Statistical Language Modeling for Information Access

Theory IV: Between IR and IE

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Outline

1. **Expertise Retrieval**
   - Setting the scence
   - Models for expertise retrieval
   - Let's evaluate
2. **Retrieving Questions from Question and Answer Archives**
3. **Wrap Up and Look Ahead**

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What Is Expertise Retrieval About?

- One line summary: **finding and profiling people** within an organizational setting
- Background, models for expertise retrieval, experimental setup and evaluation, recent developments
- Presentation mostly based on Krisztian Balog, *People Search in the Enterprise*, PhD thesis, U. Amsterdam, July 2008
  - `http://krisztianbalog.com/phd-thesis/`

From Documents to Things to People

- Increasingly, search engines become aware of entities and entity like classes: CDs, books, people, locations, answers, . . .
- This lecture: people and answers
- Why interesting
  - From a modeling point of view: entities are directly represented (yet)—you need to get to them by collecting evidence and associating it to them, somehow
  - Mixes information retrieval and information extraction, providing a level of focus not offered by document retrieval
  - People love to search for people


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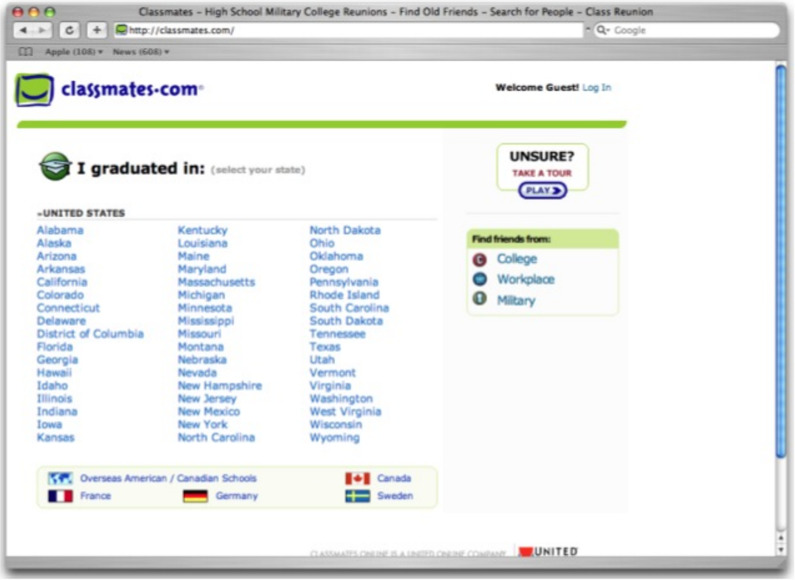
Classmates - High School Military College Reunions - Find Old Friends - Search for People - Class Reunion
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TAKE A TOUR
PLAY
UNITED STATES
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Colorado
Connecticut
Delaware
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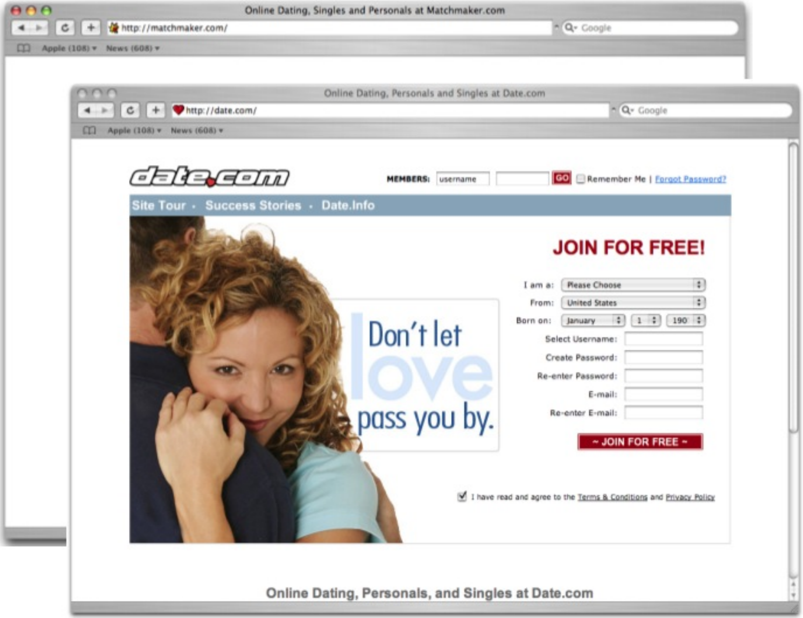
