All We (and LLMs) Need Is Fuzzy: An Argument

Olga Kosheleva and Vladik Kreinovich,
University of Texas at El Paso
500 W. University, El Paso, TX 79968, USA
olgak@utep.edu, vladik@utep.edu

1. LLMs are great but not perfect

- Modern AI techniques, in particular, Large Language Models (LLMs), have achieved many spectacular successes.
- As a result, many of us have become in awe of LLMs.
- Our only problem seems to be that they are so smart that they can take over us.
- In doing this, we forget that:
  - while, in general, ChatGPT and other LLMs produce impressive results,
  - once in a while they produce results that we humans can easily see as wrong.
- This is not just complex LLMs.

2. LLMs are great but not perfect

- Several crashes of AI-controlled self-driving cars occurred in traffic situations in which:
  - even a not-very-experienced human driver
  - would know how to avoid.
- One of the most spectacular successes of deep-learning-based AI was winning over a human world champion in Go.
- However, this success was recently kind of overturned:
  - by a not-very-highly-ranked Go player
  - who beat AI by using rather simple moves, moves that most human players would know how to react to.

3. So what is missing?

- In both examples:
  - what is missing is not the ability to deal with complex situations,
  - what is missing is simple common sense.
- So, to improve the situation, it makes sense to take common sense into account.

4. A similar challenge happened 60 years ago

- How can we take common sense into account?
- This question was first asked, in the 1960s, by Lotfi Zadeh, one of the leading control experts of that time.
- He encountered another challenge: that optimized automatic controllers often performed worse than human controllers.
- The answer to this challenge seemed to be straightforward – we need:
  - to incorporate the knowledge of expert controllers
  - into the automatic control systems.
- However, it was not clear how to follow this recommendation.
- Many expert controllers were willing to share their strategies.
- However, the problem was that they did not describe these strategies in computer-understandable precise form.
- They could only describe their strategies by using imprecise ("fuzzy") words from natural language like "small".

5. A similar challenge happened 60 years ago (cont-d)

- To overcome this challenge, Zadeh came up with a technique – that he called *fuzzy*.
- This technique transforms a natural-language description into precise computer-understandable control strategies.
- This technique indeed led to many successes – although, of course, this technique is not a panacea.

6. So maybe fuzzy technique can help here as well?

- So a natural idea is:
  - to try to use fuzzy techniques to help LLMs common sense
  - or, to be more cautious, to acquire more of common sense.

7. But will this be enough?

- Probably fuzzy techniques will lead to some successes.
- But is using these techniques the right research direction?
- Very few people in the current AI community follow this path.
- This means that the vast majority of them do not believe that using fuzzy techniques will drastically improve the situation.
- And their reasoning seems to make sense.
- After all, fuzzy successes are mainly in the past.
- These successes often pale in comparison with successes of modern deep learning techniques.

8. We arrive at the following research question

- In view of the widely spread pessimism about fuzzy:
  - to convince researchers to try fuzzy techniques,
  - it is desirable to estimate how much fuzzy can help.

9. What we do in this talk

- In this talk, we use common sense (pun intended) to provide such an estimate.
- And our estimate shows that fuzzy techniques have a potential to (almost) close the gap between:
  - current LLMs and
  - ideal future common-sense-using AI-based agents.

10. What we plan to do in this talk: plan

- Our main idea is that LLMs use only crisp – precise – part of the information.
- Namely, they use the facts.
- The LLMs do not use fuzzy (imprecise) expert knowledge.
- In order to show that fuzzy techniques have a potential to close the current gap, we need:
  - first, to gauge the size of this gap – i.e., to analyze what portion of information is missing, and
  - second, to gauge what portion of information is fuzzy.
- To perform the second task, we need to recall the main ideas behind fuzzy techniques.
- Once both tasks are performed, we will be able:
  - to compare the portions and thus,
  - to estimate to what extend fuzzy techniques can help.

11. How far are LLMs from common sense?

- In order to show that fuzzy techniques have a potential to close this gap, we need to gauge the size of this gap.
- We want a general estimate, applicable for all kinds of LLMs and AIs, not just one specific model.
- Because of this desire, we selected a 2025 paper that analyzed several different LLMs.
- This paper compares them on the example of predicting prices of gold and other precious metals.
- According to this paper, the correlation between these predictions and real data is about 20% for all the LLMs.
- One may hope that:
  - if we combine different LLMs, the gap will decrease,
  - so that some of the LLMs will pick up where others fail.

12. How far are LLMs from common sense (cont-d)

- This would have been the case if the results of these LLMs were independent.
- Then by combining them, we would indeed get more accurate results.
- Unfortunately, these hopes are in vain.
- LLMs' results are highly correlated: the correlation between every two of them is about 70-80%.
- So, the $100 - 20 = 80\%$ is not just a gap of each LLM, it is a joint gap of all LLMs.

13. Let us recall the main ideas behind fuzzy techniques

- To analyze what part of information is fuzzy, let us briefly recall how fuzzy techniques work.
- In these techniques, for each imprecise property like "x is small":
  - with each possible value of the quantity x,
  - we associate a degree $\mu(x)$ from the interval $[0,1]$ to which this value x satisfies the given property,
  - e.g., to which x is small.
- The value 1 means that we are absolutely sure that x *has* the given property.
- The value 0 means that we are absolutely sure that x *does not have* the given property.
- Values between 0 and 1 correspond to intermediate degrees of confidence.

