low probability to words or n-grams not observed in the training corpus



Smoothing methods

n-gram: α

- Change the freq. of occurrences
  - Laplace smoothing (add-one):

$$P_{add\_one}(\alpha \mid C) = \frac{|\alpha| + 1}{\sum_{\alpha_i \in V} (|\alpha_i| + 1)}$$

  - Good-Turing

    change the freq. *r* to *r**

$$r^* = (r+1)\frac{n_{r+1}}{n_r}$$

    n_r = no. of n-grams of freq. *r*
    - →redistribute the total count of words of frequency r+1 to words of frequency r

Smoothing (cont'd)

- Combine a model with a lower-order model
  - Backoff (Katz)

$$P_{Katz}(w_i \mid w_{i-1}) = \begin{cases} P_{GT}(w_i \mid w_{i-1}) & \text{if} \mid w_{i-1}w_i \mid > 0 \\ \alpha(w_{i-1})P_{Katz}(w_i) & \text{otherwise} \end{cases}$$

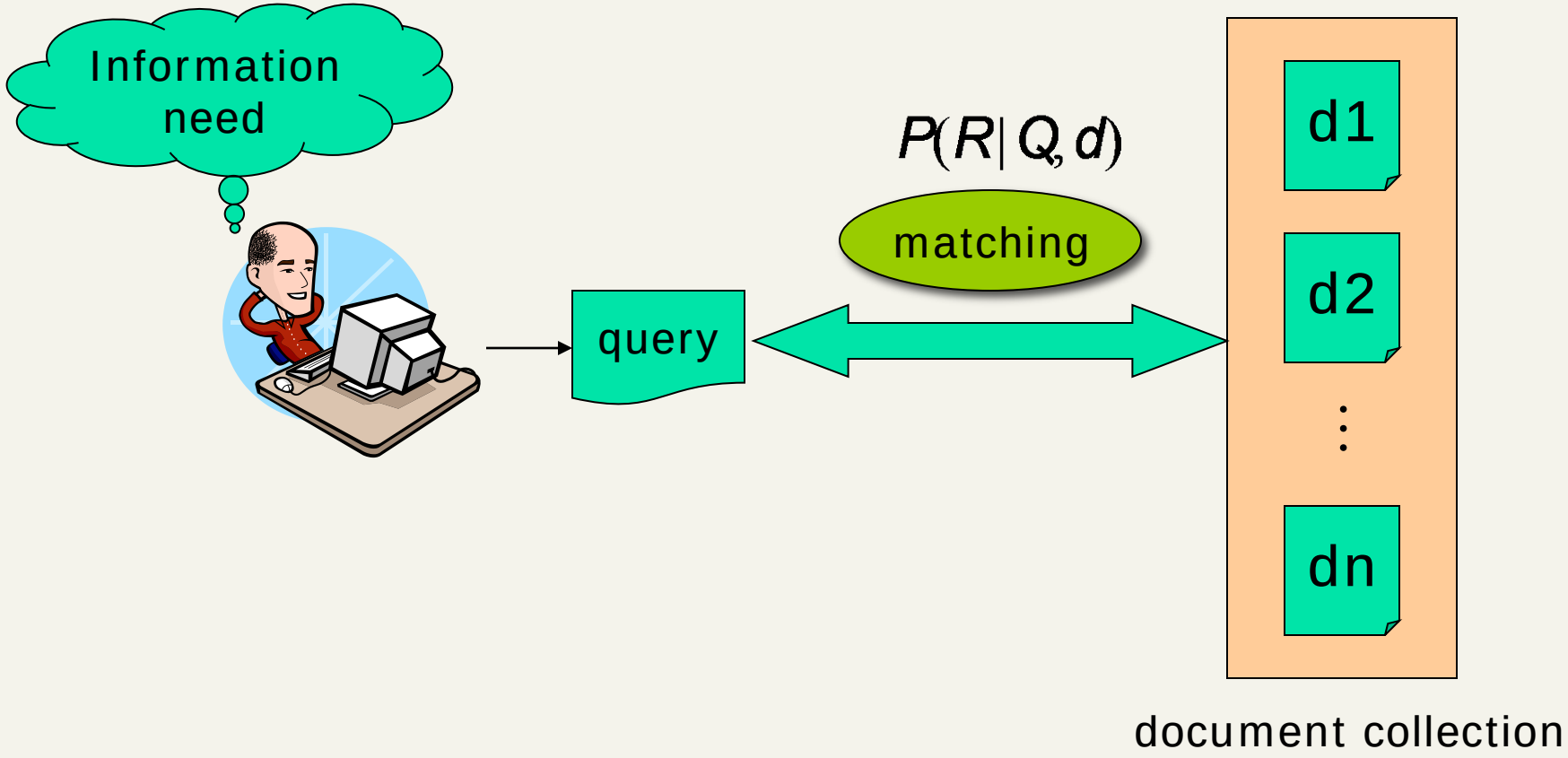
  - Interpolation (Jelinek-Mercer)

