Discovering the Neuroanatomical Correlates of Music with Machine Learning

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6.1 Introduction

Music is ubiquitous in our lives yet unique to humans. The interaction between music and the brain is complex, engaging a variety of neural circuits underlying sensory perception, learning and memory, action, social communication, and creative activities. Over the past decades, a growing body of literature has revealed the neural and computational underpinnings of music processing including not only sensory perception (e.g., pitch, rhythm, and timbre), but also local/non-local structural processing (e.g., melody and harmony). These findings have also influenced Artificial Intelligence and Machine Learning systems, enabling computers to possess human-like learning and composing abilities. Despite the plenty of evidence, more study is required for complete account of music knowledge and creative mechanisms in human brain. This chapter reviews the neural correlates of unsupervised learning with regard to the computational and neuroanatomical architectures of music processing. Further, we offer a novel theoretical perspective on the brain's unsupervised learning machinery that considers computational and neurobiological constraints, highlighting the connections between neuroscience and machine learning.

In the past decades, machine learning algorithms have been successfully used in a wide variety of fields including automatic music composition and natural language processing as well as search engine development and social network filtering. Machine Learning implements probabilistic algorithms based on input data to make predictions in the absence of explicit instructions. There are various types of machine learning algorithms (e.g., supervised, unsupervised, and reinforcement learning), each of which gives computers a particular learning ability similar to the equivalent ability of the human brain. For this reason, these algorithms also enable machines to create interpretable models revealing the brain's learning and prediction mechanisms. This knowledge allows us to design brain-inspired Artificial Intelligence (AI), potentially leading to a harmonized society of humans and computers. For example, statistical learning theory is a framework for machine learning that has given neuroscientists some interpretable ideas contributing toward understanding the implicit learning mechanisms in the human brain (Perruchet and Pacton, 2006). Implicit learning is an "*unsupervised learning*" ability that is innately equipped in the human brain and does not require explicit instructions, intention to learn, or awareness of what has been learned (Norris and Ortega, 2000). It is believed that the brain's (implicit) statistical learning machinery contributes to the acquisition of a range of auditory knowledge such as that related to music and language. Abundant evidence has suggested that statistical learning functions across different levels of processing phases in perception, memory consolidation, production (i.e.,

action), and social communication including music sessions and conversations. Recently, a growing body of literature has suggested that auditory knowledge acquired through statistical learning can be stored in different types of memory spaces through data transfer between the cortex and the subcortex, and that this knowledge is represented based on semantic/episodic, short/long-term, and implicit/explicit (procedural/declarative) processing. This chapter reviews the neural correlates of these processes with machine learning in the framework of the statistical learning hypothesis, based on a large body of literature across a broad spectrum of research areas including Neuroscience, Psychology, and AI.

6.2 Brain and Statistical Learning Machine

6.2.1 Prediction and Entropy Encoding

The auditory cortex receives external acoustic information through a bottom-up (ascending) pathway via the cochlea, the brainstem, the superior and olivary complex, the inferior colliculus in the midbrain, and the medial geniculate body of the thalamus (Langner and Ochse, 2006; Pickles, 2013; Sinex et al., 2003). For auditory perception, our brain processes space information (originating from the tonotopic organization of the cochlea) and time information (originating from the integer time intervals of neural spiking in the auditory nerve) (Moore, 2003). Importantly, the auditory pathway consists of top-down (descending) as well as bottom-up (ascending) projections. Indeed, it has been proposed that nuclei such as the dorsal nucleus of the inferior colliculus receive more top-down projections than bottom-up projections from the auditory cortices (Huffman and Henson, 1990). Furthermore, even within the neocortical circuits, auditory processing is driven by both top-down and bottom-up systems via dorsal and ventral streams (Friederici et al., 2017a). Here, we focus on the top-down and bottom-up predictive functions of (sub)cortices within the framework of the statistical learning hypothesis.

The brain is inherently equipped with computing machinery that models probability distributions about our environmental conditions. According to the internalised probabilistic model, it can also predict probable future states and optimize both perception and action to resolve any uncertainty over the environmental conditions (Pickering and Clark, 2014).

Predictive coding, currently one of the dominant theories on sensory perception (Friston, 2010), provides a neurophysiological framework of such predictive processes with regard to auditory functions. According to this theory, neuronal representations in the higher levels of the cortical hierarchies are used to predict plausible representations in the lower levels in a top-down manner and are then compared with the representations in the lower levels to assess prediction error; i.e., a mismatch between sensory information and a prediction (Kiebel et al., 2008; Mumford, 1992; Rao and Ballard, 1999). The resulting mismatch signal is passed back up the hierarchy to update higher representations and evince better predictions. Over the long term, this recursive exchange of signals suppresses prediction error and uncertainty to provide a hierarchical explanation for the input information that enters at the lowest (sensory) level. In auditory processing, the lower to higher levels of this hierarchy could comprise the auditory brainstem and thalamus, the primary auditory cortex, the auditory association cortex, the premotor cortex, and the frontal cortex in that order. Thus perceptual processes are driven by active top-down systems (i.e., backward/inverse) as well as passive bottom-up systems (i.e., forward) in a perception-action cycle (Friston et al., 2016; Rauschecker and Scott, 2009; Tishby and Polani, 2011). Thus, the processing of auditory data such as music and language subsumes a variety of cognitive systems including prediction, learning, planning, and action.

The brain's statistical learning mechanisms appear to agree with this predictive model (Harrison et al., 2006a). Statistical learning is an unsupervised and implicit mechanism by which the brain encodes the probability distributions in sequential information such as music and language (Cleeremans et al., 1998; Saffran, et al., 1996) and assesses the entropy of the distribution (i.e., the uncertainty of future states, being interpreted as the average surprise of outcomes sampled from a probability distribution) (Hasson, 2017). The brain also predicts probable future states based on an internal statistical model and chooses the optimal action to achieve a given goal (Monroy et al., 2017a; Monroy et al., 2017b). The role of statistical learning was first discovered in the lexical (word) acquisition process (Saffran et al., 1996), but an increasing number of studies has indicated that statistical or probabilistic learning also contributes to various levels of learning such as phonetic, syntactic, and grammatical processing (Saffran et al., 1997). Statistical learning is a domain-general and species-general principle, occurring for visual as well as auditory information over a wide span of ages (Saffran et al., 1999; Teinonen et al., 2009) and in both primates such as monkeys (Saffran et al., 2008) and non-primates such as songbirds (Lu and Vicario, 2014; 2017) and rats (Toro et al., 2005). The statistical learning function is not limited to within the individual but can be expanded to

communication between persons (Scott-Phillips and Blythe, 2013). That is, two persons can share a common statistical model, resulting in interplay between them (Monroy et al., 2017b). Furthermore, the generation of culture (Feher et al., 2016) and musical creativity and individuality (Daikoku, 2018b) can originate through the interplay of statistical learning. Thus, statistical learning is an indispensable ability in the developing brain that contributes to both music perception and production. Previous studies have shown that pitch prediction of novel melodies is closely linked to probability distribution sampled from a large corpus of music (Pearce, 2006; Pearce et al., 2010). In addition, the brain can process chord sequences accurately and quickly if the predictability of a chord (local event) and the uncertainty of the preceding sequence of six chords (global harmonic phrase) are correlated with each other (Tillmann et al., 2000; Tillmann et al., 1998). Thus the two levels of statistical learning (i.e., probability and uncertainty encoding) may not function independently but may rather be interdependent. Hansen and Pearce (2014) have demonstrated that uncertainty perception in melody is stronger in musicians than in non-musicians. This suggests that long-term musical training allows the brain to optimize/generalize its probabilistic model of music which decreases uncertainty. Thus the development of statistical learning machinery in the brain is indispensable for the generalization of music structure, music proficiency, and predictive processing efficiency.

6.2.2 Learning

6.2.2.1 Timbre, Phoneme, and Pitch: Distributional Learning

Although plenty of statistical learning studies have focused on lexical acquisition, statistical learning is also used to discover which phonemes, timbres, and pitch contours are important in a given language or in music (Gómez and Gerken, 2000; Kuhl, 2004; Ong et al., 2016). It is of note that this type of statistical learning differs from that used in lexical acquisition: the statistics that are learned do not represent transitional probability but rather the distributional regularity of acoustic features (e.g., pitch and formant). This is often referred to as *distributional learning* (Werker et al., 2012). Distributional learning has also been proposed as a machine learning algorithm in the framework of computational learning theory (Michael et al., 1994) although the algorithm differs from that used in psychological and neural studies. Prior to native language acquisition, infants discriminate between phonemes in many different

languages regardless of phoneme categories. Through ample exposure to the sounds in their native language, however, they gradually abstract the features of the phonemes and contrasts through statistical learning of the distributional regularities in those sounds. Infants then generalize those features into the same phonetic category even if the phonemes occur at different articulations (Maye et al., 2008; Maye et al., 2002); thus they become unable to discriminate between phonemes that do not appear in their native language. In contrast, a prototypical phoneme of a native language acts as a magnet for similar phonemes (perceptual magnet effect) (Kuhl et al., 1992; Kuhl, 2000). In the end, the brain perceives that those similar phonemes belong to the same category as the prototypical phoneme (Kuhl, 2004).

