The Basal Ganglia, Astrocyte-Ca^{2+} Neuronal Circuit, and Artificial Intelligence.

Real Requirements towards AI-Transformer-to-Natural-Language Interface: A Dual Mechanism Account.

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The most compelling evidence to date for involvement of the Basal Ganglia (BG) (Basal Ganglia[1] Grammar) [13, 16, 20, 27, 48] in natural language comes to us from theoretical *movement operations* (nested dependency, distant binding and trace-theory). This implication of BG overlaps with well-established evidence showing Broca's involvement with movement [39]. Dual pathways are a marked characteristic of BG insofar that in cascading down-stream neural networks, both direct as well as indirect paths affect admixed neuronal populations from multiple cortical areas [20]. A tentative proposal may suggest that any notion of duality at the subcortical level may have the ability to simulate what we know of local vs distant binding dependencies as found in Dual Mechanism Model accounts of natural language [2, 7]. A theoretical (meta)-synthesis which seeks to connect what we know of Natural Language (NL) with current trends in AI/Transformers may offer us a potential merging of what has up until now been two quite disparate underlying systems. If we assume that NL systems mirror what we find in Parallel Distributed Processing (PDP) across neural networks [20]—and via extension be applicable to any putative AI/Transformer-to-NL corollary [47]—then, by definition, some component of the PDP would necessarily entail a *capacity-state* which corresponds to *concepts, symbols and categorial rules*—i.e., *real recursive-based* prerequisites for natural language which up until now have been sidelined in the implementation of AI modeling: such symbolic/categorial rule formation transcends mere itemized-style connectionism (typically predominate in past PDP-connectionist models [50]). The question put here—given the recently discovered properties of 'non-linear' neurons and neural networks—is whether an AI/neurological model can be envisioned which incorporates said recursive properties found in NL.

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[1] Andrea Moro (pc) suggests that it may be specifically the ventral dorsal head of the caudate which makes-up the largest contribution to movement as found in natural language. I thank Michael Gazzaniga for his previous lecture and our discussion here at CSUN regarding his seminal work on brain lateralization and split-brain patients. The linguist Alec Marantz falls in that same group (USC talk). Much of my initial understanding on the language to brain corollary came from Paul Thompson, at LONI (lab on neuro imaging) then at UCLA. Studies in DMM/psycholinguistics comes from my former PhD mentor Harald Clasen (Essex). Maturational-based theories on child language come down from the work of my mentor and friend Andrew Radford (Essex). Special thanks to Tom Roeper (UMass) for our many exchanges of visits, talks, thoughts and data. Joseph Galasso: Open Science Framework: https://osf.io/8kdsa/

Moving beyond larger cortical areas to subcortical structures, many of which involve neuronal-modulate distributions at the synaptic level, this brief note—merely speculative at best, and synthesizing some of my recent writings on the topic [11, 14]—attempts to tease out what might be considered *real requirements* towards any putative *AI Transformer-to-Natural Language Interface.* It has long been sought out just how a dual mechanism model (dual-pathway) gives rise to natural language—viz., how the brain operates in *parallel* on gradient time scales whereby language input gets partitioned into two fundamentally different areas—relegating fast time-scales to *itemized learning*, and slower time-scales to *categorial procedures* [1, 19], (representing a morphological *dual-pathway* distinction associated with temporal vs frontal lobe partitions)[2]. (For contrast, recall that in traditional Recurrent Neural Networks (RNNs), input training is done *serially* via linear-sequential networks). The parallel time-scale distinction may be understood in neurological terms and extended to artificial neural networks (ANNs) whereby some components of stimuli show sensitivity to frequency-effects (which peg to Bayesian statistical modeling), while other stimuli remain insensitive to such probabilistic outcomes (e.g., 'token-item vs category' distinctions as found in natural language). In generative linguistic circles, talk of such a cerebral *Dual Mechanism Model* (DMM) [1,2] has largely been used to support maturational theories of child language acquisition [3] as well as a plethora of studies dealing with Second Language processing errors (known as 'shallow-processing' [4]), Specific Language Impairment and Autism. As evidenced by fMRI studies, the human brain indeed does seem to operate in *parallel* (over gradient time scales), first locally, and then over nested hierarchical domains [5].

Backwards-engineering these facts, we can see that such brain-imaging results support recent notions espoused in theoretical linguistics, where fast-signaling local/MERGE-operations (itemized learning) distinguish themselves from slower-signaling distant/MOVE operations (corresponding to manipulation of symbols and rules [6,7,8,20]). If a DMM does arise in the human brain, one question to ask is how to extend the analogy to ANNs, such that a dual partition can become realized at the sub-cortical neuronal-synaptic level—a level up until very recently thought to be quite homogeneous and serial in nature? Some recent research into what has become known as the 'astrocyte-neuronal circuity' suggests such a possible DMM at the neurological/subcortical level [21]. The hypothesis is that 'slow vs fast' *wave oscillations* (so-called *cortical volleys*) related to **Ca^{2+}**calcium-imaging might be one potential chemical neuro-transmitter capable of triggering such dual neuronal circuitry, suggesting a DMM at the neurological level. In an attempt to extend and tentatively match human brain-imaging to responses in ANNs, it's been reported that slower moving and perhaps long-distance single-neuron Ca2+ signals (action times: hundreds of milliseconds to tens of seconds) mimic what we see in slower non-linear/embedded recursive neuronal networks (RvNN) [11, 15] (see Squib [11] for a review of Marr's work [15] on recursive neurons). This is opposed to what we find regarding the faster time-scaling of RNNs. It is believed that this slower time-scaling, which recruit spatially distant and diversly disbursed neuro populations, is ultimately what leads to the unique nested coding which gives rise to natural language/syntax—where long-term memory storage and subsequent short-term retrieval (episodic rehearsals) activate cascading neurons across divergent networks [9,10].

