## CS 3100

## Data Structures and Algorithms 2 Lecture 18: Seam Carving

## Co-instructors: Robbie Hott and Tom Horton Fall 2023

Readings in CLRS $4^{\text {th }}$ edition:

- Chapter 14


## Announcements

- Upcoming dates
- PA3 (Clustering) due October 29, 2023 at 11:59pm
- PS4 (Dynamic Programming), due November 2, 2023 at 11:59pm
- PA4 (Seam Carving) due November 12, 2023 at 11:59pm
- Quizzes 3-4 (Greedy, Dynamic Programming) on November 9, 2023 in class
- Updated Late Policy!
- You must submit an extension request before the deadline
- Explain why need you need the extension (up to 48 hours past the deadline)
- Acknowledge that you're getting an extension
- The late deadline is not the real deadline $-:$
- You may then take the additional 48 hours as needed
- Course email (comes to both professors and head TAs):


## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem contains the (optimal) solutions to smaller ones
- Idea:

1. Identify the recursive structure of the problem

- What is the "last thing" done?

2. Save the solution to each subproblem in memory
3. Select a good order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest


## Log Cutting

Given a log of length $n$
A list (of length $n$ ) of prices $P$ ( $P[i]$ is the price of a cut of size $i$ ) Find the best way to cut the log


Select a list of lengths $\ell_{1}, \ldots, \ell_{k}$ such that:
$\sum \ell_{i}=n$
to maximize $\sum P\left[\ell_{i}\right]$
Brute Force: $O\left(2^{n}\right)$

## 1. Identify Recursive Structure

$P[i]=$ value of a cut of length $i$
$\operatorname{Cut}(n)=$ value of best way to cut a log of length $n$

$$
\operatorname{Cut}(n)=\max \left\{\begin{array}{l}
\operatorname{Cut}(n-1)+P[1] \\
\operatorname{Cut}(n-2)+P[2] \\
\ldots \\
\operatorname{Cut}(0)+P[n]
\end{array} \quad \begin{array}{l}
\text { 2. Save sub- } \\
\text { solutions to } \\
\text { memory! }
\end{array}\right.
$$

## 3. Select a Good Order for Solving Subproblems

Solve Smallest subproblem first


## Matrix Chaining

- Given a sequence of Matrices $\left(M_{1}, \ldots, M_{n}\right)$, what is the most efficient way to multiply them?



## 1. Identify the Recursive Structure of the Problem

- In general:

$$
\begin{aligned}
& \operatorname{Best}(i, j)=\text { cheapest way to multiply together } M_{i} \text { through } M_{j} \\
& \operatorname{Best}(i, j)=\min _{k=i}^{j-1}\left(\operatorname{Best}(i, k)+\operatorname{Best}(k+1, j)+r_{i} r_{k+1} c_{j}\right) \\
& \operatorname{Best}(i, i)=0
\end{aligned}
$$

$$
\operatorname{Best}(1, n)=\min \left\{\begin{array}{l}
\operatorname{Best}(2, n)+r_{1} r_{2} c_{n} \\
\operatorname{Best}(1,2)+\operatorname{Best}(3, n)+r_{1} r_{3} c_{n} \\
\operatorname{Best}(1,3)+\operatorname{Best}(4, n)+r_{1} r_{4} c_{n} \\
\operatorname{Best}(1,4)+\operatorname{Best}(5, n)+r_{1} r_{5} c_{n} \\
\ldots \\
\operatorname{Best}(1, n-1)+r_{1} r_{n} c_{n}
\end{array}\right.
$$

