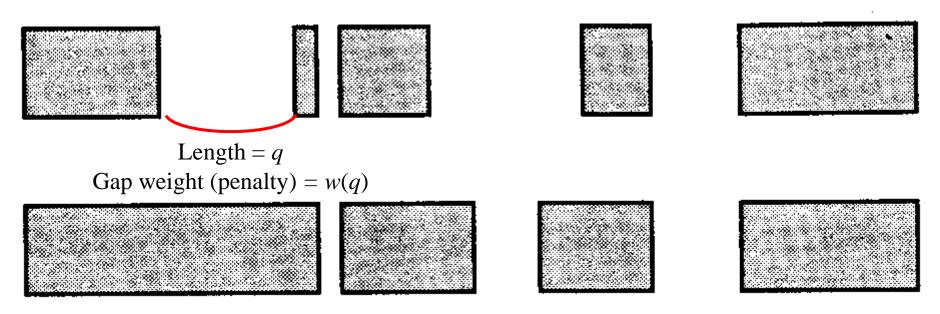
Chapter 12.6

2014. 10. 21 ISA Lab 배준우

• Gap weight

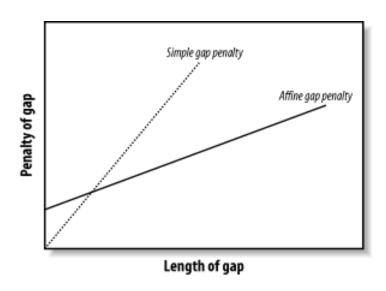


Arbitrary gap weight

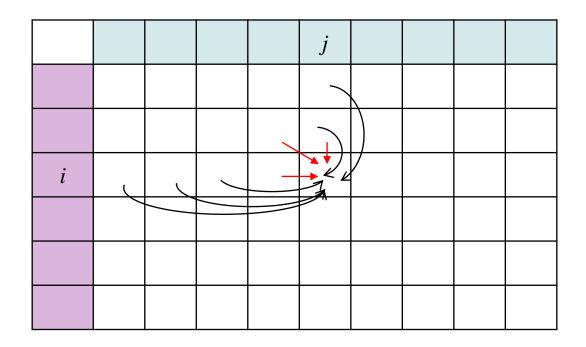
- Any gap weight function is acceptable (this is the most general case)
- Weight of a gap is an arbitrary function w(q) of its length
- The constant, affine and convex weight models are of course subcases of the arbitrary weight model

				j			
				/			
			/				
i	(/			/		
				·			

- Affine gap weight
 - The model most commonly used by molecular biologists



- Affine gap weight
 - The model most commonly used by molecular biologists



Convex gap weight

- More difficult to solve than with affine gap weights
- Not as difficult as the problem with arbitrary gap weights

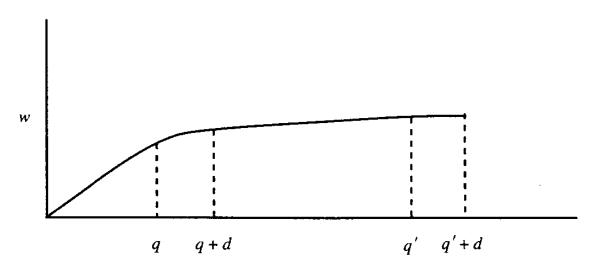


Figure 12.16: A convex function w.

Time complexity

- Arbitrary gap weights: $O(n^2m)$
- Affine gap weights: O(nm)
- Convex gap weights: $O(nm\log n)$
- Affine < Convex < Arbitrary

- We will discuss convex gap weights in terms of similarity
 - maximum weighted alignment

Definition

- Assume that w(q) is a nonnegative function of length q.
- Then w(q) is *convex* if and only if $w(q+1) w(q) \le w(q) w(q-1)$ for every q.
- It follows that $w(q+d) w(q) \ge w(q'+d) w(q')$ for q < q' for any fixed d.

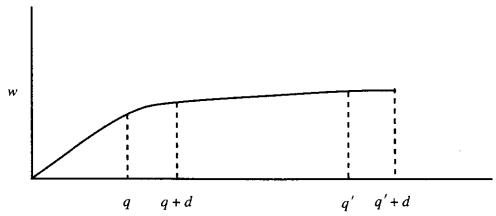
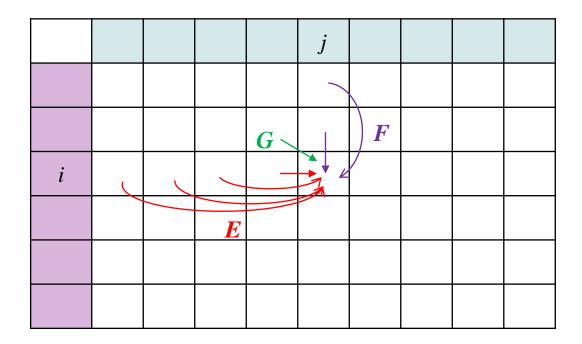


Figure 12.16: A convex function w.

