香港浸會大學
HONG KONG BAPTIST UNIVERSITY

DEPARTMENT OF
COMPUTER SCIENCE
計算機科學系

COMP7015 Artificial Intelligence

Lecture 12: Genetic Algorithm & Course Review

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December 1, 2022

Course Project

- Submit early to avoid last-minute accidence!
- The submission box closes at due automatically. Late submissions are not allowed unless prior consent is obtained.
- Present your face in the video presentation.

> 8. In the **Presentation Video**, you are required to display the presenter's faces clearly to allow the lecturers to identify your identity.

Agenda

- Genetic Algorithm

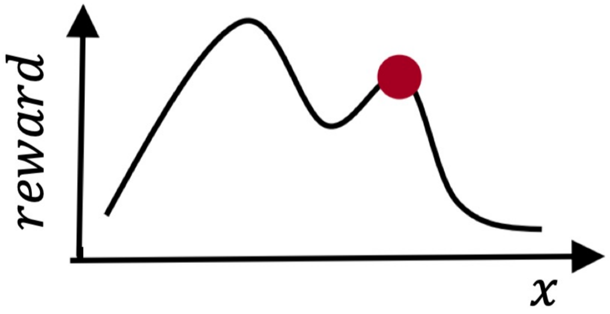
- Course Review
- Tips & Suggestions for preparing for the final

- Review of Assignments

Genetic Algorithm

Genetic Algorithm

- Why using genetic algorithm?



- Avoid getting trapped in (bad) local optima
- To handle discrete design variables $x \in \{a, b, c, d, e\}$, $x \in \{true, false\}$,
- However, genetic algorithms do not guarantee a global optimum.

Motivating Problem: Discrete Optimization

- **The Knapsack Problem**

Goal: maximize the value of items but cannot exceed the weight limit.

Maximum weight: 3kg

Value:	750	1100	180	90	3	80	120
Weight:	0.4	1.2	0.3	0.6	1.0	0.2	0.6

Motivating Problem: Discrete Optimization

- **Solution 1: Brute-force** (List out all possible combinations)
  - For each item, use a binary variable to indicate its status.
  - Complexity: 2^N where N is the number of items.

Number of items	Number of combinations	Seconds	
5	32	0.00000192	
10	1,024	0.00006144	
20	1,048,576	0.06291456	
30	1,073,741,824	64.42450944	
40	$\approx 10^{12}$	~65970.6976666	
50	$\approx 10^{15}$	~67553994.4106	
60	$\approx 10^{18}$	~69175290276.4	*(2193 years)*

