UNIVERSITÄT LEIPZIG

European Research Council

Semantic Vector Spaces and cluster analysis

Outline

- Principles of hierarchical cluster analysis
  - Case study of Romance causatives
- Semantic Vector Space Models
  - Case study: English verb classification

Cluster the Romance causatives

- We’ll cluster the Romance cognate causatives depending on how often they co-occur in translations.
  - Step 1: make a separate data frame with the Romance languages only and binarized data.
  - Step 2: compute the distances between the cognates.
  - Step 3: perform a hierarchical cluster analysis

Prepare the data frame with Romance causatives

```
> rom_cognates <- c("faire", "fazer", "hacer",
"face", "fare")
> causatives_rom <- t(causatives[, c("FRA",
"ITA", "SPA", "POR", "ROM")])
> causatives_rom[causatives_rom %in% rom_cognates]
<- "Yes"
> causatives_rom[causatives_rom != "Yes"] <- "No"
> causatives_rom <- as.data.frame(causatives_rom)
```

Distances between cognates

```
> library(cluster)
> rom.dist <- daisy(causatives_rom)
> rom.dist
Dissimilarities :
           FRA        SPA        ITA        POR
SPA 0.07500000
ITA 0.12500000 0.16666667
POR 0.13888889 0.09375000 0.25000000
ROM 0.13043478 0.05555556 0.21212121 0.05555556
```

Exercise

- Perform an MDS analysis on the distance matrix. How can you interpret the results?

Hierarchical cluster analysis: steps

- Pick the smallest distance between two objects in the distance matrix and merge them in one cluster.
- Then pick the next smallest distance between two objects and/or clusters and merge them.
- Stop when all objects are merged in one cluster tree.

Clustering methods

- OK, but how to compute distances between clusters?
  - Single (the minimally possible distances between the clusters are compared, and the smallest is taken)
  - Complete (the maximally possible distances between clusters are compared, and the smallest is taken)
  - Average (the average distances between the clusters are computed, and the smallest is taken)
  - Ward (based on variance minimization)

