Towards Local Classifier Generation for Dynamic Selection

by

Hiba ZAKANE

THESIS PRESENTED TO ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
IN PARTIAL FULFILLMENT OF A MASTER'S DEGREE
WITH THESIS IN AUTOMATED MANUFACTURING ENGINEERING
M.A.Sc.

MONTREAL, NOVEMBER 27, 2018

ÉCOLE DE TECHNOLOGIE SUPÉRIEURE
UNIVERSITÉ DU QUÉBEC

Hiba ZAKANE, 2018

This Creative Commons license allows readers to download this work and share it with others as long as the author is credited. The content of this work cannot be modified in any way or used commercially.

BOARD OF EXAMINERS

THIS THESIS HAS BEEN EVALUATED

BY THE FOLLOWING BOARD OF EXAMINERS

Mr. Robert Sabourin, Thesis Supervisor
Automated Manufacturing Engineering, École de Technologie Supérieure

Mr. George D. C. Cavalcanti, Co-supervisor
Centro de Informática, Universidade Federal de Pernambuco

Mr. Patrick Cardinal, President of the Board of Examiners
Software Engineering and Information Technology, École de Technologie Supérieure

Mrs. Eulanda dos Santos, External Independent Examiner
Instituto de Computaçao, Federal University of Amazonas

THIS THESIS WAS PRESENTED AND DEFENDED

IN THE PRESENCE OF A BOARD OF EXAMINERS AND THE PUBLIC

ON NOVEMBER 21, 2018

AT ÉCOLE DE TECHNOLOGIE SUPÉRIEURE

ACKNOWLEDGEMENTS

I would like to address special thanks to my supervisor Professor Robert Sabourin for his guidance, patience, availability, and support during the last two years. Thank you for contributing to my academic and personal development.

Many thanks to my co-supervisor, Professor George D. C. Cavalcanti, for his valuable feedback and supervision despite the distance that separates us. I also, express my deepest thanks to Dr. Rafael M.O. Cruz for his support and help throughout the elaboration of this research work.

I thank the members of the jury, Professor Eulanda dos Santos and Professor Patrick Cardinal, that kindly accepted to evaluate this master's thesis.

The support of the students services (SAE), the library facilitators, as well as the Deanship of Graduate studies.

Special thanks to all my friends from LIVIA for the constant support and the nice moments we shared during several occasions.

I thank the family and friends I have here in Montreal, I wouldn't have made this far without your precious daily encouragement and patience.

Last but not least, I would like to express my gratitude and love to my parents and my brother for their trust, love and their endless belief in my success.

Vers une génération de bassin de classificateurs adaptée à la Selection Dynamique

Hiba ZAKANE

RÉSUMÉ

Les systèmes de classificateurs multiples sont axés sur la combinaison des classificateurs, pour obtenir de meilleures performances, par rapport aux performances d'un seul classificateur robuste. Ces systèmes se déroulent en trois phases principales: la génération de bassins de classificateurs, la sélection statique ou dynamique de ces derniers et la phase d'intégration. La sélection dynamique est un sujet de recherche très en vogue au sein de la communauté d'apprentissage machine. Elle se caractérise par la sélection des classificateurs les plus compétents, pour chaque échantillon de test. La sélection dynamique fonctionne en se dotant d'un bassin (pool) de classificateurs, l'estimation du niveau de compétence des classificateurs est généralement faite à partir de la construction du voisinage de l'échantillon à classer pour la plupart des techniques, et cette région locale est appelée région de compétence. Une région de compétence composée d'instances appartenant à différentes classes est appelée : *région d'indécision* et contribue souvent aux difficultés rencontrées par les méthodes de sélection dynamiques de toujours repérer les classificateurs compétents. D'autre part, la sélection dynamique repose sur les méthodes de générations des bassins de classificateurs qui sont conçues pour les approches de combinaison statique. En d'autres termes, ces dernières adoptent une approche globale pour générer les classificateurs, ce qui n'est pas aligné avec l'aspect local qui définit le schéma de la sélection dynamique.

