Graph- and behaviour-based machine learning models to understand program semantics

Seminar Current Topics in Compiler Construction (Hauptseminar)

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July 13, 2020

Why ML for programs?

```
function fetchData(retries) {
  for (var i = 0; i < retries; i += 1) {
    print("attempt", i);

    // ...
  }
}
```

what is the type of the parameter `retries`?

Why ML for programs?

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The naturalness hypothesis

"Software is a form of human communication; software corpora have similar statistical properties to natural language corpora; and these properties can be exploited to build better software engineering tools." [Allamanis et al., 2018a]

Representing programs

Characters / Tokens

Abstract Syntax Tree

Program Graphs (data flow, control flow)

Program Behaviour (execution traces)

Representing programs

source code

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semantics

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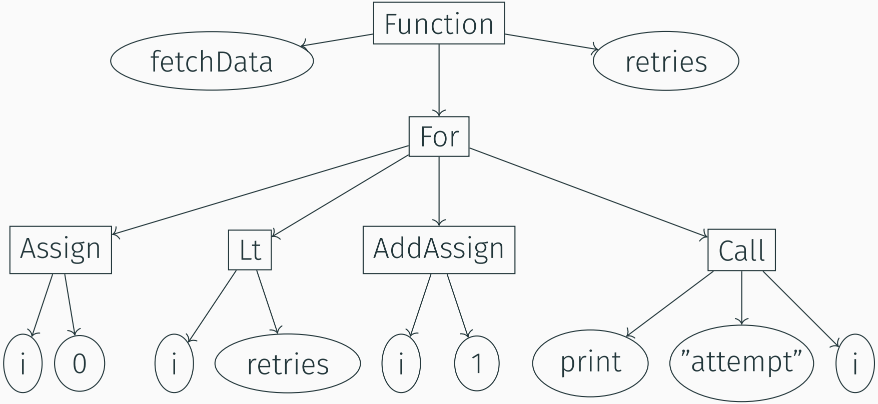
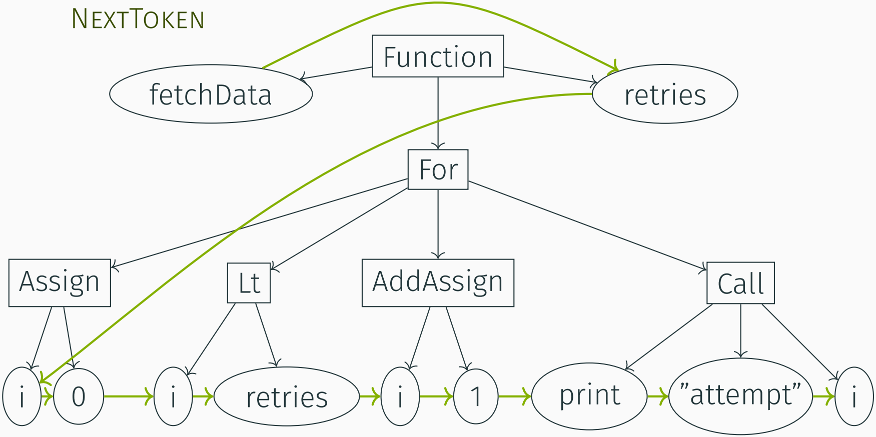
Programs as graphs [Allamanis et al., 2018b]



Programs as graphs [Allamanis et al., 2018b]



