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ARTS

Vector space models and semantic analysis

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- Harris (1954:156):
  “difference of meaning correlates with difference of distribution”
- Firth (1957):
  “a word is characterized by the company it keeps”
- Can such distributional relations be made precise?
- And specifically, can minimally different pairs (or groups) of words be identified, revealing oppositions?

Distribution as vectors

- The distribution of words can be expressed mathematically as **vectors**
- A vector is a table with a single row
- The vector for any given word records its co-occurrence with other words
  - Each entry in the row corresponds to another word
  - The entry records some information about the co-occurrence of the two words

What does a vector represent?

- Two questions:
  - What is the domain within which co-occurrence is tracked?
  - What information is stored? E.g. is it just the fact of co-occurrence or is it richer information such as distance between words?
- Example with a simple approach:
  - Domain is a sentence
  - Information stored is number of times a word occurs

Vector example

	Half	Mushrooms	Onion	The	thinly
a. Thinly SLICE half the onion	1	0	1	1	1
b. SLICE the mushrooms thinly	0	1	0	1	1

Information overload

- Vectors derived from any large corpus will be very large
  - At least each lemma will have a vector
  - For our COCA data, there are almost 0.5 million vectors
- Data is sparse – a very large proportion of the entries are zeroes
- Various algorithms have been developed to reduce the size of the output while preserving information

Spatial vectors

- One approach reduces the raw vectors to a multidimensional spatial model
- Word2vec uses this approach
  - Word2vec uses neural networks to get from text to spatial model
- Output is an n-dimensional model which locates all words (lemmas) in relation to each other
  - Still a lot of data – our 100-dimensional model is a c190mb file

- “dans la langue il n’y a que des différences” (*Cours,* 166)
- But also:
  “deux signes comportant chacun un signifié et un signifiant ne sont pas différents, ils sont seulement distincts. Entre eux il n’y a qu’opposition” (*Cours*, 167)
- Empirical investigation of oppositions is limited
  - Possible in limited domains
  - Very difficult for a language as a whole

Saussure and VSM

- Model locates every word in text relative to all the others
- Relationships can be quantified
- Is this close to a Saussurean semantic analysis?
- We look at a group of verbs:
  - CUT and BREAK concepts
  - Previously studied in detail (Majid et al 2007, 2008a, b))
- Concentrate on clustering:
  - Do clusters make intuitive sense?
  - How do they correspond to previous work?
  - Do Saussurean oppositions emerge?

What we are looking for

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- Exploring thematic cluster
  - Do the CB verbs fall into clusters?
  - If so, how many? How do we determine that?
  - What semantic theme could be explored from the clustering of particular CB words?
- Exploring “nearest” verbs to each of the CB verbs
  - Which other verbs are closely similar to each of the CB verbs?
  - Are there overlaps of the closest verbs between particular CB verbs?
- Exploring degree of similarity of the CB verbs to either *cut_v* and *break_v*

- Whole collection of COCA corpus (the POS-tagged version) (http://corpus.byu.edu/coca/)

	word	lemma	POS
561911	won't.	won't	nnu
561912	"	"	y
561913	said	say	vvd
561914	Queen	queen	nnb
561915	Esther	esther	np1
561916	.	.	y
561917	We	we	ppis2
561918	'd	have	vm
561919	come	come	vvi
561920	to	to	ii
561921	Connell	connell	np1
561922	's	's	ge
561923	Drug	drug	nn1
561924	Store	store	nn1
561925	and	and	cc
561926	both	both	db2_rr

Pre-processing steps:

1. Define words as consisting of alphabets [a-z], hyphens (to retain *machine-readable*), and single quote (to retain genitive *'s* and negation *won't*)

2. Remove punctuation and numbers

3. Collapse various *Verb-tag labels* (e.g. for infinitive, participle, etc.) into simply "v"

4. Collapse ***lemma*** and ***POS*** columns into a single, big text

```
[1] "by_ii jill_np1 mccorkle_np1 anna_np1 craven_np1 have_vhz"
```

