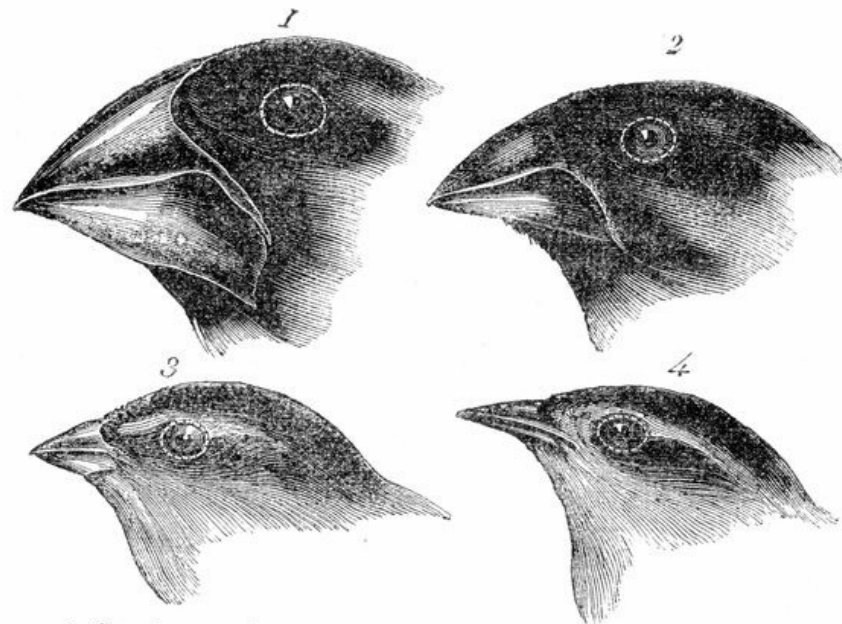


# Genetic Algorithms

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Algorithms interest group  
08/2016

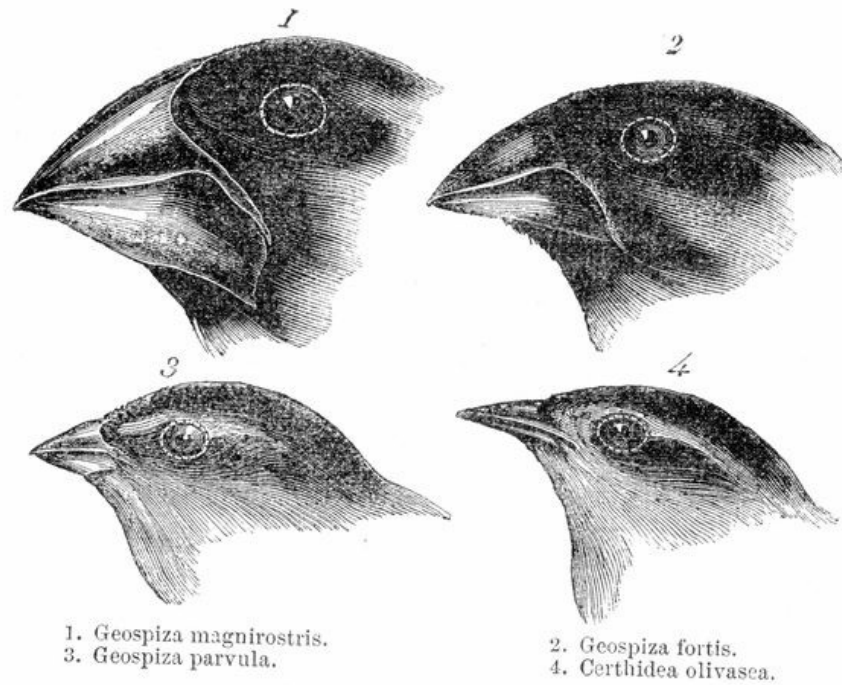


1. *Geospiza magnirostris*.  
3. *Geospiza parvula*.

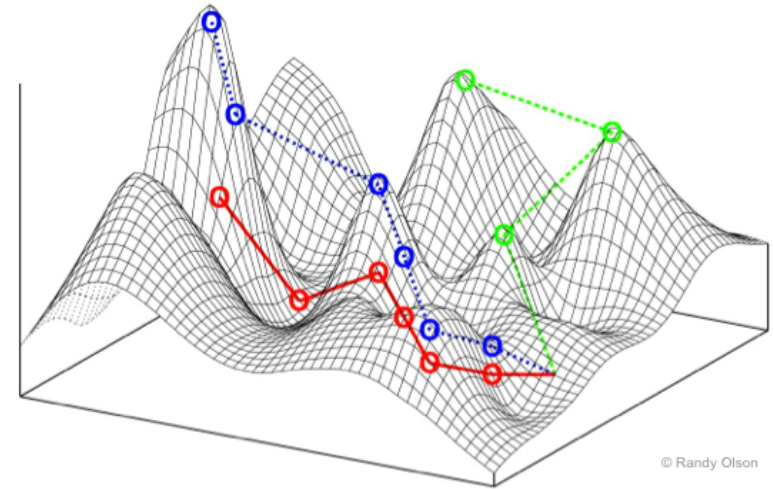
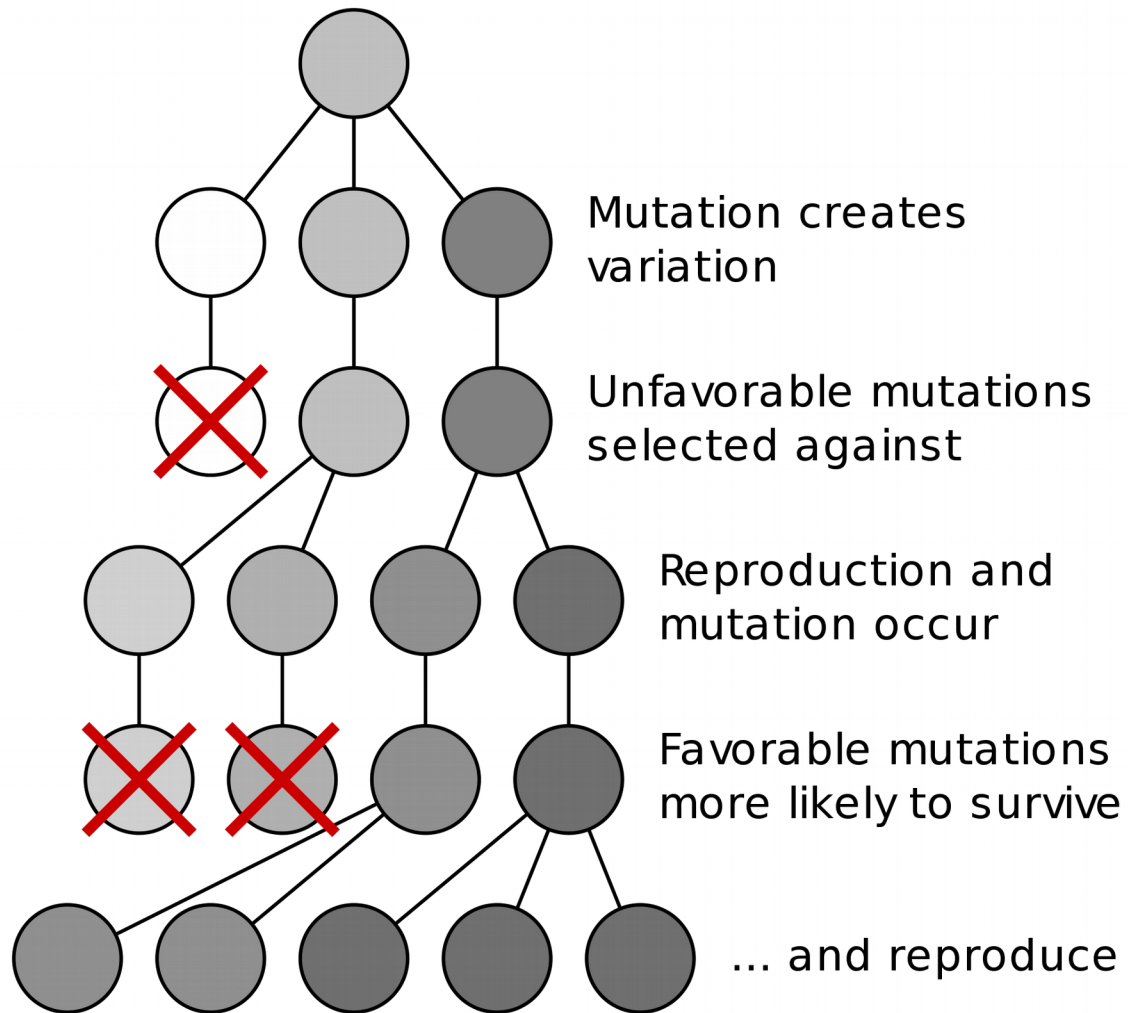
2. *Geospiza fortis*.  
4. *Certhidea olivacea*.

