Artificial Intelligence

CS482, CS682, MW 1 – 2:15, SEM 201, MS 227

Prerequisites: 302, 365

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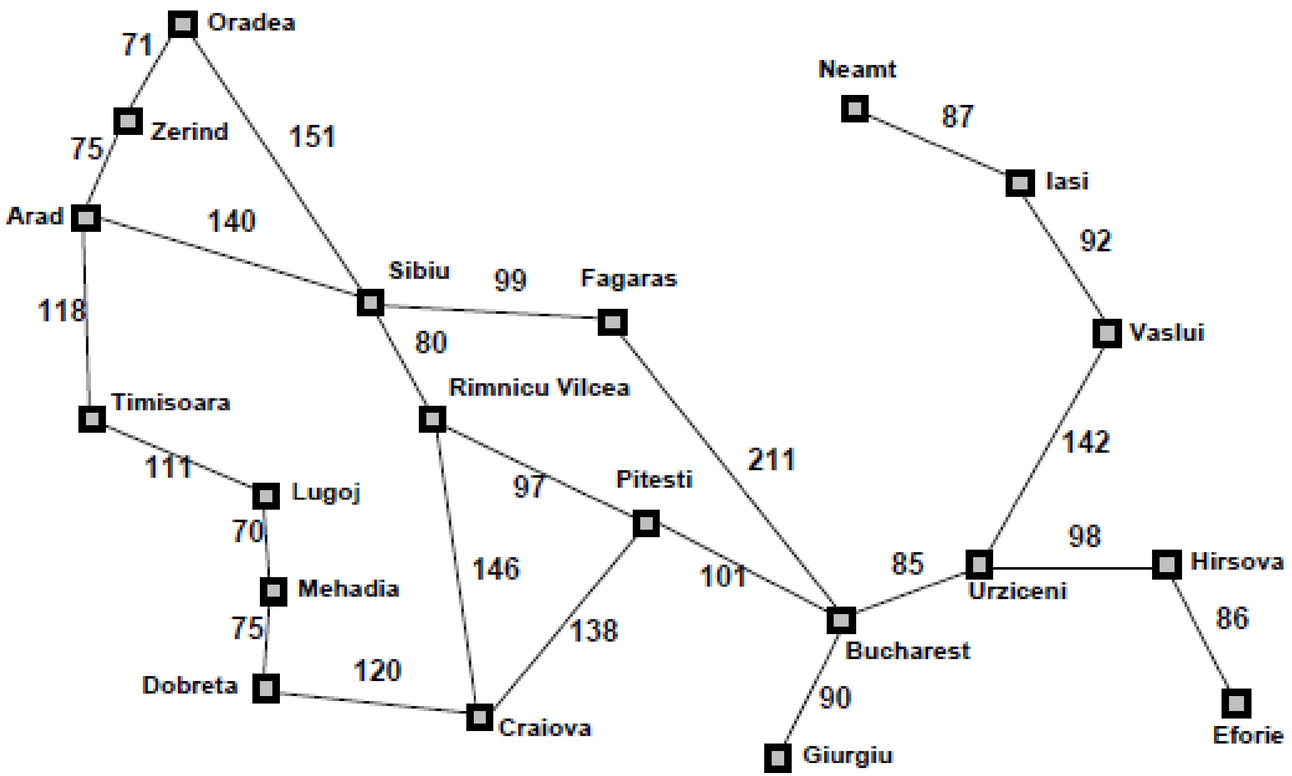
Informed Search

- **Best First Search**
  - A*
  - Heuristics

- Basic idea
  - Order nodes for expansion using a specific search strategy
    - Remember uniform cost search?
      - Nodes ordered by path length = path cost and we expand least cost
      - This function was called g(n)
  - Order nodes, n, using an evaluation function f(n)
  - Most evaluation functions include a heuristic h(n)
    - For example: **Estimated** cost of the cheapest path from the state at node n to a goal state
    - Heuristics provide domain information to guide informed search

Romania with straight line distance heuristic



Straight−line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

h(n) = straight line distance to Bucharest

Greedy search

- F(n) = h(n) = straight line distance to goal
- Draw the search tree and list nodes in order of expansion (5 minutes)

