
Metaheuristic Design Patterns
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jerry.swan@cs.stir.ac.uk
krzysztof.krawiec@cs.put.poznan.pl
john.woodward@cs.stir.ac.uk

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Premature Optimization

Claim: metaheuristic *research* is trapped in a local minimum.
Why?

1. Conceptual Parsimony - a historical preference for metaheuristics to be 'top-down, easily-described'.
2. Still in the software 'stone age' - everyone working in their own 'silo'; no metaheuristic analog of 'programming in the large'.

Consequences of Conceptual Parsimony

- **Claim**: we need to move towards *much* more sophisticated problem descriptions and solution representations, rather than the black boxes of the traditional hyper-heuristic 'domain-barrier'.
- In particular, we need to do a much better job of *knowledge engineering*, e.g. incorporating 'domain-independant domain knowledge'.
- An elementary example is the incorporation of nontrivial algebraic relationships between states and/or operators (see 'Representative' pattern later on).

The Software Stone Age - Consequences

- Parameter-tuning and algorithm selection are a manual processes, rather than being an integrated part of the researcher's toolset.
- Metaheuristic hybridization is traditionally done by hand, rather than via e.g. meta-learning or systems self-assembly.
- Automated Design of Algorithms (ADoA) researchers attempt to address this issue at the 'hyper-heuristic' level
- . . . but to some extent suffer the same problem 'one level higher-up'.

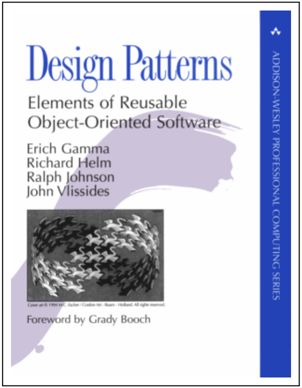
Software Development has already been here ...

- In the 1940s, a 'large' program might have 500 assembly language instructions. Modern techniques mean that codebases with $> 10^6$ LOC can be successfully maintained by distributed development teams.
- This is largely due to **modularity**. A modular system can be factored into parts that are *loosely-coupled*, i.e. their external connections are few relative to their internal complexity.
- Modularity is obviously a key concern in 'automatic programming'.
- Most interestingly, the average software engineer *has got quite a lot better at modularity*, quite recently ...

What are the drivers for progress in software development?

- **Education**: increasingly sophisticated design methodologies have become part of the common development culture.
- By contrast, much of our hard-earned knowledge as metaheuristic researchers has been gained in an *ad hoc* fashion, since relatively recent advances (∼5-10 years) are distributed across hundreds of research papers and have not yet been consolodated as ‘common practice’.
- **Componentization**: software is an ideal mechanism for describing concepts in the abstract (e.g. with pure functions or via subtype, parametric or *ad hoc* polymorphism).
- Claim we should do this with metaheuristic concepts on a much wider scale than we are currently doing.

The ‘Design Patterns’ Revolution



- One of the biggest step-changes in the overall quality of software engineering happened in 1994.
- ‘Design Patterns’ revolutionised software design and implementation.
- Over 500,000 copies sold.

Example - The Observer Pattern - 1

Intent
Define a one-to-many relationship between a subject and its observers, so that observers are updated automatically when the subject changes state.

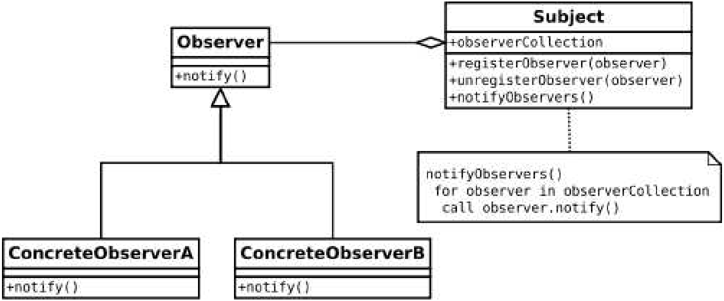
Motivation
To maintain consistency between co-operating entities.

Applicability
When a change to a subject is of interest to distributed and/or heterogenous observers.

Examples
A Model-View-Controller architecture can be greatly simplified by using the Observer pattern.

Consequences
Modularizes the update mechanism and reduces domain-specific coupling between subject and observers.

Example - The Observer Pattern - 2



More formally, a Design Pattern . . .

1. Addresses some repeatedly-observed design problem.
2. Describes the problem; the solution; when to apply the solution; consequences.
3. Gives implementation hints and examples.
4. The solution is an abstract component (or more generally a network of components) for solving the problem.
5. The generalized solution is customized to the context at hand.

