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.

Context

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

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

	• everyone has the feature.
Collectability	• it is possible to quantify the feature quantitatively
Distinctivenes	However, several studies have shown that it is not the case in practice: <i>template ageing</i> [Fenker et al., 2013].
Permanence	 feature should be invariant over time.

Context

Adaptive Biometric Systems deal with *template ageing* by <u>automatically adapting</u> 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;

Contex

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

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;

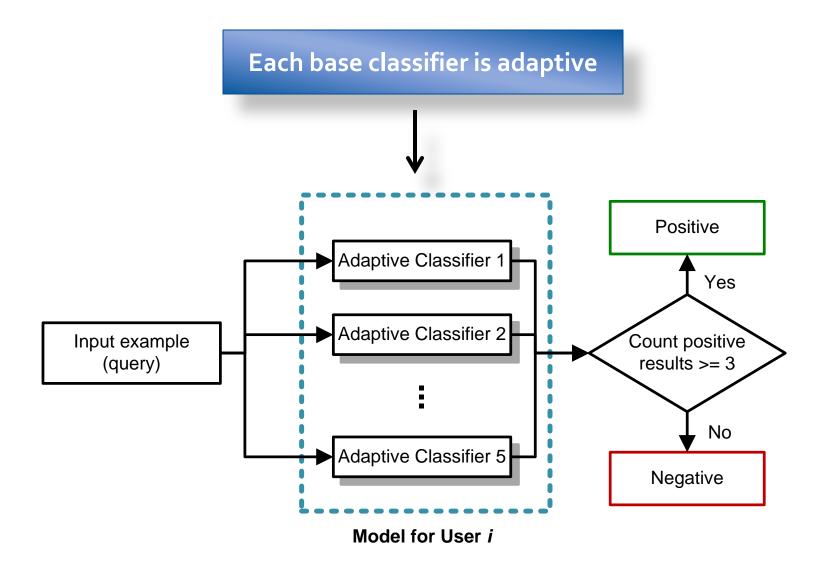
- Study of the behaviour of the ensemble with adaptive algorithms in a data stream context.

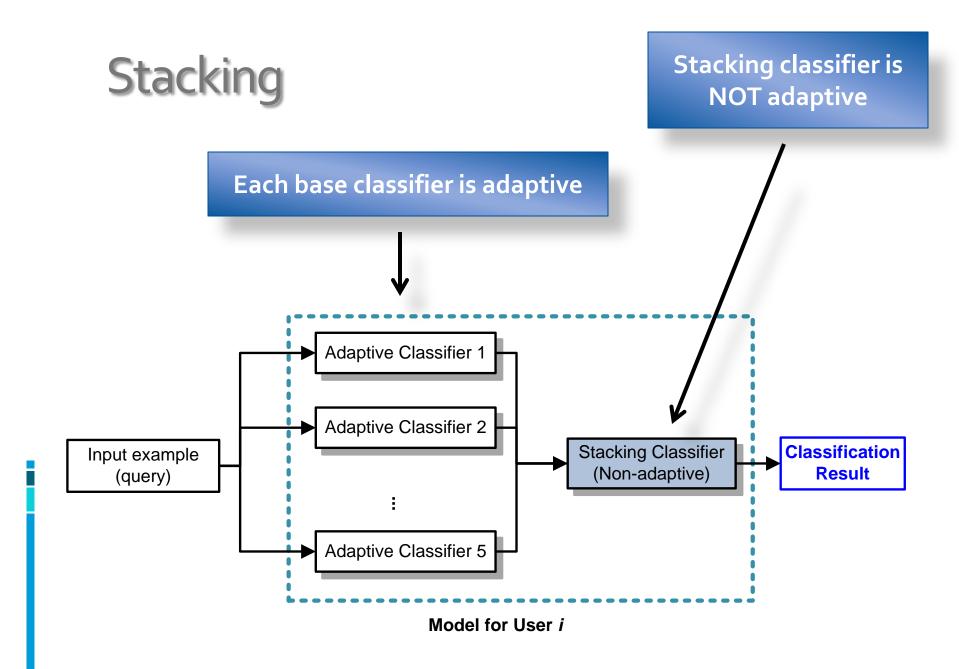
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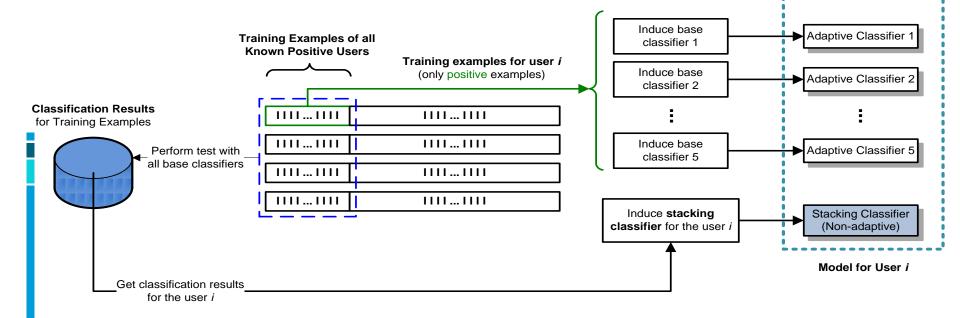
Majority Voting





