Learning Execution through Neural Code Fusion

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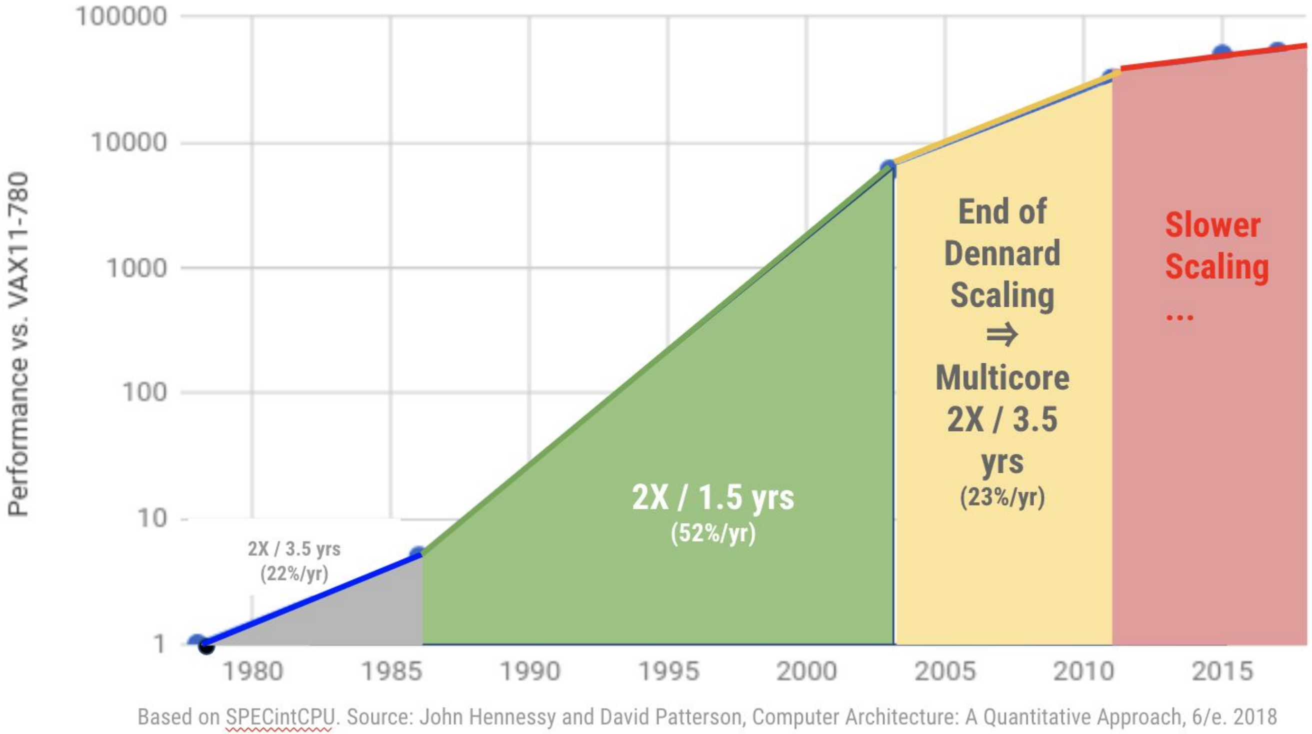
Research at Google

Overview

- Motivation
- Background
- Neural Code Fusion
- Experimental Results
- Conclusion

Motivation

2% Performance/Year is the New Normal



Source: Parthasarathy Ranganathan, More Moore: Thinking Outside the (Server) Box

Motivation

- **Dynamic** speculative execution
    - Branch prediction, value prediction, cache replacement, prefetching...

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- **Dynamic** speculative execution
  - Branch prediction, value prediction, cache replacement, prefetching...
- **Static** source code
  - Variable naming, finding bugs, algorithm classification, program synthesis...
  - Performance-related tasks: device mapping, thread coarsening, throughput prediction...
