Introduction to Information Retrieval

http://informationretrieval.org

IIR 12: Language Models for IR

Hinrich Schütze

Center for Information and Language Processing, University of Munich

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Overview

1. Recap
2. Feature selection
3. Language models
4. Language Models for IR
5. Discussion

Outline

1. Recap
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Naive Bayes classification rule

$$c_{\text{map}} = \arg\max_{c \in \mathbb{C}} \, [\log \hat{P}(c) + \sum_{1 \leq k \leq n_d} \log \hat{P}(t_k|c)]$$

- Each conditional parameter $\log \hat{P}(t_k|c)$ is a weight that indicates how good an indicator t_k is for c.
- The prior $\log \hat{P}(c)$ is a weight that indicates the relative frequency of c.
- The sum of log prior and term weights is then a measure of how much evidence there is for the document being in the class.
- We select the class with the most evidence.

Parameter estimation

- Prior:

$$\hat{P}(c) = \frac{N_c}{N}$$

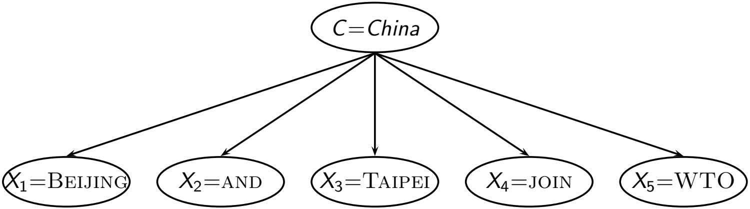
where N_c is the number of docs in class c and N the total number of docs

- Conditional probabilities:

$$\hat{P}(t|c) = \frac{T_{ct} + 1}{\sum_{t' \in V}(T_{ct'} + 1)}$$

where T_{ct} is the number of tokens of t in training documents from class c (includes multiple occurrences)

Add-one smoothing to avoid zeros

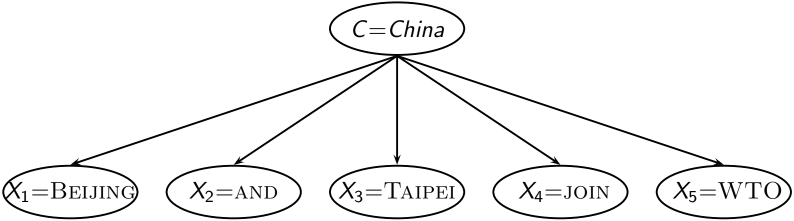


- Without add-one smoothing: if there are no occurrences of WTO in documents in class China, we get a zero estimate for the corresponding parameter:

$$\hat{P}(\mathrm{WTO}|China) = \frac{T_{China,\mathrm{WTO}}}{\sum_{t' \in V} T_{China,t'}} = 0$$

- With this estimate: $[d \text{ contains } \mathrm{WTO}] \rightarrow [P(China|d) = 0]$.
- We must smooth to get a better estimate $P(China|d) > 0$.

Naive Bayes Generative Model



$P(c|d) \propto P(c) \prod_{1 \leq k \leq n_d} P(t_k|c)$

- Generate a class with probability $P(c)$
- Generate each of the words (in their respective positions), conditional on the class, but independent of each other, with probability $P(t_k|c)$

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- Feature selection for text classification: How to select a subset of available dimensions
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- Discussion: Properties of different probabilistic models in use in IR

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- Eliminating features is called feature selection.

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- Feature selection reduces overfitting and improves the accuracy of the classifier.

Basic feature selection algorithm

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$\textsc{SelectFeatures}(\mathbb{D}, c, k)$

$V \leftarrow \textsc{ExtractVocabulary}(\mathbb{D})$

$L \leftarrow []$

for each $t \in V$

do $A(t, c) \leftarrow \textsc{ComputeFeatureUtility}(\mathbb{D}, t, c)$

$\quad \textsc{Append}(L, \langle A(t, c), t \rangle)$

return $\textsc{FeaturesWithLargestValues}(L, k)$

How do we compute A, the feature utility?

