User Authentication through Keystroke Dynamics

Johannes Luig

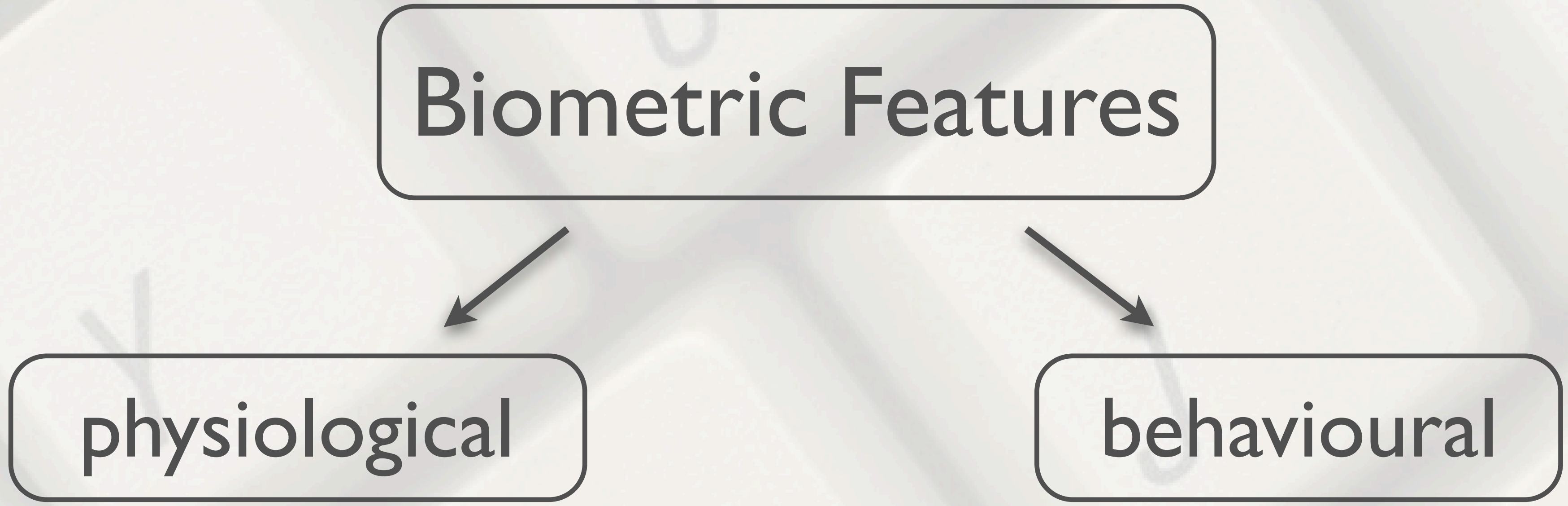
Overview

- Introduction
- Measurable Characteristics
- How to measure „Similarity"?
- User Authentication
- Performance

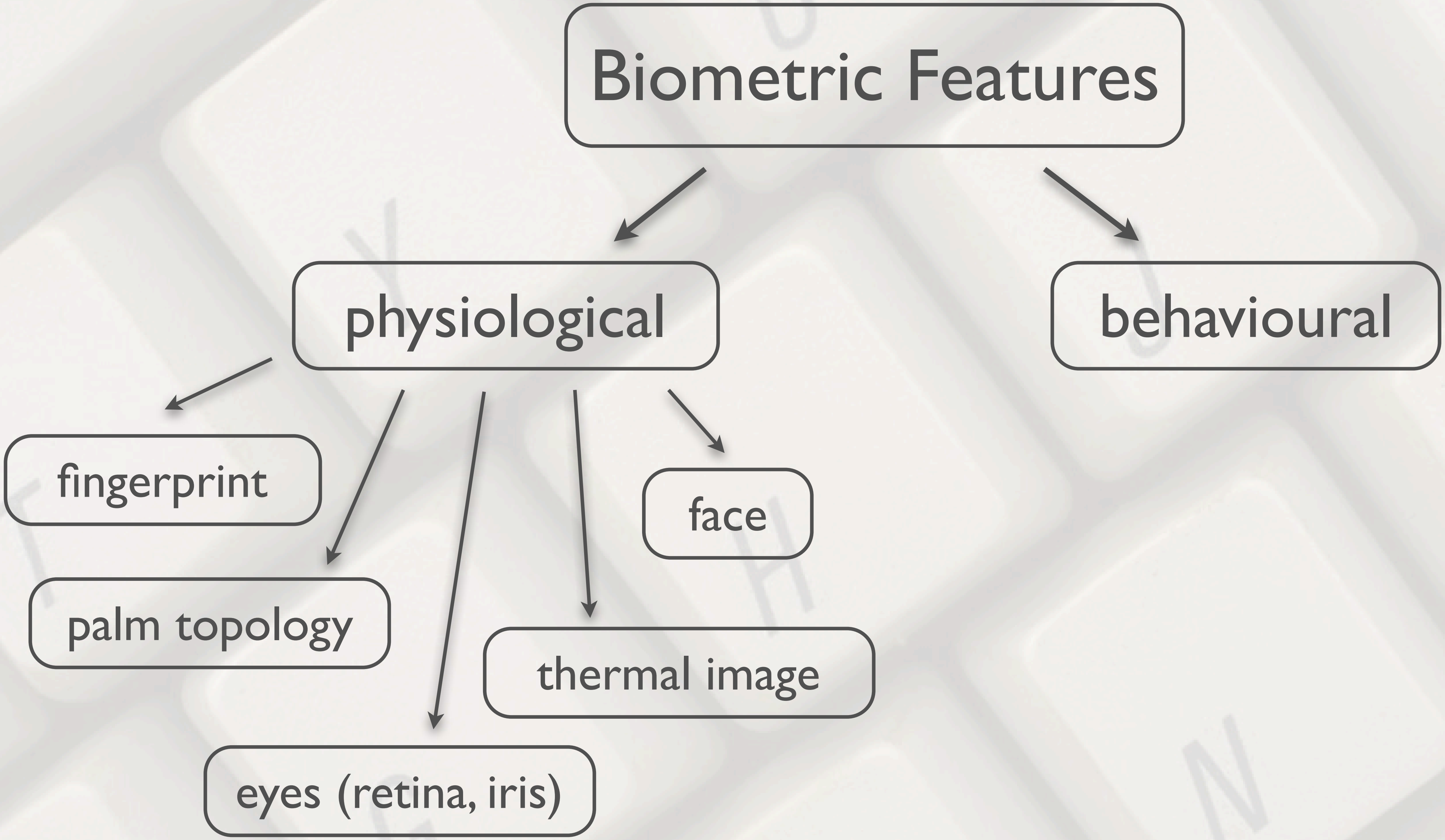
Introduction

Biometric Features

Introduction



Introduction



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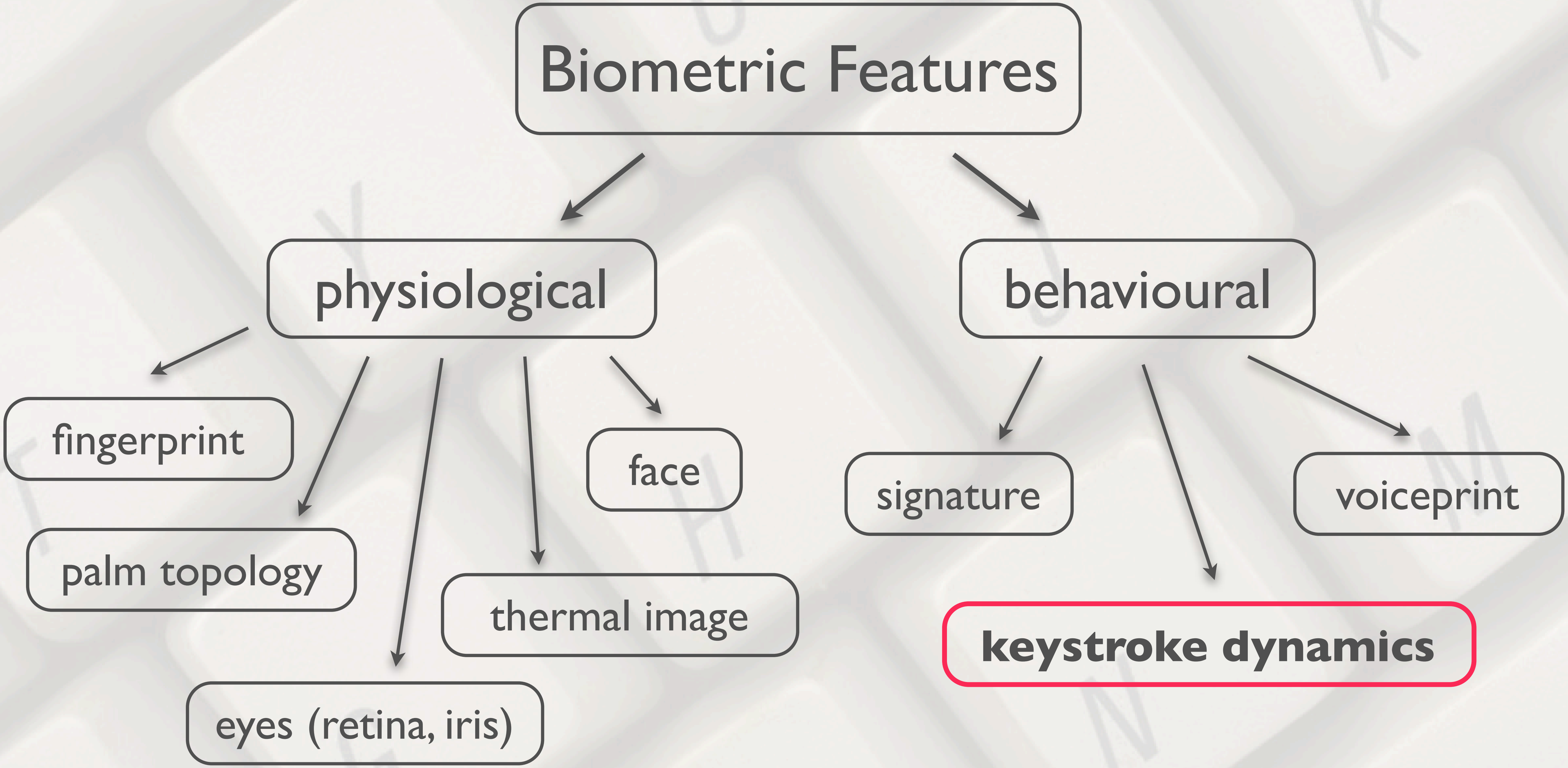

Introduction

- Motivation:
  - Typing on keyboard does not produce continuous stream of non-stop data, but distinctive patterns
  - Human actions are predictible in the performance of repetitive and routine tasks
  - No specific (expensive) tools needed
  - Method is reasonable (even „hidden check“ possible)

