Finding diachronic sense changes by Unsupervised methods

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Semantic Neologism

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example *tweet*

old sense: refers to bird song, as in (from 1995)

> When a bird **tweets**, it's telling you what it is and where it is.

recent sense: to post a status on twitter, as in (from 2009)

> An Embedded **Tweet** brings the best content created on Twitter into your article or website.

Example

gay being happy vs. homosexual

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A sample mis-translation into Tamil via Google Translate for :

S1. With Clara, however, his brow cleared, and he was gay again (from 'sons and lovers' by D.H. Lawrence 1931:)

T1. கிளாரா ஆயினும் அவரது புருவம் அகற்றப்படும் மற்றும் அவர் மீண்டும் ஓரினச்சேர்க்கையாளர்

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The question is:

Can semantic neologisms be detected from untagged text?

Representation and Notation

To talk about an occurrence of an ambiguous word will use:

$\mathbf{W}$:	words to left and right of a target
W_i:	i-th word in $\mathbf{W}$
Y:	year of occurrence
S:	sense of target occurrence of targets

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Eg. samples of **bricked**:

2001: *... In 1611 she was* **bricked** *into one of the rooms ...*
2011: *I've tried to flash a custom ROM and now I think I've* **bricked** *my phone*

become instances:

$$
\begin{array}{lll}
Y = 2001, & S = 1, & \mathbf{W} = \langle L, In, 1611, she, was, into, one, of, the, rooms \rangle \\
Y = 2011, & S = 2, & \mathbf{W} = \langle and, now, I, think, I've, my, phone, R, R, R \rangle
\end{array}
$$

Outline

Time dependent Sense Model

Without loss of generality, using the chain rule, we have

$$p(Y, S, \mathbf{W}) = p(Y) \times p(S|Y) \times p(\mathbf{W}|S, Y)$$

The $p(S|Y)$ term directly expresses the idea that the prevalence of a sense can vary with the year

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If we now assume that $p(\mathbf{W}|S, Y) = p(\mathbf{W}|S)$ ie. **$\mathbf{W}$ is conditionally independent of Y given S** we get first line below

Definition (Dynamic Sense Model)

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$$\begin{aligned} p(Y, S, \mathbf{W}) &= p(Y) \times p(S|Y) \times p(\mathbf{W}|S) & (1) \\ &= p(Y) \times p(S|Y) \times \prod_i p(W_i|S) & (2) \end{aligned}$$

Second line above by treating $\mathbf{W}$ as 'bag of words'

Outline

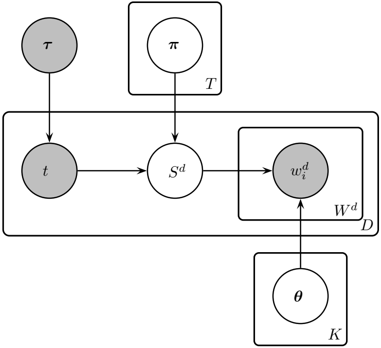
If we further assume that $p(S|Y) = p(S)$ we get:

Definition (Static Sense Model)

$$p(Y, S, \mathbf{W}) = p(Y) \times p(S) \times p(\mathbf{W}|S)$$

Outline

Generative story - EM



$\boldsymbol{\pi}_t$: parameter for senses (sense probs at t)
S^d : sense label for document d
w_i^d : word i in document d
W^d : words in document d
D : number of documents
K : total number of senses (classes)
$\boldsymbol{\theta}_k$: parameter for words (word probs at sense k)
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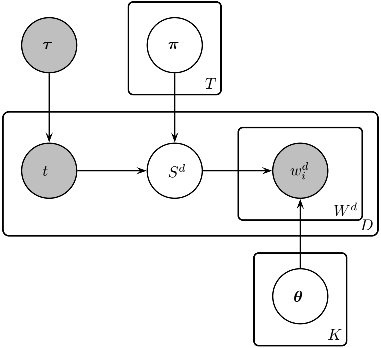
Figure: Sense emergence by EM - Graphical model

Generative story - EM



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(1) Choose sense label S^d for a document from $p(S^d|Y_t;\boldsymbol{\pi})$
(2) For each word position w_i^d in the document
    Choose a word w from $p(\mathbf{W}|S^d;\boldsymbol{\theta})$

EM-training

let $\boldsymbol{\pi}_t$ be a vector of sense parameters at time t ie., $P(\mathbf{S}|Y=t)$
let $\boldsymbol{\theta}_k$ be a vector of word parameters with sense k ie., $P(\mathbf{W}|S=k)$ and
let $\boldsymbol{\tau}$ be a vector of year probabilities ie., $p(\mathbf{Y})$

Now $P(Y, S, \mathbf{W})$ can be expressed as

$$p(d; \boldsymbol{\pi}, \boldsymbol{\theta}, \boldsymbol{\tau}) = p(Y_t; \boldsymbol{\tau}) \times p(S_d|Y_t; \boldsymbol{\pi}_t) \times \prod_i p(w_i^d|S_d; \boldsymbol{\theta}_{1:K})$$

$$p(d; \boldsymbol{\Theta}) = \tau_t \times \pi_{t,k} \times \prod_{i=1}^{W^d} \theta_{k,i}$$

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Data has no sense annotation. So use EM to make converging sequence of estimates

The training algorithm will consist of iterations to get the new estimates for $\Theta_n(\tau, \pi, \boldsymbol{\theta})$ and map them to $\Theta_{n+1}(\tau, \pi, \boldsymbol{\theta})$ by an **E-step** followed by **M-step**.

