



Error Tolerant Pattern Matching I

Algorithms for Sequence Analysis

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Overview

Previous Lecture

- Definition of distance measures, in particular edit distance
- Sequence of edit operations: copy (free), substitution, insertion, deletion (1 each)
- Global sequence alignment (full strings)
- Edit path in edit graph
- Edit distance = least-cost edit sequence
 - = least-cost alignment = least-cost path in alignment graph





Overview

Previous Lecture

- Definition of distance measures, in particular edit distance
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- Edit path in edit graph
- Edit distance = least-cost edit sequence
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Today's Lecture

- Pattern Matching with respect to edit distance
- **Semiglobal** Alignment:

Compare one full string (pattern) against substrings of a longer string (text)





Error Tolerant Pattern Matching

Problem Definition

- For two strings $P, T \in \Sigma^*$, find approximate occurrences of P in T.
- Formally: Find intervals [*i*, *j*] of *T* such that the edit distance between *P* and *T*[*i*...*j*] is below a given threshold *k*.





Error Tolerant Pattern Matching

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- For two strings $P, T \in \Sigma^*$, find approximate occurrences of P in T.
- Formally: Find intervals [i, j] of T such that the edit distance between P and T[i...j] is below a given threshold k.

Variants

- Decision Problem: Is there an interval ... ?
- **Counting Problem:** How many intervals ... ?
- **Enumeration Problem:** List all intervals
- Optimization Problem: Find an interval [i, j] with the smallest edit distance between P and T[i...j] among all (no threshold k given).





Alignment Graph for Global Alignment







Alignment Graph for Semiglobal Alignment (Pattern Matching)







Generalized Edit Graph Algorithm



- **1 Topologically sort** all nodes
- 2 Iterate over nodes in topological order
 - Compute value of that node: Minimize over incoming edges: cost at source node + edge cost
 - Mark edge(s) that gave rise to optimum
- 3 Value at final node v_{\bullet} gives solution of optimization problem
- 4 Traceback: go back along marked edges to construct alignment





Code: Semiglobal Alignment (Enumeration of End Positions)

```
def pattern_search(P, T, k):
      # compare edit ditance computation
2
      m, n = len(P), len(T)
3
      # Column O
4
      Dc = list(range(m+1)) # Dc: current column in D
5
      Dp = [0] * (m+1) # Dp: previous column in D
6
      # Iterate over columns j and characters tj=T[j] in T
7
      for j, tj in zip(count(1), T):
8
          Dp, Dc = Dc, Dp # swap to recompute Dc
9
          Dc[0] = 0 \# row 0: D[0,j] = 0, start anywhere
10
          # iterate over rows i and characters pi=P[i] in P
11
          for i, pi in zip(count(1), P):
12
              Dc[i] = min(Dp[i - 1] + (pi != tj),
13
                            Dp[i] + 1,
14
                            Dc[i - 1] + 1)
15
                   <= k: yield j 🕅 UNIVERSITAT
16
```

Traceback: Getting the Actual Alignment



Approach

- When computing the value of a graph node (cell in DP table), memorize the predecessor(s) that gave rise to the optimum.
- From bottom right cell, move to top left along these edges.





Traceback: Getting the Actual Alignment



Approach

- When computing the value of a graph node (cell in DP table), memorize the predecessor(s) that gave rise to the optimum.
- From bottom right cell, move to top left along these edges.
- Reconstructs the alignment in reverse (but easy to flip when done)





Traceback: Getting the Actual Alignment



Approach

- When computing the value of a graph node (cell in DP table), memorize the predecessor(s) that gave rise to the optimum.
- From bottom right cell, move to top left along these edges.
- Reconstructs the alignment in reverse (but easy to flip when done)

Options for managing the traceback information

- Option 1: store "predecessor edges" in extra table
- Option 2: recompute them for each cell encountered during traceback

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Ukkonen's Speed-Up of Semiglobal Alignment

Setting as in shown code

- Search for approximate occurrences with edit distance $\leq k$.
- Question: Can we omit computing parts of the graph / DP table?