# Introduction:

Nature is very good at optimizing over a huge parameter space!



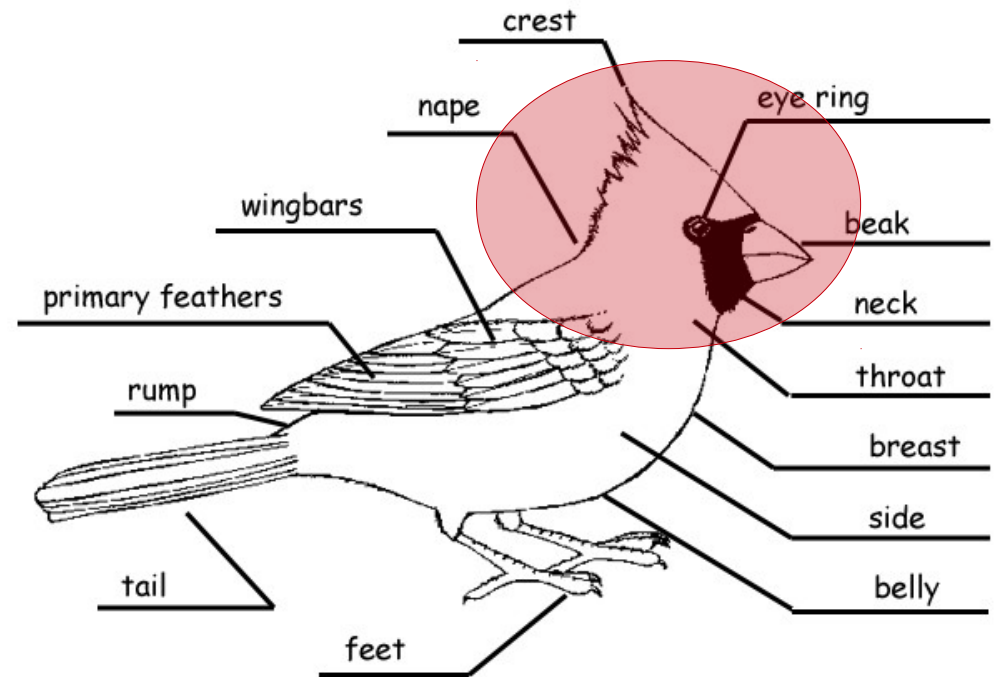
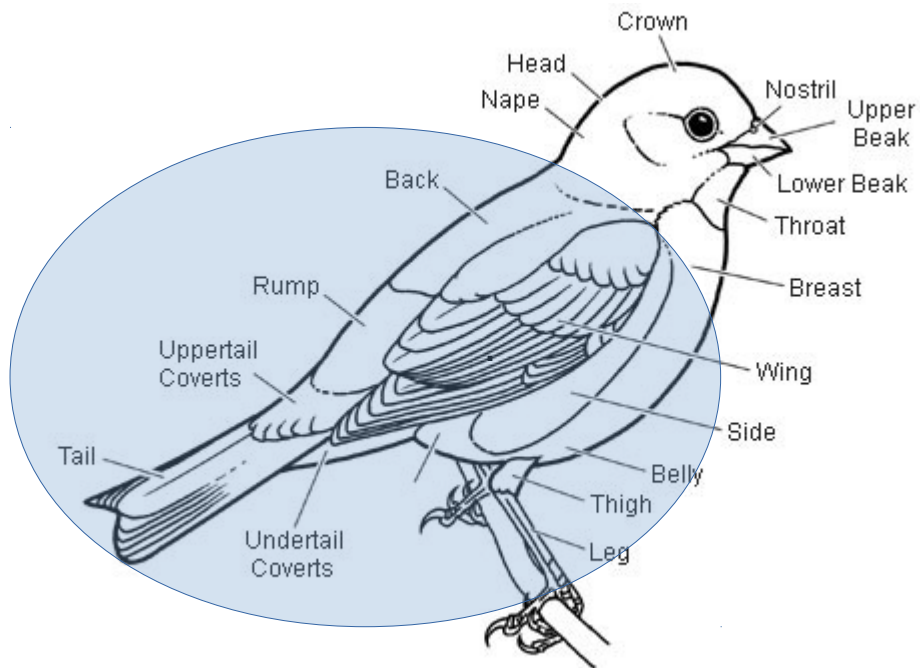
# Evolution in a nutshell.



