

Wild Experimenting in Machine Translation

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Wed Feb 15, 2012

Outline

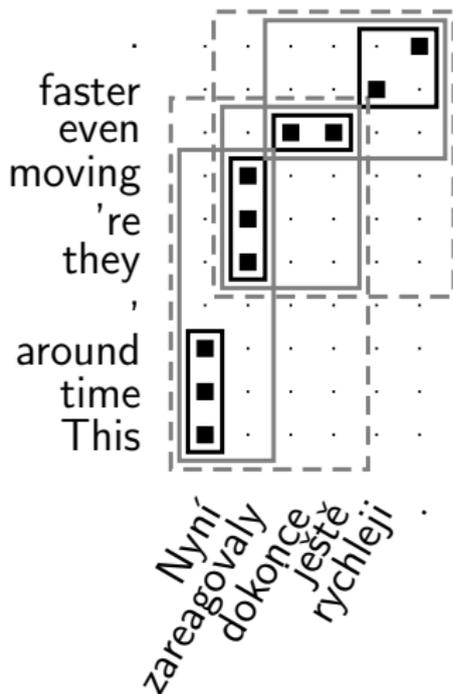
Statistical Machine Translation:

- ▶ Word order issues:
 - ▶ of PBMT, RBMT and hierarchical MT.
- ▶ Morphology issues of PBMT:
 - ▶ Along the whole MT pipeline.
 - ▶ With focus on target-side rich morphology.

Wild Experimenting:

- ▶ Motivation for experiment management.
- ▶ Key features of Eman.

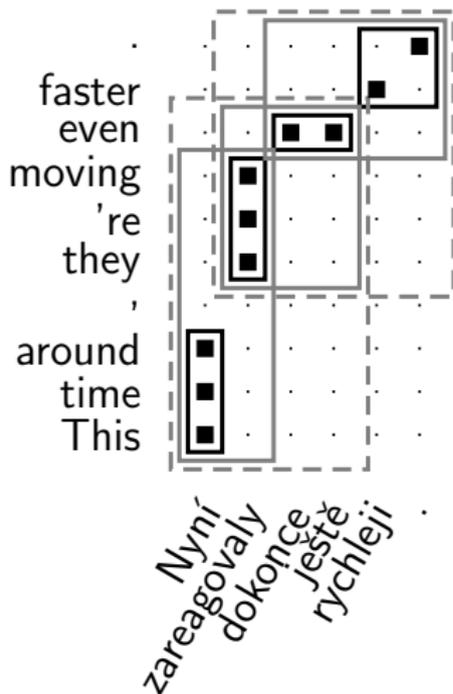
Phrase-Based Machine Translation



Training data:

- ▶ a parallel corpus (Czech sent = English sent)
- ▶ automatic word alignment (Czech word \sim English word)

Phrase-Based Machine Translation

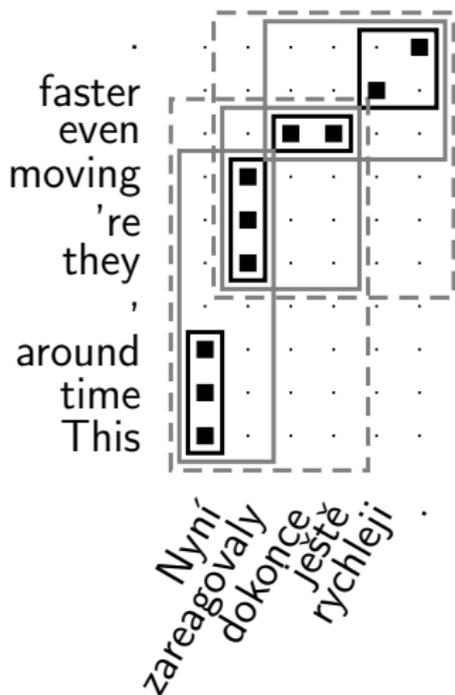


This time around = Nyní
they 're moving = zareagovaly
even = dokonce ještě
even faster = dokonce ještě rychleji
... = ...

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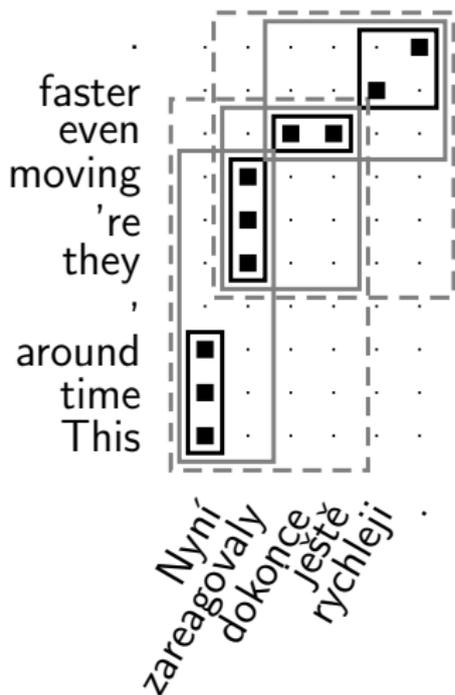
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When translating we search for:

- ▶ such a segmentation of the input sentence into “phrases”
- ▶ and such phrase translations to make the output most probable.

