Cognitive Chunks, Neural Engrams and Natural Concepts:

Bridging the Gap between Connectionism and Symbolism

Dmitry Bennett
Centre for Philosophy of Natural and Social Science
London School of Economics
London, UK
D.Bennett5@lse.ac.uk

Fernand Gobet
Centre for Philosophy of Natural and Social Science
London School of Economics
London, UK
F.Gobet@lse.ac.uk

***Abstract*—Chunking theory is among the most established theories in cognitive psychology. However, little work has been done to connect the key ideas of chunks and chunking to the neural substrate. The current study addresses this issue by investigating the convergence of a cognitive CHREST model (the computational embodiment of chunking theory) and its neuroscience-based counterpart (based on deep learning). Both models were trained from raw data to categorise novel stimuli in the real-life domains of literature and music. Despite having vastly different mechanisms and structures, both models largely converged in their predictions of classical writers and composers – in both qualitative and quantitative terms. Moreover, the use of the same chunk/engram activation mechanism for CHREST and deep learning models demonstrated functional equivalence between cognitive chunks and neural engrams. The study addresses a historical feud between symbolic/serial and subsymbolic/parallel processing approaches to modelling cognition. The findings also further bridge the gap between cognition and its neural substrate, connect the mechanisms proposed by chunking theory to the neural network modelling approach, and make further inroads towards integrating concept formation theories into a Unified Theory of Cognition (Newell, 1990).**

Keywords—chunking, symbolic, deep learning, subsymbolic, CHREST *(key words)*

I. Introduction

The brain is often said to be the most complex object in the known universe. There are multiple levels of investigating brain functions: starting from the subatomic relations between particles, to the molecular level, to whole neurons that generate action potentials, to networks of networks that link various brain regions, to cognition and behaviour that emerge from all of these multilevel relations (Purves et al., 2013). How do we approach this level of complexity?

The approach of cognitive psychology was to unravel the mechanisms that underlie cognition starting with the top levels (cognition and behaviour). For example, experiments on human processing have shed light on the cognitive functions of human attention, long-term and short-term memory modules (LTM and STM, respectively), and their interconnectedness with the perceptual apparatus. Neuroscience, in turn, focused on the investigation of the lower-level neural functions (e.g., synapses, neuronal structure, firing rates, and refractory periods) and their relationship to higher cognition. Understandably, both levels of explanation rely on different sets of assumptions and proposed mechanisms.

While many of the findings remain in the shape of verbal theories, a sizable part has been captured via computational formalisms (Anderson & Lebiere, 1998; Laird, Lebiere, & Rosenbloom, 2017; Newell, 1990; Ritter, Tehranchi, & Oury, 2019). Computational formal models form a solution to the problem of "magic parameters" associated with purely verbal theories and integrate proposed mechanisms into a more unified whole (Byrne, 2012; Lane & Gobet, 2012a; Newell, 1990).

The currently ongoing AI revolution is powered by formal models of artificial neural networks (ANNs, historically known under umbrella terms of connectionism and, more recently, deep learning) (Hambling, 2020; Jo, Nho, & Saykin, 2019; Mnih et al., 2013; Silver et al., 2016; Silver et al., 2017; Vaswani et al., 2017). Deep learning is also commonly used in psychological models (e.g., Battleday, Peterson, & Griffiths, 2020; Hoffman, McClelland, & Lambon Ralph, 2018; Sanders & Nosofsky, 2020). Indeed, its set of fundamental mechanisms was largely developed and refined through research in neuroscience and psychology (Hahnloser et al., 2000; Hinton & McClelland, 1987; Hinton et al., 2012; McCulloch & Pitts, 1943; Nair & Hinton, 2010; Rosenblatt, 1958, 1962; Rumelhart, Hinton, & Williams, 1986). A review of computational neuroscience models concluded that despite the problem of oversimplification, deep learning models can already provide profound insights into the processing of the brain (Richards et al., 2019).

On the cognitive psychology side, one of its most established theories – chunking theory – has been also embodied in computational cognitive architectures, first EPAM (Feigenbaum, 1963; Richman, Staszewski, & Simon, 1995) and now CHREST (Chunking Hierarchy REtrieval STructures) (Gobet, 1993, 2000; Gobet & Lane, 2012; Gobet & Simon, 2000). Chunking theory's key idea – a *chunk* – is defined as a meaningful unit of information made from elements that have strong associations between each other (e.g., several digits making up a telephone number). Hence, *chunking* is the process of forming and updating chunks in the cognitive system (Simon, 1974). Although the chunks themselves vary between people due to personal differences, the chunking mechanism is mostly invariant across domains, individuals and cultures (Chase & Simon, 1973; Gobet et al., 2001; Miller, 1956).

