Linguistic Information in Machine Translation

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June 16 2020

Outline

Why using linguistic information in MT?

- MT systems are learnt from (word-aligned) parallel corpora

yesterday	gestern
,	sah
the	der
man	Mann
saw	ein
a	blaues
blue	Auto
car	

the	der
man	Mann
bought	kaufte
a	eine
newspaper	Zeitung

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- Linguistic information to help generalize and to introduce knowledge that is not directly accessible

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  - morphology: varying degrees of complexity
  - syntax: free constituent order vs. strictly configurational

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- Linguistic information to model relevant information

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Morphological complexity across languages

Example: comparing nominal inflection features

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der kleine Hund *ein kleiner Hund* *dem kleinen Hund* *die kleinen Hunde* *den kleinen Hunden* ...

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⇒ more word forms observed in German corpus

Example: productive word formation

- Compounding (e.g. German)

Abfall	waste
Abfallsortierung	waste sorting
Abfallsortieranlage	waste sorting plant
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- Agglutinative concatenations (e.g. Turkish)

Turkish	English
duy(-mak)	*(to) sense*
duygu	*sensation*
duygusal	*sensitive*
duygusallaş(-mak)	*(to) become sensitive*
duygusallaştırıl(-mak)	*(to) be made sensitive*
duygusallaştırılmış	*the one who has been made sensitive*
duygusallaştırılamamış	*the one who could not have been made sensitive*
duygusallaştırılamamışlardan	*from the ones who could not have been made sensitive*

Example taken from Ataman et al. (2017)

Translating morphologically complex languages

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- NMT systems
  - typically some sort of pre-processing to keep vocabulary size manageable, such as frequency-based segmentation
  - to a certain extent, can handle unseen words
  - rich morphology still not optimally represented

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- Example: morphological forms of the Czech lemma *čéška* (plural of English *kneecap*) in different training data settings

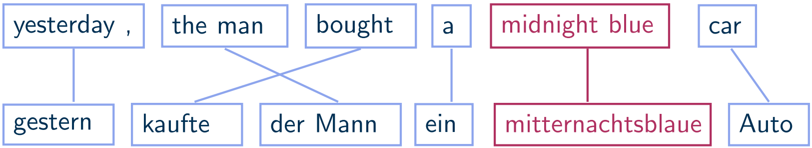
case	surface form	50K	500K	5M	50M
1	čéšky	•	•	•	•
2	čéšek	–	•	•	•
3	čéškám	–	–	•	•
4	čéšky	○	○	•	•
5	čéšky	○	○	○	○
6	čéškách	–	•	•	•
7	čéškami	–	–	–	•

Table 1: Morphological variants of the Czech lemma "čéška". For differently sized corpora (50K/500K/5M/50M), "•" indicates that the variant is present, and "○" that the same surface form realization occurs, but in a different syntactic case.

Example taken from Huck et al. (2017)

Translating into morphologically rich languages

- Data-sparsity: some inflected forms do not occur in the training data



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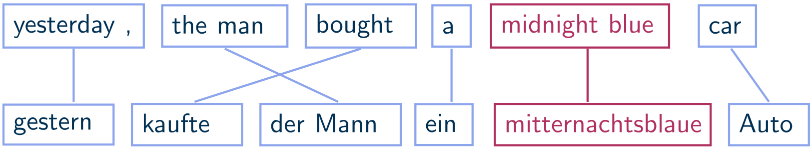

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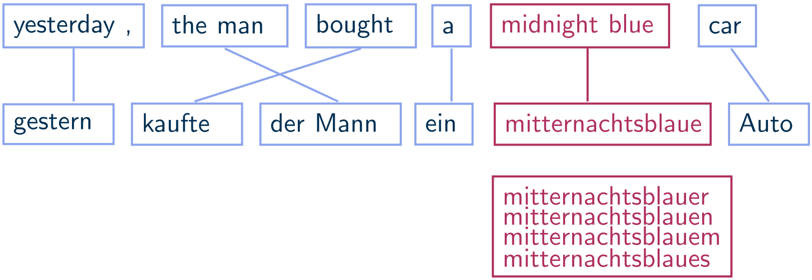

