New Resources and Ideas for Semantic Parsing

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Collaborators: Jonas Kuhn (advisor, Stuttgart) and Jonathan Berant (work on "polyglot semantic parsing", Tel Aviv), last updated 15.10.2018

Main Topic: Semantic Parsing

- **Task**: mapping text to formal (machine-readable) structured meaning representations:

Text: *Find me flights from Boston to New York.*

$$\rightarrow$$

Logical Form (LF): $\lambda x.\texttt{flight}(x) \land \texttt{depart}(x, \texttt{bos}) \land \texttt{arrive}(x, \texttt{ny})$

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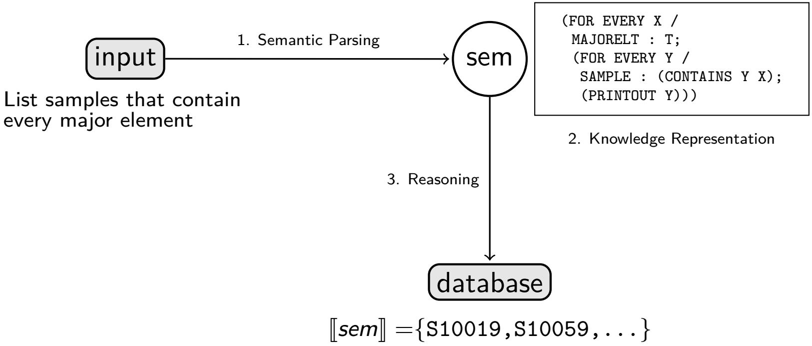
> *"**Machines and programs which attempt to answer English question have existed for only about five years**.... **Only in recent years** **have attempts been made to** **translate mechanically from English into logical formalisms** **[or LFs]**..."*

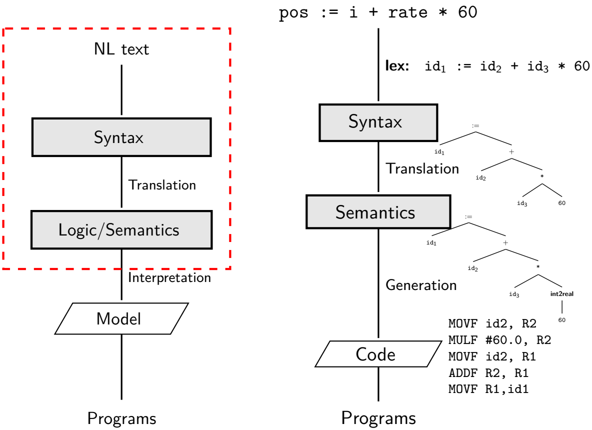
R.F. Simmons. 1965, *Answering English Question by Computer: A Survey*. Communications of the ACM

Classical Natural Language Understanding (NLU)

- Conventional **pipeline model**: focus on capturing **deep inference** and **entailment** (ex. Lunar QA system (Woods, 1973)).

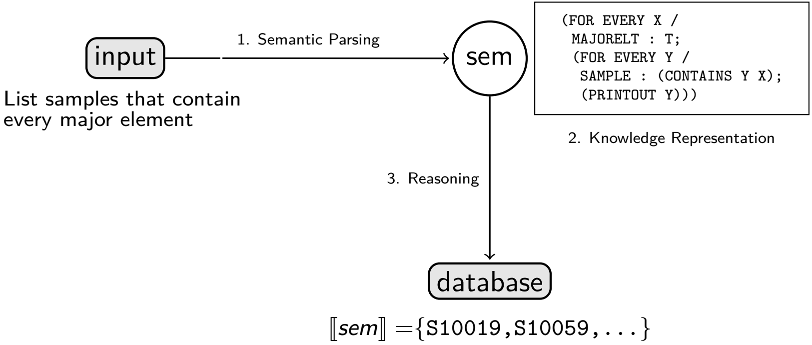


Why and How? Analogy with Compiler Design



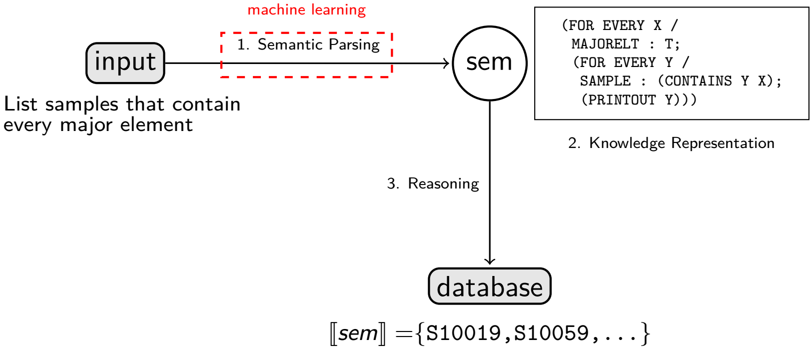
- NLU model is a kind of compiler, involves a **transduction** from NL to a formal (usually logical) language.

Data-driven NLU and Semantic Parsing



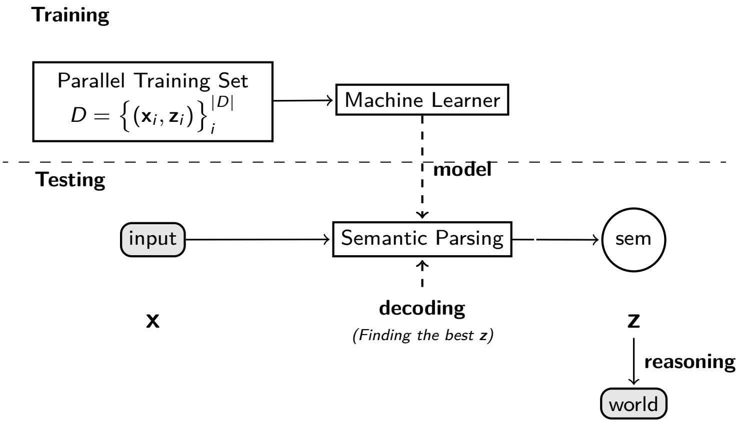
- **Data-driven NLU**: Asks an empirical question: Can we learn NLU models from examples?

Data-driven NLU and Semantic Parsing



- **Data-driven NLU**: Asks an empirical question: Can we learn NLU models from examples?
  - **Semantic Parser Induction:** Learn semantic parser (i.e., translation to LFs) automatically from example parallel data.

