Morphosyntactic features in distributional space

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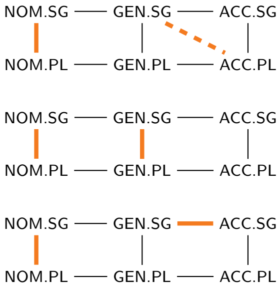
Featurally structured paradigms

- Many authors define inflectional paradigms in terms of their organization into orthogonal features, cf. Wunderlich and Fabri (1995, p. 266):

  "A paradigm is an n-dimensional space whose dimensions are the attributes (or features) used for the classification of word forms. In order to be a dimension, an attribute must have at least two values. The cells of this space can be occupied by word forms of appropriate categories."

- Implicit assumptions:
  - Some pairs of forms in a paradigms are in direct pairwise contrast, while others are not.
  - Some contrasts within the paradigm are parallel in that they involve the same variation in the same feature(s).
  - Some contrasts within the paradigm are orthogonal in that they involve variation in different features.



Limitations of feature orthogonality I

- Evidently, some situations do not lead to a system of orthogonal features.
  - Neutralization: a dimension that disappears for some feature values.
    E.g. Russian verbs (and adjectives):

	SG	PL
MAS	igral	
FEM	igrala	igrali
NEU	igralo	

Past forms of IGRÁT 'play'

  - Clusivity: a dimension that only makes sense for some feature values.
    E.g. Thulung verbs:

	SG	DU	PL	
1	buŋu	butsi	bui	INCL
		butsuku	buku	EXCL
2	buna	butsi	buni	
3	bu	butsi	buni	

Nonpast forms of BUMU 'be'

Limitations of feature orthogonality II

- Morphomic paradigm organization: systematic syncretisms are not featurally organized. E.g. English verbs:

NONFINITE	
INF	give
PRS.PTCP	giving
PST.PTCP	given

PRESENT		
	SG	PL
1	give	give
2	give	give
3	gives	give

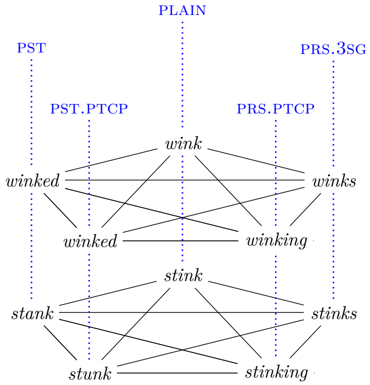
PAST		
	SG	PL
1	gave	gave
2	gave	gave
3	gave	gave

Alternatives

- A general definition should not require orthogonality.

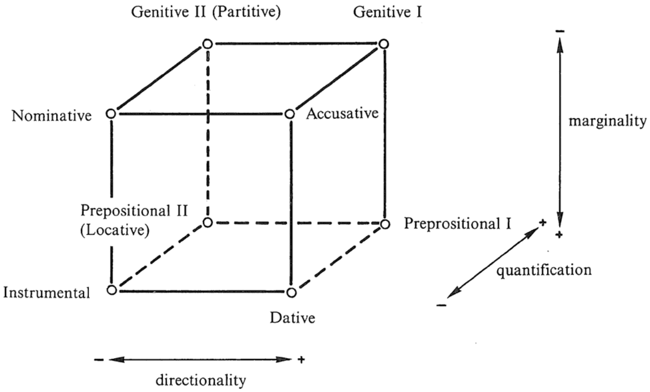
  > *"[...] we define the paradigm of a lexeme L as a complete set of cells for L, where each cell is the pairing of L with a complete and coherent morphosyntactic property set (MPS) for which L is inflectable."* (Stump and Finkel, 2013, p. 9)

- Bonami and Strnadová (2019) go further, building on Štekauer (2014):
  - Paradigms are be defined abstractively in terms of aligned pairwise contrasts
  - Analysis into orthogonal features is a further step of abstraction that is neither necessary nor always insightful.
- Hence the relationship between features and paradigms is a matter of current theoretical interest.



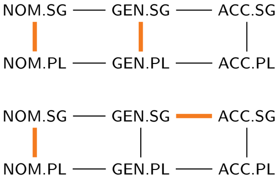
Interesting empirical questions

- Are conventional parallel contrasts really parallel?
  - Benveniste on 1SG vs. 1PL
  - Polite plurals, French *on*, etc.
- Do innovative featural analyses reflect parallel contrasts?
  - Jakobson's (1958) cube



The topic for today

- Can we find empirical evidence to support the idea that some contrasts are parallel, while others are orthogonal?