• Speeding up the general recurrences

- use the same dynamic programming recurrences developed for arbitrary gap weights
- but reduce the time needed to evaluate those recurrences



Speeding up the general recurrences

- use the same dynamic programming recurrences developed for arbitrary gap weights
- but reduce the time needed to evaluate those recurrences

$$V(i, j) = \max[E(i, j), F(i, j), G(i, j)],$$

$$G(i, j) = V(i - 1, j - 1) + s(S_1(i), S_2(j)),$$

$$E(i, j) = \max_{0 \le k \le j - 1} [V(i, k) - w(j - k)],$$

$$F(i, j) = \max_{0 \le l \le i - 1} [V(l, j) - w(i - l)],$$

$$O(n^2) \text{ per row}$$

$$O(m^2) \text{ per column}$$

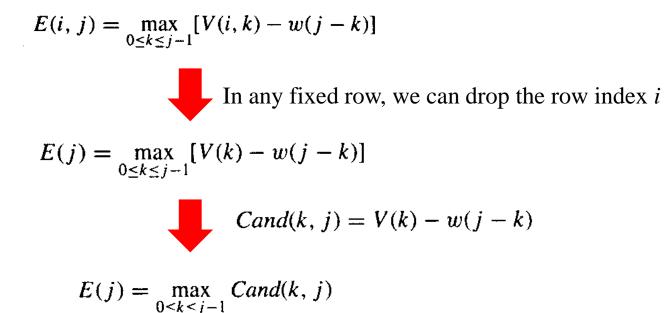
$$V(i, 0) = -w(i),$$

$$V(0, j) = -w(j),$$

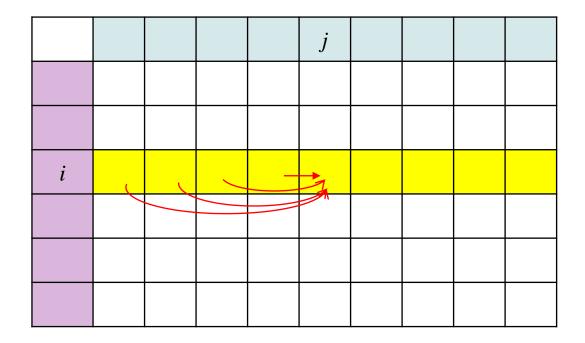
$$E(i, 0) = -w(i),$$

$$F(0, j) = -w(j).$$

Simplifying notation

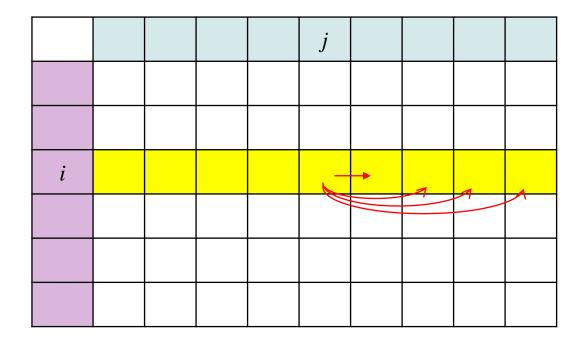


- Forward dynamic programming
 - It is more helpful in this exposition



Backward dynamic programming

- Forward dynamic programming
 - It is more helpful in this exposition



Forward dynamic programming

Forward dynamic programming

 $\bar{E}(j)$

1	2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n

E(j)

1	2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n

Forward dynamic programming

 $\bar{E}(j)$

1	2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n
<i>Cand</i> (0,1)	<i>Cand</i> (0,2)	 Cand(0,j-1)	Cand(0,j)	<i>Cand</i> (0, <i>j</i> +1)	 <i>Cand</i> (0, <i>n</i> -1)	Cand(0,n)

E(j)

1	2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n

Forward dynamic programming

 $\bar{E}(j)$

1		2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n
Cand(0,1)	<i>Cand</i> (0,2)	 <i>Cand</i> (0, <i>j</i> -1)	Cand(0,j)	<i>Cand</i> (0, <i>j</i> +1)	 <i>Cand</i> (0, <i>n</i> -1)	Cand(0,n)
E(j)							
1		2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n
$\bar{E}(1)$	\		 J I	J	J . 1	 1	- 3
L(1	.)						

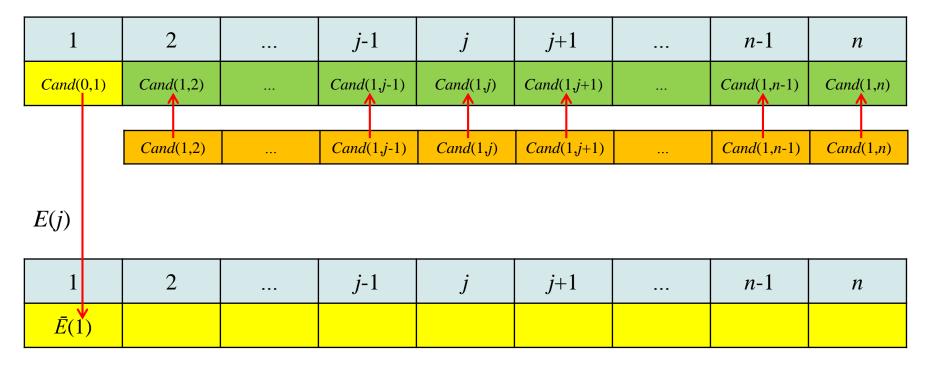
Forward dynamic programming

 $\bar{E}(j)$

1		2	 <i>j</i> -1	j	<i>j</i> +1		<i>n</i> -1	n
Cand((0,1)	<i>Cand</i> (0,2)	 <i>Cand</i> (0, <i>j</i> -1)	Cand(0,j)	<i>Cand</i> (0, <i>j</i> +1)		<i>Cand</i> (0, <i>n</i> -1)	Cand(0,n)
		<i>Cand</i> (1,2)	 <i>Cand</i> (1, <i>j</i> -1)	Cand(1,j)	<i>Cand</i> (1, <i>j</i> +1)		<i>Cand</i> (1, <i>n</i> -1)	Cand(1,n)
						Assume	>]
E(j)								
1		2	 <i>j</i> -1	j	<i>j</i> +1		<i>n</i> -1	n
$\bar{E}(1)$	()							

