Open Issues in Genetic Programming

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Tutorial Outline

- Introduction & Motivation
- Open Issues in GP
- Questions & Discussion

Introduction & Motivation

O'Neill M., Vanneschi L., Gustafon S., Banzhaf W. (2010).
Open Issues in Genetic Programming.
Genetic Programming and Evolvable Machines 11(3-4):339-363
http://www.springerlink.com/content/a058142636361453/fulltext.pdf

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Introduction

- GP in 30 seconds
- Why isn't GP more popular?
- Some stats & interesting results
- Historic time for GP with rise of Data Science
- Objective of tutorial
    - Identify roadblocks
    - Suggest future areas of research

GP in 30 Seconds

- Method for modeling data or learning behavior - regression models or robot control

Generate New Solutions w/ bias*

Data & Params

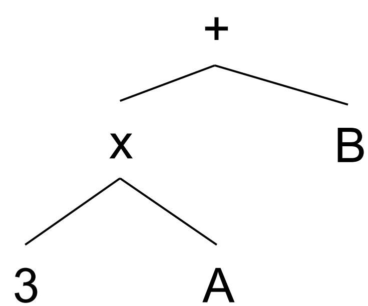
Output best “solution”

Evaluate and Rank Solutions

* First set of solutions usually “randomly” created

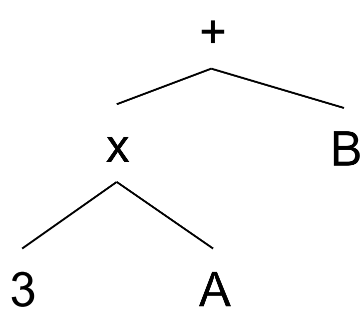
GP in 30 Seconds

- Search over solution structure & parameters



GP in 30 Seconds

- Input way of measuring success

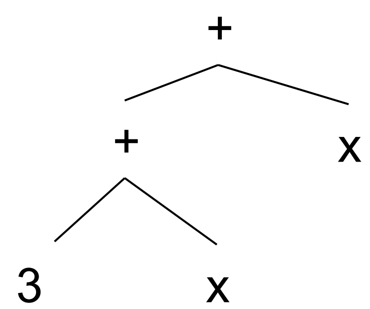


Solution A

Y	x	Solution A result
7	2	7
1	3	9
0	1	5
4	6	15

GP in 30 Seconds

- Input things a solution are built out of



% * sin() 3.14 7 9 x^(t-1)

GP in 30 Seconds

- Decide when to stop

After so many solutions sample

After no new good solutions found

After a solution of a given quality is found

Why Open Issues? Who cares?

- It is pretty popular!

- Publications, Conferences, Results in broad fields
  - Bioinformatics
  - Regression modeling
  - Robotics, and many others! (we've been to space!) ?

- How to raise the bar?
- Stochastic methods are often second choice due to lack of theory and predictable space, time complexity

Why Open Issues? Who cares?

- And… good for the community to step back and think where we need help

- And… we are at a historic time…

Historic time with Data Science

- Software, data and analytics driving new revolution in Industry, Gov't and Society!
- Data science postings and tools exploding
- Lipson named an Influential data science by a Forbes study due to GP work (Science paper)
- Data science right in GP best (SG's opinion) application: symbolic regression!

Historic time with Robots

- DARPA Humanoid challenge
- Human assisted bots (please clean my house)
- Advanced manufacturing
- More controls and cybernetics than we “probably” can scale in current way

Objective of Tutorial

- Identify and discuss issues
- Suggest possible new research areas
- Interaction and discussion

- As long members of community, we feel a bit like GP-startup-employees, we want it to succeed! Help us make it succeed!

Open Issues

1. Generalization STEVE
2. Complexity STEVE
3. Representations MIKE
4. Modularity   MIKE
5. Dynamic problems MIKE
6. Open-ended evolution MIKE
7. Fitness landscapes and problem difficulty LEO
8. Semantics LEO
9. Influence of Biology WOLFGANG
10. Benchmarks LEO

#1 Generalization

- What do we mean?
- How is it different than other ML methods?
- What can we do?

Generalization – What?

- Given a domain, we solve instances using GP
- The resulting model performs well over those instances
- Did we sample the space well? Will new data surprise us?
- Also, in practice, data ‘drifts’ and changes over time… will the GP model perform well?

Generalization – Different?

- Nope, not at all!
- All data driven methods suffer from this
- How do find a model that best represents the “true” underlying thing that generates the data?

- Unscientific evidence suggests a lot of GP papers do not adequately address this… why?

Generalization – Different?

- Asymmetrical data/algorithm in GP
- GP requires a lot of algorithm prep work, more than say a Random Forest or Neural Net
- Also, GP is often applied in data starved areas (robot control) or particularly challenging problems (nonlinear model)
- Does that effort, combined with higher computational cost, lead to lack of rigor with generalization?

Generalization – Different?

- Another difference…
- GP finds models and parameters that “can” be inspected
- Easier path to domain subject matter expert acceptance
- Easier transport of models to other environments… if (a big if) no tricks inside evaluation
- Compare to Random Forest, Neural Net, etc

Generalization - How

- Good problem setup
  - Train, test, validation and data processing
- Thoughtful objective function creation
  - No tricks or shortcuts, should be real-world like
- Good honest empirical evaluation
  - Significant, meaningful and SME validated
- After that, same as all other supervised ML
  - Put ‘control system’ around to monitor drift, etc.

Generalization – Next Steps

- More research into generalization significance, is asymmetric problem real?
- More research into solution simplification for SME validation and model transport
- More rigor in reviewing… one problem, one instance does make interesting results!
- What else?
- Questions?

Further Reading

- Kushchu, I. An evaluation of evolutionary generalization in genetic programming. Artificial Intelligence Review 18, 1 (2002), 3–14. Nice introduction, overview and example.
- Gagne, C., Schoenauer, M., Parizeau, M., and Tomassini, M. Genetic programming, validation sets, and parsimony pressure. In EuroGP2006. Using train,test,validation data plus complexity pressure was best.

#2 The Complexity of GP

- Not run time, although related
- Complexity of user experience and implementation
- How do we make it simpler out of the box?

Complexity – Run time

- Heuristic search method, slow
- Search over structure and parameters, slow
- Dependent on an evaluation function, slow
- Usually requires solution ‘compile’, slow

- In terms of algorithm complexity, no magic bullets, but many opportunities for improving
- … come back to this… but

Complexity – of GP

- How to make it simpler… what do we mean
- For example, some of the decision points
  - Functions, terminals
  - Objective function
  - Initialization
  - Operators
  - Selection pressure and operators
  - Bloat / size pressures
  - Stopping criterion
  - Oh, and generalization setup!