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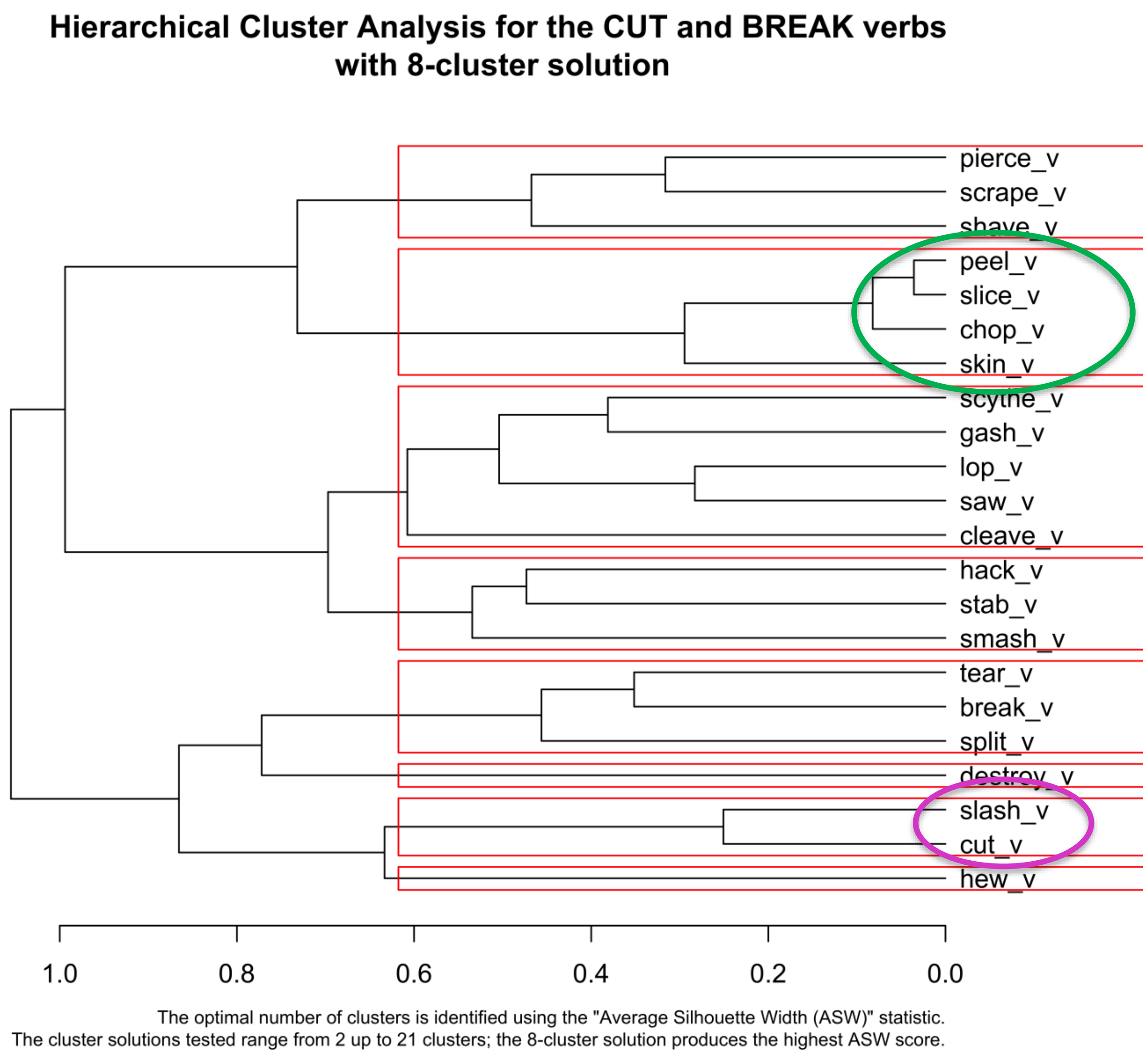
- Use the *wordVectors* R package by Ben Schmidt
  - Creates vector space model for every lemma in the COCA corpus
    - Reduces the original raw vectors into 100-dimensional vectors
    - On the basis of collocational window-span of 12 words (default in the *train_word2vec* () function)
  - Has a number of functions for exploring the vector space model
    - Finding nearest words to a particular target word
    - Computing similarity scores between words
    - *Inter alia* (cf. https://github.com/bmschmidt/wordVectors)