[2] While reaction-times studies in language certainly show fast-to-slow response times—as in the N400 millisecond for lexical semantics (Items: Wernicke's area) vs the slower P600ms response to grammatical anomalies for functional-abstract grammar (Category: Broca's area)—this somewhat simplistic Wernicke vs Broca area split perhaps only addresses the larger cortical areas governing language. In recent research, more fine-grained analyses reveal that more of the action might be taking place at the sub-cortical neuronal levels (as this paper attempts to show), with Astrocytes Glia cells being perhaps the crucial component related to a putative dual-path synaptic interaction.

These kinds of episode rehearsals generate what has been termed Dense Associated Memory, providing the neuronal network with feedback loops thus generating recursive means [21].

The following note represents a meta-synthesis in attempting to merge together what we now know of (i) the Recursive Hierarchical Implementation (RHI) (in neuro terms so-called Recursive Neural Networks (RvNNs)) with (ii) Cortical-Glial substrates in the brain. The idea here suggests that there is a dual mechanism model of sorts in the way of astrocyte-modulations which peg to fast/short vs slow/long-wave modulations in synaptic oscillation— the former being pegged to fast, reflex-like responses [46] processed in the hippocampus, while the latter pegged to slower wave-oscillation signatures found in the cortex. The 'hippocampus vs cortex' functional distinction has been long held in neuroscience and may be viewed here to help shape a dual capacity of neuromodulation, which in turn can lead to recurrent vs recursive neuronal implementation in the brain. One way to tease out such dual capacities within ANNs is to similarly evoke classic distinctions between Old-Fashioned Artificial Neural Networks (OFANNs) and very recent discoveries in RvNN Transformers (e.g., ChatGPT-3/4, Bard).[3]

It goes without saying that human-brain computation is of an emergent nature, is of a non-linear and non-sequential order, is recursive rather than recurrent in architectural design, and, perhaps above all, is defiant to all norms of statistical learning. Such computation assumes a level of abstraction which goes beyond mere levels of external input, thus creating internal models of the outside world by means of subtle abstraction—so called Theory of Mind (ToM) procedures. These abstractions proceed in stepwise-cyclical fashion by the combining and (re)re-combining (recursively) of rules, symbols, and categories to the representational mapping onto real-world token items and events [15]. The coding of such representational mapping must include the usage of algorithmic variables (a move away from item towards category). The notion of category is of interest to us since it suggests that variables are being read off by other variables in a recursive fashion—and that such 'self-attention' (bootstrapped by *embedded theories)* may play a role in higher-order cortical processes such as learning, long-term memory, and language. The aim of computational system-science is to somehow notate these cyclical processes which take place in the brain in algorithmic/mathematical terms. Neuro Computation may not be restricted to only include feed-forward, and unidirectional flows, as attested in OFANNs, but may also support the kind of internal feedback loops which allow subtle adjustments, indicating the kind of self-attention thus far unseen in typical top-down RNNs. Linear Recurrent models seem unable to support the type of self-attention indicated by these newly discovered Transformers. The question now becomes how can we implement the RvNN mechanism biologically? Might there be any way to accommodate this dual capacity in a biology

[3] Some cognitive neuroscientists take the view that Transformers can be built exclusively reliant upon recurrent operations. If so, then what we might add to that claim is that the recursive implementation is therefore somehow part of the inherent design of the platform (perhaps hidden and part of the architecture). In other words, while recurrent models may seemingly simulate much of what is behind a full-fledge GPT-Transformer, it is our view that the necessary coding behind such high-level (natural-language like) GPT operations must be recursive in nature. While just how the recursive AnBn algorithm is implemented in the platform may be of open debate, as the matter stands, a mere RNN networks fails to have generative properties to meet what would be the real requirements behind any natural language model. Recursive A^nB^n yields embedded/hierarchical nesting [a [a [a b] b] b] (distant bindings)… while Recurrent $(AB)^n$ yields so-called linear/non-hierarchical 'ABABABA'-grammars [AB], [ABAB], [ABABAB] hence, 'ABABAB(A)'-Grammars as found in stage-1 child language acquisition [3,13]. The latter is strictly dependent on brute-force BIG DATA-calculations and probabilities, a dependency otherwise not based on structure.

which otherwise suggests a neurology to be homogeneous in nature.[4] The workaround here would be to posit, at the very minimum, at least two distinct modes of Neural-Glial function which display such a putative dual makeup. Recent studies suggest that indeed a dual pathway of Neuro-Glial-Circuit connectivity does exist (presumably at the Basal Ganglia-Caudate region [16], fn.1).