Forward dynamic programming





Forward dynamic programming

 $\bar{E}(j)$

	1		2		•••	<i>j</i> -1	j	<i>j</i> +1		<i>n</i> -1	n
Ca	and(0,	,1)	Cand(1	,2)	:	Cand(1,j-1)	Cand(1,j)	<i>Cand</i> (1, <i>j</i> +1)		<i>Cand</i> (1, <i>n</i> -1)	Cand(1,n)
						<i>Cand</i> (2, <i>j</i> -1)	Cand(2,j)	<i>Cand</i> (2, <i>j</i> +1)		<i>Cand</i> (2, <i>n</i> -1)	Cand(2,n)
E((j)										
	1		2		•••	<i>j</i> -1	j	<i>j</i> +1	•••	n-1	n
	$\bar{E}(1)$)	$\bar{E}(2)$)							

Forward dynamic programming for a fixed row

```
For j := 1 to m do
begin
                              initialize
\overline{E}(j) := Cand(0, j);
end;
For j := 1 to m do
begin
E(j) := \overline{E}(j);
V(j) := \max[G(j), E(j), F(j)];
                                                                Set E(j) to the current \bar{E}(j)
{We assume, but do not show that F(j) and G(j)
have been computed for cell j in the row.
For j' := j + 1 to m do {Loop 1}
     if \overline{E}(j') < Cand(j, j') then
                                            Traverse forwards to set \bar{E}(j')
          begin
          \overline{E}(j') := Cand(j, j');
          end
end;
```

Forward dynamic programming

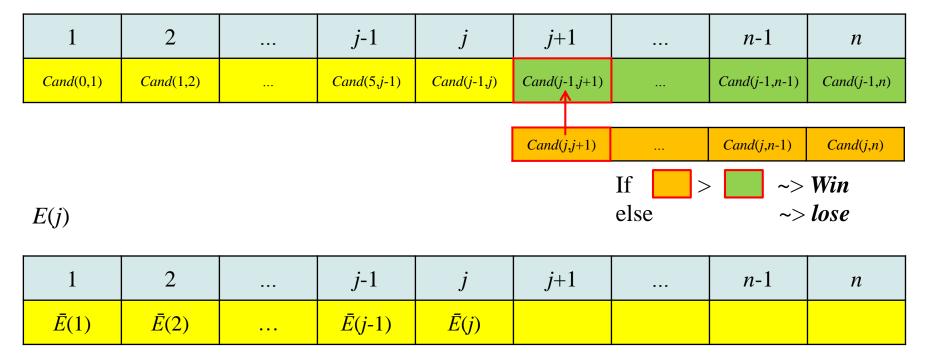
- An alternative way to think about forward dynamic programming
 ->Weighted edit graph for alignment problem
- Optimal distances = optimal alignments
- Distance algorithms(such as Dijkstra's algorithm) for shortest distance can be described as forward looking

Forward dynamic programming

- Time complexity
 - Both backward and forward dynamic programming
 - Exactly the same arithmetic operations and comparisons are done
 - Still requires $\Theta(n^2)$ time per row
 - No faster than backwards dynamic programming

The basis of the speedup





The basis of the speedup

- Candidate list approach
 - The speedup works
 - by identifying and eliminating large numbers of candidate values
 - that have no chance of winning any comparison
 - Key observation
 - Let *j* be the current cell.
 - If $Cand(j, j') \le \bar{E}(j')$ for some j' > j,
 - then $Cand(j,j'') \le \bar{E}(j'')$ for every j'' > j'

• The basis of the speedup

 $\bar{E}(j)$

1	 <i>j</i> -1	j	<i>j</i> +1	<i>j</i> +2		<i>n</i> -1	n
$ar{E}(1)$	 $ar{E}(j ext{-}1)$	$ar{E}(j)$	Ē(j+1)	Ē(j+2)	:	$\bar{E}(n-1)$	$ar{E}(n)$
			Cand(j,j+1)	Cand(j,j+2)		<i>Cand</i> (<i>j</i> , <i>n</i> -1)	Cand(j,n)

• The basis of the speedup

 $\bar{E}(j)$

1	 <i>j</i> -1	j	<i>j</i> +1	<i>j</i> +2		<i>n</i> -1	n
$ar{E}(1)$	 $ar{E}(j-1)$	$ar{E}(j)$	Cand(j,j+1)	Ē(j+2)	 ^	Ē(n-1)	$ar{E}(n)$
				X	×	X	X
			Cand(j,j+1)	Cand(j,j+2)		Cand(j,n-1)	Cand(j,n)

The basis of the speedup

- Lemma 12.6.1
 - Let k < j < j' < j'' be any four cells in the same row.
 - If $Cand(j, j') \le Cand(k, j')$ then $Cand(j, j'') \le Cand(k, j'')$

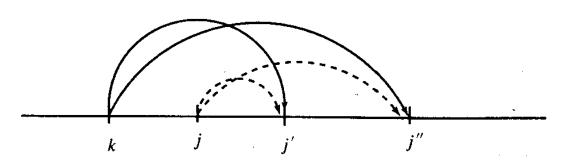


Figure 12.17: Graphical illustration of the *key observation*. Winning candidates are shown with a solid curve and losers with a dashed curve. If the candidate from j loses to the candidate from k at cell j', then the candidate from j will lose to the candidate from k at every cell j'' to the right of j'.