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  ⇒ external knowledge resources: e.g. morphological generation tools

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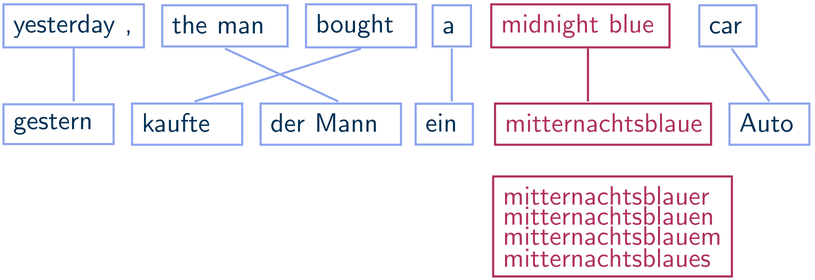

- How can we get the missing inflected forms?

  ⇒ external knowledge resources: e.g. morphological generation tools
- How to select the correct inflected form?

Translating into morphologically rich languages: some strategies

- Increase training data through **back translation**:
  create synthetic parallel data by translating target-side data

  for example Sennrich et al. (2015), Bojar et al. (2011)

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- **Two-step approach**: separation of translation and inflection step
  by translating on an abstract representation with subsequent
  generation of inflected forms (SMT+NMT)

  for example Toutanova et al. (2008), Fraser et al. (2012),
  Burlot et al. (2016), Tamchyna et al. (2017)

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- Idea: generate synthetic morphological variants to add to the phrase-table (for English–Czech translation) Huck et al. (2017)

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- Scoring the unseen variants: phrase translation and lexical translation probabilities are estimated based on lemmatized forms

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- Source-side and target-side features as independent components
  - semantic level: choosing a correct lemma
  - morpho-syntactic level: choosing the correct form
    (tag + morphological features in the given context)

Producing unseen morphological variants in SMT (3)

- Experimental results: substantial improvements in BLEU, in particular for small and medium sized settings

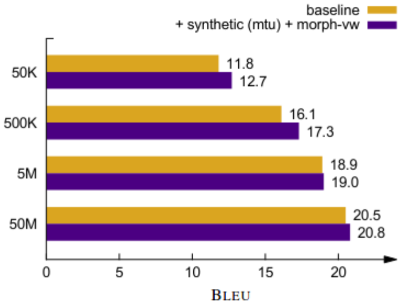

Figure 1: Visualization of the English→Czech translation quality on newstest2016, showing the benefit of our approach under different training resource conditions (50K/500K/5M/50M).

from Huck et al. (2017)

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  - integration of external knowledge:
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- SMT: nominal inflection Fraser et al. 2012
- NMT: nominal and verbal inflection Tamchyna et al. 2017

