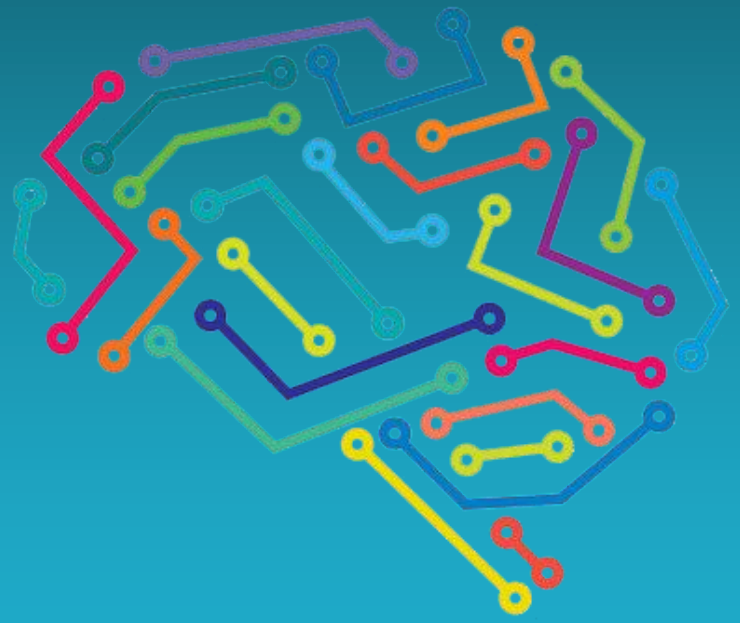
دانشگاه صنعتی شاهرود

ورای جستجوی کلاسیک



درس هوش مصنوعی

نیم‌سال اول تحصیلی 98-1397

ورای جستجوی کلاسیک

- الگوریتمهای جستجویی که تا کنون بررسی کردیم در مسائلی کاربرد داشتند که دارای سه ویژگی زیر باشند:
  - ✓ Observable
  - ✓ Deterministic
  - ✓ Known
- اگر این فرض‌های ساده‌ساز را کنار بگذاریم:
  - ✓ الگوریتم‌های جستجوی محلی (local search)
  - ✓ در مسائلی که برایشان، فقط هدف مهم است و نه مسیر رسیدن به آن

الگوریتمهای جست وجوی محلی و مسائل بهینه سازی

- معمولا در هربار فقط یک گره گسترش می‌یابد.
- ممولا مسیر نگهداری نمی‌شود.
- حافظه خیلی اندکی مصرف می‌کنند.
- در فضاهای حالت خیلی بزرگ یا بینهایت (پیوسته) جواب خوبی را می‌یابند.
- می‌توانند در مسائل بهینه‌سازی نیز مفید باشند. در این مسئله‌ها قصد ما یافتن بهترین حالت بر اساس تابع هدف است.
- وقتی بهینه هستند که مینیمم یا ماکسیمم سراسری را بیابند.

جست و جوی تپه نوردی (جست و جوی محلی حریصانه)

- این الگوریتم حلقه‌ای است که در جهت افزایش مقدار حرکت می‌کند وقتی به قله‌ای رسید که هیچ همسایه‌ای از آن بلندتر نیست خاتمه می‌یابد.

- شبیه سعی در یافتن قله اورست در مه شدید در حالی که دچار فراموشی هستید.

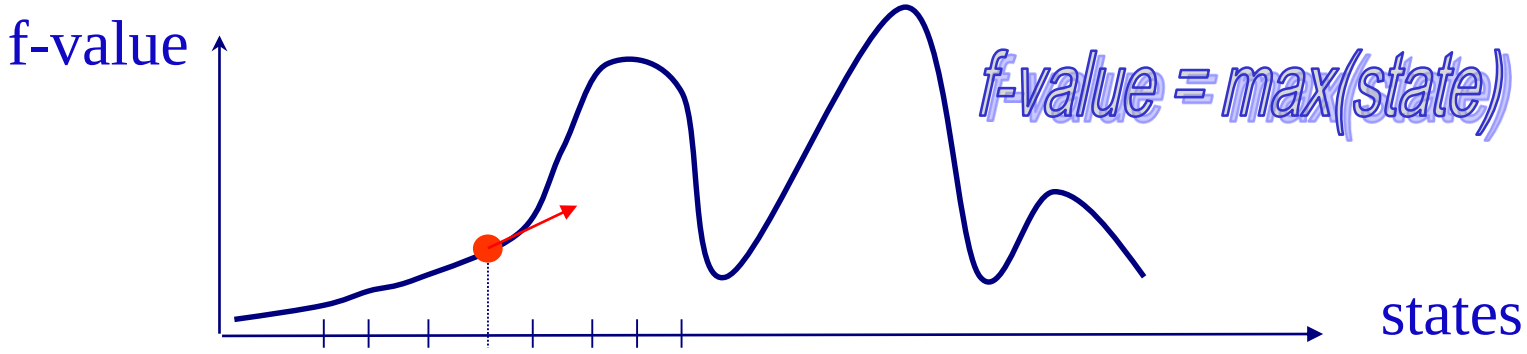
```
function HILL-CLIMBING(problem) returns a state that is a local maximum
    current ← MAKE-NODE(problem.INITIAL-STATE)
    loop do
        neighbor ← a highest-valued successor of current
        if neighbor.VALUE ≤ current.VALUE then return current.STATE
        current ← neighbor
```

Figure 4.2 The hill-climbing search algorithm, which is the most basic local search technique. At each step the current node is replaced by the best neighbor; in this version, that means the neighbor with the highest VALUE, but if a heuristic cost estimate h is used, we would find the neighbor with the lowest h.

جست و جوی تپه نوردی (جست و جوی محلی حریصانه)

• Apply the rule that increases the most the current state value

• Move in the direction of the greatest gradient



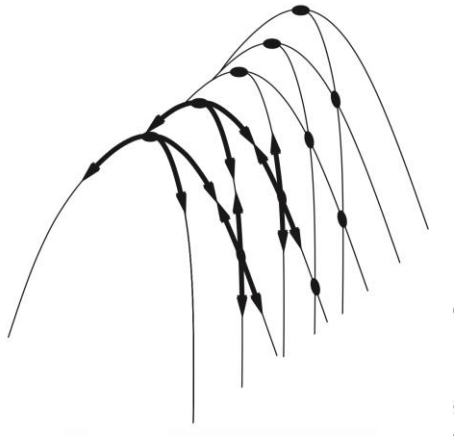
while f-value(*state*) > f-value(best-next(*state*))
    state := next-best(*state*)

دلایل شکست تپه‌نوردی

- این سیاست ساده، سه زیان عمده دارد:
- مینیمم یا ماکسیمم محلی: یک ماکزیمم محلی، برخلاف ماکزیمم عمومی، قله‌ای است که پائین‌تر از بلندترین قله درفضای حالت است. زمانی که روی ماکزیمم محلی هستیم، الگوریتم توقف خواهد نمود هرچند جواب مسئله (ماکسیمم سراسری) نباشد.

دلایل شکست تپه‌نوردی

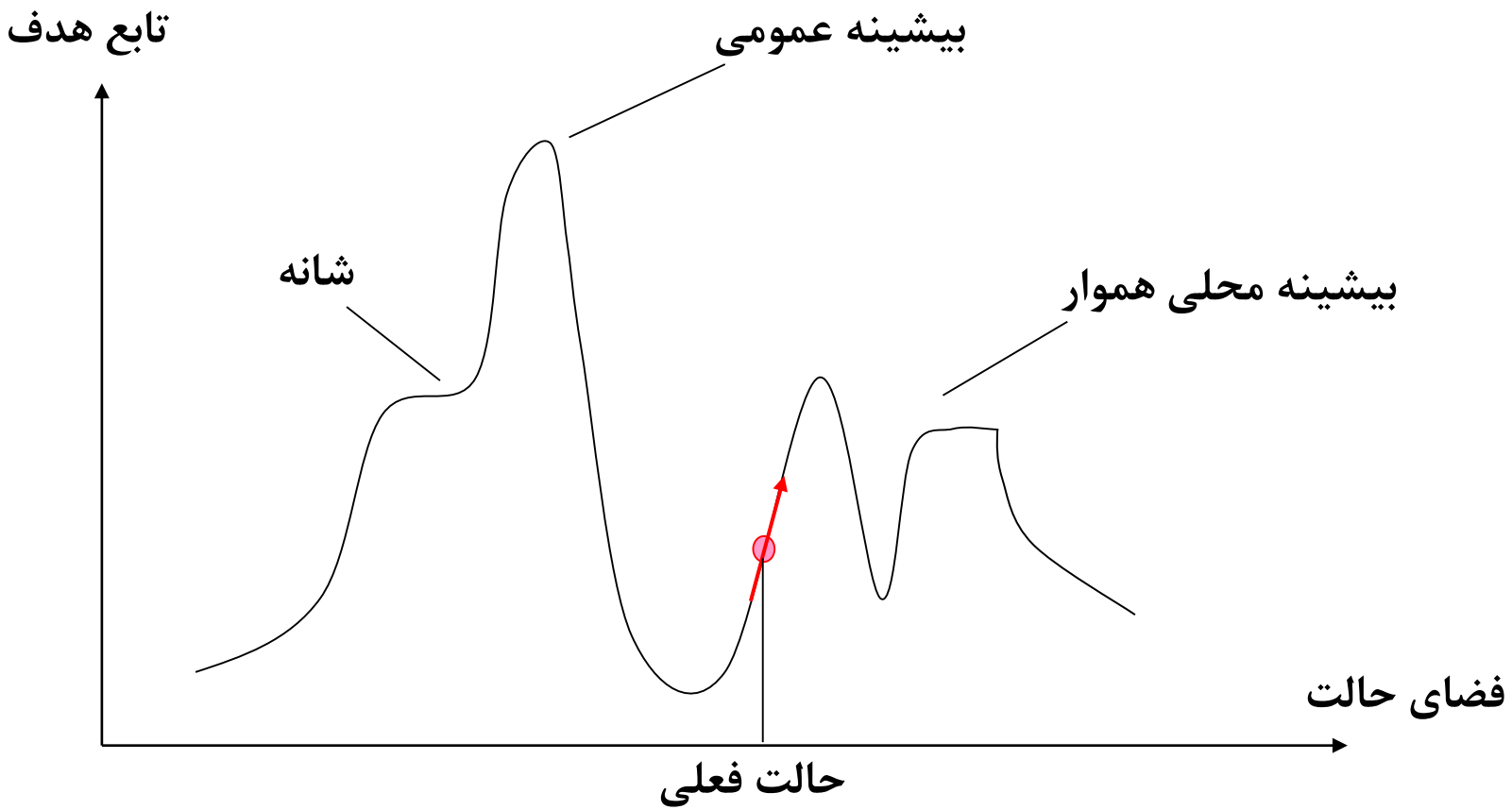
- تیغه (Ridges)، دارای لبه‌های سراشیب و ترکیبی از تعداد زیادی مینیمم محلی در مجاورت یکدیگر است است. مگر اینکه عملگرهایی موجود باشند که مستقیماً به سمت بالای نوک کوه حرکت کنند، جستجو ممکن است از لبه‌ای به لبه دیگر نوسان داشته باشد و پیشرفت کمی را حاصل نماید.