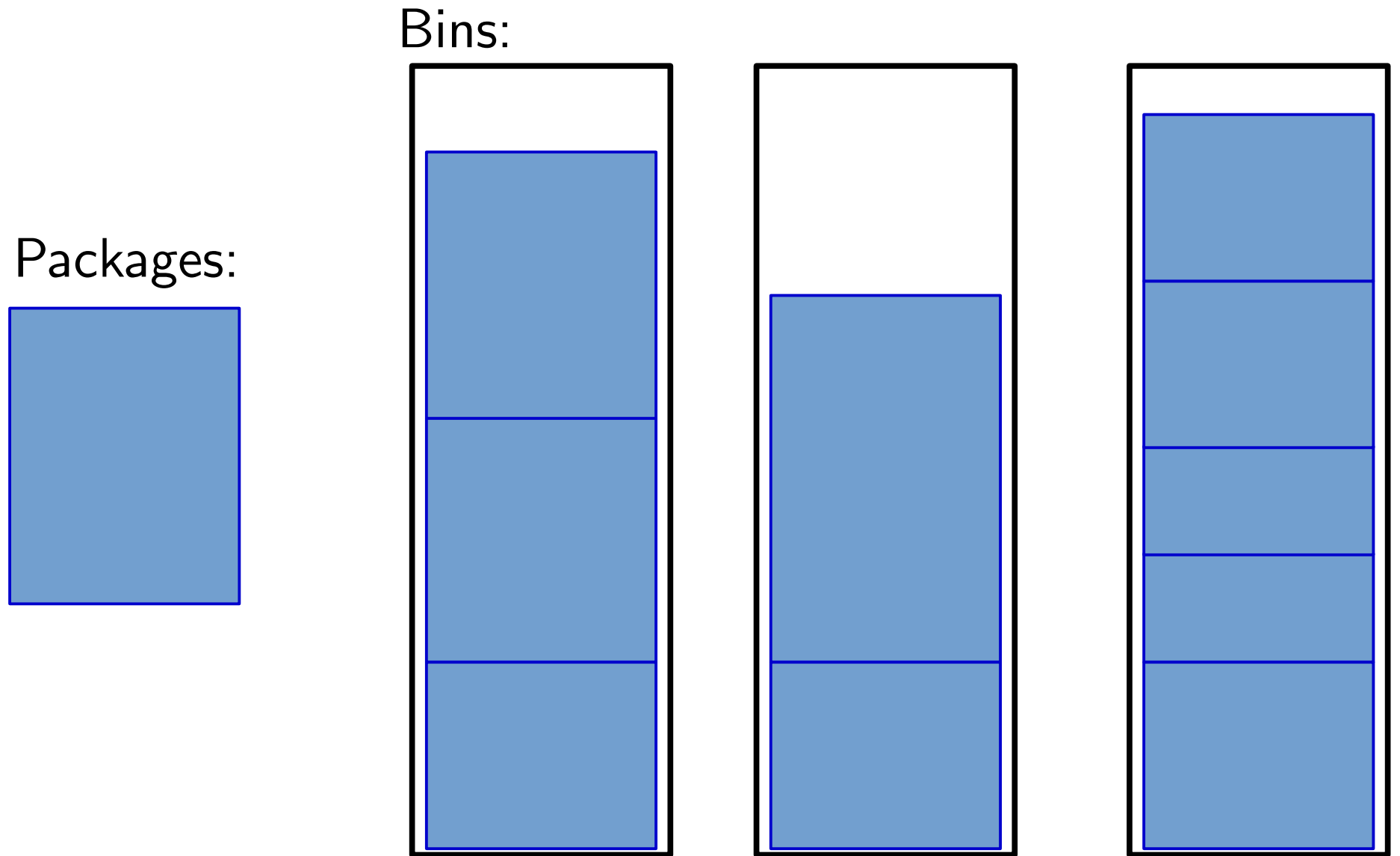
# When does it work, and why?

Building-block hypothesis:

- Don't optimize over all combinations
- Identify good "chunks"
- Construct better solutions from good partial solutions.



# Example problem: bin packing (NP-hard).



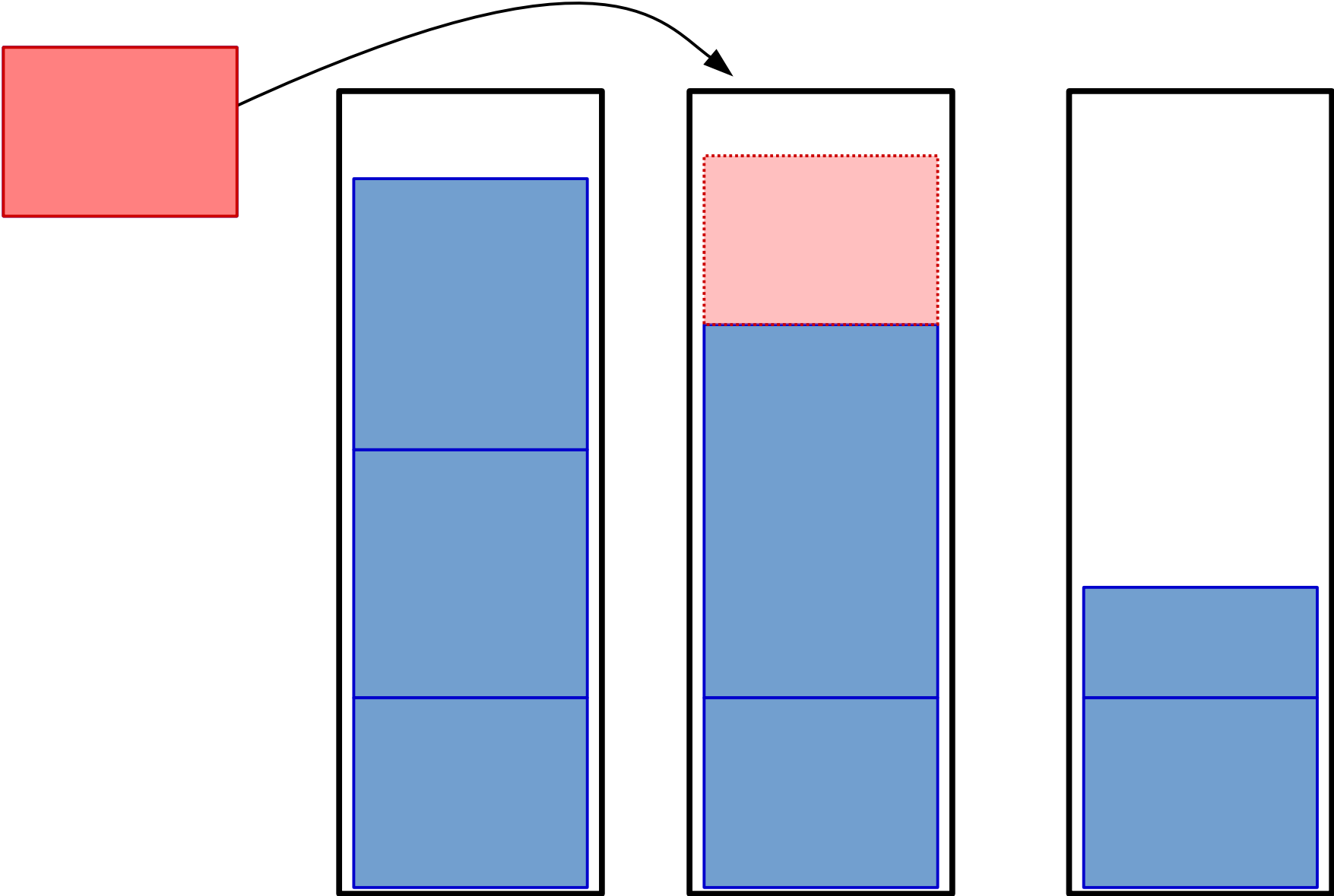
What's the least number of bins required for  $N$  packages?

