Introduction to Machine Learning
Work 3
Lazy learning exercise

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 similarity measures, feature weighting methods and instance reduction methods 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.

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 a pair of well-known data sets (**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 case base, the most used by its simplicity and applicability is a flat structure. The cases 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 cases 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 Instance-based learning algorithms. In this work you will implement three types of this algorithms: ib1, ib2, and ib3.
   a. Write a Python function for classifying, using each IBL algorithm, each instance from the `TestMatrix` using the `TrainMatrix` to a classifier called `ib1Algorithm(...)`, `ib2Algorithm(...)`, and `ib3Algorithm(...)`, respectively. You decide the parameters for these classifiers. **Justify your implementation and add all the references you have considered for your decisions.** The details of the algorithms are explained at:

      [3] David W. Aha, Dennis Kibler, and Marc K. Albert. 1991. Instance-Based Learning Algorithms. Machine Learning. 6, 1 (January 1991), 37-66. DOI: https://doi.org/10.1023/A:1022689900470.

      https://rd.springer.com/content/pdf/10.1007%2FBF00153759.pdf

   b. For evaluating the performance of the IBL algorithms, we will use the percentage of correctly classified instances. To this end, at least, you should store the number of cases correctly classified, the number of cases incorrectly classified. 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 over the 10-fold cross-validation sets. Additionally, extract the efficiency (in time).

   At the end, you will have three IBL algorithms tested with a **Euclidean** similarity measure. You should analyze the behavior of these three algorithms with **two large** enough data sets. **At least one of these data sets will contain numerical and nominal data**. You should decide and justify the reasons for the **best IBL algorithm**.

4. Departing from the **best IBL algorithm**, 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 fact, the selection of an appropriate distance metric is a key point in lazy learning algorithms. In this work you will analyze the following **similarity measures**: Euclidean, Manhattan or Cosine, Clark or Canberra, and HVDM or IVDM [4]. If necessary, adapt these distances to handle all kind of attributes (i.e., numerical and categorical).

[4] Wilson, D.R., Martínez, T.R., 1997. Improved heterogeneous distance functions. Journal of Artificial Intelligence Research 6, 1–34.

https://arxiv.org/pdf/cs/9701101.pdf

b. Assume that the kIBLAlgorithm 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.

c. To decide the solution of the ***q***, you may consider using **three voting policies:** Most voted solution, Modified Plurality, Borda count or another one that you decide.

   a. **Most voted solution** is the simplest method. Technically, a method for breaking ties should also be specified. You should decide the method in case of ties.
   b. **Modified Plurality** computes the most voted solution but in case of ties, it removes the last `k` nearest neighbors 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.
   c. **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.

d. For evaluating the performance of the K-IBL algorithm, we will use the percentage of correctly classified instances. To this end, at least, you should store the number of cases correctly classified, the number of cases incorrectly classified. 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 over the 10-fold cross-validation sets.

At the end, you will have a K-IBL algorithm with four similarity measures, different values for the `K` parameter, and three policies for deciding the solution of the **q**. You should 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, $w_f = 1$).

You can compare your results in terms of classification accuracy and efficiency (in time). Extract conclusions by analyzing **two large** enough data sets (the same as in step 3). **At least one of these data sets will contain numerical and nominal data**.

5. 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 `selectionkIBLAlgorithm(...)`.
    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 `selectionkIBLAlgorithm` 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.

1.3 Work to deliver

In this work, you will implement Instance-based learning algorithms. You will analyze the behavior of different similarity metrics, different voting rules, and feature selection methods. 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.

You will implement your own code in Python and use it to extract the performance of the different combinations. Performance will be measured in terms of classification accuracy and efficiency. 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 IBL algorithms, with the Euclidean distance and no weighting. You will analyze which is the most suitable algorithm. The one with the highest accuracy will be named as the best IBL algorithm.
2. Once you have decided the best IBL algorithm, you will analyze different similarity measures, K values and voting rules. The best combination will be named as the best k-IBL algorithm. Recall to perform a statistical analysis.
3. Once selected the best k-IBL combination, you will analyze it in front of using this combination with two feature selection methods. The idea is to analyze if reducing the feature set may increase accuracy and/or efficiency in a k-IBL algorithm and to extract conclusions of which selection method is the best one, if there is any. Recall to perform a statistical analysis.

