Data Visualization using Decision Trees and Clustering

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Abstract: Decision trees are simple and powerful tools for knowledge extraction and visual analysis. However, when applied to complex datasets available nowadays, they tend to be large and uneasy to visualize. This difficulty can be overcome by clustering the dataset and representing the decision tree of each cluster independently. In order to apply the clustering more efficiently, we propose a method for adapting clustering results with a view to simplifying the decision tree obtained from each cluster. A prototype has been implemented, and the benefits of the proposed method are shown using the results of several experiments performed on the UCI benchmark datasets.

1 INTRODUCTION

Originally used as a tool for decision support, decision trees are often used in data mining, especially for classification (Quinlan, 1986). Moreover, they are popular for the visual analysis of data (Barlow and Neville, 2001; van den Elzen and van Wijk, 2011), because they use a formalism which is intuitive and easy to understand for domain experts (Murthy, 1998).

From a dataset containing n features $A_1, \ldots, A_n$, it is possible to build a decision tree which explains the value of the feature A_i (often called *class*) according to the values of the other features ($A_j (j \neq i)$). This model is a directed graph composed of nodes, leaves and branches. A node represents a feature, and each node is followed by branches which specifiy a test on the value of the feature (for instance: A_1='value'). A leaf indicates a value of the *class* feature. From a graphical point of view, decision trees are often represented using node-link diagrams (Figure 1), but other representations like *treemaps* or concentric circles are possible (Pham et al., 2008).

A decision tree obtained from data is characterized by two important properties: its complexity and its accuracy regarding the data. The complexity of a decision tree is often measured by its size, i.e. the number of nodes (Breslow and Aha, 1997); nevertheless, others indicators such as tree width or tree depth can be used. The accuracy of the tree is estimated using the error rate, i.e. the ratio of elements which are not correctly explained using the tree (Breslow and Aha, 1997). In order to obtain this error rate, a dataset is often considered as two parts: the first one is used to induce the decision tree (*training set*), and the second one is used to compute the error rate (*testing set*). But in order to obtain a decision tree which is *representative* of the data, the whole dataset should rather be used for both induction and error rate computation (Parisot et al., 2013b).

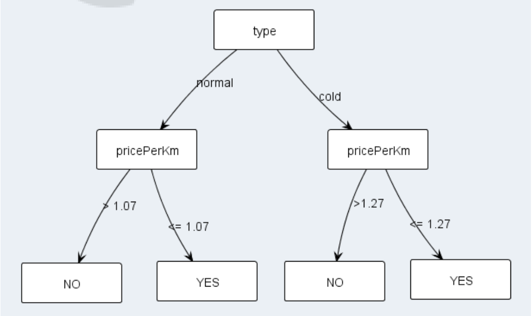

Figure 1: A decision tree.

Decision tree induction has already been extensively studied in the literature (Quinlan, 1986). The main advantage of decision tree induction is that it can be used with any kind of data, i.e. with nominal and numeric features, and only the *class* feature has to be discrete.

Unfortunately, real world datasets are traditionally complex. As a result, the decision trees obtained from these datasets are not always easily visualizable due to their size or depth (Stiglic et al., 2012; Herman et al., 1998).

Consequently, it is often useful to use other techniques to obtain simpler decision trees. One of those, clustering, allows to segment the data into homoge-

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nous groups (called *clusters*). Decision trees may then be built from each cluster.

In this work, we present a method that adapts the clusters obtained from any clustering method, according to the simplicity of the resulting decision trees.

The rest of this article is organized as follows. Firstly, related works about simplification of decision trees are discussed. Then, the presented method is described in details. Finally, a prototype is presented, and the results of experiments are discussed.

2 RELATED WORKS

Several methods have been proposed to simplify decision trees obtained from data, with a minimal impact on the decision trees accuracy (Breslow and Aha, 1997).

