Feldman & Hana 2010

NPFL096 Computational Morphology 2011

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Based on slides for an ESSLLI 2010 course by Anna Feldman & Jirka Hana

Cohen's kappa (Cohen 1960)

- The most popular measure of agreement between two annotators.
- Takes into account (somewhat) the possibility of chance agreement.

•
$$\kappa = \frac{Pr(a) - Pr(e)}{1 - Pr(e)}$$

Pr(a) - the relative observed agreement

Pr(e) - the hypothetical probability of chance agreement

$$Pr(e) = \sum_{t} \frac{t_a * t_b}{N}$$

 t_a – number of tags t assigned by annotator a

N - number of all tags

Weighted kappa – gives different weights to different errors .

- (Variant of) Kendall's tau the minimal number of operations necessary to turn one annotation into the other.
- There are other measures.
- High agreement is important but it is not everything:
 - One can use use a tagset with a single tag.
 - The annotation manual can be purely formal (Tag all sentence initial words as topics).
 - On the other hand, if iaa is below the accuracy of a tagger ...

A Resource Light MA (of Czech)

- Motivation
- Guesser
- Lexicon Acquisition
- Results

Reminder: What is MA?

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MA: form \rightarrow set(lemma \times set(tag))
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English: her \rightarrow \{ (she, \{PP\}), (her, \{PP\$\}) \}

Czech: \check{z}enou \rightarrow \{ (\check{z}ena \text{ 'woman'}, \{noun fem sing inst}), (hn\acute{a}t \text{ 'hurry'}, \{verb pres pl 3rd }) \}

\check{z}eny \rightarrow \{ (\check{z}ena \text{ 'woman'}, \{noun fem sing gen, noun fem pl nom, noun fem pl acc, noun fem pl voc }) \}
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Focus on nouns

We focus exclusively on nouns.

- Hard & interesting
 - High homonymy
 - The most open class (Names!)
- We cannot do everything at once

Two extreme approaches to MA

- Provide all information manually e.g. (Hajic 2004)
 - + High accuracy (Recall 98.5%)
 - Very costly (300K lexicon)
- Learn all information automatically e.g. (Goldsmith 2001)
 - + Cheap to use, good for understudied languages
 - Low accuracy

Corpus coverage by lemma frequency

	tr1 corpus								
Lemma	Number	Corpus noun	Cumulative	Lemmas not					
freq decile	of tokens	coverage (%)	coverage (%)	present (%)					
10	164 643	74	74	0.2					
9	22 515	10	84	6.7					
8	11 041	5.0	89	22					
7	6 741	3.0	92	36					
6	4 728	2.1	94	48					
5	3 179	1.4	96	61					
4	2 365	1.0	97	65					
3	2 364	1.0	98	70					
2	2 364	1.0	99	75					
1	2 364	1.0	100	77					

tr1/tr2: each 700K tokens; newspapers, magazine; similar Each decile contains 2364 or 2365 noun lemmas.



What does it mean? - The good news

	tr2 corpus			
Lemma	Number	Corpus noun	Cumulative	Lemmas not
freq decile	of tokens	coverage (%)	coverage (%)	present (%)
10	164 643	74	74	0.2
9	22 515	10	84	6.7
8	11 041	5.0	89	22
7	6 741	3.0	92	36
6	4 728	2.1	94	48
5	3 179	1.4	96	61
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4	2 365	1.0	97	65
3	2 364	1.0	98	70
2	2 364	1.0	99	75
1	2 364	1.0	100	77

Complete Goldsmith is not necessary

- 2.5K most frequent lemmas cover 3/4 of tokens
- 7K most frequent lemmas cover nearly 90% of tokens

What does it mean? - The bad news

				tr2 corpus					
	tr1 corpus								
Lemma	Number	Corpus noun	Cumulative	Lemmas not					
freq decile	of tokens	coverage (%)	coverage (%)	present (%)					
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1	2 364	1.0	100	77

Complete Hajič is impossible, nearly complete is hard

- Coverage gains drop quickly each of the 5 lower deciles adds ca 1%
- Infrequent lemmas are text specific 70% (!!) of the less frequent half of the lemmas from tr1 do not occur in tr2

