CS 589 Fall 2020

Probability ranking principle

Probabilistic retrieval models

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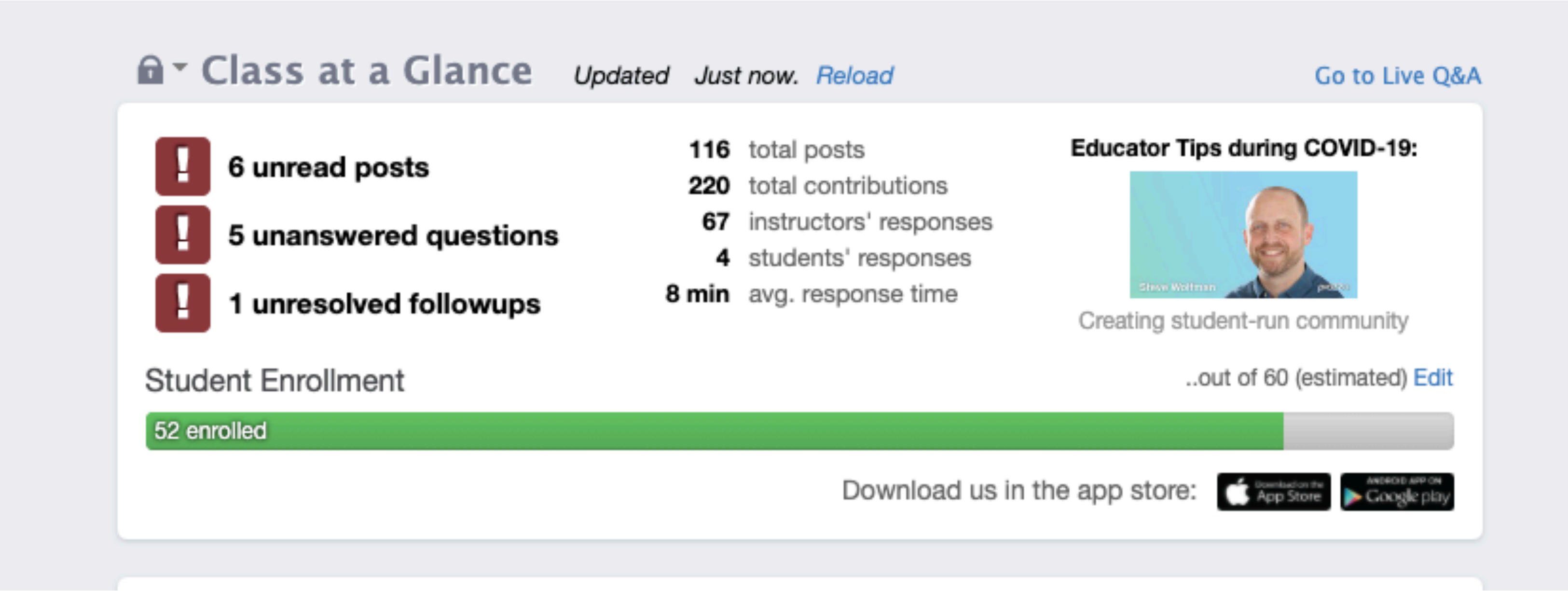
Piazza

- Only 2 students had enrolled in Piazza
- Therefore, I have to state our requirement again
  - Outside of OH, if you choose to use email, your question will be answered significantly slower, email: 2 days



Recap of last lecture

- The boolean retrieval system
- Vector-space model
  - TF: representing documents/queries with a term-document matrix
- Rescaling methods:
  - IDF: penalizing words which appears everywhere
  - Term frequency rescaling (logarithmic, max normalization)
  - Pivoted length normalization

Question from last lecture

- Between the two term-frequency rescaling methods, which one works better? Max normalization or $\boxed{\text{logarithmic}}$?

Max TF normalization

$$tf(w,d) = \alpha + (1-\alpha)\frac{count(w,d)}{max_v count(v,d)}$$

- **Max TF is unstable:**
  - max TF in a document vary with change of stop words set
  - When max TF in document d is an outlier, the normalization is incomparable with other documents
  - Does not work well with documents with different TF distribution

Today’s lecture

- Basic statistics knowledge
  - Random variables, Bayes rules, maximum likelihood estimation

- Probabilistic ranking principle

- Probability retrieval models
  - Robertson & Spark Jones model (RSJ model)
  - BM25 model
  - Language model based retrieval model

Quiz from last lecture

- Suppose we have one query and two documents:
    - q = “covid 19”
    - doc1 = “covid patient”
    - doc2 = “19 99 car wash”
    - doc3 = “19 street covid testing facility is reopened next week”

- What are the rankings of score(q, doc) using VS model (w/o IDF)?
    A. doc1 > doc2 > doc3
    B. doc1 = doc3 > doc2
    C. doc1 > doc3 > doc2
    D. doc3 > doc1 > doc2

Answer

- Recall the VS model:

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

    - q = “covid 19”
    - doc1 = “covid patient”
    - doc2 = “19 99 car wash”
    - doc3 = “19 street covid testing facility is reopen next week”
- score(q, doc1) = 1/sqrt(2)/sqrt(2) = 0.4999, score(q, doc2) = 1/sqrt(2)/sqrt(4) = 0.3535, score(q, doc3) = 2/sqrt(2)/sqrt(9) = 0.4714
- Therefore the answer is C: doc1 > doc3 > doc2

Random variables

- Random variables

sequence = 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0 **Observation**

$p(up) = \alpha, p(down) = 1 - \alpha$ α : **parameter**

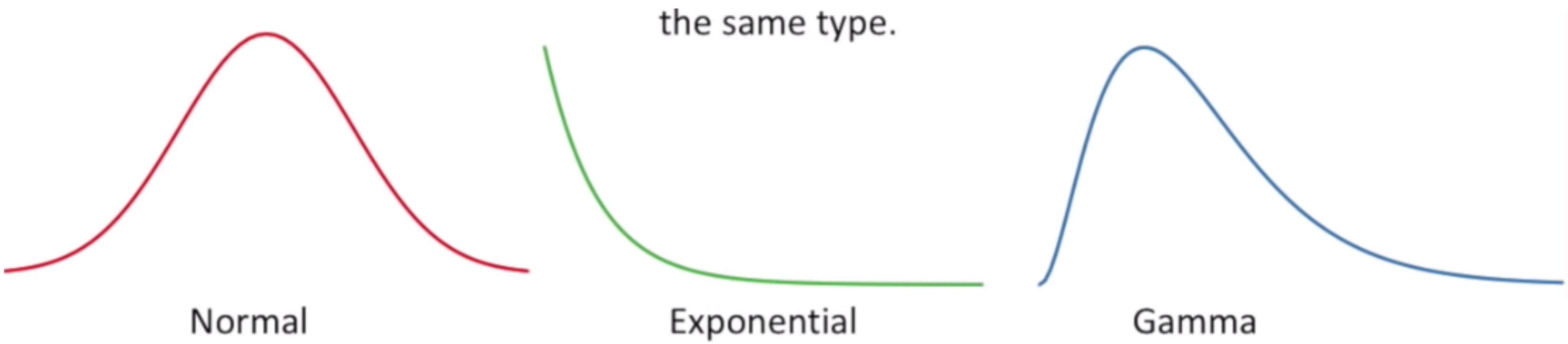
$p(sequence) = \alpha \times (1 - \alpha) \cdots \times (1 - \alpha) \times (1 - \alpha)$ **Bernoulli distribution**

