

LM Smoothing (The EM Algorithm)

PA154 Jazykové modelování (3)

Pavel Rychlý

pary@fi.muni.cz

March 16, 2021

Source: Introduction to Natural Language Processing (600.465)
Jan Hajič, CS Dept., Johns Hopkins Univ.
www.cs.jhu.edu/~hajic

The Zero Problem

- "Raw" n-gram language model estimate:
 - necessarily, some zeros
 - ▶ !many: trigram model $\rightarrow 2.16 \times 10^{14}$ parameters, data $\sim 10^9$ words
 - which are true 0?
 - ▶ optimal situation: even the least frequent trigram would be seen several times, in order to distinguish it's probability vs. other trigrams
 - ▶ optimal situation cannot happen, unfortunately (open question: how many data would we need?)
 - \rightarrow we don't know
 - we must eliminate zeros
- Two kinds of zeros: $p(w|h) = 0$, or even $p(h) = 0$!

Why do we need Nonzero Probs?

- To avoid infinite Cross Entropy:

- ▶ happens when an event is found in test data which has not been seen in training data

$H(p) = \infty$: prevents comparing data with ≥ 0 "errors"

- To make the system more robust

- ▶ low count estimates:
 - ▶ they typically happen for "detailed" but relatively rare appearances
- ▶ high count estimates: reliable but less "detailed"

Eliminating the Zero Probabilities: Smoothing

- Get new $p'(w)$ (same Ω): almost $p(w)$ but no zeros
- Discount w for (some) $p(w) > 0$: new $p'(w) < p(w)$

$$\sum_{w \in \text{discounted}} (p(w) - p'(w)) = D$$

- Distribute D to all w ; $p(w) = 0$: new $p'(w) > p(w)$
 - ▶ possibly also to other w with low $p(w)$
- For some w (possibly): $p'(w) = p(w)$
- Make sure $\sum_{w \in \Omega} p'(w) = 1$
- There are many ways of **smoothing**

Smoothing by Adding 1

■ Simplest but not really usable:

Predicting words w from a vocabulary V , training data T :

$$p'(w|h) = \frac{c(h, w) + 1}{c(h) + |V|}$$

- ▶ for non-conditional distributions: $p'(w) = \frac{c(w)+1}{|T|+|V|}$

Problem if $|V| > c(h)$ (as is often the case; even $\gg c(h)$!)

Example

Training data:

$V = \{\text{what, is, it, small, }, \langle s \rangle, \text{flying, birds, are, a, bird, }, \}$, $|V| = 12$

$p(\text{it}) = .125$, $p(\text{what}) = .25$, $p(.) = 0$

$p'(\text{it}) = .1$, $p'(\text{what}) = .15$,

$p'(\cdot) = .05$

$\langle s \rangle$ what is it what is small? $|T| = 8$

$p(\text{what is it?}) = .25^2 \times .125^2 \cong .001$

$p(\text{it is flying.}) = .125 \times .25 \times 0^2 = 0$

$p'(\text{what is it?}) = .15 \times .1^2 \cong .0002$

$p'(\text{it is flying.}) = .1 \times .15 \times .05^2 \cong .00004$

Adding *less than 1*

■ Equally simple:

Predicting word w from a vocabulary V , training data T :

$$p'(w|h) = \frac{c(h, w) + \lambda}{c(h) + \lambda|V|}, \quad \lambda < 1$$

► for non-conditional distributions: $p'(w) = \frac{c(w) + \lambda}{|T| + \lambda|V|}$

■ Example:

Training data:

<s> what is it what is small? |T| = 8

$V = \{\text{what, is, it, small, ?, <s>, flying, birds, are, a, bird, .}\}$, $|V| = 12$

$p(\text{it}) = .125$, $p(\text{what}) = .25$, $p(.) = 0$ $p(\text{what is it?}) = .25^2 \times .125^2 \cong .001$

$p(\text{it is flying.}) = .125 \times .25 \times 0^2 = 0$

Use $\lambda = .1$

$p'(\text{it}) \cong .12$, $p'(\text{what}) \cong .23$,

$p'(\text{what is it?}) = .23^2 \times .12^2 \cong .0007$

$p'(\text{.}) \cong .01$

$p'(\text{it is flying.}) = .12 \times .23 \times .01^2 \cong .000003$

- Suitable for estimation from large data
 - similar idea: discount/boost the relative frequency estimate:

$$p_r(w) = \frac{(c(w) + 1) \times N(c(w) + 1)}{|T| \times N(c(w))}$$

where $N(c)$ is the count of words with count c (count-of-counts)

specifically, for $c(w) = 0$ (unseen words), $p_r(w) = \frac{N(1)}{|T| \times N(0)}$

– good for small counts ($< 5-10$, where $N(c)$ is high)

– normalization! (so that we have $\sum_w p'(w) = 1$)

