Computational Intelligence

Unit # 5

Acknowledgement

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A Canonical EA (Source: DeJong)

- This canonical EA
  - maintains a fixed-size population of individuals,
  - each of which is a fixed-length vector (chromosome) of real-valued parameters (genes), and
  - whose objective fitness is determined by calling a "landscape" evaluation function.
- After randomly generating and evaluating the fitness of the members of the initial population, EA
  - effects population evolution by repeatedly selecting a member of the current population at random (uniformly) as a parent and
  - produces a clone offspring.

A Canonical EA (Cont'd)

- EA then introduces some variation in the offspring via a simple mutation operator which, on average picks one gene in the genome to modify by randomly adding/subtracting a small value to the current value of the selected gene.
- The new offspring is forced to immediately compete for survival against an existing member of the population selected at random.
- If the objective fitness of the child is greater than the selected member, the child survives and the old member dies off. Otherwise, the child dies without ever residing in the population.

Limitations

- It is quite possible that some members of the current population never produce any offspring in spite of the fact that they may have high fitness.
- Similarly, by randomly picking members from the current population to compete with children for survival into the next generation, it is quite possible that weak individuals may survive by the luck of the draw and not out of merit.

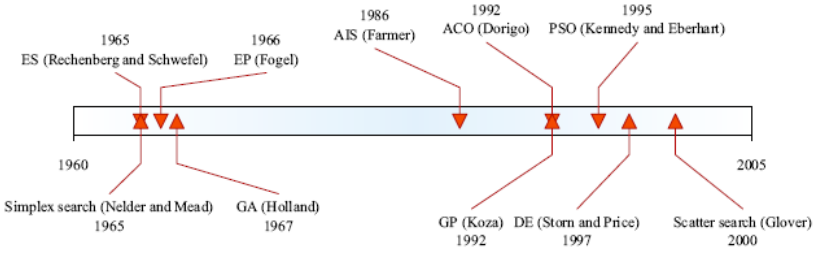
History of Evolutionary Algorithms

- Several efforts were started in parallel during 1960s
  - Evolutionary Programming (UCLA)
  - Evolution Strategies (Berlin Technical University)
  - Genetic Algorithms (University of Michigan)
- During 1990s the above communities agreed to the term "Evolutionary Computation".

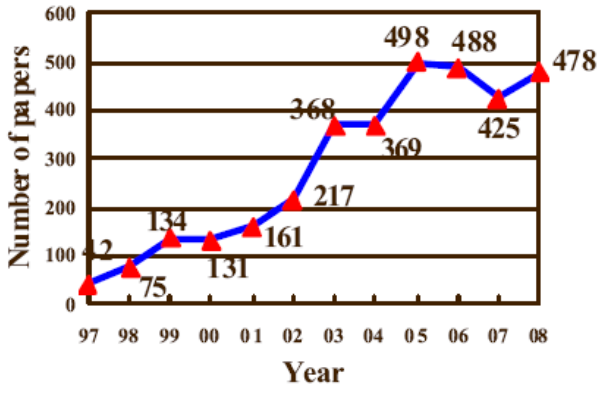
The Unifying 90s

- Till 90s, much of the R&D was done independently and in parallel without much interaction among the various groups.
- The emergence of the various EA conference in the late 1980s and early 1990s, however, changed all that as representative from various EA groups met, presented their particular viewpoints, challenged other approaches, and were challenged in return.
- The immediate result was an agreement on the term "evolutionary computation" as the name of the field and a commitment to start the field's first journal, Evolutionary Computation.

Recap: History of Evolutionary Computation



Number of EC Papers Published in ISI Indexed Journals



Evolutionary Programming

- At UCLA during the same period Fogel (1966 paper) saw the potential of achieving the goals of artificial intelligence via evolutionary techniques.
- These ideas were initially explored in a context in which intelligent agents were represented as finite state machines, and an evolutionary framework called "*evolutionary programming*" was developed which was quite effective in evolving better finite state machines (agents) over time.

Blondie24

- **Blondie24** is an artificial intelligence checkers-playing computer program.
- The screen name was used on the The Zone, an internet boardgaming site, during 1999. During this time, Blondie24 played against some 165 human opponents and was shown to achieve a rating of 2048, or better than 99.61% of the playing population of that web site.
- The design of Blondie24 is based on a minimax algorithm of the checkers game tree in which the evaluation function is an artificial neural network.
- The neural net receives as input a vector representation of the checkerboard positions and returns a single value which is passed on to the minimax algorithm.

Blondie24 (Cont'd)

- The neural net weightings were obtained by an evolutionary algorithm, in this case by having a population of Blondie24-like programs play against each other and later eliminating those with fewest earned points in which the players earned +1 for a win, 0 for a draw, and -2 for a loss, and repeating the process with a new population derived from the winners. The result was an evolutionary process selecting the programs that played better checkers games.

Canonical Evolutionary Programming

- For I = 1 to m Do:
  - Use parent I to produce 1 child and add it to the offspring population
- End Do
- From the combined pool of 2m parents and children, select only the m individuals with highest fitness to survive.

