Deep Learning and Language Adaptation

Serge Sharoff

Centre for Translation Studies
University of Leeds

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Outline

1. **Similarity between languages**
   - Variety of languages
   - Limitations of resources
2. **Task: MT quality estimation**
   - Language Adaptation via autoencoders
   - Experimental results
3. **Task: Detection of cognates**
   - Definition of cognates
   - Cross-lingual word embeddings
4. **Tasks: POS and NER tagging**
   - Relexicalisation via cognates
   - Neural Networks for Named-Entity Recognition
   - NER shared task at BSNLP'17

Variety of languages

100 languages needed to cover 85% world's population

99-100. Balochi and Konkani, ≈8M native speakers each

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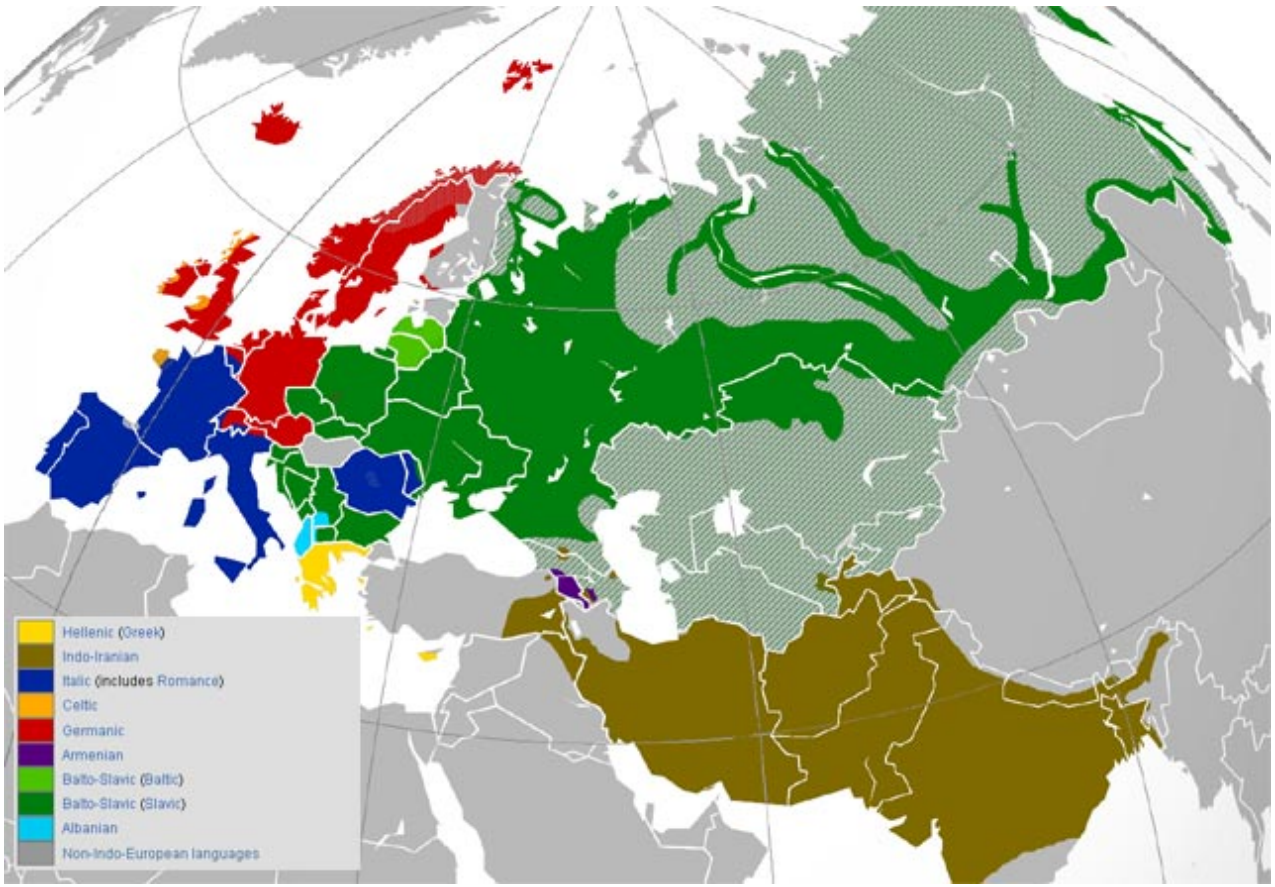