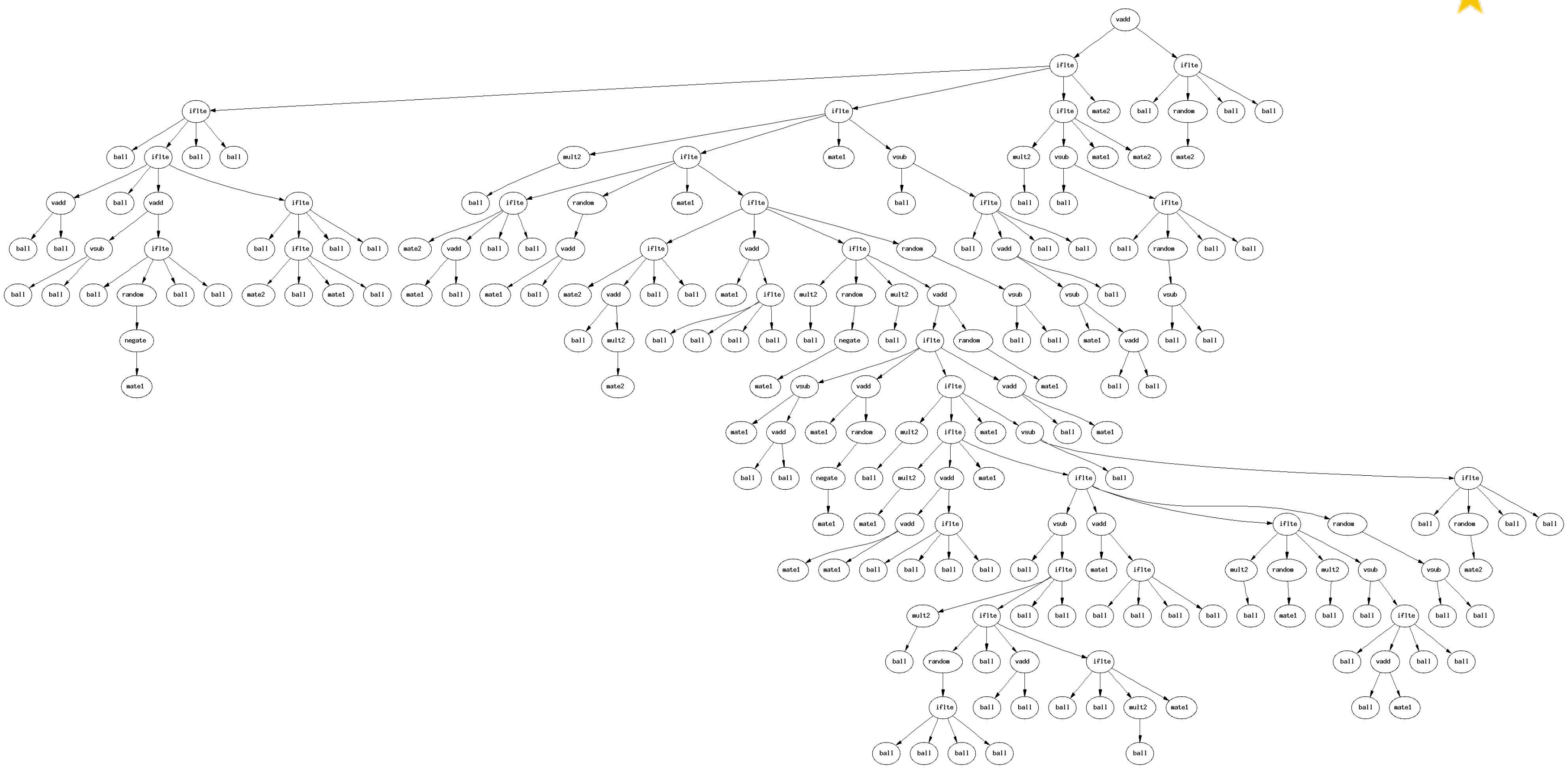
Complexity – of GP and more

- Within each decision, even more
  - Operators: interactions and mix
  - Selection pressure: replacement, archives, etc
- What is a minimal, viable GP algorithm?
  - Koza is still most often cited
  - Should it be by domain… GP-SR, GP-robot, etc
- Or, do we do meta-GP, add more algorithm complexity for simpler User Experience?

Complexity – One more thing

- Model interpretation is big benefit
- However, complexity of solutions high (big trees)
- Given a solution, which is product of evolution, i.e. non-”efficient” search, how to minimize with performance tradeoffs
- Should it be a post-search add-on or handled with Pareto archives, multi-objective, bloat / complexity control?

Complexity – One more thing



Complexity – Next Steps

- Research on simplification, approximations and Knowledge Extraction
- Research into Minimal, Viable GP (not smallest code base!)
- … and a canonical paper (not Koza '92)
- … that could be YOU!
- Research into VERY FAST systems… cloud, GPU, whatever… automating search can only help! (plug for MIT+GE work)

Further Reading

- Meta-learning – evolve an GP with a EA/GP, search parameter space
- Bloat, growth control – find least complex solutions
- Tiny GP competition and results
- GP-like alternatives: Hill-climbing like search (Poli and Langdon book, others), Incremental Program induction (Schmidhuber), others

#3 Representations

- **Identifying appropriate representations for GP**

  …..ideally based on some measure(s) of quality that capture the relationship between the fitness landscape and the search process.

Difficulty of Representation

- Hard to impossible to identify an optimal GP representation

- …but given a better understanding of the relationship between representation and search, differentiation between alternatives may be possible.

What’s a Representation?

❖ Representation = “genetic” encoding + “genetic” operators

Representation for GP

- Individual **is** *OR* **represents/encodes** a program

```
#include <stdio.h>
#include <stdlib.h>
#include <math.h>

int main(int argc, char* argv){
        float x=0.0, y=0.0, z=0.0;
        x=atof(argv[1]);
        y=atof(argv[2]);
        z=atof(argv[3]);
        x = 2.0*sin(y) + 4.0*sin(x);
        z = (x*x) + exp(z);
        printf("The answer is: z=%f\n",z);
        return(0);
}
```

```
#include <stdio.h>
#include <stdlib.h>
#include <math.h>

void turnLeft(float degrees);
void turnRight(float degrees);
void moveForward(float distance);

int main(int argc, char* argv){
        turnLeft(90);
        if(sensorValue(0) > 1000)
                moveForward(10);
        else
                turnRight(90);
        return(0);
}
```

Attributes of GP

"Tell the computer what to do, not how to do it."

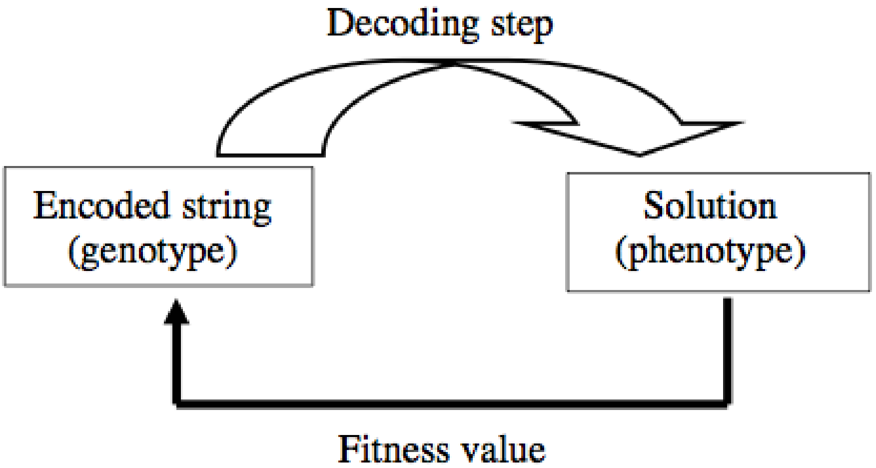
Arthur Samuel, 1959

John Koza's (1999) AP Attributes…

- Start with **high-level problem description** that results in a solution in the form of a computer program
- Automatically determine the programs **size and architecture**
- Automatically organise a group of **instructions** so that they may be **re-used** by a program
- **Problem-independence**
- **Scalability** to larger versions of the same problem
- Capability of producing **human competitive results**
- Evolutionary Automatic Programming/Genetic Programming…

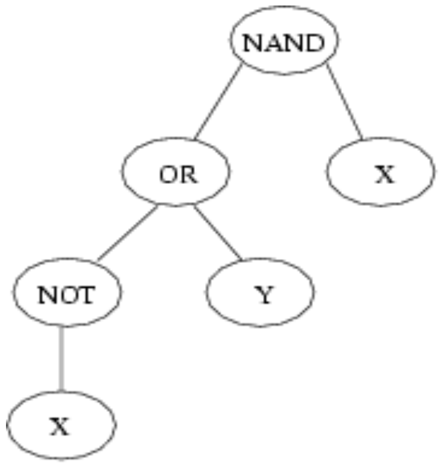
Many Representations for GP

- machine code, FSA, trees, strongly-typed, graph, linear, linear-graph, grammars, generative/developmental…



“Vanilla” GP

Koza popularised Lisp S-expressions…



(NAND (OR (NOT X) Y) X)

- Expressions (trees) generated from
  - Function Set: boolean, arithmetic, loops, user-defined functions…
  - Terminal Set: inputs, constants, variables, …

“Vanilla” GP Features

Sufficiency

- Function+Terminal sets: powerful enough to represent a solution

Parsimony

- Smaller Function+Terminal sets are better

Closure

- Each function should gracefully handle all values it ever receives
- (/ 5 0) !?!

Evolving Representation!

❖ Why not "evolve it"!?!?

❖ Examples include…
- Langdon's Data Structures
- Spector's "Autoconstructive" Evolution
- Banzhaf's Evolution of "genetic code"
- ?Hyperheuristics

Representation Open Issues

- What is the best representation for my problem?
  - computationally "sufficient"
  - facilitate navigation (e.g., see Semantic Operators later)
  - automatically identify and manipulate abstractions/modules
  - handle variable dimensions…
- How do we compare representations?
  - E.g., locality, redundancy and scaling
- Need more rigorous/formal analysis…

Representation Open Issues

- What ever happened to evolving algorithms?

#4 Modularity & Scalable GP

- Define a clear measure of success for what it means to achieve "Scalable GP" as well as modularity
- How well does GP scale to problems of increasing complexity/difficulty?
- How can we improve scalability of GP?
- Given representations in GP can evolve, what is scalability in GP anyway?

