Using Evolutionary Computation to Automatically Refactor Software Designs to Include Design Patterns

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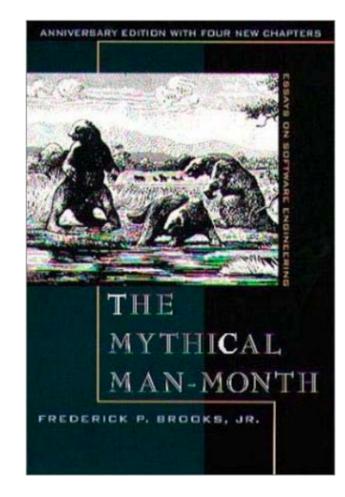
M.S. Thesis Defense

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# The Big Picture

"The total lifetime cost of maintaining a widely used program is typically 40 percent or more of the cost of developing it."

Fred Brooks, The Mythical Man Month



# The Big Picture

"... unless there is a clear reason to prefer the simpler solution, it is probably wise to choose the flexibility provided by the design pattern solution because unexpected new requirements often occur."

Prechelt et al.

L. Prechelt, B. Unger, W.F. Tichy, P. Brossler, and L.G. Votta. A controlled experiment in maintenance comparing design patterns to simpler solutions. IEEE Transactions on Software Engineering, pages 1134–1144, 2001.

### The Problem

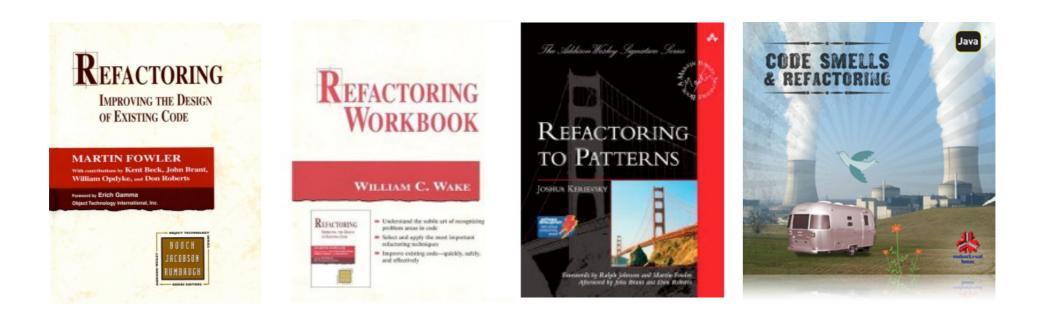
### Refactoring is

hard,

### tedious,

#### error-prone,

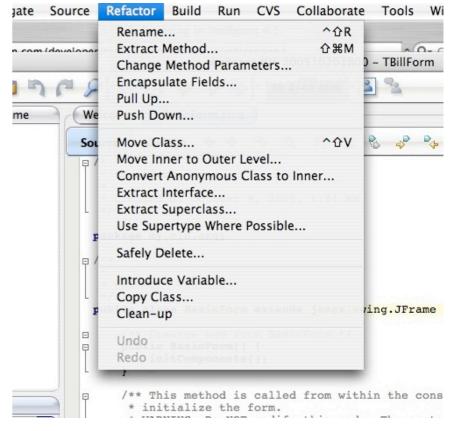
### and necessary.



# The Problem

- But there is hope. Automated refactorings include
  - Renaming classes
  - Generating get/set methods
  - Pulling up methods into a superclass
  - Generate an interface from a class

• What about larger refactorings?



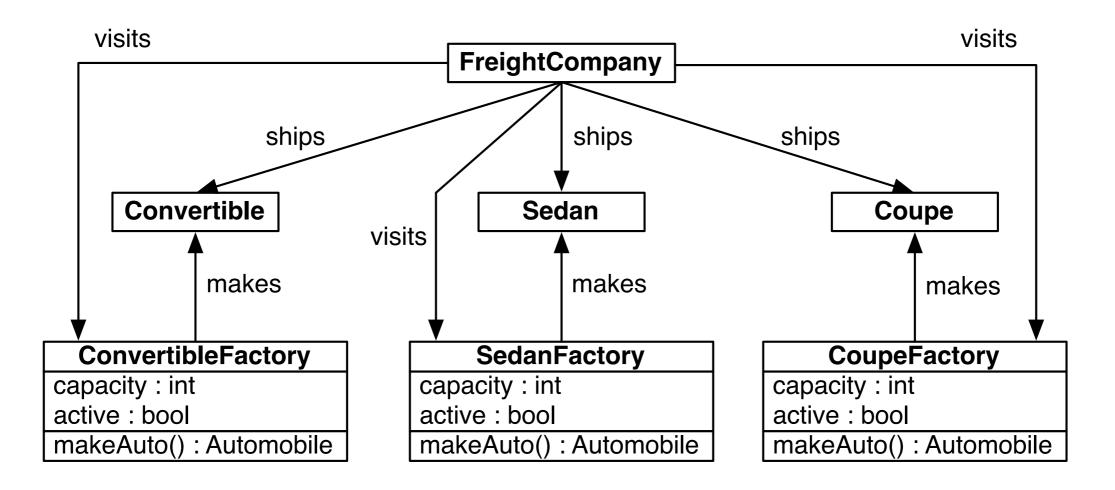
**Eclipse** 

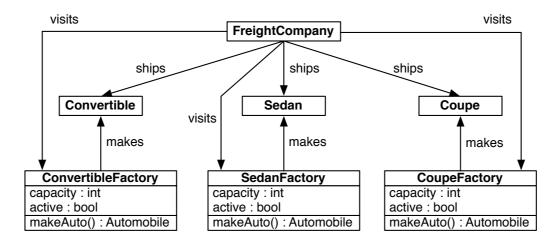
# Design Patterns

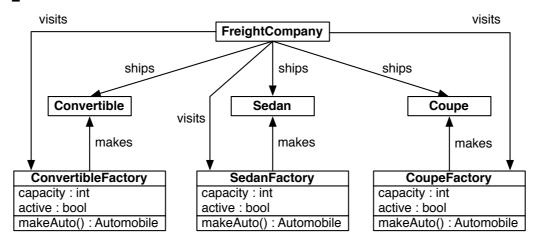
A design pattern is a reusable solution to a common design problem that occurs in a particular context. [Gamma et al.]

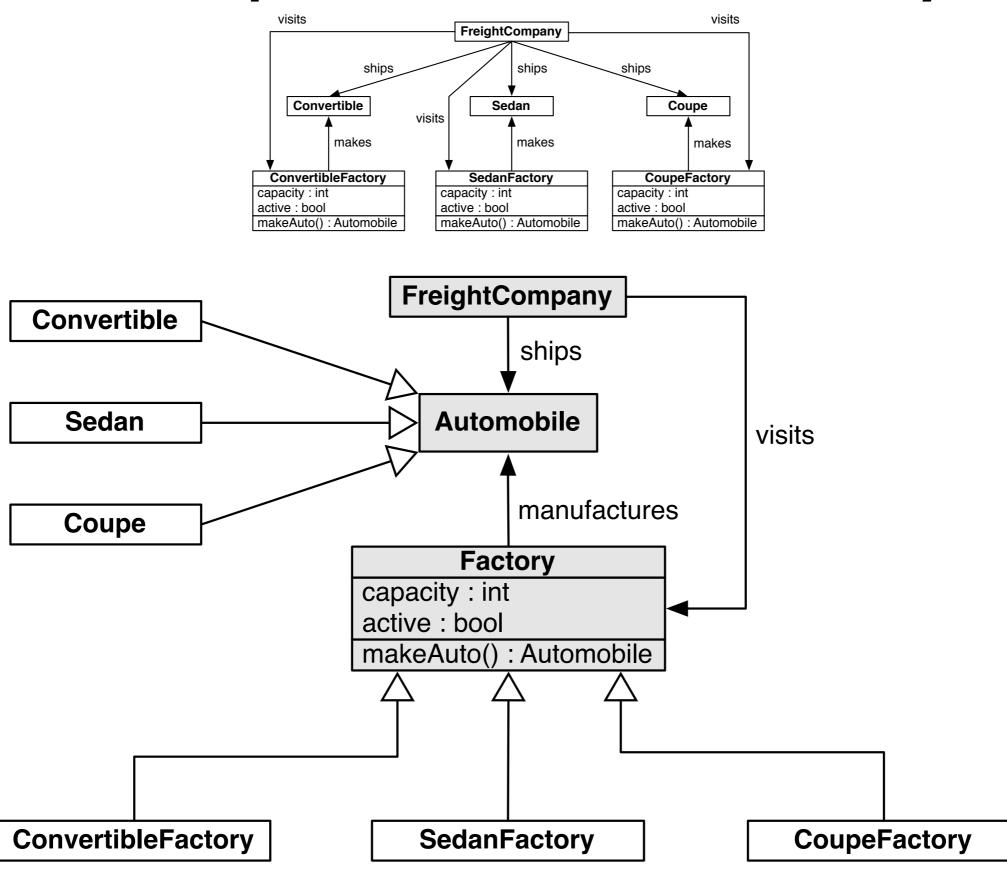
**Benefits:** 

- Captures the experience of professional designers
- Enables designers to think at a higher level of abstraction
- Improves the maintainability and reusability of software designs









### Thesis Statement

It is possible to use techniques from evolutionary computation, with guidance from software engineering metrics, in order to improve the design of existing software through the introduction of design pattern instances.

### Contributions

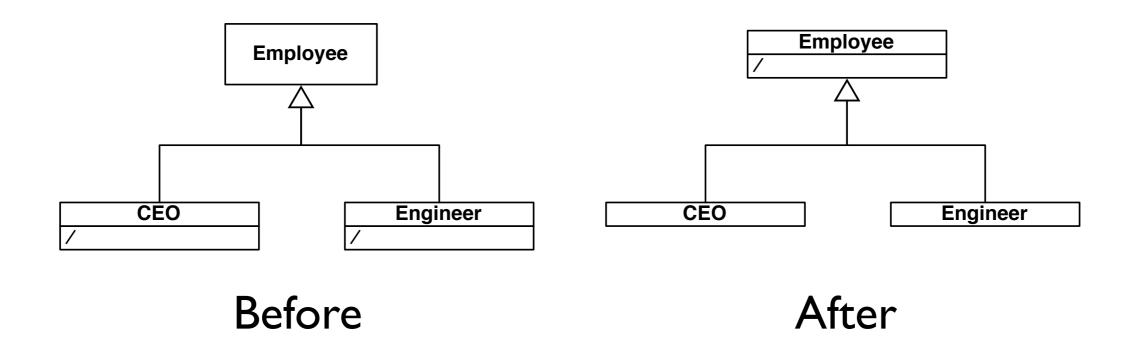
I. Novel GP encoding for refactoring software designs.

