Attempting to separate inflection and derivation using vector space representations

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The problem

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  - Apply to text
- Our focus: unsupervised methods
  - Use no annotated data
  - Discover lemmasets solely based on unannotated plain-text corpora
  - (Also interesting: semi-supervised methods, using a handful of annotated data, and/or data for another language...)

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  - Question the traditional strictly binary inflection-derivation dichotomy
    - Replace it with an empirical inflectionality score?

This work

- A modest beginning of a probably long journey
- Currently, we only present experiments for Czech language
- For evaluation, we rely on existing annotated resources
  - lemmas and their inflections: PDT (Böhmová et al., 2003), SYN (Hnátková et al., 2014)
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- Inflection: lemma → word form
  - take → take, takes, taking, took, taken
  - pes (dog) → pes, psa, psu, psovi, pse, psem, psi, psů, psům, psy, psech
  - case, number, gender, person, tense, degree, negation, voice

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    - case, number, gender, person, tense, degree, negation, voice
- Derivation: parent lemma → child lemma
    - take → overtake, taker, intake, takeout, mistake...
    - pes → pejsek, psí, psisko, psoun, psovitý, psův, zepsout...
    - perfective-imperfective, adjective-adverb, possessive, diminuitive, noun gender...

Outline

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  - We explore two kinds of similarity:
    - Orthographic similarity, via string edit distance
    - Meaning similarity, via word embeddings similarity
- Note: there are other potentially testable criteria (Stump, 1998)
  - inflection is semantically more regular than derivation (Bonami and Paperno, 2018)
  - syntax may determine inflection
  - inflection is more productive
  - ...

Orthographic similarity: string edit distance

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Additional tweak: average with distance of simplified form

- Lowercase, transliterate to ASCII, remove non-initial vowels (a e i o u y)
- “Účelový” → “uclv”

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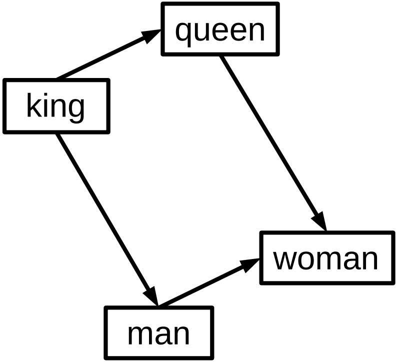
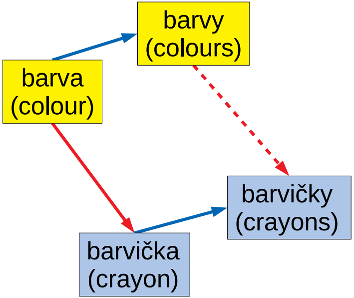
  - Also, some interesting regularities can be observed



Meaning similarity: word embeddings

- Inflection tends to correspond to a vector shift (Mikolov et al., 2013)
- Derivation tends to correspond to a vector shift (Musil et al., 2019)
- Our hypothesis: an inflectional shift should be smaller than a derivational shift



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  - $COS_{sim}(w_1, w_2) = \frac{vec(w_1) \cdot vec(w_2)}{|vec(w_1)| \cdot |vec(w_2)|}$
- FastText word embeddings, downloaded from FastText website (Grave et al., 2018)
  - Combine embeddings of full words and of character n-grams
  - Provides a vector even for out-of-vocabulary words

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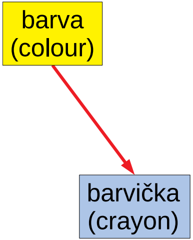
Distance measure

- For technical reasons, we need distances, not similarities
- Distance: $X_{dist} = 1 - X_{sim}$

Outline

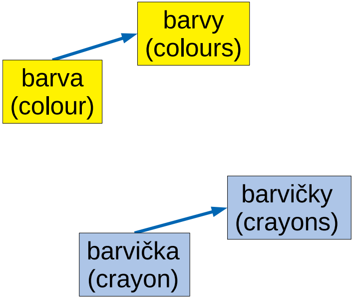
Data

- DeriNet v1.7 (Žabokrtský et al., 2016)
  - Derivational dictionary
  - Lemmas in one derivational family linked by derivational edges
  - No inflections



