Introduction to Information Retrieval

http://informationretrieval.org

IIR 12: Language Models for IR

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2011-08-29

Models and Methods

1. Boolean model and its limitations (30)
2. Vector space model (30)
3. Probabilistic models (30)
4. Language model-based retrieval (30)
5. Latent semantic indexing (30)
6. Learning to rank (30)

Take-away

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- Statistical language models: Introduction

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- Statistical language models in IR

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- Statistical language models: Introduction
- Statistical language models in IR
- Discussion: Properties of different probabilistic models in use in IR

Outline

1. Statistical language models
2. Statistical language models in IR
3. Discussion

What is a language model?

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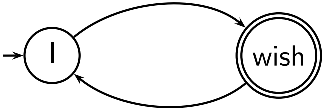

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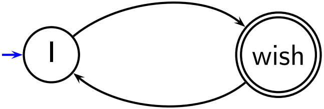

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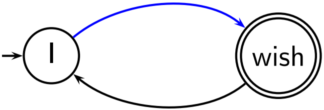

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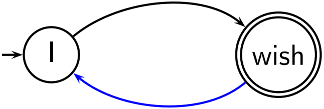

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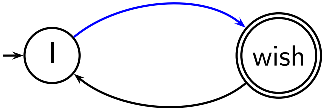

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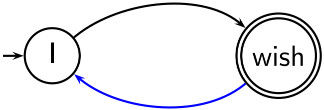

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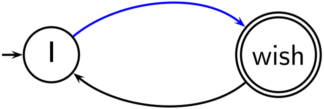

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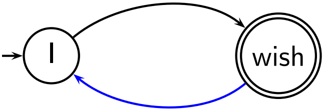

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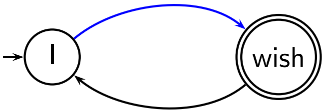

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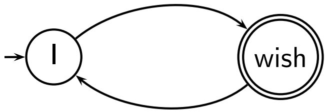

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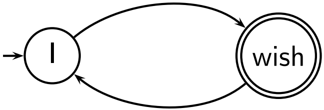

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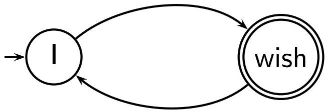

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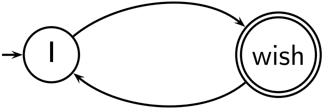
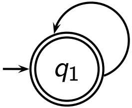


I wish I wish I wish I wish ...

Cannot generate: "wish I wish" or "I wish I"

Our basic model: each document was generated by a different automaton like this except that these automata are probabilistic.

A probabilistic language model



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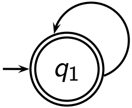

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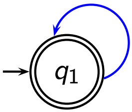

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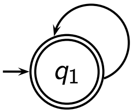

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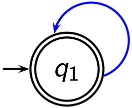

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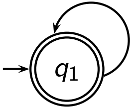

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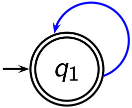

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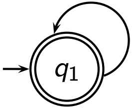

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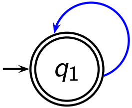

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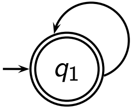

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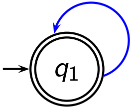

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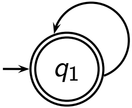

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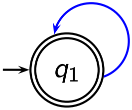

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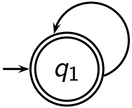

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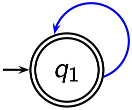

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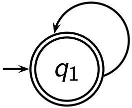

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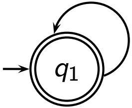

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$P(\text{string}) = 0.01 \cdot 0.03 \cdot 0.04 \cdot 0.01 \cdot 0.02 \cdot 0.01 \cdot 0.2$
$= 0.0000000000048$

A different language model for each document

language model of d_1

w	$P(w\|.)$	w	$P(w\|.)$
STOP	.2	toad	.01
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language model of d_2

w	$P(w\|.)$	w	$P(w\|.)$
STOP	.2	toad	.02
the	.15	said	.03
a	.08	likes	.02
frog	.01	that	.05
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query: frog said that toad likes frog STOP

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$P(\text{query}|M_{d1}) = 0.01 \cdot 0.03 \cdot 0.04 \cdot 0.01 \cdot 0.02 \cdot 0.01 \cdot 0.2$
$= 0.0000000000048 = 4.8 \cdot 10^{-12}$

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$$= 0.0000000000048 = 4.8 \cdot 10^{-12}$$

$$P(\text{query}|M_{d2}) = 0.01 \cdot 0.03 \cdot 0.05 \cdot 0.02 \cdot 0.02 \cdot 0.01 \cdot 0.2$$
$$= 0.0000000000120 = 12 \cdot 10^{-12}$$

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$P(\text{query}|M_{d2}) = 0.01 \cdot 0.03 \cdot 0.05 \cdot 0.02 \cdot 0.02 \cdot 0.01 \cdot 0.2$
$= 0.0000000000120 = 12 \cdot 10^{-12}$

$P(\text{query}|M_{d1}) < P(\text{query}|M_{d2})$ 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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- Under the assumptions we made, ranking documents according to $P(q|d)P(d)$ and $P(d|q)$ is equivalent.

