

# Learning to Make Inferences in a Semantic Parsing Task

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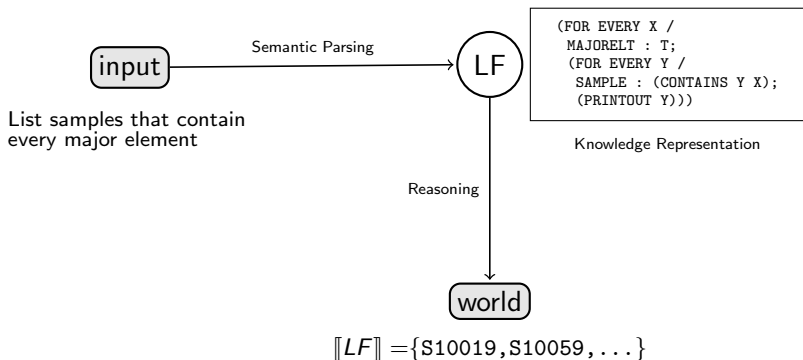
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# Natural Language Understanding and Semantic Parsing

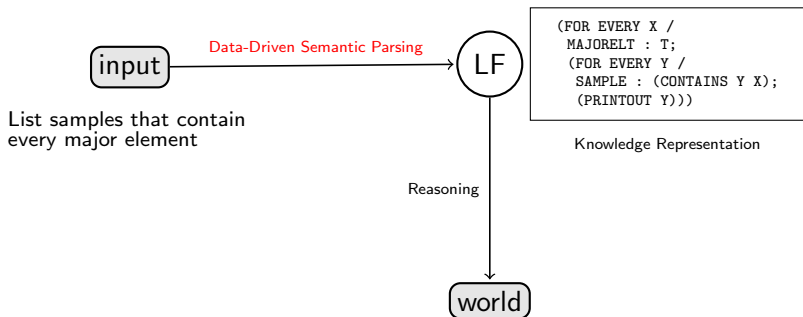
## ► Conventional pipeline model



Lunar QA system (Woods (1973))

# Natural Language Understanding and Semantic Parsing

- Semantic parsing: Learning representations from corpora and databases.

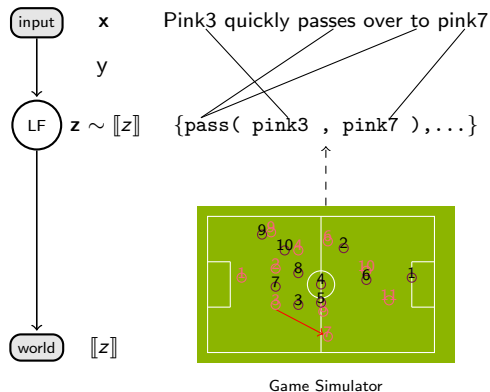


Paradigm and Supervision	Dataset	Learning Goal
Learning from LFs <sup>1</sup>	$\{(input_i, LF_i)\}_i^N$	$input \xrightarrow{Trans.} LF$
Learning from Denotation <sup>2</sup>	$\{(input_i, \llbracket input_i \rrbracket)\}_i^N$	$input \xrightarrow{LF+Trans.} \llbracket input \rrbracket$

<sup>1</sup>Zettlemoyer and Collins (2012); Wong and Mooney (2007) <sup>2</sup>Clarke et al. (2010); Liang et al. (2013)

# Learning to Sportscast

- ▶ Learning from “grounded” and ambiguous supervision
- ▶ **Objective:** Generate correct representations for unseen commentary.



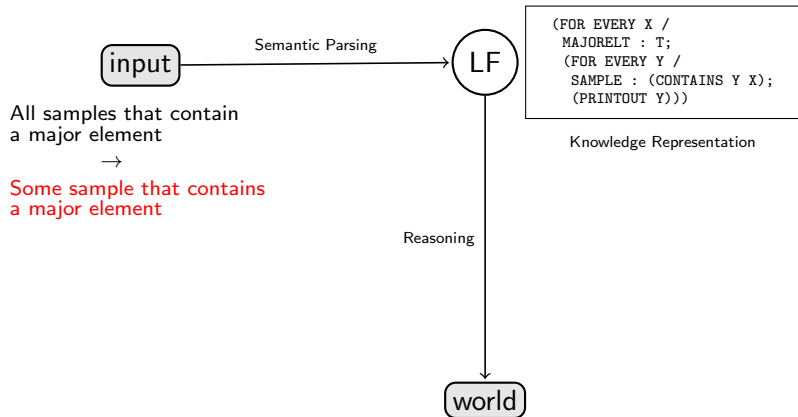
## Supervision: Dataset D

**Event Streams:**  $D = \{(x_i, \{z_1, \dots, z_k\})\}_{i=1}^N$   
*Task:* learn (latent)  $y$ , **translation**

Sportscaster corpus (Chen and Mooney (2008))

