Local overlap reduction procedure for dynamic ensemble selection

Mariana A. Souza*, Robert Sabourin*, George D. C. Cavalcanti† and Rafael M. O. Cruz*

*École de Technologie Supérieure - Université du Québec, Montreal, Quebec, Canada
Email: mariana.araujo.souza@gmail.com, robert.sabourin@etsmtl.ca, rafael.menelau-cruz@etsmtl.ca
†Centro de Informática - Universidade Federal de Pernambuco, Recife, Pernambuco, Brazil
Email: gdcc@cin.ufpe.br

Abstract—Class imbalance is a characteristic known for making learning more challenging for classification models as they may end up biased towards the majority class. A promising approach among the ensemble-based methods in the context of imbalance learning is Dynamic Selection (DS). DS techniques single out a subset of the classifiers in the ensemble to label each given unknown sample according to their estimated competence in the area surrounding the query. Because only a small region is taken into account in the selection scheme, the global class disproportion may have less impact over the system's performance. However, the presence of local class overlap may severely hinder the DS techniques’ performance over imbalanced distributions as it not only exacerbates the effects of the under-representation but also introduces ambiguous and possibly unreliable samples to the competence estimation process. Thus, in this work, we propose a DS technique which attempts to minimize the effects of the local class overlap during the classifier selection procedure. The proposed method iteratively removes from the target region the instance perceived as the hardest to classify until a classifier is deemed competent to label the query sample. The known samples are characterized using instance hardness measures that quantify the local class overlap. Experimental results show that the proposed technique can significantly outperform the baseline as well as several other DS techniques, suggesting its suitability for dealing with class under-representation and overlap. Furthermore, the proposed technique still yielded competitive results when using an under-sampled, less overlapped version of the labelled sets, specially over the problems with a high proportion of minority class samples in overlap areas. Code available at https://github.com/marianasaouza/lords.

I. INTRODUCTION

Imbalanced classification problems are characterized by a disproportion in the number of instances from the problems’ classes. Because one class is underrepresented compared to the remaining one(s), some traditional classification models may become biased towards the more well-represented labels [1]. This bias may hinder the performance over the rarer label, which is often also the most relevant class in real-world imbalanced problems, such as fraudulent transactions detection [2] and biomedical diagnosis [3].

Methods specifically tailored to deal with imbalanced datasets may fall into one of the following four categories [4]: algorithm-level approaches, which adapt traditional classifiers to deal with the class disproportion; data-level approaches, which resample the data to balance the distribution; cost-sensitive learning frameworks, which apply and incorporate class-based costs to the learning procedure; and ensemble based approaches, which usually couple ensemble methods with other methods, most commonly data-level and cost-sensitive approaches.

Among the ensemble-based approaches, dynamic selection (DS) schemes were often shown to perform rather well over imbalanced distributions [5], specially in combination with pre-processing methods [6]. DS techniques select a subset of the classifiers in the ensemble for labelling each query sample in particular, with the aim of using only the members that are perceived as competent in the area where the target instance is located. Their local approach in generalization can be an advantage in imbalanced scenarios as the global class disproportion may have a limited impact over the performance, similarly to other local methods [7].

Also due to their local approach, however, the presence of local class overlap can degrade their recognition rates not only over the positive (minority) class but also the negative (majority) class [8], [9]. In fact, the use of local adaptive distance and/or prototype selection methods that aim at minimizing the class overlap in the target region, called the Region of Competence (RoC) in the DS literature, were shown to improve their performance, including over highly imbalanced distributions [10], [11].

Thus, in this work, we propose a dynamic selection technique which dynamically edits the target region taking into account the instances’ characteristics with respect to (w.r.t.) the class overlap surrounding them. Based on the K-Nearest-Oracles Eliminate (KNORA-E) [12], the proposed method also searches for local oracles, that is, classifiers in the pool that can correctly label all instances in the RoC. Until a competent model is found, the region is iteratively reduced by removing from it the sample with the highest estimated classification difficulty. Thus, the instances considered relatively more unreliable due to their ambiguity are increasingly disregarded for estimating the competence of the classifiers.