- Looks at endings (sometimes also at the ends of stems)
- Uses manually supplied info about Czech noun paradigms:
 - endings + tags
 - permissible stem-tails
 - some stem alternation (regular tail changes, epenthesis)
 - 13 linguistic paradigms are encoded as 64 paradigms.
 - a book for general public used as a reference (Karlík et al. 1996)
- Massively overgenerates good recall, bad precision

Czech noun paradigms

Table: Examples of the žena 'woman' paradigm nouns

	woman	owl	draft	goat	iceberg	vapor	fly
S1	žen-a	sov-a	skic-a	koz-a	kr-a	pár-a	mouch-a
S2	žen-y	sov-y	skic-i	koz-y	kr-y	pár-y	mouch-y
S3	žen-ě	sov-ě	skic-e	koz-e	k ř-e	pář-e	mouš-e
S4	žen-u	sov-u	skic-u	koz-u	kr-u	pár-u	mouch-u
S5	žen-o	sov-o	skic-o	koz-o	kr-o	pár-o	mouch-o
S6	žen-ě	sov-ě	skic-e	koz-e	k ř-e	pář-e	mou š-e
S7	žen-ou	sov-ou	skic-ou	koz-ou	kr-ou	pár-ou	mouch-ou
P1	žen-y	sov-y	skic-i	koz-y	kr-y	pár-y	mouch-y
P2	žen-0	sov-0	skic-0	koz-0	ker-0	par-0	much-0
P3	žen-ám	sov-ám	skic-ám	koz-ám	kr-ám	pár-ám	mouch-ám
P4	žen-y	sov-y	skic-i	koz-y	kr-y	pár-y	mouch-y
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Inter-annotator agreement MA Tagging Motivation Guesser Lexicon Acquisition Modules & Results

Czech noun paradigms - Ending variation

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S3	žen- <mark>ě</mark>	sov-ě	skic-e	koz-e	kř-e	pář-e	mouš-e
S4	žen-u	sov-u	skic-u	koz-u	kr-u	pár-u	mouch-u
S5	žen-o	sov-o	skic-o	koz-o	kr-o	pár-o	mouch-o
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S7	žen-ou	sov-ou	skic-ou	koz-ou	kr-ou	pár-ou	mouch-ou
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P7	žen-ami	sov-ami	skic-ami	koz-ami	kr-ami	pár-ami	mouch-ami

Ending variation: žen-ě, sov-ě vs. burz-e, kř-e, pář-e
 The dative and local sg. ending is -ě after alveolar stops (d, t, n) and labials (b, p, m, v, f). It is -e otherwise.

Inter-annotator agreement MA Tagging Motivation Guesser Lexicon Acquisition Modules & Results

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S5	žen-o	sov-o	skic-o	koz-o	kr-o	pár-o	mouch-o
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Ending variation: žen-y vs. skic-i.
 Czech spelling rules require the ending -y to be spelled as -i after certain consonants, in this case: c, č, ď, ň, š. The pronunciation is the same ([i]).

Czech noun paradigms - Stem change

Table: Examples of the *žena* 'woman' paradigm nouns

	woman	owl	draft	goat	iceberg	vapor	fly
S1	žen-a	sov-a	skic-a	koz-a	k r -a	pá r -a	mou <mark>ch</mark> -a
S2	žen-y	sov-y	skic-i	koz-y	kr-y	pár-y	mouch-y
S3	žen-ě	sov-ě	skic-e	koz-e	k ř -e	pář-e	mou <mark>š</mark> -e
S4	žen-u	sov-u	skic-u	koz-u	kr-u	pár-u	mouch-u
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• Palatalization of the stem final consonant:

kr-a - kř-e, mouch-a - mouš-e.

The $-\check{e}/e$ ending affects the preceding consonant: $ch \ [x] \to \check{s}$, $g/h \to z$, $k \to c$, $r \to \check{r}$.



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P7	žen-ami	sov-ami	skic-ami	koz-ami	kr-ami	pár-ami	mouch-ami

Epenthesis: kr-a - ker.
 Sometimes, there is an epenthesis (insertion of -e-) in genitive plural.

Czech noun paradigms – Stem change

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S3	žen-ě	sov-ě	skic-e	koz-e	kř-e	pář-e	mouš-e
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• Stem internal vowel shortening: pár-a – par.

Czech noun paradigms (cont.)

