CS388: Natural Language Processing

Lecture 20: Language and Code

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credit: Deepmind

Announcements

- Sebastian Gerhmann talk on Tuesday

This Lecture

- Semantic parsing
  - Logical forms
  - Parsing to lambda calculus
  - Seq2seq semantic parsing
- Language-to-code
- Applications in software engineering

Semantic Parsing

Model Theoretic Semantics

- Key idea: can ground out natural language expressions in set-theoretic expressions called *models* of those sentences
- Natural language statement S => interpretation of S that models it

  She likes going to that restaurant

  - Interpretation: defines who *she* and *that restaurant* are, make it able to be concretely evaluated with respect to a *world*
- This is a type of truth-conditional semantics: reduce a sentence to its truth conditions (configuration of the world under which it is true)
- Our modeling language is *first-order logic*
- Entailment (statement A implies statement B) reduces to: in all worlds where A is true, B is true

First-order Logic

- Powerful logic formalism including things like entities, relations, and quantifications

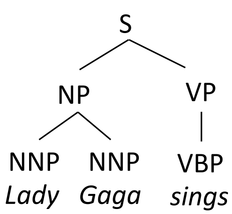
  Lady Gaga sings

- sings is a *predicate* (with one argument), function f: entity → true/false
- sings(Lady Gaga) = true or false, have to execute this against some database (*world*)
- Quantification: "forall" operator, "there exists" operator

  ∀x sings(x) ∨ dances(x) → performs(x)

  "Everyone who sings or dances performs"

Montague Semantics



Id	Name	Alias	Birthdate	Sings?
e470	Stefani Germanotta	Lady Gaga	3/28/1986	T
e728	Marshall Mathers	Eminem	10/17/1972	T

Database containing entities, predicates, etc.

- Richard Montague: operationalized this type of semantics and connected it to syntax
- Denotation: evaluation of some expression against this database

`[[`*Lady Gaga*`]] = e470` denotation of this string is an entity

`[[sings(e470)]] = True` denotation of this expression is T/F

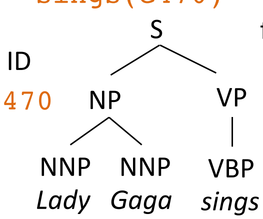
Montague Semantics

`sings(e470)`

function application: apply this to e470

ID

`e470`



`λy. sings(y)`

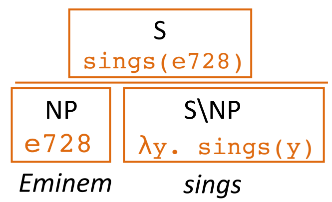
`λy. sings(y)`

takes one argument (y, the entity) and returns a logical form `sings(y)`

- We can use the syntactic parse as a bridge to the lambda-calculus representation, build up a logical form (our model) *compositionally*

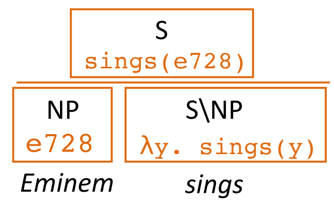
Combinatory Categorial Grammar

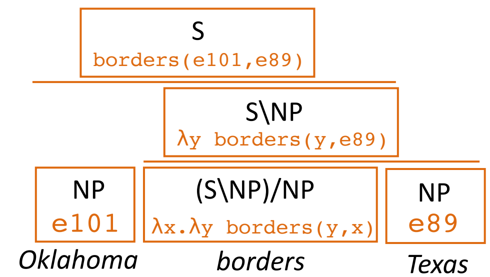
- Steedman+Szabolcsi (1980s): formalism bridging syntax and semantics
- Parallel derivations of syntactic parse and lambda calculus expression
- Syntactic categories (for this lecture): S, NP, "slash" categories
- S\NP: "if I combine with an NP on my left side, I form a sentence" — verb
- When you apply this, there has to be a parallel instance of function application on the semantics side



Combinatory Categorial Grammar

- Steedman+Szabolcsi (1980s): formalism bridging syntax and semantics
- Syntactic categories (for this lecture): S, NP, "slash" categories
  - S\NP: "if I combine with an NP on my left side, I form a sentence" — verb
  - (S\NP)/NP: "I need an NP on my right and then on my left" — verb with a direct object





CCG Parsing

What	states	border	Texas
$(S/(S\backslash NP))/N$ $\lambda f.\lambda g.\lambda x.f(x) \wedge g(x)$	N $\lambda x.state(x)$	$(S\backslash NP)/NP$ $\lambda x.\lambda y.borders(y,x)$	NP $texas$

border Texas $>$: $(S\backslash NP)$, $\lambda y.borders(y, texas)$

- "What" is a ***very*** complex type: needs a noun and needs a S\NP to form a sentence. S\NP is basically a verb phrase (*border Texas*)