De ce fait, dans ce travail, nous nous concentrons sur la couverture locale des régions d'indécision, par des classificateurs compétents localement pour la sélection dynamique. Nous proposons un système qui exploite l'information locale, dans la création des classificateurs traversant les régions d'indécision en séparant entre les échantillons appartenant aux différentes classes. Nous proposons aussi cinq nouvelles stratégies de sélection locale, pour la construction de bassins de classificateurs adaptés à la sélection dynamique. En généralisation, nous nous fions aux recommandations proposées lors de notre précédent travail, qui portait sur les raisons derrière le surpassement en terme de performances des méthodes de sélection dynamiques en comparaison de l'algorithme des K-plus proches voisins, sachant que ce dernier est exploité dans la définition de la région de compétence, dans la plupart des méthodes de sélection dynamiques. Les expériences ont montré que la sélection dynamique est efficace pour les échantillons situés dans des régions d'indécision, selon une mesure de difficulté de classification d'un échantillon donné, alors que l'algorithme des K-plus proches voisins serait plus adapté pour les échantillons ayant un faible degré de difficulté. Ceci justifie l'utilisation la mesure de difficultés des instances pour déterminer si l'on utilise un algorithme de K-Plus proches voisins ou la sélection dynamique pour la classification.

Les expériences ont été menées en utilisant plusieurs méthodes de sélection dynamique sur les cinq stratégies proposées de création de bassins de classificateurs. Les résultats de cette recherche ont montré que la focalisation sur une approche locale pour générer des classifica-

teurs pour la sélection dynamique est une voie prometteuse pour garantir l'existence de classificateurs compétents sur le plan local, car elle fournit des résultats meilleurs à ceux de la littérature et dans le cas contraire, elle présente une équivalence statistique. Cependant, il y a encore place à l'amélioration pour de telles approches qui nous mèneraient à la génération locale de classificateurs adaptés à la sélection dynamique.

Mots-clés: Apprentissage ensembliste, Sélection Dynamique, Reconnaissance de formes, classificateurs linéaires

Towards Local Classifier Generation for Dynamic Selection

Hiba ZAKANE

ABSTRACT

Multiple Classifier Systems (MCS) focus on the combination of classifiers to achieve better performance than a single robust one. These systems unravel three major phases: pool of classifiers generation, Static or Dynamic selection and integration. Dynamic Selection (DS) is an active research topic in the field of MCS. It's based on the selection of the most competent classifier(s), on the fly, for every test sample. To operate, the DS scheme needs to be provided with a pool of classifiers, it will then compute the region of competence defined as a set of the test sample's nearest neighbors (in most of DS techniques) that determines the competence of the classifiers. The regions of competence located on the decision boundaries are called "*indecision regions*" and usually contribute into the struggle of DS technique into always selecting the most competent classifiers. On the other hand, Dynamic Selection relies on classifier generation techniques that are meant for static combinations. In other words, these methods adopt a global approach into generating the classifiers, which contradicts the local aspect that defines the dynamic selection scheme.

Therefore, in this work we address the problem of covering the indecision regions with locally competent classifiers in the context of dynamic selection. We propose a system that exploits local information to build classifiers that cross the indecision regions of competence guaranteeing a separation between the samples from different classes (frienemies). We also proposed five novel local selection strategies to construct pools of these classifiers, that is adapted to the Dynamic selection system. In generalization, we rely on the recommendations of our previous work, where an investigation was conducted on the reasons behind the out-performance of the DS techniques over the K-NN classifier even though, most of the techniques rely on the definition of the nearest neighbors as a competence region. It was concluded that DS techniques deal better with instances located in indecision regions according to an instance hardness measure whereas the K-NN is well suited for the samples with a low degree of instance hardness. Therefore, we exploited the concept of the hardness of samples to determine whether to use the K-NN of DS techniques for classification.

Experiments were conducted using several DS techniques under the five proposed pool generation approaches. The results of this research have shown that focusing on a local approach to generate classifiers for Dynamic Selection is a promising path into guaranteeing the existence of locally competent classifiers as it outperformed the results of the literature for certain techniques. When there is no improvement, the results remain comparable to the literature's. Yet, there is still room for improvement for such approaches and further investigations will be lead towards the local pool generation for Dynamic Selection.