Online Dating, Singles and Personals at Matchmaker.com
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GO
Remember Me | Forgot Password?
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JOIN FOR FREE!
I am a:
Please Choose
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Select Username:
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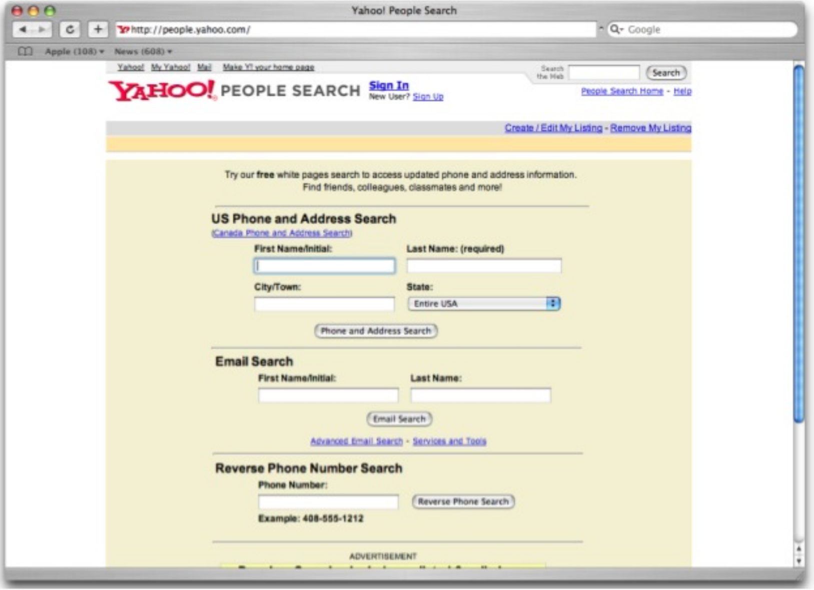
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Search
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New User? Sign Up
People Search Home - Help
Create / Edit My Listing - Remove My Listing
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Find friends, colleagues, classmates and more!
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(Canada Phone and Address Search)
First Name/Initial:
Last Name: (required)
City/Town:
State:
Entire USA
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First Name/Initial:
Last Name:
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Reverse Phone Number Search
Phone Number:
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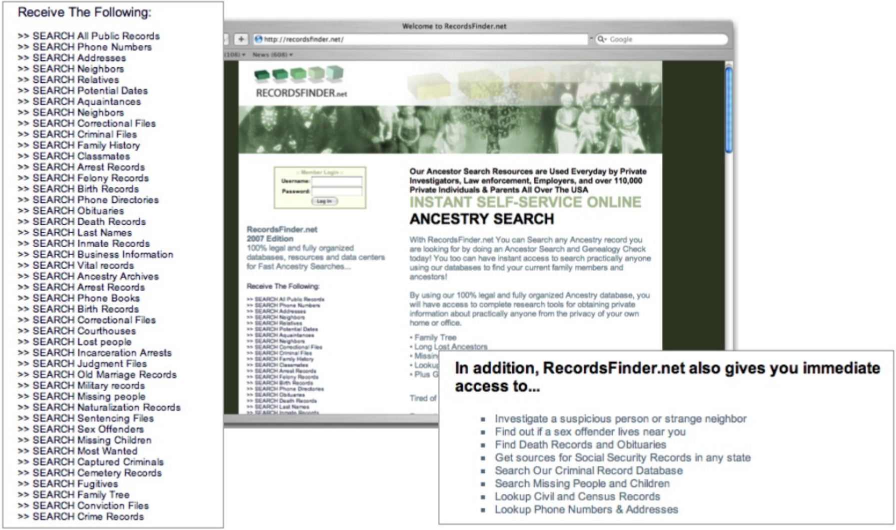
Receive The Following:
>> SEARCH All Public Records
>> SEARCH Phone Numbers
>> SEARCH Addresses
>> SEARCH Neighbors
>> SEARCH Relatives
>> SEARCH Potential Dates
>> SEARCH Aquaintances
>> SEARCH Neighbors
>> SEARCH Correctional Files
>> SEARCH Criminal Files
>> SEARCH Family History
>> SEARCH Classmates
>> SEARCH Arrest Records
>> SEARCH Felony Records
>> SEARCH Birth Records
>> SEARCH Phone Directories
>> SEARCH Obituaries
>> SEARCH Death Records
>> SEARCH Last Names
>> SEARCH Inmate Records
>> SEARCH Business Information
>> SEARCH Vital records
>> SEARCH Ancestry Archives
>> SEARCH Arrest Records
>> SEARCH Phone Books
>> SEARCH Birth Records
>> SEARCH Correctional Files
