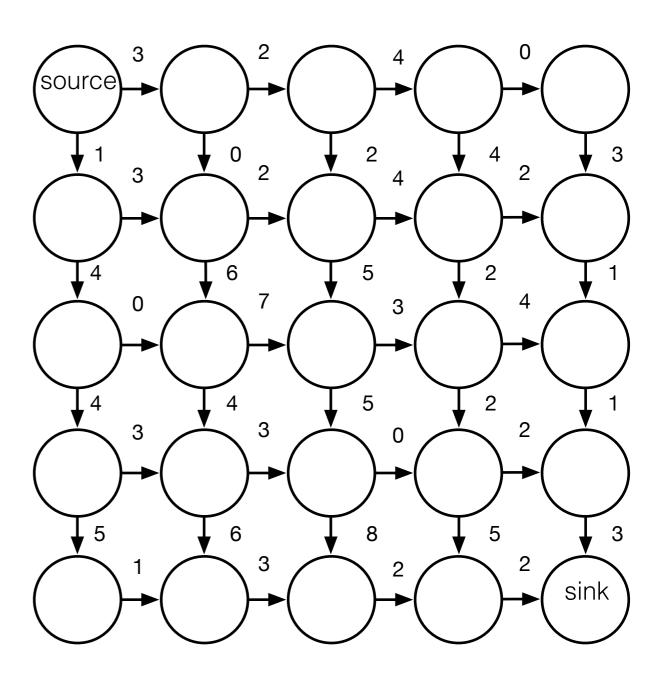
String Alignment

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Recursive Solution to Longest Path in a Grid

$$s_{i,j} = \max \begin{cases} s_{i-1,j} + \text{DOWN}_{i,j} \\ s_{i,j-1} + \text{RIGHT}_{i,j} \end{cases}$$
 move from left RIGHT



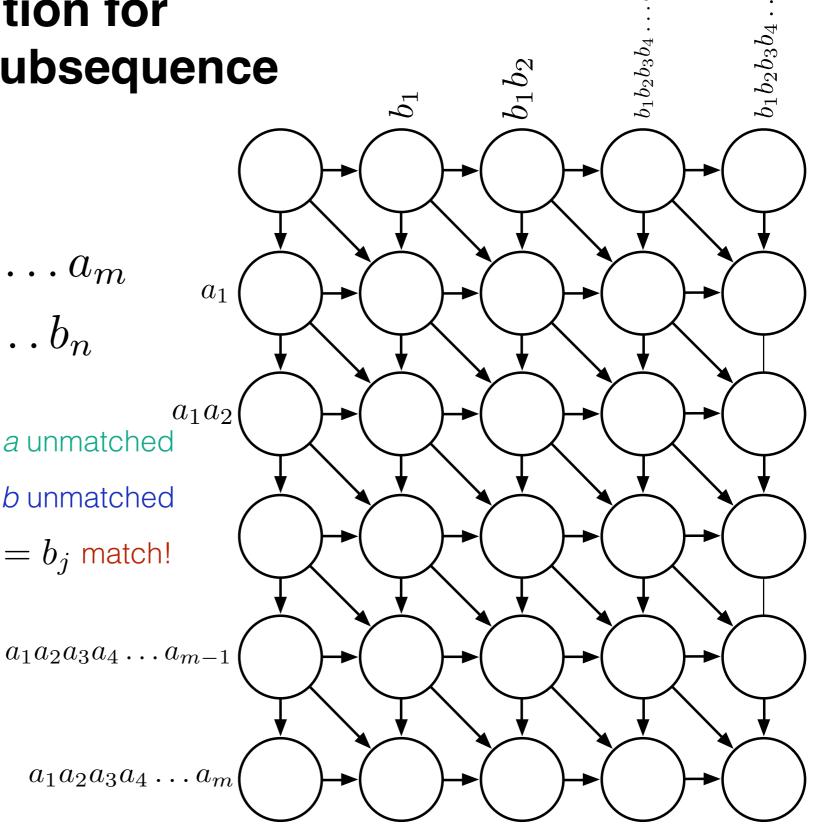
Recursive Solution for Longest Common Subsequence

$$a = a_1 a_2 a_3 a_4 \dots a_m$$
$$b = b_1 b_2 b_3 b_4 \dots b_n$$

$$s_{i,j} = \max \begin{cases} s_{i-1,j} & \text{char in a unmatched} \\ s_{i,j-1} & \text{char in b unmatched} \\ s_{i-1,j-1}+1, \text{ if $a_i=b_j$ match!} \end{cases}$$

