Statistical Language Modeling for Information Access

Theory II: Estimation, mixture models and semistructured documents

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Outline

History

- Experimental methodology prominent in IR since 1960s
  - not sufficient to develop formalisms or approaches
  - **mandatory** to demonstrate effectiveness empirically
- Early work compared manual vs. automatic indexing
  - could automatic approach manual quality?
  - assumes that manual approach was the "correct" one
- Methods evolved to compare overall system performance
  - batch mode retrieval
  - interactive information seeking

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  - tasks, calls, proceedings at `http://trec.nist.gov`
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  - retrieving documents from a gigabyte collection
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  - TREC 2011 is in November, deadlines starting from August
- Best-known IR evaluation setting
  - started with 25 participating organizations in 1992
  - nowadays: 100+ groups from 20+ countries
  - European (CLEF) and Asian counterparts (NTCIR)
  - **CLEF 2011 held in Amsterdam, in September**
  - INEX
  - MUC, DUC
  - Example widely also widely followed in other areas
    - Senseval, MTEval, ...

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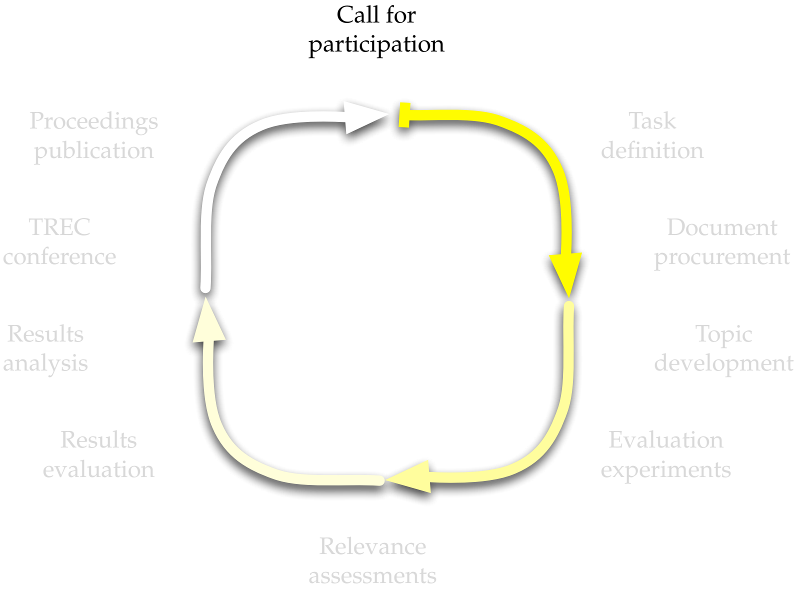
Call for participation
Task definition
Document procurement
Topic development
Evaluation experiments
Relevance assessments
Results evaluation
Results analysis
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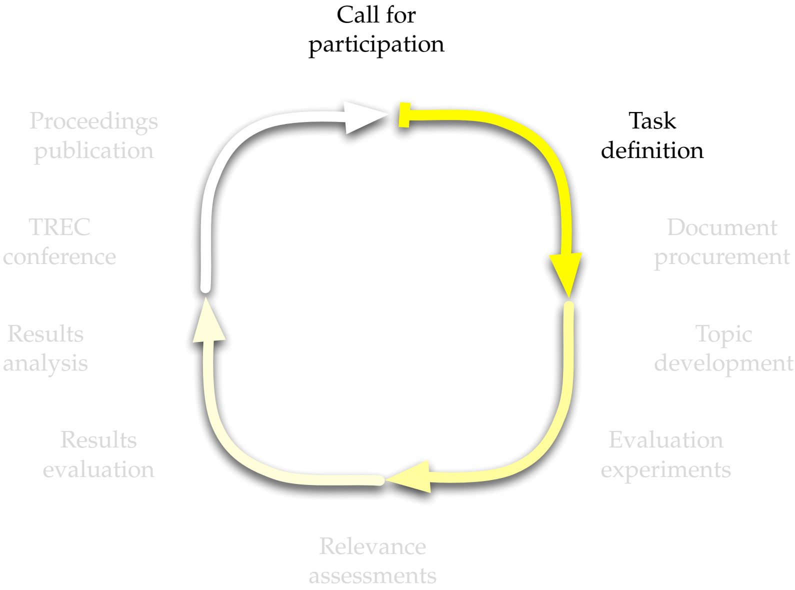

