

CS 580: Algorithm Design and Analysis

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Announcement: Homework 3 due February 14th at 11:59PM (Gradescope)

Recap

Divide and Conquer

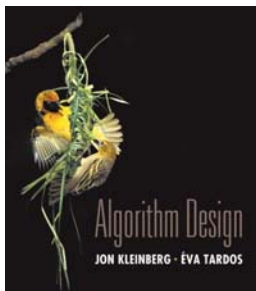
Recurrence Relationships

Examples: Merge Sort/Inversions/Integer/Matrix Multiplication

Polynomial Multiplication (Convolution)

- FFT (inverse FFT) to convert between coefficient and point value representation of polynomial $A(x)$
 - Divide: evaluate A_{odd} , A_{even} (degree $n/2-1$) at $n/2$ inputs ($(n/2)^{\text{th}}$ roots of unity).
 - Combine solutions to evaluate $A(x)$ of degree $n-1$ poly at n inputs (n^{th} roots of unity)

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Dynamic Programming

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Algorithmic Paradigms

Greedy. Build up a solution incrementally, myopically optimizing some local criterion.

Divide-and-conquer. Break up a problem into sub-problems, solve each sub-problem independently, and combine solution to sub-problems to form solution to original problem.

Dynamic programming. Break up a problem into a series of overlapping sub-problems, and build up solutions to larger and larger sub-problems.

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Dynamic Programming History

Bellman. [1950s] Pioneered the systematic study of dynamic programming.

Etymology.

- Dynamic programming = planning over time.
- Secretary of Defense was hostile to mathematical research.
- Bellman sought an impressive name to avoid confrontation.

"it's impossible to use dynamic in a pejorative sense"
"something not even a Congressman could object to"

Reference: Bellman, R. E. *Eye of the Hurricane, An Autobiography*.

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Dynamic Programming Applications

Areas.

- Bioinformatics.
- Control theory.
- Information theory.
- Operations research.
- Computer science: theory, graphics, AI, compilers, systems,

Some famous dynamic programming algorithms.

- Unix diff for comparing two files.
- Viterbi for hidden Markov models.
- Smith-Waterman for genetic sequence alignment.
- Bellman-Ford for shortest path routing in networks.
- Cocke-Kasami-Younger for parsing context free grammars.

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6.1 Weighted Interval Scheduling

Weighted Interval Scheduling

Weighted interval scheduling problem.

- Job j starts at s_j , finishes at f_j , and has weight or value v_j .
- Two jobs **compatible** if they don't overlap.
- Goal: find maximum **weight** subset of mutually compatible jobs.

Unweighted Interval Scheduling (will cover in Greedy paradigms)

Previously Shown: Greedy algorithm works if all weights are 1.

- Solution:** Sort requests by finish time (ascending order)

Observation. Greedy algorithm can fail spectacularly if arbitrary weights are allowed.

Weighted Interval Scheduling

Notation. Label jobs by finishing time: $f_1 \leq f_2 \leq \dots \leq f_n$.

Def. $p(j)$ = largest index $i < j$ such that job i is compatible with j .

Ex: $p(8) = 5, p(7) = 3, p(2) = 0$.

Dynamic Programming: Binary Choice

Notation. $OPT(j)$ = value of optimal solution to the problem consisting of job requests $1, 2, \dots, j$.

- Case 1: OPT selects job j .
 - collect profit v_j
 - can't use incompatible jobs $\{ p(j) + 1, p(j) + 2, \dots, j - 1 \}$
 - must include optimal solution to problem consisting of remaining compatible jobs $1, 2, \dots, p(j)$
- Case 2: OPT does not select job j .
 - must include optimal solution to problem consisting of remaining compatible jobs $1, 2, \dots, j-1$

optimal substructure

$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max \{ v_j + OPT(p(j)), OPT(j-1) \} & \text{otherwise} \end{cases}$$

