Language Models

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Outline

- Role of LM in ASR and SMT
- N-gram Language Models
- Evaluation of Language Models
- Frequency Smoothing
- Frequency Discounting
- Is smoothing necessary?
- ARPA LM representation
- New IRSTLM Toolkit

Fundamental Equation of ASR

Goal: find the words $\mathbf{w}^*$ in a speech signal $\mathbf{x}$ such that:

$$\mathbf{w}^* = \arg \underset{\mathbf{w}}{max} \Pr(\mathbf{x} \mid \mathbf{w}) \Pr(\mathbf{w}) \quad (1)$$

Problems:

- language modeling (LM): estimating $\Pr(\mathbf{w})$
- acoustic modeling (AM): estimating $\Pr(\mathbf{x} \mid \mathbf{w})$
- search problem: computing (1)

AM sums over hidden state sequences $\mathbf{s}$ a Markov process of $(\mathbf{x}, \mathbf{s})$ from $\mathbf{w}$

$$\Pr(\mathbf{x} \mid \mathbf{w}) = \sum_{\mathbf{s}} \Pr(\mathbf{x}, \mathbf{s} \mid \mathbf{w})$$

Hidden Markov Model: hidden states "link" speech frames to words.

Fundamental Equation of SMT

Goal: find the English string $\mathbf{f}$ translating the foreign text $\mathbf{f}$ such that:

$$\mathbf{e}^* = \arg \underset{\mathbf{e}}{max} \Pr(\mathbf{f} \mid \mathbf{e}) \Pr(\mathbf{e}) \tag{2}$$

Problems:

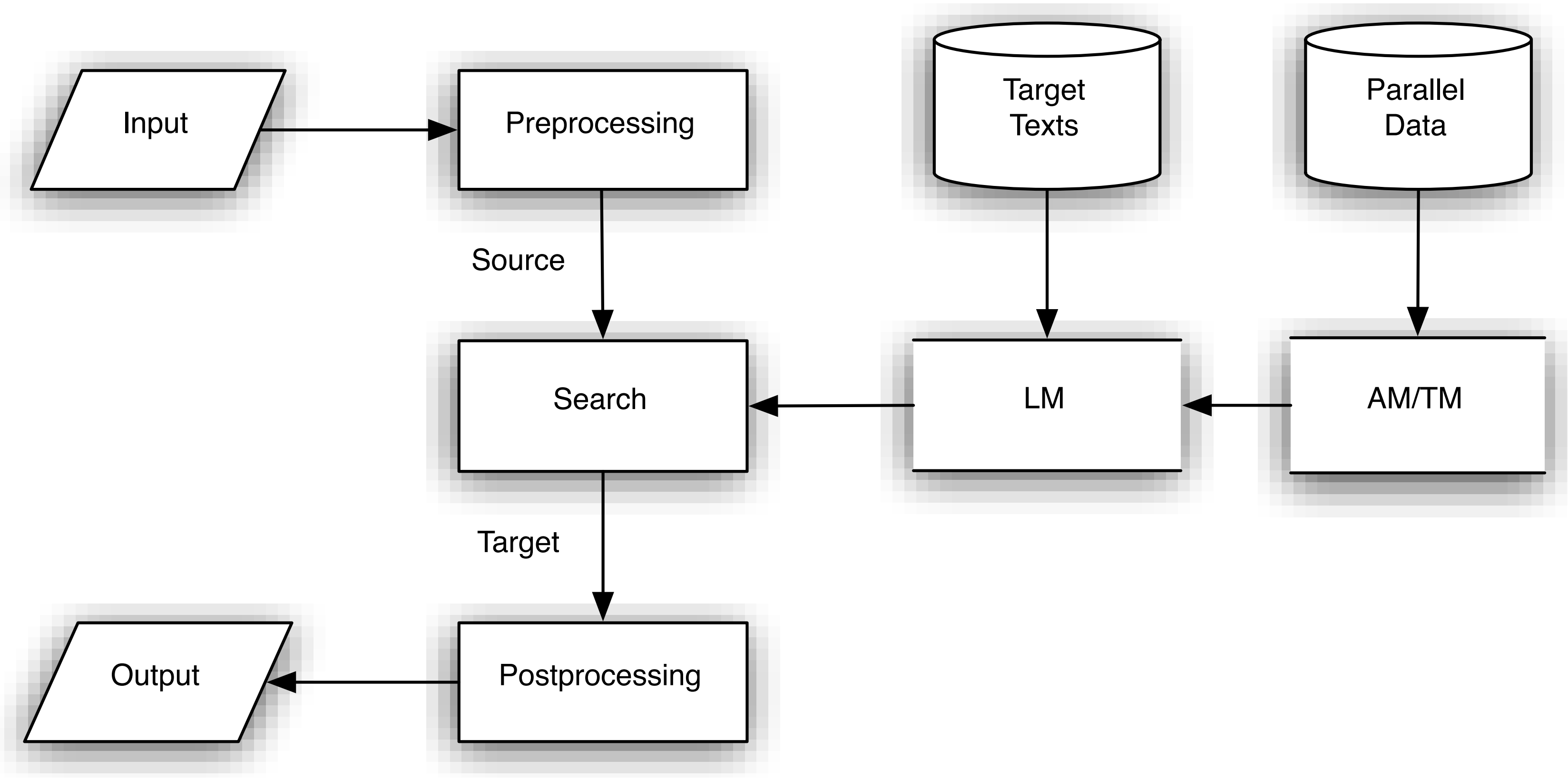
- language modeling (LM): estimating $\Pr(\mathbf{e})$
- translation modeling (TM): estimating $\Pr(\mathbf{f} \mid \mathbf{e})$
- search problem: computing (2)

