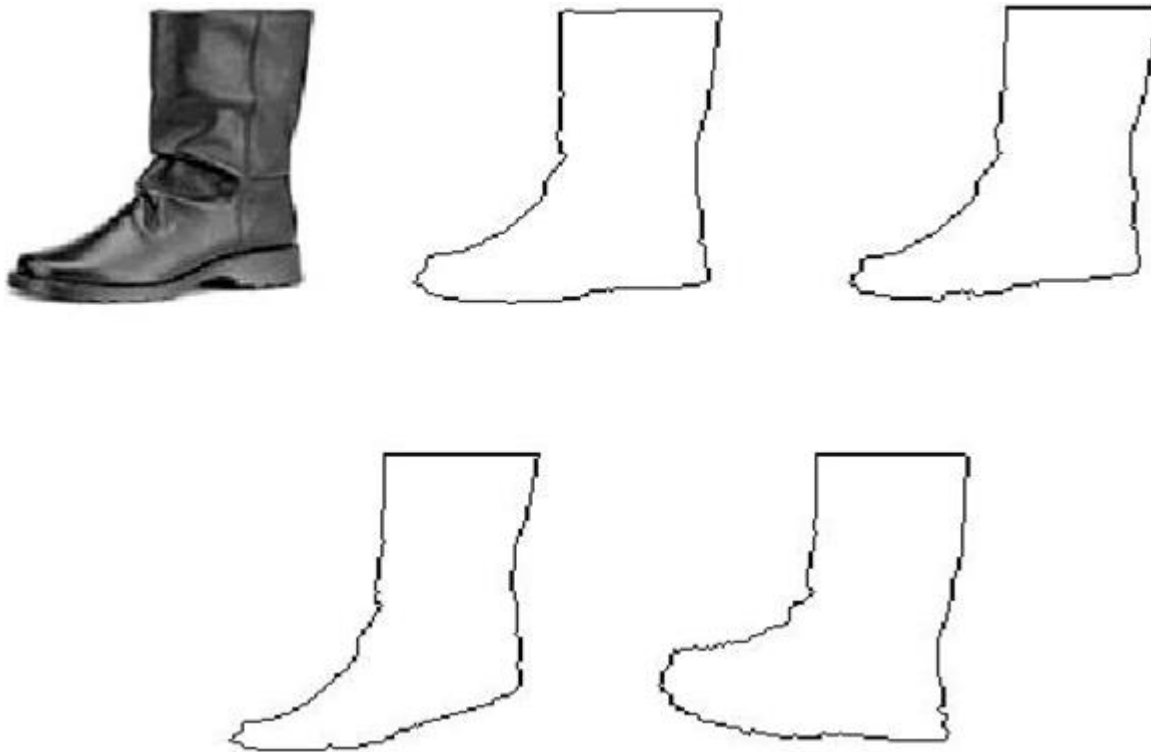


Pattern Recognition

Template Matching



Template Matching

- Typical Applications
 - Speech Recognition
 - Motion Estimation in Video Coding
 - Data Base Image Retrieval
 - Written Word Recognition
 - Bioinformatis

Template Matching

- The Goal:
 - Given a set of reference patterns known as **TEMPLATES**,
 - find the best match for unknown pattern
 - each class represented by a single typical pattern.
- requires an appropriate “measure” to quantify similarity or matching.

Template Matching

- The cost “measure” :
 - deviations between the **template** and the **test pattern**.
 - For example:
 - The word **beauty** may have been read a **beeauty** or **beuty**, etc., due to errors.
 - The **same person** may speak the **same word differently**.

Template Matching Method

- Optimal path searching techniques
- Correlation
- Deformable models

TM using Optimal Path Searching

- Representation: Represent the template by a **sequence** of **measurement vectors** or **string patterns**