*s*_{i,j} is length of LCS of:

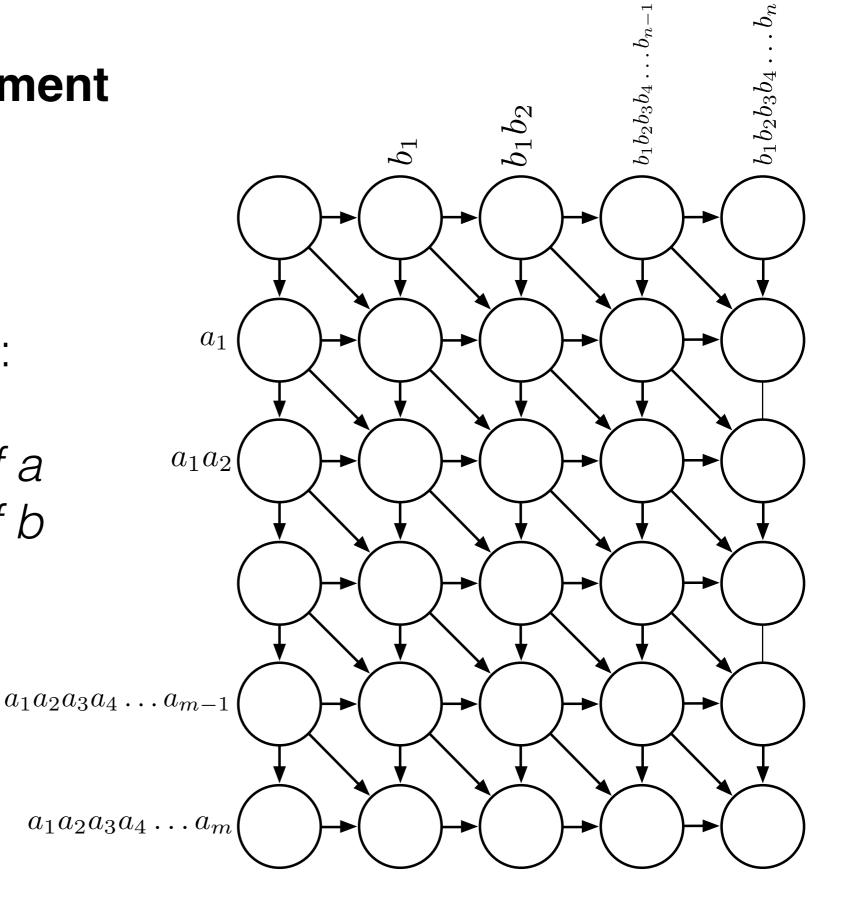
prefix of length i of a prefix of length j of b



