Analysis of Ancestry in Genetic Programming with a Graph Database

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The Big Picture

- The power of graph databases: analyzing internal data of GP
- ???????????
- Even fewer allow for plasticity during development????
- N-gram GP has natural developmental phase?????
- Can we find useful information about runs?

Bluedrakon
http://tr.im/pWUi

Outline

1. Genetic Programming
2. Graph Database
3. Experimental Setup
4. Results
5. Conclusions

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1. Genetic Programming
    - GP Overview
    - Symbolic Regression and Fitness
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Genetic Programming Overview

- Genetic Programmings is based upon biological principles.
- Individuals form a population.
- Transformations
  - Crossover (XO): sexual reproduction (root and non-root)
  - Mutation: subtrees altered
  - Reproduction: asexual reproduction
  - Elitism: reproduction based on fitness
- Transformations occur over a specified amount of generations.
- Individuals are rated by their fitness.

Sam Fraser-Smith
http://tr.im/pq7l

Symbolic Regression and Fitness

We are focusing on symbolic regression problems.

- Measured data fitted to mathematical formula.
- Collection of test points to evolve individuals.

Fitness determines individual's distance from target function.

- Lower the fitness, the better the individual.
- A zero fitness would exactly match test data.
- Anything else to add??????????

The goal of GP is to evolve an individual with a fitness as low as possible.

Outline

Neo4j

Neo4j is a graph database.

- Relatively new tool (initial release 2007 popularized in 2010).
- Information is stored like a graph.
- Nodes and relationships.
- Efficient recursive queries.

Cypher

Neo4j's query language is Cypher.

Fundamental elements of Cypher queries:

- START
- RETURN
- MATCH
- WHERE

Outline

Run Configurations

nction	sin(x)
iables	x (range from 0.0 to 6.2, incremented by steps of 0.1)
stants	range between -5.0 and 5.0
ations	addition (+), subtraction (-), multiplication (*), protected division (/)
umber	100
ration	1000 (6 runs) and 10000 (1 run)
tages	Crossover (90%), Mutation (1%), Reproduction (9%)
Elitism	best 1%

Methods

itness Absolute error between target function and individual function.

PTC2 Randomly adds operators to array of specified length (empty slots for arguments where appropriate). Empty slots divided between variables (63%) and constants (37%).

 Type Subtree Mutation

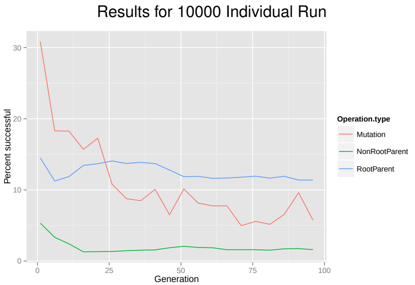
Outline

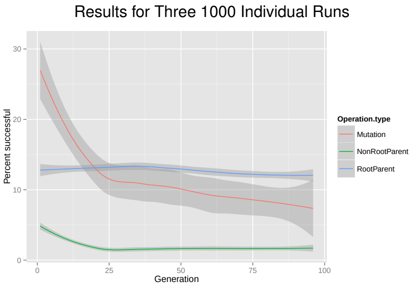
Questions Asked

1. *How often do mutations improve fitness? Also, how often do crossovers improve fitness, where the root parent is more fit than the non-root parent, and vice versa?*
2.
3. *Do a group of individuals have a common root parent ancestor and what is the latest generation where such an ancestor occurs?*
4. *How many individuals in the initial generation have any root parent descendants in the final generation?*

Percentage of Improved Transformations

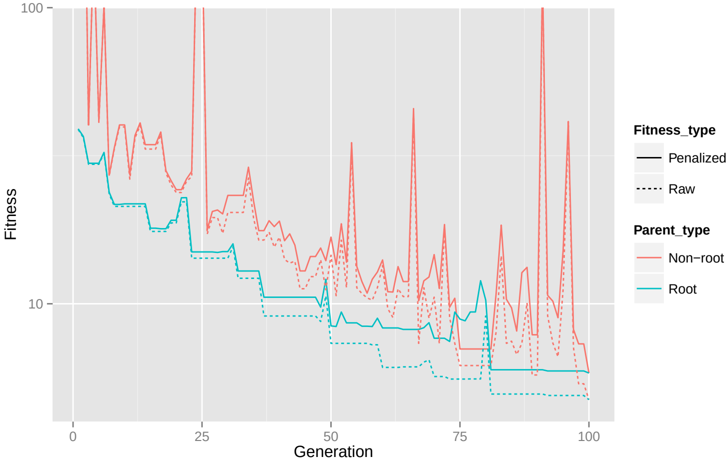
How often do mutations and crossovers improve fitness?





