Ensemble of Adaptive Algorithms for Keystroke Dynamics

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1.
Introduction

2.
Ensembles in Adaptive Biometric Systems

3.
Experimental Results and Conclusion

1. Introduction

2. Ensembles in Adaptive Biometric Systems

3. Experimental Results and Conclusion

Biometrics is considered a suitable option to improve current authentication systems.

Biometric features must meet some requirements [Jain et al., 2004]:

Universality	everyone has the feature.
Collectability	it is possible to quantify the feature quantitatively.
Distinctiveness	the feature allows to distinguish one person from another.
Permanence	feature should be invariant over time.

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Universality	• everyone has the feature.
Collectability	• it is possible to quantify the feature quantitatively
Distinctiveness	
Permanence	• feature should be invariant over time.

However, several studies have shown that it is not the case in practice: ***template ageing*** [Fenker et al., 2013].

Context

Adaptive Biometric Systems deal with *template ageing* by automatically adapting the user model over time.

Several **adaptive one-class algorithms** have been used for this purpose. However, the performance is not usually consistent over different datasets;

Context

Adaptive Biometric Systems deal with *template ageing*

Studies have shown that the combination of individual techniques in **ensembles** may lead to **more accurate and stable decision models**.

Several **adaptive one-class algorithms** have been used for this purpose. However, the

This paper investigates the use of simple **ensemble approaches** for adaptive biometric systems:

- *Proposal of a model to apply an ensemble of adaptive algorithms for biometrics;*
- *Study of the behaviour of the ensemble with adaptive algorithms in a data stream context.*

