How hard is it to automatically translate phrasal verbs from English to French?

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Outline

- Why are phrasal verbs hard to translate?
 Definitions
 Characteristics
 Scope and goals
- 2 How to measure translation quality? Evaluation protocol Annotation
- 3 How hard is it to automatically translate phrasal verbs? Experimental setup Results
- Wrapping up

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Phrasal verbs (PVs)

Main verb + prepositional or adverbial particle

take + on or away = $take \text{ on } \implies take \text{ on } a \text{ challenge}$ $take away \implies I \text{ take away your books}$

Examples

take off, give up, pull out, pick up, make up, sort out

Why phrasal verbs?

- Frequent type of MWE in (spoken) English [Sinclair, 1989]
- Complex syntactic and semantic behaviour
- Language asymmetries (take off \implies décoller)

Syntactic characterisation

Intransitive

she will show up later, the aircraft takes off

Transitive

Joint: we made up this story, he took off his shoes **Split**: we made this story up, he took them off

- Verb-particle constructions: put off, give up, move on
- Prepositional verbs: talk about, rely on, wait for

Semantic characterisation [Bolinger, 1971]

Compositionality range

- Literal or compositional: take away
- Aspectual or semi-idiomatic: fix up
- Idiomatic: pull off

Senses

- figure out, look up: 1 WN sense
- pick up: 16 WN senses
- break up: 19 WN senses

Our focus

Split transitive phrasal verbs

Verb + NP + Particle

Examples

take your clothes off, give it up, pull things out

- Word-based SMT [Brown et al., 1993] \rightarrow phrase-based SMT [Koehn et al., 2003] \rightarrow hierarchical SMT [Chiang, 2007]
- SMT can deal with some types of (contiguous) MWEs
- Intuitively, split PVs are hard to model

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Our goals

Investigate the following questions:

- What proportion of split phrasal verbs is translated correctly/acceptably by current SMT paradigms?
- Which SMT paradigm, phrase-based or hierarchical, can better handle these constructions?
- What are the main factors that influence translation quality?



Our hypotheses

- H1 Current SMT systems cannot translate PVs correctly
- H2 Hierarchical models provide better translations than phrase-based models
- H3 The quality of PV translation is determined mainly by their frequency in training data



Our experiments

- 1 Train two standard English-French SMT systems
 - phrase-based system (PBS)
 - hierarchical system (HS)
- 2 Translate a set of English sentences containing split PVs
- 3 Manually annotate PV translation quality



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Translation quality

How to measure translation quality of a specific linguistic phenomenon inside the sentence?

- BLEU, NIST, Meteor no insight into errors
- Manual annotation
 - Specific test set
 - 2 Carefully designed annotation guidelines
 - 3 Interface to highlight the target context

1) Test set selection

- **1 Automatic extraction**: Parsing with RASP + mwetoolkit
 - VERB: POS starts with VV
 - OBJECT: sequence of 1 to 5 words, excluding verbs
 - PARTICLE: POS is II, RR or RP and depends on the verb with NCMOD_PART relation
- **2** Filtering heuristics
 - Particles about, well, at
 - Verbs go, walk, do, see + locative words
 - Locative words + here, there, way
 - Verbs with double particles
 - Expressions upside down, inside out, all over
 - Long sentences (> 50 words)
- Manual validation



2) Annotation guidelines I

- Source and target (no reference) containing 1 PV
- Annotation data:
 - 250 similar PV translations once
 - 500 different PV translations consecutively in random order
- Highlight PV and its translation
- http://cameleon.imag.fr/xwiki/bin/view/Main/ Phrasal_verbs_annotation

2) Annotation guidelines II

Adequacy

Extent to which the meaning of the English PV is preserved in the French translation

- 3 FULL
- 2 PARTIAL
- 1 NONE
- 0 UNABLE TO JUDGE

2) Annotation guidelines III

Fluency

Grammatical correctness in French of the translated PV (regardless of meaning)

- 4 FLUENT
- 3 NON-NATIVE
- 2 DISFLUENT
- 1 INCOMPREHENSIBLE

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3) Annotation interface - BLAST [Stymne, 2011]



