

Key Questions to DP

- What kind of problems cannot be solved by dynamic programming effectively?
 - ⇒ if it does not follow optimal substrcture
 - ⇒ the optimal solution to a problem always contains optimal solutions to all subproblems
 - ⇒ Not "combining optimal solutions to subproblems can guarantee a optimal solution!" (What's different?)
- What kind of problems cannot be solved by dynamic programming efficiently?
 - if too few *overlapping* problems
 - ⇒ a recursive solution only needs to compute a "small" number of distinct subproblems repeated many times

DP vs. Divide-and-Conquer

- Common: solve problems by combining the solutions to subproblems ⇒ "If you cannot solve a problem, then there is an easier problem you can solve it: find it." by George Polya (1987-1985)
- Divide-and-conquer algorithms
 - partition a problem into *independent* subproblems, solve the subproblems recursively, and then combine their solutions to solve the original problem
 - what's the potential problem??
 - ⇒ inefficient to solve overlapping subproblems
- Dynamic programming (DP)
 - -applicable if *many* subproblems are *repeated*
 - ⇒ DP solves each overlapping subproblem *just once*

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DP(1): Longest Common Subsequence

- What is the problem formulation?
 - Given 2 sequences, $\mathbf{X} = \langle x_1, ..., x_m \rangle$ and $\mathbf{Y} = \langle y_1, ..., y_n \rangle$, find a common *in-order* subsequence whose length is maximum
- How to apply DP to the LCS problem?
 - 1. Define the *optimal (sub)structure* and *recurrence relationship*) and then compute the <u>length</u> of a longest-common subsequence
 - 2. Backtrack the algorithm to find one solution
- Complexity of the LCS problem
 - Space: O(mn) to construct the length table
 - Time: Computing the table: O(mn)
 Constructing an LCS: O(m+n)

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Other Similar Sequence Problems



-Given 2 sequences, $X = \langle x_1, ..., x_m \rangle$ and $Y = \langle y_1, ..., y_n \rangle$, what is the minimum number of deletions, insertions, and substitutions that you must do to change one to another?

■ Protein sequence alignment:

- -Given a score matrix on amino acid pairs, s(a,b) for $a,b\in\{\Lambda\}\cup A$, and 2 amino acid sequences, $X=\langle x_1,...,x_m\rangle\in A^m$ and $Y=\langle y_1,...,y_n\rangle\in A^n$, find the alignment with lowest score...
- Study the textbook by yourself

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Edit Distance & Example

- Suppose we have two strings x,y
 - -e.g. x = kitten and y = sitting
- And we want to transform x into y.
- We use *edit operations*:
 - -insertions
 - -deletions k i t t e n
 - -substitutions sitting
- A close look
 - -1st step: kitten ⇒ sitten (substitution)
 - -2nd step: sitten ⇒ sittin (substitution)
 - -3rd step: sittin ⇒ sitting (insertion)

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Development of a DP (revisited)

- Four steps in developing a DP algorithm
 - 1. Characterize the *optimal* structure
 - 2. **Recursively** define the formula of an optimal solution
 - 3. Compute the value of an optimal solution either **bottom-up** in a **table** or **top-down** with memorization (**caching**)
 - 4. Construct an optimal solution from computed information (this step can be omitted if only the value is required)

Developing DP for Edit Distance

- Given strings $X = \langle x_1, ..., x_m \rangle$ and $Y = \langle y_1, ..., y_n \rangle$
- Define d(i,j) = |ED(X[1..i], Y[1..j])| ⇒ Find d(m,n) = |ED(X,Y)|
- Then

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- 1. If $x_i = y_j$, then no cost on changing x_i to $y_j \Rightarrow d(i,j) = d(i-1,j-1)$.
- 2. If $x_i \neq y_i$, then d(i,j) from the minimum of
 - insert $x_i \Rightarrow d(i,j) = d(i-1,j) + 1$
 - delete y_i ⇒ d(i,j) = d(i,j-1) +1
 - substitute x_i to $y_i \Rightarrow d(i,j) = d(i-1,j-1) +1$
- How about d(i,j) as i=0 or j=0???

Modify LCS_v2.cpp

L05-7

Binomial Coefficient

A binomial coefficient is indexed by a pair of integers n ≥ k ≥ 0 and is written

$$\binom{n}{k} = \begin{cases} 1, & \text{if } k = 0 \text{ or } k = n \\ \binom{n-1}{k-1} + \binom{n-1}{k}, & \text{else} \end{cases}$$

- Write a recursive in C/C++ to implement binomial coefficient (NaiveCnk.cpp)
- Let's write this recursive again with memorization (MemCnk.cpp)
- Observe their efficiency
- ⇒ Now we shall understand *top-down caching*

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DP(2): Matrix-Chain Multiplication

- Problem Formulation:
 - Given a chain $\langle A_1, A_2, ..., A_n \rangle$ of n matrices, matrix A_i has dimension $p_{i-1} \times p_i$, parenthesize the product $\mathbf{A} = A_1 A_2 ... A_n$ to minimize the number of scalar multiplications.
- Example: 3 matrices: *A*₁:4×2, *A*₂:2×5, *A*₃:5×1
 - $-(A_1A_2)A_3$: total multiplications = $4\times2\times5+4\times5\times1=60$.
 - $-A_1(A_2A_3)$: total multiplications = $2\times5\times1+4\times2\times1=18$.
- So the order of parenthesis for multiplications can make a big difference
 - But how to find the best order??
 - -# of combinations of different parenthesizations??

