1. Uninformed Search

1.1 BFS, DFS

```
def BFS(init_state):

  q = Queue()
  q.push(init_state)

  while q is not empty:
    state = q.pop()
    viz[state] = 1

    if is_final(state):
       print(state)

    for each neigh of state:
       if is_valid(neigh) and not viz[neigh]:
          q.push(neigh)
```

```
def DFS(init_state):

  s = Stack()
  s.push(init_state)

  while s is not empty:
    state = s.pop()
    viz[state] = 1

    if is_final(state):
       print(state)

    for each neigh of state:
       if is_valid(neigh) and not viz[neigh]:
          s.push(neigh)
```

These versions may reintroduce states in the queue/stack.

1.2 Uniform Cost Search (UCS)

- In BFS, nodes are visited based on the number of the transitions from the initial state
- In Uniform cost search, nodes are visited based on the distance from the initial state
- If all transitions have same cost => BFS = Uniform Cost Search
- Finishing when removing final state from PQ, not when inserting it -> better paths can be found

```
def uniform_cost(init_state):

   d = {}
   d [init_state] = 0
   pq = priorityQueue() # ordered by d (min extracted first)
   pq.insert((init_state, d[init_state]))

   while pq is not empty:
        state = pq.pop()
        viz[state] = 1

        if is_final(state):
            return state

        for each neighbor of state:
            if is_valid(neighbor):
               if (not neighbor in pq) and (not viz[neighbor]):
                  d[neighbor] = d[state] + dist(neighbor, state)
                  pq.insert((neighbor, d[neighbor]))
               elif neighbor in pq:
                  d[neighbor] = min(d[neighbor], d[state] + dist(neighbor, state))
                  update d for neighbor in pq

   return None
```

1.3 IDDFS (Iterative Deepening Depth First Search)

- Combines the space efficiency of DFS with the fast search of states near the current state of BFS
- DFS executed in a BFS manner

```
def IDDFS(init_state, max_depth):
  for depth from 0 to max_depth:
      visited = {}
      sol = depth_limited_DFS(init_state, depth, visited):
      if sol is not None:
          return sol
  return None
```

1.4 BKT

- Difference from DFS: no need to retain visited states to avoid loops.
- One of the most computationally expensive strategies

```
def BKT(partial_solution):

   if (is_complete(partial_solution)):
      return partial_solution

   for each solution in successors(partial_solution):
       if is_valid(solution):

          res = BKT(solution)
          if res:
             return res
   return None

BKT(empty_solution)
```

1.5 Bidirectional Search

- The search is done starting from both the initial & the final state(s) with an algorithm (BFS/DFS)
- Sometimes, it is hard to define reverse transitions to reconstruct the solution
- If BFS is used, the path between the initial state and a final state has minimum number of transitions

Pseudocode using BFS (Only one final state is considered. Each BFS has associated its own queue and its own visited vector):

```
def Bidirectional_search(init_state, final_state):

   f_q = Queue(); f_q.push(init_state)
   b_q = Queue(); b_q.push(final_state)
   f_came_from = {}
   b_came_from = {}

   while not f_q.empty() and not b_q.empty():
```

```
        f_state = f_q.pop()
        viz[f_state] = 1

        if(is_final(f_state) or (viz_b[f_state]=1)):
           return reconstruct_path(f_state, b_state, f_came_from, b_came_from)

        for each neighbor of f_state: #direct transitions
           if is_valid(neighbor) and not f_viz[neighbor]:
              f_q.push(neighbor)
              f_came_from[neighbor]=f_state

        b_state = b_q.pop()
        b_viz[b_state] = 1

        if(is_initial(b_state) or (viz_f[b_state]=1)):
           return reconstruct_path(f_state, b_state, f_came_from, b_came_from)

        for each r_neighbor of b_state: #reverse transitions
           if is_valid(r_neighbor) and not b_viz[r_neighbor]:
              b_q.push(r_neighbor)
              b_came_from[r_neighbor]=b_state

  return None
```