Firstly, pruning is a well-known solution to simplify decision trees (Quinlan, 1987; Breslow and Aha, 1997). This technique removes the parts of the trees which have a low explicative power (i.e. explaining too few elements or with a high error-rate). More specific pruning techniques allow to simplify decision trees according to visual concerns: for instance, a recent work has proposed a pruning technique which is constrained by the dimensions of the produced decision tree (Stiglic et al., 2012), and another work has described an algorithm to build decision tree with a fixed depth (Farhangfar et al., 2008).

Secondly, decision tree simplification can be done by working directly on the data, by using preprocessing operations like feature selection and discretization (Breslow and Aha, 1997). As these operations tend to simplify the dataset (in term of dimensionality, number of possible values, etc.), they can also help to reduce the complexity of the associated decision tree (at the expense of accuracy): this idea has been used in a recent work (Parisot et al., 2013a).

Finally, clustering is a useful technique in data mining, but it is also a promising tool in the context of the visual analysis of data (Keim et al., 2008). A priori, by splitting the data into homogenous groups, it can be used to obtain simple decision trees. However, it is not always the case in practice. In fact, various methods of clustering exist (hierarchical, model-based, center-based, search-based, fuzzy, etc.) (Gan et al., 2007), but they often optimize a distance based-criterion, with no account of the complexity of the decision trees which are obtained from the clusters. As a consequence, a recent solution has been proposed to obtain a simple decision tree from each cluster (Parisot et al., 2013b). Nevertheless, the algorithm does not take into account the similarity between elements and the dissimilartity between clusters: it is not comparable to classic clustering results (obtained with k-means, for example), and the results are hard to interpret.

In this paper, we propose a solution to preserve interpretability, by using existing clustering results as a starting point, adapting these for simpler cluster-wise decision trees, while maintaining good cluster quality metrics.

3 CONTRIBUTION

In this section, we present a method to modify a clustering result in order to simplify the decision tree specific to each cluster. In addition, the method guarantees that the new clustering result is close to the initial clustering result.

3.1 Adaptating a Clustering Result

The input of the proposed method is an initial clustering result, which can be computed with any existing technique (k-means, EM, etc.) (Gan et al., 2007). This result is then modified by an algorithm, which is the core of our contribution.

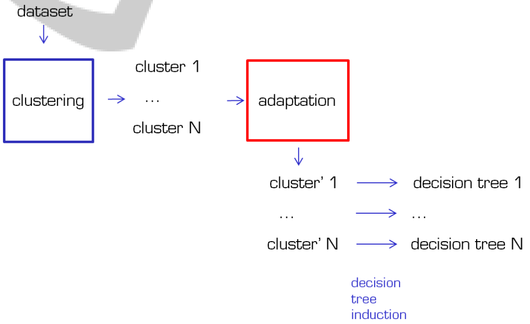


Figure 2: Clustering adaptation method.

In this work, we consider that adapting a clustering result $C_1, \dots, C_n$ amounts to move elements from C_i to $C_j (i \neq j)$. In addition, we consider that finding the cluster count, which is a complex problem (Wagner and Wagner, 2007), is managed during the creation of the initial clustering result. Therefore, the method does not modify the cluster count during the clustering adaptation (in other words, no cluster is created and/or deleted during the process).

3.2 Comparing with the Initial Clustering Result

In order to guarantee that the modified clustering result is close to the initial clustering result, we use appropriate metrics. The literature contains a lot of methods to compare two clustering results (Wagner and Wagner, 2007); in this work, the Jaccard index is used (Table 1) (Jaccard, 1908).

Table 1: Jaccard index definition.

E = initial clustering result
E' = modified clustering result

N_{11} = pairs in the same cluster in E and E'
N_{10} = pairs in the same cluster in E, not in the same cluster in E'
N_{01} = pairs in the same cluster in E', not in the same cluster in E

Jaccard index = $N_{11}/(N_{11}+N_{10}+N_{01})$

In practice, after the computation of the Jaccard index between two clustering results, we obtain the following behaviour:

- The more the Jaccard index is close to 1, the more the two clustering results are similar.
- The more the Jaccard index is close to 0, the more the two clustering results are dissimilar.

