Proceedings Paper:

Yusuf, H., Yang, K. and Panoutsos, G. orcid.org/0000-0002-7395-8418 (2021) Fuzzy multi-criteria decision-making: example of an explainable classification framework. In: Jansen, T., Jensen, R., Mac Parthaláin, N. and Lin, C.-M., (eds.) Advances in Computational Intelligence Systems (UKCI 2021). UKCI 2021: Advances in Computational Intelligence Systems, 08-10 Sep 2021, Aberystwyth, United Kingdom. Advances in Intelligent Systems and Computing, 1409 . Springer , pp. 15-26. ISBN 9783030870935

https://doi.org/10.1007/978-3-030-87094-2_2

Fuzzy Multi-Criteria Decision-Making: Example of an explainable classification framework

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Abstract. Explanation, or system interpretability, has always been important in applications where critical decisions need to be made, for example in the justice system or biomedical applications. In artificial intelligence and machine learning, there is an ever increasing need for system interpretability. This paper investigates a Fuzzy Multi-Criteria Decision-Making (MCDM) model as the basis for an interpretable framework for explainable classification. The proposed framework includes a Fuzzy Inference System paired with a modified MCDM-based model for data-driven classification. The modular nature of MCDM allows for the development of a model-based layer capable of generating factual and counterfactual explanations. Results on a 'Titanic' survivors' dataset classification, which illustrates a minimal trade-off in predictive performance while gaining textual and graphical explanation, autonomously provided by the proposed model-based MCDM framework.

Keywords: Fuzzy Logic, interpretability, multi-criteria decision making, explainable-AI

1 Introduction

Interpretability has been a topic of significant interest among researchers with the vision that it could shape how machine learning (ML) frameworks are adopted in the future [1–4]. The current state-of-the-art ML classification frameworks are not necessarily interpretable; a property of models that could enable *explainability* of the models' results. With the advent of deep learning and the power of high performance computing, data-driven ML seems to be the obvious choice for data-rich tasks. For the most part, deep learning and other state-of-the-art ML techniques are sufficiently accurate predictive models and, are constructed with data paired with minimal, if any, expert knowledge. The challenge with such models is the fact they are often black box models; hence, they are neither inherently interpretable nor explainable. The lack of transparency is an obstacle to the wide adoption of such methods, especially in applications requiring precise decision justification [1, 4, 5]; for example, safety critical applications such as nuclear, medical and advanced manufacturing.

The focus of this paper, is multi-criteria decision making, and in particular interpretable data-driven Fuzzy-Multi-Criteria Decision-Making (Fuzzy-MCDM) for classification problems. In this Section, a literature review summary on MCDM, interpretability and explainability are covered. The methodology used, in Section 2, is an expansion of Fuzzy-Amended fused TOPSIS-VIKOR for Classification (Fuzzy-ATOVIC) [11], a MCDM-based technique developed for achieving satisfactory performance while being interpretable. Fuzzy-ATOVIC is consequently augmented with an explanation framework designed for explaining the classification output. Section 3 includes the framework's application to the Kaggle 'Titanic' dataset, which presents a classification problem [6]. The results demonstrate the model's ability to provide graphical and textual explanation, while maintaining comparable classification performance. The paper finishes with concluding remarks and future work.

Multi-Criteria Decision Making (MCDM) is a set of modelling methods capable of providing decision support based on several criteria [7]. MCDM are applied in a variety of applications such as business, supply chain and manufacturing [8]. The methods often use a range of criteria to determine a *rank* for each *object*. An example of a typical MCDM application is the ranking of a supplier list. In this case, a company would compare a set of suppliers by using a set of criteria such as speed of delivery, pricing, and payment terms. Depending on the circumstances, different levels of importance can be assigned to different criteria using weights. The process results in a ranked list with the alternatives. Although MCDM was not initially intended as a classifier, nevertheless, there were attempts of developing MCDM-based classification frameworks [9, 10]. MCDM can utilise human-understandable criteria, hence it can become interpretable by nature deeming it a viable candidate for explainable AI systems, when combined with AI-based methods.