Keywords: Ensemble Learning, Dynamic Classifier Selection, Dynamic Ensemble Selection, Pool Generation, Pattern Recognition, Linear classifiers

TABLE OF CONTENTS

Page

INTRODUCTION 1

CHAPTER 1 RELATED WORK 7
1.1 The Oracle 7
1.1.1 Dynamic Selection 8
1.1.2 Region of Competence definition 11
1.1.3 Measures of competence and Dynamic Selection techniques 12
1.1.3.1 Individual-based measures of competence 13
1.1.3.2 Group-based measures of competence 18
1.1.4 Dynamic Selection Versus K-NN 20
1.1.5 Dynamic Selection in the indecision Regions 21
1.2 Ensemble Generation methods 22
1.2.1 The wisdom of crowds 22
1.2.2 Bagging 23
1.2.3 Random Subspaces Method 23
1.2.4 Boosting 24
1.2.5 Oracle-based generation method 24
1.3 Summary, discussion and a brief introduction to the proposed system 26

CHAPTER 2 TOWARDS LOCAL POOL GENERATION FOR DYNAMIC SELECTION 29
2.1 Basic concepts 29
2.1.1 Region of Competence in the context of this study 29
2.1.2 Indecision Region 29
2.1.3 frienemies samples 31
2.1.4 Instance Hardness 32
2.1.4.1 k Disagreeing Neighbors (kDN), an instance hardness measure 32
2.2 The proposed Local Pool Generation for Dynamic Selection System 33
2.2.1 How does the proposed local pool generation work? 36
2.2.2 A pairwise separation between frienemies 38
2.2.3 Strategies for local selection of classifiers 42
2.2.3.1 Strategy 1: DCS as a guide for local selection, no errors allowed 43
2.2.3.2 Strategy 2 : DCS as a guide for local selection 44
2.2.3.3 Strategy 3: KNORA-E as a guide for local selection 45
2.2.3.4 Strategy 4 : frienemies distinction as a guide for local selection, one classifier allowed 46
2.2.3.5 Strategy 5 : frienemies distinction as a guide for local selection, multiple classifiers allowed 47

2.3 The generalization phase 48
2.4 Case study:The P2 problem 48
2.4.1 Local Pool Generation for P2 49
2.4.2 Case study summary 53
2.5 Discussion 55

CHAPTER 3 EXPERIMENTS AND RESULTS 57
3.1 Experimental protocol 57
3.2 Results analyses and discussions 59
3.2.1 Comparison between the proposed local pool generation strategies and the state of the art generation methods 60
3.3 General discussion 70

CONCLUSION AND RECOMMENDATIONS 73

APPENDIX I COMMUNICATION PRESENTED IN IPTA 2017 77

APPENDIX II THE NUMERICAL RESULTS 85

BIBLIOGRAPHY 95

LIST OF TABLES

Page

Table 1.1 A summary of the the Dynamic Selection techniques and their characteristics in a chronological order inspired from (Cruz et al., 2018) 19

Table 2.1 A summary of the strategies used as guides to locally select the classi er(s) from the Temporary Pool TP and construct DSLP 42

Table 3.1 Key features of the 17 datasets used for the experiments, IR represents the Imabalance Ratio. 58

Table 3.2 Mean of the accuracy of APOS for Bagging, SGH and DSPG (Strategy 4) given the number of example on the number of features ratio (SFR) 69

LIST OF FIGURES

Page

Figure 0.1 The three phases of a MCS system: pool generation, classifiers selection and integration adapted from (Cruz et al., 2018) 1

Figure 0.2 Thesis plan 5

Figure 1.1 Taxonomy of the Dynamic Selection Scheme (Cruz et al., 2018) 9

Figure 1.2 Classical Dynamic Selection System showing the difference between the Dynamic Classifier Selection (DCS) and Dynamic Ensemble Selection (DES) adapted from (Cruz et al., 2018) 10

