Brown Clusters

Many slides from Michael Collins

The Brown Clustering Algorithm

- Input: a (large) corpus of words
- Output 1: a partition of words into *word clusters*
- Output 2 (generalization of 1): a hierarchichal word clustering

Example Clusters (from Brown et al, 1992)

Friday Monday Thursday Wednesday Tuesday Saturday Sunday weekends Sundays Saturdays
June March July April January December October November September August
people guys folks fellows CEOs chaps doubters commies unfortunates blokes
down backwards ashore sideways southward northward overboard aloft downwards adrift
water gas coal liquid acid sand carbon steam shale iron
great big vast sudden mere sheer gigantic lifelong scant colossal
man woman boy girl lawyer doctor guy farmer teacher citizen
American Indian European Japanese German African Catholic Israeli Italian Arab
pressure temperature permeability density porosity stress velocity viscosity gravity tension
mother wife father son husband brother daughter sister boss uncle
machine device controller processor CPU printer spindle subsystem compiler plotter
John George James Bob Robert Paul William Jim David Mike
anyone someone anybody somebody
feet miles pounds degrees inches barrels tons acres meters bytes
director chief professor commissioner commander treasurer founder superintendent dean custodian

A Sample Hierarchy (from Miller et al., NAACL 2004)

lawyer	1000001101000
newspaperman	100000110100100
stewardess	100000110100101
toxicologist	10000011010011
slang	1000001101010
babysitter	100000110101100
conspirator	1000001101011010
womanizer	1000001101011011
mailman	10000011010111
salesman	100000110110000
bookkeeper	1000001101100010
troubleshooter	10000011011000110
bouncer	10000011011000111
technician	1000001101100100
janitor	1000001101100101
saleswoman	1000001101100110
...	
Nike	1011011100100101011100
Maytag	10110111001001010111010
Generali	10110111001001010111011
Gap	1011011100100101011110
Harley-Davidson	10110111001001010111110
Enfield	101101110010010101111110
genus	101101110010010101111111
Microsoft	10110111001001011000
Ventritex	101101110010010110010
Tractebel	1011011100100101100110
Synopsys	1011011100100101100111
WordPerfect	1011011100100101101000
....	
John	101110010000000000
Consuelo	101110010000000001
Jeffrey	101110010000000010
Kenneth	1011100100000001100
Phillip	10111001000000011010
WILLIAM	10111001000000011011
Timothy	1011100100000001110
Terrence	10111001000000011110

The Intuition

- Similar words appear in similar contexts
- More precisely: similar words have similar distributions of words to their immediate left and right

The Formulation

- $\mathcal{V}$ is the set of all words seen in the corpus $w_1, w_2, \ldots w_n$
- Say $C : \mathcal{V} \rightarrow \{1, 2, \ldots k\}$ is a *partition* of the vocabulary into k classes
- The model:

$$p(w_1, w_2, \ldots w_n) = \prod_{i=1}^{n} e(w_i|C(w_i))q(C(w_i)|C(w_{i-1}))$$

(note: $C(w_0)$ is a special start state)

An Example

$$p(w_1, w_2, \ldots w_n) = \prod_{i=1}^{n} e(w_i | C(w_i)) q(C(w_i) | C(w_{i-1}))$$

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$$q(1|0) = 0.2, \quad q(2|1) = 0.4, \quad q(3|2) = 0.3, \quad q(1|3) = 0.6$$

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$$p(\textsf{the dog saw the cat}) =$$

The Brown Clustering Model

A Brown clustering model consists of:

- A vocabulary $\mathcal{V}$
- A function $C : \mathcal{V} \rightarrow \{1, 2, \ldots k\}$ defining a *partition* of the vocabulary into k classes
- A parameter $e(v|c)$ for every $v \in \mathcal{V}$, $c \in \{1 \ldots k\}$
- A parameter $q(c'|c)$ for every $c', c \in \{1 \ldots k\}$

Measuring the Quality of C

- How do we measure the quality of a partition C?

