

6.047/6.878/HST.507

Computational Biology: Genomes, Networks, Evolution

Lecture 2

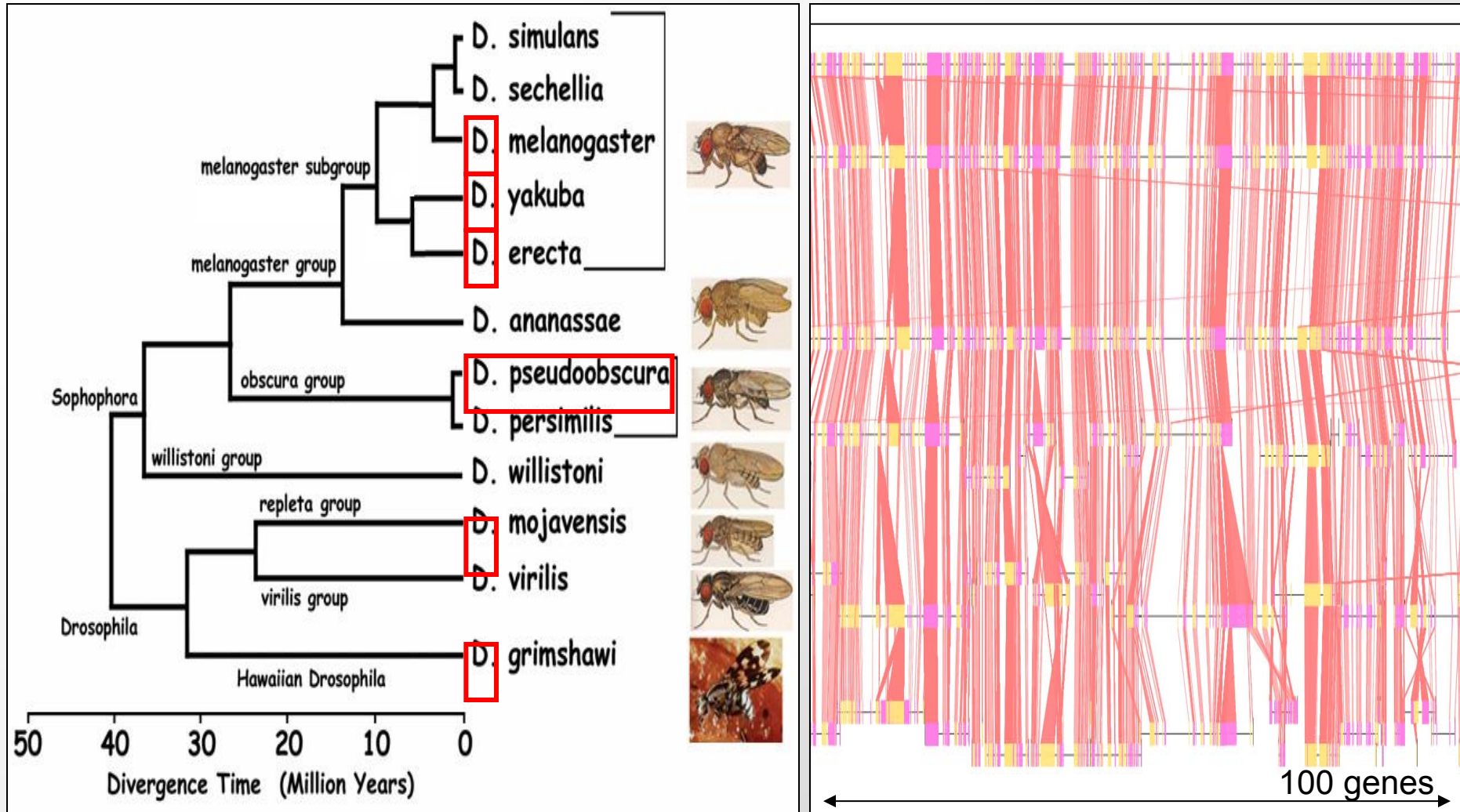
Sequence Alignment and Dynamic Programming

Module 1: Aligning and modeling genomes

Week	Date	Topic		Lec	Topic	Read*	
1	Thu, Sep 10	Introduction		L1	Intro: Biology, Algorithms, Machine Learning, Course Overview	1	
	Fri, Sep 11			R1	Recitation 1: Biology and Probability Review		
2	Tue, Sep 15	Module I: Aligning and Modeling Genomes	Foundations	L2	Alignment I: Dynamic Programming, Global and local alignment	2	
	Thu, Sep 17			L3	Alignment II: Database search, Rapid string matching, BLAST, BLOSUM	3	
	Fri, Sep 18			R2	Recitation 2: Deriving Parameters of Alignment, Multiple Alignment		
3	Tue, Sep 22		Frontiers		L4	Hidden Markov Models Part 1: Evaluation/Parsing, Viterbi, Forward algorithms	7
	Thu, Sep 24			L5	Hidden Markov Models Part 2: Posterior Decoding, Learning, Baum-Welch	8	
	Fri, Sep 25					No classes - student holiday	
	Fri, Sep 25			Project Intro: about the projects, self introductions, mentor intro, example projects, teamwork 32D-507			

- **Module 1: Computational foundations**
 - Dynamic programming: exploring exponential spaces in poly-time
 - Introduce Hidden Markov Models (HMMs): Central tool in CS
 - HMM algorithms: Decoding, evaluation, parsing, likelihood, scoring
- **This week: Sequence alignment / comparative genomics**
 - Local/global alignment: infer nucleotide-level evolutionary events
 - Database search: scan for regions that may have common ancestry
- **Next week: Modeling genomes / exon / CpG island finding**
 - Modeling class of elements, recognizing members of a class
 - Application to gene finding, conservation islands, CpG islands

Genome-wide alignments reveal orthologous segments

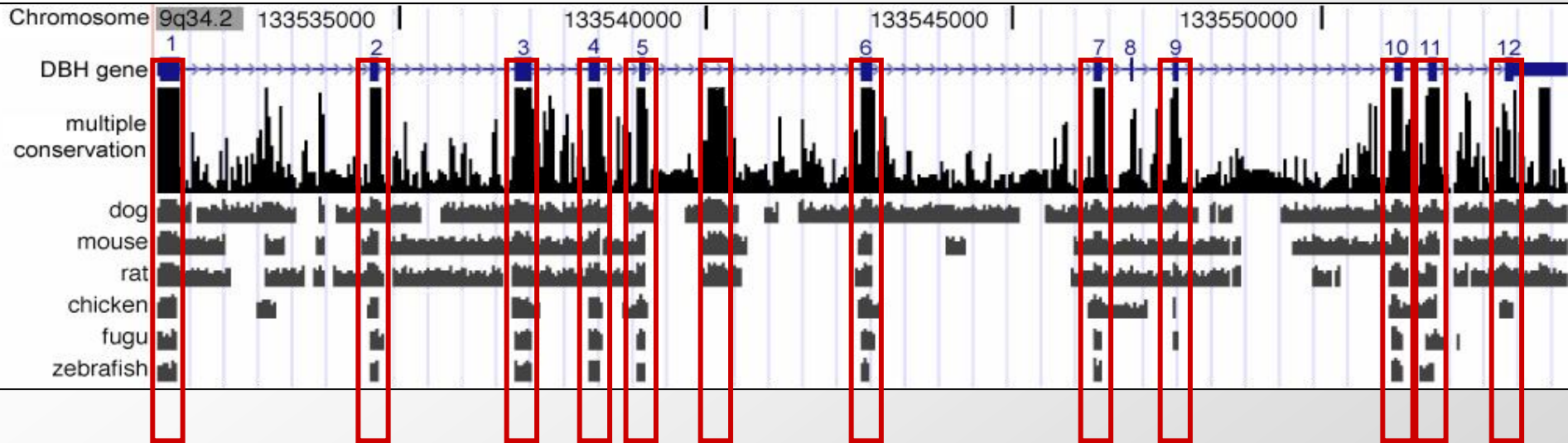


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- **Genome-wide alignments span entire genome**
- **Comparative identification of functional elements**

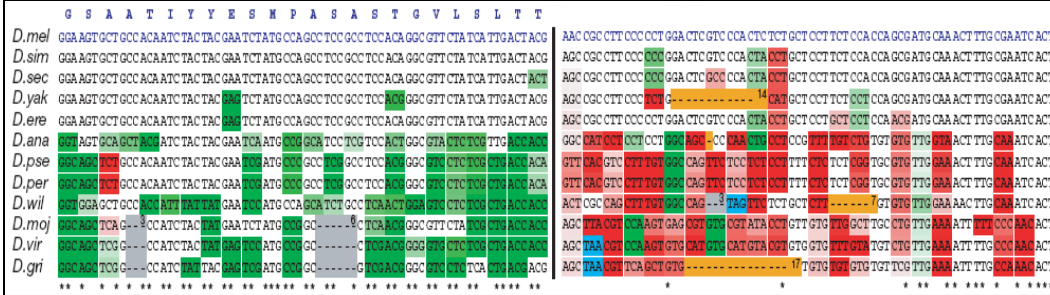
Comparative genomics reveals conserved regions



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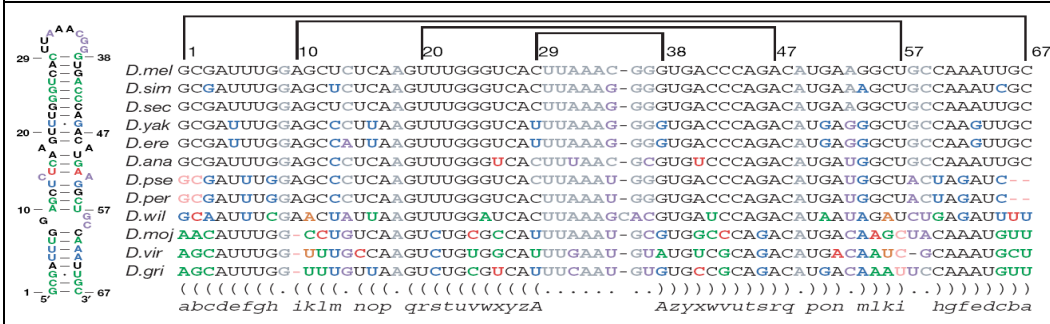
- **Comparative genomics can reveal functional elements**
 - For example: exons are deeply conserved to mouse, chicken, fish
 - Many other elements are also strongly conserved: exons / regulatory?
- **Develop methods for estimating the level of constraint**
 - Count the number of edit operations, number of substitutions and gaps
 - Estimate the number of mutations (including estimate of back-mutations)
 - Incorporate information about neighborhood: conservation ‘windows’
 - Estimate the probability of a constrained ‘hidden state’: HMMs next week
 - Use phylogeny to estimate tree mutation rate, or ‘rejected substitutions’
 - Allow different portions of the tree to have different rates: phylogenetics

Evolutionary signatures for diverse functions



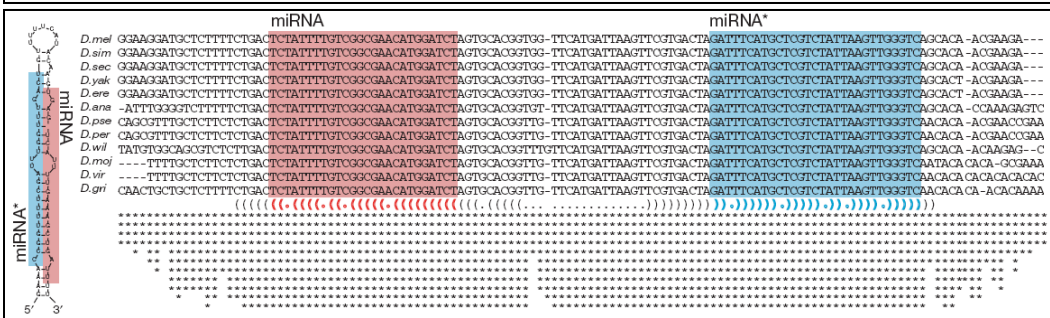
Protein-coding genes

- Codon Substitution Frequencies
- Reading Frame Conservation



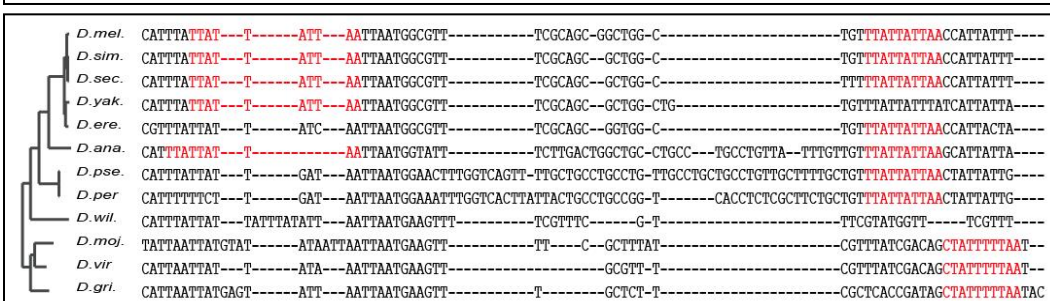
RNA structures

- Compensatory changes
- Silent G-U substitutions



microRNAs

- Shape of conservation profile
- Structural features: loops, pairs
- Relationship with 3'UTR motifs



Regulatory motifs

- Mutations preserve consensus
- Increased Branch Length Score
- Genome-wide conservation

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Source: Stark, Alexander et al. "Discovery of functional elements in 12 Drosophila genomes using evolutionary signatures." Nature 450, no. 7167 (2007): 219-232.

