Using Graph Convolutional Networks to Rank Rules in Associative Classifiers

Maicon Dall'Agnol[a], Veronica Oliveira de Carvalho[b] and Daniel Carlos Guimarães Pedronette[c]
Instituto de Geociências e Ciências Exatas (IGCE), Universidade Estadual Paulista (Unesp), Rio Claro, São Paulo, Brazil
{*maicon.dallagnol, veronica.carvalho, daniel.pedronette*}*@unesp.br*

Keywords: Associative Classifiers, Rule Ranking, GCN, Performance, Interpretability.

Abstract: Associative classifiers are a class of algorithms that have been used in diverse domains due to their inherent interpretability. For models to be induced, a sequence of steps is necessary, one of which is aimed at ranking a set of rules. This sorting usually occurs through objective measures, more specifically through confidence and support. However, as many measures exist, new ranking methods have emerged with the aim of (i) using a set of them simultaneously, so that each measure can contribute to identify the most important rules and (ii) inducing models that present a good balance between performance and interpretability in relation to some baseline. This work also presents a method for ranking rules considering the same goals ((i);(ii)). This new method, named $AC.RANK_{GCN}$, is based on ideas from previous works to improve the results obtained so far. To this end, ranking is performed using a graph convolutional network in a semi-supervised approach and, thus, the importance of a rule is evaluated not only in relation to the values of its OMs, but also in relation to its neighboring rules (neighborhood) considering the network topology and a set of features. The results demonstrate that $AC.RANK_{GCN}$ outperforms previous results.

1 INTRODUCTION

Associative classifiers (ACs) belong to a class of algorithms that have interpretability as one of their main advantages. They are based on a special type of association rule (AR), known as classification association rule (CAR), in which the antecedent contains a set of <attribute=value> pairs and the consequent a class of a given problem. It is worth mentioning that even with several XAI methods available in the literature, there are works such as that of (Rudin, 2019) that propose the use of more interpretable classifiers instead of trying to create explanation models for black box classifiers via such methods.

The induction of a model through an AC algorithm occurs in steps, namely: [A] Extraction, [B] Ranking and/or Pruning and [C] Prediction. Among the algorithms, CBA (Liu et al., 1998) stands out the most, generally used as baseline for comparison with new proposals/solutions. In most algorithms, objective measures (OMs) are used to sort the rules by their degree of importance[1] to rank them (step [B]). Support ($P(AC)$) and confidence ($P(C|A)$) are the best-known OMs, which are the ones used in the ranking step of CBA. However, more than 60 measures are found in the literature, as seen in (Tew et al., 2014) and (Somyanonthanakul and Theeramunkong, 2022). Therefore, new proposals have emerged aiming to modify the ACs ranking step. Some of them aim to merge (aggregate) a set of measures to use them simultaneously, as seen in (Dall'Agnol and Carvalho, 2024) and (Bui-Thi et al., 2022). The idea is to consider different aspects (semantics) to order the rules, so that each measure can contribute to identifying the most important rules.

In the work of (Dall'Agnol and Carvalho, 2024) a method for ranking rules via aggregation of OMs, named $AC.Rank_A$, is presented. The aim of the work is to induce models that present a better balance between performance (measured via F1-Macro) and interpretability (measured via Model Size) in relation to some baseline (CBA) when a set of OMs is used simultaneously. According to the authors, the other works present solutions that fail to balance both aspects, since an inverse relationship exists

[a] https://orcid.org/0000-0003-1172-4859
[b] https://orcid.org/0000-0003-1741-1618
[c] https://orcid.org/0000-0002-2867-4838

[1] Ranking, ordering and sorting are used as synonyms in this work.

Dall'Agnol, M., Oliveira de Carvalho, V. and Pedronette, D. C. G.
Using Graph Convolutional Networks to Rank Rules in Associative Classifiers.
DOI: 10.5220/0013364700003929

In *Proceedings of the 27th International Conference on Enterprise Information Systems (ICEIS 2025) - Volume 1*, pages 317-325
ISBN: 978-989-758-749-8; ISSN: 2184-4992

between them, i.e., when the model's performance is high, interpretability is low (and vice versa). To this end, the authors use a ranking aggregation method, specifically Borda L2-norm (**[BL]**), together with a specific group of OMs, named GF (**[GF]**). Similarly, (Bui-Thi et al., 2022) present a method for ranking rules named MoMAC. Although a complete algorithmic flow is presented, the main goal is the ranking step through the simultaneous use of multiple values (probabilities), which provide the basis for calculating the existing OMs. Thus, ranking is also seen as an aggregation of OMs (in fact, the probabilities that generate them), from which a value is obtained so that the rules can be ordered in a way that improves the performance (in this case, measured via Accuracy) and interpretability of the induced models.

