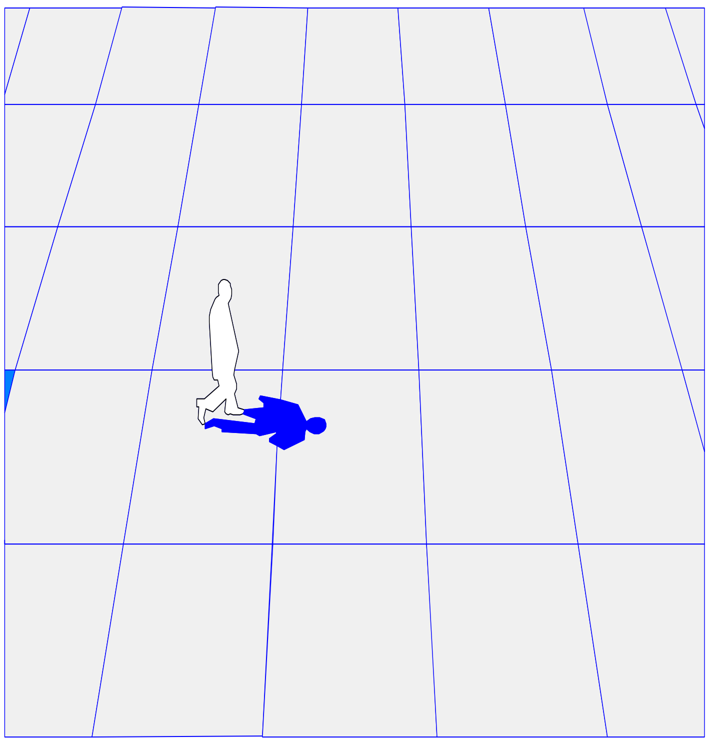
Genetic Algorithms: A Tutorial



"Genetic Algorithms are good at taking large, potentially huge search spaces and navigating them, looking for optimal combinations of things, solutions you might not otherwise find in a lifetime."

- Salvatore Mangano

Computer Design, May 1995

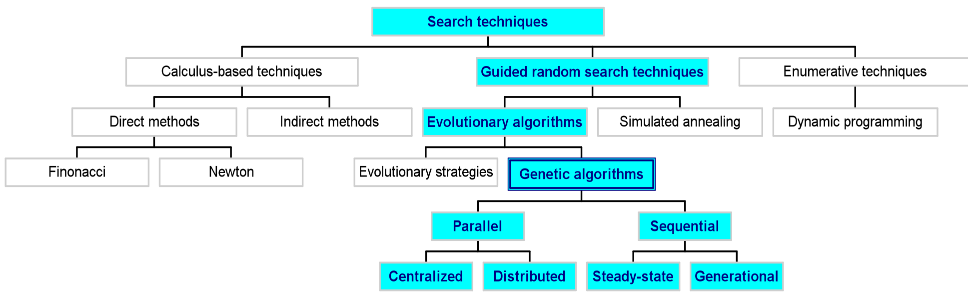
The Genetic Algorithm

- Directed search algorithms based on the mechanics of biological evolution
- Developed by John Holland, University of Michigan (1970's)
  - ♦ To understand the adaptive processes of natural systems
  - ♦ To design artificial systems software that retains the robustness of natural systems

The Genetic Algorithm (cont.)

- Provide efficient, effective techniques for optimization and machine learning applications
- Widely-used today in business, scientific and engineering circles

Classes of Search Techniques



Components of a GA

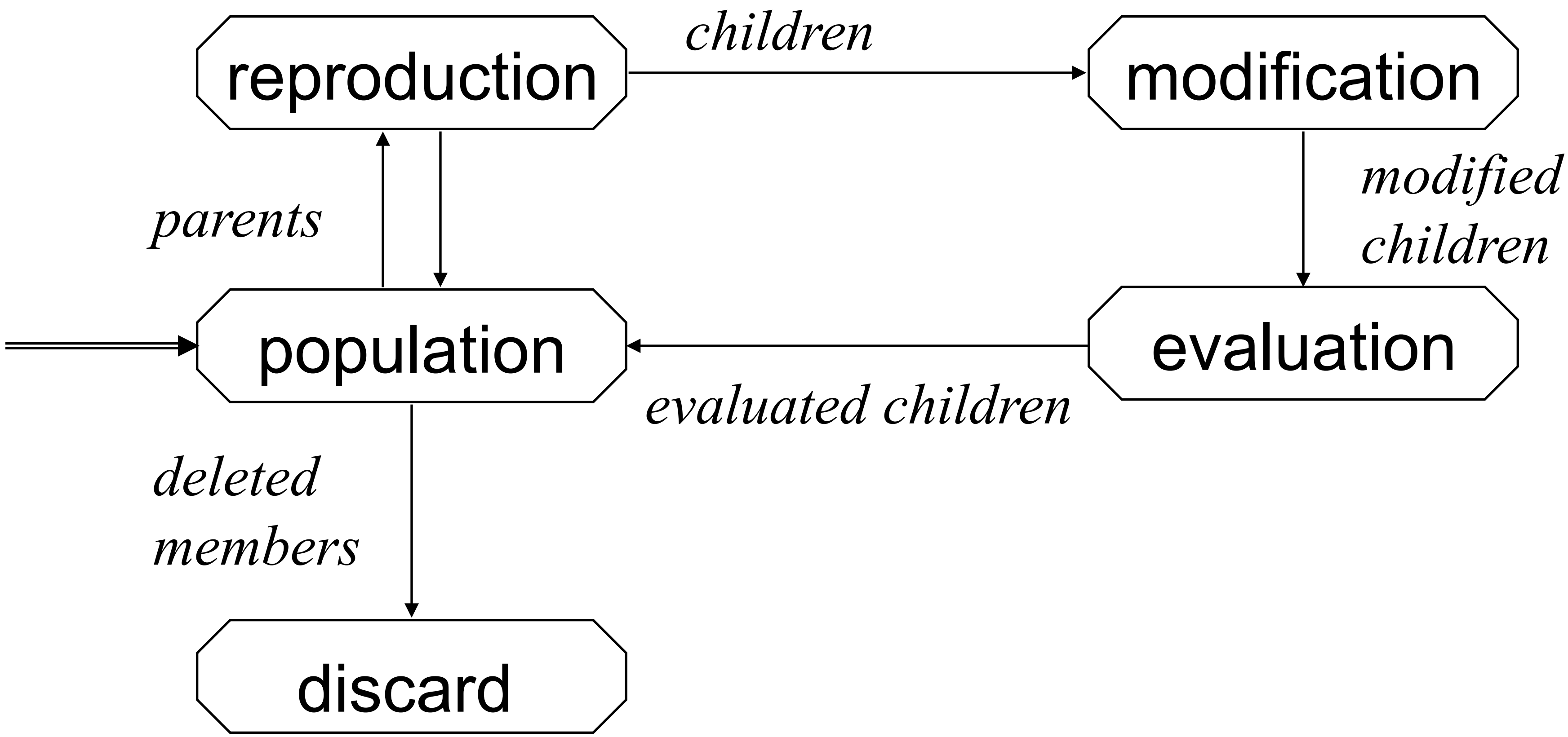
A problem to solve, and ...