Measurable Characteristics

- Hold Time
- Interkey Time
- Press/Release Latency

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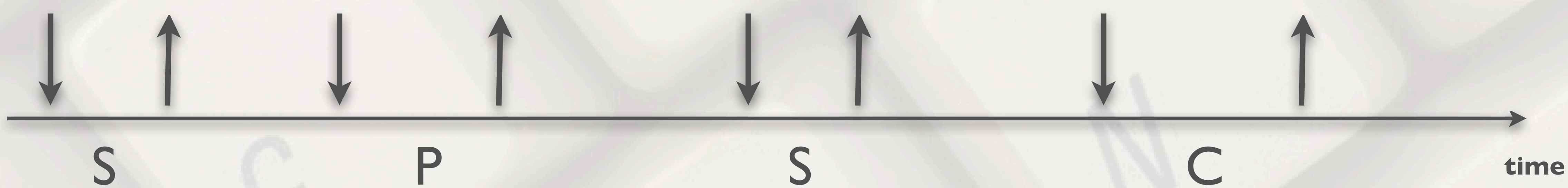

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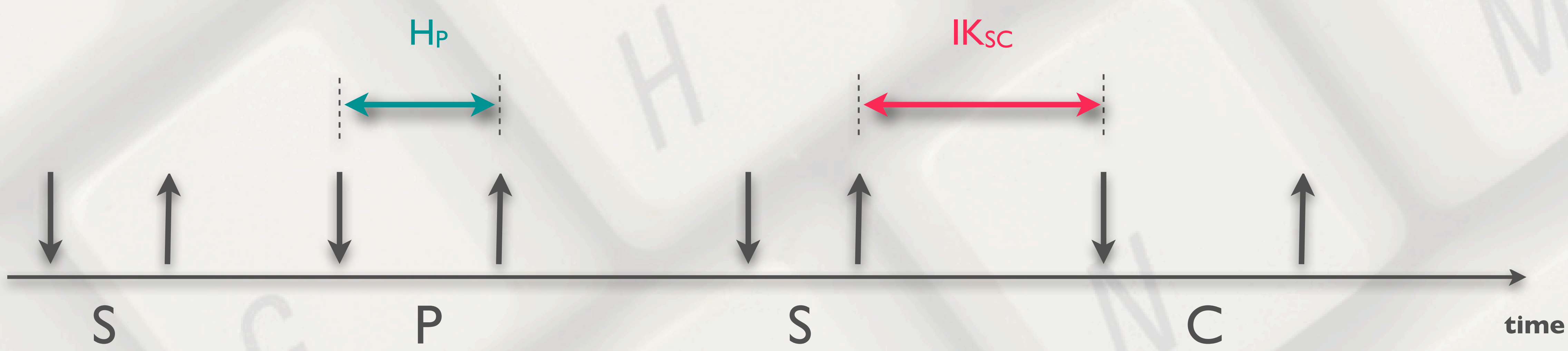

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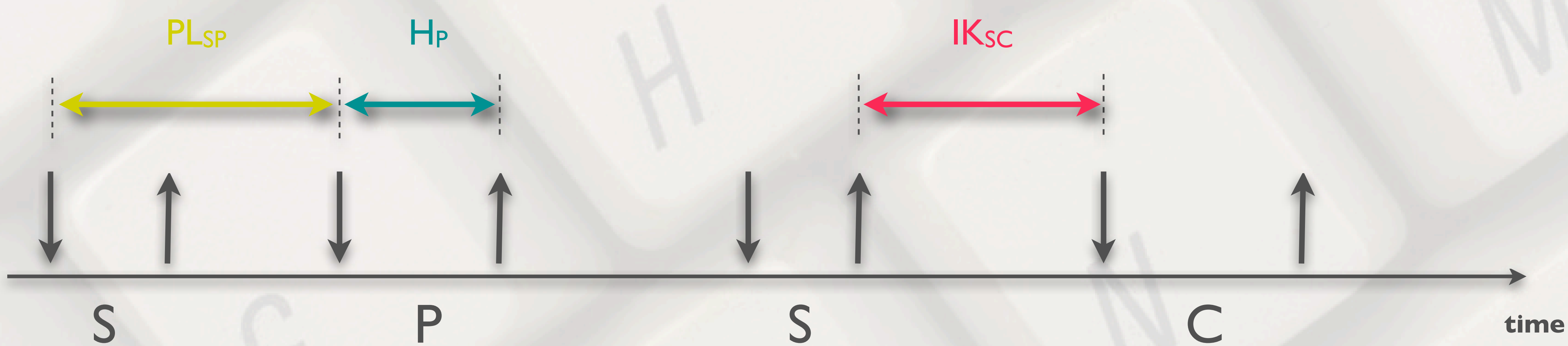

Measurable Characteristics

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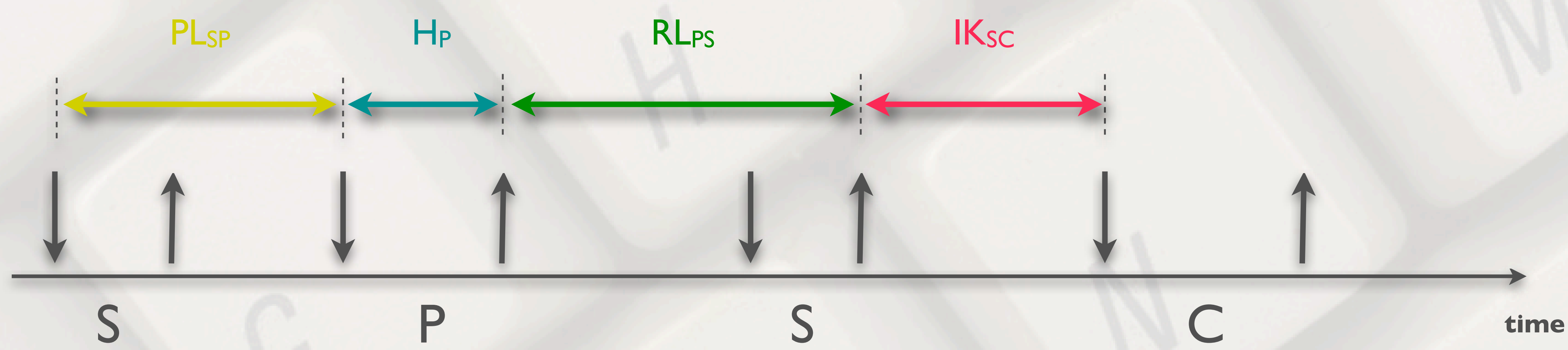
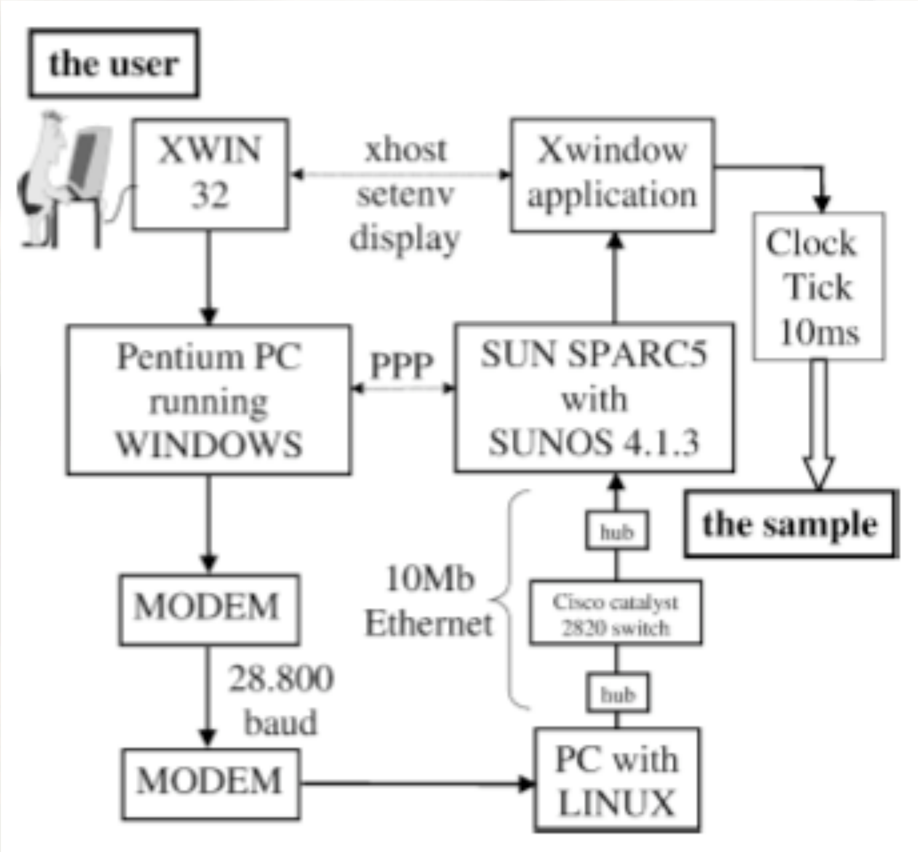


Measurable Characteristics

- Timing
  - Internal CPU clock
    - 8253 timer in IBM-compatible computers
    - BIOS microsecond timing function

Measurable Characteristics

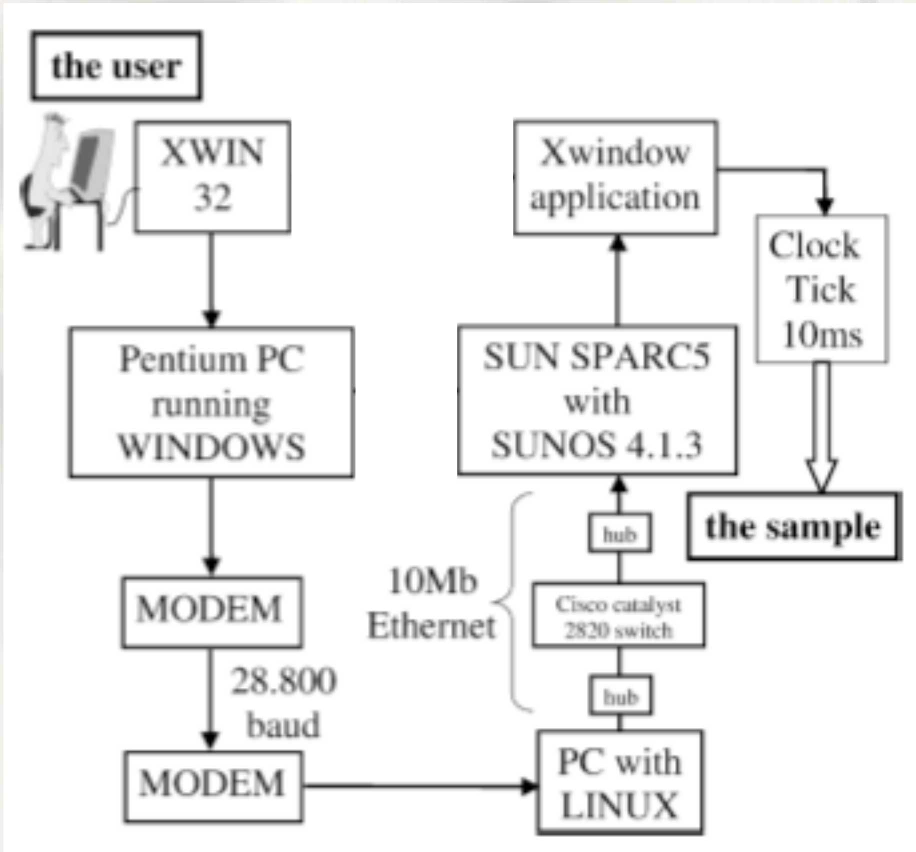
- Timing
  - Example: simulation of remote situation



from Bergadano et al.:
„User Authentication through Keystroke Dynamics“

Measurable Characteristics

- Timing
  - <u>Example:</u> simulation of remote situation



from Bergadano et al.:
„User Authentication through Keystroke Dynamics“

How to measure „Similarity“? (I)