- Roughly 13 basic noun paradigms:
 - 4 neuter
 - 3 feminine
 - 6 masculine
 - 2 paradigms for nouns with adjectival declension
- Many subparadigms and subsubparadigms, great amount of irregularity, variation, and homonymy
- Some forms have official and colloquial variants

Encoding Czech noun paradigms

Ending Homony

Table: Homonymy of the a ending in Czech

form	lemma	gloss		category	
měst-a	město	town	NS2	noun neut sg gen	
			NP1 (5)	noun neut pl nom (voc)	
			NP4	noun neut pl acc	
tém-a	téma	theme	NS1 (5)	noun neut sg nom (voc)	
			NS4	noun neut sg acc	
žen-a	žena	woman	FS1	noun fem sg nom	
pán-a	pán	man	MS2	noun masc anim sg gen	
			MS4	noun masc anim sg acc	
ostrov-a	ostrov	island	IS2	noun masc inanim sg gen	
předsed-a	předseda	president	MS1	noun masc anim sg nom	
vidě-l-a	vidět	see		verb past fem sg	
				verb past neut pl	
vidě-n-a				verb passive fem sg	
				verb passive neut pl	
vid-a				verb transgressive masc sg	
dv-a	dv-a	two		numeral masc sg nom	
				numeral masc sg acc	

Table: Ending -e and noun cases in Czech

case	form	lemma	gender	gloss
nom	kuř-e	kuře	neuter	chicken
gen	muž-e	muž	masc.anim.	man
dat	mouš-e	moucha	feminine	fly
acc	muž-e	muž	masc.anim.	man
voc	pan-e	pán	masc.anim.	mister
loc	mouš-e	moucha	feminine	fly
inst	_	_		

Lexicon Acquisition

Guesser overgenerates. Use a raw corpus to prune the results.

Lexicon Acquisition

Guesser overgenerates. Use a raw corpus to prune the results. Lemma of *talking*?

Lexicon Acquisition

Guesser overgenerates. Use a raw corpus to prune the results. Lemma of *talking*?

- talk?
- talking (à la sibling)?

Guesser overgenerates. Use a raw corpus to prune the results.

- Lemma of talking?
 - talk?
 - talking (à la sibling)?

Also found talk, talks, talked – clear

Did you see *sible*, *sibles*, *sibled*?

An Example & A Problem

forms	tokens
atom-0	48
atom-u	28
atom-em	1
atom-y	22
atom-ů	30
atom-ům	1
atom-ech	1

	inanim	found
S1	hrad-0	+
S2	hrad-ĕ/u	-/+
S3	hrad-u	+
S4	hrad-0	+
S5	hrad-e	
S6	hrad-ě/u	-/+
S7	hrad-em	+
P1	hrad-y	+
P2	hrad-ů	+
P3	hrad-ům	+
P4	hrad-y	+
P5	hrad-y	+
P6	hrad-ech	+
P7	hrad-y	+
Total		7

An Example & A Problem'

forms	tokens
atom-0	48
atom-u	28
atom-em	1
atom-y	22
atom-ů	30
atom-ům	1
atom-ech	1

	inanim	found	anim	found
S1	hrad-0	+	pán-0	+
S2	hrad-ě/u	-/+	pán-a	
S3	hrad-u	+	pán-u/ovi	+/-
S4	hrad-0	+	pán-a	
S5	hrad-e		pan-e	
S6	hrad-ě/u	-/+	pán-u	+
S7	hrad-em	+	pán-em	+
P1	hrad-y	+	pán-i/ové	-
P2	hrad-ů	+	pán-ů	+
P3	hrad-ům	+	pán-ům	+
P4	hrad-y	+	pán-y	+
P5	hrad-y	+	pán-i	
P6	hrad-ech	+	pán-ech	+
P7	hrad-y	+	pán-y	+
Total		7		7

An Example & A Problem"

forms	tokens
atom-0	48
atom-u	28
atom-em	1
atom-y	22
atom-ů	30
atom-ům	1
atom-ech	1
atom-ové	200

	inanim	found	anim	found
S1	hrad-0	+	pán-0	+
S2	hrad-ĕ/u	-/+	pán-a	
S3	hrad-u	+	pán-u/ovi	+/-
S4	hrad-0	+	pán-a	
S5	hrad-e		pan-e	
S6	hrad-ĕ/u	-/+	pán-u	+
S7	hrad-em	+	pán-em	+
P1	hrad-y	+	pán-i/ové	-/+
P2	hrad-ů	+	pán-ů	+
P3	hrad-ům	+	pán-ům	+
P4	hrad-y	+	pán-y	+
P5	hrad-y	+	pán-i	
P6	hrad-ech	+	pán-ech	+
P7	hrad-y	+	pán-y	+
Total		7		8

An Example & A Problem"

We can connect inflectional paradigms related by derivation into "super-paradigms".