Weighted Interval Scheduling: Brute Force

Brute force algorithm.

```

Input:  $n, s_1, \dots, s_n, f_1, \dots, f_n, v_1, \dots, v_n$ 
Sort jobs by finish times so that  $f_1 \leq f_2 \leq \dots \leq f_n$ .
Compute  $p(1), p(2), \dots, p(n)$ 

Compute-Opt( $j$ ) {
  if ( $j = 0$ )
    return 0
  else
    return  $\max(v_j + \text{Compute-Opt}(p(j)), \text{Compute-Opt}(j-1))$ 
}
    
```

$T(n) = T(n-1) + T(p(n)) + O(1)$
 $T(1) = 1$

Weighted Interval Scheduling: Brute Force

Observation. Recursive algorithm fails spectacularly because of redundant sub-problems \Rightarrow exponential algorithms.

Ex. Number of recursive calls for family of "layered" instances grows like Fibonacci sequence ($F_n > 1.6^n$).

$T(n) = T(n-1) + T(n-2) + 1$
 $T(1) = 1$

$p(1) = 0, p(j) = j-2$

Key Insight: Do we really need to repeat this computation?

Weighted Interval Scheduling: Memoization

Memoization. Store results of each sub-problem in a cache; lookup as needed.

```

Input:  $n, s_1, \dots, s_n, f_1, \dots, f_n, v_1, \dots, v_n$ 
Sort jobs by finish times so that  $f_1 \leq f_2 \leq \dots \leq f_n$ .
Compute  $p(1), p(2), \dots, p(n)$ 

for  $j = 1$  to  $n$ 
     $M[j] = \text{empty}$ 
 $M[0] = 0$ 
M-Compute-Opt( $j$ ) {
    if ( $M[j]$  is empty)
         $M[j] = \max(v_j + \text{M-Compute-Opt}(p(j)), \text{M-Compute-Opt}(j-1))$ 
    return  $M[j]$ 
}
    
```

Weighted Interval Scheduling: Running Time

Claim. Memoized version of algorithm takes $O(n \log n)$ time.

- Sort by finish time: $O(n \log n)$.
- Computing $p(\cdot)$: $O(n \log n)$ via sorting by start time.
- $\text{M-Compute-Opt}(j)$: each invocation takes $O(1)$ time and either
 - (i) returns an existing value $M[j]$
 - (ii) fills in one new entry $M[j]$ and makes two recursive calls
- Progress measure $\Phi = \#$ nonempty entries of $M[\cdot]$.
 - initially $\Phi = 0$, throughout $\Phi \leq n$.
 - (ii) increases Φ by 1 \Rightarrow at most $2n$ recursive calls.
- Overall running time of $\text{M-Compute-Opt}(n)$ is $O(n)$.

Remark. $O(n)$ if jobs are pre-sorted by start and finish times.

Weighted Interval Scheduling: Finding a Solution

Q. Dynamic programming algorithms computes optimal value. What if we want the solution itself?

A. Do some post-processing.

```

Run M-Compute-Opt(n)
Run Find-Solution(n)

Find-Solution( $j$ ) {
    if ( $j = 0$ )
        output nothing
    else if ( $v_j + M[p(j)] > M[j-1]$ )
        print  $j$ 
        Find-Solution( $p(j)$ )
    else
        Find-Solution( $j-1$ )
}
    
```

- # of recursive calls $\leq n \Rightarrow O(n)$.

Weighted Interval Scheduling: Bottom-Up

Bottom-up dynamic programming. Unwind recursion.

```

Input:  $n, s_1, \dots, s_n, f_1, \dots, f_n, v_1, \dots, v_n$ 
Sort jobs by finish times so that  $f_1 \leq f_2 \leq \dots \leq f_n$ .
Compute  $p(1), p(2), \dots, p(n)$ 

Iterative-Compute-Opt {
     $M[0] = 0$ 
    for  $j = 1$  to  $n$ 
         $M[j] = \max(v_j + M[p(j)], M[j-1])$ 
}
    
```

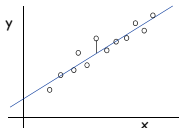
6.3 Segmented Least Squares

Segmented Least Squares

Least squares.

