Experimenting with Neuroevolution for Graal Inlining Heuristics

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Overview

- Inlining is an important optimization
- Machine Learning could help
- Evolutionary techniques may be applicable

Inlining & Heuristics

```java
public int add(int a, int b) {
    return a + b;
}
```

```java
public void foo() {
    int x = add(2, 3);
    int y = add(4, 9);
}
```

```java
public void foo() {
    int x = 2 + 3;
    int y = 4 + 9;
}
```

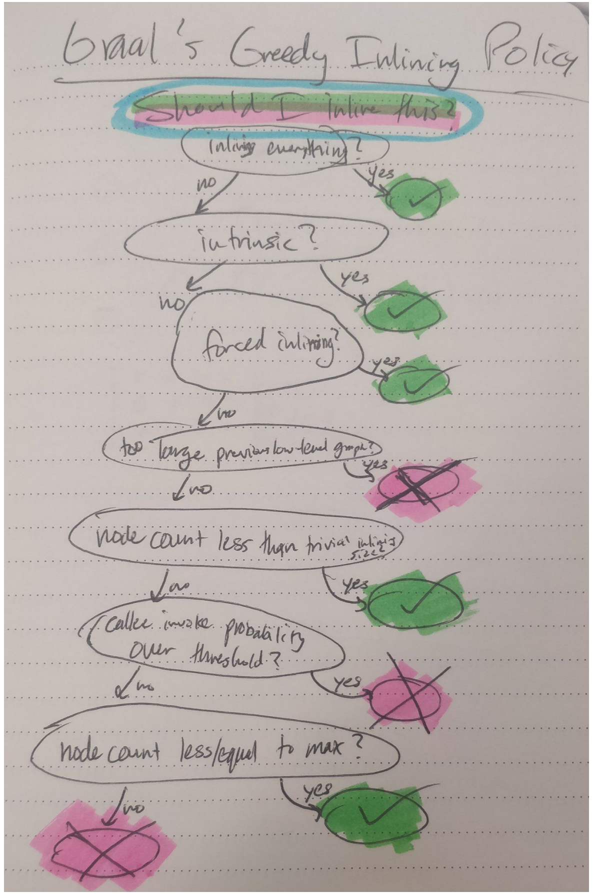
Inlining

- **Replacing callsites with bodies of callees**
- **Enables other optimizations**
- **Many interdependent decisions**
- **“How” is easy. “When” is hard.**
    - Too much is bad, too little is not optimal.

How do we decide when to inline?

Current Inlining Policy

- **Manually constructed and tuned**
- **Often tuned for a specific benchmark**
- **Same across environments and workloads**
- **Graal's current policy**
  - Simple if-statements
  - Gather some data about the decision point, run it through simple flow



Incremental Inlining Algorithm

- **Online inlining algorithm**
- **Identifies and inlines clusters of callsites**
- **Alternates between inlining and optimizations**

Aleksandar Prokopec, Gilles Duboscq, David Leopoldseder, and Thomas Würthinger. 2019. An optimization-driven incremental inline substitution algorithm for just-in-time compilers. In *Proceedings of the 2019 IEEE/ACM International Symposium on Code Generation and Optimization* (*CGO 2019*).

Machine Learning

ML helps us make decisions.
Can it tell us when to inline?
Doug Simon et al. say yes.
(about 10% speedup)

Specifically - Evolutionary Algorithms.

Douglas Simon, John Cavazos, Christian Wimmer, and Sameer Kulkarni. 2013. Automatic construction of inlining heuristics using machine learning. In Proceedings of the 2013 IEEE/ACM International Symposium on Code Generation and Optimization (CGO) (CGO '13).

The Evolution Process

1

Evaluation

Evaluate all the organisms in the current population.

2

Selection

Select the fittest organisms.

3

Crossover

Combine parent organisms to produce children

4

Mutation

With some probability, modify the children.