Data-driven Semantic Parsing in a Nutshell



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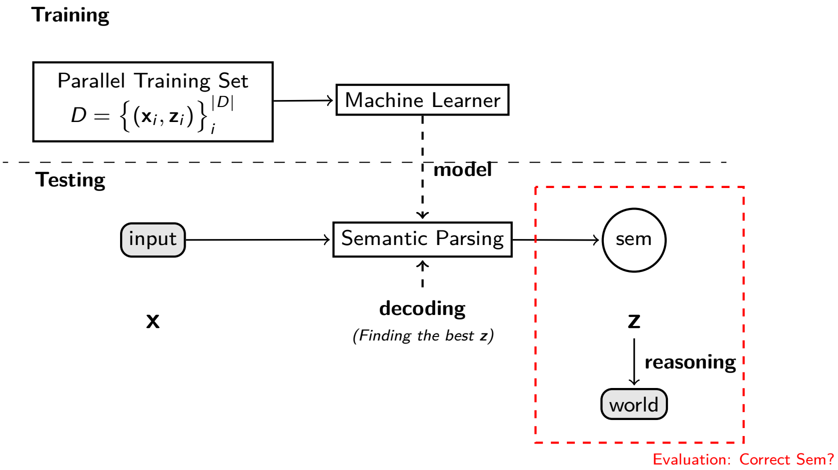

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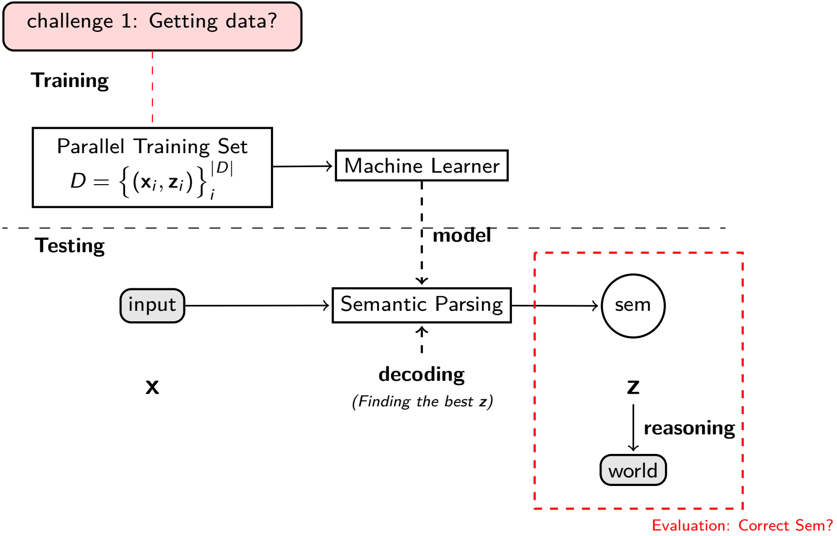

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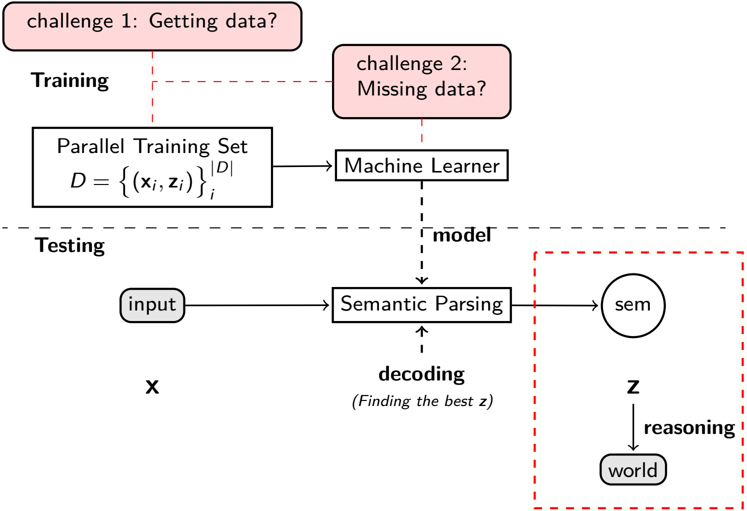

Evaluation: Correct Sem?

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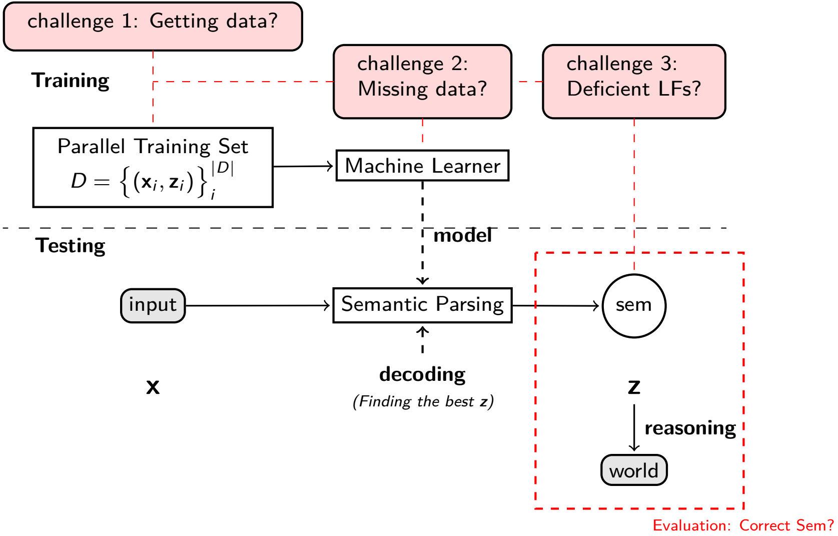


Thesis Contributions and Talk Outline

challenge 1: Getting data?

Use source code as resource for building (synthetic) parallel corpora for semantic parsing; introduce 45 new multilingual datasets and models.

Richardson *and Kuhn 2017b. ACL*
Richardson *and Kuhn 2017a. EMNLP*

challenge 2: Missing data?

Train semantic parsers on multiple datasets and domains (polyglot modeling), develop a new graph-based decoding framework.

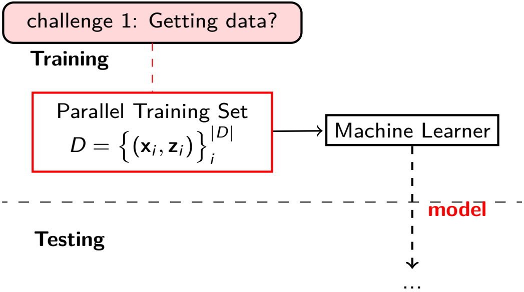
Richardson*, Berant and Kuhn 2018. NAACL*

challenge 3: Deficient LFs?

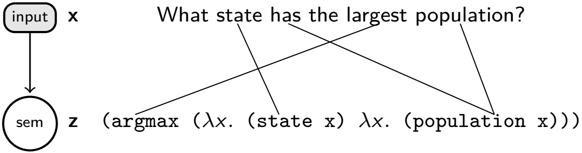
Train semantic parsers using entailment information; introduce new learning framework: *learning from entailment*.

Richardson *and Kuhn 2016. TACL*

<Challenge 1>


challenge 1: Getting data?
Training
Parallel Training Set
$D = \left\{ (\mathbf{x}_i, \mathbf{z}_i) \right\}_i^{|D|}$
Machine Learner
model
Testing
...

Semantic Parsing and Parallel Data



- **Learning from LFs**: Assumes pairs of text **x** and full logical forms **z**, goal is to learn sem : $\mathbf{x} \rightarrow \mathbf{z}$, evaluate accuracy of translation.
- **GeoQuery** (Zelle and Mooney, 1996): Benchmark dataset, available in four languages, **LFs hand annotated by domain experts**.