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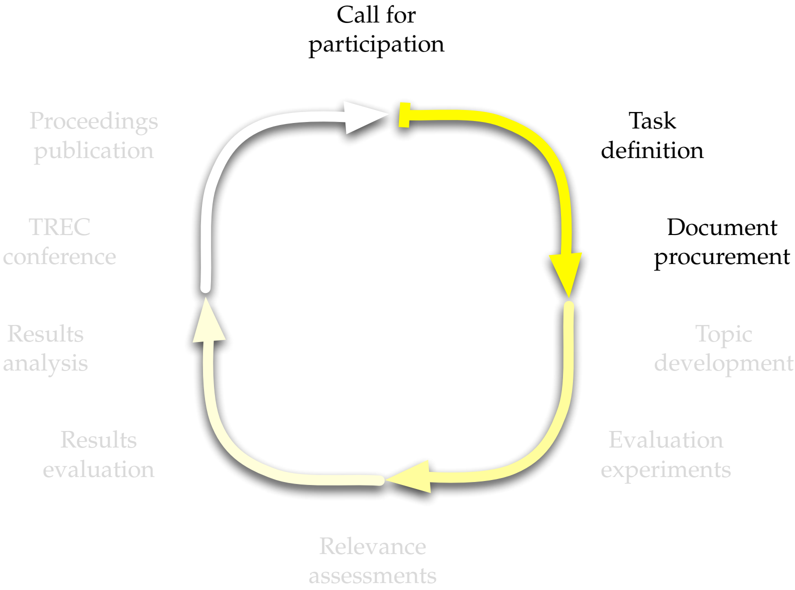
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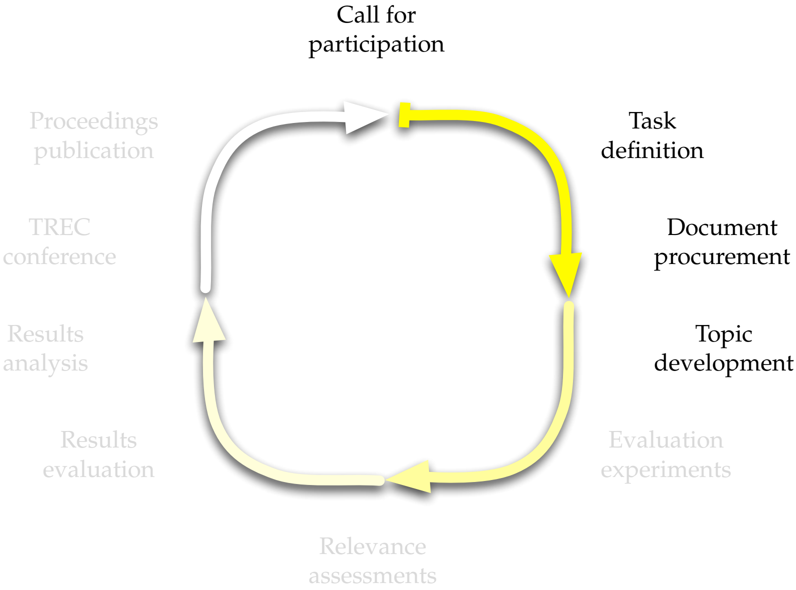
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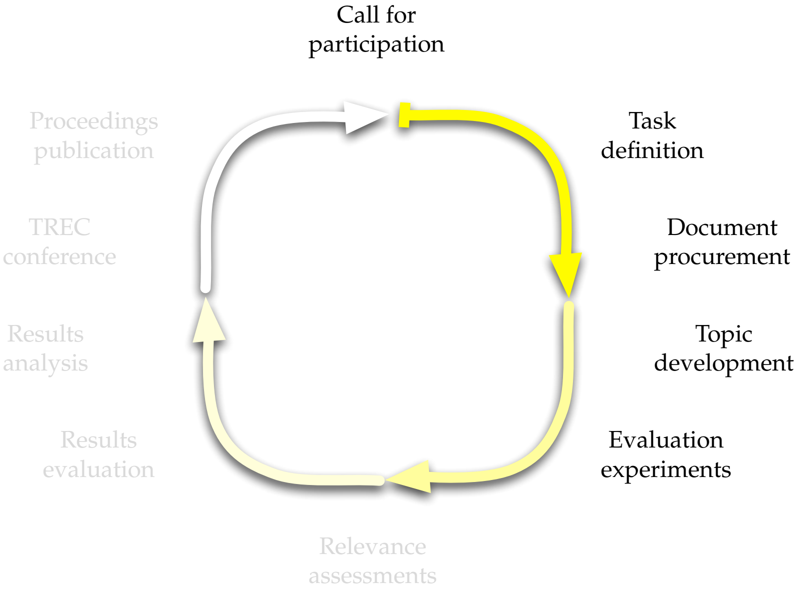

