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Incorporating target language semantic roles into a string-to-tree translation model

Key words: Machine translation; Semantic role; Syntax tree; String-to-tree model

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Motivation

- The string-to-tree model is one of the most successful syntax-based statistical machine translation models.
- Because of a lack of semantic information, the string-to-tree model often produces translation with semantic role confusion.
- Semantic roles tend to agree better between two languages than syntactic structures and constitute the skeleton of a sentence.
- We try to merge semantic roles with syntax information into one string-to-tree model, so that it can learn and choose better translation rules.

Main idea

- In natural language sentences, a syntactic structure often undertakes a semantic role.
 - A noun phrase may be a role of ARG0 (agent) or ARG1 (patient).
 - Syntactic structures can be the child node of a semantic argument in a tree.
 - Translation systems can learn which syntactic structure often takes which semantic role, and how to order the semantic chunks.

Main idea

- Furthermore, semantic roles often show some hierarchical structure:
 - a predicate and its arguments become one argument of another predicate;
 - the predicate *get* and its arguments, *ARG0 you* and *ARG1 it*, constitute the *ARGM-TMP* argument of the predicate *run*;
 - This hierarchy inspires us to build a structure-like parse tree, which can help us understand the semantic relations among the chunks and improve translation performance.

(a): When [ARG0 you] [TARGET get] [ARG1 it], run at top speed to buy a SLR.

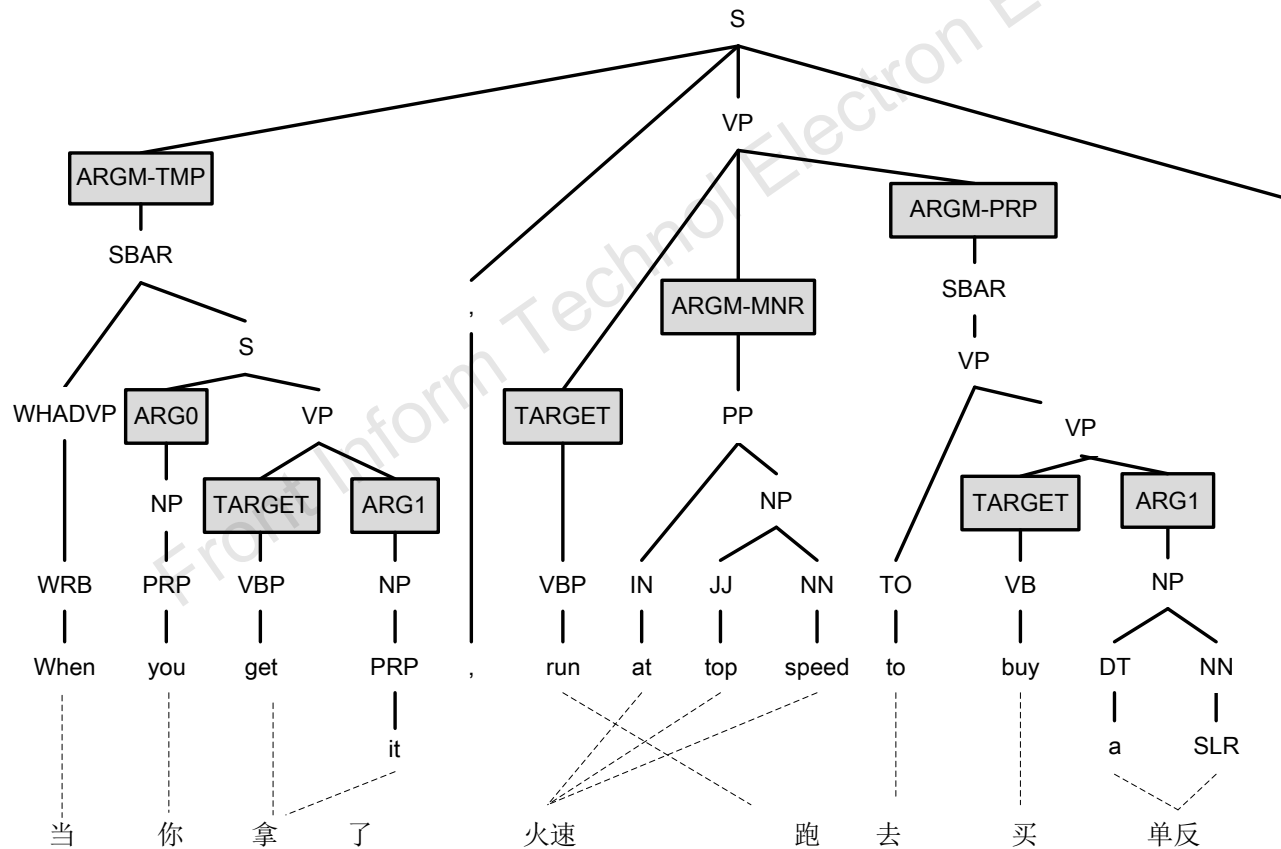
(b): [ARGM-TMP When you get it], [TARGET run] [ARGM-MNR at top speed] [ARGM-PRP to buy a SLR].