TM sums over hidden alignments $\mathbf{a}$ a stochastic process generating $(\mathbf{f}, \mathbf{a})$ from $\mathbf{e}$.

$$\Pr(\mathbf{f} \mid \mathbf{e}) = \sum_{\mathbf{a}} \Pr(\mathbf{f}, \mathbf{a} \mid \mathbf{e})$$

Alignment Models: hidden alignments "link" foreign words with English words.

ASR and MT Architectures



- Parallel data are samples of observations $(\mathbf{x}, \mathbf{w})$ and $(\mathbf{f}, \mathbf{e})$
- AM and TM can be machine-learned without observing $\mathbf{s}$ and $\mathbf{a}$.

Log-linear phrase-based SMT

- Translation hypotheses are ranked by:

$$\mathbf{e}^* = \arg\max_{\mathbf{e}} \sum_{\mathbf{a}} \sum_{k} \lambda_k \log h_k(\mathbf{e}, \mathbf{f}, \mathbf{a})$$

- Phrases are finite string (cf. n-grams)
- Hidden variable $\mathbf{a}$ embeds:
  – segmentation of $\mathbf{f}$ and $\mathbf{e}$ into phrases
  – alignment of phrases of $\mathbf{f}$ with phrases of $\mathbf{e}$
- Feature functions $h_k()$ include:
  – Translation Model: appropriateness of phrase-pairs
  – Distortion Model: word re-ordering
  – Language Model: fluency of target string
  – Length Model: number of target words
- Role of the LM is exactly the same as for the classical approach:
  – to score translations generated incrementally by the search algorithm!

N-gram Language Model

Goal: given a text $w_1^T = w_1 \ldots, w_t, \ldots, w_T$ we can compute its probability by:

$$\Pr(w_1^T) = \Pr(w_1) \prod_{t=2}^{T} \Pr(w_t \mid h_t) \tag{3}$$

where $h_t = w_1, \ldots, w_{t-1}$ indicates the history of word w_t.

- $\Pr(w_t \mid h_t)$ becomes difficult to estimate as the history h_t grows .
- hence, we take the n-gram approximation $h_t \approx w_{t-n+1} \ldots w_{t-1}$

  e.g. Full history: $\Pr(\texttt{Parliament} \mid \texttt{I declare resumed the session of the European})$
  $3 - gram$: $\Pr(\texttt{Parliament} \mid \texttt{the European})$

The choice of n determines the complexity of the LM (# of parameters):

- bad: no magic recipe about the optimal order n for a given task
- good: language models can be evaluated quite cheaply

Language Model Evaluation

- Indirect: impact on task (e.g. BLEU score for MT)
- Direct: capability of predicting words

The perplexity (PP) measure is defined as: [1]

$$PP = 2^{LP} \quad \text{where} \quad LP = -\frac{1}{M}\log_2 p(w_1^M) \tag{4}$$

- w_1^M is a sufficiently long test sample and $p(w_1^M)$ is the LM probability

Properties:

- $0 \leq PP \leq |V|$ (size of the vocabulary V)
- predictions are as good as guessing among PP equally likely options

Good: there is typical strong correlation between PP and BLUE scores!

[1] [Exercise 1. Find PP of 1-gram LM $p(\texttt{T})$=0.5 on T H T H T H T T H T T H.]

N-gram Probabilities

Estimating n-gram probabilities is not trivial due to:

- parameter space: with 10,000-word V we can form one trillion 3-grams!
- data sparseness: most of 3-grams are rare events even in large corpora.

