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LOTFI A. ZADEH,
THE VISIONARY IN EXPLAINABLE ARTIFICIAL INTELLIGENCE

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Abstract. In this paper, we describe various aspects of Explainable Artificial Intelligence (XAI) and we show that fuzzy systems can help to approach several of these aspects. We focus on the pioneering works of L.A. Zadeh that offer precious tools for the current XAI challenges. We show that they are not limited to approaches of natural language, but they also help to assist the user in understanding the meaning of the decisions made by artificial intelligence-based systems and to provide explanations about the way these decisions are made.

Keywords: artificial intelligence, eXplainable artificial intelligence (XAI), knowledge representation, fuzzy sets, Lotfi A. Zadeh.

AMS Subject Classification: 68T01, 68T05, 68T30, 68T35.

1. Introduction

To celebrate the centenary of Lotfi A. Zadeh's birth, what better way than to show how modern and visionary he was? The theory of fuzzy sets he introduced in 1965 appeared after an already long scientific life, mainly dedicated to nonlinear systems and control theory.

As early as 1950, he was forecasting that machines would "think" or at least mimic human reasoning [39]. He later explained [62] that his "interest in machine intelligence and mechanisation of human reasoning" led him to go beyond classical logic. He was a forerunner of artificial intelligence, although he was not in the main stream of AI, being more considered as a specialist of system science. He was eventually accepted as a member of the AI community, receiving several prizes: the Certificate of Commendation for AI Special Contributions Award from the International Foundation for Artificial Intelligence in 1992, the Edward Feigenbaum Medal of the International Society for Intelligent Systems in 1998, the Information Science Award of the Association for Intelligent Machinery, also in 1998, and the Allen Newell Award for seminal contributions to Artificial Intelligence from the ACM in 2000.

He very early realised that it was not possible to manage complex systems with classic mathematics. He wrote in 1962 [40]: "We need a radically different kind of mathematics, the mathematics of fuzzy or cloudy quantities which are not described in terms of probability distributions". His main objective was to facilitate interactions with human agents. He thought that natural language was the easiest way to enable machines to interact with humans and his introduction of the concept of linguistic variables [44, 45] was a first attempt towards expressible and understandable systems. This is clearly in line with the objectives f the currently highly active domain recently named eXplainable Artificial Intelligence (XAI), discussed in more details in Section 2.

After his PhD student Joseph Goguen introduced a logic of inexact concepts [19], the notion of linguistic variable led L.A. Zadeh to lay the basis for approximate reasoning based on fuzzy propositions [46, 48]. This was the necessary step to set up fuzzy rule-based systems which

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open the way for a user to understand the functioning of a decision model. This objective again matches one of the major aims of the explainable AI field, as discussed in Section 2.

This paper proposes to discuss in more details the pioneering works of L.A. Zadeh that can be seen as providing precious tools for the XAI challenges, long before this word was coined and used pervasively, as it has been the case in the last few years. Section 2 provides some backgrounds and discussion about the broad domain of explainable Artificial Intelligence, illustrating how it can be seen as a natural playground for fuzzy systems in general. Section 3 then reviews L.A. Zadeh's various approaches to natural language pertaining to explainable AI. Section 4 focuses on the notion of approximate reasoning as it has been introduced by L.A. Zadeh, that makes it possible to perform logical tasks, in a way that is both easily understandable by human agents and formally sound. Section 5 describes some other methods of Artificial Intelligence showing that L.A. Zadeh's impact on the XAI domain should not be limited to the seminal concepts he created, but embraces a huge field of research and applications. In Section 6, we will conclude on his visionary contributions to the explainability of AI systems.

2. Facets of explainable AI

The domain of explainable Artificial Intelligence, as coined in the DARPA program[1] in 2016, has seen a dramatic development in the past recent years, leading to an extremely high number of publications, special sessions, workshops or dedicated conferences. The aim of this section is not to provide an overview on this topic, to which several surveys and overviews have been devoted (see e.g. [1, 2, 3, 11, 16, 28]).

