More DP: Edit Distance and Independent Sets in Trees

Lecture 14

October 16, 2018

How many subproblems?

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

$$f(x,y) = \sum_{i=1}^{x+y-1} x * f(x+y-i, i-1),$$
$$f(0,y) = y \qquad f(x,0) = x.$$

How many distinct subproblems when computing $f(n, n)$?

- **(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.

What is the running time for each subproblem?

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

$$f(x,y) = \sum_{i=1}^{x+y-1} x * f(x+y-i, i-1),$$
$$f(0,y) = y \qquad f(x,0) = x.$$

The worst-case time to evaluate the output of a subproblem given values for its recursive subproblems when computing $f(n, n)$ is:

- **(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.

What is the total running time?

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

$$f(x, y) = \sum_{i=1}^{x+y-1} x * f(x + y - i, i - 1),$$
$$f(0, y) = y \qquad f(x, 0) = x.$$

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.

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
   1. Estimate number of different subproblems generated as a function of n. Is it polynomial or exponential in n?
   2. 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 **IsStringinL**$(string\ \ x)$ that decides whether x is in L, and non-negative integer k

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

Example

Suppose L is *English* and we have a procedure to check whether a string/word is in the *English* dictionary.

- Is the string "isthisanenglishsentence" in $English^5$?
- Is the string "isthisanenglishsentence" in $English^4$?
- Is "asinineat" in $English^2$?
- Is "asinineat" in $English^4$?
- Is "zibzzzad" in $English^1$?

Recursive Solution

When is $w \in L^k$?

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$k = 0$: $w \in L^k$ 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 $v \in L^{k-1}$

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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 Ouput 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
```

Analysis

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IsStringinLk(A[1..n], k):
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- How many distinct sub-problems are generated by **IsStringinLk**($A[1..n], k$)?

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

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- How many distinct sub-problems are generated by IsStringinLk$(A[1..n], k)$? $O(nk)$
- How much space?

Analysis

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

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```

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

Naming subproblems and recursive equation

ISLk(i, h): a boolean which is 1 if $A[i..n]$ is in L^h, 0 otherwise

Base case: **ISLk**$(n+1, 0) = 1$ interpreting $A[n+1..n]$ as ϵ

Naming subproblems and recursive equation

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Recursive relation:

- **ISLk**$(i, h) = 1$ if $\exists i < j \leq n+1$ such that (**ISLk**$(j, h-1) = 1$ and **IsStringinL**$(A[i..(j-1]) = 1$)
- **ISLk**$(i, h) = 0$ otherwise

Alternately:
ISLk$(i, h) = \max_{i<j\leq n+1}$ **ISLk**$(j, h-1)$**IsStringinL**$(A[i..(j-1)]))$

Output: **ISLk**$(1, k)$

Another variant

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

Exercise

Definition

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

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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

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

$LPS(i,j)$: length of longest palindromic subsequence of $A[i..j]$.

Recursive expression/code?

Part I

Edit Distance and Sequence Alignment

Spell Checking Problem

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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?

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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**:

$$\underline{\mathbf{F}}\mathbf{OOD} \rightarrow \mathbf{MO}\underline{\mathbf{O}}\mathbf{D} \rightarrow \mathbf{MON}\underline{\mathbf{O}}\mathbf{D} \rightarrow \mathbf{MONE}\underline{\mathbf{D}} \rightarrow \mathbf{MONEY}$$

Edit Distance: Alternate View

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

Edit Distance: Alternate View

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 $M = \{(1, 1), (2, 2), (3, 3), (4, 5)\}$.

Edit Distance: Alternate View

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.

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

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

An Example

Example

o		c	u	r	r	a	n	c	e
o	c	c	u	r	r	e	n	c	e

Cost $= \delta + \alpha_{ae}$

Alternative:

o		c	u	r	r		a	n	c	e
o	c	c	u	r	r	e		n	c	e

Cost $= 3\delta$

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

o	c	u	r	r	a	n	c	e										
									o	c	c	u	r	r	e	n	c	e

Cost $= 19\delta$.

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?

374

473

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

373

473

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(B) 2

(C) 3

(D) 4

(E) 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?

37

473

(A) 1

(B) 2

(C) 3

(D) 4

(E) 5

Sequence Alignment

Input Given two words X and Y, and gap penalty δ and mismatch costs α_{pq}

Goal Find alignment of minimum cost

Edit distance

Basic observation

Let $X = \alpha x$ and $Y = \beta y$

α, β: 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:

α	x
β	y

or

α	x
βy	

or

αx	
β	y

Observation

Prefixes must have optimal alignment!

Problem Structure

Observation

Let $X = x_1 x_2 \cdots x_m$ and $Y = y_1 y_2 \cdots y_n$. If (m, n) are not matched then either the mth position of X remains unmatched or the nth position of Y remains unmatched.

1. Case x_m and y_n are matched.
   1. 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.
   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 $y_1 \cdots y_{n-1}$

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 nδ
    If (n = 0) return mδ
    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)])
    return min(m1, m2, m3)
```

