Squibbing Against Continuity Claims in Artificial Intelligence:

Why We Can't Get There From Here

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The Pursuit of Recursive Neurons

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The fact that the brain is made up of neurons doesn't tell us much about the underlying representational mode upon which human thought is delivered, nor does it account for whether there are analogs to computer-software procedures as found in Artificial Intelligence (AI). The arguments herein contrast two types of neuronal delivery systems (local v distant, serial v parallel) in determining how short-term memory (hippocampus) tethers to 'local-domain' **connectionist models**, while long-term memory (cortex) tethers to 'distant-domain' **symbolic models**: thus, any putative interface which seeks to model the human global thought-process must require a *hybrid model*. The dual distinction, while model-based on *serial v parallel* neuronal processing, may provide insights into human language and cognition—for instance, we now know that **Cortico-Hippocampal** interplay (distant-to-local) shapes representational context in the brain[2]. Hippocampal-Neural-net models (such a connectionist multilayer-perceptrons) seem to play an important role in the 'correlation' of local, frequency-based representations ('words')—whereby such 1-1 correlations can be readily captured by statistics—while Cortico-Symbol-manipulation is crucial to a deeper 'understanding' in spawning the necessary distant and *recursive implementation* which defines human language ('rules') [1,24]. Another way to juxtapose these two distinct systems is to speak about the role 'Items' vs 'Categories' play in human language and thought—the former *Item* being advanced by brute-force statistics which promote 'local domain' *correlations,* while the latter *Categories* promote 'distant-domain' *understand*—such as logical inferences, causal relations and abstract knowledge. We believe the human mind to be uniquely defined by the latter categorical manner—viz., human thought is representational in nature, abstract in variable usage, and hierarchically recursive. We certainly know that much more goes on beneath what meets the eye in human understanding: *broad* understanding is certainly much more than the sum of its *narrow* parts. Any well-designed AI wishing to simulate human thought must capture these unique prerequisites.

It is our belief that even in today's current state of AI modelling, the platforms often chosen to be implemented fail us regarding any attempt to truly simulate human thought [16]—and, as we propose, since there is no continuity between the functions of the two neuronal distinctions as found in the brain, there too can be no continuity between human thought and current strands of AI. In other words, *'we can't get there from here'* in assuming continuity to be of a *singular* type of neuronal delivery.

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[2] See Miller, R. (1991). *Cortico-hippocampal interplay and the representation of contexts in the brain*. Springer.

Any proposal—though speculative at best since we don't begin to know enough about the brain to really address these issues properly—which somehow can bring two operating systems together would necessarily see to it that the brain's representational format manipulate variables across two (or more) operating systems, run in parallel, whereby such overlap of the systems along with their representations creates a representational hierarchy. Such hierarchical representations as Individual vs Kind, Item vs Category, can only be captured by a unique cascading of neurological functions, which spawns *recursive-neuronal framing*, exclusively found in humans. Such neurons have been referred to in the neuroscience literature as *Auto-associative* networks given their characteristic in forming loops.[3]

First, the idea here is Not to question how linguistic elements come to get represented in the brain (what is typically asked), but rather the converse, to question how the brain comes to create these neurolinguistic elements in the first place. It may seem a subtle distinction (a flipside of the same coin), but by posing the question in this manner I believe we grant the brain a bit more agency in determining how neurolinguistic structure gets formed[4]—providing vignette analyses into (*inter alia)* brain maturational in child language, types of language impairment, and how artificial neuro-networks might best come to simulate human thought. It is this latter question which is the focus of this squib.

Second, (and perhaps a bit more unorthodox) we propose that the brain doesn't hold substantive 'local-domain' **items** (*table, chair, nightstand; buy, sell, move*, [nouns, verbs, adjectives] etc.) in its long-term memory (in the form of a declarative memory list); rather, such narrowly defined lexical items are only 'stored' as long-term 'distant-domain' broad **categories** within what we call general neuro-Gestalt Frame Potentials (nGFP). How this works is that once a selected linguistic item, say the Noun *chair*, gets called up and retrieved, it takes on a precise assigned nGFP via its associative sensory-motor cortex: it's these collaborative-associative weblinks providing select **phonological & semantic** material which provoke a **Labelling Algorithm** (LA): it is only after LA has taken place can a broad *category (noun)* turn into a narrow *item (chair).* We believe it's the specifics surrounding how the neuro-frame potential provides **semantics** which define the item. (But, of course, there's more than semantics involved: only once the word is provoked and labelled—e.g., read, (*vision*/Occipital-cortex), heard *(audio* as in speech/Auditory-cortex, Wernicke's area), or even placed within an argument structure (*context/pragmatics*)—does the word become realized. (NB We can separate phonology from semantics in this respect since non-semantic/functional words also require a phonological mapping. But it's due to the absence of semantics that a word belongs to a non-substance/function class. (Phonology is not a factor in determining lexical v functional word classes, although there are theories which postulate functional words as stressless). Otherwise, lexical items (vocabulary) when tucked away in the deep recesses of long-term memory, remain dormant in the shape of a category.

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[3] **Auto-associative** networks consist of reciprocal connections in contrast to **Hetero-associative** networks which are unidirectional. Frequent corollary activation may turn a Hetero-Net into an Auto-Associative Net (with feedforward routes and back-propagation [9]. Long & short-term simultaneous repeats create **Parallel Processing neurons** (PPns), which we believe can give rise to language**. Double Disassociation** as found between language and cognition is a hallmark for such PPn processing. **Mirror-neuron** activation may also be related.

[4] The same flip questioning has been asked regarding language-brain evolution: Does language shape the brain? Or does the brain shape language? We believe it is the brain that shapes language [33].

In a sense, precise linguistic items are (by default) generic imposters in the brain/mind—viz., only once called-up by *working memory* demands do they take on a life of their own. (NB. What is of interest to us is this 'back-and-forth' torsion between short and long-term memory synapses which are supported by 'local v distant' neuronal networks: the constant ebb and flow of *recalling* then subsequent *quieting* of an item). We know that on the language-sound side of the equation, recurring speech sequences create *phonemic symbolic & categorical boundaries* due to this torsion [32]—whereby repetitive activation and disquieting of the speech-motor cortex strengthens the bundle of neurons responsible for human speech. (See 'Speech is Special' Hypothesis, Haskins Lab [29]. This same repetitive nature mimics what we find for how 'practice' shapes neuronal-web structures in word formation, where the duality of 'recall v quieting' (dishabituation v habituation) engages the two systems in parallel. It is believed the two systems merge and come to interact in the **insular cortex**, where practice (declarative) makes responses (procedural) automatic [30]. Hence, *declarative* items come into existence through the support of a dual neuro-routing system: (i) frontal cortex (housing long-term/category memory) and (ii) motor-cortex (housing short-term/item working-memory).

On the other hand, non-substantive rule-based words are categories *per excellence*. Rule-based words such as Determiners, Auxiliaries, along with Inflectional morphologies only maintain an abstract[5], non-semantic singular neuro-routing which maps long-term *distant* memory synapses directly to the inferior frontal lobe (which provides syntax). The only *local* motor-cortex/working memory demands seemingly placed on function words is phonology (absent the role of any 'theory-internal' empty categories which may fill a syntactic slot, as hypothesized in Generative Grammar frameworks[6]). Nonetheless, its categorical nature generates a recursive algorithm which defies all computational notions of local frequency and pays little if any attention to the sensitivity of semantic items [2]. Items indeed function as little calculators and abide by 'Bell-shape' learning curves—i.e., lexical words are frequency-sensitive and governed by demands placed upon them by semantics. It is the nature of such demands and governance that captures their relative ease to be represented by connectionist-multi-layer perceptrons. (Perceptrons for all intents and purposes amount to quintessential calculators which work across an array of Bigdata). Categories, on the other hand, pay no attention to such calculative demands (thus posing *catastrophic problems* for serial, connectionist AI models). It's this permissiveness to run against statistical data which gives categories the unique property of rule formulation. (See the nature of *Default* as an example of 'rule over memory' [31]).

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[5] A hallmark of such abstract functional words is what we call Agreement relation: e.g., the determiner 'these' is [+plural] and so must agree with a plural noun (these chairs/*chair). However, such agreement is abstract. While plural inflections on nouns (chairs) can be claimed to hold semantic material (number), the agreement between the plural noun and plural determiner is highly abstract and holds no semantic qualities. If a young child utters the phrase 'two car', we can obtain from the plural determiner 'two' that a number feature (plural) spreads across the phrase, despite the absence of the phonological {s} on the noun. To double mark plurals across the two words within the same phrase seems abstractly 'redundant', and in fact many languages do not mark such double agreement (providing evidence of its abstract/parameterized nature).

[6] The most Abstract SYNtactic aspect found in natural language is AGReement: most linguistics can't really explain why it shows up at all in natural language: What it is doing there? Any formal language would dispense with it straightaway and simply impose linear SEMantics on its grammar (and they do: formal computer code has nothing like). See Chomsky for a theory which suggest AGR is solely required in human language to instigate 'displacement'—viz., a long-distant domain which consolidates the 'dual operating systems' over an array of SEM & SYN [27b].

'Tadpoles to Frogs'...or is it 'Frogs all the way down?' (Gleitman 1981).

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Let's talk for a moment about 'self-learning' AI—so-called Artificial General Intelligence (AGI). We now move beyond systems trained upon select-directed data—the question now is of continuity: whether the system can still learn despite the absence of such tailored input. Generative learning procedures must now be made available, holistically via the observation of another system (the two systems must silently talk to one another). In order for AGI to work, one system must be able to observe the other and to freely move between the two in generating a commonly perceived general-learning algorithm. Humans do this all the time: in one special case, it's what we call empathy (JG) <>

The above first expression roughly captures the still ongoing debate (held-over from past decades) regarding *child language acquisition*, and whether child-to-adult language processing is to be considered as 'one in the same' (so-called continuity: 'frogs all the way down'), or, rather if an alternative discontinuity theory is more appropriate which characterizes the child's (immature) mental state of processing to be of a *fundamentally different kind* from that of adults. The second expression deals with Cognitive Science approaches to AI and sums up one of many prerequisites which must be met in order to advance from *top-down* expertise systems—'vertical-stacking' *pushdown automata* in which data are static, **hetero-associative***,* and selectively served-up as input—to *bottom-up* 'horizontal' categorical/rule-based systems (in which data-inputs are both direct and indirect (**auto-associative**), extremely noisy, and where probabilities toward learning remain stochastic) (See fn 3).

In the realm of AI/cognitive sciences, the interesting question of whether there is some form of continuity between the two systems must be considered, notwithstanding potential disparities between performances. What we mean by continuity here is to ask whether one processing mode might be qualitatively similar to the other, and where the two might easily converge, or *bleed* into one another (as in a single mechanism model), or whether there is what amounts to 'pure discontinuity' between the two systems, to such a degree that the two divergent modes are not only incongruent but are extremely heterogeneous in nature. Proponents of a single model often dismiss deficiencies with their outcomes by wishful thinking: 'Oh, if we only had more data' (hence the panacea behind the concept of ©Big Data). For them, it's not a question of the quality of the operating platform, but rather the quantity of the data. It is in this sense that I speak of 'too-strong-a-claim' continuity. Still today, those trying to sell AI/BigData offer up similar caveats and disclaimers: the problems (if any) are due to size of data, and nothing else. For those of us who are (to say the least) 'less optimistic' and a little wearier that a single mechanism model can ever handle all the properties of the human mind/language, I am reminded of the saying (to quote Hanns Johst): 'Whenever I hear the word ©BigData, I reach for my revolver'. It is at this juncture that we see the 'AI-Winter'-chickens come home to roost.