2. **Informed Search**

2.1 Greedy Best First

- Evaluate **all unexplored states accessible from the current state**
- Select the unexplored state closer to the goal (the heuristic value indicates the closeness to the goal).

```
def greedy(init_state):
    pq = priorityQueue() #ordered by heuristic value
    pq.insert( (init_state, heur_val(init_state)) )

    while pq is not empty:
         state = pq.pop() #state with the best heuristic value
         viz[state] = 1

         if is_final(state):
             return state

         for each neighbor of state:
            if (is_valid(neighbor) and
               (neighbor not in viz) and (neigbor not in pq)):

                pq.insert( (neighbor, heur_val(neighbor)) )
    return None
```

2.2 Hill Climbing

- It is a trajectory method (at each step, only a single state is retained)
- Can get stuck in local optima
- One difference from Greedy: In HC we select the next state to be at least as good as the current one. In Greedy, we can select a next state without being better than the current one.
- Multiple ways to select of the next state from the eligible neighbors: best neighbor / first neighbor / all neighbors in order (hillclimbing-backtracking).
- Debate between using:
  h(neighbor) >= h(current_state) (AI) vs h(neighbor) > h(current_state) (GA)

```
def HC(init_state):
    state=init_state

    while(not is_final(state)):
      eligible_neighbors = []
     for each neighbor of state:
        if valid(neighbor) and h(neighbor) >= h(current_state):
           eligible_neighbors.push(neighbor)
      if eligible_neighbors is empty:
        return None
      state = choose(eligible_neighbors)
```

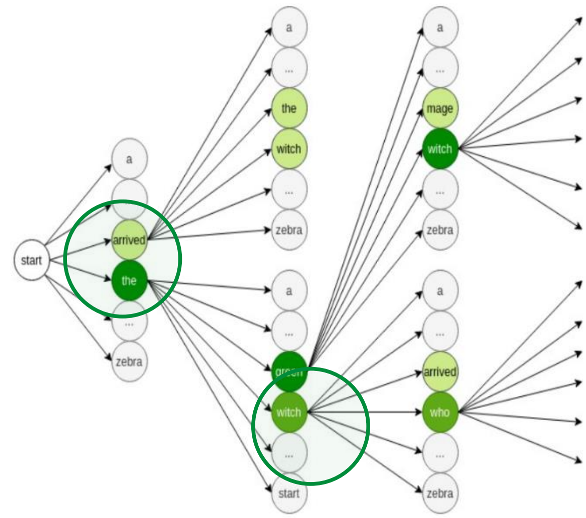
2.3 Simulated Annealing

- It is a trajectory method (at each step, only a single state is retained)
- Difference from HC: sometimes, we can go in worse states with a probability p (that decreases in time)
- Can get stuck in local optima (but is better at escaping from local optima than HC)

```
def SA(init_state):
    state=init_state
    init temperature T

    while(not stop criteria): #e.g., T>0
        neighbor = random valid neighbor of state

        if h(neighbor)> h(current_state):
           state = neighbor

        else with probability p: #high T -> high p, low T -> low p
           state = neighbor

        update temperature T
```

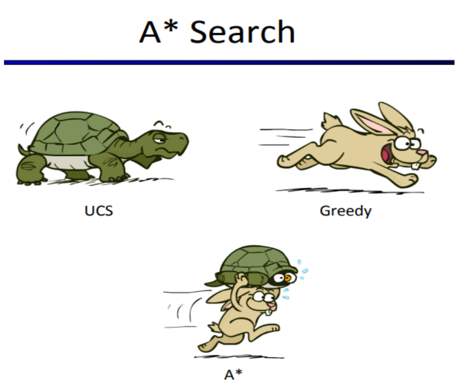
2.4 Beam Search

- Modification of BFS: only best k visited states are retained (in a *beam*), ordered based on the heuristic value
- The final state should be the first in the beam (best heuristic value)




```
def Beam_Search(init_state):
    beam = PriorityQueue()
    beam.push(init_state, h(init_state))
    viz = {}
    viz[init_state] = 1

    while(beam is not empty):

        if is_final(beam.first()):
              return beam.first()

        new_beam = PriorityQueue()
        for state in beam:
            for neighbor of state:
                if (is_valid(neighbor) and not viz[neighbor]):
                    viz[neighbor] = 1
                    new_beam.push(neighbor, h(neighbor))

        beam = new_beam.top(k)
```

2.5 [A*]



