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Morphological Processing and Word Reordering for Statistical MT of Highly Inflected Languages

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Haifa, 24 January 2011

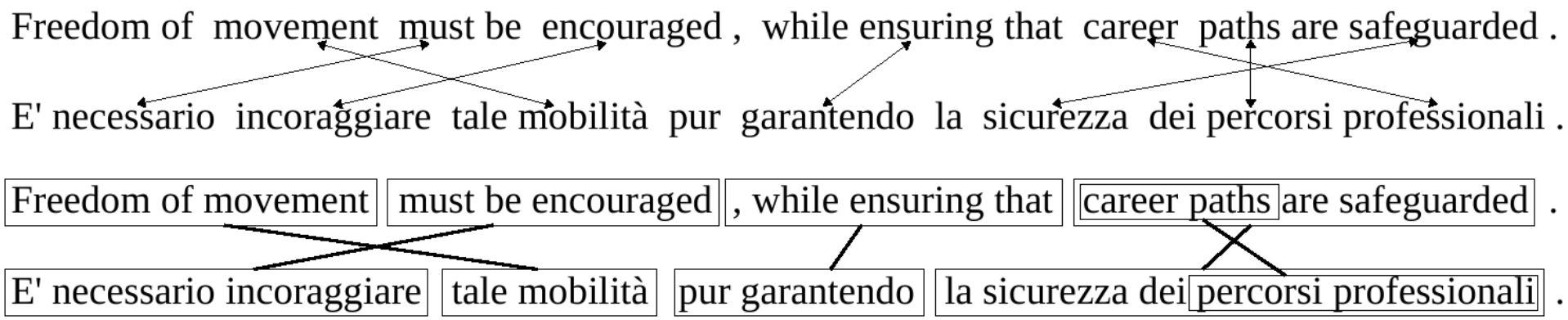
Overview

- Statistical MT in a nutshell
- When it works and when it does not
- Case study 1: Turkish to English
- Case study 2: Arabic to English
- Case study 3: German to English
- Conclusions

To take home:
embedding morpho-syntactic information into SMT is possible and it works!

This work was supported by the EuroMatrixPlus project (IST-231720), which is funded by the European Commission under the 7th Framework Programme for Research and Technological Development.

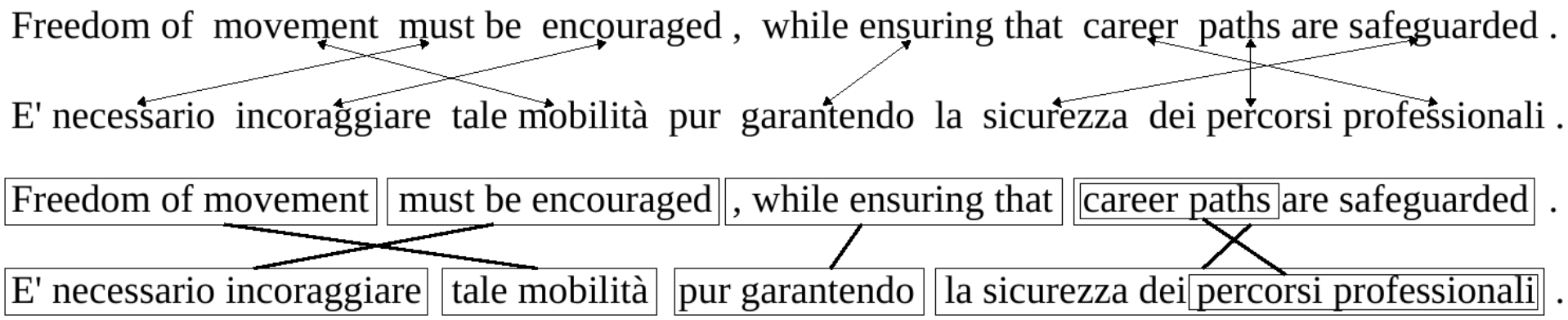
SMT: Simplistic Machine Translation



How SMT works (in a nutshell)

- operations: segment, translate, and place
- scores: linear combination of feature functions
- features: phrase pairs, target n-grams, relative phrase movement , ...
- search: efficient algorithm to compute (sub-)optimal solutions
- features and combination weights are machine learnable from parallel data

SMT: Simplistic Machine Translation



When SMT works (when "more data" is not enough)

- simple morphology of source/target
  – better n-gram models, better alignments, less OOV words, ...
- similar morphology between source and target
  – better alignments, richer phrase tables, ...
- similar syntax between source and target
  – better alignments, phrase-tables, word re-ordering,...

