Stochastic Local Search Variants

Computer Science cpsc322, Lecture 16

(Textbook Chpt 4.8)

Oct, 12, 2012

Lecture Overview

- **Recap SLS**
- SLS variants

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

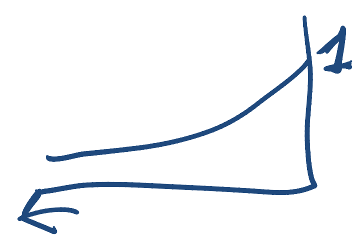
Here's how it works (for maximizing): h

- 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 $e^{(h(n')-h(n))/T}$

see next slide



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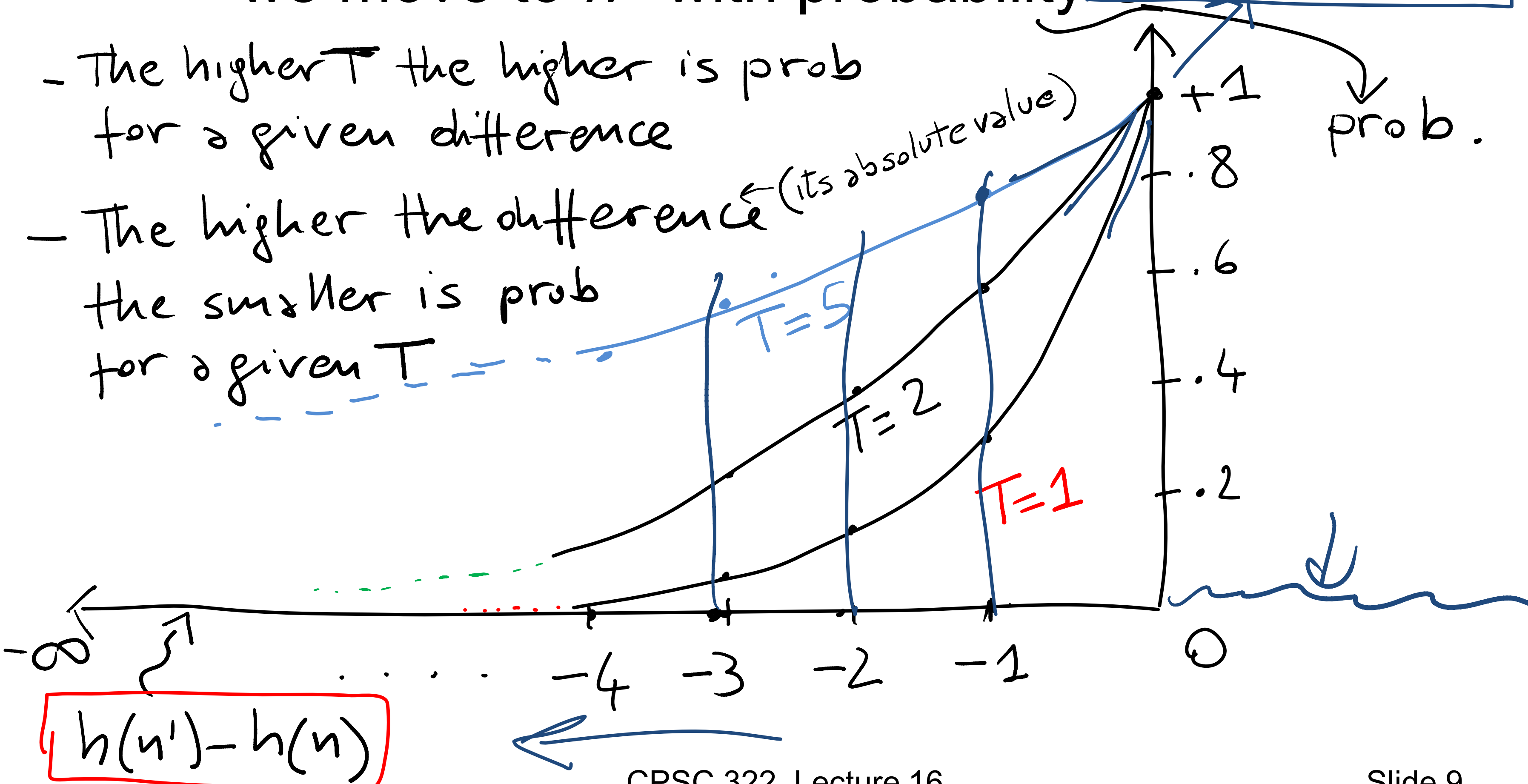


Properties of simulated annealing search

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

Lecture Overview

- Recap SLS
- SLS variants
  - 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.