Zettlemoyer and Collins (2005)

CCG Parsing

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border Texas $>$: $(S\backslash NP)$, $\lambda y.borders(y, texas)$

$>$: S, $\lambda x.state(x) \wedge borders(x, texas)$

- "What" is a ***very*** complex type: needs a noun and needs a S\NP to form a sentence. S\NP is basically a verb phrase (*border Texas*)
- **Why are we talking about this in this lecture? Because this lambda calculus expression is basically executable code.**

Zettlemoyer and Collins (2005)

CCG Parsing

- These question are *compositional*: we can build bigger ones out of smaller pieces

What states border Texas?

What states border states bordering Texas?

What states border states bordering states bordering Texas?

Zettlemoyer and Collins (2005)

Training CCG Parsers

- Training data looks like pairs of sentences and logical forms

What states border Texas	`λx. state(x) ∧ borders(x, e89)`
What borders Texas	`λx. borders(x, e89)`

…

- Unlike PCFGs, we don't know which words yielded which fragments of CCG
- Very hard to build a conventional parser for this problem

Zettlemoyer and Collins (2005)

Semantic Parsing as Translation

"what states border Texas"

↓

```
lambda x ( state ( x ) and border ( x , e89 ) ) )
```

- Write down a linearized form of the semantic parse, train seq2seq models to directly translate into this representation (similar to code generation like GitHub Copilot)
- What are some benefits of this approach compared to grammar-based?
- What might be some concerns about this approach? How do we mitigate them?

Jia and Liang (2016)

Semantic Parsing as Translation

```
GEO
x: "what is the population of iowa ?"
y: _answer ( NV , (
  _population ( NV , V1 ) , _const (
    V0 , _stateid ( iowa ) ) ) )
ATIS
x: "can you list all flights from chicago to milwaukee"
y: ( _lambda $0 e ( _and
  ( _flight $0 )
  ( _from $0 chicago : _ci )
  ( _to $0 milwaukee : _ci ) ) )
Overnight
x: "when is the weekly standup"
y: ( call listValue ( call
    getProperty meeting.weekly_standup
    ( string start_time ) ) )
```

- Prolog
- Lambda calculus
- Other DSLs

- Handle all of these with uniform machinery!

Jia and Liang (2016)

Applications

- GeoQuery (Zelle and Mooney, 1996): answering questions about states (~80% accuracy)
- Jobs: answering questions about job postings (~80% accuracy)
- ATIS: flight search
- Can do well on all of these tasks if you handcraft systems and use plenty of training data: these domains aren't that rich

Code Generation

- Suppose we are going to generate source code like in Codex/GitHub Copilot. What differs from generating natural language?
- In spite of these differences, the "obvious" thing is to do some pre-training and see how far we get!

Generating Code

CodeT5

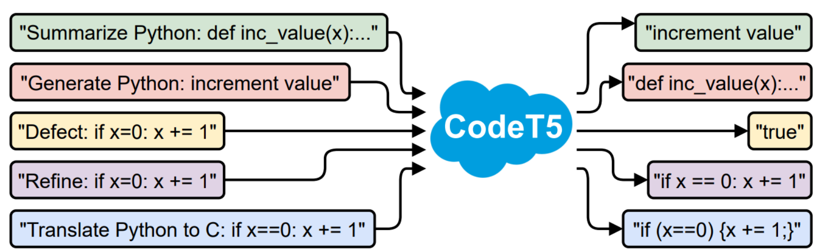
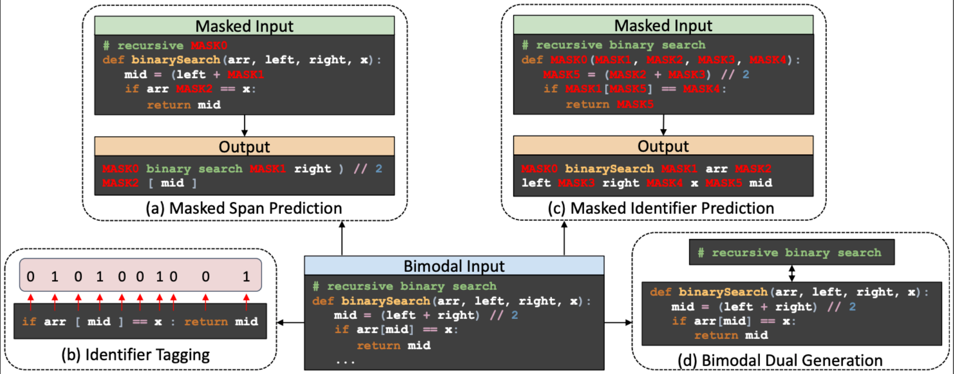


Figure 1: Illustration of our CodeT5 for code-related understanding and generation tasks.

