Natural Language Processing (CSE 517): Cotext Models (II)

Noah Smith

University of Washington
nasmith@cs.washington.edu

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Thanks to David Mimno for comments.

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Local Contexts: Distributional Semantics

Within NLP, emphasis has shifted from topics to the relationship between $v \in \mathcal{V}$ and more local contexts.

For example: LSI/A, but replace documents with "nearby words." This is a way to recover word vectors that capture distributional similarity.

These models are designed to "guess" a word at position i given a word at a position in $[i - w, i - 1] \cup [i + 1, i + 2]$.

Sometimes such methods are used to "pre-train" word vectors used in other, richer models (like neural language models).

Word2vec

(Mikolov et al., 2013a,b)

Two models for word vectors designed to be computationally efficient.

- Continuous bag of words (CBOW): $p(v \mid c)$
  - Similar in spirit to the feedforward neural language model we saw last time (Bengio et al., 2003)
- Skip-gram: $p(c \mid v)$

It turns out these are closely related to matrix factorization as in LSI/A (Levy and Goldberg, 2014)!

Skip-Gram Model

$$p(C = c \mid X = v) = \frac{1}{Z_v} \exp \mathbf{c}_c^\top \mathbf{v}_v$$

- Two different vectors for each element of $\mathcal{V}$: one when it is "v" ($\mathbf{v}$) and one when it is "c" ($\mathbf{c}$).
- Like the log-bilinear model we saw last time, normalization term Z_v is expensive, so approximations are required for efficiency.
- Can expand this to be over the whole sentence or document, or otherwise choose which words "count" as context.

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- Syntactic analogies, e.g., "*walking* is to *walked* as *eating* is to what?" Solved via:

$$\min_{v \in \mathcal{V}} \cos\left(\mathbf{v}_v, \mathbf{v}_{\textit{walking}} - \mathbf{v}_{\textit{walked}} + \mathbf{v}_{\textit{eating}}\right)$$

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Also: *extrinsic* evaluations on NLP tasks that can use word vectors (e.g., sentiment analysis).

An Older Approach to Word Representation

Recall the class-based bigram model:

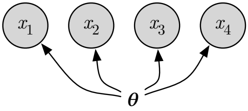
$$\begin{aligned} p(x_i \mid x_{i-1}) &= p(x_i \mid z_i) \cdot p(z_i \mid z_{i-1}) \\ &= \theta_{x_i|z_i} \cdot \gamma_{z_i|z_{i-1}} \\ p(\boldsymbol{x}, \boldsymbol{z}) &= \pi_{z_0} \prod_{i=1}^{\ell} \theta_{x_i|z_i} \cdot \gamma_{z_i|z_{i-1}} \end{aligned}$$

This is like a topic model where topic distributions are **bigram** distributed!

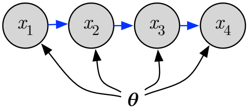
If we treat each z as latent—like in a topic model—we get to something very famous, called the **hidden Markov model** (HMM).

Comparing Five Models

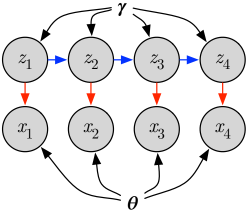
unigram



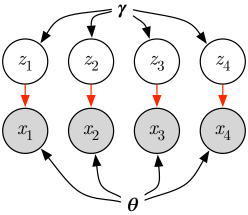
bigram
(Markov)



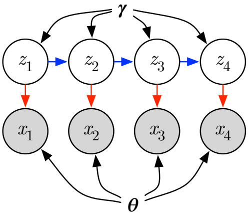
class-based
bigram



PLSA
and LDA
(topics)



hidden
Markov
model



Brown Clustering

There is a whole lot more to say about HMMs, which we'll save for later.

Brown et al. (1992) focused on the case where each $v \in \mathcal{V}$ is constrained to belong to only one cluster, $\mathsf{cl}(v)$.

They developed a greedy way to cluster words hierarchically.

Brown Clustering: Sketch of the Algorithm

Given: k (the desired number of clusters)

- Initially, every word v belongs to its own cluster.
- Repeat $V - k$ times:
  - Find the pairwise merge that gives the greatest value for $p(\boldsymbol{x}_{1:n}, \boldsymbol{z}_{1:n})$.

It turns out this is equivalent to PMI for adjacent cluster values!

This is very expensive; Brown et al. (1992) and others (later) introduced tricks for efficiency. See Liang (2005) and Stratos et al. (2014), for example.

Added Bonus to Brown Clusters

If you keep track of every merge, you have a *hierarchical* clustering.