Relative frequency estimate: MLE of any discrete conditional distribution is:

$$f(w \mid x\ y) = \frac{c(x\ y\ w)}{\sum_w c(x\ y\ w)}$$

where counts $c(\cdot)$ are taken over a large training corpus.

Problem: relative frequencies in general over-fit the training data

- if the test sample contains a "new" n-gram PP $\rightarrow +\infty$
- with 4-grams or 5-grams LM this is largely the most frequent case!

We need frequency smoothing!

Frequency Smoothing

Issue: $f(w \mid x\ y) > 0$ only if w was observed after $x\ y$ in the training data.

Idea: for each w take off some fraction of probability from $f(w \mid x\ y)$ and redistribute the total to words never observed after $x\ y$.

- the discounted frequency $f^*(w \mid x\ y)$ satisfies:

$$0 \leq f^*(w \mid x\ y) \leq f(w \mid x\ y) \qquad \forall x, y, w \in V$$

  Notice: in general $f^*(w \mid x\ y)$ does not sum up to 1!

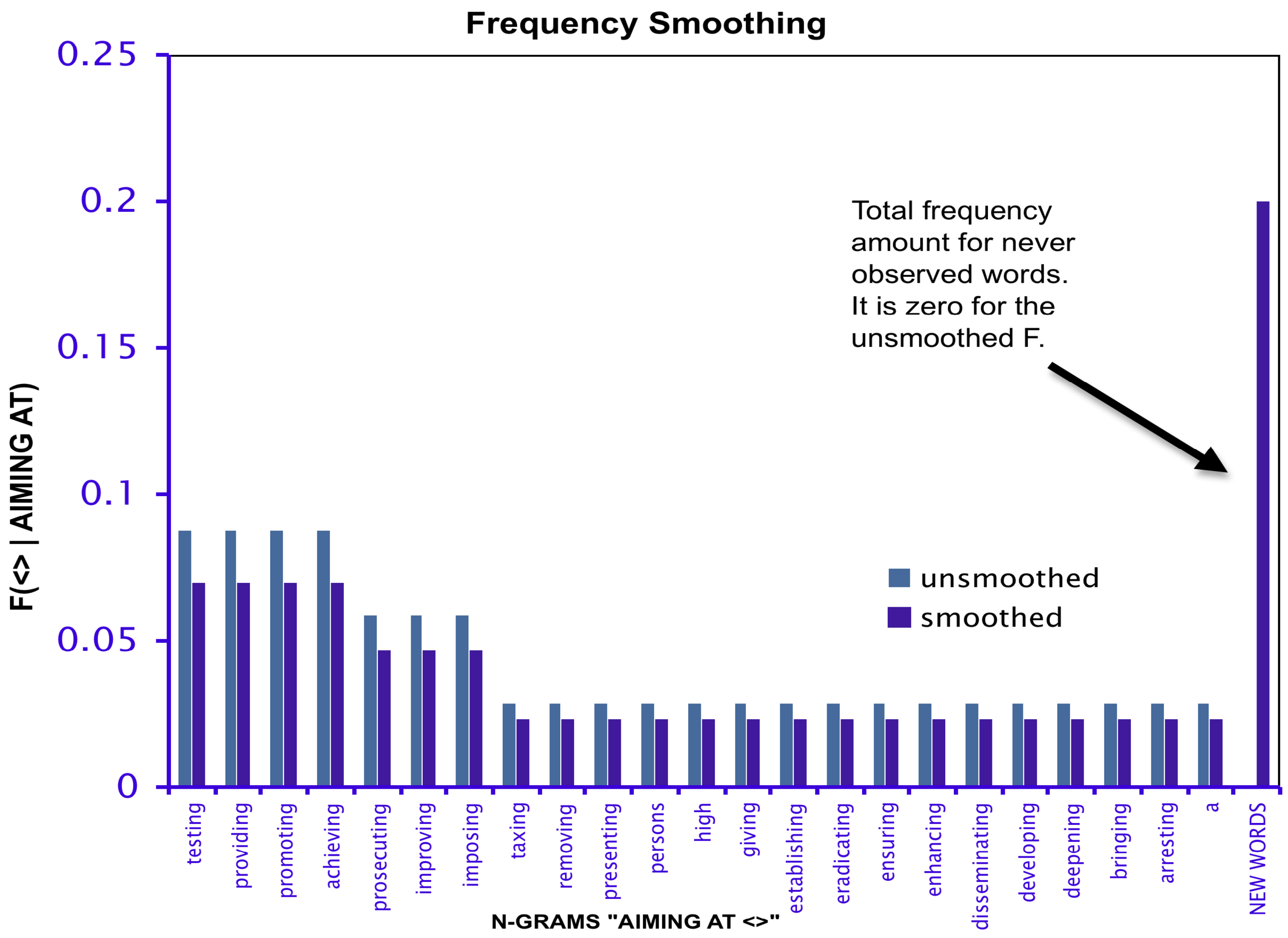
- the "total discount" is called zero-frequency probability $\lambda(x\ y)$[2]:

$$\lambda(x\ y) = 1.0\ -\ \sum_{w \in V} f^*(w \mid x\ y)$$

How to redistribute the total discount?