3.3 Algorithm

The adaptation is done using an algorithm (Algorithm 1) with the following inputs: a dataset with a *class* feature, an initial clustering result, and a minimal Jaccard index. The output is a new clustering result where each cluster leads to a simpler decision tree.

The main idea of the algorithm is to incrementally try to move the items between clusters in the limits of a parameterized minimal Jaccard index. In pratice, to handle the case when the minimal Jaccard index isn't reach, we define a maximal number of iterations (when it does not find enough moves between clusters).

The minimal Jaccard index has to be used as follows: specifying an index close to 1 amounts to configure the algorithm to do few modifications, while specifying an index close to 0 enables arbitrarily large modifications.

The following sections explain how the moves between clusters are made.

Algorithm 1: Clustering adaptation algorithm.

```
Require:
  $0 < jaccardIndexLimit < 1$
  $\wedge nbPassesLimit \geq 0$
Ensure:
  $nbPasses \leftarrow 0$
  $j \leftarrow 1$
  while $j < jaccardIndexLimit \wedge nbPasses < nbPassesLimit$ do
    for all item to mode do
      search a target cluster C' for item
      if C' exists then
        move item into C'
        $j \leftarrow$compute Jaccard index
      end if
    end for
    $nbPasses \leftarrow nbPasses + 1$
  end while
```

3.4 Selecting the Items to Move

The goal is to modify the clusters in order to simplify the decision tree of each cluster. As a result, the items which are good candidates to be moved are those which cause the decision tree complexity. We have selected two kind of items:

- The items badly classified/explained by the decision tree.
- The items explained by branches of the decision tree having a low power of classification/prediction.

A priori, it is reasonable to expect that moving these items would not have a bad effect on the decision tree generated from the initial cluster. In fact, these items correspond to the tree branches which are deleted by the classic pruning techniques.

A posteriori, for each element, it is important to check if moving the item has really a good impact on the decision tree generated from the initial cluster. To do that, we compute the decision tree before moving the item (DT), and the decision tree after moving the item (DT'). Finally, we compare the complexity of DT and DT': if the size of DT' is lower than the size of DT, then the item can be moved.

3.5 Finding a Target Cluster

When an item has been selected as a good candidate to be moved to another cluster, a target cluster has to be found. To do that, we propose to select the cluster that is the most favorably impacted by the inclusion of the candidate. In other words, we compute the decision tree for each cluster before adding the item (DT), and the decision tree after adding the item (DT'); then we compare the decision trees complexities. Two cases can occur:

- If for each cluster, the size of DT' is always higher than the size of DT, than there is no target cluster: the item is not moved.

- Else, the target cluster is the cluster for which the ratio between the size of DT' and the size of DT is minimized: the item is moved to this target cluster.

3.6 Usage of the Method

The method proposed by this paper aims at adapting a clustering result to obtain clusters whith simpler decision trees. This adapation is controlled by a parameter, the minimal Jaccard index, in order to obtain a clustering result which is close to the original clustering result. In other words, the parameter can be useful to analyze data following the Visual Analytics approach (Keim et al., 2008): adapted clustering results can be produced and refined in order to obtain decision trees which are simple to analyse visually, potentially shifting the clusters' original meaning.

Yet, using an excessively low minimal Jaccard index is likely to harm cluster quality (e.g. high intra-cluster similarity and low inter-cluster similarity). A color-coded visual cue may indicate this danger to a user.

4 EXPERIMENTS

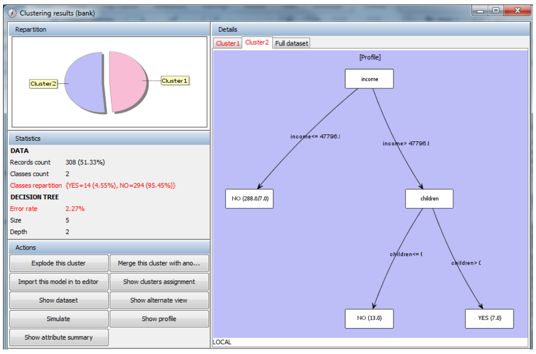
In order to validate the approach described in this paper, a prototype has been implemented and used on several datasets. This section describes the prototype and presents the experimental results.