$= \alpha^{\#up} \times (1 - \alpha)^{\#down}$

$\Rightarrow \alpha = \dfrac{\#up}{\#up + \#down}$ **Maximum likelihood estimation**

Maximum likelihood estimation

- Fitting a distribution model to the data
  - Assumes mouse weights follow an underlying distribution



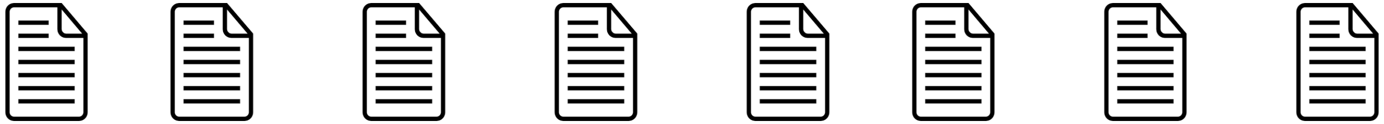
Maximum likelihood estimation

- Fitting a distribution to the data
  - Distributions of mouse weights

- Applications
  - Making estimations for probabilities for future events to happen
  - For example, predicting the probability for a document to be relevant to a query, and rank all documents by their estimated relevance score

Random variables in information retrieval

query* = *"artificial intelligence"



rel = 0, 1, 0, 0, 0, 0, 0, 0

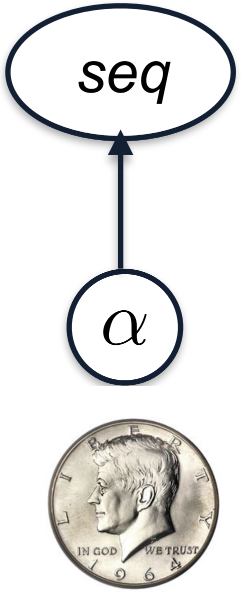
d = artificial, intelligence, machine, intelligence, information, retrieval

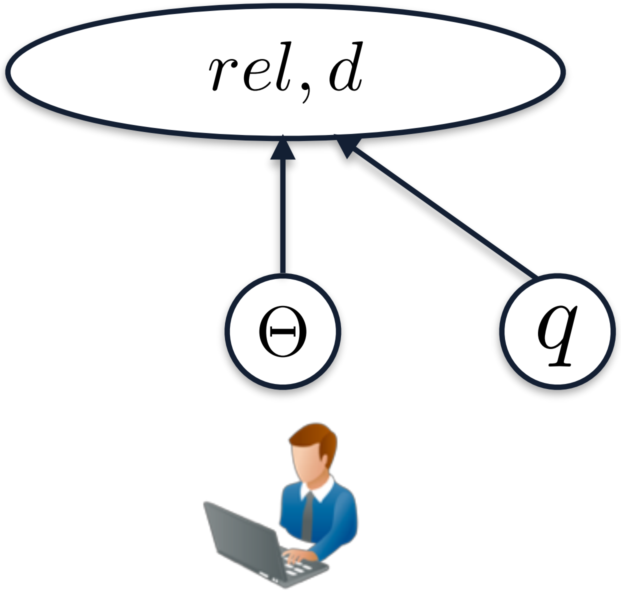
q = artificial, intelligence

Observation

Notations: *in future slides, q denotes the query, d denotes the document, rel denotes the relevance judgment*

Probabilistic graphical model (underlying distribution)





parameter	α	Θ
distribution	Bernoulli	Multinomial-Dirichlet, 2-Poisson, etc.
parameter estimation	$\alpha = \frac{\#up}{\#up + \#down}$	maximum likelihood estimation maximum a posterior estimation

Bayes' rules

Chain rule: joint distribution

$$P(A,B) = P(A \cap B) = P(A|B)P(B) = P(B|A)P(A)$$

Bayes' rule:

posterior likelihood prior

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \left[\frac{P(B|A)}{\sum_{X\in\{A,\bar{A}\}} P(B|X)P(X)}\right] P(A)$$

$$P(A|B) \propto P(B|A)P(A)$$

$$\sum_A P(A|B) = 1$$

skipping estimating $P(B)$

trick for estimating the posterior

Probability ranking principle

- Assume documents are labelled by 0/1 labels (i.e., the relevance judgement is either 0 or 1), given query q, documents should be ranked on their probabilities of relevance *(van Rijsbergen 1979)*:

PRP: rank documents by $p(rel = 1|q, d)$

- ***Theorem***. *The PRP is optimal, in the sense that it minimizes the expected loss (Ripley 1996)*

Notations: *in future slides, q denotes the query, d denotes the document, rel denotes the relevance judgment*

Estimating $p(rel = 1|q, d)$

$$\boxed{p(rel = 1|q, d)} = \frac{p(rel = 1, q, d)}{p(q, d)}$$

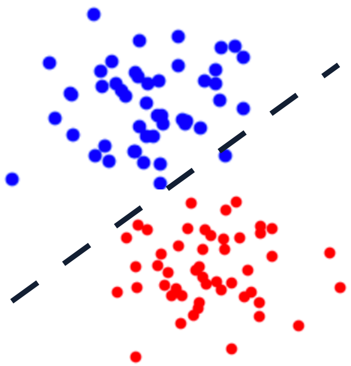
$$= \frac{count(rel = 1, q, d)}{count(q, d)}$$

$$p(rel = 1|q, d) \propto \boxed{p(d|rel = 1, q)}\, p(rel = 1)$$

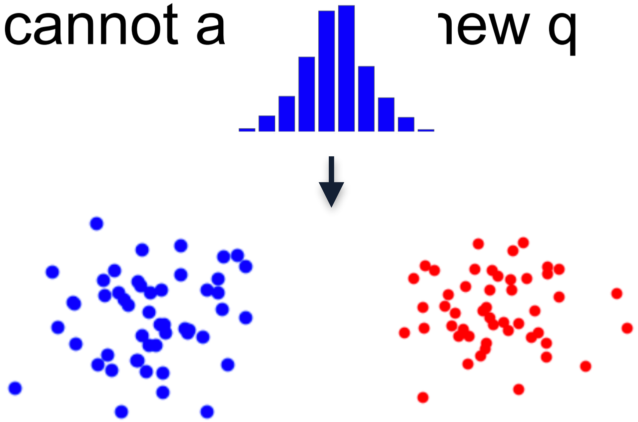
Problems with this estimation?

1. not enough data
2. cannot a [illegible] ew q

generative model



discriminative model



generative model

Estimating $p(rel = 1|q, d)$

$$p(rel = 1|q, d) \propto p(d|rel = 1, q)p(rel = 1)$$

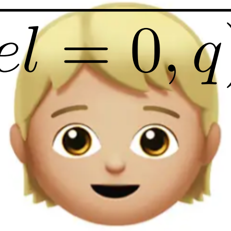
Problems with this estimation

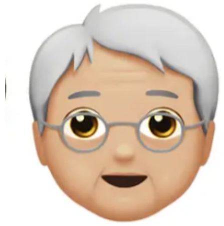
$$O(rel = 1|q, d) = \frac{p(rel = 1|q, d)}{p(rel = 0|q, d)}$$

