Automated Program Learning

MOSES

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Xiamen University
AGI Summer School 2009

Outline

What is MOSES?

MOSES (*Meta-Optimizing Semantic Evolutionary Search*)

Evolutionary program learning, PhD Moshe Looks. 

1. Search programs that maximize the fitness function

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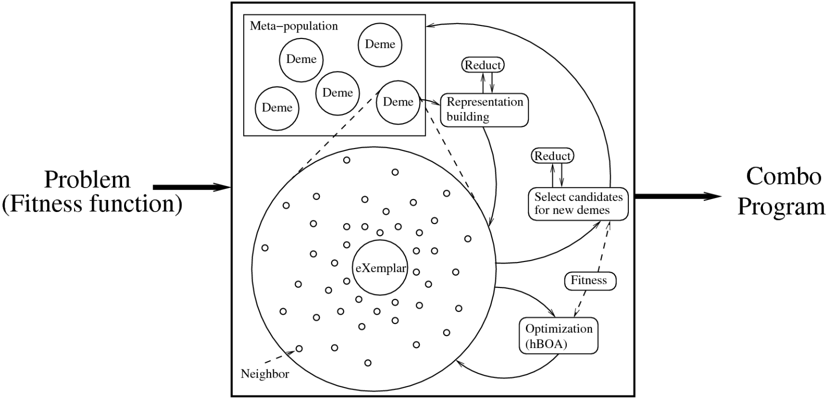
1. Search programs that maximize the fitness function
2. Take advantage of program semantics and program space topology
3. Attempt to discover fitness landscape regularities to speed up the search

How it works?


Problem
(Fitness function)
Meta–population
Deme
Deme
Deme
Deme
Deme
Reduct
Representation building
Reduct
Select candidates for new demes
eXemplar
Fitness
Optimization (hBOA)
Neighbor
Combo
Program

How it works?

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   - minimize over-representation
   - improve syntactic vs semantic distance correlation
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4. Deme management
   - Set of demes, meta-population
   - Diversity, preserving interesting demes

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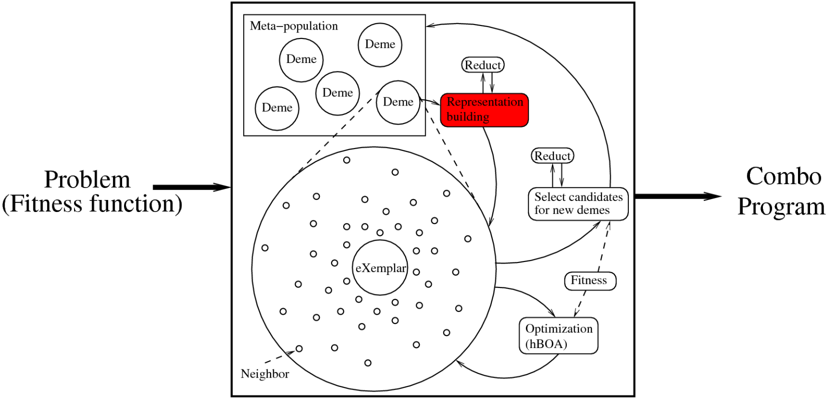
Representation-building: Build a deme's population



Building string of knobs

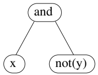
Population of a Deme

Centered around an exemplar, each neighbor is a variation of that exemplar according to the representation-building, a string of knobs.

`and(#1 not(#2))` $\Rightarrow$

Building string of knobs

Domain specific rules to create knobs, example in the Boolean domain with `and(x not(y))`:



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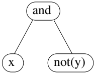
1. Under every junctor, $\forall$ v not already sibling, add [$\emptyset$, v, $not(v)$]



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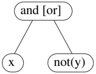

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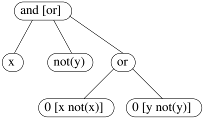

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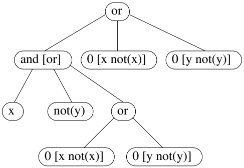

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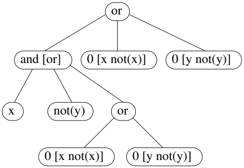
4. Insert an oposite junctor above the root + children
5. And a few more...