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Danish	89K	52M	
Dutch	286K	223M	
German	274K	783M	578K
Norwegian	245K	89M	
Swedish	131K	127M	
Romance			
Catalan	442K	181M	
French	367K	667M	432K
Italian	266K	433M	329K
Portuguese	454K	222M	321K
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Bulgarian	124K	55M	
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  Still 45 single examples of feature compbinations in ru (Syntagrus):
  колотыми
  V,Asp=Imp,Case=Ins,Num=Plur,
  Tense=Past, Voice=Pass

My story about related languages

- Automatic generation of instructions (Bateman, et al 2000)
  Rule-based grammar for Bulgarian, Czech and Russian
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KEY: Common **representation** for related languages

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- Quality Estimation measures confidence in MT output without references, e.g., by predicting Post-Editing (Specia, et al 2013)

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BUT Few languages available for training (Cs, Pl, Ru in Autodesk)

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Experimental results

- Baseline prediction of PE effort:

Upper baseline (**es**)	MAE	0.14
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- Our Language Adaptation method:

es	→	pt	it	fr
STL	MAE	0.14	0.16	0.17
	RMSE	0.17	0.21	0.22
	Correlation	**0.52**	**0.40**	**0.30**
Baseline Train: es Test: pt/it/fr	MAE	0.16	0.18	0.18
	RMSE	0.20	0.23	0.23
	Correlation	*0.35*	*0.26*	*0.24*

Power of language adaptation

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en-ru	→	en-cs	en-pl
STL	MAE	0.19	0.19
	RMSE	0.25	0.25
	Correlation	**0.41**	**0.46**
Baseline Train: ru Test: cs/pl	MAE	0.20	0.21
	RMSE	0.26	0.27
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	Correlation	*0.08*	*0.11*
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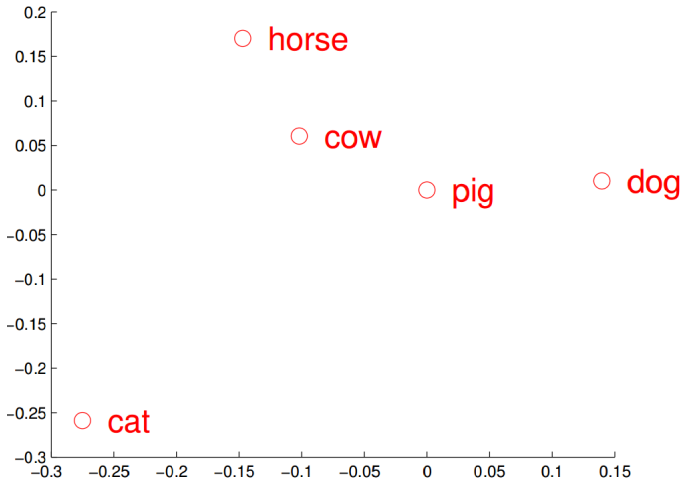
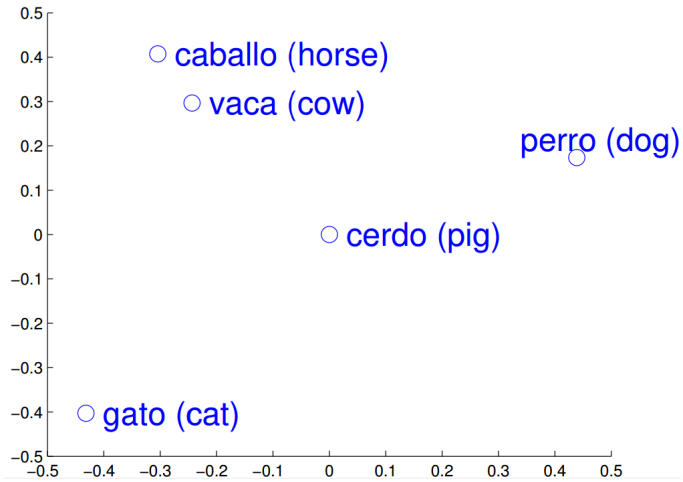
- **Frequency difference** *debuxo* vs *dibujo* 'a drawing' (Portuguese and Spanish), ranks 100,000 vs 2,000 approx (*desenho* is more common in Portuguese)

Cross-lingual word embeddings (Mikolov, 2013)





