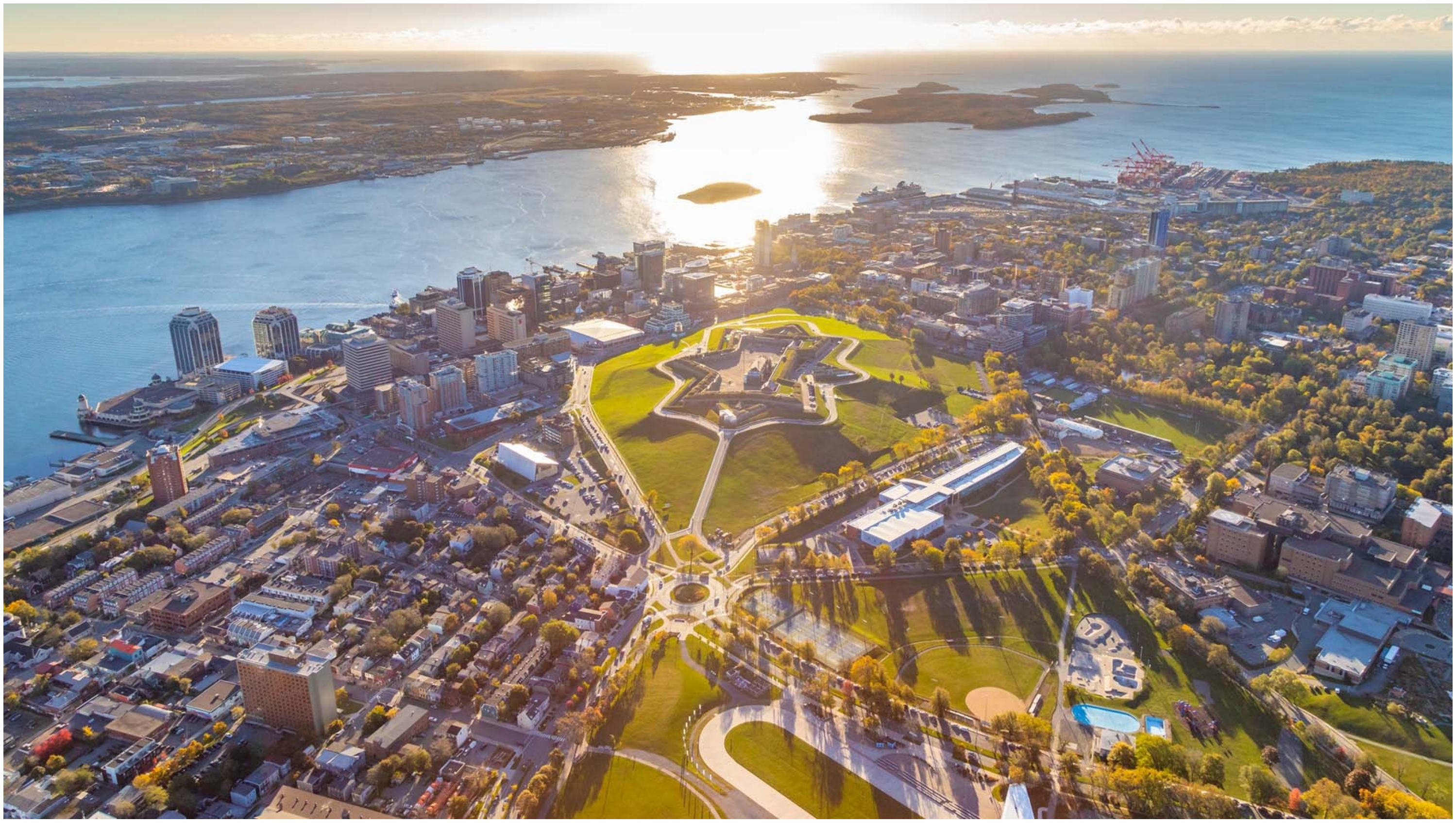

International Joint Conference on Rough Sets

BOOK OF ABSTRACTS

Organized by the International Rough Set Society and the MSc in Computing and Data Analytics (MCDA) Program at Saint Mary's University.

Friday, May 17th - Monday, May 20th, 2024
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Book of Abstracts

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Preface

This book comprises the extended abstracts selected for presentation at IJCRS 2024, the 2024 International Joint Conference on Rough Sets, held at Saint Mary's University in Halifax, Canada, on May 17-20, 2024. The annual IJCRS series conferences combine four distinct conferences linking rough sets to various paradigms: RSCTC (data analysis), RSFDGrC (granular computing), RSKT (knowledge technology), and RSEISP (intelligent systems). The first Joint Rough Set Symposium took place in Toronto, Canada, in 2007; followed by Symposiums in Chengdu, China (2012); Halifax, Canada (2013); Granada and Madrid, Spain (2014); Tianjin, China (2015), where the acronym IJCRS was proposed; and subsequent conferences IJCRS 2016 in Santiago, Chile; IJCRS 2017 in Olsztyn, Poland; IJCRS 2018 in Quy Nhon, Vietnam; IJCRS 2019 in Debrecen, Hungary; IJCRS 2020 in La Habana, Cuba (online); IJCRS 2021 in Bratislava, Slovakia (hybrid); IJCRS 2022 in Suzhou, China (hybrid); and IJCRS 2023 in Kraków, Poland (hybrid).

IJCRS 2024 continued to receive significant attention from researchers in the rough sets community. We received 53 full-length paper submissions and 40 top-quality submissions were accepted after a rigorous single-blind reviewing process. The scientific discourse at IJCRS 2024 was complemented by ten extended abstracts, describing ongoing work or research published elsewhere in the past year. These extended abstracts were rigorously reviewed by Program Committee Chairs and compiled into this Book of Abstracts edited by the Publication Chair, Xiaodong Yue, and his PhD student Zihao Li. The success of the conference owes much to the contributions of the authors, reviewers, and Program Committee Members.

The IJCRS 2024 program featured nine invited talks, including three presentations by former presidents of the International Rough Set Society, Duoqian Miao, Shusaku Tsumoto, and Wojciech Ziarko, and six keynote talks by renowned researchers in the field, Lipika Dey, Jimmy Huang, Ryszard Janicki, Eric Matson, Jesus Medina, and Jaroslaw Was. We are grateful to all the invited speakers for their visionary talks on research related to rough sets. The IJRCS 2024 also hosted two workshops on "Uncertainty, Three-way Decision, and Explainable Artificial Intelligence" and "Applications of Deep Learning and Soft Computing" and two special sessions on "General Rough Set Perspectives on Foundations of AI and Machine Learning" and "Formal Concept Analysis, General Operators and Related Topics". Our gratitude is extended to all the workshop and special session chairs, Duoqian Miao, Jianfeng Xu, Chuanlei Zhang, Ying Yu, Hong Yu, Raavee Kadam, A Mani, Stefania Boffa, Davide Ciucci, Jesús Medina, M. Eugenia Cornejo, and Eloísa Ramírez-Poussa.

The IJCRS 2024 program was further augmented by Rough Set School and Tutorials, and a Data Mining Competition. We are grateful to the chairs, Piotr Artiemjew, Zaineb Chelly Dagdia, Yasushi Akiyama, and Andrej Janusz, and the tutorial speakers, Stefania Boffa, James F. Peters, Usman Qamar, Andrzej Skowron, Dominik Ślęzak, Arkadiusz Wojna, and Yiyu Yao, and the judges and participants of the Data Mining Competition.

We appreciate the sponsorship from Springer for the Best Paper Award and the Best Student Paper Award. The awards were assigned based on a competitive process, considering scientific excellence and clarity of both articles and presentations. We are also grateful to Jimmy Huang and IEEE for their sponsorship through the IEEE TCII Fund.

IJCRS 2024 would not have been successful without the support of many people and organizations. We are grateful to the Program Committee Members and external reviewers for their effort and engagement in providing a rich and rigorous scientific program. We greatly appreciate the cooperation, support, and sponsorship from the MSc in Computing and Data Analytics (MCDA) program at Saint Mary's University and the International Rough Set Society. We acknowledge the use of the EasyChair conference system for paper submission and review. We are also grateful to Springer for publishing the proceedings as a volume of LNCS/LNAI.

Lastly, thanks are extended to Raavee Kadam, Neelam Pal, Vrushali Prajapati, and other members in the local organizational team for their logistical, technical, and administrative support, without which IJCRS 2024 would not have been possible.

May 2024

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Suggestions on the Use of Three-way Decision in Machine Learning

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1 Introduction

The use of Three-Way Decision (TWD) to handle uncertainty in Machine Learning (ML) has attracted a great interest in the last years. In order to categorize the applications of TWD-based approaches in ML, we distinguish between methods that deal with uncertainty in either the *input* or the *output* of a Machine Learning pipeline [6], as shown in Figure 1.

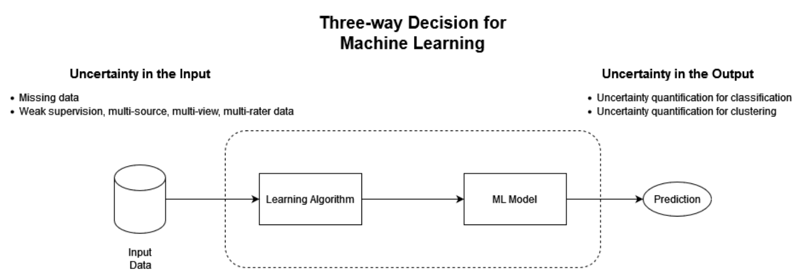

Fig. 1. A graphical representation of the framework adopted to classify applications of Three-way decision in Machine Learning.

In the context of machine learning (ML), "Uncertainty in the input" refers to situations where training datasets have instances of uncertainty [13]. This uncertainty can manifest in two primary forms: *Incomplete data* and *weak supervision*. Incomplete data happens when certain values of predictive features in the dataset are missing [18] or not fully available [19, 23].

Weak and multi-source supervision occur when the uncertainty impacts the supervision process—meaning the target or decision variable—or the relationship between predictive features and supervision is only partially defined. As a result, weak supervision is the counterpart of incomplete data, with the difference being that it affects the target space instead of the feature space [9, 17, 21].

On the other hand, "uncertainty in the output" describes what is known as cautious AI, a term that has gained popularity to describe AI systems that reveal their uncertainty instead of making definite, single-value classifications [5, 16].

This approach involves using uncertainty quantification techniques to enhance the robustness of ML models by clearly presenting their predictive uncertainty, thereby enabling models to abstain from making a decision to some extent.

The use of TWD (Three-Way Decisions) in developing uncertainty quantification methods in ML aims to address both classification and clustering problems. Initially, TWD was applied to spam detection for classification [24, 27] and later extended to clustering [26], evolving from concepts such as rough clustering and interval set clustering. A key recommendation of TWD in these scenarios is to allow classifiers or clusterers to partially abstain [25], meaning they can exclude some potential classifications, thus enhancing decision-making under uncertainty.

In this extended abstract, based on the above mentioned categorization of applications of TWD in ML, we present the observations and insights drawn from a more recent systematic survey [10] of the specialized literature through which we studied the application of TWD in ML. In this survey [10] we noted how, despite the increasing adoption of, and interest toward, TWD in ML, a lack of reporting standards and attention towards evaluation and reproducibility practices can be observed, undermining the generalizability and methodological soundness of reported results in the field. Thus, we here summarize these observations, focusing in particular on presenting recommendations and implications for future research related to TWD in ML.

2 Discussion

Areas of concern in TWD applied to ML are:

- **Issue:** a lack of reporting standard, both in regard to data and model aspects. Indeed, a majority of the surveyed studies failed to comprehensively document the main characteristics of the datasets considered for validation. Such lack of information can have a severe impact on the reproducibility, and hence credibility, of a study's results.
  Possible solution: to adopt and follow reporting checklists, including both checklists devoted specifically to data aspects [2] as well as more general reporting guidelines.
- **Issue:** many studies (especially so in the weak supervision and missing data categories) failed to provide sufficient details on crucial aspects of the ML pipeline, such as hyper-parameter optimization, which could severely impact on the generalizability and robustness of the reported results.
  Possible solution: as in the previous point, more closely follow existing standard reporting guidelines, such as [3, 11].
- **Issue:** in regard to validation design, a surprisingly large number of studies only adopted internal validation study designs: training and testing of a ML approach are performed on the same set of data. While these designs are not wrong by themselves, their sole application may limit the generalizability of the results, if the risks of overfitting and data leakage are not properly accounted for.

Possible solution: A simple approach to ensure the distinct separation of training and testing data involves using validation techniques like hold-out validation or cross-validation, and methods that incorporate randomization such as bootstrapping to mitigate overfitting risks. However, it's important to recognize that these validation techniques alone cannot confirm the generalizability of ML techniques in out-of-distribution scenarios [4, 22]. Notably, none of the studies reviewed utilized external validation. Investigating the effectiveness of TWD-inspired methods under these conditions represents a promising avenue for future research.

- **Issue:** In regard to validation metrics, most studies only focused on accuracy, which is, however, not well suited for settings affected by label imbalance. Furthermore, almost none of the surveyed studies considered metrics that go beyond the measurement of error rate, neglecting important performance dimensions such as calibration [20].
  Possible solution: the adoption of reporting guidelines could help TWD researchers in the selection of appropriate validation metrics.
- **Issue** in regard to statistical analysis, only a minority of studies assessed the significance of the observed results.
  Possible solution: it is recommended that future works in TWD research provide more comprehensive statistical analysis of the reported results, adopting approaches either based on hypothesis testing [12] or confidence intervals [1]. Importantly, following recent guidelines on the subject, TWD researchers should not only report about the significance of results, but focus on providing comprehensive discussion of p-values, effect sizes [15] as well as potential corrections needed to avoid biases and over-estimation of effects [14].