- Strategy: model contrasts between paradigm cells as contrasts between the corresponding word vectors
  - This should reflect both syntactic and semantic aspects of the relevant contrasts.

Types of contrast

- Given two cells a and b, modelled as sets of *feature* : *value* pairing:
  - $S(a,b)$ denotes the set of feature values specific to a when compared to b, i.e. $S(a,b) \overset{def}{=} \{v \mid f : v \in a \wedge \neg f : v \in b\}$
  - $C(a,b)$ denotes the set of features for which a and b contrast, i.e. $C(a,b) \overset{def}{=} \{f \mid \exists v \exists w [f : v \in a \wedge f : w \in b \wedge v \neq w]\}$
- Given two pairs of contrasting cells, (a,b) and (a',b'):
  1. (a,b) and (a',b') are parallel iff they contrast in exactly the same way, i.e. $S(a,b) = S(a',b') \wedge S(b,a) = S(b',a')$.

  2. (a,b) and (a',b') are orthogonal iff they do not contrast at all in the same way, i.e. $C(a,b) \cap C(a',b') = \emptyset$.

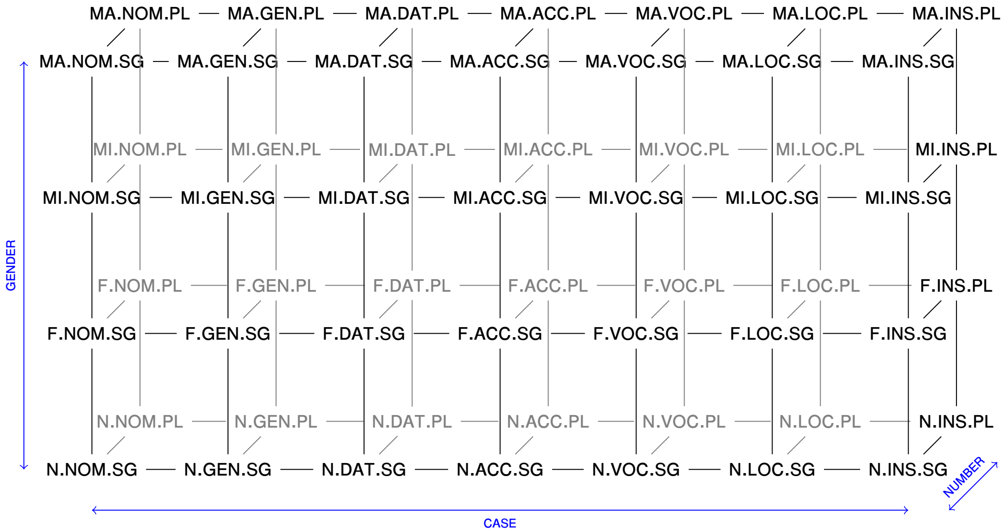
  3. (a,b) and (a',b') form a corner iff $a = a'$ or $a = b'$ or $b = a'$ or $b = b'$.

  4. (a,b) and (a',b') are not comparable iff they contrast in the same features but not the same values, i.e. $C(a,b) = C(a',b') \wedge (S(a,b) \neq S(a',b') \vee S(b,a) \neq S(b',a'))$.

Predictions

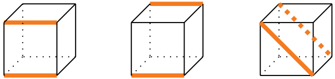
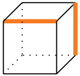
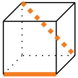
- If two pairs of cells are featurally parallel, the corresponding pairs of vectors will contrast in similar ways.
  - Possibly, they contrast in exactly the same way.
- If two pairs of cells are orthogonal, the corresponding pairs of vectors will contrast in completely different ways.
  - At the very least, they contrast in more different ways than parallel pairs.
- For corner cases, we expect odd behaviors due to sharing a cell: we exclude them from consideration.
- For non comparable cases, we have no prediction: we exclude them from consideration.

Adding dimensions (e.g. Czech adjectives)



Types of contrast in three dimensions

- With more dimensions, new situations arise:

  1. Parallel: 
  2. Orthogonal: 
  3. Neither: 

- Suggests that we need to define a gradient degree of parallelism, the proportion of contrasts shared between two pairs of cells:

$$D(p, p') = \frac{|C(a,b) \cap C(a',b')|}{|C(a,b) \cup C(a',b')|}$$

  This will be 1 in case of parallelism, 0 in case of orthogonality, and take intermediate values.