Difference in absolute probability of relevance

$$= \frac{p(d|rel = 1, q)p(rel = 1)}{p(d|rel = 0, q)p(rel = 0)}$$

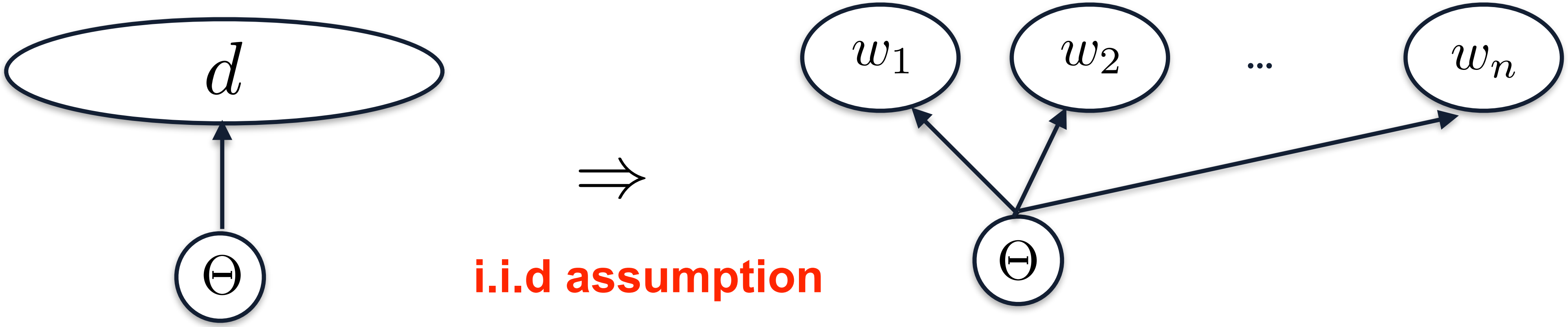
odds





agree on the relative order

Estimating the generative model $p(d|rel=1,q)$



$$p(d|rel=1,q) = \prod_i p(w_i|rel=1,q)$$

$$O(rel=1|q,d) = \prod_i \frac{p(w_i|rel=1,q)}{p(w_i|rel=0,q)} \times \frac{p(rel=1)}{p(rel=0)}$$

$$\stackrel{rank}{=} \prod_{w_i=1} \frac{\alpha_i}{\beta_i} \times \prod_{w_i=0} \frac{(1-\alpha_i)}{(1-\beta_i)} \qquad (1)$$

$$\stackrel{rank}{=} \prod_{w_i=1} \frac{\alpha_i}{\beta_i} \times \prod_{w_i=1} \frac{(1-\beta_i)}{(1-\alpha_i)} \times const \qquad (2)$$

$$= \prod_{w_i=1} \frac{\alpha_i(1-\beta_i)}{\beta_i(1-\alpha_i)} \qquad (3)$$

$$\stackrel{rank}{=} \sum_{w_i=1} \log \frac{\alpha_i(1-\beta_i)}{\beta_i(1-\alpha_i)} \qquad (4)$$

$\alpha_i = p(w_i=1|rel=1,q)$ $\qquad$ $\beta_i = p(w_i=1|rel=0,q)$

RSJ model

$$O(rel = 1|q, d) \stackrel{rank}{=} \sum_{w_i=1} \log \frac{\alpha_i(1-\beta_i)}{\beta_i(1-\alpha_i)}$$

(Robertson & Sparck Jones 76)

$$\begin{aligned}\alpha_i =& p(w_i = 1|q, rel = 1) \\ =& \frac{count(w_i = 1, rel = 1) + 0.5}{count(rel = 1) + 1}\end{aligned}$$

Probability for a word to appear in a relevant doc

$$\begin{aligned}\beta_i =& p(w_i = 0|q, rel = 0) \\ =& \frac{count(w_i = 0, rel = 0) + 0.5}{count(rel = 0) + 1}\end{aligned}$$

Probability for a word to appear in a non-relevant doc

RSJ model: Summary

- Uses only **binary word** occurrence (binary inference model), does not leverage TF information
  - RSJ model was designed for retrieving short text and abstract!
- Requires relevance judgment
  - No-relevance judgment version: [Croft & Harper 79]
- Performance is not as good as tuned vector-space model

How to improve RSJ based on these desiderata?

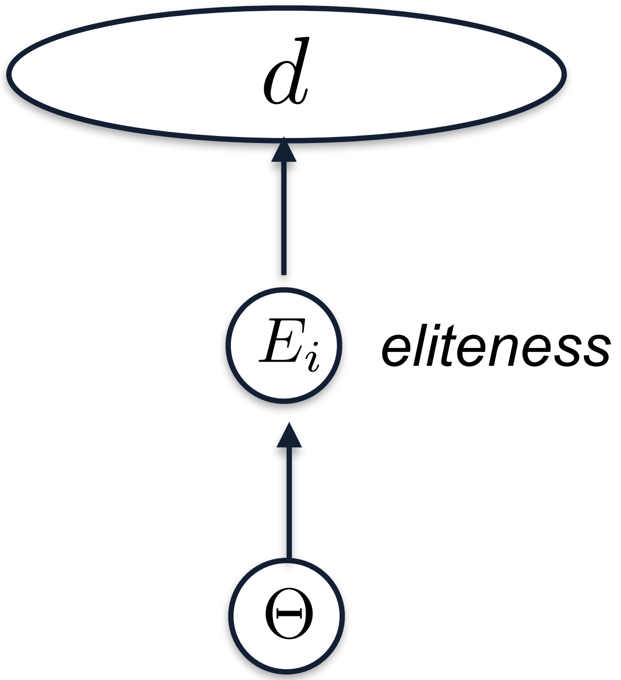
Desiderata of retrieval models

- Recall the desiderata of a retrieval models:
  - The importance of TF is sub-linear
  - Penalizing term with large document frequency using IDF
  - Pivot length normalization

How to improve RSJ based on these desiderata?

Okapi/BM25

- Estimate probability using ***eliteness***
  - *What is eliteness?*
  - *A term/word is elite if the document is* ***about the concept denoted by the term***
  - *Eliteness is binary*
  - *Term occurrence depends on eliteness*

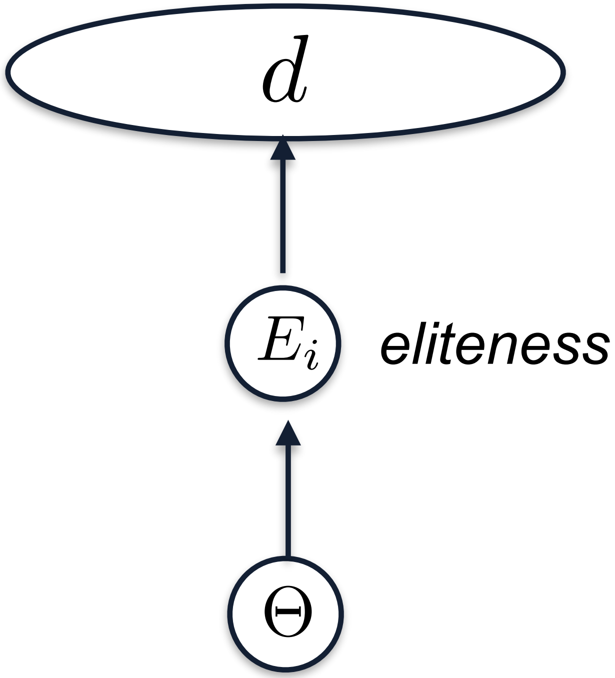


Okapi/BM25

- Introduced in 1994
  - SOTA non-learning retrieval model
- $score(q,d) = \sum_{i \in q} c_i^{elite}(tf_i)$ $\qquad tf_i = tf(i,d)$

$$c_i^{elite}(tf_i) = \log \frac{p(w_i = tf_i|q, rel = 1)p(w_i = 0|q, rel = 0)}{p(w_i = 0|q, rel = 1)p(w_i = tf_i|q, rel = 0)}$$

$$\begin{aligned} p(w_i = tf_i|q, rel = 1) &= p(w_i = tf_i|E_i = 1)p(E_i = 1|q, rel) \\ &\quad + p(w_i = tf_i|E_i = 0)p(E_i = 0|q, rel) \\ &= \pi \frac{\lambda^{tf_i}}{tf_i!} e^{-\lambda} + (1-\pi) \frac{\mu^{tf_i}}{tf_i!} e^{-\mu} \end{aligned}$$