Considering the above, this work also presents a method for ranking rules, named $AC.RANK_{GCN}$[2], also aiming to induce models that present a good balance between performance (F1-Macro) and interpretability (Model Size) when a set of OMs is used simultaneously. However, in the proposal presented here we mix ideas from both works in the literature ($AC.Rank_A$ and MoMAC) to improve the results obtained so far. To this end, rule ranking is performed using a graph convolutional network (GCN) in a semi-supervised approach. The idea is to evaluate the importance of a rule not only in relation to the values of its OMs, but also in relation to its neighboring rules (neighborhood) considering the network topology and a set of features that describe them. The results obtained demonstrate that $AC.RANK_{GCN}$ outperforms previous results in terms of interpretability while maintaining the performance of the models. It is important to mention that achieving a good balance between performance and interpretability means improving one of them without worsening the other in relation to some baseline, since, as stated by (Dall'Agnol and Carvalho, 2024), an inverse relationship between them exists.

The paper is structured as follows: Section 2 presents the concepts that support this work; Sections 3 and 4 present, respectively, the proposed method, $AC.RANK_{GCN}$, as well as its evaluation; Section 5 presents conclusion and future work.

2 FOUNDATIONS AND RELATED WORKS

This section presents a brief description of the foundations necessary to understand this work, as well as a brief description of related works.

Objective Measures (OMs). OMs exist to assess the importance of a rule. To compute the value of an OM for a given rule, i.e., its importance, it is necessary to know its contingency table. Table 1 presents the structure of a contingency table for an abstract rule $A \Rightarrow C$. A represents the antecedent, C the consequent, $\overline{A}$ the negation of the antecedent, $\overline{C}$ the negation of the consequent, $n(X)$ the frequency of X and N the number of transactions. OMs are defined as a function of these absolute frequencies. However, the most usual notation is by means of probabilities (relative frequency), obtained by dividing each element of the table by N. Rule support, for example, is defined as $P(AC) = \frac{n(AC)}{N}$ and confidence as $P(C|A) = \frac{P(AC)}{P(A)}$, where $P(A) = \frac{n(A)}{N}$. Thus, given that a set of rules must be ranked, an OM can be computed to allow the sort of them. In general, the higher the value of a rule in a given OM, the best its position (the rule with the highest value will be the first in the ranking). Although support and confidence are the best-known OMs, more than 60 measures are found in the literature, as seen in (Tew et al., 2014) and (Somyanonthanakul and Theeramunkong, 2022).

Table 1: Contingency table of an abstract rule $A \Rightarrow C$.

	C	$\overline{C}$	
A	n(AC)	n($A\overline{C}$)	n(A)
$\overline{A}$	n($\overline{A}C$)	n($\overline{A}\overline{C}$)	n($\overline{A}$)
	n(C)	n($\overline{C}$)	N

Associative Classifier (AC). In the AC literature, some algorithms have become traditional due to their uses and concepts, with CBA (Liu et al., 1998) generally being used as a baseline in most related works. However, most AC algorithms perform model induction in three or four steps, namely: [A] Extraction, [B] Ranking and/or Pruning and [C] Prediction, as seen in Figure 1. In CBA, these steps work, broadly speaking, as follows:

Figure 1: Induction steps of an AC.

- Extraction: a modified version of Apriori (Agrawal and Srikant, 1994) is run to obtain the classification association rules (CARs).
- Ranking: given the set of CARs, the obtained rules are ranked as follows: given two rules, r_i and r_j, $r_i \succ r_j$, i.e., r_i has higher precedence than r_j if: (i) the confidence of r_i is greater than that of r_j; (ii) if the confidences are equal, but the support of

[2]Name inspired by $AC.Rank_A$.

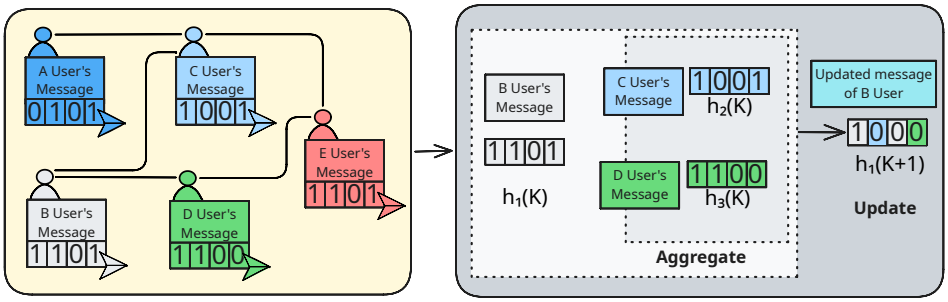


Figure 2: Message passing mechanism in GNN. Extracted and Adapted from (Khemani et al., 2024).

r_i is greater than the support of r_j; (iii) confidence and support are equal, but r_i was generated before r_j. This ranking method is known as **[CSC]** (Confidence, Support, Cardinality). This step is highlighted in Figure 1, as it refers to the step modified here, as well as in other works in the literature presented below.

- Pruning: considering the obtained ranking, pruning occurs as follows: for each rule r in the ranked list it is checked the transactions it covers and if it correctly covers at least one transaction. In this case, the rule is selected to be included in the model and all transactions covered by it are removed from the dataset.
- Prediction: given an unseen object, the class label associated with the first rule that matches the object is the one to which it will be classified.

