Frequency Trajectory Gives Rise to an Age-Limited Learning Effect as a Function of Input-Output Mapping in Connectionist Networks

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Abstract

According to the age of acquisition (AoA) hypothesis, words acquired early in life are processed faster and more accurately than words acquired later (see Juhasz, 2005; Johnston & Barry, 2006 for reviews). Connectionist models have begun to explore the influence of the age/order of acquisition of the items (and also their frequency of encounter) (Ellis & Lambon Ralph, 2000; Lambon Ralph & Ehsan, 2006; Zevin & Seidenberg, 2002). We explored age-limited learning effects in a connectionist model similar to that used by Lambon Ralph and Ehsan (2006) but with the use of a frequency trajectory (Zevin & Seidenberg, 2002), which refers to changes in the frequency of the words over long periods of age, since frequency trajectory is thought to better index age-limited learning effects than traditional AoA measures (Bonin, Barry, Méot, & Chalard, 2004). Our simulations show that the influence of frequency trajectory varies as a function of the mappings between input and output units in a similar type of neural network to that used by Lambon Ralph and Ehsan (2006).

Introduction

An important issue in psychological science is to determine whether items (words, objects, faces, etc.) which are acquired early in life are processed faster and more accurately by adults than those which are acquired later in life, namely whether there is a late influence of early acquisitions. A large number of studies have convincingly shown that words acquired early in life are processed faster and more accurately than words acquired later in life (Johnston & Barry, 2006; Juhasz, 2005 for recent reviews) using age of acquisition (AoA) norms collected from either adult ratings or from children's performance. The so-called age-of-acquisition effects have been found in a large variety of tasks (e.g., object, face and action naming, word reading, lexical decision) and in different populations (e.g., children, young and old adults, aphasics). However, despite robust AoA effects in a wide variety of lexical tasks, there is a current debate as to whether the *order of acquisition* of the words is *per se* an important factor in determining the ease of processing the words in both normal and impaired adults or whether AoA measures actually underlie other hidden factors. It is plausible that the order of acquisition of the words is a factor which is directly responsible for the ease of processing the words, and indeed this is the crucial tenet of the "AoA hypothesis". Recent attempts to independently manipulate this factor have shown a reliable influence on the learning of artificial patterns in laboratory settings (Stewart & Ellis, 2008). However, as far as the learning of the words of a language is concerned, there are obviously, factors other than the order in which the words and/or concepts were encountered also clearly underlie the speed and accuracy of acquisition (with the result that certain words are acquired before others). These factors are truly responsible for the AoA effects found in lexical processing in adults. Among these factors are (1) the frequency of encounter of the words (e.g., during certain period of life, during one's entire life) and (2) the kind of relationships (i,e., systematic, quasi-systematic, arbitrary that exists between different types of codes (e.g., between phonological and orthographic codes, between semantic codes and phonological codes). Frequency trajectories refer to the fact that some words are more frequent during certain periods of acquisition (e.g., "*dragon*" during childhood) than others (e.g., "*tax*" during adulthood) and the words which are frequently encountered are acquired earlier than those which are encountered less frequently (Bonin, Barry, Méot, & Chalard, 2004; Hazard, De Cara, & Chanquoy, in press; Zevin & Seidenberg, 2002). But as we shall explain, the question of whether words which have been frequently encountered during a period of acquisition are easier to process later in life than words encountered less frequently also depends on the kind of relationships that exists between different types of codes (and which have to be learned). In alphabetic languages such as English or French, there are quasi-systematic relationships between sound units and orthographic units, whereas the relationships between semantic units and phonological (or orthographic) units are arbitrary. When quasi-systematic relationships are present, what is learned from certain items can be generalized to other items, and as a result, the processing of new items is easier than when no such generalization is possible, as is the case with arbitrary mappings (Zevin & Seidenberg, 2002). In several studies, Zevin and Seidenberg (2002, 2004) and Bonin et al. (2004) suggested that lexical processing varies as a function of both the frequency trajectory of the words and the kind of relationships that exist between semantics, phonology and orthography. More precisely, Bonin et al. (2004) have shown age-limited learning effects in both oral and written naming (where the relationships between object names and semantics are arbitrary) but not in reading aloud and in spelling to dictation (because in alphabetic languages such as French or English, the relationships are quasi-systematic between orthography and phonology).

