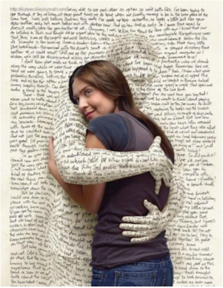
Words

and their abstractions

Jon Dehdari

November 24, 2015

Too Many Words!



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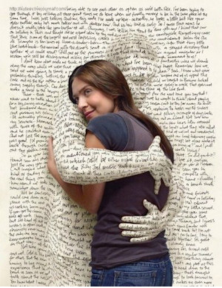

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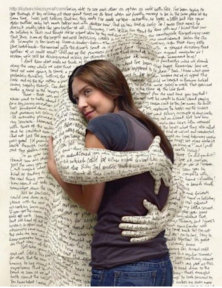

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- We need some way to generalize them
- Let's treat some words like other words

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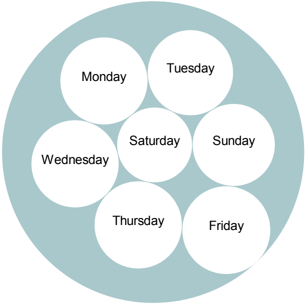

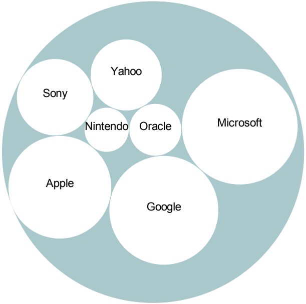

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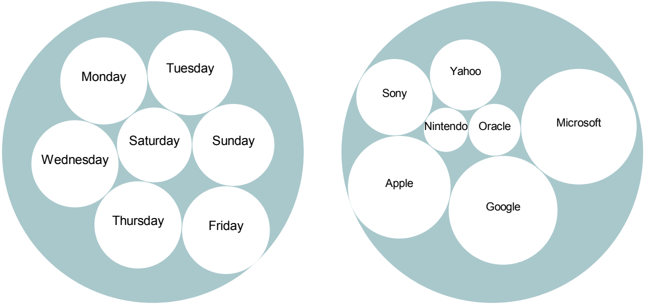

- Hand-crafted equivalence classes are called **part-of-speech tags**, and automatically induced equivalence classes are usually called **word classes** or **word clusters**

Parts of Speech and Word Clusters

- Part-of-speech example:

Pierre	Vinken	,	61	years	old	,	will	join	the	board
NNP	NNP	,	CD	NNS	JJ	,	MD	VB	DT	NN

- Word cluster example:

Pierre	Vinken	,	61	years	old	,	will	join	the	board
344	0	283	94	348	274	283	367	360	71	390

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Differences:

- Parts of speech have human-readable labels (eg. NN, VB), while word clusters usually just have numbers
- A word can have more than one part of speech (which depends on the context), while a word usually has just one word class

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- **Semi-supervised learning** uses **both** unannotated and annotated data
  - It's usually evaluated just like supervised learning tasks

[1] That's right: "data is".

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- For example: "It's raining cats and ____"
- Using word-based language models, the next word will probably be '*dogs*'
- But class-based LMs only see something like "PRP VBZ VBG NNS CC ____"
- So they would predict something like '*shares*', if they were trained on the WSJ corpus

How Many Word Classes Should I Use?

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However if you interpolate a class-based LM with a word-based LM, fewer word classes is usually better, because you get complementary information

How Can You Cluster Words?