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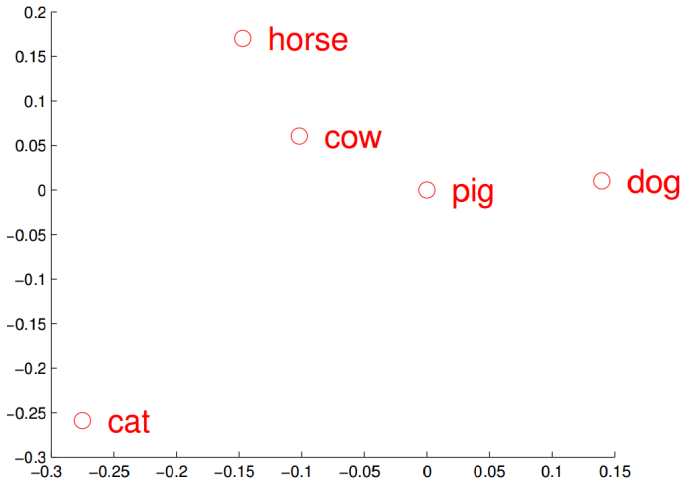

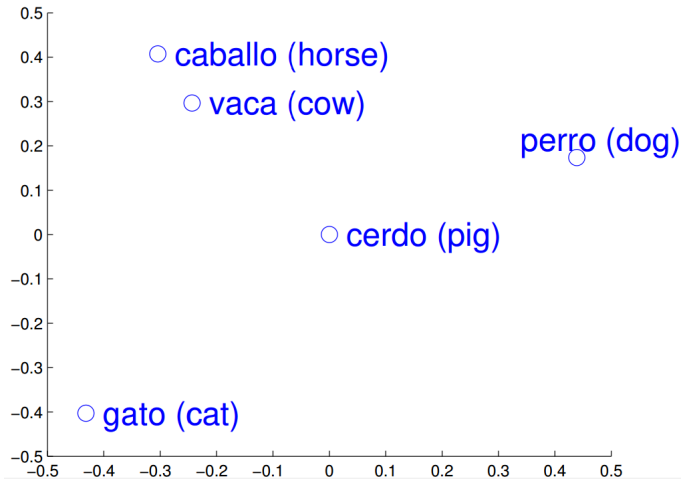

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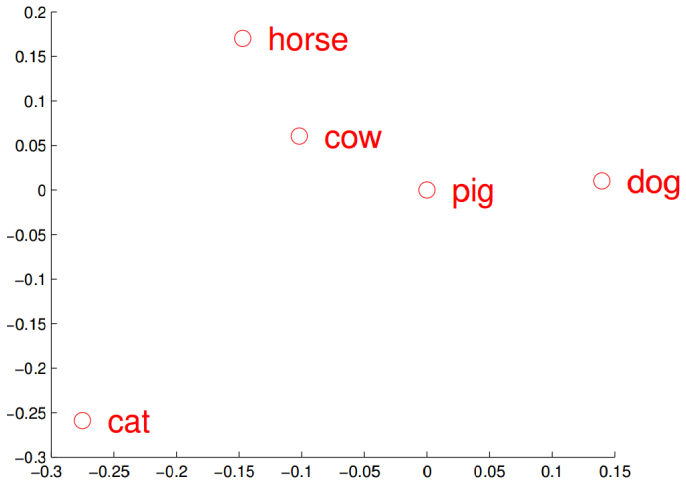

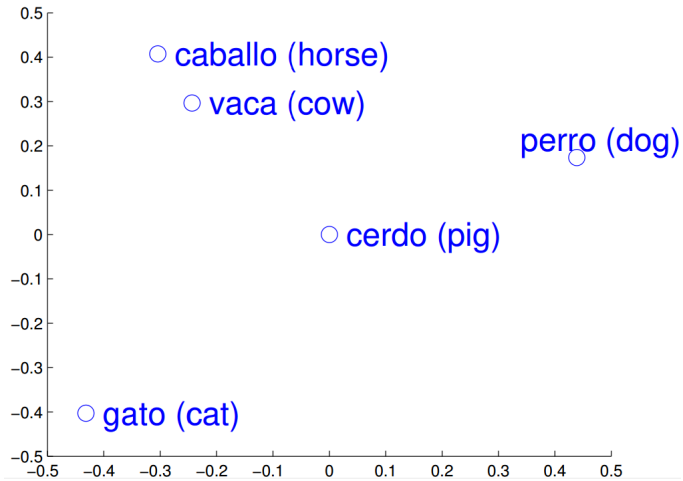

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- Linear transformation or MLP for mapping embeddings

