From morphosyntactic tagging to identification of verbal multiword expressions: a discriminative approach

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Outline

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Concraft-pl

Basic information

- A morphosyntactic tagger for Polish based on conditional random fields
- Not SOA any more (see PolEval 2017)
- Nevertheless, the set of users $\neq \emptyset$
  - Practical tagging speed
  - Compatible with Morfeusz
  - Some people just don't like deep nets

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What's new in Concraft-pl 2.0

- It's slower
- Does not rely on Maca
- Concraft-pl 2.0 can:
  - Divide sentences into paragraphs
  - Perform tokenization (segmentation)

Ambiguous segmentation

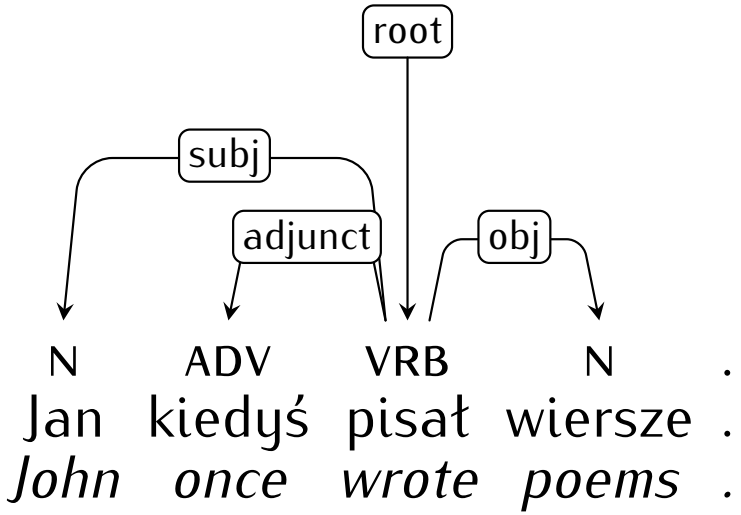
Jan ***kiedyś*** *pisał wiersze.*

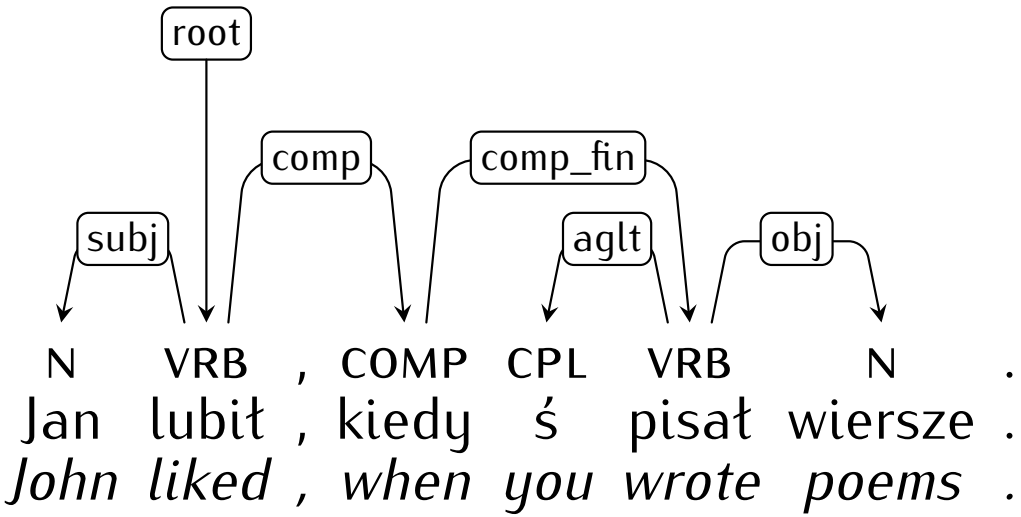
Jan lubił, ***kiedyś*** *pisał wiersze.*

(1) Jan kiedyś pisał wiersze.
John once wrote poems.

(2) Jan lubił, kiedy ś pisał wiersze.
John liked when you wrote poems.

Ambiguous segmentation





Morfeusz

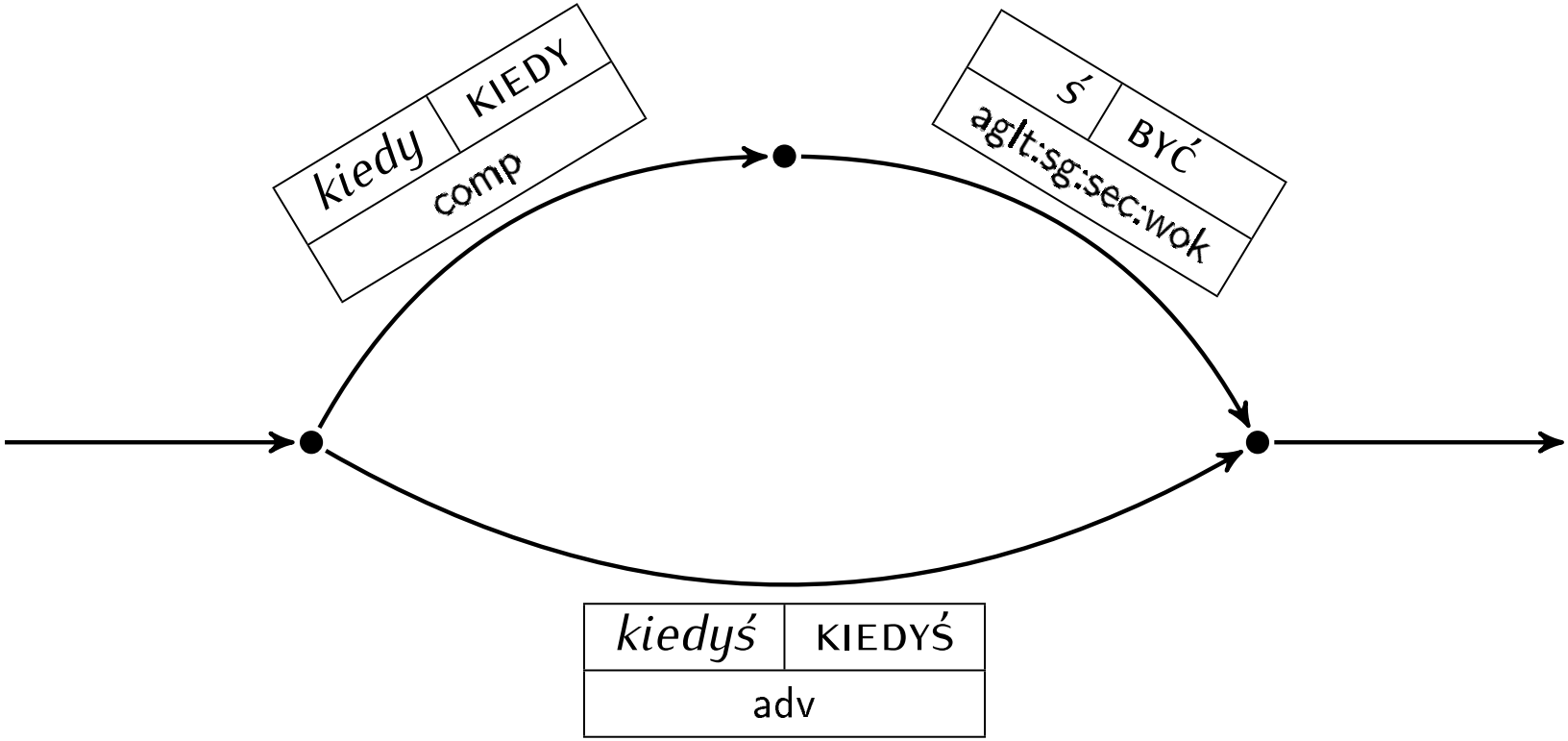


Figure 1: Directed acyclic graph (DAG) analysis of the word *kiedyś*

Existing solutions for Polish word segmentation (1)