Template: $\underline{r}(1), \underline{r}(2), \dots, \underline{r}(I)$

Test pattern: $\underline{t}(1), \underline{t}(2), \dots, \underline{t}(J)$

TM using Optimal Path Searching

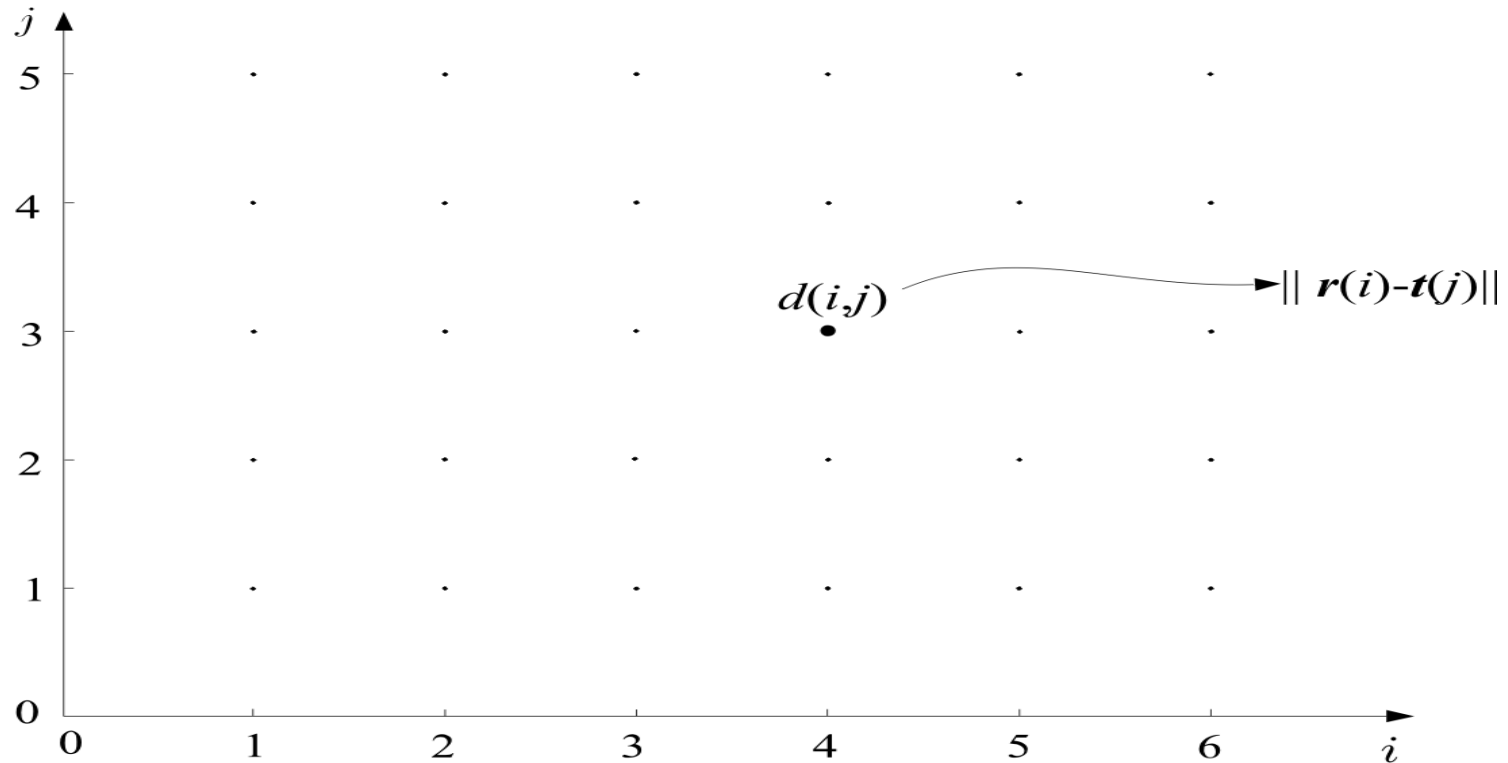
Template: $\underline{r}(1), \underline{r}(2), \dots, \underline{r}(I)$

Test pattern: $\underline{t}(1), \underline{t}(2), \dots, \underline{t}(J)$

- In general $I \neq J$
- We need to find an appropriate distance measure between test and reference patterns.

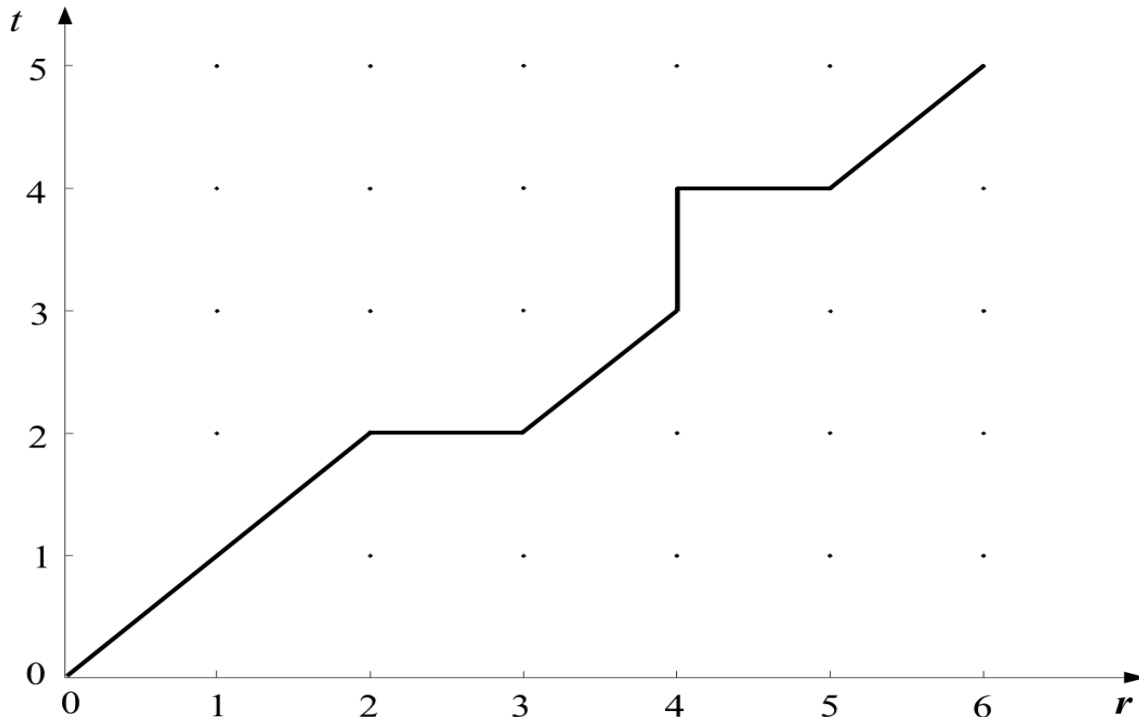
TM using Optimal Path Searching

- Form a grid with I points (template) in horizontal and J points (test) in vertical
- Each point (i,j) of the grid measures the **distance** between $\underline{r}(i)$ and $\underline{t}(j)$



