Genetic Algorithms for the Graduate TA Assignment Problem

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- The Graduate TA Assignment Problem (GTAAP)
- Formulating GTAAP as a Weighted CSP
- Genetic Algorithm Approach to Solution
- Results
- Future Work

The Graduate TA Assignment Problem

- Definition:
 - Given:
 - A set of teaching tasks *T*
 - A pool of teaching assistants *A*
 - A set of constraints restricting the assignments of members of *A* to members of *T*
 - A set of relations *P* : *T* x *A* → {0,1,2,3,4,5} describing the *preference* of each TA for each task
- Solution: A set of assignments that satisfies all constraints
- Ideal solution: A solution that maximizes total TA preference for assigned courses

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- Weighted CSP (WCSP), defined:
 - Instead of *constraints*, we have *cost functions*
 - Objective: minimize total cost
 - "Hard" constraint violation \rightarrow cost of "infinity"
- WCSP is a *combinatorial optimization* problem

- Mapping GTAAP to WCSP:
 - Domain: The set of TAs plus the special value "unassigned"
 - Variables: The teaching tasks for which TAs are needed
 - Constraints: Both "hard" and "soft"...

- Hard constraints:
 - Mutex: Two teaching tasks cannot have the same TA
 - Example: Course A and Course B occur at the same time
 - Overlap: The task cannot during a course for which the TA is registered as a student
 - Taking Course: The TA may not be enrolled in a course associated with the task
 - Example: TA enrolled in Course C cannot be the grader for Course C
 - Capacity: The TA's workload may not exceed the total number of hours for which the TA was hired to work
 - Certification: The TA assigned to the task must have ITA certification

- Soft constraints:
 - Preference: Each TA rates their preference for each task from 0 to 5, with 5 being highest
 - Because WCSP is about minimizing cost, we remap preference:

$$remapped_pref = \begin{cases} 5 - old_pref & \text{if } old_pref \neq 0 \\ \text{``infinity''} & \text{if } old_pref = 0 \end{cases}$$

• A preference of 0 is treated as a hard constraint (i.e. a cost of "infinity")

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- How GAs optimize:
 - Exploit evolution to search the problem space
 - Successive generations of solutions inherit traits from their best predecessors
- Advantages:
 - Versatile can optimize anything as long as appropriate genetic operators can be defined
 - Examples: TSP tours, neural network weights
 - Easy to parallelize

• Components of a genetic algorithm:

- Fitness function A way of quantifying how "good" a solution is
- Selection operator Forms a new population from the current population such that individuals with a higher fitness are more likely to be chosen
- Crossover operator Combines traits of two individuals to form a new individual
- Mutation operator Changes the genome of a single individual

• Generalized genetic algorithm



- Fitness function:
 - Must account for:
 - Hard constraint violations
 - Unassigned tasks
 - TA preference
 - In terms of "badness," assume:
 - (hard violation) > (unassigned task) > (low TA preference)
 - Violating one hard constraint is worse than leaving all tasks unassigned
 - Leaving one task unassigned is worse than assigning all TAs to courses with preference 1
 - Solution:
 - Treat "unassigned" as a TA with preference "cost" one greater than maximum possible for normal TAs.
 - Treat cost of "infinity" as one greater than cost of leaving all tasks unassigned.
 - Fitness = 1 / (total cost)

- Selection operator:
 - Tournament selection:
 - Choose a pair of individuals uniformly at random without replacement.
 - Select the most-fit with probability p and the least-fit with probability 1-p
 - Advantages over other methods:
 - Insensitive to magnitude of fitness difference
 - Preserves more variability in population than i.e. Roulette selection

- Crossover operator:
 - Point crossover Given two parents A and B, choose a point in the genome. Then, the child's genome consists of parent A's genome before selected point concatenated with parent B's genome after selected point.



- Mutation operator:
 - "Value change" mutation Choose a variable in the genome uniformly at random and replace its value with a different value chosen uniformly at random.
 - Before:
 - 1 5 18 2 6 7 **19** 20 0 13 24 ...
 - After:
 - 1 5 18 2 6 7 **4** 20 0 13 24 ...

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Results

- Methods:
 - Dataset: Spring 2009 CSE GTA Assignment Problem
 - 27 TAs plus 1 "unassigned"
 - 57 teaching tasks
 - 245 constraints
 - Algorithm parameters: selected based on prior experience
 - Crossover rate: 0.7
 - Mutation rate: 0.05
 - Tournament selection *p*: 1.0
 - Termination:
 - Specify maximum number of fitness function evaluations
 - Algorithm terminates after fully completing the generation that put it over the limit

Results

- "Short" tests
 - N = 128
 - Parameters: population size = 100, fitness evaluation limit = 1000
- "Medium" tests
 - N = 128
 - Parameters: pop. size = 100, fitness evaluation limit = 10000
- "Long" tests
 - N = 80
 - Parameters: pop. size = 1000, fitness evaluation limit = 50000, "die-off rate" = 0.02



Results

Test	Runs	Solutions Found
Short	128	0
Medium	128	3
Long	80	14

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Future Work

- Comparison with other search techniques:
 - Simulated Annealing
 - Greedy Local Search
- New Mutation Operators
 - Can use any local search technique

Questions?