$$\begin{aligned}
\text{Quality}(C) &= \sum_{i=1}^{n} \log e(w_i|C(w_i))q(C(w_i)|C(w_{i-1})) \\
&= \sum_{c=1}^{k} \sum_{c'=1}^{k} p(c, c') \log \frac{p(c, c')}{p(c)p(c')} + G
\end{aligned}$$

where G is a constant

- Here

$$p(c, c') = \frac{n(c, c')}{\sum_{c,c'} n(c, c')} \qquad p(c) = \frac{n(c)}{\sum_{c} n(c)}$$

where $n(c)$ is the number of times class c occurs in the corpus, $n(c, c')$ is the number of times c' is seen following c, under the function C

A First Algorithm

- We start with $|\mathcal{V}|$ clusters: each word gets its own cluster
- Our aim is to find k final clusters
- We run $|\mathcal{V}| - k$ merge steps:
  - At each merge step we pick two clusters c_i and c_j, and merge them into a single cluster
  - We greedily pick merges such that

    $$\text{Quality}(C)$$

    for the clustering C after the merge step is maximized at each stage
- Cost? Naive $= O(|\mathcal{V}|^5)$. Improved algorithm gives $O(|\mathcal{V}|^3)$: still two slow for realistic values of $|\mathcal{V}|$

A Second Algorithm

- Parameter of the approach is m (e.g., $m = 1000$)
- Take the top m most frequent words, put each into its own cluster, $c_1, c_2, \ldots c_m$
- For $i = (m+1) \ldots |\mathcal{V}|$
  - Create a new cluster, c_{m+1}, for the i'th most frequent word. We now have $m+1$ clusters
  - Choose two clusters from $c_1 \ldots c_{m+1}$ to be merged: pick the merge that gives a maximum value for Quality(C). We're now back to m clusters
- Carry out $(m-1)$ final merges, to create a full hierarchy

Running time: $O(|\mathcal{V}|m^2 + n)$ where n is corpus length

Miller et al, NAACL 2004

Name Tagging with Word Clusters and Discriminative Training

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Miller et al, NAACL 2004

At a recent meeting, we presented name-tagging technology to a potential user. The technology had performed well in formal evaluations, had been applied successfully by several research groups, and required only annotated training examples to configure for new name classes. Nevertheless, it did not meet the user's needs.