Fitness Over Time

What does the fitness of the “winning” root parent ancestry line look like over time?



Empirical comparison of IFD, N-gram GP, & TinyGP

Compare IFD, regular N-gram GP, and standard sub-tree XO GP (TinyGP)

- 11 different symbolic regression problems
- 100 independent runs for each system + problem + parameter set
- Various parameter settings (e.g., different block sizes)

2 register machine with $+$, $-$, $\times$, protected division, and swap

Normalize the clock:

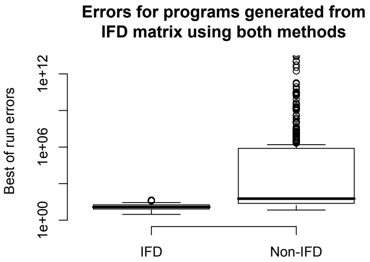
- Count instruction executions
- Allow 50M instruction evaluations per run
- Store machine state so only new block has to be executed in IFD

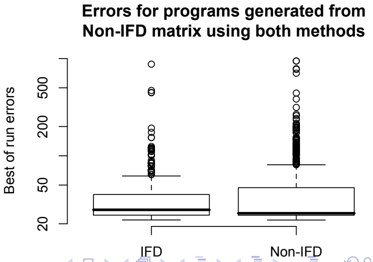
Success rates on 11 test problems

Label	Function	TinyGP	N-gram	IFD
		Successes out of 100 runs		
P1	$x + x^2 + x^3 + x^4 + x^5$	100	100	100
P2	$-x - 2x^2 + x^3$	100	100	100
P3	$1.009 + 1.419x + x^2$	100	61	100
P4	$6 + x^2 + 3x^3 + 8x^5$	0	0	0
P5	6	100	100	100
P6	$6 + x^2$	100	10	94
P7	$6 + x^2 + 3x^3$	85	0	1
P8	$8x^5$	100	100	100
P9	$3x^3 + 8x^5$	22	55	100
P10	$x^2 + 3x^3 + 8x^5$	100	7	80
Sine	$sin(x)$	0	1	63

IFD wins either way

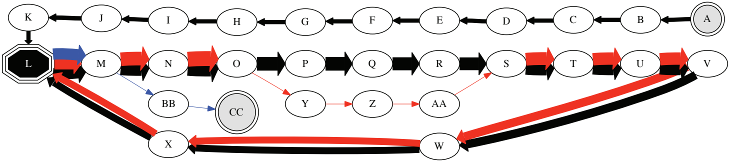
- IFD generates low-error individuals from tables evolved with IFD **and without IFD**.
- IFD's local search is valuable in all phases of the process, even if it wasn't used previously.
- N-gram GP isn't able to work effectively with the more complex probability tables that IFD generates.



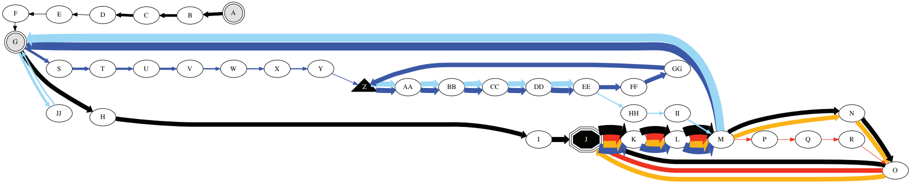


Structural differences and modularity

Standard N-gram GP tends to converge to a small set of loops with high probability edges.



With IFD there is less convergence, more variety and complexity in the modular structure, & greater use of low probability edges.



Outline

Conclusions

- Added developmental plasticity to N-gram GP using Incremental Fitness-based Development (IFD).
- IFD consistently improved N-gram GP performance on suite of test problems.
- "Knocking out" IFD shows it's valuable in all phases, even if it wasn't used earlier in a run.
- IFD generates more complex, less converged probability tables.
- IFD generates more modules/loops & uses more low-probability paths.
- Currently exploring applications to dynamic environments.

Thanks!

Thank you for your time and attention!

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Questions?

References

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See the GECCO '09 paper for additional references.