Natural Language Understanding with Common Sense Reasoning

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Microsoft Research Faculty Summit
Please...
Please...

- Identify units
- Consider multiple interpretations and representations
  - Pictures, text, spell/phonetics
- Put it all together: Determine “best” global interpretation
- Satisfy expectations
  - Slide; puzzle
Comprehension

- Dan is flying to Philadelphia this weekend. Penn is organizing a workshop on the Penn Discourse Treebank.
  - ➔ Dan is attending the workshop
  - ➔ The Workshop is in Philadelphia
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- **Interpretation** builds on **expectations** that rely on knowledge.
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Natural Language Inferences

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Natural Language Understanding

- Natural language understanding decisions are global decisions that require
  - Making (local) predictions driven by different models trained in different ways, at different times/conditions/scenarios
  - The ability to put these predictions together coherently
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Natural Language Interpretation is a Common Sense driven Inference Process that is best thought of as a knowledge constrained optimization problem, done on top of multiple statistically learned models.
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Many forms of Inference; a lot boil down to determining best assignment
Common Sense Reasoning was formulated traditionally as a “reasoning” process, irrespective of learning and the resulting knowledge representation.
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What is Needed?
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Training on the Go!
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Training on the go!
What is Needed?

- A computational Framework
- Two Examples:
  - Pronoun Resolution
  - Quantitative Reasoning
Dole’s wife, Elizabeth, is a native of N.C.
Joint Inference with General Constraint Structure [Roth&Yih’04,07,....]

Recognizing Entities and Relations

Dole’s wife, Elizabeth, is a native of N.C.

\[ E_1 \quad R_{12} \quad E_2 \quad R_{23} \quad E_3 \]

- **other** 0.05
- **per** 0.85
- **loc** 0.10

- **other** 0.10
- **per** 0.60
- **loc** 0.30

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**Key Questions:**

- How to guide the global inference?
- How to learn the model(s)?

**Joint inference gives good improvement**
Joint Inference with General Constraint Structure [Roth & Yih'04, 07,…]

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Models could be learned separately/jointly; constraints may come up only at decision time.

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Joint inference gives good improvement

An Objective function that incorporates learned (output constraints)

A Constrained Conditional Model

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Constrained Conditional Models

\[ y = \arg\max_{y \in \mathcal{Y}} w^T \phi(x, y) \]
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Weight Vector for “local” models

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\[ y = \arg\max_{y \in \mathcal{Y}} w^T \phi(x, y) + u^T C(x, y) \]

- **Weight Vector for “local” models**
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  - Decouple? Decompose? Force \(u\) to model hard constraints?

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- A way to push the learned model to **satisfy our output expectations** (or expectations from a latent representation)
  - [CoDL, Chang et. al (07, 12); Posterior Regularization, Ganchev et. al (10); Unified EM (Samdani et. al (12))]
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y = \text{argmax}_y \left( \sum \mathbf{1}_{\phi(x,y)} w_{x,y} \right) \text{ subject to Constraints } C(x,y)
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Weight Vector for “local” models
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Any MAP problem w.r.t. any probabilistic model, can be formulated as an ILP
[Roth+ 04, Taskar 04]
Examples: CCM Formulations

\[ y = \arg\max_{y \in Y} \ w^T \phi(x, y) + u^T C(x, y) \]
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\[ y = \text{argmax}_{y \in \mathcal{Y}} \ w^T \phi(x, y) + u^T C(x, y) \]

While \( \phi(x, y) \) and \( C(x, y) \) could be the same; we want \( C(x, y) \) to express high level declarative knowledge over the statistical models.
Examples: CCM Formulations

\[ y = \arg\max_{y \in \mathcal{Y}} \ w^T \phi(x, y) + u^T \mathcal{C}(x, y) \]

While \( \phi(x, y) \) and \( \mathcal{C}(x, y) \) could be the same; we want \( \mathcal{C}(x, y) \) to express high level declarative knowledge over the statistical models.

