Introduction to Natural Language Processing

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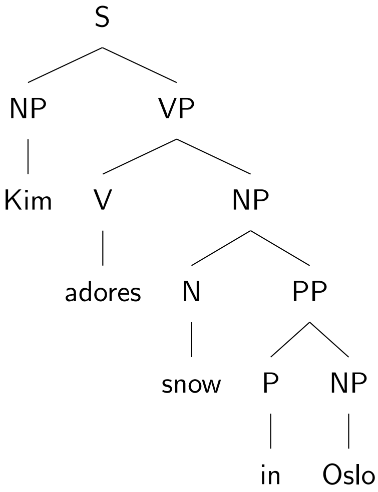
Overview

- Formal semantics, FOL, lambda-calculus
- Compositional semantics
- Semantics in computational linguistics
- Semantics in NLP

Parsing makes explicit inherent structure. So, does this tree represent meaning?



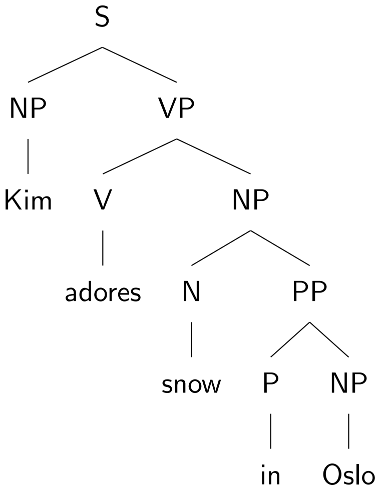
Why represent meaning computationally?

I hated this movie!

- A Dialog system:
  - Parser:
    - Yes, it is grammatical!
    - Here's the structure!
  - System: Great, but what am I supposed to DO?

Formal semantics question:

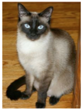
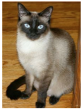
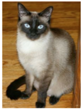
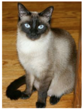
How could we put this tree in correspondence to a model of the world?



Model theoretic semantics

- Create a model of the world consisting of elements, sets of elements, and relations
  - not so much a model of what things **mean** as of **how we reason** about them
- Create an interpretation function which maps linguistic elements (parts of the semantic structure) to parts of the model
- Simple propositions are interpreted by checking their truth in the model
- Define semantics for "logical vocabulary": and, or, not, if, every, some...

Model theoretic semantics (example)

- Entities: Joey:  Fluffy:  Tiger: 
- Properties: calm: {   }; angry: {  }
- Relations: knows: { <  ,  > , <  ,  > }

Model theoretic semantics (denotations)

- [[Fluffy]] = 

- [[angry]] = { x | x is angry } = {  }

- [[Fluffy is angry]] = True *iff* the entity denoted by *Fluffy* is in the set denoted by *angry*

- Compositionality: The process of determining the truth conditions of *Fluffy is angry* based on the denotations of its parts and its syntactic structure

Logical vocabulary gets special treatment

- “First Class and Smile Members here“ (airport)
- Fluffy is angry and Joey is not angry.
  - What does *and* mean?
  - What does *not* mean?
- Every cat is angry.
  - What does *cat* mean?
  - What does *every* mean?
- Is the division into logical and non-logical vocabulary an inherent property of language or an artifact of the system of meaning representation?

Quantifiers

- The semantic type of a quantifier is a relation between sets, called the restriction and body (or scope) of the quantifier
- $[\![\textit{every}]\!]$ $\{ <P,Q> \mid P \subseteq Q\}$
- $[\![$every cat is angry$]\!]$ is True iff
  $\{ x \mid x \text{ is a cat } \} \subseteq \{ y \mid y \text{ is angry } \}$
- $[\![\textit{some}]\!]$ $\{ <P,Q> \mid P \cap Q \neq \emptyset\}$
- $[\![$some cat is angry$]\!]$ is True iff
  $\{ x \mid x \text{ is a cat } \} \cap \{ y \mid y \text{ is angry } \} \neq \emptyset$
- $[\![\textit{many}]\!]$?