As defined by the DARPA program, explainable AI mainly lies in two objectives: (i) to produce more explainable artificial intelligence models while maintaining good learning performances, (ii) to enable a user to interact easily with intelligent systems. Several words can be used to describe facets of explainability, such as transparency, expressiveness, interpretability accountability or understandability, to name a few. They are intertwined, transparency of the model being for instance a component of its understandability, and expressiveness of decisions pertaining to their understandability

These tasks can be considered highly subjective, as the interpretability and explainability of an artificial intelligence system obviously depend on the user they are aimed at: as discussed in [28], one can for instance distinguish between an *operator*, an *intermediate user* and an *end user*. The operator is concerned with the construction of the system and has to set several parameters, for instance selecting the appropriate algorithm or preparing the data. The intermediate user is for instance the medical doctor or the banker using an AI system dedicated to medical diagnosis or credit allocation, whereas the end user is for instance a patient or a bank's customer. The operator is concerned with the interpretability of the system with regard to his/her interaction with the intermediate user. The knowledge representation must be explicit to the intermediate user and the rules used for the decision must be clearly understandable. The end user wants to understand clearly the decisions and the criteria on which they are based. A natural language-based knowledge representation is certainly among the easiest ways to make a system understandable, even though some intermediate users are familiar with graphs, charts, histograms or statistics.

In this paper, we focus on the expressiveness of fuzzy set and fuzzy logic-based systems, representing their capability to easily interact with human agents. To summarise the needs in explainable AI, we propose to distinguish three levels in AI systems.

At the first level, concerning intermediate users, we consider the clarity of the description of the data used in the AI system and the explanations about features involved in the decision mechanism or the learning process. This is the kind of system interpretability that is searched for in many applications. In [18], several measures are introduced to assess the interpretability of

[1]https://www.darpa.mil/program/explainable-artificial-intelligence

rule-based systems; e.g. based on their structure, their readability and their intuitive coherence which is related to the semantic validity of involved variables. Indeed, the interpretability of a fuzzy model is usually achieved thanks to the use of linguistic terms to express the model and the relations it highlights. To measure the interpretability of a system, classic approaches are proposed based on the system complexity: its number of (fuzzy) rules, its number of variables in each rule, its use of meaningful fuzzy sets [18, 23].

The second level corresponds to the reasoning model itself and it is oriented towards the intermediate user who wants to understand how the system works, as well as the end user who must be able to access a justification of the decision. The interpretability of the construction process of the system is a crucial aim to offer to the end-user. There, it is the understandability of the algorithm that builds the system that has to be proposed. This understandability lies in the validity of the construction process that should offer a proof of the rightness of the construction and of the final system.

The third level concerns the final information provided by the AI system, either a decision or a category, which is requested to be easily understood by all parties. This important aspect of interpretability of a model lies in the decision (or output) it provides. Decisions of the system have to be u nderstandable to the end-user, thus such decisions need to be explained often in natural language to enable the end-user to receive semantically-based explanations and/or linguistic labels easily understandable.

Fuzzy models bring solutions at all levels of an AI system, first because classes or categories with imprecise boundaries are natural to intermediate and end users and they avoid the risk of an arbitrary boundary. Linguistic categories look familiar to users and easily understandable. As a consequence, fuzzy descriptions are helpful to intermediate users at the first level and to end users at the third level. At the second level, fuzzy rule-based systems and fuzzy decision trees add to the general capabilities of decision rules and decision trees with regard to explainability the flexibility and familiarity of classes with gradual boundaries. The power of fuzzy systems is not only to establish a bridge with natural language processing and automatic text generation, but more generally to authorise a flexibility and a graduality that reduces the risk of non-ethical limits and increases the acceptability of decisions by human agents.

It is well-known that a trade-off between between explainability and accuracy [17] is unmissable, and it is experimentally proved that graphical models, decision trees and classification methods are more explainable than deep learning or random forests. That is why fuzzy decision trees and fuzzy decision rules are regarded as highly explainable.

L.A. Zadeh's works are seminal for all aspects of interpretability: fuzzy sets theory, natural language representation, computing with words, computational theory of perception pertain to the easiness of interaction with all users as well as the understanding of decisions. These points are developed in the next two sections.

