Cognitive Computation Group
University of Illinois at Urbana-Champaign

Natural Language Understanding with Common Sense Reasoning

Dan Roth

Department of Computer Science

University of Illinois at Urbana-Champaign

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Microsoft Research Faculty Summit

Please…

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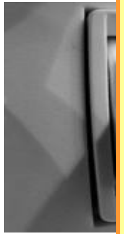
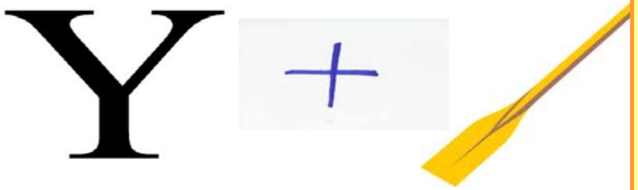
Please…





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

Comprehension

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    - ➔Dan is attending the workshop
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Natural Language Inferences

- At least 14 people have been killed in southern Sri Lanka, police say. The telecoms minister was among about 35 injured in the blast site at the town of Akuressa, 160km (100 miles) south of the capital, Colombo. Government officials were attending a function at a mosque to celebrate an Islamic holiday at the time. The defense ministry said the suicide attack was carried out by ….

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This is an Inference Problem

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
  - Knowledge, that guides the decisions so they satisfy our expectations

Natural Language Understanding

Expectation is a knowledge intensive component

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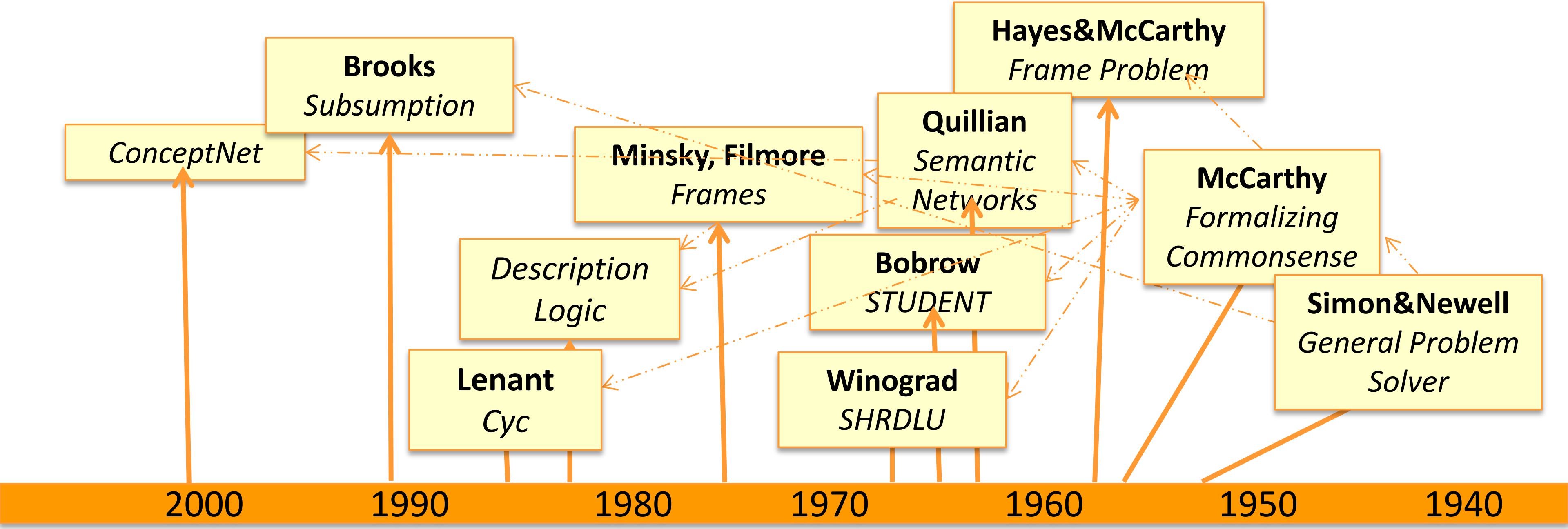
Many forms of Inference; a lot boil down to determining best assignment

A Biased View of Common Sense Reasoning



Common Sense Reasoning was formulated traditionally as a "reasoning" process, irrespective of learning and the resulting knowledge representation.

