Stochastic Local Search Variants

Computer Science cpsc322, Lecture 16

(Textbook Chpt 4.8)

June, 1, 2017

Lecture Overview

- **Recap SLS**
- SLS variants

Announcements

- Assignmnet-2 has been posted on Connect due June 8
- Midterm on June 8 – first block of class
  - Search
  - CSP
  - SLS
  - Planning
  - Possibly simple/minimal intro to logics

Stochastic Local Search

- **Key Idea:** combine greedily improving moves with randomization

  - As well as improving steps, we can allow a "small probability" of: e.g.
    - Random steps: move to a random neighbor. 1%
    - Random restart: reassign random values to all variables. 5%

  - Always keep best solution found so far

  - Stop when
    - Solution is found (in vanilla CSP …pw. satisfying all C…)
    - Run out of time (return best solution so far)

Lecture Overview

- Recap SLS
- SLS variants
  - Tabu lists
  - Simulated Annealing
  - Beam search
  - Genetic Algorithms

Tabu lists

- To avoid search to
  - Immediately going back to previously visited candidate
  - To prevent cycling

- Maintain a tabu list of the *k* last nodes visited.
  - Don't visit a poss. world that is already on the **tabu list**.

- Cost of this method depends on____ K

Simulated Annealing

- **Key idea:** Change the degree of randomness..
- Annealing: a metallurgical process where metals are hardened by being slowly cooled.
  - Analogy: start with a high ``temperature'': a high tendency to take random steps
  - Over time, cool down: more likely to follow the scoring function
- Temperature reduces over time, according to an annealing schedule

Simulated Annealing: algorithm

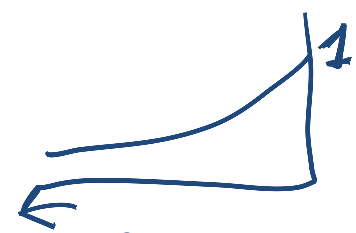
Here's how it works (for maximizing): h

- You are in node n. Pick a variable at random and a new value at random. You generate *n'*
- If it is an improvement i.e., $h(n') \geq h(n)$, adopt it.
- If it isn't an improvement, adopt it probabilistically depending on the difference and a temperature parameter, *T*.

