# Fuzzy Logics for Multiple Choice Question Answering

Jorge Martinez-Gil
Software Competence Center Hagenberg GmbH
Softwarepark 32a, 4232 Hagenberg, Austria
jorge.martinez-gil@scch.at

## Abstract

We have recently witnessed how solutions based on neural-inspired architectures are the most popular in terms of Multiple-Choice Question Answering. However, solutions of this kind are difficult to interpret, require many resources for training, and present obstacles to transferring learning. In this work, we move away from this mainstream to explore new methods based on fuzzy logic that can cope with these problems. The results that can be obtained are in line with those of the neural cutting solutions, but with advantages such as their ease of interpretation, the low cost concerning the resources needed for training as well as the possibility of transferring the knowledge acquired in a much more straightforward and more intuitive way.

**Keywords:** Knowledge engineering, Fuzzy Logics, Multiple Choice Question Answering

# 1 Introduction

Some of the most significant problems in many professional sectors are related to a large amount of information generated daily in terms of variety, volume, and velocity. This vast data stream creates many problems for professionals, overwhelmed by this constant flow of information that hinders their work and makes them more prone to errors. Some solutions tackle this problem, which attempts to automate routine and tedious tasks through techniques at the intersection of databases, decision-making processes, information retrieval, and natural language processing. The ultimate goal is to offer a wide range of methods and frameworks that can effectively and efficiently process all kinds of information of textual nature [10]. Our goal is to emulate human behavior and support decision-making processes in the domain context.

To accomplish so, we are employing Deep Learning models, which have shown to be the most effective in most areas where artificial intelligence can assist with process automation. On the other hand, these models have distinct flaws, such as the inability of human operators to interpret their insights or the considerable quantity of data they require for training. Because of these two factors, their usage is not as ubiquitous as their potential suggests [9].

We concentrate on the multiple-choice question answering (MCQA) problem in this work. Our goal is to accurately address the QA challenge in scenarios whereby the possible solutions are already known [1]. We presume that the production of candidate responses is a separate topic that should be explored separately. Furthermore, we want to accomplish it in a novel manner. That is, by aggregating (both automatically and strategically) fundamental methods for answering questions automatically.

There are various approaches to solving the MCQA issue. This is because a QA system might examine many resources in milliseconds to answer a query, saving many professionals time, money, and effort. QA design is frequently recommended as a good option for overcoming numerous constraints by automatically supplying answers to queries rather than providing an expert with a list of relevant items.

While most previous efforts relied on enhancing natural language processing techniques that to answer questions, academia and industry have recently begun to favor neural network-based solutions. These neuronal designs, however, have fundamental flaws:

- The final models' limited interpretability,
- The enormous number of resources required for their training, and
- The difficulties in transferring the taught models

The rest of the work is structured as follows: Section 2 presents the state-of-the-art computing methods for finding the correct test answer automatically. Section 3 offers our contribution based on the aggregation by fuzzy logic techniques of existing methods in the literature. Section 4 discusses our approach to other existing proposals. Finally, we note the conclusions and future lines of research.

# 2 State-of-the-art

One of the significant issues confronting many professional realms is that newly generated information is typically formatted unstructured [4, 5]. There is an information overload problem because of the massive amount and speed the information is made public. As a result, finding practical answers is regarded as a serious research topic that requires extensive investigation. In reality, there has been a surge in the number of solutions in recent years. In essence, this area is ideal for scientists and practitioners to verify their approaches since it fits all of the conditions that make the challenge appealing: There is a large amount of information, which continues to develop daily, yet this information frequently lacks organization.

It might be several reasons why structured data production is not feasible in a specific area. However, it is usually considered that creating such information would be excessively resource-intensive, that it would be prone to numerous mistakes, making it difficult and costly to maintain, and, last but not least, that it would be barely reusable. When dealing with various types of data, building solutions that can operate with unstructured text is frequently the standard [9].

The issue is that creating such scoring formula is far from simple. There are several proposals for working with texts currently available. Some of these suggestions are based on the concept of co-occurrence, while others are based on the distributional assumption, the computation of synonyms, etc. We worked on the past in this direction [2,3]. In principle, determining which technique will perform better is difficult. This is always contingent on the use case and environment in which they are used. As a result, our work does not assume any approach in advance, and instead attempts to construct a model that gives each of them a chance.