>> SEARCH Courthouses
>> SEARCH Lost people
>> SEARCH Incarceration Arrests
>> SEARCH Judgment Files
>> SEARCH Old Marriage Records
>> SEARCH Military records
>> SEARCH Missing people
>> SEARCH Naturalization Records
>> SEARCH Sentencing Files
>> SEARCH Sex Offenders
>> SEARCH Missing Children
>> SEARCH Most Wanted
>> SEARCH Captured Criminals
>> SEARCH Cemetery Records
>> SEARCH Fugitives
>> SEARCH Family Tree
>> SEARCH Conviction Files
>> SEARCH Crime Records
Welcome to RecordsFinder.net
http://recordsfinder.net/
RECORDSFINDER.net
Our Ancestor Search Resources are Used Everyday by Private Investigators, Law enforcement, Employers, and over 110,000 Private Individuals & Parents All Over The USA
INSTANT SELF-SERVICE ONLINE
ANCESTRY SEARCH
RecordsFinder.net
2007 Edition
100% legal and fully organized databases, resources and data centers for Fast Ancestry Searches...
With RecordsFinder.net You can Search any Ancestry record you are looking for by doing an Ancestor Search and Genealogy Check today! You too can have instant access to search practically anyone using our databases to find your current family members and ancestors!
By using our 100% legal and fully organized Ancestry database, you will have access to complete research tools for obtaining private information about practically anyone from the privacy of your own home or office.
Receive The Following:
• Family Tree
• Long Lost Ancestors
In addition, RecordsFinder.net also gives you immediate access to...
Investigate a suspicious person or strange neighbor
Find out if a sex offender lives near you
Find Death Records and Obituaries
Get sources for Social Security Records in any state
Search Our Criminal Record Database
Search Missing People and Children
Lookup Civil and Census Records
Lookup Phone Numbers & Addresses