Partial evaluation for FOL: Lambda calculus

- Basic idea: pass around partially evaluated functions
- feed them to other functions as arguments
- e.g. $f : y = x + 2$
- plug in $x = 3$, evaluate to 5
- or: $f : z = y * (x + 2)$
- plug in $x = 3$, evaluate to $f : z = 3y$
- then can plug in y = 2 and evaluate to 6

Lambda calculus for semantics

- Used to evaluate FOL expressions in a compositional manner
- e.g. constituent by constituent
- A constituent does not necessarily have a truth value:

$$\lambda x.gave(Kim, book, x)$$

- need to hold on to a partially evaluated constituent
- Converting multi-argument predicates to sequences of single-argument predicates
- Incrementally accumulates multiple arguments spread over different parts of the tree

Lambda calculus

- Form: λ + Variable + FOL expression
- $\lambda x.P(x)$ (evaluating the expression with respect to x)
- $\lambda x.P(x)(A) \rightarrow P(A)$ (λ-reduction; binding a formal parameter to a concrete term)
- $\lambda x.\lambda y.Near(x, y)$
- $\lambda x.\lambda y.Near(x, y)(Moscow)$
- $\lambda y.Near(Moscow, y)$
- $\lambda y.Near(Moscow, y)(Center)$
- $Near(Moscow, Center)$

Lambda calculus and composition

- One semantic composition rule per syntax rule.
- `S -> NP VP`
  VP′(NP′)
- Rover barks:
  VP *bark* is $\lambda x[\text{bark}'(x)]$
  NP *Rover* is r
  $\lambda x[\text{bark}'(x)](r) = \text{bark}'(r)$

Transitive verbs

Kitty chases Rover

- Transitive verbs: two arguments (NOTE the order)
  $\lambda x[\lambda y[\text{chase}'(y, x)]]$
- `VP -> Vtrans NP`
  $\text{Vtrans}'(\text{NP}')$
- $\lambda x \lambda y[\text{chase}'(y, x)](r) = \lambda y[\text{chase}'(y, r)]$
- `S -> NP VP`
  $\text{VP}'(\text{NP}')$
- $\lambda y[\text{chase}'(y, r)](k) = \text{chase}'(k, r)]$

Grammar fragment using lambda calculus

`S -> NP VP`	$\mathrm{VP}'(\mathrm{NP}')$
`VP -> Vtrans NP`	$\mathrm{Vtrans}'(\mathrm{NP}')$
`VP -> Vintrans`	$\mathrm{Vintrans}'$
`Vtrans -> chases`	$\lambda x \lambda y[\mathrm{chase}'(y, x)]$
`Vintrans -> barks`	$\lambda z[\mathrm{bark}'(z)]$
`Vintrans -> sleeps`	$\lambda w[\mathrm{sleep}'(w)]$
`NP -> Kitty`	k

Beyond toy examples ...

- Use first order logic where possible (e.g., event variables, next slide).
- However, First Order Predicate Calculus (FOPC) is sometimes inadequate: e.g., *most*, *may*, *believe*.
- Quantifier scoping multiplies analyses:
  Every cat chased some dog:
  $\forall x[\text{cat}'(x) \implies \exists y[\text{dog}'(y) \wedge \text{chase}'(x, y)]]$
  $\exists y[\text{dog}'(y) \wedge \forall x[\text{cat}'(x) \implies \text{chase}'(x, y)]]$
- Often no straightforward logical analysis
  e.g., Bare plurals such as *Ducks lay eggs*.
- Non-compositional phrases (multiword expressions): e.g., *red tape* meaning bureaucracy.

Event variables

- Allow first order treatment of adverbs and PPs modifying verbs by reifying the event.
- Rover barked
- instead of $\text{bark}'(r)$ we have $\exists e[\text{bark}'(e, r)]$
- Rover barked loudly
- $\exists e[\text{bark}'(e, r) \wedge \text{loud}'(e)]$
- There was an event of Rover barking and that event was loud.

Computational semantics desiderata (J&M)

- Verifiability: We must be able to compare the representation to a knowledge base
- Lack of ambiguity: A semantic representation should have just one interpretation
- Canonical form: A given interpretation should have just one representation
- Expressiveness: Must be able to adequately represent a wide range of expressions

Computational semantics desiderata (Copestake)

- Expressive Adequacy: The framework must allow linguistic meanings to be expressed correctly
- Grammatical Compatibility: clear link to other kinds of grammatical information (most notably syntax)
- Computational Tractability: Process meanings, check semantic equivalence, express relationships between semantic representations straightforwardly
- Underspecifiability: Allow resolution of partial semantic representations

