Syntactic and semantic parsing for natural language understanding

2. Syntactic and semantic parsing with CCG

Hiroshi Noji

Topics

- In the last week, we focused on the grammatical property of CCG
  - Logical forms can be obtained through syntactic derivations
  - The number of rules is small, and much information is encoded in the lexicon
- Today's topic:
  - how to efficiently obtain CCG derivation on the input sentence **= syntactic parsing**
  - Application to semantic parsing in textual entailment and QA

Outline

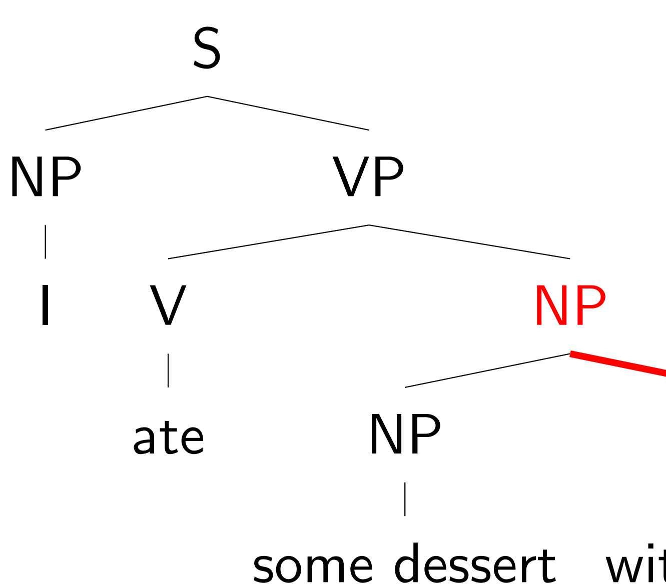
- Efficient parsing techniques for CCG
- Bottom-up semantic parsing with CCG
  - application to textual entailment
  - issues in question answering
- Top-down semantic parsing with CCG for question answering

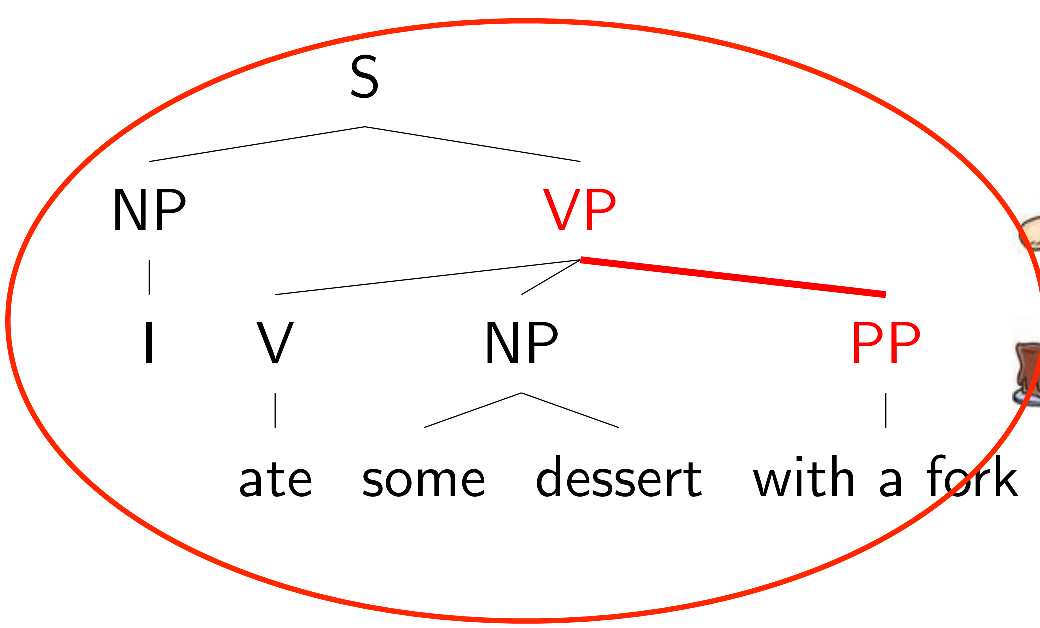
QA is moved to the next lecture (Thursday)

Goal of parsing: disambiguation

- What is the correct tree?
  - correct tree is the one **corresponding to human interpretation**
- Parsing aims at finding a tree that corresponds to human interpretation
- Example: PP-attachment ambiguity

I ate some dessert with a fork



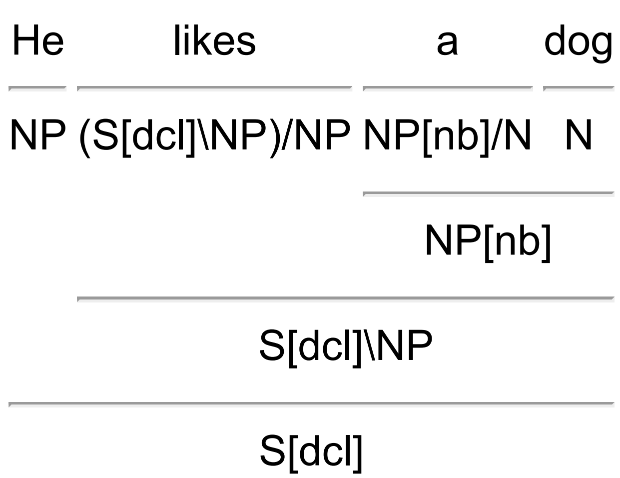


Figures from Natural Language Understanding: Foundations and State-of-the-Art (Liang, 2015)

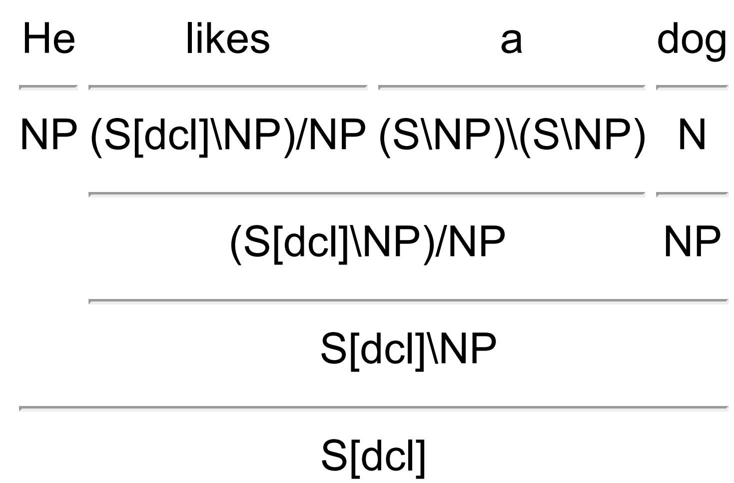
Statistical parsing

- Today most practical parsers are statistical parsers with supervised machine learning
  - Typically we use 10,000~30,000 trees to train a parser
- After training a parser, the essential problem is **search**
  - The parser can assign a score to each tree (structure)
  - How can we find the best tree for the model?
  - The number of trees is exponential to the length of the sentence
- Our recent work (Yoshikawa et al., 2017) found that CCG parsing can be more efficient than phrase-structure parsing by exploiting the property of the grammar effectively