TM using Optimal Path Searching

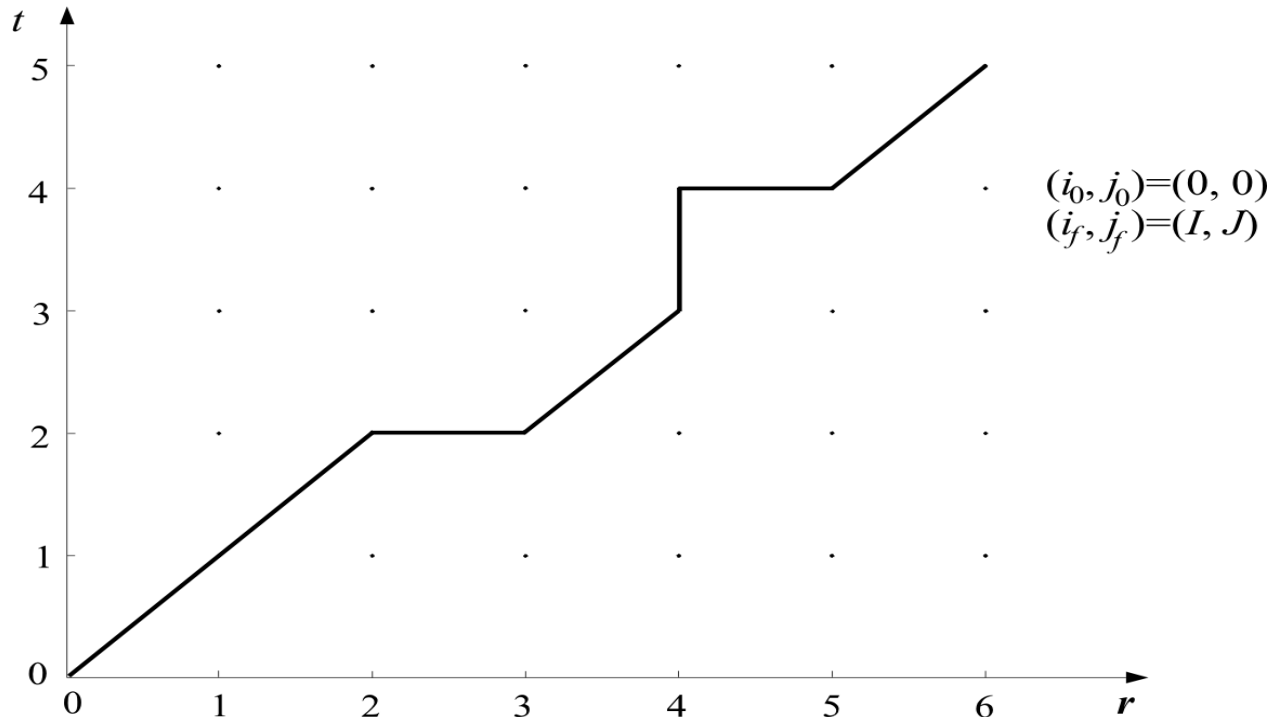
- **Path:** A path through the grid, from an **initial node** (i_0, j_0) to a **final one** (i_f, j_f) , is an **ordered set** of nodes $(i_0, j_0), (i_1, j_1), (i_2, j_2) \dots (i_k, j_k) \dots (i_f, j_f)$



TM using Optimal Path Searching

– **Path**: A path is complete path if:

$$(i_0, j_0) = (0, 0), (i_1, j_1), (i_2, j_2), \dots, (i_f, j_f) = (I, J)$$

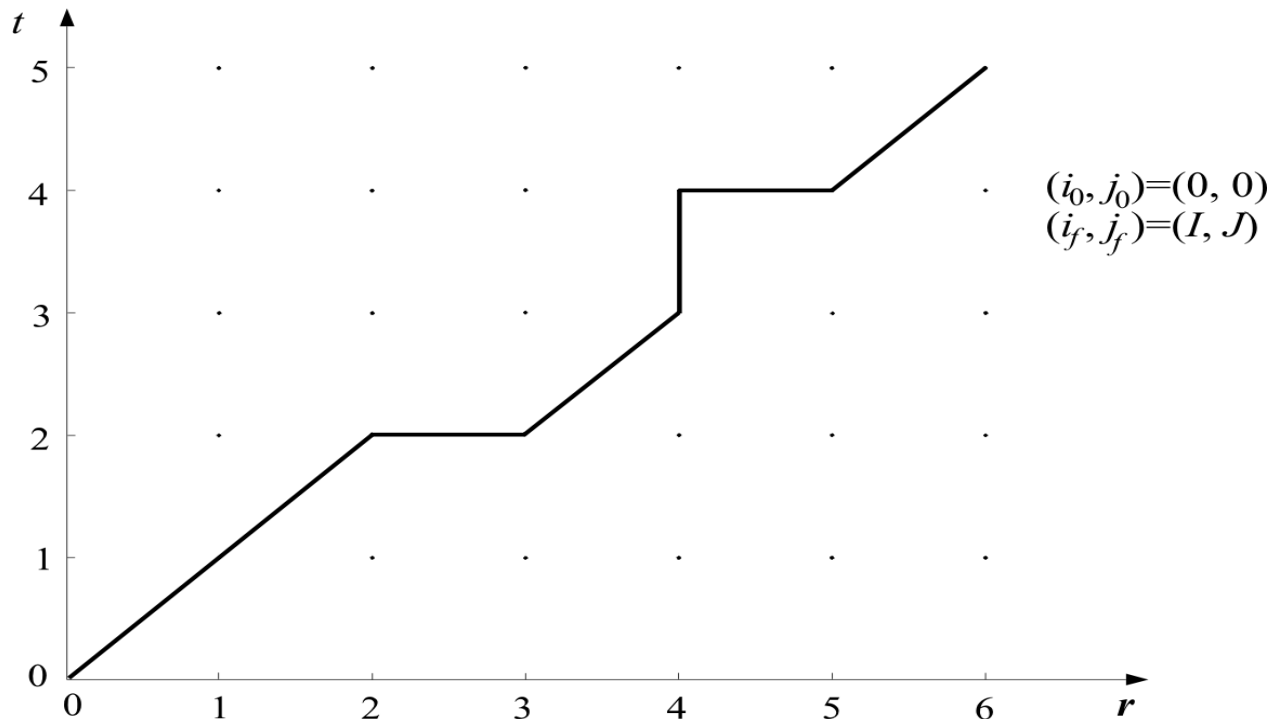


TM using Optimal Path Searching

- Each path is associated with a cost

$$D = \sum_{k=0}^{K-1} d(i_k, j_k)$$

where K is the number of nodes across the path



TM using Optimal Path Searching

- The cost up to node (i_k, j_k) is: $D(i_k, j_k)$
- By convention
 - $D(0, 0)=0$
 - $d(0,0)=0$

TM using Optimal Path Searching

- The equation

$$D = \sum_{k=0}^{K-1} d(i_k, j_k)$$

assumes that each node has been associated with some cost

TM using Optimal Path Searching

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$$D = \sum_{k=0}^{K-1} d(i_k, j_k)$$

assumes that each node has been associated with some cost

- However, each transition (i_{k-1}, j_{k-1}) to (i_k, j_k) may also associate with a cost
- The new equation is:

$$D = \sum_k d(i_k, j_k | i_{k-1}, j_{k-1})$$

TM using Optimal Path Searching

$$D = \sum_k d(i_k, j_k | i_{k-1}, j_{k-1})$$

- Search for the path with the optimal cost D_{opt} .
- The matching cost between template \underline{r} and test pattern \underline{t} is D_{opt} .
- Costly operation
- Needs efficient computation

Bellman's Optimality Principle

- Optimal path:

$$(i_0, j_0) \xrightarrow{opt} (i_f, j_f)$$

Bellman's Optimality Principle

- Optimal path:

$$(i_0, j_0) \xrightarrow{opt} (i_f, j_f)$$

- Let (i, j) be an intermediate node, i.e.

$$(i_0, j_0) \rightarrow \dots \rightarrow (i, j) \rightarrow \dots \rightarrow (i_f, j_f)$$

Bellman's Optimality Principle

- Optimal path:

$$(i_0, j_0) \xrightarrow{opt} (i_f, j_f)$$

- Let (i, j) be an intermediate node, i.e.

$$(i_0, j_0) \rightarrow \dots \rightarrow (i, j) \rightarrow \dots \rightarrow (i_f, j_f)$$

Then write the optimal path **through** (i, j)

$$(i_0, j_0) \xrightarrow[(i, j)]{opt} (i_f, j_f)$$

Bellman's Optimality Principle

- Bellman's Principle:

$(i_0, j_0) \xrightarrow{opt} (i_f, j_f)$ can be obtained as

$$(i_0, j_0) \xrightarrow{opt} (i, j) \oplus (i, j) \xrightarrow{opt} (i_f, j_f)$$

- meaning: The overall optimal path from (i_0, j_0) to (i_f, j_f) through (i, j) is the concatenation of the optimal paths from (i_0, j_0) to (i, j) and from (i, j) to (i_f, j_f)

Bellman's Optimality Principle

- Bellman's Principle:

$$(i_0, j_0) \xrightarrow{opt} (i_f, j_f) \Leftrightarrow (i_0, j_0) \xrightarrow{opt} (i, j) \oplus (i, j) \xrightarrow{opt} (i_f, j_f)$$

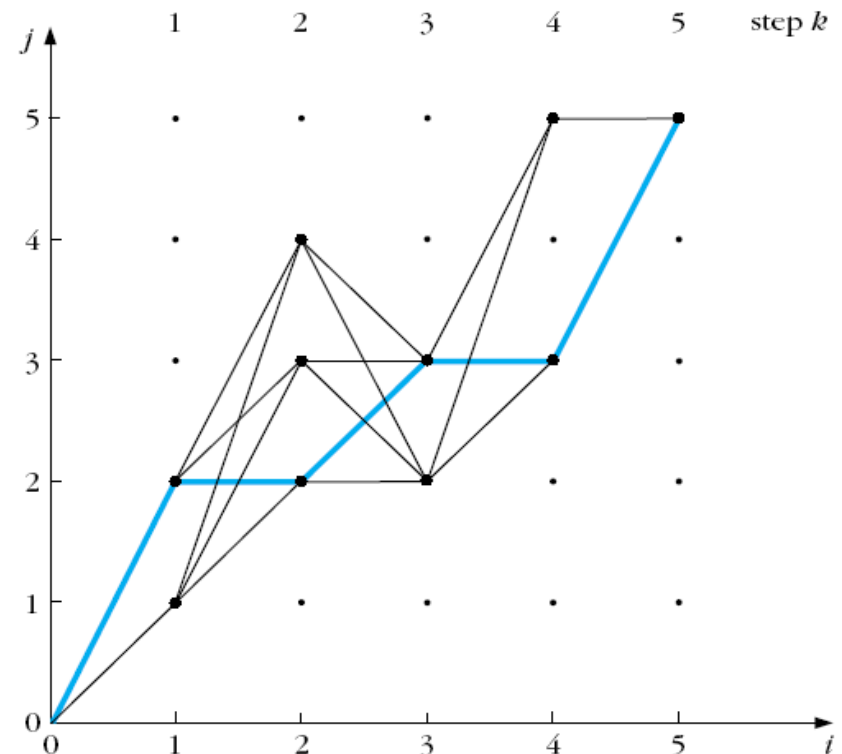
- Let $D_{opt.}(i_{k-1}, j_{k-1})$ is the optimal path to reach (i_{k-1}, j_{k-1}) from (i_0, j_0) , then Bellman's principle is stated as:

$$D_{opt}(i_k, j_k) = opt\{D_{opt}(i_{k-1}, j_{k-1}) + d(i_k, j_k | i_{k-1}, j_{k-1})\}$$