(c): When you get it, run at top speed to [TARGET buy] [ARG1 a SLR].

Fig. 1 A sample SRL result for an English sentence

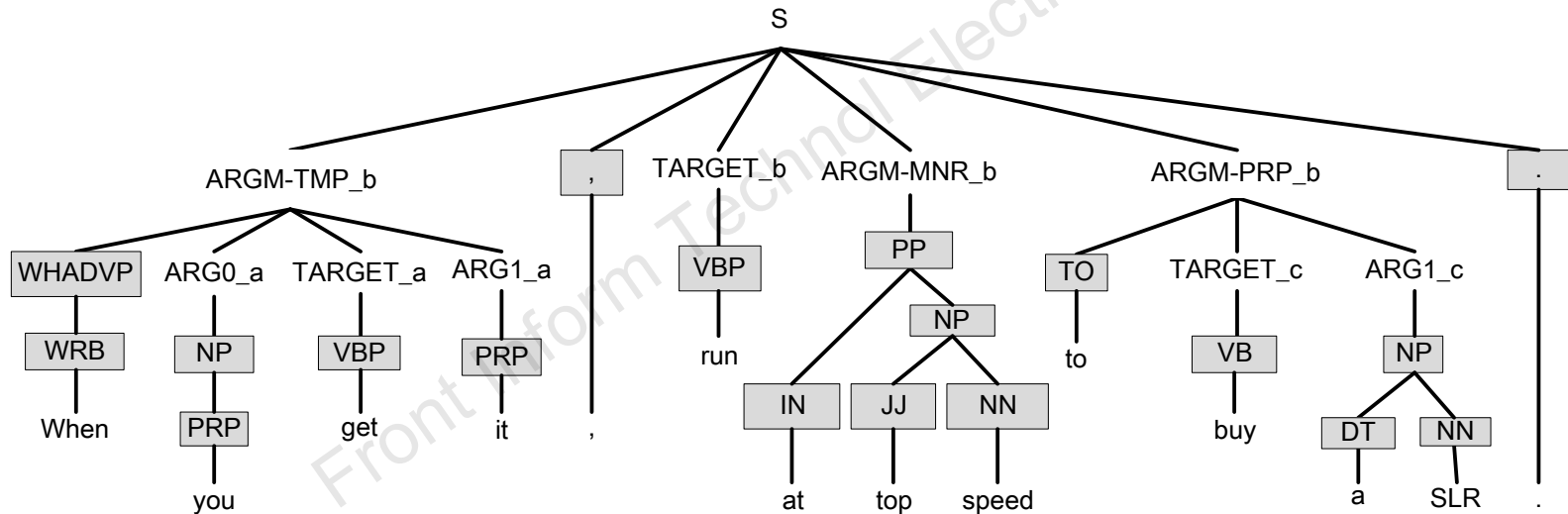
Method

1. Constructing the syntax-role tree



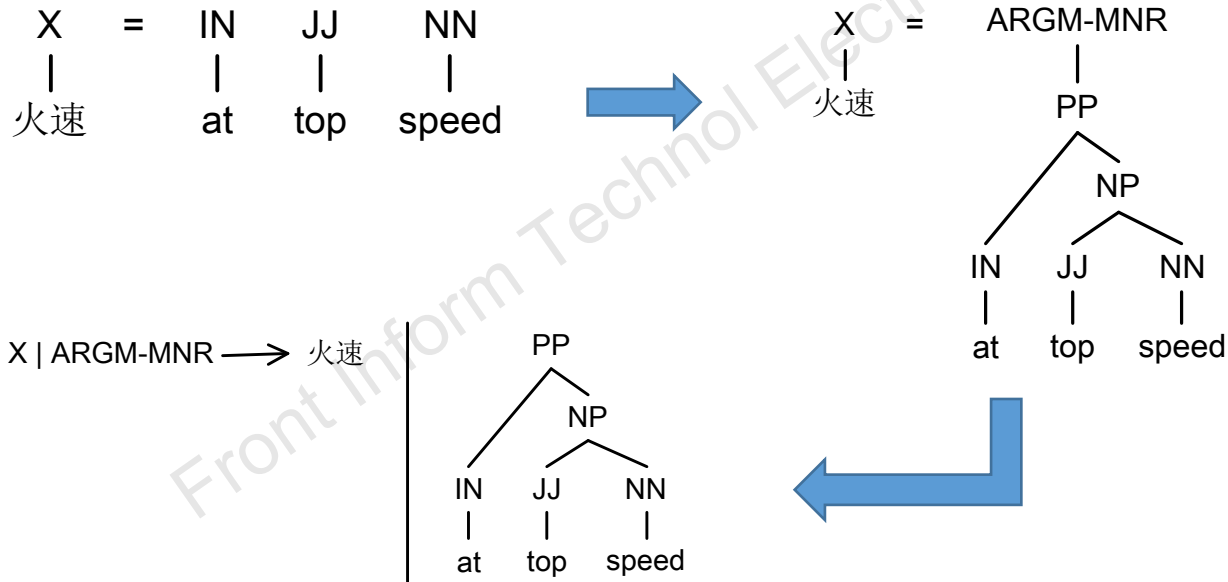
Method (Cont'd)