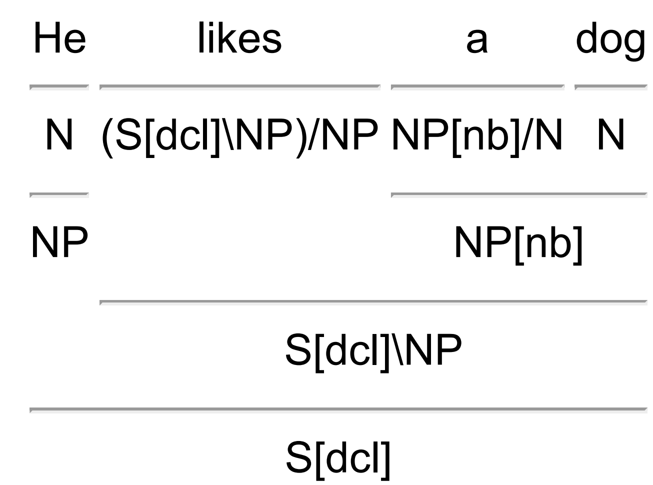
There are so many parses



1000 600

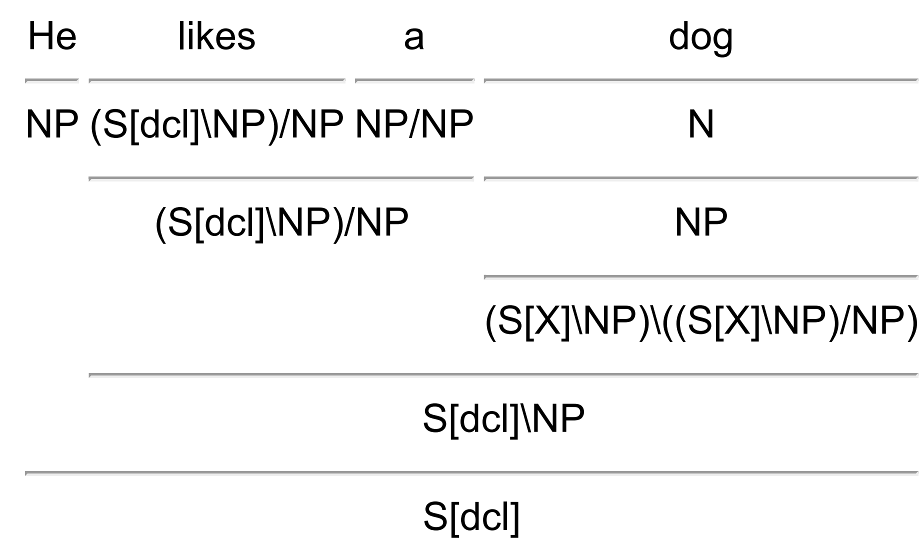


200 800



180 400

- Even for a very short sentence, the number of possible trees is large



100 200

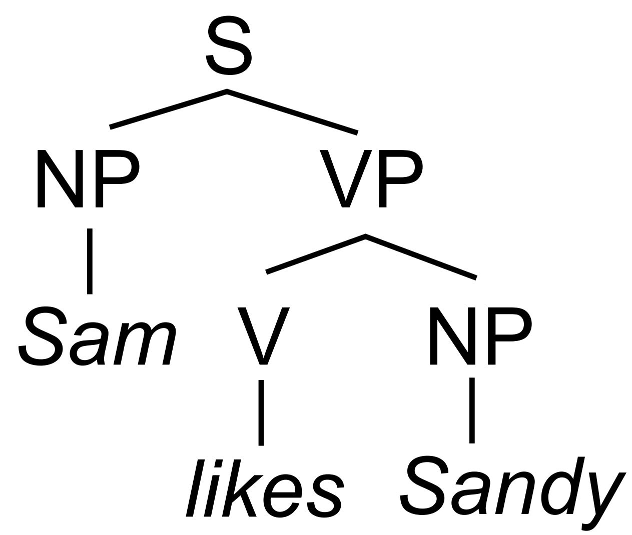
- Problems:
  - **Model:** how to obtain the model that gives the highest score to the correct tree?
  - **Search:** how to find the best tree for the model?

Model and search

- Model and search are not independent
- Generally, more complex model gets more strong (higher expressive power), but the search becomes harder
- So one critical problem in parsing is to develop a model that best balances the tradeoff between the expressivity of the model and the difficulty of search

Simple model: PCFG

Rule:	Probability:
S → NP VP	1.0
NP → *Sam*	0.7
NP → *Sandy*	0.3
VP → V NP	1.0
V → *likes*	0.8
V → *hates*	0.2



$$P(\text{Tree}) = 1.0 \times 0.7 \times 1.0 \times 0.8 \times 0.3$$

- Each rule has a different probability
- The probability of a tree is the product of all rules on the tree
- **Search:** we can find the highest score tree $\text{argmax}_t \, P(t)$ with dynamic programming called CKY in O(n^3|G|)
  - |G| is the number of rules in the grammar

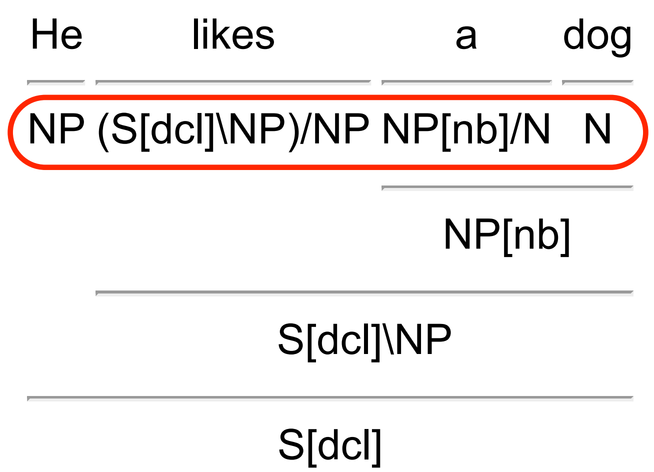
Learning is easy

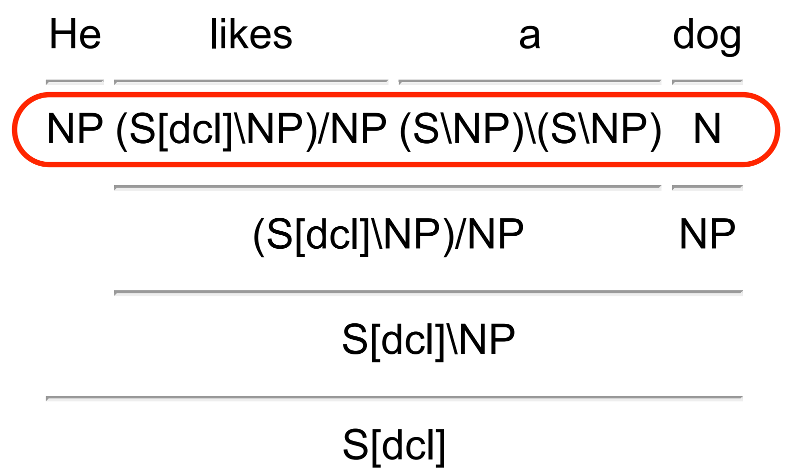
- Learning a naive PCFG from the training data (= the collection of trees, called a treebank) is very simple
- Just maximum likelihood
  - Count the number of occurrences of each rule in the treebank
  - Normalize each score to get probability

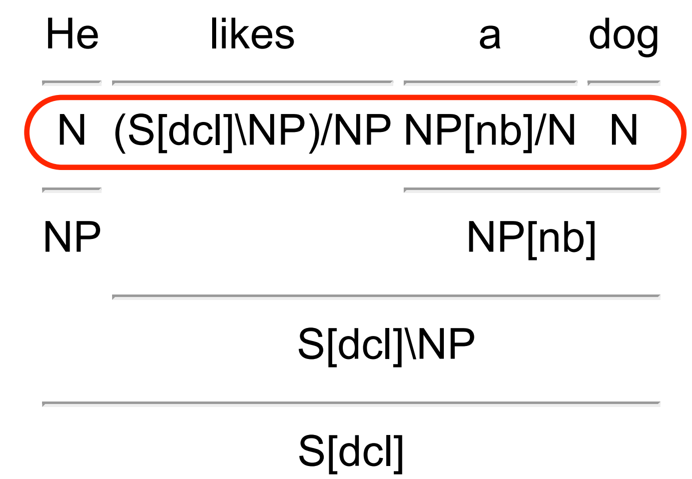
PCFG parsing for CCG?

