AI Efficacy in Sparse Data Environments: Exploring Approximate Knowledge Interpolation for Practical Applications

Qiang Shen

Department of Computer Science, Aberystwyth University, UK.
Email: qqs@aber.ac.uk

Abstract - AI stands at the forefront of transforming global industries, achieving remarkable progress in recent years, largely driven by advanced deep learning techniques adept at processing extensive datasets. However, a crucial question arises when confronted with limited and ambiguously characterised data for a novel problem: Can AI maintain its effectiveness under such constraints? This paper delves into addressing this query, emphasising the role of Fuzzy Rule Interpolation (FRI) in enabling approximate reasoning amidst sparse or incomplete knowledge. This becomes particularly significant when traditional rule based inference mechanisms struggle due to misalignment with observations. Extensive research into FRI techniques within computational intelligence has yielded various methodologies. The focus of this paper centres on a notable subset, Transformation-based FRI (T-FRI). T-FRI operates by mathematically adjusting rules that share similarities with unmatched observations, utilising linear transformations of the nearest rules chosen automatically relative to an unmatched observation. Examples are included to showcase the successful applications of T-FRI in tackling challenging real-world problems.

Keywords - AI efficacy, sparse data environments, approximate knowledge interpolation, practical applications

I. INTRODUCTION

AI stands at the forefront of transforming global industries, achieving remarkable progress in recent years, largely driven by advanced deep learning techniques adept at processing extensive datasets. However, a crucial question arises when confronted with limited and ambiguously characterized data for a novel problem: Can AI maintain its effectiveness under such constraints?

The present paper delves into addressing this query, emphasizing the role of fuzzy rule interpolation (FRI) [1] in enabling approximate reasoning amidst sparse or incomplete knowledge.

The topic becomes particularly significant when traditional rule-based inference mechanisms struggle due to misalignment with observations.

Extensive research into FRI techniques within the field of computational intelligence has yielded various methodologies. The focus of this paper centers on a notable subset, transformation-based FRI (T-FRI) [2]. T-FRI operates by mathematically adjusting rules that share similarities with unmatched observations, utilizing linear transformations of the nearest rules chosen automatically relative to an unmatched observation.

This paper will commence with an exploration of the foundational T-FRI approach, followed by a concise overview of its extended repertoire: adaptive T-FRI [3], backward T-FRI [4], higher-order T-FRI [5], dynamic T-FRI [6], and weighted T-FRI [7]. Each of these variations addresses specific limitations inherent in the original method. Subsequently, selected real-world applications of these techniques will be showcased, demonstrating their effectiveness in addressing challenges in domains such as network security and medical diagnosis. These examples underscore AI's ability to operate effectively even when faced with incomplete knowledge and ambiguous data.

The paper concludes with a glimpse into potential advancements in this critical research domain.

II. TRANSFORMATION-BASED FUZZY RULE INTERPOLATION

To perform tasks such as classification, prediction and regression with an intelligent system, a classical assumption is that the system's underlying knowledge (be it provided by experts or learned from empirical data or a mixture of both) must cover given observations. Traditional probabilistic and fuzzy approaches relax this assumption, but still require partial coverage. In reality, however, a system's knowledge base is often incomplete and does not always match, even partially, novel observations.

FRI offers a great potential to tackle this difficult and yet, common problem. It also provides a possible way of simplifying complex systems by approximating similar rules with interpolated ones. The potential of FRI to materially support approximate reasoning that would entail full interpretability of both the system model and the inference process associated has attracted a wide range of developments of effective and efficient FRI techniques.

A. Foundational Transformation-Based Fuzzy Rule Interpolation

Transformation-based Fuzzy Rule Interpolation (T-FRI) represents the foundation for a family of interpolative reasoning methods which work by means of scale and move transformations [1]. It works by constructing an intermediate inference rule via mathematically manipulating two given rules adjacent to an unmatched observation. This is realized using scale and move transformations, of the fuzzy membership functions defining the variable values within the fuzzy rules, to convert the intermediate inference results into a final conclusion in response to the unmatched observation. This method has three advantages thanks to the proposed transformations:

1) it can handle interpolation of multiple antecedent variables with simple computation;

2) it guarantees the uniqueness as well as normality and convexity of the resulting interpolated fuzzy sets; and 3) it suggests a variety of definitions for the underlying representation mechanisms, providing a degree of freedom to meet different application requirements.