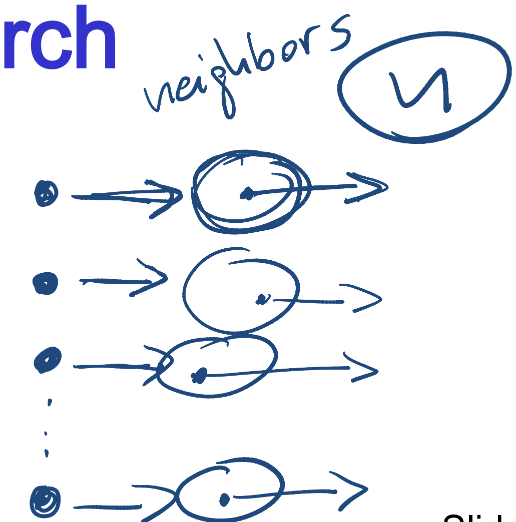
Simplest strategy: Parallel Search

- All searches are independent
- Like *k* restarts

but more memory

no reasons to use it!

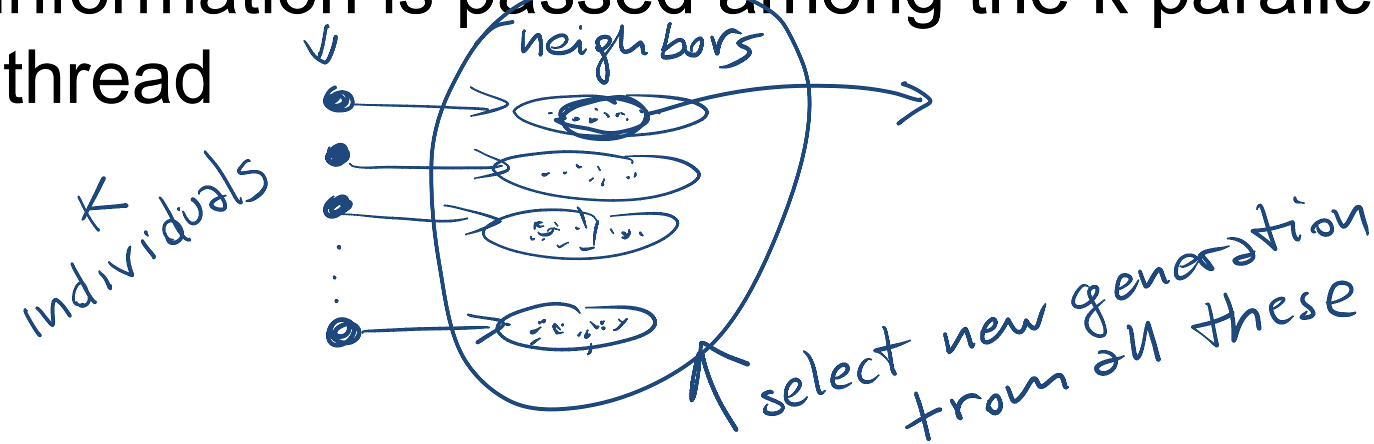
K poss. worlds



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)

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

h: scoring function

$$\text{Probability of selecting}(n_J) = \frac{h(n_J)}{\sum_{n_i} h(n_i)}$$

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)