$$P_{JM}(w_i \mid w_{i-1}) = \lambda_{w_{i-1}} P_{ML}(w_i \mid w_{i-1}) + (1-\lambda_{w_{i-1}})P_{JM}(w_i)$$

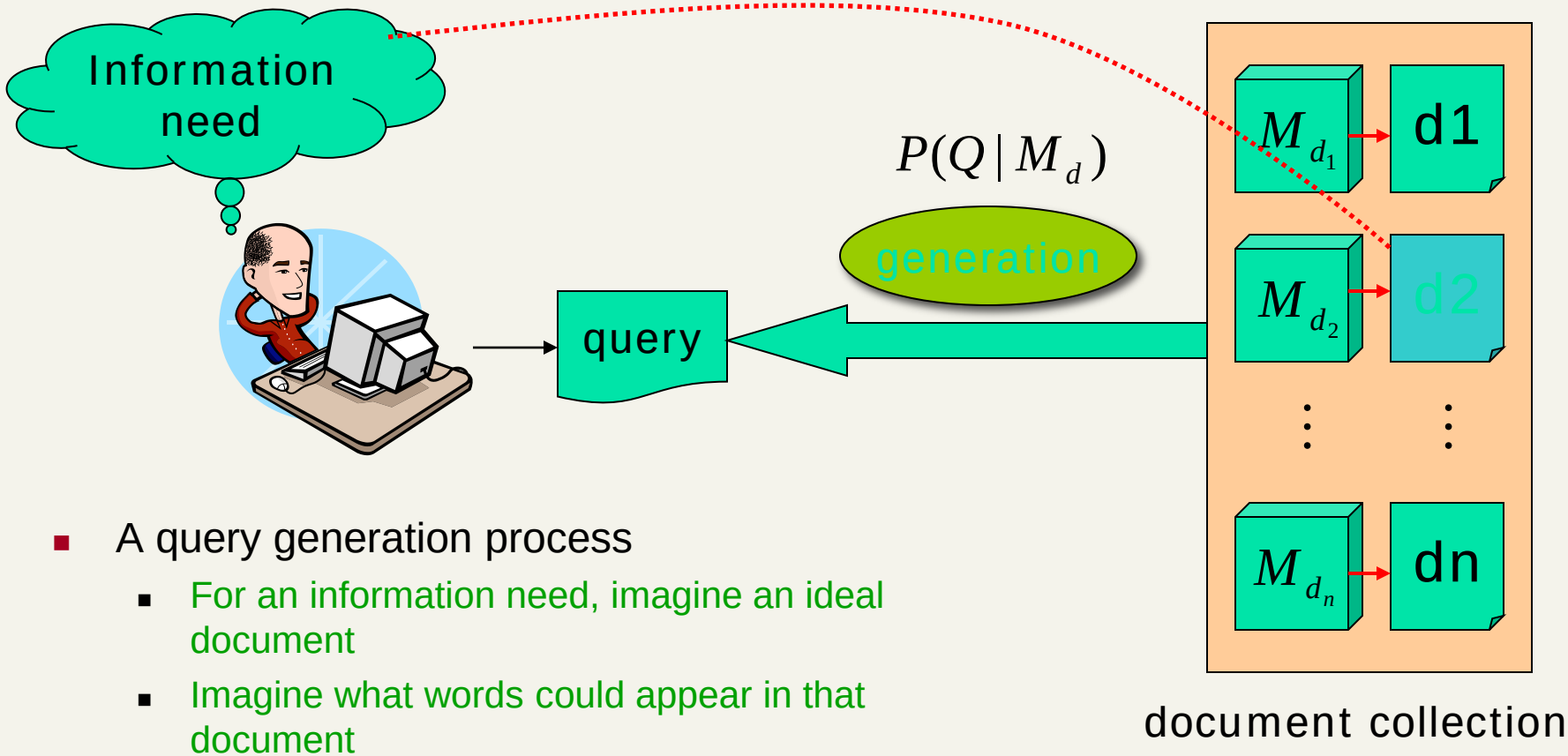
- In IR, combine doc. with corpus

$$P(w_i \mid D) = \lambda P_{ML}(w_i \mid D) + (1-\lambda)P_{ML}(w_i \mid C)$$

Standard Probabilistic IR



IR based on Language Model (LM)