Exploring thematic cluster of Cut and Break verbs

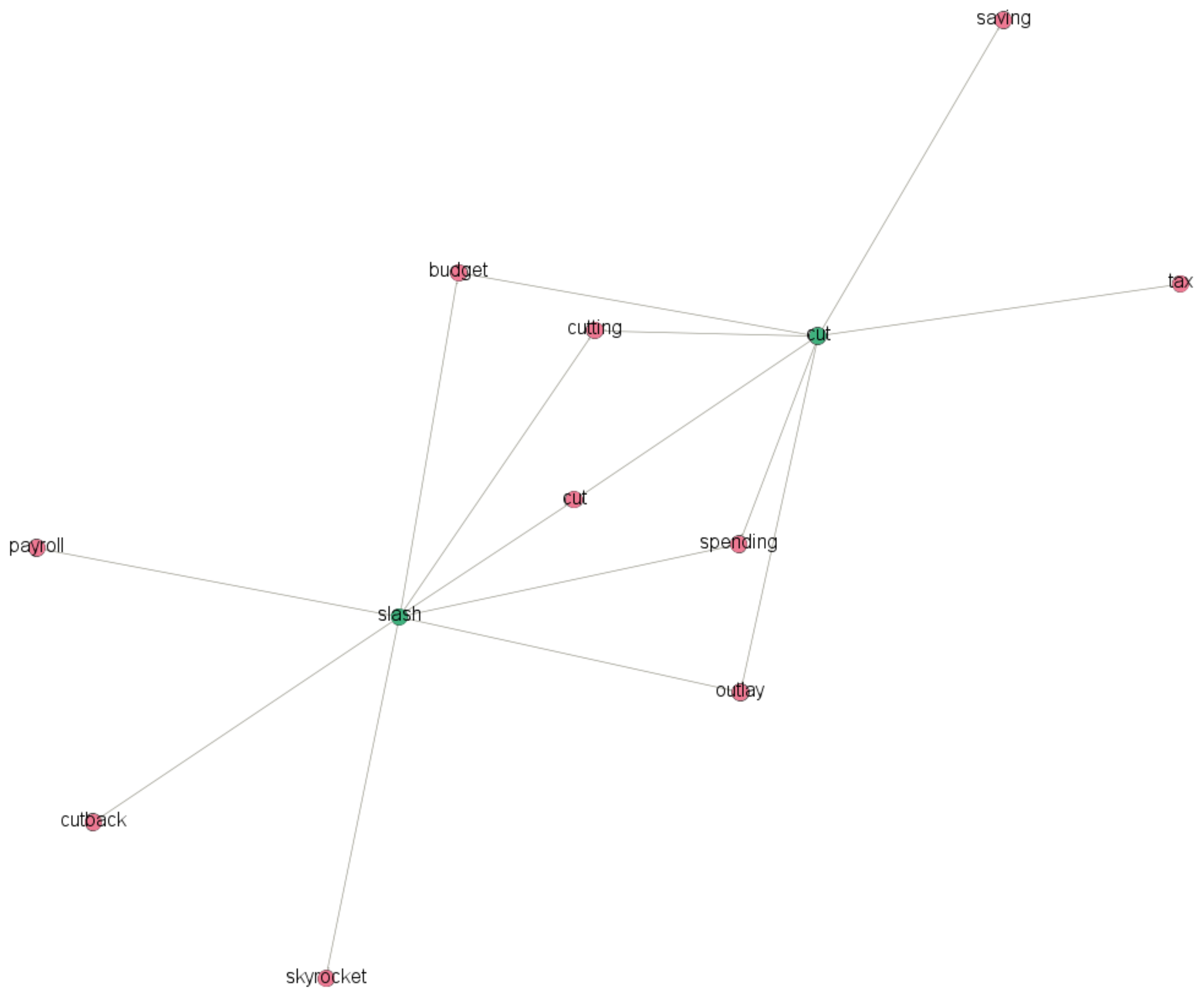
- Analyse 22 *Cut and Break* verbs (cf. the plot below)
- Retrieve the vector space matrix of these verbs' lemmas
- Compute distance matrix for the lemmas
- Perform *Hierarchical Cluster Analysis* (HCA)
  - with *hclust()* function in R
- Compute *Average Silhouette Width* (ASW) on the basis of the HCA results (cf. Levshina, 2015, p. 312)
  - To assume the optimal number of cluster solution
  - Compute ASW from 2 up to 21 clusters (i.e. N of CB verbs – 1)
  - For our data, 8-cluster solution produces the highest ASW score
- Visualise the results into a dendrogram

