Variability-based neighbor clustering with historical corpus data:
Results, new applications, and future directions

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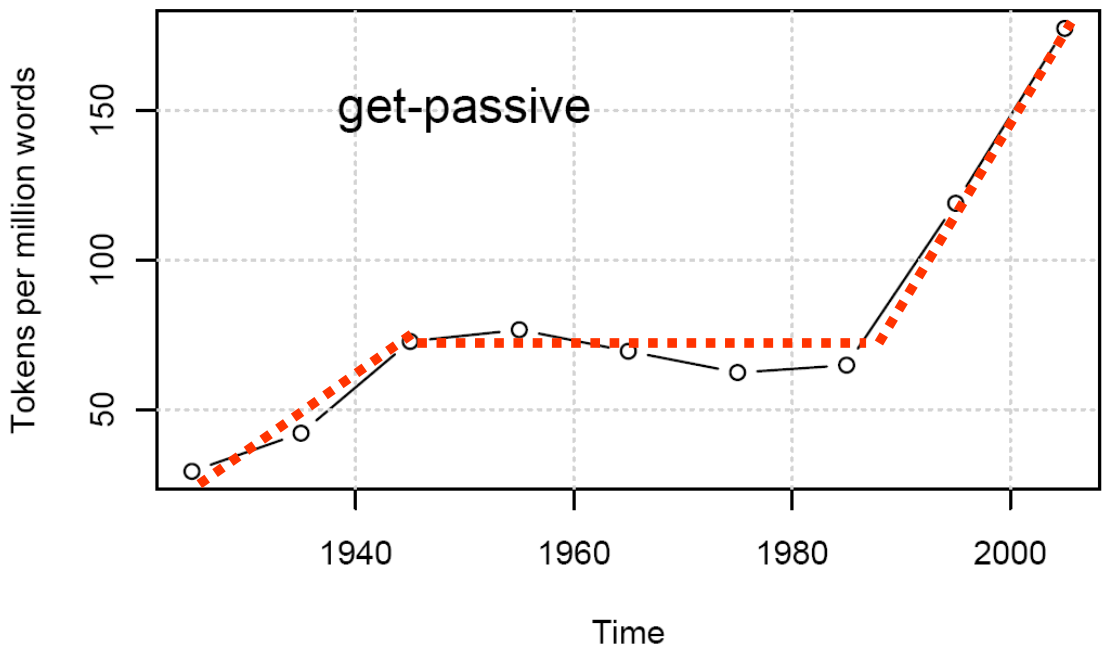
It would be nice if we had a method allowing us to divide a development in language change into a sequence of stages.

Gries & Hilpert (2008) *Corpora* 3/1

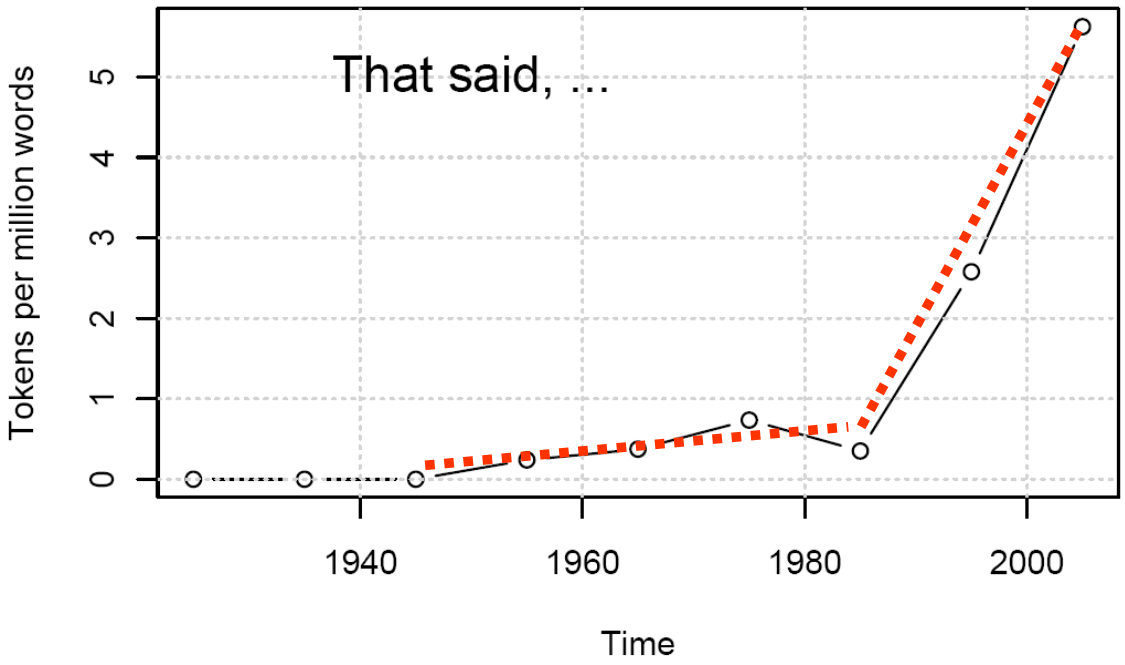
Variability-based neighbor clustering:

A technique that allows us to partition a historical development into a sequence of stages

Three stages?



Two stages?

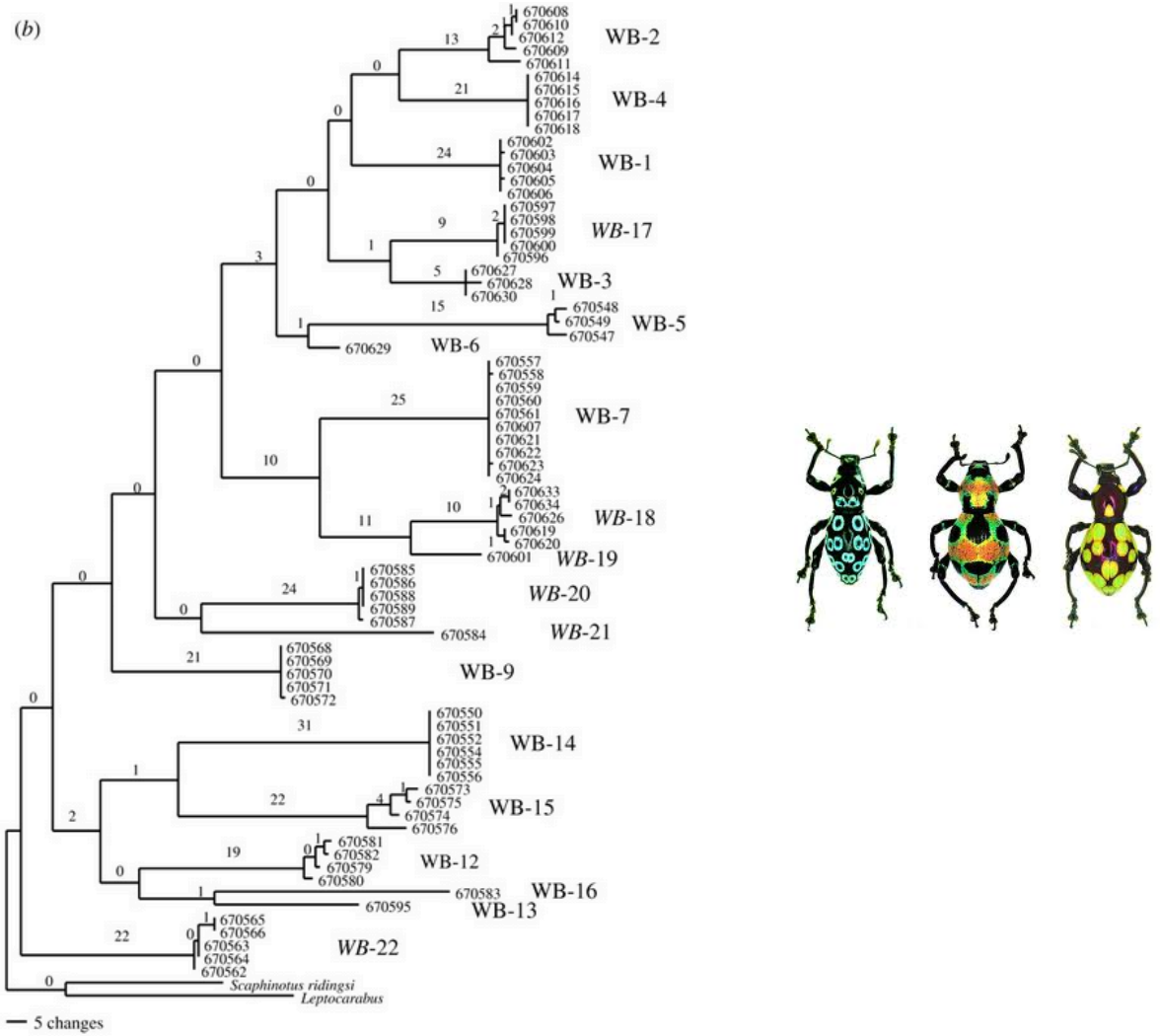

That said, ...
Tokens per million words
0
1
2
3
4
5
1940
1960
1980
2000
Time

Partitioning historical data

- Diachronic corpus work divides data into sequential periods (centuries, half-centuries, decades, ...)
- Linguistic change can move in fits, bumps, and U-shaped curves
- Averaging over a given period may be misleading
- Different time slices >> different results
- Ideal: dividing the corpus into time slices on the basis of the phenomenon that is studied (data-driven)
- One way to find structures in large bodies of data: hierarchical clustering

Hierarchical Clustering

- A technique to find categories in sets of items that are similar to varying degrees.


(b)
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WB-14
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WB-15
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670582
670579
670580
WB-12
670583
WB-16
670595
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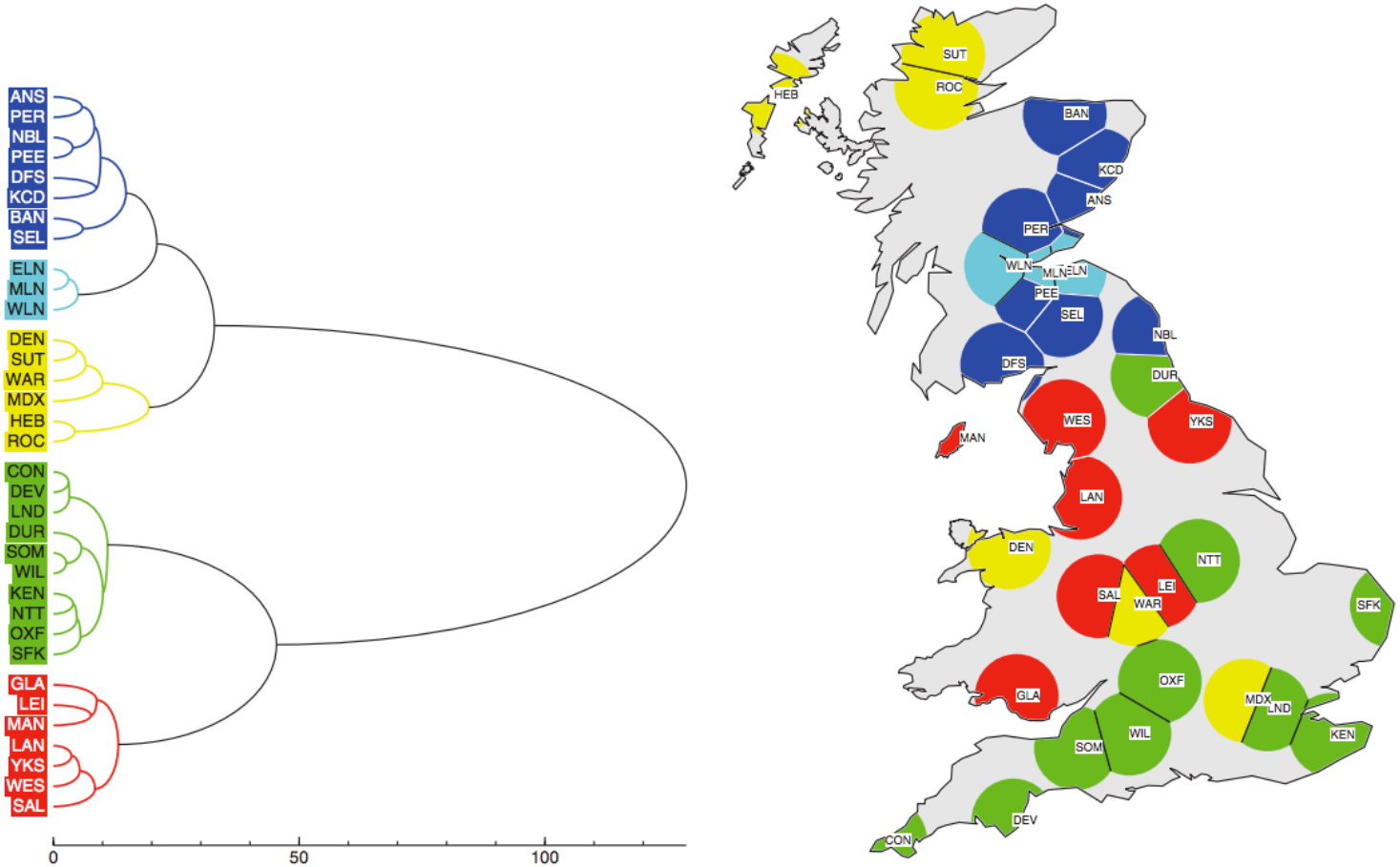
670564
670562
WB-22
Scaphinotus ridingsi
Leptocarabus
5 changes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DEV
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WIL
KEN
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WES
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DFS
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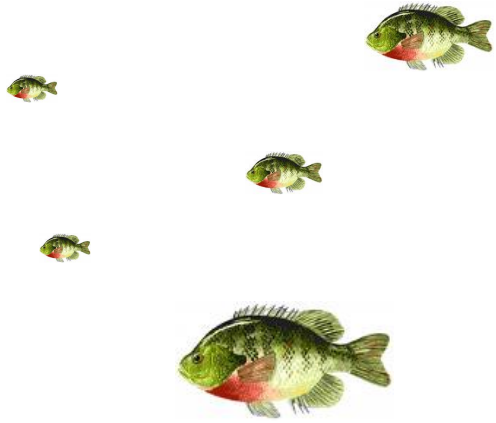


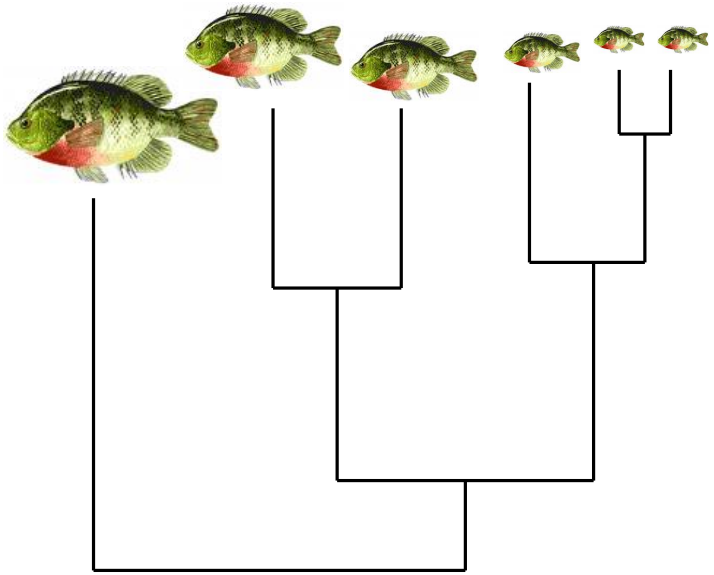
							
							
							
