Lecture 5: Search I

- When you solve this problem, try to think about how you did it. You probably simulated the scenario in your head, trying to send the farmer over with the goat and observing the consequences. If nothing got eaten, you might continue with the next action. Otherwise, you undo that move and try something else.
- But the point is not for you to be able to solve this one problem manually. The real question is: How can we get a machine to do solve all problems like this automatically? One of the things we need is a systematic approach that considers all the possibilities. We will see that search problems define the possibilities, and search algorithms explore these possibilities.

This example, taken from xkcd, points out the cautionary tale that sometimes you can do better if you change the model (perhaps the value of having a wolf is zero) instead of focusing on the algorithm.

Question
A farmer wants to get his cabbage, goat, and wolf across a river. He has a boat that only holds two. He cannot leave the cabbage and goat alone or the goat and wolf alone. How many river crossings does he need?

4
5
6
7
no solution

Course plan

Reflex
Search problems
Markov decision processes
Adversarial games
States
Constraint satisfaction problems
Variables
Bayesian networks
Logic

"Low-level intelligence"
"High-level intelligence"

Machine learning
So far, we have worked with only the simplest types of models — reflex models. We used these as a starting point to explore machine learning. Now we will proceed to the first type of state-based models, search problems.

Application: route finding

Objective: shortest? fastest? most scenic?

Actions: go straight, turn left, turn right

Route finding is perhaps the most canonical example of a search problem. We are given as the input a map, a source point and a destination point. The goal is to output a sequence of actions (e.g., go straight, turn left, or turn right) that will take us from the source to the destination.

We might evaluate action sequences based on an objective (distance, time, or pleasantness).

Application: solving puzzles

Objective: reach a certain configuration

Actions: move pieces (e.g., Move12Down)

In robot motion planning, the goal is to get a robot to move from one position/pose to another. The desired output trajectory consists of individual actions, each action corresponding to moving or rotating the joints by a small amount.

Again, we might evaluate action sequences based on various resources like time or energy.

Application: robot motion planning

Objective: fastest? most energy efficient? safest?

Actions: translate and rotate joints

In robot motion planning, the goal is to get a robot to move from one position/pose to another. The desired output trajectory consists of individual actions, each action corresponding to moving or rotating the joints by a small amount.

Again, we might evaluate action sequences based on various resources like time or energy.
• In solving various puzzles, the output solution can be represented by a sequence of individual actions. In the Rubik’s cube, an action is rotating one slice of the cube. In the 15-puzzle, an action is moving one square to an adjacent free square.
• In puzzles, even finding one solution might be an accomplishment. The more ambitious might want to find the best solution (say, minimize the number of moves).

Application: machine translation

la maison bleue

the blue house

Objective: fluent English and preserves meaning

Actions: append single words (e.g., the)

Beyond reflex

Classifier (reflex-based models):

\[ x \rightarrow f \rightarrow \text{single action } y \in \{-1, +1\} \]

Search problem (state-based models):

\[ x \rightarrow f \rightarrow \text{action sequence } (a_1, a_2, a_3, a_4, \ldots) \]

Key: need to consider future consequences of an action!

Paradigm

Modeling

Inference

Learning

Last week, we finished our tour of machine learning of reflex-based models (e.g., linear predictors and neural networks) that output either a +1 or −1 (for binary classification) or a real number (for regression).

While reflex-based models were appropriate for some applications such as sentiment classification or spam filtering, the applications we will look at today, such as solving puzzles, demand more.

To tackle these new problems, we will introduce search problems, our first instance of a state-based model.

In a search problem, in a sense, we are still building a predictor \( f \) which takes an input \( x \), but \( f \) will now return an entire action sequence, not just a single action. Of course you should object: can’t I just apply a reflex model iteratively to generate a sequence? While that is true, the search problems that we’re trying to solve importantly require reasoning about the consequences of the entire action sequence, and cannot be tackled by myopically predicting one action at a time.