$h(n') < h(n)$; $h(n') - h(n) < 0$

  - we move to *n'* with probability $e^{\boxed{(h(n') - h(n))/T}}$

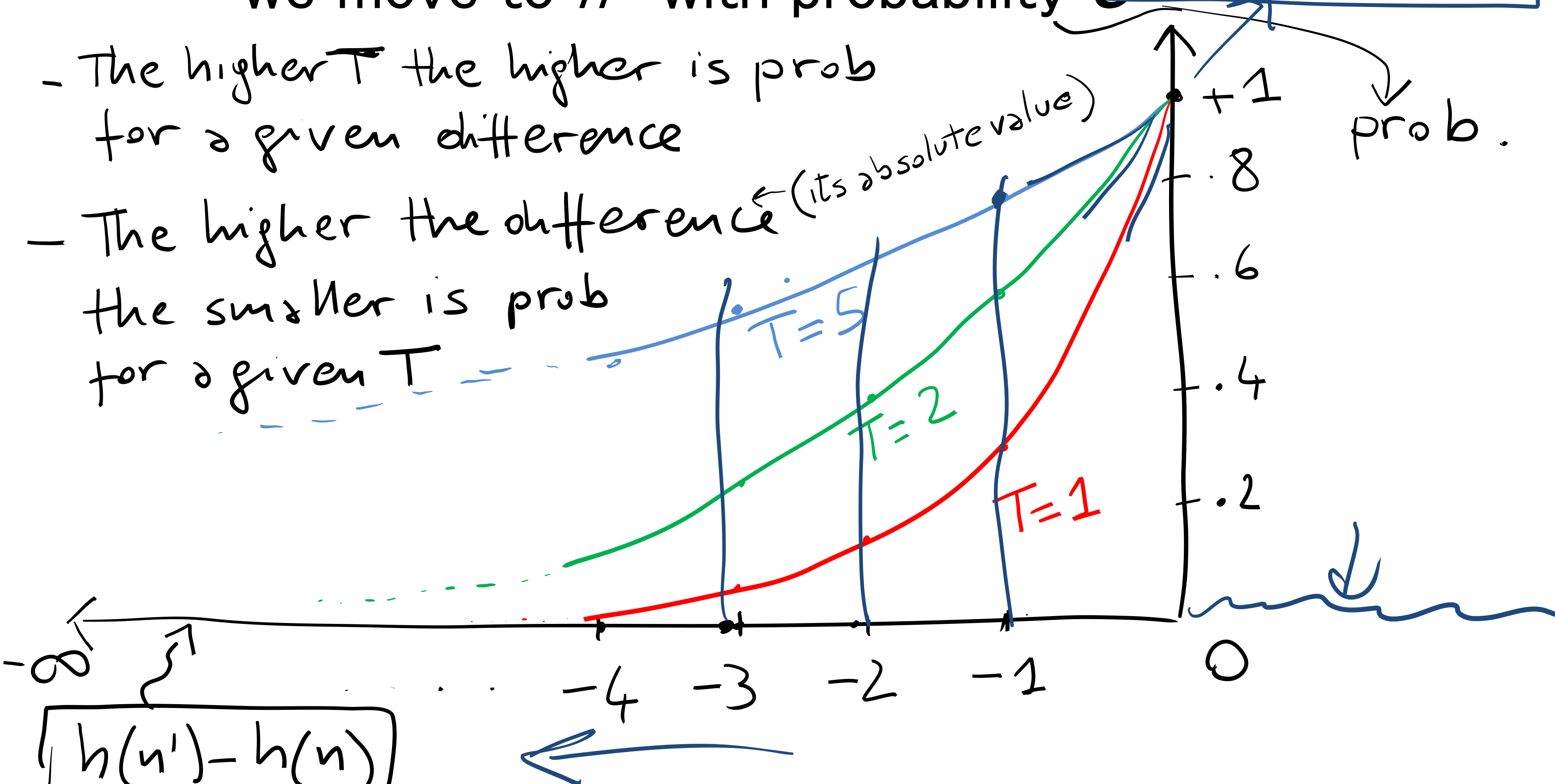
see next slide



- If it isn't an improvement, adopt it probabilistically depending on the difference and a temperature parameter, *T*.

  - we move to n' with probability $e^{(h(n')-h(n))/T}$

- The higher T the higher is prob for a given difference
- The higher the difference (its absolute value) the smaller is prob for a given T



Properties of simulated annealing search

One can prove: If ***T* decreases slowly enough**, then simulated annealing search will find a **global optimum with probability approaching 1**

Widely used in **VLSI layout**, **airline scheduling**, etc.

Finding the ideal cooling schedule is unique to each class of problems

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- Recap SLS
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  - Simulated Annealing
  - Population Based
    - ✓ Beam search
    - ✓ Genetic Algorithms

Population Based SLS

Often we have more memory than the one required for current node (+ best so far + tabu list)

Key Idea: maintain a population of *k* individuals

- At every stage, update your population.
- Whenever one individual is a solution, report it.

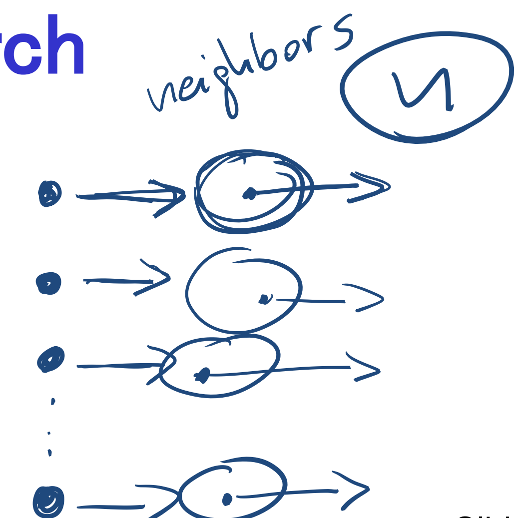
Simplest strategy: Parallel Search

- All searches are independent
- No information shared

but more memory

no reasons to use it!