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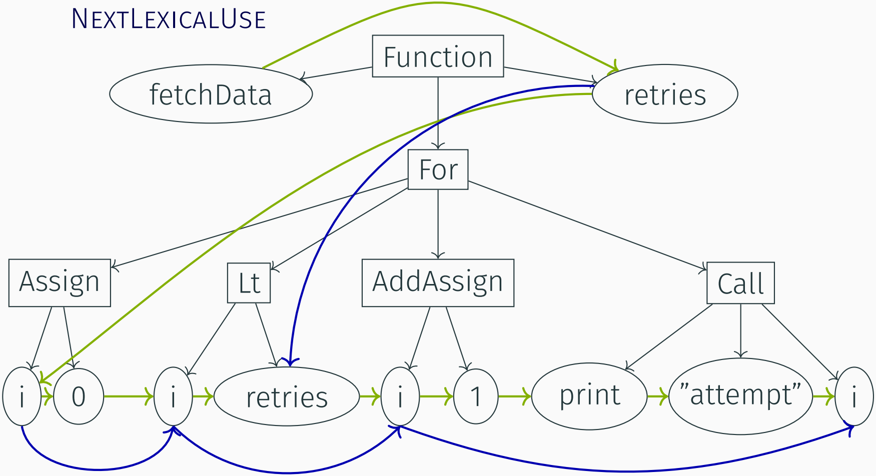

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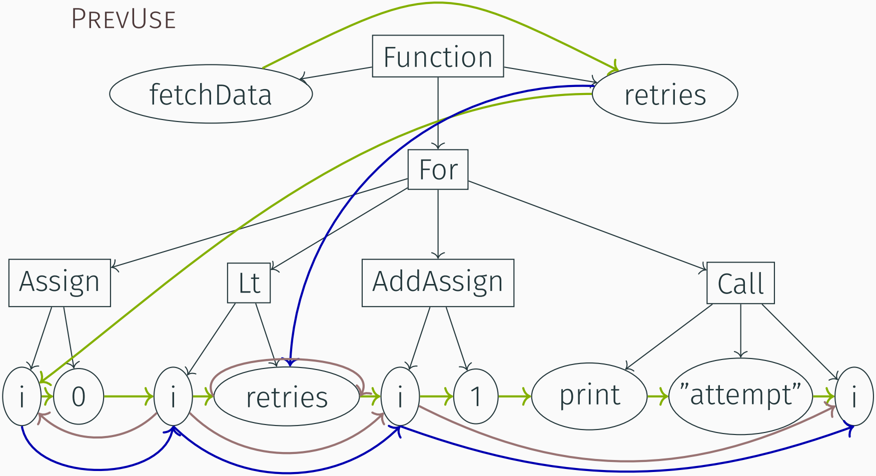

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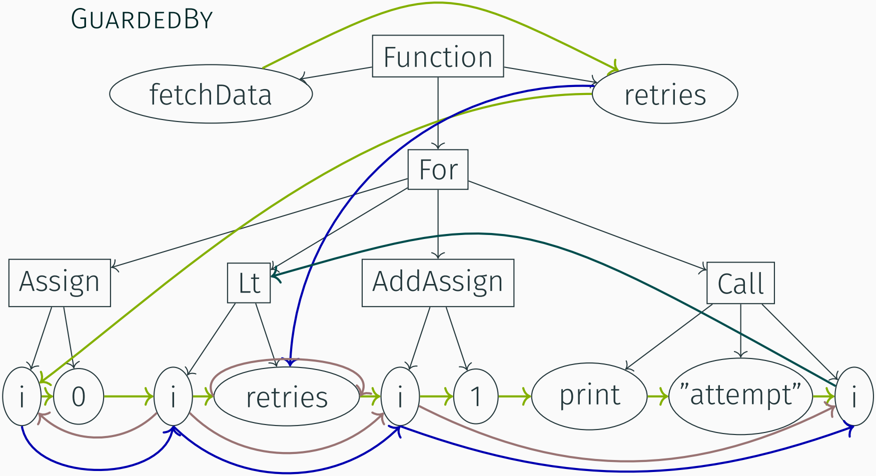

