



*Discovering Most Classificatory Patterns for  
Very Expressive Pattern Classes*

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*Distinguish two given string datasets*

*- to obtain a good **rule** and/or useful **knowledge***

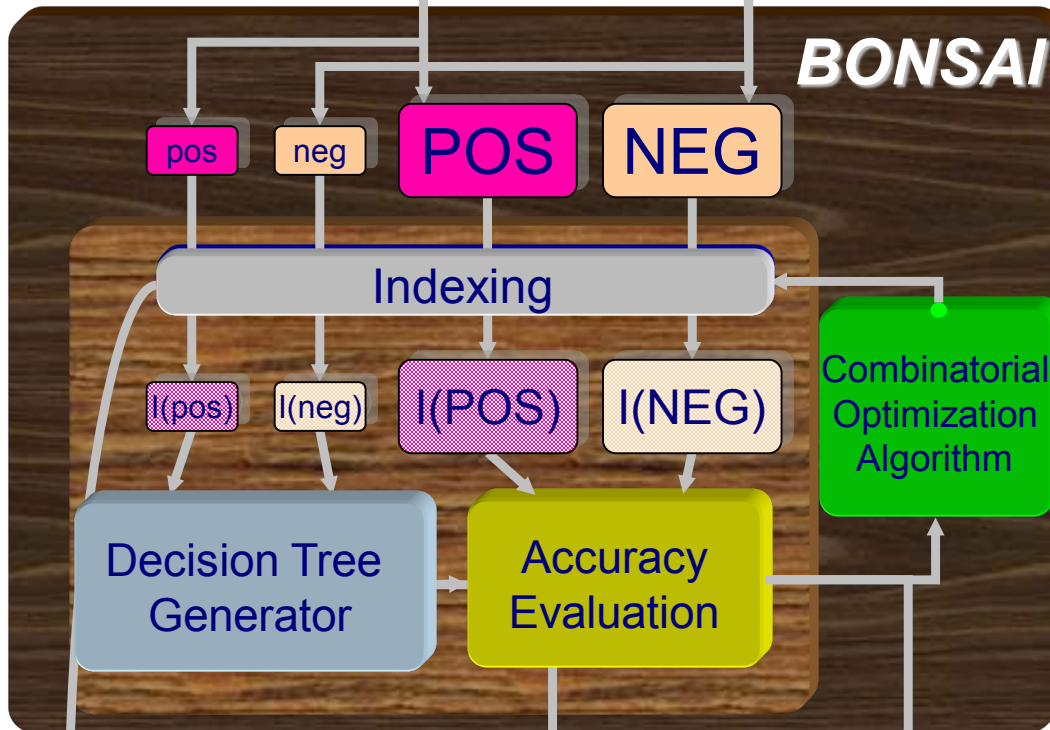
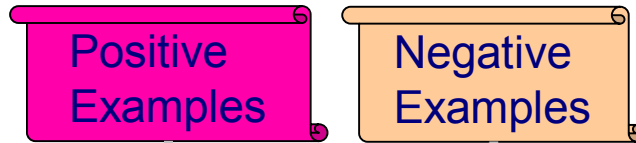
*Grade up **BONSAI** system*

*- so that it can deal with more **expressive pattern classes***

# Machine Discovery System **BONSAI**

[Shimozono et. al 1994]

Datasets

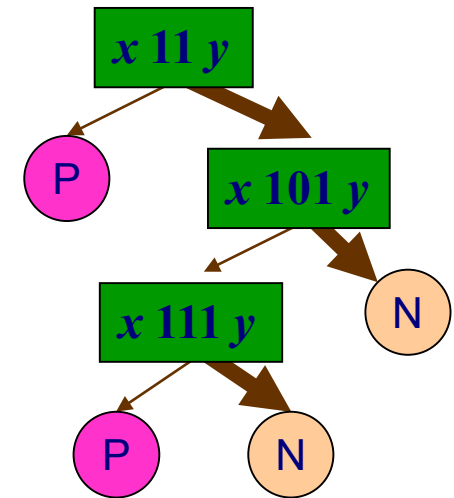


Indexing

Decision Tree

Accuracy

ABCDEFGHIJKLMN OPQRSTUVWXYZ  
0011001010001110000011010



# Pattern Discovery from Datasets

Find a pattern string that occurs **in all strings of A** and **in no strings of B**.

A

AKEBONO MUSASHIMARU  
CONTRIBUTIONS OF AI  
BEYOND MESSY LEARNING  
BASED ON LOCAL SEARCH ALGORITHMS  
BOOLEAN CLASSIFICATION  
SYMBOLIC TRANSFORMATION  
BACON SANDWICH  
PUBLICATION OF DISSERTATION

B

WAKANOHANA TAKANOHANA  
CONTRIBUTIONS OF UN  
TRADITIONAL APPROACHES  
GENETIC ALGORITHMS  
PROBABILISTIC RULE  
NUMERIC TRANSFORMATION  
PLAIN OMELETTE  
TOY EXAMPLES

Answer: **BONSAI**

## *Optimization Problem*

- *Input: Two sets  $S, T$  of strings*
- *Output: A pattern  $p$  that maximizes the score function  $f(x_p, y_p, |S|, |T|)$ .*

$x_p$  : The num. of strings in  $S$  that  $p$  matches.

