Introduction to Machine Learning
Work 3
Lazy Learning exercise

Course 2023-2024

Contents

1 Lazy learning exercise

1.1 Introduction

In this exercise, you will learn about lazy learning. In particular, you will work on a comparative study in the use of different Feature Selection techniques and Instance Selection techniques in an Instance-based Learning algorithm. You will apply lazy learning to a classification task. It is assumed that you are familiar with the concept of cross-validation. If not, you can read this paper:

[1] R. Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection. In Proceedings of the International Joint Conferences on Artificial Intelligence IJCAI-95. 1995.

Briefly, an s-fold cross validation (s = 10 in your case) divides a data set into s equal-size subsets. Each subset is used in turn as a test set with the remaining (s-1) data sets used for training. **The data sets with a predefined 10-fold cross validation are provided in Campus Virtual.** You cannot modify or perform a different cross-validation on the datasets.

For the validation of the different algorithms, you need to use a T-Test or another statistical method. Next reference is a **mandatory reading proposal** (in Campus Virtual) on this topic:

[2] Janez Demšar. 2006. Statistical Comparisons of Classifiers over Multiple Data Sets. J. Mach. Learn. Res. 7 (December 2006), 1-30.

This article details how to compare two or more learning algorithms with multiple data sets.

1.2 Methodology of the analysis

As in the previous work assignment, you will analyze the behavior of the different algorithms by comparing the results in two well-known data sets (**with medium and large size**) from the UCI repository. In that case, you will also use the class as we are testing several supervised learning algorithms. In particular, in this exercise, you will receive the data sets defined in .arff format but divided in **ten training and test sets** (they are the *10-fold cross-validation* sets you will use for this exercise).

This work is divided in several steps:

1. Read the source data for training and testing the algorithms. Improve the parser developed in previous works in order to use the class attribute, too. Now, you need to read and save the information from a training and their corresponding testing file in a `TrainMatrix` and a `TestMatrix`, respectively. **Recall that you need to normalize all the numerical attributes in the range [0..1].** For representing the instance base, the most used by its simplicity and applicability is a flat structure. The instances are represented as a feature vector approach by means of a set of attribute-value pairs. The `TrainMatrix` and the `TestMatrix` contain the set of instances for training and testing, respectively.

2. Write a Python function that automatically repeats the process described in previous step for the 10-fold cross-validation files. That is, read automatically each training case and run each one of the test cases in the selected classifier.

3. Implement a **k-Instance-Based Learning** algorithm, whose basis will be IB1. Write a Python function for classifying, using a K-NN algorithm, each instance from the `TestMatrix` using the `TrainMatrix` to a classifier called `kIBLAlgorithm(...)`. You decide the parameters for this classifier. Note that instead of retrieving the most similar instance, the similarity function will return the K most similar instances. **Justify your implementation and add all the references you have considered for your decisions.**

   Let us assume that we have a training dataset D made up of $(x_i)_{i\in[1,n]}$ training samples (where $n = |D|$). The examples are described by a set of features, F, and any numeric features have been normalized to the range $[0,1]$. Each training example is labelled with a class label $y_j \in Y$. Our objective is to classify an unknown example *q*. For each $x_i \in D$ we can calculate the distance between *q* and x_i as follows:

   $$d(q, x_i) = \sum_{f\in F} w_f\ \delta(q_f, x_{if})$$

   This is the summation over all the features in F with a weight for each feature.

   a. There are large range of possibilities for the distance metric, δ. In this work, you should consider the Euclidean. Adapt these distances to handle all kind of attributes (i.e., numerical and categorical). Assume that the kIBL algorithm returns the K most similar instances (i.e., also known as cases) from the TrainMatrix to ***q***. The value of K will be setup in your evaluation to 3, 5, and 7.

   b. There are a variety of ways in which k nearest neighbors can be used to decide the solution of the query ***q***, you may consider using **two voting policies**: Modified Plurality and Borda Count.