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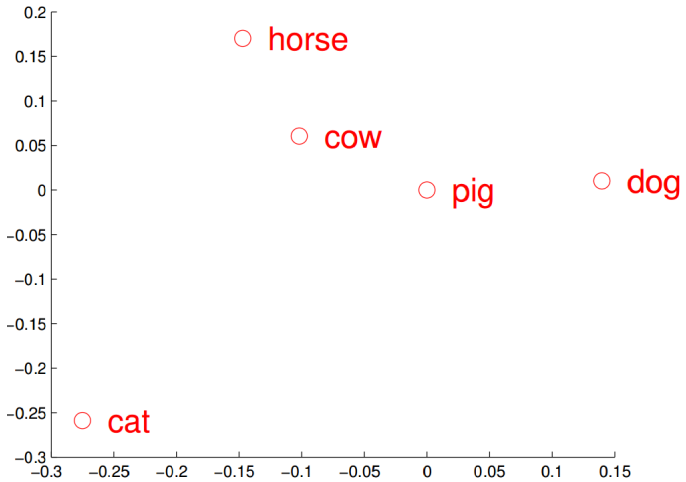

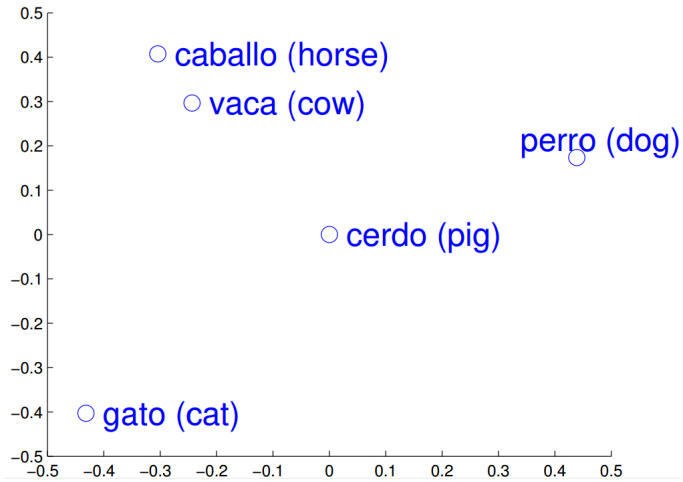

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- Small (1-2kW) bilingual dictionaries from iWiki links:
  - (sv) Slaget om Filippinen
  - (nl) Lijst van Poolse schrijvers
  - (pl) Z życia marionetek
  - (pl) Wskaźnik jakości życia
  - (de) Schlacht um die Philippinen
  - (de) Liste polnischer Schriftsteller
  - (ru) Из жизни марионеток
  - (ru) Индекс качества жизни

Levenshtein distances

- Baseline Levenshtein distance (LD):
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- Also WLD works across charsets:
  m a r i o n e t e k ż y * c ia
  м а р и о н е т о к ж и з н и

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#	**Standard**	#	**With GC**
77	bennett	10	arranged
75	curtis	10	corresponded
59	featuring	10	exists
58	laurie	10	learnt
56	james	10	milanese
56	miller	10	represents
55	elliot	10	traceable
54	gavin	9	association
51	convinced	9	chosen
47	keith	9	coincides
46	barker	9	consist
46	titled	9	forwarded
45	persuaded	9	grade

Evaluation of cognate detection for en-it

Vectors from (Dinu, et al. 2014)	
TM as in Mikolov et al. (2013b)	0.349
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Morphological structure of cognate words

- There are problems with full forms:

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ru-uk cognates for *green*

nominative	зелёный, зелёная	зелений, зелена,
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Outline

1. Similarity between languages
   - Variety of languages
   - Limitations of resources
2. Task: MT quality estimation
   - Language Adaptation via autoencoders
   - Experimental results
3. Task: Detection of cognates
   - Definition of cognates
   - Cross-lingual word embeddings
4. Tasks: POS and NER tagging
   - Relexicalisation via cognates
   - Neural Networks for Named-Entity Recognition
   - NER shared task at BSNLP'17