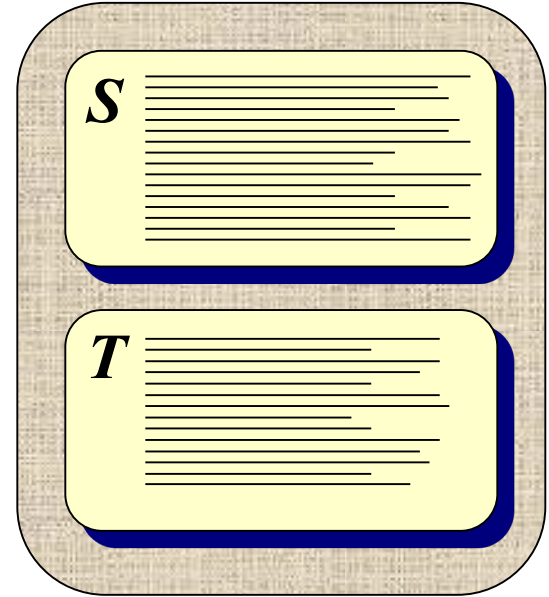
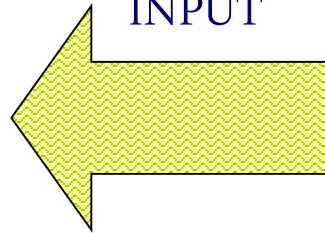
$y_p$  : The num. of strings in  $T$  that  $p$  matches.

*Score function  $f$  expresses the **goodness** of  $p$  in terms of separating the two sets  $S$  and  $T$ .*

# Process of Computation

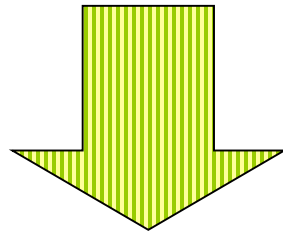


INPUT



computing the “goodness”  
for all possible patterns

OUTPUT



***as fast as possible!!***

***the pattern of best score***

## *Previous Work*

- *BONSAI*  
(discovering best **Substring** pattern), Shimozono et al., 1994
- *Discovering best Subsequence pattern*, Hirao et al., 2000
- *Discovering best Episode pattern*, Hirao et al., 2001
- *Discovering best VLDC pattern*, Inenaga et al., 2002
- *Discovering best Window Accumulated VLDC pattern*,  
Inenaga et al., 2002

*We present efficient algorithms to discover:*

- *the best **Fixed/Variable Length Don't Care Pattern***
- *the best **Approximate FVLDC Pattern***

*The aim is to apply more **expressive** pattern classes to BONSAI*

- *the best **Window Accumulated FVLDC Pattern***
- *the best **Window Accumulated Approx. FVLDC Pattern***

*The aim is to add a more **classificatory** power to the pattern classes*



The **goodness** of pattern  $p$

$$\mathit{good}(p, \mathcal{S}, \mathcal{T}) = f(x_p, y_p, |\mathcal{S}|, |\mathcal{T}|)$$

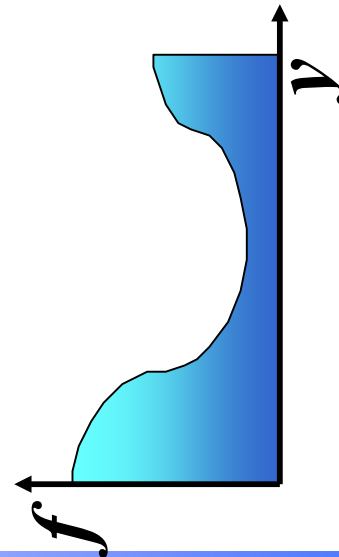
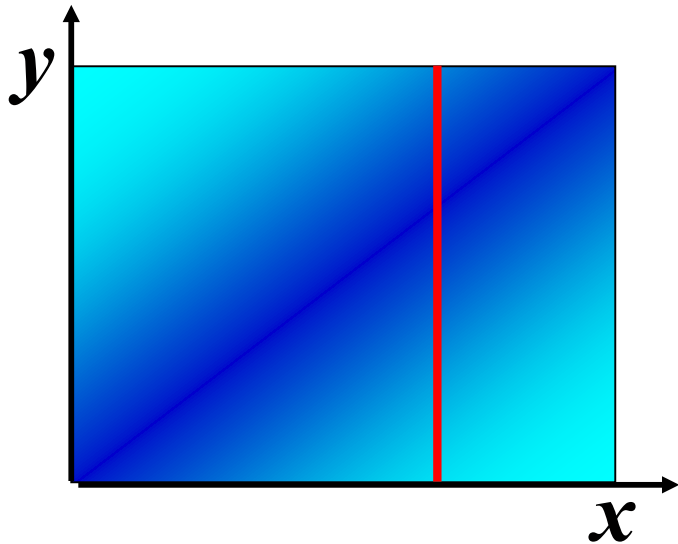
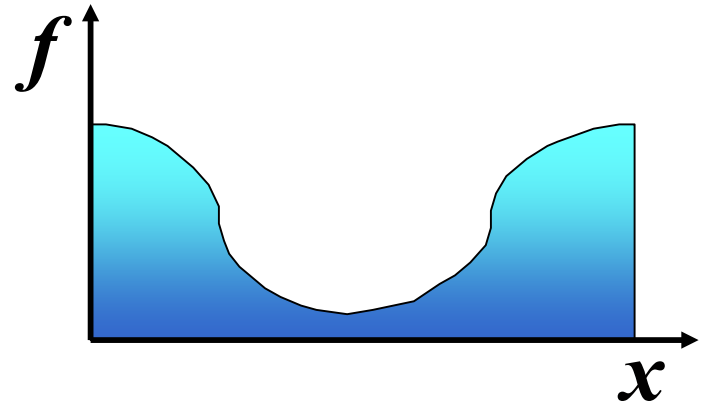
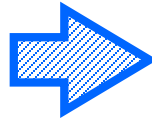
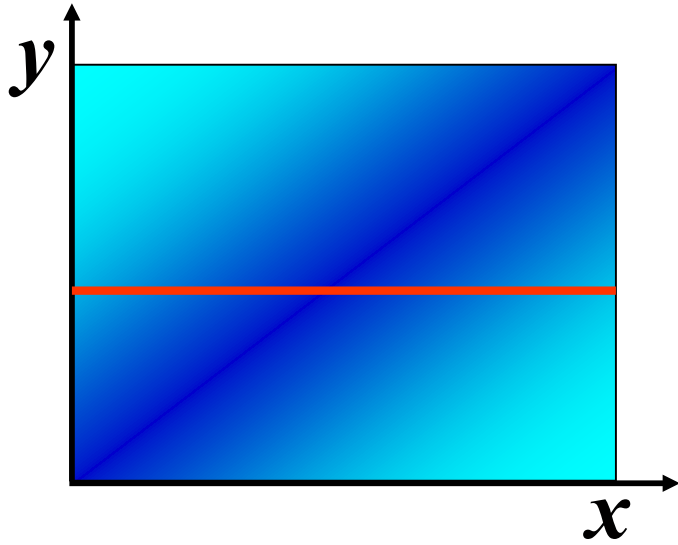
$\mathcal{S}, \mathcal{T}$  : two given sets of strings

