A computational model of bilingual semantic convergence

Shin-Yi Fang (szf4@psu.edu)
Department of Psychology, Pennsylvania State University
University Park, PA 16802 USA

Benjamin D. Zinszer (bzinszer@gmail.com)
Department of Brain and Cognitive Sciences, University of Rochester
Rochester, NY 14627 USA

Barbara C. Malt (barbara.malt@lehigh.edu)
Department of Psychology, Lehigh University
Bethlehem, PA 18015, USA

Ping Li (pul8@psu.edu)
Department of Psychology, Pennsylvania State University
University Park, PA 16802 USA

Abstract

Patterns of object naming often differ between languages, but bilingual speakers develop convergent naming patterns in their two languages that are distinct from those of monolingual speakers of each language. This convergence appears to reflect dynamic interactions between lexical representations for the two languages. In this study, we present a self-organizing neural network model to simulate semantic convergence in the bilingual lexicon and investigate mechanisms underlying semantic convergence. Our results demonstrate that connections between two languages can be established through the simultaneous activations of related words in both languages, and these connections between two languages pull the two lexicons toward each other. These results suggest that connections between words in the bilingual lexicon play a major role in bilinguals' semantic convergence. The model provides a foundation for exploring how various input variables will affect bilingual patterns of output.

Keywords: object naming; lexical categories; modeling; self-organizing map; bilingual lexicon

Introduction

The relationships between objects and names are not always consistent across languages. For example, objects labeled as *table* for English speakers are divided between two different words for Polish speakers (*stolik* for coffee tables and *stól* for dining room tables; Wierzbicka, 1992). In an early study, Kronenfeld, Armstrong, and Wilmoth (1985) asked speakers of English, Hebrew, and Japanese to sort 11 drinking vessels into categories and found that (a) some objects that were called *cup* by American speakers (e.g., paper cup, plastic cup) were named by Hebrew speakers using *cos*, a word that more closely corresponds to English *glass*, and (b) Japanese speakers distinguished paper cups and metal cups with two different names, *koppu* and *kappu*, based on the material that makes the cup. Malt, Sloman, Gennari, Shi, and Wang (1999) further investigated lexical categories across languages by asking speakers of American English, Argentinean Spanish, and Mandarin Chinese to name 60 common household containers. They found that naming patterns differed substantially as a function of the language spoken. Malt, Sloman, and Gennari (2003) identified one-to-one, one-to-multiple, multiple-to-one, and cross-cutting relationships among the lexical categories of the three languages.

These complex mapping relationships between objects and names pose a challenge for speakers of two languages. Malt and Sloman (2003) studied English naming of common household containers (e.g., plates, cups, utensils) by 68 non-native speakers of English. Even after many years of immersion in an English-language environment, the participants still showed different naming patterns from native English speakers. Ameel, Storms, Malt, and Sloman (2005) compared adult Dutch-French simultaneous bilinguals to monolingual Dutch and French speakers. They found that object naming patterns by the bilingual speakers converged toward a pattern that was different from the naming patterns of monolinguals of each language, suggesting that even simultaneous bilinguals do not behave like monolinguals in lexical categorization. Bilingual lexical representations reflect the convergence of two languages and are not simply the sum of two separate monolingual representations (Grosjean, 1989).

Recent investigations have focused on further characterizing the nature of the lexical representations and the factors that drive the particular naming patterns that emerge. Malt, Li, Pavlenko, Zhu, and Ameel (2015) examined Chinese-English bilinguals who arrived in an English-speaking environment after age 15. They found that although the bilinguals' naming patterns differed significantly from those of native English speakers, with increased second language usage, changes can occur to both L1 and L2 naming patterns. Their findings suggest that the lexical network remains plastic even in adulthood. Zinszer, Malt, Ameel, and Li (2014) examined variables characterizing both language learners and the names given to individual objects to determine conditions under which second language learners show better or poorer mastery of the second language name choice for objects. One factor of interest was name agreement: the proportion of people who agree on a name for a particular object. Name agreement has been shown to have a significant impact on naming latency

