Cross-lingual transfer of a semantic parser via parallel data

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Introduction

Meaning Annotation by Proxy

Inducing Lexical Items Using Word Alignments

Shift-reduce Parsing

Experiments and Results

Semantic parsing: what?

From Words to (Logical) Meaning

She likes to read books

```
x1 p1 e1

female(x1)

x2 e2

book(e2)

p1: read(e2)

Actor(e2, x1)

Theme(e2, x2)

like(e1)

Actor(e1, x1)

Topic(e1, p1)
```

DRT [Kamp, 1984]

Semantic parsing: why?

Translate to something a computer can "understand"

- commands for robots, e.g. [Dukes, 2014]
- queries for databases, e.g. [Reddy et al., 2014]
- formulas for (probabilistic) reasoners, e.g. [Beltagy et al., 2015]

Semantic parsing: how?

System for English [Curran et al., 2007]

System for other languages?



Goal

Learn (rudimentary) semantic parser from nothing but

- existing source language system (C&C+Boxer)
- parallel data
- (POS tagger for target language)

Method

- 1. meaning annotation by proxy
- 2. inducing lexical items using word alignments
- 3. shift-reduce parsing

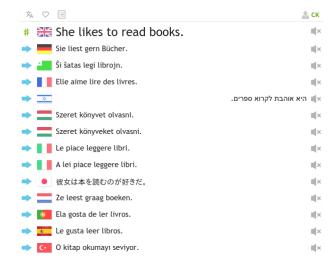
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Parallel corpus: Tatoeba.org



Automatic annotation of English sentences

She	likes	to	read	books		
NP	$\overline{(S[dcl] \setminus NP)/(S[to] \setminus NP)}$	$\overline{(S[to]\backslash NP)/(S[b]\backslash NP)}$	$\overline{(S[b]\backslash NP)/NP}$	NP		
she'	like [′]	to'	read [′]	book′ — >0		
			$S[b] \setminus NP$			
			read'@boo	~		
		$S[to]\NP$				
	to'@(read'@book')					
	like'@(to'@(read'@book'))					
S[dcl]						
	(like'@(t	e'				

Meaning annotation by proxy

(like'@(to'@(read'@book')))@she'
Ze leest graag boeken

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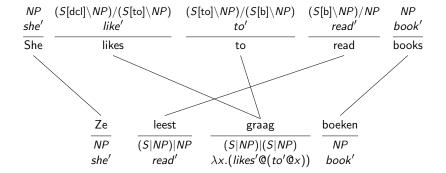
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Generating candidate lexical items

- [Zettlemoyer and Collins, 2007, Kwiatkowski et al., 2013]: hand-written lexical templates for English
- [Kwiatkowski et al., 2011]: recursively splitting gold-standard meaning representations, heuristics to constrain search space
- this work: from the English parse tree
 - use the same lexical semantics as in English
 - assign them to Dutch words, possibly one to two or two to one
 - drop category subdistinctions (dcl, b, to...)
 - · use undirected slashes

Example alignment (ideal)



Inducing Dutch lexical items

- extract one lexical item per translation unit, keep most frequent ones
- IBM model 4, all translation units from 5-best alignments in both directions
- for each word+POS, cutoff frequency is 0.1 of max

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Shift-reduce parsing

- Based on English CCG parser of [Zhang and Clark, 2011]
- Action types: shift, combine, unary, skip, finish
- Allows fragmentary parses

Forced decoding

- We have:
 - 13,122 Dutch training sentences with target semantics
 - · A CCG lexicon for Dutch
- We need:
 - Training parses for Dutch
- Solution: forced decoding with heuristic pruning based on target semantics [Zhao and Huang, 2015]
 - Training parses found for 4,038 sentences
 - Other 9,084: no parse found, or agenda explodes

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Dutch training parse (example)

Ze	leest	graag	boeken	
NP	$\overline{(S NP) NP}$	(S NP) (S NP)	NP	
she'	read'	$\lambda x.(likes'@(to'@x))$	book'	
	(${S NP) NP}$		
	$\lambda x.(likes')$	$\mathbb{Q}(to'\mathbb{Q}(read'\mathbb{Q}x)))$		
		S NP	> ₀	
	likes	'@(to'@(read'@book'))		
		S	<0	
	(likes'@(to'@(read'@book')))@book'		

Parser training

decoding

Training data: Dutch derivations obtained with forced

- ullet Averaged perceptron with beam search (b=16)
- Early update [Collins and Roark, 2004]
- Features: [Zhang and Clark, 2011]

Dealing with unknown words at test time

Pick schematic lexical entries for POS extracted from lexicon, e.g.

Introductio

Meaning Annotation by Proxy

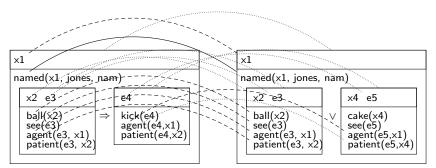
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Evaluation: graph match measure

[Allen et al., 2008, Le and Zuidema, 2012]



Evaluation: baseline and upper bound

- baseline: most frequent lexical entry/schema for each word, all unconnected
- upper bound: silver standard, unseen symbols replaced with UNKNOWN____

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Results on development test set (1,641 sentences)

	rec	prec	f1
baseline	.338	.344	.341
	260	204	070
training iterations: 0	.362	.384	.372
1	.507	.503	.505
2	.504	.510	.507
3	.508	.514	.511
4	.510	.516	.513
5	.507	.512	.510
upper bound	.962	.896	0.928

Where it goes well

NP	npers	[Will verbpressg (SNP)(SNP) Av0, Av1, Av2, (v1 @ Av3. i	p5 e6 :(v2 @ e6) }) p5: (v0 @ hv7. (v7 @ v3)) @ hv8.)	[rivet] adv (SAMP)(SAMP) AVG, Av1, Av2, (v1 @ Av3,((v0 @ Av5, (v5 @ v3]) @ v2)	[beroemd] verbpapa SNP Av0, Av1, (v0 @ Av2. (x4 :(v1 @ x4))) famous(x4) thermood, v2)	[zijn] verbprespl (SINP)(SINP) Av0, Av1, Av2, ((v0 @ v1) @ v2)
			desire(c6) agent(e6, v3) thems(e6, p5)	,5	SNP		
		(SINP)(SINP) λv0. λv1. λv2. (v1 @ λv3.	"(p6 e7 ;(v2 @ e7)))		famous(x4) theme(x4, v2)	
			p6: ((v0 @ kv8. (v8 @ v3)) @ kv0) dusine(e7) agent(e7, v3) theme(e7, p6)				
		P	5. 96 : (v1 @ e0)) 5. all famous(n0) thermole, v2) selected) (v2) semena(e0, p2)				,
	x2 person(x2) " (p5 e6 ; (v0	@ e6))					

Where it doesn't



Conclusions

- CCG suitable formalism for cross-lingual semantic parser induction
- Reasonable grammar learned Dutch
- Important areas for future work
 - Lexicon induction: tweak to get more training data
 - Treat English parses, word alignments as latent
 - Morphology
 - Lexical semantics

Interested in collaborating? Let me know!

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