To evaluate the induced model, when dealing with a classification task, evaluation measures are used (Tan et al., 2019). This work used F1-Macro to assess the performance of the models as in (Dall'Agnol and Carvalho, 2024). Furthermore, to ensure a good estimate, 10-fold stratified cross-validation was also used, as in (Dall'Agnol and Carvalho, 2024). Another important aspect used to assess rule-based models is interpretability. According to (Margot and Luta, 2021) there is no exact mathematical definition for this concept and, therefore, works evaluate this aspect using different measures. This work used the number of rules contained in the model (Model Size), as in (Dall'Agnol and Carvalho, 2024). In this case, the smaller the number of rules, the better the induced model, i.e., the more interpretable it is.

Graph Convolutional Network (GCN). Among the advantages of modeling a problem via graphs is the feasibility of making explicit the relationships (edges) that exist between the entities (nodes) in the domain, making it possible to solve a task considering both the topology of the network, i.e., the relational context, and the descriptive attributes of the entities. Through edges (relationships), algorithms can capture information from the neighbors of a node, enabling the learning of interactions that are difficult to model with traditional representations.

Recently, due to their high effectiveness, graph neural networks (GNNs) have been widely applied in graph analysis (Zhou et al., 2020). According to (Khemani et al., 2024), GNNs are a type of deep learning model that uses a message passing mechanism to aggregate information from neighboring nodes, allowing them to capture complex relationships. Figure 2 presents the general idea of how the message passing mechanism works for a given node. The messages to be passed are represented by feature vectors. Therefore, given an input graph with a set of node features (messages), at each iteration k, each node collects topological and feature information from the surrounding neighborhood to update itself. In other words, at each iteration, the neighbors of a node update its feature vector by aggregating their information into it. In the end, an embedding for each node is learned based on the aggregated information. The left side of Figure 2 presents a fictitious network. Each node is a user described by a set of features (message). On the right side, the aggregation and update operations considering node-1 (User B) are illustrated. Since this node is connected with node-2 (User C) and node-3 (User D), their message (features) are sent to node-1 and aggregated with its own message, updating its embedding. In Figure 2, $h_n(k)$ indicates an embedding h of a node n at iteration k (i.e., at layer k).

Many GNN models are available today (Ju et al., 2024), including the representative GCN model proposed by (Kipf and Welling, 2017), being one of the basic GNN variants and, therefore, easy to implement and computationally efficient (it presents fewer hyperparameters and a simpler architecture). Furthermore, GCN excels in the context of semi-supervised learning, where only a small portion of the nodes are labeled and used to label, via propagation, the rest of the unlabeled ones. The

Table 2: Set of OMs used by (Dall'Agnol and Carvalho, 2024).

Set	OMs
[TW]	Support, Prevalence, K-Measure, Least Contradiction, Confidence, TIC, Leverage, DIR, Loevinger, Odds Ratio, Added Value, Accuracy, Lift, J-Measure, Recall, Specificity, Conditional Entropy, Coverage
[GF]	Odd Multiplier, Complement Class Support, Loevinger, Odds Ratio, Confidence Causal, Confirmed Confidence Causal, J-Measure, Confidence
[C1]	Odd Multiplier, Complement Class Support, Confidence Causal, Loevinger, Added Value, One Way Support, Confirmed Confidence Causal, Lift, Confidence, Putative Causal Dependence, Leverage, Confirm Causal, TIC, DIR, Normalized Mutual Information
[G1]	Complement Class Support, Confidence, Confidence Causal, Confirmed Confidence Causal, DIR, Loevinger, Odd Multiplier, TIC
[G2]	Added Value; Lift; One Way Support; Putative Causal Dependency

message passing in GCN is expressed mathematically in Equation 1 (see (Kipf and Welling, 2017) for details):

$$H^{(k+1)} = \sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(k)}W^{(k)}), \quad (1)$$

where $H^{(k)}$ represents the matrix of activations in the k^{th} layer, $\tilde{A} = A + I_N$ the adjacency matrix of an undirected graph G with added self-connections, I_N the identity matrix, $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$, $W^{(k)}$ a layer-specific trainable weight matrix, and $\sigma(.)$ an activation function such as ReLU. For classification tasks, the cross-entropy loss function is often used for training. Therefore, the trained GCN model can be seen as a function $f(X,A)$, where X represents a matrix of node feature vectors x_i and A the adjacency matrix that represents the graph G. Finally, the learned embeddings from the final layer, i.e., $H^{(k)}$, are used to perform node classification, i.e., $\hat{Y} = \sigma(H^{(k)}W_{out})$, where softmax is often used as $\sigma(.)$ for classification tasks, and W_{out} are trainable weights to map the embeddings to class probabilities. It is worth mentioning that some hyperparameters need to the defined to execute GCN, such as number of layers, hidden units, activation functions, loss function, among others. Therefore, the implementation used here was based on the code created by (Kipf and Welling, 2017).