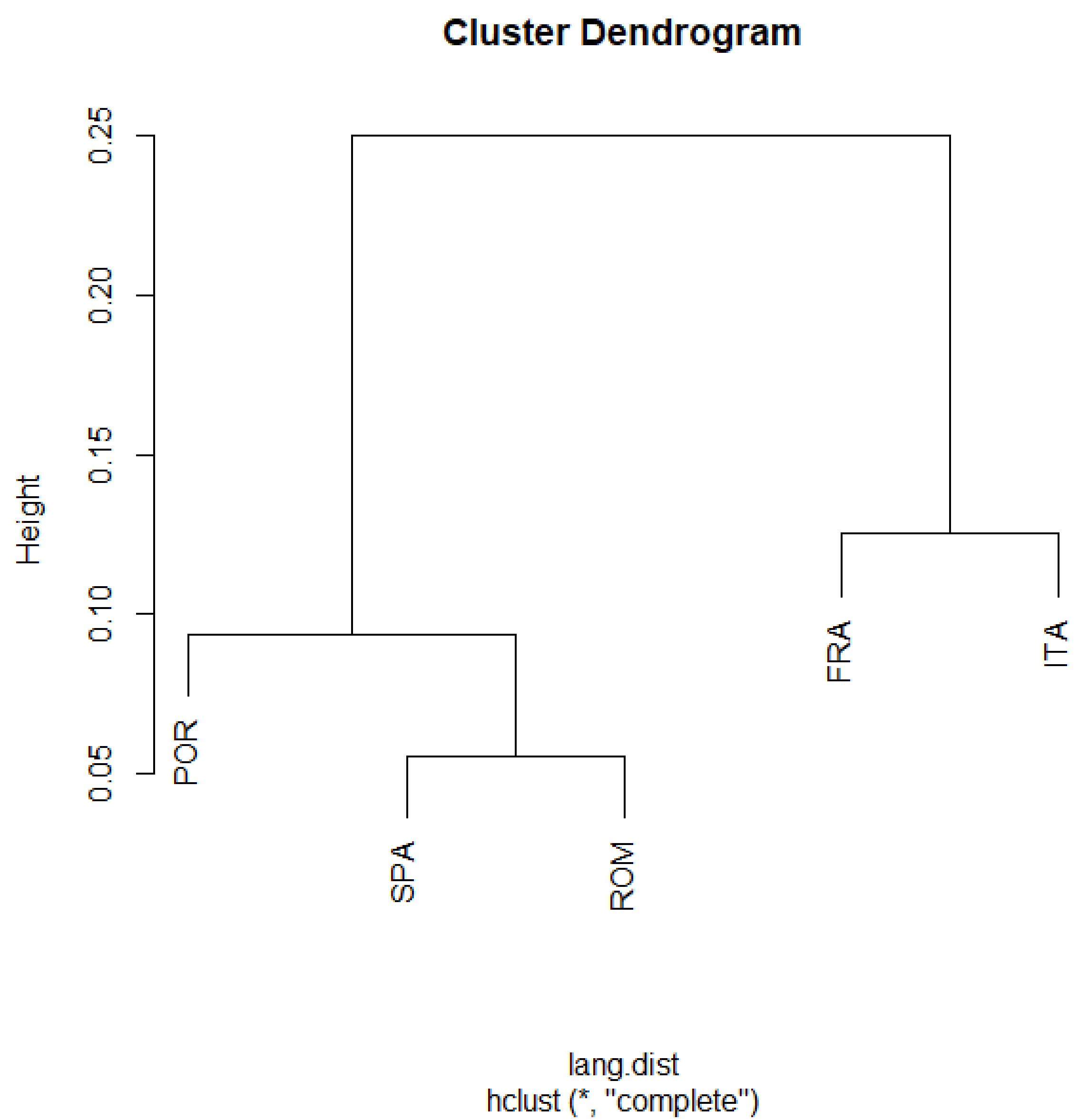
A simple analogy

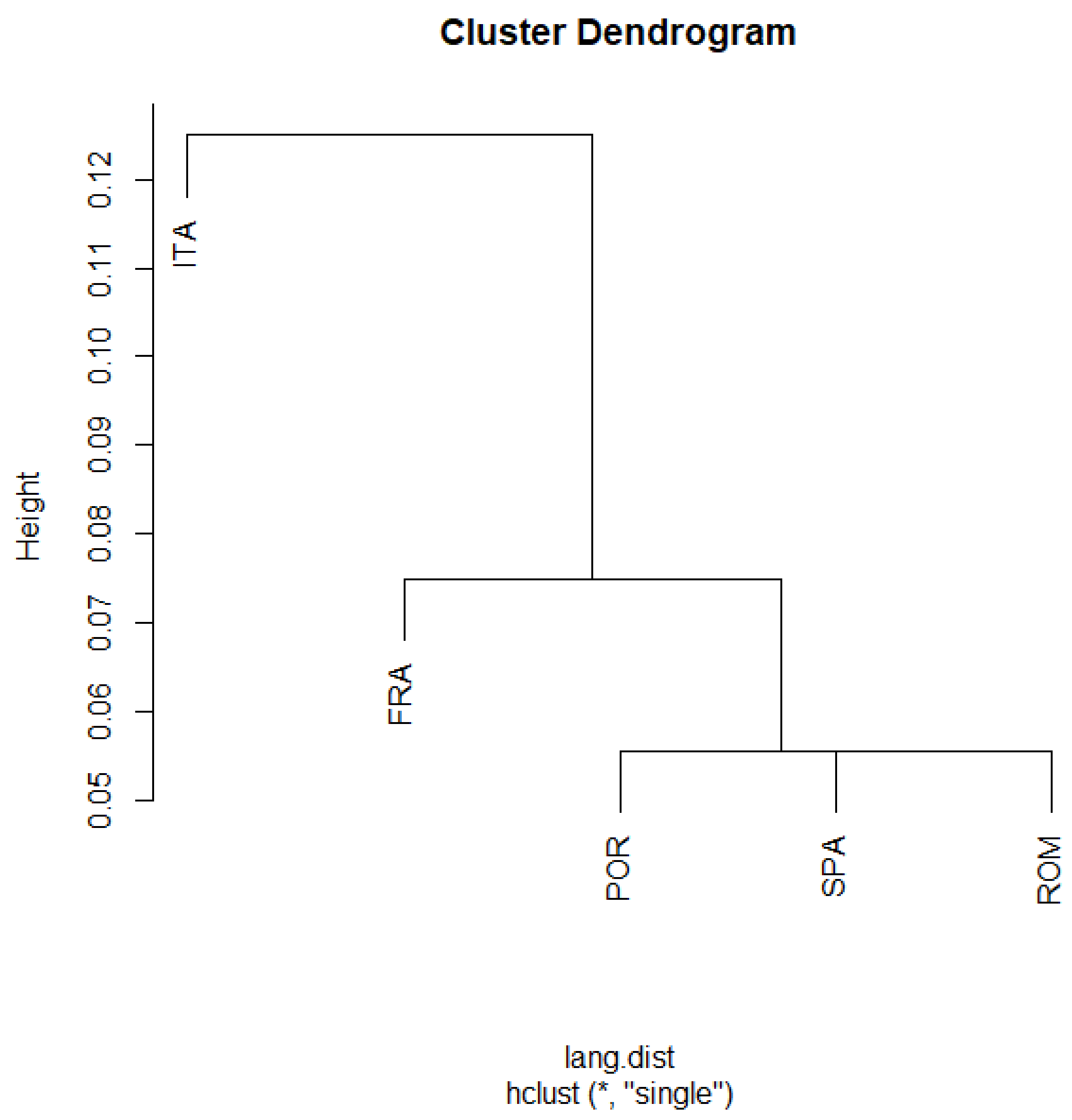
- Imagine you have a choice between two clubs. How do you decide which one to join?
  - Single: you choose the club your best friend has joined.
  - Complete: you find out which club your biggest enemy is a member of. You choose the other one.
  - Average: you choose the club which has on average more likable members.