## 2. Save Subsolutions in Memory

- In general:

$$
\begin{aligned}
& \operatorname{Best}(i, j)=\text { cheapest way to multiply together } M_{i} \text { through } M_{j} \\
& \operatorname{Best}(i, j)=\min _{k=i}^{j-1}\left(\operatorname{Best}(i, k)+\operatorname{Best}(k+1, j)+r_{i} r_{k+1} c_{j}\right) \\
& \operatorname{Best}(i, i)=\underbrace{}_{\text {Read from } \mathrm{M}[\mathrm{n}]} \\
& \text { Save to } \mathrm{M}[\mathrm{n}] \\
& \operatorname{Best}(1, n)=\min \left[\begin{array}{l}
\operatorname{Best}(2, n)+r_{1} r_{2} c_{n} \\
\operatorname{Best}(1,2)+\operatorname{Best}(3, n)+r_{1} r_{3} c_{n} \\
\operatorname{Best}(1,3)+\operatorname{Best}(4, n)+r_{1} r_{4} c_{n} \\
\operatorname{Best}(1,4)+\operatorname{Best}(5, n)+r_{1} r_{5} c_{n} \\
\ldots \\
\operatorname{Best}(1, n-1)+r_{1} r_{n} c_{n}
\end{array}\right.
\end{aligned}
$$

## 3. Select a good order for solving subproblems




Time!
In Season 9 Episode 7 "The Slicer" of the hit 90s TV show Seinfeld, George discovers that, years prior, he had a heated argument with his new boss, Mr. Kruger. This argument ended in George throwing Mr. Kruger's boombox into the
 ocean. How did George make this discovery?


## Seam Carving

- Method for image resizing that doesn't scale/crop the image


## Seam Carving

- Method for image resizing that doesn't scale/crop the image



## Cropping

- Removes a "block" of pixels



## Scaling

- Removes "stripes" of pixels



## Seam Carving

- Removes "least energy seam" of pixels
- https://trekhleb.dev/js-image-carver/


Carved


## Seam Carving

- Method for image resizing that doesn't scale/crop the image

Cropped


Scaled


Carved


## Seattle Skyline



## Energy of a Seam

- Sum of the energies of each pixel

$$
e(p)=\text { energy of pixel } p
$$

- Many choices for pixel energy
- E.g.: change of gradient (how much the color of this pixel differs from its neighbors)
- Particular choice doesn't matter, we use it as a "black box"
- Goal: find least-energy seam to remove


## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem contains the solutions to smaller ones
- Idea:

1. Identify the recursive structure of the problem

- What is the "last thing" done?

2. Save the solution to each subproblem in memory
3. Select a good order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest


## Identify Recursive Structure

Let $S(i, j)=$ least energy seam from the bottom of the image up to pixel $p_{i, j}$


## Finding the Least Energy Seam

Want to delete the least energy seam going from bottom to top, so delete:

$$
\min _{k=1}(S(n, k))
$$



## Computing $S(n, k)$

Assume we know the least energy seams for all of row $n-1$
(i.e. we know $S(n-1, \ell)$ for all $\ell$ )


## Computing $S(n, k)$

Assume we know the least energy seams for all of row $n-1$ (i.e. we know $S(n-1, \ell)$ for all $\ell$ )


## Computing $S(n, k)$

Assume we know the least energy seams for all of row $n-1$ (i.e. we know $S(n-1, \ell)$ for all $\ell$ )
$S(n, k)=\min \left\{\begin{array}{l}S(n-1, k-1)+e\left(p_{n, k}\right) \\ p_{n, k} \\ s(n-1, k)+e\left(p_{n, k}\right) \\ S(n-1, k+1)+e\left(p_{n, k}\right)\end{array}\right.$
$s(n-1, k-1)=s(n-1, k)$
$s(n-1, k+1)$

## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem contains the solutions to smaller ones
- Idea:

1. Identify the recursive structure of the problem

- What is the "last thing" done?

2. Save the solution to each subproblem in memory
3. Select a good order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest



## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem contains the solutions to smaller ones
- Idea:

1. Identify the recursive structure of the problem

- What is the "last thing" done?

2. Save the solution to each subproblem in memory
3. Select a good order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest



## Longest Common Subsequence

Given two sequences $X$ and $Y$, find the length of their longest common subsequence

Example:
$X=$ ATCTGAT
$Y=$ TGCATA
$L C S=T C T A$

Brute force: Compare every subsequence of $X$ with $Y$
$\Omega\left(2^{n}\right)$


## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem is the (optimal) solutions to a smaller one plus one "decision"
- Idea:

1. Identify the substructure of the problem

- What are the options for the "last thing" done? What subproblem comes from each?