Cross-lingual tagging and parsing

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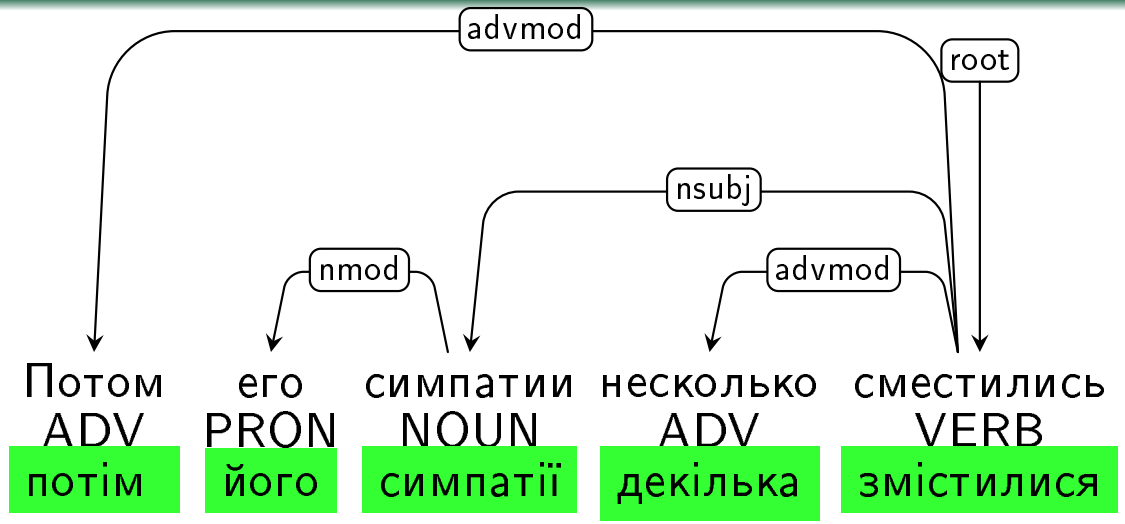
Relexicalisation via cognates



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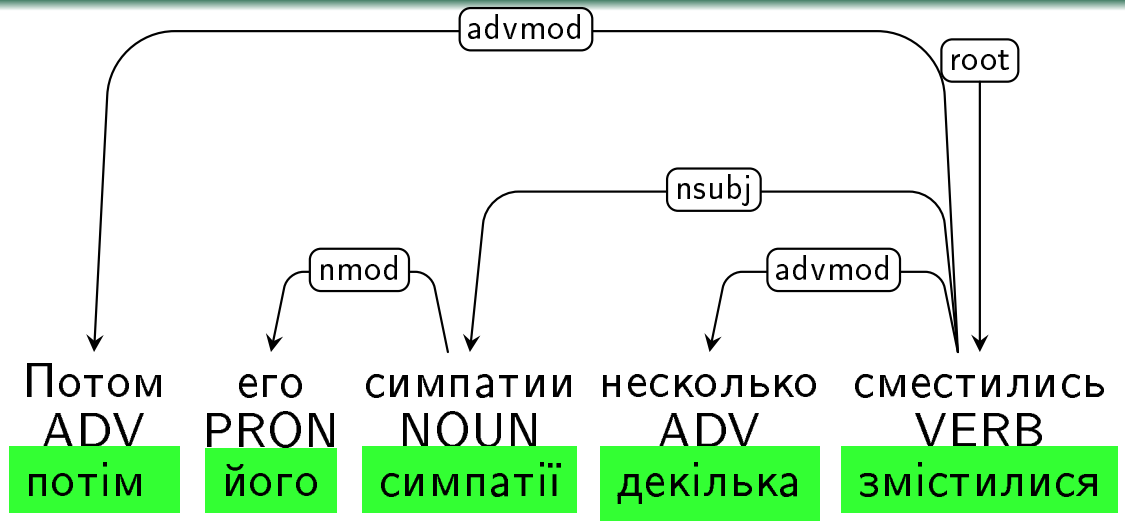