دلایل شکست تپه‌نوردی

- یک فلات محوطه‌ای از فضای حالت است که تابع ارزیاب یکنواخت باشد.
- راه‌حل: Sideways Move

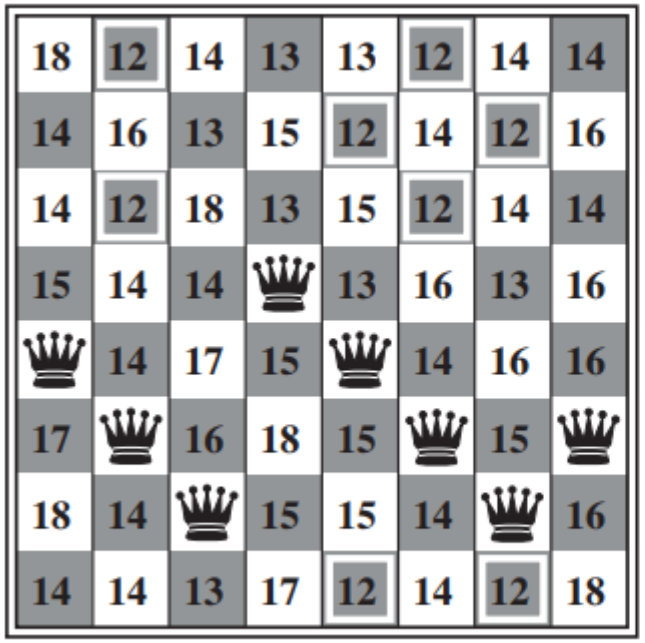
جست و جوی تپه نوردی (جست و جوی محلی حریصانه)



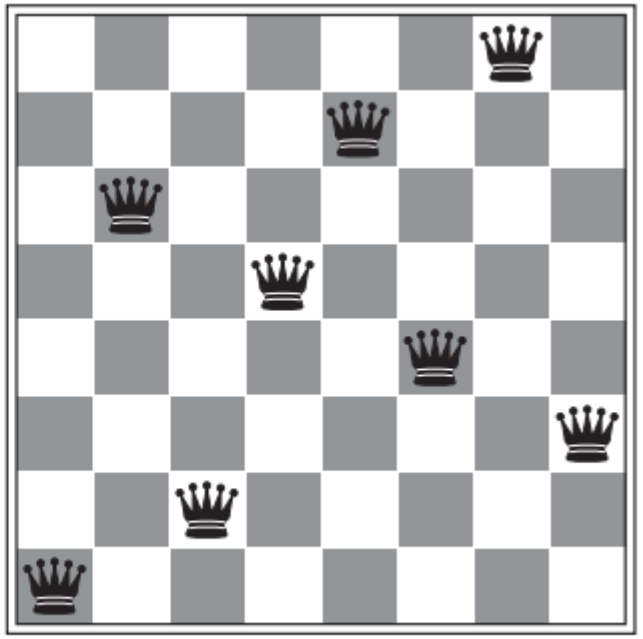
مساله ۸ وزیر با استفاده از جست و جوی تپه نوردی

- استفاده از فرمول بندی کامل
- هر حالت ۵۶ جانشین دارد
- تابع اکتشافی h تعداد جفت‌هایی از وزیران است که یکدیگر را می‌زنند.

مساله ۸ وزیر با استفاده از جست و جوی تپه نوردی



(a)



(b)

Local minimum

- (a) An 8-queens state with heuristic cost estimate $h = 17$, showing the value of h for each possible successor obtained by moving a queen within its column. The best moves are marked.
- (b) A local minimum in the 8-queens state space; the state has h = 1 but every successor has a higher cost.

Escaping Shoulders: Sideways Move

- If no downhill (uphill) moves, allow sideways moves in hope that algorithm can escape
  - ✓ Must limit the number of possible sideways moves to avoid infinite loops
- For 8-queens
  - ✓ Allow sideways moves with limit of 100
  - ✓ Raises percentage of problems solved from 14 to 94%
  - ✓ However....
    - 21 steps for every successful solution
    - 64 for each failure
  - ✓ Without sideway moves:
    - 4 steps for every successful solution
    - 3 for each failure

Hill Climbing Properties

- Not complete.
- Terrible worst case running time.
- Simple, O(1) space, and often very fast.

Hill Climbing: Stochastic Variations

- When the state-space landscape has local minima, any search that moves only in the greedy direction cannot be complete
- Idea: Combine random & greedy selection
- At each step do one of the following:
  - ✓ Greedy: With prob. p move to the neighbor with largest value
  - ✓ Random: With prob. 1-p move to a random largest neighbor neighbor

Hill-climbing with random restarts

- If at first you don't succeed, try, try again!
- Different variations
  - ✓ For each restart: run until termination vs. run for a fixed time
  - ✓ Run a fixed number of restarts or run indefinitely
- Analysis
  - ✓ Say each search has probability p of success
  - ✓ e.g., for 8-queens, p = 0.14 with no sideways moves
- Expected number of restarts?
- Expected number of steps taken?

Hill-Climbing with Both Random Walk & Random Sampling

- At each step do one of the three
  - ✓ **Greedy**: move to the neighbor with largest value
  - ✓ **Random Walk**: move to a random neighbor
  - ✓ **Random Restart**: Start over from a new, random state

Simulated Annealing

- Idea: escape local maxima by allowing some "bad" moves
  - ✓ **but gradually decrease their size and frequency**
  - ✓ method proposed in 1983 by IBM researchers for solving VLSI layout problems
- A Physical Analogy:
  - ✓ Imagine letting a ball roll downhill on the function surface
  - ✓ Now shake the surface, while the ball rolls,
  - ✓ Gradually reducing the amount of shaking

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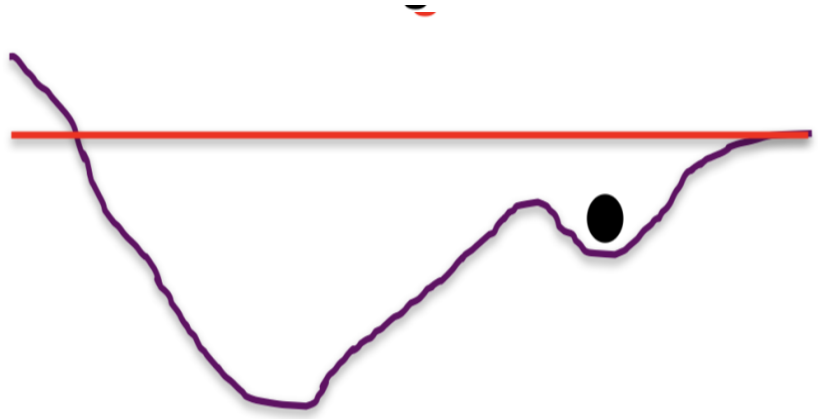

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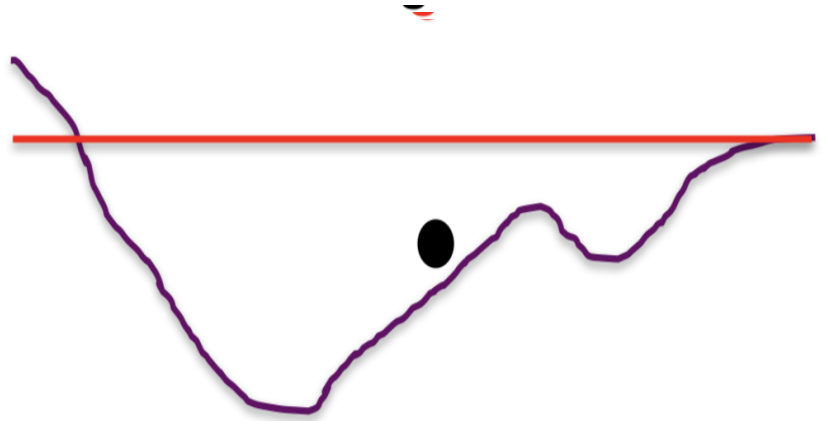