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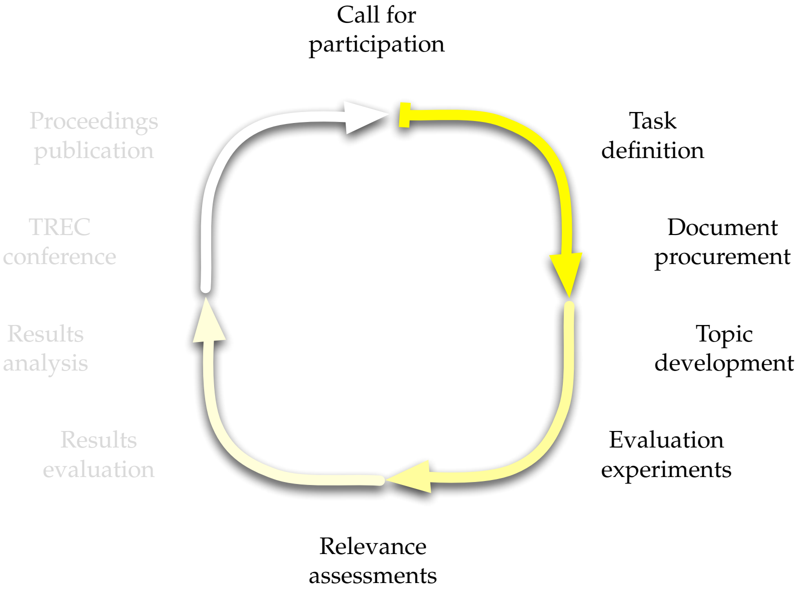
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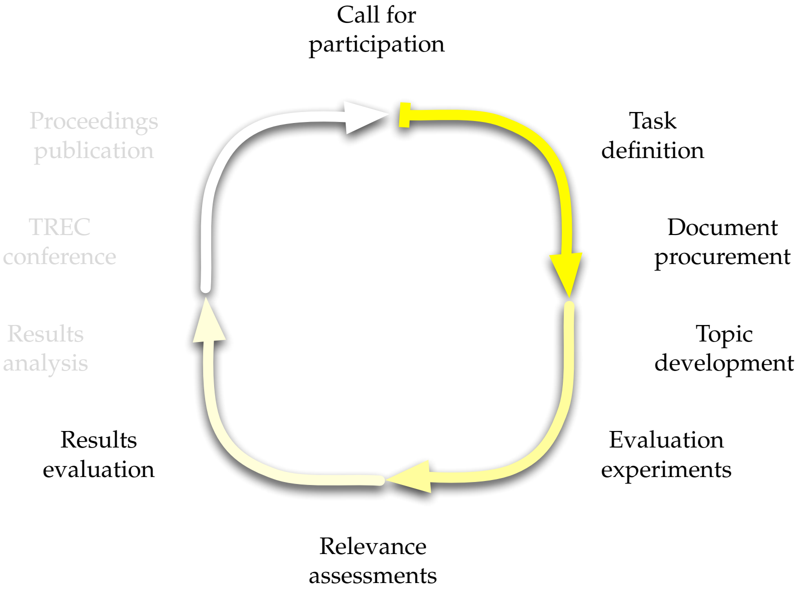
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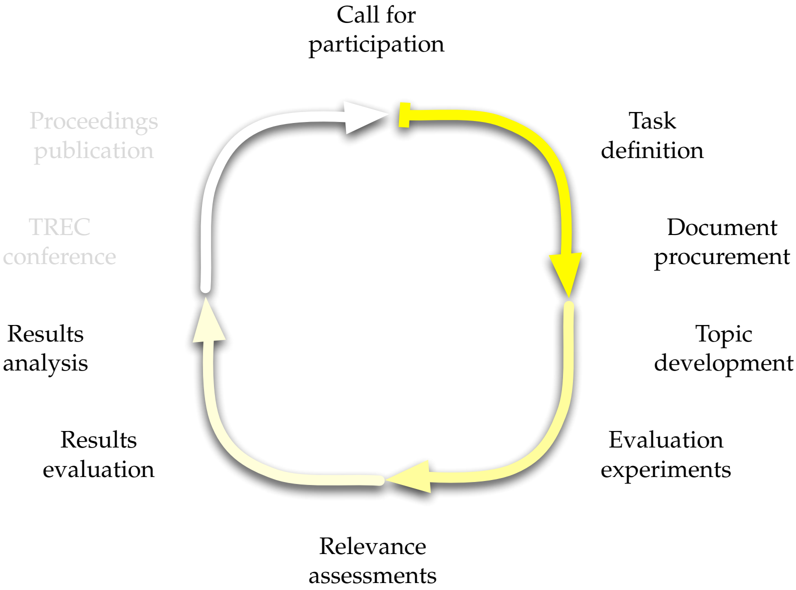
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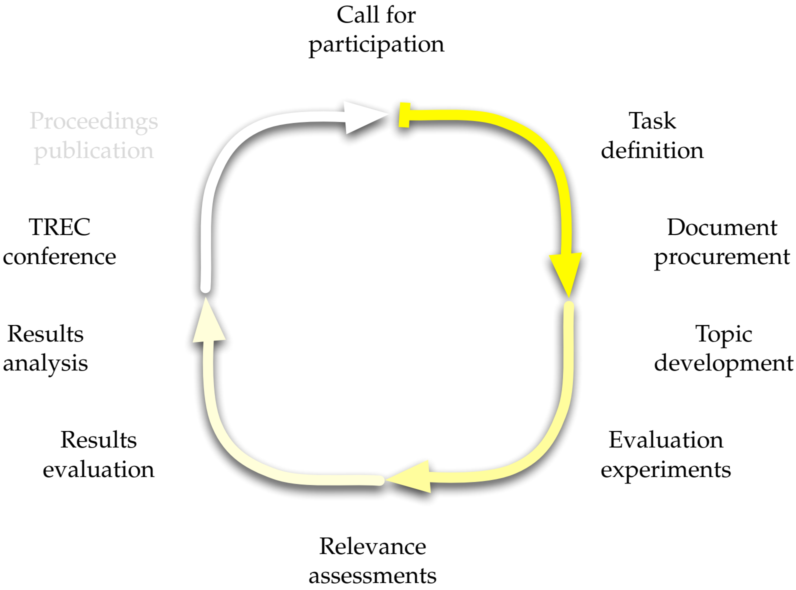
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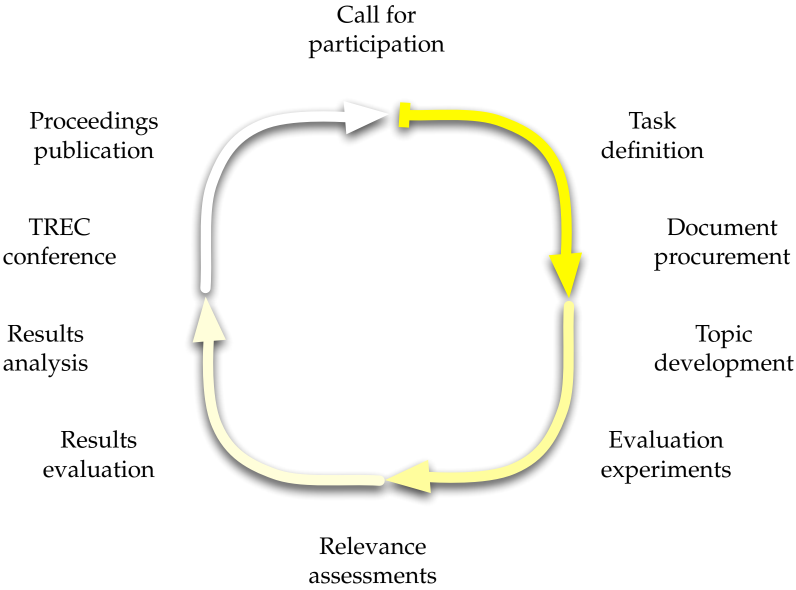
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TREC Cycle