Alleviates two important problems:

- The $ov\acute{e}$ problem above $ov\acute{e} = ov-\acute{e}$
- Data sparsity.

Very rough (overgenerating) information seems to be enough.

- MA of a corpus & Create all possible hypothetical lexical entries
- Cluster entries & Filter out the bad ones. Simply put: the entry that covers the highest number of forms wins.
 - Size of the wining crust can be specified. In relative or absolute terms.
 - Minimal number of tokens for an entry can be specified.
 - Exclude strange entries contains infrequent forms (voc), but not frequent (nom)
 - Etc.

Limited memory: several passes, etc.

MA modules

Running a cascade of modules. High precision first, high recall last.

- Word list
- Abbreviation identification
- Numbers
- Lexicon based analyzer
- Paradigm-based guesser

Lexicon	_	_	_	+	+	+	+	Hajič ¹
Top forms list	0K	5K	10K	0K	5K	10K	10K	
Derivation suff:	0	0	0	0	0	0	20	
Error rate	3.6	2.9	2.7	5.8	3.9	3.6	3.4	1.3
Ambiguity tag/w	19.6	13.1	11.5	11.7	8.5	7.8	4.0	3.8

Results for other POS than noun are better.

¹(Hajic 2004, p.c.): 300K lexicon

Evaluation of the Russian morphological analyzer

Lexicon		no	yes	no	yes
LEO		no	no	yes	yes
All	Recall error:	2.9	4.3	12.7	6.6
	ambiguity (tag/w)	9.7	4.4	3.3	2.8
N	Recall error:	2.6	4.9	41.6	13.7
	ambiguity (tag/w)	18.6	6.8	6.5	4.3
A	Recall error:	6.2	7.0	8.1	7.5
	ambiguity (tag/w)	21.6	10.8	3.3	5.7
V	Recall error:	0.8	2.0	2.3	2.3
	ambiguity (tag/w)	14.7	4.8	1.5	1.5

No Top-frequency lists, no derivation used.

Resource light morphology - Why?

- Traditional taggers and analyzers are very accurate, but very costly (money, time, resources)
- Most languages and dialects have no realistic prospect for morphological tools created in this way

Main Assumption

- target-language model can be approximated by language models of related source language(s)
- inclusion of a limited amount of high-impact and/or low-cost manual resources is greatly beneficial and desirable

Using TnT (Brants 2000), a second order Markov Model tagger

- emissions: approximated by the source-language emissions + resource-light morphological analysis
- transitions: approximated by the source-language transitions

See (Feldman and Hana 2010)

Languages

- We have experimented with several language pairs
 - Russian via Czech
 - Catalan via Spanish
 - Portuguese via Spanish
- Currently working on
 - Lithuanian via Russian/Czech
 - Romanian via Bulgarian/Spanish
- Planning to do Old Czech.

Here, we present our approach on Czech and Russian.

Russian East Slavonic, Czech West Slavonic

Syntax/Morphosyntax

- Grammatical functions by inflection
- Constituent order determined mostly by Information Structure.
- Agreement: subj-verb (person, nr), subj-participle (gender, nr), within NP (gender, nr, case)
- No articles; (in)definiteness is expressed using other means, e.g., word order.
- Certain rigid word order combinations, such as noun modifiers, clitics (in Czech), and negation (in Russian).

Russian & Czech Morphology

- The order and value of morphemes nearly identical
- Similar shape of morphemes (modulo scripts)
- Nominal categories inflect for gender, number, case.
 - 3 genders (masculine, feminine, neuter)
 - 2 numbers (some remnants of dual in Czech).
 - 6 cases with roughly the same meaning (nominative, genitive, dative, accusative, local, instrumental).
 In addition, Czech has vocative.
- Nouns and verbs are grouped into paradigms.
- Numerals use declensional strategies which range from near indeclinability to adjective-like declension.

