Dynamic Programming

Divide & Conquer + Lookup Table

Overview

- The key idea of Divide & Conquer is to break a problem into smaller sub-problems and combine the result of those subproblems
- Some Problem can be divided into subproblems that is overlapping, i.e., same subproblem that happens more than once
 - If we use general D&C, each copies of the same subproblem will be solved repeatedly, wasting time
 - Dynamic Programming is a technique that use a look up table to store result of each sub-problem and immediately use it if any subproblem is required multiple times

Fibonacci Number

Fibonacci Number

- Problem: compute F(N), the Fibonacci function of N
- Input:
 - An integer N >= 0
- Output:
 - F(N), according to

$$F(N) = \begin{cases} F(N-1) + F(N-2) & ; n > 1 \\ 1 & ; n = 1 \\ 0 & ; n = 0 \end{cases}$$

Can be solve directly using Divide & Conquer

Recursion Tree

```
int fibo(int n) {
                                        if (n == 1 || n == 0)
                                          return n;
                                        if (n >= 2)
                                          return fibo(n-1) + fibo(n-2);
                                F(4)
               F(5)
                                                                                      F(0)
                                                                    F(1)
                                                                    F(1)
                                F(3)
 Some subproblems
 (F(3) \text{ and } F(2)) \text{ are}
                                                                    F(0)
 computed multiple
times, they should not
                                                                    F(1)
                                                                    F(0)
```

Memoization: Simplest form of Dynamic Programming

- Top-Down approach
- Remember what have been done, if the subproblem is needed again, use the remembered result

```
ResultType DC(Problem p) {
  if (p is trivial) {
    solve p directly
    return the result
  } else {
    divide p into p_1, p_2, \ldots, p_n
    for (i = 1 \text{ to } n)
       r_i = DC(p_i)
    combine r_1, r_2, \ldots, r_n into r
     return r
```

```
ResultType DP(Problem p) {
  if (p is trivial) {
    solve p directly
    return the result
    else {
    if p is solved
      return table.lookup(p);
    divide p into p_1, p_2, \ldots, p_n
    for (i = 1 \text{ to } n)
      r_i = DP(p_i)
    combine r_1, r_2, \ldots, r_n into r
    table.save(p,r);
                                   remember
    return r
```

Fibonacci: Top-Down DP

table is an array[1..n] initialized by 0

```
int fibo_memo(int n) {
  if (n == 1 || n == 0)
    return n;
 if (n >= 2) {
   if (table[n] > 0) {
      return table[n];
                                                     use
    int value = fibo_memo(n-1) + fibo_memo(n-2);
    table[n] = value;
                                               remember
    return value;
```

Exercise

• Draw recursion tree when we call fibo memo(7)

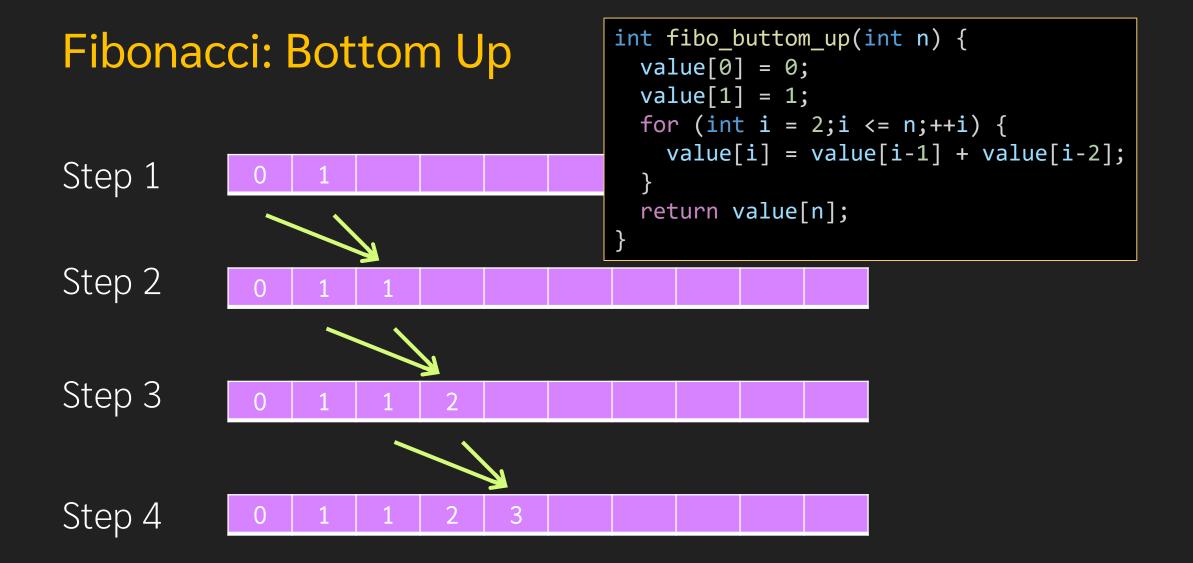
```
//table is a global variable
int fibo_memo(int n) {
  if (n == 1 || n == 0)
    return n;
  if (n >= 2) {
    if (table[n] > 0) {
      return table[n];
    int value = fibo_memo(n-1) + fibo_memo(n-2);
    table[n] = value;
    return value;
```

Bottom-up dynamic programming

- Instead of relying on recursion to discover repetition of subproblems, we analyze the recursion directly and build table constructively from smaller subproblems
 - The initial subproblems are the ones from trivial case of Divide & Conquer recurrent relation
- Benefit: no-recursion, better runtime performance, (usually) easier to analyze
- Drawback: sometime, we build unnecessary sub-problem

Fibonacci: Bottom-Up DP

- From the definition of F(N), we know that
 - F(n) needs to know F(n-1) and F(n-2)
 - In other words, if we know F(n-1) and F(n-2), then we can construct F(N)
- Initial Condition:
 - F(0) = 0, F(1) = 1
 - i.e., table[0] = 0; table[1] = 1;
- From the recurrent
 - table[3] = table[2] + table[1]
 - table[4] = table[3] + table[2]
 - ...