# Example problem: bin packing (NP-hard)

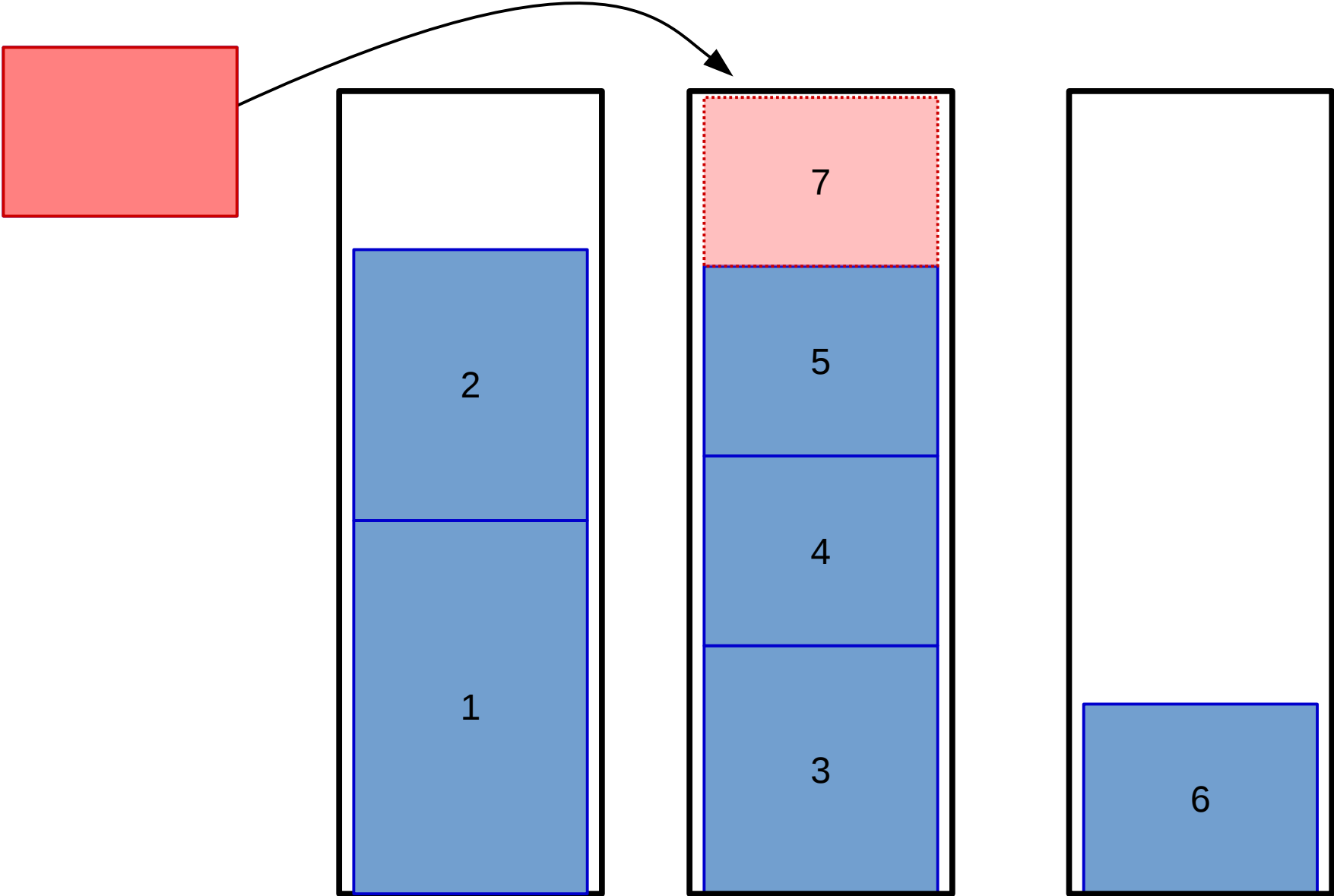
Important details:

- 1-d binpacking (only worry if package fits in 1 direction).
- Bins are all some fixed size  $\equiv 1$ .
- Package sizes randomly sampled  $U(0, M)$ ,  $M < 1$ .
- Figure of merit:  $V_{\text{packages}}/V_{\text{bins}}$  “filled fraction”.