Today's goal:

How do we actually align two genes?

Goal: Sequence Alignment / Dynamic Programming

1. Introduction to sequence alignment

- Comparative genomics and molecular evolution
- From Bio to CS: Problem formulation
- Why it's hard: Exponential number of alignments

2. Introduction to principles of dynamic programming

- Computing Fibonacci numbers: Top-down vs. bottom-up
- Repeated sub-problems, ordering compute, table lookup
- DP recipe: (1) Parameterization, (2) sub-problem space, (3) traversal order, (4) recursion formula, (5) trace-back

3. DP for sequence alignment

- Additive score, building up a solution from smaller parts
- Prefix matrix: finite subproblems, exponential paths
- Duality: each entry \Leftrightarrow prefix alignment score; path \Leftrightarrow alignment

4. Advanced topics: Dynamic Programming variants

- Linear-time bounded DP(heuristic). Linear-space DP. Gaps
- Importance of parameterization: 2-D vs. 4-D decomposition

Genomes change over time

begin

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

mutation

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

deletion

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

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

insertion

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

end

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

Goal of alignment: Infer edit operations

begin

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

?

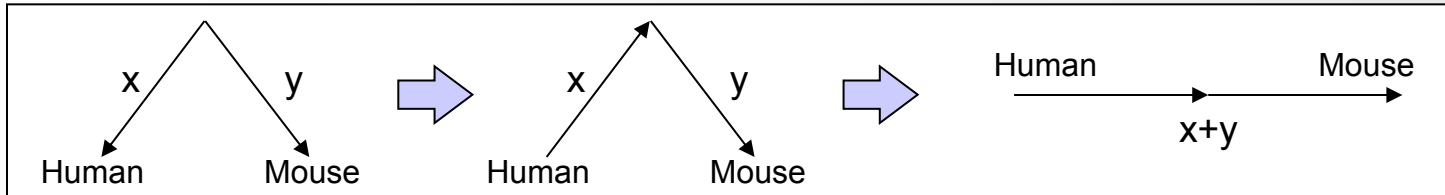


end

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

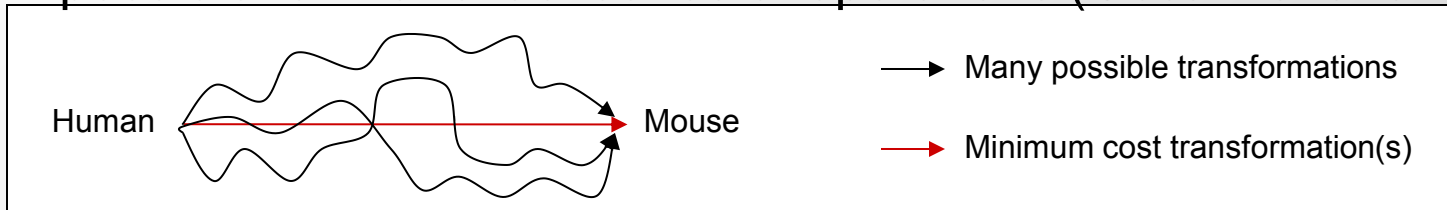
From Bio to CS: Formalizing the problem

- Define set of evolutionary operations (insertion, deletion, mutation)
 - Symmetric operations allow time reversibility (part of design choice)

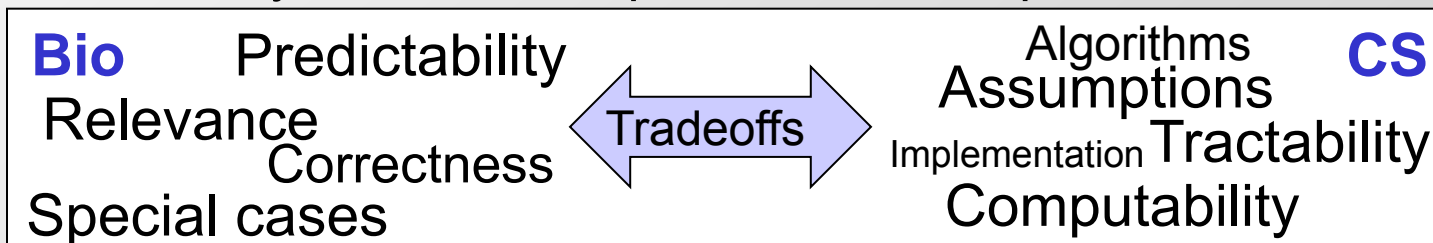


(Exception: methylated CpG dinucleotides → TpG/CpA non-symmetric)

- Define optimality criterion (min number, min cost)
 - Impossible to infer exact series of operations (Occam's razor: find min)



- Design algorithm that achieves that optimality (or approximates it)
 - Tractability of solution depends on assumptions in the formulation



Note: Not all decisions are conflicting (some are both relevant and tractable) (e.g. Pevzner vs. Sankoff and directionality in chromosomal inversions)

Formulation 1: Longest common substring

- Given two possibly related strings S1 and S2
 - What is the longest common substring? (no gaps)

S1

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

S2

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



S1

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

S2

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



S1

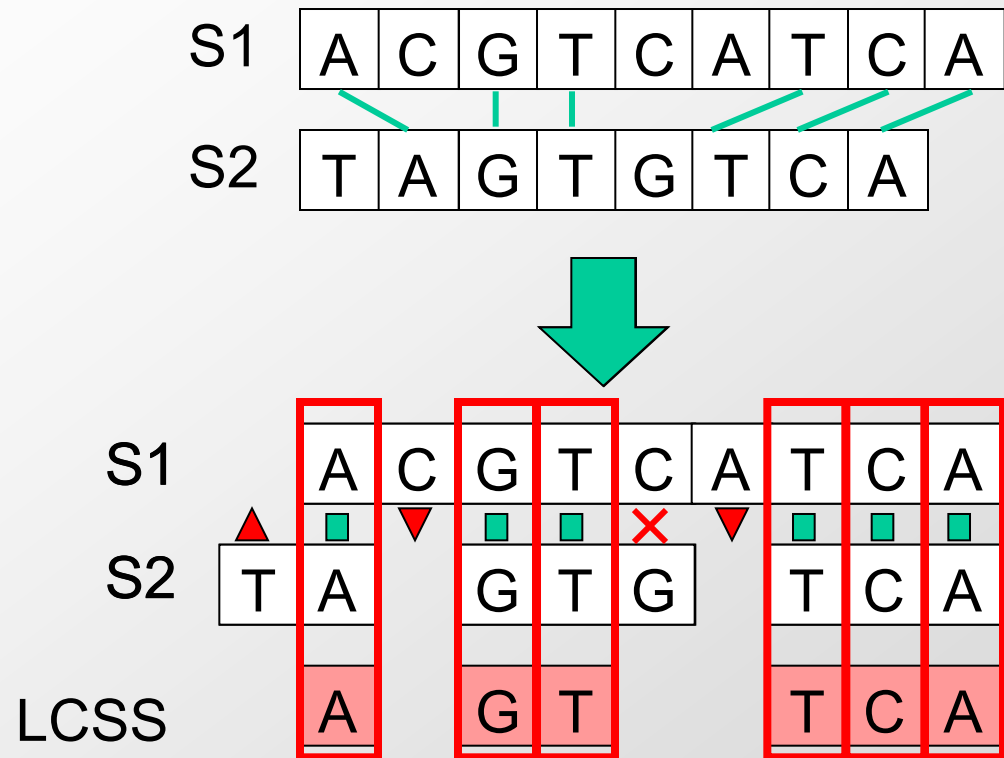
		A	C	G	T	C	A	T	C	A
--	--	---	---	---	---	---	---	---	---	---

S2

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

Formulation 2: Longest common subsequence

- Given two possibly related strings S1 and S2
 - What is the longest common subsequence? (gaps allowed)



Related to:

Edit distance:

- Number of changes needed for $S1 \rightarrow S2$
- Uniform scoring function

Formulation 3: Sequence alignment

- Allow gaps (fixed penalty)
 - Insertion & deletion operations
 - Unit cost for each character inserted or deleted
- Varying penalties for edit operations
 - Transitions (Pyrimidine \leftrightarrow Pyrimidine, Purine \leftrightarrow Purine)
 - Transversions (Purine \leftrightarrow Pyrimidine changes)
 - Polymerase confuses Aw/G and Cw/T more often

Scoring function:

Match(x,x) = +1

Mismatch(A,G) = $-\frac{1}{2}$

Mismatch(C,T) = $-\frac{1}{2}$

Mismatch(x,y) = -1

	A	G	T	C
A	+1	$-\frac{1}{2}$	-1	-1
G	$-\frac{1}{2}$	+1	-1	-1
T	-1	-1	+1	$-\frac{1}{2}$
C	-1	-1	$-\frac{1}{2}$	+1

purine pyrimid.

Transitions:

$A \leftrightarrow G$, $C \leftrightarrow T$ common
(lower penalty)

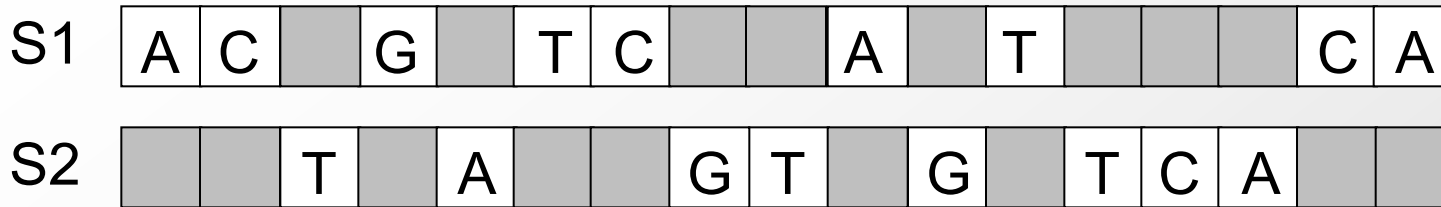
Transversions:

All other operations

Formulation 4: Varying gap cost models

1. Linear gap penalty
 - Same as before
2. Affine gap penalty
 - Big initial cost for starting or ending a gap
 - Small incremental cost for each additional character
3. General gap penalty
 - Any cost function
 - No longer computable using the same model
4. Frame-aware gap penalty
 - Multiples of 3 disrupt coding regions
5. Seek duplicated regions, rearrangements, ...
 - Etc

How many alignments are there?



- Longest 'non-boring' alignment: $n+m$ entries
 - Otherwise a gap will be aligned to a gap \rightarrow condense
- Alignment is equivalent to gap placement
 - $(n+m \text{ choose } n)$ ways to choose S1 placement
 - At each position yes/no answer of placing character
 - Exponential number of possible placements
- Exponential number of sequence alignment
 - Enumerating and scoring each of them not an option
 - Need faster solution for finding best alignment

Need **polynomial** algorithm to find best alignment amongst an **exponential** number of possible alignments!