5

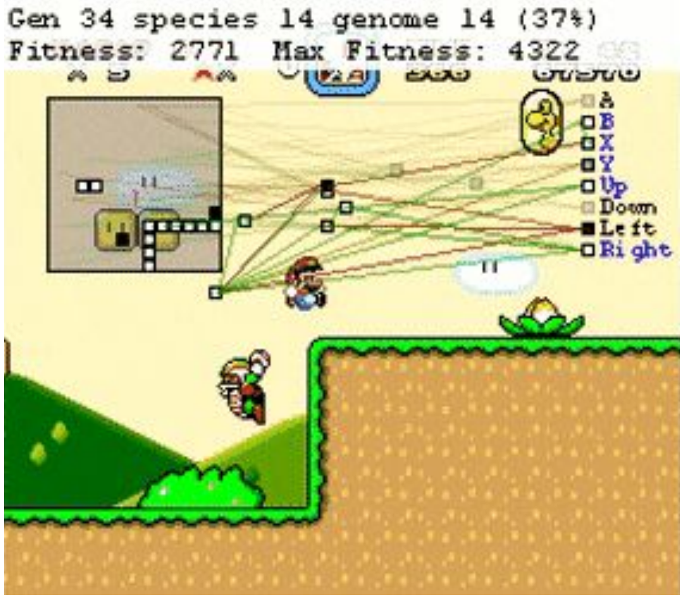
Repeat!

As the new generation is created, repeat the process until convergence or a maximum limit.

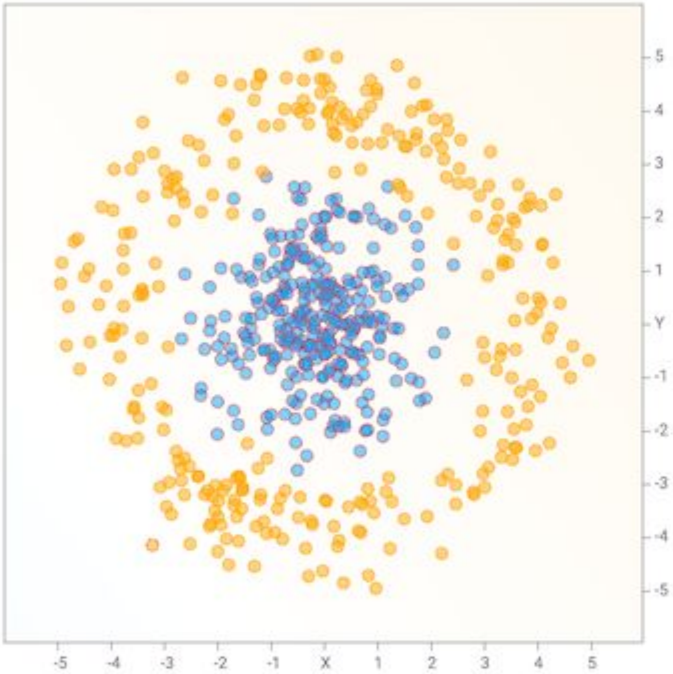
Neuroevolution of Augmenting Topologies (NEAT)

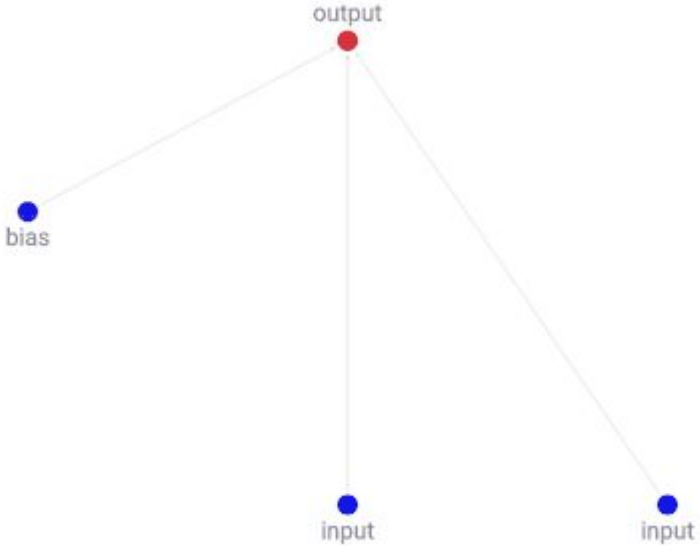
NEAT

- Applying evolution to Neural Networks
- Neuroevolution algorithm developed by Kenneth O. Stanley in 2002
- Can evolve structure and weights



Kenneth Owen Stanley. 2004. Efficient Evolution of Neural Networks Through Complexification. Ph.D. Dissertation. The University of Texas at Austin.