2. Process for automatically instantiating design patterns in existing software designs.

3. Step-by-step traceability for realizing a suggested design refactoring to enable manual or automated application.

### Related Work

- [Seng et al.]: GA for optimizing a class hierarchy
- Key insight:
  - Moving operations between classes in a hierarchy can improve design quality
  - Evolution can efficiently explore sequences of refactorings to apply
  - Example: promoting a common operation to a superclass



### Related Work

- [O'Keeffe & Ó Cinnéide]: "search-based refactoring"
- Key insight:
  - Perhaps other (non-GA) evolutionary approaches are more suitable for searchbased refactoring
- Study compared evolutionary approaches
  - Genetic Algorithm, Simulated Annealing, and Hill Climbers
  - Objective: to choose the optimal sequence of 14 refactoring steps, using software engineering metrics to evaluate solution quality
  - Conclusion: Multiple-restart hill-climber is most effective.

Existing approaches are effective for automating simple, incremental changes.

- No support for *composition* of multiple changes.
- They do not address larger refactoring strategies, such as design patterns.

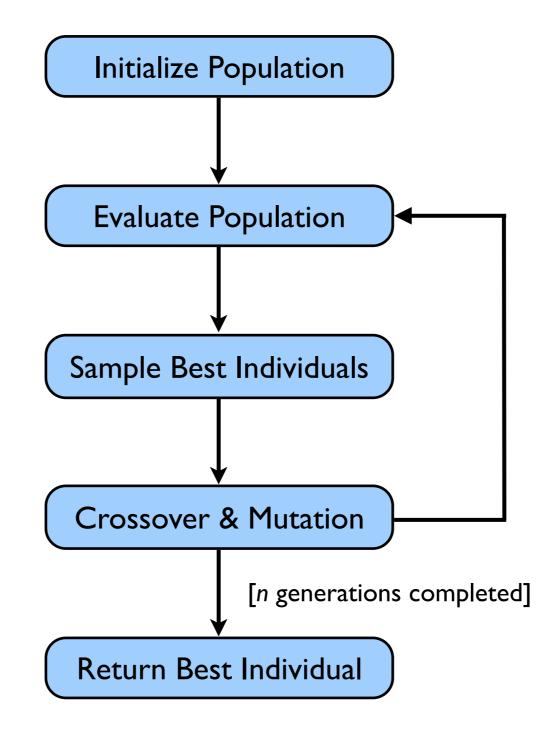
# Our Approach

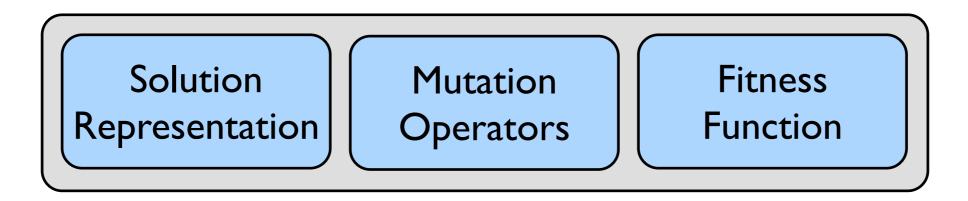
- Focus on the introduction of design patterns.
- Use genetic programming (GP), with a tree-based genotype, to leverage composition of mutation operators.
- Use metrics to evaluate fitness of modified designs.

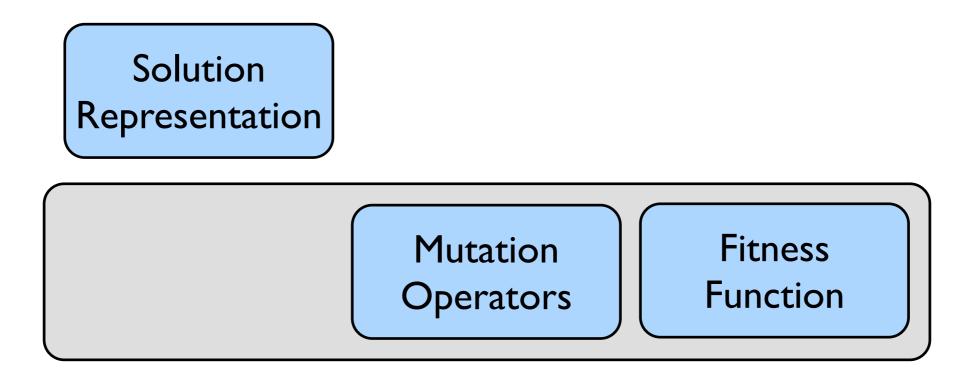
# Design Patterns

This approach supports seven Gamma design patterns:

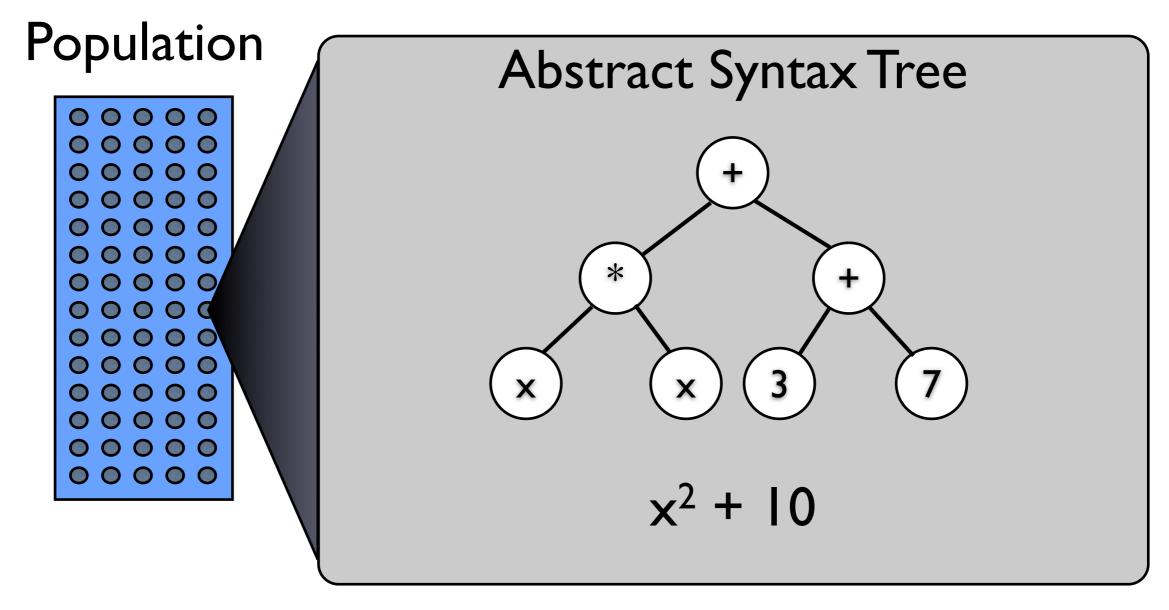
- Abstract FactoryAdapter
- Bridge
- Composite
- Decorator
- Prototype
- Proxy