Czech and Russian paradigms

	Czech	Russian	Gloss
sg.			
nom	žen-a	ženščin-a	'woman'
gen	žen-y	ženščin-y	
dat	žen-ě	ženščin-e	
acc	žen-u	ženščin-u	
voc	žen-o	_	
loc	žen-ě	ženščin-e	
ins	žen-ou	ženščin-oj/ou	
pl.			
nom	žen-y	ženščin-y	
gen	žen	ženščin	
dat	žen-ám	ženščin-am	
acc	žen-y	ženščin	
voc	žen-y	_	
loc	žen-ách	ženščin-ax	
ins	žen-ami	ženščin-ami	

Czech and Russian Morphology

Morphology in both languages exhibits

- a high number of fusion several morphemic categories whose values are combined in clusters, each of which is expressed by a single ending (e.g., number, gender, and case with nouns or adjectives, or tense, number, and person with finite verbs),
 - the Russian knig-oj, 'book', -oj stands for feminine, singular, instrumental;
 - pročital-a -a stands for past tense and feminine.
- a high degree of ambiguity of the endings. See the two next slides.
- a relatively common synonymy of the endings.

Questions we try to address

- Are word order properties of Czech and Russian similar enough to approximate the target language word order by the source language word order?
- What kind of morpho-syntactic descriptions are relevant for these languages in general and for the annotation transfer in particular?
- How close is a particular pair of languages in the lexicon?
- Can lexical similarities be used to improve the morpho-syntactic transfer?
- How can the data sparsity problem be addressed in the cross-lingual induction of morpho-syntactic features of highly inflected languages?

Tagging Russian via Czech

- Direct
- Approximating Emissions
 - Even
 - Cognates
- Approximating Transitions

Using TnT (Brants 2000), a second order Markov Model tagger

- emissions: approximated by the source-language emissions + resource-light morphological analysis
- transitions: approximated by the source-language transitions

Resources

- Limited language dependent resources:
 - Manually created list of paradigms and closed class words
 - Annotated development corpus: 1,788 tokens from Orwell's 1984
 - Raw Russian corpus: 1M tokens of Uppsala Corpus²
- Testing corpus: 4,011 tokens from Orwell's 1984
- Russian Positional tagset
 Size: Russian 2000+; Czech 4000+, English 45 (Penn Treebank)

²http://www.slaviska.uu.se/ryska/corpus.html 🐶 🔻 🖘 😩 🔻 🗨

Tagset

Table: Overview and comparison of the Czech and Russian tagsets

Pos	Description	Abbr.	No. of v	alues	
			Czech	Russian	
1	POS	р	12	12	
2	SubPOS - detailed POS	s	69	45	
3	Gender	g	11	5	
4	Number	n	6	4	
5	Case	С	9	8	
6	Possessor's Gender	f	5	5	
7	Possessor's Number	m	3	3	
8	Person	e	5	5	
9	Tense	t	5	5	
10	Degree of comparison	d	4	4	
11	Negation	a	3	3	
12	Voice	V	3	3	
13	Unused		1	1	
14	Unused		1	1	
15	Variant, Style	i	10	8	

Tag translation

- Translate to the corresponding category in Russian (if obvious)
 - \bullet e.g., vocative \to nominative; Pronominal clitics \to pronouns, etc.
- Drop distinctions Russian does not make.
 - e.g., short adjectives do not distinguish case, verbs do not distinguish negation.
- Ignore rare tags.
- Some translations are not obvious:
 - Czech participles: QW (fem, sg OR neutr.pl) can be translated as Russian FS (fem,sg) or NP (neutr,pl), but Russian particples do not distinguish gender in plural (XP).

Script Modification

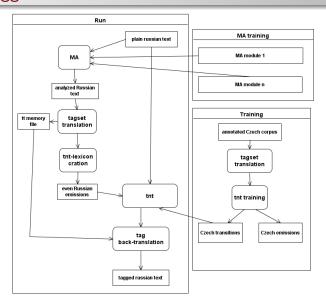
- Russian and Czech use different scripts
- Cannot use emissions directly
- Transliterate Russian, using Scientific Transliteration
 - e.g., it produces \check{s} for $[\![j \!]]$ and \check{c} for $[\![tj \!]]$.
- Replace Czech characters not present in the transliterated Russian with their obvious (or most likely) counterparts.
 - e.g., long vowels are shortened $(\acute{a} \rightarrow a)$, palatalization is expressed using the soft sign $(\check{n} \rightarrow n')$, etc.

