AGI for dummies

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Language models and how they are trained

As of 2022, the most "intelligent" AI systems are **language models** such as BERT, GPT-3, ... and their variants.

These systems are trained to understand natural language, using a revolutionary technique by **masking out** words in a text corpus and asking the AI to **predict** them. For example:

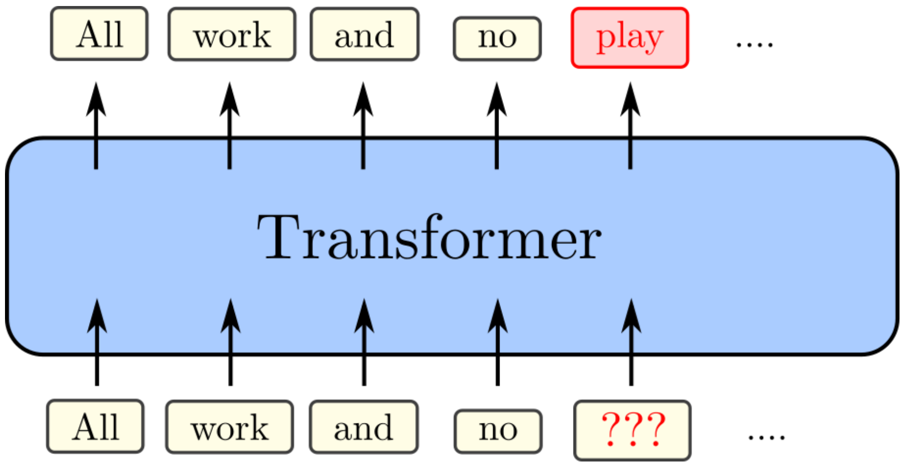
$$\begin{gathered}\boxed{\text{All}}\ \boxed{\text{work}}\ \boxed{\text{and}}\ \boxed{\text{no}}\ \boxed{\text{play}}\ \ \boxed{\text{makes}}\ \boxed{\text{Jack}}\ \boxed{\text{a}}\ \boxed{\text{dull}}\ \boxed{\text{boy}} \\ \Downarrow \\ \boxed{\text{All}}\ \boxed{\text{work}}\ \boxed{\text{and}}\ \boxed{\text{no}}\ \boxed{\text{???}}\ \ \boxed{\text{makes}}\ \boxed{\text{Jack}}\ \boxed{\text{a}}\ \boxed{\text{dull}}\ \boxed{\text{boy}}\end{gathered} \tag{1}$$

When a neural network is **forced** to make such predictions, it will gradually start to acquire knowledge similar to human's. This knowledge is stored in the (massive number of) **weights** in the neural network.

Using the masked-word trick, there is no longer the need to prepare **annotated** data to train the AI, solving one of the biggest bottlenecks in AI development.