(2 Poisson model)

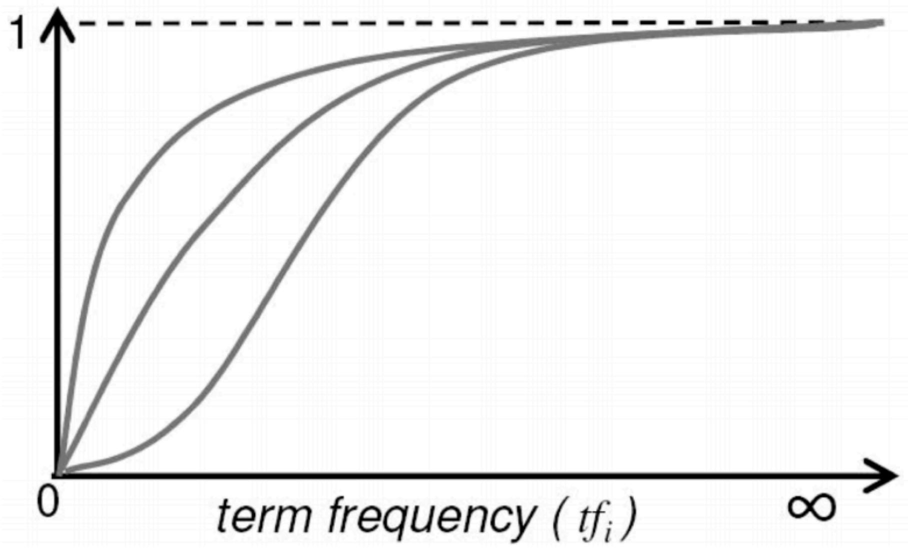
Okapi/BM25

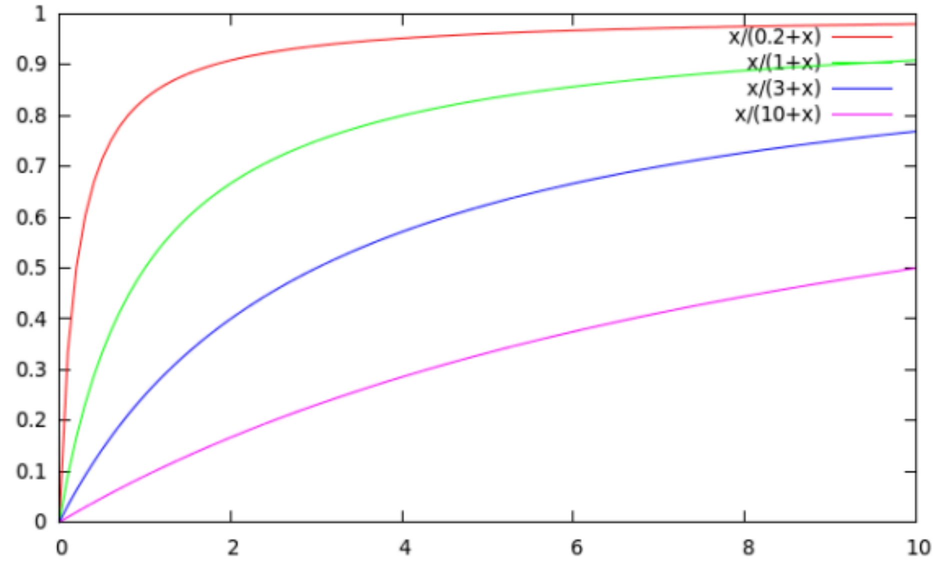
$$p(w_i = tf_i | q, rel = 1) = \boxed{\pi \frac{\lambda^{tf_i}}{tf_i!} e^{-\lambda} + (1 - \pi) \frac{\mu^{tf_i}}{tf_i!} e^{-\mu}}$$

- We do not know λ, μ, π
- Can we estimate λ, μ, π ? Difficulty to estimate
- Designing a parameter-free model such that it simulates $p(w_i = tf_i | q, rel = 1)$

Simulating the 2-Poisson model

$c_i^{elite}(tf_i)$





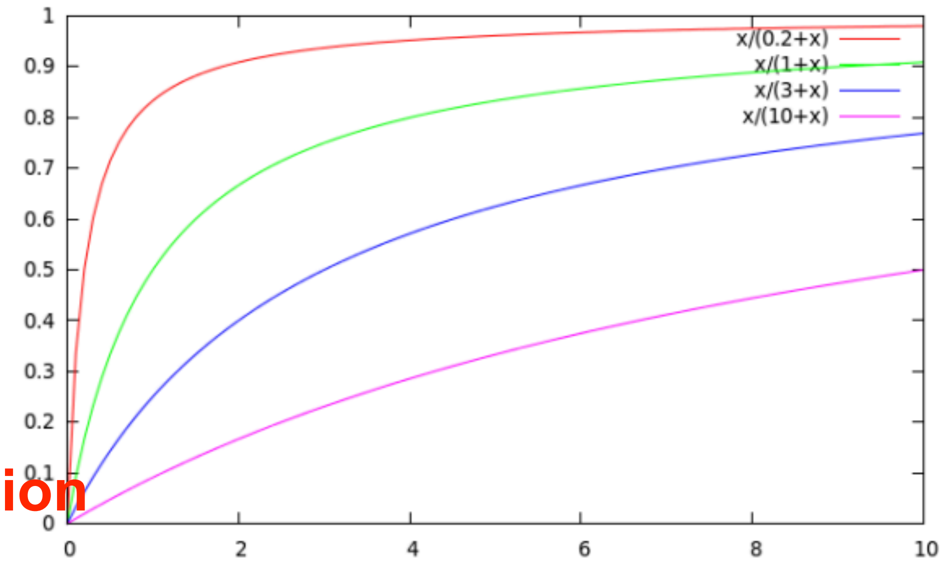
$$\frac{tf_i}{k_1 + tf_i}$$

$$c_i^{BM25}(tf_i) \approx \log \frac{N}{df_i} \times \frac{tf_i(k_1+1)}{k_1(1-b+b\frac{|dl|}{|avgdl|}) + tf_i} \qquad b = 0.75, k_1 \in [1.2, 2.0]$$

slides from Stanford CS276 Information retrieval

Analysis of BM25 formulation

$$c_i^{BM25}(tf_i) \approx \boxed{\log \frac{N}{df_i}} \times \frac{tf_i(k_1+1)}{k_1\boxed{(1-b+b\frac{|dl|}{|avgdl|})}+tf_i}$$



$$\frac{tf_i}{k_1+tf_i}$$

IDF

Pivoted document length normalization

$$b = 0.75, k_1 \in [1.2, 2.0]$$

$$(1.0 - slope) + slope \times \frac{old\ normalization}{average\ old\ normalization} \leftarrow 1-b+b\frac{|dl|}{|avgdl|}$$

Multi-field retrieval

How should I cite presentation slides?

title

Asked 6 years, 10 months ago Active 5 years, 9 months ago Viewed 8k times

9

A friend has made some nice slides that I could reuse (similar topics). He sent me the slides and commented that if I use them and could cite him that would be nice, I asked him how should I cite the slides but he said that whatever suits better to me he said "Just add my surname in some place where it's not very intrusive".