SMT: Smarter Machine Translation

For many language pairs we are far from the ideal condition.

What can we do? what has been done?

- **Enhance SMT features** to capture more information
  – factored models, shallow/deep syntax models, hierarchical re-ordering model
- **Integrate language knowledge** within the existing models
  – morphology pre-preprocessing, word-order pre-processing

We report recent work on the second approach for three translation directions:

- Turkish to English, IWSLT BTEC task
- Arabic to English, NIST MT 2009 task
- German to English, WMT 2010 task

All case studies are carried out with the Moses and IRSTLM toolkits.

Morphological Pre-processing for Turkish SMT

A. Bisazza, M. Federico. "Morphological Pre-Processing for Turkish to English SMT." Proc. of International Workshop on Spoken Language Translation, 2009.

A. Bisazza, I. Klasinas, M. Cettolo, M. Federico. "FBK @ IWSLT 2010." Proc. of the International Workshop on Spoken Language Translation, 2010.

IWSLT BTEC Turkish-English task

Tourist expressions: simple task but limited training data

Rich morphology of Turkish has negative impact on SMT

	Training		OOV on Test
	$\|W\|$	$\|V\|$	(iwslt04)
TR	139.5K	17.6K	6.7%
EN	182.6K	8.3K	

Examples:

SRC: Belki bir doktora görünmelisin.
REF: Perhaps you should see a doctor.
OUT: Maybe *[görünmelisin]* a doctor.

SRC: Bu film rulolarını banyo ettirip basabilir miydiniz?
REF: Could you develop and print these rolls of film?
OUT: Could you reissue *[ettirip]* *[rulolarını]* this film developed ?

Turkish

Several linguistic features can negatively affect an SMT system:

- **Agglutination**
  → vocabulary built by a wide range of suffix combinations

oda	'room'
*oda**m***	'**my** room'
*odam**da***	'**in** my room'
*odamda**yım***	'**I am** in my room'

- **Vowel harmony** and other phoneme alternation phenomena
  → systematic stem and suffix *allomorphy*

saç+(I)m	→	*saç**ım***	'my hair'
el+(I)m	→	*el**im***	'my hand'
kol+(I)m	→	*kol**um***	'my arm'
göz+(I)m	→	*göz**üm***	'my eye'
kafa+(I)m	→	*kafa**m***	'my head'

Turkish - Morphological Decomposition

Idea: selectively isolating or removing suffixes from the words

Workflow:

1. Morphological analysis and suffix normalization [Oflazer, 94]:
   suffix boundaries are detected and surface forms are replaced by tags
   to address vowel harmony and allomorphy.
2. Morphological disambiguation in context [Sak and Saraclar, 2007]:
   only the most likely analysis is taken for each word
3. Rules for splitting/removal of suffix tags:
   15 segmentation schemes developed and tested. Best performing schemes:
   - *MS11*: handles **nominal** suffixes (case, possessive) and copula;
   - *MS13*: also isolates **verbal** negation suffix;
   - *MS15*: also isolates other **verbal** suffixes: subject person, ability & voice.

Turkish - Morphological Decomposition

Examples: surface form *vs* normalized representation:

I was in my room
= odamdaydım → *oda /m/ da/ydı/m*
[room-my-in-was-I] [room] [my] [in] [was] [I]

I can not explain
= anlatamıyorum → *anla / t / a /mı /yor/um*
[understand-make-can-not-I] [understand] [make] [can] [not] [I]

Turkish - Morphological Decomposition

Examples: surface form *vs* normalized representation:

I was in my room
= odamdaydım → *oda /m/ da/ydı/m*
[room-my-in-was-I] [room] [my] [in] [was] [I]

oda+A3sg/+P1sg/+Loc/+Zero+Past/+A1sg
↑ ↑ ↑ ↑ ↑
lemma poss. case copula person

I can not explain
= anlatamıyorum → *anla / t / a /mı /yor/um*
[understand-make-can-not-I] [understand] [make] [can] [not] [I]

anla+Prog1/+Caus/+Able/+Neg/+A1sg
↑ ↑ ↑ ↑ ↑
lemma+tense causative ability negation person

⇒ The underlying representation is used to train the SMT system.