Context

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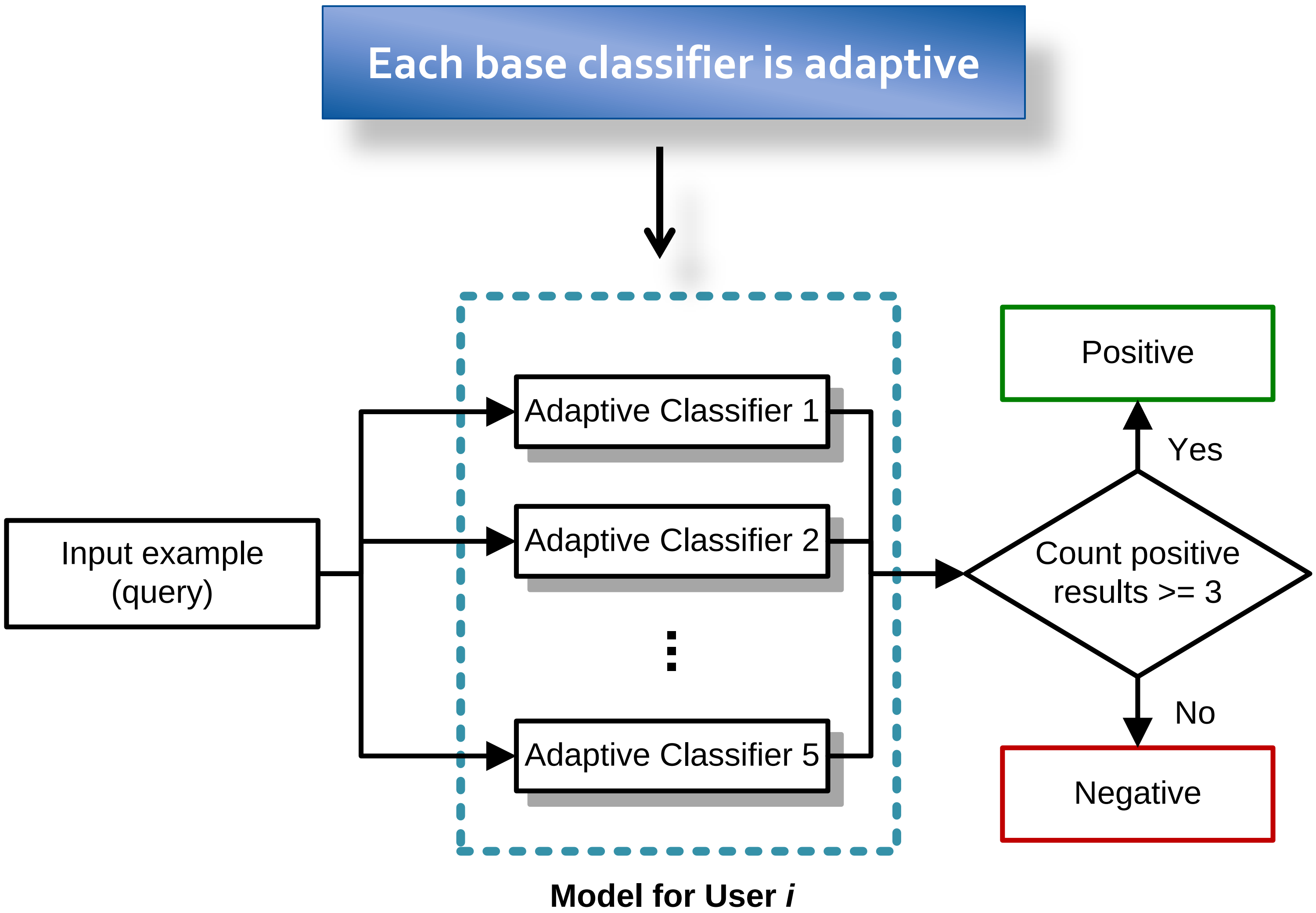
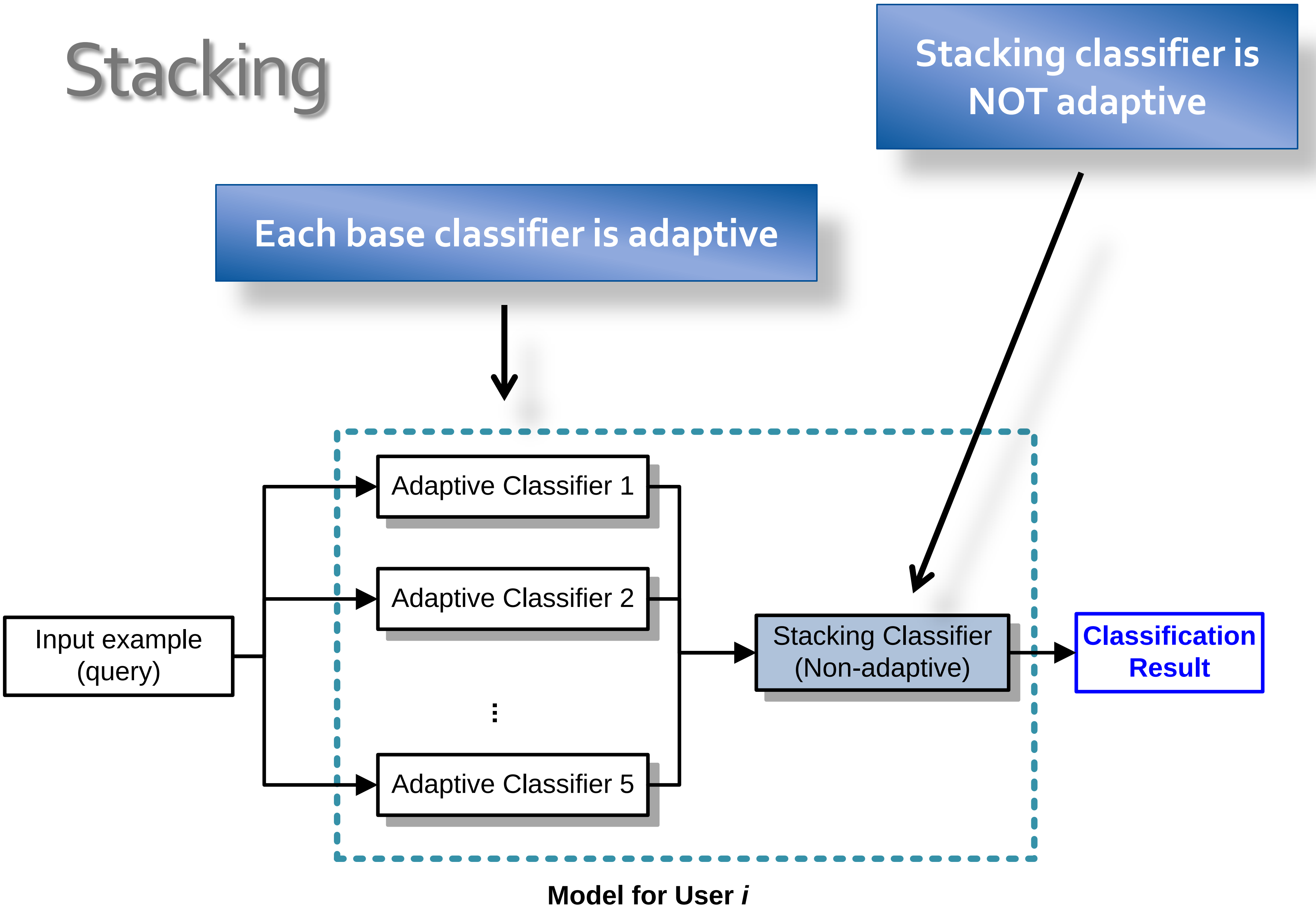
Majority Voting

