4th ECADA
Evolutionary Computation for the Automated Design of Algorithms
GECCO WORKSHOP 2014

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Welcome + Outline

- Schedule
- Proposing many algorithm
- Template method + type signatures
- Base and meta-level learning
- Problem Classes (probability of an instance)
- Example: Bin Packing
- Outlook.

Schedule

- **8:30-9:00** Introduction and Overview.
- **9:00-9:30** Automated Design of Algorithms and Genetic Improvement: Contrast and Commonalities
- Saemundur O. Haraldsson, John R. Woodward
- **9:30-10:00** Benchmarks that Matter for Genetic Programming
- John R. Woodward, Simon P. Martin, Jerry Swan
- **10:00-10:40** Coffee Break
- **10:40-11:10** A Problem Configuration Study of the Robustness of a Black-Box Search Algorithm Hyper-Heuristic
- Matthew A. Martin, Daniel R. Tauritz
- **11:10-11:40** A Step Size Based Self-Adaptive Mutation Operator for Evolutionary Programming
- Libin Hong, John H. Drake, Ender Ozcan
- **11:40-12:10** Discussion

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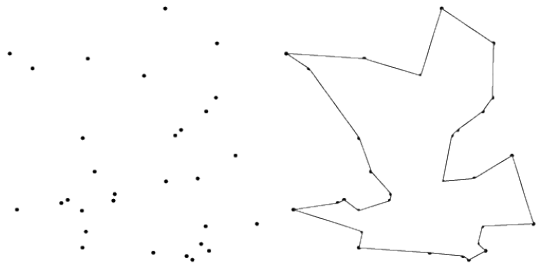
Conceptual Overview

Combinatorial problem e.g. TSP salesman
Exhaustive search?



Genetic Algorithm
heuristic – permutations

Travelling Salesman

Tour

Single tour NOT EXECUTABLE!!!

Genetic Programming
code fragments in for-loops.

Travelling Salesman Instances

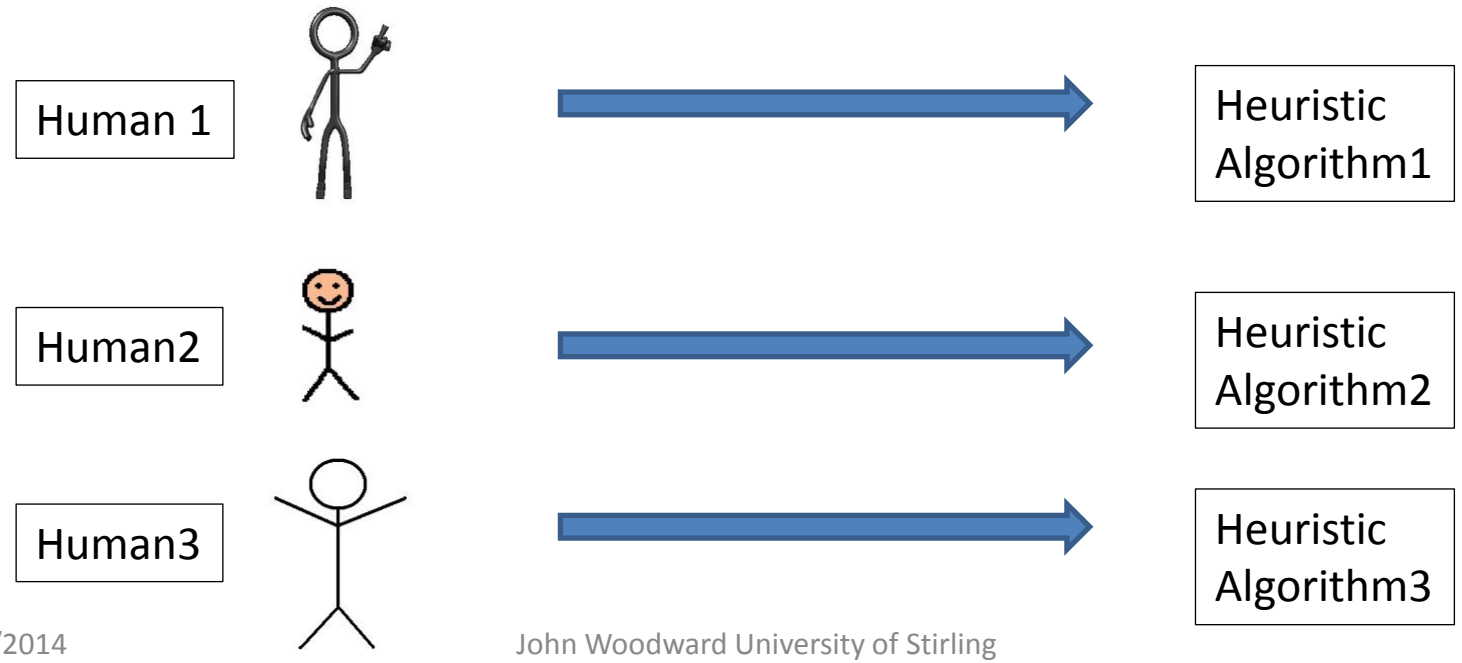
TSP algorithm

EXECUTABLE on MANY INSTANCES!!!