The initial work on T-FRI as per [1] and indeed almost all early approaches to FRI make strong assumptions that there are two closest adjacent rules available to an unmatched observation, and that such rules must flank the observation for each attribute. To remove this significant limitation, a practically more applicable approach has been established [8], enabling both interpolation and extrapolation that involve multiple fuzzy rules, where each rule may consist of multiple antecedents. In recognition of the great potential of T-FRI in supporting reasoning with sparse approximate knowledge, many follow-on techniques have been developed since the inception of this work. The following are just a few representatives within the T-FRI family.

B. Adaptive Fuzzy Rule Interpolation

T-FRI strengthens the power of fuzzy inference by offering the power for the enhancement of the robustness of fuzzy systems and the reduction of the systems' complexity. However, when applied, after a series of interpolations, it is possible that multiple object values for a common underlying variable are inferred, leading to inconsistency in interpolated results. Such inconsistencies may result from defective interpolated rules or incorrect interpolative transformations. Adaptive fuzzy rule interpolation [3] provides an improved approach which is capable of identifying and correcting defective rules during the process of interpolative transformations, thereby removing the inconsistencies. For this, the popular assumption-based truth-maintenance system (ATMS) is used to record dependences between interpolations, and the classical general diagnostic engine built on the ATMS that was employed for physical fault localization is adapted to isolate possible faulty interpolated rules and their associated interpolative transformations. From this, the linear interpolation method underpinning the original T-FRI is modified to become first-order piecewise linear.

This work has been further developed by considering observations, rules, and interpolation procedures, all as diagnosable and modifiable system components [9]. In addition, given the common practice in fuzzy systems that observations and rules are often associated with certainty degrees, the identified candidates are ranked by examining such degrees of its components and their derivatives. The candidate modification is then carried out based on the resultant ranking.

This study significantly improves the efficacy of the existing adaptive FRI system by exploiting more information during both the diagnosis and modification processes.

C. Backward Fuzzy Rule Interpolation

In real-world applications of interconnected (fuzzy) rule bases, situations may arise where certain crucial antecedents are absent from given observations. If such missing antecedents were involved in the subsequent interpolation process, the conclusion would not be deducible using conventional FRI means. To address this important issue, backward fuzzy rule interpolation has been introduced [4], allowing the observations directly relating to the conclusion to be inferred or interpolated from the known antecedents and conclusion. This approach supports both backward interpolation and extrapolation that involve multiple fuzzy rules, with each having multiple antecedents. Considering that there may be more than one antecedent value missing in an application problem, different algorithms have also been created in an attempt to perform backward interpolation with multiple missing antecedent values.

D. Higher-Order Fuzzy Rule Interpolation

In the FRI literature, very little of the existing work can conjunctively handle more than one form of uncertainty in the rules or observations. Particularly, the difficulty in defining the required precise-valued membership functions for the fuzzy sets that are used in conventional FRI techniques significantly restricts their application, until higher-order methods are introduced. A specific and powerful approach for higher-order FRI is to employ rough-fuzzy sets to address such difficulties [5]. The resulting approach entails the representation, handling and utilisation of different levels of uncertainty in knowledge. This facilitates T-FRI techniques to model and harness additional type of uncertain information, other than that of value imprecision that is captured by fuzzy sets, while implementing an effective fuzzy interpolative reasoning system.

E. Dynamic Fuzzy Rule Interpolation

FRI offers an effective approach for making inference possible in sparse rule-based systems.

However, requirements of fuzzy systems may change over time and hence, the use of a static rule base may affect the accuracy of FRI applications. Interestingly, an FRI system in action will produce interpolated rules in abundance during the interpolative reasoning process. Such interpolated results can be utilised to facilitate the development of a dynamic rule base in supporting subsequent inference. This leads to a dynamic fuzzy rule interpolation (D-FRI) approach to improve the overall system's coverage and efficacy [6]. The resulting D-FRI system can select, combine, and generalise informative, frequently used interpolated rules for merging with the existing rule base while performing interpolative reasoning. To reinforce the practicability of DFRI it has been extended most recently, exploiting the information on ranking the fuzzy rules [10].

F. Weighted Fuzzy Rule Interpolation

Whilst offering a potentially powerful inference mechanism, typical representation of fuzzy rules in the FRI literature assumes that all attributes in the rules are of equal significance in deriving the consequents. This is a strong assumption in practical applications, thereby often leading to less accurate interpolated results. To address this problem, feature selection techniques are innovatively applied, adjudging the relative significance of individual attributes, to differentiate the contributions of the rule antecedents and their impact upon FRI [11]. Without requiring any acquisition of real observations, based on the originally given sparse rule base, the individual scores can be computed using a set of training samples that are artificially created from the rule base through an innovative reverse engineering procedure. The attribute scores are integrated within T-FRI, forming a method for attribute ranking-supported fuzzy interpolative reasoning.