And while exactly how the brain works currently eludes us, we do know *how the brain doesn't work* [40]. The question confronting those of us working within Artificial Intelligence (AI) (neurocognitive scientist and linguists alike) is to ask how such non-linear human brain capacity can become represented within current AI frameworks. While how the brain works is still not well understood, there is an overwhelming consensus that mere 'input-to-output' strength-weighted **[ ]–[ ]** modeling (feed-forward or hidden-layer connectionism) falls well short of capturing human-like thought. In fact, all such recurrent top-down trained devices (current as well as bygone artificial neural connective networks) simply cannot capture human thought: not only are their performances dismal, they are catastrophic! [29]. What is now well appreciated is that human language is of a quite exotic 'recursive-embedded nature'—viz, a 'many to one' // 'one to many' **[[ ]]** unfolding algorithm whereby manifold of overlapping matrixes layer upon a singular event potential, and that such overlaps may in fact recursively generate a kind of 'shadowing' effect whereby the 'brightening and dimming' of any given neuro-stimulus complexity becomes part of the neural network. It is the promise of a new kind of neural network, referred to herein as Transformer, which we speak of in testing whether such modeling is brain-like in nature and is given to human-like performance. This 'ebb and flow' (brightening and dimming) of the on-line holding of memory during decision-making tasks [17], and memory rehearsal and replay during memory consolidation [18, 11] seems to activate the kind of neuronal distinctions which cut across astrocyte-wave oscillations. (Nb. What seems to be a unique feature of human thought processes is this interplay between working and long-term memory [44]. In the *declarative/procedural* model [1], an overlap of such processing distinctions may play out in what we find in natural language between lexical words (items) vs syntax (category), respectively.

In order for an AI-Language Transformer to perform similarly, its processing must have simultaneous access to both a (vertical stacking) of a list of words (a lexicon) as well as a list of sentence strings stored (a syntax). One way to do this might be to treat all sentences as unsegmented lexical chunks (i.e., as lexical items, *per se*). But this gains us nothing beyond mere item-based learning. So, while the devil is in the details regarding the real architecture behind CHATGPT/Transformer transcription, it minimally must have a dual capacity to process (i) items on one hand and (ii) a symbolic syntax on the other (See Marcus for review [28]).

This short synthesis highlights what I think are the REAL requirements behind any putative Transformer-to-Human Language (THL) interface (e.g., ChatGPT-4, Bard, or other bio-implementations towards AI). The five requirements outlined below do not represent an exhaustive list but are presented merely as pointers to what many in the cognitive sciences believe to be real and necessary prerequisites to a viable THL interface. The one analogy I provide below is that of '*Pentimento*'[5] (a kind of modulating

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[4] Despite acknowledgement of heterogeneous cortical functionality, it was always assumed that the make-up and function of sub-cortical neurons and neuronal networks were homogeneous in design and function.

[5] The notion of Pentimento is based on a Lellian Hellman poem 'Pentimento' where surface imagery my overlap and superimpose onto hidden deep-structured layers.

dimmer-effect between *brightening and dimming* which creates 'shadow' overlaps which mediate between surface (short-oscillating) and deep (long-oscillating) networks. This oscillating factor is, I believe, quite essential in determining the putative Ca2 wave fluxes correlating to (i) short-term memory (hippocampus) vs (ii) long-term memory (cortex): the latter now seemingly being related to so-called **Astrocyte** Glia cells, now widely discussed in the literature [19-22]. The idea currently being pursued is that such Astrocyte three-prong formations—*three-prong* since they don't constitute the traditional 1-1 neuron-to-axion nexus, but rather lay down an overcoat sheath (similar to myelination)—undergird relevant neuro networks responsible for human language[6].

Regarding this 'dimming effect', this would have been referred to in early connective networks as so-called 'strengthening & weakening' of weighted values. Such previously held (top-down) Artificial Intelligence (AI) networks—which tried to seek bio-relevance, originating as early as the 1940's Hebbian school of 'What fires together wires together'—has been very recently supplanted by bottom-up transformers which, being trained on a very minimum innate architecture, become not only *self-learning*, but also *self-aware* (i.e., self-attentive). Cognitive scientists like to say that Transformers are 'mysterious' in this way and rather opaque, like the human brain/mind, precisely because transformers are based on an untrained bottom-up platform. On the other hand, Old-Fashioned Artificial Neural Networks (OFANNs) are not so mysterious as their modeling is quite transparent based on the human input trainer.

Circuit Dynamics.

Some circuit dynamics which fall within the range of <millisecond> (ms) seem to control fast-reflexive and compulsive behaviors, tethered to short-term memory (e.g., perception and decision making, lexical selectivity of vocabular [23, 46]). Slower-moving synaptic changes <high-length ms range: up to lasting minutes and hours> may control long-term memory, learning and language [24]. It is this latter slow-wave which is able to seek new information against the backdrop of previously constructed embedded models [20]—the core of such embedded operations seems to be responsible for selective attention and language.

The dynamics of Connectivity suggest two main patterns (RNN vs. RvNN, respectively): (i) linear feedforward, supporting a unidirectional flow of sequential information, and (ii) recurrent, composed of positive and negative feedback loops that lead to self-sustained multiple activity patterns [22]. It is the second, recurrent dynamic which we believed, if heightened in response, may move beyond being a mere statistical tool, and rather lead to substrate codes in the brain capable of handling variables and algorithms (i.e., a recursive-hierarchical implementation in the brain). One way to look at this is to say that linear sequential feed-forward flows may indeed become superimposed (onto itself, e.g., degerming self-attention) if the right kind of neuronal circuitry is employed. The idea here is that it is the unique features of astrocytes (a three-pong glial sheath) which enable the circuitry of RNN to backslide onto itself, which in turn leads to self-attention. By self-attention, we mean the ability to read not only the input bits coded

[6] The magic number 3: it is well known in physics that measurements are complicated when three or more variables enter into measurement/calculations (similar to Heisenberg's *uncertain principle)*. Similarly, the unique 3-pronged glial astrocyte functions very differently from typical neuronal bidirectional heads as they seem to provide feedback loops necessary for approximate values/variable over brute-force statistics [15]. This may give the computational function an added feature having to do with category/variable functions.

in the representation, but also the source of coded material itself, triggering a recursive A^nB^n/RvNN computational signature [13]—namely, an RvNN operating scheme at the neuro-substrate level is necessitated by the evaluation of new information against the backdrop of previously constructed embedded information, hence a nested construct.

