A Distributional Approach to Inflection *vs.* Derivation in Czech

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Delineating the border between inflection and derivation

Changes of an affix affect grammatical or lexical meaning of a word, the former ones are treated as inflectional, while the latter ones as derivational categories

- Affix *]r0s* for **3rd singular person as inflection**, e.g., *§09H\ ! §09H\0*
- Affix *]0}* for **agent name as derivation**, e.g., *§09H\ ! §09H\0}*

When delineating border between inflection–derivation, the available literature insists on

- Either a ***categorical*** distinction and look for corresponding criteria (Anderson, 1982),
- Or an elusiveness of the distinction, which is seen as ***gradient*** and/or ***multidimensional*** (Dressler 1989; Booij 1996; Haspelmath 1996; Corbett 2010; Spencer 2013; Štekauer 2015)

Recent work has applied computational methods from distributional semantics (e.g. Boleda 2020) to the issue of the border between inflection and derivation (cf. Bonami and Paperno 2018, Rosa and Žabokrtský 2019), but consider smaller sets of morphological categories.

Three views of the inflection–derivation distinction

+	derivation
−	inflection

−	derivation
+	inflection

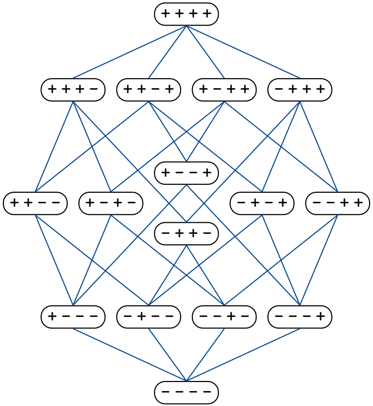
Monodimensional, categorical

↑ canonical derivation

↓ canonical inflection

Monodimensional, gradient

canonical derivation



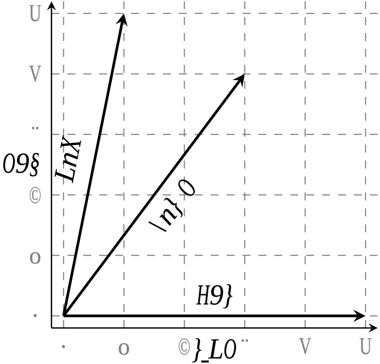
canonical inflection

Multidimensional, categorical

Outline

Distributional semantics

The distributional hypothesis (see Harris 1954, Firth 1957) from (Lenci, 2008, p. 3):
Ȳ¦ \0 L0X}00 nT 0h9j§_H _h_e9}_§´ @0§°00j §°n e_jX«_ §_H 0²q}0 _nj A 9jL B _
9 T«jH§_nj nT §\0 _h_e9}_§´ nT §\0 e_jX«_ §_H Hnj§0²§ _j °_H\ A 9jL B H9j 9qq09}w̄Ȳ
Contemporary computational linguistics deduce semantic representations from large corpora to follow this idea.

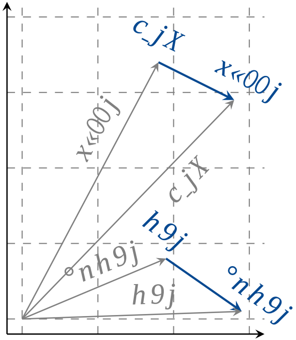


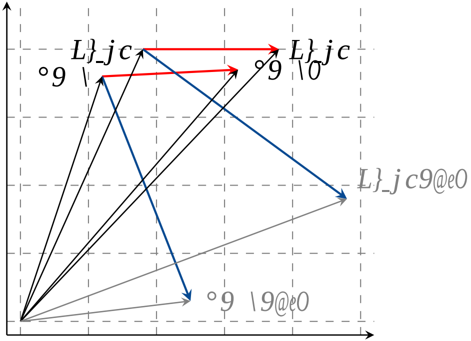
Distributional semantics for morphology

Proportional analogy, accessible through vector arithmetic (Mikolov et al., 2013), works to the extent that differences between pairs of words are similar.

These **difference vectors** represent the shift in distribution from word to the next.

