Orthography in Language Modeling of Mutual Intelligibility

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Slavic languages:
intercomprehensible
to various degrees

Objective:
find mechanisms
of linguistic coding
+ statistical evidence
of mutual intelligibility

Source: http://en.wikipedia.org/wiki/Slavic_languages

Focus: reading intercomprehension

Aspects:
orthography, morphology, lexis, syntax, semantics

Methods:
statistics, language modeling, machine translation
information theory, Slavic linguistics

Meaningful Units of Language

Certain **constructions** encode specific information

V Evropském *parlamentu* ... (CS), meaning: "parliament"
Noun, singular, male, locative case, preceded by adjective, part of PP

possibly stark differences between languages

(RU) В Европейском парламенте — -ом + -е: prepositive case
(BG) В Европейския парламент — -ия: determiner (male adjective short)

Identifying Encoding Schemes of Natural Languages

Objective: well-founded **statistical model** of natural language understanding
→ fundamental advance in computational linguistics research

We expect:
- Diminished intelligibility through missing units
- Confusion through mis-recognition of units

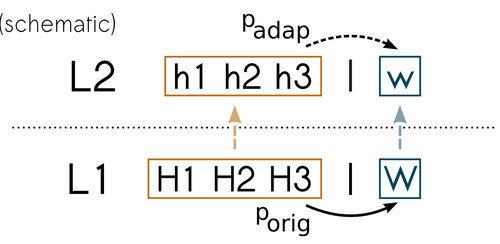
→ discover informative elements of natural language

Modeling: Language as Domain

Basic idea: surprisal of statistical **n-gram language models** correlates with cognitive effort, but n-grams need to be adapted to process a different language

Smith, Nathaniel J., and Roger Levy. 2013.
The Effect of Word Predictability on Reading Time Is Logarithmic.
In Cognition 128.3 (2013). 302-319.

(schematic)



Decoding as Domain Adaptation

Explicit "latent" space describing each language
Decompose words into meaningful units
→ decode the words from unknown languages by similarity to known units
→ treat them exactly as in-language words would be

Soft Class Language Model for Adaptation

N-gram class language model
→ relax notion of hard classes to soft ones → *features*

$$p(w \mid h) = \sum_{f \in F(w)} p(w \mid f) \sum_{f_h \in F_\times(w)} p(f \mid f_h) \prod_{i=1}^{N} p(f_{h_i} \mid w_{h_i})$$

feature importance in context
word is mixture of features
feature importance in word

Each individual word is agglomerate of meaningful units: list of features
→ each feature contributes individually to the word's identity

Preliminary Results: Orthography

Diachronically-based assumptions tested on parallel list of Pan-Slavic vocabulary for each language pair (high cognate rate)

English	Czech	Polish	Bulgarian	Russian
'horse'	kůň	koń	кон	конь
'body'	tělo	ciało	тяло	тело
'sea'	moře	morze	море	море
'brush'	štětka	szczotka	четка	щётка
'head'	hlava	głowa	глава	голова
'cow'	kráva	krowa	крава	корова

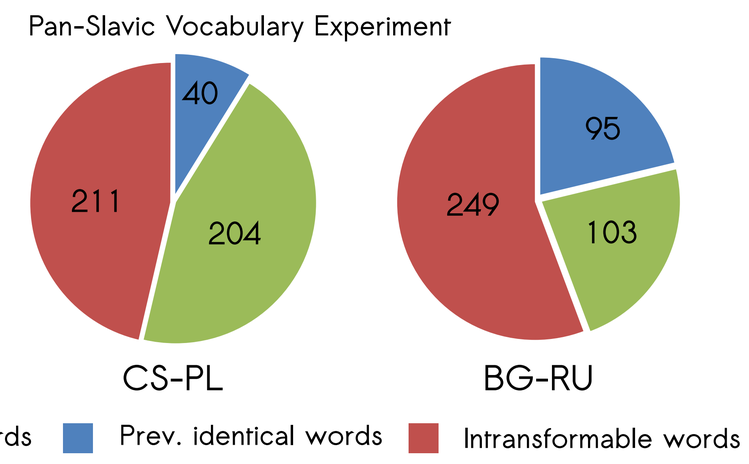
http://www.eurocomslav.de/BIN/inhalt.htm

Applicability of Diachronically-Based Rules

1) Orthographically identical words (8.79% in CZ-PL vs. 21.25% in BG-RU),
2) Application of transformation rules on remaining word pairs: (91.21% vs. 79.75%), but
3) not all word pairs could be covered by rules: morphological differences

→ will be explored in next project phase
→ rules also tested on other word sets (internationalisms)

Swadesh lists with wider vocabulary range/ higher (non-)cognate rates



Modeling Orthographic Differences -- Levenshtein Weights

From this, derive asymmetric substitution costs for Levenshtein distance

Use these as feature weights for individual letters as features
project words and use LM

→ relative perplexity of L2 text to L1 gives intercomprehensibility score
→ currently constructing experiments to test correlations

However,
1) letters are likely not the basic units of reading comprehension
2) model is still parametric in **both** languages

→ articulation experiments
→ build lexing model of native L1 speaker

Model is sensitive to individual texts and scores comprehensibility as conformity to alphabet usage of L1

CS-PL

a	a	0.031	t	c	0.976
	ę	0.997		t	0.433
	ó	0.997		ć	0.590
	i	0.997	n	ń	0.966
	o	0.976		n	0.034
o	u	0.983	ý	y	0.0
	ó	0.928			
	ą	0.971			
	o	0.118			

PL-CS

o	a	0.974	ą	á	0.745
	á	0.989		u	0.745
	e	0.964		_	0.941
	ů	0.985		o	0.568
	o	0.099	ń	ň	0.583
	_	0.986		n	0.417
y	y	0.769			
	ý	0.231			

Levenshtein substitution/deletion costs: 1-prob(L2|L1)
x → _ indicates deletion of letter x

Summary

Goal: identify mechanisms by which languages en- and decode information
Ideas: - surprisal of language models correlates with intelligibility
- adapt N-gram LMs for cross-language use via latent space and similarity
- analyse information-theoretical results with linguistic knowledge

Next Steps

Linguistically:
Lexis: "false friends" and closed word classes
Morphology: correspondences in grammar
Syntax: word order, complexity of constructions

Information-Theoretically:
Suitable model classes
Most informative features
Inter/intra-language patterns

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