`Maca` [Radziszewski and Śniatowski, 2011a]

- **Idea**: transform and simplify the segmentation graph to a sequence of tokens based on heuristic rules
- **Taggers**: `WMBT` [Radziszewski and Śniatowski, 2011b], `WCRFT` [Radziszewski, 2013], `Concraft` [Waszczuk, 2012], `KRNNT` [Wróbel, 2017]
- **Disadvantage**: segmentation performed in pre-processing

Example

```
Jan     newline
    Jan     subst:sg:nom:m1
kiedyś     space
    kiedyś     adv
pisał     space
    pisać     praet:sg:m1:imperf
    pisać     praet:sg:m2:imperf
    pisać     praet:sg:m3:imperf
wiersze     space
    wiersz     subst:pl:nom:m3
    wiersz     subst:pl:acc:m3
    wiersz     subst:pl:voc:m3
    wiersza     subst:pl:nom:f
    wiersza     subst:pl:acc:f
    wiersza     subst:pl:voc:f
.     none
    .     interp
```

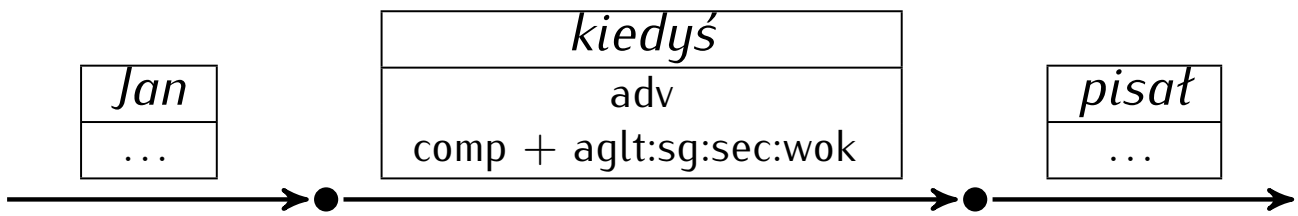
```
Jan     newline
    Jan     subst:sg:nom:m1
lubił     space
    lubić     praet:sg:m1:imperf
    lubić     praet:sg:m2:imperf
    lubić     praet:sg:m3:imperf
,     none
    ,     interp
kiedyś     space
    kiedyś     adv
pisał     space
    pisać     praet:sg:m1:imperf
    pisać     praet:sg:m2:imperf
    pisać     praet:sg:m3:imperf
wiersze     space
    wiersz     subst:pl:nom:m3
    wiersz     subst:pl:acc:m3
    ...
```

Figure 2: Maca (v. 1.0.7) output for the two example sentences

Existing solutions for Polish word segmentation (2)

`MorphoDiTa-pl` [Piasecki and Walentynowicz, 2017]

- **Idea**: encode all segmentation ambiguities as morphosyntactic labeling ambiguities



- **Disadvantage**: hard to generalize (spelling errors, speech processing, multiword units, etc.)

Sequential CRF

Basics

- **Structure**: sequence of labels (morphosyntactic tags)
- **Model**: multiclass logistic regression
  - any sequence of labels y is reduced to a feature vector f_y
  - given a sentence x and a parameter vector θ:

$$p_\theta(y|x) = \frac{\exp(\theta \cdot f_y)}{\sum_{y' \in \mathbf{Y}(x)} \exp(\theta \cdot f_{y'})}$$

  - $\mathbf{Y}(x)$ is the solution space for sentence x
- **Inference**: efficient due to factorization of the model

Factorization in Concraft

Input sequence

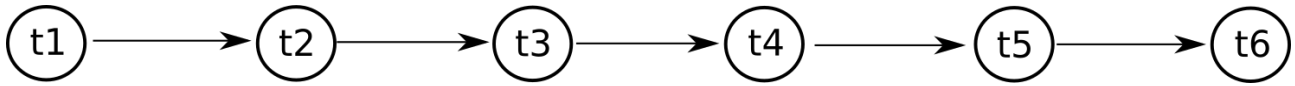
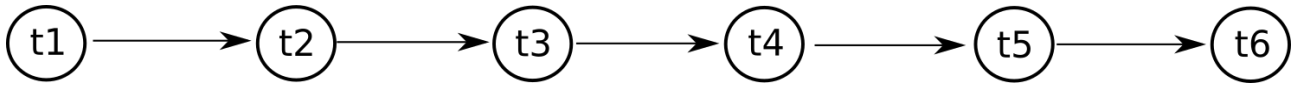


Figure 3: The circles represent the tags assigned to the subsequent words in the sentence.

Factorization in Concraft

Input sequence



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Factorization in 2-order sequential CRFs

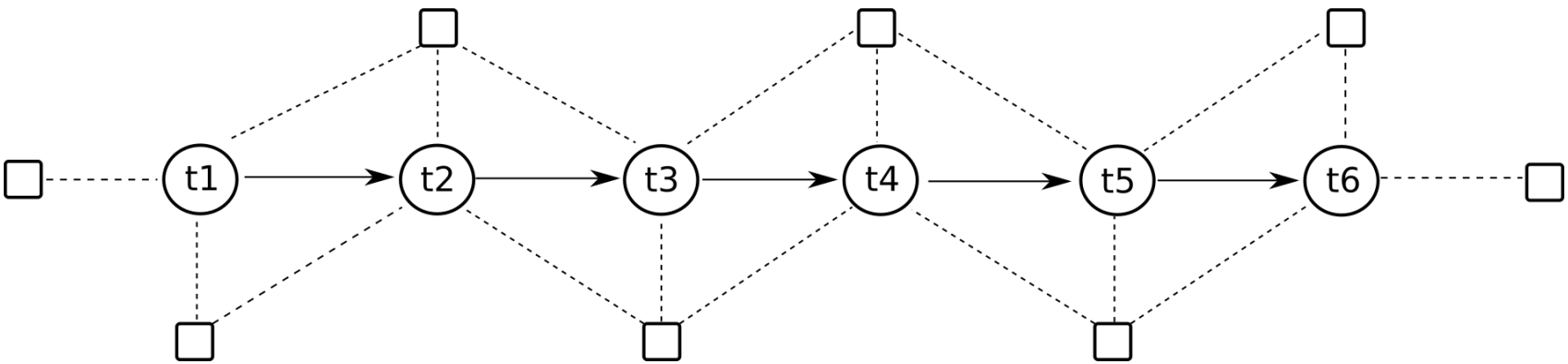


Figure 4: The squares represent the factors, which capture relations between triples of adjacent words.