- The basis of the speedup
 - Lemma 12.6.1
 - Let k < j < j' < j'' be any four cells in the same row.
 - If $Cand(j, j') \le Cand(k, j')$ then $Cand(j, j'') \le Cand(k, j'')$
 - PROOF
 - Cand(k, j) = V(k) w(j k)

$$V(k) - w(j' - k) \ge V(j) - w(j' - j)$$

 $V(k) - V(j) \ge w(j' - k) - w(j' - j)$

- The basis of the speedup
 - Lemma 12.6.1
 - Let k < j < j' < j'' be any four cells in the same row.
 - If $Cand(j, j') \le Cand(k, j')$ then $Cand(j, j'') \le Cand(k, j'')$
 - PROOF
 - Cand(k, j) = V(k) w(j k)

$$V(k) - w(j' - k) \geq V(j) - w(j' - j)$$

$$V(k) - V(j) \geq w(j' - k) - w(j' - j)$$

- By convexity, $w(j'-k) w(j'-j) \ge w(j''-k) w(j''-j)$
- $V(k) V(j) \ge w(j'' k) w(j'' j)$
- $V(k) w(j'' k) \ge V(j) w(j'' j)$

The basis of the speedup

- Lemma 12.6.1
 - Let k < j < j' < j'' be any four cells in the same row.
 - If $Cand(j, j') \le Cand(k, j')$ then $Cand(j, j'') \le Cand(k, j'')$

PROOF

• Cand(k, j) = V(k) - w(j - k)

$$V(k) - w(j' - k) \geq V(j) - w(j' - j)$$

$$V(k) - V(j) \geq w(j' - k) - w(j' - j)$$

- By convexity, $w(j'-k) w(j'-j) \ge w(j''-k) w(j''-j)$
- $V(k) V(j) \ge w(j'' k) w(j'' j)$
- $V(k) w(j'' k) \ge V(j) w(j'' j)$

The basis of the speedup

Forward dynamic programming for a fixed row

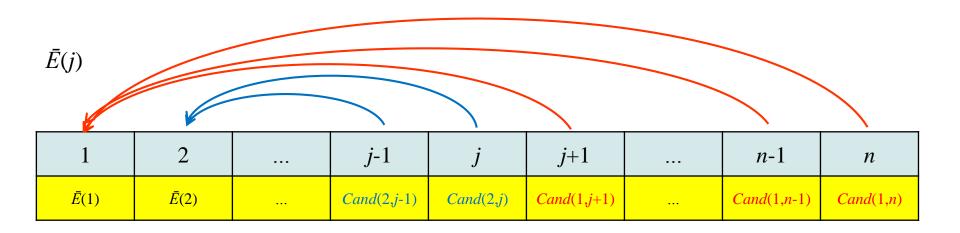
```
For j := 1 to m do
begin
                                            But this improvement does not lead
\overline{E}(j) := Cand(0, j);
end;
                                            directly to a better (worst-case) time
                                            bound
For j := 1 to m do
begin
E(j) := \overline{E}(j);
V(j) := \max[G(j), E(j), F(j)];
{We assume, but do not show that F(j) and G(j)
have been computed for cell j in the row.}
For j' := j + 1 to m do {Loop 1}
     if \overline{E}(j') < Cand(j, j') then
          begin
          \overline{E}(j') := Cand(j, j');
                                              else then
          end
end;
                                                   break
```

Cell pointers and row partition

Forward dynamic programming for a fixed row

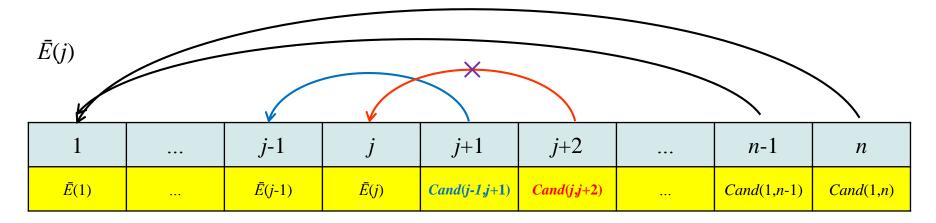
```
For j := 1 to m do
begin
\overline{E}(j) := Cand(0, j);
b(j) := 0
end;
For j := 1 to m do
begin
E(j) := \overline{E}(j);
V(j) := \max[G(j), E(j), F(j)];
(We assume, but do not show that F(j) and G(j)
have been computed for cell j in the row.}
For j' := j + 1 to m do {Loop 1}
     if \overline{E}(j') < Cand(j, j') then
          begin
          \vec{E}(j') := Cand(j, j');
          b(j') := j; {This sets a pointer from j' to j to be explained later.}
          end
end;
```

Cell pointers and row partition



Cell pointers and row partition

- Lemma 12.6.2
 - Consider the point when *j* is the current cell
 - but before *j* sends forward any candidate values
 - At that point, $b(j') \ge b(j'+1)$ for every cell j' from j+1 to m-1



Cell pointers and row partition

- Lemma 12.6.2
 - Consider the point when *j* is the current cell
 - but before *j* sends forward any candidate values
 - At that point, $b(j') \ge b(j'+1)$ for every cell j' from j+1 to m-1

PROOF

- Suppose b(j') < b(j'+1)
- By Lemma 12.6.1, $Cand(b(j'), j'+1) \ge Cand(b(j'+1), j'+1)$
- b(j'+1) should be set to b(j'), not b(j'+1)
- Hence $b(j') \ge b(j'+1)$

Cell pointers and row partition

- Corollary 12.6.1
 - *j* is the current cell, but before *j* sends forward any candidates
 - The values of the *b* pointers form a nonincreasing sequence from left to right
 - Therefore, cells $j, j+1, j+2, \ldots, m$ are partitioned into maximal blocks of consecutive cells
 - such that all b pointers in the block have the same value
 - and the pointer values decline in successive blocks

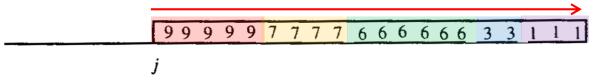


Figure 12.18: Partition of the cells j + 1 through m into maximal blocks of consecutive cells such that all the cells in any block have the same b value. The common b value in any block is less than the common b value in the preceding block.

Cell pointers and row partition

- Given Corollary 12.6.1
 - The algorithm doesn't need to explicitly maintain a b pointer for every cell
 - Only record the **common** *b* **pointer** for each block

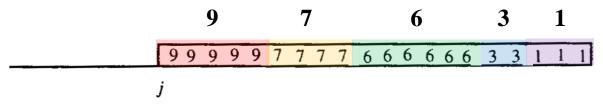


Figure 12.18: Partition of the cells j + 1 through m into maximal blocks of consecutive cells such that all the cells in any block have the same b value. The common b value in any block is less than the common b value in the preceding block.