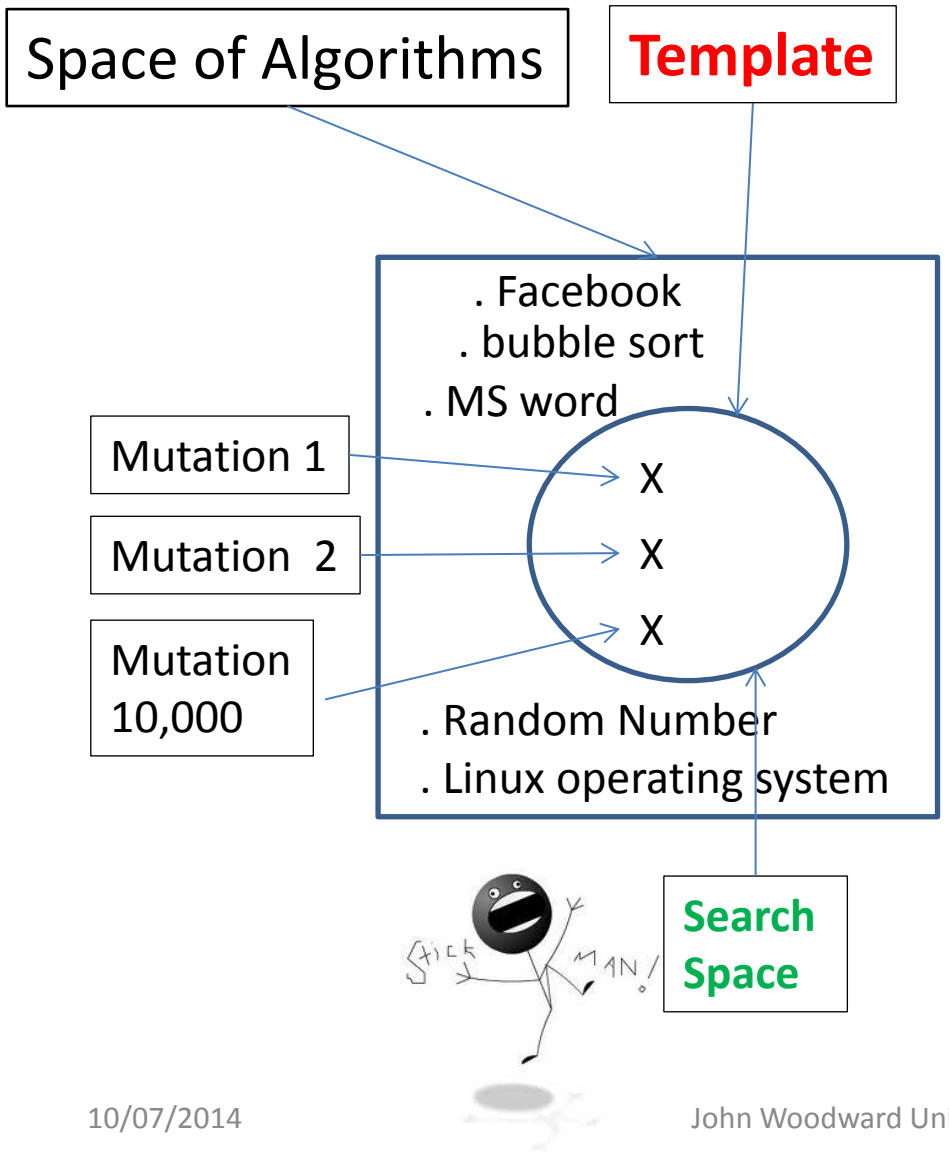
Give a man a fish and he will eat for a **day**.
Teach a man to fish and he will eat for a **lifetime.**

One Man – One Algorithm

1. Researchers design heuristics by hand and test them on problem instances or arbitrary benchmarks off internet.
2. Presenting results at conferences and publishing in journals. In this talk/paper we propose a new algorithm…
3. What is the target problem class they have in mind?



One Man ….Many Algorithms



1. Challenge is defining an algorithmic framework (**set**) that **includes** useful algorithms, and **excludes** others.

2. Let Genetic Programming **select the best algorithm for the problem class at hand.** **Context!!!** Let the data speak for itself without imposing our assumptions.

Proposing Sets of Algorithms

In the *template method*, one or more algorithm steps can be **overridden** by subclasses to allow **differing** behaviours while ensuring that the **overarching** algorithm is still followed.

- **Concrete** methods/classes **constrain** the **behaviour** of the program.
- **Abstract** methods/classes allow variation.

A template is a **skeleton**.

Template Method Hyper-heuristics

- **Template Method** is a design pattern.
- Some methods of a class have specified type signatures but no implementation (body) i.e. **abstract class**.
- The abstract class(es) can be **supplied later** by another programmer.
- OR can be supplied by Automatic Programming Technique such as **Genetic Programming**.