Computational semantics

- Semantic parsing: mapping surface sentence to a semantic representation
- Should this representation be a structure?
  - Sentence meaning: probably yes
  - Speaker meaning: unclear

(But sentence meaning is usually directly involved in speaker meaning)

Sentence vs. Speaker meaning (Grice 1968)

- Through experience within our speech communities, we learn (and help create) shared linguistic conventions.
- These conventions support fairly consistent calculation of **sentence meaning** by different speakers in the same community.
- The sentence meaning of an utterance (together with its form) serves as a clue which a listener can use to construct his/her representation of the speaker's **speaker meaning**

Sentence vs. Speaker meaning

Could you pass me the salt? – No, I couldn't pass you the salt!

- Sentence meaning, but not speaker meaning, is compositional
- Systems attempting to understand speaker meaning directly from surface: resolve the same problems around grammatical structure for each task unlikely to scale

Semantic compositionality

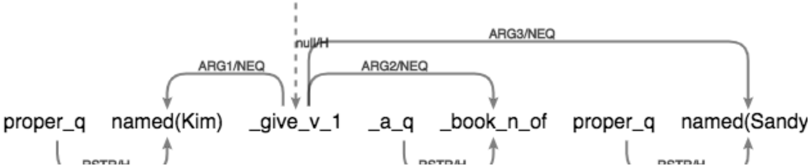
- The meaning of the whole must be directly assembled from its parts
- E.g. *Agent/patient* information comes from the *subject/object constituents*
- The syntactico-semantic formalism must explicitly ensure such connections and assembly

Compositional layer and syntax-semantics interface

- Predicate-argument structure
- Scope of negation and other operators
- Restriction of quantifiers
- Modality
- Tense/aspect/mood
- Information structure
- Discourse status of referents of NPs
- Politeness

Minimal Recursion Semantics (MRS)

- An example of a compositional computational semantics approach
- Copestake et al. (2005)
- A semantic formalism (not a semantic theory)



Kim gave a book to Sandy

Minimal Recursion Semantics (MRS)

TOP	*h0*
INDEX	*e2*

RELS ⟨

proper_q⟨0:3⟩	
LBL	*h4*
RSTR	*h5*
ARG0	*x3*
BODY	*h6*

,

named⟨0:3⟩	
LBL	*h7*
ARG0	*x3*
CARG	*Kim*

,

_give_v_1⟨4:8⟩	
LBL	*h1*
ARG3	*x10*
ARG2	*x9*
ARG1	*x3*
ARG0	*e2*

,

_a_q⟨9:10⟩	
LBL	*h11*
RSTR	*h12*
ARG0	*x9*
BODY	*h13*

,

_book_n_of⟨11:15⟩	
LBL	*h14*
ARG1	*i15*
ARG0	*x9*

,

proper_q⟨19:24⟩	
LBL	*h16*
RSTR	*h17*
ARG0	*x10*
BODY	*h18*

,

named⟨19:24⟩	
LBL	*h19*
ARG0	*x10*
CARG	*Sandy*

⟩

HCONS ⟨

qeq	
HARG	*h17*
LARG	*h19*

,

qeq	
HARG	*h12*
LARG	*h14*

,

qeq	
HARG	*h0*
LARG	*h1*

,

qeq	
HARG	*h5*
LARG	*h7*

⟩

Kim gave a book to Sandy

Machine translation by transfer

- Assuming a canonical form for semantic structure, we can generate sentences in one language given a semantic structure which was obtained by parsing a sentence in another language
- A **symbolic** approach to MT
- Requires **grammars** for both languages
- Ensures **precision and grammaticality** of the translations
- Disadvantage: lack of **robustness**: not every sentence will be translated.

```
ace -g grammar.dat -Tf1 | ace -g grammar.dat -e
```

MRS: MINIMAL recursion semantics

- Syntactic structure may sometimes be irrelevant to the truth conditions
- *fierce black cat* vs *gato negro y feroz*
- with syntax insufficiently abstracted away, hard to do transfer
- the LFs produced by the two grammars will look different:

a. $\lambda x[\text{fierce}(x) \wedge (\text{black}(x) \wedge \text{cat}(x))]$
b. $\lambda x[\text{gato}(x) \wedge (\text{negro}(x) \wedge \text{feroz}(x))]$
c. $\lambda x[\text{cat}(x) \wedge (\text{black}(x) \wedge \text{fierce}(x))]$

- $\textit{fierce}(x) \wedge \textit{black}(x) \wedge \textit{cat}(x)$ – solution?