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Number of Different Parenthesizations

- Catalan Number: For any n,
 # ways to fully parenthesize the product of a chain of n+1 matrices
 - = # of binary trees with *n* nodes.
 - = # of permutations generated from 1 2 ... *n* through a stack.
 - = # of *n* pairs of fully matched parentheses.
 - = *n*-th Catalan Number
 - $= C(2n,n)/(n+1) = \Omega(4^n/n^{3/2})$
- The Brute-Force algorithm is hopeless!
 - -What else can we try?
 - ⇒ Dynamic Programming

Apply DP to Matrix-Chain Multiplication

- Step 1: Characterize the optimal structure Let m[i, j] be the minimum number of multiplications to compute matrix $A_{i..j} = A_i$ $A_{i+1}...A_i$, $1 \le i \le j \le n$
 - $-A_1, A_2, ..., A_n$ with sizes in $p_0 \times p_1, p_1 \times p_2, ..., p_{n-1} \times p_n$
 - -m[1, n]: the cheapest cost to compute $A_{1..n}$ Suppose the optimal parenthesization of $A_{i..j}$ splits the product between A_k and A_{k+1} , then the parenthesizations of $A_{i..k}$ and $A_{k+1..j}$ must be optimal
 - -Why? How to prove?? (by contradiction!)

Apply DP to Matrix-Chain Multiplication (cont'd)

- Step 2: Define the recurrence relationship $m[i,j] = \{ min_{i \le k < j} m[i,k] + m[k+1,j] + p_{i-1}p_k p_j, i < j \}$
- Step 3: Compute costs tabularly (top-down)
 input: dimension sequence $p = \langle p_0, p_1, ..., p_n \rangle$

```
Naive_Matrix_Chain(p,i,j)

1 if i = j then return 0;

2 m[i,j] \leftarrow \infty; //or INT_MAX

3 for k \leftarrow i to (j-1)

4 q \leftarrow N_M_C(p,i,k)+N_M_C(p,k+1,j)+p_{i-1}p_kp_j;

5 if q < m[i,j] then m[i,j] \leftarrow q

6 return m[i,j];
```

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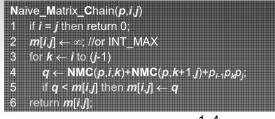
Example of Matrix-Chain-Order (cont'd)

Consider an example with sequence of dimensions <5,2,3,4,6,7,8> m[i,j] = min_{i≤k<j} { m[i,k]+m[k+1,j]+p_{i-1}p_kp_j }

Ex: m[1,1]+m[2,6]+5*2*8=0+268+80=348, m[1,2]+m[3,6]+5*3*8=30+366+120=516, ...

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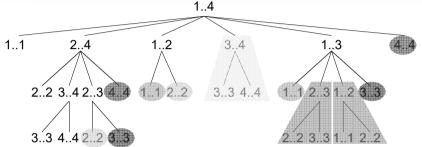
Example of Matrix-Chain-Order



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Problem: repeat on computing the same subproblems!!

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Memorization for Top-down DP

Simple idea: maintain a table M to memorize solutions to the computed subproblems

```
Memorized_Matrix_Chain(p)

1 n \leftarrow \text{length}[p]-1;

2 for i \leftarrow 1 to n

3 for j \leftarrow 1 to n

4 m[i,j] \leftarrow \infty;

5 return Lookup_Chain(p,1,n);
```

```
Lookup_Chain(p, i, j)

1 if m[i,j] < \infty

2 return m[i,j];

3 if i = j then m[i,j] \leftarrow 0;

4 else

5 for k \leftarrow i to (j-1)

6 q \leftarrow \text{Lookup\_Chain}(p,i,k) + \text{Lookup\_Chain}(p,k+1,j) + p_{i-1}p_kp_j;

7 if q < m[i,j] then m[i,j] \leftarrow q;

8 return m[i,j];
```

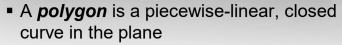
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Apply DP to Matrix-Chain Multiplication (cont'd)

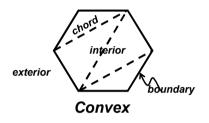
- Step 4: Construct an Optimal Solution
 - -Optimal matrix $A_{1,n}$ multiplication:
 - $A_{1..s[1,n]} \times A_{s[1,n]+1..n}$
 - Backtrack the Lookup-Chain table *M* to find the current splitting *k*
- Complexity analysis
 - -Space: $O(n^2)$ for the memorization table **M**
 - -Time: total runtime $O(n^3)$. Why??
 - \because each entry in **M** takes O(n) time

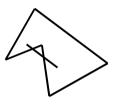
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DP(3): Application on Polygon



■ Def: A polygon P is **convex** if, when you connect any two points p, q in the polygon (interior + boundary), the entire line segment pq lies in the polygon.