Studying the similarity of these difference vectors, tells us about stability of contrasts.





Existing data resources for Czech

Distributional semantics

1. **Word2vec** (Mikolov et al., 2013)
2. **SYN v9 corpus** (Křen et al., 2021)
   - large representative corpus of Czech
   - 362M sentences; 4,719M tokens; 7.3M lemmas

! ¯0 }0e´ nj §\0 Hn}q« qn]§9X 9j jn§9§_nj 9 °0 §}9_j ®0H§n} Tn} Hn h@_j9§_nj nT §nc0j 9jL §9X u

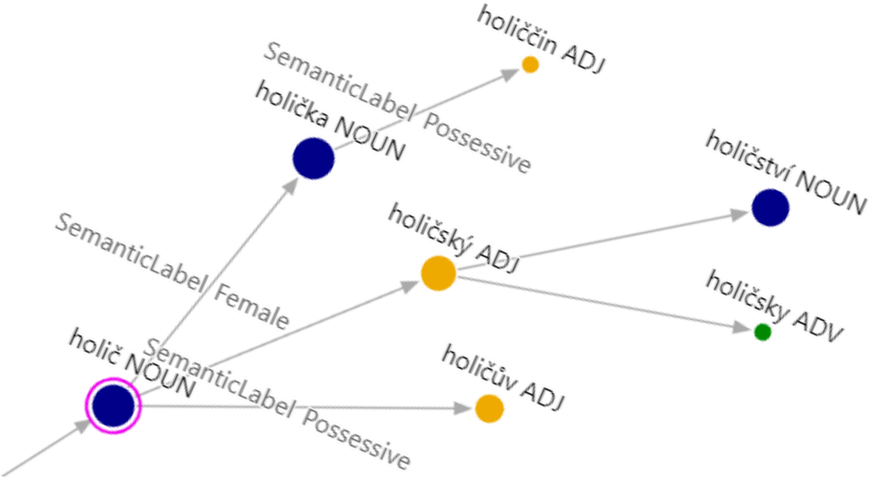
Morphological data

1. **MorfFlexCZ 2.0** (Hajič et al., 2020)
   - inflectional morphological lexicon
   - 125.3M lemma-tag-wordform triples
2. **DeriNet 2.1** (Vidra et al., 2021)
   - derivational morphological lexicon
   - 1M lemmas; 782,814 derivations

Example from MorfFlexCZ: inflection of *'barber'*

Lemma	Tag	Word form
\ne_ċ	NNMS1-----A----	\ne_ċ
\ne_ċ	NNMS2-----A----	\ne_ċ0
\ne_ċ	NNMS3-----A----	\ne_ċ_
\ne_ċ	NNMS3-----A---1	\ne_ċn®_
\ne_ċ	NNMS4-----A----	\ne_ċ0
\ne_ċ	NNMS5-----A----	\ne_ċ_
\ne_ċ	NNMS6-----A----	\ne_ċ_
\ne_ċ	NNMS6-----A---1	\ne_ċn®_
\ne_ċ	NNMS7-----A----	\ne_ċ0
\ne_ċ	NNMP1-----A----	\ne_ċ_
\ne_ċ	NNMP2-----A----	\ne_ċʧ
\ne_ċ	NNMP3-----A----	\ne_ċʧ h
\ne_ċ	NNMP4-----A----	\ne_ċ0
\ne_ċ	NNMP5-----A----	\ne_ċ_
\ne_ċ	NNMP6-----A----	\ne_ċ∂H\
\ne_ċ	NNMP7-----A----	\ne_ċ_

Example from DeriNet: derivation of *'barber'*



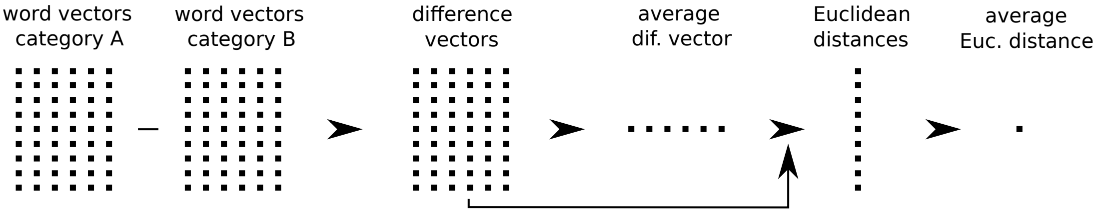
We process 24 types of morphological contrasts (difference vectors)