Concluding, we provide suggestions for future directions of research in the application of TWD to ML:

1. Clustering-based TWD approaches for weakly supervised learning seem to improve robustness to the curse of dimensionality, especially in comparison with traditional clustering-based methods. This hypothesis should be further investigated in future research;
2. TWD-based approaches for missing data management seem to offer a distinct advantage over traditional techniques adopted in the ML literature, in that they do not necessarily require imputation, a data processing step that may negatively impact the generalizability of ML studies. Future research should be devoted at exploring this advantage of TWD-based methods, as well as at comparing them with other ML techniques that likewise do not require imputation (e.g., missing indicators);
3. For classification tasks, TWD-based methods often blend feature selection with classification, a practice rooted in the extensive use of rough set-theoretic (RST) techniques in TWD research. This suggests a need for ablation studies to separately evaluate the effects of feature selection and classification on performance. Moreover, the heavy reliance on RST-inspired techniques opens up opportunities to investigate other TWD-based strategies that do

not depend on RST, especially those that merge TWD with cautious inference techniques or related methods like conformal prediction or active learning.
4. In regard to both the classification and clustering tasks, we observed that only a minority of the surveyed articles properly accounted for the uncertainty quantification properties of TWD-based approaches in the validation phase. As for the classification task, we believe that future research should be focused at better exploring the accuracy-coverage trade-off offered by commonly adopted TWD-based methods, both from an empirical point of view as well as from a theoretical one [6]. As for the clustering task, we believe that future studies that more accurately and precisely investigate their advantages with respect to hard clustering methods, using appropriate validation metrics [7, 8], are particularly needed;
5. Finally, in regard to clustering, most of the surveyed studies focused on techniques based on generalizing existing partitional (e.g., k-means) and density (e.g., DBSCAN) clustering methods. On the one hand, this suggests that further attention should be focused toward other clustering methods' families, such as hierarchical clustering. On the other hand, due to three-way clustering's ability to more comprehensively represent clustering uncertainty, a particularly interesting direction for future research would be the investigation of the trade-offs between these different forms of uncertainty.

References

1. Berrar, D.: Confidence curves: an alternative to null hypothesis significance testing for the comparison of classifiers. Machine Learning **106**, 911–949 (2017)
2. Boyd, K.L.: Datasheets for datasets help ml engineers notice and understand ethical issues in training data. Proceedings of the ACM on Human-Computer Interaction **5**(CSCW2), 1–27 (2021)
3. Cabitza, F., Campagner, A.: The need to separate the wheat from the chaff in medical informatics: Introducing a comprehensive checklist for the (self)-assessment of medical ai studies. International Journal of Medical Informatics **153**, 104510 (2021)
4. Cabitza, F., Campagner, A., Soares, F., de Guadiana-Romualdo, L.G., Challa, F., Sulejmani, A., Seghezzi, M., Carobene, A.: The importance of being external. methodological insights for the external validation of machine learning models in medicine. Computer Methods and Programs in Biomedicine **208**, 106288 (2021)
5. Campagner, A., Cabitza, F., Berjano, P.L., Ciucci, D.: Three-way decision and conformal prediction: Isomorphisms, differences and theoretical properties of cautious learning approaches. Information Sciences **579**, 347–367 (2021)
6. Campagner, A., Cabitza, F., Ciucci, D.: Three-way decision for handling uncertainty in machine learning: A narrative review. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) **12179 LNAI**, 137–152 (2020)
7. Campagner, A., Ciucci, D., Denœux, T.: A distributional framework for evaluation, comparison and uncertainty quantification in soft clustering. International Journal of Approximate Reasoning **162**, 109008 (2023)
8. Campagner, A., Ciucci, D., Denœux, T.: A general framework for evaluating and comparing soft clusterings. Information Sciences **623**, 70–93 (2023)

9. Campagner, A., Ciucci, D., Svensson, C.M., Figge, M.T., Cabitza, F.: Ground truthing from multi-rater labeling with three-way decision and possibility theory. Information Sciences **545**, 771 – 790 (2021)
10. Campagner, A., Milella, F., Ciucci, D., Cabitza, F.: Three-way decision in machine learning tasks: a systematic review. Artificial Intelligence Review (Under Revision)
11. Crossnohere, N.L., Elsaid, M., Paskett, J., Bose-Brill, S., Bridges, J.F.: Guidelines for artificial intelligence in medicine: literature review and content analysis of frameworks. Journal of Medical Internet Research **24**(8), e36823 (2022)
12. Demšar, J.: Statistical comparisons of classifiers over multiple data sets. The Journal of Machine learning research **7**, 1–30 (2006)
13. Destercke, S.: Uncertain data in learning: challenges and opportunities. In: Johansson, U., Boström, H., An Nguyen, K., Luo, Z., Carlsson, L. (eds.) Proceedings of the Eleventh Symposium on Conformal and Probabilistic Prediction with Applications. Proceedings of Machine Learning Research, vol. 179, pp. 322–332 (2022)
14. García-Pérez, M.A.: Use and misuse of corrections for multiple testing. Methods in Psychology **8**, 100120 (2023)
15. Greenland, S., Senn, S.J., Rothman, K.J., Carlin, J.B., Poole, C., Goodman, S.N., Altman, D.G.: Statistical tests, p values, confidence intervals, and power: a guide to misinterpretations. European journal of epidemiology **31**, 337–350 (2016)
16. Hüllermeier, E., Waegeman, W.: Aleatoric and epistemic uncertainty in machine learning: An introduction to concepts and methods. Machine Learning **110**(3), 457–506 (2021)
17. Lienen, J., Hüllermeier, E.: Credal self-supervised learning. Advances in Neural Information Processing Systems **34** (2021)
18. Little, R.J., Rubin, D.B.: Statistical analysis with missing data, vol. 793. John Wiley & Sons (2019)
19. Miao, X., Gao, Y., Guo, S., Liu, W.: Incomplete data management: a survey. Frontiers of Computer Science **12**(1), 4–25 (2018)
20. Ojeda, F.M., Jansen, M.L., Thiéry, A., Blankenberg, S., Weimar, C., Schmid, M., Ziegler, A.: Calibrating machine learning approaches for probability estimation: A comprehensive comparison. Statistics in Medicine **42**(29), 5451–5478 (2023)
21. Poyiadzi, R., Bacaicoa-Barber, D., Cid-Sueiro, J., Perello-Nieto, M., Flach, P., Santos-Rodriguez, R.: The weak supervision landscape. In: 2022 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops). pp. 218–223. IEEE (2022)
22. Steyerberg, E.W., Harrell, F.E.: Prediction models need appropriate internal, internal–external, and external validation. Journal of clinical epidemiology **69**, 245–247 (2016)
23. Williams, D., Liao, X., Xue, Y., Carin, L., Krishnapuram, B.: On classification with incomplete data. IEEE transactions on pattern analysis and machine intelligence **29**(3), 427–436 (2007)
24. Yao, Y.: Three-way decisions with probabilistic rough sets. Information sciences **180**(3), 341–353 (2010)
25. Yao, Y.: An outline of a theory of three-way decisions. In: Rough Sets and Current Trends in Computing. pp. 1–17. Springer Berlin Heidelberg (2012)
26. Yu, H.: A framework of three-way cluster analysis. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) **10314 LNAI**, 300–312 (2017)
27. Zhou, B., Yao, Y., Luo, J.: A three-way decision approach to email spam filtering. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) **6085 LNAI**, 28–39 (2010)

Privacy-Preserving Federated Learning: Insights and Perspectives

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Abstract. Federated learning is a distributed machine learning approach where learning occurs directly on devices without central data collection. This approach processes data where it is generated, significantly enhancing user privacy and system security. This innovative approach promises substantial benefits across various domains, from healthcare to smart cities, by enabling collaborative model training while safeguarding sensitive information. Despite its potential, it faces various challenges, such as privacy preservation, communication efficiency, heterogeneity, and security. The issue of privacy preservation becomes even more complex with the advent of advanced technologies. There is a need to address these privacy-preserving challenges to enhance the applicability of federated learning in real-world scenarios. This work aims at the essence of federated learning, exploring its architecture, data partitioning strategies, and the pressing need for innovative privacy-preserving methods.

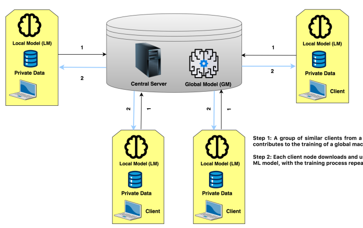
Keywords: Artificial Intelligence · Federated Learning · Privacy-Preserving

1 Introduction

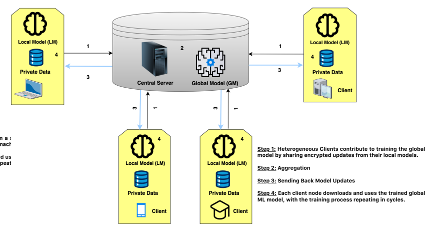
Federated Learning (FL) is a distributed machine learning approach that trains models across multiple devices or servers holding local data samples, without exchanging them [4]. This method significantly enhances data privacy, security, and access across various devices. By addressing data privacy and fragmentation challenges, FL allows for the collaborative training of models without compromising individual data privacy, strengthening the path for a more trusted and expansive adoption of technologies [7]. FL is revolutionizing machine learning by offering a more private and efficient way to train models. This makes FL especially useful in fields like healthcare and marketing, where data is sensitive but crucial for developing powerful models. By keeping data on local devices and reducing reliance on big data centers, FL not only keeps data safer but also makes machine learning more accessible and scalable, even in areas where data sharing is restricted [1].

FL is commended for its privacy-preserving capabilities, but it faces its own set of challenges in maintaining this privacy. The process of exchanging model information between devices may still create openings for attackers to hack the system or manipulate data. Therefore, securing FL against these threats is a critical area of ongoing research. Additionally, FL must deal with the diversity of data and device capabilities, which can complicate the learning process and impact the accuracy of models. Communication efficiency is another challenge, requiring solutions to handle bandwidth limits and the cost of sending data across networks [6]. These challenges highlight the need for FL to continuously evolve in addressing security concerns, managing data and device diversity, and improving communication to maintain its privacy advantages.

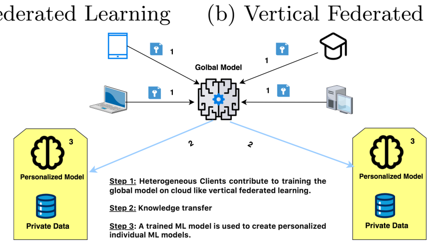
Various methods have been developed to address privacy-preserving challenges, including homomorphic encryption [3], differential privacy [2], secure multi-party computation [4], game-theory and three-way decisions each offering a way to perform computations on encrypted data to prevent the disclosure of sensitive information [10]. However, these methods introduce some limitations, such as increased computational complexity, potential degradation in model performance, and the complex balance between privacy and utility.



(a) Horizontal Federated Learning



(b) Vertical Federated Learning



(c) Transfer Federated Learning

Fig. 1: Federated Learning Data Partition Strategies

2 Federated Learning: Architecture

In FL, the network architecture is categorized into two main types: centralized and fully decentralized. The centralized FL architecture typically relies on a single server to aggregate models from participants, enhancing trust and managing the learning process. In a fully decentralized FL method, there is no need for a central server to aggregate the models. Instead, it establishes trust and reliability among participants. Unlike centralized models with a single global model, in a decentralized setup, each participant improves their model by sharing information with nearby nodes in a peer-to-peer network [7].

The architecture of FL encompasses three main data partition strategies: horizontal federated learning, vertical federated learning, and federated transfer learning. horizontal federated learning involves datasets on various devices sharing identical features but representing different instances [4]. This form of FL is particularly suitable for scenarios where clients possess similar feature spaces as shown in Fig. 1a. Vertical federated learning as shown in Fig. 1b, shared data from different domains trains a global machine learning model. Usually, an intermediate third party ensures encryption to protect shared data statistics. In practical scenarios, vertical federated learning proves useful, data features are divided vertically among parties, with one party usually holding labels and acting as the FL manager. Federated transfer learning as shown in Fig. 1c is an extension of traditional transfer learning techniques, allowing a pre-trained model to be adapted for solving new problems in federated environments [4].

Existing research on privacy-preserving in FL goes beyond basic techniques like secure multi-party computation and differential privacy. They explore advanced methods such as the VerifyNet framework and adversarial training [8]. These strategies aim to enhance data protection while keeping the collaborative learning process effective and secure. The integration of game theory and three-way decision-making further illustrates this trend, providing robust approaches to privacy preservation. Game theory offers a strategic framework for modeling interactions among participants, encouraging cooperative behavior, and improving security. Similarly, the three-way decision method allows for dynamic and flexible privacy settings. However, implementing these methods presents challenges, including increased computational demands and potential impacts on model performance [4, 7, 10].

3 Concluding Remarks

FL represents a revolutionary approach to machine learning. While it offers many benefits, it also faces challenges in privacy-preserving. Although existing privacy mechanisms keep a solid foundation for data protection, advancing technologies demand innovative solutions to safeguard privacy effectively without losing system performance. Exploring federated learning has revealed many challenges and opportunities, directing researchers to areas that require further investigation.