Type Signatures

- H = history, P = population

$$initialization : Void \rightarrow P$$

$$selection : P \times H \rightarrow P$$

$$variation : P \times H \rightarrow P$$

$$succession : P \times H \rightarrow P$$

$$termination : H \rightarrow Bool$$

Evolutionary Algorithm Template

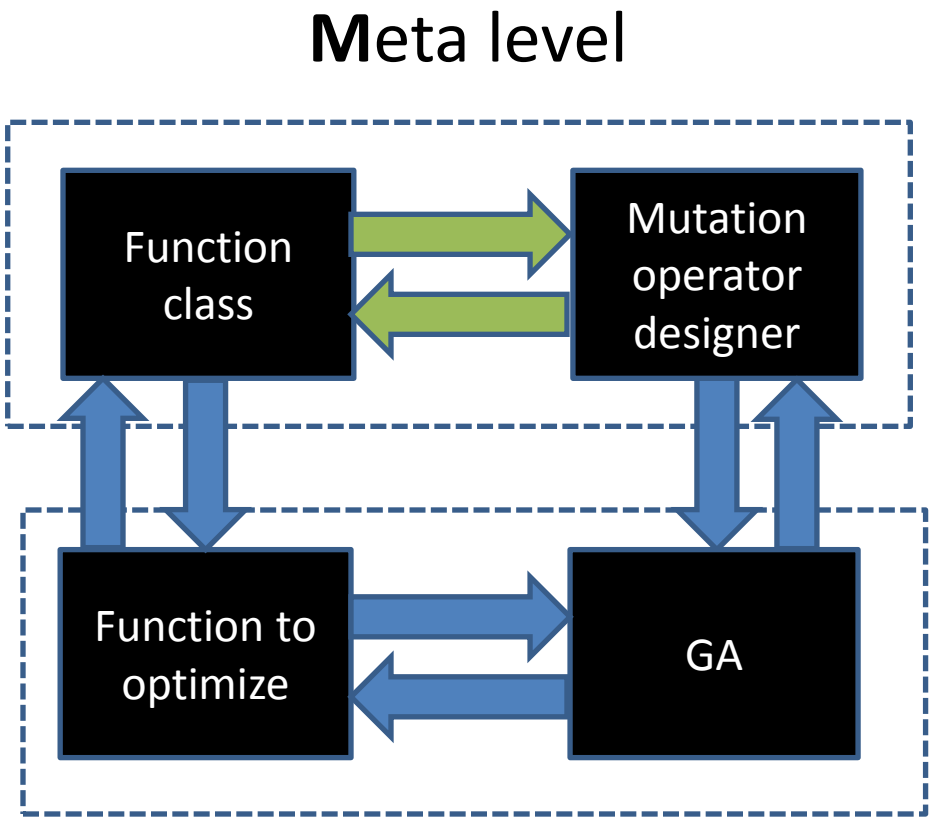
```
procedure evolve
begin
   pop = initialization()
   history = []
   repeat
      parents =  selection( pop, history )
      offspring =  variation( parents, history )
      pop  = succession( offspring, history )
      history =  history.append( pop )
   until termination( history )
end
```

Example – mutation for GA.

- **Examples:** one point and uniform mutation.
- **Behaviour:** Given a bit string of length n, return a bit string of length n.
- We could write another mutation operator.
- **NO NO NO** – lets let Genetic Programing DO ALL THE HARD (and boring) WORK.
- **Generate-and-test a Generate-and-test method**

Meta and Base Learning

1. At the **base** level we are learning about a **specific** function.
2. At the **meta** level we are learning about the problem **class**.
3. We are just doing **"generate and test"** on **"generate and test"**
4. What is being passed with each **blue arrow**?
5. Training/Testing and Validation



Compare Signatures (Input-Output)

Genetic Algorithm	Genetic Algorithm Designer
• (B^n -> R) -> B^n	• [(B^n -> R)] -> ((B^n -> R) -> B^n)
Input is an objective function mapping bit-strings of length n to a real-value.	**Input** is a *list of* functions mapping bit-strings of length n to a real-value (i.e. sample problem instances from the problem class).
Output is a (near optimal) bit-string	**Output** is a (near optimal) mutation operator for a GA
i.e. the solution to the problem instance	i.e. the solution method (algorithm) to the problem class

We are **raising the level of generality** at which we operate.
Give a man a fish and he will eat for a day, teach a man to fish and…

Additions to Genetic Programming

1. final program is part human constrained part (for-loop) machine generated (body of for-loop).

2. In GP the initial population is **typically randomly created**. Here we (can) initialize the population with **already known good solutions** (which also confirms that we can express the solutions). (improving rather than evolving from scratch) – standing on shoulders of giants. Like genetically modified crops – we start from existing crops.

3. Evolving on **problem classes** (samples of problem instances drawn from a problem class) not instances.

In a Nutshell

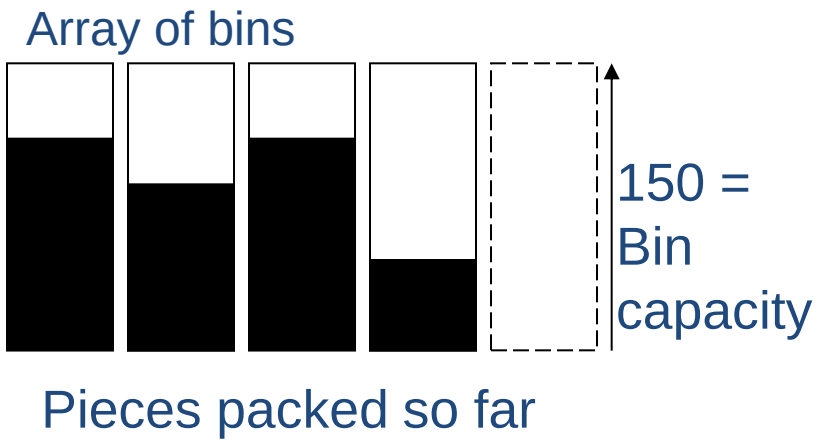
- **Humans** design the **structure** of the program e.g. the for-loops (GP is bad at that) (INVARIANT)
- Let **GP** build the **body** of the for-loop (VARIANT).
- The final program is part **man made** and part **machine made**.
- We used the **Object Oriented** approach but could be expressed in terms of e.g. **Functional programming** (pass in a mutation operator).

