



Three Short Stories on Computerised Presupposition Projection

Johan Bos

University of Rome "La Sapienza"

Dipartimento di Informatica

A little introduction

- My work is in between formal semantics and natural language processing/computational linguistics/AI
- Aim of my work is to use insights/adopt linguistic theories in applications that require natural language understanding

Surprise

- Surprisingly, very little work of formal semantics make it to real applications
- Why?
 - Requires interdisciplinary background
 - Gap between formal semantic theory and practical implementation
 - It is just not trendy --- statistical approaches dominate the field

Rob's Algorithm

- Van der Sandt 1992
 - Presupposition as Anaphora
 - Accommodation vs. Binding
 - Global vs. Local Accommodation
 - Acceptability Constraints
 - Uniform way of dealing with a lot of related phenomena
- Influenced my work on computational semantics

Three Short Stories

- **World Wide Presupposition Projection**
 - The world's first serious implementation of Rob's Algorithm, with the help of the web
- **Godot, the talking robot**
 - The first robot that computes presuppositions using Rob's Algorithm
- **Recognising Textual Entailment**
 - Rob's Algorithm applied in wide-coverage natural language processing

The First Story

World Wide Presupposition Projection

Or how the world came to see the first serious implementation of Rob's Algorithm, with the help of the internet...



1993-2001

How it started

- Interested in implementing presupposition
 - Already a system for VP ellipsis in DRT
 - Read JofS paper, also in DRT
- Lets add presuppositions
 - Met Rob at Summerschool ESSLLI Lisbon
 - Enter DORIS

The DORIS System

- Reasonable grammar coverage
- Parsed English sentences, followed by resolving ambiguities
 - Scope
 - Pronouns
 - Presupposition
- Rob's Algorithm caused hundreds of possible readings, sometimes thousands

Studying Rob's Algorithm

- The DORIS system allowed one to study the behaviour of Rob's Algorithm
- Examples such as:
 - If Mia has a husband, then her husband is out of town.
 - If Mia is married, then her husband is out of town.
 - If Mia is dating Vincent, then her husband is out of town.



Adding Inference

- One of the most exciting parts of Rob's theory are the

Acceptability Constraints

- But it is a right kerfuffle to implement them!
- Some form of automated reasoning required...

Theorem Proving

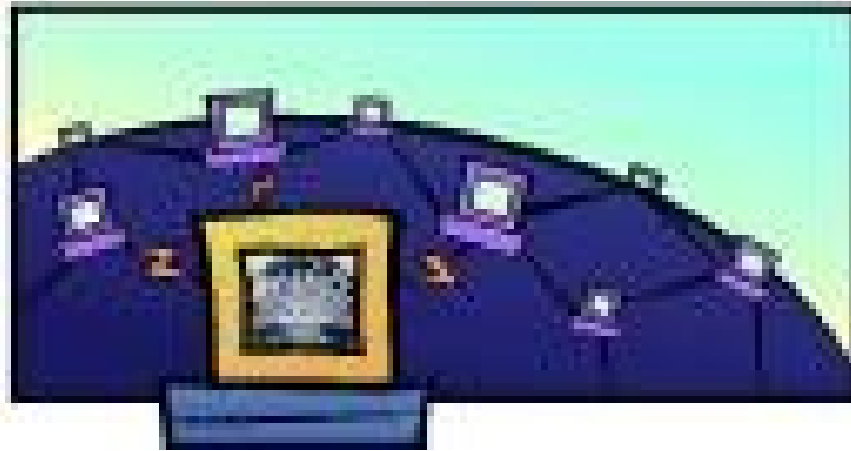
- First attempt
 - Translate DRS to first-order logic
 - Use general purpose theorem prover
 - Bliksem [by Hans de Nivelle]
- This worked, but...
 - Many readings to start with, explosion...
 - The Local Constraints add a large number of inference tasks
 - It could take about 10 minutes for a conditional sentence

MathWeb



- MathWeb [by Michael Kohlhase & Andreas Franke] came to the rescue
- Theorem proving services via the internet
- Interface Doris with MathWeb
- At the time this was a sensation!
- What happened exactly?

