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Neurosymbolic AI for Studying the Quality of Life's Dimensions of People with Intellectual Disability

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Abstract. The model of quality of life (QOL) used in Catalonia to assess the QOL level of people with intellectual disability considers eight dimensions defined operationally by core indicators. In this paper, to advance the knowledge about these dimensions regarding social service Catalonia users, we employ logic explained networks to generate global explanations of the correlations between these dimensions and present the results obtained.

Keywords. Disability, intellectual disability, quality of life, logic explained networks, neurosymbolic AI, explainable artificial intelligence, ethics and AI

1. Introduction

Deep learning (DL) has shown great success and delivered results that outperform, in many cases, symbolic approaches to artificial intelligence (AI). In recent years, however, the need for designing explainable models has become more and more of a central problem in the discipline, motivated by the general goals of integrating an ethical dimension into AI and reaching a closer and richer notion of intelligence (indeed, explaining is a must for the intelligence). In that context, neurosymbolic AI [1] (a field of AI aspiring to build AI models by combining the strengths of neural and symbolic AI) contributes towards explainable AI (XAI), intending to maintain the symbolic AI value and incorporate it into deep learning to not lose the strengths of the latter approach. In this paper, we present a real-world application of one of the XAI frameworks, the family of interpretable DL models named Logic Explained Networks (LENs) introduced by Ciravegna et al. [2]. This research forms part of an ongoing project aimed at broadening the knowledge of the quality of life dimensions of people with intellectual disability [3].

In the 1980s, the concept of quality of life (QOL) was presented in diverse domains (e.g., health care and social services), and nowadays, it is fundamental for quality improvement strategies and evaluating the effectiveness of these processes. Taking disabil-

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ity as the interaction between the skills (performance competence) and the support (integration facilities) of their context, Schalock and Verdugo [4] introduced a model of QOL with eight dimensions defined operationally by core indicators, and in 2008, the Institute on Community Integration (University of Salamanca) and the Catalonian Institute of Assistance and Social Services (Government of Catalonia) presented the still-in-use GENCAT scale [5,6]: a questionnaire for users of social services that has 69 questions divided into eight blocks, one for each QOL dimension, allowing four answers. In [7], the authors use the GENCAT scale and propose to use lazy induction of descriptors to estimate the correlation between three dimensions, but only 90 records are considered. That research was improved in [8], wherein a filtered tree and 5158 records were used. However, in contrast to our approach, the QOL level classes were restricted to three (*low*, *medium*, and *high*), resulting in less detailed explanations than those presented in this paper. In [9], the authors used ML methods to predict the QOL level using the 8 dimensions. The multiple linear regression algorithm results show better performance for root mean squared error (1.47) and R^2 score (0.99), whereas no explanation is generated.

2. LENs to analyze the QOL dimensions of people with intellectual disability

We use the database named IntDisCat [3], whose data was provided to us by ICASS. IntDisCat contains records corresponding to 6104 social service users, indicating the answers to the GENCAT scale from multiple practitioners in diverse institutions. With these data, punctuations of the eight QOL dimensions are computed, and then categorized them into five levels[2]: *very low*, *low*, *medium*, *high*, and *very high*. The eight QOL dimensions are: emotional well-being (EW), interpersonal relations (IR), material well-being (MW), personal development (PD), physical well-being (PW), self-determination (SD), social inclusion (SI), and rights (RI).

As a general method to XAI, Ciravegna et al. [2] introduced LENs, a family of interpretable DL models that, among other tasks, generate global explanations of predictions established by other (black-box) classifiers or by the proper LENs (see [2, Sections 2 & 3]). The function computed by the LEN is $f : C \to E$, where $C = \{0,1\}^k$ is the space of activations of the k-input, $E = \{0,1\}^r$ relates to the activations of the r-outputs, and so that the inputs are conceived as human-understandable concepts. In our case study, the explanations provided by LENs are interpreted as propositional logic formulas.

Regarding LENs, three are the computational pipelines (end-to-end, concept-bottleneck, and cascading). We take the end-to-end configuration and adapt the approach to explore the relations between the QOL dimensions, also considering its levels. We use a LEN for each dimension and level, also integrating the framework for entropy-based LENs in [10]. Given a dimension and a level, the human-interpretable inputs considered are 35 concepts related to the other dimensions, whereas the output of each LEN is a quantitative categorization (i.e., a 5-bit vector) and a global explanation of the result.

3. Explaining the correlations between the QOL dimensions

In this section, we show and discuss five examples of global explanations regarding the dimensions IR, MW, PD, PW, and SD, with respect to the levels considered.

[2] See `https://github.com/dfp97/LENsIntDisCatQOLDimensions`.

Table 1. Means of the explanation metrics of the interrelations between the QOL dimensions.

Level		Explanation metrics and related data		
		Explanation complexity	Explanation accuracy	Number of dimensions appearing in the explanation
Means	very low	8.143	0.737	4.429
	low	17.5	0.727	5.125
	medium	19.125	0.779	5.625
	high	25.5	0.758	5.375
	very high	9.6	0.875	4.8
	total	**15.974**	**0.775**	**5.071**

The term *explanation complexity* refers to the number of the variables in the explanation, counting repetitions. Being the explanations in DNF, we restricted them (using *max_minterm_complexity*) to fix a maximum of 8 variables in each disjunct. Then, the experimentation conducted generated 38 global explanations about the levels considered for the eight dimensions. The *low* level got the worst explanation accuracy results, *very high* obtained the best (0.737 and 0.875, respectively), whereas the mean of the five levels is 0.775. No explanations resulted for the level *very high* of MW, PD, and RI since no cases for this level in those dimensions are present in the database. The reader is referred to Table 1 for the means of the results obtained. The first illustrative example is about the relationships between the lowest level for IR (i.e., *very low*) and the rest of dimensions, where its explanation accuracy is 0.911:

$SD_{very-low} \land EW_{low} \land MW_{low} \land PD_{low} \land PW_{medium} \land SI_{medium}$.

The low level for MW is explained as follows (the explanation accuracy is 0.803):

$IR_{medium} \land PD_{low} \land PW_{medium} \land SD_{medium} \land SI_{high}$.

The global explanation for a medium PD obtained is (explanation accuracy is 0.734):

$MW_{high} \land SD_{very-high} \land \neg EW_{very-high} \land \neg IR_{very-high} \land \neg SI_{high} \land \neg RI_{high}$.

Regarding high level of PW, the explanation is (the explanation accuracy is 0.787):

$IR_{low} \land MW_{medium} \land SI_{medium} \land RI_{high} \land \neg PD_{medium}$.

The highest level for the SD dimensions is (the explanation accuracy is 0.880):

$PD_{very-high} \land SI_{very-high} \land \neg PW_{high} \land \neg RI_{low} \land \neg RI_{medium}$.

4. Conclusions and future work

We have focused on the task of providing human-interpretable explanations with competitive accuracy metrics results that are informative and have low syntactic complexity. As future work, an exhaustive comparison with the proposals [7,8,11] will be conducted. In addition, we will evaluate the explanations using different frameworks for this purpose (e.g., [12,13]). Our next step will be the discussion with the experts and practitioners about the semantics of the explanations presented here. Debates on improving the GENCAT scale have been reopened in the last years [14], and more generally, about the role of AI in the validation and construction of psychological tests and scales [15]. Contributing to developing tools such that, we presented in [3] a reduced GENCAT scale. We intend to use the correlations presented in this paper to improve that reduced GENCAT scale.

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