$x_p$  : num. of strings in  $\mathcal{S}$  that  $p$  matches

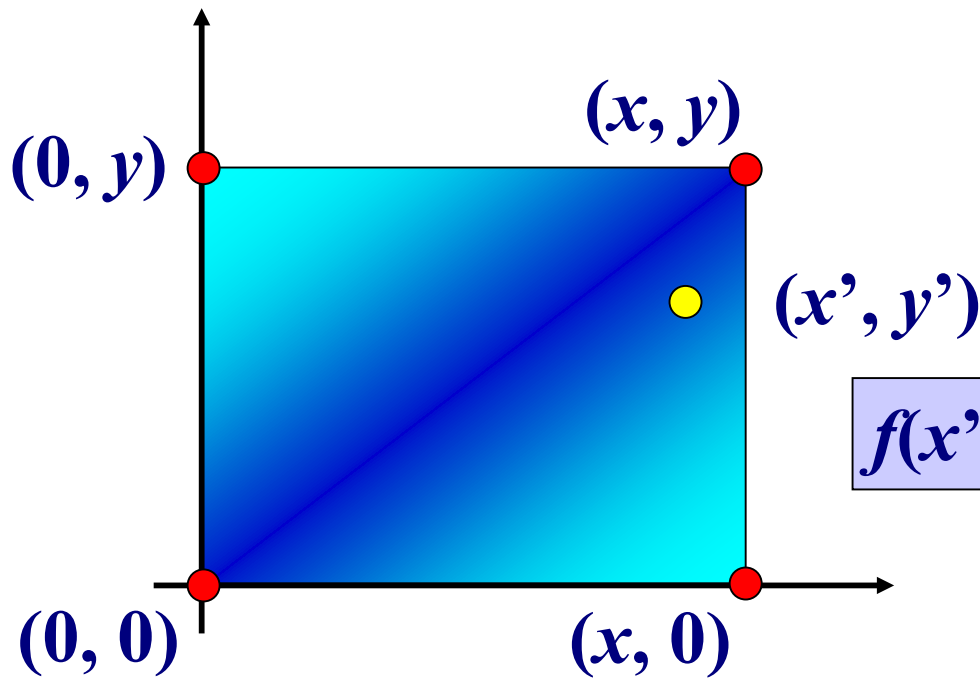
$y_p$  : num. of strings in  $\mathcal{T}$  that  $p$  matches

*If score function  $f$  is **conic**, then we can apply an efficient pruning technique for speeding up the computation.*

