The Semantic State Machine

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The current approach to finding semantic distance between words , expressions, sentences, bodies of text relies on training a model (usually based on Encoder-Decoder pair) with large volume of usually labeled data in supervised learning mode (Word Embedding, 2021), (Reimers, 2021). The problem with this approach is that it offers very few insights on how the thought processes occur internally and does not capture internal interactions necessary to improve and refine the model. This issue with these kind of semantic models is that they are not essentially based on an understanding of the rules governing the low level interactions happing inside a state machine but rather they identify and match patterns based on very large volume of training data applied to what essentially is a black box.

In order to gain additional insights we could pose the problem differently. What if we have some algorithm which *continuously* processes thoughts, thereby updating its internal state with new semantic structures created by parsing a new thought. This internal state is a representation of *processed to this moment thoughts*. When a new semantic structure is added to the internal representation of stored thoughts a set of connections are created between the new semantic structure and the internal representation (state). The semantic distance between any pair of thoughts already incorporated in the internal state can be found by exploring the connectedness between the pair of thoughts. Every new semantic structure being added to the internal representation will trigger an update of the internal state which may remove or create new connections between the incorporated in the internal state semantic structures. Thus, the semantic distance between two thoughts would *change dynamically* with more thoughts being processed and added to the internal representation. That is not surprising because the semantic distance between a pair of thoughts should depend on the context. The context of a semantic structure is defined to be that part of the internal representation which is most connected to this semantic structure. Let us call this abstraction *semantic state machine*.

The real question here is: Under what conditions the defined in the previous paragraph abstraction will evolve in a meaningful way such that the semantic distances will retain their significance and will continue to be realistic representation of the closeness of every pair of thoughts within the chosen context. Note that the context will change dynamically with processing more thoughts.
The answer to this question could be found if we choose well a set of rules:
1) converting a parsed thought to a set of internal semantic structures
and
2) integrating the newly created semantic structures with the current internal representation.

The bottom line is that it will be instructive to look into the semantic distance in this way as in the process we would get additional insights on the laws governing the behavior of these semantic structures which are the building blocks of processed thoughts. What I find curious here is that at certain level the rules according to which these semantic structures should be assembled, interact, create / remove connections, updating the internal representation are reminiscent of the laws which govern our physical world.

Meet the semantic state machine (SSM). It understands basic E language. It can recognize words, figures of speech and expressions in E. It parses thoughts expressed in basic E. It learns new words, expressions and concepts by making inferences, conjectures and hypotheses which will prove or refute using new data in some future moment.

SSM can be in one of multiple operating modes which can be refined by learning: each mode has a dominant component and supporting components. A set of components are pre-defined: for example, building inferences (problem solving) component, empirical relation discovery (intuition) component, resource preserving mode (practicality) component and custom components learned with experience.

References

Reimers, N. (2021). *Semantic Textual Similarity.* Retrieved from SBERT.net Sentence-Transformers: https://www.sbert.net/docs/usage/semantic_textual_similarity.html

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., . . . Polosukhin, I. (2017). Attention Is All You Need. *31st Conference on Neural Information Processing Systems (NIPS 2017)* (p. 15). Long Beach: Google.

Word Embedding. (2021). Retrieved from Wikipedia: https://en.wikipedia.org/wiki/Word_embedding