Motivating Problem: Discrete Optimization

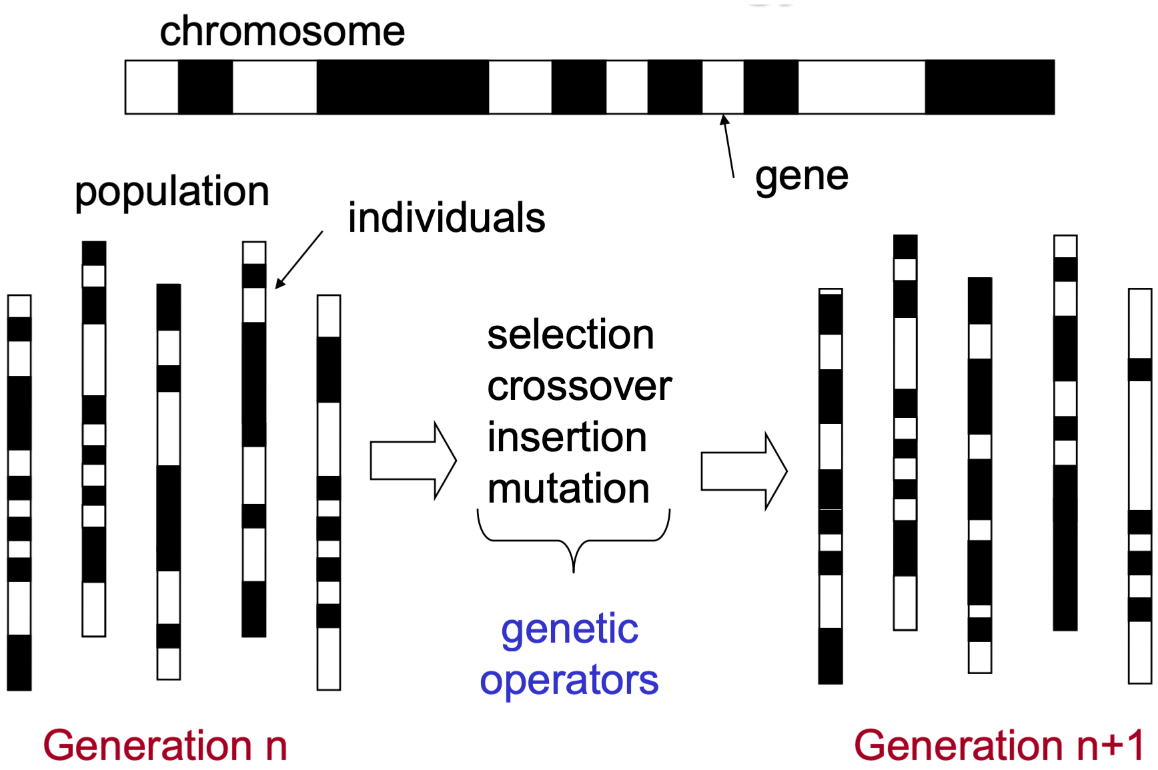
- **Solution 2: Genetic Algorithm**

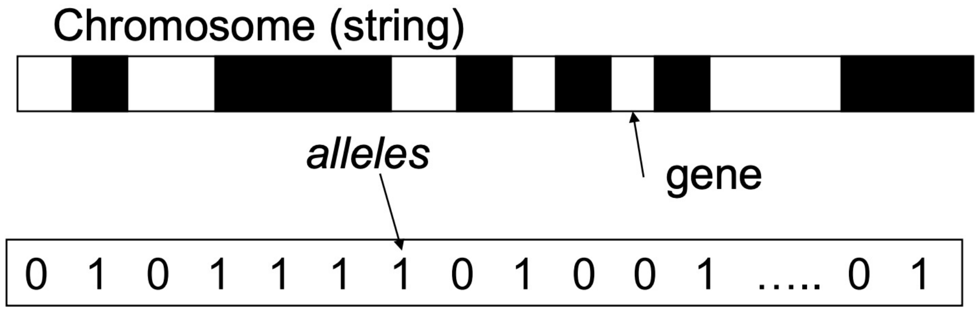
Number of items	Time using Brute-force	Time using Genetic Algorithm	Accuracy of Genetic Algorithm
5	0.00000192	0.000460147	100.00%
10	0.00006144	0.001574755	100.00%
20	0.06291456	0.003477812	100.00%
30	64.42450944	0.007086039	100.00%
40	~65970.6976666	0.0159061	100.00%
50	~67553994.4106	0.0206821	97.57%
60	~69175290276.4	0.0238941	94.32%

Idea of Genetic Algorithm

- Genetic algorithm (GA) belongs to a larger class of “Evolutionary algorithms”.
- It is inspired by the process of natural selection.
- Natural Selection is a very successful organizing principle for optimizing individuals and populations of individuals.
- It is argued that if we can mimic natural selection, then we will be able to optimize more successfully.
- Only the fittest survive – define a fitness function.

Terminologies

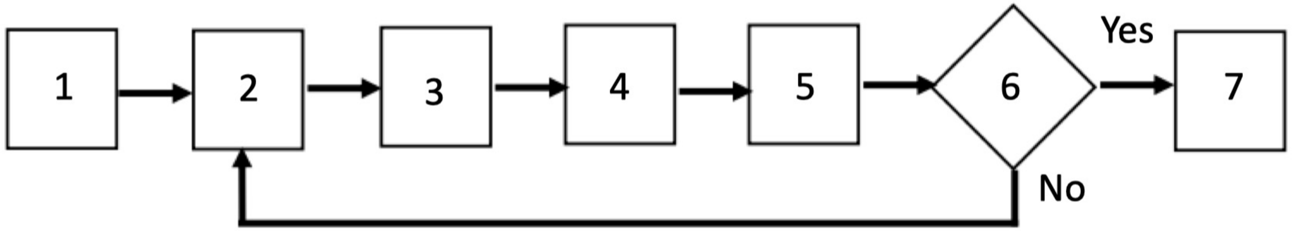




Each chromosome represents a solution, often using strings of 0's and 1's. Each bit typically corresponds to a gene. This is called binary encoding.

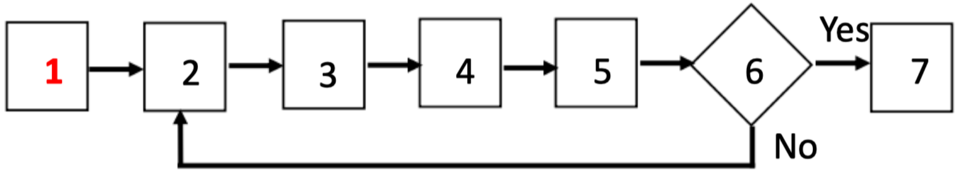
https://ocw.mit.edu/courses/ids-338j-multidisciplinary-system-design-optimization-spring-2010/resources/mitesd_77s10_lec11/

Framework of GA

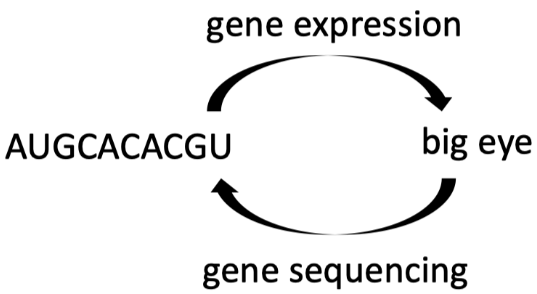


1. Initialize Population
2. Select individual for mating
3. Mate individuals and produce children
4. Mutate children
5. Insert children into population
6. Check whether termination conditions are met
7. Output