SMOR: morphological analysis and generation

- **Analysis**

```
analyze> blaue
------------------------------------------
blau<+ADJ><Pos><Neut><Acc><Sg><Wk>
blau<+ADJ><Pos><Neut><Nom><Sg><Wk>
blau<+ADJ><Pos><Masc><Nom><Sg><Wk>
blau<+ADJ><Pos><NoGend><Acc><Pl><St>
blau<+ADJ><Pos><NoGend><Nom><Pl><St>
blau<+ADJ><Pos><Fem><Acc><Sg><Wk>
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generate> blau<+ADJ><Pos><Fem><Nom><Sg><Wk>
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blaue
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Inflection prediction approach: data representation

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Translation model on abstract lemmatized representation

- Inflected forms (nominal phrases) are replaced with lemmas
  blau, *blaue*, *blaues*, *blauem*, *blauen*, *blauer* → `blau<+ADJ><Pos>`
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Inflect the lemmatized translation output

- Predict inflectional features: *case*, *number*, *gender* and *strong/weak*
- Generation step:

$$\underbrace{\texttt{blau<+ADJ><Pos>}}_{\text{lemma}}\underbrace{\texttt{<Neut><Acc><Sg><Wk>}}_{\text{features}} \rightarrow \texttt{blaue}$$

Features for German Nominal Inflection

	English	**German**
number	✓	target-side number of a phrase is determined by the source-side
gender	∅	innate to the noun
strong/weak inflection	∅	depends on the particular setting of definite/indefinite article, number and case within the NP
case	∅	depends on the syntactic function of the NP (→ semantic dimension)

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Feature prediction:
CRF sequence models trained on local context information

Wapiti toolkit: Lavergne et al. (2010)

Markup for Feature Prediction

- The markup helps to predict inflectional features
- Markup sets values which are propagated over the phrase
  - *add markup* for features that are innate or given by the source-side
  - *no markup* for features that entirely depend on target-side context

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			markup
noun	Apfel<+NN><**Masc**><**Sg**>	*apple*	gender, number
adjective	lustig<+ADJ><Pos>	*funny*	∅
article	die<+ART><Def>	*the*	∅
preposition	in<APPR><**Dat**>	*in*	case (positional vs. directional)
verb	kauft<VVFIN>	*buys*	fully inflected

Process of Inflection Prediction

English input … these buses may have access to that country …

SMT output with markup	**predicted features**	**inflected forms**	**gloss**
solche<+INDEF><Pro>			such
Bus<+NN><Masc><Pl>			buses
haben<VAFIN>			have
dann<ADV>			then
zwar<ADV>			though
Zugang<+NN><Masc><Sg>			access
zu<APPR><Dat>			to
die<+ART><Def>			the
betreffend<+ADJ><Pos>			respective
Land<+NN><Neut><Sg>			country

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haben<VAFIN>	haben<V>			have
dann<ADV>	ADV			then
zwar<ADV>	ADV			though
Zugang<+NN><Masc><Sg>	NN-Masc	Sg		access
zu<APPR><Dat>	APPR-Dat			to
die<+ART><Def>	ART			the
betreffend<+ADJ><Pos>	ADJA			respective
Land<+NN><Neut><Sg>	NN-Neut	Sg		country

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Zugang<+NN><Masc><Sg>	NN-Masc.Acc.Sg.St	**Zugang**	access
zu<APPR><Dat>	APPR-Dat	zu	to
die<+ART><Def>	ART-Neut.Dat.Sg.St	**dem**	the
betreffend<+ADJ><Pos>	ADJA-Neut.Dat.Sg.Wk	**betreffenden**	respective
Land<+NN><Neut><Sg>	NN-Neut.Dat.Sg.Wk	**Land**	country

Results: Inflection Prediction

- English–German phrase-based SMT system (MOSES)
- 4.5M parallel sentences, 5-gram language model of 45M sentences

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	news'14	**news'15**	**news'14**	**news'15**
Surface	19.17	20.86	19.03	20.80
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- Similar results in other domains (e.g. medical domain)
- BLEU is not an ideal measure: evidence that BLEU underestimates performance in WMT human evaluation

Example: Inflection Prediction

Input	in particular , the actresses play a major role in the sometimes rather dubious staging .