[2]Notice: by convention $\lambda(x\ y) = 1$ if $f(w \mid x\ y) = 0$ for all w, i.e. $c(x\ y) = 0$.

Discounting Example



Frequency Smoothing

Insight: redistribute $\lambda(x\ y)$ according to the lower-order smoothed frequency.

Two major hierarchical schemes to compute the smoothed frequency $p(w \mid x\ y)$:

- Back-off, i.e. select the best available n-gram approximation:

$$p(w \mid x\ y) = \begin{cases} f^*(w \mid x\ y) & \text{if } f^*(w \mid x\ y) > 0 \\ \alpha_{xy}\lambda(x\ y)p(w \mid y) & \text{otherwise} \end{cases} \quad (5)$$

  where α_{xy} is an appropriate normalization term.[3]

- Interpolation, i.e. sum up the two approximations:

$$p(w \mid x\ y) = f^*(w \mid x\ y) + \lambda(x\ y)p(w \mid y). \quad (6)$$

Smoothed frequencies are learned bottom-up, starting from 1-grams ...

[3][Exercise 2. Find and expression for α_{xy} s.t. $\sum_w p(w \mid x\ y) = 1$.]

Frequency Smoothing of 1-grams

Unigram smoothing permits to treat out-of-vocabulary (OOV) words in the LM.

Assumptions:

- $|U|$ is an upper-bound estimate of the size of language vocabulary
- $f^*(w)$ is strictly positive on the observed vocabulary V
- λ is the total discount reserved to OOV words

Then: 1-gram back-off and interpolation collapse to:

$$p(w) = \begin{cases} f^*(w) & \text{if } \; w \in V \\ \lambda(|U| - |V|)^{-1} & \text{otherwise} \end{cases} \tag{7}$$

Notice: LMs make also other approximations when an OOV word x appears:

$$p(w \mid h_1 \; x \; h_1) = p(w \mid h_2) \;\; \text{and} \;\; p(x \mid h) = p(x)$$

Important: use a common value $|U|$ when comparing/combining different LMs!

Discounting Methods

Witten-Bell estimate (WB) [Witten and Bell, 1991]

- Insight: learn $\lambda(x\ y)$ by counting "new word" events in 3-grams `x y *`
  - corpus: `x y u x x y t t x y u w x y w x y t u x y u x y t`
  - then $\lambda(x\ y) \propto$ number of "new word" events (i.e. 3)
  - and $f^*(w \mid x\ y) \propto$ relative frequency (linear discounting)
- Solution:

$$\lambda(x\ y) = \frac{n(x\ y\ *)}{c(x\ y) + n(x\ y\ *)} \quad \text{and} \quad f^*(w \mid xy) = \frac{c(x\ y\ w)}{c(x\ y) + n(x\ y\ *)}$$

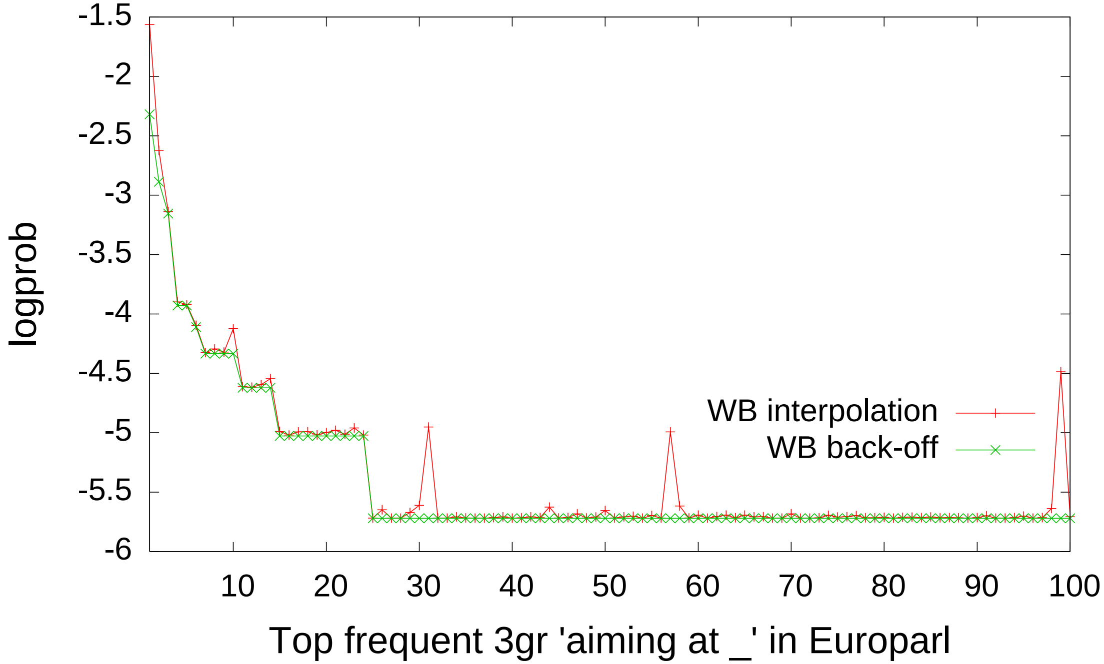
where $c(x\ y) = \sum_w c(x\ y\ w)$ and $n(x\ y\ *) = |\{w : c(x\ y\ w) > 0\}|$. [4]