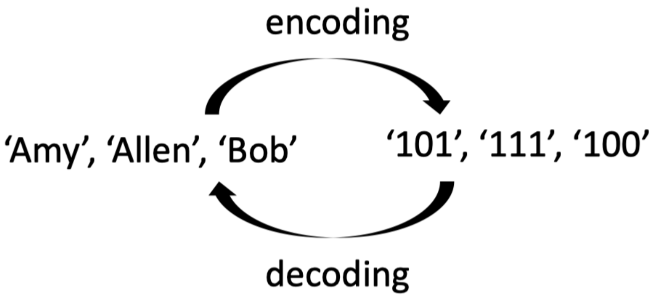
Framework of GA



1. Initialize Population



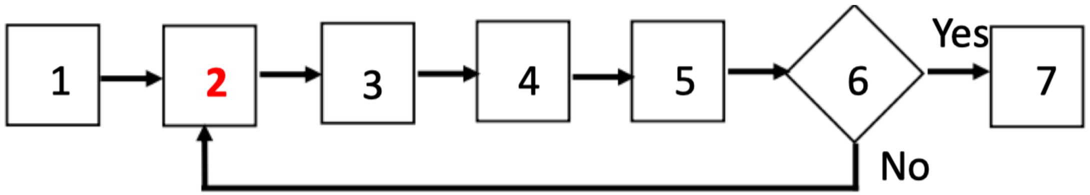
Biology



Design

(binary coding)

Framework of GA



2. Select individual for mating

a) Choosing the right fitness function

b) Evaluating genes with fitness functions

c) Selecting genes with higher value, e.g., top k

Selection by Ranking

- Goal is to select parents for crossover
- Should create a bias towards more fitness
- Must preserve diversity in the population

(1) Selection according to RANKING

Example: Let $D = \sum_{j \in P} 1/j$

select the k^th most fit member of a population

to be a parent with probability $P_k = \left(\frac{1}{k}\right) D^{-1}$

Better ranking has a higher probability of being chosen, e.g. 1st $\propto 1$, 2nd $\propto 1/2$, 3rd $\propto 1/3$ ...

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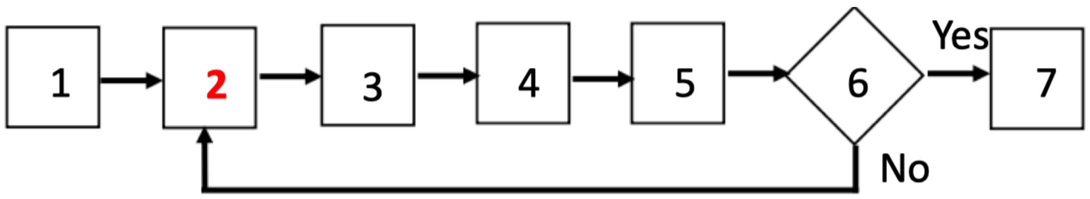
Framework of GA