The contributions of this work are then:

- A novel DS technique which integrates instance characterization, including two proposed adaptations for imbalanced distributions, into the definition of the RoC for dynamically reducing the class overlap in it.
- An experimental analysis over 64 imbalanced datasets in which we assess the performance of the proposed technique against 11 DS techniques, as well as the
impact of the proposed dynamic overlap-reducing scheme compared to using a pre-processing technique with the same goal.

This work is organized as follows. Section II presents a brief background on DS techniques. Then, in Section III we lay out the problem statement. The proposed method is introduced in Section IV. The experimental analysis is presented in Section V. Lastly, we summarize our conclusions in Section VI.

II. BACKGROUND

Dynamic selection techniques select a subset of a pool of base-classifiers to label each given query sample according to their perceived competence in the task, estimated over a region around the target instance. DS techniques are usually performed in three steps: RoC definition, competence estimation and classifier selection [13]. In the first step, the RoC is defined over a labelled set, called the DSEL set, using the nearest neighbors rule [12], clustering methods [14], distance-based potential functions [15], among others. Then, the competence of the classifiers in the pool is estimated using the samples in the RoC according to some criteria, for instance local accuracy [12]. Lastly, the classifier(s) deemed competent is(are) selected to label the query. If only one the most competent one is selected, the method is a Dynamic Classifier Selection (DCS) technique while if more than one can be selected the method is a Dynamic Ensemble Selection (DES) technique, which requires a combination scheme to join the selected classifiers’ responses.

It has been observed in the literature that the RoC definition has a large impact over the performance of the DS techniques [16], as the classifiers’ competence is estimated as a function of the instances included in it. In fact, a few DS techniques present a RoC editing scheme with the purpose of improving the classifiers’ competence estimation. The Multiple Classifier Behavior [17] uses only the subset of instances from the RoC that have a similar output profile, that is, the aggregate of classifiers’ responses, as the query’s. In [18], Item Response Theory (IRT) is applied over the ensemble to filter out from a set of linear classifiers and label blue to their right and green to their left, as indicated by the arrows.

As shown in this example, the RoC editing procedure from the KNORA-E may lead to the entire elimination of one of the classes in the region, which can bias the selection towards the remaining class, often the less sparse or under-represented one. Two methods based on the KNORA-E, the K-Nearest Oracles-Borderline (KNORA-B) and K-Nearest Oracles-Borderline-Imbalanced (KNORA-BI) propose to fix this issue by forcing the presence of all classes in the RoC. However, the three methods still assume the samples that are the closest to the query are more relevant for estimating the classifiers’ competences. This may not be true if the RoC presents a certain degree of class overlap, as in the example from Fig. 1. In fact, by disregarding the query’s closest neighbor (x1), which is located in the most overlapped area of the RoC, the classifier c1 would be recognized as a local oracle and would correctly label xq.

IV. PROPOSED TECHNIQUE

We propose a dynamic selection technique based on the KNORA-E which performs the RoC editing based on the samples’ estimated classification difficulty. The classification difficulty is estimated using an instance hardness measure [20], [21] which attempts to capture the degree of class overlap where the instance is located. That is, for a given unknown sample, we remove from the RoC the neighbors with higher instance hardness first, instead of the ones with largest distance to the query, in the search for the nearest local oracles. That way, the samples which are perceived as more reliable (that is, that are easier to classify) have a larger impact on the classifiers’ competence estimation compared to the more unreliable ones in the RoC. Thus, the proposed neighborhood editing procedure functions similarly to a dynamic instance selection over the RoC in which the samples with higher class ambiguity are sequentially removed until a competent classifier is found.

Algorithms 1 and 2 present in more detail the proposed dynamic selection scheme. The instance hardness estimation step described in Algorithm 1 occurs in memorization, while
the selection of the ensemble of classifiers (Algorithm 2) happens in generalization.

A. Instance hardness estimation

With regards to the hardness estimation procedure, Algorithm 1 requires the DSEL set and returns the hardness estimates of each sample in the DSEL. The hardness estimate consists of the score obtained from an instance hardness measure computed over the DSEL set. Thus, from Line 1 to Line 4, the instance hardness of each sample $x_i$ in the DSEL ($V$) is estimated and stored. The instance hardness measures that are computed in estimate hardnes($()$ are explained next. The hardness estimates of all instances in the DSEL are then returned in Line 5.