							
							
							
							

						
	0	5	7	9	10	10.5
		0	2	6	7	7.5
			0	2	3	3.5
				0	1	1.5
					0	0.5
						0

					
	0	5	7	9	10.25
		0	2	6	7.25
			0	2	3.25
				0	1.25
					0

				
	0	5	7	9.625
		0	2	6.625
			0	2.625
				0

			
	0	6.5	9.625
		0	6.125
			0

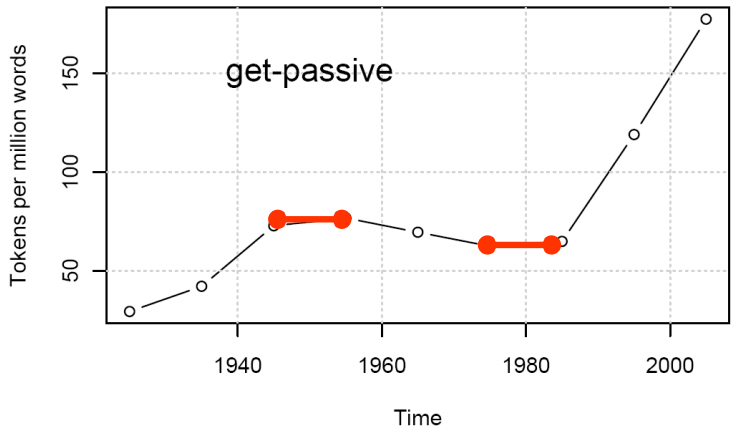


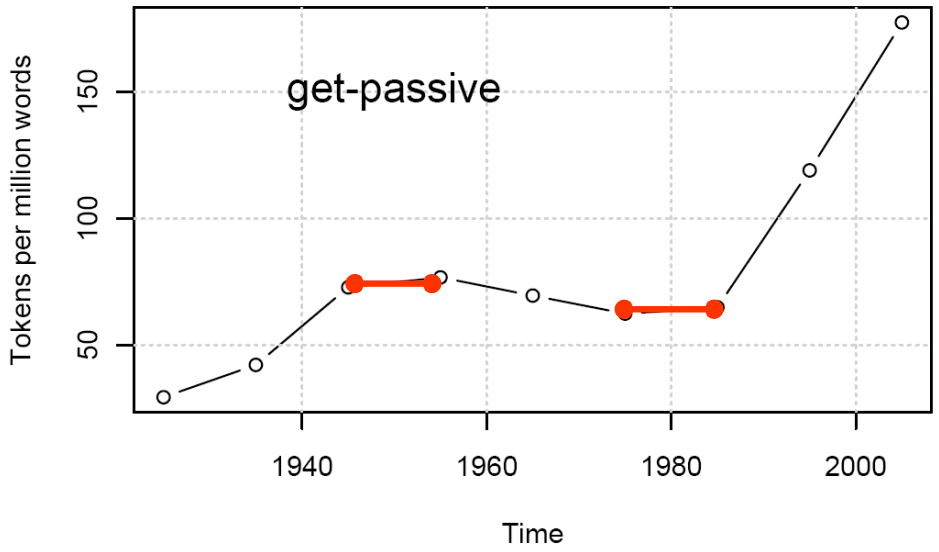
Hierarchical Clustering

- Idea: Use clustering to find out how the development of a given linguistic unit can be divided into stages.
    - Data from different historical periods are coded for a parameter (frequency, range of collocates,...) and grouped according to their similarity.
- Problem: Clustering algorithms are blind to temporal sequence.
    - If, for instance, 1993 is more similar to 2000 than to 1994, we end up with nonsensical clusters.
- Proposal: Variability-based Neighbor Clustering (VNC)
    - Only temporally adjacent nodes are allowed to merge.

Variability-based Neighbor Clustering

- find the two closest neighbors
- merge them and take the mean value
- now find again the two closest neighbors
- merge them and take the mean value
- ...
- until all periods are merged





Decade	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Tokens per MW	29.5	42.2	72.8	76.7	69.6	62.4	64.9	119.0	177.3

Decade	1920s	1930s	1940s	1950s	1960s	1970s and 1980s	1990s	2000s
Tokens per MW	29.5	42.2	72.8	76.7	69.6	63.65	119.0	177.3

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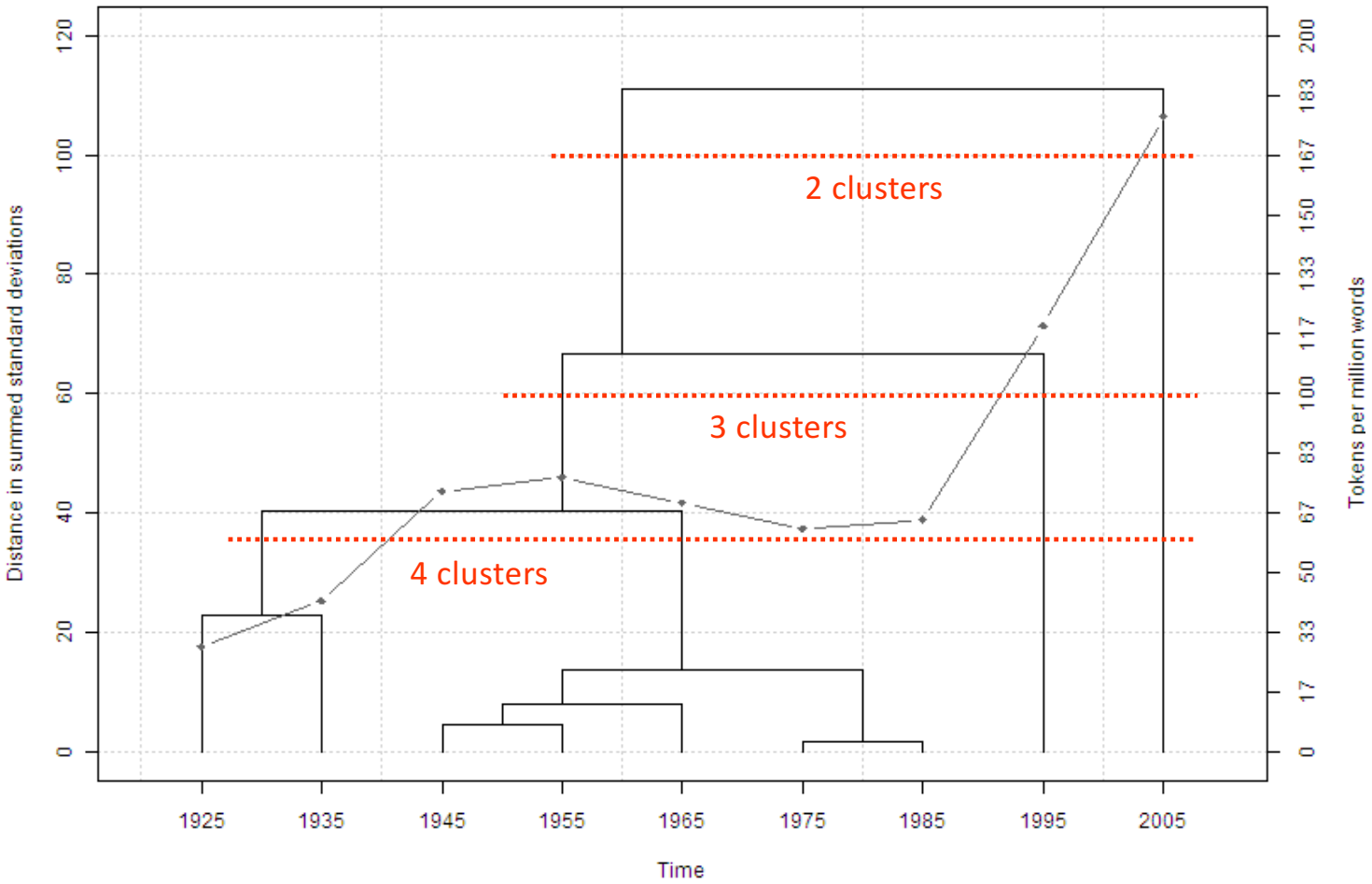
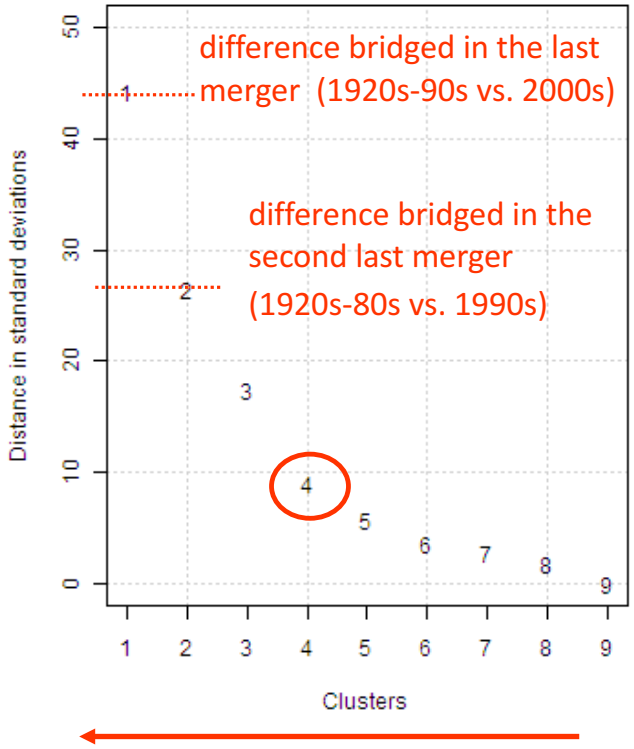
Tokens per MW	29.5	42.2	74.75	69.6	63.65	119.0	177.3


2 clusters
3 clusters
4 clusters
Distance in summed standard deviations
Tokens per million words
Time
0
20
40
60
80
100
120
0
17
33
50
67
83
100
117
133
150
167
183
200
1925
1935
1945
1955
1965
1975
1985
1995
2005

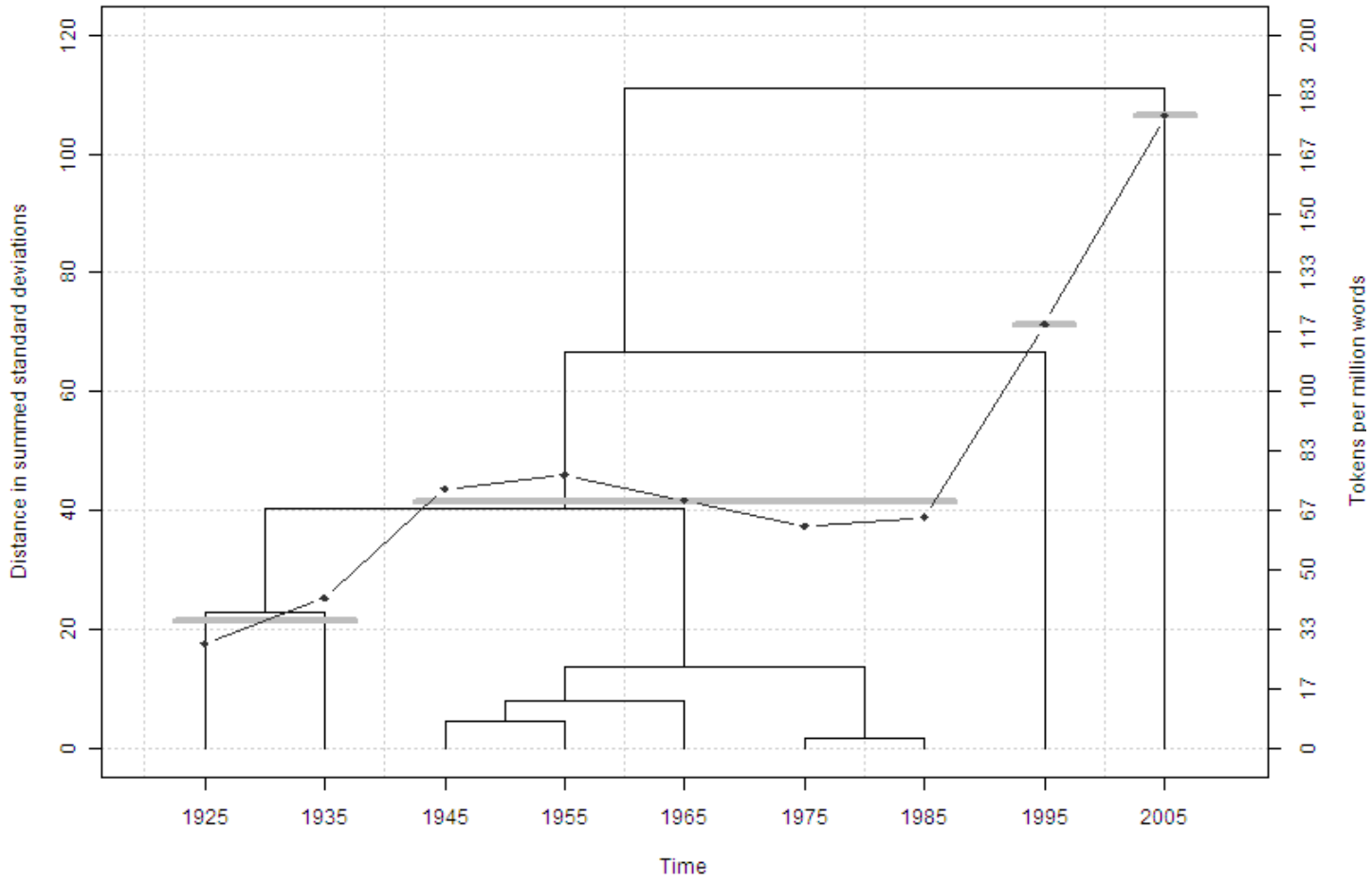
How many clusters?

as low as possible



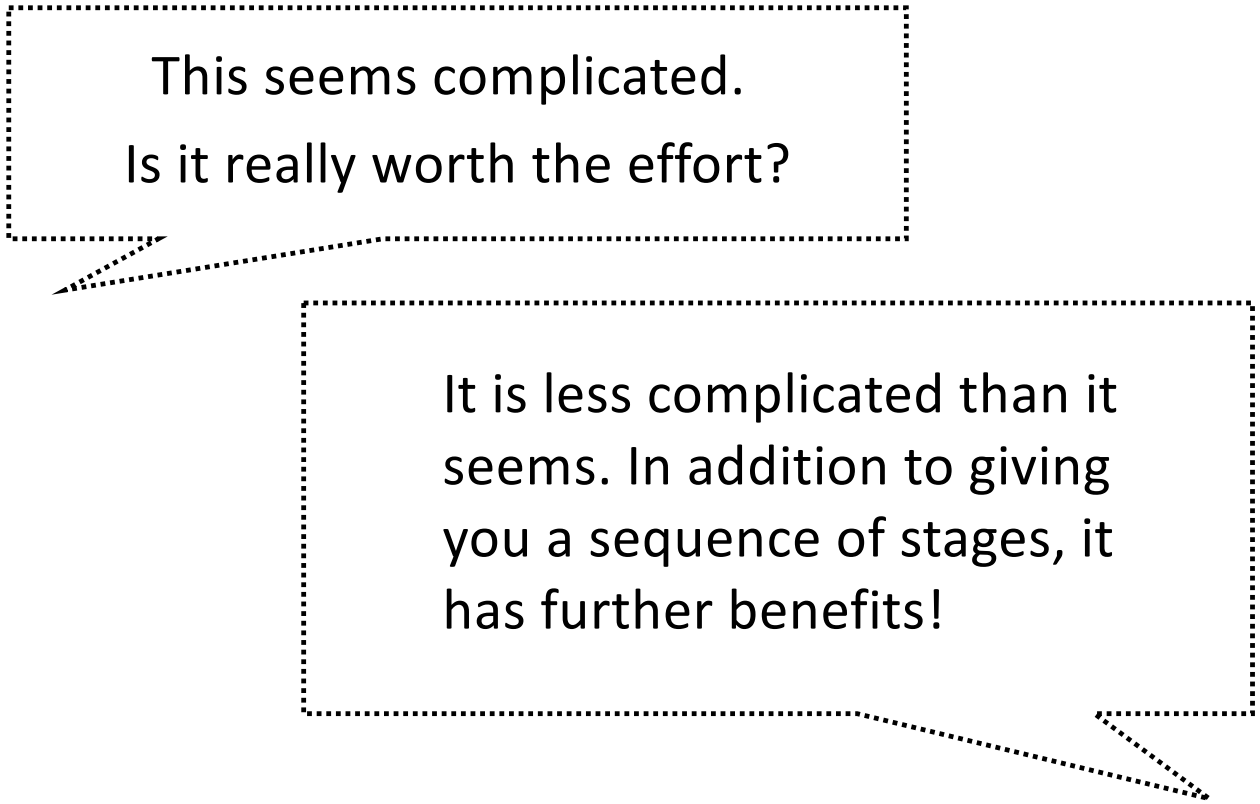
as few as possible

4-cluster solution for the *get*-passive



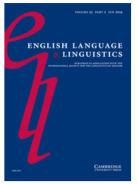
VNC: interim conclusions

- VNC shows that
  - the trend has four different temporal stages
  - provides their lengths
  - provides their average frequencies
- VNC can detect structure that may otherwise go unnoticed / be hard to characterize objectively


This seems complicated.
Is it really worth the effort?
It is less complicated than it seems. In addition to giving you a sequence of stages, it has further benefits!