4.1 Prototype

The prototype is a standalone tool implemented in Java. It is based on Weka, a widely-used data mining library (Hall et al., 2009), in order to use the implementations of the decision trees induction algorithm and the k-means clustering algorithm. For the graphical representation of the decision trees, the tool uses Jung, a graphical library (O'Madadhain et al., 2003). In addition to these building block components, the prototype is completed with the implementation of our clustering adaptation method, and with a graphical user interface for the results exploration (statistics about the datasets, graphical representation of the clusters, etc. . .) (Figure 3).

4.2 Test Procedure

Some tests have been performed on a selection of 10 well-known academic datasets (Bache and Lichman, 2013). This selection tries to cover several kinds of datasets (number of records, features count, features type, size and depth of decision trees, etc. . .).



DATA
Records count 308 (51.33%)
Classes count 2
Classes repartition {YES=14 (4.55%), NO=294 (95.45%)}
DECISION TREE
Error rate 2.27%
Size 5
Depth 2

Figure 3: Prototype.

In order to check the impact of our method, for each dataset we have compared the decision trees obtained in the following cases:

- CASE 1: Decision tree induction on the full dataset.
- CASE 2: Clustering with k-means (k=2,3,4), and decision tree induction for each cluster.
- CASE 3: Clustering with k-means (k=2,3,4), adaptation of the clustering result with our method, and induction of the decision tree for each cluster.

For the k-means clustering, the Euclidean distance has been used. Moreover, the J48 algorithm has been used to generate decision trees from data: it is a widely used implementation of the C4.5 algorithm (Quinlan, 1993). In practice, the J48 algorithm has to be configured with several parameters; for these experiments, we have disabled the 'pruning' phase, in order to initially obtain large decision trees and check the benefits of our method.

4.3 Results

The experimental results (Tables 2,3,4) show the decision trees obtained in the three cases previously described. According to the case, the metrics are chosen as follows: for CASE 1, we indicate the size and the error rate of the decision tree generated from the full dataset; for CASE 2 and CASE 3, we indicate the mean sizes and error rates of the decision trees generated from the clusters. Moreover, we indicate for CASE 3 the value of *ji*, the minimal Jaccard index specified when running the adaptation method.

From these results, we can observe that it is possible to obtain simpler decision trees by simply using a clustering technique like k-means, in comparison to the decision trees obtained from the full dataset. For instance, the dataset *cmc* leads to an initial decision

Table 2: Results for 2 clusters. In CASE 1, we indicate the size and the error-rate for the full decision tree. In CASE 2 and 3, we indicate the means of the sizes and the error-rates of the decision trees obtained from the clusters.

Dataset	CASE 1 (full)	CASE 2 (k-means)	CASE 3 mji=0.95	CASE 3 mji=0.90	CASE 3 mji=0.85	CASE 3 mji=0.80
cmc	457/0.24	229/0.23	198/0.23	196/0.22	171/0.22	167/0.22
vehicle	173/0.06	71/0.07	53/0.11	51/0.09	50/0.09	n/a
autos	76/0.04	48/0.06	42/0.06	32/0.08	n/a	n/a
credit-a	120/0.06	61/0.06	52/0.05	48/0.04	47/0.04	n/a
spectrometer	149/0.14	75/0.19	70/0.20	n/a	n/a	n/a
landsat	435/0.03	210/0.03	185/0.02	165/0.02	n/a	n/a
credit-g	334/0.099	173/0.095	153/0.095	143/0.09	134/0.08	125/0.06
mushroom	47/0.33	95/0.33	61/0.33	n/a	n/a	n/a
anneal	59/0.009	37/0.005	26/0.004	n/a	n/a	n/a
bank-marketing	5120/0.04	2768/0.04	2246/0.03	1997/0.02	n/a	n/a
adult	2442/0.09	1245/0.08	970/0.08	840/0.07	778/0.07	697/0.06

Table 3: Results for 3 clusters. In CASE 1, we indicate the size and the error-rate for the full decision tree. In CASE 2 and 3, we indicate the means of the sizes and the error-rates of the decision trees obtained from the clusters.