6.2.2.2 Chunk and Word: Transitional Probability

Saffran et al. (1996) initially reported on human statistical learning ability in lexical acquisition. After four minutes of exposure to speech sequences in which three-syllable pseudo-words were randomly concatenated, infants discriminated the pseudo-words from non-words (non-words consisted of the same syllables but were sequenced in a different order from the pseudo-words). Because there were no cues (such as pauses, intonation, etc.) indicating word boundary information other than transitional probabilities between words, the results indicate that infants can learn words based on statistical learning of adjacent transitional probability. Several studies have demonstrated that statistical learning based on adjacent transitional probability is also indispensable for learning the sequential structures of musical pitches (Saffran et al., 1999; Saffran et al., 2005), timbre (Koelsch et al., 2016), and chord sequences (Daikoku et al., 2016; Kim et al., 2011). Actually, this type of statistical learning has frequently been used in machine learning such as natural-language processing and automatic music composition (Brent, 1999; Raphael and Stoddard, 2004); these models are referred to as *n*-gram or *n*th-order Markov models. The statistical learning that occurs during lexical acquisition has generally been assumed to represent the early stages of native language and music acquisition. Statistical learning based on local dependency (i.e., adjacent transitional probability) alone, however, may not be sufficient to account for all levels of music and language knowledge. In other words, music structures consist of both local and non-local (hierarchically organized and non-adjacent) dependencies. Some reports have indicated that different types of statistical or probabilistic learning can partially explain the acquisition of higher-level structures such as syntactic processing (Saffran and Wilson, 2003; Seidenberg,

1997). Indeed, in machine learning as well as in natural language processing, the n-gram models of words have been applied to generate artificial sentences (i.e., a word is recognized as one unit and a computer calculates the statistical relationships between words). It is, however, still debatable whether the human brain also performs the same underlying computation used in lexical acquisition to acquire syntactic structure, or whether the two processes tap into different mechanisms. In the next section, we review recent advances in exploring the underpinnings of syntactic learning mechanisms and how nonlocal/nonadjacent (i.e., long-distance) dependency interacts with adjacent dependency.

6.2.2.3 Syntax and Grammar: Local vs. Non-Local Dependencies

The important question consists of how statistically chunked words are syntactically ordered and how nonlocal/nonadjacent (i.e., long-distance) dependency interacts with adjacent dependency. In many experimental paradigms, however, the processes of local dependency (e.g., musical expectancy formation between adjacent events) and non-local dependency (hierarchically organized musical structure building) have often been confounded (as is usually the case in real music and language). For example, in the sentence “The books on the desk are old.”, the plural verb form “are” corresponds to the plural subject “books” occurring several words earlier, creating a nonadjacent hierarchical dependency between “the books” and “are old”. Learning such rules can be difficult because the adjacent singular form “desk” must be ignored. Analogous hierarchical structures are found in music. For example, in a wide variety of musical genres (but most commonly by far in Jazz), the subdominant – dominant – tonic progression referred to as a two-five-one (II – V – I) progression is a common cadential chord progression. Jazz improvisers partially chunk harmony progressions to create the hierarchical structure of a larger phrase. Figure 6.1 shows an example of non-local dependency in a piece of Jazz music entitled *Misty* as played by Errol Garner (a simplified arrangement is shown).

As can be seen in Figure 6.1, the chord names and symbols are also simplified (just major/minor, and 7th note) to account for the two-five-one (II – V⁽⁷⁾ – I) progression. In this phrase, the chord “IV” (E ♭ maj7) in the fourth measure corresponds to the chord “I” (E ♭ maj7) in the second measure occurring several chords earlier, creating a nonadjacent hierarchical dependency between the “I” and the “IV” in a recursive fashion. The local

dependency between the first and second chords ($E \flat \text{ maj7} - B \flat \text{ m7}$) is less likely according to traditional music theory, but this second chord lays the groundwork for the non-local dependency between “I” and “IV” by generating a $\text{II} - \text{V} - \text{I}$ progression (i.e., $B \flat \text{ m7} - E \flat 7 - A \flat \text{ maj7}$). Another type of interaction can be seen in the latter half of the phrase (i.e., adjacent: $\text{II} - \text{V} - \text{VI} - \text{IV}$, non-adjacent: $\text{IV} - \text{I}$). Near the end of the piece, the higher hierarchy of the harmony structure “ $\text{I} - \text{IV} (- \text{IV}) - \text{I}$ ” nests the lower hierarchy of the structures “ $\text{II} - \text{V} - \text{I}$ ” and “ $\text{II} - \text{V} - \text{VI} - \text{IV}$ ”. Hofstadter (1979) has also indicated that a key change embedded in a superordinate key forms hierarchical nonadjacent structures in a recursive fashion. Thus, composers generally design hierarchical nonadjacent structures in a recursive fashion, potentially using this technique to organize as much as an entire movement of a symphony or sonata (Schenker and Jonas, 1956). Some researchers have proposed computational and generative models for such hierarchical structures in music; e.g., Generative Theory of Tonal Music (GTTM) by (Lerdahl and Jackendoff, 1983) and the Generative Syntax Model (GSM) by (Rohrmeier, 2011).

non-adjacent (non-local) I IV IV I

adjacent (local) (II → V → I) (II → V → VI → IV)

E^b_{maj7} B^b_{m7} E^b₇ A^b_{maj7} A^b_{m7} D^b₇ E^b_{maj7} C_{m7}

Figure 6.1: *Misty* by Errol Garner, composed in 1954. This is simplified arrangement.

With respect to the question of how nonadjacent dependency interacts with adjacent dependency, categorization (Jones and Mewhort, 2007), non-adjacent (non-local) transitional probabilities (Frost and Monaghan, 2016; Pena, 2002), and higher-order transitional probabilities (Daikoku, 2018c) may be key insights into generating advanced statistical learning models that are as similar as possible to those used for natural music and language processing. For example, humans can learn which words belong to certain categories such as nouns and verbs by tracking the similar contexts in which words of the same category appear and creating templates of possible sentence structures based on the statistical regularities of the ordering of these different categories, regardless of explicit (declarative) knowledge of labels on their categories (Jones and Mewhort, 2007; Landauer and Dumais, 1997; Lund and Burgess, 1996). For example, when the verb “drink” occurs, the models predict subsequent words referring to things that can be drunk. This hypothesis is partially supported by a behavioural study (Gómez and Gerken, 2000). In this study, after exposure to novel grammatical and ungrammatical sentences, infants could discriminate between grammatical and ungrammatical sentences even when the individual words were exchanged for others in the same category. This generalization indicates that infants were not learning vocabulary-specific grammatical structures but rather abstracting the general rules of those grammatical structures and applying those rules to novel vocabulary (Gomez and Gerken, 1999). Furthermore, Gomez demonstrated that both adults and infants can learn non-adjacent transitional probabilities of words (Gómez, 2002). This study also suggested conditions that might lead learners to focus on nonadjacent versus adjacent dependencies. Each learner was exposed to several types of pseudo-word streams (e.g., pel-wadim-rud and pel-kicey-rud). Each type of stream contained the same adjacent dependencies (e.g., $P(\text{wadim}|\text{pel}) = P(\text{kicey}|\text{pel})$ and $P(\text{rud}|\text{wadim}) = P(\text{rud}|\text{kicey})$), so learners could distinguish among the languages only by acquiring data on dependencies between the first and third elements (the nonadjacent dependencies: $P(\text{pel}|\text{rud})$). The size of the pool from which the middle words were drawn was systematically varied to investigate whether increasing variability (in the form of decreasing predictability between adjacent words) would lead to better detection of nonadjacent dependencies. The participants acquired non-adjacent dependencies only when adjacent dependencies were least predictable. That is, the adjacent elements were recognised as invariant when the adjacent transitional probabilities were high, whereas learners might seek alternative sources of predictability such as non-adjacent transitional probabilities when adjacent dependencies were lower. A similar finding has also been observed from a different viewpoint in a study on the order of transitional probability (Daikoku et al., 2017). In this study,

when the variability of transitional probability distribution was increased, participants focused on higher-order transitional probability. For example, in the sentence “the books on the desk are old” mentioned above, an increase in variability could lead to a shift in the statistical learning strategy from a lower order (e.g., first-order: $P(\text{are}|\text{desk})$) to a higher order (e.g., fourth-order: $P(\text{are}|\text{books-on-the-desk})$). In the end, the adjacent singular form “desk” does not have to be ignored when predicting the plural verb form “are” based on a higher-order transitional probability. In other words, “are” accompanied by “desk” (i.e., first-order transitional probability of $P(\text{are}|\text{desk})$) is less likely and the uncertainty of predictability is high, whereas “are” accompanied by “books-on-the-desk” (i.e., first-order transitional probability of $P(\text{are}|\text{desk})$) is likely and the uncertainty of predictability is low. Importantly, Shannon’s information theory also offers evidence that a higher-order transitional-probability distribution shows lower conditional entropy (i.e., uncertainty). Thus the order of transitional probability may partially represent the relationship between local and non-local dependencies (Shannon, 1948). It is of note, however, that composers sometimes design hierarchical nonadjacent structures, potentially even consisting of “entire” movements of music (Schenker and Jonas, 1956). It may not be reasonable to create a transitional probability that is long enough and of a high enough order to cover an entire piece of music. In summary, many researchers have suggested a relationship between adjacent and non-adjacent dependency in syntactic structure, but the matter is still open to debate.