(Kremin, Hamerel, Dordain, De Wilde, & Perrier, 2000), and lead to different profiles in event-related potential (Cheng, Schafer, & Akyürek, 2010) and fMRI response patterns (Kan & Thompson-Schill, 2004). Objects with high name agreement have stronger object-name associations and more robust representations. The same object could have a different degree of name agreement across languages and result in different level of robustness and entrenchment. Zinszer *et al.* found that the name agreement level in both the first and second language plays an important role in L2 naming patterns. Learner characteristics such as age of immersion also mattered, suggesting complex dynamic interactions underlying the acquisition of L2 patterns in object naming.

The study of the dynamic interactions in a lexical network lends itself naturally to connectionist representation and computational modeling. We can think of the lexical network in terms of a conceptual representation that includes features, exemplars, and associations rather than unitary concept nodes in a connectionist network. Influences of one language on the other can be thought of in terms of the connection weights that hold between features of the word meaning and the word form. When a new L2 word form is taught as a translation equivalent of an L1 word, the network will set initial weights to match those of the L1 word. The L2 word will be activated by the same features as the L1 word, and non-native L2 patterns of production will result. Over time, however, these weights will be modified by L2 experience and will move away from a uniform pattern driven by L1. The weights may settle into a pattern that is the convergence of L1 and L2.

Previous studies implementing a computational model to test lexical categorization in L1 and L2 object naming have been models of an individual at fixed state of learned representation. To capture phenomena such as lexical interaction, a model is needed that allows manipulating learning conditions longitudinally. With such a model, it will ultimately be possible to identify how important learner characteristics such as age of exposure and proficiency in each language affect output, as well as lexical input variables such as frequency of input and similarities between the lexical items. It will also be possible to examine both the learning trajectory and the mature state, and to see how behavior changes with shifts in the relative degree of first and second language use.

In this study, we build a model based on self-organizing maps (SOM) to study cross-language lexical interaction. By building and testing this computational model against existing data of Ameel *et al.*, this work will provide the foundation for further modeling studies manipulating variables such as those just mentioned. SOM is a type of unsupervised learning that extracts and represents input similarities (Kohonen, 2001). It achieves this by projecting the complex stimulus representations from a high-dimensional space onto a two-dimensional space while preserving their topographical structure. Because of this dimensionality-reduction ability, SOM is also a powerful

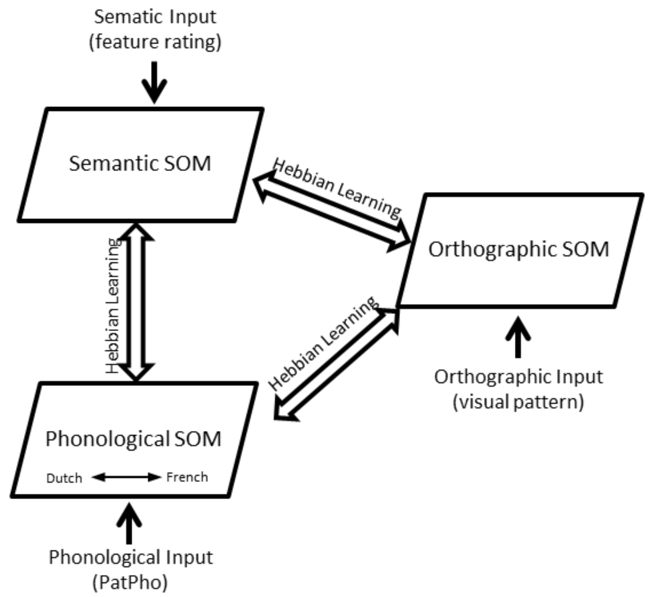

Figure 1: The model is composed of three self-organizing maps. The connection weights between SOMs were through Hebbian learning.

tool to visualize the complex stimulus relationships in a 2D space. Past studies have applied SOMs successfully to model child lexical development and to simulate bilingual language processing (see Li & Zhao, 2013 for a recent review). As a first connectionist model of L1-L2 lexical categorization, the goal of the present study is to identify the computational mechanisms underlying bilingual lexical semantic convergence.

