COMP 5970/6970/6976 Fall 2019 Final Exam 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 "COMP 5970/6970/6976 Fall 2019 Final Exam". 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 79, but note that the max exam score will be capped at 75 (i.e., there are 4 bonus points but you can't score more than 100%). You have exactly 150 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. In an EA which utilizes truncation survival selection: [2]
   - (a) the chance of premature convergence is lower than other elitist EAs *(false because truncation survival has the highest selective pressure of all the regular elitist survival mechanisms)* [0]
   - **(b) the parent selection should be stochastic to decrease the chance of premature convergence**
   - (c) the parent selection may not be elitist because that would cause premature convergence *(elitist means that the fittest solution is guaranteed to survive which by itself doesn't cause premature convergence)* [1]
   - (d) all of the above [1]
   - (e) none of the above [0]
2. To increase selective pressure for an EA employing tournament parent selection one can: [2]
   - (a) switch from truncation survivor selection (i.e., deterministically replacing the worst individuals) to an elitist stochastic survivor selection [0]
   - (b) decrease the tournament size used in parent selection [0]
   - (c) both of the above [0]
   - **(d) none of the above**
3. One advantage of implementing survivor selection by employing a so-called reverse k-tournament selection to select who dies is that: [2]
   - (a) you guarantee (k)-elitism [1]
   - (b) **you guarantee** $(k-1)$**-elitism**
   - (c) the probability of surviving is proportional to your fitness rank [0]
   - (d) you guarantee 1-elitism (i.e., the fittest individual is guaranteed to survive) [$\frac{1}{2}$]
   - (e) none of the above [0]
4. Is it possible for a haploid EA to be both pleitropic and polygenetic at the same time: [2]
   - (a) no, because this would require a diploid EA [0]
   - (b) no, because the one excludes the other regardless of whether it's a haploid or a diploid EA [0]
   - (c) yes, because the decoder function can be both surjective and injective at the same time [$\frac{1}{2}$]
   - **(d) yes, because the decoder function can be both not surjective and not injective at the same time**
   - (e) none of the above [0]

5. Genetic drift and natural selection: [2]

   (a) are different terms for the same concept [0] *(false because they are different concepts)*

   (b) are different non-related concepts [$\frac{1}{2}$] *(false because while different, they are certainly related)*

   (c) complement each other because natural selection without genetic drift would select based on phenotypes without regard for genotypes [1] *(bad answer because natural selection selects based on phenotype, whether or not there is genetic drift)*

   (d) complement each other because genetic drift without natural selection would result in random search

6. In an arbitrary unimodal problem there are: [2]

   (a) no local optima, but multiple global optima *(false as every global optimum is also a local optimum)* [0]

   (b) **a single local optimum and a single global optimum**

   (c) multiple local optima but only one global optimum *(false because per definition a unimodal problem has a single local optimum)* [$\frac{1}{2}$]

   (d) none of the above [0]

7. Mutation has the potential to modify an individual's: [2]

   (a) genotype [$\frac{1}{2}$]

   (b) phenotype [$\frac{1}{2}$]

   (c) alleles [$\frac{1}{2}$]

   (d) fitness [$\frac{1}{2}$]

   (e) all of the above

   (f) a, b, and c, but not d [$1\frac{1}{2}$]

8. A Hamming cliff is: [2]

   (a) **A pair of binary strings which differ in many of their bits *(i.e., have a large Hamming distance)* exhibit a Hamming cliff**

   (b) a population of individuals with binary representation whose genotypes are very similar and who all have a large Hamming distance to the global optimum causing premature convergence [$\frac{1}{2}$]

   (c) a cliff-like plot associated with a binary encoded fitness function belonging to an NP-Complete problem class [0]

   (d) all of the above [0]

   (e) none of the above [0]

9. Binary gray code is: [2]

   (a) a binary coding system specifically developed to represent gray scales in digital images [$\frac{1}{2}$]

   (b) a binary coding system with consecutive corresponding integers differing by no more than 2 bits [$1\frac{1}{2}$]

   (c) a binary coding system where the Hamming distance between consecutive corresponding integers is proportional to their magnitude [1]

   (d) all of the above [0]