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Training data:

- ▶ a parallel corpus (Czech sent = English sent) ... **9 mil. sent. pairs**
- ▶ automatic word alignment (Czech word ~ English word) ~ **2×90 M**

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- ▶ such a segmentation of the input sentence into “phrases”
- ▶ and such phrase translations to make the output most probable.

Warm-Up: Prove Google is Phrase-Based

Natáhnout bačkory.

Kick the bucket.



Warm-Up: Prove Google is Phrase-Based

Natáhnout bačkory.

Proč musel natáhnout bačkory?

Kick the bucket.

Why did he kick the bucket?



Warm-Up: Prove Google is Phrase-Based

Word form variations:

Natáhnout bačkory.

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Proč natáhl bačkory?

Kick the bucket.

Why did he kick the bucket?

Why stretched slippers?



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Pumping words into phrases:

Jan s Marií se vzali.

John and Mary were married.



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Pumping words into phrases:

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John and Mary married yesterday.



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Jan s Marií se včera v kostele vzali.

John and Mary are married in church yesterday.



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John and Mary are married in church yesterday.



Jan s Marií se včera v kostele svatého Ducha vzali.

John and Mary yesterday in the Church of the Holy Spirit took.



PBMT vs. RBMT

(Prove Systran is not phrase-based.)

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Stell dir das vor.

Google Imagine that.

Systran Imagine.



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Stell dir ein Haus vor.

Google Imagine a house before.

Systran Imagine a house.



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Stell dir ein kleines Haus vor.

Google Imagine a small house in front.

Systran Imagine a small house.



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Stell dir ein kleines Haus vor.

Google Imagine a small house in front.

Systran Imagine a small house.



Stell dir ein kleines Haus mit vierzehn Fenster vor.

Google Imagine a small house with fourteen windows in front.

Systran Imagine a small house with fourteen windows.



Limitations of RBMT

- ▶ “Pump” grammatical constructions, not just words.

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Stell dir ein Haus vor.

⇒ Imagine a house.



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Stell dir ein Haus, das einen Garten hat, vor.

⇒ Imagine a house, which has a garden.



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Stell dir ein Haus, das einen Garten, der berühmt ist, hat, vor.

⇒ Place to you a house, which a garden, which has is famous, forwards.



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- ▶ “Pump” grammatical constructions, not just words.

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⇒ Imagine a house.



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⇒ Place to you a house, which a garden, which has is famous, forwards.



- ▶ What's worse: non-grammatical input breaks it.

Stell dir ein Haus, das \emptyset Garten hat, vor.

⇒ Place to you a house, the garden intends.



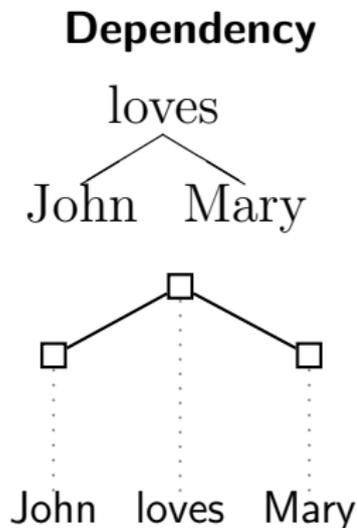
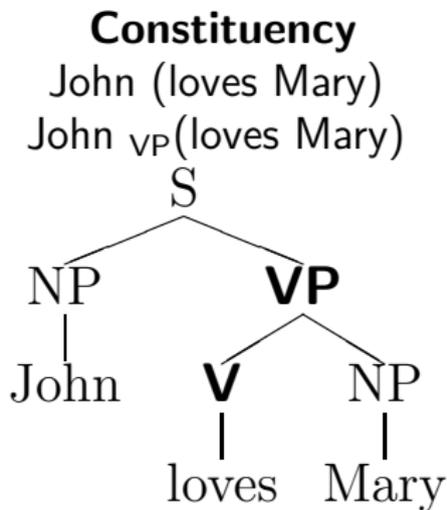
Constituency vs. Dependency

Constituency trees (CFG) represent only bracketing:

= which adjacent constituents are glued to each other.

Dependency trees represent which words depend on which.

+ usually, some agreement/conditioning along the edge.



What Dependency Trees Tell Us

Input: The **grass** around your house should be **cut** soon.

Google: **Trávu** kolem vašeho domu by se měl **snížit** brzy.