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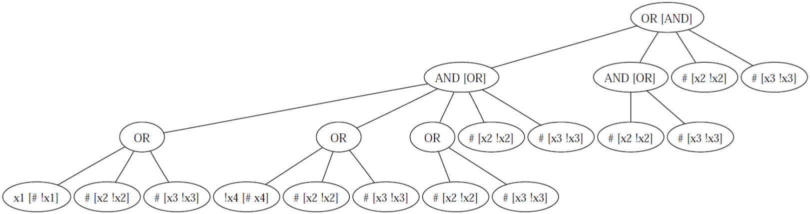

Figure: Built knobs for $\mathit{and}(x_1\,\mathit{not}(x_4))$, *extracted from Moshe's PhD*.

Optimization problem takes place on the knob string

For example:

knob setting	combo (reduced)	distance
(and, $\emptyset$, $\emptyset$, $\emptyset$, $\emptyset$)	and(x not(y))	0
(or, $\emptyset$, $\emptyset$, $\emptyset$, $\emptyset$)	or(x not(y))	1
(and, $\emptyset$, $\emptyset$, not(x), $\emptyset$)	or(not(x) not(y))	1
(or, $\emptyset$, $\emptyset$, not(x), $\emptyset$)	true	2

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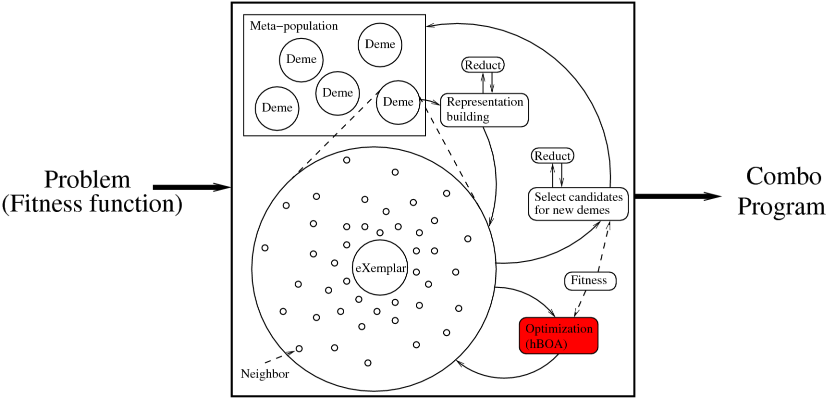
Optimization: Find the best candidates inside a deme



MOSES' Optimization algorithms

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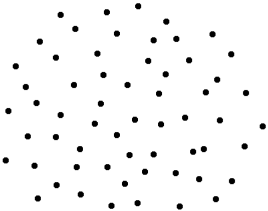
3. Building-Block Hill-Climbing (being ported to the OpenCog version)

Hierarchical Bayesian Optimization Algorithm (hBOA)

Candidate	*score*
00001010	0.2
00011010	0.6
01000100	0.01
00110110	0.5
10010010	0.6
⋮	⋮



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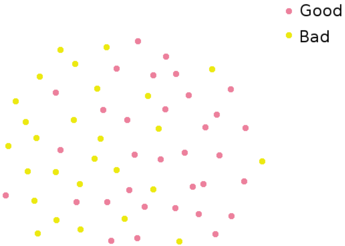

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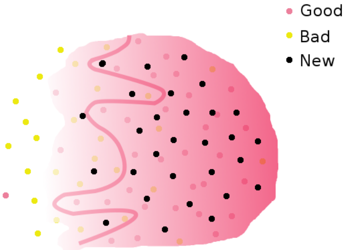

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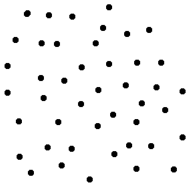
Hierarchical Bayesian Optimization Algorithm (hBOA)

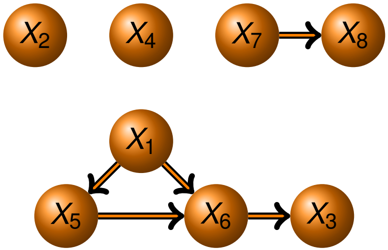
Candidate	*score*
10011010	0.5
00111011	0.6
11111001	0.7
00111010	0.4
10000001	0.1
⋮	⋮



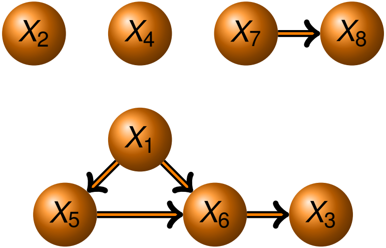
- Split the population in good vs bad candidates
- Learn a classifier, but not too strict or incorrect
- Probabilistic classifier, distribution of good candidates
- Sample new candidates according to the distribution
- Repeat on the new population