Dataset	CASE 1 (full)	CASE 2 (k-means)	CASE 3 mji=0.95	CASE 3 mji=0.90	CASE 3 mji=0.85	CASE 3 mji=0.80
cmc	457/0.24	57/0.13	49/0.12	37/0.11	37/0.10	31/0.10
vehicle	173/0.06	49/0.04	41/0.04	37/0.05	31/0.05	25/0.05
autos	76/0.04	30/0.06	25/0.06	21/0.09	n/a	n/a
credit-a	120/0.06	40/0.05	27/0.03	27/0.03	25/0.03	20/0.02
spectrometer	149/0.14	51/0.16	47/0.16	43/0.18	41/0.18	41/0.16
landsat	435/0.03	75/0.02	53/0.02	n/a	n/a	n/a
credit-g	334/0.10	108/0.08	98/0.07	91/0.06	80/0.05	74/0.06
mushroom	47/0.33	16/0.26	16/0.25	16/0.23	n/a	n/a
anneal	59/0.009	19/0.003	18/0.001	n/a	n/a	n/a
bank-marketing	5120/0.04	1916/0.04	1492/0.03	1347/0.02	1158/0.02	n/a
adult	2442/0.09	391/0.07	308/0.06	260/0.04	231/0.03	188/0.01

Table 4: Results for 4 clusters. In CASE 1, we indicate the size and the error-rate for the full decision tree. In CASE 2 and 3, we indicate the means of the sizes and the error-rates of the decision trees obtained from the clusters.

Dataset	CASE 1 (full)	CASE 2 (k-means)	CASE 3 mji=0.95	CASE 3 mji=0.90	CASE 3 mji=0.85	CASE 3 mji=0.80
cmc	457/0.24	78/.18	57/.20	48/.19	42/.19	37/.19
vehicle	173/0.06	10/.01	7/.01	5/.01	n/a	n/a
autos	76/0.04	24/.10	20/.09	16/.10	n/a	n/a
credit-a	120/0.06	24/.04	21/.06	18/.04	n/a	n/a
spectrometer	149/0.14	39/.19	37/.19	34/.20	n/a	n/a
landsat	435/0.03	53/.02	39/.02	32/.01	n/a	n/a
credit-g	334/0.10	71/.09	50/.09	47/.08	45/.06	n/a
mushroom	47/0.33	64/.31	37/.31	n/a	n/a	n/a
anneal	59/0.009	22/.01	19/.00	n/a	n/a	n/a
bank-marketing	5120/0.04	1375/.05	1168/.04	971/.03	850/.02	n/a
adult	2442/0.09	438/.09	370/.08	318/.07	279/.05	254/.04

tree with a size of 457, and using the k-means algorithms allows to obtain decisions trees with a mean size of 229 for 2 clusters and 57 for 3 clusters. In addition, the results show that our clustering adaptation method significantly simplifies the decision trees of the clusters. For the dataset *cmc*, our technique allows to reduce the mean size of the decision trees: up to 27% for 2 clusters, and up to 46% for 3 clus-