- Encoding technique (*gene, chromosome*)
- Initialization procedure *(creation)*
- Evaluation function *(environment)*
- Selection of parents *(reproduction)*
- Genetic operators *(mutation, recombination)*
- Parameter settings *(practice and art)*

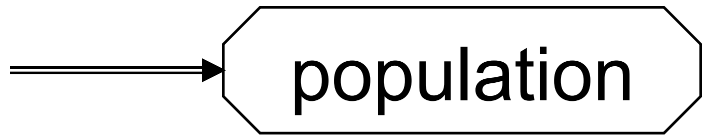
Simple Genetic Algorithm

```
{
    initialize population;
    evaluate population;
    while TerminationCriteriaNotSatisfied
    {
        select parents for reproduction;
        perform recombination and mutation;
        evaluate population;
    }
}
```

The GA Cycle of Reproduction



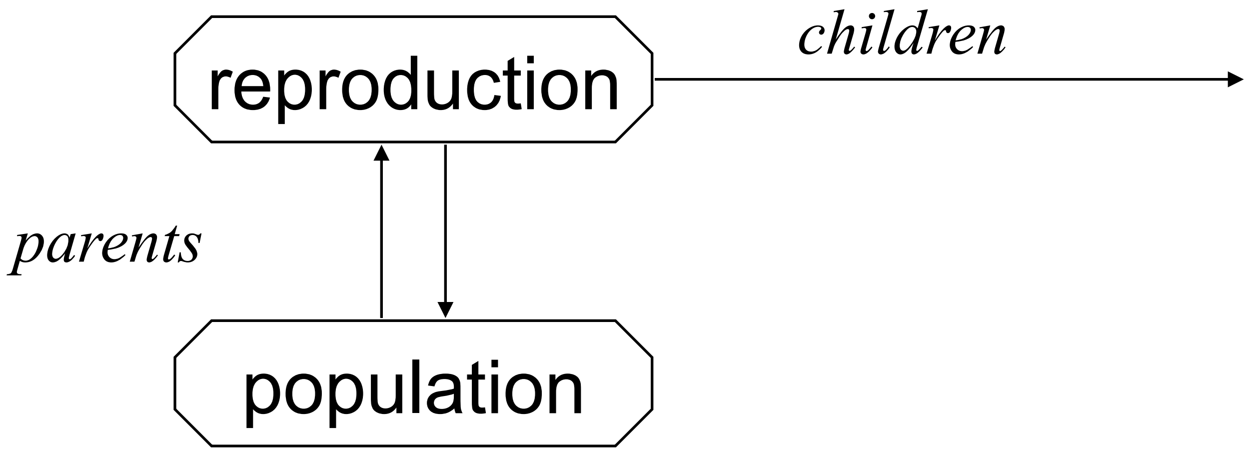
Population



Chromosomes could be:

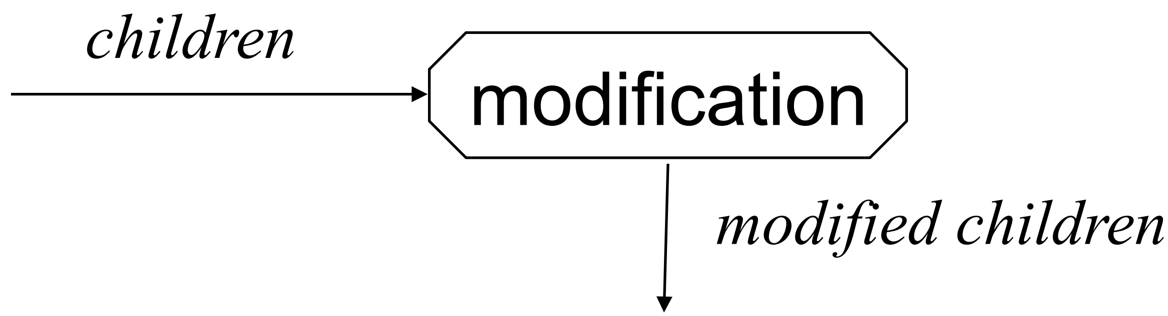
♦ Bit strings	(0101 ... 1100)
♦ Real numbers	(43.2 -33.1 ... 0.0 89.2)
♦ Permutations of element	(E11 E3 E7 ... E1 E15)
♦ Lists of rules	(R1 R2 R3 ... R22 R23)
♦ Program elements	(genetic programming)
♦ ... any data structure ...	

Reproduction



Parents are selected at random with selection chances biased in relation to chromosome evaluations.

