More Dynamic Programming

Lecture 9
February 18, 2014
What is the running time of the following?

Consider computing $f(x, y)$ by recursive function + memoization.

$$f(x, y) = \sum_{i=1}^{x+y-1} x \cdot f(x + y - i, i - 1),$$

$$f(0, y) = y \quad f(x, 0) = x.$$

The resulting algorithm when computing $f(n, n)$ would take:

(A) $O(n)$
(B) $O(n \log n)$
(C) $O(n^2)$
(D) $O(n^3)$
(E) The function is ill defined - it can not be computed.
Part I

Maximum Weighted Independent Set in Trees
Maximum Weight Independent Set Problem

Input  Graph $G = (V, E)$ and weights $w(v) \geq 0$ for each $v \in V$

Goal  Find maximum weight independent set in $G$

Maximum weight independent set in above graph: $\{B, D\}$
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**Goal** Find maximum weight independent set in $G$

Maximum weight independent set in above graph: $\{B, D\}$
Maximum Weight Independent Set in a Tree

Input  Tree $T = (V, E)$ and weights $w(v) \geq 0$ for each $v \in V$

Goal Find maximum weight independent set in $T$

Maximum weight independent set in above tree: ??
Independent set in a tree...

In a tree with $n$ nodes, there is always an independent set of size (bigger is better [this is America!])

(A) $\Omega(1)$
(B) $\Omega(\log n)$
(C) $\Omega(\sqrt{n})$
(D) $n/2$
(E) $n - 5$
Towards a Recursive Solution

For an arbitrary graph $G$:

1. Number vertices as $v_1, v_2, \ldots, v_n$
2. Find recursively optimum solutions without $v_n$ (recurse on $G - v_n$) and with $v_n$ (recurse on $G - v_n - N(v_n)$ & include $v_n$).
3. Saw that if graph $G$ is arbitrary there was no good ordering that resulted in a small number of subproblems.

What about a tree? Natural candidate for $v_n$ is root $r$ of $T$?
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Towards a Recursive Solution

Natural candidate for $v_n$ is root $r$ of $T$? Let $O$ be an optimum solution to the whole problem.

**Case** $r \notin O$ : Then $O$ contains an optimum solution for each subtree of $T$ hanging at a child of $r$.

**Case** $r \in O$ : None of the children of $r$ can be in $O$. $O - \{r\}$ contains an optimum solution for each subtree of $T$ hanging at a grandchild of $r$.

Subproblems? Subtrees of $T$ hanging at nodes in $T$. 
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A Recursive Solution

\(T(u)\): subtree of \(T\) hanging at node \(u\)

\(OPT(u)\): max weighted independent set value in \(T(u)\)

\[OPT(u) = \max \left\{ \sum_{v \text{ child of } u} OPT(v), w(u) + \sum_{v \text{ grandchild of } u} OPT(v) \right\}\]
A Recursive Solution

$T(u)$: subtree of $T$ hanging at node $u$

$OPT(u)$: max weighted independent set value in $T(u)$

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\end{cases}$$
Iterative Algorithm

1. Compute $\text{OPT}(u)$ bottom up. To evaluate $\text{OPT}(u)$ need to have computed values of all children and grandchildren of $u$.

2. What is an ordering of nodes of a tree $T$ to achieve above?
   Post-order traversal of a tree.
Iterative Algorithm

1. Compute $\text{OPT}(u)$ bottom up. To evaluate $\text{OPT}(u)$ need to have computed values of all children and grandchildren of $u$.