Prediction

- There is a monotonous relation between the degree of parallelism between pairs of cells and the similarity of the corresponding distributional contrasts: the more parallel in terms of feature, the more distributionally parallel.

Outline

Training the model of distributional semantics for Czech

- We train the semantic representations of words by applying **Word2vec** (Mikolov et al., 2013) to **SYN v9 corpus** (Křen et al., 2021).

- SYN v9 corpus
  - large representative corpus of Czech
  - 362M sentences; 4,719M tokens; 7.3M lemmas
  - tagged by MorphoDiTa (accuracy above 95%; Straková et al., 2014)

- Semantic representations (vectors) are trained for combinations of tokens and tags; we rely on the corpus pos-tag annotations.

Existing morphological data resources for Czech

- We use data from **MorfFlexCZ 2.0** (Hajič et al., 2020).
- MorfFlexCZ 2.0
  - inflectional morphological lexicon
  - 125.3M lemma-tag-wordform triples
- Its data has served for a development of MorphoDiTa (tagging SYN v9 corpus).
- We exploit the data when creating samples for our two studies.

Example from MorfFlexCZ: inflection of *'barber'*.

Lemma	Tag	Word form
holič	NNMS1-----A----	holič
holič	NNMS2-----A----	holiče
holič	NNMS3-----A----	holiči
holič	NNMS3-----A---1	holičovi
holič	NNMS4-----A----	holiče
holič	NNMS5-----A----	holiči
holič	NNMS6-----A----	holiči
holič	NNMS6-----A---1	holičovi
holič	NNMS7-----A----	holiče
holič	NNMP1-----A----	holiči
holič	NNMP2-----A----	holičů
holič	NNMP3-----A----	holičům
holič	NNMP4-----A----	holiče
holič	NNMP5-----A----	holiči
holič	NNMP6-----A----	holičích
holič	NNMP7-----A----	holiči

(1) Classifying contrasting word vectors

- **Data:** combinations of two samples of unpaired words for the studied inflectional contrasts
- **Task:** binary classification of a target word on the basis of its vector
- **Evaluation:**
    - **intrinsic** assesses discriminative power of a given feature for classifying word vectors
    - **extrinsic** assesses stability of classifying word vectors in a different context

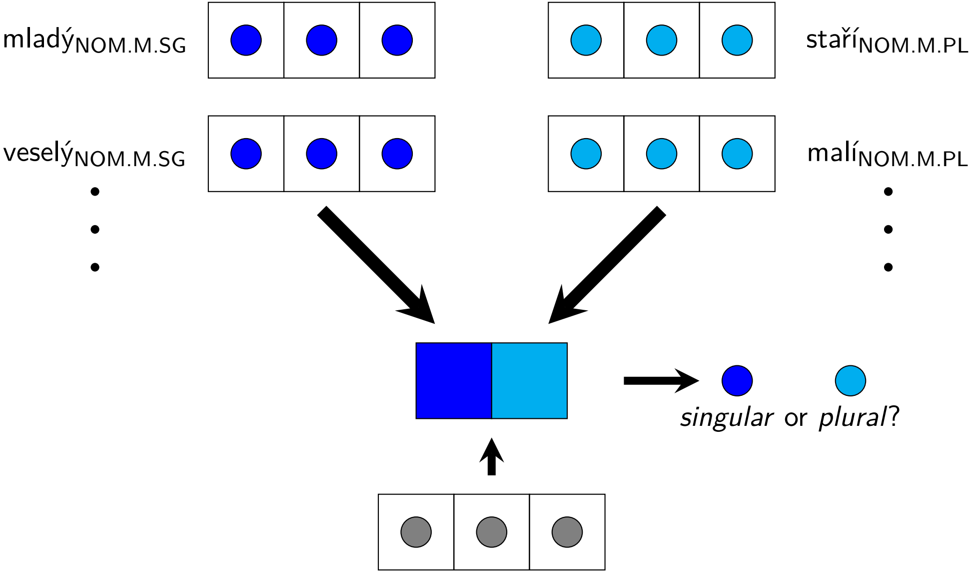
Sampling research data for classification study

- 500 word vectors (only words with freq>50 in SYN v9) for each studied inflectional category were sampled from SYN v9.
- It resulted in 30 samples for nouns and 30 samples for adjectives; combinations of gram.
  - cases [NOM, GEN, ACC],
  - numbers [SG, PL], and
  - genders [MASC.ANIM, MASC.INANIM, FEM, NEUT] (only for adjectives).

