# Forms Wanted: Training SMT on Monolingual Data



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## **Outline**



- Targeting Czech.
  - Vocabulary sizes.
  - Source of the morphological explosion.
  - OOV rates.
  - Caveat: BLEU much less reliable.
- Failed: Factored attempts to generate forms on the fly.
- Promising: Two-Step Translation.
- Black Art: **Reverse Self-Training.**
- Summary.

# Vocabulary Sizes for en and cs



WMT10 (Bojar and Kos, 2010)	Large	Small	Dev
Sentences	7.5M	126.1k	2.5k
Czech Tokens	79.2M	2.6M	55.8k
English Tokens	89.1M	2.9M	49.9k
Czech Vocabulary	923.1k	138.7k	15.4k
English Vocabulary	646.3k	64.7k	9.4k
Czech Lemmas	553.5k	60.3k	9.5k
English Lemmas	611.4k	53.8k	7.7k

	Czech	English
Rich morphology	$\geq$ 4,000 tags possible	50 used
	$\geq$ 2,300 tags seen	
Word order	free	rigid

# Morphological Explosion in Czech



(In)flective lang.: many categories expressed in a single suffix:

- Czech nouns and adjectives: 7 cases, 4 genders, 3 numbers, . . .
- Czech verbs: gender, number, aspect (im/perfective), . . .

I	saw	two	green	striped	cats	
já	pila	dva	zelený	pruhovaný	kočky	
	pily	dvě	zelená	pruhovaná	koček	
		dvou	zelené	pruhované	kočkám	
	viděl	dvěma	zelení	pruhovaní	kočkách	
	viděla	dvěmi	zeleného	pruhovaného	kočkami	
			zelených	pruhovaných		
	uviděl		zelenému	pruhovanému		
	uviděla		zeleným	pruhovaným		
			zelenou	pruhovanou		
vid	lěl jsem		zelenými	pruhovanými		
vid	ěla jsem					

Wide margin for improvement: Standard BLEU  ${\sim}12\%$  vs. lemmatized BLEU  ${\sim}21\%$ 

## **OOV** Rates



Dataset	n-grams Out of: Corpus Voc.		Phrase-T	able Voc.	
(# Sents)	Language	1	2	1	2
	Czech	2.2%	30.5%	3.9%	44.1%
7.5M	English	1.5%	13.7%	2.1%	22.4%
	Czech + English input sent	1.5%	29.4%	3.1%	42.8%
	Czech	6.7%	48.1%	12.5%	65.4%
126k	English	3.6%	28.1%	6.3%	45.4%
	Czech + English input sent	5.2%	46.6%	10.6%	63.7%
	Czech lemmas	4.1%	36.3%	5.8%	52.6%
126k	English lemmas	3.4%	24.6%	6.9%	53.2%
	Czech + English input lemmas	3.1%	35.7%	5.1%	38.1%

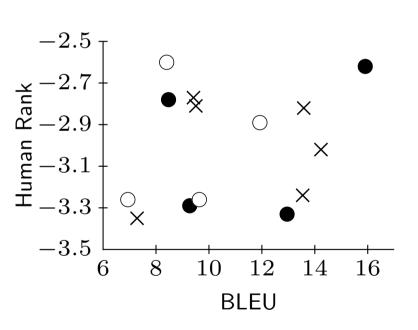
- Significant vocabulary loss during phrase extraction:
  - e.g.  $2.2\% \rightarrow 3.9\%$  for 7.5M Czech.
- ullet OOV of Czech forms  $\sim$ twice as bad as in English, cf. the reds.
- OOV of Czech lemmas lower than in English, see the greens.

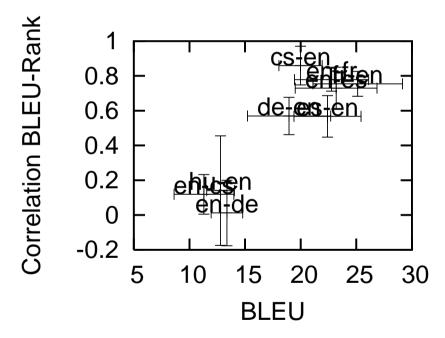
# Side Note: BLEU vs. Human Rank



Large vocabulary impedes the performance of BLEU.

En→Cs Systems Various Language Pairs WMT08, WMT09 WMT08, WMT09, MetricsMATR





 $\Rightarrow$  BLEU does not correlate with human rank if below  $\sim$ 20.