Factorization in Concraft

Potential in 1-order sequential CRFs

$$\exp(\theta \cdot f_y) = \prod_{i=1}^{|y|} \exp(\theta \cdot f(y_i, y_{i-1}, i)) \tag{1}$$

Factorization in Concraft

Potential in 1-order sequential CRFs

$$\exp(\theta \cdot f_y) = \prod_{i=1}^{|y|} \exp(\theta \cdot f(y_i, y_{i-1}, i)) \tag{1}$$

Viterbi decoding

$$\alpha(y, i) = \max_{y' \in Y} \big(\exp(\theta \cdot f(y, y', i)) \cdot \alpha(y', i-1)\big) \tag{2}$$

Sequential CRF

Jan (*John*)	kiedyś (*once*)	pisał (*wrote*)	wiersze (*poems*)
subst:sg:nom:m1	subst:sg:nom:m1	subst:sg:nom:m	subst:sg:nom:m
...	...	...	...
subst:pl:acc:m3	subst:pl:acc:m3	subst:pl:acc:m3	**subst:pl:acc:m3**
...	...	...	...
adj:sg:nom:m1:pos	adj:sg:nom:m1:pos	adj:sg:nom:m1:pos	adj:sg:nom:m1:pos
...	...	...	...
adv	**adv**	adv	adv
...	...	...	...
praet:sg:m1:imperf	praet:sg:m1:imperf	**praet:sg:m1:imperf**	praet:sg:m1:imperf
...	...	...	...
prep:gen	prep:gen	prep:gen	prep:gen
...	...	...	...
interp	interp	interp	interp

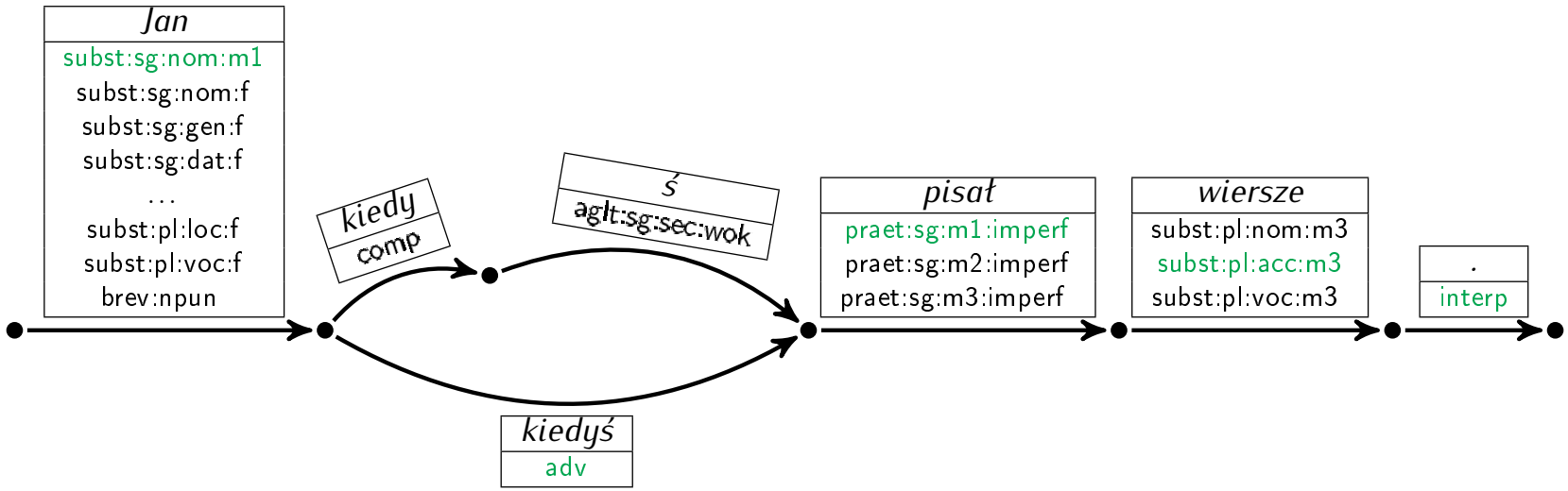
Solution space: $\mathsf{Y}(x) = T^{|x|}$, where T is a tagset

Constrained CRF (Concraft 1.0)

Jan (*John*)	kiedyś (*once*)	pisał (*wrote*)	wiersze (*poems*)	.
subst:sg:nom:m1	**adv**	**praet:sg:m1:imperf**	subst:pl:nom:m3	**interp**
subst:sg:nom:f		praet:sg:m2:imperf	**subst:pl:acc:m3**	
subst:sg:gen:f		praet:sg:m3:imperf	subst:pl:voc:m3	
subst:sg:dat:f				
...				
subst:pl:loc:f				
subst:pl:voc:f				
...				
brev:npun				

Solution space: $Y(x) = \prod_{i=1}^{|x|} r_i$, where r_i is the set of possible labels (tags) assigned to position i ($r_i = T$ for out-of-vocabulary words)

DAG-based CRF (Concraft 2.0)



Solution space: $\mathsf{Y}(x)$ is the set of labeled paths in the input DAG

DAG-based CRF (`Concraft 2.0`)

Inference

The standard algorithms for CRFs [Wainwright et al., 2008]:

- *max-product* – for Viterbi decoding
- *sum-product* – for forward and backward sums

can be straightforwardly adapted to DAG-based CRFs.

DAG-based CRF (Concraft 2.0)

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The standard algorithms for CRFs [Wainwright et al., 2008]:

- *max-product* – for Viterbi decoding
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can be straightforwardly adapted to DAG-based CRFs.

Viterbi decoding (1-order)

$$\alpha(e) = \max_{e' \in \mathrm{pred}(e)} \left(\exp(\theta \cdot f(e, e')) \cdot \alpha(e') \right) \tag{3}$$

where:

- e – edge in the DAG
- $\mathrm{pred}(e)$ – the set of edges preceding e in the DAG

DAG-based CRF (Concraft 2.0)

Features

The same as in Concraft 1.0:

- 2-order *transition* features (t_{i-2}, t_{i-1}, t_i)
- *observation* features (o_i, t_i), where o_i is an observation (wordform, suffix, prefix, shape, etc.) related to word i

"*the wordform of the token on position* $i - 2$"

Issue

$i - 2$ may not be uniquely defined

Solution

- $i - 1$ is defined as the shortest edge preceding i
- $i + 1$ is defined as the shortest edge following i

Evaluation datasets

Baroque Corpus of Polish [Kieraś et al., 2017]

- 500,000 tokens large manually annotated subcorpus of the Baroque Corpus of Polish (1601–1772)
- 3% of tokens have ambiguous segmentation

Corpus of Polish 1830–1918 [Kieraś and Woliński, 2018]

- 625,000 tokens large manually annotated corpus of Polish texts published between 1830 and 1918
- 1.3% of tokens have ambiguous segmentation

NCP: 0.3% tokens have ambiguous segmentation

Evaluation results

	Baroque	1830-1918
Tagging:		
precision	0.882724	0.903176
recall	0.88303	0.903335
Guessing:		
precision	0.60125	0.610493
recall	0.601214	0.609796
Segmentation:		
precision	0.937455	0.951261
recall	0.948684	0.965946

Segm. baselines	Baroque	1830-1918
shortest path:		
precision	0.712871	0.694111
recall	0.503595	0.517577
longest path:		
precision	0.264848	0.294253
recall	0.41452	0.47628
freq. based:		
precision	0.838571	0.911858
recall	0.724294	0.823025

Table 1: Results (our system on the left, baselines on the right)

Where to find more

Implementation

- **Repository**: `https://github.com/kawu/concraft-pl`
- **Languages**: Haskell + Dhall (configuration – NEW)
- **License**: 2-clause BSD
- **Model**: pre-trained on NKJP1M merged with Morfeusz
- **„Bindings“**: Python client for the client/server mode
- **Concraft-pl 1.0**: avaliable in branch `maca`

Conclusions and future work

Polish word segmentation

- Potentially hard to resolve in pre-processing
- Neglected so far due to relatively low frequency

Concraft-pl 2.0's approach

- More principled than what was proposed before
- Segmentation as a by-product of disambiguation, or
- No segmentation at all! (just output marginal probabilities)

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Future work

?

