CS/COE 1501

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Greedy Algorithms and Dynamic Programming

Consider the change making problem

- What is the minimum number of coins needed to make up a given value k?
- If you were working as a cashier, what would your algorithm be to solve this problem?

This is a greedy algorithm

- At each step, the algorithm makes the choice that seems to be best at the moment
- Have we seen greedy algorithms already this term?
 - Yes!
 - Building Huffman trees
 - Nearest neighbor approach to travelling salesman

... But wait ...

- Nearest neighbor doesn't solve travelling salesman
 - Does not produce an optimal result
- Does our change making algorithm solve the change making problem?
 - For US currency...
 - But what about a currency composed of pennies (1 cent),
 thrickels (3 cents), and fourters (4 cents)?
 - What denominations would it pick for k=6?

So what changed about the problem?

- For greedy algorithms to produce optimal results, problems must have two properties:
 - Optimal substructure
 - Optimal solution to a subproblem leads to an optimal solution to the overall problem
 - The greedy choice property
 - Globally optimal solutions can be assembled from locally optimal choices
- Why is optimal substructure not enough?

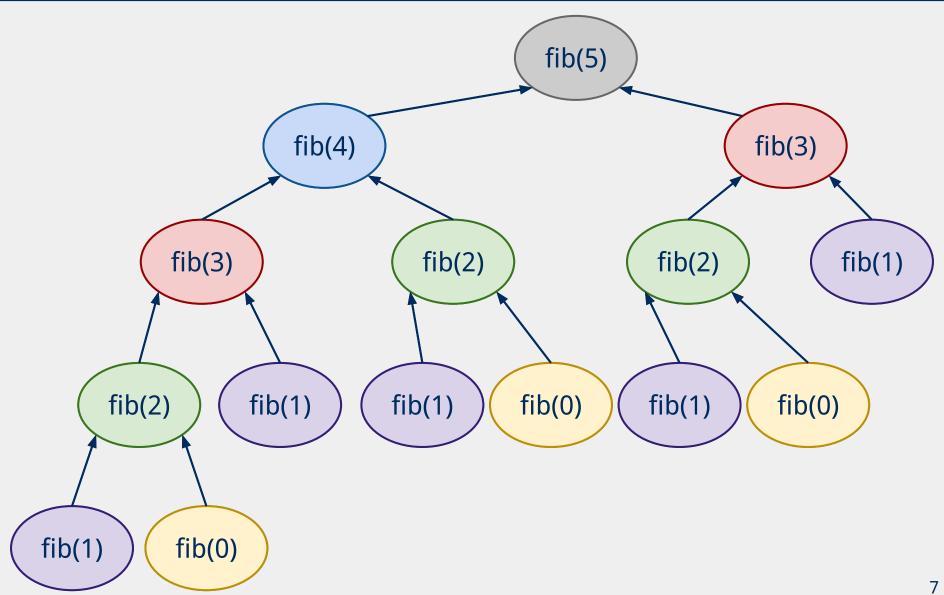
Finding all subproblems solutions can be inefficient

Consider computing the Fibonacci sequence:

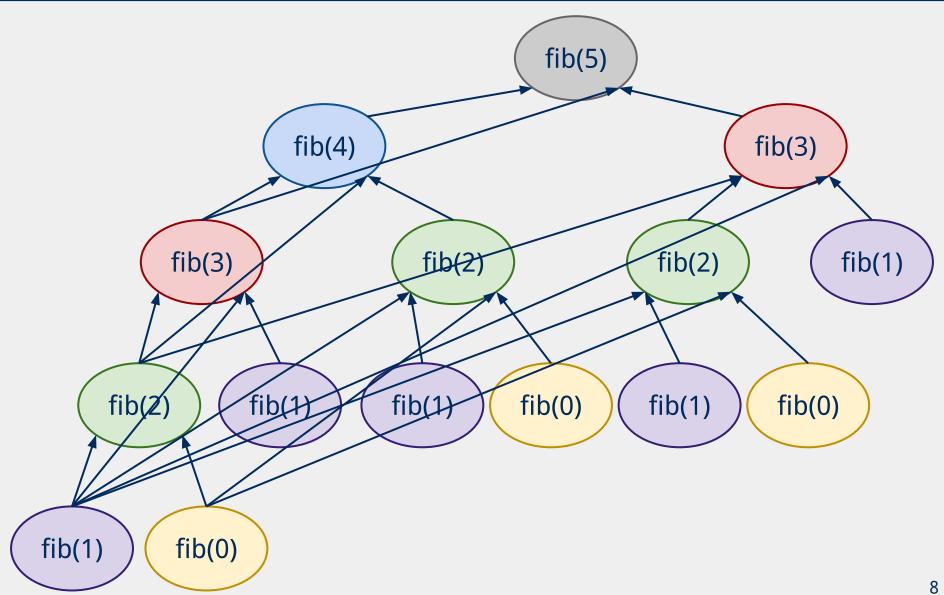
```
int fib(n) {
    if (n == 0) { return 0 };
    else if (n == 1) { return 1 };
    else {
        return fib(n - 1) + fib(n - 2);
    }
}
```