EM-updates

(E-step) Compute the completions for each of the training instances $(Y^d, \mathbf{W}^d)$ of the dataset $\mathbf{D}$ with a sense $(Y^d, S, \mathbf{W}^d)$, by computing the conditional probability $P(S|Y = t, \mathbf{W}^d)$ under the current estimate $\Theta_n(\boldsymbol{\tau}, \boldsymbol{\pi}, \boldsymbol{\theta})$.

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(M-step) Use maximum likelihood estimate to derive the new estimates for $\Theta_{n+1}(\tau_t, \boldsymbol{\pi}_t, \boldsymbol{\theta}_k)$.

Compute the conditional probabilities $\gamma[d][k_i] = p(S = k_i|Y = t^d, \mathbf{W} = \mathbf{W}^d)$ for each sense of $\mathbf{K} = \{k_1, k_2, \ldots, k_n\}$, in dataset D. The updates are:

$$p(S = k_i|Y = t; \Theta_{n+1}) = \frac{\sum_d (\text{if } Y^d = t \text{ then } \gamma[d][k_i] \text{ else } 0)}{\sum_d (\text{if } Y^d = t \text{ then } 1 \text{ else } 0)}$$

$$p(w|S = k_i; \Theta_{n+1}) = \frac{\sum_d (\gamma[d][k_i] \times freq(w \in \mathbf{W}^d))}{\sum_d (length(\mathbf{W}^d))}$$

Outline

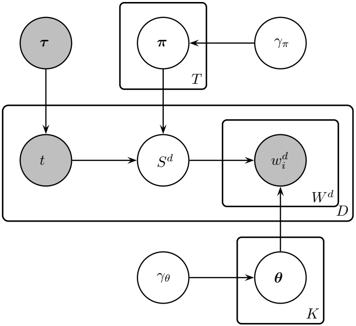

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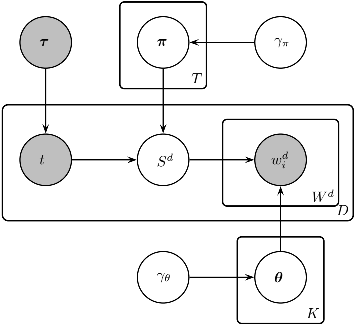
Figure: Sense emergence by Gibbs sampling - Graphical model



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(3) Choose sense label S^d from $p(S^d|t;\boldsymbol{\pi})$
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Difference from EM:

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1. Compute $\gamma[d][k_i] = p(S = k_i | Y = t^d, \mathbf{W} = \mathbf{W}^d)$ (as in EM) and sample for sense label from $\gamma[d][k_i]$
2. Sample for posteriors π and θ from Dirichlet distribution based on the document-sense counts and word-sense counts respectively.

Outline

Dataset

The data needed timestamp for a number of years

1. Google 5-gram dataset
2. Google timeline search

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Here is a sample of dataset for *mouse* from 1821:

5-gram	count
diligence and patience the mouse	2
and patience the mouse ate	2
patience the mouse ate in	2
the mouse ate in two	2
mouse ate in two the	2

Google timeline search: Data (text snippets) collected by searching for target using Google time-line search feature.

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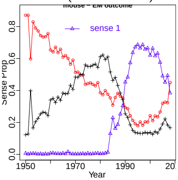
Google timeline search datasets for the following targets were tested: bricked, crawled, smashed it, me time, going forward, biological clock

Outline

Google 5-gram: Evaluation - by *introspection* comparing with tracks plot. For any word w let *track*(w) be the sequence of its *per-year probabilities* of occurrence in the 5-grams for a given target.

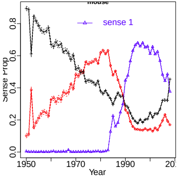
Neologism target: Mouse

mouse (EM outcome)



sense 1 words(:corp) *button, pointer, left, right, release, over, move, down, your, drag, you, hold, to, then, on, when, Release, cursor, use, clicking, click, Move, position, press, Click, while, changes, When, moving, user*

Gibbs outcome



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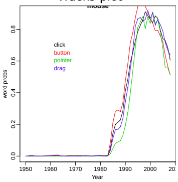
Tracks-plot



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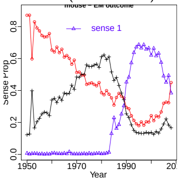

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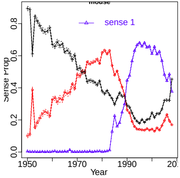

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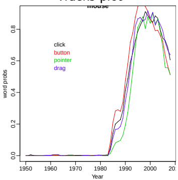

Additionally *Oxford English Dictionary* provides first citation date - used to verify

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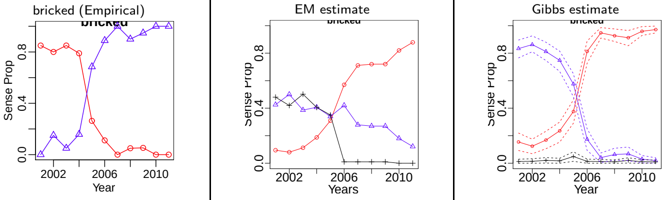

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The emerging sense from unsupervised estimates closely follow the empirical estimates.

Thank you