5
4
3
2
1
Y
-1
-2
-3
-4
-5
-5 -4 -3 -2 -1 X 1 2 3 4 5


output
bias
input
input

Applying NEAT

NEAT for the Inlining Problem

- **Inlining requires making decisions using a heuristic**
- **Neural Networks can be used as a heuristic**
  - Input is the same data the current policy receives
  - Output is YES/NO
- **They cannot be trained for inlining using traditional Gradient Descent**
  - No way of knowing the correct decisions
- **A heuristic can be evolved**
- **Evaluating an organism means getting running time on benchmarks**

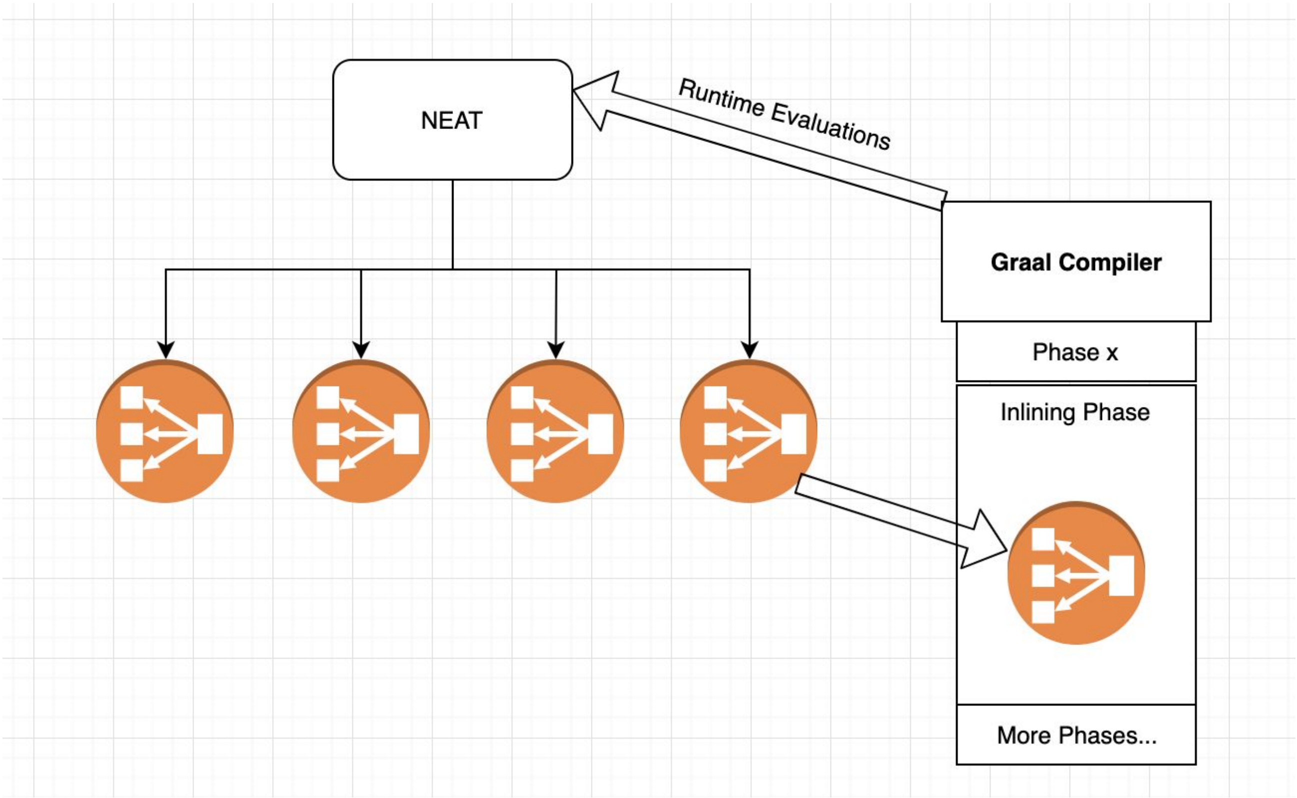
Thank you.