Optimized version of Bottom-Up Fibo

- From bottom up approach, we know that we only need two prior
 Fibonacci numbers (F(n-1) and F(n-2)) to compute the current
 Fibonacci number (F(n))
 - There is no need to lookup for F(n-3), F(n-4), ... if we know F(n-1), and F(n-2)
 - Hence, no need to use entire table
 - Just remember two previous Fibonacci number

```
def fibo(n)
  if (n == 0 || n == 1)
    return n
 f2 = 0
  f1 = 1
  for i from 2 to n
    #calculate current
    f = f2 + f1
    #prepare f1 and f2 for next round
   f2 = f1
    f1 = f
 end
  return f
end
```

Binomial Coefficient

choose r things from n things

Example 2: Binomial Coefficient

- $C_{n,r}$ =how to choose r things from n things
 - We have a closed form solution

•
$$C_{n,r} = n!/(r!*(n-r)!)$$

We also have recurrence relation of C_{n,r}

•
$$C_{n,r} = C_{n-1,r} + C_{n-1,r-1}$$

= 1 ; r = 0
= 1 ; r = n

- What is the subproblem?
- Do we have overlapping subproblem?

- Input:
 - Two integer r and n $(0 \le r \le n)$
- Output:
 - C_{n,r}

Binomial Coefficient

- Each subproblem is represented by 2 numbers, r and n
 - Hence, the table should be 2D

```
int bino_naive(int n,int r) {
  if (r == n) return 1;
  if (r == 0) return 1;

int result = bino_naive(n-1,r) + bino_naive(n-1,r-1);
  return result;
}
```

Binomial Coefficient: Top-Down (Memoization)

• table[0..n][0..n] is initialized by -1

```
int bino_memoize(int n,int r) {
  if (r == n) return 1;
  if (r == 0) return 1;

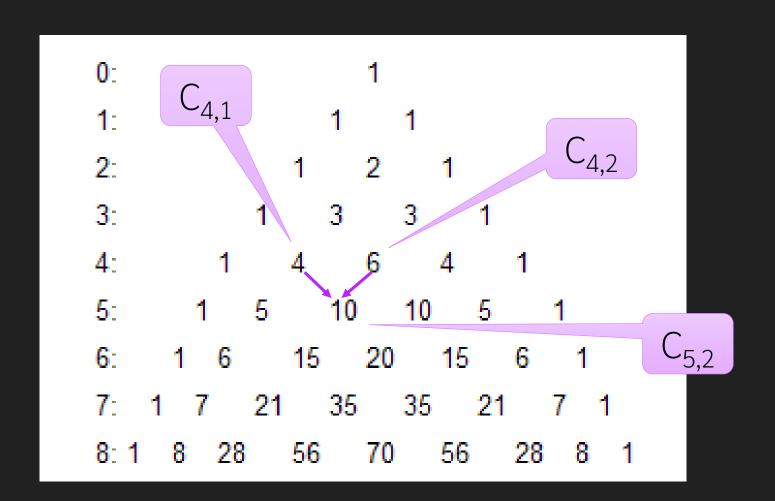
  if (table[n][r] != -1)
    return table[n][r];

  int result = bino_memoize(n-1,r) + bino_memoize(n-1,r-1);
  table[n][r] = result;

  return result;
}
```

Binomial Coefficient: Bottom Up

• Pascal triangle is a by-hand bottom-up DP of Binomial Coeff.



Binomial Coefficient: Bottom Up

	0	1	2	3	4	5	6
0	1						
1	1	1					
2	1		1				
3	1			1			
4	1				1		
5	1					1	
6	1						1

```
int bino_DP(int n,int r) {
   for (int i = 0;i <= n;i++) {
      table[i][0] = 1;
      table[i][i] = 1;
   }
   for (int i = 1;i <= n;i++) {
      for (int j = 1;j < i;j++) {
       table[i][j] = table[i-1][j] + table[i-1][j-1];
      }
   }
   return table[n][r];
}</pre>
```

Question

- Is it possible to fill the table in different order?
- Does previous code solve subproblem that we does not need?
 - If yes, how to avoid?

Maximum Subarray Sum

Revisiting

The problem

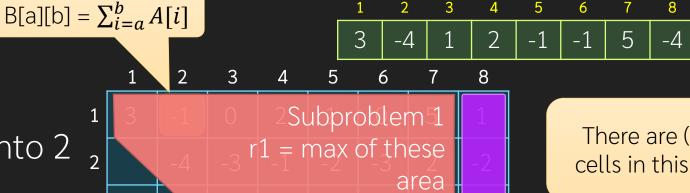
- Given array A[1..n] of numbers, may contain negative number
 - Find a non-empty subarray A[p..q] such that the summation of the values in the subarray is maximum
- Input:
 - A[1..n]
- Output:
 - p and q, where $1 \le p \le q \le n$ and summation of A[p..q] is maximum
- Example:
 - A = [1, 4, 2, 3] output: 1 and 4
 - A = [-2, -1, -3, -5] output: 2 and 2
 - A = [2, 3, -6, 4, -2, 3, -5, -4, 3] output: 4 and 6

D&C by n-1

- Instead of divining n into 2 of n/2 as previously done, we divide by n-1 and 1
 - The real work is solved by another D&C

```
def mss(A, stop)
  if (stop == 1)
    return A[1]
  r1 = mss(A, stop-1)
  r2 = A[stop]
  r3 = max suffix(A, stop-1)+A[stop]
  return max(r1,r2,r3)
end
```

```
\max_{1 \le k \le m} \sum_{i=k}^{m} A[i]
```