# Semantic Parsing and Entailment

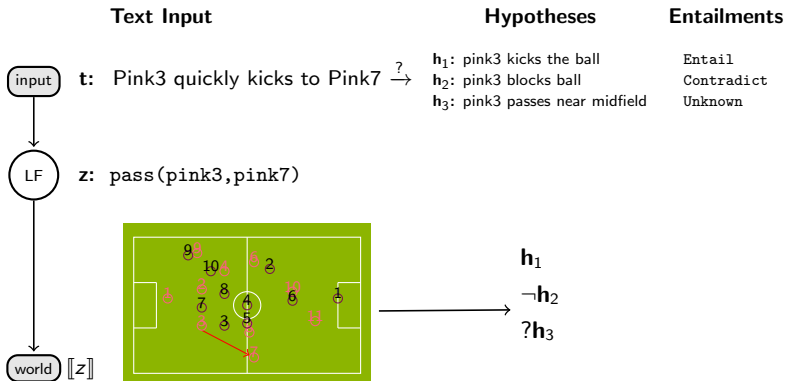
- ▶ **Entailment:** One of the *basic aims* of semantics. (Montague (1970))
- ▶ Representations should be *grounded* in judgements about entailment.



$$\llbracket LF \rrbracket = \{S10019, S10059, \dots\} \supseteq \{S10019\}$$

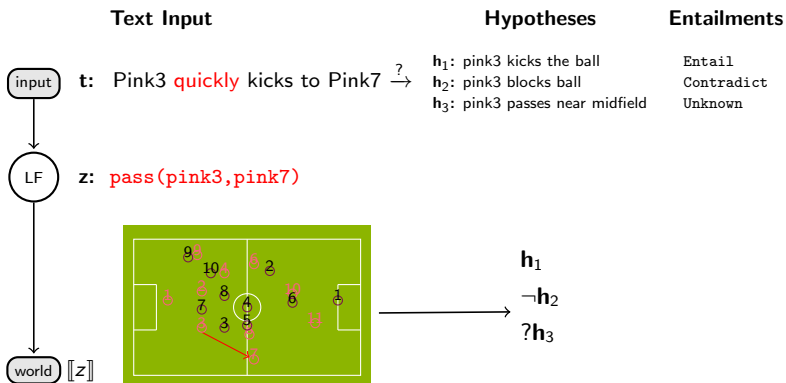
# Requirements for Semantic Representations

- ▶ **Minimal requirement:** Semantic parser should be able to recognize certain types of entailments.
- ▶ **RTE:** Would a human reading  $t$  infer  $h$ ? Dagan et al. (2005)



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# Problem 1: Crude Representations

- ▶ Target representations are **not expressive, underspecified**
- ▶ Not based on background logical theory (no knowledge)

	Text $t$	Hypothesis $h$	Entailment	
			$t \rightarrow h$ $h \rightarrow t$	Naive (do reps match?)
1.	Pink 3 <b>quickly</b> kicks to pink 1 <code>pass(pink3,pink1)</code>	Pink 3 kicks over to pink 1 <b>near midfield</b> <code>pass(pink3,pink1)</code>	Unknown Unknown	Entail
2.	Purple player 10 <b>kicks the ball</b> <code>kick(purple10)</code>	Purple 10 <b>again</b> <b>shoots</b> for the goal <code>kick(purple10)</code>	Unknown Entail	Entail

- ▶ **Desiderata:** **explicit treatment of modifiers, sense distinctions**

## Problem 2: Missing Knowledge

- ▶ Target representations are not expressive, underspecified
- ▶ **Not based on background logical theory** (no knowledge)

Text $t$	Hypothesis $h$	Entailment	
		$t \rightarrow h$ $h \rightarrow t$	Naive (do reps match?)
1. Pink 3 quickly kicks to pink 1 <code>pass(pink3,pink1)</code>	Pink 3 kicks over to pink 1 near midfield <code>pass(pink3,pink1)</code>	Unknown Unknown	Entail
2. <b>Purple player 10</b> kicks the ball <code>kick(purple10)</code>	<b>Purple team</b> scores another goal <code>playmode(goal_1)</code>	Unknown Unknown	Contradict

- ▶ **Desiderata:** explicit treatment of modifiers, sense distinctions **abstract relations between symbols**

## How to improve this?

- ▶ **General Problem:** Semantic representations are underspecified, fail to capture entailments, background knowledge missing.
- ▶ **Goal:** Capture the missing knowledge and inferential properties of text.

