Transformation-based Learning for Semantic Parsing

F. Jurcicek, M. Gasic, S. Keizer, F. Mairesse, B. Thomson, K. Yu, S. Young
Cambridge University Engineering Department | {fj228, mg436, sk561, f.mairesse, brmt2, ky219, sjy}@eng.cam.ac.uk

Goals & Motivation

- **Develop a fast semantic decoder for dialogue systems**
- **Capability to parse 10 – 100 ASR hypotheses in real time**
- **Robust to speech recognition noise**

- **Semantic parsing maps natural language to formal language**
- **In current dialogue systems, most of the mapping is fairly simple (cities, times, ...)**

what are the lowest airfares from Washington to Boston		
GOAL	=	airfare
airfare.type	=	lowest
from.city	=	Washington
to.city	=	Boston

- **Transformation based – error driven learning was shown to be efficient and fast on this type of task**

Transformations

Triggers	Transformations
"Seattle"	add the slot "to.city=Seattle"
"connecting"	replace the slot "to.city=*" by "stop.city=*"
"from * Francisco"	delete the slot "toloc.city=San Francisco"

Example of parsing

find all flights between Toronto and San Diego that arrive on Saturday

1. **Parser assigns initial semantics to input sentence**

GOAL	=	flight

2. **Rules are sequentially applied, whenever a trigger matches the sentence a the hypothesised semantics**

#	Trigger	Transformation
1	"between Toronto"	add the slot "from.city=Toronto"
2	"and San Diego"	add the slot "to.city=Sand Diego"
3	"Saturday"	add the slot "departure.day=Saturday"

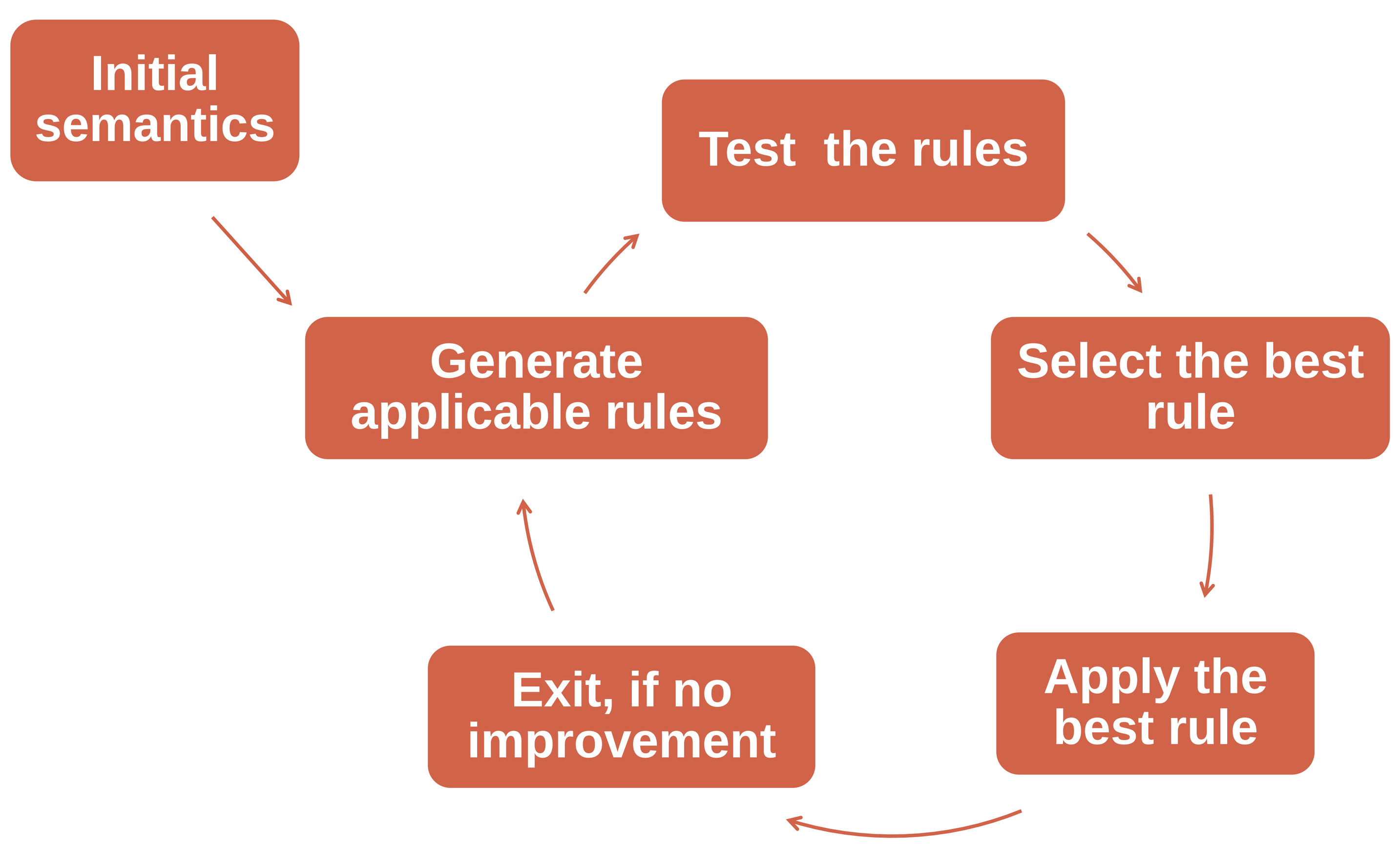
GOAL	=	flight
from.city	=	Toronto
to.city	=	San Diego
departure.day	=	Saturday