Figure 2.1 Three type of samples: safe samples (labeled as S), borderline samples (labeled as B), and noisy samples (labeled as N). The continuous line shows the indecision region(Adapted from (Oliveira et al., 2017)). 30

Figure 2.2 Representation of pairs of frienemies (A, B), (A, D), (B, C), (B, E), (B, F), (B,G) (C, D), (D, E), (D, F), (B,G) in the region of competence of the query in a black diamond shape (Adapted from (Oliveira et al., 2017)). 31

Figure 2.3 General overview of the proposed framework. In the training phase, we use the proposed Dynamic Selection Pool Generation method (DSPG) to create the Dynamic Selection Local Pool (DSLP). Then, depending on the hardness of the test query sample in generalization, the system uses either KNN to take the decision or DS with the generated pool (DSLP) as suggested in [71]. 34

Figure 2.4 Summary of the Dynamic Selection Pool Generation (DSPG) part with the different selection strategies 35

Figure 2.5 Region of competence for a given query represented by a black diamond. Red circle represents class 1, and blue cross represents class 2. 38

Figure 2.6 The frienemies separation proposed that is closer to the minority class (blue cross) with the pink classifier for $\alpha = \frac{1}{7}$. 40

Figure 2.7 The difference between the frienemies separation in the midpoint (in gray) and the proposed separation (blue cross) 41

Figure 2.8 Local Selection Strategy 1 43

Figure 2.9 Local Selection Strategy 2 44

Figure 2.10 Local Selection Strategy 3 45

Figure 2.11 Local Selection Strategy 4 46

Figure 2.12 Local Selection Strategy 5 47

Figure 2.13 The P2 Problem with decision boundaries, the red circle refers to class 1 49

Figure 2.14 A Region of Competence in an indecision region from the P2 problem 51
(a) The features space 51
(b) The rst region of competence 51

Figure 2.15 First iteration: the generation of a Temporary Pool (TP) for a hard sample in a Region of Competence and the local selection of the most competent classi er to be added to DSLP 51
(a) The construction of TP 51
(b) The remaining classi er after strategy application 51

Figure 2.16 The second iteration: the generation of a Temporary Pool (TP) for the second hard sample in a Region of Competence followed by the chosen classi er to integrate DSLP 52
(a) Iteration 2: TP construction 52
(b) Iteration 2: remaining classi ers 52

Figure 2.17 A snapshot of the classi ers chosen applying the rst local selection strategy and a nal coverage of the space (b) of that speci c replication 53
(a) The chosen classi ers within their RoCs 53
(b) The nal DSLP 53

Figure 3.1 Instance Hardness measure for the joint use of kNN and DS in generalization. 59

Figure 3.2 Bonferroni-Dunn post hoc test for a critical value of $\alpha = 0.05$ (on top) and $\alpha = 0.01$ (on the bottom). The strategies in which the difference in average rank is lower than the critical value are connected with a bar. 62
(a) Bonferoni Post-hoc test for $\alpha = 0.05$ 62
(b) Bonferoni Post-hoc test for $\alpha = 0.01$ 62

Figure 3.3 Bonferroni-Dunn post hoc test for a critical value of $\alpha = 0.05$ (a) and $\alpha = 0.01$ (b). The DS techniques in which the the difference in average rank is lower than the critical value are connected with a bar. 64
(a) Bonferoni Post-hoc test for $\alpha = 0.05$ 64
(b) Bonferoni Post-hoc test for $\alpha = 0.01$ 64

Figure 3.4 Strategy 4 compared with SGH using the different DS techniques. The colored lines (left to right) illustrate the critical values n_c considering significance levels of $\alpha = \{0.10, 0.05, 0.01\}$, respectively 66

Figure 3.5 Strategy 4 compared with Bagging using the different DS techniques. The colored lines (left to right) illustrate the critical values n_c considering significance levels of $\alpha = \{0.10, 0.05, 0.01\}$, respectively 67

LIST OF ALGORITHMS

Page

Algorithm 1.1 Self-generating Hyperplane Method (SGH), from (Souza et al., 2017) 26