Dectecting outliers with VNC

- Frequencies from diachronic corpus data are often messy.
- There is no principled way to identify certain data points as outliers.
- Picking outliers manually is dangerous because you might fit the data to your expectations.
- VNC provides a solution.

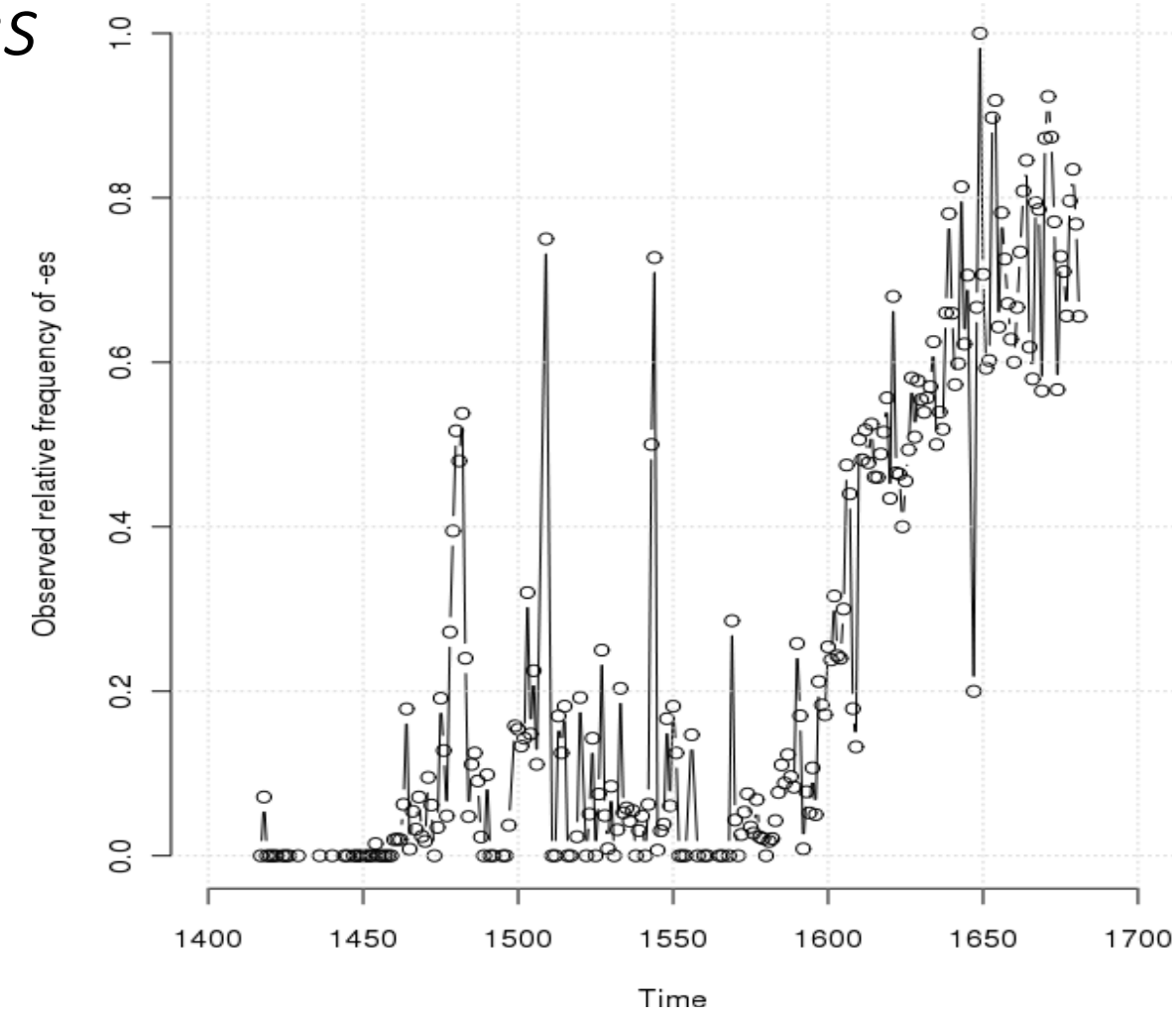


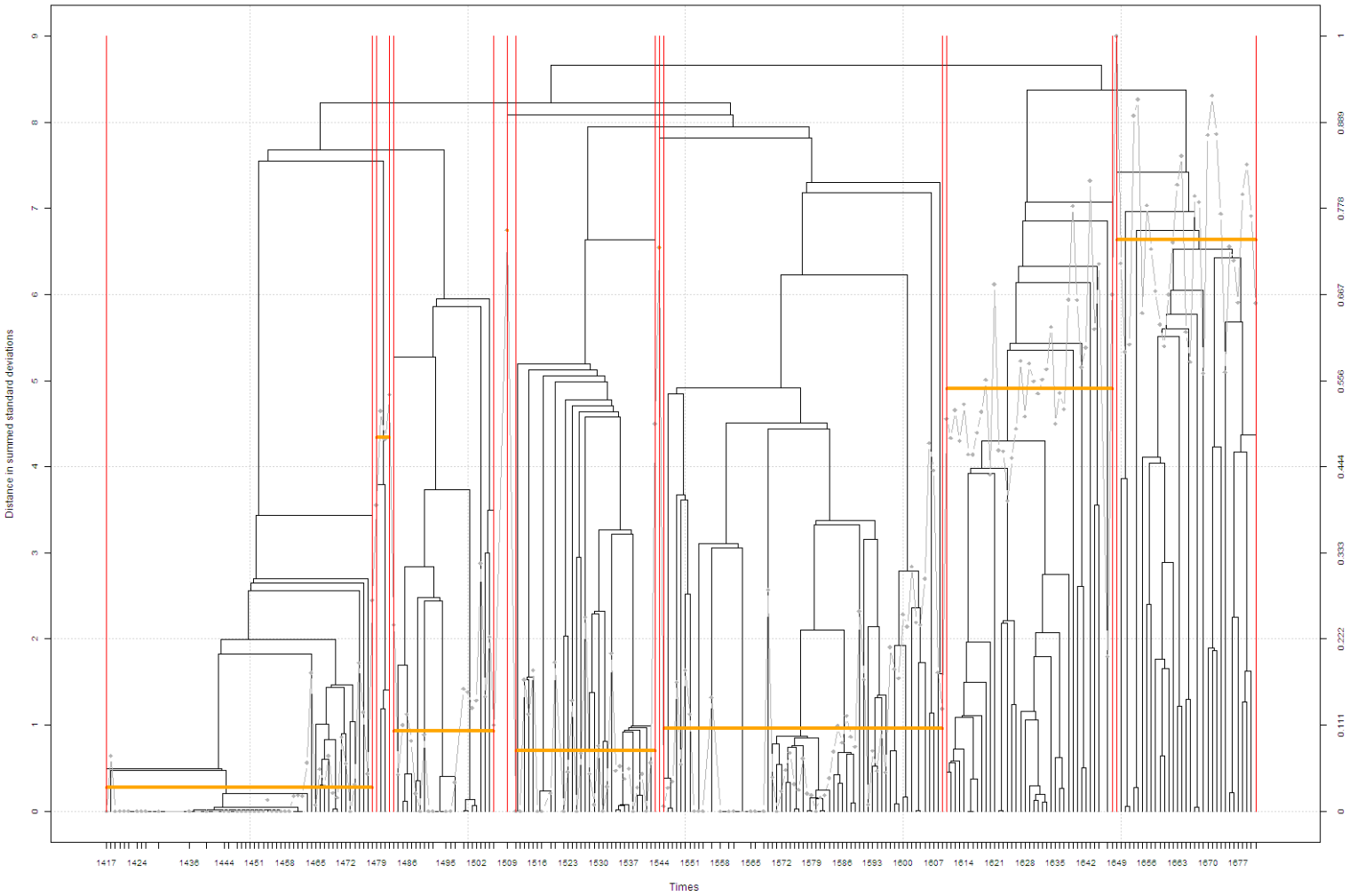
Gries & Hilpert (2010) *English Language and Linguistics* 14/3

