

Greedy Algorithms

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Greedy algorithms

- An algorithm that always makes locally optimal moves is called greedy
- For some kinds of problems this will give a globally optimal solution as well
- Seeing when this is the case can be very tricky, and if used in the wrong context the solution will get a WA verdict

Submitting greedy solutions

- The tricky thing with these solutions are that it's often hard to know if you've made a mistake and thus get WA or if there's some hole in the greedy algorithm
- It's often easy to think of all kinds of greedy solutions, but they are very often wrong
- Generally one would like to consider complete search or dynamic programming (will see this later) first, but some problems do require greedy solutions

Coin change

- A classical example is making change. Say you want to sum up
 n and have only denominations of 1, 5 and 10, what's the least
 amount of coins you can give back?
- The greedy solution would be to just always give the biggest coin you can that's not too much. So for say 24 we'd do 10,10,1,1,1,1.
- Is this always optimal?

Coin change

- Well, it turns out to depend on the denominations. Say we have denominations of 1,8 and 20.
- For n=24 we then give back 20,1,1,1,1 instead of the optimal 8,8,8.
- We will come back to this problem when we solve the general case using dynamic programming.

Lilypad jump

- Consider a frog jumping on a sequence of lily pads, there is one at x=0 and one at x=n, with some amount of lilypads in between
- ullet The frog can jump at most distance r
- When at a given lily pad, what's the best move?

Lilypad jump

- Clearly just jump as far right as possible!
- \bullet But be careful, this is very contingent on the frog being able to jump any distance in [0,r]
- If it could jump any distance in [r/2,r], it would not be true for example

Taxi assignment

- ullet Let's consider another problem. You are managing a taxi company and today n drivers showed up and you have m cars.
- But not all drivers and cars are created equal. Car i has h_i horsepower and driver j can only handle at most g_j horsepower.
- What's the greatest number of drivers you can pair to cars such that they can handle their car?

The greedy step

- The greedy idea here is to simply pair each car to the worst driver that can still handle that car.
- Thus we start by sorting the drives and cars and then simply linearly walk through each and pair them together.
- It might not be obvious, but this actually gives the best answer.

Implementation

```
int main() {
 int n, m; cin >> n >> m;
 vi a(n). b(m):
 for(int i = 0; i < n; ++i) cin >> a[i];
 for(int i = 0; i < m; ++i) cin >> b[i];
 sort(a.begin(), a.end());
 sort(b.begin(), b.end());
 int ans = 0:
 for(int i = 0, j = 0; i < m; ++i) {
     while(j < n \&\& a[j] < b[i]) j++;
     if(j < n) ans++, j++;
 cout << ans << '\n';
```

Sorting

- Greedy algorithms very often involve sorting
- More generally they often involve always picking the "extremal" option out of the local options, in some sense
- Biggest, shortest, cheapest, first, etc.

Job scheduling

- \bullet Say we have a list of jobs, each starting at some time s_j and finishing at some time f_j
- What's the largest amount of jobs we can complete if they can't overlap?

Solution

- The solution is shockingly simple, but not obviously correct
- ullet Order the jobs by completion time f_j and then walk through them
- If you can complete a job in addition to the ones you've already picked, pick it
- The jobs you've picked by the end are the solution

Proof of correctness

- Why is this correct though? Let's prove it.
- Suppose the algorithm is not optimal. Say we pick jobs of indices i_1, i_2, \ldots, i_k but a better solution picks j_1, j_2, \ldots, j_l .
- Say the solutions agree on the first r jobs (possibly 0).
- Now neither i_{r+1} nor j_{r+1} clash with the jobs $i_1=j_1, i_2=j_2, \ldots, i_r=j_r$. But because we ordered things by end time, we must have that job i_{r+1} ends no later than j_{r+1} . But then we could just as well have picked i_{r+1} . But this holds for any r, so by induction we have that i_1, \ldots, i_k is no worse than j_1, \ldots, j_l , which gives a contradiction.
- Thus the algorithm is optimal.

Many more

- There are many many more and we will see plenty in the course
- Many famous algorithms are famous because they perform non-trivial greedy steps
- Dijkstra's algorithm, Huffman coding, Kruskal's algorithm, Horn satisfiability and many more

- How do we prove the greedy algorithms are correct?
- When in programming contests this is usually overkill, but at a workplace it is generally not
- There are two main common arguments that tackle this, but often novel methods are needed
- These are usually called "Greedy stays ahead" and "Exchange arguments"

- "Greedy stays ahead" aims to prove that during each greedy step it consistently stays ahead of all other possible choices
- "Exchange arguments" aims to show that you can turn any solution into the greedy solution with a sequence of "exchanges" without making them any worse, so the greedy solution is as good as it gets
- Sometimes a part of this is showing that the greedy solution outputs a valid solution at all, as that is not obvious in every case

- Consider the lilypads again.
- We'll now prove it's optimal, which is more work than it may seem at first
- First we prove that the greedy solution reaches the final lily pad if there is a path there
- Note again this is not true for many minor variants of the problem!