World Wide Presupposition Projection



- In order to find out whether Mia was married or not, thousands of computers world wide were used
- Just because of Rob's algorithm...

Six feet under

- The DORIS system †
1993-2001
- Why?
 - Limited grammatical coverage
 - Unfocussed application domain
 - It would take at least 20 years to develop a parser that was and robust and accurate [at least that was my belief]

The Second Story

Godot the talking robot

*Or how a mobile, talking robot
computed his presuppositions using
Rob's Algorithm...*



2001-2004

Human-Computer Dialogue

- Focus on small domains
 - Grammatical coverage ensured
 - Background knowledge encoding
- Spoken Dialogue system = killer app
 - Godot the robot
 - Speech recognition and synthesis
 - People could give Godot directions, ask it questions, tell it new information
 - Godot was a REAL robot

Godot the Robot



Godot with Tetsushi Oka

Typical conversation with Godot

- Simple dialogues in beginning
 - Human: **Robot?**
 - Robot: **Yes?**
 - Human: **Where are you?**
 - Robot: **I am in the hallway.**
 - Human: **OK. Go to the rest room!**
- Using the components of DORIS, we added semantics and inference

Advanced conversation with Godot

- Dealing with inconsistency and informativeness
 - Human: **Robot, where are you?**
 - Robot: **I am in the hallway.**
 - Human: **You are in my office.**
 - Robot: **No, that is not true.**
 - Human: **You are in the hallway.**
 - Robot: **Yes I know!**
- Obviously, we also looked at presupposition triggers in the domain