Transformers – the most advanced AI component

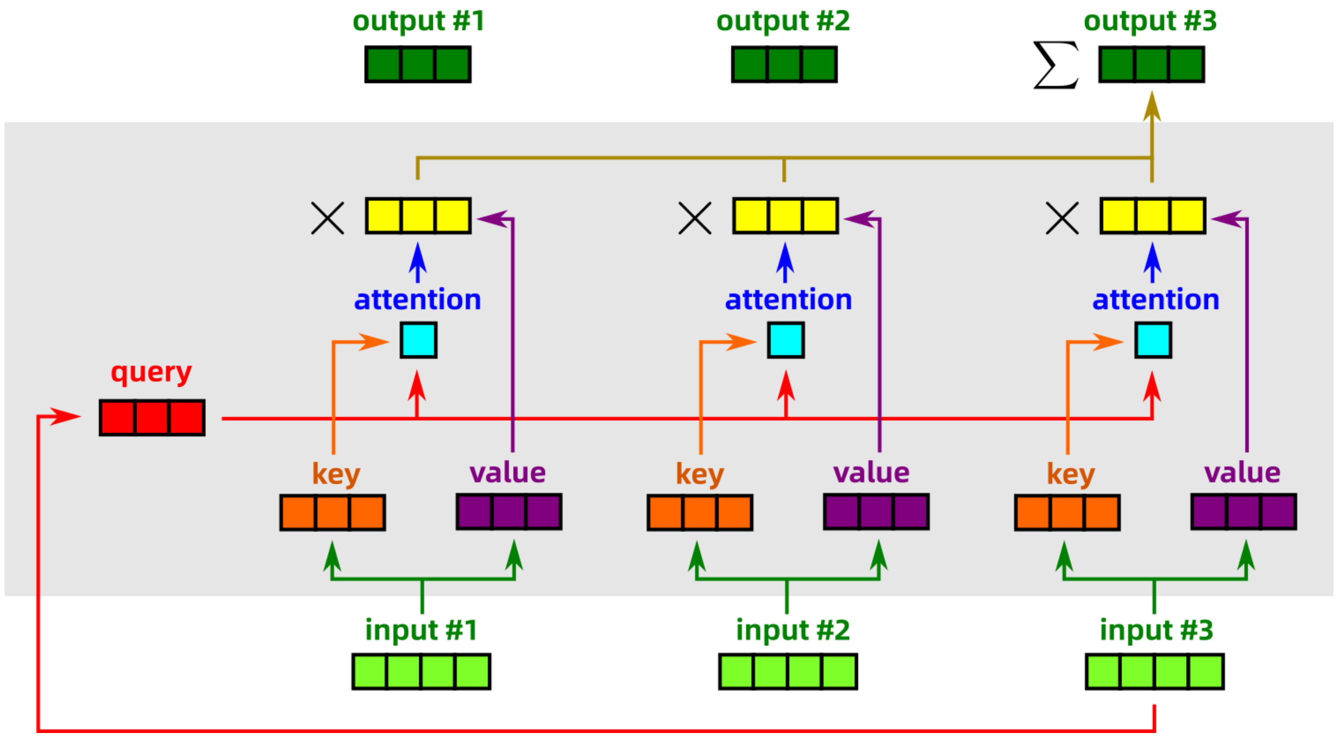
The above language models are based on a key component known as **Transformers**, invented by a research team in Google:



(2)

In principle, we only need a "fully-connected" neural network and train it to predict the masked words. But such a network without **additional structure** is too inefficient to learn the desired knowledge. One of the key ideas in machine learning is to give a machine some "**bias**" to make it learn faster. An example of bias is to "cut" some connections in a fully-connected neural network, so that it looks like partitioned into blocks.

The Transformer has an internal structure known as the **Attention** mechanism. It looks like this:



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This is not widely accepted, but my hypothesis is that the Transformer performs logic reasoning.

Logic as a form of rewriting

The following are examples of **logic rules**:

"All humans are mortal":

$$\forall x.\ \text{human}(x) \Rightarrow \text{mortal}(x) \tag{4}$$

"The father's father is the grand-father":

$$\forall x, y, z.\ \text{father}(x, y) \wedge \text{father}(y, z) \Rightarrow \text{grand-father}(x, z) \tag{5}$$

The symbol $\forall$ means "for all", $\wedge$ means "and", $\Rightarrow$ means "imply".

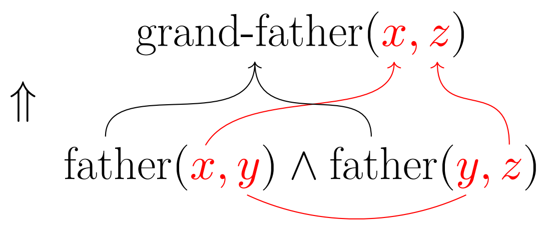
In order for the logic formulas to work, variables such as x, y, z need to be **copied** from the left-hand-side **premise** to the right-hand-side **conclusion**. For example:

$$\begin{tikzcd}
\text{human}(\text{Socrates}) \arrow[rr, bend left] & \Rightarrow & \text{mortal}(\text{Socrates}) \\
\text{human}(\text{Plato}) \arrow[rr, bend left] & \Rightarrow & \text{mortal}(\text{Plato})
\end{tikzcd} \tag{6}$$