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- Stemmed language model representation:
  `fragwürdig[ADJ] Inszenierung<Fem><Sg>[NN]`

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- Nominal vs. verbal inflection
  - SMT: only modeling of nominal inflection verbal inflection in this setting is very difficult Ramm et al. (2016)
  - NMT: both nominal and verbal inflection better capturing of global sentence context enables verbal inflection

Inflection prediction: NMT

- Inflection prediction in NMT generally works Tamchyna et al. (2017)
  - English → Czech
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  - → this language pair is of current interest, but rather difficult ...
- Currently ongoing work: modeling word formation in NMT
  - abstract lemma-tag representation provides a sound basis to integrate further linguistic information
  - learn word-formation processes across languages
  - → later in this talk ...

Outline

Reducing the complexity of words: overview

- Translating *compounds* in SMT
  - Splitting compounds on the source side — Koehn and Knight (2003)
  - Modeling compounds on the target side — Cap et al. (2014)

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  - Linguistically informed segmentation approaches
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- Transparent vs. semantically opaque compounds
  → we assume that compounds are transparent ...

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- Splitting options for *Aktionsplan* (*plan for action*)

  aktionsplan
  aktion plan
  aktions plan
  akt ion plan

  → all parts have been observed in the training data

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aktion (960) – plan (710)	*action – plan*	825.6
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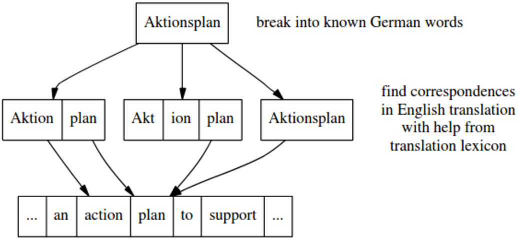

Figure 2: Acquisition of splitting knowledge from a parallel corpus: The split *Aktion–plan* is preferred since it has most coverage with the English (two words overlap)

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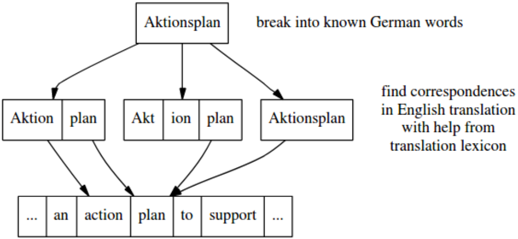

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⇒ Improved splitting precision

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$\Rightarrow$ Improved splitting precision

Source-side compound splitting in SMT: results

- System variants (English → German):

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- Word-based translation

Method	BLEU
raw	0.291
eager	0.222
frequency based	**0.317**
using parallel	0.294
using parallel and POS	0.306

Phrase-based translation

Method	BLEU
raw	0.305
eager	**0.344**
frequency based	**0.342**
using parallel	0.330
using parallel and POS	0.326

taken from Koehn et al. (2003)

Compound splitting in SMT

- So far: compound splitting on the source side
  split compounds: intermediate representation

- How to generate compounds on the target side?
  more difficult: need to generate correctly inflected compounds

Generating target-side compounds in SMT

- How to generate (new) compounds? Cap et al. (2014)

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- Generation and inflection of compounds
  - generate the correct surface form
  - find the correct inflection (→ combine with inflection-prediction system)

Compound representation

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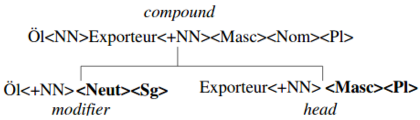

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  compound
  Öl<NN>Exporteur<+NN><Masc><Nom><Pl>

  Öl<+NN>**<Neut><Sg>** — Exporteur<+NN> **<Masc><Pl>**
  modifier — *head*

- Representation of modifier and head is the same
  - all components are accessible during training
  - all components can be merged into "new" and "old" compounds

    Haus<+NN><Neut><Sg> + *Boot<+NN><Neut><Pl>*
    → *Haus<NN>Boot<+NN><Neut><Pl>* (merged)

Examples taken from Cap et al. (2014)