Method

Model Architecture

Figure 1 presents a diagrammatic sketch of our model. The model is a multi-layer SOM network, which includes three basic SOMs (i.e., semantic, phonological, and orthographic). As in the standard SOM architecture (Kohonen, 2001), for each input stimulus, the SOM identifies a node that is most similar to the input vector as the Best Matching Unit (BMU), and adjusts the weights of the BMU so that over time, it can best represent the input. In addition to adjusting the weights of the BMU, the model also adjusts the weights of the BMU's neighbors using a Gaussian kernel. As training progresses, the weight vectors of the BMU and its neighboring nodes become more similar to the input vector. As a result, similar input vectors activate nodes that are located near one another on the SOMs. All SOMs were implemented on a two-dimensional square grid (Kohonen, 1982) and composed of 30 × 40 nodes. Each node on the grid consists of a high-dimensional weight vector. In our model, the number of dimensions is based on an input structure defined by empirical data (see Stimuli). The three SOMs are connected via associative links updated by bi-directional Hebbian learning (Hebb, 1949). The three

SOMs were shared between two languages. The associative links between SOMs were distinct for each language.

In addition to the basic SOM architecture, we added lateral connections (see Sirosh & Miikkulainen, 1994) between languages in the model to simulate between-language interactions. The lateral connections are implemented with the nodes that are fully connected with each other. The connection weights are updated via the Hebbian learning rule. Lateral connections have been shown to play an important role in the neocortex, and computational models of the primary visual cortex have relied on lateral connections (Sirosh & Miikkulainen, 1994). Zhao and Li (2013) also used lateral connections successfully to simulate a cross-language priming effects, and Shook and Marian (2013) used lateral connections to simulate competition between languages in speech comprehension. Many studies have shown that phonological representations from both languages may be activated when bilinguals read in only one language, due to parallel bilingual lexical activation (Dijkstra, Grainger, & van Heuven, 1999). Through lateral connections, lexical items across the two languages can be linked to enter into cooperation or competition regardless of physical distance. In our model we assume that when an object is presented to the semantic SOM, names of both languages will be activated on phonological SOMs through Hebbian connections, and the lateral connection between them is then strengthened via the Hebbian learning rule. As a result, object naming in the model in either L1 or L2 can be influenced by both languages through lateral connections.

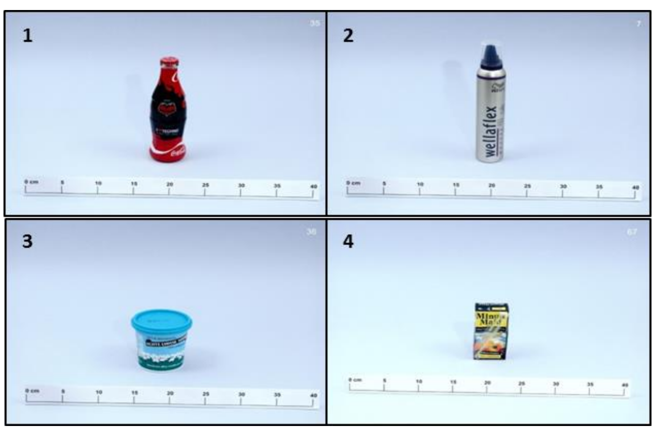

Figure 2: Examples of *fles*, *bus*, *pot*, and *brik* (pictures from 1 to 4 respectively) for Dutch monolinguals. Adapted from Ameel *et al.* (2005).

Stimuli

As a starting point we used the monolingual naming data from Ameel *et al.* (2005) as the basis of input to the model. We trained the model on representations of pictures of 73 bottle-like objects that are typically named as *bottle*, *jar*, or *container* in American English or else to have one or more salient properties in common with objects called by those names. In Ameel *et al.*'s study, the objects were photographed in color against a neutral background with a ruler included in front of each object to provide additional size information. Figure 2 (adapted from Ameel *et al.*, 2005) provided 4 example pictures, which are usually named as *fles*, *bus*, *pot*, and *brik* by Dutch monolinguals (Ameel *et al.*, 2005).