However, Ellis and Lambon Ralph (2000) or Lambon Ralph and Ehsan (2006) obtained age-limited learning effects by manipulating the age of acquisition of the items. The authors manipulated the order of introduction of the patterns instead of the frequency trajectory of the items. Thus, for systematic and quasi-systematic relationships, it remains to be determined whether frequency trajectory, as proposed by Zevin and Seidenberg (2002), can generate age-limited learning effects similar to what was obtained by Ellis and Lambon Ralph (2000) and Lambon-Ralph and Ehsan (2006) when manipulating the order of introduction of the items. As far as arbitrary mappings are concerned, Zevin and Seidenberg (2002) have shown that frequency trajectory had an effect on network performance. However, it is worth stressing that this effect was obtained when background items were not included in the simulation (Simulation 3). Also, a potential problem is that their Simulations 3 and 4 significantly differ from what Ellis and Lambon Ralph (2000) and Lambon Ralph and Ehsan (2006) have defined as "arbitrary mappings". Zevin and Seidenberg (2002) used "critical" items having few neighbors in order to manipulate arbitrary mapping, whereas in the simulations performed by both Ellis and Lambon Ralph (2000) and Lambon Ralph and Ehsan (2006) completely arbitrary mappings were used (it should be remembered that this situation is thought to approximate to picture naming which involves arbitrary relationships between semantics and names). In other words, Zevin and Seidenberg (2002) did not actually test the effect of frequency trajectory on items having arbitrary relationships. Instead, what they have shown was a very specific age-limited learning effect produced by the manipulation of the frequency trajectory of the items under exceptional conditions (when the neural network was trained on critical items but with all the background items removed). The main purpose of our study is to reduce the gap between the Lambon Ralph and Ehsan (2006) and the Zevin and Seidenberg (2002) approaches by using the same networks and procedures used by Lambon Ralph and Ehsan (2006) to investigate the influence of the frequency trajectory of the items instead of their order of introduction. Of importance also is the fact that we included items having a flat frequency trajectory as baseline items in order to better index the true influence of high-to-low frequency trajectory items and low-to-high frequency trajectory items.

Simulation 1
Frequency trajectory effects in artificial neural systems for arbitrary mappings

The goal of Simulation 1 is to test the influence of frequency trajectory as reported by Zevin and Seidenberg (2002) on arbitrary relationship between input-output units. The initial findings suggested that the nature of the relationships between input and output patterns is crucial if age-limited learning effects on network performance are to emerge. Thus, whereas age-limited learning effects should emerge in tasks requiring the involvement of arbitrary mappings such as in face or object naming, little or no age-limited learning effects should be found in tasks requiring the involvement of componential (i.e. systematic or quasi-systematic) representations. This pattern of findings has indeed been observed on behavioral data (Bonin et al., 2004). At a computational level, Lambon Ralph and Ehsan (2006) identified a significant effect of the order of introduction of the patterns when the relationships between input-output patterns were arbitrary. Zevin and Seidenberg (2002) did not find a reliable effect of frequency trajectory on network performance when cumulative frequency was equalized across each training regime and background items were introduced in the network, even when a high level of arbitrariness was introduced between the input-output patterns (Simulation 4). According to these latter authors, what is learned from early items can be generalized to later items by means of associative learning functions which are provided by the background items. To our knowledge, the influence of frequency trajectory, when cumulative frequency is controlled for, has never been tested using a simple back-propagation neural network and arbitrary items.