Algorithm 2.1 Pseudo code of the Dynamic Selection Pool Generation technique 36

Algorithm 2.2 The joint use of the K-NN rule and DS techniques in generalization depending on the instance hardness level 48

LIST OF ABREVIATIONS

DCS	Dynamic Classi er Selection
DES	Dynamic Ensemble Selection
DSEL	Dynamic Selection Dataset
DSLP	Dynamic Selection Local Pool
DSPG	Dynamic Selection Pool Generation
ÉTS	École de Technologie Supérieure
KNN	Dynamic Selection Dataset
RoC	Region of Competence
SFR	Number of sample on the number of features ratio
TP	Temporary Pool

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

c_i	i-th classi er
C	Pool of classi ers
C	Ensemble of most competent classi ers
c	The most competent classi er
W	Set of class labels of x_k
w_k	Class label
L	Number of class labels
N	Number of instances in a dataset
T_r	Training dataset
T_e	Testing dataset
V_a	Validation dataset
q	Region of competence
x_q	test query
x_j	j-th sample
$d_{i;j}$	Level of competence of the classi er c_i for classifying the instance x_q

INTRODUCTION

Through the decades, various research projects have been conducted in the area of classi cation in a wide range of sectors. Despite the innumerable classi cation methods that cover different aspects of classi cation problems, empirical and theoretical results drove the researchers to jointly agree that building a single robust classi er isn't always the right t to deal with all the complex pattern recognition problems (Britto et al., 2014). Therefore, it took years to the computational intelligence community to converge to a research trend that focuses on Ensembles of classi ers (EoC) or commonly called Multiple Classi er Systems (MCS).

Multiple Classi er Systems tend to mimic the human nature that usually seeks for different opinions before making a nal decision (Rokach, 2010). Researchers from diverse disciplines such as pattern recognition, statistics, and machine learning have explored the use of ensemble methods since the late seventies (Rokach, 2010). They have been acknowledged for their conceptual simplicity and the top-level performance in many classi cation tasks (Tamponi, 2015; Friedman et al., 2001). The process of MCS is constituted of three major phases: generation, selection and integration (Britto et al., 2014). As shown in Figure 0.1, during the rst phase, a pool of classi ers is generated; in the second step, one classi er or a non-empty subset of these classi ers is selected, while in the last one, a nal decision is made based on the prediction(s)/opinion(s) of the selected classi er(s) (Britto et al., 2014).

Figure 0.1 The three phases of a MCS system: pool generation, classi ers selection and integration adapted from (Cruzet al., 2018)

Among these phases, intensive work on the selection phase became a key cause for the evolution of MCS. Selection can be achieved in two ways, static and dynamic. In the Static Selection approach, the subset of classi ers is determined during the training of MCS; therefore, the same subset is applied for all test samples. On the contrary, Dynamic Selection (DS) considers different subsets of classi ers for individual test samples (Roy et al., 2016). Several techniques have been developed through the years (Ko et al., 2008; Cruz, 2016) aiming to enhance the strength of the recognition rates. However, there is no single algorithm that is better than any other over all possible classes of problems as stated in the “No free lunch” theorem (Cruz, 2016; Cruz et al., 2018; Britto et al., 2014).

Problem statement

In the traditional process of Multiple Classi er Systems for DS, the phases consist on generating a diverse pool of classi ers with mass generation techniques such as Bagging, Boosting, Random Subspace etc (Britto et al., 2014; Cruz et al., 2018). Then comes the step where dynamic selection techniques select a classi er or a subset of classi ers, for each test sample.

The issue with these generation approaches is that they were designed for static combination methods. In other words, they use a global approach in generating the base classi ers (Souza et al., 2017; Cruz et al., 2018).

Although, the results of this process are ef cient enough through the advancement of the eld, the performance in generalization for DS depends on the initial base classi ers of the pool. Furthermore, the main philosophy of dynamic selection, is to select the most competent classi ers locally.

However, with ensembles generated with the static combination methods, this condition is not taken into consideration. It means that there is no guaranty for the the presence of local experts,

which leads to the incapacity of the DS technique to always select local competent classi ers (Cruz et al., 2018; Oliveira et al., 2017).