- Pros: easy to compute, robust for small corpora, works with artificial data.
- Cons: underestimates probability of frequent n-grams

[4] [Exercise 3. Compute $f^*(\mathtt{u} \mid \mathtt{x\ y})$ with WB on the above artificial text.]

Discounting Methods

- interpolation and back-off with WB discounting
- trigram LMs estimated on the English Europarl corpus
- logprobs of 3-grams of type `aiming at _` observed in training



- peaks correspond to very probable 2-grams interpolated with f^* respectively: `at that`, `at national`, `at European`
- Practically, interpolation and back-off perform similarly

Absolute Discounting (AD) [Ney and Essen, 1991]

- Insight:
  - discount by subtracting a small constant β $(0 < \beta \leq 1)$ from each counts
  - estimate β by maximizing the leaving-one-out likelihood of the training data
- Solution: (notice: one distinct β for each n-gram order)

$$f^*(w \mid x\ y) = max\left\{\frac{c(xyw) - \beta}{c(xy)}, 0\right\} \text{ which gives } \quad \lambda(xy) = \beta\frac{\sum_{w:c(xyw)>1} 1}{c(xy)}$$

where $\beta \approx \frac{n_1}{n_1+2n_2} < 1$ and $n_r = |\{x\ y\ w : c(x\ y\ w) = r\}|$. [5]

- Pros: easy to compute, accurate estimate of frequent n-grams.
- Cons: problematic with small and artificial samples.

[5] [Exercise 4. Given the text in WB slide find the number of 3-grams, n_1, n_2, β, $f^*(\mathtt{w} \mid \mathtt{x\ y})$ and $\lambda(\mathtt{x\ y})$]

Discounting Methods

Kneser-Ney method (KN) [Kneser and Ney, 1995]

- Insight: 2-grams counts should be correspond to the "back-off" cases
  - count all "back-off" events in 3-grams of type `* y w` (cf. WB method)
  - corpus: `x y w x t y w t x y w u y w t y w u x y w u u y w`
  - corrected counts $n(*\ y\ w)$ = number of observed back-offs (i.e. 3)

- Solution: (for 3-gram normal counts)

$$f^*(w \mid y) = max\left\{\frac{n(*\ y\ w) - \beta}{n(*\ y\ *)}, 0\right\} \text{ which gives } \quad \lambda(y) = \beta\frac{\sum_{w:n(*\ y\ w)>1} 1}{n(*\ y\ *)}$$

where $n(*\ y\ w) = |\{x : c(x\ y\ w) > 0\}|$ and $n(*\ y\ *) = |\{x\ w : c(x\ y\ w) > 0\}|$

- Pros: better back-off probabilities, can be applied to other methods
- Cons: LM cannot be used to compute lower order n-gram probs

Discounting Methods

Modified Kneser-Ney (MKN) [Chen and Goodman, 1999]