   (e) **none of the above**

10. Koza states that the aim of the fields of artificial intelligence and machine learning is to generate human-competitive results with a high artificial-to-intelligence (AI) ratio where the AI ratio of a problem-solving method means: [2]

    (a) the ratio of automation (generality) to human intelligence (speciality) needed by the problem-solving method to solve a particular problem [1]

    (b) **the ratio of that which is delivered by the automated operation of the problem-solving method to the amount of intelligence that is supplied by the human applying the method to a particular problem**

    (c) the ratio of artificial intelligence to human intelligence employed by the problem-solving method [1]

    (d) none of the above [0]

11. Panmictic mating (aka panmictic mixing) is: [2]

    (a) mating between genotypically similar individuals [0]

    (b) mating between phenotypically similar individuals [0]

    (c) unrestricted mating between any individuals in a population

    (d) mating between parents and their offspring [0]

    (e) none of the above [0]

12. 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 [0]

    (c) all of the above [$\frac{1}{2}$]

    (d) none of the above [0]

13. Alice and Bob are competing in the Pac-Man vs. the Ghosts competition. Alice's EA evolves a controller which in her experiments scored a higher final best fitness on average than what Bob's evolved controller scored in his experiments. Should the judge on that basis declare Alice the winner for best controller? [2]

    (a) yes, because fitness is per definition an absolute measure and Alice's evolved controller scored higher than Bob's [0]

    (b) yes, because although fitness is a relative measure in co-evolution, Alice's evolved controller scored higher on average, not just in one instance [1]

    (c) no, because although fitness is per definition an absolute measure, without knowing the variance in their results, one cannot statistically conclude that Alice beat Bob [1]

    (d) no, because fitness is a relative measure in co-evolution, so Alice's best evolved controller may have a high fitness due to her controllers being relatively weak and Bob's low due to his controllers being relatively strong

    (e) none of the above [0]

14. 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 [1]

    (b) this cannot be done because it is inherently impossible to self-adapt any part of the evaluation function [$\frac{1}{2}$]

    (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 [0]

15. 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 higher than the average fitness of the smaller population [1]

    (b) the larger population is stuck in a local minimum but the average fitness of the smaller population is larger than the average fitness of the larger population [$1\frac{1}{2}$]

    (c) **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**

    (d) none of the above [0]

16. Alice wants to employ a hyper-heuristic to target a computationally expensive algorithm to execute as efficiently as possible on a specific mobile device. She should: [2]

    (a) Reject this approach as hyper-heuristics need to execute on the targeted architecture to ensure fitness accurately reflects the target architecture, but mobile devices do not have the computational power to execute hyper-heuristics [1]

    (b) Pursue this approach and execute the hyper-heuristic on the targeted architecture to ensure fitness accurately reflects the target architecture. [$\frac{1}{2}$]

    (c) Pursue this approach and execute the hyper-heuristic on an HPC system capable of handling the high computational load. [1]

    (d) **Pursue this approach and execute the hyper-heuristic on an HPC system capable of handling the high computational load, but with a fitness function which reflects the estimated performance on the target architecture.**

    (e) None of the above [0]

Regular Questions

17. Think of, and then describe, a shortcoming of the GPS-EA + ELOOMS hybrid in terms of population size control. [3]

    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.

18. Assuming an elitist evolutionary algorithm with whose global optimum has a fitness of 100 and given a population consisting of the following bit strings v_1 through v_5 and schema S
    $v_1 = (11110110011001)$ $fitness(v_1) = 19$
    $v_2 = (10110111011011)$ $fitness(v_2) = 11$
    $v_3 = (10110110011101)$ $fitness(v_3) = 2$
    $v_4 = (10111110011001)$ $fitness(v_4) = 100$
    $v_5 = (11111110111001)$ $fitness(v_5) = 10$
    $S = (10111110011001)$

    (a) Compute the *order* of S. [1]
    14

    (b) Compute the *defining length* of S and show your computation. [1]
    14-1=13

    (c) Compute the fitness of S and show your computation. [1]
    $fitness(S) = fitness(v_4)/1 = 100$

    (d) Do you expect the number of strings matching S to increase, decrease, or stay the same in subsequent generations? Explain your answer! [4]
    As S matches exactly one of the current strings and that string has maximum fitness and so is guaranteed to survive due to the elitism except in the unlikely event where a whole population of maximum fitness individuals is evolved, the number will not decrease; however, considering its maximum order and maximum defining length, the fact that genotypically similar individuals have much lower fitness, and the absence of any other high fitness individuals in the current population, it is questionable whether any clones will appear, so increasing seems somewhat tenuous and most likely it will stay the same till termination.