Arad	366	Mehadia	241
Bucharest	0	Neamt	234
Craiova	160	Oradea	380
Drobeta	242	Pitesti	100
Eforie	161	Rimnicu Vilcea	193
Fagaras	176	Sibiu	253
Giurgiu	77	Timisoara	329
Hirsova	151	Urziceni	80
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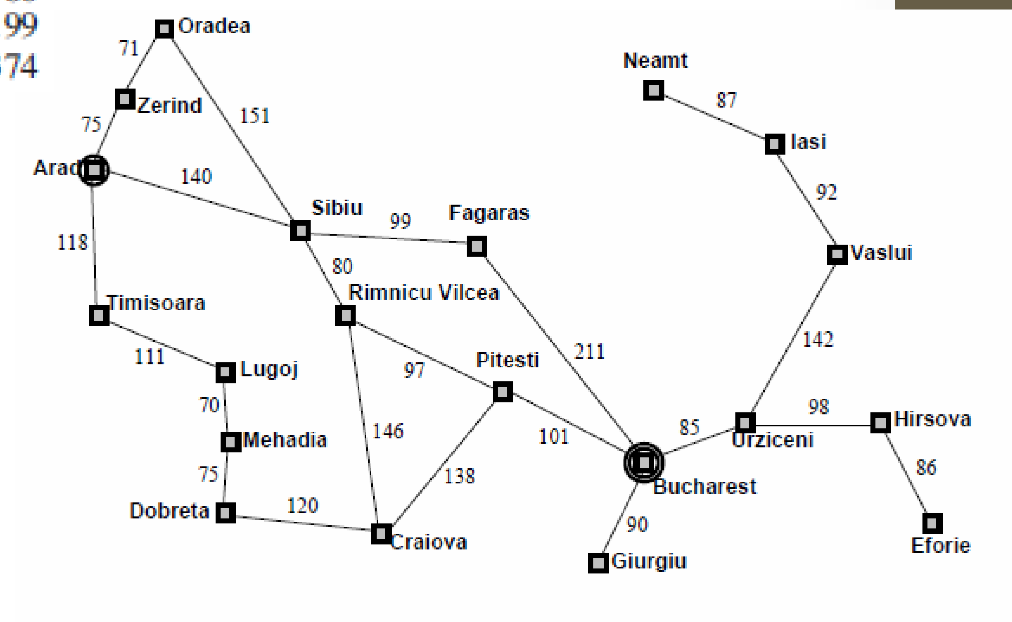
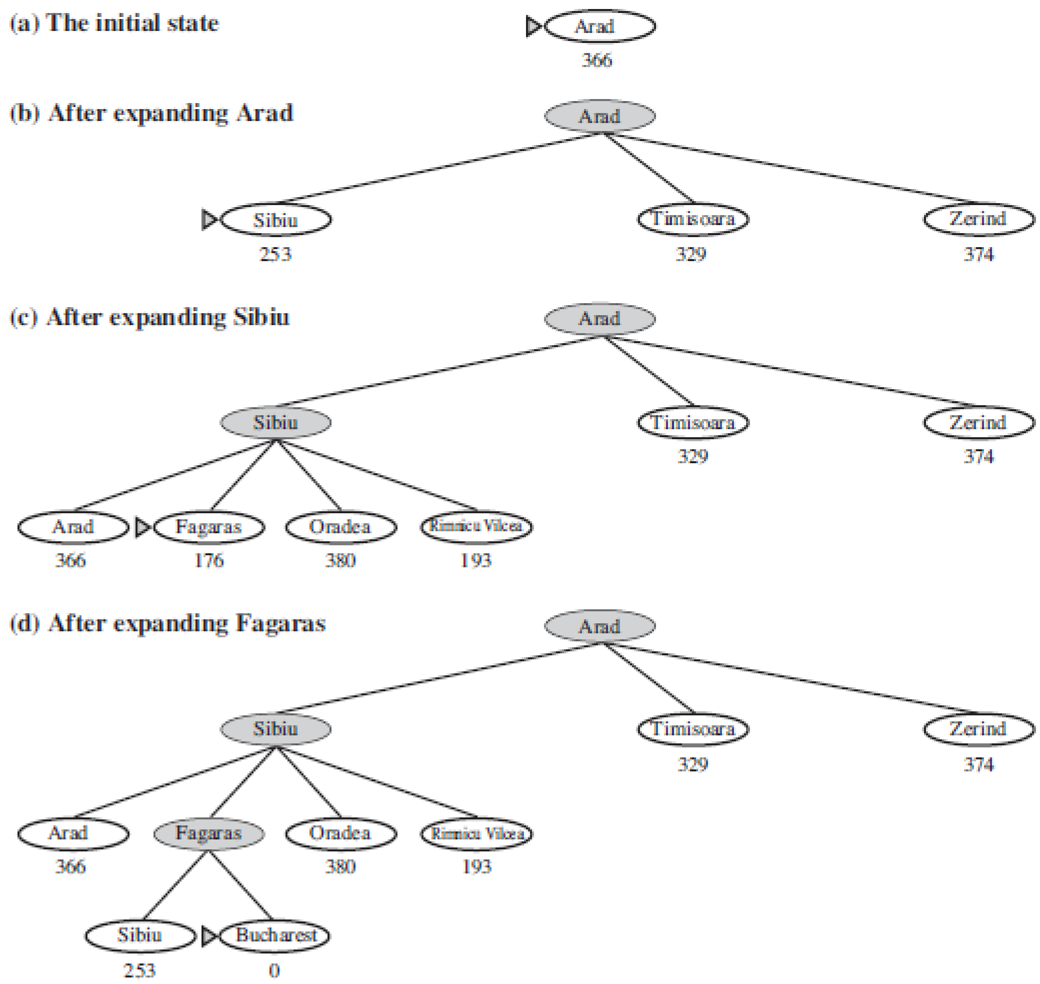
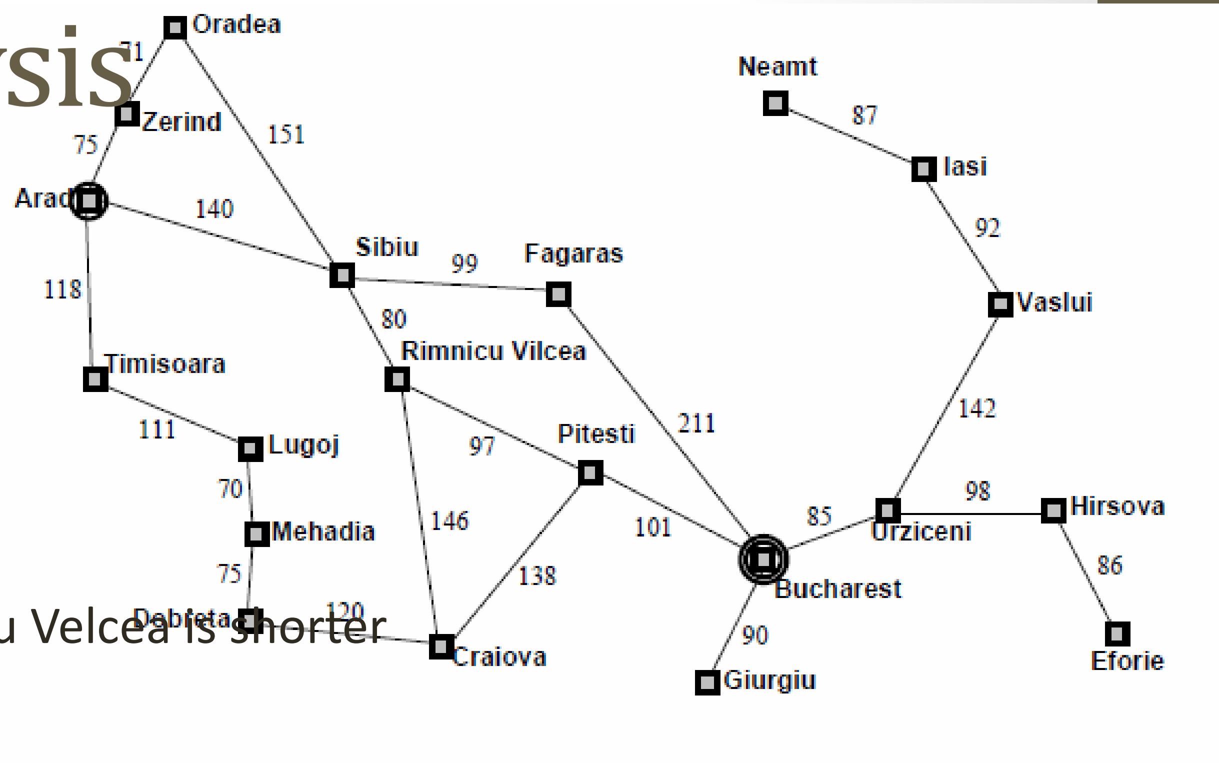
Time?
Space?
Complete?
Optimal?