- Most TREC tracks are organized as follows
  - November: track approved by TREC community
  - winter: track's members finalize format for track
  - spring: researchers train system based on specification
  - summer: researchers carry out formal evaluation
    - usually a "blind" evaluation: researchers do not know answer
  - fall: NIST carries out evaluation
  - November: Group meeting (TREC) to find out:
    - how well your site did
    - how others tackled the problem
  - some tracks are run by volunteers outside of NIST (e.g., Web)

+/−

- Widely recognized, premier annual IR evaluation
- What is good
  - brings together a wide range of active researches
  - huge distributed resources applied to common task
  - substantial gains on tasks rapidly
- What is less good
  - annual evaluation can divert resources from research
    - evaluations often require significant engineering effort
    - some tracks evaluation bi-annually as a result
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TREC Format

- TREC consists of IR research tracks
  - Past examples
    - ad-hoc retrieval, routing, cross-language, scanned documents, speech recognition, video, genomics, question answering, interactive, novelty, Web, NLP, robust, enterprise, blogs, SPAM
- TREC 2011
  - microblog, legal, session, medical, web, chemical, crowdsourcing, entity
- NLP spun off into TAC (Text Analysis Conference)
  - Knowledge base population task, Text entailment, Summarization

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Outline

1. A bit more on evaluation
2. Modeling retrieval
3. Mixture models and priors
4. Applications to semistructured document retrieval

What is a Retrieval Model?