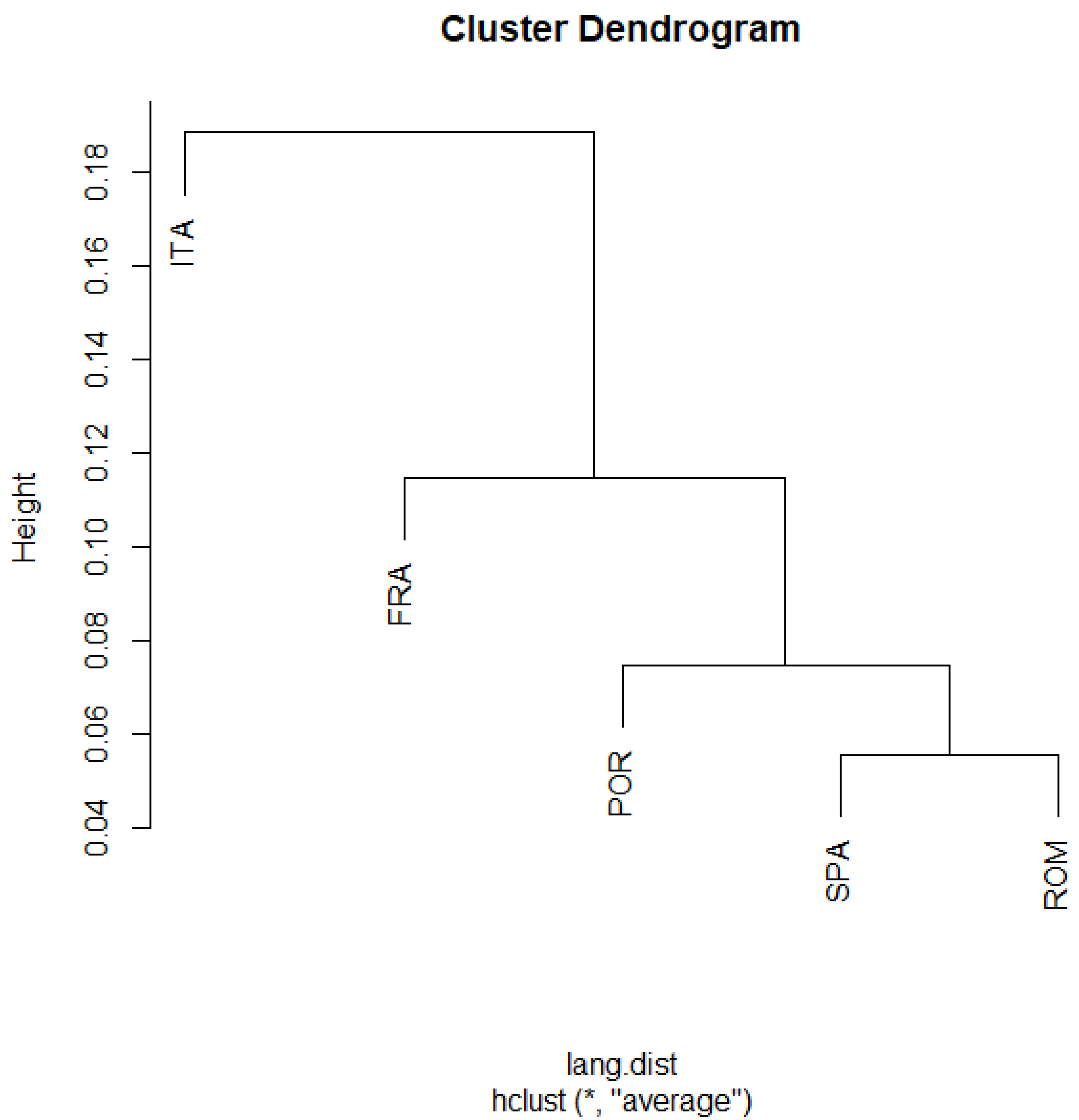
What is your own social strategy?