Videos of Godot

Video 1:
***Godot in the basement
of Buccueuch Place***



Video 2:
***Screenshot of dialogue manager
with DRSs and camera view of
Godot***

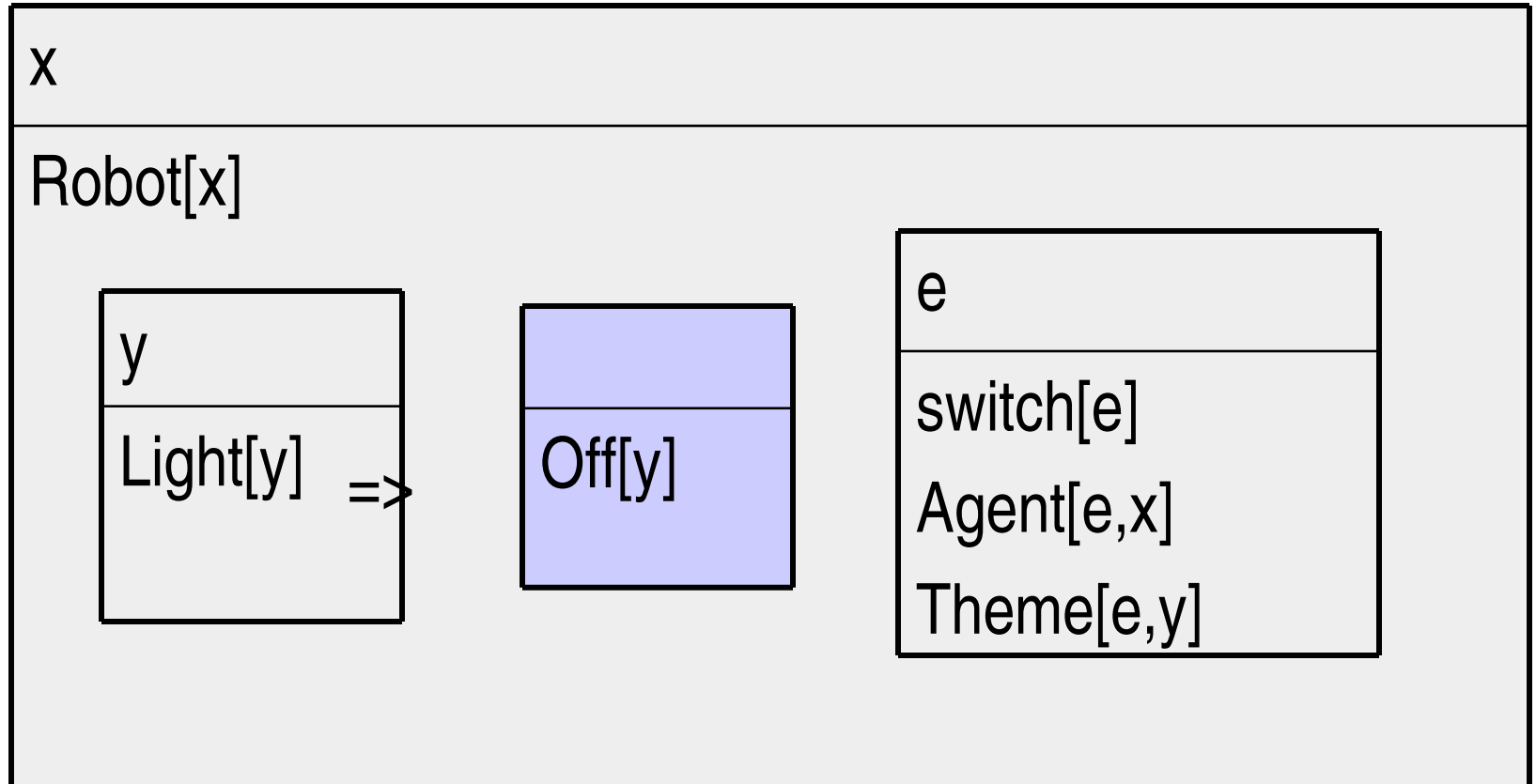
Adding presupposition

- One day, I asked Godot to switch on all the lights [Godot was connected to an automated home environment]
- However, Godot refused to do this, responding that it was unable to do so.
- Why was that?
 - At first I thought that the theorem prover made a mistake.
 - But it turned out that one of the lights was already on.