Good-Turing: An Example

Remember:
$$p_r(w) = \frac{(c(w)+1) \times N(c(w)+1)}{|T| \times N(c(w))}$$

Training data: <s> what is it what is small? |T| = 8

V = {what, is, it, small, ?, <s>, flying, birds, are, a, bird, .}, |V| = 12

$p(\text{it}) = .125$, $p(\text{what}) = .25$, $p(.) = 0$ $p(\text{what is it?}) = .25^2 \times .125^2 \cong .001$

$p(\text{it is flying.}) = .125 \times .25 \times 0^2 = 0$

- Raw estimation ($N(0) = 6$, $N(1) = 4$, $N(2) = 2$, $N(i) = 0$, for $i > 2$):

$$p_r(\text{it}) = (1+1) \times N(1+1) / (8 \times N(1)) = 2 \times 2 / (8 \times 4) = .125$$

$$p_r(\text{what}) = (2+1) \times N(2+1) / (8 \times N(2)) = 3 \times 0 / (8 \times 2) = 0:$$

keep orig. $p(\text{what})$

$$p_r(.) = (0+1) \times N(0+1) / (8 \times N(0)) = 1 \times 4 / (8 \times 6) \cong .083$$

- Normalize (divide by $1.5 = \sum_{w \in |V|} p_r(w)$) and compute:

$$p'(\text{it}) \cong .08, p'(\text{what}) \cong .17, p'(\text{.}) \cong .06$$

$$p'(\text{what is it?}) = .17^2 \times .08^2 \cong .0002$$

$$p'(\text{it is flying.}) = .08^2 \times .17 \times .06^2 \cong .00004$$

Smoothing by Combination: Linear Interpolation

- Combine what?
 - ▶ distribution of various level of detail vs. reliability
- n-gram models:
 - ▶ use (n-1)gram, (n-2)gram, ..., uniform
 - reliability
 - ← detail
- Simplest possible combination:
 - sum of probabilities, normalize:
 - ▶ $p(0|0) = .8$, $p(1|0) = .2$, $p(0|1) = 1$, $p(1|1) = 0$,
 $p(0) = .4$, $p(1) = .6$
 - ▶ $p'(0|0) = .6$, $p'(1|0) = .4$, $p'(1|0) = .7$, $p'(1|1) = .3$

Typical n-gram LM Smoothing

- Weight in less detailed distributions using $\lambda = (\lambda_0, \lambda_1, \lambda_2, \lambda_3)$:

$$p'_{\lambda}(w_i | w_{i-2}, w_{i-1}) = \lambda_3 p_3(w_i | w_{i-2}, w_{i-1}) + \\ \lambda_2 p_2(w_i | w_{i-1}) + \lambda_1 p_1(w_i) + \lambda_0 / |V|$$

- Normalize:

$$\lambda_i > 0, \sum_{i=0}^n \lambda_i = 1 \text{ is sufficient } (\lambda_0 = 1 - \sum_{i=1}^n \lambda_i) (n = 3)$$

- Estimation using MLE:

- fix the p_3, p_2, p_1 and $|V|$ parameters as estimated from the training data
- then find such $\{\lambda_i\}$ which minimizes the cross entropy (maximizes probability of data): $-\frac{1}{|D|} \sum_{i=1}^{|D|} \log_2(p'_{\lambda}(w_i | h_i))$

■ What data to use?

– try training data T : but we will always get $\lambda_3 = 1$

- ▶ why? let p_{iT} be an i -gram distribution estimated using r.f. from T
- ▶ minimizing $H_T(p'_\lambda)$ over a vector λ , $p'_\lambda = \lambda_3 p_{3T} + \lambda_2 p_{2T} + \lambda_1 p_{1T} + \lambda_0 / |V|$
 - remember $H_T(p'_\lambda) = H(p_{3T}) + D(p_{3T} || p'_\lambda)$; p_{3T} fixed $\rightarrow H(p_{3T})$ fixed, best
 - which p'_λ minimizes $H_T(p'_\lambda)$? Obviously, a p'_λ for which $D(p_{3T} || p'_\lambda) = 0$
 - ...and that's p_{3T} (because $D(p || p) = 0$, as we know)
 - ...and certainly $p'_\lambda = p_{3T}$ if $\lambda_3 = 1$ (maybe in some other cases, too).
 - ($p'_\lambda = 1 \times p_{3T} + 0 \times p_{2T} + 1 \times p_{1T} + 0 / |V|$)

– thus: do not use the training data for estimation of λ !

- ▶ must hold out part of the training data (**heldout** data, \underline{H})
- ▶ ...call remaining data the (true/raw) **training** data, \underline{T}
- ▶ the **test** data \underline{S} (e.g., for comparison purposes): still different data!

