# Comp 555 - BioAlgorithms - Spring 2019 



- problem set \#3 is due tonicht
- Problem set \#4 is posted
"Really? - my people always say multiply and conquer."

Divide and Conquer Algorithms

## The Essence of Divide and Conquer

- Divide problem into sub-problems
- Conquer by solving sub-problems recursively.
- If the sub-problems are small enough, solve them in brute force fashion
- Combine the solutions of sub-problems into a solution of the original problem
- This is the tricky part



## Divide and Conquer Applied to Sorting

## Problem

- Given an unsorted array of items


## $\begin{array}{llllllll}5 & 2 & 4 & 7 & 1 & 3 & 2 & 6\end{array}$

- Reorder them such that they are in a non-decreasing order

$$
\begin{array}{llllllll}
1 & 2 & 2 & 3 & 4 & 5 & 6 & 7
\end{array}
$$

## Merge Sort

Step 1. The Divide Phase

$\log _{2}(n)$ divisions to split an array of size n into single elements

## Merge Sort

## Merging

- 2 arrays of size 1 can be easily merged to form a sorted array of size 2

- Move the smaller first value of the two arrays to the next slot in the merged array. Repeat.
- 2 sorted arrays of size $p$ and $q$ can be merged in $O(p+q)$ time to form a sorted array of size $p+q$


## Merge Sort

Step 2. Conquer Phase

$O(n) \quad \downarrow$
$\downarrow$

| 2 | 4 | 5 | 7 | 1 | 2 | 3 | 6 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

$\log _{2}(n)$ iterations, each iteration takes $O(n)$ time, for a total time $O\left(n \log _{2}(n)\right)$

\[

\]

## Now back to Biology

## All algorithms for aligning a pair of sequences thus far have required quadratic memory

The tables used by the dynamic programming method

- Space complexity for computing alignment path for sequences of length $n$ and $m$ is $O(n m)$
- We kept a table of all scores and arrival directions in memory to reconstruct the final best path (backtracking)



## Computing Alignments with Linear Memory



- If appropriately ordered, the space needed to compute just the score can be reduced to $\mathrm{O}(\mathrm{n})$
- For example, we only need the previous column to calculate the current column, and we can throw away that previous column once we're done using it


## Recycling Columns

Only two columns of scores are needed at any given time


## An Aside

Suppose that we reverse the source and destination of our Manhattan Tour

- Does the path with the most attractions change?



## More Aside

Now suppose that we made two tours

- One from the source towards the destination
- A second from the destination of towards the source
- And we stop both tours at the middle column

- Can we combine these two separate solutions to find the overall best score?


## A Divide \& Conquer Alignment Approach



- We want to calculate the longest path from $(0,0)$ to $(\mathrm{n}, \mathrm{m})$ that passes through ( $\mathrm{i}, \mathrm{m} / 2$ ) where $i$ ranges from 0 to $n$ and represents the $i$-th row
- Define Score(i) as the score of the path from $(0,0)$ to $(n, m)$ that passes through vertex $(i, m / 2)$


## Finding the Midline

Define ( $\mathrm{mid}, \mathrm{m} / 2$ ) as the vertex where the best score crosses the middle column.


- How hard is the problem compared to the original DP approach?
- What does it lack?


## We know the Best Score

How do we find the best path?

- We actually know one vertex on our path, (m/2, mid).
- How do we find more?

- Hint: Knowing mid actually constrains where the paths can go


## A Mid's Mid

We can now solve for the paths from $(0,0)$ to ( $\mathrm{m} / 2, \mathrm{mid}$ ) and ( $\mathrm{m} / 2, \mathrm{mid}$ ) to ( $\mathrm{m}, \mathrm{n}$ )


## And Mid-Mid's Mids (recursively)

And repeat this process until the path is from ( $\mathrm{i}, \mathrm{j}$ ) to ( $\mathrm{i}, \mathrm{j}$ )


## Algorithm's Performance

- On the first level, the algorithm fills every entry in the matrix, thus it does $\mathrm{O}(\mathrm{nm})$ work



## Work done on a second pass

- On second level, the algorithm fills half the entries in the matrix, thus it does $0(\mathrm{~nm}) / 2$ work



## Work done on an Alternate second pass

- This is true regardless of what mid is



## Work done on a third pass

- On the third pass, the algorithm fills a quarter of the entries in the matrix, thus it does $0(n m) / 4$ work