In the past, it has been proposed that such evaluation is probabilistic in nature [25, 26]; however, rethinking such shortcoming based on Bayesian models has led to a reanalysis of the necessary recursive implementation. Surely, natural language goes well beyond Bayesian statistical operations [43]—hence, any such crude statistical tools such as generalized linear models (GLMs) deemed worthy of governing Transformer and/or Natural Language most certainly would fly in the face of what we know of natural language (Chomsky). It is worth noting here that Chomsky often talks about the brain/language as a 'black box', even a 'ghost in the machine': we really don't know what is going on inside (the brain), how it works. This is because natural language is an unsupervised 'bottom-up' phenomenon: okey! to a certain extent 'top-down' if you consider the Faculty of Language (FL) to be 'Innately Design', but bottom-up in terms of a self-learning procedure. There is no top-down, language-specific guide to supervise the child in her language acquisition, and even if there were, we know that children go well beyond their supervised data, while at the same time never producing so-called unconstrained 'wild' grammars [27]. It goes without saying that there is no preselected labelling of language beyond the basic instruction: MERGE items {α,β}, with local vs distant MOVE options [6]. Well, the same analogy recently seems to be employed when talking about ChatGPT: We say things like ChatGPT is 'mysterious' (a black box) and that we don't really know how it works. We claim we don't know how the transformer goes about learning or correcting itself. Well, this mystery can only be maintained because there is no top-down 'software engineer' behind the scenes guiding the selection of choices to be considered. There is only the bottom-up accumulation of BIG DATA. (Nb. Though I think we do carry this analogy too far: we really DO know how GPT works—that is, if it is a model solely reliant on (OFANN) probabilities (which still seems to be the operating platform of choice these days [28, 29]).

If, on the other hand, GPT is truly a recursive design operating on variables, analogous to nature language (child language acquisition), then I accept the premise. I must point out here that in the past, GPT modelers have been extremely weary of using true rule-like symbolic procedures (such as symbolic tree diagrams) precisely because of the sticky problems imposed by an operating network reliant upon the tree diagram (top-down) as the source of linguistic data[7]. In other words, the tree-diagram itself introduces inductive biases (i.e., the assumption that the data must flow from the tree diagram, (rather than the other way around)). Recall, that in linguistics, the tree is simply a notational device (albeit physiologically real in notation); the data a tree might provide might only represent a surface-phonological string (the upper

[7] One great advantage of symbolic systems is that they are not overly depended on data size: they can work over an array of low latent variables across nested hierarchy. OFANNs and other strictly recurrent ANNs solely rely on BIGDATA in order to meet probabilistic tendencies (See [30], 'Sentence no. 4' for an instructive account of how language is not 'data dependent' (= *count every example*), but rather is 'structure dependent', a more abstract property (= *every example counts*).

spell-out, or left periphery post movement). We know that children go well beyond the data in consistent ways. If assumptions (biases) dictate that the [tree = data], say on a 1-to-1 sound to meaning, then the model will surely fall short: the dilemma is rather than acquiring new representations bottom-up, GPT modeling may simply reuse a preselected tree diagram in order to recombine the same old structure. We know that surface strings while seemingly similar in sound structure (phonology) may take on very different deep structures (whereby semantics/pragmatics are required for interpretation). In other words, a wrongly selected inductive-bias assumption which directs the data to follow a specifically pre-selected tree hierarchy (top-down) may cause a failure at interpretation (and thus prevent the learning mechanism from expanding). This is just one such problem. The best example of this is the classic textbook sentence: 'John saw Mary with a telescope': while having the same surface phonology, only one of two possible trees gives the right interpretation that it is 'Mary' (and not 'John') who is holding the telescope.

In today's Chomskyan 'Minimalist Program' terms, Merge of {α,β} [6, 7] (leading to phrase projection) is an exclusively bottom-up enterprise (though guided by top-down semantic-pragmatic sources). Such a fountain effect of top-down (Language Faculty) but bottom-up merge-based phrase projection may certainly wreak havoc for any OFANN recurrent operation. So, if the GPT operating algorithm believes it is the actual tree (top-down) which is the computation source (inductive bias), then we are in trouble. Symbolic tree diagrams are still not commonly employed in ANNs for this reason— symbols are hard to work with, not as robust as recurrent Bayesian models, and may be better suited for specific tasks (so-called expert systems).

Neural Substrates: Brain Oscillations.