Since its emergence in 1959, cognitive chunking has been found to be central in verbal learning (Feigenbaum & Simon, 1984; Richman & Simon, 1989; Richman, Simon, & Feigenbaum, 2002), perception and memory systems involved in expert behaviour (Gobet & Simon, 2000; Richman et al., 1996; Richman et al., 1995; Simon & Chase, 1973; Simon & Gilmartin, 1973), concept learning and categorisation (Bennett, Gobet, & Lane, 2020; Lane & Gobet, 2012b), developmental abilities and cognitive decline due to ageing (Mathy et al., 2016; R. Smith, Gobet, & Lane, 2007), acquisition of grammar in children (Freudenthal et al., 2016; Gegov et al., 2012), and the list goes on. Thus, the idea of a chunk is one of the key ideas in all of cognitive psychology.

One classic example of chunking theory is the finding that stronger chess players are able to recall more novel chess positions from a given chessboard when compared to weaker players, but this effect is much more pronounced when the said novel positions come from an actual game, and not just randomly placed chess pieces. According to CHREST – a computational model based on chunking – this is due to the experts possessing more chunks in their LTM (Gobet & Simon, 1996) (see Figure 1).

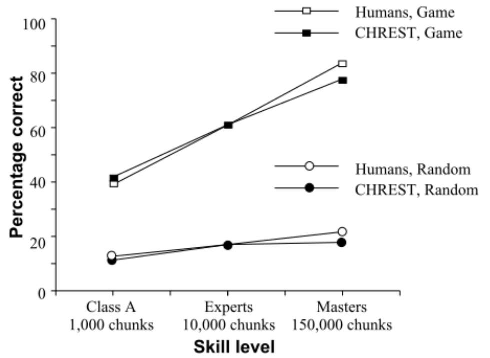

Figure 1. Recollection of game and random chess positions as a function of ELO rating in humans and number of chunks in CHREST. From Gobet and Simon (1996).

The neural basis of chunking was investigated using neuroimaging techniques. It was found that experts possess large domain-specific knowledge structures that activate in the areas of the brain associated with episodic LTM memory. While novices primarily rely on the prefrontal cortex to form new primitives and update their shallow chunking networks, experts show less activation in the prefrontal areas, but large activations in the medial temporal lobe, presumably due to rapid utilisation of large knowledge structures (see Figure 2) (for a review, see Guida et al., 2012). While these findings were important for establishing a link between chunking and the neural function, they were presented in a form of a verbal theory that was difficult to operationalise, e.g., using a connectionist model of chunking.

The current paper aims to address this issue by investigating the correspondence between the rigorous cognitive CHREST model that is based on chunking and a neuroscience-based model based on deep learning.

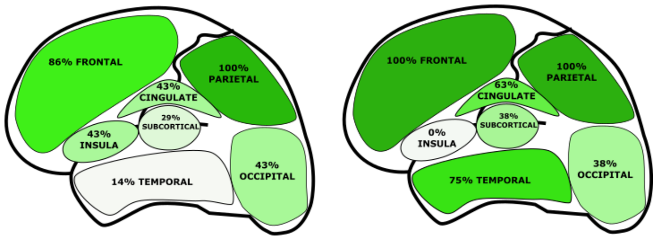

Figure 2. Experts' brains (on the right) have more activations in the temporal regions associated with LTM, and fewer activations in the prefrontal STM regions when compared to novices (on the left). Darker shades of green signify stronger activation. Adapted from Guida et al. (2012).

II. CHREST and Deep Learning

CHREST is a self-organising computer model that simulates human learning processes via interacting cognitive mechanisms and structures. For CHREST, learning implies gradual growth of a network of chunks in LTM, a process influenced both by the environmental stimuli and the data that have already been stored (Gobet & Lane, 2012). CHREST's STM structure allows for additional ways to create links between chunks, such as linking chunks across visual and verbal modalities.

Another way to present CHREST is to say that it is analogous to deep learning – both in terms of its power and simplicity, with the caveat that CHREST's level of investigating the brain function starts with the top level (cognition and behaviour) as opposed to neural mechanisms. With regard to power, like the multi-layer artificial neural nets, CHREST is an example of a universal function approximator (Fredkin, 1960; Gobet, 1996; Hornik, Stinchcombe, & White, 1989). Thus, like deep learning, CHREST is capable of classifying complex multidimensional stimuli while learning from raw data, using both supervised and unsupervised approaches.

As for simplicity, like deep learning, CHREST is very simple at its core. While a perceptron is an idealised model of a neuron, CHREST presents an idealised model of a cognitive system. But, where deep learning relies on linear algebra, partial differentials and the differentiation chain rule, CHREST relies on a different set of formalisms. They include

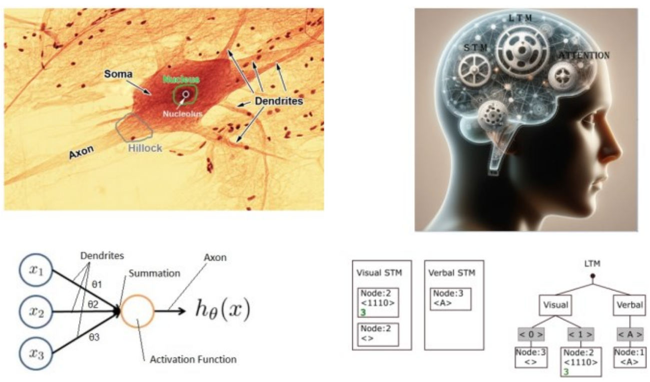

Figure 3. Some of the core neural (on the left) and cognitive mechanisms (on the right), and their respective formalisms (below) in deep learning and CHREST respectively. The microscopy image was taken from Olexik (2015).