Tangent: Of course, saying “cannot” is a bit strong, since sometimes a search problem can be solved by a reflex-based model. You could have a massive lookup table that told you what the best action was for any given situation. It is interesting to think of this as a time/memory tradeoff where reflex-based models are performing an implicit kind of caching. Going on a further tangent, one can even imagine compiling a state-based model into a reflex-based model; if you’re walking around Stanford for the first time, you might have to really plan things out, but eventually it kind of becomes reflex.

We have looked at many real-world examples of this paradigm. For each example, the key is to decompose the output solution into a sequence of primitive actions. In addition, we need to think about how to evaluate different possible outputs.
Recall the modeling-inference-learning paradigm. For reflex-based classifiers, modeling consisted of choosing the features and the neural network architecture; inference was trivial forward computation of the output given the input; and learning involved using stochastic gradient descent on the gradient of the loss function, which might involve backpropagation.

Today, we will focus on the modeling and inference part of search problems. The next lecture will cover learning.

Farmer Cabbage Goat Wolf

Actions:

- $F\triangleright$: build a search tree (“what if?”)

Approach: build a search tree (“what if?”)

Search problem

- $s_{start}$: starting state
- $\text{Actions}(s)$: possible actions
- $\text{Cost}(s, a)$: action cost
- $\text{Succ}(s, a)$: successor
- $\text{IsEnd}(s)$: reached end state

Definition: search problem

Roadmap

- Tree search
- Dynamic programming
- Uniform cost search
We will build what we will call a search tree. The root of the tree is the start state $s_{\text{start}}$, and the leaves are the end states ($\text{IsEnd}(s) = \text{true}$). Each edge leaving a node $s$ corresponds to a possible action $a \in \text{Actions}(s)$ that could be performed in state $s$. The edge is labeled with the action and its cost, written $a : \text{Cost}(s, a)$. The action leads deterministically to the successor state $\text{Succ}(s, a)$, represented by the child node.

In summary, each root-to-leaf path represents a possible action sequence, and the sum of the costs of the edges is the cost of that path. The goal is to find the root-to-leaf path that ends in a valid end state with minimum cost. Note that in code, we usually do not build the search tree as a concrete data structure. The search tree is used merely to visualize the computation of the search algorithms and study the structure of the search problem.

For the boat crossing example, we have assumed each action (a safe river crossing) costs 1 unit of time. We disallow actions that return us to an earlier configuration. The green nodes are the end states. The red nodes are not end states but have no successors (they result in the demise of some animal or vegetable). From this search tree, we see that there are exactly two solutions, each of which has a total cost of 7 steps.

Now let’s consider another problem and practice modeling it as a search problem. Recall that this means specifying precisely what the states, actions, goals, costs, and successors are.

To avoid the ambiguity of natural language, we will do this directly in code, where we define a SearchProblem class and implement the methods: startState, isEnd and succAndCost.

Let’s put modeling aside and suppose we are handed a search problem. How do we construct an algorithm for finding a minimum cost path (not necessarily unique)?

We will start with backtracking search, the simplest algorithm which just tries all paths. The algorithm is called recursively on the current state $s$ and the path leading up to that state. If we have reached a goal, then we can update the minimum cost path with the current path. Otherwise, we consider all possible actions $a$ from state $s$, and recursively search each of the possibilities.

Graphically, backtracking search performs a depth-first traversal of the search tree. What is the time and memory complexity of this algorithm?

To get a simple characterization, assume that the search tree has maximum depth $D$ (each path consists of $D$ actions/edges) and that there are $b$ available actions per state (the branching factor is $b$).

It is easy to see that backtracking search only requires $O(D)$ memory (to maintain the stack for the recurrence), which is as good as it gets.

However, the running time is proportional to the number of nodes in the tree, since the algorithm needs to check each of them. The number of nodes is $1 + b + b^2 + \ldots + b^D = b^{D+1} - 1 = O(b^D)$. Note that the total number of nodes in the search tree is on the same order as the number of leaves, so the cost is always dominated by the last level.