Compound merging: when to merge

- How to decide what words to merge? Just merge adjacent nouns?

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merge	ein erhöhtes verkehrs aufkommen sorgt für chaos an increased traffic volume causes chaos (S...(NP(DT an)(VN increased (NN traffic) (NN volume)) ...)
don't merge	für die finanzierung des verkehrs aufkommen pay for the financing of transport (VP(V pay)(PP(IN for)(NP(NP(DT the)(NN financing))(PP(IN of) (NP(NN transport)...))

Compound generation and inflection

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- Use inflection prediction system (Fraser et al. 2012)
  to inflect the entire text

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- No improvement in BLEU over inflection-prediction baseline
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- Examples for compound translations

reference	English source	UNSPLIT baseline		STR	
Teddybären	teddy bear	4b	Teddy tragen (Teddy, to bear)	1a	Teddybären (teddy bear)
Emissionsreduktion	emissions reduction	3b	Emissionen Reduzierung (emissions, reducing)	3a	Emissionsverringerung (emission decrease)
Geldstrafe	fine	4b	schönen (fine/nice)	3a	Bußgeld (monetary fine)
Tischtennis	table tennis	2b	Tisch Tennis (table, tennis)	4a	Spieltischtennis (play table tennis)
Kreditkartenmarkt	credit-card market	2b	Kreditkarte Markt (credit-card, market)	4a	Kreditmarkt (credit market)
Rotationstempo	rotation rate	2b	Tempo Rotation (rate, rotation)	4a	Temporotation (rate rotation)

Table 6: Examples of the detailed manual compound analysis for **UNSPLIT** and **STR**.

taken from Cap et al. (2003)

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Reducing the vocabulary size with BPE

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- Obtained segmentation is often not lingusitically optimal

  Forschungsinstituten (*research institutes*)

  Forschungs|*instituten* vs. *Forsch*|*ungsinstitu*|*ten*

Linguistically informed segmentation

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- Better open vocabulary translation
  - generation of new compounds or morphological variants (stem+suffix)
  - better learning of word formation processes
    through linguistic segmentation

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suffixes
-e, -em, -en, -end, -enheit, -enlich, -er, -erheit, -erlich, -ern, -es, -est, -heit, -ig, -igend, -igkeit, -igung, -ik, -isch, -keit, -lich, -lichkeit, -s, -se, -sen, -ses, -st, -ung

Set of suffixes from Huck et al. (2017)

Examples: relations between English and German suffixes

-los with consistent English counterpart *-less*
taktlos – tactless
reglos – motionless
rastlos – restless
schamlos – shameless
German participles ending with *-end*
hängend – hanging
stehend – standing
schlafend – sleeping
lachend – laughing

Examples from Huck et al. (2017)

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prefixes
ab-, an-, anti-, auf-, aus-, auseinander-, außer-, be-, bei-, binnen-, bitter-, blut-, brand-, dar-, des-, dis-, durch-, ein-, empor-, endo-, ent-, entgegen-, entlang-, entzwei-, epi-, er-, extra-, fehl-, fern-, fest-, fort-, frei-, für-, ge-, gegen-, gegenüber-, grund-, heim-, her-, hetero-, hin-, hinter-, hinterher-, hoch-, homo-, homöo-, hyper-, hypo-, inter-, intra-, iso-, kreuz-, los-, miss-, mit-, mono-, multi-, nach-, neben-, nieder-, non-, pan-, para-, peri-, poly-, post-, pro-, prä-, pseudo-, quasi-, schein-, semi-, stock-, sub-, super-, supra-, tief-, tod-, trans-, ultra-, um-, un-, unab-, unan-, unauf-, unaus-, unbe-, unbei-, undar-, undis-, undurch-, unein-, unent-, uner-, unfehl-, unfort-, unfrei-, unge-, unher-, unhin-, unhinter-, unhoch-, unmiss-, unmit-, unnach-, unter-, untief-, unum-, ununter-, unver-, unvor-, unweg-, unwider-, unzer-, unzu-, unüber-, ur-, ver-, voll-, vor-, voran-, voraus-, vorüber-, weg-, weiter-, wider-, wieder-, zer-, zu-, zurecht-, zurück-, zusammen-, zuwider-, über-