2. What is an ordering of nodes of a tree $T$ to achieve above? Post-order traversal of a tree.
Iterative Algorithm

**MIS-Tree**(*T*):

Let \(v_1, v_2, \ldots, v_n\) be a post-order traversal of nodes of \(T\)

```plaintext
for \(i = 1\) to \(n\) do

\[
M[v_i] = \max \left( \sum_{v_j \text{ child of } v_i} M[v_j], \quad w(v_i) + \sum_{v_j \text{ grandchild of } v_i} M[v_j] \right)
\]

return \(M[v_n]\) (* Note: \(v_n\) is the root of \(T\) *)
```

**Space:** \(O(n)\) to store the value at each node of \(T\)

**Running time:**

1. Naive bound: \(O(n^2)\) since each \(M[v_i]\) evaluation may take \(O(n)\) time and there are \(n\) evaluations.
2. Better bound: \(O(n)\). A value \(M[v_j]\) is accessed only by its parent and grand parent.
Iterative Algorithm

**MIS-Tree**($T$):

Let $v_1, v_2, \ldots, v_n$ be a post-order traversal of nodes of $T$

for $i = 1$ to $n$

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M[v_i] = \max \left( \sum_{\text{child of } v_i} M[v_j], w(v_i) + \sum_{\text{grandchild of } v_i} M[v_j] \right)
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Example

Chandra (UIUC)
Part II

Edit Distance and Sequence Alignment
Spell Checking Problem

Given a string “exponen” that is not in the dictionary, how should a spell checker suggest a nearby string?

What does nearness mean?

**Question:** Given two strings $x_1x_2\ldots x_n$ and $y_1y_2\ldots y_m$ what is a distance between them?

**Edit Distance:** minimum number of “edits” to transform $x$ into $y$. 
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**Edit Distance:** minimum number of “edits” to transform $x$ into $y$. 
Edit Distance

**Definition**

Edit distance between two words $X$ and $Y$ is the number of letter insertions, letter deletions and letter substitutions required to obtain $Y$ from $X$.

**Example**

The edit distance between FOOD and MONEY is at most 4:

$$
\text{FOOD} \rightarrow \text{MOOD} \rightarrow \text{MONOD} \rightarrow \text{MONED} \rightarrow \text{MONEY}
$$
Alignment

Place words one on top of the other, with gaps in the first word indicating insertions, and gaps in the second word indicating deletions.

F O O D
M O N E Y

Formally, an alignment is a set $M$ of pairs $(i, j)$ such that each index appears at most once, and there is no “crossing”: $i < i'$ and $i$ is matched to $j$ implies $i'$ is matched to $j' > j$. In the above example, this is $M = \{(1, 1), (2, 2), (3, 3), (4, 5)\}$. Cost of an alignment is the number of mismatched columns plus number of unmatched indices in both strings.
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Alignment

Place words one on top of the other, with gaps in the first word indicating insertions, and gaps in the second word indicating deletions.

\[
\begin{array}{ccc}
  & F & O & O & D \\ 
M & O & N & E & Y
\end{array}
\]

Formally, an alignment is a set \( M \) of pairs \((i, j)\) such that each index appears at most once, and there is no “crossing”: \( i < i' \) and \( i \) is matched to \( j \) implies \( i' \) is matched to \( j' > j \). In the above example, this is \( M = \{(1, 1), (2, 2), (3, 3), (4, 5)\} \). Cost of an alignment is the number of mismatched columns plus number of unmatched indices in both strings.
Edit Distance Problem

Problem

Given two words, find the edit distance between them, i.e., an alignment of smallest cost.
Applications

1. Spell-checkers and Dictionaries
2. Unix `diff`
3. DNA sequence alignment ... but, we need a new metric
Similarity Metric

**Definition**

For two strings $X$ and $Y$, the cost of alignment $M$ is

1. **[Gap penalty]** For each gap in the alignment, we incur a cost $\delta$.

2. **[Mismatch cost]** For each pair $p$ and $q$ that have been matched in $M$, we incur cost $\alpha_{pq}$; typically $\alpha_{pp} = 0$.

Edit distance is a special case when $\delta = \alpha_{pq} = 1$. 
For two strings $X$ and $Y$, the cost of alignment $M$ is

1. **[Gap penalty]** For each gap in the alignment, we incur a cost $\delta$.
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Edit distance is special case when $\delta = \alpha_{pq} = 1$. 