graph data structures, first-in-first-out queues, with the whole system being trained by a process of chunking that is functionally equivalent to deep learning's backpropagation. (Backpropagation is the process of adjusting synaptic weights based on the error rate of the artificial neural network (Rumelhart et al., 1986)). Chunks are operationalized as graph nodes and chunking is the process of adding new data to the LTM (see Figure 3). This is done via two psychologically plausible cognitive processes: discrimination and familiarisation. Discrimination is the process of adding a new node to the network. Familiarisation updates existing nodes with new information.

An important difference between CHREST and connectionism/deep learning is that CHREST is an example of a symbolic architecture, while the connectionist neural nets are subsymbolic (the question of which approach better models cognition was hotly debated) (Simon, 1991). In practice, this means that CHREST's patterns are meaningful and are represented as symbols (i.e., text) for objects inside (cognition) and outside (input) the architecture. This is in contrast to deep learning, where, for example, meaningful input text is converted into numbers which are then manipulated by the internal functions to generate a desired output (see Figure 4). We should also add that CHREST is different to many symbolic models (like "expert systems") and is closer to deep learning in its focus on perception as the primary driver of intelligence. Gobet and Lane (2012) offer an in-depth introduction to the chunking theory; for deep learning, see LeCun, Bengio, and Hinton (2015).

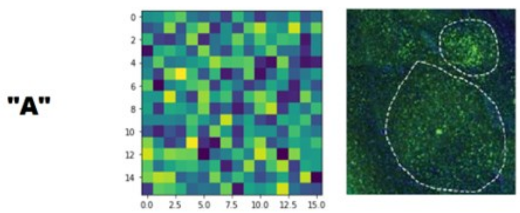

Figure 4. Representations in cognitive, ANN and biological systems. From left to right: a chunk with letter "A" in CHREST; numerical neural heatmap corresponding to letter "A" in a deep learning model; biological neuronal engram corresponding to "safe place" in an optogenetically modified mouse (from Liu, Ramirez, and Tonegawa (2013)). Yellow colour represents strong positive activations and dark blue represents strong negative activations.

III. Concepts and Chunks

As was mentioned above, chunking plays a crucial role in a wide range of cognitive phenomena. We focused on chunking in concept learning/categorisation as this field is particularly complex, and, "in some way, everything is concepts" (Murphy, 2002, p. 3).

What *are* concepts? One definition is that concepts are "mental representations of classes of things", with "classes of things" themselves being categories (Murphy, 2002). Historically, the psychological literature on concept formation was dominated by formal models that operated on artificial categories with a few and often binary dimensions (e.g., Anderson, 1991; Love, Medin, & Gureckis, 2004; Nosofsky, 2011), or natural categories that were pre-processed (into a few and often binary dimensions) (e.g., Nosofsky et al., 2017; Nosofsky et al., 2018). This led to reformulating the definition of concepts as either prototypes (summary descriptions) (Frixione & Lieto, 2012), clusters of specific instances (exemplars) (Nosofsky, 2011), or clusters based on Bayesian inference (Anderson, 1991) and other clustering algorithms (Murphy, 2002). More recently, a number of psychological deep learning models moved towards processing *raw natural* categories, for example, classifying real-life images using their pixel data (Battleday et al., 2020; Sanders & Nosofsky, 2020), or finding false sentences (e.g., "fur has cat") in a natural language text (Bhatia & Richie, 2022). Moreover, Battleday et al. (2020) concluded that intuitions about theory and model performance for low-dimensional categories do not transfer to higher-dimensional ones.

Chunking theory's CHREST has also been used to model concept learning in tasks with high-dimensional real-life complexity. One CHREST model was able to categorise novel chess positions as one of two types of opening – a French, or a Sicilian (in chess, an opening concerns the first 10-20 moves of a game, with there being billions of potential different sequences of moves) (Lane & Gobet, 2012b). A more recent CHREST model was able to categorise novel literature pieces and music scores by predicting their respective author or composer (Bennett et al., 2020). The latter model was also notable for being domain general. For example, while the chess model relied on chess-specific heuristics/mechanisms that were hand-crafted by a chess expert (e.g., one of the heuristics guided model's attention towards chess pieces under attack), the literature and music categorisation did not have such pre-built knowledge structures and feature detectors. Instead, the model automatically formed chunking hierarchies during the learning phase (exposure to different literature and music pieces). During the test phase, the model automatically activated the largest of the formed chunks to "vote" for a category. In broader terms, this meant that a concept (e.g., a mental representation such as "Mozart" or "Homer") was a collection of chunks in a cognitive LTM-like structure – as operationalised by chunking theory's CHREST.