- Key idea: code analogue of T5 that should be able to map language to source code

Wang et al. (2021)

CodeT5



- Predict (a) spans; (c) identifiers; (d) language from code and vice versa
- What's different from normal T5?

Wang et al. (2021)

CodeT5

- Pre-trained on data from several language and NL
- Applied to several generation tasks: code summarization, generation, and translation (between programming languages)

	PLs	W/ NL	W/o NL	Identifier
CodeSearchNet	Ruby	49,009	110,551	32.08%
	JavaScript	125,166	1,717,933	19.82%
	Go	319,132	379,103	19.32%
	Python	453,772	657,030	30.02%
	Java	457,381	1,070,271	25.76%
	PHP	525,357	398,058	23.44%
Our	C	1M	-	24.94%
	CSharp	228,496	856,375	27.85%
	Total	3,158,313	5,189,321	8,347,634

- Also used for classification like bug detection (can be fine-tuned like BERT-style models)

Wang et al. (2021)

CodeT5

- Generation task from CONCODE (Iyer et al., 2018):

```
public class SimpleVector implements Serializable {
  double[] vecElements;
  double[] weights;

  NL Query: Adds a scalar to this vector in place.
  Code to be generated automatically:
  public void add(final double arg0) {
    for (int i = 0; i < vecElements.length; i++){
      vecElements[i] += arg0;
    }
  }
```

- What do you think about this evaluation?

Methods	EM	BLEU	CodeBLEU
GPT-2	17.35	25.37	29.69
CodeGPT-2	18.25	28.69	32.71
CodeGPT-adapted	20.10	32.79	35.98
PLBART	18.75	36.69	38.52
CodeT5-small	21.55	38.13	41.39
+dual-gen	19.95	39.02	42.21
+multi-task	20.15	35.89	38.83
CodeT5-base	22.30	40.73	43.20
+dual-gen	**22.70**	**41.48**	**44.10**
+multi-task	21.15	37.54	40.01

Table 3: Results on the code generation task. EM denotes the exact match.

Wang et al. (2021)

Codex

- GPT-3 additionally fine-tuned on code (although they state that pre-training on NL isn't really helpful)
  - Modified tokenizer to handle whitespace better. Otherwise, no real modifications!
- Up to 12B parameter models fine-tuned on Python
- One challenge is evaluation. How to go beyond BLEU/EM?

Mark Chen et al. (2021)

HumanEval

- Generate standalone Python functions from docstrings **and execute them!**

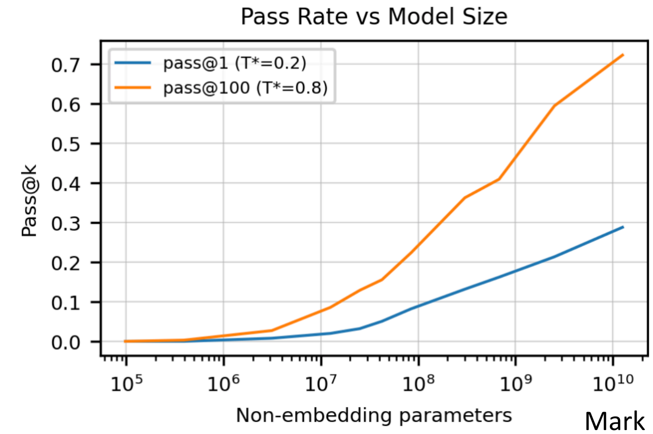
```python
def solution(lst):
    """Given a non-empty list of integers, return the sum of all of the odd elements
    that are in even positions.

    Examples
    solution([5, 8, 7, 1]) ==>12
    solution([3, 3, 3, 3, 3]) ==>9
    solution([30, 13, 24, 321]) ==>0
    """
    return sum(lst[i] for i in range(0,len(lst)) if i % 2 == 0 and lst[i] % 2 == 1)
```

- Handwritten benchmarks evaluated for correctness (“pass@k”: generate k, see if one of them works)

Mark Chen et al. (2021)