- Formal representation of the process of matching a query and a document
- Theory of relevance topical or user relevance
- Typically based on a statistical view of language
- Basis of a ranking algorithm
- Explicit or implicit

Retrieval Models

- Older models
  - Query languages, indexing (Boolean)
  - introducing ranking and weighting (Vector Space)
- Topical relevance models
  - IR as Bayesian classification, relevance information, tf.idf weights (BM25)
  - probabilistic models of documents, queries, topics (language models)
- More on Thursday

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What makes it an language modeling technique?

- When is a given model an LM?
- LM is generative
  - at some level, an LM can be use to generate text
  - explicitly computes probability of observing a string of text
  - e.g., probability of obsserving a query string from a document model
  - model an entire population
- Discriminative approaches
  - model just the decision boundary
  - e.g., is this document relevant? does it belong to class X or Y?

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LM-ing: pros and cons

- Pros
  - formal mathematical model
  - simple, well-understood framework
  - integrates both indexing and retrieval models
  - natural use of collection statistics, no heuristics
  - avoids "philosophical" concepts such as *relevance*, *aboutness*, etc.
- Cons
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Issues in applying LMs

- What kind of LM should we use?
  - unigram or higher-order models?
  - multinomial or multiple Bernouilli?
- How can we estimate model parameters?
  - basic model
  - (translation models, aspect models, relevance models)
- How can we use the model for ranking?
  - query likelihood
  - document likelihood
  - (divergence of query and document models)

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Unigram LMs

- Words are sampled independently from each other
  - "randomly pulling out words from an urn (with replacement)"
  - joint probability decomposes into a product of marginals
  - estimation of probabilities: simple counting
- Basic modeling: determine a posteriori most likely documents, i.e., for which $p(d|q)$ is highest:

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

$$p(d|q) \propto p(q|d) \cdot p(d)$$

Query-likelihood term

Query-independent term (often uniform)

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Higher-Order Models

- Unigram model assumes word independence
  - cannot capture surface form
  - $P(\text{"brown fox"}) = P(\text{"fox brown"})$
- Higher-order models
  - n-gram: condition on preceding words
  - cache: condition on a window
  - grammar: condition on parse tree
- Are they useful?
  - no improvements from n-gram, grammar-based modules
  - some research on cache-like (proximity, passages, etc)
  - parameter estimation is prohibitively expensive

Higher-order Models

- Song and Croft, A general language model for information retrieval, *CIKM* 1999
- Combining unigrams with bigrams:
  - $p(t_{i-1}, t_i|d) = \lambda_1 \cdot p_1(t_i|d) + \lambda_2 \cdot p_2(t_{i-1}, t_i|d)$
  - $\lambda_1 + \lambda_2 = 1$
  - $p_2(t_1, t_2|d) = p_1(t_1|d) \cdot p_1(t_2|d, t_1)$
- Evaluation on the WSJ (250Mb, 74K docs) and TREC 4 (2Gb, 570K docs; WSJ $\subseteq$ TREC 4) data sets

Higher-order Models

Table 3. Experimental Results on the WSJ Data Set

Retrieval Methods	11-pt Average	%Change	%Change
INQUERY	0.2172	-	
LM	0.2027	- 6.68%	-
GLM(40)	0.2198	+ 1.20%	+ 8.44%
GLM2(40+90)	0.2359	+ 8.61%	+ 16.38%

Table 4. Experimental Results on the TREC4 Data Set

Retrieval Methods	11-pt Average	%Change	%Change
INQUERY	0.1917	-	
LM	0.1890	- 1.41%	-
GLM(40)	0.1905	- 0.63%	+ 0.79%
GLM2(40+90)	0.1923	+ 0.31%	+ 1.75%

- Interesting improvements on small collection
- Neglible on more realistic collection sizes
- Findings corroborated in later work
- See tomorrow's lecture for an alternative way of modeling higher-order aspects (Gao et al.)

Multinomial or multiple-Bernouilli?

- Predominant model is the **multinomial**
  - Modeling word frequency
  - observation is a sequence of events, one for each query token
  - $P(t_1, \ldots, t_k|M) = \prod_{i=1}^{k} P(t_i|M)$
- Some flavors are multiple-Bernouilli
  - Modeling word presence/absence
  - Observation is a vector of binary events, one for each possible word
  - $P(t_1, \ldots, t_k|M) = \prod_{w \in t_1,\ldots,t_k} P(w|M) \cdot \prod_{w \notin t_1,\ldots,t_k} (1 - P(w|M))$

Multinomial or multiple-Bernouilli?