Lecture Overview

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

Population Based SLS: Genetic Algorithms

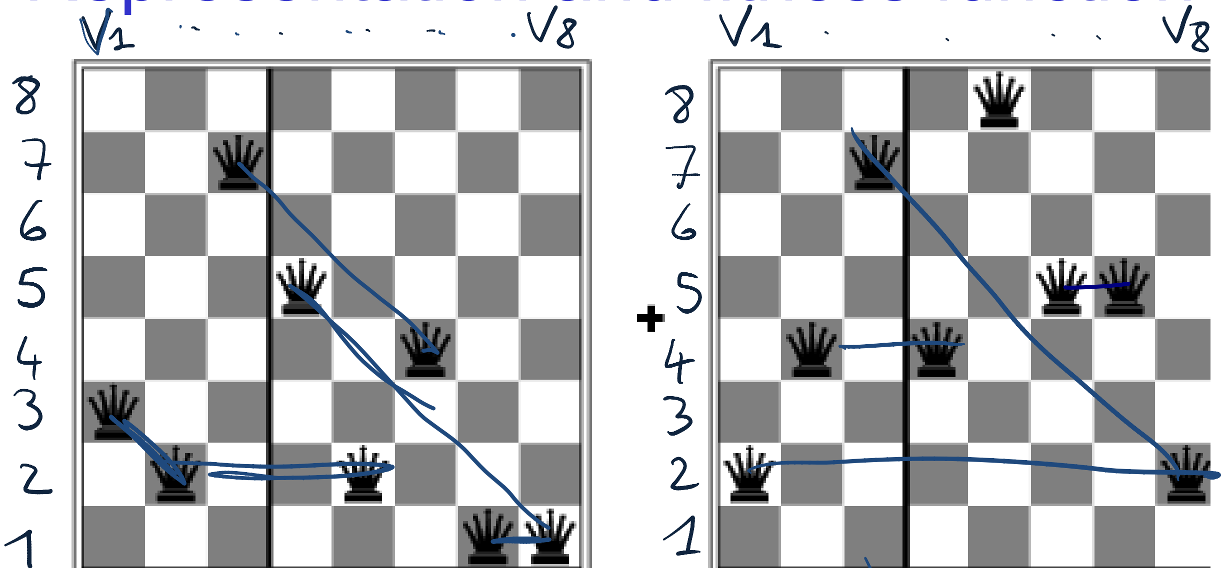
- Start with *k* randomly generated individuals (population)
- An individual is represented as a string over a finite alphabet (often a string of 0s and 1s)
- A successor is generated by combining two parent individuals (loosely analogous to how DNA is spliced in sexual reproduction)
- Evaluation/Scoring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