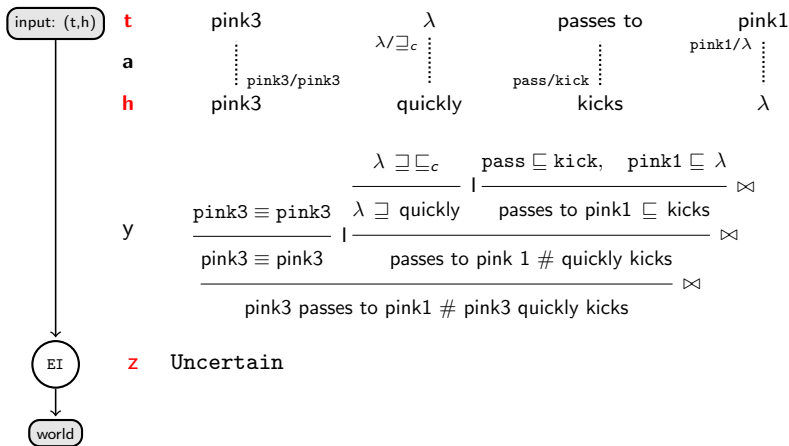
# How to improve this?

- ▶ **General Problem:** Semantic representations are underspecified, fail to capture entailments, background knowledge missing.
- ▶ **Goal:** Capture the missing knowledge and inferential properties of text.
- ▶ **Solution:** Use entailment information (EI) as weak signal to train parser and logical reasoning (an alternative to annotating representations).

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Learning from Denotation	$\{(input_i, \llbracket input_i \rrbracket)\}_i^N$	$input \xrightarrow{LF+Trans.} \llbracket input \rrbracket$
Learning from Entailment	$\{(input_t, input'_h)_i, EI_i\}_i^N$	$(input_t, input'_h) \xrightarrow{Proof} EI$

# Learning from Entailment: Illustration

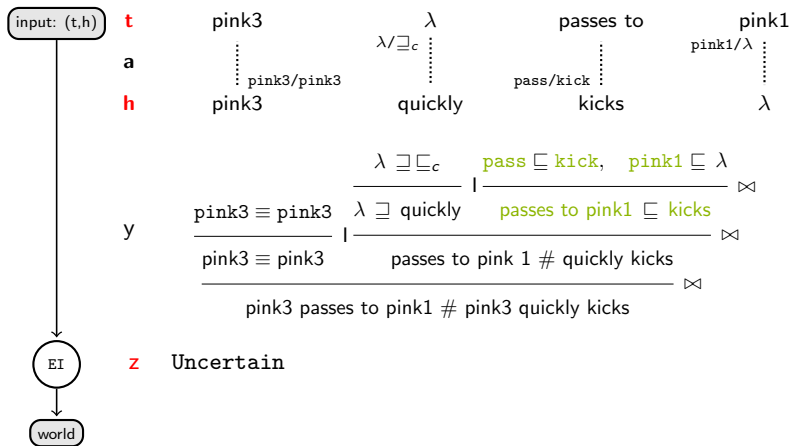
- Entailments are used to reason about target symbols and find holes in the analyses.