Method

The connectionist network was a standard 3-layer back-propagation neural network. It was in all respects identical to the one used by Lambon Ralph and Ehsan (2006), namely a 100-50-100 neural network architecture. Like Ellis and Lambon Ralph (2000) and Lambon Ralph and Ehsan (2006), we did not include background items in the simulation relating to arbitrarily mapped items. For these items, the input and output vectors were 100 randomly generated binary vectors. The first 33 vectors were encoded with a frequency of 16.7 % (each vector was presented once at each iteration of the neural network), the next 34 vectors with a frequency of 33.3 % (each vector was presented twice at each iteration of the neural network) and the remaining 33 with a frequency of 50 % (each vector was presented three times at each iteration of the neural network) during a first training stage consisting of 5,000 epochs. During the second training stage of 5,000 epochs, all the vectors were encoded with the same frequency, namely 33.3% (each vector was presented once at each iteration of the neural network). Finally, during the last training stage of 5,000 epochs, the first 33 vectors were encoded with a frequency of 50 %, the 34 next vectors with a frequency of 33.3 % and the remaining 33 vectors with a frequency of 16.7 %. To summarize, the first 33 vectors had a low-to-high frequency trajectory, the next 34 vectors were perfectly stable over time (i.e., they had a flat frequency trajectory) and the last 33 vectors had a high-to-low frequency trajectory. However, by the end of training, the cumulative frequency of the items was as shown in Table 1. Initial synaptic weights were randomly initialized between 0 and 1 at the beginning of the first training phase. The learning rate was fixed to 0.1 and momentum to 0.9.

	Time		
	1	2	3
Low-to-high trajectories	16.7	33.3	50
Flat trajectories	33.3	33.3	33.3
High-to-low trajectories	50	33.3	16.7

Table 1. *Frequency trajectories used in Simulation 1, 2 and 3*

Results

Like previous connectionist simulations, we used the Sum Squared Error (SSE) as the standard dependent variable (Ellis & Lambon Ralph, 2000; Lambon-Ralph & Ehsan, 2006 and Zevin & Seidenberg, 2002).

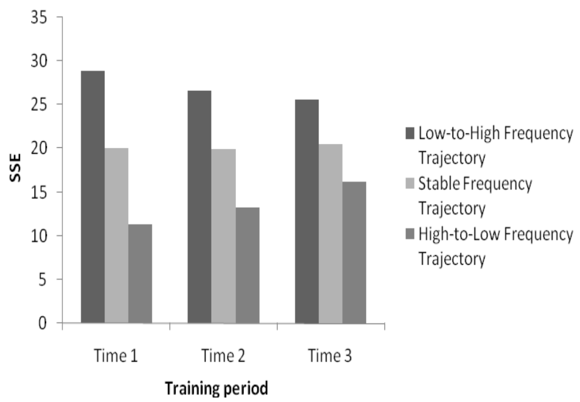

Figure 1. Frequency trajectory effect on Sum Square Error for arbitrary items.

As far as the first training period is concerned, there were more errors on low-to-high items than on flat items, $F(1, 291) = 41.75$, $MSE = 31.28$, $p < .001$, and more errors on stable items than on high-to-low frequency items, $F(1, 291) = 41.35$, $MSE = 31.28$, $p < .001$. In the second training period, the frequency trajectory effect was also significant. There were more errors for the low-to-high items (mean SSE = 26.57) than the flat items (mean SSE = 19.94; $F(1, 291) = 21.36$, $MSE = 34.43$, $p < .001$), and more errors on flat items than on high-to-low items (mean SSE = 11.28; $F(1, 291) = 34.43$, $MSE = 21.5$, $p < .001$). More importantly, the frequency trajectory effect was significant during the last training period (representing adult performance). More errors were observed for low-to-high items (mean SSE = 25.59) than for flat items (mean SSE = 20.48; $F(1, 291) = 10.66$, $MSE = 41.14$, $p < .001$), and more errors for flat items than for high-to-low items (mean SSE = 16.22; $F(1, 291) = 7.39$, $MSE = 41.14$, $p < .01$).