Word category A	Word category B	Type of contrast
i n«j u**NOM**uSN g u~W	i n«j u**GEN**uSN g u~W	Hn}0 H9 0 r i ∼ i s
i n«j u**NOM**uSN g upd	i n«j u**GEN**uSN g upd	Hn}0 H9 0 r i ∼ i s
Ṛ	Ṛ	Ṛ
i n«j u**DAT**uSN g u~W	i n«j u**LOC**uSN g u~W	j nj]Hn}0 H9 0 r i ∼ i s
i n«j u**DAT**uSN g upd	i n«j u**LOC**uSN g upd	j nj]Hn}0 H9 0 r i ∼ i s
Ṛ	Ṛ	Ṛ
i n«j u**NOM**uSN g u~W	i n«j u**DAT**uSN g u~W	h_²0L H9 0 r i ∼ i s
i n«j u**NOM**uSN g upd	i n«j u**DAT**uSN g upd	h_²0L H9 0 r i ∼ i s
Ṛ	Ṛ	Ṛ
i n«j u i m g uSN g u~W	i n«j u**DIM**u i m g uSN g u~W	L_h_j«§_®0 r i ∼ i s
i n«j uWN i uSN g upd	i n«j u**DIM**uWN i uSN g upd	L_h_j«§_®0 r i ∼ i s
Ṛ	Ṛ	Ṛ
-0}@u_jT	i n«j u**AGENT**u i m g u g 8~Gu~W	9X0j§ r - ∼ i s
-0}@u_jT	i n«j u**AGENT**u i m g u g 8~Gupd	9X0j§ r - ∼ i s

core cases: nom, gen, acc; **non-core cases**: dat, voc, loc, ins;
mixed cases: contrasts between core and non-core cases

Method

We sampled 200 word pairs (freq>50) for each contrast and calculated average difference vectors on the basis of individual difference vectors. Then we measured Euclidean distances between the individual difference vectors and the average difference vector. The individual distances were averaged to obtain one average Euclidean distance for the analysed contrast.

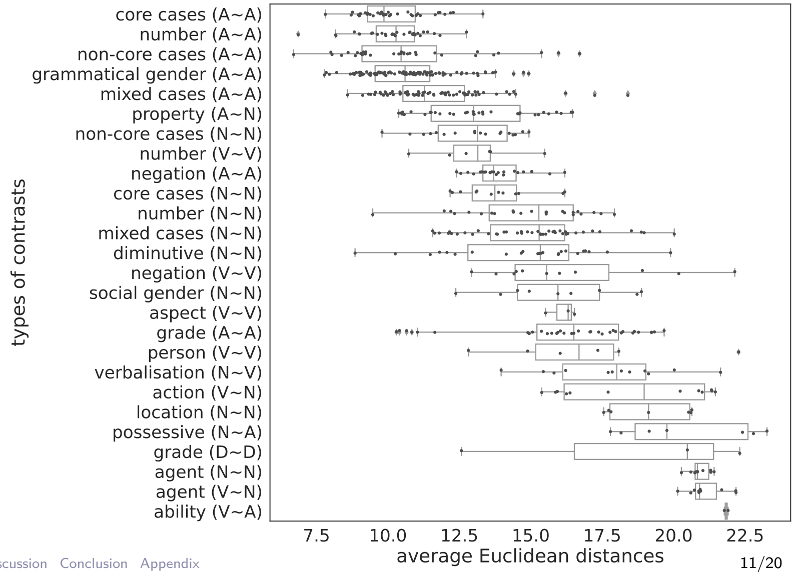


Results in a single sample

Points in the graph show dispersion of the average Euclidean distances for individual contrasts.

Boxes in the graph aggregate the contrasts into individual types of contrasts.