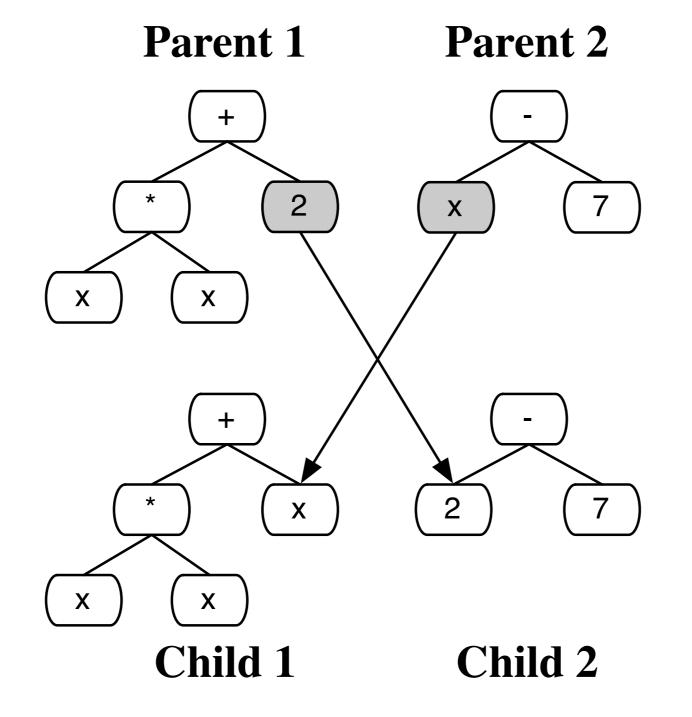


# Traditional GP

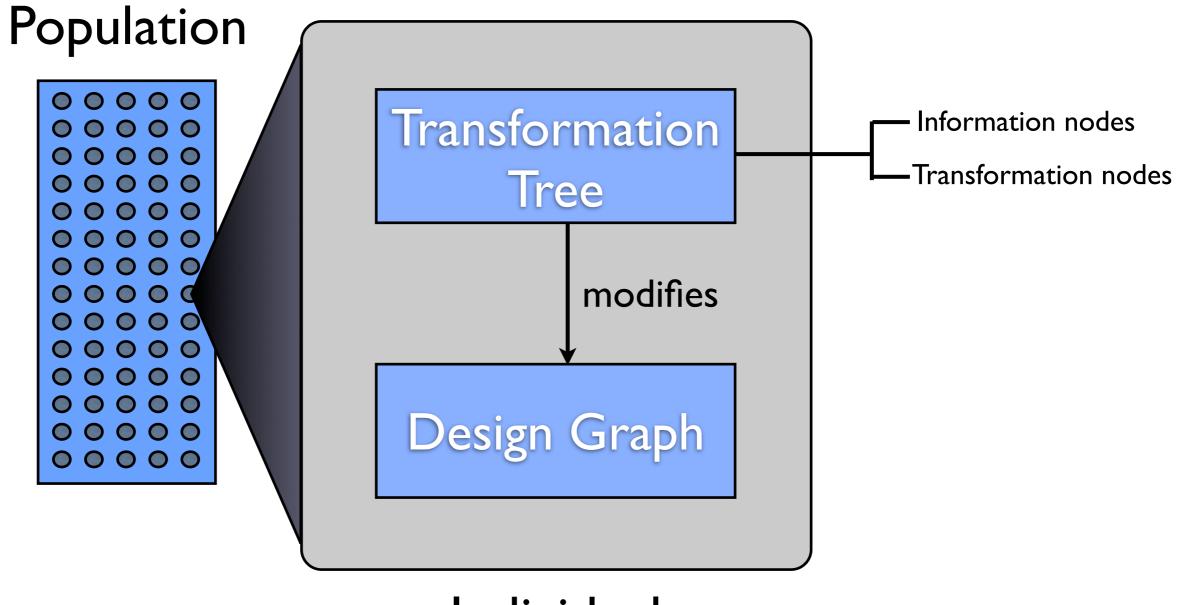


Individual

### Subtree Crossover

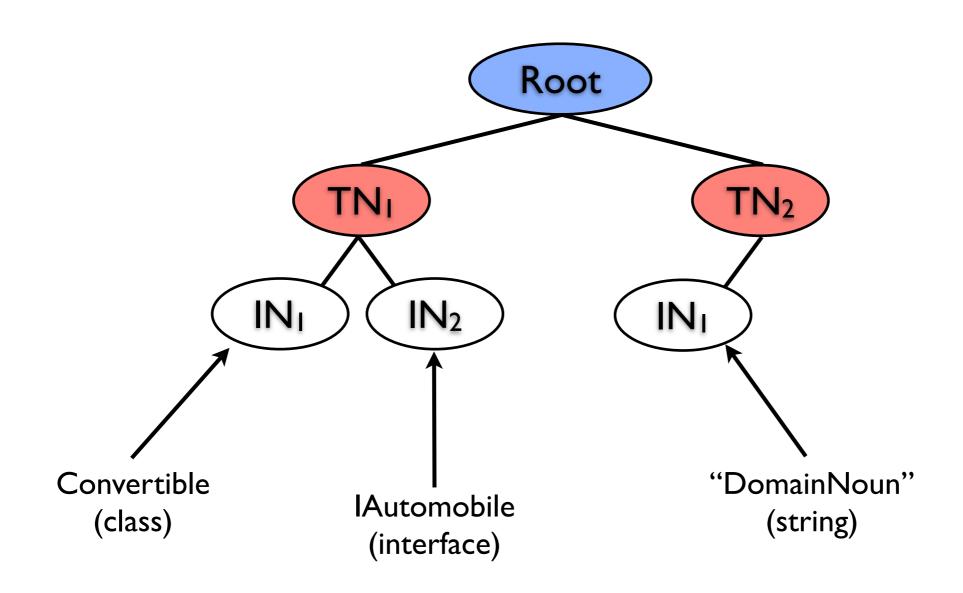


# Extended GP

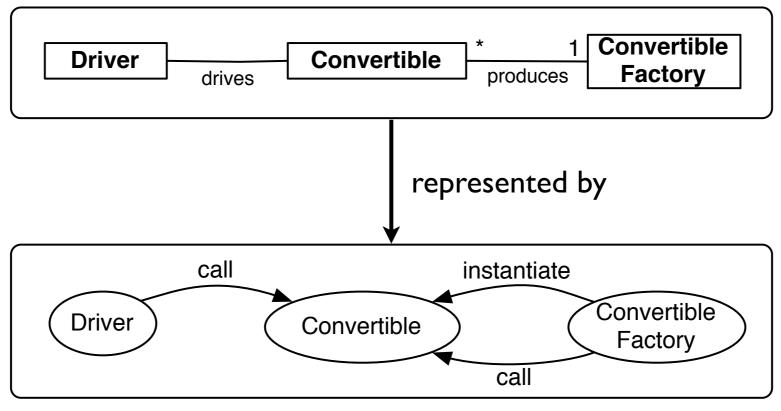


#### Individual

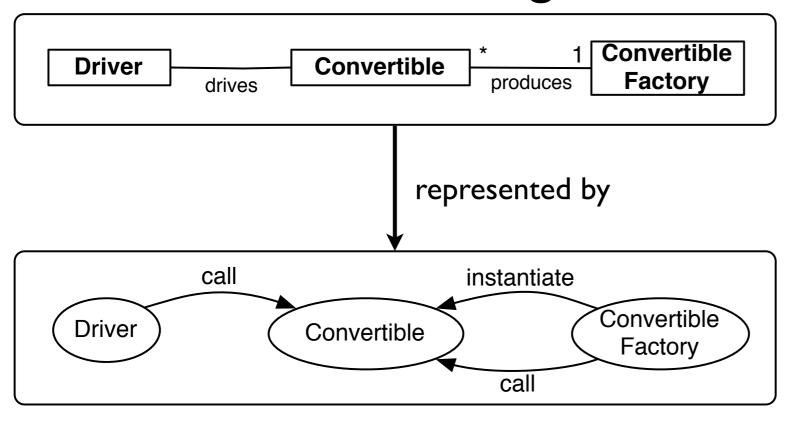
### Transformation Tree



### Software Design

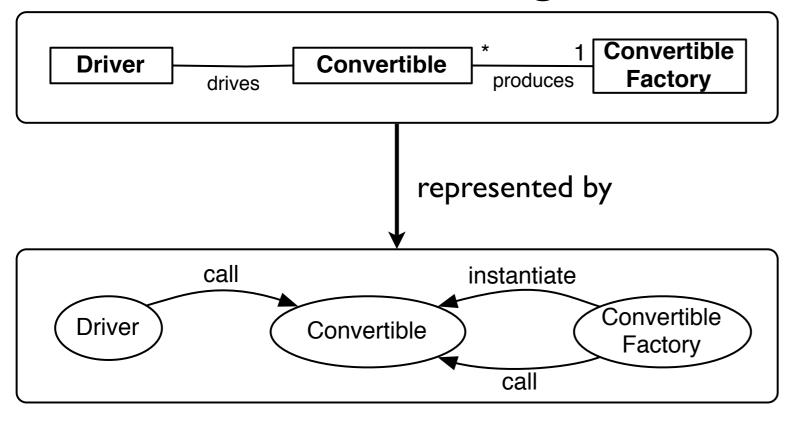


### Software Design



### Design Graph Elements:

### Software Design

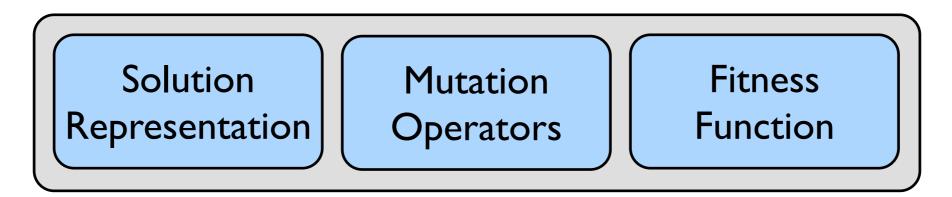


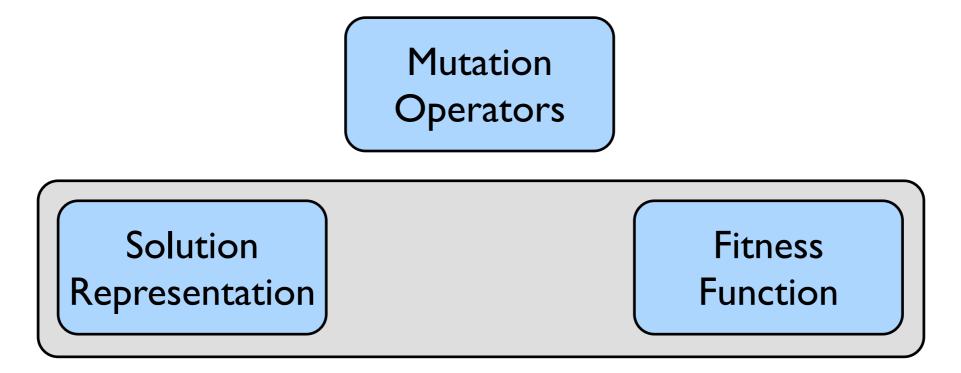
### Design Graph Elements:



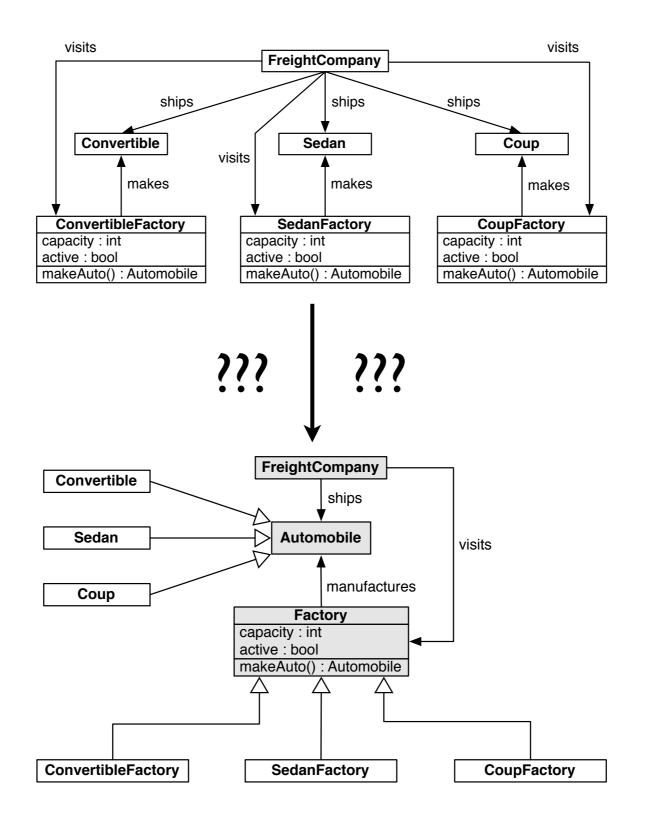
- Classes
- Interfaces
- Operations
- Edges
  - Aggregations
  - Associations
  - Function calls
  - Inheritance
  - Instantiations

#### Software Design Convertible 1 Convertible Driver Factory drives produces represented by call instantiate Convertible Driver Convertible Factory call