Flavors of People Search

- Locating classmates and old friends
- Finding dates, partners
- White/yellow pages (name, addres, phone, . . .)
- Background check (recordsfinder.com: "investigate a susicious person or strange neighbor")
- Interest in this lecture: professional or work-related people search applications
  - A personnel officer wants to find information about a person who applied for a specific position
  - A company requires the state-of-the-art in some field, therefore they want to contact with someone from a knowledge institute
  - An enterprise needs to set up a task force to accomplish some objective

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Two Main Tasks

- Expert finding
  - Identifying a list of people who are knowledgeable about a given topic Who are the experts on topic X?
- Expert profiling
  - Returning a list of topics that a person is knowledgeable about
  - What topics does person Y know about?
- Concretely:

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- Concretely: `http://www.uvt.nl/webwijs/`

Additional Tasks

- Mining contact details
  - Essential for an operational system
- Finding similar experts
  - Counterpart of “find similar pages” feature of Web search engines
- Enterprise document search
  - Not just names, but documents relevant to the topic

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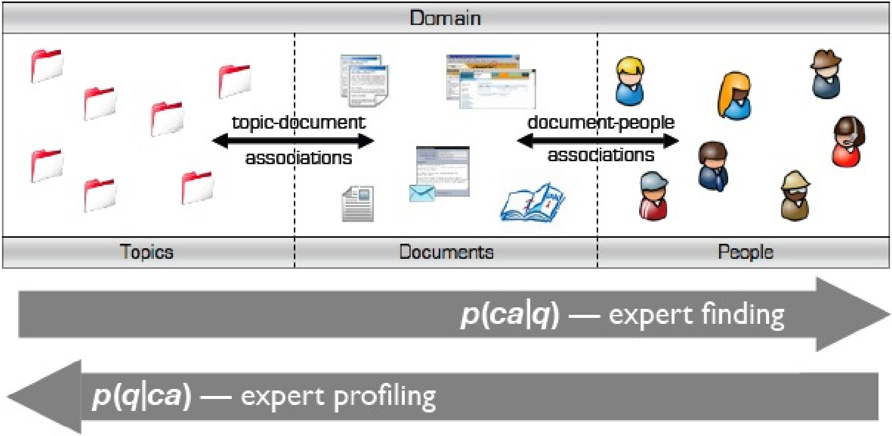
Language Modeling Framework

- Expert finding: $p(ca|q)$ — the probability of a candidate being an expert given the query topic q?
- Expert profiling: $p(q|ca)$ — the probability of a knowledge area (topic) being part of the candidate's profile?
- Use Bayes to reduce to $p(q|ca)$

Main Building Blocks



Quickly: Two Models for Expertise Retrieval

- Estimating $p(q|ca)$... how do we find experts?
  how do **you** find experts?

- An association finding problem
  - **candidate-based**: create a textual model candidates' knowledge according to the document with which they associated
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Model 1: Candidate Model

- Collect all term information from all documents associated with given candidate
- Smooth it with a background model
- Use this to represent candidate
- In a few steps
  - $p(t|M_{ca}) = (1-\lambda) \cdot p(t|ca) + \lambda \cdot p(t)$
  - $p(t|ca) = \sum_d p(t|d) \cdot p(d|ca)$
  - $p(q|M_{ca}) = \prod_{t \in q} p(t|M_{ca})^{n(t,q)}$
- Putting it altogether:
  $p(q|M_{ca}) =$
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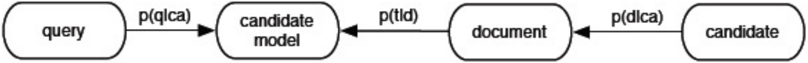

Model 2: Document Model

- Find docs relevant to query and determine who's most strongly associated with the relevant docs
- Step by step:
  - $p(q|ca) = \sum_d p(q|d)p(d|ca)$
  - $p(q|M_d) = \prod_{t \in q} p(t|M_d)^{n(t,q)}$
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- All in one:
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Document-Candidate Associations

- *Need*: estimate the probability that a doc is associated with a candidate — $p(d|ca)$
- *Assume*: extraction component produces $n(d, ca)$, the number of times person ca appears in doc d

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

- Multiple choices
  - Boolean: associations are binary; $p(ca|d) = 1$ if $n(ca, d) > 0$, 0 otherwise
  - TF.IDF like features
  - KL divergence (see below)
  - …

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Smoothing

- JM
- Dirichlet $\lambda = \frac{\beta}{\beta + n(x)}$
  where $n(x)$ is
  - Model 1: sum of lengths of all docs assocated with a given candidate ($x = ca$)
  - Model 2: document lenght ($x = d$)

  and β is the avg representation length
  - Model 1: of a candidate representation
  - Model 2: of a doc