- **Both views provide useful features**

Example: a “Simple” Case for Branch Prediction

```
for (i = 0; i < k; i++)
{
}
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Highly biased

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Highly biased

Branch history doesn’t help

- Jump out when “close enough”
- Predictable if we knew the relation
  [Static] i and k are compared
  [Dynamic] values of i and k

Background: Graph Neural Networks

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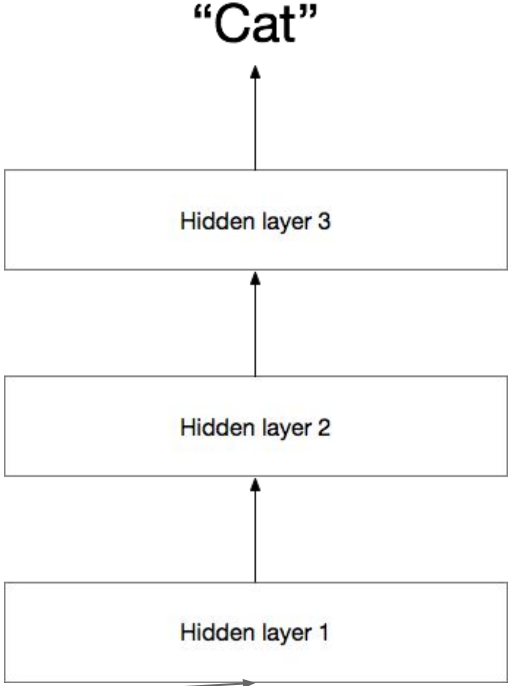
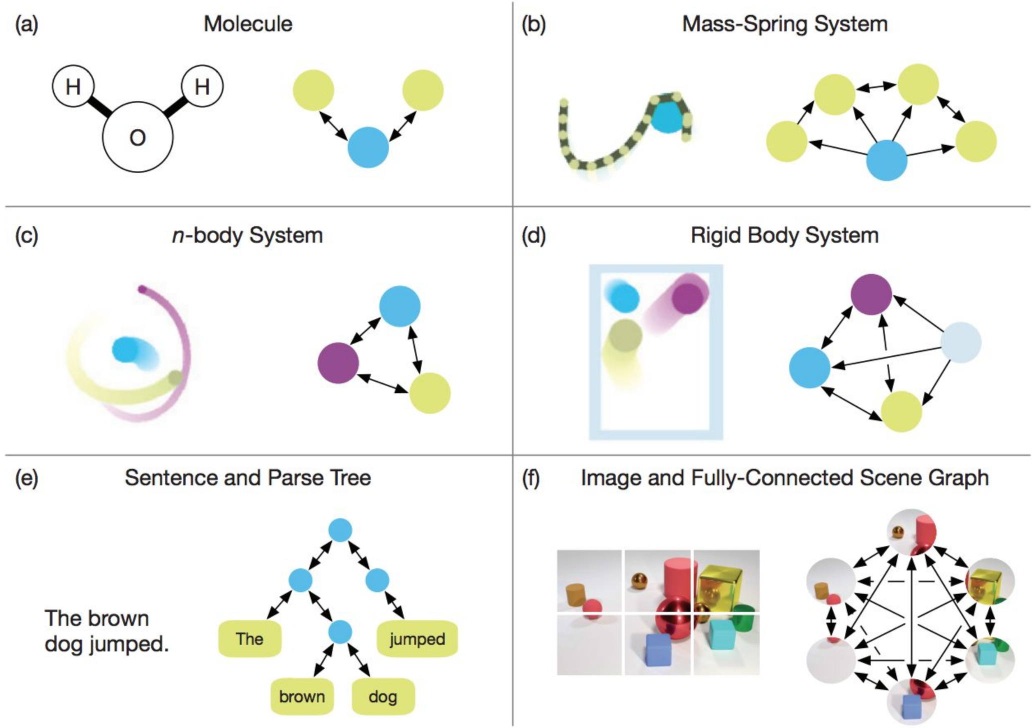
- Typical deep learning operates on IID data points.



Background: Graph Neural Networks

- What if the data points had *relational* information?