- ▶ Bad lexical choice for *cut* = *sekat/snížit/krájet/řezat/...*
 - ▶ Due to long-distance lexical dependency with *grass*.
 - ▶ One can “pump” many words in between.
 - ▶ Could be handled by full source-context (e.g. maxent) model.
- ▶ Bad case of *tráva*.
 - ▶ Depends on the chosen active/passive form:

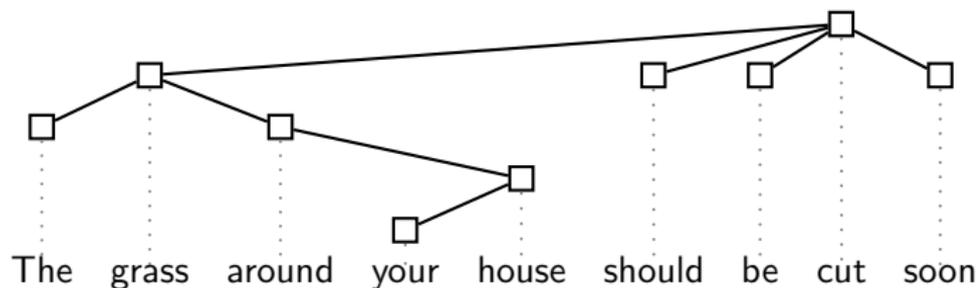
active⇒accusative

trávu ... by **ste** ~~se~~ měl posekat

passive⇒nominative

tráva ... by **se** měla posekat
tráva ... by měla **být** posekána

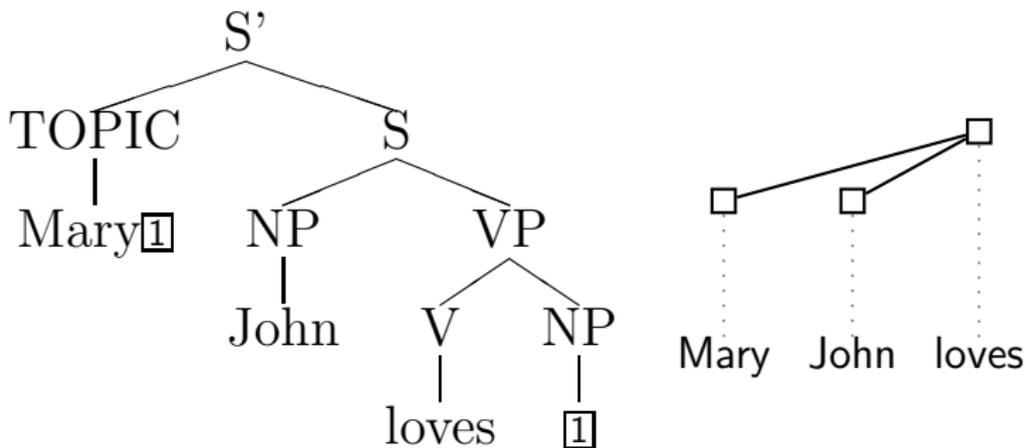
Tree vs. Linear Context



- ▶ Tree context (neighbours in the dependency tree):
 - ▶ is better at predicting lexical choice than n -grams.
 - ▶ often equals linear context:
Czech manual trees: 50% of edges link neighbours,
80% of edges fit in a 4-gram.
- ▶ Phrase-based MT is a very good approximation.
- ▶ Hierarchical MT can even capture the dependency in one phrase:
 $X \rightarrow \langle \text{the grass } X \text{ should be cut, trávu } X \text{ byste měl posekat} \rangle$

“Crossing Brackets”

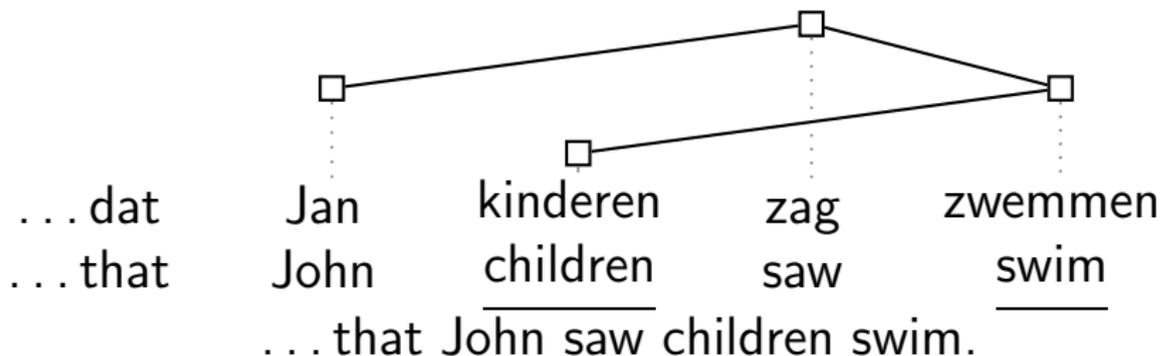
- ▶ Constituent outside its father’s span causes “crossing brackets.”
 - ▶ Linguists use “traces” (⊠) to represent this.
- ▶ Sometimes, this is not visible in the dependency tree:
 - ▶ There is no “history of bracketing”.
 - ▶ See Holan et al. (1998) for dependency trees including derivation history.



Non-Projectivity

= a gap in a subtree span, filled by a node higher in the tree.

Ex. Dutch “cross-serial” dependencies, a non-projective tree with one gap caused by *saw* within the span of *swim*.



- ▶ 0 gaps = projective tree \Rightarrow representable in CFG.
- ▶ ≤ 1 gap & “well-nested” \Rightarrow mildly context sensitive (TAG). See Kuhlmann and Möhl (2007) and Holan et al. (1998).

Why Non-Projectivity Matters?