Approaches to Modularity

- Many approaches…
  - E.g., ADF's, architecture-altering operators (Koza), Genetic Library Builder (GLiB - Angeline & Pollack), Adaptive Representation through Learning (Rosca), Automatically defined macros (Spector), reuse of "concepts" (Seront), lambda abstraction (Yu), linear-gp register reuse & repeated patterns (Langdon & Banzhaf), module repository (Majeed & Ryan), sub-graph encapsulation (Walker & Miller), Run Transferable Libraries (Keijzer et al), functional modularity (Krawiec & Wieloch), grammar-defined functions (O'Neill, Hemberg, Harper, Swafford), Swafford PhD thesis (2013)

Modularity & Evolution

- Modularity & Evolvability (Altenberg)…modularity may have positive effect on “alignment” between spaces of phenotypic variation and selection gradients

- Evidence for dynamic environments leading to emergent modularity (Kashtan)

Modularity

- Mechanism to
  - protect parts of individuals from disruption
  - achieve abstraction and parameterisation

- What's the best way to
  - automatically **identify** modules?
  - achieve automatic **abstraction**
  - achieve automatic **manipulation** of modules
    - E.g., architecture altering operators

- Is modularity critical to scalability?
- How are modules used? Can their use guide search operators?

- Can we achieve modularity, hierarchy and reuse in a more principled manner? (e.g., software eng – or should we even consider these human-centric approaches?)

#5 Dynamic Problems

- The "natural environment" for artificial evolution.
- Dynamic in so many ways:
  - Type of change (e.g., constraints, fitness landscape, combinations)
  - Degree
  - Frequency
  - Combinations of all of the above!
- Mind-shift from optimisation to "survival"

Dynamic Problems with GP

- Can borrow strategies from broader EC literature
  - E.g., Branke (2001) and Morrison (2004)

- GP inherently dynamic!
  - Co-evolving
    - Structure
    - Parameters
  - Dimensionally dynamic!

Dynamic Problems – lots to do!

- Little formal analysis of GP in dynamic env's
  - E.g., Bloat - Langdon & Poli (1998), population sizing - Tu & Banzhaf (2009) & Vanneschi (2009), constant evolution – time series - Dempsey (2009)

- Recall (Kasthan) emergent modularity
  - Also, dynamic environments can provide more efficient search
  - some evidence for GP in specific cases (O'Neill)

#6 Open-ended Evolution

- Designing an evolutionary system capable of continuously adapting and searching…(can also mean un-directed search)

- Essential
  - Feedback loops
    - Dynamic environment
    - Co-evolutionary processes
  - Continuously injected randomness

#6 Open-ended Evolution

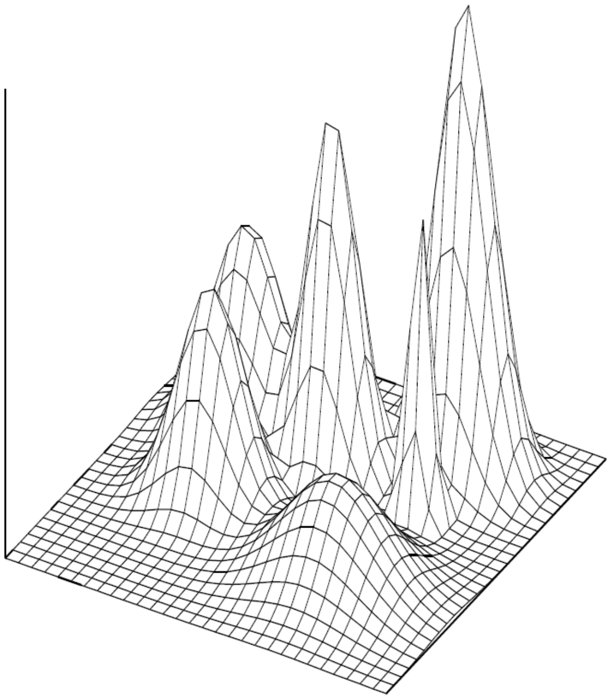
- EC & ALife have failed!
  - What are the missing ingredients for artificial evolution to achieve the open-ended emergence of complexity, innovation and adaptation witnessed in nature?

#7 Fitness Landscapes and Problem Difficulty in GP

Fitness Landscape

Fitness landscape $(\mathcal{S}, \mathcal{V}, f)$:

- $\mathcal{S}$: set of potential solutions,
- $\mathcal{V} : \mathcal{S} \rightarrow 2^{\mathcal{S}}$: neighborhood function,
- $f : \mathcal{S} \rightarrow \mathbb{R}$: fitness function.



$\mathcal{V} : \mathcal{S} \rightarrow 2^{\mathcal{S}}$: neighborhood function

$\forall x \in \mathcal{S}$,

$$\mathcal{V}(x) = \{y \in \mathcal{S} \mid y = op(x)\}$$

$$\mathcal{V}(x) = \{y \in \mathcal{S} \mid d(y, x) \leq 1\}$$

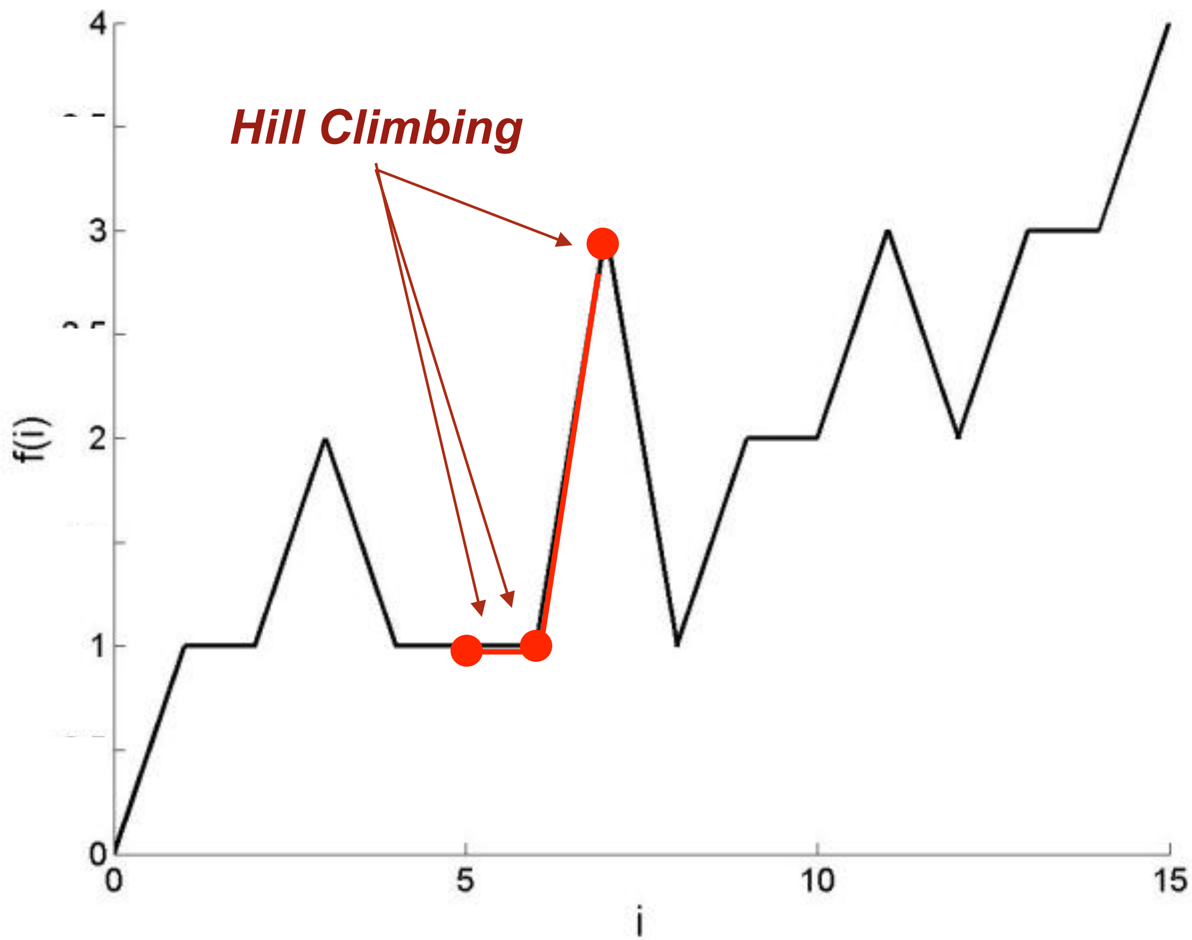
Example

$S = \{ i \mid \quad i \in \mathbb{N} \quad \& \quad 0 \leq i \leq 15 \}$

$\forall i \in S, \quad f(i)$ = number of "1"s in the binary representation of i

Neighborhood: $\quad j \in N_i \Leftrightarrow |j - i| = 1$

Fitness Landscape



Remark that...

if we consider exactly the same problem, but with a ***different neighborhood structure***:

$S = \{ i \mid \quad i \in \mathbb{N} \quad \& \quad 0 \leq i \leq 15 \}$

$\forall i \in S, \quad f(i)$ = number of "1"s in the binary representation of i

Neighborhood: $j \in N_i \Leftrightarrow j$ and i differ by just 1 bit

There are ***no local optima*** in this fitness landscape!
(every individual that is different from the global optimum has at least one neighbor better than him, that can be obtained by changing a 0 into a 1).