The results (sorted by medians) correspond well to the linguistic tradition, but variances of the types of contrasts are high in a single sample.

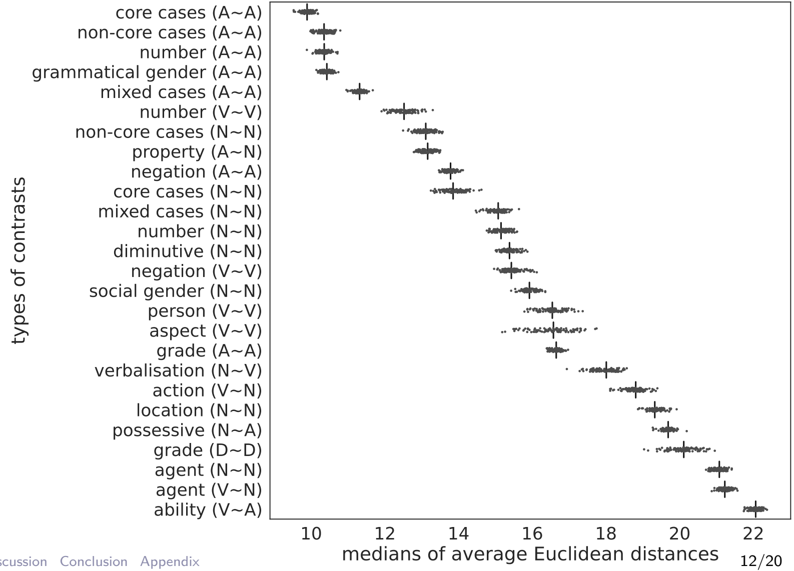


Global overview of the inflection–derivation scale (monodimensional gradient)

Making a bootstrap of medians of individual types of contrasts (100 iter.) shows more stable results with lower variances.

Inherent inflection and category changing ® u denotation changing derivation stand at the extremes.

Intermediate situations (e.g., diminution, social gender) stand between the extremes but are hardly comparable.



Assigning properties of the contrasts

(multidimensional categorical)

We assign 4 properties to the contrasts (inspired by Bauer 2004 and Spencer 2013):

- pv different part of speech
- ^v inherent (® ı contextual)
- dv different lexeme
- ~v different semantic type (individual ® ı eventuality ® ı property)

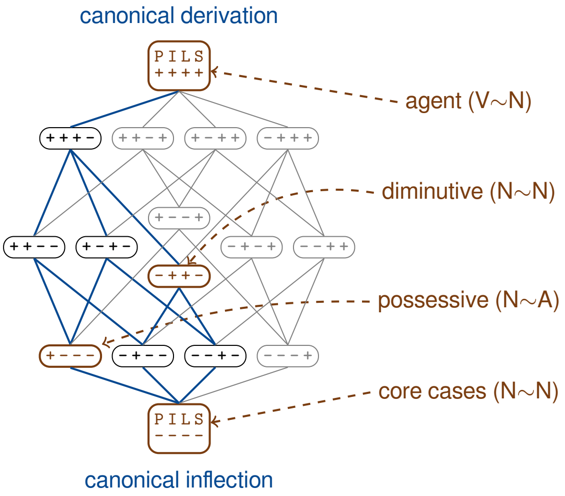
Type of contrast	p	^	d	~
core cases (N N)	−	−	−	−
grammatical gender (A A)	−	−	−	−
...		...		
possessive (N A)	+	+	−	−
...		...		
diminutive (N N)	−	+	+	−
social gender (N N)	−	+	+	−
...		...		
action (V N)	+	+	+	−
property (A N)	+	+	+	−
...		...		
ability (V A)	+	+	+	+
agent (V N)	+	+	+	+

Predictions of partial order

We expect partial order in the feature lattice to predict differences in vector dispersion, e.g.

- agents should be more dispersed than diminutives
- diminutives should be more dispersed than core case contrasts
- no prediction for possessive adjectives vs. diminutives, as these are not ordered.

Most of the predicted multidimensional categorical comparisons follow the expected partial order made by the assigned properties (82%).