- It has been tried at the very beginning of CCG parsing
  - Hockenmaier (2001). *Statistical Parsing for CCG with Simple Generative Models*. ACL student research workshop.
- Problem:
  - The search space (= size of grammar) is quite huge
  - r = (S\NP)/NP → (S\NP)/(S\NP)   S\NP/NP …
  - A number of occurrences of each rule is small = **sparsity issue**
- The popular parser (Clark and Curran, 2008) employs a log-linear model for scoring each rule
  - Score(r) = Score(top=(S\NP)/NP) + Score(Right= S\NP/NP) + …
  - **breaking independence assumption of each rule**

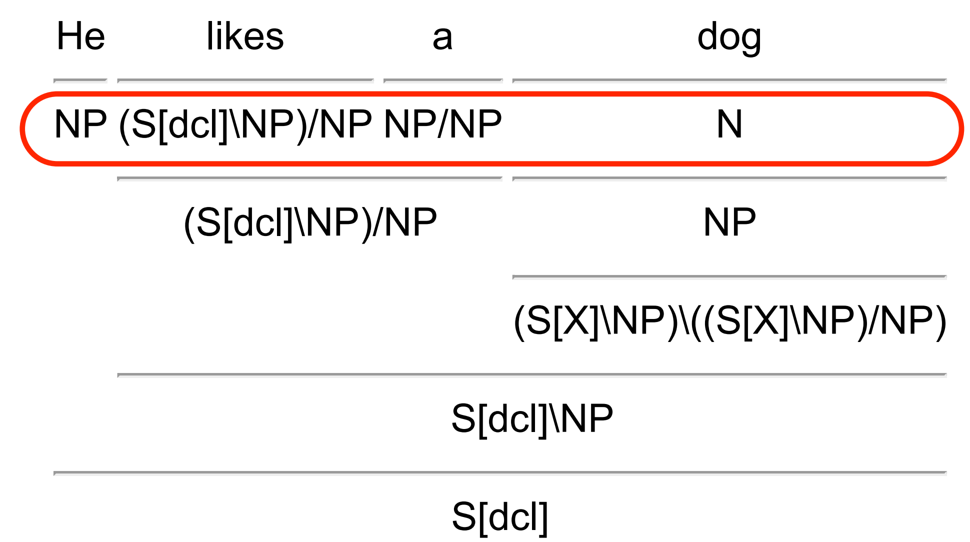
Can we exploit the property of CCG?





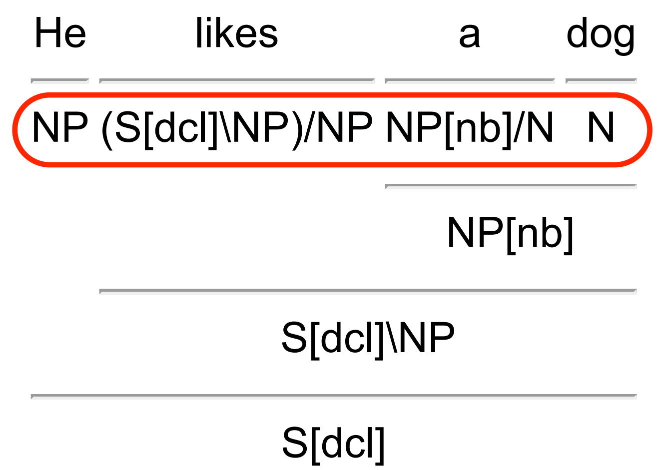


- All structures differs in **category assignments for words**
  - **In other words, if we find the correct category assignments, we can find the correct tree**



- This is because each CCG category is syntactically highly informative ⇒ categories drastically reduce search space

Supertagging



- CCG categories are highly informative
  - When correct categories are given to all words, random choice from all grammatical trees achieves >95% accuracy
  - So it is essential to assign correct category to every word
- In previous CCG parsing (e.g., Clark and Curran, 2008), **the process of assigning categories** is called **supertagging**
  - Before scoring a derivation (tree), supertagging restricts the possible categories to each word
    - This reduces the search space, and speeds up the search

Supertagging

He	likes	a	dog
N	N	N	**N**
NP	NP	NP	**NP**
S\NP/NP	**S\NP/NP**	S\NP/NP	S\NP/NP
NP/N	NP/N	**NP/N**	NP/N
NP/NP	NP/NP	**NP/NP**	NP/NP
(S\NP)/(S\NP)	(S\NP)/(S\NP)	**(S\NP)/(S\NP)**	(S\NP)/(S\NP)

- For longer sentences, this approach is quite effective
- Supertagger model can be trained by a standard machine learning technique (e.g., linear classifier, neural networks)

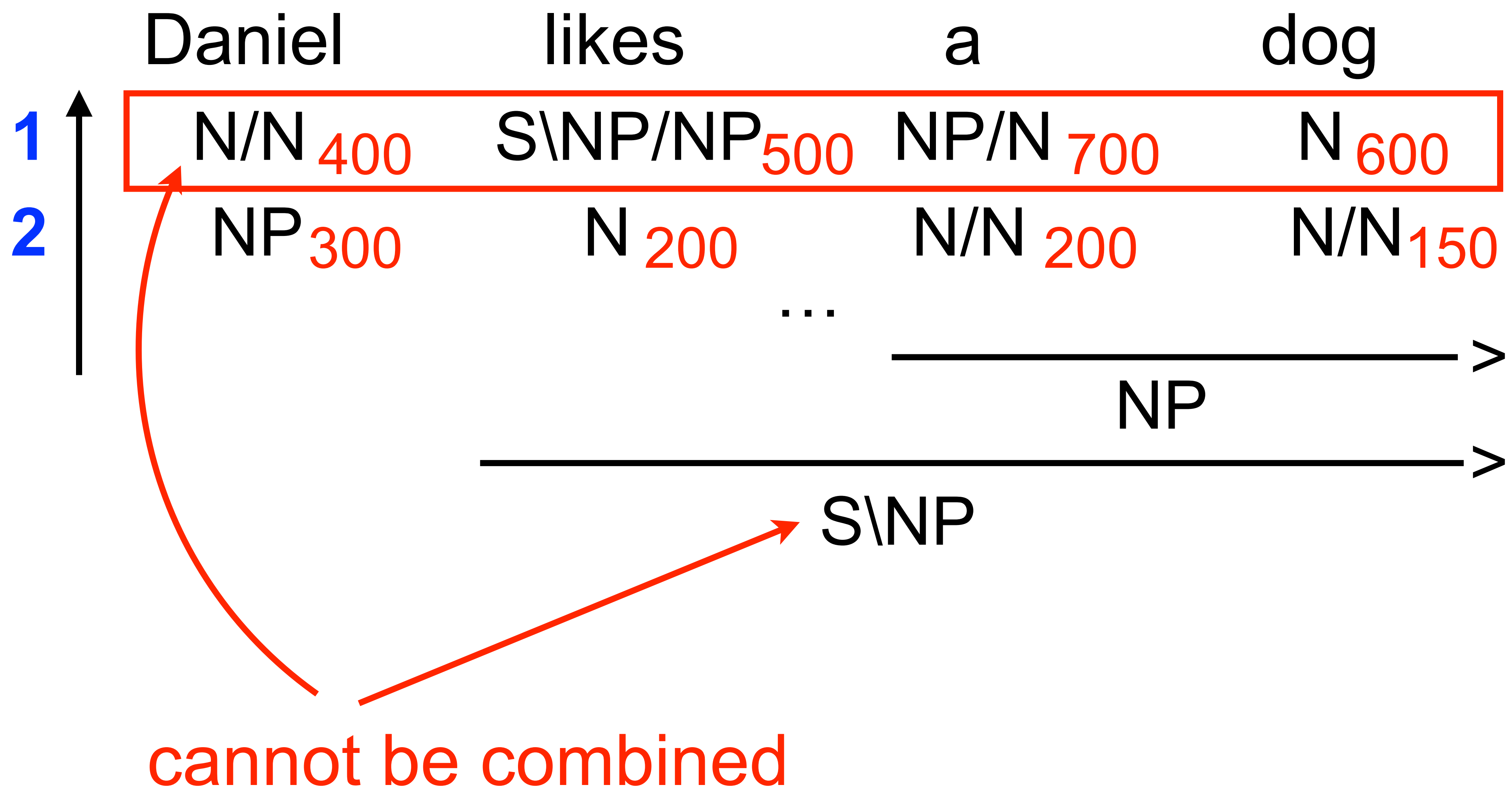
A* CCG parsing

Lewis et al., 2014. *A* CCG Parsing with a Supertag-factored Model.* In EMNLP.