Future research in the domain of privacy-preserving mechanisms in FL presents an approach aimed at enhancing both privacy and efficiency while maintaining the utility of shared data. The exploration of advanced game-theoretical models promises to develop dynamic and adaptive privacy-protection mechanisms that respond in real-time to changes in FL environments and participant behaviors, offering robust privacy without compromising model accuracy or high computational costs [10]. The integration of anonymization techniques like differential privacy and secure multi-party computation into the three-way decision model could significantly balance privacy, data utility, and computational efficiency [5]. Further, there is a need for developing adaptive and granular privacy measures capable of adjusting based on real-time assessments of data usage and associated risks [9]. Moreover, the development of lightweight, efficient FL frameworks that support real-time processing and decision-making, without sacrificing scalability or adaptability, is essential. Collectively, these future research directions highlight a comprehensive and integrated approach to advancing the field of privacy-preserving federated learning.

References

1. Kaylani Bochie. An analysis of federated learning on mobile networks. *Netw. Comput. Appl.*, 194:103213–103258, 2021.
2. Oshamah Khalaf Ibrahim, Sameer Algburi, Anupallavi S, Dhanasekaran Selvaraj, Mhd Saeed Sharif, and Wael Elmedany. Federated learning with hybrid differential privacy for secure and reliable cross-iot platform knowledge sharing. *Security and Privacy*, page e374, 2024.
3. Wenchao Liu, Tanping Zhou, Long Chen, Hongjian Yang, Jiang Han, and Xiaoyuan Yang. Round efficient privacy-preserving federated learning based on mkfhe. *Computer Standards & Interfaces*, 87:103773, 2024.
4. Viraaji Mothukuri, Reza M Parizi, Seyedamin Pouriyeh, Yan Huang, Ali Dehghantanha, and Gautam Srivastava. A survey on security and privacy of federated learning. *Future Generation Computer Systems*, 115:619–640, 2021.
5. Jin Qian, Haoying Jiang, Ying Yu, Hui Wang, and Duoqian Miao. Multi-level personalized k-anonymity privacy-preserving model based on sequential three-way decisions. *Expert Systems with Applications*, 239:122343, 2024.
6. Prohim Tam, Riccardo Corrado, Chanthol Eang, and Seokhoon Kim. Applicability of deep reinforcement learning for efficient federated learning in massive iot communications. *Applied Sciences*, 13(5):3083, 2023.
7. Omar Abdel Wahab, Azzam Mourad, Hadi Otrok, and Tarik Taleb. Federated machine learning: Survey, multi-level classification, desirable criteria and future directions in communication and networking systems. *IEEE Comm. Surveys & Tutorials*, 23(2):1342–1397, 2021.
8. Guowen Xu, Hongwei Li, Sen Liu, Kan Yang, and Xiaodong Lin. Verifynet: Secure and verifiable federated learning. *IEEE Trans. on Information Forensics and Security*, 15:911–926, 2019.
9. Yang Xu, Md Zakirul Alam Bhuiyan, Tian Wang, Xiaokang Zhou, and Amit Kumar Singh. C-fdrl: Context-aware privacy-preserving offloading through federated deep reinforcement learning in cloud-enabled iot. *IEEE Transactions on Industrial Informatics*, 19(2):1155–1164, 2022.
10. Lihua Yin, Sixin Lin, Zhe Sun, Ran Li, Yuanyuan He, and Zhiqiang Hao. A game-theoretic approach for federated learning: a trade-off among privacy, accuracy and energy. *Digital Communications and Networks*, 2023.

Interfacing with a Machine Learning Framework to Detect Drug-Related Harms on Social Media*

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1 Introduction

The use of social media platforms has emerged as a primary method for public health agencies to disseminate information, including trends related to drug use [2,5]. Recognizing the potential of this data source to act as a real-time indicator for drug trends across Canada, a study published by our group in the Journal of Medical Internet Research (JMIR) introduced a novel framework that leverages artificial intelligence (AI) to monitor and analyze content from Twitter/X [3]. This extended abstract describes a project that expands upon this framework, aiming to create a comprehensive user interface for both public health professionals and the general public, facilitating the tracking and analysis of drug-related trends on social media.

2 Framework and Motivation

Our previous research represents an effort to automate the identification of drug-related content on social media by applying zero-shot classification algorithms [1,3]. This initiative arose from a need to enhance public health surveillance mechanisms, enabling quick identification and response to emerging drug trends [4]. By offering an automated method for detecting drug-related trends, our framework aimed to facilitate interventions and support evidence-based policy making in the realms of public health as well as substance abuse prevention.

3 Project Motivation and Goals

This abstract builds upon the capabilities of our previous work [3], driven by the motivation of making nuanced, real-time data on drug trends accessible to both experts and the general public. It aims to bridge the gap between complex data analytics and user-friendly information dissemination, thereby providing individuals with the knowledge necessary to understand substance abuse in their community. By having an informed dialogue around drug trends, the project strives to contribute to a more proactive and preventive approach in public health surveillance.

* Supported by the Canadian Centre on Substance Use and Addiction

4 Homepage and Interactive Map View

The platform's homepage presents users with a dynamic map view, acting as a visual aid to interpret drug-related trends across different geographical locations. This is achieved by systematically monitoring the social media accounts of public health organizations, police departments, and harm reduction agencies to gather any new posts they publish on the Twitter/X platform. Then, the zero-shot classification algorithm from our previous work [3] is applied to assess the relevance of each post to our Early Warning System (EWS). It accomplishes this by categorizing each post into one of the predefined categories listed in Table 1. Posts that do not align with these categories are maintained in the database but hidden from the user interface.

Table 1. The distribution of labels and categories used on the CCSA EWS

Label	**Meaning**	**Category (sub label)**
Public Health	Posts that point to drug-related health risks, harms, and adverse events, including drug poisoning events	increased drug overdoses or risk or poisoning, opioid emergency or crisis or advisory or overdose signs
Public Safety	Posts that point to drug manufacture and supply routes through law enforcement responses	drug trafficking or possession, drug-related seizure or investigation
Drug Supply	Posts that point to the contents of the unregulated drug supply, including adulterants and emergence of NPS	drug supply or mixing, drug supply alert

The homepage enables users to interact with the data by applying filters to narrow their search according to keywords, time frames, and regions. Furthermore, users can vote on the accuracy of each categorization, providing a feedback mechanism that helps to refine the algorithm further. This tool provides an simple way to navigate through extensive, geographically diverse data, allowing users to streamline the information and obtain more relevant results. For further understanding, please refer to Figure 1, which is annotated as follows:

1. **Province Filter:** This filter can be used to only display tweets from a certain province
2. **Label Filter:** This filter can be used to only display tweets under one of the three labels: public health, public safety, or drug supply
3. **Time Filter:** This filter can be used to only display posts within a certain time range
4. **Summarized Results:** This table will display a summary of the posts as constrained by the filters. The **Map View (6)** will adjust dynamically alongside. The tweet counts can be clicked on to zoom the map into the corresponding location
5. **Visualize Button:** Users that are signed into the interface can click on this button to access the analysis tool

6. **Map View:** This view displays clusters of posts that meet the current filter criteria. Moving around the map or changing the zoom level will dynamically change the **Summarized Results (4)** alongside

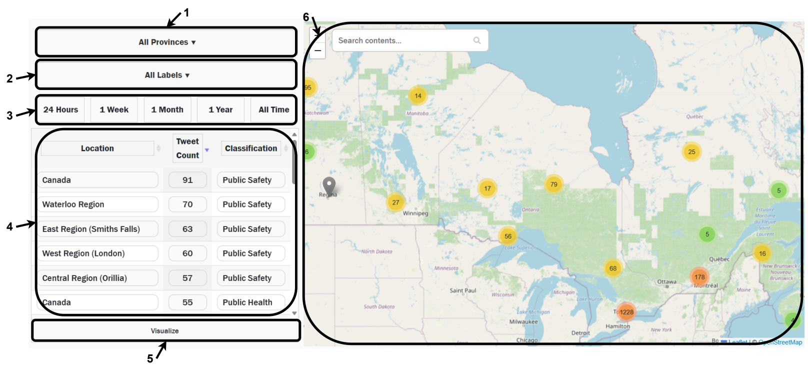

Fig. 1. An annotated screenshot of the homepage in the proposed interface

Additionally, consider Figure 2 which is annotated as follows:

7. **Tweet Text:** This column provides the exact results that are currently visible in the **Map View (6)** and counted in the **Summarized Results (4)**. Any changes to the filters or map view will update the table that this column is in
8. **Category:** This column provides the category for the given tweet text that was determined by the zero-shot classification algorithm. The confidence that the algorithm had in the classification is also provided
9. **Accuracy:** This column allows users that are signed into the interface to provide feedback on the categorization. If they feel it is inaccurate, they can click on the button and will be asked to provide the correct classification. This information will eventually be used to improve the zero-shot classification algorithm by providing it with examples of inaccurate categorizations
10. **Summarized Plot:** This plot provides a summative count over time of the label distribution in the current map view. The labels at the top of the plot can be clicked on to hide them from the plot

5 Current Status

The development roadmap includes conducting usability studies to enhance the user experience, incorporating additional social media platforms to expand the data collection scope, and integrating diverse media formats, including videos.

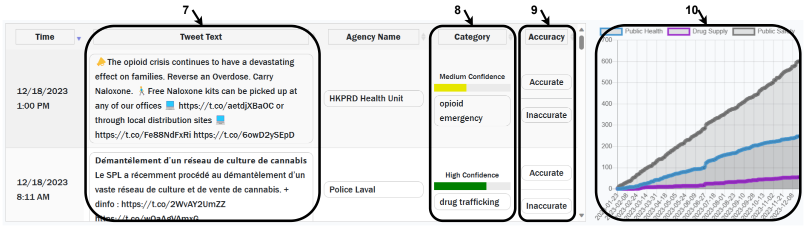

Fig. 2. A continued annotated screenshot of the homepage in the proposed interface

A continuous priority is the improvement of the classification model, with the goal of increasing the accuracy and relevance of trend detection. Moreover, to provide more in-depth insights into the collected data, we are exploring the use of Kibana and Elasticsearch, with initial results showcased in a tutorial video on YouTube[1]. These initiatives aim to ensure the platform remains at the forefront of public health surveillance technology.

6 Conclusion

By integrating the processing capabilities of artificial intelligence into a simple platform, this extended abstract presents a notable advancement in the field of public health surveillance. It showcases a combination of data science and user experience design, rendering it a valuable tool for monitoring and understanding drug-related trends. As the project advances, its goal is to enhance public health strategies through proactive and informed participation from both experts and the public in understanding substance abuse.

References

1. Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L., Stoyanov, V.: Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116 (2019)
2. Fisher, A., Sharma, R., Mago, V.: Analyzing the trends of responses to COVID-19 related tweets from news stations: An analysis of three countries. In: International Workshop on Health Intelligence. pp. 273–288. Springer (2023)
3. Fisher, A., Young, M.M., Payer, D., Pacheco, K., Dubeau, C., Mago, V.: Automating detection of drug-related harms on social media: Machine learning framework. Journal of Medical Internet Research **25**, e43630 (2023)
4. Higgins, K., O'Neill, N., O'Hara, L., Jordan, J.A., McCann, M., O'Neill, T., Clarke, M., O'Neill, T., Campbell, A.: Evidence for public health on novel psychoactive substance use: A mixed-methods study. Public Health Research **7**(14), 1–150 (2019)
5. Kazemi, D.M., Borsari, B., Levine, M.J., Dooley, B.: Systematic review of surveillance by social media platforms for illicit drug use. Journal of Public Health **39**(4), 763–776 (2017)

[1] https://www.youtube.com/watch?v=1QdKZSIuo4I

Generalized multi-adjoint fuzzy rough set*

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Keywords: Galois connection, Multi-adjoint property-oriented concept lattice, Rough sets, Approximation operators.

Rough set theory, introduced by Pawlak [14] in the eighties, is a mathematical tool with many applications [2, 6, 7] and relationships with other approaches [1, 8, 9, 15]. Many researchers have extended the definition of rough set into different backgrounds; e.g., based on neighborhoods [16], based on Galois connections [10] or based on fuzzy set theory [3]. In this work, we will focus on the extensions proposed in the context of fuzzy sets and specifically, in the framework given by the multi-adjoint paradigm [5]. Such an approach has proven to be useful in different areas, such as Formal Concept Analysis [12] or logic programming [13], among others. This fuzzy framework provides two main advantages:

- The first one is that the considered fuzzy operators do not need to be commutative nor associative, allowing to model a wider range of real situation.
- The second one is that different operators can be considered to model conjunctions and implications, allowing to establish different degrees of preferences in the elements of the considered universe [4].

This multi-adjoint paradigm has already been considered in the definition of fuzzy rough sets in [5]. In this first extension of rough set, the natural extension to the fuzzy case was considered in which the lower and

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March 16, 2024

upper approximations were directly defined from the necessity and possibility operators, respectively. As it could also be reasonable, some properties true in the Bolean case do not hold in this new approach. For example, the proposed lower and upper approximation operators require extra conditions in order to guarantee that the lower approximation is contained in the referential set and the upper approximation contains the referential set. However, it is possible to introduce new natural definitions satisfying this last property

In this paper, considering also the multi-adjoint property-oriented framework, and following the idea presented in [10], we propose a new definition of the upper and lower approximation operators based on Galois connections which satisfies the previous mentioned property, as well as other desirable properties.