- ▶ CFGs cannot handle non-projective constructions:

Imagine John **grass** saw **being cut**!

- ▶ No way to glue these crossing dependencies together:

- ▶ Lexical choice:

$X \rightarrow \langle \text{grass } X \text{ being cut, } \text{trávu } X \text{ sekát} \rangle$

- ▶ Agreement in gender:

$X \rightarrow \langle \text{John } X \text{ saw, Jan } X \text{ viděl} \rangle$

$X \rightarrow \langle \text{Mary } X \text{ saw, Marie } X \text{ viděla} \rangle$

- ▶ Phrases can memorize fixed sequences containing:

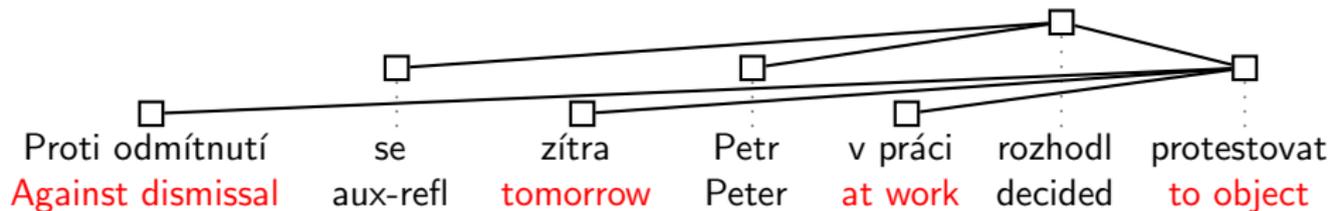
- ▶ the non-projective construction
- ▶ and all the words in between! (\Rightarrow extreme sparseness)

Is Non-Projectivity Severe?

Depends on the language.

In principle unlimited:

- ▶ Czech allows long gaps as well as many gaps in a tree.



Peter decided to object against the dismissal at work tomorrow.

In treebank data:

- ⊖ 23% of Czech sentences contain a non-projectivity.
- ⊕ 99.5% of Czech sentences are well nested with ≤ 1 gap.

Parallel View

- ▶ Ignoring formal linguistic grammar, do we have to reorder beyond swapping constituents?
 - ▶ This is the ITG (Hiero with ≤ 2 nonterminals) limitation.

| Domain | Alignment | English-Czech Parallel Sents | |
|--------|--------------|------------------------------|------------|
| | | Total | Beyond ITG |
| WSJ | manual Sure | 515 | 2.9% |
| WSJ | manual S+P | 515 | 15.9% |
| News | GIZA++, gdfa | 126k | 10.6% |
| Mixed | GIZA++, gdfa | 6.1M | 3.5% |

- ▶ searched for (discontinuous) 4-tuples of alignment points in forbidden shapes (3142 and 2413).
- ▶ additional alignment links were allowed to intervene (and could force different segmentation to phrases) \Rightarrow we overestimate.
- ▶ no larger sequences of tokens were considered as a unit \Rightarrow we underestimate.

Don't Care Approach (cs→en)

Input: Zítra **se** v kostele Sv. Trojice budou **brát** Marie a Honza.

Ref: Mary and John get married in the Holy Trinity church tomorrow.

Goog: Tomorrow **is** the Holy Trinity church will **take** Mary and John.

- ▶ Bad lexical choice:
brát = take vs. brát se = get married
- ▶ Superfluous *is*:
 - ▶ *se* is very often mis-aligned with the auxiliary *is*.

The straightforward bag-of-source-words model fails here:

- ▶ *se* is very frequent and it often means just *with*.
- ▶ An informed model would use the source parse tree.
 - ▶ Remember to use a non-projective parser!

Tentative Conclusion on Reordering

For Indo-European languages, PBMT seems acceptable.

- ▶ Dependencies are most often local enough.
- ▶ Distant dependencies can be non-projective
⇒ Hierarchical model does not help much either.

Other languages?

- ▶ We will try Tamil (Dravidian language, SOV) in the lab.
- ▶ ...but you'll see we will first hit another issue:
rich morphology.

Rich Morphology in PBMT Pipeline

- ▶ Word Alignment.
- ▶ Extraction of Translation Units.
- ▶ Translation of New Text.
- ▶ (Reordering.)
- ▶ Language Modelling.
- ▶ MT Evaluation.
- ▶ Model Optimization.

Rich Morphology in PBMT Pipeline

- ▶ Word Alignment.
 - ▶ Extraction of Translation Units.
 - ▶ Translation of New Text.
 - ▶ New forms of known words.
 - ▶ Unknown words.
 - ▶ (Reordering.)
 - ▶ Language Modelling.
 - ▶ Sparser unigrams and higher-grams (reordering).
 - ▶ MT Evaluation.
 - ▶ Fewer matches with the reference.
 - ▶ Model Optimization.
- ... rich morphology makes everything harder.