IV. The Present Study

The present study intended to establish the level of convergence between the chunking theory and connectionism/deep learning. We replicated and compared CHREST's artificial category learning performance, as well as literature and music categorisation experiment, with a deep learning model. While deep learning models have a rich history in text classification, with over 150 models built in recent years alone (Minaee et al., 2020), models of music scores classification are less numerous. Dor and Reich (2011) analysed MIDI data and achieved over 90% accuracy on classification of composer pairs (e.g., Bach or Chopin, Bach or Mozart). Herremans, Martens, and Sörensen (2015) achieved over 80% accuracy on a 3-way classification of a large dataset containing MIDI music by Bach, Beethoven and Haydn. However, both of the studies above relied on hand engineered musical features such as "melodic fifth frequency", "note count feature" and "melodic octave frequency", instead of training from raw music score data. Indeed, Dor and Reich (2011) considered classification of raw music scores to be impossible for the then current machine learning methods.

The approach of the current study included training linguistic and non-linguistic domains in one pass (i.e. *simultaneous* learning of *both* the literature authors and music composers – as was done in the CHREST study). Also, the training sets were kept to raw data only. To our knowledge, this approach is novel. We should also note that our deep learning model is meant to be supplementary to CHREST research – while our model is not trivial, it makes no claim to state-of-the-art categorisation performance. Instead, it was designed to aid comparison and to provide important theoretical neuroscience context to the state-of-the-art cognitive model of concept learning (CHREST). We trained both CHREST and deep learning models on the same set of unabridged works by various authors and composers. We tested categorisation on previously unseen pieces produced by the same authors and composers.

V. Method

A. The Training and Testing

The training and testing procedure was meant to mostly replicate the experiment by Bennett et al. (2020). There were 10 categories altogether, with 6 literature authors (Homer, Chaucer, Shakespeare, Scott, Dickens, Joyce) and 4 music composers (Bach, Mozart, Beethoven, Chopin). For each category (i.e., a literature author or a music composer), the training set contained approximately 300Kb of text in total.

The test dataset was expanded from the original study's 50 pieces of literature and music – to 120 pieces (60 literature pieces and 60 music scores; these were not part of the training set). This was done both to further test the CHREST model and to broaden the scope of comparison to the ANN model.

B. CHREST Model

Our CHREST model architecture was replicated from the original experiment by Bennett et al. (2020): it once again contained an LTM data structure that acquired chunks through learning, an STM structure that allowed to create category naming links between chunks, and a sliding attention window. The model also had a "chunk activation" mechanism: if there are *m* categories, the vector of categories is $c = [\boldsymbol{c_1}, \boldsymbol{c_2}, \dots \boldsymbol{c_m}]$, the vector of category specific chunk activations is $a = [\boldsymbol{a_1}, \boldsymbol{a_2}, \dots \boldsymbol{a_m}]$ and the confidence of a prediction that a stimulus belongs to category $\boldsymbol{c_i}$ would be calculated using the equation

$$C(c_i \mid x) = a_i \;/\; \sum_{k=1}^{m}(a_k)$$

where $C(c_i \mid x)$ is confidence that the category is c_i, given a literature or music stimulus *x*; a_i is the LTM chunks' activation corresponding to that category, and the summation part being the sum of chunk activations across all *m* categories. See Bennett et al. (2020) for the full details of CHREST categorisation model.

C. Deep Learning Model

A common way to model sequence processing in neural networks is with a recurrent type of neural architecture, also referred to as Recurrent Neural Networks (RNN) (Elman, 1990). Our model was also of this type. An RNN neuron has an axon that branches and outputs signal into that neuron itself, as well the subsequent neurons. Concretely, RNN neuron's output at time *t* is $h_t = ReLU(W_{xh}x_t + W_{hh}h_{t-1})$, where $ReLU$ is the threshold activation function (see below for more details), x_t is the input at time *t*, W_{xh} is the synapse weight between the input and the neuron, h_{t-1} is the output of that neuron at the previous time step *t-1,* and the W_{hh} is the synapse weight between the neuron's output and itself. The backward propagation of RNN is also known as "backward propagation through time" (Elman, 1990), but, despite the added time component, the basic logic remains the same.

As was mentioned above, simple off-the-shelf RNNs could not categorise raw music scores – presumably due to the network "forgetting" input that is above approximately ten time steps (Bengio, Frasconi, & Schmidhuber, 2001; Goodfellow, Bengio, & Courville, 2016). Thus, our model was enriched with four additional psychologically plausible mechanisms.

Firstly, the model featured random shutdown of neurons (also known as "Dropout") (Hinton et al., 2012). This can be viewed as an approximation for the neural refractory period – the short period of time when the neuron may not fire again (Deutsch, 1964). Functionally, the dropping out of neurons from the learning process prevents overfitting and excessive synaptic co-adaptation to patterns. Indeed, recent neuroscience research suggests that artificially inducing higher levels of neuronal dropout in biological brains (e.g., via Deep Brain Stimulation) can both disrupt and improve memory (Tan et al., 2020).