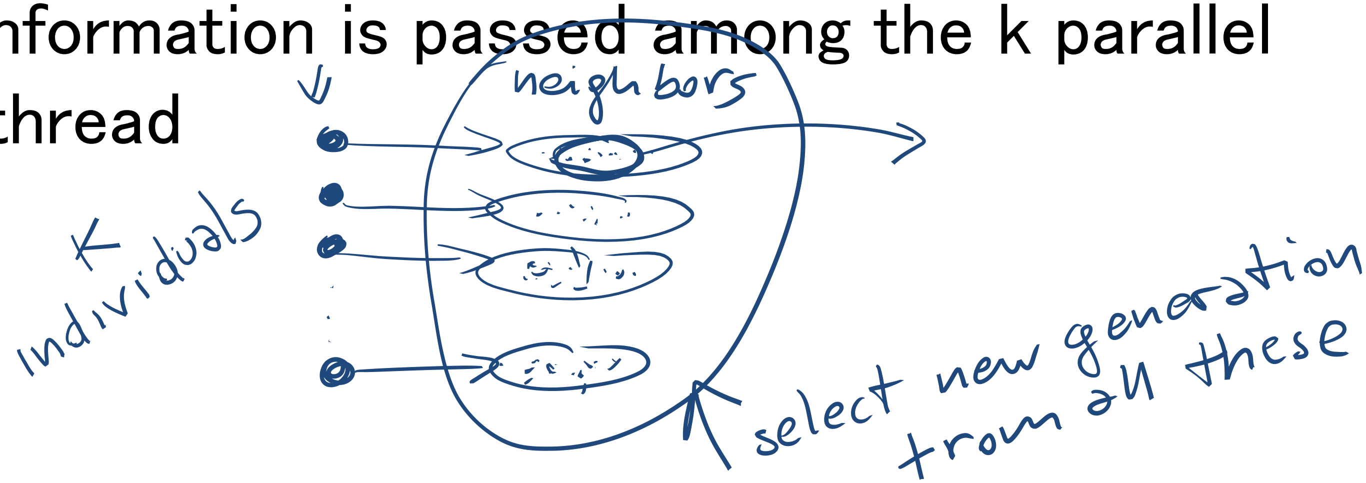
K poss. worlds



Population Based SLS: Beam Search

Non Stochastic

- Like parallel search, with *k* individuals, but you choose the *k* best out of all of the neighbors.
- Useful information is passed among the k parallel search thread



- **Troublesome case:** If one individual generates several good neighbors and the other k−1 all generate bad successors..

the next generation will comprise very similar individuals

Population Based SLS: Stochastic Beam Search

- **Non Stochastic** Beam Search may suffer from lack of diversity among the k individual (just a more expensive hill climbing)
- **Stochastic** version alleviates this problem:
  - Selects the k individuals at random
  - But probability of selection proportional to their value (according to scoring function)

iclicker.

m neighbors $\{n_1 \dots n_m\}$

h: scoring function

$Prob\ of\ selecting\ n_j\ ?=$

A. $\dfrac{n_j}{\sum_i n_i}$

B. $\dfrac{h(n_j)}{\sum_i h(n_i)}$

C. $\dfrac{\sum_i h(n_i)}{h(n_j)}$

Stochastic Beam Search: Advantages

- It **maintains diversity** in the population.
- **Biological metaphor** (asexual reproduction):
  - ✓ each individual generates "mutated" copies of itself (its neighbors)
  - ✓ The scoring function value reflects the fitness of the individual
  - ✓ the higher the fitness the more likely the individual will survive (i.e., the neighbor will be in the next generation)

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Population Based SLS: Genetic Algorithms