## Reason 1: Focus on Forms



SRC	Prague Stock Market falls to minus by the end of the trading day
REF	pražská burza se ke konci obchodování propadla do minusu
cu-bojar	praha stock market klesne k minus na konci obchodního dne
pctrans	praha trh cenných papírů padá minus do konce obchodního dne

- Only a single unigram in each hyp. confirmed by the reference.
- Large chunks of hypotheses are not compared at all.

Confirmed by Reference	Yes	Yes	No	No
Contains Errors	Yes	No	Yes	No
Running words	6.34%	36.93%	22.33%	34.40%

# Reason 2: Sequences Overvalued



#### BLEU overly sensitive to sequences:

- Gives credit for 1, 3, 5 and 8 four-, three-, bi- and unigrams,
- Two of three serious errors not noticed,
  - ⇒ Quality of cu-bojar overestimated.

```
SRC Congress yields: US government can pump 700 billion dollars into banks kongres ustoupil : vláda usa může do bank napumpovat 700 miliard dolarů cu-bojar kongres výnosy : vláda usa může čerpadlo 700 miliard dolarů v bankách pctrans kongres vynáší : us vláda může čerpat 700 miliardu dolarů do bank
```

 $\Rightarrow$  Bojar et al. (2010) use SemPOS, a coarse metric that correlates better with humans for Czech and English.

## Factored Phrase-Based MT



Both input and output words can have more factors.

## Mapping steps $(\rightarrow)$

Translate (phrases of) source factors to target factors.

two green → dvě zelené

## **Generation steps** (↓)

Generate target factors from target factors.

```
dv\check{e} \rightarrow \textit{fem-nom}; dva \rightarrow \textit{masc-nom}
```

 $\Rightarrow$  To ensure "vertical" coherence.

## Target-side language models (+LM)

Applicable to various target-side factors.

```
p(dvě kočkách) < p(dvě kočky); p(fem-nom masc-nom) < p(fem-nom fem-nom)
```

⇒ To ensure "horizontal" coherence.

(Koehn and Hoang, 2007)

## **Translation Scenarios**



#### Vanilla

#### Translate+Check (T+C)

English	Czech	
form ->	form	+LM
lemma	lemma	
morphology	morphology	

English	Czech	
form ->	form —	+LM
lemma	lemma	
morphology	morphology <del>&lt;</del>	+LM

#### Translate+2·Check (T+C+C)

#### 2.Translate+Generate (T+T+G)

English	Czech	
form -		1 + LM
lemma	lemma <b>←</b>	+LM
morphology	morphology <del>&lt;</del>	+LM

English	Czech	
form	form <	$\frac{1}{1}$ +LM
lemma	→ lemma —	+LM
morphology	∕→morphology—	$^{J}+LM$

# Factored Attempts (WMT09)



Sents	System	BLEU	NIST	Sent/min
2.2M	Vanilla	14.24	5.175	12.0
2.2M	T + C	13.86	5.110	2.6
84k	T+C+C&T+T+G	10.01	4.360	4.0
84k	Vanilla MERT	10.52	4.506	_
84k	Vanilla even weights	08.01	3.911	_

- In WMT08, T+C was still the effort (Bojar and Hajič, 2008).
- In WMT09, our computers could handle 7-grams of forms.
  - $\Rightarrow$  No gain from T+C.
- T+T+G too big to fit and explodes the search space.
  - $\Rightarrow$  Worse than Vanilla trained on the same dataset.

# T+T+G Failure Explained



- Factored models are "synchronous", i.e. Moses:
  - 1. Generates fully instantiated "translation options".
  - 2. Appends translation options to extend "partial hypothesis".
  - 3. Applies LM to see how well the option fits the previous words.
- There are too many possible combinations of lemma+tag.
- $\Rightarrow$  Less promising ones must be pruned.
  - ! Pruned before the linear context is available.
- Hieu Hoang wasted a year on trying asynchronous factors.
  - Pruning hard to design (no clear comparison for partial translation options).
- In a completely different decoder Bojar et al. (2009) use "delayed factors".
  - The final value generated only after the full hypothesis is ready.