- Insight: specific discounting coefficients for unfrequent n-grams
- Solution:

$$f^*(w \mid x\ y) = \frac{c(x\ y\ w) - \beta(c(x\ y\ w))}{c(x\ y)}$$

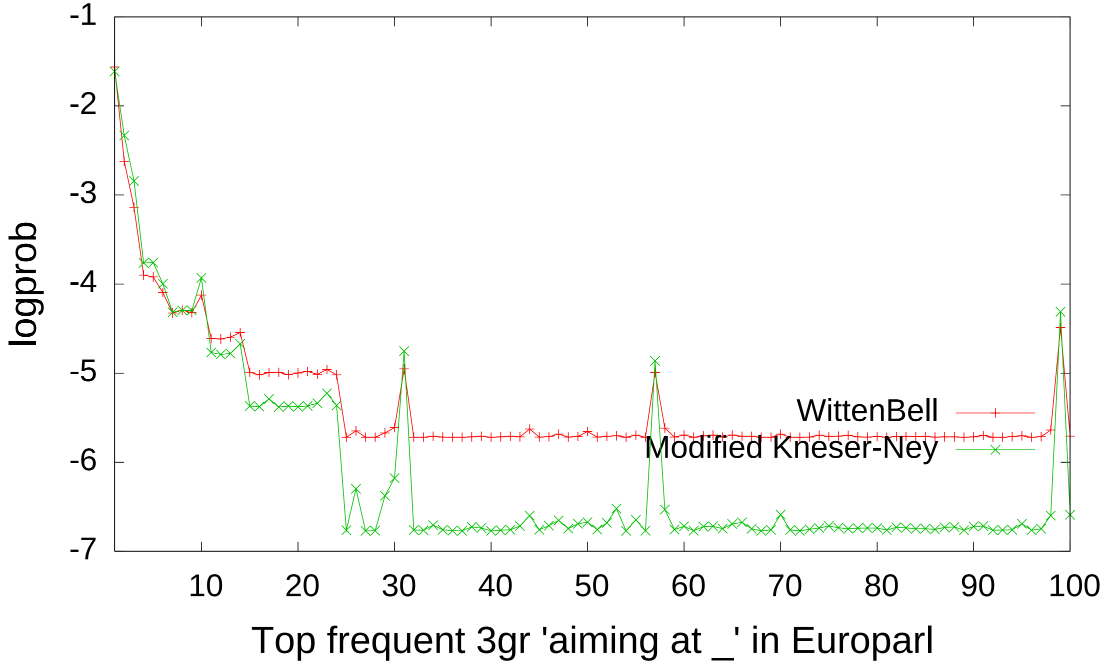
where $\beta(0) = 0$, $\beta(1) = D_1$, $\beta(2) = D_2$, $\beta(c) = D_{3+}$ if $c \geq 3$, coefficients are computed from n_r statistics, corrected counts used for lower order n-grams

- Pros: see previous + more fine grained smoothing
- Cons: see previous + more sensitiveness to noise

Important: LM interpolation with MKN is the most popular training method. Under proper training conditions it gives the best PP and BLEU scores!

Discounting Methods

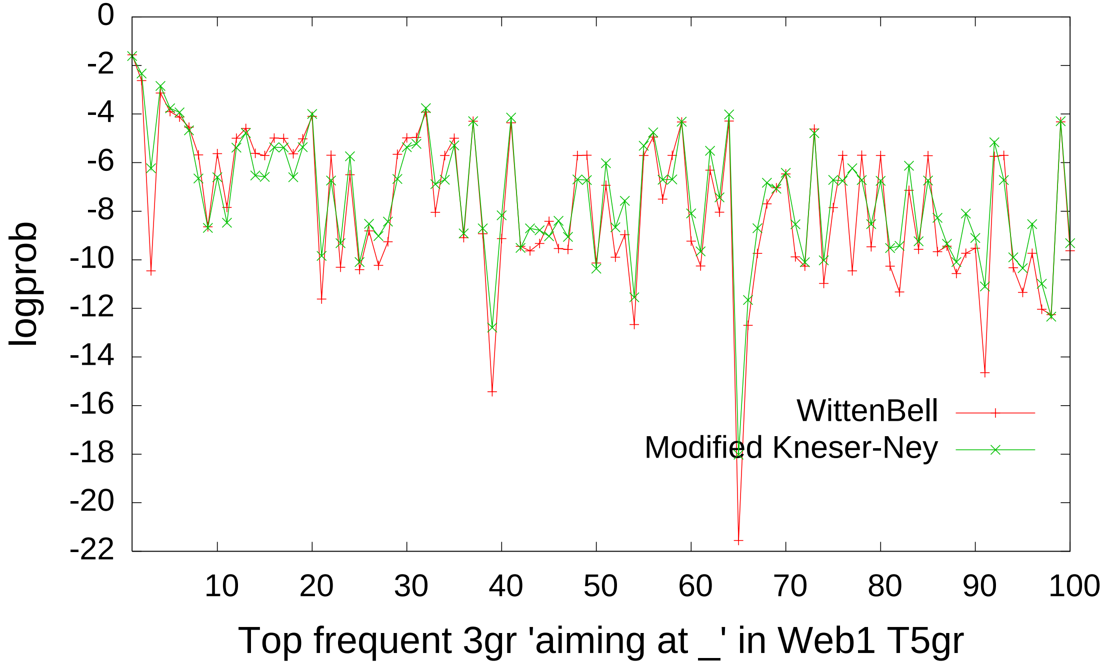
- interpolation with WB and MKN discounting trained on Europarl
- the plot shows the logprob of observed 3-grams of type `aiming at _`