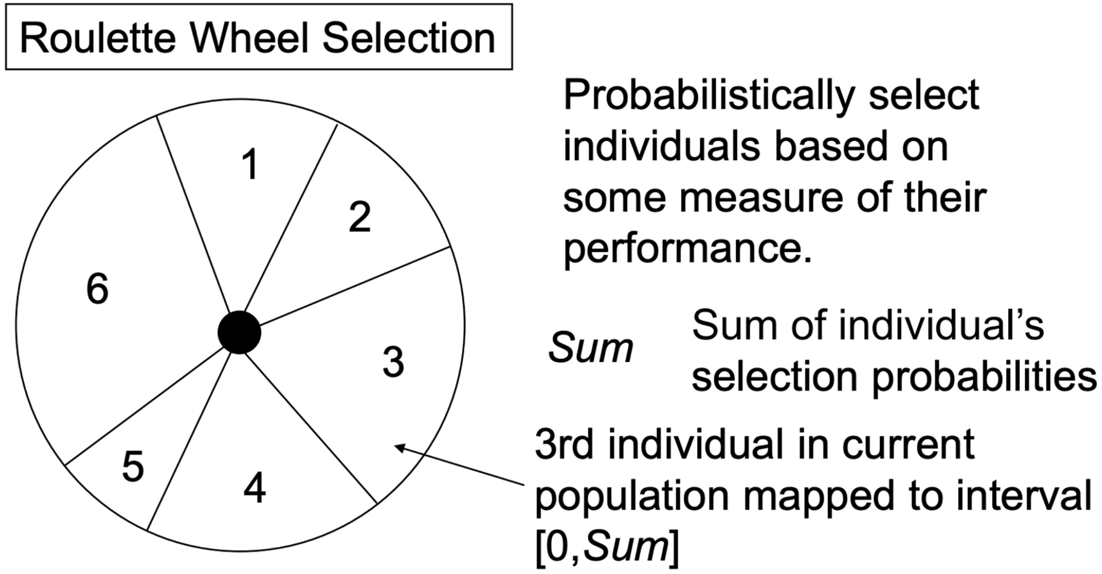
2. Select individual for mating

a) Choosing the right fitness function

b) Evaluating genes with fitness functions

c) Selecting genes with higher value, e.g., top k

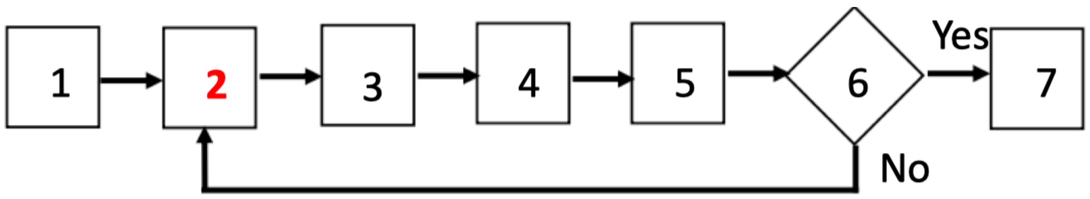
Roulette Wheel Selection



Selection: generate random number in [0,*Sum*]
Repeat process until desired # of individuals selected
Basically: stochastic sampling with replacement (SSR)

https://ocw.mit.edu/courses/ids-338j-multidisciplinary-system-design-optimization-spring-2010/resources/mitesd_77s10_lec11/