Problem Classes Do Occur

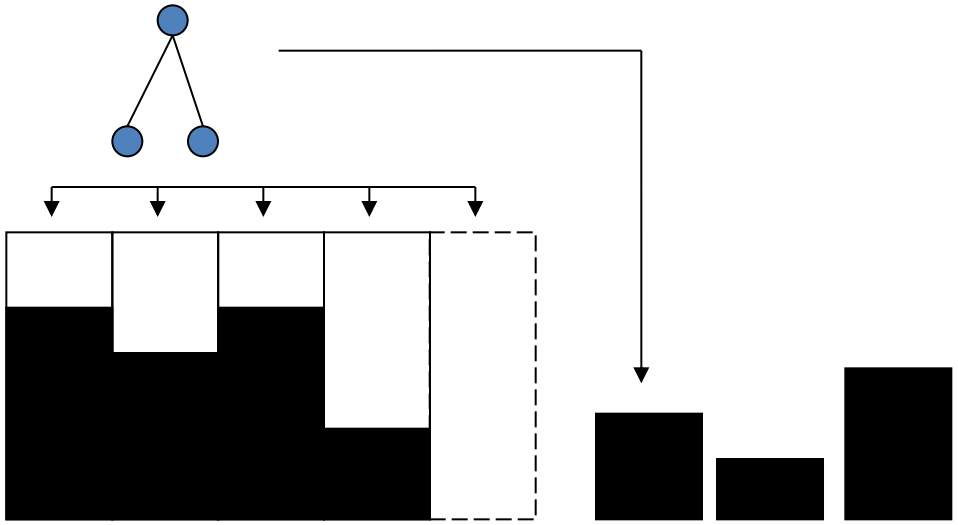
1. Travelling Salesman
    1. Distribution of cities over different counties
    2. E.g. USA is square, Japan is long and narrow.
2. Bin Packing & Knapsack Problem
    1. The items are drawn from some probability distribution.
3. Problem classes do occur in the real-world
4. Next 6 slides demonstrate **problem classes** and **scalability** with on-line bin packing.

On-line Bin Packing

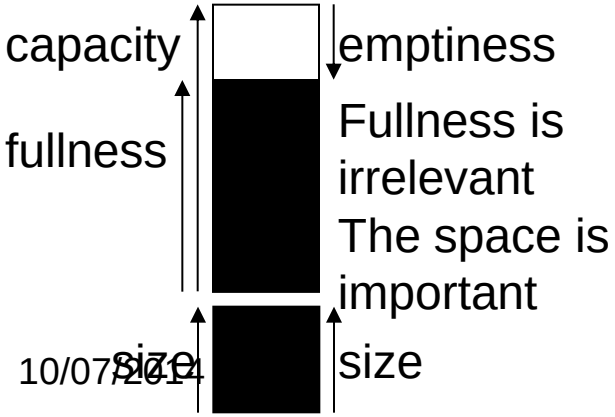
A *sequence* of pieces is to be packing into as few a bins or containers as possible.
Bin size is 150 units, pieces uniformly distributed between 20-100.
Different to the off-line bin packing problem where the *set* of pieces to be packed is available for inspection at the start.
The “best fit” heuristic, puts the current piece in the space it fits best (leaving least slack). It has the property that this heuristic does not open a new bin unless it is forced to.



Genetic Programming applied to on-line bin packing

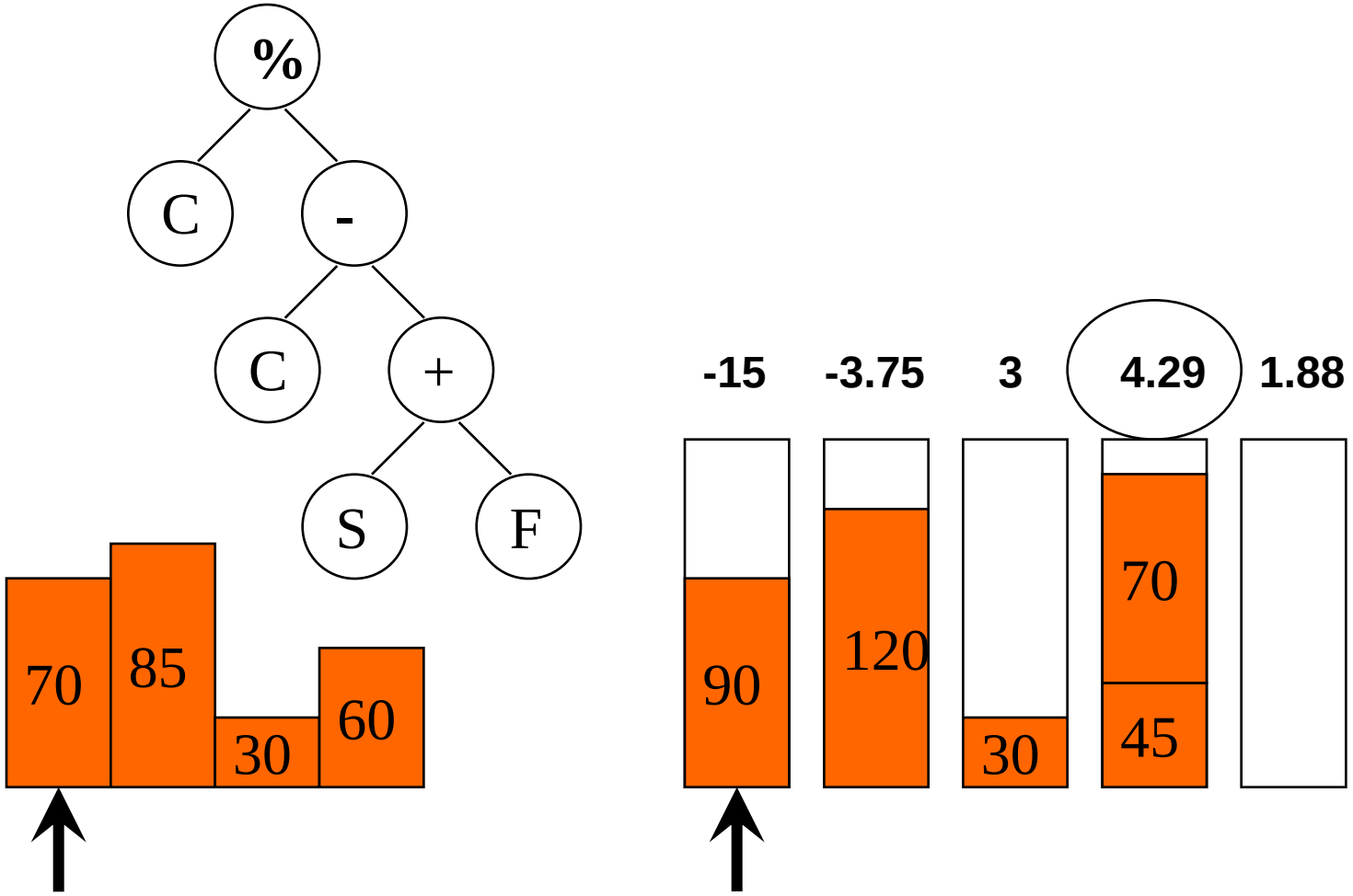


Not immediately obvious how to link
Genetic Programming to apply to combinatorial problems.
See previous paper.
The GP tree is applied to each bin with the current piece put in the bin which gets maximum score



Terminals supplied to Genetic Programming
Initial representation {C, F, S}
Replaced with {E, S}, E=C-F
We can possibly reduce this to *one variable*!!