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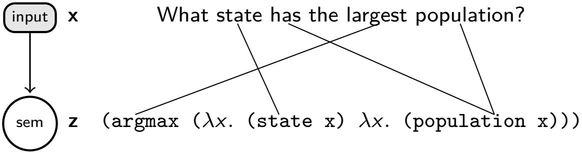

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- **GeoQuery** (Zelle and Mooney, 1996): Benchmark dataset, available in four languages, **LFs hand annotated by domain experts**.
- **Underlying Challenge**: Getting pairs of text and full LFs without expensive annotation effort.

Source Code and API Documentation

```
* Returns the greater of two long values
*
* @param a an argument
* @param b another argument
* @return the larger of a and b
* @see java.lang.Long#MAX_VALUE
*/
 public static Long max(long a, long b)
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- **Source Code Documentation:** High-level descriptions of internal software functionality paired with code.

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- **Source Code Documentation:** High-level descriptions of internal software functionality paired with code.
- **Idea**: Treat as a parallel corpus (Allamanis et al., 2015), or **synthetic semantic parsing** dataset.

Source Code as a Parallel Corpus

- Tight coupling between high-level text and code, easy to extract text/code pairs automatically (no annotation).

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$\Downarrow$ extraction

text	*Returns the greater...*
code	lang.Math long max(long...)

```
(ns ... clojure.core)