Previous work in the literature, focused on the elaboration of several new Dynamic Selection methods, by creating new competence measures, and new frameworks to improve the performances(Lustosa Filho et al., 2018; Oliveira, 2018). Recently, Cruz et al., (Cruz et al., 2018), addressed the issue of rethinking the generation phase of these base classi ers, before applying the DS techniques.

To the best of our knowledge, there exists no pool generation method that uses local information to suit dynamic selection, in its classical scheme (Cruz et al., 2018; Oliveira, 2018), apart from an online generation of classi ers conducted recently by souza (Souza et al., 2019).

Therefore, this work aims to provide an approach leading towards local classi er generation for dynamic selection, by taking into consideration local criteria within the creation of the classi ers. Which, we believe is a promising subject to explore.

How can we generate locally competent classi ers that are adapted to the Dynamic Selection scheme?

To achieve the creation of locally competent classi ers we believe that the following criteria must be met:

- The presence of at least one classi er that crosses the Region of Competence of the patterns located in indecision regions.
- The use of different guides borrowed from the Dynamic Selection scheme for pool generation.

Research goals and Contributions

Therefore, our research question leads us to propose the following :

1. A novel procedure to generate local classi ers that cross the region of competence (RoC). The method takes into account the different local information regarding the samples that constitute RoC.
2. A heuristic to gather the previously generated classi ers given different types of guides for the construction of the Dynamic Selection Local Pool (DSLP), that will be detailed in chapter 2.
3. A classi cation system that takes in considerations the hardness of its test samples to decide whether to use the KNN classi er and Dynamic Selection techniques based on the recommendations provided in our previous work (Cruz et al., 2017).

Pursuing the research goal to rethink the usual pool generations methods by including information, holds promise towards the generation of local classi ers for Dynamic Selection.

Organization of the thesis

This document is organized as shows the gure 0.2: chapter one presents the related work about Dynamic Selection and Ensemble generation methods. The second chapter describes the proposed system heading towards local pool generation for Dynamic Selection, we presented in the orange boxes the titles of the most important aspects of the chapters. We expose in chapter three, the experimental protocol, as well as the results, the comparison to the state of the art and their discussion. The related work and the other chapters are linked with a dashed line to Appendix I, representing a conference paper that performs an analysis of the performances of the Dynamic Selection scheme and the K-NN classi er. This is a complementary reading that supports our research direction. Finally, we conclude by summarizing this study and give recommendations for future work.

Figure 0.2 Thesis plan

CHAPTER 1

RELATED WORK

This chapter regroups the literature review concerning the Oracle as an important concept in the Multiple Classi ers Systems. It then presents the Dynamic selection scheme and the Ensemble generation methods. It also contains complementary sections that narrows down the understanding of the problem and introduces the motivations of the solutions proposed in the next chapter.

1.1 The Oracle

In the process of the ideal selection of classi ers, the concept of the Oracle is de ned as an abstract function that always chooses the classi er that predicts the correct label for each instance (Kuncheva, 2002, 2004b; Cruz et al., 2018), if there exists such a classi er. That is to say, it represents the ideal classi er selection scheme. For a given dataset, the classi er c_i gives an output vector y_j (Kuncheva, 2004b) so that :

$$y_{i,j} = \begin{cases} 1 & \text{if classi er } c_i \text{ correctly classi es } x_j \\ 0 & \text{otherwise} \end{cases} \tag{1.1}$$

In the area of Multiple Classi ers Systems, the concept of the Oracle is exploited at different stages. It is used to the construction of diverse pools (Kuncheva, 2004b). Diversity is agreed that it measures how complementary the classi ers are in terms of making different mistakes in the features space (Kuncheva, 2004b). Kuncheva (Kuncheva, 2004b) states the following concerning the diversity concept: "If we have a perfect classi er which makes no errors, then we do not need an ensemble. However, if the classi er does make errors, then we seek to complement it with another classi er which makes errors on different objects. The diversity of the classi er outputs is therefore a vital requirement for the success of the ensemble." Moreover, empirical results showed that there exists a positive correlation between accuracy of the en-

semble and diversity among the base classi ers, which leads to a high accuracy of the Oracle when the diversity rate is high (Kuncheva, 2004b; Shipp & Kuncheva, 2002; Tang et al., 2006).

