Analysis of Ancestry in Genetic Programming with a Graph Database

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The Big Picture

- Genetic programming (GP) demonstrably works.
- Difficult to determine how this process works.
- Databases allow examination of the internal interactions of a run.
- Graph databases more efficient for this task than relational DBs.
- Analysis may allow us to improve GP tools.

Outline

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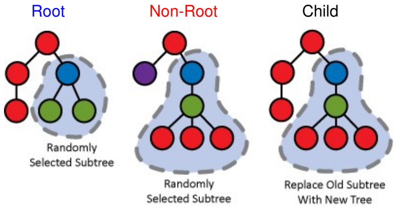
Transformations and genealogical history

Crossover sexual reproduction (root and non-root)

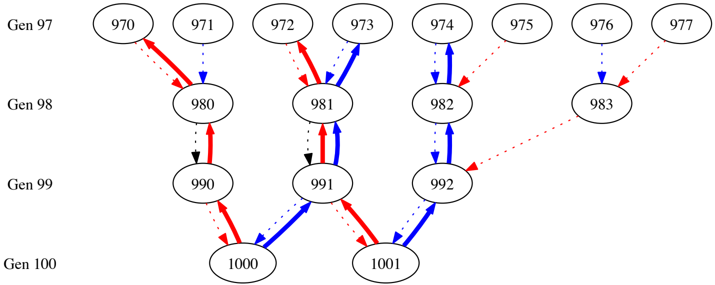
Mutation subtrees altered

Reproduction asexual reproduction

Elitism reproduction based on fitness



geneticprogramming.us

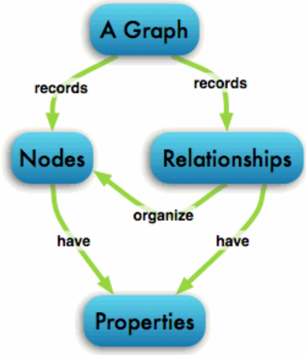


Outline

Neo4j

Neo4j is a graph database.

- Relatively new tool
    - Initial release 2007
    - V1.0 in 2010, V2.0 last December
- Information is stored using a graph consisting of nodes and relationships
- Efficient recursive queries compared with traditional databases



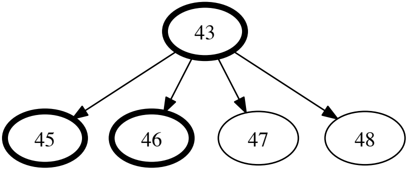
Neo4j `http://goo.gl/nzRWSV`

Cypher

Neo4j's query language is Cypher.

Fundamental elements of Cypher queries:

- START
- MATCH
- WHERE
- RETURN



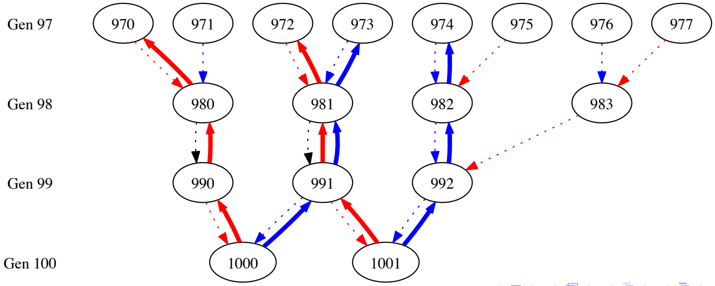
START parent=node(43)
MATCH (parent)-[:PARENTOF]->(child)
WHERE id(child) < 47
RETURN parent, child;

DB setup

We store:

- Individuals as nodes + data, e..g, program, fitness, generation
- XO, mutation, replication events as edges between nodes

Different edge types indicate relationship types, e.g., *ROOT_PARENT* edge from 991 to 1000 says 991 is the root-parent of 1000.



Finding the “winning” fitness and individual

Finding the minimal fitness across all individuals (nodes) in the DB:

```
start n=node(*)
return min(n.penalizedFitness);
```

Finding one (arbitrary) “winning” individual:

```
start n=node(*)
return n
order by n.penalizedFitness
limit 1;
```

These are not unlike queries in relational databases.