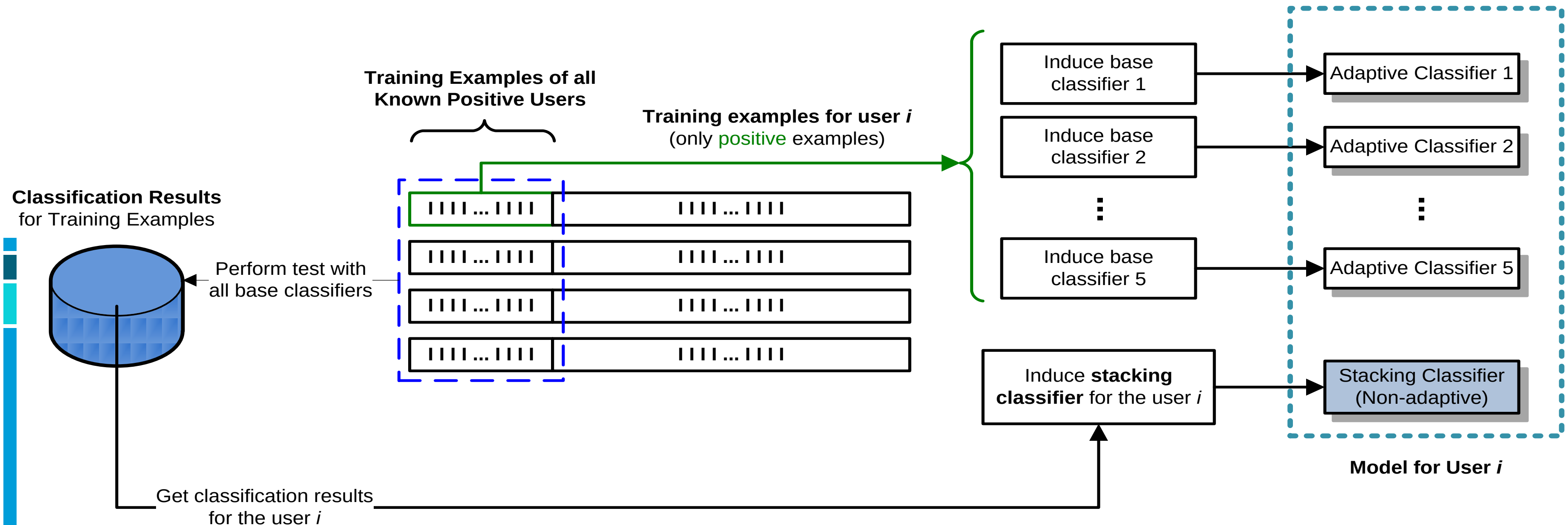


Stacking


Stacking classifier is NOT adaptive
Each base classifier is adaptive
Adaptive Classifier 1
Adaptive Classifier 2
⋮
Adaptive Classifier 5
Input example (query)
Stacking Classifier (Non-adaptive)
Classification Result
Model for User *i*

Stacking Training

- Stacking classifier requires both positive and negative examples
- Biometric system has access to data from all enrolled users