- General approach:
  - Measure hold and/or interkey times
  - Measurement data = vectors in vector space
  - Identify typing person using traditional pattern recognition techniques or Neural Network paradigms

How to measure „Similarity“? (I)

- Pattern recognition techniques include:
  - **k-Means Clustering**
  - Cosine Measure
  - Minimum Distance
  - Bayes‘ Rule
  - Potential Function

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- cluster data into k partitions
- try to find centers of „natural“ clusters
- minimize intra-cluster variance (squared error):

$$V = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2$$

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- cosine of angle between two feature vectors:

$$s^{(C)}(\mathbf{x}_a, \mathbf{x}_b) = \frac{\mathbf{x}_a^{\dagger}\mathbf{x}_b}{\|\mathbf{x}_a\|_2 \cdot \|\mathbf{x}_b\|_2}$$

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- euclidean distance:

$$\sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$$

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- relates conditional and marginal probability distributions of random variables to each other

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

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  - **Potential Function**

- A vector v has a potential function F, if

  grad(F) = v

How to measure „Similarity“? (I)

- Neural Network paradigms include:
  - **Backpropagation**
  - Fuzzy ARTMAP
  - Radial Basis Functions
  - Learning Vector Quantization
  - (Hybrid) Sum-of-Products

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- feed-forward multilayer network
- input for each unit = sum of outputs of previous units
- „gradient descent algorithm“ (weigths are moved along negative gradient)

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- supervised Neural Network with very fast convergence
- comparable to Multilayer Perceptron

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- real-valued functions, whose values depend only on the distance from center
- popular: Gaussians

$$y(\mathbf{x}) = \sum_{i=1}^{N} w_i \, \phi(||\mathbf{x} - \mathbf{c}_i||),$$

How to measure „Similarity“? (I)

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- Neural Network paradigms include:
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  - **Learning Vector Quant.**
  - (Hybrid) Sum-of-Products

- supervised competetive network
- goal: find some kind of structure in data by determining in which way it is clustered

How to measure „Similarity“? (1)

- Neural Network paradigms include:
  - Backpropagation
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  - **(Hybrid) Sum-of-Products**

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- Neural Network paradigms include:
  - Backpropagation
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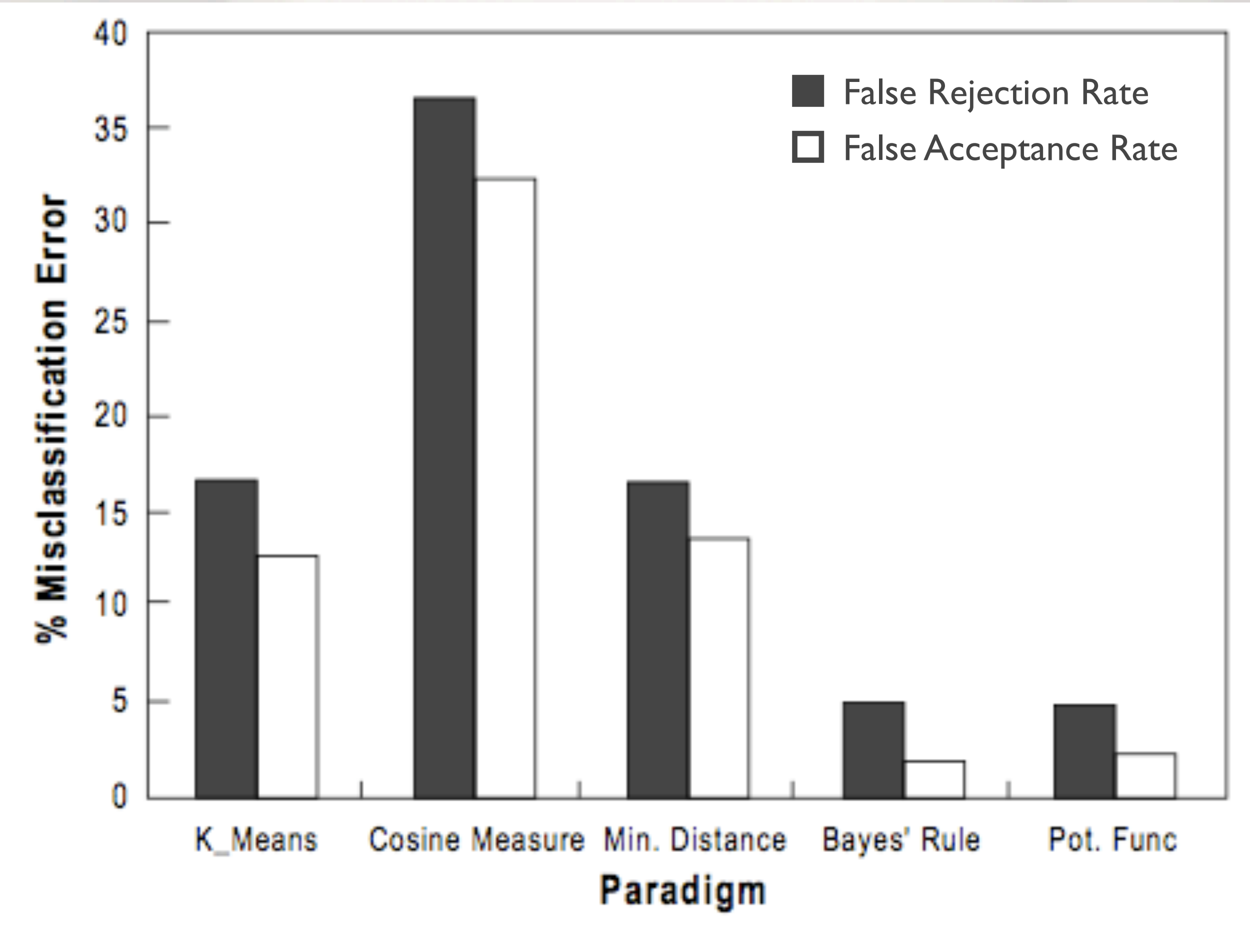
  - Learning Vector Quantization
  - **(Hybrid) Sum-of-Products**

- backpropagation network with modified layer connections
- input for each unit = product of outputs of previous unit with weighting factor