Turkish - Morphological Decomposition

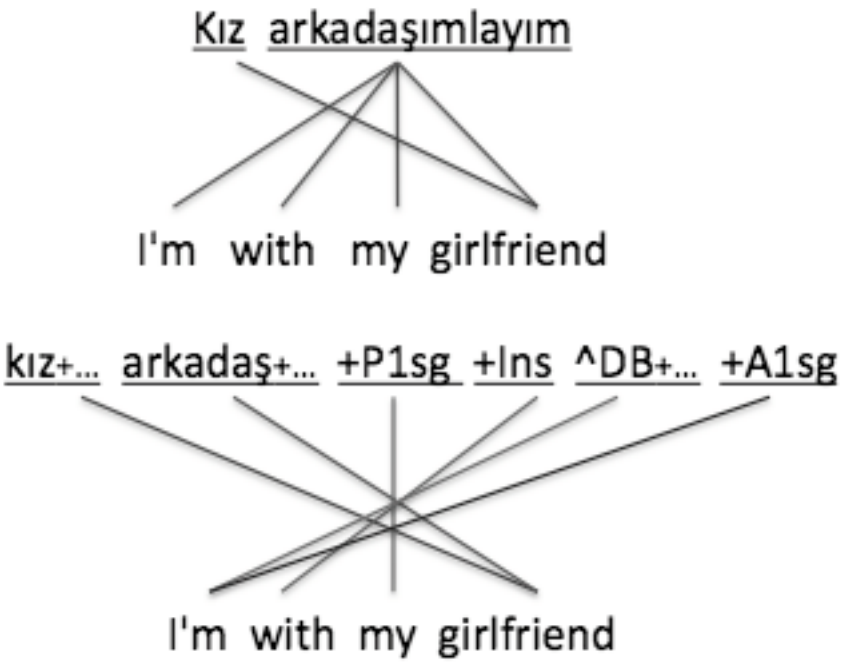
Results:

- minimizes differences in word granularity between TR and EN,
- abstracts from allomorphy by using a tag-like notation,
- reduces data sparseness, training dictionary size, OOV rate of test:

	Preprocessing	Training $\|W\|$	Training $\|V\|$	OOV on Test (iwslt04)
TR	basic tokenization	139.5K	17.6K	6.7%
	MS11	168.1K	10.4K	2.6%
	MS15	174.5K	9.5K	2.0%
EN	*basic tokenization*	*182.6K*	*8.3K*	–

Turkish - Morphological Decomposition

- yields more refined alignments:



Turkish - Lexical Approximation

Idea: replace OOVs in the test by morphologically similar words seen in training:

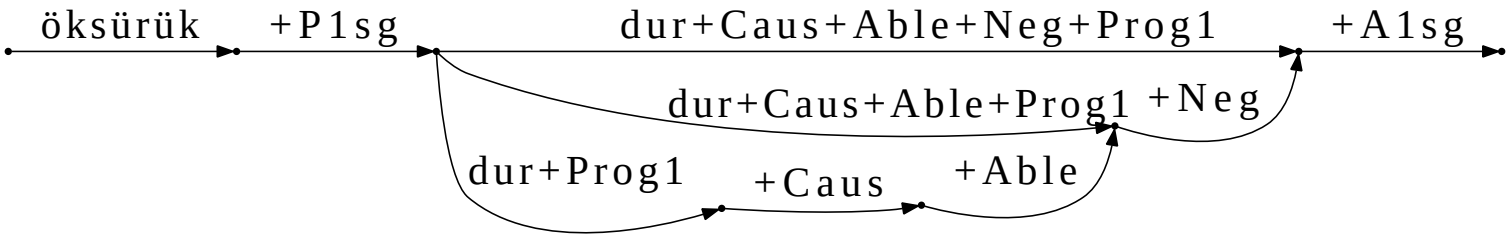
- possible replacers: all words sharing the same lemma
- heuristic: choose candidates with tag sequence most similar to the OOV word
- OOVs replaced by n-best candidates in a confusion network input

Word	Gloss	Preprocessed (MS11)	Score[1]
çıkışlar	***exits***	çık+Verb+Pos^DB+Noun+Inf3+A3pl	
çıkış	exit	çık+Verb+Pos^DB+Noun+Inf3+A3sg	**93**
çıkma	going out	çık+Verb+Pos^DB+Noun+Inf2+A3sg	66
çıkacak	will go out	çık+Verb+Pos^DB+Noun+FutPart+A3sg	66
çıkan	who goes out	çık+Verb+Pos^DB+Adj+PresPart	44
çıkıyor	is going out	çık+Verb+Pos+Prog1	27
çıkmıyor	isn't going out	çık+Verb+Neg+Prog1	0
çıkarır	takes out	çık+Verb^DB+Verb+Caus+Pos+Aor	-15

[1] Score $= 20C$ - $2D_1$ - $5D_2$, where C: # of shared contiguous tags, D_1: # of different tags in the OOV, D_2: # of different tags in the candidate.