- notice that for less frequent 3-grams WB assigns higher probability
- we have three very high peaks corresponding large corrected counts:
  `n(*at that)=665 n(* at national)=598 n(* at European)=1118`
- also an interesting peak at rank #26: n(* at very)=61

Discounting Methods

- train: interpolation with WB and MKN discounting on Europarl
- test: 3-grams of type `aiming at _` are from the Google 1TWeb sample

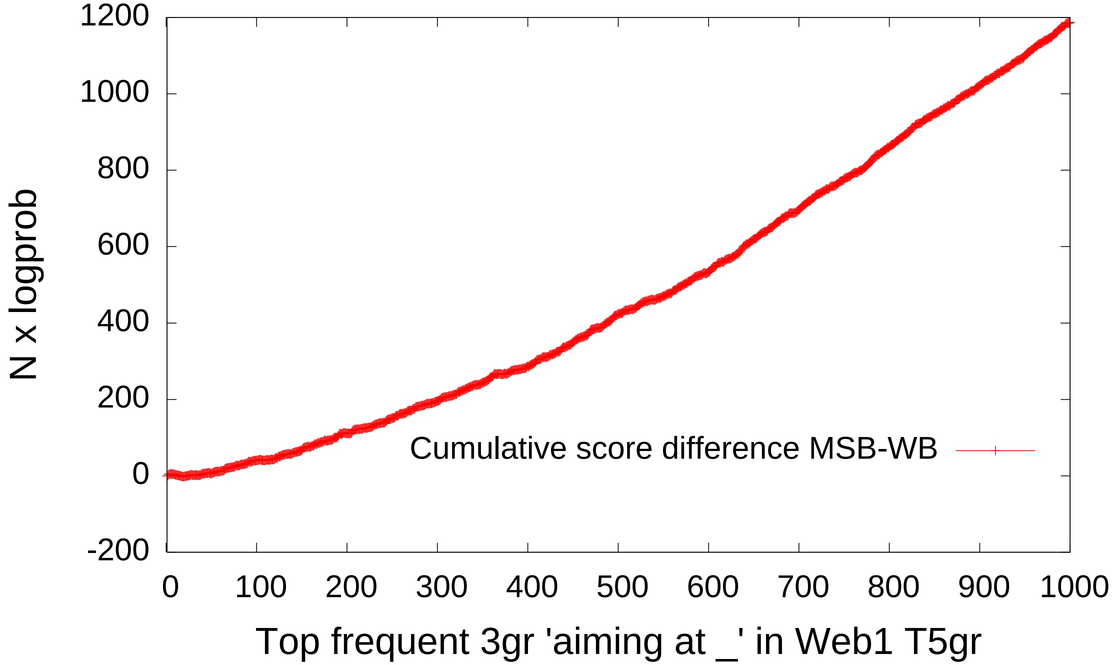


- the trend is the same but MKN outperforms WB smoothing

If you don't believe, check the next slide ....

Discounting Methods

- train: interpolation with WB and MKN discounting on Europarl
- test: 3-grams of type `aiming at _` are from the Google 1TWeb sample
- plot: cumulative score differences between MKN and WB on top 1000 3-grams



Is LM Smoothing Necessary?