EP Differences

- EP emphasizes phenotypic evolution, instead of genotypic evolution.
- Due to the above, EP does not make use of any recombination operator. There is no exchange of genetic material.
- Selection is based on competition. Those individuals that perform best against a group of competitors have a higher probability of being included in the next generation.
- Parents and offspring compete for survival.
- The behavior of individuals is influenced by strategy parameters, which determine the amount of variation between parents and offspring.

EP - Mutation

- As mutation is the only means of introducing variation in an EP population, it is very important that the design of a mutation operator considers the exploration–exploitation trade-off.
- The variation process should facilitate exploration in the early stages of the search to ensure that as much of the search space is covered as possible.
- After an initial exploration phase, individuals should be allowed to exploit obtained information about the search space to fine tune solutions.

EP – Mutation (Cont'd)

- In general, mutation is defined as

$$x'_i(t) = x_i(t) + \Delta x_i(t)$$

- where $x'_i(t)$ is the offspring created from parent $x_i(t)$ by adding a step size $\Delta x_i(t)$ to the parent.
- The step size is noise sampled from some probability distribution, where the deviation of the noise is determined by a strategy parameter, σ_i .
- Generally, the step size is calculated as

$$\Delta x_i(t) = \Phi(\sigma_i(t))\eta_i(t)$$

- where $\Phi : R \rightarrow R$ is a function that scales the contribution of the noise, $\eta_i(t)$.

EP – Scaling Functions

- Based on the characteristics of the scaling function, Φ, EP algorithms can be grouped into three main categories of algorithms:
- ***non-adaptive EP,*** in which case Φ(σ) = σ. In other words, the deviations in step sizes remain static.
- ***dynamic EP,*** where the deviations in step sizes change over time using some deterministic function, Φ.
- ***self-adaptive EP,*** in which case deviations in step sizes change dynamically.

Canonical EP (Cont'd)

- Producing a very small number of offspring from a parent is not a very reliable sample of its potential for producing useful progeny.
- Computationally, it is quite easy to extend the EP paradigm to encompass this idea by just allowing the size of the offspring population n to be greater than m, the size of the parent population.

Summary EP

Representation	Real-valued vectors
Parent Selection	Deterministic (each parent creates one offspring via mutation)
Recombination	None
Mutation	Gaussian perturbation
Survival Selection	Probabilistic (mu + mu)

Evolution Strategies

- At the Technical University Berlin, Rechenberg and Schwefel (1965 paper) began formulating ideas about how evolutionary processes could be used to solve difficult real-valued parameter optimization problems.
- From these early ideas emerged a family of algorithms called "*evolution strategies*" which today represent some of the most powerful evolutionary algorithms for function optimization.

Canonical Evolution Strategy

- Having done so raises two interesting questions:
  - How many offspring should each parent produce, and given that we are now using parents more efficiently,
  - Can we reduce the size of the parent population
- These ideas correspond directly to the early Evolutionary Strategy algorithms.
- Perhaps most striking about this early work was the focus on (1 + λ)-ES models in which the entire next generation was produced from a single parent.

ES - Recombination

- The basic recombination scheme in evolution strategies involves two parents that create one child.
- To obtain λ offspring recombination is performed λ times.
- There are two recombination variants distinguished by the manner of recombining parent alleles.
  - Using discrete recombination one of the parent alleles is randomly chosen with equal chance for either parents.
  - In intermediate recombination the values of the parent alleles are averaged.

ES – Step-Size Adjustment

- Theoretical studies motivated an on-line adjustment of step sizes by the famous 1/5 success rule of Rechenberg.
- This rule states that the ratio of successful mutations to all mutations should be 1/5.
- If the ratio is greater then 1/5 the step size should be increased to make a wider search of the space, and if the ratio is less than 1/5 then it should be decreased to concentrate the search more around the current solution.

ES - Survival Selection

- After creating λ offspring and calculating their fitness, the best μ of them are chosen deterministically, either from the offspring only, called (μ, λ) selection, or from the union of the parents and offspring, called $(\mu + \lambda)$ selection.
- Both schemes are strictly deterministic and are based on rank rather than an absolute fitness value.

ES - Survival Selection (Cont'd)

- (μ, λ) is typically preferred over $(\mu + \lambda)$ for the following reasons
  - The (μ, λ) discards all parents and is there in principle able to leave (small) local optima, so it is advantageous in the case of multimodal topologies
  - If the fitness function is not fixed, but changes in time, the $(\mu + \lambda)$ selection preserves outdated solutions, so it is not able to follow the moving optimum well.
  - $(\mu + \lambda)$ selection hinders the self-adaptation mechanism because mis-adapted parameter may survive for a relatively large number of generations

Summary of ES

Representation	Real-valued vectors
Parent Selection	Uniform random
Recombination	Discrete or intermediary
Mutation	Gaussian perturbation
Survival Selection	(mu, lambda) or (mu + lambda)

Probability Distributions for Mutation

- All EAs follows a stochastic search process.
- Stochasticity is introduced by computing step sizes as a function of noise, η_{ij} , *sampled from some* probability distribution. The most popular distributions are
  - Uniform
  - Gaussian

Uniform

- Noise is sampled from a uniform distribution

$$\eta_{ij}(t) \sim U(x_{min}, x_{max})$$

- where x_{min} *and* x_{max} *provide lower and upper bounds for the values of* η_{ij}.