In this fuzzy generalization, we fix a multi-adjoint property-oriented frame $(P, L, L, \&_1, \ldots, \&_k)$ where P is a partially ordered set, L is a complete lattice and $\{(\&_i, \nwarrow_i, \swarrow_i) \mid i \in \{1, \ldots, k\}\}$ is a family of adjoint triples with respect to P, L and L (see [11] for more details). We also consider an approximation space (X, R), where X is a non-empty set of objects and R is any arbitrary P-fuzzy relation (i.e., $R\colon X \times X \to P$); and a mapping $\tau\colon X \times X \to \{1, \ldots, k\}$ used to associate each pair of objects in X with an adjoint triple in the frame.

In this environment, given an L-fuzzy set $A \in L^X$, since the considered P-fuzzy relation R may be non symmetric, we have two possibilities to define the possibility and necessity operators as: ${}^{\uparrow_\pi}\colon L^X \to L^X$, ${}^{\downarrow^N}\colon L^X \to L^X$:

$$
\begin{aligned}
A^{\uparrow^r_\pi}(x) &= \sup\{R(x, y) \&_{\tau(x,y)} A(y) \mid y \in X\} \\
A^{\uparrow^l_\pi}(x) &= \sup\{R(y, x) \&_{\tau(y,x)} A(y) \mid y \in X\} \\
A^{\downarrow^N_r}(y) &= \inf\{A(x) \nwarrow_{\tau(y,x)} R(y, x) \mid x \in X\} \\
A^{\downarrow^N_l}(y) &= \inf\{A(x) \nwarrow_{\tau(x,y)} R(x, y) \mid x \in X\}
\end{aligned}
$$

Note that, the operators previously defined satisfy that $({\downarrow^N_r}, {\uparrow^l_\pi})$ and $({\downarrow^N_l}, {\uparrow^r_\pi})$ are isotone Galois connections [11]. Hence, we propose to use the closure and interior operators related to $({\downarrow^N_r}, {\uparrow^l_\pi})$ and $({\downarrow^N_l}, {\uparrow^r_\pi})$, as lower and upper approximations, as the following definition states.

Definition 1. Given a fuzzy sets $A \in L^X$, the *lower approximations of* A are defined as:

$$A^{\downarrow^N_r \uparrow^l_\pi} \quad \text{and} \quad A^{\downarrow^N_l \uparrow^r_\pi}$$

and the *upper approximations of A* are defined as:

$$A^{\uparrow^l_\pi \downarrow^N_r} \quad \text{and} \quad A^{\uparrow^r_\pi \downarrow^N_l}.$$

A set $A \in L^X$ is called *a generalized multi-adjoint fuzzy rough set* if is different from the two lower approximations and from the two upper approximations.

The use of interior and closure operators under the umbrella of the theory of Galois connections imply the following properties of our proposed upper and lower approximations:

- the essential property holds, i.e., for every fuzzy set A, both lower approximations of A are included in A, which, in turn, is included in both upper approximations;
- the upper and lower approximations are monotonic;
- the upper and lower approximations are idempotent.

Moreover, due to the flexibility of the multi-adjoint paradigm, a kind of duality is satisfied: for each upper approximation (resp. lower approximation) is possible to define, from the framework, the mapping τ and involutive negation, a dual lower approximation (resp. upper approximation).

References

[1] M. J. Benítez-Caballero, J. Medina, E. Ramírez-Poussa, and D. Ślęzak. Rough-set-driven approach for attribute reduction in fuzzy formal concept analysis. *Fuzzy Sets and Systems*, 391:117–138, 2020.

[2] F. Chacón-Gómez, M. E. Cornejo, and J. Medina. Decision making in fuzzy rough set theory. *Mathematics*, 11(19), 2023.

[3] M. D. Cock, C. Cornelis, and E. E. Kerre. Fuzzy rough sets: The forgotten step. *Fuzzy Systems, IEEE Transactions on*, 15(1):121–130, feb. 2007.

[4] M. E. Cornejo, J. Medina, E. RamÌrez-Poussa, and C. Rubio-Manzano. Preferences in discrete multi-adjoint formal concept analysis. *Information Sciences*, 650:119507, 2023.

[5] C. Cornelis, J. Medina, and N. Verbiest. Multi-adjoint fuzzy rough sets: Definition, properties and attribute selection. *International Journal of Approximate Reasoning*, 55:412–426, 2014.

[6] A. Gaeta, V. Loia, and F. Orciuoli. An explainable prediction method based on fuzzy rough sets, topsis and hexagons of opposition: Applications to the analysis of information disorder. *Information Sciences*, 659:120050, 2024.

[7] R. Gul, M. Shabir, and M. Naeem. A comprehensive study on (α, β)-bipolar fuzzified rough set model based on bipolar fuzzy preference relation and corresponding decision-making applications. *Computational and Applied Mathematics*, 42:310, 2023.

[8] A. Janusz, A. Zalewska, L. Wawrowski, P. Biczyk, J. Ludziejewski, M. Sikora, and D. Slezak. Brightbox – a rough set based technology for diagnosing mistakes of machine learning models. *Applied Soft Computing*, 141:110285, 2023.

[9] D. Lobo, V. López-Marchante, and J. Medina. Reducing fuzzy relation equations via concept lattices. *Fuzzy Sets and Systems*, 463:108465, 2023.

[10] N. Madrid, J. Medina, and E. Ramírez-Poussa. Rough sets based on galois connections. *International Journal of Applied Mathematics*, 30(2):299–313, 2020.

[11] J. Medina. Multi-adjoint property-oriented and object-oriented concept lattices. *Information Sciences*, 190:95–106, 2012.

[12] J. Medina, M. Ojeda-Aciego, and J. Ruiz-Calviño. Formal concept analysis via multi-adjoint concept lattices. *Fuzzy Sets and Systems*, 160(2):130–144, 2009.

[13] J. Medina, M. Ojeda-Aciego, and P. Vojtáš. Multi-adjoint logic programming with continuous semantics. Technical report, Dept. Matemática Aplicada. Univ. Málaga, 2001. Available at `http://www.satd.uma.es/aciego/TR/malp-tr.pdf`.

[14] Z. Pawlak. Information systems theoretical foundations. *Information Systems*, 6(3):205 – 218, 1981.

[15] Y. Song, H. Lin, and Z. Li. Outlier detection in a multiset-valued information system based on rough set theory and granular computing. *Information Sciences*, 657:119950, 2024.

[16] Y. Yao. Relational interpretations of neighborhood operators and rough set approximation operators. *Information Sciences*, 111(1):239 – 259, 1998.

Aspect-Based Sentiment Analysis in the LLM Era

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Abstract. In this extended abstract, we present the outcomes of our pilot experiment, which concentrates on the in-context learning (ICL) abilities of Large Language Models (LLMs) for the Aspect-Based Sentiment Analysis (ABSA) task. This task utilizes a novel dataset designed to reduce the memorization effect. Our experiments indicate that LLMs are capable of performing comparably to one of the current state-of-the-art models without the need for additional fine-tuning or adaptation. Moreover, the experiment highlights the inadequacies of traditional classification metrics in evaluating models on ABSA tasks and suggests further research directions in this domain.

Keywords: LLM · Sentimend Analysis · NLP · Aspect-Based Sentiment Analysis · Metrics

1 Introduction

Large Language Models have ushered in a transformative era in the field of Natural Language Processing (NLP), reshaping the landscape of classic NLP tasks, including aspect-based sentiment analysis. The rapid development and deployment of LLMs, such as the Generative Pre-trained Transformer (GPT) series, Bidirectional Encoder Representations from Transformers (BERT), and their successors, have enhanced the ability of machines to understand, generate, and interpret human language with unprecedented accuracy and nuance.

Historically, ABSA has posed a significant challenge within the field of NLP, necessitating the identification of specific aspects mentioned in the text and determining the sentiment polarity expressed towards each of those aspects. Traditional approaches often depended on manually crafted features, rule-based systems, or machine learning models which, although somewhat effective, were constrained by their limited capacity to fully comprehend the complexities and subtleties of language. The advent of LLMs has shifted this paradigm, offering a new approach that enhances the ability to analyze sentiment at a more granular level [2].

This study endeavors to examine the role of LLMs in transforming ABSA, discussing the methodologies that utilize these models, the challenges faced in adapting them to ABSA tasks, and the opportunities they offer for future research and applications.

2 Aspect-Based Sentiment Analysis

Aspect-based Sentiment Analysis is a nuanced form of sentiment analysis that focuses on identifying the sentiment toward specific aspects within a text [3]. For instance, in the sentence "The soup was delicious", the aspect term (AT) "soup" refers to the specific item being evaluated, while the aspect category (AC) could be "food", and the opinion term (OT) is "delicious". Generally, ABSA task for identifying sentiments towards specific aspects mentioned in a text can be formulated as follows. Given a text document d, the task involves two main steps: aspect extraction and sentiment classification. First, identify a set of aspects $A_d = \{a_1, a_2, \ldots, a_M\}$ mentioned in d by applying a function:

$$F_a : \mathcal{D} \to P(\mathcal{A}) \tag{1}$$

that maps a document $d \in \mathcal{D}$ to a set of aspects $A_d \subseteq \mathcal{A}$, where $\mathcal{D}$ is the domain of all documents and $\mathcal{A}$ is the set of all possible aspects.

Second, for each aspect $a_i \in A_d$, we determine the sentiment polarity $p_{a_i} \in \mathcal{P}$ expressed towards it in $d \in \mathcal{D}$. We can express it as a function

$$F_s : \mathcal{A} \times \mathcal{D} \to \mathcal{P} \tag{2}$$

that assigns a sentiment polarity to an aspect a from $\mathcal{A}$ identified in a document d from $\mathcal{D}$, where $\mathcal{P}$ represents the set of possible sentiment polarities, e.g., $\{\text{positive}, \text{neutral}, \text{negative}\}$.

The overall objective of ABSA can be formulated as a joint task of extracting aspects and classifying polarities towards these aspects. In a case of supervised learning, given a dataset $\mathscr{D} = \{(d_i, \{(a_{ij}, p_{ij}) \mid j = 1, 2, \ldots, n_i\}) \mid i = 1, 2, \ldots, N\}$, where $d_n \in \mathcal{D}$ is a document, $a_{ij} \in A_d$ an aspect in d_n, and $p_{ij} \in \mathcal{P}$ a polarity towards a_{ij}, the goal is to accurately learn the two functions F_a and F_s from the given data. Various studies extend the ABSA task to include opinion extraction [4] and attribute labeling [3]; however, we consider these subtasks to be auxiliary and thus do not cover them in our study.

Our partner organization supplied us with survey data from a sporting event, which included 630 documents containing feedback from volunteers. For our experiment, we selected a sample of 40 documents and manually annotated them for the Aspect-Based Sentiment Analysis (ABSA) task by identifying aspects and their corresponding polarities. As a baseline model, we utilized the DeBERTa-v2-based PyABSA framework [1] [5]. To assess the performance of Large Language Models (LLMs) on the ABSA task, we employed three models: ChatGPT-3.5, ChatGPT-4, and LLaAMA-2-7b-chat.

3 Preliminary Results

The results for the aspect detection subtask reveal that GPT-3.5 surpasses other models in recall ($R_{absa} = 0.70$) and F1-score ($F1_{absa} = 0.53$), suggesting its superior ability to align with human judgments regarding aspects within the novel dataset. In contrast, PyABSA (DeBERTa-v2), GPT-4, and LLaMA-2-7b demonstrate a more balanced, yet overall lower, performance. Notably, the performance of GPT-4 ($P_{absa} = 0.28$, $R_{absa} = 0.48$, $F1_{absa} = 0.35$) is particularly interesting, considering its architectural improvements and the extensive size of its training corpus. A closer examination of the results indicates that GPT-4 tends to produce longer, albeit valid, descriptions of aspects. This observation underscores the limitations of our evaluation metric in capturing the semantic similarity between aspects.

In the polarity classification subtask, GPT-4 stands out with the highest precision (0.84), recall (0.85), and F1-score (0.84), demonstrating its proficiency in discerning and categorizing sentiment once aspects are identified. Meanwhile, PyABSA (DeBERTa-v2) and LLaMA-2-7b show moderate performance, with LLaMA-2-7b experiencing a notable decline in recall (0.51), which may indicate challenges in consistently recognizing the correct sentiment for all aspects. This could point to constraints in model pre-training or an intrinsic difficulty in differentiating subtle sentiment nuances within the dataset.

Overall, this pilot experiment underscores the feasibility of employing unmodified LLMs in ABSA, highlighting their potential to excel in ABSA tasks without the need for specific fine-tuning or adaptation.

4 Future Work and Conclusions

This pilot study critically examines the use of state-of-the-art LLMs including GPT-3.5, GPT-4, and LLaMA-2-7b, in the context of aspect detection and polarity classification, evaluated against a novel dataset. It contributes to the field of natural language processing by underscoring the strengths and weaknesses of these models in tasks that require a nuanced understanding of text without necessitating additional training. Furthermore, it underscores the necessity for a more sophisticated metric to evaluate the aspect detection task—one that can align sets of predicted aspects based on their semantic similarity.

The incorporation of a novel dataset is crucial in reducing the memorization effect commonly observed in models trained on frequently utilized benchmarks. By testing the models with previously unseen data, the study sheds light on their authentic understanding and generalization capabilities, thereby providing a more accurate measure of their suitability for real-world applications.

The study highlights the importance of continued exploration in ABSA for our next iteration, focusing on several critical areas. Initially, we aim to improve aspect matching accuracy by integrating semantic similarity measures into the aspect detection process. Utilizing methods like word embeddings, contextual embeddings from transformer-based models, or a combination of lexical and semantic similarities could enable the system to recognize and match aspects that are semantically related but not lexically identical. This enhancement is expected to refine the accuracy of aspect detection and polarity classification.