Another Case ("CONO" Problem)

S = { vectors of prefixed length of real numbers included in [0,10] }

$\forall\, i \in S$, $f(i)$ = distance to a prefixed (and known and unique) global optimum

Neighborhood: $j \in N_i \Leftrightarrow$ *j is equal to i except for the random perturbation of some of its coordinates of a quantity included in [0,1].*

Example

The global optimum → [8.0, 6.0, 4.0, 7.0, 5.0]

A solution i → [5.2, 6.4, 2.1, 4.9, 3.7]

A solution j neighbor of i → [5.8, 6.4, 2.9, 4.9, 3.6]

closer!

Unimodal Fitness Landscape

Importance of Fitness Landscape

It gives a *visual intuition* of the *facility* or *difficulty* of a search agent (like Hill Climbing, but also Evolutionary Algorithms) ***to find the global optimum***.

- Smooth landscape, with only one "peak" (global optimum)
  easy problem
- Rugged landscape, with many local optima
  hard problem

Limitation of fitness landscapes

It is generally ***impossible to draw*** a fitness landscape:

- Huge search space
- Huge neighborhoods *(multi-dimensionality!)*

Objective of Problem Hardness Studies

Find indicators of problem hardness (that typically capture some important characteristics of the fitness landscape and) that can give insight on the ability of a GP configuration to solve the problem....

- Without having to run GP
- Without having to draw the fitness landscape

Autocorrelation [Kinnear, 1994]

Proposed measure of problem hardness for GP: ***autocorrelation function*** (Weinberg in 1990 and Manderick in 1991 had studied the same measure for GAs).

Autocorrelation of $(f(s_1), f(s_2), \ldots)$ along a random walk $(s_1, s_2, \ldots)$ (Weinberger 1990 [29]) :

$$\rho(n) = \frac{E[(f(s_i) - \bar{f})(f(s_{i+n}) - \bar{f})]}{var(f(s_i))}$$

autocorrelation length $\tau = \frac{1}{\rho(1)}$

- small τ : rugged landscape
- long τ : smooth landscape

Basically no clear relationship between autocorrelation values and problem hardness was observed for GP

Difficulty and Neutrality [T. Yu, J. Miller 2001]

Larger amount of neutrality allow GP to generate fitter individuals, in particular for hard problems

(results criticized in [Collins, 2005])

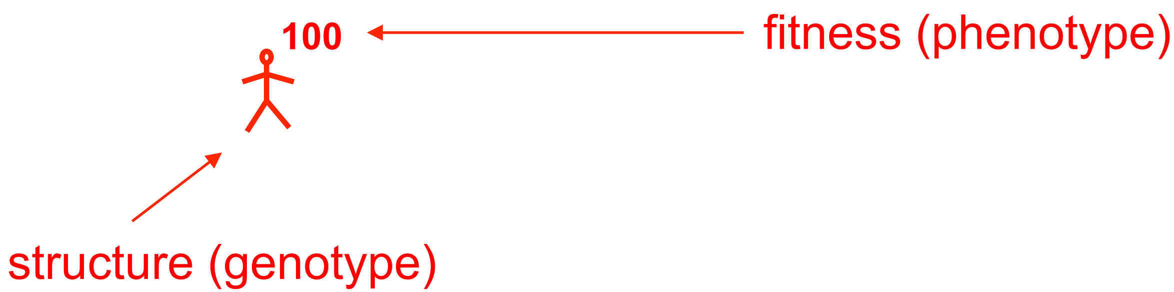
Fitness-Distance Correlation (fdc)

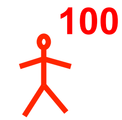
(Introduced in [Jones et al., 1995] for GAs)

Hypothesis: what makes a problem *easy* or *hard* is the ***relationship*** between ***fitness*** of individuals and the ***structural similarity*** of individuals to the optimum.

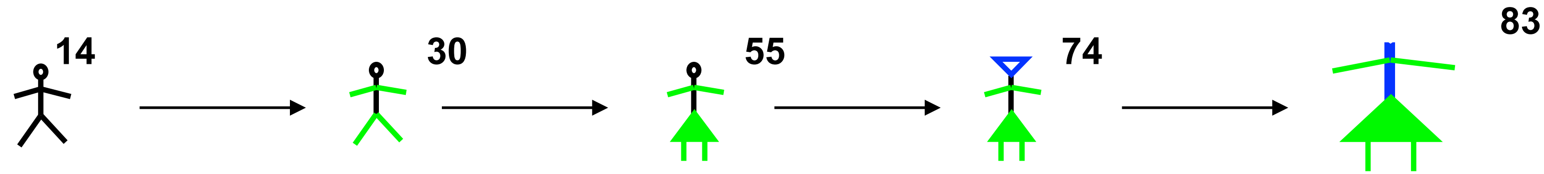
Example

Let's suppose that the global optimum is:



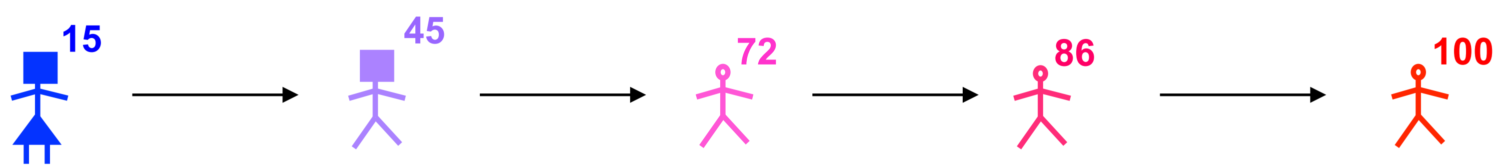
optimum = 

Difficult Problem



the more fitness increases (improves), the more individuals are <u>different</u> from the optimum

Easy Problems



the more fitness increases (improves), the more individuals are <u>similar</u> to the optimum

Fitness Distance Correlation (*fdc*) *[T. Jones, 1995]*

Given a sample of *n* individuals, let's suppose to know:

- the set $F = \{f_1, f_2, \ldots, f_n\}$ of the individual fitnesses
- the genotype of the global optimum (individual with the best fitness)
- a measure to express the genotypic distance between individuals

Let $D = \{d_1, d_2, \ldots, d_n\}$ be the *n* distances to the global optimum, then

fdc* is the correlation between sets *F* and *D

Summary of the Results obtained by *fdc* in GP [Vanneschi et al., 2004]

Fdc is a ***very reliable*** measure of difficulty for a large set of problems.

Fdc also has some drawbacks:

- Counterexamples exist
- It is not predictive

  Optima must be known « a priori »
  (this makes fdc « almost» unusable in practice)

A new measure must be defkned to quantify the difficulty of real-life problems.

A measure that has been proposed is based on the concept of ***fitness cloud.***

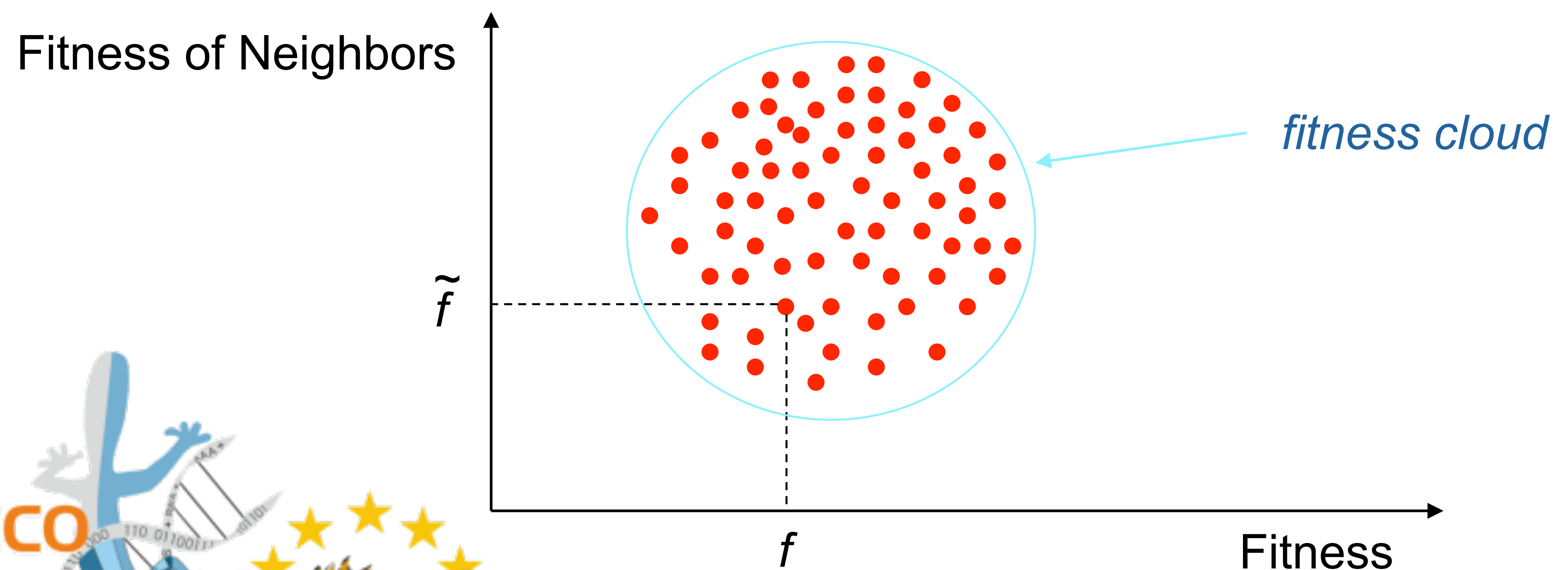
Fitness Clouds

(First introduced for binary landscapes in [Vérel et al., 2003])