Bellman's Optimality Principle

$$D_{opt}(i_k, j_k) = \text{opt}\{D_{opt}(i_{k-1}, j_{k-1}) + d(i_k, j_k | i_{k-1}, j_{k-1})\}$$

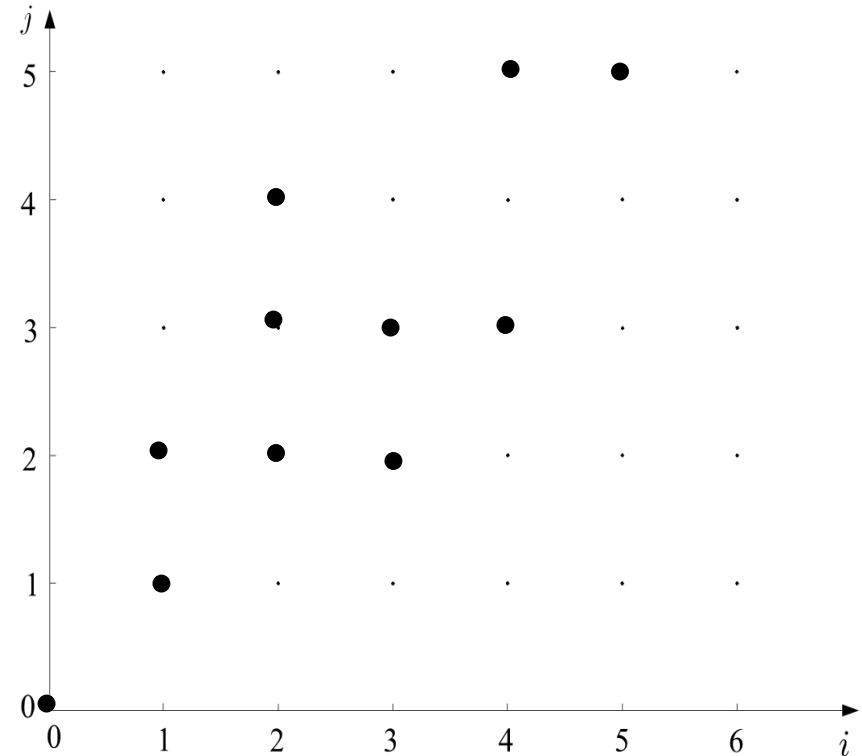
- We don't need to search the whole space to find the optimal path
- Global and local constraints may be imposed to reduce the search space



Bellman's Optimality Principle

$$D_{opt}(i_k, j_k) = \text{opt}\{D_{opt}(i_{k-1}, j_{k-1}) + d(i_k, j_k | i_{k-1}, j_{k-1})\}$$

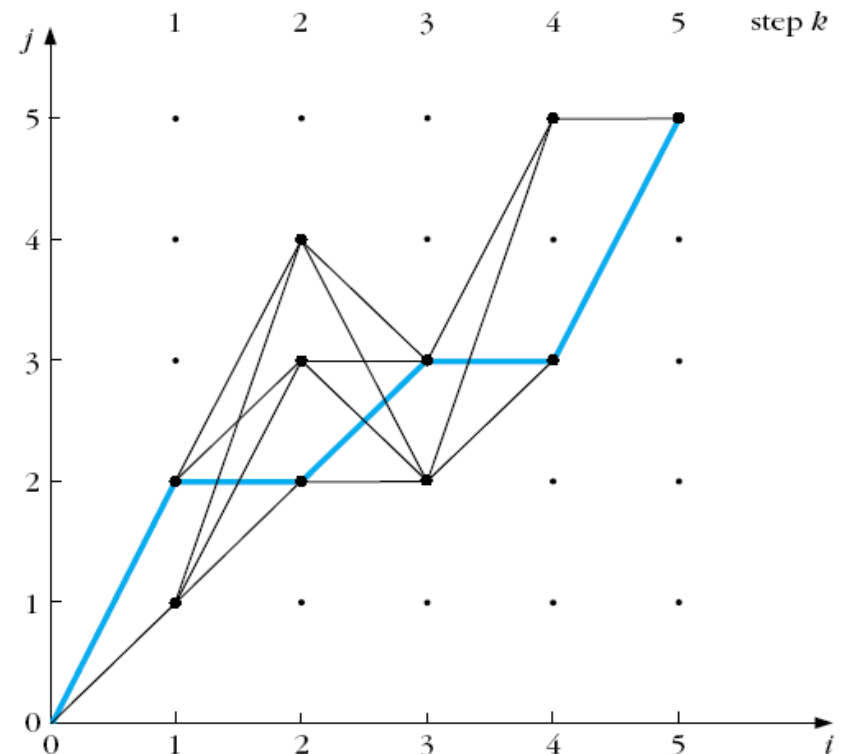
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Bellman's Optimality Principle

$$D_{opt}(i_k, j_k) = \text{opt}\{D_{opt}(i_{k-1}, j_{k-1}) + d(i_k, j_k | i_{k-1}, j_{k-1})\}$$

- We don't need to search the whole space to find the optimal path
- Global and local constraints may be imposed to reduce the search space



Application of TM in Text Matching: The Edit Distance

- The Edit distance
 - It is used for matching written words.
- Applications:
- Automatic Editing
 - Text Retrieval

Application of TM in Text Matching: The Edit Distance

- The Edit distance
 - It is used for matching written words.
Applications:
 - Automatic Editing
 - Text Retrieval
 - The measure to be adopted for matching, must take into account:
 - **Wrongly identified** symbols
e.g. “befuty” instead of “beauty”
 - **Insertion errors**, e.g. “bearuty”
 - **Deletion errors**, e.g. “beuty”

Examples:

- **Input:** str1 = “geek”, str2 = “gesek”
- **Output:** 1
- **Explanation:** We can convert str1 into str2 by inserting a ‘s’.