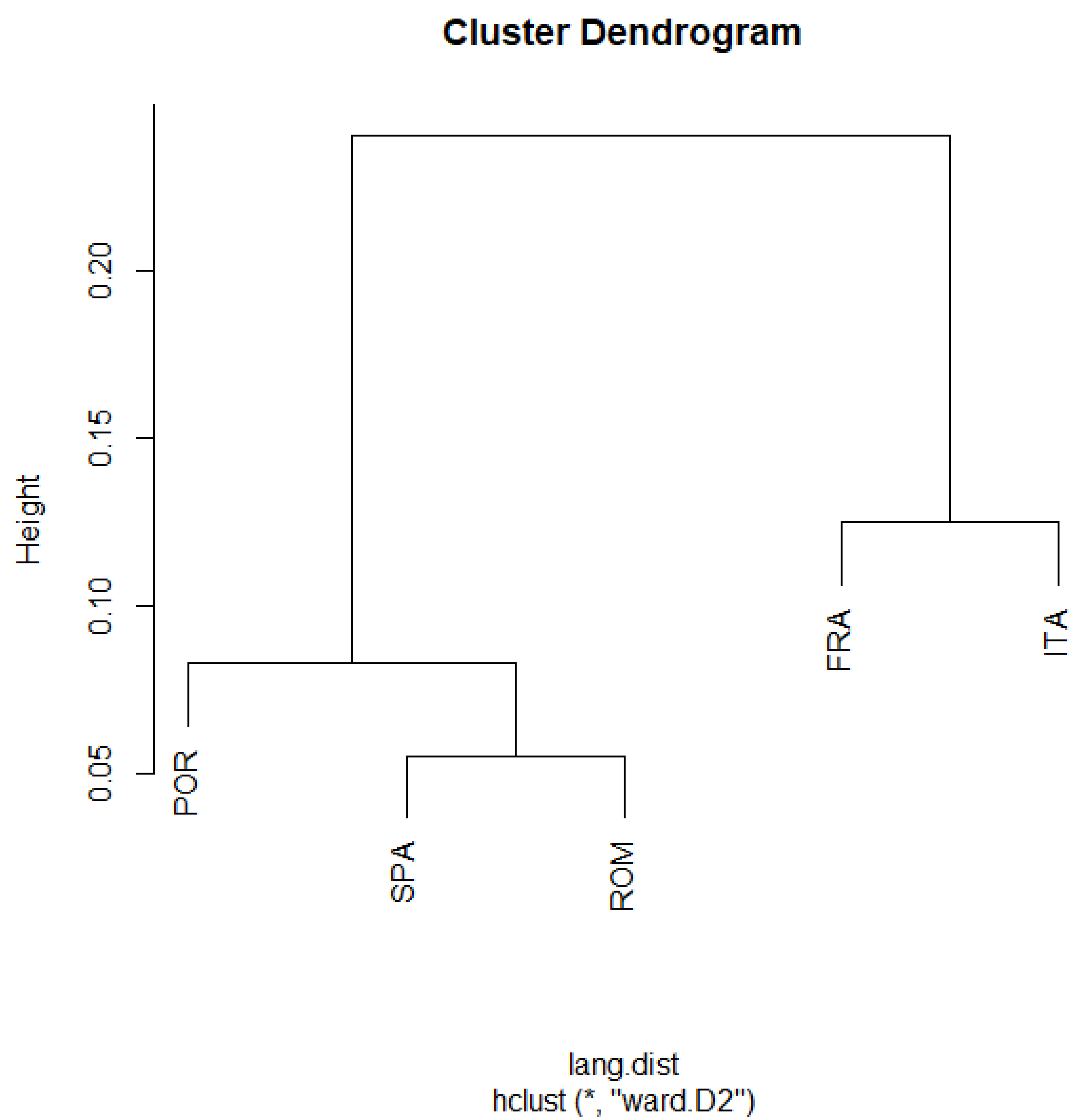
Hierarchical clustering with hclust

```
> plot(hclust(rom.dist)) #complete
> plot(hclust(rom.dist, method = "single"))
> plot(hclust(rom.dist, method = "average"))
> plot(hclust(rom.dist, method = "ward.D2"))
```


Cluster Dendrogram
Height
0.25
0.20
0.15
0.10
0.05
POR
SPA
ROM
FRA
ITA
lang.dist
hclust (*, "complete")


Cluster Dendrogram
Height
0.05
0.06
0.07
0.08
0.09
0.10
0.11
0.12
ITA
FRA
POR
SPA
ROM
lang.dist
hclust (*, "single")


Cluster Dendrogram
Height
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0.18
ITA
FRA
POR
SPA
ROM
lang.dist
hclust (*, "average")


Cluster Dendrogram
Height
0.20
0.15
0.10
0.05
POR
SPA
ROM
FRA
ITA
lang.dist
hclust (*, "ward.D2")

Exercise

- Perform HCA of the Germanic verbs of letting. The languages are “ENG”, “GER”, “DUT”, “SWE”, “NOR”. Compare the results produced by different clustering methods. Are they stable?

Outline

- Principles of cluster analysis
  - Case study of Romance causatives
- Semantic Vector Space Models
  - Case study: English verb classification

Semantic Vector Space Models

- Main inspiration:
  - "You shall know the word by the company it keeps" (Firth 1957)
  - Words that occur in the same contexts tend to have similar meaning (Harris 1959)
- Origins in Computational Linguistics (cf. Deerwester et al. 1990, Schütze 1992, Lin 1998)
- Various applications in lexical and constructional corpus-based semantics (e.g. Levshina & Heylen 2014; Perek 2016)

A compact overview for linguists

- See my paper with Kris Heylen (Levshina & Heylen 2014)

The main steps

1. Create the vectors of co-occurrence frequencies of target words and contextual features (other words, subcategorization frames, etc.).

2. Normalize the frequencies (usually by transforming them into Pointwise Mutual Information scores), so that more surprising frequencies get more weight.

3. Compute the distances between the vectors (usually using the cosine measure).

4. Perform cluster analysis, MDS or use another exploratory technique.

What are contextual features?

- Bag-of-words models:
  - Take all words that occur within a certain window around a word (e.g. 5 words on the left and 5 words on the right).

-5	-4	-3	-2	-1	0	1	2	3	4	5
I	wandered	lonely	as	a	**cloud**	that	floats	on	high	ov'r

  - Large window: topic-related information

Topic: hospital





What are contextual features like?

