Semantic Parsing: transforming sentences to logical forms using machine learning models

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Syntactic and Semantic Natural Language Learning

- Most computational research in natural-language learning has addressed "low-level" syntactic processing.
  - Morphology (e.g. past-tense generation)
  - Part-of-speech tagging
  - Chunking
  - Syntactic parsing
- Learning for semantic analysis has been restricted to relatively "shallow" meaning representations.
  - Word sense disambiguation (e.g. SENSEVAL)
  - Semantic role assignment (determining agent, patient, instrument, etc., e.g. FrameNet, PropBank)
  - Information extraction

Semantic Parsing

- Semantic parsing is the process of mapping a natural-language sentence to a complete, detailed semantic representation: ***logical form*** or ***meaning representation*** (***MR***).
- For many applications, the desired output is immediately executable by another program.
- Application domains:
  - CLang: RoboCup Coach Language
  - GeoQuery: A Database Query Application
  - Legal domain

CLang: RoboCup **Coach** **Lang**uage

- In RoboCup Coach competition teams compete to coach simulated players
- The coaching instructions are given in a formal language called CLang

Coach

If the ball is in our penalty area, then all our players except player 4 should stay in our half.

Semantic Parsing

CLang

((bpos (penalty-area our))
(do (player-except our{4}) (*pos* (half our)))

Simulated soccer field

GeoQuery: A Database Query Application

- Query application for U.S. geography database containing about 800 facts [Zelle & Mooney, 1996]

User

How many cities are there in the US?

Semantic Parsing

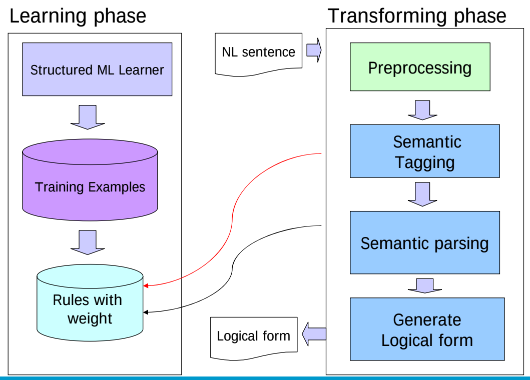
Query

answer(A,
count(B, (city(B), loc(B, C),
const(C, countryid(USA))),A))

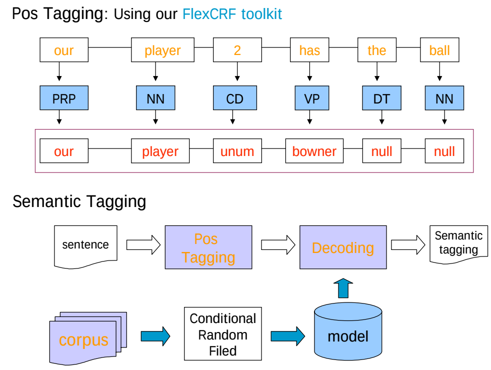
Approach

- Applying ML to the transforming problem
- Motivations
  - Robustness, reduction of development rules
  - Treating ambiguity
  - Handling with the difficulty of consistent rules
- Current work
  - ML for query database language / robocup controlled language
  - ML for legal domain