- Combines Uniform Cost Search (Dijkstra) + a heuristic
- Dijkstra (distances to all nodes) vs Uniform Cost (dist. to goal)
- At each step we consider the state S, such that the length of the path from the initial state to the goal, which passes through S, is minimum.
  - f[S] = d[S] + h(S) (the length of the path)
  - d[S] = distance from the initial state to S (updated according to Uniform Cost Search)
  - h(S) = heuristic function approximating the distance from S to the goal
- To find the shortest path from an initial state, A* needs an admissible heuristic
- "An admissible heuristic never overestimates the shortest distance between a state and the goal."
- A consistent heuristic satisfies: h(A) <= dist(A, B) + h(B) if B is reachable from A, where:
  - h(X) = distance from state X to the goal
  - dist(X,Y) = distance between X and Y (e.g., we can consider it being the number of moves to reach Y from X).
- A consistent heuristic is also admissible.

For tests/ the final exam, use A* version from the course, not this one.
The course version is more efficient.

A beginner friendly version, resembling in some ways the ones from here and here is:

```
def A_star(init_state):
    came_from = {}
    d = {}
    f = {}
    d[init_state] = 0
    f[init_state] = h(init_state)

    pq = priorityQueue() #ordered by f, min value first
    pq.insert((init_state, f[init_state]))

    while pq is not empty:
         state = pq.pop()

         for each neighbor of state
             if is_valid(neighbor) and
               ( neighbor not in d or
                 d[neighbor] > d[state] + dist(neighbor, state) ):

                d[neighbor] = d[state] + dist(neighbor, state)
                f[neighbor] = d[neighbor] + h(neighbor)
                came_from[neighbor] = state

                pq.insert((neighbor, f[neighbor]))

    return None
```

Obs1: Do not stop when encountering the final state (but when finding the shortest path)

3. **Algorithms' properties**

Alg.	Always finds a solution	Solution found in minimum number of transitions/ at minimum distance from the initial state	Needs to mark visited states to not revisit them again	Advantages Disadvantages
Random	✗ (the algorithm is stopped after a number of steps and all solutions might be in an unexplored region)	✗	✗ (states can be revisited)	1. The path towards the solution may be very long; states may be revisited 2. Some search regions might be avoided if we stop after a certain number of transitions
DFS	✓ (exception: infinite graphs)	✗	✓	1. In some cases, it can be fast even if a solution is not close to the initial state 1. Memory costly 2. May be slow even though there is a solution close to the initial state
BFS	✓ (exception: infinite graphs)	✓ (minimum nb. of transitions)	✓	1. Fast if a solution is close to the initial state 1. Memory costly 2. Slow if all solutions are far away from the initial state
Uniform cost	✓ (exceptions: infinite graphs, negative cycles)	✓ (minimum distance)	✗ (states can be revisited)	1. Can determine the/a solution with minimum distance from the initial state 1. Doesn't stop if it enters a cycle with negative costs on the edges
BKT	✓ (exception: infinite graphs)	✗	✗ (it does not revisit states due to the way the partial solution is constructed)	1. It does not need to memorize visited states to avoid loops (revisiting states) 1. Slow approach
IDDFS	✗ (the algorithm is stopped after reaching a max. depth and all solutions might be in an unexplored region)	✓ (minimum nb. of transitions)	✓	1. Much more memory efficient than BFS. Also, the DFS is depth limited. 2. Many nodes are revisited as we increase the depth.

Bidirectional	✓ (exception: infinite graphs)	If the used algorithm is BFS, then ✓ (minimum nb. of transitions)	✓ (two visited vectors are needed, one for each side)	1. Sometimes it is hard to define the reverse transitions 2. Needs to memorize visited states
Greedy Best First	✓ (exception: infinite graphs)	✗	✓ (if we do not keep the evidence of the visited nodes, we might get stuck in a loop)	1. Fast strategy 2. At worst: DFS with bad choices
Hill Climbing	✗ (trajectory method)	✗	✗	1. Fastest strategy 1. Can get stuck in local optima
Simulated Annealing	✗ (trajectory method)	✗	✗	1. Fast strategy 2. Better at avoid local optima than Hill Climbing, but still can get stuck
Beam Search	✗ (only a subspace is explored)	✗	✓	1. More time and space efficient than BFS 1. Might not find a solution
A*	✓ (exception: infinite graphs, negative cycles)	✓ (minimum distance) only if the heuristic is admissible	✗ (states can be revisited)	1. Combines advantages of Greedy Best First and Uniform Cost Search 1. Might not be very time and space efficient