AC.Rank$_A$. Works have been proposed aiming to modify the ACs ranking step since a large number of OMs exists and none of them is suitable for all explorations (Sharma et al., 2020). The idea is to use a set of measures simultaneously to reduce the need to choose a single measure, also considering different aspects (semantics) for sorting the rules. One of these works is *AC.Rank$_A$*, presented in Figure 3. The idea is to incorporate its ranking mechanism into ACs induction flows aiming to induce models that present a good balance between performance and interpretability. The authors analyzed *AC.Rank$_A$* in different induction flows, comparing it when ranking occurs via **[CSC]** (CBA sorting (baseline)). In general, the *AC.Rank$_A$* mechanism works as follows: given a set of rules, a set of OMs is computed for each of them. To do so, it is necessary to specify the set of OMs to be used. The authors explored 5 different sets, namely: **[TW]**, **[GF]**, **[C1]**, **[G1]** and **[G2]**. Table 2 presents the OMs that make up each set, whose definitions (equations) can be found in (Tew et al., 2014). Details about the sets can be found in (Dall'Agnol and Carvalho, 2024)[3], (Dall'Agnol and De Carvalho, 2023a) and (Dall'Agnol and De Carvalho, 2023b). Based on the selected set a "Rules" x "OMs" matrix is constructed and used by one of the aggregation methods explored by the authors, namely: **[WS]** (WSM), **[WP]** (WPM), **[TS]** (TOPSIS), **[BM]** (Borda Arithmetic Mean), **[BD]** (Borda Median), **[BG]** (Borda Geometric Mean) and **[BL]** (Borda L2-norm). According to the authors, the best combination is **[GF]+[BL]**, and the one that should actually be used. For this reason, in Section 4, the method presented here will be compared to *AC.Rank$_A$* in this configuration. Basically, **[BL]** computes the rank $Rank_i$ of each rule i as follows: $Rank_i = \sqrt[n]{\frac{\sum_{j=1}^{n} Mat_{ij}^2}{n}}$, where i indicates a rule, j an OM, n the number of OMs and Mat_{ij} the position of rule i in a list ordered by an OM j (position i,j of the matrix). After that, considering this new ranking, the flow goes on, i.e., the rules are pruned and the model is finalized aiming at the predictions.

MoMAC. Aiming to modify the ACs ranking step, similarly as the *AC.Rank$_A$* work, (Bui-Thi et al., 2022) proposed MoMAC, presented in Figure 4. The goal is to find a ranking that ensures a good balance between performance, in this case estimated by Accuracy, and interpretability. However, they do not work directly with the OMs, but rather with the probabilities that generate the measures. In general,

[3]Regarding the **[GF]** group, in this reference the authors forgot to remove the equivalent measures from the list.

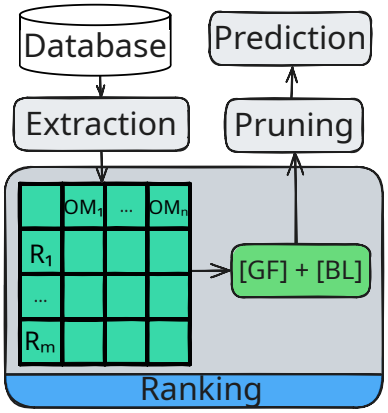


Figure 3: Ranking mechanism of $AC.Rank_A$.

MoMAC works as follows: given a set of rules, their contingency table, as in Table 1, are computed. Based on the table of each rule, 15 probabilities are considered and a "Rules" x "Probabilities" matrix is constructed. The 15 probabilities are: $P(A)$, $P(\overline{A})$, $P(C)$, $P(\overline{C})$, $P(AC)$, $P(A\overline{C})$, $P(\overline{A}C)$, $P(\overline{A}\overline{C})$, $P(A|C)$, $P(\overline{A}|\overline{C})$, $P(\overline{A}|C)$, $P(A|\overline{C})$, $P(C|A)$, $P(\overline{C}|A)$, $P(A)P(C)$. Then, given the matrix, a Multi-Layer Perceptron (MLP) is trained using the probabilities as input to predict a value (I(r)) for each rule that will be used to rank them. In other words, the network has to learn the right weights to generate a ranking that will provide a model with a good balance between performance and interpretability. The predicted value (I(r)) is seen as the aggregation of many "implicit" OMs, since all measures are derived from the probabilities of the contingency table. Since the weights are learned through a genetic algorithm (NSGAII), the process is iterative, i.e., after evaluating each individual in the population (a vector of weights) through ranking, pruning and prediction, the best individuals are selected, a new population is generated and the flow starts again, using new weights to generate new rankings and, therefore, new models, until reaching a certain stopping criterion. At the end, a two-dimensional graphic is presented to the user so that he can choose the individual from the final population that best balances, according to his analysis, performance and interpretability.

3 $AC.RANK_{GCN}$

This section presents the method proposed here, named $AC.RANK_{GCN}$, which, like other literature works, aims to modify the ranking step to obtain models that present a good balance between performance (F1-Macro) and interpretability (Model Size) when a set of OMs is used simultaneously.

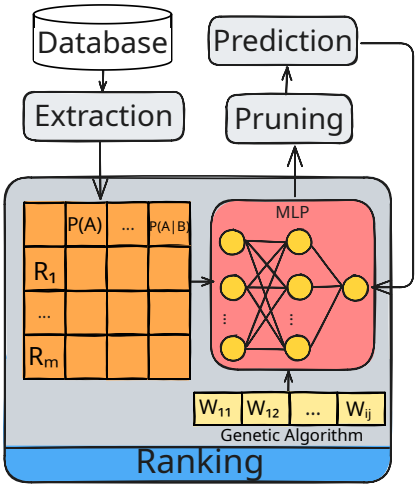


Figure 4: Ranking mechanism of MoMAC.