I'm not sure if he doesn't care or he doesn't want to be too picky, but I'd like to cite him, to each one his own.

AFAIK, they are related to a paper (but not in the paper) and to his thesis, where they could be as a diagram but definitively not animated. The slides (as such) may be available at some URL, he said they will be but they are not available yet (so I don't have the URL yet). If citing by the URL I guess I could use this: "How to cite a website URL?"

Should I cite slides? If yes, how?

citations

question

BM25F

$$score^{BM25F}(q,d) = \log \frac{N}{df_i} \times \frac{tf_i^F(k_1+1)}{k_1(1-b+b\frac{|dl|^F}{|avgdl|^F})+tf_i^F}$$

- Each variable is estimated as the weighted sum of its field value

$$tf_i = \sum_f \alpha_f \times tf_{i,f} \qquad dl = \sum_f \alpha_f \times dl_f \qquad avgdl = \sum_f \alpha_f \times avgdl_f$$

parameter estimation using grid search

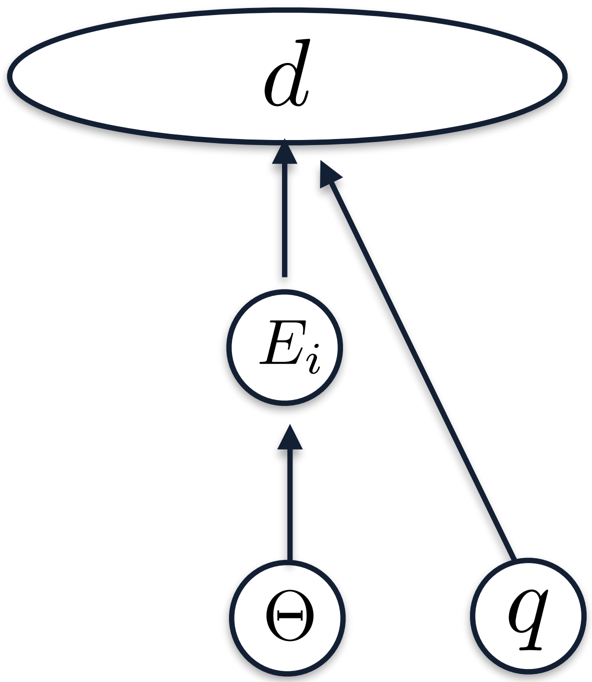
Multi-field retrieval

- BM25 outperforms TF-IDF in every field & combined

	[1.0, 0.0, 0.0]	[0.0, 1.0, 0.0]	[0.0, 0.0, 1.0]	[1.0, 0.5, 0.5]
Python, bm2, ndcg@10	0.319	0.322	0.293	0.378
Python, tfidf, ndcg@10	0.317	0.274	0.276	0.355
Java, bm2, ndcg@10	0.327	0.287	0.254	0.376
Java, tfidf, ndcg@10	0.315	0.258	0.238	0.349
Javascript, bm2, ndcg@10	0.349	0.330	0.267	0.407
Javascript, tfidf, ndcg@10	0.346	0.289	0.247	0.374

Analysis on the n-Poisson model

- **Advantage:** BM25 is based on the 2-Poisson model



eliteness: *d satisfies q's information need, when q is a* ***single term***

- **Disadvantages:**
  - For single term, documents will not fall cleanly into elite/non-elite set
  - For multiple term, requires a combinatorial explosion of elite set
  - Requires explicit indexing of the 'elite' words

Language model-based retrieval

- A language model-based retrieval method [Ponte and Croft, 1998]

$$score(q,d) = \log p(q|d) = \prod_{i, w_i \in q} p(w_i = 1|d) \prod_{i, w_i \notin q} (1.0 - p(w_i = 1|d))$$

- Bernoulli -> multinomial

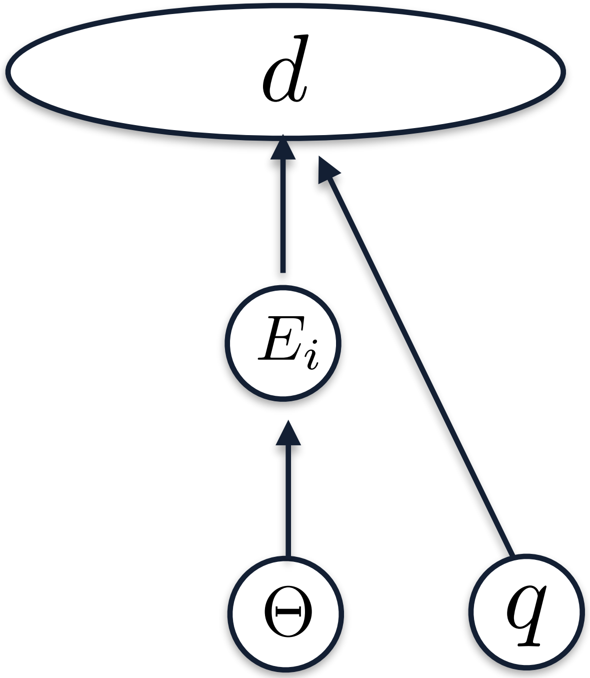
$$score(q,d) = \log p(q|d) = \prod_{w_i=1}^{V} p(w_i|d)^{c(w_i,q)}$$

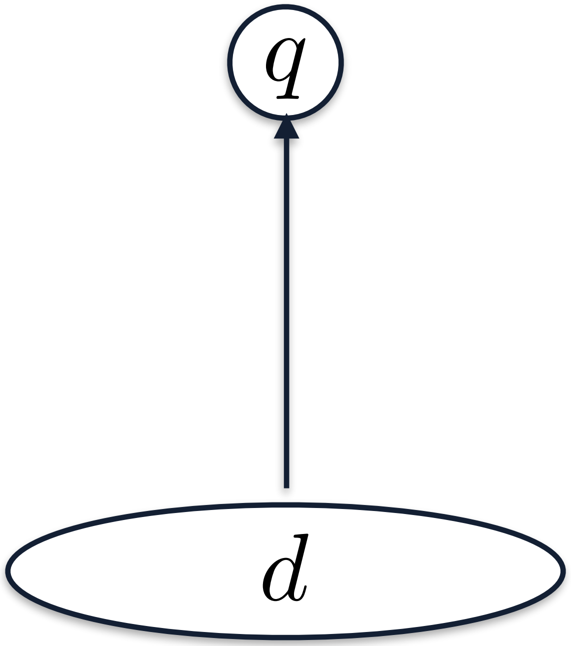
$$\stackrel{rank}{=} \sum_{w_i=1}^{V} c(w_i,q) \log p(w_i|d)$$

$$p(w_i|d) = \begin{cases} p_{seen}(w_i|d) & \text{if } w_i \text{ is seen in d} \\ \alpha_d p(w_i|C) & o.w. \end{cases}$$

corpus unigram LM

Language model-based retrieval





Disclaimer: the right figure is a schematic model, not a rigorous graphical model