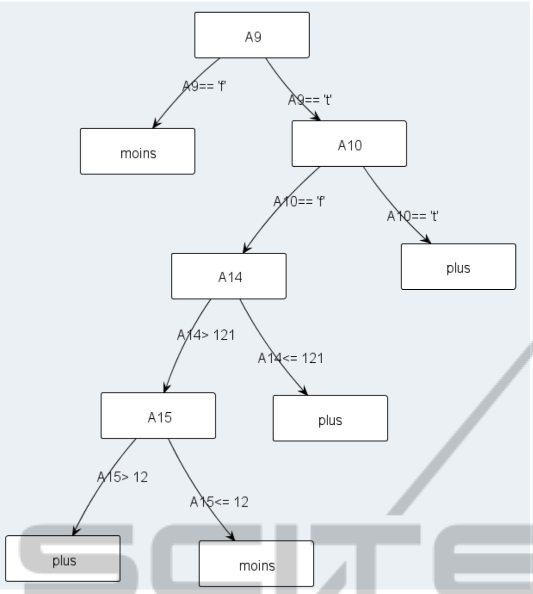


Figure 4: '*credit-a*' clustered with k-means (k=2) and adapted with our method: the first cluster's decision tree.

ters. The most important gains are observed for the *vehicle*, *credit-a*, and *adult* datasets: in these cases, the mean sizes of the decision trees for the clusters can be reduced up to 50% for 3 clusters. But it is not always so efficient: in some cases (like *mushroom* split in 3 clusters), k-means produces clusters for which decision trees are very simple: our method hardly simplifies them further. It is important to say that the decision trees obtained with our method do not lose accuracy: the computed error rates tend to decrease. By comparison, the classical decision tree simplification methods tend to produce decision trees with higher error rates (Breslow and Aha, 1997).

Finally, the results show that for the majority of the tested datasets, it is not possible to drop below a certain value of Jaccard index (the most significative case is *spectrometer*, 2 clusters): it means that after a certain count of moves, the algorithm can not find others moves which can simplify decision trees. It is not a problem, because our method aims to provide clustering results which globally keep the meaning of the original clustering results.

4.4 Impact for Decision Trees Visualization

The method presented in this paper allows to simplify decision trees by adapting clustering results. If we combine this method with existing pruning techniques, we can obtain decision trees which are simple to visualize. For instance, the *credit-a* dataset leads to a decision tree with a size of 63 by using the J48 induction algorithm with pruning enabled. And if we apply our method by setting the minimum Jaccard index to 0.9, we obtain two clusters with simpler decision trees (sizes=9 and 13), which are easily visualizable (Figures 4,5).

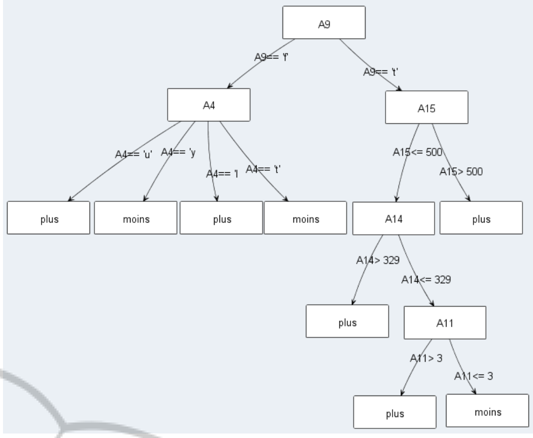


Figure 5: '*credit-a*' clustered with k-means (k=2) and adapted with our method: the second cluster's decision tree.

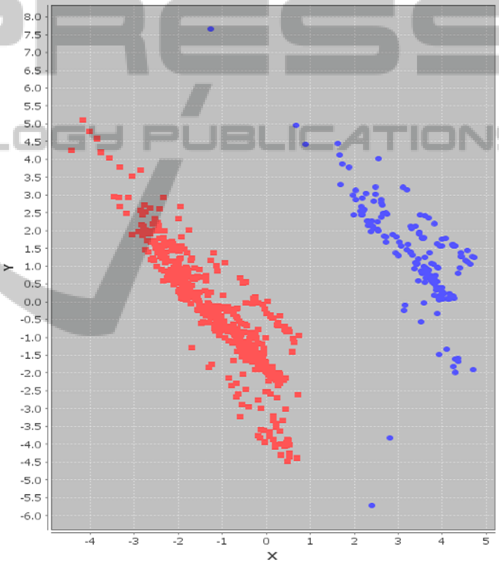


Figure 6: PCA projection for '*credit-a*', colored using k-means (k=2): the x axis represents the first principal component, and the y axis represents the second principal component.