To facilitate discussion, the two systems [7] will be labelled as <u>system-2</u> (overt: a more deliberate strain of processing) vs <u>system-1</u> (covert: a faster reflexive strain, more sporadic and intuitive in nature). (In referring to this duality, I often overlap the use of terms <u>Vertical vs Horizontal, Item vs Category</u> respectively). [3,4]

Overview

What's at play here in this squib is that we believe there are two Cortical-specific **neuro-Gestalt Frame Potentials** (nGFP) found in the human brain/mind—i.e., two framing algorithms, one juxtaposed against the other—but in which potential *recursive cascades* of the two can be formed—which must work in tandem to fully generating human thought (see Appendix-1).

1. We say potential 'recursive cascades' in the sense that a given Long-Term (LT) memory frame originating in the Cortex (CORTX) must undergo *consolidation in order to bring it online to working memory*: viz., where a given neural frame (i) first collapses, (ii) ultimately reduces just short of neural elimination, and then (iii) gets re-rewired. Due to these oscillating fluxes—from Long-Term (LT/COTRX) to Short-Term (ST/HIPPO) and back to LT/CORTX memory-nodes located in the HIPPO(campus)—neuro-frames build-up local & distant neuronal webs which exhibit recursive overlaps in connectivity. It's believed that consolidation of small amounts of prior neuro-information must carry over since original neuropathway '*memory-traces*' remain within the embedded oscillation, with each progressive nGFP *time-step* taking on amplification of past stimuli:
   nGFP transitions which produce embedded amplification.

   Long-term > Short-term > Long-term

   [GFP-LT (CORTX) **[**GFP-ST (HIPPO) **[**GFP-LT (CORTX) **]]]**

2. We say *cortical-specific* because we believe that the two processes are attributed to two specific cortical regions of the brain: accepting the traditional oft-cited (albeit imperfect) cortical-area distinctions as found between the Front-Left-Hemisphere (FLH) (e.g., Brodmann's area 45, 44 and the Temporal Lobe Brodmann area 22).

The twin nGFPs come in a variety of nomenclatures, spanning the literature ranging from morphosyntactic processing [1], child language acquisition [20], brain processing [8], and extending to Artificial Intelligence (AI) [16,18]. It is this latter point, the scope of Artificial General Intelligence (AGI) in particular, that I'd like to address in this squib. (NB. Of course, and what is the very rationale behind writing the present squib, it goes without saying that not every cognitive scientist/linguist agrees with the necessity for a dual model, as demonstrated by those who claim that a *single mechanism model* can suffice to explain both human language and AI computation [5, *pace* 8,16]. Such a single mechanism model, one would think, might be buttressed and gain favor by the notion that since there is only one single 'Off-On' binary functor behind the neuro-mechanism in the brain—viz., the functor that 'wires and fires together' [6] based on a network of pulled associative means—then the default assumption, one would guess, should be to promote the same single model: 'How the brain goes, so too goes AI' (and natural language for that matter). In fact, much of the impetus behind the pioneering efforts of AI in the latter part of the last century (1950-1990's) was that the modelling of such straightforward input-to-output schemes were (so they thought) well understood. And so, the essence of AI research was to simulate in artificial-electronic ways what we knew of the brain: 'What-goes-in-comes-out' models (sometimes referred to as 'Plug and Play') were all the rave of the day. It has only recently come to light that such simplistic 'plug & play' models have been questioned as being unforgivably naïve, with consequential catastrophic failures washing-up in its wake [16,18,21].

As we now know, the 'brain just doesn't work that way' [22 *pace* 26, 27,28]: there are roughly 150 different areas of the brain divided between the two hemispheres, each of which houses very specific types and signatures of neuro-glial-cell formations—the number and unique function of these precise glial-cell functions are still largely unknown and rather mysterious to us. It's no longer enough to cite the four or five traditional neuron-types, such as sensory, motor, pyramidal, interneuron, etc., but we must in addition begin to realize that there are individual 'fingerprints' to these bundle of neurons which are responsible for unique (and perhaps mysterious)[7] architectures which shape, *inter alia*, circuity of movement (e.g., long v local distance connectivity, serial vs parallel processes), orchestration, transcription-factor expressions, etc. The sheer number of cortical neurons could be visualized as follows: say, in a randomly selective minimal slice of 1,000 neurons per every $0.5mm^2$ of cortical surface, the minimal capacity of every one neuron would be the connection of nine hundred million synaptic links per same cortical space. This amounts to a 1,000-neuron connection to 900,000,000-synaptic ratio within the cortical space of $0.5mm^{2.}$ In addition to this, we believe the ratio of glia to neuron ranges to approximately 9 to 1. And further still, merely citing these astronomic factors doesn't serve us in understanding just how specific neuron-to-glia cell tandems work in orchestration throughout global human thought-processing.

Two Systems (nGFP). Let's refer to these two GFPs as meeting the criteria (using computer-software metaphors) for either: (i) a specified top-down algorithmic system, or (ii) bottom-up system. These two systems [7] overlap with what we know of the processing distinctions between *Items (Words) vs Categories (Rules*) in language [1], and *Declarative vs* Procedural in knowledge [8] Ullman). Let's take each in turn:

1. (System-2). The first most primitive nGFP algorithm (system-2) is said to be 'top down' in the sense of what is often understood in the cognitive science literature as *pushdown automata memory.* This type of GFP pertains to context-free grammars which obey strict criterion for what can and can't proceed to enter into a given frame. It's called pushdown because the algorithm is unidirectional in memory, where the last (old) piece of information gets pushed out as new information comes in, like a vertical stack. New relevant information is entered from the top, as prescribed by the 'fine-tuning' of the frame criteria, with older information being removed. Fine-tuning is essential in sharpening the conceptual frame: (think of it as a focusing mechanism). This is what we find of *Declarative*, explicit knowledge-based processes.

[7] Noam Chomsky often refers to such Mysteries as 'Hopeful Monsters', which can only be rescued by some 'innate blueprint' of design. A young child's ability to generate a recursive grammar is one such example: https://www.philosophysciencehumanitiescontroversies.com/listviewdetails.php?id=913879&a=t&first_name=Terrence%20W.&author=Deacon&concept=Hopeful%20Monsters

Regarding the back-and-forth retrievals of memories, the signaling for the move (as regulated by the thalamus) from the cortex (long-term memory) to the hippocampus (short-term memory) may help to fine-tune and sharpen memories over time, whereby the new neuropathway rewired in the process may generate new gestalt frames for the memory. This is not to say that a given memory *fossilizes* by getting better or stronger due to such repetitive retrieval action: in fact, memories seem to weaken and reduce over time due to these same processes, so much so that what were the strength of our earlier memories may now become hostage to newer rewiring, rendering old memories delusional to newer perceptions. (See system-3 below). Nevertheless, researchers now observe that such new information, such as new experiences, activate old neurons in the hippocampus that express two Genes, Fos and Scg2—these gene expressions allow neurons to 'fine-tune' input from interneurons. Within the gestalt parameters of the frame, defining material comes more and more into focus. The static nature of such GFP stacking attributed to pushdown memory allows the concept to avoid otherwise noisy and stochastic background interference. In natural language, this type of GFP is what *generates substantive 'Lexical Words' (Nouns, verbs, adjectives), List of Items, Image/Iconic Memory, Declarative Knowledge*, *Vertical Stacking, etc.*

The interesting criterion for such an algorithm is that the frame must stay consistent, despite this ebb and flow of old-to-new information. One way to think about pushdown automata frames is that only a certain amount of information can be stored within the parameters of the GFP. There is thought to be a *threshold* that can be reached which then forces a decision: either the previously held old/irrelevant information must be pushed out (as there is no room for it), or, if the info is still deemed essential, then a second frame must be reconstructed circumventing the first. This seems to be the case with *categorization* found in natural languages—viz., where one frame reaches its pushdown-memory threshold, another frame must be recreated to take-in the framing spillage.

In a similar manner, consider what happens in natural language when we move from 'Item to Category', (also seen as a move from system-2 to system-1). Items are pushdown automata memory GFP *per excellence*. For example, for items such as [*tables], [chairs] and [nightstands],* while each item-frame maintains its respective GFP algorithm, it may become over-extended by another matrix frame we call [*furniture […]].* In fact, there may be something to the notion, at least found in natural language, that such categorization poses problems for pure pushdown-automata systems, and where extremely non-congruent *embedded recursive* structures may need to take their place and be implemented (recursive embedding being referred to here as a bottom-up rule-based GFP (system no. 2). 'It does seem that the need to incorporate more and more sophisticated rules which go into categorization has led to extensions which make the resulting device somewhat more difficult to relate to neuronal structure' [9]. I suggest that categorization gives birth to system-2, which then becomes fully manifest in recursive embeddings:

[Category [items………………………..]] (= recursive embedding)

a. [Furniture [table, chair, nightstand]]

b. [Vehicle [car, train, boat, plane]]

A personal note: I have a long-held belief that the evolution of human recursive/categorial rule-formation as exclusively found in human language was/is a result of such **over-spillage** of 'Items into Categories'. In other words, the move from system-2 to system-1 facilitated language. Perhaps the shift was forced upon us early homo-sapiens (Cro-magnum), some 40-60KYA (thousand years ago) by our insistent increase of memory: once the vertical stacking of system-2 pushdown memory of 'Items' became increasingly over-loaded, a second system-1 which provide the algorithmic ingredients for 'Rules' emerged. The famous paper by George Miller [10] entitled *The magic number seven, plus or minus two* I think represents just one kind of a constraint/parameter which might go into the framing problem as posed by pushdown memory—once memory is overloaded, we seek out rules. '*From overabundance of items comes categories' sound just about right to me*).

Other constraints placed upon gestalt framing would be space/time constraints (such as speech-phonology, e.g., in the word 'spay' one can't utter phonemes /s/ and /p/ at the same space & time), labelling constraints (such as Saussure's 1-to-1 / sound-meaning association as arbitrary but necessary), linguistics structure-dependency, (language structure is not positional)[8] etc. Regarding specific neurons in the brain, researchers are now looking into how the pattern of connections between neurons might constrain how information flows through neural circuits (i.e., how frames are made). Following this line of thought regarding frame constraints on memory, as a thought-experiment, consider the following: Let's say you have seven books [items] on a shelf. To recall their sequential order as they sit on the shelf is quite easy: (with a small amount of items memory serves just fine). Now increase the items to seventy thousand books: to recall their order would be impossible if solely using pushdown memory. However, if you utilize a symbolic rule (such as the library of congress classification), one can easily know the relative place for each book.