Chromosome Modification



- Modifications are stochastically triggered
- Operator types are:
  - Mutation
  - Crossover (recombination)

Mutation: Local Modification

Before:	(1 0 1 $\boxed{1}$ 0 1 1 0)
After:	(0 1 1 $\boxed{0}$ 0 1 1 0)

Before:	(1.38 $\boxed{-69.4}$ 326.44 0.1)
After:	(1.38 $\boxed{-67.5}$ 326.44 0.1)

- Causes movement in the search space (local or global)
- Restores lost information to the population

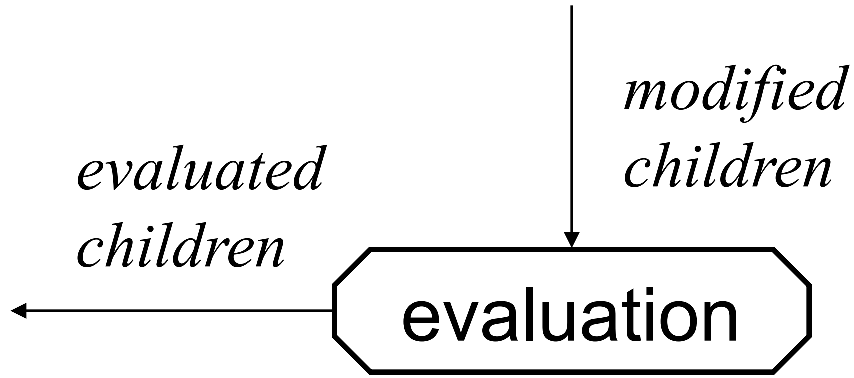
Crossover: Recombination

	*			
P1	(0 1 1 0 1 0 0 0)	→	(0 1 0 0 1 0 0 0)	C1
P2	(1 1 0 1 1 0 1 0)		(1 1 1 1 1 0 1 0)	C2

Crossover is a critical feature of genetic algorithms:

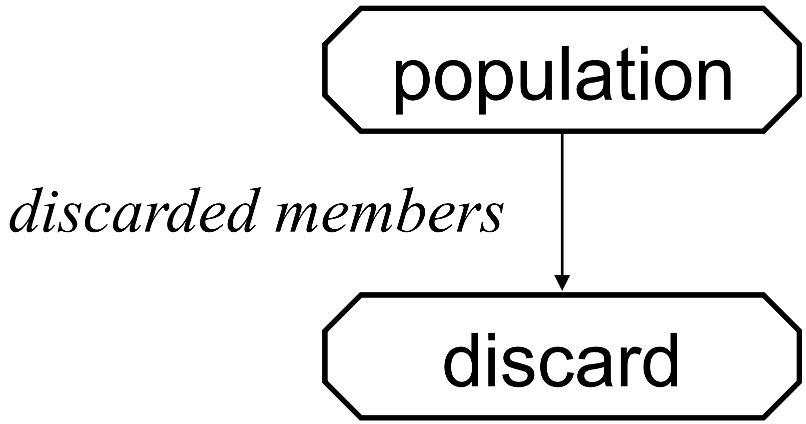
- It greatly accelerates search early in evolution of a population
- It leads to effective combination of schemata (subsolutions on different chromosomes)

Evaluation



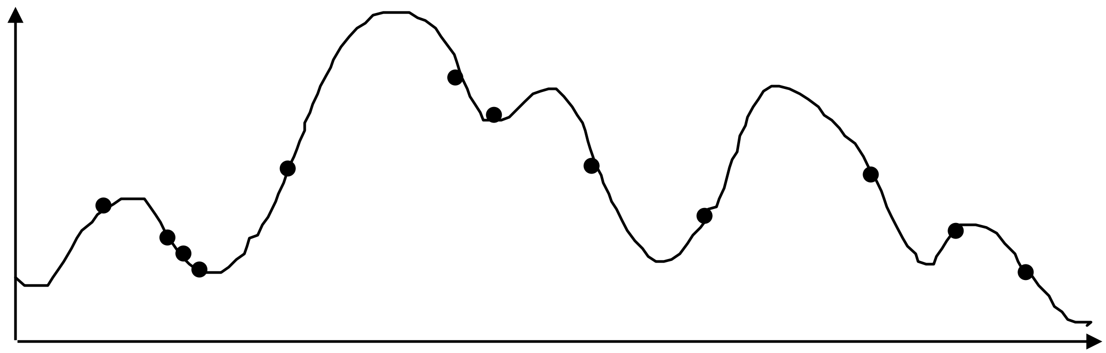
- The evaluator decodes a chromosome and assigns it a fitness measure
- The evaluator is the only link between a classical GA and the problem it is solving

Deletion

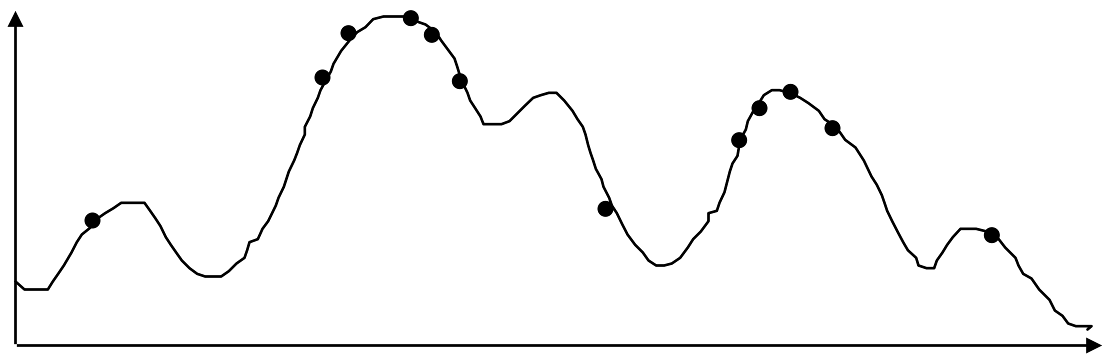


- *Generational* GA:
  entire populations replaced with each iteration
- *Steady-state* GA:
  a few members replaced each generation