Gaussian

- For the Gaussian mutation operators, noise is sampled from a zero-mean, normal distribution.
- For completeness sake, and comparison with other distributions, the Gaussian density function is given as (assuming a zero mean)

$$f_G(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-x^2/(2\sigma^2)}$$

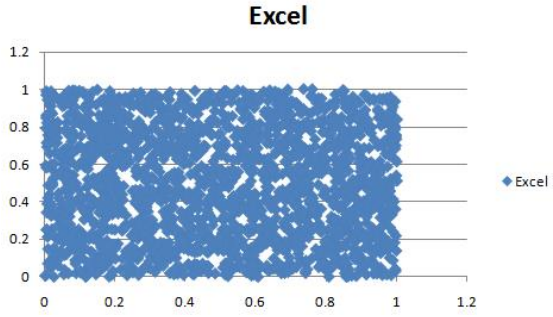
- where σ is the deviation of the distribution

C# Program

```
using System;
using System.Collections.Generic;
using System.Linq;
using System.Text;
using System.IO;

namespace ConsoleApplication1
{
  class Program
  {
    static void Main(string[] args)
    {
      StreamWriter strOut = new StreamWriter("output.txt");

      Random r1 = new Random(1111);
       Random r2 = new Random(1729);

      for (int i = 0; i < 2000; i++)
        strOut.WriteLine(r1.Next(10000)/10000.0 + " , " + r2.Next(10000) / 10000.0);

      strOut.Flush();
      strOut.Close();
    }
  }
}
```

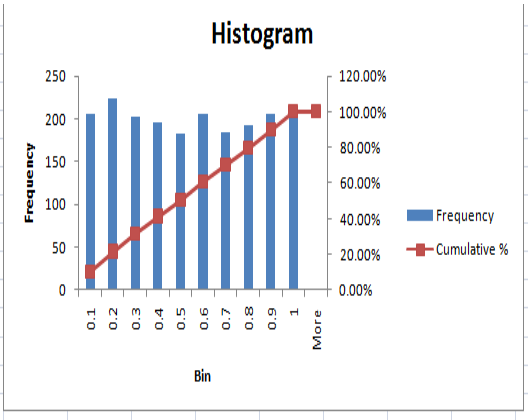
Excel Random Numbers

	Random 1 Series	Random 2 Series
Q1	0.234332	0.24797
Median	0.495124	0.486396
Q3	0.748964	0.743278



Excel Random Numbers Histogram

Bin	Frequency	Cumulative %
0.1	205	10.25%
0.2	224	21.45%
0.3	202	31.55%
0.4	195	41.30%
0.5	182	50.40%
0.6	205	60.65%
0.7	185	69.90%
0.8	192	79.50%
0.9	206	89.80%
1	204	100.00%
More	0	100.00%

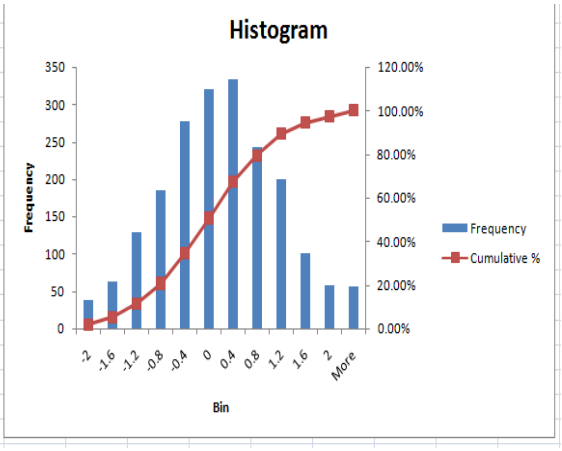


Normal (Gaussian) Random Numbers

- The most important transformation functions is known as the **Box-Muller** (1958) transformation.
- It allows us to transform uniformly distributed random variables, to a new set of random variables with a Gaussian (or Normal) distribution.
- The most basic form of the transformation looks like:
  - y1 = sqrt(- 2 ln(x1)) cos(2 pi x2)
  - y2 = sqrt(- 2 ln(x1)) sin(2 pi x2)
- We start with *two* independent random numbers, x1 and x2, which come from a uniform distribution (in the range from 0 to 1).
- Then apply the above transformations to get two new independent random numbers which have a Gaussian distribution with zero mean and a standard deviation of one.

Normal Distribution

Bin	Frequency	Cumulative %
-2	38	1.90%
-1.6	63	5.05%
-1.2	128	11.45%
-0.8	185	20.70%
-0.4	277	34.55%
0	321	50.60%
0.4	333	67.25%
0.8	242	79.35%
1.2	199	89.30%
1.6	101	94.35%
2	57	97.20%
More	56	100.00%



Normal Random Numbers

	Random 1 Series	Random 2 Series
Q1	-0.66701	-0.69655
Median	-0.00948	0.022777
Q3	0.624935	0.69396