In general, there might not be a finite upper bound on the depth of a search tree. In this case, there are two options: (i) we can simply cap the maximum depth and give up after a certain point or (ii) we can disallow visits to the same state.

It is worth mentioning that the greedy algorithm that repeatedly chooses the lowest action myopically won’t work. Can you come up with an example?

### Transportation example

**Example: transportation**

Street with blocks numbered 1 to $n$.
Walking from $s$ to $s+1$ takes 1 minute.
Taking a magic tram from $s$ to $2s$ takes 2 minutes.
How to travel from 1 to $n$ in the least time?

[live solution: TransportationProblem]

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### Backtracking search

**Algorithm: backtracking search**

```python
def backtrackingSearch(s, path):
    if isEnd(s):
        update minimum cost path
    for each action $a \in \text{Actions}(s)$:
        extend path with $\text{Succ}(s, a)$ and $\text{Cost}(s, a)$
        call backtrackingSearch($\text{Succ}(s, a)$, path)
    return minimum cost path
```

[live solution: backtrackingSearch]
**Depth-first search**

Assumption: zero action costs

Assume action costs $\text{Cost}(s,a) = 0$.

Idea: Backtracking search + stop when find the first end state.

If $b$ actions per state, maximum depth is $D$ actions:
- **Space**: still $O(D)$
- **Time**: still $O(b^D)$ worst case, but could be much better if solutions are easy to find.

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**Breadth-first search**

Assumption: constant action costs

Assume action costs $\text{Cost}(s,a) = c$ for some $c \geq 0$.

Idea: explore all nodes in order of increasing depth.

Legend: $b$ actions per state, solution has $d$ actions

- **Space**: now $O(b^d)$ (a lot worse!)
- **Time**: $O(b^d)$ (better, depends on $d$, not $D$)

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**DFS with iterative deepening**

Assumption: constant action costs

Assume action costs $\text{Cost}(s,a) = c$ for some $c \geq 0$.

Idea:
- Modify DFS to stop at a maximum depth.
- Call DFS for maximum depths $1, 2, \ldots$

DFS on $d$ asks: is there a solution with $d$ actions?

Legend: $b$ actions per state, solution size $d$

- **Space**: $O(d)$ (saved!)
- **Time**: $O(b^d)$ (same as BFS)

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- Backtracking search will always work (i.e., find a minimum cost path), but there are cases where we can do it faster. But in order to do that, we need some additional assumptions — there is no free lunch.
- Suppose we make the assumption that all the action costs are zero. In other words, all we care about is finding a valid action sequence that reaches the goal. Any such sequence will have the minimum cost: zero.
- In this case, we can just modify backtracking search to not keep track of costs and then stop searching as soon as we reach a goal. The resulting algorithm is depth-first search (DFS), which should be familiar to you. The worst time and space complexity are of the same order as backtracking search. In particular, if there is no path to an end state, then we have to search the entire tree.
- However, if there are many ways to reach the end state, then we can stop much earlier without exhausting the search tree. So DFS is great when there are an abundance of solutions.

- Breadth-first search (BFS), which should also be familiar, makes a less stringent assumption, that all the action costs are the same non-negative number. This effectively means that all the paths of a given length have the same cost.
- BFS maintains a queue of states to be explored. It pops a state off the queue, then pushes its successors back on the queue.
- BFS will search all the paths consisting of one edge, two edges, three edges, etc., until it finds a path that reaches an end state. So if the solution has $d$ actions, then we only need to explore $O(b^d)$ nodes, thus taking that much time.
- However, a potential show-stopper is that BFS also requires $O(b^d)$ space since the queue must contain all the nodes of a given level of the search tree. Can we do better?