Flat semantics: quantifier problem

- *Every white horse is old*
- every (x, white (x) $\wedge$ horse (x), old (x))
- Flat: every(x), horse(x), old(x), white(x)
- problem?

Flat semantics: quantifier problem

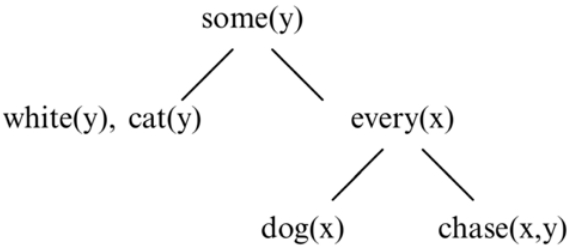
- *Every white horse is old*
- every (x, white (x) $\wedge$ horse (x), old (x))
- Flat: every(x), horse(x), old(x), white(x)
- problem?
- *Every old horse is white*?

Quantifier scope

Every dog chases some white cat

a. $\text{some}(y, \text{white}(y) \wedge \text{cat}(y), \text{every}(x, \text{dog}(x), \text{chase}(x, y)))$

b.



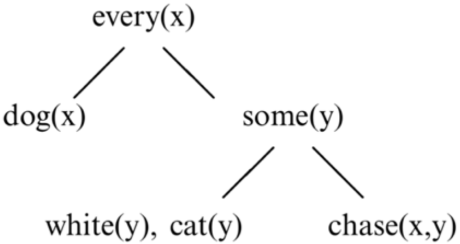
c. $h1: \text{every}(x, h3, h4), h3: \text{dog}(x), h7: \text{white}(y), h7: \text{cat}(y),$
$h5: \text{some}(y, h7, h1), h4: \text{chase}(x, y)$

Quantifier scope

Every dog chases some white cat

a. every(x, dog(x), some(y, white(y) $\wedge$ cat(y), chase(x, y)))

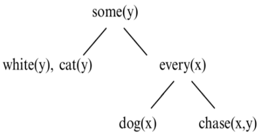
b.



c. $h1$: every(x, $h3$, $h5$), $h3$: dog(x), $h7$: white(y), $h7$: cat(y),
$h5$: some(y, $h7$, $h4$), $h4$: chase(x, y)

Scope underspecification

a. $\text{some}(y, \text{white}(y) \wedge \text{cat}(y), \text{every}(x, \text{dog}(x), \text{chase}(x, y)))$
b.



c. $h1\colon \text{every}(x, h3, h4), h3\colon \text{dog}(x), h7\colon \text{white}(y), h7\colon \text{cat}(y),$
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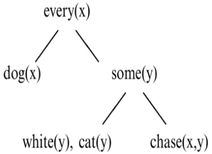
b.



c. $h1\colon \text{every}(x, h3, h5), h3\colon \text{dog}(x), h7\colon \text{white}(y), h7\colon \text{cat}(y),$
$h5\colon \text{some}(y, h7, h4), h4\colon \text{chase}(x, y)$

$$h1\colon \text{every}(x, h3, h8), h3\colon \text{dog}(x), h7\colon \text{white}(y), h7\colon \text{cat}(y),$$
$$h5\colon \text{some}(y, h7, h9), h4\colon \text{chase}(x, y)$$

- *Every dog chases some white cat*
- Can say EITHER $h9 = h1$ or $h8 = h5$

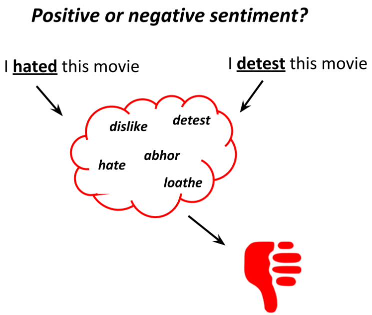
NLP business with semantics

- Construct knowledge base or model of the world
  - wikidata, DbPedia, ConceptNet
  - TBOX vs ABOX
- Extract meaning representations from linguistic input
- Match input to world knowledge
- Produce replies/take action (or queries) on the basis of the results