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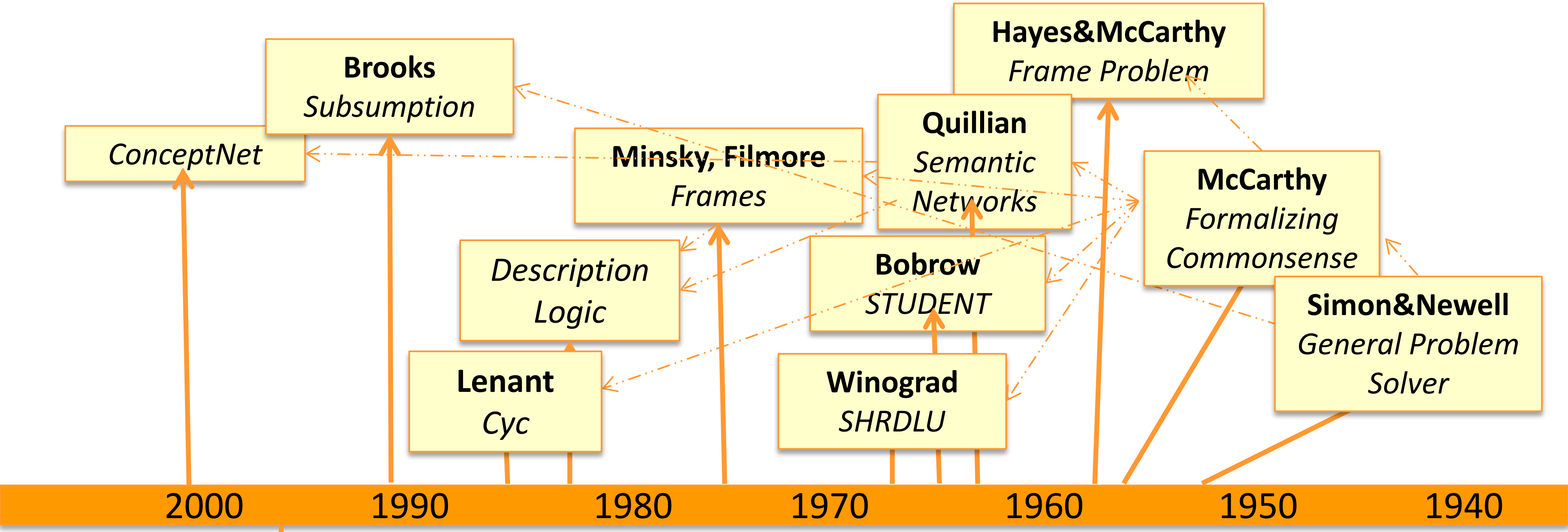

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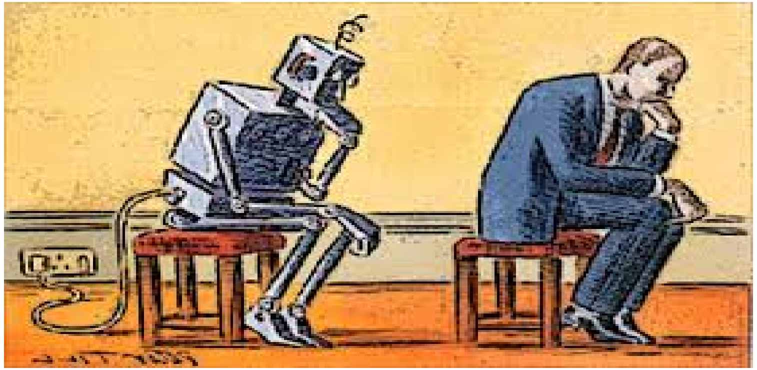