Discussion

An effect of frequency trajectory on the age-limited learning effect in terms of network performance was found when the mappings between the input and output units were arbitrary. Compared to previous connectionist data, this finding means that it is possible to obtain an age-limited learning effect on arbitrary items without any reference to the order of introduction of the encounters (Ellis & Lambon Ralph, 2000, Lambon-Ralph & Ehsan, 2006). Instead, these effects were obtained through the simple manipulation of the frequency trajectories of the items. These results are consistent with the hypotheses proposed by Zevin & Seidenberg (2002). Moreover, we have to remember that these results were obtained using the same neural network (standard back-propagation algorithm) and the same material as Lambon-Ralph & Ehsan (2006). This effect mimics that observed on behavioral picture naming data (Bonin, Barry et al., 2004) when cumulative frequency is controlled for. In line with previous data (Munro, 1986), these findings suggest that age-limited effects arise from a generic aspect of learning, that is to say that the plasticity of the network reduces with learning. The consequence of the reduction of network plasticity is that the point during learning at which items are first encountered has a long-term, stable effect on behavioral data *if relationship between input/output units is arbitrary*.

Simulation 2

Frequency trajectory effects in artificial neural systems for quasi-systematic mappings

A second simulation was run using a new pattern of vectors (generated from Lambon Ralph and Ehsan, 2006) having a quasi-systematic relationship between the input and the output layers. As in the previous simulation, the frequency trajectory of the items was manipulated while their cumulative frequency was held constant. This context is thought to operationalize reading aloud in alphabetic languages. The input and output representations were based on data provided by Lambon Ralph and Ehsan (2006). These data instantiate the quasi-regular mapping of English or French languages. Based on the findings reported by Zevin and Seidenberg (2002), no reliable effect of frequency trajectory was predicted on neural network performance with a quasi-systematic coding of the input-output relationship (except in one very specific condition, namely critical items without background items). This represents a clear contrast to Lambon Ralph and Ehsan's (2006) study which obtained small but significant age-limited learning effects for quasi-systematic relationships in a simulation which used the order of introduction of the items as independent variable.

Method

The network was identical to the one used in Simulation 1. For the quasi-systematic items, we used the structure relationship provided by Lambon Ralph and Ehsan (2006). The quasi-regular mappings were created by dividing the 100 unit vectors into three sections (33; 34; 33) in order to represent a CVC-like word. We used the identical abstract patterns for 10 consonant and 10 vowel components generated by Lambon Ralph and Ehsan (2006) to produce a hundred representations that were formed by joining the CVC patterns using a Latin-square type combination. In other words, each input vector Cn Vn Cn was associated with an output vector Cn Vn Cn+1. Likewise, all the ten consonant and vowel patterns were used 10 times each in both the onset and offset positions. As in the previous simulation, the first 33 vectors had a low-to-high frequency trajectory, the next 34 vectors had a flat trajectory and the last 33 vectors a high-to-low frequency trajectory. The cumulative frequency of the items was controlled for.

Results

Unlike in Simulation 1, at the end of the training period, no reliable differences were observed between the different types of items (see Figure 2). Although small differences between item types were found at the end of the first training period, none of these was significant. There was a dramatic reduction in the error rate on quasi-systematic items compared to that observed for the arbitrary items, $F(1, 291) = 621.37$, $MSE = 99.07$, $p < .001$.

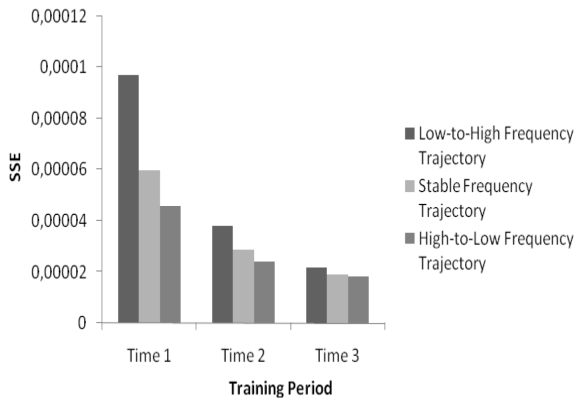

Figure 2. Frequency trajectory effect on SSE for systematic items.