Algorithm 1 Instance hardness estimation.

```plaintext
Input: $V = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$ // DSEL set
Output: $H = \{h_1, h_2, \ldots, h_N\}$ // Hardness estimates

1: for every $(x_i, y_i)$ in $V$ do
2: $h_i \leftarrow$ estimate hardness($((x_i, y_i), V$) // Estimate instance hardness
3: $H \leftarrow H \cup h_i$
4: end for
5: return $H$
```

In order to characterize the hardness of the samples in the DSEL, we make use of instance hardness measures found in the literature. We have selected two measures to investigate in this work: the K-Disagreeing Neighbors (KDN) [20] and the Local Set Cardinality [21]. We chose these measures because they attempt to convey the classification difficulty associated with the local class overlap of the region where the sample is located. Since the dynamic selection technique is based on the concept of local oracles, the information regarding how ambiguous that region is may be valuable to assess the instance’s reliability for the competence estimation step. Moreover, local class overlap was shown to correlate the most with classification difficulty on the instance level in [20]. Lastly, since both measures are based on sample counts, their adaptation for class imbalanced scenarios can be quite straightforward.

We describe next the two chosen measures, as well as their proposed adaptation for imbalanced datasets. We also illustrate the hardness estimation using the example from Fig. 1, and to calculate the scores of the instances within the RoC we assume the total number of samples in the DSEL set is $|V| = 100$ and its imbalance ratio (IR), that is, the ratio between the majority and minority class sizes, is $IR = 3.0$.

a) K-Disagreeing Neighbors (KDN): The KDN score indicates the proportion of neighbors of a given sample which belong to a different class. The computation of the KDN measure is shown in (1), in which the k-neighborhood $\theta_k$ of the target instance $x_i$ is obtained over the remaining samples in the labelled set $V$. Fig. 2a shows the KDN scores, with $k = 3$ and rounded to two decimal points, of the instances from the toy example.

$$KDN((x_i, y_i), V, k) = \frac{|\{(x_j, y_j) \in \theta_k : y_i \neq y_j\}|}{k}$$ (1)

Since the KDN measure disregards the differences between the classes’ frequencies, in highly imbalanced scenarios the scores of the positive instances in overlap regions may be estimated much higher than the negative samples. This could negatively impact their recognition rates, as they would be removed first in the RoC editing procedure of the proposed technique. Thus, we propose and evaluate an adaptation of the KDN measure which attempts to even out the scores according to the classes’ frequencies. The adaptation, K-Disagreeing Neighbors-imbalance (KDNi) is shown in (2). It consists of the regular KDN score of the sample, according to (1), divided by the proportion of samples in the dataset that belong to the opposite class of the target instance ($p_o$). Since the KDN score includes the value 0.0, we add a very small number $e = 10^{-3}$ to it before computing the KDNi. Moreover, as the KDNi score can reach quite large values due to the division, we apply the function $f(x) = 1 - 1/(1 + x)$ to bound the base score from (2) and keep it in the range (0.0, 1.0), with the higher values for harder instances and lower values for easier samples.

$$KDNi((x_i, y_i), V, k) = \frac{KDN((x_i, y_i), V, k)}{p_o}$$ (2)

The KDNi scores of the example from Fig. 1 are shown in Fig. 2b. We can see, comparing the KDNi scores to the original KDN scores, that the instances very close to the border had their estimated hardness changed, while the ones further from the border changed little to nothing.

b) Local Set Cardinality (LSC): The LSC is an instance hardness measure based on the Local Set (LS) concept [22]. The LS of a given sample is comprised of the instances whose distance to it is smaller than the distance between the target sample and its nearest enemy, that is, the closest instance from the opposite class. The LSC measure of an instance is then the cardinality of its LS averaged by the number of samples in the dataset, as shown in (3), where $d(\cdot)$ is the Euclidean
distance and $x_{ne}$ is the nearest enemy of $x_i$. In order to yield a higher score to a harder to classify instance, we do as in [23] and calculate the measure as one minus the score shown in (3). The LSC scores of the instances from Fig. 1 are shown in Fig. 2c.

$$LSC((x_i, y_i), V) = \frac{|\{(x_j, y_j) \in V : d(x_i, x_j) < d(x_i, x_{ne})\}|}{|V|}$$ (3)