- Bag-of-words models:
  - Take all words that occur within a certain window around a word (e.g. 5 words on the left and 5 words on the right).

-5	-4	-3	-2	-1	0	1	2	3	4	5
I	wandered	lonely	as	a	**cloud**	that	floats	on	high	ov’r

  - Small window: semantic relatedness

Some semantic relationships

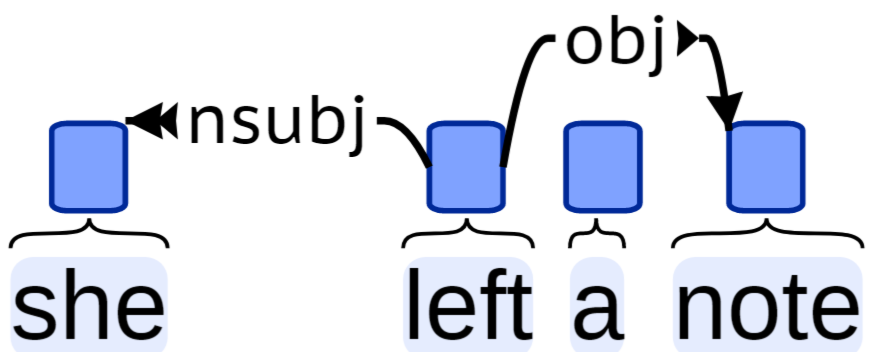
- Synonyms, e.g. *begin – start*
- Co-hyponyms, e.g. *fox terrier – beagle*

- Hyper- and hyponyms, e.g. *dog - beagle*

Images from Wikipedia

What are contextual features like?

- Syntactically enriched models:
  - Take into account the syntactic dependencies between the targets and other lexemes

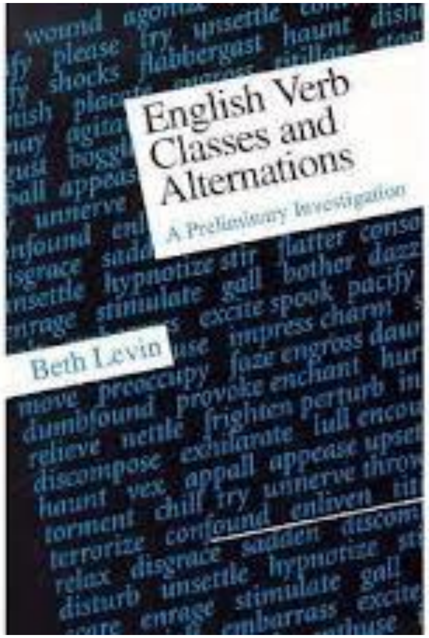


  - Good for capturing semantic similarity.

Image from http://universaldependencies.org/u/overview/simple-syntax.html

What are contextual features like?

- Fully syntactic information
  - E.g. subcategorisation frames for verbs, such as Subj_V_Indirect Object_Direct Object.
- Yields classes similar to Levin's (1993)



Of cabbages and kings (COCA)

	vegetable.n	**grow.v**	**crown.n**	**royal.adj**	**make.v**	**…**
cabbage	76	43	3	1	109	**…**
king	11	90	134	236	1122	**…**
queen	3	92	56	127	312	**…**
…	…	…	…	…	…	…

Of cabbages and kings (COCA)

	vegetable.n	grow.v	crown.n	royal.adj	make.v	…
cabbage	76	43	3	1	**109**	…
king	11	90	134	236	**1122**	…
queen	3	92	56	127	**312**	…
…	…	…	…	…	…	…

Weighting: PMI

- Pointwise Mutual Information

$$\text{PMI(target, context)} = \log_2 \frac{\text{P (target, word)}}{\text{P (target) * P (word)}}$$

Can be expressed as log (Observed / Expected) in a contingency table (Evert 2005).

- Negative values are replaced with zero.
- As a result of this weighting, the co-occurrence frequencies with highly frequent words (e.g. *like*) are less important, and infrequent events become more prominent.

Positive PMI

	vegetable.n	grow.v	crown.n	royal.adj	make.v	…
cabbage	76	43	3	1	**109**	…
king	11	90	134	236	**1122**	…
queen	3	92	56	127	**312**	…
…	…	…	…	…	…	…

	vegetable.n	grow.v	crown.n	royal.adj	make.v	…
cabbage	3.14	0.99	0	0	**0**	…
king	0	0	0.07	0	**0.14**	…
queen	0	0.74	0.25	0.51	**0**	…
…	…	…	…	…	…	…

