# Statistical Language Modeling for Information Access

## Practical IV: Pseudo Relevance Feedback

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## Outline of the Course

- Day 1: Installing and Indexing
- Day 2: Retrieval and Evaluation
- Day 3: Retrieval Parameters and Indri
- Day 4: Pseudo Relevance Feedback and Some More Evaluation; Additional bells, whistles and requests



## Outline

1. **Pseudo Relevance Feedback**
   - Lemur
   - Indri
2. **A Bit More On Evaluation**
   - Plotting
   - Statistical Testing
3. **Exercises**



## Lemur

- Lemur comes with five blind relevance feedback methods
- You can easily develop your own! Subclass RetrievalMethod and override the method updateQuery with your new method.
- All methods use, besides their own parameter values, two "global" parameter values:
  - `feedbackDocCount` – The number of documents to use for blind relevance feedback
  - `feedbackTermCount` – The number of terms to use



## Lemur

- To use them, put the `queryUpdateMethod` parameter in your retrieval parameter file
  - **mix** – Mixture
  - **div** – Divergence Minimization
  - **mc** – Markov Chain Translation Model
  - **rm1** – Relevance Model 1 (independent)
  - **rm2** – Relevance Model 2 (conditional)
- The first three use the parameter `feedbackMixtureNoise`
- Relevance models
  - only require the `feedbackDocCount` and `feedbackTermCount` parameters
  - require query-likelihood scores, so use `<adjustedScoreMethod>ql</adjustedScoreMethod>`



## Mixture

- Assume that each term $w$ in the set of feedback documents $\mathcal{F}$ is generated *independently* from some model $R$ (Zhai and Lafferty, *CIKM* 2001):

$$P(\mathcal{F}|R) = \prod_i \prod_w P(w|R)^{n(w,d_i)}$$

- Mix in a background model

$$P(\mathcal{F}|R) = \prod_i \prod_w ((1-\lambda)P(w|R) + \lambda P(w|GE))^{n(w,d_i)}$$

- Take the log to obtain the log-likelihood of the feedback documents:

$$\log P(\mathcal{F}|R) = \sum_i \sum_w n(w,d_i) \log((1-\lambda)P(w|R) + \lambda P(w|GE))$$



## Mixture

- Use an EM algorithm to determine $P(w|R)$

$$t(w) = n(w_i, d) \cdot \frac{(1-\lambda)P(w|R)}{(1-\lambda)P(w|R) + \lambda P(w|GE)}$$

$$P(w|R) = \frac{\sum_d t(w)}{\sum_{w'} \sum_d t(w')}$$

- Difference with yesterday's EM formula?
- `feedbackMixtureNoise` $= \lambda$
- One more parameter for this method: `emIterations`, which is the maximum number of iterations the EM algorithm will run (default: 50)
- The EM algorithm terminates earlier if the log-likelihood converges



## Divergence Minimization

- Minimize the divergence between the query model and each feedback document $d \in \mathcal{F}$ (Zhai and Lafferty, *CIKM* 2001):

$$D_c(M; \mathcal{F}, GE) = \frac{1}{\mathcal{F}} \sum_{i=1}^{n} D(M||\hat{M}_{d_i}) - \lambda D(M||P(\cdot|GE))$$

- This query model will give the *best average score over the feedback documents*
- After some rewriting, we obtain

$$P(w|R) \propto \exp\left(\frac{1}{1-\lambda}\frac{1}{|\mathcal{F}|}\sum_i \log P(w|M_{d_i}) - \frac{1}{1-\lambda}\log P(w|GE)\right)$$

- `feedbackMixtureNoise` $= \lambda$

## Markov Chain Translation Model

- Lafferty and Zhai, *SIGIR* 2001
- Inspired by Berger and Lafferty, *SIGIR* 1999
- Imagine a user looking to formulate a query for an information need
- She "surfs" the index in the following random manner
  - A word $w_0$ is chosen
  - A document $d_0$ containing that word is chosen (a choice which will be influenced by the number of times the word appears in $d_0$)
  - From that document, a new word $w_1$ is sampled
  - A new document containing $w_1$ is chosen
  - Etc.
  - After each step, there is some chance the user will stop browsing with probability $\alpha$