- Recently, the idea of supertagging was further promoted
- **New simpler model:**
  - **The score of tree = The score of supertags**
  - Do not score the internal of derivation (applied rules) at all!
  - Lewis et al. found that if the supertagger model is strong (with neural networks), this approach can achieve near state-of-the-art
- **Advantage of simpler model**: Search gets simpler as well
  - They found that efficient A* search can be applied to this model
  - A* search finds the derivation of a single connected tree that has the highest score

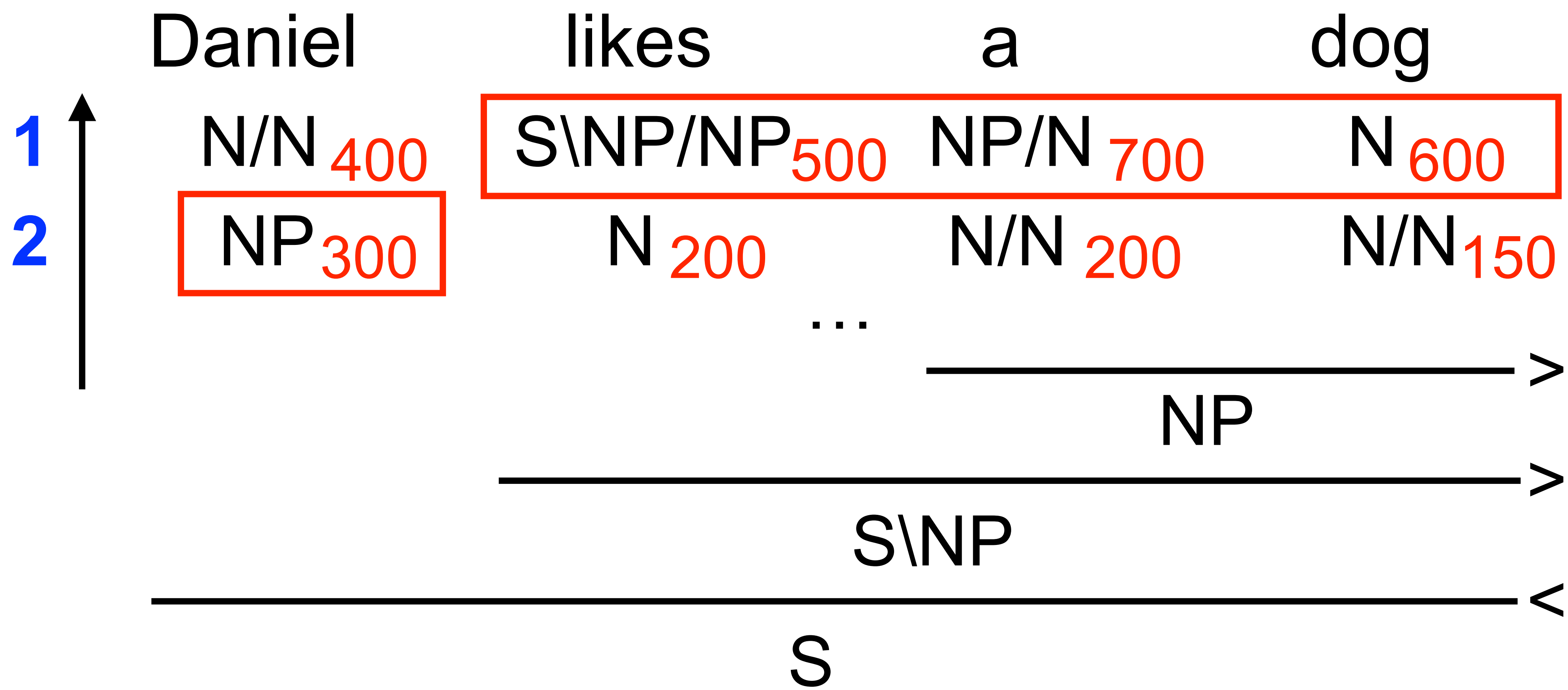
A* CCG parsing

- Note: If we pick up the best supertag on each word, they do not (generally) realize the single connected tree



A* CCG parsing

- A* search finds the best supertag sequence that realizes a single connected tree

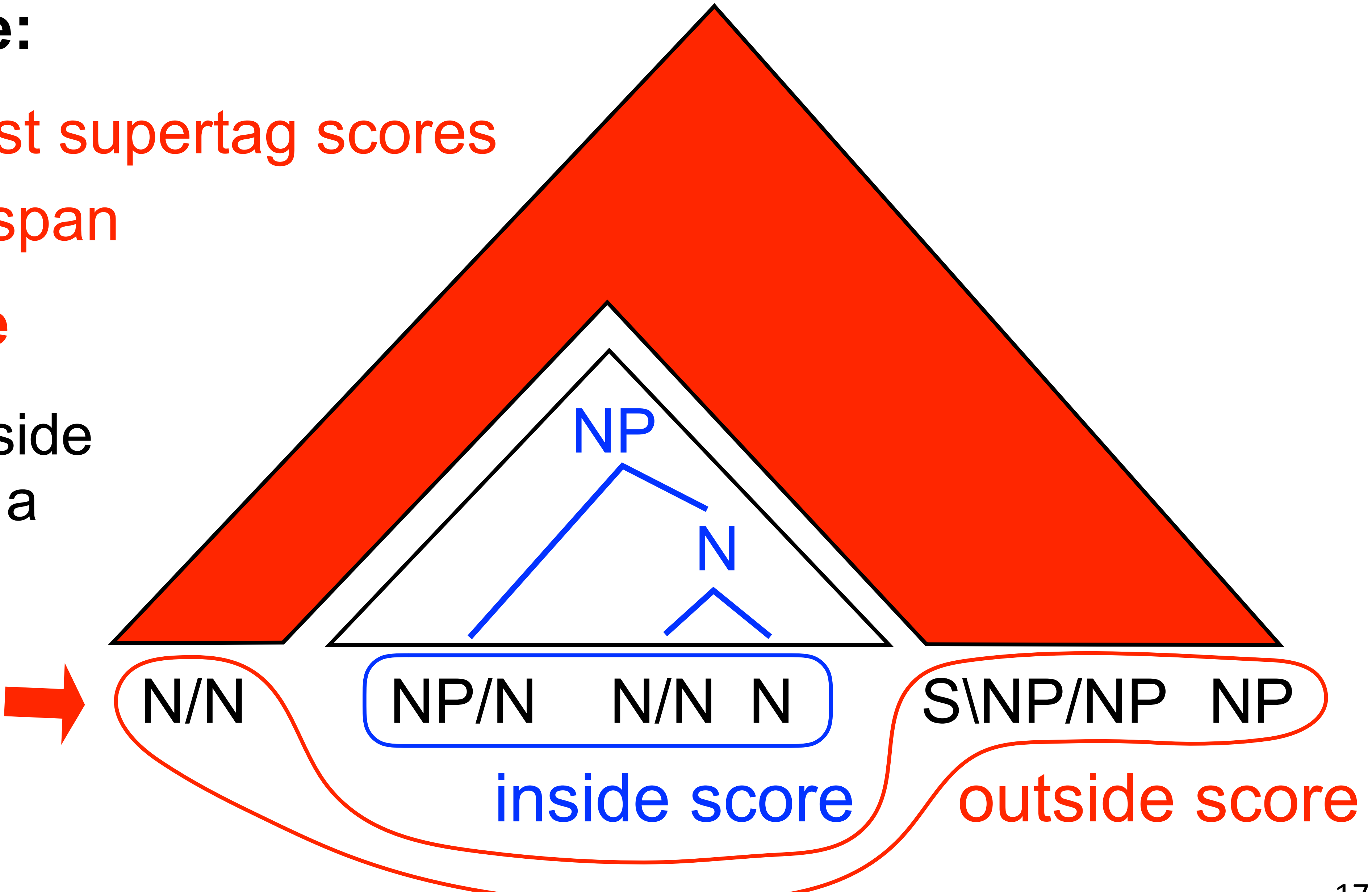


How A* search works?