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CS473  
Spring 2014
An Example

Example

Cost = \delta + \alpha_{ae}

Alternative:

Cost = 3\delta

Or a really stupid solution (delete string, insert other string):

Cost = 19\delta.
What is the minimum edit distance for the following two strings, if insertion/deletion/change of a single character cost 1 unit?

HAR–PELED
SHARP_EYED

(A) 1
(B) 2
(C) 3
(D) 4
(E) 5
Sequence Alignment

**Input**  Given two words $X$ and $Y$, and gap penalty $\delta$ and mismatch costs $\alpha_{pq}$

**Goal**  Find alignment of minimum cost
Let $X = \alpha x$ and $Y = \beta y$

$\alpha, \beta$: strings.

$x$ and $y$ single characters.

Think about optimal edit distance between $X$ and $Y$ as alignment, and consider last column of alignment of the two strings:

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>$y$</td>
</tr>
</tbody>
</table>

or

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>$x$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta y$</td>
<td></td>
</tr>
</tbody>
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</tr>
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<td>$\beta$</td>
<td>$y$</td>
</tr>
</tbody>
</table>

**Observation**

Prefixes must have optimal alignment!
Let $X = x_1x_2 \cdots x_m$ and $Y = y_1y_2 \cdots y_n$. If $(m, n)$ are not matched then either the $m$th position of $X$ remains unmatched or the $n$th position of $Y$ remains unmatched.

1. **Case** $x_m$ and $y_n$ are matched.
   - Pay mismatch cost $\alpha_{x_m y_n}$ plus cost of aligning strings $x_1 \cdots x_{m-1}$ and $y_1 \cdots y_{n-1}$

2. **Case** $x_m$ is unmatched.
   - Pay gap penalty plus cost of aligning $x_1 \cdots x_{m-1}$ and $y_1 \cdots y_n$

3. **Case** $y_n$ is unmatched.
   - Pay gap penalty plus cost of aligning $x_1 \cdots x_m$ and $y_1 \cdots y_{n-1}$
Subproblems and Recurrence

Optimal Costs

Let $\text{Opt}(i, j)$ be optimal cost of aligning $x_1 \cdots x_i$ and $y_1 \cdots y_j$. Then

$$\text{Opt}(i, j) = \min \begin{cases} 
\alpha_{x_i y_j} + \text{Opt}(i - 1, j - 1), \\
\delta + \text{Opt}(i - 1, j), \\
\delta + \text{Opt}(i, j - 1) 
\end{cases}$$

Base Cases: $\text{Opt}(i, 0) = \delta \cdot i$ and $\text{Opt}(0, j) = \delta \cdot j$
Let $\text{Opt}(i, j)$ be optimal cost of aligning $x_1 \cdots x_i$ and $y_1 \cdots y_j$. Then

$$\text{Opt}(i, j) = \min \begin{cases} 
\alpha_{x_i y_j} + \text{Opt}(i - 1, j - 1), \\
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\end{cases}$$

Base Cases: $\text{Opt}(i, 0) = \delta \cdot i$ and $\text{Opt}(0, j) = \delta \cdot j$
Dynamic Programming Solution

\[
\begin{align*}
&\text{for all } i \text{ do } M[i, 0] = i\delta \\
&\text{for all } j \text{ do } M[0, j] = j\delta \\
&\text{for } i = 1 \text{ to } m \text{ do} \\
&\quad \text{for } j = 1 \text{ to } n \text{ do} \\
&\quad \quad M[i, j] = \min \left\{ \alpha_{x_i,y_j} + M[i - 1, j - 1], \right. \\
&\quad \quad \left. \delta + M[i - 1, j], \delta + M[i, j - 1] \right\}
\end{align*}
\]

Analysis

Running time is \(O(mn)\).
Dynamic Programming Solution

for all i do $M[i, 0] = i\delta$

for all j do $M[0, j] = j\delta$

for $i = 1$ to $m$ do

for $j = 1$ to $n$ do

$$M[i, j] = \min \begin{cases} 
\alpha_{xi, yj} + M[i - 1, j - 1], \\
\delta + M[i - 1, j], \\
\delta + M[i, j - 1]
\end{cases}$$