[Library of Congress [Book-1,2,3…]] = [Rule/Category [Item…]] = recursive embedding

The question for future neuroscientists is to seek out how and where these recursive rules get encoded within our neurons, as observed in transcription-factor expressions.[9]

2. (System-1) The second, most recently evolved species-specific algorithm involves our ability to override local environmental stimuli and to proceed from inward intuition. For example, when we perceive data which run counter to what we know of the world, we can quickly avoid it. We have no idea how we do it; it just happens. The ability to use this fast form of native, tacit knowledge to override otherwise stimuli right in front of us suggests that this thought-process is not of a step-by-step overt and analytical kind, but rather is opaque and part of our subconscious, inner awareness. This processing is covert

[8] An example of how language is structure-dependents and not positional can be witnessed by the simple test in considering the nature of the final /s/ in the words 'fix' /fIks/ vs 'speaks' /spiks/, showing internal structure of /s/ in [fIks] as part of the stem [__s] vs /s/ in [[spik]s] as recursive inflectional affix [[ ] s]. Even though the {s} for both words are located in final 'position', the two maintain different 'structure' (lexical v functional respectively). [23a].

[9] FOXP2 has been one such gene candidate for language evolution (though the verdict is still out on that): a better bet is that many cascading gene-expressions are involved in establishing human recursive language.

and fast, and if it informs the basis for some decision, the choice provided by system-1 is usually correct. (If you must decide on something, the best probabilistic outcomes in the norm seem to arise from your first, fast intuition: over-thinking a thought, over-analyzing an action or performance often leads to bad outcomes: as the saying goes: *Just do it*!) [7].

In sum: system 2 is a deliberate and conscious step-by-step process of thinking, while system 1 is automatic. This same distinction between the two systems equates to what we find regarding *Declarative* (system-2) vs *Procedural* (system-1) knowledge [8]. As an overlap to these distinctions, the terms Vertical (as in stacking) vs Horizontal (as in spreading for rules: x + y = z) respectively have also been used. (See Galasso [4]). *Most importantly, we may begin to define the qualitative 'species-split' found in our last rendezvous between pongid and homo lines some 6MYA (million years ago) by addressing the evolutionary emergences of the two systems—viz., by assigning a 'system-2' processing to higher-order Bonobo Chimpanzees primates, and assigning system-2 (as a recursive design) to human-specific cognitive processing, presumably having evolved late on the scene (as recently as 60 KYA).

The upshot of this discussion thus far regarding the shift between the two systems is that we believe it doesn't represent a traditional form of continuity (albeit, of course, on a mere material basis, the same brain is involved with the shift)—namely, one system does not (cannot) bleed into the other. The 'over-spillage' of system-2 we talk about above which creates system-1 must be of **a categorically different order.** We believe there can be 'NO Bootstrapping' involved (as the term 'bootstrapping' is commonly understood) which derives a newly formed system-1 from out of an archaic system 2. The strong discontinuity claim would have it that the latter system is of a qualitatively different kind. How the brain/mind does this discontinuous paradigm shift is still beyond our understanding of how the brain works. One idea, in line with those who wish to promote notions of *quantum effects* in the brain [11, 12], is to speculate that perhaps there are certain bundles of orchestrated neurons which can work together to form recursive loops [34], that is 'neurological recursive loops', which render a kind of *dreamscape* towards mental processing (the hallmark of system-1).

Again, I say dreamscape as a way to include these loops as 'Alice-in-Wonderland-like', creating *Dreams, Intuition, Imagination, Music and the Arts, Wordplay, Nonsense*, and more seriously *Religion, Ceremonial practices/Taboo*, (as well as the ability linguistically to shift from a public objective language to a private inner and subjective language—a language which is said to escape all antecedence of Darwinian biological pressures) [27b].

Note: In short, the idea here is that it is not enough to simply assert that the more excess data and items are forced through a pushdown automata channel, beyond its threshold, the more likely categorization will appear. There must also be some *off-ramp*, waiting in the wings (if you will), perhaps of an innate design. A 'materialist reductionist' stance, (or *eliminative-connectionism* which promotes a single mechanism model [5,13]) would be to claim that since the *same* brain/neurons are involved (even if a dual system is granted), then there must be continuity with no off-ramp.

On the other hand, if it were only owing to this mere excess in size of (external) environmental data which forced an (internal) 'Item to Category' shift in processing, then why should this shift be exclusively of a 'species-specific' kind, as other higher-order primates are surely as likely as us to encounter newly perceived framing-data beyond given thresholds, as borne out in their environments? No: This can't be the explanation. What allows for the data to grow, both in quantity and in quality, within our own species, rather suggests some innate *off-ramp machinery* giving rise to its formation: (a Top-down, non-Darwinist account given that no bottom-up biological pressure seems to trigger the change). And here comes the discontinuity claim: this new, innate mechanism is completely untethered to lower-level cognitive schemes. In linguistic terms, this constitutes a pure 'double disassociation' between cognition and language. But beyond these two systems, which overlap neurologically between local-short term v distant-long term memory[10], we can speculate that transitions between the two provide quite important **feedback loops**. In recent studies, such feedback loops may be understood in the following manner.

Feedback loops arise from movement between system 1 & system 2 (= system-3). (See Appendix-1)

System-3 (interplay). As it turns out, the two systems don't work in a mutually exclusive manner. In fact, both may be simultaneously excited. One question to ask: How does such an interplay work?

Let's speculate on this by examining this Procedural/Long-term Memory (system-1) vs Declarative/Short-term Working Memory (system-2)—an interplay referred to in neuroscience as **Memory Reconsolidation**. Here is one instance of how such an interplay might work in creating feedback loops. It has to do with memory retrieval (perhaps an interplay unique to our species). Every time we retrieve a long-term, stored memory pulled from the cortex, and surface it to our short-term working memory in the hippocampus, we in fact destroy that memory's connection. True, the memory trace may remain pegged, say, to an assigned sensory neuron, remaining cortex *in situ*, but once we recall it 'locally' into working-memory service, the 'distant-bound' neurons largely get pruned (which later must be rewired again in a slightly different fashion, as the neurons have incorporated newly acquired 'noise' picked-up along the pathway of the neuro-transition).

The 'local-bound' working memory neurons, found in the hippocampus (a more local connection) are activated, perhaps allowing us to speak e.g., a word (phonology), remember an image (vision), etc. But once performed, the concept must be rewired and stored back to the cortex via new neurological pathways. In other words, by remembering something, we actually 'weaken' it by adding additional neurological noise picked-up in the transitive connection. Just to restate: the so-called *noise* is picked-up along the way due to the many distinct hetero-areas of the brain which become simultaneously activated (interplay) along the orchestral pathway of neuronal connections (e.g., movement/motor control regarding speech/mouth movement (motor-strip area), vision (optic region), auditory regarding speech (temporal lobe/auditory cortex), emotion (amygdala), etc. This ebb-and-flow of recall—(i) from storage in long-term, (ii) to retrieval and performance in short-term working memory, (iii) back to long-term storage, with potential intermediate interplays (involving the thalamus, and insular cortex)—forces the potential for recursive neuro-connections which must accommodate and consolidate the added noise. (Interplay here is seen as a kind of rehearsed *practice*).

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[10] We acknowledge here two distinct types of neurons and glia-cell formations: one which carries out local firing (short-term memory associated with the hippocampus) and another which carries out distant firing (long-term memory associated with the cortex).

In one sense, the continuous interplay in this manner for look-up retrieval of a given singular thought may increase neuro-recursive pathways: while old neuron pathways get reduced, new pathways form, rendering the ‘frame-of-thought’ (nGFP) to include *embedded neuro bundles*. Of course, this is speculative at best [14a], but the idea here would be that *practice over time* creates neuron bundles which may have qualities similar to what we find in *mirror neurons*. ‘Practice doesn’t just make perfect’, as the old adage expresses, but rather ‘*Practice creates mirror image’*. Mirror neurons have been a hot topic over the past two decades, looking into whether higher-order primates (Bonobo chimps) too have access to mirror potentials. It is in this sense that subtle mimicking, a highly developed human skill, has become a benchmark for higher-order thought processes. In several recent studies, Chimps consistently demonstrate an ‘inability towards subtle human-like mimicking’ [14b].

One piece of solid evidence that suggests that the ebb-and-flow of recall establishes recursive neuronal framing is to examine what actually takes place in the enfant’s brain. At birth, with over 100billions neurons innately provided, (more than double the amount to that of adults), the neurons are still unspecified (in terms of their nGFPs) as they await cortical assignment. The proliferation of these neurons is vast and overly broad (as there has yet to be any practice) and are viewed to be without parameterized directionality. (These broad and unpracticed neurons are apparently universal and brain-stem-like in nature). If infantile neurons were to remain broad, a good wager could be made that the child’s mental processing would remain stuck in a primitive (primate) state. (NB. We can speculate here that the profound qualitative differences found between humans and higher-order primates is that this quantity/quality of pruning of brain cells only takes place among homo-sapiens). So, what takes place over time—in what we call a series of critical periods—is that the human process of pruning carries out due to interplay practice over time (Certain thresholds of practiced are reached which delimit the early and mid-life critical periods of humans). This pruning (elimination of overly broad connections), we believe, is the result of an innately-guided migration, (an off-ramp) which initiates the capacity for this ‘ebb-and-flow’ of short-term to long-term back to short-term memory cycles.

These cycles form in the aggregate the 1-1 mapping between neuron-type and distinct region (e.g., distant-bound neurons being assigned to the cortex in establishing long-term memory nodes while local-bound neurons remain in the hippocampus regulating short-term memory nodes). By the time this critical cycle is complete, with specific neurons being delimited and assigned specific cortical regions, the size of the child’s brain has been neurologically pruned in half. Recent studies have shown that the *thalamus* region, an area controlling such local v distant movement (among other functions) begins from birth with double the glia cell count (11.2 million) as compared to adults (6.4 million). However, what takes place over a span of critical periods is that the adult glia count increases four-fold, from 10 million at birth to 36 million in the adult. It is believed that the interplay between these two memories is what starts the cascade leading to abundant recursive neuronal framing.

The persistence of the continuity debates might be said to rely on misunderstandings: the arguments are fraught with notational squabbles and confused terms (viz., What exactly do we mean by discontinuity?)—of course, no one disputes that the child and adult neocortex is made-up of the same substantive brain-matter (continuity). It seems to me that if such debates are to remain credible, and not reducible to red herrings, (which is what happens when sides take on too strong a position), then in a somewhat weaker versions, we must make sense of the debates by suggesting that indeed stages of processing both develop over time and proceed untethered to any known cerebral-substance distinction. (NB. One plausible substance-distinction argument might claim that certain substantive-regions which undergo *brain-myelination* (Broca's area) have yet to neurologically materialize (come online) in early stages of child language processing, thus delimiting processing in the child as distinct from that of adults [20]. But again, this is not a true different-substance argument, but rather a neuro myelinization-onset argument. Even granting this, there should be no debate about the progression of processing: it goes without saying that the *null hypothesis* is that biological processes evolve and change over time. (If this is what we mean by 'discontinuity', fair enough). Bio organisms/processes mature (a maturational hypothesis) and flow from bioprogram trajectories of brain maturation. Given this null hypothesis, all versions of maturation subscribe to continuity theories.