From *giveth* to *gives*

~270 data points

relative frequencies of
–es range from 0 to 1




Distance in summed standard deviations
Observed relative frequency of 'es'
Times
0
1
2
3
4
5
6
7
8
9
0
0.111
0.222
0.333
0.444
0.556
0.667
0.778
0.889
1
1417
1424
1436
1444
1451
1458
1465
1472
1479
1486
1495
1502
1509
1516
1523
1530
1537
1544
1551
1558
1565
1572
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1586
1593
1600
1607
1614
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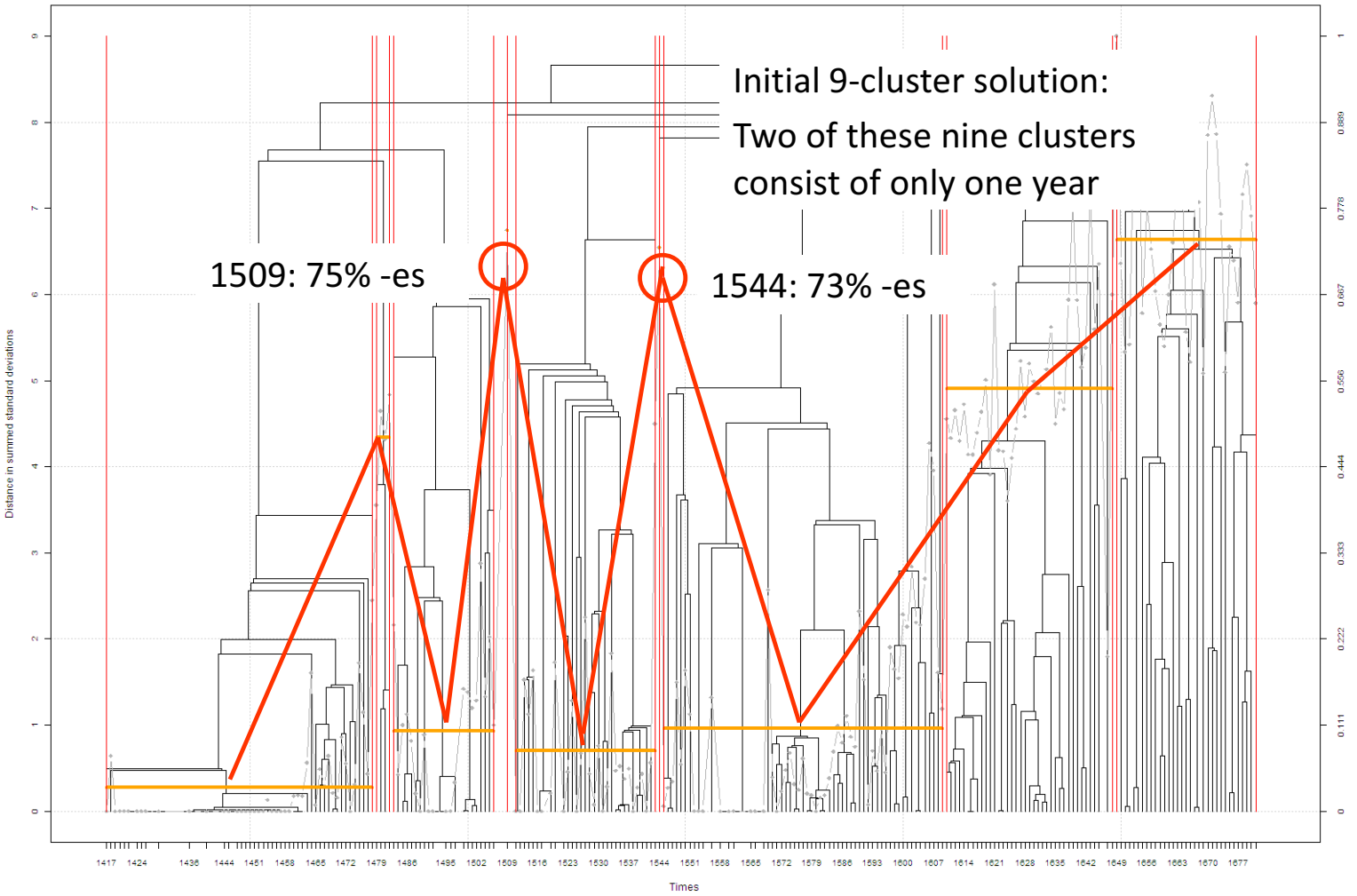
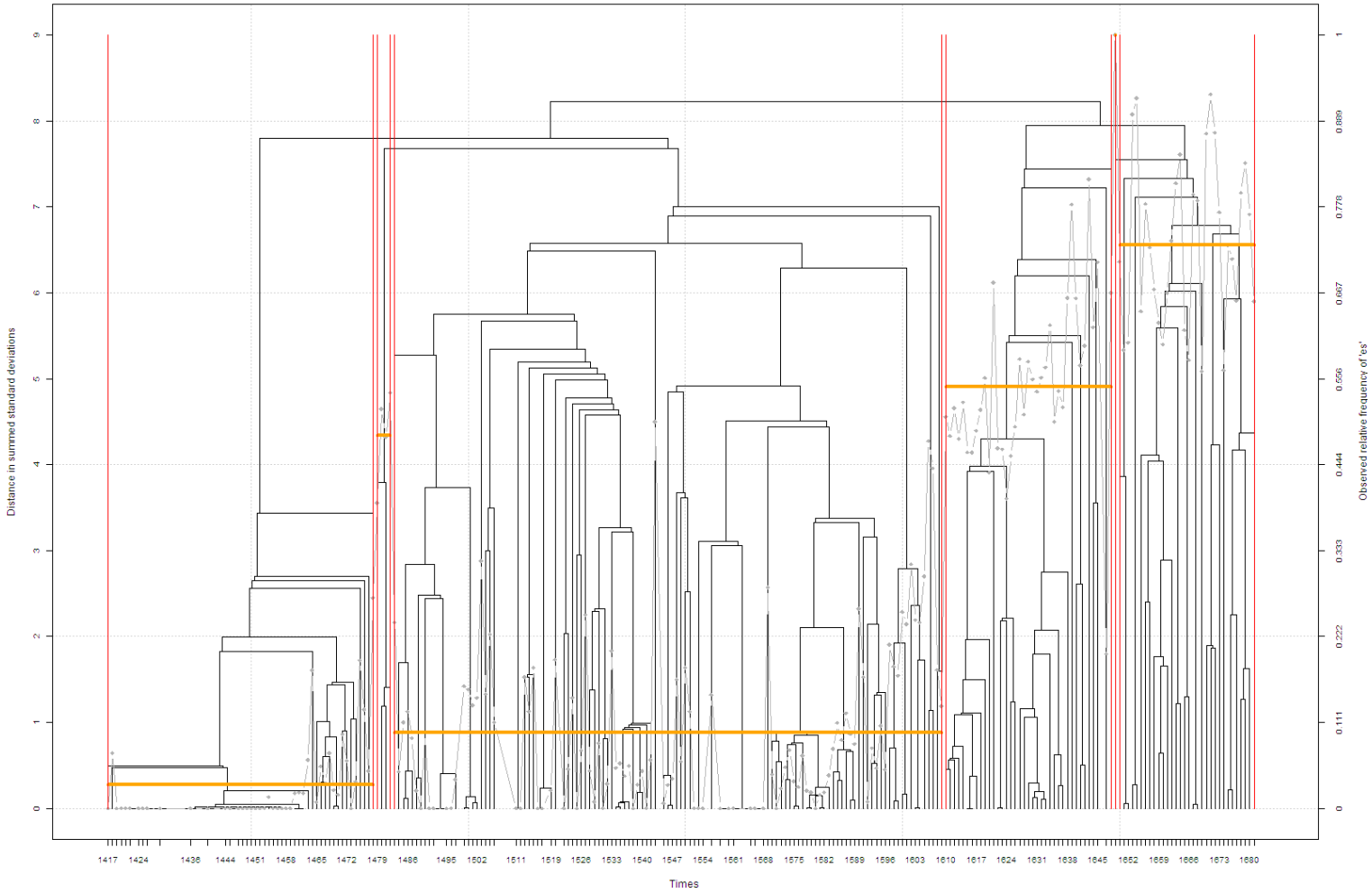
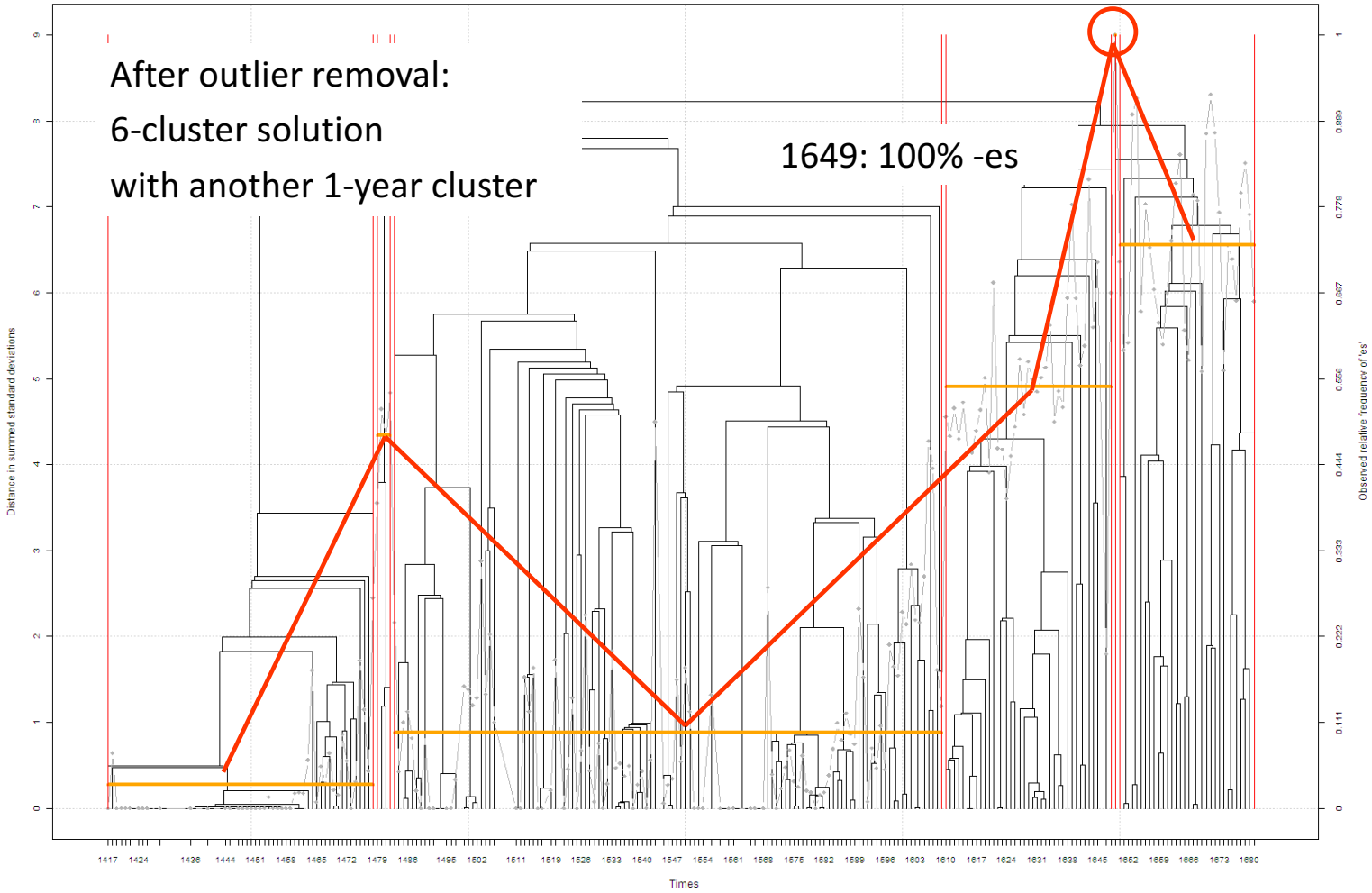
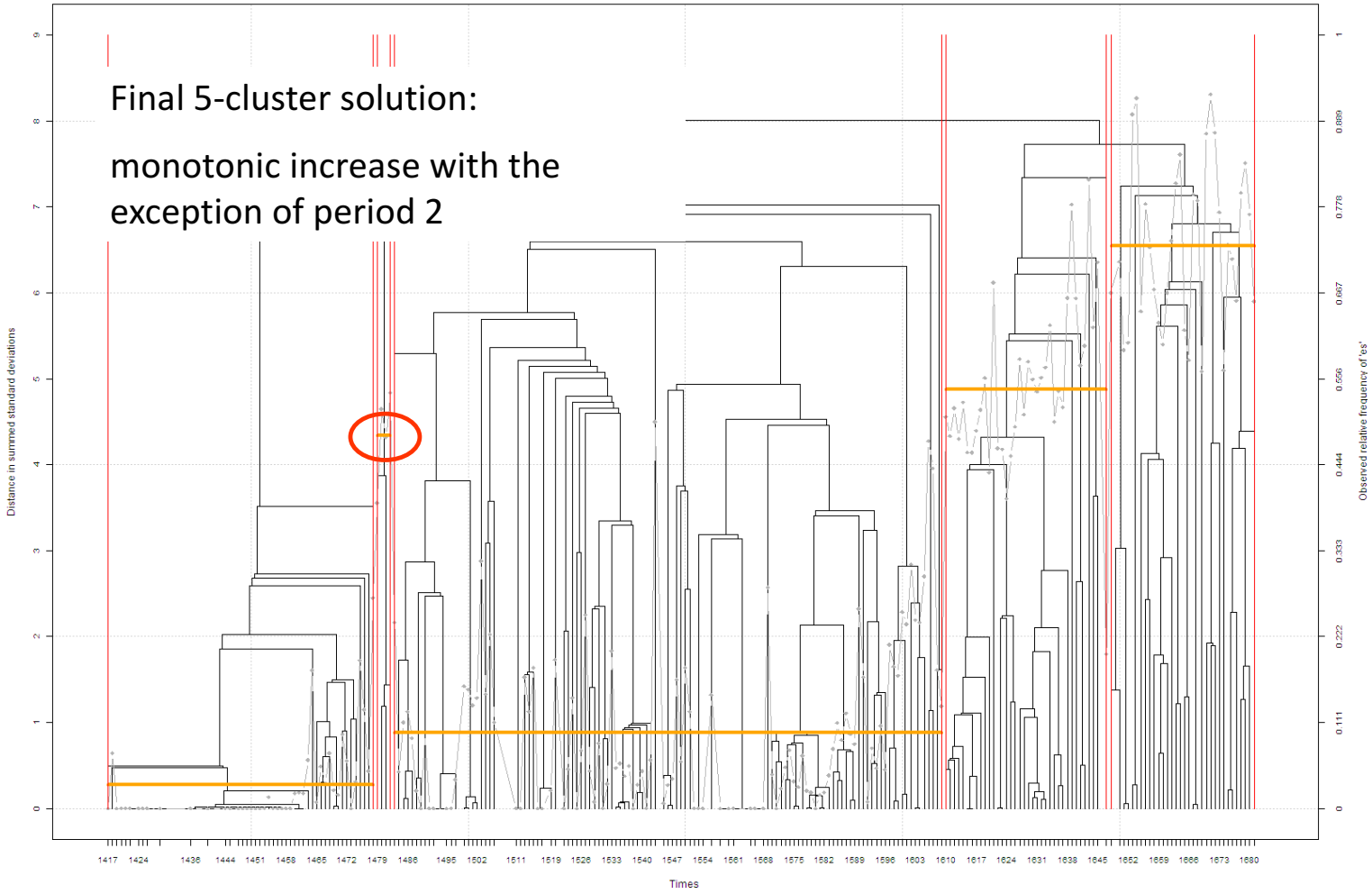
1628
1635
1642
1649
1656
1663
1670
1677


Initial 9-cluster solution:
Two of these nine clusters consist of only one year
1509: 75% -es
1544: 73% -es
Distance in summed standard deviations
Observed relative frequency of 'es'
Times
1417 1424 1436 1444 1451 1458 1465 1472 1479 1486 1495 1502 1509 1516 1523 1530 1537 1544 1551 1558 1565 1572 1579 1586 1593 1600 1607 1614 1621 1628 1635 1642 1649 1656 1663 1670 1677


Distance in summed standard deviations
0
1
2
3
4
5
6
7
8
9
Observed relative frequency of 'es'
0
0.111
0.222
0.333
0.444
0.556
0.667
0.778
0.889
1
1417
1424
1436
1444
1451
1458
1465
1472
1479
1486
1495
1502
1511
1519
1526
1533
1540
1547
1554
1561
1568
1575
1582
1589
1596
1603
1610
1617
1624
1631
1638
1645
1652
1659
1666
1673
1680
Times

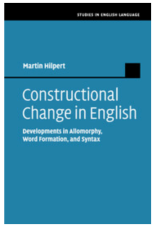

After outlier removal:
6-cluster solution
with another 1-year cluster
1649: 100% -es
Distance in summed standard deviations
Observed relative frequency of 'es'
Times
1417 1424 1436 1444 1451 1458 1465 1472 1479 1486 1495 1502 1511 1519 1526 1533 1540 1547 1554 1561 1568 1575 1582 1589 1596 1603 1610 1617 1624 1631 1638 1645 1652 1659 1666 1673 1680


Final 5-cluster solution:
monotonic increase with the exception of period 2
Distance in summed standard deviations
Observed relative frequency of 'es'
Times
0
1
2
3
4
5
6
7
8
9
0
0.111
0.222
0.333
0.444
0.556
0.667
0.778
0.889
1
1417 1424 1436 1444 1451 1458 1465 1472 1479 1486 1495 1502 1511 1519 1526 1533 1540 1547 1554 1561 1568 1575 1582 1589 1596 1603 1610 1617 1624 1631 1638 1645 1652 1659 1666 1673 1680

Dectecting outliers with VNC

- Especially when year-by-year data from historical sources is used (OED, TIME, PCEEC, PPCEME, etc.), searches often yield extreme and odd data points.
- If data points are really bad neighbors, VNC will find them.
- They can then be evicted.

Sometimes the most important change in a development is not token frequency. What about type frequency and different measures of productivity?



Hilpert (2013) *Cambridge University Press*

VNC with similarity measures other than token frequency

The V-ment construction

- Combination of a lexical stem and a suffix with the phonemic structure [mənt].
- The stem strongly tends to be verbal (judgment, punishment, but of course: merriment, scholarment).
- Typically conveys the meaning of an action (adjustment), the result of an action (assortment), or the means to accomplish an action (refreshment).

A very short history of -ment

- Isolated Latin loans during OE
- Wave of French loans after 1066
- Nativization between 1250 and 1350
- Rate of new loans recedes after 1600
- Overall productivity recedes
- In PDE, a residue of ~1000 types remains, but the construction is non-productive

  (jogment?, kissment?)

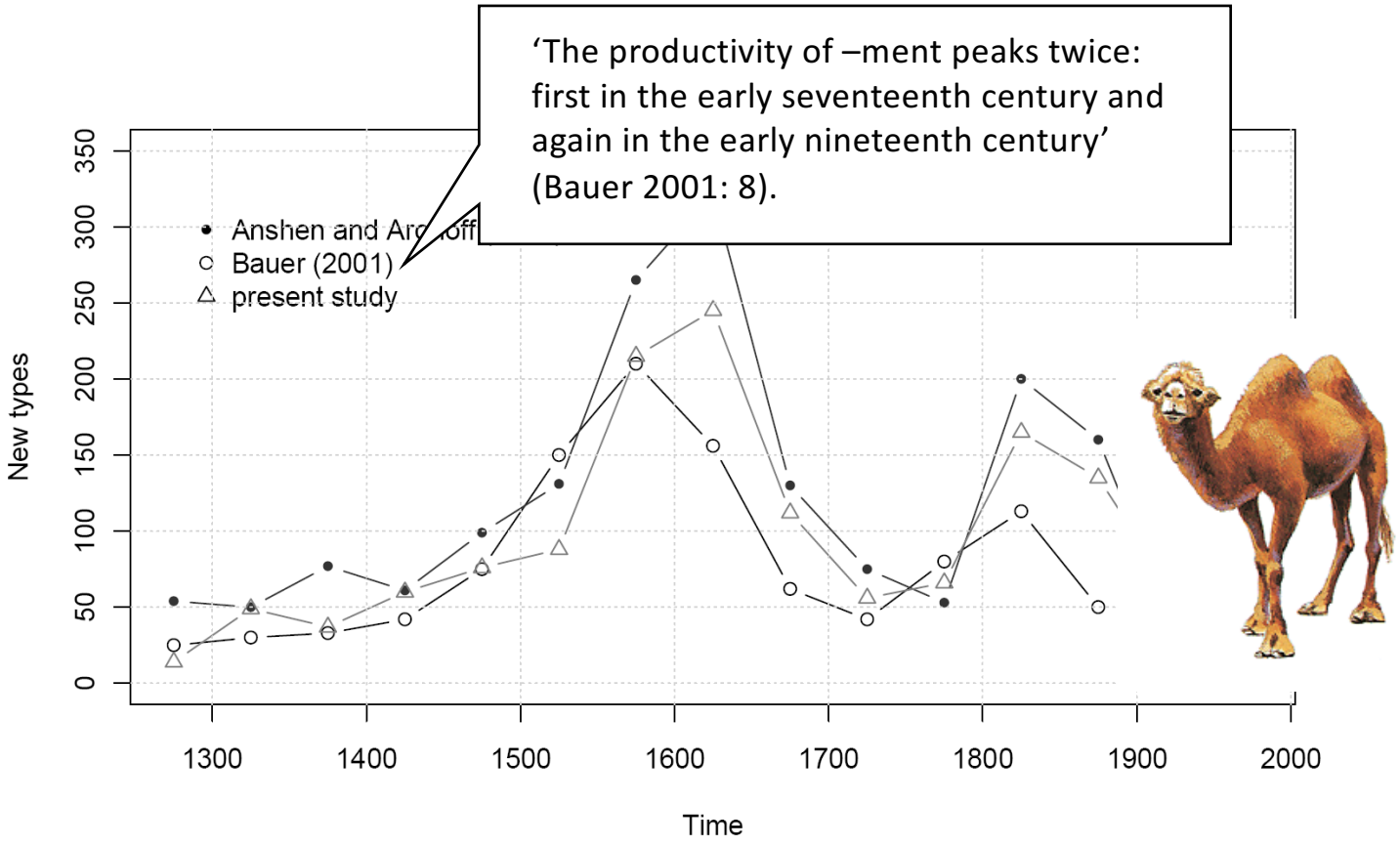
Are there stages in this development that VNC can identify?