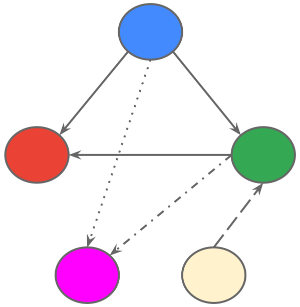


Battaglia et al., 2018

Background: Graph Neural Networks

- Message passing

Input graph



Background: Graph Neural Networks

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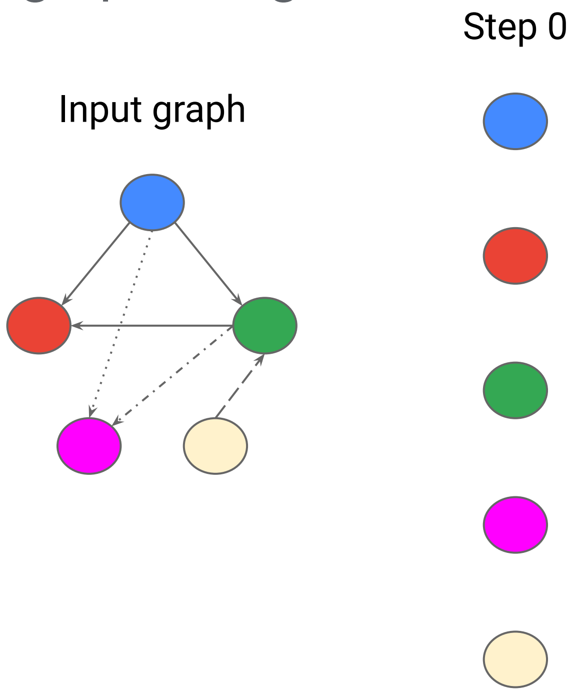

Background: Graph Neural Networks

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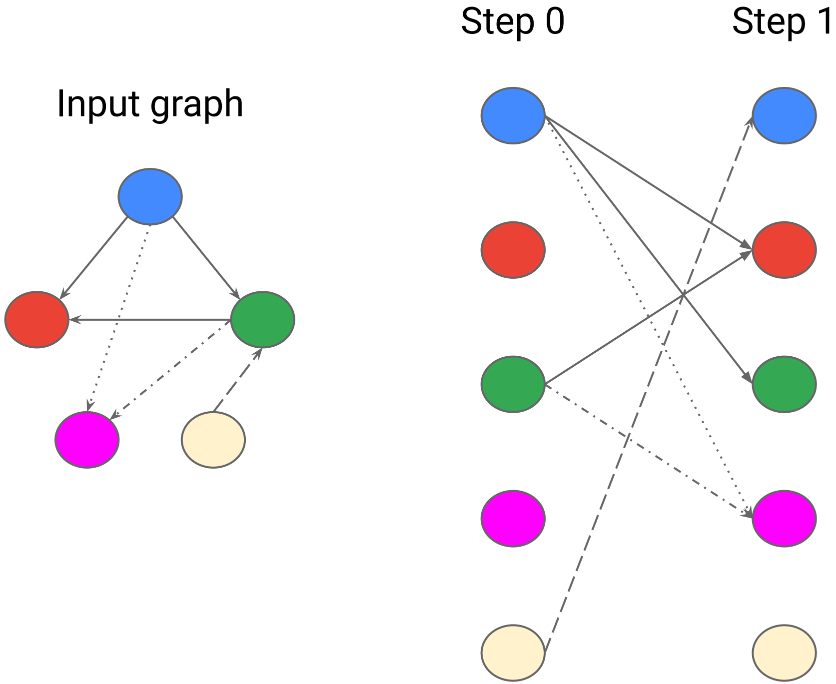