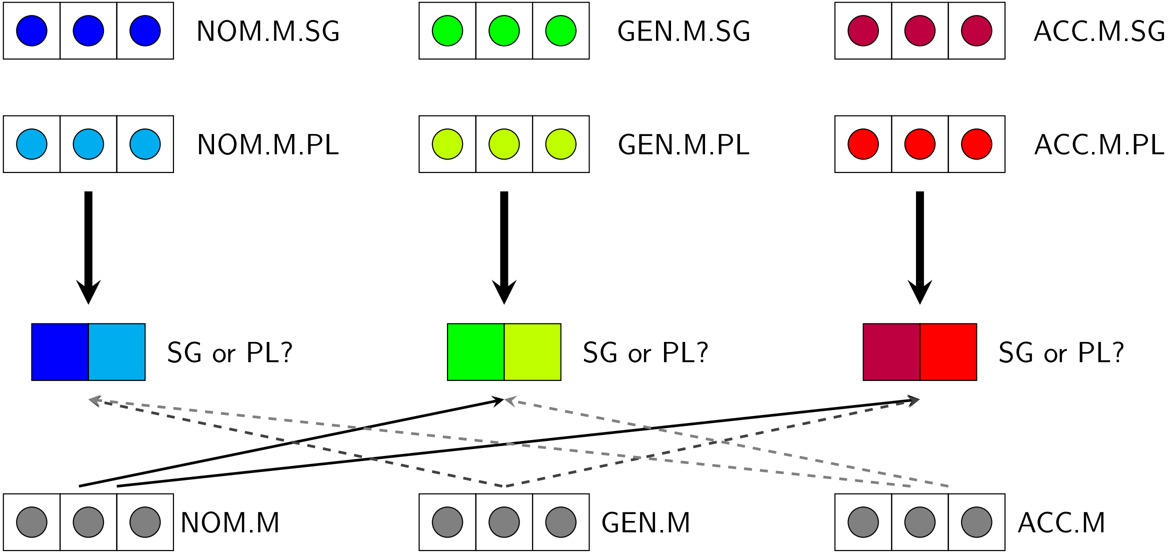
Example for the category *'NFS1'* (NOUN.FEM.SG.NOM).

Word	Vector
`pastelka>NNFS1-----A----`	*100-dim vector*
`tichost>NNFS1-----A----`	*100-dim vector*
`meduňka>NNFS1-----A----`	*100-dim vector*
...	...
`práce>NNFS1-----A----`	*100-dim vector*
`letargie>NNFS1-----A----`	*100-dim vector*
`paměť>NNFS1-----A----`	*100-dim vector*