4.5 Impact on the Clustering Results

It can be useful to show the impact of our adaptation method on the clustering results: to do that, well-known cluster interpretation methods like projections can be used (Gan et al., 2007). For the *credit-a* dataset, a PCA projection (Principal Component Analysis) allows to show that the clusters are less *correct* after adaptation (Figures 6,7), as confirmed by a Silhouette plot (Figures 8,9) (Rousseeuw, 1987). The clustering results are less *correct*, but the decision trees are simpler: so our method allows to influence the tradeoff between *simplicity of decision trees* and *similarity with the initial clustering*.

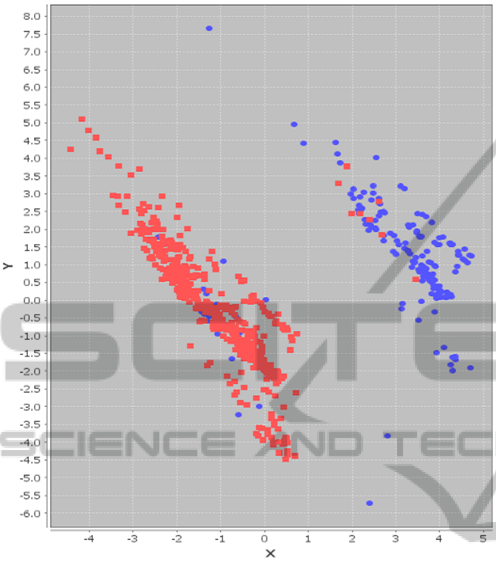


Figure 7: PCA projection for '*credit-a*', colored with k-means (k=2) adapted with our method (minimum Jaccard index=0.9): the x axis represents the first principal component, and the y axis represents the second principal component.

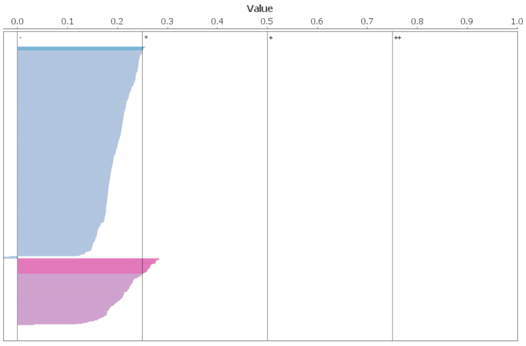


Figure 8: Silhouette plot for '*credit-a*', using k-means clustering(k=2): the x axis represents the Silhouette value, and the y axis represents the elements (sorted by clusters and Silhouette values). In practice: larger Silhouette values indicate a better quality of the clustering result.

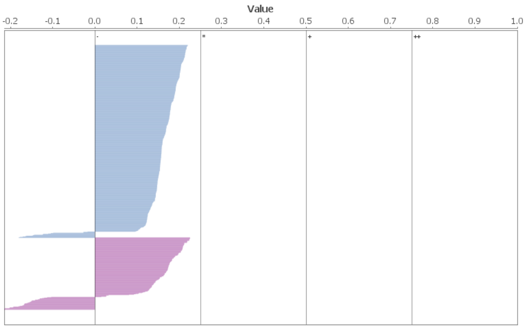


Figure 9: Silhouette plot for '*credit-a*', using k-means (k=2) adapted with our method (minimum Jaccard index=0.9): the x axis represents the Silhouette value, and the y axis represents the elements (sorted by clusters and Silhouette values). In practice: larger Silhouette values indicate a better quality of the clustering result.