Stacking Training

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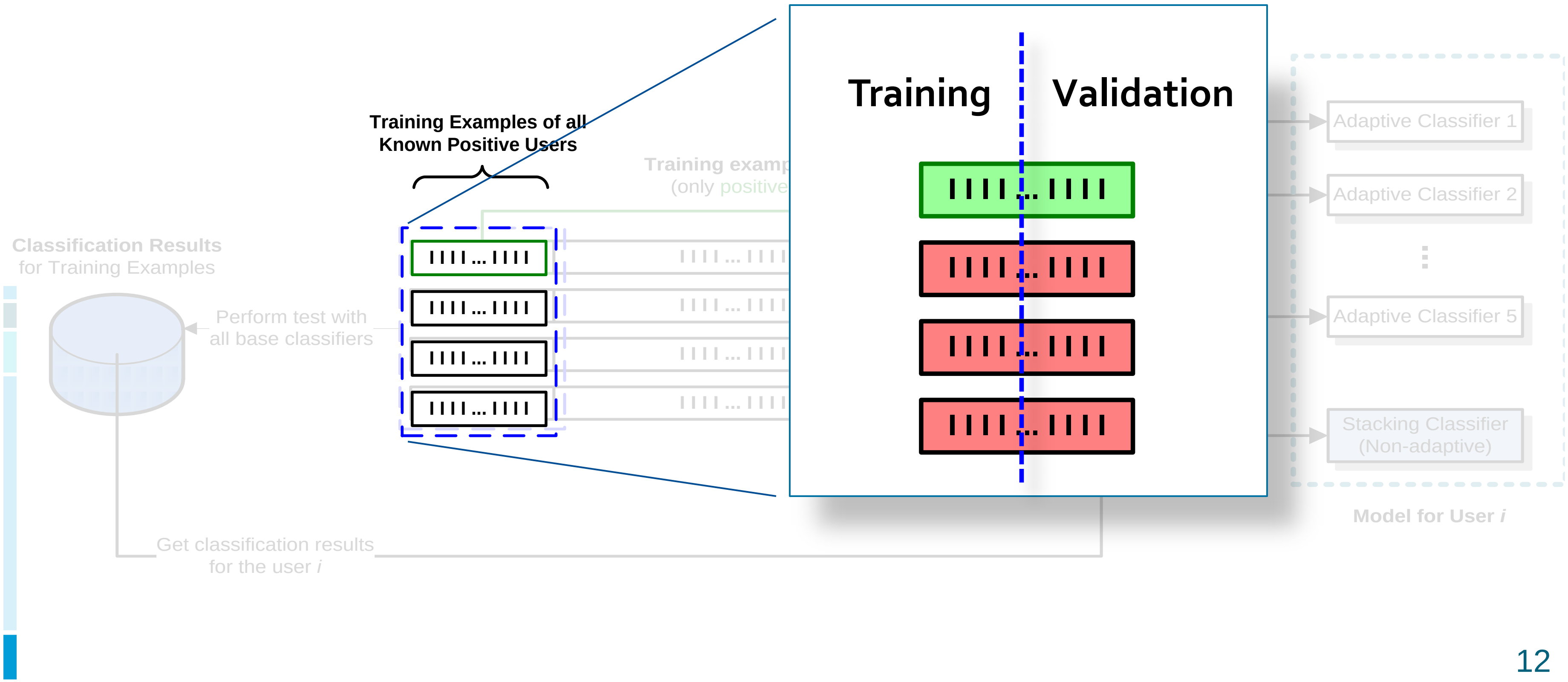

Stacking Training

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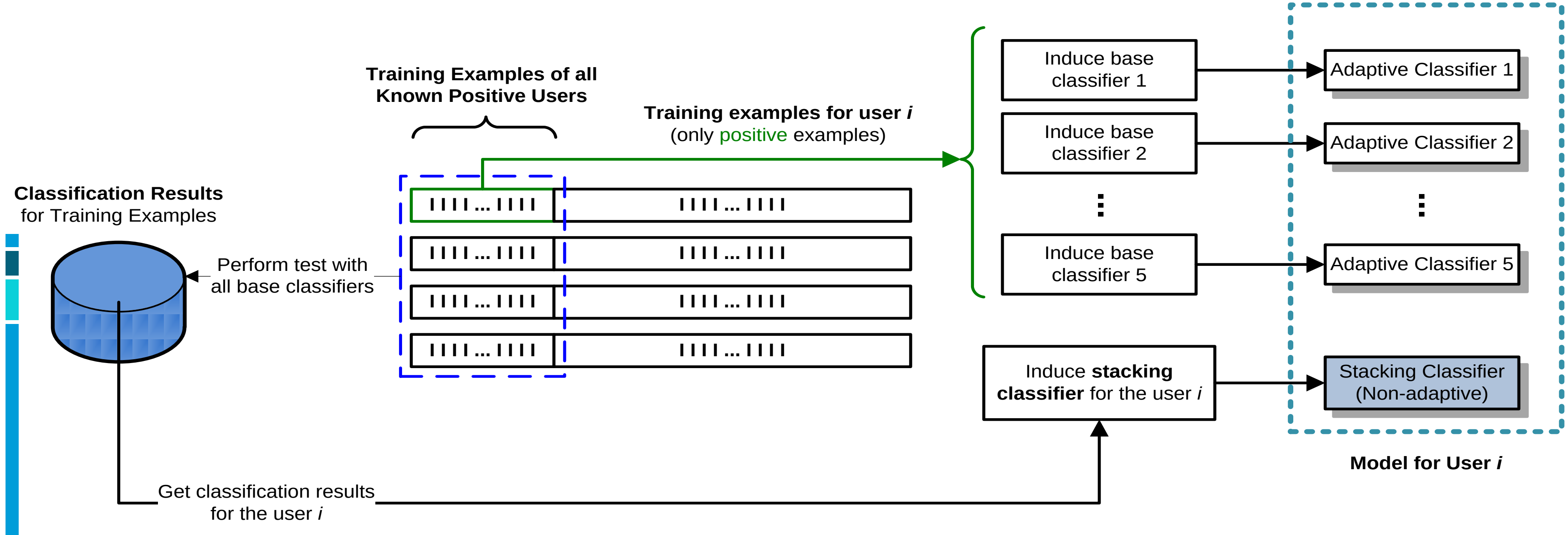