Intrinsic classification task



Extrinsic prediction task

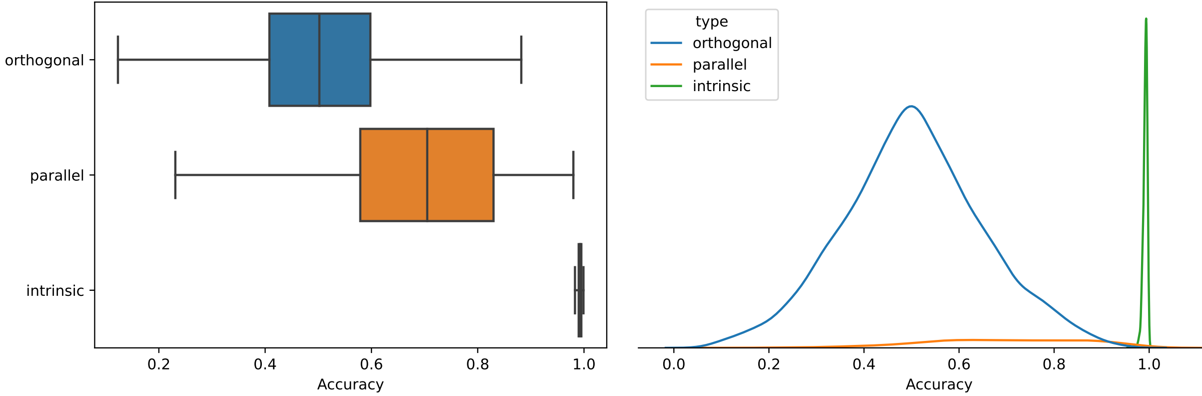


Method

- We train classifiers with gradient boosting (Friedman, 2001, Mason et al., 2000) applied on decision trees
  - 500 estimators, learning rate of 0.01, max depth of 2, random state of 0, and ‘deviance’ as the loss function
  - 1000 unpaired words (500 by condition)
- Intrinsic classification is evaluated by means of 10-fold cross validation on the 1000-word dataset
- Extrinsic classification is by means of a confusion matrix based on aligned labels (eg. SG for both masculine and feminine nominative adjectives)

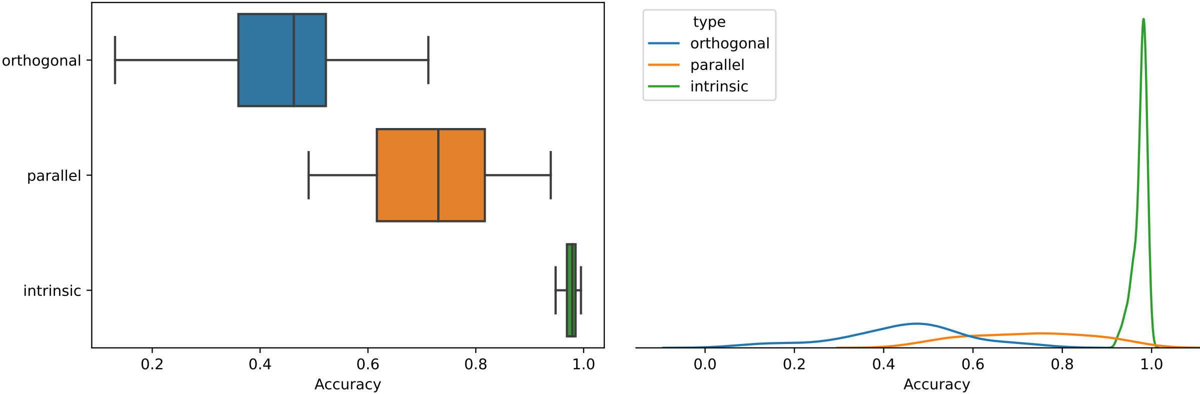
Classification results I

- Distribution of classification of contrasts for adjectives, by type



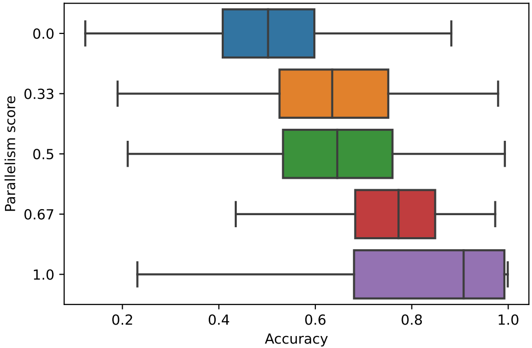
Classification results II

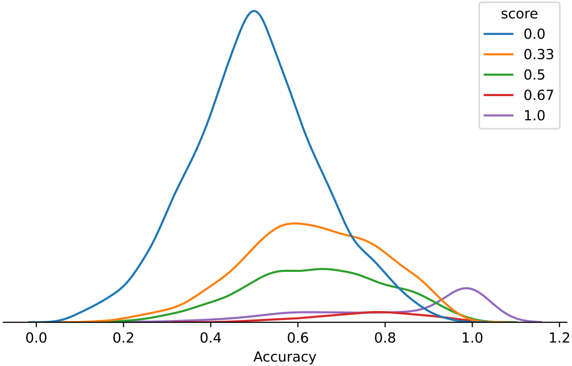
- Distribution of classification of contrasts for nouns, by type



Classification results III

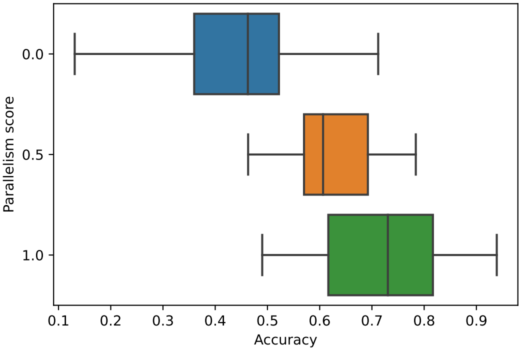
- Distribution of classification of contrasts for adjectives, by parallelism score