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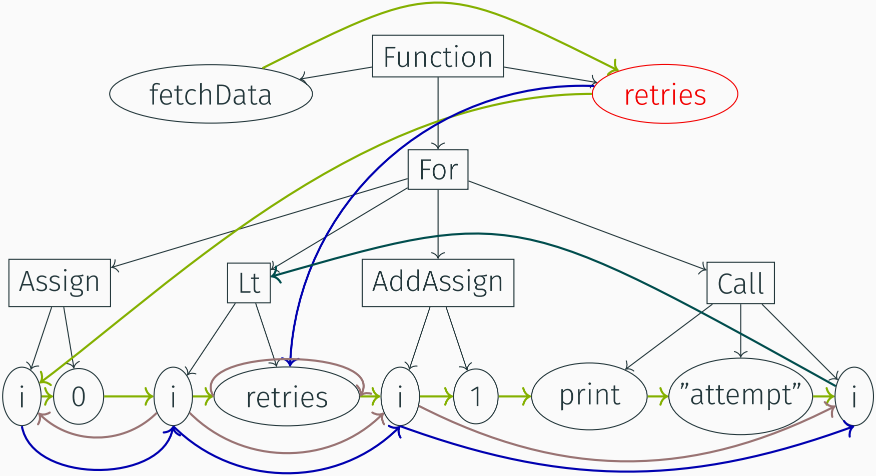
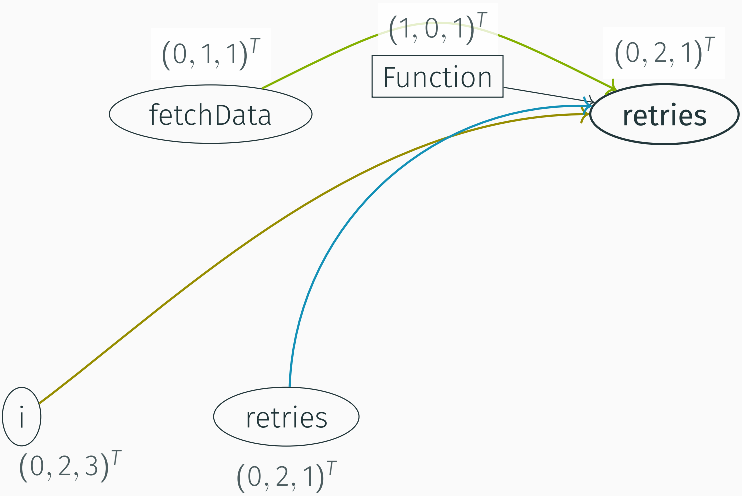
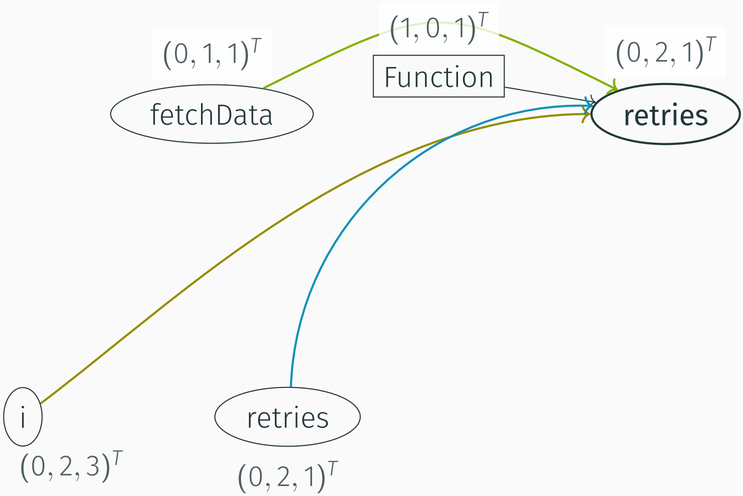


