

Combining Axiom Injection and Knowledge Base Completion for Efficient Natural Language Inference

Masashi Yoshikawa♦, Koji Mineshima★, Hiroshi Noji♥, Daisuke Bekki★

♦ Nara Institute of Science and Technology

★ Ochanomizu University

♥ Artificial Intelligence Research Center, AIST

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NAIST®



Recognizing Textual Entailment

a.k.a. Natural Language Inference

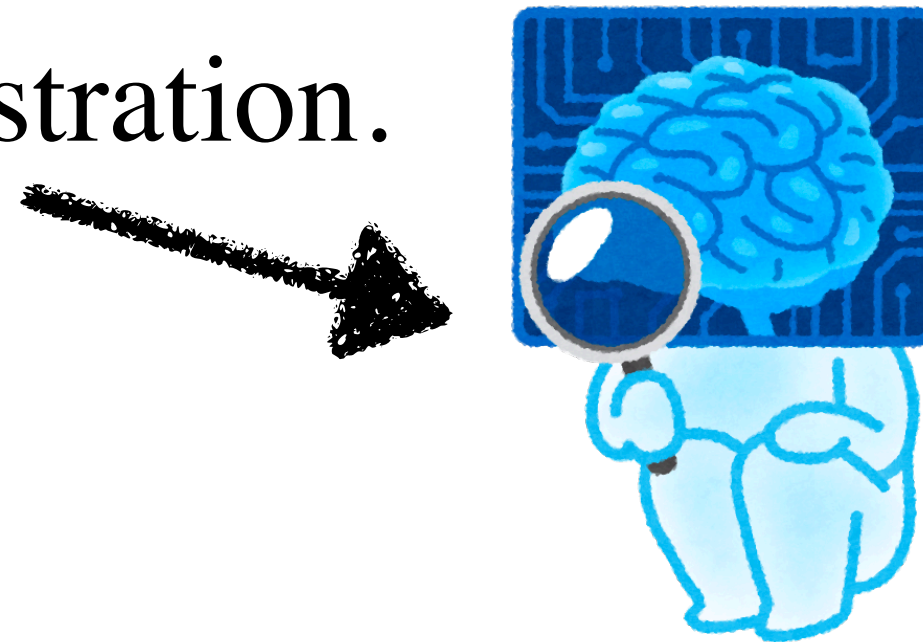
Premise(s)

P1: Clients at the demonstration were all impressed by the system's performance.

P2: Smith was a client at the demonstration.

Hypothesis

H: Smith was impressed by the system's performance.

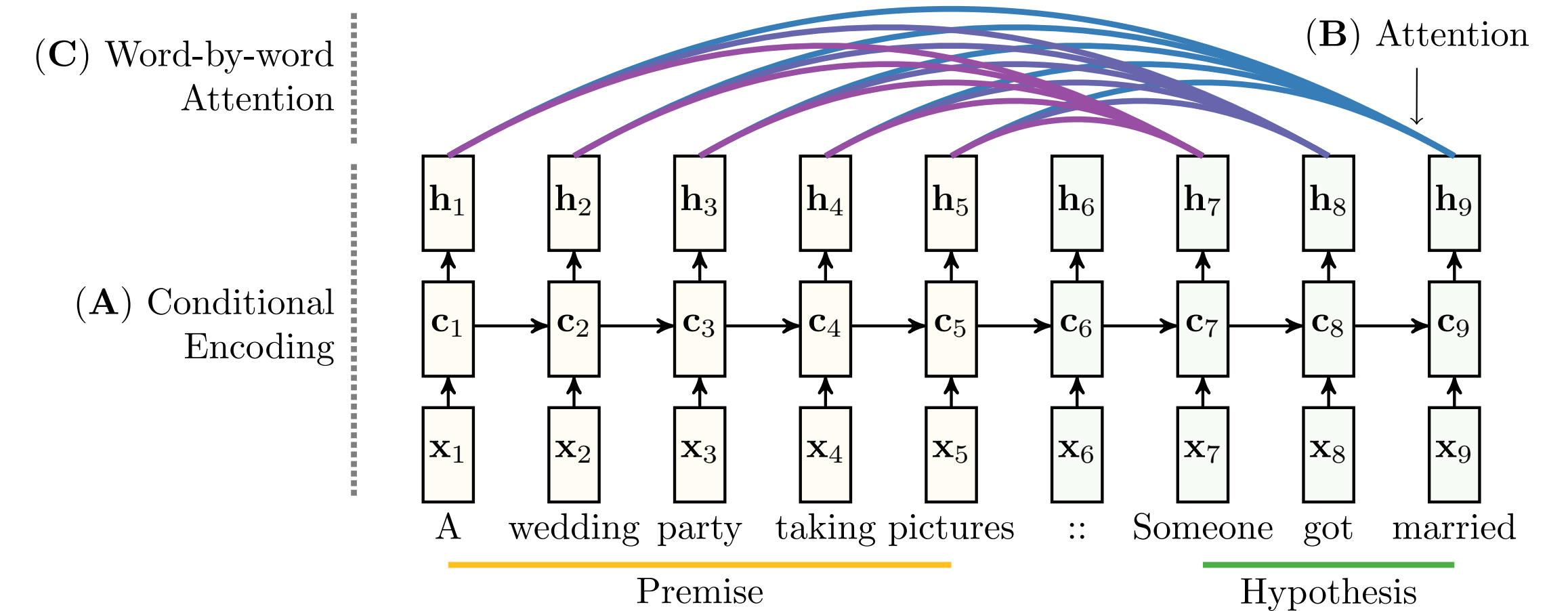


{entailment, contradiction, unknown}

- A testbed to evaluate if a machine can reason as we do
 - lexical, logical, syntactic phenomena, etc.
- Elemental technology for improving other NLP tasks
 - Question answering, reading comprehension, etc.

Approaches to RTE

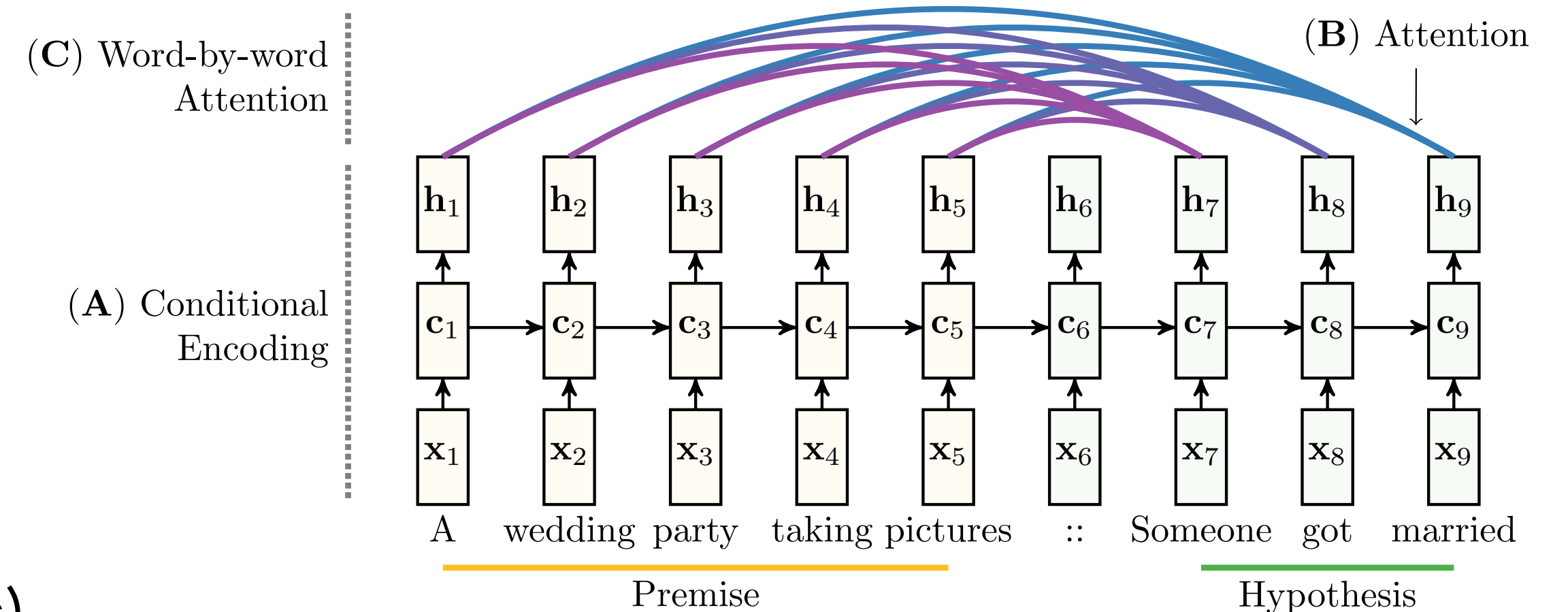
- Machine learning (Rocktäschel et al., 2016, etc.)
- e.g. Neural Networks



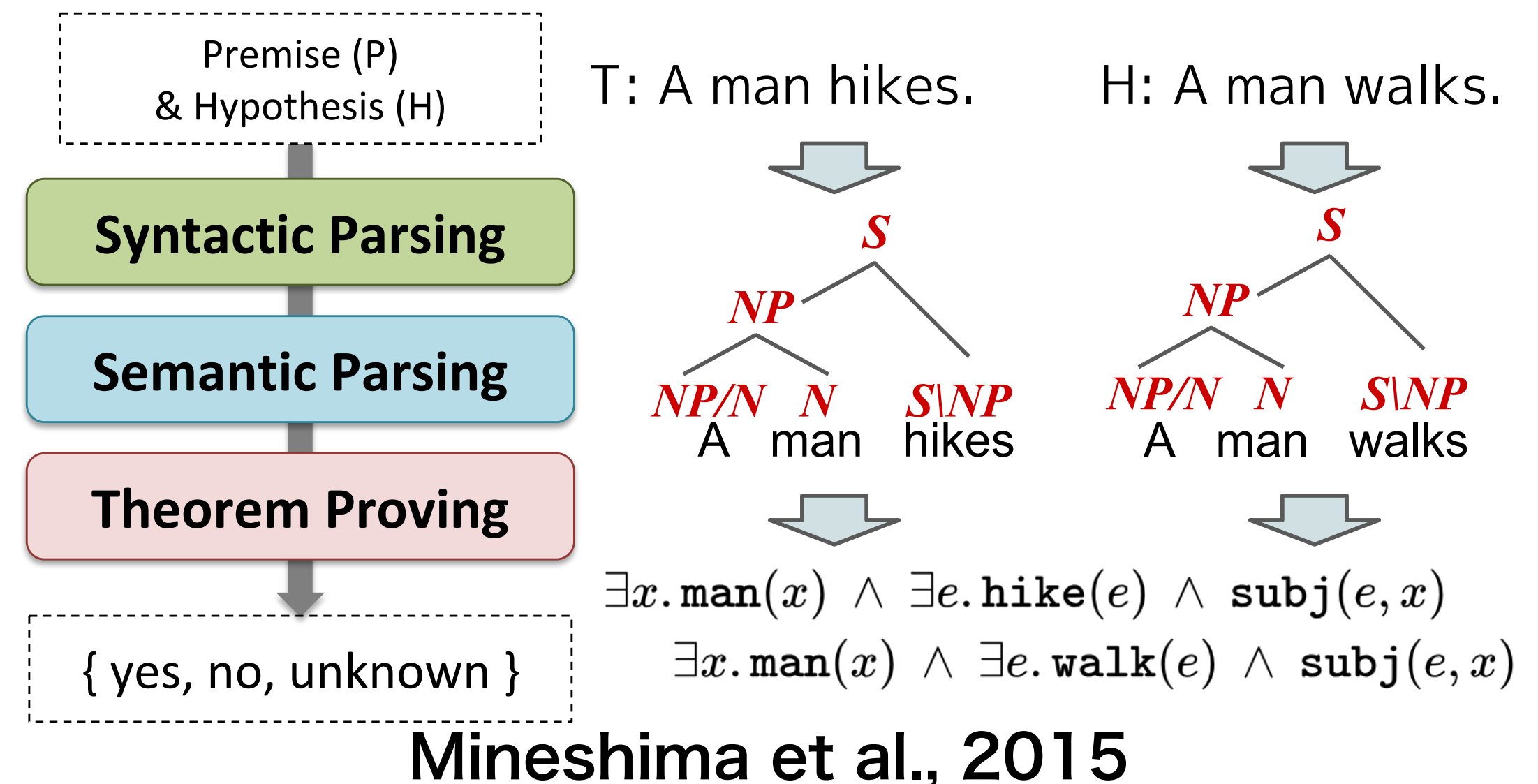
Rocktäschel et al., 2016

Approaches to RTE

- Machine learning (Rocktäschel et al., 2016, etc.)
- e.g. Neural Networks
- Logic (Mineshima et al., 2015, Abzianidze 2017, etc)
- Traditional pipeline systems
- Theorem prover (e.g. Coq)