3. L.A. Zadeh and expressible AI

We focus on two of the facets of explainable AI: the capacity for an artificial intelligence to use words from natural language and categories with imprecise boundaries, familiar to the human agent, and the possibility for the agent to understand how the artificial intelligence makes a decision concerning him/her. They are not independent in L.A. Zadeh's framework and we begin with his attempts to deal with simple forms of natural language. He explored several directions to describe linguistic knowledge in a computable form. E. Trillas [35] gives a very comprehensive view of the progression of L.A. Zadeh's thought. We dedicate this section to expressible AI, as the aspect of explainable AI related to the possibility for the users to understand the descriptions of criteria involved in decisions, the categories underlying them and the meaning of decisions. The next section is devoted to the understanding of the reasoning part of AI systems.

L.A. Zadeh first approached the notion of meaning [41] and the possibility to treat it quantitatively by means of fuzzy sets. Regarding at this point meaning as a fuzzy subset of a universe of discourse, he defined language as a fuzzy binary relation from a set of terms, like *young* or *far* to a universe of discourse such as the universe of ages or distances, a definition that he considered close in spirit to the traditional concept of language in linguistics. Then, to show the subtlety of fuzzy semantics, he represented linguistic hedges [43], or modifiers, such as *very* or *relatively.* Indeed, the latter correspond to the essence of fuzzy knowledge representation, a symbolic rather than numerical graduality in descriptions. The three descriptions *relatively far*, *far*, *very far* are for instance gradually ordered to describe a distance, without any crisp passage from one to the other.

He introduced linguistic variables [44] as variables taking values that are not numerical, but "words or sentences in a natural or artificial language", in order to authorise linguistic or approximate descriptions of some of the features of complex or ill-defined systems. His main goal was what he called *humanistic systems*, to solve problems involving humans. He mentioned societal, political and economic problems and it turns out that economy was one of the major domains of applications in the 70s. It appears that most of the decision and control systems have a human component, be it the observer, the expert who provides the knowledge, the user of the machine automatically controlled (e.g. the passenger of a train or the worker using a smart crane), the decision-maker or the addressee of the decision.

L.A. Zadeh precised shortly after [45, 46] the concept of linguistic variable as a quintuple composed of a name, a basic set of linguistic values represented by fuzzy sets, a universe of discourse on which they are defined, a syntactic rule regarded as a grammar to generate other linguistic values, and a semantic rule defining the fuzzy sets, or meanings, representing the linguistic values through fuzzy sets. This definition has been simplified later to keep the only three first components to define a linguistic value. L.A. Zadeh was considering that approximate reasoning is one of the important areas of application of the concept of linguistic variable. He described the fields of application as artificial intelligence, linguistics or human decision processes, to cite a few. He also mentioned *truth* as particular linguistic variable, paving the way for fuzzy logic.

The last brick of his approach to natural language and meaning representation was his definition of fuzzy quantifiers [54], opening the door to fuzzy summaries briefly discussed in Section 5. Symbolic quantifiers like *most* or *a few*, common in natural language, are gradual versions of the universal and existential quantifiers and the basis of fuzzy propositions that are used in approximate reasoning.

All these concepts point out the effort of L.A. Zadeh to approach natural language and natural knowledge representation. They show that his constant preoccupation was to enable automatic systems to interact easily with human agents.

4. L.A. Zadeh and explainable decision models

The other side of L.A. Zadeh's seminal proposals for an explainable AI lies in his construction of explainable models on the basis of approximate reasoning easily understandable by human agents. L.A. Zadeh coined the term Fuzzy Logic in [47], as a fuzzy extension of a multi-valued logic, the truth values being fuzzy subsets of the unit interval with linguistic labels such as *true*, *very true*, or *not very false.* After his introduction of linguistic variables, which is the pivotal point of his construction of approximate reasoning, he was still looking for an automatic means to process linguistic variables in a way similar to the management of numerical values. The cornerstone of his construction was the introduction of a theory of possibility [50] to take into account the fuzziness of natural language and the possible values of a variable described by means of a linguistic term. Possibility distribution and possibility measure were at the basis of his first proposal of an artificial language representing the meaning, PRUF, standing for Possibilistic

Relational Universal Fuzzy [51]. The concept of truth is there regarded as a measure of the possible compatibility between a given fuzzy proposition and a reference proposition.