As the LSC measure also does not take into account the disproportion between the classes’ sizes, we adapt it to imbalanced distributions. The Local Set Cardinality-imbalance is a straightforward adaptation in which instead of dividing the size of the local set by the total number of instances in the dataset $|V|$, we divide it by the number of samples that share the same label as the target instance, as shown in (4). As in the LSC score used in this work, we also compute the LSCI as one minus the score shown in the equation for it to have a higher value for harder samples.

$$LSCI((x_i, y_i), V) = \frac{|\{(x_j, y_j) \in V : d(x_i, x_j) < d(x_i, x_{ne})\}|}{|\{(x_j, y_j) \in V : y_i = y_j\}|}$$ (4)

Fig. 2d shows the computed scores of the LSCI. We can see that the adaptation for imbalanced scenarios with this measure affected more instances than in the KDN adaptation case.

B. Ensemble selection

Algorithm 2 describes the dynamic ensemble of classifiers selection procedure. It takes as input the query sample $x_q$, the region of competence (RoC) size $k$, the DSEL set, the pool of classifiers $C$ and the hardness estimates $H$ obtained in memorization, and returns the selected ensemble of classifiers $C' \subseteq C$. First, the RoC $\theta_q$ of size $k$ is obtained using the nearest neighbors rule in Line 1. Then, in Line 2, the subset of classifiers in $C$ which correctly label all instances in the RoC are singled out. If there are local oracles with regards to the original RoC $\theta_q$, they are returned in Line 9. Otherwise, the procedure enters the loop from Line 4 to Line 8 until there can be found a classifier able to correctly label all instances in the RoC. In Line 5, the hardness estimates of the instances in the current RoC $\theta_q'$, which starts as the original $\theta_q$, are obtained. The size of the current RoC $\theta_q'$ is then reduced by one in Line 6 by removing from it the instance with highest hardness estimate. If there are more than one instance with the maximum hardness score in the current RoC, the furthest one from the query sample is removed. Then, we update the subset $C'$ with the classifiers in $C$ which have $100\%$ accuracy over the reduced RoC in Line 7. If at least one classifier is in $C'$, then the loop is exited and the procedure returns the ensemble $C'$, which is aggregated using majority voting to produce the predicted label of the query. However, if no local oracle is found at that iteration, the RoC editing process is repeated with the current RoC $\theta_q'$.

Now, going back to the example from Fig. 1, we can see that based on the neighboring samples’ instance hardness scores obtained in memorization (Fig. 2), the proposed technique would remove the sample $x_1$ from the RoC (Line 6) in the first iteration of the loop from Line 4 to Line 8, if using the KDN, KDNi or LSCI measures. In this case, the edited RoC $\theta_q'$ obtained after the first RoC edit is shown in Fig. 3a. If using the LSC measure, the first sample to be removed from the original RoC would be the $x_4$, as it presents the same (highest) hardness estimate as $x_1$ but it is further away from the query. In the second iteration, however, $x_1$ would be removed as well based on the LSC scores of the remaining instances in the RoC. The RoC configuration obtained after the removal of $x_1$ in the case of using the LSC measure is shown in Fig. 3b. Using any of the presented instance hardness measures, we can see from Fig. 3 that, after the removal of $x_1$, the method reaches its stop criteria as in Line 7 the classifier $c_1$ is identified as a local oracle in $C$, since it labels all instances in the current RoC correctly. Thus, the ensemble $C'$ which is returned in Line 9 contains the classifier $c_1$, which is then used to label the query instance.

V. EXPERIMENTS

A. Experimental protocol

a) Datasets: In order to evaluate the performance of the proposed technique over class imbalanced scenarios, we use the 64 two-class datasets from the Knowledge Extraction based on Evolutionary Learning (KEEL) repository [24] presented in Table I. The datasets present an IR ranging from 1.82 to 41.40. Moreover, we obtained for each dataset the proportion of safe instances according to the categorization proposed in [25].

![Algorithm 2 Ensemble of classifiers selection](image-url)
which is based on the local class distribution of the positive class samples. A minority class sample is considered safe if at least 4 of its 5 neighbors also belong to the minority class. The datasets in Table I are sorted in descending order of $S(\%)$, that is, the percentage of safe minority class instances. We refer to the first 36 problems in Table I as safe datasets, since at least half of its positive class samples are safe ($S(\%) \geq 50$), and the remaining problems as unsafe, as in [26].