**Data:**  $D = \{((t, h)_i, z_i)\}_{i=1}^N$ , **Task:** learn (latent) proof y

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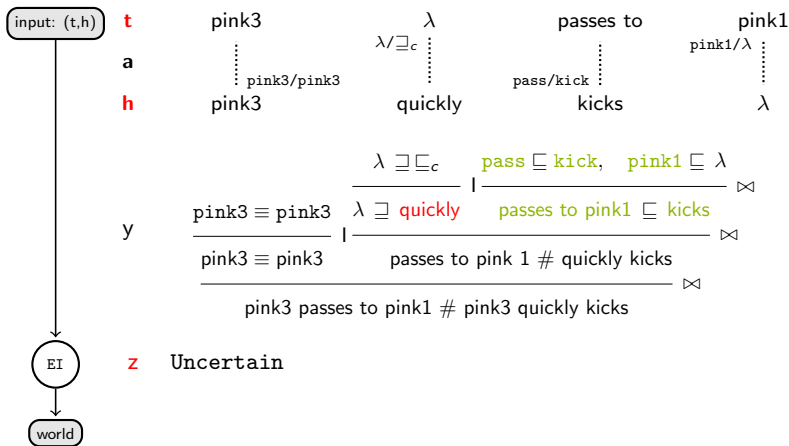
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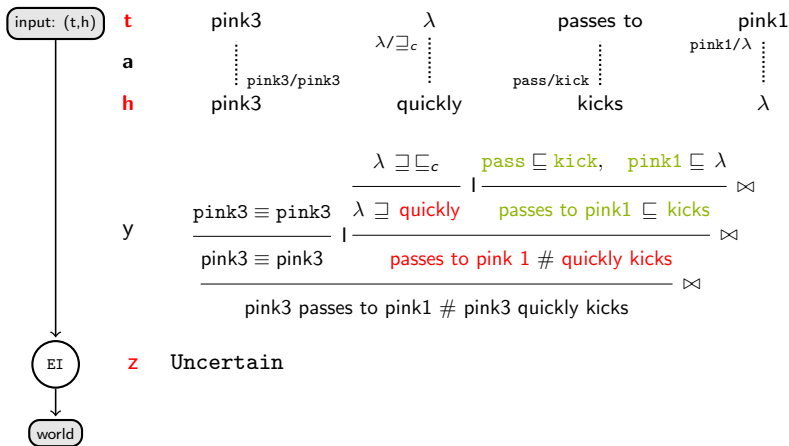
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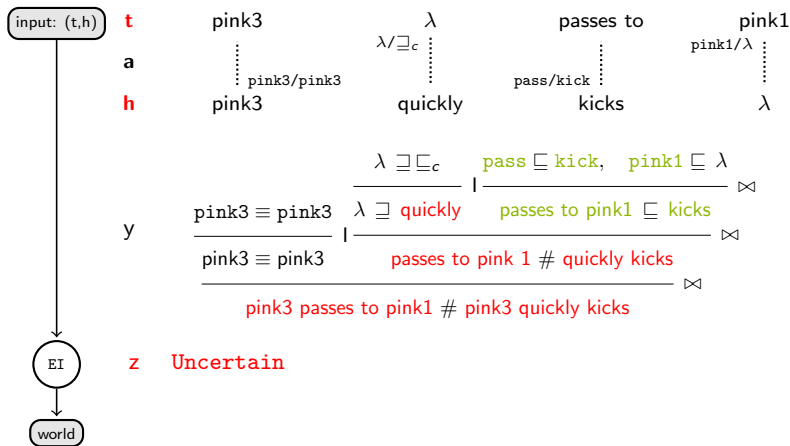


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- Entailments are used to reason about target symbols and find holes in the analyses.



**Data:**  $D = \{((t, h)_i, z_i)\}_{i=1}^N$ , **Task:** learn (latent) proof y

# Learning from Entailment: Proofs

$$\frac{\frac{\frac{\text{pink3} \equiv \text{pink3}}{\lambda \sqsupseteq \text{quickly}} \quad \frac{\lambda \sqsupseteq \sqsubseteq_c \quad \text{pass} \equiv \text{pass}, \text{pink1} \sqsubseteq \text{pink team}}{\text{passes to pink1} \sqsubseteq \text{kicks to the pink team}}}{\text{pink3} \equiv \text{pink3} \quad \text{passes to pink 1} \# \text{quickly kicks to the pink team}}}{\text{pink3 passes to pink1} \# \text{pink3 quickly kicks to the pink team}}$$

- **Logic:** Natural logic calculus (MacCartney and Manning (2009)).

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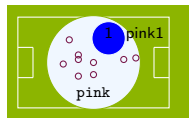
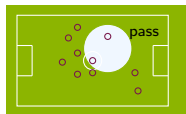
- ▶ **Logic:** Natural logic calculus (MacCartney and Manning (2009)).

- ▶  $I$ : axioms, set-theoretic relations between symbols.

pass  $\equiv$  pass

pink1  $\sqsubseteq$  pink team

$\forall x. \text{pink1}(x) \rightarrow \text{pink-team}(x)$  (**FOL**)



# Learning from Entailment: Proofs

$$\begin{array}{c}
 \frac{\text{pink3} \equiv \text{pink3}}{\text{pink3} \equiv \text{pink3}} \quad \left| \frac{\lambda \sqsupseteq \sqsubseteq_c \quad \text{pass} \equiv \text{pass}, \quad \text{pink1} \sqsubseteq \text{pink team}}{\lambda \sqsupseteq \text{quickly passes to pink1} \sqsubseteq \text{kicks to the pink team}} \right. \bowtie \\
 \hline
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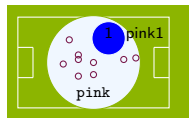
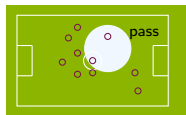
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- ▶  $\bowtie$ : natural logic inference rule:  $\equiv \bowtie \sqsubseteq = \sqsubseteq$

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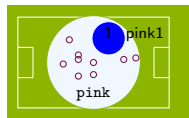
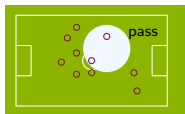
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pink1  $\sqsubseteq$  pink team

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- ▶  $\boxtimes$ : natural logic inference rule:  $\equiv \boxtimes \sqsubseteq = \sqsubseteq$

- ▶ **Latent variable:** axioms or relations in proofs.