(defn random-sample
   "Returns items from coll with random
   probability of prob (0.0 - 1.0)"
   ([prob] ...)
   ([prob coll] ...))
```

$\Downarrow$ extraction

text	*Returns items from coll...*
code	(core.random-sample prob...)

- **Function signatures:** Header-like representations, have similar predicate-argument structure to atomic predicate logic.

$$\text{Signature} ::= \underbrace{\texttt{lang}}_{\texttt{namespace}}\ \underbrace{\texttt{Math}}_{\texttt{class}}\ \underbrace{\texttt{long}}_{\texttt{return}}\ \underbrace{\texttt{max}}_{\texttt{name}}\left(\underbrace{\texttt{long a, long b}}_{\texttt{named/typed arguments}}\right)$$

New Resources: Stdlib and Py27 Datasets

Dataset	#Pairs	#Symbols	#Words	Vocab.	Example Pairs (**x**, **z**)
Java	7,183	4,072	82,696	3,721	x : Compares this Calendar to the specified Object. z : `boolean util.Calendar.equals(Object obj)`
Ruby	6,885	3,803	67,274	5,131	x : Computes the arc tangent given y and x. z : `Math.atan2(y,x)` $\to$ `Float`
PHP_{en}	6,611	8,308	68,921	4,874	x : Delete an entry in the archive using its name. z : `bool ZipArchive::deleteName(string $name)`
Python	3,085	3,991	27,012	2,768	x : Remove the specific filter from this handler. z : `logging.Filterer.removeFilter(filter)`
Elisp	2,089	1,883	30,248	2,644	x : Returns the total height of the window. z : `(window-total-height window round)`
Geoquery	880	167	6,663	279	x : What is the tallest mountain in America? z : `(highest(mountain(loc_2(countryid usa))))`

- **Stdlib**: Datasets 18 standard libraries, 10 programming languages, 7 natural languages.
- **Py27**: 27 open-source Python projects from GitHub.

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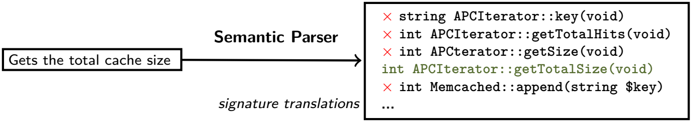
New Task: Text to Signature Translation

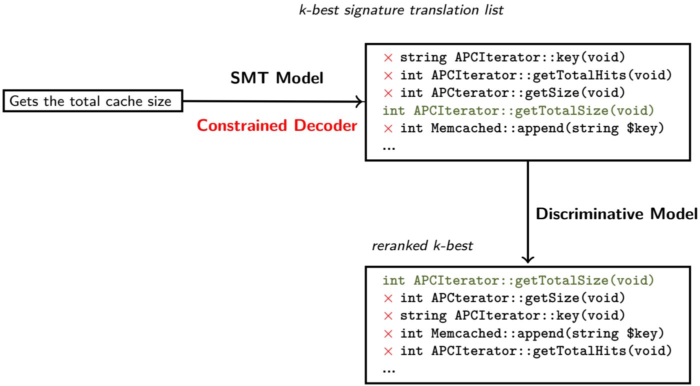
text	*Returns the greater of two long values*
signature	`lang.Math long max( long a, long b )`

- **Task**: Given text/signatures training pairs, learn a *semantic parser*: text $\rightarrow$ `signature`, predicting within finite signature/translation space.



Text to Signature Translation: How hard is it?

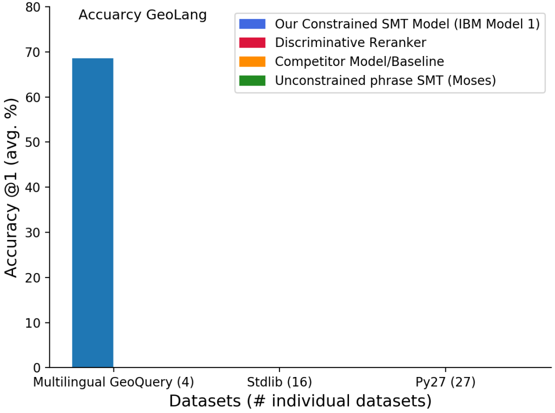
- **A First Model**: Use statistical (word-based) machine translation (SMT) (Deng and Chrupała, 2014) and reranking.



- **Decoding**: finding the best output given input, **unconstrained** versus **constrained** (assign probability to wellformed output only).

Text to Signature Translation: How Hard Is It?

- How does such a simple approach fare on benchmark tasks and our task?



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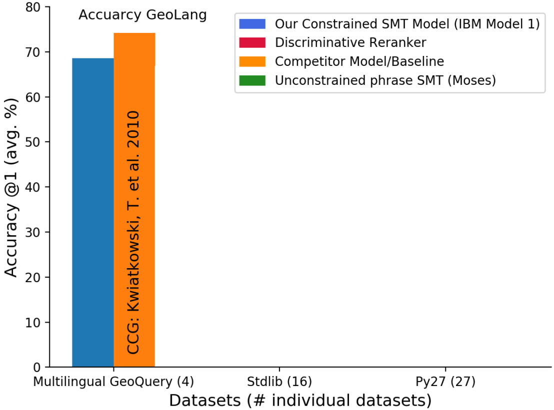

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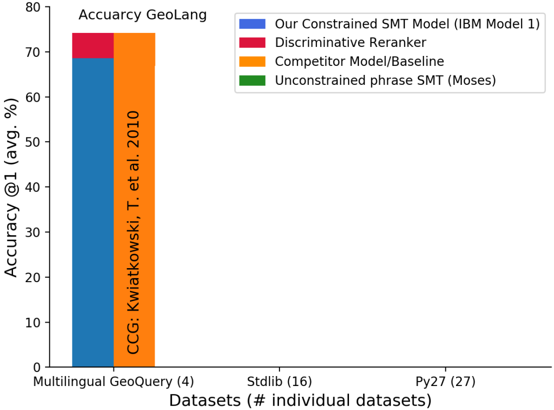

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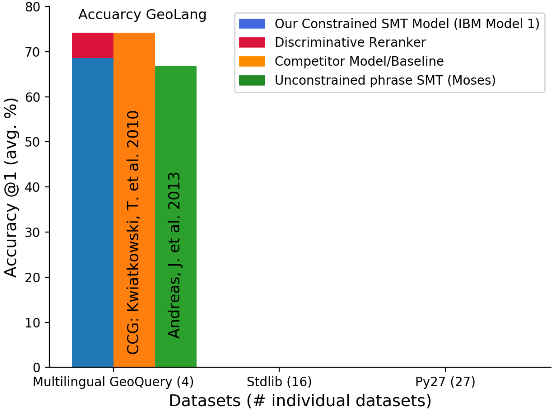

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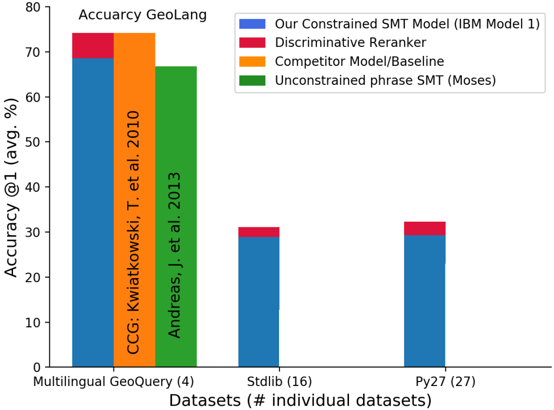

- **Result**: achieving high accuracy is not easy, not a trivial problem.

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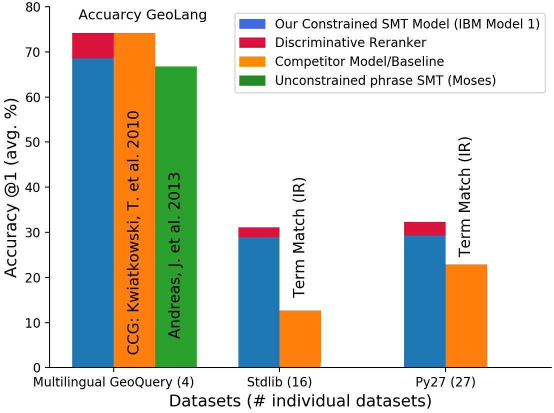

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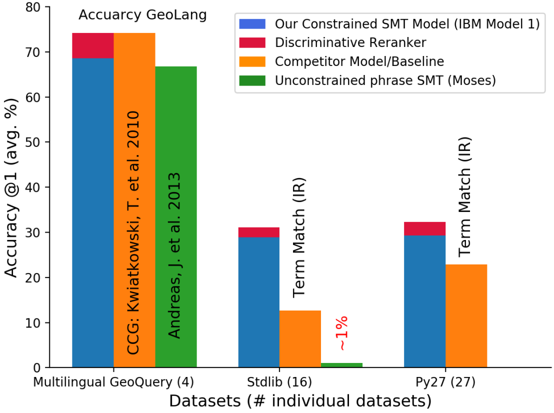

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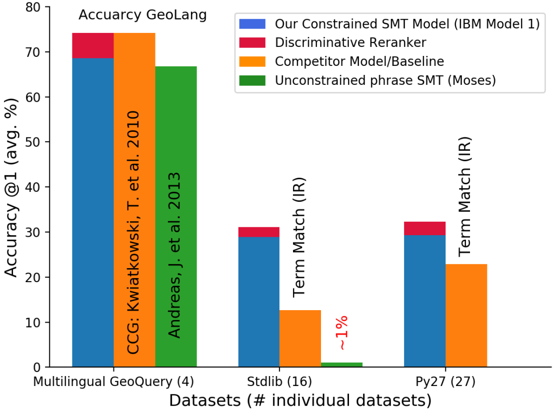
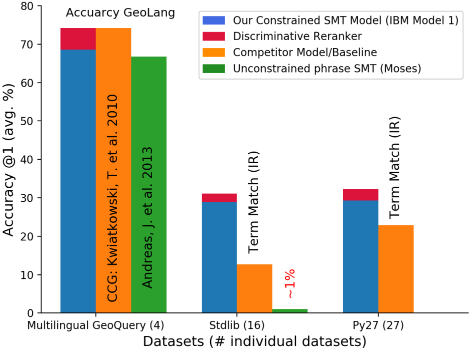


Text to Signature Translation: How Hard Is It?

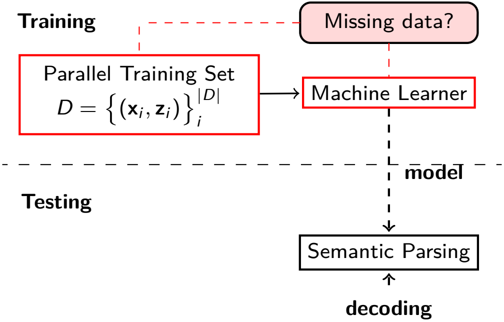
text	*Returns the index of the first occurrrence of char in the string*
Moses	(`start end occurrence lambda char string string string`)

- **Observation:** Semantic Parsing is not an unconstrained translation problem, constraining the search is very important.



- Introduced 45 new datasets and novel text-to-signature task.
- This work is of interest to semantic parsing:
  - Reveals the limitations of existing techniques in sparse settings, better benchmark (realistic vocabulary/domain size).
  - Requires asking fundamental questions about how decoding and search work.

<Challenge 2>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Missing data?
Parallel Training Set
$D = \left\{(\mathbf{x}_i, \mathbf{z}_i)\right\}_i^{|D|}$
Machine Learner
model
Testing
Semantic Parsing
decoding

Challenge 2: Insufficient and Missing Data

(en,PHP) → $\theta_{\texttt{en}} \rightarrow$ `Java`