\rightarrow DP

Goal: Sequence Alignment / Dynamic Programming

1. Introduction to sequence alignment

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- Why it's hard: Exponential number of alignments

2. Introduction to principles of dynamic programming

- Computing Fibonacci numbers: Top-down vs. bottom-up
- Repeated sub-problems, ordering compute, table lookup
- DP recipe: (1) Parameterization, (2) sub-problem space, (3) traversal order, (4) recursion formula, (5) trace-back

3. DP for sequence alignment

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4. Advanced topics: Dynamic Programming variants

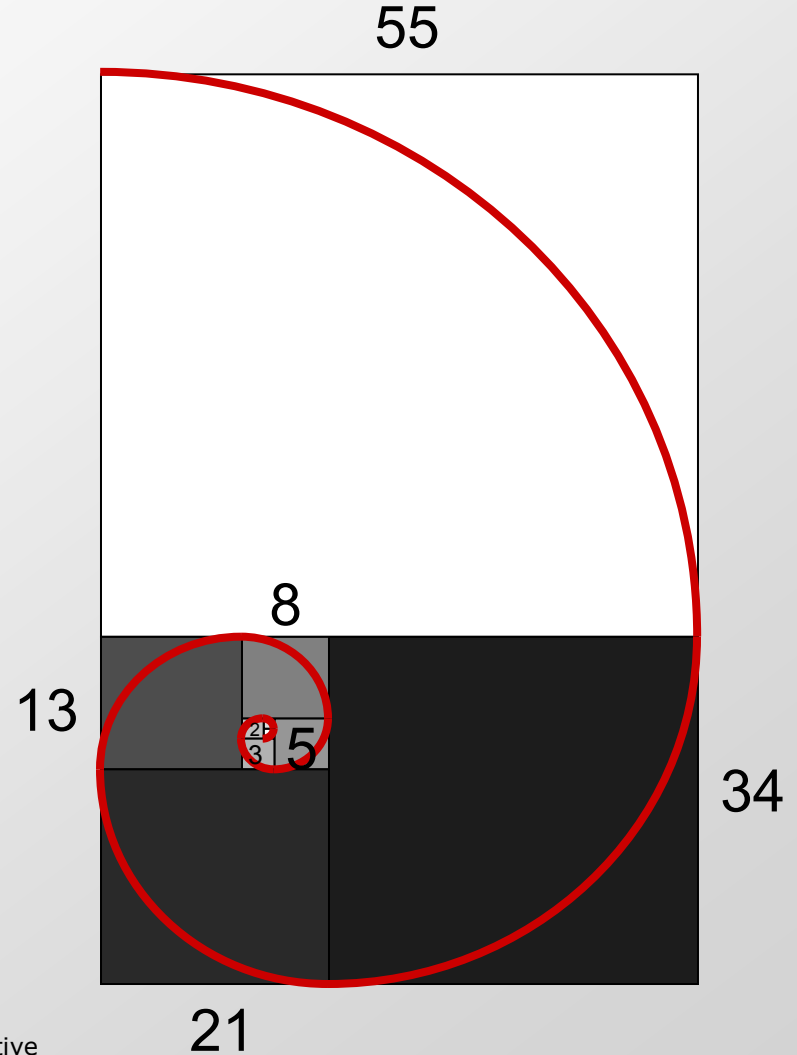
- Linear-time bounded DP(heuristic). Linear-space DP. Gaps
- Importance of parameterization: 2-D vs. 4-D decomposition

A simple introduction to the principles of Dynamic Programming

Turning exponentials into polynomials

Computing Fibonacci Numbers

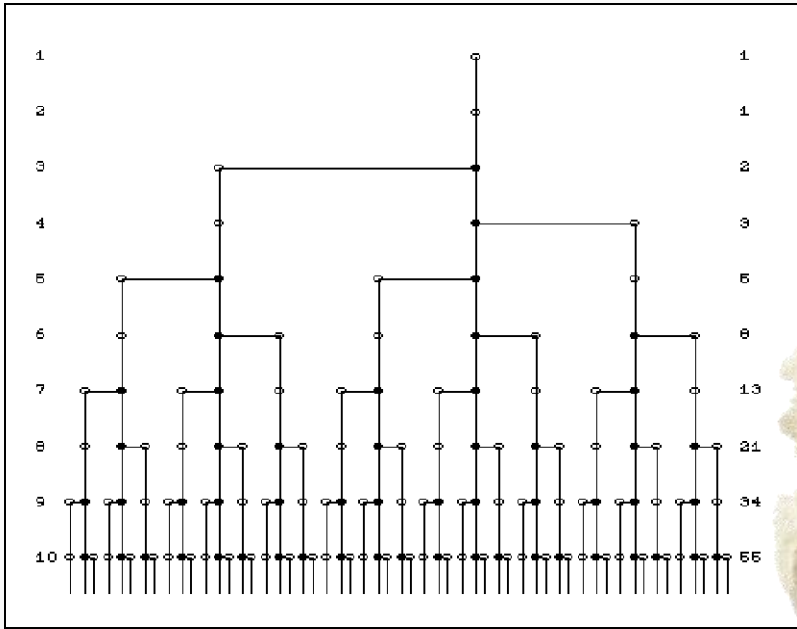
- Fibonacci numbers



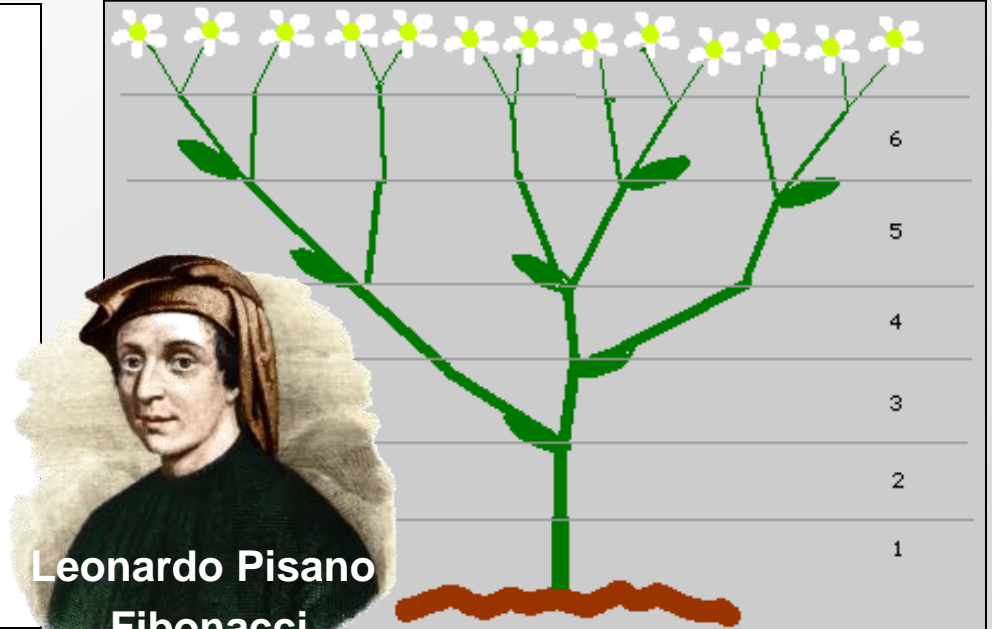
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$$F_6 = F_5 + F_4 = (F_4 + F_3) + (F_3 + F_2) = \dots = (3 + 2) + (2 + 1) = 5 + 3 = 8$$

Fibonacci numbers are ubiquitous in nature



Rabbits per generation



Leonardo Pisano
Fibonacci

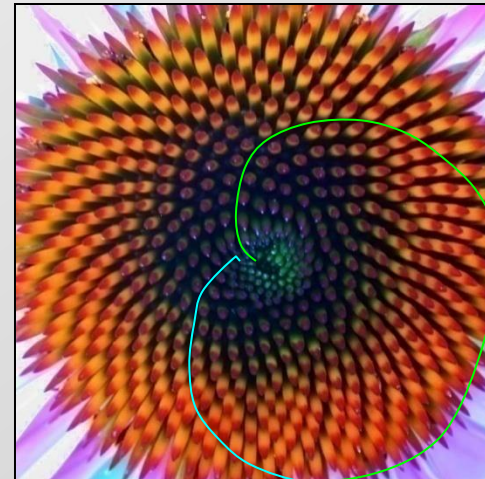
Leaves per height



Romanesque spirals



Nautilus size



Coneflower spirals



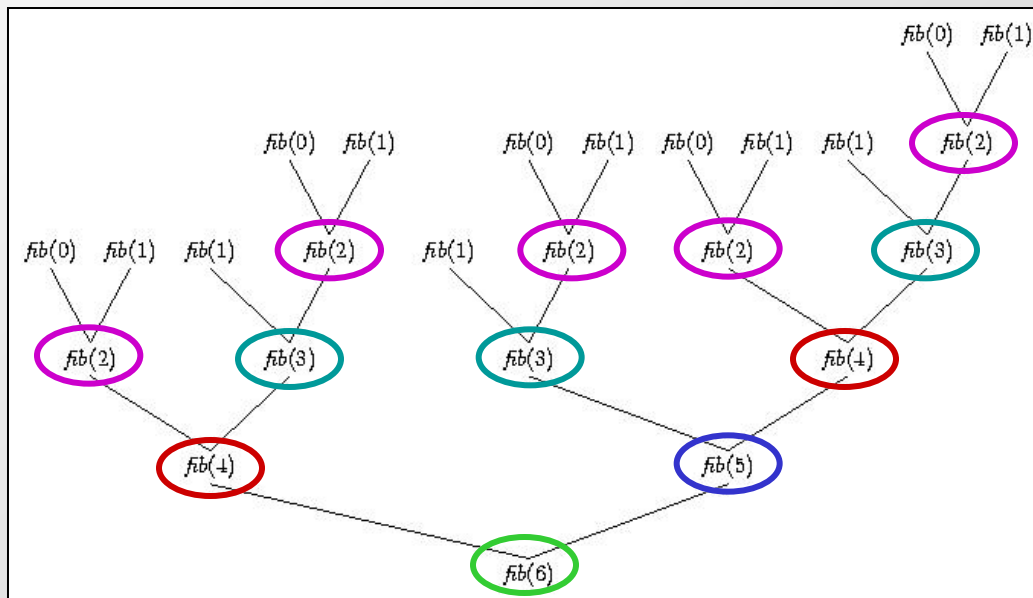
Leaf ordering

Computing Fibonacci numbers: Top down

- Fibonacci numbers are defined recursively:
 - Python code

```
def fibonacci(n):  
    if n==1 or n==2: return 1  
    return fibonacci(n-1) + fibonacci(n-2)
```

- Goal: Compute n^{th} Fibonacci number.
 - $F(0)=1, F(1)=1, F(n)=F(n-1)+F(n-2)$
 - 1,1,2,3,5,8,13,21,34,55,89,144,233,377,...
- Analysis:
 - $T(n) = T(n-1) + T(n-2) = (\dots) = O(2^n)$