2. Save the solution to each subproblem in memory
3. Select an order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest


## 1. Identify Recursive Structure

Let $\operatorname{LCS}(i, j)=$ length of the LCS for the first $i$ characters of $X$, first $j$ character of $Y$ Find $\operatorname{LCS}(i, j)$ :

$$
\text { Case 1: } X[i]=Y[j] \quad \begin{aligned}
X & =\operatorname{ATCTGCGT} \\
Y & =\operatorname{TGCATAT} \\
\operatorname{LCS}(i, j) & =\operatorname{LCS}(i-1, j-1)+1
\end{aligned}
$$

Case 2: $X[i] \neq Y[j]$

$$
\begin{array}{cc}
X=A T C T G C G A & X=A T C T G C G T \\
Y=T G C A T A T & Y=T G C A T A C \\
\operatorname{LCS}(i, j)=\operatorname{LCS}(i, j-1) & \operatorname{LCS}(i, j)=\operatorname{LCS}(i-1, j)
\end{array}
$$

$$
\operatorname{LCS}(i, j)= \begin{cases}0 & \text { if } i=0 \text { or } j=0 \\ \operatorname{LCS}(i-1, j-1)+1 & \text { if } X[i]=Y[j] \\ \max (\operatorname{LCS}(i, j-1), \operatorname{LCS}(i-1, j)) & \text { otherwise }\end{cases}
$$

## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem is the (optimal) solutions to a smaller one plus one "decision"
- Idea:

1. Identify the substructure of the problem

- What are the options for the "last thing" done? What subproblem comes from each?

2. Save the solution to each subproblem in memory
3. Select an order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest


## 1. Identify Recursive Structure

Let $\operatorname{LCS}(i, j)=$ length of the LCS for the first $i$ characters of $X$, first $j$ character of $Y$ Find $\operatorname{LCS}(i, j)$ :

$$
\text { Case 1: } X[i]=Y[j] \quad \begin{aligned}
X & =\operatorname{ATCTGCGT} \\
Y & =\operatorname{TGCATAT} \\
\operatorname{LCS}(i, j) & =\operatorname{LCS}(i-1, j-1)+1
\end{aligned}
$$

Case 2: $X[i] \neq Y[j]$

$$
\begin{array}{cc}
X=A T C T G C G A & X=A T C T G C G T \\
Y=T G C A T A T & Y=T G C A T A C \\
\operatorname{LCS}(i, j)=\operatorname{LCS}(i, j-1) & \operatorname{LCS}(i, j)=\operatorname{LCS}(i-1, j)
\end{array}
$$

X = "alkjdflaksjdf"
$Y=$ "lakjsdflkasjdlfs"
$M=2 d$ array of len $(X)$ rows and len $(Y)$ columns, initialized to -1
def LCS(int i, int j):
\# returns the length of the LCS shared between the length-i prefix of $X$ and length-j prefix of $Y$ \# memoization
if $M[i, j]>-1$ :
return $\mathrm{M}[\mathrm{i}, \mathrm{j}]$
\#base case:
if $i=0$ or $j=0$ :
ans $=0$
elif $X[i]==Y[j]$ :
ans $=\operatorname{LCS}(\mathrm{i}-1, \mathrm{j}-1)+1$
else:

$$
\text { ans }=\max (\operatorname{LCS}(\mathrm{i}, \mathrm{j}-1), \operatorname{LCS}(\mathrm{i}-1, \mathrm{j}))
$$

$M[i, j]=$ ans
return ans
$\operatorname{print}(\operatorname{LCS}(\operatorname{len}(X)+1, \operatorname{len}(Y)+1))$ \# the answer for the entirety of $X$ and $Y$

$$
\operatorname{LCS}(i, j)=\left\{\begin{array}{l}
0 \\
\operatorname{LCS}(i-1, j-1)+1 \\
\max (\operatorname{LCS}(i, j-1), \operatorname{LCS}(i-1, j))
\end{array}\right.
$$

if $i=0$ or $j=0$
if $X[i]=Y[j]$
otherwise

## Dynamic Programming

- Requires Optimal Substructure
- Solution to larger problem is the (optimal) solutions to a smaller one plus one "decision"
- Idea:

1. Identify the substructure of the problem

- What are the options for the "last thing" done? What subproblem comes from each?