6.2.3. Memory

6.2.3.1 Semantic vs. Episodic

It has been suggested that semantic memory is partially acquired through statistical learning of episodic experience (Altmann, 2017; Rogers and McClelland, 2004). In other words, an individual episodic experience is abstracted on a statistical basis to generate semantic knowledge that captures the statistical common denominator across experienced information (Sloutsky, 2010). This suggests that statistical learning underlying chunk formation and word acquisition consists in part of statistical accumulation across multiple episodes. On the other hand, an opposing statistical learning process appears to be happening simultaneously: semantic memory can be integrated to generate novel episodic memory through statistical learning (Altmann, 2017). This can be regarded as a syntactic process in contrast to chunking and the lexical process. Altman et al. (2017) has suggested that language learning (e.g.,

semantic tokens) requires a route from episodic experience to semantic representation (via abstraction), while language comprehension (e.g., grammar and sentences) requires a route from semantic to episodic representation. Thus it has been suggested that two interdependent processes should be incorporated to generate a complete account of statistical learning (Thiessen et al., 2013):

(a) Abstraction (chunking) of statistically coherent events from the input information (i.e., abstraction to generate semantic memory on lexicon

(b) Comparison and integration between those chunked units (i.e., comparison between semantic memories to generate episodic memory on syntax).

6.2.3.2 Short-term vs. Long-term

Recent neurophysiological studies have demonstrated that the statistical learning effect is reflected in neuronal response even after short-duration exposure (5 to 10 minutes) (Daikoku et al., 2014; François et al., 2017; Koelsch et al., 2016). Few studies, however, have investigated how long statistical knowledge can persist (Ellis, 2009). It has been suggested that statistical learning shares properties with artificial grammar learning (Reber, 1967) because of their implicit nature in memory (Conway and Christiansen, 2006; Perruchet and Pacton, 2006). According to artificial grammar learning studies, implicit memory persists over the long term; as long as two years (Allen and Reber, 1980). Considering its shared properties with artificial grammar learning, implicit memory acquired by statistical learning may also have both short-term and long-term properties. Indeed, some researchers have reported that statistical learning persists for at least 24 hours (Kim et al., 2009). Recent studies indicate that slow-wave sleep (SWS) contributes to retention of statistical knowledge (Durrant et al., 2013; Durrant, Taylor et al., 2011). Interestingly, memory consolidation could modulate the structure of short-term memory into different forms of long-term memory in which the information may be minimized, possibly to enhance information efficiency in long-term storage (Diekelmann and Born, 2010; Lewis and Durrant, 2011). Furthermore, it has been indicated that memory consolidation transforms implicit memory into explicit memory (Fischer et al., 2006). In the next section, we review recent studies on consolidation within the statistical learning framework and discuss how memory can be transformed by consolidation.

6.2.3.3 Consolidation

An initially acquired memory is labile and easily forgotten. To retain temporary but important memories over the long term, memory can be stabilized by the memory consolidation system in the brain. This memory consolidation process allows the brain to extract useful knowledge and discard (forget) irrelevant information, contributing to the efficiency of memory capacity in the brain (Kumaran et al., 2016). It is still debatable, however, how the brain discriminates between important and irrelevant knowledge among the massive quantities of information it receives. Recent studies have proposed that the algorithm underlying the brain's memory consolidation will prove to be a key insight for improving the efficiency of information processing in machine learning (Wiggins, 2018a) and understanding the links between neuroscience and machine learning (Kumaran et al., 2016).

Active Systems Consolidation (ASC), a leading theory of memory consolidation, proposes a two-stage model of memory consolidation across short- and long-term storage (Diekelmann and Born, 2010). This model describes a way in which the brain's neuronal networks could overcome the stability-plasticity dilemma; i.e., how it could acquire new information (plasticity) without overriding older knowledge (stability) (Frankland and Bontempi, 2005; Marr, 1971; McClelland et al., 1995; Rasch and Born, 2007). The model assumes two types of memory stores: one serves as storage for fast and short-term learning and memory while the other serves as storage for long-term learning and memory. First, novel information is encoded in both stores. Then, the short-term memory is repeatedly re-activated in the fast-learning store. This processing is followed by re-activation in the long-term store to re-organize and strengthen the memory. Through these re-activations of novel information, the short-term learning store acts like an internal trainer for the long-term-learning store, allowing it to gradually adapt the novel information to the pre-existing long-term memories. This process also promotes the extraction of invariant repeating features from the new memories. These processes occur when there is no interference from novel information; i.e., during sleep. Neuronal studies have suggested that these two stores for short-term and long-term learning are reflected in the hippocampus and neocortex activities, respectively (Durrant et al., 2013; Rasch and Jan, 2013). On the other hand, whether memory consolidation merely passively protects memories from decay or actively refreshes memory representations remains an open

question (Ellenbogen et al., 2006; Wixted, 2004). The ASC posits that consolidation during both Slow-Wave Sleep (SWS), which is typically referred to as deep sleep and which consists of stages 3 and 4 of non-rapid eye movement (nonREM) sleep, and Rapid Eye Movement (REM) sleep promotes both quantitative and qualitative changes in memory representations (Ellenbogen et al., 2007; Wagner et al., 2004). For example, through ASC, memory representation in the short-term space is consolidated and then re-organized in the long-term space. This consolidation also leads to chunking of the memory as a single unit, improvement of performance, and enhancement of novel and creative processing (Walker et al., 2002; Walker and Stickgold, 2006). The consolidated memory can be integrated into the network of pre-existing long-term memories (Lewis and Durrant, 2011), which allows the brain to generate creative information (Von Fange, 1959). Furthermore, the consolidation facilitates the inference of relationships between distant (non-local) objects that had not been learned before sleep (Ellenbogen et al., 2007). Together, the brain's consolidation system may give AI researchers new ideas to use in pursuing an innovative future machine learning algorithm; this will be discussed in more detail in section 6.4.2 below.

6.2.4. Action and Production

Statistical learning also influences human actions and decision-making (Friston et al., 2015; 2014; Monroy et al., 2017a; Monroy et al., 2018; Monroy et al., 2017c; Pezzulo et al., 2015; Schwartenbeck et al., 2013; Zubicaray et al., 2013). Using sequential paradigms based on various-order Markov models, Karlaftis et al. (2019) demonstrated that the brain alters its decision strategies and engages dissociable neural circuits in response to changes in statistics pertaining to the environment: the ability to extract exact sequence statistics relates to neural plasticity in the motor corticostriatal circuits, while the ability to select the most probable outcomes relates to plasticity in the motivational and executive corticostriatal circuits. The same study also provided evidence that learning-dependent changes in these circuits predict individual decision strategy. Statistical learning of motor and action sequences is partially supported by the chunking hypothesis (Boyd et al., 2009), i.e., the hypothesis that learning is based on extracting, storing, and combining small chunks of information. Statistical knowledge formed in the cerebral cortex is sent to the cerebellum, which is thought to play important roles in procedural learning such as motor skill learning (Ito, 2008) and habit learning (Karl Friston et al., 2016) as well as the generalization or abstraction of statistical knowledge

(Shimiz et al., 2017) and prediction of sequences (Lesag et al., 2012; Moberget et al., 2014).

6.2.5. Social Communication

Humans are more sensitive to the statistical regularities of action sequences between two persons than to those that occur within one person (Monroy et al., 2018). This implies that social-communicative interaction facilitates statistical learning (Monroy et al., 2017b). Some evidence also suggests the importance of communication in the distributional learning of phonemes (Kuhl, 2004). In these studies, infants who spent time in a laboratory with a native Mandarin speaker could discriminate among Mandarin but not among English phonemes, whereas infants raised under comparable circumstances who were exposed to English rather than Mandarin failed to discriminate among Mandarin phonemes (Kuhl et al., 2003). This shows that, when infants are merely exposed to auditory speech sounds rather than engaged in social interaction, they cannot use the statistical cues included in the sounds. Hence, social and communicative interaction may allow infants to conduct statistical learning more effectively. Within the predictive coding framework, a recent study on human-robot interaction (Nagai, 2019) likewise indicated that interacting with other individuals often increases prediction error, which can be minimized by executing one's own action corresponding to others' actions. Using robotic systems, Nagai and colleagues replicated developmental dynamics observed in infants. The abilities of self-other cognition and goal-directed action were acquired through updating an immature predictor through sensorimotor experiences, whereas imitation and prosocial behaviours emerged by executing the action anticipated by the predictor. Thus, social and communicative interaction modulates learning and prediction abilities in the developing brain and may be an important key to developing advanced machine learning algorithms similar to that used by the human brain.

6.3 Computational Model

6.3.1 Mathematical Concepts of the Brain's Statistical Learning

According to the statistical learning hypothesis, the brain automatically computes transitional probability distributions in sequences, grasps uncertainty/entropy in distributions, and

predicts probable states based on its internal statistical models to minimize prediction error. Thus statistical learning includes at least two mechanisms:

(a) Probability encoding of each local event

(b) Uncertainty encoding of probability distribution.