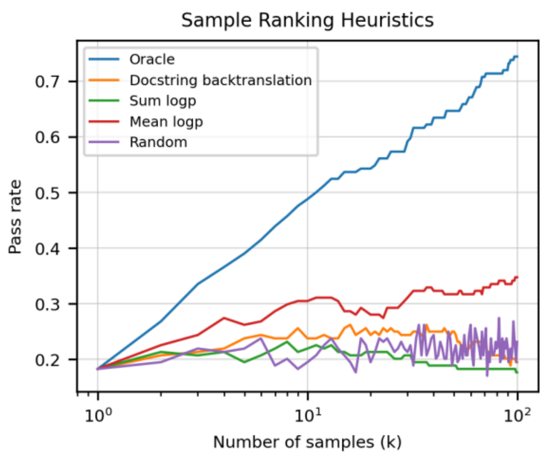
HumanEval



Mark Chen et al. (2021)

HumanEval

- Another setting: can we generate a bunch of samples and then pick the correct one? This would be useful for rejection sampling
- Other experiments: additional fine-tuning on competitive programming problems, docstring generation



Reflexion

> go to desk 2
On the desk 2, you see a alarmclock 1, a bowl 1, a mug 3, a pencil 3, and a pencil 2.
> think: Now I find a desklamp (1). Next, I need to use it.
OK.
> use desklamp 1
Nothing happens.
> use desklamp 1
Nothing happens.
Status: Fail

Reflection: In this environment, my plan was to find a mug then find and use a desklamp. However, the task says to examine the mug with the desklamp. I should have looked for the desklamp first, then looked for the mug. I noticed that the desklamp was found on desk 1. In the next trial, I will go to desk 1, find the lamp, then look for the mug and examine it with the desklamp.

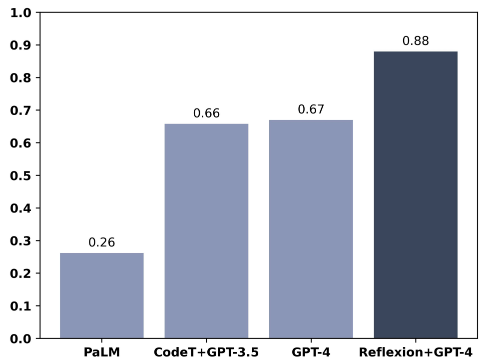
Trial #2
> go to desk 1
On the desk 1, you see a creditcard 3, a desklamp 1, a laptop 2, a mug 1, a pen 1, and a pencil 1.
> think: To solve the task, I need to find and take a mug, then find and use a desklamp.
OK.
> take mug 1 from desk 1
You pick up the mug 1 from the desk 1.

https://twitter.com/johnjnay/status/1639362071807549446

Shinn et al. (2023)

Reflexion

- Interact with environment, generate a "reflection" about that interaction, then condition on that interaction for the next round
- Very little details about this, but very strong results on HumanEval!



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Shinn et al. (2023)

NL Feedback

Prompt

OLD CODE:
```
"""
Write a python function to find
the sum of the three lowest
positive numbers from a given list
of numbers.
>>> Example:
sum_three_smallest_nums([10,20,30,
40,50,60,7]) = 37
"""
def sum_three_smallest_nums(lst):
    lst.sort()
    return sum(lst[:3])
```

FEEDBACK:
This code finds the sum of the smallest 3 numbers, not the smallest 3 positive numbers. It needs to disregard negatives and 0.

REFINEMENT:

Expected completion

```
"""
Write a python function to find
the sum of the three lowest
positive numbers from a given list
of numbers.
>>> Example:
sum_three_smallest_nums([10,20,30,
40,50,60,7]) = 37
"""
def sum_three_smallest_nums(lst):
    lst = [x for x in lst if x >
0]
    lst.sort()
    return sum(lst[:3])
```

Improving Code Generation by Training with Natural Language Feedback

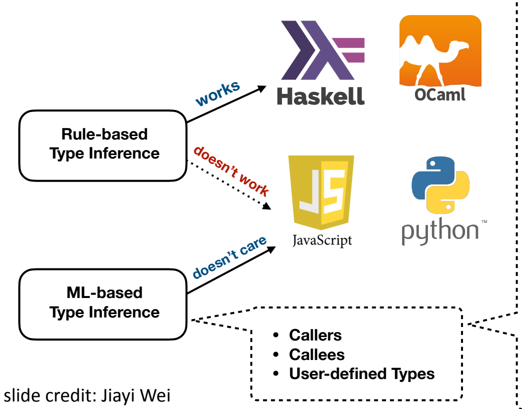
Angelica Chen et al. (2023)