Annotation process

- 750 sentences, 4 annotators
- Proficient in English and French
- Access to Wordnet and online dictionaries
- Fluency and adequacy annotated in two passes



Inter-annotator agreement

- Pilot dataset of 156 sentences, 5 annotators
- *Fluency*: $\kappa = 0.50$
- Fluency pairwise: $\kappa = .33$ to $\kappa = .72$
- *Adequacy*: *κ* = .35
- Adequacy pairwise: $\kappa = .23$ to $\kappa = .52$



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Training and test data

English-French TED Talks parallel corpus [Cettolo et al., 2012]¹

	# sentences		
	Sys. 1	Sys. 2	
Shared training set	137,319	137,319	
PVs training set	1,034	1,037	
Shared dev. set	2,000	2,000	
PVs test set	1,037	1,034	
Total	141,390	141,390	

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¹https://wit3.fbk.eu/

Machine translation systems

Phrase-based system (PBS) and Hierarchical system (HS)

- Moses toolkit [Koehn et al., 2007], standard training parameters²
- Word-alignment: GIZA++
- Phrase table extraction: grow-diag-final heuristic
- Language model: 5-grams, IRSTLM, monolingual part of training corpus
- Tuning: MERT
- Print out alignment information

How hard is it to automatically translate PVs from English to French

Sanity check

Compare with Google Translate - automatic metrics

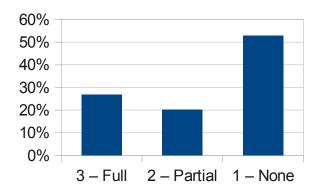
BLEU			TER		
PBS	HS	Google	PBS	HS	Google
29.5	25.1	32.3	52.6	55.7	50.3

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Translation examples

	could boil this poem down to saying
PBS	pourriez furoncle ce poème jusqu' à dire
HS	pourriez bouillir ce poème descendu à dire
	he would think it through and say
Both	il pense que ça à travers et dire
	you couldn 't figure it out
HS	vous ne pouvais pas le comprendre
PBS	vous ne pouviez pas le découvrir
	Then we 'll test some other ideas out
Both	puis nous allons tester certains autres idées

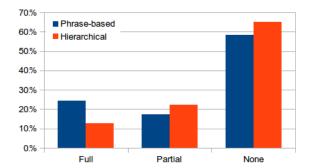
Finding 1: both systems are quite bad



Distribution of annotations - adequacy

Finding 2: PBS is better than HS

	Overall	PBS	HS	PBS-Diff.	HS-Diff.
Fluency (1-4) Adequacy (1-3)		2.67 1.75		2.63 1.65	2.25 1.48



Why does the HS perform poorly?

- Some hypotheses
 - Insufficient training material
 - Standard parameters are inadequate
 - In the PBS, generally 2 bi-phrases are enough (make up, make it up)

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Finding 3: similar translations are better

Similar	Different
2.82	2.44
2.07	1.56
	2.82

Finding 4: frequency is not the only explanation

Kendall τ rank correlation between PV's average translation quality and:

	Adequacy		Fluency	
	PBS	HS	PBS	HS
Frequency split	0.173	0.203	0.168	0.260
Frequency joint	0.125	0.096	0.197	0.166
Verb-particle distance	0.073	0.061	0.083	0.151

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Wrapping up

Contributions

- A reusable pipeline to build test set (RASP + mwetk + filter)
- An evaluation protocol including detailed guidelines
- A systematic evaluation of EN-FR split PV translation



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Main contribution

Even though SMT is a mature framework, flexible constructions like PVs cannot be modelled appropriately



Moving on

- Improve base SMT systems (larger corpora)
- Develop better automatic PV identification
- Conceive clearer guidelines, annotator training, ranking task
- Investigate why the HS performs poorly
- Investigate why PV translation is poor
- Extend to other types of PVs (joint instances, double particles)
- Extend to other types of MWEs (idioms, support-verb constructions)



Thank you! Questions?

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Datasets available at http://cameleon.imag.fr/xwiki/bin/view/Main/Phrasal_verbs_annotation

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