• What does the call tree for n = 5 look like?

fib(5)



How do we improve?



Memoization

```
int[] F = new int[n+1];
F[0] = 0;
F[1] = 1;
for(int i = 2; i <= n; i++) { F[i] = -1 };
int dp_fib(x) {
   if (F[x] == -1) {
       F[x] = dp_fib(x-1) + dp_fib(x-2);
   return F[x];
```

Note that we can also do this bottom-up

```
int bottomup_fib(n) {
   if (n == 0)
       return 0;
   int[] F = new int[n+1];
   F[0] = 0;
   F[1] = 1;
   for(int i = 2; i <= n; i++) {
       F[i] = F[i-1] + F[i-2];
   return F[n];
```

Can we improve this bottom-up approach?

```
int improve_bottomup_fib(n) {
   int prev = 0;
   int cur = 1;
   int new;
   for (int i = 0; i < n; i++) {
       new = prev + cur;
       prev = cur;
       cur = new;
   return cur;
```

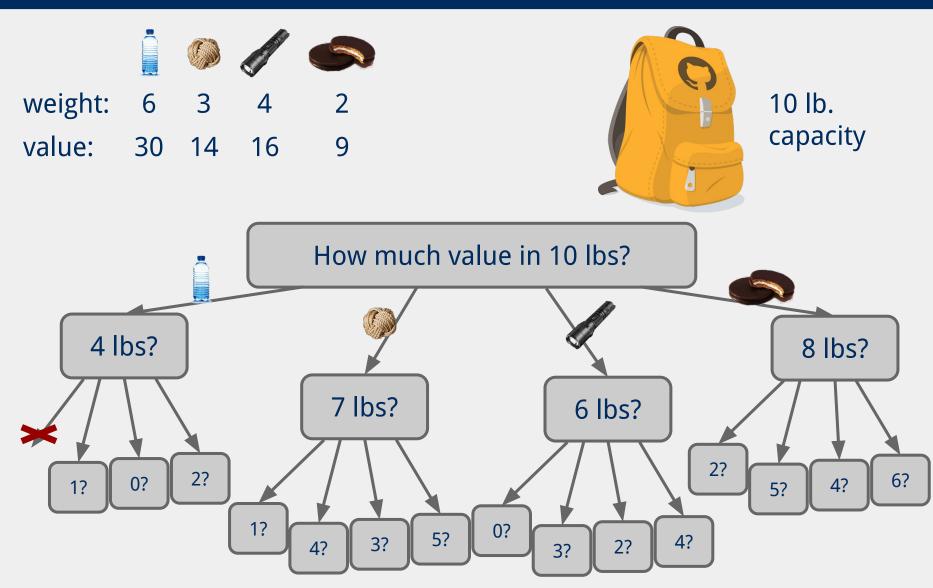
Where can we apply dynamic programming?