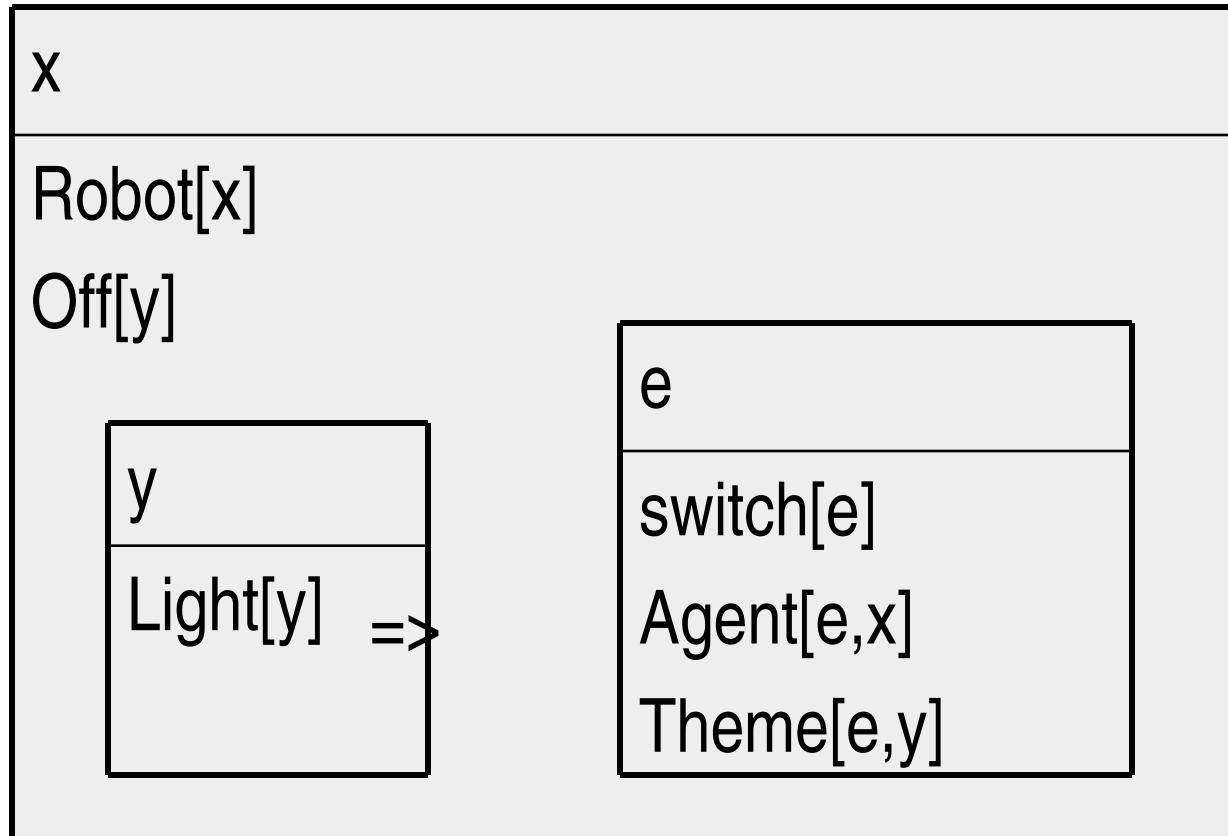
Intermediate Accommodation

- Because I had coded *to switch on X* having a **precondition** that *X is not on*, the theorem prover found a proof.
- Coding this as a **presupposition**, would not give an inconsistency, but a beautiful case of **intermediate accommodation**.
- In other words:
 - Switch on all the lights!
[≠ All lights are off; switch them on.]
[=Switch on all the lights that are currently off]