With such an extension, empirically, it has been shown that for typical problems where T-FRI techniques are applied to resolve only two (i.e., the least number of) nearest neighboring rules to an unmatched observation are required [12].

III. EXAMPLE APPLICATIONS OF TRANSFORMATION-BASED FUZZY RULE INTERPOLATION

T-FRI has found a wide range of real-world applications internationally, covering a variety of problems which lack sufficient knowledge while involving sparse historical data. This paper outlines two representatives of such successful applications, as examples.

A. Application to Strengthening Computer Network Security

Computer network security is one of the major concerns of any organization regardless of their size and nature of work. It is therefore, not a surprise that T-FRI has been applied to accomplish various network security analysis tasks, including intrusion detection [6] and sting operation [13].

Network security attacks and their types are countless, while network intrusion attack is one of the key concerns, being an illicit attempt that compromises the confidentiality, integrity, or availability of any organizational IT infrastructure. Having taken notice of this, D-FRI's application for network intrusion detection is introduced here as the first example. This is implemented through devising a dynamic intrusion detection system, via integrating D-FRI and the Snort software, one of the most popular open-source systems for detecting network intrusion attacks.

The resulting D-FRI-Snort integration delivers an extra amount of intelligence to predict the level of potential threats. Experimental results show that with the inclusion of a dynamic rule base, by generalizing newly interpolated rules based on the current computer network traffic conditions, D-FRI-Snort can reduce both false positives and false negatives in network intrusion detection.

B. Application to Improving Medical Risk Analysis

Being the highest cause for women's death globally, breast mass cancer remains a great challenge for devising advanced computer-aided diagnosis (CADx) systems. Such systems are aimed at assisting medical professionals for the determination of benignancy or malignancy of masses.

Selected as the second successful example of applying FRI techniques, weighted T-FRI [11] is herein employed to develop a fuzzy rule-based CADx system for mass classification in mammographic images. The resulting inference system helps ensure interpretable classification of masses through firing the rules that match given observations, while having the capability of classifying unmatched observations through FRI. In particular, a feature weight-guided T-FRI scheme is exploited to realize the interpolative reasoning process, whose implementation is facilitated with the individual feature weights estimated by a feature evaluation procedure (taken from any popular filter-based feature selection algorithm). The efficacy of the proposed CADx system is systematically evaluated using two real-world mammographic image datasets, demonstrating its explicit interpretability and accurate risk level estimation.

IV. CONCLUSION

This paper has presented a high-level description of the popular family of transformation-based approximate rule interpolation methods, together with selected applications to real-world problems. This demonstrates the efficacy of existing AI techniques, developed within the framework of computational intelligence, in addressing the challenges of their working with situations in which limited and ambiguously characterized data are confronted.

Restricted by space, many other established FRI mechanisms have not been included here, but readers may find them in the literature. Particular relevant to the family of T-FRI techniques are: closed form T-FRI of mathematical rigor [15], bidirectional T-FRI [16], T-FRI with different distance functions [17] or attribute ranking [18], FRI based on system models differing from classical rule representation (e.g., TSK [19] and ANFIS [20]) or involving different learning mechanisms [21], alternative T-FRI foundations (e.g., [22]), and integration of T-FRI and conventional compositional rule of inference [23]. A good summary of most of these recent advances can be found in [24].

Whilst promising, much remains to be further developed, however. Example on-going work includes: vector-based T-FRI of mathematical rigor, D-FRI with dynamic rule-pruning using FRI, T-FRI with different aggregation functions, theoretical analysis of empirically revealed FRI properties, integration of FRI methodologies, and widening applications to solving real-life problems.

ACKNOWLEDGEMENT

The series of works presented in this short paper were the result of significant team efforts spanning over a long period of time. The author is deeply grateful to many past PhD students who conducted the actual work, particularly to: T. Chen, C. Cheng, R. Diao, Z. Huang, S. Jin, F. Li, N. Naik, J. Yang, L. Yang, P. Zhang, and M. Zhou, for their valuable contributions.

REFERENCES

[1] F. Li, C. Shang, Y. Li, J. Yang and Q. Shen. Approximate reasoning with fuzzy rule interpolation: Background and recent advances. Artificial Intelligence Review, 54:4543-4590, 2021.

[2] Z. Huang and Q. Shen. Fuzzy interpolative reasoning via scale and move transformation. IEEE Transactions on Fuzzy Systems, 14(2):340-359, 2006.

[3] L. Yang and Q. Shen. Adaptive fuzzy interpolation. IEEE Transactions on Fuzzy Systems, 19(6):1107-1126, 2011.