However, the point of this squib goes well beyond bygone continuity debates by suggesting that the duality of the human mind-brain split is unique, and not derived from what we typically see as biological continuity at work. Rather, we suggest that the mind, while indeed arising from the brain (bootstrapping), subsequently takes on such an aloof processing dimension that it no longer becomes meaningful or productive to speak about 'brain>mind' continuity. When it comes to Brain/Mind, Continuity is no longer attainable. In other words, any naïve notion that the brain can 'bootstrap' itself in creating a mind runs counter to this *fundamental difference* between the two operational platforms of mind/brain. What we are claiming here is that 'We can't get there from here'—namely, that a human mind can't simply flow from out of a human brain, as if once some mysterious threshold is reached, voila, we have a mind. We rather suggest that there are yet unknowable aspects of the mind which evade our current human capacity for understanding how the mind works, and it is much too vague and overly simplistic to speak of the mind as simply the by-product *sum* of its turbo-charged circuity of *parts. In other words, the 'mind' doesn't work like that [22].*

> (NB. While we acknowledge that great advances will certainly come from AI, greatly impacting world societies, these benefits will exclusively come from *expert systems* dealing with medicine, scans and diagnoses for cancer, agricultural maintenance and conservation, energy distribution, security such as face/voice recognition, etc. But these expert systems are trained on compartmentalized and highly selective data, with little if any understanding of compositionality—of how the vital parts of the expertise come together to be understood holistically. The human mind, as argued herein, is of a quite unique nature in this respect of compositionality).

Having said this, the same analogy then can be applied in the dualism debate between AI and the human mind (where AI is akin to associative bundling-networking of the 01 binary code) vs how the human mind which is a 'symbolic processor'—yielding a sum of compositionality beyond that of its parts—often and necessarily disregards frequency-based associative means by instigating 'distant *jumps*', referred to as *saltation*…a kind of 'quantum jump' if you will [11,12]. (School-day saltations in the early schoolyears are what brings on the teacher to say, 'Listen-up Johnny: Pay attention in class!')

There is something to be said about the incapacity of AI systems to daydream, to go off-line. One thing we know, off-line thinking as 'daydreaming', or 'thought-wandering' is essential not just for creativity humans engage in, but also for day-to-day mental consolidation. (The arts are now hot topics with book titles such as '*Your brain on art'*)[11]. Whereas a frequency-sensitive AI/Brain might be easily brought-up to scale (since there is no daydream 'waste of time'), the human symbolic mind is not so

[11] E.g., *Your Brain on Art* (Susan Magsamen, Ivy Ross). *This is Your Brain on Music* (Daniel Levitin).

availably suited. I suggest that the ease in which AI can scale-up is pegged to *low-cost of processing: symbolic minds, on the other hand, don't easily scale-up due to extreme cost in processing* (much to the chagrin of those in the industry trying to bring AI up to scale). Let's look at some problems below.

Problems with current AI[12].

Let's begin by posing the following question to any number of CEO/Co-Founders of our nation's 'Autonomous Self-Driving Vehicle' (ASDV) start-ups:

<u>Q: What are the most pressing problems facing your Company/Industry today?</u>

You would discover that most CEOs respond categorically. Their remarks are twofold in nature:

(i) Firstly, as a Public Relations (PR) concern, we find in survey after survey that it's not the technology *per se* that most people mistrust…it's rather the perception of 'humans' behind the technology. The public is afraid of hidden agendas—an agenda, in their view, on a scale so vast and complex that the individual feels forced to surrender one's autonomy. (It's the *Big Brother* concern of Orwell brought to the 21st century).

(ii) Secondly, an overwhelming problem on the technical side related to ASDVs is simply 'other people'. Our largest safety concern (for ASDV) is *understanding* other drivers on the road (people), and how to react to them. (Humans are messy as they deal in compositionality).

> Recall, ASDV technology is equivalent to the power of 'speed of light', manifold! Data points redundantly built-up over an array of billions of light reflections, each point traveling close to the speed of light, allows, (so it is thought) only minuscule chance for error, at least on the observable/empirical side of things (the environment). As we see from such statements above, it's not the data-points found in the environment which pose the greatest potential for errors (the *clocks* are right-on all the time), it's rather the chaotic, inconsistent, unpredictable mess of determining the nature of people's behavior that poses the greatest problem—It's those god-damme ungovernable *Clouds* which worry us to the bone. *Clocks* on the other hand are perfect! ([15] See clouds & clocks argument below).
>
> *(Personally, I feel these ASDV CEOs are living in 'never-never land'. They believe the current problems only to be relegated to PR, and completely miss the big picture of how ASDV, even in its best of days, will never be able to really scale-up for general public use).

This first point shows just how well the AI/ASDV industry has sold us on their technology, over-hyped as it is (to a degree that many AI experts warn of a coming AI Winter [16], in which billions, even trillions of investment dollars may be at stake globally). Interestingly, if you think about the above CEO

[12] For a full discussion into what can only be considered as 'catastrophic failures' with current AI, see Gary Marcus' book entitled *Rebooting AI* (2019). Also, for some theoretical background of how AI relates to language acquisition, see Galasso's book entitled *Recursive Syntax (2019), Note-4. [3].*

remarks just a little, the problem is on the human side of the leger, not on the tech side: both in terms of PR, as well as with technology. 'People are the problem'!

Well, this 'people problem'—[people vs tech]—has been borne out in many historical analogies [respectively]: starting with Plato v Aristotle (rationalism v empiricism [27]) where Plato comes down on the 'people-as-rational' side, moving through to the mechanics metaphors behind classical physics of 'Clouds v Clocks' [15], culminating with the metaphors of 'Brain as computer hardware, Mind as software'. (Updating to recent metaphors as 'The brain as a quantum computer') [11,12].

Regarding AI specifically, this same debate comes in the form of 'Rule-based & Symbolic Processing' (a hallmark of the human *mind*) vs. 'Neuro-net & Associative Connectionism (a hallmark of the *brain*), as captured by the Minsky v Rosenblatt debates presented below [17]. The former symbolic processing being much messier in nature, what I term *horizontal* processing [4] by which many different embedded points recursively converge on a singular subject, such as *context, mood, intuition, nuance*, (just to name a few). In forming a complete human-like understanding of a given subject, such complete convergence is required. Otherwise, we are left with only the outer shell of the subject, void of its inner dreamscape existence. This is the problem, only rephrased, as given by our CEOs. Though they may not spell it out in precisely these terms—which would go counter to their over-zealous hype, putting investment dollars at risk—what they are really admitting to is the non-trivial fact that *AI only sees outer-shells of items*; they see factums (albeit at the speed-of light). That's all they can see—What I call 'vertical processing' awareness: their knowledge (map of the world) is flat[13]. This flatness of AI processing doesn't offer the kind of dynamic interactions sufficient to carry out human-like response. The AI only sees a lamp, either turned on or off…its response is digital, flat and binary, whereas the human response to something so trivial as our table lamp is rich and dynamic.

The Table Lamp Test. The test can be rephased as follows: 'If we really want AI to understand us humans, we need to give their platforms the ability to use an array of *broad* knowledge which leads to complete understanding, and not merely provide factum-correlations between interconnected data points. In addition to mere factum-correlations, spread across an environmental continuum as offered by our bit-speed-of-light technology, we further need the unique kind of processing platform which can house all sorts of 'messy' knowledge about 'messy' human subjects and behavior. I emphasize *messy* here as indeed 'a certain type of knowledge' which on one hand may not seem relevant to the *narrow* calculation of ITEMs at hand, but as it turns out, is quite critical for the *broad* CATEGORICAL understanding of a given thought (compositionality). For example, take this lamp in front of me…we still do not know, neurologically speaking, how the brain/mind recognizes, perceives, and handles such information as ubiquitous as a table lamp. What do I think about when I see this lamp? Is it something that was given to me, once broken and I repaired? Is the cord worn out, does the bulb need replacing? Was it gifted to me from my former girlfriend who unceremoniously broke up with me years ago? etc.

In other words, such mundane objects we find in the world come replete with 'emotional dreamscapes' in which myriad neurons simultaneously fire, whether we wish to acknowledge this or not. (Perhaps the more scientific reader might take a more objective stance on human understanding. But when you take a moment, step back, and evaluate exactly what we humans know of the world, and how we come to know of it, the fuzziness of broad correlations immediately comes to light. Part

[13] My favorite all-time book on 'Flatness' is Edwin Abbott's 'Flatland' (1884).

of being human is to insert such broad understandings into narrow facts)[14]. And all these apparently random and chaotic points intersect for me (in my mind) in what constitutes my perception ('my neurological-compositionality') of this lamp in front of me…In other words, we should think of this lamp as something like a 'dreamscape'. That's what humans do—we form dreamscapes out of mental maps of our worlds. The upshot here is that if AI really wishes to simulate all that human thought-possesses have to offer, than we in some way have to capture what lays behind this dreamscape for a simple *lamp*, then proceed to all other such scapes accordingly…(No easy lift!)

The initial 'mind v brain' debates within the AI world began with Marvin Minsky (mind) vs Frank Rosenblatt (brain) [17], with Minsky claiming that humans' ability towards general intelligence (at least as exhibited by the human mind) was something of a 'kludge'—meaning something quite unpredictable and stochastic which otherwise would not arise from of a well-conceived engineering design. In other words, what we mean by *kludge* here is that the human mind—to be distinguished from the human brain—is cataclysmically messy and remote from any mere statistical-based algorithm of zeros & ones (0,1) that a brute-force binary code could offer: viz., the human mind is rather *ad hoc* as a processor and clumsily put together seemingly via a patchwork of poorly matched elements (or co-opted via an 'adaptive process' (using Steven J. Gould's terms) of elements originally intended for other applications).

Minsky's view in this regard was that natural human intelligence resulted from perhaps a series of 'dream-like states' (dreamscapes)—while apparently a product of thousands of special-purpose mechanisms, but not necessarily derived by them. That the interactive networks of thought were rather loosely connected, sometimes co-operating, and sometimes competing in order to solve the myriad of environmental problems faced by evolving humans. In Minsky's words, the brain's functions simply aren't based on any small set of general principles or constraints. Instead, they're based on thousands of them, orchestrated in what would seem a chaotic fashion. What Minsky is saying here is that each part/area of the brain is what engineers call a kludge – that is, a jerry-rigged solution to a problem, accomplished by the evolutionary add-on of bits of machinery wherever needed, without any general, overall plan: the result is that the blueprint of human mind –which is believed what the brain bootstraps into–should be regarded as a collection of kludges (hidden compartments, false rooms, trap doors, smoke and mirrors, to rival 'The Hall of Mirrors' at the Palace of Versailles).

This squib is directed towards a seemingly common-sense view, (perhaps ubiquitously held, but wrongly in my view), that the human brain can bootstraps itself in creating the human mind—taking what is a lower primitive form of processing and obtaining an extreme, qualitative shift in higher processing. The *bootstrapping myth* axiom is that the uniqueness of the human mind came about due to a phenomenal gain derived by over-amped lower-level processes. For instance, given the low-level brain as an associative mechanism, in which frequency plays a chief role in memorization, what the myth proposes is that the uniqueness of the human mind is 'nothing more than a quantitative repurposing of the same lower-cognitive functions'. The old adage [6] of 'What fires together wires together' may work for such low-level processes, whereby bundle of *adjacent* neurons (nGFPs) work in tandem over an array of processes; however, where such an adage becomes obsolete is in the

[14] For example, humans take for granted the knowledge that two things may be similar in 'kind', but different in 'item', hence, the tenants of categorization. Young children work this out for themselves very early in life, and yet the AP modeling has a hard time handling such processing [35].

observed *spooky phenomena* showing how things may work, in fact be 'correlated', at a *distance*. The former observation is well known in classical-contact physics, albeit a physics which is no longer a viable perspective of how the world works: (It was Newton would destroy the classical world of 'local contact' and left us with the ghost of 'action at a distance'). The idea here is that the two planes of physics (viz., classical v quantum) is equivalent to our linguistic description of recurrent v recursive.