Direct Tagger

Table: Direct Tagger: Czech tagger applied to Russian

tagg	ger name		direct	
		Scientific transliteration	Better transliteration	
Unknown tokens (%)		59.0	55.3	
All	Full tag:	44.9	48.1	
	SubPOS	61.0	63.8	
N	Full tag:	32.8	37.3	
	SubPOS	84.0	81.1	
A	Full tag:	20.7	31.7	
	SubPOS	33.8	51.7	
V	Full tag:	36.1	39.9	
	SubPOS	44.6	48.1	

Even Tagger



Even Tagger: Results

Table: Tagging with evenly distributed output of Russian MA

tagger name		Direct	Even	
transitions		Czech	Czech	
emissions		Czech	uniform Russian MA	
All	Full tag:	48.1	77.6	
	SubPOS	63.8	91.2	
N	Full tag:	37.3	54.4	
	SubPOS	81.1	89.6	
A	Full tag:	31.7	53.1	
	SubPOS	51.7	86.9	
V	Full tag:	39.9	90.1	
	SubPOS	48.1	95.7	

Approximating emissions

- Thus far, we used evenly distributed emissions, i.e. we lost some useful information
 - Identify source-target cognate pairs
 - Transfer the information about the source cognate word to the target cognate word

Cognates: Hypotheses

Cognate words

- will have similar morphological and distributional properties.
- are similar in form and this tendency is strong enough to be useful.

Cognates (cont.)

We are aware of the fact that

- Cognates could have departed in their meaning, and thus probably have different distributions.
 - život 'life' in Czech vs. život 'belly' in Russian, and krásný (adj.) 'nice' in Czech vs. krasnyj (adj.) 'red' in Russian.
- Cognates could have departed in their morphological properties.
 - tema 'theme', borrowed from Greek, is neuter in Czech and feminine in Russian.
- There are false cognates unrelated, but similar or even identical words.
 - dělo 'cannon' in Czech vs. delo 'matter, affair' in Russian, jel [jɛl] 'drove' in Czech vs. el [jɛl] 'ate' in Russian, pozor 'attention' in Czech vs. pozor 'disgrace' in Russian, ni 'she_{loc}' in Czech vs. ni negative particle in Russian (corresponding to Czech ani).

Automatic cognate detection

- A variant of the edit distance where the cost of operations is dependent on the arguments:
 - Characters sharing certain phonetic features are closer than characters not sharing them (we use spelling as an approximation of pronunciation; E.g., b is closer to p than to, say, j.
 - Costs are refined based on some well-known and common language-specific phonetic-orthographic regularities. E.g.,
 - Russian è and e have zero distance from Czech e.
 - Czech h and g have zero distance from Russian g (in Czech, the original Slavic g was replaced by h, in Russian it was not).
 - The length of Czech vowels is ignored (in Russian, vowel length is not phonemic)
 - y and i are closer to each other than other vowels (modern Czech does not distinguish between them in pronunciation)

Cognates (cont.)

- Cognates are translated back to their original spelling.
- ED is affected by the number of arguments (characters) it needs to consider → normalize by word length.
- The list of cognates includes all Czech-Russian pairs of words whose distance is below a certain threshold.
- We require that the words have the same morphological features (except for the gender of nouns and the variant as they are lexical features).

Using cognates

- Map the Czech emission probabilities to Russian emissions.
 - Assume w_{cze} and w_{rus} are cognate words.
 - Let T_{cze} denote the tags that w_{cze} occurs with in the Czech training corpus.
 - Let $p(w_{cze}|t)$ be the emission probability of w_{cze}
 - Let T_{rus} denote tags assigned to w_{rus} by the morphological analyzer; $\frac{1}{|T_{rus}|}$ is the even emission probability.
 - Then, assign the new emission probability $p'(w_{rus}|t)$ to every tag $t \in T_{rus}$ (followed by normalization):

$$(1) \ p'(w_{rus}|t) = \begin{cases} p(w_{cze}|t) + \frac{1}{|T_{rus}|} & \text{if } t \in T_{rus} \\ 0 & \text{otherwise} \end{cases}$$

Approximating transitions

- Czech transitions are a fairly good approximation of Russian transitions.
- Nevertheless, there's a drop in accuracy (especially for verbs), when compared to the native Russian transitions.
- Russify data.