Semiglobal Alignment: Ukkonen's Trick



• Define: $last_k(j) := max\{i | T[i, j] \le k, T[i', j] > k \text{ for all } i' > i\}$

 Trick: last_k(j + 1) ≤ last_k(j) + 1 Why? Difference between neighboring cells is at most 1 (proof follows).
 Speedup: average runtime improves from O(mn) to O(kn) (hard proof!)

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Edit Distance DP Table: Horizontal, Vertical, and Diagonal Properties

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Motivation

Setting

DP table for edit distance computations: global and semi-global alignment

We astated that the **difference of neighboring cells is at most 1**. Needed for speed-ups:

- Ukkonen's trick (just seen)
- Myers' bit-parallel algorithm (next)

Goal

State precise properties and prove them.





Properties

Let T be a DP table satisfying the edit distance recurrence.

Lemma: Vertical Property

The value difference between any two vertically adjacent cells is at most 1: $|T[i,j] - T[i-1,j]| \le 1$.

Lemma: Horizontal Property

The value difference between any two **horizontally adjacent** cells is at most 1: $|T[i,j] - T[i,j-1]| \le 1$.

Lemma: Diagonal Property

The value of **diagonally adjacent** cells is non-decreasing, and the value difference is at most 1, i.e., $0 \leq T[i,j] - T[i-1,j-1] \leq 1$.

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Vertical Property

Lemma: Vertical Property

The value difference between any two vertically adjacent cells is at most 1: $|T[i,j] - T[i-1,j]| \le 1$.

Proof idea

Show separately:

•
$$T[i,j] - T[i-1,j] \le 1 \Leftrightarrow T[i,j] \le T[i-1,j] + 1$$

$$T[i-1,j] - T[i,j] \le 1 \Leftrightarrow T[i-1,j] - 1 \le T[i,j]$$





Vertical Property

Lemma: Vertical Property

The value difference between any two vertically adjacent cells is at most 1: $|T[i,j] - T[i-1,j]| \le 1$.

Proof idea

Show separately:

$$T[i,j] - T[i-1,j] \le 1 \Leftrightarrow T[i,j] \le T[i-1,j] + 1$$

Follows immediately from recurrence

•
$$T[i-1,j] - T[i,j] \le 1 \Leftrightarrow T[i-1,j] - 1 \le T[i,j]$$

Left to be shown.





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Left to be shown.

d v
$$x \le v+1 \checkmark$$

h x $v-1 \le x$ (to be shown)

To be shown: $v - 1 \le x$





To be shown: $v - 1 \le x$





To be shown: $v - 1 \le x$







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To be shown: $v - 1 \le x$

Case 1: Minimum from vertical neighbor d vh $v+1 = x \rightarrow v-1 \le x \checkmark$ h x



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To be shown: $v - 1 \le x$

Case 3: Minimum from horizontal neighbor

$$v_1 \quad \dots \quad v_k \quad v_k$$

$$h_1 \longleftarrow \dots \longleftarrow h_k \longleftarrow x$$

Proof by induction:





To be shown: $v - 1 \le x$

Case 3: Minimum from horizontal neighbor

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$$h_1 \longleftarrow \dots \longleftarrow h_k \longleftarrow x$$

Proof by induction:

• Induction base $(v_1 - 1 \le h_1)$: (follows from Case I or II)





To be shown: $v - 1 \le x$

Case 3: Minimum from horizontal neighbor

$$v_1 \quad \dots \quad v_k \quad v_k$$

$$h_1 \longleftarrow \dots \longleftarrow h_k \longleftarrow x$$

- Induction base $(v_1 1 \le h_1)$: (follows from Case I or II)
- Induction step $(v_{j-1} 1 \le h_{j-1} \Rightarrow v_j 1 \le h_j)$: we have:





To be shown: $v - 1 \le x$

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- Induction step $(v_{j-1} 1 \le h_{j-1} \Rightarrow v_j 1 \le h_j)$: we have:
 - $h_{j-1} + 1 = h_j$ (by definition, minimum is horizontal)





To be shown: $v - 1 \le x$

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 - $h_{j-1} + 1 = h_j$ (by definition, minimum is horizontal)
 - $v_{j-1} \leq h_{j-1} + 1$ (by induction assumption)





To be shown: $v - 1 \le x$

Case 3: Minimum from horizontal neighbor

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$$h_1 \longleftarrow \dots \longleftarrow h_k \longleftarrow x$$

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 - $h_{j-1} + 1 = h_j$ (by definition, minimum is horizontal)
 - $v_{j-1} \leq h_{j-1} + 1$ (by induction assumption)
 - $v_j 1 \le v_{j-1}$ (by recurrence relation)





To be shown: $v - 1 \le x$

Case 3: Minimum from horizontal neighbor

$$v_1 \quad \dots \quad v_k \quad v_k$$

$$h_1 \longleftarrow \dots \longleftarrow h_k \longleftarrow x$$

Proof by induction:

- Induction base $(v_1 1 \le h_1)$: (follows from Case I or II)
- Induction step $(v_{j-1} 1 \le h_{j-1} \Rightarrow v_j 1 \le h_j)$: we have:
 - $h_{j-1} + 1 = h_j$ (by definition, minimum is horizontal)
 - $v_{j-1} \leq h_{j-1} + 1$ (by induction assumption)
 - $v_j 1 \le v_{j-1}$ (by recurrence relation)

Taken together: $v_j - 1 \le v_{j-1} \le h_{j-1} + 1 = h_j$

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Horizontal Property

Lemma: Horizontal Property

The value difference between any two **horizontally adjacent** cells is at most one, that is, $|T[i,j] - T[i,j-1]| \le 1$.

Proof

Symmetric to the proof for the vertical property.





Diagonal Property

Lemma: Diagonal Property

The value of **diagonally adjacent** cells is non-decreasing and the value difference is at most one, that is, $0 \le T[i,j] - T[i-1,j-1] \le 1$.





Diagonal Property

Lemma: Diagonal Property

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Proof idea

Show separately:

■
$$T[i,j] - T[i-1,j-1] \le 1 \Leftrightarrow T[i,j] \le T[i-1,j-1] + 1$$

$$0 \leq T[i,j] - T[i-1,j-1] \Leftrightarrow T[i-1,j-1] \leq T[i,j]$$





Diagonal Property

Lemma: Diagonal Property

The value of **diagonally adjacent** cells is non-decreasing and the value difference is at most one, that is, $0 \le T[i,j] - T[i-1,j-1] \le 1$.

Proof idea

Show separately:

- $T[i,j] T[i-1,j-1] \le 1 \Leftrightarrow T[i,j] \le T[i-1,j-1] + 1$
 - Follows immediately from recurrence

$$0 \leq T[i,j] - T[i-1,j-1] \Leftrightarrow T[i-1,j-1] \leq T[i,j]$$

Left to be shown.





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Case	1:	Minimum	from	vertical	neighbor	
d	Ĭ	7				
h	2	ζ				





Case 1: Minimum from vertical neighbor

 $d \qquad v \qquad d \leq v+1$ (horizontal property)

h x





Case 1: Minimum from vertical neighbor d v $d \le v+1$ (horizontal property) \uparrow v+1 = x (origin of minimum) h x





Case 1: Minimum from vertical neighbor d v $d \le v+1$ (horizontal property) $\downarrow v+1 = x$ (origin of minimum) h x $\longrightarrow d \le x$





Case	1: N	linimum from vertical neighbor	
d	v ▲		
h	x	\rightarrow d \leq x \checkmark	