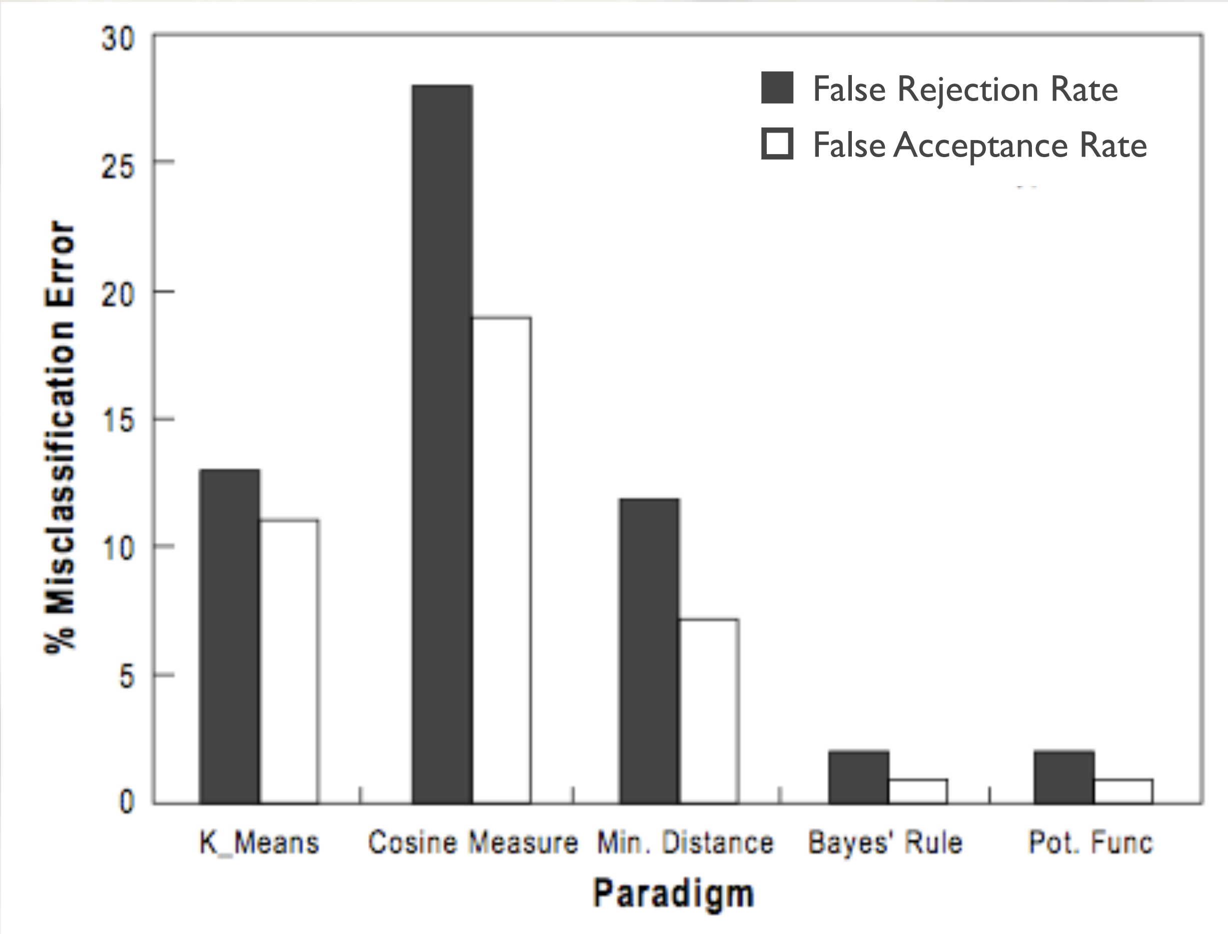
Performance

- Pattern Recognition Techniques

from Obaidat/Sadoun:
„Keystroke Dynamics based Authentication“



Classification based on **Interkey Times**



Classification based on **Hold Times**

Performance

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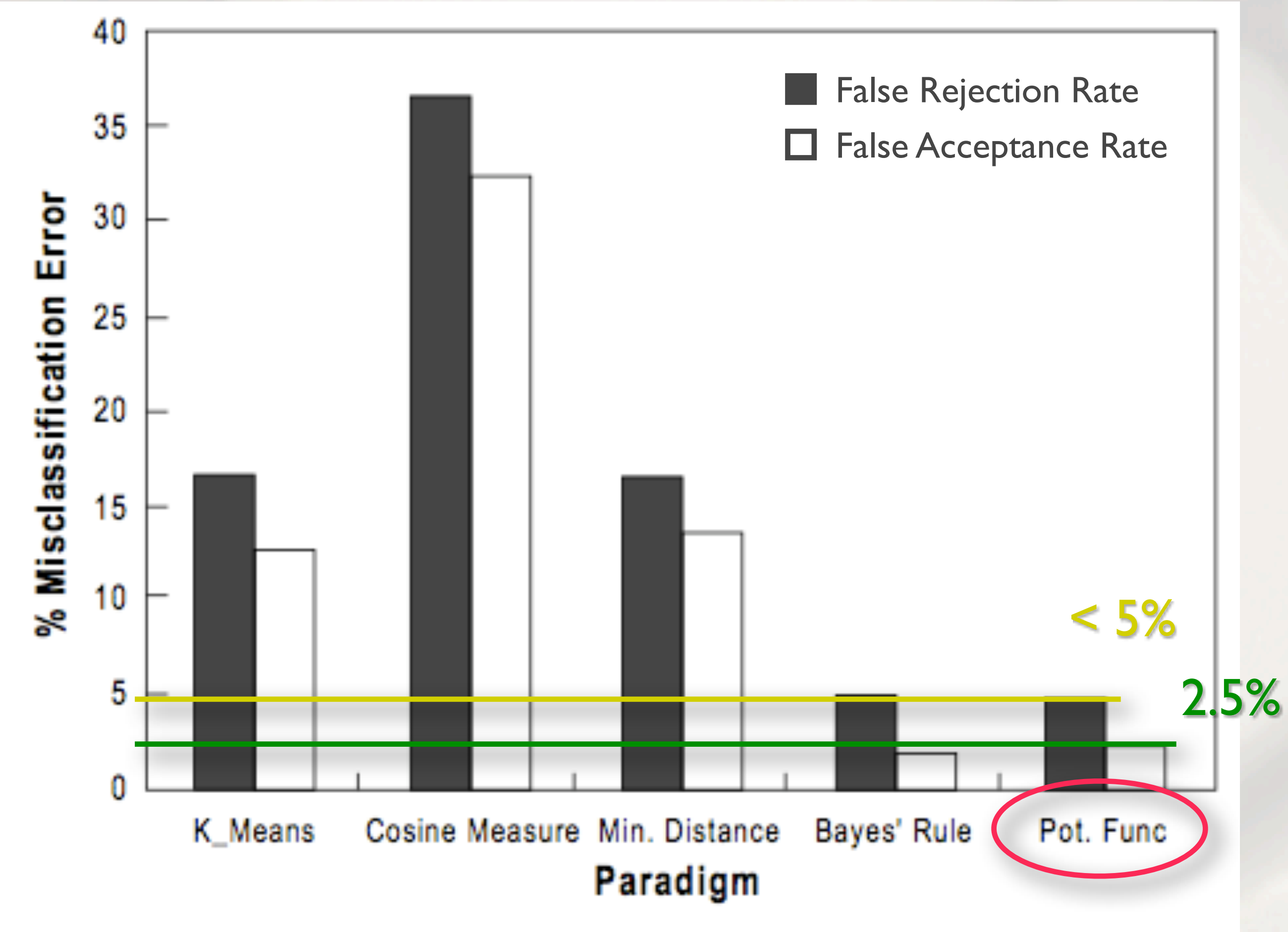

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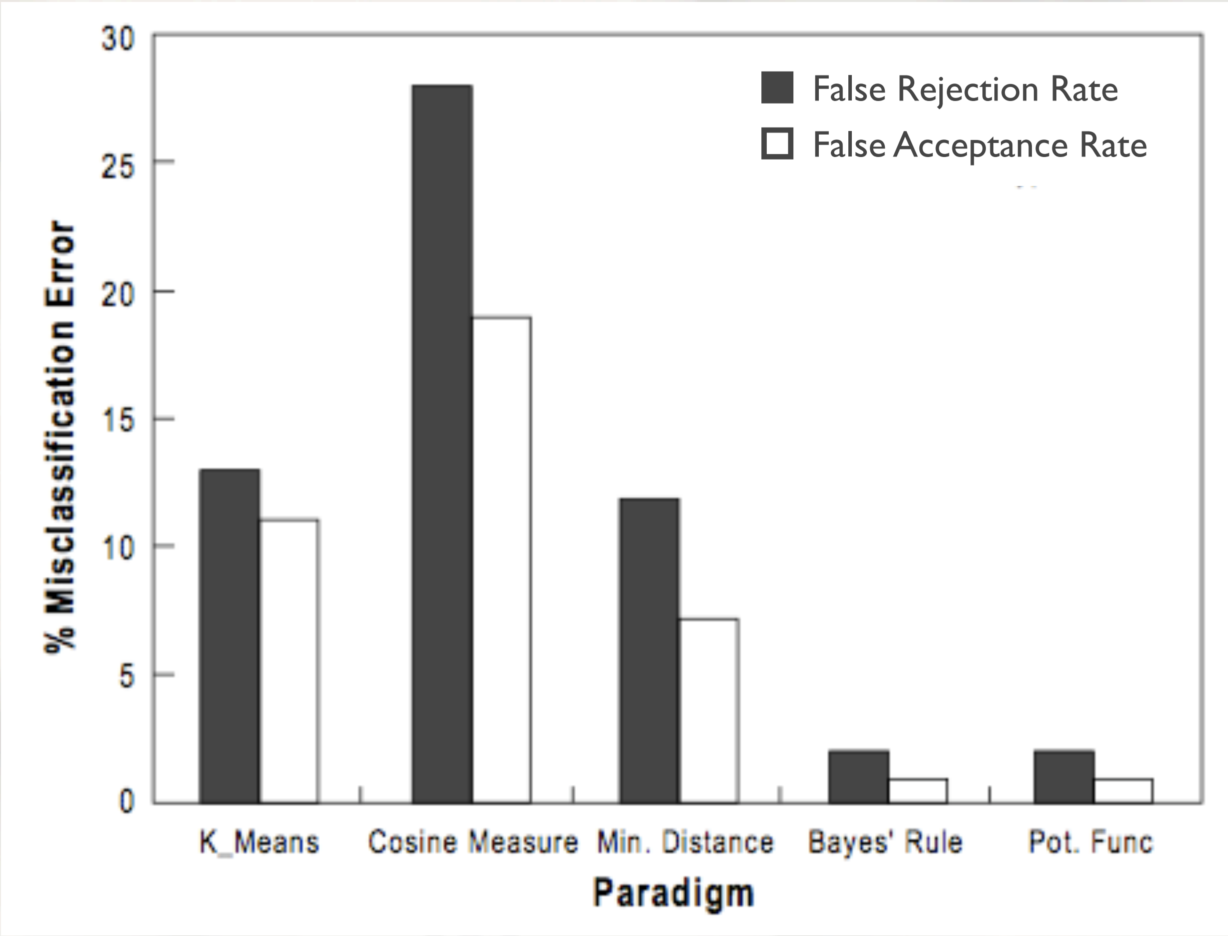

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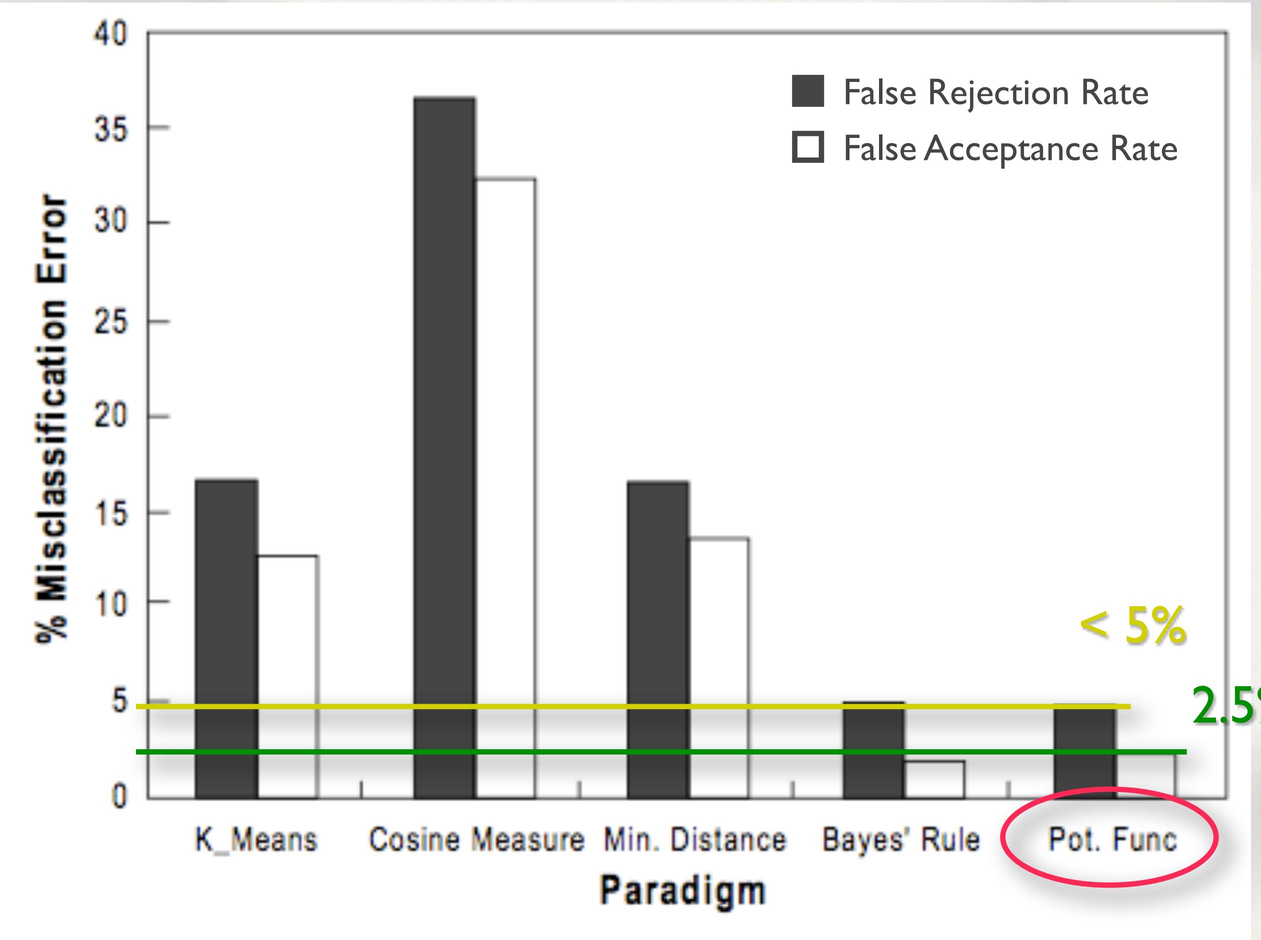