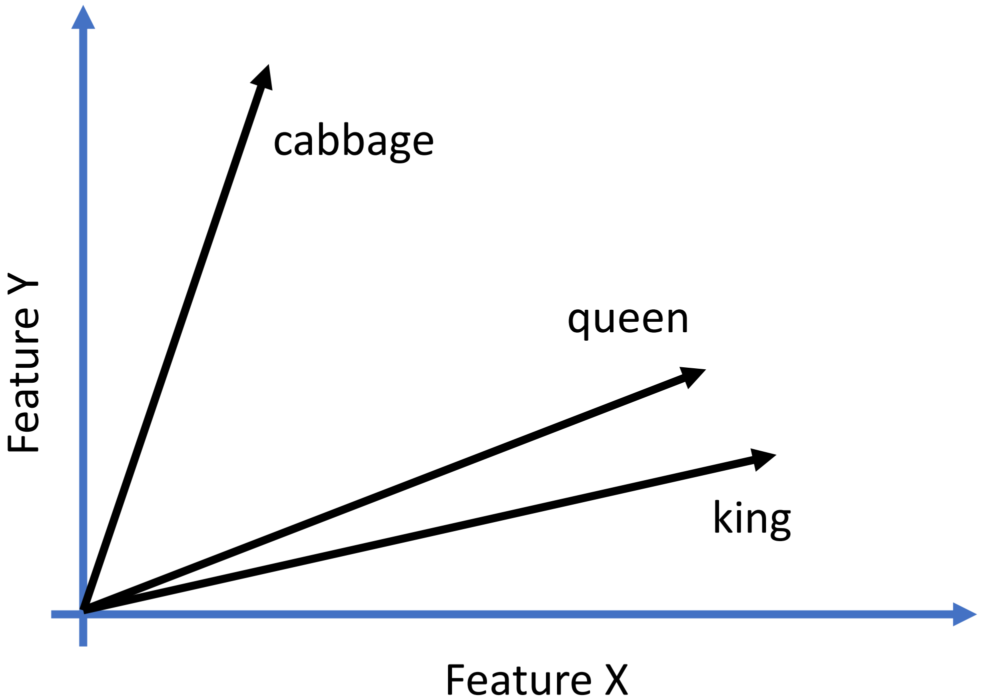
Why vector space?

- We speak about distributional vectors (sequences of PMI scores).

	vegetable.n	grow.v	crown.n	royal.adj	make.v	…
cabbage	3.14	0.99	0	0	0	…
king	0	0	0.07	0	0.14	…
queen	0	0.74	0.25	0.51	0	…
…	…	…	…	…	…	…

Why vector space?

- The weighted frequencies can be seen as coordinates defining the position of a target word in a multidimensional semantic feature space.



What is the cosine measure of similarity?

- If the angle between two vectors is small, the cosine will be large (up to 1), e.g. king and queen.
- If the angle is large, the cosine will be small (around 0), e.g. cabbage and king.
- **The greater the cosine of the angle between two vectors, the more similar the corresponding words.**

Data

- Universal Dependencies Corpus
  - http://universaldependencies.org/
- English subcorpus (254K): blogs, social media, reviews
- > 2K verbs (types)
- 28 subcategorization frames with various arguments and adjuncts, e.g.
  - Subject + Verb + Adverbial Modifier (e.g. John runs fast.)
  - Subject + Verb + Indirect Object + Direct Object (e.g. John gives Mary a book).

Data set verbframes

```
> dim(verbframes)
[1] 598  28
> verbframes[1:8, 1:8]
        Intr1 Intr2 Intr3 Intr4 Intr5 Intr6 Intr8 Trans1
come       20    22    21    64    67    48    26      2
replace     0     6     1     0     0     0     0      4
retire      2     6     0     0     0     2     1      0
attack      0     1     2     0     0     0     0      7
launch      0     2     2     0     0     0     0      2
kill        0     4     7     0     0     0     1     13
have      188    28     2    14    71     4     5    586
found       2     1     2     0     0     0     1      0
```

Weighting the frequencies

1. Transform frequencies into Pointwise Mutual Information scores

```
> verbframes.exp <-
chisq.test(verbframes)$expected
```

```
> verbframes.pmi <-
log2(verbframes/verbframes.exp)
```

2. Transform PMI into Positive PMI

```
> verbframes.ppmi <- verbframes.pmi
```

```
> verbframes.ppmi[verbframes.ppmi < 0] <- 0
```

Selecting a smaller list of verbs

```
> verblist <- c("give" ,"send", "offer","hand",
"create", "build", "produce", "jump", "come",
"go", "walk", "tell", "say", "speak", "talk",
"communicate","think","believe","assume",
"understand", "discuss", "expect", "see", "hear",
"feel",  "watch", "listen", "start", "begin",
"finish")

> verbframes.short <-
verbframes.ppmi[rownames(verbframes) %in%
verblist,]
```

Computing the cosine measures

- Function cosine from add-on package lsa. Note that we need to transpose the data (i.e. swap the rows and columns).

```
> library(lsa)
> verbframes.cos <- cosine(t(verbframes.short))
```

- We'll assign zeros to diagonal elements (similarity of a word to itself), for convenience:

```
> diag(verbframes.cos) <- 0
```

Which verbs are the most similar?

```
> max(verbframes.cos)
[1] 0.9557553

> which(verbframes.cos == max(verbframes.cos),
arr.ind = TRUE)
      row col
walk  27  11
go    11  27
```

Which verbs are similar to give?

```
> verbframes.cos[rownames(verbframes.cos) ==
"give", ]
```

[output omitted]

For convenience, round the numbers up to three decimal points:

```
> round(verbframes.cos[rownames(verbframes.cos) ==
"give", ], 3)
```