# Experiments with Sportscaster

- ▶ **Step 1:** Train a normal semantic parser, sentences  $\rightarrow$  logical forms.
- ▶ **Step 2:** Jointly retrain on original data and inference pairs, sentences  $\rightarrow$  logical forms, pairs  $\rightarrow$  proofs.
- ▶ **Evaluation:** generating logical representations (**standard**), recognizing textual entailment (**novel**)

## Semantic Parsing: Sentences to Logical Form

- ▶ Use a semantic CFG, rules constructed from target representations using small set of templates (Börschinger et al. (2011))

$(x : \text{purple } 10 \text{ quickly kicks}, z : \{\text{kick}(\text{purple}10), \text{block}(\text{purple}7), \dots\})$

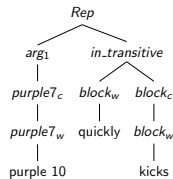
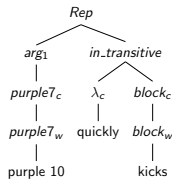
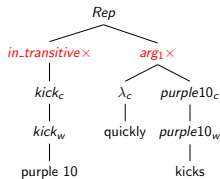
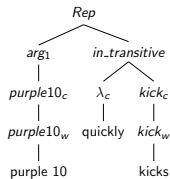
↓ (rule extraction)

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( $x$  : purple 10 quickly kicks,  $z$  : {kick(purple10), block(purple7),...})

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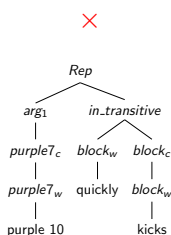
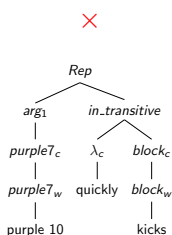
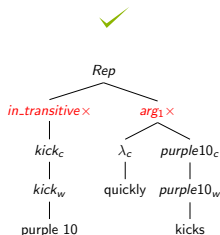
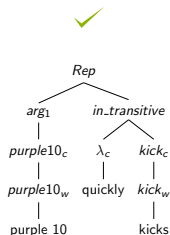


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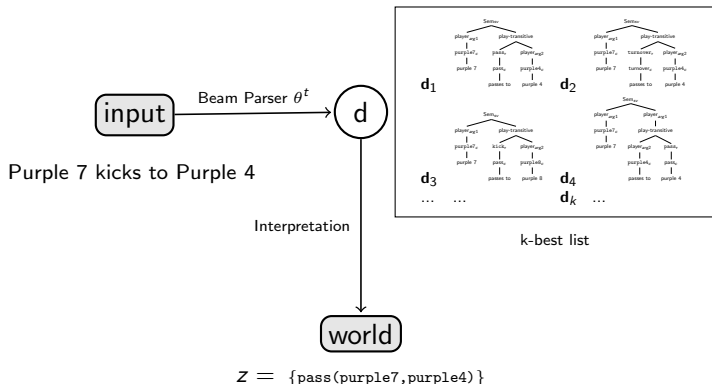
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# Learning for Semantic Parsing

- ▶ Rules used to define a PCFG  $\mathcal{G}_\theta$ , learn correct derivations.
- ▶ **Learning:** EM bootstrapping approach (Angeli et al. (2012)), **objective:**

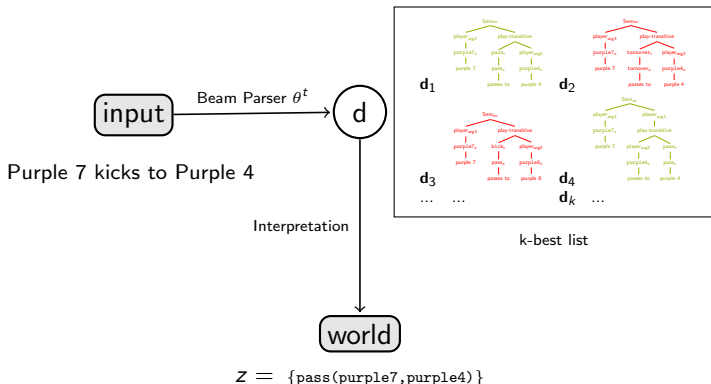
$$\max_{\theta} \sum_{i=1}^N \log p_{\theta}(z_i | x_i)$$