Greedy search



Greedy analysis



- Optimal?
  - Path through Rimniu Velcea is shorter
- Complete?
  - Consider Iasi to Fagaras
  - Tree search no, but graph search with no repeated states version → yes
    - In finite spaces
- Time and Space
  - Worst case b^m where m is the maximum depth of the search space
  - Good heuristic can reduce complexity

A^*

- f(n) = g(n) + h(n)
- = cost to state + estimated cost to goal
- = estimated cost of cheapest solution through *n*

A^*

Arad	366	Mehadia	241
Bucharest	0	Neamt	234
Craiova	160	Oradea	380
Drobeta	242	Pitesti	100
Eforie	161	Rimnicu Vilcea	193
Fagaras	176	Sibiu	253
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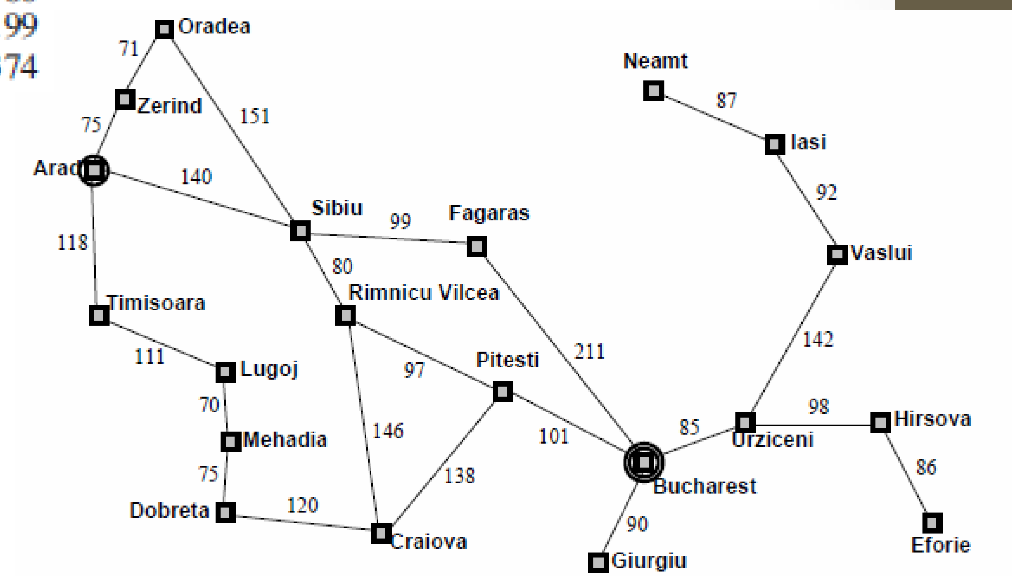
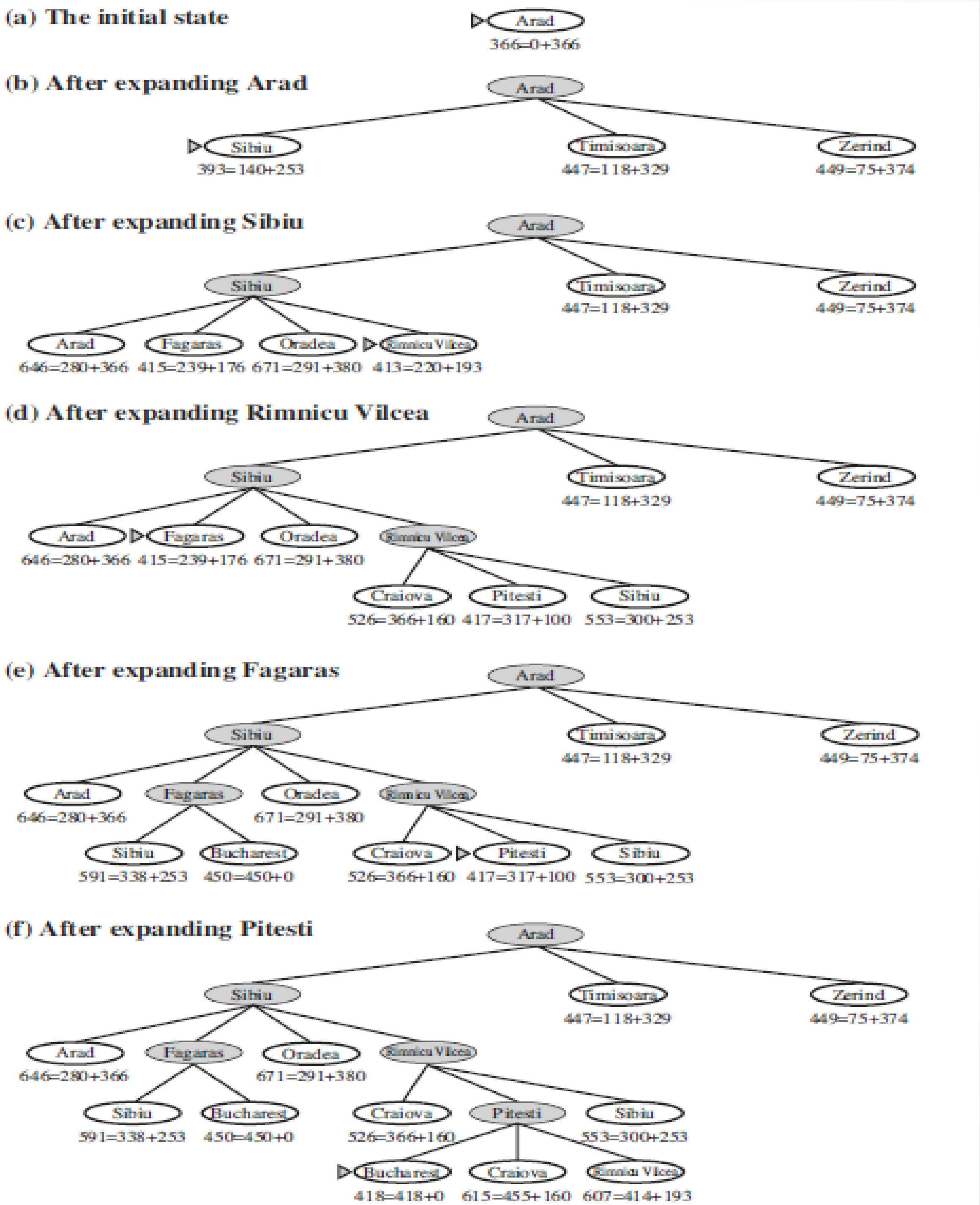
Lugoj	244	Zerind	374

Draw the search tree and list the nodes and their associated cities in order of expansion for going from Arad to Bucharest
5 minutes