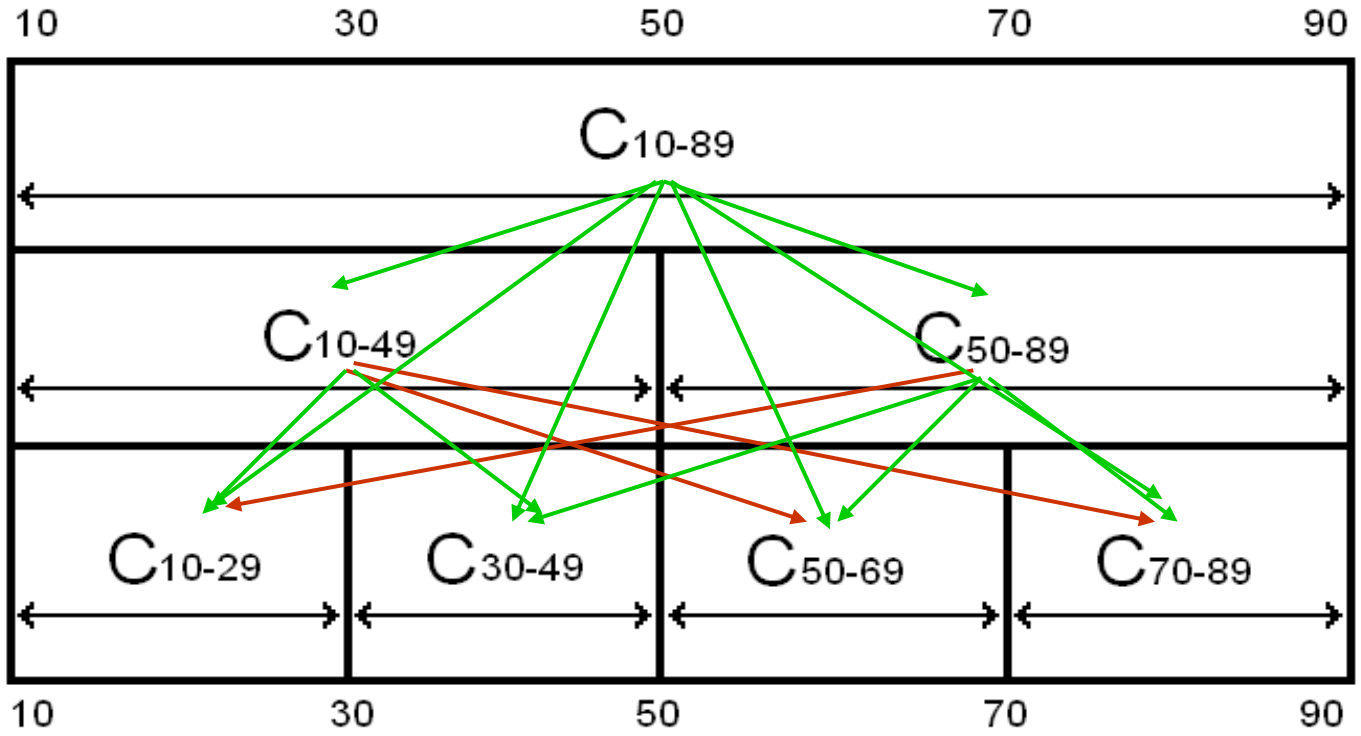
How the heuristics are applied



Robustness of Heuristics

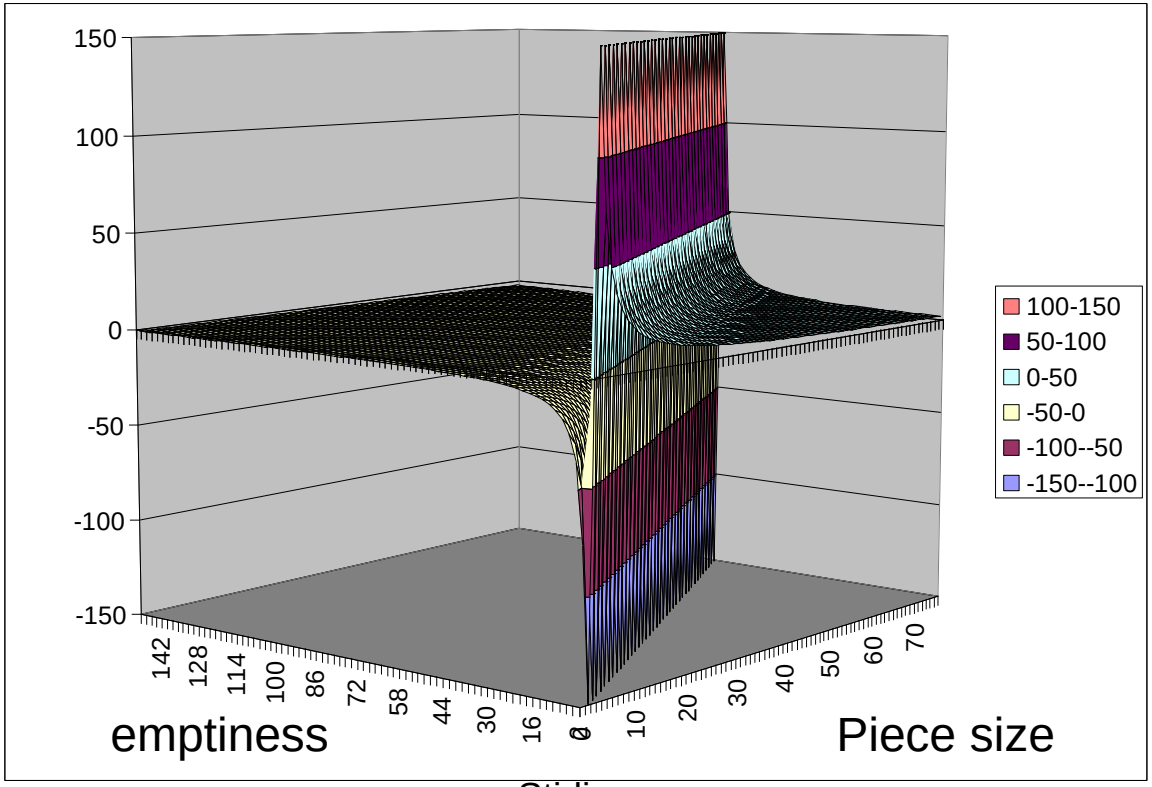
= all legal results

= some illegal results

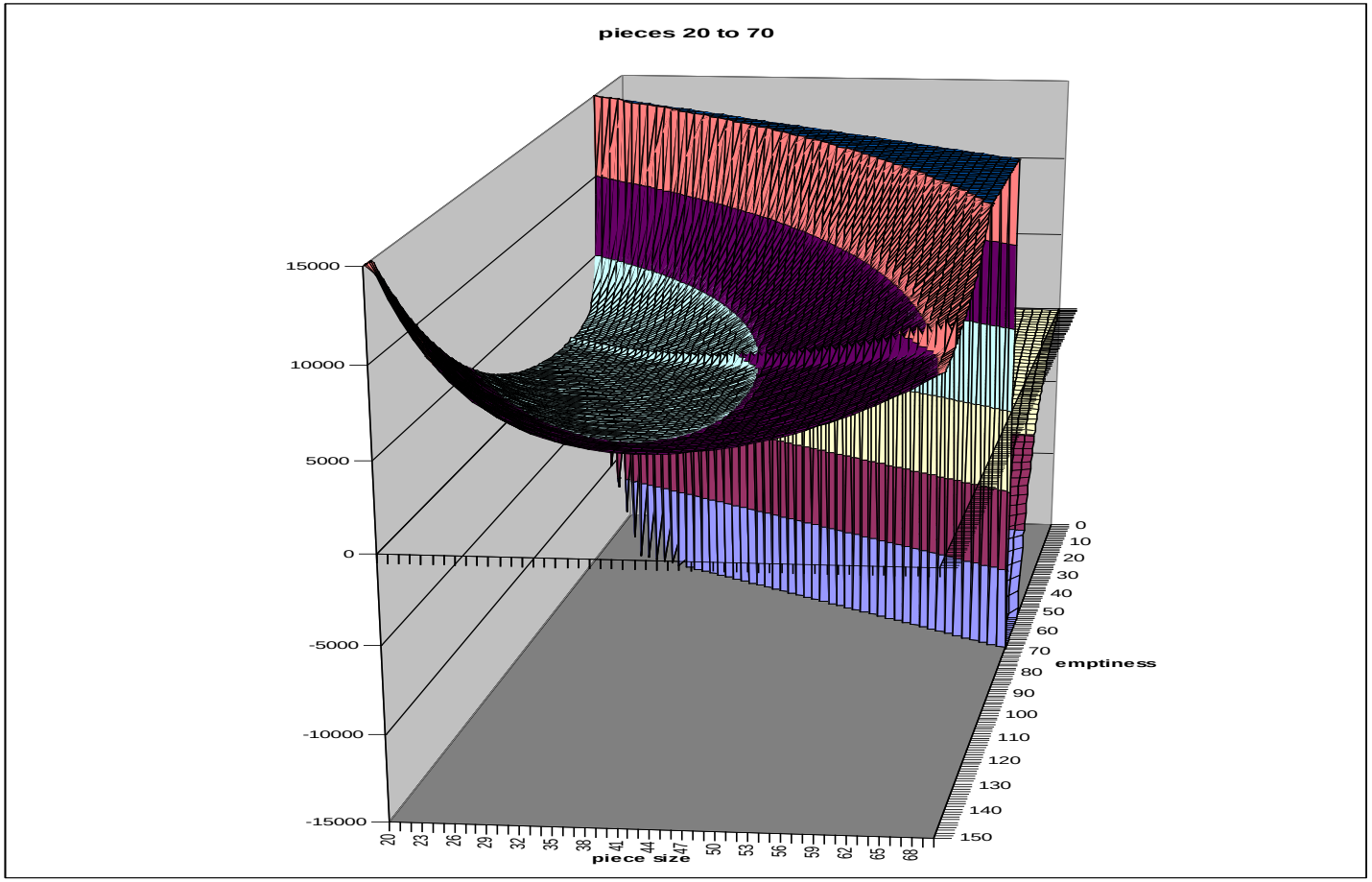


The Best Fit Heuristic

Best fit = 1/(E-S). Point out features.
Pieces of size S, which fit well into the space remaining E, score well.
Best fit applied produces a set of points on the surface,
The bin corresponding to the maximum score is picked.