On the other hand, in the context of the Dynamic Selection literature, the Oracle is used to determine whether the results obtained by dynamic selection techniques is close to the ideal accuracy (Cruz et al., 2018; Souza et al., 2017; Giacinto & Roli, 2001). In other words, it acts as an upper bound for DS techniques performances for a given pool of classi ers. It also contributes in the elaboration of many ensemble generation methods (Souza, 2017; Dos Santos et al., 2008; Santos & Sabourin, 2011; Kuncheva & Rodriguez, 2007) as well as Dynamic selection techniques and frameworks (Cruz, 2016; Ko et al., 2008; Oliveira, 2018).

Given the quick introduction about the Oracle as an important element in the context of MCS, the next sections present the Dynamic Selection concept followed by the Ensemble generation scheme as a solid background to support the research question concerning the creation of locally competent classi ers for Dynamic Selection.

1.1.1 Dynamic Selection

In the context of MCS, the selection of classi ers can be either static or dynamic (Britto et al., 2014; Cruz et al., 2018). The former considers a subset of base classi ers for all the test patterns whereas the latter assumes that each classi er is an expert in a speci c region of the features space (Britto et al., 2014; Cruz et al., 2015b; Cruz, 2016; Cruz et al., 2018). Therefore, each query instance is classi ed by a single classi er or an ensemble of classi ers. Empirical studies showed that Dynamic Selection (DS) is well suited for ill de ned problems, i.e., for small sized datasets and when there is insuf cient training data (Britto et al., 2014; Cruz et al., 2015b; Cruz, 2016; Cruz et al., 2018). Moreover, several research projects have been focusing on Dynamic Selection, which can be applied in several domains such as : music genre classi cation, credit scoring, face recognition, signature veri cation, bug predictions and many more (Cruz, 2018).

Based on a pool of supposedly diverse classifiers $C = \{c_1, \ldots, c_M\}$, dynamic selection consists on finding the most competent classifier or ensemble of classifiers C to predict the class label for each test sample x_q (Kuncheva, 2004b). In Dynamic Selection, the classification of a new test samples unfolds the following steps:

1. The definition of a local region in which the selection will operate called, Region of Competence (RoC).
2. The selection criterion used to estimated the competence of the base classifiers.
3. The selection scheme. Dynamic selection techniques can be divided into two categories: Dynamic Classifier Selection (DCS) or Dynamic Ensemble Selection (DES). In dynamic classifier selection, a single classifier is selected for each test sample whereas in dynamic ensemble selection, a subset of competent classifiers is selected for each test pattern.

Figure 1.1 shows a diagram of the Taxonomy of DS adapted from (Cruz et al., 2018). It shows the different processes of Dynamic Selection, enumerating the region of competence definition, the selection criteria (individual-based and group-based measures of competence) and the Selection Approach.

Figure 1.1 Taxonomy of the Dynamic Selection Scheme
(Cruz et al., 2018)

Figure 1.2 shows a basic dynamic classi er selection system differentiating between the Dynamic Classi ers Selection (DCS) and Dynamic Ensemble Selection (DES). Indeed, the prior uses only one classi er de ned as the most competent one to identify the test sample whereas the latter uses an ensemble of competent classi er for the recognition task (Britto, 2014; Cruz et al., 2018).

In this section, we address the different concepts used in the elaboration of the Dynamic Selection systems, we will rst give a de nition of the local regions where the decisions of the system occurs. Then, we expose the measures of competence evaluated for the DS techniques and introduce them in the same subsection. Furthermore, we exhibit complementary information about the behavior of the DS scheme in certain situations to provide a broad motivation to our research question.

Figure 1.2 Classical Dynamic Selection System showing the difference between the Dynamic Classi er Selection (DCS) and Dynamic Ensemble Selection (DES) adapted from (Cruz et al., 2018)