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- For example, for query [Michael Jackson top hits] a document about "Michael Jackson top songs" (but not using the word "hits") would have $P(q|M_d) = 0$. – That's bad.
- 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
- Tuning λ is important for good performance.

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- $P(q|d)$ is 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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- Ranking: $d_2 > d_1$ □

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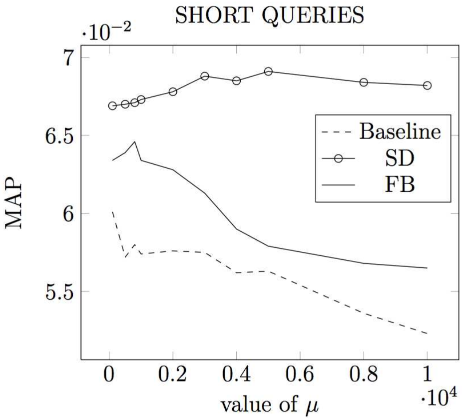
- The weighting factor α determines how strong an effect the prior has.

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)

Vector space (tf-idf) vs. LM

	precision			significant
Rec.	tf-idf	LM	%chg	
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6. Present most likely document(s) to user

Outline

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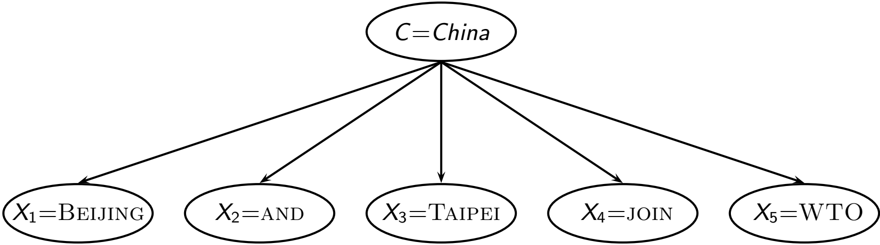
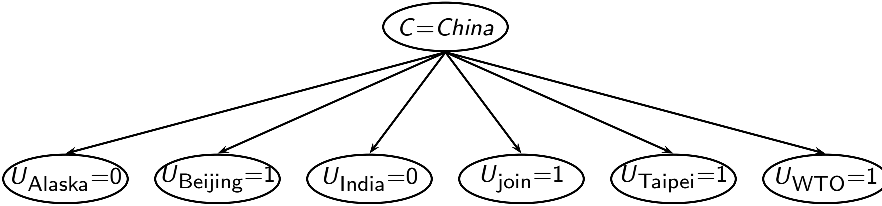
Naive Bayes Multinomial model / IR language models



Naive Bayes Bernoulli model / Binary independence model



Comparison of the two models

	multinomial model / IR LM	Bernoulli model / BIM
event model	generation of (multi)set of tokens	generation of subset of vocabular
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	$\hat{P}(X = t \mid c)$	$\hat{P}(U_i = e \mid c)$
dec. rule: maximize	$\hat{P}(c) \prod_{1 \leq k \leq n_d} \hat{P}(X = t_k \mid c)$	$\hat{P}(c) \prod_{t_i \in V} \hat{P}(U_i = e_i \mid c)$
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	$\hat{P}(X = \text{the} \mid c) \approx 0.05$	$\hat{P}(U_{\text{the}} = 1 \mid c) \approx 1.0$

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  - BM25: tuning parameters for optimizing length normalization

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- Collection frequency (LMs) vs. document frequency (BM25, vector space)

Take-away

- Statistical language models: Introduction
- Statistical language models in IR
- Discussion: Properties of different probabilistic models in use in IR

Resources

- Chapter 12 of Introduction to Information Retrieval
- Resources at http://informationretrieval.org/essir2011
  - 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)
  - Bernoulli vs multinomial models

Exercise: Compute ranking

- Collection: d_1 and d_2
- d_1: Xerox reports a profit but revenue is down
- d_2: Lucene narrows quarter loss but revenue decreases further
- Query q: revenue down
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- $P(q|d_1) = [(1/8 + 2/16)/2] \cdot [(1/8 + 1/16)/2] = 1/8 \cdot 3/32 = 3/256$
- $P(q|d_2) = [(1/8 + 2/16)/2] \cdot [(0/8 + 1/16)/2] = 1/8 \cdot 1/32 = 1/256$
- Ranking: $d_1 > d_2$