Automatic Generation of Wide-Coverage Semantic Representations in NLTK

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Semantic Parsing: Mapping natural language (NL) sentences to a machine readable meaning representation (MR).

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John admires Mary. $\Rightarrow$ $admires(Mary, John)$

Supervised approaches

(Ge & Mooney, 2005; Wong & Mooney, 2006; Kate & Mooney, 2006)

- Learn a mapping from NL to constituent predicates in the target meaning representation language (MRL).
- Requires annotated training data, e.g. NL-MR pairs.

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- Requires annotated training data, e.g. NL-MR pairs.
- Issues: Limited domain/methods generalize poorly to other MRLs. Require gold-standard MRs for each NL input sentence.

Minimally-supervised approaches

(Clarke, Goldwasser, Chang, & Roth, 2010; Goldwasser, Reichart, Clarke, & Roth, 2011)

- Training data is NL query and gold-standard answer.
- Treat MR as a latent variable. Find best MR out of possible MRs for an input sentence using a weight vector learned via a feedback signal (e.g. +1 if MR gets correct answer, -1 if incorrect).

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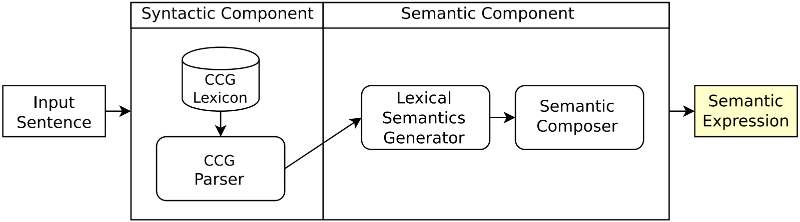
Requirements:

1. Wide-coverage: determine semantic representation for input sentence in any domain.
2. Compositionality: semantic representation of a NL sentence determined by the semantic representations of its constituent words and how they combine.

System Structure



Two components:

1. Syntactic Component: syntactic parse of the input sentence using CCG.
2. Semantic Component: generation of lexical semantics and composition.

Combinatory Categorial Grammar (CCG)

$$\cfrac{\cfrac{John}{NP} \qquad \cfrac{\cfrac{admires}{(S\backslash NP)/NP} \qquad \cfrac{Mary}{NP}}{S\backslash NP}\,>}{S}\,<$$

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Information provided by the CCG parse

- Syntactic category of constituents, e.g. admires :: $(S \setminus NP)/NP$.
- Combinatory rules, e.g. forward application ($>$).

Lexical semantics

- Translate syntactic category into an expression in Neo-Davidsonian event semantics.
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Approach adopted from GraphParser developed by (Reddy et al., 2014).

Composition

- Compose constituent semantic expressions guided by the syntactic parse tree.
- Recursively build subexpressions according to the structure of the parse tree and the CCG combinatory rules used.
- E.g. CCG application rule $\mapsto$ functional application.

An example parse

$$
\dfrac{\dfrac{\textit{John}}{\begin{array}{c} NP \\ john \end{array}} \quad \dfrac{\dfrac{\textit{admires}}{\begin{array}{c} (S\backslash NP)/NP \\ \lambda z \lambda y.\exists e.[admires.agent(e,y) \wedge admires.patient(e,z)] \end{array}} \quad \dfrac{\textit{Mary}}{\begin{array}{c} NP \\ mary \end{array}}}{\begin{array}{c} S\backslash NP \\ \lambda y.\exists e.[admires.agent(e,y) \wedge admires.patient(e,mary)] \end{array}}>}{\begin{array}{c} S \\ \boldsymbol{\exists e.[admires.agent(e,john) \wedge admires.patient(e,mary)]} \end{array}}<
$$

Evaluation

- Implemented as a package within the NLTK framework (`nltk.semparse`).
- Preprocessing performed using the NLTK tokenizer (`nltk.word_tokenize`) and NLTK POS tagger (`nltk.pos_tag`).
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Coverage of syntactic and semantic components on GEOQUERY880:

Component	Questions Parsed	Coverage
Syntactic	825	93.75%
Semantic	366	41.59%
Total	**880**	

Limitations of the current system:

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- **Syntactic component**: NLTK CCG parser is not probabilistic. Also not as expressive as current standard systems such as C&C parser, easyCCG parser.
- **Semantic component**: Some special-case linguistic phenomena have not been addressed. E.g. gerunds which act as adjectives, “the running man”.

Further tasks

Current system is preliminary work towards a semantic parser in NLTK.

- Address the limitations described above.
  - It is possible to use external tools for tokenization and POS tagging.
  - Make the NLTK CCG parser probabilistic. Develop method for reading in CCG parses from more reliable parsers.
  - Identify special cases.
- Develop methods for grounding the output expressions in a knowledge base.
  - Evaluate the system on standard question-answering and information retrieval tasks.

Thank you.

Code available at `https://github.com/jvasilakes/nltk/tree/develop/nltk/semparse`.

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