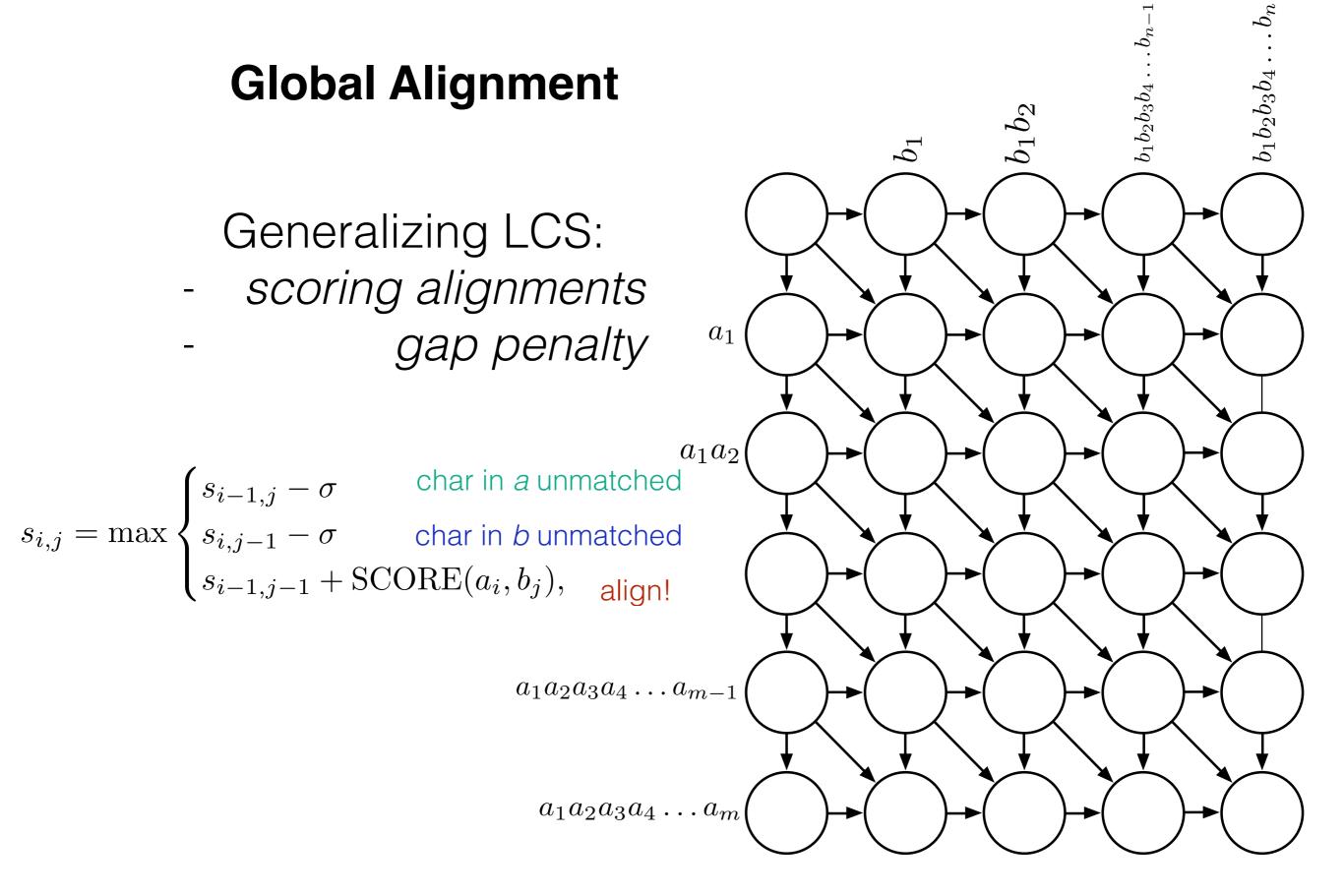
Global Alignment

 $s_{i,j}$ is the score of optimally aligning:

prefix of length i of a
prefix of length j of b



Global Alignment



Guiding principles of scores in alignments

- Sequence is said to have diverged from a common ancestor through mutations
 - Substitutions
 - Insertions and deletions (gaps)
- Score evolutionarily close alignments higher than those that are not
- That is we compute the likelihood ratio of an alignment given the two sequences are related versus not related

Log odds score

- Let *X* be a random variable representing an alignment
- Let M_1 and M_2 be two probabilistic models for X
- Log odds score S(X)

$$S(X) = \log \frac{P(X|M_1)}{P(X|M_2)}$$

- If S(X)>0, X is more likely to come from model M_1
- If S(X) < 0, X is more likely to come from model M_2

What are M_1 and M_2 in our sequence alignment problem

- M_1 : foreground model, that is the sequences are "related by evolution".
- M_2 : background model, that is the sequences are unrelated
- Need to compute the probability of an alignment X, under the two models M_1 and M_2
- Assume alignments on protein sequences with no gaps.