**Greedy solution: put it in the first bin it fits!**

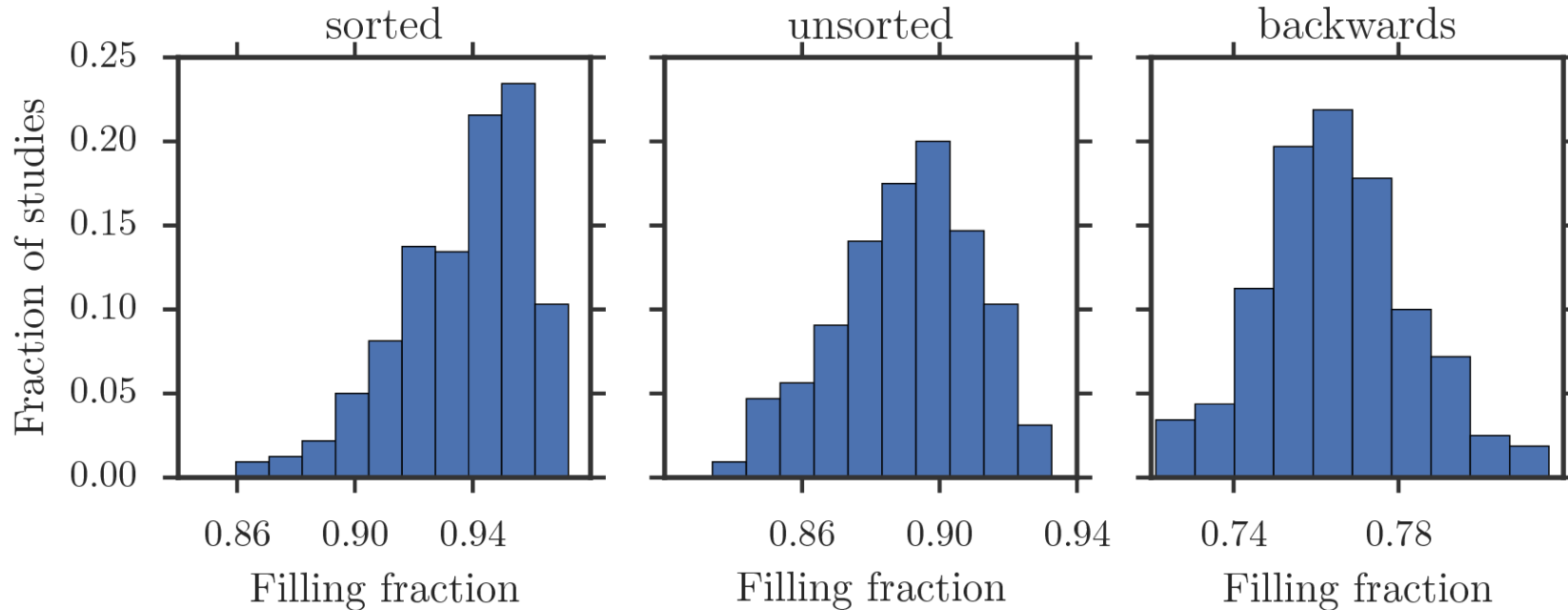


**Improvement: sort, then greedy pack.**



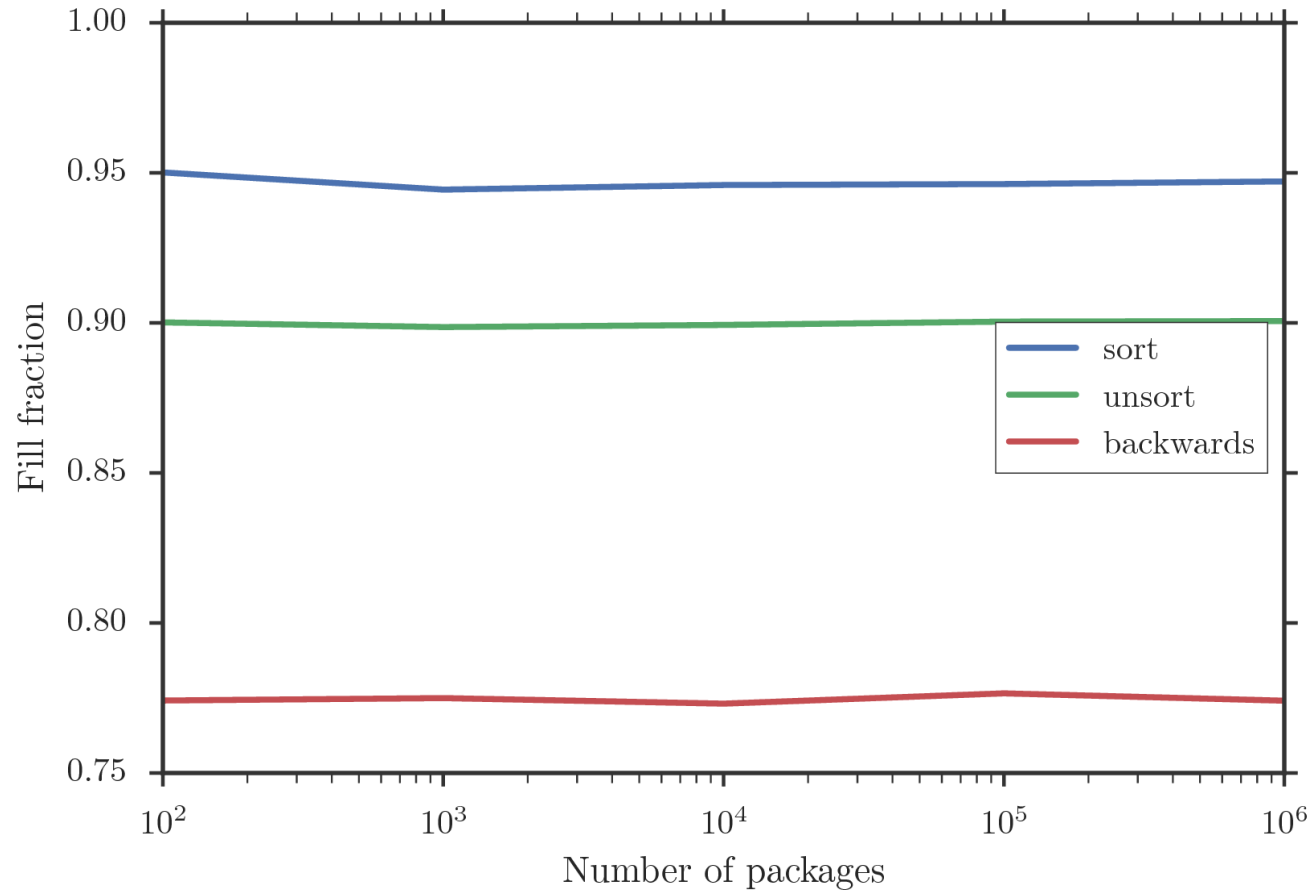


# Statistics of greedy solutions.



- Sorting improves performance slightly.
- Sorting backwards hinders performance dramatically.
- Generally, greedy packing leaves roughly 10% unfilled space.

# Performance doesn't depend on size!



## **Genetic algorithm:**

1. Initialize populations.
2. Cycle:
  - (a) Measure fitness of all solutions.
  - (b) Sample solutions weighted by fitness for breeding.
  - (c) Mutate all new solutions.

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## **Bin packing implementation:**

Greedy solutions, packing in random orders and in order of package size

## Genetic algorithm:

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## Bin packing implementation:

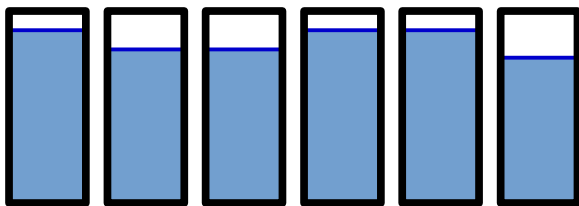
Figure of merit:  $\frac{V_{\text{packages}}}{V_{\text{bins}}}$

## Genetic algorithm:

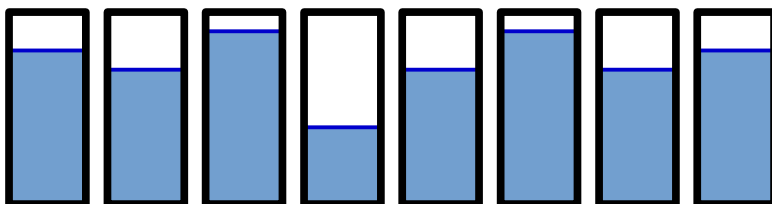
1. Initialize populations.
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## Bin packing implementation:

Solution 1



Solution 2

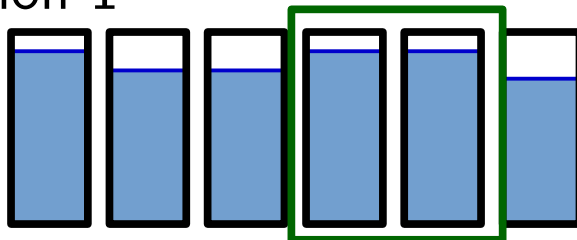


## Genetic algorithm:

1. Initialize populations.
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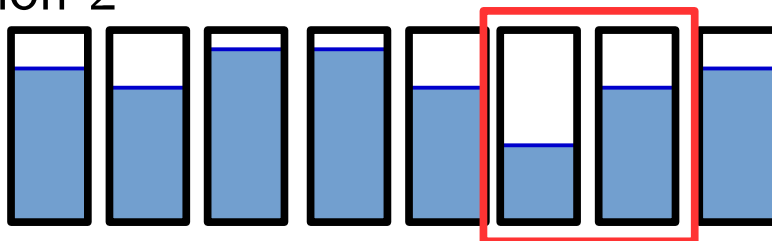
## Bin packing implementation:

Solution 1



Copy over

Solution 2

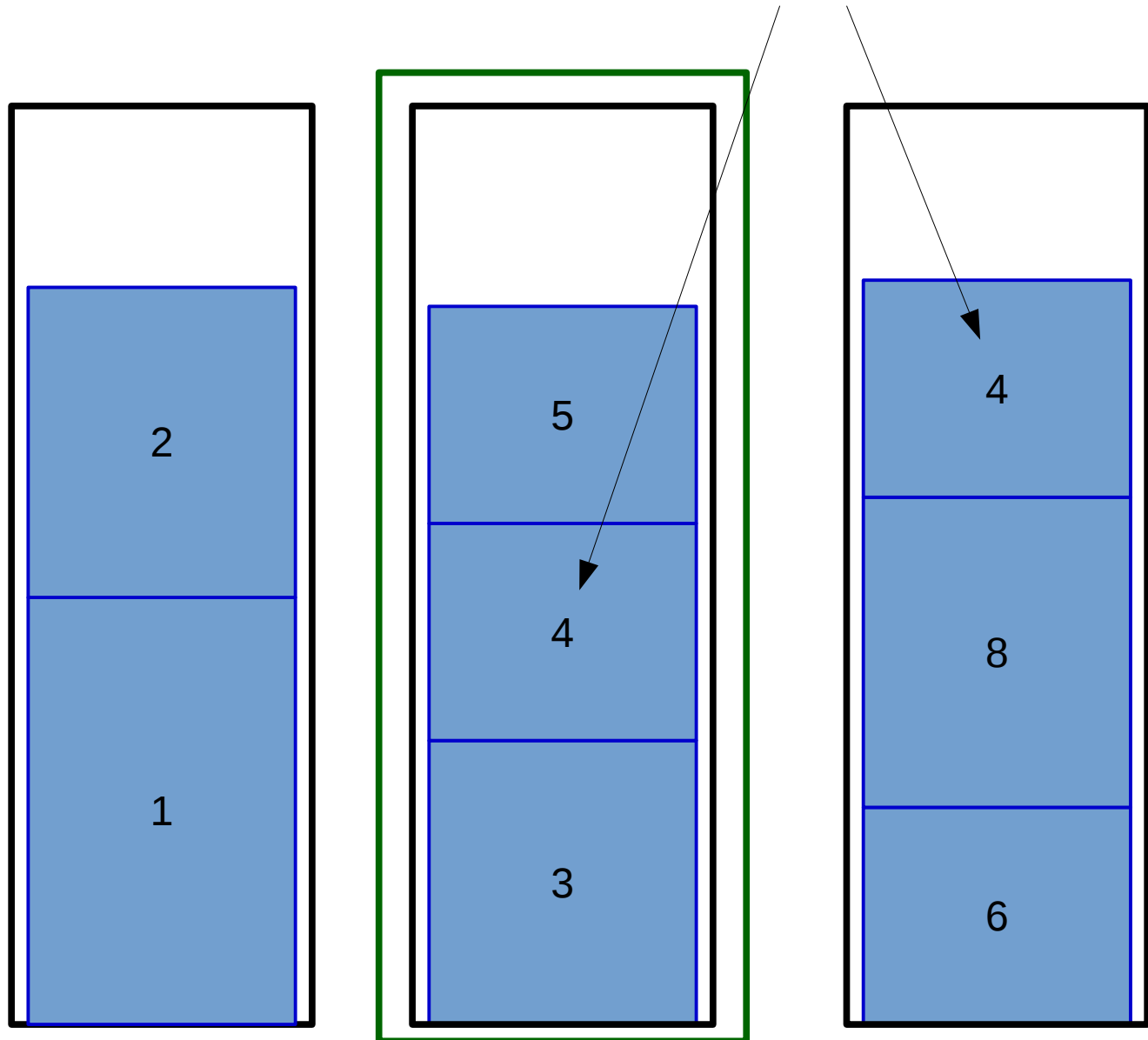


Delete

# Repair bin packing: greedy pack

Package 7 not packed!

Same package, two bins





# Genetic algorithm:

1. Initialize populations.

2. Cycle:

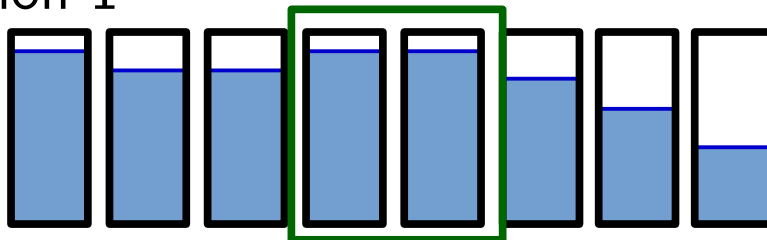
(a) Measure fitness of all solutions.

(b) Sample solutions weighted by fitness for breeding.

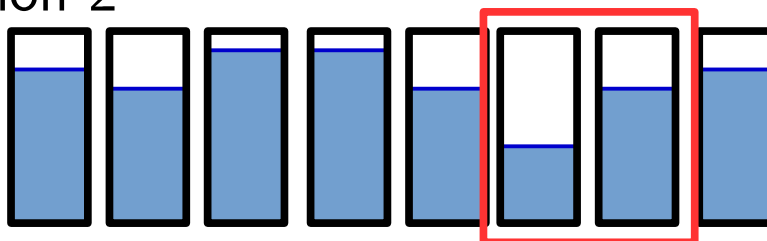
(c) Mutate all new solutions.