- Foundational problem in statistic and numerical analysis.
- Given n points in the plane: $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$.
- Find a line $y = ax + b$ that minimizes the sum of the squared error:

$$SSE = \sum_{i=1}^n (y_i - ax_i - b)^2$$



Solution. Calculus \Rightarrow min error is achieved when

$$a = \frac{n \sum x_i y_i - (\sum x_i)(\sum y_i)}{n \sum x_i^2 - (\sum x_i)^2}, \quad b = \frac{\sum y_i - a \sum x_i}{n}$$

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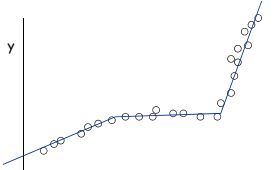
Segmented Least Squares

Segmented least squares.

- Points lie roughly on a sequence of several line segments.
- Given n points in the plane $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ with $x_1 < x_2 < \dots < x_n$, find a sequence of lines that minimizes $f(x)$.

Q. What's a reasonable choice for $f(x)$ to balance accuracy and parsimony?

\uparrow
number of lines



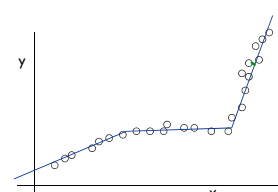
\uparrow
goodness of fit

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Segmented Least Squares

Segmented least squares.

- Points lie roughly on a sequence of several line segments.
- Given n points in the plane $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ with $x_1 < x_2 < \dots < x_n$, find a sequence of lines that minimizes:
 - the sum of the sums of the squared errors E in each segment
 - the number of lines L
- Tradeoff function: $E + cL$, for some constant $c > 0$.



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Dynamic Programming: Multiway Choice

Notation.

- $OPT(j)$ = minimum cost for points p_1, p_{i+1}, \dots, p_j .
- $e(i, j)$ = minimum sum of squares for points p_i, p_{i+1}, \dots, p_j .

To compute $OPT(j)$:

- Last segment uses points p_i, p_{i+1}, \dots, p_j for some i .
- Cost = $e(i, j) + c + OPT(i-1)$.

$$OPT(j) = \begin{cases} 0 & \text{if } j=0 \\ \min_{1 \leq i \leq j} \{ e(i, j) + c + OPT(i-1) \} & \text{otherwise} \end{cases}$$

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Segmented Least Squares: Algorithm

```

INPUT:  $n, p_1, \dots, p_n, c$ 
Segmented-Least-Squares() {
   $M[0] = 0$ 
  for  $j = 1$  to  $n$ 
    for  $i = 1$  to  $j$ 
      compute the least square error  $e_{ij}$  for
      the segment  $p_i, \dots, p_j$ 

  for  $j = 1$  to  $n$ 
     $M[j] = \min_{1 \leq i \leq j} (e_{ij} + c + M[i-1])$ 
  return  $M[n]$ 
}
        
```

Running time. $O(n^3)$. can be improved to $O(n^2)$ by pre-computing various statistics

- Bottleneck = computing $e(i, j)$ for $O(n^2)$ pairs, $O(n)$ per pair using previous formula.

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6.4 Knapsack Problem

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Knapsack Problem

Knapsack problem.

- Given n objects and a "knapsack."
- Item i weighs $w_i > 0$ kilograms and has value $v_i > 0$.
- Knapsack has capacity of W kilograms.
- Goal: fill knapsack so as to maximize total value.

Ex: { 3, 4 } has value 40.

| # | value | weight |
|---|-------|--------|
| 1 | 1 | 1 |
| 2 | 6 | 2 |
| 3 | 18 | 5 |
| 4 | 22 | 6 |
| 5 | 28 | 7 |

W = 11

Greedy: repeatedly add item with maximum ratio v_i / w_i .

Ex: { 5, 2, 1 } achieves only value = 35 \Rightarrow greedy not optimal.