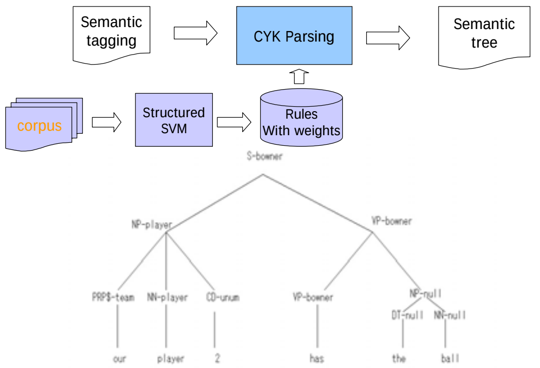
Machine Learning Framework



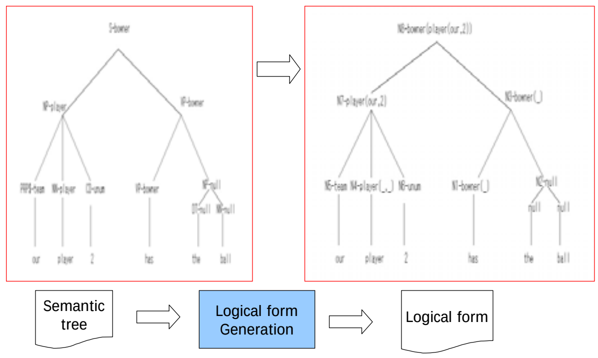
Semantic Tagging



Semantic parsing



Example: Generate LF from a semantic tree



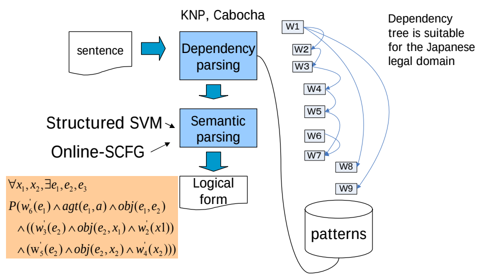
Current Work

- English Data (CLANG)
  - **Structured SVM** (Robocup)
    - Precision: 85%
    - Recall: 74%
  - Maximum entropy model (DB query)
    - Precision 89%
    - Recall 51%
- Japanese Data
  - Splitting long sentences into a set of short sentences
  - Mapping NL Japanese sentence to logical form

$$precision = \frac{\#correct-representation}{\#completed-representation}$$

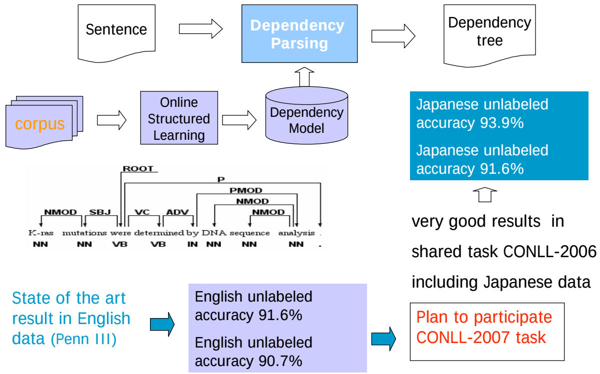
$$recall = \frac{\#correct-representation}{\#sentences}$$

Legal domain



Correspondences between DT's node and predicate in LF

Dependency Parsing



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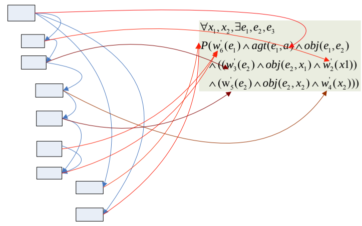
Patterns learning

- Input: set of dependency trees and their logical forms
- Output: the correspondences of each node in DT with a predicate in LF
- Method: Using statistical machine translation to align a node in DT to a predicate a LF

Example: W1 W2 W3 W4 W5 W6 W7 W8 W9



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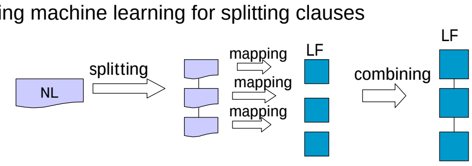
Splitting clauses in legal domain

- Using machine learning for splitting clauses



zenjou ni gaitou suru mono ga aru toki ha, kuchou ha, kore o kokuhatsu suru mono to suru

前条に該当する者があるときは、区長は、これを告発するものとする。

前条に該当する者があるときは、区長は これを告発するものとする。

- Collected 108 sentences and their logical form
- 9/10 for training and 1/10 for testing data
- The accuracy of the model is 93.10%!