Outline

Multiword expressions

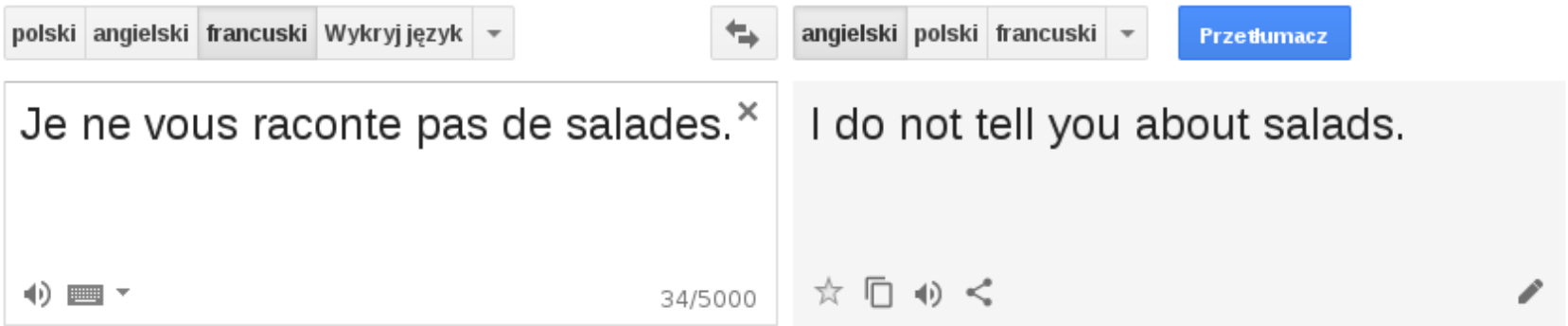
Properties

- Contain two or more words and show **idiosyncratic** behavior at different levels

  by and large
  to pull one's socks up
  white wine

- Non-compositional meaning

MWEs and NLP


polski angielski francuski Wykryj język
angielski polski francuski
Przetłumacz
Je ne vous raconte pas de salades.
34/5000
I do not tell you about salads.

MWEs and parsing

Syntactic parsing

- Syntactic structure: describes syntactic relations between the words of a sentence
- The goal of parsing: find the correct syntactic structure for a given input sentence

Interactions between MWEs and parsing

- MWE identification and syntactic parsing can mutually enhance each other [Nivre and Nilsson, 2004, Finkel and Manning, 2009, Wehrli et al., 2010, Constant et al., 2013, Nasr et al., 2015, Constant and Nivre, 2016]

Syntax and MWEs

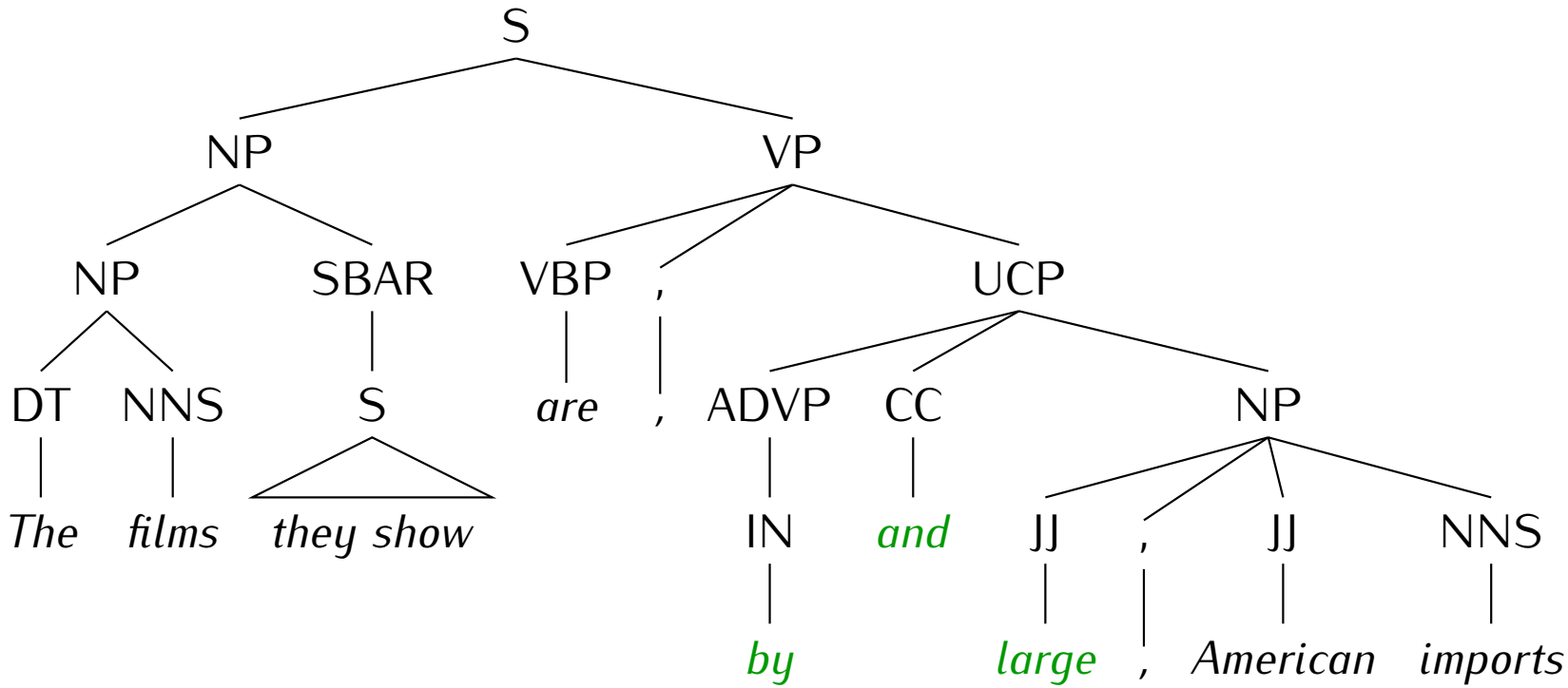
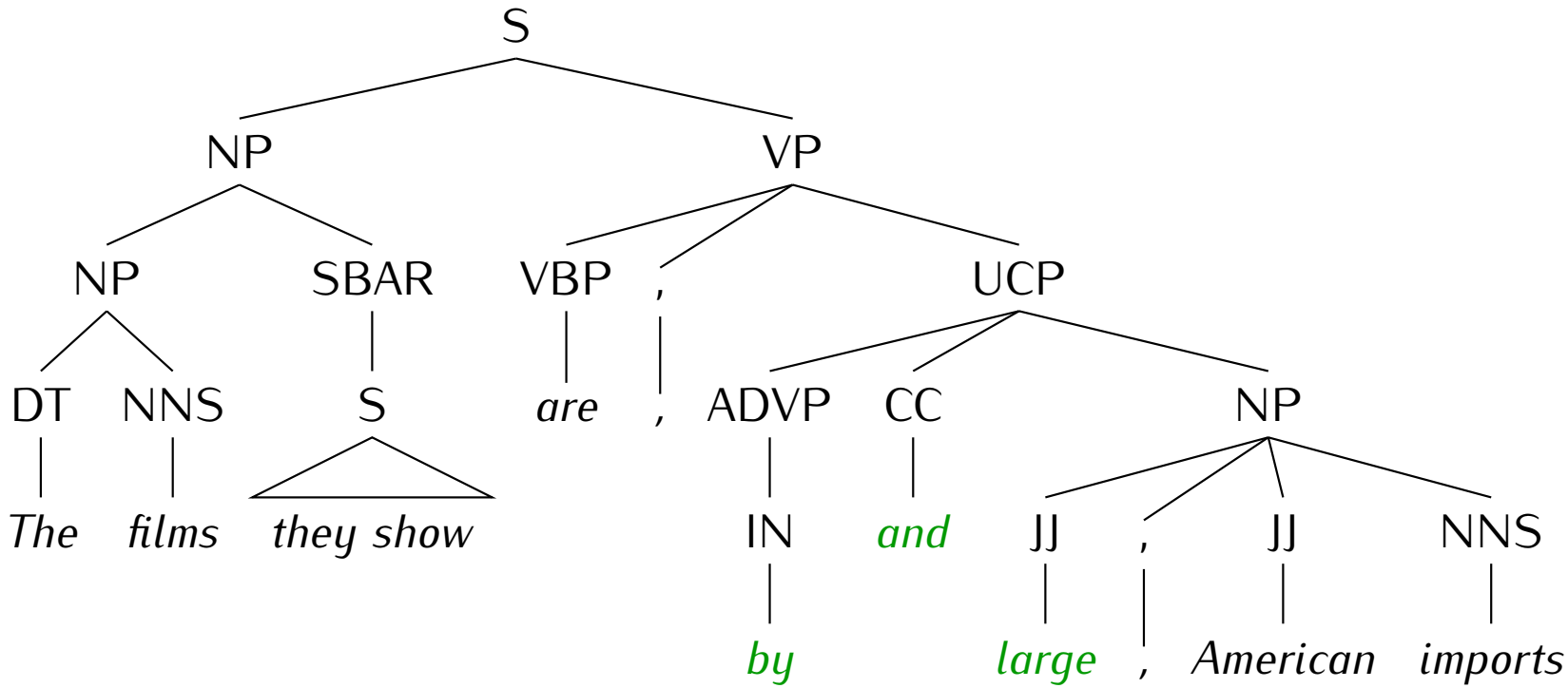