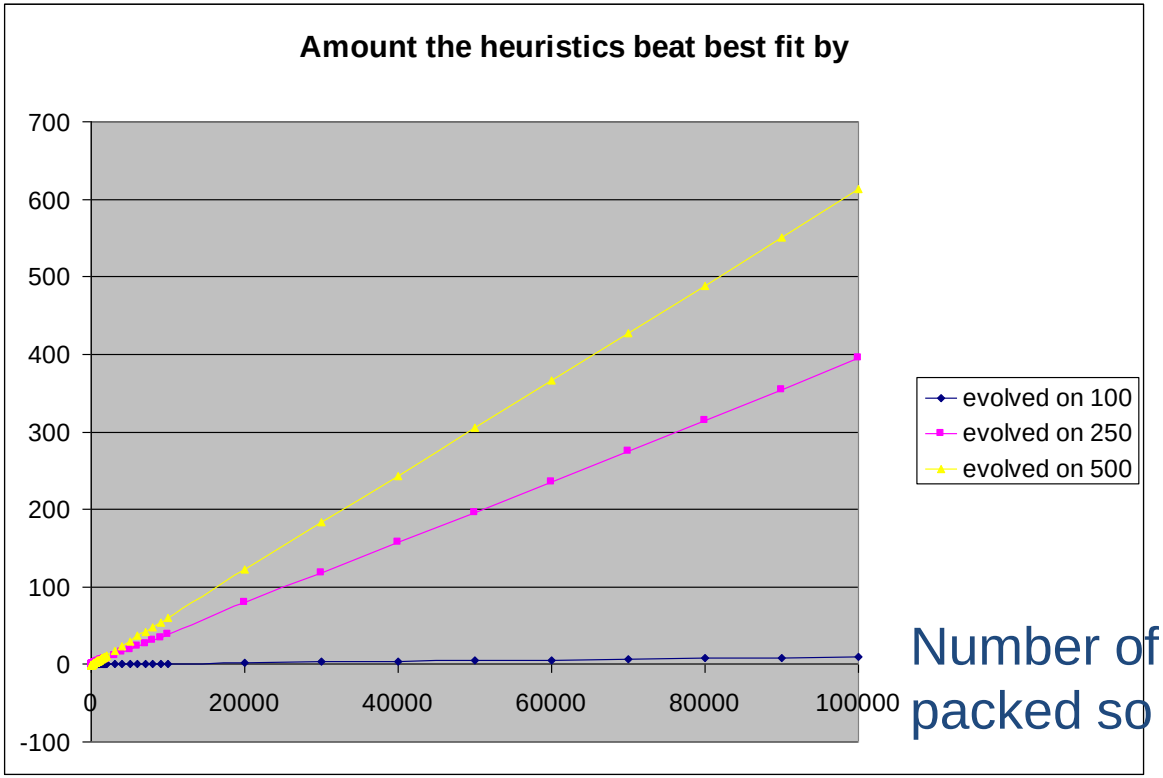
Our best heuristic.



Similar shape to best fit – but curls up in one corner.
Note that this is rotated, relative to previous slide.

Compared with Best Fit

Amount evolved heuristics beat best fit by.

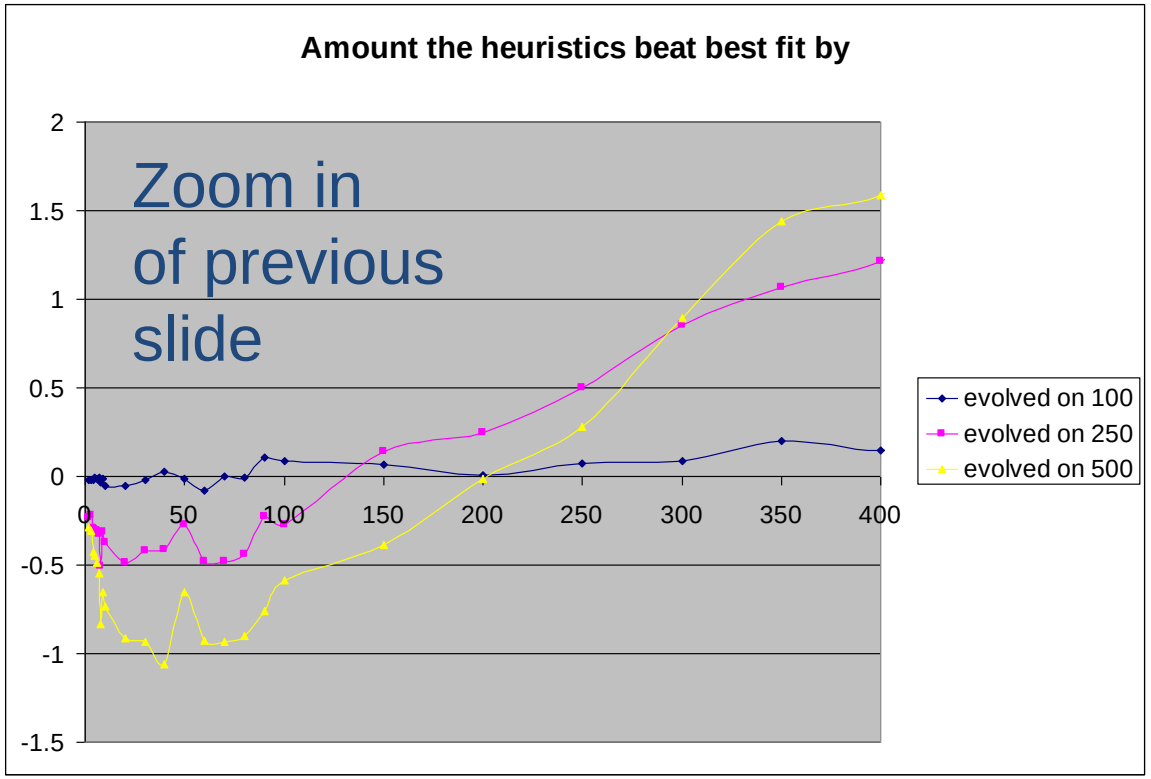


Number of pieces packed so far.