The implication here is that the brain codes/oscillates (at the neural substate) at multi-levels: (i) at fast/linear levels of encoding of Evoked Action Potentials (EAP), and (ii) at slow/non-linear potentials— whereby the former could be seen as a strictly recurrent operation (RNN equivalent), and the latter a potentially recursive operation (RvNN equivalent). This means that different arrival-onsets of stimuli within millisecond intervals can impact individual firings of neurons (see (1) below). These arrival-onsets are determined by Ca2+ transients. What this means is that a singular bidirectional neuron can take on varies dynamic roles as determined by these transients. What has been uncovered is that fast reflex decision-making tasks can be as ultrafast as 10ms (falling within the range of <100ms), while that same neuron can adapt to encoding slower astrocyte wave-functions (up to minutes) when deliberation occurs (with language and higher cortical reasoning falling on the slow side, as would be expected of RvNN delivery systems). Recall, that grammatical/recursive anomalies based on recursive-systems errors peak at around 600ms (P600) [31]. Further still, we now know that short-term memory time-scales incur fast-wave fluxes (hippocampus related/RNN), while long-term memory incurs longer-spatial wave fluxes (cortex related/RvNN). The ebb and flow of pulling long-term memory up to short-term working memory (as in a temporary file for a computer) and then pushing the same short-term code back to long-term residence (as the default) constantly rearranges the actual neuronal infrastructure such that new neurological connections/rewiring have to be made [see Squib [11] for review). Given that fast time-fluxes involved with working memory have to be constantly reset (to the default slower-cortical signature), the persistent firing of ebb and flow neurological activity achieves 'exquisite tuning' of recurrent circuits [32].

Extending the analogy of probabilistic Hebbian modeling (OFANNs) to fast-wave lower-level cognitive domains, we can begin to tease out findings which show that category and variable coding (presumably at the Basal Ganglia-Caudate regions of the brain) becomes selected whenever higher-brain functions are call upon. **Ca^{2+}** (a chemical neurotransmitter) is the transient marker, with slow-wave oscillations serving higher functioning (cortex) canonical operations [33]. The marker may encode additional, external feedback-(loop) variable information to the dynamic circuitry (synergistic and/or complementary in nature [34]. Neuromodulations refer to this ebb and flow of rapid to slow oscillations of circuits whereby any reconfiguration of such chemical neurotransmitters (acetylcholine, dopamine, noradrenaline, and serotonin) can reconfigure the electrical releases of the subcortical and brainstem nuclei [19]. It has been assumed that fast **Ca^{2+}** fluctuations surrounding 'local-domain' circuitries are too anatomically fixed to be utilized for more distant, and perhaps 'global-domain' circuits, whereas slow-wave **Ca^{2+}** correspond to highly complex and content-dependent variables and may continue to have down-stream effects on other non-local domain circuitry. This same 'local vs distant' distinction is similarly a feature which shows up in natural language theories (Chomsky 1995 [6]), whereby the bottom-up phrase-projection of local/linear Merge {α,β} is then extended (superadded by extension) to a distant/non-linear MOVE operation {α {α,β}}, showing recursive hierarchy [7].

Astrocytes. Astrocytes—behaving as switches (Janus-headed gatekeepers of neurons)—have the benefit (a unique property) of not being too/overly sensitive to electrical excitable neurons. Given that their release is chemical in nature, slow percolation of firings coupled with potential cascading downstream effects can give rise to more global computations (e.g., variables & algorithms) across distant neural networks. An added feature is that astrocytes are not neurons *per se* (but rather Glia formations which serve as a sheath-like covering to neurons). This allows them to interact with a bidirectional neuron/axion in manifold ways. The nature of their three-prong tripartite-head may allow continuous feedback loops to enter into the otherwise bidirectionally-fed neuron. The unique design/function of astrocytes suggests that they may generate so-called logic gates, the kind of formal, canonical operations which may govern natural language (e.g., AND, OR, NOT, XOR, NAND-operations) [35][8]. Other factors may play a role in astrocyte global/canonical computations—viz., other interactions involving neuro-messenger molecules (such as Na+, IP3, cAMP, which work alongside Ca2+ in creating ion-based signals [36]. Such a dynamic astrocyte system has been unpacked in recent research showing an underwriting of 'movement-based' and (potential) recursive implementations, as would be found in language [37]. On this higher end of the dynamic spectrum, non-linear ANNs are increasingly being used to replace old-fashion linear (OFANNs) for machine learning. However, it is our belief that in order for non-linear ANNs to truly live up to their name—to be generative models, to manipulate low numbers of latent variable, and not be simply turbo-charged Bayesian models—their underling computational systems must approach recursive implementation, or, at the very least, be a system which utilizes both (local) linear statistics alongside (global) hierarchal symbolic 'tree-like' structures, thus promoting *hybrid systems* which simulate Dual Mechanism Models a found implemented in natural language ([3,28,29]. As far as 'natural language' goes, we know that it is the frontal cortex which is responsible for man's ability to create internal cognitive maps and representations of our external worlds. It is the frontal lobe which diverts token items (+Freq(uency) sensitive) into -Freq

[8] I would like to consider 'OF' also as a canonical operation (recursive in nature where nested expression are looked-up and 'negated' upon <NOT>, as in the expression: [an enemy [OF an enemy [is a friend]]].

categories. A buffer-zone of sorts would need to be in place to act as an interface. With this kind of ongoing work into neurological equivalence, it goes without saying that the exact nature of this astrocyte-Ca2+ interface, I believe, is quickly becoming the holy grail in understanding not only the dynamics behind machine-learning (and the like) but will also inform a more complete understanding of lies beneath natural language.