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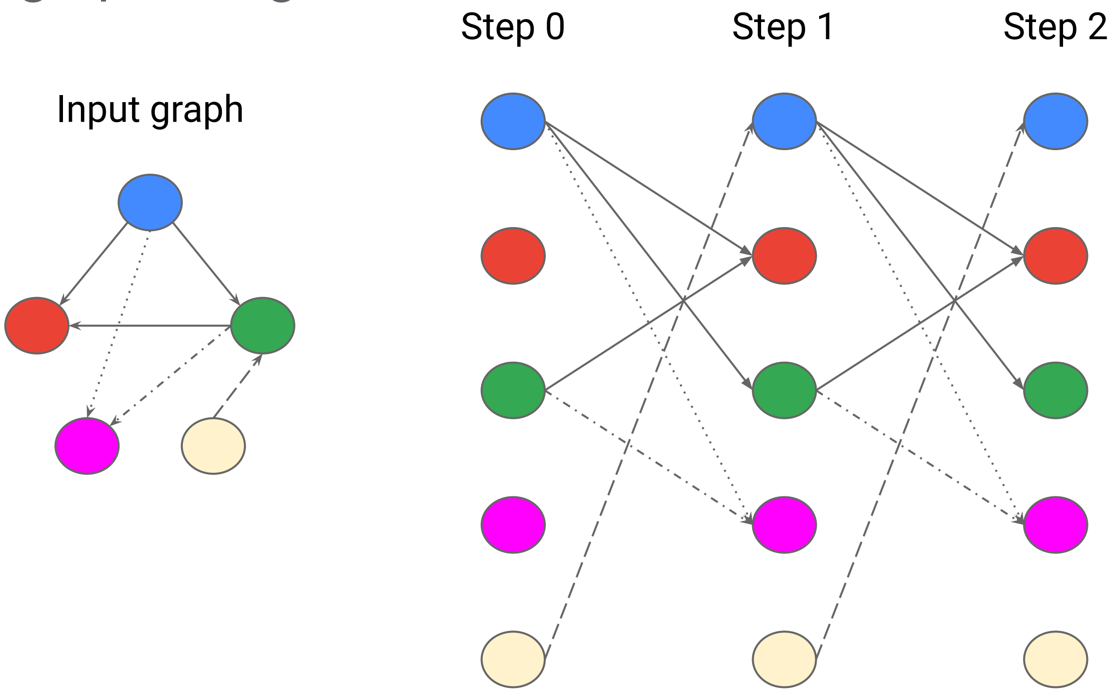

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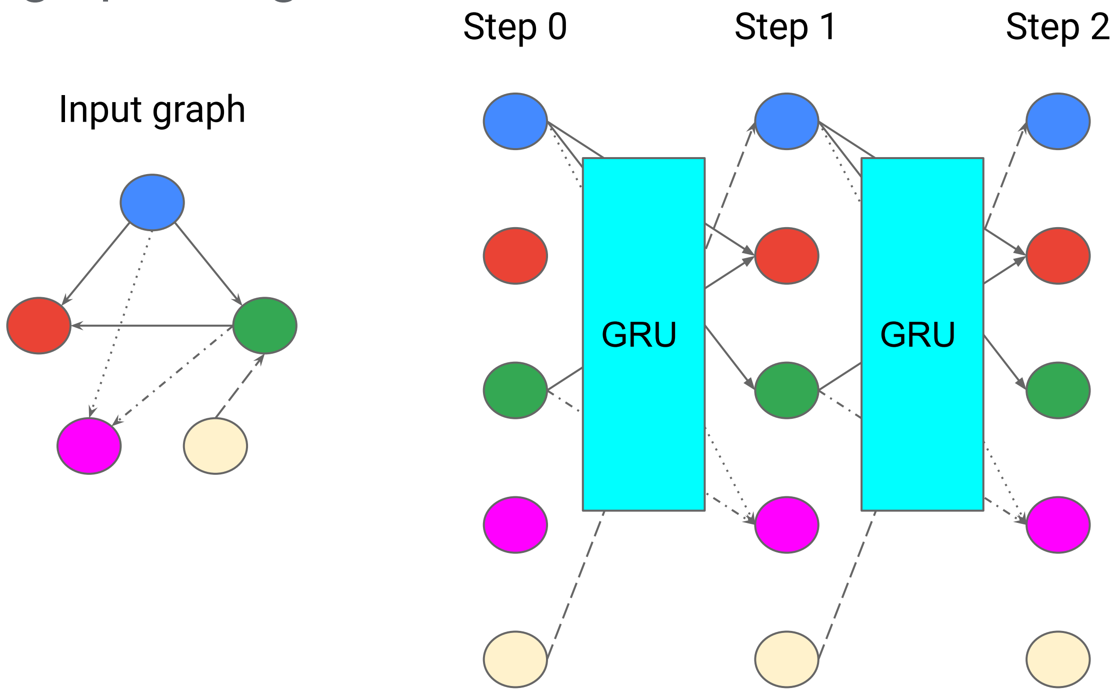
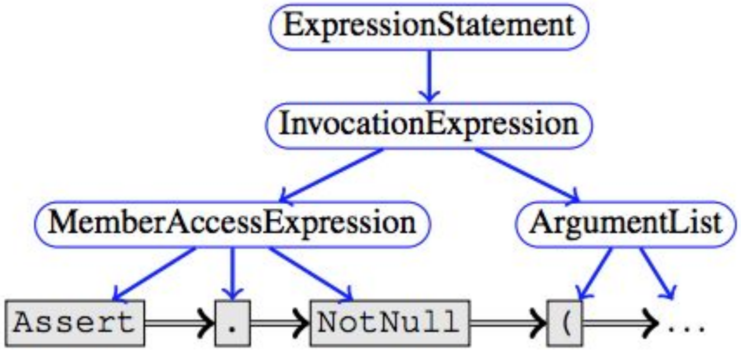
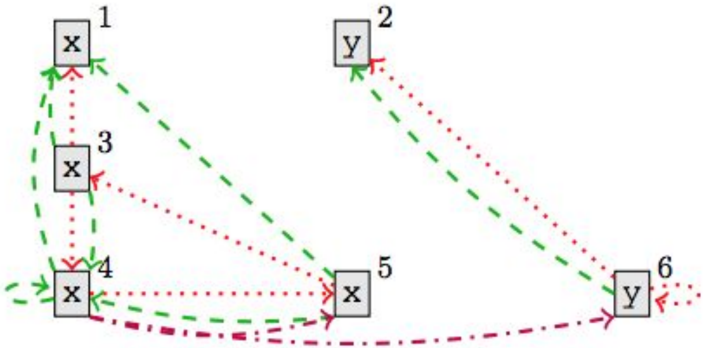


Programs as Graphs Allamanis et al., 2017



(a) Simplified syntax graph for line 2 of Fig. 1, where