More Dynamic Programming

Lecture 14
Tuesday, March 5, 2019
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:

- $O(n)$
- $O(n \log n)$
- $O(n^2)$
- $O(n^3)$
- The function is ill defined - it can not be computed.
Recipe for Dynamic Programming

1. Develop a recursive backtracking style algorithm \( \mathcal{A} \) for given problem.

2. Identify structure of subproblems generated by \( \mathcal{A} \) on an instance \( I \) of size \( n \)
   - Estimate number of different subproblems generated as a function of \( n \). Is it polynomial or exponential in \( n \)?
   - If the number of problems is “small” (polynomial) then they typically have some “clean” structure.

3. Rewrite subproblems in a compact fashion.

4. Rewrite recursive algorithm in terms of notation for subproblems.

5. Convert to iterative algorithm by bottom up evaluation in an appropriate order.

6. Optimize further with data structures and/or additional ideas.
A variation

Input A string $w \in \Sigma^*$ and access to a language $L \subseteq \Sigma^*$ via function $\text{IsStringinL}(\text{string } x)$ that decides whether $x$ is in $L$, and non-negative integer $k$

Goal Decide if $w \in L^k$ using $\text{IsStringinL}(\text{string } x)$ as a black box sub-routine

Example

Suppose $L$ is $\text{English}$ and we have a procedure to check whether a string/word is in the $\text{English}$ dictionary.

- Is the string “isthisenganlishsentence” in $\text{English}^5$?
- Is the string “isthisenganlishsentence” in $\text{English}^4$?
- Is “asinineat” in $\text{English}^2$?
- Is “asinineat” in $\text{English}^4$?
- Is “zibzzzzad” in $\text{English}^1$?
Recursive Solution

When is $w \in L^k$?

$k = 0$: $w \in L^k$ iff $w = \epsilon$

$k = 1$: $w \in L^k$ iff $w \in L$

$k > 1$: $w \in L^k$ if $w = uv$ with $u \in L$ and $v \in L^{k-1}$

Assume $w$ is stored in array $A[1..n]$

**IsStringinLk($A[1..n]$, $k$):**

If ($k = 0$)

If ($n = 0$) Output YES
Else Output NO

If ($k = 1$)

Output $\text{IsStringinL}(A[1..n])$

Else

For ($i = 1$ to $n - 1$) do

If ($\text{IsStringinL}(A[1..i])$ and $\text{IsStringinLk}(A[i+1..n], k-1)$)

Output YES

Output NO
Recursive Solution

When is $w \in L^k$?

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Assume $w$ is stored in array $A[1..n]$

IsStringinLk($A[1..n]$, $k$):

- If $(k = 0)$
  - If $(n = 0)$ Output YES
  - Else Output NO

- If $(k = 1)$
  - Output IsStringinL($A[1..n]$)

- Else
  - For $(i = 1$ to $n - 1$) do
    - If (IsStringinL($A[1..i]$) and IsStringinLk($A[i + 1..n]$, $k - 1$))
      - Output YES

Output NO
Recursive Solution

When is $w \in L^k$?

$k = 0$: $w \in L^k$ iff $w = \epsilon$

$k = 1$: $w \in L^k$ iff $w \in L$

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Assume $w$ is stored in array $A[1..n]$

**IsStringinLk**($A[1..n], k$):

If ($k = 0$)

If ($n = 0$) Output YES
Else Output NO

If ($k = 1$)

Output **IsStringinL**($A[1..n]$)

Else

For ($i = 1$ to $n - 1$) do

If (**IsStringinL**($A[1..i]$) and **IsStringinLk**($A[i + 1..n], k - 1$))

Output YES

Output NO
IsStringinLk(A[1..n], k):
    If (k = 0)
        If (n = 0) Output YES
        Else Output NO
    If (k = 1)
        Output IsStringinL(A[1..n])
    Else
        For (i = 1 to n − 1) do
            If (IsStringinL(A[1..i]) and IsStringinLk(A[i + 1..n], k − 1))
                Output YES
        Output NO

- How many distinct sub-problems are generated by IsStringinLk(A[1..n], k)? \( O(nk) \)
- How much space? \( O(nk) \) pause
- Running time? \( O(n^2k) \)
Analysis

**IsStringinLk**($A[1..n], k$):

If ($k = 0$)
  
  If ($n = 0$) Output YES
  Else Output NO

If ($k = 1$)
  
  Output **IsStringinL**($A[1..n]$)

Else
  
  For ($i = 1$ to $n - 1$) do
    
    If (**IsStringinL**($A[1..i]$) and **IsStringinLk**($A[i + 1..n], k - 1$))
      Output YES

Output NO

- How many distinct sub-problems are generated by **IsStringinLk**($A[1..n], k$)? $O(nk)$
- How much space? $O(nk)$ pause
- Running time? $O(n^2k)$
Analysis

\textbf{IsStringinLk}(A[1..n], k):

If \((k = 0)\)
  
  If \((n = 0)\) Output YES
  
  Else Output NO

If \((k = 1)\)
  