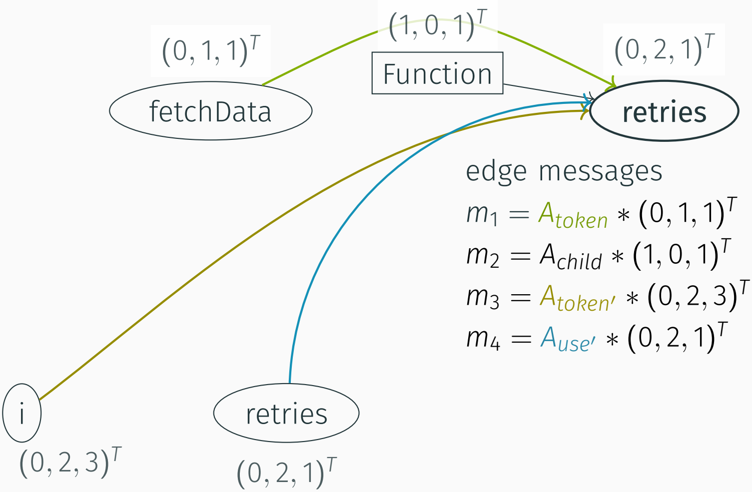
Message Passing Neural Network





$(0, 1, 1)^T$
$(1, 0, 1)^T$
$(0, 2, 1)^T$
Function
fetchData
retries
i
retries
$(0, 2, 3)^T$
$(0, 2, 1)^T$