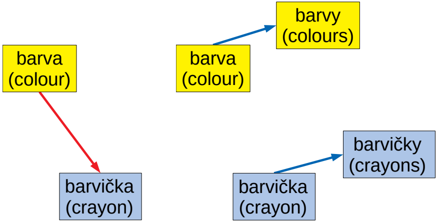
Data

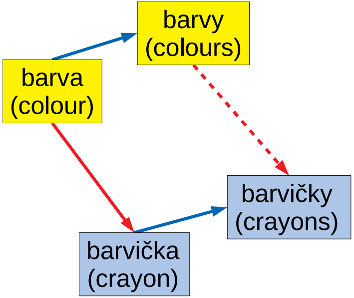
- SYN v4 (Hnátková et al., 2014)
    - Tagged corpus
    - Words in sentences annotated by lemmas and morphological features
    - No derivational annotation



Data

- Combine the resources
  - DeriNet derivational trees with lemmas
  - Add inflections from SYN to each lemma
  - Add secondary derivational edges





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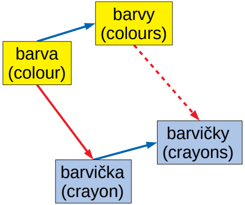

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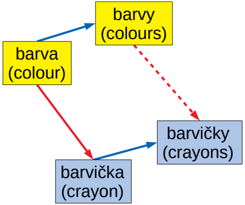

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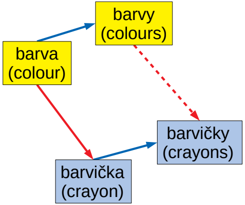

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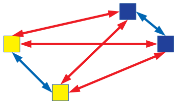
  - Small derivational families are uninteresting (not many derivational relations)
  - 561 derivational families with at least 50 lemmas
    → sample 42 families
    → 4,514 lemmas
    → 69,743 word forms

Evaluation types

Pairwise evaluation

- Is the distance of the two words higher than a threshold?
- Inflections should be below the threshold, derivations above
- Oracle threshold



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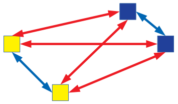
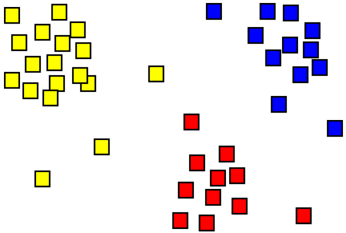


Clustering-based evaluation

- Use the word distances to find clusters of nearby words
- Agglomerative clustering algorithm
- Inflections of one lemma should fall into one cluster, derivations into separate clusters
- Oracle number of clusters



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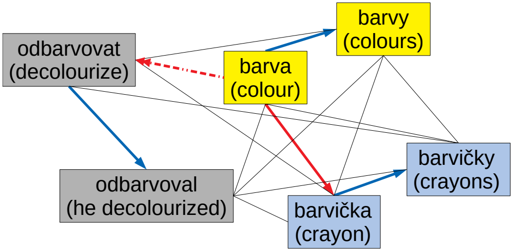

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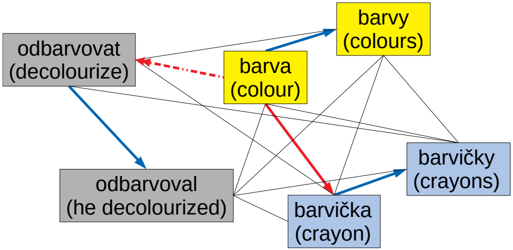
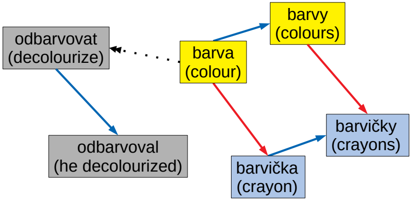
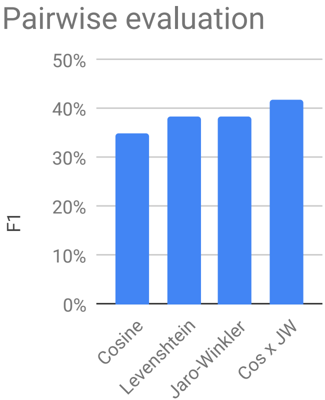
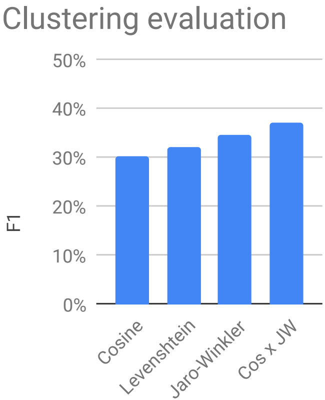