Data

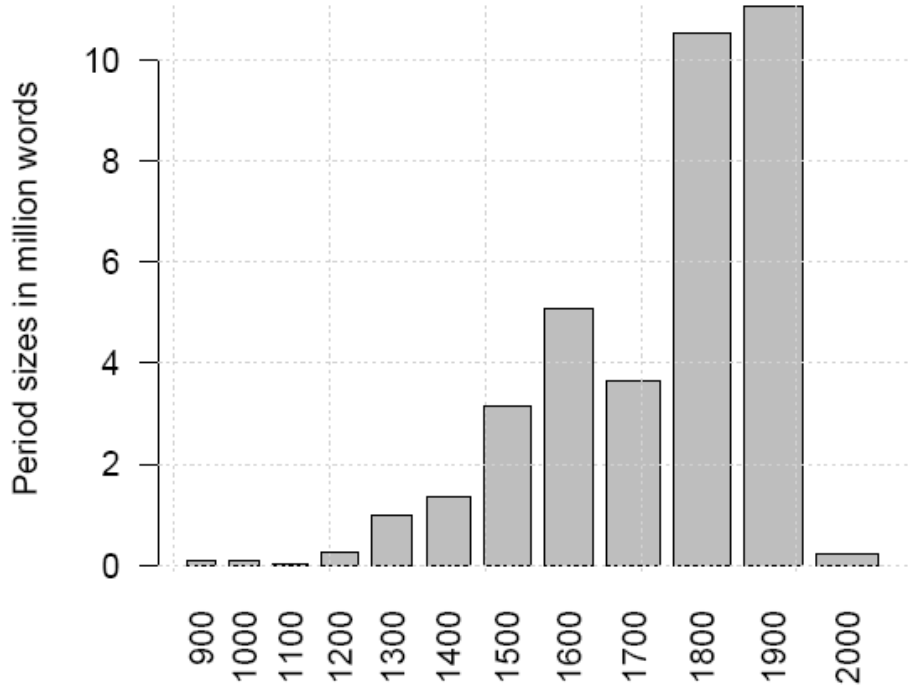
- retrieve all types from the Oxford English Dictionary
- retrieve all quotations with these types from the OED


Oxford English Dictionary a...
http://dictionary.oed.com/cgi/entry/50001680?query_type=word&queryword=hatchment&first=1&
Oxford English Dictionary
Lost for Words?
Find Word
Results
Entry
achievement, n.
DRAFT REVISION Dec. 2009
Earlier
Acheulean, adj. (and n.)
[achevisaunce, n.
achiasmate, adj.
achiasmatic, adj.
achievability, n.
achievable, adj.
achievance, n.
achieve, v.
achieved, adj.
achievement, n.
achiever, n.
achieving, n.
achieving, adj.
achill, adj.
achillea, n.
Achillean, adj.
Achilles, n.
Achilles heel, n.
Achillize, v.
achime, adj.
achimenes, n.
Pronunciation
Spellings
Etymology
Quotations
Date chart
[< Anglo-Norman and Middle French achevement, Middle French achievement (French achèvement) the action of finishing or completing something (mid 13th cent. in Old French), accomplishment (1338) < achever ACHIEVE v. + -ment -MENT suffix. Compare earlier ACHIEVING n.
With sense 2 compare HATCHMENT n.1; it is possible that this sense may have originated as a reinterpretation of HATCHMENT n.1, understood as a contracted form (compare forms at that entry).]
1. a. The action of achieving something; completion, accomplishment, successful execution.
Also with modifying prefix, as non-achievement, over-, under-achievement, etc. (see at first element).
1477 CAXTON tr. R. Le Fèvre Hist. Jason (1913) 149 With thachieuement of these deuises the kyng Oetes approched..the shippe. 1490 CAXTON tr. Eneydos sig. A i, Alle thystorye of his aduentures that he had er he cam to the achieuement of his conquest of ytalye. 1576 T. NEWTON tr. L. Lemnie Touchstone of Complexions ii. f. 15, All the instruments..of the Senses..attayne thereby stablenes, for the atchieuement of their functions and charges. c1592 Faire Em sig. A3, The blisse That hangs on quicke atchiuement of my loue. 1603 R. KNOLLES
List by entry
List by date
Entry map
Simple search
Advanced search
Print
Mail
Help
Sign out
Subscriber: Universitaetsbibliothek Freiburg
OXFORD UNIVERSITY PRESS

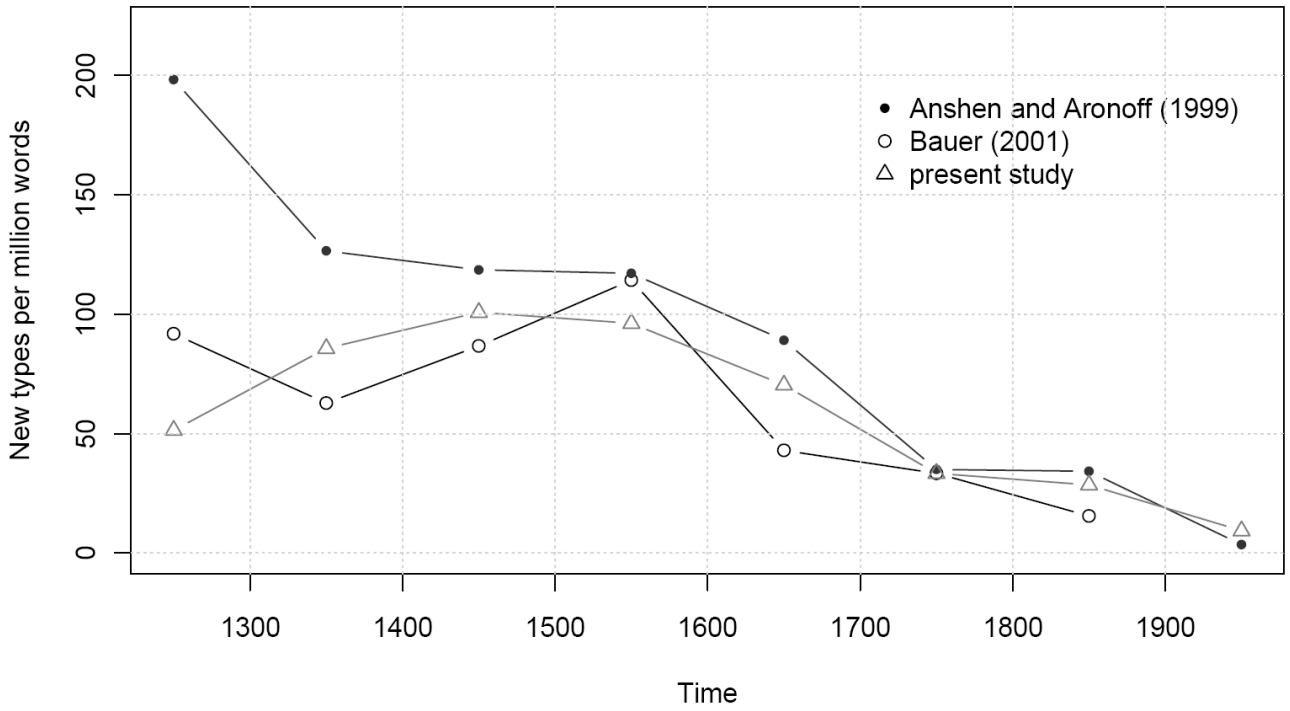
Data from the OED (~1400 types)



Words in OED quotations

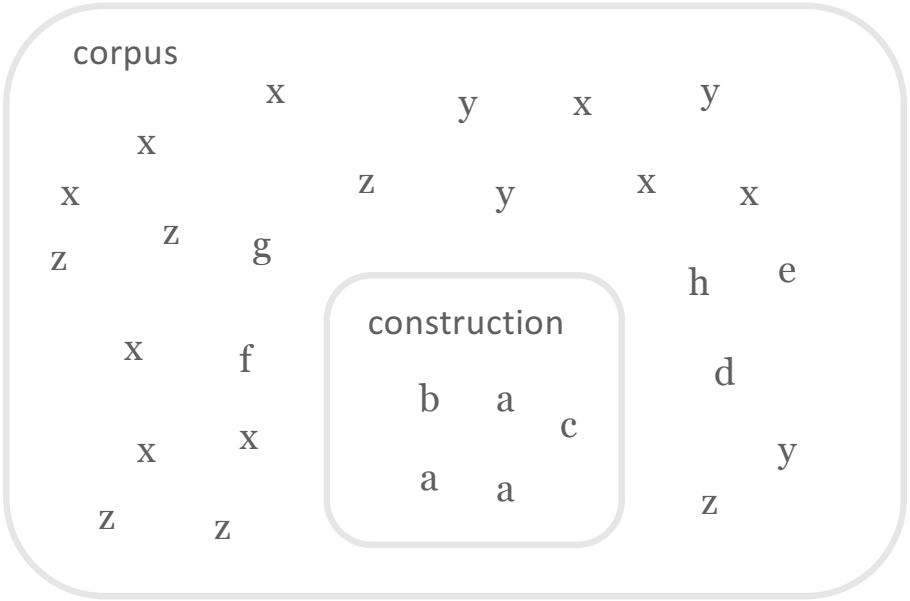


Normalized type frequencies



Expanding productivity

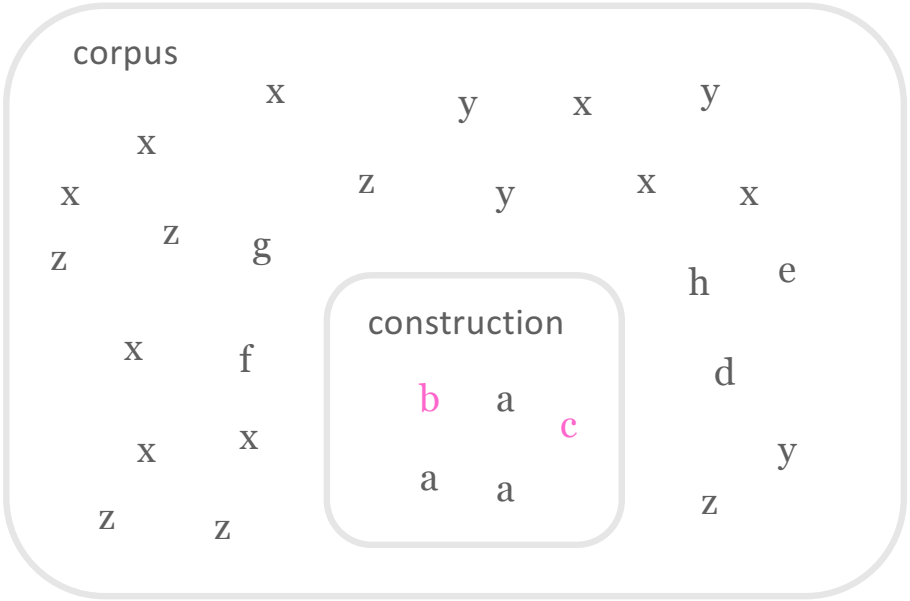
- computed as a ratio:



Expanding productivity

- computed as a ratio:

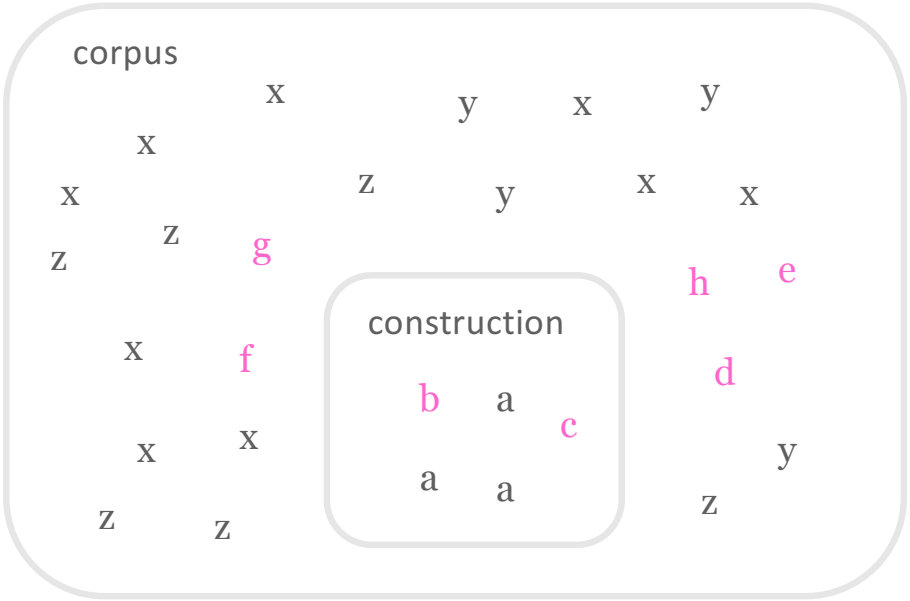
  all hapax legomena of a construction



Expanding productivity

- computed as a ratio:

$$\frac{\text{all hapax legomena of a construction}}{\text{all hapax legomena of the corpus}}$$