(en,Lisp) → $\theta_{\texttt{en}} \rightarrow$ `Lisp`

(es, PHP) → $\theta_{\texttt{es}} \rightarrow$ `PHP`

(ja, Python) → $\theta_{\texttt{ja}} \rightarrow$ `Python`

(en, Haskell) → $\theta_{\texttt{en}} \rightarrow$ `Haskell`

...

?$\theta_{\texttt{es}} \rightarrow$ `Java`?

- Traditional approaches to semantic parsing train individual models for each available parallel dataset.
- **Underlying Challenge**: Datasets tend to be small, hard and unlikely to get certain types of parallel data, e.g., (es,Java).

Polyglot Models: Training on Multiple Datasets

(en,`Java`)
(en,`Lisp`)
(es, `PHP`)
(ja, `Python`)
(en, `Haskell`)
...

$\longrightarrow \theta_{\texttt{polyglot}}$

- **Idea**: concatenate all datasets, build a single-model with shared parameters, capture redundancy (Herzig and Berant, 2017).
- **Polyglot Translator:** translates from any input language to any output (programming) language.

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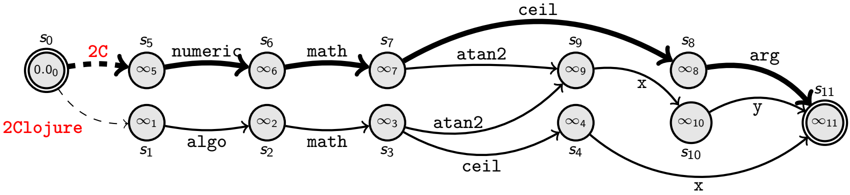
- **Polyglot Translator:** translates from any input language to any output (programming) language.
  1. **Multiple Datasets:** Does this help learn better semantic parsers?
  2. **Zero-Short Translation** (Johnson et al., 2016): Can we translate between unobserved language pairs?

Graph-Based Constrained Decoding



- **Idea**: Represent full translation search space as directed graph, add *artifical language tokens*.

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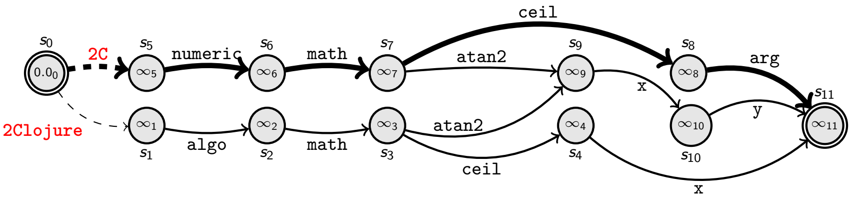

- **Idea**: Represent full translation search space as directed graph, add *artifical language tokens*.

- **Decoding/Search** (test time): Find a path given an input $\mathbf{x}$:

$$\mathbf{x}: \text{ The ceiling of a number}$$

Formulate as weighted shortest-path search (use translation models as dynamic weight functions), defines a general decoding framework.

Shortest Path Decoding in a Nutshell

- **Standard SSSP**: Traverse labeled edges E (label z) in order (e.g., sorted or best-first order), and solve for each node v the following recurrence:

$$\underbrace{d[v]}_{\substack{\uparrow \\ \text{node score}}} = \min_{(u,v,z)\in E} \Big\{ \underbrace{d[u]}_{\substack{\uparrow \\ \text{incoming node score}}} + \underbrace{w(u,v,z)}_{\substack{\uparrow \\ \text{edge score}}} \Big\}$$

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  - Use trained **translation model** to dynamically weight edges, general framework for directly comparing models (Richardson et al., 2018).

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  - **constrained decoding**: ensure that output is well-formed, related efforts: Krishnamurthy et al. (2017); Yin and Neubig (2017).

DAG Decoding for Neural Semantic Parsing (Example)

- **Seq2Seq**: popular in semantic parsing (Dong and Lapata, 2016), variants of (Bahdanau et al., 2014), direct decoder model (unconstrained):

$$\begin{aligned} p(\mathbf{z} \mid \mathbf{x}) &= \textsc{ConditionalRNNLM}(\mathbf{z}) \\ &= \prod_{i}^{|\mathbf{z}|} p_{\Theta}(z_i \mid z_{<i}, \mathbf{x}) \end{aligned}$$

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- **DAGs** $\mathcal{G} = (V, E)$, **numerically sorted nodes** (acyclic), trained decoder.

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for node v ∈ V in topologically sorted order
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0: $d[b] \leftarrow 0.0$
1: **for** node $v \in V$ in topologically sorted order
2: **do** $d(v) = \min_{(u,v,z_j) \in E} \left\{ d(u) + -\log p_\Theta(z_j \mid z_{<j}, \mathbf{x}) \right\}$

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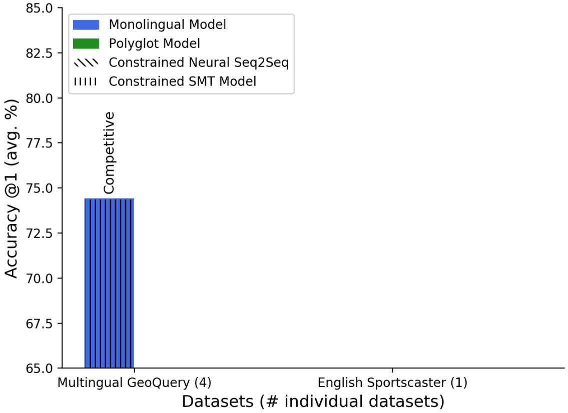
3: $s[v] \leftarrow$ `RNN` state for min edge and z_j
4: **return** $\min_{v \in V} \Big\{ d(v) \Big\}$

Shortest Path Decoding: Comparing Models

- **Shortest Path Decoding Framework**: Directly compare the performance of different semantic parsing models under a single search procedure.



- **Neural Seq2Seq**: popular in semantic parsing (Dong and Lapata, 2016; Jia and Liang, 2016).

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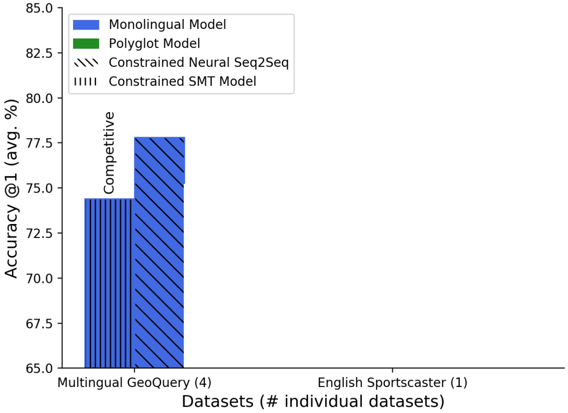

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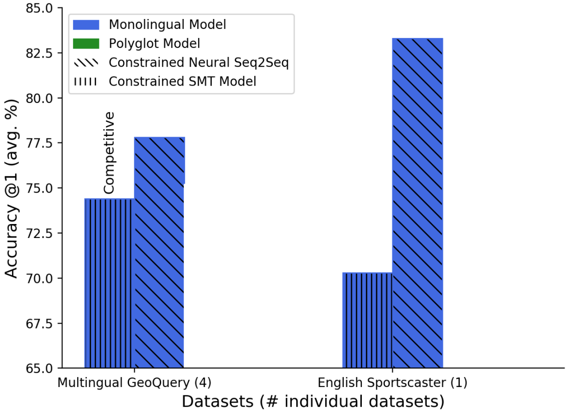

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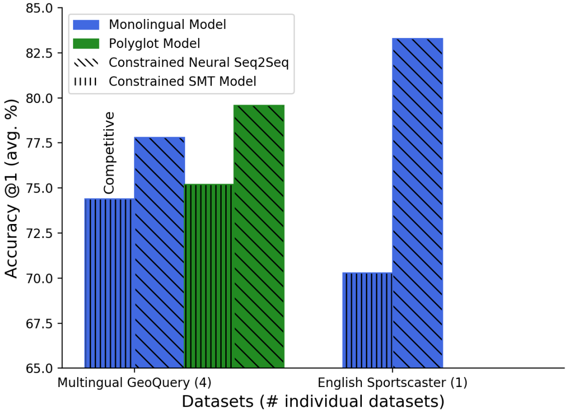