Segmentation lattice

- Choice of optimal decomposition ruleset depends on task & target language
- Possible approach: combine various degrees of decomposition in input
  $\Rightarrow$ decoder can choose word-level-optimal segmentation path
- Training set = differently segmented versions of train, concatenated
- Example lattice combining MS11 + MS13 + MS15:



TR: öksürüğümü durduramıyorum

(EN: I cannot make my cough stop)

Experimental Results

System\BLEU	iwslt04	iwslt09	iwslt10
baseline	54.80	–	–
segm. ruleset MS11	60.30	57.21	52.14
segm. ruleset MS15	60.32	**58.28**	52.46
MS11 + lexical approx.(3-best)	59.68	57.11	51.76
segm. lattice MS11+13+15	**60.41**	57.70	**53.29**

- Morphological decomposition yields substantial improvements on baseline
- Adding rules for verbal inflection (MS15) helps slightly but consistently
- Lexical approximation unfortunately doesn't help
- Decomposition lattice works best for two of the three test sets

Conclusions: choice of pre-processing technique depends on task and dataset.

Morphological Pre-processing for Arabic SMT

N. Bertoldi, A. Bisazza, M. Cettolo, M. Federico and G. Sanchis-Trilles. "FBK @ IWSLT 2009". Proc. of the International Workshop on Spoken Language Translation, 2009.

Arabic

Rich morphology, but also orthographic variations and different vowelization styles.
$\rightarrow$ specific preprocessing reduces data sparseness and improves alignments.

Arabic tokenization: Unicode characters and digits normalization, removal of diacritics and $tatweel$ (justification character).

Morphological decomposition: isolates clitics from words.

Two state-of-the-art linguistic tools compared:

- MADA
  - heavy-weight: based on linguistic features produced by Buckwalter analyzer,
  - optimised use of the tool to run on large corpora
- AMIRA
  - light-weight: SVM classifier based on a $-5/+5$ character context.

Arabic - Morphological Decomposition

Two different segmentation schemes:

- MADA (scheme D2) splits prefixes: conjunctions (`w+` 'and', `f+` 'then'), prepositions (`b+` 'by', `k+` 'as', `l+` 'to'), future tense mark (`s+`).
  Also normalizes orthography (beginning *alef*, *tah marbutah*, *alef maksura*. . .)
- AMIRA doesn't split future mark, but splits suffixes: object and poss. pronouns.

'and she will say it to her colleague':

Baseline	`wstqwlh`	`lzmylhA`
	`[and-she-will-say-it]`	`[to-her-colleague]`
MADA	`w+` `s+` `tqwlh`	`l+` `zmylhA`
	`[and]` `[will]` `[she-say-it]`	`[to]` `[her-colleague]`
AMIRA	`w+` `stqwl` `+h`	`l+` `zmyl` `+hA`
	`[and]` `[she-will-say]` `[it]`	`[to]` `[colleague]` `[her]`

On the NIST task MADA slightly outperforms AMIRA, but AMIRA is faster and includes shallow chunking.

Verb Reordering for Arabic SMT

A. Bisazza and M. Federico. "Chunk-based verb reordering in VSO sentences for Arabic-English SMT." Proc. of ACL Workshop on SMT and Metrics, 2010.

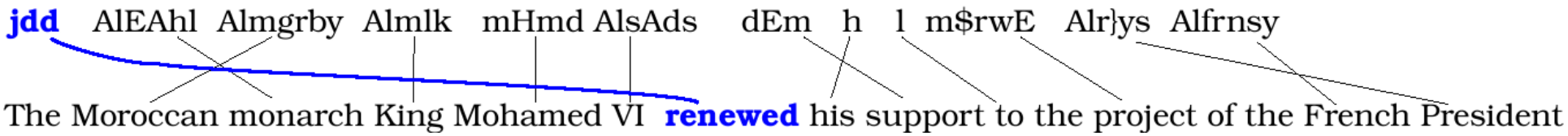
A. Bisazza, D. Pighin, M. Federico. "Chunk-Lattices for Verb Reordering in Arabic-English SMT". *Machine Translation*, 2010. (Accepted for publication).

The Problem of Arabic VSO Sentences

Problem:

Word reordering is a challenge for phrase-based SMT between distant languages

English: mainly Subject-Verb-Object *VS* Arabic: both SVO and VSO



Typical errors in phrase-based SMT outputs:

**The Moroccan monarch King Mohamed VI ∅ his support to the French President*

**He renewed the Moroccan monarch King Mohamed VI his support to the French President*

First attempt: rule-based verb reordering

- Focus on verbs *say, declare, note...* in pre-subject position of news
- Apply simple surface pattern-matching reordering rules, without syntax
- Rule: move verb before trigger element (*'that', colon, quotation mark, etc.*)

Example 1

original

src: qAlt hh AlwkAlp : nZrA l+ AlwDE AlHAly fy AlErAq ...
mt: She said the agency: In view of the current situation in Iraq . . .

reordered

src: h*h AlwkAlp qAlt : nZrA l+ AlwDE AlHAly fy AlErAq ...
mt: The agency said due to the current situation in Iraq . . .