The transitional probability is a conditional probability of an event B given that the latest event A has occurred, written as $P(B|A)$. From a psychological perspective, it can be interpreted as positing that the brain predicts a subsequent event B after observing the preceding events A in a sequence. Learners expect an event with a higher transitional probability based on the latest event A, whereas they are likely to be surprised by an event with a lower transitional probability. Entropy can be calculated from the probability distribution and used to evaluate the neurobiology of higher levels of predictive coding and statistical learning (Harrison et al., 2006a). Conditional entropy has been defined as the average surprise (uncertainty) of an outcome (Friston, 2010). Furthermore, the motivation to resolve uncertainty is sometimes interpreted as curiosity (Kagan, 1972). Curiosity can be regarded as the drive toward novelty-seeking behaviour, which has often been evaluated by mutual information $I(X;Y)$ between hidden states (Y) and observations (X) (Friston et al., 2016; Krebs et al., 2009; Schwartenbeck et al., 2013; Wittmann et al., 2008). In general, mutual information is an information theoretic measure of dependency between two variables (Cover and Thomas, 1991). Mutual information corresponds to a reduction in entropy (uncertainty) about hidden states (Y) afforded by observations (X). According to psychological and information-theoretical concepts, mutual information means that the amount of uncertainty remaining about Y after X is known. The brain's prediction ability is correlated with mutual information (uncertainty reduction) (Harrison et al., 2006a). When an observer is curious about sequential information, observation of an event X may lead to stronger (and correct) expectation of Y, resulting in an increase in mutual information (reduction in uncertainty). In contrast, a lack of curiosity about event X can be simply perceived as having no expectation of a subsequent event, resulting in less mutual information (increasing uncertainty). Several researchers have proposed advanced computational models for expressing a variety of brain functions such as reward system and action. The next section discusses these brain-inspired models in the framework of music and language statistical learning.

6.3.2. Statistical Learning and the Neural Network

Computational modelling has been used to understand the brain's statistical learning mechanisms (Daikoku, 2018a; Pearce and Wiggins, 2012; Rohrmeier and Rebuschat, 2012; Wiggins, 2018b). Although experimental approaches are necessary for understanding the brain's function in the real world, the modelling approaches partially outperform experimental results under conditions that are difficult to replicate in an experimental approach (e.g., long-term statistical variation over the decades within a person and across cultures). Computational modelling can also represent the relevant neural hardware in the sensory cortices (Roux and Uhlhaas, 2014; Turk-Browne et al., 2009). For example, the simple recurrent network (SRN), which is classified as a neural network and was first hypothesized by Elman (Elman, 1990), learns sequential co-occurrence statistics through error-driven learning in which the gap between the predicted next input and the actual next input drives changes to the weights on its internal connections. The SRN (Rogers and McClelland, 2004) and a modified SRN (Altmann, 1999; Dienes et al., 1999) implement a similarity space in which words referring to similar objects or actions were located more closely to one another than to words referring to dissimilar objects or actions. The neural network and deep learning such as Long-Short Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997), however, are not intended to serve as a model for the human episodic and semantic memory systems, although they proceed in this direction (Huebner, 2018). Corpus-based approaches such as Hyperspace Analogue to Language (HAL) (Lund and Burgess, 1996), Bound Encoding of the AGgregate Language Environment (BEAGLE) (Jones and Mewhort, 2007), and Latent Semantic Analysis (LSA) (Landauer and Dumais, 1997) are based on abstraction of episodic information and encoding in a multidimensional semantic space. These models can also generate semantic similarity spaces in a similar way. For example, when the verb "drink" occurs, the models predict subsequent words referring to things that can be drunk. PARSER (Perruchet and Vinter, 1998), Competitive Chunker (Servan-Schreiber and Anderson, 1990), Information Dynamics of Music (IDyOM) (Pearce and Wiggins, 2012), Information Dynamics of Thinking (IDyOT) (Wiggins, 2018b), and other Markovian models including the n-gram and nth-order Markov models (Daikoku, 2018b) incorporate the chunking hypothesis in which learning is based on extracting, storing, and combining small chunks of information. The Markov Decision Process (MDP) (Karl Friston et al., 2015, 2014; Pezzulo et al., 2015; Schwartenbeck et al., 2013), which has often been used for reinforcement learning in machine learning and robotics, extends the

simple perceptive process by adding an active process (controlling predictability by choice, called ‘policy’) and rewards (giving motivation). The IDyOM is also an extension of the Markov model (i.e., the variable-order Markov model) for precisely modelling the statistical learning of musical sequences concomitantly combining several types of information such as pitch, duration, onset, scale degree, and so on. The IDyOT takes advantage of information theory to represent statistical learning mechanisms that cover both music and language (Wiggins, 2018b). This model implements semantic and episodic memory systems and captures the hierarchical learning process from lower to higher levels using boundary entropy: the spectrum of an auditory sequence is chunked into phonemes, then morphemes, then words (Wiggins, 2019).

Rohrmeier et al. (2014) compared the n-gram Markov, Competitive Chunker, and neural network SRN models to examine how each of these models simulates human implicit learning. They showed a strong learning effect for n-gram models and Competitive Chunker and a weaker effect for SRN. Their results suggest that the SRN and n-gram models represent the abilities of ordinary humans and those of music experts, respectively. These findings are important because they can provide useful information for devising an AI algorithm that simulates the development of learning ability in the human brain. It is of note, however, that such neural networks and deep learning (LeCun et al., 2015) are inscrutable because some integrated components as opposed to independent components may be learned. The statistical (machine) learning model, on the other hand, is time-based and the learning effect is dynamically represented. Importantly, pitch prediction in novel melodies is closely tied with probability distribution sampled from a large corpus of music (Pearce, 2006; Pearce et al., 2010). For example, the transitional probability between two pitches that are a whole-tone apart is higher than other transitional probabilities in Beethoven’s piano sonatas (Daikoku, 2018d), Jazz improvisation (Daikoku, 2018b), and Bach’s *Well-Tempered Clavier* (Daikoku, 2019). These properties are clearer when the order of transitional probabilities is higher (e.g., fifth-order transitional probability: $P(VI|I-II-III-IV-V)$, corresponding to $P(A|C-D-E-F-G)$ in C major (Daikoku, 2018d). The transition probability distribution of chords extracted from a corpus of Bach chorales also captures musical expectancy (Rohrmeier and Cross, 2008), showing, for example, that a tonic chord follows the dominant seventh chord with the highest transitional probability.

These statistical learning models have also been applied to neurophysiological experiments

(Daikoku, 2018c; Pearce et al, 2010; Pearce and Wiggins, 2012; Yumoto and Daikoku, 2016; 2018), which have consistently indicated that neural activity is higher in response to stimuli with high information content (i.e., low probability) than in response to those with low information content (i.e., high probability), which is in keeping with the predictive coding hypothesis. Furthermore, these statistical learning effects are larger when humans are exposed to stimulus sequences with less information entropy (uncertainty) than when they are exposed to stimulus sequences with more information entropy (Daikoku et al., 2017). This neural phenomenon is in agreement with the *Bayesian* hypothesis in which the brain encodes probabilities (beliefs) about the causes of sensory data and updates these beliefs in response to new sensory evidence based on Bayesian inference (Doya et al., 2007; Friston, 2010; Kersten et al., 2004; Knill and Pouget, 2004; O'Reilly et al., 2012; Parr and Friston, 2018; Parr et al., 2018). Hence, the statistical (machine) learning model can capture a variety of neurophysiological phenomena pertaining to statistical learning such as prediction and uncertainty. The next section reviews how these statistical learning models are reflected in neurophysiological activity based on the abundant neuroimaging literature.

6.4 Neurobiological Model

6.4.1. Temporal Mechanism

Electroencephalography (EEG) and magnetoencephalography (MEG) directly measure neural activity during statistical learning and represent a more sensitive method as compared to the observation of behavioural effects (Koelsch et al., 2016; Paraskevopoulos et al., 2012). When the brain encodes the probability distribution in a stimulus sequence, it expects a probable future stimulus with a high probability and inhibits the neural activity that would occur in response to that predictable stimulus. Finally, the statistical learning effect manifests as a difference in neuronal activity between predictable and unpredictable stimuli (Figure 6.2). Studies on Event-Related Potentials (ERP) and Event-Related Magnetic Fields (ERF) have suggested that statistical learning is reflected in:

(a) Early components, such as:

- Auditory Brainstem Response (ABR) (Sko et al., 2015)
- P5 (Daikoku and Yumoto, 2017; Daikoku et al., 2016; Paraskevopoulos et al., 2012)

- N100 (Daikoku et al., 2014; Daikoku et al., 2015b; Furl et al., 2011; Sander et al., 2002)
- MisMatch Negativity (MMN) (François et al., 2017; Stefan Koelsch et al., 2016; Moldwi et al., 2017; Tsogli et al., 2019)

(b) Late components such as:

- P200 (Balaguer et al., 2007; Cunillera et al., 2006; Francois and Schön, 2011; Furl et al., 2011),
- N200–250 (François et al., 2017; Rao et al., 2017)
- P300 (Laura et al., 2015)
- N400 (Balaguer et al., 2007; Cunillera et al., 2009, 2006; François et al., 2013; François and Schön, 2014; Sanders et al., 2002)

The suppression of the early components of responses in the lower cortical areas to auditory stimuli with higher transitional probabilities has been interpreted as the transient expression of prediction error that is suppressed by top-down predictions from higher cortical areas (Daikoku, 2018c; Skoe et al., 2015). Within the predictive coding framework, neuronal representations in the higher levels of cortical hierarchies predict plausible representations in the lower levels in a top-down manner and are compared with the representations in the lower levels to yield prediction error, usually associated with the activity of superficial pyramidal cells (Kiebel et al., 2008; Mumford, 1992; Rao and Ballard, 1999). The resulting mismatch signal is passed back up the hierarchy to update higher representations (associated with the activity of deep pyramidal cells). This recursive exchange of signals suppresses prediction error at each level to provide a hierarchical explanation for inputs that enter at the lowest (sensory) level.