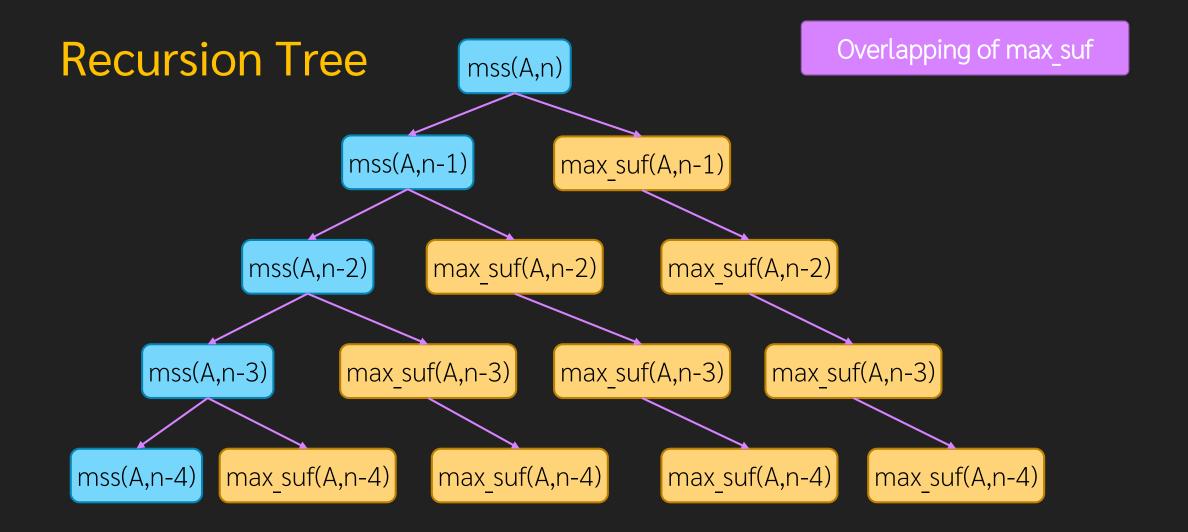


There are (n-1) cells in this area

Question

- Can you make max suffix as a D&C (try $n \rightarrow n-1$)
- Can you draw a recursion tree?
- Does it has overlapping subproblem?

```
def max_suffix(A,stop)
 if stop == 1
    return A[1]
 return max(A[stop],
             A[stop]+max suffix(A,stop-1))
end
```



MSS with Dynamic Programming

```
def mss(A,stop)
  if (stop == 1)
    return A[1]
  r1 = mss(A,stop-1)
  r2 = A[stop]
  r3 = max_suffix(A,stop-1)+A[stop]
  return max(r1,r2,r3)
end
```

- Memoization (top-down) approach
- Since the value of max_suffix can be negative, we need another table to determine whether this subproblem is already solved
 - done[1..n] is initialized as false

Bottom-Up approach

- Direct version
 - Build max sur first
 - Calculate mss from 1 to n
- Optimized version (Kadane's Algorithm)
 - See that we need only one max_suf

```
def mss_bottom_up(A[1..n])
  max_suf is array [1..n]
  max_suf[1] = A[1]
  for i from 2 to n
    max_suf[i] = max(max_suf[i-1]+A[i],A[i])
  mss = A[1]
  for i from 2 to n
    mss = max(mss,
              max(A[i],
                  max_suf[i-1]))
  return mss
end
```

Kadane's Algorithm

```
def kadane(A[1..n])
    suf = A[1]
    mss = A[1]
    for i from 2 to n
        suf = max(A[i], suf+A[i])
        mss = max(mss, suf)
    return mss
end
```

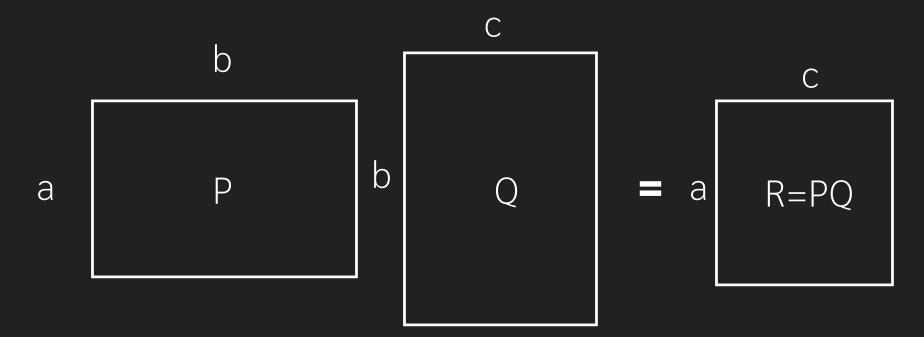


- Calculate both mss and suf on the fly
- Original problem was proposed by Ulf Grenander in 1977
 - Originally 2D problem, convert to 1D to gain insight
- O(n log n) D&C proposed by Michael Shamos
- Joseph Born Kadane heared the problem in a seminar and propose O(n)