Framework of GA



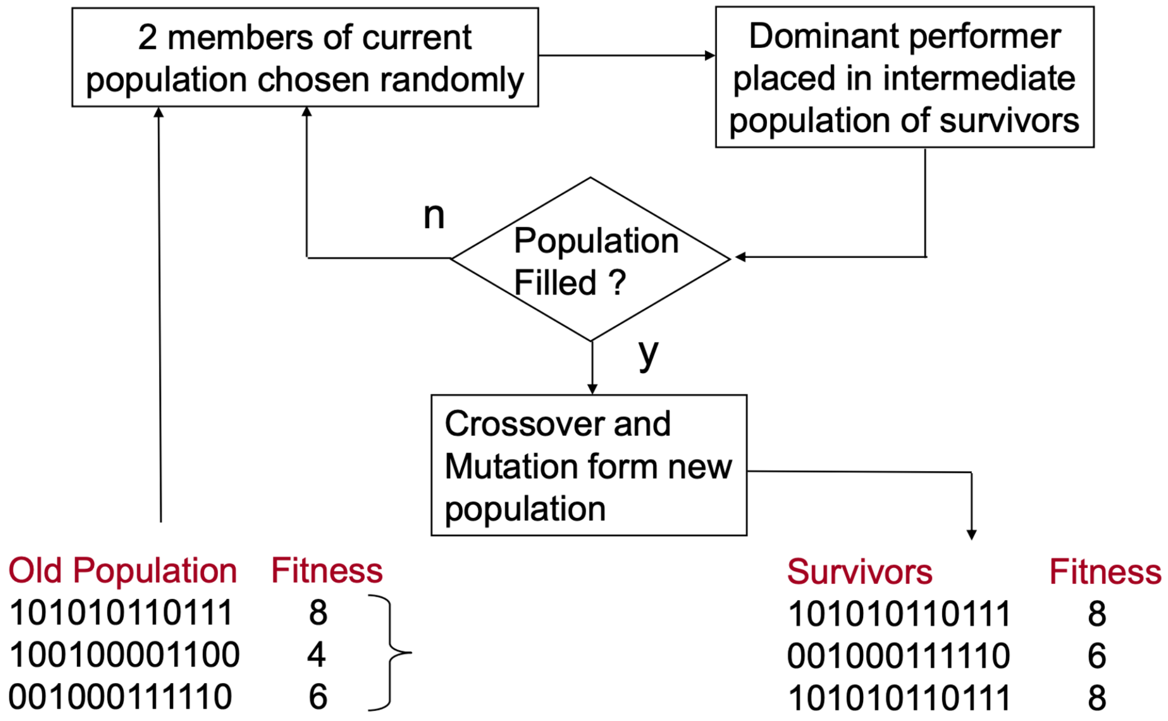
2. Select individual for mating

   a) Choosing the right fitness function

   b) Evaluating genes with fitness functions

   c) Selecting genes with higher value, e.g., top k

Tournament Selection



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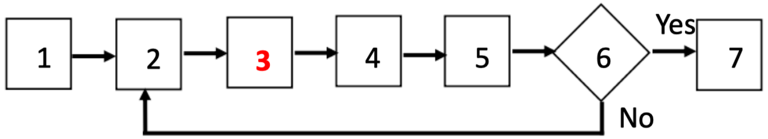
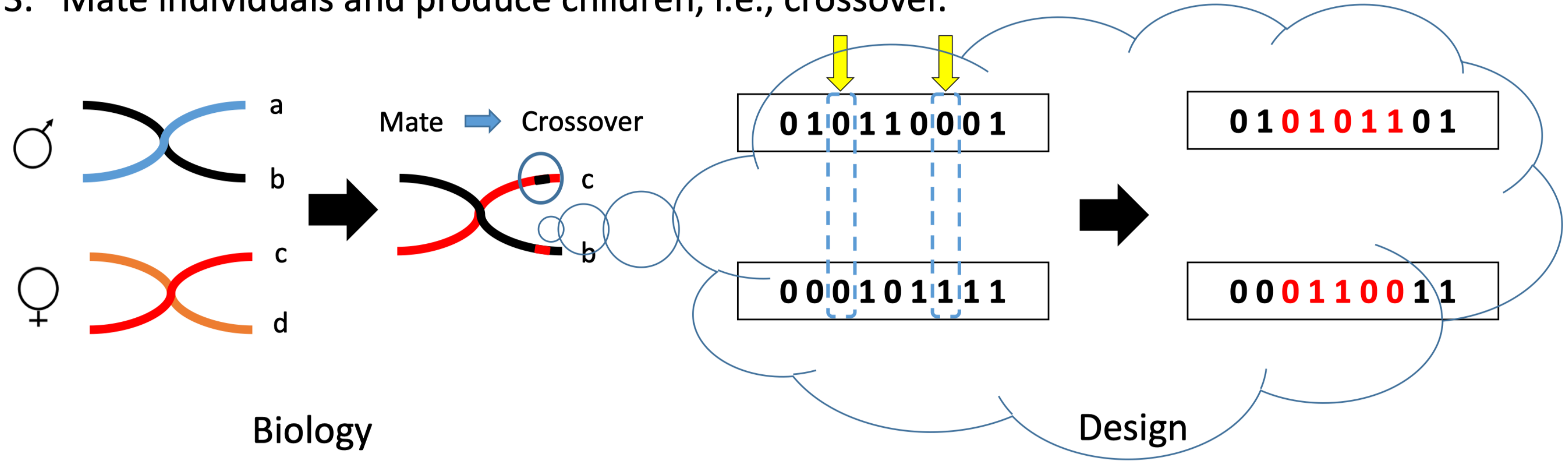
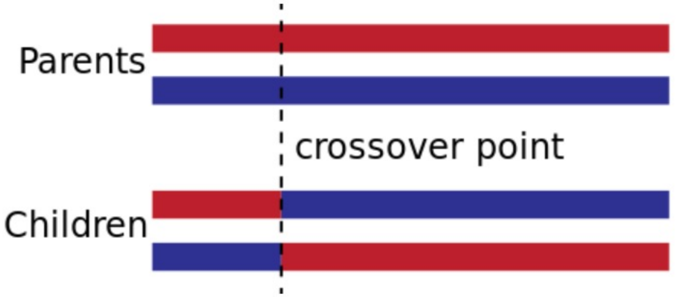
Framework of GA



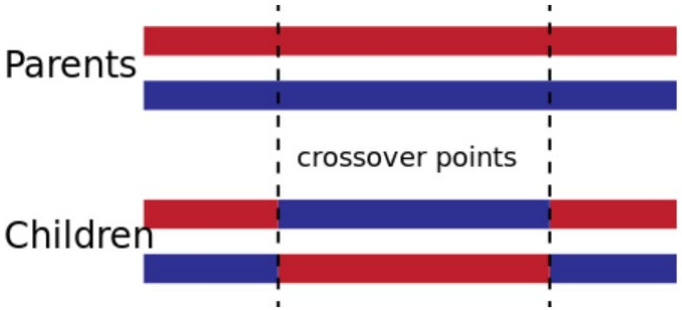
3. Mate individuals and produce children, i.e., crossover.