- Yes, we can do better with a trick called iterative deepening. The idea is to modify DFS to make it stop after reaching a certain depth. Therefore, we can invoke this modified DFS to find whether a valid path exists with at most $d$ edges, which as discussed earlier takes $O(d)$ space and $O(b^d)$ time.
- Now the trick is simply to invoke this modified DFS with cutoff depths of $1, 2, \ldots$ until we find a solution or give up. This algorithm is called DFS with iterative deepening (DFS-ID). In this manner, we are guaranteed optimality when all action costs are equal (like BFS), but we enjoy the parsimonious space requirements of DFS.
- One might worry that we are doing a lot of work, searching some nodes many times. However, keep in mind that both the number of leaves and the number of nodes in a search tree is $O(b^d)$ so asymptotically DFS with iterative deepening is the same time complexity as BFS.
Tree search algorithms

Legend: $b$ actions/state, solution depth $d$, maximum depth $D$

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Action costs</th>
<th>Space</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>DFS</td>
<td>zero</td>
<td>$O(D)$</td>
<td>$O(b^D)$</td>
</tr>
<tr>
<td>BFS</td>
<td>constant $\geq 0$</td>
<td>$O(b^d)$</td>
<td>$O(b^d)$</td>
</tr>
<tr>
<td>DFS-ID</td>
<td>constant $\geq 0$</td>
<td>$O(d)$</td>
<td>$O(b^D)$</td>
</tr>
<tr>
<td>Backtracking</td>
<td>any</td>
<td>$O(D)$</td>
<td>$O(b^D)$</td>
</tr>
</tbody>
</table>

- Always exponential time
- Avoid exponential space with DFS-ID

Roadmap

- Tree search
- Dynamic programming
- Uniform cost search

Dynamic programming

Minimum cost path from state $s$ to a end state:

$$\text{FutureCost}(s) = \begin{cases} 
0 & \text{if IsEnd}(s) \\
\min_{a \in \text{Actions}(s)} \{ \text{Cost}(s, a) + \text{FutureCost}(\text{Succ}(s, a)) \} & \text{otherwise}
\end{cases}$$

Motivating task

**Example: route finding**

Find the minimum cost path from city 1 to city $n$, only moving forward. It costs $c_{ij}$ to go from $i$ to $j$.

Observation: future costs only depend on current city
Now let us see if we can avoid the exponential time. If we consider the simple route finding problem of traveling from city 1 to city n, the search tree grows exponentially with n.

However, upon closer inspection, we note that this search tree has a lot of repeated structures. Moreover (and this is important), the future costs (the minimum cost of reaching a end state) of a state only depends on the current city! So therefore, all the subtrees rooted at city 5, for example, have the same minimum cost!

If we can just do that computation once, then we will have saved big time. This is the central idea of dynamic programming.

We’ve already reviewed dynamic programming in the first lecture. The purpose here is to construct one generic dynamic programming solution that will work on any search problem. Again, this highlights the useful division between modeling (defining the search problem) and algorithms (performing the actual search).

Let us collapse all the nodes that have the same city into one. We no longer have a tree, but a directed acyclic graph with only n nodes rather than exponential in n nodes.

Note that dynamic programming is only useful if we can define a search problem where the number of states is small enough to fit in memory.

The dynamic programming algorithm is exactly backtracking search with one twist. At the beginning of the function, we check to see if we’ve already computed the future cost for s. If we have, then we simply return it (which takes constant time if we use a hash map). Otherwise, we compute it and save it in the cache so we don’t have to recompute it again. In this way, for every state, we are only computing its value once.

For this particular example, the running time is \(O(n^2)\), the number of edges.

One important point is that the graph must be acyclic for dynamic programming to work. If there are cycles, the computation of a future cost for \(s\) might depend on \(s'\) which might depend on \(s\). We will infinite loop in this case. To deal with cycles, we need uniform cost search, which we will describe later.