- To problems with two properties:
 - Optimal substructure
 - Optimal solution to a subproblem leads to an optimal solution to the overall problem
 - Overlapping subproblems
 - Naively, we would need to recompute the same subproblem multiple times

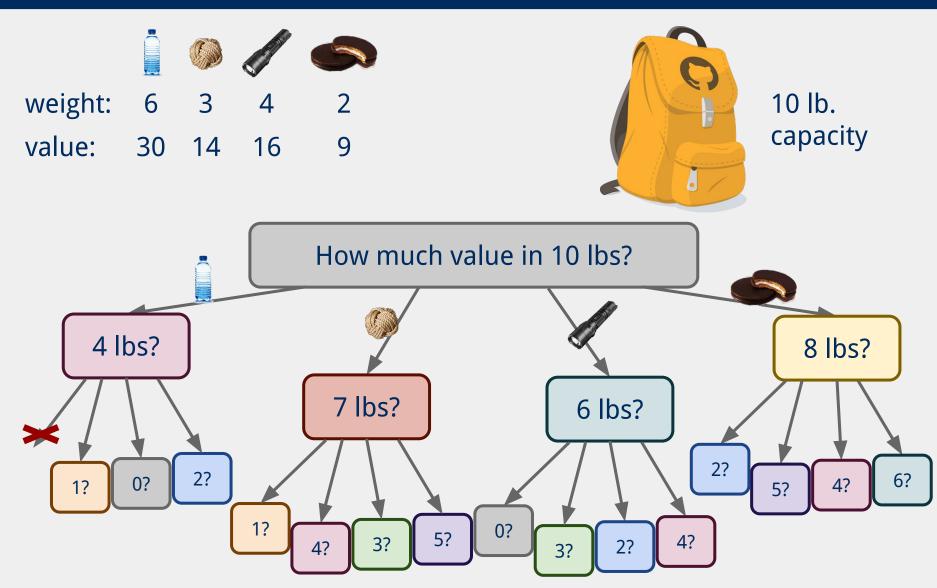
The unbounded knapsack problem

• Given a knapsack that can hold a weight limit L, and a set of n types items that each has a weight (w_i) and value (v_i), what is the maximum value we can fit in the knapsack if we assume we have unbounded copies of each item?

Recursive example



Recursive example



Bottom-up example



weight: 6 3 4 2

value: 30 14 16 9

Size:	0	1	2	3	4	5	6	7	8	9	10
Max val:	0	0	9	14	18	23	30	32	39	44	48

Bottom-up solution

```
K[0] = 0
for (1 = 1; 1 <= L; 1++) {
    int max = 0;
   for (i = 0; i < n; i++) {
       if (w_i \le 1 \& v_i + K[1 - w_i]) > max) {
           max = v_i + K[1 - w_i];
   K[1] = max;
```

What would have happened with a greedy approach?

- Try adding as many copies of highest value per pound item as possible:
 - \circ Water: 30/6 = 5
 - Rope: 14/3 = 4.66
 - Flashlight: 16/4 = 4
 - Moonpie: 9/2 = 4.5
- Highest value per pound item? Water
 - Can fit 1 with 4 space left over
- Next highest value per pound item? Rope
 - Can fit 1 with 1 space left over
- No room for anything else
- Total value in the 10 lb knapsack?
 - 0 44
 - Bogus!

The 0/1 knapsack problem

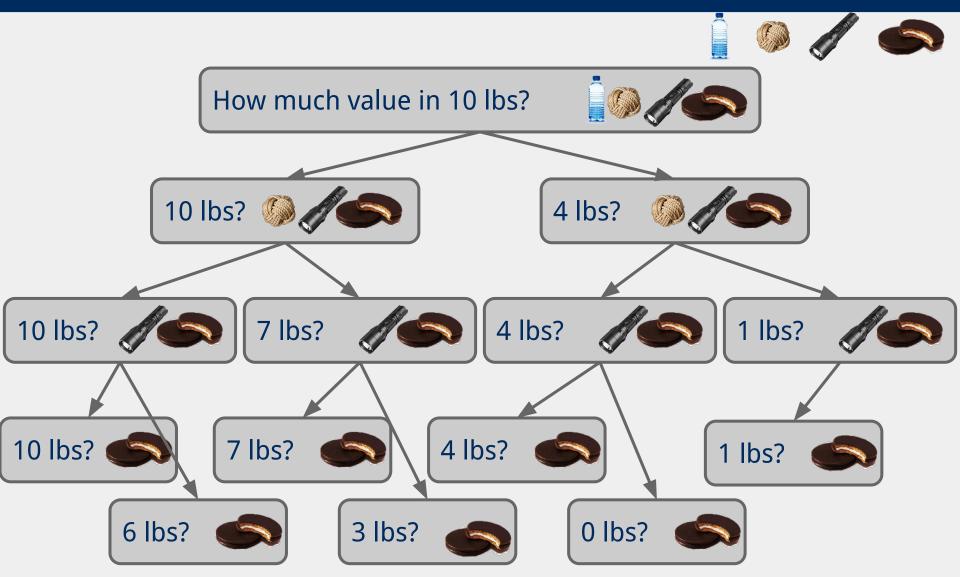
 What if we have a finite set of items that each has a weight and value?