14. Main ideas behind fuzzy techniques (cont-d)

- The resulting function $\mu(x)$ is known as a *membership function*, or, alternatively, as a *fuzzy set*.
- It is well known that:
  - to process fuzzy data,
  - it is convenient to use an alternative representation of fuzzy sets – via so-called α-*cuts*,
  - i.e., sets $\mathbf{x}(\alpha) \stackrel{\text{def}}{=} \{x : \mu(x) \geq \alpha\}$ for $\alpha > 0$ and $\mathbf{x}(0) \stackrel{\text{def}}{=} \overline{\{x : \mu(x) > 0\}}$ for $\alpha = 0$.
- Here $\overline{S}$ denotes the closure of the set S.
- It is known that once we have all the α-cuts, we can uniquely reconstruct the original membership function.

15. Main ideas behind fuzzy techniques (cont-d)

- The meaning of α-cuts is as follows.
- For each α and for each $x \notin \mathbf{x}(\alpha)$, our degree of confidence that this x is possible is smaller than α.
- Thus, our degree of confidence that this x is *not* possible is larger than $1 - \alpha$.
- Thus, with degree of confidence $1 - \alpha$, we are sure that all possible values x are located in the corresponding α-cut $\mathbf{x}(\alpha)$.

16. Let us estimate which portion of information is stored in non-crisp (fuzzy) form

- From the purely theoretical viewpoint:
  - to reconstruct the membership function,
  - we need to know α-cuts corresponding to *all* infinitely many values α from the interval $[0, 1]$.
- The reason for this need is that in principle, a degree $\mu(x)$ can be any value from the interval $[0, 1]$.
- However, it is not possible for an expert to meaningfully distinguish between, e.g., degree 0.8 and degree 0.81.
- According to the psychological seven-plus-minus-two law:
  - a human being can meaningly distinguish only between 7 ± 2 different values,
  - i.e., at best, between $7 + 2 = 9$ values.

17. Let us estimate which portion of information is stored in non-crisp (fuzzy) form (cont-d)

- We want possible values to include 0 (absolutely false) and 1 (absolutely true).
- This leaves us with 7 intermediate values.
- For simplicity, it makes sense to assume that these intermediate values are uniformly spread on the interval $[0, 1]$.
- So, they have the form
$$0, \frac{1}{8}, \frac{2}{8}, \ldots, \frac{7}{8}, \text{ and } 1.$$
- We may have other values of $\mu(x)$, but these values are indistinguishable from these nine ones.
- So, without losing any expert information, we can safely assume that all the values $\mu(x)$ are equal to one of these nine numbers.
- For such membership functions, we do not need to know all infinitely many α-cuts.

18. Let us estimate which portion of information is stored in non-crisp (fuzzy) form (cont-d)

- It is sufficient to use α-cuts corresponding to the above nine values α.
- Using the above general meaning of α-cuts, we can make the following conclusions:
  - we are fully confident that the actual value is in $\mathbf{x}(0)$;
  - with confidence $7/8$, we are sure that the actual value is in $\mathbf{x}(1/8)$;
  - $\ldots$
  - with confidence $1 - i/8$, we are sure that the actual value is in $\mathbf{x}\left(i/8\right);$
  - $\ldots$

19. Let us estimate which portion of information is stored in non-crisp (fuzzy) form (cont-d)

- So, in this sense, we have nine pieces of information:
  - one piece with confidence 1 – this is the crisp (non-fuzzy) piece,
  - and eight fuzzy pieces with confidences, correspondingly,

$$\frac{7}{8}, \frac{6}{8}, \ldots, \text{ and } 0.$$

- To get the amount of information contained in each piece, it makes sense to multiply:
  - the average amount of knowledge in a corresponding statement
  - by the degree of confidence.
- For example, if our degree of confidence in a statement is 0, this means that we have no information at all.

20. Let us estimate which portion of information is stored in non-crisp (fuzzy) form (cont-d)

- Thus, the overall amount of information contained in all 9 pieces is proportional to the sum

$$1 + \frac{7}{8} + \frac{6}{8} + \ldots + \frac{1}{8} + 0 = \frac{8 + 7 + 6 + \ldots + 1 + 0}{8} =$$

$$\frac{1}{8} \cdot (1 + 2 + \ldots + 8) = \frac{1}{8} \cdot \frac{8 \cdot (8+1)}{2} = \frac{9}{2} = 4.5.$$

- On the other hand, the amount of information contained in the crisp part is proportional to 1.

- Hence, the proportion of information contained in the fuzzy part is equal to $\dfrac{4.5 - 1}{4.5} \approx 0.78.$

21. Conclusion

- What is missing is approximately 80% of the information.
- What fuzzy can bring is about 78%.
- Taking into account that these are crude estimates, we can reasonably conclude that fuzzy information can:
  - fill the gap between current LLMs and the ideal AI-based agents,
  - or at least fill in the significant portion of the bill.

22. Remaining open question

- First, what we provide are crude quantitative estimates.
- It is desirable to come up with better estimates.
- Also, the big question is how to incorporate fuzzy knowledge into LLMs.
- We still do not know how to do it.
- But the fact that we do not know how to do it does not mean that this idea is useless.
- Our analysis – presented in this talk – shows that fuzzy knowledge has a potential of filling the gap.
- So hopefully this will inspire more researchers to try to incorporate imprecise (fuzzy) expert knowledge into the LLMs.

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