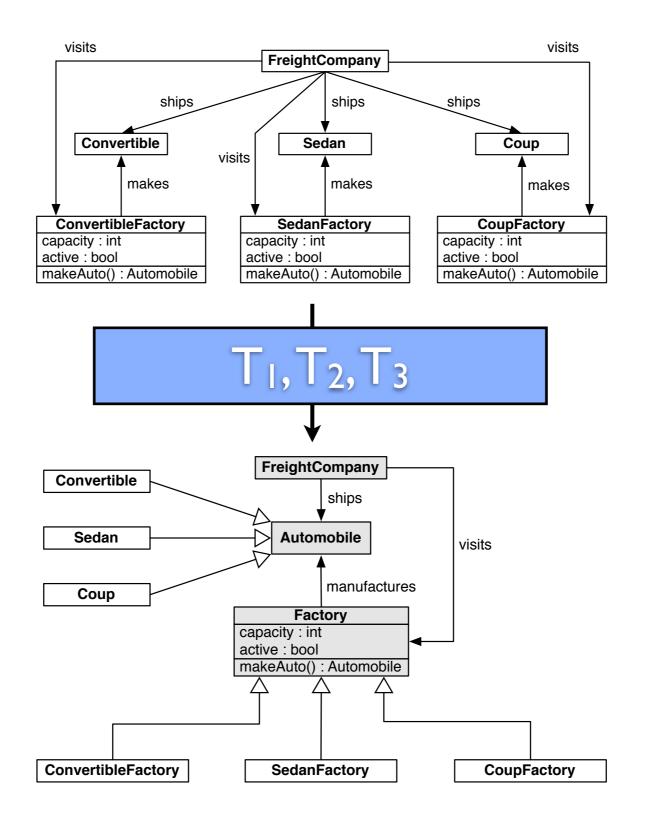




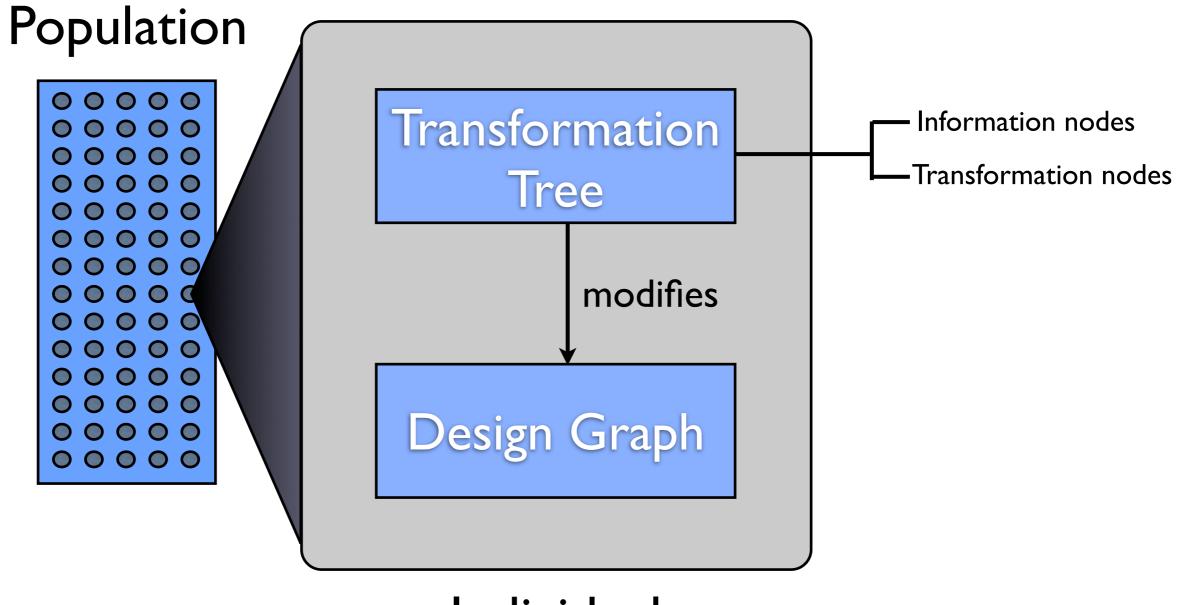
## Course-Grained Refactorings



# Course-Grained Refactorings

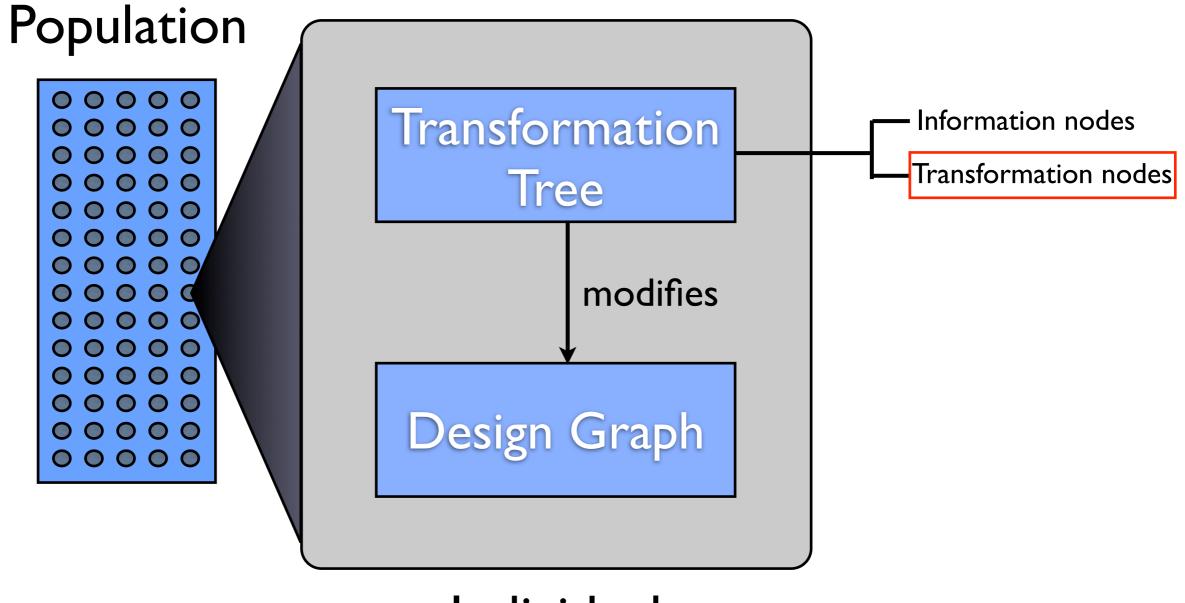


# Extended GP



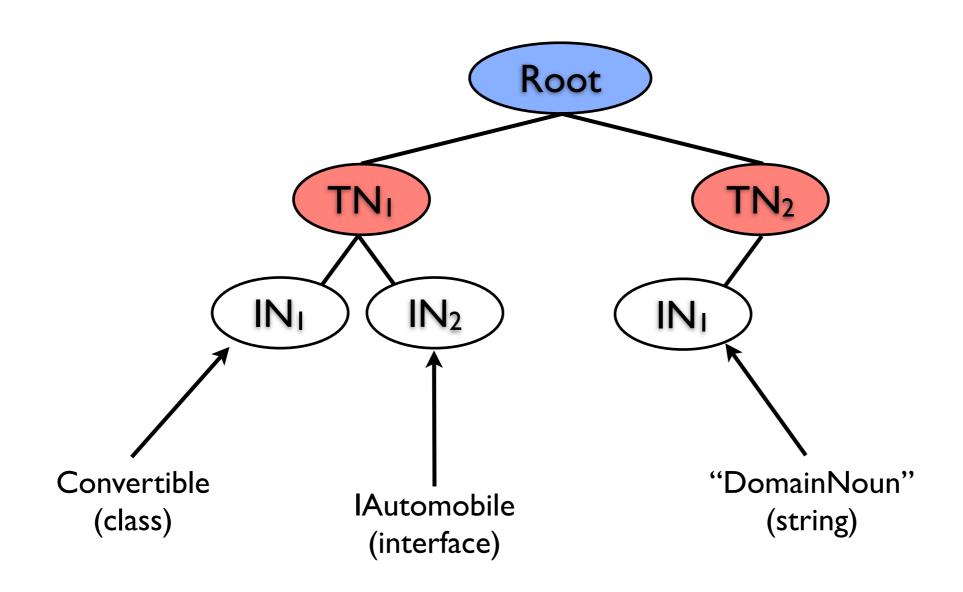
#### Individual

# Extended GP

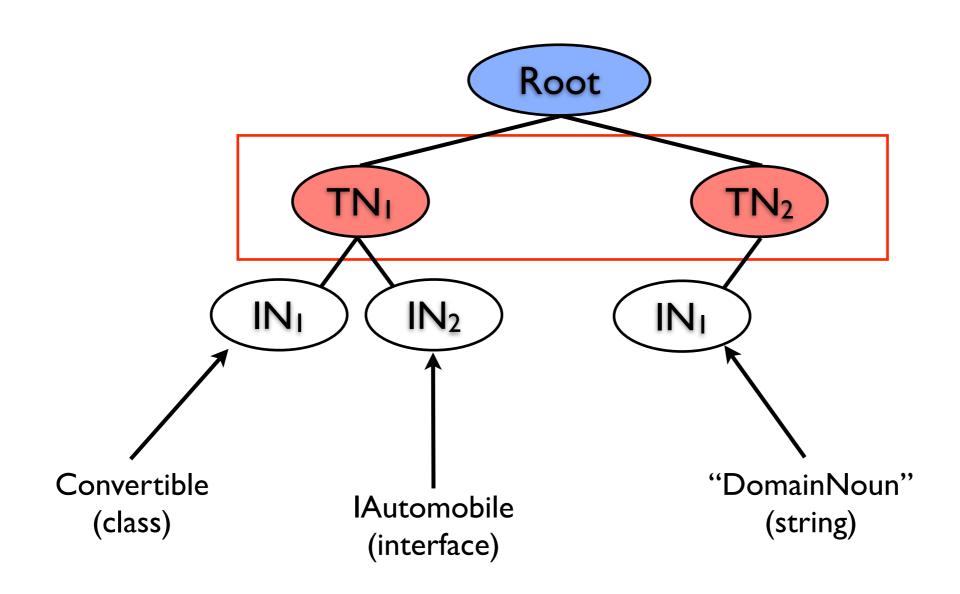


### Individual

### Transformation Tree



### Transformation Tree

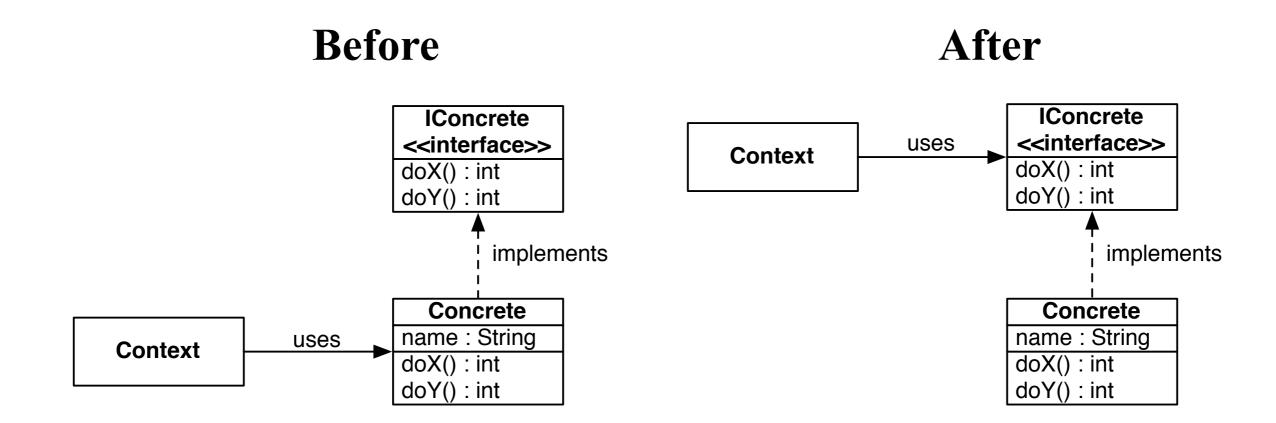


## Minitransformations

- Six mini-patterns, or *minitransformations*:
  - I. Abstract Access
  - 2. Abstraction
  - 3. Delegation
  - 4. Encapsulate Construction
  - 5. Partial Abstraction
  - 6. Wrapper

#### Abstract Access Transformation

**Purpose**: to modify a class *Context* to access another class *Concrete* more abstractly through an interface *IConcrete*.