For reproducibility, each dataset was evaluated using a stratified 5-fold cross validation procedure, one fold for test and the remaining for training, using the same partitions provided in the KEEL website. Due to the small-sized datasets and their high imbalance ratio, we use the training set as the DSEL set for all dynamic selection techniques evaluated, as in [10], [11].

b) Performance measures: We evaluate the models in this work in terms of two frequently used measures for imbalance learning: the $F_1$ score [27] and the Geometric Mean (G-mean) [28]. For the statistical comparisons between the techniques’ performances over multiple datasets, we use the pairwise Wilcoxon signed-rank test, as recommended in [29].

c) Dynamic Selection techniques: We compare our proposed technique against 11 DES techniques, including the baseline KNORA-E. The chosen techniques are shown in Table II. We use their implementation from the Python library DESLib [30], and evaluate them with the RoC size $k = 7$, and their remaining hyperparameters as the default. W.r.t. the proposed method, we use the same RoC size, and evaluate it using each of the hardness measures presented in Section IV-A. The only extra hyperparameter necessary is the neighborhood size of the KDN (as in (1) and (2)), which we set to $k = 5$ as recommended in [20].

All techniques except for the OLP use the same pool of classifiers containing 100 Perceptrons (learning rate $\alpha = 0.001$ and number of iterations $n_{iter} = 100$) that was generated using Bagging [31], as in [11]. To obtain the output class probabilities of the base-classifiers, we apply the sigmoid function over the hyperplanes’ decision function.

Lastly, since the proposed technique performs a dynamic RoC definition that takes into account the degree of class overlap associated with the location of each instance, the result may be similar to performing an instance selection/noise removal over the DSEL set. Thus, we also include in the analysis the use of the Edited Nearest Neighbors (ENN) [32] pre-processing method, available in the Python library imbalanced-learn [33], over the DSEL set only. The ENN, in this case, removes from the DSEL set the negative class samples which contain a majority of its $k = 3$ neighbors from the positive class.

B. Experimental results

We start by observing the difference in the behavior of the baseline KNORA-E and the proposed technique. Fig. 4 shows the average proportion of test instances whose sample removal order in the RoC editing scheme was different from the baseline KNORA-E and the proposed technique. Fig. 4 shows the average proportion of test instances whose sample removal order in the RoC editing scheme was different from the baseline KNORA-E, over the safe and unsafe datasets. Of course, this does not necessarily mean the selected ensemble of classifiers was different than the one KNORA-E would select. As expected due to the higher local class overlap, changes in the sample removal order were much more frequent over the unsafe datasets compared to the safe ones, considering all measures. Another trend we can observe in Fig. 4 is that the LSC-based measures have a larger effect in the ranking of the RoC samples compared to the KDN-based. This is likely due to the local set size, which can vary on a greater scale among close-by instances compared to the amount of disagreeing neighbors of a small fixed k-neighborhood. More score variation in a small area leads to falling fewer times on the tie rule, which is the distance-based ranking from the KNORA-E.

As to whether the proposed RoC editing scheme was able to outperform the KNORA-E’s distance-based procedure,
In terms of G-mean, the DES-KNN obtained the highest rank, followed again by the proposed method using the KDN, LSC and KDNi. Considering both performance measures, the OLP obtained the highest number of wins over the safe datasets, though the proposed method still obtained more wins than the baseline. Over the unsafe datasets, however, the proposed method obtained the two highest mean performance and average ranks in both $F_1$ and G-mean when using the adapted hardness measures, as well as the two highest numbers of wins.

Table IV shows the p-values obtained from the pairwise Wilcoxon signed-rank test with significance $\alpha = 0.05$, per-
formed over the average performances of the DS techniques. First, we can see that compared to the baseline, the proposed technique yielded a statistically similar $F_1$ score over the safe datasets except when using the LSCI measure, which obtained a significantly worse performance. As observed previously, the LSCI prompts a change in the RoC editing order much more often than the KDN-based measures, all the while favoring the positive class, so over the safe problems the precision may have been hindered. In fact, both adapted measures obtained a poorer $F_1$ score compared to the DES-KNN, META-DES and OLP over the safe datasets. However, the proposed method using the original measures was significantly better over the safe datasets than the KNORA-B and KNORA-BI. Moreover, in terms of G-mean, the proposed technique significantly outperformed both the baseline and KNORA-B over the safe datasets, using the KDN and LSC as hardness estimates.