## Bin packing implementation:

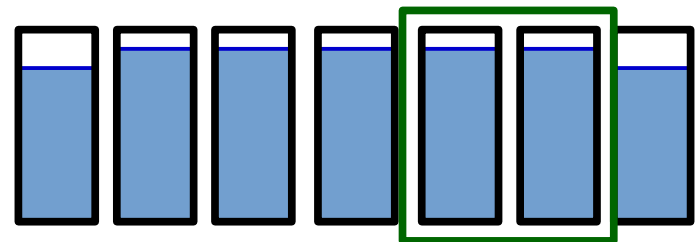
Solution 1



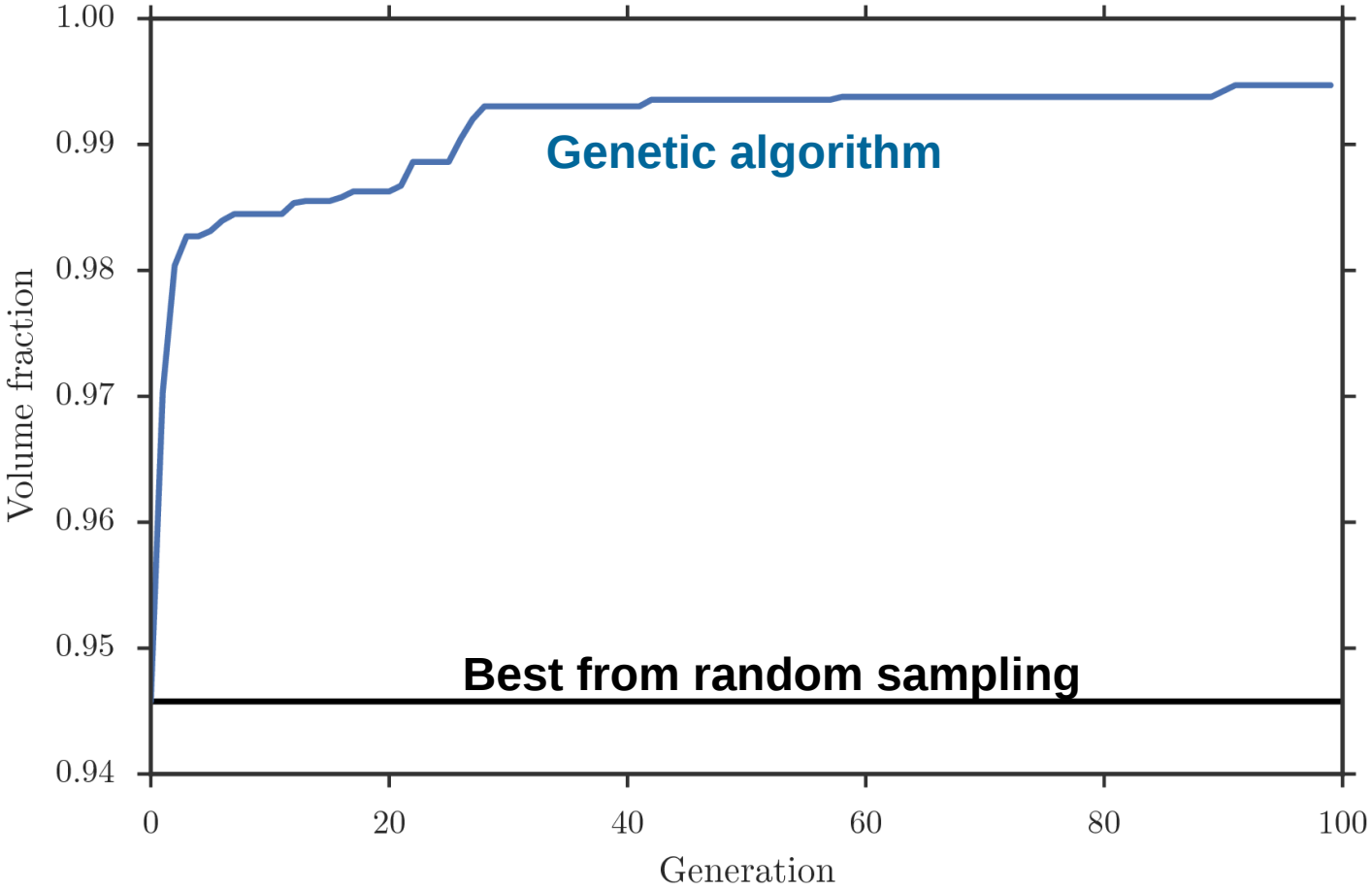
Solution 2



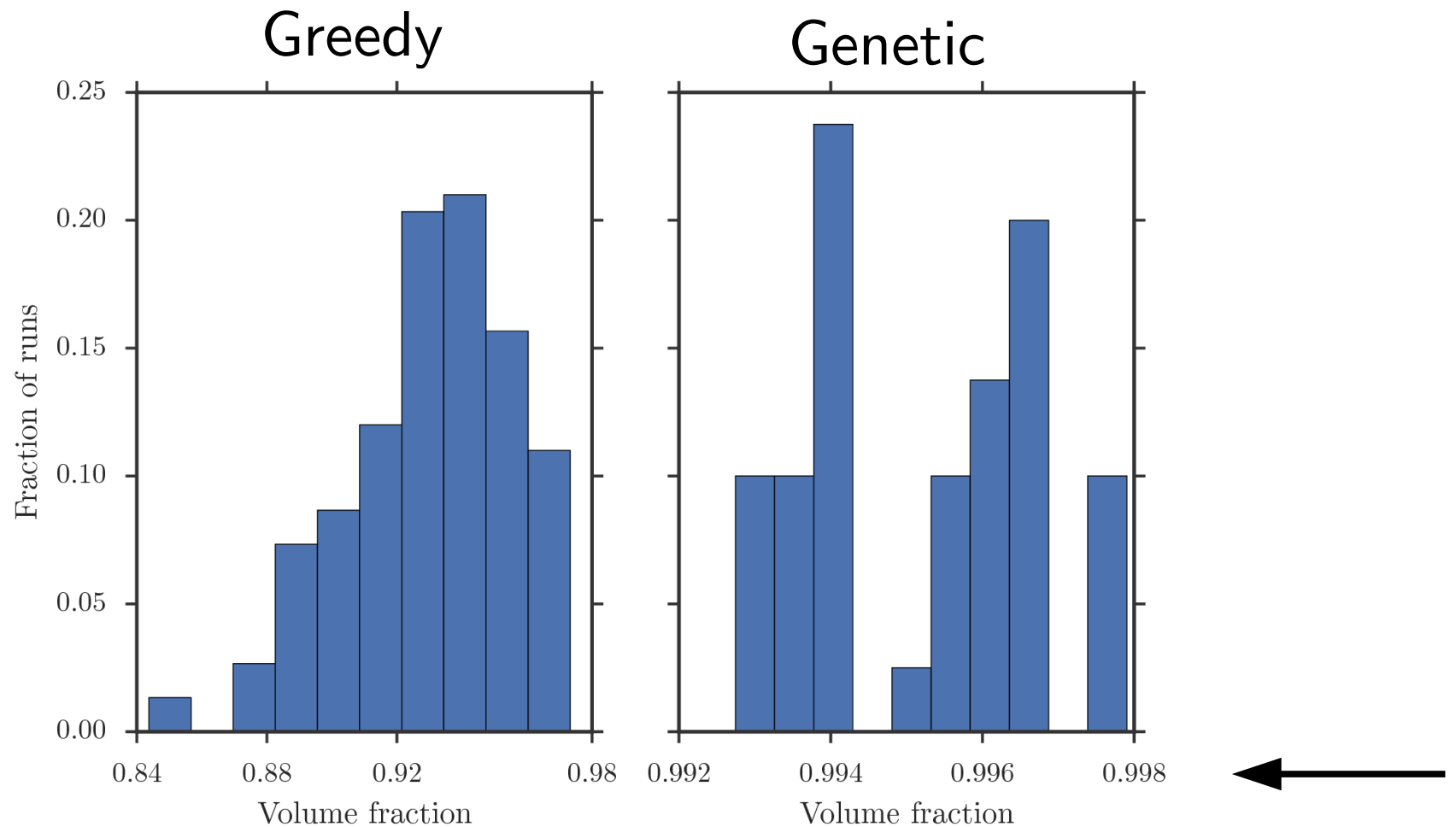
Child Solution



# Genetic algorithm demonstration:

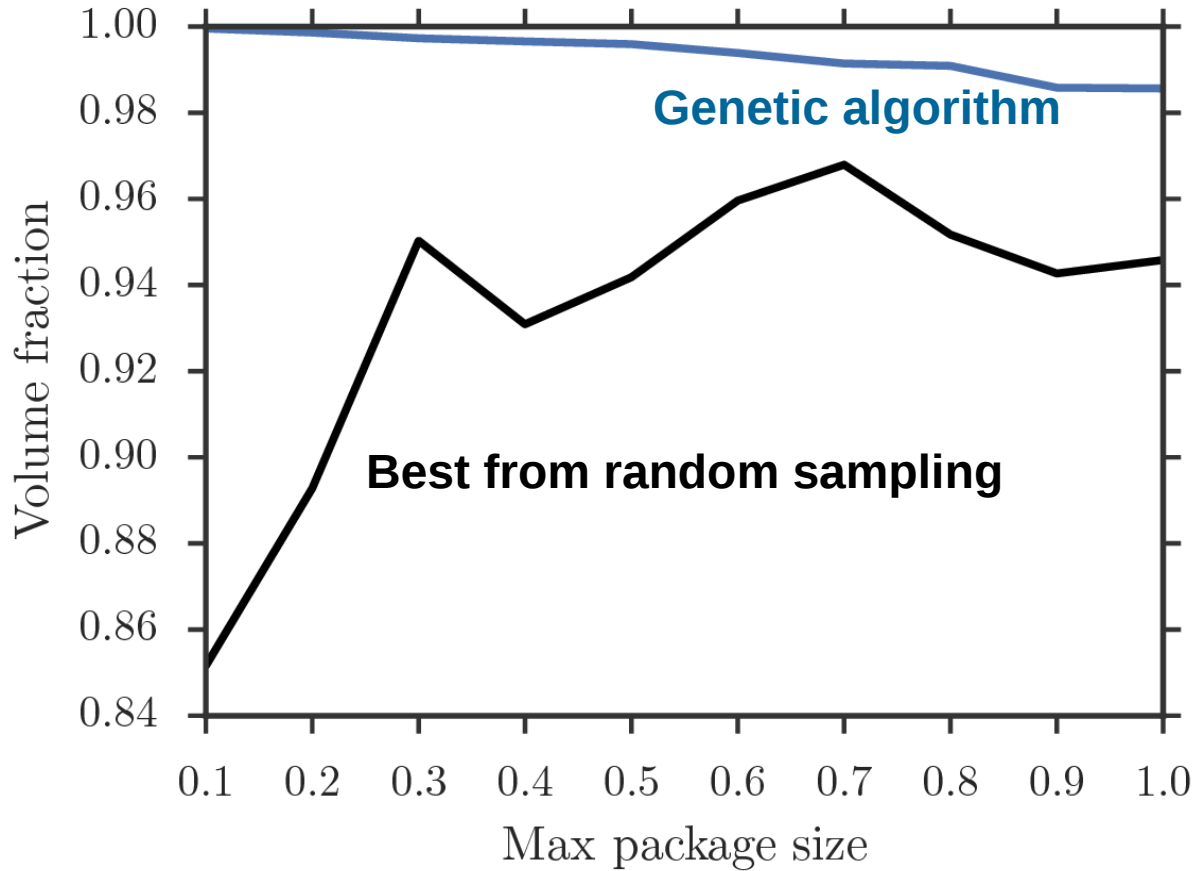


# Statistics of genetic algorithm performance.

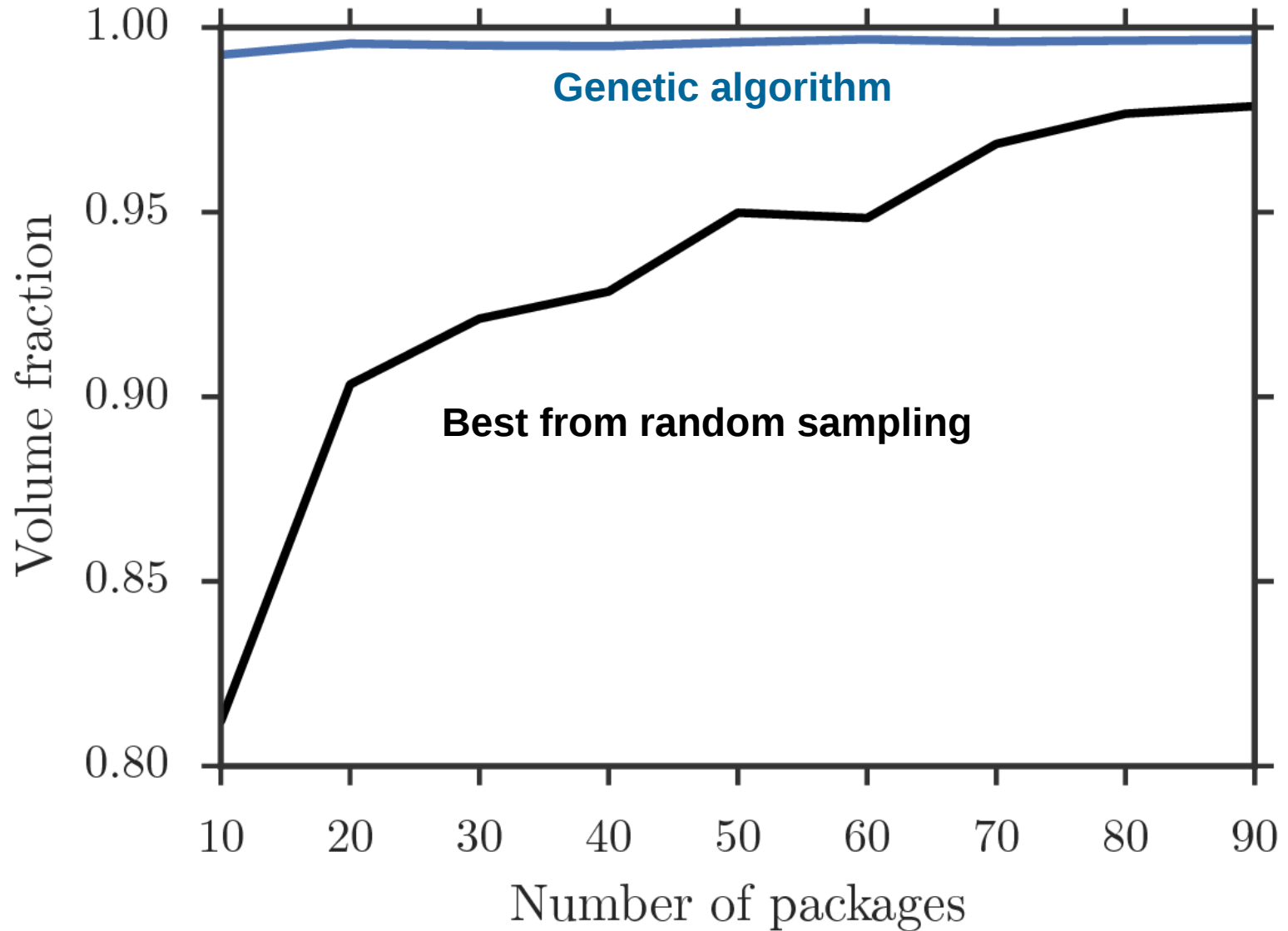