The semantic SOM was trained using input vectors with weighted object features. These features are derived from participants' judgments of the object features (e.g., "it is made of glass"; "it is deep and you can put something in it"). The phonological SOM was trained using vectors generated from PatPho, a generic phonological pattern generator for neural networks (Li & MacWhinney, 2002). The phonological forms of words were represented as sequences of phonemes, obtained from dictionaries of the two target languages (New Routledge Dutch Dictionary, 2003, for Dutch; The Oxford-Hachette French Dictionary. 2001, for French). The orthographic SOM was trained using vectors that are based on the pixel patterns of the images of the alphabets in a word (see Mikkulainen, 1997, for a similar method). Each Dutch and French alphabet (the 26 alphabets and è, é, & î) was typed in 12 point, Arial font in black on a while background measuring 90 × 90 pixels. Each alphabetic image was divided into 9 cells (3-by-3, each cell has 900 pixels). The proportion of black pixels in each cell (i.e., number of black pixels / 900) was then calculated and used to create a 9-dimension vector for each letter within a word.

Training

Figure 3 presents the training timeline of the model: (1) the semantic and phonological SOMs independently (without the orthographic SOM) to simulate the learning of the properties of objects and the pronunciation of words; (2) Hebbian learning started after 50 epochs, which enabled the learning of the association between object features and phonological forms; the orthographic SOM also started at the 50th epoch to simulate the learning of written words; and (3) Hebbian learning between the semantic and orthographic SOMs and between the phonological and orthographic SOMs began at epoch 100, to simulate the learning to read process.

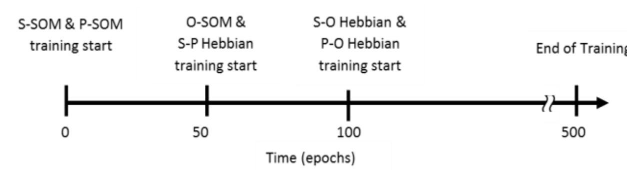

Figure 3: Schematic representation of the training timeline. S-SOM: semantic SOM. P-SOM: phonological SOM. O-SOM: orthography SOM. S-P Hebbian: Hebbian connections between semantic SOM and phonological SOM. S-O Hebbian: Hebbian connections between semantic SOM and Orthography SOM. P-O Hebbian: Hebbian connections between phonological SOM and Orthography SOM.

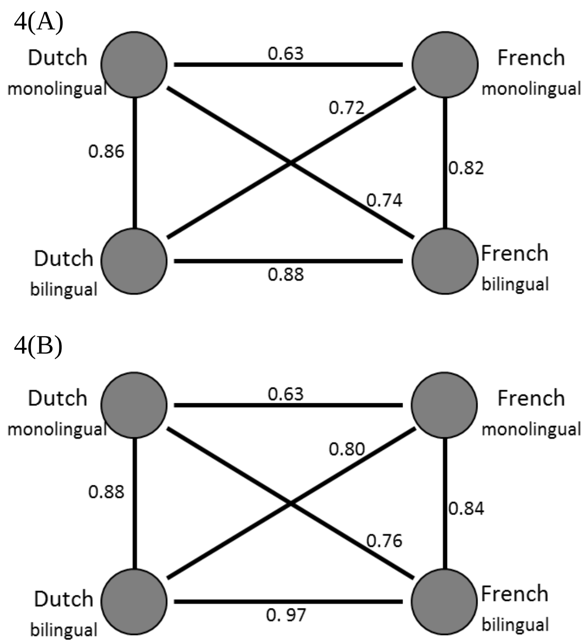

Figure 4: Patterns of correlations between the name distributions of the language groups. $Dutch_{monolingual}$ denotes the naming pattern of the Dutch-speaking monolinguals, $French_{monolingual}$ the naming pattern of the French-speaking monolinguals, $Dutchbi_{bilingual}$ and $French_{bilingual}$ the Dutch and French naming pattern of the bilinguals. (4A) the correlation reported from Figure 5D in Ameel *et al.* (2005). (4B) the correlation from our model. The circles represent the naming patterns. The lines between the circles express the relations between the naming patterns. The numbers next to the lines show the correlation coefficient between the naming patterns.