- A query generation process
  - For an information need, imagine an ideal document
  - Imagine what words could appear in that document
  - Formulate a query using those words

Stochastic Language Models

- Models *probability* of generating strings in the language (commonly all strings over alphabet ∑)

Model M

0.2	the
0.1	a
0.01	man
0.01	woman
0.03	said
0.02	likes
…	

the	man	likes	the	woman
0.2	0.01	0.02	0.2	0.01

multiply

P(s | M) = 0.00000008

Stochastic Language Models

- Model *probability* of generating any string

Model M1	
0.2	the
0.01	class
0.0001	sayst
0.0001	pleaseth
0.0001	yon
0.0005	maiden
0.01	woman

Model M2	
0.2	the
0.0001	class
0.03	sayst
0.02	pleaseth
0.1	yon
0.01	maiden
0.0001	woman

the	class	pleaseth	yon	maiden
0.2	0.01	0.0001	0.0001	0.0005
0.2	0.0001	0.02	0.1	0.01

$$P(s|M2) > P(s|M1)$$

Using Language Models in IR

- Treat each document as the basis for a model (e.g., unigram sufficient statistics)
- Rank document d based on P(d | q)
- P(d | q) = P(q | d) x P(d) / P(q)
  - P(q) is the same for all documents, so ignore
  - P(d) [the prior] is often treated as the same for all d
    - But we could use criteria like authority, length, genre
  - P(q | d) is the probability of q given d's model
- Very general formal approach

Language Models for IR

- Language Modeling Approaches
  - Attempt to **model query generation process**
  - Documents are ranked by **the probability that a query would be observed as a random sample from the respective document model**
    - Multinomial approach

$$P(Q|M_D) = \prod_w P(w|M_D)^{q_w}$$

Retrieval based on probabilistic LM

- Treat the generation of queries as a random process.
- Approach
  - Infer a language model for each document.
  - Estimate the probability of generating the query according to each of these models.
  - Rank the documents according to these probabilities.
  - Usually a unigram estimate of words is used

Retrieval based on probabilistic LM

- Intuition
  - Users …
    - Have a reasonable idea of terms that are likely to occur in documents of interest.
    - They will choose query terms that distinguish these documents from others in the collection.
- Collection statistics …
  - Are integral parts of the language model.
  - Are not used heuristically as in many other approaches.
    - In theory. In practice, there's usually some wiggle room for empirically set parameters

Query generation probability (1)

- Ranking formula

$$p(Q,d) = p(d)\,p(Q \mid d)$$

$$\approx p(d)\,p(Q \mid M_d)$$

- The probability of producing the query given the language model of document d using MLE is:

$$\hat{p}(Q \mid M_d) = \prod_{t \in Q} \hat{p}_{ml}(t \mid M_d)$$

$$= \prod_{t \in Q} \frac{tf_{(t,d)}}{dl_d}$$

Unigram assumption:
Given a particular language model, the query terms occur independently

M_d : language model of document d

$tf_{(t,d)}$: raw tf of term t in document d

dl_d : total number of tokens in document d

Insufficient data

- Zero probability $p(t \mid M_d) = 0$
  - May not wish to assign a probability of zero to a document that is missing one or more of the query terms [gives conjunction semantics]
- General approach
  - A non-occurring term is possible, but no more likely than would be expected by chance in the collection.
  - If $tf_{(t,d)} = 0$, $p(t \mid M_d) \propto \frac{cf_t}{cs}$

cs : raw collection size(total number of tokens in the collection)

cf_t : raw count of term t in the collection

Insufficient data

- Zero probabilities spell disaster
  - We need to smooth probabilities
    - Discount nonzero probabilities
    - Give some probability mass to unseen things
- There's a wide space of approaches to smoothing probability distributions to deal with this problem, such as adding 1, ½ or ε to counts, Dirichlet priors, discounting, and interpolation
- A simple idea that works well in practice is to use a mixture between the document multinomial and the collection multinomial distribution

Mixture model

- $P(w|d) = \lambda P_{mle}(w|M_d) + (1 - \lambda)P_{mle}(w|M_c)$
- Mixes the probability from the document with the general collection frequency of the word.
- Correctly setting λ is very important
- A high value of lambda makes the search "conjunctive-like" – suitable for short queries
- A low value is more suitable for long queries
- Can tune λ to optimize performance
  - Perhaps make it dependent on document size (cf. Dirichlet prior or Witten-Bell smoothing)

Basic mixture model summary

- General formulation of the LM for IR

$$p(Q,d) = p(d)\prod_{t\in Q}((1-\lambda)\,p(t)+\lambda p(t\mid M_d))$$

general language model

individual-document model

  - The user has a document in mind, and generates the query from this document.
  - The equation represents the probability that the document that the user had in mind was in fact this one.