Those steps seem rather familiar . . .

- As metaheuristic researchers, we use our own expert knowledge to perform these steps all the time.
- **Proposal**: Techniques of ubiquitous value should be explicitly documented as Design Patterns.
- The least we might aspire to is to codify repeated patterns (including more recent advances) as a kind of 'Metaheuristics 102': a cookbook for researchers in the field.

“That’s Impossible/Trivial . . .”

- This has of course already been done on a number of (less overtly Design Pattern-centric) levels.
- Standard EC or LS framework is clearly a kind of design pattern, customised (mainly by hand) to problem-specific needs.
- Krasnogor used a pattern-language to define families of memetic algorithms [4].
- PMML - A generic language for describing classifiers [3].
- PDDL - Generic planning DSL [2].

Example - Selection

Intent
Choose members of a collection according to some context-specific criterion.

Motivation
Original motivation comes from EC, where the context is defined as a quantitative fitness measure.

Applicability
When it is desirable to promote certain features of a population.

Collaborations
May benefit from access to an archive of previous items.

Consequences
Generally acts as an intensification mechanism.

The Pattern Catalog

The original GOF categories were:

- Creational – concerned with generation.
- Structural – concerned with composition.
- Behavioural – concerned with interaction/division of responsibility.

Some additional categories for metaheuristics ...

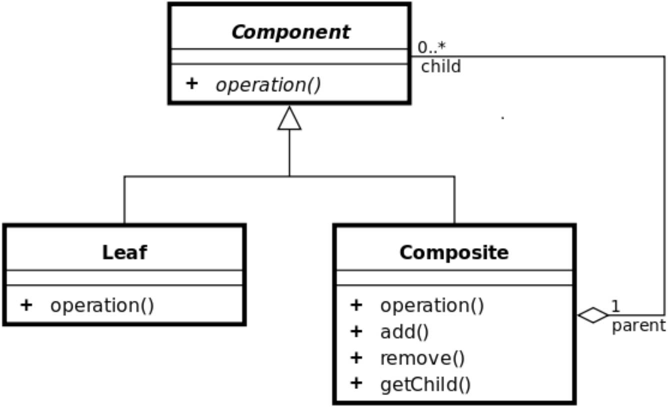
- Semantic – Representative, Repair, Locality.
- Methodological – Templates for: the design of experiments; performance of statistical tests ...
- Metrics – Euclidian and other norms, Jaquard, Mutual information, MDL ...)

Example metaheuristic patterns

Here are some examples of metaheuristic design patterns:

- **Structural**: Composite Metaheuristics. Relation=Graph=Matrix. Archive. Structured Population (e.g. Spatial and Island Models).
- **Behavioural**: Template method metalearning. Blackboard. Stigmergy (c.f. Visitor). Sampler.
- **Semantic**: Representative. Repair. Locality.

Examples: 1. The ‘Composite’ Pattern



Hyper-heuristics as Composites

- From [8], we can recursively define a hyper-heuristic as:

$$
\begin{aligned}
\mathcal{H}_0 &: ([S] \times [S \to S]) \to ([S] \times [S \to S]) \\
\mathcal{H}_1 &: ([S] \times [\mathcal{H}_0]) \to ([S] \times [\mathcal{H}_0]) \\
&\ldots \\
\mathcal{H}_n &: ([S] \times [\mathcal{H}_{i<n}]) \to ([S] \times [\mathcal{H}_{i<n}])
\end{aligned}
$$

- A metaheuristic such as steepest-ascent hillclimbing can be considered as $\mathcal{H}_0$ with an operator list of length 1.
- Hence, by the usual definition of hyper-heuristic, it can be seen as a composite metaheuristic, i.e. it IS-A metaheuristic that USES-A list of metaheuristic.

Examples: 2. The Template Method Pattern

- The Template Method pattern divides a framework into fixed and variant parts.
- The fixed parts orchestrate the behaviour of the variant parts.
- Simple example: Quicksort with variant partition function.

```
qsort( arr : Array[ T ] ) =
    qsort( lesser ) ++ equal ++ qsort( greater )
where
(lesser,equal,greater) = partition( arr )
```

Template Method Hyper-heuristics

- If we can express an algorithmic framework in template method terms, then we can learn good implementations for the variant parts.
- By ‘good’, we mean ‘biased towards the distribution to which they are exposed’.
- If our algorithms are metaheuristics, such meta-bias is actually a necessity (by NFL) [9].
- Successfully demonstrated this approach for GA selection and mutation operators ([12, 11]).