Semantics in NLP

- The hottest area in NLP right now
- all kinds of NLU tasks are associated with semantic annotation and semantic parsing
  - sentiment analysis
  - dialog systems
  - news/ads ranking etc.
- NLP semantics today is usually task-oriented and domain-tailored e.g. a grammar/semantic system for cooking recipes often have nothing to do with theoretical semantics ambitions

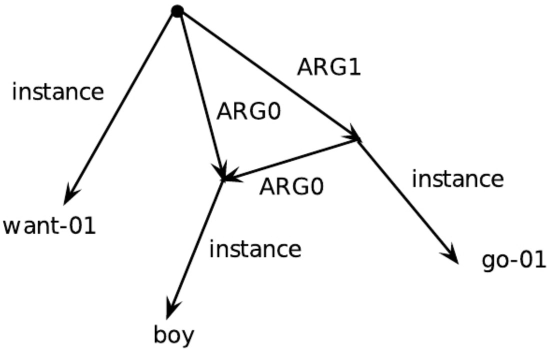
Semantics in NLP



- Linguistic models, syntactic or semantic (or morphological...) tend to be too unwieldy for today's NLP
- NLP goals: perform well on a task, not necessarily precisely and not necessarily providing explanations
- Tacit expectation to map directly from *surface* to *speaker meaning*

(pre-vector space) semantics in NLP

- e.g. Abstract Meaning Representation (AMR; Banarescu et al., 2013)
- Note similarities with dependency parse
- https://amr.isi.edu



AMR: a widely adopted formalism

"We describe Abstract Meaning Representation (AMR), a semantic representation language in which we are writing down the meanings of thousands of English sentences. We hope that a sembank of simple, whole-sentence semantic structures will spur new work in statistical natural language understanding and generation, like the Penn Treebank encouraged work on statistical parsing." (Banarescu et al., 2013)

this came true!! we look at it as an example of a widely adopted formalism!

AMR: Pros and Cons

+ very simple representation
+ yields nice immediate results
+ wide paraphrase sets
- Plateaus: like WJS, AMR-based research keeps reusing the same dataset and ends up overfitting to it
- Inconsistent and task-dependent annotation

Thematic Roles

- describe semantic roles of verbal arguments
- capture commonality across verbs
- e.g. subject *break/open* is AGENT (volitional cause). THEME (things affected by action)
- enables generalization over surface order of arguments
  - John$_{agent}$ broke the window$_{theme}$
  - The rock$_{instrument}$ broke the window$_{theme}$
  - The window$_{theme}$ was broken by John$_{agent}$

Thematic Role Issues

Hard to produce:

- standard set of roles. Fragmentation: often need to make more specific. E.g. INSTRUMENT can be subject?
- standard definition of roles: most AGENTs (animals, volitional, sentient, causal. . .) but not all.

strategies:

- generalized semantic roles (proto-agent, proto-patient etc)
- definied heuristically (propbank)
- define roles specific to verbs/nouns: FrameNet

Even if we come up with a standard set of some sort, we will have low inter-annotator agreement. Hard to expect that people will interpret the roles exactly the same

Sembanks, Propbanks...

- Representations like AMR can be stored in "sembanks"
- Compare to treebanks
- Challenge: **interannotator agreement**
  - ...is a problem with treebanks, too, unless a grammar is used
  - is even a bigger problem in sembanks
  - role-labeling is more vague than syntactic structure
  - e.g. what kind of granularity?
- Familiar issues with overfitting

PropBank

(22.11) **agree.01**

Arg0: Agreer
Arg1: Proposition
Arg2: Other entity agreeing

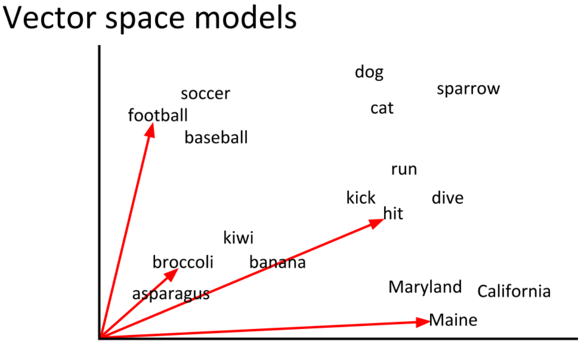
Ex1: [$_{\text{Arg0}}$ The group] *agreed* [$_{\text{Arg1}}$ it wouldn't make an offer].
Ex2: [$_{\text{ArgM-TMP}}$ Usually] [$_{\text{Arg0}}$ John] *agrees* [$_{\text{Arg2}}$ with Mary] [$_{\text{Arg1}}$ on everything].