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  - Chi-square (see book)

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- For example, if a term's occurrence is independent of the class (same proportion of docs within/without class contain the term), then MI is 0.
- Definition:

$$I(U; C) = \sum_{e_t \in \{1,0\}} \sum_{e_c \in \{1,0\}} P(U = e_t, C = e_c) \log_2 \frac{P(U = e_t, C = e_c)}{P(U = e_t) P(C = e_c)}$$

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- Based on maximum likelihood estimates, the formula we actually use is:

$$
\begin{aligned}
I(U;C) \quad = \quad & \frac{N_{11}}{N}\log_2\frac{NN_{11}}{N_{1.}N_{.1}} + \frac{N_{01}}{N}\log_2\frac{NN_{01}}{N_{0.}N_{.1}} \\
& + \frac{N_{10}}{N}\log_2\frac{NN_{10}}{N_{1.}N_{.0}} + \frac{N_{00}}{N}\log_2\frac{NN_{00}}{N_{0.}N_{.0}}
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$$

- N_{10}: number of documents that contain t ($e_t = 1$) and are not in c ($e_c = 0$); N_{11}: number of documents that contain t ($e_t = 1$) and are in c ($e_c = 1$); N_{01}: number of documents that do not contain t ($e_t = 1$) and are in c ($e_c = 1$); N_{00}: number of documents that do not contain t ($e_t = 1$) and are not in c ($e_c = 1$); $N = N_{00} + N_{01} + N_{10} + N_{11}$.

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- Alternative way of computing MI:

$$I(U;C) = \sum_{e_t \in \{1,0\}} \sum_{e_c \in \{1,0\}} P(U=e_t, C=e_c) \log_2 \frac{N(U=e_t, C=e_c)}{E(U=e_t)E(C=e_c)}$$

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- $N(U=e_t, C=e_c)$ is the count of documents with values e_t and e_c .
- $E(U=e_t, C=e_c)$ is the expected count of documents with values e_t and e_c if we assume that the two random variables are independent.

MI example for *poultry*/EXPORT in Reuters

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	$e_c = e_{poultry} = 1$	$e_c = e_{poultry} = 0$
$e_t = e_{\text{EXPORT}} = 1$	$N_{11} = 49$	$N_{10} = 27{,}652$
$e_t = e_{\text{EXPORT}} = 0$	$N_{01} = 141$	$N_{00} = 774{,}106$

Plug these values into formula:

$$\begin{aligned} I(U;C) &= \frac{49}{801{,}948}\log_2\frac{801{,}948\cdot 49}{(49+27{,}652)(49+141)} \\ &+\frac{141}{801{,}948}\log_2\frac{801{,}948\cdot 141}{(141+774{,}106)(49+141)} \\ &+\frac{27{,}652}{801{,}948}\log_2\frac{801{,}948\cdot 27{,}652}{(49+27{,}652)(27{,}652+774{,}106)} \\ &+\frac{774{,}106}{801{,}948}\log_2\frac{801{,}948\cdot 774{,}106}{(141+774{,}106)(27{,}652+774{,}106)} \\ &\approx 0.000105 \end{aligned}$$

MI feature selection on Reuters

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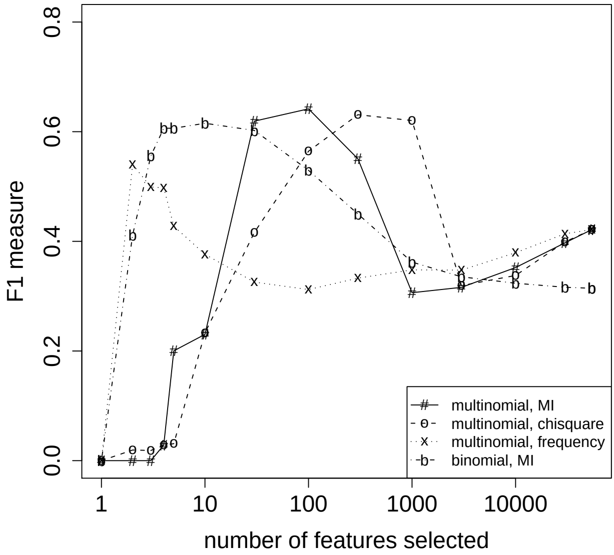
Class: *coffee*

term	MI
COFFEE	0.0111
BAGS	0.0042
GROWERS	0.0025
KG	0.0019
COLOMBIA	0.0018
BRAZIL	0.0016
EXPORT	0.0014
EXPORTERS	0.0013
EXPORTS	0.0013
CROP	0.0012

Class: *sports*

term	MI
SOCCER	0.0681
CUP	0.0515
MATCH	0.0441
MATCHES	0.0408
PLAYED	0.0388
LEAGUE	0.0386
BEAT	0.0301
GAME	0.0299
GAMES	0.0284
TEAM	0.0264

Naive Bayes: Effect of feature selection



(multinomial = multinomial Naive Bayes, binomial = Bernoulli Naive Bayes)

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- Also true for many other learning methods in text classification: you need feature selection for optimal performance.

