Language Adaptation experiments

Cross-lingual embeddings for related languages

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University of Leeds

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Outline

1. **Rationale for Language Adaptation**
   - Universal Dependencies
   - Multilingual terminology
   - Limitations of resources
2. **Detection of cognates**
   - Cross-lingual word embeddings
   - Weigted Levenshtein Distance
3. **Predicting morphology**
   - Syncretism across related languages
   - Impact of prediction
4. **Terminology augmentation**
   - Similarity across the forms
   - Cross-lingual prediction methods

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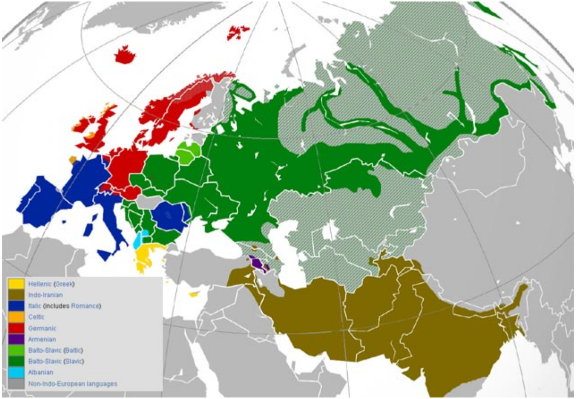

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BUT Farsi and Hindi are

UD examples: German and English

Stuttgart tagset (German) vs Penn tagset (English)

1	Ich	ich	PPER	PRON	Case=Nom|Num=Sing|Person=1|Type=Pers
2	kann	können	VMFIN	AUX	Num=Sing|Person=1|Tense=Pres|VerbForm=Fi
3	es	es	PPER	PRON	Case=Acc|Gender=Neut|Num=Sing|Person=3|T
4	nur	nur	ADV	ADV	
5	empfehlen	empfehlen	VVINF	VERB	VerbForm=Inf
6	.	.	.	PUNCT	

1	I	I	PRP	PRON	Case=Nom|Num=Sing|Person=1|Type=Pers
2	ca	can	MD	AUX	Tense=Pres|VerbForm=Fin
3	n't	not	RB	PART	
4	thank	thank	VB	VERB	VerbForm=Inf
5	you	you	PRP	PRON	Case=Acc|Person=2|Type=Pers
6	enough	enough	RB	ADV	
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acceptable risk	risque acceptable
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Two smallest subject domains: id4206, id360

acquisition cost	coût d'achat
reverse osmosis	osmose inverse

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33,311	29,382	36,165	33,899	57,725	39,613	35,930	43,706	**16,728**

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→ Similar terms: *druhé čtení* (cs) or *второ четене* (bg)

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French	367K	667M	432K
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- 45 single examples in ru vs 237 in uk:
  колотыми V,Aspect=Imperf,Case=Inst,
  Num=Plur,Tense=Past,Voice=Passive
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  ADJ,Case=Gen,Degree=Sup,Gender=Fem

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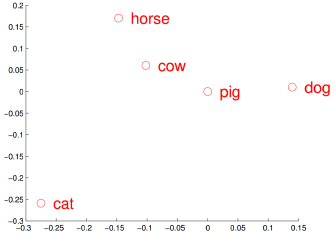

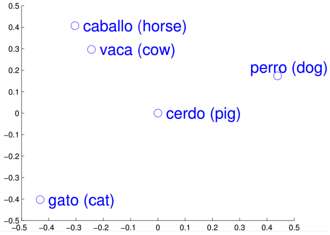

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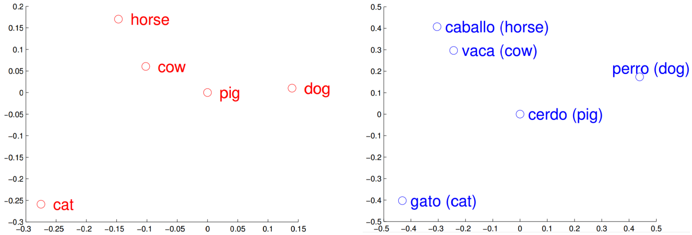

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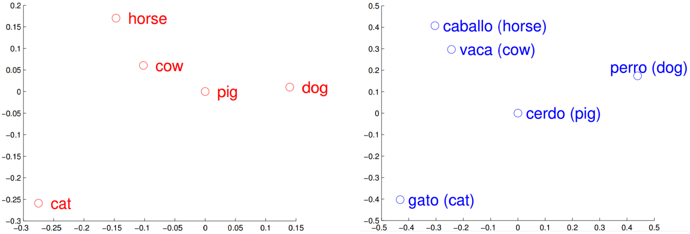

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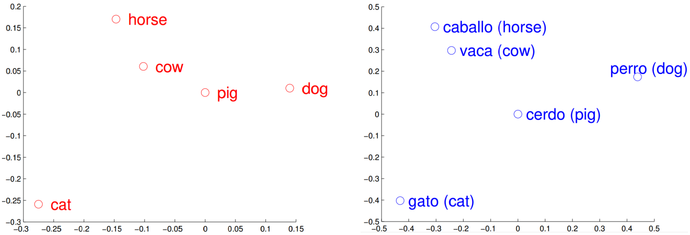

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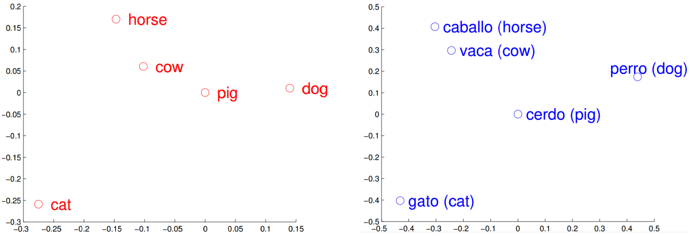