Approximating transitions (examples)

Negation in Czech is expressed by the prefix ne, whereas in Russian it is very common to see a separate particle (ne) instead:

(2) a. Nic neřekl.
 nothing not-said
 'He didn't say anything.'

[Cz]

b. On ničego ne skazal.he nothing not said'He didn't say anything.'

[Ru]

Approximating transitions (examples)

Reflexivization of verbs is expressed by a separate word in Czech, and by affixation in Russian.

(3) a. Filip se ještě neholí.
Filip REFL-CL still not-shaves
'Filip doesn't shave yet.' [Cz]
b. Filip esče ne breet+sja.
Filip still not shaves+REFL.SUFFIX

'Filip doesn't shave yet.' [Ru]

Approximating transitions (examples)

Even though auxiliaries and the copula are the forms of the same verb $b\acute{y}t/byt'$ 'to be', both in Czech and in Russian, the use of this verb is different in the two languages. For example, Russian does not use an auxiliary to form past tense:

```
(4) a. Já jsem psal.
```

I aux_{1sg} wrote

'I was writing/I wrote.'

[Cz]

b. Ja pisal.

l wrote

'I was writing/I wrote.'

[Ru]

Russified transitions: examples

Czech Russian

Já bych spal. Ja by spal. 'I would sleep.'

Ty bys spal. Ty by spal. 'You.sg would sleep.'

On by spal. On by spal. 'He would sleep.'

Russified transitions: results

Table: Tagging Russian using Russified Czech transitions

tagger name		cognates	russified	
transitions		Czech	Russified Czech	
emissions		cognates	cognates	
All	Full tag:	79.5	80.0	
	SubPOS	92.2	92.3	
N	Full tag:	57.3	57.1	
	SubPOS	89.9	89.3	
A	Full tag:	54.5	55.9	
	SubPOS	86.9	86.9	
V	Full tag:	90.6	92.7	
	SubPOS	96.1	96.6	

Russified transitions: discussion

- Russifications are language specific and therefore do not fit into our goal of developing a resource- and knowledge-light framework.
- The penalty for using Czech transitions is very small (although this might be different for other languages)
- Some improvements in transitions are the results of the tagset translation, which are part of the most basic tagger.

Tag decomposition

- Data sparsity problem (large tagset): with 1,000 tags there are 1,000³ potential trigrams.
- Decompose the tag into subtags to reduce the tagset
- We focus on six positions POS (p), SubPOS (s), gender (g), number (n), case (c), and person (e). The selection of the slots is based on linguistic intuition.
- Train the tagger on the subtags
- Combine them

Combination of subtaggers

There are many possible formulas that could be used. E.g.,

(6)
$$bestTag = argmax_{t \in T_{MA}} val(t)$$

where:

- 1. T_{MA} is the set of tags offered by MA
- 2. $val(t) = \sum_{k=0}^{14} N_k(t)/N_k$
- 3. $N_k(t)$ is the # of taggers voting for k-th slot of t
- 4. N_k is the total # of taggers on slot k

This formula means that the best tag is the tag that receives the highest average percentage of votes for each of its slots.

• No significant improvement in performance

Summary of results

		direct	even	cog	russif
emissions		CZ	MA	cog	cog
transitions		CZ	CZ	CZ	CZ _{ru}
All	Full tag:	45.6	77.6	79.3	79.7
	SubPOS	62.3	90.4	91.4	91.3
N	Full tag:	36.7	59.6	61.2	62.1
	SubPOS	81.9	89.5	89.8	89.8
Α	Full tag:	18.9	62.5	64.7	65.8
	SubPOS	36.1	86.5	86.8	86.8
V	Full tag:	44.1	93.0	93.2	93.9
	SubPOS	54.3	95.5	95.7	95.7

Comparisons with other tools

- Czech taggers (Hajic et al. 2001) significantly better (4.84% error r.)
 - However, extensive lexicon (300K entries) with 1.5% recall error
 - Taggers trained and tested on the same language
- Xerox Russian Tagger worse (but not a real evaluation)
 - Much smaller tagset (63 tags, collapsing some cases, ...)
 - Error rate comparison on 201 tokens of the testing corpus: Xerox tagger: 18%; our tagger: 8.5%;