Rich Morphology in PBMT Pipeline

- ▶ Word Alignment. ⇒ Lab: Stem, chop (or lemmatize or LEAF).
 - ▶ Extraction of Translation Units.
 - ▶ Translation of New Text.
 - ▶ New forms of known words. ⇒ Here: Two-Step; Lab: Split+Join.
 - ▶ Unknown words. ⇒ Word derivations in Treex.
 - ▶ (Reordering.)
 - ▶ Language Modelling.
 - ▶ Sparser unigrams and higher-grams (reordering).
 - ▶ MT Evaluation. ⇒ Here: Problems of BLEU.
 - ▶ Fewer matches with the reference.
 - ▶ Model Optimization. ⇒ Here: SemPOS+BLEU.
- ... rich morphology makes everything harder.

Morphological Explosion in Czech

(In)flective lang.: suffix encodes many categories:

- ▶ Czech nouns and adjs: 7 cases, 4 genders, 3 nums, ...
- ▶ Czech verbs: gender, num, 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 | | |
| | viděl jsem | | zelenými | pruhovanými | | |
| | viděla jsem | | ... | ... | | |

Result: Out-of-Vocabulary Rates

| Dataset (# Sents) | Language | n -grams Out of: Corpus Voc. | | Phrase-Table Voc. | |
|----------------------|------------------------------|--------------------------------|-------|-------------------|-------|
| | | 1 | 2 | 1 | 2 |
| 7.5M | Czech | 2.2% | 30.5% | 3.9% | 44.1% |
| | English | 1.5% | 13.7% | 2.1% | 22.4% |
| | Czech + English input sent | 1.5% | 29.4% | 3.1% | 42.8% |
| 126k | Czech | 6.7% | 48.1% | 12.5% | 65.4% |
| | English | 3.6% | 28.1% | 6.3% | 45.4% |
| | Czech + English input sent | 5.2% | 46.6% | 10.6% | 63.7% |
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- ▶ OOV of Czech lemmas **lower than** in English.
- ▶ Free word order of Czech **apparent**.

Two-Step Moses 1/2

- ▶ English → lemmatized Czech
 - ▶ meaning-bearing morphology preserved
 - ▶ max phrase len 10, distortion limit 6
 - ▶ large target-side (lemmatized LM)
- ▶ Lemmatized Czech → Czech
 - ▶ max phrase len 1, monotone

| | | | | |
|-------|--------------|--------------------|----------------|----------------|
| 0 | Src | after a sharp drop | | |
| <hr/> | | | | |
| 1 | Mid | po+6 | ASA1.prudký | NSA-.pokles |
| | Gloss | after+voc | adj+sg...sharp | noun+sg...drop |
| <hr/> | | | | |
| 2 | Out | po | pruškém | poklesu |

- ▶ Only 1-best output passed, lattices on our todo list.
- ▶ See also works by Alex Fraser for targetting German.
- ▶ Alternative: Exponential models (Subotin, 2011).

Two-Step Moses 2/2

| Data Size | | Simple | | Two-Step | | Diff |
|-----------|------|------------|--------|------------|--------|-------|
| Parallel | Mono | BLEU | SemPOS | BLEU | SemPOS | B. S. |
| 126k | 126k | 10.28±0.40 | 29.92 | 10.38±0.38 | 30.01 | ↗↗ |
| 126k | 13M | 12.50±0.44 | 31.01 | 12.29±0.47 | 31.40 | ↘↗ |
| 7.5M | 13M | 14.17±0.51 | 33.07 | 14.06±0.49 | 32.57 | ↘↘ |

Manual micro-evaluation of ↘↗, i.e. 12.50±0.44 vs. 12.29±0.47:

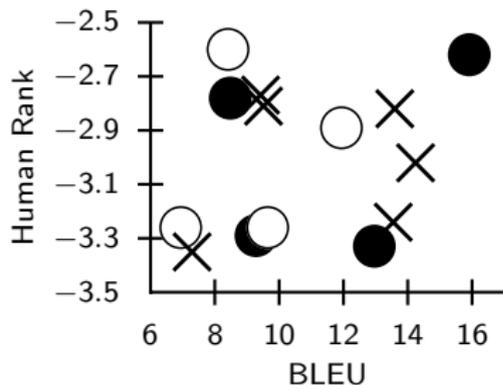
| | Two- -Step | Both Fine | Both Wrong | Simple | Total |
|------------|---------------|--------------|---------------|-----------|-----------|
| Two-Step | 23 | 4 | 8 | - | 35 |
| Both Fine | 7 | 14 | 17 | 5 | 43 |
| Both Wrong | 8 | 1 | 28 | 2 | 39 |
| Simple | - | 3 | 7 | 23 | 33 |
| Total | 38 |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

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

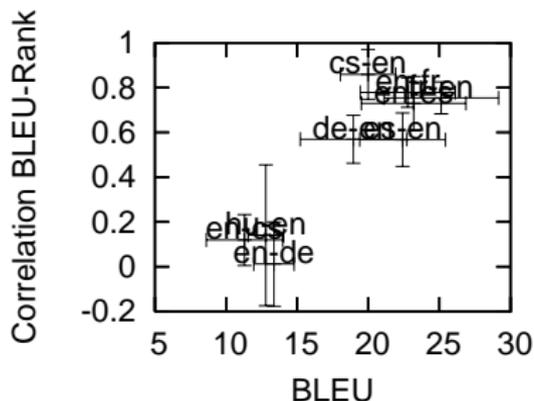
Effect of Rich Morphology on BLEU

- ▶ Large vocabulary impedes the performance of BLEU.