Exercise

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(i) Compute the "export"/POULTRY contingency table for the "Kyoto"/JAPAN in the collection given below. (ii) Make up a contingency table for which MI is 0 – that is, term and class are independent of each other.

"export"/POULTRY table:

	$e_c = e_{poultry} = 1$	$e_c = e_{poultry} = 0$
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Collection:

	docID	words in document	in c = Japan?
training set	1	Kyoto Osaka Taiwan	yes
	2	Japan Kyoto	yes
	3	Taipei Taiwan	no
	4	Macao Taiwan Shanghai	no
	5	London	no

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9. Note that 4–7 is very similar to what we did in Naive Bayes.

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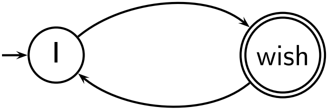

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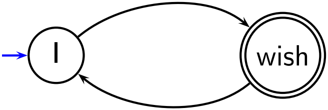

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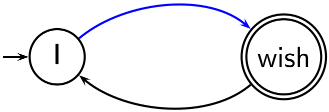

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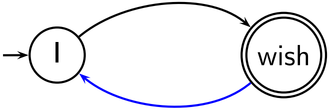

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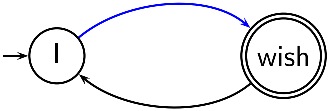

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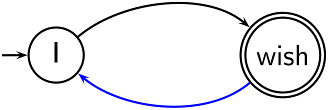

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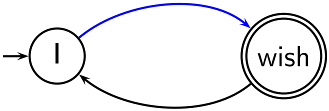

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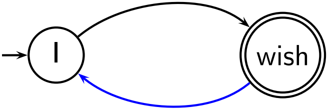

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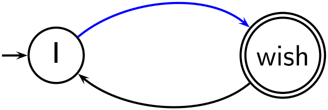

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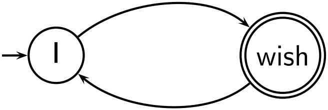

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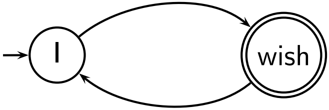

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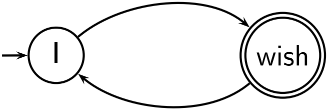

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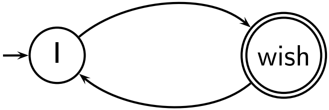

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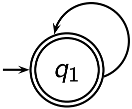
A probabilistic language model



w	$P(w\|q_1)$	w	$P(w\|q_1)$
STOP	0.2	toad	0.01
the	0.2	said	0.03
a	0.1	likes	0.02
frog	0.01	that	0.04
		...	...

This is a one-state probabilistic finite-state automaton – a unigram language model – and the state emission distribution for its one state q_1.

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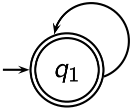

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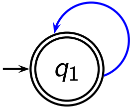

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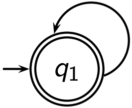

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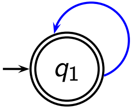

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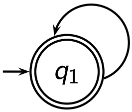

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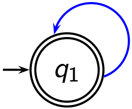

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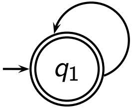

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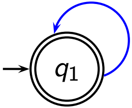

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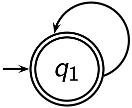

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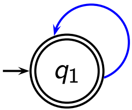

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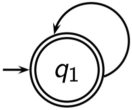

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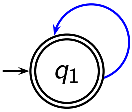

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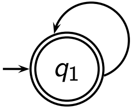

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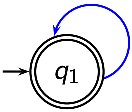

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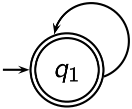

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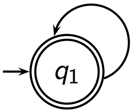

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$= 0.0000000000048$

A different language model for each document

language model of d_1

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language model of d_2

w	$P(w\|.)$	w	$P(w\|.)$
STOP	.2	toad	.02
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$P(\text{query}|M_{d1}) < P(\text{query}|M_{d2})$ Thus, document d_2 is "more relevant" to the query "frog said that toad likes frog STOP" than d_1 is.