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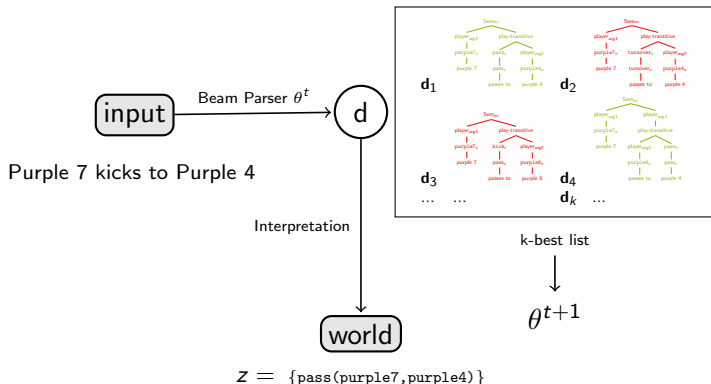
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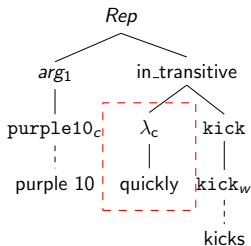


# Semantic Parsing: Sentences to Logical Form

- ▶ Representations are a rough approximation, unknown items are ignored

( $x$  : purple 10 quickly kicks,  $z$  : {kick(purple10), block(purple7),...})

↓ (parsing)



# Entailment Modeling: Sentence Pairs to Proofs

- ▶ **Alignment:** heuristic alignment between target/hypothesis parse trees.

((**t:** purple7 kicks the ball, **h:** purple team scores a goal), Uncertain)

transform.            kick  $\xrightarrow{sub.}$  score            purple7  $\xrightarrow{sub.}$  purple team  
relation.

?

inference

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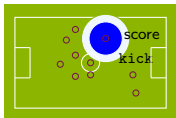
transform.

relation.

symbol	definition
$\sqsubset$	$x \subset y$
$\supset$	$x \supset y$
$\equiv$	$x = y$
	neg.
#	other

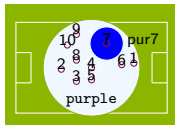
kick  $\xrightarrow{sub.}$  score

$\sqsupset$



purple7  $\xrightarrow{sub.}$  purple team

$\sqsubset$



inference

# Entailment Modeling: Sentence Pairs to Proofs

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kick  $\xrightarrow{\text{sub.}}$  score

purple7  $\xrightarrow{\text{sub.}}$  purple team

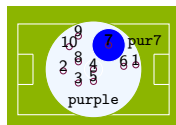
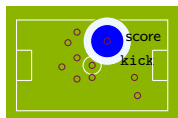
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$\sqsupseteq$

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$\sqsubseteq$	$x \subset y$
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$\equiv$	$x = y$
	neg.
#	other



inference

$(\sqsupseteq \boxtimes \sqsubseteq) = \#(\text{Uncertain})$

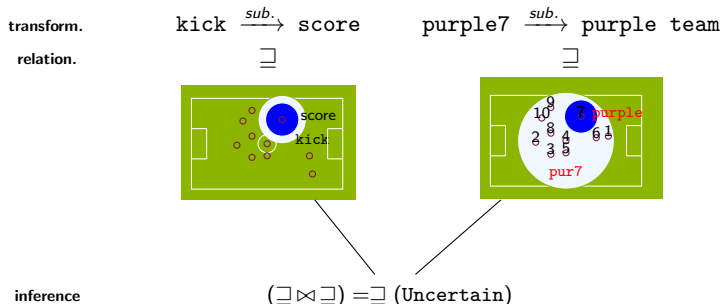
$\boxtimes$	$\equiv$	$\sqsubseteq$	$\sqsupseteq$		#
$\equiv$	$\equiv$	$\sqsubseteq$	$\sqsupseteq$		#
$\sqsubseteq$	$\sqsubseteq$	$\sqsubseteq$	#		#
$\sqsupseteq$	$\sqsupseteq$	#	$\sqsupseteq$		#
		#			#
#	#	#	#	#	#



# Entailment Modeling: Sentence Pairs to Proofs

- **Alignment:** heuristic alignment between target/hypothesis parse trees.