- Start with *k* randomly generated individuals (population)
- An individual is represented as a string over a finite alphabet (often a string of 0s and 1s)
- A successor is generated by combining two parent individuals (loosely analogous to how DNA is spliced in sexual reproduction)
- Evaluation/Scoring function (fitness function). Higher values for better individuals.
- Produce the next generation of individuals by selection, crossover, and mutation

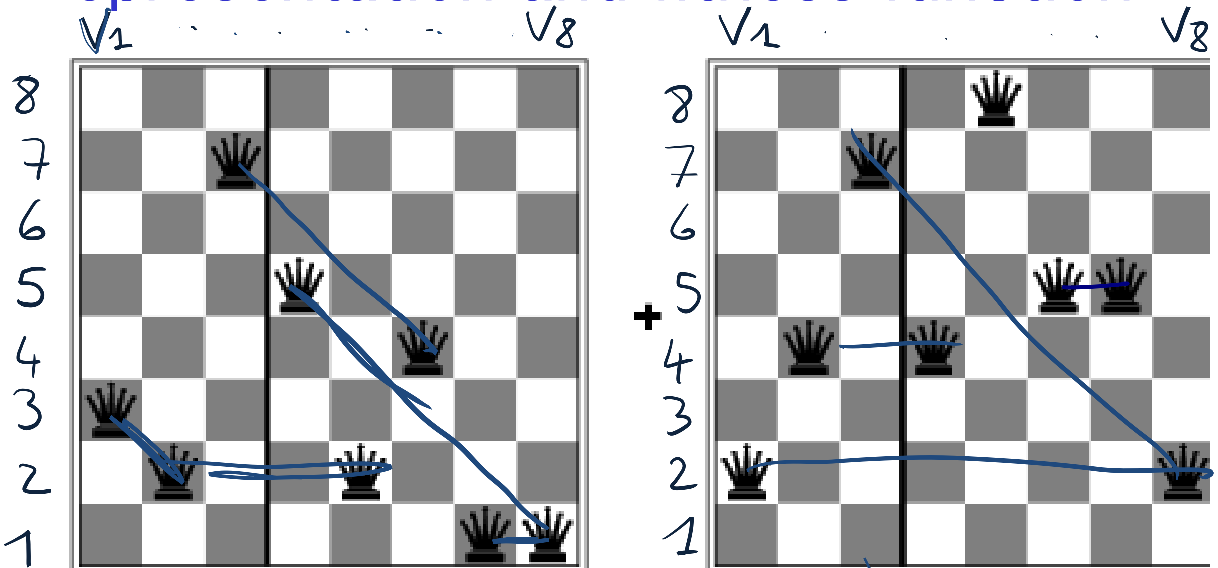
Genetic algorithms: Example

8-queen

Representation and fitness function

\# of queen pairs possibly attacking each other

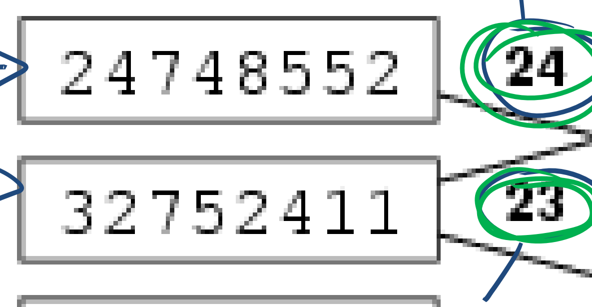
$$\frac{8 \cdot 7}{2} = 28$$



5 attacks

4 attacks

28 − 4



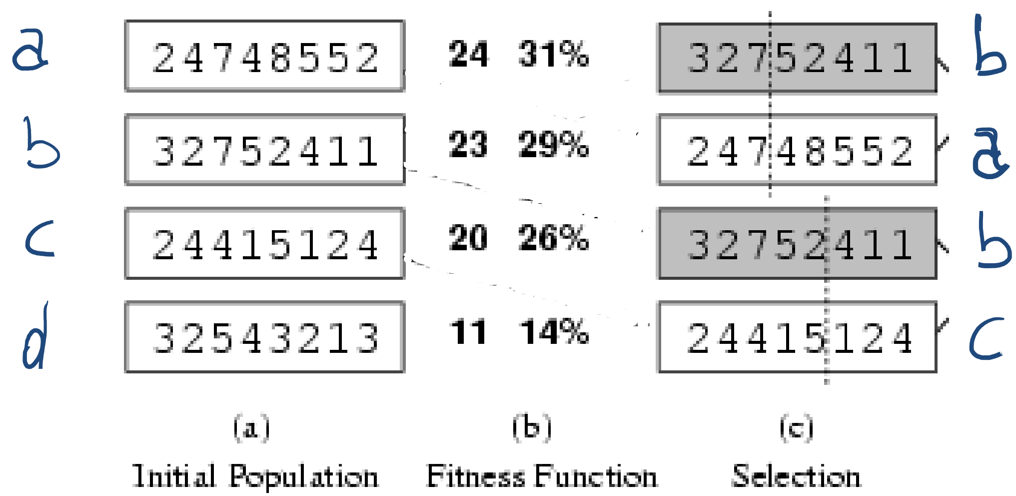
(28 − 5)

State: string over finite alphabet

Fitness function: higher value better states. # queen pairs not attacking each other

Genetic algorithms: Example

Selection: common strategy, probability of being chosen for reproduction is directly proportional to fitness score