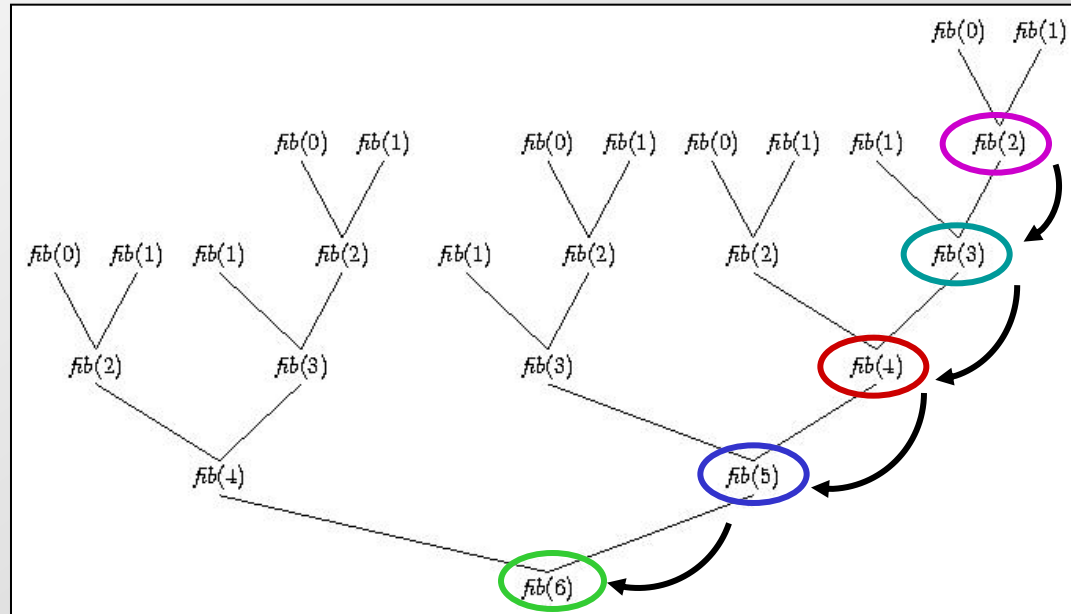
Computing Fibonacci numbers: Bottom up

- Bottom up approach
 - Python code

fib_table	
F[1]	1
F[2]	1
F[3]	2
F[4]	3
F[5]	5
F[6]	8
F[7]	13
F[8]	21
F[9]	34
F[10]	55
F[11]	89
F[12]	?

```
def fibonacci(n):  
    fib_table[1] = 1  
    fib_table[2] = 1  
    for i in range(3,n+1):  
        fib_table[i] = fib_table[i-1]+fib_table[i-2]  
    return fib_table[n]
```

- Analysis: $T(n) = O(n)$



Lessons from iterative Fibonacci algorithm

fib_table	
F[1]	1
F[2]	1
F[3]	2
F[4]	3
F[5]	5
F[6]	8
F[7]	13
F[8]	21
F[9]	34
F[10]	55
F[11]	89
F[12]	?



- What did the iterative solution do?
 - Reveal identical sub-problems
 - Order computation to enable result reuse
 - Systematically filled-in table of results
 - Expressed larger problems from their subparts
- Ordering of computations matters
 - Naïve top-down approach very slow
 - results of smaller problems not available
 - repeated work
 - Systematic bottom-up approach successful
 - Systematically solve each sub-problem
 - Fill-in table of sub-problem results in order.
 - Look up solutions instead of recomputing

Dynamic Programming in Theory

- **Hallmarks of Dynamic Programming**
 - **Optimal substructure:** Optimal solution to problem (instance) contains optimal solutions to sub-problems
 - **Overlapping subproblems:** Limited number of distinct subproblems, repeated many many times
- **Typically for optimization problems (unlike Fib example)**
 - Optimal choice made locally: $\max(\text{subsolution score})$
 - Score is typically added through the search space
 - Traceback common, find optimal path from indiv. choices
- **Middle of the road in range of difficulty**
 - Easier: greedy choice possible at each step
 - DynProg: requires a traceback to find that optimal path
 - Harder: no opt. substr., e.g. subproblem dependencies

Hallmarks of optimization problems

Greedy algorithms

Dynamic Programming

1. Optimal substructure

An optimal solution to a problem (instance) contains optimal solutions to subproblems.

2. Overlapping subproblems

A recursive solution contains a “small” number of distinct subproblems repeated many times.

3. Greedy choice property

Locally optimal choices lead to globally optimal solution

*Greedy Choice is not possible
Globally optimal solution requires trace back through many choices*

Dynamic Programming in Practice

- **Setting up dynamic programming**
 1. Find 'matrix' parameterization (# dimensions, variables)
 2. Make sure sub-problem space is finite! (not exponential)
 - If not all subproblems are used, better off using memoization
 - If reuse not extensive, perhaps DynProg is not right solution!
 3. Traversal order: sub-results ready when you need them
 - Computation order matters! (bottom-up, but not always obvious)
 4. **Recursion formula: larger problems = F(subparts)**
 5. Remember choices: typically F() includes min() or max()
 - Need representation for storing pointers, is this polynomial !
- **Then start computing**
 1. Systematically fill in table of results, find optimal score
 2. Trace-back from optimal score, find optimal solution

Goal: Sequence Alignment / Dynamic Programming

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3. DP for sequence alignment

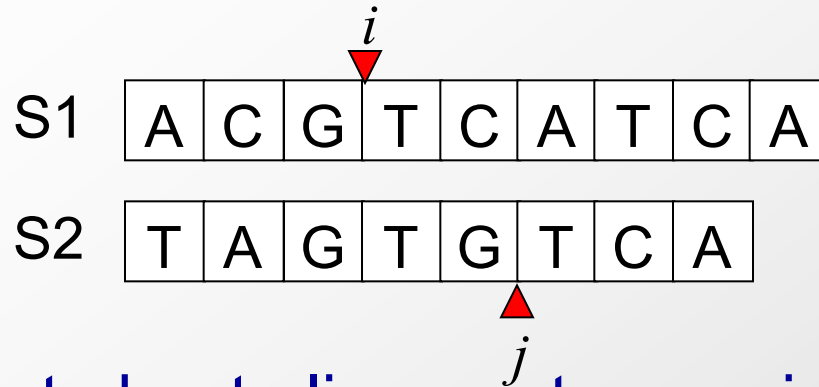
- Additive score, building up a solution from smaller parts
- Prefix matrix: finite subproblems, exponential paths
- Duality: each entry \Leftrightarrow prefix alignment score; path \Leftrightarrow alignment

4. Advanced topics: Dynamic Programming variants

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- Importance of parameterization: 2-D vs. 4-D decomposition

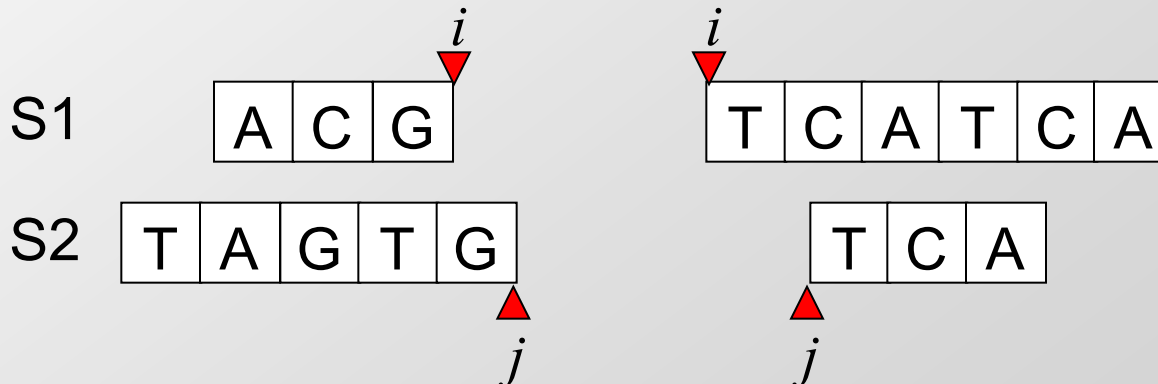
**(3) How do we apply dynamic programming
to sequence alignment ?**

Key insight #1: Score is additive, smaller to larger



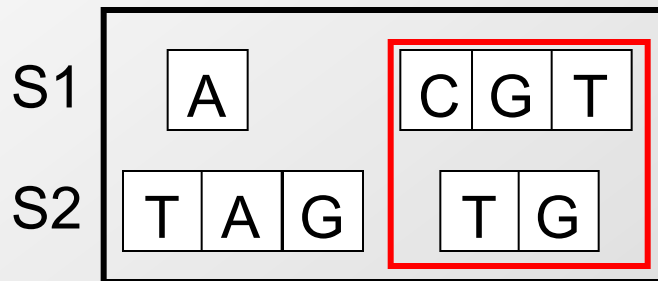
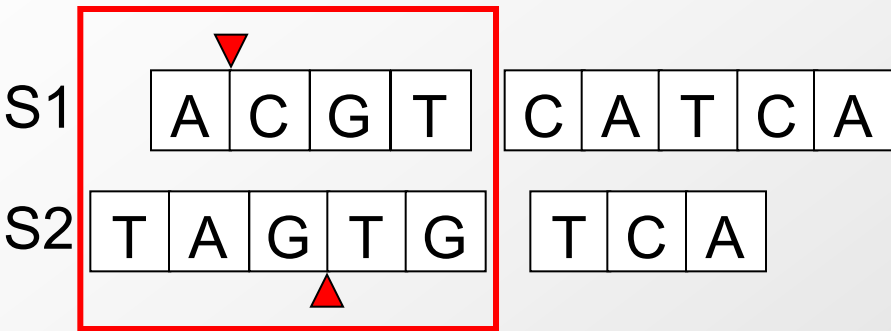
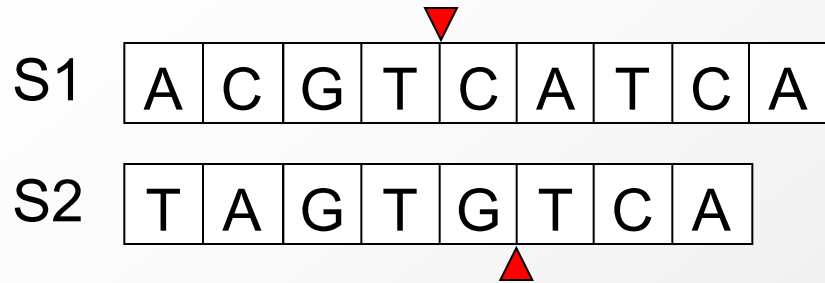
- Compute best alignment recursively

- For a given aligned pair (i, j) , the best alignment is:
 - Best alignment of $S1[1..i]$ and $S2[1..j]$
 - + Best alignment of $S1[i..n]$ and $S2[j..m]$
- Proof: cut-and-paste argument (see 6.046)