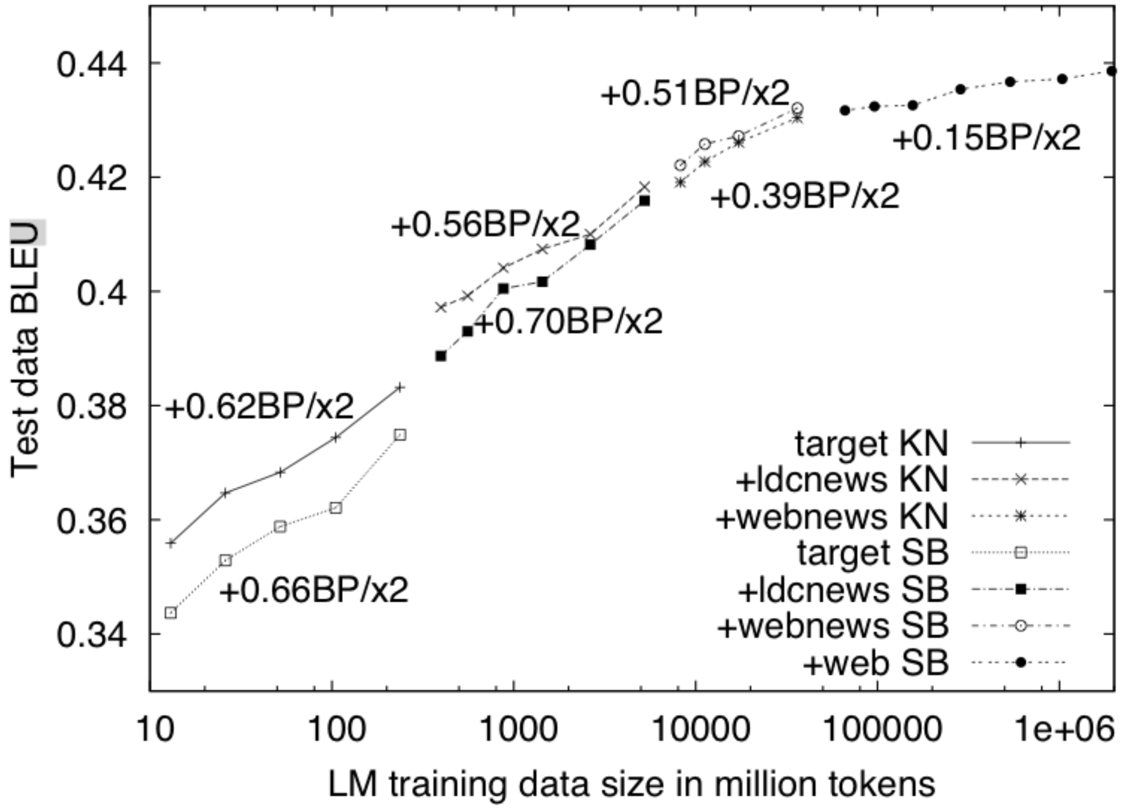
- LM Quantization [Federico and Bertoldi, 2006]
  - Idea: one codebook for each n-gram/back-off level
  - Pros: improves storage efficiency
  - Cons: reduces discriminatory power
  - Experiments with 8bit quantization on ZH-EN NIST task showed:
    * 2.7% BLUE drop with a 5-gram LM trained on 100M-words
    * 1.6% BLUE drop with a 5-gram LM trained on 1.7G words.
- Stupid back-off [Brants et al., 2007]
  - simple smoothing, no correct normalization

$$p(w \mid x\ y) = \begin{cases} f(w \mid x\ y) & \text{if } f(w \mid x\ y) > 0 \\ k \cdot p(w \mid y) & \text{otherwise} \end{cases} \tag{8}$$

where $k = 0.4$ and $p(w) = c(w)/N$.

Is LM Smoothing Necessary?

Stupid back-off (SB) versus Modified Kneser-Ney (KN)



From [Brants et al., 2007].

- Conclusion: proper smoothing useful up to 1 billion word training data?

ARPA File Format (srilm, irstlm)

Represents both interpolated and back-off n-gram LMs

- format: log(smoothed-freq) :: n-gram :: log(back-off weight)
- computation: look first for smoothed-freq, otherwise back-off

```
\data\
ngram 1= 86700
ngram 2= 1948935
ngram 3= 2070512
\1-grams:
-2.88382        !       -2.38764
-2.94351        world       -0.514311
-6.09691        dublin       -0.15553
...
\2-grams:
-3.91009     world !     -0.351469
-3.91257     hello world  -0.24
-3.87582     hello dublin    -0.0312
..
\3-grams:
-0.00108858     hello world  !
-0.000271867    , hi hello  !
...
\end\
```

```
logPr(!| hello dublin) = -0.0312 + logPr(!| dublin)
logPr(!| dublin) = -0.15553 - 2.88382
```

New IRSTLM Toolkit

Main Features [Federico et al., 2008]

- Single thread training for standard LMs
  - all major smoothing methods: WB, AD, MKN, ...
  - LM pruning, internal/external interpolation, adaptation
- Distributed training for huge LMs
  - simple smoothing methods: interpolation with WB, KN
  - split dictionary into balanced n-gram prefix lists
  - collect n-grams for each prefix lists
  - estimate and merge single LMs for each prefix list
- Space optimization
  - n-gram collection uses dynamic storage to encode counters
  - distributed LM estimation just requires reading disk files
  - probs and back-off weights are quantized
  - run-time LM data structure is loaded on demand
- LM caching
  - computations of probs, access to internal lists, LM states, ...

References

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