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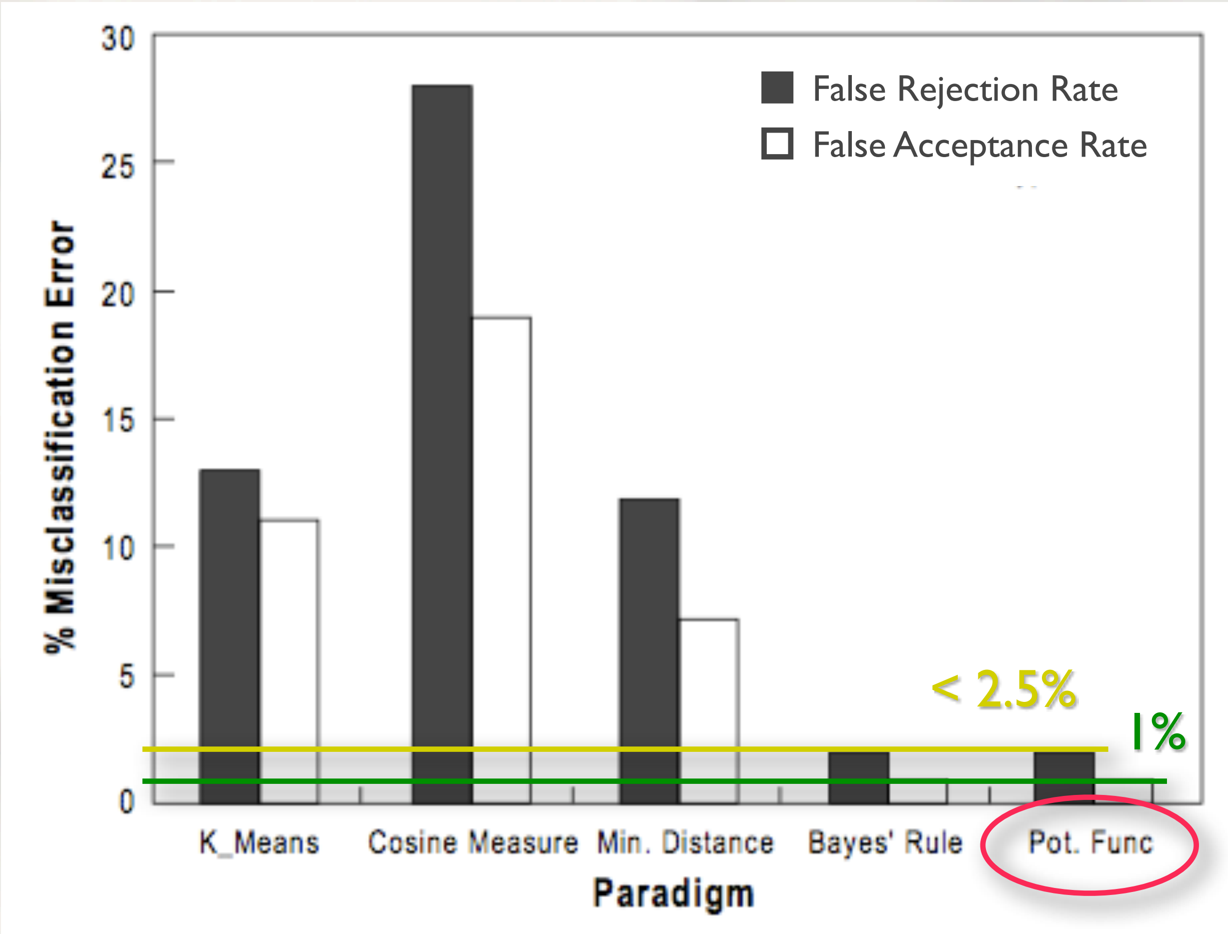

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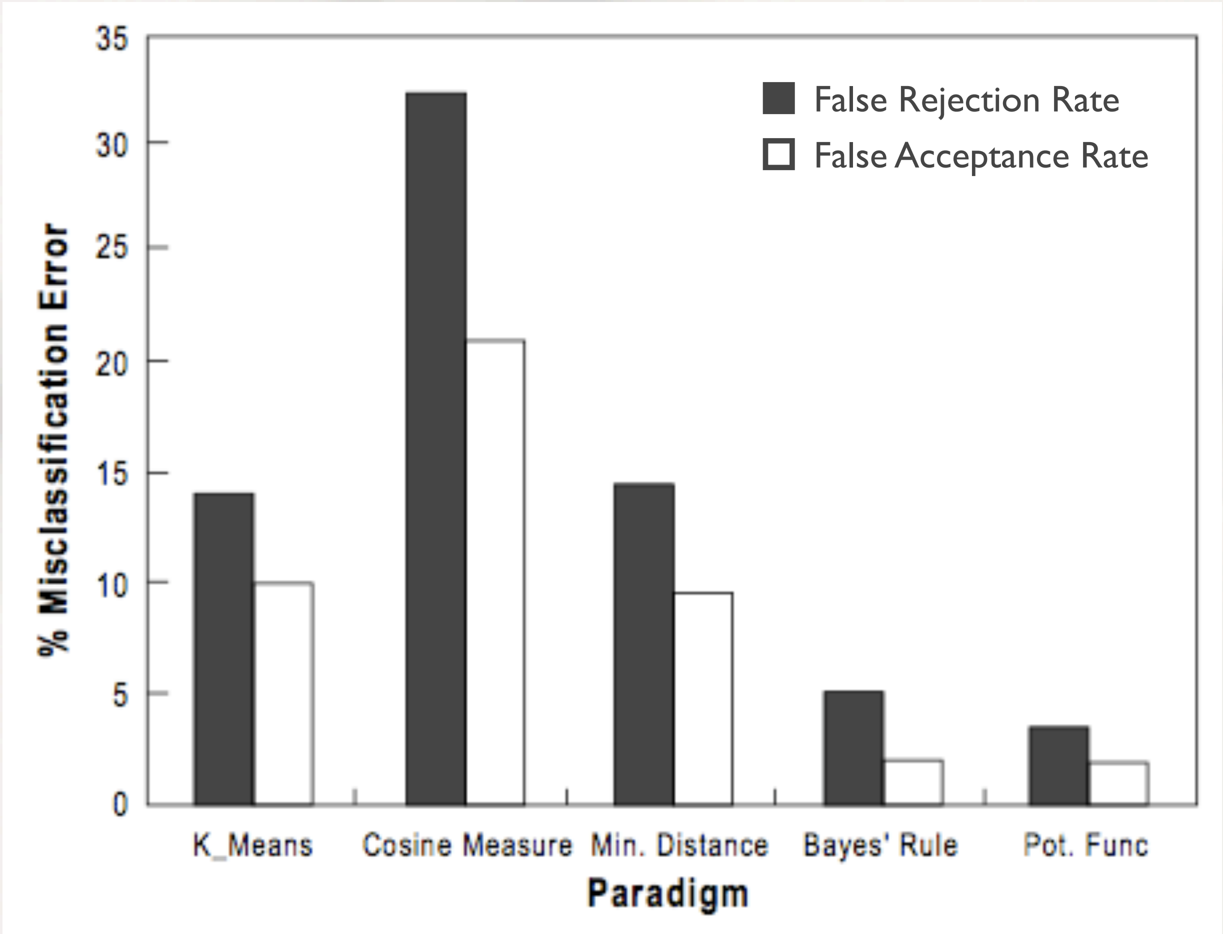

Classification based on **Hold and Interkey Times**

Performance

- Pattern Recognition Techniques

from Obaidat/Sadoun:
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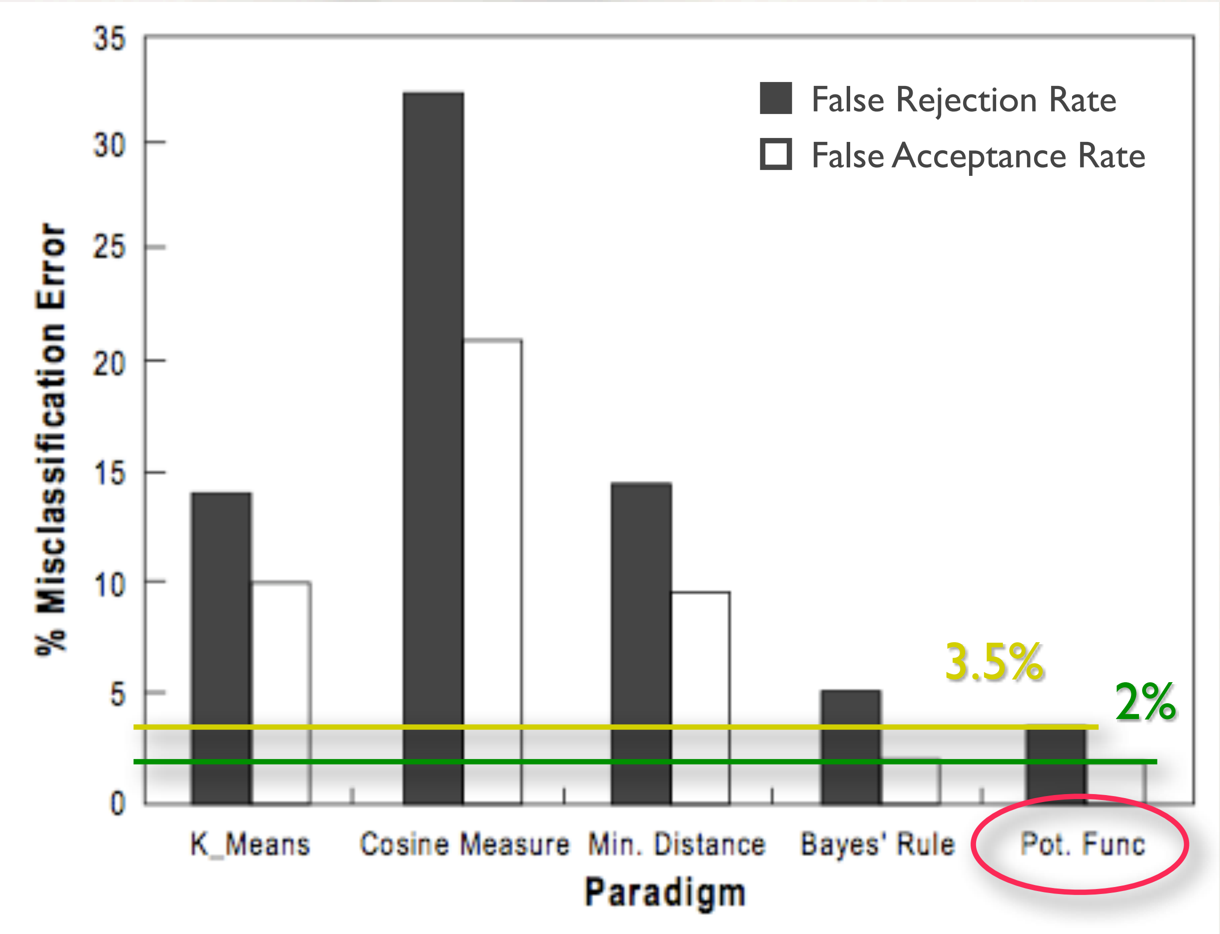

