CS348 FS2011 Exam 3 Key

This is a closed-book, closed-notes exam. The only items you are allowed to use are writing implements. Mark each sheet of paper you use with your name and the string “cs348fs2011 exam3”. If you are caught cheating, you will receive a zero grade for this exam. The max number of points per question is indicated in square brackets after each question. The sum of the max points for all the questions is 48, but note that the max exam score will be capped at 45 (i.e., there are 3 bonus points but you can’t score more than 100%). You have exactly 75 minutes to complete this exam. Keep your answers clear and concise while complete. Good luck!

Multiple Choice Questions - write the letter of your choice on your answer paper

1. Parameter Control is important in EAs because: [2]
   (a) optimal strategy parameter values may change during evolution
   (b) it may somewhat relieve users from parameter tuning as parameter control may make an EA less sensitive to initial strategy parameter values
   (c) all of the above
   (d) none of the above

2. “Blind Parameter Control” is a better name for the class of parameter control mechanisms named “Deterministic Parameter Control” in the textbook because that class: [2]
   (a) includes stochastic mechanisms [1]
   (b) does not use any feedback from the evolutionary process [1]
   (c) all of the above
   (d) none of the above [0]

3. Speciation is: [2]
   (a) when geographically separated sub-populations of a species adapt to their local environmental niches to the extent that they become mating-incompatible
   (b) when sub-populations of different species in the same local environmental niche adapt homogeneously to the extent that they become mating-compatible
   (c) all of the above
   (d) none of the above

4. In Diffusion Model EAs: [2]
   (a) individuals are modeled by diffusion equations and only panmictic mating is permitted [0]
   (b) the population is conceptually distributed on a grid and mating is restricted to demes [0]
   (c) all of the above [0]
   (d) none of the above [0]

5. If we employ self-adaptation to control the value of penalty coefficients for an EA with an evaluation function which includes a penalty function, then: [2]
   (a) the penalty coefficients will be self-adapted to cause fitness improvement just like, for instance, mutation step sizes
   (b) this cannot be done because it is inherently impossible to self-adapt any part of the evaluation function [0]
   (c) the penalty coefficients will be self-adapted, but the increase in fitness achieved may not be correlated with better performance on the objective function
   (d) none of the above
6. In an EA employing Lamarckian evolution: [2]
   (a) improved EA performance is obtained through the Baldwin effect [0]
   (b) improved EA performance is obtained through local search [1]
   (c) **acquired traits are passed on genetically** [2]
   (d) all of the above [2]
   (e) none of the above [0]

7. The Baldwin Effect is: [2]
   (a) improved EA performance obtained by applying local search after fitness calculation [1]
   (b) **improved EA performance obtained by applying local search prior to fitness calculation** [1]
   (c) improved EA performance obtained by combining local search with Lamarckian evolution [1]
   (d) none of the above [0]

8. Learning Classifier Systems are technically speaking: [2]
   (a) a type of Condition-Action Rule-Based System [1]
   (b) a type of Reinforcement Learning System [1]
   (c) a type of Evolutionary Algorithm [0]
   (d) **both of the first two types, but not the third** [2]
   (e) all three types [1]
   (f) none of the above [0]

   (a) in the Pitt approach each individual represents a complete rule set, while in the Michigan approach each individual represents a single rule and the entire population represents the complete rule set [2]
   (b) in the Pitt approach each individual represents a single rule and the entire population represents the complete rule set, while in the Michigan approach each individual represents a complete rule set [2]
   (c) in the Pitt approach each individual represents a single rule and the entire population represents the complete rule set, while in the Michigan approach each individual has the option of either representing a single rule or a rule set [1]
   (d) in the Pitt approach each individual represents a complete rule set, while in the Michigan approach each individual has the option of either representing a single rule or a rule set [1]
   (e) in the Pitt approach each individual has the option of either representing a single rule or a rule set, while in the Michigan approach each individual represents a single rule and the entire population represents the complete rule set [1]
   (f) none of the above [0]

10. The Limiting Cases in the Greedy Population Sizing EA (GPS-EA) are those instances when: [2]
    (a) both populations are stuck in a local minimum and the average fitness of the larger population is lower than the average fitness of the smaller population [2]
    (b) the larger population is stuck in a local minimum but the average fitness of the smaller population is higher than the average fitness of the larger population [2]
    (c) both populations are stuck in a local minimum and the average fitness of the larger population is higher than the average fitness of the smaller population [1]
    (d) none of the above [0]
11. In the hybridization of the GPS-EA and ELOOMS, the Limiting Cases are detected by: [2]
   