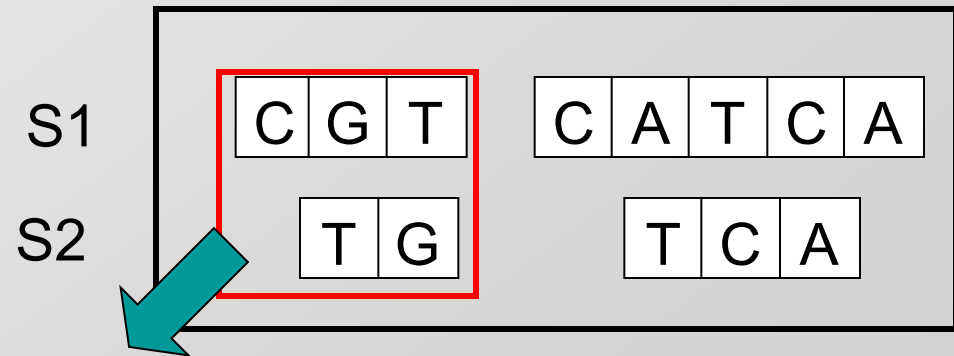
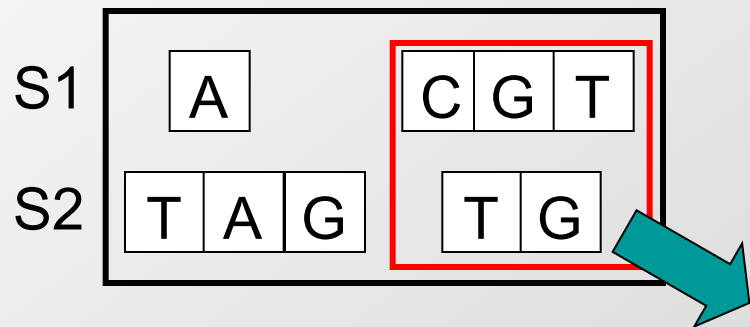
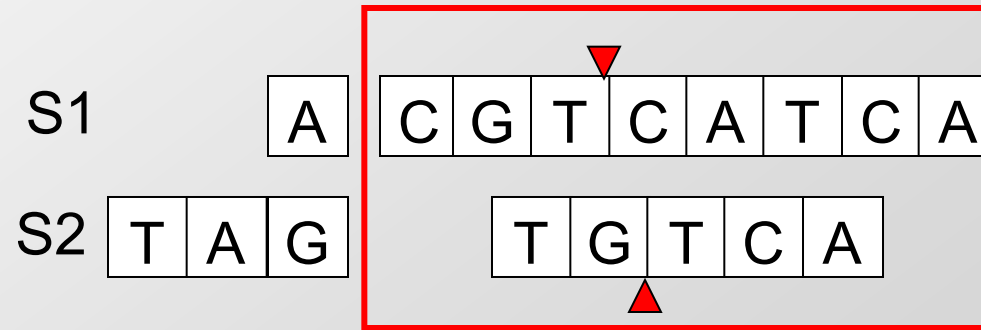
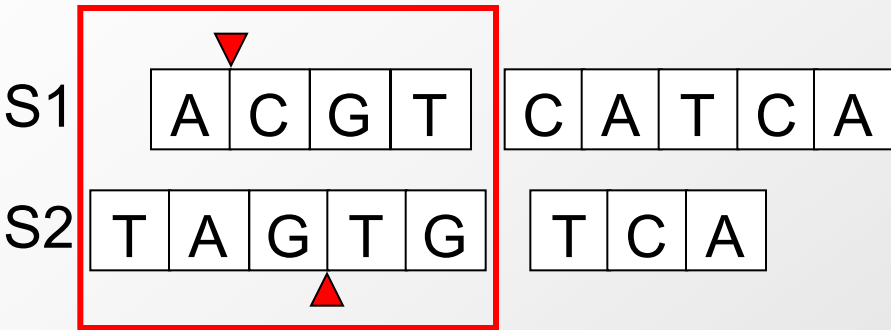
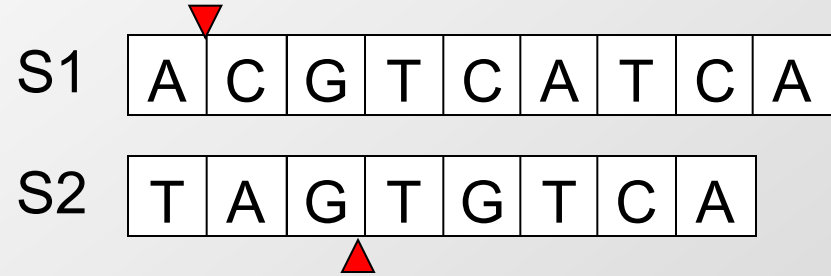
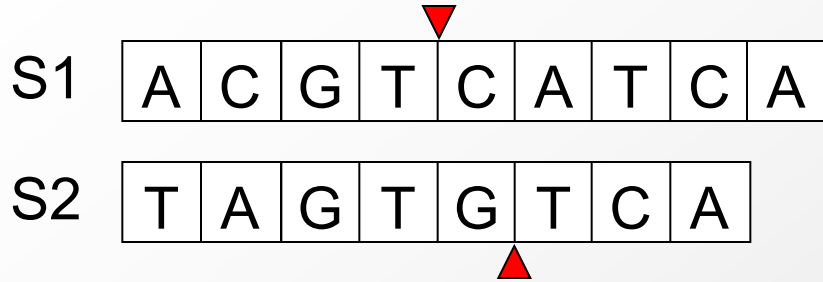
This allows a single recursion (top-left to bottom-right) instead of two recursions (middle-to-outside top-down)

Key insight #2: compute scores recursively



→ Compute alignment of CGT vs. TG exactly once

Key insight #3: sub-problems are repeated → reuse!



→ Identical sub-problems! We can reuse our work!

Solution #1 – Memoization

- Create a big dictionary, indexed by aligned seqs
 - When you encounter a new pair of sequences
 - If it is in the dictionary:
 - Look up the solution
 - If it is not in the dictionary
 - Compute the solution
 - Insert the solution in the dictionary
- Ensures that there is no duplicated work
 - Only need to compute each sub-alignment once!

Top down approach

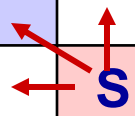
Solution #2 – Dynamic programming

- Create a big table, indexed by (i,j)
 - Fill it in from the beginning all the way till the end
 - You know that you'll need every subpart
 - Guaranteed to explore entire search space
- Ensures that there is no duplicated work
 - Only need to compute each sub-alignment once!
- Very simple computationally!

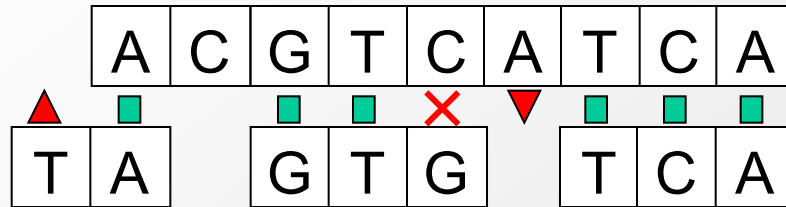
Bottom up approach

Key insight #4: Optimal prefix almt score \Leftrightarrow Matrix entry

	$S_1[1..i]$						i	$S_1[i..n]$					
$S_2[1..j]$													
j							S						
$S_2[j..m]$													



Key insight #5: Optimal alignment \Leftrightarrow Matrix path

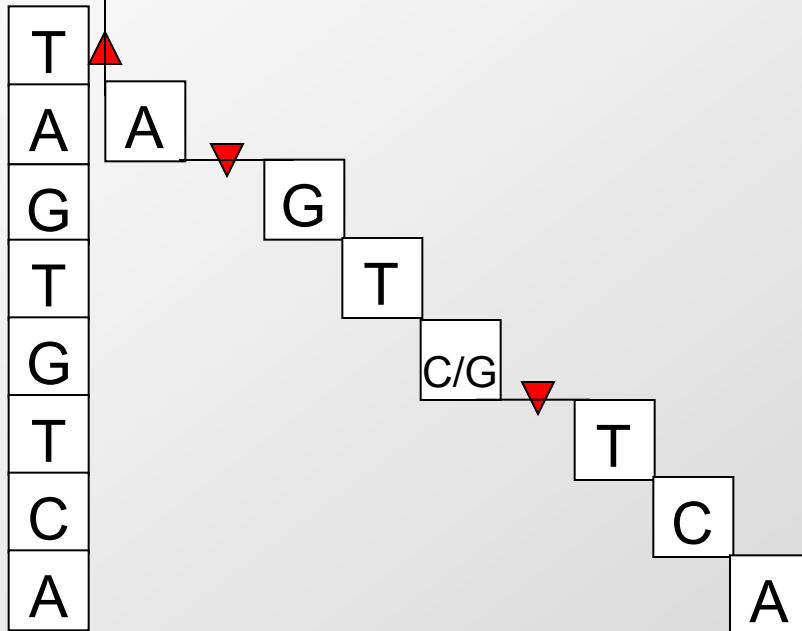


Best alignment \Leftrightarrow Best path through the matrix

S1

A C G T C A T C A

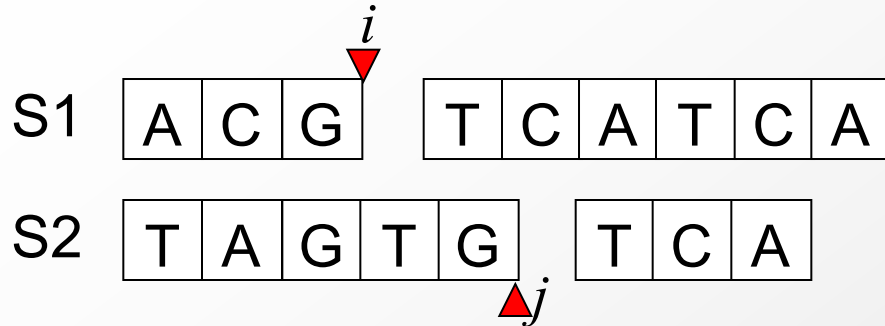
S2



Goal:

Find best path
through the matrix

DP approach: iteratively grow best alignment soltn



- Compute all alignment scores from the bottom up
 - Define $M[i,j]$ prefix alignment score of $S_1[1..i]$ and $S_2[1..j]$
 - Fill up table recursively from smaller to bigger alignments
- Express alignment of $S_1[1..i+1]$ and $S_2[1..j+1] \rightarrow M[i+1,j+1]$
 - One of three possibilities: (1) extend alignment from $M[i,j]$
 - (2) extend from $M[i-1,j]$, or (3) extend from $M[i,j-1]$
 - Only a local computation, takes $O(1)$ time!
- Proof of correctness (cut-and-paste argument from 6.006)
 - Best alignment of $S_1[1..i+1]$ and $S_2[1..j+1]$ must be composed of best alignments of smaller prefix
 - Proof: otherwise could replace sub and get better overall

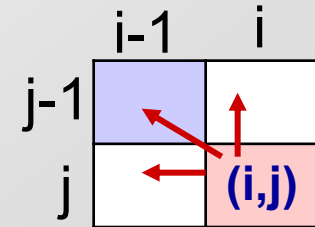
Computing alignments recursively: $M[i,j]=F(\text{smaller})$

- Local update rules, only look at neighboring cells:
 - Compute next alignment based on previous alignment
 - Just like Fibonacci numbers: $F[i] = F[i-1] + F[i-2]$
 - Table lookup avoids repeated computation
- Computing the score of a cell from smaller neighbors

$$M(i-1, j) - \text{gap}$$

$$- M(i,j) = \max\{ M(i-1, j-1) + \text{score} \}$$

$$M(i, j-1) - \text{gap}$$



- Only three possibilities for extending by one nucleotide: a gap in one species, a gap in the other, a (mis)match
- Compute scores for prefixes of increasing length
 - Start with prefixes of length 1, extend by one each time, until all prefixes have been computed
 - When you reach bottom right, alignment score of $S_1[1..m]$ and $S_2[1..n]$ is alignment of full S_1 and full S_2
 - (Can then trace back to construct optimal path to it)

Dynamic Programming for sequence alignment

- **Setting up dynamic programming**

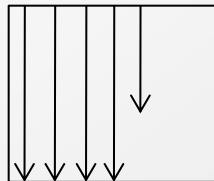
1. Find 'matrix' parameterization

- Prefix parameterization. $\text{Score}(S_1[1..i], S_2[1..j]) \rightarrow M(i,j)$
- (i,j) only prefixes vs. (i,j,k,l) all substrings \rightarrow simpler 2-d matrix

2. Make sure sub-problem space is finite! (not exponential)

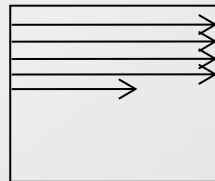
- It's just n^2 , quadratic (which is polynomial, not exponential)

3. Traversal order: sub-results ready when you need them



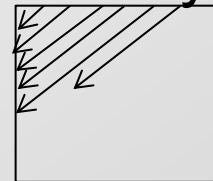
Cols

L \rightarrow R



Rows

top \rightarrow bot



Diags

topR \rightarrow botL

4. Recursion formula: larger problems = Func(subparts)

- Need formula for computing $M[i,j]$ as function of previous results
- Single increment at a time, only look at $M[i-1,j]$, $M[i,j-1]$, $M[i-1,j-1]$ corresponding to 3 options: gap in S_1 , gap in S_2 , char in both
- Score in each case depends on gap/match/mismatch penalties

5. Remember choice: $F()$ typically includes $\min()$ or $\max()$

- Remember which of three cells (top, left, diag) led to maximum

Step 1: Setting up the scoring matrix $M[i,j]$

	-	A	G	T
-	0			
A				
A				
G				
C				

Initialization:

- Top left: 0

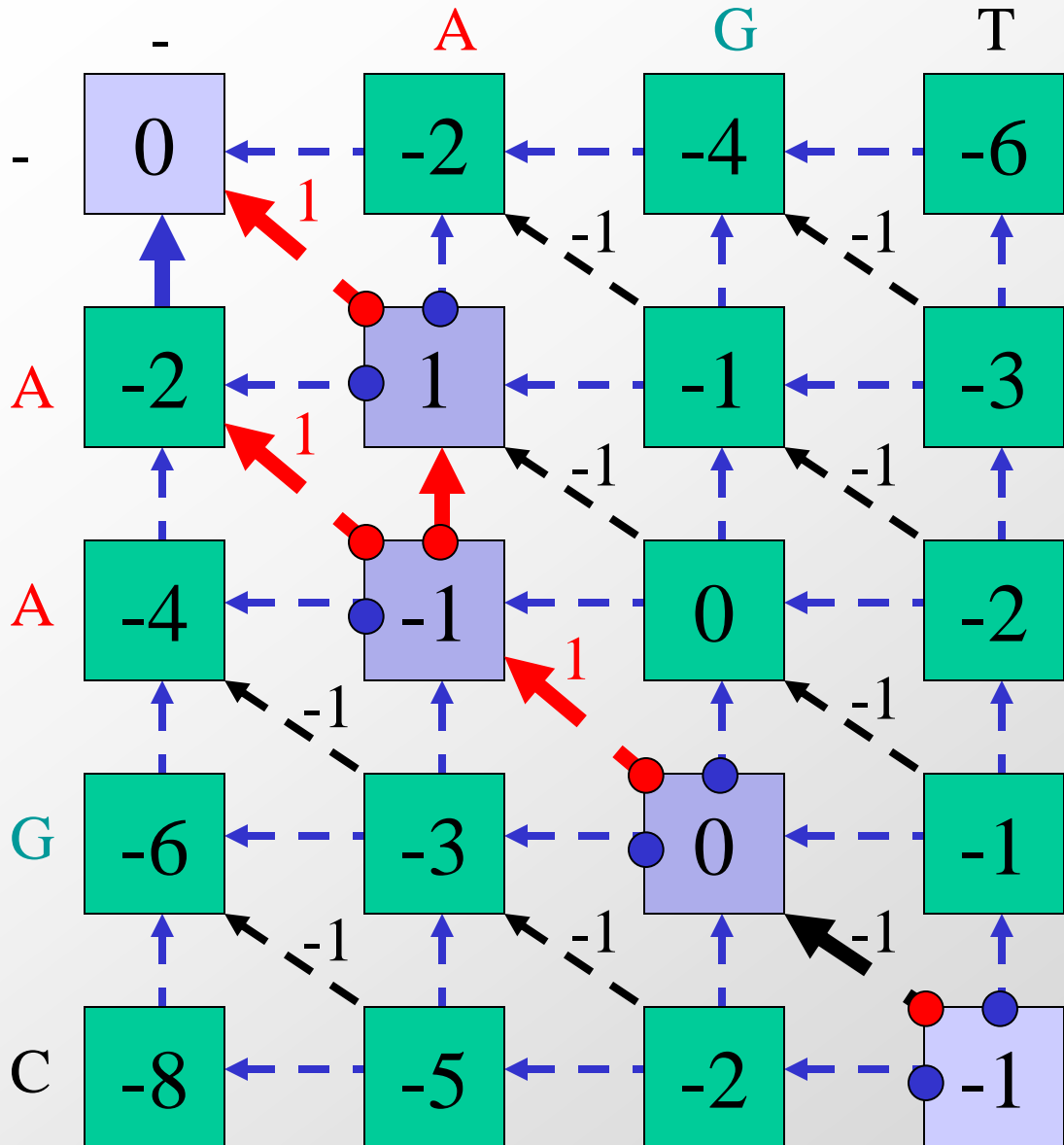
Update Rule:

$$M(i,j) = \max\{$$

Termination:

- Bottom right

Step 2: Filling in the optimal scores from top left



Initialization:

- Top left: 0

Update Rule:

$$M(i,j) = \max\{$$

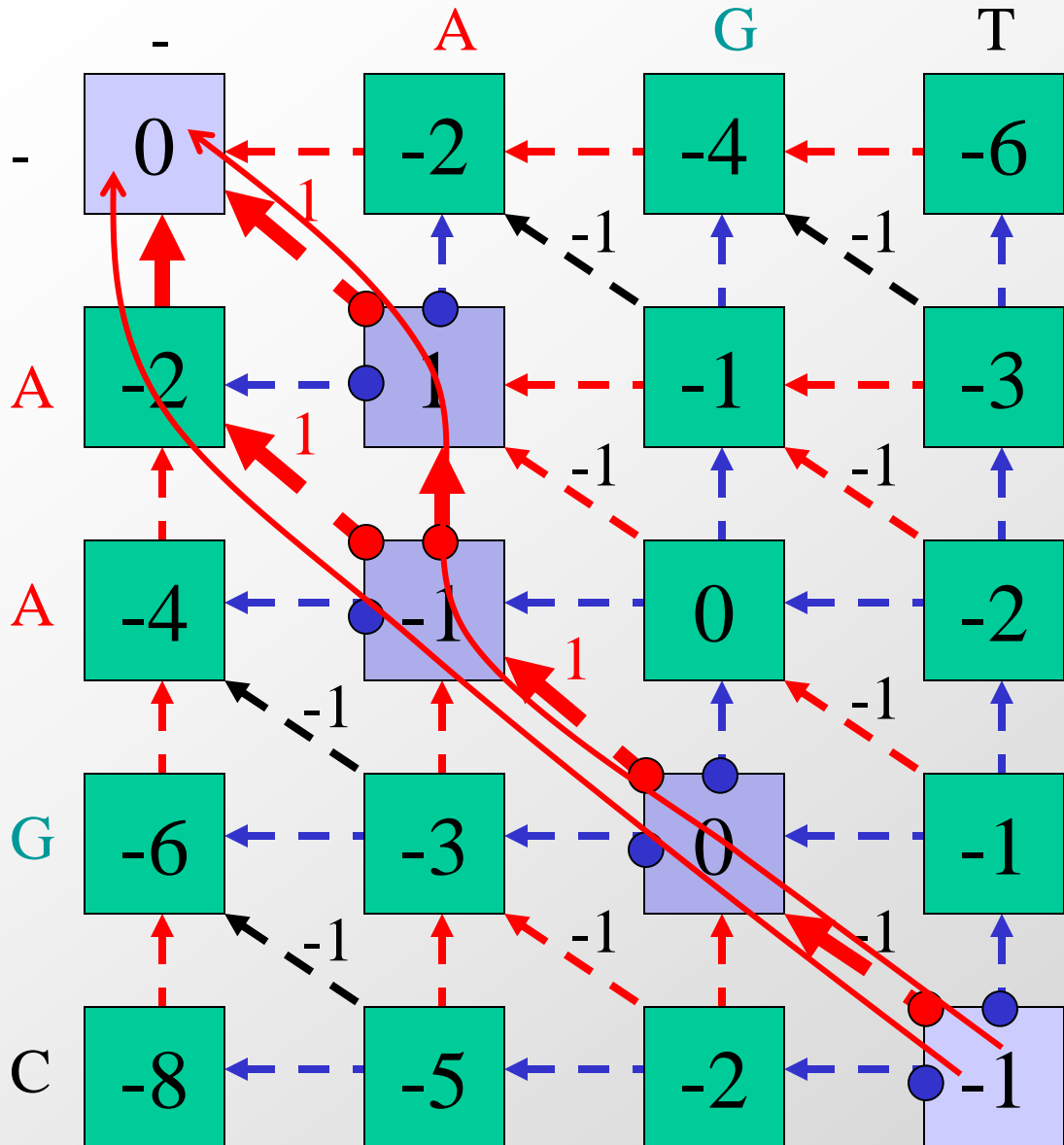
- $M(i-1, j) - 2$ gap
- $M(i, j-1) - 2$ gap
- $M(i-1, j-1) - 1$ mismatch
- $M(i-1, j-1) + 1$ match

Termination:

- Bottom right

● Path segment that lead to the optimal choice

Step 3: Trace back pointers to construct alignment



Initialization:

- Top left: 0

Update Rule:

$$M(i,j) = \max\{$$

- $M(i-1, j) - 2$ gap
- $M(i, j-1) - 2$ gap
- $M(i-1, j-1) - 1$ mismatch
- $M(i-1, j-1) + 1$ match

Termination:

- Bottom right

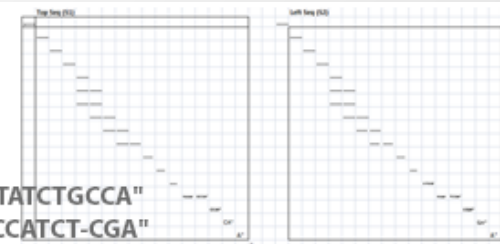
----- Path segments that lead to locally optimal choices

==== Path segments that lead to the globally optimal solution

Genome alignment in an excel spreadsheet

	A	G	C	T	Gap
A	1.0	0.0	-1.0	-1.0	-1.0
G	0.0	1.0	-1.0	-1.0	
C	-1.0	-1.0	1.0	0.0	
T	-1.0	-1.0	0.0	1.0	

S1[1..i]	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	
Prefixes	T	TA	TAA	TAAC	TAAAC	TAAACT	TAAACCT	TAAACCTT	TAAACCTTT	TAAACCTTTA	TAAACCTTTAT	TAAACCTTTATC	TAAACCTTTATCT	TAAACCTTTATCTG	TAAACCTTTATCTGC	TAAACCTTTATCTGCC	TAAACCTTTATCTGCCA



S1:"TAAC-CTTTATCTGCCA"
S2:"TAACGGCCCATCT-CGA"

S2[1..j]	Prefixes
1	T
2	TA
3	TAA
4	TAAC
5	TAACG
6	TAACGG
7	TAACGGC
8	TAACGGCC
9	TAACGGCCC
10	TAACGGCCCA
11	TAACGGCCCAT
12	TAACGGCCCATC
13	TAACGGCCCATCT
14	TAACGGCCCATCTC
15	TAACGGCCCATCTCG
16	TAACGGCCCATCTCGA