blue rounded boxes are syntax nodes, black rectangular boxes syntax tokens, blue edges Child edges and double black edges NextToken edges.



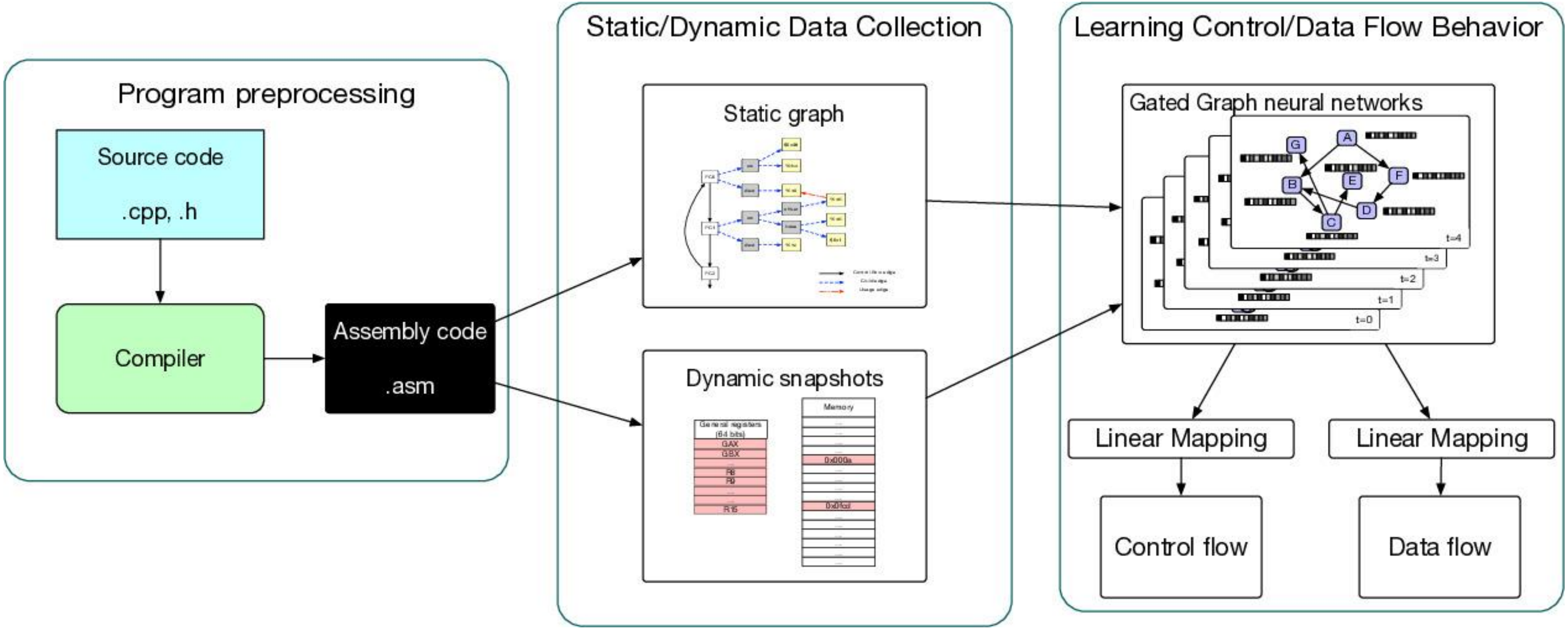
(b) Data flow edges for (x^1,y^2) = Foo(); while (x^3 > 0) x^4 = x^5 + y^6 (indices added for clarity), with red dotted LastUse edges, green dashed LastWrite edges and dashdotted purple ComputedFrom edges.