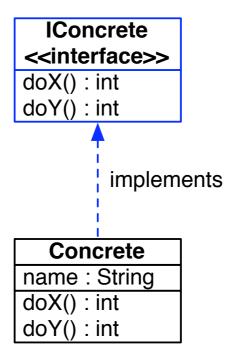
#### Abstraction Transformation

**Purpose**: to derive an interface from an existing class Concrete, enabling other classes to view Concrete more abstractly.

#### Before

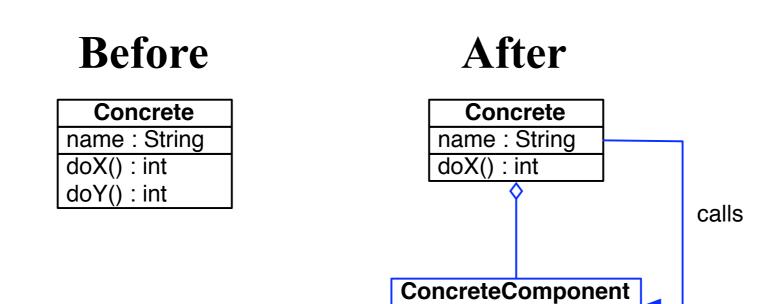
Concrete
name : String
doX() : int
doY() : int

#### After



#### **Delegation Transformation**

**Purpose**: to delegate a subset of the functionality of one class to another class.



doY() : int

#### Encapsulate Construction Transformation

# **Purpose**: to localize class instantiations into a dedicated operation.

#### Before

ShapeManager		
numShapes : int		nu
CopyShape() : Shape		Со
RandomizeShape() : Shape		Ra
TransformShape() : Shape		Tra
	' I	_

#### After

ShapeManager
numShapes : int
CopyShape() : Shape
RandomizeShape() : Shape
TransformShape() : Shape
CreateShape() : Shape

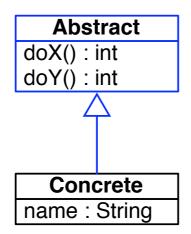
#### Partial Abstraction Transformation

**Purpose**: to create an abstract class with the same interface as an existing class.

#### Before

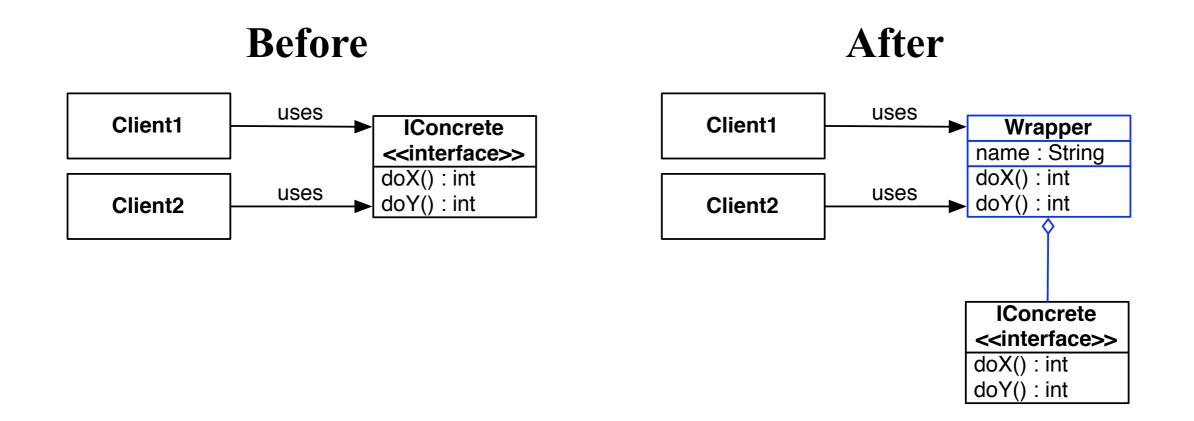
Concrete
name : String
doX() : int
doY() : int

#### After

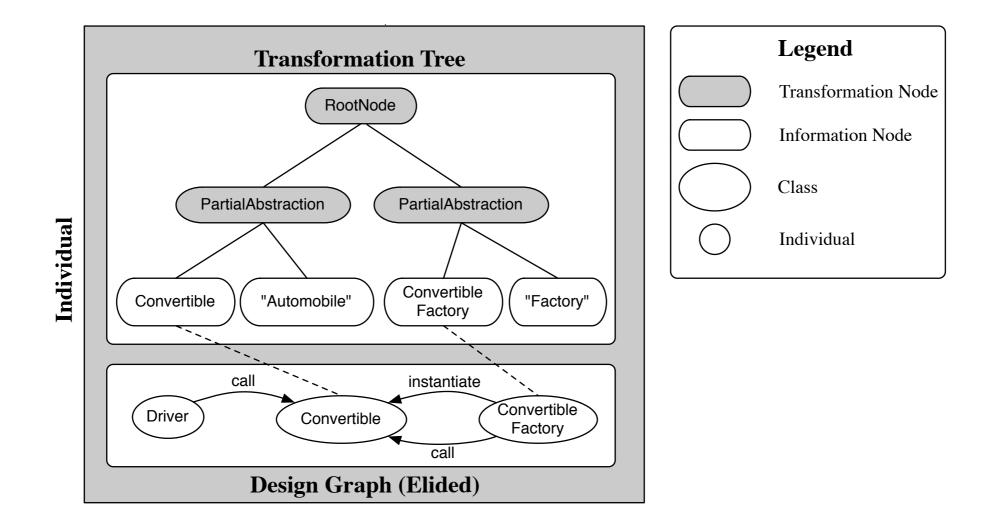


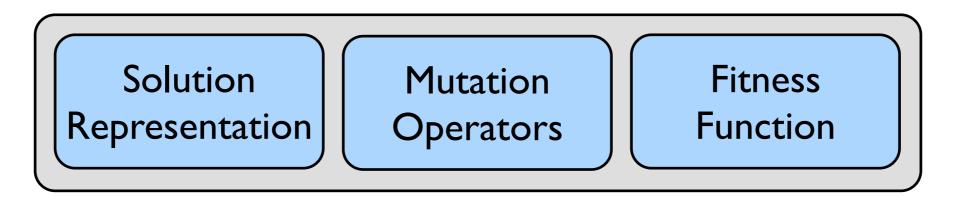
#### Wrapper Transformation

**Purpose**: to wrap a class with another, thus enabling run-time replacement of the wrapped class.

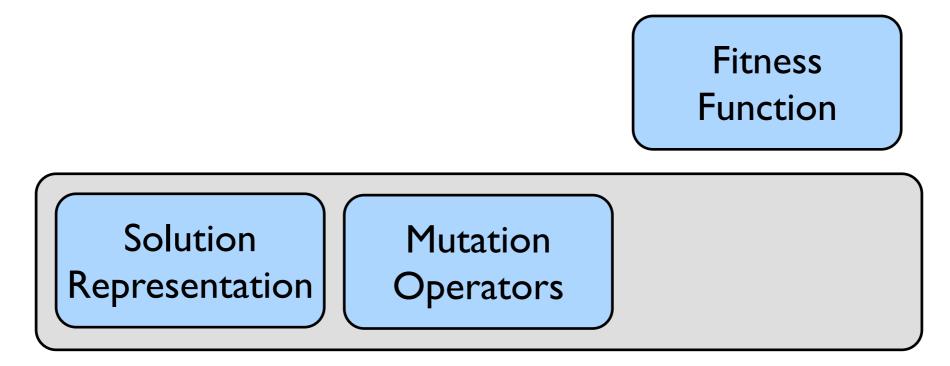


#### Minitransformations in Context





#### **Evolutionary Approach**



#### Evolutionary Approach

### Fitness Function

#### **Two initial terms:**

I. Quality of evolved software design

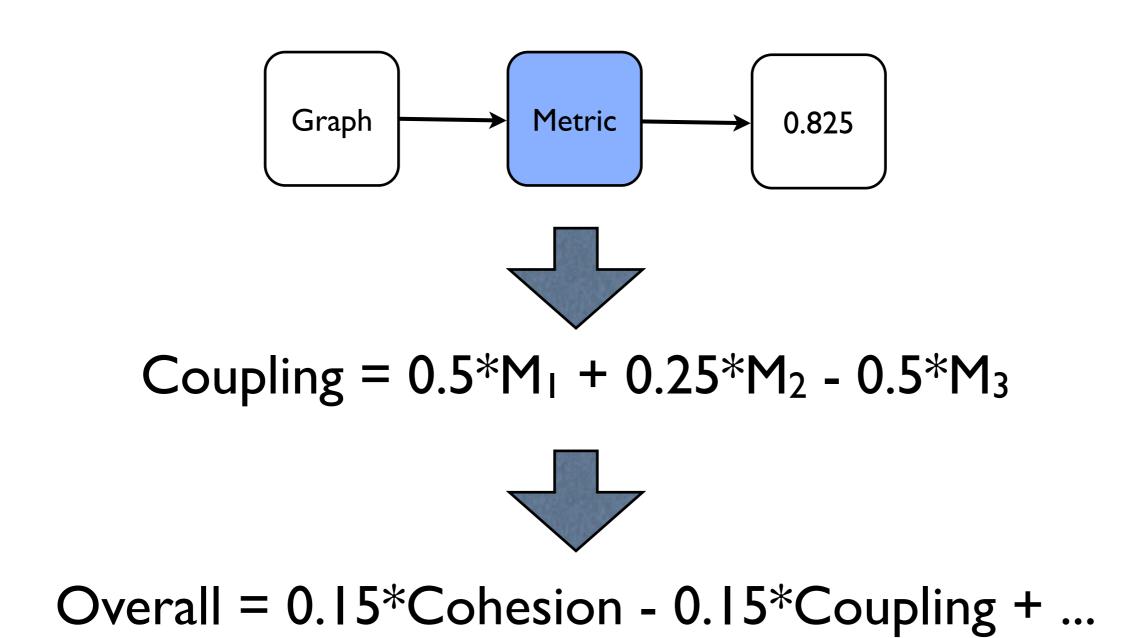
• Metrics

- 2. Presence of design patterns
  - Design pattern detector

## Metrics

- Hierarchical Metrics for Object-Oriented Design Quality [Bansiya & Davis]
  - Known as "QMOOD"
  - Comprises II metrics
  - Evaluates multiple characteristics: cohesion, coupling, design size, etc.
  - Amenable to automation
  - Implemented naturally as a set of graph algorithms