Matrix Chain Multiplication

Non-trivial bottom-up

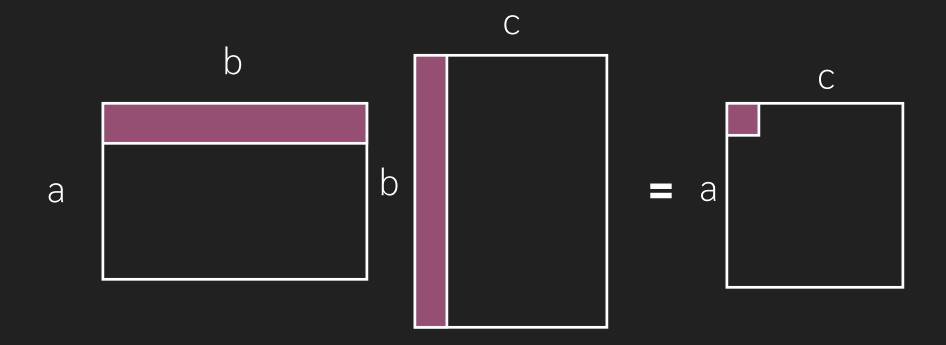
Matrix Multiplication



P = matrix with a rows and b columns

Q = matrix with b rows and c columns

Multiplying the Matrix

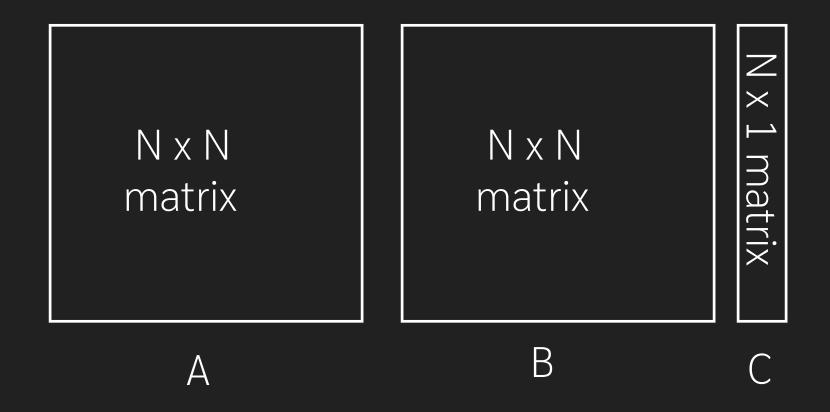


Time used = $\Theta(abc)$

Naïve Method

```
for (i = 1; i <= a;i++) {
  for (j = 1; i <= c;j++) {
    sum = 0;
  for (k = 1;k <= b;k++) {
    sum += P[i][k] * Q[k][j];
  }
  R[i][j] = sum;
}</pre>
```

Matrix Chain Multiplication



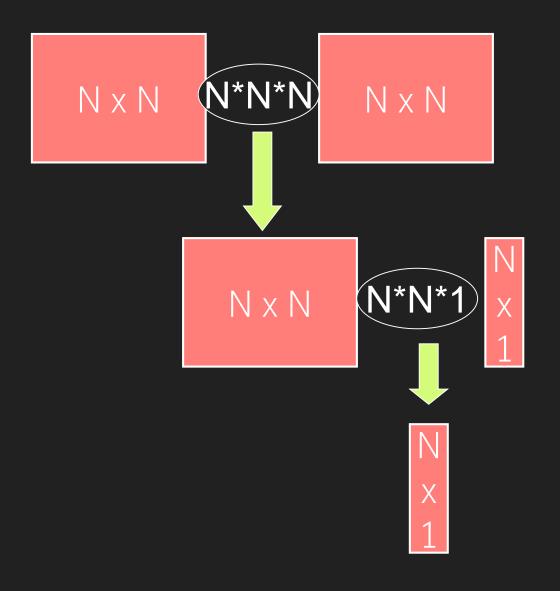
How to compute ABC?

Matrix Multiplication

- ABC = (AB)C = A(BC)
- (AB)C differs from A(BC)?
 - Same result, different efficiency

- What is the cost of (AB)C?
- What is the cost of A(BC)?

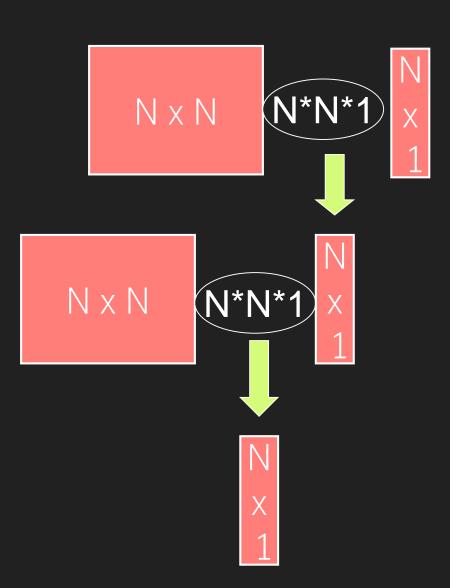
(AB)C



• Total = $N^3 + N^2$

A(BC)

• Total = 2N2



The Problem

- Input:
 - a₁,a₂,a₃,....,a_n
- Output:
 - The order of multiplication
 - How to parenthesize the chain
 - How many multiplication is needed
- Example Instance:
 - Input: 10 10 10 1

These represents the size of the n-1 matrices B_1 .. B_{n-1}

$$a_1 \times a_2 \qquad B_1 \\ a_2 \times a_3 \qquad B_2 \\ a_3 \times a_4 \qquad B_3$$

 $a_{n-1} \times a_n$ B_{n-1}

Output: $(B_1(B_2B_3))$ 200

More Example

INPUT

- a₁ a₂ a₃ a₄ a₅ a₆
- 10 x 5 x 1 x 5 x 10 x 2
 B₁ B₂ B₃ B₄ B₅

Possible Output

$$((B_1B_2)(B_3B_4))B_5$$

 $(B_1B_2)((B_3B_4)B_5)$

$$(B_1((B_2B_3)B_4))B_5$$

And much more...

Consider the Output

What do

 $(B_1B_2)((B_3B_4)B_5)$

 $(B_1B_2)(B_3(B_4B_5))$

have in common?

What do

 $((B_1B_2)(B_3B_4))B_5$

 $(((B_1B_2)B_3)B_4))B_5$

have in common?

Solving B₁ B₂ B₃ B₄ ... B_{n-1}

Min cost of

- (1) $B_1 B_2 B_3$ Subproblem (2) Subproblem B_3 Subproblem B_3 Subproblem B_4
- (3) Subproblem Subproblem

•••

$$(n-2)$$
 B_1 Subproblem B_{n-1}

- Each options ((1)..(n-2)) has 1
 or 2 subproblems
- Sub problem is described by indices of left and right matrix
 - Needs 2 integers to describe a subproblem
- No overlapping subproblem (yet)

Overlapping Subproblem

Have to dig deeper to identify existence of overlapping $B_{1}...B_{N-1}$ subproblem $(B_1)(B_2...B_{N-1})$ $(B_1B_2)(B_3...B_{N-1})$ $(B_1...)(B_{N-1})$ $(B_{...})(B_{2}...B_{N-2})$ $(B_2...B_{N-2})(B_{N-1})$

Deriving the Recurrence Relation for D&C

- mcm(l,r)
 - The least cost to multiply B₁ ... B_r

• The solution is mcm(1,n-1)