Representing Static and Dynamic Information

- Graphs are an effective representation for static code
- How do we generally represent **dynamic information** in a model?

Neural Code Fusion

Full System



Program preprocessing
Source code
.cpp, .h
Compiler
Assembly code
.asm
Static/Dynamic Data Collection
Static graph
Dynamic snapshots
Memory
0x000a
Learning Control/Data Flow Behavior
Gated Graph neural networks
A
B
C
D
E
F
G
t=4
t=3
t=2
t=1
t=0
Linear Mapping
Linear Mapping
Control flow
Data flow

Assembly vs Source Code

- Highly structured

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if-else	Ternary	Assembly	Semantics
if (a<b)	i= a<b ? a : b;	4004da: mov -0xc(%rbp),%eax	# fetch a
i = a;		4004dd: cmp -0x8(%rbp),%eax	# compare a and b
else		4004e0: jge 4004ea	# jump to i = b if a >= b
i = b;		4004e2: mov -0xc(%rbp),%eax	# fetch a
		4004e5: mov %eax,-0x4(%rbp)	# i = a
		4004e8: jmp 4004f0	# jump out
		4004ea: mov -0x8(%rbp),%eax	# fetch b
		4004ed: mov %eax,-0x4(%rbp)	# i = b
		4004f0: mov $0x1,%eax	

Assembly vs Source Code

- Highly structured
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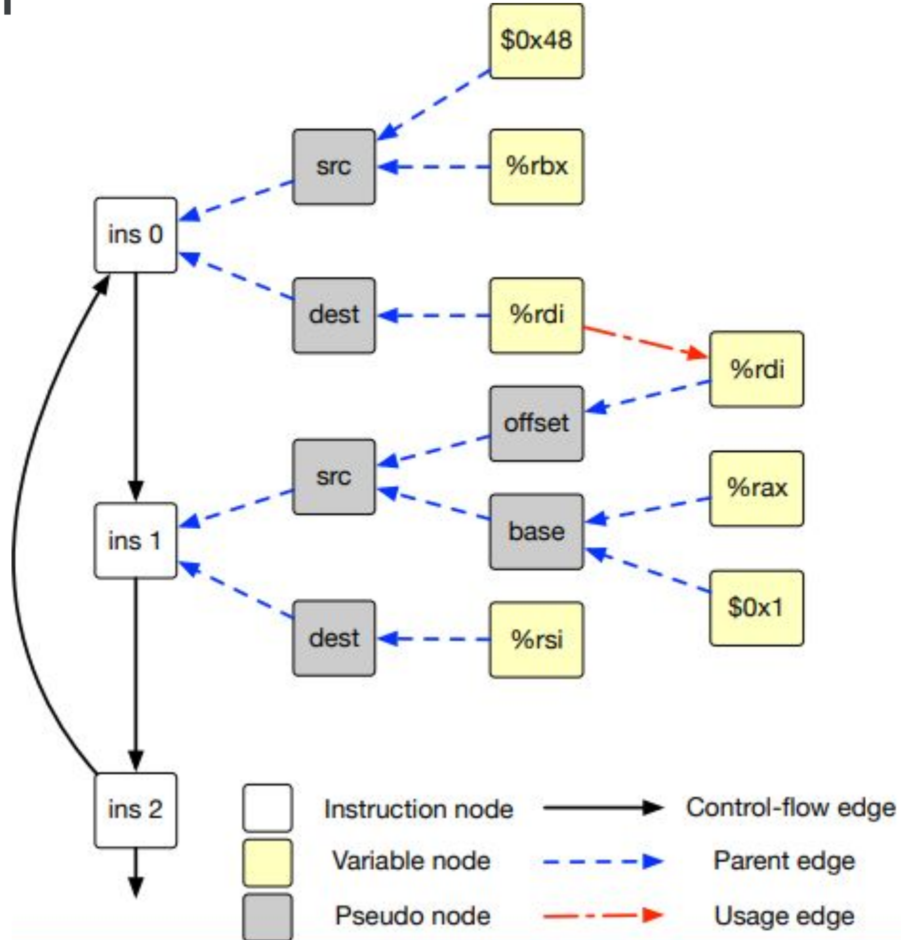
Assembly vs Source Code

- Highly structured
- Directly relate data to program semantics
- Easy to use for architecture tasks

Code Fusion Graph Representation

```
PC0: mov $0x48(%rbx), %rdi
PC1: cmp (%rdi, %rax, 1), %rsi
PC2: jne PC0
```



Dynamic Tasks: Control Flow and Data Flow

- Control flow (branch prediction)
  - predict whether a branch statement will be taken or not taken.