L.A. Zadeh then formalised approximate reasoning [52] to infer conclusions from imprecise premises, formalising the compositional rule of inference at the root of rule-based systems. He developed several means to deal with what he called "commonsense reasoning" [55] in a continued attempt to have systems work similarly to human beings.

All these efforts led him to the major concept of "Computing With Words" [58], a means to use words instead of numbers in computing and reasoning, which can be regarded as a methodology encompassing all aspects of fuzzy logic, as well as the management of fuzzy constraints. It is based on the concept of granule [59], regarded as a fuzzy set of elements drawn together by similarity.

His final attempt to facilitate the interaction with humans and to help them understand the functioning of a reasoning model was the use of what he called *perceptions* [60]. Human beings substitute them for precise measurements in their daily life: they use perceptions of distance, size, colour, likelihood, to make decisions and actions, whether precise or imprecise. Constructing a reasoning model that takes perceptions of such features into account to make decisions is certainly a good way to make the human agents understand the way decisions are made. The computational theory of perceptions proposed in [61] can be declined in various environments: to name a few, perception-based system modelling is based on if-then rules and perceptions of the values of the variables; perception-based time-series analysis considers time-series with perceptions as values. Reasoning with perceptions is then based on imprecise constraint propagation. This computational theory of perceptions shows L.A. Zadeh's concern for various aspects of artificial intelligence and more specifically a human-friendly artificial intelligence.

5. Various contributions of fuzzy systems to explainable AI

It would be reductive to limit the potency of fuzzy systems to the concepts which were explicitly introduced by L.A. Zadeh, namely fuzzy sets, hedges and quantifiers, linguistic variables, approximate reasoning and fuzzy logic, possibility theory, computing with words. The power of his seminal ideas also lies in all the concepts that were introduced by others and contribute to explainable AI. He mentioned the concept of fuzzy branching questionnaire [49] in a very preliminary form, that was developed later [9] and gave rise to fuzzy decision trees which were proposed [31, 36] as models of inductive learning accepting features with imprecise or linguistic values and decisions admitting uncertainty.

Other important concepts in explainable AI that were made possible because of L.A. Zadeh's inception of fuzzy sets, but that he did not create are fuzzy ontologies [33], as well as fuzzy and possibilistic description logic [6, 7, 25, 30, 34]. They are important knowledge representation tools that define a kind of dictionary enabling the user to understand the meaning of imprecise concepts and classes and their relations.

A major field where fuzzy propositions make an AI system really understandable concerns the construction of linguistic summaries (see e.g. [8, 12, 22, 37, 38]), which is not related to text summarisation, but to the extraction of easily understandable relevant information from possibly large numerical data sets or time series.

Another substantial concept tackled by L.A. Zadeh was the concept of similarity that he only regarded as a gradual degree of resemblance between crisp elements [42], that was extensively developed as the measure of the resemblance between imprecisely or linguistically characterised objects. This led to a natural approach of similar cases easily understandable by human agents [13] and in particular to the construction of prototypes compatible the approach of prototypes in psychology [32], starting again from L.A. Zadeh's seminal definition [53], and reinforced [26] in order to allow natural and expressible representatives of classes used for instance in case-based or similarity-based reasoning.

Before concluding, it should be remarked that L.A. Zadeh introduced the concept of Soft Computing [56, 57], whose components are fuzzy logic, neural network theory, probabilistic reasoning and optimisation methods, a concept close to Computational Intelligence. Evolutionary-fuzzy systems clearly have a role to play, in particular for the optimisation of the interpretability of fuzzy systems together with their complexity [16, 20].

6. Conclusion

All concepts proposed by L.A. Zadeh were oriented towards the interpretability and expressiveness of automated systems, through the interface of fuzzy set-based methods with natural language and by taking into account imprecise or vague categories very natural to human agents. In addition, his approach of approximate reasoning and fuzzy rule-based systems made possible the understanding by users of the way decisions are made.