Message Passing Neural Network



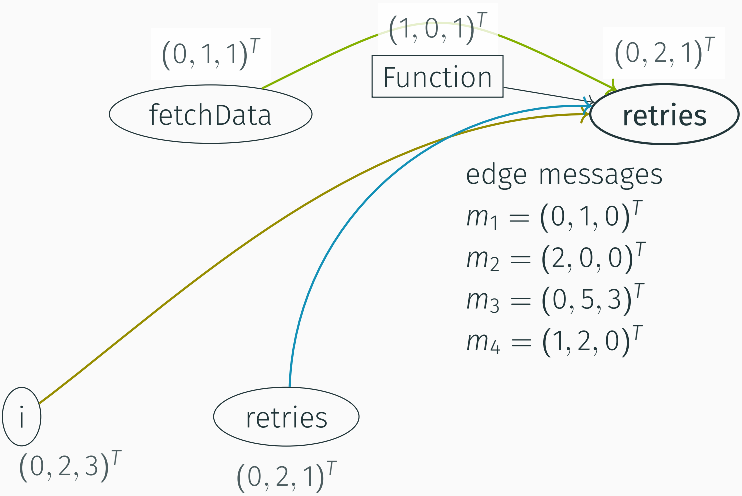
edge messages

$m_1 = A_{token} * (0,1,1)^T$

$m_2 = A_{child} * (1,0,1)^T$

$m_3 = A_{token'} * (0,2,3)^T$

$m_4 = A_{use'} * (0,2,1)^T$



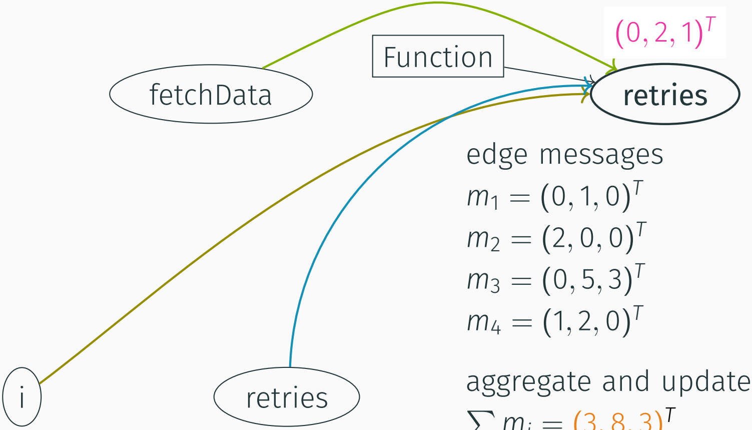
edge messages

$m_1 = (0, 1, 0)^T$

$m_2 = (2, 0, 0)^T$

$m_3 = (0, 5, 3)^T$

$m_4 = (1, 2, 0)^T$



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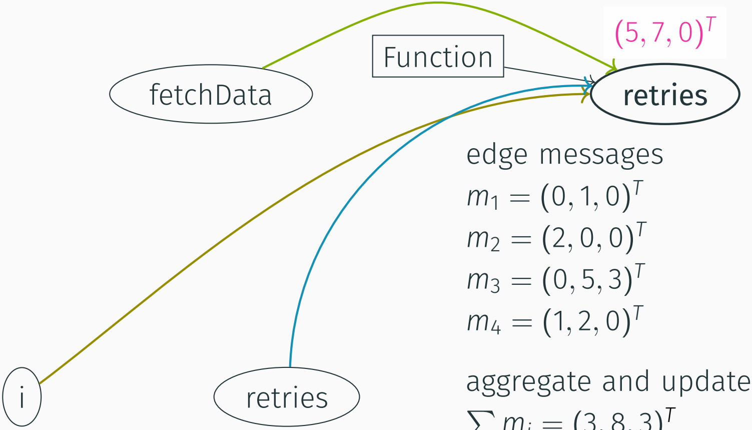
aggregate and update

$\sum m_i = (3, 8, 3)^T$

$h_{t+1} = GRU((0, 2, 1)^T, (3, 8, 3)^T)$

Message Passing Neural Network



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semantics

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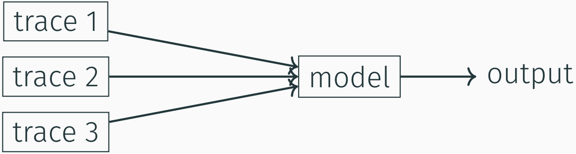
Programs as traces

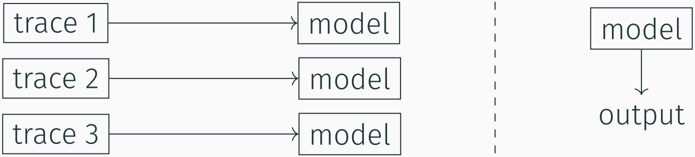
trace 1	trace 2	trace 3
…	…	…
retries=3 i=0	retries=5 i=0	retries=1 i=0
retries=3 i=1	retries=5 i=1	retries=1 i=1
retries=3 i=2	retries=5 i=2	…
retries=3 i=3	retries=5 i=3	
…	retries=5 i=4	
	retries=5 i=5	
	…	

Learning from traces

variant 1: learn program embedding



variant 2: learn model to “emulate” program (synthesis)



Evaluation

Evaluation: MethodNaming

```
boolean f(Set<String> set, String value) {
    for (String entry : set) {
        if (entry.equalsIgnoreCase(value)) {
            return true;
        }
    }
    return false;
}
```

prediction: contains ignore case

Evaluation: MethodNaming

java dataset (java-*)

code2seq [Alon et al., 2019] → SNS [Fernandes et al., 2019]

code2seq [Alon et al., 2019] → DyPro [Wang, 2019]

code2seq [Alon et al., 2019] → LiGer [Wang and Su, 2020]

DyPro [Wang, 2019] → LiGer [Wang and Su, 2020]

POJ-104 dataset

NCC [Ben-Nun et al., 2018] ⟶ ProGraML [Cummins et al., 2020]

Evaluation: Invariant inference

```
x = 1; y = 0;
while (y < 100000) {
  x = x + y;
  y = y + 1;
}
assert(x >= y);
```

Example invariant: $x > y$

Evaluation: Invariant inference

GGNN [Hellendoorn et al., 2019]
gated graph neural network for checking dynamically generated invariants

DyPro [Wang, 2019]
checking loop invariants with behaviour-based model

code2inv [Si et al., 2018]
synthesis using graph-neural network representation as memory

GCLN [Yao et al., 2020]
synthesis by fitting gated continuous logic networks to trace data

Conclusion and future research directions

- Graph-based models improve on simpler models
- Behaviour-based models better at semantics (as expected)
- But require execution traces

Research directions

datasets: standarized, to evaluate different models
architectures: combine static/dynamic, performance, pretrain
analysis: adversarial examples, different languages

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