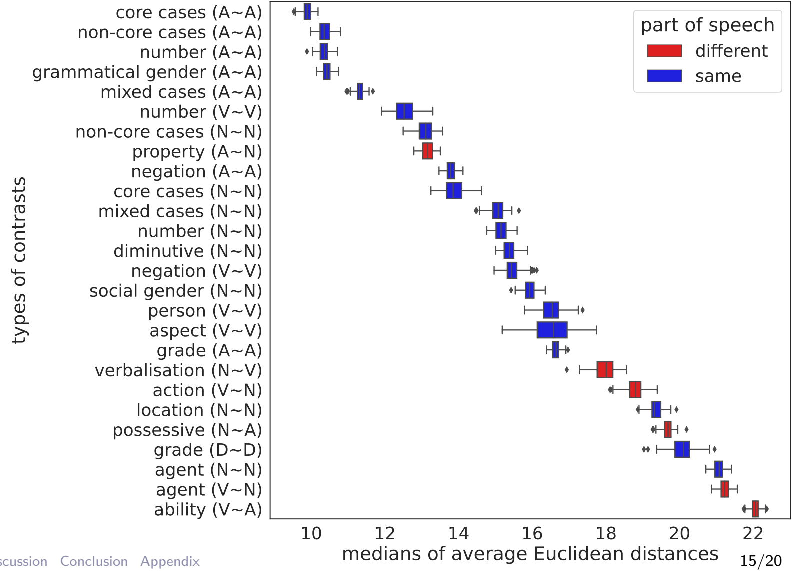


Feature p : part of speech

Most of the pos-changing contrasts have higher distances, except for **property (A N)**.

The opposite exceptions:

- location (N N)
- grade (D D)
- agent (N N)

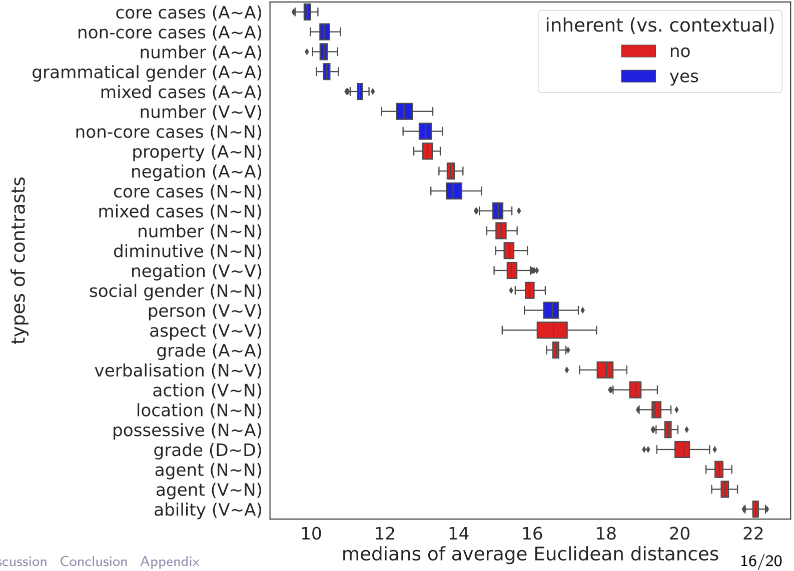


Feature ^ : inherent (*vs.* contextual)

Most of the canonical inflectional contrasts have lower distances, except for **person (V V)**.

The opposite exceptions:

- property (A N)
- negation (A A)



Feature d : lexeme

Most of the contrasts represented by different lexemes have higher distances, except for **property (A N)**, **diminutive (N N)**, and **social gender (N N)**.

The opposite exceptions:

- person (V V)
- grade (A A)
- possessive (N A)
- grade (D D)

Feature ~ : semantic type

Most of the contrasts denoting different semantic type have higher distances, except for **action (V   N)**, **possessive (N   A)**, and **grade (D   D)**.

There are no opposite exceptions.