A*

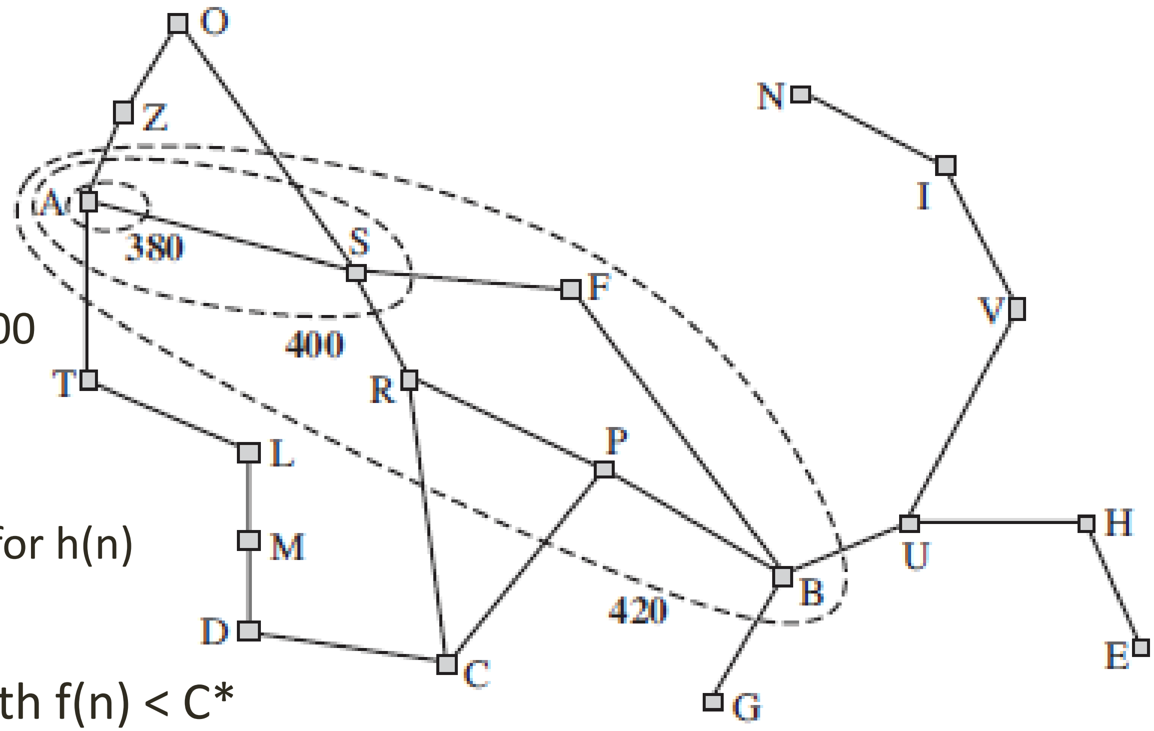

(a) The initial state
Arad
366=0+366
(b) After expanding Arad
Arad
Sibiu
393=140+253
Timisoara
447=118+329
Zerind
449=75+374
(c) After expanding Sibiu
Arad
Sibiu
Timisoara
447=118+329
Zerind
449=75+374
Arad
646=280+366
Fagaras
415=239+176
Oradea
671=291+380
Rimnicu Vilcea
413=220+193
(d) After expanding Rimnicu Vilcea
Arad
Sibiu
Timisoara
447=118+329
Zerind
449=75+374
Arad
646=280+366
Fagaras
415=239+176
Oradea
671=291+380
Rimnicu Vilcea
Craiova
526=366+160
Pitesti
417=317+100
Sibiu
553=300+253
(e) After expanding Fagaras
Arad
Sibiu
Timisoara
447=118+329
Zerind
449=75+374
Arad
646=280+366
Fagaras
Oradea
671=291+380
Rimnicu Vilcea
Sibiu
591=338+253
Bucharest
450=450+0
Craiova
526=366+160
Pitesti
417=317+100
Sibiu
553=300+253
(f) After expanding Pitesti
Arad
Sibiu
Timisoara
447=118+329
Zerind
449=75+374
Arad
646=280+366
Fagaras
Oradea
671=291+380
Rimnicu Vilcea
Sibiu
591=338+253
Bucharest
450=450+0
Craiova
526=366+160
Pitesti
Sibiu
553=300+253
Bucharest
418=418+0
Craiova
615=455+160
Rimnicu Vilcea
607=414+193

A^*

- f(n) = g(n) + h(n)
- = cost to state + estimated cost to goal
- = estimated cost of cheapest solution through *n*
- Seem reasonable?
  - If heuristic is *admissible*, A^* is optimal and complete for Tree search
    - Admissible heuristics underestimate cost to goal
  - If heuristic is *consistent*, A^* is optimal and complete for graph search
    - Consistent heuristics follow the triangle inequality
    - If n' is successor of n, then $h(n) \leq c(n, a, n') + h(n')$
    - Is less than cost of going from n to n' + estimated cost from n' to goal
      - Otherwise you should have expanded n' before n and you need a different heuristic
  - f costs are always non-decreasing along any path

A^* contours

- Non decreasing f implies
  - We can draw contours
  - Inside the 400 contour
    - All nodes have f(n) ≤ 400
  - Contour shape
    - Circular if h(n) = 0
    - Elliptical towards goal for h(n)



- If C* is optimal path cost
  - A* expands **all** nodes with f(n) < C*
  - A* may expand some nodes with f(n) = C* before getting to a goal state
  - If b is finite and all step costs > e, then A* is complete since
    - There will only be a finite number of nodes with f(n) < C*
      - Because b is finite and all step costs > e