# Score Function to be Conic



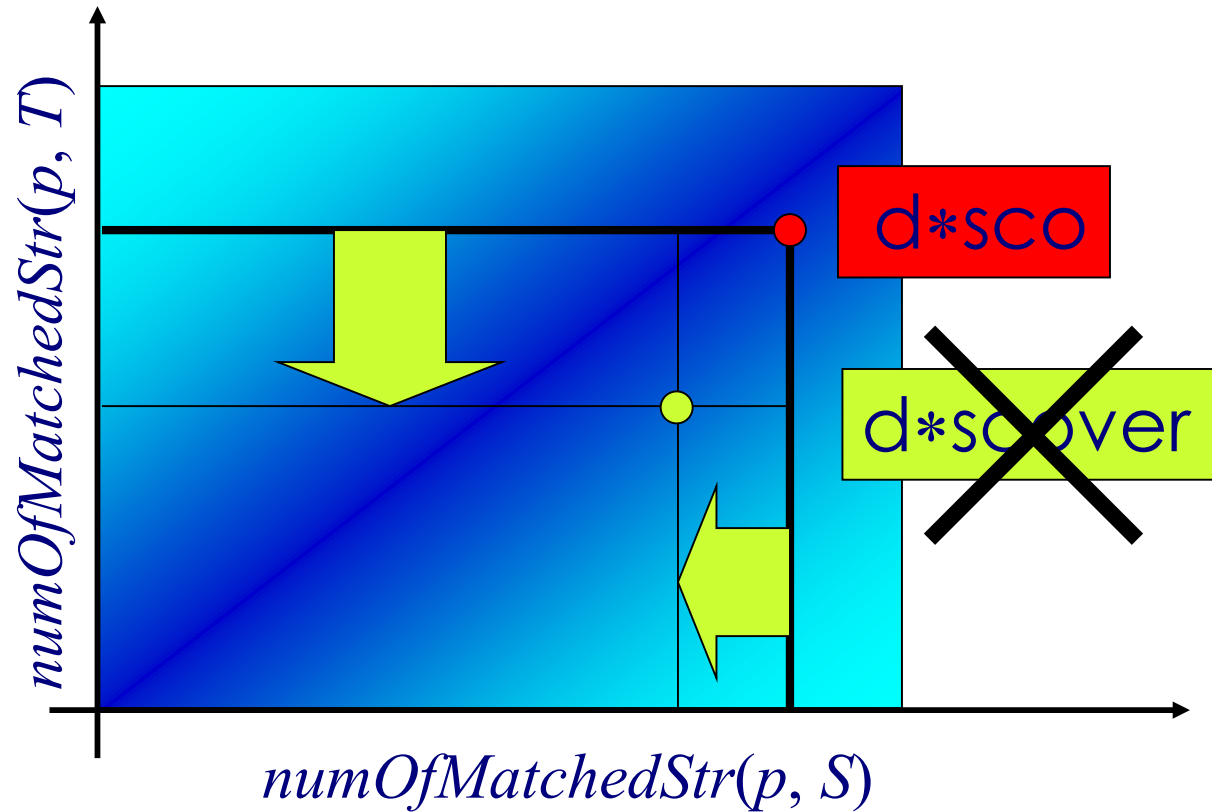
## Conic Function Property



$$f(x', y') \leq \text{upperBound}(x, y)$$

$\text{upperBound}(x, y)$  : the max value on the square  
 $= \max\{f(0, 0), f(x, 0), f(0, y), f(x, y)\}$

# Pruning Technique



~~The goodness of  $d*scover$~~

$\geq$

The *upperBound* of  $d*sco$

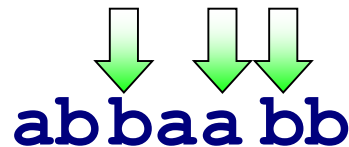
$<$

The current best score

**A *Fixed/Variable Length Don't Care Pattern***

is an element of  $\Pi = (\Sigma \cup \{ \circ, \star \})^*$ , where  $\circ$  matches any character and  $\star$  matches any string.

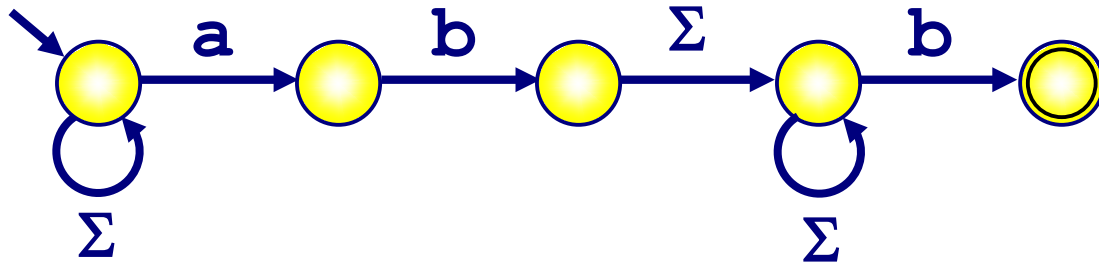
e.g. FVLDC pattern **ab $\circ$ a $\circ$  $\star$ b** matches **abbaabbb**.

  
abbaabbb

## *FVLDC Pattern Matching*

We use an **NFA** that recognizes the language of a given FVLDC pattern  $p$ . The num. of states is  $m+1$ , where  $m$  is the num. of constants and O's in  $p$ .

$$p = \star abO\star b$$



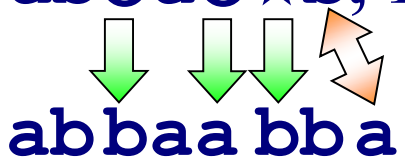
Using the **bit-parallel technique**, we can do matching for  $p$  in  $O(m|\Sigma|)$  preprocessing time and  $O(n)$  running time .

## Approximate FVLDC Pattern

An **Approximate FVLDC Pattern** is an element of  $\Pi \times \mathbb{N}$ , where  $\mathbb{N}$  is the set of non-negative integers.

Approx. FVLDC pattern  $\langle p, k \rangle$  is said to match a string  $w$  within distance  $k$  if the **Hamming Distance** between  $p$  and  $w$  is within  $k$ .

e.g. Approx. FVLDC pattern  $\langle \text{ab} \circ \text{a} \circ \star \text{b}, 1 \rangle$   
matches **abbaabba**.



The diagram illustrates the Hamming distance between the pattern  $\text{ab} \circ \text{a} \circ \star \text{b}$  and the string **abbaabba**. The pattern has three wildcards: a circle  $\circ$  at the 3rd position, a circle  $\circ$  at the 5th position, and a star  $\star$  at the 7th position. The string is **abbaabba**. Green arrows point from the 'a' at position 1 to 'a' at position 1, 'b' at position 2 to 'b' at position 2, and 'a' at position 4 to 'a' at position 4. An orange arrow points from the 'b' at position 6 to 'b' at position 6, but it is dashed, indicating a mismatch. The star  $\star$  at position 7 matches the 'b' at position 7.

## *Approx. FVLDC Pattern Matching*

*We use an **NFA** that recognizes the language of a given approx. FVLDC pattern  $\langle p, k \rangle$ .*

*The NFA has  $(m+1)(k+1)$  states, but  $(m-k+1)(k+1)$  bits are actually enough.*

*If  $(m-k+1)(k+1)$  is not larger than the computer word length, our bit-parallel algorithm runs in  $O(|n|)$  time after  $O(m|\Sigma|)$ -time preprocessing for  $p$ .*