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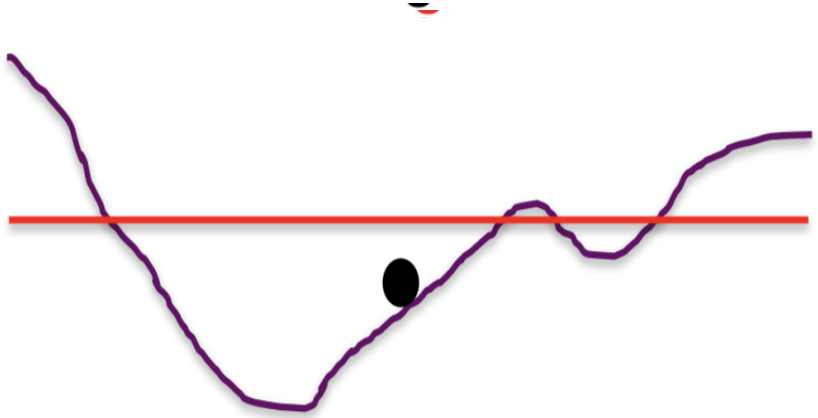

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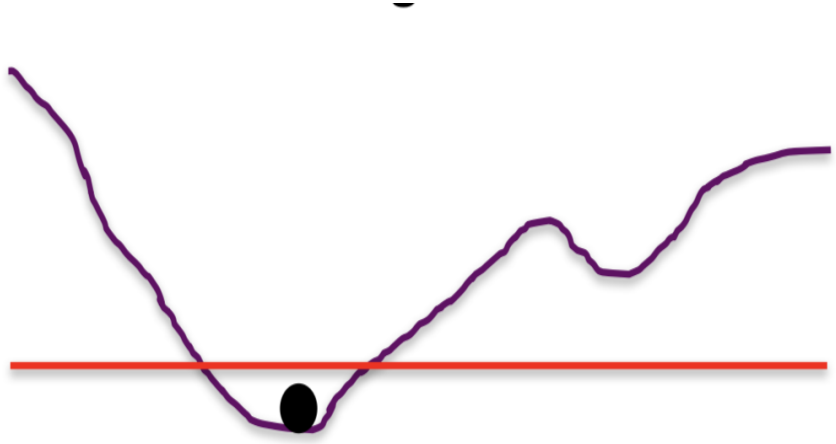


Simulated Annealing (cont.)

- Annealing = physical process of cooling a liquid → frozen
- simulated annealing:
  - ✓ free variables are like particles
  - ✓ seek "low energy" (high quality) configuration
  - ✓ slowly reducing temp. T with particles moving around randomly
- high T: probability of "locally bad" move is higher
- low T: probability of "locally bad" move is lower
- typically, T is decreased as the algorithm runs longer
  - ✓ i.e., there is a "temperature schedule"

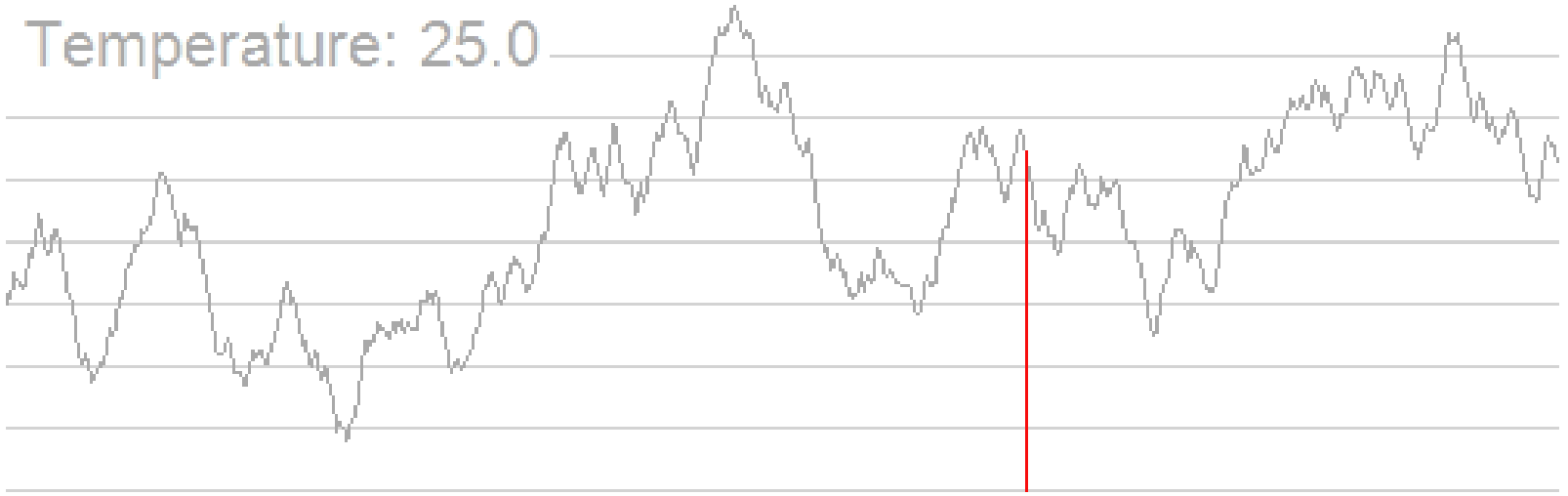
Simulated Annealing (cont.)

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
    inputs: problem, a problem
            schedule, a mapping from time to "temperature"
    local variables: current, a node
                     next, a node
                     T, a "temperature" controlling prob. of downward steps