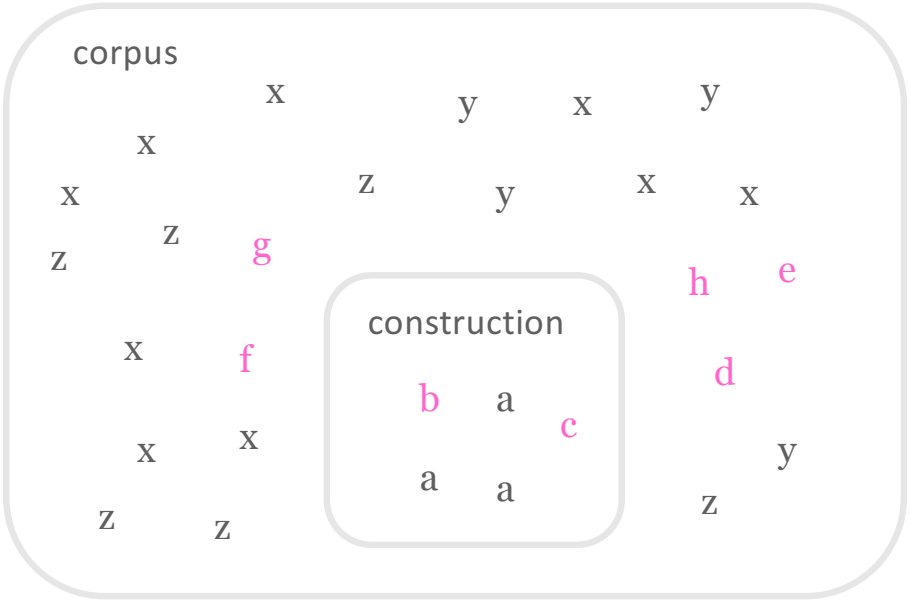


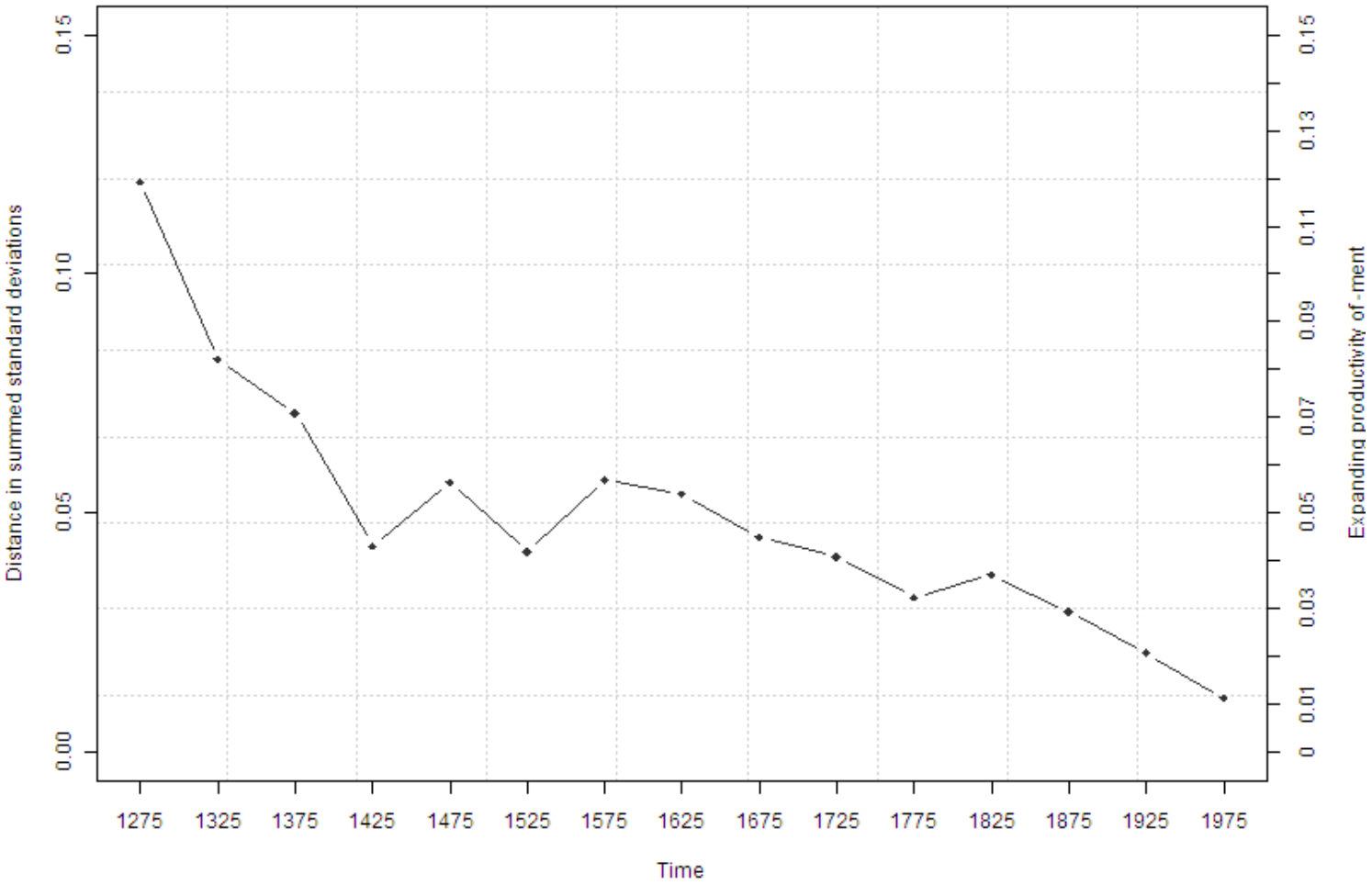
Expanding productivity

- computed as a ratio:

$$\frac{\text{all hapax legomena of a construction}}{\text{all hapax legomena of the corpus}}$$

- in this example 2/7 = 0.29
- the construction holds 29% of the creative business in the corpus




Distance in summed standard deviations
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0.05
0.10
0.15
Expanding productivity of -ment
0
0.01
0.03
0.05
0.07
0.09
0.11
0.13
0.15
1275
1325
1375
1425
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1525
1575
1625
1675
1725
1775
1825
1875
1925
1975
Time


Distance in summed standard deviations
0.00
0.05
0.10
0.15
Expanding productivity of -ment
0
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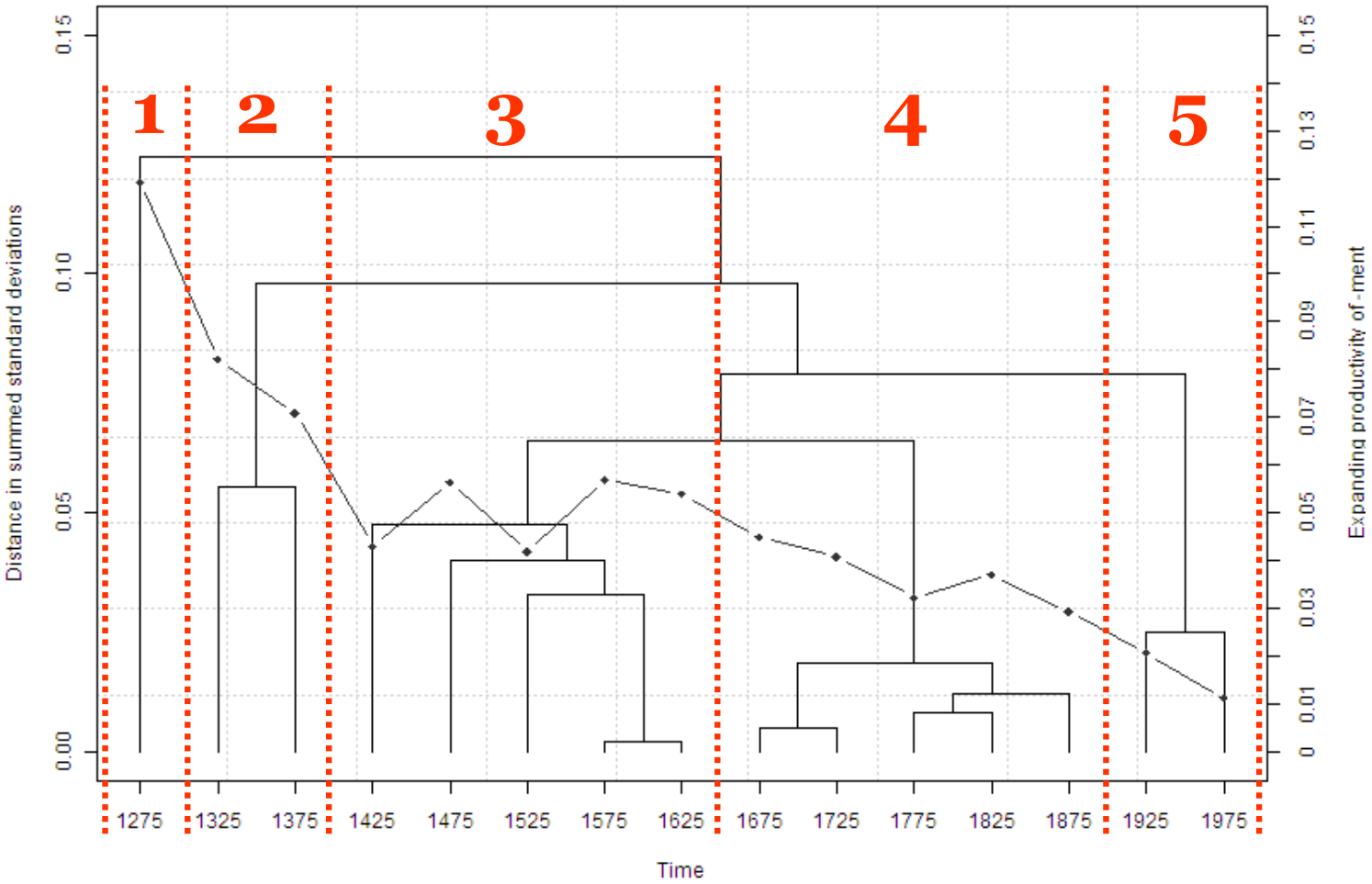
1925
1975
Time


1
2
3
4
5
Distance in summed standard deviations
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0.05
0.10
0.15
Expanding productivity of -ment
0
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0.11
0.13
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1275
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1475
1525
1575
1625
1675
1725
1775
1825
1875
1925
1975
Time

Analytical steps

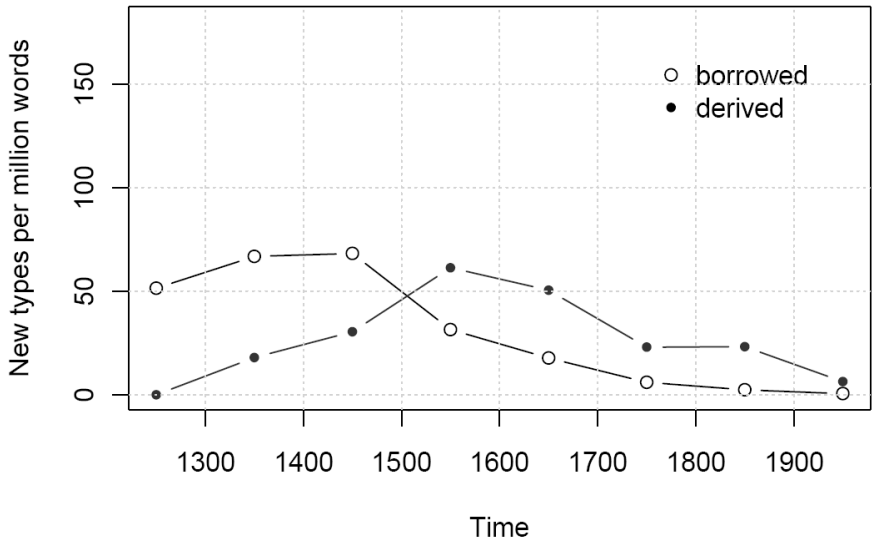
- determine relevant variables
- annotate all 1400 types in the database for these variables
- explore whether patterns of variation change over time, using a multivariate analysis

Variable 1: Etymological source

Is a form borrowed or derived?

B: achievement, detachment, enforcement

D: bickerment, erasement, shipment



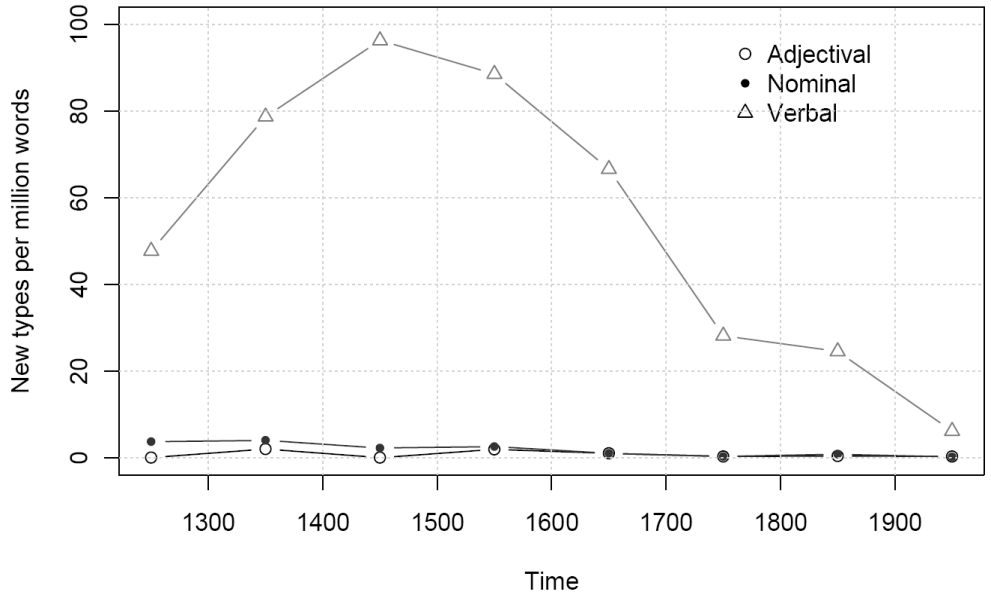
Variable 2: Stem type

What is the lexical category of the stem?

V: achievement, enforcement

A: merriment, unruliment

N: scholarment, utensilment



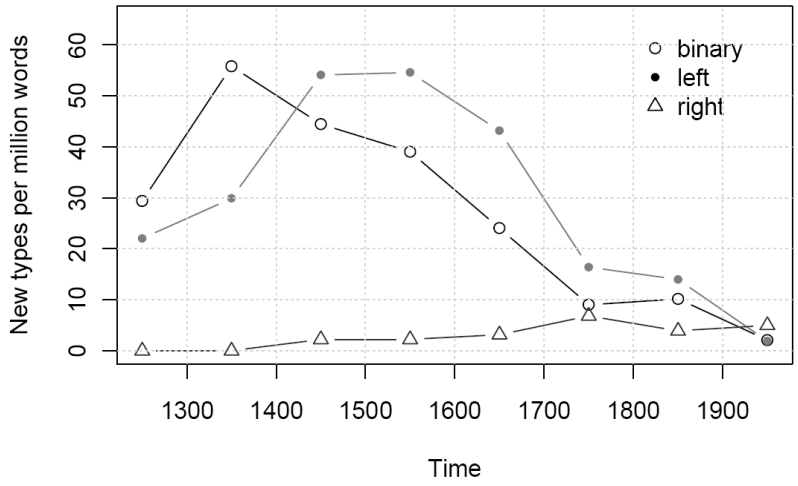
Variable 3: Branching structure

What is the internal hierarchical structure?