These are "patterns" of a **rewriting system**. My hypothesis is that the Transformer is a kind of rewriting system. If we write the logic $\Rightarrow$ vertically as $\Uparrow$, it will look even more like the Transformer:

$$\begin{tikzcd}
 & \text{mortal} & (x) \\
\Uparrow & & \\
 & \text{human} \arrow[uu] & (x) \arrow[uu]
\end{tikzcd} \tag{7}$$

A more complicated example:



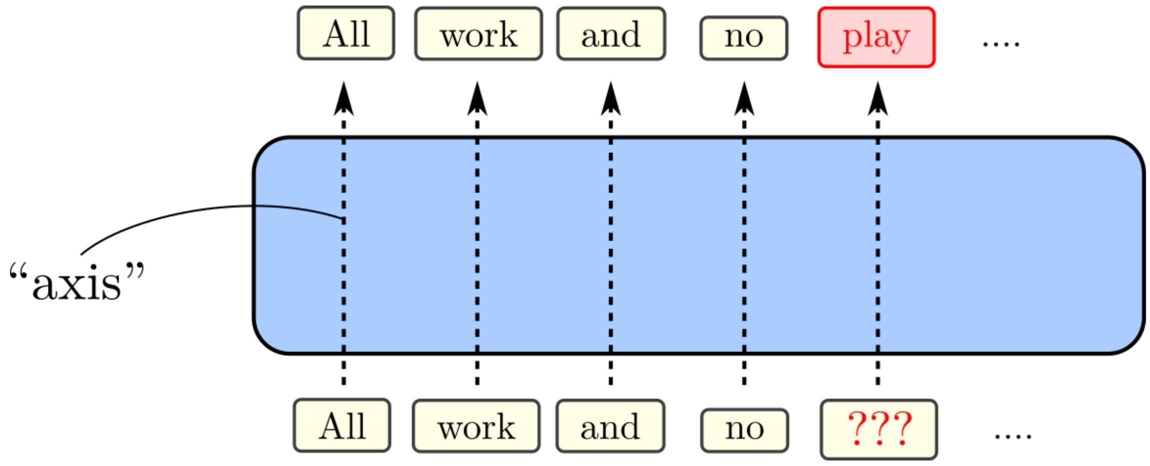
(8)

Notice that the bottom link $y - y$ signifies a requirement of **pattern matching**: the two y's must be substituted by the **same** object, otherwise the pattern does not match and the rule will not be applied.

How the Transformer performs rewriting

The Transformer's rewriting style is similar to the logical syntax above, but they differ in some details.

First, in the Transformer, each token has an "axis" for which it plays the role of the **Query**. We can think of each token as one proposition, and each token gives rise to one new proposition along that axis. So the Transformer layer takes N input propositions and spits out N new propositions:



(9)

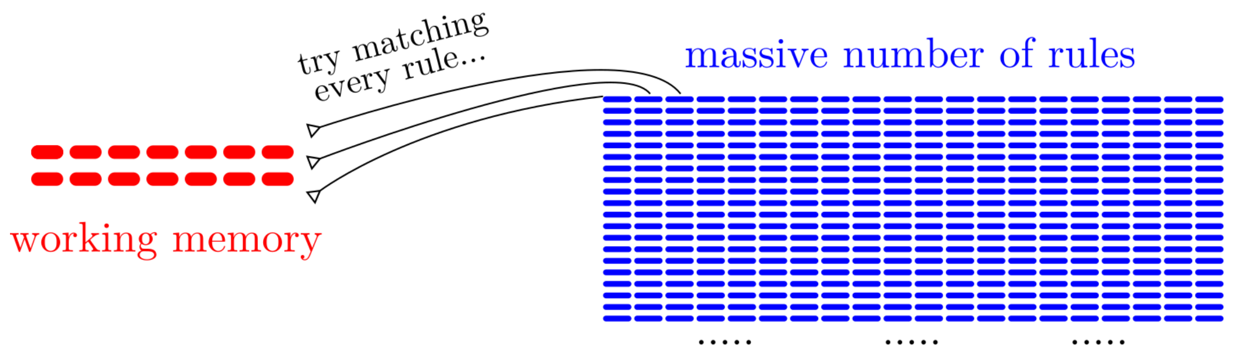
In the logic view, however, we may want to break a proposition into multiple tokens.