By contradiction; suppose it did not. Let the positions of the lilypads be $x_1 < x_2 < \cdots < x_m$. Since our algorithm didn't find a path, it must have stopped at some lilypad x_k and not been able to jump to a future lilypad. In particular, this means it could not jump to lilypad k+1, so $x_k+r < x_{k+1}$. Since there is a path from lilypad 1 to the lilypad m, there must be some jump in that path that starts before lilypad k+1 and ends at or after lilypad k+1. This jump can't be made from lilypad k, so it must have been made from lilypad s for some s < k. But then we have $x_s + r < x_k + r < x_{k+1}$, so this jump is illegal. We have reached a contradiction, so our assumption was wrong and our algorithm always finds a path.

- Let's now show it actually stays ahead of any optimal solution
- ullet Let J be the set of jumps from our greedy algorithm and J^* be an optimal set of jumps
- Then $|J| \ge |J^*|$ since it's optimal
- Let p(i, J) be the position after taking the first i jumps in J
- Let's prove that for all i we have $p(i, J) \ge p(i, J^*)$

We proceed by induction. As a base case, if i=0, then $p(0,J)=0\geq 0=p(0,J*)$ since the frog hasn't moved. For the inductive step, assume that the claim holds for some $0\leq i<|J^*|$. We will prove the claim holds for i+1 by considering two cases:

- Case 1: $p(i,J) \geq p(i+1,J^*)$. Since each jump moves forward, we have $p(i+1,J) \geq p(i,J)$, so we have $p(i+1,J) \geq p(i+1,J^*)$.
- Case 2: $p(i,J) < p(i+1,J^*)$. Each jump is of size at most r, so $p(i+1,J^*) \le p(i,J^*) + r$. By the inductive hypothesis, we know $p(i,J) \ge p(i,J^*)$, so $p(i+1,J^*) \le p(i,J) + r$. Therefore, the greedy algorithm can jump to position at least $p(i+1,J^*)$. Therefore, $p(i+1,J) \ge p(i+1,J^*)$.

So $p(i+1,J) \ge p(i+1,J^*)$, completing the induction.

- And now we are almost done!
- Finally we just have to prove that $|J|=|J^*|$, which would mean the greedy is always optimal

Since J^* is an optimal solution, we know that $|J^*| \leq |J|$. We will prove $|J^*| \ge |J|$. Suppose for contradiction that $|J^*| < |J|$. Let $k=|J^*|$. From before, we have $p(k,J^*) < p(k,J)$. Because the frog arrives at position n after k jumps along series J^* , we know $n \leq p(k,J)$. Because the greedy algorithm never jumps past position n, we know $p(k, J) \le n$, so n = p(k, J). Since $|J^*| < |J|$, the greedy algorithm must have taken another jump after its k-th jump, contradicting that the algorithm stops after reaching position n. We have reached a contradiction, so our assumption was wrong and $|J^*| = |J|$, so the greedy algorithm produces an optimal solution.

- That was a lot of effort!
- Now, which kind of greedy proof was that?

- That was a lot of effort!
- Now, which kind of greedy proof was that?
- It was a "Greedy stays ahead" proof, so let us next see an exchange proof

- To consider exchange arguments we have to do things slightly out of order and nab an algorithm from the future week of graph theory
- Consider a set of houses, we want to lay fibre cable between them such that each house is connected to every other house through some set of cables
- Doesn't have to be a direct connection, just some path exists between them
- For each pair of houses we are given the cost of laying a cable between them
- What's the cheapest cable-laying procedure?

- Our greedy algorithm will be as follows
- Start with just a single house and consider it "active"
- Choose the cheapest cable that goes between an active house and one that is not active
- Make the newly connected house active, and keep going
- Now we prove this is optimal!

Let T be the set of cables chosen by our algorithm and T^* be some optimal set. Let c(T) denote the total cost of a set of cables. We will prove $c(T) = c(T^*)$. If $T = T^*$ the result is obvious, so we can assume $T \neq T^*$. Then let (u, v) be a cable in $T \setminus T^*$. Let S be the set of active houses when (u, v) was added to T and H be the set of all houses. Then (u, v) is the cheapest edge between S and $H \setminus S$. Since T^* connects all houses it must contain some path from u to v. This path begins in S and ends in $H \setminus S$ so there must be some cable (x, y) such that $x \in S$ and $y \in H \setminus S$. Since (u,v) is the cheapest such edge we must have $c(\{(u,v)\}) \le c(\{(x,y)\})$. Let $T' = T^* \cup \{(u,v)\} \setminus \{(x,y)\}$.

Since every house in S can reach every other house in S without using (u, v), T' is valid for those houses, and the same goes for $H \setminus S$. But then T' allows any house in S to reach u, then go to v, then to any house in $H \setminus S$. So T' is a valid set of connections. But note that $c(T') = c(T^*) - c(\{(x,y)\}) + c(\{(u,v)\}) \le c(T^*)$. Since T^* is optimal this means $c(T') \ge c(T^*)$, so $c(T') = c(T^*)$. Note that $|T \setminus T'| = |T \setminus T^*| - 1$, so if we repeat this same argument once for each edge in $T \setminus T^*$ we will have converted T^* into T without changing T, thus $c(T) = c(T^*)$.

- Very mathy!
- But that is an example of an "Exchange argument" proof of correctness