2. Constructing the role-syntax tree



Method (Cont'd)

3. Learning translation rules



Experimental setup

- Training corpora: BOLT, FBIS, and large-scale data
- Tuning set: NIST MT02
- Test sets: NIST MT03, MT04, MT05, MT06 (NIST), MT08, MT12 (general), and MT08-12 (progress)
- Parsing: Berkeley parser
- SRL tool: ASSERT
- Word-align tool: Mgiza
- LM: 5-gram

Major results

- Both SRT and RST outperform the baseline on the BOLT spoken corpus.

Table 2 Experimental results on the BOLT corpus

Method	BLEU score	Meteor score
Str2tr	13.29	22.52
SRT	13.85* (+0.56)	23.14* (+0.62)
RST	13.51 (+0.22)	22.73 (+0.21)
Phb	14.17	23.25

Major results (Cont'd)

- In terms of the FBIS news corpus, SRT performs better than RST and exhibits an improvement of 1.33 BLEU points.

Table 3 Experimental results on the FBIS corpus

Test set	BLEU score (%)				Meteor score (%)			
	Str2tr	SRT	RST	Phb	Str2tr	SRT	RST	Phb
MT03	28.83	30.35* (+1.52)	29.29 (+0.46)	29.57	28.20	28.71* (+0.51)	28.01 (-0.19)	28.84
MT04	31.33	33.15*# (+1.82)	31.87* (+0.54)	31.46	29.31	30.11*# (+0.80)	29.53* (+0.22)	29.97
MT05	28.27	29.92*# (+1.65)	28.69 (+0.42)	28.33	28.66	29.26* (+0.60)	28.62 (-0.04)	29.47
MT06	27.76	29.27*# (+1.51)	28.32* (+0.56)	28.72	27.03	27.97* (+0.94)	27.20 (+0.17)	28.10
MT08	22.27	22.71*# (+0.44)	21.76 (-0.51)	22.11	24.09	24.40* (+0.31)	23.59 (-0.50)	24.37
MT08-12	21.12	22.39*# (+1.27)	21.00 (-0.12)	21.84	23.82	24.35* (+0.53)	23.26 (-0.56)	24.57
MT12	20.57	21.68*# (+1.11)	20.79 (+0.22)	21.00	22.90	23.34 (+0.44)	22.81 (-0.09)	23.45
Average	25.74	27.07 (+1.33)	25.96 (+0.22)	26.14	26.29	26.88 (+0.59)	26.15 (-0.14)	26.97

* and # denote that the result is significantly better than those of Str2tr and Phb, respectively (at significance level $p < 0.01$)

Major results (Cont'd)

- In terms of large-scale data, both SRT and RST beat the baseline. RST shows an improvement of 1.13 BLEU points.