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TREC enterprise track

- Tasks at the enterprise track

Task	TREC 2005	TREC 2006	TREC 2007
Expert search	x	x	x
E-mail known item search	x		
E-mail discussion search	x	x	
Document search			x

- Standard metrics: MAP, MRR, both for expert finding and for expert profiling
- Multiple collections, with their own characteristics...
    - W3C (TREC 2006, 2006): w3c.org
    - CSIRO (TREC 2007, 2008): csiro.au
    - UvT Epert Collection: uvt.nl/webwijs

Expert Finding: Model 1 vs Model 2

Model	TREC 2005		TREC 2006		TREC 2007	
	MAP	MRR	MAP	MRR	MAP	MRR
1	.1883	.4692	.3206	.7264	.3700	.5303
2	**.2053**	**.6088**$^{(2)}$	**.4660**$^{(3)}$	**.9354**$^{(3)}$	**.4137**$^{(1)}$	**.5666**

Table 5.1: Model 1 vs. Model 2 on the expert finding task, using the TREC 2005–2007 test collections. Best scores for each year are in boldface.

Expert Finding: Model 1 vs Model 2

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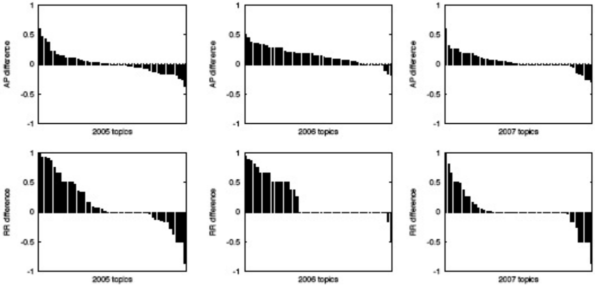

Figure 6.2: Topic-level differences in scores, Model 1 (baseline) vs Model 2. (Top): AP; (Bottom): RR. From left to right: TREC 2005, 2006, 2007.

Expert Profiling

Language	UvT ALL				UvT MAIN			
	Model 1		Model 2		Model 1		Model 2	
	MAP	MRR	MAP	MRR	MAP	MRR	MAP	MRR
English	.2023	.3913	**.2682**$^{(3)}$	**.4968**$^{(3)}$	.3003	.4375	**.3549**$^{(3)}$	**.5198**$^{(3)}$
Dutch	.2081	.4130	**.2503**$^{(3)}$	**.4963**$^{(3)}$	.2782	.4155	**.3102**$^{(3)}$	**.4854**$^{(3)}$

Table 5.5: Model 1 vs. Model 2 on ALL vs. MAIN topics of the UvT collection. Best scores for each language are in boldface.

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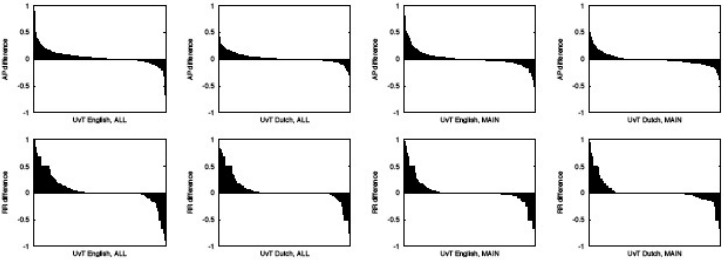

Figure 6.5: Topic-level differences in scores, Model 1 (baseline) vs Model 2. (Top): AP; (Bottom): RR. From left to right: English ALL, Dutch ALL, English MAIN, and Dutch MAIN.