### Dynamic programming

**State:** past sequence of actions, current city

- Now let us see if we can avoid the exponential time. If we consider the simple route finding problem of traveling from city 1 to city n, the search tree grows exponentially with n.
- Let us collapse all the nodes that have the same city into one. We no longer have a tree, but a directed acyclic graph with only n nodes rather than exponential in n nodes.
- Note that dynamic programming is only useful if we can define a search problem where the number of states is small enough to fit in memory.

The dynamic programming algorithm is exactly backtracking search with one twist. At the beginning of the function, we check to see if we’ve already computed the future cost for \(s\). If we have, then we simply return cached answer. If IsEnd\((s)\): return solution

For each action \(a \in \text{Actions}(s)\): ...

[ live solution ]

### Assumption: acyclicity

The state graph defined by \(\text{Actions}(s)\) and \(\text{Succ}(s, a)\) is acyclic.

### Key idea: state

A **state** is a summary of all the past actions sufficient to choose future actions **optimally**.

<table>
<thead>
<tr>
<th>past actions (all cities)</th>
<th>1 3 4 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>state (current city)</td>
<td>1 3 4 6</td>
</tr>
</tbody>
</table>
• So far, we have only considered the example where the cost only depends on the current city. But let’s try
to capture exactly what’s going on more generally.
• This is perhaps the most important idea of this lecture: state. A state is a summary of all the past actions
sufficient to choose future actions optimally.
• What state is really about is forgetting the past. We can’t forget everything because the action costs in
the future might depend on what we did on the past. The more we forget, the fewer states we have, and
the more efficient our algorithm. So the name of the game is to find the minimal set of states that suffice.
It’s a fun game.

Handling additional constraints

Example: route finding
Find the minimum cost path from city 1 to city n, only moving forward. It costs $c_{ij}$ to go from $i$ to $j$.

Constraint: Can’t visit three odd cities in a row.

State: (whether previous city was odd, current city)

Let’s add a constraint that says we can’t visit three odd cities in a row. If we only keep track of the current
city, and we try to move to a next city, we cannot enforce this constraint because we don’t know what the
previous city was. So let’s add the previous city into the state.

This will work, but we can actually make the state smaller. We only need to keep track of whether the
previous city was an odd numbered city to enforce this constraint.

Note that in doing so, we have $2n$ states rather than $n^2$ states, which is a substantial savings. So the
lesson is to pay attention to what information you actually need in the state.

State graph

State: (min(number of odd cities visited, 3), current city)

Our first thought might be to remember how many odd cities we have visited so far (and the current city).
But if we’re more clever, we can notice that once the number of odd cities is 3, we don’t need to
keep track of whether that number goes up to 4 or 5, etc. So the state we actually need to keep is
(min(number of odd cities visited, 3), current city). Thus, our state space is $O(n)$ rather than $O(n^2)$.

We can visualize what augmenting the state does to the state graph. Effectively, we are copying each node
4 times, and the edges are redirected to move between these copies.

Note that some states such as (2, 1) aren’t reachable (if you’re in city 1, it’s impossible to have visited 2
odd cities already); the algorithm will not touch those states and that’s perfectly okay.

Question

Objective: travel from city 1 to city n, visiting at least 3 odd cities.

What is the minimal state?
Question

Objective: travel from city 1 to city n, visiting more odd than even cities. What is the minimal state?

State: summary of past actions sufficient to choose future actions optimally

Dynamic programming: backtracking search with memoization — potentially exponential savings

Summary

Dynamic programming only works for acyclic graphs...what if there are cycles?

Ordering the states

Observation: prefixes of optimal path are optimal

Key: if graph is acyclic, dynamic programming makes sure we compute PastCost(s) before PastCost(s')

If graph is cyclic, then we need another mechanism to order states...

Roadmap

Tree search

Dynamic programming

Uniform cost search

• An initial guess might be to keep track of the number of even cities and the number of odd cities visited.
• But we can do better. We have to just keep track of the number of odd cities minus the number of even cities and the current city. We can write this more formally as (n1 - n2, current city), where n1 is the number of odd cities visited so far and n2 is the number of even cities visited so far.