Recent advances made in OPenAI, GPT-4, and future prospects steering for a General AI (AGI, Artificial General Intelligence) seem to suggest that the only barrier from 'getting there from here' is quantitative in nature— viz., more data, faster processing speed, and perhaps even what I'd call a paradigm shift in processing which might be offered by future quantum computing. However, this squib here says No*: We can't get there from here*! Why? Because the two processes are of such a different order, (on an extreme 'unlikeness' qualitative plane). It's not enough to call the two processes out as merely two different sides of a single mechanism model (i.e., the singular human brain/mind), but rather, what we propose here is that while the human brain does indeed have real antecedents both to our earlier mammalian class and more recent primate order, the magnitude of the human mind as such is on a qualitatively different plane, of such a different nature, situated on such a different platform, on an order perhaps not even measurable, that continuity between the two is not a viable option. Noam Chomsky's famous saying goes something like this (paraphrasing):

> *'We don't know exactly what happens when you squeeze 88 billion neurons into a space roughly the size of a softball'.*

Chomsky goes on to suggest that such 'spookiness' is delivered to natural language in the form of **Displacement** (a form of movement, action at a distance). As to why such recursive displacement takes place in language, Chomsky only speculates that it may be an 'optimal' way to bring the two operator systems together (i.e., the duality of semantics). [27b].

An analogy (Analogy-A) of likeness might be to show how, say, a primitive dog of the dinosaur-age evolved into today's blue whale. Fine! Evolution works over a very, very long time-span, on an array of physical parameters and constraints, some of which are physical in nature and fixed (such as the laws of gravity), others which are bio-specific and varied to ensure survival of the individual life (such as conservation of energy to calory absorption, etc.)

Analogy-B (unlikeness) would be better described as a stone evolving into a tree. Now true, both are physical items seen on earth, both being prone to degradation of the environment, etc. but one doesn't go around claiming that trees came from rocks. We have kingdoms to sort out such things). Simply put, the two are of such a different (unlikeness) being. The language we can use here is to say that the two items while placed along the physical trajectory, occupy such different planes on the spectrum of typology that no interaction can be expected from the two. So, the claim here is that *the human mind is of such a qualitative distinction that no amount of amplification of lower-level brain processes can bootstrap themselves in forming an entirely different processing platform* (Analogy-B):

Low level: Mammalian Class>Primate Order>(Human brain): motor-cortex, cognition, reflex, neuro bundling, = the associative brain.

High-level: Homo-sapiens>(Human mind): abstract reasoning>theory of mind (false believe, altruism), neuro looping (neuro entanglement) = the recursive mind.

***Recursive Indexing: An Overview*.**

One example of how High-Level recursive indexing works is to show ruled-based/embedded applications as found in syntax, as seen in the following examples which require embedded trace-operations. For example, consider 'look-ahead/trace' features which requires the [+/- Definiteness] feature on a Determiner (*A, The*) to select its proper verb (*are/is*) matrix. Ask yourself which of the two verbs correctly applies to the matrix Determiner:

a. A number of students is/are dropping.
b. The number of students are/is dropping.

   You quickly see that part of our inherent knowledge of English grammar relies on a recursive/syntax of the $[A_i[A_k[AB_j]B_k]B_i]$ type: where indexing of an element must be able to **Move** as a *PROBE* across an array of lexical items to link up with its *GOAL* relation (Probe-Goal Union). In other words, recurrent/adjacency is a not a governing principle for syntax of the [AB], [ABAB]-type. Rather, movement, even at times very 'distant-movement', is required in order to achieve proper syntactic values. Note the distance between words that such indexing must cover—clearly, trace-theory is not a recurrent/adjacency operation, but rather is reliant on movement at a distance. (Our most advanced Deep-Learning/Artificial Intelligence algorithms—in addition to how young children, and Aphasia Tests (see below)—suffer catastrophic failures when dealing with such distant operations) [21a,b].

c. **A** number of students are/*is dropping. (plural verb 'are' indexes with [–Def] 'A')

d. **The** number of students *are/**is** dropping. (singular verb 'is' indexes with [+Def] 'The').

Aphasia Tests Applied to Neural Networks. Contrasts what we find above regarding recursive embedding to earlier cited properties of AI neural networks—namely, recall that *Phonology & Semantics* (both 'local-domains') are the calling cards behind neuro-net architecture (local nGFPs). Why? Because they are the poster-child OFF & ON-switch processes of local, frequency-based algorithms upon which the architecture of AI is designed. In addition, we consider a third *Adjacency* principle which takes 'closeness' as a major determining factor in processing (also, highly favorable towards an AI design). But these poster-child processes pose major problems if we wish to truly simulate human thought. The weakness with AI neural networks is that their underlying processes are too sensitive to these three locality dynamics (which otherwise don't pose problems for symbolic/categorial rule systems found in human thought). The three dynamics include sensitivities toward: (i) sound analogy (phonology), (ii) meaning associations (semantics), and (iii) adjacency (closeness). All three serve us nicely regarding our current-state of neuro-net architectures, but their *Achilles Heel* is two-fold in nature: 1. That they are too sensitive to either brute-force memorization and locality of structure—they too neatly follow 'Bell-shape' learning curves[15] and, in addition, require

[15] For discussion of how language doesn't follow Bell-shape learning, see Galasso [21a, p107].

massive amounts of data inputs (no amount of which could ever attempt to adequately cover my dreamscapes for something as simple as a table lamp, least of all the vast complexity of context, subtlety of background knowledge, commonsense, and the holy grail of what lays behind human consciousness). 2. That their architecture is rather opaque in nature (unlike classical expert systems which can easily be understood in terms of top-down installed rule-procedures). Opaque to such a degree that when AI flies off the handle and gets things *catastrophically* wrong that cognitive scientists have no way of knowing exactly what went wrong[16]. In this respect, we pose the following *aphasia test* as a litmus test in evaluation human cognition (below).

Phonology/Sound Analogy. One very strong feature of AI is that its brute-force memory easily captures irregular vowel-shift/sound-pattern (umlaut) analogies as found in natural language (e.g., *speak>spoke, mouse>mice,* etc.) We say *irregular* due to the fact that such examples are *exceptions* to the rule. Irregulars are in the minority and run against their matrix majority rule-based options ({ed}, {s} (receptively). At first blush, it seems the mere size and distribution of the token affix, as found in the language corpus, is what's driving the status of the default rule. But size of token count can't be the sole explanation, since in some languages, German being one, e.g., the plural rule [N+{s}] is absolutely in the minority. And yet, whenever a German speaker is confronted in selecting a plural marker for a completely novel Noun, with no help or hint of any stem+affix sound-pattern analogy Umlaut, etc.), the German speaker selects the default plural {s}. The fact that German here seems to go against brute frequency (against 'bell-shape' distribution) provides a very interesting corollary, proving that rules are altogether abstract and have no relationship to frequency effects: it seems that it is the (German) exception that proves the rule. [31].

Semantics, Adjacency vs Syntax. The other two factors, Semantics and Adjacency (also 'local domains' regarding neuro-connectivity) can be juxtaposed against abstract syntax (which is a 'distance-domain'). Consider the examples below, often used to diagnose Broca's Aphasia (BA):

(i) *The girl that the boy chased is tall.* (Who is tall?)

Aphasics have a hard time processing such move-required operations. The typical Aphasic (non-correct) reading is that 'The Boy is tall.'

a. Recurrent-[ ] reading: *[The girl that the boy chased is tall] (BA error)
b. Recursive-[[ ]] reading: [The girl [that the boy] chased is tall] (Correct)

This error in (ia) relies on a misanalysis which treats 'locality' to be the main operator: the fact that 'boy' is closer than 'girl' to the adjective 'tall' suggests a processing which is flat [ ], rather than recursive [[ ]]. (A different analysis may claim that 'Boy' is selected because it has an inherent 'Tall' semantic feature [Boy: +Masculine/+Tall], [Girl: -Masculine/-Tall], based on yet another semantic

[16] See Marcus and Davis [16] for plethora of examples showing AI catastrophic failures. Failure to understand such errors has recently been euphemized as 'Emergent Properties' (as if there is some magic involved). This is utter nonsense: the failures if taken the time to be properly unpacked—which is no easy feat given the opaque nature and extreme numbers behind the neuro-nets—would all be ultimately traced back to their antecedent data.

feature [Gender]. (One way to tease this out would be to invert the syntactic subject Girl [-Tall] with Boy [+Tall], and to see how the processing plays out. If it's mere adjacency, 'Girl should be Tall' since Girl is closer. If semantics continue to be used on a feature basis, then 'Boy' might remain as matrix subject). In both cases, either adjacency or semantic, the response is correctly given its tether to 'local domains']. (Flatness without embedding is a quintessential feature of locality).

Consider (ii) below:

(ii) *The apple that the boy ate is red*. (What is red?)

Such questions don't pose problems.

In (ii) semantics helps: we know only 'apples' are red, and not '*boys': [The Apple ____is red]. BA subjects have a relatively easier time handling the semantics (as part of their preserved pragmatic 'world knowledge) since they know 'boys can't be red'. Hence, (ii) gets processed not via syntax, but rather gets co-opted by semantics (a local domain). The upshot of this discussion is that there is a hybrid/dual mechanism model at work in the underlying processing which must be hardwired into any AI architecture.

The most exotic case of AI's complete bias towards adjacency/closely comes from a French structure. In French, (like English) there are two verbs for 'work' ('function' when done by a [-person] object Fr. *Fonctionne*), versus 'work' when done by a [+person] person (Fr. *Travaille*). (This is similar to the English distinction between 'labor' (person) vs 'function' (thing)[17]. In a wonderful example provided by Marcus [16a], Google Translate completely fails, whereby only the closeness factor seems to play out in the translation. Consider the error derived by ©Google Translate.

Let's consider first the error/flat structure in (i), then turn to the correct/recursive translation:

The electrician whom we called to fix the <u>phone works/fonctionne o</u>n Sunday
(where the French verb should correct to 'travaille'*).*

*(i) Fr. **[**L' électricien que nous avons appelé pour réparer le **<u>téléphone fonctionne</u>** le Dimanche**].***

*(ii) Fr. **[**L' **électricien [**que nous avons appelé pour réparer le <u>telephone**] travaille**</u> le Dimanche**].***

Noting the flat/error structure in (i) showing the non-appropriate agreement between adjacent words only [***<u>téléphone fonctionne</u>***] (showing a flat-[ ] structure), since 'telephone' [-person] is an object which therefore must trigger the appropriate verb for 'work' associated with objects, (English equivalent of 'function').

In the correct/recursive structure in (ii), the agreement between the two items are distant but appropriate: [***électricien** [……..<u>] **travaille**],</u>* showing a recursive-[[ ]] structure.

[17] Another interesting fact is that while English can use the verb 'run' (for 'function', but not for 'labor': e.g., 'Is the computer running'), French uses the verb 'walk' (ça marche).

