THESIS PROPOSAL

LEARNING REPRESENTATIONS FOR TEXT-LEVEL DISCOURSE PARSING

Copyright © 2015 gw0 [http://gw.tnode.com/] <gw.2015@tnode.com>

OVERVIEW

- motivation
- discourse parsing
 - PDTB-style
- deep learning architectures
 - sequence processing
 - word embeddings
- our approach
 - key ideas
 - guided layer-wise multi-task learning
- progress

MOTIVATION

- natural language processing (NLP)
 - large pipelines of independently-constructed components or subtasks
 - traditionally hand-engineered sparse features based on language/domain/task specific knowledge
 - still room for improvement on challenging NLP tasks

• deep learning architectures

- backpropagation could be the one learning algorithm to unify learning of all components
- latent features/representations are automatically learned as distributed dense vectors
- surprising results for a number of NLP tasks

DISCOURSE PARSING

- **discourse**: a piece of text meant to communicate specific information (clauses, sentences, or even paragraphs)
- understood only in relation to other discourses, their joint meaning is larger than individual unit's meaning alone

```
[Index arbitrage doesn't work]<sub>arg1</sub>,

and [it scares natural buyers of stock]<sub>arg2</sub>.

— PDTB-style, id: 14883, type: explicit, sense: Expansion.Conjunction
```

```
if [this prompts others to consider the same thing]<sub>arg1</sub>,
then [it may become much more important]<sub>arg2</sub>.

— PDTB-style, id: 14905, type: explicit, sense: Contingency.Condition
```

PDTB-STYLE EXAMPLES

He added [that "having just one firm do this isn't going to mean a hill of beans]_{arg1}.

 \underline{But} [if this prompts others to consider the same thing, then it may become much more important]_{arg2}."

— PDTB-style, id: 14904, type: explicit, sense: Comparison.Concession

In addition, Black & Decker had said it would sell two other undisclosed Emhart operations if it received the right price. [Bostic is one of the previously unnamed units, and the first of the five to be sold.]_{arg1}

[The company is still negotiating the sales of the other four units and expects to announce agreements by the end of the year]_{arg1}. [The five units generated sales of about \$1.3 billion in 1988, almost half of Emhart's \$2.3 billion revenue]_{arg2}. Bostic posted 1988 sales of \$255 million.

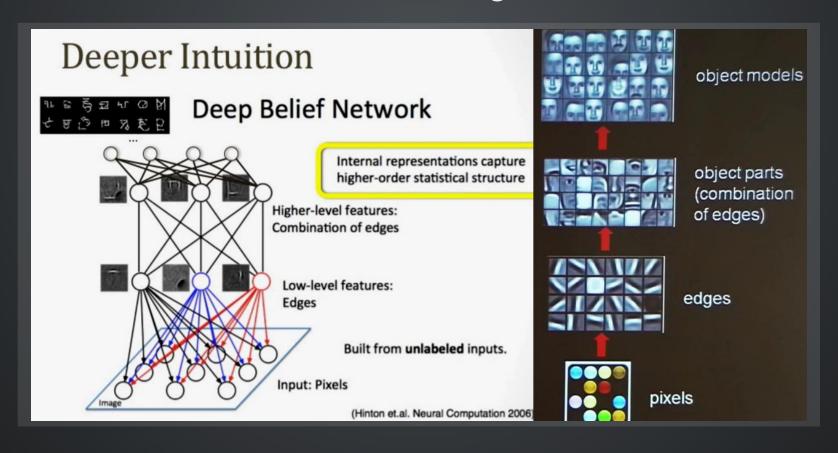
— PDTB-style, id: 12886, type: entrel, sense: EntRel

PDTB-STYLE DISCOURSE PARSING

- Penn Discourse Treebank adopts the predicate-argument view and independence of discourse relations
 - 2159 articles from the Wall Street Journal
 - 4 discourse sense classes, 16 types, 23 subtypes
- also called shallow discourse parsing
 - discourse relations are not connected to each another to form a connected structure (tree or graph)
 - adjacent/non-adjacent units in same/different sentences
- primary goals
 - locate explicit or implicit discourse connective
 - locate text spans for argument 1 and 2
 - predict sense that characterizes the nature of the relation

DEEP LEARNING ARCHITECTURES

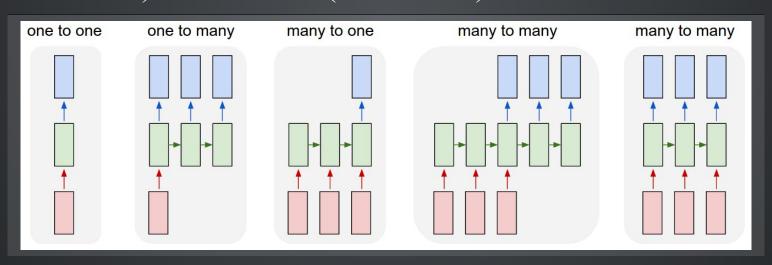
- multiple layers of learning blocks stacked on each other
- beginning with raw data, its representation is transformed into increasingly higher and more abstract forms in each layer, until final low-dimensional features for a given task



SEQUENCE PROCESSING

Text documents of different lengths are usually treated as a sequence of words:

- transition-based processing mechanisms
- recurrent neural networks (RNNs)
 - applying the same set of weights over the sequence (temporal dimension) or structure (tree-based)



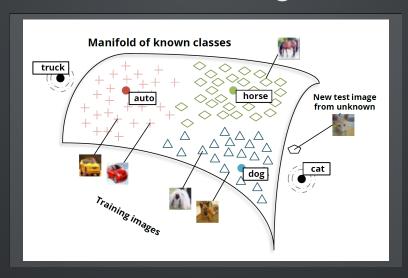
WORD EMBEDDINGS

Represent text as numeric vectors of fixed size:

- word embeddings: SGNS (word2vec), GloVe, ...
- feature/phrase/document embeddings
- character-level convolutional networks

Unsupervised pre-training helps develop natural abstractions.