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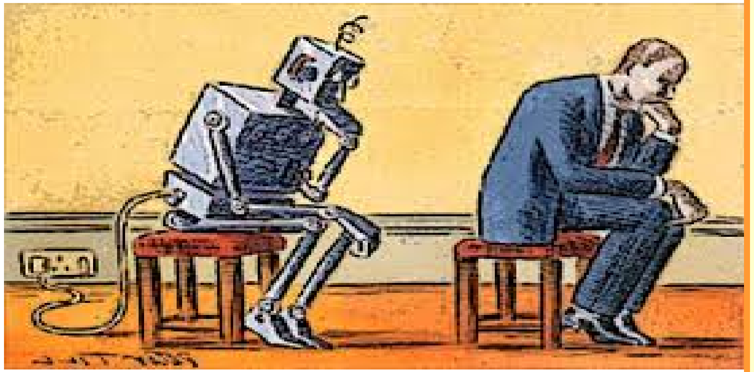
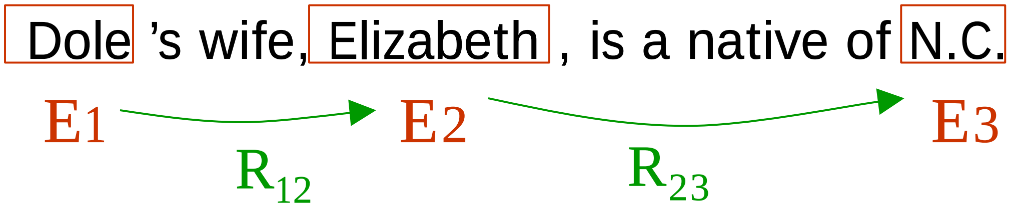


- A computational Framework
- Two Examples:
  - Pronoun Resolution
  - Quantitative Reasoning

Joint Inference with General Constraint Structure [Roth&Yih'04,07,….]

Recognizing Entities and Relations



Joint Inference with General Constraint Structure [Roth&Yih'04,07,….]

Recognizing Entities and Relations

other	0.05
per	0.85
loc	0.10

other	0.10
per	0.60
loc	0.30

other	0.05
per	0.50
loc	0.45

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

E1 → E2 → E3

R_{12} R_{23}

irrelevant	0.05
spouse_of	0.45
born_in	0.50

irrelevant	0.10
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Joint Inference with General Constraint Structure [R

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Joint inference gives good improvement

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Key Questions:

How to guide the global inference?

How to learn the model(s)?

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An Objective function that incorporates learned models with knowledge (output constraints)

A Constrained Conditional Model

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Weight Vector for "local" models

Features, classifiers; log-linear models (HMM, CRF) or a combination

Constrained Conditional Models

$$\mathbf{y} = \mathbf{argmax}_{\mathbf{y} \in \mathcal{Y}} \; \mathbf{w}^{\mathsf{T}}\phi(\mathbf{x}, \mathbf{y}) + \mathbf{u}^{\mathsf{T}}\mathcal{C}(\mathbf{x}, \mathbf{y})$$

Knowledge component: (Soft) constraints

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  - [CoDL, Chang et. al (07, 12); Posterior Regularization, Ganchev et. al (10); Unified EM (Samdani et. al (12)]

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$y = \text{argmax}_{y} \sum \mathbf{1}_{\phi(x,y)}\, w_{x,y}$ subject to Constraints C(x,y)

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Constrained Conditional Models

Any MAP problem w.r.t. any probabilistic model, can be formulated as an ILP [Roth+ 04, Taskar 04]

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Sequential Prediction

HMM/CRF based:

Argmax $\sum \lambda_{ij} x_{ij}$

Knowledge/Linguistics Constraints

Cannot have both A states and B states in an output sequence.