## Markov Chain Translation Model

- The posterior probability of sampling document $d_i$ after term $w_i$ is

$$P(d_i|w_i) = \frac{P(w_i|d_i)P(d_i)}{\sum_d P(w_i|d)P(d)}$$

- Having chosen a document $d_i$, a new word $w_{i+1}$ is sampled from it according to $P(\cdot|d_i)$
- If we have evidence in the form of (pseudo-)relevant documents, we can use this approach to sample expansion terms:

$$P(w|q,\mathcal{F}) \propto P(w) \sum_{d \in \mathcal{F}} P(d|w)P(q|d)$$

- `feedbackMixtureNoise` $= 1 - \alpha$ (!)



## Example RetEval parameter file

```
<parameters>
<index>/path/to/your/index</index>
<retModel>kl</retModel>
<textQuery>path/to/queries.ldf</textQuery>
<resultCount>1000</resultCount>
<resultFile>queries.res</resultFile>
<TRECResultFormat>1</TRECResultFormat>
<smoothMethod>jm</smoothMethod >
<JelinekMercerLambda>0.15</JelinekMercerLambda>
<feedbackDocCount>10</feedbackDocCount>
<feedbackTermCount>5</feedbackTermCount>
<queryUpdateMethod>rm1</queryUpdateMethod>
<adjustedScoreMethod>ql</adjustedScoreMethod>
</parameters>
```



## Interpolation

- After generating the expanded model using one of the methods, the original query may be blended in
- The following parameter values apply:
  - `feedbackCoefficient` – the coefficient of the feedback model for interpolation
    - The value ranges from 0-1
    - 0 meaning using only the original model (thus no updating/feedback)
    - 1 meaning using only the feedback model (thus ignoring the original model)
  - `feedbackTermCount` – Truncate the feedback model to no more than a given number of terms
  - `feedbackProbThresh` – Truncate the feedback model to include only words with a probability higher than this threshold (default 0.001)
  - `feedbackProbSumThresh` – Truncate the feedback model until the sum of the probability of the included words reaches this threshold (default 1)



## Indri

- Indri only implements relevance model 1 (independent)
- The initial retrieval of pseudo-relevant documents is **always** done using Dirichlet smoothing
- Specify one of the parameter settings below to enable feedback
  - `fbDocs` – number of feedback documents
  - `fbTerms` – number of terms to use
  - `fbOrigWeight` – interpolation weight of the original query (note that this is the inverse of Lemur!)

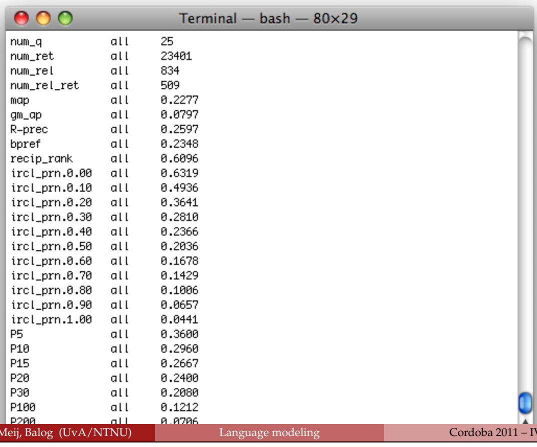


## Indri Example

```
<parameters>
<index>/path/to/your/index</index>
<rule>method:jm,lambda:0.15</rule>
<count>1000</count>
<trecFormat>1</trecFormat>
<fbTerms>5</fbTerms>
<fbDocs>10</fbDocs>
<fbOrigWeight>0.2</fbOrigWeight>
</parameters>
```