      a. **Modified Plurality** computes the most voted solution but in case of ties, it removes the last k nearest neighbor and computes again the most voted solution. In case of ties, the process is repeated. The process finishes when there is a winner solution or when just one nearest neighbor remains.
      b. **Borda count** voting rule, whose name comes from the French mathematician, physicist, political scientist and sailor Jean-Charles de Borda (1733-1799). Borda voting rule assigns k – 1 points to the solution of the most similar instance, k – 2 points to the second `k` nearest neighbor, or k – k to the solution that is ranked in k-th. The winner is the solution that amasses the highest total number of points. A method for breaking ties should also be specified. You should decide what to do in this case.

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c. Instance-based learning algorithms may learn during the generalization process. In this work, you will implement different retention policies.
    a. **Never retain (NR)**. The algorithm never retains the current instance q in the instance base. The generalization process is based exclusively on the instances present in the training set.
    b. **Always retain (AR)**. The algorithm retains all new solved instances in the instance base.
    c. **Different Class retention (DF)**. The algorithm retains all the instances that have been solved incorrectly.
    d. **Degree of Disagreement (DD)**. This strategy is based on a measure of dispersion -or disagreement- of the k most similar instances. It is inspired by the active learning policy, which, in turn, uses a variation of the Query by Committee (QbC) algorithm. The proposal is to use the k set as a virtual committee. So, each member of the committee can be seen as a case in k, and the vote it generates as the class associated to this case. The formula is as follows:

$$d = \frac{\#remaining\_cases}{(\#classes - 1) \times \#majority\_cases}$$

The equation measures d as the degree of disagreement over the K retrieved instances, where #classes is the number of different classes[1] in the instance base, where #majority_cases is the number of instances with the most assigned class (i.e., the majority class in K) and #remaining_cases is the number of instances with classes other than the majority one. In this manner, |k|= #majority_cases + #remaining_cases. Thus, disagreement value d reaches value 1 when every instance in K yields to a different classification and so, instances disagree the most, while it approximates to 0 when there is a clear majority. #classes -1 is introduced in order to normalize disagreement from 0 to 1. As an implementation detail, it is important that the K set is ordered according to the similarity. In case of ties, you will solve ties by just considering the first one that has been found. So, it is the most assigned and most similar class since K is ordered according to similarity.

d. For evaluating the performance of the K-IBL algorithm, we will use the classification **accuracy** (i.e., the average of correctly classified instances) and the **efficiency** (i.e., average problem-solving time). To this end, at least, you should store the number of cases correctly classified, the number of cases incorrectly classified, and the problem-solving time. This information will be used for the evaluation of the algorithm. You can store your results in a memory data structure or in a file. Keep in mind that you need to compute the average accuracy and the average efficiency over the 10-fold cross-validation sets.

[1]This is a general definition which, in our case, could correspond to all the classes in the instance base or just the classes appearing in k. We take the former option, so all classes are considered at each iteration step.

At the end, you will have a K-IBL algorithm with different values for the K parameter, two policies for deciding the solution of the current_instance q, and four different retention policies. You will analyze the behavior of these parameters in the K-IBL algorithm and decide which combination results in the **best k-IBL algorithm**. Assume that you use equal weights in all the features (i.e, $w_f = 1$). Use statistical tests to decide which is the best option.

You can compare your results in terms of classification accuracy and efficiency (in time). Extract conclusions by analyzing **two datasets (should be large enough). At least one of these data sets will contain numerical and nominal data**. The suggestion is that you continue with the same data sets you have used in Work 2. However, if you want to modify them, you are free to modify one of them, just justifying your decision at the beginning of the report that describes your Work 3.