Discussion

Property (A N) type of contrast is modelled like inflection in distributional semantics (have lower distance) but we would expect it will behave more like action (V N) type of contrast. The two ends up on different parts of the scale.

core cases (A A)
non-core cases (A A)
number (A A)
grammatical gender (A A)
mixed cases (A A)
number (V V)
non-core cases (N N)
! property (A N)
negation (A A)
core cases (N N)
mixed cases (N N)
number (N N)
diminutive (N N)
negation (V V)
social gender (N N)
person (V V)
aspect (V V)
grade (A A)
verbalisation (N V)
action (V N)
location (N N)
possessive (N A)
grade (D D)
agent (N N)
agent (V N)
ability (V A)

Discussion

Property (A   N) type of contrast is modelled like inflection in distributional semantics (have lower distance) but we would expect it will behave more like action (V   N) type of contrast. The two ends up on different parts of the scale.

Person (V   V) contrast has surprisingly high distance, indicating derivational behaviour; it may be caused by the complicated resolution of person in past participles.

core cases (A   A)
non-core cases (A   A)
number (A   A)
grammatical gender (A   A)
mixed cases (A   A)
number (V   V)
non-core cases (N   N)
property (A   N)
negation (A   A)
core cases (N   N)
mixed cases (N   N)
number (N   N)
diminutive (N   N)
negation (V   V)
social gender (N   N)
! person (V   V)
aspect (V   V)
grade (A   A)
verbalisation (N   V)
action (V   N)
location (N   N)
possessive (N   A)
grade (D   D)
agent (N   N)
agent (V   N)
ability (V   A)

Discussion

Property (A N) type of contrast is modelled like inflection in distributional semantics (have lower distance) but we would expect it will behave more like action (V N) type of contrast. The two ends up on different parts of the scale.

Person (V V) contrast has surprisingly high distance, indicating derivational behaviour; it may be caused by the complicated resolution of person in past participles.

There are differences across part of speech for the same type of contrast

- negation (A A) ® u (V V), and
- number (A A) ® u (V V) ® u (N N), and
- grade (A A) ® u (D D).

	core cases (A A)
	non-core cases (A A)
!	number (A A)
	grammatical gender (A A)
	mixed cases (A A)
!	number (V V)
	non-core cases (N N)
	property (A N)
!	negation (A A)
	core cases (N N)
	mixed cases (N N)
!	number (N N)
	diminutive (N N)
!	negation (V V)
	social gender (N N)
	person (V V)
	aspect (V V)
!	grade (A A)
	verbalisation (N V)
	action (V N)
	location (N N)
	possessive (N A)
!	grade (D D)
	agent (N N)
	agent (V N)
	ability (V A)

Conclusion

We exploited models of distributional semantics to approach the issue of inflection–derivation distinction on a larger set of semantic contrasts in Czech.

The results clearly show the inflection-derivation divide as gradient and/or multidimensional.

- Inherent inflection and category changing, denotation changing derivation stand at the opposite extremes with a few exceptions.
- Intermediate situations and the properties of the same category across parts of speech (e.g., number on nouns or adjectives, negation on verbs and adjectives) stand between the two extremes.

This is an instance of convergence of computational modelling and linguistics, which leads us to new theoretical questions.

Acknowledgement

Thank you for your attention.

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Appendix A: Euclidean distance *vs.* Cosine distance I