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

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

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

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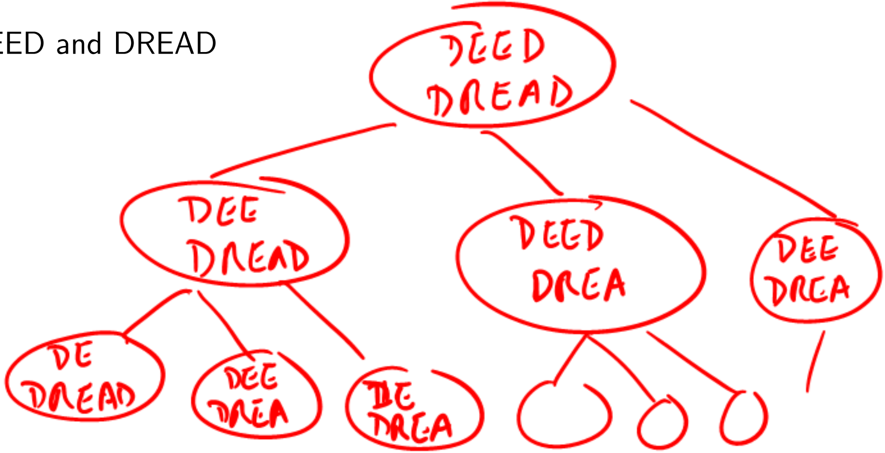
Base Cases: $\text{Opt}(i, 0) = \delta \cdot i$ and $\text{Opt}(0, j) = \delta \cdot j$

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

```
EDIST(A[1..m], B[1..n])
    int  M[0..m][0..n]
    for i = 1 to m do M[i, 0] = iδ
    for j = 1 to n do M[0, j] = jδ

    for i = 1 to m do
        for j = 1 to n do
```

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

Removing Recursion to obtain Iterative Algorithm

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Analysis

Removing Recursion to obtain Iterative Algorithm

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Analysis

1. Running time is $O(mn)$.
2. Space used is $O(mn)$.

Matrix and DAG of Computation

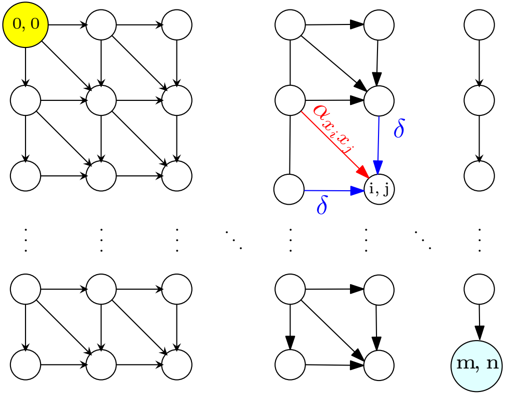

Figure: Iterative algorithm in previous slide computes values in row order.

Example

DEED and DREAD

Sequence Alignment in Practice

1. Typically the DNA sequences that are aligned are about $\mathbf{10^5}$ letters long!
2. So about $\mathbf{10^{10}}$ operations and $\mathbf{10^{10}}$ bytes needed
3. The killer is the 10GB storage
4. Can we reduce space requirements?