The Formulas

Repeat: minimizing $\frac{-1}{|H|} \sum_{i=1}^{|H|} \log_2(p'_\lambda(w_i|h_i))$ over λ

$$\begin{aligned} p'_\lambda(w_i|h_i) &= p'_\lambda(w_i|w_{i-2}, w_{i-1}) = \\ &= \lambda_3 p_3(w_i|w_{i-2}, w_{i-1}) + \lambda_2 p_2(w_i|w_{i-1}) + \lambda_1 p_1(w_i) + \lambda_0 \frac{1}{|V|} \end{aligned}$$

"Expected counts of lambdas": $j = 0..3$

$$c(\lambda_j) = \sum_{i=1}^{|H|} \frac{\lambda_j p_j(w_i|h_i)}{p'_\lambda(w_i|h_i)}$$

"Next λ ": $j = 0..3$

$$\lambda_{j,next} = \frac{c(\lambda_j)}{\sum_{k=0}^3 c(\lambda_k)}$$

The (Smoothing) EM Algorithm

- 1 Start with some λ , such that $\lambda > 0$ for all $j \in 0..3$
 - 2 Compute "Expected Counts" for each λ_j .
 - 3 Compute new set of λ_j , using "Next λ " formula.
 - 4 Start over at step 2, unless a termination condition is met.
- Termination condition: convergence of λ .
 - Simply set an ε , and finish if $|\lambda_j - \lambda_{j,next}| < \varepsilon$ for each j (step 3).
 - Guaranteed to converge: follows from Jensen's inequality, plus a technical proof.

Remark on Linear Interpolation Smoothing

■ "Bucketed Smoothing":

– use several vectors of λ instead of one, based on (the frequency of) history: $\lambda(h)$


- ▶ e.g. for $h = (\text{micrograms,per})$ we will have

$$\lambda(h) = (.999, .0009, .00009, .00001)$$

(because "cubic" is the only word to follow...)

– actually: not a separate set for each history, but rather a set for "similar" histories ("bucket"):

$\lambda(b(h))$, where $b: V^2 \rightarrow N$ (in the case of trigrams)
 b classifies histories according to their reliability (\sim frequency)



Bucketed Smoothing: The Algorithm

- First, determine the bucketing function \underline{b} (use heldout!):
 - decide in advance you want e.g. 1000 buckets
 - compute the total frequency of histories in 1 bucket ($f_{max}(b)$)
 - gradually fill your buckets from the most frequent bigrams so that the sum of frequencies does not exceed $f_{max}(b)$ (you might end up with slightly more than 1000 buckets)
- Divide your heldout data according to buckets
- Apply the previous algorithm to each bucket and its data

Simple Example

- Raw distribution (unigram only; smooth with uniform):
 $p(a) = .25, p(b) = .5, p(\alpha) = 1/64$ for $\alpha \in \{c..r\}$, $= 0$ for the rest: s, t, u, v, w, x, y, z
- Heldout data: baby; use one set of λ
(λ_1 : unigram, λ_0 : uniform)
- Start with $\lambda_0 = \lambda_1 = .5$:

$$p'_\lambda(b) = .5 \times .5 + .5/26 = .27$$

$$p'_\lambda(a) = .5 \times .25 + .5/26 = .14$$

$$p'_\lambda(y) = .5 \times 0 + .5/26 = .02$$

$$c(\lambda_1) = .5 \times .5 / .27 + .5 \times .25 / .14 + .5 \times .5 / .27 + .5 \times 0 / .02 = 2.27$$

$$c(\lambda_0) = .5 \times .04 / .27 + .5 \times .04 / .14 + .5 \times .04 / .27 + .5 \times .04 / .02 = 1.28$$

Normalize $\lambda_{1,next} = .68, \lambda_{0,next} = .32$

Repeat from step 2 (recompute p'_λ first for efficient computation, then $c(\lambda_i), \dots$).

Finish when new lambdas almost equal to the old ones (say, < 0.01 difference).

Some More Technical Hints

- Set $V = \{\text{all words from training data}\}$.
 - ▶ You may also consider $V = T \cup H$, but it does not make the coding in any way simpler (in fact, harder).
 - ▶ But: you must *never* use the test data for your vocabulary
- Prepend two "words" in front of all data:
 - ▶ avoids beginning-of-data problems
 - ▶ call these index -1 and 0: then the formulas hold exactly
- When $c_n(w,h) = 0$:
 - ▶ Assigning 0 probability to $p_n(w|h)$ where $c_{n-1}(h) > 0$, but a uniform probability ($1/|V|$) to those $p_n(w|h)$ where $c_{n-1}(h) = 0$ (this must be done both when working on the heldout data during EM, as well as when computing cross-entropy on the test data!)

Back-off model

- Combines n-gram models
- using lower order in not enough information in higher order
-

$$\begin{aligned} P_{bo}(w_i | w_{i-n+1} \dots w_{i-1}) &= \\ &= d_{w_{i-n+1} \dots w_i} \frac{C(w_{i-n+1} \dots w_{i-1} w_i)}{C(w_{i-n+1} \dots w_{i-1})} && \text{if } C(w_{i-n+1} \dots w_i) > k \\ &= \alpha_{w_{i-n+1} \dots w_{i-1}} P_{bo}(w_i | w_{i-n+2} \dots w_{i-1}) && \text{otherwise} \end{aligned}$$