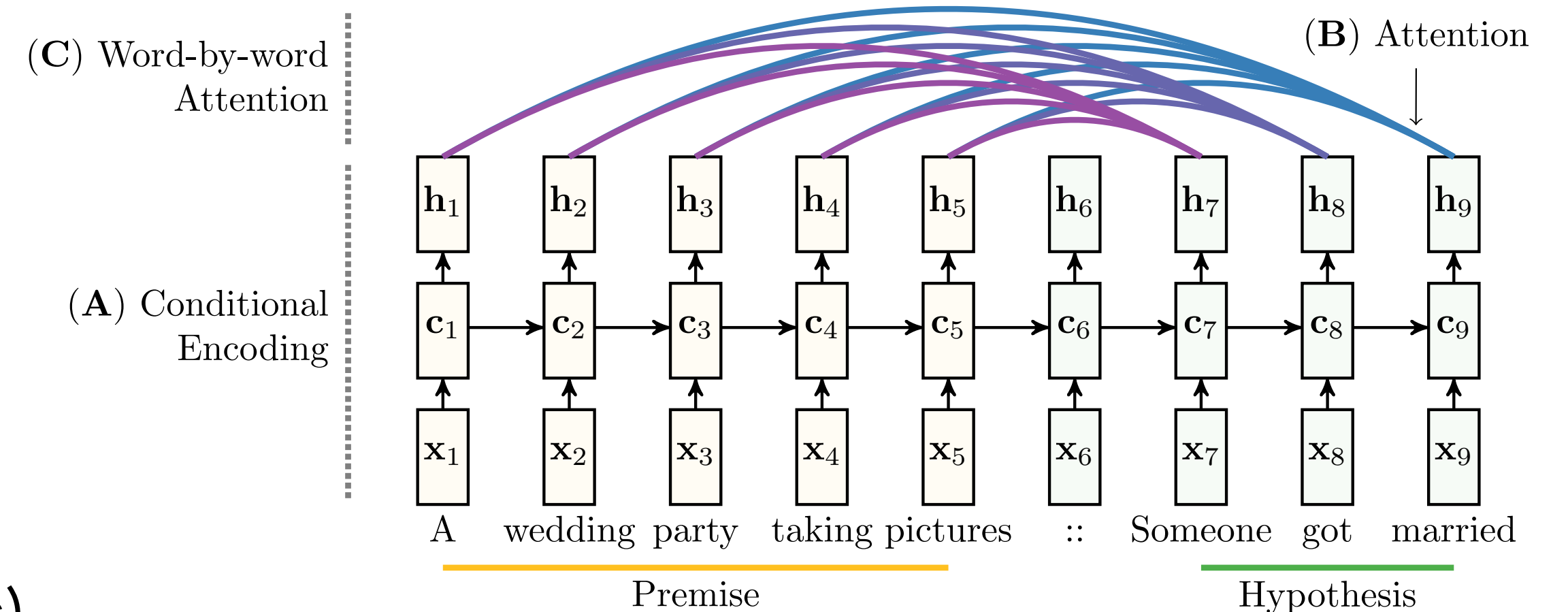
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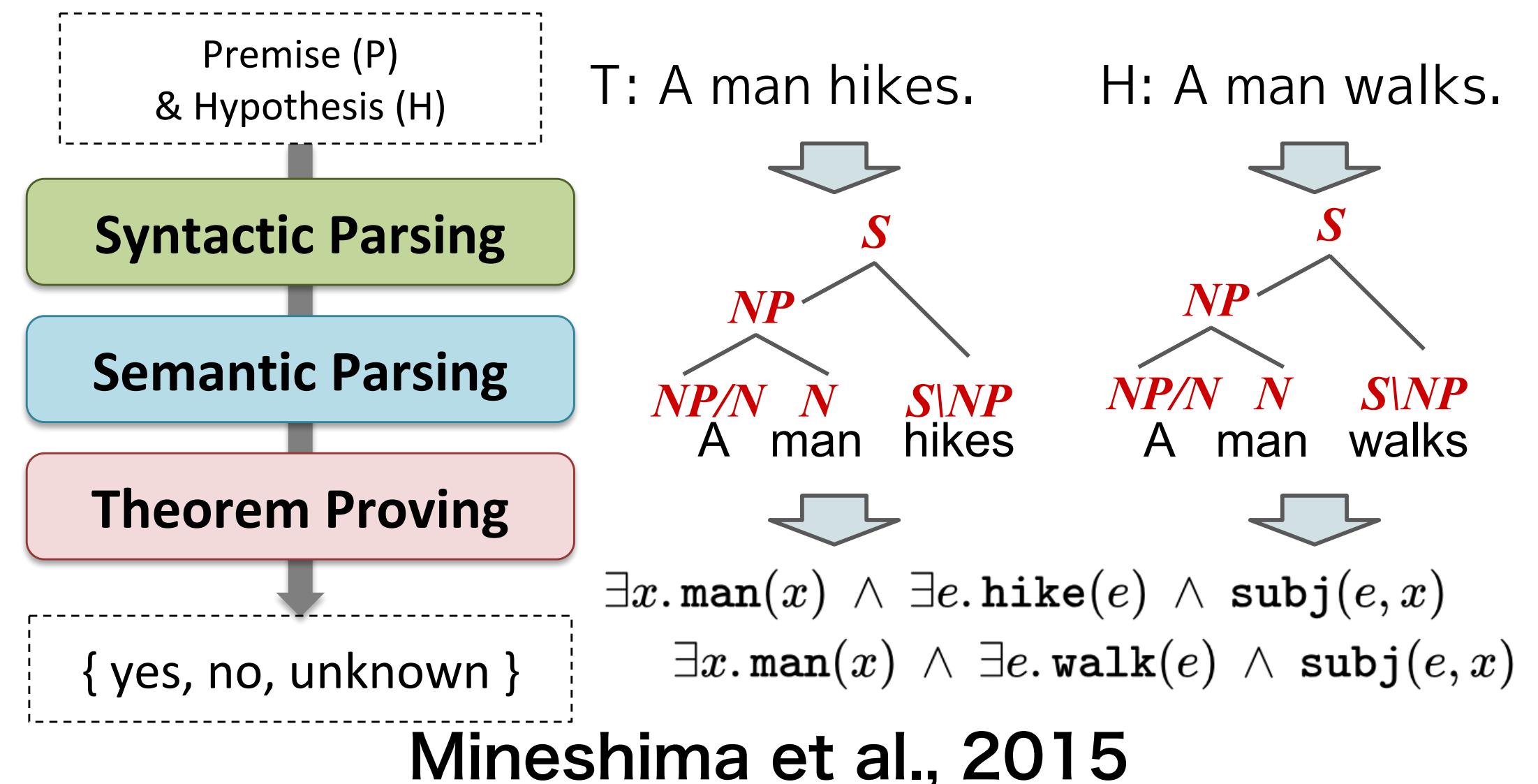
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- Traditional pipeline systems
- Theorem prover (e.g. Coq) 🐓
- **Ours:** logic-based, extended by ML! (Hybrid)



Rocktäschel et al., 2016



Mineshima et al., 2015

ccg2lambda (Mineshima et al., 2015)

Premise (P)
& Hypothesis (H)

Syntactic Parsing

CCG Derivations

Semantic Parsing

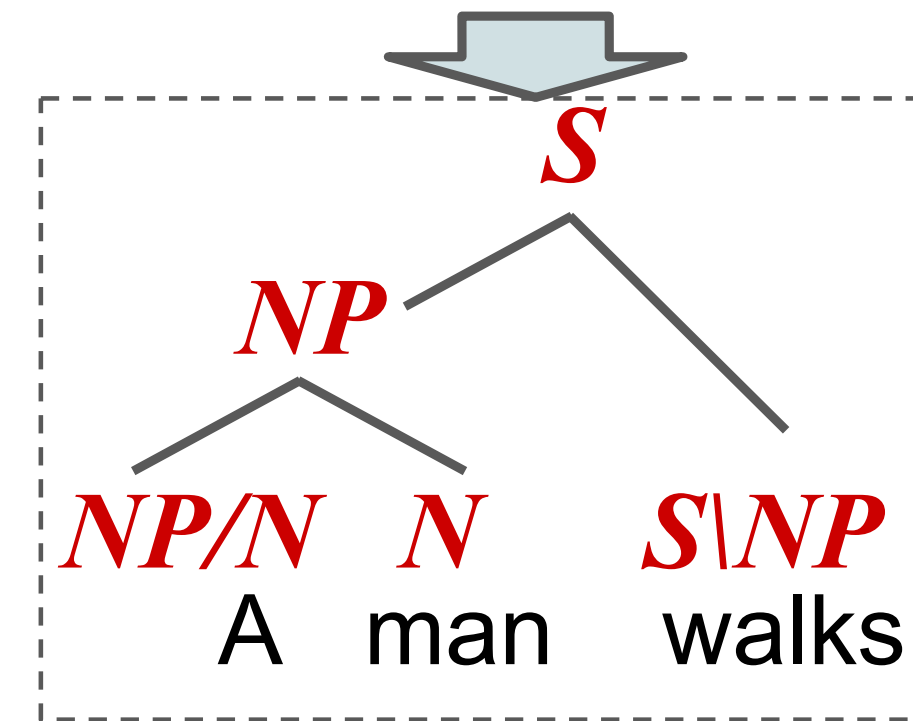
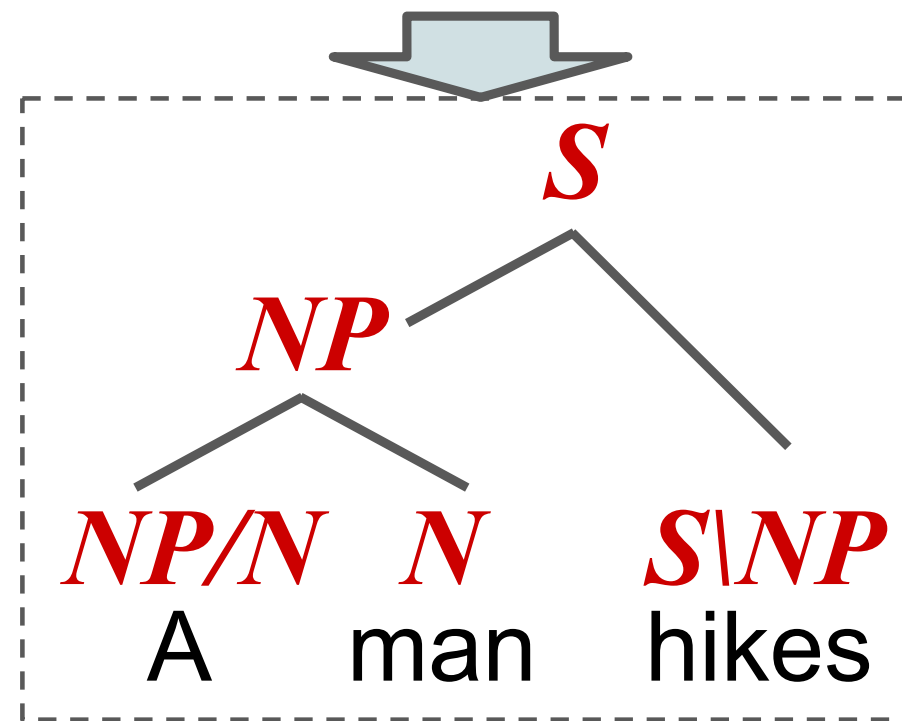
Logical Formulas

Theorem Proving

{ yes, no, unknown }

P: A man hikes.

H: A man walks.