M_1 : foreground model

- Assume each pair of aligned positions evolved from a common ancestor
- Let p_{ab} be the probability of observing a pair $\{a,b\}$
- Probability of an alignment between x and y is

$$P(x, y|M_1) = \prod_{i=1} p_{x_i y_i}$$

M₂: background model

- Assume the individual amino acids at a position are independent of the amino acid in another position.
- Let q_a be the probability of amino acid a
- The probability of an n-character alignment of x and y is

$$P(x, y|M_2) = \prod_{i=1}^{n} q_{x_i} \prod_{i=1}^{n} q_{y_i}$$

Computing the log odds ratio to score an alignment

• The score of an alignment is the log odds ratio of the two sequences from M_1 and M_2

$$S = \log \frac{P(x, y|M_1)}{P(x, y|M_2)}$$

$$S = \log \frac{\prod_{i=1}^{n} p_{x_i y_i}}{\prod_{i=1}^{n} q_{x_i} q_{y_i}}$$

Computing the log odds ratio to score an alignment

$$S = \sum_{i=1}^{n} \log \frac{p_{x_i y_i}}{q_{x_i} q_{y_i}}$$

Score of an alignment

$$s(a,b) = \log \frac{p_{a,b}}{q_a q_b}$$

Substitution matrix entry

Some common substitution matrices

- BLOSUM matrices [Henikoff and Henikoff, 1992]
 - BLOSUM45
 - BLOSUM50
 - BLOSUM62
 - Number represents percent identity of sequences used to construct substitution matrices
- PAM [Dayhoff et al, 1978]
- Empirically, BLOSUM62 works the best

How to estimate the probabilities?

- Need a good set of confirmed alignments
- Depends upon what we know about when the two sequences might have diverged
 - p_{ab} for closely related species is likely to be low if a!=b
 - p_{ab} for species that have diverged a long time ago is likely close to the background.

BLOSUM matrices

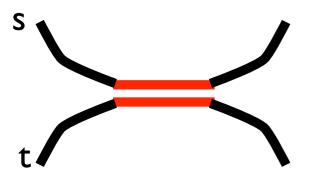
- BLOck Substitution Matrix
- Derived from a set of aligned ungapped regions from protein families called BLOCKS
- Cluster proteins such that they have no less than L
 % of similarity

Different BLOSUM matrices

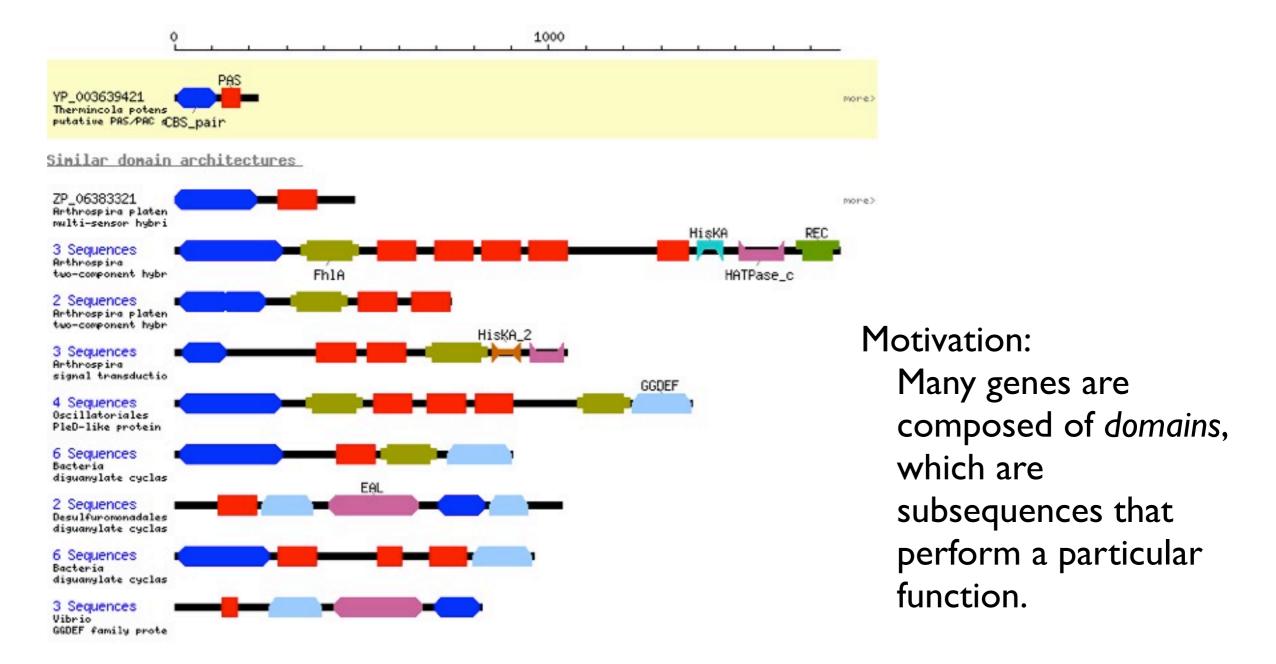
- BLOSUM50
 - Proteins >50% similarity are in the same group
- BLOSUM62
 - Proteins >62% similarity are in the same group