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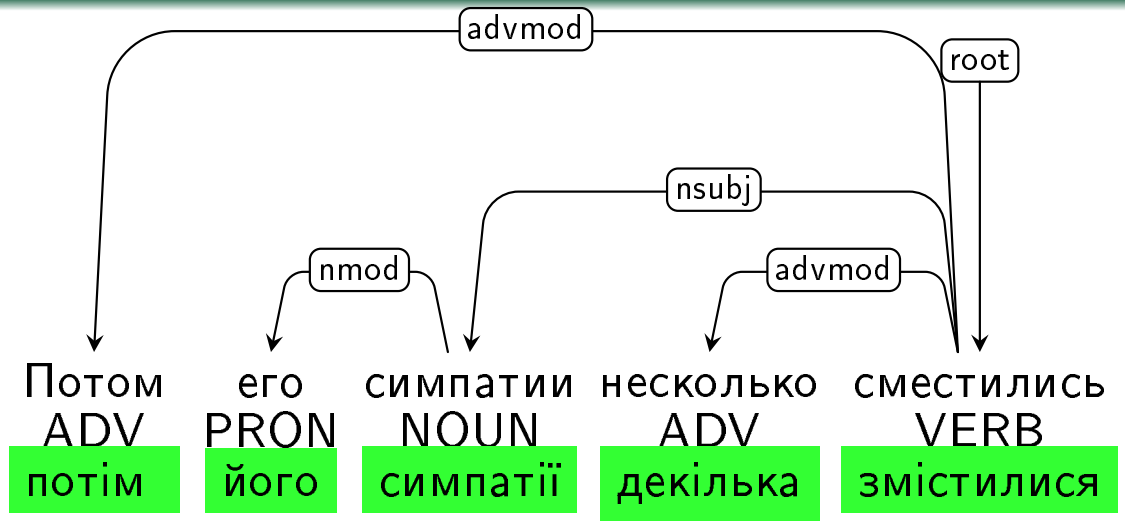

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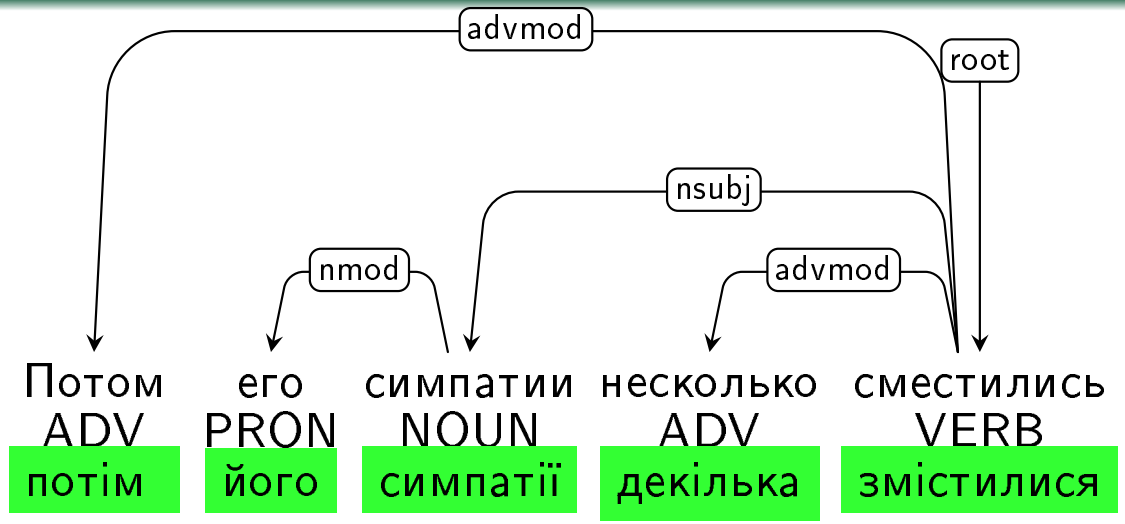