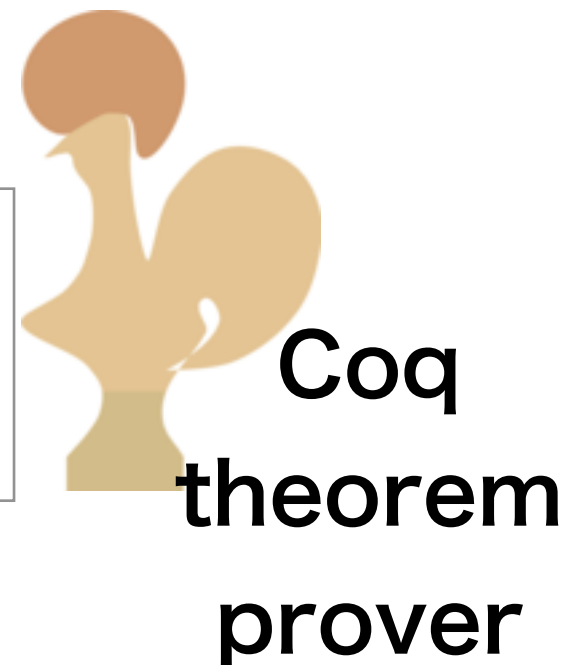


$\exists x. \text{man}(x) \wedge \exists e. \text{hike}(e) \wedge \text{subj}(e, x)$

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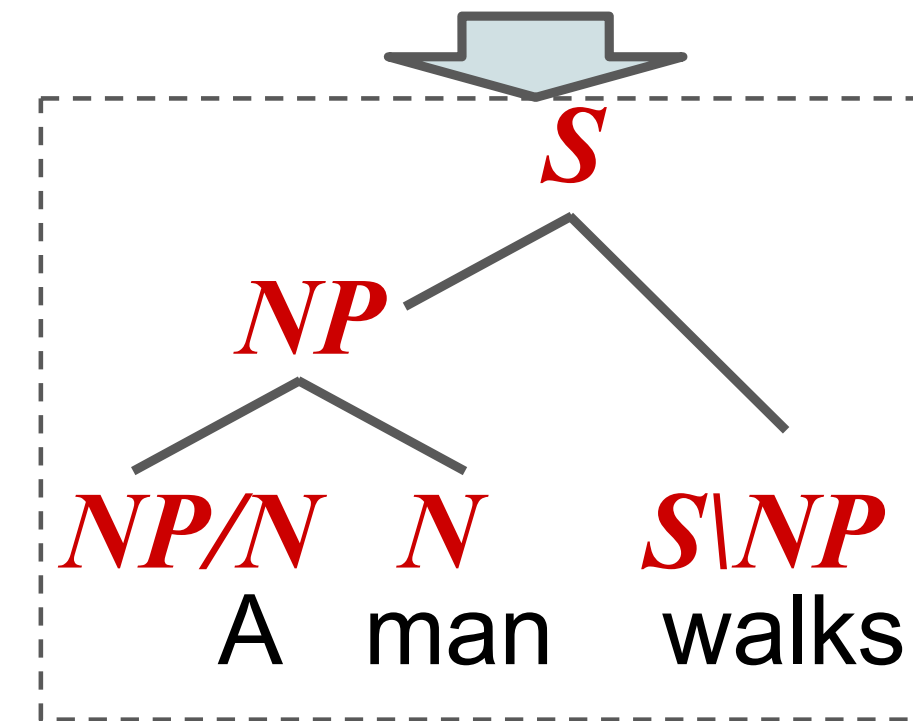
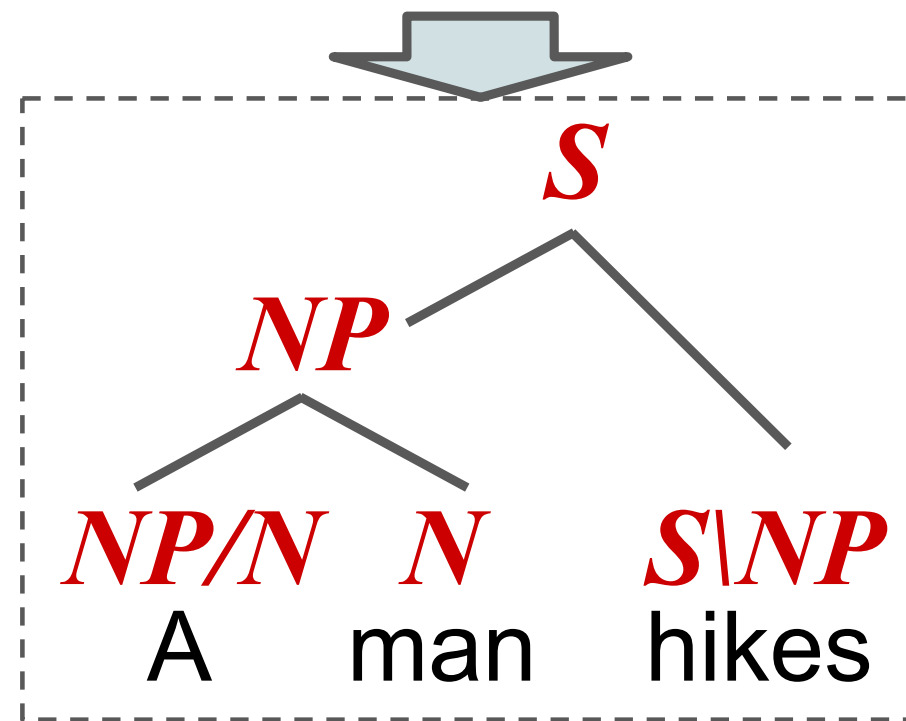
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👍 Unsupervised

👍 Captures linguistic phenomena
- 83.6 % accuracy in SICK

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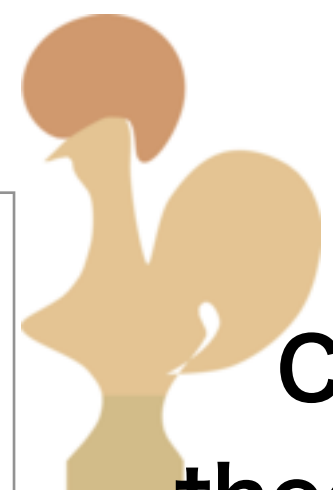


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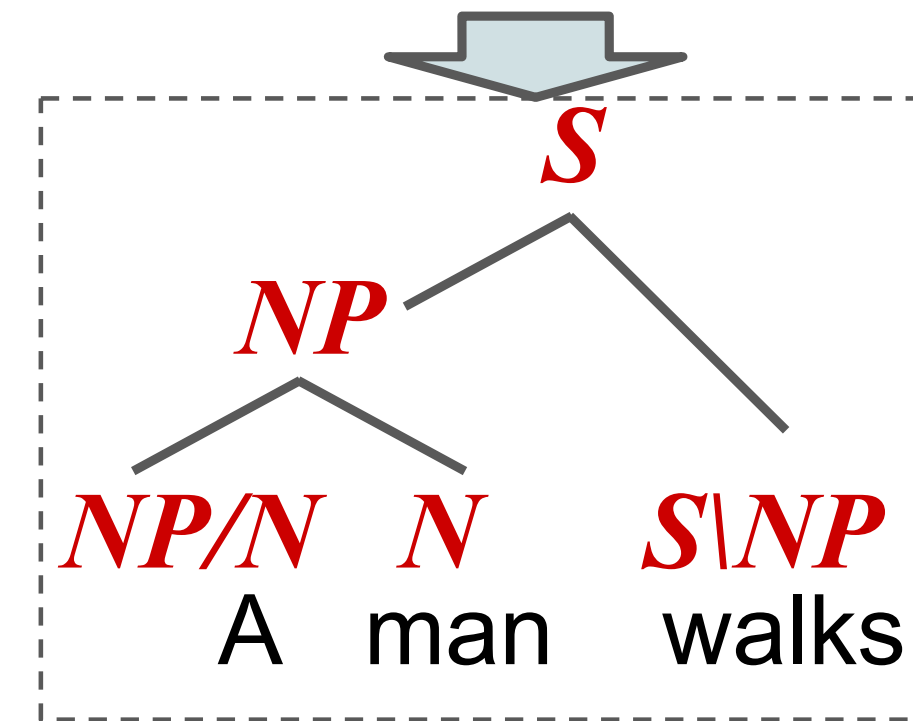
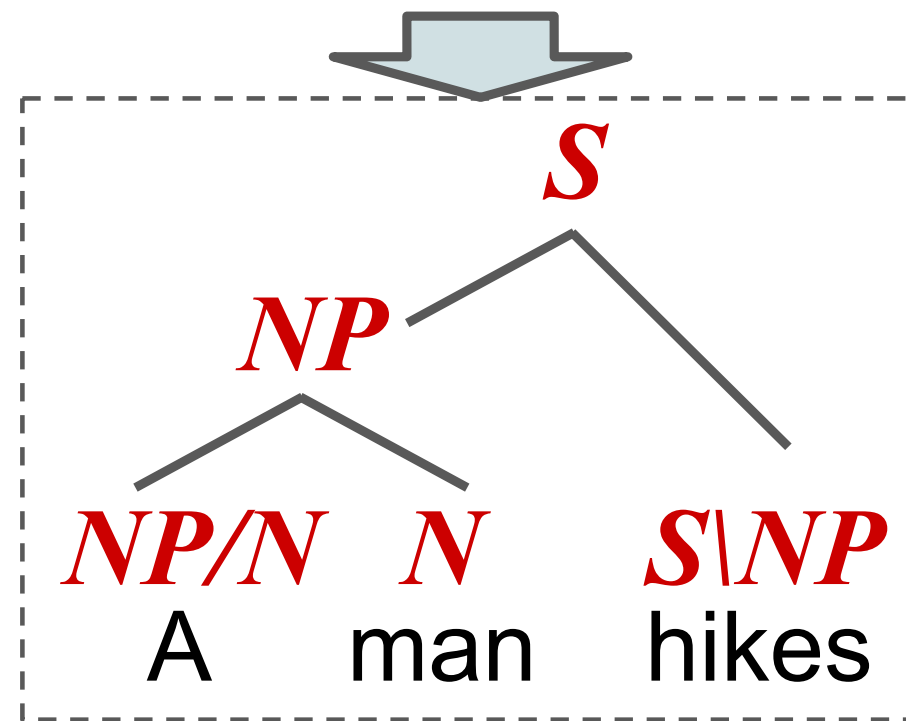
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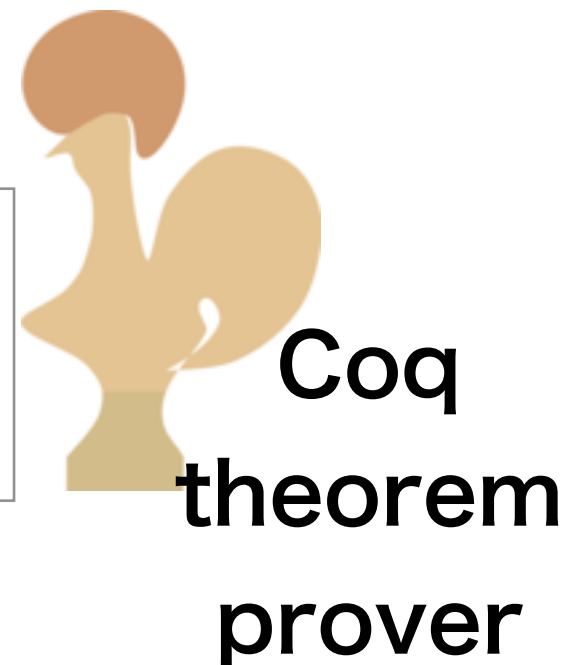
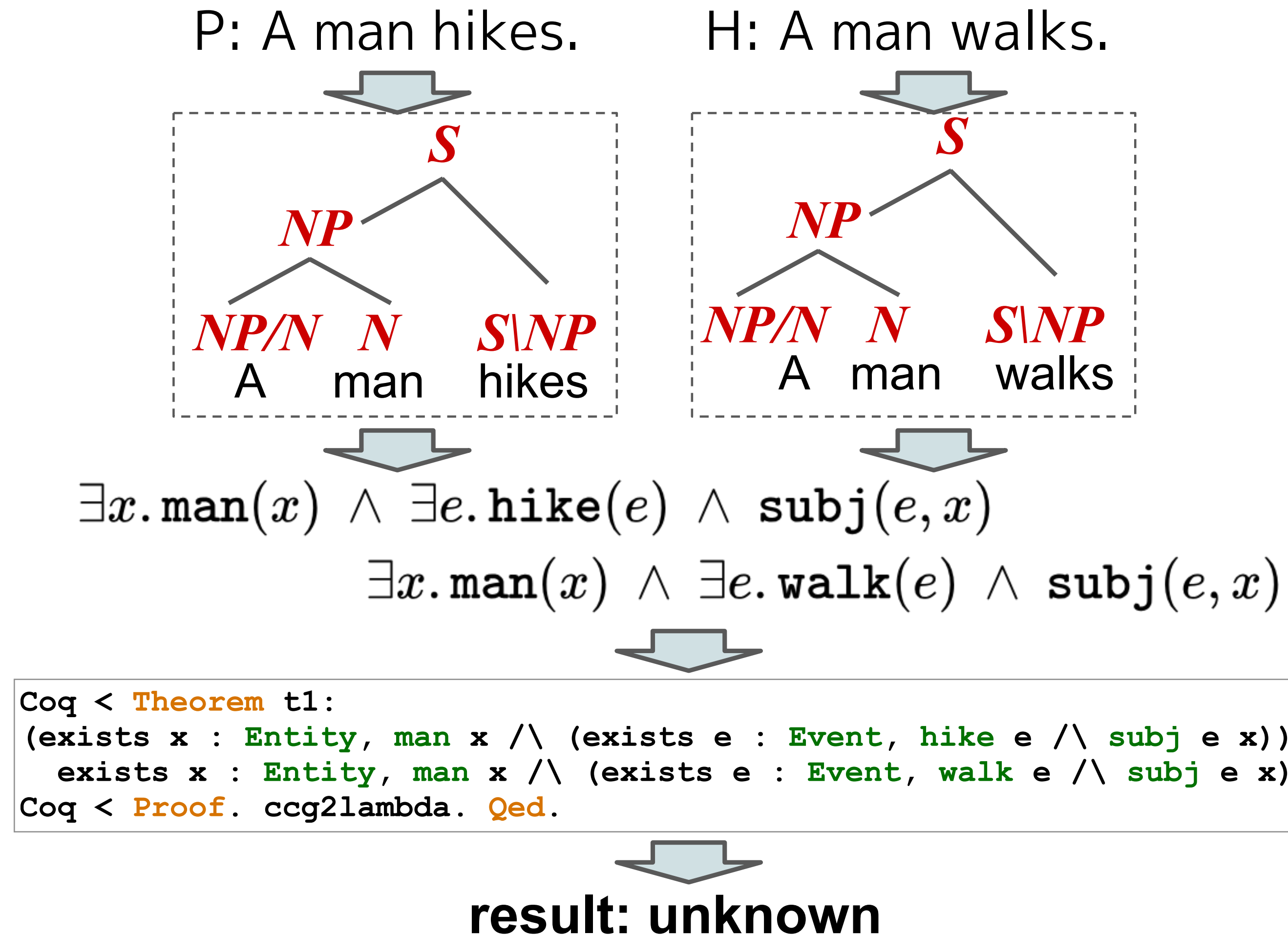
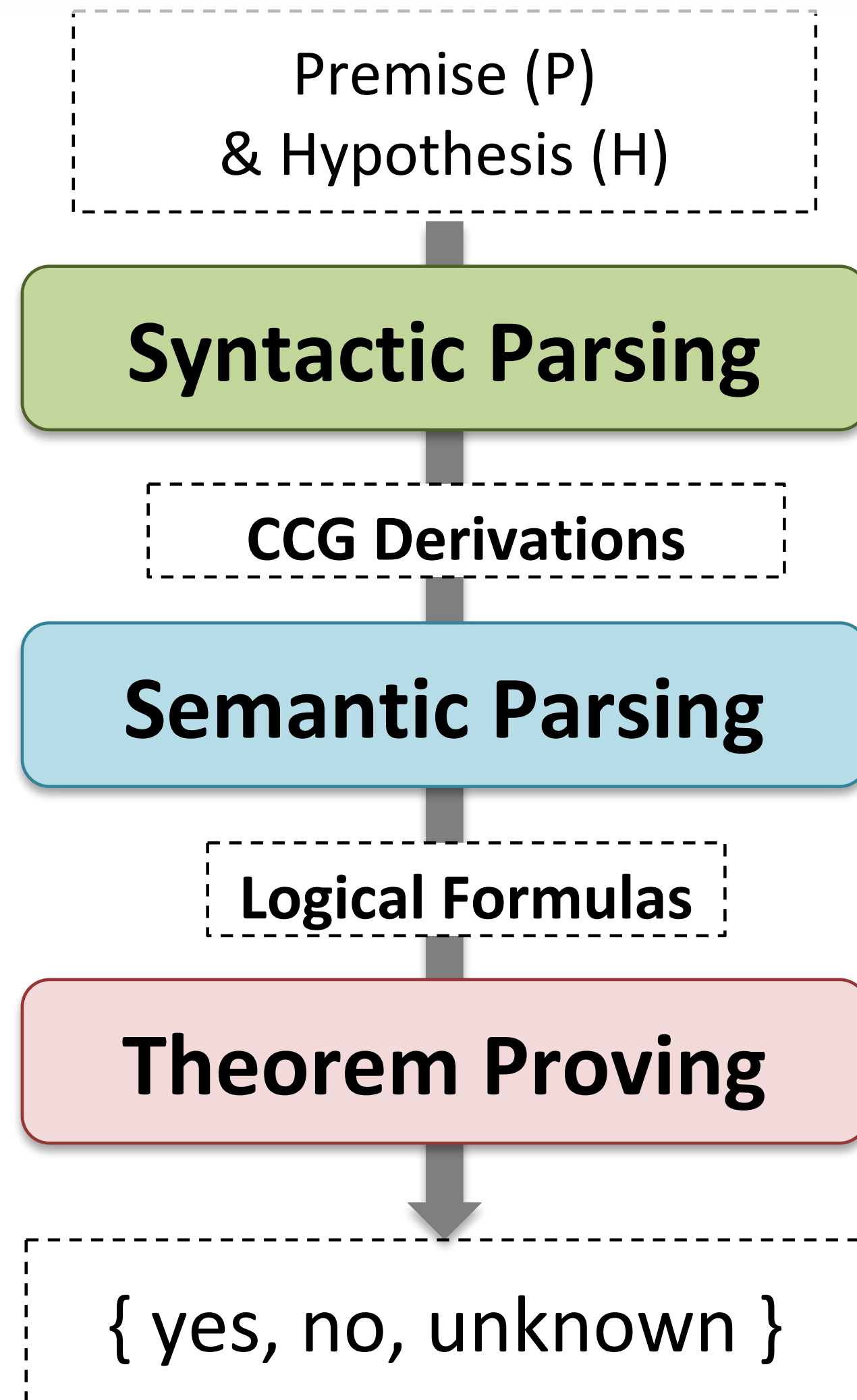
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🤔 How to handle external knowledge?