An Abstract Example

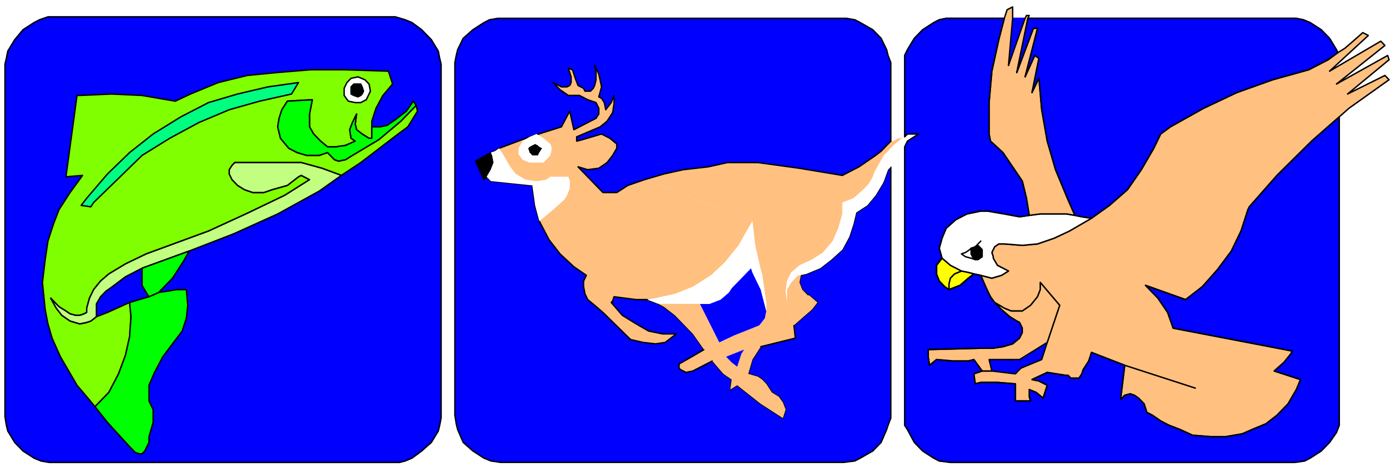


Distribution of Individuals in Generation 0



Distribution of Individuals in Generation N

A Simple Example



"The Gene is by far the most sophisticated program around."

- Bill Gates, *Business Week*, June 27, 1994

A Simple Example

The Traveling Salesman Problem:

Find a tour of a given set of cities so that

- each city is visited only once
- the total distance traveled is minimized

Representation

Representation is an ordered list of city numbers known as an *order-based* GA.

1) London	3) Dunedin	5) Beijing	7) Tokyo
2) Venice	4) Singapore	6) Phoenix	8) Victoria

CityList1 (3 5 7 2 1 6 4 8)

CityList2 (2 5 7 6 8 1 3 4)

Crossover

Crossover combines inversion and recombination:

			*			*		
Parent1	(3	5	7	2	1	6	4	8)
Parent2	(2	5	7	6	8	1	3	4)
Child	(2	5	7	2	1	6	3	4)

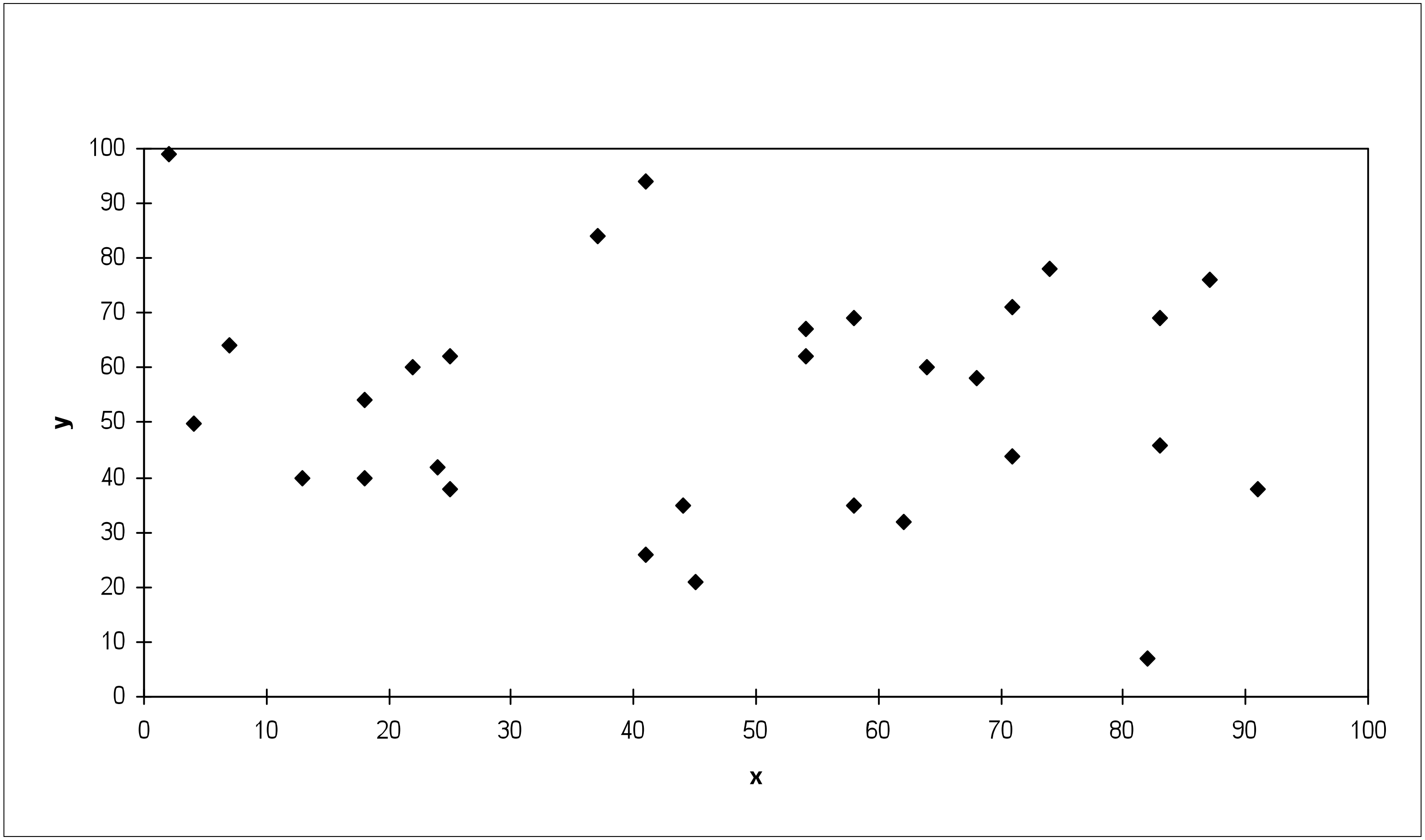
This operator is called the *Order1* crossover.