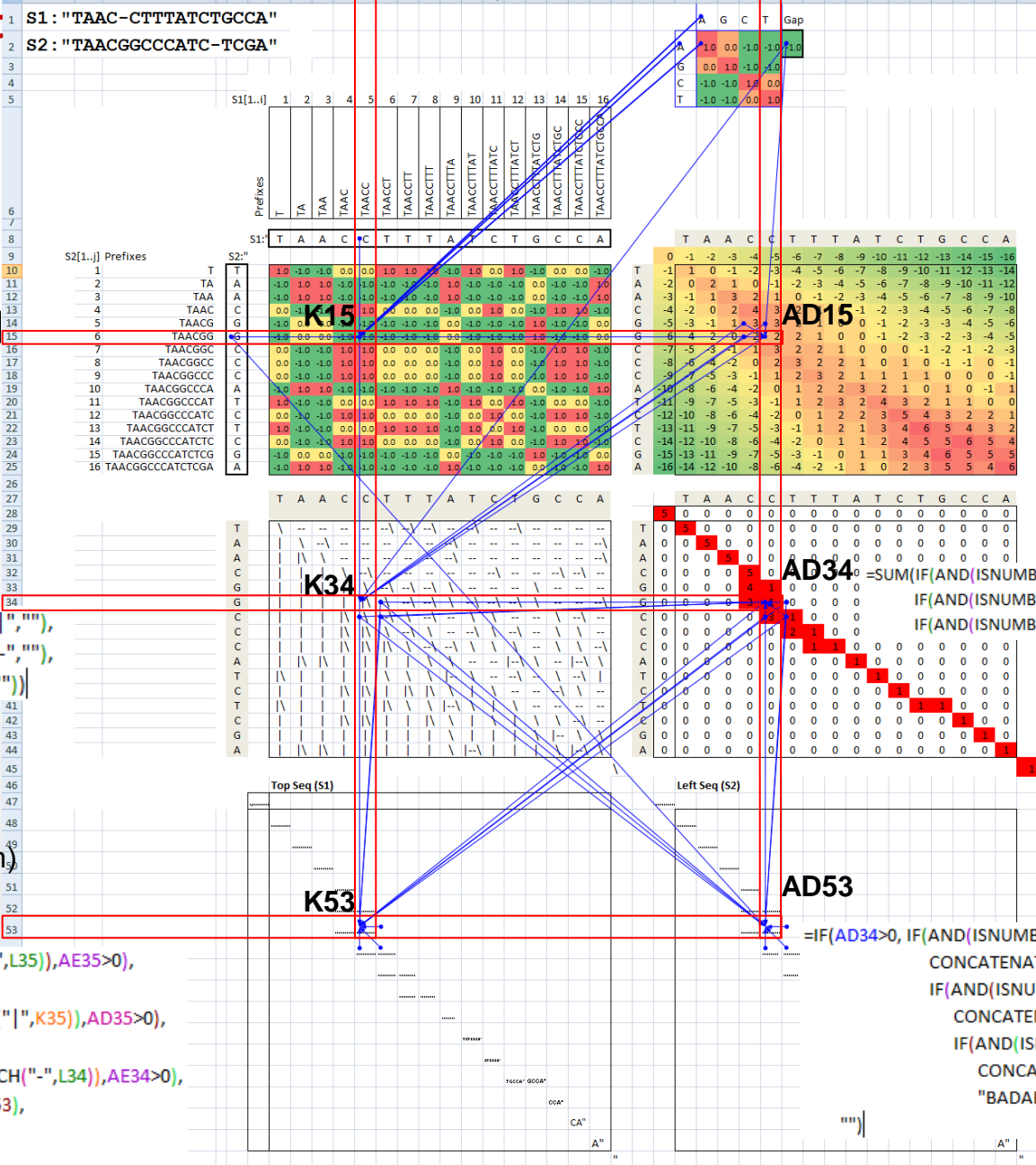
S1:	T	A	A	C	C	T	T	T	A	T	C	T	G	C	C	A
S2:"	T	A	A	C	C	T	T	T	A	T	C	T	G	C	C	A
1	1.0	-1.0	-1.0	0.0	0.0	1.0	1.0	1.0	-1.0	1.0	0.0	1.0	-1.0	0.0	0.0	-1.0
2	-1.0	1.0	1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	1.0
3	-1.0	1.0	1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	1.0
4	0.0	-1.0	-1.0	1.0	1.0	0.0	0.0	0.0	-1.0	0.0	1.0	0.0	-1.0	1.0	1.0	-1.0
5	-1.0	0.0	0.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	0.0
6	-1.0	0.0	0.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	0.0
7	0.0	-1.0	-1.0	1.0	1.0	0.0	0.0	0.0	-1.0	0.0	1.0	0.0	-1.0	1.0	1.0	-1.0
8	0.0	-1.0	-1.0	1.0	1.0	0.0	0.0	0.0	-1.0	0.0	1.0	0.0	-1.0	1.0	1.0	-1.0
9	0.0	-1.0	-1.0	1.0	1.0	0.0	0.0	0.0	-1.0	0.0	1.0	0.0	-1.0	1.0	1.0	-1.0
10	-1.0	1.0	1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	1.0
11	1.0	-1.0	-1.0	0.0	0.0	1.0	1.0	1.0	-1.0	1.0	0.0	1.0	-1.0	0.0	0.0	-1.0
12	0.0	-1.0	-1.0	1.0	1.0	0.0	0.0	0.0	-1.0	0.0	1.0	0.0	-1.0	1.0	1.0	-1.0
13	1.0	-1.0	-1.0	0.0	0.0	1.0	1.0	1.0	-1.0	1.0	0.0	1.0	-1.0	0.0	0.0	-1.0
14	0.0	-1.0	-1.0	1.0	1.0	0.0	0.0	0.0	-1.0	0.0	1.0	0.0	-1.0	1.0	1.0	-1.0
15	-1.0	0.0	0.0	-1.0	-1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	0.0
16	-1.0	1.0	1.0	-1.0	-1.0	-1.0	-1.0	-1.0	1.0	-1.0	-1.0	-1.0	0.0	-1.0	-1.0	1.0

	T	A	A	C	C	T	T	T	A	T	C	T	G	C	C	A	
0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15	-16	
T	-1	1	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14
A	-2	0	2	1	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12
A	-3	-1	1	3	2	1	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10
C	-4	-2	0	2	4	3	2	1	0	-1	-2	-3	-4	-5	-6	-7	-8
G	-5	-3	-1	1	3	3	2	1	0	0	-1	-2	-3	-3	-4	-5	-6
G	-6	-4	-2	0	2	2	2	1	0	0	-1	-2	-3	-2	-3	-4	-5
C	-7	-5	-3	-1	1	3	2	2	1	0	0	0	-1	-2	-1	-2	-3
C	-8	-6	-4	-2	0	2	3	2	2	1	0	1	0	-1	-1	0	-1
C	-9	-7	-5	-3	-1	1	2	3	2	1	1	1	1	0	0	0	-1
A	-10	-8	-6	-4	-2	0	1	2	2	3	2	1	0	1	0	-1	1
T	-11	-9	-7	-5	-3	-1	1	2	3	2	4	3	2	1	1	0	0
C	-12	-10	-8	-6	-4	-2	0	1	2	2	3	5	4	3	2	2	1
T	-13	-11	-9	-7	-5	-3	-1	1	2	1	3	4	6	5	4	3	2
C	-14	-12	-10	-8	-6	-4	-2	0	1	1	2	4	5	5	6	5	4
G	-15	-13	-11	-9	-7	-5	-3	-1	0	1	1	3	4	6	5	5	5
A	-16	-14	-12	-10	-8	-6	-4	-2	-1	1	0	2	3	5	5	4	6

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

	T	A	A	C	C	T	T	T	A	T	C	T	G	C	C	A
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0
C	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	4	1	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0	0
C	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0
C	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
C	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Genome alignment in an excel spreadsheet



```

K15
=INDEX($AA$2:$AD$5,
MATCH(K$8,$Z$2:$Z$5,0),
MATCH($E15,$AA$1:$AD$1,0))
    
```

Local score of matching characters S₁[i] and S₂[j]

```

AD15
=MAX(AD14+$AE$2,
AC15+$AE$2,
AC14+K15)
    
```

Max alignment score of aligning prefix S₁[1..i] and prefix S₂[1..j]

```

K34
=CONCATENATE(IF(AD15=AD14+$AE$2,"|",""),
IF(AD15=AC15+$AE$2,"-",""),
IF(AD15=AC14+K15,"\",""))
    
```

Is the max alignment score coming from the top ("|"), from the left ("-") or from the diagonal up ("\") (show all of them, cuz we can.)

```

AD34
=SUM(IF(AND(ISNUMBER(SEARCH("|",K35)),AD35>0),AD35,0),
IF(AND(ISNUMBER(SEARCH("-",L35)),AE35>0),AE35,0),
IF(AND(ISNUMBER(SEARCH("\",L34)),AE34>0),AE34,0))
    
```

Is the [i,j] part of an optimal path? (i.e. are chars S₁[i] and S₂[j] aligned to each other in an optimal path) (also count number of optimal paths/alignment through [i,j], cuz we can)

```

K53
=IF(AD34>0, IF(AND(ISNUMBER(SEARCH("|",L35)),AE35>0),
CONCATENATE(K$8,L54),
IF(AND(ISNUMBER(SEARCH("|",K35)),AD35>0),
CONCATENATE("-",K54),
IF(AND(ISNUMBER(SEARCH("-",L34)),AE34>0),
CONCATENATE(K$8,L53),
"BADABOOM!"))),
"")
    
```

Construct the optimal alignment for sequence S₁ by adding in characters or gaps to increasingly large suffixes (and arbitrarily choose one path when multiple using nested if's)

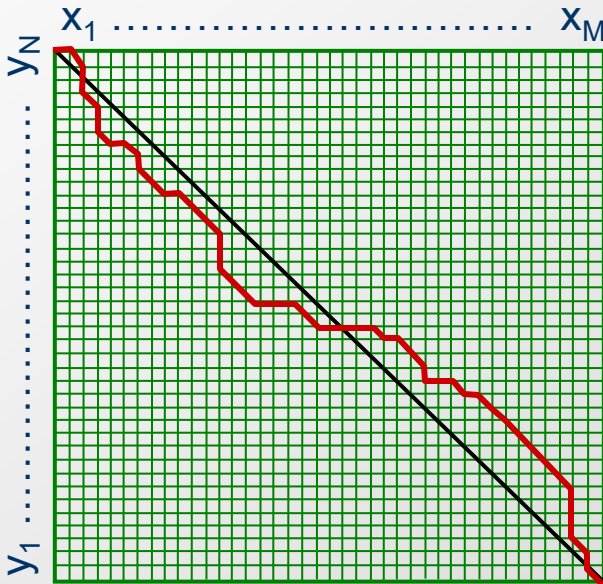
```

AD53
=IF(AD34>0, IF(AND(ISNUMBER(SEARCH("\",L35)),AE35>0),
CONCATENATE($E15,AE54),
IF(AND(ISNUMBER(SEARCH("|",K35)),AD35>0),
CONCATENATE($E15,AD54),
IF(AND(ISNUMBER(SEARCH("-",L34)),AE34>0),
CONCATENATE("-",AE53),
"BADABOOM!"))),
"")
    
```

Construct the optimal alignment for sequence S₂ similarly to S₁

What is missing? (5) Returning the actual path!

- We know how to compute the best score
 - Simply the number at the bottom right entry
- But we need to remember where it came from
 - Pointer to the choice we made at each step
- Retrace path through the matrix
 - Need to remember all the pointers



Time needed: $O(m*n)$

Space needed: $O(m*n)$

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- Additive score, building up a solution from smaller parts
- Prefix matrix: finite subproblems, exponential paths
- Duality: each entry \Leftrightarrow prefix alignment score; path \Leftrightarrow alignment

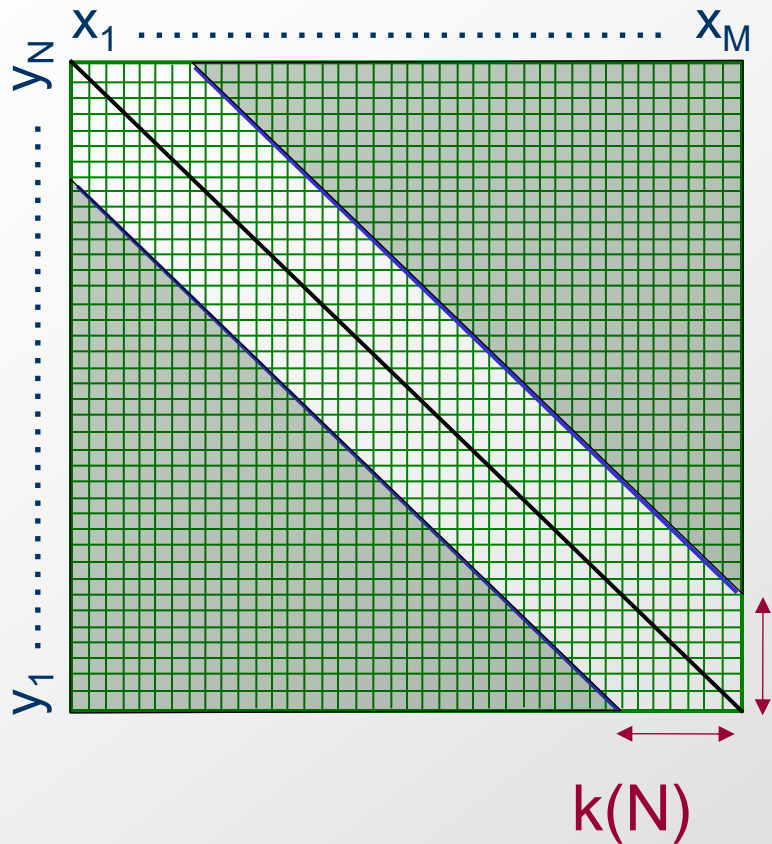
4. Advanced topics: Dynamic Programming variants

- Linear-time bounded DP(heuristic). Linear-space DP. Gaps
- Importance of parameterization: 2-D vs. 4-D decomposition

If time permits...