Not convex

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Optimal Polygon Triangulation

- A *triangulation* of a polygon $P = \langle v_0, v_1, ..., v_{n-1} \rangle$ is a set of *non-intersecting diagonals* that partitions the polygon into triangles.
 - -an edge v_iv_j is called a *diagonal* if v_i and v_j
 are not adjacent vertices
- Optimal Polygon Triangulation Problem:

Given a convex polygon $P = \langle v_0, v_1, ..., v_{n-1} \rangle$ and a weight function w defined on triangles, find a triangulation that minimizes $\sum_{\forall \land} \{w(\Delta)\}$.

Optimal Polygon Triangulation Problem

- Input: a convex polygon $P = \langle v_0, v_1, ..., v_{n-1} \rangle$
- Output: an optimal triangulation with minimum w_P





• One possible weight function on triangle:

$$w(\Delta v_i v_j v_k) = |v_i v_j| + |v_j v_k| + |v_k v_i|,$$

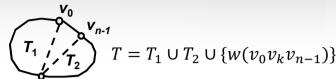
where $|v_i v_j|$ is the Euclidean distance
–total weight = boundary+2×(length of all diagonals)

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Apply DP to Optimal Polygon Triangulation

- Matrix-chain multiplication is a special case of the optimal polygonal triangulation problem.
- Complexity: Runs in $O(n^3)$ time and uses $O(n^2)$ space.

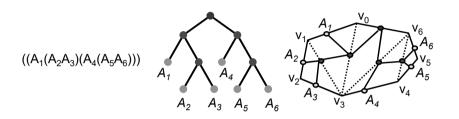
Hint:



- Step 1:
 - Suppose the optimal polygon triangulation of $P_{i..j}$ connect at v_k , then the polygon triangulation of $P_{i..k}$ and $P_{k+1..j}$ must be optimal
- $\textbf{Step 2:} \\ t[i,j] = \begin{cases} 0 & \text{, if } i = j \\ \min_{i \le k \le j-1} \{t[i,k] + t[k+1,j] + w(\Delta v_{i-1} v_k v_j)\} & \text{, if } i < j \end{cases}$

Correspondence between DP Problems

- Between full parenthesization, full binary tree (parse tree), and triangulation
- full parenthesization: multiplication pairs
 - ⇔ full binary tree: non-leaf nodes
 - ⇔ triangulation: mid-points on diagonals

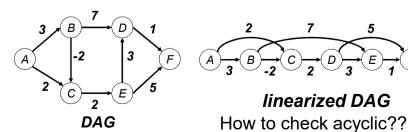


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DP(4): Shortest Path Problem

(Single Source) Shortest Path

- -Input: given a weighted graph G=(V,E), a source $s \in V$, and a sink $t \in V$,
- Output: a path of minimum weight betweens and t.



Apply DP to Shortest Path Problem

- Step 1: Characterize the optimal substructure
 Any part of the shortest path is also shortest.
- Step 2: Define the recurrence relationship
 - -where d(v) is the shortest distance from s to v and d(s)=0
- Complexity analysis:
 - -Runs in O(|E|) time and uses O(|V|) space.
 - -Why?

3 Types of Overlapping Problems

- ① input is $x_1, x_2, ..., x_n$ and a subproblem is $x_1, x_2, ..., x_i$ \Rightarrow # of subproblems is O(n).
 - EX: (single source) shortest path problem on DAGs
- ② input is $x_1, x_2, ..., x_n$ and $y_1, y_2, ..., y_m$, a subproblem is $x_1, x_2, ..., x_i$ and $y_1, y_2, ..., y_j$
 - \Rightarrow # of subproblems is $\mathbf{O}(nm)$.

triangulation

- EX: longest common subsequence, edit distance, protein sequence alignment
- ③ input is $x_1, x_2, ..., x_n$ and a subproblem is $x_i, x_{i+1}, ..., x_j$ \Rightarrow # of subproblems is $O(n^2)$. EX: matrix-chain multiplication, convex polygon

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Summary

- How to apply DP to your problem?
 - ① Characterize the optimal structure
 - ② Define the recurrence formula (relationship)
 - ③ Compute costs tabularly (bottom-up/top-down)
 - Construct an Optimal Solution
- Matrix-Chain Multiplication in top-down
 - think about bottom up
 - Time complexity? Space complexity?
 - Optimal Polygon Triangulation and its correspondence w/ Matrix-Chain Multiplication
- 3 Types of common overlapping problems
- Next Lecture ⇒ Knapsack problem and Greedy Algorithms

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