### Metrics



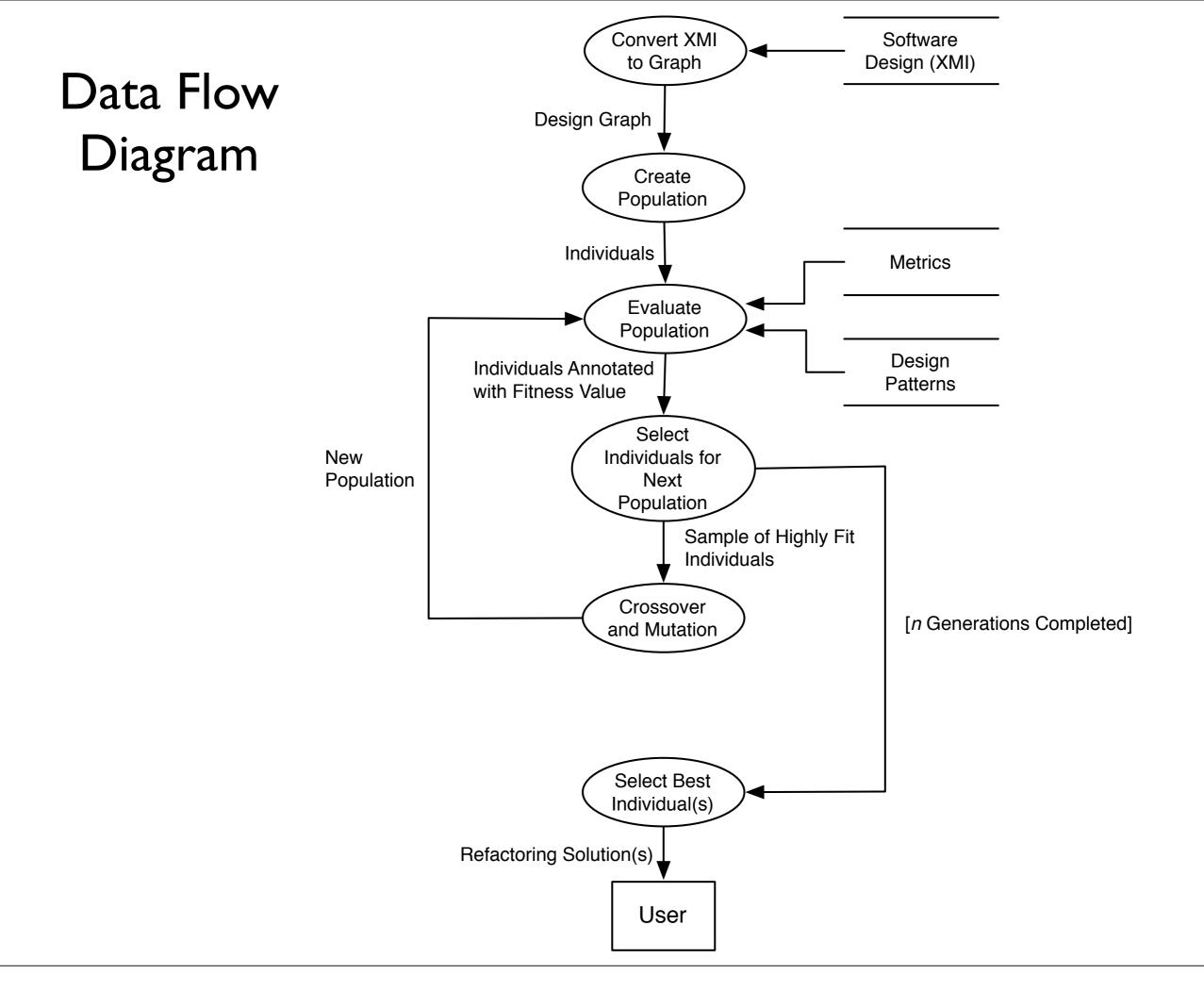
## **Design Pattern Detection**

- Design patterns have a characteristic signature
  - Can be detected using a logic or query language (e.g., Prolog or SQL)
  - Example Prolog query for the Abstract Factory pattern:

```
abstract_factory(AFact,CFact,AProd,CProd,Client) :-
cls(AFact), cls(CFact), cls(AProd), cls(CProd),
cls(Client), inherit(CFact,AFact),
inherit(CProd,AProd), instantiate(CFact,CProd),
fcall(Client,CProd), AFact \= CFact,
AProd \= CProd, AFact \= Client,
CFact \= Client, AProd \= Client,
CProd \= Client, AFact \= AProd,
AProd \= CFact.
```

### Fitness Function

F= Metrics -C<sub>1</sub>\*nodeCountPenalty + C<sub>2</sub>\*patternReward + C<sub>3</sub>\*matchingSequencesReward



### Implementation

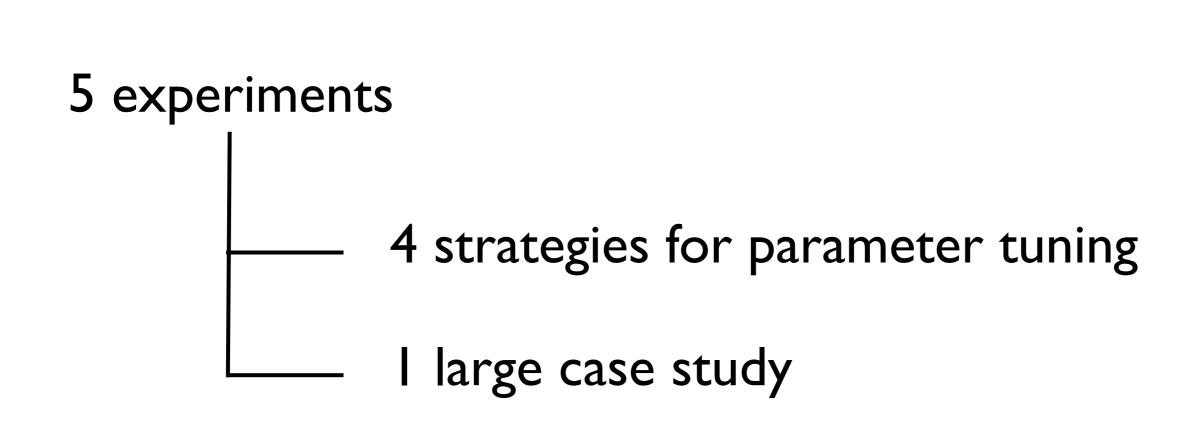
• <u>Input model format</u>: ArgoUML XMI

• <u>GP Framework</u>: Evolutionary Computation for Java (ECJ)

• <u>Graph support</u>: jGraph

• <u>Detection of Design Patterns</u>: jLog and HSQLDB

### Validation



## Parameter Tuning

- I. Plain vanilla
- 2. Constraining the number of transformation nodes
- 3. Rewarding design pattern presence
- 4. Rewarding known sequences of transformation nodes

## Setup

#### Parameters

- 100 individuals
- 100 generations
- Tournament selection with tournament size = 7
- 90% crossover+mutation; 10% reproduction

#### • Experiments I-IV

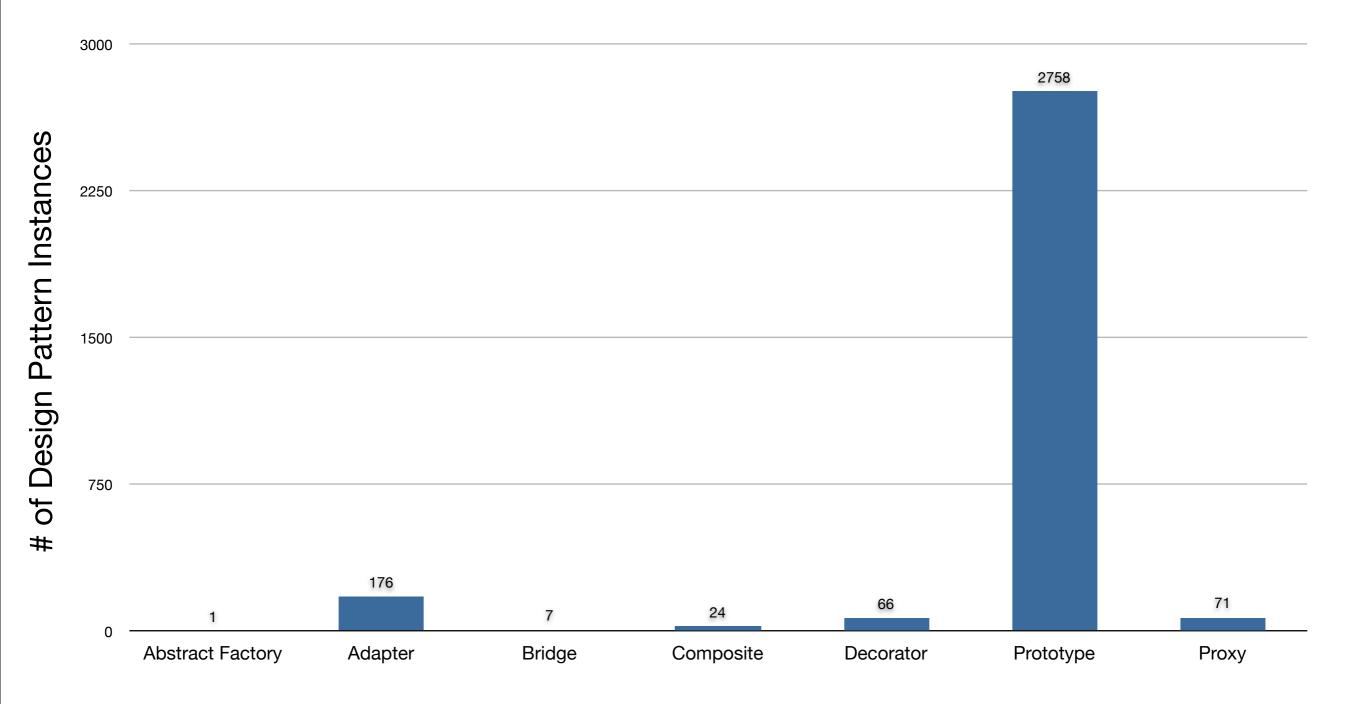
- 290 software designs
- 5 trials per design, each with a unique random seed

## Experiment I

- Purpose: to establish a baseline.
- No rewards or penalties; only metrics are considered
- Fitness function:
  - F = Metrics + 0.0\*nodeCountPenalty 0.0\*patternReward + 0.0\*matchingSequenceReward
- Hypothesis: at least one new design pattern instance will evolve in each of the 290 models.
- Result: hypothesis validated.