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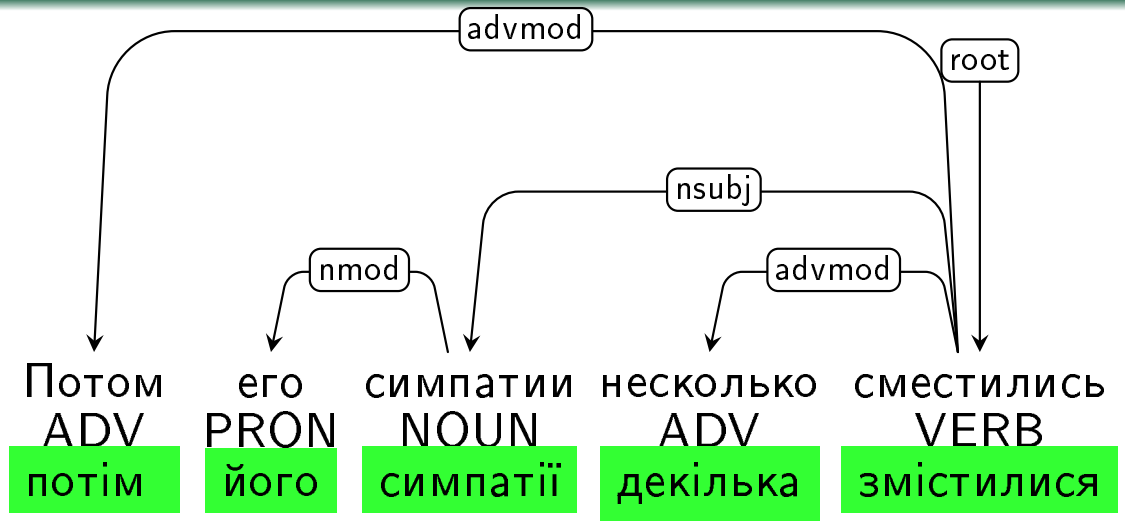

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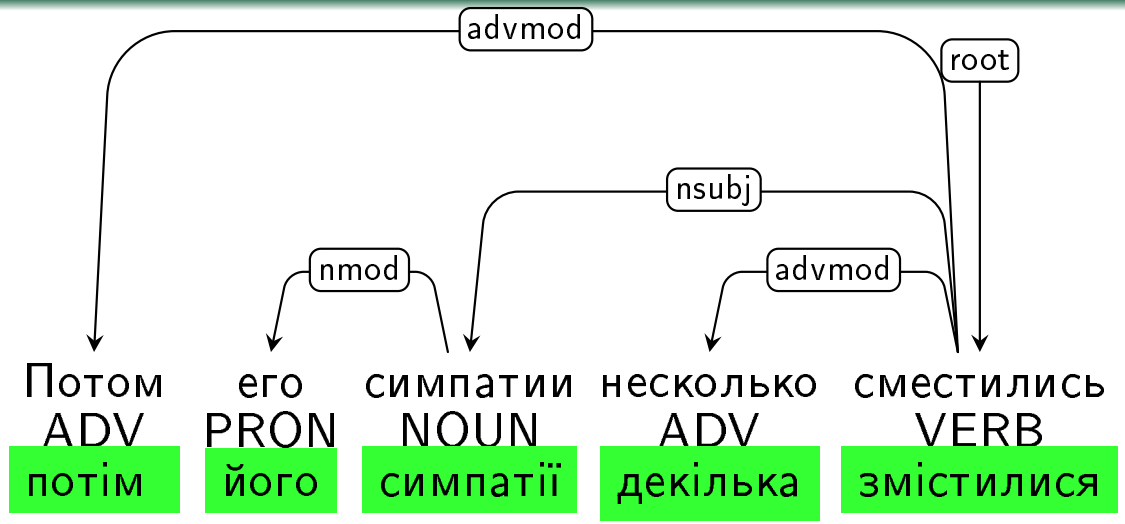

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- Disambiguated RNC with Ukrainian cognates using TnT:
  ru: 0.95 (Sharoff, Nivre, 2011),
  uk: 0.92 (Babych, Sharoff, 2016)

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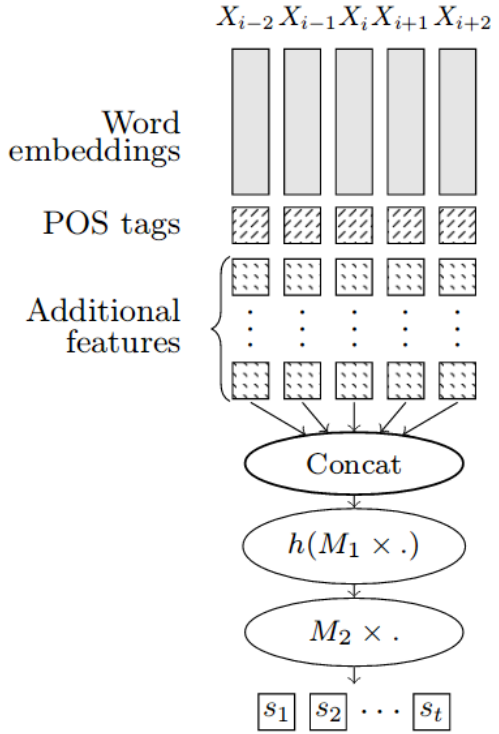