Language model-based retrieval

$$\log p(q|d) = \sum_{w_i}^{V} c(w_i, q) \log p(w|d)$$

$$= \sum_{w_i, w_i \in d} c(w_i, q) \log p_{seen}(w_i|d) + \sum_{w_i, w_i \notin d} c(w_i, q) \log \alpha_d p(w_i|C)$$

$$\cdot \quad \cdot \quad \cdot$$

$$= \sum_{w_i, w_i \in d} c(w_i, q) \log \frac{p_{seen}(w_i|d)}{\alpha_d p(w_i|C)} + |q| \log \alpha_d + \boxed{\sum_{w_i=1}^{V} c(w_i, q) \log p(w_i|C)}$$

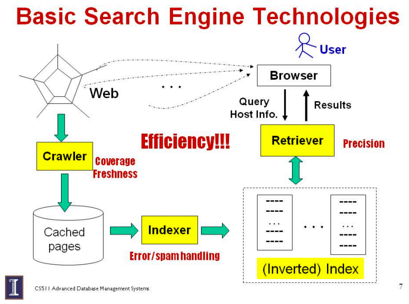
$$score^{LM}(q, d) \overset{rank}{=} \sum_{\boxed{w_i, w_i \in d}} c(w_i, q) \log \frac{p_{seen}(w_i|d)}{\boxed{\alpha_d p(w_i|C)}} + |q| \log \alpha_d$$

constant

efficient to compute, general formulation

Different senses of ‘model’ [Ponte and Croft, 98]

- First sense (high level): an abstraction of the retrieval task itself



decouple → **retrieval model** **+** **other problems (e.g., indexing)**

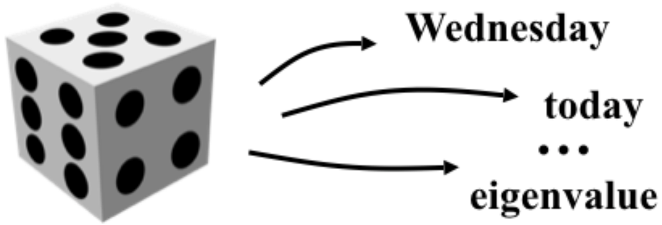
- Second sense (mid level): modeling the distribution, e.g., 2-Poisson model

- Thirds sense (low level): which **statistical language model** is used in $p_{seen}(w_i|d)$

RSJ model without relevance judgment

Statistical language model

- A probability distribution over word sequences
  - p("*Today is Wednesday*") ≈ 0.001
  - p("*Today Wednesday is*") ≈ 0.0000000000001
  - p("*The eigenvalue is positive*") ≈ 0.00001
- Unigram language model
  - Generate text by generating each word INDEPENDENTLY
  - Thus, $p(w_1\ w_2\ ...\ w_n)=p(w_1)p(w_2)\ldots p(w_n)$
  - Parameters: $\{p(t_i)\}$ $p(t_1)+\ldots+p(t_N)=1$ (N is voc. size)



$$p(\text{"}today\ is\ Wed\text{"}) \\ = p(\text{"}today\text{"})p(\text{"}is\text{"})p(\text{"}Wed\text{"}) \\ = 0.0002 \times 0.001 \times 0.000015$$

Notes on language model-based retrieval

- **Advantages**:
  - Avoided the disadvantages in eliteness
  - Defines a general framework, more accurate $p_{seen}(w_i|d)$ can further improve the model
  - In some cases, has outperformed BM25

- **Disadvantages**:
  - The assumed equivalence between query and document is unrealistic
  - Only studied unigram language model
  - Performance is not always good

Equivalence to KL-divergence retrieval model

$$score^{LM}(q,d) \overset{rank}{=} \sum_{w_i, w_i \in d} \boxed{c(w_i,q) \log} \frac{p_{seen}(w_i|d)}{\alpha_d p(w_i|C)} + |q| \log \alpha_d$$

- KL divergence

$$D(p\|q) = \sum_x p(x) \log \frac{p(x)}{q(x)}$$

$$-D(\hat{\theta}_q \| \hat{\theta}_d) = \sum_{w_i=1}^{V} p(w_i|\hat{\theta}_q) \log p(w_i|\hat{\theta}_q) + \boxed{(-\sum_{w_i=1}^{V} p(w_i|\hat{\theta}_q) \log p(w_i|\hat{\theta}_d))}$$

smoothed ***constant***

. . .

why not the opposite?

$$\overset{rank}{=} \sum_{w_i, w_i \in d} \boxed{p(w_i|\hat{\theta}_q) \log} \frac{p_{seen}(w_i|d)}{\alpha_d p(w_i|C)} + \log \alpha_d$$

(Eq. 1)

Notes on the KL-divergence retrieval formula and Dirichlet prior smoothing

Estimating $p_{seen}(w_i|d)$

- Estimating $p_{seen}(w_i|d)$ based on the maximum likelihood estimation

$$p_{seen}(w_i|d) = \frac{count(w_i)}{|dl|}$$

- Disadvantage: if the word is unseen, probability will be 0

- Solution: language model smoothing:

$$p_s(w_i|d) = \frac{c(w_i, d) + \mu p(w_i|C)}{|d| + \mu} \qquad \alpha_d = \frac{\mu}{\mu + |d|}$$

(plug in Eq. 1)

$$= \frac{|d|}{|d| + \mu} p(w_i d) + \frac{\mu}{|d| + \mu} p(w_i|C)$$

Dirichlet smoothing

Estimating $p_{seen}(w_i|d)$

- Dirichlet smoothing

$$score^{Dir}(q,d) = \sum_{w_i, w_i \in d, p(w_i|\hat{\theta}_q)} p(w_i|\hat{\theta}_q) \log{(1 + \frac{count(w_i,d)}{\mu p(w_i|C)})} + \log\frac{\mu}{\mu + |dl|}$$

- Jelinek-Mercer smoothing

$$score^{JM}(q,d) = \sum_{w_i, w_i \in d, p(w_i|\hat{\theta}_q)} p(w_i|\hat{\theta}_q) \log{(1 + \frac{(1-\lambda)count(w_i,d)}{\lambda p(w_i|C)})}$$

Other smoothing methods

- Additive smoothing
- Good-Turing smoothing
- Absolute discounting
- Kneser-ney smoothing

Tuning parameters in smoothing models [Zhai and Lafferty 02]

$$score^{Dir}(q,d) = \sum_{w_i, w_i \in d, p(w_i|\hat{\theta}_q)} p(w_i|\hat{\theta}_q) \log\left(1 + \frac{count(w_i, d)}{\mu p(w_i|C)}\right) + \log \frac{\mu}{\mu + |dl|}$$

- Tuning parameter μ using "leave-one-out" method

$$\hat{\mu} = argmax_{\mu} \sum_{w_i=1}^{V} \sum_{d} \log p(w_i|d; w_i \notin d)$$

remove w_i

- Estimating parameter using Newton's method (2nd derivative)

Two-stage language models for information retrieval

Tuning parameters in smoothing models [Zhai and Lafferty 02]

$$score^{JM}(q,d) = \sum_{w_i, w_i \in d, p(w_i|\hat{\theta}_q)} p(w_i|\hat{\theta}_q) \log(1 + \frac{(1-\lambda)count(w_i,d)}{\lambda p(w_i|C)})$$

- Tuning parameter λ using MLE for the query probability

$$p(q|\lambda, C) = \sum_d \pi_d \prod_{w_i \in q} ((1-\lambda)p(w_i|d) + \lambda p(w_i|C))$$