Preparation for the speedup

- Our goal
 - To reduce the time per row used in computing the E values
 - $\Theta(n^2) \rightarrow O(n \log n)$
- The main work done in a row
 - 1. Update the \bar{E} values

2. Update the current block-partition with its associated pointer

Preparation for the speedup

- Our goal
 - To reduce the time per row used in computing the E values
 - $\Theta(n^2) \rightarrow O(n \log n)$
- The main work done in a row
 - 1. Update the \bar{E} values
 - Assume that all the \bar{E} values are maintained for free
 - 2. Update the current block-partition with its associated pointer

Preparation for the speedup

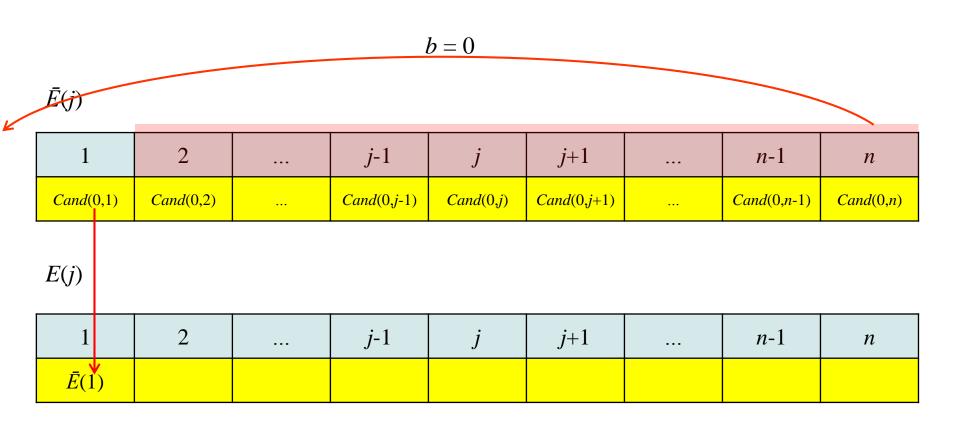
 $\bar{E}(j)$

1	2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n
<i>Cand</i> (0,1)	<i>Cand</i> (0,2)	 Cand(0,j-1)	Cand(0,j)	<i>Cand</i> (0, <i>j</i> +1)	 <i>Cand</i> (0, <i>n</i> -1)	Cand(0,n)

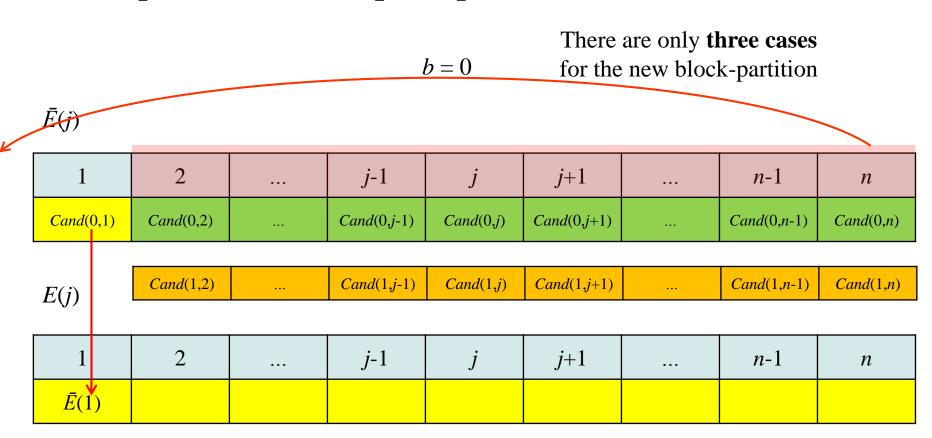
E(j)