Two-point Crossover

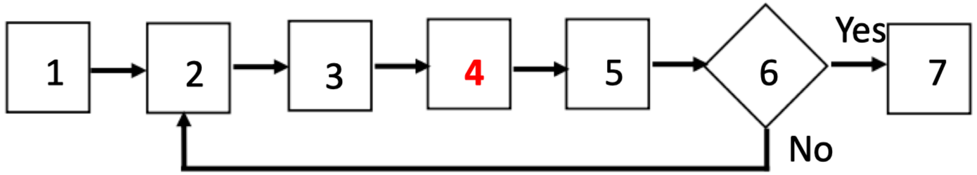


One-point crossover

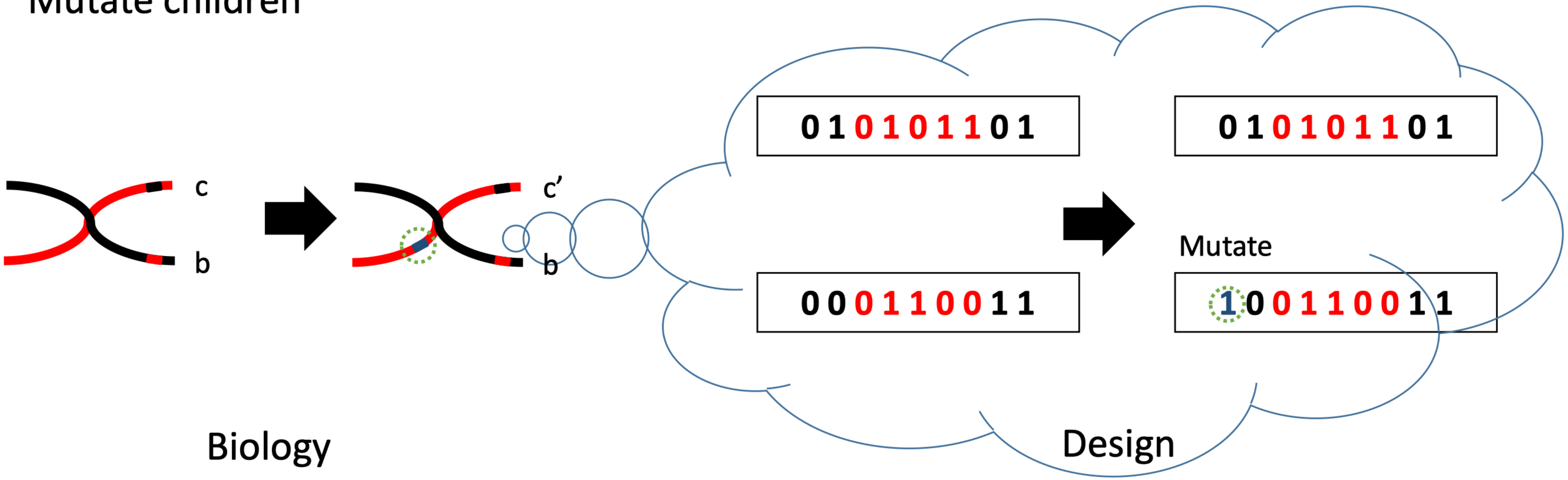


Two-point crossover

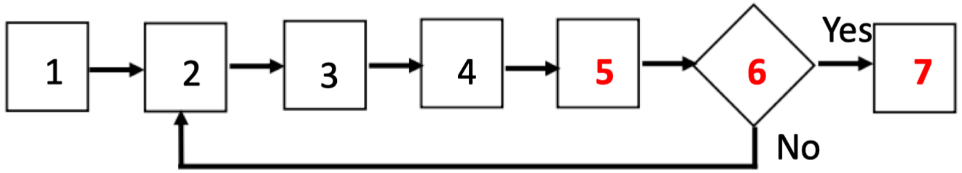
Framework of GA



4. Mutate children



Framework of GA



5. Insert children into population

6. Check whether termination conditions are met

   a) Iteration:

      The maximum number of generations completed.

   b) Design variable:

      All genes become almost the same.

   c) Fitness:

      The improvement of the fitness (reward) is marginal.

7. Output the design variables

An example of GA: The Knapsack Problem

Value:	750	1100	180	90	3	80	120
Weight:	0.4	1.2	0.3	0.6	1.0	0.2	0.6
binary coding	1	0	0	0	1	1	0

An example of GA: The Knapsack Problem

Step 1: Initialize population

Value:	750	1100	180	90	3	80	120
Weight:	0.4	1.2	0.3	0.6	1.0	0.2	0.6

Generation 0 (just random)

1000110 1000001 1100001 1111001 0110100

0101011 0100010 1010110 0010011 1101001

An example of GA: The Knapsack Problem

Step 2: Select Individuals for matting

Value:	750	1100	180	90	3	80	120
Weight:	0.4	1.2	0.3	0.6	1.0	0.2	0.6

Generation 0 (just random)

1000110 1000001 1100001 1111001 0110100 0101011 0100010 1010110 0010011 1101001

Fitness function: sum of the values

$$\text{Fitness} = \begin{cases} 750\ b_1 + 1100\ b_2 + 180\ b_3 + 90\ b_4 + 3\ b_5 + 80\ b_6 + 120\ b_7 & \text{if weight} \leq 3 \\ 0 \quad \text{if weight} > 3 \end{cases}$$

An example of GA: The Knapsack Problem

Step 2: Select Individuals for matting

Value:	750	1100	180	90	3	80	120
Weight:	0.4	1.2	0.3	0.6	1.0	0.2	0.6

Generation 0 (just random)

1000110	1000001	1100001	1111001	0110100	0101011	0100010	1010110	0010011	1101001

Fitness function: sum of the values

833	**870**	**1970**	**0**	**1283**	**1390**	**1180**	**1180**	**380**	**2060**

An example of GA: The Knapsack Problem

Step 2: Select Individuals for matting (e.g., Roulette Wheel selection method)