19. Show how one can configure an EA to be functionally equivalent to Simulated Annealing (SA) by copying and filling out the provided table on your answer paper, or, if you believe it is inherently impossible, explain why. [5]

For your convenience, here is some SA pseudo-code:

function SimulatedAnnealing($problem, schedule$) **returns** a solution state
  $current \leftarrow MakeNode(InitialState[problem])$
  for $t \leftarrow 1$ to ∞ **do**
    $T \leftarrow schedule[t]$
    if $T = 0$ **then**
      return current
    end if
    $next \leftarrow$ a randomly selected successor of $current$
    $\Delta E \leftarrow Value[next] - Value[current]$
    if $\Delta E > 0$ **then**
      $current \leftarrow next$
    else
      $current \leftarrow next$ with probability $e^{\Delta E/T}$
    end if
  end for

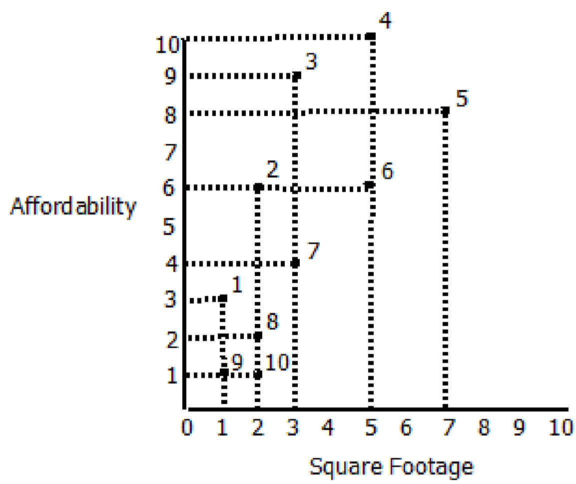
An EA can be configured to be functionally equivalent to SA as follows:

μ	*1*
λ	*1*
Initialization	*the single pop member is uniform randomly selected* *t=1*
Parent selection	*the lone population member is always selected to be the parent*
Recombination rate	*0%*
Mutation rate	*100%*
Mutation	*offspring = random successor of the parent*
Survival selection type	$(\mu + \lambda)$
Survival selection	*fitness F[] is defined to be equal to Value[]* *T=schedule[t]* *IF* $F[offspring] - F[parent] > 0$ *THEN offspring survives* *ELSE offspring survives with probability* $e^{\frac{F[offspring]-F[parent]}{T}}$ *t++*
Termination condition	*T==0*

20. Say you want to purchase a new house and care most about maximizing space and affordability. You collect square footage data and pricing on ten different houses and then you normalize both the square footage data and the pricing which results in the following table, where higher space numbers indicate greater square footage and higher affordability numbers indicate lower prices:

ID	Space	Affordability
1	1	3
2	2	6
3	3	9
4	5	10
5	7	8
6	5	6
7	3	4
8	2	2
9	1	1
10	2	1

(a) Plot the above table using dotted lines to indicate the area of domination for each element, with space on the horizontal axis and affordability on the vertical axis. [2]



(b) List for each element which elements it dominates; indicate elements with their IDs. [2]

ID	Dominates
1	9
2	1,8,9,10
3	1,2,7,8,9,10
4	1,2,3,6,7,8,9,10
5	1,2,6,7,8,9,10
6	1,2,7,8,9,10
7	1,8,9,10
8	9,10
9	None
10	9

(c) Show the population distributed over non-dominated levels, like some multi-objective EAs employ, after each addition of an element, starting with element 1 and ending with element 10 increasing the element number one at a time; indicate elements with their IDs. So you need to show ten different population distributions, the first one consisting of a single element, and the last one consisting of ten elements. [6]

After adding element 1:

Level 1: 1

After adding element 2:

Level 1: 2

Level 2: 1

After adding element 3:

Level 1: 3

Level 2: 2

Level 3: 1

After adding element 4:

Level 1: 4

Level 2: 3

Level 3: 2

Level 4: 1

After adding element 5:

Level 1: 4,5

Level 2: 3

Level 3: 2

Level 4: 1

After adding element 6:

Level 1: 4,5

Level 2: 3,6

Level 3: 2

Level 4: 1

After adding element 7:

Level 1: 4,5

Level 2: 3,6

Level 3: 2,7

Level 4: 1

After adding element 8:

Level 1: 4,5

Level 2: 3,6

Level 3: 2,7

Level 4: 1,8

After adding element 9:

Level 1: 4,5

Level 2: 3,6

Level 3: 2,7

Level 4: 1,8

Level 5: 9

After adding element 10:

Level 1: 4,5

Level 2: 3,6

Level 3: 2,7

Level 4: 1,8

Level 5: 10

Level 6: 9

21. (a) What is the binary gray code for the standard binary number 000111001011? [2]
000100101110
(b) What is the standard binary number encoded by the binary gray code 10101011000? [2]
11001101111

22. Given the following two parents with permutation representation:
$p1 = (829137465)$
$p2 = (986375421)$

(a) Compute the first offspring with Cycle Crossover. [4]
Cycle 1: 8-9-6-2, cycle 2: 1-3-7-5, cycle 3: 4
Construction of first offspring by scanning parents from left to right, starting at parent 1 and alternating parents:
i. Add cycle 1 from parent 1: $829 \cdots \cdot 6 \cdot$
ii. Add cycle 2 from parent 2: $829375 \cdot 61$
iii. Add cycle 3 from parent 1: 829375461

(b) Compute the first offspring with PMX, using crossover points between the 2nd and 3rd loci and between the 6th and 7th loci. [4]
i. $\cdot \cdot 9137 \cdot \cdot \cdot$
ii. $6 \cdot 9137 \cdot \cdot \cdot$
iii. $6 \cdot 9137 \cdot \cdot 5$
iv. 689137425

(c) Compute the first offspring with Edge Crossover, except that for each random choice you instead select the lowest element. [8]

Original Edge Table:

Element	Edges	Element	Edges
1	9+,3,2	6	4,5,8,3
2	8,9,4,1	7	3+,4,5
3	1,7+,6	8	5,2,9,6
4	7,6,5,2	9	2,1+,8
5	6,8,7,4		

Construction Table:

Element selected	Reason	Partial result
1	Lowest	1
9	Common edge	19
2	Shortest list	192
8	Shortest list	1928
5	Equal list size, so lowest	19285
4	Equal list size, so lowest	192854
6	Equal list size, so lowest	1928546
3	Only element	19285463
7	Last element	**192854637**

Edge Table After Step 1:

Element	Edges	Element	Edges
1	9+,3,2	6	4,5,8,3
2	8,9,4	7	3+,4,5
3	7+,6	8	5,2,9,6
4	7,6,5,2	9	2,8
5	6,8,7,4		

Edge Table After Step 2:

Element	Edges	Element	Edges
		6	4,5,8,3
2	8,4	7	3+,4,5
3	7+,6	8	5,2,6
4	7,6,5,2	9	2,8
5	6,8,7,4		

Edge Table After Step 3:

Element	Edges	Element	Edges
		6	4,5,8,3
2	8,4	7	3+,4,5
3	7+,6	8	5,6
4	7,6,5		
5	6,8,7,4		

Edge Table After Step 4:

Element	Edges	Element	Edges
		6	4,5,3
		7	3+,4,5
3	7+,6	8	5,6
4	7,6,5		
5	6,7,4		

Edge Table After Step 5:

Element	Edges	Element	Edges
		6	4,3
		7	3+,4
3	7+,6		
4	7,6		
5	6,7,4		

Edge Table After Step 6:

Element	Edges	Element	Edges
		6	3
		7	3+
3	7+,6		
4	7,6		

Edge Table After Step 7:

Element	Edges	Element	Edges
		6	3
		7	3+
3	7+		

(d) Compute the first offspring with Order Crossover, using crossover points between the 3rd and 4th loci and between the 7th and 8th loci. [2]

i. Child 1: $\cdot\cdot\cdot 1374 \cdot\cdot$

ii. Child 1: **865137429**