Dynamic Programming: False Start

Def. $OPT(i) = \max$ profit subset of items $1, \dots, i$.

- Case 1: OPT does not select item i .
 - OPT selects best of $\{1, 2, \dots, i-1\}$
- Case 2: OPT selects item i .
 - accepting item i does not immediately imply that we will have to reject other items
 - without knowing what other items were selected before i , we don't even know if we have enough room for i

Conclusion. Need more sub-problems!

Dynamic Programming: Adding a New Variable

Def. $OPT(i, w) = \max$ profit subset of items $1, \dots, i$ with weight limit w .

- Case 1: OPT does not select item i .
 - OPT selects best of $\{1, 2, \dots, i-1\}$ using weight limit w
- Case 2: OPT selects item i .
 - new weight limit = $w - w_i$
 - OPT selects best of $\{1, 2, \dots, i-1\}$ using this new weight limit

$$OPT(i, w) = \begin{cases} 0 & \text{if } i = 0 \\ OPT(i-1, w) & \text{if } w_i > w \\ \max\{OPT(i-1, w), v_i + OPT(i-1, w-w_i)\} & \text{otherwise} \end{cases}$$

Knapsack Problem: Bottom-Up

Knapsack. Fill up an n -by- W array.

```

Input: n, W, w1, ..., wn, v1, ..., vn
for w = 0 to W
    M[0, w] = 0
for i = 1 to n
    for w = 1 to W
        if (wi > w)
            M[i, w] = M[i-1, w]
        else
            M[i, w] = max {M[i-1, w], vi + M[i-1, w-wi]}
return M[n, W]
```

Knapsack Algorithm

| | | W + 1 | | | | | | | | | | | |
|-------|-------------------|-------|---|---|---|---|----|----|----|----|----|----|----|
| | | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| n + 1 | ϕ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | { 1 } | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | { 1, 2 } | 0 | 1 | 6 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| | { 1, 2, 3 } | 0 | 1 | 6 | 7 | 7 | 18 | 19 | 24 | 25 | 25 | 25 | 25 |
| | { 1, 2, 3, 4 } | 0 | 1 | 6 | 7 | 7 | 18 | 22 | 24 | 28 | 29 | 29 | 40 |
| | { 1, 2, 3, 4, 5 } | 0 | 1 | 6 | 7 | 7 | 18 | 22 | 28 | 29 | 34 | 34 | 40 |

| Item | Value | Weight |
|------|-------|--------|
| 1 | 1 | 1 |
| 2 | 6 | 2 |
| 3 | 18 | 5 |
| 4 | 22 | 6 |
| 5 | 28 | 7 |

W = 11

OPT: { 4, 3 }
value = 22 + 18 = 40

Knapsack Problem: Running Time

Running time. $\Theta(nW)$.

- Not polynomial in input size!
 - Only need $\log_2 W$ bits to encode each weight
 - Problem can be encoded with $O(n \log_2 W)$ bits
- "Pseudo-polynomial."
- Decision version of Knapsack is NP-complete. [Chapter 8]

Knapsack approximation algorithm. There exists a poly-time algorithm that produces a feasible solution that has value within 0.01% of optimum. [Section 11.8]

6.5 RNA Secondary Structure

RNA Secondary Structure

RNA. String $B = b_1b_2\dots b_n$ over alphabet $\{A, C, G, U\}$.

Secondary structure. RNA is single-stranded so it tends to loop back and form base pairs with itself. This structure is essential for understanding behavior of molecule.

Ex: GUCCAUUGAGCGAAUGUUAACACGUGGCUACGGCGAGA

complementary base pairs: A-U, C-G

RNA Secondary Structure

Secondary structure. A set of pairs $S = \{(b_i, b_j)\}$ that satisfy:

- [Watson-Crick.] S is a matching and each pair in S is a Watson-Crick complement: A-U, U-A, C-G, or G-C.
- [No sharp turns.] The ends of each pair are separated by at least 4 intervening bases. If $(b_i, b_j) \in S$, then $i < j - 4$.
- [Non-crossing.] If (b_i, b_j) and (b_k, b_l) are two pairs in S , then we cannot have $i < k < j < l$.