Analysis

Running time is $O(mn)$. 
Dynamic Programming Solution

for all \( i \) do \( M[i, 0] = i \delta \)
for all \( j \) do \( M[0, j] = j \delta \)

for \( i = 1 \) to \( m \) do
  for \( j = 1 \) to \( n \) do
    \[
    M[i, j] = \min \left\{ \alpha_{x_i y_j} + M[i - 1, j - 1], \delta + M[i - 1, j], \delta + M[i, j - 1] \right\}
    \]

Analysis

1. Running time is \( O(mn) \).
2. Space used is \( O(mn) \).
Matrix and DAG of Computation

Figure: Iterative algorithm in previous slide computes values in row order. Optimal value is a shortest path from \((0, 0)\) to \((m, n)\) in the DAG.
Typically the DNA sequences that are aligned are about $10^5$ letters long!

So about $10^{10}$ operations and $10^{10}$ bytes needed.

The killer is the 10GB storage.

Can we reduce space requirements?
Recall

\[ M(i, j) = \min \begin{cases} 
\alpha_{x_i y_j} + M(i - 1, j - 1), \\
\delta + M(i - 1, j), \\
\delta + M(i, j - 1) 
\end{cases} \]

Entries in \( j \)th column only depend on \((j - 1)\)st column and earlier entries in \( j \)th column

Only store the current column and the previous column reusing space; \( N(i, 0) \) stores \( M(i, j - 1) \) and \( N(i, 1) \) stores \( M(i, j) \)
Computing in column order to save space

Figure: $M(i, j)$ only depends on previous column values. Keep only two columns and compute in column order.
Space Efficient Algorithm

for all i do  $N[i, 0] = i\delta$
for j = 1 to n do
  $N[0, 1] = j\delta$ (* corresponds to $M(0, j)$ *)
for i = 1 to m do
  $N[i, 1] = \min \begin{cases} 
    \alpha_{x_iy_j} + N[i - 1, 0] \\
    \delta + N[i - 1, 1] \\
    \delta + N[i, 0]
  \end{cases}$
for i = 1 to m do
  Copy $N[i, 0] = N[i, 1]$

Analysis

Running time is $O(mn)$ and space used is $O(2m) = O(m)$
1. From the $m \times n$ matrix $M$ we can construct the actual alignment (exercise)

2. Matrix $N$ computes cost of optimal alignment but no way to construct the actual alignment

Part III

DAGs and Dynamic Programming
Observation

Let $A$ be a recursive algorithm for problem $\Pi$. For each instance $I$ of $\Pi$ there is an associated DAG $G(I)$.

1. Create directed graph $G(I)$ as follows...
2. For each sub-problem in the execution of $A$ on $I$ create a node.
3. If sub-problem $v$ depends on or recursively calls sub-problem $u$ add directed edge $(u, v)$ to graph.
4. $G(I)$ is a DAG. Why? If $G(I)$ has a cycle then $A$ will not terminate on $I$. 
Recursion and **DAGs**

**Observation**

Let \( A \) be a recursive algorithm for problem \( \Pi \). For each instance \( I \) of \( \Pi \) there is an associated **DAG** \( G(I) \).

1. Create directed graph \( G(I) \) as follows...
2. For each sub-problem in the execution of \( A \) on \( I \) create a node.
3. If sub-problem \( v \) depends on or recursively calls sub-problem \( u \) add directed edge \((u, v)\) to graph.
4. **G(I)** is a **DAG**. Why? If **G(I)** has a cycle then **A** will not terminate on \( I \).
An iterative algorithm $B$ obtained from a recursive algorithm $A$ for a problem $\Pi$ does the following:

For each instance $I$ of $\Pi$, it computes a topological sort of $G(I)$ and evaluates sub-problems according to the topological ordering.