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  - But we can give a higher prior to "high-quality" documents, e.g., those with high PageRank.
- $P(q|d)$ is the probability of q given d .
- For uniform prior: ranking documents according according to $P(q|d)$ and $P(d|q)$ is equivalent.

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- This is equivalent to:
$$P(q|M_d) = \prod_{\text{distinct term } t \text{ in } q} P(t|M_d)^{\mathrm{tf}_{t,q}}$$
- $\mathrm{tf}_{t,q}$: term frequency (# occurrences) of t in q
- Multinomial model (omitting constant factor)

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- We need to smooth the estimates to avoid zeros.

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- $$\hat{P}(t|M_c) = \frac{\mathrm{cf}_t}{T}$$
- We will use $\hat{P}(t|M_c)$ to "smooth" $P(t|d)$ away from zero.

Jelinek-Mercer smoothing

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- Low value of λ: more disjunctive, suitable for long queries
- Correctly setting λ is very important for good performance.

Jelinek-Mercer smoothing: Summary

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- The equation represents the probability that the document that the user had in mind was in fact this one.

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- Collection: d_1 and d_2

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Exercise: Compute ranking

- Collection: d_1 and d_2
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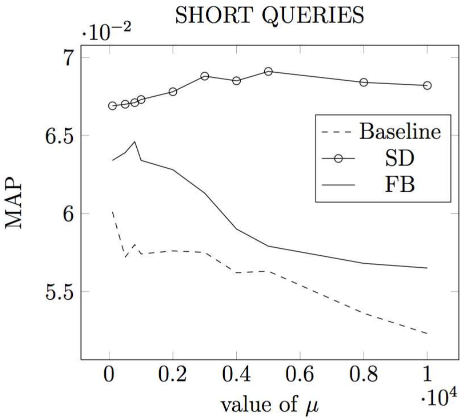
- As we read the document and count terms we update the background distribution.
- The weighting factor α determines how strong an effect the prior has.

Jelinek-Mercer or Dirichlet?

- Dirichlet performs better for keyword queries, Jelinek-Mercer performs better for verbose queries.
- Both models are sensitive to the smoothing parameters – you shouldn't use these models without parameter tuning.

Sensitivity of Dirichlet to smoothing parameter



μ is the Dirichlet smoothing parameter (called α on the previous slides)

Outline

Language models are generative models

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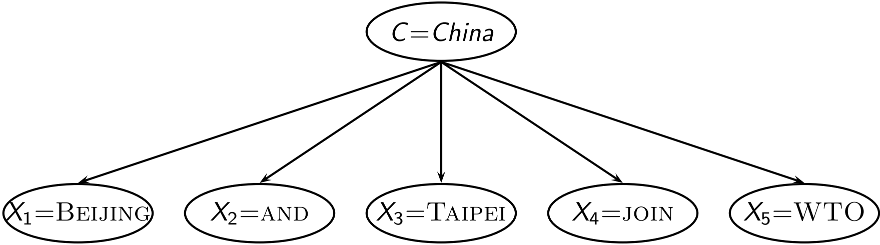

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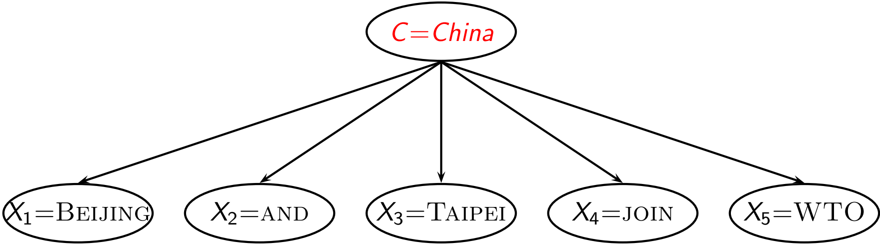