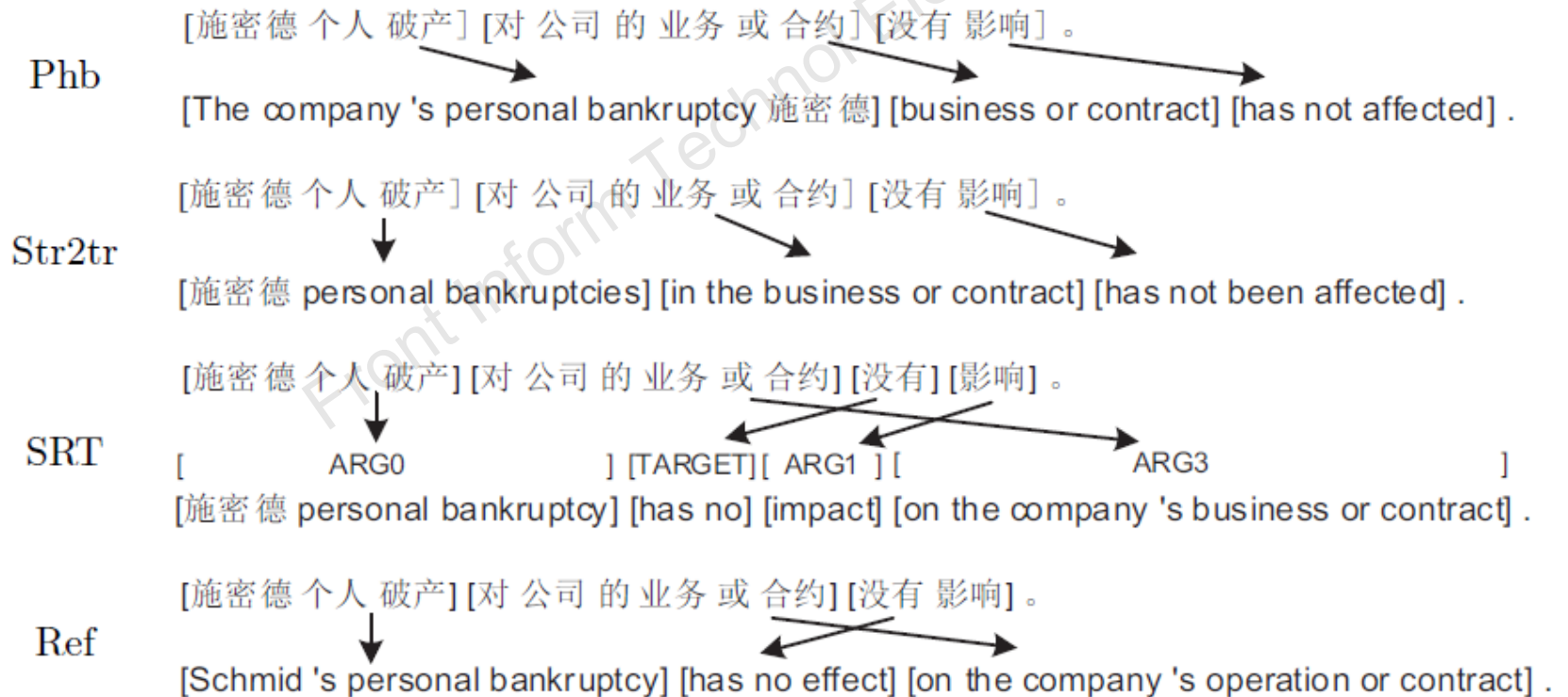
Table 4 Experimental results on the large-scale corpus

Test set	BLEU score (%)				Meteor score (%)			
	Str2tr	SRT	RST	Phb	Str2tr	SRT	RST	Phb
MT03	31.80	33.74 [*] (+1.94)	34.26^{*#} (+2.46)	33.50	30.55	30.92 [#] (+0.37)	31.50^{*#} (+0.95)	30.64
MT04	34.29	35.60 ^{*#} (+1.31)	36.28^{*#} (+1.99)	34.79	31.20	31.57 [#] (+0.37)	32.13^{*#} (+0.93)	31.09
MT05	33.19	34.24 [*] (+1.05)	34.73^{*#} (+1.54)	33.92	31.55	31.51 (-0.04)	32.41^{*#} (+0.86)	31.56
MT06	32.85	32.89 [#] (+0.04)	33.28[#] (+0.43)	31.93	29.76	29.75 [#] (-0.01)	30.28^{*#} (+0.52)	29.15
MT08	26.11	26.32[#] (+0.21)	26.29 [#] (+0.18)	23.99	26.48	26.61 [#] (+0.13)	26.84[#] (+0.36)	25.39
MT08-12	25.34	25.13 [#] (-0.21)	25.39[#] (+0.05)	24.06	26.32	26.20 [#] (-0.12)	26.60[#] (+0.28)	25.70
MT12	22.88	23.72 [*] (+0.84)	24.08^{*#} (+1.20)	23.48	24.89	25.15 [#] (+0.26)	25.44^{*#} (+0.55)	24.94
Average	29.49	30.23 (+0.74)	30.62 (+1.13)	29.38	28.68	28.82 (+0.14)	29.31 (+0.63)	28.35

* and # denote that the result is significantly better than those of Str2tr and Phb, respectively (at significance level $p < 0.01$)

Example analysis

- SRT successfully recognizes the prepositional phrase *on the company's business or contract* as an ARG3 argument and moves it to the end of sentence.



Conclusions

- We have presented an effort that uses semantic information for SMT.
- Our methods improve the translation performance in the following aspects:
 - (1) They use the semantic roles in the target language to reorder the semantic chunks in output;
 - (2) They use the hierarchy of predicate-argument structure to generate semantic chunks and gather them together.
- In future work, we will explore in detail the situations in which our models work and how to use the overlapped semantic roles dropped in this work.