Suppose the two get selected

Individual	Fitness Function	Selection Probability
1000110	833	0.07
1000001	870	0.08
1100001	1970	0.18
1111001	0	0
0110100	1283	0.12
0101011	1390	0.12
0100010	1180	0.11
1010110	1180	0.11
0010011	380	0.03
1101001	2060	0.18
	Sum = 11146	Sum = 1

An example of GA: The Knapsack Problem

Step 3: Mate individuals and produce children (cross-over)

parents		Children (offsprings)
100 | 00 | 01	→	100 10 01
010 | 10 | 11		010 00 11

parents

Children (offsprings)

An example of GA: The Knapsack Problem

Step 4: Mutate children

children	mutation
100 10 01	100 11 01
010 00 11	011 00 11

children *mutation*

An example of GA: The Knapsack Problem

Step 5: Insert children into population

Generation 1

1000110

1000001

1100001

1111001

0110100

1001101

0101011

0100010

1010110

0010011

1101001

0110011

An example of GA: The Knapsack Problem

Step 6: Check Termination

If one of the following conditions is met, terminate:

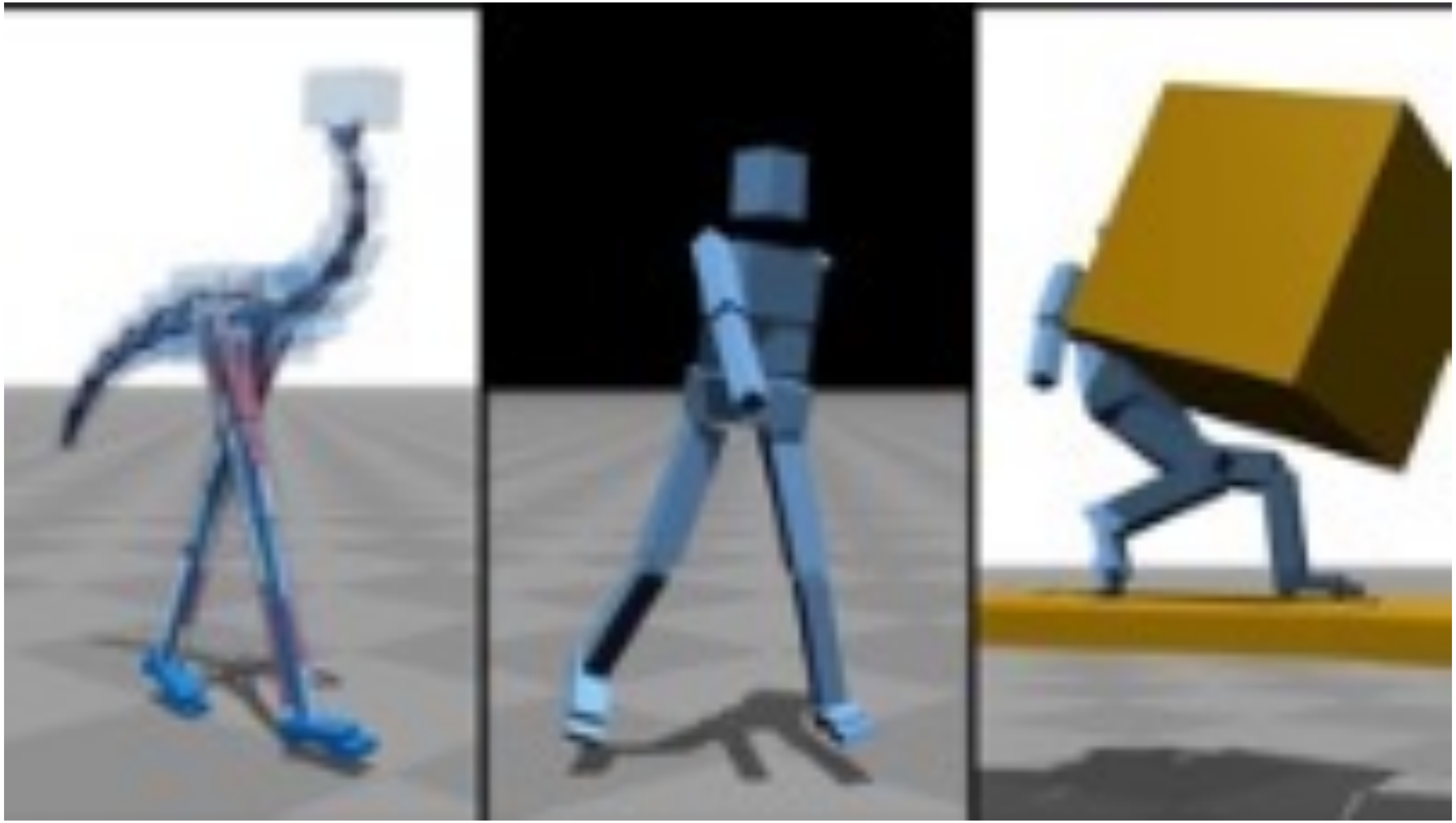
- The maximum number of generations completed.
- All genes become almost the same.
- The improvement of the fitness is marginal.