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- BPE benefits from the linguistic segmentation
  - inflectional suffixes already split off:
    no more arbitrary splitting of the last characters
  - compound/prefix splitting:
    meaningful sub-word units provide a better basis for BPE splitting

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  - target-side segmentation needs to be reversible in post-processing: introduce special markup

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- Experimental results:
  Improved translation quality with +0,5 BLEU and −0.9 TER
  for English→German translation

Morphologically guided segmentation

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- Morphological analysis on source side and target side
- Comparison of translating lexically close and distant languages
  - English–Hindi, English–Bengali, Bengali–Hindi
  - Linguistically distant language-pairs: Morfessor-based segmentation is better than BPE
  - Linguistically close language-pairs: BPE is better
  - Combined segmentation of Morfessor and BPE is best

Outline

Modeling word formation in NMT

- Lack of generalization in word-level approaches to NMT at the level of inflectional variants and derivations of shared word stems
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  ungovernability $\leftrightarrow$ *Unregierbarkeit*

  un_{PREF} $govern_{V}$ $able_{SUFF-ADJ}$ $ity_{SUFF-NOUN}$

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- Sound morphological processing:
  - better generalization on the word-level and morpheme-level
  - model processes such as compounding and derivation
  - enables the generation of new words

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  - transitional elements: *Grenz|kontroll|politik* → *Grenze, Kontrolle*
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- Segmentation strategy that takes into account fusional morphology
  - implementing an English morphological analyzer
  - exploiting an existing tool for German

⇒ Obtain a consistent linguistics-informed sub-word representation

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word	**analysis**
conspiracy	conspire|V acy|SUFF/N/e
conspiratorial	conspire|V ator|SUFF/N/e ial|SUFF/ADJ/-
conspirator	conspire|V ator|SUFF/N/e
conspire	conspire|V
acquire	acquire|V
acquisition	acquire|V ition|SUFF/N/s→re
acquisitive	acquire|V itive|SUFF/ADJ/s→re
acquisitiveness	acquire|V itive|SUFF/ADJ/s→re ness|SUFF/N/-

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Word	*atomwaffenfrei*
SMOR	Atom<NN>Waffe<NN>frei<+ADJ>
	nuclear weapon free
Word	*Forschungsergebnis*
SMOR	forschen<V>ung<NN><SUFF>Ergebnis<+NN>
	research result
Word	*gefährlich*
SMOR	Gefahr<NN>lich<SUFF><+ADJ>
	danger -ous

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EN Morph-Markup-Split
enthusiasm <N> tic<SUFF_ADJ> ally<SUFF_ADV> explode <V> ion<SUFF_N>

EN Morph-noMarkup-Split
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- Non-split morphological analyses: enables BPE splitting
  into valid and existing sub-words

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	Source (EN)	Target (DE)	Small (250k)	Medium (1M)	Large (2M)	Larger (4M)
1	plain	plain	21.77	26.60	28.66	33.71
2	plain	oldLemTag	22.25	26.96	28.87	33.97
3	plain	LemTag	22.47	27.05	28.61	33.90
4	LemTag	LemTag	23.32	27.36	28.88	34.28
5	LemTag	LemTagSplit	22.55	27.22	29.07	34.21
6	LemTag Markup-Split	LemTag	21.85	26.90	29.33	33.96
7	LemTag noMarkup-Split	LemTag	22.86	27.05	29.20	34.10
8	LemTag noMarkup-noSplit	LemTag	22.82	27.18	29.18	34.12
9	LemTag Markup-Split	LemTagSplit	22.25	27.12	29.39	34.38
10	LemTag noMarkup-Split	LemTagSplit	22.53	26.90	29.10	34.12
11	LemTag noMarkup-noSplit	LemTagSplit	23.23	27.55	29.42	34.19

- Improvements over standard lemma-tag system
- Best system variants: morphological analysis on source and target side

Translation experiments: example