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Online-SCFG Methods

- Preprocessing
  - Generate a sequence of word tokens
  - Transform a logical form representation into a sequence of atomic logical form.
- Using GIZA++ to generate alignment between each word in NL to each token in LF
- Using synchronous grammar to estimate the model for generating logical form
- Using online structured prediction learning to estimate the SCFG grammar
- Some issues for Japanese data
  - Require a formal grammar representation for LF
  - In the case there is no formal grammar it becomes phrase based SMT models

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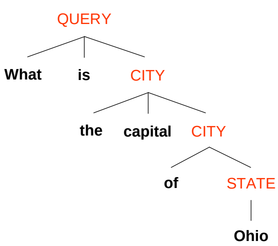
Context-Free Semantic Grammar

QUERY → What is CITY

CITY → the capital CITY

CITY → of STATE

STATE → Ohio



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Synchronous Context-Free Grammars (SCFG)

- Developed by Aho & Ullman (1972) as a theory of compilers that combines *syntax analysis* and *code generation* in a single phase
- Generates a pair of strings in a single derivation

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Synchronous Context-Free Grammars

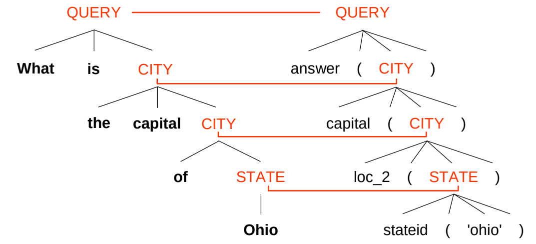
Developed by Aho & Ullman (1972) as a theory of compilers that combines *syntax analysis* and *code generation* in a single phase

Generates a pair of strings in a single derivation

pattern *template*

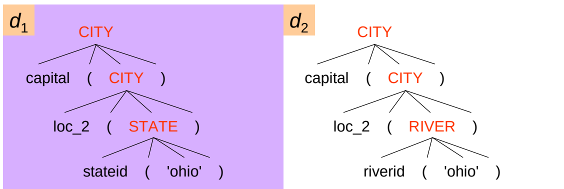
QUERY → **What is** CITY / answer(CITY)

Synchronous Context-Free Grammars



What is the cap[...]**2(stateid('ohio'))))

Probabilistic Parsing Model



d_1		d_2	
CITY → **capital** CITY / capital(CITY)	0.5	CITY → **capital** CITY / capital(CITY)	0.5
CITY → **of** STATE / loc_2(STATE)	0.3	CITY → **of** RIVER / loc_2(RIVER)	0.05
STATE → **Ohio** / stateid('ohio') +	0.5	RIVER → **Ohio** / riverid('ohio') +	0.5

λ λ

Pr(d_1|**capital of Ohio**) = exp(**1.3**) / *Z*

Pr(d_2|**capital of Ohio**) = exp(**1.05**) / *Z*

normalization constant

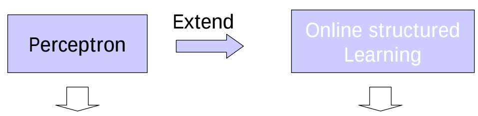
Parsing Model

- **N** (non-terminals) = {QUERY, CITY, STATE, …}
- *S* (start symbol) = QUERY
- $\mathbf{T}_m$ (MRL terminals) = {answer, capital, loc_2, (,), …}
- $\mathbf{T}_n$ (NL words) = {**What**, **is**, **the**, **capital**, **of**, **Ohio**, …}
- **L** (lexicon) =
  QUERY → **What is** CITY / answer(CITY)
  CITY → **the capital** CITY / capital(CITY)
  CITY → **of** STATE / loc_2(STATE)
  STATE → **Ohio** / stateid('ohio')
- λ (parameters of probabilistic model) = **?**

Online structured prediction learning

Online structured prediction learning

- Extend the traditional Perceptron learning



Two class labels learning problem

Many class labels, tree structure

Results

- English data (CLANG)
  - It is applicable for Robocup language
    - Precision 89.5 (best precision)
    - Recall 61.2
  - The result is good because we do not need fully semantic tree annotation
- Japanese data (110 sentences)
  - Because of spare data problem so the alignment of each word in NL sentence and each token in LF is not good.
  - It is need to verify this problem in detail for improving the accuracy of our model
    - Enlarge the training data ?

Conclusions

- Learning is applicable for transforming NL to logical form
- The number of training data should be enlarged to make sure the accuracy of the models
- The splitting result for legal Japanese data is attractive

We should integrate this model with the rule-based model

Future work

- Experiment on a larger corpus of Japanese data
- Integrate with the rule-based models
- Transforming a logical form representation to a NL sentence
- Semi-supervised learning models for semantic parsing