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  - Binary classification

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- Data flow (prefetching)
    - predict which address will be accessed next.
    - Set src node to be the target node.
    - Predict 64-bit address

Multi-Task Representation

- Many other static/dynamic tasks can be defined on the graph simultaneously
  - Value prediction, indirect branch prediction, memory disambiguation, caching...

Dynamic Snapshots

- Snapshots
  - The values of the set of variable nodes
  - Captured during program execution
- Used to initialize the graph neural network

Representation Study

- Number “3” in different representations
  - Categorical: [1, 0, 0, 0]
  - Scalar: 3
  - Binary: 11

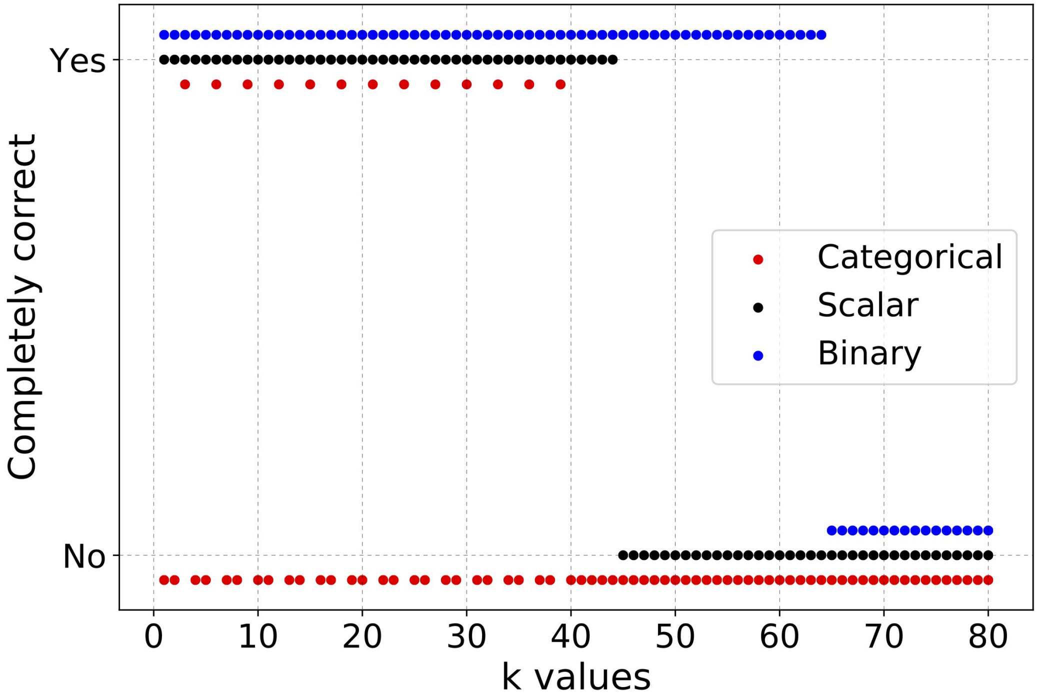
Representation Study

- Correctly predict when to jump out
- Sample k values as training data

```
for(k=0; k < n; k+=3){
    for (i = 0; i < k; i++)
    {
    }
}
```

Representation Study:

- Results
  - Binary > scalar > categorical

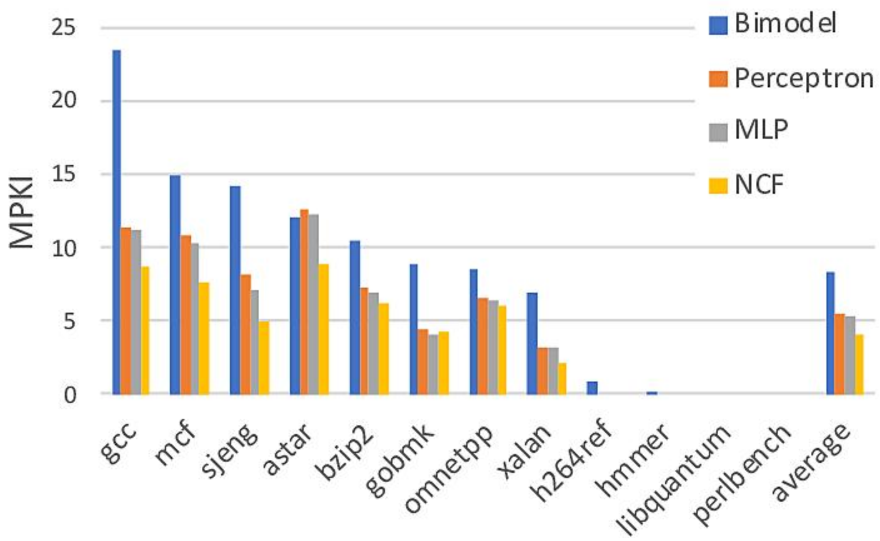