Amended fused TOPSIS-VIKOR for Classification (ATOVIC) is a supervised learning MCDM framework that can be trained by a combination of data and expert knowledge [9]. A Fuzzy Logic-based extension of the method, Fuzzy-ATOVIC, makes use of a Fuzzy Inference System (FIS) to replace the final step in the decision making process, introducing greater potential for interpretability to the overall MCDM framework [11]. Fuzzy-ATOVIC as an initial proposal was the first step towards adapting ATOVIC as a fully data-driven classification framework while maintaining its interpretability [11]. Achieving explainability in complex ML structures has always been a challenge due to the inherent non-interpretable nature of many such models. The lack of explanatory information in such models delayed the long awaited wide adoption in several industries. Explanation, as a functional requirement, is considered important in areas where the wrong decision is likely to have a major or catastrophic consequence. In these applications, it is imperative that ML models can provide *explanation* because without it, the user is faced with relying on their own calculations to make decisions, defying the ultimate purpose of the model - improving the overall efficiency and accuracy of the process.

Interpretability has two main categories: model-based or post-hoc [3]. Model-based, as the name suggests, is interpretability that utilises the model itself (its parameters and variables), as the source of interpretation. In contrast, post-hoc interpretability relies solely on the input(s) and output(s) as the source of interpretation [3]. Many researchers have attempted to utilise post-hoc to attempt to explain the output [12, 13]. One of the weaknesses of post-hoc interpretability is the fact that it does not directly explain how the model arrived at a certain decision, rather it is in some way an explanation estimator. On that account, model-based interpretability offers the potential for a direct explanation of the models' decision making process. One of the main challenges in pursuing model-based interpretability is to overcome the trade-off of performance (accuracy, interpretability) [1].

2 Methodology

2.1 ATOVIC and Fuzzy-ATOVIC

Amended Fused TOPSIS-VIKOR for Classification (ATOVIC) is an MCDM-based classification technique introduced by Baccour in 2018 [9]. ATOVIC is a fusion of two MCDM-based techniques: TOPSIS and VIKOR [9]. As opposed to most MCDM techniques, ATOVIC is supervised and data-driven: however, it relies on expert knowledge for setting whether a feature is a *cost* or *benefit*. It is vital to set features as costs or benefits effectively to maximise performance. Furthermore, relying on expert knowledge for data-driven applications could be problematic for datasets where such knowledge does not exist; thus, a method was implemented, as will be explained in Step 2 of model construction, to numerically classify a feature as a cost or benefit. Fuzzy-ATOVIC is a fuzzy extension of ATOVIC that uses a Fuzzy Inference System (FIS) for the final step of decision making [11].

Construction of the ATOVIC model is achieved using the following steps. The procedure is based on Baccour's literature [9], while steps 2 and 3 were modified to enhance the methods of weight calculation and feature classification; to improve the accuracy performance and eliminate the requirement of expert knowledge.

1. Training dataset normalisation using (1, 2) where θ is the normalised term, r denotes the reference matrix, x is the non-normalised term and h is the normalisation coefficient, p is the class number, i is the object number and j is the feature number.
2. Weight calculation using (3) where w_j is the weight and ρ_j is the Pearson correlation coefficient [15]; of feature j.
3. Classifying features as a benefit or cost is determined using ρ. If $\rho_j \leq 0$ then j is a cost for Class 2 and a benefit for Class 1; while if $\rho_j > 0$ then j is a cost for Class 1 and a benefit for Class 2. Where j is the feature number. To achieve this, the labels for class 1 and 2 data have to be set as 1 and 2 respectively.
4. Ideal solutions calculation using (4, 5) where two sets of ideal solutions f are calculated: positive and negative. For positive ideal solutions f_p^+, the maximum is used for a *benefit* feature while the minimum is used for a *cost* feature. Intuitively, it is vice versa for negative ideal solutions, as shown in (5). The ideal solutions are later used for classification.