1. Sometimes the DAG $G(I)$ can be obtained directly without thinking about the recursive algorithm $A$
2. In some cases (not all) the computation of an optimal solution reduces to a shortest/longest path in DAG $G(I)$
3. Topological sort based shortest/longest path computation is dynamic programming!
A quick reminder...

A Recursive Algorithm for weighted interval scheduling

Let $O_i$ be value of an optimal schedule for the first $i$ jobs.

$$
\text{Schedule}(n) :
\begin{align*}
&\text{if } n = 0 \text{ then return } 0 \\
&\text{if } n = 1 \text{ then return } w(v_1) \\
&O_{p(n)} \leftarrow \text{Schedule}(p(n)) \\
&O_{n-1} \leftarrow \text{Schedule}(n - 1) \\
&\text{if } (O_{p(n)} + w(v_n) < O_{n-1}) \text{ then} \\
&\quad O_n = O_{n-1} \\
&\text{else} \\
&\quad O_n = O_{p(n)} + w(v_n) \\
&\text{return } O_n
\end{align*}
$$
Given intervals, create a DAG as follows:

1. Create one node for each interval, plus a dummy sink node 0 for interval 0, plus a dummy source node s.
2. For each interval i add edge (i, p(i)) of the length/weight of v_i.
3. Add an edge from s to n of length 0.
4. For each interval i add edge (i, i − 1) of length 0.
Example

$p(5) = 2, p(4) = 1, p(3) = 1, p(2) = 0, p(1) = 0$
Relating Optimum Solution

Given interval problem instance \( I \) let \( G(I) \) denote the DAG constructed as described.

**Claim**

Optimum solution to weighted interval scheduling instance \( I \) is given by longest path from \( s \) to \( 0 \) in \( G(I) \).

Assuming claim is true,

1. If \( I \) has \( n \) intervals, \( G(I) \) has \( n + 2 \) nodes and \( O(n) \) edges. Creating \( G(I) \) takes \( O(n \log n) \) time: to find \( p(i) \) for each \( i \). How?

2. Longest path can be computed in \( O(n) \) time — recall \( O(m + n) \) algorithm for shortest/longest paths in DAGs.
Given interval problem instance $I$ let $G(I)$ denote the DAG constructed as described.

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Optimum solution to weighted interval scheduling instance $I$ is given by longest path from $s$ to $0$ in $G(I)$.

Assuming claim is true,

1. If $I$ has $n$ intervals, DAG $G(I)$ has $n + 2$ nodes and $O(n)$ edges. Creating $G(I)$ takes $O(n \log n)$ time: to find $p(i)$ for each $i$. How?

2. Longest path can be computed in $O(n)$ time — recall $O(m + n)$ algorithm for shortest/longest paths in DAGs.
DAG for Longest Increasing Sequence

Given sequence $a_1, a_2, \ldots, a_n$ create DAG as follows:

1. add sentinel $a_0$ to sequence where $a_0$ is less than smallest element in sequence
2. for each $i$ there is a node $v_i$
3. if $i < j$ and $a_i < a_j$ add an edge $(v_i, v_j)$
4. find longest path from $v_0$
DAG for Longest Increasing Sequence

Given sequence $a_1, a_2, \ldots, a_n$ create DAG as follows:

1. add sentinel $a_0$ to sequence where $a_0$ is less than smallest element in sequence
2. for each $i$ there is a node $v_i$
3. if $i < j$ and $a_i < a_j$ add an edge $(v_i, v_j)$
4. find longest path from $v_0$
Dynamic programming is based on finding a recursive way to solve the problem. Need a recursion that generates a small number of subproblems.

Given a recursive algorithm there is a natural DAG associated with the subproblems that are generated for given instance; this is the dependency graph. An iterative algorithm simply evaluates the subproblems in some topological sort of this DAG.

The space required to evaluate the answer can be reduced in some cases by a careful examination of that dependency DAG of the subproblems and keeping only a subset of the DAG at any time.