Examples: 3. Blackboard - Motivation

- Blackboard architectures offer a generic solution mechanism for problems which are:
  - Data-driven\opportunistic.
  - Not easily solved by an *apriori* fixed strategy.
- These are certainly properties of hyper-heuristic search.
- Concurrency support built-in to the architecture.

Blackboard - Implementation and Consequences

- Concurrent agents share search trajectories via a *workspace*.
- Places *minimal* restrictions on agent (metaheuristic) implementation (selective vs generative, constructive vs perturbative etc).
- Facilitates metaheuristic *racing*, interleaving of offline and online activites etc [8].
- Readily supports varying process granularities and transaction costs.
- Has potential as a *very* high-level interoperability mechanism.

Example: 4. Representative

Intent
Transform data (solutions/operators/algorithms) into a canonical (or normal) form.

Motivation
Such a transformation can be used to reduce the size of the search space.

Applicability
When it is possible to define a (relatively efficient) set of transformations.

Examples

- Polynomials can be represented by their roots [10]. See also [5].
- Operator sequences that form a *monoid* can be reduced to normal via the Knuth-Bendix algorithm [7].

The real goal - using Patterns in ADoA

- As ADoA researchers, the real advantages will come if we can obtain a *declarative* description of our patterns, i.e. one that is ammenable to *automated reasoning*.
- What we might want from our formalization?
  - Based on function signatures and contracts.
  - Strongly (even dependantly?) typed

Selection - signature and semantics

```
select( pop : List[T], howMany : ℕ₁ ) : NonEmptyList[ℕ]
require( !pop.isEmpty )
ensure(result.len == howMany && ∀ i∈result, i<pop.len)

selectProportional( pop : List[T], howMany : ℕ₁,
    fitnessFn : T → ℝ⁺, random : Random ) : NonEmptyList[ℕ]

selectTournament( pop : List[T], howMany : ℕ₁,
    fitnessFn : T → ℝ⁺, random : Random,
    tournamentSize : ℕ₁ ) : NonEmptyList[ℕ]
```

1. Strong typing helps enforce semantics.
2. Variant implementations may require extended signatures.

Towards ‘Metaheuristics in the large’ . . .

- Computer scientists don’t design algorithms ‘at random’ . . .
- Good researchers don’t hybridize metaheuristics ‘for no reason’ . . .
- How can we better learn the criteria for good designs?
- One starting point is to think about possible ‘Universal’ features of metaheuristic components . . .

Blum's I&D Frames

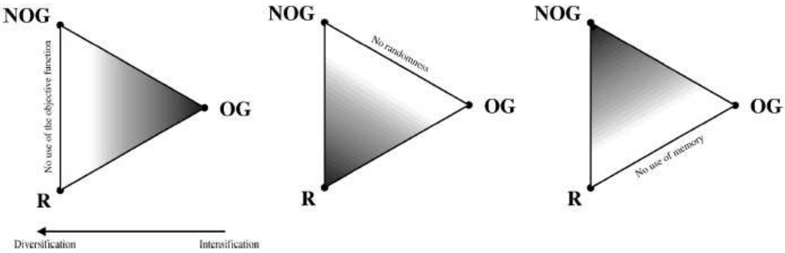


Fig. 18. The *I&D frame* provides a unified view on intensification and diversification in metaheuristics (**OG** = I&D components solely guided by the objective function, **NOG** = I&D components solely guided by one or more function other than the objective function, **R** = I&D components solely guided by randomness).

Declarative Representation

- Static features
  - Signature.
  - Semantics.
  - Fan-in and fan-out.
  - I&D Frame coordinate position.
  - Units and dimensions? (c.f. Mars Climate Orbiter ‘metric mixup’)
- Dynamic features
  - Induced semantics.
  - I&D Frame coordinate position (e.g. as modified by RL).

Other suggestions . . . ?

Assembling larger systems

- Given declarative descriptions of components, we can combine these descriptions to indicate how assemblies of these components might behave.
- For example, an Iterative Local Search procedure that uses SA as an operator will have higher diversity and randomness components than one that uses a hillclimber.
- This process applies recursively: for example, we can consider the construction of an SA metaheuristic to be parameterized by its source of 'thermal noise' values.
- By using a Markov chain c of order 2 as the source, then an instance of SA that uses c would have a lower I&D frame value for randomness than one that used a Random Number Generator for which samples are independant.

An ADoA Component Framework

- As per Pappa et al. [6], the time is right for principled integration of ML and ADoA.
- Having a common repertoire of features to describe components facilitates the creation of learning algorithms that can operate at heirarchical levels of modularity.
- Modules and learning algorithms can be shared across the community, moving metaheuristic design closer to electronic and software component design [1].

Thanks for listening

Questions?

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