3. **Rules can correct previous errors**

#	Trigger	Transformation
4	"arrive"	replace the slot "departure.day=*" by "arrival.day=*"

GOAL	=	flight
from.city	=	Toronto
to.city	=	San Diego
arrive.day	=	Saturday

Learning



- **On average 1 million of rules is tested in each iteration**
- **Training takes about 24 hours on an Intel Pentium 2.8 GHz**

Efficiency

- **Inferred list of rules is very small for domains such as ATIS or TownInfo**

Dataset	# of inferred rules	concepts	# of rules/concepts
ATIS	372	83	4.5
TownInfo	195	28	6.9

- **Average number of semantic concepts in a sentence is 5**
- **Python implementation of the parser needs 6ms per sentence**

Evaluation

Compare TBL Semantic Parser with:

- **A handcrafted Phoenix grammar**
- **The Hidden Vector State model (He & Young, 2006)**
- **Probabilistic Combinatory Categorial Grammar Induction (Zettlemoyer & Collins, 2007)**
- **Markov Logic networks (Meza-Ruiz et al., 2008)**
- **Semantic Tuple Classifiers (Mairesse et al., 2008)**

Evaluation metrics is precision, recall and F-measure of dialogue act items (e.g. *food=Chinese*, *toloc.city=New York)*

Semantic decoder	Item precision	Item recall	Item F
ATIS dataset with transcribed utterances:			
Semantic Tuple Classifiers	96.7	92.4	94.5
Hidden Vector State			90.3
PCCG Induction	95.1	96.7	95.9
Markov Logic Networks	93.4	89.8	91.6
TBL Semantic Parser	96.4	95.1	95.7
TownInfo dataset with transcribed utterances:			
Semantic Tuple Classifiers	97.4	94.0	95.7
Phoenix grammar	96.3	94.2	95.3
TBL Semantic Parser	92.7	94.7	95.4
TownInfo dataset with ASR output:			
Semantic Tuple Classifiers	94.0	83.7	88.6
Phoenix grammar	90.3	79.5	85.5
TBL Semantic Parser	92.7	83.4	87.8

Conclusion: TBL Semantic Parser is robust to noise and competitive with the state of the art.

Open source

The code is available at http://code.google.com/p/tbed-parser

Acknowledgements

This research was partly funded by the UK EPSRC under grant agreement EP/F013930/1 and by the EU FP7 Programme under grant agreement 216594 (CLASSiC project: www.classic-project.org).