Furthermore, we will explore the impact of model fine-tuning or adaptation for ABSA tasks on public datasets to assess how these adjustments might affect performance on new datasets. This investigation stands as another crucial area for our forthcoming research efforts.

Extending the analysis to include the identification of emotions towards aspects offers a promising yet challenging research direction. For instance, the sentence "The sight of the cherry blossoms reminded her of the beauty in the world" would associate the aspect term "cherry blossoms" with the emotion "Joy". The main challenge here is compiling and annotating a comprehensive dataset that covers a wide spectrum of emotions, potentially adapting this task to the unsupervised learning domain. Such an approach could be particularly beneficial for developing human-centered AI applications in various fields.

Looking forward, future research should explore leveraging and improving in-context learning capabilities of LLMs within ABSA, and investigate knowledge distillation techniques to enhance computational efficiency. By focusing on these areas, researchers can further unlock the potential of LLMs in ABSA, allowing for more accurate, flexible, and efficient model performances.

References

1. He, P., Liu, X., Gao, J., Chen, W.: Deberta: Decoding-enhanced bert with disentangled attention (2021)
2. Kheiri, K., Karimi, H.: Sentimentgpt: Exploiting gpt for advanced sentiment analysis and its departure from current machine learning. arXiv preprint arXiv:2307.10234 (2023)
3. Pontiki, M., Galanis, D., Papageorgiou, H., Androutsopoulos, I., Manandhar, S., AL-Smadi, M., Al-Ayyoub, M., Zhao, Y., Qin, B., De Clercq, O., et al.: Semeval-2016 task 5: Aspect based sentiment analysis. In: ProWorkshop on Semantic Evaluation (SemEval-2016). pp. 19–30. Association for Computational Linguistics (2016)
4. Scaria, K., Gupta, H., Sawant, S.A., Mishra, S., Baral, C.: Instructabsa: Instruction learning for aspect based sentiment analysis. arXiv preprint arXiv:2302.08624 (2023)
5. Yang, H., Zhang, C., Li, K.: Pyabsa: A modularized framework for reproducible aspect-based sentiment analysis. In: Proceedings of the 32nd ACM International Conference on Information and Knowledge Management. p. 5117–5122. CIKM '23, Association for Computing Machinery, New York, NY, USA (2023). https://doi.org/10.1145/3583780.3614752, https://doi.org/10.1145/3583780.3614752

Interactive Machine Learning and Data Labeling – Can Rough Sets Help?

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Abstract. We discuss the Label-In-The-Loop (LITL) software solution which is aimed at interactive data labeling. We consider some of possible rough set extensions of LITL. We focus on the aspects of machine learning (ML), data selection, uncertainty modeling, different scenarios of labeling, as well as making the outputs of LITL more insightful.

Keywords: Interactive ML · Data Labeling · LITL · Rough Sets.

1 Introduction

A machine learning (ML) process needs to explore a huge space of possible models to find the one which fits the available data and assures the highest chance for good performance after deploying it within a production environment. The complexity of the space of possible models can be determined by the ranges of parameters of a selected ML algorithm and a variety of information sources and attributes that can be used by the algorithm. On top of that, to learn a good model, one needs the data of a sufficiently good quality. In particular, the data needs to be representative and correctly labeled, at least partially.

Given the above kind of complexity, it may be useful to design some human-computer interaction mechanisms so subject matter experts (SMEs) can help (if they want and know how) the ML process to focus on the most promising model subspaces and the most valuable data cases. For example, if there is a chance to get SMEs involved into the phase of feature selection, then they can help the algorithm to omit attributes that they would not like to see in a later decision process anyway. (This way the algorithm can sooner concentrate on a smaller subspace of features, its work becomes faster, and its results become more acceptable for SMEs.) As another example, if there is a chance to get SMEs involved into the phase of data labeling, then they can help the algorithm by feeding it with information required for the model training. (This is particularly important if the data is unlabeled and its labeling requires high expertise. In such cases the mechanism of selecting the most valuable data cases to be labeled is crucial because the time of SMEs is limited and expensive.)

In this report, we consider an example of an interactive ML technology, called Label-In-The-Loop (LITL) [8, 9], which aims at semi-automatic data labeling. We discuss its current state of development and elaborate on its further roadmap, with a special emphasis on its rough-set-related extensions [13, 15].

2 The LITL Technology

LITL has been developed by QED Software to support commercial ML projects in which data sets available for training are not labeled or are labeled insufficiently. The conceptual design of LITL follows the principles of active learning [12, 5]. From a software architecture viewpoint, besides monitoring, administration and other typical functions, LITL is composed of the following layers:

- **Data processing**. This part supports continuous updates to a data store (arrivals of new data cases, recording labels added by SMEs), as well as maintaining data cases in both "SME-friendly" and a transformed "ML-friendly" form (so they are ready to show them to SMEs and feed ML algorithms with them). This part also collects metadata which may be useful while producing the final LITL outputs (the attribute importance rankings, the quality and uncertainty scores of ML models and so on) and monitoring whether it works correctly (e.g. the history of human labelings and ML model inferences).
- **Data displaying**. This part embraces "widgets" adjusted to visualize different data types, such as texts, images, logs, time series and so on. Thanks to that, based on information about the underlying original "SME-friendly" data schema, data cases can be shown effectively. Data cases can be multimodal, e.g., tuples consisting of images and standard attributes. This part also takes care of different display modes, e.g., case by case, in batches (wherein one can label each case independently or sort cases due to their likelihood to be assigned with a specific label) and so on.
- **Data selection**. Based on the previous data selection phases, as well as on the performance of an ML model learnt up to now on both labeled and unlabeled data, this part needs to choose the next cases to be examined by SMEs. In principle, LITL takes into account ML models' uncertainty about particular cases, similarity of those cases to the previously labeled cases, as well as potential mistakes in the human labeling processes.
- **Machine learning**. This part is responsible for continuous training and applying ML models for the purposes of uncertainty estimation and SMEs' verification. We used to assume that the users of LITL might wish to upload their own ML methods for training. However, a general business requirement is rather that LITL trains reasonable ML models by itself. The final outcome of LITL is a set of labeled data. However, the users may also request a final serialized ML model or at least some insights about attributes which can be important for further learning stages. On the other hand, in some scenarios the users may wish LITL to become their everyday inference engine.

From a research perspective, our efforts up to now concentrated on designing the aforementioned ML model uncertainty measures and applying them to the phase of data selection [8], as well as modeling and resolving inconsistencies among SMEs' labelings [9]. In the next section, we discuss some ideas how to utilize rough set algorithms and paradigms in the overall LITL process.

3 How Rough Sets Can Help?

There are several opportunities of strengthening LITL with rough sets:

- **Rough sets for ML**. One can rely on reducts and their ensembles as ML models. Particularly the ensembles of approximate reducts and bireducts can be promising [6, 13]. Moreover, one can adapt some methods for incremental reduct calculations [3], which seems to be useful from the viewpoint of continuous re-learning of ML models within the active learning loop.
- **Rough sets for data selection**. There are a number of rough set algorithms for selecting not only attributes but also instances [2]. Moreover, one of data selection principles used in LITL is to avoid showing too similar cases to SMEs. Therefore, some data clustering techniques can be applied, in particular rough clustering [11]. Interestingly, rough sets can be also used to define and calculate similarities. Actually, in LITL we used to consider some advanced similarity structures that would let us quickly generate representative data batches for labeling [17]. However, somewhat analogously to Locality Sensitive Hashing (LSH) [16], it is also possible to define a similarity measure by means of counting how many common decision rules are triggered for the given two data cases within a precomputed ensemble of decision reducts [7]. To keep the things simple, one can use the same ensemble of reducts as an ML model and as the basis for similarity calculations.
- **Rough sets for uncertainty**. ML model uncertainties for the given data cases are usually expressed based on the analysis of label distributions observed for their most similar cases. Then one can apply, e.g., the Dempster-Shafer's theory of evidence to represent the uncertainties of ML models and human labelings [5, 8]. However, we also intend to consider rough set approximations and generalized decision functions for this purpose [4].
- **Rough sets for data labeling**. Rough-set-related paradigms can be also used to support SMEs while labeling complex cases, whereby labelings are sometimes too hard to decide or should be replaced by operting with preferences or rankings. The three-way decisions [18] and the dominance rough set models [15] can be applied here, respectively. Going further, instead of labeling the whole data cases, SMEs can annotate some fragments of their corresponding images, texts and so on. In such a scenario, rough set approximations can be useful to deal with uncertain and complex objects [1].
- **Rough sets for more insights**. Finally, as outlined before, we can extend the current LITL's functionality by delivering not only the labeled data but also information about the most important attributes. It is worth mentioning that rough set algorithms can produce high-quality attribute rankings [6]. It is also possible to enrich those algorithms with some elements of interactive feature selection [14], which can be combined within a single user interface with interactive data labeling. Going further, we can extend LITL's interface by letting SMEs lead chat-based discussions about the hardest data cases and use some NLP methods [10] to analyze those discussions to search for attributes that seem to be most important in SMEs' decision making.

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References

1. Beaubouef, T., Petry, F.E., Ladner, R.: Spatial Data Methods and Vague Regions: A Rough Set Approach. Applied Soft Computing **7**(1), 425–440 (2007)
2. Cornelis, C.: Hybridization of Fuzzy Sets and Rough Sets: Achievements and Opportunities. In: Proc. of FedCSIS 2022. pp. 7–14 (2022)
3. Dong, L., Chen, D.: Incremental Attribute Reduction with Rough Set for Dynamic Datasets with Simultaneously Increasing Samples and Attributes. International Journal of Machine Learning and Cybernetics **11**(6), 1339–1355 (2020)
4. Dutta, S., Ślęzak, D.: Nature of Decision Valuations in Elimination of Redundant Attributes. International Journal of Approximate Reasoning **165**, 109091 (2024)
5. Hoarau, A., Martin, A., Dubois, J., Gall, Y.L.: Imperfect Labels with Belief Functions for Active Learning. In: Proc. of BELIEF 2022. pp. 44–53 (2022)
6. Janusz, A., Ślęzak, D., Stawicki, S., Stencel, K.: A Practical Study of Methods for Deriving Insightful Attribute Importance Rankings Using Decision Bireducts. Information Sciences **645**, 119354 (2023)
7. Janusz, A., Zalewska, A., Wawrowski, Ł., Biczyk, P., Ludziejewski, J., Sikora, M., Ślęzak, D.: BrightBox – A Rough Set Based Technology for Diagnosing Mistakes of Machine Learning Models. Applied Soft Computing **141**, 110285 (2023)
8. Kałuża, D., Janusz, A., Ślęzak, D.: On Several New Dempster-Shafer-Inspired Uncertainty Measures Applicable for Active Learning. In: Proc. of IJCRS 2023. pp. 479–494 (2023)
9. Kałuża, D., Janusz, A., Ślęzak, D.: Robust Assignment of Labels for Active Learning with Sparse and Noisy Annotations. In: Proc. of ECAI 2023. pp. 1207–1214 (2023)
10. Laskar, M.T.R., Bari, M.S., Rahman, M., Bhuiyan, M.A.H., Joty, S., Huang, J.X.: A Systematic Study and Comprehensive Evaluation of ChatGPT on Benchmark Datasets. In: Proc. of ACL 2023. pp. 431–469 (2023)
11. Lingras, P., Peters, G.: Rough Clustering. WIREs Data Mining and Knowledge Discovery **1**(1), 64–72 (2011)
12. Settles, B.: Active Learning. Morgan & Claypool (2012)
13. Skowron, A., Ślęzak, D.: Rough Sets Turn 40: From Information Systems to Intelligent Systems. In: Proc. of FedCSIS 2022. pp. 23–34 (2022)
14. Ślęzak, D., Grzegorowski, M., Janusz, A., Stawicki, S.: Toward Interactive Attribute Selection with Infolattices – A Position Paper. In: Proc. of IJCRS 2017, Part II. pp. 526–539 (2017)
15. Słowiński, R.: Multiple Criteria Decision Aiding by Constructive Preference Learning (Keynote Lecture – Extended Abstract). In: Proc. of FedCSIS 2023. p. 39 (2023)
16. Ullman, J.: Big-Data Algorithms That Are Not Machine Learning. In: Proc. of BigData 2023. p. 5 (2023)
17. Wu, P., Hoi, S.C.H., Nguyen, D.D., He, Y.: Randomly Projected KD-Trees with Distance Metric Learning for Image Retrieval. In: Proc. of MMM 2011, Part II. pp. 371–382 (2011)
18. Yao, Y.: An Outline of a Theory of Three-Way Decisions. In: Proc. of RSCTC 2012. pp. 1–17 (2012)

Attribute Ranking Method Based on Conditional Comparison Matrices

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Abstract. This paper presents an extension to the rough-fuzzy hybrid method for attribute ranking ranking problem [5], [6]. We propose a new method for the attribute comparison with the constraint that some other attributes must be chosen based on expert knowledge. The proposed comparison method can be applied to the attribute ranking problem in the RAFAR framework [6], resulting in the building of a conditional interval value fuzzy preference relation. The suggested approach enables the users to impose certain attributes–designated by an expert or belonging to the kernel–at the top of the ranking list. We also propose new methods for finding optimal rankings compatible with the comparison matrix

Keywords: Rough fuzzy hybridization · attribute ranking · Fuzzy preference relation · optimization models

1 Introduction

In rough set theory, training data set can be presented in form of a decision table, which is a tuple $\mathbf{T} = (U, A \cup \{d\})$, where $U = \{u_1, \cdots, u_m\}$ is the set of objects, $A = \{a_1, \cdots a_n\}$ is the set of attributes and d is the decision attribute.

