Polyglot Semantic Parsing in APIs

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Understanding Source Code Documentation

```
* Returns the greater of two long values
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* @param a an argument
* @param b another argument
* @return the larger of a and b
* @see java.lang.Long#MAX_VALUE
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- **Docstrings:** High-level descriptions of internal software functionality.

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- **Docstrings:** High-level descriptions of internal software functionality.
- **Difficult:** Understanding goes beyond information in software library.
- **First step:** Learning to translate high-level text to code representations.

Return the greater of two long values $\longrightarrow$ `Long max(long a, long b)`

Source Code as a Parallel Corpus

- Tight coupling between high-level text and code, easy to extract text/code pairs automatically.

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⇓ 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)"
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text	*Returns items from coll...*
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- **Function signatures:** Header-like representations, containing function name, (optionally typed) arguments, (optional) return value, namespace.

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

Main Task: Text to Function Signature Translation

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

- **Task**: Given a training corpus of text/signatures pairs, learn a *semantic parser*: text $\rightarrow$ `signature` (Deng and Chrupała, 2014; Richardson and Kuhn, 2017b)
  - **Assumption**: predicting within finite signature/translation space.

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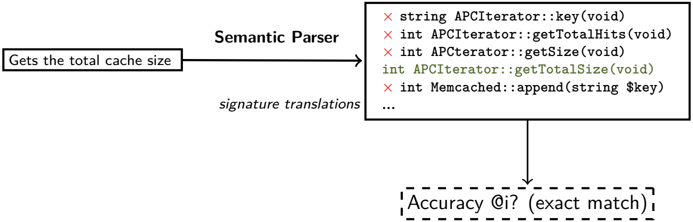
- **Code Retrieval Analogy**: Ordinary train/test split, at test time, *retrieve* function signature that matches input text *specification*:



Conventional Approach to Semantic Parsing

Approach of Richardson and Kuhn (2017b,a)

(en,PHP) → $\theta_{\texttt{en}} \rightarrow$ `PHP`
(en,Lisp) → $\theta_{\texttt{en}} \rightarrow$ `Lisp`
(de, PHP) → $\theta_{\texttt{de}} \rightarrow$ `PHP`
(ja, Python) → $\theta_{\texttt{ja}} \rightarrow$ `Python`
(en, Haskell) → $\theta_{\texttt{en}} \rightarrow$ `Haskell`
...

- Train individual models for each available parallel dataset, below current resources from Richardson and Kuhn (2017b,a)

dataset	**description**
`Stdlib`	45 Stdlib docs, 11 programming languages, 8 natural languages.
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dataset	**description**
`Stdlib`	45 Stdlib docs, 11 programming languages, 8 natural languages.
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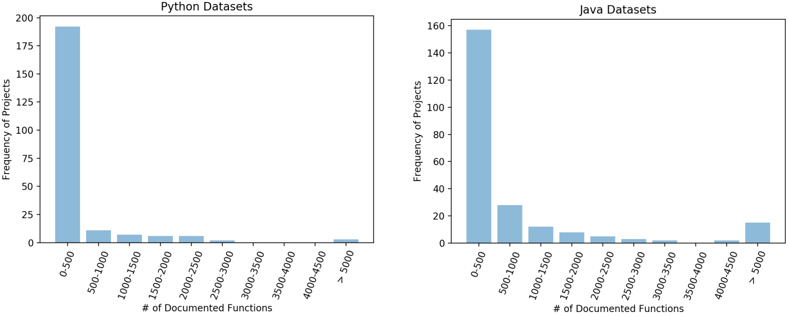
- **Resource Problem**: Individual datasets tend to be small, hard and unlikely to get certain types of parallel data, e.g., (de,`Haskell`).

Code Domain: Projects often lack documentation



- Ideally, we want to find large sets of function documentation specific to each target software project or API.
- Easy to find in bulk (focus of most studies in this area), but most projects are low-resourced, hard to build models to *specific domains/projects*.

Polyglot Models: Training on Multiple Datasets

Approach in this talk

- **Idea**: concatenate all datasets into one, 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 translators?
2. **Zero-Short Translation** (Johnson et al., 2016): Can we translate between different APIs and unobserved language pairs?