- Two models are fundamentally different
  - entirely different event spaces
  - both assume word independence (though it has different meanings)
  - both use smoothed relative-frequency (counting) for estimation
- Multinomial
  - can account for multiple word occurrences in the query
  - well understood
  - possibility for integration with ASR/MT/NLP (same event space)
- Multiple-Bernouilli
  - highly suited for IR (directly checks presence of query terms)
  - provision for explicit negation of query terms ("A but not B")
  - no issues with observation length
- See Lavrenko *A General Theory of Relevance*, PhD thesis, UMass, 2004 for experimental assessment
  - Multinomial seems to work better

Ranking with LMs

- Standard approach: **query likelihood**
  - estimate language model M_D for every doc D in collection
  - rank docs by the probability of "generating" the query

$$P(q|M_D) = \prod_{t \in q}^{k} P(t|M_D)^{n(t,q)}$$

  - Computation often performed in the **log** domain:

$$\log P(q|M_D) = \sum_{t \in q} n(t,q) \cdot \log P(t|M_D)$$

- Drawbacks
  - no notion of relevance in the model: everything is random sampling
  - user feedback/query expansion not part of the model
    - examples of relevant documents cannot help improve M_D
    - only option is augmenting the original query Q with extra terms
    - could, in principle, make use of sample queries for which D is relevant
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Ranking with LMs

- Document likelihood: flip the direction of the query likelihood approach
  - estimate a language model M_Q for the query Q
  - rank docs D by the likelihood of being random sample from M_Q
  - M_Q expected to "predict" a typical relevant document

$$P(D|M_Q) = \prod_{w \in D} P(w|M_Q)$$

- Drawbacks
  - different doc lengths, probabilities not comparable
  - favors docs that contain frequent (low content) words
  - consider "ideal" (highest-ranked) document for a given query

$$\max_D \prod_{w \in D} P(w|M_Q) = \max_{w \in D} P(w|M_Q)^n$$

Ranking with LMs

- Other choices in the literature
  - Likelihood ratio
    - "fix" document likelihood
    - related to probability ranking principle
  - Model comparison
    - estimate query model and doc model
    - use measure such as cross-entropy, KL-divergence to compare them
  - Hang on, let's throw in some formulas… from query likelihood to KL divergence…

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From Query Log-Likelihood to KL Divergence

- $p(q|M_d) = \prod_{t \in q} p(t|M_d)^{n(t,q)}$
- $\log p(q|M_d) = \sum_{t \in q} n(t,q) \cdot \log p(t|M_d)$
- Generalize $n(t,q)$ to $p(t|M_q)$:
  - $\log p(q|M_d) = \sum_{t \in q} p(t|M_q) \cdot \log p(t|M_d)$
- Recall KL-divergence: measuring the difference between two probability distributions:

$$\mathrm{KL}(M_q \| M_d) = -\sum_t p(t|M_q) \log p(t|M_d) + cons(q)$$

  - For those of you in the know: $cons(q)$ is document-independent, the entropy of the query model M_q
  - $cons(q)$ does not affect the ranking of documents
  - Hence, maximizing the query log-likelihood provides the same ranking as minimizing the KL-divergence

From Query Log-Likelihood to KL Divergence

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- Generalize $n(t,q)$ to $p(t|M_q)$:
  - $\log p(q|M_d) = \sum_{t \in q} p(t|M_q) \cdot \log p(t|M_d)$
- Recall KL-divergence: measuring the difference between two probability distributions:

$$\mathrm{KL}(M_q \| M_d) = -\sum_t p(t|M_q) \log p(t|M_d) + cons(q)$$

  - For those of you in the know: $cons(q)$ is document-independent, the entropy of the query model M_q
  - $cons(q)$ does not affect the ranking of documents
  - Hence, maximizing the query log-likelihood provides the same ranking as minimizing the KL-divergence

From Query Log-Likelihood to KL Divergence

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Constructing a Document Model

- So far: retrieval = unigram language model estimation problem
- How to infer a document model?
  - Represent d by a multinomial probability distribution over the vocabulary of terms, $p(t|d)$
  - Maximum likelihood estimate of a term given by relative frequency:

$$p(t|d) = \frac{n(t,d)}{n(d)}$$

  - … plus smoothing
    - Jelink Mercer: linear interpolation with collection model

$$p(t|M_d) = (1-\lambda) \cdot p(t|d) + \lambda \cdot p(t)$$

    - Bayes smoothing aka Dirichlet smoothing

$$p(t|M_d) = \frac{n(t,d) + \beta \cdot p(t)}{n(d) + \beta}$$

(β often set to average doc length)

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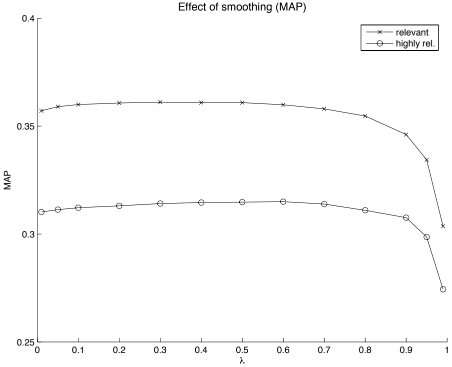
Experimental Results on Smoothing