Example substitution scoring matrix (BLOSUM62)

```
BLOSUM62
                       Positive for chemically similar substitution
                          Common amino acids have low weights
                               Rare amino acids have high weights
     0 -1 -1 -1 -1 -2 -2 -1 -1 -1 -1 -2 -1
-3 -3 -4 -4 -2 -2 -3 -2 -2 -3 -2 -3 -1 1 -4 -3 -2(11)
```

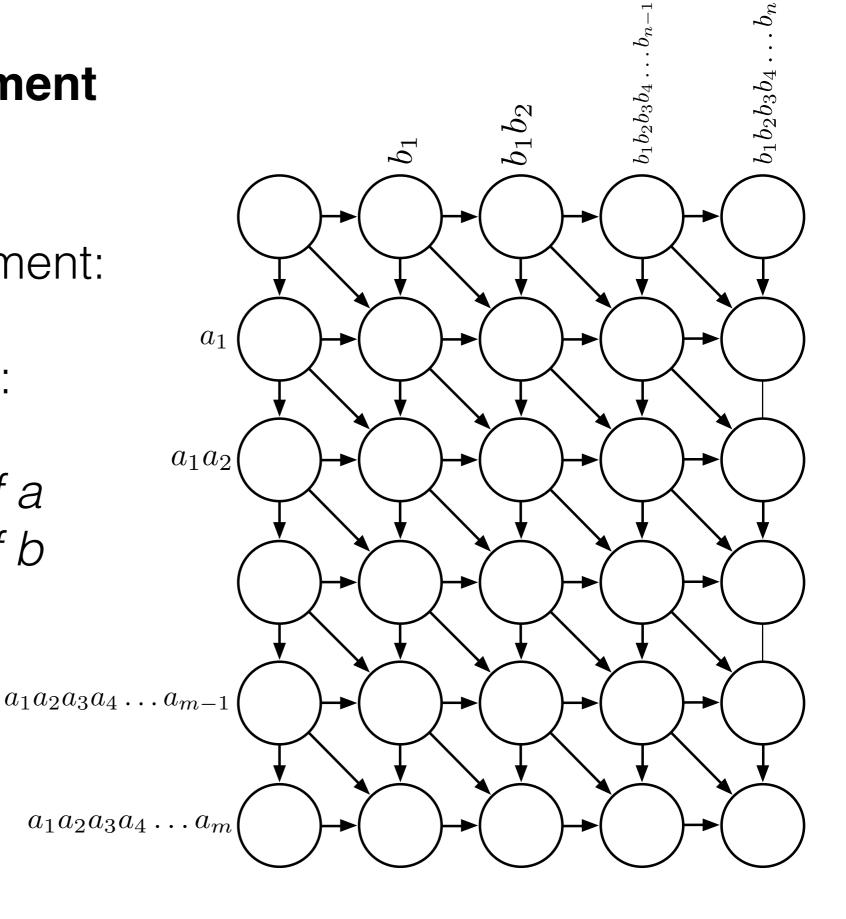


Local alignment between s and t: Best alignment between a subsequence of s and a subsequence of t.