Case 2: Minimum from horizontal neighbor $\mathbf{d} = \mathbf{v}$

h **←** x





Case	1:	Minimum from vertical neighbor
d	v ↑	$d \le v+1$ (horizontal property) v+1 = x (origin of minimum)
h	X	$u \leq x$

Case 2: Minimum from horizontal neighbor

 $d \qquad v \qquad d \leq h{+}1 \text{ (vertical property)}$

h **←** x





Case	1: N	Ainimum from vertical neighbor	
d	v ≜		
h	x	\rightarrow d \leq x \checkmark	

Case 2: Minimum from horizontal neighbor d v $d \le h+1$ (vertical property) h+1 = x (origin of minimum) h $\longleftarrow x$





Case	1: N	linimum fron	n vertical	neighbor
d	v ∳	$d \le v + v + 1 = x$	1 (horizont (origin of	al property) ⁻ minimum)
h	I X	\rightarrow	$d \leq x$ V	

Case 2: Minimum from horizontal neighbor $d v d \le h+1$ (vertical property) h+1 = x (origin of minimum) $h \longleftarrow x d \le x \checkmark$





Case	1: N	linimum from vertical neighbor	
d	v ∳	$d \le v+1$ (horizontal property) v+1 = x (origin of minimum)	
h	T X	\rightarrow d \leq x \checkmark	

Case 2: Minimum from horizontal neighbor

$$\begin{array}{ccc} d & v & d \leq h+1 \text{ (vertical property)} \\ h+1 = x & (\text{origin of minimum}) \\ h \longleftarrow x & \longrightarrow d \leq x \checkmark \end{array}$$





Case	1: M	inimum	from	vertical	neighbor
d	v ≜	$d \le v+1 =$	v+1 x	(horizont (origin of	al property) minimum)
h	T X		► d	≤ x 💙	

Case 2: Minimum from horizontal neighbor

$$\begin{array}{ccc} d & v & d \leq h+1 \text{ (vertical property)} \\ & h+1 = x & (\text{origin of minimum}) \\ h \longleftarrow x & \longrightarrow & d \leq x \checkmark \end{array}$$

Case 3: Minimum from diagonal neighbor d v x = d or x = d+1 (match) (mismatch) h x Algorithmic Bioinformatics





Case	1: N	linimum from	vertical neighbor
d	v ∱	$d \le v+1$ $v+1 = x$	(horizontal property) (origin of minimum)
h	X	→ d	$\leq x$ 🗸

Case 2: Minimum from horizontal neighbor

$$\begin{array}{ccc} d & v & d \leq h+1 \text{ (vertical property)} \\ & h+1 = x & (\text{origin of minimum}) \\ h \longleftarrow x & \longrightarrow & d \leq x \checkmark \end{array}$$

Case 3: Minimum from diagonal neighbor d v x = d or x = d+1(match) or (mismatch) h x \rightarrow $d \le x$ V Algorithmic Bioinformatics

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Myers' Fast Bit Vector Algorithm for Edit Distance

A Fast Bit-Vector Algorithm for Approximate String Matching Based on DP,

Gene Myers, 1999, Journal of the ACM





Ideas

- We only need to keep one active column in memory
- Consecutive cells in the DP matrix can only differ by {-1,0,1}.
 → We can store differences instead of absolute values.







Definitions

Instead of considering absolute values, we track differences between adjacent rows and columns in the DP matrix:

$$\begin{array}{ll} \Delta h_{i,j} := \ensuremath{\mathcal{T}}[i,j] - \ensuremath{\mathcal{T}}[i,j-1] \in \{-1,0,1\} & (\mbox{horizontal}) \\ \Delta v_{i,j} := \ensuremath{\mathcal{T}}[i,j] - \ensuremath{\mathcal{T}}[i-1,j] \in \{-1,0,1\} & (\mbox{vertical}) \\ \Delta d_{i,j} := \ensuremath{\mathcal{T}}[i,j] - \ensuremath{\mathcal{T}}[i-1,j-1] \in \{0,1\} & (\mbox{diagonal}) \end{array}$$