The brain computes the uncertainty/entropy of each probability distribution as well as the probability of each local event. The distinction between the uncertainty and probability encodings may partially be explained by the findings of ERP studies (Koelsch et al., 2018). An early component called MMN (100–200 ms after stimulus onset) is typically elicited by deviant stimuli of oddball sequences and is not affected by explicit and prior knowledge about upcoming deviant stimuli (Garrido et al., 2008; Rinne et al., 2001; Sussman et al., 2003; Winkler and Czigler, 2012). In contrast, a later component called P300 or P3 is elicited by novel stimuli rather than repeated deviant stimuli (Friedman et al., 2001) and is reduced by prior knowledge of an upcoming syntactic deviant stimulus (Ritter et al., 1999; Sussman et al., 2003). This

suggests that, if an upcoming stimulus is predictably unpredictable (i.e., the event has a low probability but the sequence has low uncertainty), the later rather than earlier components may be decreased. It has generally been considered that, as compared to earlier components, later components reflect higher levels of auditory processing such as semantic and syntactic learning (Garrido et al., 2007). Neurophysiological (Donchin and Coles, 1988; Frens and Donchin, 2009) and computational studies (Feldman and Friston, 2010) suggest that later components reflect a change in context or predictability. For example, N400 reflects a semantic meaning in language and music (Koelsch et al., 2004; Kutas and Federmeier, 2010; Tillmann et al., 2006). Thus, statistical learning's effect on N400 (Balaguer et al., 2007; Cunillera et al., 2009, 2006; François et al., 2013; François and Schön, 2014; Sanders et al., 2002) may support the hypothesis that semantic memory can be acquired through statistical learning (Altmann, 2017; Rogers and McClelland, 2004).

N400 and Early Anterior Negativity (EAN) components distinguishing between high and low transitional probability are also influenced by long-term musical experiences (François and Schön, 2011; Kim et al., 2011). It is widely known that Early Right Anterior Negativity (ERAN) has a larger amplitude in individuals with musical training (Koelsch, 2012). Furthermore, Zhang et al (2018) have shown evidence of ERAN's effects on non-local prediction. ERAN can be elicited not only in harmony processing but also in melody processing (Carrus et al., 2013; Miranda and Ullman, 2007) and in rhythmic syntactic processing (Sun et al., 2018). Importantly, random feedback including false and correct feedback regarding participants' detection of out-of-key tones in melodies may modulate ERAN (Vuvan et al., 2018), as could attention-driven changes in the confidence of predictions (i.e., uncertainty). A recent study offered evidence that long-term experience of music also modulates another earlier component called P50. In this study, the effects of statistical learning on P50 were larger in musicians than in non-musicians (Paraskevopoulos et al., 2012), suggesting that long-term experience may facilitate prediction of each content type as well as uncertainty of context. Hence both the prediction of individual events and the uncertainty of the context can be reflected in many ERP components, but different levels of statistical learning may involve different ERP components.

Statistical learning is reflected in oscillatory activity as well as ERP/ERF. According to neurophysiological studies, low-frequency oscillations in the speech motor cortex track the envelope of the speech signal (Park et al., 2015), while high-frequency oscillations dominate in tracking the fine structure of speech (Giraud and Poeppel, 2012) and bottom-up processing

(Fontolan et al., 2014). Furthermore, in each frequency band, statistical learning and the chunking function control the coupling and synchronisation between phase-locked neural oscillations and speech frequencies (e.g., ~20Hz: phoneme, ~4Hz: syllable, ~1Hz: word and phrase) (Assaneo et al., 2019; Ding et al., 2016). This has also been suggested by simulations and models based on cochlea function (Ding et al., 2017; Leong and Goswami, 2015). Furthermore, the N400 and phase-locked coherence (~1Hz: word frequency) as semantic chunking effects can be detected in parallel (Batterink and Paller, 2017). Thus a number of electrophysiological experiments have shown that both oscillation and ERP/ERF represent statistical learning processes including probability and uncertainty encodings.

Figure 6.2: Representative statistical learning effect. Equivalent Current Dipole (ECD) locations (dots) and orientations (bars) for auditory ERP (N1) responses superimposed on the magnetic resonance images (a) and the auditory statistical learning effects (b) Reprinted from (Daikoku, 2018) with permission.

As shown in Figure 6.2, when the brain encodes the transitional probability in a auditory sequence, it expects a probable future stimulus with a high transitional probability and inhibits the neural response to predictable stimuli. In the end, the statistical learning effects manifest as a difference in amplitudes of neural responses to stimuli with lower and higher transitional probability.

6.4.2. Spatial Mechanism

6.4.2.1 Domain Generality vs. Domain Specificity

It has generally been assumed that the networks that are instrumental in statistical learning involve a variety of brain areas including the neocortex, hippocampus and corticostriatal systems (Gomez, 2017; McClelland et al., 1995; Reddy et al., 2015; Schapiro et al., 2014). In other words, the neuroanatomical mechanisms of statistical learning are associated with both modality-general (e.g., hippocampus and striatum) and modality-specific processing (e.g., auditory: Superior Temporal Gyrus (STG) and Superior Temporal Sulcus (STS); visual: cuneus, fusiform gyrus) (Nastase et al., 2014; Strange, 2005). Some studies have suggested that the sensory type of statistical learning modulates the cortical networks. For example, the neuronal system underlying audiovisual statistical learning is partly in common with and partly distinct from the unimodal networks of visual and auditory statistical learning, comprising the right temporal (Roser et al., 2011) and left inferior frontal sources, respectively (Paraskevopoulos et al., 2018). That is, statistical learning essentially reflects contributions from domain-general mechanisms that share brain regions between different modalities yet are constrained to operate in specific modalities (Frost et al., 2015; Nastase et al., 2014; Strange et al., 2005). In terms of the two distinct types of statistical learning mechanisms (i.e., encoding probability and uncertainty, presumably corresponding to prediction of local events and predictability of whole events, respectively), recent studies have consistently shown that the neocortex is likely to play an important role in probability encoding, while the hippocampus is thought to be associated with uncertainty encoding (Harrison et al., 2006a; Hasson, 2017; Thiessen and Pavlik, 2013). On the other hand, many other studies have implied that these two levels of statistical learning do not function independently but rather are interdependent (Hansen and Pearce, 2014; Tillmann et al., 2000; 1998).

6.2.4.2 Probability Encoding

According to findings obtained through functional magnetic resonance imaging (fMRI) (Cunillera et al., 2009), MEG (Paraskevopoulos, 2017), and near-infrared spectroscopy (NIRS) (Abla and Okanoya, 2008), the networks instrumental in statistical learning are associated with a variety of brain areas. For example, recent studies report contributions from motor

areas including the Preotor Cortex (PMC) (Cunillera et al., 2009) and the primary motor cortex (Zubicaray et al., 2013) as well as the superior temporal cortex including the STG (Trembla et al., 2013) and the STS (Farthouat et al., 2017), areas for speech processing and forward prediction, respectively (Hickok, 2012; Overath et al., 2007). The left dorsal stream including the superior temporal areas, auditory-motor areas, PMC, and prefrontal cortex plays an important role in statistical learning (Elmer et al., 2018) in the contexts of infant speech (Friederici et al., 2017b) and music processing (Oechslin et al., 2010). The basal ganglia are also thought to be associated with chunk formation, which is underpinned by statistical learning (Graybiel, 1998; Sakai et al., 2003). In particular, the striatum, which is part of the basal ganglia and thought to be associated with motivational circuits, has been proposed as a region implicating prediction (McNealy et al., 2006; Plante et al., 2015; Turk-browne et al., 2009). Using sequential paradigms based on various-order Markov models, Karlaftis et al. (2019) have demonstrated that individuals alter their decision strategies in response to changes in the statistics of their environments and engage dissociable circuits; extraction of exact sequence statistics is related to neural plasticity in the motor corticostriatal circuits, while selection of the most probable outcomes is related to plasticity in the motivational and executive corticostriatal circuits. Karlaftis et al. (2019) also provided evidence that learning-dependent changes in these circuits predict individual decision strategies.

Previous studies have also reported contributions from functional connectivity between the auditory and motor language networks, that is, from the link between the prefrontal cortex including the IFG and Broca's area and that between the superior temporal cortex and Wernicke's area (Lopez-Barroso et al., 2013; McNealy et al., 2006). It is important, however, to differentiate between local and non-local processing in prediction (Dehaene et al., 2015). A growing body of literature claims that hierarchically organized (nested) non-local dependencies are processed in the pars opercularis of the posterior IFG corresponding to BA 44v (Amunts et al., 2010), whereas the processing of local dependency violations is mainly associated with the ventral PMC (Friederici, 2004; Friederici et al., 2006; Makuuchi et al., 2009; Opitz and Kotz, 2012). The ventral parts of Broca's area is involved in left- and right-hemispheric weighting in language- and music-syntactic processing, respectively (Friederici et al., 2006; Makuuchi et al., 2009). Furthermore, the ventral parts of Broca's area is involved not only in language- and music-syntactic processing but also in the hierarchical processing of action sequences (Fazio et al., 2009; Koechlin and Jubault, 2006) and presumably in the processing of hierarchically organized mathematical formulas (Friedrich and Friederici,

2009). Music syntax has both local and non-local regularities. Therefore, there is no doubt that music-syntactic processing involves not only the IFG but also the ventral PMC (Janata et al., 2002; Parsons, 2001) and the STG (Tremblay et al., 2013). The IFG and ventral PMC, however, are likely to contribute mainly to non-local and local processing, respectively. Dehaene et al. (2015) have indicated that tree structures, which are used to explain hierarchical syntactic structures in language and music (e.g., context-free grammar) (Hauser et al., 2002; Lerdahl et al., 1983), require a specific recursive neural code. Importantly, the processing of context-free grammar is available to humans but not to non-human primates (Fitch and Hauser, 2004). Thus this type of processing may be unique to humans, which may explain the singularity of human language and music cognition.