[output omitted]

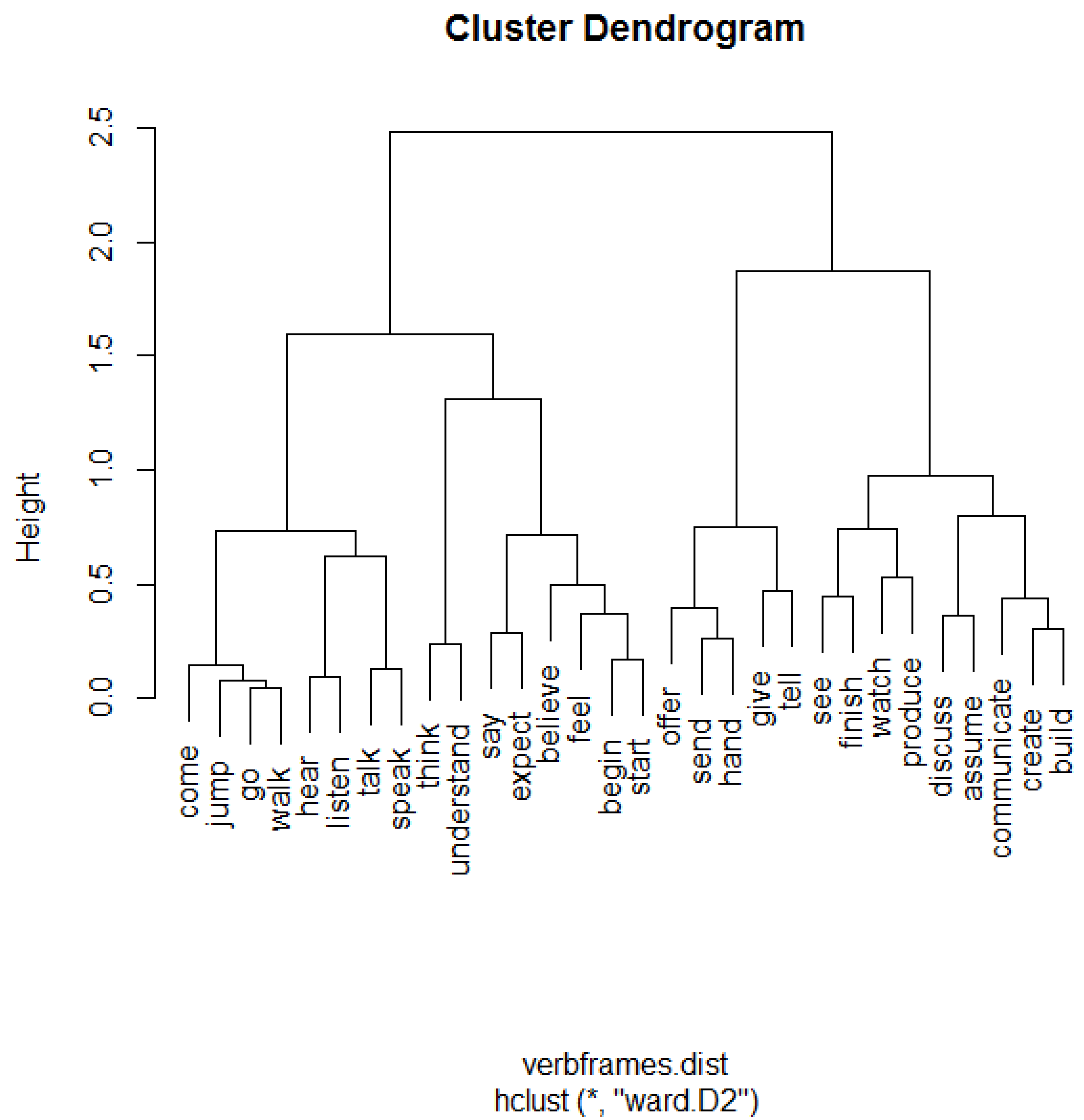
Hierarchical cluster analysis

1. Transform the similarity scores into distances by subtracting the cosines from 1:

```
> verbframes.dist <- as.dist(1 - verbframes.cos)
```

2. Perform HCA (see previous lecture):

```
> verbframes.clust <- hclust(verbframes.dist,
method = "ward.D2")
> plot(verbframes.clust)
```


Cluster Dendrogram
Height
0.0
0.5
1.0
1.5
2.0
2.5
come
jump
go
walk
hear
listen
talk
speak
think
understand
say
expect
believe
feel
begin
start
offer
send
hand
give
tell
see
finish
watch
produce
discuss
assume
communicate
create
build
verbframes.dist
hclust (*, "ward.D2")

Comparing properties of clusters

```
> verbs1 <- c("come", "go", "walk", "jump")
> verbs2 <- c("hear", "listen", "talk", "speak")
> cluster1 <-
verbframes.short[rownames(verbframes.short) %in%
verbs1,]
> cluster2 <-
verbframes.short[rownames(verbframes.short) %in%
verbs2,]
```