- A* search expands the span, where the best internal structure (= supertag sequence) was found
  - **Dynamic programming**: solve the small problems first
  - **Heuristic score:**
    - The sum of best supertag scores outside of the span
    - **Outside score**

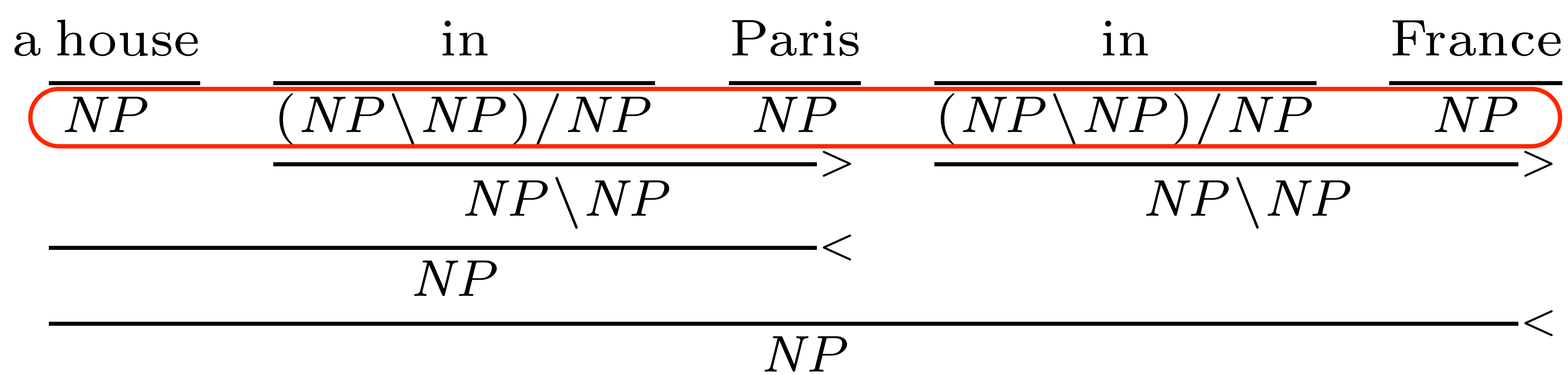
The sequence for outside score may not realize a single tree

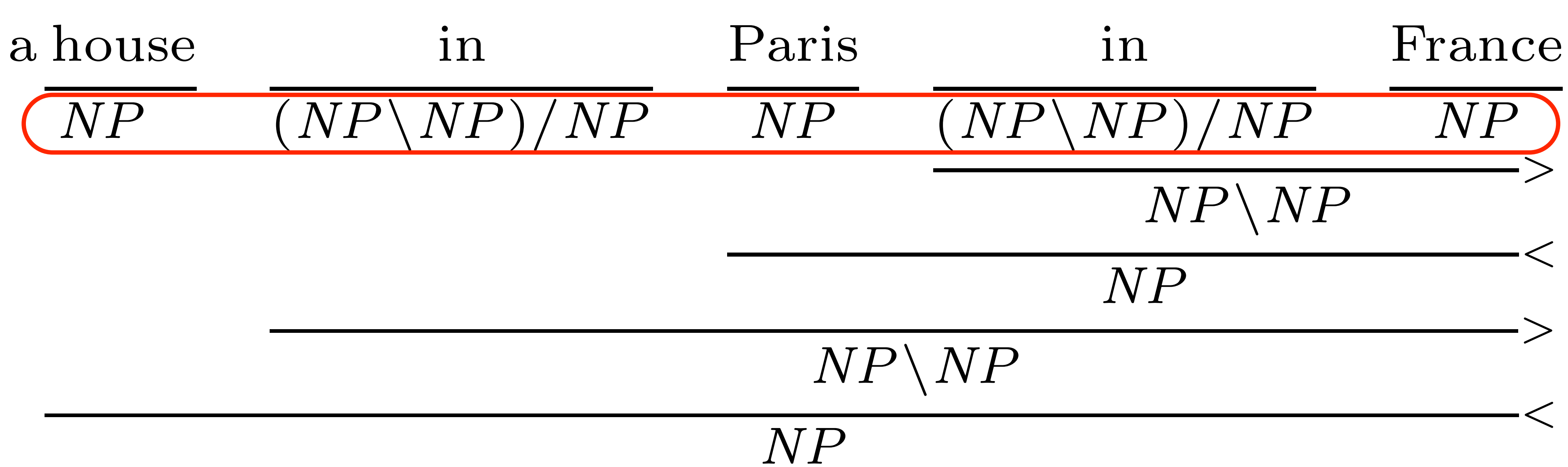
But can be a good approximation of the **upper bound** of the true best score



Limitation

- For some supertag sequence, the derivation on that cannot be uniquely determined
  - Lewis et al. select the one using some heuristic rule