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- SGD (Mikolov, et al 2013), CCA (Faruqui, et al 2014), multivariate regression (Dinu, et al 2014), regression with orthogonalisation constraints (Artetxe, et al 2016)

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- Lists of geonames and persons: filtering by frequency
  Alapajevsk, Alarich, Alasdair MacIntyre, Alaska, Alassio, Alastair G.W. Cameron, Alata, Alathfar, Alatri, Alatyr

Levenshtein distances

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- Two alignment cycles: most likely **cognate** pairs

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  2. Re-alignment of spaces using this dictionary

Evaluation of cognate detection for en-it

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TM as in Mikolov et al. (2013b)	0.349
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Adversarial NN (Conneau et al, 2017)	0.451
CSLS cost (Joulin et al, 2018)	0.453

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- Producing cross-lingual Panslavonic embeddings:

	sl-hr	sl-cs	sl-pl	sl-ru	ru-uk	cs-sk
SOTA:	0.429	0.611	0.584	0.566	0.929	0.814
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- In-family embedding spaces are better than multilingual ones: Success in NER Shared task at BSNLP'17

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Forms of *green*	Russian		Ukrainian	
	Masc	Fem	Masc	Fem
Nominative	зелёный	зелёная	зелений	зелена
Genitive	зелёного	зелён**ой**	зеленого	зеленої
Dative	зелёному	зелён**ой**	зелен**ому**	зеленій
Instrumental	зелёным	зелён**ой**	зеленим	зеленою
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- **Problem:** Cross-lingual mappings between the forms are not one-to-one even across closely related languages

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- Direct prediction and by using cross-lingual embedding for training: Cs→Sk, Ru→Uk

Prediction results: Language adaptation

- Prediction is by Multi-layer Perceptron (300, 75, tanh)

O training on the original UD lexicon

T using cross-lingual embedding by transfer from related languages: Cs→Sk, Ru→Uk

	POS	$Tags_O$	$Tags_T$	$Train_O$	$Train_T$	MLP_O	MLP_T
Slovak	adj	23	202	1061	10778	45%	52%
	nouns	45	78	3537	8919	31%	43%
	verbs	30	61	1333	4695	49%	54%
Ukrainian	adj	45	54	1394	6235	40%	47%
	nouns	47	58	4187	14054	50%	58%
	verbs	32	54	2123	5765	55%	59%

Impact of prediction

Proportion of OOV words in the lexicons

	Cs	Ru	Pl	Sk	Be	Uk
Train	108257	97749	19344	19100	1628	5080
Test	32461	26567	4778	5425	662	271
OOV #	7891	8034	2327	3385	436	192
OOV %	24.31%	30.24%	48.70%	62.40%	65.86%	70.85%

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Precision of UDPipe POS taggers

	Pl (Cs)	Sk (Cs)	Sk (Ru)	Be (Ru)	Uk (Ru)
Baseline (train only)	70.33	79.82	79.82	58.79	70.01
With added lexicon	**82.34**	**83.03**	**81.42**	**71.20**	**82.79**

Future cross lingual morphology prediction

- Signals beyond embeddings: endings, morphology clusters
  ой is a strong signal in Russian (60% adjectives)
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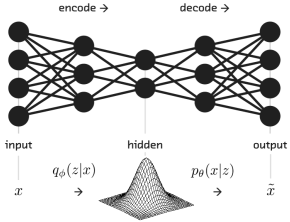

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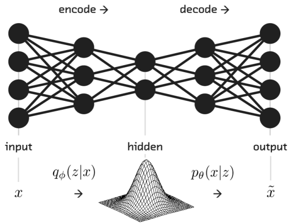

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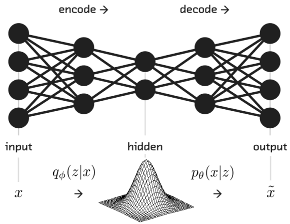

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- Proper transfer learning:
  train on related languages with morph prediction

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Similarity across the forms

Single-word terms

English	Polish	Slovenian
minority	mniejszość	manjšina
homelessness	bezdomność	brezdomstvo
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drug, narcotic	narkotyk	droga, narkotik

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Multiword terms

English	Polish	Slovenian
Graham's salt	sól Grahama	grahamova sol
Maddrell's salt	sól Maddrella	maddrellova sol
sodium hexametaphosphate	heksametafosforan sodu	natrijev heksametafosfat
sodium metaphosphate	metafosforan sodu	natrijev metafosfat
glassy sodium polyphosphate	szklisty polifosforan sodu	steklast natrijev polifosfat

Single-word term augmentation

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	bg		cs		sl	
Test #	2229		2186		2194	
Found #	792		862		766	
	Orth	WLD	Orth	WLD	Orth	WLD
prec@1	0.225	0.480	0.413	0.541	0.251	0.433
prec@5	0.393	0.595	0.580	0.668	0.422	0.555
prec@10	0.458	0.621	0.633	0.701	0.490	0.584
recall@1	0.220	0.467	0.397	0.519	0.234	0.408
recall@5	0.383	0.576	0.557	0.644	0.395	0.527
recall@10	0.447	0.604	0.609	0.678	0.460	0.555

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- (Iwai, et al, 2017): term inference on a graph
  information processing, information retrieval, data retrieval → *data processing*

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Term variation

brass plate company	compagnie écran
dummy company	entreprise boîte aux lettres
front company	filiale sans support matériel
letterbox company	société boîte aux lettres
money box company	société boîte à lettres
paper company	société coquille
shell company	société de façade
shell corporation	société fantôme
	société fictive

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- Place for linguistics: what is shared?
  UD annotation or Term structure