4. Departing from the best k-IBL algorithm. Modify the k-IBL algorithm so that it includes a preprocessing for selecting the best set of features from the training set, you will call this algorithm as `fs_KIBLAlgorithm(...)`.
   a. Modify the distance metric in the k-IBL so that it uses the preprocessed feature's weights. Note that a weight value of 1.0 denotes that the feature will be used by the distance metric. By contrast, a weight value of 0.0 shows that the feature is useless and it is not going to be used.
      The selection can be done using different metrics. You may choose **two algorithms** (filter or wrapper, as you wish). Use them as a preprocessing step. This means that you will only compute the selection in the initial training set. For example, you can use ReliefF, Information Gain, or the Correlation, among others. There are several Python Libraries that also include most of the well-known metrics for feature weighting and feature selection. You can use the implementations that exist in Python for your feature selection implementations. The following paper may help you in your selection of algorithms.

      [5] Feature Selection Tutorial with Python Examples. Padraig Cunningham, Bahavathy Kathirgamanathan, Sarah Jane Delany https://arxiv.org/abs/2106.06437

   b. Analyze the results of the `fs_KIBLAlgorithm` in front of the previous `kIBLAlgorithm` implementation. To do it, setup both algorithms with the best combination obtained in your previous analysis. In this case, you will analyze your results in terms of classification accuracy.

5. Departing from the best k-IBL algorithm. Modify the k-IBL algorithm so that it includes a preprocessing for reducing the training set, you will call this algorithm as `is_KIBLAlgorithm(...)`. In general instance-based learning algorithms retain all the training instances. However, the training set may be too large and it may also contain inconsistent and noisy instances. For this reason, it is important to decide which instances to store for use during the generalization. In this work, you will implement your own code for several preprocessing instance selection techniques:

a. Selective Nearest Neighbour Rule (SNN), TCNN, or MCNN
b. Edited Nearest Neighbour rule (ENN), allKNN, or MENN
c. IB3 or ICF
d. Analyze the results of the `is_KIBLAlgorithm` in front of the previous `kIBLAlgorithm` and `fs_KIBLAlgorithm` implementation. To do it, setup all the algorithms with the best combination obtained in your previous analysis. In this case, you will analyze your results in terms of classification accuracy, efficiency and storage (i.e, the average percentage of instances stored from the training to generalize the testing instances). Accordingly, the storage of the kIBLAlgorithm is 100%.

Note that all the reduction algorithms are detailed in:

[3] D. Randall Wilson and Tony R. Martinez. 2000. Reduction Techniques for Instance-BasedLearning Algorithms. Mach. Learn. 38, 3 (March 2000), 257-286. DOI: https://doi.org/10.1023/A:1007626913721 https://link.springer.com/content/pdf/10.1023%2FA%3A1007626913721.pdf

1.3 Work to deliver

In this work, you will implement Instance-based learning algorithms. You will analyze the behavior of different parameters in the k-IBL algorithm and the use of feature and instance selection techniques in a preprocessing process for reducing the memory requirements and to increase the execution speed. You may select two data sets (large enough to extract conclusions) for your analysis. At the end, you will find a list of the data sets available.

The idea is that you implement **your own code in Python 3.7 and PyCharm I**DE and you will use it to produce the results of the analysis, and to extract the performance of the different combinations. Performance will be measured in terms of classification accuracy, efficiency, and storage. The accuracy measure is the average of correctly classified cases. That is the number of correctly classified instances divided by the total of instances in the test file. The efficiency is the average problem-solving time. For the evaluation, you will use a T-Test or another statistical method [2].

From the accuracy and efficiency results, you will extract conclusions showing graphs of such evaluation and reasoning about the results obtained.

In your analysis, you will include several considerations.

1. You will analyze the k-IBL algorithm, with different parameter combinations. You will analyze which is the most suitable algorithm. The one with the highest accuracy will be named as the best k-IBL algorithm. *Recall to perform a statistical analysis over the different configurations*.