- Example from the medical domain (Large 4M setting):

Input	normally involves coagulation tests on the patient's blood.
Surface	beinhalten normalerweise Coagulationstests am Blut des Patienten.
Morph	handelt es sich in der Regel um Gerinnungstests am Blut des Patienten.
Ref	beinhaltet normalerweise Gerinnungstests der Blut des Patienten.

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- Segmentation of *coagulation* (f=19) and *coagulate* (f=3)

Surface (BPE)	Morph. System (morph + BPE)
co@@ ag@@ ulation	co@@ ag@@ ulate ion<SUFF_N>
co@@ ag@@ ulate	co@@ ag@@ ulate

  - even with BPE splitting: better generalization
  - enables matches between *coagulate* and *coagulation* (and other inflected variants: *coagulates*, *coagulated*, ...)

Recap: inflection and segmentation strategies

- Methods to model inflectional morphology for SMT and NMT
  - generally successful ...
  - inflection-prediction: basis for target-side linguistic modeling
  - target-side compound generation, modeling word formation
  - modeling complement types: subcategorization and choice of prepositions Weller-Di Marco et al. (2016)

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- Segmentation approaches with varying degrees of complexity
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- Potential problems
  - at least to some extent language-specific
  - resource-intensive: requires morphological annotation tools, parsers, ...
  - morphological analysis is error prone → errors in translation

Outline

Compositional representation of morphologically-rich input

- Replace source-language embeddings with a bi-directional RNN that generates compositional representations of the input

Ataman et al. (2018)

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- Composition to learn morphology and lexical meaning in a bilingual context
- Composition layer computes final input representation passed to the encoder to generate translations

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- Obtain input representation from composing smaller units, such as character n-grams
- Composition to learn morphology and lexical meaning in a bilingual context
- Composition layer computes final input representation passed to the encoder to generate translations
- Avoids explicit and potentially sub-optimal segmentation

Compositional representation of morphologically-rich input

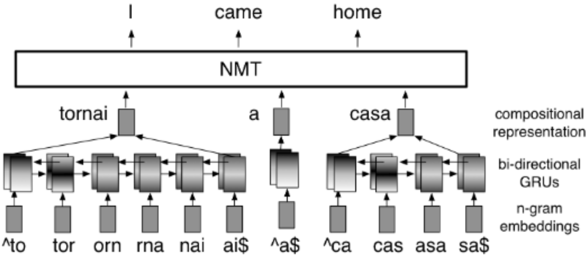

Figure 1: Translation of the Italian sentence *tor-nai a casa* (*I came home*) with a word-level representation composed from character trigrams.

Taken from Ataman et al. (2018)

Languages and Results

- Experiments with five languages from different morphological typologies in a low-resource setting (translating into English)

Language	Morphological Typology	Morphological Complexity
Turkish	*Agglutinative*	*High*
Arabic	*Templatic*	*High*
Czech	*Fusional, Agglutinative*	*High*
German	*Fusional*	*Medium*
Italian	*Fusional*	*Low*

Table 1: The languages evaluated in our study and their morphological characteristics.

Language Pair	# tokens Src	# tokens Tgt	# types Src	# types Tgt
Tr - En	2,7M	2,0M	171K	53K
Ar - En	3,9M	4,9M	220K	120K
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Table 2: Sizes of the training sets and vocabularies in the TED Talks benchmark. Development and test sets are on average 50K to 100K tokens. (*M*: Million, *K*: Thousand.)

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- Results: compositional models improve over simple BPE models
- Best setting: character trigrams as input symbols and words as final input representation

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Modeling syntax in machine translation

- Different syntactic structures are hard to capture in machine translation

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  NMT: can capture long-distance relations, but can still benefit from syntactic information