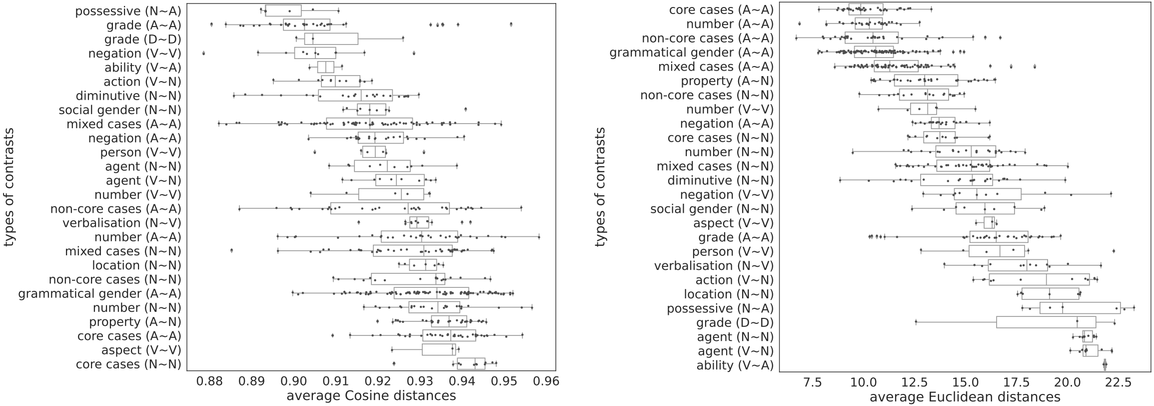


Figure: Prototypical sample before bootstrapping (from left: Cosine, Euclidean distances).

Appendix A: Euclidean distance *vs.* Cosine distance II

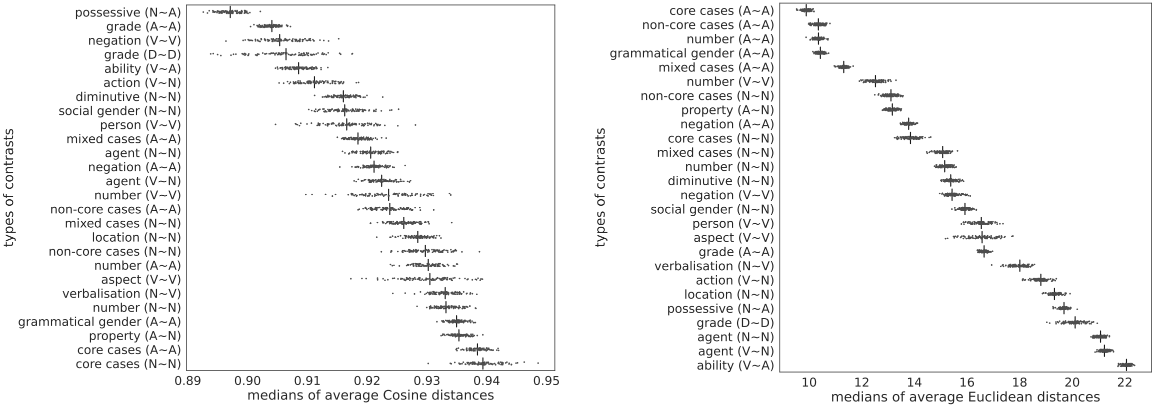
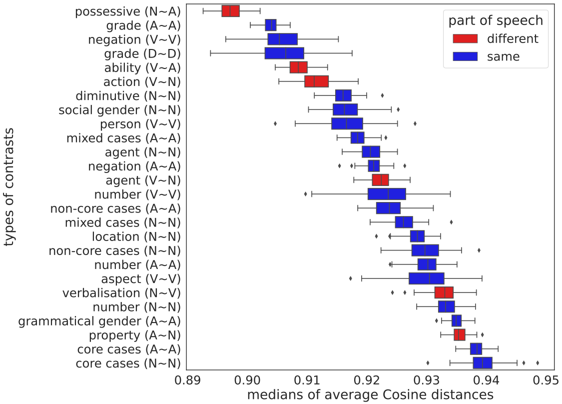


Figure: Bootstrapping (from left: Cosine, Euclidean distances).

Appendix A: Euclidean distance *vs.* Cosine distance III



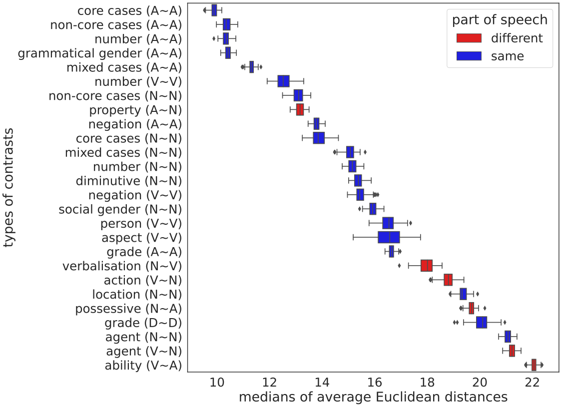


Figure: Bootstrapping, feature POS (from left: Cosine, Euclidean distances).