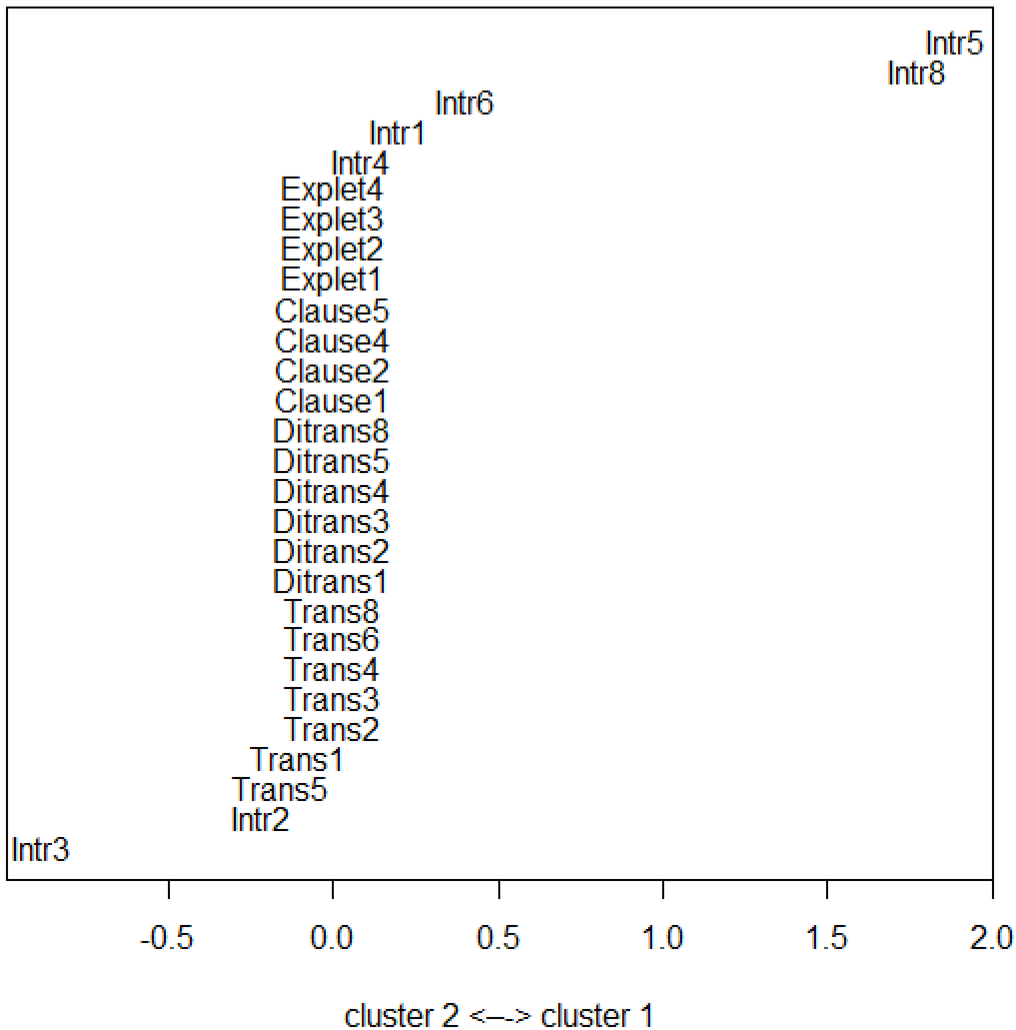
Compute the mean PMIs and the differences between them:

```
> cluster1.means <- colMeans(cluster1)
> cluster2.means <- colMeans(cluster2)
> diff <- cluster1.means - cluster2.means
```

Making a “snake plot”

```
> plot(sort(diff), 1:length(diff), type = "n",
xlab = "cluster 2 <--> cluster 1", yaxt = "n",
ylab = "")

> text(sort(diff), 1:length(diff),
names(sort(diff)))
```


Intr5
Intr8
Intr6
Intr1
Intr4
Explet4
Explet3
Explet2
Explet1
Clause5
Clause4
Clause2
Clause1
Ditrans8
Ditrans5
Ditrans4
Ditrans3
Ditrans2
Ditrans1
Trans8
Trans6
Trans4
Trans3
Trans2
Trans1
Trans5
Intr2
Intr3
-0.5
0.0
0.5
1.0
1.5
2.0
cluster 2 <--> cluster 1

Distinctive subcategorization frames

- Frame Intr3: V + Oblique
  - Talk **to** your academic **adviser**, see what they recommend.
- Frame Intr5: Subj + V + AdvMod
  - **Now** comes the fun part.
- Frame Intr8: V + AdvMod
  - Coming **soon**!

Exercise

- Compare the clusters [give, tell] and [offer, send, hand]. What is the difference?

References

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- Levshina, N., & Heylen, K. (2014). A radically data-driven construction grammar: Experiments with Dutch causative constructions. In R. Boogaart, T. Colleman, & G. Rutten (Eds.), *Extending the Scope of Construction Grammar,* 17–46. Berlin/New York: Mouton de Gruyter.
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- Schütze, H. (1992). Dimensions of meaning. In *Proceedings of Supercomputing 92,* 787–796. Minneapolis, MN.