  Output \textbf{IsStringinL}(A[1..n])

Else

  For \((i = 1\) to \(n - 1\)) do
    
    If \((\text{IsStringinL}(A[1..i]) \text{ and } \text{IsStringinLk}(A[i + 1..n], k - 1))\)
      
      Output YES

Output NO

- How many distinct sub-problems are generated by \textbf{IsStringinLk}(A[1..n], k)? \(O(nk)\)
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**IsStringinLk(\(A[1..n], k\))**:

- If \(k = 0\)  
  - If \(n = 0\) Output YES  
  - Else Output NO  
- If \(k = 1\)  
  - Output \(\text{IsStringinL}(A[1..n])\)  
- Else  
  - For \(i = 1\) to \(n - 1\) do  
    - If (\(\text{IsStringinL}(A[1..i])\) and \(\text{IsStringinLk}(A[i+1..n], k-1)\))  
      - Output YES  
  - Output NO

- How many distinct sub-problems are generated by \(\text{IsStringinLk}(A[1..n], k)\)? \(O(nk)\)
- How much space? \(O(nk)\) pause
- Running time? \(O(n^2k)\)
**Analysis**

IsStringinLk(A[1..n], k):

1. If (k = 0)
   - If (n = 0) Output YES
   - Else Output NO
2. If (k = 1)
   - Output IsStringinL(A[1..n])
3. Else
   - For (i = 1 to n − 1) do
     - If (IsStringinL(A[1..i]) and IsStringinLk(A[i + 1..n], k − 1))
       - Output YES
   - Output NO

- How many distinct sub-problems are generated by IsStringinLk(A[1..n], k)? \( O(nk) \)
- How much space? \( O(nk) \) pause
- Running time? \( O(n^2k) \)
Another variant

**Question:** What if we want to check if $w \in L^i$ for some $0 \leq i \leq k$? That is, is $w \in \bigcup_{i=0}^{k} L^i$?
Exercise

Definition

A string is a palindrome if $w = w^R$.
Examples: $I$, $RACECAR$, $MALAYALAM$, $DOOFFOOD$

Problem: Given a string $w$ find the longest subsequence of $w$ that is a palindrome.

Example

$MAHDYNAMICPROGRAMZLETMESHOWYOUTHEM$ has $MHYMRORMYHM$ as a palindromic subsequence
Exercise

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Example

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Exercise

Assume $w$ is stored in an array $A[1..n]$  

$LPS(A[1..n])$: length of longest palindromic subsequence of $A$.  

Recursive expression/code?
Part I

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 $x_1 x_2 \ldots x_n$ and $y_1 y_2 \ldots y_m$ what is a *distance* between them?

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

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Chan, Har-Peled, Hassanieh (UIUC)
Spell Checking Problem

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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.

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

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.
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.

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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.
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.

\[ \text{FOOD} \]
\[ \text{MONEY} \]

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
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 special case when $\delta = \alpha_{pq} = 1$. 

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 special case when $\delta = \alpha_{pq} = 1$. 
An Example

Example

\[ \text{o c c u r r a n c e} \quad \text{o c c u r r e n c e} \quad \text{Cost} = \delta + \alpha_{ae} \]

Alternative:

\[ \text{o c c u r r a n c e} \quad \text{o c c u r r e n c e} \quad \text{Cost} = 3\delta \]

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

\[ \text{o c c u r r a n c e} \quad \text{o c c u r r e n c e} \quad \text{Cost} = 19\delta. \]
What is the minimum edit distance for the following two strings, if insertion/deletion/change of a single character cost 1 unit?

374
473

1
2
3
4
5
What is the minimum edit distance for the following two strings, if insertion/deletion/change of a single character cost 1 unit?

373
473

1
2
3
4
5
What is the edit distance between...

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

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

37
473
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>
<th>or</th>
<th>$\alpha$</th>
<th>$x$</th>
<th>or</th>
<th>$\alpha x$</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>$y$</td>
<td></td>
<td>$\beta$</td>
<td>$y$</td>
<td></td>
<td>$\beta$</td>
<td>$y$</td>
</tr>
</tbody>
</table>

**Observation**

*Prefixes must have optimal alignment!*
Observation

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.
   1. Pay mismatch cost $\alpha_{x_my_n}$ plus cost of aligning strings $x_1 \cdots x_{m-1}$ and $y_1 \cdots y_{n-1}$

2. Case $x_m$ is unmatched.
   1. 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.
   1. 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 $\text{Opt}(0, j) = \delta \cdot j$
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

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

Base Cases: $\text{Opt}(i, 0) = \delta \cdot i$ and $\text{Opt}(0, j) = \delta \cdot j$
Recursive Algorithm

Assume $X$ is stored in array $A[1..m]$ and $Y$ is stored in $B[1..n]$. Array $COST$ stores cost of matching two chars. Thus $COST[a, b]$ give the cost of matching character $a$ to character $b$.