However, the goal was to improve the results obtained so far evaluating the importance of a rule not only in relation to the values of its OMs, but also in relation to its neighboring rules (neighborhood) and their features. To this end, the problem was modeled using a graph approach via semi-supervised learning, in which the importance (rank) of each rule is a label to be learned considering its neighborhood and features. Since Graph Convolutional Networks (GCNs) are applied in semi-supervised contexts and take into account, during learning, both the network topology and the node attributes, they were used in this work. The proposal is a mix of ideas from both previously described literature works, i.e., $AC.Rank_A$ and MoMAC. It is important to mention, as already stated, that achieving a good balance between performance and interpretability means improving one of them without worsening the other in relation to some baseline, since, as stated by (Dall'Agnol and Carvalho, 2024), an inverse relationship between them exists. Figure 5 presents $AC.RANK_{GCN}$ flow, which is described below.

Matrices Generation. Given a set of rules, two matrices are obtained: "Rules" x "OMs" ($Mat.M$), as in (Dall'Agnol and Carvalho, 2024), and "Rules" x "Probabilities" ($Mat.P$), as in (Bui-Thi et al., 2022). However, in this case, 16 probabilities are considered: $P(A)$, $P(\overline{A})$, $P(C)$, $P(\overline{C})$, $P(AC)$, $P(A\overline{C})$, $P(\overline{A}C)$, $P(\overline{A}\overline{C})$, $P(A|C)$, $P(\overline{A}|\overline{C})$, $P(\overline{A}|C)$, $P(A|\overline{C})$, $P(C|A)$, $\boldsymbol{P(\overline{C}|\overline{A})}$, $P(\overline{C}|A)$, $\boldsymbol{P(C|\overline{A})}$. In (Bui-Thi et al., 2022) those highlighted in bold were not considered, although they are variations of others considered, and different from (Bui-Thi et al., 2022) we did not consider $P(A)P(C)$, since both probabilities were already considered separately[4]. Regarding the OMs,

[4]When $P(AC) = P(A)P(C)$, A and C are statistically independent, i.e., there is no relationship between the

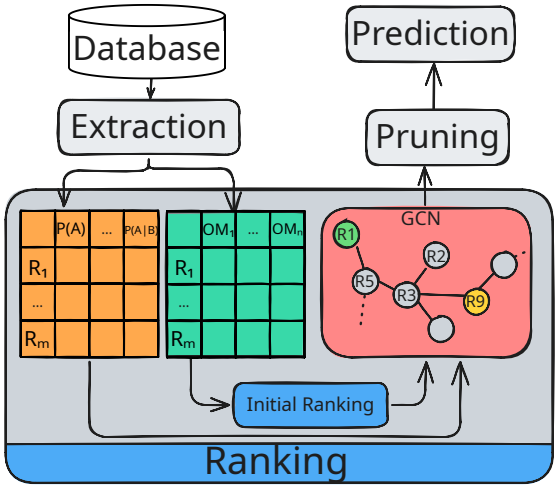


Figure 5: Ranking mechanism of $AC.RANK_{GCN}$.

the sets **[TW]**, **[GF]**, **[G1]** and **[G2]** were explored, as in (Dall'Agnol and Carvalho, 2024) (see Table 2). Set **[C1]** was not used because it is a previous version of sets **[G1]** and **[G2]**.

Graph Construction. Based on the two matrices, a graph is constructed. Each node in the graph represents a rule, which is described by a set of features extracted from $Mat.P$. Using $Mat.M$, each edge represents the similarity between two rules with respect to their set of OMs. However, edges are only created between rules that present high similarity ($\geqslant 99\%$)[5], i.e., high agreement regarding their ranks, since we assume that only nodes that belong to the same class should be connected. The similarity between two rules i and j is computed by $1 - \frac{\sum_{k=1}^{n} |Mat.M_{ik} - Mat.M_{jk}|}{n}$ (normalized Manhattan), where n indicates the number of OMs considered and $Mat.M_{ik}$ the position of rule i in a list ordered by an OM k (position i,k of $Mat.M$) (the same for $Mat.M_{jk}$). Therefore, it is possible to learn a node representation (embedding) that considers, at the same time, the graph structure (defined by a set of OMs), the node features (described by a set of probabilities) and neighborhood information.

Labeling. As mentioned, the problem was modeled via semi-supervised learning. The idea is that GCN learns the embeddings of each rule (node) considering the importance (class) of some initial rules. Since

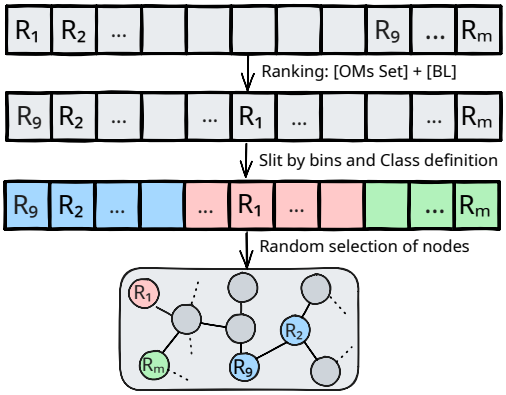


Figure 6: Labeling step.