Secondly, the activation function for the neurons was chosen to be "ReLU" (rectified linear unit *f(x) = max(0,x)*). Originally proposed as a more biologically plausible depiction of the neural threshold function that is analogue as well as digital in nature (Hahnloser et al., 2000), ReLU became one of the key drivers behind the breakthrough with training artificial neural networks with many layers (Nair & Hinton, 2010). Because ReLU is so similar to a linear function – while being non-linear – it significantly diminished gradient saturation (and the ensuing vanishing gradient problem) that was associated with the traditional neural activation function *sigmoid(x)* and its variants like the *tanh(x)*.

Our third addition was the "sliding attention window" – as it was used with CHREST. The sliding attention window passed the retrieved short word sequences to the model and the model generated a vote/prediction for each of the sequences.

The fourth addition was the "LTM activation" mechanism that aimed to resolve conflicts between votes for different categories. As the model generated category "votes", these votes were then aggregated and the overall winner was declared by the confidence formula. The multidomain confidence criterion was calculated by the same formula as was used in CHREST model and still had the aim of resolving conflicting "voting" among category representations. The important difference was that, this time, the voting conflict was among different neural activations/engrams (as opposed to different cognitive chunks with CHREST):

$$C(c_i \mid x) = a_i \;/ \sum_{k=1}^{m}(a_k)$$

where $C(c_i|x)$ is confidence that category (i.e., author or composer) is c_i, given a novel literature or music stimulus *x*; a_i is the neural engrams' activation score corresponding to that category (i.e., author or composer), and the summation part being the sum of neural engram activations across all *m* categories.

Training and testing text files were converted to numeric vectors using the TensorFlow Tokenizer library to streamline processing. It should be noted that text vectorisation was done in the name of convenience – despite the psychological questionability of such a mechanism. The plausibility of the overall model would not be affected by this particular decision as artificial neural nets are capable of character recognition at approximately human level of performance (LeCun et al., 1999). The order of the training samples was randomised. No notes or words were removed from either training or testing patterns.

The model had around 8.5 million trainable parameters and was trained for 20 epochs. The vocabulary size was set to 50,000; the size of the attention window was set to 20 words/chords/notes; the embedding dimension was set to 1.

In all other aspects, the current experiment was a complete replica of the CHREST music and literature categorisation experiment discussed above.

See https://github.com/Voskod for Python3 source code; for Java implementation of CHREST with graphical user interface and more documentation see www.chrest.info.

VI. Results

Both CHREST and deep learning models were able to learn complex categories in the real-world music and literature domains. They required no ad hoc additions to the core architecture in order to simultaneously process music or literature specific nuances. The descriptive statistics for both models are summarised in Table 1.

CHREST's categorisation performance was substantially above chance – of the 120 tests across 10 categories (implying 12 correct answers by pure chance), 83 were classed correctly. Within modalities, CHREST correctly categorised 41 out of 60 literature works and 42 out of 60 music scores. The deep learning model's categorisation performance was also substantially above chance – of the 120 tests across 10 categories, 93 were classed correctly.

CHREST and ANN models made similar quantitative predictions. The CHREST model had the highest true predictions for Bach, Mozart, and Beethoven in music and Chaucer, Homer, Shakespeare, and Dickens in literature. Bach and Chaucer had the highest confidence scores for their respective modalities. Chopin and Joyce had the lowest confidence scores as well as the lowest true prediction rates. The same pattern of results was true for the deep learning model. One notable outlier was the discrepancy on the Walter Scott category, where CHREST had 4/10 correct predictions while the deep learning model had a 9/10 score.

There were no mistakes across modalities by either model – literature was never categorised as music and vice versa. This implies that while the models were taught to classify 10 types of regularities, they formed (empirically) distinct memory chunks/engrams that separate the domains of music and literature – as was evident from the overall winning confidence scores. However, while CHREST had no activations across modalities, they were occasionally present for the deep learning model. For example, the first four Scott pieces generated various activations across literature authors but had zero activations for any music composer. On the other hand, some stimuli did generate exactly that kind of "multi-modality" engram activation pattern. For instance, Mozart's *Fantasia in D* activated an engram that was made up from 76% of Mozart's representations, but also with 3% of Joyce's (see Table 2).

VII. Discussion

A. Summarising the Results

Both cognitive and neural models were able to learn real-life highly multidimensional categories while learning from raw data only, without bootstrapping to pre-made knowledge structures and feature detectors.

The comparison of the performance obtained by the CHREST and deep learning models provides for intriguing analysis and warrants further investigation. From a high-level perspective, both models demonstrated the capability of learning concepts in complex, dissimilar domains (*linguistic* in the case of literature and *non-linguistic* in the case of music).

Beyond the qualitative similarity, the CHREST and deep-learning models also made similar quantitative predictions. CHREST and deep learning also share functional similarities. This was demonstrated using the *same* activation mechanism for both CHREST and deep-learning models. Indeed, the proposed activation formula/code was completely interchangeable between the models and required no adjustment to measure the activation of *chunks* or the activation of *neural engrams*. In this technical sense, cognitive chunks may be said to be *equivalent* to neural engrams. The attention window mechanism was also similar for the two types of models.