- Two choices for each item:
 - Goes in the knapsack
 - Is left out

0/1 Recursive example

weight: 6 3 4 2

value: 30 14 16 9



Recursive solution

```
int knapSack(int[] wt, int[] val, int L, int n) {
   if (n == 0 | L == 0) { return 0 };
   if (wt[n-1] > L) {
       return knapSack(wt, val, L, n-1)
   else {
       return max( val[n-1] + knapSack(wt, val, L-wt[n-1], n-1),
                   knapSack(wt, val, L, n-1)
                  );
```

i\l	0	1	2	3	4	5
0	0	0	0	0	0	0
1						
2						
3						
4						

i\l	0	1	2	3	4	5
0	0	0	0	0	0	0
1						
2						
3						
4						

i\l	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	0	3	3	3	3
2						
3						
4						

i\l	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	0	3	3	3	3
2	0	0	3	4	4	7
3						
4						

i\l	0	1	2	3	4	5
0	0	0	0	0	0	0
1	0	0	3	3	3	3
2	0	0	3	4	4	7
3	0	0	3	4	5	7
4						

The 0/1 knapsack dynamic programming solution

```
int knapSack(int wt[], int val[], int L, int n) {
   int[][] K = new int[n+1][L+1];
   for (int i = 0; i <= n; i++) {
       for (int l = 0; l <= L; l++) {
           if (i==0 \mid | 1==0) \{ K[i][1] = 0 \};
           else if (wt[i-1] > 1) \{ K[i][1] = K[i-1][1] \};
           else {
               K[i][1] = max(val[i-1] + K[i-1][1-wt[i-1]],
                               K[i-1][1]);
   return K[n][L];
```