Binary: judgment, treatment

Left-branching: [en+rich]ment, [be+little]ment

Right-branching: eco[manage+ment], non[agree+ment]

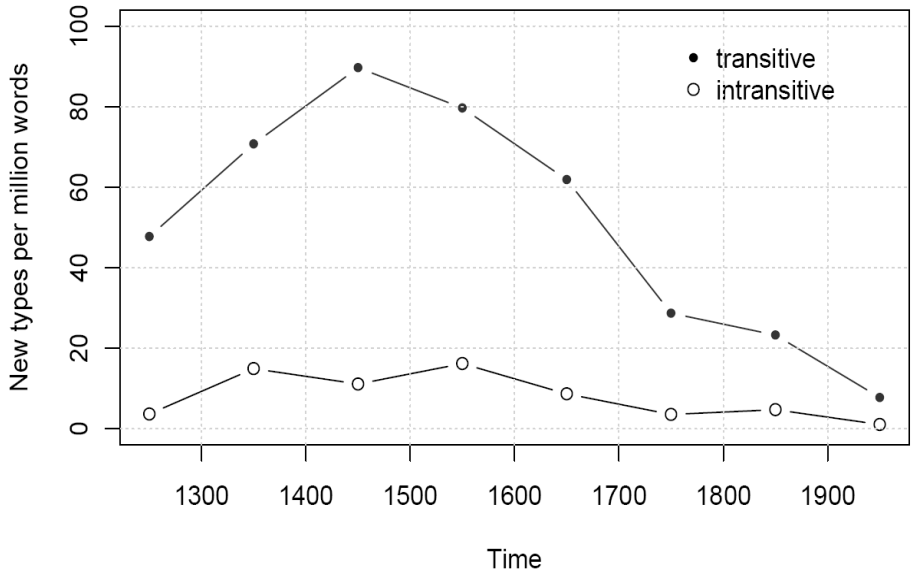


Variable 4: Transitivity

Does the form evoke an entity that is acted upon?

Transitive: arousement, punishment

Intransitive: flourishment, merriment



Variable 5: Semantic types

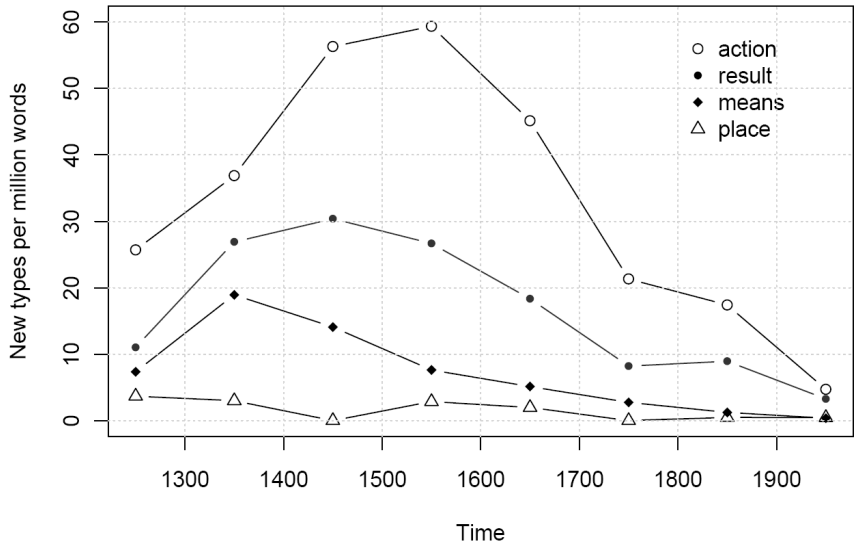
Which overall meaning is conveyed by the form?

Action: confrontment, dismantlement

Result: settlement, scholarment

Means: ornament, refreshment

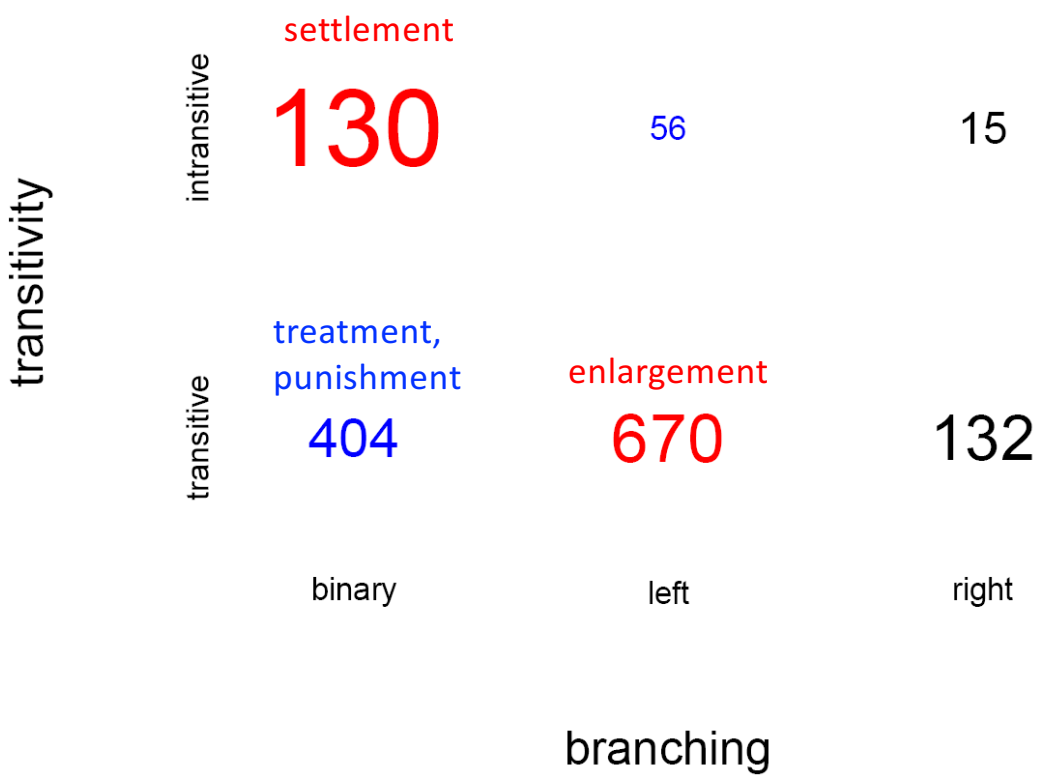
Place: parliament, environment



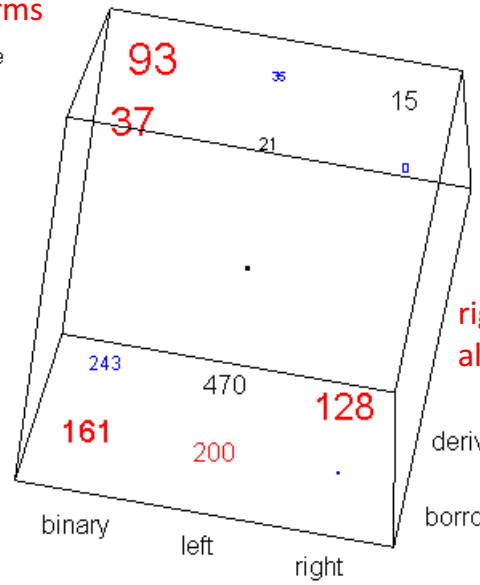
Analysis

transitivity	binary	left	right
intransitive	130	56	15
transitive	404	670	132

branching


transitivity
intransitive
transitive
settlement
130
56
15
treatment,
punishment
404
enlargement
670
132
binary
left
right
branching

binary-branching intransitive:
native and borrowed forms



right-branching transitive:
always native, never borrowed

binary-branching transitive:
borrowed forms are
overrepresented

Configural Frequency Analysis

- cross-tabulate all 1400 types for the following variables:

VARIABLE	VALUES
Period:	1,2,3,4,5
Source:	borrowed, derived
Stem:	verb, noun, adjective
Branching:	binary, left, right
Transitivity:	transitive, intransitive
Semantics:	action, result, means, place

- determine configurations of values that occur with greater than chance frequency
- see if early types differ from later types

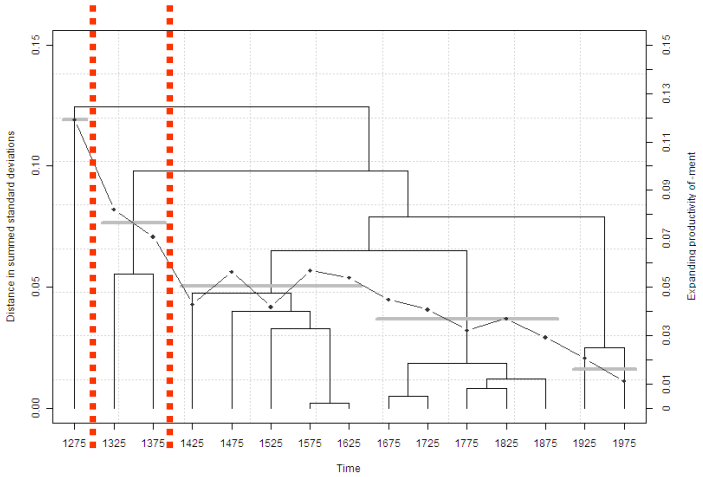
Results

1250-1299

- Type1: commencement
  - borrowed, transitive verbal stem
  - imprisonment, confirmment, enchantment, judgment, ...
  - consonant with previous claims that early ment-types typically had transitive verbs as hosts
    (Gadde 1910, Dalton-Puffer 1996)

1300-1399

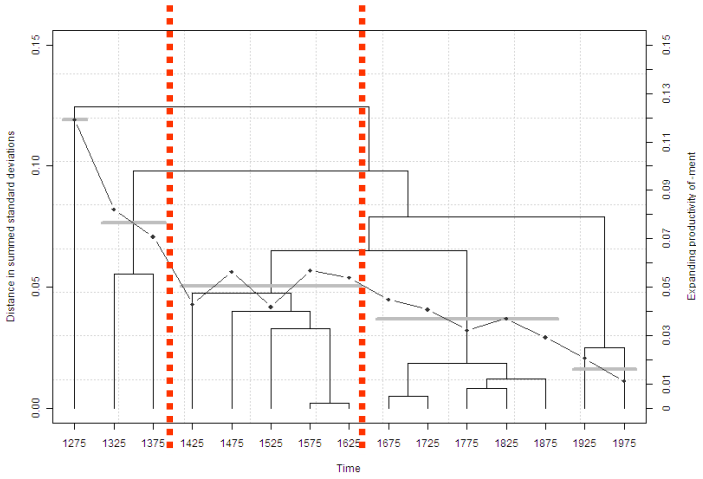
- Type 2: ointment
  - borrowed, verbal, transitive, binary, means
  - vestment, supplement, ornament, ...
  - semantic type of means is not very frequent but rises to a moderate level during the 14th century
  - the forms are classified as transitive because in each case, a ‘patient’ can be identified



- Type 3: vesselment
  - borrowed, nominal, transitive, binary, means
  - monument, odorament, and vesselment
  - highly infrequent, but still more frequent than expected
  - both nominal and means are rare, their combination rarer still

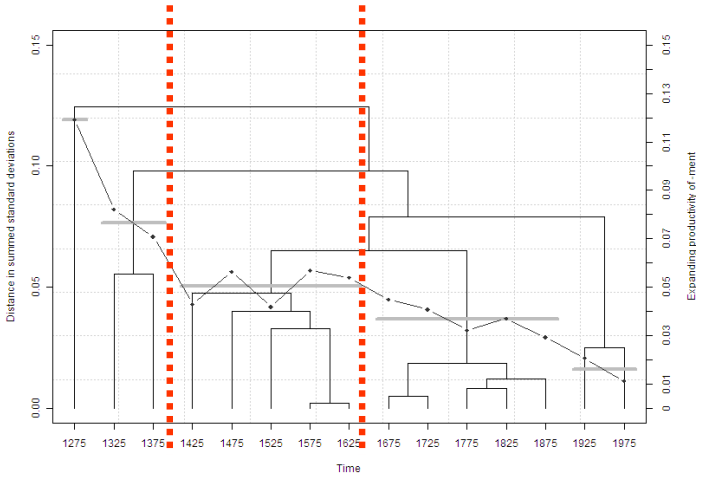
1400-1650

- Type 4: enlargement
  - derived, verbal, transitive, left, action
  - disbursement, misusement, renewment, ...
  - the most frequent configuration in the database (174 instances in period 3 alone, 339 in total)
  - Plag (1999: 16): unattested forms such as encodement or envisionment sound fully acceptable to modern speakers
  - Type 4 explains this: neologisms are OK if the host is a prefixed transitive verb



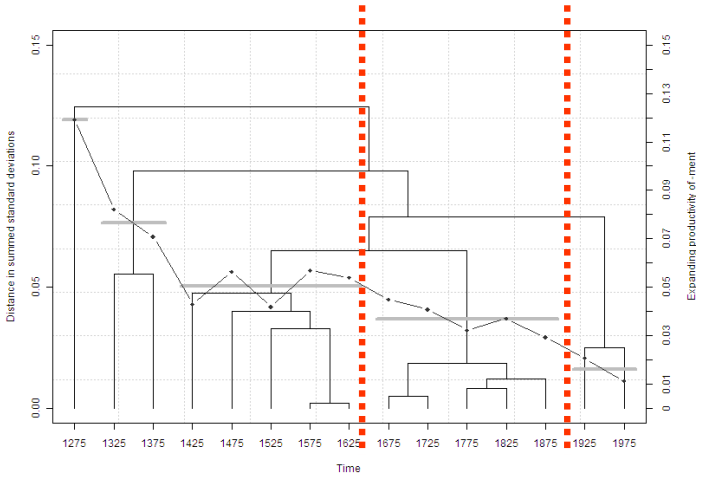
1400-1650

- Type 5: merriment
  - adjectival, derived, action, intransitive, binary
  - coldment, dreariment, jolliment, justment, and wariment
  - genuinely English pattern that is not based on borrowed coinages
  - an innovative but short-lived fad; all types coined between 1548 and 1611



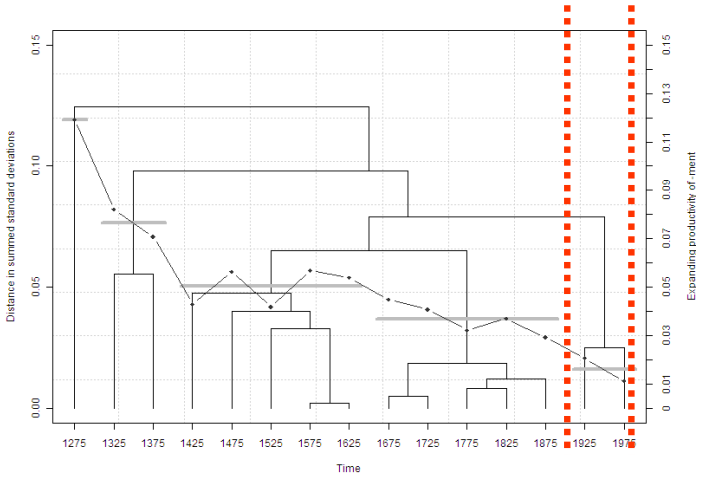
1650-1899

- Type 6: disembodiment
  - right-branching, verbal, action, transitive, derived,
  - maltreatment, overenrichment, reemplacement, selfchastisement
  - typically coined on the basis of Type 4 (enlargement) forms
  - outgrowth of the V-ment prototype
  - independent of the productivity of the suffix –ment: host element is an already existing form of the V-ment construction
  - hence, this type can continue to thrive while other types of the V-ment construction are in demise



1900-2000

- Type 7: semiretirement
  - right-branching, verbal, transitive, derived, result
  - malnourishment, misalignment, noninvolvement, semiretirement, ...
  - this type dodges the strong bias towards the meaning of action
  - metonymic shift from actions to results is a recent semantic trend that is confined to right-branching structures