Distribution of Good Candidates: Bayesian Network

Candidate (X_i) i : 12345678	*score*
00001010	0.2
00011010	0.6
01000100	0.01
00110110	0.5
10010010	0.6
⋮	⋮

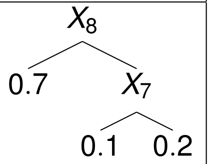


Decomposing the problem into sub-problems



Conditional Probability with Decision Tree

Marginal	*Prob*
$P(X_1 = 1)$	0.3
$P(X_2 = 1)$	0.05
$P(X_4 = 1)$	0.9
$P(X_7 = 1)$	0.88

Conditional	*Prob*
$P(X_8 \| X_7)$	
$P(X_5 \| X_1)$	...
$P(X_6 \| X_1, X_5)$	...
$P(X_3 \| X_6)$	...

In OpenCog for the moment only univariate

Univariate

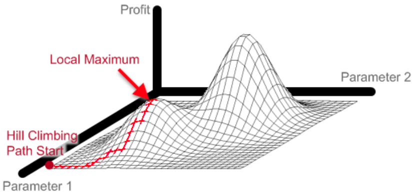
Only marginal probabilities

Marginal	*Prob*
$P(X_1 = 1)$	0.3
$P(X_2 = 1)$	0.05
$P(X_3 = 1)$	0.2
$P(X_4 = 1)$	0.5
$P(X_5 = 1)$	0.4
$P(X_6 = 1)$	0.7
$P(X_7 = 1)$	0.88
$P(X_8 = 1)$	0.1

Hill-Climbing, Building-Block Hill-Climbing

- Hill-Climbing

The problem with hill climbing is that it gets stuck on "local-maxima"



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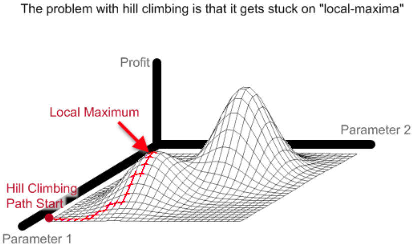

- Building-Block Hill-Climbing $\Rightarrow$ Redefine neighborhood to take short-cuts.

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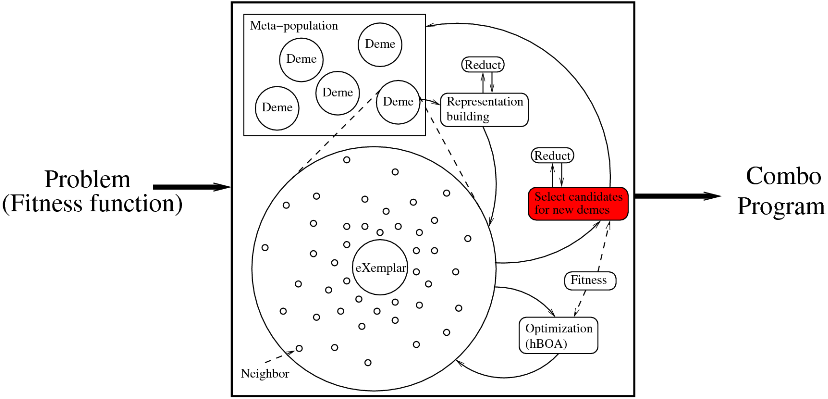
Select Candidates for Future Demes



Preserving Diversity, candidates that behave differently and non-dominated

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- Neither one dominates the other

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- Neither one dominates the other
- But “Moshe Lewis” dominates then both

Behavioral score

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Partial order

- if c1 < c2 then c1 is dominated by c2

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For instance: vector of floats $(f_1, \ldots, f_n)$ where each f_i measure how well a candidate is doing for that particular feature.
If for all features i, $c1$ is doing better than $c2$, then $c1$ dominates $c2$.

Deme selection

Keep non-dominated exemplars as potential deme.

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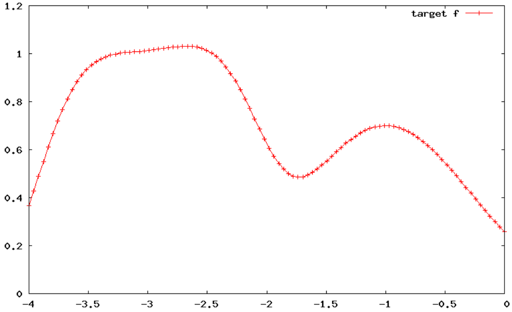
We want to learn $f(x)$.