- Initial Case, when $(r l) \le 1$ (one or two matrices)
 - mcm(x,x) = 0
 - mcm(x,x+1) = a[x] * a[x+1] * a[x+2]

The Recurrence Relation

Subproblems Final multiplication Recursion Case min cost of mcm(l+1,r) B_{I} $+ a_l \bullet a_{l+1} \bullet a_{r+1}$ min cost of mcm(l, l+1) mcm(l+2,r) $+ a_1 \bullet a_{1+2} \bullet a_{r+1}$ mcm(l,r) = min ofmcm(l, l+2)mcm(l+3,r)min cost of $+ a_{l} \cdot a_{l+3} \cdot a_{r+1}$... mcm(l, r-1) min cost of B_r $+ a_l \bullet a_r \bullet a_{r+1}$

Divide & Conquer

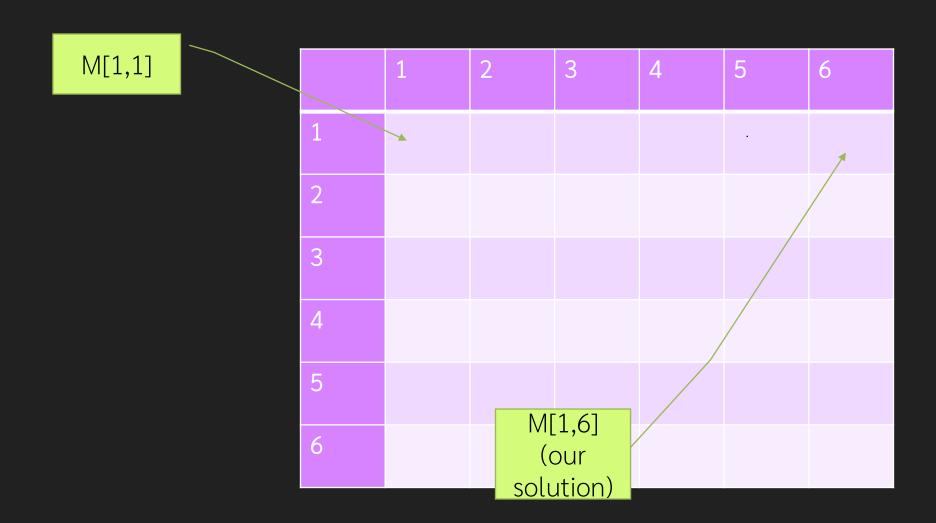
```
int mcm(int 1,int r) {
  if (1 < r) {
    minCost = MAX_INT;
    for (int i = 1;i < r;i++) {
      my_cost = mcm(l,i) + mcm(i+1,r) + (a[l] * a[i+1] * a[r+1]);
      minCost = min(my_cost,minCost);
    return minCost;
  } else {
    return 0;
```

Using bottom-up DP

- Design the table
 - M[i][j] = the best solution (min cost) for multiplying B_i...B_i
 - M[i][j] stores mcm(i,j)
 - The solution is at M[1][n-1]
- Trivial Case
 - What is M[x][x] ?
 - No multiplication, M[x][x] = 0
- Simple case
 - What is M[x][x+1]?
 - $B_x B_{x+1}$
 - Only one solution = $a_x * a_{x+1} * a_{x+2}$

What is M[i,j]?

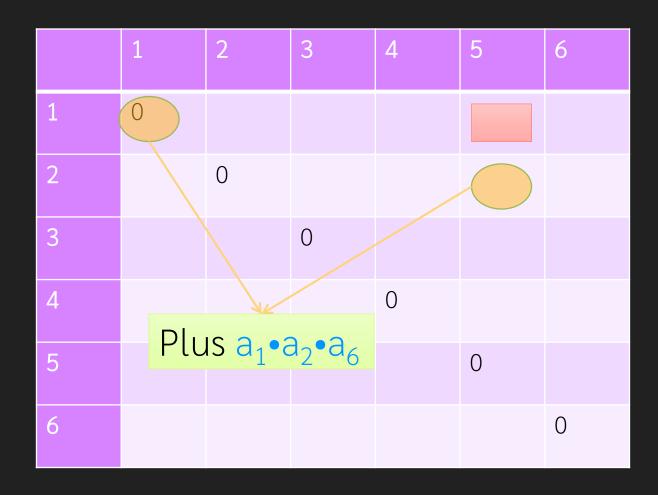
- General case
 - What is M[x][x+k]?
 - $\bullet B_x B_{x+1} B_{x+2} ... B_{x+k}$