    current ← MAKE-NODE(INITIAL-STATE[problem])
    for t ← 1 to ∞ do
        T ← schedule[t]
        if T = 0 then return current
        next ← a randomly selected successor of current
        ΔE ← VALUE[next] – VALUE[current]
        if ΔE > 0 then current ← next
        else current ← next only with probability e^(Δ E/T)
```

maximization

T نماینده دماست و دائم در حال کم شدن است.


Temperature: 25.0

Simulated Annealing in practice

- Other applications:
  - ✓ Traveling salesman, Graph partitioning, Graph coloring, Scheduling, Facility Layout, Image Processing, ...
- Optimal, given that T is decreased **sufficiently slow**.
- Convergence can be guaranteed if at each step, T drops no more quickly than C/log n, C=constant, n = # of steps so far.

Local beam search

- Idea: Keeping only one node in memory is an extreme reaction to memory problems.
- Keep track of *k* states instead of one
  - ✓ Initially: *k* randomly selected states
  - ✓ Next: determine all successors of *k* states
  - ✓ If any of successors is goal → finished
  - ✓ Else select *k* best from successors and repeat

Local Beam Search

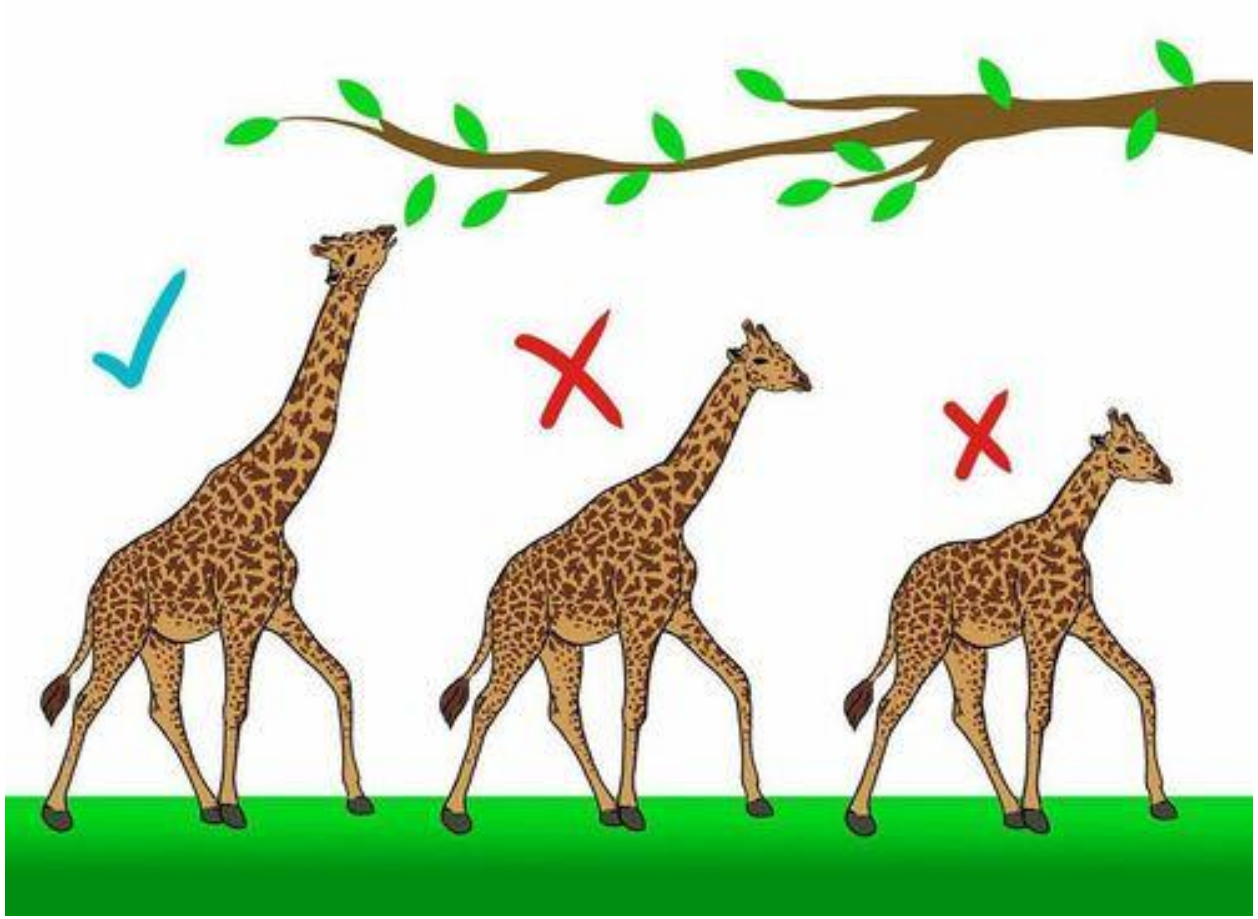
- Not the same as *k random-start searches that run in parallel!*
  - ✓ Searches that find good states recruit other searches to join them
- Problem: quite often, all *k states end up on same local hill*
- Idea: Stochastic beam search
  - ✓ Choose *k successors randomly, biased towards good ones*
- Observe the close analogy to natural selection!

Genetic Algorithm (GA)

- Local beam search, but…
  - ✓ A successor state is generated by ***combining two parent states***
- Start with *k* randomly generated states (population)
- A state is represented as a ***string*** over a finite alphabet (often a string of 0s and 1s)
- Evaluation function (fitness function). Higher = better
- Produce the next generation of states by selection, crossover, and mutation

Natural selection

Natural selection

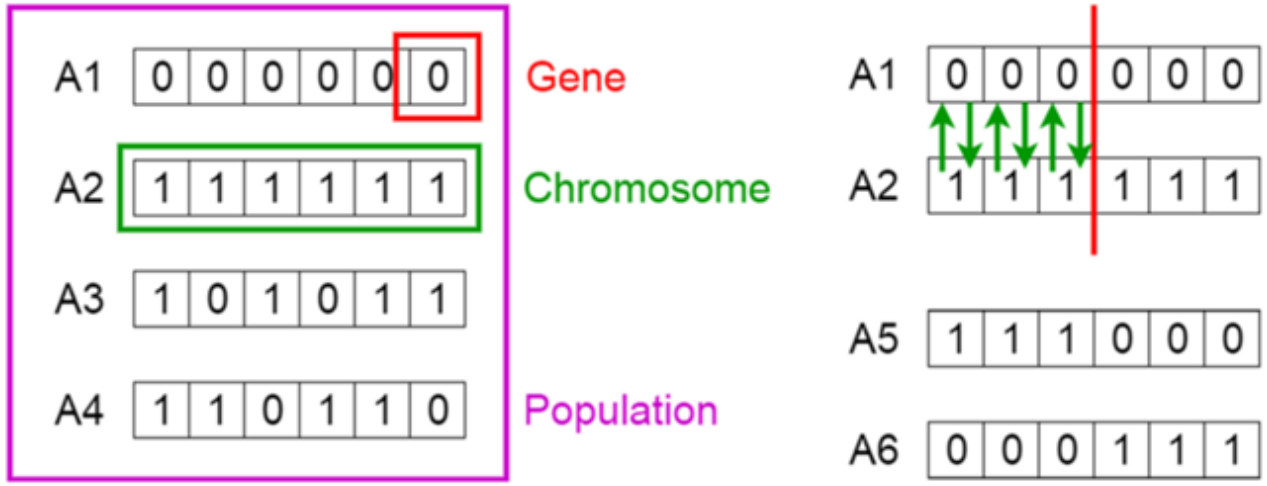


Natural selection

- The process of natural selection starts with the selection of fittest individuals from a population.
- They produce offspring which probably inherit the superior characteristics of the parents and will be added to the next generation.
- Their offspring who inherit the superior characteristics have a better chance at surviving.
- This process keeps on iterating and at the end, a generation with the fittest individuals will be found.

GA

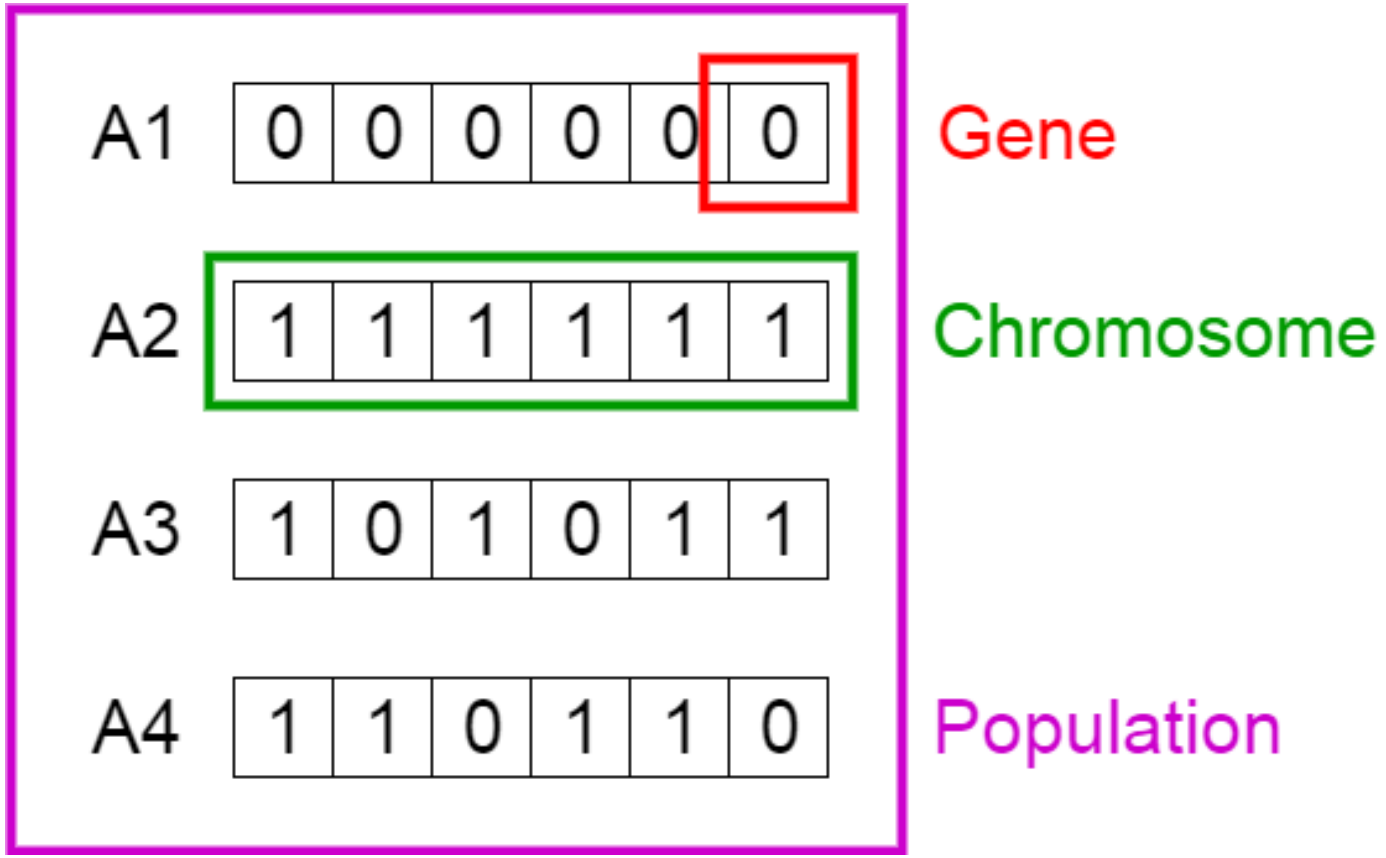
- Five phases are considered in a genetic algorithm.
  - ✓ Initial population