Usually, the description of objects are represented by attributes or features, namely $a_1, ..., a_n$. Each attribute a_i is in fact a function of form: $a_i : U \to V_{a_i}$, where V_{a_i} is called the domain of a_i. In another words, $\mathbf{x}_i = (a_1(u_i), \cdots, a_n(u_i))$. If a is a measurement such as a person's weight, height, blood pressure or the weather temperature, i.e. V_a is a real interval, then a is called the numeric or quantitative attribute. Otherwise, if the values in V_a are not comparable, or if they can not be ordered in a linear order, then a is called categorical, symbolic or qualitative attribute. The decision attribute is a categorical attribute and the values of its domain V_d are called the decision class labels.

The goal of the attribute ranking problem for decision table $\mathbf{T} = (U, A \cup \{d\})$ is to order the feature in a ranking list so that the more important features are at the beginning of the list while the less important features are located at the end of the ranking list.

In [5], we proposed a new method for feature ranking called RAFAR (Rough-fuzzy Algorithm For Attribute Ranking). This is a hybrid method that combines discernibility relation of the rough set theory and the ranking method described in the previous section. The RAFAR method consists of two main steps:

(1) construction of a pairwise comparison matrix for the set of attributes and
(2) searching for the optimal *weight vector*, which is consistent (defined later) with the comparison matrix. This step has two options:
   2a) searching for *real-value weight vector* $\mathbf{w} = (w_1, \ldots, w_n)$ *such that* $w_i \in [0, 1]$ *for* $i = 1, \cdots, n$ *and* $\sum_{i=1}^{n} w_i = 1$*,*
   2b) searching for normalized interval-value weight vector, i.e. (see [3] and [7]) the vector $\mathbf{w} = ([l_1, r_1], \cdots, [l_n, r_n])$, where $[l_i, r_i] \subset [0, 1]$ and:

$$\sum_{j=1, j\neq i}^{n} l_j + r_i \leq 1 \leq l_i + \sum_{j=1, j\neq i}^{n} r_j \quad \text{for each } i \in \{1, \cdots, n\} \tag{1}$$

Each weight value w_i or weight interval $[l_i, r_i]$ corresponds to attribute $a_i \in A$ so that the higher weight means the more preferred choice.

Recall that for any attribute $a_k \in A$, the *discernibility relation* D_{a_k} is defined as the set of pairs of objects that are discernible by a_k. In particular,

- if a_k is a symbolic attribute, then

$$D_{a_k} = \{(u_i, u_j) \in U \times U : d(u_i) \neq d(u_j) \text{ and } a_k(u_i) \neq a_k(u_j)\} \tag{2}$$

- In the case when $a_k \in A$ is a continuous attribute, the domain V_{a_k} is discretized into b equal length intervals, where b is a predefined constant, and D_{a_k} denotes the discernibility relation for the discretized attribute.

In [6], to compare a pair of attributes $(a_i, a_j) \in A \times A$, we proposed to use a pair of two real values p^l_{ij}, p^r_{ij} defined by

$$p^l_{ij} = \begin{cases} 1 - \dfrac{|D_j|}{|D_i \cup D_j|} & \text{if } i \neq j \\ 0.5 & \text{if } i = j \end{cases}; \qquad p^r_{ij} = \begin{cases} \dfrac{|D_i|}{|D_i \cup D_j|} & \text{if } i \neq j \\ 0.5 & \text{if } i = j. \end{cases} \tag{3}$$

Notice that if we consider the set $\Omega_{\mathbf{T}} = \{(u_k, u_l) \in U \times U : d(u_k) \neq d(u_l)\}$ as a probability space with uniform distribution, then we have the following interpretation

$p^l_{ij} = \mathcal{P}(D_i - D_j | D_i \cup D_j)$**:** is the probability that a pair of objects is not distinguishable by a_j, assuming that it is distinguishable by $\{a_i, a_j\}$.
$p^r_{ij} = \mathcal{P}(D_i | D_i \cup D_j)$**:** is the probability that a pair of objects are distinguishable by a_i, assuming that it is distinguishable by $\{a_i, a_j\}$.

Informally, if $P(a_i > a_j)$ denotes the probability that a_i is better than a_j, then

$$P(a_i > a_j) \in [p^l_{ij}, p^r_{ij}] \subset [0, 1]$$

The matrix $\mathbf{P_T} = ([p^l_{ij}, p^r_{ij}])_{n\times n}$, containing pairwise comparison intervals between all pairs of attributes is called *the interval-valued fuzzy preference relation* (IV-FPR) over the set of attributes.

In [5], 4 optimization models including additive consistent models **(A1)**, **(A2)** and multiplicative consistent models **(M1)** or **(M2)** were applied to generate the probability weight vector for the set of attributes. In [6], another two optimisation models based on IV-FPR and interval-valued fuzzy vectors (IV-FV) were presented.

2 Conditional Comparison

The limitation of the above method is the lack of taking into account expert knowledge in the attribute ranking process. This also often happens when kernel attributes that appear in all reducts but are not placed at the top of the ranking list.

In this article, we propose a new method for attribute comparison in the situation when an expert prefers certain attributes or a user requires that kernel attributes be at the beginning of the ranking list.

Firstly, let's extend the discernibility relation defined in Eq. 2. Let $B \subset A$ be an arbitrary subset of attributes. A pair of objects $(u_k, u_l) \in U \times U$ is called distinguishable by B if $d(u_k) \neq d(u_l)$ and there exists an attribute $a \in B$ such that $a(u_k) \neq a(u_l)$. The set of all pairs of objects distinguishable by $B \subset A$ is denoted by

$$D_B = \{(u_k, u_l) \in U \times U : d(u_k) \neq d(u_l) \text{ and } (u_k, u_l) \text{ is distinguishable by } B\}.$$

D_B is the discernibility relation, which is the building block in rough set theory [1].

In this paper, we propose a generalization of Eq. 3. For any $B \subset A$, we consider the set $\Omega_{\mathbf{T}} - D_B$, i.e. the pairs that are not discernible by B. We define $p^l_{ij}(B)$ and $p^r_{ij}(B)$ as the probabilities that a pair of objects is not distinguishable by a_j (distinguishable by a_i), assuming that it is distinguishable by $\{a_i, a_j\}$ but not by B. Formally, $p^l_{ii}(B) = p^r_{ii}(B) = 0.5$ and if $i \neq j$ then

$$p^l_{ij}(B) = \frac{|D_i - D_j - D_B|}{|D_i \cup D_j - D_B|} = \frac{|D_{B\cup\{a_i,a_j\}}| - |D_{B\cup\{a_j\}}|}{|D_{B\cup\{a_i,a_j\}}| - |D_B|}$$
$$p^r_{ij}(B) = \frac{|D_i - D_B|}{|D_i \cup D_j - D_B|} = \frac{|D_{B\cup\{a_i\}}| - |D_B|}{|D_{B\cup\{a_i,a_j\}}| - |D_B|}$$

Obviously, $[p^l_{ij}(B), p^r_{ij}(B)]$ evaluates which of the attributes a_i, a_j is a better compliment to B, i.e.

$$P(a_i > a_j|B) \in [p^l_{ij}(B), p^r_{ij}(B)] \subset [0, 1]$$

The conditional comparison matrix $\mathbf{P_T}(B) = ([p^l_{ij}(B), p^r_{ij}(B)])$ is also an IV-FPR and is called B-conditional IV-FPR. It is obvious that $\mathbf{P_T} = \mathbf{P_T}(\emptyset)$.

Let us illustrate our approach by the following example:

Table 1. A sample decision table with 5 attributes and 10 objects

$\mathbf{T_1}$	a_1	a_2	a_3	a_4	a_5	dec
ID	outlook	temp.	hum.	windy	smog	play
1	sunny	hot	high	FALSE	no	no
2	sunny	hot	high	TRUE	no	no
3	overcast	hot	high	FALSE	yes	yes
4	rainy	mild	high	FALSE	yes	yes
5	rainy	cool	normal	FALSE	no	yes
6	rainy	cool	normal	TRUE	no	no
7	overcast	cool	normal	TRUE	no	yes
8	sunny	mild	high	FALSE	no	no
9	sunny	cool	normal	FALSE	no	yes
10	rainy	mild	normal	FALSE	no	yes

Example 1. Table 1 provides an example of a small decision table, $\mathbf{T_1}$. The first ten objects from the well-known "weather data set" were used to produce this table, and a new attribute smog was included as the fifth attribute.

The discernibility relations for attributes of $\mathbf{T_1}$ are presented in Table 2. One can check that this decision table has exactly 2 reducts: $R_1 = \{a_1, a_2, a_4\}$ and $R_2 = \{a_1, a_3, a_4\}$. According to [2], the features a_1 and a_4 are called the *core attributes*, and a_5 is the *redundant attribute*.

Now we can calculate the IV-FPR for this table. Let us illustrate our approach for a few pairs of attributes:

$$(a_1, a_2): \quad |D_1| = 18; |D_2| = 17; |D_{a_1,a_2}| = 23 \qquad \Longrightarrow [p^l_{1,2}, p^r_{1,2}] = \left[\frac{6}{23}, \frac{18}{23}\right]$$

$$(a_2, a_5): \quad |D_2| = 17; |D_5| = 8; |D_{a_2,a_5}| = 20 \qquad \Longrightarrow [p^l_{2,5}, p^r_{2,5}] = \left[\frac{12}{20}, \frac{17}{20}\right]$$

$$(a_3, a_4): \quad |D_3| = 14; |D_4| = 12; |D_{\{a_3,a_4\}}| = 19 \qquad \Longrightarrow [p^l_{3,4}, p^r_{3,4}] = \left[\frac{7}{19}, \frac{14}{19}\right]$$

Now, let compare the attributes a_3 and a_4 assuming that an expert wishes to place the set $B = \{a_2\}$ at the begin of the final ranking:

$$|D_2| = 17; |D_{\{a_2,a_3\}}| = 18; |D_{\{a_2,a_4\}}| = 20; |D_{\{a_2,a_3,a_4\}}| = 21$$
$$\Longrightarrow [p^l_{3,4}(a_2), p^r_{3,4}(a_2)] = \left[\frac{1}{4}, \frac{1}{4}\right]$$

This example presents the fact that, even a_3 is slightly preferable to a_4, but probably a_3 is a worse compliment to $B = \{a_2\}$ than a_4.

3 Searching for Consistent Weight Vectors

In this paper we also propose some new methods for searching for the optimal normalized weight vectors that are consistent with a given pairwise comparison

Table 2. The discernibility relations $D_i = D_{a_i}$ of attributes in decision table $\mathbf{T_1}$.

$\Omega_{\mathbf{T_1}}$	D_1	D_2	D_3	D_4	D_5
(3,1)	1	0	0	0	1
(3,2)	1	0	0	1	1
(3,6)	1	1	1	1	1
(3,8)	1	1	0	0	1
(4,1)	1	1	0	0	1
(4,2)	1	1	0	1	1
(4,6)	0	1	1	1	1
(4,8)	1	0	0	0	1
(5,1)	1	1	1	0	0
(5,2)	1	1	1	1	0
(5,6)	0	0	0	1	0
(5,8)	1	1	1	0	0

...	D_1	D_2	D_3	D_4	D_5
(7,1)	1	1	1	1	0
(7,2)	1	1	1	0	0
(7,6)	1	0	0	0	0
(7,8)	1	1	1	1	0
(9,1)	0	1	1	0	0
(9,2)	0	1	1	1	0
(9,6)	1	0	0	1	0
(9,8)	0	1	1	0	0
(10,1)	1	1	1	0	0
(10,2)	1	1	1	1	0
(10,6)	0	1	0	1	0
(10,8)	1	0	1	0	0

matrix (generated by the presented above methods). As an example, the IV-FPR for $\mathbf{T_1}$ is as follows:

$$\mathbf{P}_{\mathbf{T}_1} = \begin{pmatrix} [0.50, 0.50] & [0.26, 0.78] & [0.36, 0.82] & [0.45, 0.82] & [0.58, 0.95] \\ [0.22, 0.74] & [0.50, 0.50] & [0.22, 0.94] & [0.40, 0.85] & [0.60, 0.85] \\ [0.18, 0.64] & [0.06, 0.78] & [0.50, 0.50] & [0.37, 0.74] & [0.60, 0.70] \\ [0.18, 0.55] & [0.15, 0.60] & [0.26, 0.63] & [0.50, 0.50] & [0.50, 0.75] \\ [0.05, 0.42] & [0.15, 0.40] & [0.30, 0.40] & [0.25, 0.50] & [0.50, 0.50] \end{pmatrix}$$

The first method is converting the IV-FPR $\mathbf{P_T} = ([p^l_{ij}, p^r_{ij}])_{n\times n}$ into a Fuzzy Preference Relation $\mathbf{R_T} = (p_{ij})_{n\times n}$, where

$$p_{ij} = \frac{p^l_{ij} + p^r_{ij}}{2}$$

Recall that the fuzzy matrix $\mathbf{R_T} = (p_{ij})_{n\times n}$ is called the Fuzzy Preference Relation (FPR) if $p_{ij} + p_{ji} = 1$ for all $i, j \in \{1, ..., n\}$. In our example:

$$\mathbf{R}_{\mathbf{T}_1} = \begin{pmatrix} 0.5 & 0.52 & 0.59 & 0.64 & 0.77 \\ 0.48 & 0.5 & 0.58 & 0.63 & 0.73 \\ 0.41 & 0.42 & 0.5 & 0.56 & 0.65 \\ 0.36 & 0.37 & 0.44 & 0.5 & 0.63 \\ 0.23 & 0.27 & 0.35 & 0.37 & 0.5 \end{pmatrix}$$