Discussion

We shall return to these results in the Discussion of Simulation 3.

Simulation 3

Frequency trajectory effects in artificial neural systems for systematic mappings

In Simulation 3, the influence of frequency trajectory was examined for systematic input-output relationships. As in the previous simulation, we used the input and output patterns provided by Lambon Ralph and Ehsan (2006). Given the findings from Simulation 2, in which quasi-systematic relationships were used, we expected the systematic regularities of the input-output patterns to completely suppress age-limited learning effects in the artificial neural network.

Method

As in the case of the quasi-systematic data, one hundred unit vectors were created to form CVC-like words based on the 10 consonant and 10 vowel components generated by Lambon Ralph and Ehsan (2006). The only difference to Simulation 2 was that each input vector Cn Vn Cn was associated with itself as an output vector. In other words, the connectionist network was an auto-associator neural network which permitted the reproduction of perfectly predictable input-output correspondences. As in the previous simulations, the first 33 vectors had a low-to-high frequency trajectory, the next 34 vectors had a flat trajectory and the remaining 33 vectors had a high-to-low frequency trajectory. The cumulative frequency of the items was controlled for.

Results

As in Simulation 2, no reliable differences were observed between the different types of items (see Figure 3). Therefore, the effect of frequency trajectory, which was reliable on the SSE when arbitrary patterns were used (Simulation 1), was eliminated when the relationships between input and output units were systematic. Moreover, the mean SSE were very similar to those of quasi-systematic items ($F<1$).

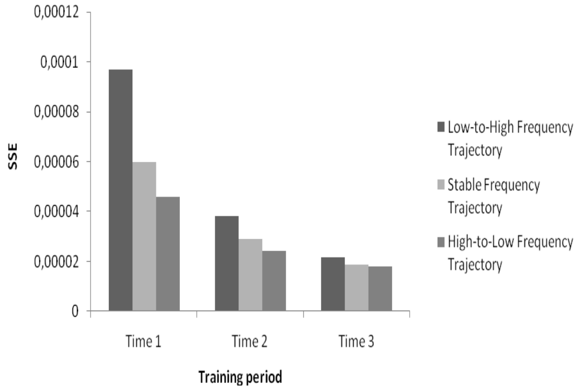

Figure 3. Frequency trajectory effect on SSE for quasi-systematic items.

Discussion of Simulation 2 and 3

The findings obtained for systematic mappings are consistent with previous behavioral (Bonin et al., 2004; Zevin & Seidenberg, 2004) and computational studies (Lambon Ralph & Ehsan, 2006; Zevin & Seidenberg, 2002), thus showing that no age-limited learning effect emerges when grapheme-to-phoneme correspondences are perfectly predictable. Early in training, the network performance is better (albeit not significantly so) on items which are trained more often, that is to say a frequency effect occurs during the early phase of the training regime. However, as training continues, the performance of the network for the different kinds of items converges to the same level. The effect of frequency trajectory occurs early in training, but then decreases rapidly and no residual effect of this factor is observed at the end of training, when the cumulative frequencies are equalized. The results of Simulation 2 (on quasi-systematic relationships) were more ambiguous with respect to the previous connectionist data reported by Lambon-Ralph & Ehsan (2006). Whereas Lambon-Ralph & Ehsan (2006) identified a small but significant age-limited learning effect with quasi-systematic relationships, we did not find this effect in our simulations. This difference was probably due to a quantitative difference in the training regime since we used more iterations during the different stages of the training (we used 5,000 iterations for each stage whereas Lambon-Ralph & Ehsan (2006) used 5,000 iterations in total and added late patterns to the training set after 750 epochs of training). Even if convergence is very fast using the back-propagation algorithm, the improvement we added at the level of each training period might qualitatively change the size of the effect (in the same way that training improves cognitive performance in humans). However, our results are consistent with behavioral data which indicates no age-limited learning effect in quasi-systematic languages like French or English (Bonin et al., 2004; Zevin & Seidenberg, 2004). With the exception of this difference, the findings obtained from Simulations 2 and 3 are compatible with the hypothesis that age-limited learning effects are not expected when the mappings between input and output units are quasi-systematic (or systematic) as has been empirically observed in word reading in alphabetic languages such as French (Bonin et al., 2004), English (Zevin & Seidenberg, 2004) or Italian (Burani, Arduino, & Barca, 2007). At a computational level, the findings from Simulation 2 suggest that the reduction of plasticity phenomenon demonstrated by Munro (1986) might be considerably reduced in componential representations when cumulative frequency is adequately controlled for. Furthermore, these three simulations have shown that the theoretical framework proposed by Zevin and Seidenberg (2002) is able to explain the results reported by Lambon Ralph and Ehsan (2006). Neither background items nor attractor networks seem necessary to observe a reliable influence of frequency trajectory in connectionist networks. At a behavioral level, we suggest that frequency trajectories better quantify age-limited learning effects than the simple order of introduction of the encounters. We therefore suggest that the influence of frequency trajectories on age-limited learning effects should be widely generalized to artificial but also to biological cognitive systems.