  - ✓ Fitness function
  - ✓ Selection
  - ✓ Crossover
  - ✓ Mutation



GA

- The process begins with a set of individuals which is called a **Population**. Each individual is a solution to the problem you want to solve.
- An individual is characterized by a set of parameters (variables) known as **Genes**. Genes are joined into a string to form a **Chromosome** (solution).
- In a genetic algorithm, the set of genes of an individual is represented using a string, in terms of an alphabet. Usually, binary values are used (string of 1s and 0s). We say that we encode the genes in a chromosome.

GA


A1
0 0 0 0 0 0
Gene
A2
1 1 1 1 1 1
Chromosome
A3
1 0 1 0 1 1
A4
1 1 0 1 1 0
Population

GA

❑ Fitness Function

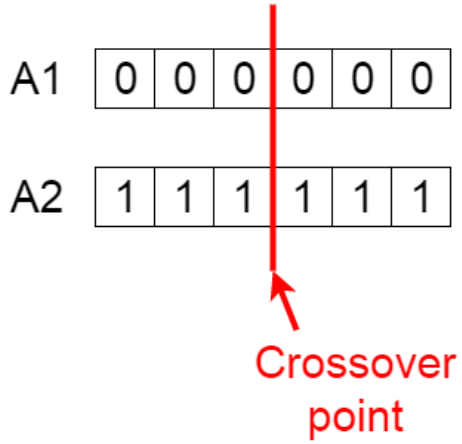
- ✓ The **fitness function** determines how fit an individual is (the ability of an individual to compete with other individuals). It gives a **fitness score** to each individual. The probability that an individual will be selected for reproduction is based on its fitness score.

❑ Selection

- ✓ The idea of **selection** phase is to select the fittest individuals and let them pass their genes to the next generation.
- ✓ Two pairs of individuals (**parents**) are selected based on their fitness scores. Individuals with high fitness have more chance to be selected for reproduction.

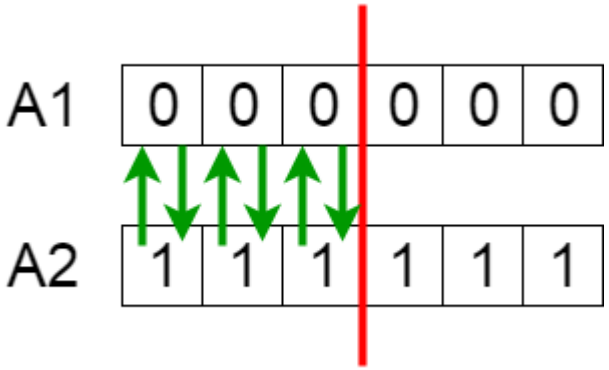
GA - crossover

- **Crossover**
  - ✓ **Crossover** is the most significant phase in a genetic algorithm. For each pair of parents to be mated, a **crossover point** is chosen at random from within the genes.
- For example, consider the crossover point to be 3 as shown below.

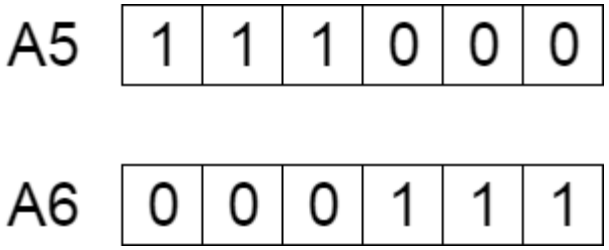


GA - crossover

- **Offspring** are created by exchanging the genes of parents among themselves until the crossover point is reached.



- The new offspring are added to the population.



GA - Mutation

Mutation

- ✓ Sometimes, new offspring can be subjected to a **mutation** with a low random probability. This implies that some of the bits in the bit string can be flipped.

- Mutation occurs to maintain diversity within the population and prevent premature convergence.

Before Mutation

A5	1	1	1	0	0	0

After Mutation

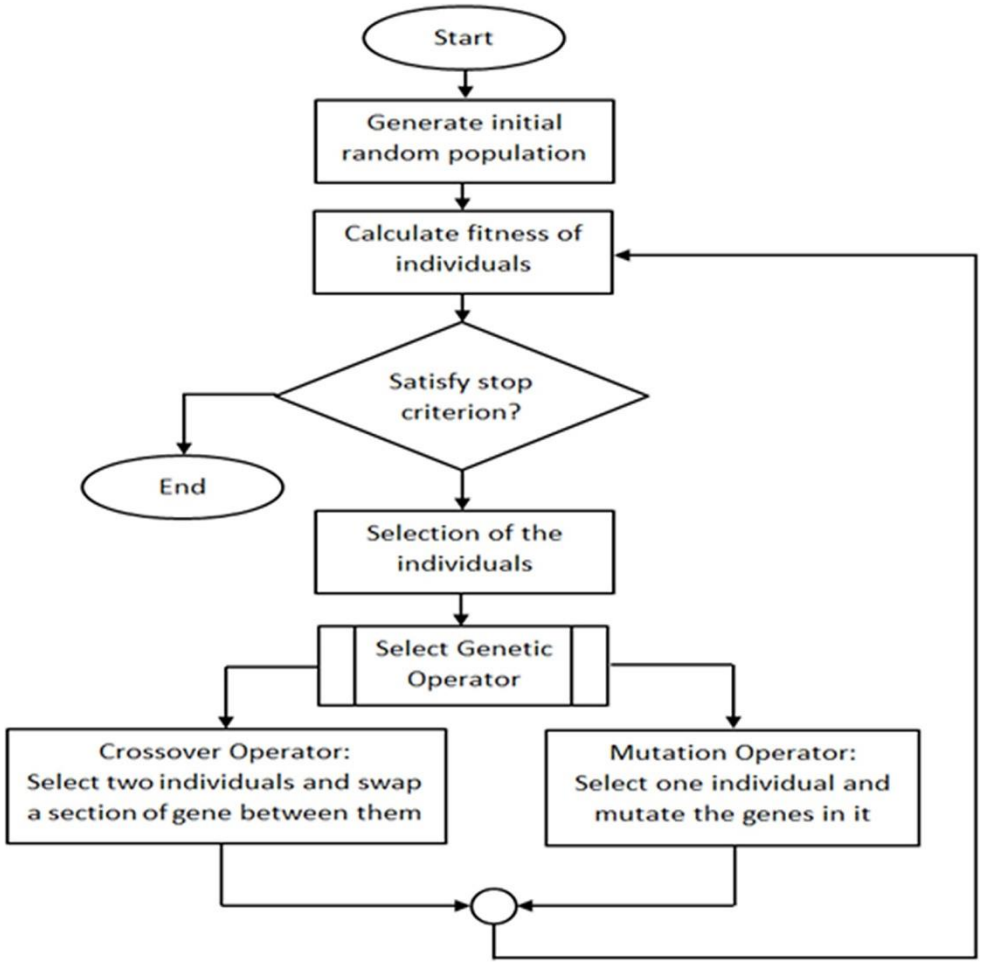
A5	1	1	0	1	1	0

GA- other factors

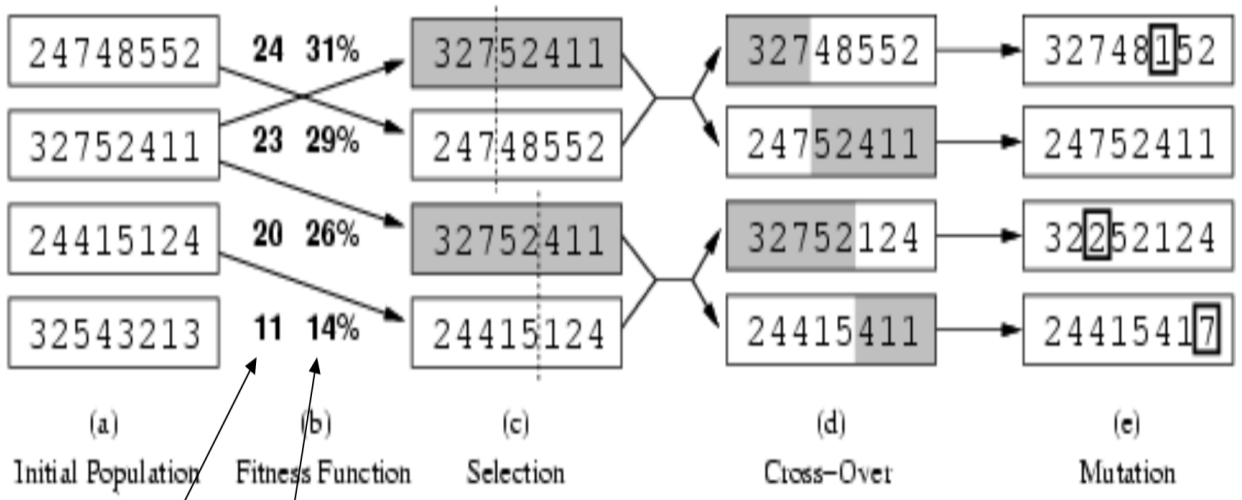
- **Heuristics**
  - ✓ In addition to the main operators above, other heuristics may be employed to make the calculation faster or more robust. The *speciation* heuristic penalizes crossover between candidate solutions that are too similar.