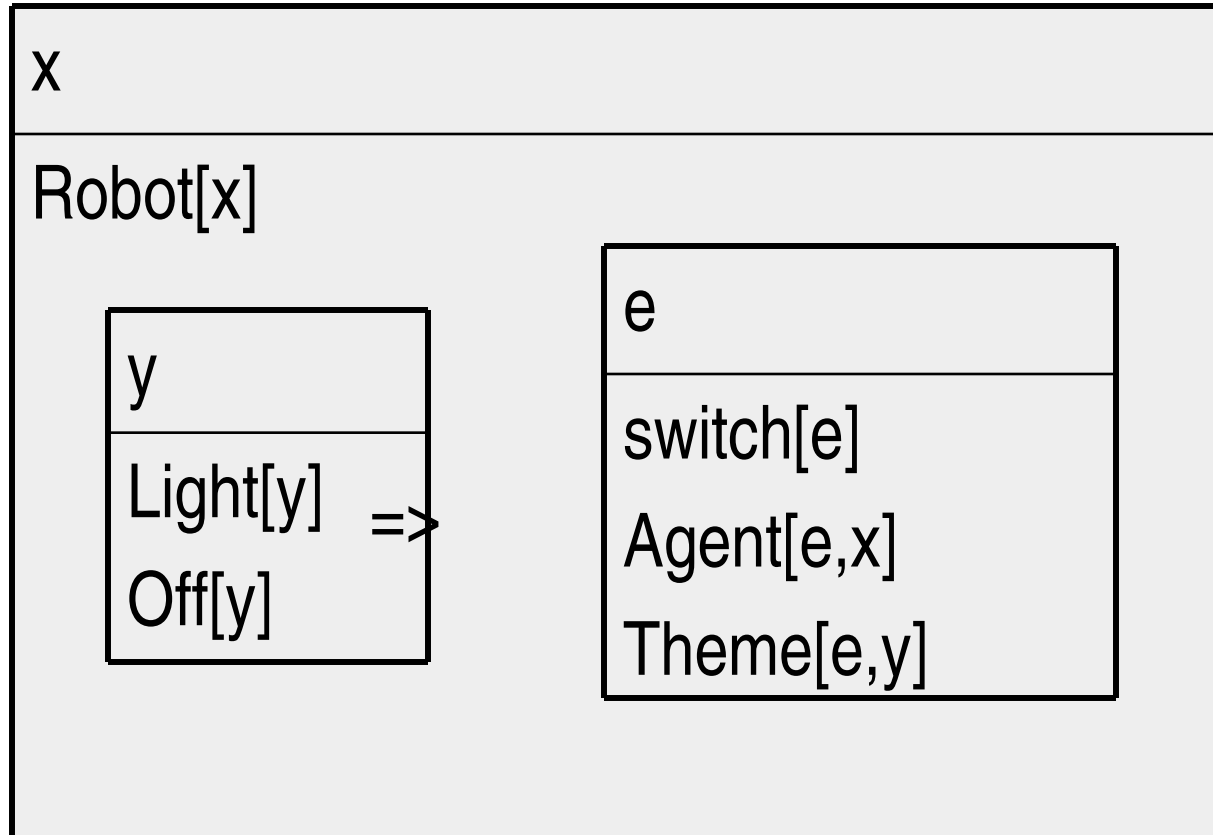
Sketch of resolution



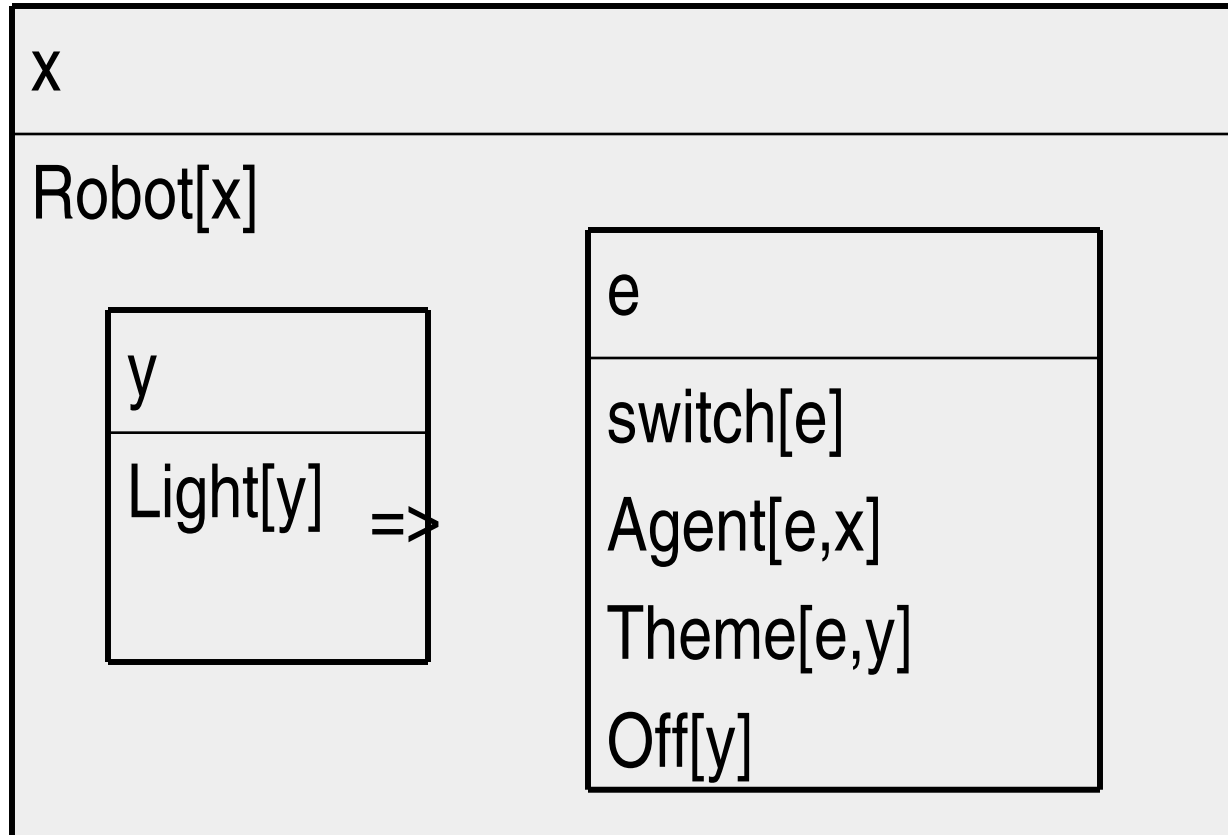
Global Accommodation



Intermediate Accommodation



Local Accommodation



Godot the Robot [later]



Godot at the Scottish museum

The Third Story

Recognising Textual Entailment

*Or how Rob's Algorithm is applied
to wide-coverage semantic
processing of texts*



2005-present

Recognising Textual Entailment

- What is it?
 - A task for NLP systems to recognise entailment between two (short) texts
 - Proved to be a difficult, but popular task.
- Organisation
 - Introduced in 2004/2005 as part of the PASCAL Network of Excellence, RTE-1
 - A second challenge (RTE-2) was held in 2005/2006
 - PASCAL provided a development and test set of several hundred examples

RTE Example (entailment)

RTE 1977 (TRUE)

His family has steadfastly denied the charges.

The charges were denied by his family.