Free energy. Usual hypothesis is that an RNA molecule will form the secondary structure with the optimum total free energy.

approximate by number of base pairs

Goal. Given an RNA molecule $B = b_1b_2\dots b_n$, find a secondary structure S that maximizes the number of base pairs.

RNA Secondary Structure: Examples

Examples.

ok sharp turn crossing

RNA Secondary Structure: Subproblems

First attempt. $OPT(j)$ = maximum number of base pairs in a secondary structure of the substring $b_1b_2\dots b_j$.

Difficulty. Results in two sub-problems.

- Finding secondary structure in: $b_1b_2\dots b_{t-1}$.
- Finding secondary structure in: $b_{t+1}b_{t+2}\dots b_{n-1}$.

need more sub-problems

Dynamic Programming Over Intervals

Notation. $OPT(i, j)$ = maximum number of base pairs in a secondary structure of the substring $b_{i+1}\dots b_j$.

- Case 1.** If $i \geq j - 4$.
 - $OPT(i, j) = 0$ by no-sharp turns condition.
- Case 2.** Base b_j is not involved in a pair.
 - $OPT(i, j) = OPT(i, j-1)$
- Case 3.** Base b_j pairs with b_t for some $i \leq t < j - 4$.
 - non-crossing constraint decouples resulting sub-problems
 - $OPT(i, j) = 1 + \max_t \{ OPT(i, t-1) + OPT(t+1, j-1) \}$

take max over t such that $i \leq t < j - 4$ and b_t and b_j are Watson-Crick complements

Remark. Same core idea in CKY algorithm to parse context-free grammars.

Bottom Up Dynamic Programming Over Intervals

Q. What order to solve the sub-problems?
 A. Do shortest intervals first.

```

    RNA(b1, ..., bn) {
      for k = 5, 6, ..., n-1
        for i = 1, 2, ..., n-k
          j = i + k
          Compute M[i, j]
      return M[1, n]
    }
    
```

using recurrence

| | | | | | |
|--|---|---|---|---|---|
| | 4 | 0 | 0 | 0 | |
| | 3 | 0 | 0 | | |
| | 2 | 0 | | | |
| | 1 | | | | |
| | | 6 | 7 | 8 | 9 |
| | | | | | j |

Running time. $O(n^3)$.

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Dynamic Programming Summary

Recipe.

- Characterize structure of problem.
- Recursively define value of optimal solution.
- Compute value of optimal solution.
- Construct optimal solution from computed information.

Dynamic programming techniques.

- Binary choice: weighted interval scheduling.
- Multi-way choice: segmented least squares. Viterbi algorithm for HMM also uses DP to optimize a maximum likelihood tradeoff between parsimony and accuracy.
- Adding a new variable: knapsack.
- Dynamic programming over intervals: RNA secondary structure. CKY parsing algorithm for context-free grammar has similar structure.

Top-down vs. bottom-up: different people have different intuitions.

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6.6 Sequence Alignment

String Similarity

How similar are two strings?

o c u r r a n c e -
 o c c u r r e n c e
 6 mismatches, 1 gap

o c - u r r a n c e
 o c c u r r e n c e
 1 mismatch, 1 gap

o c - u r r - a n c e
 o c c u r r e - n c e
 0 mismatches, 3 gaps

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Edit Distance

Edit distance. [Levenshtein 1966, Needleman-Wunsch 1970]

- Gap penalty δ ; mismatch penalty α_{pq} .
- Cost = sum of gap and mismatch penalties.

C T G A C C T A C C T - C T G A C C T A C C T
C C T G A C T A C A T C C T G A C - T A C A T

$\alpha_{TC} + \alpha_{GT} + \alpha_{AG} + 2\alpha_{CA}$ $2\delta + \alpha_{CA}$

Applications.

- Basis for Unix diff.
- Speech recognition.
- Computational biology.