$$\theta^r_{ij_p} = \frac{x^r_{ij}}{h^r_{j_p}} \tag{1}$$

$$h_{j_p} = \sqrt{\sum_{i=1}^{m^r} (x^r_{ij_p})^2} \tag{2}$$

$$w_j = \frac{\rho^r_j}{\sum_{j=1}^{n} \rho^r_j} \tag{3}$$

$$f_p^{+} = \{\theta_1^{r^+}, \theta_2^{r^+}, \ldots, \theta_n^{r^+}\} = \left\{(max_i \theta_{ij_p}^{r} / j \in B), (min_i \theta_{ij_p}^{r} / j \in C)\right\} \quad (4)$$

$$f_p^{-} = \{\theta_1^{r^-}, \theta_2^{r^-}, \ldots, \theta_n^{r^-}\} = \left\{(min_i \theta_{ij_p}^{r} / j \in B), (max_i \theta_{ij_p}^{r} / j \in C)\right\} \quad (5)$$

After model construction, the data is classified by executing the steps below.

1. Testing data normalisation using (1) and, based on the values of $h_{j_p}^{r}$ defined during model construction.
2. Distance measures S and R are the Manhattan and Chebyshev distances, respectively. They are obtained by calculating the distance types from the ideal solutions for class c = 1 to 2. This implementation of ATOVIC, as opposed to the original version, does not use the Q measure - a weighted sum of S and R. The purpose is to improve traceability and simulatability [1].
3. Comparing distance measures for classification by use of a FIS.

$$S_{c_i} = \sum_{j=1}^{n} w_j * (f_{ij_c}^{+} - \theta_{ij_c}^{t}) / (f_{ij_c}^{+} - f_{ij_c}^{-}),\ S_{c_i} \in [0, 1] \quad (6)$$

$$R_{c_i} = \max_j \left[w_j * (f_{ij_c}^{+} - \theta_{ij_c}^{t}) / (f_{ij_c}^{+} - f_{ij_c}^{-})\right],\ R_{c_i} \in [0, 1] \quad (7)$$

The measures S and R (6, 7), are input into a FIS to compute the fuzzy class. The FIS has six inputs as defined by (8, 9) where ΔM_c is calculated for $M = \{S, R\}$ and class $c = 1$ to 2.

$$\Delta M_c = M_{c,2} - M_{c,1} \quad (8)$$

$$n_M = |\Delta M_2| - |\Delta M_1| \quad (9)$$

Furthermore, the input-output membership functions (MFs) were configured as below.

– S_c, R_c: two MFs: `class_1`, `class_2`
– n_S, n_R: two MFs: `positive` (positive outcome model is used for decision), `negative` (negative outcome model is used for decision)
– Output: four MFs: `class_c_strong`, `class_c_normal`, for class `c` = 1 to 2.

Consequently, a set of 16 rules were configured to cover all possible combinations of inputs; this includes cases where the two sub-models are in agreement or conflict. The S measures are utilised to take a decision, while the R measures translates to a higher chance of certainty; if it is in agreement with S. If the measures are in agreement, a *strong* output MF, corresponding to the class, is set while a *normal* one is used in the case of conflict, as illustrated in Figure 1. The updated configuration of ATOVIC means the FIS had to be modified to process the measures S and R, instead of just the weighted sum measure Q; in the first iteration of Fuzzy-ATOVIC [11].

Despite ATOVIC not utilising user-defined linguistic terms, using human-understandable features meant this is not necessary for interpretation. However, for features that are not human-understandable, it would be essential to introduce interpretability by pre-processing techniques suitable for the problem.