For each individual γ (in a sample or in the whole search space) a point is plotted:

- **abscissa** = fitness value of γ
- **ordinate** = fitness value of a "particular" neighbor (chosen randomly or by some particular techniques).

here: *neighbor = individual obtained by applying <u>one step of mutation</u> to* γ



Negative Slope Coefficient (nsc) [Vanneschi et al., 2004]
Summary of results

- Good hardness indicator for:
  - Trap Functions
  - Royal Trees
  - Binomial-3 Problem [Daida *et al.*, 2001]
  - Even Parity Problem [Koza, 1992]
  - Artificial Ant on the Santa Fe Trail [Koza, 1992]
  - ... (also some real-life applications)
- Many ways of calculating the *nsc* have been used:
  - Number of neighbors for each sampled individual
  - Number of mutations to generate neighbors
  - Different types of mutations to generate neighbors
  - Different techniques to partition the fitness clouds into bins

- *nsc* is predictive $\Rightarrow$ it can be used on *any* problem
- *nsc* has not been normalized yet into a given range (classification of different problems by their difficulty)
- A theoretical justification for nsc in [Poli, Vanneschi, GECCO 2007]. Some problems of the nsc for GAs in [Vanneschi, Valsecchi, Poli, GECCO 2009]

#8 Semantics in GP

GP as a Machine Learning Method (supervised learning)

- **Known**: the correct outputs for a fixed given set of inputs $\{I_i, O_i\}$
- **Sought**: a function belonging to a certain class that interpolates those points, i.e., $f(I_i) = O_i$ for any i
- **Output vector**: the vector of the outputs of f is $f(I)=(f(I_i))$
- **Fitness** on the error on the training set, i.e.,***distance*** betw tors of f and the target output vector $F(f)=D$ (ERROR AS DISTANCE)

semantics ([Moraglio et al., 2012] and many others...)

Semantic Diversity #1

[McPhee et al., 2008]

Use of truth tables to analyze behavioral changes in crossover for boolean problems

Considered the semantics of two components in each tree: semantics of **subtrees** and semantics of **context** (the remainder of an individual after removing a subtree).

Measured the **variation** of these semantic components throughout the GP evolutionary process.

Fixed-semantic subtrees: subtrees such that the semantics of the entire tree does not change when they are replaced by another subtree.

There may be **many fixed semantic subtrees** ***when the tree size increases*** during evolution; thus it becomes very difficult to change the semantics of trees with crossover and mutation.

Semantic Diversity #2

[Beadle and Johnson, 2008]

Semantic is used to define an algorithm called **Semantically Driven Crossover** (**SDC**).

SDC has been developed based on analysis of the behavioral changes caused by crossover.

Use of a canonical representation of members of the population (Reduced Ordered Binary Decision Diagrams-ROBDDs) to check for semantic equivalence without having to access the fitness function: two trees are semantically equivalent if and only if they reduce to the same ROBDD.

This is used to determine which participating individuals are copied into the next generation.

If the offspring are semantically equivalent to their parents, the children are discarded and the crossover is repeated.

Increased semantic diversity in the evolving population, and a consequent improvement in the GP performance.

Semantic Diversity #3

[Beadle and Johnson, 2009]

Previous work extended to mutation: semantics is used to test the effects of behavioral control at the point of the mutation operator.

Presented **Semantically Driven Mutation** (**SDM**), which can explicitly detect and apply behavioral changes caused by the syntactic modifications in programs caused by mutation.

SDM does not allow mutated programs to be produced when they are behaviorally equivalent to the original program. The aim of this is to avoid getting stuck in areas of the semantic/search space that have already been investigated.

As in [Beadle and Johnson, 2008], the key feature of the semantically driven operator is the ability to canonically represent programs in such a way that it is possible to compare them, looking for equivalent behaviors.

Semantic Locality

[Nguyen et al., 2010]

Investigation of the role of **syntactic** locality and **semantic** locality of **crossover**.

The results show that improving syntactic locality reduces code growth, and that leads to a slight improvement of the ability to generalize.

By comparison, improving semantic locality significantly enhances GP performance, reduces code growth and substantially improves the ability of GP to generalize.

Semantic Diversity + Locality #1

[Nguyen et al, 2009(a)]

Semantics Aware Crossover (**SAC**), a crossover operator promoting semantic diversity, based on checking semantic equivalence of subtrees.

[Nguyen et al, 2011]

Extended to **Semantic Similarity based Crossover** (**SSC**), which turned out to perform better than both standard crossover and SAC

Objective: *incorporate semantics* into the design of new crossover operators, so as to maintain greater semantic diversity and provide higher locality than standard crossover.

Semantic Diversity + Locality #2

[Nguyen et al, 2009(b)]

SSC extended to mutation leading to **Semantic Similarity based Mutation** (**SSM**).

Superior performance of SSM compared to standard mutation.

Geometry in the Semantic Space

[Krawiec and Lichocki, 2009] + [Krawiec, 2012]

Proposed a class of crossover operators for GP aimed at making offspring programs intermediate (or medial) with respect to parent programs in the semantic space (**geometric**).

Suggested that the prospects of designing a crossover operator that works in the genotype space and behaves geometrically in the corresponding semantic space are gloomy in GP, given the *complexity of the genotype-phenotype mapping*.

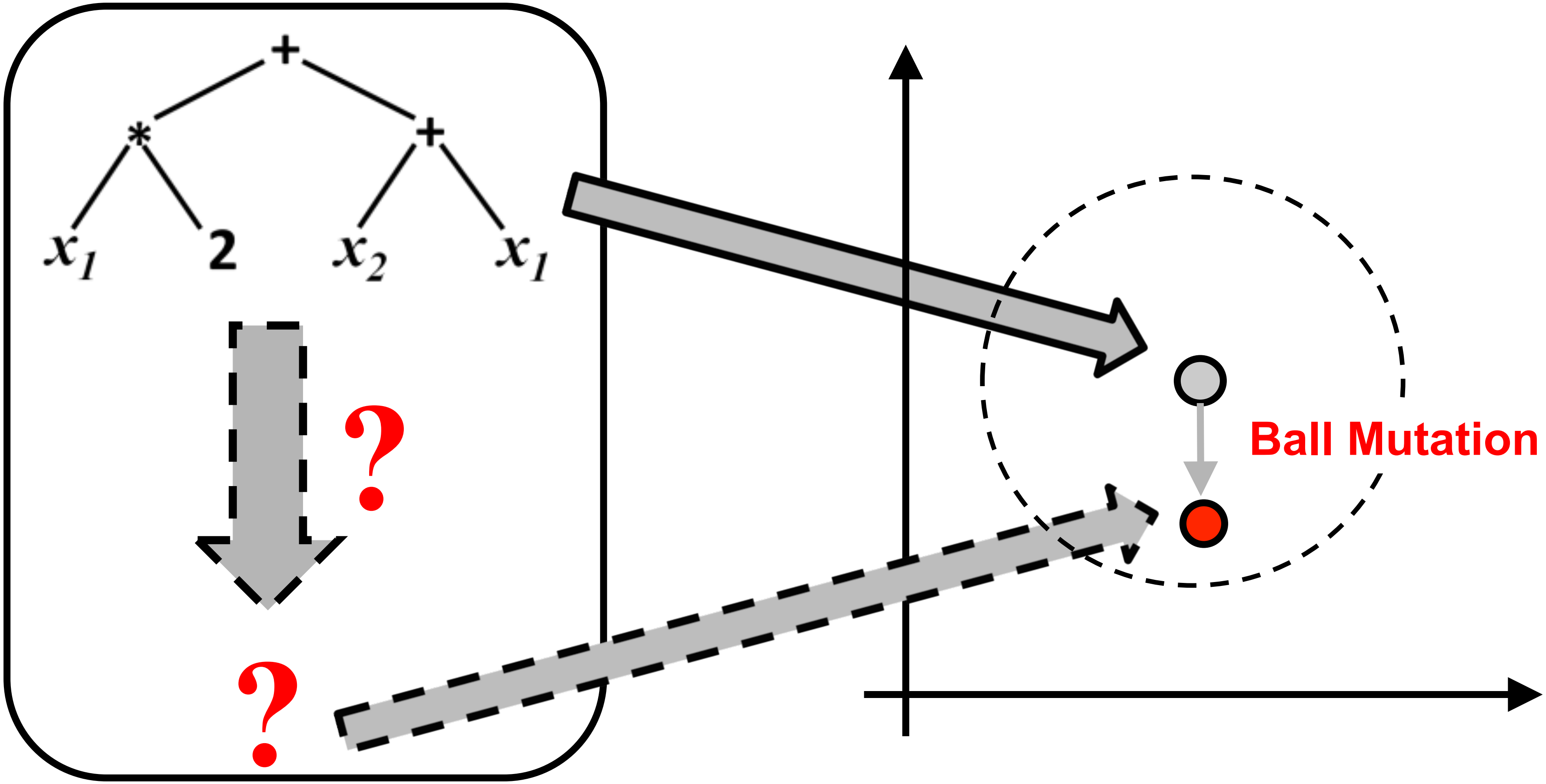
Hence, rather than guaranteeing the geometric behavior, their operator tries to approximate it by analyzing the offspring after it has been created.