- EM algorithm:

$$\pi_d^{(k+1)} = \frac{\pi_d^{(k)} \prod_{w_i \in q} \left(\left(1-\lambda^{(k)}\right) p\left(w_i \mid d\right) + \lambda^{(k)} p\left(w_i \mid C\right)\right)}{\sum_d \pi_d^{(k)} \prod_{w_i \in q} \left(\left(1-\lambda^{(k)}\right) p\left(w_i \mid d\right) + \lambda^{(k)} p\left(w_i \mid C\right)\right)}$$

$$\lambda^{(k+1)} = \frac{1}{|q|} \sum_d \pi_d^{(k+1)} \sum_{w_i \in q} \frac{\lambda^{(k)} p\left(w_i \mid C\right)}{\left(1-\lambda^{(k)}\right) p\left(w_i \mid d\right) + \lambda^{(k)} p\left(w_i \mid C\right)}$$

Two-stage language models for information retrieval

Feedback language model [Zhai and Lafferty 01]

protect passengers, accidental/malicious harm, crime, rules

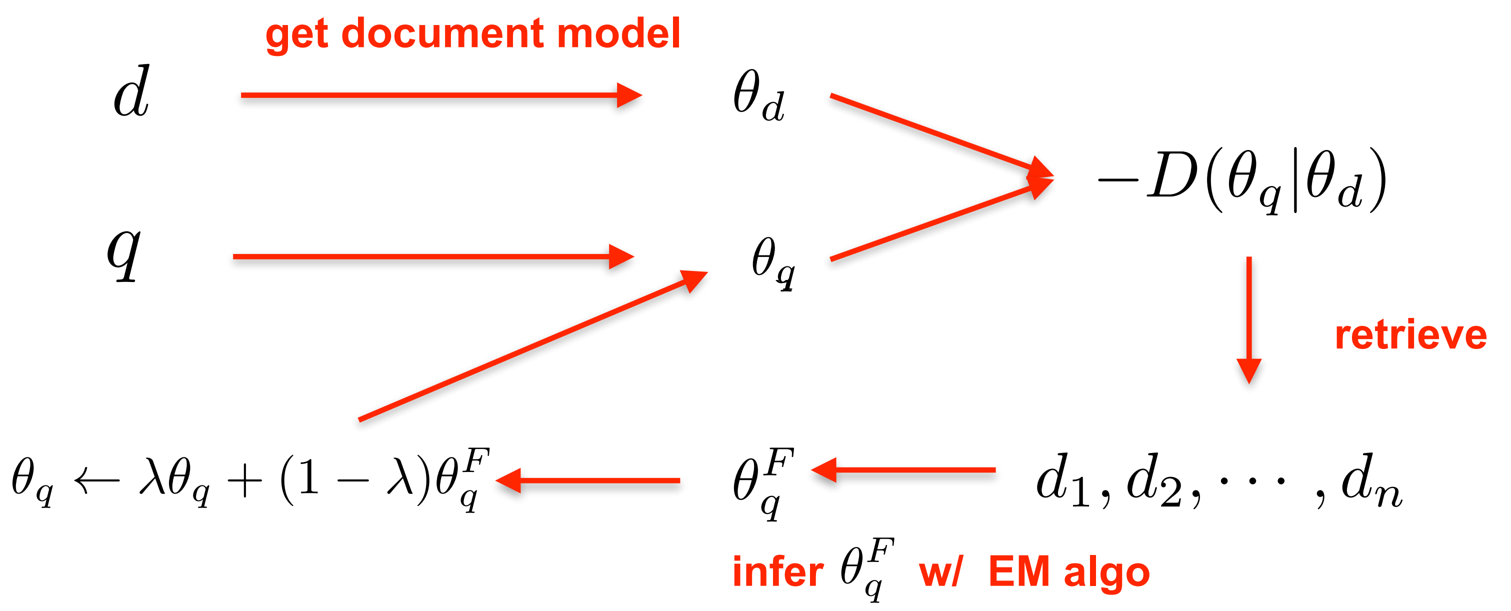
Model-based feedback in the language modeling approach to information retrieval

Feedback language model [Zhai and Lafferty 01]

$$score^{JM}(q,d) = \sum_{w_i, w_i \in d, p(w_i|\hat{\theta}_q)} \boxed{p(w_i|\hat{\theta}_q)} \log\left(1 + \frac{(1-\lambda)count(w_i,d)}{\lambda p(w_i|C)}\right)$$

$$p(w_i|q) = \frac{count(w_i,q)}{|q|}$$

sparsity



Model-based feedback in the language modeling approach to information retrieval

Evaluation on smoothing methods [Zhai & Lafferty 02]

Collection	query	Optimal-JM	Optimal-Dir	Auto-2stage
AP88-89	SK	20.3%	23.0%	22.2%*
	LK	36.8%	37.6%	37.4%
	SV	18.8%	20.9%	20.4%
	LV	28.8%	29.8%	29.2%
WSJ87-92	SK	19.4%	22.3%	21.8%*
	LK	34.8%	35.3%	35.8%
	SV	17.2%	19.6%	19.9%
	LV	27.7%	28.2%	28.8%*
ZIFF1-2	SK	17.9%	21.5%	20.0%
	LK	32.6%	32.6%	32.2%
	SV	15.6%	18.5%	18.1%
	LV	26.7%	27.9%	27.9%*

Two-stage language models for information retrieval

Evaluation on smoothing methods [Zhai & Lafferty 01b]

collection		Simple LM	Mixture	Improv.	Div.Min.	Improv.
AP88-89	AvgPr	0.21	0.296	+41%	0.295	+40%
	InitPr	0.617	0.591	-4%	0.617	+0%
	Recall	3067/4805	3888/4805	+27%	3665/4805	+19%
TREC8	AvgPr	0.256	0.282	+10%	0.269	+5%
	InitPr	0.729	0.707	-3%	0.705	-3%
	Recall	2853/4728	3160/4728	+11%	3129/4728	+10%
WEB	AvgPr	0.281	0.306	+9%	0.312	+11%
	InitPr	0.742	0.732	-1%	0.728	-2%
	Recall	1755/2279	1758/2279	+0%	1798/2279	+2%

Comparison between BM25 and LM [Bennett et al. 2008]

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)
Trec8 TD	Okapi BM25	Okapi	0.2528	0.2908	0.4640
	JM	$\lambda = 0.7$	0.2582 (p=0.5226)	0.3038 (p=0.1886)	0.4600 (p=0.8372)
	Dir	$\mu = 2,000$	**0.2621** (p=0.3308)	0.3043 (p=0.1587)	0.4460 (p=0.3034)
	Dis	$\delta = 0.7$	0.2599 (p=0.1737)	**0.3105** (p=0.0203)	**0.4880** (p=0.1534)
	Two-Stage	auto	0.2445 (p=0.2455)	0.2933 (p=0.7698)	0.4400 (p=0.1351)

However, BM25 outperforms LM in other cases

Summary on parameter tuning

- RSJ: no parameter
- BM25: Due to the formulation of two-Poisson, parameters are difficult to estimate, so use a parameter free version to replace it
- Language model
  - Leave-one-out
  - EM algorithm