Formulate NLP Problems as ILP problems (inference may be done otherwise)

1. Sequence tagging \( \text{(HMM/CRF + Global constraints)} \)
2. Sentence Compression \( \text{(Language Model + Global Constraints)} \)
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Sequential Prediction

HMM/CRF based:
\[ \text{Argmax} \sum \lambda_{ij} x_{ij} \]

Knowledge/Linguistics Constraints

Cannot have both A states and B states in an output sequence.
Examples: CCM Formulations

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Sentence Compression/Summarization:
Language Model based:
Argmax \( \sum \lambda_{ijk} x_{ijk} \)

Knowledge/Linguistics Constraints
If a modifier chosen, include its head
If verb is chosen, include its arguments
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Constrained Conditional Models Allow:
- Decouple complexity of the learned model from that of the desired output
- Learn a simple model (multiple; pipelines); reason with a complex one.
- Accomplished by incorporating constraints to bias/re-rank global decisions to satisfy (minimally violate) expectations.
I. Coreference Resolution

(ENGLAND, June, 1989) - Christopher Robin is alive and well. He lives in England. He is the same person that you read about in the book, Winnie the Pooh. As a boy, Chris lived in a pretty home called Cotchfield Farm. When Chris was three years old, his father wrote a poem about him. The poem was printed in a magazine for others to read. Mr. Robin then wrote a book. He made up a fairy tale land where Chris lived. His friends were animals. There was a bear called Winnie the Pooh. There was also an owl and a young pig, called a piglet. All the animals were stuffed toys that Chris owned. Mr. Robin made them come to life with his words. The places in the story were all near Cotchfield Farm. Winnie the Pooh was written in 1925. Children still love to read about Christopher Robin and his animal friends. Most people don't know he is a real person who is grown now. He has written two books of his own. They tell what it is like to be famous.
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Pronoun Resolution can be Really Hard

- When Tina pressed Joan to the floor she was punished.
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State-of-the-art co-reference resolution makes random decisions on problems of this type.
Pronoun Resolution can be Really Hard

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- Requires, among other things, thinking about the structure of the sentence – who does what to whom
Hard Co-reference Problems

- Requires knowledge Acquisition
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Knowledge representation called “predicate schemas”
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- Requires an inference framework that can make use of this knowledge
ILP Formulation of Coreference Resolution

\[ y = \arg \max_y \sum_{uv} w_{uv} \cdot y_{uv} \]

s.t \[ \sum_u < v y_{uv} \leq 1, \ \forall v \]

\[ y_{uv} \in \{0,1\} \]
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\[ y = \arg \max_y \sum_{uv} w_{uv} \cdot y_{uv} \]

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Variable \( y_{uv} \) indicates a coreference link \( u \rightarrow v \)
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Best Link Approach: only one of the antecedents \( u \) is linked to \( v \)
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Results in a state-of-the-art coreference that at the same time also handles hard instances at close to 90% Precision.
II. Quantities & Quantitative Reasoning

- A crucially important natural language understanding task.
- Election results; Stock Market; Casualties,...
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Gwen was organizing her book case making sure each of the shelves had exactly 9 books on it. She has 2 types of books – mystery books and picture books. If she had 3 shelves of mystery books and 5 shelves of picture books, how many books did she have total?
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$$E^* = \arg\max \sum_q R(q) \mathbf{1}_q + \bigoplus_{(q, q')} \text{Pair}(q, q', \odot(q, q')) \mathbf{1}_{q, q'}$$
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- **Subject to commonsense constraints.**
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Results in a state-of-the-art results on multiple types of arithmetic word problems
Conclusion

- Natural Language Understanding is a Common Sense Inference problem.

- We would gain by thinking in a unified way on Learning, Knowledge (Representation and Acquisition) and Reasoning.

- Provided some recent samples from a research program that addresses
  - Learning, Inference and Knowledge via
  - A constrained optimization framework that guides “best assignment” inference, with (declarative) output expectations.
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