(NB. Recently, one of my linguistics students who worked on google translate as an AI/syntax project quickly discovered that while at times the translation surfaces correctly, it nonetheless then radically alters when the (syntactic) subject-position is changed from *electrician* to say, *monkey* or *dwarf*, etc. (and with other subject choices, even by as little as a shift from a lower to upper case letter in the word). The new calculus thus seems completely reliant not on proper syntax but on the nature of the frequency of the data inputted in the system. Recall, the rallying cry for AI is BigData, because of the claim that all deficiencies are due to such lack of data. Here, we show it is much more than data, but is due to the underlying deficiency of a flat/recurrent-based architecture (and the absence of a recursive/embedded architecture) [21].

Summary: In (i) syntactic recursion is required: [The girl [*that the boy chased*] is tall]. Hence, it seems recursive movement poses problems for BA, as well as for neuro networks which don't/can't implement the 'spreading of rules' in the underlying architecture. BA subjects' responses breakdown since semantics can't help with what is an otherwise ambiguous construct (viz., both a 'Girl' and 'Boy' can be 'Tall'). Thus, BA fails in the processing of (i). In (ii), BA subjects have no problems since semantic features can guide the processing. The crucial distention is that only in (i) is distant/syntactic movement required—hence, the hypothesis that Broca's area of the brain (BA 44/45) is the cite responsible for movement—What Noam Chomsky defines as the quintessential prerequisite for human language [24].

Analogies Based on Word Vectors (Bit Info) vs Logical Operations (Spreading of Rules)

In the beginning, it struck me somewhat as a curiosity as to why certain types of analogies did well with neuro-deep learning, while others were utter failures [16]. Later, I came to see that two distinct operator-distinctions were involved, based on whether the analogy was either:

(i) a pure/**recurrent** [combine] + [combine] (= logical-&/ITEM) with well-defined *bit information & semantic-feature overlaps* pegged to a pure 1-1 relation, or whether,

or,

(ii) there were other 'logical-&&' (=logical-of/SET**)** **recursive**-*embedded-combine operations* which *spread the 'bit info' over an array of logical reasonings* making the correlation rather opaque[18].

Take for example what appears to be two cases of simple logical-& analogies [16, p. 130]. At first blush, the two (below) seem completely congruent. However, while analogy (a) is easily and correctly processed by combine-search procedures which are easily transparent in mapping 'word-to-vector' features [e.g., 1-1 semantics-word) (so-called Word2Vec), (b) shows an embedded [combine [combine]] operation with absence of feature overlap, sometimes referred to as Logical-&& which deals with the *sum logic* of bit-piece information.

[18] I use the terms 'Vertical' for recurrent vs 'Horizontal' for recursive processes. These two distinctions also play as an overlap between 'Declarative'/itemized vs 'Procedural' spreading of rules [8]. (Also See [4]).

Consider below two different types of analogies.

a. Man is to woman as king is to___
b. Short is to tall as beautiful is to___

	Processing:	Combine:	Feature:
a' 'Logical-&' Combine Analogy:	recurrent:	[man + king] =>	[+masc]
[Man] is to woman as [king] is to___		[woman + queen] >	[-masc]

Recurrent logical-& analogies as shown in (a) above are of the combine A + B type where local domains serve nicely. On the other hand, notice (in b) how non-combine/recursive Logical-&& analogies pose processing difficulties. Recursive non-combine would notate as: [short + beautiful [tall + beautiful]].

	Processing:	Non-combine:	Feature:
b' Logical-& Non-combine analogy:	recursive:	[short = beautiful]	[?]
[Short is to [tall as beautiful]] is to ___		[tall = beautiful]*	[?]

In analogy (b), Deep-learning Word2Vectors fail due to the fact that the logic is not of a prosaic combine A+B feature value. This differs to analogy (a) where 'King & Man' can both easily be coded as having overlapping SEMantic [+Masculine] features, hence facilitating look-up. Conversely, the value of 'Beautiful & Short' doesn't share common overlapping semantic features. Rather, the analogy is based on [opposites], a rather abstract value with SEM featural naturality. It seems the logical analogy in (b) is rather difficult to code[19]. [Note: This embedded Logical-&& operation reminds me of how we were once taught that a negative number multiplied by another negative number yields a positive number (since the inverse of an inverse returns you to the starting point positive: [- (-) = +]].

Consider the infamous phrase where multiplication operates logically over the array of embedded sets: 'An enemy **of** my enemy is my friend'.

Multiplication operates {**of** set}: recursive: [[ ]]...
[-Enemy [-Enemy = [+ Friend]]]

I like to call this *logical-"of"* (which combines **SET/categories**) as opposed to *logical-"and"* which combines **BIT/items**:

'An enemy **and** an enemy is an enemy'
Addition operates {**and** bit}]: recurrent: [ ] [ ]…
[-Enemy] [-Enemy] = [two enemies].

---

[19] In fact, the top five answers to the analogy-b were: tall, gorgeous, lovely, stunningly beautiful, and majestic. Some logisticians might suggest the differences lay between 'logical &' vs 'logical &&' (the former being operations on bits/features, the latter on logic spread across the computation).

We can play out these analogy-games even further, showing just how complex they can become—not easily being squeezed into a semantic-feature training corpus. Take for example how these last two analogies might become complicated by a simple feature specificity: (c) defining feature as 'relation', (d) defining feature as 'opposite':

(c) A mother is to a daughter what a grandmother is to a _____

(d) The opposite of a VW Beatle is _____

In (c), most people complete the analogy and fill in the blank with <u>granddaughter</u>. This seems to make perfect sense—by simply inserting the prefix 'grand' for both elements seems to secure the analogy. Fine, you say: this is a typical response. However, if the computer were trained on 'hierarchical logic' (based on generations, and not on prefix matching), then the response from AI might rather be <u>daughter</u> (c') (preserving one-generation gap):

(c') A mother is to her daughter what a grandmother is to her <u>daughter.</u>

Hence, the difference in responses between granddaughter or daughter can't be easily captured unless hierarchical relations (mother-daughter, sister-sister relations) have been encoded in the algorithm. (Prefix matching ('grand') being an instance of flat/non-hierarchical *'sister-sister'* relation, what in generative linguistics we call (sister-sister) *MERGE*. Hierarchy (mother-daughter) is referred to in generative linguistics as *MOVE* [21a,b], a processing distinction similarly found in Broca's Aphasia Tests.

What about this:

(d) A mother is to a son what a __ is to a mother.

You say easy: a 'reciprocal' mother-son analogy and fill in the blank as <u>son</u>:

(d') 'A mother is to a son what a <u>son</u> is to a mother'.

Fine! This is gender natural based on relation. But what if it is the Gender-feature and not reciprocal Relation-feature which enters into the operation—due to weighted factors (innately programmed in the architecture) strengthened by the training data? A trained algorithm based on Gender-feature analogies might answer <u>daughter</u>.

(d'') A mother is to a son what a <u>daughter</u> is to a mother.

Humans take such background analogies for granted; we don't think about it because it is built-in as an essential part of our intuitive 'fast thinking' [7]. But in trained algorithms—and even for self-learning/general intelligence (AGI) algorithms (the very sort of problem which general AGI is purported to solve—such background reasoning is a 'hard problem'.

Finally, consider 'opposite' analogies (another hard problem).

(e) What is the opposite of a VW Beetle?

Most people respond to such a question by first assuming that we keep 'opposition' confined to the same 'category' (car), and thus consider *quality, value, expense*…as potential features driving opposition: hence, the typical response might be Mercedes-Benz, Rolls-Royce (etc). But let's entertain what AGI might do: perhaps the opposition is not [Categorical] but rather based on a feature [Shape], *round-top* (beetle) vs *flat-top* (Mercedes-Benz). (And this is only one such entertainment…a multitude can as easily be applied). Perhaps with such a feature specificity of opposites, we get the same types of results the first time around. But let's play it out a second time, and a third time, etc…Here's only one of many possible scenarios:

Input to AGI: What's the opposite of a 'VW beetle'?

Output from AGI: A 'North American Woodpecker'

People would find such a response (woodpecker) utterly bizarre, a catastrophic failure'. But let's look into it just a bit[20].

Here, for the AI algorithm, an 'opposition-feature' of shape has over-extended to Features of Insects (from the search 'beetle' (VW Beetle)), and since Beetles (Lady Bug) have the feature-shape quality of 'soft-roundness', the opposite might me Woodpecker since its beak is hard and straight. Yes, it may be hard to believe, but a self-learning algorithm could actually 'rationalize' precisely in this manner—a manner which is completely 'off the mark' for human reasoning, but perfectly obtainable for *weighted measurement* (built into the AI architecture in the form of 'hidden-layer' feedback/back-propagation loops). Such 'off the mark' search-patterns could extract such bizarre outcomes. In fact, as it turns out, the hardest problems for AI/AGI are essentially how to control and minimize *wild*[21] search-patterns (which result in catastrophic outcomes): Current AI has a hard time with certain forms of deduction: namely, *kindness of* (category), *likeness to* (Item), *identical with, similar to, relationship of, compositionality in,* (moving beyond the sum of its parts), and *analogy* and *opposition to* (as seen above), etc. etc. [22]

(NB. Cognitive scientists can't really explain how AI comes up with such wild responses, whether correct or catastrophically off the mark. We really don't know how AI works in this respect.… and some leading AI voices refer to such alternative learning schemes as **Emergent Properties**. Again, as I have already stated, I am very weary of adding 'super learning' to AI, learning which goes beyond input calculations. I don't believe in any mystery that befuddles us regarding emergent properties in AI. What they really are are just 'defiant analogies and learning patterns' which go against what humans might expect (based on our human biases and common-sense reasoning as shown above). There is no 'superhuman' mystery which takes AI learning (or even AGI) beyond their input (See Endnote, Appendix 2). But rather, the complexity of vast data, coupled with the speed of learning procedures, can easily overwhelm human understanding—like what happened

[20] Marcus [16a] shows such bizarre examples of deep-learning catastrophic visual failures: e.g., a picture of a 'baseball with foam' being labeled as an 'expresso', or a 'stop sign' with a sticker being labelled as a 'refrigerator'.
[21] Not 'Wild' because they are unconstrained (they are indeed constrained by the algorithm, they must be), but 'wild' because the **common-sense** behind the search is completely off the **human** mark.
[22] The promise of General-Deductive Learning AI ((AGI), somewhat removed for what is today being offered by Chat GPT-4+, is that Autonomous Learning AGI (Auto AI) algorithms will move well and beyond these constraints.

in the ultimate ‘human vs computer’ chess-off between IBM’s ©Deep Blue supercomputer vs Garry Kasparov (New York, 1997). The computer won the series: but it was not due to some mysterious emergent property: it was not magic! It was, as it turned out, quite simply the result of a faster mathematical calculus which easily outstripped Garry’s chess capacity).

Recurrent vs Recursive Analogies. In sum, (recalling the two types of analogies above) in order to break with a feature-specified-analogy parameter, any future AUTO-GPT (AGI)—one which could create its own AUTOnomous algorithm tailored to any task—would have to see that recurrent SEMantic/ITEM features alone can’t handle the analogy, since it is based on Recursive SET ‘opposites’. The ability for AI/AGI to move from one analogy-algorithm to another is what is currently preventing us from modelling true human thought. Whether this flux—this ebb and flow between analogy-algorithms, (if it should ever come to pass in the technology)—should be considered as real ‘bootstrapping’ will most likely remain an open question. But until we can see the kind of inner workings which provide for ‘analogy modulations’, as it currently stands, bootstrapping remains beyond the technology.