Ancestry of an individual (hard for relational DBs)

Find all the root ancestors of individual 99,000:

```
start n=node(99000)
match ps =
(n)<-[r:ELITISM|PARENTOF|ROOT_XOOF|MUTANTOF*]-(p)
return distinct ps;
```

Find the fitness of all the root ancestors of individual 99,000:

```
start n=node(99000)
match ps =
(n)<-[:ELITISM|PARENTOF|ROOT_XOOF|MUTANTOF*]-(p)
where p.generation=1
return extract(x in nodes(ps) | x.fitness);
```

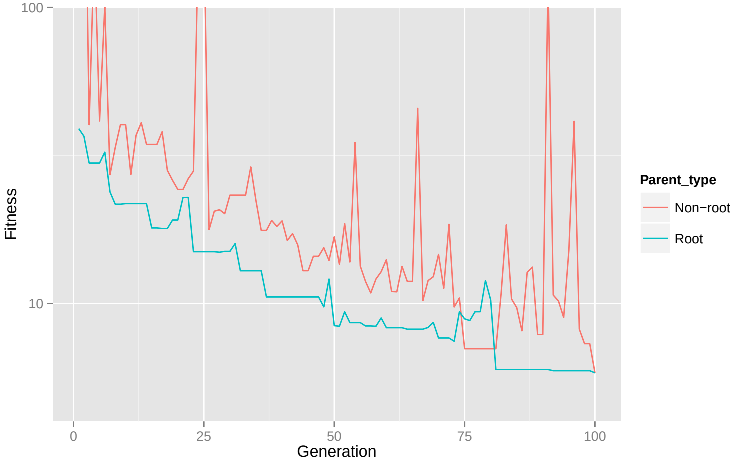
Outline

A few questions

1. What does the fitness of the “winning” individual’s ancestry line look like over time?
2. How often does mutation improve fitness? Also, how often does crossover improve fitness, where the root parent is more fit than the non-root parent, and vice versa?
3. Does 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?

Fitness Over Time

What does the fitness of the “winning” individual’s ancestry line look like over time?



Percentage of Improved Transformations

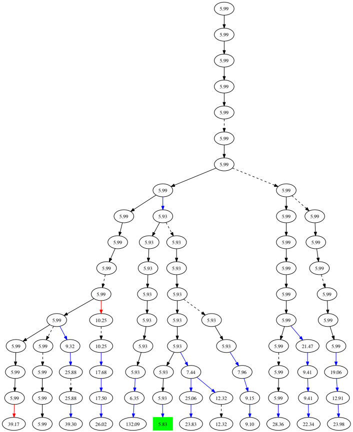
How often do mutation and crossover improve fitness?

Common Ancestor

How far back to a common root parent ancestor? How many initial generation individuals have descendants in the final generation?

In run w/ 10K individuals for 100 gens:

- Final pop consists of 2 clades
- One clade *strongly* dominates (only 24 left in small clade)
- Each clade root-descends from single individual in initial population



Outline

Conclusions

Conclusions

- We can collect & extract useful data about evolutionary dynamics
- More detailed analysis that moves beyond statistical summaries
- Suggests interesting avenues to explore
  - Importance of having root parent be more fit
  - Changing role of mutation over the life of a run
  - Potential for clades/quasi-species and their impact

Future Work

- Enforcing the root parent to have better fitness in XO
- Exploring equivalents in other EC systems (e.g., Push)

Thanks!

Thank you for your time and attention!

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- Paper: https://github.com/NicMcPhee/MICS-2014-GraphDB-EC

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Questions?

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Run Configurations

Target Function	sin(x)
Variables	x (range 0.0 to 6.2, incremented by steps of 0.1)
Constants	range between -5.0 and 5.0
Operations	addition (+), subtraction (-), multiplication (*), protected division (/)
Generation Number	100
Population Size Per Gen	1,000 (3 runs) and 10,000 (1 run)
Transform Percentages	crossover (90%), mutation (1%), reproduction (9%)
Elitism	best 1%
Fitness	absolute error between target function and individual function