$$EDIST(A[1..m], B[1..n])$$
- If ($m = 0$) return $n\delta$
- If ($n = 0$) return $m\delta$
- $m_1 = \delta + EDIST(A[1..(m-1)], B[1..n])$
- $m_2 = \delta + EDIST(A[1..m], B[1..(n-1)])$
- $m_3 = COST[A[m], B[n]] + EDIST(A[1..(m-1)], B[1..(n-1)])$
- return $\min(m_1, m_2, m_3)$
Example

DEED and DREAD
Memoizing the Recursive Algorithm

```
int M[0..m][0..n]
Initialize all entries of M[i][j] to ∞
return EDIST(A[1..m], B[1..n])
```

```
EDIST(A[1..m], B[1..n])
If (M[i][j] < ∞) return M[i][j]    (* return stored value *)

If (m = 0)
    M[i][j] = nδ
ElseIf (n = 0)
    M[i][j] = mδ
Else
    m₁ = δ + EDIST(A[1..(m − 1)], B[1..n])
    m₂ = δ + EDIST(A[1..m], B[1..(n − 1)])
    m₃ = COST[A[m], B[n]] + EDIST(A[1..(m − 1)], B[1..(n − 1)])
    M[i][j] = min(m₁, m₂, m₃)
return M[i][j]
```
Removing Recursion to obtain Iterative Algorithm

\[
\text{EDIST}(A[1..m], B[1..n])
\]
\[
\text{int } M[0..m][0..n]
\]
\[
\text{for } i = 1 \text{ to } m \text{ do } M[i, 0] = i\delta
\]
\[
\text{for } j = 1 \text{ to } n \text{ do } M[0, j] = j\delta
\]
\[
\text{for } i = 1 \text{ to } m \text{ do }
\]
\[
\text{for } j = 1 \text{ to } n \text{ do }
\]
\[
M[i][j] = \min \left\{ \alpha_{x_i y_j} + M[i-1][j-1], \delta + M[i-1][j], \delta + M[i][j-1] \right\}
\]

Analysis

Running time is \(O(mn)\).
Removing Recursion to obtain Iterative Algorithm

\[ \text{EDIST}(A[1..m], B[1..n]) \]

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

Analysis

Running time is \( O(mn) \).
Removing Recursion to obtain Iterative Algorithm

\[
EDIST(A[1..m], B[1..n])
\]

\[
\text{int } M[0..m][0..n]
\]

\[
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\]

\[
\text{for } j = 1 \text{ to } n \text{ do } M[0, j] = j\delta
\]

\[
\text{for } i = 1 \text{ to } m \text{ do }
\]

\[
\text{for } j = 1 \text{ to } n \text{ do }
\]

\[
M[i][j] = \min \left\{ \alpha_{x_i, y_j} + M[i - 1][j - 1], \delta + M[i - 1][j], \delta + M[i][j - 1] \right\}
\]

Analysis

1. Running time is \(O(mn)\).
2. Space used is \(O(mn)\).
Figure: Iterative algorithm in previous slide computes values in row order.
Example

DEED and DREAD
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?
Optimizing Space

1. Recall

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

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

3. 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
  $N[i, 1] = \min \begin{cases} 
  \alpha_{x_i,y_j} + N[i - 1, 0] \\
  \delta + N[i - 1, 1] \\
  \delta + N[i, 0] \end{cases}$

for $i = 1$ to $m$ do
  Copy $N[i, 0] = N[i, 1]$

Analysis

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

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

Part II

Longest Common Subsequence Problem
**LCS Problem**

**Definition**

LCS between two strings $X$ and $Y$ is the length of the longest common subsequence between $X$ and $Y$.

**Example**

LCS between ABAZDC and BACBAD is 4 via ABAD

Derive a dynamic programming algorithm for the problem.
LCS Problem

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Part III

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: $\{B, D\}$
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\}
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: ??
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 $T$?
Towards a Recursive Solution

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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 $T$?
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 $T$ rooted at nodes in $T$.

How many of them? $O(n)$
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Example
A Recursive Solution

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

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

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

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

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

$$OPT(u) = \max \left\{ \sum_{\text{child of } u} OPT(v), \ w(u) + \sum_{\text{grandchild of } u} OPT(v) \right\}$$
Iterative Algorithm

1. Compute $OPT(u)$ bottom up. To evaluate $OPT(u)$ 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 $OPT(u)$ bottom up. To evaluate $OPT(u)$ 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

\textbf{MIS-Tree(}T\textbf{)}:

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

\begin{verbatim}
for i = 1 to n do
    M[v_i] = max ( \(\sum_{v_j \text{ child of } v_i} M[v_j], \)
                     \(w(v_i) + \sum_{v_j \text{ grandchild of } v_i} M[v_j])\)
\end{verbatim}

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

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

\textbf{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

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

For $i = 1$ to $n$ do

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

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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 $n$ do

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**Iterative Algorithm**

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

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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

```
  r
 / \ 10
a / 5  \ b 8
  c   d  e  f  g
  4   4  9  3
 / \ / \          / \\
2 h i 7  f g  j 8
```

Chan, Har-Peled, Hassanieh (UIUC)

CS374 47

Spring 2019 47/48
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.