Mutation

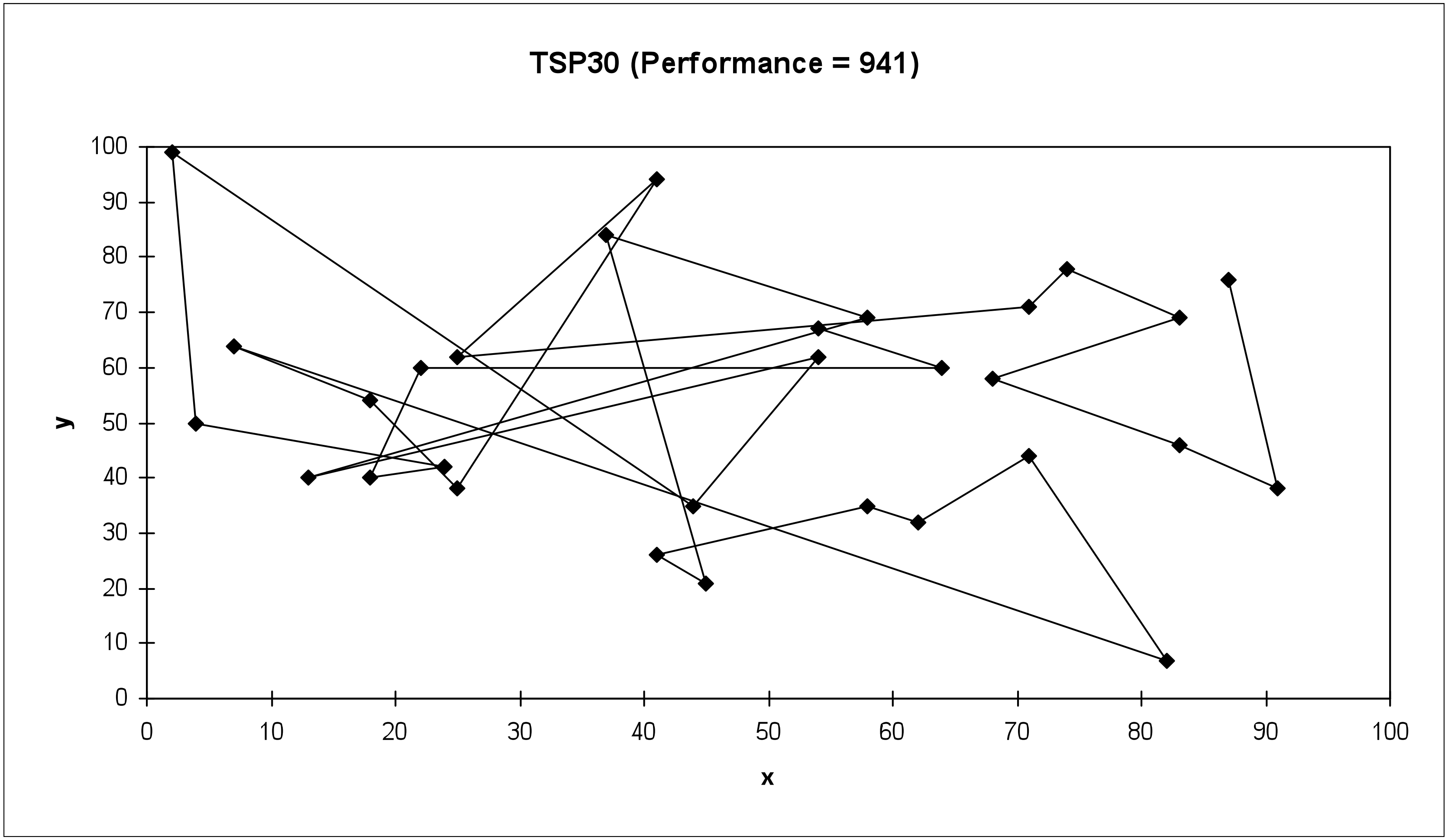
Mutation involves reordering of the list:

		*			*			
Before:	(5	8	7	2	1	6	3	4)
After:	(5	8	6	2	1	7	3	4)