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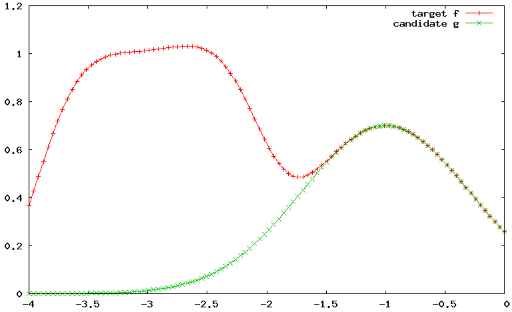

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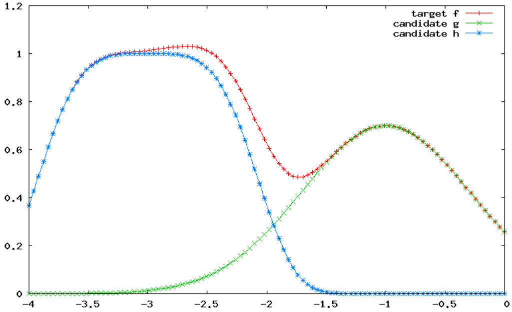

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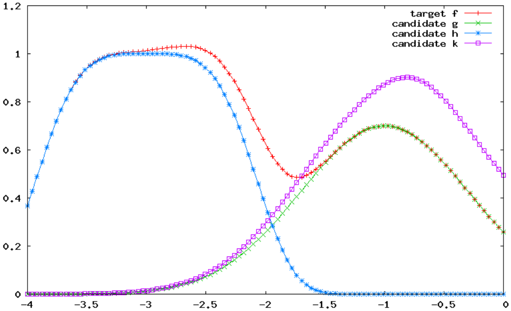

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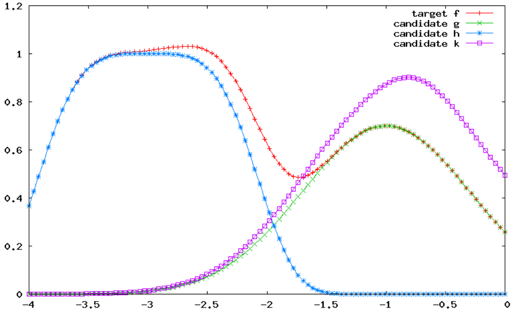
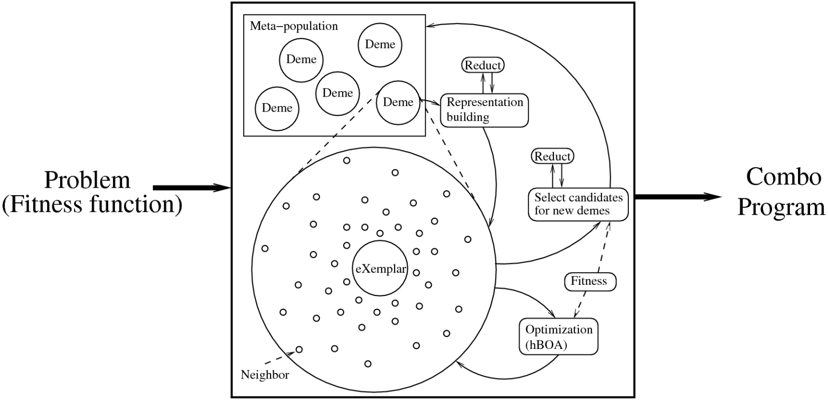


$k(x)$ is dominates by $g(x)$ and will not be included in the meta-population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Some benchmark

Technique	Computational Effort			
	3-parity	4-parity	5-parity	6-parity
Univariate MOSES	6,151	73,977	2,402,523	342,280,092
Evolutionary programming [15]	28,500	181,500	2,100,000	no solutions
Genetic programming [49]	96,000	384,000	6,528,000	no solutions
MOSES	5,112	72,384	1,581,212	100,490,013

Figure: Computational effort to find solution of n-parity 99% of the time *(extracted from Moshe's PhD thesis)*

$$n\text{-}parity(b_1, \ldots, b_n) = even\left(\sum_{i=1}^{n} int(b_i)\right)$$

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3. Maintain diversity in the meta-population (deme managment)

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1. minimize over-representation (Reduction in normal form)
2. build expressive deme population by taking into account operator semantics (representation-building)
3. Maintain diversity in the meta-population (deme managment)
4. Attempt to find regularities in one deme's population to speed up optimization (model-building)

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3. Model-building is slow
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4. No transfer learning across problem instances
   $\Rightarrow$ Integrative AGI, Attention Allocation, PLN, etc.