2. Save the solution to each subproblem in memory
3. Select an order for solving subproblems

- "Top Down": Solve each recursively
- "Bottom Up": Iteratively solve smallest to largest


## 3. Solve in a Good Order

$$
\operatorname{LCS}(i, j)= \begin{cases}0 & \text { if } i=0 \text { or } j=0 \\ \operatorname{LCS}(i-1, j-1)+1 & \text { if } X[i]=Y[j] \\ \max (\operatorname{LCS}(i, j-1), \operatorname{LCS}(i-1, j)) & \text { otherwise }\end{cases}
$$

| \& $X=$ |  | 0 | A 1 | $T$ 2 | $C$ 3 | $T$ 4 | $G$ 5 | A 6 | $T$ 7 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $T$ | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| G | 2 | 0 | 0 | 1 | 1 | 1 | 2 | 2 | 2 |
| C | 3 | 0 | 0 | 1 | 2 | 2 | 2 | 2 | 2 |
| A | 4 | 0 | 1 | 1 | 2 | 2 | 2 | 3 | 3 |
| $T$ | 5 | 0 | 1 | 2 | 2 | 3 | 3 | 3 | 4 |
| A | 6 | 0 | 1 | 2 | 2 | 3 | 3 | 4 | 4 |

To fill in cell $(i, j)$ we need cells $(i-1, j-1),(i-1, j),(i, j-1)$
Fill from Top->Bottom, Left->Right (with any preference)

## Run Time?

$$
\begin{aligned}
& \operatorname{CCS}(i, j)= \begin{cases}0 & \text { if } i=0 \text { or } j=0\end{cases} \\
& \operatorname{LCS}(i, j)= \begin{cases}\operatorname{LCS}(i-1, j-1)+1 & \text { if } X[i]=Y[j] \\
\max (\operatorname{LCS}(i, j-1), \operatorname{LCS}(i-1, j)) & \text { otherwise }\end{cases}
\end{aligned}
$$

Run Time: $\Theta(n \cdot m)($ for $|X|=n,|Y|=m)$

## Reconstructing the LCS

$$
\begin{array}{ll}
0 & \text { if } i=0 \text { or } j=0
\end{array}
$$

| \& $X=$ |  | 0 | A1 | $T$2 | C3 | T | G | A <br> 6 | $T$7 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  |  |  |  |  |
|  | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $T$ | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| $G$ | 2 | 0 | 0 | 1 | 1 | 1 | 12 | 2 | 2 |
| $C$ | 3 | 0 | 0 | 1 | 2 | 2 | 2 | 2 | 2 |
| $A$ | 4 | 0 | 1 | 1 | 2 | 2 | 2 | / 3 | 3 |
| $T$ | 5 | 0 | 1 | 2 | 2 | 3 | 3 | 3 | ${ }^{4}$ |
| A | 6 | 0 | 1 | 2 | 2 | 3 | 3 | 4 | 4 |

Start from bottom right,
if symbols matched, print that symbol then go diagonally
else go to largest adjacent

## Reconstructing the LCS

$$
\begin{array}{ll}
0 & \text { if } i=0 \text { or } j=0
\end{array}
$$



Start from bottom right,
if symbols matched, print that symbol then go diagonally
else go to largest adjacent

## Reconstructing the LCS

$$
\begin{array}{ll}
0 & \text { if } i=0 \text { or } j=0
\end{array}
$$



Start from bottom right,
if symbols matched, print that symbol then go diagonally
else go to largest adjacent