Results

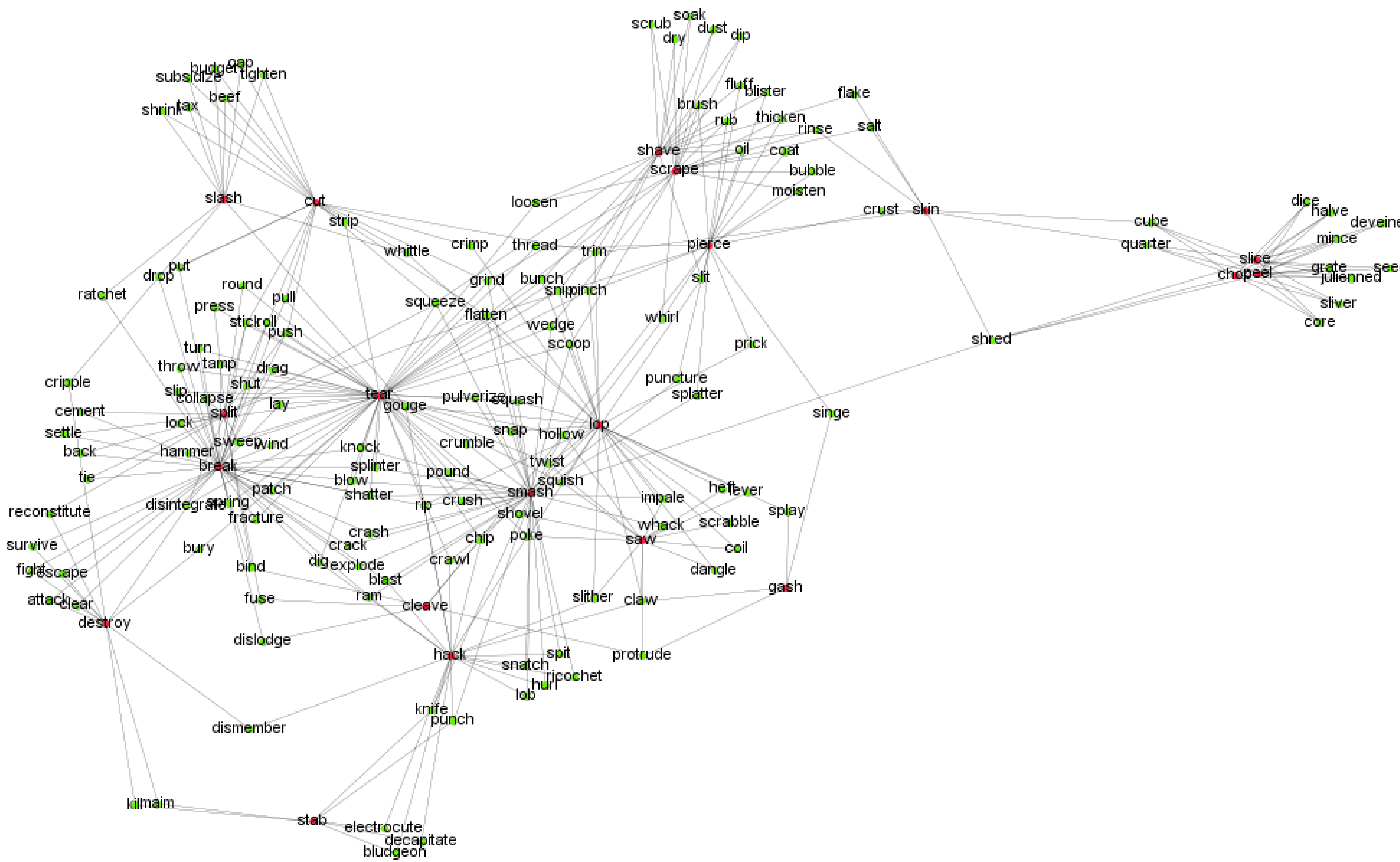
Exploring thematic cluster of Cut and Break verbs