Example

- Document collection (2 documents)
  - d_1: Xerox reports a profit but revenue is down
  - d_2: Lucent narrows quarter loss but revenue decreases further
- Model: MLE unigram from documents; $\lambda = ½$
- Query: *revenue down*
  - $P(Q|d_1) = [(1/8 + 2/16)/2] \times [(1/8 + 1/16)/2]$
    $= 1/8 \times 3/32 = 3/256$
  - $P(Q|d_2) = [(1/8 + 2/16)/2] \times [(0 + 1/16)/2]$
    $= 1/8 \times 1/32 = 1/256$
- Ranking: $d_1 > d_2$

Ponte and Croft Experiments

- Data
  - TREC topics 202-250 on TREC disks 2 and 3
    - Natural language queries consisting of one sentence each
  - TREC topics 51-100 on TREC disk 3 using the concept fields
    - Lists of good terms

<num>Number: 054

<dom>Domain: International Economics

<title>Topic: Satellite Launch Contracts

<desc>Description:

... </desc>

<con>Concept(s):

1. Contract, agreement
2. Launch vehicle, rocket, payload, satellite
3. Launch services, ... </con>

Precision/recall results 202-250

	tf.idf	LM	%chg	I/D	Sign	Wilc.
Rel:	6501	6501				
Rret.:	3201	3364	+5.09	36/43	0.0000⋆	0.0002⋆
Prec.						
0.00	0.7439	0.7590	+2.0	10/22	0.7383	0.5709
0.10	0.4521	0.4910	+8.6	24/42	0.2204	0.0761
0.20	0.3514	0.4045	+15.1	27/44	0.0871	0.0081⋆
0.30	0.2761	0.3342	+21.0	28/43	0.0330⋆	0.0054⋆
0.40	0.2093	0.2572	+22.9	25/39	0.0541	0.0158⋆
0.50	0.1558	0.2061	+32.3	24/35	0.0205⋆	0.0018⋆
0.60	0.1024	0.1405	+37.1	22/27	0.0008⋆	0.0027⋆
0.70	0.0451	0.0760	+68.7	13/15	0.0037⋆	0.0062⋆
0.80	0.0160	0.0432	+169.6	9/10	0.0107⋆	0.0035⋆
0.90	0.0033	0.0063	+89.3	2/3	0.5000	undef
1.00	0.0028	0.0050	+76.9	2/3	0.5000	undef
Avg:	0.1868	0.2233	+19.55	32/49	0.0222⋆	0.0003⋆
Prec.						
5	0.4939	0.5020	+1.7	10/21	0.6682	0.4106
10	0.4449	0.4898	+10.1	22/30	0.0081⋆	0.0154⋆
15	0.3932	0.4435	+12.8	19/26	0.0145⋆	0.0038⋆
20	0.3643	0.4051	+11.2	22/34	0.0607	0.0218⋆
30	0.3313	0.3707	+11.9	28/41	0.0138⋆	0.0070⋆
100	0.2157	0.2500	+15.9	32/42	0.0005⋆	0.0003⋆
200	0.1655	0.1903	+15.0	35/44	0.0001⋆	0.0000⋆
500	0.1004	0.1119	+11.4	36/44	0.0000⋆	0.0000⋆
1000	0.0653	0.0687	+5.1	36/43	0.0000⋆	0.0002⋆
RPr	0.2473	0.2876	+16.32	34/43	0.0001⋆	0.0000⋆