First attempt: rule-based verb reordering

- Focus on verbs *say, declare, note...* in pre-subject position of news
- Apply simple surface pattern-matching reordering rules, without syntax
- Rule: move verb before trigger element (*'that', colon, quotation mark, etc.*)

Example 2

original

src: tAbE byAn SAdr En mktb hnyp >n Al>xyr ...
mt: He went on to say, a statement issued by the office of Hania that the latter

reordered

src: byAn SAdr En mktb hnyp tAbE >n Al>xyr ...
mt: A statement issued by the office of Hania continued that the latter . . .

First attempt: rule-based verb reordering

- Focus on verbs *say, declare, note...* in pre-subject position of news
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- Rule: move verb before trigger element (*'that', colon, quotation mark, etc.*)

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mt: He went on to say, a statement issued by the office of Hania that the latter

reordered

src: `byAn SAdr En mktb hnyp tAbE >n Al>xyr ...`
mt: A statement issued by the office of Hania continued that the latter . . .

Unfortunately, no significant BLEU improvement on the NIST task.

We introduce more linguistic knowledge and extend to all verbs!

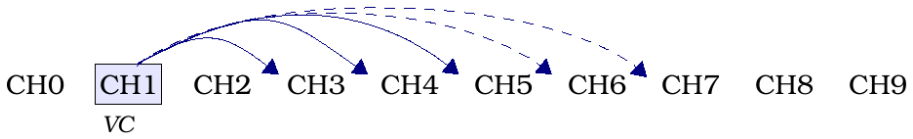
Chunk-based Verb Reordering

Assumptions:

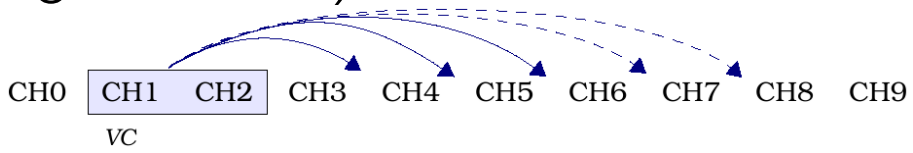
1) verb reordering only between shallow syntax chunks
2) no overlap between consecutive verb movements

Define a class of possible movements:

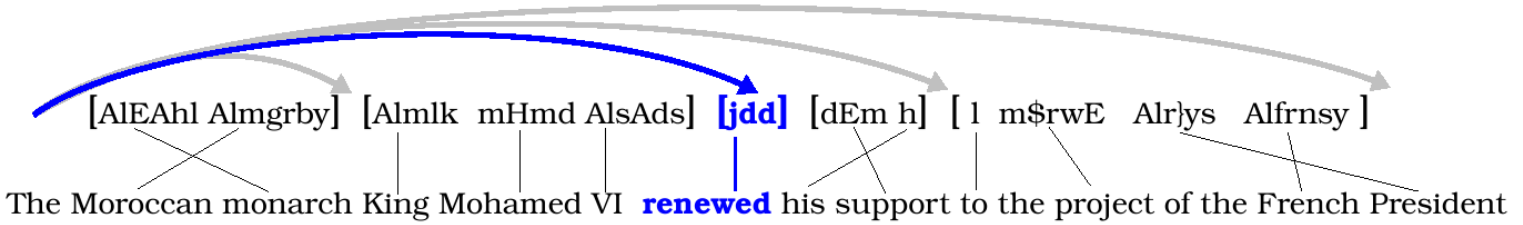
i) move verb chunk...



ii) ... or verb chunk + next chunk (e.g. adverbials) by up to N chunks to the right



Best movement in parallel corpus:
minimizes global distortion wrt to English translation