Result of NEAT

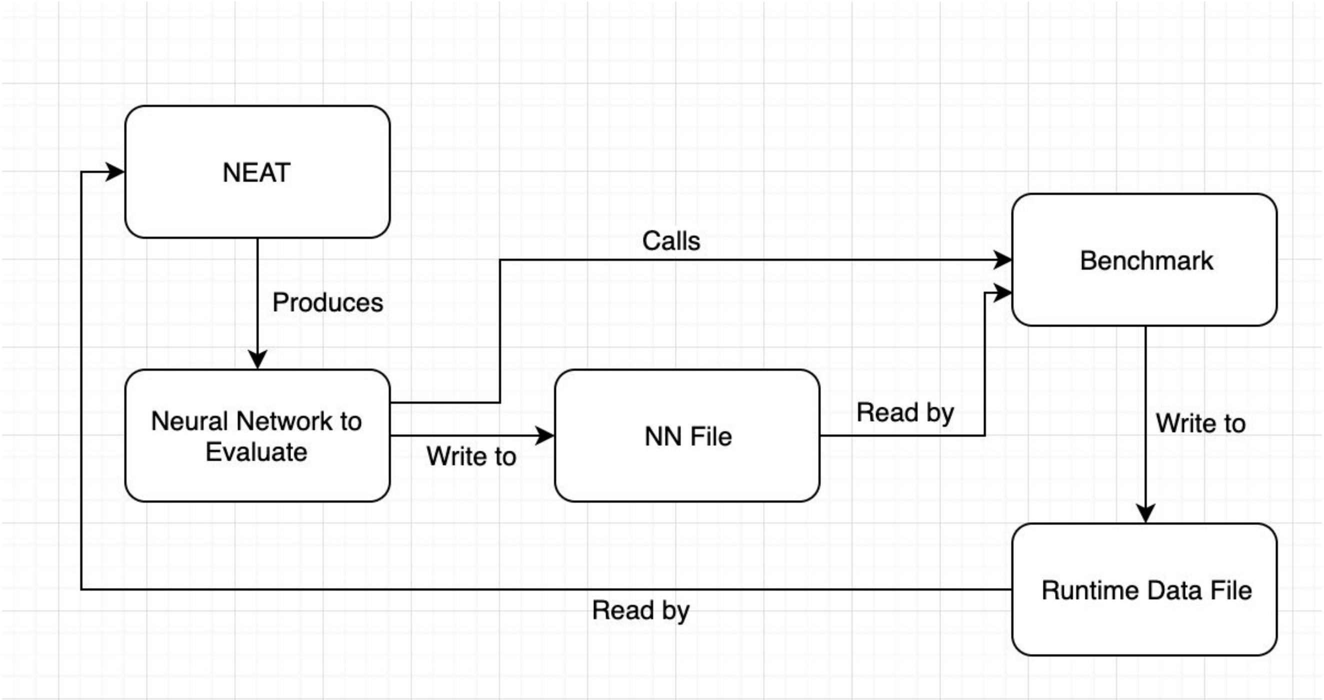
- When NEAT ends, it gives you the best organism of the last generation
- “Bake” this into the compiler, totally offline
- Can make different network/policies for different environments

Benefits of NEAT for Inlining

- Automatic construction of heuristic without expert work
- Easy to customize for environments, workloads
- Done offline
    - Result is a single heuristic
- Doug Simon et al. showed improvements over default algorithm in MaxineVM (C1X)


NEAT
Runtime Evaluations
Graal Compiler
Phase x
Inlining Phase
More Phases...

In More Detail

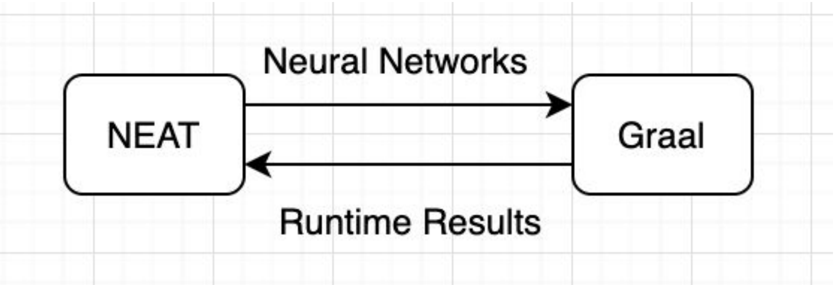


Libraries

Neuroph is used for Neural Network support.
There is a NEAT for Neuroph implementation.

Why Neuroph? Easy to transfer.