RTE Example (no entailment)

RTE 2030 (FALSE)

Lyon is actually the gastronomical capital
of France.

Lyon is the capital of France.

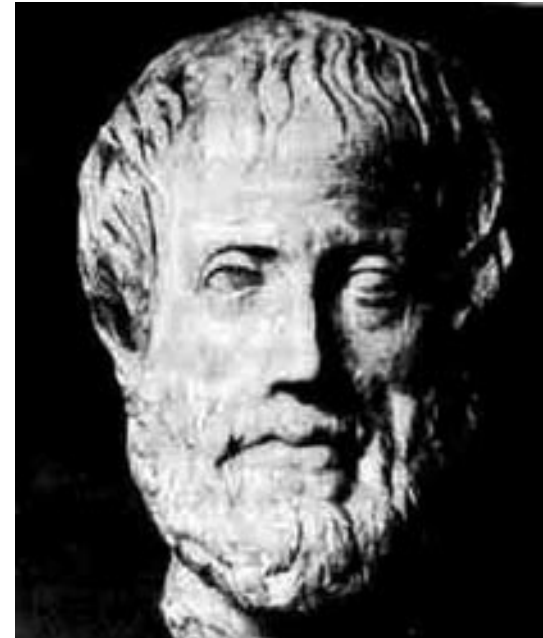
Aristotle's Syllogisms

ARISTOTLE 1 (TRUE)

All men are mortal.

Socrates is a man.

Socrates is mortal.



Recognising Textual Entailment

Method A:
Flipping a coin



Flipping a coin

- Advantages
 - Easy to implement
 - Cheap
- Disadvantages
 - Just 50% accuracy

Recognising Textual Entailment

Method B:
Calling a friend



Calling a friend

- Advantages
 - High accuracy (95%)
- Disadvantages
 - Lose friends
 - High phone bill

Human Upper Bound

RTE 893 (TRUE)

The first settlements on the site of Jakarta were established at the mouth of the Ciliwung, perhaps as early as the 5th century AD.

The first settlements on the site of Jakarta were established as early as the 5th century AD.