e.g. $\forall x. \text{hike}(x) \rightarrow \text{walk}(x)$

- Use WordNet as axioms blows up
the search space of theorem proving!

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Search on KBs

PRINCETON UNIVERSITY
WordNet
A lexical database for English

New Axioms

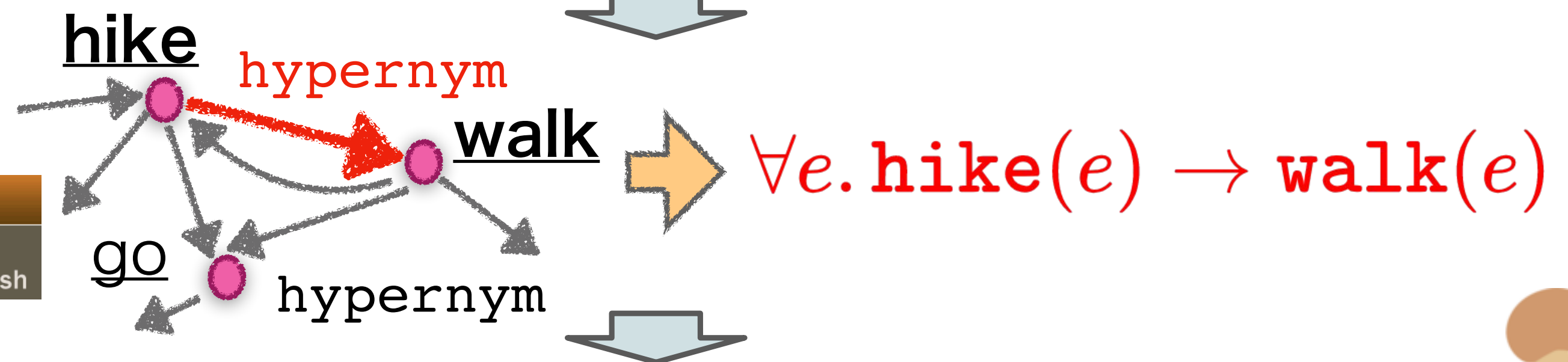
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result: yes



More steps when the 1st theorem proving is unsuccessful

1. Search KBs (e.g. WordNet) for useful lexical relations
2. Rerun Coq with additional axioms

"Abduction" Mechanism (Martínez-Gómez et al., 2017)

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- Do not want to run Coq again and again for real applications 😞
 - Ideally, the mechanism should be tightly integrated with the inference for efficiency



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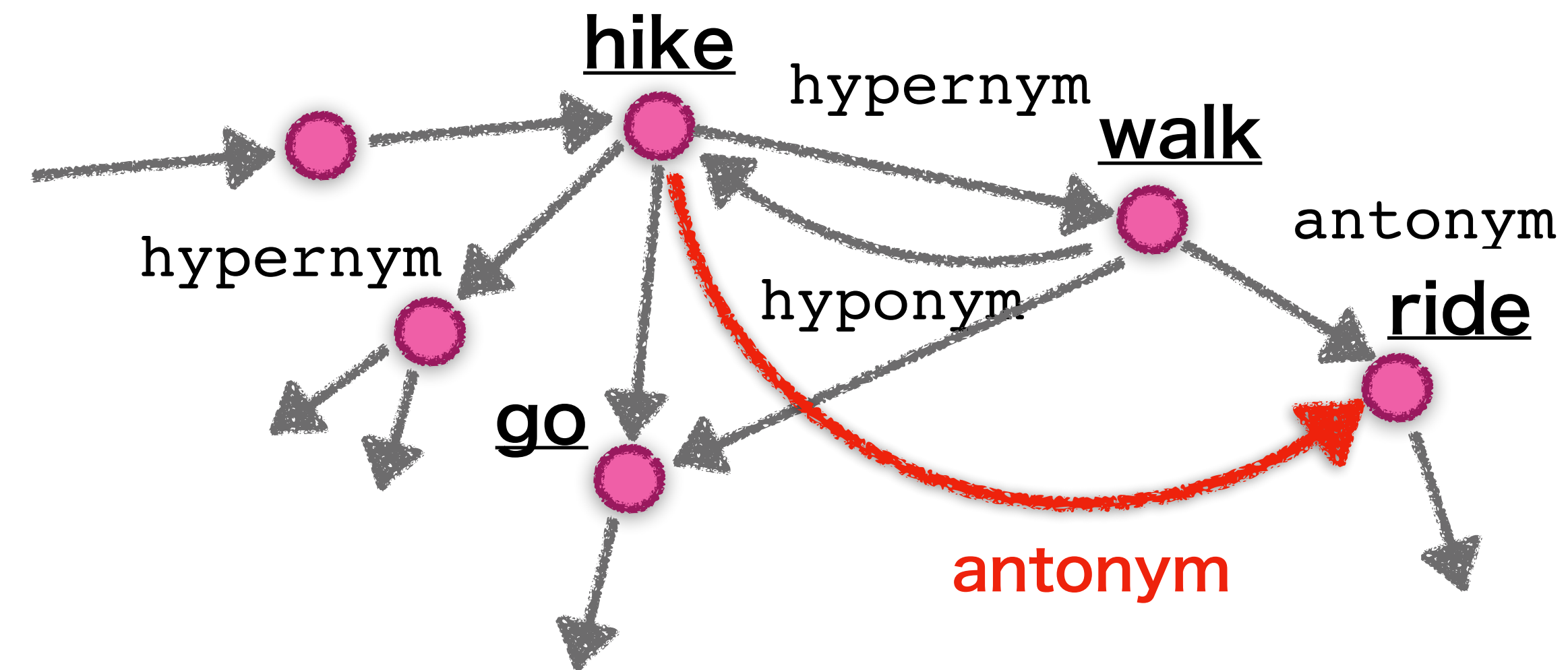


👉 We solve these issues by:

1. Replacing search on KBs by techniques of "Knowledge Base Completion"
2. Developing "**abduction**" Coq plugin

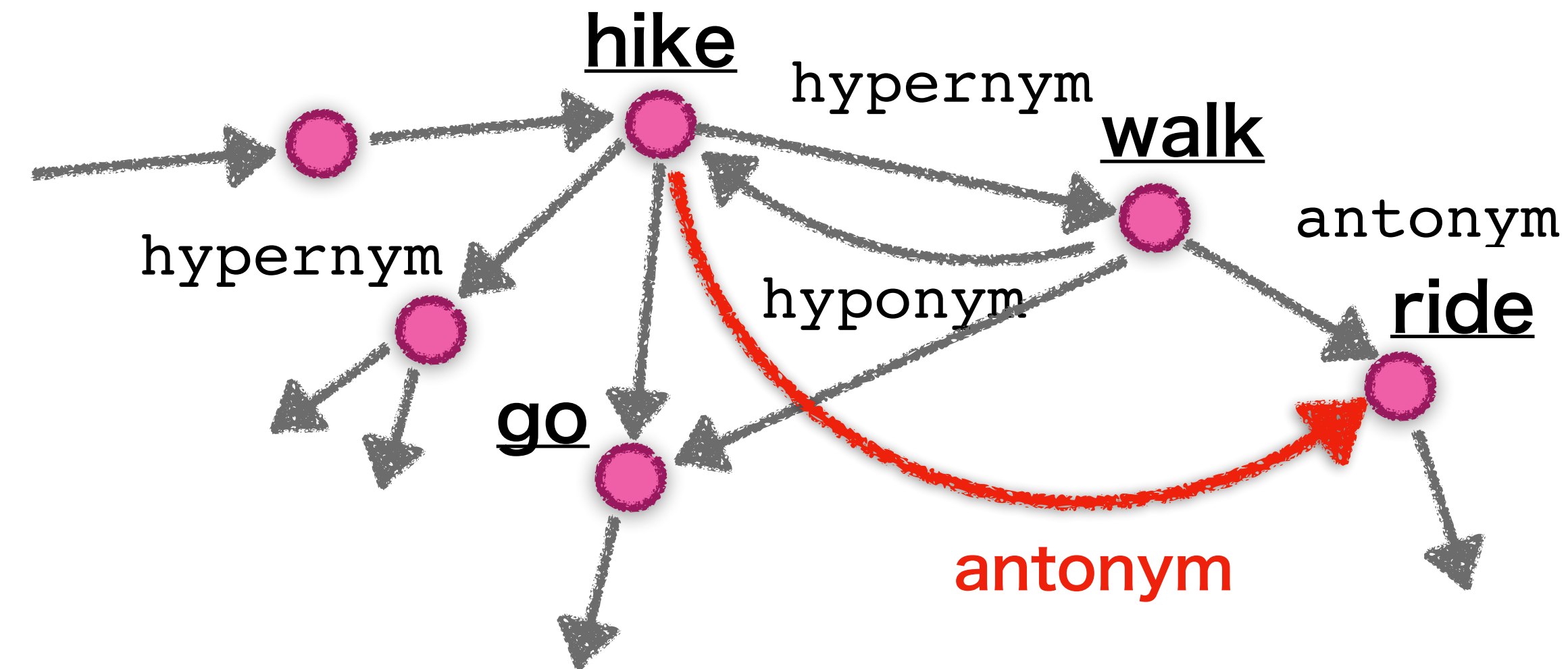


1. Extending Abduction Mechanism with KBC



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- **Knowledge Base Completion:**
 - A task to complement missing relations
 - recent huge advancement



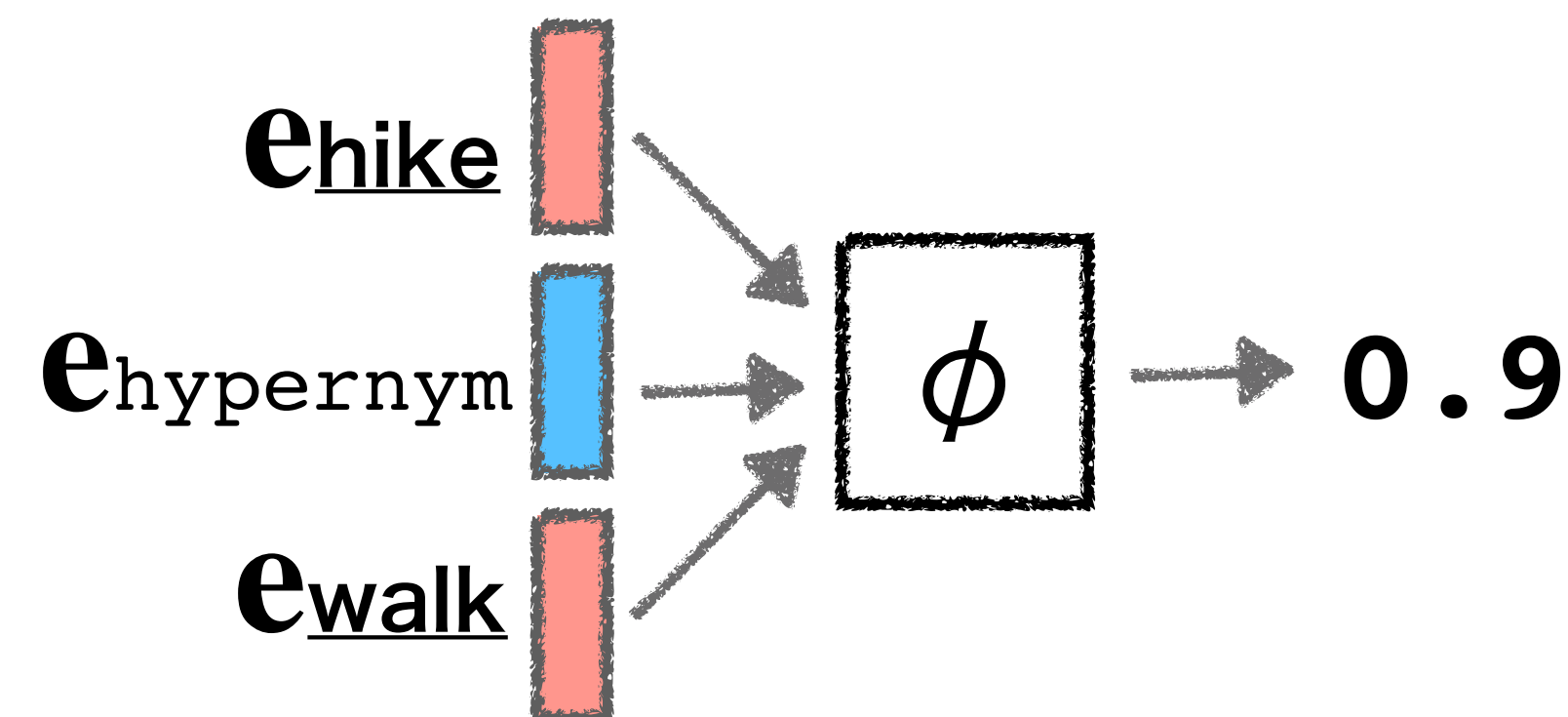
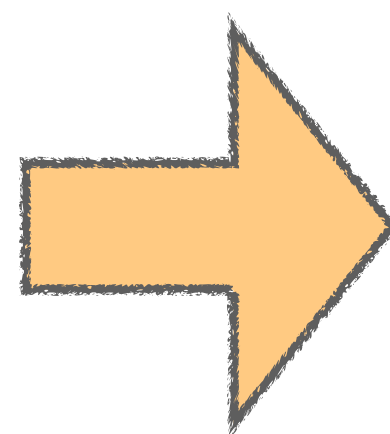
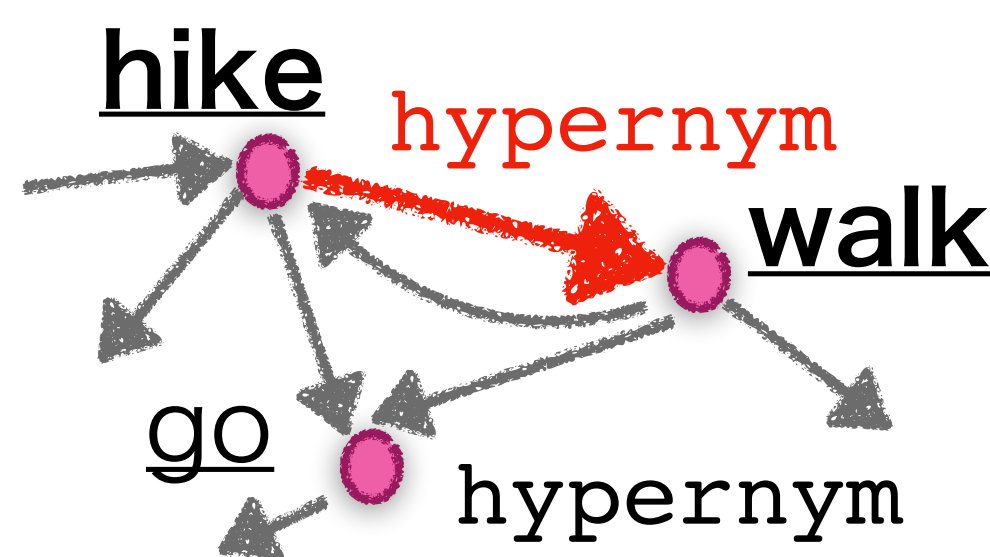
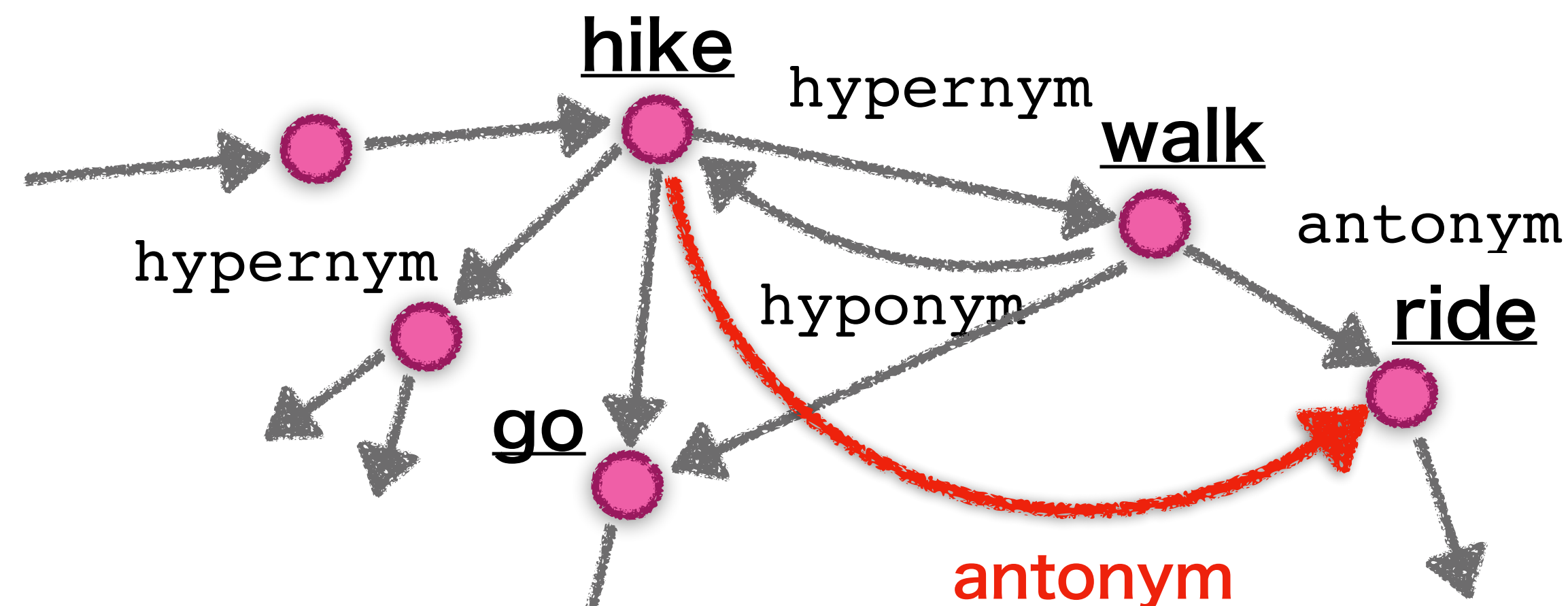
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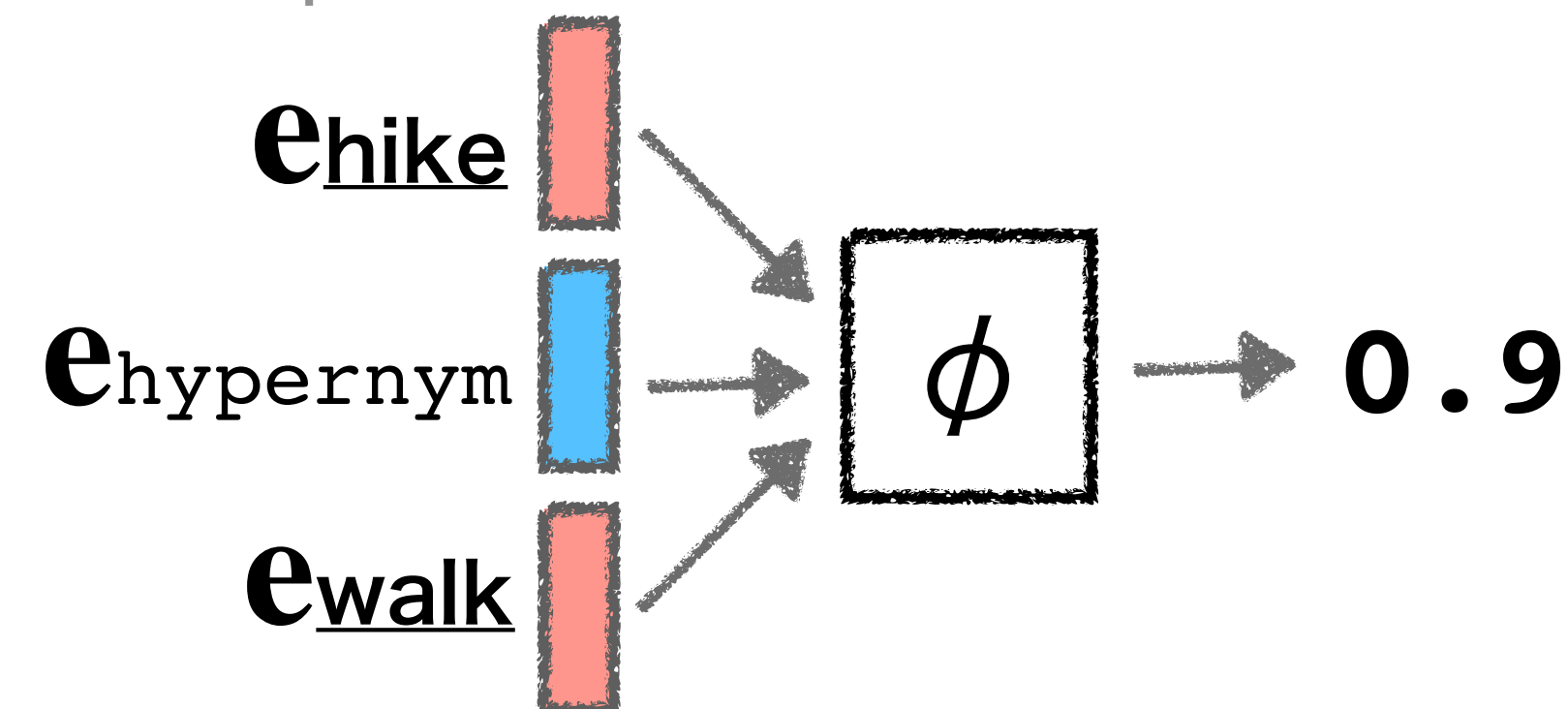
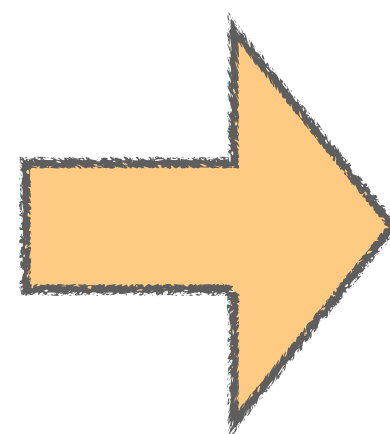
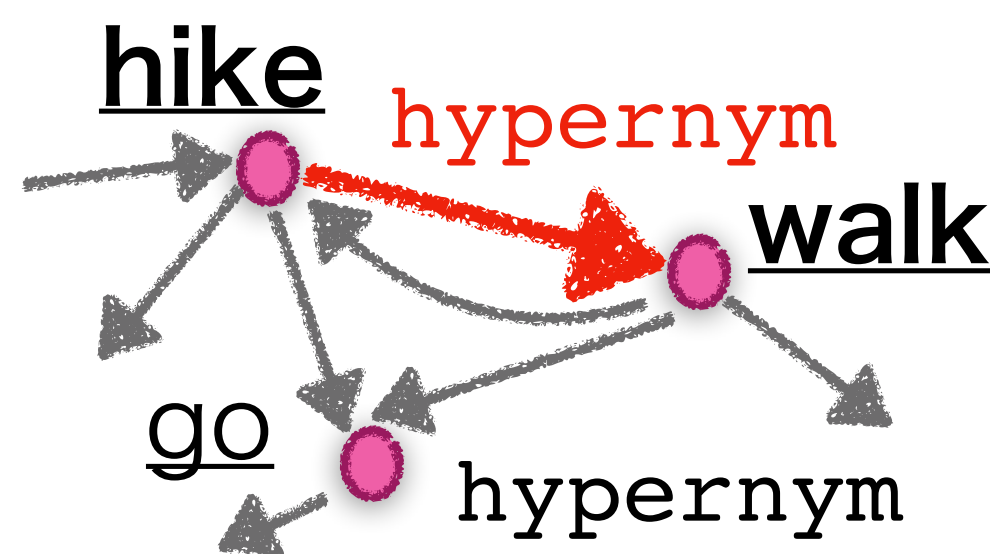
- We propose an **abduction mechanism based on KBC:**

