

# Cormen Ch 15 - Dynamic Programming

- "programming" in dynamic programming means tabular method (i.e. of or relating to the use of a table) not to writing code
- much like divide-and-conquer, but applies when the subproblems overlap
- typically used for optimization problems
- procedure:
  - i. characterize the structure of an optimal solution
  - ii. recursively define the value of an optimal solution
  - iii. compute the value of an optimal solution -> typically bottom up
  - iv. construct an optimal solution from computed information

## 15.1 - Rod cutting

- given a rod of length  $n$  and a table of prices,  $p_i$  for  $i = 1, 2, \dots, n$ , obtain max revenue obtained by cutting the rod and selling the pieces
- can cut  $2^{n-1}$  ways
- the problem has an optimal substructure
- input:
  - $p[1..n]$  -> prices for sizes
  - $n$  -> size of rod
  - returns maximum value possible for rod size
- recursive top-down:

```
cut_rod(p, n):  
    if n == 0  
        return 0  
    q = -inf  
    for i == 1 to n  
        q = max(q, p[i] + cut_rod(p, n - i))  
    return q
```

- inefficient because it solve the same problems over and over again
- recursion tree

```
{  
  4: {  
    3: {  
      2: {  
        1: {  
          0: null
```

```

        },
        0: null
    },
    1: {
        0: null
    },
    0: null
},
2: {
    1: {
        0: null
    },
    0: null
},
1: {
    0: null
},
0: null
}
}

```

- dynamic programming for rod cutting (top-down with memoization)

```

memoized_cut_rod(p, n):
    let r[0...n]
    for i = 0 to n
        r[i] = -inf
    return memoized_cut_rod_aux(p, n, r)

memoized_cut_rod_aux(p, n, r):
    if r[n] >= 0
        return r[n]
    if n == 0
        q = 0
    else q = -inf
        for i = 1 to n
            q = max(q, p[i] + memoized_cut_rod_aux(p, n - 1, r))
    r[n] = q
    return q

```

- bottom-up dynamic cut rod

```

bottom_up_cut_rod(p, n):
    let r[0...n]
    r[0] = 0
    for j = 1 to n
        q = -inf
        for i = 1 to j
            q = max(q, p[i] + r[j - 1])

```

```
    r[j] = q
return r[n]
```

- subproblems form a graph, the subproblem graph, that embodies the relationship between subproblems, with a directed edge from one subproblem to another if the initial is dependent on the subsequent
- the size of the subproblem graph can help determine the running time
- can extend the dynamic programming example to include both a value and the choice that led to that value (or a set of all permutations of possible choices)

```
extended_bottom_up_cut_rod(p, n):
    let r[0...n] and s[1...n]
    r[0] = 0
    for j = 1 to n
        q = -inf
        for i = 1 to j
            if q < p[i] + r[j - i]
                q = p[i] + r[j - i]
                s[j] = i
        r[j] = q
    return r and s
```

```
print_cut_rod_solution(p, n):
    (r, s) = extended_bottom_up_cut_rod(p, n)
    while n > 0
        print s[n]
        n = n - s[n]
```

## 15.2 Matrix-chain multiplication

- fully parenthesized - matrix multiplication string that parenthesizes all pairs so each is of the form  $(A * B)$  or  $A * (()) * A$ , i.e. there is only one pair that is of the form  $(A * B)$  and the rest are of the second form

```
matrix_multiply(A, B)
    if A.columns != B.rows
        error "incompatible dimensions"
    else let C be a new A.rows x B.columns matrix
        for i = 1 to A.rows
            for j = 1 to B.columns
                c sub ij = 0
                for k = 1 to A.columns
```

```

        c sub ij = s sub ij + a sub ik * b sub kj
    return C

```

- matrix-chain multiplication problem:
  - given a chain of  $n$  matrices, fully parenthesize the product in a way that minimizes the number of scalar multiplications
- checking all parenthesizations does not yield an efficient algorithm
  - characterized by recurrence:

$$P(n) = \begin{cases} 1 & \text{if } n = 1, \\ \text{Sum from } k = 1 \text{ to } n - 1 \text{ of } P(k) * P(n - k) & \text{if } n \geq 2 \end{cases}$$

- similar to Catalan numbers
- dynamic programming:
  - substructure of optimal parenthesization:
    - the optimal parenthesization of a prefix subchain of matrices is a component of the solution
  - recursive solution

$$m[i, j] = \begin{cases} 0 & \text{if } i = j, \\ \min_{i \leq k < j} \{m[i, k] + m[k + 1, j] + p_{\text{sub } i - 1} * p_{\text{sub } k}\} & \end{cases}$$

### 3. computing optimal costs

```

matrix_chain_order(p)
    n = p.length - 1
    let m[1...n, 1...n] and s[1...n - 1, 2...n] (tables)
    for i = 1 to n
        m[i, i] = 0
    for l = 2 to n
        for i = 1 to n - l + 1
            j = i + l - 1
            m[i, j] = inf
            for k = i to j - 1
                q = m[i, k] + m[k + 1, j] + p sub i - 1 * p sub k * p sub j
                if q < m[i, j]
                    m[i, j] = q
                    s[i, j] = k
    return m and s

```

### 4. constructing an optimal solution

```

print_optimal_parens(s, i, j)
    if i == j
        print "A" sub i

```

```
else print "("
    print_optimal_parens(s, i, s[i, j])
    print_optimal_parens(s, s[i, j] + 1, j)
    print ")"
```

## 15.3 Elements of dynamic programming

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- optimal substructure: an optimal solution to a problem contains within it optimal solutions to subproblems
- pattern:
  - i. show a solution consists of making a choice which leaves one or more subproblems to be solved
  - ii. make the assumption that the choice leads to an optimal solution
  - iii. this assumption allows for determination of the resulting space of subproblems
  - iv. show that solutions to subproblems within an optimal solution to the problem must be optimal solutions to subproblems by assuming they aren't and showing a contradiction
- overlapping subproblems\*\*\*\*:
  - recursive algorithm revisits the same problem repeatedly
  - NOTE: this is why dynamic programming uses tables -> store results of repeated subproblems
- memoization:
  - maintain a table of the subproblem solutions and allow control structure to work recursively
  - uses a sentinel value to indicate a solution has not yet been determined for a subproblem