Definitions

Instead of considering absolute values, we track differences between adjacent rows and columns in the DP matrix:

$\Delta h_{i,j} := T[i,j] - T[i,j-1] \in \{-1,0,1\}$	(horizontal)
$\Delta v_{i,j} := T[i,j] - T[i-1,j] \in \{-1,0,1\}$	(vertical)
$\Delta d_{i,j} := \mathcal{T}[i,j] - \mathcal{T}[i-1,j-1] \in \{0,1\}$	(diagonal)

Note

Indices i, j denote the same cell as in the DP matrix.

However, during the algorithm we never have the full matrix with all boolean variables in memory, but only single columns, each of which is stored as a bit vector.





Original costs from vertical differences

The original values of the full edit distance DP matrix (left) can be retrieved from the matrix of $\Delta v_{i,j}$ values (right):

 $T[i,j] = \sum_{r=0}^{i} \Delta v_{r,j}$







Horizontal connections in last row

We can keep track of the relevant last row with $cost_j := T[m, j]$ by using

$$cost_0 = m \, , \ cost_j = cost_{j-1} + \Delta h_{m,j}$$



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Definitions and Encodings

The differences cann be tracked using bit vectors as follows:

$$\begin{split} VP_{i,j} &= \begin{cases} 1 & \text{if } \Delta v_{i,j} = 1, \\ 0 & \text{otherwise.} \end{cases} \quad VN_{i,j} = \begin{cases} 1 & \text{if } \Delta v_{i,j} = -1, \\ 0 & \text{otherwise.} \end{cases} \\ HP_{i,j} &= \begin{cases} 1 & \text{if } \Delta h_{i,j} = 1, \\ 0 & \text{otherwise.} \end{cases} \quad HN_{i,j} = \begin{cases} 1 & \text{if } \Delta h_{i,j} = -1, \\ 0 & \text{otherwise.} \end{cases} \\ D0_{i,j} &= \begin{cases} 1 & \text{if } \Delta d_{i,j} = 0, \\ 0 & \text{otherwise.} \end{cases} \end{split}$$





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$$\Delta v_{i,j} = VP_{i,j} - VN_{i,j}$$
$$\Delta h_{i,j} = HP_{i,j} - HN_{i,j}$$
$$\Delta d_{i,j} = 1 - D0_{i,j}$$

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Dependencies between variables

Observation

 $HN_{i,j} \Leftrightarrow VP_{i,j-1} \text{ and } D0_{i,j}$

Proof idea





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Dependencies between variables

More dependencies

$$\begin{array}{l} HN_{i,j} \Leftrightarrow VP_{i,j-1} \text{ and } D0_{i,j} \\ VN_{i,j} \Leftrightarrow HP_{i-1,j} \text{ and } D0_{i,j} \\ VP_{i,j} \Leftrightarrow HN_{i-1,j} \text{ or not } (HP_{i-1,j} \text{ and } D0_{i,j}) \\ HP_{i,j} \Leftrightarrow VN_{i,j-1} \text{ or not } (VP_{i,j-1} \text{ and } D0_{i,j}) \\ D0_{i,j} \Leftrightarrow (p_i == t_j) \text{ or } VN_{i,j-1} \text{ or } HN_{i-1,j} \end{array}$$





Dependencies between variables

More dependencies

$$HN_{i,j} \Leftrightarrow VP_{i,j-1} \text{ and } D0_{i,j}$$

$$VN_{i,j} \Leftrightarrow HP_{i-1,j} \text{ and } D0_{i,j}$$

$$VP_{i,j} \Leftrightarrow HN_{i-1,j} \text{ or not } (HP_{i-1,j} \text{ and } D0_{i,j})$$

$$HP_{i,j} \Leftrightarrow VN_{i,j-1} \text{ or not } (VP_{i,j-1} \text{ and } D0_{i,j})$$

$$D0_{i,j} \Leftrightarrow (p_i == t_j) \text{ or } VN_{i,j-1} \text{ or } HN_{i-1,j}$$

Idea of Myers' algorithm

- Store full columns (length *m*) of each quantity in a bit vector.
- Apply bit-parallel update formulas based on dependencies and text character.