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Sequence Alignment

Goal: Given two strings $X = x_1 x_2 \dots x_m$ and $Y = y_1 y_2 \dots y_n$ find alignment of minimum cost.

Def. An alignment M is a set of ordered pairs $x_i - y_j$ such that each item occurs in at most one pair and no crossings.

Def. The pair $x_i - y_j$ and $x_i' - y_j'$ **cross** if $i < i'$, but $j > j'$.

$$\text{cost}(M) = \underbrace{\sum_{(x_i, y_j) \in M} \alpha_{x_i y_j}}_{\text{mismatch}} + \underbrace{\sum_{i: x_i \text{ unmatched}} \delta + \sum_{j: y_j \text{ unmatched}} \delta}_{\text{gap}}$$

Ex: CTACCG VS. TACATG.
Sol: $M = x_2 - y_1, x_3 - y_2, x_4 - y_3, x_5 - y_4, x_6 - y_6$.

| | | | | | | |
|--|-------|-------|-------|-------|-------|-------|
| | x_1 | x_2 | x_3 | x_4 | x_5 | x_6 |
| | C | T | A | C | C | G |
| | - | T | A | C | A | T |
| | y_1 | y_2 | y_3 | y_4 | y_5 | y_6 |

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Sequence Alignment: Problem Structure

Def. $OPT(i, j)$ = min cost of aligning strings $x_1 x_2 \dots x_i$ and $y_1 y_2 \dots y_j$.

- Case 1: OPT matches $x_i - y_j$.
 - pay mismatch for $x_i - y_j$ + min cost of aligning two strings $x_1 x_2 \dots x_{i-1}$ and $y_1 y_2 \dots y_{j-1}$.
- Case 2a: OPT leaves x_i unmatched.
 - pay gap for x_i and min cost of aligning $x_1 x_2 \dots x_{i-1}$ and $y_1 y_2 \dots y_j$.
- Case 2b: OPT leaves y_j unmatched.
 - pay gap for y_j and min cost of aligning $x_1 x_2 \dots x_i$ and $y_1 y_2 \dots y_{j-1}$.

$$OPT(i, j) = \begin{cases} j\delta & \text{if } i = 0 \\ \alpha_{x_i, y_j} + OPT(i-1, j-1) & \text{otherwise} \\ i\delta & \text{if } j = 0 \end{cases}$$

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Sequence Alignment: Algorithm

```

Sequence-Alignment(m, n, x1x2...xm, y1y2...yn, δ, α) {
  for i = 0 to m
    M[i, 0] = iδ
  for j = 0 to n
    M[0, j] = jδ

  for i = 1 to m
    for j = 1 to n
      M[i, j] = min(α[xi, yj] + M[i-1, j-1],
                   δ + M[i-1, j],
                   δ + M[i, j-1])

  return M[m, n]
}
    
```

Analysis. $\Theta(mn)$ time and space.
English words or sentences: $m, n \leq 10$.
Computational biology: $m = n = 100,000$.
 10 billions ops OK, but 10GB array?

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6.7 Sequence Alignment in Linear Space