Otherwise, go back to step 2 and iterate.

The individual with maximum fitness function is the result.

https://www.youtube.com/watch?v=pgaEE27nsQw&t=1s

A Demo: Flexible Muscle-Based Locomotion for Bipedal Creatures



https://www.youtube.com/watch?v=pgaEE27nsQw

Suggested Readings

- David E. Goldberg, Genetic Algorithms in Search, Optimization and Machine Learning, 1989

COMP7015 Artificial Intelligence Course Review

Artificial Intelligence

- Searching
- Knowledge Representation & Logics
- Machine Learning
- Deep Learning
- Bayesian Learning
- Reinforcement Learning
- Genetic Algorithms

I. Searching

- How to formulate a search problem: states, initial state, goal state, & actions
- Uninformed Search (blind search):
  - BFS, graph DFS, uniform-cost search
  - Tree-like search: tree-like DFS, depth-limited search, iterative deepening search
- Informed Search (heuristic search; have hints about the how close a state is to the goal state):
  - Heuristic functions: admissible? Which is better?
  - Greedy search & A* search
- Constraint Satisfaction Problems (CSPs):
  - Variables and domains
  - Backtracking with forward checking
- Which algorithm to use?

II. Knowledge Representation and Logics

- Goal: Represent and store information and derive conclusions from the available information.
  (example: virtual assistant)
- Why logics? Natural language is not precise. Need a precise way to store and process knowledge.

- Ingredients of logic: Syntax, Semantics, and Inference Rules.
- Propositional Logics
  - Syntax: propositional atoms and propositional connectives
  - Semantics: models, satisfaction, truth table
  - Knowledge base: entailment, satisfiability, Tell and Ask operations.
  - Inference Rules: Modus Ponens, Resolution
- First-order Logics
  - Syntax and Semantics: quantifiers (universal and existential)
  - Inference Rules: generalized Modus Ponens rule

III. Machine Learning (1/2)

- Supervised Machine Learning Algorithms
  - Linear regression, logistic regression: loss minimization framework, gradient descent
  - Decision tree (ID3) algorithm
    - Entropy, information gain, information gain ratio
    - Bi-partition for continuous attributes
- Generalization and Model Selection
  - How to evaluate model performance? Hold-out, repeated hold-out, K-fold, leave-one-out
- Performance Measures for Classification Problems
  - Confusion matrix
  - Metrics: accuracy, precision, recall, f1-scores
- Ensemble Learning:
  - Why and when ensemble learning could help?
  - Random forest.

III. Machine Learning (2/2)

- Multi-class classification
  - OvO and OvR approach
  - Performance Evaluation

- Feature Engineering
  - Hypothesis class: a feature extractor (or feature mapping) determines the hypothesis class.

IV. Deep Learning

- Neural Networks: Feature (representation) learning
- Feedforward Neural Network
  - Neurons, layers, nonlinear activation functions
  - Computational graphs and backpropagation
  - Stochastic gradient descent
- Regularization Techniques
- Convolutional Neural Networks
  - Convolution, padding, stride, receptive field, pooling
  - Why CNN?
- Recurrent Neural Networks
  - Sequential data
  - RNN, vanilla RNN, LSTM
- Language Models: word embeddings
- Pre-trained CNN and language models and fine-tuning

V. Bayesian Learning

- Probabilities
  - Independence vs conditional independence
- Bayesian Decision Theory: MAP decision
  - Bayes’ rule
  - Prior, posterior & likelihood
  - Naïve Bayes classifier
- Bayesian Network
  - Why do we need Bayes net? Space complexity
  - Structure of Bayesian network
  - Belief propagation

VI. Reinforcement Learning

- Markov Decision Process
  - Why? Uncertainty
  - State, chance nodes, transition function, reward.
  - Policy evaluation: how good a given policy is?
    - Utility, discounting, value, Q-value.
  - Value iteration: what is the optimal value and optimal policy?
    - Optimal value, optimal policy, iterative algorithm
- Reinforcement Learning
  - Why? No access to transition function and reward.
  - Framework
  - Monte Carlo methods
    - Model-based: estimate the MDP
    - Model-free: estimate the Q-value directly.
  - Q-learning
  - ϵ-greedy algorithm: exploration vs exploitation

VII. Genetic Algorithm

- Why genetic algorithm?
- Algorithm process:
    - Initialize population
    - Select individuals for mating: selection methods
    - Mate individuals and produce children: crossover
    - Mutate children
    - Insert children into population
    - Check termination and return output

The final exam

- Materials for preparation:
  - Slides (you can safely skip parts we did not cover in class)
  - Lab materials
  - Assignments (written/programming)
  - Quiz
- Give short explanation when you are not certain about your answer.
- Give intermediate steps.
- You can use a calculator.
- There are in total 8 questions. There will be less calculation than the quiz.
- Scan through the questions before start: not ordered by difficulty.