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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

Examples: CCM Formulations

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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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- Big Problem; essential to text understanding; hard.
- Requires: good learning and inference models & knowledge

Recent Advances in Co-reference [Chang, Peng, Samdani, Khashabi]

- Latent Left-linking Model (L3M) model [ICML 14]
- Joint mention identification & co-reference resolution [CoNLL'15]
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- When Tina pressed Joan to the floor she was punished.
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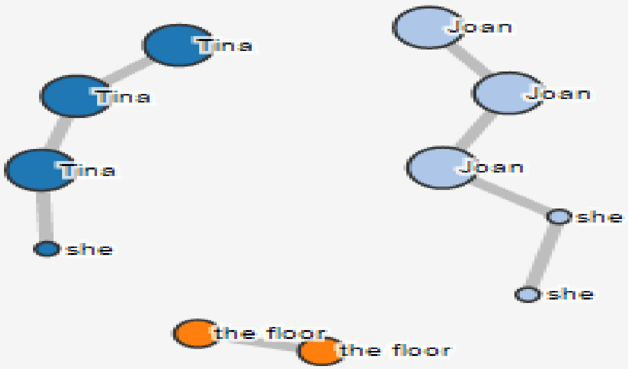
Coref Demo Results

The coreference resolution system has identified the following coreferent mentions.

When [Tina] pressed [Joan] to [the floor] [she] was punished . When [Tina] pressed [Joan] to [the floor] [she] was hurt . When [Tina] pressed charges against [Joan] [she] was jailed .

State-of-the-art co-reference resolution makes random decisions on problems of this type.



Pronoun Resolution can be Really Hard

- When Tina pressed Joan to the floor she was punished.
- When Tina pressed Joan to the floor she was hurt.
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  - Requires, among other things, thinking about the structure of the sentence – who does what to whom

Hard Co-reference Problems

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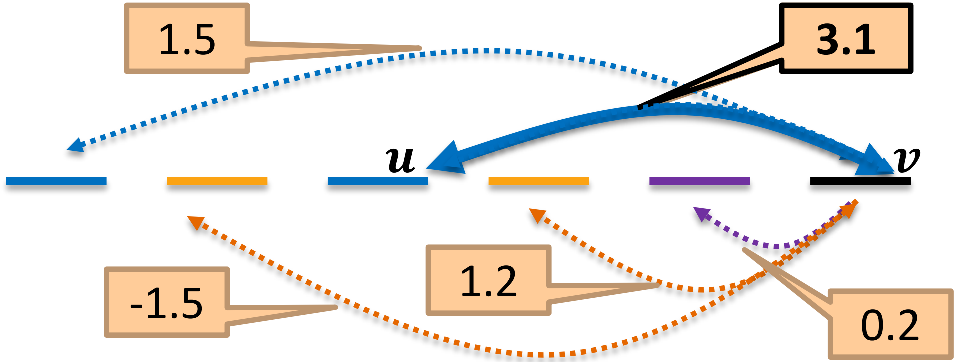
- Requires an inference framework that can make use of this knowledge

ILP Formulation of Coreference Resolution

- $y = \arg\max_y \sum_{uv} \mathrm{w}_{\mathrm{uv}} \cdot y_{uv}$

  s.t $\sum_{u\ <\ v} yu_v$ <= 1, ∀v

  y_{uv} ε {0,1}



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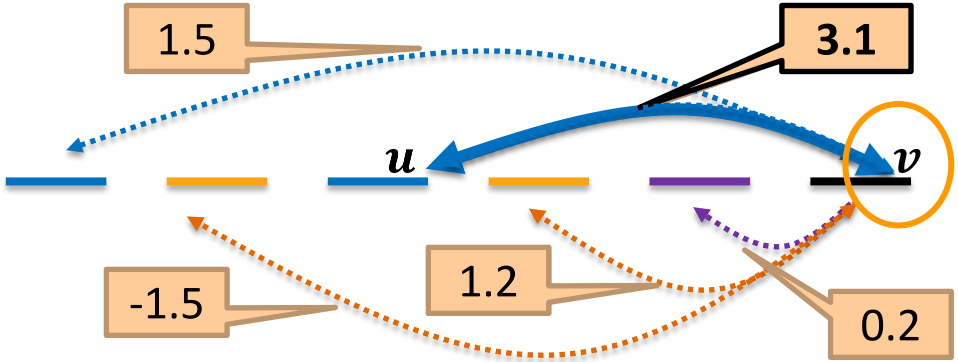