According to [8], a given fuzzy preference relation $P = (p_{ij})_{n\times n}$ is called

1. a-consistent if and only if there exists a normalized vector $w = (w_1, \cdots, w_n)$, such that $p_{ij} = \frac{w_i - w_j + 1}{2}$;
2. P is m-consistent if and only if there exists a normalized vector $w = (w_1, \cdots, w_n)$, such that $p_{ij} = \frac{w_i}{w_i + w_j}$;

In other words, for any normalized weight vector $\mathbf{w} = (w_1, \cdots, w_n)$, one can construct 2 fuzzy preference relations: $\mathbf{A}(\mathbf{w}) = [a_{ij}]$ and $\mathbf{M}(\mathbf{w}) = [m_{ij}]$, where

$$a_{ij} = \frac{1}{2}(1 + w_i - w_j) \qquad \text{and} \qquad m_{ij} = \frac{w_i}{w_i + w_j}$$

Most of the existing a-consistent models are minimizing the norm $\|\mathbf{P} - \mathbf{A}(\mathbf{w})\|_1$, see [9], [4]. In this paper we propose a ranking method by minimization of the following functions

$$\mathcal{A}(w_1, \cdots, w_n) = \|\mathbf{P} - \mathbf{A}(\mathbf{w})\|_F^2 = \sum_{i,j=1}^{n} \left(\frac{w_i - w_j + 1}{2} - p_{ij} \right)^2 \tag{4}$$

$$\mathcal{M}(w_1, \cdots, w_n) = \|\mathbf{P} - \mathbf{M}(\mathbf{w})\|_F^2 = \sum_{i,j=1}^{n} \left(\frac{w_i}{w_i + w_j} - p_{ij} \right)^2 \tag{5}$$

The first function is in fact the square of the Frobenius norm of $\mathbf{P} - \mathbf{A}(\mathbf{w})$ or the sum of square errors between $\mathbf{P}$ and $\mathbf{A}(\mathbf{w})$. The second function is the sum of square errors between $\mathbf{P}$ and $\mathbf{M}(\mathbf{w})$.

Fortunately, the minimum of function $\mathcal{A}(w_1, \cdots, w_n)$ is unique and can be found by analytical method. Indeed,

$$\frac{\partial \mathcal{A}}{\partial w_k} = n \cdot w_k - 1 + n - 2\sum_{j=1}^{n} p_{kj}$$

$$\frac{\partial \mathcal{A}}{\partial w_k} = 0 \Leftrightarrow w_k = \frac{2P_k + 1}{n} - 1,$$

where P_k is the sum of values in the k^{th} row of the matrix $\mathbf{P}$. The function $\mathcal{M}(w_1, \cdots, w_n)$ is more complex and its minimum can be found using gradient descent technique.

This approach can be applied for different types of preference matrices (FPR or IV-FPR), different types of consistency (a-consistency or m-consistency) as well as different types of weight vectors (real-value or interval-value). The other results will be presented in the full version of our paper.

4 Conclusions

In this version (extended abstract) we briefly presented some new rough-fuzzy hybrid methods for the attribute ranking problem. The complete result and the experiment results will be presented in the full version of our peper.

References

1. Nguyen, H.S.: Approximate Boolean Reasoning: Foundations and Applications in Data Mining, p. 334–506. Springer-Verlag, Berlin, Heidelberg (2006)

2. Nguyen, L.G., Nguyen, H.S.: On elimination of redundant attributes from decision table. In: Ganzha, M., Maciaszek, L.A., Paprzycki, M. (eds.) Federated Conference on Computer Science and Information Systems - FedCSIS 2012, Wroclaw, Poland, 9-12 September 2012, Proceedings. pp. 317–322 (2012)
3. Sugihara, K., Ishii, H., Tanaka, H.: Interval priorities in ahp by interval regression analysis. European Journal of Operational Research **158**, 745–754 (02 2004)
4. Torun, H.: Group decision making with intuitionistic fuzzy preference relations. Knowledge-Based Systems **70** (04 2014)
5. Vo, B.K., Nguyen, H.S.: Feature selection and ranking method based on intuitionistic fuzzy matrix and rough sets. In: Proceedings of the 17th Conference on Computer Science and Intelligence Systems. Annals of Computer Science and Information Systems, vol. 30, pp. 279–288 (2022)
6. Vo, B.K., Nguyen, H.S.: Application of interval valued fuzzy sets in attribute ranking. In: Huynh, V.N., Le, B., Honda, K., Inuiguchi, M., Kohda, Y. (eds.) Integrated Uncertainty in Knowledge Modelling and Decision Making. Lecture Notes in Computer Science, vol. 14375, pp. 61–72. Springer Nature Switzerland, Cham (2023)
7. Wang, Z.J., Li, K.W.: Goal programming approaches to deriving interval weights based on interval fuzzy preference relations. Information Sciences **193**, 180–198 (2012)
8. Xu, Z.: A survey of preference relations. International Journal of General Systems **36**(2), 179–203 (2007)
9. Xu, Z., Yager, R.R.: Intuitionistic and interval-valued intutionistic fuzzy preference relations and their measures of similarity for the evaluation of agreement within a group. Fuzzy Optimization and Decision Making **8**, 123–139 (2009)

Cross-domain Structural Damage Identification based on Deep Domain Adaptation Algorithm

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Abstract. Against the backdrop of rapid socio-economic progress and the continuous increase in traffic volume, bridges play a crucial role as essential components of transportation hubs, ensuring road traffic safety. However, with the aging of bridges and dynamic changes in the surrounding environment, the safety of bridge structures has become a prominent concern. Existing methods for bridge damage detection have not thoroughly explored the monitoring data collected by sensors. Moreover, due to the dynamic changes in the loads borne by bridges, existing deep learning methods often suffer from insufficient generalization performance, failing to meet the real-time and high-precision requirements of bridge monitoring. Therefore, researching and developing data-driven methods for bridge structural damage identification, prioritizing real-time performance and high accuracy, becomes particularly important.

Considering the shortcomings of existing deep learning-based methods for bridge structural damage identification, we have undertaken the following research efforts:

1. Construction of a bridge damage dataset with dynamic load variations. Due to considerations of cost-effectiveness and safety, there is a scarcity of datasets related to bridge structural damage that meet the experimental exploration requirements. In light of this, the present study utilizes ANSYS simulation software to construct four distinct bridge damage scenarios. For each scenario, transient analyses are conducted under various load conditions to acquire the acceleration responses of the bridge structure as an evaluation metric for bridge damage. These scenarios include the passage of a single vehicle (car1), two vehicles (car2), and three vehicles (car3).

2. Multi-Channel Data Fusion. Existing deep learning methods often only consider dividing data obtained from individual sensors into windows as single-channel samples to train models. However, they neglect the correlation between various sensors within the entire sensor system, leading to unnecessary waste of computational resources. In order to fully exploit data information while taking into account the inter-sensor correlations, this study performs data-level fusion on multiple data streams acquired by the sensor system under the same scenario. This approach constructs multi-channel samples for model training.

3. Integration of attention mechanism in multi-scale parallel Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (BiGRU) feature extractors. We propose an algorithm incorporating an attention mechanism into

a multi-scale parallel CNN and BiGRU as a damage feature extractor. Firstly, the multi-scale CNN is employed to extract spatial feature information at different granularities from the input data. Concurrently, the parallel BiGRU, operating alongside the CNN, is utilized to capture temporal feature information from the acceleration responses, mitigating the issue of information loss caused by the serial nature of CNN processing. Finally, the addition of the attention mechanism allows the neural network model to focus more on the mutation signals that represent damage, capturing more valuable damage features and enhancing the data's representational capacity.

4. Cross-Domain Structural Damage Identification. Considering the dynamic variations in load moments on bridge structures, the Mean Maximum Discrepancy (MMD) is employed as a domain loss evaluation metric to construct a domain adaptation algorithm. This algorithm aims to extract domain-invariant features from the structure, thereby enhancing the model's generalization performance. The model utilizes a multi-scale parallel CNN and BiGRU network structure, incorporating an attention mechanism as a feature extractor. It performs feature extraction separately on source domain samples and a limited amount of target domain samples. Subsequently, a domain adaptation algorithm is employed for feature alignment. Through iterative backpropagation, the model continuously optimizes parameters, yielding the best-trained model for cross-domain structural damage identification.

To validate the model's generalization and robustness, this study defined six different cross-domain damage scenarios, including car1→car2, car1→car3, car2→car3, car3→car1, car3→car2, and car2→car1. The model achieved accuracy rates of 93.08%, 91.15%, 92.31%, 95.38%, 97.69%, and 98.46%, respectively, in the six different cross-domain damage recognition scenarios.

Keywords: Deep Learning; Transfer Learning; Attention Mechanism; Structural Health Monitoring; Domain Adaption.

Sequential Three-way Detection Method of Hybrid Concept Drift

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Keywords: Streaming Data · Concept Drift · Detection.
Concept drift refers to the phenomenon that the distribution characteristics of data may change over time in a streaming data environment [2], which has negative influence on the model decision accuracy [1, 5]. Most research mainly focus on the single type of concept drift currently [4], while little literature study the hybrid concept drift [7].

In practical application scenarios, concept drift is often uncertain, which means that the change of data distribution may occur suddenly or may be a gradual process [6,8]. Some scholars divide concept drift into two types according to the speed at which it occurs: abrupt drift and gradual drift [9]. Abrupt or rapid changes between different concepts are referred to as abrupt drift, while relatively slow changes between different concepts are referred to as gradual drift.

This work introduces three-way decisions [10], one of the important results in granular computing [3], and proposes a sequential three-way detection method of hybrid concept drift (S3-HDD).

Suppose that there is a stream data set $SD = \{S_0, S_1, S_2, \cdots S_n\}$ with a time series relationship in stream computing, and any two adjacent elements in SD have the same time interval. Most elements $S_x \in SD$ in the streaming data $SD = \{S_0, S_1, S_2, \cdots S_i\}$ obey the same distribution characteristics and satisfy the same conceptual model f. In order to detect the concept drift of the subsequent data flowing into SD starting from the current latest data node S_i. We first define two forward detection windows, namely the short forward detection window $FD_{w_1} = \{S_{i+1}, \cdots S_{i+w_1}\}$ and the long forward drift detection window $FD_{w_2} = \{S_{i+1}, \cdots S_{i+w_2}\}$, whose lengths are w_1 and w_2 respectively and $w_1 < w_2$; secondly, we define a backward detection window $BD_w = \{S_{i-w+1}, \cdots S_{i-1}, S_i\}$,which has a fixed length w.

Based on the above definition, the initial conceptual model f is used to test the data in the backward detection window BD_w and the forward detection windows FD_{w_1} and FD_{w_2}. The prediction accuracy obtained respectively can be defined as the backward detection window accuracy ACC_{BD_w}, short forward detection window accuracy $ACC_{FD_{w_1}}$ and long forward detection window accuracy $ACC_{FD_{w_2}}$.

When there is a streaming data $SD = \{S_0, S_1, S_2, \cdots S_i\}$ that obeys the same distribution characteristics, two forward detection windows FD_{w_1}, FD_{w_2} and a backward detection window BD_w are set from the latest data node S_i. Then the corresponding value ratio between $ACC_{FD_{w_1}}$ and ACC_{BD_w} can be defined as a short-time drift measurement metric, recorded as DM_{St} (Short-time drift metric); the value ratio between $ACC_{FD_{w_2}}$ and ACC_{BD_w} can be defined as a long-time drift measurement metric, recorded as DM_{Lt} (Long-time drift metric).

The calculation formulas of the above short-time drift measurement metric and long-time drift measurement metric are as follows:

$$DM_{St} = \frac{ACC_{FD_{w_1}}}{ACC_{BD_w}} \times 100 \tag{1}$$

$$DM_{Lt} = \frac{ACC_{FD_{w_2}}}{ACC_{BD_w}} \times 100 \tag{2}$$

Based on the basic idea of three-way decisions, we set a pair of three-way detection thresholds $\langle \alpha, \beta \rangle$, $0 < \beta < \alpha < 1$; and a two-way detection threshold γ, $0 < \gamma < 1$. Starting from the latest data node S_i, based on the values of DM_{St} and DM_{Lt} and the above decision thresholds, the following sequential three-way detection of hybrid concept drift can be performed. The sequential three-way detection of hybrid concept drift includes two decision-making levels.