(4) Extensions to basic DP solution

Bounded Dynamic Programming



Initialization:

$F(i,0), F(0,j)$ undefined for $i, j > k$

Iteration:

For $i = 1 \dots M$

For $j = \max(1, i - k) \dots \min(N, i + k)$

$$F(i, j) = \max \begin{cases} F(i - 1, j - 1) + s(x_i, y_j) \\ F(i, j - 1) - d, \text{ if } j > i - k(N) \\ F(i - 1, j) - d, \text{ if } j < i + k(N) \end{cases}$$

Termination: same

Can we do better than $O(n^2)$ in the general case?

- Reduced Orthogonal Vectors to PATTERN
- Reduced PATTERN to EDIT DISTANCE
- Proved EDIT DISTANCE is a SETH-hard problem

Abstract removed due to copyright restrictions.

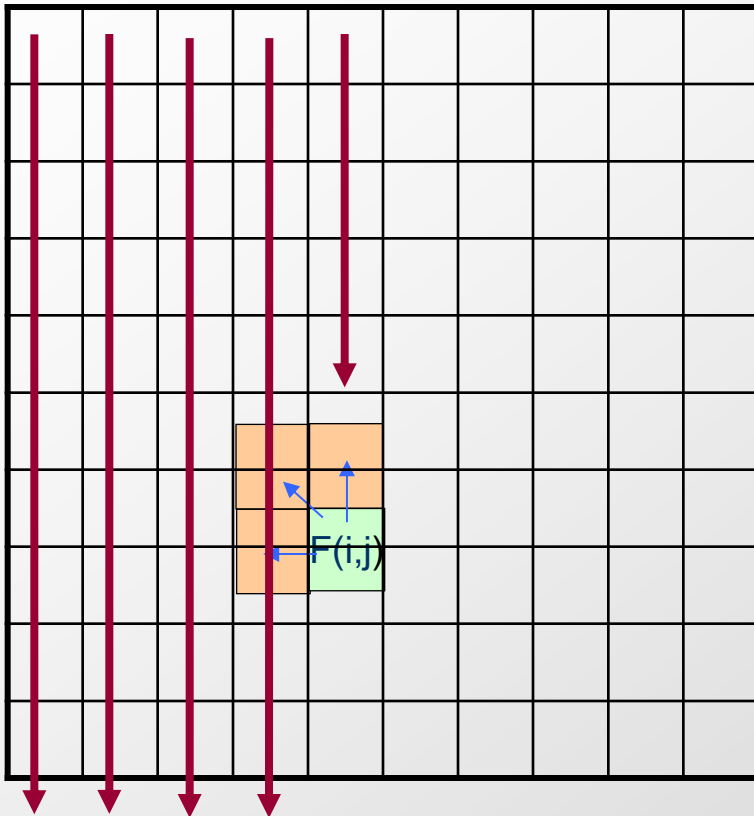
Source: Backurs, Arturs, and Piotr Indyk. "[Edit Distance Cannot Be Computed in Strongly Subquadratic Time \(unless SETH is false\)](#)."

In Proceedings of the Forty-Seventh Annual ACM on Symposium on Theory of Computing, pp. 51-58. ACM, 2015.

- Faster edit dist. algorithm probably not a good term project

Linear space alignment

It is easy to compute $F(M, N)$ in linear space



Allocate (column[1])

Allocate (column[2])

For $i = 1 \dots M$

If $i > 1$, then:

Free(column[$i - 2$])

Allocate(column[i])

For $j = 1 \dots N$

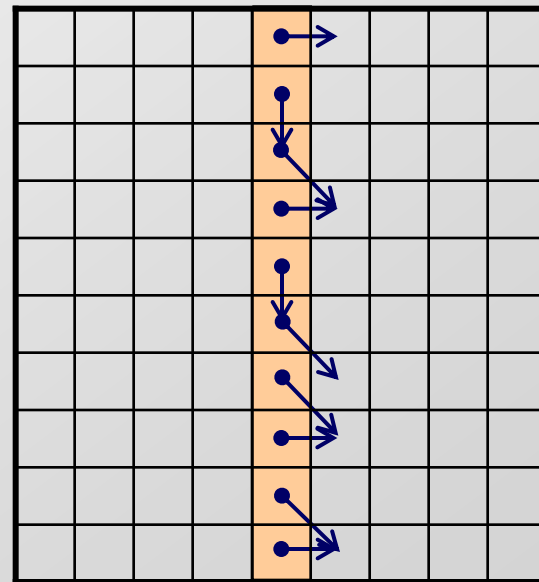
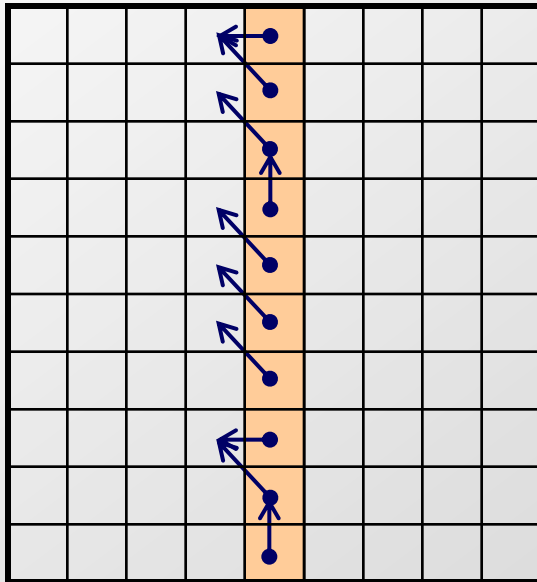
$F(i, j) = \dots$

What about the pointers?

Finding the best back-pointer for current column

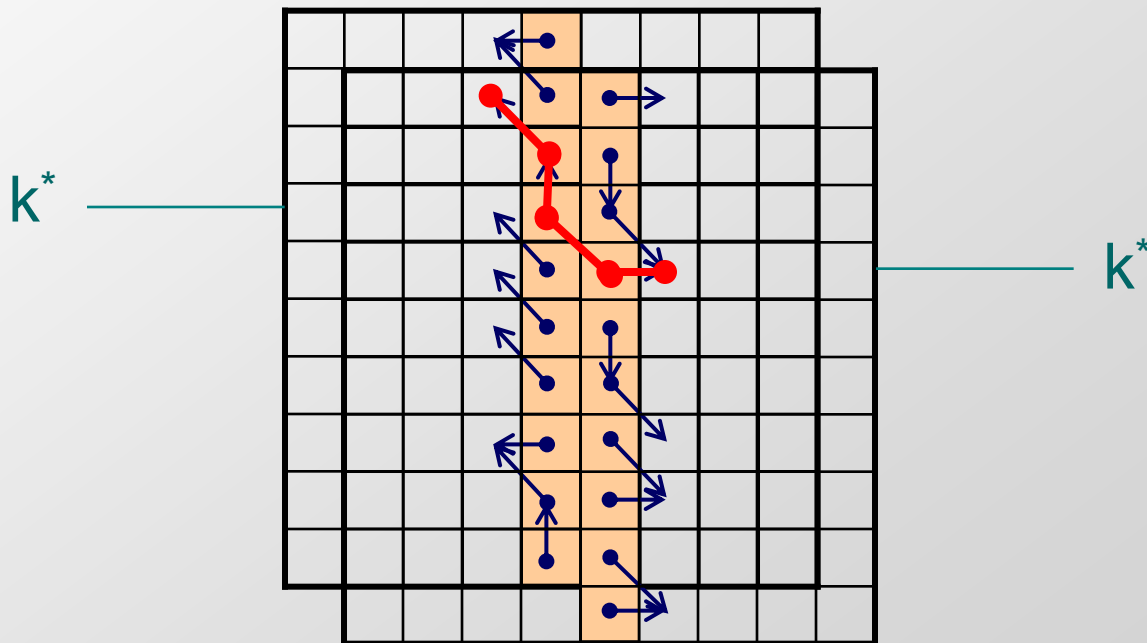
- Now, using 2 columns of space, we can compute for $k = 1 \dots M$, $F(M/2, k)$, $F^r(M/2, N-k)$

PLUS the backpointers



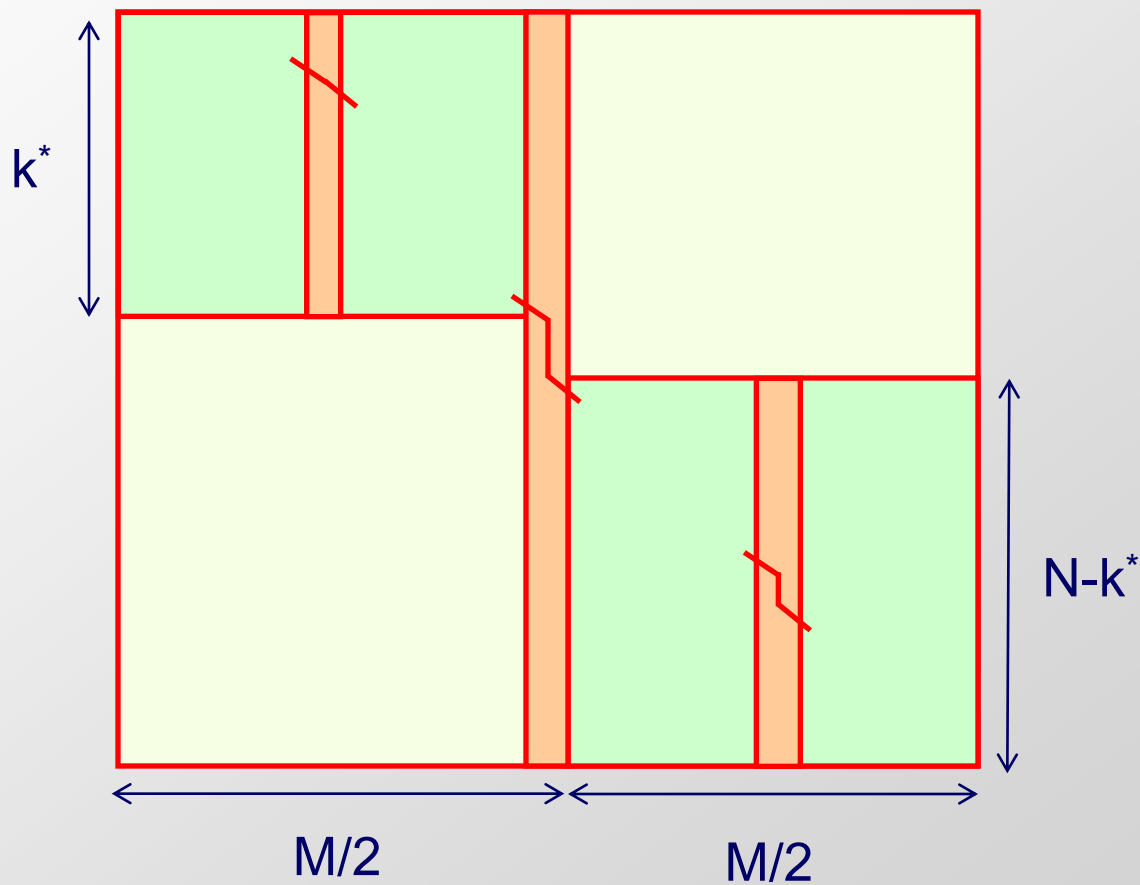
Best forward-pointer for current column

- Now, we can find k^* maximizing $F(M/2, k) + F^r(M/2, N-k)$
- Also, we can trace the path exiting column $M/2$ from k^*



Recursively find midpoint for left & right

- Iterate this procedure to the left and right!



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Additional insights

Why the 2-dimensional parameterization worked

Summary

- **Dynamic programming**
 - Reuse of computation
 - Order sub-problems. Fill table of sub-problem results
 - Read table instead of repeating work (ex: Fibonacci)
- **Sequence alignment**
 - Edit distance and scoring functions
 - Dynamic programming matrix
 - Matrix traversal path \Leftrightarrow Optimal alignment
- **Thursday: Variations on sequence alignment**
 - Local/global alignment, affine gaps, algo speed-ups
 - Semi-numerical alignment, hashing, database lookup
- **Recitation:**
 - Dynamic programming applications
 - Probabilistic derivations of alignment scores

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