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2\.
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3\.
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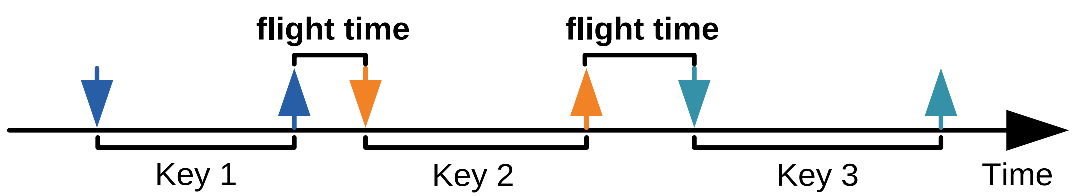
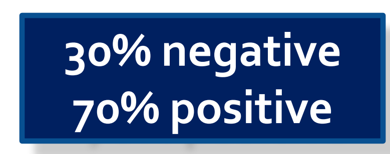
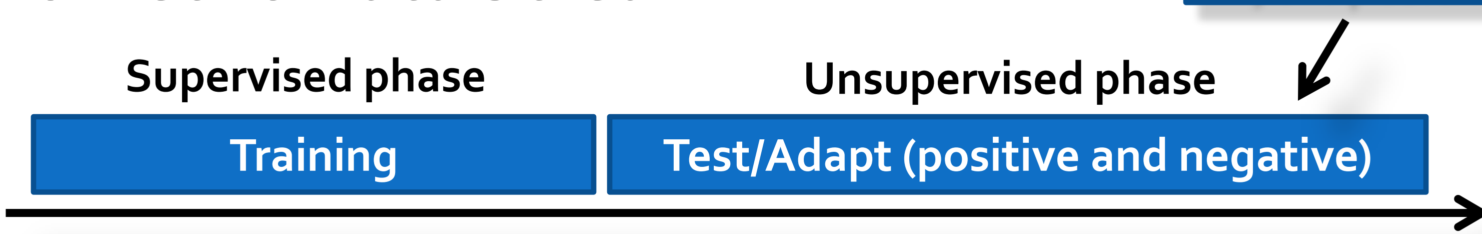
Experimental Setup

- Datasets:
  - GREYC: 100 users (2 months)
  - CMU: 51 users (8 sessions)
  - GREYC-Web: 35 users (> 1 year)
- Extracted features:



- Biometric Data Stream:





Experimental Setup

- **Base** Classification Algorithms (adaptive):
  - **M2005** (I. Double Parallel)
  - **Self-Detector** (Sliding, Usage Control R, Usage Control S, Usage Control 2)
- **Stacking** Classification Algorithms (static):
  - Multilayer Perceptron
  - Decision Tree (J48)
  - Random Forest
  - Naïve Bayes

Experimental Results

	GREYC Dataset			
	Algorithm	**FMR**	**FNMR**	**Acc (balanc.)**
B	*Self-Detector (No adaptation)*	0.090 (0.010)	0.165 (0.005)	0.872 (0.006)
	Self-Detector (Sliding)	0.092 (0.011)	0.129 (0.004)	$\boxed{\textbf{0.890}\ (0.006)}$
	Self-Detector (Usage Control R)	0.092 (0.010)	0.140 (0.005)	0.884 (0.006)
	Self-Detector (Usage Control S)	0.089 (0.010)	0.149 (0.005)	0.881 (0.006)
	Self-Detector (Usage Control 2)	**0.069** (0.009)	0.168 (0.006)	0.882 (0.006)
	M2005	0.221 (0.019)	0.130 (0.003)	0.824 (0.009)
	M2005 (I. Double Parallel)	0.210 (0.018)	**0.092** (0.004)	0.849 (0.008)
E	*Ensemble (Voting)*	**0.087** (0.010)	0.126 (0.005)	$\boxed{0.893\ (0.006)}$
	Ensemble (MLP)	0.181 (0.016)	0.054 (0.004)	0.882 (0.008)
	Ensemble (Random Forest)	0.185 (0.016)	**0.053** (0.004)	0.881 (0.008)
	Ensemble (Naive Bayes)	0.116 (0.012)	0.094 (0.005)	**0.895** (0.007)
	Ensemble (Decision Tree)	0.184 (0.013)	0.066 (0.005)	0.875 (0.006)