- **Termination**

  This generational process is repeated until a termination condition has been reached. Common terminating conditions are:
  - ✓ A solution is found that satisfies minimum criteria
  - ✓ Fixed number of generations reached
  - ✓ Allocated budget (computation time/money) reached
  - ✓ The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results
  - ✓ Manual inspection
  - ✓ Combinations of the above

GA - Flowchart

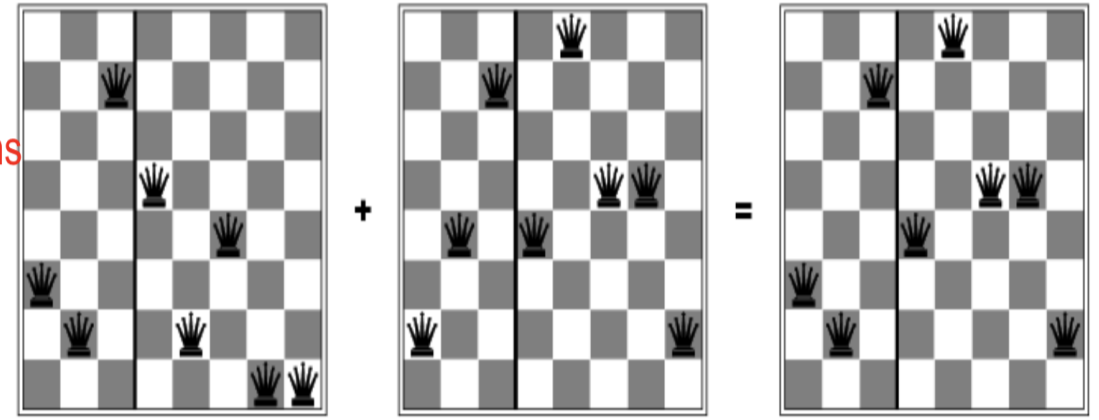


n-queens example

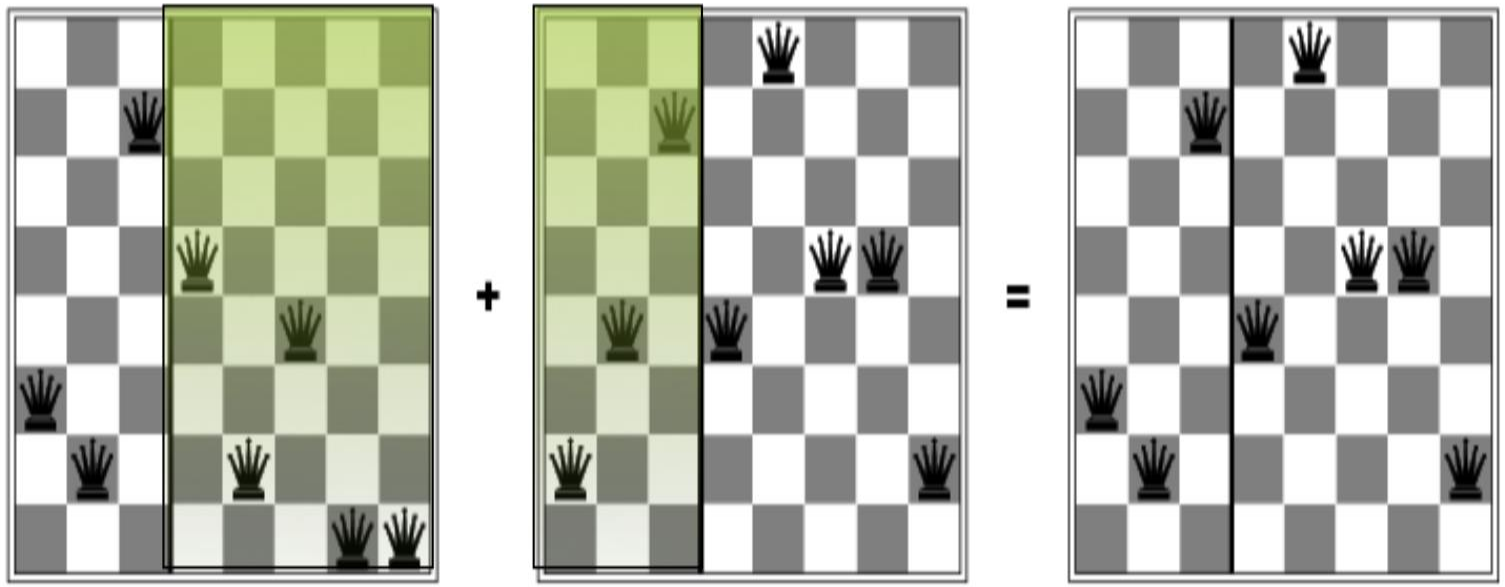


fitness:
#non-attacking queens

probability of being
regenerated
in next generation



n-queens example (cont.)



Has the effect of “jumping” to a completely different new part of the search space (quite non-local)

Comments on Genetic Algorithms

- Genetic algorithm is a variant of "stochastic beam search"
- Positive points
  - ✓ Random exploration can find solutions that local search can't
    - (via crossover primarily)
  - ✓ Appealing connection to human evolution
    - "neural" networks, and "genetic" algorithms are **metaphors**!
- Negative points
  - ✓ Large number of "tunable" parameters
    - Difficult to replicate performance from one problem to another
  - ✓ Lack of good empirical studies comparing to simpler methods
  - ✓ Useful on some (small?) set of problems but no convincing evidence that GAs are better than hill-climbing w/random restarts in general

Genetic Programming

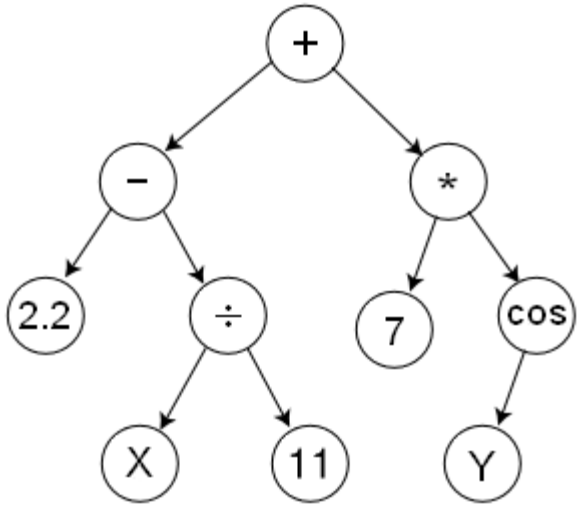
- In artificial intelligence, **genetic programming** (**GP**) is a technique whereby computer programs are encoded as a set of genes that are then modified (evolved) using an evolutionary algorithm (often a genetic algorithm, "GA").
- It is an application of (for example) genetic algorithms where the space of solutions consists of computer programs.
- The results are computer programs that are able to perform well in a predefined task..

Evolutionary Algorithms

- In artificial intelligence, an **evolutionary algorithm** (EA) is a generic population-based metaheuristic optimization algorithm.
- An EA uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination, and selection.
- Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the quality of the solutions (see also loss function).
- Evolution of the population then takes place after the repeated application of the above operators.

GP

- GP evolves computer programs, traditionally represented in memory as tree structures. Trees can be easily evaluated in a recursive manner. Every tree node has an operator function and every terminal node has an operand, making mathematical expressions easy to evolve and evaluate.