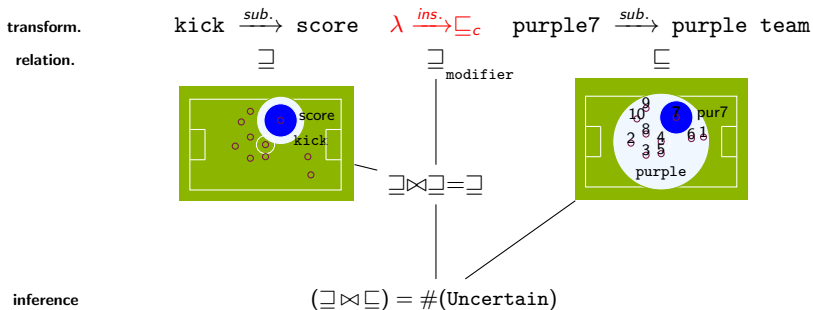
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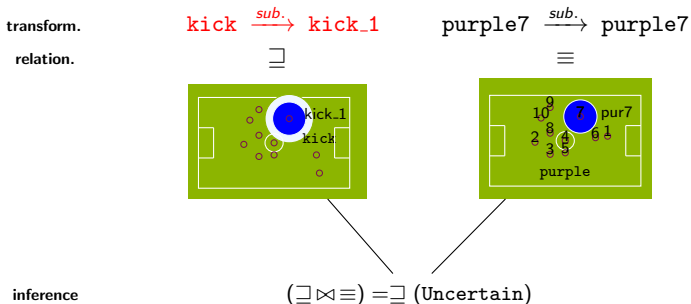
((**t**: purple7 kicks the ball, **h**: purple team scores a goal **again**), Uncertain)



# Entailment Modeling: Sentence Pairs to Proofs

- **Alignment:** heuristic alignment between target/hypothesis parse trees.

((**t**: purple7 kicks the ball, **h**: purple7 shoots for the goal), Uncertain)



# Natural Logic Rules as a PCFG

- ▶ Rules of the logic are encoded as probabilistic rewrite rules.
- ▶ **Proof example**

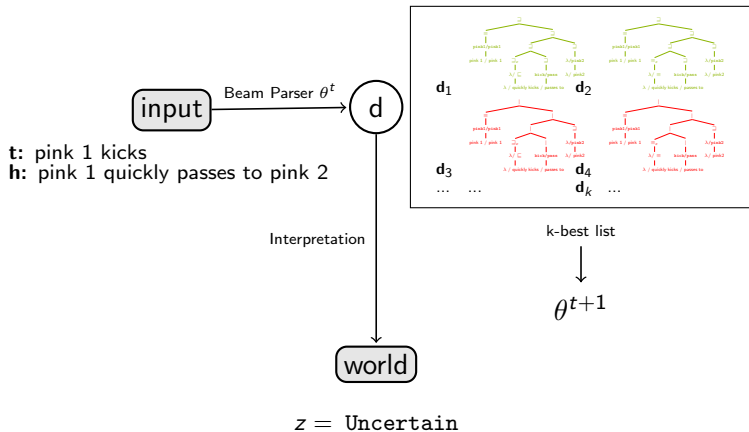
$$\begin{array}{c}
 \frac{\lambda \sqsupseteq \sqsubseteq_c \quad \text{pass} \equiv \text{pass}, \text{pink1} \sqsubseteq \text{pink team}}{\text{pink3} \equiv \text{pink3} \quad \lambda \sqsupseteq \text{quickly} \quad \text{passes to pink1} \sqsubseteq \text{kicks to the pink team}} \quad \boxtimes \\
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 \end{array}$$

- ▶ **PCFG rules**

$(X \boxtimes Y)$	$\rightarrow_{\boxtimes}$	$X / Y$
$0.5 \equiv_{\text{arg1}}$	$\rightarrow_I$	pink3 / pink3
$0.5 \equiv_{\text{arg1}}$	$\rightarrow_I$	pink1 / pink1
$0.9 \sqsubseteq_{\text{arg1}}$	$\rightarrow_I$	pink1 / pink team
$0.1 \sqsubseteq_{\text{arg1}}$	$\rightarrow_I$	pink team / pink1
$1.0 \sqsupseteq$	$\rightarrow_I$	$\lambda / \sqsubseteq_c$
$1.0 \sqsubseteq$	$\rightarrow_I$	$\sqsubseteq_c / \lambda$
$0.8 \sqsubseteq_{\text{rel}}$	$\rightarrow_I$	pass / kick
$0.2 \sqsubseteq_{\text{rel}}$	$\rightarrow_I$	kick / pass
$0.7 \sqsupseteq_{\text{rel}}$	$\rightarrow_I$	kick / pass
$0.3 \sqsupseteq_{\text{rel}}$	$\rightarrow_I$	pass / kick

# Learning Entailment Rules

- ▶ Rules define an inference PCFG  $\mathcal{G}'_{\theta}$ , learn correct proofs.
- ▶ **Learning:** Grammatical inference problem as before, EM bootstrapping.



## Experiment: Datasets

- ▶ **Sportscaster:** 4 games, 1872 sentences, 46 concept types.
- ▶ **Inference Dataset:** 461 pairs from training annotated (155 using AMT, 306 using local annotators).
  