- If (s, r, o) is missing, use it as axiom if $\phi(s, r, o) \geq \delta$ (threshold)
- ComplEx (Trouillon et al., 2016): $\phi(s, r, o) = \sigma(\text{Re}(\langle \mathbf{e}_s, \mathbf{e}_r, \mathbf{e}_o \rangle))$, $\forall \mathbf{e}_v \in \mathbb{C}^n$



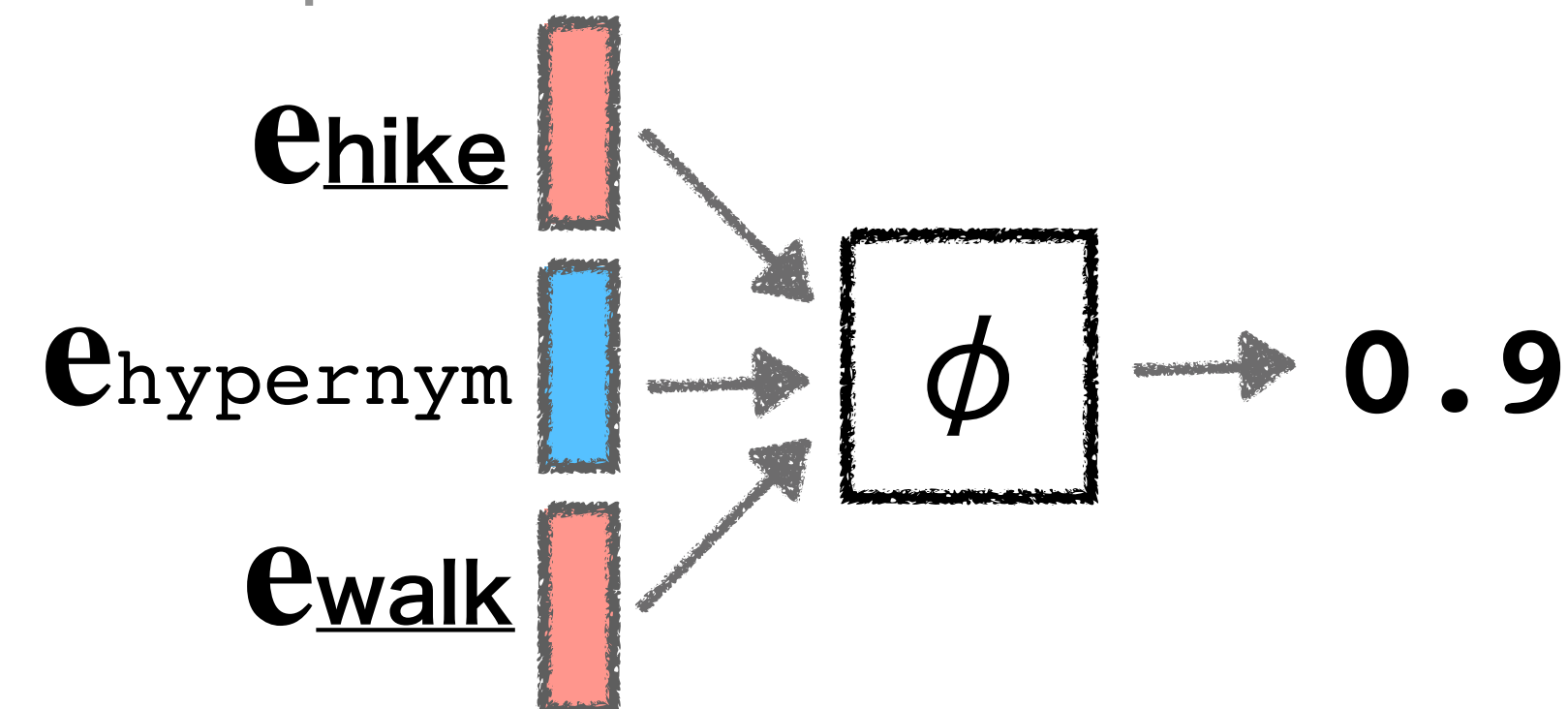
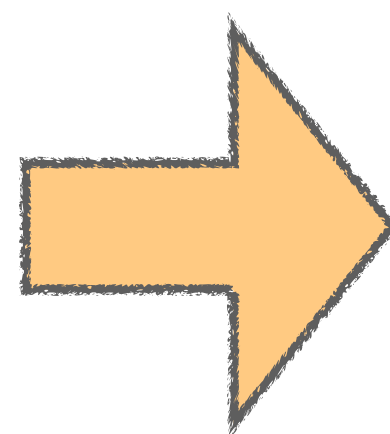
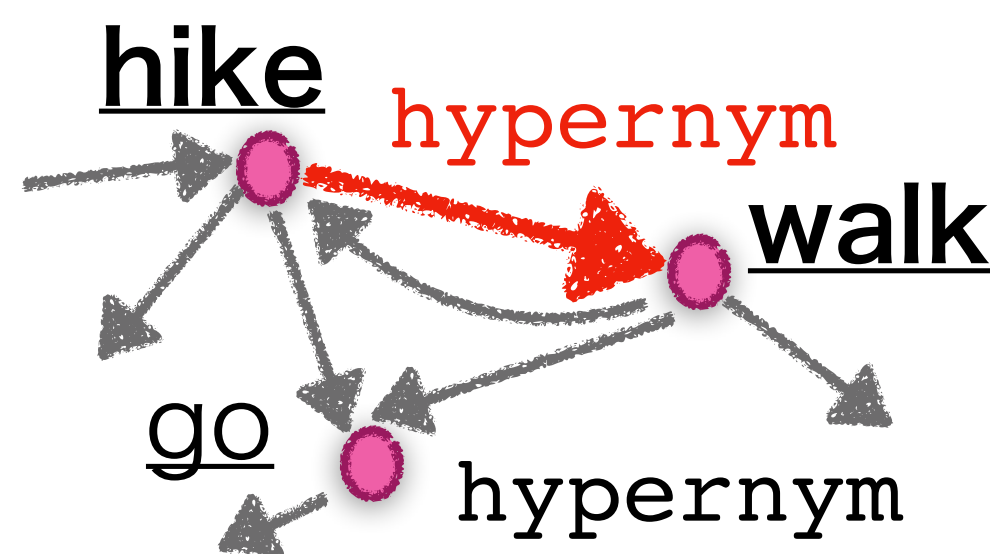
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| | Search on KB | KBC |
|------------------|---|--|
| Latent Knowledge | Hand-crafted rules (e.g. transitive closure of hypernym) | KBC models learn accurately |
| Efficiency | Multi-hop reasoning takes time | One dot product (ComplEx) |
| Scalability | Adding more knowledge harms the search time | Knowledge from VerbOcean (Chklovski et al., 2004) are added for free |