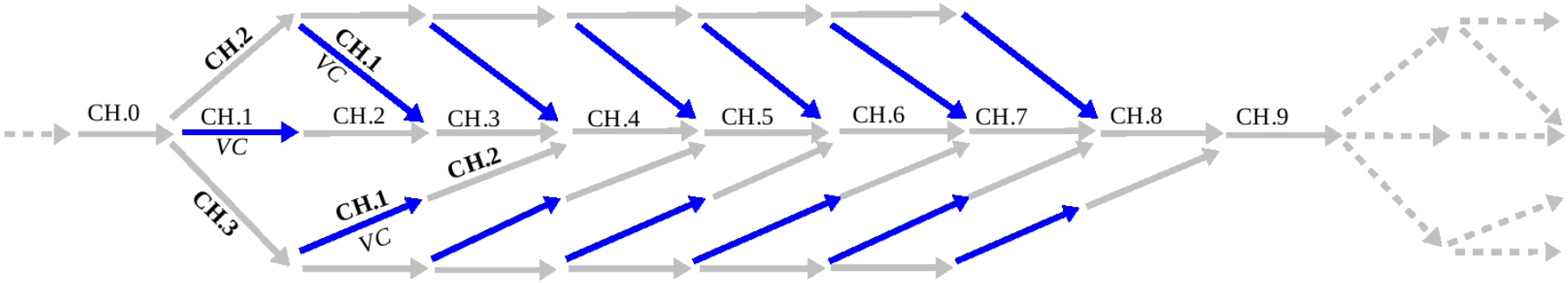
Verb Reordering Lattice

The reordered parallel corpus is used to train the SMT system.
As for the test, we use word **reordering lattices**.

Given the initial assumptions, we can build compact lattices and run non-monotonic decoding on them (Dyer & al. 2008)

Hybrid approach:
- for verb reordering: lattices
- for other reorderings: standard (phrase-internal and local distortion)

Lattice representation of the rule:
"move 1 or 2 chunks by up to 6 chunk positions right"



Evaluation

High-end baseline: Moses, 30M words newswire from NIST09 with lexicalized reordering models (Och &al. 2004; Koehn &al. 2007)

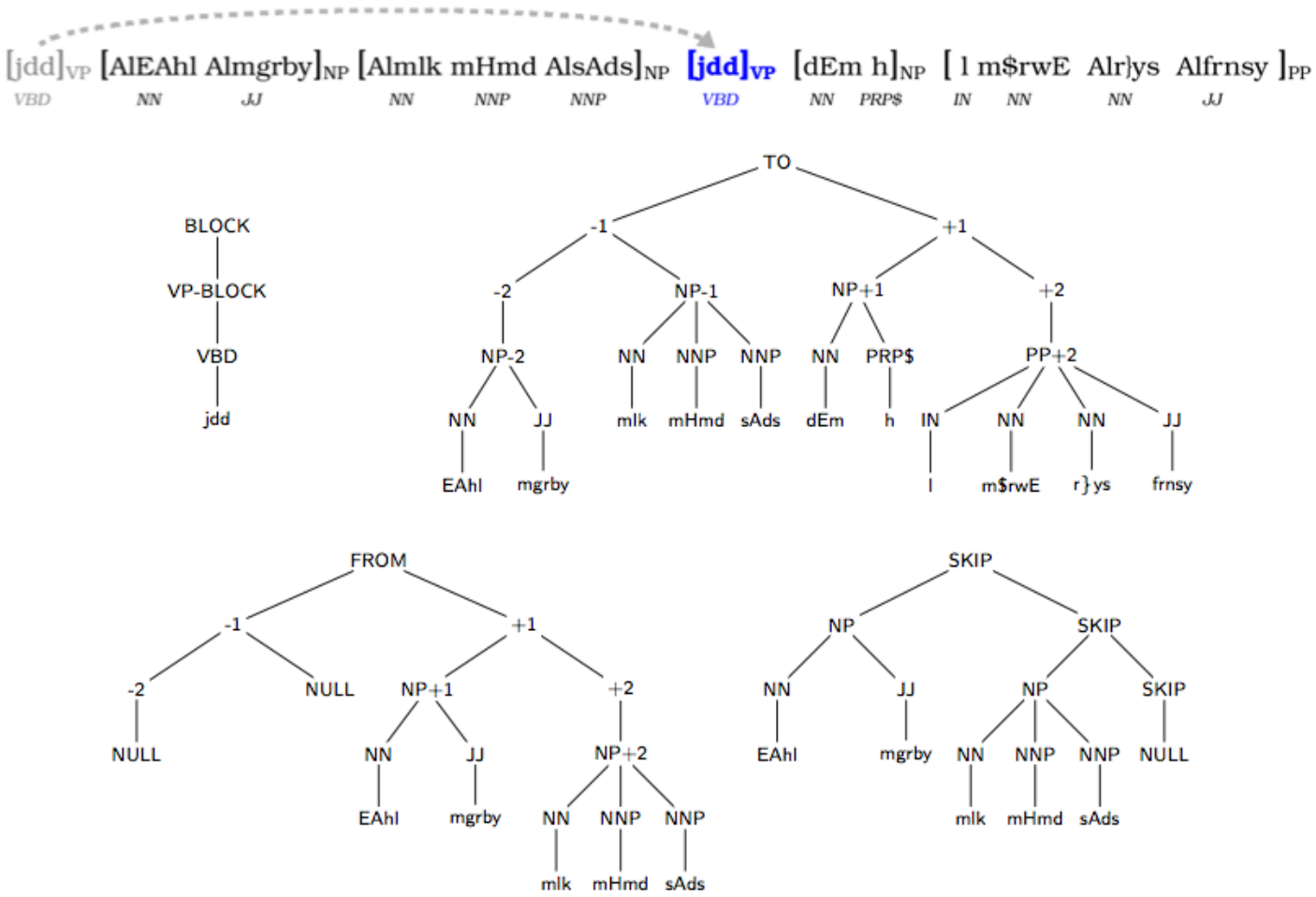
Different experimental conditions:

- whole system re-trained and tuned on verb-reordered data
- translation of plain input (text)
- translation of reordering lattice

		Eval08-NW		Eval09-NW	
System	DL	bleu	krs[2]	bleu	krs
baseline	6	43.10	80.57	48.13	83.17
reord. training +					
plain input	6	43.67	80.62	48.53	83.58
lattice	4	**44.04**	**80.93**	**48.96**	**83.75**
oracle reordered	*4*	*44.36*	*81.29*	*49.26*	*84.30*

[1]Kendall Reordering Score: similarity btw word order of outputs and of references (Birch &al.2010)

Discriminative lattice pruning



We use *syntactic tree kernel* to represent verb chunk movements; Fig. shows forest corresponding to one specific movement. We train a SVM by optimizing global distortion in the training data.

Conclusions

System	DL	Eval08-NW bleu	Eval08-NW krs	Eval09-NW bleu	Eval09-NW krs
baseline	6	43.10	80.57	48.13	83.17
reord. training +					
full lattice	4	44.04	80.93	48.96	83.75
1-best-pruned	4	**44.34**	81.18	49.10	**84.15**
2-best-pruned	4	44.29	**81.30**	**49.19**	84.02
3-best-pruned	4	44.11	81.13	49.05	83.90

- Simply reordering of the training data is beneficial:
  more monotone alignments $\Rightarrow$ better phrase extraction
- Providing likely reordering in the lattice yields further improvement
- Interesting: reordering-specific metric correlates well with BLEU
- Further improvement:
  – pruning the lattice with discriminative approach (SVM)

Morphological Reduction and Reordering for German

C. Hardmeier, A. Bisazza and M. Federico. "FBK at WMT 2010: word lattices for morphological reduction and chunk-based reordering." Proc. of ACL Workshop on SMT and Metrics, 2010.

Problems with German to English SMT

Morphology

- Inflectional morphology: much more prolific in German
  Nouns have case, verbs have many forms, etc.
- Derivational morphology:
  German has one-word-compounds that must be split

$\longrightarrow$ many vocabulary types, high OOV rate

Word order

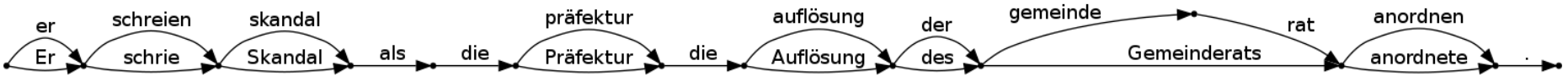
- English: strict SVO word order
- German: SVO in main clauses, SOV in subordinate clauses

$\longrightarrow$ word order mismatch

Approach: morphological reduction and chunk-based reordering

Morphological Reduction

- We use Gertwol to split compounds and reduce words to their base form. Gertwol: commercial two-level finite-state morphology
- Gertwol analyses are disambiguated with POS tags and heuristic disambiguation rules (courtesy of the University of Zurich).
- Decoding: supply reduced forms as alternative paths in a lattice:



- Training: concatenate original and processed parallel texts.