His seminal works led to the birth of the Fuzzy Set research community that has been concerned since the end of the sixties with building interpretable systems and explainable models. The paradigms created by L.A. Zadeh generated very early research on the interpretability and explainability of fuzzy models [4, 5, 10, 14, 15, 18, 21, 24, 28, 29, 27].

Nowadays, the research topic on explainable AI developed in the Machine Learning community offers a natural playground for the heritage handed down by L. A. Zadeh and highlights his visionary approach of automated systems.

References

[1] Alonso, J.M., Castiello, C., Magdalena, L., and Mencar, C., (2021), Explainable Fuzzy Systems: Paving the Way from Interpretable Fuzzy Systems to Explainable AI Systems, Studies in Computational Intelligence, Springer International Publishing, 970.

[2] Alonso, J.M., Castiello, C., and Mencar, C., (2015), Interpretability of fuzzy systems: Current research trends and prospects, In K. J. and P. W., eds., Handbook of Computational Intelligence, Springer, pp.219-237.

[3] Alonso, J.M., Castiello, C., and Mencar, C., (2018), A bibliometric analysis of the explainable artificial intelligence research fields, In Proc. of IPMU 2018, Cadiz, Spain.

[4] Alonso, J.M. and Magdalena, L., (2011), Special issue on interpretable fuzzy systems, , Inf. Sci., 181, pp.4331-4339.

[5] Alonso, J.M., Magdalena, L., and Gonzlez-Rodrguez, G., (2009), Looking for a good fuzzy system interpretability index: An experimental approach, Int. J. Approx Reason., 51(1), pp.115-134.

[6] Bobillo, F., Cerami, M., Esteva, F., Garcaa-Cerdana, A., Penaloza, R., and Straccia, U., (2015), Fuzzy description logics. In Handbook of Mathematical Fuzzy Logic, College Publications, Studies in Logic, Mathematical Logic and Foundations, 58. pp.1105-1181.

[7] Bobillo, F. and Straccia, U., (2016), The fuzzy ontology reasoner fuzzyDL, Knowl.-Based Syst., 95, pp.12-34.

[8] Boran, F.E., Akay, D., and Yager, R.R., (2016), An overview of methods for linguistic summarization with fuzzy sets, Expert Syst. Appl., 61, pp.356-377.

[9] Bouchon, B., (1981), Fuzzy questionnaires, Fuzzy Sets Syst., 6(1), pp.1-9.

[10] Bouchon-Meunier, B., (2015), Interpretability, a silver lining to a fuzzy cloud, In E.F. Magdalena L. Verdegay J., ed., Enric Trillas: A Passion for Fuzzy Sets, Springer, Cham, 322, pp.223-231.

[11] Bouchon-Meunier, B., Laurent, A., and Lesot, M.J., (2021), XAI: a natural application domain for fuzzy set theory, In A. Smith, ed., Women in Computational Intelligence, Key Advances and Perspectives on Emerging Topics, Springer.

[12] Bouchon-Meunier, B. and Moyse, G., (2012), Fuzzy linguistic summaries: Where are we, where can we go? In Proc. of the 2012 IEEE Int. Conf. on Computational Intelligence for Financial Engineering & Economics (CIFEr). pp.317-324.

[13] Bouchon-Meunier, B., Rifqi, M. and Bothorel, S., (1996), Towards general measures of comparison of objects, Fuzzy Sets Syst., 84(2), pp.143-153.

[14] Bouchon-Meunier, B. and Marsala, C., (2015), Fuzzy modifiers at the core of interpretable fuzzy systems, In A.K. D. Tamir N. Rishe, ed., Fifty Years of Fuzzy Logic and its Applications, Springer, Studies in Fuzziness and Soft Computing, 326, pp.51-63.

[15] Bouchon-Meunier B., (2009), Interpretable decisions by means of similarities and modifiers, In Proc. of the IEEE International Conference on Fuzzy Systems, FUZZ-IEEE, pp.524-529.