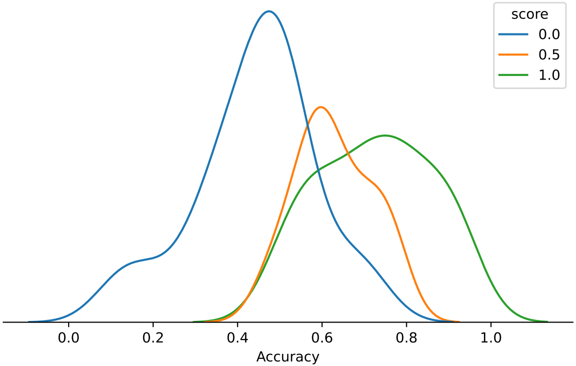




Classification results IV

- Distribution of classification of contrasts for nouns, by parallelism score





(2) Predicting relations between word vectors

- **Data**: samples of pairs of word vectors for the studied inflectional contrasts
- **Task**: to predict a target word vector on the basis of a source word vector
- **Evaluation**:
    - **intrinsic** assesses discriminative power for predicting word vectors
        - 10-fold cross-validation
        - prediction of the same contrast as for the one on which the model was trained
    - **extrinsic** assesses stability of predicting word vectors in different context
        - prediction of different contrasts than the one on which the model was trained

Sampling research data for prediction study

- 1000 pairs of word vectors (only words with freq>50 in SYN v9) for each studied inflectional contrast were sampled from SYN v9 (linked by lemmas from MorfFlexCZ).
- It resulted in 60 samples for nouns and 276 for adjectives; combinations of gram.
  - cases [NOM, GEN, ACC],
  - numbers [SG, PL], and
  - genders [MASC.ANIM, MASC.INANIM, FEM, NEUT] (only for adjectives).

Example for the contrast *'NF(PS)1'* (NOUN.FEM.SG.NOM ∼ NOUN.FEM.PL.NOM).

Word A	Word B	Vector A	Vector B
výpůjčka>NNFS1-----A----	výpůjčky>NNFP1-----A----	*100-dim vector*	*100-dim vector*
hmotnost>NNFS1-----A----	hmotnosti>NNFP1-----A----	*100-dim vector*	*100-dim vector*
nádrž>NNFS1-----A----	nádrže>NNFP1-----A----	*100-dim vector*	*100-dim vector*
...	...	...	...
rosa>NNFS1-----A----	rosy>NNFP1-----A----	*100-dim vector*	*100-dim vector*
dojnice>NNFS1-----A----	dojnice>NNFP1-----A----	*100-dim vector*	*100-dim vector*
líheň>NNFS1-----A----	líhně>NNFP1-----A----	*100-dim vector*	*100-dim vector*

Predicting vectors

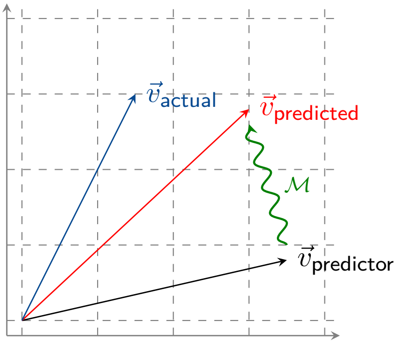
- Following Marelli and Baroni (2015), we train one linear model per dimension in the target vector: each model predicts one dimension in the target from all dimensions in the predictor.

$$
\begin{aligned}
\texttt{target\_val\_1} &\sim \texttt{pred\_val\_1} + \texttt{pred\_val\_2} + \cdots + \texttt{pred\_val\_100} \\
\texttt{target\_val\_2} &\sim \texttt{pred\_val\_1} + \texttt{pred\_val\_2} + \cdots + \texttt{pred\_val\_100} \\
&\vdots \\
\texttt{target\_val\_100} &\sim \texttt{pred\_val\_1} + \texttt{pred\_val\_2} + \cdots + \texttt{pred\_val\_100}
\end{aligned}
$$