En→Cs Systems
WMT08, WMT09



Various Language Pairs
WMT08, WMT09, MetricsMATR



⇒ BLEU does not correlate with human rank if below ~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 <u>konci</u> obchodního dne |
| pctrans | praha trh cenných papírů padá minus <u>do</u> 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 | | | | | | | |
| REF | kongres ustoupil : vláda usa může do bank napumpovat 700 miliard dolarů | | | | | | | |
| cu-bojar | <u>kongres</u> | výnosy | <u>:</u> | <u>vláda usa může</u> | čerpadlo | <u>700 miliard dolarů</u> | v | <u>bankách</u> |
| pctrans | <u>kongres</u> | <u>vynáší</u> | <u>:</u> | <u>us</u> | <u>vláda</u> | <u>může</u> | <u>čerpat</u> | <u>700 miliardu dolarů do bank</u> |

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

Optimizing Towards SemPOS

SemPOS compares bags of lemmas, not sequences of forms.

- ▶ Sequences not overvalued
⇒ better correlation with human ranking.
- ▶ Not fit for selecting best output from n-best list.
⇒ Need to combine with e.g. BLEU.

WMT11 Tunable Metrics Task, manual ranking:

| System | \geq others | $>$ others |
|-----------------|---------------|-------------|
| bleu● | 0.79 | 0.28 |
| bleu-single● | 0.77 | 0.27 |
| cmu-meteor● | 0.76 | 0.27 |
| rwth-cder | 0.76 | 0.26 |
| cu-sempos-bleu● | 0.74 | 0.29 |
| stanford-dcp● | 0.73 | 0.27 |
| nus-tesla-f | 0.68 | 0.28 |
| sheffield-rose | 0.05 | 0.00 |

- ▶ Among the many “winners” (●).
- ▶ Best in “ $>$ others”, i.e. when ties are not rewarded.

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- ▶ Among the many “winners” (●).
- ▶ Best in “ $>$ others”, i.e. when ties are not rewarded.
- ▶ Generally hard to interpret the ranking.

Motivation for Experiment Mgmt (1/2)

Research needs reproducibility.

- ▶ Console-based environment alone helps a lot:
 - ▶ Bash history of past commands.
 - ▶ Log files.
- ▶ Complications:
 - ▶ Experiments carried out in parallel.
Experiments can take days.
⇒ Easy to lose track.
 - ▶ Should reuse large intermediate files.
 - ▶ Different versions of the research software.
(Both daily updates as well as yearly updates.)

Motivation for Experiment Mgmt (2/2)

Research is search.

(for the best procedure, the best configuration, . . .)

You can think of research in AI/machine-learning terms.

- ▶ Heuristics:
 - ▶ Run quick probes (small data) first, then replicate on full.
- ▶ Beam Search: Increase *your* beam size:
 - ▶ Run ~10 variations of each experiment.
- ▶ Genetic Algorithms:
 - ▶ Clone and modify most successful experiments.
- ▶ (“The best” varies based on the metric chosen.)
 - ▶ So look at more metrics at once.

Features of Eman

- ▶ Console-based \Rightarrow easily scriptable (e.g. in bash).
- ▶ Versatile: “seeds” are up to the user, any language.
- ▶ Support for the manual search through the space of experiment configurations.
- ▶ Support for finding and marking (“tagging”) experiments of interest.
- ▶ Support for organizing the results in 2D tables.
- ▶ Integrated with SGE
 \Rightarrow easy to run on common academic clusters.

eman --man will tell you some details.

Eman's View

- ▶ Experiments consist of processing STEPS.
- ▶ Steps are:
 - ▶ of a given type, e.g. **align**, **tm**, **lm**, **mert**,
 - ▶ defined by immutable variables, e.g. **ALISYM=gdfa**,
 - ▶ all located in one directory, the “**playground**”,
 - ▶ timestamped unique directories, e.g.
s.mert.a123.20120215-1632
 - ▶ self-contained in the dir as much as reasonable.
 - ▶ dependent on other steps, e.g. first **align**, then build **tm**, then **mert**.

Lifetime of a step:



Eman is Versatile

What types of steps should I have?

- ▶ Any, depending on your application.

What language do I write steps in?

- ▶ Any, e.g. bash.

What are the input and output files of the steps?

- ▶ Any, just make depending steps understand each other.
- ▶ Steps can have many output files and serve as prerequisites to different types of other steps.

What are measured values of my experiments?

- ▶ Anything from any of the files any step produces.

What the User Implements: Just Seeds

Technically, a seed is any program that:

- ▶ responds to arbitrary environment variables,
- ▶ runs **eman defvar** to register step variables with eman,
- ▶ produces another program, **./eman.command** that does the real job.

The seed is actually run twice:

- ▶ At “init”: to check validity of input variables and register them with eman.
- ▶ At “prepare”: to produce **eman.command**.

The user puts all seeds in **playground/eman.seeds**.