This limitation is overcome by the geometric semantic operators proposed in [Moraglio et al., 2012], discussed in the continuation.

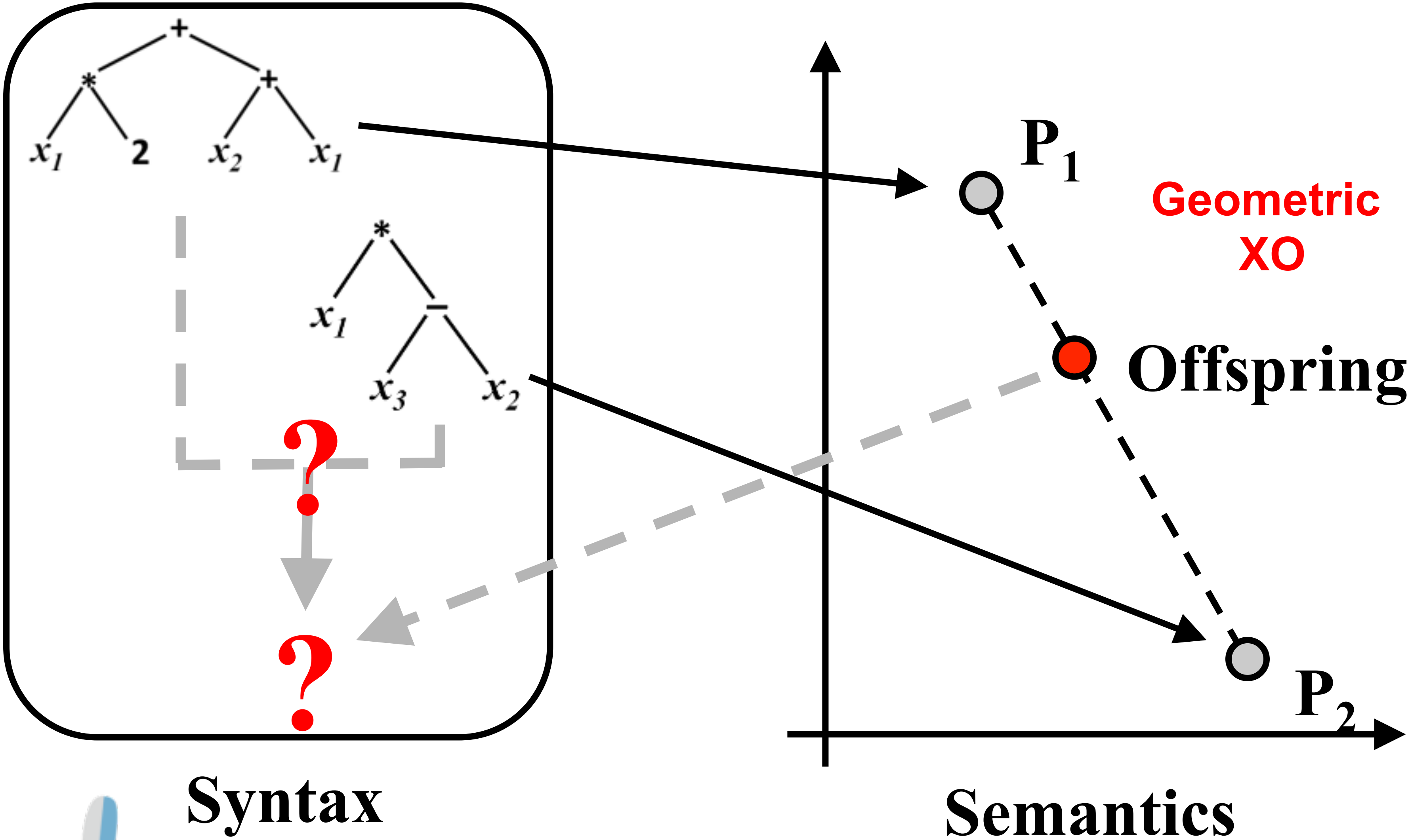
GP Geometric Semantic Operators
[Moraglio et al., 2012]

Objective:

Is it possible to define transformations on the syntax of individuals that have **known effects** on their semantics?



Syntax **Semantics**



+
*
+
x1
2
x2
x1
*
x1
–
x3
x2
?
?
P1
Geometric XO
Offspring
P2
Syntax
Semantics

Ball Mutation on the Semantic Space

If
a transformation on the syntax of an individual whose effect is ***ball mutation on the semantic*** space can be found

Then

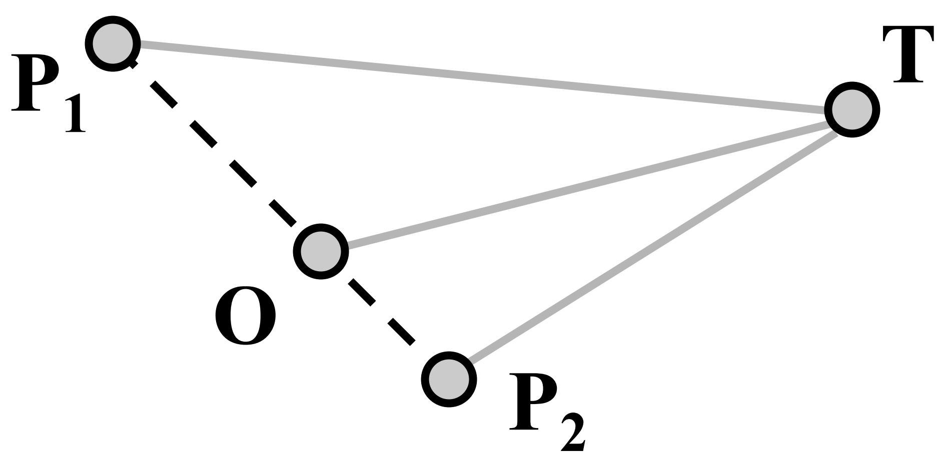
a **unimodal fitness landscape** can be induced on ***any*** problem consisting in matching input data into known targets (e.g. regressions and classifications)

Problem mapped into the "CONO".

Geometric XO on the Semantic Space

If
a transformation on the syntax of individuals whose effect is ***geometric crossover on the semantic*** space can be found

Then
the offspring is **not worse than the worst of its parents**



Is it a dream?

Yes... but turning into reality

Those operators have been defined:

A. Moraglio, K. Krawiec, and C. G. Johnson.
Geometric semantic genetic programming.
In C. A. Coello Coello, et al., editors, *Parallel Problem Solving from Nature, PPSN XII* (part 1), volume 7491 of Lecture Notes in Computer Science, pages 21–31. Springer, 2012.

Geometric Semantic Crossover [Moraglio et al., 2012]

Definition 1. (Geometric Semantic Crossover). *Given two parent functions* $T_1, T_2 : \mathbb{R}^n \rightarrow \mathbb{R}$*, the geometric semantic crossover returns the real function* $T_{XO} = (T_1 \cdot T_R) + ((1 - T_R) \cdot T_2)$*, where* T_R *is a random real function whose output values range in the interval* $[0, 1]$.