Neuroph
Java Neural Network Framework



Neuroph
Java Neural Network Framework

Running

- Aurora/Mesos
- Running on dedicated JVM cluster machine
- No interference

Evolution Hyperparameters

- Population Size
- Number of Generations (or Termination Condition)
- Mutation rates
- Selection
- Speciation

Other Knobs & Dials

- **What benchmarks to run**
  - How to evaluate a neural network
- **Warmup run count**
- **How to turn neural net output into YES/NO**
  - Threshold
  - Probability

Output

- **Fitness of every organism evaluated**
- **Generation Statistics**
  - Best Organism
  - No. of Species
- **Save each generation**
  - Can resume from any point later

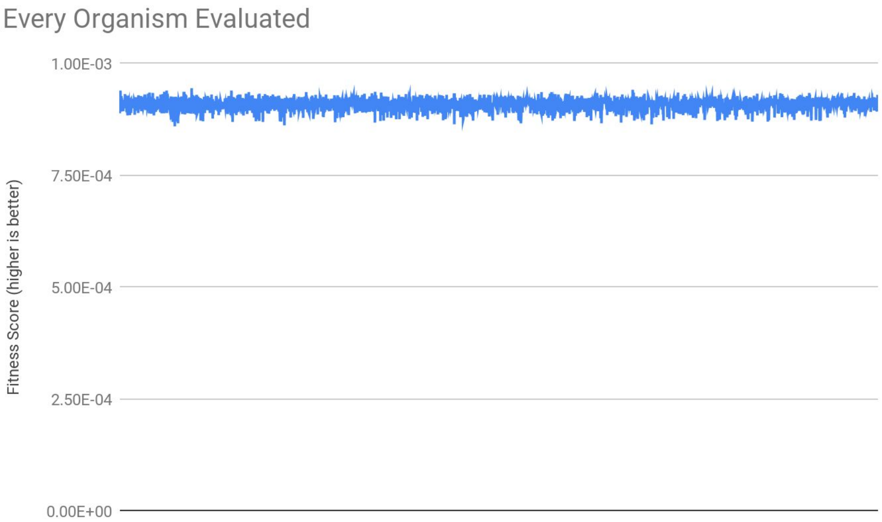
Results

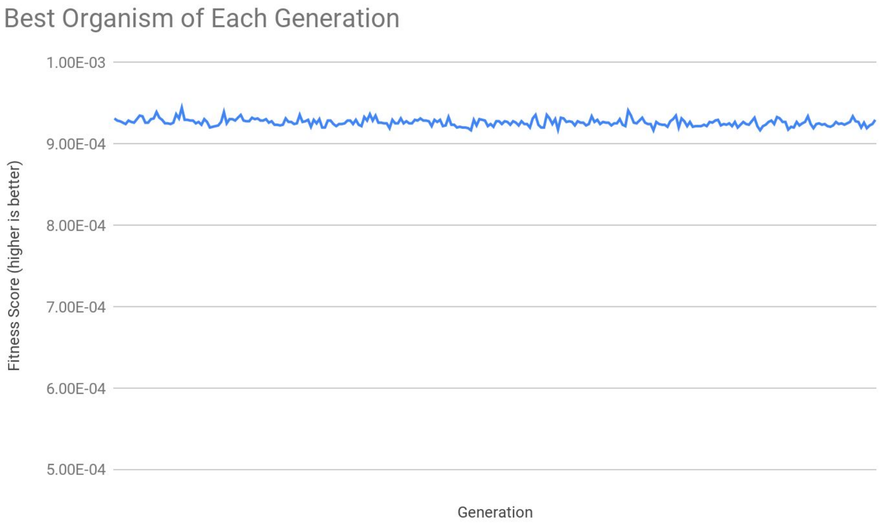
The Experiment

- **Population Size = 12**
- **Warmups = 12**
- **Benchmarks**
  - "dacapo:lusearch"
  - "dacapo:jython"
  - "dacapo:pmd"
  - "dacapo:avrora"
  - "dacapo:luindex"
  - "dacapo:sunflow"
  - "dacapo:xalan"
  - "dacapo:fop"

The Outcome

Ran for ~271 Generations before kill





The Secondary Experiment

Something Faster.

Optimize for only a single benchmark, reduce warm up runs.