embeddings encode for each node both the aggregated features of its neighbors and the graph structure, it is possible to identify the importance of each rule considering not only its values in a set of OMs, but also these values in relation to its neighboring rules and the attributes that describe them, that is, their expanded contingency matrices. As the class of any rule is not known at this point, a labeling is performed considering an initial ranking of the rule set. The labeling works as described below (Figure 6):

- Given the set of rules, a ranking is generated. The ranking is done as described in (Dall'Agnol and Carvalho, 2024)'s work, depending on the set of OMs used in the Graph Construction step ($Mat.M$). Regardless of the set, the **[BL]** aggregation method is used, as it has proven to be stable across the sets of measures.
- Based on the ranking generated, the rules, now sorted, are divided into 20[6] bins of equal size (such as equal width), so that the rules contained in the first bin are considered as belonging to class 1 (label 1), those in the second bin to class 2 (label 2), and so on. Thus, rules belonging to the first classes (first bins) are more relevant than those belonging to the final classes (last bins). After that, 20%[7] of the rules are randomly selected to identify the nodes that will be labeled according to the classes defined via bins so that the embeddings are learned and the label propagation is performed. It is possible that a certain class may be left out, since the selection

occurrences of A and C (Tan et al., 2019). On the other hand, when $P(AC) > P(A)P(C)$, A and C are positively correlated; otherwise, negatively correlated (Tan et al., 2019). Thus, we did not consider $P(A)P(C)$ in the list of probabilities, since we assumed that the information is implicit through $P(AC)$, $P(A)$ and $P(C)$.

[5]This similarity threshold could be a hyperparameter (HyP-1) to be better explored in the future.

[6]The number 20 was chosen experimentally to avoid generate an excessively large number of classes. However, this may be a hyperparameter (HyP-2) to be better explored in future work.

[7]This percentage was chosen experimentally, representing the proportion of labeled nodes. However, this may be a hyperparameter (HyP-3) to be better explored in future work.

of rules is done randomly. However, in this case, this does not pose a problem, as the labels are actually pseudo-labels, which are used to direct the learning of the embeddings.

Label Prediction. Based on the labels previously defined, GCN is trained to find the labels of the unlabeled nodes based on the learned embeddings. The idea is to find the importance of each rule not only in relation to a set of measures, but also in relation to its neighbors, that are described by a set of features.

Ranking. After training, unlabeled nodes are labeled as belonging to the highest probability class in their output embedding. Given that each rule is then labeled, their ranking is performed as follows: the rules are ordered from the best class to the worst class and among the rules of the same class, priority is given to those with the highest support value (as in the CBA tiebreaker criterion).

Finally, as in other works, after modifying the ranking step, the induction flow continues until prediction. It is noticed that the proposed method can be seen as a mixture of previous works available in the literature aiming to obtain better results.

4 EXPERIMENTS, RESULTS AND DISCUSSION

Experiments were carried out to evaluate the method proposed here ($AC.RANK_{GCN}$). For that, as in (Dall'Agnol and Carvalho, 2024), CBA was used as baseline, i.e., we changed the CBA ranking step by $AC.RANK_{GCN}$ and compared it with CBA to verify whether the induced models presented a better balance between performance and interpretability. We also compared $AC.RANK_{GCN}$ with $AC.Rank_A$ instantiated with **[GF]+[BL]**, since (Dall'Agnol and Carvalho, 2024) demonstrated its best result in relation to CBA; on the other hand, MoMAC was not considered, as it does not achieve good results according to the authors.

To execute CBA, $AC.Rank_A$ and $AC.RANK_{GCN}$, some requirements are needed. Regarding the datasets, their treatments (pre-processing) and aspects related to rule extraction, we used the configurations as described in (Dall'Agnol and Carvalho, 2024), aiming to guarantee a fair comparison between the works. However, among the 43 datasets presented in (Dall'Agnol and Carvalho, 2024), 41 were used[8], as 2 of them were disregarded because they produced less than 100 rules, making it difficult to apply the method proposed here.

[8]https://bit.ly/gcn-datasets.

Regarding $AC.RANK_{GCN}$, it was executed with the following configurations: **[TW;TW+BL]**, **[GF;GF+BL]**, **[G1;G1+BL]** and **[G2;G2+BL]**. The notation before the ";" refers to the set of OMs in $Mat.M$ used in the construction of the graph ("Graph Construction" step). The notation after the ";" refers to the way of obtaining the ranking to define the labels ("Labeling" step). Regarding the GCN hyperparameters (HyP-GCN), we used the same configurations described in (Kipf and Welling, 2017) (activation functions, loss function, etc.), except for the number of layers, which was set to 1, and the number of hidden units, which were set to 32, since the features vector has dimension 16. As mentioned before, the implementation was based on the code[9] created by (Kipf and Welling, 2017).

Regarding the evaluation criteria, the measures considered were F1-Macro, in terms of performance, and Model Size, in terms of interpretability, both estimated through 10-fold stratified cross-validation. Furthermore, to compare the obtained results, statistical tests were carried out using the Friedman test with $\alpha = 0.05$ and the Nemenyi post-hoc test (Friedman+Nemenyi), together with the critical difference (CD) diagrams, as recommend by (Demsar, 2006). Therefore, a total of 2,460 experiments were executed (6 flows × 41 datasets × 10-fold cross-validation).