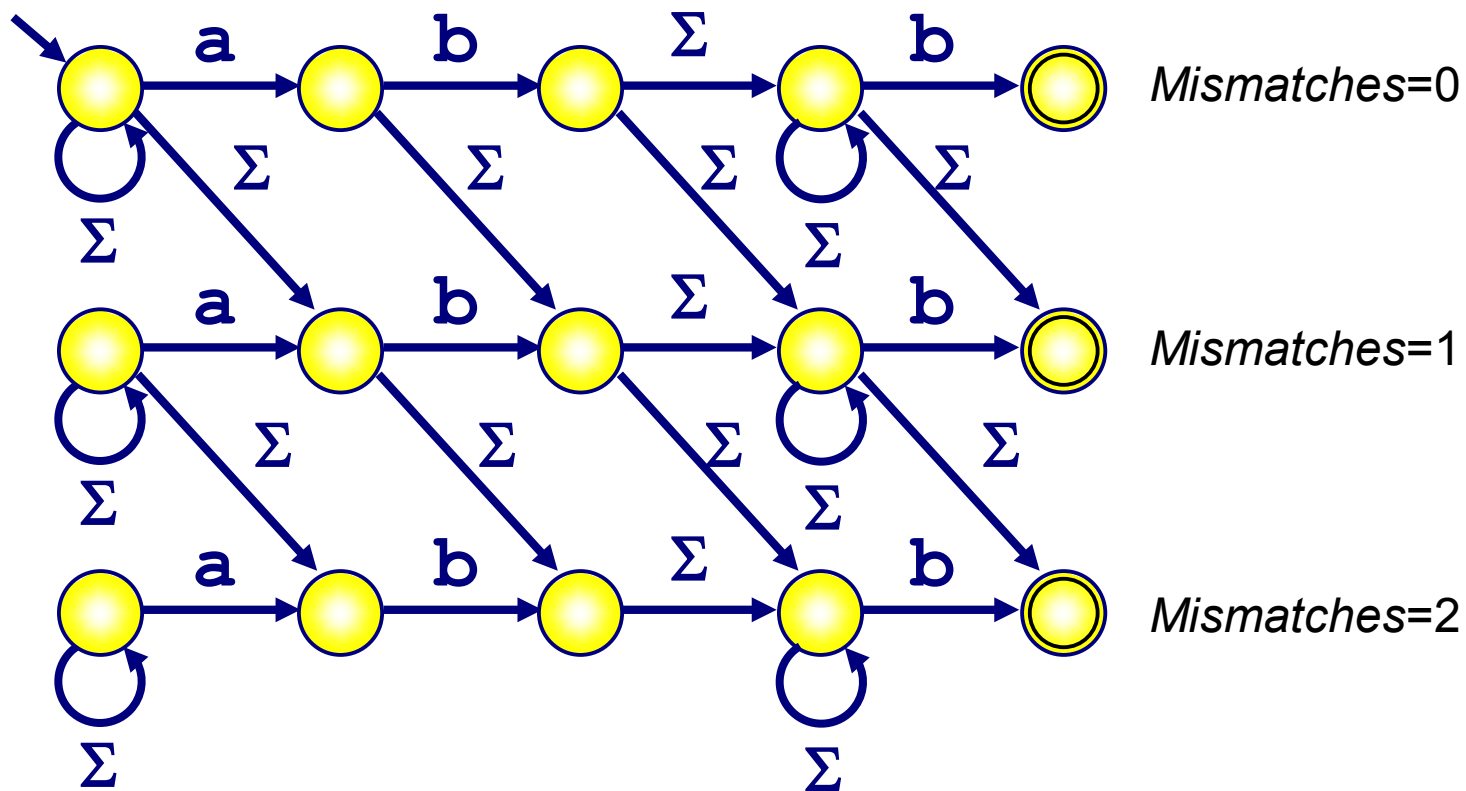


# Approx. FVLDC Pattern Matching

$p = \langle \star abO\star b, 2 \rangle$

$m=4$

$k=2$

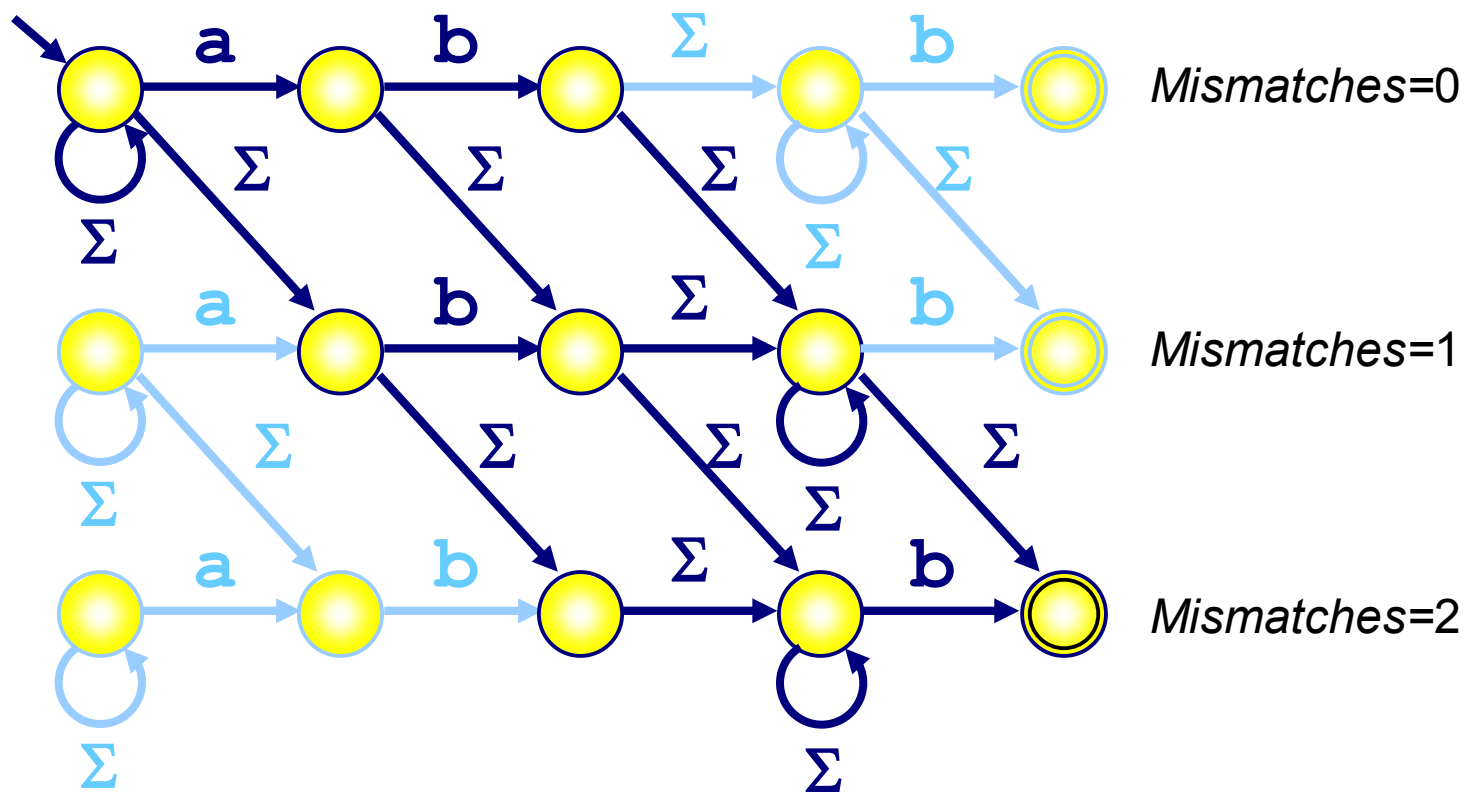


The NFA has  $(m+1)(k+1)$  states.

# Approx. FVLDC Pattern Matching

$p = \langle \star abO\star b, 2 \rangle$

$m=4$   
 $k=2$



Only  $(m-k+1)(k+1)$  states are necessary.

## More Classificatory Pattern Class

$p = \star dO\star scO\star very\star$

any pattern similar  
to "discovery"?

$w = fh$ **di**hertlhglehgliogfrg  
xawpolmkhhjqirvnbotuhxxxxr  
ylnv**hb**tr**is**co**v**bgneinmvgerig  
eooitrnrnvevroigreintnnvoi  
woireohirlneroi**very**niritro  
eitruijnbrymxbairive

They're far apart!!