Variations and Improvements

- Better estimates of candidate-document associations
- Bring in organisational structure
  - Smooth with documents from colleagues in the same group
- Proximity-based models
  - Passage/window based (M1B, M2B)
- Weigh candidate's weight in doc using KL-divergence between candidate's LM and doc LM
- Boosting underlying doc retrieval (BFB, query expansion using expert profiles, doc priors, . . .)
- Careful combination leads to MAP scores of **0.5267** on TREC 2007 data (M1B; SIGIR 2009)
- Up to **0.5405** with some "secret" ingredients (M1B; SIGIR 2009)
- Up to **0.5747** without secret sauce but with rich query model based on example documents (M1B; CIKM 2008)

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Variations and Improvements

- Better estimates of candidate-document associations
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- Finding Similar Experts task
  - Balog and De Rijke, SIGIR 2007
- Complement topic-centric models with contextual factors
  - Media experience, “up-to-date-ness”, organizational structure, reliability, proximity, position, …
  - Model as priors
- Experiment with Tilburg University science communicators
  - If the expert you’d normally recommend is not available, whom would you recommend?
- Contextual factors significantly improve early precision (MRR): $0.54 \rightarrow 0.59$
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Expertise Retrieval Upshot

- Going beyond documents
  - After all, document search has become a commodity (on the web, at least)
- Language models offer a flexible setting for modeling ER, accommodating priors, mixtures, etc.
- Very competitive performance on a range of ER tasks
- Lots of modeling work left to be done, lots of work on the interface of IR/IE left to be done
  - Be creative

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Hang on

If You Have A Hammer…

- Apply the underlying type-topic associations elsewhere
  - Stakeholders in the news
  - Influential authors on a given topic (digital library setting)
  - Intelligence
  - Blog distillation
  - Spotting moods associated with a given topic
  - Getting to know your politician
  - Automatic composition of committees, PCs, …
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- What's next
  - Web-based ER
  - Result presentation
  - New evaluation/application settings

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Outline

1. Expertise Retrieval
   - Setting the scence
   - Models for expertise retrieval
   - Let's evaluate
2. **Retrieving Questions from Question and Answer Archives**
3. Wrap Up and Look Ahead

Question Answering vs Question Retrieval

- QA has been around since the early 1960s
- Initially as a front end to (structured database)
  - Early fame for systems provided access to baseball data, data on rocks collected by NASA during its moon missions, ...
- Since late 1990s lot of attention for *corpus-based* QA: given a text corpus and a question, a system has to identify and return "the answer" (in the corpus)
- Recent rise in interest in *community-based QA*: retrieving questions that are similar to a given input query
  - FAQs (Jijkoun and de Rijke, CIKM 2005)
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Combining a Translation-Based LM with a QL Model

- Given a question, find a good answer in the repository
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- Xue et al combine a translation-based language model for the question part with a query likelihood approach for the answer part
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The Models

- Setting: query ("the user's question"): $\mathbf{q}$, archive consisting of (q, a) pairs

- $p(\mathbf{q}|(q,a)) = \prod_{w \in \mathbf{q}} p(w|(q,a))$
- $p(w|(q,a)) = \frac{|(q,a)|}{|(q,a)|+\lambda} p_{mx}(w|(q,a)) + \frac{\lambda}{|(q,a)|+\lambda} p_{ml}(w|GE)$
- $p_{mx}(w|(q,a)) = \alpha p_{ml}(w|q) + \beta \sum_{t \in q} p(w|t) p_{ml}(t|q) + \gamma p_{ml}(w|a)$

- Huh?
  - Generation probability of the question:

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  - Briefly: EM plus maximum likelihood estimates
- Compare: standard mixture LM ($\beta = 0$), translation model ($\gamma = 0$), everything together ($\alpha \cdot \beta \cdot \gamma > 0$)
- Evaluation: using 50 TREC QA questions, against a 1M (q, a) collection

Model	MAP	P@10
$\beta = 0$	0.3791	0.2368
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full	0.4885	0.3053

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What's Next Here?

- Parameter estimation
- Bringing in additional factors
  - Social features (number of stars)
  - Question class specific features
- ...

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Wrap Up and Look Ahead

- Summary
  - Getting started with expertise retrieval
  - A bit on retrieving questions and answers
- What else?
  - Learning to rank
  - Discriminative vs generative models
  - So many ranking criteria
  - Learning to rank (offline, online)
  - Semantic search
  - Query modeling
  - Evaluation methodology
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- So many things **you** can work on!

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