Increasing Coverage of Syntactic Subcategorization Patterns in FrameNet Using Verbnet

Introduction/Problem

Supervised semantic parsers (semantic role labelers) are trained on manually annotated example sentences that illustrate syntax/semantics mappings. Sparsity of this training data limits parser performance:

- Unknown pairs of words and frames, and pairs without examples limit parser performance on unseen data to 50%. [3]
- Lexicographic examples do not allow statistical learning. FrameNet 'fulltext' corpus is small (5946 sentences) and scarcely annotated (50.5%).
- Low syntactic coverage: Non-illustrated syntax/semantics patterns. (this work)

Contribution

- We analyze the extent of the syntactic coverage problem of FrameNet lexicographic annotations on FrameNet fulltext corpora. The lexicographic annotations contain the correct syntax/semantics mapping for only 53.4% of all annotations.
- We propose a simple method to apply existing annotations to new verbs within the same frame. Our algorithm uses Verbnet to ensures syntactic compatibility of annotations.
- As the result of our method we release a comprehensive dictionary of syntax/semantics mappings that covers most verb/frame pairs. The new mappings are syntactically correct (93.8%). The corresponding example sentences and mostly semantically well-formed (78.7%).

The dictionary is available at

http://www.cs.columbia.edu/~speech/text2scene/resources.html

Sample Subcategorization Patterns and Sentences Applied to New Verbs

Frame	Subcat Mapping	Example Text (new verbs in bold)
Attaching	{ subj/Agent obj/Item dep(into)/Goal }	Data can also be pasted/ pinned into word processing documents.
Appointing	{ subj/Selector obj/Official dep(vpto)/Function}	In 893, Tsar Simeon appointed/designated Clement to be the first Slav bishop of
Grooming	{ subj/Agent dep(with)/Medium}	Ian gave Sue 's hair a good trim before shampooing/soaping with Natural Stylin
Categorization	{ subj/Cognizer obj/Item dep(as)/Category obj/Cognizer }	Rosa interpreted/stereotyped this behavior as a desire to upset her.
Cause_to_be_wet	{ subj/Agent dep(avp)/Manner obj/Undergoer }	He sucked at his cigarette and then wet/ humidified his lips distastefully.
Scrutiny	{ subj/Cognizer obj/Ground dep(pping)/Phenomenon}	I scanned/ surveyed the street for lurking strangers as I came near , and no one w
Experiencer_obj	{ subj/Stimulus obj/Experiencer }	The soundlessness of nature impressed and solaced/ beguiled her .
Cooking_creation	{ subj/Cook obj/Rcpient dep(np)/Produced_food dep(in)/Place }	Instead she set about cooking/ baking herself a suitable supper

References

- [2] Karin Kipper Schuler. Verbnet: A Broad-Coverage, Comprehensive Verb Lexicon. PhD thesis, University of Pennsylvania, 2005.

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Frameinet					
FrameNet[1] groups lexi	cal items into <i>frames</i>	\frown	Duplication		
which share contextual	structure, i.e. they	copy.v	clone.n	\setminus	
have the same set of frar	ne elements (seman-	/ duplica photoc	te.v copy.n opy.v duplicate.n		
tic roles; color-coded in t	he following sample	redupli	cate.v duplication.r	1)	
definition).		replication (run_off.	v photocopy.n		
DUDIICATION This frame involves a creator making a duplicate, the copy of some Original entity. A source the location of the Original and Goal, the location of the Copy, may be expressed. None-core frame elements: Manner Purpose Lexical items form <i>lexical units</i> with frames. Verbs in one frame are <i>semantically sim-</i> <i>ilar</i> . Example apportations illustrate syntax (semantics mappings)					
like the hebrew scriptures	which were ritually copied	by scribes	to forestall their wearin	a-out	
NP	AVP	PP	VPto		
Subj	Dep	Dep	Dep		
Original	Manner	Creator	Purpose		

Subcategorization Mappings and Coverage Analysis

For each example annotation from the FrameNet *lexicographic annotations* we extract subcategorization patterns and their mapping to frame elements (normalized to active voice).

 $\langle copy.v, Duplication \rangle$:

{subj/Creator, obj/Original, dep(AVP)/Manner, dep(VPto)/Purpose}.

We evaluate coverage of these patterns on FrameNet 1.5 *fulltext annotations*.

	#vorhs	#anno		%seen scats	
				per anno	per TR_LU
	13510	6828(50.5%)	77.6	53.4	68.9
-	-				-

#verbs = number of verbs in the corpus. #anno = number of annotated verbs. %TR_LU = perc. of annotations with any subcat pattern for lexical unit. %seen_scats = perc. of annotations with correct subcat pattern for lexical unit.

[1] Collin F. Baker, Charles J. Fillmore, and John B. Lowe. The Berkeley FrameNet Project. In COLING-ACL 1998, pages 86–90, Montréal, 1998.

[3] Alexis Palmer and Caroline Sporleder. Evaluating FrameNet-style semantic parsing : the role of coverage gaps in FrameNet. In COLING 2010, Beijing, 2010.

the diocese... ng Perm Hair Bath.

vas there.

Verbnet

Verbnet[2] groups verbs into classes, according to diathesis alternations, which are sets of possible subcategorization patterns a verb can occur in. Verbs in one class behave *syntactically equivalent*.

	bre	eak-45.1
	break	snap
	crack	splinter
	chip	fracture
	dissolve	fragment
)	rip	tear
	shatter	split

Increasing Coverage - Algorithm

The algorithm partitions verbs in each FrameNet frame into syntactic equivalence classes (equal set of Verbnet classes). Annotations can be shared safely between verbs in an equivalence class.

For instance, we wish to prevent:

- John sprayed/***covered** paint on the wall.
- John painted/*buttered wall plaster on the wall.

Results

- 209,475 new example sentences (see sample).
- Syntactically adequate
- Obey semantic selectional restrictions 78.7%
- Repeated coverage analysis on *fulltext annotations*:

%TR_I

Acknowledgments

- Tony broke the window (with a hammer). NP V NP (PP.instrument)
- The window broke. NP.patient V
- The hammer broke the window. NP.Instrument V NP
- Tony broke the window to pieces. NP V NP PP.oblique



• Precision of new examples evaluated by independent judge: 93.8% • Recall for subcat patterns on 10% leave-out lexicographic annotations: 99.6%

гтт	%seen scats	
LU	per anno	per TR_LU
9.1	78.7	99.5 (+30.6)