Concluding Remarks: AI and the Dual Model of the Mind/Brain.

It seems the one narrow piece which is (still) missing in the broad AI puzzle—an absent piece which yields such catastrophic failures, along with AI’s inability to derive consistent human-like reasoning—is the piece pegged to *symbolic/rule-based* learning. If this second piece were implemented within current AI platforms, what one would fine is a *Dual Mechanism Mode (DMM)l* [23] (of the sort which shows up in natural language between, e.g., memorized/recurrent single-mechanism-[ ] found in irregular verbs ([go]>[went])/nouns [mouse]>[mice]), vs rule-based/recursive dual-mechanism-[[ ]] found in regular morphology formations (Verb + {ed} = Past}: talk>talked, Noun + {s} = plural: [book]>[[book]s]) [1].

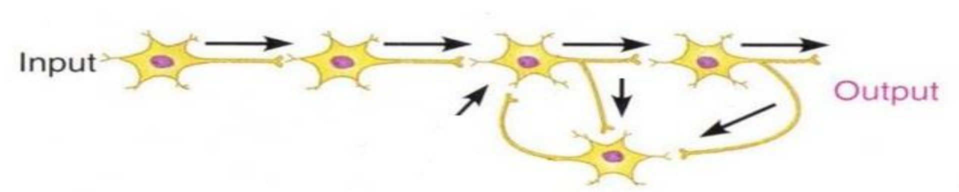
The nature of this squib has been to first establish that there is no continuity between the types of neuronal structure which provide short-term memory and long-term memory, the former being structural composed via a nGFPs of a ‘local domain’, and latter of a ‘distant-domain’. The argument herein has been to suggest that it is the torsion, this flux between local and distant connectivity, which eventually creates a recursive neuron—a qualitatively different neuronal composition which leads to the ability to deduct in abstract ways, leading to all the integrated corollaries which go into a Language Faculty-narrow [24]. The string of Dual Mechanism Models (DMM) behind *system-2 vs system-1, serial v parallel, declarative v procedural, vertical v horizontal, lexical v functional, connectionist v symbolic*, are each the result of this singular neuronal ebb and flow which, by their loop-forming corollaries, coordinate in creating the essential ingredients for language. The most articulated proposal for such a dual mechanism model [23] which incorporates both (i) a *recurrent*/**brain-like** neuro-network coupled with (ii) the *recursive*/**mind-like** symbolic processing comes from cognitive scientist Gary Marcus [18]. Gary is perhaps the most outspoken critic of the assumption ‘we can get there from here’, and while he acknowledges the many benefits a well-modelled AI can provide, particularly in the expertise realm (so-called encyclopedic expert systems), he is quite explicit about the pitfalls and rabbit-holes which lay ahead. But regarding a DMM implementation for AI, Gary would be the first to tell you ‘*We don’t know how to do it’* [16b]. Any scientific breakthrough of bringing the *digital* neuro-network world (brain) to converge onto the *analog* symbolic world (mind) is so far off into the future that we don’t even know how to adequately begin to address the issues…

Appendix-1a Recursive Neurons

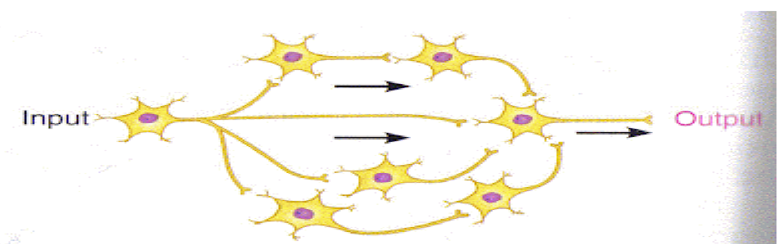
The neuroscientist David Marr [14a], I Believe, is the first to ever proposal that neuronal connections take on recursive functions. The closest analog to recursiveness, happening at such micro-levels, probably relates to what we think is happening with *mirror neurons*, whereby <external-internal:inputs-outputs> might be mirroring each other in forming feedback loops. The notion that the transition of GFPs from (i) short-term to (ii) long-term, back to (iii) short-term memory retrievals, which indeed adds noise to the neuron, nonetheless may not necessarily mean that the neuron is completely eliminated, as is sometimes suggested. Rather, given a recursive neuron connection, *amplification*s may ripple through the neuron-bundles via dendrite-axion pathways in quite dynamic ways, allowing memory-traces of the original stimuli (first time-step GFP) to remain, while also incorporated additional information, (sometimes referred to as 'noise'), rendering *embedded feedback loops*.

Marr goes further in suggesting that neural networks can exhibit **pure recursive functions** having to do with *reverberating circuits.* Marr suggests that while synapses become excited, information packages will pass along the chain of neurons, with the last neuron in the chain be amplified or attenuated. Mars states '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. (See Marieb et al [14b]).



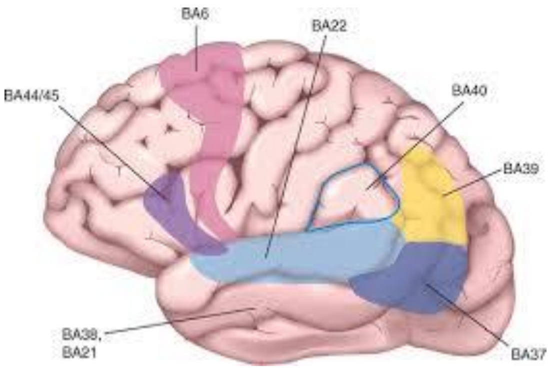
(e) Reverberating circuit



(f) Parallel after-discharge circuit

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 time-steps and regions. It is believed that it is this parallel processing which allows human neurons to take-on recursive functions.

Appendix-1b Neural Networks of Language Representations in the Brain



The Vertical v Horizontal Brian Porcessing.

Motor-cortex BA6 extends down to perisylvian region BA22 in comprising of Declarative 'Vertical Processing' (recurrent/multi-layer neuro-net functionality). Frontal Lobe BA44/45 laterally spreads connecting temporal region BA22 comprising of Procedural/'Horizontal' processing (recursive/symbolic- rule functionality):

Items: X=X Where Items can be stacked as a memorized vocabulary list: [ ]

[table]* [ ]

[chair] [ ]

[nightstand] [ ]

[[table]s] (plural rule): [[N] + s]= PL [[ ]]

Categories: X+Y=Z Where Categories are created out of rule-formation which takes on a 'spreading effect' over items [[ ]]…

NeuroNet Deep learning is very good at associating correlations on a 1-1 level (a vertical process), such processes can easily handle *image, sound, and labels* as long as the input is without *noise* which then requires some background understanding (as in our analogy games). What neuro nets struggle with is how such internal nodes (for labelling) relate to their parts (like how words relate to a phrase, a phrase to a sentence). It seems what is missing is **compositionality** (i.e., how the sum is more than its parts, and in turn, how parts move (ebb and flow) to combine and create compositionality).

* [Category [Items…..]]

[Furniture [table, chair, and nightstand]]

The above processing distinction can be referred to as 'Fascinating' vs 'Celebrating' Typologies [4] (in term of language typologies of morphological processing) when considering the morphological nature of the affix {ing}:

(i) This is a 'fascinating' class = {ing} is Derivational/Adjective Phrase

[AdjP fascinating class] = [ ] recurrent combine

(ii) Mary is 'celebrating' her birthday = {ing} is Inflectional (progressive-aspect)

Progressive Rule : Be + [[Verb] + ing]: $^{\text{is}}$ **[[celebrat]$_{\textbf{ing}}$]** = [[ ]] recursive

What we find regarding the content/lexical word vs. abstract/function word distribution is that lexical word formations appear vertically beginning with the sensory-action motor cortex (BA6) and descend to the perisylvian area (BA 22) (Temporal lobe/Wernicke's area) where semantics link up, while non-substantive grammatical-functional words isolate predominately in BA 44/45 (Frontal/Broca's area). This dual distinction suggests that a dual-hybrid mechanism model is required in any attempt to map language in the brain. Frequency-sensitive multi-layer perceptrons, as proposed by connectionist models, work well with the vertical processing areas where semantic corollaries can easily be assigned by connectionist nodes, while recursively-sensitive and rule-based systems work well with horizontal rule-based functional words. This same overlap roughly corresponds with what we find regarding (sematic) anomia vs (syntactic) agrammatism respectively. Further still, this same distribution holds with frequency-based Derivational affixes vs rule-based Inflectional affixes (e.g., plural {s}, past tense {ed}, etc. (See Galasso recursive syntax pp 13ff [3]. In fact, one of the most interesting findings show that in languages which have a high-frequency and irregular adjoining derivational affix (such as {-n} in go>gone), defaults upon novel word formations nonetheless show a rule-based inflection, such that past tense {ed} of 'go' would inflect as 'goed' (as default). (See Pinker 1999 for discussion [1]). In the phrase 'How *do* you DO?' the first *do* (Auxiliary verb) as functional is allowed to be deleted in spontaneous speech (How__ you DO?) while the second lexical main verb DO can't delete (*How *do* you__?).

Regarding another distinction between lexical and functional elements of language, it is believed that it is the recurring sound sequences (of phoneme to morpheme association) which eventually creates a symbolic category of the element, leading to rule formation e.g., Noun + s = plural. We know that not all things can be *a table, chair or nightstand* (**item**), but all things can be either singular or plural (**category**). Hence, the task of distribution is very different between Nouns/Verbs. And their respective inflections. It is in this manner that the recurring sound-sequences, as mapped onto lexical items, take on qualitative different characteristics. Such recurring sound sequences which may have originated in BA 6, shift to BA 44/45. This is one of the many factors behind language change. For instance, the now lexicalized {m} was an inflectional Case marker (Accusative Case) as found in (he) /hi/ > (him) /hi-m/, (they) /the/ > (them) /the-m/, (or who> who-m). In the last case (whom), the {m}, not being *lexicalized* as part of the stem has now become an optional affix in standard English (e.g., Who_ does she like?/*Whom does she like (the latter which is now *marked). In the first two cases (him/them), the {m} has become lexicalized and thus is required. Think of lexical {m} as local combine.

Appendix-2: A Dual System Model (Kahneman) [8].

System-2	System-1
Brain Area: Gyrus triangularis (Temporal Lobe)	Gyrus opercularis (Frontal Lobe)
Wernicke's area 22	Broca's area 45, 44
Language Models: AI: Single Mechanism Model (5)	AGI: Dual Mechanism Model [20, 21b,23a)
Multi-layer perceptron [5,13]	Symbol-manipulation [16]
Processing:	
Serial/Recurrent/Declarative	Parallel/Recursive/Procedural [8]
Recursive:	
No	Yes. [24]
Representational Format:	
Images, Sounds, Labels,	Propositions
Neuro-nets	Rule-based algorithms [18]
Connectionist models [5]	Hybrid models [18]
Child Language Acquisition: (Maturational Theory)	
Lexical stage-1	Functional stage-2 [20]
Word Level:	
Substantive/Lexical/Word	Abstract/Functional/Syntax
Theory of Mind:	
No.	Yes.
Faculty of Language: *broad vs narrow:	
FLb	FLn [24]
Language Impairment/Aphasia:	
Anomia (semantic)	Agrammatic/Syntactic
Autism/Impairment:	
Asperger's Syndrome	Williams' syndrome / *SLI [1, 26]
Cerebral Degenerative Disease:	(*Specific Language Impairment)
Alzheimer's	Parkinson's
Primate Order: Ability to Mimic;	
Pongid: NO	Homo-sapiens: Yes [25]

EndNote on Learnability: Innate Mechanisms Behind Language learning.