*Bound the length of occurrence of  $p$  by a **window size  $h$** .*

$p = \star \text{dO} \star \text{scO} \star \text{very} \star$



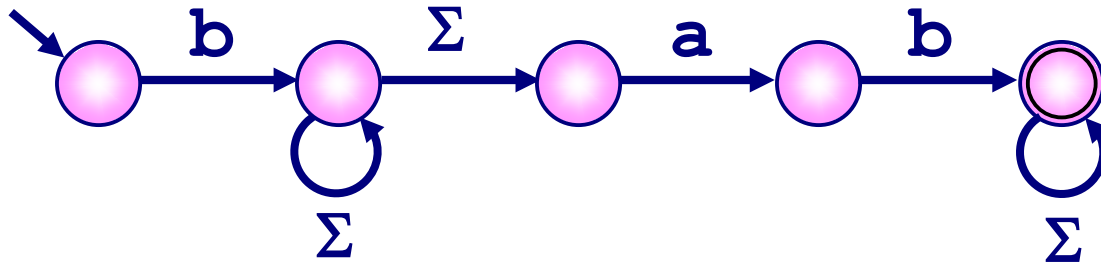
*$h$*

*This way we can get rid of redundant matches, and obtain better classification!*

## Window Accumulated Pattern Matching

We use two **NFAs** each recognizes the language of either a given FVLDC pattern  $p$  or its reversal.

$$p^{\text{rev}} = \mathbf{b} \star \mathbf{O} \mathbf{a} \mathbf{b} \star$$



Using the **bit-parallel technique**, we can do pattern matching for  $\langle p, h \rangle$  in  $O(m|\Sigma|)$  preprocessing time and in  $O(n^2)$  running time .

Same for Win-Acc. approx. FVLDC patterns.