Figure 5: An example of a tree obtained with the *Berkeley Parser* (`http://tomato.banatao.berkeley.edu:8080/parser/parser.html`)

Syntax and MWEs



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MWE-related issues: irregular syntax, syntactic ambiguity

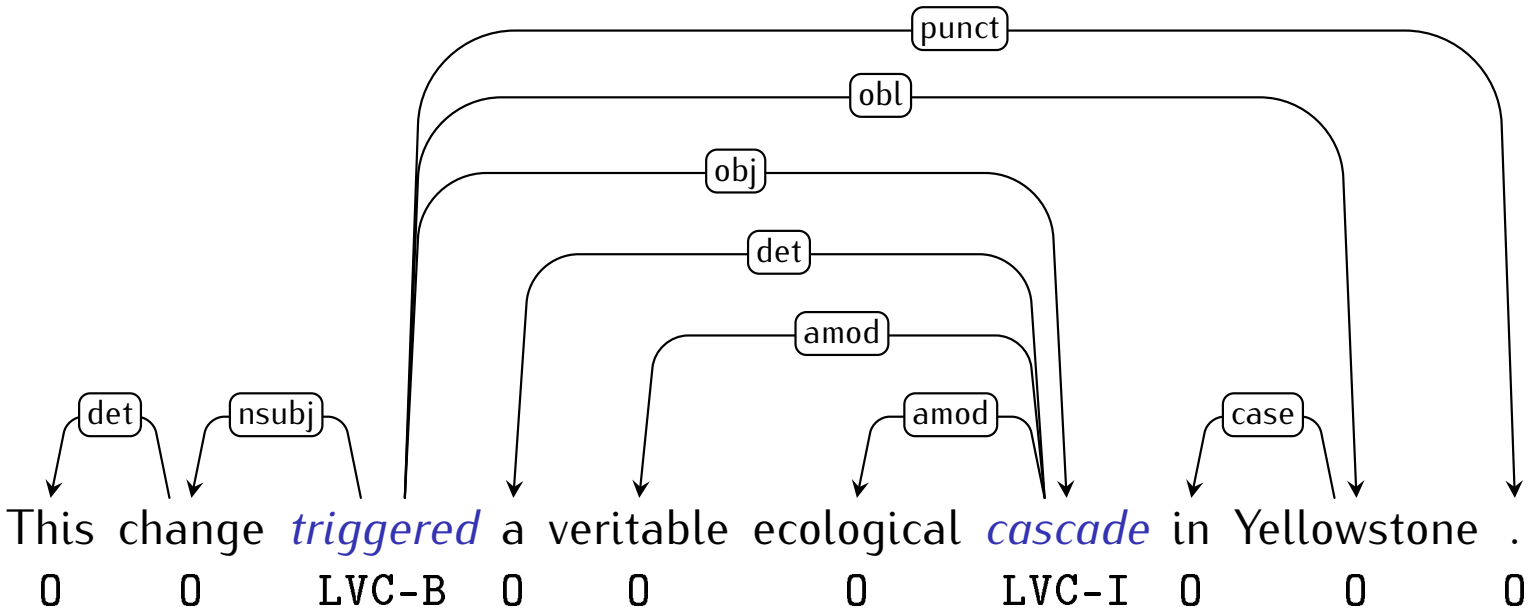
(example: *. . . and it was a fantastic protest – lots of interest from people passing by and large numbers of conversations which were uplifting and positive in the main.*)

Outline

PARSEME Shared Task 2018

- **Task**: automatic identification of verbal MWEs (VMWEs)
- **Data**: manually annotated with VMWEs for 19 languages (including PL)
- **Syntax**: UD trees provided on input (some manually annotad, some obtained using UDPipe)
- **Tracks**: *open* and *closed*

VMWEs, (dis)continuity, and sequential models



Sequential models:

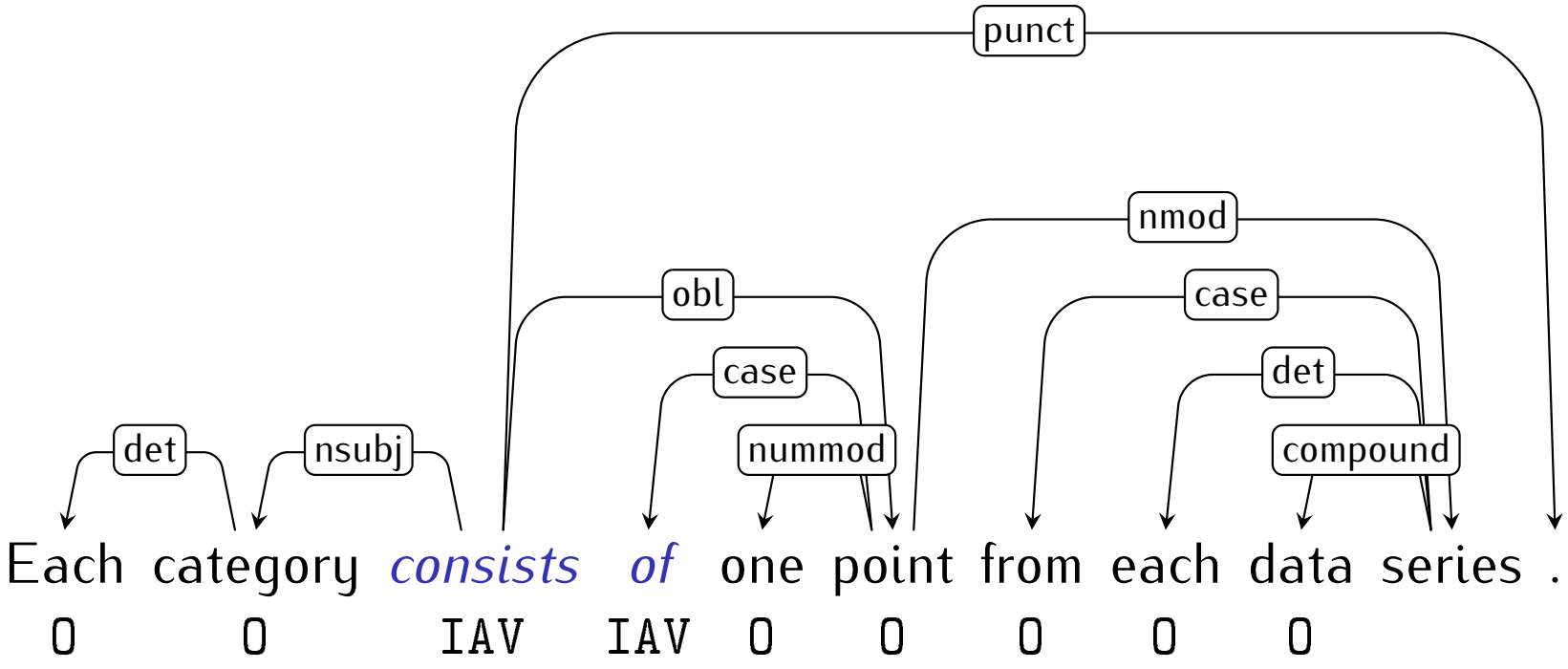
- Don't directly capture the relation between `LVC-B` and `LVC-I`.
- **CRF**: labeling *triggered* with `LVC-B` is independent from labeling *cascade* with `LVC-I` (provided that the material in between is labeled with `O`s).