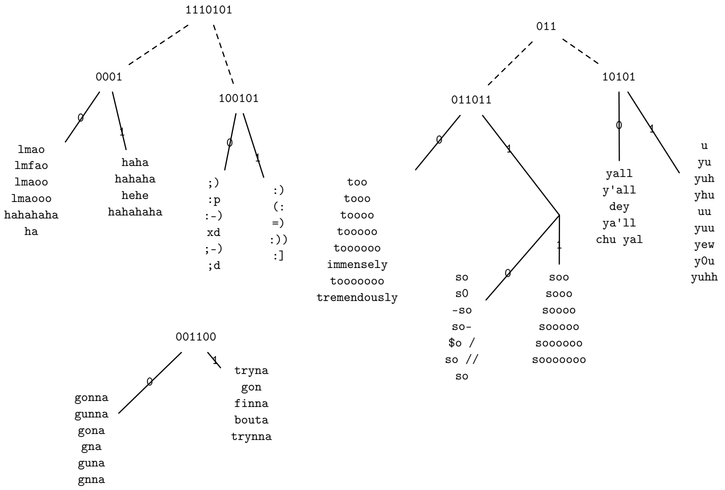
Each cluster is a binary tree with words at the leaves and internal nodes corresponding to merges.

Indexing the merge-pairs by 0 and 1 gives a bit-string for each word; prefixes of each word's bit string correspond to the hierarchical clusters it belongs to.

These can be seen as word embedings!

Brown Clusters from 56,000,000 Tweets

http://www.cs.cmu.edu/~ark/TweetNLP/cluster_viewer.html



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Bitext

Let $\boldsymbol{f}$ and $\boldsymbol{e}$ be two sequences in $\mathcal{V}^\dagger$ (French) and $\bar{\mathcal{V}}^\dagger$ (English), respectively.

We're going to define $p(\boldsymbol{F} \mid \boldsymbol{e})$, the probability over French translations of English sentence $\boldsymbol{e}$.

In a noisy channel machine translation system, we could use this together with source/language model $p(\boldsymbol{e})$ to "decode" $\boldsymbol{f}$ into an English translation.

Where does the data to estimate this come from?

IBM Model 2

(Brown et al., 1993)

Let ℓ and m be the (known) lengths of $\boldsymbol{e}$ and $\boldsymbol{f}$.

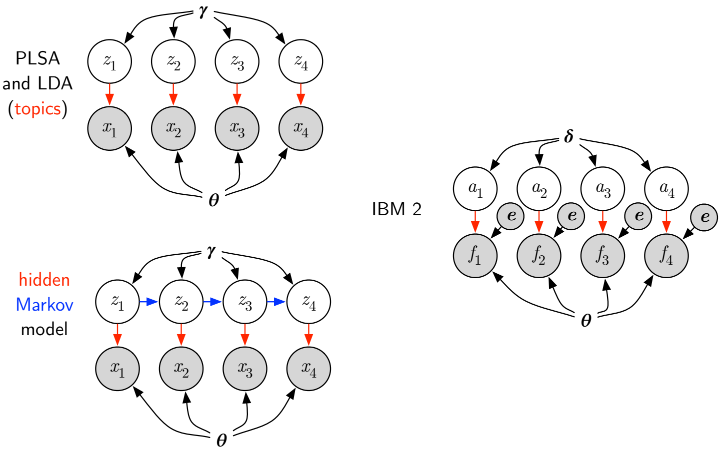
Latent variable $\boldsymbol{a} = \langle a_1, \ldots, a_m \rangle$, each a_i ranging over $\{0, \ldots, \ell\}$ (positions in $\boldsymbol{e}$).

- E.g., $a_4 = 3$ means that f_4 is "aligned" to e_3.

$$p(\boldsymbol{f} \mid \boldsymbol{e}, m) = \sum_{\boldsymbol{a} \in \{0,\ldots,n\}^m} p(\boldsymbol{f}, \boldsymbol{a} \mid \boldsymbol{e}, m)$$

$$\begin{aligned} p(\boldsymbol{f}, \boldsymbol{a} \mid \boldsymbol{e}, m) &= \prod_{i=1}^{m} p(a_i \mid i, \ell, m) \cdot p(f_i \mid e_{a_i}) \\ &= \delta_{a_i \mid i, \ell, m} \cdot \theta_{f_i \mid e_{a_i}} \end{aligned}$$

IBM Model 2, Depicted



Parameter Estimation

Use EM!

E step: calculate posteriors over all a_i, and then soft counts (left as an exercise: what soft counts do you need?)

M step: use relative frequency estimation from soft counts to get $\boldsymbol{\delta}$ and $\boldsymbol{\theta}$

Variations

- IBM Model 1 is the same, but fixes $\delta_{j|i,\ell,m} = \frac{1}{\ell+1}$.
  - Log-likelihood is convex!
  - Often used to initialize IBM Model 2.
- Dyer et al. (2013) introduced a new parameterization:

$$\delta_{j|i,\ell,m} \propto \exp -\lambda \left| \frac{i}{m} - \frac{j}{\ell} \right|$$

  (This is called `fast_align`.)
- IBM Models 3–5 (Brown et al., 1993) introduced increasingly more powerful ideas, such as "fertility" and "distortion."

Wow! That was a lot of models!

We covered:

- Topic models: LSI/A, PLSA, LDA
- Distributional semantics models: Skip-gram, Brown clustering
- Translation models: IBM 1 and 2

All of them are probabilistic models that capture patterns of cooccurrence between words and cotext.

They do *not* have: morphology (word-guts), syntax (sentence structure), or translation dictionaries . . .

Readings and Reminders

- Collins (2011)
- Submit a suggestion for an exam question by Friday at 5pm.
- Form your project team by Wednesday 1/27.
- Project details will be finalized this week.

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