Self-Attention. It has been reported [38] that slow-wave modulations (a default mode of cortical higher function) can provide the kind of feed-back loops which can recruit self-attention of neuronal firing. In other words, this self-attention allows the evaluation of new information against the backdrop of previously constructed embedded information (a kind of mirror onto itself: perhaps not unlike what we know of actual 'mirror neurons'). It is speculated that such stimulating 'ebb and flow' between (i) feedforward down-stream effects (RNNs) followed by +/- feed-backs loops (RvNNs) lead to this kind of self-attention. Of course, there are still cognitive-science holdouts that ANN (even OFANNs recurrent RNNs) might be in a position to similarly give rise to self-attending processes. However, it is our claim that any self-attention would have to be embedded in the kind of dual processing which utilizes as one of its two forms a proper recursive operation.

Five Requirements (minimally) for AI-to-Natural Language Interface:

1. *Graceful Degradation*. Where gradient even cascading errors do not necessarily bring a system to terminal status (stoppage). While catastrophic failures (total malfunctions) are a typical feature of top-down (supervised) systems, (e.g., linear-sequential Recurrent Neural Networks (RNNs)), bottom-up self-attending RvNNs tend to allow processing to approximate in light of systems errors and noise. Humans' capacity to think on one's feet (using background knowledge, experience, content, even intuition and guesswork) are all hallmarks of the abstract/high cognitive levels of human thought.

   Top-down vs Bottom-up Processing: The ability to incorporate what has been learned in its prior knowledge. This incorporation happens at two different and distinct levels of processing and speaks to a unique ability to approximate information from the two networks—viz., where bottom-up represents environmental (bits of info) as delivered to the closest surface-interface system, but where top-down context (prior knowledge, inference) may approximate otherwise direct 1-1 bits to a 1-many scattering, putting environmental stimuli in check. The result of the two reaches a final state, referred to as a *constellation state*, whereby attractor bundle of features become calculated via *strengths* and eventually settle on an appropriate assembly of linking networks (the so-called **binding problem**). Here's a way to think about the two processes. Let's take a simple *visual cortex* scenario and apply a binding of 'item to category'- constellation: suppose you see two items: a *car* waiting in front of a *stop sign.* Ok, you say: there's two bits of neuro inputs (item) which can easily be accessed together via association rendering a 'traffic scenario' (category). The ITEM/OBJECT [CAR] fires its appropriate high-level/categorial networks of thematic and taxonomic neurons & [STOPSIGN] fires its appropriate neurons. But now, say, a third bit of info enters into the binding (a *theatrical stage*) [STAGE]. This subsequent third bit of info (item) will force new modulations, enacting different levels of binding across the constellation-states imposed on by the prior first two firings (via hundreds of back-and-forth volleys across distant cortical regions). This amounts to a new approximation inferring that this visual field is no longer a (real) 'traffic scene'—viz., that the AGENT *car* is not in an ACTION state of being *driven,* so that the neuro scheme *[AGENT + (ACTION) + INSTRUMENT]* no longer gets processed since the INSTRUMENT *stop sign* cannot deliver any thematic value. This inference will produce a new subsequent settled state (with a new bundle of neuro wiring and firing)—viz., that this is a (fake) 'staged production'. (Note how the actual visual SEM/thematic items themselves don't change, but only the *intensity* of their bound constellation of their *attractor states)*. Such modulated constellation of top-down knowledge in this way is an accumulative result of this 'dimming & brightening', 'slowing & quickening' oscillations of neural networks, pulled from local and distant multiple cortical areas [49])—deriving context, inference, and pragmatic world-understanding. The functions of *basal ganglia cortico-thalamus* connectivity seem to play a critical role in pulling these diverse areas together in settling a constellation-state [20]). In this same context, see [29] (p. 23) for how a [STOPSIGN] graffitied with stickers generates such a level of (unrecoverable) bottom-up *noise* that a 'google captioning system' mistakenly identifies it as a 'refrigerator door' covered with 'posty-notes' (since brute-force probabilities as gathered from BIG DATA algorithms pull such [flat surface objects + cluttering of stickers] to neuro-associate with American-style refrigerators). In this sense, deep learning can be very *brittle*, and not robust enough to eliminate noise in the input. In sum, top-down is not merely the sum of its bottom-up parts, but rather 'bootstraps' itself to an entirely higher/different level (a level which may altogether be disconnected from the bottom-up source). Having a 'deep-embedded theory' about how the world 'categorically' works around us, independent for the day's 'itemized' surroundings is such an epi-phenomenal bootstrap.

2. *Manifold shadowing*. The ability to create transparent-like overlaps (what I have called *pentimento effects*) at the subcortical-neuronal level. Presumably, such a dual mechanism model would have similar inner-workings to what we find in natural language (and may mimic what we find between recurrent v recursive processing distinctions). Such a dualling direct vs indirect cascading pathway model which affects/modulates admixed neural populations may play an essential role in any Basal Ganglia-Astrocyte interface system, further informing our understanding of the dualism behind natural language.

   For instance, in (1) above, while the items 'car' and 'stop sign' would bundle in local neurological domains such that the two items prime together, the third item 'theatrical stage' incurs no such local/bundled-priming and would rather trigger distant neuro-connectivity. When a distant neuronal triggering sits and overlaps onto local networks (pentimento), one can think of this as a kind of 'shadowing' (or superimposing of neurological connections). Such shadowing gives rise to neuro approximation, context and inference—all essential properties needed for any AI system to be deemed human-like in understanding. Part of this problem has been written about regarding *Binding*—viz., the capacity to link neural representations in the brain both a local as well as distant domains. Also, potential back-and-forth (volleys) between the two processing may further add to the complexity of thought [20].