- Averaged over 30 heuristics over 20 problem instances
- Performance does not deteriorate
- The larger the training problem size, the better the bins are packed.

Compared with Best Fit

Amount evolved heuristics beat best fit by.

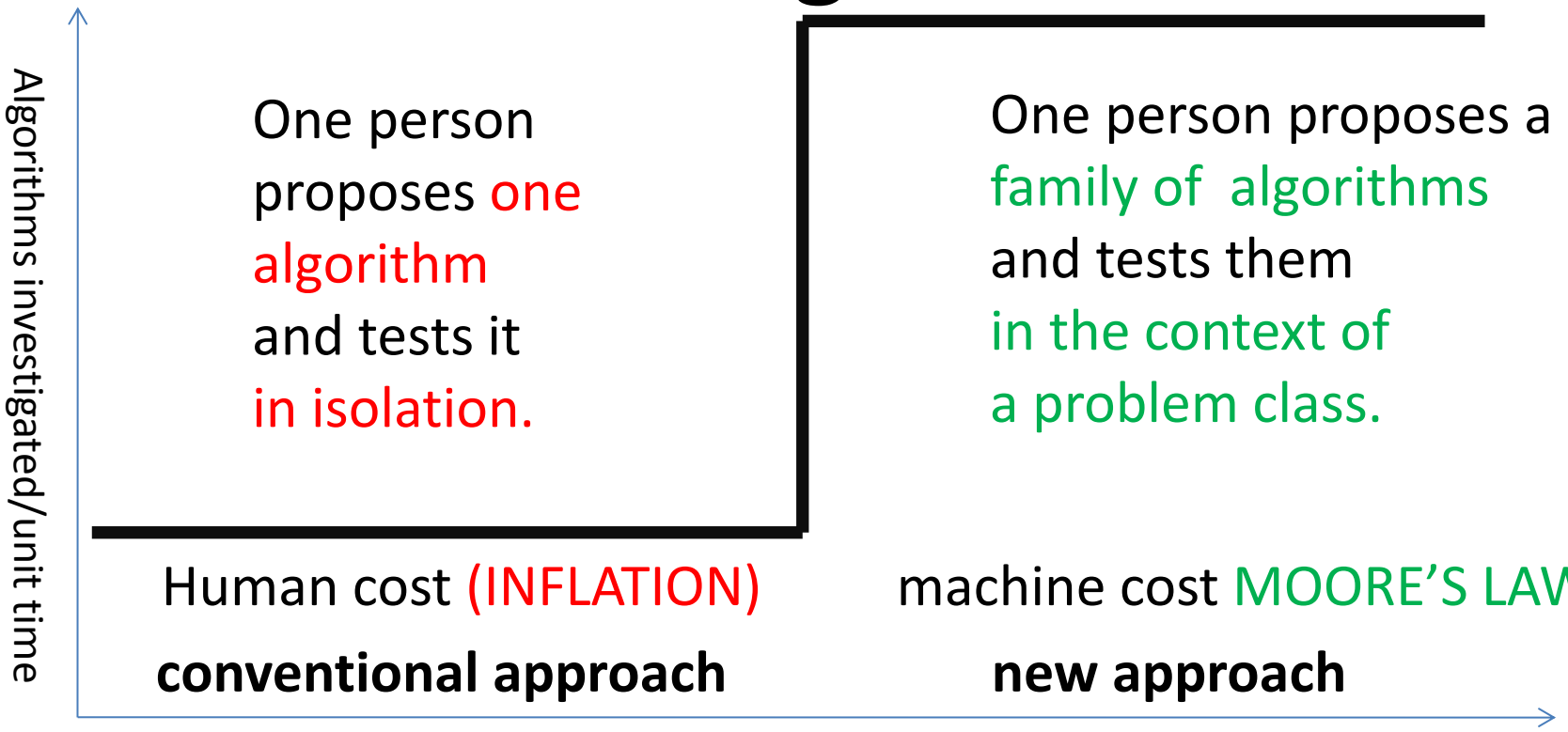


- The heuristic seems to learn the number of pieces in the problem
- Analogy with sprinters running a race – accelerate towards end of race.
- The "break even point" is approximately half of the size of the training problem size
- If there is a gap of size 30 and a piece of size 20, it would be better to wait for a better piece to come along later – about 10 items (similar effect at upper bound?).

A Brief History (Example Applications)

1. **Image Recognition** – Roberts Mark
2. **Travelling Salesman Problem** – Keller Robert
3. **Boolean Satifiability** – Fukunaga, Bader-El-Den
4. **Data Mining** – Gisele L. Pappa, Alex A. Freitas
5. **Decision Tree** - Gisele L. Pappa et. al.
6. **Selection Heuristics** – Woodward & Swan
7. **Bin Packing 1,2,3 dimension** (on and off line) Edmund Burke et. al. & Riccardo Poli et. al.

A Paradigm Shift?



- Previously **one** person proposes **one** algorithm
- Now **one** person proposes **a set of** algorithms
- Analogous to "industrial revolution" from hand to machine made. Automatic Design.

Consequences

1. Instead of proposing a **single algorithm**, “In this paper we propose a novel algorithm”…
2. We can now propose a set of algorithms, “In this paper we propose **10,000 algorithms**”
3. The resulting algorithm is **typically better** than a human designed algorithm.
4. If the problem changes, **we can instantly call** on Genetic Programming **again**.

Conclusions

1. Algorithms are **reusable**, "solutions" aren't (e.g. TSP).
2. We can automatically design algorithms that **consistently outperform human designed algorithms (on various domains)**.
3. Heuristic are **trained to fit a problem class**, so are designed in context (like evolution). Let's close the feedback loop! Problem instances live in classes.
4. We can design algorithms on **small** problem instances and **scale** them apply them to **large** problem instances (TSP, child multiplication).