Nevertheless, this similarity of the two models was not absolute. While CHREST had no cross-modality activations at all, the deep-learning model had slight (mostly around 1-5%) activations on some of the cross-modal representations. This being said, the overall distinct clustering of literature and music was true for both models. The occasional and mostly small cross modal activations of the deep-learning model may need further investigation: while the result above may represent statistical noise of the artificial neurons, similar mechanism may also potentially elucidate the complex phenomenon of synaesthesia (Ward & Simner, 2022).

B. Constraining the Infinite Space of Candidate Theories

One potential criticism of our study is that having two models arriving at similar behaviour by different means does not necessarily imply that the models are equivalent in any but the broadest sense. Indeed, in a trivial example where $x = 2$ and $f(x) = 4$, it does not make sense to talk about the equivalence of functions such as $f(x) = 2x$; $f(x) = x^3 - x^2$; $f(x) = 4*sin(\pi / x)$, and so on. Of the similarly infinite number of functions that may potentially represent a working cognitive system, which one did nature choose to make a human categorise a novel music piece as a "Beethoven"? Similarly, to what extent can psychological models claim convergence with humans and

Table 1. Categorisation performance summary for CHREST and deep learning models.

		CHREST		Deep Learning	
		Accuracy rate (%)	Mean confidence	Accuracy rate (%)	Mean confidence
Music	Bach	100	0.50	93	0.56
	Beethoven	93	0.44	87	0.46
	Chopin	20	0.31	27	0.34
	Mozart	67	0.42	67	0.52
Literature	Chaucer	100	0.50	100	0.85
	Dickens	70	0.26	100	0.49
	Homer	90	0.31	100	0.58
	Joyce	20	0.17	40	0.37
	Scott	40	0.20	90	0.39
	Shakespeare	90	0.34	90	0.50

Table 2. An excerpt of individual categorisation confidence scores by CHREST and deep learning models. Red colour signifies zero memory activation and darker shades of green signify stronger activation. Numbers in bold denote the highest confidence prediction on a given novel test.