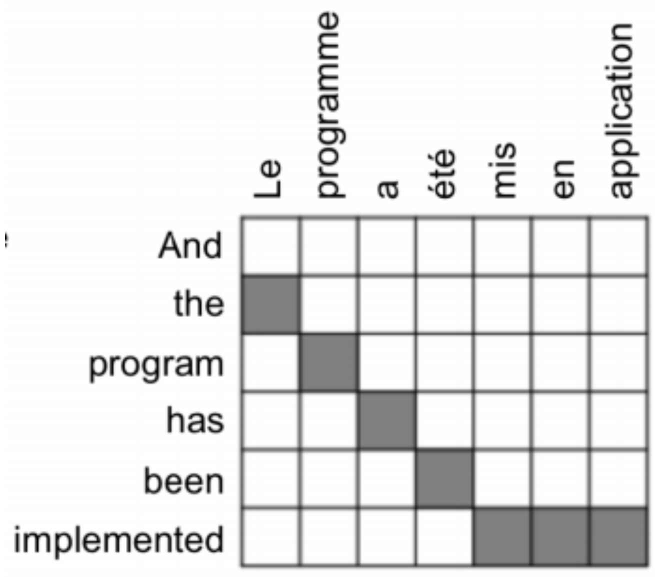
Translation-based language model [Xue et al. 2008]

- The retrieval model can benefit from incorporating knowledge in the formulation

$$p_{(}w_i|d) = \frac{|dl|}{|dl| + \lambda} p_{mix}(w_i|d) + \frac{\lambda}{|dl| + \lambda} p(w_i|C)$$

$$p_{mix}(w_i|d) = (1 - \beta) p(w_i|d) + \beta \sum_{t \in d} p_{tr}(w_i|t) p(t|d)$$

- Translation matrix:



Performance of translation based LM [Xue et al. 2008]

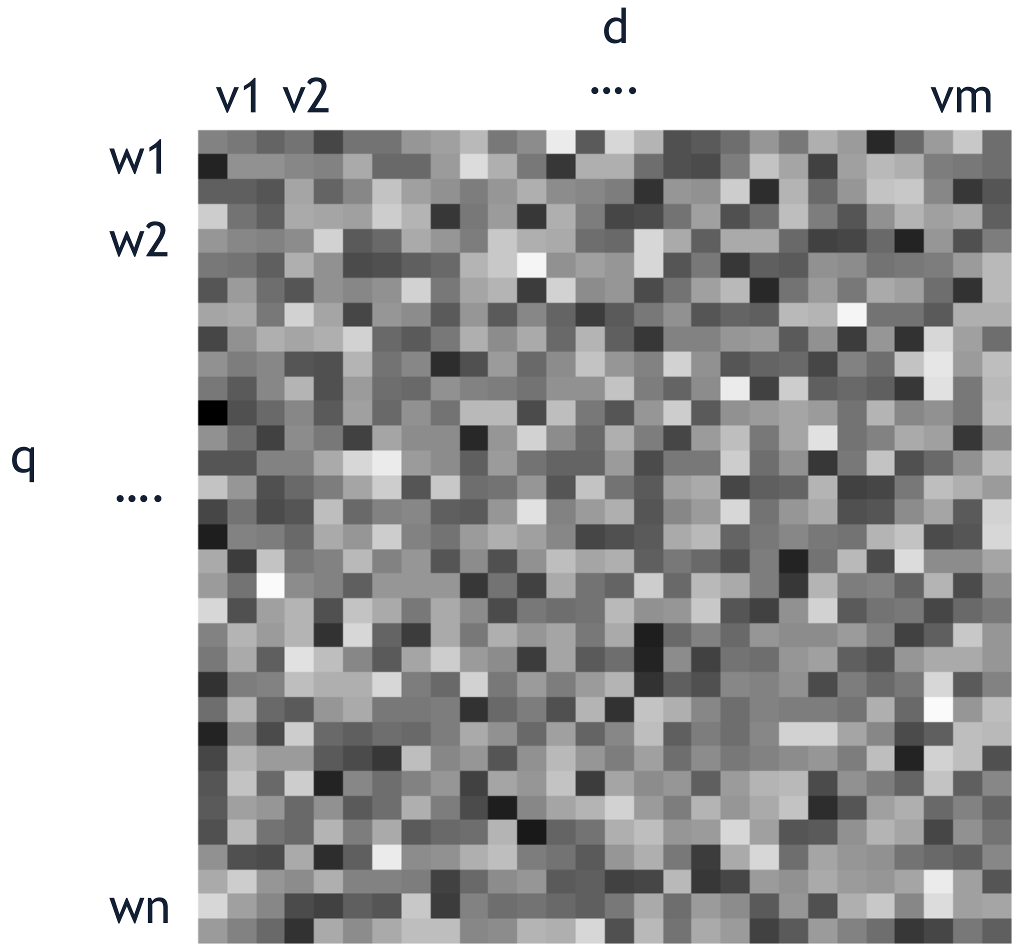
	Python			Java			JavaScript		
	R	@5	@10	R	@5	@10	R	@5	@10
TF-IDF	.299	.301	.360	.285	.282	.352	.305	.315	.378
BM25	.313	.320	.384	.311	.321	.382	.329	.344	.412
TransLM	.468	.502	.553	.455	.487	.544	.483	.528	.573

			Wondir	
Type	Model	Trans Prob	MAP	P@10
Type I	LM		0.3217	0.2211
	Okapi		0.3207	0.2158
	RM		0.3401	0.2395
Type II	LM-Comb		0.3791	0.2368
Type III	Murdock	$P(Q\|A)$	0.3566	0.25
	Murdock	$P(A\|Q)$	0.3658	0.2526
	Jeon	$P(Q\|A)$	0.3546	0.25
	Jeon	$P(A\|Q)$	0.3658	0.2526
	TransLM	$P(Q\|A)$	0.379	0.2658
	TransLM	$P(A\|Q)$	0.4059	0.2684

Discussion on query length

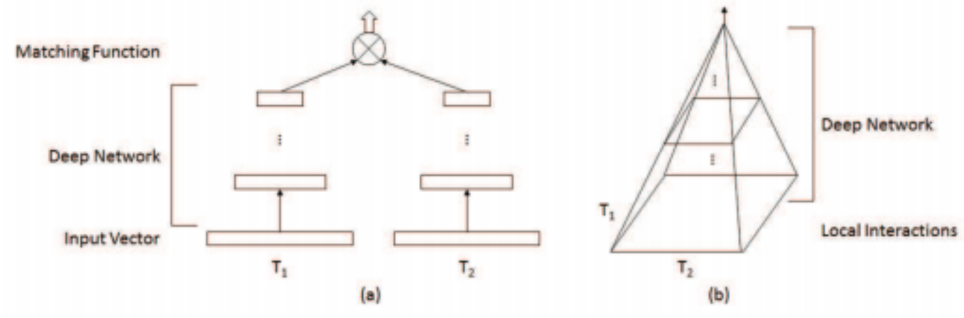
- What if the query is very long?
  - For example, the query is a paragraph or a document
  - The problem of retrieval is turned into a matching problem
    - i.e., semantic matching

Deep semantic matching [Pang et al. 2016]



each cell:

distributed representation of words (word2vec)



A Study of MatchPyramid Models on Ad-hoc Retrieval

Question asking protocol

- Regrading requests: **email TA**, cc myself, titled [CS589 regrading]
- Deadline extension requests: **email** myself, titled [CS589 deadline]
- Dropping: email myself, titled [CS589 drop]
- All technical questions: **Piazza**
  - Homework description clarification
  - Clarification on course materials
- Having trouble with homework: join my **office hour** directly, no need to **email** me
  - If you have a time conflict, **email me** & schedule another time
- Project discussion: join my **office hour**
- **Ask any common questions shared by the class on Piazza**

Homework 1

- Homework 1 is released in Canvas:

- Implementing TF-IDF and BM25 on the LinkSO dataset:
    - https://sit.instructure.com/courses/44342/assignments/218604