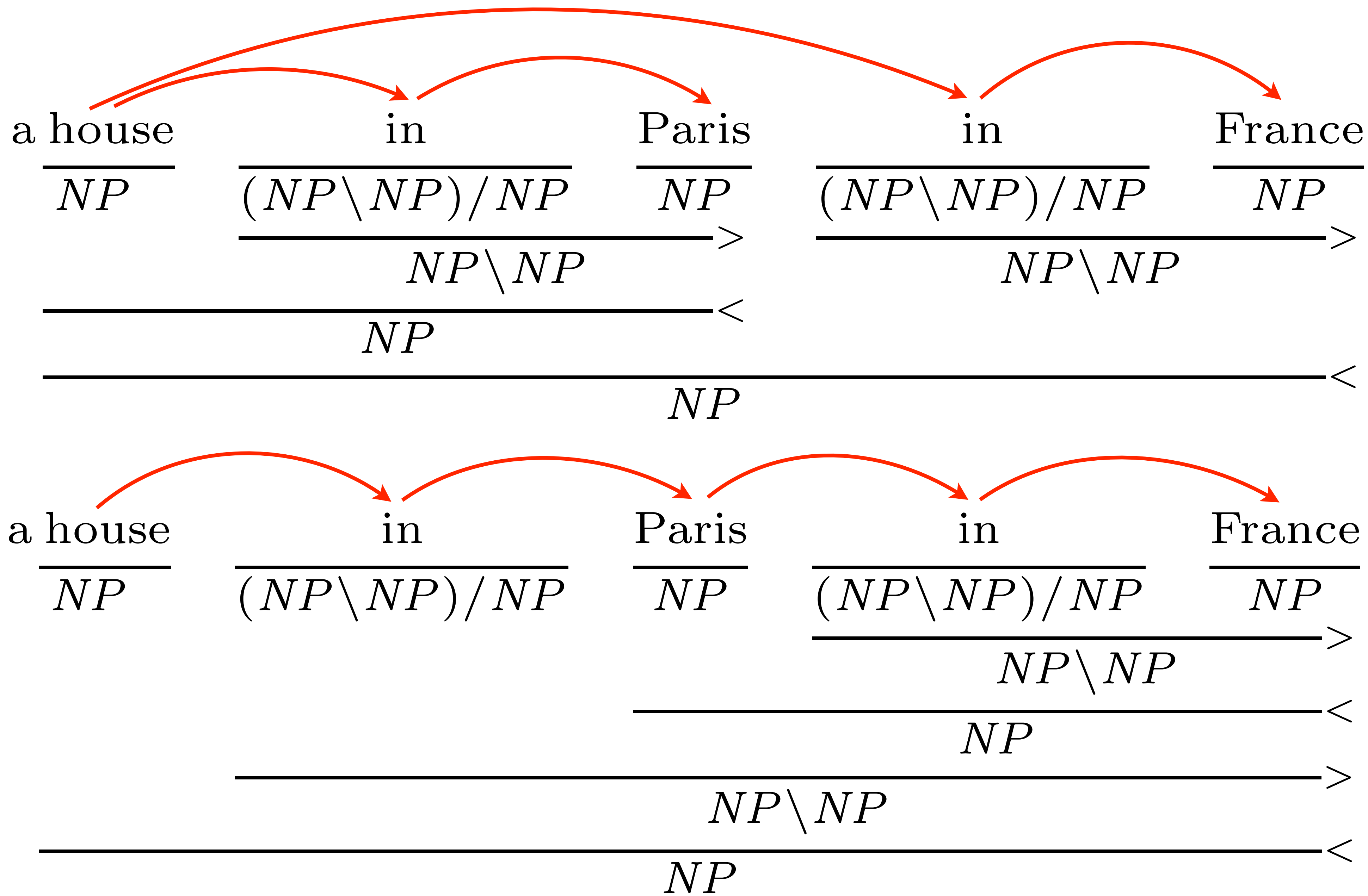




A* CCG + dependency parsing

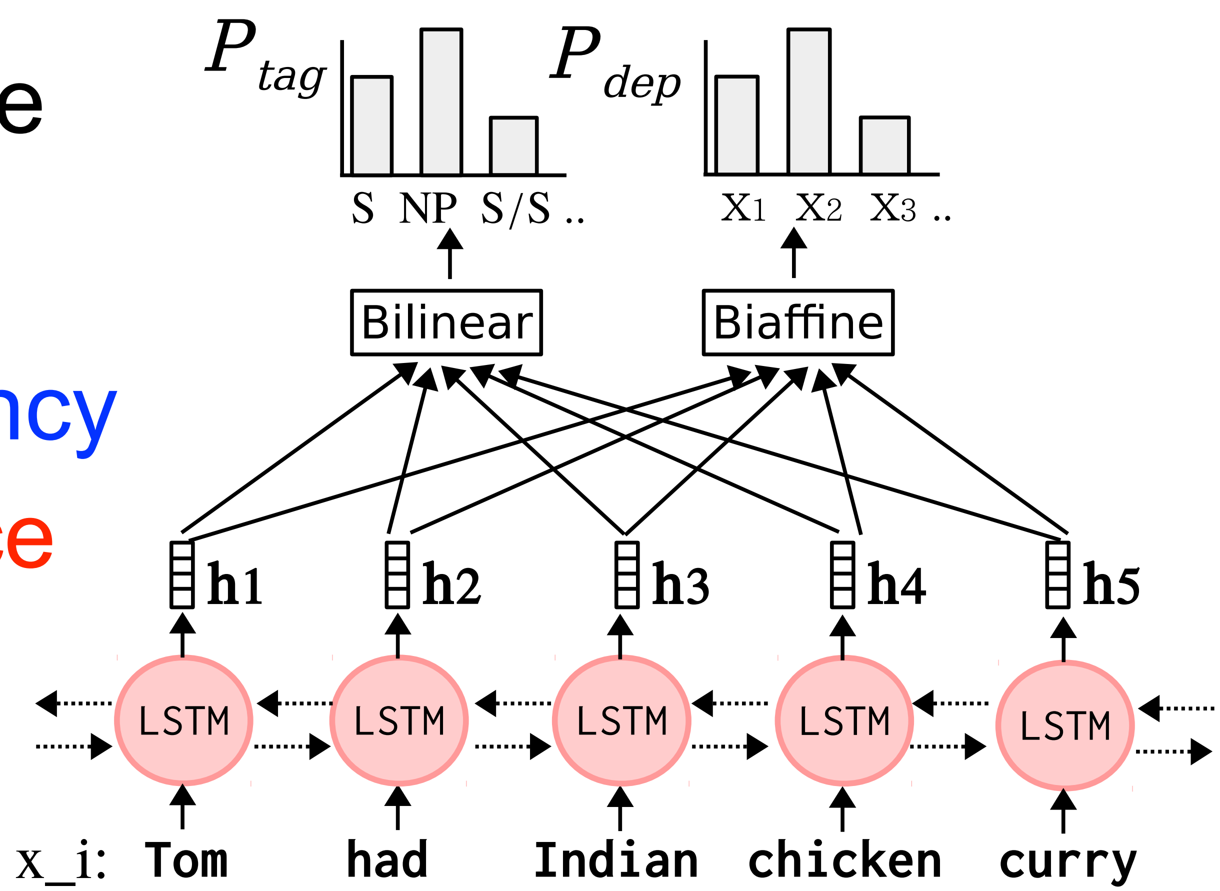
Yoshikawa, Noji, and Matsumoto (2017 ACL)

- **Problem:** supertags cannot resolve all ambiguities
- **Propose:** joint model of supertag and **word-to-word dependencies**



A* search can still be applied

- We use a simpler dependency model for keeping A* search applicable
- We use **bidirectional LSTMs** to model both CCG supertags and dependencies (multi-task learning)
  - Bi-LSTMs are very powerful neural networks for sequence prediction tasks
  - **Point:** we cast the dependency prediction task as a sequence prediction task to enable A* search



depccg

- https://github.com/masashi-y/depccg
- Current state-of-the-art for English and Japanese CCG parsing

Outline

- Efficient parsing techniques for CCG
- Bottom-up semantic parsing with CCG
  - application to textual entailment
  - issues in question answering
- Top-down semantic parsing with CCG for question answering

QA is moved to the next lecture (Thursday)

ccg2lambda

- System for RTE using CCG parsers and logics
  - Developed mainly by researchers in NII, AIST, Ochanomizu univ.
  - Mineshima et al. (2015, 2016), Martínez-Gómez et al. (2016)