Training on Multiple Datasets: Does this help?

- **Polyglot Models**: Directly compare if training on multiple datasets improves translation.



- **Benchmark Datasets**: Training *polyglot models* on multiple datasets can increase performance, makes learning more robust

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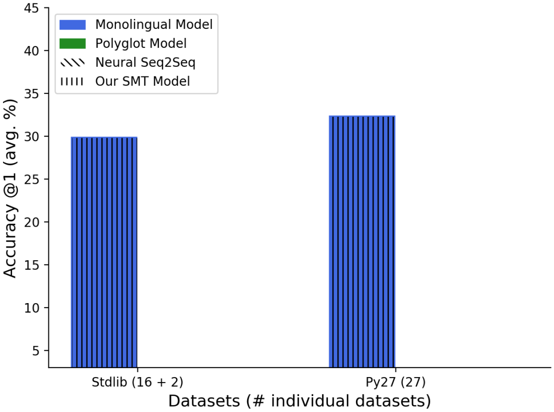

- **Code Datasets**: Training *polyglot models* on multiple datasets can increase performance, depending on the model.

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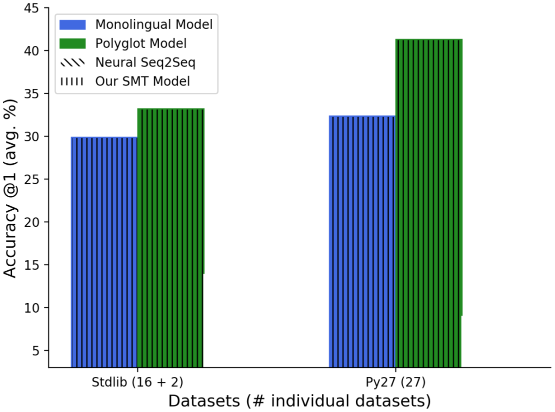

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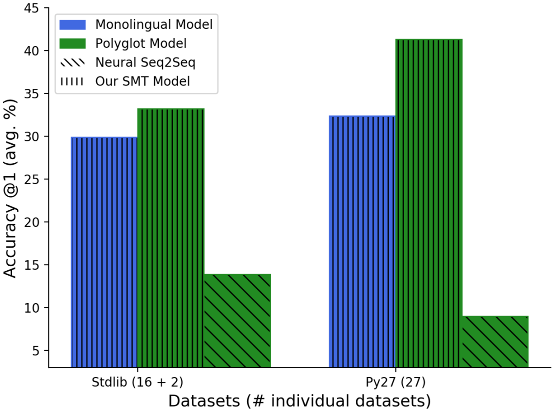


- **Code Datasets**: Training *polyglot models* on multiple datasets can increase performance, depending on the model.

Advantages: Any/Mixed Language Decoding

- **Any Language Decoding**: translating between multiple APIs, letting the decoder decide output language, zero-shot translation.

1.	Source API (stdlib): (***es*, PHP**)	**Input**: Devuelve el mensaje asociado al objeto lanzado.
Output	Language: **PHP**	Translation: `public string Throwable::getMessage ( void )`
	Language: **Java**	Translation: `public String lang.getMessage( void )`
	Language: **Clojure**	Translation: `(tools.logging.fatal throwable message & more)`
2.	Source API (stdlib): (***ru*, PHP**)	**Input**: конвертирует строку из формата UTF-32 в формат UTF-16.
Output	Language: **PHP**	Translation: `string PDF_utf32_to_utf16 ( ... )`
	Language: **Ruby**	Translation: `String#toutf16 => string`
	Language: **Haskell**	Translation: `Encoding.encodeUtf16LE :: Text -> ByteString`
3.	Source API (py): (***en*, stats**)	**Input:** Compute the Moore-Penrose pseudo-inverse of a matrix.
Output	Project: **sympy**	Translation: `matrices.matrix.base.pinv_solve( B, ... )`
	Project: **sklearn**	Translation: `utils.pinvh( a, cond=None,rcond=None,... )`
	Project: **stats**	Translation: `tools.pinv2( a,cond=None,rcond=None )`

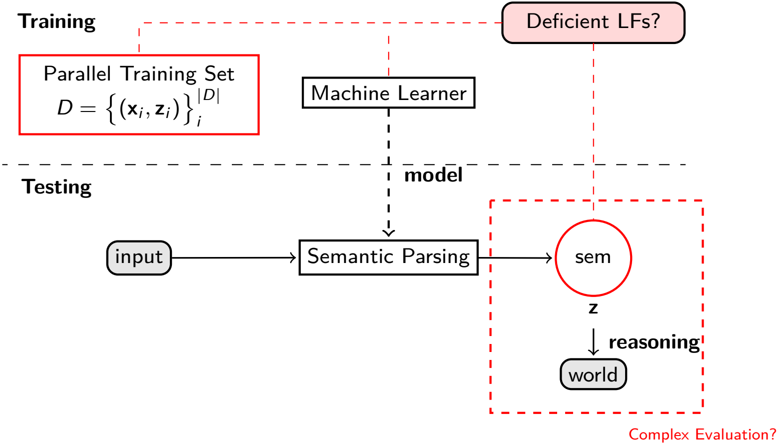
Advantages: Any/Mixed Language Decoding

- **Mixed Language Decoding**: translating from input with NPs from multiple languages, introduced a new mixed GeoQuery test set.

Mixed Lang.	**Input**: Wie hoch liegt der höchstgelegene punkt in Αλαμπάμα?
LF: `answer(elevation_1(highest(place(loc_2(stateid('alabama'))))))`	

- Polyglot modeling: training on multiple datasets, helps to make models more robust and learn across domains.
- Developed a graph-based constrained decoding framework:
  - Supports polyglot and mixed language decoding.
  - Allows for directly comparing models using a single search protocol.

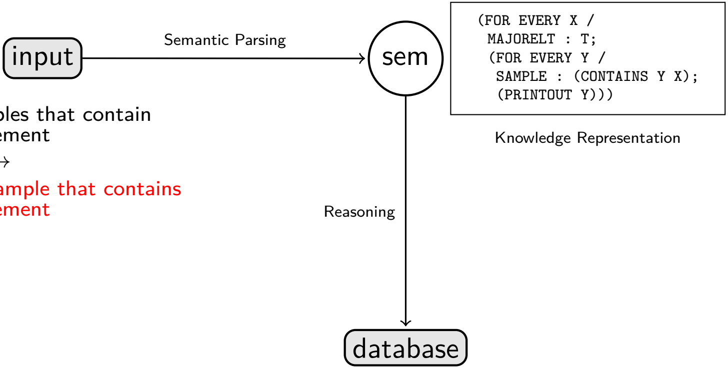
<Challenge 3>



Training
Deficient LFs?
Parallel Training Set
$D = \left\{(\mathbf{x}_i, \mathbf{z}_i)\right\}_i^{|D|}$
Machine Learner
model
Testing
input
Semantic Parsing
sem
z
reasoning
world
Complex Evaluation?

Semantic Parsing and Entailment

- **Entailment:** One of the *basic aims* of semantics (Montague, 1970)[1].



t. All samples that contain
a major element

$\rightarrow$

h. Some sample that contains
a major element

$[\![\textit{sem}]\!] = \{\texttt{S10019}, \texttt{S10059}, \ldots\} \supseteq \{S10019\}$

[1] Recognizing Textual Entailment (RTE): would a person reading `t` usually infer `h`? (Dagan et al., 2005), answers: { `Entail` (yes), `Contradict` (no), `Unknown` (possible) }

Semantic Parsing and Entailment

- **Question**: What happens if we *unit test* our semantic parsers using an RTE test?
- **Sportscaster**: ≈1,800 soccer descriptions paired with logical forms (LFs) (Chen and Mooney, 2008).

	sentence	LF
t	*Pink 3 passes to Pink 7*	`pass(pink3,pink7)`
h	*Pink 3 quickly kicks to Pink 7*	`pass(pink3,pink7)`
inference (human) `t` → `h`		`Unknown` (RTE)
inference (LF match) `t` → `h`		`Entail` (RTE)

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	sentence	**LF**
t	*The pink goalie passes to pink 7*	`pass(pink1,pink7)`
h	*Pink 1 kicks the ball*	`kick(pink1)`
inference (human) $\texttt{t} \rightarrow \texttt{h}$		`Entail` (RTE)
inference (LF match) $\texttt{t} \rightarrow \texttt{h}$		`Contradict` (RTE)

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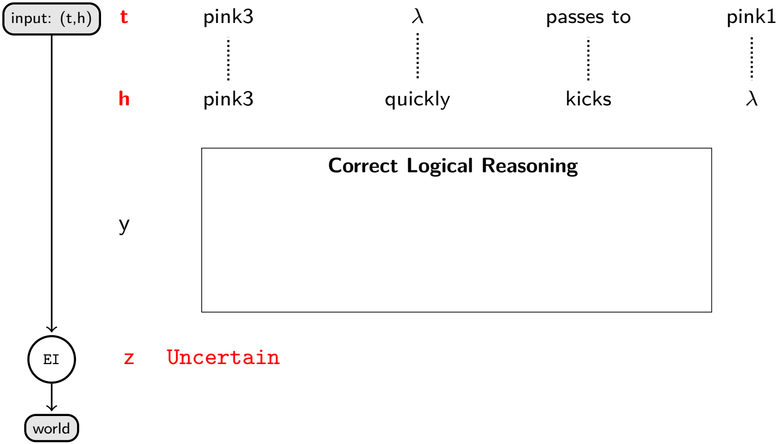
- **Sportscaster**: ≈1,800 soccer descriptions paired with logical forms (LFs) (Chen and Mooney, 2008).

Inference Model	**Accuracy**