- ▶ Eman runs a local copy of the seed in a fresh step dir.

Why INITED→PREPARED→RUNNING?

The call to **eman init** *seed*:

- ▶ Should be quick, it is used interactively.
- ▶ Should only check and set vars, “turn a blank directory to valid eman step”.

The call to **eman prepare** *s.step.123.20120215*:

- ▶ May check for various input files.
 - ▶ Less useful with heavy experiments where even corpus preparation needs cluster.
- ▶ Has to produce **eman.command**.
⇒ A chance to check it: are all file paths correct etc.?

The call to **eman start** *s.step.123.20120215*:

- ▶ Sends the job to the cluster.

Bells and Whistles

Experiment management:

- ▶ **ls**, **vars**, **stat** for simple listing,
- ▶ **select** for finding steps,
- ▶ **traceback** for full info on experiments,
- ▶ **redo** failed experiments,
- ▶ **clone** individual steps as well as whole experiments.

Meta-information on steps:

- ▶ **status**,
- ▶ **tags**, autotags,
- ▶ **collecting** results,
- ▶ **tabulate** for putting results into 2D tables.

eman select

- ▶ Step dirs don't have nice names.
- ▶ You need to locate steps of given properties.

What all language models do I have?

- ▶ **eman ls lm**
- ▶ **eman select t lm**

If we need just the finished ones:

- ▶ **eman stat lm | grep DONE**
- ▶ **eman select t lm d**

And just 5-gram ones for English:

- ▶ **eman select t lm d vre ORDER=5 vre
CORPAUG=en**

eman traceback

eman traceback s.evaluator.8102edfc.20120207-1611

```
+-- s.evaluator.8102edfc.20120207-1611
| +- s.mosesgiza.b6073a00.20120202-0037
| +- s.translate.b17f203d.20120207-1604
| | +- s.mert.272f2f67.20120207-0013
| | | +- s.model.3e28def7.20120207-0013
| | | | +- s.lm.608df574.20120207-0004
| | | | | +- s.srilm.117f0cfe.20120202-0037
| | | | | +- s.mosesgiza.b6073a00.20120202-0037
| | | | | +- s.tm.527c9342.20120207-0012
| | | | | | +- s.align.dec45f74.20120206-0111
| | | | | | | +- s.mosesgiza.b6073a00.20120202-0037
| | | | | | | +- s.mosesgiza.b6073a00.20120202-0037
| | | +- s.mosesgiza.b6073a00.20120202-0037
```

Options: **--vars** **--stat** **--log** ... **--ignore=steptype**

eman redo

On cluster, jobs can fail nondeterminically.

- ▶ Bad luck when scheduled to a swamped machine.
- ▶ Bad estimate of hard resource limits (RAM exceeds the limit \Rightarrow job killed).

Eman to the rescue:

- ▶ **eman redo** *step* creates a new instance of each failed step, preserving the experiment structure.
- ▶ **eman redo** *step* **--start** starts the steps right away.

To make sure eman will do what you expect, first try:

- ▶ **eman redo** *step* **--dry-run**

eman clone

CLONING is initing a new step using vars of an existing one.

Cloning of individual steps is useful:

- ▶ when a step failed (used in **eman redo**),
- ▶ when the seed has changed,
- ▶ when we want to redefine some vars:

ORDER=4 eman clone s.lm.1d6f791c...

Cloning of whole tracebacks:

- ▶ The text of a traceback gets instantiated as steps.
- ▶ Existing steps are reused if OK and with identical vars.
- ▶ **eman traceback *step* | eman clone**
- ▶ **eman traceback *step* | mail bojar@ufal**
followed by **eman clone < the-received-mail.**

Deriving Experiments using **clone**

The text form of traceback allows to tweak the experiment:

- ▶ **eman tb step | sed 's/cs/de/' | eman clone**
replicates our experiment on German instead of Czech.

The derivation is now available in eman itself:

- ▶ **eman tb step -s '/cs/de/' -s '/form/lc/'**
shows the traceback with the substitutions highlighted.
 - ▶ A good chance to check if the derivation does the intended.
- ▶ **eman tb step -s '/cs/de/' -s '/form/lc/' **
| eman clone --dry-run
 - ▶ Last chance to check if existing steps get reused and what vars will new steps be based on.
 - ▶ Drop **--dry-run** to actually init the new steps.

eman tag or eman ls --tag shows tags

TAGS and AUTOTAGS are:

- ▶ arbitrary keywords assigned to individual steps,
- ▶ inherited from dependencies.

Tags are:

- ▶ added using **eman add-tag** *the-tag steps*,
- ▶ stored in `s.stepdir.123/eman.tag`.

⇒ Use them to manually mark exceptions.

Autotags are:

- ▶ specified in `playground/eman.autotags` as regexes over step vars, e.g.: `/ORDER=(.*)/$1gr/` for LM,
- ▶ (re-)observed at **eman retag**.