3. *Short term vs long-term intermingling of synapses.* The Ca2+ fluxes seemingly are what's behind the aforementioned neuronal dual pathway. With potential analogies between local vs distant volleys as stated in (2) above, this 'ebb and flow' of neural recall—recall to working

memory/Hippocampus, followed then by reconsolidation back to long-term memory/Cortex—instigates a pruning and rewiring of neural circuitry to the extent that the oscillating patters ultimately seek out self-attentive/recursive processes (see *Dense Associated Memory*, providing the neuronal network with feedback loops thus generating recursive means [21]).

4. *Looping effects* (which require three-prong astrocyte glial cells). There is no question that perhaps the holy grail of human language has to do with such a recursive looping effect (3 above). Chomsky's Faculty of Language (FL) [42]. Hauser, Chomsky and Fitch characterize this as FLn (Narrow) which perhaps only involves recursive syntax, with LFb (broad) being relegated to everything else (phonology, semantics, working memory, problem-solving). The ability for a system to look inside of itself via embedded theories, (say, at a deep-level, or even at its architectural hidden level) and gain additional information to percolate back to surface-level inputs may be what is behind this unique process termed 'Dense Associative Memory'. Looping capacity has long been sought after as the quintessential feature separating a system of *understanding* from that of a mere system of *knowledge*—the former being a horizontal rule-based/symbolic system, the latter being a vertical/associative push-down stacking system.

   *Whereas in AI terms, FLb might be considered as operations reliant upon BIG DATA, FLn would be reliant on abstract and rule-based causal relations governed by recursive operations. Others suggest that the dual distinction can be viewed as network distinctions between auto-associator networks (FLn) vs pattern associators (FLb) [20].

5. *Sleep for consolidation* (a very bio-specific activity). As part of any biologically based *reconsolidation*, (a calming of back-and-forth volleys spread across cortico-thalamic networks) sleep becomes are overwhelming factor. I'd like to think that what makes us humans special is our capacity to sleep and reconsolidate the day's events into compartmentalized classification, too a self-attending matter at the cortical and perhaps even subcortical levels of the human brain. While dubious, there may some attempt to consider non-bio/AI analogues to sleep: computers may be capable of a 'kind of sleep' if they can parallel process both online and offline (IN SYNC), as humans do. (Again, I am personally very suspect of any real AI analog to human sleep—but the notion has been bandied-about in the literature). If indeed there's evidence of AI on/offline processing, I would count the offline part as a mode of sleep. The following is how one might go about assessing the notion of AI/computer sleep (perhaps some components of this can be instructive for us):

Note: Online AI-algorithms work with specific input/data. Such declarative/online algorithms improve incrementally as new info gets incorporated into the training/data-set. Stochastic systems with back-propagation, as used in RNNs, are a good example of traditional online sequential/incremental processing. Offline learning algorithms on the other hand work with data in bulk (i.e., all at once over an array of local and/or distant domains). Offline algorithms may often require secondary components such as generative models to support their online counterpart, enabling adjustments of the underlying algorithm. Such top-down offline learning algorithms need to be re-run from scratch at each take in order to (re)learn acquired data reallocated from previous data (and therefore may have the computational ability to infer casual relations between the two on/off-line processes). Similarly (though not necessarily as a result of off-line reasoning) humans' unique ability to formalize *causal relations* (cause-effect) has recently been found as being one of the few special properties required before any deep-learning system can be putatively claimed as having human-like reasoning skills [41, 43].

EndNote: Distant Binding from Linguistics to Neuro-computation and Marr's recursive neuron.

As an endnote, I'd like to make explicit how I think a basal ganglia (BG) grammar, coupled with astrocyte wave fluxes, might generate natural-language (NL) outcomes [45]. Firstly, let's review a few findings, tentative though they may be.

1. *Distant Binding* (anaphoric/antecedent trace-coindexing, word/phrase-level displacement, nested structures) is a well-known feature of NL syntax, and theoretical distinctions on the SEMantic level can easily be made between (i) SEM/Local associations (attributed to lexical MERGE of {α, β} in forming phrases—e.g., as found in [VP drink milk], [AdjP red apple] and (ii) non-local SEM constituencies which may cut across intervening phrasal boundaries (thus reliant upon SYN). For example, consider how sentence (a) replete with SEM survives correct processing by Broca Aphasics (BA), while the same subjects suffer catastrophic syntax failure (b) (noting that BA subjects perform poorly on MOVE-based SYN [39]):

(a) [The apple [the boy ate] is red].
(a') What is red? BA response: 'the apple' : (correct: [apple = red]/SEM

(b) [The girl [*the boy chased] is tall].
(b') Who is tall? BA response: *'the boy'. : (*incorrect: girl and/or boy = tall]/SYN

(Note: BA subjects default back to a flat-[ ] linear SEM processing devoid of any recursive SYN [[ ]]-embedding). (BA subjects process the closest item/subject of the modifier). (See [13]).

Normal functioning distant-binding would process as:

(b'') [The girl [the boy chased] is tall]. : (showing embedded hierarchy).