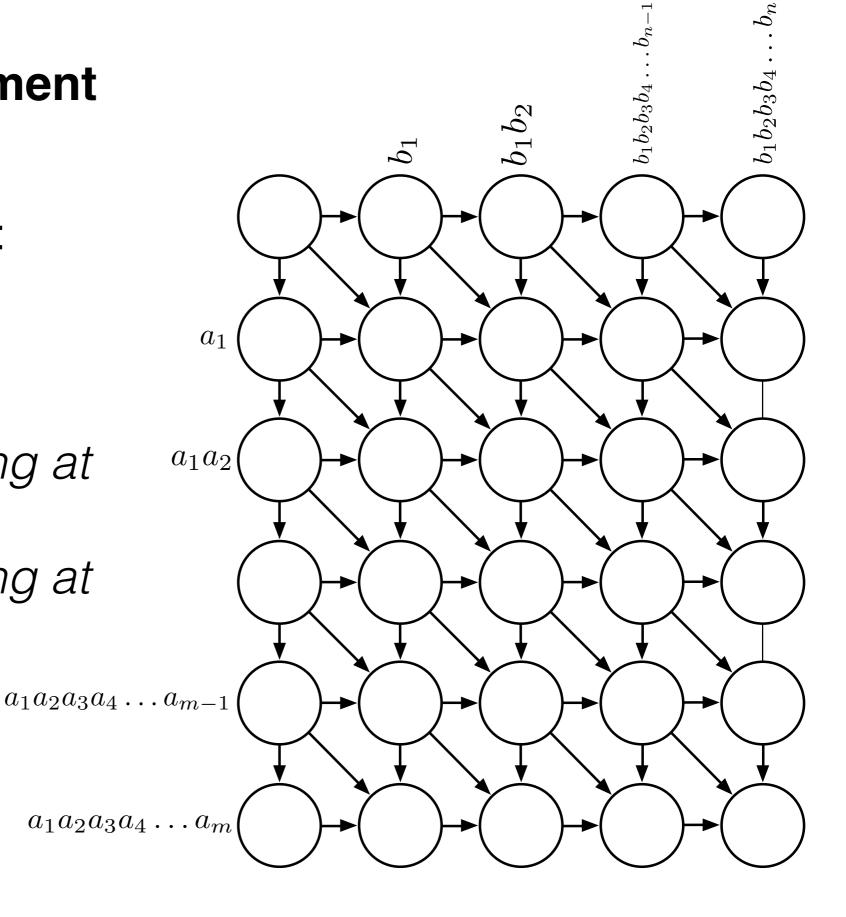
Recall in **global** alignment: $s_{i,j}$ is the score of optimally aligning:

prefix of length i of a
prefix of length j of b



In **local** alignment: $s_{i,j}$ is the score of optimally aligning:

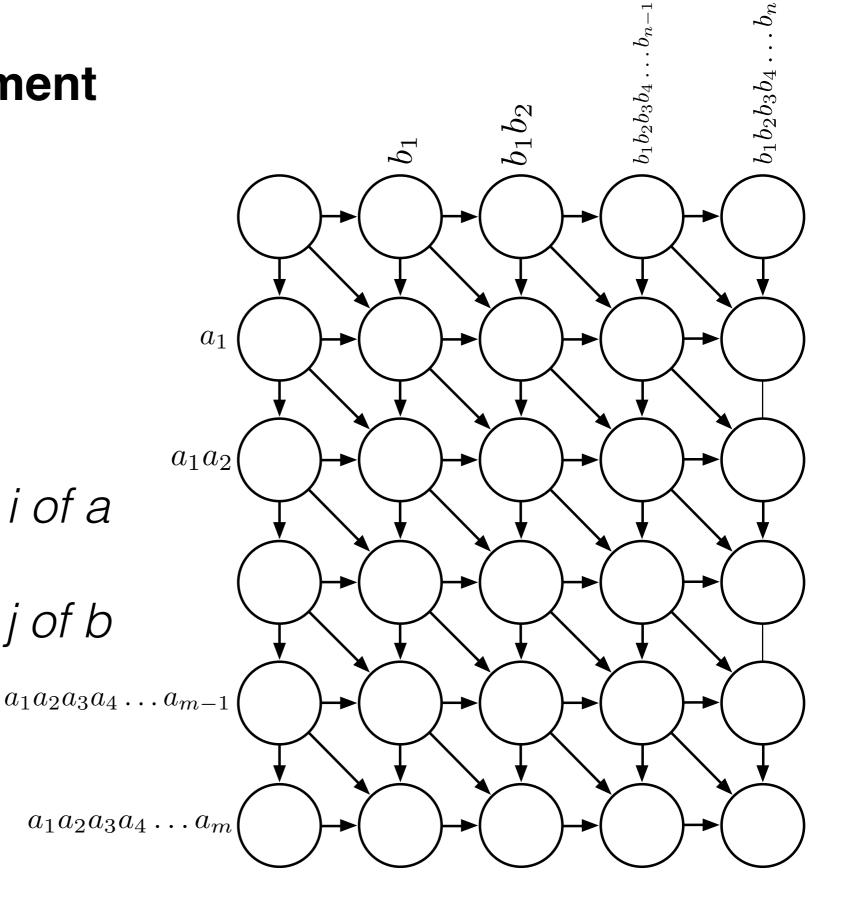
some **substring** ending at position i of a some **substring** ending at position j of b



In **local** alignment: $s_{i,j}$ is the score of optimally aligning:

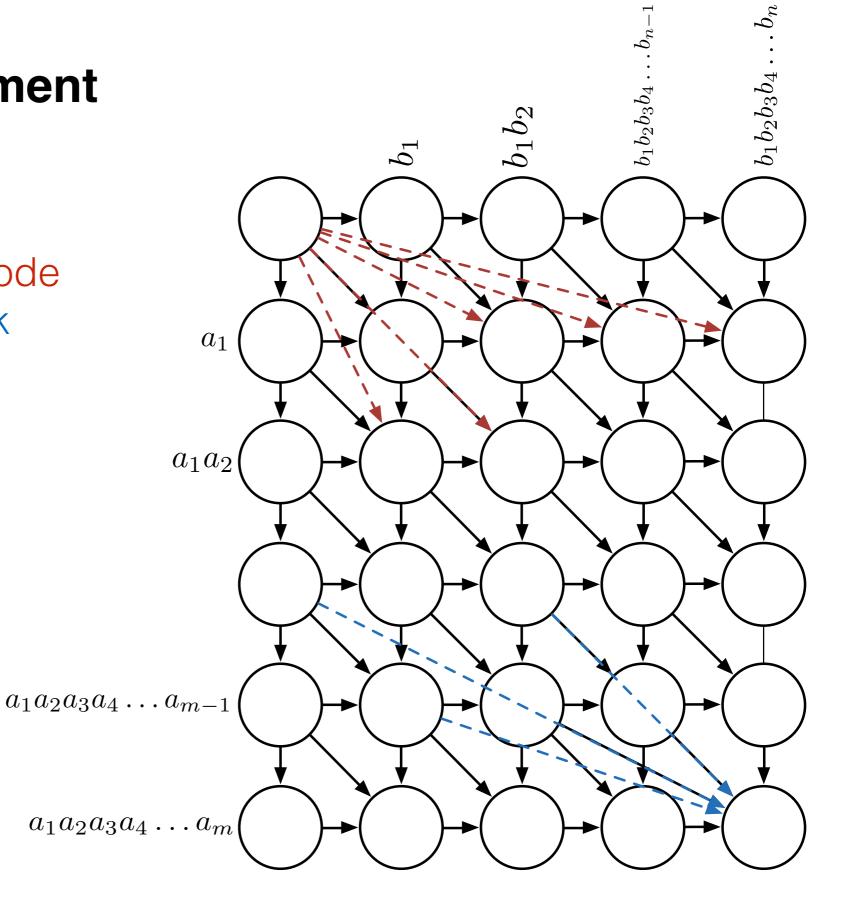
some **suffix** of the **prefix** of length i of a