Recognising Textual Entailment

Method C:
Semantic Interpretation

Robust Parsing with CCG

- Rapid developments in statistical parsing the last decades
- Yet most of these parsers produced syntactic analyses not suitable for systematic semantic work
- This changed with the development of CCGbank and a fast CCG parser

Combinatorial Categorical Grammar

- CCG is a lexicalised theory of grammar (Steedman 2001)
- Deals with complex cases of coordination and long-distance dependencies
- Lexicalised
 - Many lexical categories
 - Few combinatorial rules

CCG: lexical semantics

Category	Semantics	Example			
N	$\lambda x.$ <table border="1" style="display: inline-table; vertical-align: middle;"> <tr><td> </td></tr> <tr><td>spokesman(x)</td></tr> </table>		spokesman(x)	<i>spokesman</i>	
spokesman(x)					
NP/N	$\lambda p. \lambda q. (($ <table border="1" style="display: inline-table; vertical-align: middle;"> <tr><td>x</td></tr> <tr><td> </td></tr> </table> $)q(x)); q(x))$	x		<i>a</i>	
x					
NP/N	$\lambda p. \lambda q. (($ <table border="1" style="display: inline-table; vertical-align: middle;"> <tr><td>x</td></tr> <tr><td> </td></tr> </table> $)q(x)) \alpha q(x))$	x		<i>the</i>	
x					
S\NP	$\lambda y.$ <table border="1" style="display: inline-table; vertical-align: middle;"> <tr><td>e</td></tr> <tr><td>lie(e)</td></tr> <tr><td>agent(e,y)</td></tr> </table>	e	lie(e)	agent(e,y)	<i>lied</i>
e					
lie(e)					
agent(e,y)					

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda z.$

spokesman(z)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda z.$

spokesman(z)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

(FA)

NP: a spokesman

$\lambda p. \lambda q.$

x

 $p(x);q(x)(\lambda z.$

spokesman(z)

)

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda z.$

spokesman(z)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

(FA)

NP: a spokesman

$\lambda q.$

x

spokesman(x)

)

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda z.$

spokesman(z)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

----- (FA)

NP: a spokesman

$\lambda q.$

x
spokesman(x)

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda x.$

spokesman(z)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

(FA)

NP: a spokesman

$\lambda q.$

x
spokesman(x)

(BA)

S: a spokesman lied

$\lambda q.$

x
spokesman(x)

e
lie(e)
agent(e,y)

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda x.$

spokesman(z)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

(FA)

NP: a spokesman

$\lambda q.$

x
spokesman(x)

(BA)

S: a spokesman lied

x
spokesman(x)

e
lie(e)
agent(e,x)

CCG derivation

NP/N:a

$\lambda p. \lambda q.$

x

 $p(x);q(x)$

N:spokesman

$\lambda x.$

spokesman(x)

S\NP:lie

$\lambda y.$

e
lie(e)
agent(e,y)

(FA)

NP: a spokesman

$\lambda q.$

x
spokesman(x)

(BA)

S: a spokesman lied

x e
spokesman(x)
lie(e)
agent(e,x)

Implementation

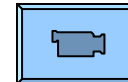
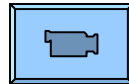
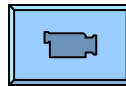
- Use standard statistical techniques
 - Robust wide-coverage parser
 - Clark & Curran (ACL 2004)
- Grammar derived from CCGbank
 - 409 different categories
 - Hockenmaier & Steedman (ACL 2002)

Example Output

- Example:

Pierre Vinken, 61 years old, will join the board as a nonexecutive director Nov. 29. Mr. Vinken is chairman of Elsevier N.V., the Dutch publishing group.