Over the unsafe datasets, the proposed technique using the adapted measures obtained a statistically similar $F_1$ and a significantly better G-mean compared to the baseline, META-DES and DES-KNN. It also significantly surpassed the OLP, KNORA-B and KNORA-BI when using the LSCI measure in both $F_1$ and G-mean. Compared to the remaining techniques, the proposed method significantly outperformed them using all of the hardness measures investigated. This suggests that reducing the local overlap in the RoC in generalization may be advantageous for the classifier selection step, specially over the unsafe datasets.

Fig. 6. Difference in performance between the proposed method using the indicated hardness measure, (a-b) without and (c-d) with pre-processing (ENN), and the baseline technique with pre-processing (KNORA-E + ENN), averaged over the indicated datasets (Table I).

We now analyze the performance of the proposed technique relative to the use of the ENN. In order to observe the impact of such procedure over the DS techniques, we only apply it to the DSEL set, thus the pool of classifiers is the same as in the previous analysis. Fig. 6a and Fig. 6b show the difference in average $F_1$ and G-mean between the proposed method without pre-processing and the baseline with pre-processing (KNORA-E + ENN). We can observe that applying the ENN over the DSEL yielded a greater improvement to the KNORA-E method compared to the proposed hardness-based RoC editing procedure. This may be due to the fact that, after applying the ENN over the DSEL, the initial RoC contains more reliable samples since the most unreliable ones in that area were already removed. Therefore, even if the proposed technique eventually removes such samples, comparatively fewer instances will remain in the RoC which may negatively impact the competence estimation. Thus, starting off the ensemble selection procedure with a less overlapped RoC seems to provide a better overall performance for the KNORA-E. However, for some datasets the dynamic sample removal used in the proposed method still yielded slightly better average results, which may motivate the design of an approach that can combine this desirable characteristic from a pre-processing procedure for an online RoC editing scheme.

Table V Average performance and mean rank of the DES techniques with the ENN pre-processing method over the groups of safe and unsafe datasets. Wins shows the total number of first positions. Solo wins count as 1 while ties in the first position count as 1/# tied techniques. Best results are in bold.

| Technique | Mean Rank | Mean Rank | Wins |
|-----------|-----------|-----------|------|
| KNORA-E   | 5.318     | 6.250     | 4     |
| KNORA-B   | 4.892     | 6.661     | 3     |
| KNORA-U   | 4.645     | 7.292     | 2     |
| DESP      | 4.972     | 7.639     | 1     |
| DESK      | 4.365     | 9.013     | 0     |
| DES-KNN   | 3.830     | 9.804     | 0     |
| DES-RRC   | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |
| META-DES  | 3.847     | 9.804     | 0     |

Applying the ENN over the DSEL for all DS techniques investigated in this work, we obtain the results from Table V. We can see that the OLP still yielded the best average rank over the safe datasets in terms of $F_1$, as well as the highest number of wins considering both performance measures, but the proposed method (with the KDN and LSC) and the baseline KNORA-E obtained the highest rank in terms of G-mean. Over the unsafe datasets, the proposed method obtained the two highest average ranks w.r.t. $F_1$ using the original measures, and w.r.t. G-mean using the adapted measures. The second highest number of wins was also achieved by...
the proposed technique, using the KDNi. Interestingly using the original measures yielded a better $F$-value than using the adapted measures over the unsafe datasets, as opposed to the previous results without the pre-processing, possibly due to the slightly less biased hardness estimation after removing the most overlapped majority class samples.