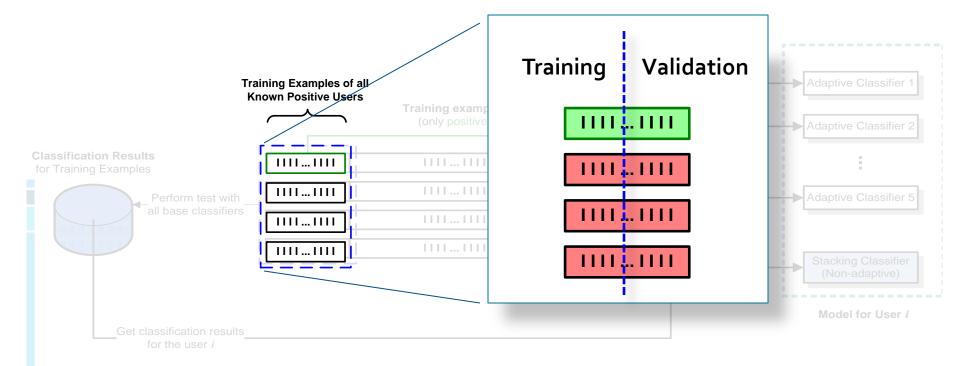
Stacking Training

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



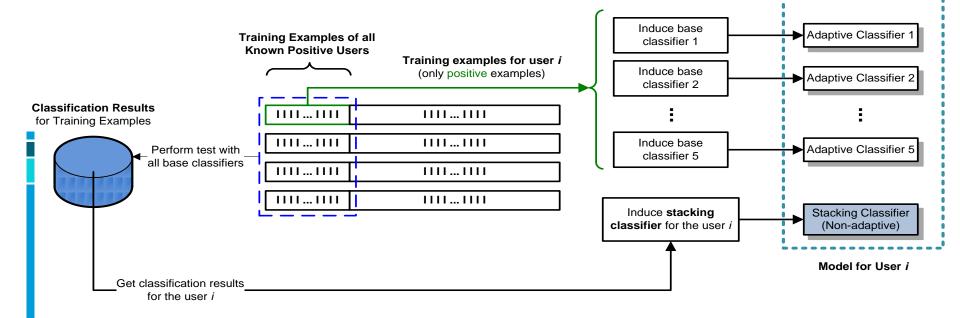
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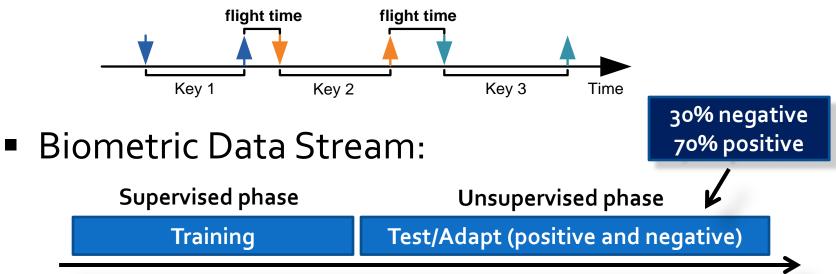
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3-Experimental Results and Conclusion