## trec_eval



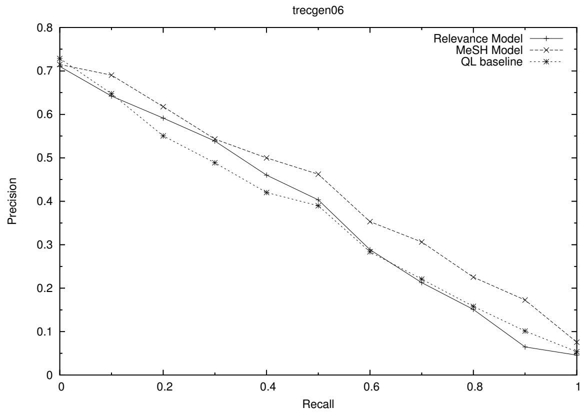
```
Terminal — bash — 80×29
num_q          all   25
num_ret        all   23401
num_rel        all   834
num_rel_ret    all   509
map            all   0.2277
gm_ap          all   0.0797
R-prec         all   0.2597
bpref          all   0.2348
recip_rank     all   0.6096
ircl_prn.0.00  all   0.6319
ircl_prn.0.10  all   0.4936
ircl_prn.0.20  all   0.3641
ircl_prn.0.30  all   0.2810
ircl_prn.0.40  all   0.2366
ircl_prn.0.50  all   0.2036
ircl_prn.0.60  all   0.1678
ircl_prn.0.70  all   0.1429
ircl_prn.0.80  all   0.1006
ircl_prn.0.90  all   0.0657
ircl_prn.1.00  all   0.0441
P5             all   0.3600
P10            all   0.2960
P15            all   0.2667
P20            all   0.2400
P30            all   0.2080
P100           all   0.1212
P200           all   0.0706
```



## Plotting

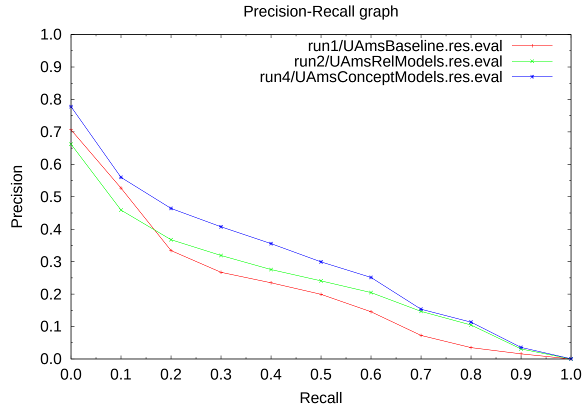
- Scripts on the course web site
  - Requires Perl and Gnuplot
  - If you run Windows, consider using cygwin
- Precision-Recall graphs
  - Displays precision at fixed recall points
  - Used often in IR evaluations
  - Script: `ProcessPR.pl [trec_eval_output_files]`

## Precision-Recall graphs






## Precision-Recall graphs



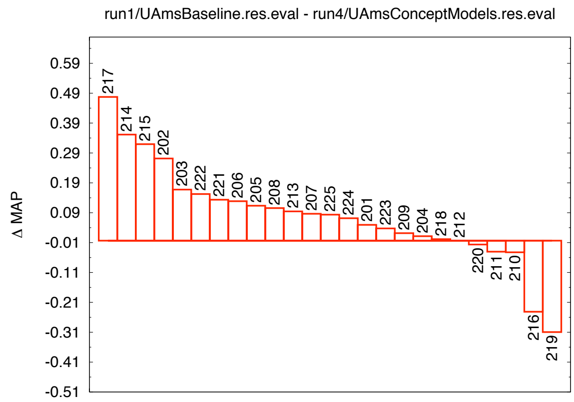



## Plotting

- Per-topic differences
  - Displays a per-topic comparison between two runs on a chosen measure
  - Useful for determining which topics are hurt/helped as well as to get a general feel for how many topics were helped/hurt
  - Script: `plotRunDifference.pl <measure> <trec_eval_output_file_1> < trec_eval_output_file_2>`



## Per-topic differences






## Statistical Testing

- Which test to use?
  - Sign test (weakest)
  - Wilcoxon
  - Paired t-test (strongest)
- Paired t-test script for comparing two retrieval runs on the course web site



## Outline





## Exercises

- Choose the KL-divergence retrieval model, a smoothing method, and a set of smoothing parameters
- Compare results of different relevance feedback approaches
  - Different strategies
  - Different settings
- Report on (interesting) differences
- Plot the results
- Perform statistical tests to determine whether two runs are significantly different
- Where does relevance feedback help? hurt? In terms of precision, recall or some average? Why?