## *Experimental Environment*

*Machine: Alpha Station XP1000*

*CPU: Alpha21264 processor of 667MHz*

*OS: Tru64 Unix OS V4.0F*

*Datasets:*

*(1) completely random data*

*(2) VLDC pattern embedded data*

*(3) FVLDC pattern embedded data*

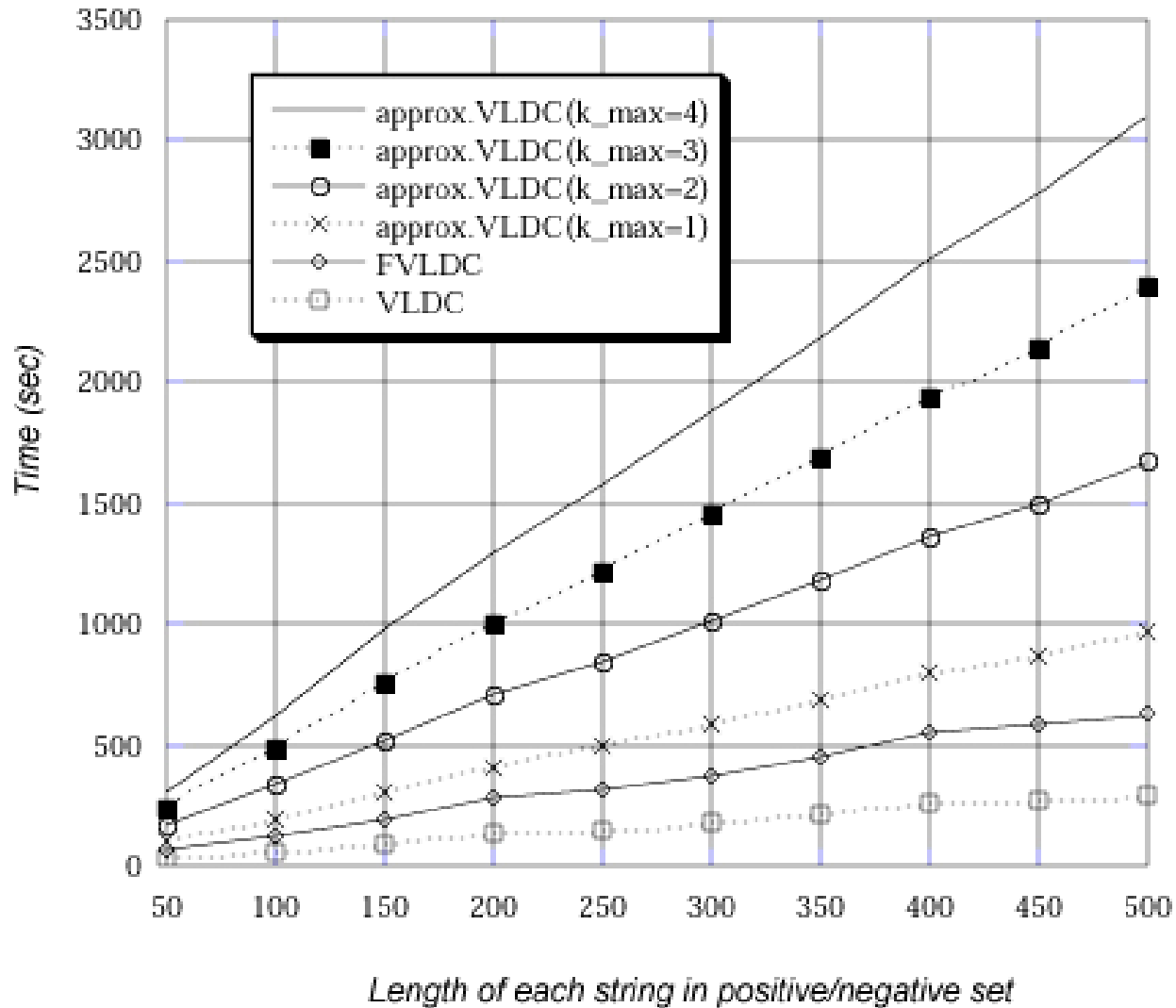
*(4) 2-approx. VLDC pattern embedded data*

*(5) window-accumulated 2-approx.*

*VLDC pattern embedded data*

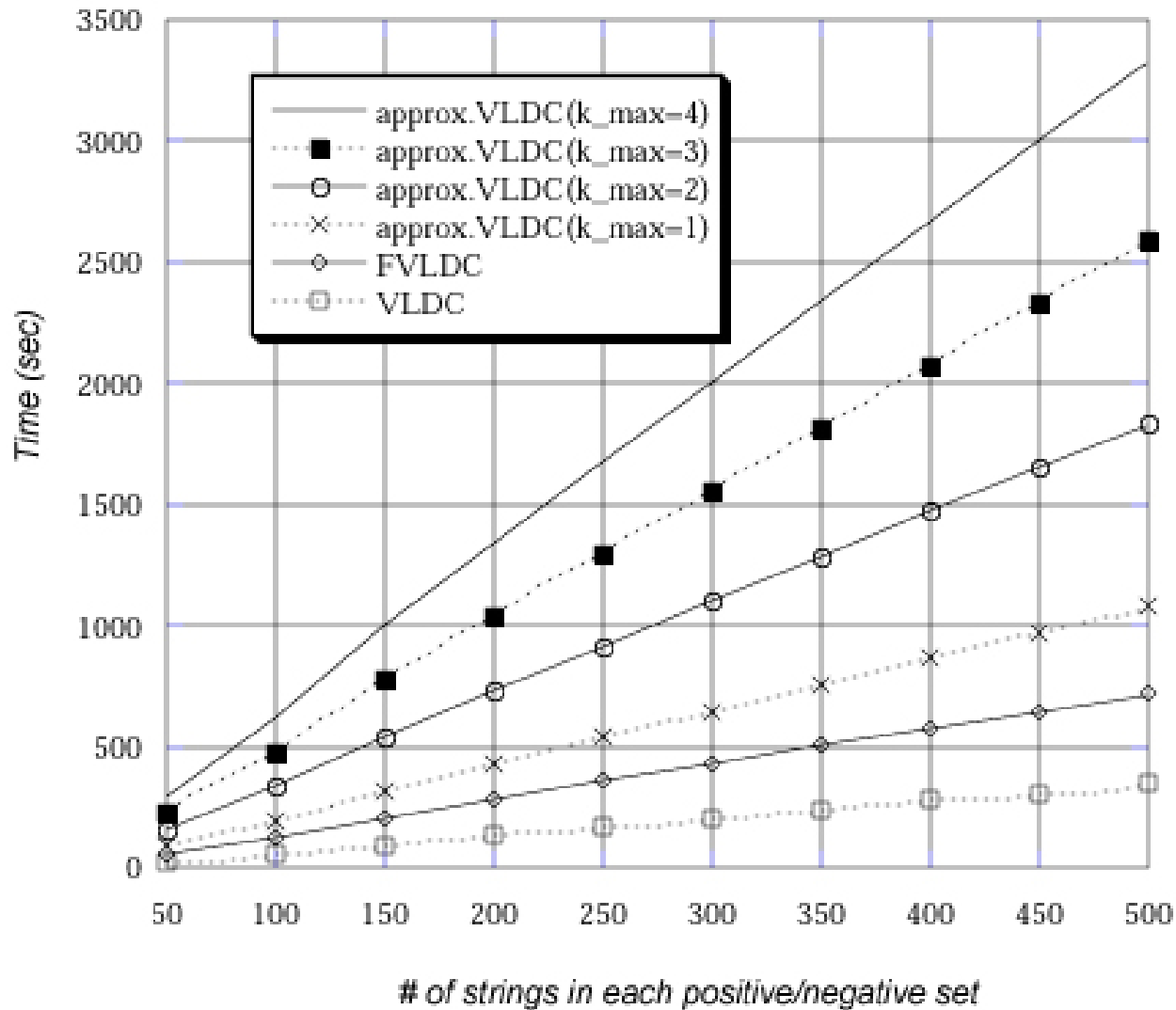
# Experimental Result 1

Execution time for 100 positive/100 negative completely random data of length 100  
(maximum pattern size=6)