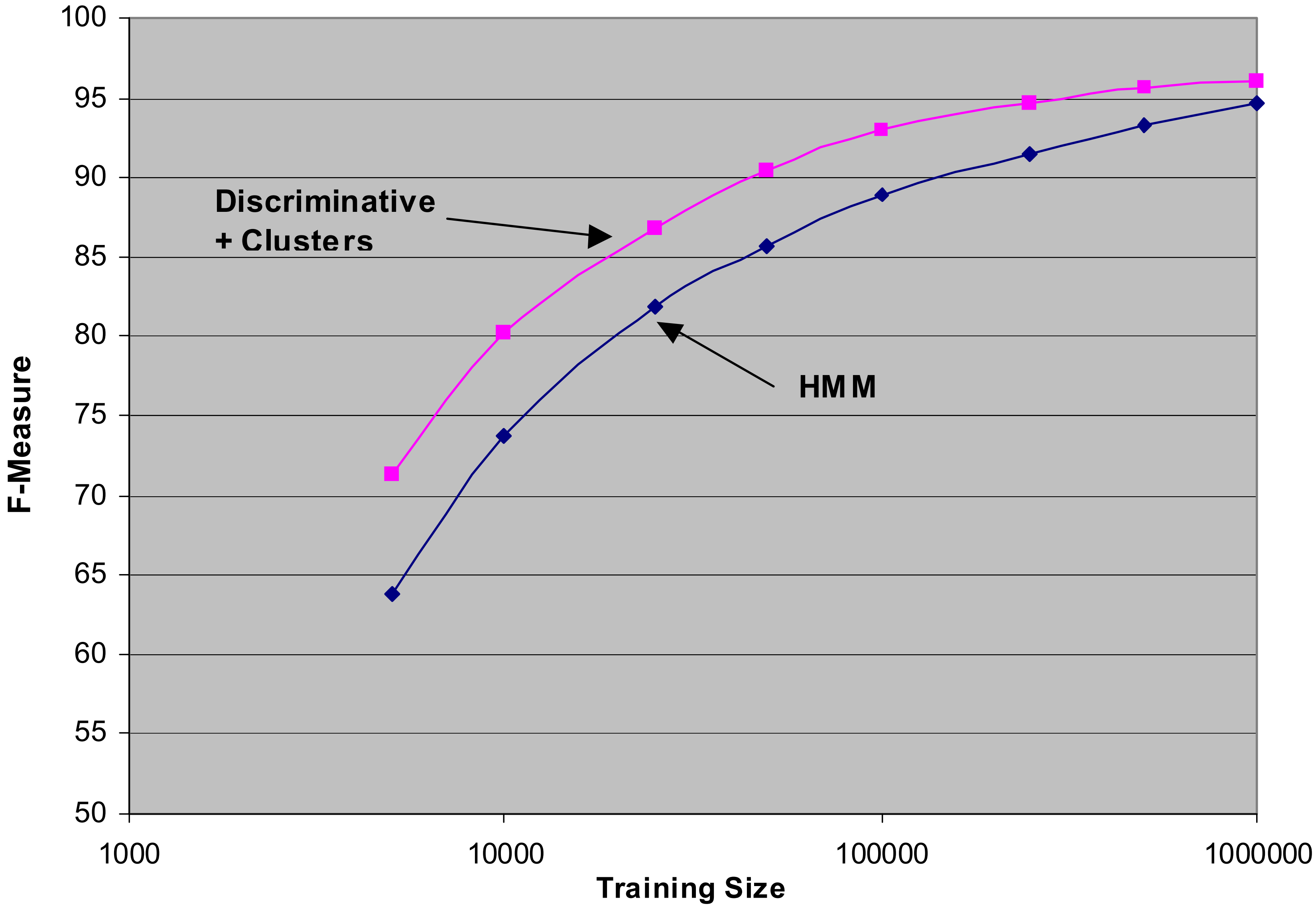
Miller et al, NAACL 2004

To achieve reasonable performance, the HMM-based technology we presented required roughly 150,000 words of annotated examples, and over a million words to achieve peak accuracy. Given a typical annotation rate of 5,000 words per hour, we estimated that setting up a name finder for a new problem would take four person days of annotation work – a period we considered reasonable. However, this user's problems were too dynamic for that much setup time. To be useful, the system would have to be trainable in minutes or hours, not days or weeks.