	BLEU	
	DEV	EVAL
Baseline	18.8	20.1
with morphological reduction	19.3	20.6

Chunk Reordering

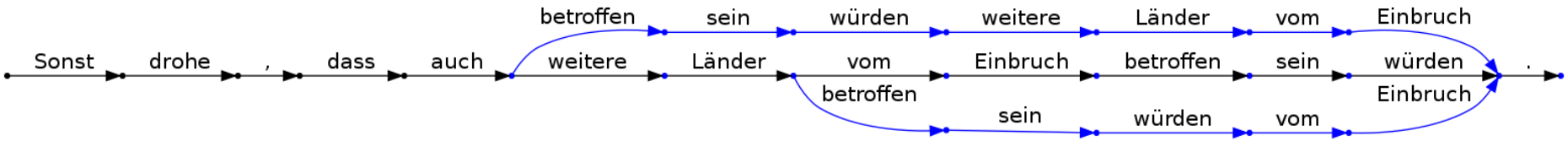
- Same mechanism as for Arabic-English, but different rules.
- We concentrate on a few patterns involving verbs.
- Simplifying assumption:
  Verb reordering only occurs between shallow syntax chunks.
- Tagging and chunking done with the TreeTagger.
- Small number of hand-written reordering rules that can generate multiple reorderings for each matching verb chunk.

Example: Subordinate clause rule

Motivation	Move clause-final verbs in German SOV subordinates left to match English SVO word order.
Moving block	Verb chunk immediately followed by punctuation.
Movement	to the left 1 to 3 chunks after most recent subordinating conjunction

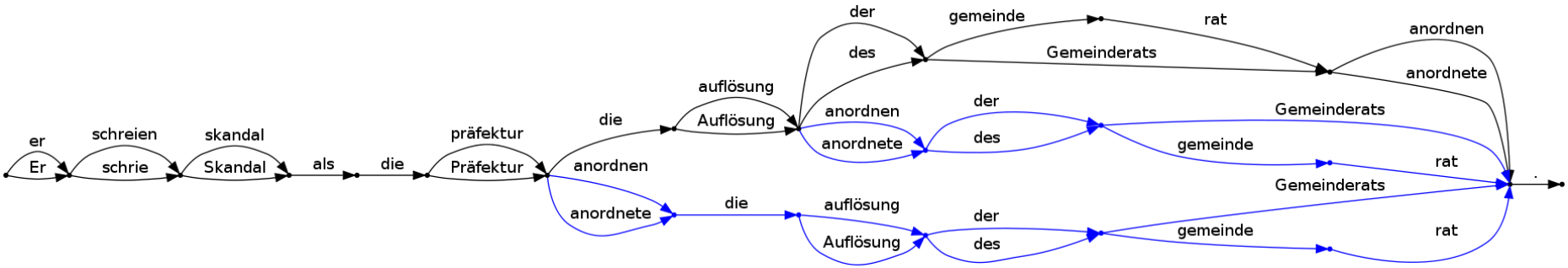
Chunk Reordering: Examples

Sonst [drohe]$_{VC}$, dass auch [weitere Länder]$_{NC}$ [vom Einbruch]$_{PC}$ [betroffen sein würden]$_{VC}$.



It is straightforward to merge a morphological reduction lattice with a chunk reordering lattice:

[Er]$_{NC}$ [schrie]$_{VC}$ [Skandal]$_{NC}$ als [die Präfektur]$_{NC}$ [die Auflösung]$_{NC}$ [des Gemeinderats]$_{NC}$ [anordnete]$_{VC}$.



English-German: Results

	BLEU			
	DEV		EVAL	
	–	MR	–	MR
Baseline	18.8	19.3	20.1	20.6
with reordering	18.9	19.8	20.3	21.1

MR = morphological reduction

- Chunk reordering on its own helps very little: around 0.2 BLEU points.
- In combination with morphological reduction, the gain is much greater: half a point for morphological reduction + half a point for reordering = one point total improvement
- Reordering with lattices strongly depends on the language model to choose the right path.

Conclusions

- We showed methods to exploit morpho-syntactic information for SMT
  – that also resulted in performance improvements on strong baselines
- Language expertise of the source/target languages definitely helps
  – to identify, analyze, and describe issues from a linguistic perspective
- Statistical modeling expertise is required
  – to conceive, implement, and integrate new features in the decoder
  – to exploit or extend existing features
- The phrase-based SMT framework is simple, flexible, and extensible
  – there are more and more things that can be explored, improved, integrated
- Current evolution of the presented approaches:
  – re-ordering models embedding language specific syntactic constraints/preferences
  – context models to enforce cohesive MT across different sentences

Conclusions

- We showed methods to exploit morpho-syntactic information for SMT
  – that also resulted in performance improvements on strong baselines
- Language expertise of the source/target languages definitely helps
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- The phrase-based SMT framework is simple, flexible, and extensible
  – there are more and more things that can be explored, improved, integrated
- Current evolution of the presented approaches:
  – integrate language-specific word-order knowledge directly in the decoder
  – embed syntactic knowledge in re-ordering models and future cost estimation

thank you