| Technique | Prop. (KDN) | Prop. (KDNi) | Prop. (LSC) | Prop. (LSCi) |
|-----------|-------------|--------------|-------------|--------------|
| KNORA-U   | 0.005       |              |             |              |
| DES-KNN   | 0.190 0.445 | 0.241 0.707  |              |              |
| META-DES  | 0.439 0.982 | 0.600 0.820  | 0.106       |              |
| DES-RRC   | 0.029       |              |             |              |
| KNORA-B   | 0.305 0.927 | 0.316 0.733  | 0.716 0.179  | 0.733 0.029  |
| KNORA-E   | 0.404       |              |             |              |
| DES-RE    | 0.582 0.052 | 0.620        |             |              |
| KNOP      | 0.370 0.111 | 0.268 0.072  | 0.076 0.133  | 0.063 0.155  |
| DES-KNN   | 0.740 0.883 | 0.734 0.083  | 0.249 0.287  | 0.138 0.813  |
| META-DES  | 0.706 0.897 | 0.724 0.083  | 0.409 0.535  | 0.404 0.545  |
| DES-RRC   | 0.881 0.409 | 0.904 0.530  | 0.465 0.666  | 0.620 0.700  |
| OLCP      | 0.001 0.001 | 0.072 0.002  | 0.344 0.313  | 0.212 0.126  |
| KNORA-BI  | 0.013 0.012 | 0.102 0.102  | 0.318 0.623  | 0.358 0.358  |
| KNORA-BII | 0.018 0.013 | 0.013 0.049  | 0.305 0.683  | 0.281 0.221  |

Table VI shows the resulting p-values of the Wilcoxon signed-rank test on the average performances of the techniques with the ENN over the safe and unsafe datasets. We can observe that, over the safe datasets, the proposed method with the adapted measures was statistically worse than several methods including the baseline with the original measures it surpassed the KNORA-B and KNORA-BI in terms of $F_1$. Over the unsafe datasets, however, the proposed method with the LSCI statistically outperformed all techniques except for the KNORA-BI, in terms of G-mean.

C. Lessons learned

All in all, the results suggest that there is a performance improvement to be had by characterizing the hardness of the instances in the RoC, and prioritizing the ones that seem more reliable for the classifiers’ competence estimation. Using an overlap reducing pre-processing technique tailored for imbalanced data seems to have an overall better impact over the classifier selection procedure compared to the proposed dynamic RoC editing scheme alone, possibly due to the region being less ambiguous from the start. However, we observed an advantage in not outright removing the instances in memorization for some datasets. Moreover, the proposed technique still presented a performance improvement after reducing the local class overlap in the data using the pre-processing technique, which further supports the integration of instance characterization into the RoC definition for DS techniques.

Furthermore, we observed that the instance characterization within the proposed method had a large effect on performance, so choosing which hardness measure to use should be based on the distribution of the positive class in the problem. For a minority class composed of mostly safe samples, the original measures seemed to provide a good estimate of the instances’ reliability in the region, even in the presence of high global imbalance ratios. On the other hand, over the unsafe datasets, the adapted measures were a much more effective guide in the proposed RoC editing scheme. Lastly, while the corresponding KDN-based and LS-based measures yielded somewhat similar performances, likely because they both attempt to quantify the local class overlap using a concept of neighborhood, we would recommend using the LS-based measures as they not only presented slightly better overall results but also do not require any hyperparameter.

VI. Conclusion

In this work, we proposed a Dynamic Selection technique which dynamically edits the target region in the search for a local oracle. Motivated by the observation that a class-overlapped region can hinder the system’s recognition rates, specially over the locally under-represented class, the proposed method removes the samples perceived as most unreliable from the RoC one by one until at least one classifier can label all remaining instances in it. For characterizing the known instances in the problem, we use two instance hardness measures that convey the degree of local overlap in the area. We also propose and evaluate an adapted version of these measures as they can often be biased towards the majority class.

Experiments were conducted over 64 imbalanced datasets, which were split into two groups according to the percentage of safe positive class instances in the problem. The proposed method yielded very competitive results against a baseline and 10 other DS techniques, specially over the unsafe datasets, which suggests that the overlap-reducing procedure on the RoC can improve the competence estimation and thus the selection of the classifiers. Moreover, the most adequate instance characterization to use within the proposed technique appears to depend on the positive class distribution, as the original instance hardness measures present a high bias towards the majority class on the unsafe problems.

Future work in this line of research may involve a further investigation on the impact of using pre-processing methods to remove the local overlap for DS techniques, as opposed to dynamically editing the RoC. This may lead to the study of a scheme which can provide some advantages from both approaches, in order to improve the competence estimation of
the classifiers and thus the DS techniques' recognition rates over all classes.

ACKNOWLEDGMENTS

The authors would like to thank the Canadian agencies FRQ (Fonds de Recherche du Québec) and NSERC (Natural Sciences and Engineering Research Council of Canada), and the Brazilian agencies CAPES (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior), CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) and FACEPE (Fundação de Amparo à Ciência e Tecnologia de Pernambuco).