Evaluating prediction accuracy

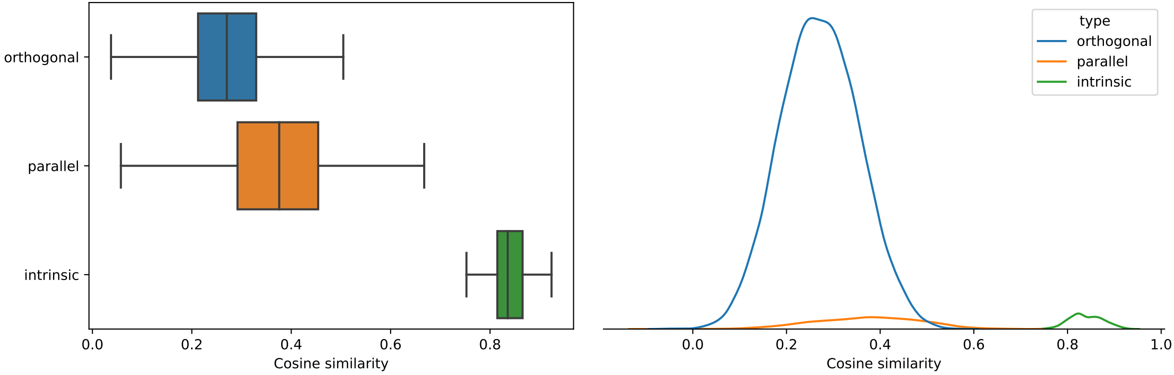
- We then measure how good the model collection $\mathcal{M}$ is at capturing the semantics of the morphological relation by examining the cosine between the predicted and the actual target vector.

- The average value of $\cos(\vec{v}_{\text{predicted}}, \vec{v}_{\text{actual}})$ is indicative of how predictable the meaning of targets is from that of predictors for that particular morphological relation.