TRAVERSAL

Principles

- **Assumption**: VMWEs continuous in dependency structures
- **Division**: VMWE identification = labeling + segmentation
- **Labeling**: multiclass logistic regression
- **Segmentation**: two simple heuristics

Breaking cases (attested)



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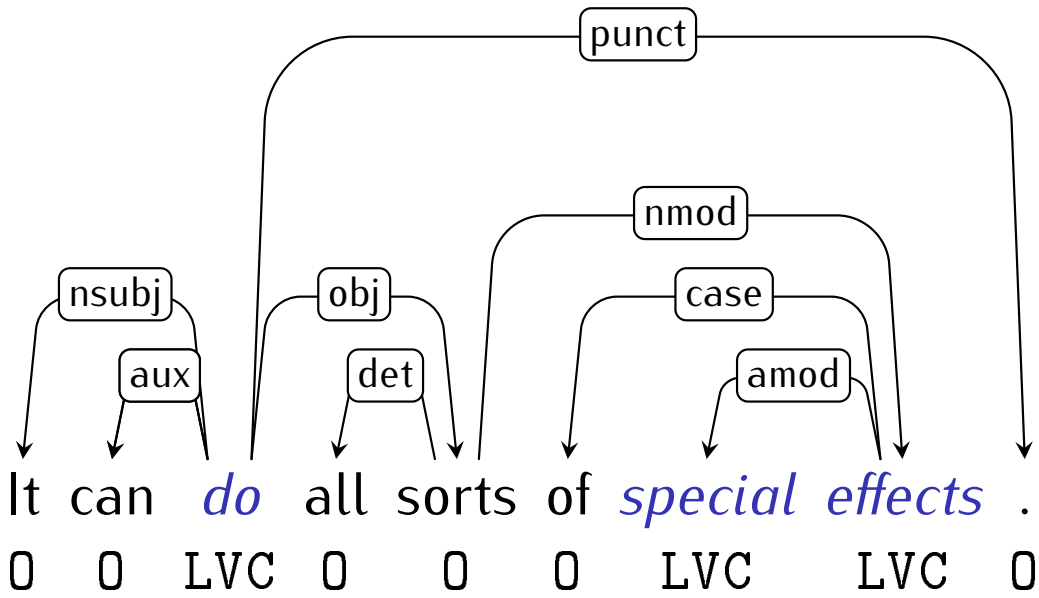


Dataset statistics

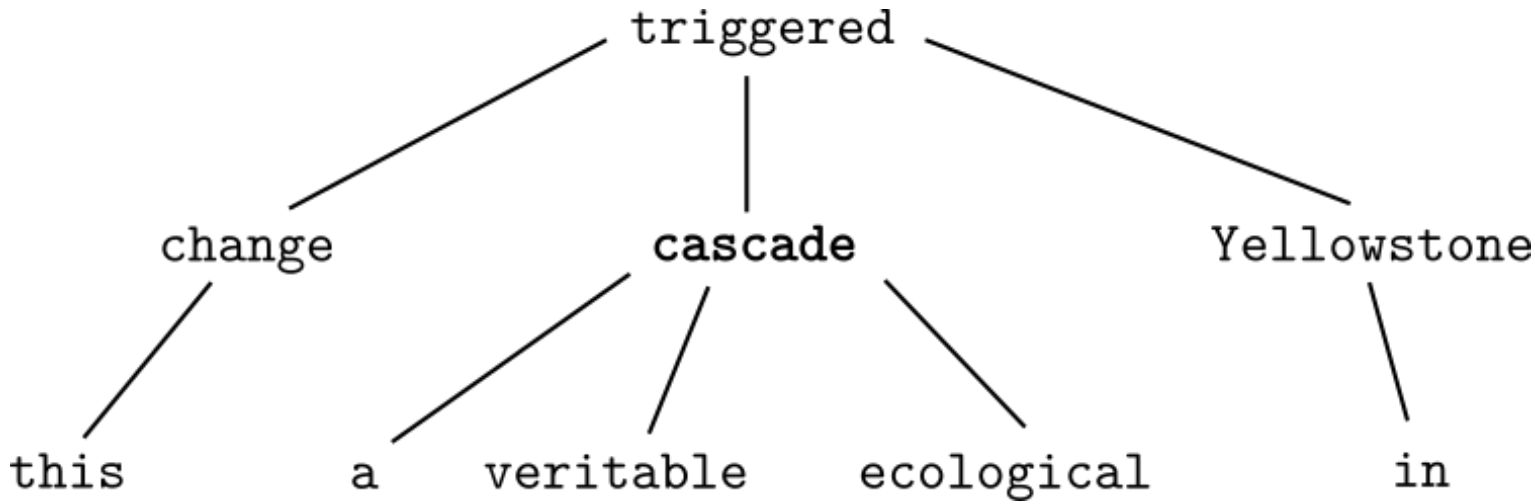
	% Continuous	
	Seq	Dep
BG	80.39	95.0
DE*	57.39	90.76
EL	48.58	92.86
EN**	68.28	91.84
ES	74.05	76.55
EU*	80.62	95.28
FA*	85.09	94.48
FR**	58.1	98.17
HE	75.82	76.45
HI	91.2	98.5

	% Continuous	
	Seq	Dep
HR	57.23	63.38
HU**	92.78	99.53
IT	64.78	94.62
LT†	58.33	n/a
PL*	70.26	80.87
PT*	53.5	95.54
RO	68.96	98.64
SL*	44.51	71.61
TR	49.5	55.54

Table 2: The % of continuous VMWEs in terms of sequences and dependency trees in the Train+Dev datasets for the individual languages. The datasets with dependencies annotated manually, partially manually, or not at all, are marked with **, *, or †, respectively. For the other datasets/sentences, dependencies were obtained automatically.

Factorization

Goal: capture the relations between `MWE` labels of adjacent nodes.