The training order of each stimulus was randomly assigned. During training, the learning rate of the SOM, following previous practice, was linearly decreased from 0.2 to 0.1 during the first 100 epochs and it remained at 0.1 for the rest of the training. The learning rate for Hebbian learning was set at 0.2. The initial radius of the neighborhood size was set at 15, and was adjusted according to the network's learning outcome. We used a self-adjustable neighborhood function according to Li, Zhao and MacWhinney (2007).

The Hebbian connections between semantic and phonological SOMs within each language (Dutch or French) were based on the monolingual naming data from Ameel *et al.* (2005), which were also scaled according to the name agreement scores. For example, if an object was named 81.25% as *fles* and 18.75% as *bus* in Dutch, the adjusted connection weights were rescaled by 81.25% for *fles* and 18.75% for *bus*. To avoid uncontrolled weight growth, a multiplicative normalization was applied to the associative weight vectors to ensure that the largest possible connection weight is no more than one (Miller & MacKey, 1994).

Assessment of the model

We tested each model at epoch 500. During testing, we presented all 73 bottle-like objects to the semantic SOM and examined their activations propagating to the phonological SOM (simulating the name production process). In order to distinguish specific language output (i.e., whether the name given was Dutch or French), we labeled the phonological BMUs by their language memberships in this process and only examined the output of the to-be-named language in the analysis.

We conducted three analyses to evaluate model's naming patterns, following the methods used in the empirical studies of lexical categorization in Ameel *et al.* (2005; 2008) and Malt *et al.* (1999). In the first analysis, we used the correlation of the name distributions for each object based on the model's naming patterns in different languages. The correlation indicates the extent to which the same object would elicit same or similar name distributions in each language (Ameel *et al.*, 2005; Malt *et al.*, 1999). For this analysis, in the first step, we constructed the name distribution for each object. The name distribution consists of a vector of numbers to indicate the number of times a given name was produced for each object. For example, for one object, 11 participants called it *fles*, 10 called it *flacon* and 4 called it *pot*, and none called it by any other name. This would lead to a vector in which the dimensions for *fles*, *flacon*, and *pot* are filled with values 11, 10, 4, respectively, with all other dimensions as 0s. In the second step, given the name distribution as calculated, we can compute the similarity of objects with regard to name distributions within each language, by calculating pairwise Pearson correlations for each object against every other object. There are n(n-1)/2 correlations, and thus 2628 correlations for 73 bottle-like objects. We can then correlate these name similarity values between two language groups. In the last step, the correlations of name distributions were converted to Z-values using Fisher's r-to-z transformation to normalize the sampling distribution of the correlations.

In order to estimate the correspondence between simulation and empirical data, we conducted two further analyses to directly compare the outputs from simulations and the empirical data. Specifically, we used the correlations of name distributions for each object to compare the naming patterns from the empirical data and the simulation data. For each language group (monolingual Dutch, monolingual French, bilingual Dutch-French), we correlated the name similarity values (i.e., the correlation matrices between object pairs within each language group) between the empirical data and the simulation data. Moreover, we compared the dominant category names for each object between our simulations and the empirical data from Ameel *et al.* (2005). Finally, to identify the effect of lateral connections, we also constructed a model in which there are no lateral connections between languages.

Results

Before reporting our simulation results, we briefly summarize the empirical findings from Ameel *et al.* (2005). Ameel *et al.* reported the correlations of the name distributions between monolingual and bilingual language groups as shown in Figure 4(A) (adapted from Figure 5D in Ameel *et al.*, 2005). There are four circles in the figure, one for each language of a language group (naming in Dutch by Dutch monolinguals, naming in French by French monolinguals, and naming in Dutch by the bilinguals, and naming in French by the bilinguals). The figure indicates that the correlation between two bilingual circles is higher than the correlation between the two monolingual circles showing that bilinguals arrive at a convergent pattern in object naming, distinct from monolinguals in each language.