[16] Casillas, J., Cordn, O., Herrera, F., and Magdalena, L., (2003), Interpretability improvements to find the balance interpretability-accuracy in fuzzy modeling: An overview, In C. J., C. O., H. F., and M. L., eds., Interpretability Issues in Fuzzy Modeling, Springer, Heidelberg, 128, pp.3-22.
[17] Dam, H.K., Tran, T., and Ghose, A., (2018), Explainable software analytics, In N. Sinha and M. Gupta, eds., Proc. ICSE18 NIER, Association for Computing Machinery.
[18] Gacto, M., Alcalá, R., and Herrera, F., (2011), Interpretability of linguistic fuzzy rule-based systems: an overview of interpretability measures, Inf. Sci., 181, pp.4340-4360.
[19] Goguen, J., (1969), The logic of inexact concepts, Synthese, 19, p.325-373.
[20] H. Wang, S., Kwong, Y.J., (2005), A multi-objective hierarchical genetic algorithm for interpretable rule-based knowledge extraction, Fuzzy Sets Syst., 149(1), pp.149-186.
[21] Jin, Y., (2000), Fuzzy modeling of high-dimensional systems: Complexity reduction and interpretability improvement, IEEE Transactions on Fuzzy Systems, 8(2), pp.212-221.
[22] Kacprzyk, J. and Zadrozny, S., (2005), Linguistic database summaries and their protoforms: towards natural language based knowledge discovery tools, Inf. Sci., 173, pp.281-304.
[23] Kruse, R., Borgelt, C., and Nauck, D., (1999), Fuzzy data analysis: Challenges and perspectives, In Proc. of the IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 3, pp.1211-1216.
[24] Laurent, A., Marsala, C., and Bouchon-Meunier, B., (2003), Improvement of the interpretability of fuzzy rule based systems: Quantifiers, similarities and aggregators, In A.R. J. Lawry J. Shanahan, ed., Modelling with Words, Springer-Verlag, Lecture Notes in Artificial Intelligence, pp.102-123.
[25] Lesot, M.J., Couchariere, O., Bouchon-Meunier, B., and Rogier, J.L. (2008), Inconsistency degree computation for possibilistic description logic: an extension of the tableau algorithm, In Proc. of the Annual Meeting of the North American Fuzzy Information Processing Society, NAFIPS'08.
[26] Lesot, M.J., Rifqi, M., and Bouchon-Meunier, B., (2008), Fuzzy prototypes: From a cognitive view to a machine learning principle, In Fuzzy Sets and Their Extensions: Representation, Aggregation and Models, Springer, pp.431-452.
[27] Lesot, M.J., Moyse, G. and Bouchon-Meunier, B., (2016), Interpretability of fuzzy linguistic summaries, Fuzzy Sets Syst., 292, pp.307-317.
[28] Marsala, C. and Bouchon-Meunier, B., (2015), Fuzzy data mining and management of interpretable and subjective information, Fuzzy Sets Syst., 281, pp.252-259.
[29] Mencar, C., (2013), Interpretability of fuzzy systems, In International Workshop on Fuzzy Logic and Applications, Springer, pp.22-35.
[30] Qi, G., Pan, Z., and Ji, Q., (2007), Extending description logics with uncertainty reasoning in possibilistic logic, In Proc. of ECSQARU'07, pp.828-839.
[31] Ramdani, M., (1993), Apprentissage à partir de données imparfaites, In 1er congrès biennal de l'association française des sciences et technologies de l'information et des systèmes, AFCET'93, pp.209-218.
[32] Rosch, E., (1978), Principles of categorization, In E. Rosch and B. Lloyd, eds., Cognition and categorization, Lawrence Erlbaum associates, pp.27-48.
[33] Sanchez, E., Yamanoi, T., and D'Amico, A., (2006), Fuzzy ontologies for the semantic web, In Proc. of the Int. Conf. on Flexible Query Answering Systems, FQAS.
[34] Straccia, U., (2001), Reasoning within fuzzy description logics, J. Artif. Intell. Res., 14, pp.137-166.
[35] Trillas, E., (2011), L. A. Zadeh: on the man and his work, Scientia Iranica, 18(3), pp.574-579.
[36] Weber, R., (1992), Fuzzy-ID3: A class of methods for automatic knowledge acquisition, In IIZUKA'92 Proceedings of the 2nd International Conference on Fuzzy Logic, pp.265-268.
[37] Wilbik, A., Keller, J., and Alexander, G., (2011), Linguistic summarization of sensor data for eldercare, In Proc. of SMC-2011, pp.2595-2599.
[38] Yager, R., (1982), A new approach to the summarization of data, Inf. Sci., 28, pp.69-86.
[39] Zadeh, L.A., (1950), Thinking machines - a new field in electrical engineering, Columbia Engineering Quarterly, pp.12-13, pp.30-31.
[40] Zadeh, L.A., (1962), From circuit theory to system theory, Proceedings of the IRE, 50(5), pp.856-865.
[41] Zadeh, L.A., (1971), Quantitative fuzzy semantics, Inf. Sci., 3(2), pp.159-176.
[42] Zadeh, L.A., (1971), Similarity relations and fuzzy orderings, Inf. Sci., 3(2), pp.177-200.
[43] Zadeh, L.A., (1972), A fuzzy-set-theoretic interpretation of linguistic hedges, Journal of Cybernetics, 2(2), pp.4-34.
[44] Zadeh, L.A., (1973), Outline of a new approach to the analysis of complex systems ans decision processes, IEEE Trans. Systems, Man and Cybernetics, 3, pp.28-44.
[45] Zadeh, L.A., (1975), The concept of a linguistic variable and its application to approximate reasoningpart 1, Inf. Sci., 8, pp.199-249.
[46] Zadeh, L.A., (1975), The concept of a linguistic variable and its application to approximate reasoningpart 2, Inf. Sci., 8, pp.301-357.
[47] Zadeh, L.A., (1975), Fuzzy logic and approximate reasoning, Synthese, 30(3-4), pp.407-428.