The labeling model can be seen as:

- Extension of sequential CRFs to tree structures
- Variant of the 2-order Eisner's graph-based parser
- Multiclass logistic regression model with special factorization allowing efficient computation

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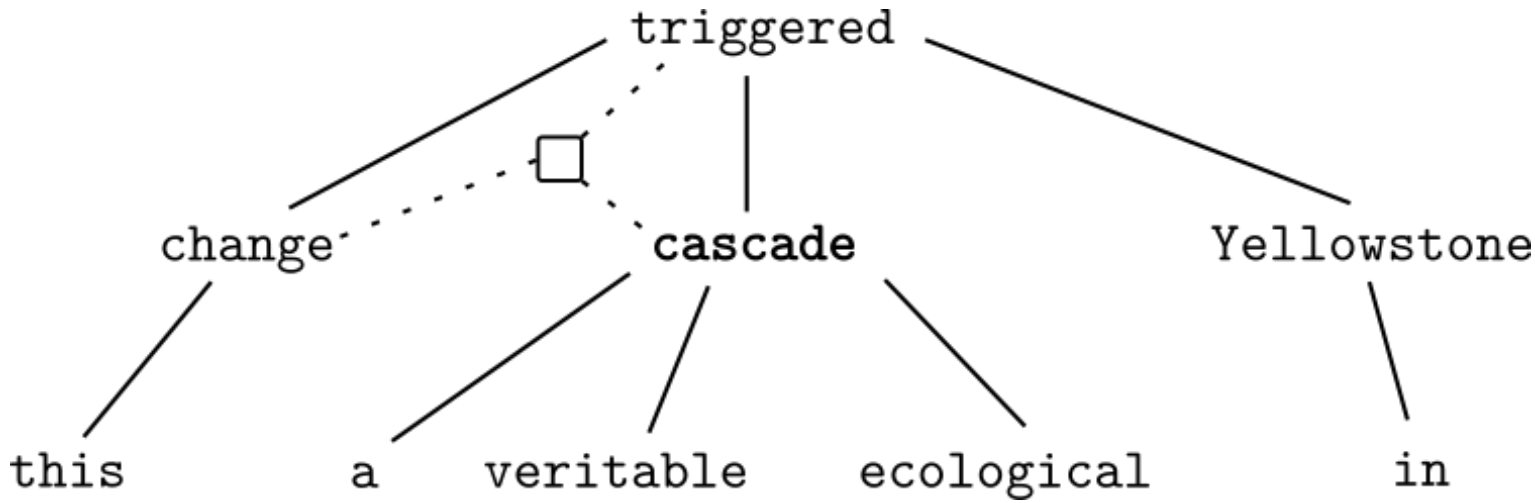

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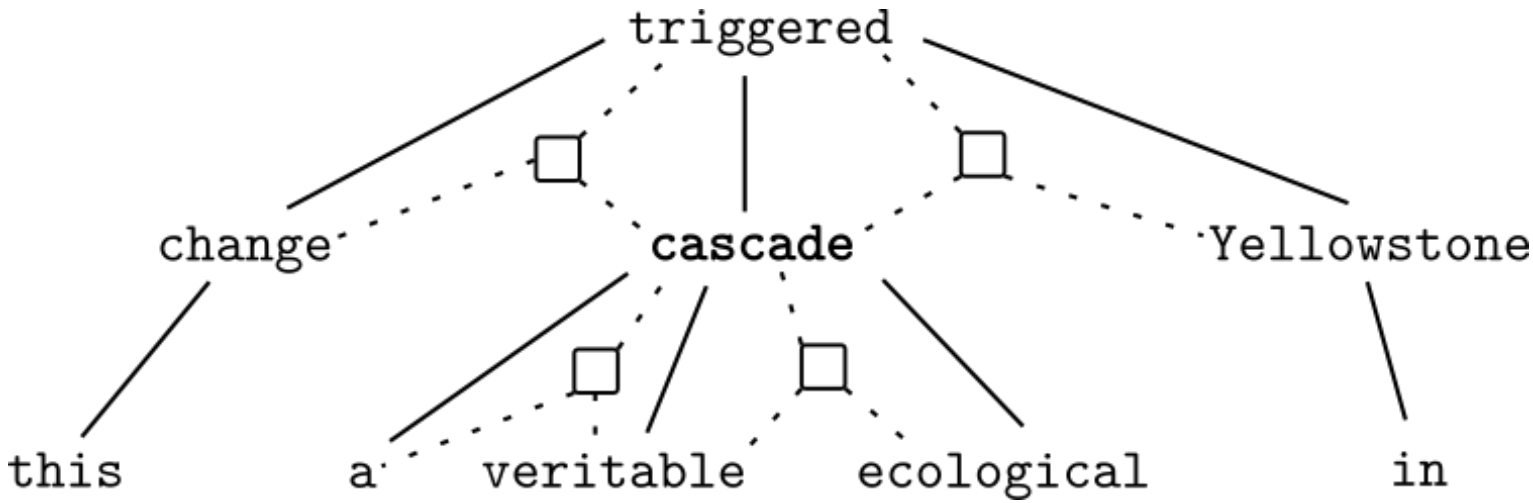

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- Extension of sequential CRFs to tree structures
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- Multiclass logistic regression model with special factorization allowing efficient computation

Encoding

Goal: given a dependency tree d, construct a *hypergraph* $\mathcal{H}(d)$ encoding all labelings of d. The individual *hyperarcs* should locally capture relations between adjacent nodes and their labels.

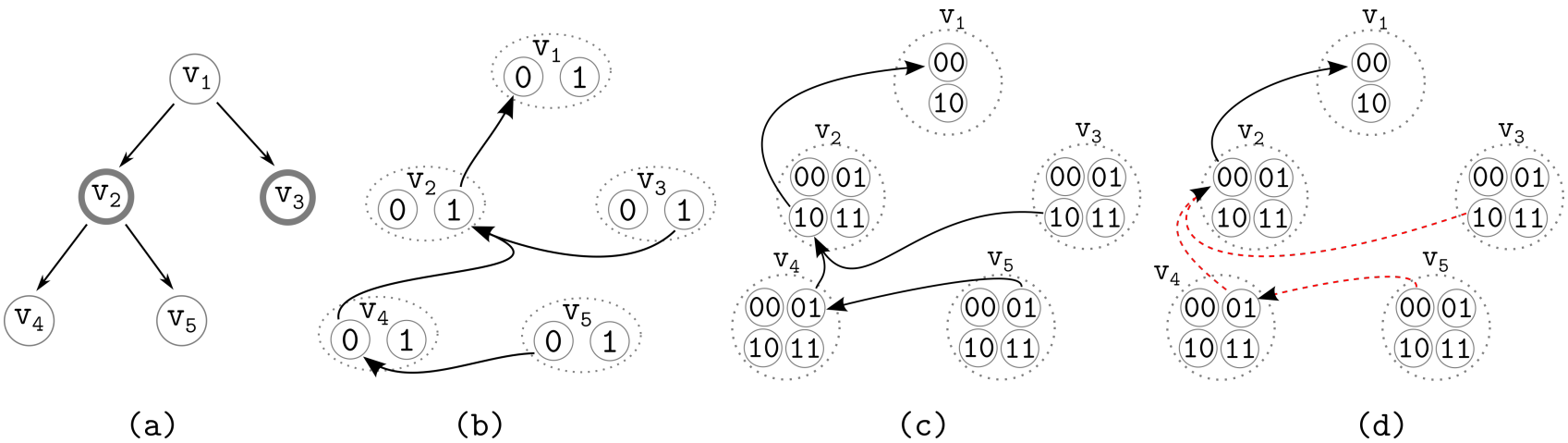


Figure 6: Encoding example. (a) A dependency tree with v_2 and v_3 marked as `MWE`s. (b) The corresponding hyperpath. (c) The corresponding hyperpath with copying of parent labels. (d) An invalid hyperpath, not encoded in the hypergraph.

Labeling model

- **Reduction**. Labeling boils down to finding the best-score hyperpath $h \in \mathcal{H}(d)$ among the set of hyperpaths $\mathcal{H}(d)$.
- **Representation**. Each hyperpath h is reduced to a feature vector f^h of a fixed length n, where n is the number of features, with each hyperarc $a \in h$ represented as a binary feature vector f^a such that $f^a_k = 1$ iff the k-th feature holds within the context of a:

$$f^h = \sum_{a \in h} f^a \tag{4}$$

- **Probability**. Given a vector of parameters θ of length n, the probability of a hyperpath $h \in \mathcal{H}(d)$ given a dependency tree d is defined as:

$$p_\theta(h|d) = \exp(\theta \cdot f^h) \; / \; \sum_{h' \in \mathcal{H}(d)} \exp(\theta \cdot f^{h'}) \tag{5}$$

Labeling model

- **Training**. Training consists in finding the *maximum likelihood estimates* (w.r.t. training data T) given the following (log-)likelihood function (with normal priors over θ):

$$\ell(\theta) = \sum_{(d,h)\in T} \log p_\theta(h|d) - \sum_{k=1}^{n} \frac{\theta_k^2}{2\sigma^2} \tag{6}$$

- **Optimization**. The maximum likelihood estimates are approximated using *stochastic gradient descent* with momentum.
- **Complexity**. The necessary calculations can be performed efficiently using the *inside-outside* algorithm.