$$\left(2.2 - \left(\frac{X}{11}\right)\right) + \left(7 * \cos(Y)\right)$$

Ants Colony Optimization

- In the natural world, ants of some species (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but instead to follow the trail, returning and reinforcing it if they eventually find food.
- Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones.

ACP

- Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.
- The influence of pheromone evaporation in real ant systems is unclear, but it is very important in artificial systems.
- The overall result is that when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to many ants following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve.

Other EAs

- **Artificial bee colony algorithm** (ABC) is an optimization algorithm based on the intelligent foraging behaviour of honey bee swarm, proposed by Karaboga in 2005.
- **Particle swarm optimization** (PSO) was first intended for simulating social behaviour, as a stylized representation of the movement of organisms in a bird flock or fish school. The algorithm was simplified and it was observed to be performing optimization.

جستجو در محیط‌های پیوسته

- در فضاهاي پيوسته، در هر حالت، تعداد حالات بعدي نامحدود است.
- تابع هدف به صورت تابعي از متغيرهاي پيوسته تعريف مي‌شود.
- نزول (صعود) در امتداد گرادیان شناخته شده ترین تکنیك جستجو در این محیط‌ها است.
- در هر گام به اندازه آلفا در جهت گرادیان حرکت می‌کنیم :

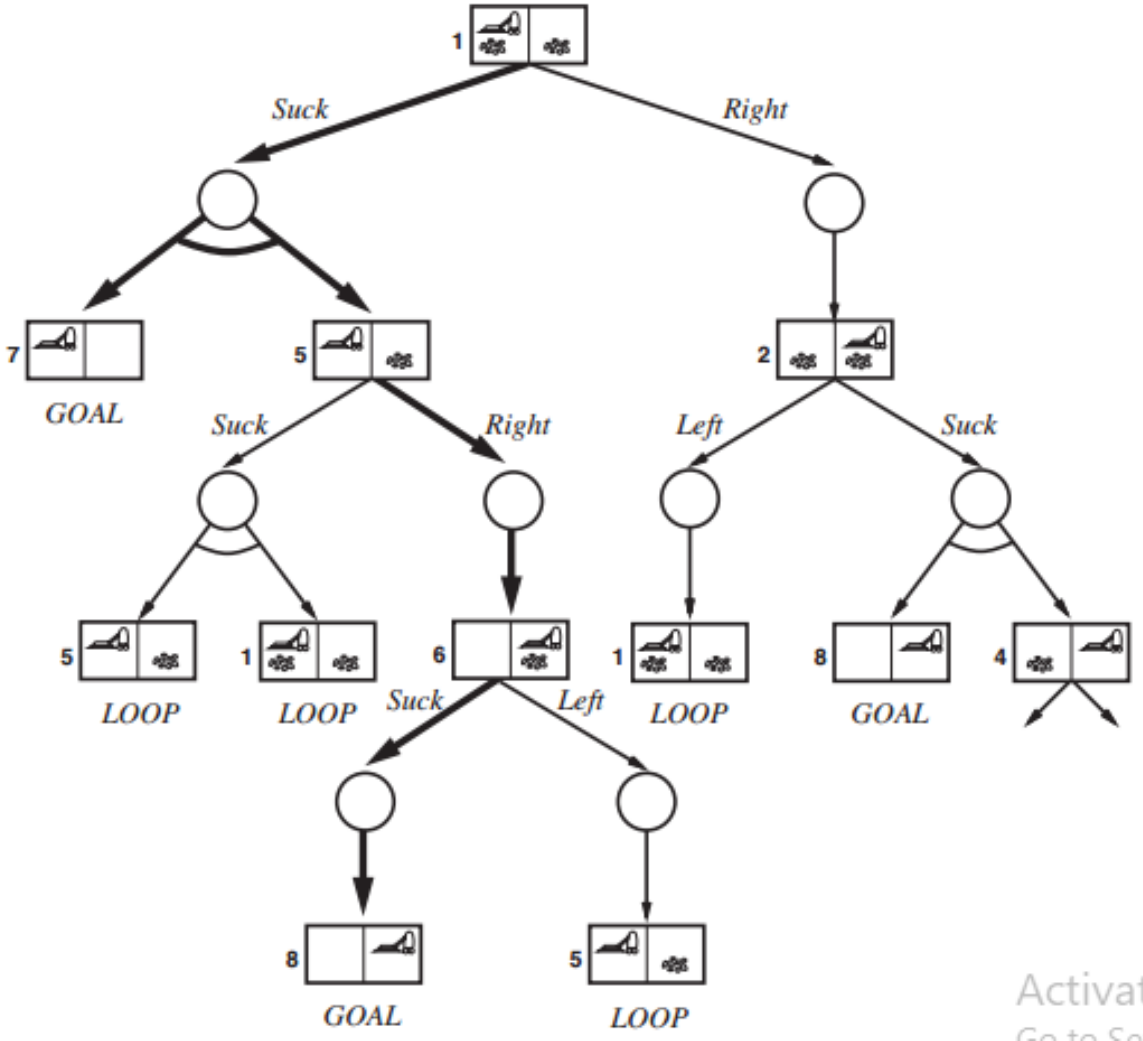
$$X \leftarrow X + \alpha \sum \nabla f(X)$$

- روش هاي مختلفي براي تنظيم مقدار آلفا (اندازه گام) پيشنهاد شده است.
- آنقدر در جهت گرادیان پیش می‌رویم تا به یک نقطه بهینه برسیم. این نقطه به عنوان حالت بعد در نظر گرفته می‌شود. نقاط بهينه محلي نقاطي هستند كه گراديان تابع در آنها صفر است : روش نیوتن-رافسون برای یافتن ریشه گرادیان

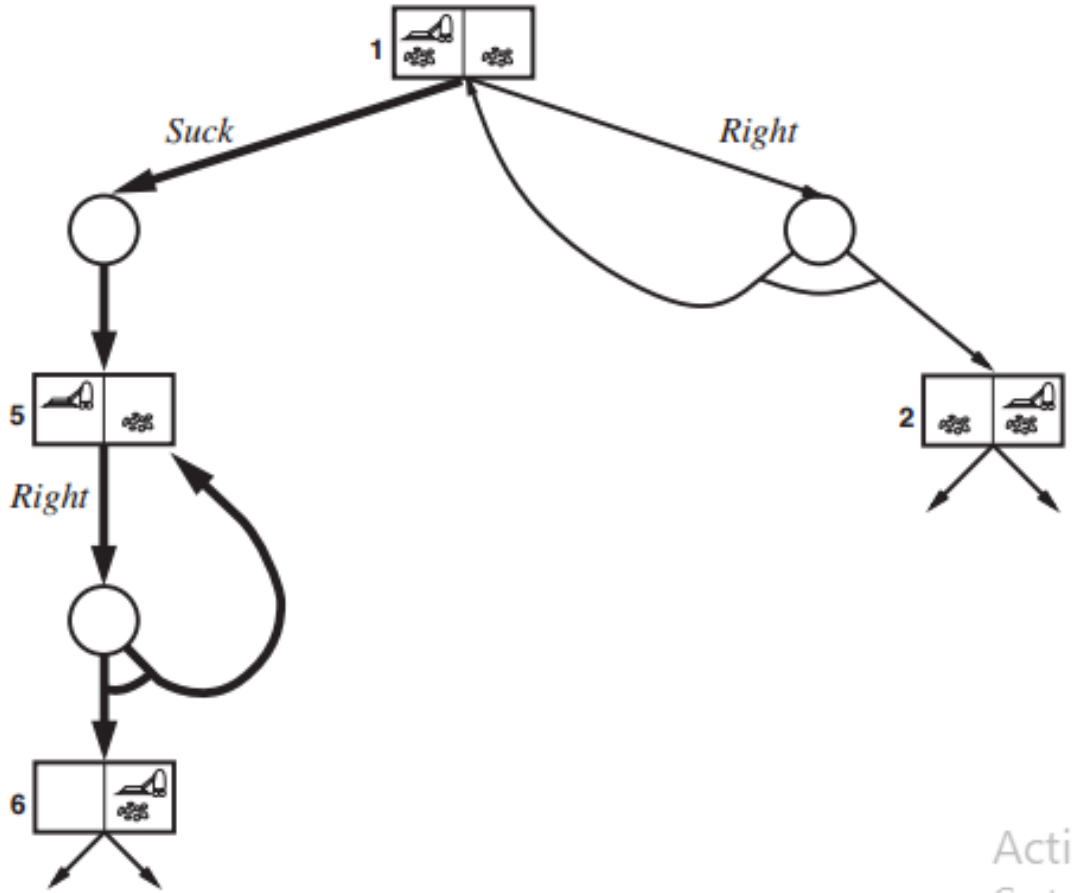
جستجو با اعمال غیرقطعی

- غیرقطعي بودن عمل‌ها:
  - ✓ محیط غیرقطعی
  - ✓ محیط نیمه‌قابل مشاهده
  - ✓ محیط ناشناخته
- تفاوت با جستجو در محیطهاي قطعي:
  - ✓ راه حل مسأله دنباله ثابتي از عمل ها نیست بلکه یک استراتژی از دنباله‌های مشروط به مشاهدات عامل از محیط است.
  - ✓ خروجي هر عمل مجموعه اي از حالات است نه و يك حالت خاص.
- درخت جستجو به شکل درخت جستجوي AND-ORخواهد بود.
- راه حل يك درخت AND-OR زيردرختي است که
  - ✓ همه برگهاي آن حالت هدف باشد.
  - ✓ در هر گره ORيك عمل مشخص را انتخاب کرده باشد.
  - ✓ در هر گره ANDکليه خروجي‌هاي ممکن را شامل شود

درخت AND-OR



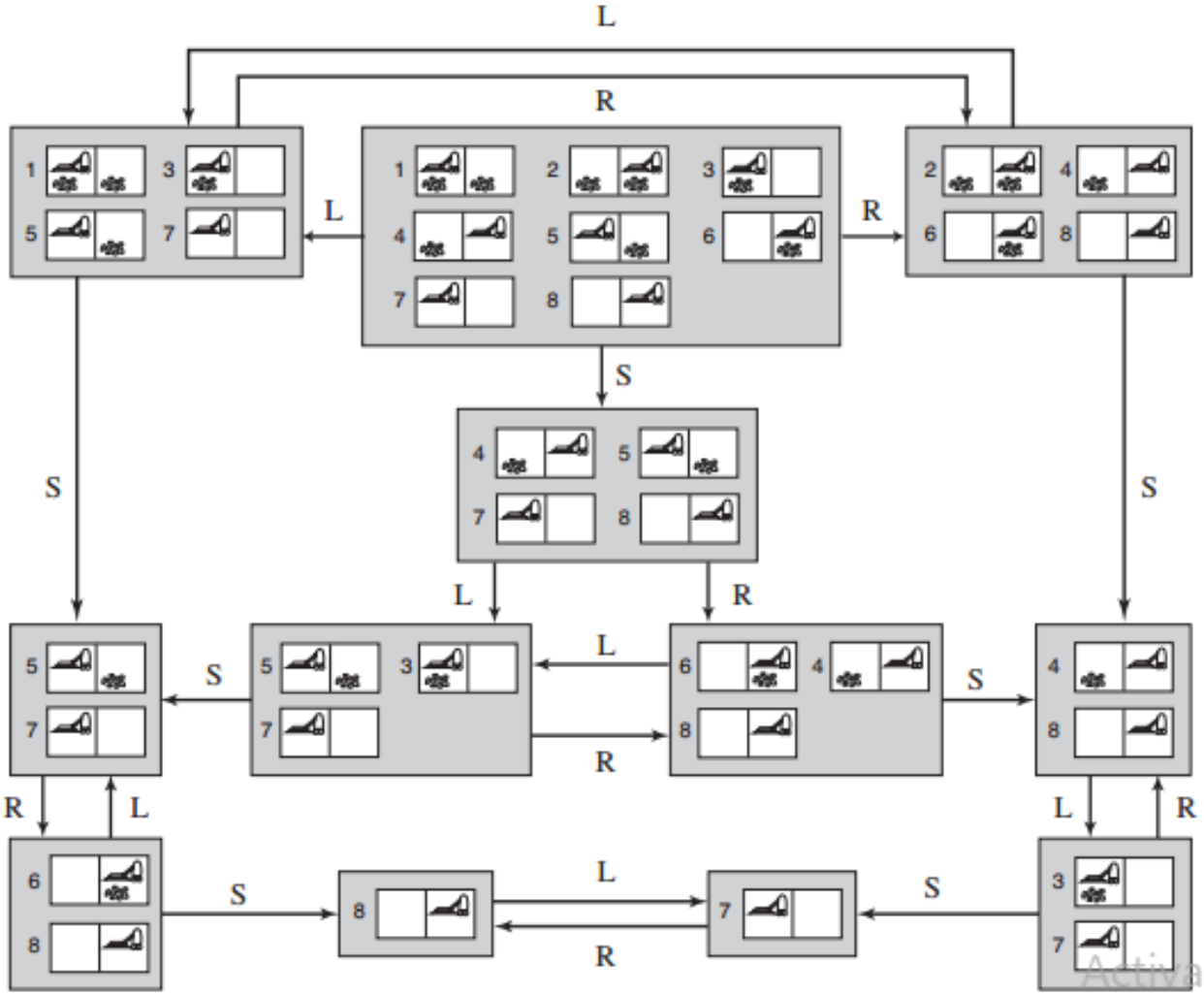
درخت AND-OR



جستجو در محیط‌های نیمه‌مشاهده‌پذیر