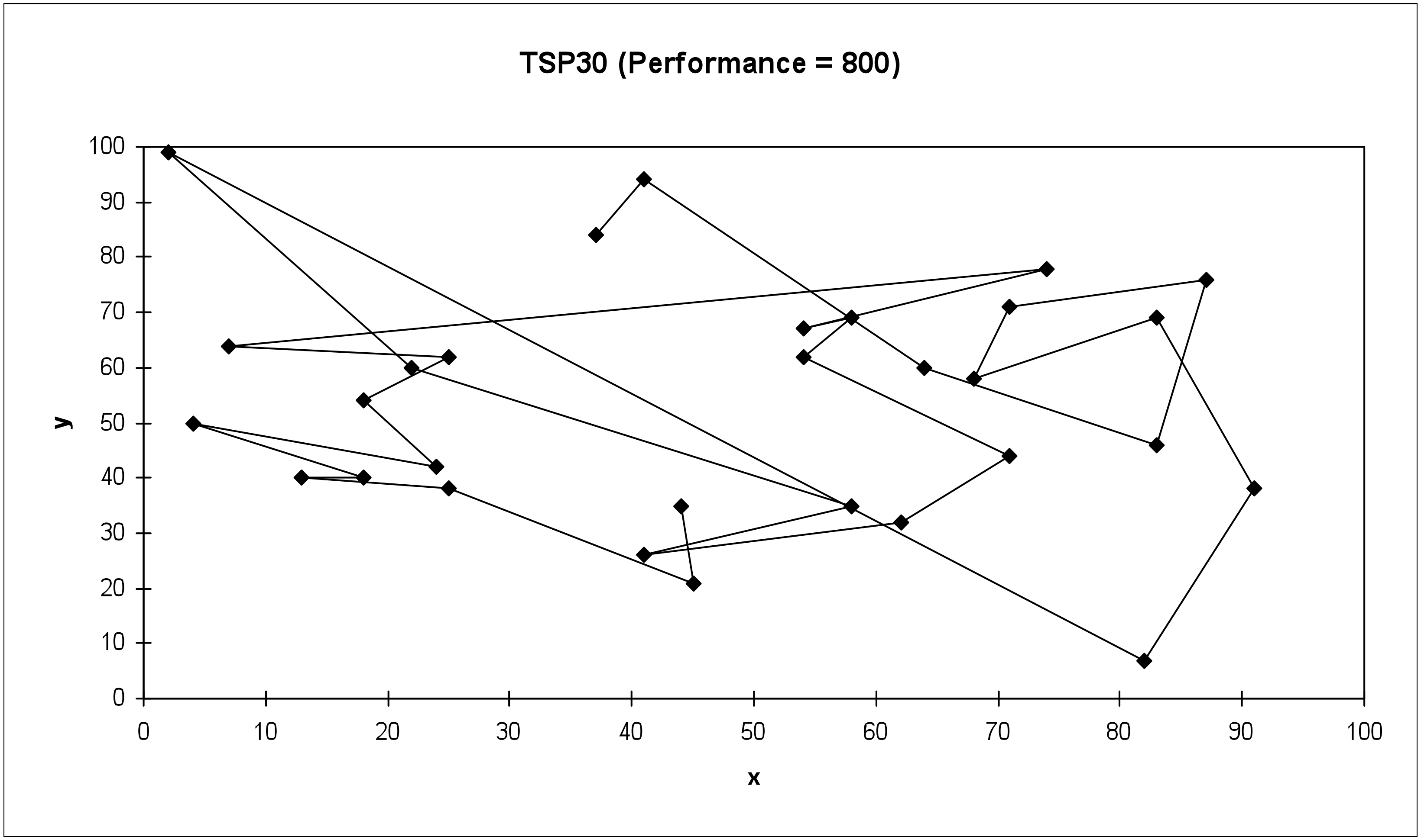
TSP Example: 30 Cities



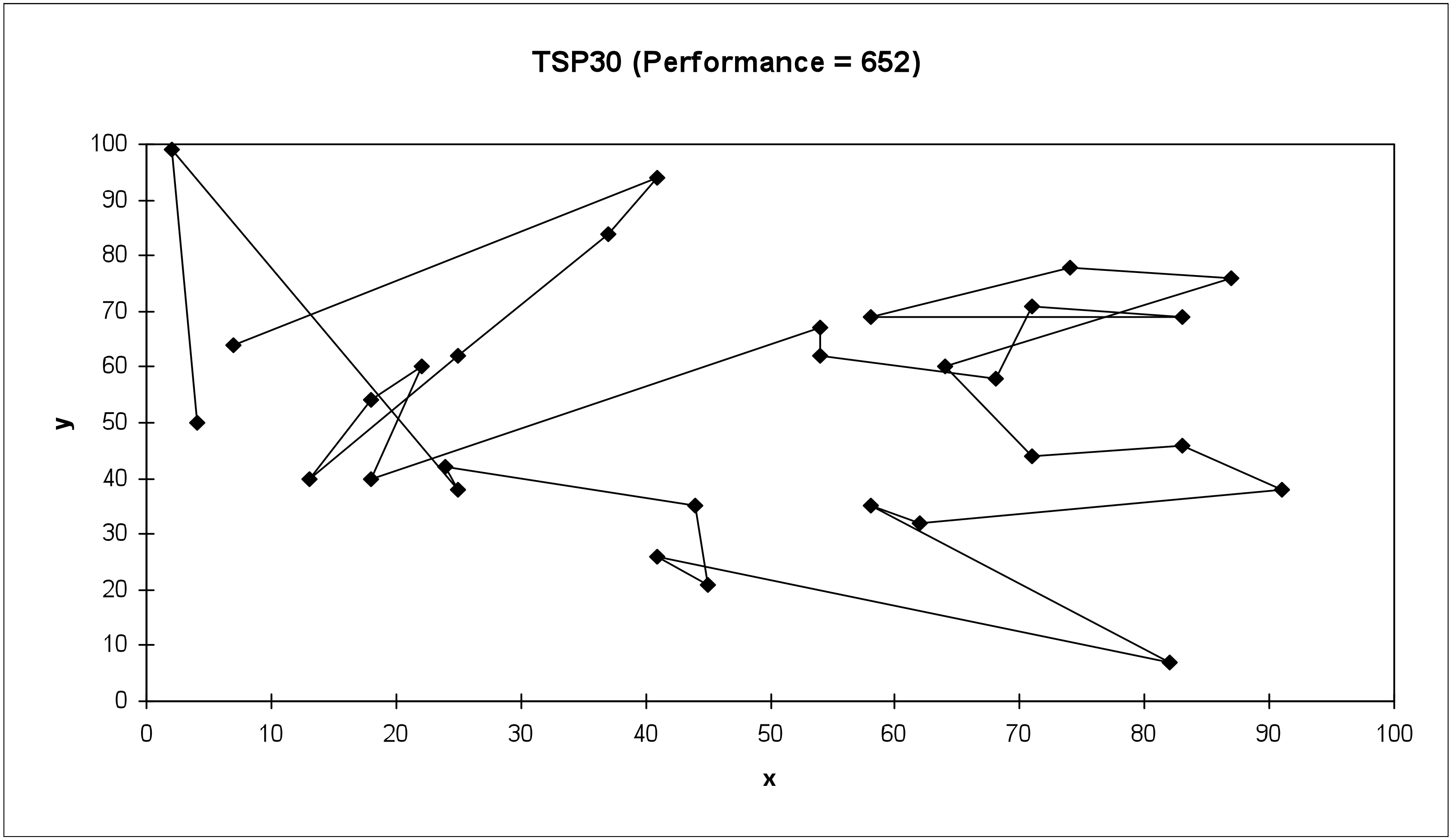
Solution $_i$ (Distance = 941)