Experimental Setup

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



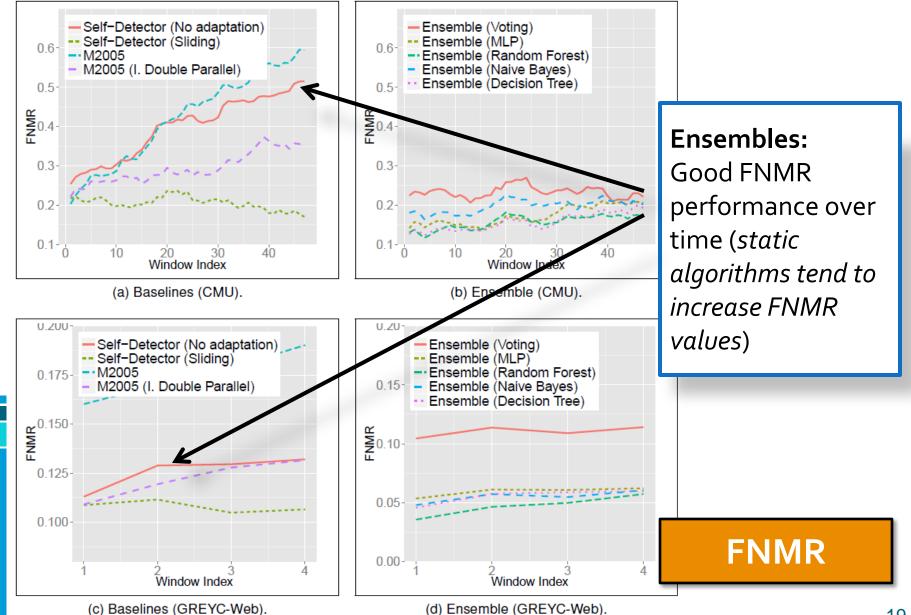
Experimental Setup

- 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

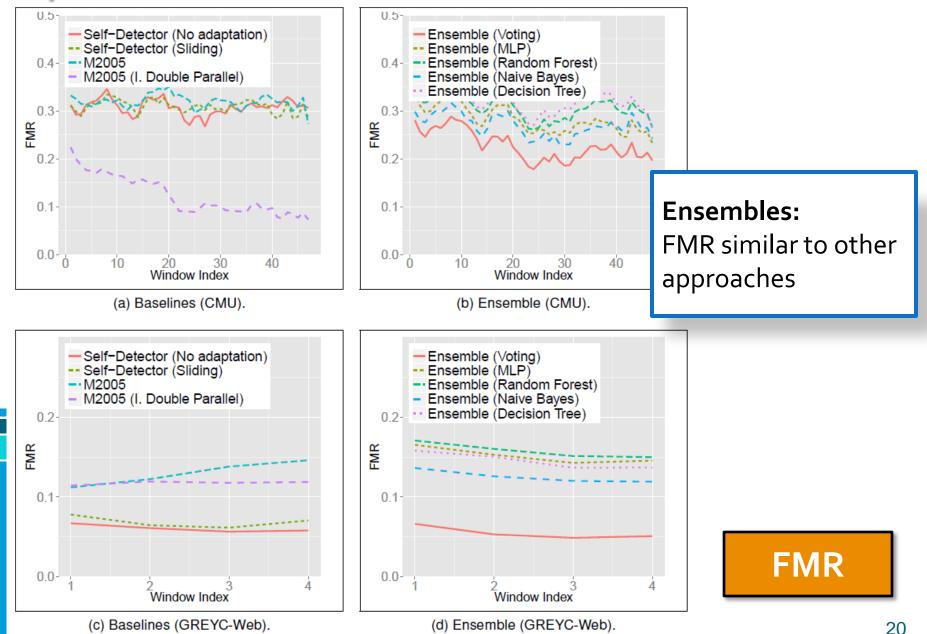
	G	REYC Dataset			-
	Algorithm	FMR	FNMR	Acc (balanc.)	Experimental Decute
	Self-Detector (No adaptation)	0.090 (0.010)	0.165 (0.005)	0.872 (0.006)	Experimental Results
	Self-Detector (Sliding)	0.092 (0.011)	0.129 (0.004)	0.890 (0.006)	1
	Self-Detector (Usage Control R)	0.092 (0.010)	0.140 (0.005)	0.884 (0.006)	
m	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)	
	Ensemble (Voting)			0.893 (0.006)	
	Ensemble (MLP)			0.882 (0.008)	
<u>ц</u>	Ensemble (Random Forest)			0.881 (0.008)	
	Ensemble (Naive Bayes)		0.094 (0.005)		Najority Voting
	Ensemble (Decision Tree)		0.066 (0.005)	0.875 (0.006)	inajoney voering
		CMU Dataset			Ensemble:
	Algorithm	FMR	FNMR	Acc (balanc.)	
	Self-Detector (No adaptation)	· · · · · · · · · · · · · · · · · · ·	· · · · · ·	0.651 (0.009)	Consintent high
	Self-Detector (Sliding)			0.749 (0.016)	
Ω	Self-Detector (Usage Control R)				performance
	Self-Detector (Usage Control S)				periormanee
	Self-Detector (Usage Control 2)				
	M2005			0.638 (0.013)	ר א <i>ר</i>
_	M2005 (I. Double Parallel)			0.786 (0.006)	
	Ensemble (Voting)			0.776 (0.009)	
ш	Ensemble (MLP) Ensemble (Random Forest)			0.781 (0.012) 0.775 (0.014)	
	Ensemble (Naive Bayes) Ensemble (Decision Tree)			0.772 (0.015) 0.766 (0.014)	
_				0.766 (0.014)	= /
	Algorithm	YC-Web Datas	FNMR	Acc (balanc.)	. /
	Self-Detector (No adaptation)		0.141 (0.005)		- /
	Self-Detector (Sliding)			0.920 (0.007)	ר /
	Self-Detector (Usage Control R)				
	Self-Detector (Usage Control S)				
	Self-Detector (Usage Control 2)				
	M2005			0.829 (0.008)	Ovorall
	M2005 (I. Double Parallel)			0.887 (0.008)	Overall
	Ensemble (Voting)			0.928 (0.005)	
	Ensemble (MLP)			0.911 (0.008)	performance
ш	Ensemble (Random Forest)			0.913 (0.012)	performance
	Ensemble (Naive Bayes)			0.923 (0.008)	
	Ensemble (Decision Tree)			0.908 (0.007)	. 17