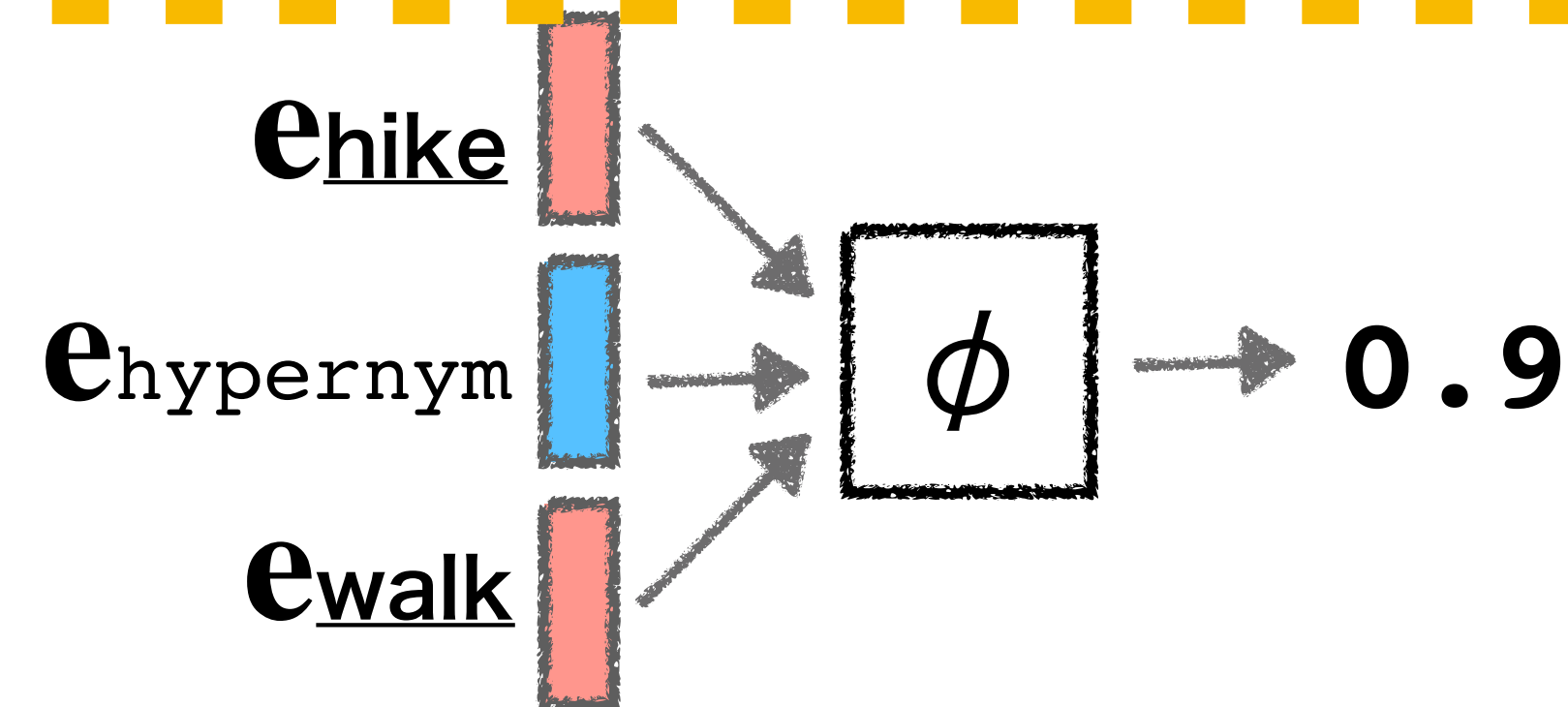
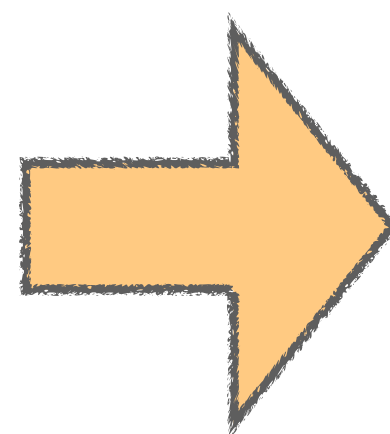
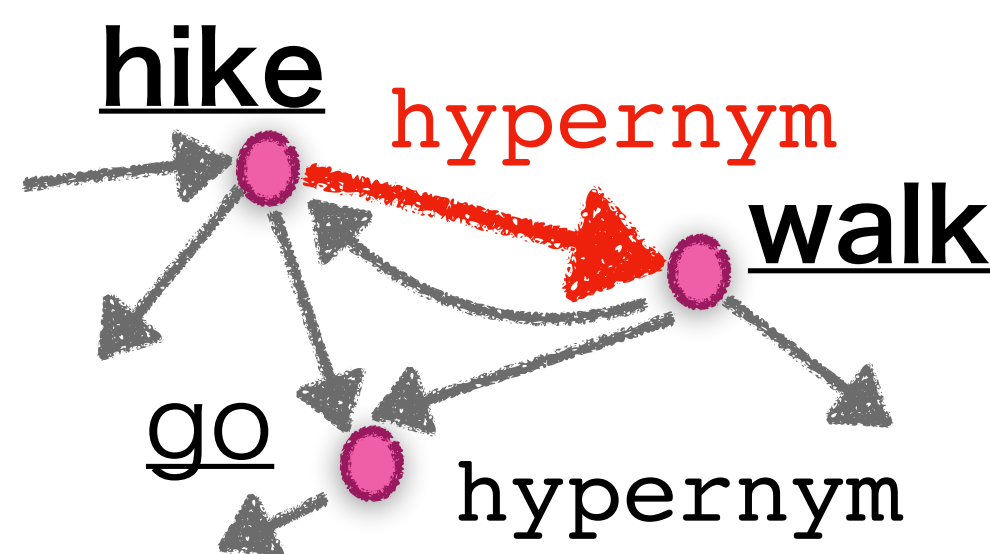
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2. Faster Reasoning with "**abduction**" Coq plugin

Coq Interactive Session

1 subgoal

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H : exists x : Entity, man x /\ (exists e : Event, hike e /\ subj e x)
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exists x : Entity, man x /\ (exists e : Event, walk e /\ subj e x)
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Lexical gap!

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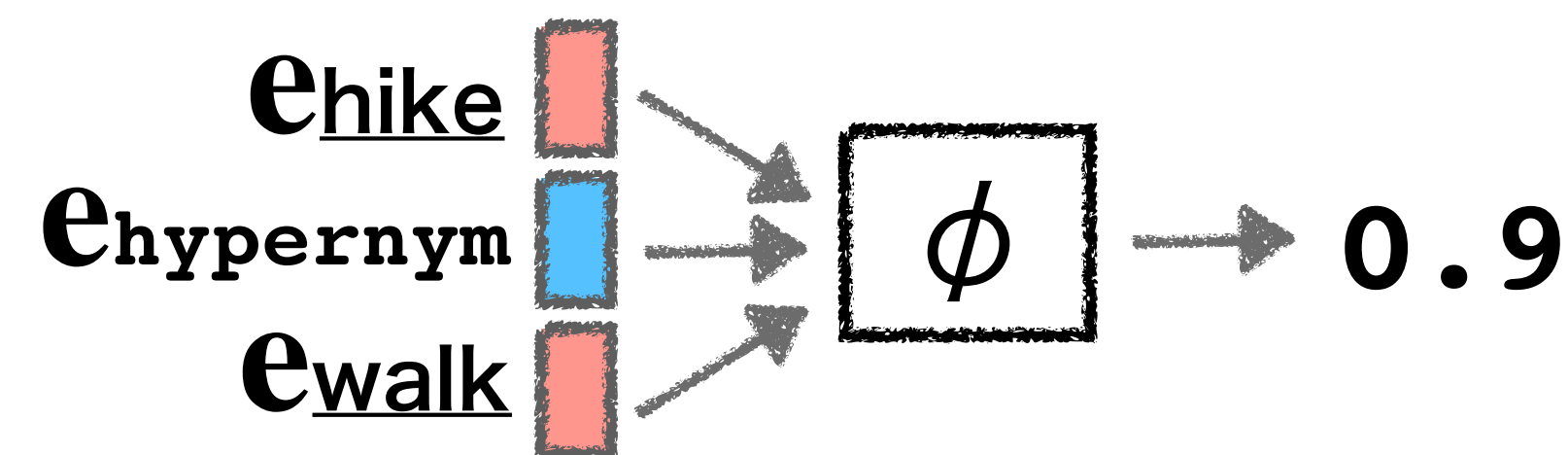
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Lexical gap!

(man, walk)
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Construct a list of predicate pairs from context and goal

Evaluate all the predicate pairs using ComplEx



Filter them by score

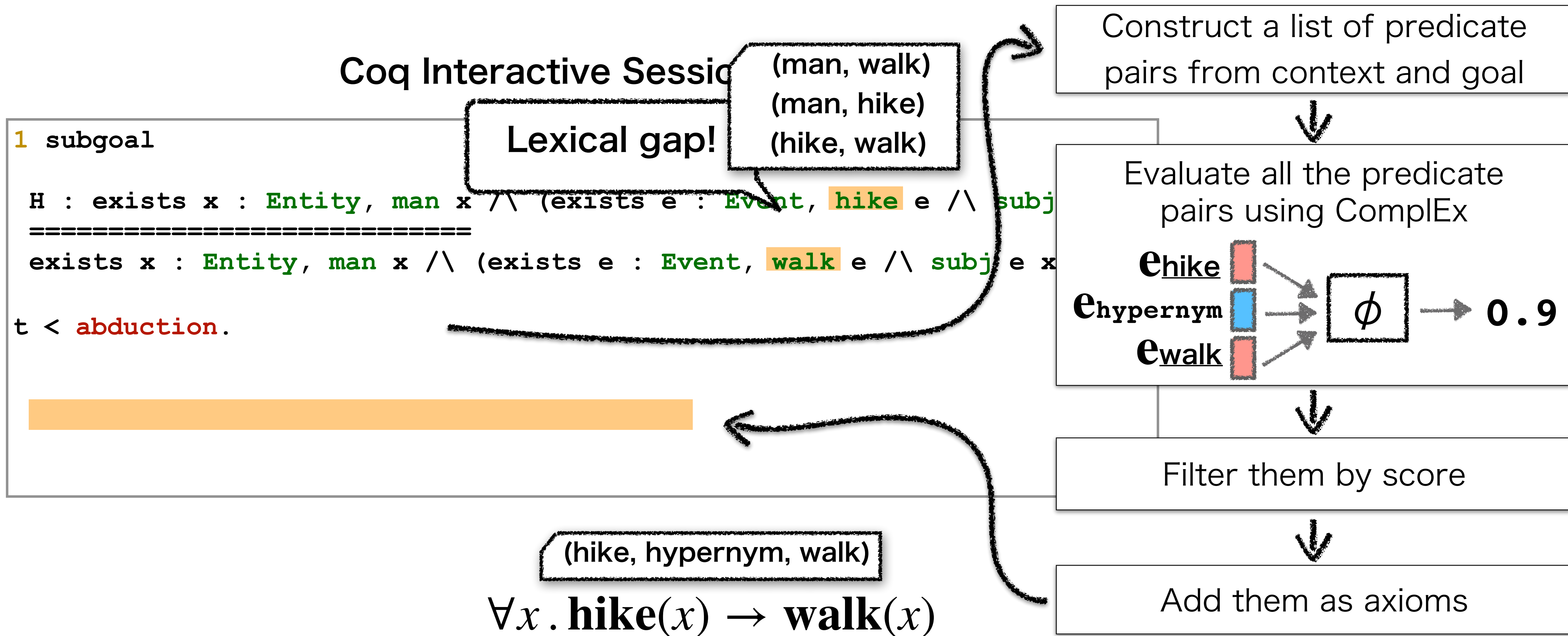
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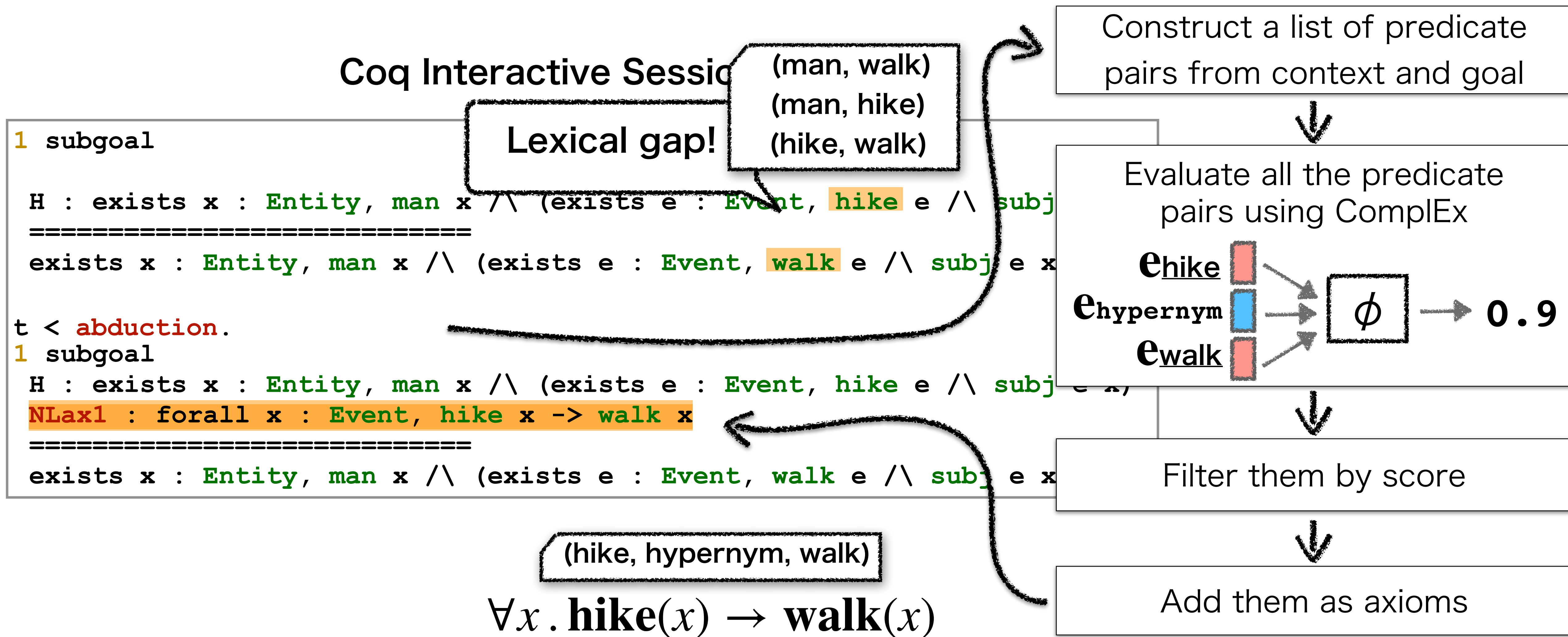
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Semantic Parsing

Logical Formulas

Theorem Proving

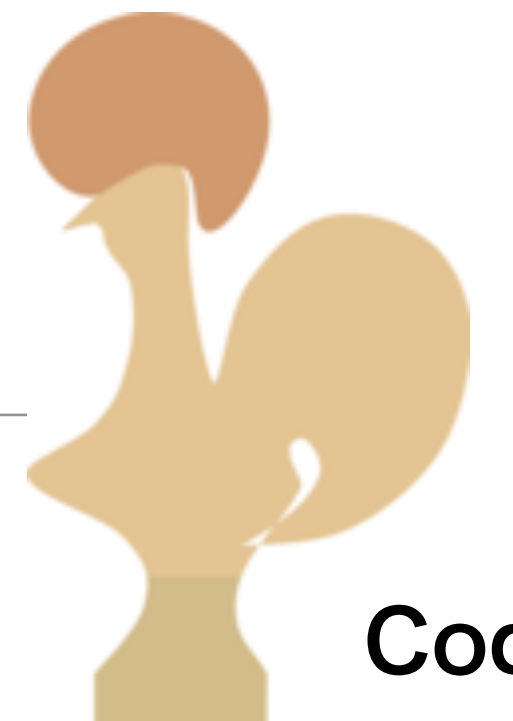
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Summary so far...