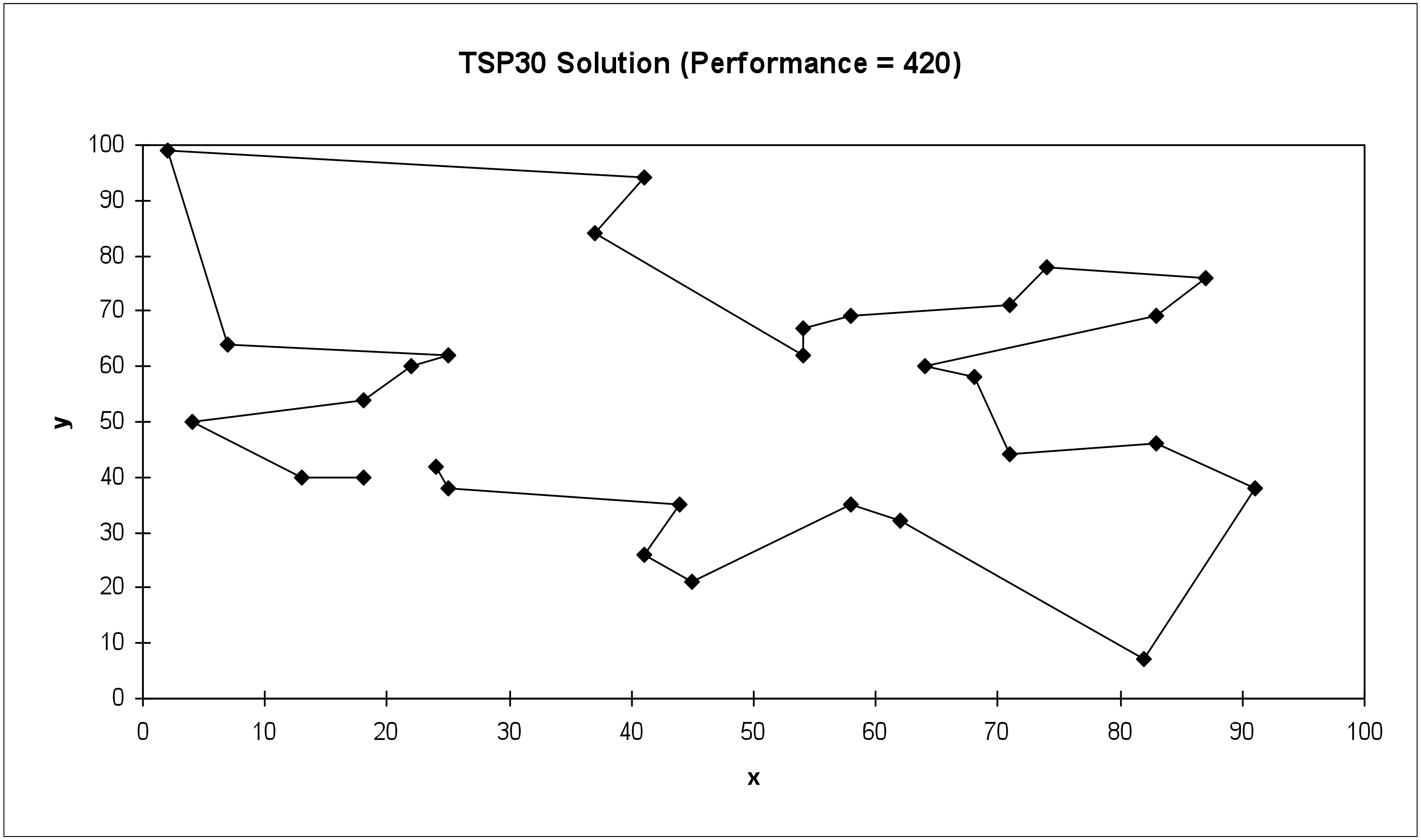
Solution $_j$(Distance = 800)



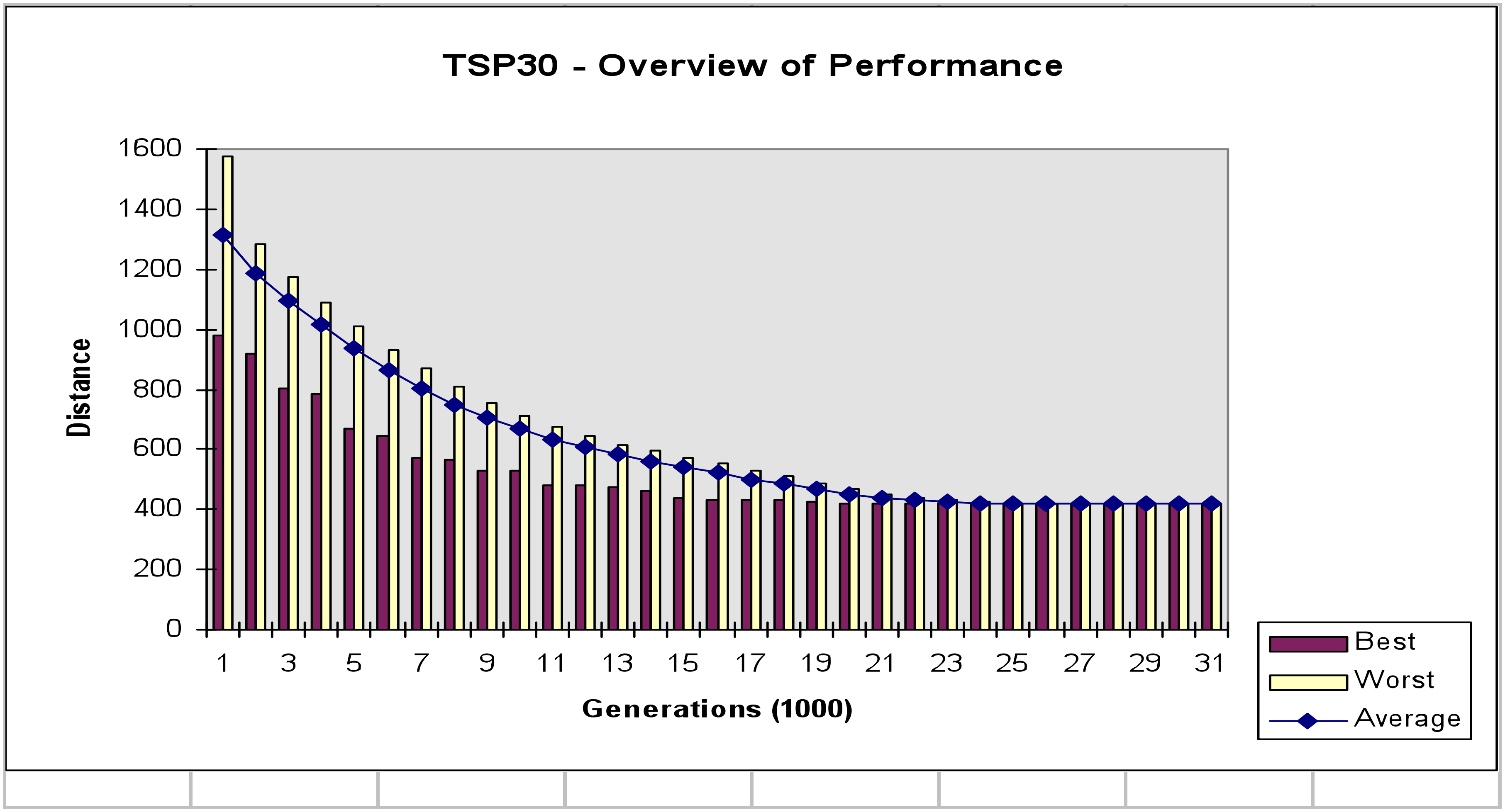
Solution $_k$(Distance = 652)