Majority Baseline	33.1%
RTE Classifier	52.4%
LF Matching	59.6%

- **Challenge 3**: Model cannot solve RTE, can we teach our model to reason logically about entailment?

Learning from Entailment: Illustration

- Add pairs of sentences with entailment judgements to training, jointly train model to reason logically about entailment and soccer.



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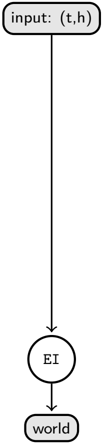

t	pink3	λ	passes to	pink1
h	pink3	quickly	kicks	λ

y

Correct Logical Reasoning

✓ passes to pink 1 $\Rightarrow$ kicks

z `Uncertain`

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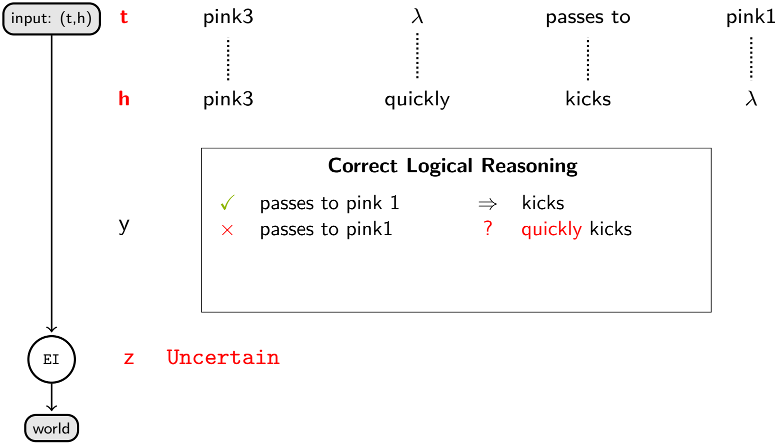

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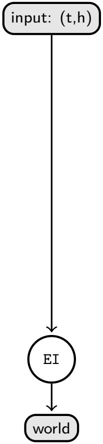

t	pink3	λ	passes to	pink1
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Correct Logical Reasoning

✓	passes to pink 1	$\Rightarrow$	kicks
×	passes to pink1	?	quickly kicks
×	pink 3 passes to pink1	?	pink3 quickly kicks

? = Uncertain

z Uncertain

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input: (t,h)

t	pink3	λ	passes to	pink1
h	pink3	quickly	kicks	λ

y

Incorrect Reasoning

✓	passes to pink 1	$\Rightarrow$	kicks
✓	passes to pink1	$\Rightarrow$	quickly kicks
✓	pink 3 passes to pink1	$\Rightarrow$	pink3 quickly kicks

$\Rightarrow$ = `Entail`

EI

z `Uncertain`

world

Grammar Approach: Sentences to Logical Form

- Translation rules as probabilistic grammar rewrites, constructed from target representations using templates (Börschinger et al. (2011))

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

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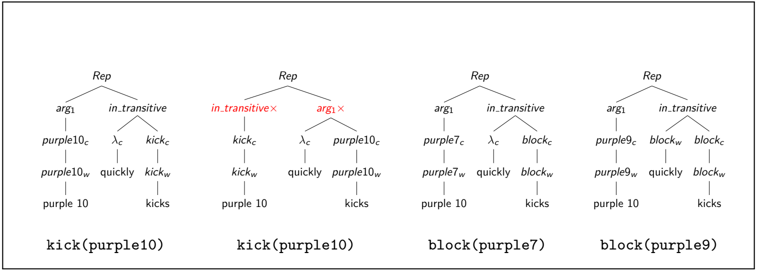

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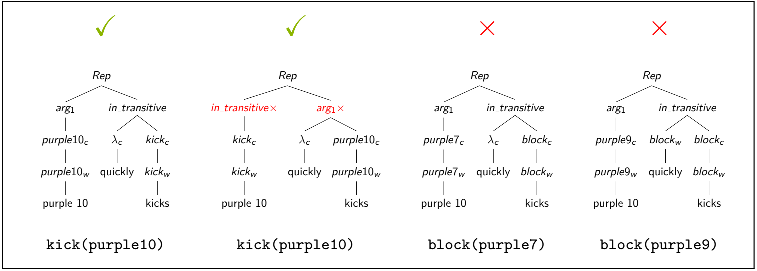
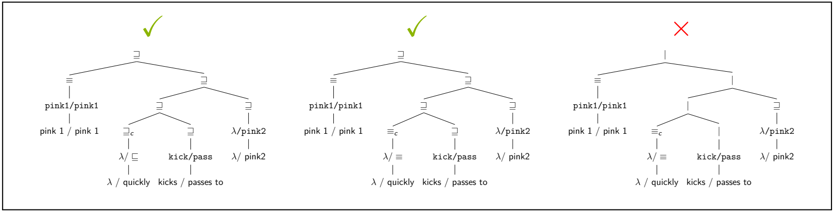


Modeling Entailments as Structured Proofs

- Define a novel probabilistic language and logic based on the natural logic calculus (MacCartney and Manning, 2009).
- Rules decompose to probabilistic rewrites, allows for joint training with ordinary semantic parser using single generative model.

$$\Big(\big(\textbf{t}\text{: pink 1 kicks}, \textbf{h}\text{: pink 1 quickly passes to pink 2}\big)\text{ ,z: }\texttt{Uncertain}\Big)$$

$$\Big\downarrow \text{(inference rules)}$$



Joint Entailment Modeling and Reasoning

- Weakly-supervised semantic parsing (Liang et al., 2013; Berant et al., 2013), treat as partially-observed random process (Guu et al., 2017).

$$\mathbf{x} = (\mathtt{t}, \mathtt{h}),\ \mathbf{z} \in \{\mathtt{Entail}, \mathtt{Contradict}, \mathtt{Unknown}\}$$

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$$p(\mathbf{z} \mid \mathbf{x}) = \sum_{\underbrace{y \in \mathcal{Y}_{\mathbf{x}}}_{\text{proofs}}} \underbrace{p(\mathbf{z} \mid y)}_{\substack{\uparrow \\ \text{valid inference?}}} \times \underbrace{p_\theta(y \mid \mathbf{x})}_{\substack{\uparrow \\ \text{proof score}}}$$

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  - $p_\theta(y \mid \mathbf{x})$: Model proof structures and rules as PCFG, use variant of natural logic calculus (MacCartney and Manning, 2009).
    - Results in an interesting probabilistic logic, efficient proof search via reduction to (P)CFG search.

Improved Semantic Parsing and RTE Testing

- **New Evaluation**: Can my semantic parser solve RTE tasks? New Sportscaster inference corpus, ≈460 RTE pairs.

	sentence	analysis
t	*Pink 3 passes to Pink 7*	`pass(pink3,pink7)`
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Inference Model	Accuracy
Majority Baseline	33.1%
LF Matching	59.6%
Logical Inference Model	73.4%

- Jointly training semantic parsers to reason about entailment.
- Created a novel semantic parsing model that supports joint probabilistic symbolic reasoning:
  - We achieve state-of-the-art performance on the original semantic parsing task.
  - Allows for evaluating semantic parsers on entailment tasks, perform domain-specific reasoning.

<Conclusions>

Introduced several new algorithmic/learning techniques, tasks and resources for helping making semantic parsing easier.

- 45 new multilingual datasets in the software domain, and a novel text-to-signature task and set of models.
- A new graph decoding framework, which allows for polyglot modeling, new mixed language dataset and task, improve results on code datasets.