2. Once you have decided the best k-IBL algorithm, you will analyze different feature selection and instance selection techniques. The idea is to analyze if these techniques may increase accuracy, efficiency and storage in a k-IBL algorithm and to extract conclusions of which feature or instance selection technique is the best one. *Recall to perform a statistical analysis*.

For example, some of questions that it is expected you may answer with your analysis:

- Which is the best value of K at each dataset?

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- Which k-IBL algorithm is the best one at each dataset?
- Did you find useful the use of a voting scheme for deciding the solution of the current_instance?
- Which is the best feature selection technique for the k-IBL? Or by the contrary, feature selection does not help.
- Which is the best instance selection technique for the k-IBL? Or by the contrary, instance selection does not help.
- Did you find differences in performance among the k-IBL and the feature/instance selection k-IBL?
- According to the data sets chosen, which feature selection method provides you more advice for knowing the underlying information in the data set?
- Do you think it will be much better to improve the retention process rather than reducing the training set?
- Do you think it will be much better to perform feature selection rather than reducing the training set with an instance selection technique?
- Do you think that the combination of both, feature selection and instance selection, will be the best option to obtain the best k-IBL algorithm? Since the experiments do not include this analysis, just make your reasoning and explain what do you think about this.

Apart from explaining your decisions and the results obtained, it is expected that you reason each one of these questions along your evaluation.

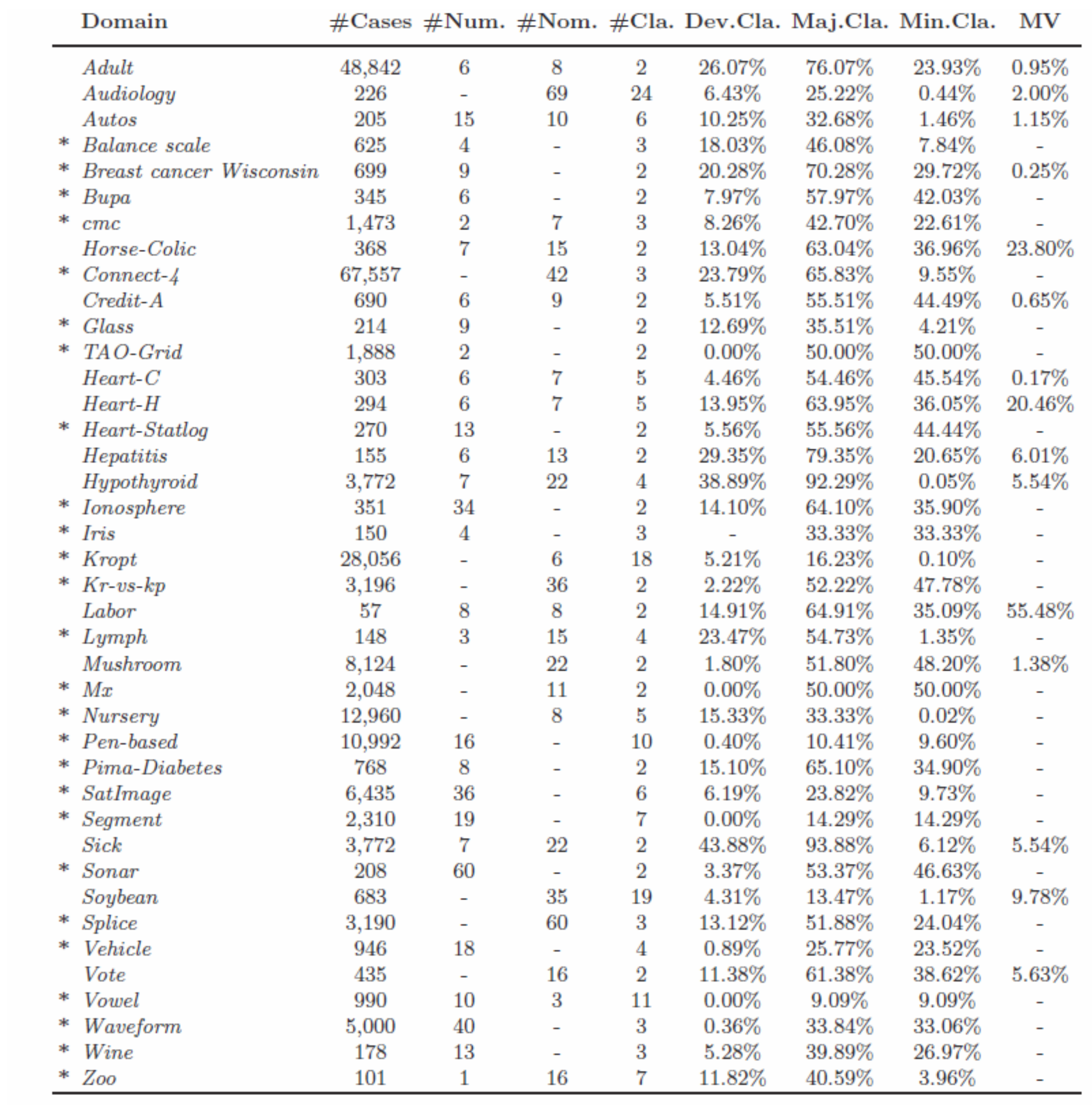
Additionally, **you should explain how to execute your code in the README.md and include the requirements.txt in your code folder**. Remember to add any reference that you have used in your decisions.