Precision/recall results 51-100

	tf.idf	LM	%chg	I/D	Sign	Wilc.
Rel:	10485	10485				
Rret.:	5818	6105	+4.93	32/42	0.0005⋆	0.0003⋆
Prec.						
0.00	0.7274	0.7805	+7.3	10/22	0.7383	0.2961
0.10	0.4861	0.5002	+2.9	26/44	0.1456	0.1017
0.20	0.3898	0.4088	+4.9	24/45	0.3830	0.1405
0.30	0.3352	0.3626	+8.2	28/47	0.1215	0.0277⋆
0.40	0.2826	0.3064	+8.4	25/45	0.2757	0.0286⋆
0.50	0.2163	0.2512	+16.2	26/40	0.0403⋆	0.0007⋆
0.60	0.1561	0.1798	+15.2	20/30	0.0494⋆	0.0025⋆
0.70	0.0913	0.1109	+21.5	14/22	0.1431	0.0288⋆
0.80	0.0510	0.0529	+3.7	8/13	0.2905	0.2108
0.90	0.0179	0.0152	−14.9	1/4	0.3125	undef
1.00	0.0005	0.0004	−11.9	1/2	0.7500	undef
Avg:	0.2286	0.2486	+8.74	32/50	0.0325⋆	0.0015⋆
Prec.						
5	0.5320	0.5960	+12.0	15/21	0.0392⋆	0.0125⋆
10	0.5080	0.5260	+3.5	14/30	0.7077	0.1938
15	0.4933	0.5053	+2.4	14/28	0.5747	0.3002
20	0.4670	0.4890	+4.7	16/34	0.6962	0.1260
30	0.4293	0.4593	+7.0	20/32	0.1077	0.0095⋆
100	0.3344	0.3562	+6.5	29/45	0.0362⋆	0.0076⋆
200	0.2670	0.2852	+6.8	29/44	0.0244⋆	0.0009⋆
500	0.1797	0.1881	+4.7	30/42	0.0040⋆	0.0011⋆
1000	0.1164	0.1221	+4.9	32/42	0.0005⋆	0.0003⋆
RPr	0.2836	0.3013	+6.24	30/43	0.0069⋆	0.0052⋆

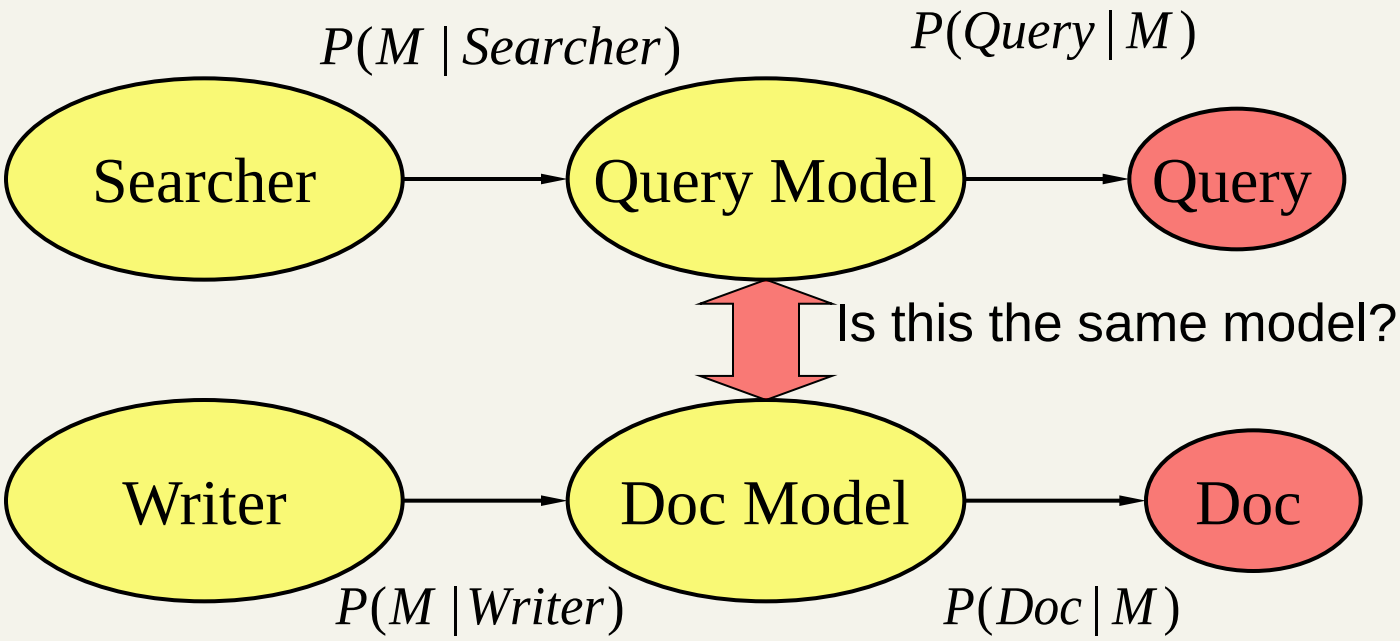
LM vs. Prob. Model for IR

- The main difference is whether “Relevance” figures explicitly in the model or not
  - LM approach attempts to do away with modeling relevance
- LM approach asssumes that documents and expressions of information problems are of the same type
- Computationally tractable, intuitively appealing