Sharing word embedding in **multi-task learning** improves their performance in the absence of hand-engineered features.



OUR APPROACH

- PDTB-style end-to-end discourse parser
- one deep learning architecture instead of multiple independently-constructed components
- almost without any hand-engineered NLP knowledge

Input:

• tokenized text documents (from CoNLL 2015 shared task)

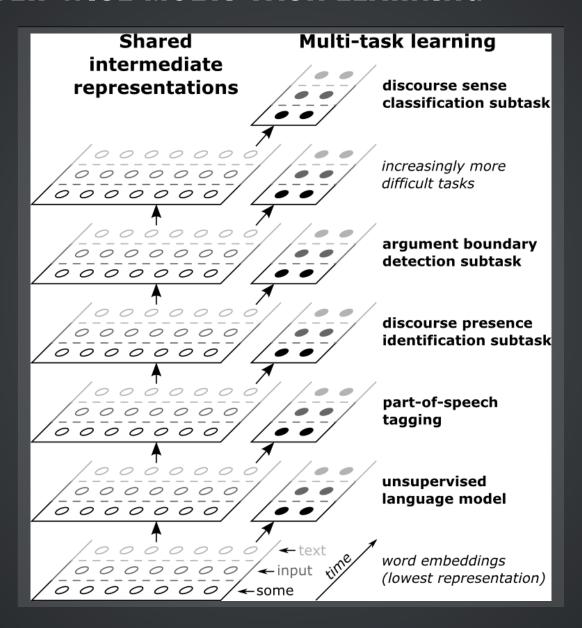
Output:

- extracted PDTB-style discourse relations
 - connectives
 - arguments 1 and 2
 - discourse senses

KEY IDEAS

- unified end-to-end architecture
 - backpropagation as the one learning algorithm for all discourse parsing subtasks and related NLP tasks
- automatic learning of representations
 - in hidden layers of deep learning architectures (bidirectional deep RNN/LSTM)
- shared intermediate representations
 - partially stacked on top of each other to benefit from each others representations
- guided layer-wise multi-task learning
 - jointly learning all discourse parsing subtasks and related NLP tasks including unsupervised pre-training

GUIDED LAYER-WISE MULTI-TASK LEARNING

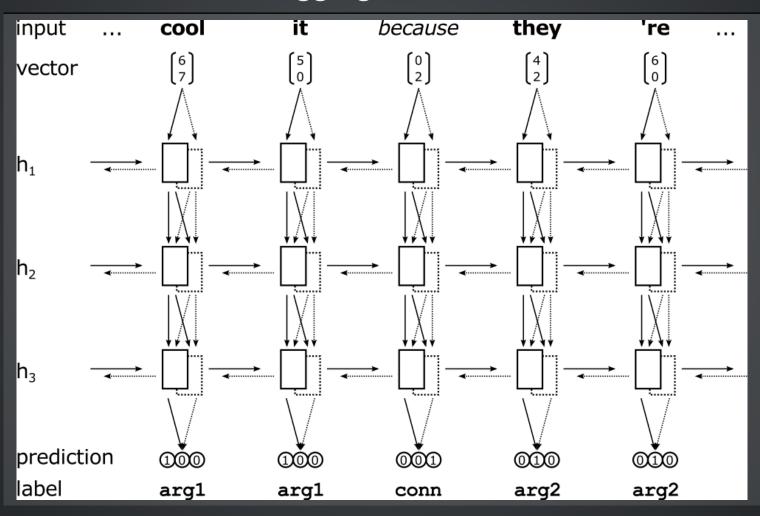


PROGRESS

- technology
 - Python
 - *Theano*: fast tensor manipulation library
 - *Keras*: modular neural network library
- resources and inputs
 - pre-trained word2vec lookup table (on Google News)
 - tokenized text documents as input
 - POS tags of input tokens
- evaluation (from CoNLL 2015 shared task)
 - performance in terms of precision/recall/F1-score
 - explicit connectives, argument 1, 2 and combined extraction, sense classification, overall

COMPLICATION OR USEFUL?

Experiments with single-task learning with bidirectional deep RNN for discourse sense tagging:



SINGLE-TASK RESULTS

- long training time for randomly initialized weights
 - lower tasks improve initialization
- overfitting training data
 - more tasks improve generalization

FUTURE EXPERIMENTS

- various discourse parsing subtasks
- various related NLP tasks (chunking, POS, NER, SRL, ...)
- different representation structures
- different activation, optimization, architectures
- long short-term memory (LSTM)
- neural Turing machines (NTM)

DOES IT MAKE SENSE?

I would like to hear your *feedback* and *ideas* for my thesis proposal.

THANK YOU

http://gw.tnode.com/deep-learning/acl2015-presentation/

Copyright © 2015 gw0 [http://gw.tnode.com/] <gw.2015@tnode.com>