Figures 7 to 10 present the results. Each CD diagram[10] refers to the average results[11] obtained by the methods on the 41 datasets with respect to an evaluation measure (F1-Macro or Model Size) over the 10-folds. It is possible to notice that:

- regarding performance (F1-Macro), the Friedman test did not detect a difference between $AC.RANK_{GCN}$ (GCN for short) executed with **[GF;GF+BL]**, **[G1;G1+BL]** and **[G2;G2+BL]** in relation to $AC.Rank_A$ and CBA (the null hypothesis was not rejected (p-values $\cong$ 0.21, 0.07 and 0.15 respectively). However, GCN executed with **[TW;TW+BL]** presented a statistical difference and, therefore, the post-hoc Nemenyi test was applied along with a CD diagram, as shown in Figure 7. Therefore, although GCN was able to maintain the performance of the models in the **[GF;GF+BL]**, **[G1;G1+BL]** and **[G2;G2+BL]** configurations, in the **[TW;TW+BL]** configuration the performance was below the baselines, not being an interesting configuration to be used;

[9]https://github.com/tkipf/gcn.

[10]For more details on CD diagrams see (Demsar, 2006).

[11]Available in https://bit.ly/results-acrankgcn.

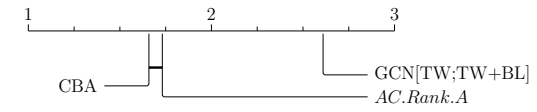
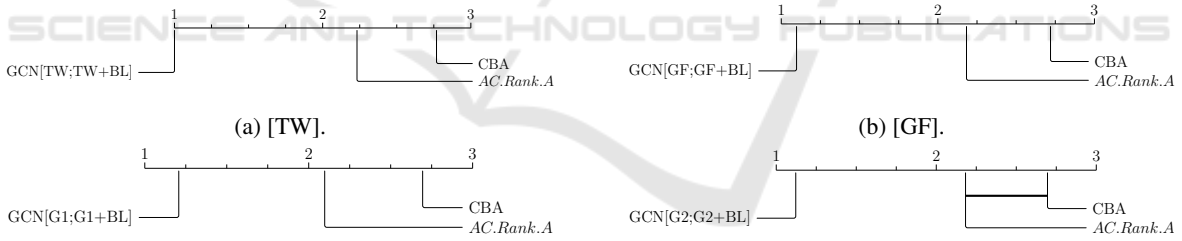


Figure 7: CD diagram between $AC.RANK_{GCN}$ and baselines ($AC.Rank_A$ and CBA) regarding performance (F1-Macro) in [TW;TW+BL] configuration.

- regarding interpretability (Model Size), all GCN configurations presented a statistically significant difference in relation to $AC.Rank_A$ and CBA. In this case, a diagram was generated for each set of OMs, as seen in Figure 8. In all of them it is clear that GCN outperforms $AC.Rank_A$ and CBA. Therefore, considering both performance and interpretability, the only configuration that does not perform well is **[TW;TW+BL]**;
- comparing all GCN configurations (Figure 9), it is possible to notice that regarding F1-Macro, **[TW;TW+BL]** is the only configuration that differs from the others, presenting a worse performance (Figure 9a). On the other hand, it is the best configuration regrading interpretability (Figure 9b). As stated by (Dall'Agnol and Carvalho, 2024), there is an inverse relationship between performance and interpretability. Since the aim here is to achieve a balance between both, it can be noticed that **[G2;G2+BL]** is the most suitable GCN configuration: it appears in the second position of the first group regarding F1-Macro (Figure 9a) and is the second best option regarding interpretability (Figure 9b). Therefore, $AC.RANK_{GCN}$ achieves its aim with this configuration;
- comparing all GCN configurations with the baselines (Figure 10), it is possible to notice that, in fact, **[G2;G2+BL]** is the configuration that guarantees a better balance between performance and interpretability, since it maintains performance (Figure 10a), but improves interpretability (Figure 10b) in relation to baselines.

5 CONCLUSION

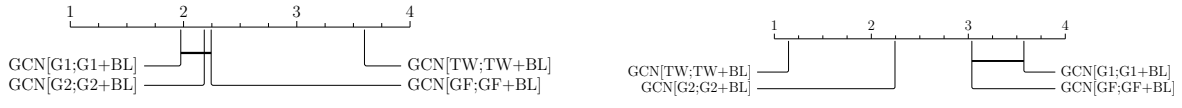
This work presented a method ($AC.RANK_{GCN}$) for ranking rules in ACs induction flows. The aim is to induce models that present a good balance between performance (F1-Macro) and interpretability (Model Size) when a set of OMs is used simultaneously. The method mixes ideas from previous literature works ($AC.Rank_A$ and MoMAC) to improve the results obtained so far. The method uses a graph convolutional network (GCN) in a semi-supervised approach. The idea is to evaluate the importance of a given rule considering its neighboring rules



(a) [TW]. (b) [GF].