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

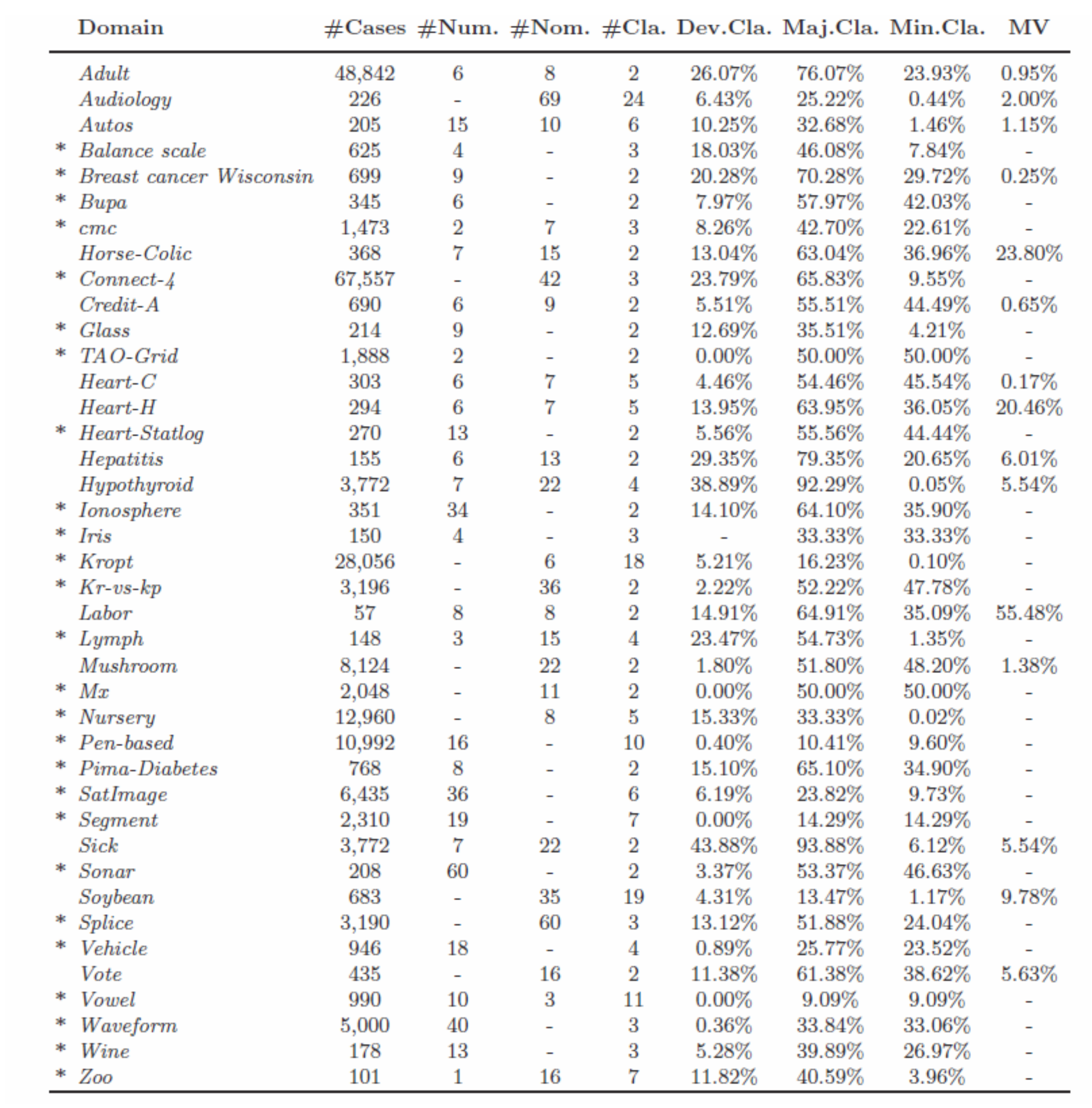
- Which is the best value of K at each dataset?
- Which IBL algorithm is the best one at each dataset?
- Did you find useful the use of a voting scheme for deciding the solution of the query ***q***?
- Which is the best similarity function for the k-IBL?
- Did you find differences in performance among the k-IBL and the 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? (look at the relative weight to each feature).
- Do you think it will be much better to weight the features rather than removing some of them in the similarity function?

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**. 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, 23rd, 2021**. Remember that the maximum size of the report is 20 pages (one column), including description and graphs. Excluded are the cover page 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%	-