• Recall that we used dynamic programming to compute the future cost of each state s, the cost of the minimum cost path from s to a end state.
• We can analogously define PastCost(s), the cost of the minimum cost path from the start state to s. If instead of having access to the successors via Succ(s,a), we had access to predecessors (think of reversing the edges in the state graph), then we could define a dynamic program to compute all the PastCost(s).
• Dynamic programming relies on the absence of cycles, so that there is always a clear order in which to compute all the past costs. If the past costs of all the predecessors of a state s are computed, then we could compute the past cost of s by taking the minimum.
• Note that PastCost(s) will always be computed before PastCost(s') if there is an edge from s to s'. In essence, the past costs will be computed according to a topological ordering of the nodes.
• However, when there are cycles, no topological ordering exists, so we need another way to order the states.
Uniform cost search (UCS)

Key idea: state ordering
UCS enumerates states in order of increasing past cost.

Assumption: non-negativity
All action costs are non-negative: Cost(s, a) ≥ 0.

UCS in action:

High-level strategy
Frontier
Explored
Unexplored

- Explored: states we’ve found the optimal path to
- Frontier: states we’ve seen, still figuring out how to get there cheaply
- Unexplored: states we haven’t seen

Uniform cost search example

Example: UCS example

Start state: A, end state: D

Minimum cost path:
A → B → C → D with cost 3
Uniform cost search (UCS)

Algorithm: uniform cost search [Dijkstra, 1956]

Add \( s_{\text{start}} \) to frontier (priority queue)
Repeat until frontier is empty:
  Remove \( s \) with smallest priority \( p \) from frontier
  If IsEnd(\( s \)):
    return solution
  Add \( s \) to explored
  For each action \( a \in \text{Actions}(s) \):
    Get successor \( s' \leftarrow \text{Succ}(s, a) \)
    If \( s' \) already in explored: continue
  Update frontier with \( s' \) and priority \( p + \text{Cost}(s, a) \)

Analysis of uniform cost search

Theorem: correctness
When a state \( s \) is popped from the frontier and moved to explored,
its priority is \( \text{PastCost}(s) \), the minimum cost to \( s \).

Proof:

DP versus UCS

\( N \) total states, \( n \) of which are closer than end state

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Cycles?</th>
<th>Action costs</th>
<th>Time/space</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP</td>
<td>no</td>
<td>any</td>
<td>( O(N) )</td>
</tr>
<tr>
<td>UCS</td>
<td>yes</td>
<td>( \geq 0 )</td>
<td>( O(n \log n) )</td>
</tr>
</tbody>
</table>

Note: UCS potentially explores fewer states, but requires more overhead
to maintain the priority queue

Note: assume number of actions per state is constant (independent of \( n \) and \( N \))
Summary

- **Tree search**: memory efficient, suitable for huge state spaces but exponential worst-case running time

- **State**: summary of past actions sufficient to choose future actions optimally

- **Graph search**: dynamic programming and uniform cost search construct optimal paths (exponential savings!)

- **Next time**: learning action costs, searching faster with A*

We started out with the idea of a search problem, an abstraction that provides a clean interface between modeling and algorithms.

- Tree search algorithms are the simplest: just try exploring all possible states and actions. With backtracking search and DFS with iterative deepening, we can scale up to huge state spaces since the memory usage only depends on the number of actions in the solution path. Of course, these algorithms necessarily take exponential time in the worst case.

- To do better, we need to think more about bookkeeping. The most important concept from this lecture is the idea of a state, which contains all the information about the past to act optimally in the future. We saw several examples of traveling between cities under various constraints, where coming up with the proper minimal state required a deep understanding of search.

- With an appropriately defined state, we can apply either dynamic programming or UCS, which have complementary strengths. The former handles negative action costs and the latter handles cycles. Both require space proportional to the number of states, so we need to make sure that we did a good job with the modeling of the state.