⇒ Use them to systematically mark experiment branches.

eman collect

Based on rules in **eman.results.conf**, e.g.:

```
BLEU */BLEU.opt BLEU\s*=\s*([\s,]+)
Snts s.eval*/corpus.translation CMD: wc -l
```

eman collects results from all steps into **eman.results**:

| # Step Name | Status | Score | Value | Tags and Autotags |
|------------------------------------|----------|-------|-------|--------------------------------|
| s.evaluator.11ccf590.20120208-1554 | DONE | TER | 31.04 | 5gr DEVwmt10 LMc-news towards- |
| s.evaluator.11ccf590.20120208-1554 | DONE | PER | 44.61 | 5gr DEVwmt10 LMc-news towards- |
| s.evaluator.11ccf590.20120208-1554 | DONE | CDER | 33.97 | 5gr DEVwmt10 LMc-news towards- |
| s.evaluator.11ccf590.20120208-1554 | DONE | BLEU | 12.28 | 5gr DEVwmt10 LMc-news towards- |
| s.evaluator.11ccf590.20120208-1554 | DONE | Snts | 3003 | 5gr DEVwmt10 LMc-news towards- |
| s.evaluator.29fa5679.20120207-1357 | OUTDATED | TER | 17.66 | 5gr DEVwmt10 LMc-news |
| ... | ... | ... | ... | |
| s.evaluator.473687bb.20120214-1509 | FAILED | Snts | 3003 | |

- ▶ Perhaps hard to read.
- ▶ Easy to grep, sort, whatever, or **tabulate**.

eman tabulate to Organize Results

The user specifies in the file **eman.tabulate**:

- ▶ which results to ignore, which to select,
- ▶ which tags contribute to col labels, e.g. **TER, BLEU**,
- ▶ which tags contribute to row labels, e.g. **[0-9]gr, towards-[A-Z]+, PRO**.

Eman tabulates the results, output in **eman.nicerresults**:

| | | PER | CDER | TER | BLEU |
|-----|--------------|-------|-------|-------|-------|
| 5gr | towards-CDER | 44.61 | 33.97 | 31.04 | 12.28 |
| 5gr | | 44.19 | 33.76 | 31.02 | 12.18 |
| 5gr | PRO | 43.91 | 33.87 | 31.49 | 12.09 |
| 5gr | towards-PER | 44.44 | 33.52 | 30.74 | 11.95 |

Hacking Welcome

Eman is designed to be hacking-friendly:

- ▶ Selfcontained steps are easy to inspect:
 - ▶ all logs are there,
 - ▶ all (or most of) input files are there,
 - ▶ the main code (**eman.command**) is there,
 - ▶ often, even the binaries are there, or at least clearly identifiable.
- ▶ Step halfway failed?
 - ⇒ Hack its **eman.command** and use **eman continue**.
- ▶ Seed not quite fit for your current needs?
 - ⇒ Just init the step and hack **eman.seed**.
 - ⇒ Or also prepare and hack **eman.command**.

Remember to **eman add-tag** *tag step* for further reference.

Fit for Cell-Phone SSH ☺

- ▶ Experiments run long but fail often.
- ▶ You don't want to be chained to a computer.

Most eman commands have a short nickname.

- ▶ How are my last 10 merts?
eman sel t mert l 10 --stat

Specify steps using any part of their name/hash or result:

- ▶ s.foobar.a0f3b123.20120215-1011 failed, retry it:
eman redo a0f3 --start
- ▶ How did I achieve this great BLEU score of 25.10?
eman tb 25.10 --vars | less

Related Experiment Mgmt Systems

Eman is just one of many, consider also:

- ▶ LoonyBin (Clark et al., 2010)
 - ⊖ Clickable Java tool.
 - ⊕ Support for multiple clusters and scheduler types.
- ▶ Moses EMS (Koehn, 2010)
 - ▶ Experiment Management System primarily for Moses.
 - ▶ Centered around a single experiment which consists of steps.
- ▶ Pure Makefiles

Yes, you can easily live with fancy Makefiles.

 - ▶ You will use commands like **make init.mert** or **cp -r exp.mert.1 exp.mert.1b**
 - ▶ You need to learn to use **\$***, **\$@** etc.
 - ▶ You are likely to implement your own eman soon. 😊

There are also the following workflow management systems: DAGMan, Pegasus, Dryad.

Work in Progress

- ▶ Eman is being heavily used by a rather few people.
- ▶ Eman is still evolving
 - ⇒ not everything well documented (read the source code).
 - ⇒ not everything well tested.

Halfway finished: eman teamwork!

- ▶ **eman add remote** */home/fred/playground freds-exps*
- ▶ You can re-interpret Fred's results.
- ▶ You can clone Fred's experiments.
- ▶ You can make your steps depend on Fred's steps.

Summary

- ▶ Word order issues of PBMT, RBMT and hierarchical MT.
- ▶ Rich morphology issues in PBMT:
 - ▶ Producing target forms never seen in parallel data.
 - ▶ Evaluating MT to morphologically rich languages.
 - ▶ Model optimization.
- ▶ General motivation for experiment management.
- ▶ Introduced eman.
- ▶ Highlighted useful tricks in experimenting.
 - ▶ Experiment cloning or deriving.
 - ▶ Tabulating results.
 - ? Team experimenting.

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