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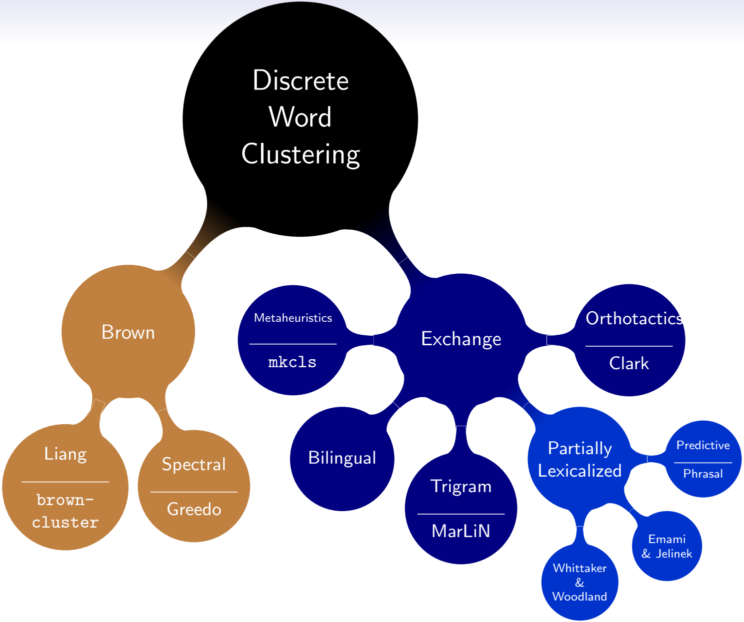
- You can also use discrete versions of these two algorithms, to cluster words directly from plaintext
- Discrete agglomerative word clustering is usually called **Brown clustering**
- Discrete k-means word clustering is usually called **exchange algorithm clustering**



Discrete Word Clustering
Brown
Liang
brown-cluster
Spectral
Greedo
Exchange
Metaheuristics
mkcls
Orthotactics
Clark
Bilingual
Trigram
MarLiN
Partially Lexicalized
Predictive
Phrasal
Emami & Jelinek
Whittaker & Woodland

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- Thus it's fairly fast for small clusters (< 400), but slow for large clusters (> 800)

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- There's a little more added complexity is how you calculate training-set likelihood

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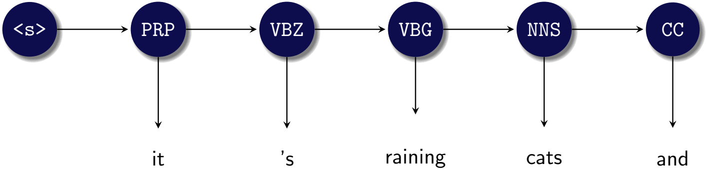
- The most common form (c_i is the word class of word w_i):

$$P(w_i|w_{i-1}) \triangleq P(w_i|c_i)\,P(c_i|c_{i-1})$$



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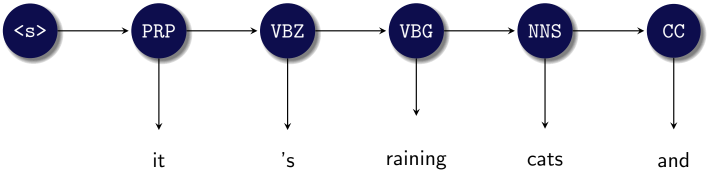

- Notice c_i, which is called a **bottleneck variable**
- The history is 'squeezed' through this point, in order to summarize and generalize the history

Predictive Exchange and Conditional Exchange

- The previous model is used in both Brown clustering and exchange algorithm clustering to determine the likelihood of the training set. We can use different models as well.

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- The *predictive exchange algorithm* uses this model:

$$P(w_i|w_{i-1}) \triangleq P(w_i|c_i)\,P(c_i|w_{i-1})$$

- The *conditional exchange algorithm* uses this model:

$$P(w_i|w_{i-1}) \triangleq P(w_i|c_{i-1})$$

Uses of Word Clusters

Machine Translation

- Word alignment (Brown et al, 1993; Och & Ney, 2000)
- Factored/class-based translation models (Koehn & Hoang, 2007; *inter alia*)
- Reordering models (Cherry, 2013)
- Preordering (Stymne, 2012)
- Target-side inflection (Chahuneau et al, 2013)
- Syntax-augmented machine translation (Zollmann & Vogel, 2011)
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Other NLP Tasks

- Training Neural Net Lang. Models (Goodman, 2001; Mnih & Hinton, 2009; ...)
- Parsing (Koo et al, 2008; Candito & Seddah, 2010; Kong et al, 2014)
- Semantic Parsing (Zhao et al, 2009)
- Chunking (Turian et al, 2010)
- NER (Miller et al, 2004, *inter alia*)
- Tagging of Twitter Feeds (Owoputi et al, 2013; Nooralahzadeh et al, 2014)
- Structure Transfer (Täckström et al, 2012)
- Discourse Relation Discovery (Rutherford & Xue, 2014)

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