- TREC enterprise document retrieval task: finding relevant documents in an enterprise collection
- Balog, Weerkamp, de Rijke, A few Examples Go A Long Way: Constructing Query Models from Elaborate Query Formulations, *SIGIR* 2008
- To set up baseline:
    - empirically best
    - maximize average precision of a small set user-provided documents
    - maximize query likelihood, again using that small set of user provided documents

Experimental Results on Smoothing

- Note peculiarites in the paper
  - $p(t|M_d) = (1 - \lambda) \cdot p(t|d) + \lambda \cdot p(t)$
  - Jelinek-Mercer smoothing
- Empirical exploration:



Further remarks about smoothing

- Jelinek-Mercer and Dirichlet generally work well for IR
- Zhai and Lafferty (2002) consider a two-stage smoothing method
  - explain unseen words
  - explain noise in the query
  - $p(t|d) = (1-\lambda)\frac{n(t,d)+\beta p(t)}{n(d)+\beta} + \lambda p(t|U)$
    where U is a user background model, which can be approximated by $p(t|GE)$
- Parsimonious language models: instead of blindly modeling language use (through MLE and/or smoothing), model what language usage distinguishes a relevant document from other documents
  - See tomorrow

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Outline

Exploiting Multiple Sources of Evidence

Some examples

- Document structure
  - Newspaper articles (lead, title)
  - HTML documents (content, meta tags, anchor texts)
- Collection structure
  - Digitial library, with multiple media types, multiple collections, multiple journals, etc.
  - Expert finding, with multiple sources of evidence (e.g., publications, profiles, course material, annual reports, ...)

Query Independent Factors
Some examples

- Factors other than content-similarity that may/should influence document ranking
- Examples
  - Time: searching a news archive; prefer more recent items over old items
  - Credibility:
    - Link structure: use page rank to identify "authoritative" pages
  - Quality indicators: language usage, host
  - Opinionatedness (for marketing analysts): lexical scoring plus (perhaps #comments)
  - Expert finding: approachability, media experience?
  - Past search behavior? Past click behavior?

Putting Things Together

- Recall: baseline model

$$p(d|q) \;\propto\; p(d) \cdot p(q|d) \;=\; p(d) \cdot \prod_{t_i \in q} p(t_i|d)$$

- Multiple sources of evidence combined into a *mixture model*:

$$p(d|q) \;\propto\; p(d) \cdot \prod_{t_i \in q} ((1 - \lambda_1 - \ldots - \lambda_k) p(t_i|S_{k+1}) + \lambda_1 p(t_i|S_1) + \ldots + \lambda_k p(t_i|S_k))$$

- and we use $p(d)$ to model the *priors*
  - assume independence and use product for multiple priors

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App 1: Entry Page Search

- Task: to find the home page of an institution ("the entry page")
  - E.g., *Hunt Memorial Library*
- Priors
  - The prior probability of relevance vs doc length
  - The prior probability of relevance vs #inlinks
  - URL depth ("slash counting")
- Sources of evidence
  - Anchor text
  - Content
- $p(d|q) \propto$
  $p(d) \prod_i ((1 - \lambda - \mu) p(t_i|GE) + \lambda p_{content}(t_i|d) + \mu p_{anchor}(t_i|d))$
- JM smoothing of $p_{content}$ and p_{anchor}

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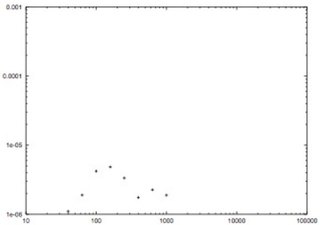
- Prior probabilities (doc length, #inlinks, log-log scales; url type)



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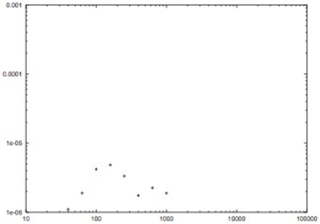

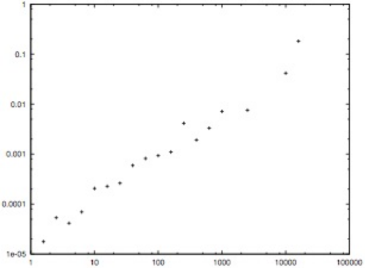

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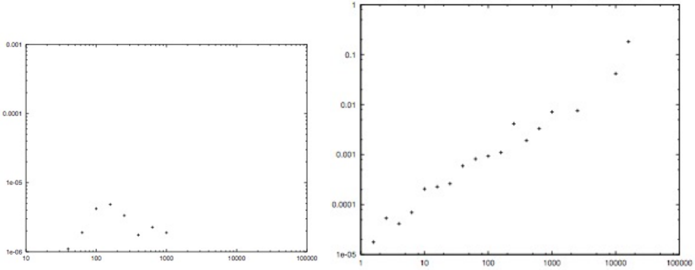