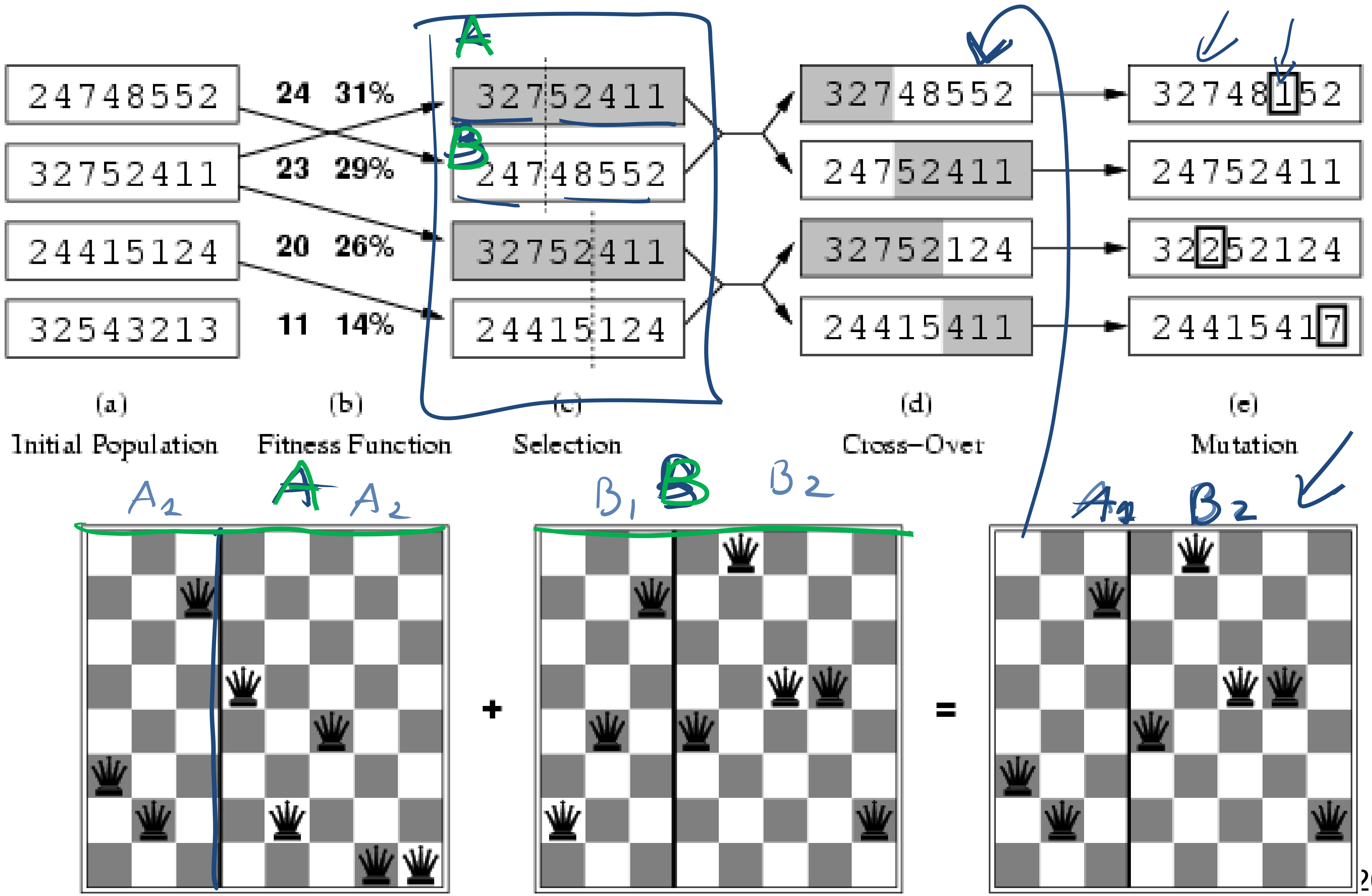
→ 24/(24+23+20+11) = 31%

→ 23/(24+23+20+11) = 29% etc

same as Beam Search slide 14

Genetic algorithms: Example

Reproduction: cross-over and mutation



Genetic Algorithms: Conclusions

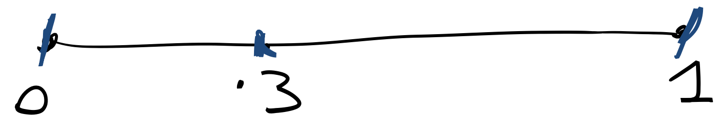
- Their performance is very sensitive to the choice of state representation and fitness function
- **Extremely slow** (not surprising as they are inspired by evolution!)

Sampling a discrete probability distribution

e.g. Sim. Annealing. Select n' with probability p

$p = .3$

generate random number in [0,1]



If $< .3$ accept n'

e.g. Beam Search: Select K individuals. Probability of selection proportional to their value

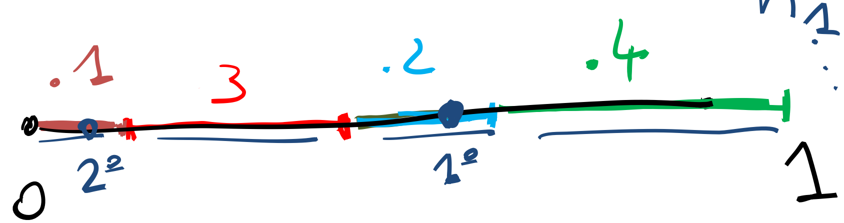
SAME HERE

$\rightarrow n_1$ $p_1 = .1$

$\rightarrow n_2$ $p_2 = .3$

$\rightarrow n_3$ $p_3 = .2$

$\rightarrow n_4$ $p_4 = .4$



n_3 first sample

n_1 second sample

Learning Goals for today's class

You can:

- Implement a tabu-list.
- Implement the simulated annealing algorithm
- Implement population based SLS algorithms:
  - Beam Search
  - Genetic Algorithms.
- Explain pros and cons of different SLS algorithms .

Modules we'll cover in this course: R&Rsys

Environment

Problem		Deterministic	Stochastic
Static	Constraint Satisfaction	Arc Consistency *Vars + Constraints* Search SLS for CSP	
	Query	*Logics* Search for Inference	*Belief Nets* Var. Elimination
Sequential	Planning	*STRIPS* actions Search for complex planning	*Decision Nets* Var. Elimination *Markov Processes* Value Iteration

Representation

Reasoning Technique

Next class

How to select and organize a sequence of actions to achieve a given goal…

………………

Start Planning (Chp 8.1-8.2 *Skip 8.1.1-2*)