[4] S. Jin, R. Diao, C. Quek and Q. Shen. Backward fuzzy rule interpolation. IEEE Transactions on Fuzzy Systems, 22(6): 1682-1698, 2014.

[5] C. Chen, N. MacParthalain, Y. Li, C. Price, C. Quek and Q. Shen. Rough-fuzzy rule interpolation. Information Sciences, 351:1-17, 2016.

[6] N. Naik, R. Diao and Q. Shen. Dynamic fuzzy rule interpolation and its application to intrusion detection. IEEE Transactions on Fuzzy Systems, 26(4):1878-1892, 2018.

[7] F. Li, Y. Li, C. Shang and Q. Shen. Fuzzy knowledge-based prediction through weighted rule interpolation. IEEE Transactions on Cybernetics, 50(10):4508-4517, 2020.

[8] Z. Huang and Q. Shen. Fuzzy interpolative and extrapolative reasoning: a practical approach. IEEE Transactions on Fuzzy Systems, 16(1):13-28, 2008.

[9] L. Yang, F. Chao and Q. Shen. Generalised adaptive fuzzy interpolation. IEEE Transactions on Fuzzy Systems, 25(4):839-853, 2017.

[10] M. Zhou, C. Shang and Q. Shen. Rule-ranking-based approximate knowledge interpolation with directional monotonicity. IEEE Transactions on Cybernetics, DOI:10.1109/TCYB.2023.3335472, 2024.

[11] F. Li, Y. Li, C. Shang and Q. Shen. Fuzzy knowledge-based prediction through weighted rule interpolation. IEEE Transactions on Cybernetics, 50(10):4508-4517, 2020.

[12] F. Li, C. Shang, Y. Li, J. Yang and Q. Shen. Interpolation with just two nearest neighbouring weighted fuzzy rules. IEEE Transactions on Fuzzy Systems, 28(9):2255-2262, 2020.

[13] N. Naik, C. Shang, P. Jenkins and Q. Shen. D-FRI-Honeypot: a secure sting operation for hacking the hackers using dynamic fuzzy rule interpolation. IEEE Transactions on Emerging Topics in Computational Intelligence, 5(6): 893-907, 2021.

[14] F. Li, C. Shang, Y. Li and Q. Shen. Interpretable mammographic mass classification with fuzzy interpolative reasoning. Knowledge-Based Systems, 191:105279, 2020.

[15] L. Yang and Q. Shen. Closed form fuzzy interpolation. Fuzzy Sets and Systems, 225:1-22, 2013.

[16] S. Jin, J. Peng, Z. Li and Q. Shen. Bidirectional approximate reasoning-based approach for decision support. Information Sciences, 506:99-112, 2020.

[17] M. Zhou, C. Shang, G. Li, L. Shen, N. Naik, S. Jin, J. Peng and Q. Shen. Transformation-based fuzzy rule interpolation with Mahalanobis distance measures supported by Choquet integral. IEEE Transactions on Fuzzy Systems, 31(4):1083-1097, 2023.

[18] F. Li, C. Shang, Y. Li, J. Yang and Q. Shen. Fuzzy rule-based interpolative reasoning supported by attribute ranking. IEEE Transactions on Fuzzy Systems, 26(5):2758-2773, 2018.

[19] P. Zhang, C. Shang and Q. Shen. Fuzzy rule interpolation with k-neighbours for TSK models. IEEE Transactions on Fuzzy Systems, 40(10):4031-4043, 2022.

[20] J. Yang, C. Shang, Y. Li, F. Li and Q. Shen. ANFIS construction with sparse data via group rule interpolation. IEEE Transactions on Cybernetics, 51(5):2773-2786, 2021.

[21] J. Yang, C. Shang, Y. Li, F. Li, L. Shen and Q. Shen. Constructing ANFIS with sparse data through group-based rule interpolation: an evolutionary approach. IEEE Transactions on Fuzzy Systems, 30(4):893-907, 2022.

[22] T. Chen, C. Shang, J. Yang, F. Li and Q. Shen. A new approach for transformation based fuzzy rule interpolation. IEEE Transactions on Fuzzy Systems, 28(12):3330-3344, 2020.

[23] H. Lv, F. Li, C. Shang and Q. Shen. W-Infer-polation: Approximate reasoning via integrating weighted fuzzy rule inference and interpolation. Knowledge-Based Systems, 258:109995, 2022.
[24] F. Li and Q. Shen. Fuzzy Rule-Based Inference: Advances and Applications in Reasoning with Approximate Knowledge Interpolation. Springer Nature, 2024.