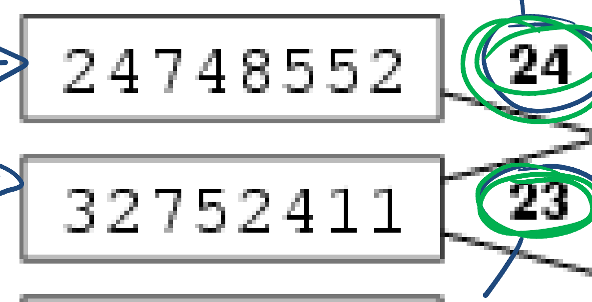
Genetic algorithms: Example 8-queen

Representation and fitness function

of queen pairs possibly attacking each other

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



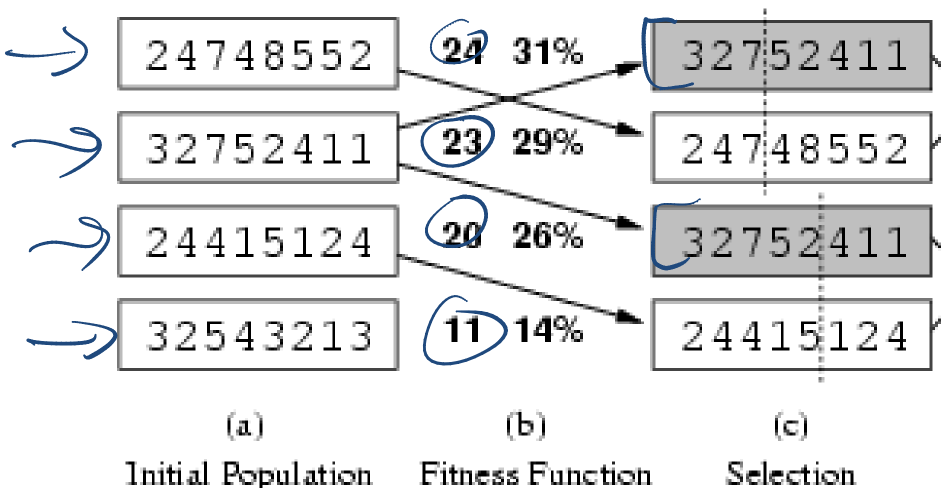


State: string over finite alphabet

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



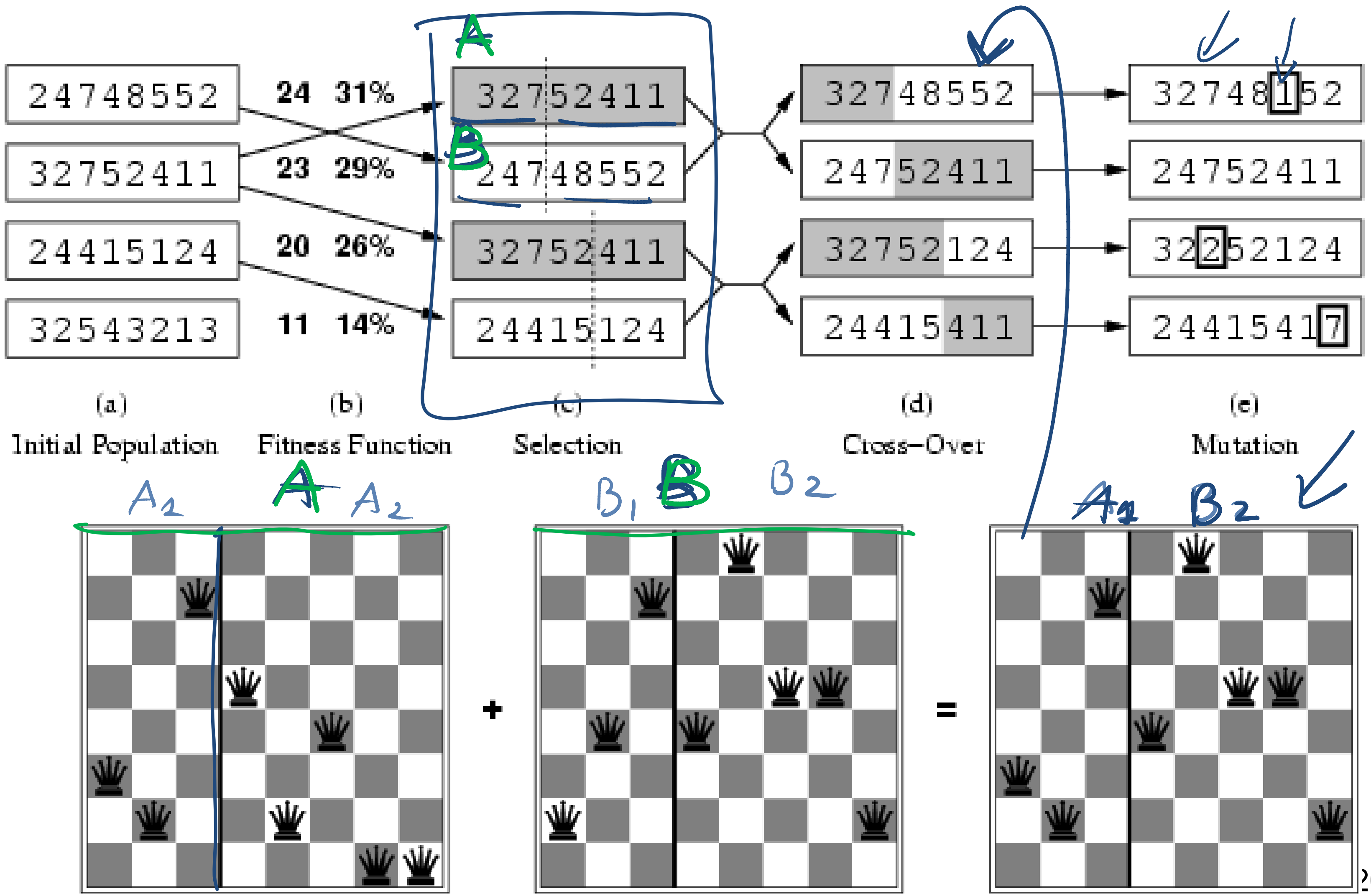
24/(24+23+20+11) = 31%

23/(24+23+20+11) = 29% etc

same as Beam Search slide 14

Genetic algorithms: Example

Reproduction: cross-over and mutation



Genetic Algorithms: Conclusions

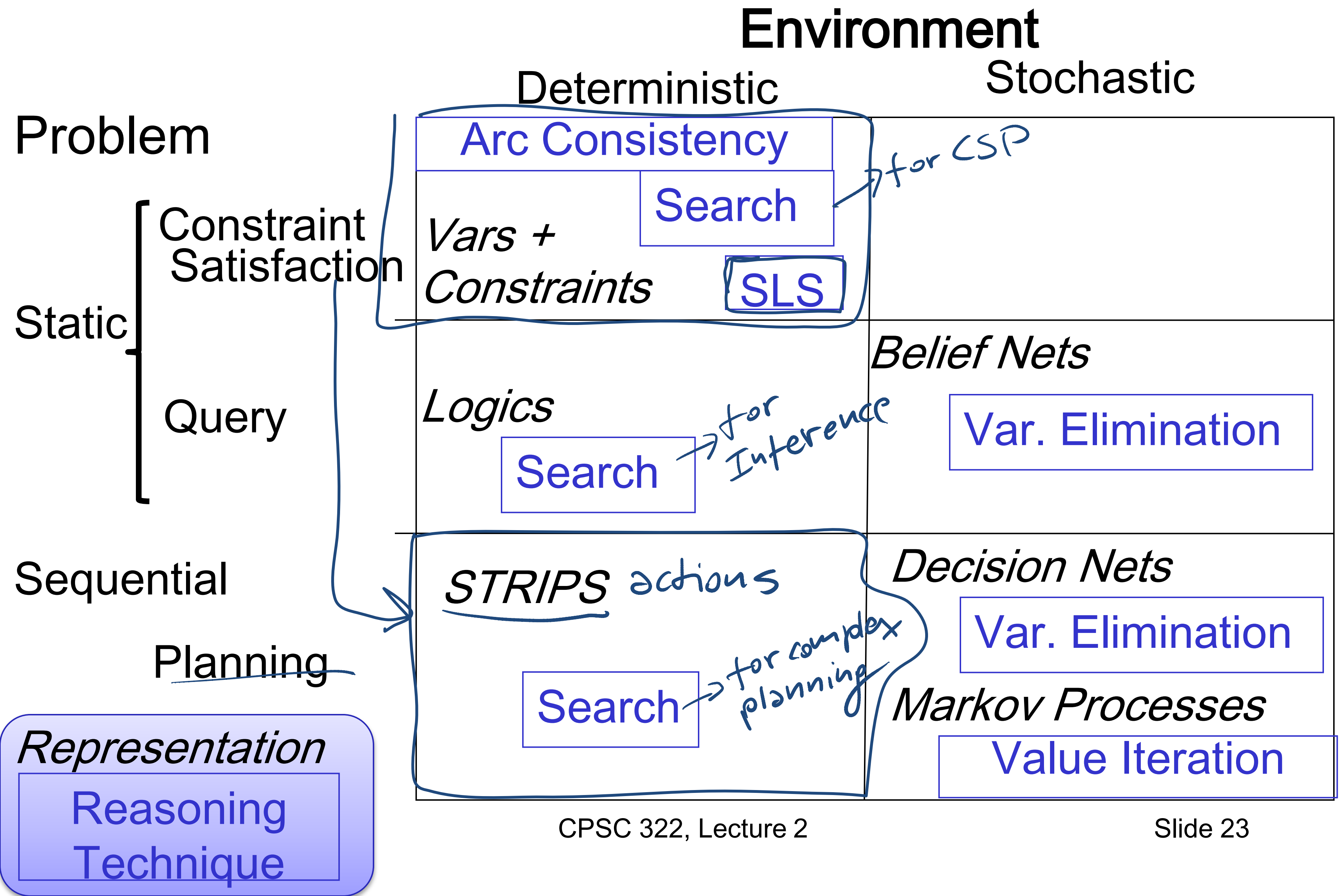
- Their performance is very sensitive to the choice of state representation and fitness function
- **Extremely slow** (not surprising as they are inspired by evolution!)

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



Assignment-2 on CSP will be out this evening (programming!)

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***)

322 Feedback ☺ or ☹

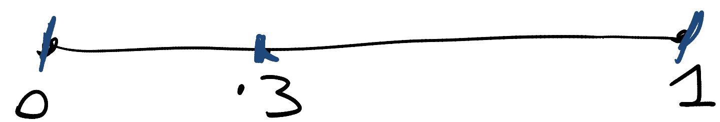
- Lectures
- Slides
- Practice Exercises
- Assignments
- AIspace
- ……
- Textbook
- Course Topics / Objectives
- TAs
- Learning Goals
- ……

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

→ n_1 $P_1 = .1$

→ n_2 $P_2 = .3$

→ n_3 $P_3 = .2$

→ n_4 $P_4 = .4$

n_3 first sample

n_1 second sample