- SMT: reordering as pre-processing Collins et al. (2005)
- Syntactic information in NMT
  - Modeling target syntax through CCG tags Nadejde et al. (2017)
  - More strategies to model Syntax in NMT

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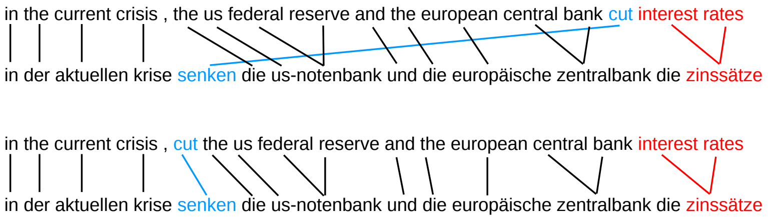

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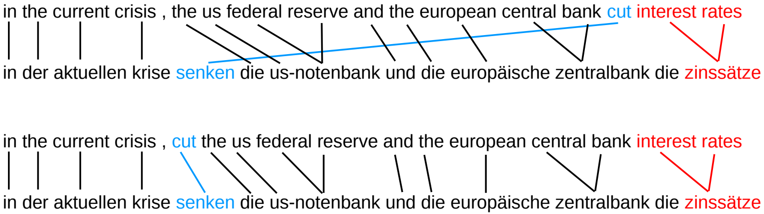
Colins et al. (2005)



- Source-side reordering typically leads to improvements in BLEU

Modeling target syntax through CCG tags

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  - sequences of CCG-tag word pairs
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- CCG tags provide global syntactic information
  - subcategorization information
  - attachment
  - tense/morphological aspects of a word in its context

Interleaving with CCG tags: example

Source-side

BPE:	Obama	receives	Net+	an+	yahu	in	the	capital	of	USA
IOB:	O	O	B	I	E	O	O	O	O	O
CCG:	NP	((S[dcl]\NP)/PP)/NP	NP	NP	NP	PP/NP	NP/N	N	(NP\NP)/NP	NP

Target-side

NP Obama ((S[dcl]\NP)/PP)/NP receives NP Net+ an+ yahu PP/NP in NP/N the N capital (NP\NP)/NP of NP USA

Figure 1: Source and target representation of syntactic information in syntax-aware NMT.

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Figure 1: Source and target representation of syntactic information in syntax-aware NMT.

- There are two PPs with different attachment possibilities
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- There are two PPs with different attachment possibilities
  - *in* → *Netanyahu* or *receives*?
  - *of* → *capital* or *Netanhayu* or *receives*?
- Disambiguation through suptertags
  - *((S[dcl]\NP)/PP)/NP* of *receives* indicates that *in* attaches to the verb
  - *(NP\NP)/NP* of *of* indicates that it attaches to *capital*

Interleaving with CCG tags: results

- German → English and Romanian → English
  - improvement for both language pairs with target-side CCG annotation
  - no CCG tags available for DE/RO:
    additional source-side annotation with dependency labels:

    small improvement for German → English
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- Observation: large improvements for longer sentences involving syntactic phenomena such as subordinated clauses and PP attachment

More strategies to model syntax in NMT

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- String-to-Tree translation Aharoni et al. (2017)
  - propose translation into a serialized constituency tree
  - mixed results for German → English translation using large data
  - consistent improvement for a low-resource setting
    for DE-EN, RU-EN, CS-EN

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- Tree-to-Sequence Attentional Neural Machine Translation Eriguchi et al. (2016)
  - propose using a parse tree on the source side to guide the attention model
  - improvements for English–Japanese translation

More strategies to model syntax in NMT

- Graph Convolutional Encoders for Syntax-aware NMT

  Bastings et al. (2017)

  - GCNs use source-side syntactic dependency trees to produce representations of words
  - improvements for English-German and English-Czech

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- Incorporating Source Syntax into Transformer-Based NMT

  Currey et al. (2019)

  - propose to incorporate constituency parse information
  - leverage linearized parses of the source training sentences
  - multi-task model with a shared encoder/decoder: translate and parse
  - translating from English into 20 languages in low-resource settings: consistent improvements using the multi-task setup
  - no improvements for large-scale settings

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- Brief look into incorporating syntactic information

- Integrating linguistic information can lead to improvements on many levels

Thank you!

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