- Pairs of words linked by a single derivational or inflectional operation
  - Not realistic, many close pairs omitted
  - Focuses on the hard cases – interesting
  - Use this for further manual analysis



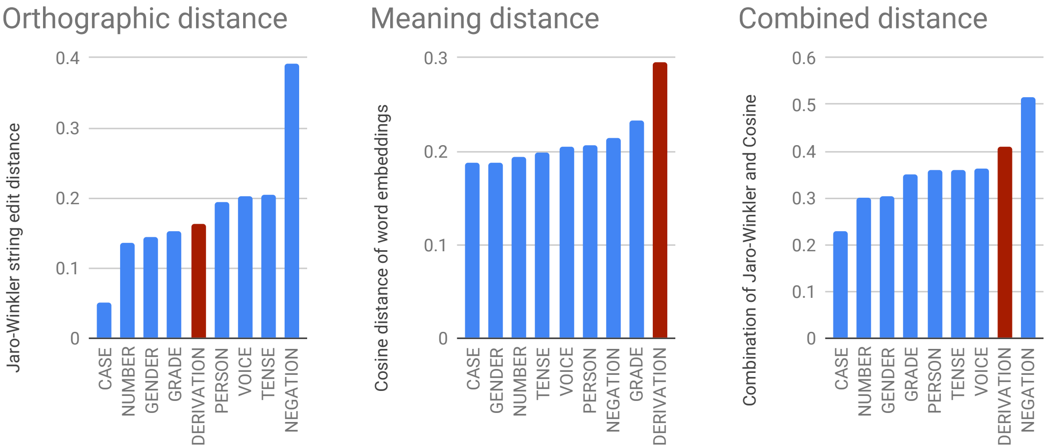
Quantitative evaluation: identification of inflection





- Inflection and derivation separable to some extent
- Combination better than individual measures

Further analysis: average count-weighted distances



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- Inflection-derivation dichotomy: a strictly binary categorization or a continuous scale?

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- Inflection-derivation boundary is vague

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References I

Željko Agić and Ivan Vulić. JW300: A wide-coverage parallel corpus for low-resource languages. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3204–3210, Florence, Italy, July 2019. Association for Computational Linguistics. URL `https://www.aclweb.org/anthology/P19-1310`.

Alena Böhmová, Jan Hajič, Eva Hajičová, and Barbora Hladká. The Prague dependency treebank. In *Treebanks*, pages 103–127. Springer, 2003.

Olivier Bonami and Denis Paperno. Inflection vs. derivation in a distributional vector space. *Lingue e linguaggio*, 17(2):173–196, 2018.

Edouard Grave, Piotr Bojanowski, Prakhar Gupta, Armand Joulin, and Tomas Mikolov. Learning word vectors for 157 languages. In *Proceedings of the International Conference on Language Resources and Evaluation (LREC 2018)*, 2018.

Milena Hnátková, Michal Kren, Pavel Procházka, and Hana Skoumalová. The SYN-series corpora of written Czech. In *LREC*, pages 160–164, 2014.

Vladimir Iosifovich Levenshtein. Binary codes capable of correcting deletions, insertions, and reversals. In *Soviet physics doklady*, volume 10, pages 707–710, 1966.

Thomas Mayer and Michael Cysouw. Creating a massively parallel Bible corpus. In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC-2014)*, pages 3158–3163, Reykjavik, Iceland, May 2014. European Languages Resources Association (ELRA). URL `http://www.lrec-conf.org/proceedings/lrec2014/pdf/220_Paper.pdf`.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

Tomáš Musil, Jonáš Vidra, and David Mareček. Derivational morphological relations in word embeddings. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 173–180, Florence, Italy, August 2019. Association for Computational Linguistics. URL `https://www.aclweb.org/anthology/W19-4818`.

Gregory T Stump. Inflection. In Andrew Spencer and Arnold M. Zwicky, editors, *The Handbook of Morphology*, pages 13–43. London: Blackwell, 1998.

William E. Winkler. String comparator metrics and enhanced decision rules in the Fellegi-Sunter model of record linkage. In *Proceedings of the Section on Survey Research Methods (American Statistical Association)*, pages 354–359, 1990. URL `http://www.amstat.org/sections/srms/Proceedings/papers/1990_056.pdf`.

Zdeněk Žabokrtský, Magda Ševčíková, Milan Straka, Jonáš Vidra, and Adéla Limburská. Merging data resources for inflectional and derivational morphology in Czech. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016)*, pages 1307–1314, 2016.