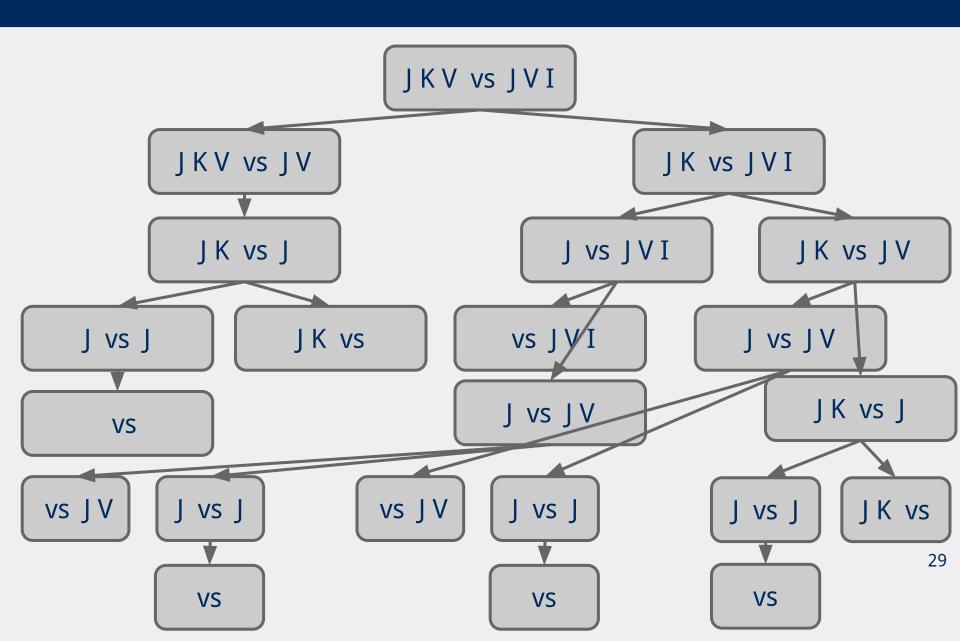
Longest Common Subsequence

 Given two sequences, return the longest common subsequence

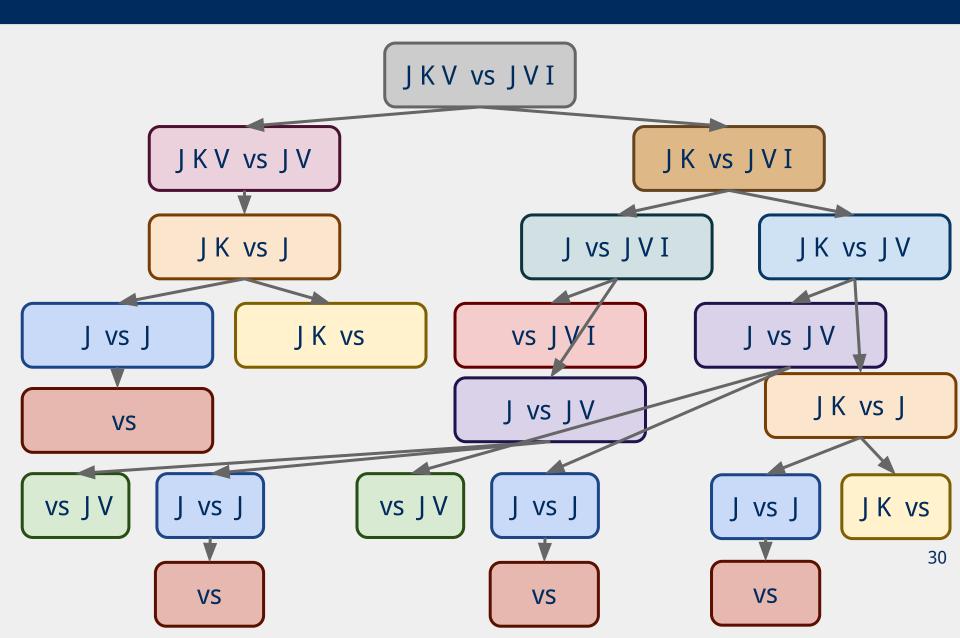
```
A Q S R J K V B IQ B W F J V I T U
```

 We'll consider a relaxation of the problem and only look for the *length* of the longest common subsequence

LCS recursive example



LCS recursive example



LCS recursive solution

```
int LCSLength(String x, String y, int m, int n) {
   if (m == 0 | | n == 0)
      return 0;
   if (x.charAt(m-1) == y.charAt(n-1))
      return 1 + LCSLength(x, y, m-1, n-1);
   else
      return max(LCSLength(x, y, m, n-1),
                 LCSLength(x, y, m-1, n)
                 );
```

LCS dynamic programming example

X	=	Α	0	S	R	J	В	Ι
			T.					

$$y = Q B I J T U T$$

i\j	0	1	2	3	4	5	6	7
0								
1								
2								
3								
4								
5								
6								
7								

LCS dynamic programming solution

```
int LCSLength(String x, String y) {
   int[][] m = new int[x.length + 1][y.length + 1];
   for (int i=0; i <= x.length; i++) {
      for (int j=0; j \leftarrow y.length; j++) {
          if (i == 0 | | j == 0) m[i][j] = 0;
          if (x.charAt(i) == y.charAt(j))
             m[i][j] = m[i-1][j-1] + 1;
          else
             m[i][j] = max(m[i][j-1], m[i-1][j]);
   return m[x.length][y.length];
```

To review...

- Questions to ask in finding dynamic programming solutions:
 - Does the problem have optimal substructure?
 - Can solve the problem by splitting it into smaller problems?
 - Can you identify subproblems that build up to a solution?
 - Does the problem have overlapping subproblems?
 - Where would you find yourself recomputing values?
 - How can you save and reuse these values?

The change-making problem

Consider a currency with n different denominations of coins
 d₁, d₂, ..., d_n. What is the minimum number of coins needed
 to make up a given value k?