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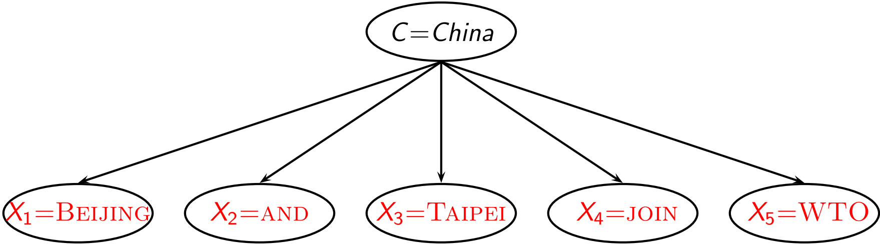

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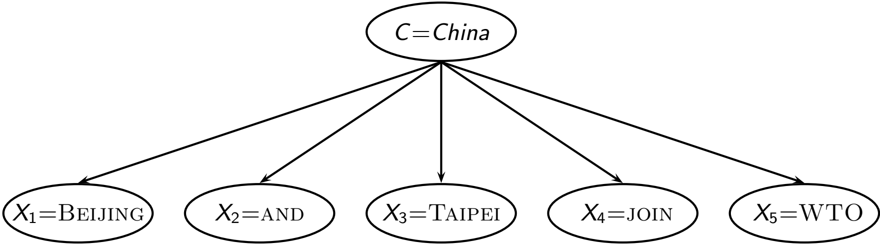
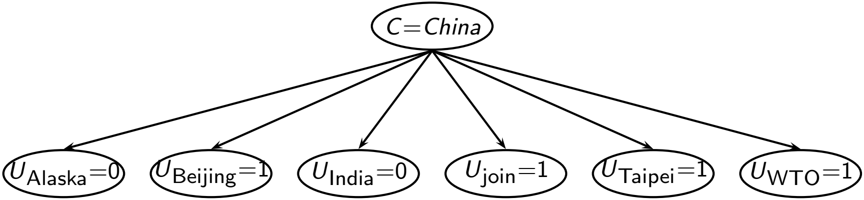
Naive Bayes Multinomial model / IR language models



Naive Bayes Bernoulli model / Binary independence model



Comparison of the two models

	multinomial model / IR language model	Bernoulli model / BIM
event model	generation of (multi)set of tokens	generation of subset of voc
random variable(s)	$X = t$ iff t occurs at given pos	$U_t = 1$ iff t occurs in doc
doc. representation	$d = \langle t_1, \ldots, t_k, \ldots, t_{n_d} \rangle, t_k \in V$	$d = \langle e_1, \ldots, e_i, \ldots, e_M \rangle$, $e_i \in \{0, 1\}$
parameter estimation	$\hat{P}(X = t\|c)$	$\hat{P}(U_i = e\|c)$
dec. rule: maximize	$\hat{P}(c) \prod_{1 \leq k \leq n_d} \hat{P}(X = t_k\|c)$	$\hat{P}(c) \prod_{t_i \in V} \hat{P}(U_i = e_i\|c)$
multiple occurrences	taken into account	ignored
length of docs	can handle longer docs	works best for short docs
# features	can handle more	works best with fewer
estimate for THE	$\hat{P}(X = \text{the}\|c) \approx 0.05$	$\hat{P}(U_{\text{the}} = 1\|c) \approx 1.0$

Vector space (tf-idf) vs. LM

	precision			significant
Rec.	tf-idf	LM	%chg	
0.0	0.7439	0.7590	+2.0	
0.1	0.4521	0.4910	+8.6	
0.2	0.3514	0.4045	+15.1	*
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0.6	0.1024	0.1405	+37.1	*
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1.0	0.0028	0.0050	+76.9	
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- Collection frequency (LMs) vs. document frequency (BM25, vector space) □

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- Cleaner statement of assumptions than vector space
- Thus, better theoretical foundation than vector space
  - . . . but "pure" LMs perform much worse than "tuned" LMs.

Take-away today

- Feature selection for text classification: How to select a subset of available dimensions
- Statistical language models: Introduction
- Statistical language models in IR
- Discussion: Properties of different probabilistic models in use in IR

Resources

- Chapter 13 of IIR (feature selection)
- Chapter 12 of IIR (language models)
- Resources at `http://cislmu.org`
  - Ponte and Croft's 1998 SIGIR paper (one of the first on LMs in IR)
  - Zhai and Lafferty: A study of smoothing methods for language models applied to information retrieval. ACM Trans. Inf. Syst. (2004).
  - Lemur toolkit (good support for LMs in IR)