2.2 Explanation Framework

The type of interpretability utilised in this framework is model-based; it uses components from the classification model, including traits of the Fuzzy Logic Inference system to explain the result as opposed to relying on post-processing. Two types of explanation are generated here, textual and graphical. The textual explanation is implemented by using sentence templates and a series of logical operations. Three statements are generated for each data record; this includes one statement for each of the negative/positive outcome models and one statement for the overall decision model. The models are:

– Negative outcome model: This model is optimised using Negative records however, capturing the similarity for both classes.
– Positive outcome model: This model is optimised using Positive records however, capturing the similarity for both classes.
– Overall decision: This model captures the overall decision between the two classes using the Positive and Negative outcome models as inputs to a FIS.

Sentence templates are a simple way to generate textual explanation [14]. A text sentence template

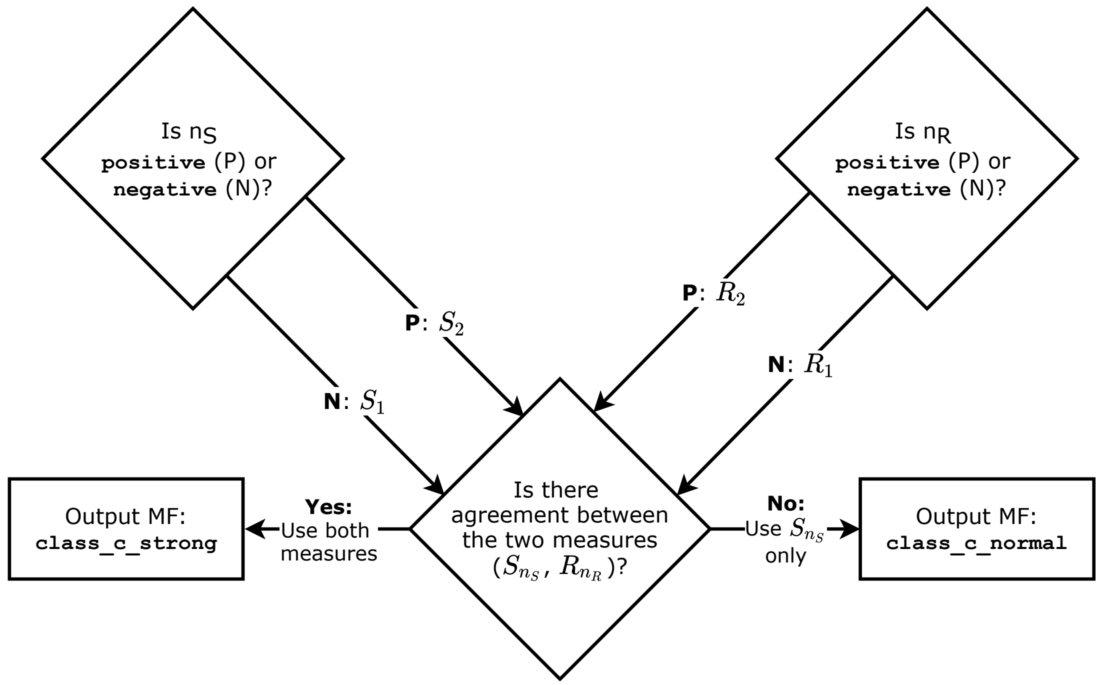

Fig. 1: Flowchart explaining the conditions for formulating the fuzzy rules: binary classification

for the outcome models is shown below as an example. It is used to generate a statement for each of the outcome models, where `sim_class` and `dis_class` are replaced with the names of the similar and dissimilar classes, respectively. To provide greater insight into the level of similarity, the distance measures S for both classes (similar and dissimilar) are included in the template as S_{sim} and S_{dis} respectively. In addition, an overall explanation statement is generated to describe whether the two outcome models are in agreement, and states the FIS class output - `Fuzzy_class`.