	CMU Dataset			
	Algorithm	**FMR**	**FNMR**	**Acc (balanc.)**
B	*Self-Detector (No adaptation)*	0.287 (0.023)	0.410 (0.016)	0.651 (0.009)
	Self-Detector (Sliding)	0.291 (0.031)	**0.211** (0.013)	0.749 (0.016)
	Self-Detector (Usage Control R)	0.311 (0.030)	0.220 (0.013)	0.735 (0.015)
	Self-Detector (Usage Control S)	0.213 (0.014)	0.275 (0.012)	0.756 (0.008)
	Self-Detector (Usage Control 2)	0.143 (0.012)	0.323 (0.014)	0.767 (0.009)
	M2005	0.273 (0.028)	0.451 (0.019)	0.638 (0.013)
	M2005 (I. Double Parallel)	**0.122** (0.011)	0.306 (0.008)	$\boxed{\textbf{0.786}\ (0.006)}$
E	*Ensemble (Voting)*	**0.208** (0.017)	0.239 (0.013)	$\boxed{0.776\ (0.009)}$
	Ensemble (MLP)	0.257 (0.039)	0.182 (0.018)	**0.781** (0.012)
	Ensemble (Random Forest)	0.283 (0.044)	**0.168** (0.020)	0.775 (0.014)
	Ensemble (Naive Bayes)	0.255 (0.025)	0.202 (0.010)	0.772 (0.015)
	Ensemble (Decision Tree)	0.299 (0.043)	0.169 (0.016)	0.766 (0.014)

	GREYC-Web Dataset			
	Algorithm	**FMR**	**FNMR**	**Acc (balanc.)**
B	*Self-Detector (No adaptation)*	0.066 (0.008)	0.141 (0.005)	0.896 (0.005)
	Self-Detector (Sliding)	0.074 (0.011)	**0.085** (0.004)	0.920 (0.007)
	Self-Detector (Usage Control R)	0.069 (0.009)	0.086 (0.004)	$\boxed{\textbf{0.922}\ (0.006)}$
	Self-Detector (Usage Control S)	0.053 (0.007)	0.123 (0.005)	0.912 (0.005)
	Self-Detector (Usage Control 2)	**0.035** (0.007)	0.148 (0.010)	0.908 (0.007)
	M2005	0.096 (0.013)	0.245 (0.016)	0.829 (0.008)
	M2005 (I. Double Parallel)	0.095 (0.015)	0.131 (0.011)	0.887 (0.008)
E	*Ensemble (Voting)*	**0.052** (0.007)	0.091 (0.004)	$\boxed{\textbf{0.928}\ (0.005)}$
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Majority Voting Ensemble:
Consintent high performance

Overall performance

Experimental Results

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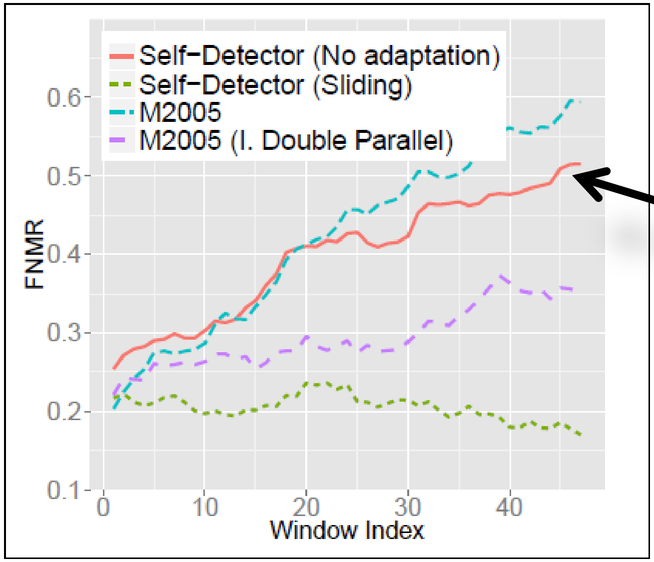
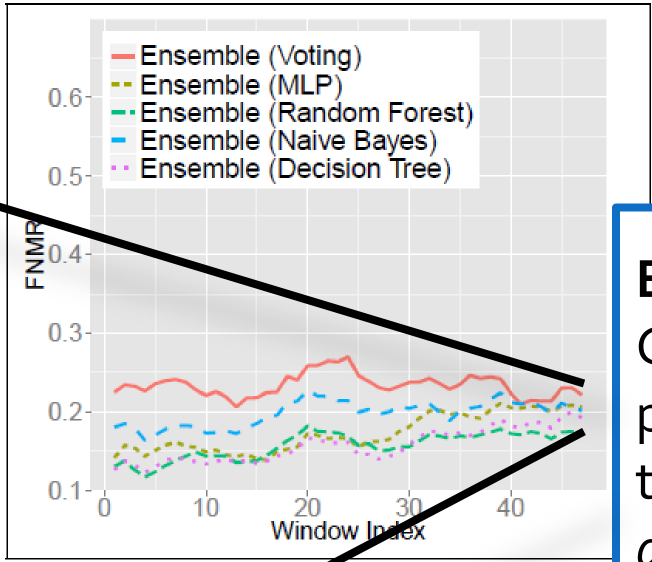
Staking: lower FNMR (may be a result of the imbalanced biometric data stream)