Optimizing Space

1. Recall

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

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

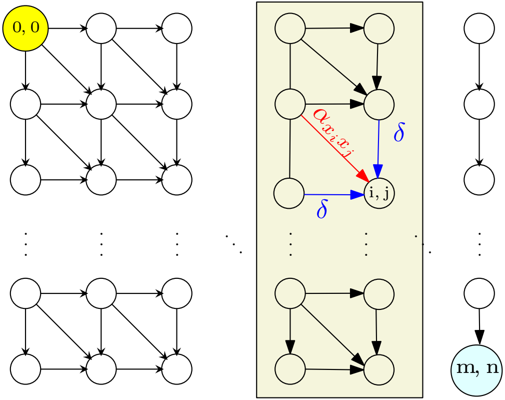

Figure: $\boldsymbol{M(i,j)}$ only depends on previous column values. Keep only two columns and compute in column order.

Space Efficient Algorithm

```
for all i do N[i,0] = iδ
for j = 1 to n do
    N[0,1] = jδ (* 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 $O(2m) = O(m)$

Analyzing Space Efficiency

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
3. Space efficient computation of alignment? More complicated algorithm — see notes and Kleinberg-Tardos book.

Part II

Longest Common Subsequence Problem

LCS Problem

Definition

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

Example

LCS between ABAZDC and BACBAD is

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Derive a dynamic programming algorithm for the problem.

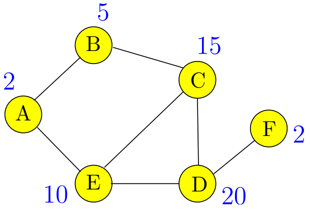
Part III

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



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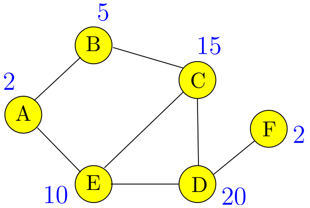
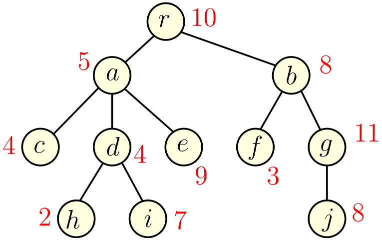


Maximum weight independent set in above graph: $\{B, D\}$

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: ??

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.

Towards a Recursive Solution

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What about a tree?

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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 $\mathcal{O}$ be an optimum solution to the whole problem.

Case $r \not\in \mathcal{O}$: Then $\mathcal{O}$ contains an optimum solution for each subtree of T hanging at a child of r.

Towards a Recursive Solution

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

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

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

Towards a Recursive Solution

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

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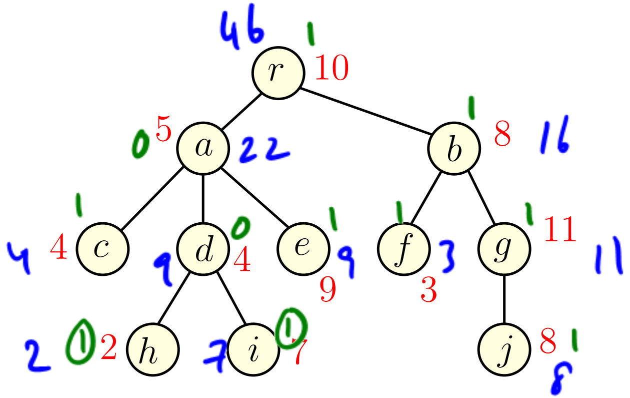
How many of them? $O(n)$

Example



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

1. Compute $OPT(u)$ bottom up. To evaluate $OPT(u)$ need to have computed values of all children and grandchildren of u
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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
    for $i = 1$ to n **do**

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

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

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

Running time:

Iterative Algorithm

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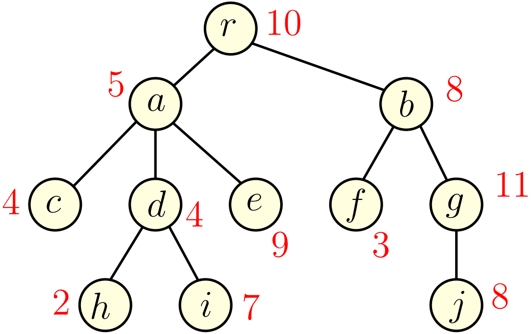
Running time:

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.

Example



Takeaway Points

1. Dynamic programming is based on finding a recursive way to solve the problem. Need a recursion that generates a small number of subproblems.
2. 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.
3. 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.