You should deliver a report as well as the code in Python in a PyCharm project in Campus Virtual by **December, 18th, 2023**.

Remember that the maximum size of the report is 20 pages, including description and graphs. Excluded are the cover page, table of contents, and the references.

2 Data sets

Below, you will find a table that shows in detail the data sets that you can use in this work. All these data sets are obtained from the UCI machine learning repository. First column describes the name of the domain or data set. Next columns show #Cases = Number of cases or instances in the data set, #Num. = Number of numeric attributes, #Nom = Number of nominal attributes, #Cla. = Number of classes, Dev.Cla. = Deviation of class distribution, Maj.Cla. = Percentage of instances belonging to the majority class, Min.Cla. = Percentage of instances belonging to the minority class, MV = Percentage of values with missing values (it means the percentage of unknown values in the data set). When the columns contain a '-', it means a 0. For example, the Glass data set contains 0 nominal attributes and it is complete as it does not contain missing values.



Domain	#Cases	#Num.	#Nom.	#Cla.	Dev.Cla.	Maj.Cla.	Min.Cla.	MV
Adult	48,842	6	8	2	26.07%	76.07%	23.93%	0.95%
Audiology	226	-	69	24	6.43%	25.22%	0.44%	2.00%
Autos	205	15	10	6	10.25%	32.68%	1.46%	1.15%
* *Balance scale*	625	4	-	3	18.03%	46.08%	7.84%	-
* *Breast cancer Wisconsin*	699	9	-	2	20.28%	70.28%	29.72%	0.25%
* *Bupa*	345	6	-	2	7.97%	57.97%	42.03%	-
* *cmc*	1,473	2	7	3	8.26%	42.70%	22.61%	-
Horse-Colic	368	7	15	2	13.04%	63.04%	36.96%	23.80%
* *Connect-4*	67,557	-	42	3	23.79%	65.83%	9.55%	-
Credit-A	690	6	9	2	5.51%	55.51%	44.49%	0.65%
* *Glass*	214	9	-	2	12.69%	35.51%	4.21%	-
* *TAO-Grid*	1,888	2	-	2	0.00%	50.00%	50.00%	-
Heart-C	303	6	7	5	4.46%	54.46%	45.54%	0.17%
Heart-H	294	6	7	5	13.95%	63.95%	36.05%	20.46%
* *Heart-Statlog*	270	13	-	2	5.56%	55.56%	44.44%	-
Hepatitis	155	6	13	2	29.35%	79.35%	20.65%	6.01%
Hypothyroid	3,772	7	22	4	38.89%	92.29%	0.05%	5.54%
* *Ionosphere*	351	34	-	2	14.10%	64.10%	35.90%	-
* *Iris*	150	4	-	3	-	33.33%	33.33%	-
* *Kropt*	28,056	-	6	18	5.21%	16.23%	0.10%	-
* *Kr-vs-kp*	3,196	-	36	2	2.22%	52.22%	47.78%	-
Labor	57	8	8	2	14.91%	64.91%	35.09%	55.48%
* *Lymph*	148	3	15	4	23.47%	54.73%	1.35%	-
Mushroom	8,124	-	22	2	1.80%	51.80%	48.20%	1.38%
* *Mx*	2,048	-	11	2	0.00%	50.00%	50.00%	-
* *Nursery*	12,960	-	8	5	15.33%	33.33%	0.02%	-
* *Pen-based*	10,992	16	-	10	0.40%	10.41%	9.60%	-
* *Pima-Diabetes*	768	8	-	2	15.10%	65.10%	34.90%	-
* *SatImage*	6,435	36	-	6	6.19%	23.82%	9.73%	-
* *Segment*	2,310	19	-	7	0.00%	14.29%	14.29%	-
Sick	3,772	7	22	2	43.88%	93.88%	6.12%	5.54%
* *Sonar*	208	60	-	2	3.37%	53.37%	46.63%	-
Soybean	683	-	35	19	4.31%	13.47%	1.17%	9.78%
* *Splice*	3,190	-	60	3	13.12%	51.88%	24.04%	-