Overall performance

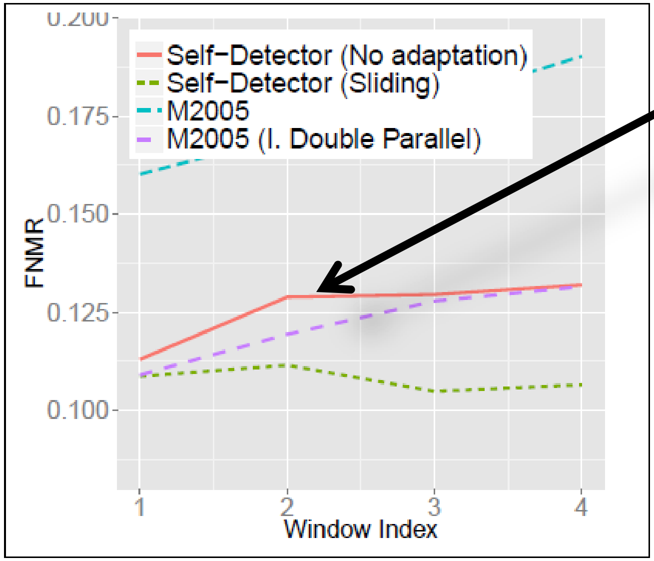
Experimental Results



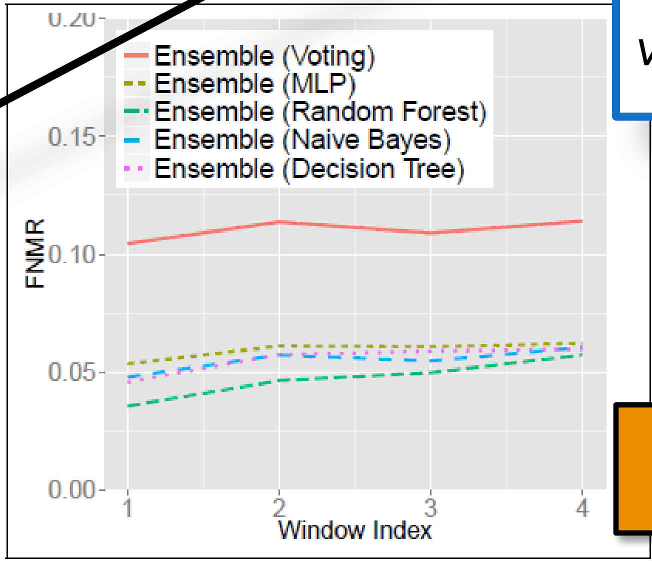
(a) Baselines (CMU).



(b) Ensemble (CMU).



(c) Baselines (GREYC-Web).

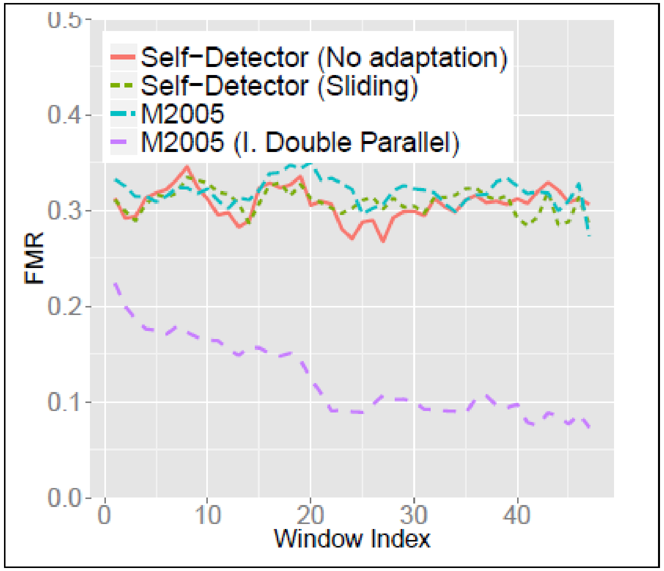


(d) Ensemble (GREYC-Web).