	CHREST model											
Author	**File**	**Chaucer**	**Dickens**	**Homer**	**Joyce**	**Scott**	**Shakespeare**	**Bach**	**Beethoven**	**Chopin**	**Mozart**	**Correct**
Mozart	A Piece For Piano K176	0.00	0.00	0.00	0.00	0.00	0.00	**0.60**	0.16	0.03	0.21	FALSE
	Adagio In B Flat	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.04	0.29	**0.55**	TRUE
	Fantasia In C K.475	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.20	0.28	**0.38**	TRUE
	Fantasia In D, K397	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.06	0.31	**0.58**	TRUE
	K309 Piano Sonata N10 1mov	0.00	0.00	0.00	0.00	0.00	0.00	**0.44**	0.24	0.11	0.22	FALSE
Scott	Talisman Part 2	0.05	0.22	0.21	0.08	**0.26**	0.17	0.00	0.00	0.00	0.00	TRUE
	Talisman Part 3	0.05	0.21	0.20	0.14	**0.25**	0.16	0.00	0.00	0.00	0.00	TRUE
	Talisman Part 4	0.11	0.21	0.21	0.10	0.16	**0.22**	0.00	0.00	0.00	0.00	FALSE
	Talisman Part 5	0.11	0.17	**0.26**	0.11	0.17	0.19	0.00	0.00	0.00	0.00	FALSE
	The Lay Of The Last Minstrel	0.04	0.13	0.11	0.15	0.17	**0.39**	0.00	0.00	0.00	0.00	FALSE
Beethoven	Piano Sonata N08 Op13 1mov	0.00	0.00	0.00	0.00	0.00	0.00	0.31	**0.44**	0.14	0.10	TRUE
	Piano Sonata N08 Op13 3mov	0.00	0.00	0.00	0.00	0.00	0.00	**0.46**	0.32	0.12	0.11	FALSE
	Piano Sonata N09_1	0.00	0.00	0.00	0.00	0.00	0.00	0.33	**0.50**	0.10	0.06	TRUE
	Piano Sonata N09_2	0.00	0.00	0.00	0.00	0.00	0.00	0.34	**0.51**	0.09	0.06	TRUE
	Piano Sonata N10 1mov	0.00	0.00	0.00	0.00	0.00	0.00	**0.41**	**0.41**	0.08	0.09	TRUE
Joyce	A_Portrait_Of_The_Artist _1	0.05	**0.25**	0.14	0.24	0.20	0.11	0.00	0.00	0.00	0.00	FALSE
	A_Portrait_Of_The_Artist _2	0.04	0.20	0.14	**0.24**	0.21	0.16	0.00	0.00	0.00	0.00	TRUE
	A_Portrait_Of_The_Artist _3	0.02	**0.23**	0.20	**0.23**	0.10	0.21	0.00	0.00	0.00	0.00	TRUE
	Finnegans_Wake_1	0.12	0.12	0.19	0.18	0.10	**0.29**	0.00	0.00	0.00	0.00	FALSE
	Finnegans_Wake_2	0.13	0.16	0.18	0.09	0.16	**0.29**	0.00	0.00	0.00	0.00	FALSE
	Deep Learning model											
Author	**File**	**Chaucer**	**Dickens**	**Homer**	**Joyce**	**Scott**	**Shakespeare**	**Bach**	**Beethoven**	**Chopin**	**Mozart**	**Correct**
Mozart	A Piece For Piano K176	0.00	0.00	0.00	0.00	0.00	0.00	**0.57**	0.14	0.05	0.24	FALSE
	Adagio In B Flat	0.00	0.00	0.02	0.10	0.00	0.01	0.01	0.08	0.16	**0.61**	TRUE
	Fantasia In C K.475	0.00	0.00	0.00	0.05	0.00	0.01	0.01	0.09	0.40	**0.43**	TRUE
	Fantasia In D, K397	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.21	**0.76**	TRUE
	K309 Piano Sonata N10 1mov	0.00	0.00	0.00	0.00	0.00	0.00	0.25	**0.46**	0.11	0.18	FALSE
Scott	Talisman Part 2	0.00	0.13	0.20	0.04	**0.51**	0.11	0.00	0.00	0.00	0.00	TRUE
	Talisman Part 3	0.00	0.11	0.09	0.05	**0.54**	0.21	0.00	0.00	0.00	0.00	TRUE
	Talisman Part 4	0.00	0.15	0.15	0.09	**0.38**	0.24	0.00	0.00	0.00	0.00	TRUE
	Talisman Part 5	0.00	0.11	0.25	0.05	**0.38**	0.22	0.00	0.00	0.00	0.00	TRUE
	The Lay Of The Last Minstrel	0.04	0.02	0.07	0.11	0.26	**0.48**	0.00	0.00	0.02	0.00	FALSE
Beethoven	Piano Sonata N08 Op13 1mov	0.00	0.00	0.00	0.02	0.00	0.02	0.13	**0.38**	0.14	0.30	TRUE
	Piano Sonata N08 Op13 3mov	0.00	0.00	0.00	0.00	0.00	0.00	**0.43**	0.42	0.05	0.10	FALSE
	Piano Sonata N09_1	0.00	0.00	0.00	0.00	0.00	0.00	0.18	**0.49**	0.18	0.16	TRUE
	Piano Sonata N09_2	0.00	0.00	0.00	0.00	0.00	0.02	0.23	**0.58**	0.12	0.05	TRUE
	Piano Sonata N10 1mov	0.00	0.00	0.00	0.00	0.00	0.00	**0.41**	0.40	0.05	0.15	FALSE
Joyce	A_Portrait_Of_The_Artist _1	0.00	**0.45**	0.07	0.35	0.11	0.02	0.00	0.00	0.01	0.01	FALSE
	A_Portrait_Of_The_Artist _2	0.00	**0.47**	0.01	0.34	0.09	0.09	0.00	0.00	0.00	0.00	FALSE
	A_Portrait_Of_The_Artist _3	0.00	0.38	0.04	**0.46**	0.07	0.04	0.00	0.00	0.00	0.00	TRUE
	Finnegans_Wake_1	0.00	**0.42**	0.05	0.41	0.03	0.09	0.00	0.00	0.00	0.00	FALSE
	Finnegans_Wake_2	0.03	**0.41**	0.03	0.34	0.06	0.12	0.00	0.00	0.00	0.00	FALSE

with each other? To put it yet another way, given two points "A" and "B", there is an infinite number of paths that lead from point "A" to point "B"; how would we decide on which path to take? On the one hand, there is no real answer – a "solution" that is commonly known as Hume's problem of induction (Hume, 1748). We relied on three pragmatic means to address this problem in the current study.

Firstly, the simplest answer would be to choose the path that satisfies some other constraints. For example, the shortest path, a path through the gates "X", "Y", "Z" and so on. In terms of choosing a psychologically plausible computational approach, one should choose a method that satisfies multiple constraints – e.g., postdicting past psychological experimental data as well as predicting findings that have not yet been reported (Newell, 1990). Our CHREST and deep-learning models both satisfy these constraints as they incorporate fundamental psychological mechanisms and structures, and are rooted in decades of psychological research. For example, our CHREST model features the STM, LTM, chunking, familiarisation, discrimination, association and attention; while our ANN model has dendrites, axons, threshold activation and a refractory period. While not the focus of the current study, CHREST family of models also successfully simulates human timings and learning rates in a variety of cognitive experiments (Gobet, Lane, & Lloyd-Kelly, 2015). As was mentioned above, a recent Nature review concluded that deep learning models offer profound insights into the working of the brain (Richards et al., 2019). This means that, in terms of the "path from A to B" analogy above, our models not only connect the "A" and "B", but also pass the "X", "Y", "Z" gates/constraints that are relevant to psychology. This is unlike other hypothetical models of categorisation (e.g., semantic parsers, support vector machines, etc) that connect the "A" and "B" without passing the gates and thus make up the unconstrained infinite space of candidate models. More broadly, this aspect forms a crucial difference between computer science (where all models are "equal" as long as they succeed at a task) and psychology (where "psychologically plausible" models are desired). For instance, Deep Blue is not considered to be a psychologically plausible model of human chess playing (Gobet, 1997a) due to its reliance on brute search, but AlphaZero is more psychological in how it relies on pattern recognition (as well as incorporating some neural mechanisms) (Gobet & Waters, 2023; Silver et al., 2017).