   (a) none of the individuals desiring to mate with any other individual [1]
   
   (b) **none of the individuals desiring to mate with an individual who reciprocates that desire**
   
   (c) the average fitness of the mating pool being higher than the average population fitness [0]
   
   (d) the average fitness of the mating pool being lower than the average population fitness [0]
   
   (e) none of the above [0]

**Regular Questions**

12. Think of, and then describe, a shortcoming of the GPS-EA + ELOOMS hybrid in terms of population size control. [4]

   The GPS-EA + ELOOMS hybrid is very good at determining high quality fixed population sizes, but does not support dynamic population size control. As it has been shown to be beneficial to be able to vary population size during the run of an EA, this is a shortcoming.


   Island model EAs run multiple populations of the same species in parallel in some kind of communication structure. After a usually fixed number of generations, a number of individuals are selected from each population to be exchanged with others from neighboring populations. During this migration, the injection of individuals of potentially high fitness, and with possibly radically different genotypes, facilitates exploration. In terms of the theory of punctuated equilibria, these injections interrupt periods of evolutionary stasis by rapid growth when the main population is invaded by individuals from a previously spatially isolated group of individuals of the same species.

14. Explain the difference between fitness sharing and crowding. [4]

   In fitness sharing the fitness of individuals immediately prior to selection is adjusted according to the number of individuals falling within some prespecified distance of each other, while in fitness crowding new individuals replace similar population members; the resulting difference is that in fitness sharing the number of individuals per niche is dependent on the niche fitness, while in fitness crowding the population is equally distributed over the niches.

15. Alice is writing an EA to solve the binary knapsack constraint satisfaction problem. Given the following constraint handling approaches:

   (a) Ignore the constraints under the motto: all is well that ends well.
   
   (b) Upon generating an infeasible solution, immediately kill it and generate a new solution; repeat this step until a feasible solution is generated.
   
   (c) Employ a penalty function that reduces the fitness of infeasible solutions, preferably so that the fitness is reduced in proportion to the number of constraints violated, or to the distance from the feasible region.
   
   (d) Employ a repair function that takes infeasible solutions and “repairs” them by transforming them into a related feasible solution, typically as close as possible to the infeasible one.
   
   (e) Employ a closed feasible solution space which guarantees that the initial population consists of feasible solutions only and all evolutionary operations on feasible solutions are guaranteed to result in feasible solutions. Typically a combination of custom representation, initialization, recombination, and mutation is employed to achieve this.
   
   (f) Employ a decoder function that maps genotype space to phenotype space such that the phenotypes are guaranteed to be feasible even when the genotypes are infeasible. Typically this involves mapping multiple different genotypes to the same phenotype.
Which of these six constraint handling approaches do you recommend Alice employs? Explain your answer!

There are three cases:

**Case 1** If the sum of the item costs is smaller or equal to the constraint value, then use the first approach where the constraints are simply ignored.

**Case 2** If Alice knows that the ratio of invalid to total solutions is extremely low, for instance if the sum of the item costs barely exceeds the constraint value, then use the second approach where invalid solutions are immediately discarded and use either stochastic survival or a mutation with for instance a Gaussian distributed mutation rate to guarantee global optimum reachability.

**Case 3** Otherwise use a high quality decoder function which will guarantee valid solutions while imposing no limitations on the search of the genotype space.

16. Given the following bit strings $v_1$ through $v_5$ and schema $S$

$v_1 = (11101101111101) \quad fitness(v_1) = 0.3$
$v_2 = (10110010001101) \quad fitness(v_2) = 0.1$
$v_3 = (00010100110110) \quad fitness(v_3) = 1.0$
$v_4 = (010011110111001) \quad fitness(v_4) = 1.9$
$v_5 = (11001011110101) \quad fitness(v_5) = 1.7$

$S = (*************** )$

(a) Compute the order of $S$. [1]

0

(b) Compute the defining length of $S$ and show your computation. [1]

*It can’t be computed per the definition, but it has to be 0 to be consistent with the concept of defining length.*

(c) Compute the fitness of $S$ and show your computation. [2]

\[
\frac{0.3 + 0.1 + 1.0 + 1.9 + 1.7}{5} = 1.0
\]

(d) Do you expect the number of strings matching $S$ to increase or decrease in subsequent generations? Explain your answer! [3]

*Because $S$ matches all possible strings, the number of strings matching $S$ will never increase nor decrease.*