Realizing Linguistic Functions via the Whole Brain Architecture Approach

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Abstract: This article argues that the whole brain architecture approach will be an advantageous way to realize human-level linguistic functions for AGI. The WBA approach aims for realizing AGI by mimicking the entire architecture of the brain. The article also gives a review of current researches in areas such as cognitive science, artificial neural nets and neural science related to the subject.

1. Introduction

This article argues that the whole brain architecture approach will be an advantageous way to realize human-level linguistic functions for AGI. The WBA approach aims for realizing AGI by mimicking the entire architecture of the brain [†]. While it regards the brain mechanism as cognitive architecture consisting of brain organs, it does not require biological fidelity, so that state-of-the-art machine learning techniques could be used for functional modeling.

Since the only being realizing general intelligence where we live is the human (*homo sapiens*), it would be reasonable to look into the human brain when one sets out for realizing AGI. In particular, for the ability to deal with (human) language is unique to the human, the knowledge on the human brain would be of greater significance for realizing the linguistic function for AGI. In recent years, the accelerated accumulation of cognitive neuroscientific knowledge and rapid advancement or researches in artificial neural nets (ANNs) have made it possible to think of brain-like cognitive architecture as the combination of functions realizable with ANNs.

The following are reasons why the WBA approach would be effective to realize human-like linguistic functions.

- We can learn from the human brain that implements the functions.
- The mechanism for the linguistic functions realized as combination of other cognitive functions should be thought as holistic architecture rather than by a piecemeal way.
- As linguistic functions are practical functions of a social agent rather than mere symbol manipulation and its realization thus would require the consideration of the entire function of an agent, when one looks into the brain for linguistic functions, s/he should look at its entire function.

2. Issues around Linguistic Functions

2.1. Learning phonemes and morphemes

Human children learn phonemes and morphemes through interaction with speakers around without being fed with them articulated. In artificial systems, it is known to be difficult to manually create and maintain proper and ever-changing sets of grammars and lexicons. Thus, it would be desirable for AGI to have language acquisition capability similar to human beings.

The issue of how symbols such as morphemes could attain their meaning is known as *the symbol grounding problem*. Humans relate linguistic expressions with exterior things by learning language in their environment. The symbol grounding for artifacts is claimed to be solved in principle, according to researches in robotics [1][2][3].

Tomasello et al. point out that the key for human infant language acquisition is the recognition of the fact that other speakers refer to some things and what are referred to by words. Such ability appears around one year of age to serve subsequent language acquisition. If the ability is necessary for language acquisition at all, its realization will be a key issue for AGI's linguistic function.

2.2. Acquisition of Grammar

Human language contains at least context-free language, which generally cannot be learned only from positive examples [4]. In addition, linguists such as Noam Chomsky argued that a certain innate mechanism would be necessary to choose a specific grammar from infinite possible ones with too few linguistic data that human children receive. As humans somehow learn language, the human language grammar must have characteristics with which a *certain* mechanism could acquire it. Some evolutionary linguists who adopt the Chomskian minimalist theory look for brain regions where the *merge*, which is presumed to be the only operation required to explain syntactic phenomena, takes place [5]. Meanwhile, other linguists such as Tomasello claim that human infants acquire language by learning usages [6].

2.3. Representation of Situations

Phrases or their semantic contents are thought to represent situations. When the brain generates a phrase or a sentence, it is thought to gather relevant information by traversing semantic representation, which may be stored in the form of an associative network, to linearize it [7]. When the brain understands a sentence, a linear symbol sequence is conversely translated to semantic representation.

3. Language Processing by Machines

In computer science, the field of natural language processing deals with human language. In a classical way, processing has been done by giving machines manually constructed lexicons and grammars. In recent years, data-driven methods, such as statistical speech recognition and machine translation with data from massive parallel corpora, have been used.

Meanwhile, research for realizing linguistic functions with ANNs or mechanisms inspired by the brain would have the following motivations:
1) to use the results of rapidly advancing ANN researches
2) to use the semantic structure emerged with ANNs in cognitive architecture
3) to realize linguistic functions in a way similar to the brain to create a human-like AGI
As for 1), ANN researches are having notable results in language processing:

3.1. Distribution analysis and semantic representation

Morphemes cluster by their occurring context (or distribution, i.e., preceding and following morphemes) and those having a similar meaning are situated in a similar place in the statistical feature space. It is known that in such a feature space, meaning can be represented as the relation among feature vectors (e.g., $X_{king} - X_{man} + X_{woman} \approx X_{queen}$) [8]. With ANNs such as Word2vec, one can make basic analyses (word embedding) for syntactic and semantic categorization of morphemes.

3.2. Syntactic analysis

It is known that RNNs such as LSTM can represent nested structure in languages (such as in XML, though it is an artificial one) [9]. As nested structure in language can be represented with the context-free grammar, by which most of the structure of human language can be described, ANNs like LSTM would represent most of the syntactic structure of human language.

3.3. Visual data and captions

Researches in caption generation for images and motion pictures and image generation from captions are in progress. Some researches in caption generation use attention mechanisms (e.g., [10]). Linguistic expressions can be generated by linking morphemes and syntax with shifting attentions on the representation of *what* there are and *where* they are with ANNs such as LSTM.