The second important constraint is the inherent difficulty of problems that were long considered to be "ill-posed", yet routinely solved by the brains/minds of various organisms – such as inverse optics and inverse kinematics (Palmer, 1999; Pizlo, 2001). Musical and literature categorisation is one type of this "ill-posed" problem. Psychological models of concept learning traditionally struggled with such tasks and resorted to either artificial categories with a few dimensions (e.g., Braunlich & Love, 2022; Nosofsky, 2011), pre-processed natural categories into a few dimensions (e.g., Konovalova & Le Mens, 2018; Nosofsky, 2011), or bootstrapping to hand-crafted knowledge structures such as semantic dictionaries (e.g., Lieto, 2019). More recently, there was a move to combine psychological models with deep learning, where ANNs do the heavy lifting of learning from raw data (Battleday et al., 2020). In the current study, both models learn from highly multidimensional raw data without bootstrapping, with CHREST performing all the learning required with its own mechanisms.

The third crucial constraint is the "single algorithm hypothesis", which proposes that visual, auditory, motor, and somato-sensory cortices utilise approximately the same algorithm to extract approximately one type of data structure from various types of information (i.e., visual, auditory, motor, etc) (Hawkins & Blakeslee, 2004; Mountcastle, 1978). In this context, the similarity between CHREST and deep learning is constrained in two important ways. Firstly, chunks-based and engrams-based models converged in classification of relatively dissimilar complex domains. Secondly, both approximations of this "single algorithm" shared a common activation mechanism which works on both cognitive chunks *and* neural engrams. Having said that, of course, a conclusive guarantee that the models' overlap provides a unique explanation is impossible (Lakatos, 1970). See Lieto (2022) for more discussion on "function only" (functionalist) versus "function + constraints" (structural) models as well as a more general framework of evaluating bio-inspired models.

C. Future Research and Conclusions

We focused on one of the most complex, yet most fundamental psychological processes – concept learning. Future research, while utilising a similar methodology, may focus on other cognitive phenomena that involve chunking (e.g., working memory, expertise, acquisition of grammar, verbal learning, reasoning, and the list goes on) to further ground chunking mechanisms in the neural substrate. For example, it has been established that human working memory contains around seven chunks at a time (Baddeley, 1986; Miller, 1956; Robbins, 1995); and, that human experts' LTM typically possess between one to five hundred thousand chunks with information specific to their domain (Gobet & Simon, 1998; Richman et al., 1996). One natural extension of the current study would be to adapt the chunk/engram activation mechanisms proposed in the current paper to translate the above work on chunking to connectionist models. Such work would be of obvious benefit to both psychology and AI. On the psychology side, this would further bridge cognitive psychology, the neuroimaging studies of chunking (Guida et al., 2012) and computational neuroscience. On the AI side, establishing chunking mechanisms in deep learning architectures would allow for better interpretability of the models.

The correspondence of chunking and other, non-RNN, deep learning architectures also warrants further investigation. We chose the RNNs as they have deep roots in psychology (this was important for the constraint saturation aspects that were discussed above). RNNs may also be considered to be closely related to CNNs (Convolutional Neural Networks) (LeCun et al., 1999), LSTMs (Long Short-term Memory) (Hochreiter & Schmidhuber, 1997) and GRUs (Gated Recurrent Units) (Cho et al., 2014) – indeed, our current engram activation mechanism is compatible with all of these architectures. On the other hand, the latest advancements in deep learning – based on the transformer architecture (Vaswani et al., 2017) – are radically different in important ways (e.g., in modelling of the attention function) and require a separate study.

The current study addresses a long historical feud between the symbolic/serial processing and subsymbolic/parallel processing approaches to modelling cognition. Generally, the focus on perception and bottom up processes is attributed to the subsymbolic approach, while the focus on heuristics, symbol manipulation and high levels of abstraction is considered to be the way of the symbolic approach (for a review, see Lieto, 2021). It is important to note that such differentiation was not universally accepted. Indeed, Simon and Newell considered perception to be a vital component in symbolic models of intelligence, together with a physical symbol system (Newell, 1990; Simon, 1981). Our CHREST model also adheres to their view (which is natural, as it is closely related to their models). However, contrary to Simon's intuitions (Simon, 1991, pp. 81-83) and more in line with Newell's thinking (Newell, 1990, p. 487), our results demonstrate both serial and parallel approaches to be convergent in important ways (with cognitive chunks and neural engrams being equivalent in a narrow technical sense), and with there being multiple levels of explicit representation – a mind-level representation and a brain-level representation.

To conclude, the current paper further bridges the gap between cognition and its neural substrate by demonstrating profound convergence between a rigorous cognitive psychology-based model and its neuroscience-based counterpart. Our findings connect the mechanisms proposed by chunking theory to the neural network modelling approach, and make further inroads towards a Unified Theory of Cognition (Newell, 1990).

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