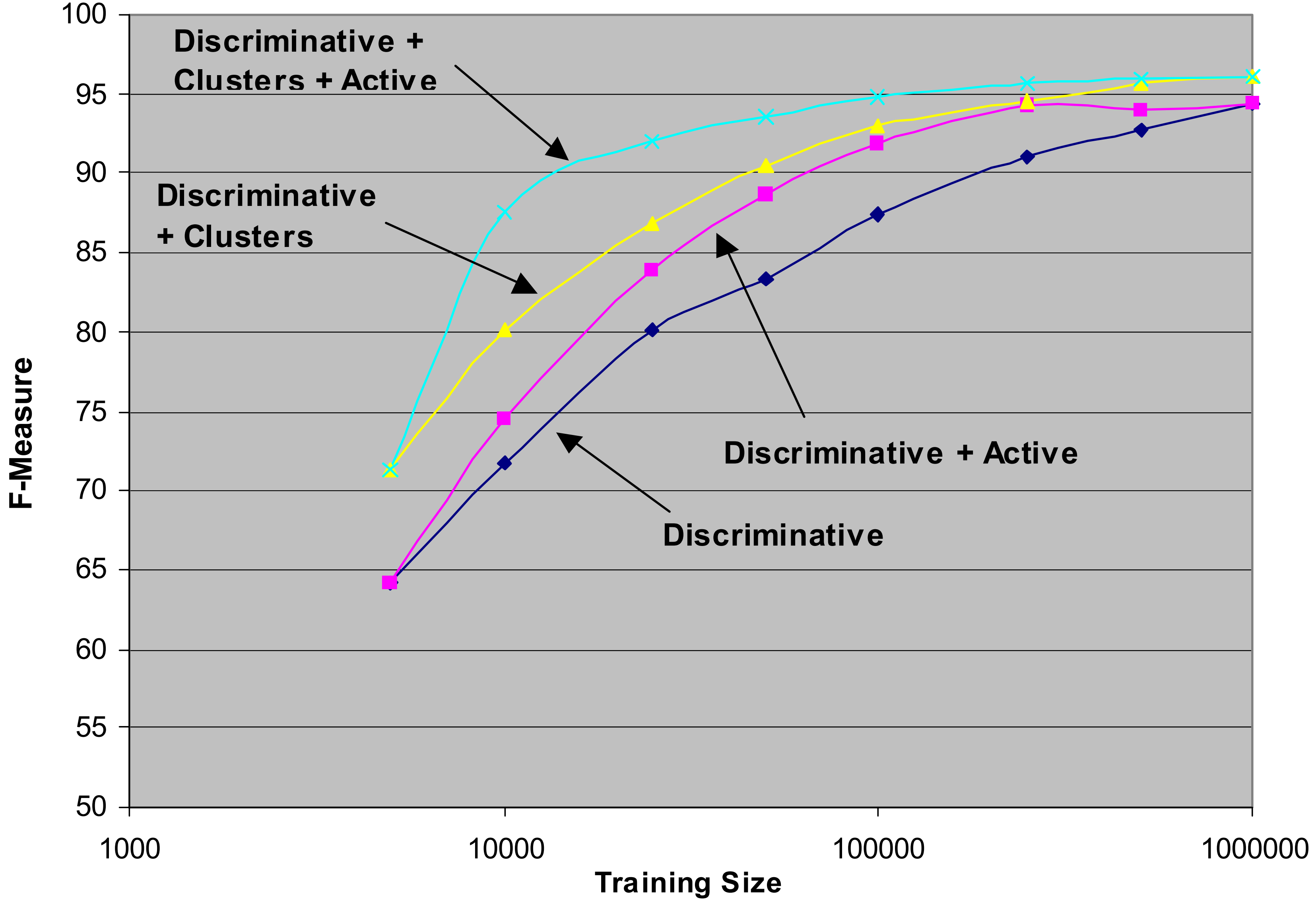
Miller et al, NAACL 2004

1. Tag + PrevTag
2. Tag + CurWord
3. Tag + CapAndNumFeatureOfCurWord
4. ReducedTag + CurWord
   //collapse start and continue tags
5. Tag + PrevWord
6. Tag + NextWord
7. Tag + DownCaseCurWord
8. Tag + Pref8ofCurrWord
9. Tag + Pref12ofCurrWord
10. Tag + Pref16ofCurrWord
11. Tag + Pref20ofCurrWord
12. Tag + Pref8ofPrevWord
13. Tag + Pref12ofPrevWord
14. Tag + Pref16ofPrevWord
15. Tag + Pref20ofPrevWord
16. Tag + Pref8ofNextWord
17. Tag + Pref12ofNextWord
18. Tag + Pref16ofNextWord
19. Tag + Pref20ofNextWord

Miller et al, NAACL 2004



Miller et al, NAACL 2004



Owoputi et. al. ACL 2013

Improved Part-of-Speech Tagging for Online Conversational Text with Word Clusters

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Owoputi et. al. ACL 2013

	Binary path	Top words (by frequency)
A1	111010100010	lmao lmfao lmaoo lmaooo hahahahaha lool ctfu rofl loool lmfaoo lmfaooo lmaoooo lmbo **lololol**
A2	111010100011	haha hahaha hehe hahahaha hahah aha hehehe ahaha hah hahahah kk hahaa ahah
A3	111010100100	yes yep yup nope yess yesss yessss ofcourse yeap likewise yepp yesh yw yuup yus
A4	111010100101	yeah yea nah naw yeahh nooo yeh noo noooo yeaa **ikr** nvm yeahhh nahh nooooo
A5	11101011011100	**smh** jk #fail #random #fact smfh #smh #winning #realtalk smdh #dead #justsaying
B	011101011	**u** yu yuh yhu uu yuu yew y0u yuhh youh yhuu iget yoy yooh yuo yue juu dya youz yyou
C	11100101111001	w fo fa fr fro ov fer **fir** whit abou aft serie fore fah fuh w/her w/that fron isn agains
D	111101011000	facebook **fb** itunes myspace skype ebay tumblr bbm flickr aim msn netflix pandora
E1	0011001	tryna gon finna bouta trynna boutta gne fina gonn tryina fenna qone trynaa qon
E2	0011000	gonna gunna gona gna guna gnna ganna qonna gonnna gana qunna gonne goona
F	0110110111	soo sooo soooo sooooo soooooo sooooooo soooooooo sooooooooo soooooooooo
G1	11101011001010	;) :p :-) xd ;-) ;d (; :3 ;p =p :-p =)) ;] xdd #gno xddd >:) ;-p >:d 8-) ;-d
G2	11101011001011	:) (: =) :)) :] ☺ :') =] ^_^ :))) ^.^ [: ;)) 😊 ((: ^__^ (= ^-^ :))))
G3	1110101100111	:(:/ -_- -.- :-(:'(d: :| :s -__- =(=/ >.< -___- :-/ </3 :\ -____- ;(/: :((>_< =[:[#fml
G4	111010110001	<3 ♥ xoxo <33 xo <333 ❤ ♡ #love s2 <URL-twitition.com> #neversaynever <3333