For the first analysis, the correlations between language groups are presented in Figure 4(B). Similar to Ameel *et al.* (2005), our computational model shows higher correlation between bilinguals' two languages (0.97) than between two monolingual languages (0.63), indicating that our model simulated convergence naming patterns and captured this aspect of bilinguals' lexical categorization.

In the second analysis, we compared the empirical and simulated name distributions, and found that the model that incorporated lateral connections has higher correlations with the empirical data than the model in which there was no lateral connection mechanism: $t(38) = 14.02$, $p < .001$ for Dutch, $t(38) = 13.35$, $p < .001$ for French. We also compared the dominant names produced by the model with the empirical data from Ameel *et al.* (2005). We identified that averaged across 20 individual simulations, there were 93.22% and 92.26% dominant names that were matched in Dutch and French. The model without lateral connections showed 82.95% and 86.03% dominant name match in Dutch and French. Thus, the model with lateral connections performed significantly better than the model without lateral connections ($t(38) = 18.29$, $p < .001$ for Dutch; $t(38) = 10.47$, $p < .001$ for French).

We further examined the model to explore what properties in the model might have influenced the naming patterns. For each object, its name could be determined by two sources: (1) activation from the to-be-named language; (2) cross-activation from the other language. The level of activation is proportional to the strength of name agreement. In the empirical study, name agreement is reflected as the likelihood of a name for an object. The naming pattern was considered as the sum of both of these two sources of activation. Our model shows that if an object elicited a strong level of activation for a word in the to-be-named language, the output name of the model for bilingual naming will be the same as the name for monolingual naming. However, if the activation level is weak in the to-be-named language and the cross-activation from the other language is strong, the output names of the model could be different between bilingual naming and monolingual naming. For example, if a bottle-like object elicited strong activation of the word *fles* in Dutch, both the monolinguals and bilinguals will produce *fles* in Dutch; whereas if the activation of *fles* in Dutch is weak, the activation of *bus* in Dutch may outperform *fles*, due to a combination of its original activation from Dutch and the strong lateral activation from French. In this example, the monolinguals will produce *fles*, but the bilinguals will produce *bus*.

Discussion

In this study, we successfully built a bilingual lexical categorization model based on a connectionist SOM architecture that has been previously tested in other domains of language acquisition and bilingual processing. Our model simulated bilingual semantic convergence in the naming of common household objects as reported in the empirical literature (Ameel *et al.*, 2005).

Our simulation also showed that the strength of name agreement is an important factor to determine lexical naming patterns for bilinguals. If the object has high name agreement in one language, the influence from the other language through lateral connection cannot easily change its name and vice versa. Such changes can occur only if the influence from other language is very strong. This is consistent with Zinser *et al.* (2014) who found that the level of agreement can predict the native-likeness of responses. Furthermore, our model suggested that the relatioship between the two languages in the levels of name agreement are competition and cooperation, as reflected in the associative mapping between languages.

Our model with additional lateral connections also performed significantly better than the model in which lateral connections are not included. This is particularly important as our model is designed to simulate the dynamic interactions between two languages, and lateral connections play a critical role in bilingual lexical categorization, consistent with findings from Zhao and Li (2013). Our results demonstrate how, for simultaneous bilinguals, the processing of one language can be influenced by the other language (i.e., bi-directional influences between languages). The viability of our model paves the way to use modeling to study a wide range of learner and object name variables that may influence behavioral outcomes for simultaneous and sequential bilinguals (such as variables discussed before, including age of onset, proficiency, and frequency of input).

Our simulations also provide a mechanistic account for the idea of retrieval-induced reconsolidation as applied to cross-language lexical interaction, as proposed by Wolff and Ventura (2009). The idea of retrieval-induced reconsolidation originated from memory research (Alberini, 2005) in which consolidated memories become labile and vulnerable to change when they are re-activated through retrieval. During this vulnerable period, other active information can alter or modulate the original memory. Eventually, the activated memory will re-stabilize through reconsolidation, but it may be different from the original memory. Wolff and Ventura suggested that processing of one language is affected by the other language when the one language is activated in the labile stage. Our simulation is consistent with this hypothesis and provides a concrete instantiation of such an idea. When an object activates names in both languages, the connections between two languages begin to be established.