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Algorithm FMR FNMR Acc (balanc.) Self-Detector (No adaptation) 0.090 (0.010) 0.165 (0.005) 0.872 (0.006) Self-Detector (Siding) 0.092 (0.011) 0.129 (0.004) 0.890 (0.006) Self-Detector (Usage Control S) 0.092 (0.010) 0.140 (0.005) 0.884 (0.006) Self-Detector (Usage Control S) 0.092 (0.010) 0.140 (0.005) 0.881 (0.006) Self-Detector (Usage Control S) 0.221 (0.019) 0.130 (0.003) 0.822 (0.008) Ensemble (MLP) 0.181 (0.016) 0.053 (0.004) 0.881 (0.008) Ensemble (Nuice Bayes) 0.186 (0.013) 0.092 (0.004) 0.881 (0.008) Ensemble (Nuice Bayes) 0.184 (0.013) 0.094 (0.005 0.893 (0.006) Ensemble (Naire Bayes) 0.184 (0.013) 0.095 (0.007) Ensemble (Decision Tree) 0.184 (0.013) 0.490 (0.005) Self-Detector (No adaptation) 0.287 (0.023) 0.410 (0.016) 0.651 (0.009) Self 0.005 0.897 (0.016) Self-Detector (Usage Control R) 0.111 (0.030) 0.291 (0.031) 0.716 (0.018) 0.756 (0.008) Self 0.016) Self 0.016)						REYC Dataset	6	
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Self-Detector (Sliding) 0.074 (0.011) 0.085 (0.004) 0.920 (0.007)								
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Self-Detector (Usage Control 2) 0.035 (0.007) 0.148 (0.010) 0.908 (0.007)								
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Ensemble (Voting) 0.052 (0.007) 0.091 (0.004) 0.928 (0.005) Ensemble (MLP) 0.126 (0.015) 0.052 (0.006) 0.911 (0.008) Ensemble (MLP) 0.126 (0.025) 0.052 (0.006) 0.911 (0.008)		performance		0.911 (0.008)	0.052 (0.006)	0.126 (0.015)	Ensemble (MLP)	
L Ensemble (Random Forest) 0.122 (0.026) 0.052 (0.004 0.913 (0.012)				0.913 (0.012)	0.052 (0.004)	0.122 (0.026)	Ensemble (Random Forest)	ш
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Experimental Results



Experimental Results





2. Ensembles in Adaptive Biometric Systems

3-Experimental Results and Conclusion

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 <u>consistent high predictive</u> <u>performance over all datasets</u>;
- 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

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