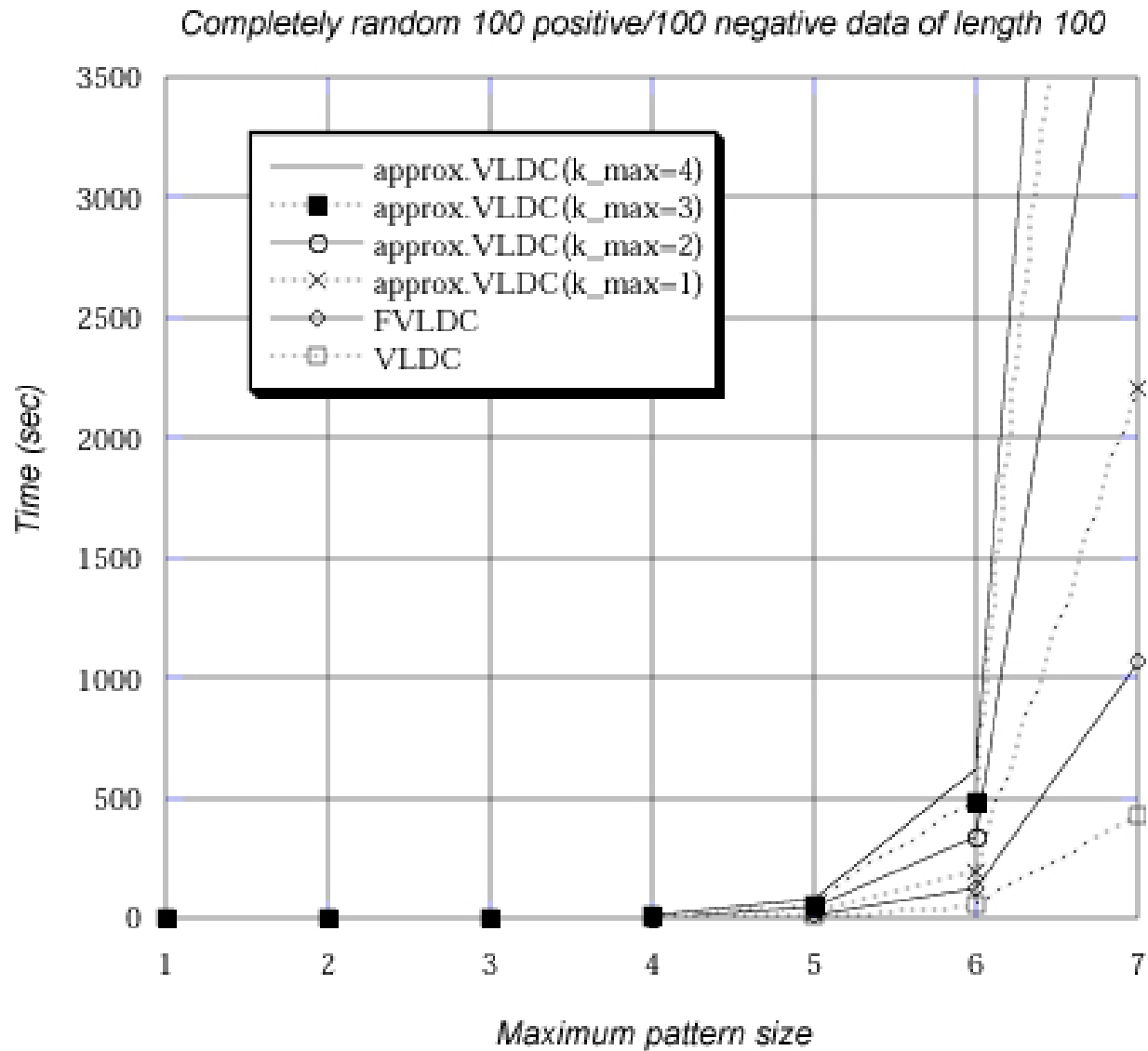
## Experimental Result 2

Execution time for completely random set of length 100 (maximum pattern size=6)





# Experimental Result 3



## *Experimental Result 4*

<i>pattern class</i>	<i>dataset</i>					
	(1)	(2)	(3)	(4)	(5)	(5)
<i>VLDC</i>	423	109	236	182	224	(554)
<i>FVLDC</i>	1068	331	645	514	623	(1579)
<i>approx. VLDC (<math>k_{max}=1</math>)</i>	2203	725	1088	853	1026	(1820)
<i>approx. VLDC (<math>k_{max}=2</math>)</i>	4569	1660	2185	1790	2035	(3558)
<i>approx. VLDC (<math>k_{max}=3</math>)</i>	6973	2739	3324	2868	3146	(5679)
<i>approx. VLDC (<math>k_{max}=4</math>)</i>	9396	3880	4492	4008	4304	(8377)

*Execution times (in seconds) for different pattern classes:*

*The maximum pattern length was set to 7.*

*Execution time for each window-accumulated version with dataset (5) is shown in parentheses.*