# Two-Step Attempts (WMT10) 1/2



- 1. English  $\rightarrow$  lemmatized Czech
  - meaning-bearing morphology preserved
  - max phrase len 10, distortion limit 6
  - large target-side (lemmatized LM)
- 2. Lemmatized Czech  $\rightarrow$  Czech
  - trained on much more data
  - max phrase len 1, monotone

Src	after a shar	rp drop	
Mid	ро+6	ASA1.prudký	NSApokles
Gloss	after+voc	adj + sgsharp	noun+sgdrop
Out	ро	prudkém	poklesu

# Two-Step Attempts (WMT10) 2/2

	ÚFAL
$\vdash$	\ · cc' \
L	Diff

Training	g Sents	Vani	lla	Two-S	Step	Diff
Parallel	Mono	BLEU	SemPOS	BLEU	SemPOS	B.S.
126k	126k	$10.28 \pm 0.40$	29.92	$10.38 \pm 0.38$	30.01	アア
126k	13M	$12.50 \pm 0.44$	31.01	$12.29 \pm 0.47$	31.40	7
7.5M	13M	$14.17{\pm}0.51$	33.07	$14.06 \pm 0.49$	32.57	XX

Manual micro-evaluation of  $\nearrow$ , i.e.  $12.50\pm0.44$  vs.  $12.29\pm0.47$ :

	Two-	Both	Both		
	-Step	Fine	Wrong	Vanilla	Total
Two-Step	23	4	8	-	35
Both Fine	7	14	17	5	43
Both Wrong	8	1	28	2	39
Vanilla	_	3	7	23	33
Total	38	22	60	30	150

- Each annotator weakly prefers Two-step
  - but they don't agree on individual sentences.

# Reverse Self-Training



Goal: Learn from monolingual data to produce <u>new</u> target-side word forms in correct contexts.

	Source English		Target Czech
Para	a cat chased	=	kočka honila
126k			kočka honit (lem.)
	I saw a cat	=	viděl jsem <b>kočku</b>
			vidět být kočka (lem.)
Mono	?		četl jsem o <b>kočce</b>
2M			číst být o kočka (lem.)
			Use reverse translation
	I read about a cat	$\leftarrow$	backed-off by lemmas.

 $<sup>\</sup>Rightarrow$  New phrase learned: "about a cat" = "o **kočce**".

# The Back-off to Lemmas



- The key distinction from self-training used for domain adaptation (Bertoldi and Federico, 2009; Ueffing et al., 2007).
- We use simply "alternative decoding paths" in Moses:

Czech English	0 14	Czech English	
form → form +LM	Or	lemma→ form	+LM

- We even don't correct the bug that phrases available only in one of the tables score better than phrases scored by both paths.
- Other languages (e.g. Turkish, German) need different back-off techniques:
  - Split German compounds.
  - Separate and allow to ignore Turkish morphology.
    - ⇒ See the talks by Chris Dyer and Marcello Federico.

# Mixing Para+Mono



## Simple concatenation (denoted ".").

Just append the baseline parallel and the monolingual texts.

### Interpolated in MERT (denoted "+").

- Separate weight for the LM trained on the monolingual data.
- Separate five weights for the phrase table extracted from the monolingual data.

## Results



BLEU	TM	LM	Manual
$10.56 \pm 0.39$	para	para	
$10.70 \pm 0.40$	mono	mono	
$10.98 {\pm} 0.38$	mono	para+mono	
$11.06 \pm 0.40$	mono	para.mono	
$12.20 \pm 0.40$	para	para+mono	
$12.24 \pm 0.44$	para	para.mono	baseline
$12.27 \pm 0.41$	para.mono	para+mono	
$12.33 \pm 0.43$	para.mono	para.mono	29 over 19 better
$12.65 {\pm} 0.42$	para+mono	para.mono	35 over 27 better

- For LM, interpolation ("+") usually beats concat. (".").
  - Here domains match exactly  $\Rightarrow$  no gain.
- Reverse self-training works (TM "+") for en $\rightarrow$ cs small data.
- 2M monolingual (alone!) make a reasonable baseline (10.70±0.40).

# Summary



- Czech is an interesting target language for MT.
  - http://ufal.mff.cuni.cz/czeng
  - 8 million parallel sents ( $\sim$ 90 milion words per lang.)
- BLEU unreliable if below 20.
- Naive factored setup to generate unseen forms fails.
  - Search space explodes.
- Two-step approach (translate to lemmas first) promising.
  - Future: pass lattice between step 1 and 2.
  - Future: better model for step 2 (see Alex Fraser's talk).
- Reverse-self training works on small datasets.
  - Future: test on larger dataset.
  - Future: back-off for the reverse step in other languages.

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