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LSTM: 89%; LSTM+CRF: 91%

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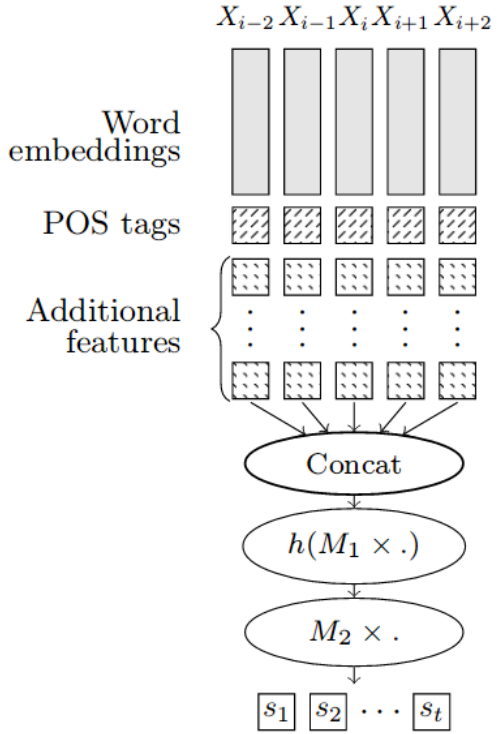

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- Embeddings from recipient Wikipedias (2015), training on Slovenian SSJ500 (200kW)

Shared task results: F1

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cs	hr	pl	ru	sl	ua	
47.2	**46.2**	**44.8**	46.5	47.8	10.8	JHU
41.2	30.0	34.6	**53.7**	37.5	**20.8**	JRC
47.7	44.3	44.2	33.6	**59.5**	13.7	Sharoff

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- Trump:

cs	hr	pl	ru	sl	ua	
46.1	50.4	41.0	41.8	46.2	33.2	JHU
42.2	37.4	48.0	**55.6**	44.2	**50.8**	JRC
52.6	**52.4**	**55.2**	21.0	**62.6**	20.7	Sharoff

Closer look at Sl-Hr transfer

- Slovenian: Upper baseline

sl→sl	P	R	F1	N
Accuracy: 97.47	74.08	73.87	73.98	
loc	81.92	76.72	79.23	354
misc	30.77	17.52	22.33	78
org	64.06	57.68	60.70	217
per	77.49	88.73	82.73	813

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- Croatian SE Times test corpus (180kW)

sl→hr	P	R	F1	N
Accuracy: 93.98	67.40	63.64	65.47	
loc	81.66	61.27	70.01	709
misc	0.00	0.00	0.00	105
org	56.40	59.11	57.73	851
per	77.96	72.85	75.32	599

Gold vs test results

en	hr	Gold	Output
Bosnian	Bosanska	O	O
model	manekenka	O	O
in	u	O	O
dress	modelu	O	O
from	iz	O	O
collection	kolekcije	O	O
Omnia	Omnia	O	B-misc
Mei	Mei	O	I-misc
Serbian	srbijanske	O	I-misc
fashion	modne	O	I-misc
designer	kreatorice	O	I-misc
Slavica	Slavice	B-per	B-per
Aleksijev	Aleksijev	I-per	I-per

en	hr	Gold	Output
at	na	O	O
autumn	jesenjem	O	O
Sarajevo	Sarajevskom	O	B-org
week	tjednu	O	I-org
fashion	mode	O	I-org
2006	2006	O	O
	.	O	O
	(	O	O
Getty	Getty	O	B-misc
Images	Images	O	I-misc
	)	O	O

NLP: slipping into the Dark Ages

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  Human intuition and knowledge

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NLP is kind of like a rabbit in the headlights waiting to be flattened by the Deep Learning steam train.

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Jelinek vs Church

Jelinek: Every time I fire a linguist, the performance goes up

Church: Fire everybody and buy more data

Neil Lawrence quoted by Chris Manning

NLP is kind of like a rabbit in the headlights waiting to be flattened by the Deep Learning steam train.

- In Deep Learning everything is a black box

The Zero Theorem by Terry Gilliam

Counteracting the Dark Ages with linguistics

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- Place for linguistics: what is shared?