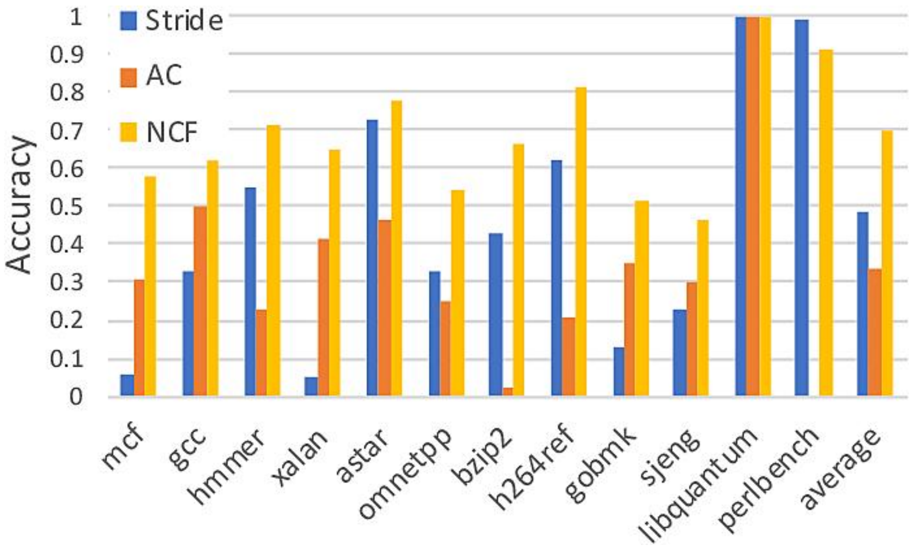
Experimental Results

Experimental Setup

- Benchmarks
  - SPEC06 INT
- Tasks
  - Dynamic: control flow (branch prediction) and data flow (prefetching)
  - Static: algorithm classification
- Offline evaluation for both NCF and baselines
  - 70% training
  - 30% testing

Control-flow (Branch Prediction) and Data-flow (Prefetching)





Algorithm Classification

- **Test the usefulness of the learned representation**
- We **pre-train our GNN on the *control-flow* task**
- A simple linear SVM model
- We get 96% vs 95.3% (50M lines of LLVM IR) using 200k lines of assembly with no external data sources.

Summary

- NCF combining **static** and **dynamic** information
  - creates useful representations
- Different from the **traditional dynamic models** in architecture
  - Data is usually purely dynamic
  - Model is history-based
- Enhances **static models** with dynamic program behavior
  - Learned representation can also transfer to a unseen static task

Thank you!

Questions?

Research at Google