Best Solution (Distance = 420)



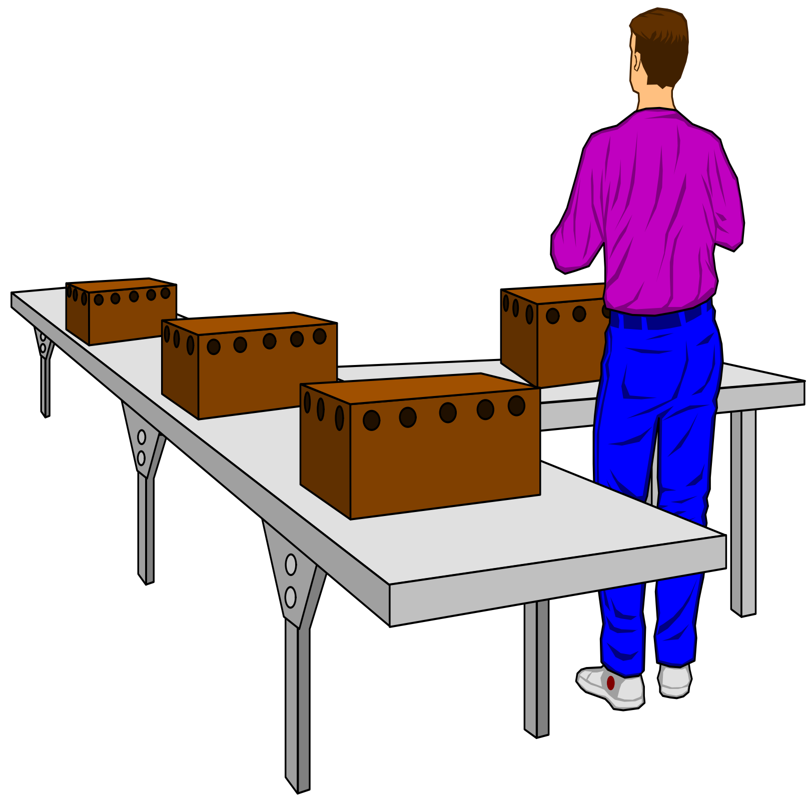
Overview of Performance



Considering the GA Technology

*"Almost eight years ago ...
people at Microsoft wrote
a program [that] uses
some genetic things for
finding short code
sequences. Windows 2.0
and 3.2, NT, and almost all
Microsoft applications
products have shipped
with pieces of code created
by that system."*

- Nathan Myhrvold, Microsoft Advanced Technology Group, *Wired*, September 1995



Issues for GA Practitioners

- Choosing basic implementation issues:
  - representation
  - population size, mutation rate, ...
  - selection, deletion policies
  - crossover, mutation operators
- Termination Criteria
- Performance, scalability
- Solution is only as good as the evaluation function (often hardest part)

Benefits of Genetic Algorithms

- Concept is easy to understand
- Modular, separate from application
- Supports multi-objective optimization
- Good for “noisy” environments
- Always an answer; answer gets better with time
- Inherently parallel; easily distributed

Benefits of Genetic Algorithms (cont.)

- Many ways to speed up and improve a GA-based application as knowledge about problem domain is gained
- Easy to exploit previous or alternate solutions
- Flexible building blocks for hybrid applications
- Substantial history and range of use

When to Use a GA

- Alternate solutions are too slow or overly complicated
- Need an exploratory tool to examine new approaches
- Problem is similar to one that has already been successfully solved by using a GA
- Want to hybridize with an existing solution
- Benefits of the GA technology meet key problem requirements

Some GA Application Types

Domain	Application Types
Control	gas pipeline, pole balancing, missile evasion, pursuit
Design	semiconductor layout, aircraft design, keyboard configuration, communication networks
Scheduling	manufacturing, facility scheduling, resource allocation
Robotics	trajectory planning
Machine Learning	designing neural networks, improving classification algorithms, classifier systems
Signal Processing	filter design
Game Playing	poker, checkers, prisoner's dilemma
Combinatorial Optimization	set covering, travelling salesman, routing, bin packing, graph colouring and partitioning

Conclusions

Question: 'If GAs are so smart, why ain't they rich?'

Answer: 'Genetic algorithms ***are*** *rich - rich in application across a large and growing number of disciplines.'*

- David E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*