* *Vehicle*	946	18	-	4	0.89%	25.77%	23.52%	-
Vote	435	-	16	2	11.38%	61.38%	38.62%	5.63%
* *Vowel*	990	10	3	11	0.00%	9.09%	9.09%	-
* *Waveform*	5,000	40	-	3	0.36%	33.84%	33.06%	-
* *Wine*	178	13	-	3	5.28%	39.89%	26.97%	-
* *Zoo*	101	1	16	7	11.82%	40.59%	3.96%	-

3 Report guidelines

I believe that it will be of great help for you some general **guidelines** for writing the report. It is not a complete list, it contains some comments and suggestions that you may consider in the assignments.

First of all, include a **front cover** with the name and surnames of the group members and a title of the work (this front cover is not part of the length of the report). The font size should be 11 or 12, not smaller and recall that figures should be also large enough for easier readability.

Analyze the different parameters and use tables or plots to show the results of your evaluation, and justify your decision of the final parameters. Not just saying we have tested several parameters and the best one is X or Y.

Additionally, it is important to **justify your findings**, not to just plot the graph with no comments on it about your observations and your judgement of the behavior of the algorithm in your data. Recall that when you add a comment on a plot, you should also link the comment to the figure/table/plot you are talking about. For example, as shown in Figure X .... or this result indicates that ... (see Figure X).

For the reader of a report, it is difficult to compare graphs if they contain different ranges in their axes and if they are placed in different pages (i.e., more than one page in the middle). It is supposed that **your findings are based on the experiments and the results obtained**. You cannot extract a conclusion if your results do not support it.

Presenting the results in isolation for every one of the datasets helps you to **fix the parameters** and extract conclusions considering the properties of a particular dataset. However, an **overall evaluation** of the methods/algorithms tested over the different datasets is also important to denote the applicability of the method/algorithm to different domains.

If you have read and implemented improvements on the basic algorithms, please add the comment and the references that justify your decision too. The report should contain a section with **references** or bibliography. Remember to add references at the end of the report. (references are not part of the length of the report)

Apart from showing your results and describing them, you **should also answer the questions that are requested in the description of the work**.

Conclusions in a report are important, please, remember to add them in your reports. Not only the general conclusions about what you have done, the conclusions of your findings and your observations of the results.