Segmentation

Problem

- It's not enough to label nodes as `MWEs` or `not-MWEs`
- The **boundaries** of VMWEs need to be determined

Solutions

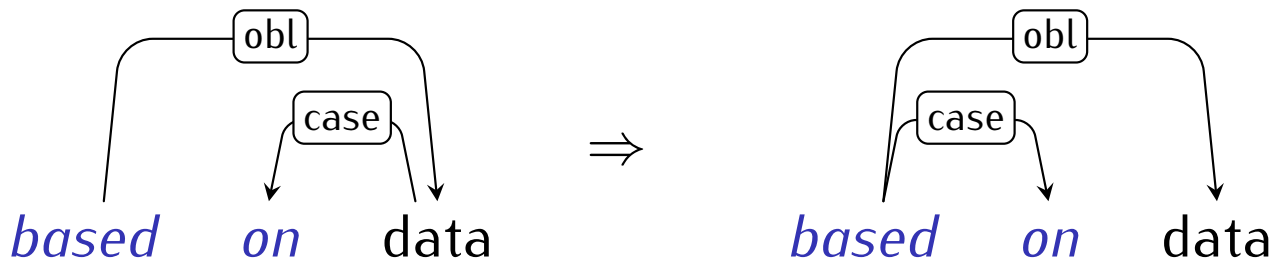
- Consider all adjacent nodes marked as `MWEs` of the same category as a single MWE occurrence (default heuristic)
- If a group of adjacent nodes is marked as `MWEs` but it contains two (or more) verbs, the group is divided into two (or more) distinct MWEs (heuristic applied only to `FA`)
- Variant of IOB encoding adapted to trees (not in the shared task)

Implementation

- **Repository**: `https://github.com/kawu/traversal`
- **Languages**: Haskell + Dhall (configuration)
- **License**: 2-clause BSD

Setup

- **Pre-processing**: *case lifting* (among others)



- **Feature engineering**: `PL` and `FR`
- **Backoff model**: 2-order sequential CRF (`LT`)

Feature templates

Unary	(l_v, m_v)
Binary	$\{(l_v, m_v), (l_w, m_w)\}$ (*unordered pair*)
Sibling Binary	(m_v, m_w), (l_v, l_w, m_v, m_w), (m_v, m_w, d_v, d_w), (l_v, p_w, m_v, m_w), (p_v, l_w, m_v, m_w)
Parent Binary	(m_v, m_w), (l_v, l_w, m_v, m_w), (m_v, m_w, d_v), $(l_v, p_w, m_v, m_w, d_v)$, $(p_v, l_w, m_v, m_w, d_v)$
Ternary	(*none, even though possible to capture*)

Table 3: v is the current node, w is its sibling or parent, l_u is the u's lemma, m_u is the u's MWE label, p_u is the u's universal POS tag, d_u is the dependency label of the arc incoming to u.

Dataset statistics after pre-processing

	%VMWE$_{(train+dev)}$		
	Con	**Con$_p$**	**Iso$_p$**
BG	95.0	**97.34**	**93.42**
DE	90.76	**93.17**	**87.69**
EL		**92.86**	**84.66**
EN	91.84	**98.19**	**95.17**
ES	76.55	**90.13**	**84.59**
EU		**95.28**	**84.38**
FA		**94.48**	**57.83**
FR		**98.17**	**92.62**
HE		**76.45**	**73.69**
HI	98.5	**98.88**	**85.58**

	%VMWE$_{(train+dev)}$		
	Con	**Con$_p$**	**Iso$_p$**
HR	63.38	**96.56**	**87.03**
HU		**99.53**	**90.35**
IT		**94.62**	**88.12**
LT		**58.33**	**58.33**
PL	80.87	**86.09**	**82.42**
PT		**95.54**	**90.01**
RO		**98.64**	**95.38**
SL	71.61	**88.12**	**86.14**
TR	55.54	**98.21**	**91.08**

- `Con` – % of connected VMWEs (no value $\Longrightarrow$ `Con`=`Con`$_p$)
- `Con`$_p$ – % of connected VMWEs after pre-processing
- `Iso`$_p$ – % of connected and isolated (with no adjacent VMWEs of the same category) VMWEs after pre-processing

Results

	MWE-based					Token-based				
	P	R	F1	Rank	**Delta**	P	R	F1	Rank	Delta
SL	79.41	54	64.29	1/10	**21.95**	83.61	54.54	66.01	1/10	14.04
HR	68.04	46.59	55.3	1/10	**11.03**	78.14	50.73	61.52	1/10	11.55
IT	63.09	40.32	49.2	1/12	**10.68**	74.42	42.11	53.78	1/12	7.27
...	...	...	...	...	**...**	...	...	...	...	...
PL	77.02	59.22	66.96	1/11	**6.42**	81.85	59.03	68.59	1/11	3.67
FR	77.19	44.18	56.19	1/13	**5.65**	84.72	48.76	61.9	1/13	6.18
...	...	...	...	...	**...**	...	...	...	...	...
DE	62.93	32.73	43.06	3/11	**-2.21**	76.17	38.36	51.02	2/11	-0.64
...	...	...	...	...	**...**	...	...	...	...	...
FA	73.8	58.48	65.26	7/10	**-12.57**	90.19	65.23	75.7	6/10	-5.58
LT	29.61	13.8	18.83	3/10	**-13.34**	55.56	16.92	25.94	3/10	-8.49
AVG	*67.58*	*44.97*	*54*	*1/13*	***4.26***	*77.41*	*48.55*	*59.67*	*1/13*	*5.04*

Table 4: Results for selected languages ordered by the difference between TRAVERSAL's `F1` and `F1` of the other best-performing system (`Delta`)

Results

	Cont.	Discont.	Multi-tok.	Single-tok.	Seen	Unseen	Variant	Identical
F1	57.55	44.36	55.83	25.96	72.92	17.35	63.1	81.88
Delta	2.17	6.96	6.45	-6.86	0.85	-2.36	-1.92	-1.85

Table 5: Macro-average MWE-based F_1-scores for specialized phenomena

	IAV	IRV	LVC.cause	LVC.full	MVC	VID	VPC.full	VPC.semi	LS.ICV
F1	44.31	68.07	23.81	46.03	17.65	34.45	34.84	42.70	30.77
Delta	8.89	8.51	-8.34	6.30	-11.39	8.01	2.07	2.2	10.77

Table 6: Macro-average MWE-based F_1-scores for MWE categories

Conclusions

- State-of-the-art results (at least for some languages)
  - Last-year's winner [Al Saied et al., 2017] still better on average
- Tree-structured input pays off (especially for discontinuous MWEs)
- It's not clear if deep nets outperform the more traditional ML methods in this task
  - Since VMWEs are local in dependency trees, tree-structured CRFs might be good enough
  - Word embeddings can possibly help with identification of more productive categories (VPC), but what about idioms?

Ideas for future work

- Experiment with ternary features
- Improve the configuration language
- Allow input from lexical reasources
- Higher-order model (code optimization)
- Joint labeling and segmentation (IOB schemes for trees)
- Integrate sequential with tree-based models (dual decomposition, loopy belief propagation)

Dziękuję!

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