T_{XO} =

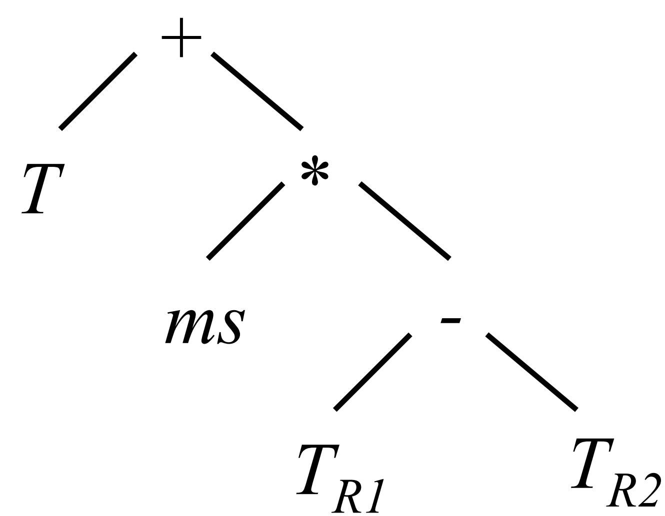
```
              +
            /   \
          *       *
         / \     / \
       T1   TR  -    T2
               / \
              1   TR
```

T_R = Random function with codomain [0, 1]

Geometric Semantic Mutation [Moraglio et al., 2012]

Definition 2. (Geometric Semantic Mutation). *Given a parent function* $T : \mathbb{R}^n \to \mathbb{R}$*, the geometric semantic mutation with mutation step* ms *returns the real function* $T_M = T + ms \cdot (T_{R1} - T_{R2})$*, where* T_{R1} *and* T_{R2} *are random real functions.*

T_M =



T_{R1} , T_{R2} = Random functions

Drawback of Geometric Semantic Operators

These operators, by construction, always produce offspring that are larger than their parents, causing an ***exponential*** growth in the size of the individuals [Moraglio et al., 2012]

This renders them ***useless in practice***.

A solution that has been proposed: "***simplification***" of the individuals during the evolution. But….

An Efficient Implementation

In:
A New Implementation of Geometric Semantic GP Applied to Predicting Pharmacokinetic Parameters.
L. Vanneschi, M. Castelli, L. Manzoni, S. Silva.
Accepted for publication in the *EuroGP 2013* Proceedings
Lecture Notes in Computer Science.

We propose a ***new implementation*** of Moraglio's geometric semantic operators that is ***efficient*** and does not imply any online simplification phase and thus allows us to use them on complex real-life applications!

Summary of the results obtained

- An ***efficient implementation*** of geometric semantic operators, that has allowed us to use them on real-life applications.
- ***Excellent results*** on the studied ***applications***.
- ***New insights about the generalization*** ability of geometric semantic operators (without the novel implementation that allowed us to use geometric semantic GP on these complex real-life problems, this interesting property would probably remain unnoticed).

Major open issue

The ***reconstruction of the expression of the best individual***, even though we do it only once and after the termination of the run, is still an issue:

Individuals after hundreds of generations get so huge that it may be *impossible* to reconstruct their entire expression (even though it is possible to get some information about it, such as the features or primitives it uses...).

Models generated by geometric semantic GP are ***black*** (or at least ***"dark gray"***) boxes!

We are working on this!

GECCO 2013

#9 The Influence of Biology

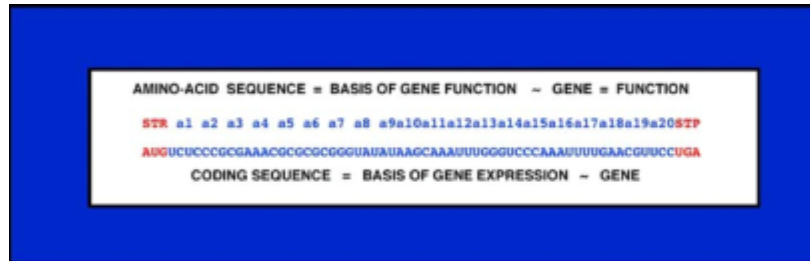
- Weaknesses of current paradigm
- The trade-off
- Opportunities
- Reversing the flow

Weaknesses of current Paradigm

- Fixed representation
- Static fitness functions
- Closed systems
- Our notion of genes
- Simple maps from genotype to phenotype
- Pre-determined operator features
- No role for non-expressed material
- Direct passing of genes without further qualifications
- Scalability

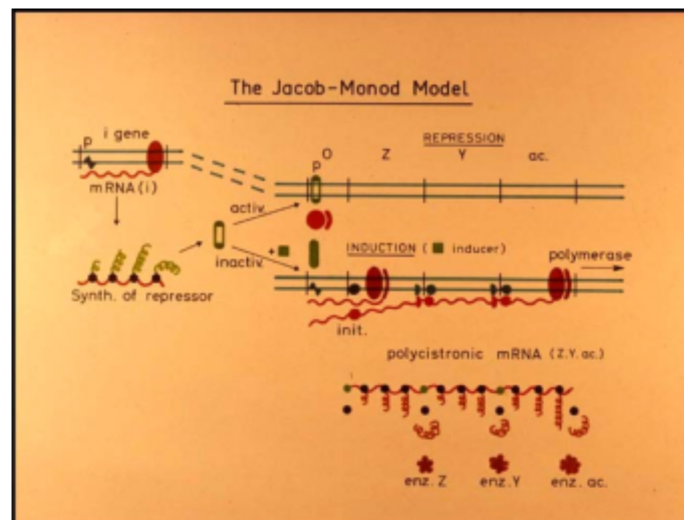
Our Notion of Genes …

- From …
- EC genes that fully determine phenotypic outcomes
- Genes as "coding sequences"



From: Scherrer/Jost: Theory Biosci., 2007

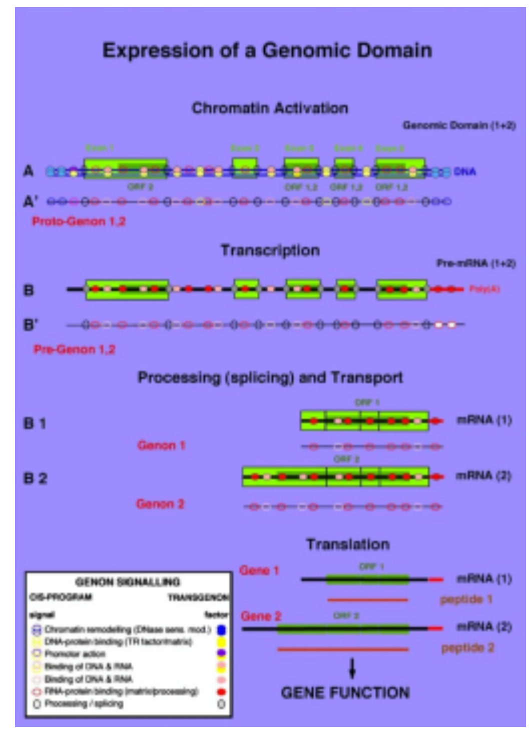
- … to …
- Genes as regulating units
- The operon model



… has to develop …

- … to
- Expression management of
- Highly intricate complexes

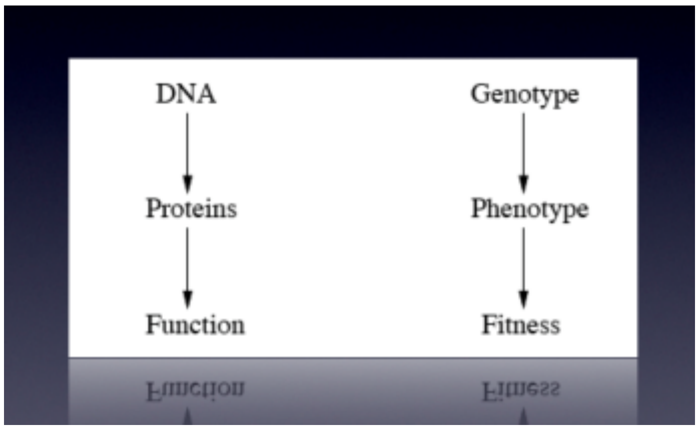
- Chromosomes and chromatin structures
- Regulation, transcription, splicing
- Editing of intermediate products (RNA)
- Translation in ribosomes
- …. to function



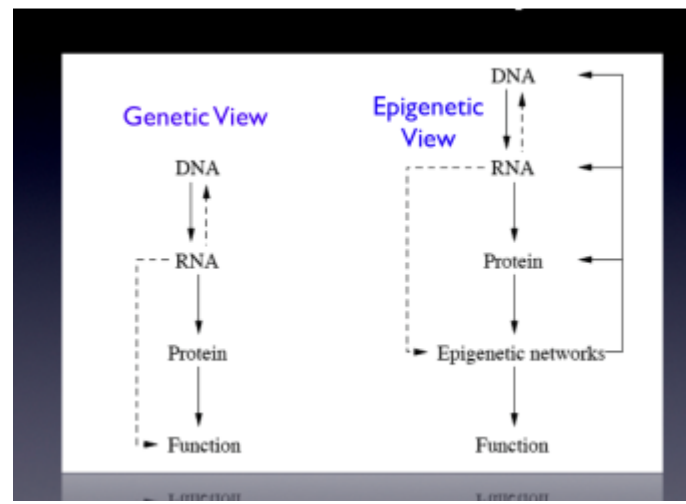
From: Scherrer/Jost: Theory Biosci., 2007