- **حتی مسائل بدون حسگر (sensorless)نیز قابل حل هستند:**
  - ✓ محيطه‌هايي كه در آنها عامل هيچ حسگري براي درك محيط اطراف ندارد.
  - ✓ علت: امكان حل مسأله بدون نياز به حسگر، هزينه بالاي حسگرها و ...
- **در محیط‌های نیمه‌مشاهده‌پذیر:**
  - ✓ حالت محيط به صورت مجموعه‌اي از حالات ممكن يا حالات باور (belief states) بيان مي‌شود.
- **اندازه مجموعه حالات باور در این محیط‌ها بسیار بزرگ است.**
- **جستجو در فضای باور به جای جستجو در فضای حالت:**
  - ✓ حالت شروع، مجموعه تمام حالات فیزیکی ممکن است.
  - ✓ اعمال ممکن در هر حالت باور، اشتراک تمام اعمال ممکن در حالات فیزیکی موجود در آن حالت باور است.
  - ✓ مجموعه حالات فیزیکی ممکن در اثر انجام هر یک از اعمال مذکور، حالت باور بعدی را می‌سازند.
  - ✓ حالت باوری، حالت هدف محسوب می‌شود که تمام حالات فیزیکی موجود در آن، حالت هدف باشد.

Belief search



جستجوي آنلاين

- **جستجوي آفلاين (برون خط):**
  - ✓ اجراي كامل فرآيند جستجو و يافتن راه حل كامل پيش از شروع اجراي آن در دنياي واقعي.
- **جستجوي آنلاين (برخط):**
  - ✓ جستجو و اجراي همزمان راه حل
  - ✓ تار زمانی که در موقعیت جاری قرار نگرفته‌ایم، حالات بعدی را نمی‌دانیم
  - ✓ مناسب براي :
    - محيط هاي پويا يا نيمه پويا : مواردي كه گذشت زمان هزينه (جريمه) دارد
    - محیطهای نامعین
    - محيطهاي ناشناخته (مسأله اكتشاف : exploration problem)

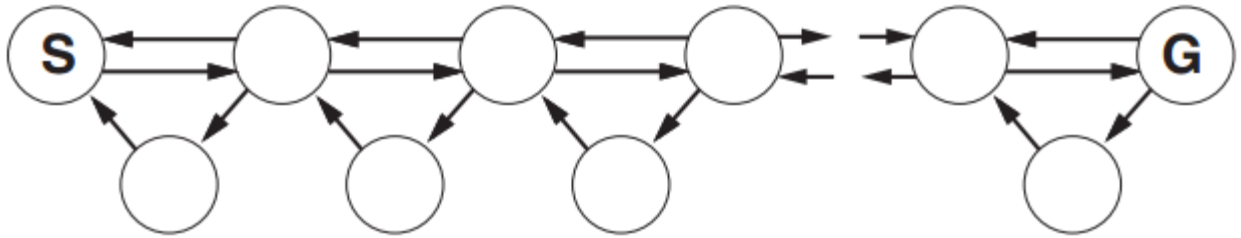
جستجوي آنلاين

- **جستجوي آنلاين:**
  - ✓ در هر لحظه، عامل در نقطه‌اي از محيط واقعي قرار دارد و تنها مي‌تواند جستجوي خود را به صورت محلي از اين نقطه دنبال كند.
  - ✓ براي ادامه جستجو از بخش ديگري از محيط لازم است عامل به صورت فيزيكي به آن حالت برگردد.
- **جستجو بايد ماهيت محلی داشته باشد، چون نمی‌توان جستجو را در لحظه جاری به موقعيت غيرشناخته شده‌ای از فضای حالت منتقل كرد.**
- **الگوريتم هاي قابل استفاده:**
  - ✓ جستجوي اول عمق آنلاين
  - ✓ تپه نوردي با گردش تصادفي يا حافظه
  - ✓ جستجوي A* يادگيرنده real-time (LRTA*)

جستجوي آنلاين

تپه نوردي آنلاين:

- ✓ الگوريتم تپه نوردي به دليل نگهداری تنها، حالت فعلي، في‌نفسه يك الگوريتم جستجوي آنلاين است.
- ✓ ولی ناكارآمد است، چون حالت شروع مجدد تصادفي به دليل عدم اطلاع از نقشه محيط، قابل پياده سازي نيست.
- ✓ مي‌توان از random walk براي اكتشاف محيط استفاده كرد ولی ممكن است خيلی زمان‌بر باشد.

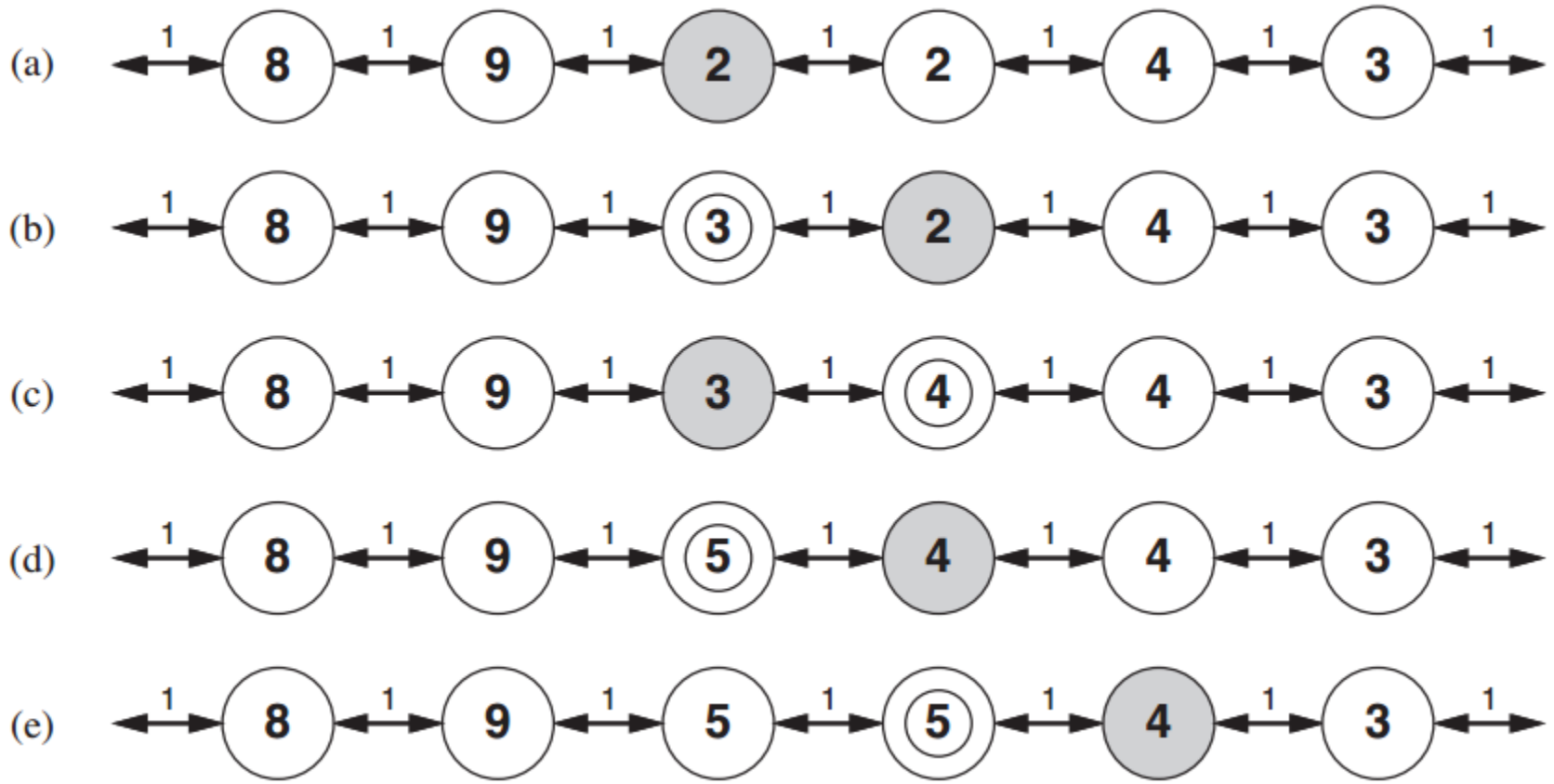


جستجوي آنلاين

- صرف حافظه بيشتر، جواب بهتری می‌دهد.
- در توسعه مبتني بر حافظه اين الگوريتم، مقدار H(s) يعني بهترين تخمين الگوريتم براي رسيدن به هدف از حالت s، بر اساس تجربيات عامل در محيط واقعي بروز مي‌شود.
- مقدار اوليه H(s) برابر با مقدار حاصل از يک تابع هيوريستيک قرار داده می‌شود.

LRTA*

LRTA*


(a)
1 8 1 9 1 2 1 2 1 4 1 3 1
(b)
1 8 1 9 1 3 1 2 1 4 1 3 1
(c)
1 8 1 9 1 3 1 4 1 4 1 3 1
(d)
1 8 1 9 1 5 1 4 1 4 1 3 1
(e)
1 8 1 9 1 5 1 5 1 4 1 3 1