# Determining the Semantic Compositionality of Croatian Multiword Expressions

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# The problem

- MWEs require special attention in NLP

**Semantic compositionality**

Degree to which the features of the parts of an MWE combine to predict the features of the whole [Baldwin, 2006].
Compositional MWEs: *world war, yellow tape*
Non-compositional MWEs: *cold war, red tape*

- In reality, MWEs populate a continuum between two extremes [Bannard et al., 2003]
- Determining compositionality useful for many NLP tasks (machine translation, information retrieval, word sense disambiguation...)

# Our approach

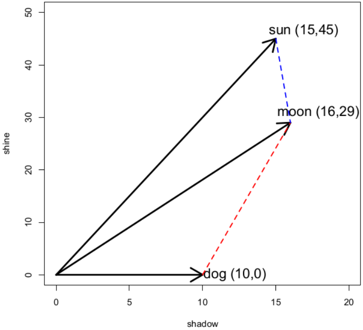
- We follow up on the works of Katz and Giesbrecht [2006] and Biemann and Giesbrecht [2011]
- Idea: compare the meaning of an MWE against the meaning of the composition of its parts
  $\rightarrow$ world $\oplus$ war $=$ world war ?
- To model the meanings of words, we use *distributional semantics*
- Our contribution:
  - we build a small dataset of Croatian MWEs annotated with semantic compositionality scores
  - we build and evaulate a semantic compositionality model based on **Latent Semantic Analysis** [Landauer et al., 1998]
  - results comparable to relevant RW

# Distributional semantics

- Representation of word meaning based on distributional hypothesis [Harris, 1954]:
  - correlation between similarity of words' contexts and words' semantic similarity
- Words represented as vectors of context features obtained from corpus
- Semantic similarity predicted via vector similarity
- Distributional semantic models used in many applications [Turney and Pantel, 2010]

# Distributional semantic models

| | planet | night | full | shadow | shine | crescent |
|---|---|---|---|---|---|---|
| moon | 10 | 22 | 43 | 16 | 29 | 12 |
| sun | 14 | 10 | 4 | 15 | 45 | 0 |
| dog | 0 | 4 | 2 | 10 | 0 | 0 |




(Marco Baroni's EACL 2012 tutorial: Compositionality in Distributional Semantics)

# Dataset

- Corpus: fHrWaC [Šnajder et al., 2013], filtered version of hrWaC [Ljubešić and Erjavec, 2011]
- Three MWE types:
  1. **AN**: *žuti karton (yellow card)*
  2. **SV**: *podatak govori (data says)*
  3. **VO**: *popiti kavu (drink coffee)*
- We extracted the most frequent MWEs and pre-annotated each as compositional (C) or non-compositional (NC)
- Final dataset was balanced to include roughly equal number of C and NC MWEs

# Annotation

- Setup: 200 MWEs, 24 annotators
- Score aggregation: median

| MWE | Score |
|---|---|
| *maslinovo ulje (olive oil)* | 5 |
| *telefonska linije (telephone line)* | 4 |
| *pružiti pomoć (to offer help)* | 4 |
| *kućni ljubimac (a pet)* | 3.5 |
| *crno tržište (black market)* | 3 |
| *voditi brigu (to worry)* | 3 |
| *ostaviti dojam (to leave an impression)* | 2.5 |
| *zeleno svjetlo (green light)* | 1 |
| *hladni rat (cold war)* | 1 |
| ⋮ | ⋮ |

- Average Spearman's correlation coefficient: 0.77
- Dataset split in development (100 MWEs) and test set (100 MWEs)

# Compositionality model

**Step 1:** model the meaning of constituent words and MWEs

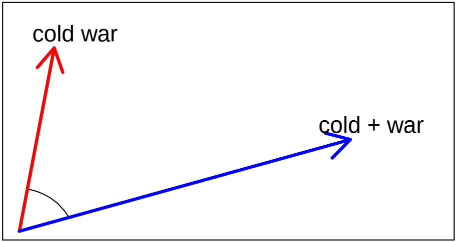
- Latent Semantic Analysis
- $\pm 5$ words context window, 10K most freq. words (excl. stopwords)

**Step 2:** model the composed meaning from constituents

- six compositional models

**Step 3:** compare composed meaning against MWE meaning

- cosine similarity between word vectors



# Distributional semantic composition

($\vec{z}$ – composed vector; $\vec{x}$, $\vec{y}$ – constituents' vectors)

- **multiplicative**: $\vec{z} = \vec{x} \odot \vec{y}$
- **simple additive**: $\vec{z} = \vec{x} + \vec{y}$
- **weighted additive**: $\vec{z} = \alpha\vec{x} + \beta\vec{y}$
  - opt: weights optimized globally on the train set
  - dyn: constituent more similar to MWE more important (*gray economy*)

$$\alpha = \frac{\cos(\overrightarrow{xy}, \vec{x})}{\cos(\overrightarrow{xy}, \vec{x}) + \cos(\overrightarrow{xy}, \vec{y})}, \quad \beta = 1 - \alpha$$

- **first constituent**: $\vec{z} = \vec{x}$
- **second constituent**: $\vec{z} = \vec{y}$
- **linear combination**:

$$\lambda = a_0 + a_1 \cdot \cos(\overrightarrow{xy}, \overrightarrow{x + y}) + a_2 \cdot \cos(\overrightarrow{xy}, \overrightarrow{x \odot y}) + a_3 \cdot \cos(\overrightarrow{xy}, \vec{x}) + a_4 \cdot \cos(\overrightarrow{xy}, \vec{y})$$