Conclusions

Following previous studies (Bonin et al., 2004; Bonin, Méot, Mermillod, Ferrand, & Barry, *in press*; Zevin & Seidenberg, 2002, 2004), a new theoretical framework has been put forward to account for age-limited learning effects in mature cognitive systems. This theory is explicit regarding the influence of AoA, cumulative frequency and frequency trajectory in lexical processing. Objective or rated AoA measures constitute a performance variable which has to be accounted for. Among other factors, the frequency trajectory of the items has an influence on the age/order of acquisition of the words. Frequency trajectory can thus be used to investigate age-limited learning effects in lexical processing. According to this theory, the influence of frequency trajectory is confined to the specific cases where learning about some items cannot be generalized to new items (when specific links between input-output patterns have to be learned). No or only a reduced influence of frequency trajectory is predicted when generalization is possible. This theory has been confirmed by both computational and empirical data (Bonin et al., 2004; Zevin & Seidenberg, 2002, 2004). The aim of this paper was to provide further computational evidence in support of this general connectionist theory.

In the present study, we have used the same networks and procedures employed by Lambon Ralph and Ehsan (2006), but we have investigated the influence of the frequency trajectory of the items instead of their order of introduction. The kind of relationships between input and output units was also manipulated (Simulations 1, 2 and 3). We also included items having a flat frequency trajectory in order to gain a better approximation of the true influence on the network performance of high-to-low frequency trajectory items compared to low-to-high frequency trajectory items. Simulations 1, 2 and 3 showed that frequency trajectory had a reliable influence when arbitrary mappings, but not quasi-systematic or systematic mappings, were used. These findings are consistent with previous empirical findings showing an effect of frequency trajectory on spoken and written picture naming latencies but not on word reading and spelling to dictation (Bonin, Barry, Méot, & Chalard, 2004).

In the theoretical framework that we suggest, the order/age of acquisition of the items is partly dependent on their frequency of encounter. Items which are more frequent during a certain period of life are those which are learned first. From this perspective, AoA should not be considered as an independent variable for further behavioral experiment but rather as an outcome variable which is actually determined by frequency trajectories.

In other words, the precise quantification of frequency trajectory should be a better method in order to carefully address the question of age limited learning effects.

Acknowledgments

This work has been supported in part by the National Center for Scientific Research (CNRS UMR 6024) in addition with 2 grants from the french Research National Agency (ANR Grant BLAN06-2_145908 and ANR Project BLAN08-1_353820) to Martial Mermillod. We specially thank Matt Lambon-Ralph and Andrew Ellis for useful comments on a previous version of this manuscript.

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