Applications in Software Development

Applications

- Generating complete code is nice, but is very challenging: can't read the user's mind, if generated code has errors they may be time-consuming to spot
- There are a range of applications in software engineering: bug detection, type inference, etc. — solving these subproblems can still help save developers time
- Here: focus on type inference

Type Inference




```
def predict(
    self,
    data: ChunkedDataset,
    n_seqs: Optional[int] = None,
) -> dict[int, list[PythonType]]:
    pred_types = dict()
    for batch in data.data:
        batch["input_ids"] = batch["input_ids"].to(device)
        preds, _ = self.predict_on_batch(batch, n_seqs)
        for i, c_id in enumerate(batch["chunk_id"]):
            if n_seqs is None:
                pred_types[c_id] = preds[i]
            else:
                span = i * n_seqs : (i + 1) * n_seqs
                pred_types[c_id] = preds[span]
    return pred_types
```

Callee

```
def predict_on_batch(
    self, batch: dict,
    n_seqs: Optional[int] = None
) -> tuple[list[PythonType], dict]:
    ...
```

Caller

```
chunks = chunk_srcs(data, window)
return model.predict(chunks, n_seqs=None)
```

slide credit: Jiayi Wei

Type Inference

- Typing this code snippet:

```
chunks = chunk_srcs(data, window)
return model.predict(chunks, n_seqs=None)
```

...requires looking at this function:

```
def predict(
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    return pred_types
```
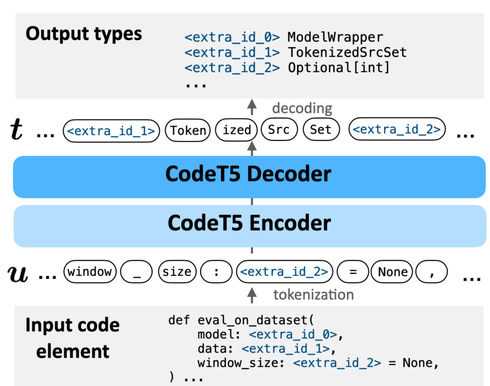

- Changes are non-local: even with GPT-4-length contexts, you usually can't have a whole project in Transformer context

slide credit: Jiayi Wei

Type Inference

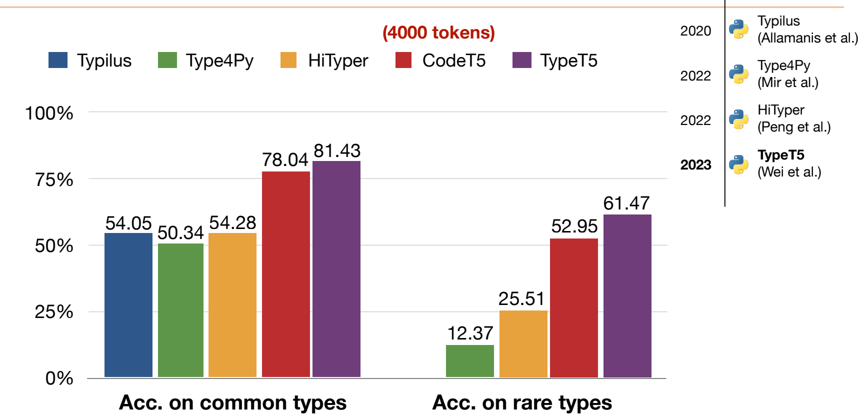
- Can use CodeT5 to predict the types…but what context do we feed it?
- Solution: use **static analysis** to determine relevant parts of the program
- Use the call graph to assemble a context for CodeT5 consisting of callers, callees, and skeletons of various files



slide credit: Jiayi Wei

Jiayi Wei, Durrett, Dillig (ICLR 2023)

Type Inference



slide credit: Jiayi Wei

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Other Applications

- Bug detection: spot bugs in code
- Comments: code-to-comment translation, updating comments when code has changed, and more (see papers by Sheena Panthaplackel)
- Debugging: ask GPT-4 to fix code given an error message (see Greg Brockman's GPT-4 demo)
- Program synthesis: have some specification other than language (e.g., input-output examples, formal spec) and produce code to follow that

Takeaways

- Language was being interpreted into logical forms that looked like code for a long time (including in formal semantics)
- Rather than doing this with parsers, now we just use seq2seq models
  - Powerful enough models will almost always generate code that compiles. You don't need special constraints on the output.
- …and because of pre-training, rather than using customized DSLs, we just use source code because models have seen more of it