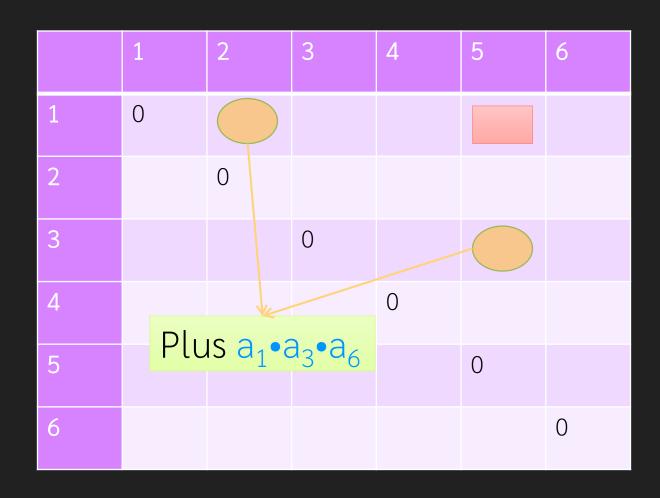


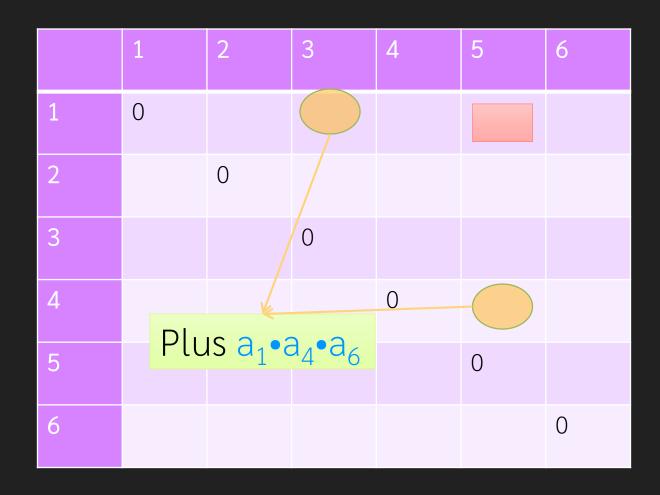
Trivial case

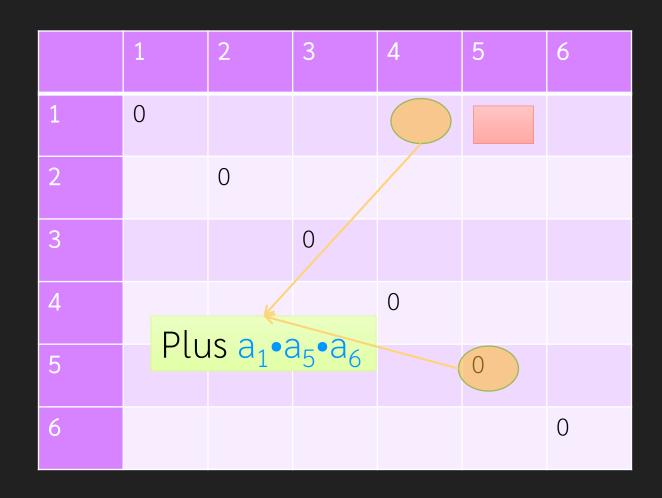
	1	2	3	4	5	6
1	0					
2		0				
3			0			
4				0		
5					0	
6						0

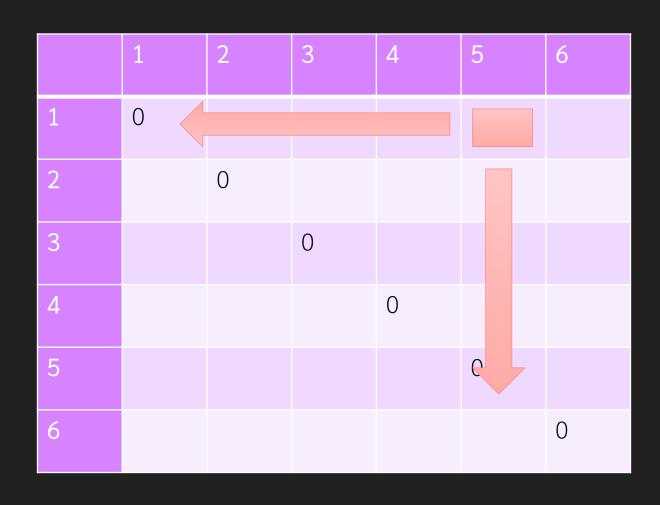
	1	2	3	4	5	6
1	0					
2		0				
3			0			
4				0		
5					0	
6						0

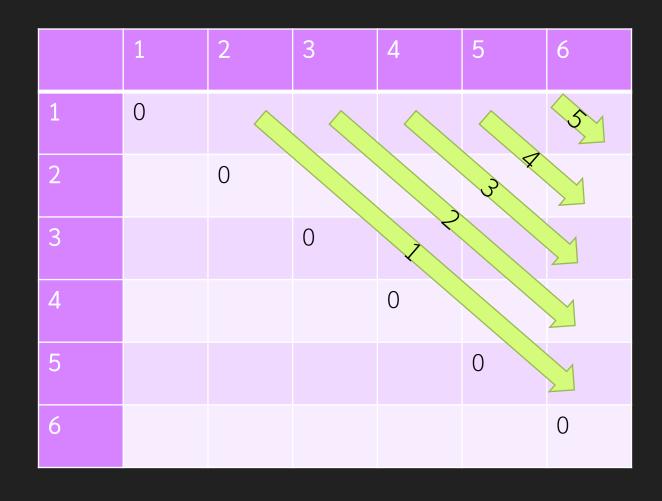




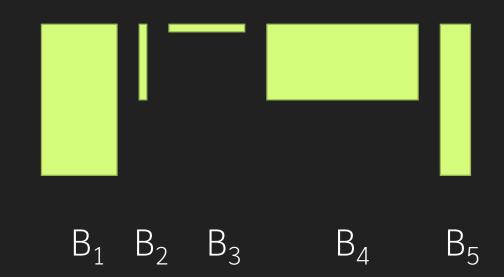




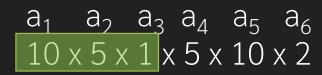




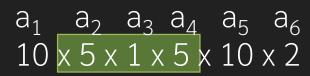
- \bullet a_1 a_2 a_3 a_4 a_5 a_6
- 10 x 5 x 1 x 5 x 10 x 2
 B₁ B₂ B₃ B₄ B₅



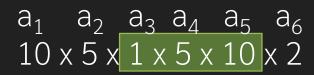
	1	2	3	4	5
1	0				
2		0			
3			0		
4				0	
5					0



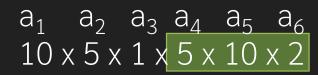
	1	2	3	4	5
1	0	50			
2		0			
3			0		
4				0	
5					0