#### Experiment I

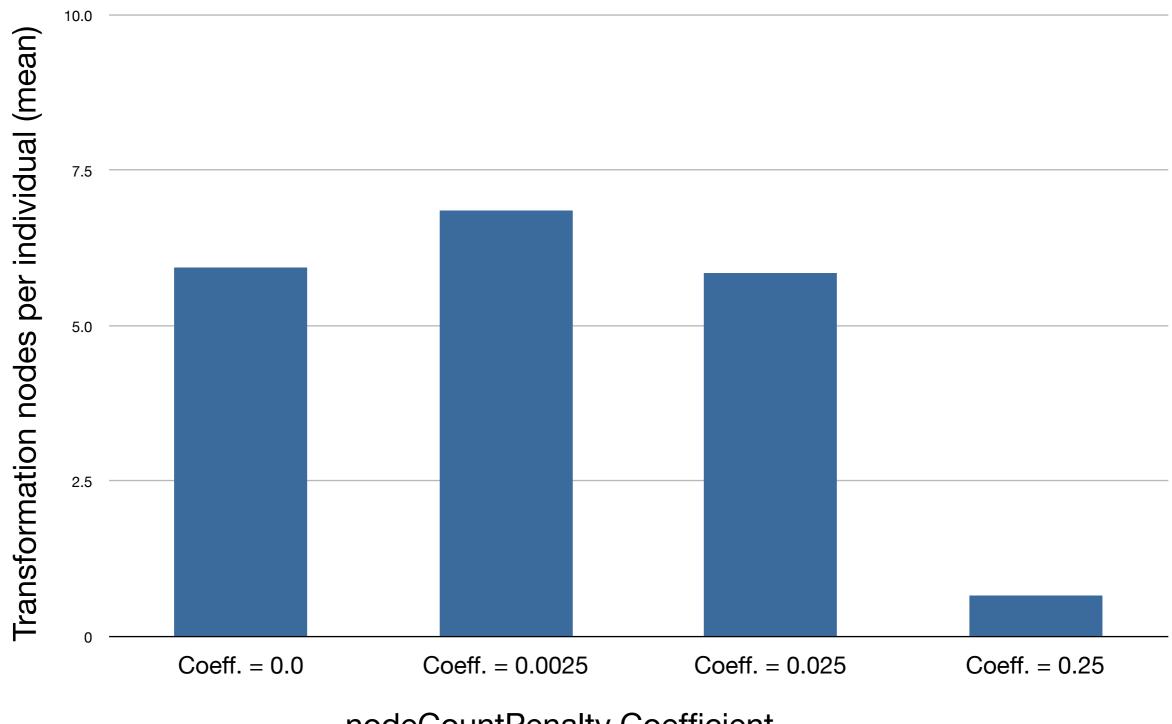
Mean # of transformation nodes: 5.94 New design pattern instances per model: 10.7



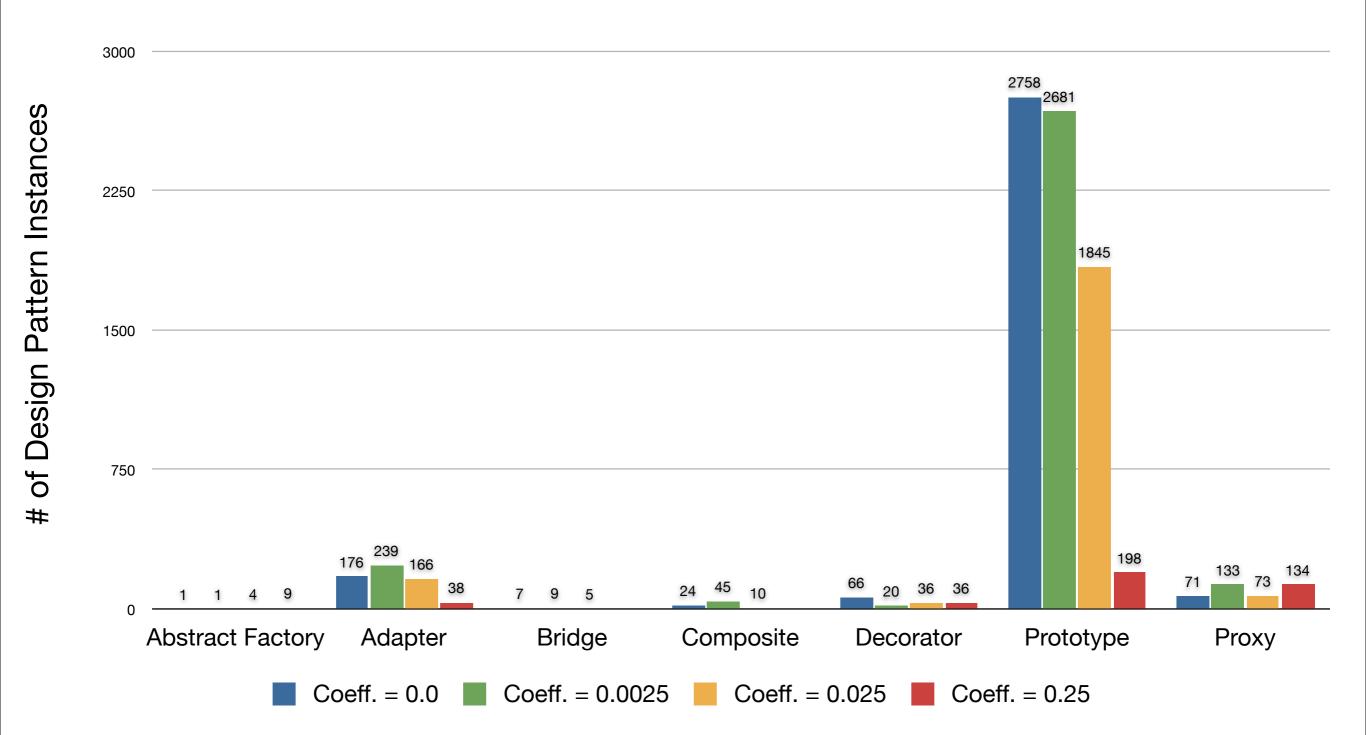
## Experiment II

- Purpose: to penalize large numbers of transformations
- New term in fitness function: nodeCountPenalty
  - We vary the coefficient on this term: 0.0025, 0.025, 0.25, 0.5
- Fitness function:
  - F = Metrics + X\*nodeCountPenalty + 0.0\*patternReward + 0.0\*matchingSequencesReward
- Hypothesis: a larger coefficient will reduce the number of transformations in the average individual
- Result: hypothesis validated.

#### Experiment II



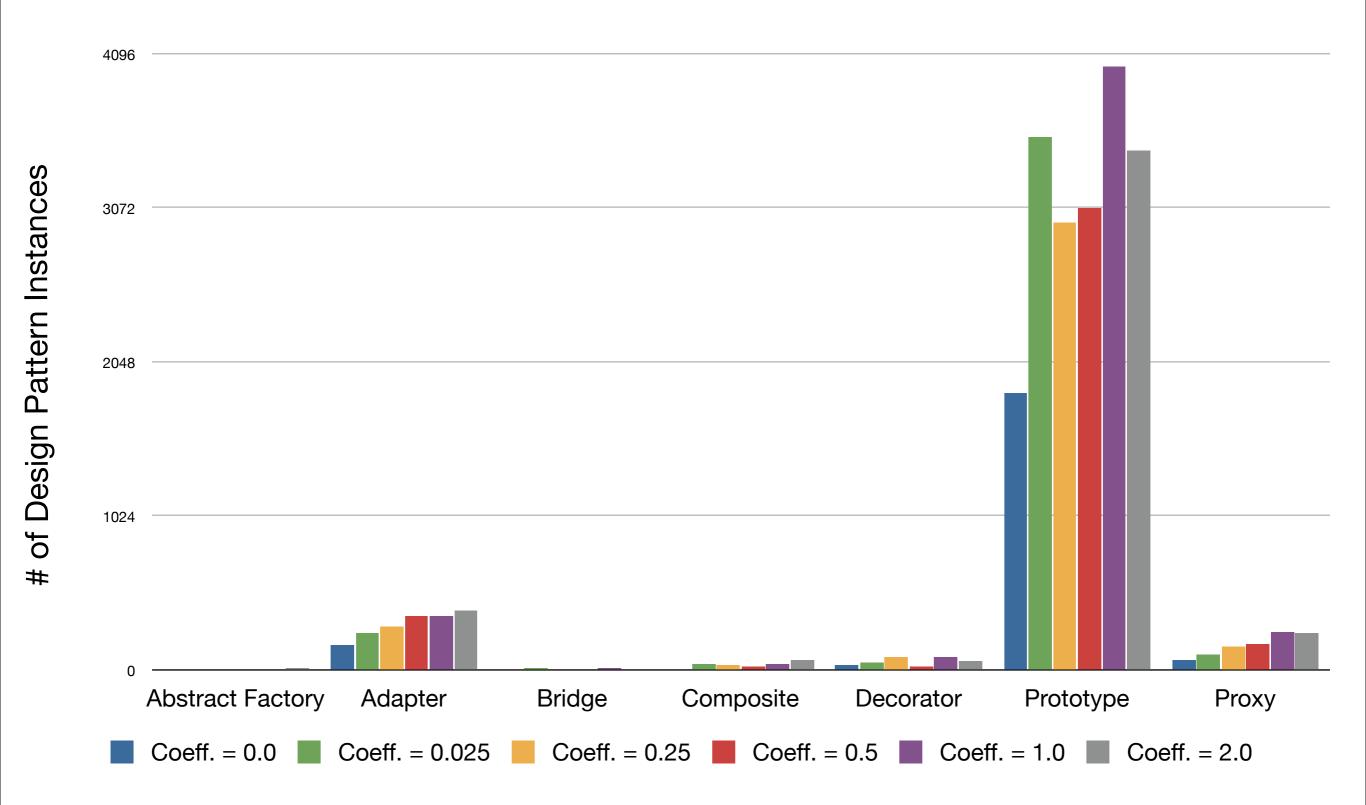
### Experiment II



## Experiment III

- Purpose: to reward creation of design pattern instances
- New term in fitness function: patternReward
  - We vary the coefficient on this term: 0.025, 0.25, 0.5, 1.0, 2.0
- Fitness function:
  - F = Metrics + 0.025\*nodeCountPenalty + X\*patternReward + 0.0\*matchingSequencesReward
- Hypothesis: a larger coefficient will lead to a larger number of design pattern instances on average.
- Result: hypothesis validated.