6.2.4.3 Uncertainty Encoding

The mechanisms underlying uncertainty encoding are considered to be partially independent of those underlying prediction (Hasson, 2017; Thiessen and Pavlik, 2013). For example, the m Medial Temporal Lobe (MTL) including the hippocampus (Turk-browne et al., 2009; Turk-Browne et al., 2010) and the lateral temporal region (Cunillera et al., 2009) including Wernicke's area (Bischoff-Grethe et al., 2000) are considered to play roles in encoding uncertainty (Harrison et al., 2006a). The interactive neuronal networks between prediction and uncertainty may be partially explained by the Complementary Learning System (CLS) (McClelland et al., 1995), which is a model for the memory system in the neocortex and hippocampus. This model suggests that the neocortex contributes slow and long-term encoding of semantic memory based on statistical knowledge through smaller changes in connectivity within the neocortex, whereas the hippocampus contributes rapid, sparse, and long-term encoding of episodic memory through large changes in connectivity between the hippocampus and the neocortex as well as within the hippocampus (Frost et al., 2015).

6.2.4.4 Consolidation of Statistically Learned Knowledge

Many studies have suggested that neural replay in the MTL contributes to memory consolidation in the cortex (Diekelmann and Born, 2010; Mölle et al., 2002). A previous study has demonstrated that, after 24 hours of consolidation of statistical knowledge during sleep,

the memory system is less dependent on the hippocampus and more dependent on the corticostriatal pathway and the planum temporale (Durrant et al., 2013) in a process known as Active System Consolidation (ASC). That study indicated that, prior to consolidation, the striatum has greater connectivity with both the MTL and the ventromedial prefrontal cortex, whereas after consolidation the striatum is directly connected to the STG. The system of interaction between the hippocampus and the neocortex that is involved in statistical learning has also been discussed from the perspective of a different consolidation system that activates during development, between infancy and adulthood (Durrant et al., 2011; Gomez, 2017; Swain et al., 1993). The ability to predict each type of content improved after 24 hours consolidation in adults (Durrant et al., 2011), whereas infants tend to show weak retention of statistical knowledge (Gomez, 2017; Swain et al., 1993). Furthermore, infants' statistical knowledge is drastically altered by novel input (Benavides-Varela et al., 2011), suggesting that infants, compared with adults, may encode statistical information in a noisier representation, and have more difficulty integrating novel input with pre-existing memory (Thiessen, 2017). It has been suggested that the connectivity between hippocampal and other memory systems including the prefrontal cortex (Gómez and Edgin, 2016) develops more fully after two years of age (Gao et al., 2009). Prior to two years of age, therefore, the networks that are instrumental in statistical learning involve the cortex, corticostriatal loop, and monosynaptic circuit of the hippocampus. Together, the previous studies suggest that the hippocampus-neocortex loop contributes to the consolidation of statistical knowledge. That hypothesis leads one to wonder how the consolidation networks between the MTL and the neocortex are related to the interactive system between uncertainty and prediction in statistical learning. Again, the CLS and ASC models suggest that the hippocampus plays an important role in the formation of novel episodic memory through rapid, sparse, and short-term encoding, whereas the neocortex contributes to slow and long-term encoding of semantic memory based on statistical knowledge (Durrant et al., 2013; Frost et al., 2015). Thus, to retain a memory, the brain must consolidate a short-term memory in the hippocampus and shift it into long-term memory in the neocortex through the pathway between the hippocampus and the neocortex. Then novel input can be integrated into the consolidated memory without destroying it (Lewis and Durrant, 2011). According to previous studies, the MTL contributes the abstraction in statistical learning (Cohen and Eichenbaum, 1993; Konkel et al., 2008; Moscovitch et al., 2016) and uncertainty perception (Harrison et al., 2006a; Harrison et al., 2006b; Turk-browne et al., 2009; Turk-Browne et al., 2010). This abstracted information is sparse and represents only a fragment of the whole, but is statistically important and enhances predictability under

conditions of limited uncertainty (Figure 1). In contrast, syntactic processing associated with the integration of semantic knowledge depends on neocortical areas including the language network; e.g. IFG, STG, etc. (Friederici, 2011) as well as other areas associated with the integration of semantic knowledge, such as the medial prefrontal cortex (van Kesteren et al., 2012) and the perirhinal cortex (Taylor et al., 2006). Thus, integration between pre-existing long-term information sent from the MTL through consolidation and novel input information may occur in the neocortex. Statistical knowledge may also be sent to the cerebellum which is thought to play important roles in generalization or abstraction, prediction of sequences (Lesage et al., 2012; Moberget et al., 2014), motor skill acquisition (Ito, 2008), and transference into novel circumstances (Shimizu et al., 2017) to enable more efficient performance in a learned context. A previous study has suggested that the cerebellum, in conjunction with the premotor cortex, inferior parietal lobule and medial occipital cortex, mediates the probabilistic inferences that guide decision-making under conditions of uncertainty (Blackwood et al., 2004). The cerebellum as well as the hippocampus and the cerebellum-hippocampus network (Babayan et al., 2017) may play a role in resolving uncertainty (Khilkevich et al., 2018) to optimize action and prediction via statistical learning. An fMRI study (Karuza et al., 2016) has suggested that, during statistical learning, participants with strong statistical learning effects of a familiar language on which they had been pretrained (e.g., their native language) exhibited decreased recruitment of the fronto-subcortical and posterior parietal regions, as well as a dissociation between downstream regions and the early auditory cortex. Some studies have indicated that IFG activity may reflect recognition of accumulated statistical information (Karuza et al., 2016; Plante et al., 2014). This finding may suggest that, through long-term learning, the brain optimizes probabilistic models with less uncertainty in the long-term space in order to predict input information efficiently. In summary, these previous studies suggest that the dorsal stream (namely, the superior temporal areas, motor areas, PMC, and prefrontal cortex) plays an important role in online prediction of each event during statistical learning. In addition, these networks in the neocortex may interact with the functions of the basal ganglia through the corticostriatal pathway. In contrast, the hippocampus may serve as a short-term space associated with perceptive mechanisms of uncertainty. Furthermore, these two distinct systems are not independent but interdependent via the hippocampus-neocortex gateway, which contributes memory consolidation from short-term to long-term memory.

Within the framework of CLS theory, Kumaran et al. (2016) have also asserted the relevance of the hippocampus-neocortex interplay to the design of Artificial Intelligence, highlighting

connections between neuroscience and machine learning. The CLS theory proposes two learning systems. The first gradually acquires structured knowledge representations in the neocortex while the second quickly learns the specifics of individual experiences in the hippocampus. Both the brain and AI systems benefit from the second system that stores specific experiences in the hippocampus. That is, once structured knowledge has been acquired in the hippocampus-neocortex networks, new consistent information can be rapidly integrated. The network replays memories stored in the hippocampus, contributing to the integration of new information into the neocortex (O'Neill et al., 2010). It is thought that the replay of recent experiences occurs during offline periods (e.g., during sleep and rest). Furthermore, the hippocampus and the neocortex interact during replay (Ji and Wilson, 2007). This recurrent activation of multiple memories can be used to discover links between experiences, supporting generalization and memory-based reasoning. Thus this mechanism could support a variety of cognitive functions, including goal-related manipulation of experience statistics such that the neocortex is not a slave to the statistics of its environment (Kumaran et al., 2016). The fast-learning hippocampal system can circumvent the general statistics of the environment by reweighting experiences that are of unequal significance. This mechanism may link the cognitive and machine-learning models in that both operate by computing the similarity of a new input pattern to stored experiences, though the first is an exemplar model and the second is an instance-based model. On the other hand, the hippocampal replay of experiences can be modulated according to each experience's degree of surprise and its novelty, that is, its relative reward value (either positive or negative) and the amount of new informational content that it provides (e.g., its value in terms of reducing uncertainty about the best action to take in a given situation), acting to rebalance the general statistics of the environment (Kumaran et al., 2016). Kumaran et al. (2016) have also indicated that the hippocampus plays an important role in marking salient but statistically infrequent experiences, ensuring that such events are not swamped by the wealth of typical experiences but are instead preferentially stabilized and replayed to the neocortex, thereby allowing knowledge structures to incorporate this new information. Importantly, recent machine-learning research has been inspired by the role of hippocampal experience replay within the framework of CLS theory. In AI research, experience replay stores experiences including state transitions, rewards and actions, which are necessary for creating mini-batches to update neural networks and increase learning speed. For example, implementation of an experience replay mechanism was crucial to developing the neural network called Deep Q-network (DQN). This neural network achieved human-level performance across a wide variety of Atari 2600 games by successfully harnessing the power of

deep neural networks and reinforcement learning (Mnih et al., 2015). In machine-learning research, continual learning, which is the ability to learn successive tasks in sequential fashion (e.g., tasks A, B, C) without catastrophic forgetting of non-local earlier tasks (e.g., task A), remains a fundamental challenge. This is believed to be a prerequisite to developing artificial agents that we would consider truly intelligent. A principal motivation for incorporating a fast-learning hippocampal system as a complement to the slow neocortical system was to support continual learning in the neocortex: hippocampal replay was proposed to mediate interleaved training of the neocortex (i.e., intermixed examples from tasks A, B, C). In sum, a number of recent studies have identified the neural correlates of music with machine learning. Actually, a number of AI models have been inspired by neural function in the human brain, and compose many genres of music as if human brain does. On the other hand, many computational and neurophysiological studies in music processing had mainly focused into optimal, likelihood, efficient problem solving. However, the human brain often behaves inefficiently. For example, creative thinking such as music composition is a process by which we resolve an open-ended problem from a different perspective that has not been emerged before. In the next section, we propose future directions for interdisciplinary research in Neuroscience and AI for music processing.