<Polyglot Decoding>

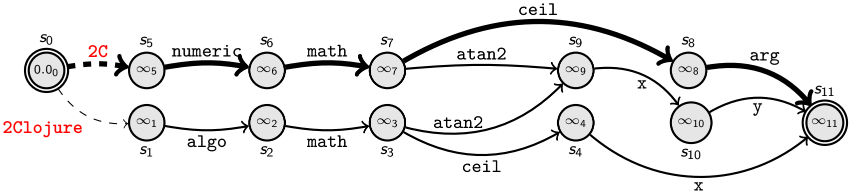
Polyglot Models: Training on Multiple Datasets

- **Challenge**: Building a polyglot decoder, or translation mechanism that facilitates crossing between (potentially unobserved) language pairs.

Polyglot Models: Training on Multiple Datasets

- **Challenge**: Building a polyglot decoder, or translation mechanism that facilitates crossing between (potentially unobserved) language pairs.
  - **Constraint 1**: Ensure well-formed code output (not guaranteed in ordinary MT, cf. Cheng et al. (2017); Krishnamurthy et al. (2017))
  - **Constraint 2**: Must be able to translate to target APIs/programming languages on demand.

Graph Based Approach



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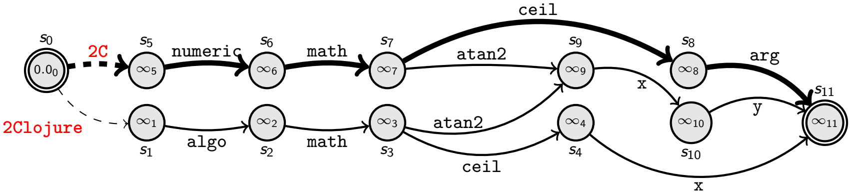

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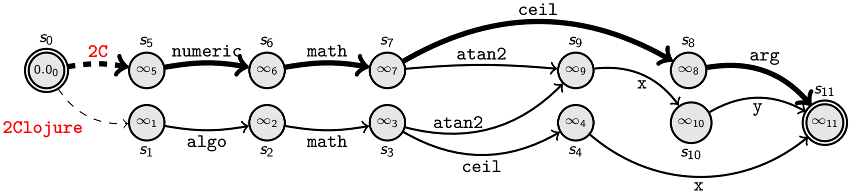

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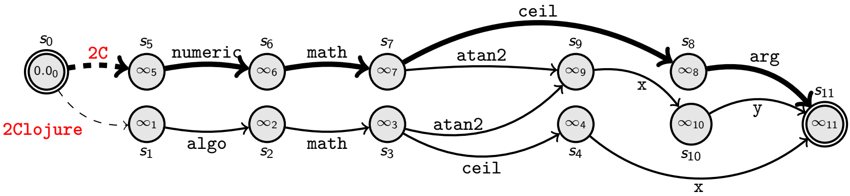
- **Decoding**: Reduces to finding a path given an input $\mathbf{x}$:

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

Can be solved using variant of single-source shortest path (SSSP) problem (Cormen et al., 2009), extendible to k-SSSP paths.

Graph Decoder: Constrained Shortest Path Decoding



- **Standard SSSP:** assumes a DAG $\mathcal{G} = (V, E)$, a weight function: $w : E \to \mathbb{R}$, (initialized) vector $d \in \infty^{|V|}$, unique source node b

0: $d[b] \leftarrow 0.0$
1: **for** vertex $u \in V$ in top sorted order
2: **do** $d(v) = \min_{(u,v,z) \in E} \left\{ d(u) + w(u, v, z) \right\}$
3: **return** $\min_{v \in V} \left\{ d(v) \right\}$

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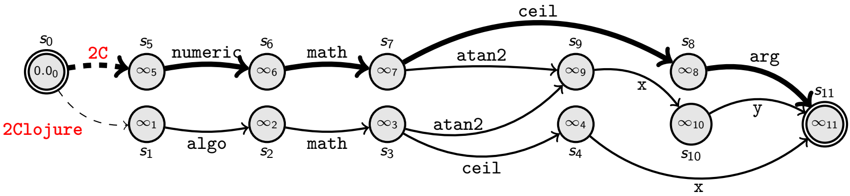

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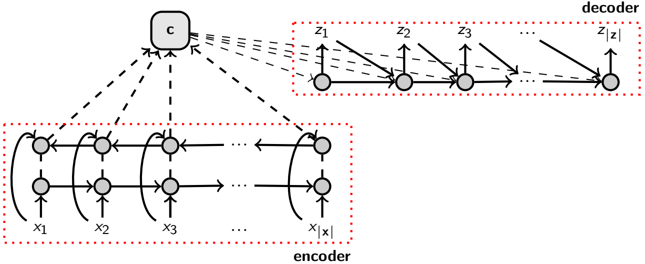
- **Variant:** replace $w(..)$ with translation model, dynamically generates weights correspond. to translation scores for **x** and labels in SSSP search.