Sequence Alignment: Linear Space

Q. Can we avoid using quadratic space?

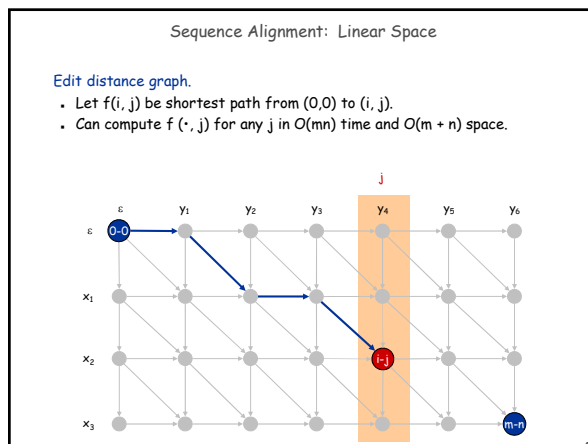
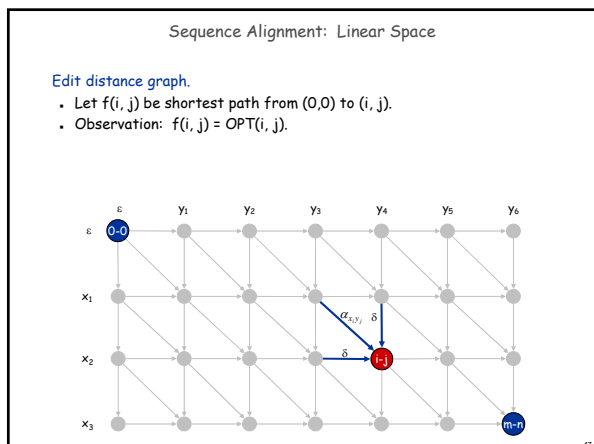
Easy. Optimal value in $O(m+n)$ space and $O(mn)$ time.

- Compute $OPT(i, \cdot)$ from $OPT(i-1, \cdot)$.
- No longer a simple way to recover alignment itself.

Theorem. [Hirschberg 1975] Optimal alignment in $O(m+n)$ space and $O(mn)$ time.

- Clever combination of divide-and-conquer and dynamic programming.
- Inspired by idea of Savitch from complexity theory.

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Sequence Alignment: Linear Space

Edit distance graph.

- Let $g(i, j)$ be shortest path from (i, j) to (m, n) .
- Can compute by reversing the edge orientations and inverting the roles of $(0, 0)$ and (m, n)

Sequence Alignment: Linear Space

Edit distance graph.

- Let $g(i, j)$ be shortest path from (i, j) to (m, n) .
- Can compute $g(\cdot, j)$ for any j in $O(mn)$ time and $O(m + n)$ space.

Sequence Alignment: Linear Space

Observation 1. The cost of the shortest path that uses (i, j) is $f(i, j) + g(i, j)$.

Sequence Alignment: Linear Space

Observation 2. let q be an index that minimizes $f(q, n/2) + g(q, n/2)$. Then, the shortest path from $(0, 0)$ to (m, n) uses $(q, n/2)$.

Sequence Alignment: Linear Space

Divide: find index q that minimizes $f(q, n/2) + g(q, n/2)$ using DP.

- Align x_q and $y_{n/2}$.

Conquer: recursively compute optimal alignment in each piece.

Sequence Alignment: Running Time Analysis Warmup

Theorem. Let $T(m, n) = \max$ running time of algorithm on strings of length at most m and n . $T(m, n) = O(mn \log n)$.

$$T(m, n) \leq 2T(m, n/2) + O(mn) \Rightarrow T(m, n) = O(mn \log n)$$

Remark. Analysis is not tight because two sub-problems are of size $(q, n/2)$ and $(m - q, n/2)$. In next slide, we save $\log n$ factor.

Sequence Alignment: Running Time Analysis

Theorem. Let $T(m, n)$ = max running time of algorithm on strings of length m and n . $T(m, n) = O(mn)$.

Pf. (by induction on n)

- $O(mn)$ time to compute $f(\cdot, n/2)$ and $g(\cdot, n/2)$ and find index q .
- $T(q, n/2) + T(m - q, n/2)$ time for two recursive calls.
- Choose constant c so that:

$$\begin{aligned} T(m, 2) &\leq cm \\ T(2, n) &\leq cn \\ T(m, n) &\leq cmn + T(q, n/2) + T(m - q, n/2) \end{aligned}$$

- Base cases: $m = 2$ or $n = 2$.
- Inductive hypothesis: $T(m, n) \leq 2cmn$.

$$\begin{aligned} T(m, n) &\leq T(q, n/2) + T(m - q, n/2) + cmn \\ &\leq 2cq(n/2) + 2c(m - q)(n/2) + cmn \\ &= cq(n/2) + cmn - cq(n/2) + cmn \\ &= 2cmn \end{aligned}$$

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