- ▶ **Elicitation:** Directions from Snow et al. (2008). Those without agreement discarded (standard).

Text $t$	Hypothesis $h$	Entail?
purple 7 kicks the ball	purple 7 makes a bad pass	{Entail,Contradict,Uncertain}

## Experiment: Evaluation and Results

- ▶ **Old Evaluation:** Can we generate the correct target representations for held-out examples? (*state-of-the-art results reported*)
- ▶ **New Evaluation:** Can we generate correct entailments given held-out pairs? (*positive results using our method*)

## Experiment: Evaluation and Results

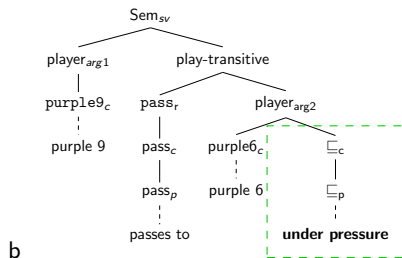
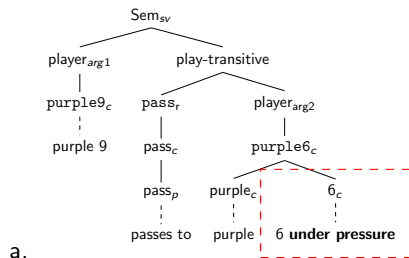
- ▶ **Old Evaluation:** Can we generate the correct target representations for held-out examples? (*state-of-the-art results reported*)
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Inference Task	Accuracy
Majority Baseline	0.33
RTE classifier	0.52
Naive Inference	0.60
SVM Flat Classifier	0.64
<b>Inference Grammar</b>	<b>0.73</b>



# Qualitative Analysis

- ▶ Improving the internal representations (before, a, after, b).

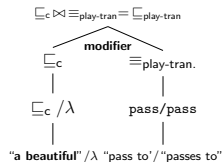


# Qualitative Analysis

- ▶ Learned modifiers from example proofs trees.

$(t, h)$ :

(a beautiful pass to, passes to)

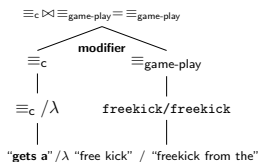


analysis:

generalization:

$\text{beautiful}(X) \sqsubseteq X$

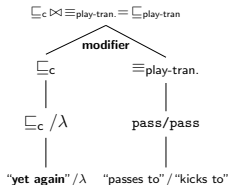
(gets a free kick, freekick from the)



$\text{get}(X) \equiv X$

$(t, h)$ :

(yet again passes to, kicks to)

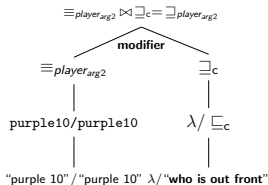


analysis:

generalization:

$\text{yet-again}(X) \sqsubseteq X$

(purple 10, purple 10 who is out front)



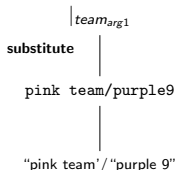
$X \sqsupset \text{out\_front}(X)$

# Qualitative Analysis

## ► Learned lexical relations from example proof trees

$(t, h)$ :

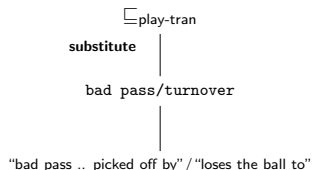
(pink team is offside, purple 9 passes)



analysis:  
relation:

pink team | purple9

(bad pass.., loses the ball to)

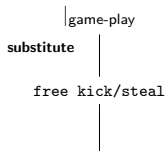


"bad pass .. picked off by"/"loses the ball to"

bad pass ⊆ turnover

$(t, h)$ :

(free kick for, steals the ball from)

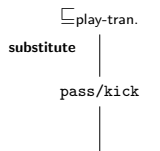


analysis:  
relation:

"free kick for"/"steals the ball from"

free kick | steal

(purple 6 kicks to, purple 6 kicks)



"kicks to"/"kicks"

pass ⊆ kick

# Conclusion

- ▶ **Learning from Entailment:** Use entailment information and reasoning to help train semantic parsers.
  - ▶ *Improve learning:* learn background knowledge, find gaps.
  - ▶ *Evaluation:* provides a new way to evaluate semantic parsers.

# Conclusion

- ▶ **Learning from Entailment:** Use entailment information and reasoning to help train semantic parsers.
  - ▶ *Improve learning:* learn background knowledge, find gaps.
  - ▶ *Evaluation:* provides a new way to evaluate semantic parsers.
- ▶ **Conceptually:** Make our semantic learner behave more like a semanticist, ground representation decisions in entailments.

Thank You

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