(22.12) **fall.01**

Arg1: Logical subject, patient, thing falling
Arg2: Extent, amount fallen
Arg3: start point
Arg4: end point, end state of arg1
Ex1: [$_{\text{Arg1}}$ Sales] *fell* [$_{\text{Arg4}}$ to \$25 million] [$_{\text{Arg3}}$ from \$27 million].
Ex2: [$_{\text{Arg1}}$ The average junk bond] *fell* [$_{\text{Arg2}}$ by 4.2%].

http://propbank.github.io

Vector space semantics



- The core of today's NLP
- Are word vectors semantic representations?
- Yes, but not necessarily compositional

Word senses and Word sense disambiguation

- A problem from which word vectors arise
- How close/distinct are the senses of two words?
- How to determine this computationally?

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  - See which contexts they appear in: N-grams! (or, these days, word vectors) $\rightarrow$ Compute distance $\rightarrow$ Closer distance $=$ closer meaning?
- What is one problem with this?

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- What is one problem with this?
  - This place is very **loud**
  - This place is very **quiet**
- Antonyms tend to occur in the same context

Natural language inference

- Inference on a knowledge base: convert natural language expression to KB expression, valid inference according to KB.
  - \+ Precise
  - \+ Formally verifiable
  - \+ Disambiguation using KB state
  - \- Limited domain, requires KB to be formally encodable
- Language-based inference: does one utterance follow from another?
  - \+ Unlimited domain
  - +/- Human judgement
  - -/+ Approximate/imprecise
- Both approaches may use logical form of utterance.

Lexical meaning and meaning postulates

- Some inferences validated on logical representation directly, most require lexical meaning.
- meaning postulates: e.g.,

$$\forall x[\text{bachelor}'(x) \rightarrow \text{man}'(x) \wedge \text{unmarried}'(x)]$$

- usable with compositional semantics and theorem provers
- e.g. from 'Kim is a bachelor', we can construct the LF bachelor$'$(Kim) and then deduce unmarried$'$(Kim)
- Problematic in general, OK for narrow domains or micro-worlds.

Recognising Textual Entailment (RTE) shared tasks

T: The girl was found in Drummondville earlier this month.

H: The girl was discovered in Drummondville.

- DATA: pairs of text (T) and hypothesis (H). H may or may not follow from T.
- TASK: label TRUE (if follows) or FALSE (if doesn't follow), according to human judgements.

Many approaches

- https://aclanthology.org/S14-2125/ and https://aclanthology.org/W15-2205/
- Natural Logic https://aclanthology.org/W09-3714/
- Combining symbolic and ML/DL https://aclanthology.org/2020.coling-demos.9/ and https://aclanthology.org/P16-2079/

RTE using logical forms

- T sentence has logical form T′, H sentence has logical form H′
- If $T' \implies H'$ conclude TRUE, otherwise conclude FALSE.

T The girl was found in Drummondville earlier this month.

T′ $\exists x, u, e[\text{girl}'(x) \wedge \text{find}'(e, u, x) \wedge \text{in}'(e, \text{Drummondville}) \wedge \text{earlier-this-month}'(e)]$

H The girl was discovered in Drummondville.

H′ $\exists x, u, e[\text{girl}'(x) \wedge \text{discover}'(e, u, x) \wedge \text{in}'(e, \text{Drummondville})]$

MP $[\text{find}'(x, y, z) \implies \text{discover}'(x, y, z)]$

- So $T' \implies H'$ and we conclude TRUE

More complex examples

T: Four Venezuelan firefighters who were traveling to a training course in Texas were killed when their sport utility vehicle drifted onto the shoulder of a highway and struck a parked truck.

H: Four firefighters were killed in a car accident.

Systems using logical inference are not robust to missing information: simpler techniques can be effective (partly because of choice of hypotheses in RTE).

More examples

T: Clinton's book is not a big seller here.

H: Clinton's book is a big seller.

T: After the war the city was briefly occupied by the Allies and then was returned to the Dutch.

H: After the war, the city was returned to the Dutch.

T: Lyon is actually the gastronomic capital of France.

H: Lyon is the capital of France.