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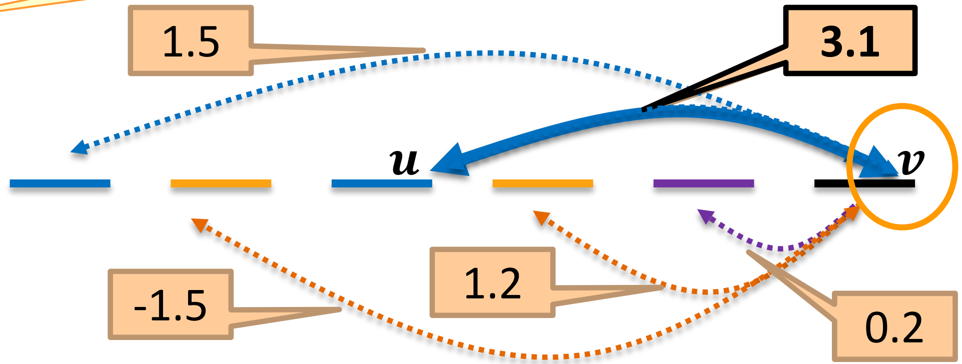

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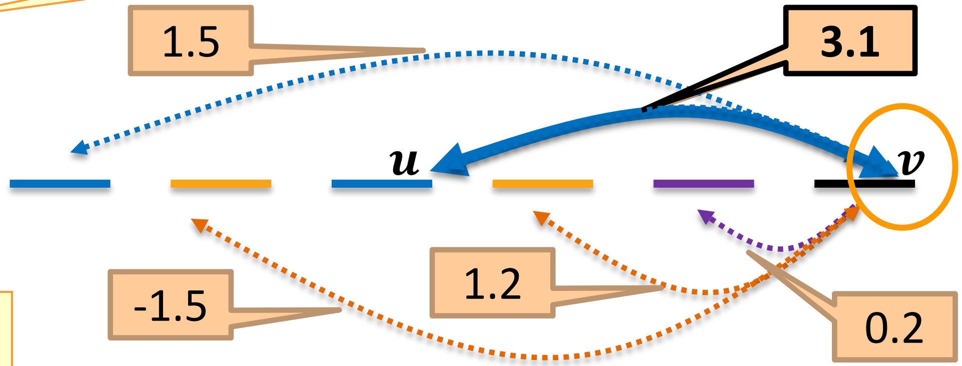
Best Link Approach: only one of the antecedents **u** is linked to **v**



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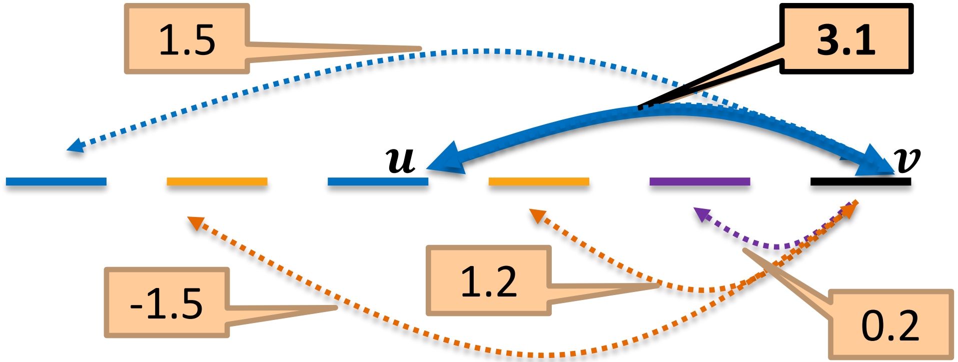

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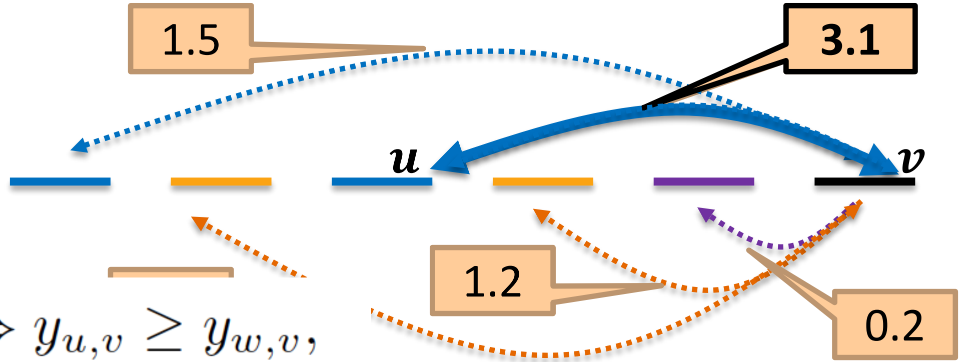