Pruning, IDA*, RBFS, MA/SMA

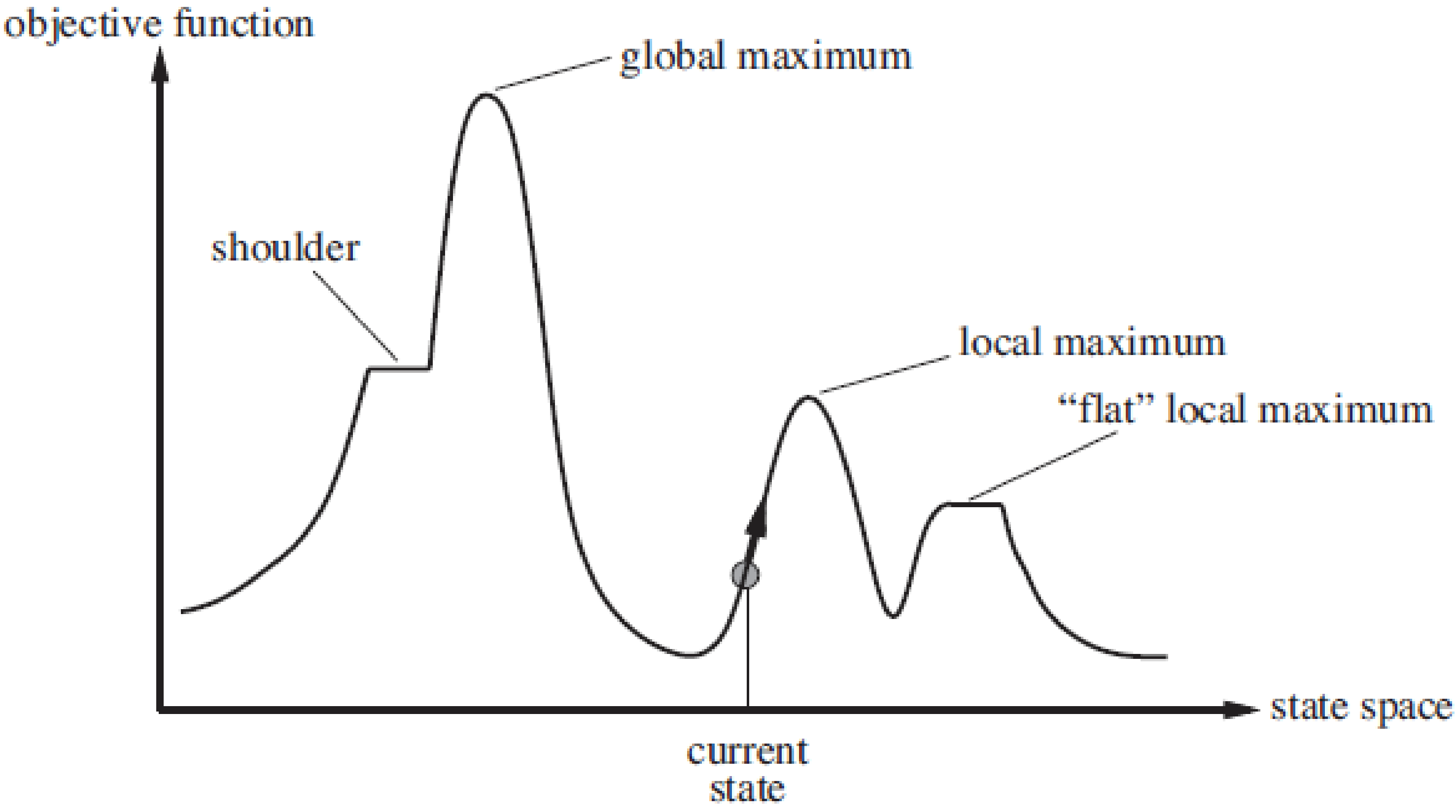
- A* does not expand nodes with f(n) > C*
  - The sub-tree rooted at Timisoara is **pruned**
- **A*** may need too much memory
- **Iterative Deepening A* (IDA*)**
  - Iterative deepening using f(n) to limit depth of search
  - Much less memory
  - Depth cutoff used: min f(n) from prior step
- **Recursive Best First Search (RBFS)**
  - Best first search
  - Again uses f(n) to limit depth
  - Whenever current f(n) > next best alternative, explore alternative
  - Keep track of best alternative
- **Memory Bounded A* (MA) or Simple Memory Bounded A*(SMA)**
  - A* with memory limit
  - When memory limit exceeded drop worst leaf, and back up f-value to parent
  - Drops **oldest** worst leaf, and expands **newest** best leaf

Heuristic functions

- Some consistent heuristics are better than others
- Analysis
  - Consider the **effective** branching factor, b*
  - The better the heuristic, the closer that b* is to 1
- N+1 = 1 + b* + $(b*)^2$ + … + $(b*)^d$
- If d = 5, and N = 52, then b* = 1.92

- There are techniques for generating admissible heuristics
  - Relax a problem
  - Learn from pattern database

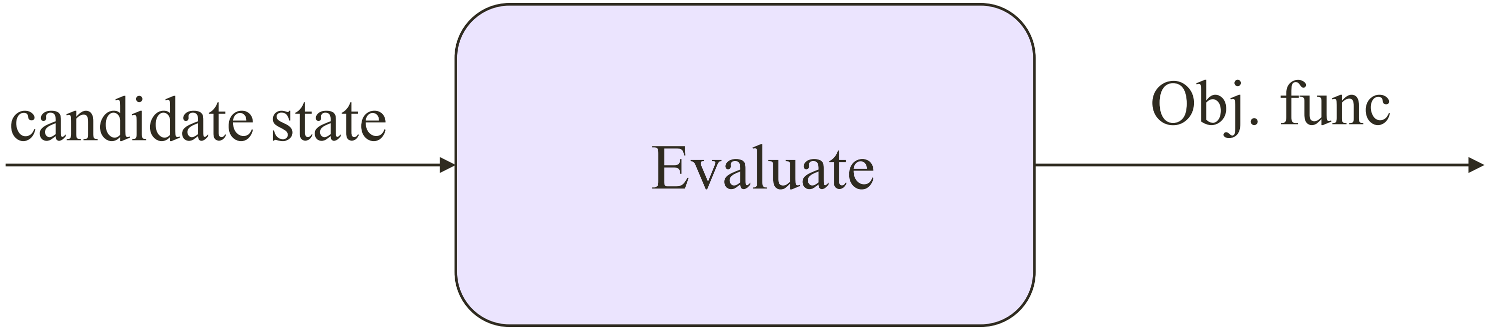
Non-classical search



- Path does not matter, just the final state
- Maximize objective function

Model

- We have a black box "evaluate" function that returns an objective function value