Definition 1 (The first level decision of sequential three-way detection for concept drift).

$$\begin{aligned}
&POS_{(\alpha,\beta)}\left(FD_{w_1}\right) = \left\{FD_{w_1} | DM_{St} \geq \alpha\right\}, \\
&BND_{(\alpha,\beta)}\left(FD_{w_1}\right) = \left\{FD_{w_1} | \beta < DM_{St} < \alpha\right\}, \\
&NEG_{(\alpha,\beta)}\left(FD_{w_1}\right) = \left\{FD_{w_1} | DM_{St} \leq \beta\right\}.
\end{aligned} \tag{3}$$

The semantics of $POS_{(\alpha,\beta)}\left(FD_{w_1}\right)$ in the above Equation 3 are: no concept drift occurs in the forward detection window FD_{w_1} of the streaming data SD starting from the S_i node; the semantics of $NEG_{(\alpha,\beta)}\left(FD_{w_1}\right)$ are: the streaming data SD starting from the S_i node and the forward detection window ST_{w_1} occur mutation concept drift. The semantics of $BND_{(\alpha,\beta)}\left(FD_{w_1}\right)$ are: The type of concept drift that occurs in the data flow in FD_{w_1} cannot be determined. Therefore, when FD_{w_1} is decided to be $BND_{(\alpha,\beta)}\left(FD_{w_1}\right)$, in order to further determine its drift type, it is necessary to implement the second-level decision-making of sequential three-way concept drift detection based on the values of the long forward drift detection window FD_{w_2} and its DM_{Lt}.

Definition 2 (The second level decision of sequential three-way detection for concept drift).

$$\begin{aligned}
&POS_{\gamma}\left(FD_{w_2}\right) = \left\{FD_{w_2} | DM_{Lt} \geq \gamma\right\}, \\
&NEG_{\gamma}\left(FD_{w_2}\right) = \left\{FD_{w_2} | DM_{Lt} < \gamma\right\}.
\end{aligned} \tag{4}$$

The semantics of $POS_\gamma\left(FD_{w_2}\right)$ in the above Equation 4 are: in the streaming data SD, a gradual concept drift occurs in the forward detection window FD_{w_2} starting from S_i; the semantics of $NEG_\gamma\left(FD_{w_2}\right)$ are: there is no concept drift occurs in the forward detection window FD_{w_2} starting from S_i.

By using the S-3WD method, the S3-HDD can hierarchically determine the type of concept drift according to the change of model accuracy, which improves the concept drift detection accuracy and reduces the time cost of concept drift countermeasure calculation. Experiments show that the proposed S3-HDD algorithm can accurately determine the type of concept drift and ensure the accuracy of the concept drift adaptation algorithm, and reduce the time cost of concept drift countermeasure calculation.

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References

1. Abbasi, A., Javed, A.R., Chakraborty, C., Nebhen, J., Zehra, W., Jalil, Z.: Elstream: An ensemble learning approach for concept drift detection in dynamic social big data stream learning. IEEE Access **9**, 66408–66419 (2021)
2. Agrahari, S., Singh, A.K.: Concept drift detection in data stream mining: A literature review. Journal of King Saud University-Computer and Information Sciences **34**(10), 9523–9540 (2022)
3. Bargiela, A., Pedrycz, W.: Granular computing. In: Handbook on Computer Learning and Intelligence: Volume 2: Deep Learning, Intelligent Control and Evolutionary Computation, pp. 97–132. World Scientific (2022)
4. Gama, J., Medas, P., Castillo, G., Rodrigues, P.: Learning with drift detection. In: Advances in Artificial Intelligence–SBIA 2004: 17th Brazilian Symposium on Artificial Intelligence, Sao Luis, Maranhao, Brazil, September 29-Ocotber 1, 2004. Proceedings 17. pp. 286–295. Springer (2004)
5. Guo, H., Li, H., Ren, Q., Wang, W.: Concept drift type identification based on multi-sliding windows. Information Sciences **585**, 1–23 (2022)
6. Liu, W., Zhang, H., Ding, Z., Liu, Q., Zhu, C.: A comprehensive active learning method for multiclass imbalanced data streams with concept drift. Knowledge-Based Systems **215**, 106778 (2021)
7. Maaradji, A., Dumas, M., La Rosa, M., Ostovar, A.: Fast and accurate business process drift detection. In: Business Process Management: 13th International Conference, BPM 2015, Innsbruck, Austria, August 31–September 3, 2015, Proceedings 13. pp. 406–422. Springer (2015)
8. Mohawesh, R., Tran, S., Ollington, R., Xu, S.: Analysis of concept drift in fake reviews detection. Expert Systems with Applications **169**, 114318 (2021)
9. Yang, L., Shami, A.: A lightweight concept drift detection and adaptation framework for iot data streams. IEEE Internet of Things Magazine **4**(2), 96–101 (2021)
10. Yao, Y.: The geometry of three-way decision. Applied Intelligence **51**(9), 6298–6325 (2021)

Representing Pedagogic Content Knowledge Through Rough Sets

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Concepts of knowledge can be associated with granular and nongranular semantics of rough sets from multiple perspectives such as those based on classical rough ideas, mereological axiomatic granular perspectives [5,6], classical granular computing, interpretations of modal logic [13], constructive logic, concept analysis [14,6], evidence theory, and machine learning. These ideas of knowledge are not uniformly well-developed across these types of rough sets. Possible applications of these to education research, and specifically mathematical education research is a very domain-specific matter. Many aspects of these are explored by the present author in her earlier papers [7,11,8,9].

Application of rough sets and other artificial intelligence methodologies to education research is important for all the fields involved. This is because of the intense complexity of knowledge representation in education research. The subject is substantially population specific, and is strongly influenced by socioeconomic, psychological, and cultural factors. The very idea of *core content* for a level of learning as understood from the perspective of a subject specialist is not reasonably definable without additional constraints. However, the idea of core content in mathematics (for example) for regular courses in middle school or higher can be specified though not exactly as one would want to. *Details of proposed models are relegated to the full version of this report*.

In the modern view [1], three components that determine a teacher's knowledge base are knowledge of mathematics content, knowledge of student epistemology, and pedagogical knowledge. The first is about the breadth and depth of a teacher's knowledge of the subject. The second concerns understanding of the psychological principles of learning, concept formation, assimilation, and maturation. Teacher's understanding of teaching in the light of the other components is knowledge of pedagogy. Many instructive application of the concepts that demonstrate how a teacher's fixation with computational procedures for understanding can adversely affect conceptual learning outcomes of the class may be found in the literature. Further associations between a teacher's beliefs about the nature of the subject (such as school mathematics is a fixed set of concepts and procedures that are to be delivered to and remembered by students), and the fixations are deducible. These aspects matter for both the training of,

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and designing intelligent software aids for teachers (and additionally for the development of curricula and textbooks).

A student's understanding of a mathematics textbook in relation to the instructional context is distinct from a teacher's understanding of the pedagogic content (including psychological aspects) and context – the latter, in turn typically differs from a subject expert's view on the matter (see [1] for a detailed discussion). The categories of students, teachers and experts may be classifiable into a number of finer categories on the basis of subsets of features. The classification of conceptual knowledge as evidenced by the work produced by learners (using any form of expression or in any settings or context) takes many forms. While concept inventories are useful to access over many types of contexts, they do not typically have the breadth to consider atypical reasoning, and related errors. *Teachers understanding of the pedagogic content is in relation to all these, and specifically to the meta-level language used for the context*. The purpose of this research to propose a framework for this idealized understanding. Teachers and students, in a classroom, actually approximate a body of knowledge formed in a distributed cognition perspective [12] in different ways.

The real numbers are taught in certain languages with much interspersed vagueness in middle school. Further, mathematical problem-solving methods, and concepts have vagueness in related discourse. Making use of predicates such as is an approximation of, is a superset of, is a subset of, and is definitely a part of much of the formalization is possible. The harder problem of expressing them through general rough approximations is additionally explored in this research after formalizing the school real numbers typically ignored by formal mathematicians. Work in the area is primarily limited because of the need to systematically confront the varieties of vagueness inherent in it [4,2]. However, there is much work on pragmatic approaches to the ontology of the real numbers in the context. They serve as sources for building viable models.

In the context of mathematics education research, the very idea of *formal language or model* is open for some debate. In [9], it is argued that mereology combined with a language of approximations can potentially be used to build higher order formalizations of concepts that go beyond the restrictions envisaged in [4] or in earlier work [2].

Further, a common practice in teaching mathematics is to use everyday language when describing and explaining ideas. Teachers may use phrases such as *plug in* a value to evaluate a function, and *cancel* instead of dividing by the common factor. These and the overuse of pronouns can obscure the meaning of the procedures and concepts being used. The use of imprecise, loose language, and unidentified errors by teachers can be counterproductive. These and related studies motivate the need to build reasonably formal models to study teachers' knowledge of content, and more so for the purpose of building intelligent aids for teachers. ML approaches based on numeric simplifications of language features or keywords cannot succeed in the context, and none are attempted in the literature.

The following are done in the full version of this research (within the domain of pedagogic knowledge):

- A much improved applicable model of the vague version of real numbers is proposed;
- The model is intended for use with a companion model that involves multiple general rough approximation operators, mereological and rough predicates (possibly functional), and
- a justification of aspects of the above is argued for through equational reasoning contexts.

Let a representation of the students' knowledge of content be SC, and the objective content be C. Now, an ideal teacher of the subject can be required to know a lot more about C, the learning of SC by a student of type $\tau \in \mathcal{T}$ (where $\mathcal{T}$ is a categorization of students by their sociocultural context) TC, and the relation of SC to the teacher's understanding of the content T, and relevant concepts Co. Partial models MP of Co, and sufficient models MS of the ideal teachers' knowledge of content T may be constructed from the information. Thus, the components of the ecosystem may be represented by the interrelationship diagram Fig 1 (the hierarchies are left to the reader to understand).

$$\begin{tikzcd}
 & \mathrm{MP} \arrow[r, leftrightarrow] \arrow[d, leftrightarrow] & \mathrm{MS} \arrow[dl, leftrightarrow] \arrow[d, leftrightarrow] \\
\mathrm{C} \arrow[d, leftrightarrow] \arrow[dr, leftrightarrow] & \mathrm{Co} \arrow[r, leftrightarrow] \arrow[d, leftrightarrow] & \mathrm{TC} \arrow[dl, leftrightarrow] \\
\mathrm{SC} \arrow[r, leftrightarrow] & \mathrm{T} &
\end{tikzcd}$$

Fig. 1: Components of the Ecosystem

The proposed system consists of three major blocks:

- an improved better suited description of the real numbers as understood in school mathematics,
- formal systems for reasoning about mathematical assertions that accommodate ontology, mereology and vagueness, and psychosocial factors, and
- a granular extension of the same based on earlier work of the present author.

Student-centric rough concept inventories [7] can additionally be handled more smoothly through the companion models introduced as automatic evaluation of explanations is dependent on the latter. The coherent formalizability issue in the education research literature is thus addressed to an extent. Higher-order formalizations of equational reasoning (including [12]), described in detail in the full version, are not unique, and making these more unique is an important problem. Issues relating to use of multiple approximation operators, ideas of overlap predicates, generalized overlap functions, weak rough implications, rationality, and substantial parthood [10], will be investigated further in future work. Additionally, this research motivates higher order approaches in rough sets, that would have been previously glossed over through hybrid layers.

References

1. Ball, D., Thames, M., Phelps, G.: Content Knowledge for Teaching: What Makes it Special? Journal of Teacher Education **59**(5), 389–407 (2008)
2. Barwell, R., Others (eds.): Mathematics Education and Language Diversity –The 21st ICMI Study. Springer (2021). https://doi.org/10.1007/978-3-319-14511-2
3. Harel, G., Lim, K.H.: Mathematics teachers' knowledge base:preliminary results. In: Proceeedings of 28th PME. vol. 3, pp. 25–32 (2004)
4. Jayasree, S., Subramaniam, K., Ramanujam, R.: Coherent Formalisability as Acceptability Criterion for Students' Mathematical Discourse. Research in Mathematics Education (2022). https://doi.org/10.1080/14794802.2022.2041469
5. Mani, A.: Algebraic Methods for Granular Rough Sets. In: Mani, A., Düntsch, I., Cattaneo, G. (eds.) Algebraic Methods in General Rough Sets, pp. 157–336. Trends in Mathematics, Birkhauser Basel (2018)
6. Mani, A.: Dialectical Rough Sets, Parthood and Figures of Opposition-I. Transactions on Rough Sets **XXI**(LNCS 10810), 96–141 (2018)
7. Mani, A.: Towards Student Centric Rough Concept Inventories. In: Bello, R., et al. (eds.) IJCRS' 2020, LNAI, vol. 12179, pp. 251–266. Springer International (2020)
8. Mani, A.: What May be a Table in Education Research? In: Kollosche, D., et al. (eds.) Proc. of Eleventh International Mathematics Education and Society Conference, vol. 1, pp. 651–661. Tredition (2021). https://doi.org/10.5281/zenodo.5415451
9. Mani, A.: Mereology for STEAM and Education Research. In: Chari, D., Gupta, A. (eds.) EpiSTEMe 9, vol. 9, pp. 122–129. TIFR, Mumbai (2022), https://www.researchgate.net/publication/359773579
10. Mani, A.: Granular knowledge and rational approximation in general rough sets-i. Journal of Applied Non-Classical Logics **34**, 1–36 (2023). https://doi.org/10.1080/11663081.2024.2336387
11. Mani, A.: Mereological methods for education research, and school and college-level mathematics. ICME, Accepted **15**, 1–8 (2023)
12. Mani, A.: Rough algebraic semantics of concepts in a distributed cognition perspective. In: Hu, M., Others (eds.) Rough Sets IJCRS 2024, pp. 16–30. Springer Nature (2024)
13. Mani, A., Düntsch, I., Cattaneo, G. (eds.): Algebraic Methods in General Rough Sets. Trends in Mathematics, Birkhauser Basel (2018). https://doi.org/10.1007/978-3-030-01162-8
14. Yao, Y.: Rough-Set Concept Analysis: Interpreting Rs-Definable Concepts Based on Ideas From Formal Concept Analysis. Information Sciences **347**, 442–462 (2016)

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