Neural Sequence to Sequence Models



- **Encoder Model:** neural sequence model, builds a *distributed* representation of the source sentence and its words $\mathbf{x} = (h_1, h_2, .., h_{|\mathbf{x}|})$:
- **Decoder Model**: RNN language model additionally conditioned on input $\mathbf{x}$/Encoder states.

$$p(\mathbf{z} \mid \mathbf{x}) = \prod_{i}^{|\mathbf{z}|} p_{\Theta}(z_i \mid z_{<i}, \mathbf{x})$$

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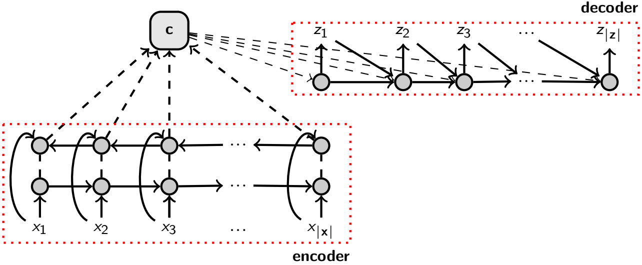

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  - **Modification** (at decode/test time): Constrain search (each new z_i) to ensure well-formed translation output.

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- **Translation models:** Any model can be used, we experiment with lexical SMT models (see paper) and attentive encoder-decoder models.

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- **Neural Variant:** assumes input x, $\mathcal{G}$, neural decoder parameters Θ (trained normally), d, and s (state map):

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3: $s[v] \leftarrow$ RNN state for min edge
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- **Making Our Decoders Behave** by restricting search to paths in the graph (represents full search space, similar to grammar constraints).
  - big topic now in neural SP (Yin and Neubig, 2017; Krishnamurthy et al., 2017), see NAACL tutorial by Neubig and Allamanis.

<Results>

Polyglot vs. Monolingual Decoding

- The difference is the type of input data, and starting point (i.e., source node) in the graph search.
- **Any Language Decoding**: Letting the decoder decide.

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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 )`

Polyglot vs. Monolingual Decoding: Tech Doc Task

- **Our Focus**: Does training on multiple datasets (i.e., *polyglot models*) improve monolingual decoding?
  - **Monolingual models**: current best models, primarily SMT based.

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	poly.	Lexical SMT SSSP	**33.2**	70.7	45.9
		Best Seq2Seq SSSP	13.9	36.5	21.5
py27	**mono.**	Best Monolingual Model	32.4	73.5	46.5
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- **Findings:** Polyglot models can improve performance using SMT models, do not work for Seq2Seq models.
  - Standard set of tricks: copying à la Jia and Liang (2016), lexical biasing (Arthur et al., 2016).

Polyglot Modeling on Benchmark SP Tasks

- **Our Focus**: Does this help on benchmark semantic parsing tasks?

		Method	Acc@1 (averaged)
Multilingual Geoquery	mono.	UBL Kwiatkowski et al. (2010)	74.2
		TreeTrans Jones et al. (2012)	76.8
		Lexical SMT SSSP	68.6
		Best Seq2Seq SSSP	78.0
	poly.	Lexical SMT SSSP	67.3
		Best Seq2Seq SSSP	**79.6**

- **Multilingual Geoquery**: *monolingual/polyglot* models on Geoquery in *en*, *de*, *gr*, *th*, polyglot setting improves accuracy, neural Seq2Seq models perform best (consistent with recent findings, (Dong and Lapata, 2016)).

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  - Recall that these same Seq2Seq models do not work in the technical documentation tasks.

Benchmark SP Tasks: Mixed Language Decoding

- Introduced a new *mixed language* GeoQuery test set, each sentence contains NPs from two or more languages.

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

	Method	Acc@1 (averaged)	Acc@10 (averaged)
Mixed	Best Monolingual Seq2Seq	4.2	18.2
	Polyglot Seq2Seq	**75.2**	90.0

Learning from multiple datasets: Conclusions

- **Polyglot modeling**: Useful technique for improving semantic parsing (SP), transfer learning, zero-shot translation, mixed language parsing.
- **Constrained MT**: Constrained MT decoding using **graphs**, related to other efforts in neural SP that use grammar constraints.
- **Technical Docs**: has features of a low-resource translation task, difficult for neural SPs, shows limitations of benchmark tasks.

Code	`https://github.com/yakazimir/zubr_public`
Datasets	`https://github.com/yakazimir/Code-Datasets`

Thank You

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