Application dependent fitness function

Local Hill Climbing

```
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
```

- Move in the direction of increasing value
- Very greedy
- Subject to
  - Local maxima
  - Ridges
  - Plateaux
- 8-queens: 86% failure, but only needs 4 steps to succeed, 3 to fail

Hill climbing

- Keep going on a plateau?
  - Advantage: Might find another hill
  - Disadvantage: infinite loops → limit number of moves on plateau
    - 8 queens: 94% success!!
- Stochastic hill climbing
  - randomly choose from among better successors (proportional to obj?)
- First-choice hill climbing
  - keep generating successors till a better one is generated
- Random-restarts
  - If probability of success is *p*, then we will need 1/p restarts
  - 8-queens: p = 0.14 ~= 1/7 so 7 starts
  - 6 failures (3 steps), 1 success (4 steps) = 22 steps
  - In general: Cost of success + (1-p)/p * cost of failure
  - 8-queens sideways: 0.94 success in 21 steps, 64 steps for failure
    - Under a minute

Simulated annealing

```
function SIMULATED-ANNEALING(problem, schedule) returns a solution state
  inputs: problem, a problem
          schedule, a mapping from time to "temperature"

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

- Gradient descent (not ascent)
- Accept bad moves with probability $e^{dE/T}$
- T decreases every iteration
- If *schedule(t)* is slow enough we approach finding global optimum with probability 1

Genetic Algorithms

- Stochastic hill-climbing with information exchange
- A population of stochastic hill-climbers

```
function GENETIC-ALGORITHM(population, FITNESS-FN) returns an individual
  inputs: population, a set of individuals
          FITNESS-FN, a function that measures the fitness of an individual

  repeat
     new_population ← empty set
     for i = 1 to SIZE(population) do
        x ← [redacted]-SELECTION(population, FITNESS-FN)
        y ← [redacted]-SELECTION(population, FITNESS-FN)
        child ← REPRODUCE(x, y)
        if (small random probability) then child ← MUTATE(child)
        add child to new_population
     population ← new_population
  until some individual is fit enough, or enough time has elapsed
  return the best individual in population, according to FITNESS-FN
```

```
function REPRODUCE(x, y) returns an individual
  inputs: x, y, parent individuals

  n ← LENGTH(x); c ← random number from 1 to n
  return APPEND(SUBSTRING(x, 1, c), SUBSTRING(y, c + 1, n))
```

More detailed GA

- Generate pop(0)
- Evaluate pop(0)
- T=0
- While (not converged) do
  - Select pop(T+1) from pop(T)
  - Recombine pop(T+1)
  - Evaluate pop(T+1)
  - T = T + 1
- Done

Generate pop(0)

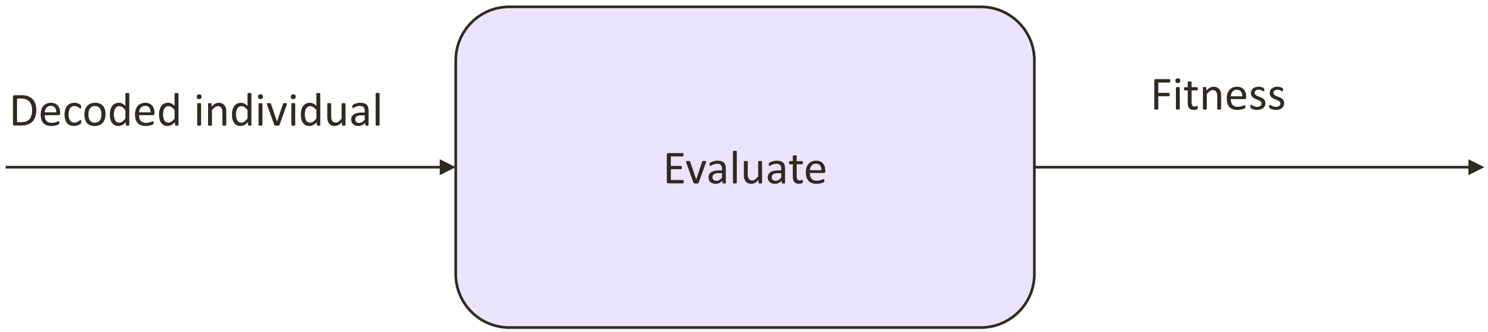
Initialize population with randomly generated strings of 1's and 0's