5 CONCLUSIONS

We presented a method based on clustering and decision tree induction that optimize the visual representation of complex datasets. This method proceeds by modifying a clustering result to obtain simpler decision trees for all clusters. The method has been implemented in a prototype, and its effectiveness was demonstrated on well-known UCI datasets.

We are now adapting the solution in order to support data streams, by using incremental decision trees induction methods and stream clustering algorithms. Moreover, we have in view to extend the method by using other heuristics such as genetic algorithms.

REFERENCES

Bache, K. and Lichman, M. (2013). UCI machine learning repository.

Barlow, T. and Neville, P. (2001). Case study: Visualization for decision tree analysis in data mining. In *Proceedings of the IEEE Symposium on Information Visualization 2001 (INFOVIS'01)*, INFOVIS '01, pages 149–, Washington, DC, USA. IEEE Computer Society.

Breslow, L. A. and Aha, D. W. (1997). Simplifying decision trees: A survey. *Knowl. Eng. Rev.*, 12(1):1–40.

Farhangfar, A., Greiner, R., and Zinkevich, M. (2008). A fast way to produce optimal fixed-depth decision trees. In *ISAIM*.

Gan, G., Ma, C., and Wu, J. (2007). *Data clustering - theory, algorithms, and applications*. SIAM.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., and Witten, I. H. (2009). The weka data mining software: an update. *SIGKDD Explor. Newsl.*, 11(1):10–18.

Herman, I., Delest, M., and Melancon, G. (1998). Tree visualisation and navigation clues for information visualisation. Technical report, Amsterdam, The Netherlands, The Netherlands.

Jaccard, P. (1908). *Nouvelles recherches sur la distribution florale*. Bulletin de la Société vaudoise des sciences naturelles. Impr. Réunies.

Keim, D., Andrienko, G., Fekete, J.-D., Görg, C., Kohlhammer, J., and Melançon, G. (2008). Information visualization. chapter Visual Analytics: Definition, Process, and Challenges, pages 154–175. Springer-Verlag, Berlin, Heidelberg.

Murthy, S. K. (1998). Automatic construction of decision trees from data: A multi-disciplinary survey. *Data Min. Knowl. Discov.*, 2(4):345–389.

O'Madadhain, J., Fisher, D., White, S., and Boey, Y. (2003). The JUNG (Java Universal Network/Graph) framework. Technical report, UCI-ICS.

Parisot, O., Bruneau, P., Didry, Y., and Tamisier, T. (2013a). User-driven data preprocessing for decision support. In Luo, Y., editor, *Cooperative Design, Visualization, and Engineering*, volume 8091 of *Lecture Notes in Computer Science*, pages 81–84. Springer Berlin Heidelberg.

Parisot, O., Didry, Y., Tamisier, T., and Otjacques, B. (2013b). Using clustering to improve decision trees visualization. In *Proceedings of the 17th International Conference Information Visualisation (IV)*, pages 186–191, London, United Kingdom.

Pham, N.-K., Do, T.-N., Poulet, F., and Morin, A. (2008). Treeview, exploration interactive des arbres de dcision. *Revue d'Intelligence Artificielle*, 22(3-4):473–487.

Quinlan, J. R. (1986). Induction of decision trees. *Machine Learning*, 1:81–106.

Quinlan, J. R. (1987). Simplifying decision trees. *Int. J. Man-Mach. Stud.*, 27(3):221–234.

Quinlan, J. R. (1993). *C4.5: programs for machine learning*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of computational and applied mathematics*, 20:53–65.

Stiglic, G., Kocbek, S., Pernek, I., and Kokol, P. (2012). Comprehensive decision tree models in bioinformatics. *PLoS ONE*, 7(3):e33812.

van den Elzen, S. and van Wijk, J. (2011). Baobabview: Interactive construction and analysis of decision trees. In *Visual Analytics Science and Technology (VAST), 2011 IEEE Conference on*, pages 151–160.

Wagner, S. and Wagner, D. (2007). *Comparing clusterings: an overview*. Universität Karlsruhe, Fakultät für Informatik.