some **suffix** of the **prefix** of length j of b



Conceptually:

connect source to every node connect every node to sink

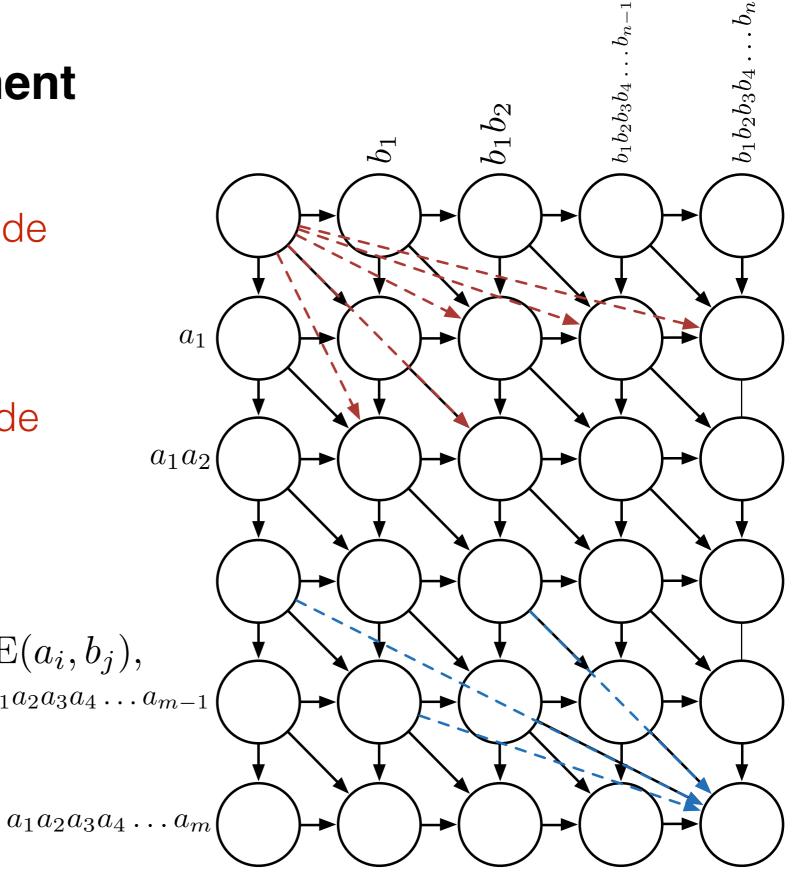


Conceptually:

connect source to every node connect every node to sink

Implementation: connect source to every node

$$s_{i,j} = \max \begin{cases} 0 \\ s_{i-1,j} - \sigma \\ s_{i,j-1} - \sigma \\ s_{i,j-1} + \text{SCORE}(a_i, b_j), \\ a_1 a_2 a_3 a_4 \dots a_{m-1} \end{cases}$$



Conceptually:

connect source to every node connect every node to sink

Implementation: connect every node to sink

start backtrack at node with max score anywhere in the graph

 $a_1 a_2 a_3 a_4 \dots a_{m-1}$

stop backtrack if O option taken

 $b_1b_2b_3b_4\dots b_n$ $b_1b_2b_3b_4$. b_1 a_1 a_1a_2 $a_1a_2a_3a_4\ldots a_m$

Global/Local Alignment Recap

- Scoring matrices: based on probabilistic models of amino acid evolution
- Algorithm for global alignment sometimes called "Needleman-Wunsch"
- Algorithm for **local** alignment sometimes called "Smith-Waterman"
- Same basic algorithmic framework