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- Neural Networks

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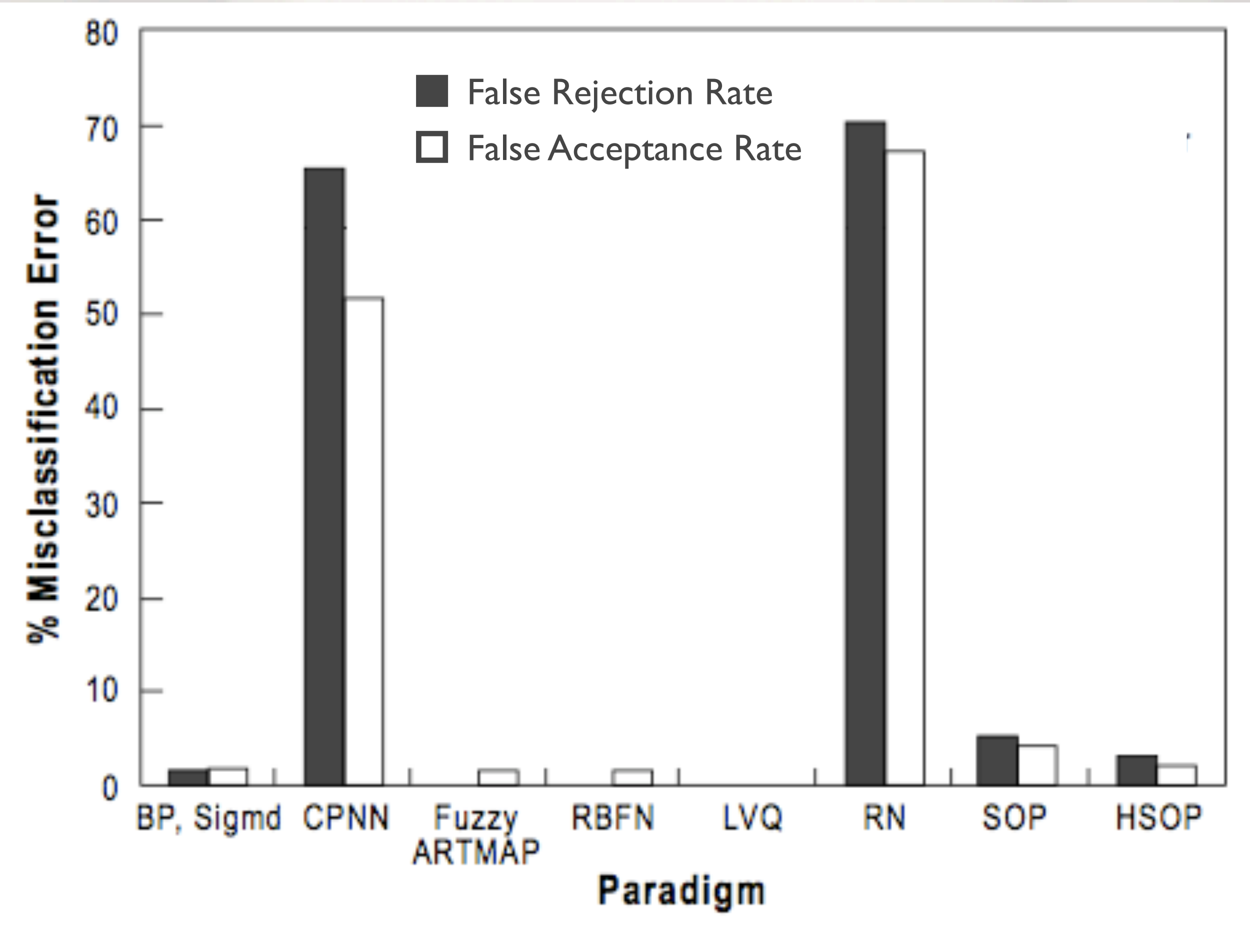

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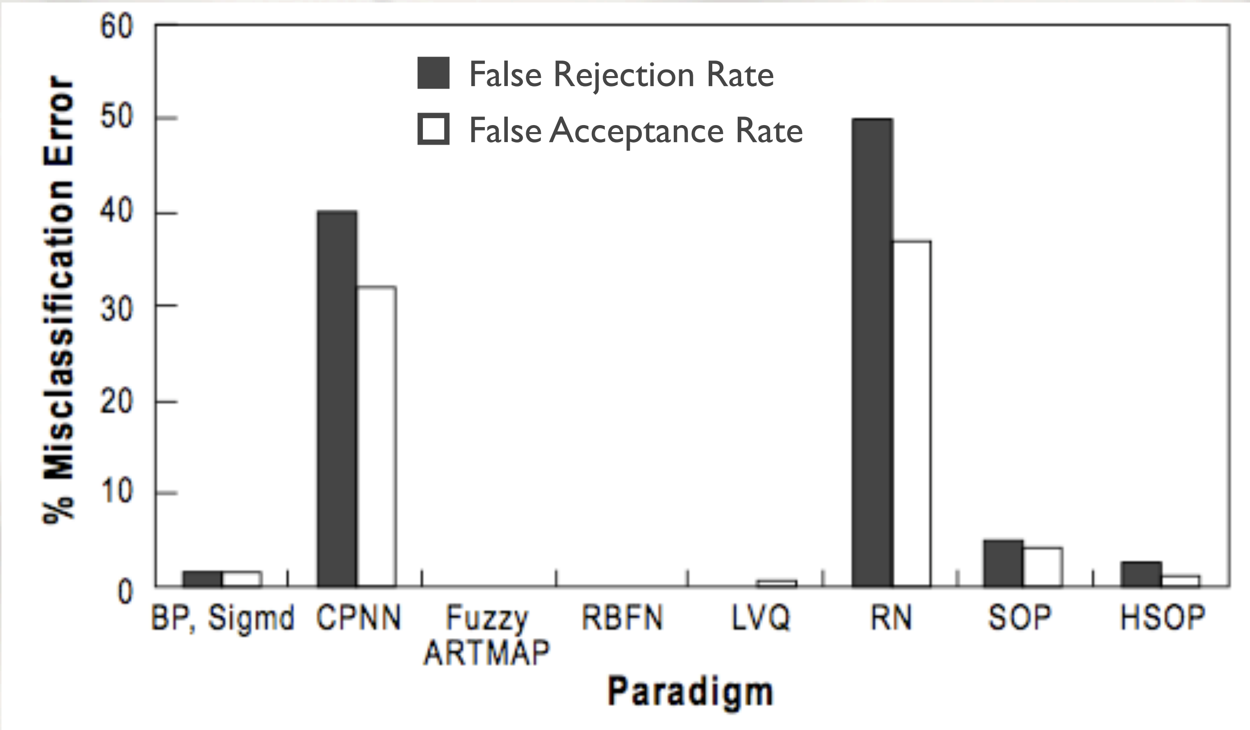

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Performance

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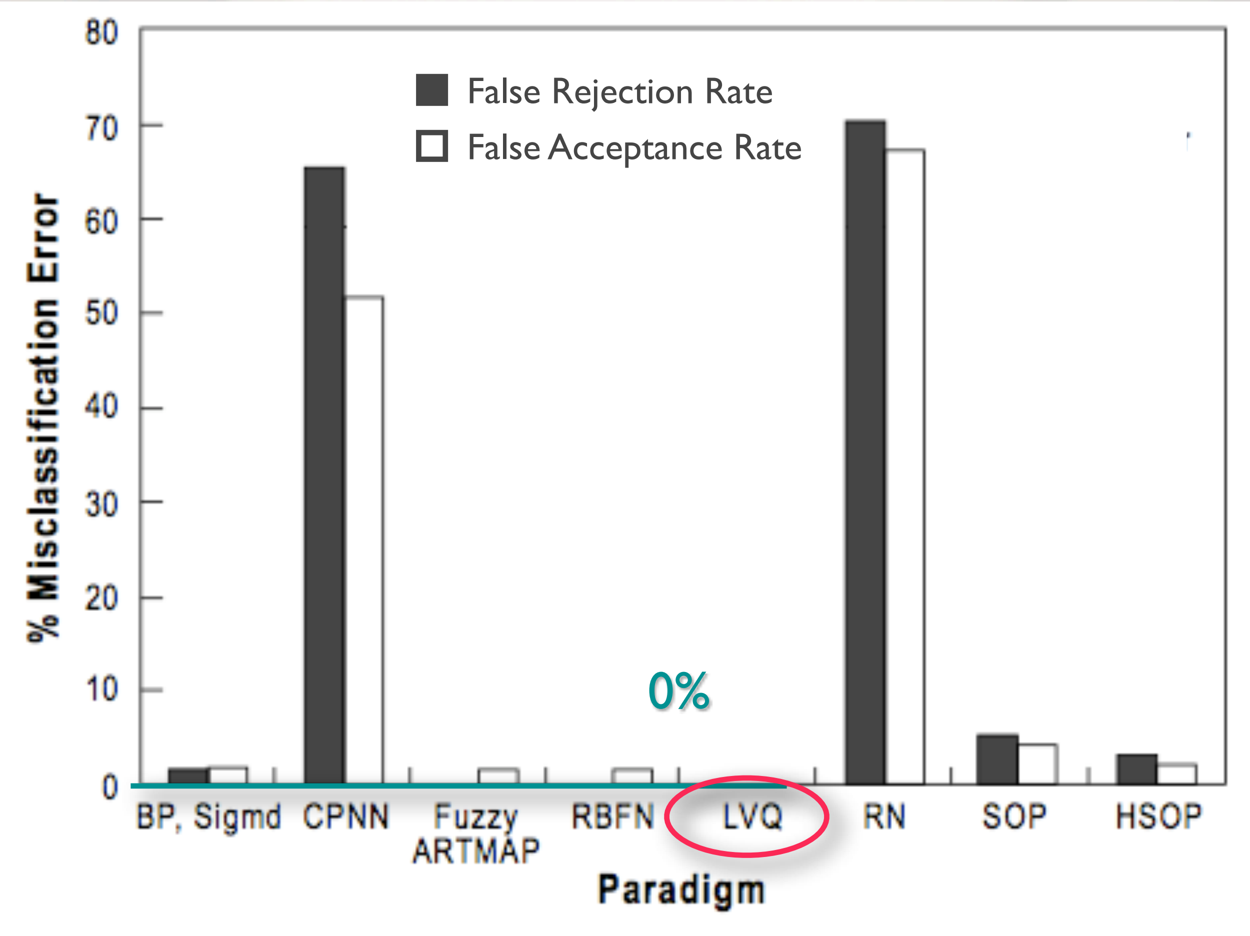