- A new learning framework and dataset for entailment modeling and semantic parsing, state-of-the-art results on original task.

Thank You

References I

Allamanis, M., Tarlow, D., Gordon, A., and Wei, Y. (2015). Bimodal modelling of source code and natural language. In *International Conference on Machine Learning*, pages 2123–2132.

Bahdanau, D., Cho, K., and Bengio, Y. (2014). Neural Machine Translation by Jointly Learning to Align and Translate. *arXiv preprint arXiv:1409.0473*.

Berant, J., Chou, A., Frostig, R., and Liang, P. (2013). Semantic Parsing on Freebase from Question-Answer Pairs. In *in Proceedings of EMNLP-2013*, pages 1533–1544.

Börschinger, B., Jones, B. K., and Johnson, M. (2011). Reducing grounded learning tasks to grammatical inference. In *Proceedings of EMNLP-2011*, pages 1416–1425.

Chen, D. L. and Mooney, R. J. (2008). Learning to sportscast: A test of grounded language acquisition. In *Proceedings of ICML-2008*, pages 128–135.

Dagan, I., Glickman, O., and Magnini, B. (2005). The pascal recognizing textual entailment challenge. In *Proceedings of the PASCAL Challenges Workshop on Recognizing Textual Entailment*.

Deng, H. and Chrupała, G. (2014). Semantic approaches to software component retrieval with English queries. In *Proceedings of LREC-14*, pages 441–450.

Dong, L. and Lapata, M. (2016). Language to Logical Form with Neural Attention. *arXiv preprint arXiv:1601.01280*.

Guu, K., Pasupat, P., Liu, E., and Liang, P. (2017). From Language to Programs: Bridging Reinforcement Learning and Maximum Marginal Likelihood. In *Proceedings of ACL*.

References II

Herzig, J. and Berant, J. (2017). Neural semantic parsing over multiple knowledge-bases. In *Proceedings of ACL*.

Jia, R. and Liang, P. (2016). Data Recombination For Neural Semantic Parsing. *arXiv preprint arXiv:1606.03622*.

Johnson, M., Schuster, M., Le, Q. V., Krikun, M., Wu, Y., Chen, Z., Thorat, N., Viégas, F., Wattenberg, M., Corrado, G., et al. (2016). Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. *arXiv preprint arXiv:1611.04558*.

Krishnamurthy, J., Dasigi, P., and Gardner, M. (2017). Neural Semantic Parsing with Type Constraints for Semi-Structured Tables. In *Proceedings of EMNLP*.

Liang, P., Jordan, M. I., and Klein, D. (2013). Learning dependency-based compositional semantics. *Computational Linguistics*, 39(2):389–446.

MacCartney, B. and Manning, C. D. (2009). An extended model of natural logic. In *Proceedings of the eighth International Conference on Computational Semantics*, pages 140–156.

Montague, R. (1970). Universal grammar. *Theoria*, 36(3):373–398.

Richardson, K. (2018). A Language for Function Signature Representations. *arXiv preprint arXiv:1804.00987*.

Richardson, K., Berant, J., and Kuhn, J. (2018). Polyglot Semantic Parsing in APIs. In *Proceedings of NAACL*.

References III

Richardson, K. and Kuhn, J. (2012). Light Textual Inference for Semantic Parsing. In *Proceedings of COLING-12*.

Richardson, K. and Kuhn, J. (2014). Unixman corpus: A resource for language learning in the unix domain. In *Proceedings of LREC-2014*.

Richardson, K. and Kuhn, J. (2016). Learning to Make Inferences in a Semantic Parsing Task. *Transactions of the Association for Computational Linguistics*, 4:155–168.

Richardson, K. and Kuhn, J. (2017a). Function Assistant: A Tool for NL Querying of APIs. In *Proceedings of EMNLP*.

Richardson, K. and Kuhn, J. (2017b). Learning Semantic Correspondences in Technical Documentation. In *Proceedings of ACL*.

Richardson, K., Zarrieß, S., and Kuhn, J. (2017). The Code2Text Challenge: Text Generation in Source Code Libraries. In *Proceedings of INLG*.

Woods, W. A. (1973). Progress in natural language understanding: an application to lunar geology. In *Proceedings of the June 4-8, 1973, National Computer Conference and Exposition*, pages 441–450.

Yin, P. and Neubig, G. (2017). A Syntactic Neural Model for General-Purpose Code Generation. *arXiv preprint arXiv:1704.01696*.

Zarrieß, S. and Richardson, K. (2013). An Automatic Method for Building a Data-to-Text Generator. In *Proceedings of the 14th European Workshop on Natural Language Generation*.

Zelle, J. M. and Mooney, R. J. (1996). Learning Parse Database Queries using Inductive Logic Programming. In *Proceedings of AAAI-1996*, pages 1050–1055.