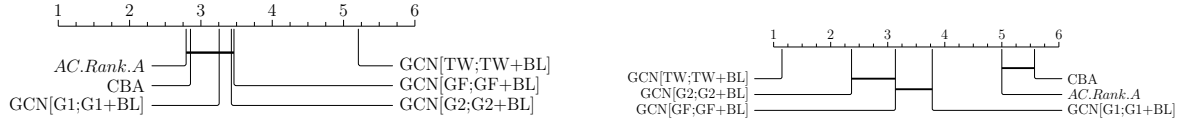
(c) [G1]. (d) [G2].

Figure 8: CD diagram between $AC.RANK_{GCN}$ and baselines ($AC.Rank_A$ and CBA) regarding interpretability (Model Size).



(a) F1-Macro. (b) Model Size.

Figure 9: CD diagram between $AC.RANK_{GCN}$ configurations.



(a) F1-Macro. (b) Size.

Figure 10: CD diagram between $AC.RANK_{GCN}$ configurations and baselines ($AC.Rank_A$ and CBA).

(neighborhood), the network topology and a set of features that describe them. The method outperformed *AC.Rank*$_A$ and CBA in terms of interpretability while maintaining the performance of the models. The best results were achieved with **[G2;G2+BL]** configuration.

We believe that this study presents promising results, which can be better explored in future works regarding (i) the impact of hyperparameters on the process (HyP-1, HyP-2, HyP-3, HyP-GCN), (ii) the possibility of using GCNs in other steps of the induction process, as well as in other flows (as explored by (Dall'Agnol and Carvalho, 2024)), (iii) the construction of solutions that incorporate black-box approaches to improve inherently interpretable (white-box) solutions.

ACKNOWLEDGEMENTS

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES). The authors are also grateful to the São Paulo Research Foundation - FAPESP (grant #2024/04890-5) and the Brazilian National Council for Scientific and Technological Development - CNPq (grants #313193/2023-1 and #422667/2021-8) for their financial support.

REFERENCES

Agrawal, R. and Srikant, R. (1994). Fast algorithms for mining association rules in large databases. In *Proceedings of the 20th International Conference on Very Large Data Bases (VLDB)*, pages 487—499. Morgan Kaufmann Publishers Inc.

Bui-Thi, D., Meysman, P., and Laukens, K. (2022). MoMAC: Multi-objective optimization to combine multiple association rules into an interpretable classification. *Applied Intelligence*, 52(3):3090—3102.

Dall'Agnol, M. and Carvalho, V. O. (2024). AC.RankA: Rule ranking method via aggregation of objective measures for associative classifiers. *IEEE Access*, 12:88862–88882.

Dall'Agnol, M. and De Carvalho, V. O. (2023a). Clustering the behavior of objective measures in associative classifiers. In *18th Iberian Conference on Information Systems and Technologies (CISTI)*, pages 1–6.

Dall'Agnol, M. and De Carvalho, V. O. (2023b). Ranking rules in associative classifiers via borda's methods. In *18th Iberian Conference on Information Systems and Technologies (CISTI)*, pages 1–6.

Demsar, J. (2006). Statistical comparisons of classifiers over multiple data sets. *J. Mach. Learn. Res.*, 7:1—30.

Ju, W., Fang, Z., Gu, Y., Liu, Z., Long, Q., Qiao, Z., Qin, Y., Shen, J., Sun, F., Xiao, Z., Yang, J., Yuan, J., Zhao, Y., Wang, Y., Luo, X., and Zhang, M. (2024). A comprehensive survey on deep graph representation learning. *Neural Networks*, 173:106207.

Khemani, B., Patil, S., Kotecha, K., and Tanwar, S. (2024). A review of graph neural networks: concepts, architectures, techniques, challenges, datasets, applications, and future directions. *J Big Data*, 11(18).

Kipf, T. N. and Welling, M. (2017). Semi-supervised classification with graph convolutional networks. In *International Conference on Learning Representations (ICLR)*.

Liu, B., Hsu, W., and Ma, Y. (1998). Integrating classification and association rule mining. In *In Proceedings of the 4th International Conference on Knowledge Discovery and Data Mining (KDD),*, pages 27–31.

Margot, V. and Luta, G. (2021). A new method to compare the interpretability of rule-based algorithms. *Ai*, 2(4):621–635.

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead.

Sharma, R., Kaushik, M., Peious, S. A., Yahia, S. B., and Draheim, D. (2020). Expected vs. Unexpected: Selecting right measures of interestingness. In *Big Data Analytics and Knowledge Discovery - 22nd International Conference (DaWaK)*, volume 12393, pages 38–47.

Somyanonthanakul, R. and Theeramunkong, T. (2022). Scenario-based analysis for discovering relations among interestingness measures. *Information Sciences*, 590:346–385.

Tan, P.-N., Steinbach, M., Karpatne, A., and Kumar, V. (2019). *Introduction to Data Mining*. 2 edition.

Tew, C., Giraud-Carrier, C., Tanner, K., and Burton, S. (2014). Behavior-based clustering and analysis of interestingness measures for association rule mining. *Data Mining and Knowledge Discovery*, 28(4):1004–1045.

Zhou, J., Cui, G., Hu, S., Zhang, Z., Yang, C., Liu, Z., Wang, L., Li, C., and Sun, M. (2020). Graph neural networks: A review of methods and applications. *AI Open*, 1:57–81.