1	2	 <i>j</i> -1	j	<i>j</i> +1	 <i>n</i> -1	n

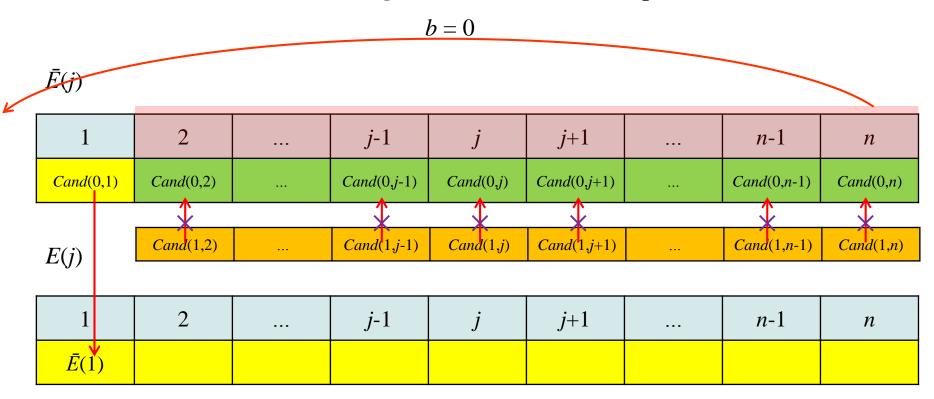
Preparation for the speedup



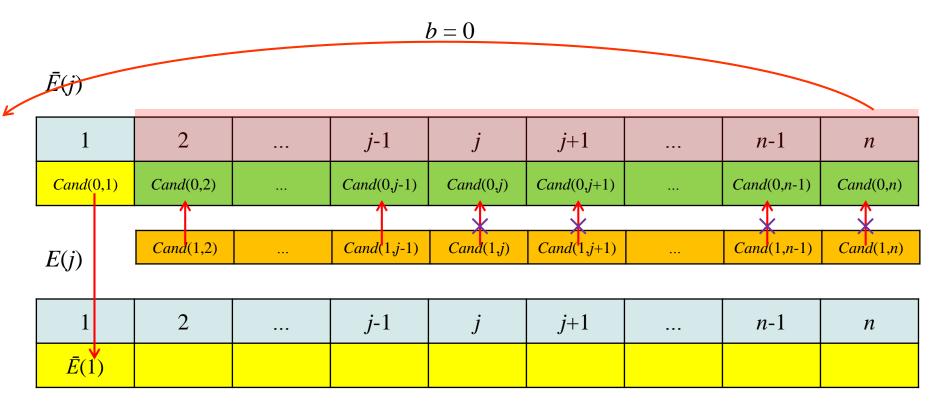
Preparation for the speedup



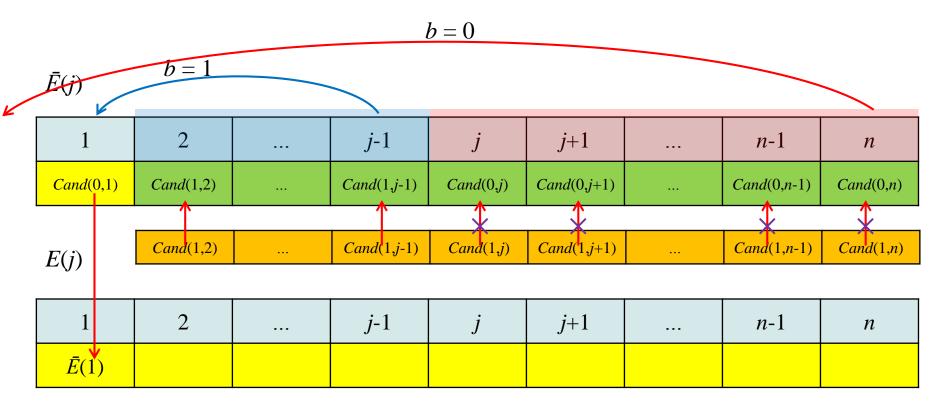
- Preparation for the speedup
 - Case 1: remain in a **single block** with common pointer b = 0



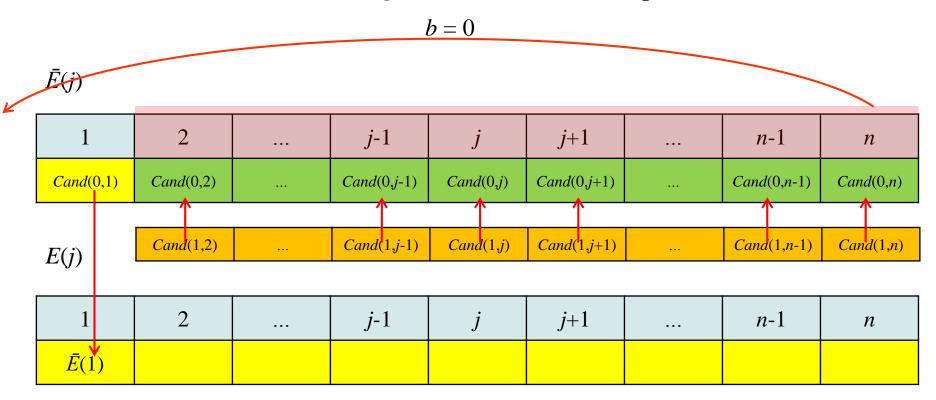
- Preparation for the speedup
 - Case 2: divided into two blocks



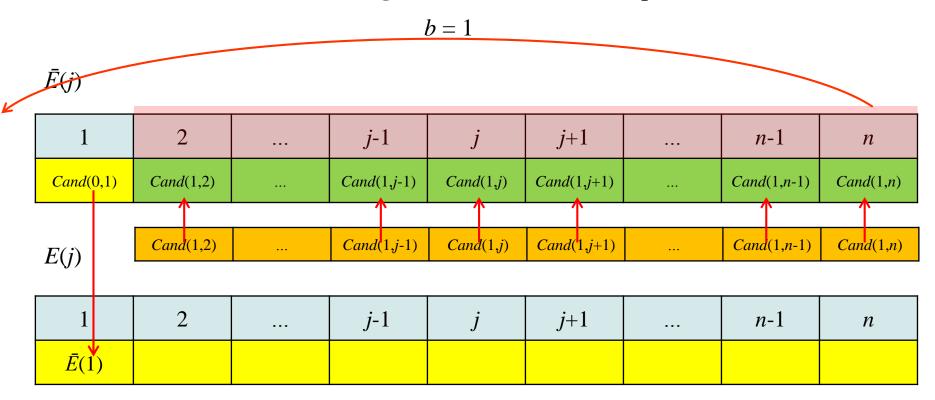
- Preparation for the speedup
 - Case 2: divided into two blocks



- Preparation for the speedup
 - Case 3: remain in a **single block** with common pointer b = 1



- Preparation for the speedup
 - Case 3: remain in a **single block** with common pointer b = 1



Preparation for the speedup

- The punch line
 - Search for the left-most cell j' > 2 such that $\bar{E}(j') \ge Cand(1, j')$
 - Win ... Win **Lose** Lose ... Lose
 - can be done by **binary search**
 - $O(\log n)$ comparisons
 - at most one pointer update
 - Since we only record one *b* pointer per block