4. Language Processing in the Brain

Researches of aphasia since the mid 19th century have revealed that the Broca area (Brodmann Areas 44 and 45) is related to language generation and the Wernicke area (BA22), language understanding (Fig. 1) on the cerebrum [11]. More recently, for example, Friederici made detailed analyses of EEG during speech perception to investigate its relation with brain areas, and Hickok et al. argue that speech perception, as well as visual perception, is done in two streams, i.e., the ventral (semantic) and the dorsal (perception-motor integration) processing [13].

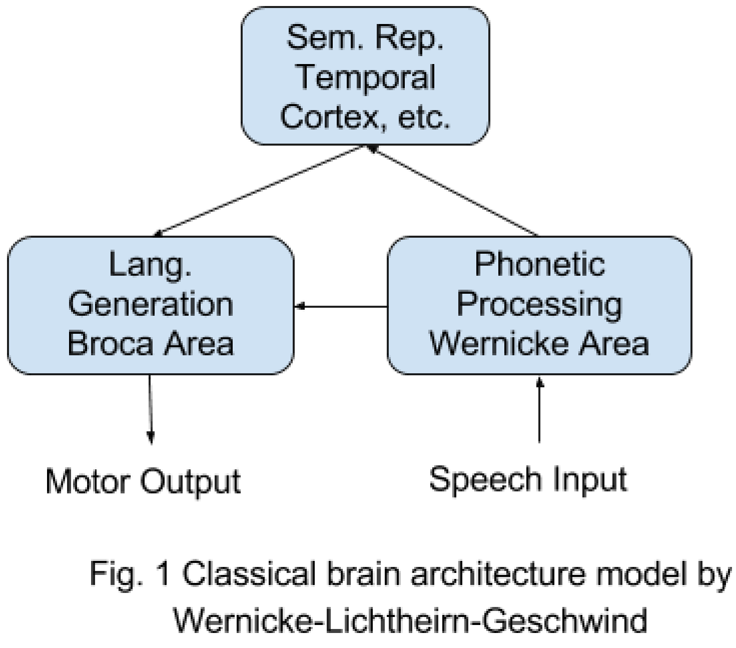

Fig. 1: Classical Linguistic Architecture of the Brain by Wernicke-Lichtheirn-Geschwind

Researches by, e.g., Friederici and Hashimoto et al. [14], have revealed that syntactic processing are at least partly dealt in the Broca area and its surrounding. In a more computational vein, Dominey has proposed a whole brain semantic understanding model combining models by Hickok and Friederici with reservoir computation [15]. While researchers have various theories on the linguistic functions of brain areas [11], engineers could profit from them for realizing functions in mind.

5. Linguistic Functions are of the Entire Brain

The human linguistic function is part of the overall cognitive and behavioral function of an individual or the entire brain. Thus, language understanding is part of recognition and language generation behavior is determined practically from the content of recognition. In the cerebrum, recognition is mostly subserved by the posterior part and the decision by the anterior part. This division of labor is largely true of linguistic function.

Characteristics unique to human language include *double articulation*, in which meaningless phonemes are combined into meaningful morphemes, *generativity*, in which morphemes are combined with syntax to form an indefinite number of phrases, and *compositionality* of meaning, in which syntactically generated phrases have their meaning according to its composition. While enough explanation has not be done for these characteristics with brain models nor ANNs, generativity and syntactic-semantic relation have been implemented by ANNs such as LSTM. Besides, double articulation is known to have a statistical solution [16].

While conversion between syntactic and semantic information with ANN has been studied, semantics for an individual does not only reside in the interpretation of images seen in caption generation, but also in perceptual changes along with action, the result of action, and the availability of things (affordance). For example, semantics (ontology) of three-dimensional objects can be derived from interaction with object through action. The representation of such multi-modal semantics in the brain is an issue for brain modeling.

Another issue is found in modeling an individual (brain) to carry out speech acts adequate for the situation. As the brain model for taking adequate action would be of that of the prefrontal cortex (PFC) (and related brain areas), one would have to build a prefrontal cortex model for speech acts (see [17][18][19] for the functions of PFC). When PFC decides action, it should gather related information such as episodic memory (of particular situations), rules, and the result of simulation, from the entire brain. With an ANN, collection and manipulation of information might be implemented by expanding, e.g., Neural Turing Machine [20]. In speech acts, when lexical, syntactic, semantic and pragmatic information has been gathered for an adequate utterance, linearization occurs as one utters. Such serialization could be implemented with a mechanism similar to those in the current caption generation.

Yet another issue is that of the amount of learning data. While many of the current ANNs use massive data for training, it is known that a smaller amount of data is used for human language acquisition (fast mapping). A method for one-shot learning is transfer learning [21] and another is episodic memory. Transfer learning requires information structure to be formed beforehand, which could be created by deep learning (or by the cerebral cortices in the brain). Episodic memory requires the hippocampus in the brain (for an standard model of hippocampal episodic memory, see [22], while computational models in this area have been debated).

6. Summary

The overall linguistic function is part of cognitive and behavioral function at the individual level, and many parts of the brain participate in it. As the functions of brain parts could be implemented with ANNs, it would be worthwhile to look at the architecture of the entire brain when one tries to create the overall linguistic function by combining them.

As we are getting a perspective of the entire issues, we expect that AGI with human-level linguistic function could be realized in the not-so-distant future if research resources are amply brought into this field.

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