– The negative or positive outcome model would yield a text explanation as follows: The `neg (or pos)` outcome model resulted in a similarity to `sim_class` (S_{sim}) and dissimilarity to `dis_class` (S_{dis}).
– The overall decision model would yield a text explanation as follows (if the neg/pos models are in conflict): Models are in conflict however, the measures pointed towards a larger similarity towards `sim_class` (`Fuzzy_class`), or if the two models are in agreement:
– Models are in consensus hence the subject was predicted to be a `sim_class` (`Fuzzy_class`)

To provide further insight into how the different input features of the models impact the classification result, a graphical explanation was designed to illustrate how the values of the features contribute to the models' prediction. There are two outcome models, each optimised for the respective class by means of a unique set of ideal solutions. Similarity measures for each outcome model are determined by calculating the measures, as defined in Section 2.1. To make the distances calculated as part of the measures more readable, they have been scaled between 0 and 5, plotted on a bar graph and named a feature *score* - a more user-friendly terminology than *normalised distance*. The further a feature is from the negative ideal solution $f^-_{j_c}$, the closer it gets to the positive ideal solution $f^+_{j_c}$. This translates to higher similarity to the class' ideal solution, which is represented with a higher feature score as defined by (10).

$$F = 5\left(\frac{\theta^t - f^-_{j_c}}{f^+_{j_c} - f^-_{j_c}}\right) \tag{10}$$

3 Results & Discussion

3.1 Kaggle Titanic case study

Kaggle's Titanic dataset is used for this case study, which is pre-divided into training and testing datasets [6]. The dataset contains attributes describing the ship's passengers. The attributes are listed in Table 1, along with their data types and possible values. The objective of the classification is to classify (hence predict) whether a passenger survived based on the six attributes. Two simulation trials were conducted on the following divisions of data as described below.

- The Kaggle version of the dataset was used in which the data was pre-divided into training and testing; in order to compare the proposed model with models tested by other researchers.
- Performing cross-validation by k-fold: partitioning the data into 5-fold and 10-fold. The aim of this is to evaluate the performance of the proposed model independently.

Table 1: Titanic Dataset: Attribute Information

Attribute	Type	Possible Values
ID	Integer	[1..891]
Ticket Class	Integer	[1..3]
Sex	Category	M, F
Age	Real	$[0, 80]$
Sibling(s)/Spouse(s)	Integer	[0..8]
Parent(s)/Children	Integer	[0..6]
Embarked	Category	C, Q, S

Table 2: Titanic Dataset: Class Information

No.	Class	Count
1	Casualty	549
2	Survivor	342
	Total	891

3.2 Predictive Performance

The methodologies defined in Section 2 were implemented to obtain a Fuzzy-ATOVIC classification model that achieved satisfactory performance for classifying passengers into one of two classes: Casualty or Survivor. In addition, the model generated two modes of explanation: graphical and textual. The classification performance was compared to Ekini et al.'s results on the same dataset [16]. As shown in Table 3, Fuzzy-ATOVIC performance is in a comparable range, however it was not the highest performing. Table 4 shows the detailed performance figures for 5-fold and 10-fold datasets respectively. Increasing the number of folds results in a marginally higher standard deviation, however, the predictive performance figures remain largely similar, with less than a percent increase across the different number of folds for the metrics measured.

Table 3: Comparison of Fuzzy-ATOVIC Titanic Testing Dataset Results with Various Algorithms Tested by Ekinci et al [16]

Model	ACC %	F-Score	Kaggle
Fuzzy-ATOVIC	79.2	75.9	76.6
Gradient Boosting	86.9	82.0	79.4
Decision Tree	81.7	73.8	78.9
Naive Bayes	78.9	71.4	76.2

Table 4: Comparison of Fuzzy-ATOVIC 5-fold and 10-fold performance

Fuzzy-ATOVIC Metrics ($\mu \pm \sigma\%$)		
Metric	5-fold	10-fold
Accuracy	78.3 ± 2.3	79.2 ± 3.6
Sensitivity	67.3 ± 3.2	68.1 ± 5.5
Specificity	85.2 ± 2.6	86.3 ± 4.3
F-Score	75.1 ± 2.0	75.9 ± 4.4