	1	2	3	4	5
1	0	50			
2		0	25		
3			0		
4				0	
5					0



	1	2	3	4	5
1	0	50			
2		0	25		
3			0	50	
4				0	
5					0



	1	2	3	4	5
1	0	50			
2		0	25		
3			0	50	
4				0	100
5					0

	1	2	3	4	5
1	0	50			
2		0	25		
3			0	50	
4				0	100
5					0

Option
$$1 = 0 + 25 + 10 \times 5 \times 5 = 275$$

Option $2 = 50 + 0 + 10 \times 1 \times 5 = 100$

$$a_1$$
 a_2 a_3 a_4 a_5 a_6 $10 \times 5 \times 1 \times 5 \times 10 \times 2$

	1	2	3	4	5
1	0	50			
2		0 (25		
3			0	50	
4				0	100
5					0

$$a_1$$
 a_2 a_3 a_4 a_5 a_6 $10 \times 5 \times 1 \times 5 \times 10 \times 2$

(2) means that the minimal solution is by dividing at B₂

	1	2	3	4	5
1	0	50	100 (2)		
2		0	25		
3			0	50	
4				0	100
5					0

Option
$$1 = 0 + 50 + 5x 1 x 10 = 100$$

Option
$$2 = 25 + 0 + 5x 5 \times 10 = 275$$

	1	2	3	4	5
1	0	50	100 (2)		
2		0	25		
3			0	50	
4				0	100
5					0

	1	2	3	4	5
1	0	50	100 (2)		
2		0	25	100 (2)	
3			0	50	70 (4)
4				0	100
5					0

Option
$$1 = 0 + 100 + 10x 5 \times 10 = 600$$

Option $2 = 50 + 50 + 10x 1 \times 10 = 200$
Option $2 = 100 + 0 + 10x 5 \times 10 = 600$
 $a_1 \quad a_2 \quad a_3 \quad a_4 \quad a_5 \quad a_6$
 $10 \times 5 \times 1 \times 5 \times 10 \times 2$

	1	2	3	4	5
1 (0	50	100 (2)		
2		0	25	100	
3			0	50	70 (4)
4				0	100
5					0

	1	2	3	4	5
1	0	50	100 (2)	200 (2)	
2		0	25	100 (2)	
3			0	50	70 (4)
4				0	100
5					0

	1	2	3	4	5
1	0	50	100 (2)	200 (2)	
2		0	25	100 (2)	80 (2)
3			0	50	70 (4)
4				0	100
5					0

	1	2	3	4	5
1	0	50	100 (2)	200 (2)	140 (2)
2		0	25	100 (2)	80 (2)
3			0	50	70 (4)
4				0	100
5					0

Analysis

- There is $O(n^2)$ cell to be filled
 - Each cell has O(n) options
- This totals to $O(n^3)$

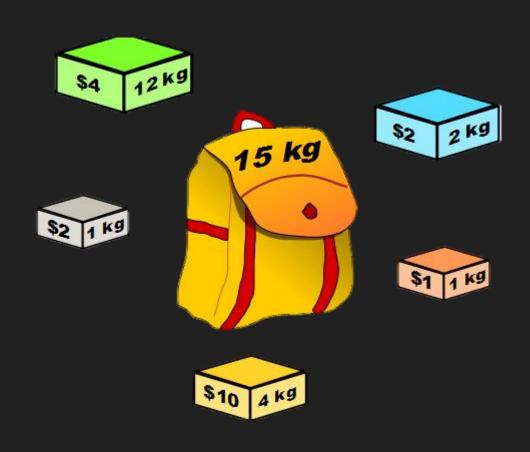
Can you write a code for Bottom-up DP of Matrix Chain Multiplication Problem?

Also can your code build the actual solution (the parenthesis of Bi, not just the minimum cost)

0-1 Knapsack Problem

Knapsack Problem

- Given a sack, able to hold W kg
- Given a list of objects
 - Each has a value and a weight
- Try to pack the object in the sack so that the total value is maximized



Variation

- Rational Knapsack
 - Object is like a gold bar, we can cut it into pieces, each has the same value/weight ratio
- 0-1 Knapsack
 - Object cannot be broken, we have to choose to take (1) or leave (0) the object
 - W = 50
 - Objects = (60, 10) (100, 20) (120, 30)
 - Best solution = second and third

The Problem

• Input:

- A number W, the capacity of the sack
- n values of weight and price
 - W_i = weight of the ith items
 - p_i = price of the ith item

• Output:

- A subset *S* of {1,2,3,...,n} such that
 - $\sum_{i \in S} p_i$ is maximum
 - $\sum_{i \in S} w_i \leq W$

• Example Instance

- W = 50
- Pi = 60, 100, 120
- wi = 10, 20, 30
- Best solution = second and third

Naïve approach

```
def knapsack(W,w[1..n],p[1..n],idx,pick[1..n])
  if (idx == 0)
    sum price = 0
    sum weight = 0
   for i from 1 to n
      if pick[i]
        sum price += p[i]
        sum weight += w[i]
    if (sum weight <= W && sum price > max)
      max = sum_price
  pick[idx] = false
  knapsack(W,w,p,idx-1,pick)
  pick[idx] = true
  knapsack(W,w,p,idx-1,pick)
end
```

- Try every possible combination of {1,2,3,...n}
- Test whether a combination satisfies the weight constraint
 - If so, remember the best one
 - Start with knapsack(W,w,p,n,[1..n])
 - max is global var
 - $\theta(2^{n*}n)$

Another Naïve approach

- Keep track of remaining weight, sum the total price along the way
- What is the benefit of this approach?

```
def knapsack(W,w[1..n],p[1..n],idx,remain)
  if (idx == 0)
    return 0
  if (remain >= w[idx])
    #r1 is that we don't pick item #idx
    r1 = knapsack(W,w,p,idx-1,remain)
    #r2 is that we pick item #idx
    r2 = knapsack(W,w,p,idx-1,remain - w[idx]) + p[idx]
    return max(r1,r2)
  else
    return knapsack(W,w,p,idx-1,remain)
end
```

The Recurrence Relation

• K(a,b) = the best total price when and only item number 1 to number a is considered and the knapsack is of size b

- K(a,b) = 0 when a = 0 or b = 0
- K(a,b) = K(a-1,b) when $W_a > b$
- $K(a,b) = \max(K(a-1,b-w_a) + p_a, K(a-1,b))$
- The solution is at K(n,W)

The Failed Attempt #1

- Let *K(a)* be the best total value when we consider only item number *1* to number *a* and the weight limit is *W*
 - The answer is at K(n)
 - By definition, K(n) and K(n-1) and K(n-2)... all consider the same weight limit
- Let's say that the answer contains item number n
 - Also by definition, its means that K(n) = K(n-1) + pn
 - However, K(n-1) will consider the problem thinking that the weight limit is the same (not reduced by weight of item number n)
 - It is wrong to say that $K(a) = \max(K(a-1) + p_a, K(a-1))$
 - It is not possible to have a recurrence relation that does not consider W