VNC on the basis of distributional semantic information

cabbage

jacket

mouse

sheep

beans

trousers

shirt

pig

potatoes

wheat

hat

boots

cow

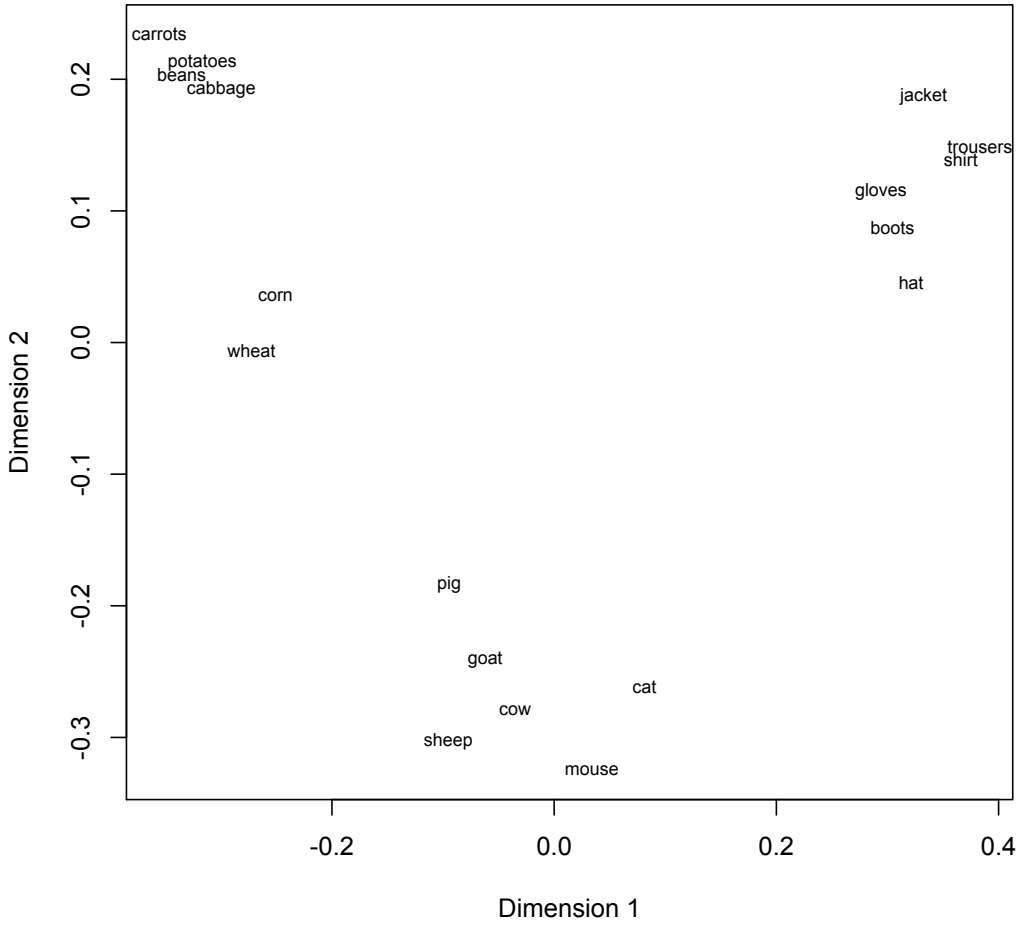
gloves

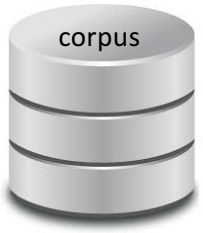
goat

carrots

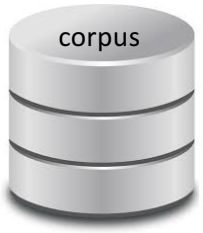
cat

corn


carrots
potatoes
beans
cabbage
jacket
trousers
shirt
gloves
boots
hat
corn
wheat
pig
goat
cat
cow
sheep
mouse
Dimension 2
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.2
0.0
0.2
0.4
Dimension 1



much hope there . He has his	goat	clinic on Fridays . I hope you
established . Within the mountain	goat	community , this leads to continual
is to get a dead mountain	goat	down from a mountain -- it simply
driving a donkey laden with	goat	fodder . As he passed our party
he wouldn't be a tethered	goat	from choice . He went into
was in good spirits . The	goat	had been sacrificed at the shrine
her a tart or because her pet	goat	had gone missing ; she always
usually from a combination of	goat	hair , cotton and jute , and
And have that lecherous old	goat	hanging round my door



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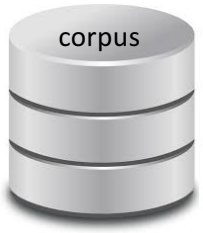
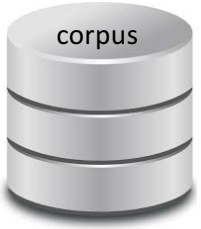
And have that lecherous old goat hanging round my door

stop words



hope goat clinic Fridays hope
established mountain goat community leads continual
dead mountain goat mountain simply
driving donkey laden goat fodder passed party
tethered goat choice
good spirits goat sacrificed shrine
tart pet goat missing always
usually combination goat hair cotton jute
lecherous old goat hanging round door



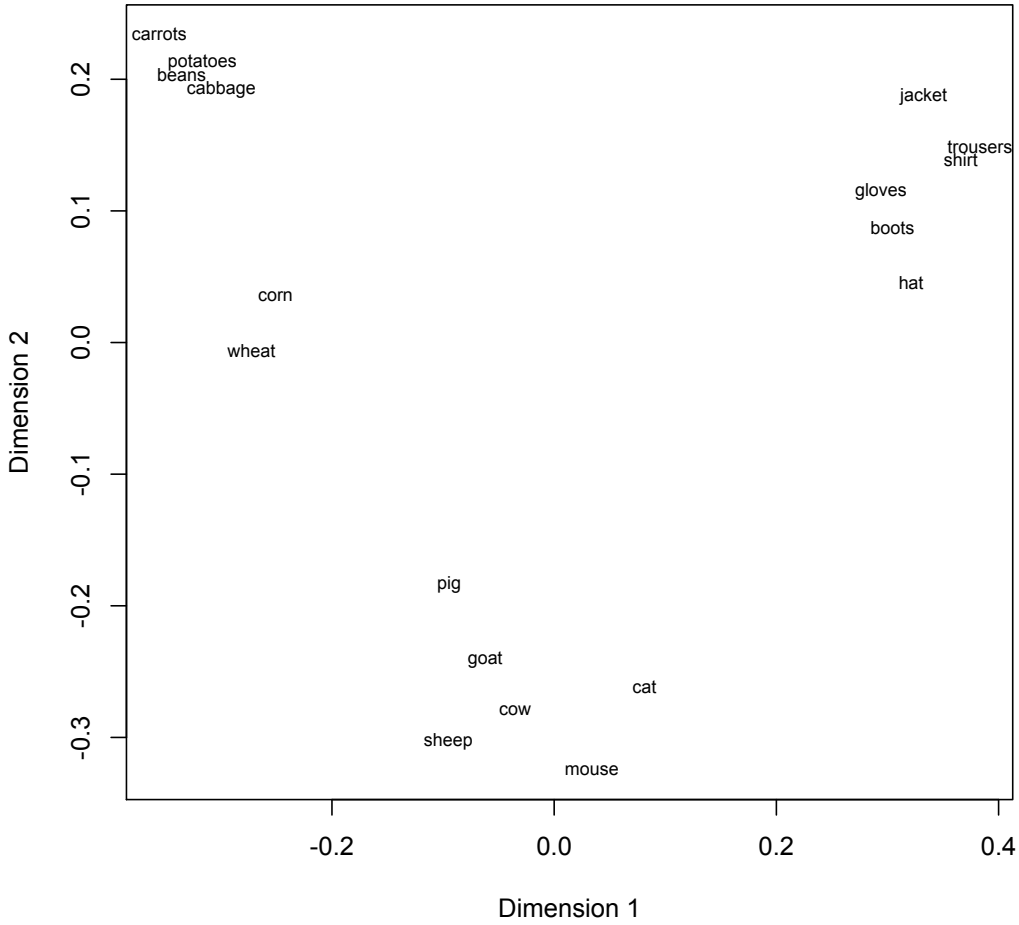
goat
goat
goat
goat
goat
goat
goat
goat
goat

CONTEXT ITEM	FREQUENCY
mountain	48
goat	32
milk	30
cheese	20
sheep	13
meat	9
horns	8
antibodies	8
black	8
gets	7
hens	7
eat	6
tiger	6
head	6
hand	6

CONTEXT ITEM	FREQUENCY
milk	119
cow	80
mad	39
stupid	38
disease	34
silly	28
parsley	26
sheep	21
calf	18
per	17
sacred	17
say	16
little	16
dairy	15
bull	14

CONTEXT ITEM	FREQUENCY
pig	84
wild	27
head	24
pigs	23
iron	20
says	17
farm	16
meat	14
farmer	14
food	13
fact	13
dog	13
thought	12
prices	12
pot	12

CONTEXT ITEM	FREQUENCY
shirt	150
pair	133
jacket	123
white	108
black	107
trousers	80
wearing	67
shoes	60
grey	58
blue	55
wore	54
boots	51
dressed	48
wear	48
cotton	44


carrots
potatoes
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cabbage
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trousers
shirt
gloves
boots
hat
corn
wheat
pig
goat
cat
cow
sheep
mouse
Dimension 2
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.2
0.0
0.2
0.4
Dimension 1

the *hell* construction

- That scared the hell out of me.
- They beat the hell out of that poor guy.
- Leave it to Patrick to take a simple issue and complicate the hell out of it.

- data from COHA
- 362 tokens with 105 verb types

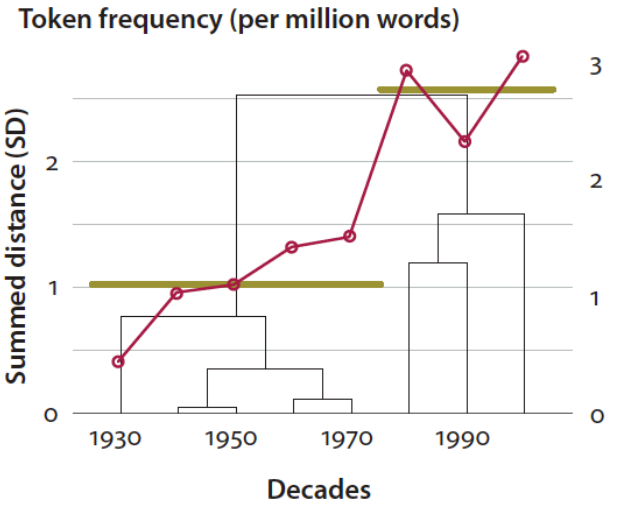
Perek & Hilpert (2017) *IJCL* 22/4

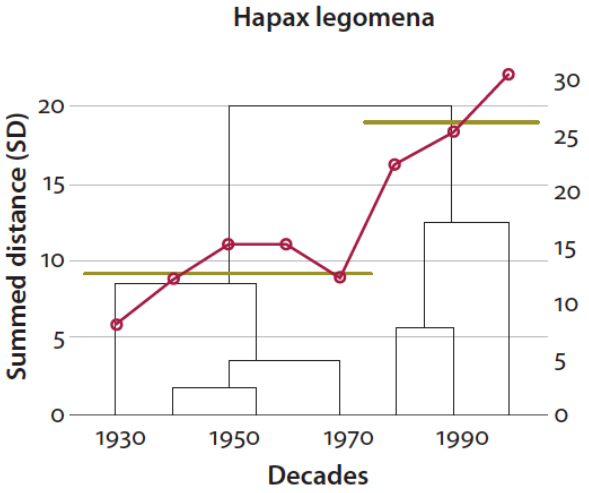
Perek & Hilpert (2017) *IJCL* 22/4

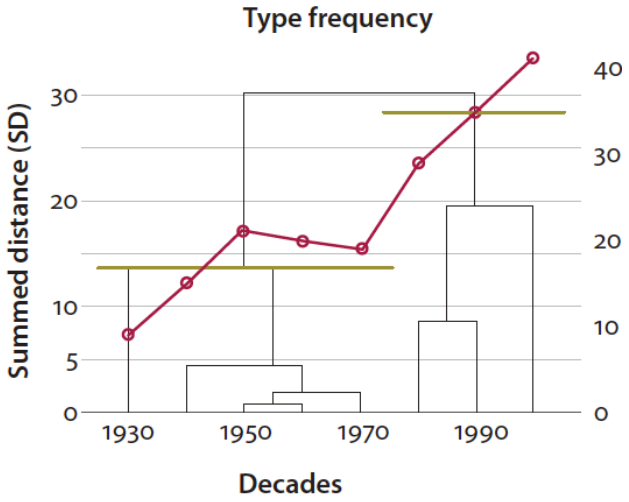
VNC with distributional information

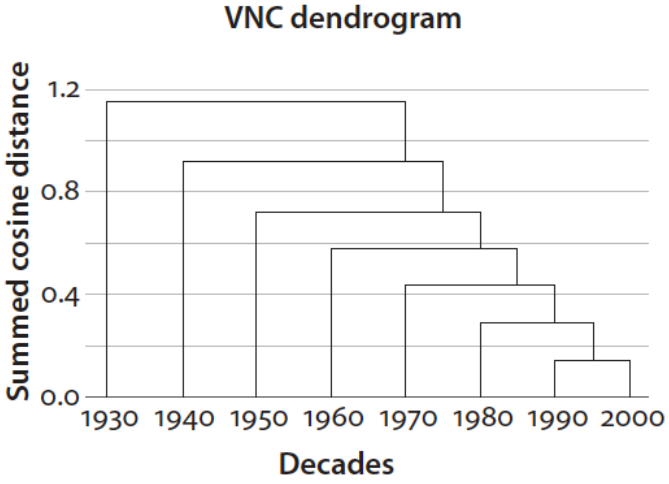
- Each decade in the COHA contains examples of the *hell* construction with several verb types.
- For each verb type, a collocate vector was created.
- All collocate vectors of a given decade were combined by averaging into a single ‘decade vector’.
- VNC was applied to a sequence of decade vectors.

Perek & Hilpert (2017) *IJCL* 22/4







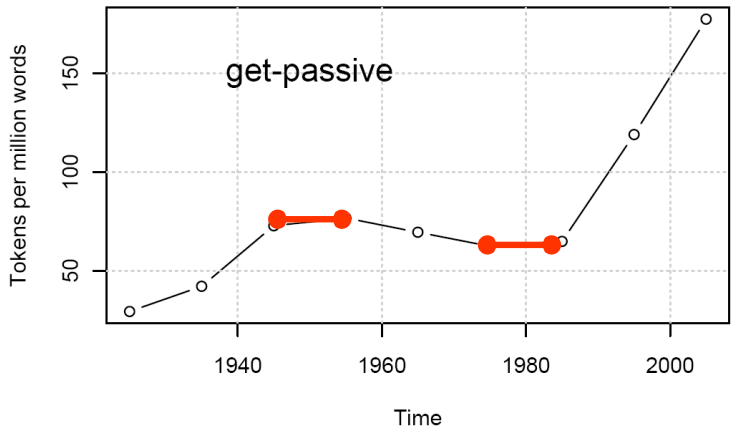


Perek & Hilpert (2017) *IJCL* 22/4

Conclusions

Variability-based Neighbor Clustering

- find the two closest historically adjacent neighbors
- merge them and take the mean value
- now find again the two closest neighbors
- merge them and take the mean value
- ...
- until all periods are merged



- Upsides:
  - VNC can find stages in a data-driven, bottom-up way
  - identifying stages is useful, sometimes necessary, for the decription of changes
  - VNC can be used for the detection of outlier data points
  - finding different stages for two forms can show that they are indeed different constructions

- Downsides:
  - clustering does not provide divine truths: results reflect the similarity measure used in the input
  - determining stages is usually just a first step in an analysis

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