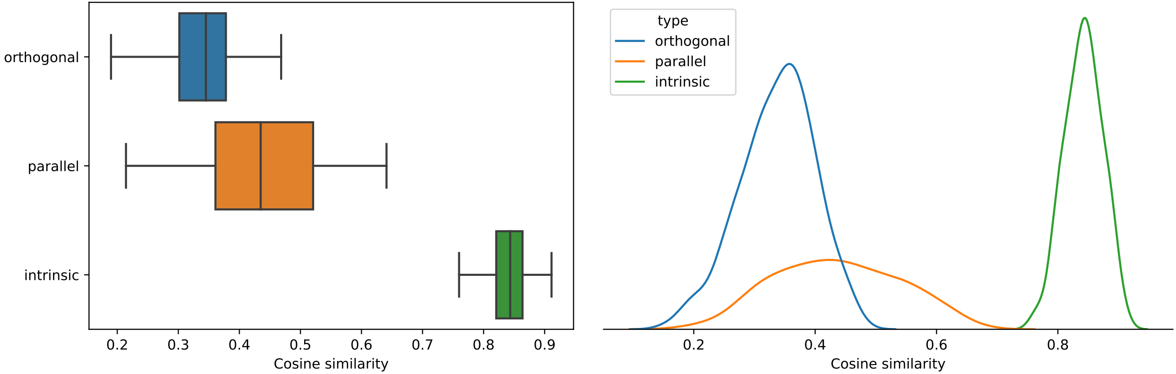
Vector prediction results I

- Distribution of quality of prediction for adjectives, by type

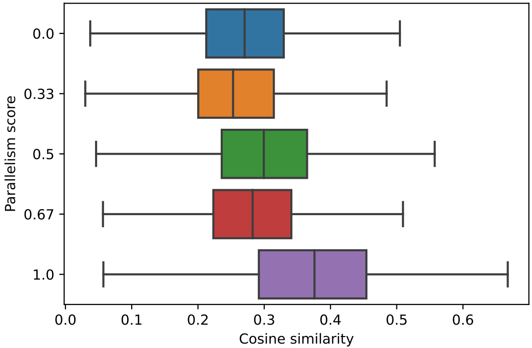


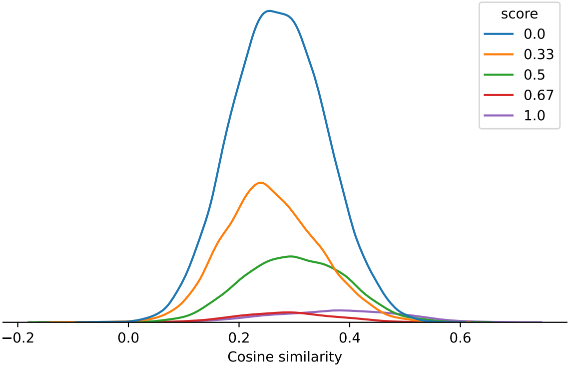
Vector prediction results II

- Distribution of quality of prediction for nouns, by type



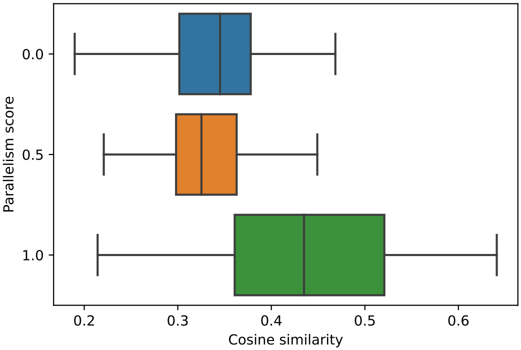
- Distribution of quality of prediction for adjectives, by parallelism score

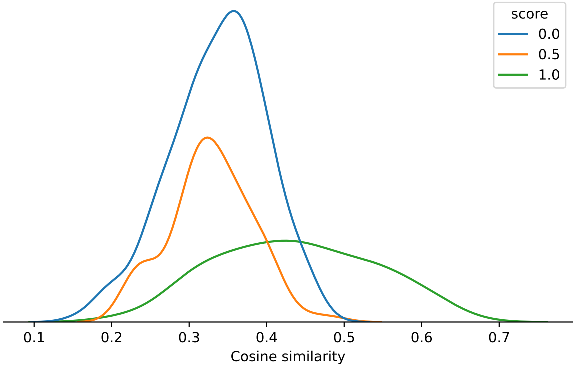




Vector prediction results IV

- Distribution of quality of prediction for nouns, by parallelism score





Conclusion

- High perfomance of cross-validated intrinsic prediction, with both methods.
  - Shows that distributional semantics captures contrasts between paradigm cells.
- While orthogonal contrasts lead to chance-level performance in extrinsic prediction, parallel contrasts lead to performance above chance level.
  - Shows that parallel contrasts in features capture some degree of parallelism in terms of actual content, as measured by distributional methods.
  - Hence the analysis of paradigms in terms of orthogonal features does capture interesting aspects of paradigm structure.
- Parallel contrasts in extrinsic prediction still lead to much poorer performance than intrinsic prediction.
  - Shows that the difference between two paradigm cells is not reducible to the featural description of those paradigm cells.
  - Hence, paradigm cells have properties that are not reducible to their description in terms of features.
  - Calls into question the reducibility of paradigmatic organisation in terms of orthogonal features, à la Wunderlich and Fabri (1995), and supports the view of paradigm organisation defended by Bonami and Strnadová (2019).

Future work

- The same methodology can be applied to more complicated paradigms such as to verbs.
- Future challenges:
  - Are number contrasts the same in the context of person (in the present) vs. gender (in the past)?
  - PAST tense of PERF verbs *vs.* PAST tense of IMPF verbs
  - FUT tense of PERF verbs *vs.* PRES tense of IMPF verbs
  - technical issue of auxiliaries in PAST and FUT tenses when training word vectors

Inflectional paradigm of the perfective verb *'udělat'* (*'to complete'*) and the imperfective verb *'dělat'* (*'to do'*).

	PERS	PRES.SG	PRES.PL	PAST.SG	PAST.PL	FUT.SG	FUT.PL
PERF	1.	–	–	udělal-[∅|a|o] (jsem)	udělal-[i|y|a] (jsme)	udělá-m	udělá-me
	2.	–	–	udělal-[∅|a|o] (jsi)	udělal-[i|y|a] (jste)	udělá-š	udělá-te
	3.	–	–	udělal-[∅|a|o]	udělal-[i|y|a]	udělá-∅	uděla-jí
IMPF	1.	dělá-m	dělá-me	dělal-[∅|a|o] (jsem)	dělal-[i|y|a] (jsme)	(budu) dělat	(budeme) dělat
	2.	dělá-š	dělá-te	dělal-[∅|a|o] (jsi)	dělal-[i|y|a] (jste)	(budeš) dělat	(budete) dělat
	3.	dělá-∅	děla-jí	dělal-[∅|a|o]	dělal-[i|y|a]	(bude) dělat	(budou) dělat

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