The Failed Attempt #2

- Let *K(b)* be the best total value when the weight limit of the sack is *b*
 - The answer is at K(W)
- If the ith item is in the best solution
 - $K(W) = K(W W_i) + p_i$
- But, we don't really know that the ith item is in the optimal solution
 - So, we try everything
 - $K(W) = \max_{1 \le i \le n} (K(W W_i) + p_i)$
- Is this our algorithm?
 - Yes, if and only if we allow each item to be selected multiple times (that is not true for this problem)

Exercise: Top-Down approach

 Write a top down dynamic programming approach using this recurrence relation

```
• K(a,b) = 0 when a = 0 or b = 0

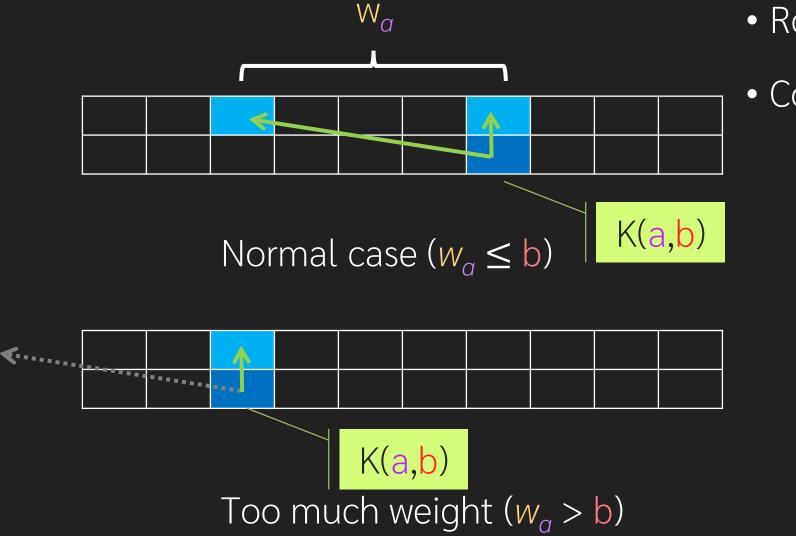
• K(a,b) = K(a-1,b) when w_a > b

• K(a,b) = \max(K(a-1,b-w_a) + p_a,

K(a-1,b)
```

- Which data structure should we use to store result?
 - Should we use 2D array?
 - Should we use associative data structure such as std::map or std::unordered_map?

The Table for Bottom-Up



Row = item id (a)

• Col = weight (b)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0																
1																
2																
3																
4																
5																

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0															
2	0															
3	0															
4	0															
5	0															

$$K(a,b) = 0$$
 when $a = 0$ or $b = 0$

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 1 $(p_1=4 \ w_1=12)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0															
2	0															
3	0															
4	0															
5	0															

Fill row 1 $(p_1=4 \ w_1=12)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0				
2	0															
3	0															
4	0															
5	0															

$$K(a,b) = K(a-1,b)$$

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 1 $(p_1=4 \ w_1=12)$

$$K(a,b) = \max(K(a-1,b-w_a) + p_a, K(a-1,b))$$

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 2 $(p_2=2 \ w_2=2)$

K(a,b) = K(a,b-1) when $w_b > a$

Fill row 2 $(p_2=2 \ w_2=2)$

$$K(a,b) = K(a-1,b)$$

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 2 $(p_2=2 \ w_2=2)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	√ 2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0															
4	0															
5	0															

$$K(a,b) = \max(K(a-1,b-w_a) + p_a, K(a-1,b))$$

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 2 $(p_2=2 \ w_2=2)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0															
4	0															
5	0															

$$K(a,b) = \max(K(a-1,b-w_a) + p_a, K(a-1,b))$$

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 3 $(p_3=2 \ w_3=1)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0															
5	0															

$$K(a,b) = \max(K(a-1,b-w_a) + p_a, K(a-1,b))$$

Fill row 3 $(p_3=2 \ w_3=1)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0															
5	0															

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 4 $(p_4=1 w_4=1)$

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0	2	3	4	5	5	5	5	5	5	5	5	5	6	7	8
5	0															

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 4 (p₄=1 w_4 =1)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0	2	3	4	5	5	5	5	5	5	5	5	5	6	7	8
5	0															

Fill row 5 ($p_5=10 \text{ w}_5=4$)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0	2	3	4	5	5	5	5	5	5	5	5	5	6	7	8
5	0	2	3	4	10	12	13	14	15	15	15	15	15	15	15	15

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Fill row 5 ($p_5=10 \text{ w}_5=4$)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0	2	3	4	5	5	5	5	5	5	5	5	5	6	7	8
5	0	2	3	4	10	12	13	14	15	15	15	15	15	15	15	15

$$p = \{4, 2, 2, 1, 10\}$$

 $w = \{12, 2, 1, 1, 4\}$ $W = 15$

Trace the solution backward to get the actual item number We have item number 5,4,3,2

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	4
2	0	0	2	2	2	2	2	2	2	2	2	2	4	4	6	6
3	0	2	2	4	4	4	4	4	4	4	4	4	4	6	6	8
4	0	2	3	4	5	5	5	5	5	5	5	5	5	6	7	8
5	0	2	3	4	10	12	13	14	15	15	15	15	15	15	15	15

Bottom-Up Code

Can you write a code that generate the list of actual item that we take?

- Does this code generate too much subproblem?
- Does it generates one that we does not need?
- Is it better to use Top-Down approach?
 - Can you show some instance that Top-Down is better than Bottom-up (this code)

Analysis

- From Bottom-Up, it is clear that this is O(Wn)
- Original generate-all-solution method is O(2ⁿ)
- Which one is better
 - In what case that O(Wn) Dynamic Programming will benefit greatly (because there are several overlapping subproblems)