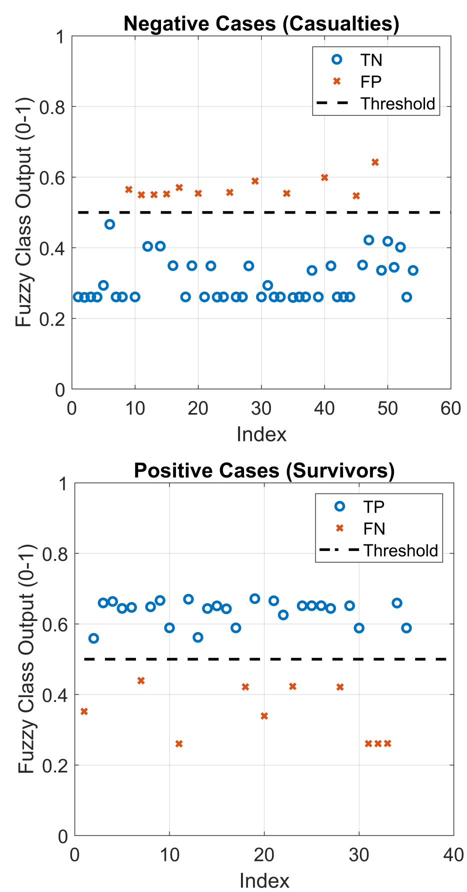

Fig. 2: Fuzzy class output plotted for negative and positive cases

As described in Section 2, the FIS computes the fuzzy class output based on the measures S and R. Hence, the fuzzy class output has to be converted into an integer to determine the class. Figure 2, illustrates the range of the fuzzy class output for negative and positive cases and how the threshold set at 0.5 is used to determine the class (set at 0.5, halfway between the range, however a different threshold can be set to optimise the performance for a given case study, as a hyperparameter).

3.3 Linguistic and Graphical Explanation

The model-generated explanation consists of two types; graphical in the form of a bar graph to illustrate the features' impact on classification and, textual in the form of language statements explaining the sub-models' parameters. Key information is extracted from the model through the ATOVIC and FIS components. The former provides information about the similarity measures while, the latter about the decision making process.

The first example is for a True Positive case where the passenger was correctly identified as a *survivor*. The textual explanation (Table 5) describes the result of the two outcome models with a statement of the distance measures as described in Section 2. Finally, the explanation is concluded with a remark that explains whether the models are in consensus or not and, states the fuzzy class output.

The graphical explanation (Figure 3) illustrates which features are the most impactful in the respective model's decision making process; a larger score implies a stronger impact. In this example, the Pcass and Embarked are the most impactful for a negative classification, while Sex and Sib/Spo were the most impactful for a positive classification. Despite the higher mean feature score for the negative class, the model correctly classified this passenger as positive; attributable to the feature weights which affect the measures' final values.

The second example is a False Positive case where the two outcome models were in conflict as shown in Table 6. The fuzzy class output is further away from the threshold compared to the first example (True Positive), hence there is no obvious distinguishing factor between the two examples. Furthermore, when comparing ID. 329 to another true positive case (ID: 609), it appears the model's positive classification of ID. 609 was more conclusive due to an agreement between the models and, the value of the fuzzy class output which is further away from the threshold (at 0.66).

Certainty is important when justifying a decision. Experts utilise mathematical formulae to quantify the suitability of a decision. The results show how textual explanation conveys certainty by stating the models are in agreement or consensus. On the other hand, uncertainty is conveyed by stating the models' conflict. In spite of the precise wording provided in the textual explanation, the variability of the model's accuracy means some explanation will be, inevitably, misleading. Nonetheless, explanations provide an indication of the result's certainty and most impactful features.