# Results – Predicting compositionality scores

| Model | AN+SV+VO | AN | SV+VO |
|---|---|---|---|
| Multiplicative | $-0.19$ | $-0.20$ | $-0.18$ |
| Simple additive | 0.45 | 0.54 | **0.35** |
| Weighted additive (Opt) | 0.46 | 0.56 | 0.28 |
| Weighted additive (Dyn) | 0.46 | **0.57** | 0.26 |
| First constituent | 0.41 | 0.50 | 0.19 |
| Second constituent | 0.28 | 0.31 | 0.31 |
| Linear combination ($\lambda$) | **0.48** | 0.56 | 0.34 |
| Annotators | 0.77 | 0.77 | 0.74 |

- Combining multiple models beneficial
- AN compositionality easier to predict (AN easier to model?)

# Results – Compositionality classification

- Dataset: score $\leq 3 \Rightarrow$ MWE is non-compositional
- Linear combination model
- The threshold optimized on the train set by optimizing the F1-score

| | AN+SV+VO | AN | SV+VO |
|---|---|---|---|
| Precision | $0.58$ | $0.74$ | $0.43$ |
| Recall | $0.73$ | $0.65$ | $0.77$ |
| Accuracy | $0.65$ | $0.72$ | $0.54$ |
| F1-score | $0.65$ | $0.69$ | $0.56$ |

# Conclusion

- A composition-based model for determining semantic compositionality of Croatian MWEs
- The best-performing model combines the additive and the multiplicative compositional models and the representations of the two individual words
- Annotated dataset available from takelab.fer.hr/cromwesc
- Future work wishlist:
  - enlarge the dataset
  - consider using an unbalanced dataset
  - error analysis
  - supervised compositionality classification
  - experiment with neural word embeddings
  - token based semantic compositionality detection

# References I


Timothy Baldwin. Compositionality and multiword expressions: Six of one, half a dozen of the other. In *Invited talk given at the COLING/ACL'06 Workshop on Multiword Expressions: Identifying and Exploiting Underlying Properties*, 2006.

Colin Bannard, Timothy Baldwin, and Alex Lascarides. A statistical approach to the semantics of verb-particles. In *Proc. of the ACL 2003 Workshop on Multiword Expressions: Analysis, Acquisition and Treatment - Volume 18*, MWE '03, pages 65–72. ACL, 2003. doi: 10.3115/1119282.1119291. URL http://dx.doi.org/10.3115/1119282.1119291.

Chris Biemann and Eugenie Giesbrecht. Distributional semantics and compositionality 2011: Shared task description and results. In *Proc. of the Workshop on Distributional Semantics and Compositionality*, pages 21–28. ACL, 2011. URL http://dl.acm.org/citation.cfm?id=2043121.2043125.

Zelig S. Harris. Distributional structure. *Word*, 10(23):146–162, 1954.

# References II


Graham Katz and Eugenie Giesbrecht. Automatic identification of non-compositional multi-word expressions using latent semantic analysis. In *Proc. of the Workshop on Multiword Expressions: Identifying and Exploiting Underlying Properties*, pages 12–19. ACL, 2006.

T. K. Landauer, P. W. Foltz, and D. Laham. An introduction to latent semantic analysis. *Discourse Processes*, 25:259–284, 1998. URL http://lsa.colorado.edu/papers/dp1.LSAintro.pdf.

Nikola Ljubešić and Tomaž Erjavec. hrWaC and slWaC: Compiling web corpora for Croatian and Slovene. In *Text, Speech and Dialogue*, pages 395–402. Springer, 2011.

Jan Šnajder, Sebastian Padó, and Željko Agić. Building and evaluating a distributional memory for Croatian. In *In Proc. of the 51st Annual Meeting of the Association for Computational Linguistics*, pages 784–789. ACL, 2013.

Peter D. Turney and Patrick Pantel. From frequency to meaning: Vector space models of semantics. *Journal of Artificial Intelligence Research*, 37:141–188, 2010.

# Annotation (1)

Annotation setup:

- 200 MWEs randomly split in 4 groups (A, B, C, D)
- 24 annotators $\Rightarrow$ each MWE annotated by 6 annotators
- 10% overlap
- question: how literal an MWE is on the scale from 1 (non-compositional) to 5 (compositional)?
- one context sentence provided for each MWE
- final score: median

# Annotation (2)

Inter-annotator agreement (Krippendorff's $\alpha$):

| Sample | AN+SV+VO | AN | SV+VO |
|---|---|---|---|
| Group A | 0.587 | 0.620 | 0.535 |
| Group B | 0.506 | 0.510 | 0.478 |
| Group C | 0.490 | 0.544 | 0.337 |
| Group D | 0.586 | 0.505 | 0.648 |
| Overlap (10%) | 0.456 | 0.452 | 0.439 |

# Levels of compositionality

- MWEs come in different "flavors of compositionality"
- In an attempt to identify different levels of non-compositionality, we developed the following typology:
  - **NC3**: completely non-compositional
    $\rightarrow$ *žuti karton (yellow card)*
  - **NC2**: partially compositional
    $\rightarrow$ *siva ekonomija (gray economy)*
  - **NC1**: non-compositional considering the dominant senses
    $\rightarrow$ *planinski lanac (mountain chain)*

# Results analysis

- Moderate level of correlation
- Comparable to Biemann and Giesbrecht [2011] and Katz and Giesbrecht [2006]
- Possible causes of error:
  - low quality of vector representations for some words
  - polysemy