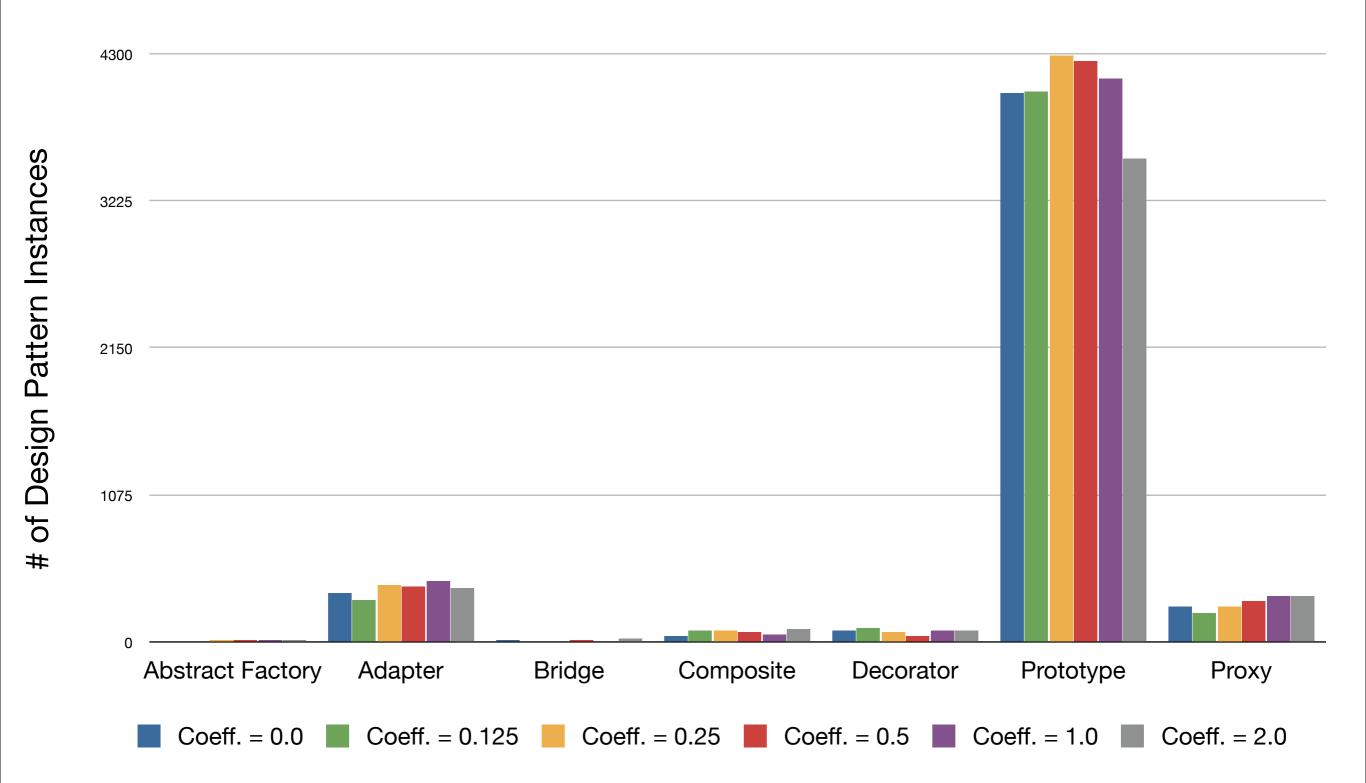
### Experiment III



## Experiment IV

- Purpose: to reward specific sequences of transformations
- New term in fitness function: matchingSequencesReward
  - We vary the coefficient on this term: 0.025, 0.25, 0.5, 1.0, 2.0
- Fitness function:
  - F = Metrics + 0.025\*nodeCountPenalty + 1.0\*patternReward +
     X\*matchingSequencesReward
- Hypothesis: a larger coefficient will lead to a larger number of design pattern instances on average.
- Result: hypothesis validated.

### Experiment IV

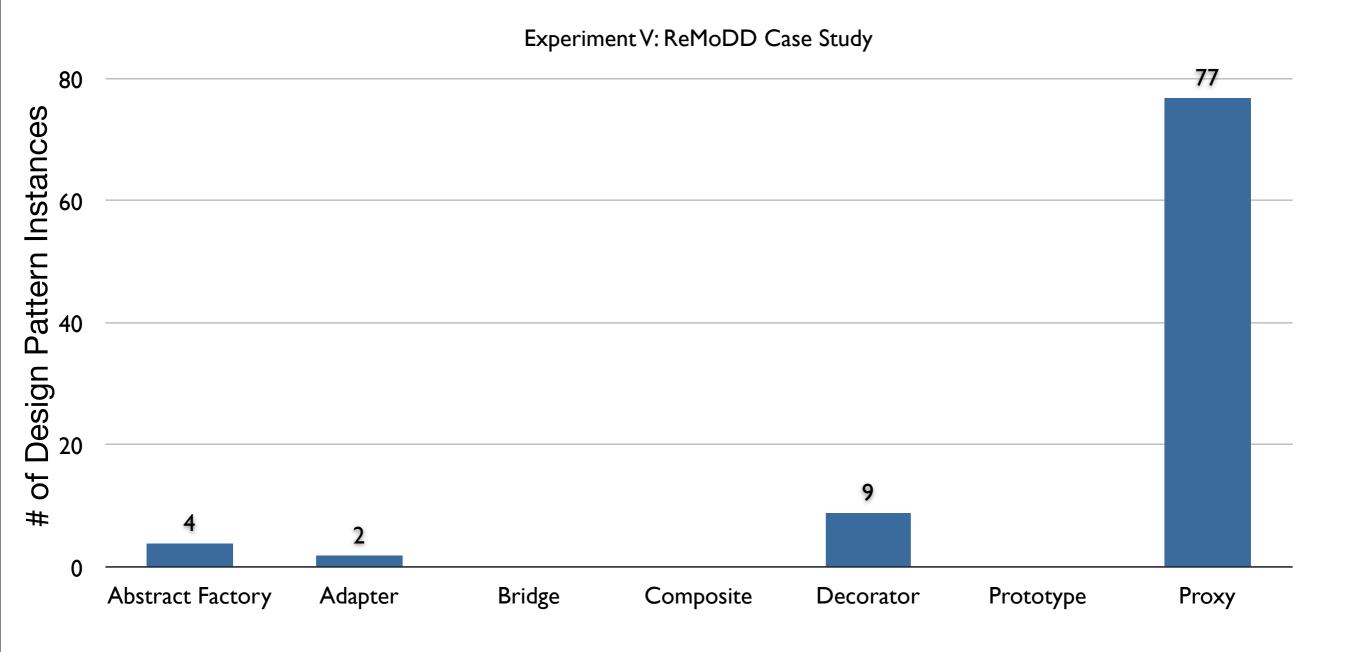


### Experiment V

- Purpose: to test the approach on a large design.
- Parameters
  - 25 generations
- Fitness function:
  - F = Metrics + 0.025\*nodeSizePenalty + 1.0\*patternReward + 0.5\*matchingSequencesReward
- Hypothesis: at least one instance of each supported design pattern type will evolve during the run.
- Result: **FIXME**.

### Experiment V

#### • ReMoDD case study



### Discussion

- Pattern complexity affects instance frequency
- Trends are not always monotonic
- Trials with no DP instances had higher quality than other trials for the same model
- In experiment IV, average design quality increased by 2.6

## Conclusions

- EC can be used to support automated design refactoring
- Validated on large body of designs.
  - 290 models
  - real-world case study
  - exploration of several rewards and penalties
- Impact:
  - design assistance tools
  - step-by-step process for automated refactoring

## Future Work

- Consider fitness for purpose of specific metrics and design patterns
- Explore synergy between metrics and DPs
- Look for other metric suites

## Questions / Comments

#### References

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[Prechelt2001] L. Prechelt, B. Unger, W.F. Tichy, P. Brossler, and L.G. Votta. A controlled experiment in maintenance comparing design patterns to simpler solutions. IEEE Transactions on Software Engineering, pages 1134–1144, 2001.

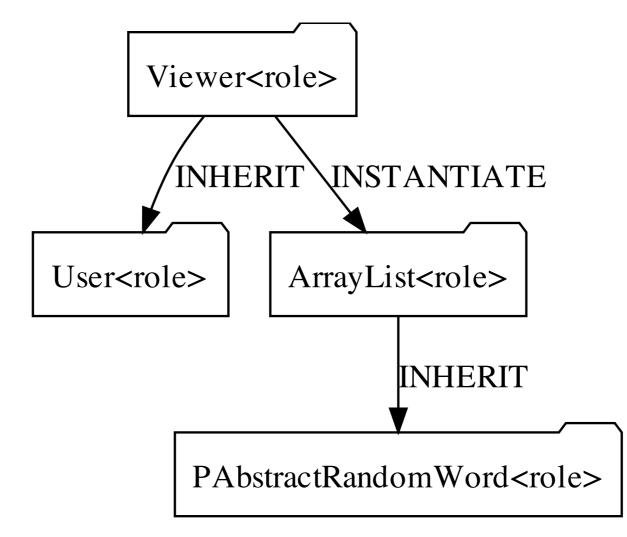
[Seng2006] O. Seng, J. Stammel, and D. Burkhart. Search-based determination of refactorings for improving the class structure of ob ject-oriented systems. In Proceedings of the 8th annual conference on Genetic and evolutionary computation, pages 1909–1916. ACM New York, NY, USA, 2006.

## Acknowledgements

- Funding support from
  - Ford
  - QFC
  - ► NSF

QMOOD	Metric Name and Ab- breviation	Description
QMOOD Metrics	Design size in classes (DSIC)	The number of classes in the software design.
	Number of hierarchies (NOH)	The number of class hierarchies in the software design.
Bansiya & Davis	Average number of ances- tors (NOA)	The average number of other classes that a class inherits.
	Number of polymorphic methods (NOPM)	The number of methods in the software design that exhibit polymorphic behavior.
	Class interface size (CIS)	The average number of public methods in a class.
	Direct class coupling (DCC)	A count of the number of classes that a given class is directly related to by attribute declaration or method return type.
	Cohesion among methods of class (CAM)	The relatedness among methods of a class, com- puted using the summation of the intersection of parameters of a method with the maximum inde- pendent set of all parameter types in the class.
	Number of methods (NOM)	The average number of methods in a class.
	Data access metric (DAM)	The ratio of non-public (i.e., private or protected) attributes to the total number of attributes de- clared in a class. This is interpreted as the average of the ratios for all classes in the software design.
	Measure of aggregation (MOA)	The average number of data declarations (e.g., fields) in a class whose data types are user-defined classes. We exclude classes that are part of the Java standard library and language.
	Measure of functional ab- straction (MFA)	The ratio of the total number of methods inher- ited by a class to the number of methods that are accessible by member methods of that class.

## **Evolved Design Fragment**



# Sample AST