Ensembles:
Good FNMR performance over time (*static algorithms tend to increase FNMR values*)

FNMR

Experimental Results



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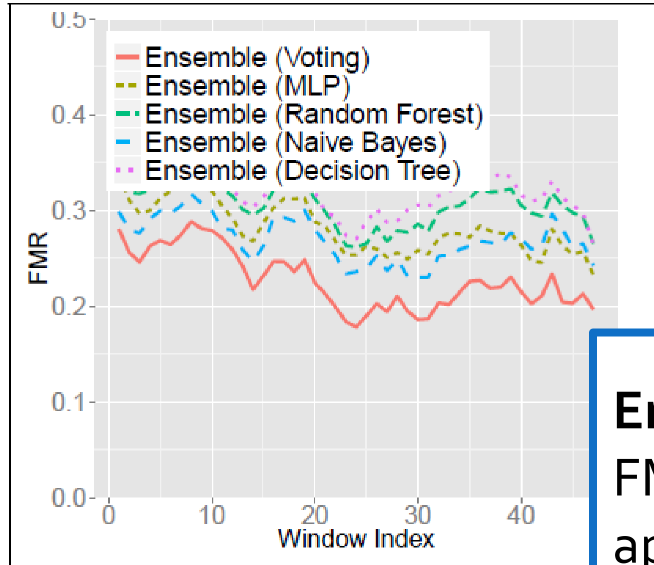
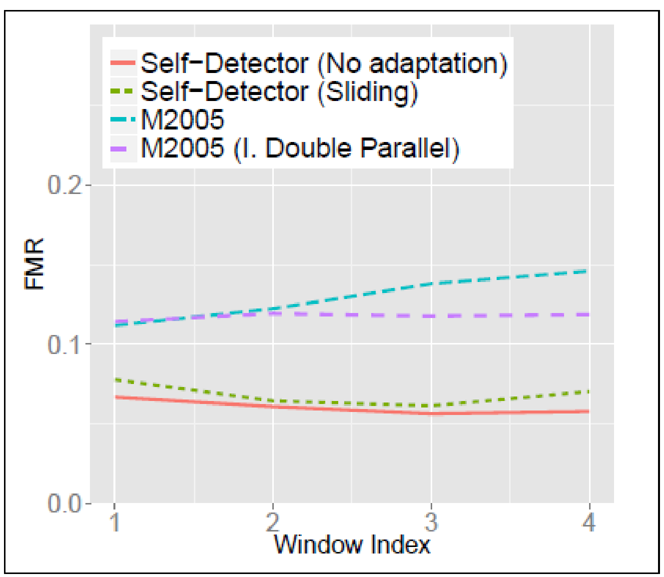
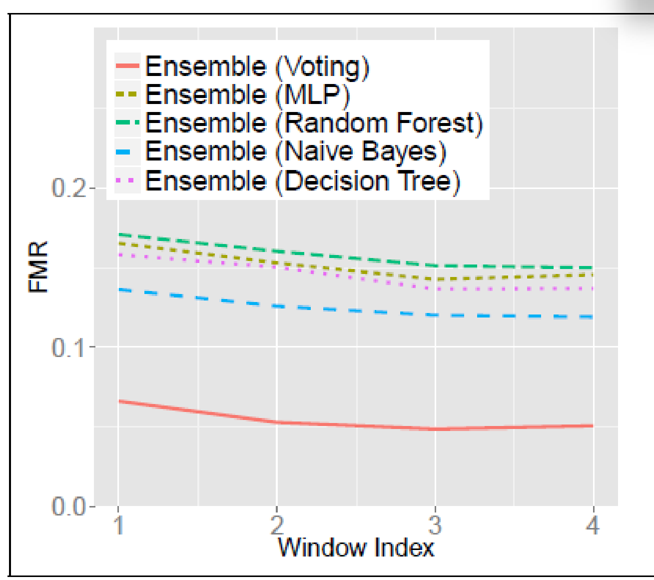


(b) Ensemble (CMU).

Ensembles:
FMR similar to other approaches



(c) Baselines (GREYC-Web).



(d) Ensemble (GREYC-Web).

FMR

1.
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2.
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3.
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Conclusion

- This paper investigated the use of **ensemble approaches** for adaptive biometric systems (and how to implement them in this context).
- Ensemble approaches resulted in consistent high predictive performance over all datasets;
- Majority Voting (the simplest one) obtained accuracy better than baselines on two datasets;
- Although ensemble implies in high use of computational resources, it may justify its use by the high predictive performance.

- **Future Work**:
  - Change the way of selecting data for stacking classifier training;
  - Additional ensemble approaches.

Ensemble of Adaptive Algorithms for Keystroke Dynamics

- Universidade de São Paulo (USP)
  - Instituto de Ciências Matemáticas e de Computação (ICMC)

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