- Unresolved DRS
- Resolved DRS
- Complete Wall Street Journal



Back to RTE

- Given a textual entailment pair T/H with text T and hypothesis H:
 - Produce DRSs for T and H
 - Translate these DRSs into FOL
 - Generate Background Knowledge in FOL
- Use theorem provers and model builders to determine the likelihood of entailment
 - Theorem Proving: $[\mathbf{BK} \ \& \ \mathbf{T}'] \rightarrow \mathbf{H}'$
 - Model Building: $\mathbf{BK} \ \& \ \mathbf{T}'$ and $\mathbf{BK} \ \& \ \mathbf{T}' \ \& \ \mathbf{H}'$

Example

RTE-2 100 (TRUE)

This document declares the irrevocable determination of Edward VIII to abdicate. By signing this document on December 10th, 13, he gave up his right to the British throne.

King Edward VIII abdicated on the 10th of December, 13.

Example

RTE-2 100 (TRUE)

This document declares the irrevocable determination of Edward VIII to abdicate. By signing this document on December 10th, 13, he gave up his right to the British throne.

King Edward VIII abdicated on the 10th of December, 13.

- Vampire [theorem prover]:
 - no proof

Example

RTE-2 100 (TRUE)

This document declares the irrevocable determination of Edward VIII to abdicate. By signing this document on December 10th, 13, he gave up his right to the British throne.

King Edward VIII abdicated on the 10th of December, 13.

- Paradox/Mace [model builders]:
 - similar models, i.e. difference between models for T and T+H small

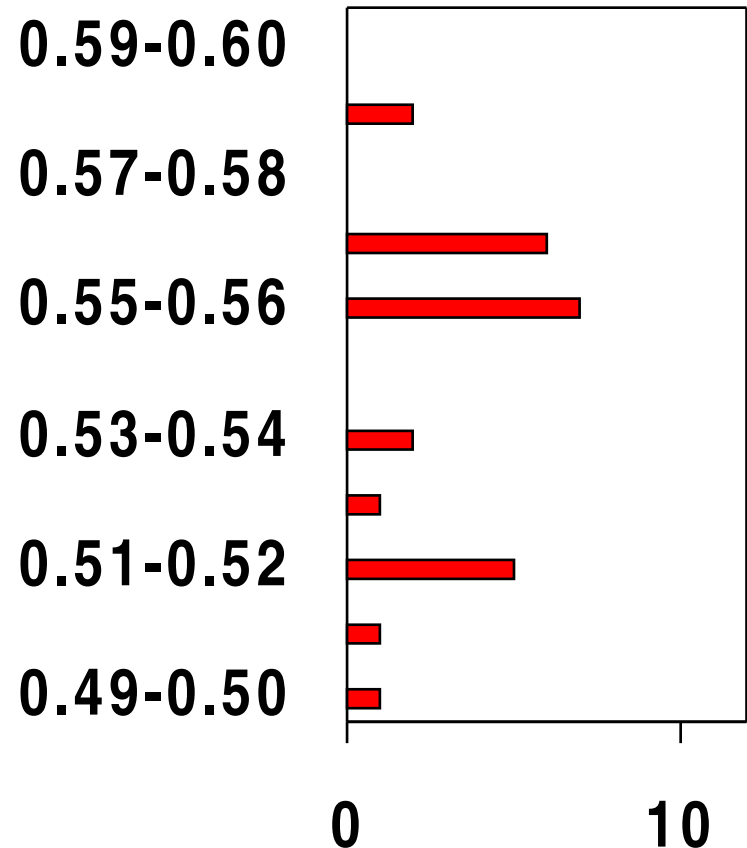
How well does this work?

- We tried this at the RTE-1 and RTE-2
- Using standard machine learning methods to build a decision tree using features
 - Proof (yes/no)
 - Domain size difference
 - Model size difference
- Better than baseline, still room for improvement

RTE State-of-the-Art

- Pascal RTE-1 challenge
- Hard problem
- Requires semantics
- Requires a lot of background knowledge

Accuracy RTE 2004/5 (n=25)



Summary

- Rob's Algorithm had a major influence on how computational semantics is perceived today
 - Implementations used in pioneering work of using first-order inference in NLP
 - Implementations used in spoken dialogue systems
 - Now also used in wide-coverage NLP systems