In 80 trials, genetic algorithms fills  $> 99\%$  of bins, better than all greedy.

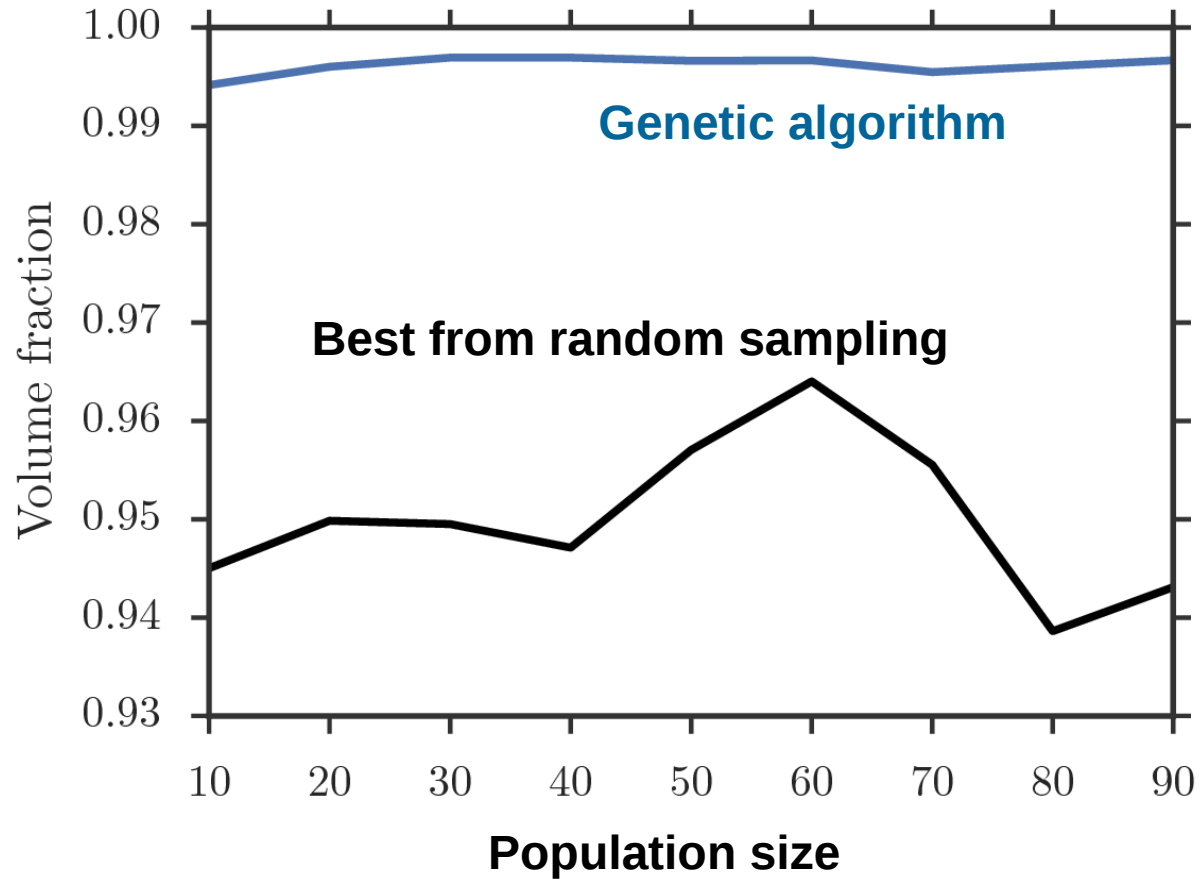
# Increasing difficulty: larger packages.



# Increasing difficulty: more packages.



# Increasing accuracy: larger populations.



# Conclusions

## Genetic algorithms

- Identify high-fitness partial solutions and attempt to combine.
- Consistent strong improvement over random search.