[48] Zadeh, L.A., (1976), The concept of a linguistic variable and its application to approximate reasoningpart 3, Inf. Sci., 9, pp.43-80.
[49] Zadeh, L.A., (1976), A fuzzy-algorithmic approach to the definition of complex systems and decision processes, Int. J. Man-Machine Studies, 8, pp.249-291.
[50] Zadeh, L.A., (1978), Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets Syst., 1(1), pp.3-28.
[51] Zadeh, L.A., (1978), PRUF: a meaning representation language for natural languages, International Journal of Man-Machine Studies, 10(4), pp.395-460.
[52] Zadeh, L.A., (1979), A theory of approximate reasoning, In J. Hayes, D. Michie, and L. Mikulich, eds., Machine Intelligence, Halstead Press, 9, pp.249-194.
[53] Zadeh, L.A., (1982), A note on prototype theory and fuzzy sets, Cognition, 12, pp.291-297.
[54] Zadeh, L.A., (1983), A computational approach to fuzzy quantifiers in natural languages, Computers & Mathematics with Applications, 9(1), pp.149-184.
[55] Zadeh, L.A., (1984), A theory of commonsense knowledge, In S. H.J., T. S., and T. E., eds., Aspects of Vagueness, Springer, 30, pp. 257-296.
[56] Zadeh, L.A., (1994), Fuzzy logic, neural networks, and soft computing, Communications of the ACM, 37(3).
[57] Zadeh, L.A., (1994), k Soft computing and fuzzy logic, IEEE Software, 11(6).
[58] Zadeh, L.A., (1996), Fuzzy logic = computing with words, IEEE Trans. Fuzzy Syst., 4, pp.103-111.
[59] Zadeh, L.A., (1997), Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic, Fuzzy Sets Syst., 90(1), pp.111-127.
[60] Zadeh, L.A., (1999), From computing with numbers to computing with words from manipulation of measurements to manipulations of perceptions, IEEE Trans. Circuits Syst., 45, pp.105-119.
[61] Zadeh, L.A., (2001), A new direction in AI: Toward a computational theory of perceptions, AI Magazine, 22, pp.73-84.
[62] Zadeh, L.A., (2005), Fuzzy logic - forty years later, a personal perspective, In Conference BISCSE'05. Berkeley, USA.

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