To accomplish so, we aim to combine techniques carefully. The most popular aggregation operations are arithmetical mean, median, and geometric mean. On the other hand, their aggregation technique is short-sighted since it fails to account for the interaction between the input variables [8]. As we shall see later, this typically indicates that these approaches do not produce ideal outcomes. As a result, researchers prefer to seek more advanced operators.

# 3 Fuzzy Logics for Multiple Choice Question Answering

Many application domains have previously exploited fuzzy logic [11,12]. We focus on training a fuzzy system to combine inputs of various types in this work. Based on expert knowledge, linguistic rules (also known as fuzzy rules) describe a fuzzy logic controller. A fuzzy rule is a structure that looks like this: IF (specific criteria are met) THEN (some consequences are inferred). However, when the expert is absent, these rules can be derived analytically. It is also worth noting that terms and fuzzy rules are entirely interdependent. One of the most fundamental aspects is that any analytically determined rules will depend on the input techniques.

An evolutionary strategy guides our learning process, which aims to identify the optimal parameters in the fuzzy system. To accomplish this, we have chosen a genetic evolution model with a low mutation probability, which allows for automated exploration of the candidate solutions while still allowing for a reduced level of unpredictable leaps in pursuit of better alternatives.

Each of the inputs corresponds to each of the methods we want to aggregate to the model. Besides, we want a single output that will give us the absolute value of each choice associated with each question. This value is expected to be between 0 (the present choice has no probability of answering the question) and 1 (the present choice has the highest possible probability of being the answer we are looking for). To facilitate the learning of a simple model to understand and not fall into over-fitting problems, we propose limiting the number and structure of the rules. Besides the terms and fuzzy rules, it is also necessary to determine the number of additional parameters such as defuzzification, i.e., how to calculate the result through a defuzzification process and the methods of accumulation for the fuzzy rules.

The ideal evolutionary strategy should allow us to properly calibrate the following parameters: the fuzzy model to be used, fuzzy sets and membership functions, the best-fitting IF-THEN rules, and the defuzzification method. Please note that we will only consider a maximum of 20 fuzzy rules in this work, each with a maximum of two priors. Furthermore, the operators AND, OR, and NOT will be permitted. Furthermore, multi-objective evolutionary approaches may always be used if a trade-off between model accuracy and interpretability needs to be modeled.

As a result, we have those fuzzy systems have better features to facilitate interpretability. Moreover, their performance can also be tuned based on IF-THEN rules. However, acquiring the knowledge is quite complicated; many parameters need to be configured and therefore, often require the help of a domain expert. For that reason, our approach is different since it allows to automatically derive the model.

# 4 Discussion

Many application domains stand out due to their characteristics and great importance and impact on society. The mainstream of research is developing new architectures of a neural nature that will allow even better results to be achieved. However, this research line has always brought problems such as its lack of interpretability, a large number of resources for training, and its difficulties for transfer learning. We have studied an alternative approach that have provided promising results without significant disclaimers in other aspects to solve these problems.

Our technique is based on generating a ranking of answers without the necessity for a data training phase. Unlike most other approaches, ours does not need the consumption of textual corpora in which the correct answer to the query is explicitly given. Furthermore, the method described here can explain the findings such that a human operator may understand them.

However, it is clear that neural networks and fuzzy systems alone have significant advantages and disadvantages. In neural networks, knowledge can be automatically acquired from data. However, the learning process is relatively slow as it requires a massive amount of data, and the understanding of the final model is very complicated. Moreover, it is impossible to extract structured knowledge, and domain knowledge cannot be injected to simplify the learning process. Fuzzy systems make up for many of these shortcomings, although they often do not achieve as much accuracy as neural networks.

# 5 Conclusions

We have seen how the design of a fuzzy controller to strategically aggregate the results of existing methods based on a set of already solved cases has achieved good results. More importantly, the model is expressed in a format of rules close to natural language that is easily interpretable. Therefore, as novel results of our work, it should be noted that we have been able to implement a strategy for the MCQA challenge that

- obtain good levels of accuracy,
- do not require training over resources where the answers are explicitly contained,
- facilitate their interpretation by a human operator, and
- makes it possible to implement methods for transfer learning and recalibration.

As a result, they can be helpful in situations where a few hundredths greater precision is not enough to compensate for the other drawbacks of neural models.

As lines of future work, we intend to explore other types of learning to train our models in an efficient way. We have designed a classic approach to evolutionary learning, but many more approaches could be considered. We want to learn more about the differences between them in this context. We also intend to study the possibility of working with multilingual solutions since it would be pretty interesting to study how these solutions behave when working with other different languages.

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