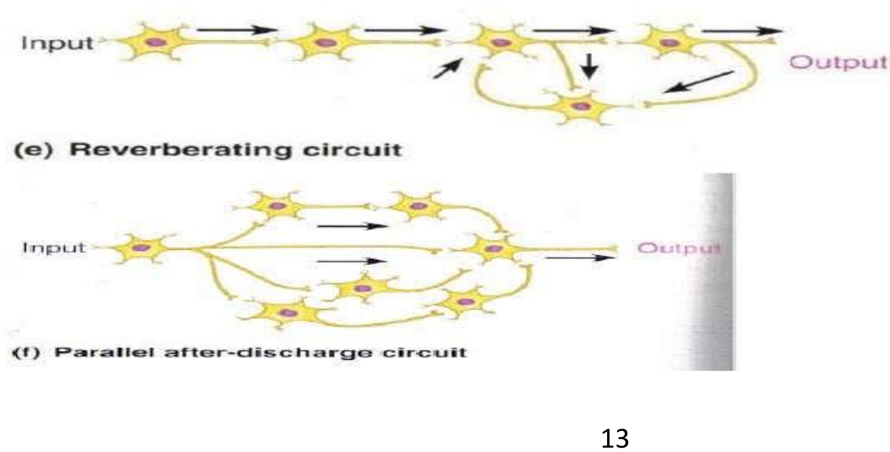
Neurologically, this can only be achieved by a recursive implementation in the brain. (See below for Marr's seminal work on the notion of recursive neurons).

Though the response in (a) seemingly shows correct embedded processing, a closer look reveals otherwise: the info in (a) is readily available based on local/surface-string info (semantics/pragmatics). This is not so the case for (b) which is ambiguous since both a 'girl' and 'boy' can be 'tall'. Hence, in order to get at the correct response, embedded/SYN hierarchy must be employed. Several studies [7, 39, 48] indicate that BA subjects have trouble when it comes to non-local & non-linear (distant) SYN-operations which rely on the ability to process embedded structures. In terms of an AI-transformer-to NL transcription, it seems universally that SEM features also encode fast and locally (as measured based on their EAP signatures).

In sum, regarding EAP distributions overall, fast-wave-related EAPs tie to recurrent SEM (RNNs) while slower-wave tie to recursive SYN (RvNNs). In child language, we see the same early distribution with recurrent/Thematic <AGENT VERB PATIENT> constructs emerging before more abstract/SYN constructs. Such neuromodulations—*back and forth cortical volleys* (between long-term and short-term memory involving of *insular cortex* [44])—have become an important factor in the ongoing research [20] and poses a problem as to what might be the 'relegating-factor' involved. Certainly, Hebbian neuro-to-neuron states make sense in providing the faster EAPs, but the question is how do these EAP signatures come to be represented at the subcortical level. One idea presented in much of the research cited herein suggests that it is the intervening astrocyte (perhaps buttressed by BG-Thalamus system [20]) which acts as a kind of buffer between SEM and SYN operations. If so, then there might be good reason to speculate that indeed a DMM becomes realized at the subcortical level, whereby lexical items (heavily frequency sensitive) take on sequential processing (as found in e.g., the verb phrase), while categorical SYN representation (reliant more so on abstract rules and less frequency sensitive) take on recursive cortico-cortical 'feedback loops which may bring together and bind divergent brain regions for consolidative processing. (Consider below). Given this feedback loop, AI/Transformers (as found with neuro circuity) can enjoy long-range dependencies between words and thematic-structured sentences.

Marr's Recursive Neurons. The late (and sorely missed) neuroscientist David Marr, I Believe, was the first to ever proposal that neuronal connections may take-on recursive-loop functions. The closest analog to recursiveness, at that time, at such micro-levels, probably related to what we thought was happening with *mirror neurons,* whereby interlocking bidirectional neuronal firings might mirror each other in forming feedback loops. The notion that the transition loops of GFPs (gestalt frame potential) from (i) short-term to (ii) long-term, back to (iii) short-term memory retrievals, which indeed increasingly adds *noise* to the neuron, nonetheless may not necessarily mean that the neuron is completely eliminated, as was at that time sometimes suggested. Rather, it is currently thought that given a recursive neuron connection, amplifications may ripple through the neuron-bundles via dendrite-axion pathways in quite dynamic ways, allowing memory-traces (pentimento) of the original stimuli (first time-step GFP) to remain, while also incorporating additional overlapping information, (sometimes referred to as 'noise'), rendering embedded feedback loops. Marr went on further in suggesting that neural networks can exhibit pure recursive functions having to do with *reverberating circuits.* Marr suggested that while synapses become excited, information packages will pass along the chain of neurons, with the last neuron in the chain being amplified or attenuated. Marr stated: 'However, the output neuron also feeds back the same output message back to another neuron, which then loops the information back to the penultimate neuron in the chain'. In Reverberating or oscillating circuits, the incoming signal travels through a chain of neurons, each of which makes collateral synapses with neurons in a previous part of the pathway. It is this 'collateral' aspect which suggests the potential for recursive reverberation. Notice how input impulses run parallel, reaching the output cell at different GFP time-steps. In parallel processing, the input travels along several different pathways to be integrated in different GFPs timesteps and regions. It is believed that it is this parallel processing which allows human neurons to take on recursive functions. Marr had always speculated that it was the *pyrimidine neuron* which held the key to such recursive looping. Coupling this with what we now know today of astrocyte-basal ganglia-thalamus function, perhaps there is a path forward in bringing AI/Transformer systems even closer to natural language. While current state-of-the-art AI/Transformers may not be there yet [29]—and there are still plenty of cognitive scientists [28] and linguists [6] willing to bet the house that we will 'never get there from here' (and I count myself amongst them)—nonetheless, we seem to be approaching a *pivotal point* in realizing a possible convergence, bringing AI/Transformers on par with our understanding of the neuro-circuity behind a brain-to-language corollary.

Below, we see Marr's original scheme for a recursive 'reverberating-circuit' neuron.



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