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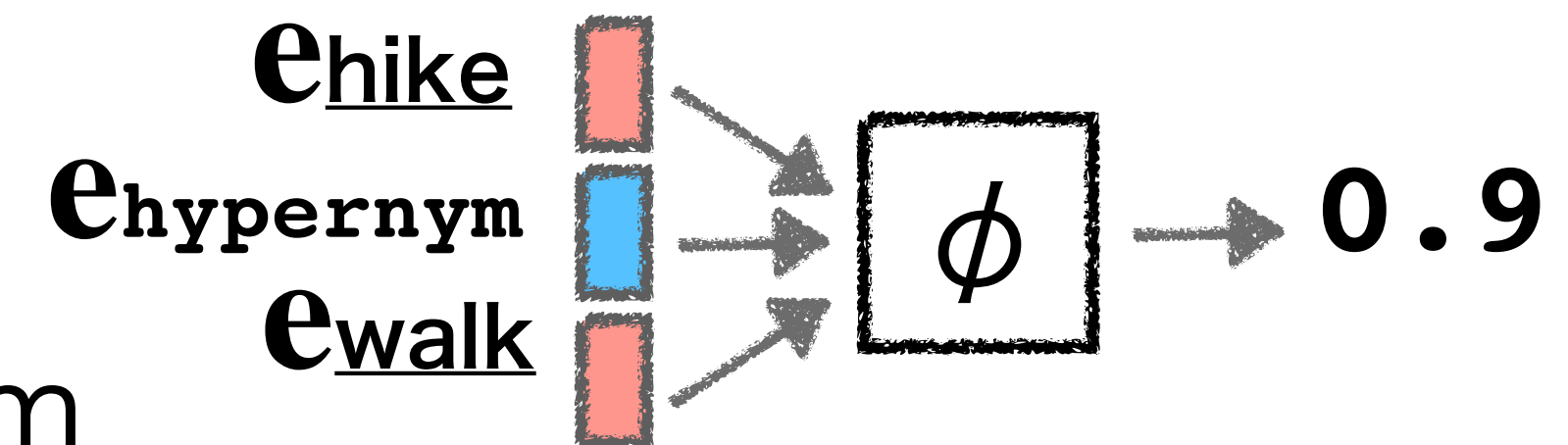
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Coq

result: yes

+abduction



- 👍 Efficient and scalable abduction mechanism
- 👍 No need to rerun Coq in abduction
 - Our method is applicable to other logic-based systems
 - e.g. Modern Type Theory (Bernandy and Chatzikyriakidis, 2017)

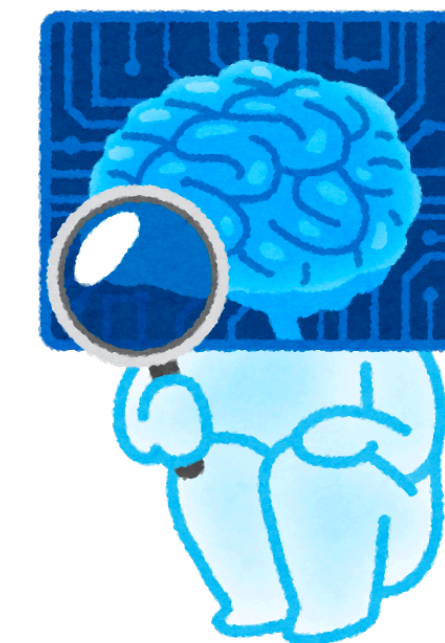
Experiments

- SICK RTE dataset (Marelli et al., 2014)
- Metrics: accuracy and processing time
- ComplEx is trained on logistic loss: $\sum_{((s,r,o),t) \in \mathcal{D}} t \log f(s,r,o) + (1-t) \log(1-f(s,r,o))$
- The training data is constructed using WordNet
 - synonym, antonym, hyponym, hypernyms, etc.
- The trained ComplEx model achieves MRR of 77.68%

P: A flute is being played in a lovely way by a girl.

H: One woman is playing a flute.

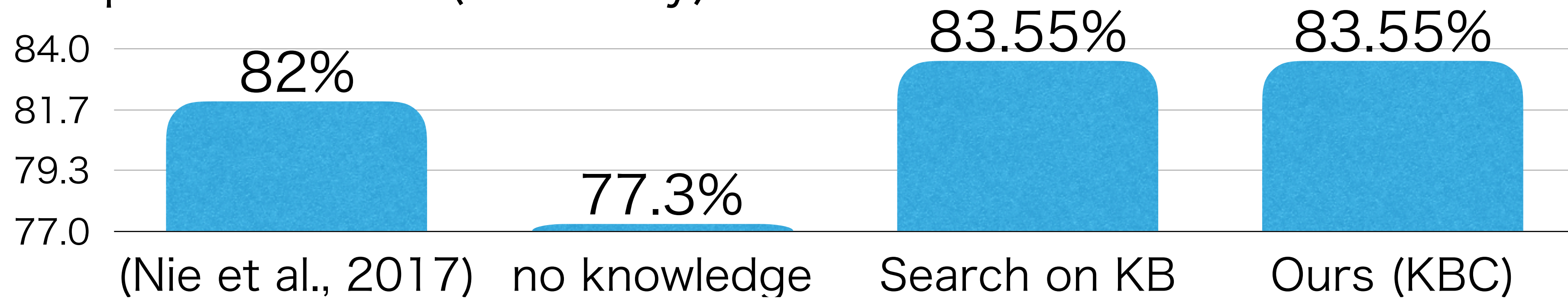
logical lexical
syntactic phenomena



entailment

Experimental Results on SICK

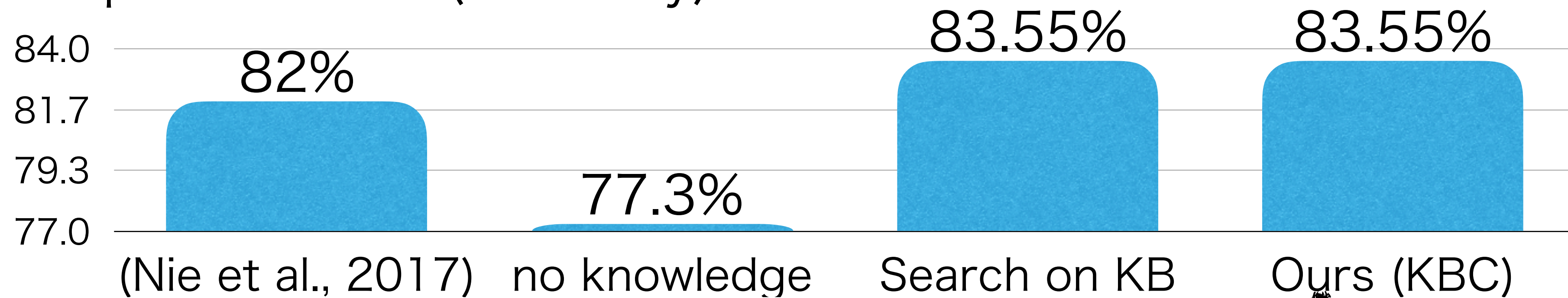
- RTE performance (accuracy)



- Baselines: Search on KB (Martínez-Gómez et al., 2017), NN-based (Nie et al., 2017)

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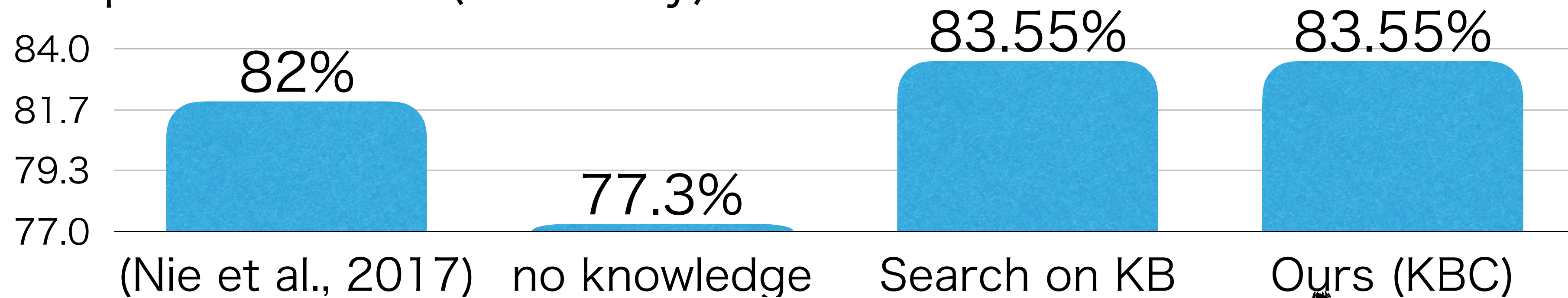


**Achieves the same accuracy,
improving significantly
from "no knowledge" case**

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Experimental Results on SICK

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- Processing speed (second per a problem)

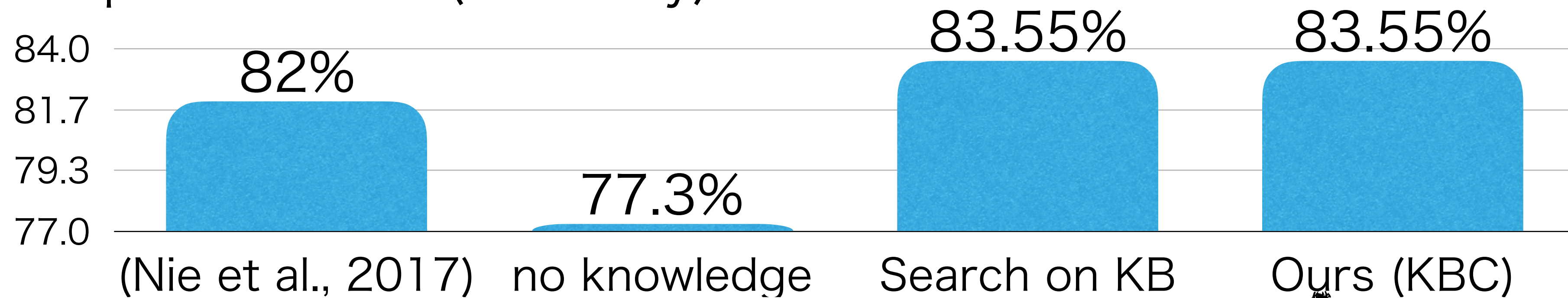


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**Our method halves the time
to process an RTE problem!**

Thank you!

- A KBC-based axiom injection for logic-based RTE systems
 - Efficient, scalable, and it provides latent knowledge
- **abduction** tactic for further faster reasoning
- **Come to my poster (#1319) for other topics:**
 - Adding other KB (VerbOcean) without losing efficiency
 - Evaluating learned latent knowledge in terms of RTE (LexSICK dataset)
- **All the codes, dataset and slides are available:**
 - <https://masashi-y.github.io>