6.5 Future Direction: Creativity

6.5.1 Optimization For Creativity Rather Than Efficiency

The brain is generally motivated to optimize prediction and minimize uncertainty for information efficiency (Friston, 2010). This uncertainty resolution results in rewards. Until the last few decades, many computational and neurophysiological studies in music processing had mainly focused on optimal, likely, and efficient solutions to specific problems. Yet these specific problem-solving approaches are not ideal for revealing how the brain deals with open-ended problems. For example, creative thinking such as music composition is a process by which we resolve a specific or open-ended problem from a different perspective that has not been encountered before. This mechanism has been broadly investigated in a variety of analyses of creative people (Gardner, 1993), products (Amabile, 1996), creative processes (Simonton, 2010), and neuroimaging during creation (Beaty et al., 2018). For example, *motivation* is a key

insight into understanding creativity from both neuronal and computational perspectives. Generally, motivation stems from two different sources: intrinsic and extrinsic motivation (Schmidhuber, 2010). Intrinsic motivation is a drive originating inside an individual toward personal interest, satisfaction, goals, etc., whereas extrinsic motivation is a drive originating outside of a person toward external factors such as specific rewards, approval from others, etc. Although both extrinsic and intrinsic motivation increases creativity in certain cases, extrinsic motivation can sometimes impede creativity (Prabhu et al., 2008). Excessively predictable patterns and very low uncertainty of information essentially give rise to boredom because they do not allow for the pursuit of curiosity rewards. A certain degree of uncertainty may be necessary to maintain curiosity about information and thus the motivation to learn it, given that uncertainty allows the brain to anticipate further rewards through the resolution of the unknown. That is, for sustainable curiosity and motivation, humans may seek a slightly suboptimal solution if it is afforded at a significantly low uncertainty. Recent studies indicate that fluctuations in uncertainty may contribute to aesthetic appreciation of art and music (Daikoku, 2019; Koelsch, 2014) and that this phenomenon may encourage humans to create and learn new regularities (Schmidhuber, 2006). This suggests that an algorithm optimizing not for efficiency but for creativity is an important goal in statistical learning (probability and uncertainty encodings) of creative information such as music. Creative information is not just pastiche and replication of previous information but is regarded as an artefact that is difficult to anticipate based on information that is already known.

Over the past decade, however, statistical learning mechanisms have essentially been discussed based on optimization of prediction and information efficiency at the lowest possible informational cost and uncertainty. Creativity, however, does not necessarily generate information-theoretically optimal, efficient, and certain information, but sometimes gives rise to uncertain, unpredictable information. We sometimes derive pleasure from prediction errors under conditions such as music listening due to our curiosity and our drive toward novelty-seeking behaviour in connection with our anticipation of the resolution of uncertainties. That is, humans appear to seek certain forms of optimality between uncertain and certain situations through actions from which we expect to receive maximal curiosity rewards, and hence our actions give rise to increasing as well as decreasing uncertainty. Nevertheless, few studies have investigated how creativity interacts with the brain's statistical learning machinery including probability and uncertainty encoding. The next section reviews some computational literature on this challenging question from the viewpoint of the brain's

functions including prediction, learning, memory consolidation, and intrinsic/extrinsic rewards systems. Then we discuss the neuroanatomical correlates of creativity and music with machine learning and statistical learning.

6. 5.2 Cognitive Architectures

Until a few decades ago, computational modelling was mostly focused on seeking an optimal, likely, and efficient solution to a specific problem by a reductionist means. These problem-solving approaches, however, are not ideal for implementing divergent thinking as humans do. How to deal with open-ended problems is a contemporary challenge in AI studies. Computational creativity and Artificial General Intelligence (AGI) aims at breaking free from the problem-solving approaches (Besold et al., 2015) and instead dealing with conditions where there is no solution and no problem. The Dual Process Theory of Intelligence has proposed two types of intelligence models that give rise to creativity (Kaufman et al, 2013). One is a conscious and explicit process in response to a specific goal-directed thought. The other, in contrast, is an unconscious and implicit process of spontaneous cognition associated with implicit learning ability. Hélie et al. (2010) have also proposed the Explicit–Implicit Interaction (EII) theory of creativity as a unified theory of creativity. This theory, which attempts to integrate various fragmentary theories, consists of five basic principles:

- 1) The co-existence of and the difference between explicit and implicit knowledge
- 2) The simultaneous involvement of implicit and explicit processes in most tasks
- 3) The redundant representation of explicit and implicit knowledge
- 4) The integration of the results of explicit and implicit processing
- 5) The existence of iterative (and possibly bidirectional) processing.

A cognitive architecture called Connectionist Learning with Adaptive Rule Induction On-line (CLARION) (Hélie and Sun, 2010) computationally implements EII theory and simulates relevant human data. This work represents an initial step in the development of process-based theories of creativity encompassing incubation, insight, and various other related phenomena. For example, explicit knowledge can be encoded as directional associative rules that link chunks (of declarative knowledge), while implicit knowledge is learned by an algorithm related to standard back propagation using both implicit and explicit networks. In the end, the given

explicit knowledge affects the learned implicit knowledge.

Schmidhuber (2006; 2010) has proposed a theory of learning that affords creativity based on information theory. This theory indicates that creativity and curiosity are by-products of a computational principle for optimizing learning progress. That is, a human's acts afford a "*black box*" optimization through reinforcement learning that maximizes the extrinsic rewards for achieving a given goal. In this model, the intrinsic rewards, i.e., the so-called wow-effect, motivates creative behaviour even if there is no specific goal. The agent keeps improving its performance over time because it is invariably predicting and encoding a growing history of actions and sensory information. A sudden improvement in data compression or computational speed, which can be measured as a decrease in computational cost at each time point (e.g., errors, time, number of required synapses, storage size), gives rise to the wow-effect. This effect finally becomes an intrinsic reward signal for the action selector. Thus, unknown (uncertain), novel, and regular information motivates the agent to perform continual, open-ended, active, creative exploration, whereas random data, already known (certain) information, and predictable patterns are essentially boring because they do not give rise to wow-effects and rewards. Recent computational studies on music have found that the conditional entropies (i.e., uncertainties) in Beethoven's music gradually increased (Daikoku, 2019) with time over the composer's lifetime. These findings were prominent in higher- rather than lower-order statistical learning models. Improvisational music also shows a similar phenomenon: lower-order statistical learning models represent the general characteristics shared among musicians, whereas higher-order statistical learning models detected specific characteristics unique to each musician (Daikoku, 2018b). These findings may suggest that higher- rather than lower-order statistical knowledge (Daikoku, 2018a) may be more susceptible to the effects of long-term experience on the brain's probabilistic models and individuality of creativity. In sum, it is thought that new structured information may intrinsically motivate humans to discover the regularities. In response, they perform open-ended and creative exploration due to the absence of pre-established knowledge or instruction on the regularities. This behaviour, however, may increase creativity and provide intrinsic rewards when the hidden regularity is finally detected. In terms of statistical learning, "how" and "when" the intrinsic motivation occurs during statistical (machine) learning appears to be a key insight into new frontiers for both neural and computational fields. In the next section, we discuss neuroanatomical mechanisms involved in creativity and music.

6.5.3 Neuroanatomical Correlates

In contrast to the large number of studies on statistical learning and memory, there are few neuronal studies on creativity based on statistical learning theory. On the other hand, behavioural and neuroimaging studies have begun to uncover mechanisms that give rise to novel ideas using various paradigms on divergent thinking, musical improvisation, poetry composition, and art production. Here, we review neural studies on creativity across several paradigms. Then, based on a number of previous findings across neuronal and computational studies, we hypothesize possible mechanisms of creativity within the statistical learning framework including prediction and uncertainty encoding.