```
for(i = 0 ; i < popSize; i++){
  for(j = 0; j < chromLen; j++){
    Pop[i].chrom[j] = flip(0.5);
  }
}
```

Genetic Algorithm

- Generate pop(0)
- Evaluate pop(0)
- T=0
- While (not converged) do
  - Select pop(T+1) from pop(T)
  - Recombine pop(T+1)
  - Evaluate pop(T+1)
  - T = T + 1
- Done

Evaluate pop(0)



Application dependent fitness function

Genetic Algorithm

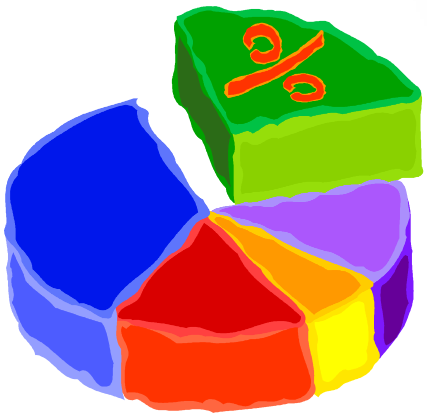
- Generate pop(0)
- Evaluate pop(0)
- T=0
- While (T < maxGen) do
  - Select pop(T+1) from pop(T)
  - Recombine pop(T+1)
  - Evaluate pop(T+1)
  - T = T + 1
- Done

Genetic Algorithm

- Generate pop(0)
- Evaluate pop(0)
- T=0
- While (T < maxGen) do
  - Select pop(T+1) from pop(T)
  - Recombine pop(T+1)
  - Evaluate pop(T+1)
  - T = T + 1
- Done

Selection

- Each member of the population gets a share of the pie proportional to fitness relative to other members of the population
- Spin the roulette wheel pie and pick the individual that the ball lands on
- Focuses search in promising areas



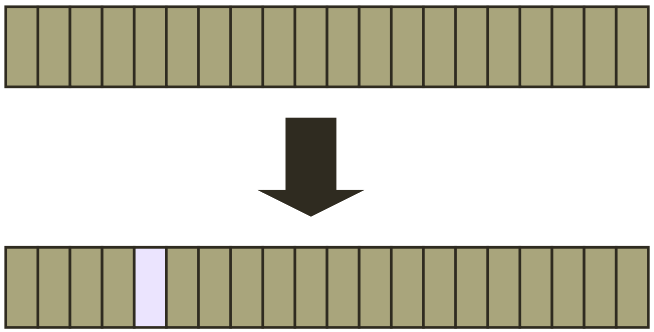
Code

```
int roulette(IPTR pop, double sumFitness, int popsize)
{

  /* select a single individual by roulette wheel selection */

  double rand,partsum;
  int i;

  partsum = 0.0; i = 0;
  rand = f_random() * sumFitness;

  i = -1;
  do{
    i++;
    partsum += pop[i].fitness;
  } while (partsum < rand && i < popsize - 1) ;

  return i;
}
```

Genetic Algorithm

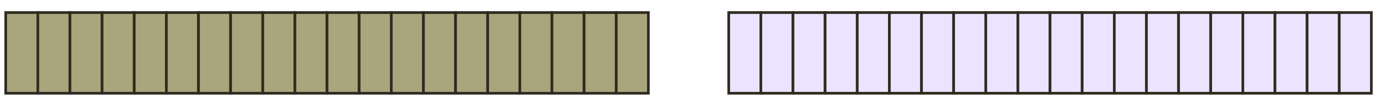
- Generate pop(0)
- Evaluate pop(0)
- T=0
- While (T < maxGen) do
  - Select pop(T+1) from pop(T)
  - Recombine pop(T+1)
  - Evaluate pop(T+1)
  - T = T + 1
- Done

Crossover and mutation



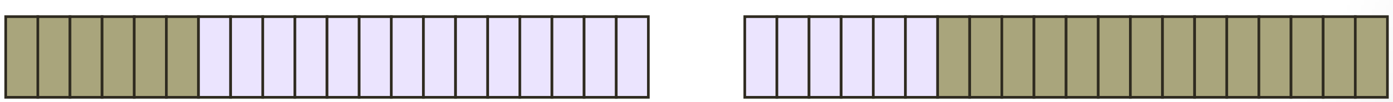
Mutation Probability = 0.001

Insurance



Xover Probability = 0.7

Exploration operator



Crossover code

```
void crossover(POPULATION *p, IPTR p1, IPTR p2, IPTR c1, IPTR c2)
{
/* p1,p2,c1,c2,m1,m2,mc1,mc2 */
  int *pi1,*pi2,*ci1,*ci2;
  int xp, i;

  pi1 = p1->chrom;
  pi2 = p2->chrom;
  ci1 = c1->chrom;
  ci2 = c2->chrom;

  if(flip(p->pCross)){

    xp = rnd(0, p->lchrom - 1);
    for(i = 0; i < xp; i++){
      ci1[i] = muteX(p, pi1[i]);
      ci2[i] = muteX(p, pi2[i]);
    }
    for(i = xp; i < p->lchrom; i++){
      ci1[i] = muteX(p, pi2[i]);
      ci2[i] = muteX(p, pi1[i]);
    }
  } else {
    for(i = 0; i < p->lchrom; i++){
      ci1[i] = muteX(p, pi1[i]);
      ci2[i] = muteX(p, pi2[i]);
    }
  }
}
```

Mutation code

```
int muteX(POPULATION *p, int pa)
{
  return (flip(p->pMut) ? 1 - pa  : pa);
}
```

Search

- Problem solving by searching for a solution in a space of possible solutions
- Uninformed versus Informed search
- Atomic representation of state
- Solutions are fixed sequences of actions