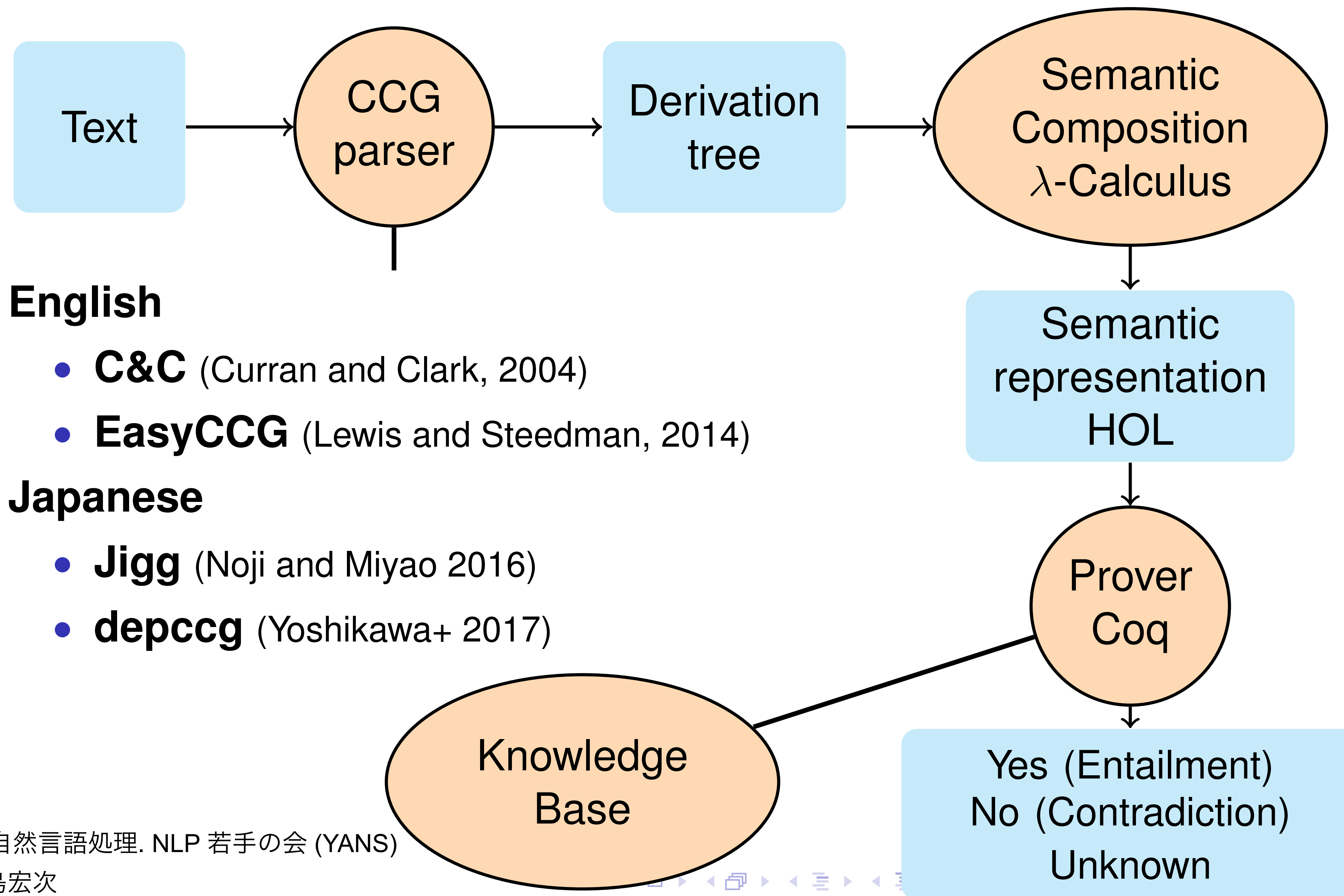


Figure from 形式意味論と自然言語処理. NLP 若手の会 (YANS) 第 12 回シンポジウム. 峯島宏次

Recognizing textual entailment (RTE)

- **Task:** judge whether the input sentences (premise; 前提) semantically **entail** another sentence (hypothesis; 仮定)
  - Given **P**, **H** is true or false?

P Smoking in restaurants is prohibited by low in most cities in Japan

---

H Some cities does not allow smoking in public spaces

⇒ **true (entail)**, because **most cities does not mean all cities**

- *The best way of testing an NLP system's semantic capacity* (Cooper, et al., 1994)
- Applications: Summarization, QA on articles, etc.

Challenges

P Smoking in restaurants is prohibited by low in most cities in Japan

H Some cities does not allow smoking in public spaces

- Relationships between content words:
  - prohibited → not allowed, restaurants → public spaces
- Logical relations arose with function words:
  - most, some, not, etc.
  - Implicit logical relations: e.g.,
    - extensional complement: *saw* *NP VP* → *NP VP(ed)*
    - intentional complement: *believe* *NP VP* $\not\rightarrow$ *NP VP(ed)*
- We need to handle both (lexical and logical) aspects

Entailment as logical proof

P Smoking in restaurants is prohibited by low in most cities in Japan

H Some cities does not allow smoking in public spaces

$\downarrow$ CCG helps

P $\exists x.(smoking(x) \wedge most(\lambda y.city(y), \lambda y.prohibited(x) \wedge in(x, y))$

H $\exists x.(smoking(x) \wedge \exists y(city(y) \wedge \neg\, allowed(x) \wedge in(x, y)))$

- Approach:
  - try to prove the statement: **P** $\rightarrow$ **H**
  - We can use a prover system, which receives a logical form (P$\rightarrow$H) and returns the following values:
    - yes (entail), no (contradict), and unknown
  - ccg2lambda uses Coq as a automatic theorem prover

CCG and logical forms

- One attractive property of CCG is its transparency between syntax and semantics (among syntactic theories)
- By assigning a logical form to each word, the sentence logical form can be obtained automatically
  - some: *λFλG.∃x.(Fx∧Gx)*
  - woman: *λx.woman(x)*

$$\dfrac{\dfrac{\begin{array}{c}\text{Some}\\ NP/N\\ \lambda F \lambda G.\exists x.(Fx \wedge Gx)\end{array} \quad \begin{array}{c}\text{woman}\\ N\\ \lambda x.\mathsf{woman}(x)\end{array}}{\begin{array}{c}NP\\ \lambda G.\exists x(\mathsf{woman}(x) \wedge G(x))\end{array}}> \qquad \dfrac{\begin{array}{c}\text{ordered}\\ (S\backslash NP)/NP\\ \lambda Q_1 \lambda Q_2.Q_2(\lambda x.Q_1(\lambda y.\mathsf{order}(x,y)))\end{array} \quad \dfrac{\begin{array}{c}\text{tea}\\ N\\ \lambda y.\mathsf{tea}(y)\end{array}}{\begin{array}{c}NP\\ \lambda F.\exists y.(\mathsf{tea}(y) \wedge F(y))\end{array}}\text{lex}}{\begin{array}{c}S\backslash NP\\ \lambda Q_2.Q_2(\lambda x.\exists y.(\mathsf{tea}(y) \wedge \mathsf{order}(x,y)))\end{array}}>}{\begin{array}{c}S\\ \exists x.(\mathsf{woman}(x) \wedge \exists y.(\mathsf{tea}(y) \wedge \mathsf{order}(x,y)))\end{array}}<$$

Figure from Martínez-Gómez et al., 2016. ccg2lambda: A Compositional Semantics System.

Pipeline

- CCG parser does not output logical forms
- We first parse the CCG with a CCG parser, and then assign a logical form on each node
  - We only have to assign a logical form to each word
  - Logical forms on the internal nodes are calculated based on the definition of each rule
    - e.g, X/Y: f Y/Z: g $\rightarrow$ X/Z: $\lambda x.f(g\ x)$ (>B)

Templates for assigning logical forms

1. For closed words: lexical entries directly assigned to surface form: 100 entries (English) and 113 entires (Japanese)

Example

- category: NP/N
- semantics: $\lambda F \lambda G \lambda H . \forall x (Fx \wedge Gx \rightarrow H)$
- surf: every

2. For open words: semantic templates for syntactic categories: 129 entries (English) and 37 entries (Japanese)

Example

- category: N
- semantics: $\lambda x.\mathrm{E}(x)$

“E” is a position in which a particular lexical item appears.

Adding lexical knowledge

P $\exists x.(smoking(x) \wedge most(\lambda y.city(y), \lambda y.prohibited(x) \wedge in(x, y))$

H $\exists x.(smoking(x) \wedge \exists y(city(y) \wedge \neg\, allowed(x) \wedge in(x, y)))$

- Logical relations (e.g., most, every) can well be handled by a theorem prover
- But a prover does not have any world knowledge (e.g., prohibited → ¬ allowed)
- ccg2lambda supports adding such lexical knowledge in a proof step:
  - Martínez-Gómez et al., On-demand injection of lexical knowledge for recognizing textual entailment. In EACL 2017.

Adding lexical knowledge

T: *men are sawing logs.*

$$\exists x.(\mathrm{man}(x) \wedge \exists y.(\mathrm{log}(y) \wedge \mathrm{saw}(x, y))$$

H: *men are cutting wood.*

$$\exists x.(\mathrm{man}(x) \wedge \exists y.(\mathrm{wood}(y) \wedge \mathrm{cut}(x, y))$$

Method: to inject lexical knowledge into the proof.

- Word relations can be found in ontologies (e.g. WordNet, etc.)

$$\forall x \forall y.\mathrm{saw}(x, y) \rightarrow \mathrm{cut}(x, y)$$

$$\forall x.\mathrm{log}(x) \rightarrow \mathrm{wood}(x)$$

SICK dataset

- The standard dataset for evaluating RTE system
  - ccg2lambda is an unsupervised system (does not use training data)
    - Size: $4,500/500/4,927$ for training, dev. and testing.
    - Label distribution: $.29/.15/.56$ for yes/no/unk.
    - About $212,000$ running words.
    - Average premise and conclusion length: 10.6.