REFERENCES

[1] R. C. Prati, G. E. Batista, and D. F. Silva, “Class imbalance revisited: a new experimental setup to assess the performance of treatment methods,” Knowledge and Information Systems, vol. 45, no. 1, pp. 247–270, 2015.

[2] W. Wei, J. Li, L. Cao, Y. Ou, and J. Chen, “Effective detection of sophisticated online banking fraud on extremely imbalanced data,” World Wide Web, vol. 16, no. 4, pp. 449–475, 2013.

[3] M. A. Mazurowski, P. A. Habas, J. M. Zurada, J. Y. Lo, J. A. Baker, and G. D. Tourassi, “Training neural network classifiers for medical decision making: The effects of imbalanced datasets on classification performance,” Artificial Intelligence in Medicine, vol. 21, no. 2-3, pp. 427–436, 2001.

[4] A. Fernández, S. García, M. Galar, R. C. Prati, B. Krawczyk, and F. Herrera, Learning from Imbalanced Data Sets. Springer International Publishing, 2018.

[5] D. V. Oliveira, G. D. Cavalcanti, and R. Sabourin, “Online pruning of base classifiers for dynamic ensemble selection,” Pattern Recognition, vol. 72, pp. 44–58, 2017.

[6] R. M. Cruz, L. G. Hafemann, R. Sabourin, and G. D. Cavalcanti, “A study on combining dynamic selection and data preprocessing for imbalance learning,” Neurocomputing, vol. 286, pp. 179–192, 2018.

[7] V. García, R. A. Mollineda, and J. S. Sánchez, “On the k-nn performance in a challenging scenario of imbalance and overlapping,” Pattern Analysis and Applications, vol. 11, no. 3-4, pp. 269–280, 2008.

[8] R. C. Prati, G. E. Batista, and M. C. Monard, “Class imbalances versus class overlapping: an analysis of a learning system behavior,” in Mexican international conference on artificial intelligence. Springer, 2004, pp. 312–321.

[9] V. García, J. Sánchez, and R. Mollineda, “An empirical study of the behavior of classifiers on imbalanced and overlapped data sets,” in Iberoamerican Congress on Pattern Recognition. Springer, 2007, pp. 397–406.

[10] R. M. Cruz, D. V. Oliveira, G. D. Cavalcanti, and R. Sabourin, “Fire-dess++: Enhanced online pruning of base classifiers for dynamic ensemble selection,” Pattern Recognition, vol. 85, pp. 149–160, 2019.

[11] M. A. Souza, G. D. Cavalcanti, R. M. Cruz, and R. Sabourin, “On evaluating the online local pool generation method for imbalance learning,” in International Joint Conference on Neural Networks (IJCNN). IEEE, 2019, pp. 1–8.

[12] A. H.-R. Ko, R. Sabourin, and A. de Souza Britto Jr, “A new dynamic ensemble selection method for numeral recognition,” in 7th International Conference on Multiple Classifier Systems. Springer-Verlag, 2007, pp. 431–439.

[13] R. M. O. Cruz, R. Sabourin, and G. D. C. Cavalcanti, “Dynamic classifier selection: Recent advances and perspectives,” Information Fusion, vol. 41, pp. 195–216, May 2018.

[14] R. G. Soares, A. Santana, A. M. Canuto, and M. C. P. de Souto, “Using accuracy and diversity to select classifiers to build ensembles,” in The 2006 IEEE International Joint Conference on Neural Network Proceedings. IEEE, 2006, pp. 1310–1316.

[15] T. Wołoszyński and M. Kurzyński, “A probabilistic model of classifier competence for dynamic ensemble selection,” Pattern Recognition, vol. 44, no. 10, pp. 2656–2668, 2011.

[16] R. M. Cruz, R. Sabourin, and G. D. Cavalcanti, “Prototype selection for dynamic classifier and ensemble selection,” Neural Computing and Applications, vol. 29, no. 2, pp. 447–457, 2018.

[17] G. Giacinto, F. Roli, and F. G. Fumera, “Selection of classifiers based on multiple classifier behaviour,” in Joint IAPR International Workshops on Statistical Techniques in Pattern Recognition and Structural and Syntactic Pattern Recognition. Springer-Verlag, 2000, pp. 87–93.