LM vs. Prob. Model for IR

- Problems of basic LM approach
  - Assumption of equivalence between document and information problem representation is unrealistic
  - Very simple models of language
  - Can’t easily accommodate phrases, passages, Boolean operators
- Several extensions
  - putting relevance back into the model,
  - query expansion
  - term dependencies,
  - etc.

Alternative Models of Text Generation



Model Comparison

- Estimate query and document models and compare
- Suitable measure is KL divergence $D(Q_m||D_m)$

$$D(Q_m \| D_m) = \sum_{x \in X} Q_m(x) \log \frac{Q_m(x)}{D_m(x)} \propto -\sum_{x \in X} Q_m(x) \log D_m(x)$$

  - equivalent to query-likelihood approach if simple empirical distribution used for query model (why?)
- More general risk minimization framework has been proposed
  - Zhai and Lafferty 2001
- Better results than query-likelihood

Comparison With Vector Space

- There's some relation to traditional tf.idf models:
  - (unscaled) term frequency is directly in model
  - the probabilities do length normalization of term frequencies
  - the effect of doing a mixture with overall collection frequencies is a little like idf: terms rare in the general collection but common in some documents will have a greater influence on the ranking

Comparaison: LM v.s. tf*idf

$$P(Q \mid D) = \prod_i P(q_i \mid D)$$

$$= \prod_{q_i \in Q \cap D} (\lambda \frac{tf(q_i, D)}{|D|} + (1-\lambda) \frac{tf(q_i, C)}{|C|}) \prod_{q_j \in Q-D} ((1-\lambda) \frac{tf(q_j, C)}{|C|})$$

$$= \prod_{q_i \in Q \cap D} (\lambda \frac{tf(q_i, D)}{|D|} + (1-\lambda) \frac{tf(q_i, C)}{|C|}) \prod_{q_j \in Q} ((1-\lambda) \frac{tf(q_j, C)}{|C|}) / \prod_{q_j \in Q \cap D} ((1-\lambda) \frac{tf(q_j, C)}{|C|})$$

$$= const \prod_{q_i \in Q \cap D} (\frac{\lambda \frac{tf(q_i, D)}{|D|} + (1-\lambda) \frac{tf(q_i, C)}{|C|}}{(1-\lambda) \frac{tf(q_i, C)}{|C|}}) = const \prod_{q_i \in Q \cap D} (\frac{\lambda}{1-\lambda} \frac{\frac{tf(q_i, D)}{|D|}}{\frac{tf(q_i, C)}{|C|}} + 1)$$

idf

- Log P(Q|D) ~ VSM with tf*idf and document length normalization
- Smoothing ~ idf + length normalization

Comparison With Vector Space

- Similar in some ways
  - Term weights based on frequency
  - Terms often used as if they were independent
  - Inverse document/collection frequency used
  - Some form of length normalization useful

- Different in others
  - Based on probability rather than similarity
    - Intuitions are probabilistic rather than geometric
  - Details of use of document length and term, document, and collection frequency differ

Resources

J.M. Ponte and W.B. Croft. 1998. A language modeling approach to information retrieval. In *SIGIR 21.*

D. Hiemstra. 1998. A linguistically motivated probabilistic model of information retrieval. *ECDL 2*, pp. 569–584.

A. Berger and J. Lafferty. 1999. Information retrieval as statistical translation. *SIGIR 22*, pp. 222–229.

D.R.H. Miller, T. Leek, and R.M. Schwartz. 1999. A hidden Markov model information retrieval system. *SIGIR 22*, pp. 214–221.

Chengxiang Zhai, Statistical language models for information retrieval, in the series of Synthesis Lectures on Human Language Technologies, Morgan & Claypool, 2009

[Several relevant newer papers at *SIGIR* 2000–now.]

Workshop on Language Modeling and Information Retrieval, CMU 2001. http://la.lti.cs.cmu.edu/callan/Workshops/lmir01/ .

The Lemur Toolkit for Language Modeling and Information Retrieval. http://www-2.cs.cmu.edu/~lemur/ . CMU/Umass LM and IR system in C(++), currently actively developed.