One last way to tease out these two systems is to examine what takes place in the language learning of young children. Peter Gordon [19] [asked children to produce compounds such as (irregular plural) *mice-eater* and (regular plural) *rats-eater.* Gordon found that children over four-years of age[23] had a seemingly built-in bias against regular-plurals (which embed inflectional {s} between compounds) *rat-s-eater. (The children never produced them). But this sort of biased 'Learning' goes well beyond the given input the child would receive[24], since plurals inside of compounds are extremely rare in the input. Such a built-in bias is linguistically consistent, close to universally so, across languages: the bias involves a linguistic constraint which disallows an inflectional marker to embed within a stem+stem compound. Such compounds are seldom accepted, (save rare exceptions e.g., *mother**s**-in-law*, *attorney**s**-general*, etc.) One way to understand this constraint is via our dual system approach—namely, since all [stem]+[stem] formations are of a short-term memory storage process (their being lexical in nature), any intervening variable/rule (such as {Noun + s = plural} (a long-term process) would break the cohesion of the frame. (Note: plural inflection for 'Rats' is recursively structured: [[rat]s] .

*[lexical-stem] $_{\text{[functional-affix]}}$ [lexical-stem] (*rat-s-eater)

Such a biased morphological processing 'Auto-Corrects' to:

[lexical-stem] + [lexical-stem] (rat-eaters).

In other words, where Lexical items (such as substantive words, derivational affixes) are assigned to the Temporal Lobe regions (housing vertical processed items), Functional items (such as non-substantive words and inflectional affixes) are assigned to Broca's area. Whenever the two must be called upon to form a linguistic expression, both regions of the brain must simultaneously activate, calling for a **Dual Mechanism Model.**

Word/Derivational morpheme

[rat-]

*[-s-]… Affix/INFLectional morphology (See [23a]).

[[-eater] s]

[23] Children up to the age of three demonstrate insensitivity to such grammatical distinction between stems and affixes typically treating word formations holistically, least of all treating abstract distinctions between regular vs irregular formations. This suggest that the bias is maturational in nature and connected to the growth and development of certain areas of the brain responsible for functional categories [20, 21].

[24] The mere fact that young children seemingly have easy access to linguistic knowledge 'beyond their input' poses serious challenges for any AI system which wishes to emulate true human-like knowledge of language, given that the hallmark of AI algorithms closely tie to their training input.

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[35] Galasso, taken from class lecture on AI syntax:

A fun example of factum/ITEM (AI) vs background human knowledge/CATEGORY is to play-out the scenario where a robot-student is standing in front of its professor's office hoping for a chat. The door has a sticky-post which says: 'Back in 5 minutes', and so the robot reads the note, times the duration and waits (these are the Item-based factum-points). A minute later, a human student passes the robot and says, 'Oh, never mind, that sticky-post has been on the door all week' and walks away. Now, we humans realize that this sticky-post is old, irrelevant information, and perhaps even for the robot, such new info might be processed via a pushdown automata system. However, the problem here is that the human student's info (word of mouth) is fleeting and doesn't remain in a constant reinforcement stream (within the stimulus & response (S&R) environment, citing Behavioristic norms), while the constant visual cue in the sticky-post remains on the door to be re-re-read/processed constantly, (the sticky-post is constantly being reinforced). Here, the calculus, (division of work) is between 'fleeting incidental info' which has now faded into the background, vs 'repetitive consistent S&R information' continually being fed into the computer. In such cases, the AI algorithm may force the robot to wait indefinitely due to the brute force of the same continual S&R input stream. In order for the robot to change its decision-making capacity, (its algorithm), a new tact must be coded, allowing for environmental feedback to be overridden by new but fleeting information. (This new tact would be consistent of *reasoning, critical thinking* skills). This same scenario plays out regarding narrow Items over broad Categories: here the actual sticky-post represents the 'item' while the human student's new passing information shifts this item to be relabeled as a category: 'an old sticky-post left on the door, no longer relevant, background noise' (item to category: to be filed and put away).

Glossary: Recurrent Neural Network vs. Recursive Neural Networks

• **Recursive Neural Networks** (RvNNs) operate on symbolic, hierarchical data modelled after syntactic tree structures as found in NLPs. Symbolic Tree structures which include both MERGE serial/items (sister-relation nodes), as well as MOVE parallel/symbolic (mother-daughter categorical nodes) in executing hierarchical operations. Due to their tree-like structure, RvNNs can operate over hierarchical data, recursively setting child nodes, sister-sister relation, which sets parent nodes.

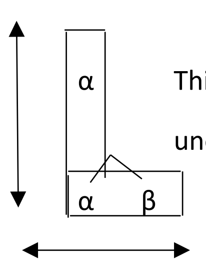
	RNN: Merge	RvNN: Move	
(i)	*a. Sister-sister {X, Y}*	*b. Mother-daughter {Z {X, Y}}*	
	[X Y]	*[Z [X Y]]*	
(ii)	*a. Sister-sister {X, Y}*	*b. Mother-daughter {Z {X, Y}}*	
	[drink milk]	*[drink*	
	[milk drink]	*[house [~~drink~~ milk]]*	*[VP: Drink milk]*
	[boat house]	*[boat ~~house~~]*	*= a kind of boat*
	[house boat]		

In early child syntax, the word-order of a phrase may be varied due to an RNN sister-relation (where no hierarchy has come on-line). So, in (iia) a child may say 'drink milk', or 'milk drink'. It is not until an RvNN phrase comes on-line (iib) that hierarchical *word order* is set (via myelination of Broca's area which provides recursive hierarchy). Similarly, due to a non-hierarchical phrase structure found at stage-1, young children cannot discriminate between the expressions 'boat-house' vs 'house boat' (the former a kind of house, the latter a kind of boat).

For a fuller discussion, see: file:///C:/Users/jgjos/Downloads/galasso_23_The-Recurrent-.2%20(12).pdf

This two-prong axis is what we find regarding the two stages of child syntax:

RNN **MERGE** (vertical): stage-1 (linear stacking {of a, b}; non-hierarchical)



This dual pathway is expressed as Merge {a, b} which gives you an unordered SET, while Move provides a hierarchical PAIR: < α, <α, b>>.

RvNN **MOVE** (Horizontal/Hierarchical {a {a, b}}): stage-2

Move = the spreading of hierarchical rules.

• **Recurrent Neural Networks** (RNNs) are considered Flat-ABABABA-grammars [21] to the extent that 'local domain' constraints serve as their scaffolding (Natural Language analogs include phonology, (sound-pattern analogy), semantics and principles of closeness/adjacency), noting that such aspects fall under Language Faculty-Broad [24]. Such operations are consistent with 'Logical-&' operations which are governed by constraints on proximity and bundled associations. Connectionist-Network (CN) Models are supported by RNN-type networks. It has been proposed that early child syntax first passes through this kind of stage (i.e., the lexical stage-1 [20,21]).

RNNs represent temporal sequenced logical-& applications when governing Natural Language Processing (NLP). Such NLP-operations are substantive/Lexical in nature in serving phonological/Semantic material (so-called Faculty of Language-Broad [24]. RNNs are usually designed to operate across a chain (nGFP time-steps), whereby their connected 'weights' are shared across the length of the chain.

• **Disadvantages vs Advantages of Recursive-modeling RvNNs for AI.**

The main disadvantage of RvNNs is that by the use of rather abstract Syntactic Tree structures—whereby sentence parsing can be 'slowed' by ambiguity, focus, context and interpretation—cognitive scientist may be hard-pressed to achieve any real simulation of how such operations might take hold in the delivery system of the brain. Clearly, RNNs hold the advantage here since they seem to have a closer 'neurological mechanism' in this respect: (RNNs support a recurrent logical-& behavior with a strictly weighted associative binary operation, similar to what actually takes place at the neurological-level in the brain). Another drawback is that any such RvNN simulated model would be hard to bring-up to scale, since such models have a unique fingerprint between inputs and output (just as we say every human brain/mind is different). Labelling and training such particular data would be time-consuming and labor intensive. Early Classical Expert systems were able to use symbolic rules precisely because they weren't required to be brought-up to scale. (But any attempt for a General expert system (AGI) would have to scale up enormously. This poses perhaps the direst problem for RvNNs. Early AI pioneers of the 1960's were buttressed by their connections/multi-layer perceptron models precisely because they felt that such artificial modeling were in fact the closest mechanism to what actually took place neurologically in the human brain/mind.

Of course, the singular and most critical advantage that recursive-symbolic/rule-based operations hold for AI is that it co-opts much of what many cognitive scientists confirm is an imperative ingredient in obtaining human-like understanding. It's one thing to 'know' something in a strict associative 1-1 linear manner (as in list-memorization), but quite another to 'understand'. Humans are not mere robust memory calculators, but rather glean a human 'understanding' from a variety of means.

Neural Nets and The Broca's Aphasia Test:

1. (RNN) Recurrent Neural Net (sequential chain processing)

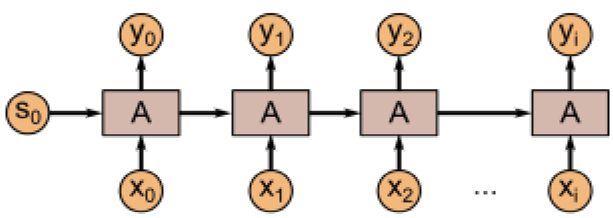
   [The girl that chased the boy is tall]: Who is tall? * The boy.
   (*Broca Aphasia (BA) error based on flat recurrent [ ]-processing.

2. (RvNN) Recursive Neural Net (syntactic tree processing).

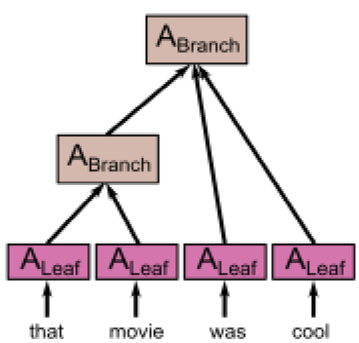
   [The girl [that chased the boy] is tall: Who is tall? The Girl.

   (Correct recursive/embedded [[ ]]-processing)

Recurrent 'Combine' vs Recursive 'Tree-like' Neural Nets



Recurrent Neural Net



Recursive Neural Net

(Apple's Siri, Alexa's smart speaker, Google's voice search, translate, capturing, Stanford's SQuAD (Stanford Question and Answering Dataset), just to name a few are all RNN models built around sequential data. For Hybrid-model application, see Marcus' 2023 Tedtalk [16b]).

For recent studies on RvNN models, see:

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8046141/

https://www.simplilearn.com/recursive-neural-network-in-deep-learning-article

https://proceedings.neurips.cc/paper/2014/file/2cfd4560539f887a5e420412b370b361-Paper.pdf