The Central Dogma is dead

- The linear flow of information from DNA
- to function is a grave oversimplification



- The picture now is complex and bidirectional,
- closing loops and forming networks



From: Banzhaf et al: Nature Rev. Gen., 2006

No role for non-expressed material

Organism	No. of protein coding genes	Genome Size (Mb)	Coding sequences (Mb)	Coding sequences (%)	Transcribed non-coding sequences (Mb)	Transcribed non-coding sequences (%)	Ratio
Human	20-25,000	2851	34	1.2	1619	57	48:1
Mouse	20-25,000	2490	31	1.3	1339	54	43:1
Fruit Fly	~13,500	120	22	18	53	44	2.4:1
Nematode	~19,000	100	26	26	33	33	1.3:1

From: Frith,Pheasant, Mattic: Eur. J. Hum., 2005

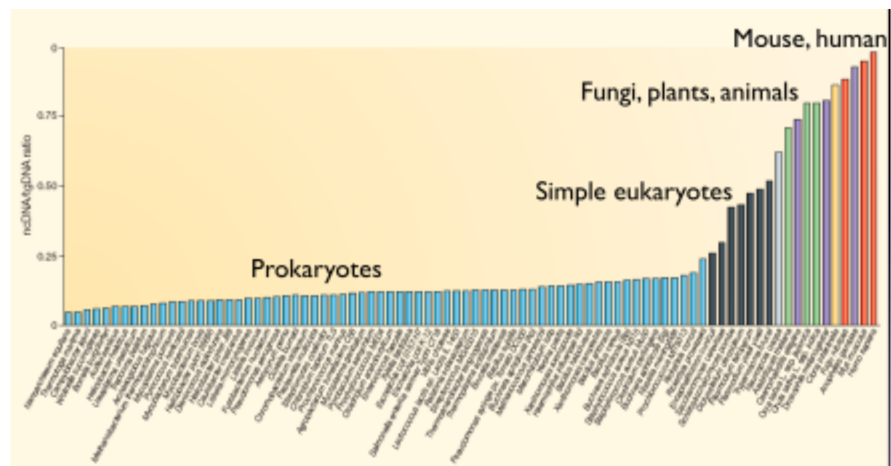


Figure 1 | **The ratio of non-coding to protein-coding DNA rises as a function of developmental complexity.** Prokaryotes have less than 25% non-coding DNA, simple eukaryotes have between 25 and 50% non-coding DNA and more complex fungi, plants and animals have more than 50%, rising to approximately 98.5% non-coding DNA in humans — which also have a genome size that is three orders of magnitude larger than prokaryotes. Note that this analysis corrects for ploidy, whereas pre-genomic estimations of the amount of DNA in different organisms did not. The different colours represent prokaryotes (bacteria and archaea) (blue), simple eucharyotes (black), *Neurospora crassa* (grey), plants (green), non-chordate invertebrates (nematodes, insects) (purple), *Ciona intestinalis* (urochordate) (yellow) and vertebrates (red). ncDNA, non-coding DNA; tgDNA, total genomic DNA. Reproduced with permission from REF. 77 © (2003) BioMed Central Ltd.

Tafts, Mattick, Increasing biological complexity is positively correlated with the relative genome-wide expansion of non-protein-coding DNA sequences, <www.arxiv.org/abs/q-bio.GN/0401020>, 2003

Trade-Offs

- Level of abstraction in models
- Potential for harvesting useful features
- Increased simulation time for evolutionary processes
- More emergent phenomena ?

Opportunities

- Epigenetics
- Multi-level selection
- Regulatory networks
- Multi-cellularity and Development
- Self-modifying genomes
- Research into novelty, innovation and creativity

#10 GP Needs Benchmarks

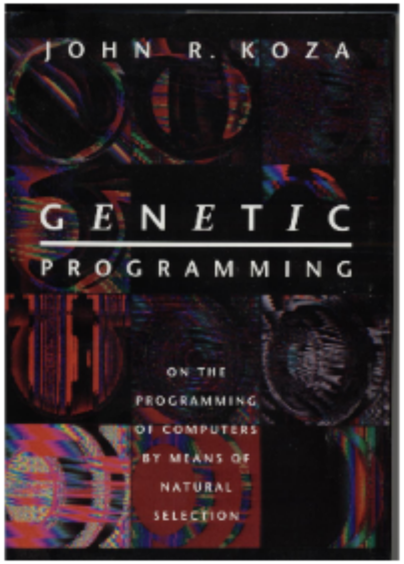
Published Use of Benchmarks

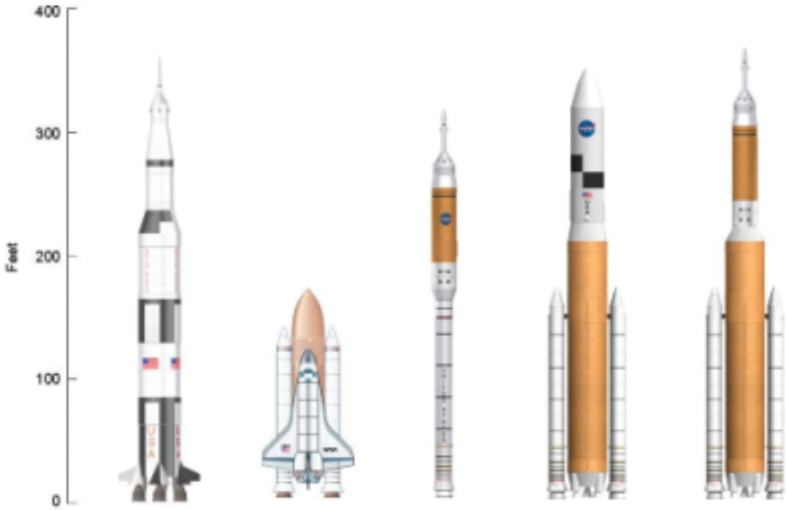
Survey of EuroGP and GECCO's GP Track from 2009 to 2011.
183 articles using 471 problem instances.

	Percentage (nearest percent)
Symbolic Regression	32
Classification	27
Path Finding and Planning	10
Boolean Functions	9
Traditional Programming	8
Predictive Modelling	7
Constructed Problems	3
Control Problems	1
Others	4

Limited variety e.g. 26% of papers involving symbolic regression used the quartic equation.

“De Facto” Banchmarks





What makes for a good benchmark?

- Tunably Dicult
- Varied
- Relevant (Real World? Constructed?)
- Fast (?)
- Accommodating to Implementors
- Supports good empirical method (e.g. problem generation)
- Easy to interpret and compare
- Representation Independent
- Precisely Defined (to an extent!)
- Known global optimum?

A Good Starting Point

GP Benchmarks.org

James McDermott
David R. White
Sean Luke
Luca Manzoni
Mauro Castelli
Leonardo Vanneschi
Wojciech Jaskowski
Krzysztof Krawiec
Robin Harper
Kenneth De Jong
Una-May O'Reilly
... and many many others (sorry if I forgot to include your name!)

#11 Miscellany…

- Algorithm Induction
- Halting Problem
- Domain Knowledge
- Usability
- GP Theory
- Constants
- Visualisation…

(…and we never mentioned BLOAT! ☺)

Conclusions

So many open issues...

- Can we increment GP generalization ability?
- Is there a better way to deal with programs' complexity?
- How to choose the right representation for a problem?
- What is the best way of using GP in dynamic environments?
- How can we measure/predict the ability of GP to solve a problem?
- How can we use sematic awareness to improve GP?
- Can we exploit the richness of nature better then we currently do?
- ...

One big objective...

Let GP become a trusted mainstream member of the computational problem solving toolkit.

Why not yet?

Questions & Discussion

Acknowledgements

- The impetus for this article arose out of the EuroGP 2008 debate on Grand Challenges of Genetic Programming which took place on 27 March 2008 at the Evo* event in Naples, Italy. In particular we thank the two other panel members, Nic McPhee and Riccardo Poli, and also the many members of the audience who participated in the debate. Many of these issues have been raised on multiple occasions at previous (and subsequent) EuroGP debates so this inspired us to put these ideas on paper to open the debate to a wider audience. MO’N acknowledges support of Science Foundation Ireland under Grant No. 08/IN.1/I1868 and 08/SRC/FM1389. WB acknowledges support from the Canadian National Science and Engineering Research Council (NSERC) under discovery grant RGPIN 283304-07.

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