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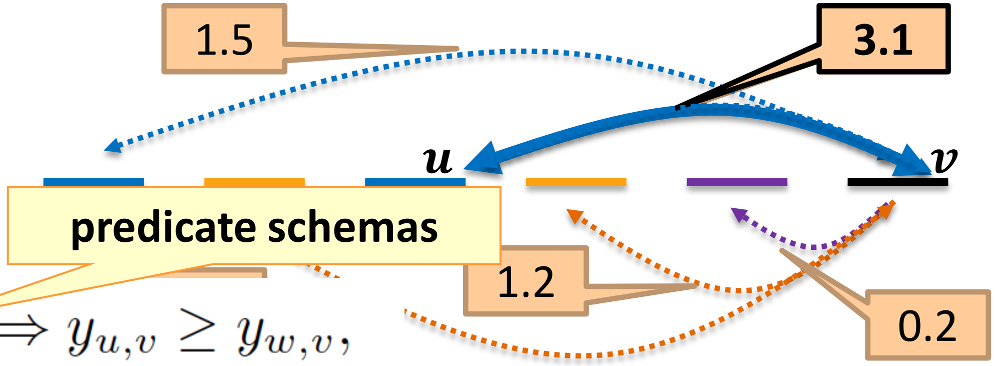

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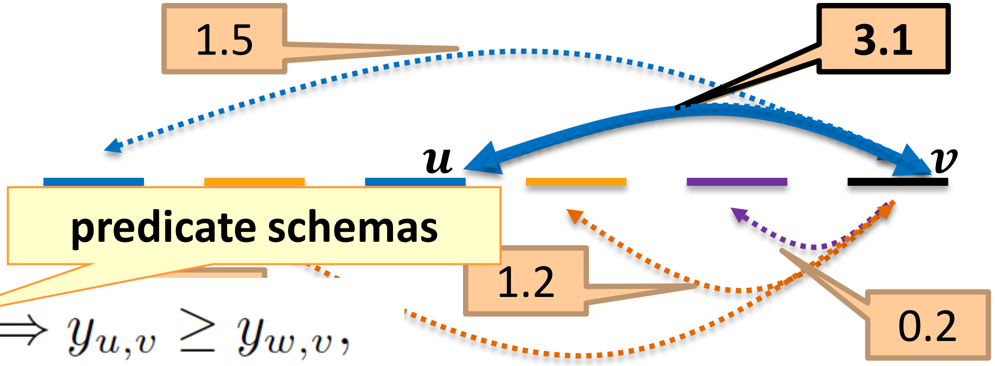

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Results in a state-of-the-art coreference that at the same time also handles hard instances at close to 90% Precision.

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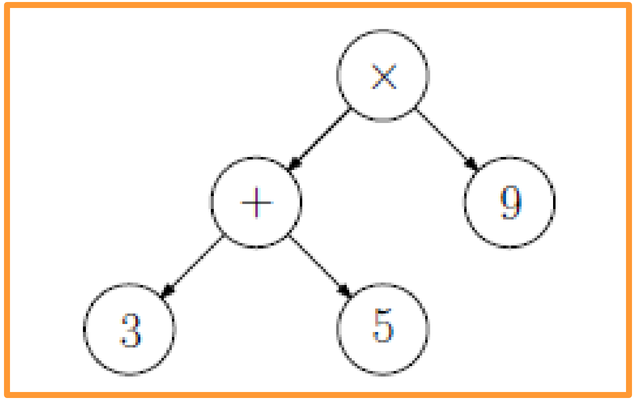

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Results in a state-of-the-art results on multiple types of arithmetic word problems

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Expectations developed given a text snippet

Conclusion

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