Table 5: Explanation Example: ID No. 329, True Positive

Model	Explanation
Negative	The Casualty outcome model resulted in a similarity to Survivor (0.00) and dissimilarity to Casualty (0.47)
Positive	The Survivor outcome model resulted in a similarity to Casualty (0.34) and dissimilarity to Survivor (0.54)
Overall	Models are in conflict however, the measures pointed towards a larger similarity towards Survivor (fuzzy class: 0.56)

Table 6: Explanation Example: ID No. 437, False Positive

Model	Explanation
Negative	The Casualty outcome model resulted in a similarity to Survivor (0.00) and dissimilarity to Casualty (0.49)
Positive	The Survivor outcome model resulted in a similarity to Casualty (0.35) and dissimilarity to Survivor (0.53)
Overall	Models are in conflict however, the measures pointed towards a larger similarity towards Survivor (fuzzy class: 0.57)

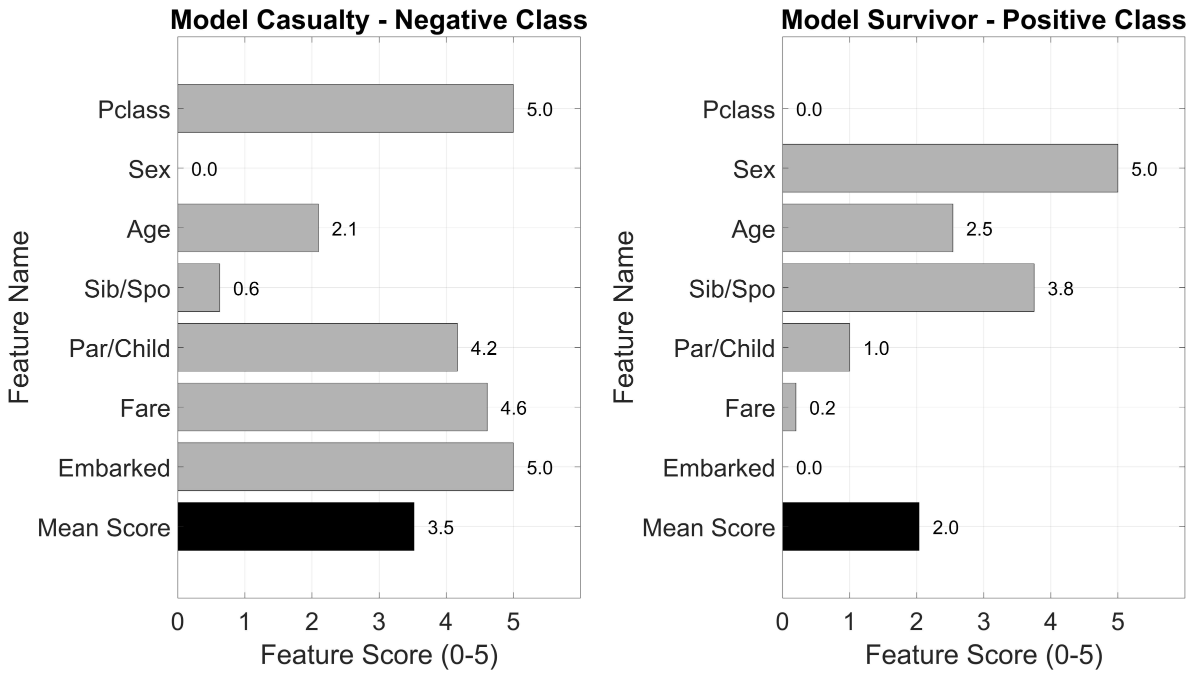

Fig. 3: Graphical Explanation of features ID No. 329, True Positive

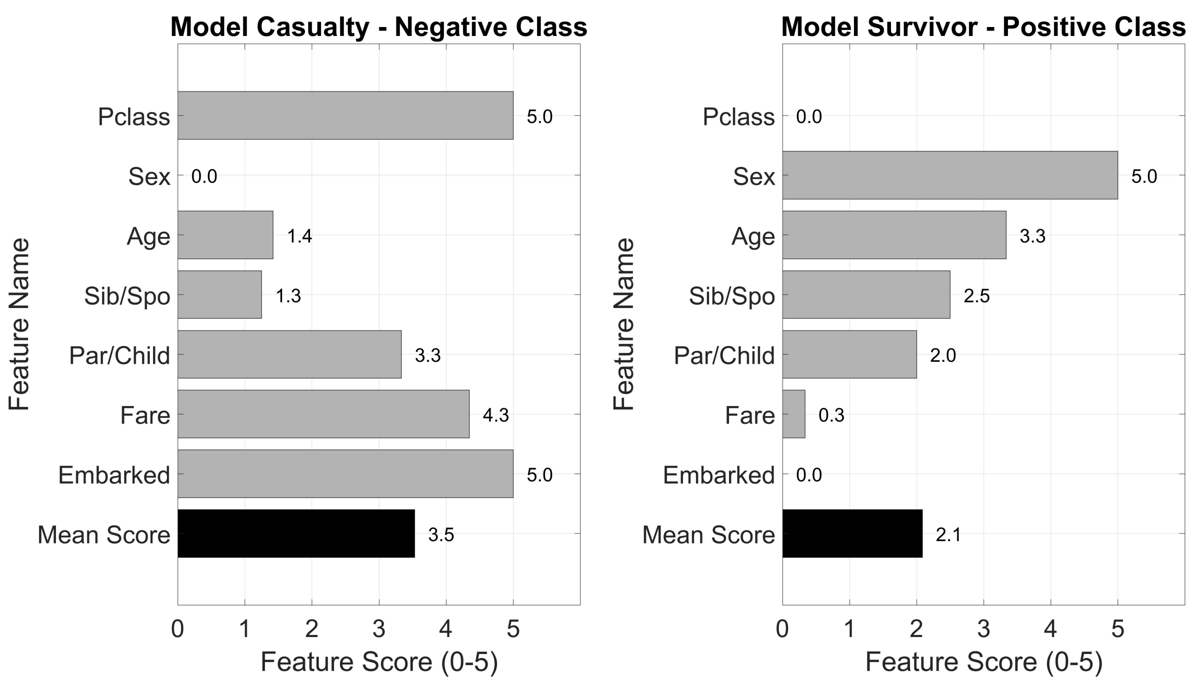

Fig. 4: Graphical Explanation of features ID No. 437, False Positive

4 Conclusion and Future Work

In summary, the proposed enhancement to ATOVIC omits its reliance on expert knowledge, and automatically sets classes, thereby making it entirely data-driven. When extended with a fuzzy component, the result is Fuzzy-ATOVIC; a data-driven MCDM framework for classification with traits that are amenable to textual and graphical explanation inherent to the models involved. While the resulting predictive accuracy is not the highest, the main benefit of using such a method for classification is the higher potential of model-based interpretability.