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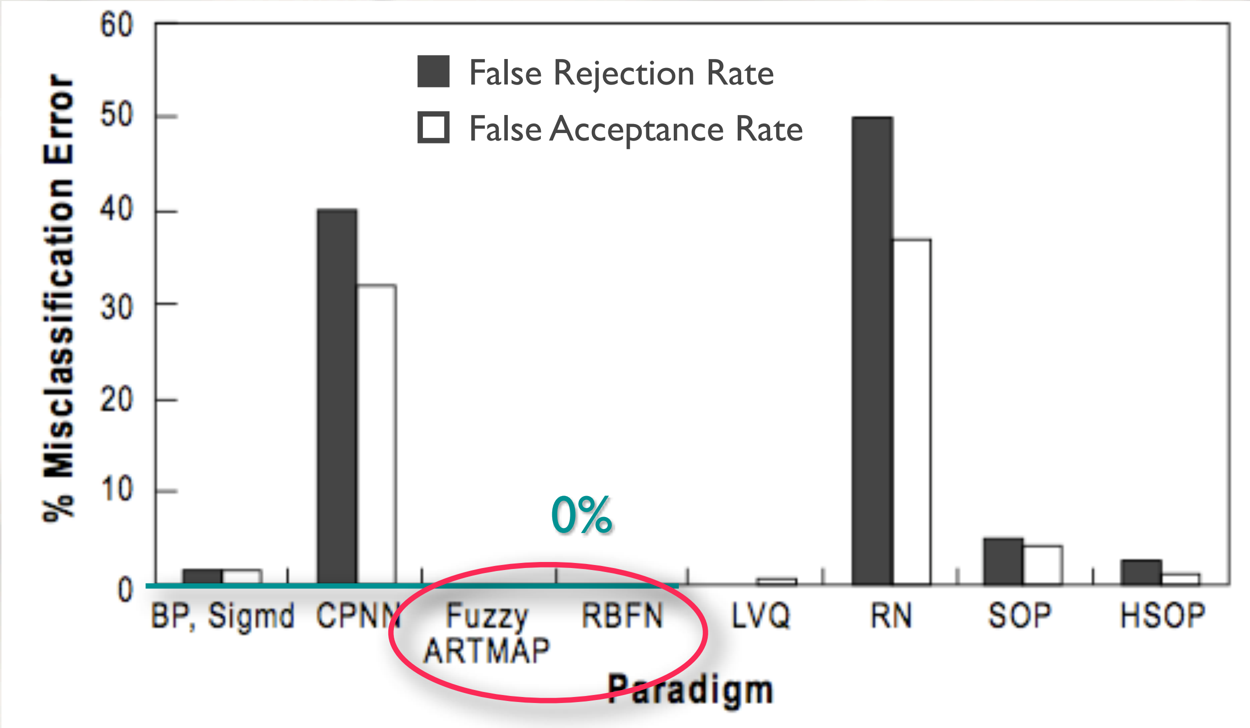

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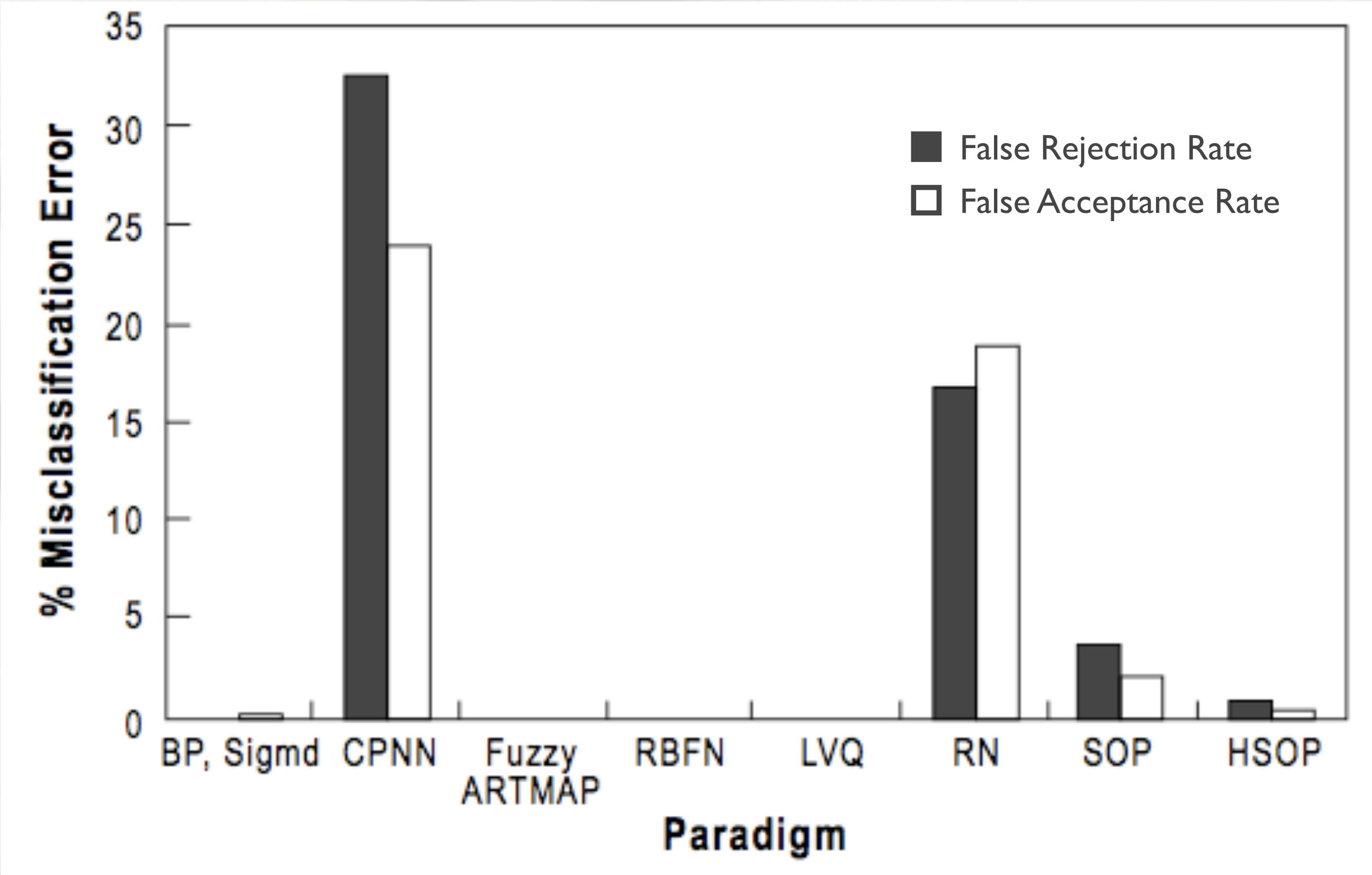

Classification based on **Hold and Interkey Times**

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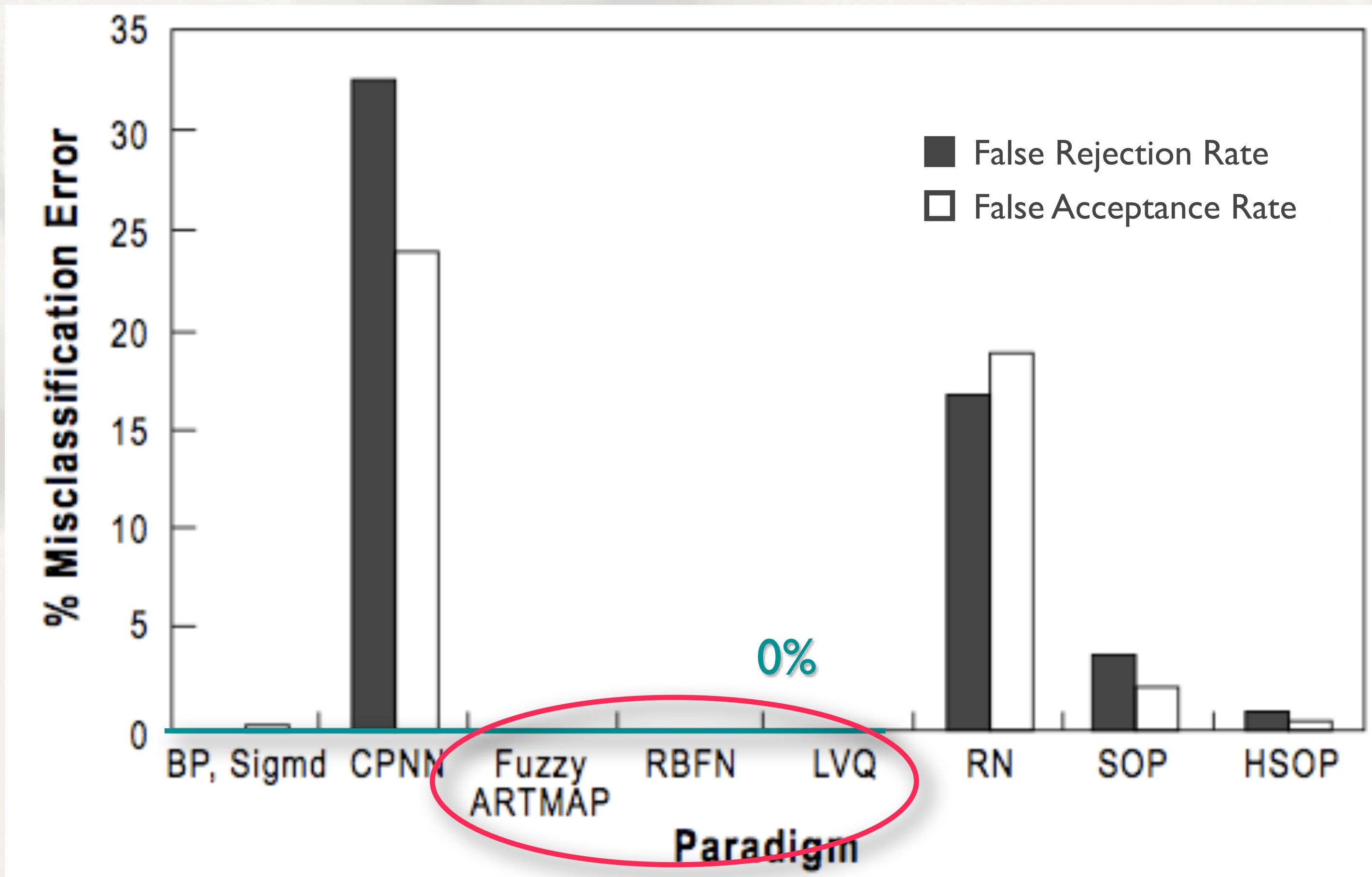

Classification based on **Hold and Interkey Times**

How to measure „Similarity“? (2)

- Alternative Approach (*Bergadano* et al.):
  - Measure duration (latency) of trigraphs and sort them in ascending order
  - Define distance between two samples as the „degree of disorder“ between sorted trigraphs
  - Normalize distance by maximum degree of disorder

How to measure „Similarity“? (2)

Example: User is asked to type ***austria***

Trigraph	aus	ust	str	tri	ria
Duration	277 ms	231 ms	281 ms	248 ms	295 ms

How to measure „Similarity“? (2)

<u>Example:</u> User is asked to type ***austria***

Trigraph	aus	ust	str	tri	ria
Duration	277 ms	231 ms	281 ms	248 ms	295 ms

sorted version

ust	tri	aus	str	ria
231	248	277	281	295

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Example: User is asked to type ***austria***

Trigraph	aus	ust	str	tri	ria
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sorted version

ust	tri	aus	str	ria
231	248	277	281	295

d = 1 d = 2 d = 2 d = 1 d = 0

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Example: User is asked to type ***austria***