- **Input:** str1 = “cat”, str2 = “cut”
- **Output:** 1
- **Explanation:** We can convert str1 into str2 by replacing ‘a’ with ‘u’.

- **Input:** str1 = “sunday”, str2 = “saturday”
- **Output:** 3
- **Explanation:** Last three and first characters are same. We basically need to convert “un” to “atur”. This can be done using below three operations. Replace ‘n’ with ‘r’, insert t, insert a

The Edit Distance

- Edit distance: **Minimal** total number of **changes**, ***C***, **insertions** ***I*** and **deletions** ***R***, required to change pattern A into pattern B ,

$$D(A, B) = \min_j [C(j) + I(j) + R(j)]$$

where j runs over **All** possible variations of symbols, in order to convert $A \longrightarrow B$

The Edit Distance

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$$D(A, B) = \min_j [C(j) + I(j) + R(j)]$$

where j runs over **All** possible variations of symbols, in order to convert $A \longrightarrow B$

- *Example*: many ways to change **beuty** to **beauty**

The Edit Distance

- The optimal path search algorithm can be used, provided we know
 - Initial conditions
 - Search space
 - Allowable transitions
 - Distance measure

The Edit Distance

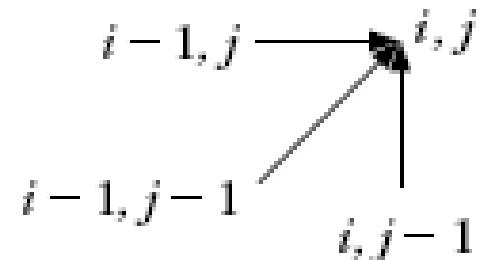
- Cost $D(0,0) = 0$,
- Complete path is searched
- Allowable predecessors and costs

– $(i-1, j-1) \rightarrow (i, j)$

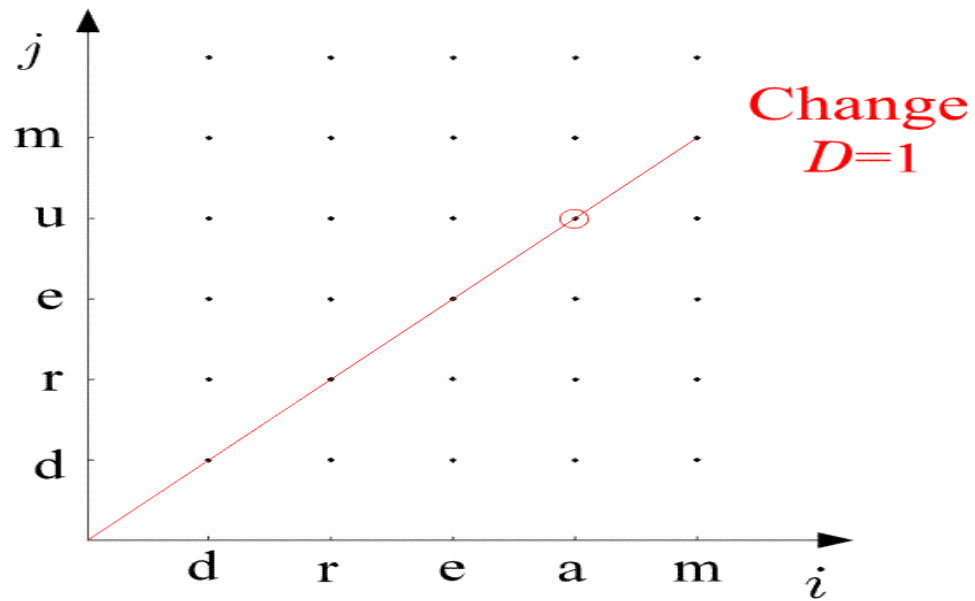
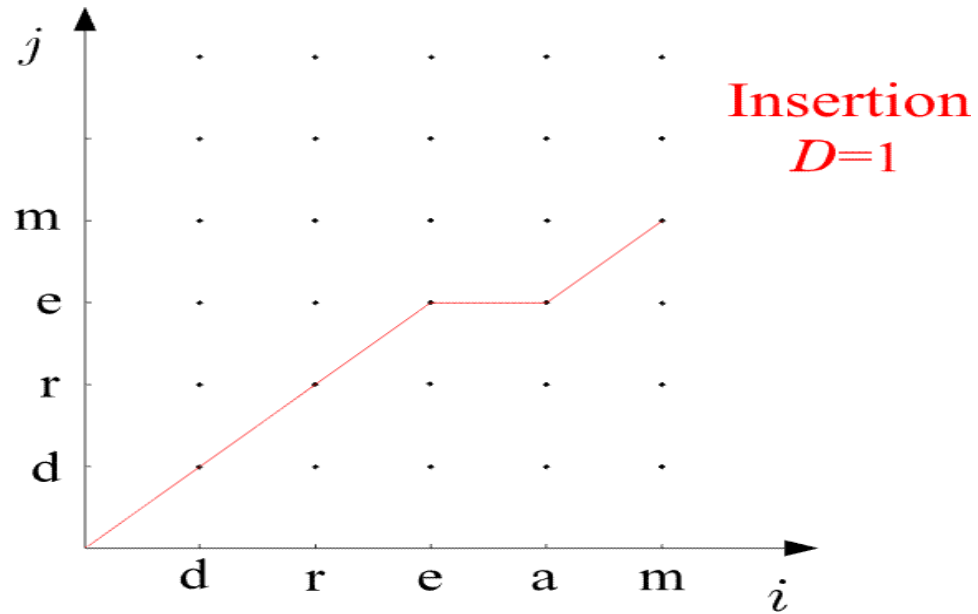
$$d(i, j | i-1, j-1) = \begin{cases} 0, & \text{if } t(i) = r(j) \\ 1, & t(i) \neq r(j) \end{cases}$$

