

From neighborhood to parenthood: the advantages of dependency representation over bigrams in Brown clustering

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Word representations

- Falls into following categories:
 - Word-space models (DS) + dimensionality reduction
 - Clustering
 - Word embeddings
 - Other probabilistic models
- Improve generalization
- Clustering: grouping similar words (semantic, paradigmatic & orthographic variants)

Brown clusters

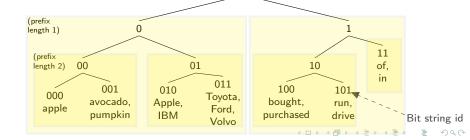
- Popular: POS-tagging, NER, parsing, question answering etc.
- Easy-to-understand parameters
- Simplicity and <u>robustness</u>
- Word embeddings' recent momentum:
 - Brown clusters hard to beat in real tasks (Turian et al 2010;
 Bansal et al 2014; Nepal and Yates 2014; Passos et al 2014)
- Brown clusters admittedly less scalable

Our contribution

- Original Brown clustering uses bigram contexts
- Adapt to dependencies: helpful for semantic similarity
- Tool for dependency Brown clustering

How does Brown clustering work

- Maximize data likelihood defined on a class-based bigram LM
- In practice, done through average Mutual Information
- 1 assign some word types to unique classes
- 2 put each remaining word type to one of these classes by minimizing the MI loss
- 3 when all word types are merged, further merge the resulting classes to create a hierarchy



From Brown to dependency Brown

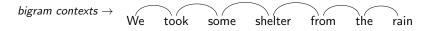
Original formulation

- Factorization includes class transitions with conditioning on previous word's class
- Such representation is local

Our modification

- Adopt dependency representation: less local, more precise (assuming we can trust the parser)
- (Class-based) dependency language model: conditioning on parent's class

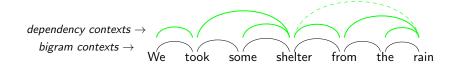
Contexts



Contexts



Contexts



Extract parent-child pairs:

(took, We), (took, shelter), (shelter, some),

...

(Optional) 2nd order dependency: collapse on preposition (shelter, rain)

Evaluation

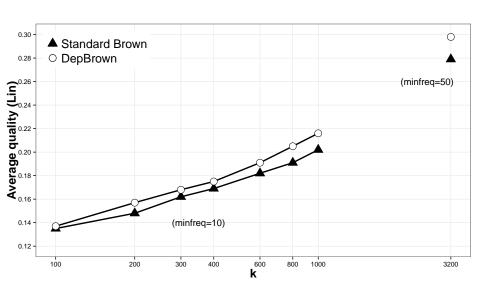
- Parse a 46M-word reference corpus sample
- Obtain counts of dependency instances as input for the clustering tool
- Semantic similarity task on Dutch wordnet
 - Average similarity over all clusters, as measured by Lin score

Group Cluster id		Most frequent words	
A1	001010001011	contractor, family doctor, baker, lawyer, pharmacist, real	
A2	001010001011	estate agent, property developer, postman, analyst, reviewer, observer, expert, commentator, people's rights organisation, insider,	
A3	0010100010111110	entrepreneur, businessman, manager, self-employed, merchant, starter, craftsman,	
B1	<u>011101111011</u> 110	me	
B2	<u>011101111011</u> 10	him/herself, myself, yourself	
B3	<u>011101111011</u> 00	them	
C1	00110010010	Bush, Obama, Clinton, Putin,	
C2	<u>001100</u> 0111010	Sarah, Kim, Nathalie, Justine,	
C3	<u>001100</u> 0111011	David, Jimmy, Benjamin,	
D1	001011100010101	email, mail, sms, sms_DIM, e-mail, mail_DIM,	
D2	001011100010100	telephone, satellite, telephony, telephone line, Explorer, music player, iTunes, \dots	
E	001000010110101	income, energy consumption, minimum wage, cholesterol, IQ, alcohol content,	
(trans	translated from Dutch)		

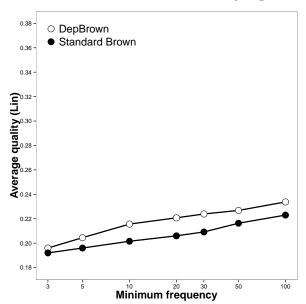
Different contexts, different clusters?

- No strong evidence in our case (manual inspection)
- Word embedding and distributional-semantic literature:
 - Bow: words associated with target word (topical similarity)
 - DEP: words behaving like target word
- Bigram contexts in original Brown clustering too narrow for topical similarity

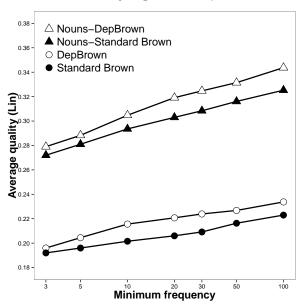
Varying *k* number of clusters



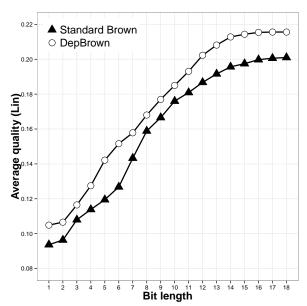
Varying minfreq



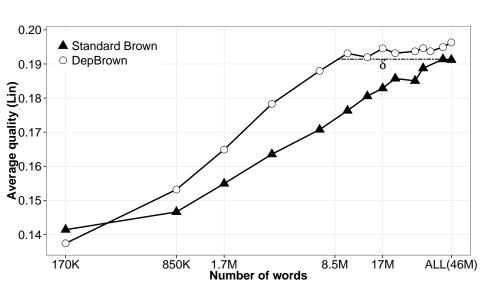
Varying *minfreq* + Nouns only



Prefix length



Amount of data



Leveraging syntactic functions

- Select parent-child pairs based on dependency label
- Further improvements in semantic similarity by using:
 - subjects
 - direct objects
 - directional complements
 - 2-nd order relations (intervening preposition)
 - directional and prepositional complements

Thank you!

Data & clustering tool at:

github.com/rug-compling/dep-brown-cluster