Problem: Circular Dependencies

Problem

For example, D0 and HN depend on each other (same j)!

$$HN_{i,j} \Leftrightarrow VP_{i,j-1} \text{ and } D0_{i,j}$$

 $D0_{i,j} \Leftrightarrow (p_i == t_j) \text{ or } VN_{i,j-1} \text{ or } HN_{i-1,j}$





Problem: Circular Dependencies

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For example, D0 and HN depend on each other (same j)!

$$\begin{array}{l} HN_{i,j} \Leftrightarrow VP_{i,j-1} \text{ and } D0_{i,j} \\ D0_{i,j} \Leftrightarrow (p_i == t_j) \text{ or } VN_{i,j-1} \text{ or } HN_{i-1,j} \end{array}$$

Solution

- Denote another bit vector X with $X_j = (p[i] == t[j])$.
- Pre-compute the bit vector for every possible text character t[j].
- The following formula computes the complete bit vector *D*0 from the previous *VP*: $D0 = (((VP\&X) + VP) \land VP) \mid X$





Code: Myers' Algorithm

```
def myers(P,T,k):
1
       B = defaultdict(int)
2
       i = 1
3
       for c in P:
4
         B[c] = B[c] | i
5
         i = i << 1
6
       m = len(P)
7
       VP = (1 << m) - 1 \# \text{ set } m \text{ bits}
8
       VN = 0
9
       cost = m
10
       # ... (next slide)
11
```

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Code: Myers' Algorithm

```
def myers(P,T,k):
1
      # ... preprocessing (previous slide)
2
      for i, c in enumerate(T):
3
           Eq = B[c]
4
           Xv = Eq | VN
5
           Xh = (((Eq \& VP) + VP) \land VP) | Eq
6
           HP = VN | ~ (Xh | VP)
7
           HN = VP \& Xh
8
           if HP & (1<<(m-1)):
9
                cost += 1
10
           elif HN & (1<<(m-1)):
11
                cost -= 1
12
           if cost \leq k:
13
               yield i
14
           HP = HP << 1
15
           VP = (HN < <1) | ~(Xv | HP)
16
               = HP & Xv
17
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```

Summary: Myers' Bit-Vector Algorithm

Idea

- Neighboring cells in DP table can differ by at most one
- Encode these differences using bit vectors
- Keep track of score in bottom row
- Formulate algorithm in terms of bit-parallel operations

Complete description of Myers' algorithm



Mäkinen, Belazzougui, Cunial, Tomescu Genome-Scale Algorithm Design: Biological Sequence Analysis in the Era of High-Throughput Sequencing

(see Section 6.1.3 for Myers' algorithm)

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Summary

- Variants of the error-tolerant pattern matching problem
- Global vs. semi-global alignment and their edit graphs
- General graph alignment algorithm
- Traceback: follow back edges that led to optima
- Ukkonen's speed-up: $last_k(j+1) \le last_k(j) + 1$
- Proof of differences in DP table: horizontal, vertical, and diagonal properties
- Ideas of Myers' bit-parallel algorithm: difference encoding





Exam Questions

- Define variations of the error tolerant pattern matching problem.
- How does error-tolerant pattern search relate to semi-global alignment?
- How does the edit / alignment graph differ from that for global alignment?
- Explain Ukkonen's speed-up (in theory / on a small example)
- Explain the horizontal, vertical, and diagonal properties.
- What are the ideas to prove these properties?
- Why are these properties helpful?
- What is the idea behind Myers' bit vector algorithm?
- How does the original DP matrix relate to the used bit vectors?