While the presented preliminary results only demonstrate a simple case study of a binary classification problem, there is further work required towards scaling up the framework to more complex and multi-class case studies. Developing a FIS structure that is able to handle more than two sub-models is the first step towards multi-class support. However, with increasing complexity it is imperative that the framework is adequately simplified to ensure interpretability.

Acknowledgement This publication was made possible by the sponsorship and support of Lloyd's Register Foundation. A charitable foundation, helping to protect life and property by supporting engineering-related education, public engagement and the application of research www.lrfoundation.org.uk. The work was enabled through, and undertaken at, the National Structural Integrity Research Centre (NSIRC), a postgraduate engineering facility for industry-led research into structural integrity established and managed by TWI through a network of both national and international Universities. This research was also financially supported by The University of Sheffield, Department of Automatic Control and Systems Engineering.

This is an Author Accepted Manuscript version of the following chapter: H. Yusuf, K. Yang and G. Panoutsos, "Fuzzy Multi-Criteria Decision-Making: Example of an explainable classification framework", published in Advances in Computational Intelligence Systems, edited by T. Jansen, R. Jensen, N. M. Parthaláin and C.-M. Lin, 2022, Springer reproduced with permission of Springer International Publishing. The final authenticated version is available online at: https://dx.doi.org/10.1007/978-3-030-87094-2_2.

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