URL type	Entry pages		WT10g	
root	79	(73.1%)	12258	(0.7%)
subroot	15	(13.9%)	37959	(2.2%)
path	8	(7.4%)	83734	(4.9%)
file	6	(5.6%)	1557719	(92.1%)

App 1: Entry Page Search

- Kraaij, Westerveld, Hiemstra, Importance of Prior Probabilities for Entry Page Search, *SIGIR 2002*
  - TREC Web track 2001 data

Ranking method	Content ($\lambda = 0.9$)	Anchors($\lambda = 0.9$)
$P(Q\|D)$	0.3375	0.4188
$P(Q\|D)P_{doclen}(D)$	0.2634	0.5600
$P(Q\|D)P_{URL}(D)$	**0.7705**	0.6301
$P(Q\|D)P_{inlink}(D)$	0.4974	0.5365

Table 4: Results for different priors

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Table 4: Results for different priors

α	MRR
0.5	0.3978
0.7	0.4703
0.8	**0.4920**
0.9	0.4797

Table 5: Combining web page text and anchor text

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Ranking method	Content+Anchors ($\alpha = 0.8$)
$P(Q\|D)$	0.4920
$P(Q\|D)P_{URL}(D)$	**0.7748**
$P(Q\|D)P_{inlink}(D)$	0.5963

Table 6: Results for different priors(content+anchor)

App 2: Blog post retrieval

- Task: blog post retrieval
  - given a topic, identify blog posts ("utterances") that discuss the topic
  - E.g., *Macdonalds* or *iPhone* or *Basque*
  - $\neq$ blogger finding $\sim$ people with a recurring interest in the topic
- Weerkamp and De Rijke, Credibility Improvess Topical Blog Post Retrieval, *ACL 2008*
- Credibility indicators
  - Post level: capitalization, emoticons, shouting, spelling, post length, timeliness, semantic
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indicator	topic dependent?	post level/ blog level	related Rubin & Liddy indicator
capitalization	no	post	4b
emoticons	no	post	4b
shouting	no	post	4b
spelling	no	post	4b
post length	no	post	3a
timeliness	yes	post	3d
semantic	yes	post	3b, 3c
spam	no	blog	3b, 3c, 3f, 3g
comments	no	blog	1b
regularity	no	blog	2f
consistency	no	blog	2f

Table 1: Credibility indicators

App 2: Blog post retrieval

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  - $p(d) = \lambda \cdot p_{pl}(d) + (1 - \lambda) \cdot p_{bl}(d)$
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- Topic dependent indicators: create a query model that mixes a temporal query model and a semantic query model:
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App 2: Blog post retrieval

- But does it work?
- TREC Blog track post finding task, 2006, 2007
- Develop on 200x, test on 200y

App 2: Bl

- But doe
- TREC B
- Develop

	2006		2007	
	map	p@10	map	p@10
baseline	0.2156	0.4360	0.2820	0.5160
capitalization	0.2155	0.4500	0.2824	0.5160
emoticons	0.2156	0.4360	0.2820	0.5200
shouting	0.2159	0.4320	0.2833	0.5100
spelling	0.2179△	0.4480△	0.2839▲	0.5220
post length	0.2502▲	0.4960▲	0.3112▲	0.5700▲
timeliness	0.1865▼	0.4520	0.2660	0.4860
semantic	0.2840▲	0.6240▲	0.3379▲	0.6640▲
spam filtering	0.2093	0.4700	0.2814	0.5760▲
comments	0.2497▲	0.5000▲	0.3099▲	0.5600▲
regularity	0.1658▼	0.4940△	0.2353▼	0.5640△
consistency	0.2141▼	0.4220	0.2785▽	0.5040
post level (topic indep.)	0.2374▲	0.4920▲	0.2990▲	0.5660▲
post level (topic dep.)	0.2840▲	0.6240▲	0.3379▲	0.6640▲
post level (all)	0.2911▲	0.6380▲	0.3369▲	0.6620▲
blog level	0.2391▲	0.4500	0.3023▲	0.5580▲
all	0.3051▲	0.6880▲	0.3530▲	0.6900▲

Table 2: Retrieval performance on 2006 and 2007 topics, using $\lambda = 0.3$, $\beta = 0.4$, and $\mu = 0.0$.

Wrap Up and Look Ahead

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  - Mixture models and priors to incorporate document structure and aspects that go beyond relevance
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  - Cluster-based LMs
  - Applications to biomedical IR and more
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