Appendix A: Euclidean distance *vs.* Cosine distance IV

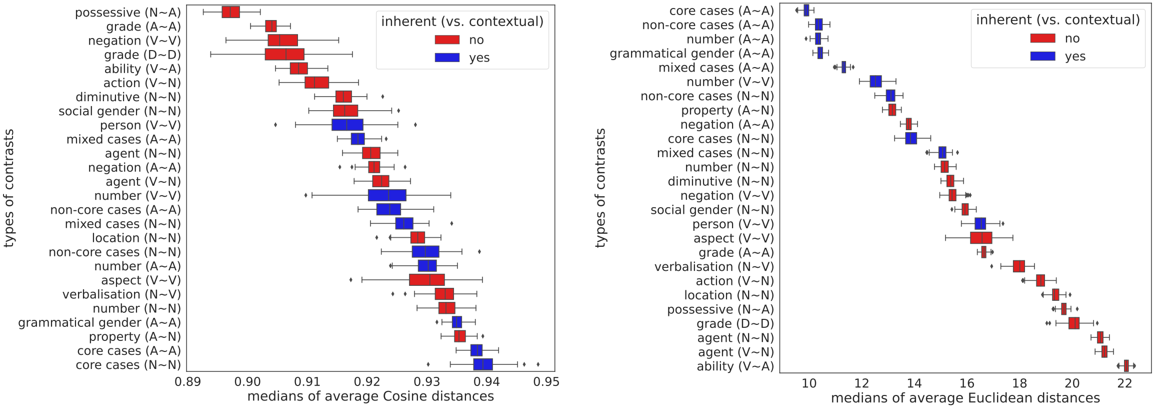


Figure: Bootstrapping, feature INHERENT (from left: Cosine, Euclidean distances).

Appendix A: Euclidean distance *vs.* Cosine distance V

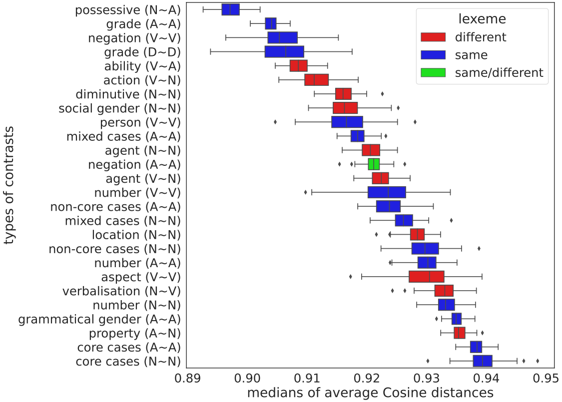


Figure: Bootstrapping, feature LEXEME (from left: Cosine, Euclidean distances).

Appendix A: Euclidean distance *vs.* Cosine distance VI

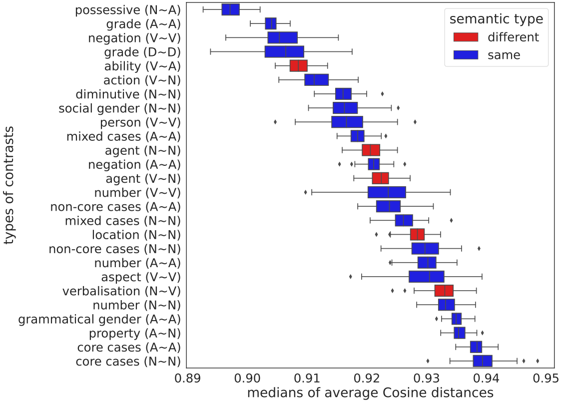


Figure: Bootstrapping, feature SEMANTIC TYPE (from left: Cosine, Euclidean distances).

Appendix B: Comparison of the features

Feature expectation	Counts	
Cosine correct	98	42%
Cosine incorrect	135	58%
Euclidean correct	**190**	**82%**
Euclidean incorrect	43	18%
Same correct results	63	27%
Same incorrect results	8	3%
Different results	162	70%

Cosine distance does not model the multidimensional distinction properly, while Euclidean distance does so.