– Horizontal $d(i, j | i-1, j) = 1$

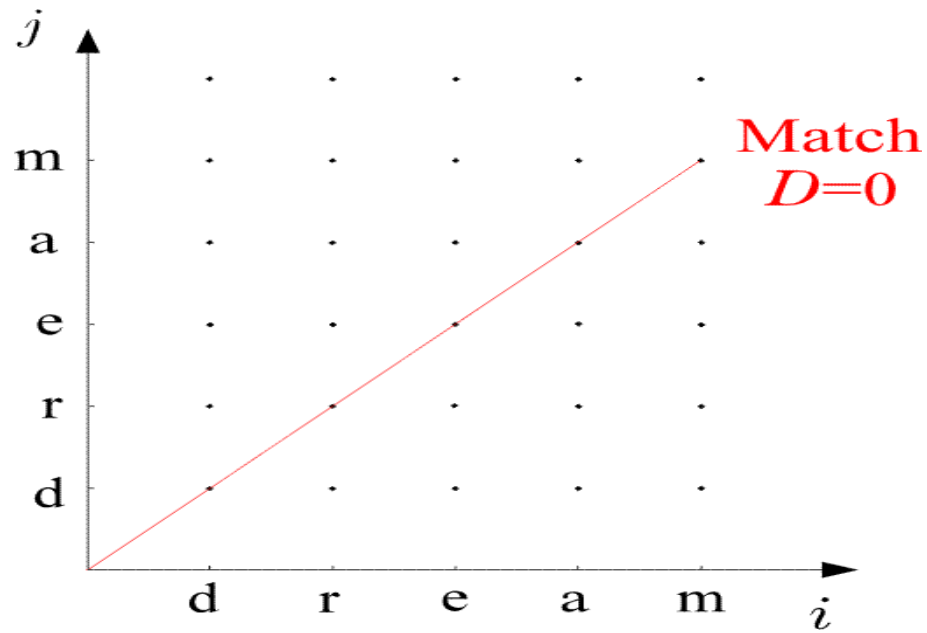
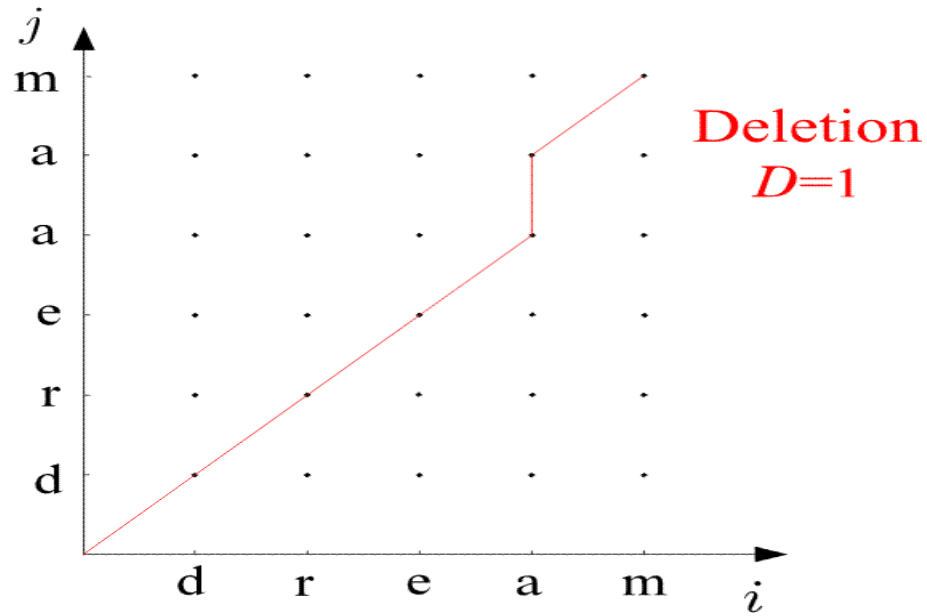
– Vertical $d(i, j | i, j-1) = 1$



- Examples:

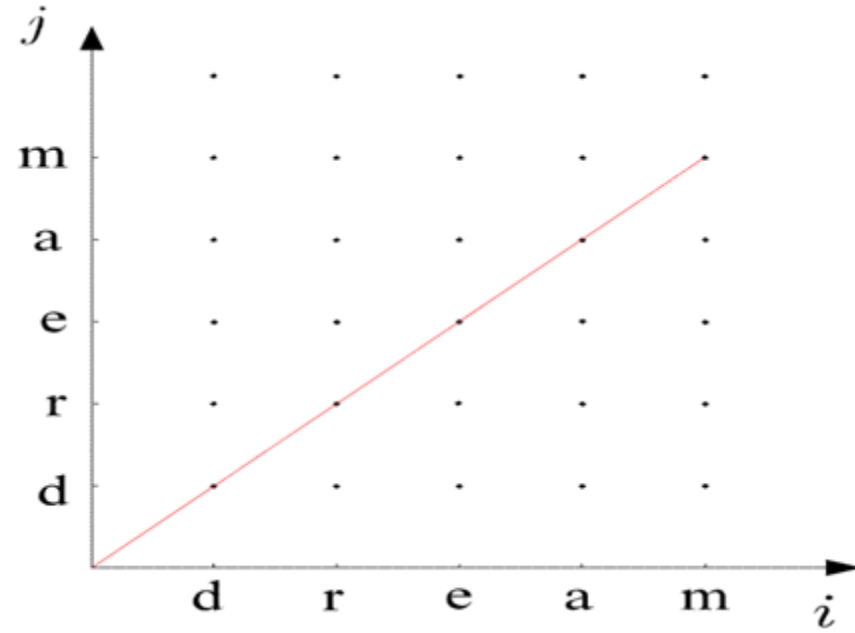


- Examples:



The Edit Distance

- The Algorithm
 - $D(0,0)=0$
 - For $i=1$, to I
 - $D(i,0)=D(i-1,0)+1$
 - END {FOR}
 - For $j=1$ to J
 - $D(0,j)=D(0,j-1)+1$
 - END{FOR}
 - For $i=1$ to I
 - For $j=1$, to J
 - $C_1=D(i-1,j-1)+d(i,j \mid i-1,j-1)$
 - $C_2=D(i-1,j)+1$
 - $C_3=D(i,j-1)+1$
 - $D(i,j)=\min(C_1,C_2,C_3)$
 - END {FOR}
 - END {FOR}
 - $D(A,B)=D(I,J)$



Dynamic Program Table for String Edit

Measure distance between strings

PARK

SPAKE

Edit operations
for turning
SPAKE
into
PARK

		P	A	R	K
	delete ↓				
S					
P					
A			insert →		
K					substitute ↘
E					

Dynamic Program Table for String Edit

Measure distance between strings

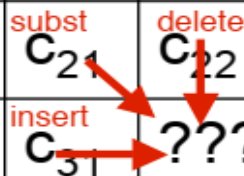
PARK

SPAKE

		P	A	R	K
	C ₀₀	C ₀₂	C ₀₃	C ₀₄	C ₀₅
S	C ₁₀	C ₁₁	C ₁₂	C ₁₃	C ₁₄
P	C ₂₀	C ₂₁	C ₂₂	C ₂₃	C ₂₄
A	C ₃₀	C ₃₁	???		
K					
E					

Dynamic Program Table for String Edit

		P	A	R	K
	C ₀₀	C ₀₂	C ₀₃	C ₀₄	C ₀₅
S	C ₁₀	C ₁₁	C ₁₂	C ₁₃	C ₁₄
P	C ₂₀	C ₂₁	C ₂₂	C ₂₃	C ₂₄
A	C ₃₀	C ₃₁	???		
K					
E					



$D(i,j)$ = score of **best** alignment from $s1..si$ to $t1..tj$

$$= \min \begin{cases} D(i-1,j-1), & \text{if } si=tj & //copy \\ D(i-1,j-1)+1, & \text{if } si \neq tj & //substitute \\ D(i-1,j)+1 & & //insert \\ D(i,j-1)+1 & & //delete \end{cases}$$

Dynamic Program Table Initialized

		P	A	R	K
	0	1	2	3	4
S	1				
P	2				
A	3				
K	4				
E	5				

$D(i,j)$ = score of **best** alignment from $s1..si$ to $t1..tj$

$$= \min \left\{ \begin{array}{ll} D(i-1,j-1)+d(s_i,t_j) & //substitute \\ D(i-1,j)+1 & //insert \\ D(i,j-1)+1 & //delete \end{array} \right.$$

Dynamic Program Table ... filling in

		P	A	R	K
	0	1	2	3	4
S	1	1			
P	2				
A	3				
K	4				
E	5				

$D(i,j)$ = score of **best** alignment from $s1..si$ to $t1..tj$

$$= \min \left\{ \begin{array}{ll} D(i-1,j-1)+d(s_i,t_j) & //substitute \\ D(i-1,j)+1 & //insert \\ D(i,j-1)+1 & //delete \end{array} \right.$$

Dynamic Program Table ... filling in

		P	A	R	K
	0	1	2	3	4
S	1	1	2	3	4
P	2				
A	3				
K	4				
E	5				

$D(i,j)$ = score of **best** alignment from $s1..si$ to $t1..tj$

$$= \min \left\{ \begin{array}{ll} D(i-1,j-1)+d(si,tj) & //substitute \\ D(i-1,j)+1 & //insert \\ D(i,j-1)+1 & //delete \end{array} \right.$$

Dynamic Program Table ... filling in

		P	A	R	K
	0	1	2	3	4
S	1	1	2	3	4
P	2	1			
A	3				
K	4				
E	5				

$D(i,j)$ = score of **best** alignment from $s1..si$ to $t1..tj$

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Dynamic Program Table ... filling in

		P	A	R	K
	0	1	2	3	4
S	1	1	2	3	4
P	2	1	2	3	4
A	3	2	1	2	3
K	4	3	2	2	2
E	5	4	3	3	3

Final cost of aligning all of both strings.

$D(i,j)$ = score of **best** alignment from $s1..si$ to $t1..tj$

$$= \min \left\{ \begin{array}{ll} D(i-1,j-1)+d(s_i,t_j) & // \text{substitute} \\ D(i-1,j)+1 & // \text{insert} \\ D(i,j-1)+1 & // \text{delete} \end{array} \right.$$