Secondly, in the Transformer, the Attention mechanism determines the **weights** by which the tokens combine, by summing up into a final token vector. In other words, the new token is a weighted sum of old tokens. In the logic view, a proposition is represented by multiple tokens, so we may need an alternative Attention mechanism to **move** tokens around.

Rete algorithm for rules-matching

In classical logic-based AI, **rules-matching** is a very inefficient problem that is solved by the **Rete algorithm**.

Naively, one's first idea is to try to match *each and every* rule to Working Memory items, which of course is very inefficient:



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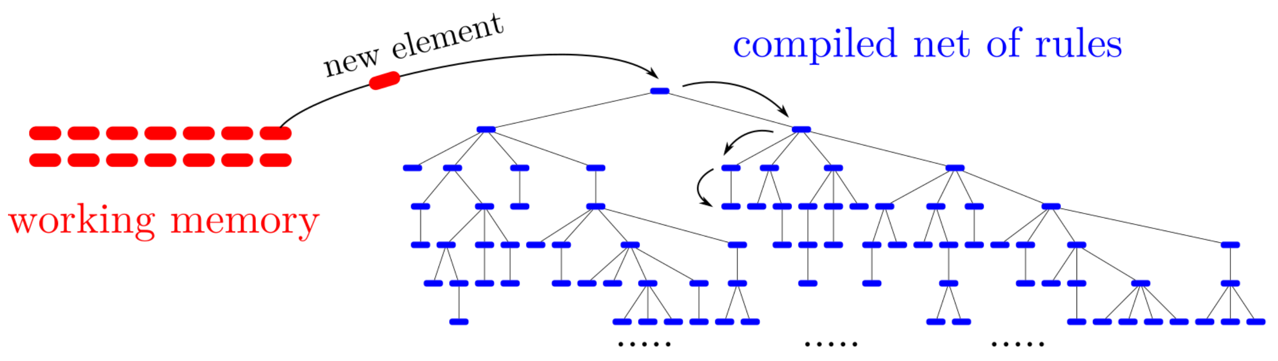
Instead, the **Rete algorithm** compiles the rules into a **classification tree**, so that each new Working Memory item is matched by "filtering" through the tree:



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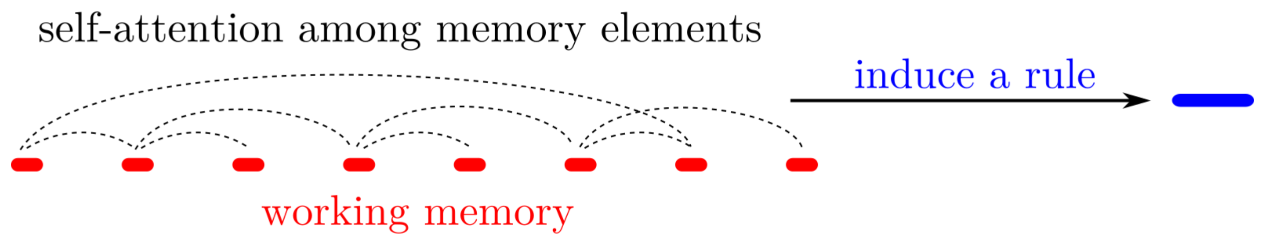
So how does the Transformer perform rules matching? It seems that rules are stored in the Q, K, V matrices. The Self-Attention mechanism is like a **message-passing** algorithm that yields a logic rule as its result:



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