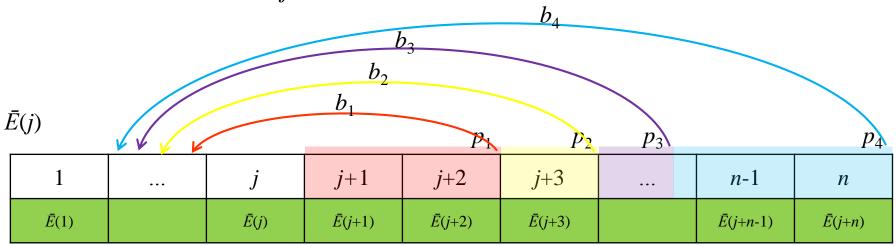
- Preparation for the speedup
 - General case of j > 1

		r blocks							
Ì	$ar{E}(j)$			$p_1 = j + 2$	$p_2 = j + 3$	p_3	p	$p_4 = p_r = n$	
	1	 j	<i>j</i> +1	<i>j</i> +2	<i>j</i> +3		<i>n</i> -1	n	
	$ar{E}(1)$	$ar{E}(j)$	$\bar{E}(j+1)$	$\bar{E}(j+2)$	$\bar{E}(j+3)$		$\bar{E}(j+n-1)$	$ar{E}(j+n)$	

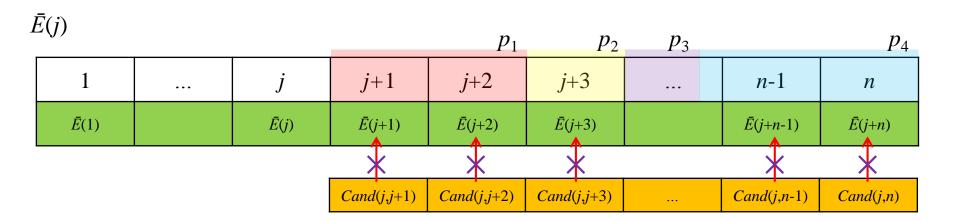
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Preparation for the speedup

• General case of j > 1

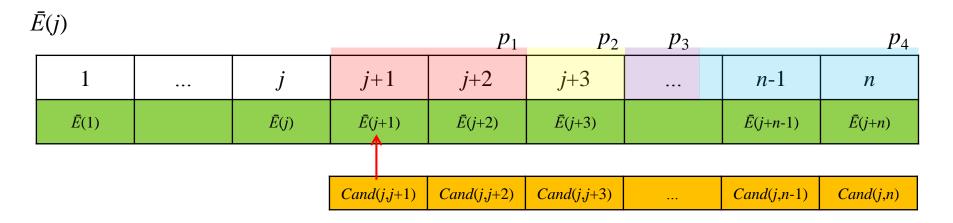


- Preparation for the speedup
 - Case 1: if $\bar{E}(j+1) \ge Cand(j, j+1)$ **Lose**

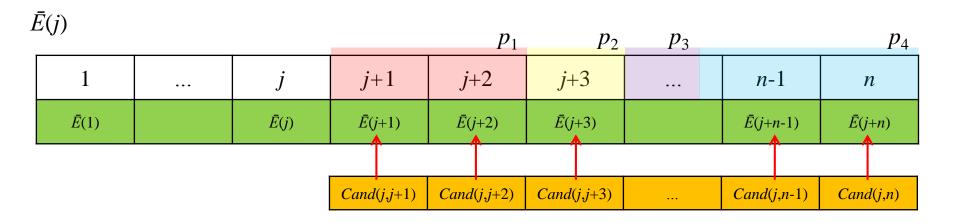


Preparation for the speedup

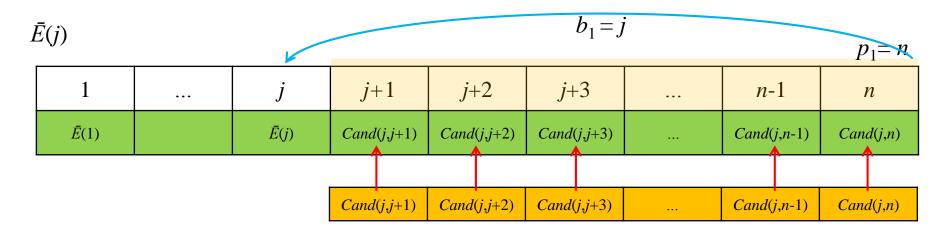
- Case 2: if $\bar{E}(j+1) < Cand(j, j+1)$ **Win**
 - A. until end-of-block list is exhausted
 - B. until it finds the first index s with $\bar{E}(p_s) \ge Cand(j, p_s)$



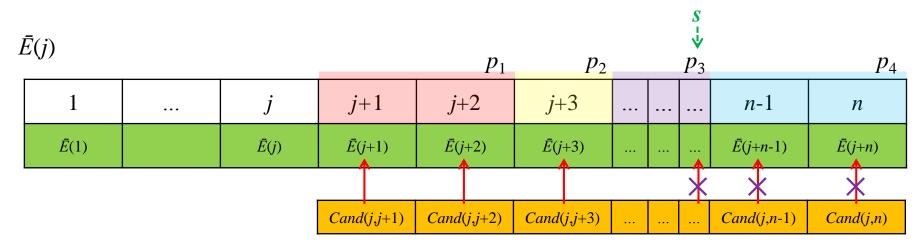
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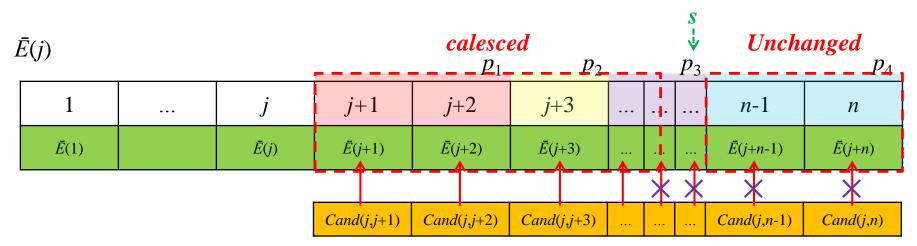
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 - Case 2: if $\bar{E}(j+1) < Cand(j, j+1)$ **Win**
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 - B. until it finds the first index s with $\bar{E}(p_s) \ge Cand(j, p_s)$

