CoEvolving Memetic Algorithms (COMA) A framework for algorithm creation and adaptation

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Overview

- Memetic Algorithms in a broader context
- What do I mean by memes?
- Co-evolving Gene and Memes
  - COMA framework
  - Key findings and open questions
- Conclusions
Positioning

Adaptive Search – but to what?

- An instance of a problem?
  - Algorithm Selection Problem (ML) / NELLI
- A history of search on an instance?
  - Adaptive Operator Selection (meta-heuristics)
  - Hyper-heuristics / VNS etc.
- Distinct regions of search space?
  - Self-Adaptation (meta-heuristics)
  - (some) Multimeme Algorithms
Memetic algorithms as adaptive systems

- Typical Viewpoint: MA = EA + Local Search
- Get better results with multiple LS operators
  - (Krasnogor & Smith, Gecco '01 ->, Ong & Keane '04 IEEE TEC)
  - Blurred distinction to Hyper-Heuristics
- Adaptive MAs (Ong et al. 2006 IEEE SMC-B)
  - as a more general framework
  - AMA = Meta-heuristic + set of LS + choice function
# Ong et al.'s classification

<table>
<thead>
<tr>
<th>Nature of adaptation mechanism</th>
<th>Source of information To adaptation mechanism</th>
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<table>
<thead>
<tr>
<th>Adaptive Type</th>
<th>Adaptive Level</th>
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<tbody>
<tr>
<td></td>
<td><strong>External</strong></td>
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<tr>
<td></td>
<td><strong>Local</strong></td>
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<tr>
<td></td>
<td><strong>Global</strong></td>
</tr>
<tr>
<td>Static</td>
<td>Basic meta-Lamarckian learning / Simplerandom</td>
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<tr>
<td>Qualitative</td>
<td>Randomdescent / Randompermdescent</td>
</tr>
<tr>
<td>Adaptive Quantitative</td>
<td>Sub-Problem Decomposition/ Greedy</td>
</tr>
<tr>
<td>Self-Adaptive</td>
<td>Multi-memes/ Co-evolution MA</td>
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</table>
Meuth *et al.* categorisation of MAs

- **First Generation:**
  - Global search paired with local search

- **Second Generation:**
  - Global search with multiple local optimizers.
  - Memetic information (Choice of optimizer) passed to offspring (Lamarckian evolution)

- **Third Generation:**
  - Global search with multiple local optimizers.
  - Memetic information (Choice of local optimizer) passed to offspring (Lamarckian Evolution).
  - A mapping between evolutionary trajectory and choice of local optimizer is learned

- **Fourth Generation:**
  - Mechanisms of recognition, generalization, optimization, and memory are utilized *to search meme space*

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How do we classify Meme Transmission?

With respect to the:

1. **Search space?**
   - Global /local – depends on move operator/distance metric

2. **Individual choosing a meme?**
   - Credit assignment problem

3. **Memepool?**
   - Social theories (Vertical/horizontal/diagonal)
Or more generally...

AMA = population of solutions
    + population of memes

- Both adapted by meta-heuristics,
- Individual’s behavioural responses can be modified by memes
  - Could think of as individual or social learning
- But why not also teaching?
- Or task sharing more generally?
Co-Evolving Memetic algorithms

- Framework for investigating meme-gene co-adaptation from 1-4G
- Separate populations of genes and memes
- Run a search algorithm in each space,
- Could use any representation and model, needn’t be EAs
  - For example Nogueras and Cottas use EDAs

“Perturbative” rather than constructive.
CO-evolving Memetic Algorithms (COMA)

- Memes match and replace patterns in genotypes
  - Syntactic string rewriting
  - Set of possible matches ↔ LS neighbourhood
  - Gives really good optimisation results
    - Smith: PPSN ’02, IEEE SMC-B ’07, ECJ 2012
    - Nogueras and Cotta PPSN ’14, J NMA ’15
- Evolved memes capture underlying problem structure
  - E.g., solve concatenated trap functions in linear time,
  - “rediscover” Protein folding rules
- Changing LS neighbourhoods facilitate escape from local optima

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Illustration: 4 trap problem

Linear with $R^2 > 0.8$
Population of evolving solutions

<table>
<thead>
<tr>
<th>r d d l u l u u r u r d r d r d d d l u</th>
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<tbody>
<tr>
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<td>u r r l l u l u r u r d r d d d l u</td>
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- This example from protein structure prediction
- Offspring created by normal processes of selection, crossover and mutation
# Population of Rules

<table>
<thead>
<tr>
<th>Condition</th>
<th>Action</th>
<th>Pivot</th>
<th>Depth</th>
<th>Linkage</th>
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<tbody>
<tr>
<td>r #1 u#r</td>
<td>r u l d u l</td>
<td>S</td>
<td>1</td>
<td>L</td>
</tr>
<tr>
<td>1#r</td>
<td>l r d</td>
<td>S</td>
<td>-1</td>
<td>L</td>
</tr>
<tr>
<td>11#d</td>
<td>l r u u</td>
<td>G</td>
<td>2</td>
<td>F</td>
</tr>
<tr>
<td>#u u #</td>
<td>#u r r</td>
<td>S</td>
<td>3</td>
<td>L</td>
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</tbody>
</table>

- **Linkage** indicates gene-meme pairing
  - *Self-adaptive linkage, Random, Fitness based*
- **Pivot**: *Steepest / Greedy search of neighbourhood.*
- **Depth**: *-1 indicates search to local optima.*
One application

offspring solution

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The Neighbourhood to be searched i.e. the set of points which can be reached by applying this operator to this solution

offspring rule

u ≠ u : uuu : s : 1 : 1
Some key results

- **Different spaces need different search algorithms:**
  - Obvious if the encoding is very different, but also true if the same
  - e.g. Nogueras & Cotta showed Laplacian correction to maintain entropy was useful in solution but not meme space

- **The credit assignment issue differs between spaces**
  - Solutions: Maturana et al showed *extreme* reward gave best results for operator adaptation in solution space (IEEE CEC’09)
  - Memes: *mean* reward is better for various 2G and 4G strategies
  - Best results: *local* adaptation using piecewise linear fitness

- **Ideas can overwhelm geography**
  - More rapid dispersion in meme space can reduce effects of deme separation in gene space
Some open questions

- **Rate of adaptation:**
  - So far work has used synchronous adaptation of memes,
  - is this necessary or desirable?

- **Richer transformations?**
  - Extend the regular expressions used for rewriting
  - Or use GP (cf. Fukunaga ECJ 2002 did it offline),
  - Simoes et al (PPSN14) self-adapted neural transformations (effectively endosymbiotic memes),

- **Extension to modelling problems**
  - Memes for genetic improvement of software?

- **Memes for teaching as well as learning?**
And more: How does all this work within the context of

- **Dynamic Optimisation/Modelling**
  - What is needed for continuous adaptation

- **Interactive Machine Learning / Optimisation**
  - Longer term adaption/selection of memes according to human behaviour and reactions
  - Being explored with IPAT tool
    - Allows interaction with anything that can be shown/heard/watched via HTML5
    - Shortly to be available as open source framework

- **Expensive problems that need surrogate models**
  - How approximate can you get and still adapt?

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Conclusions

- COMA framework support research into the co-adaption of problem solving strategies with the solutions to the problem being solved.
  - So closely linked with Hyperheuristics etc.
- Premise: even for simple problems the optimal strategies will vary during search
  - So online adaptation methods are necessary
  - And may not be designable in advance
- Available on request as C libraries, welcome ports to other languages

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What more might we be able to get?