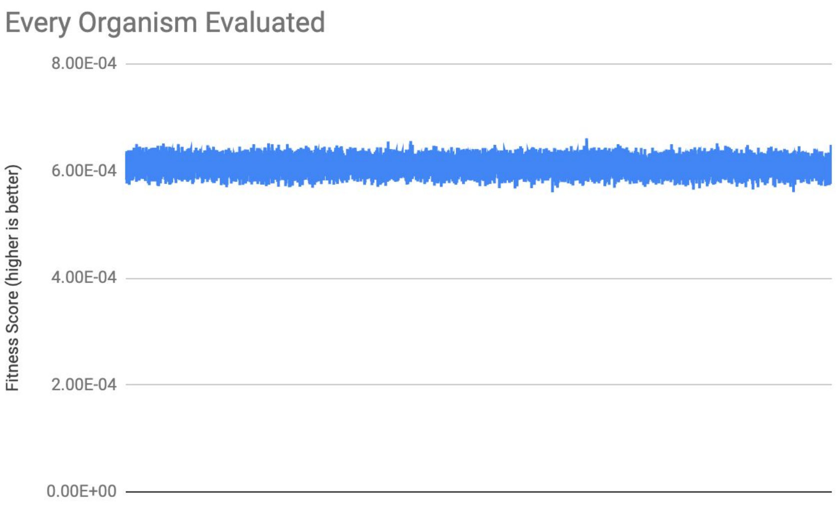
Only Benchmark = dacapo:pmd

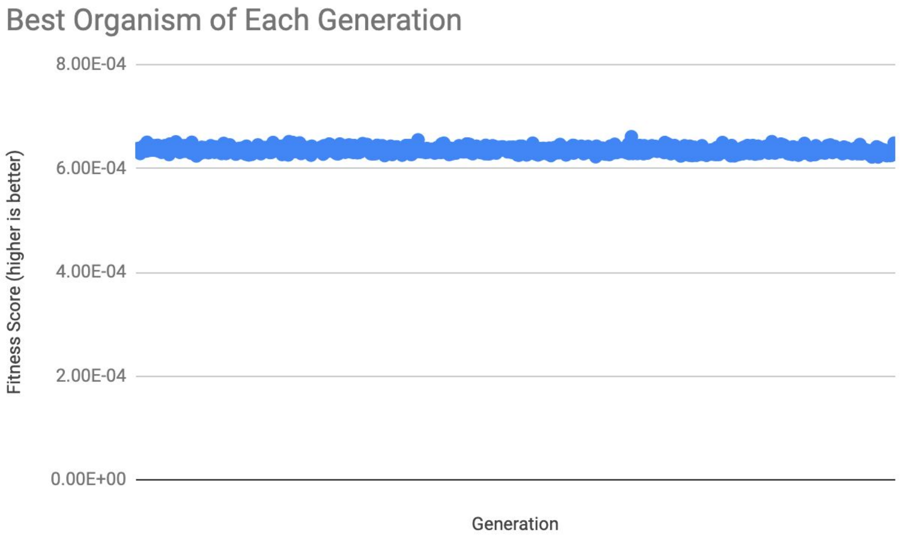
Why? Demonstrated variance between policies

Warmups = 6

The Secondary Outcome

Ran for 1000 Generations





What Happened?

- **No significant improvements over the generations**
- **Theory: Maybe inlining policies don't matter?**
  - Unlikely, running these benchmarks with varying policies led to large differences in running time
  - E.g. for dacapo:pmd –
    - never inline - 910ms
    - always inline - 1515ms
    - default graal - 301ms
- **Theory: Search is not wide enough**
  - Mutation rate was manually increased over default
  - Could use further experimentation

What Happened?

- **Theory: Network Sensitivity**
  - Generally, near the beginning the networks do not seem to be sensitive to inputs, thus essentially always being always-inline or never-inline
  - Investigate input normalization, mutation rates, binarization
- **Theory: NEAT isn’t suited for this**
  - Doug Simon et al. says otherwise
  - The other theories are credible enough to merit further investigation before this
- **Theory: Implementation Bugs**
  - NEAT program is able to solve other problems
  - Further testing

Future Work & Potential Improvements

- **Workload Testing**
  - Create/Use benchmark that models different Twitter workloads
- **Experimental**
  - Mutation
  - Binarization
  - Input normalization
  - Testing
- **Parallelism**
  - Evaluate organisms simultaneously
- **Other Applications**
  - Autovectorization

Applicability

- **Heuristics/Policies are everywhere**
- **In a compiler alone,**
  - Instruction selection
  - Register allocation
  - Instruction scheduling
  - Software pipelining
- **NEAT could help**
- **Investing in this work could mean returns in many different areas**
  - Anywhere decisions need to be made using a policy

Addendum: Reinforcement Learning

- **RL used for Go, Chess, Robotics, Chemistry**
- **Agent, Environment, Reward**
- **Network is Agent, Benchmark is Environment, Running Time is Reward**
- **RL Literature/Techniques may be applicable to Inlining & other optimizations**
    - Q Learning
    - Actor-Critic Model
    - Deep Deterministic Policy Gradient