Examples:

Problem ID	T-H pairs	Entailment
1412	T: *Men are sawing logs.* H: *Men are cutting wood.*	Yes
4114	T: *There is no man eating food.* H: *A man is eating a pizza.*	No
718	T: *A few men in a competition are running outside.* H: *A few men are running competitions outside.*	Unknown

SICK results

System	Prec.	Rec.	Acc.
Baseline (majority)	–	–	56.69
MLN (Beltagy+ ACL14)	–	–	73.40
Nutcracker	–	–	74.30
Nutcracker-WN	–	–	77.50
Nutcracker-WN-PPDB	–	–	78.60
MLN-WN-PPDB	–	–	80.40
LangPro Hybrid-800 (Abzianidze, EMNLP2015)	97.95	58.11	81.35
The Meaning Factory (Bjerva+ SemEval14)	93.63	60.64	81.60
ccg2lambda, No axioms	98.90	46.48	76.65
ccg2lambda, Naïve	92.99	59.70	80.98
ccg2lambda, Abduction (WN,VerbOcean)	97.04	63.64	**83.13**
SemantiKLUE	85.40	69.63	82.32
UNAL-NLP	81.99	76.80	83.05
ECNU	84.37	74.37	83.64
Illinois-LH	81.56	81.87	84.57
MLN-eclassif (Beltagy+ CL2016)	–	–	85.10
Yin-Schutze (EACL2017)	–	–	**87.10**

logic-based

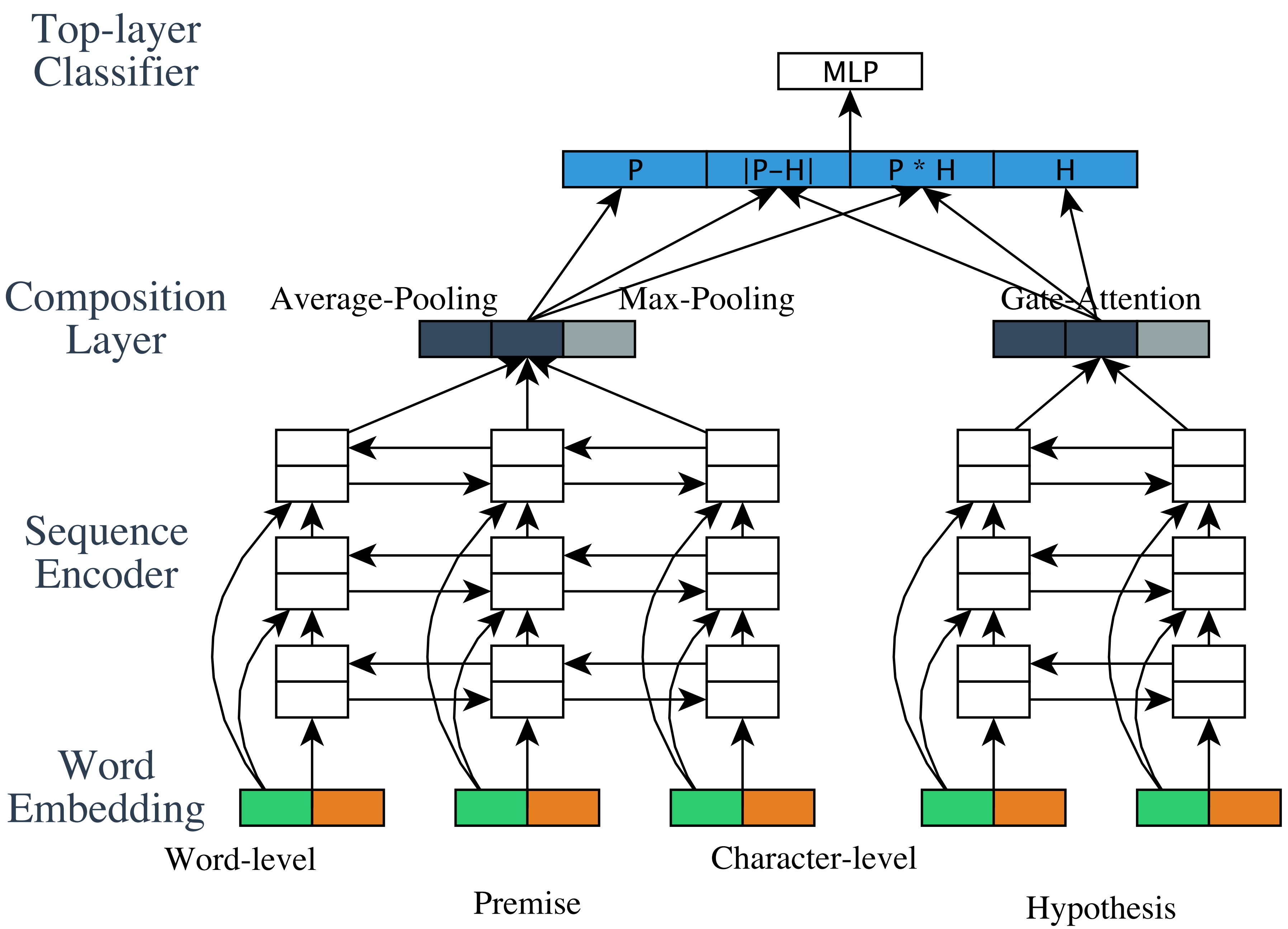
supervised machine learning

Bottleneck in knowledge

- Logic-based system (including ccg2lambda) shows high-precision and low-recall
  - High-precision: If the system answers “yes” or “no”, often that is correct
  - Low-recall: The system answers “unknown” too aggressively
  - Low-recall is essentially due to the lack of word knowledge
    - WordNet does not cover all relationships between the words
    - Relationships between more than one word (paraphrase, etc.)
      - P: A woman is sewing with a machine
      - H: A woman is using a machine made for sewing
      - Required knowledge: “sewing with a machine” → “using a machine made for sewing”

Challenges

Alternative approach: deep learning



- We train a neural-network model where an input sentence is encoded in a vector, and some classifier is applied

Chen et al., Recurrent Neural Network-Based Sentence Encoder with Gated Attention for Natural Language Inference. RepEval. 2017.

Deep learning can learn logics?

- DL methods use a very large corpus (<500K training pairs) to learn the classifier
- In other words, it only requires a training data (and machine resource = GPU)
- This indicates we may sidestep the complexity of most linguistic phenomena, including qualification (e.g., every, most), with machine learning?
    - like visual recognition on ImageNet?

FraCaS dataset

fracas-067	
Premise 1	All residents of the North American continent can travel freely within Europe.
Premise 2	Every Canadian resident is a resident of the North American continent.
Hypothesis	All Canadian residents can travel freely within Europe.
Answer	Yes
fracas-074	
Premise 1	Most Europeans can travel freely within Europe.
Hypothesis	Most Europeans who are resident outside Europe can travel freely within Europe.
Answer	Unknown

There are multi-premise problems

quantifier section

- A dataset developed by a theoretical linguist
- Divided into sections by the relevant linguistic phenomena
  - Generalized quantifier, Plurals, Comparatives, etc.
  - A collection of logically difficult problems

Mineshima et al., Higher-order logical inference with compositional semantics. EMNLP 2015.

Deep learning on FraCaS

Section	#	Ours	Nut	Bow16
Quantifiers	74	.77	.53	.64*
Plurals	33	**.67**	.52	.54*
Adjectives	22	**.68**	.32	.47*
Comparatives	31	**.48**	.45	.56*
Verbs	8	.62	.62	.62*
Attitudes	13	**.77**	.46	.67*
Total	181	**.69**	.50	

- Ours: ccg2lambda
- Nut: Previous logic-based system (Nutcracker)
- Bow16: A deep learning model learned with a huge amount of training data (called SNLI)
- Note (*): Single premise problems only (Bow16 cannot handle multi-premises)

Mineshima et al., Higher-order logical inference with compositional semantics. EMNLP 2015.

Discussion

- Currently deep learning models do not work well on FraCaS
- It is a very open problem whether a strong machine learning technique, and big data, are enough to be able to understand the language
- Advantage of bottom-up approach (ccg2lambda):
  - High interpretability of the results:
    - we can see the reason why the system fails (e.g., missing knowledge)
  - Extensibility: e.g., we can add more lexical knowledge, if we have
- **Can we integrate these two very different approaches?**