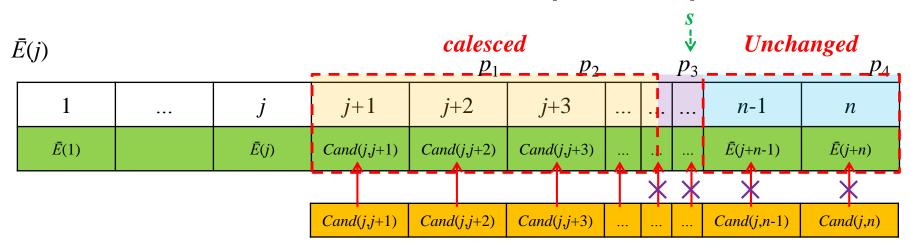


- Preparation for the speedup
 - Case 2: if $\bar{E}(j+1) < Cand(j, j+1)$ **Win**
 - A. until end-of-block list is exhausted
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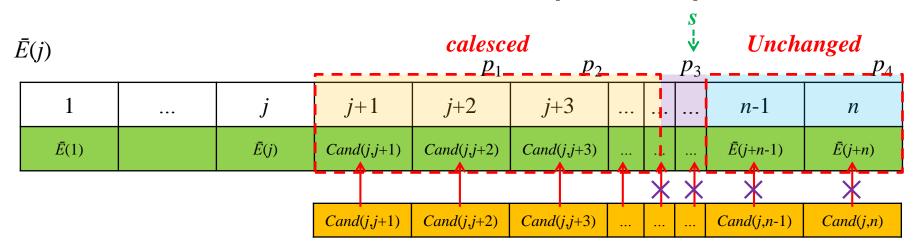


- The algorithm finds the proper place to split block s
 - by doing binary search over the cells in the block

- Preparation for the speedup
 - Case 2: if $\bar{E}(j+1) < Cand(j, j+1)$ Win
 - A. until end-of-block list is exhausted
 - B. until it finds the first index s with $\bar{E}(p_s) \ge Cand(j, p_s)$



- Preparation for the speedup
 - Case 2: if $\bar{E}(j+1) < Cand(j, j+1)$ Win
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- Our goal
 - To reduce the time per row used in computing the E values
 - $\Theta(n^2) \rightarrow O(n \log n)$
- The main work done in a row
 - 1. Update the \bar{E} values
 - Assume that all the \bar{E} values are maintained for free
 - 2. Update the current block-partition with its associated pointer

- The key observation
 - retrieves $\bar{E}(j)$
 - only when *j* is the current cell

- retrieves $\bar{E}(j')$
 - only when examining cell j' in the process of updating the block-partition

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 - retrieves $\bar{E}(j)$
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$$b(j) = b_1$$

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 - which can be computed in **constant time** when needed
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- retrieves $\bar{E}(j')$
 - only when examining cell j' in the process of updating the block-partition
 - The algorithm knows the block that j' falls into, say block i,
 - and hence it knows b_i
 - $\bar{E}(j') = Cand(b_i, j')$
 - which can be computed in **constant time** when needed

Final implementation details

Revised forward dynamic programming for a fixed row

Initialize the end-of-block list to contain the single number m. Initialize the associated pointer list to contain the single number 0.

```
For j := 1 to m do begin

Set k to be the first pointer on the b-pointer list.

E(j) := Cand(k)j);

V(j) := \max[G(j), E(j), F(j)];

{As before we assume that the needed F and G values have been computed.}
```

```
{Now see how j's candidates change the block-partition.}
Set(j') equal to the first entry on the end-of-block list.
{look for the first index s in the end-of-block list where j loses}
If Cand(b(j'), j + 1) < Cand(j, j + 1) then \{j' \text{s candidate wins one}\}
begin
     While
     The end-of-block list is not empty and Cand(b(j'), j') < Cand(j, j') do
          begin
          remove the first entry on the end-of-block list,
          and remove the corresponding b-pointer
          If the end-of-block list is not empty then
          set j' to the new first entry on the end-of-block list.
          end:
     end {while};
```

```
If the end-of-block list is empty then
    place m at the head of that list;
    Else {when the end-of-block list is not empty}
         begin
         Let p_s denote the first end-of-block entry.
         Using binary search over the cells in block s, find the
         right-most point p in that block such that Cand(j, p) > Cand(b_s, p).
         Add p to the head of the end-of-block list;
         end:
    Add j to the head of the b pointer list.
    end;
end.
```

Time analysis

- The total time for the algorithm
 - Proportional to the number of comparisons
 - Find block s ~> l >2 comparisons, at least l -1 full blocks coalesce into a single block
 - Binary search to split s ~> splits at most one block into two
 - Hence if the algorithm does l > 2 comparisons to find s,
 - Then the total number of blocks at most increases by one.
 - The algorithm begins with a single block and *n* iterations
 - To find every s: At most O(n) comparisons
 - To find split cell (binary search): $O(\log n)$

• Theorem 12.6.1

• For any fixed row, all the E(j) values can be computed in $O(n \log n)$ total time.

- The case of F values is essentially symmetric
 - One point that might cause confusion
 - The computations of *E* and *F* are actually *interleaved*
 - since each V(i, j) value depends on both E(i, j) and F(i, j)

V(i,j)			j		
i					

 \boldsymbol{E}

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			l	\setminus /		
				X		

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 \boldsymbol{F}

Total time

- E value: $O(n \log n)$
- F value: $O(m \log m)$
- G value: O(nm)
- V value: O(nm) once E and F is known
- Theorem 12.6.2
 - When the gap weight w is a convex function of the gap length
 - An optimal alignment can be computed in $O(nm \log n)$ time
 - where n > m are the lengths of the two strings