6.5.3.1 Frontal Lobe

It is generally considered that frontal lobe function, which is involved in top-down control of executive function and decision-making (Dalley et al., 2011; Dosenbach et al., 2008; Gold and Shadlen, 2007; Heekeren et al., 2008), is one of the most important keys to understanding creativity and statistical learning in the brain (Flaherty, 2005), although multiple neural networks also interact with each other (Mayseless et al., 2015). For example, EEG (Fink et al., 2006; Fink et al., 2009; Lustenberger et al., 2015) and fMRI studies (Bengtsson et al., 2007; Berkowitz and Ansari, 2008; de Manzano and Ullén, 2012a; 2012b; Limb and Braun, 2008) have examined brain activity during exposure to fixed melodies (less creative) or free-improvised melodies (more creative). The results indicate that more creative conditions lead to stronger alpha power (Fink et al., 2006; Lopata et al., 2017; Lustenberger et al., 2015) in the right frontal and parietal regions (Fink et al., 2009). The increased oscillatory activity in the alpha band is considered to reflect inhibition of the top-down process (Klimesch, 2012) and the dorsal stream (Jokisch and Jensen, 2007). Other studies, in contrast, have suggested that alpha power reflects internally oriented attention in which external bottom-up stimulation is suppressed (Fink and Benedek, 2014). One study that investigated both the neural and genetic correlates of creativity has suggested that a system of interaction between strong top-down and weak bottom-up processes underpins creativity, which is modulated by competition between the glutamate and GABA neurotransmitter systems (Liu et al., 2018). Furthermore, a computational model (Collins and Koechlin, 2012) inspired the hypothesis that the frontal

lobes create an expanding repertoire of flexible behavioural strategies for driving action in uncertain, changing, and open-ended environments and suggested that frontal lobe function including executive control and decision-making supports integration between reasoning, learning and creativity through uncertainty monitoring. Green et al. (2017) have also suggested that neural activity in the frontopolar cortex facilitates creative intelligence. The contradiction between these two opposing findings on inhibition and enhancement of top-down control may be explained by the different tasks set in the different studies (Adhikari et al., 2016). In fMRI studies (Pinho et al., 2015), however, improvisation using a defined pitch set resulted in activation of the dorsolateral Prefrontal Cortex (dlPFC) because participants had to maintain available note choices in the working memory, whereas free improvisation leads to deactivation of the dlPFC because participants are able to take advantage of their implicit learning systems to create improvisations in which top-down control from the dlPFC would be disadvantageous (Dhakal et al., 2019). Using fMRI, Liu et al. (2015) has examined brain mechanisms during poetry composition and the assessment (revision) process. The results indicated that dlPFC activity was attenuated during composition and re-engaged during revision, whereas the Medial Prefrontal Cortex (MPFC), which is associated with multiple cognitive functions such as motivation (Kouneiher et al., 2009) and unconscious decision-making (Soon et al., 2008), was active during both phases. Furthermore, expert poets showed significantly stronger deactivation of the dlPFC during composition but no significant difference in activity of the MPFC. Thus expert poets may more effectively suspend top-down control while maintaining their motivation. Together, these findings show that open-ended creative behaviours may suppress top-down controls as expressed through dlPFC activity level while maintaining motivation as expressed through MPFC activity level, whereas fixed behaviours enhance top-down control.

6.5.3.2 Cerebellum

The cerebellum as well as the frontal lobe is known to be an important area in creativity. de Manzano and Ullen (2012a) found that rhythmic improvisation enhanced connectivity between the Supplementary Motor Area (SMA) and the cerebellum. Furthermore, the cerebellum (Sagar et al., 2016) and the caudate, which is part of the striatum (Beaty et al., 2017; Jauk et al., 2015), also contribute to creative cognition. Vandervort et al. (2007) have explained how the frontal lobes and the cerebellum collaborate to produce creativity. The

cerebellum adaptively models all movement and thought (Schmahmann, 2004). The cerebellum's adaptive models then forward this information to the frontal lobes' working memory which it uses in its control processes (Miller and Cohen, 2001). Frontal lobe function then leads to idea generation (Vandervort et al., 2007). Furthermore, the temporal lobe, as a region where idea editing and evaluation occurs (Flaherty, 2005), triggers creative insight or the "aha" experience (Jung-Beeman et al., 2004). This hypothesis may be partially supported by computational studies (Schmidhuber, 2006; 2010). Due to the improvements in performance speed and efficiency and the reduction of uncertainty that occur through repetitive mental prototyping in the cerebro-cerebellar blending process, the human brain receives intrinsic rewards in the form of the so-called wow-effect, which then motivates further creative behaviour. Furthermore, statistical learning studies have also suggested that statistical knowledge can be sent to the cerebellum for more efficient performance in a learned context (Shimizu et al., 2017). The cerebellum, in conjunction with the premotor cortex, inferior parietal lobule and medial occipital cortex, mediates the probabilistic inferences under the control of uncertainty (Babayan et al., 2017; Blackwood et al., 2004; Khilkevich et al., 2018).

6.5.3.3 Neural Network

Recently, to explain the dynamics of creativity processes, three types of neuronal networks have been proposed (Beaty et al., 2018). One is the Default Mode Network (DMN), which consists of the cortical midline and posterior inferior parietal regions and contributes to idea generation via flexible, spontaneous, and self-generated thought involved in mental simulation (Zabelina and Andrews-Hanna, 2016), mind-wandering (Mason et al., 2007), social cognition, and episodic future thinking. A second proposed network is the Executive Control Network (ECN), which consists of the lateral prefrontal and anterior inferior parietal regions and plays a role in idea evaluation through involvement in cognitive processes that require externally-directed attention, working memory, and relational integration (Beaty et al., 2016). The third is the Salience Network (SN), which consists of the bilateral insula and anterior cingulate cortex and which underpins the dynamic transitions between DMN and ECN (Uddin, 2014) and forwards candidate ideas originating from the DMN to the ECN for high-order processing such as idea evaluation, elaboration, or revision (Beaty et al., 2015; 2016; 2018). Thus, creative behaviours may involve an interaction between an automatic bottom-up process (DMN) that supplies possible choices and a top-down control process (ECN) that guides those

choices according to hierarchical rules (Beaty et al., 2015; 2016). The ECN (Axelrod et al., 2015) and the DMN (Mason et al., 2007) have also been considered to contribute to mind wandering, which is important for many mental functions such as future planning (Bar, 2009) and creativity (Baird et al., 2012). Using a divergent-thinking task, a recent study (Beaty et al., 2015) reported that coupling between the DMN and the SN preceded coupling between the DMN and the ECN, suggesting dynamic shifts in idea generation and evaluation. They also indicated that more creative participants showed higher global efficiency within a network; i.e., a smaller number of paths to traverse between brain regions). This suggests that communication efficiency is higher in more creative people. Interestingly, a recent study has suggested that the hippocampus, which is thought to be related to uncertainty, is linked to the DMN (Ward et al., 2014). Thus it is hypothesized that uncertainty perception and divergent thinking are interdependent with each other. It has generally been considered that the DMN and the ECN usually do not work concurrently (Anticevic et al., 2012). A recent study, however, has demonstrated that creative people have the ability to simultaneously engage these large-scale brain networks (Beaty et al., 2018; Boccia et al., 2015). This suggests that individual variation in the ability to simultaneously engage the DMN, ECN, and SN can be a neurophysiological marker of creativity.

In summary, the brain is equipped with unsupervised statistical learning machinery that makes Bayesian predictions without explicit instructions. For this reason, AI algorithms also enable machines to create interpretable models representing the brain's methods of prediction, learning, and memory consolidation in music and language acquisition. These machine learning models, however, are still unable to account for all levels of music and language learning including hierarchically organized and non-local regularities. It also remains an open question how the unsupervised statistical learning machinery in the human brain gives rise to creative information. Hence, an algorithm optimizing not for efficiency but for creativity is a key option to pursue to improve music processing both by the brain and by computers. To understand how and when creativity originates through learning processes, future interdisciplinary study is needed to verify the present conclusions from both computational and neuronal perspectives.

6.6 Concluding Remarks

A body of studies demonstrated that the brain makes Bayesian predictions without explicit instructions: unsupervised learning. The AI algorithms also enable machines to create interpretable models revealing the brain's predictive and learning function. Nonetheless, it remains unknown how our brains produce creative and innovative ideas, which are an essential capacity unique to natural intelligence and which have recently been an important and challenging topic for advanced machine learning algorithms as they attempt to break free from the specific problem-solving approaches that have been a mainstream of AI. Given that composers do not observe their own brains' activity in writing music, music itself does not necessarily require input from the fields of neuroscience and computing. Yet music offers (computational) neuroscientists a new perspective from which to explore a wide range of the brain's natural intelligences including idea generation and to devise creative machine learning algorithms that can resolve open-ended problems.

In sum, further research is required to generate a complete explanation of music knowledge both in the human brain and in computers. One of the key questions for future research will be how local dependency (e.g., musical expectancy formation between adjacent events) interacts with non-local dependency (hierarchically organized musical structure building) in the computation of music, and whether these interactions can explain both AI models' and the brain's function. A second key question is how music processing benefits from ubiquitous (domain-general) phenomena such as curiosity, creativity, and reward systems. Statistical learning essentially reflects contributions from domain-general mechanisms that share brain regions between different modalities (e.g., auditory, visual, and somatosensory) but are constrained to operate in their respective specific modalities. A third key question is how and when unsupervised statistical learning machinery such as that in the brain computationally and neurophysiologically gives rise to creative information. Creativity is part of human nature and is an important ability for advanced machine learning algorithms that are expected to imitate the human brain. Hence an algorithm that is optimized not for efficiency but rather for creativity may be a key step toward a complete account of music knowledge both in the brain and in computers, potentially leading to a harmonized society of humans and computers. Here we offer a novel theoretical perspective on statistical learning, highlighting the connections between Neuroscience and Machine Learning.

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