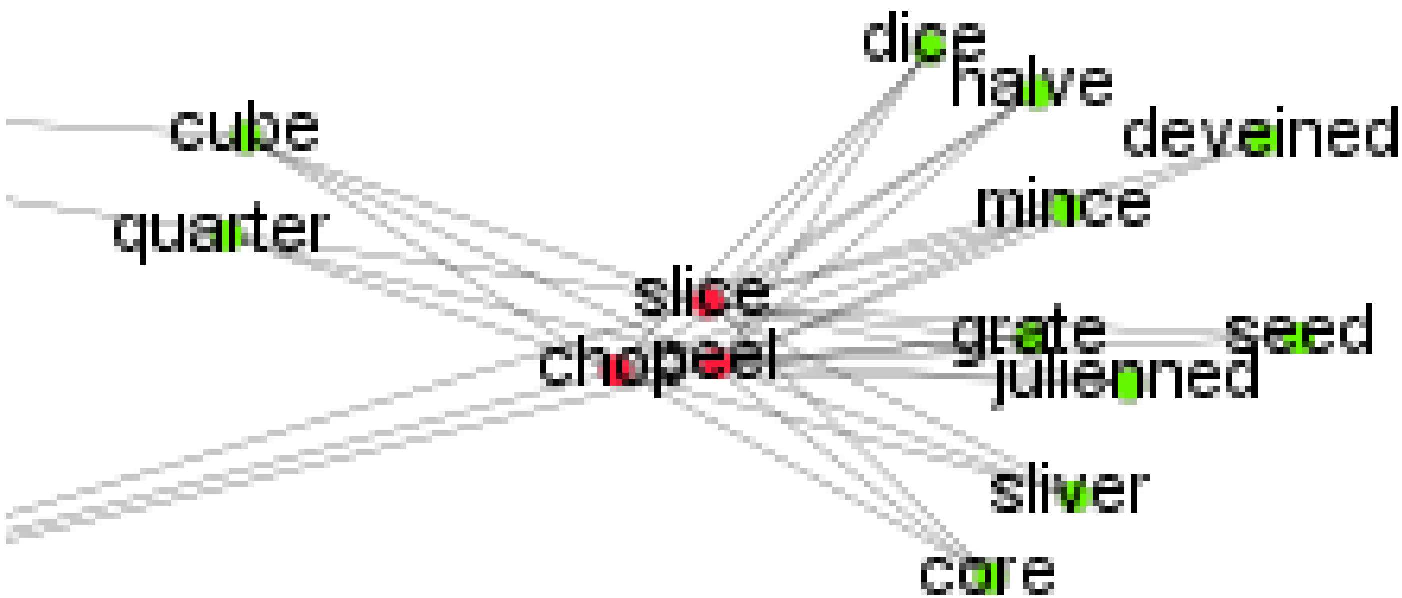
Similarity spaces – *cut* and *slash*



Similarity spaces – *peel* and *slice*



Similarity spaces – *peel* and *slice*



An alternative approach

Majid et al.:

`event ➔ verb ➔ similarity space`

To what extent do these converge?

Musgrave et al.:

`verb ➔ collocates ➔ similarity space`

Next steps

- Build models for:
  - German
  - Swedish
  - Dutch
- Comparison for Majid et al 2007
- Compare clusterings produced by two different approaches

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