## Sum of a Geometric Series



Total Space: $\mathrm{O}(\mathrm{n})$ for score computation, $\mathrm{O}(\mathrm{n}+\mathrm{m})$ to store the optimal alignment

- Time complexity is still $O(m n)$. Actually, we expect it to take about twice as long as the approach using $O(m n)$ space


## Can We Do Even Better?

- Align in Subquadratic Time?
- Dynamic Programming takes $O(n m)$ for global alignment, which is quadratic assuming $n \approx m$
- Yes, using the Four-Russians Speedup



## Partitioning the Alignment Grid

Into smaller blocks


## Block Logic

- How does a block relate to a correct alignment?
- the alignment path passes through block
- the path does not use the block
- The alignment passes through $O(n / t)$ total blocks
- Paths enter from the top or left and exit from the right or bottom
- If we know the best score at the boundaries, perhaps we can peice together a solution as we did before.



## Recall our Bag of DP Tricks

- A key insight of dynamic programming was to reuse repeated computations by storing them in a tableau
- Are there any repeated computations in Block Alignments?
- Let's check out some numbers...
- Lets assume $\mathrm{n}=\mathrm{m}=4000$ and $\mathrm{t}=4$
- $n / t=1000$, so there are $1,000,000$ blocks
- How many possible many blocks are there?
- Assume we are aligning DNA with DNA, so there sequences are over an alphabet of $\{A, C, G, T\}$
- Possible sequences are $4^{\mathrm{t}}=4^{4}=256$,
- Possible alignments are $4^{t} \times 4^{t}=65536$
- There are fewer possible alignments than blocks, thus we must be frequently revisiting block alignments!

|  |  | A | C | A | T |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | $v$ | w | $x$ | $y$ | z |
| A | $u$ | $\max (\mathrm{u}-1, \mathrm{v}+1, \mathrm{w}-1)$ | $\max (\max (\mathrm{u}-1, \mathrm{v}+1, \mathrm{w}-1)-1, \mathrm{w}-1, \mathrm{x}-1)$ | $f(u, v, w, x, y)$ | $f(u, v, w, x, y, z)$ |
| T | $t$ | x(u-1,v+1,w-1)-1) | $\mathrm{f}(\mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w}, \mathrm{x})$ | $f(t, u, v, w, x, y)$ | $f(t, u, v, w, x, y, z)$ |
| A | $s$ | $\mathrm{f}(\mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w})$ | $\mathrm{f}(\mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w}, \mathrm{x})$ | $\mathrm{f}(\mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w}, \mathrm{x}, \mathrm{y})$ | $\mathrm{f}(\mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w}, \mathrm{x}, \mathrm{y}, \mathrm{z})$ |
| G | $r$ | $\mathrm{f}(\mathrm{r}, \mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w})$ | $\mathrm{f}(\mathrm{r}, \mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w}, \mathrm{x})$ | $f(r, s, t, u, v, w, x, y)$ | $f(r, s, t, u, v, w, x, y, z)$ |

- $\quad \max (\max (\mathrm{u}-1, \mathrm{v}+1, \mathrm{w}-1)-1, \mathrm{w}-1, \mathrm{x}-1) \rightarrow \max (\mathrm{u}-2, \mathrm{v}, \mathrm{w}-2, \mathrm{w}-1, \mathrm{x}-1) \rightarrow \max (\mathrm{u}-2, \mathrm{v}, \mathrm{w}-1, \mathrm{x}-1)$
- $\quad \max (\mathrm{t}-1, \mathrm{u}-1, \max (\mathrm{u}-1, \mathrm{v}+1, \mathrm{w}-1)-1) \rightarrow \max (\mathrm{t}-1, \mathrm{u}-1, \mathrm{u}-2, \mathrm{v}, \mathrm{w}-2) \rightarrow \max (\mathrm{t}-1, \mathrm{u}-1, \mathrm{v}, \mathrm{w}-2)$
- All functions are maxs of the 7 block inputs ( $\mathrm{r}, \mathrm{s}, \mathrm{t}, \mathrm{u}, \mathrm{v}, \mathrm{w}, \mathrm{x}, \mathrm{y}, \mathrm{z}$ ), which can be precomputed.


## Next Time

## HIdden Markov Models