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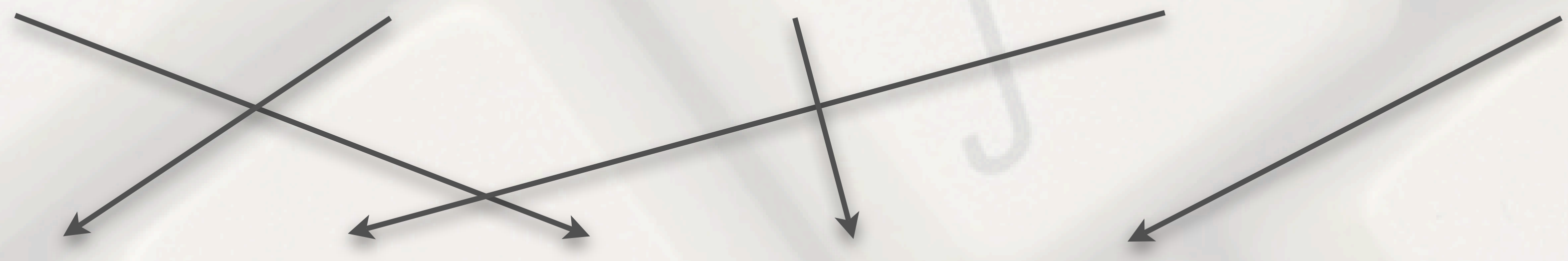


sorted version

ust	tri	aus	str	ria
231	248	277	281	295
d = 1	d = 2	d = 2	d = 1	d = 0

max. degree of disorder: $\frac{|array|^2 - 1}{2}$ → $d_{norm} = \frac{1+2+2+1+0}{12} = 0.5$

How to measure „Similarity“? (2)

Sample 1 (sorted)

ust	tri	aus	str	ria
231	248	277	281	295

How to measure „Similarity“? (2)

Sample 1 (sorted)

ust	tri	aus	str	ria
231	248	277	281	295

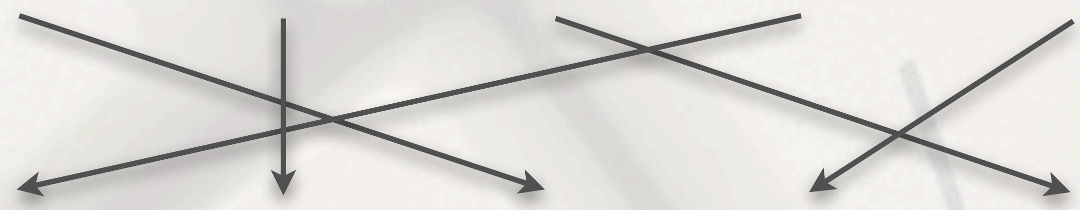
Sample 2 (sorted)

str	tri	ust	ria	aus
222	236	254	269	280
d = 3	d = 0	d = 2	d = 1	d = 2

How to measure „Similarity“? (2)

Sample 1 (sorted)

ust	tri	aus	str	ria
231	248	277	281	295



Sample 2 (sorted)

str	tri	ust	ria	aus
222	236	254	269	280
d = 3	d = 0	d = 2	d = 1	d = 2

$$d(S1, S2) = \frac{3+0+2+1+2}{12} = 0.6666$$

How to measure „Similarity“? (2)

- User Classification
  - Compute „mean distance“ of incoming sample to each user‘s model (all available samples of that user)

$$md(A, X) = (d(A_1, X) + d(A_2, X) + d(A_3, X) + d(A_4, X)) / 4$$

$$md(B, X) = (d(B_1, X) + d(B_2, X) + d(B_3, X)) / 3$$

$$md(C, X) = (d(C_1, X) + d(C_2, X) + d(C_3, X) + d(C_4, X) + d(C_5, X)) / 5$$

X .... current incoming sample

A, B, C ... user models consisting of Samples $A_{1...n}$, $B_{1...n}$, $C_{1...n}$

User Authentication

- Access Control System
  - Samples may be provided by illegal users with unknown typing patterns
  - ➡ <u>even if FAR = 0%, best possible IPR = (100/N)%</u>

- Condition:
  - Input sample must not only be closer to a certain model than to any other model; it must be <u>sufficiently</u> close to this model

User Authentication

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➡ even if FAR = 0%, best possible IPR = (100/N)%

„Impostor Pass Rate“ (IPR)

„False Alarm Rate“ (FAR)

- Condition:
  - Input sample must not only be closer to a certain model than to any other model; it must be sufficiently close to this model

User Authentication

- Use of Thresholds
  - Compute mean value of „inner-model“ distances:

$$m(A) = (d(A_1,A_2) + d(A_1,A_3) + d(A_1,A_4) + d(A_2,A_3) + d(A_2,A_4) + d(A_3,A_4)) / 6$$

  - Classify sample X as belonging to A, if (and only if):

$$md(A, X) < m(A) + | k * (md(B, X) - m(A)) |$$

md(B, X) ... mean value of „second closest“ model

A, B, C ... user models consisting of Samples $A_{1...n}$, $B_{1...n}$, $C_{1...n}$

User Authentication

- Values for k:
  - k = 1: plain classification scenario
  - k = 0.5: md(A, X) closer to m(A) than to any other md(B,X)
  - k = 0.33: md(A, X) twice as close to m(A) than to md(B,X)

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  - k = 0.33: md(A, X) twice as close to m(A) than to md(B,X)

Value of k	$k = 1$	$k = 0.66$	$k = 0.5$	$k = 0.33$	$k = 0.3$
N. of successful attacks out of 71500 attempts	1650	98	30	2	0
N. of failed legal connections out of 220 attempts	0	0	4	13	16
Impostor Pass Rate	2.3077%	0.1371%	0.042%	0.0028%	0%
False Alarm Rate	0%	0%	1.8182%	5.9091%	7.2727%

from Bergadano et al.:
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md(B, X) ... mean value of „second closest" model

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md(B, X) ... mean value of „second closest" model

A, B, C ... user models consisting of Samples $A_{1...n}$, $B_{1...n}$, $C_{1...n}$

User Authentication

- Additional filtering
  - Thresholds improve classification results but may have counterintuitive behavior:

$$md(A, X) = 0.307025 \qquad d(A_1, A_2) = 0.212378$$
$$md(B, X) = 0.420123 \qquad d(A_1, A_3) = 0.204381$$
$$md(C, X) = 0.423223 \qquad d(A_2, A_3) = 0.226024$$
$$m(A) = 0.214261$$

$$md(A, X) < m(A) + | k * (md(B, X) - m(A)) |$$

User Authentication

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$$md(A, X) = 0.307025 \qquad d(A_1, A_2) = 0.212378$$
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$$0.307025 < 0.214261 + | 0.5 * (0.420123 - 0.214261) |$$ ✓

User Authentication

- Additional filtering
  - Thresholds improve classification results but may have counterintuitive behavior:

$md(A, X) = 0.307025$
$md(B, X) = 0.420123$
$md(C, X) = 0.423223$

$d(A_1, A_2) = 0.212378$
$d(A_1, A_3) = 0.204381$
$d(A_2, A_3) = 0.226024$

$m(A) = 0.214261$

?

$0.307025 < 0.214261 + | 0.5 * (0.420123 - 0.214261) |$ ✓

User Authentication

- Additional filtering
  - For each sample, compute mean distance w.r.t. all the other samples in the model:

$$m(A_{xyz}) = (d(A_x,A_y) + d(A_x,A_z) + d(A_y,A_z)) / 3$$

$$dA_1 = | (d(A_1,A_2) + d(A_1,A_3) + d(A_1,A_4)) / 3 - m(A_{234}) |$$
$$dA_2 = | (d(A_2,A_1) + d(A_2,A_3) + d(A_2,A_4)) / 3 - m(A_{134}) |$$
$$dA_3 = | (d(A_3,A_1) + d(A_3,A_2) + d(A_3,A_4)) / 3 - m(A_{124}) |$$
$$dA_4 = | (d(A_4,A_1) + d(A_4,A_2) + d(A_4,A_3)) / 3 - m(A_{123}) |$$

User Authentication

- Additional filtering
  - For each sample, compute mean distance w.r.t. all the other samples in the model:

$$m(A_{xyz}) = (d(A_x,A_y) + d(A_x,A_z) + d(A_y,A_z)) / 3$$

$$dA_1 = | (d(A_1,A_2) + d(A_1,A_3) + d(A_1,A_4)) / 3 - m(A_{234}) |$$
$$dA_2 = | (d(A_2,A_1) + d(A_2,A_3) + d(A_2,A_4)) / 3 - m(A_{134}) |$$
$$dA_3 = | (d(A_3,A_1) + d(A_3,A_2) + d(A_3,A_4)) / 3 - m(A_{124}) |$$
$$dA_4 = | (d(A_4,A_1) + d(A_4,A_2) + d(A_4,A_3)) / 3 - m(A_{123}) |$$

$$md(A, X) < m(A) + a * max(dA_1, dA_2, dA_3, dA_4) + b * std(dA_1, dA_2, dA_3, dA_4)$$

User Authentication

- Additional filtering
  - For each sample, compute mean distance w.r.t. all the other samples in the model:

value of k value of a value of b	$k=0.5$ $a=1$ $b=1.5$	$k=0.5$ $a=1$ $b=1.75$	$k=0.5$ $a=1.5$ $b=0$	$k=0.5$ $a=1.5$ $b=0.5$	no k $a=1.5$ $b=0.5$	$k=0.55$ $a=1.22$ $b=1.25$
Successful attacks (out of 71500)	3	5	4	7	1032	7
Failed legal connections (out of 220)	12	9	10	8	5	4
IPR FAR	0.0042% 5.4545%	0.007% 4.0909%	0.0056% 4.5454%	0.0098% 3.6364%	1.4433% 2.2727%	0.0098% 1.8182%

from Bergadano et al.:
„User Authentication through Keystroke Dynamics“

$$md(A, X) < m(A) + a * \max(dA_1, dA_2, dA_3, dA_4) + b * std(dA_1, dA_2, dA_3, dA_4)$$

User Authentication

- Additional filtering
  - For each sample, compute mean distance w.r.t. all the other samples in the model:

value of k value of a value of b	$k=0.5$ $a=1$ $b=1.5$	$k=0.5$ $a=1$ $b=1.75$	$k=0.5$ $a=1.5$ $b=0$	$k=0.5$ $a=1.5$ $b=0.5$	no k $a=1.5$ $b=0.5$	$k=0.55$ $a=1.22$ $b=1.25$
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from Bergadano et al.: **„User Authentication through Keystroke Dynamics“**

$$md(A, X) < m(A) + a * \max(dA_1, dA_2, dA_3, dA_4) + b * \mathrm{std}(dA_1, dA_2, dA_3, dA_4)$$

How to measure „Similarity“? (2)

- Advantages
  - Measure considers relative relative values of various typing features only
  - No need for specific tuning or training
  - Typing errors allowed (additional pre-filtering to keep only the shared trigraphs)

Bibliography

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Thank you.