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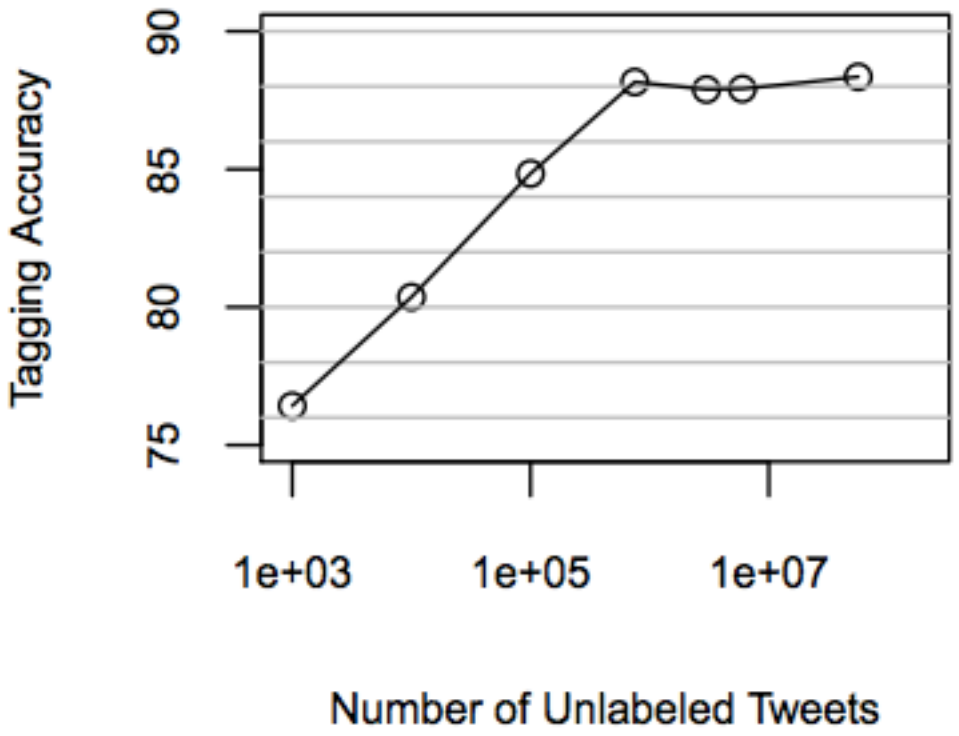

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Feature set	OCT27TEST	DAILY547	NPSCHATTEST	
All features	91.60	92.80	91.19	1
with clusters; without tagdicts, namelists	91.15	92.38	90.66	2
without clusters; with tagdicts, namelists	89.81	90.81	90.00	3
only clusters (and transitions)	89.50	90.54	89.55	4
without clusters, tagdicts, namelists	86.86	88.30	88.26	5
Gimpel et al. (2011) version 0.2	88.89	89.17		6
Inter-annotator agreement (Gimpel et al., 2011)	92.2			7
Model trained on all OCT27		93.2		8

Table 2: Tagging accuracies (%) in ablation experiments. OCT27TEST and DAILY547 95% confidence intervals are roughly ±0.7%. Our final tagger uses all features and also trains on OCT27TEST, achieving 93.2% on DAILY547.

Software for Brown Clusters

- Percy Liang's code: https://github.com/percyliang/brown-cluster
- "A bit of progress in language modeling" Joshua Goodman
  - More sophisticated smoothing
  - JCLUSTER: http://research.microsoft.com/en-us/downloads/0183a49d-c86c-4d80-aa0d-53c97ba7350a/default.aspx