Conclusion

This study used a connectionist self-organizing model to simulate object naming patterns in bilinguals and to identify mechanisms of lexical semantic convergence. We successfully replicated the lexical convergence patterns reported in empirical data from Ameel *et al.* (2005), and we further investigated the mechanisms and important factors that modulate bilinguals' naming categorization. We demonstrated that lateral connections play an important role in lexical convergence. Finally, we have identified the role of name agreement strength on bilinguals' object naming. This study provides a first computational model that examines the dynamic interaction between two lexicons in the process of naming objects in monolingual or bilingual language contexts.

Acknowledgments

This research was supported by a grant from the National Science Foundation (BCS-1057855) to BCM and PL.

References

Alberini, C. M. (2005). Mechanisms of memory stabilization: Are consolidation and reconsolidation similar or distinct processes? *Trends in Neuroscience*, 28, 51–56.

Cheng, X., Schafer, G., & Akyurek, E. (2010). Name Agreement in Picture Naming: An ERP study. *Internatinal Journal of Psychophysiology*. 76(3):130-41

Grosjean, F. (1989). Neurolinguists, beware! The bilingual is not two monolinguals in one person. *Brain and Language*, *36*, 3-15.

Hebb, D. (1949). *The organization of behavior: A neuropsychological theory*. New York, NY: Wiley.

Kan, I. P. & Thompson-Schill, S. L. (2004). Selection from perceptual and conceptual representations. *Cognitive, Affective, & Behavioral Neuroscience, 4,* 466-482.

Kremin, H., Hamerel, M., Dordain, M., De Wilde, M., & Perrier, D. (2000). Age of acquisition and name agreement as predictors of mean response latencies in picture naming of French adults. *Brain & Cognition*, 43, 286-291.

Kohonen, T. (1982). Self-organized formation of topologically correct feature maps. *Biological Cybernetics*, 43, 59–69.

Kohonen, T. (2001). *The self-organizing maps*. (3rd ed.). Berlin: Springer.

Kronenfeld, D. B., Armstrong, J. D., & Wilmoth, S. (1985). Exploring the internal structure of linguistic categories: An extensionist semantic view. In J. W. D. Dougherty (Ed.), *Directions in cognitive anthropology* (pp. 91–113). Urbana: University of Illinois Press.

Li, P. & MacWhinney, B. (2002). PatPho : A phonological pattern generator for neural networks, *Behavior Research Methods Instruments and Computers*, 34(3), 408–415.

Li, P., & Zhao, X. (2013). Self-organizing map models of language acquisition. *Frontiers in psychology*, 4(November), 828. doi:10.3389/fpsyg.2013.00828

Li, P., Zhao, X., & MacWhinney, B. (2007). Dynamic self-organization and early lexical development in children. *Cognitive Science*, 31, 581–612.

Malt, B. C., Li, P., Pavlenko, A., Zhu, H., & Ameel, E. (2015). Bidirectional lexical interaction in late immersed Mandarin-English bilinguals. *Journal of Memory and Language*, 82, 86–104.

Malt, B. C., & Sloman, S. A. (2003). Linguistic diversity and object naming by non-native speakers of English. *Bilingualism: Language and Cognition*, 6, 47–67.

Malt, B. C., Sloman, S. a., & Gennari, S. P. (2003). Universality and language specificity in object naming. *Journal of Memory and Language*, 49(1), 20–42.

Malt, B. C., Sloman, S. A., Gennari, S., Shi, M., & Wang, Y. (1999). Knowing versus naming: Similarity and the linguistic categorization of artifacts. *Journal of Memory and Language*, 40, 230–262.

Miller, K. D., & MacKay, D. J. (1994). The role of constraints in Hebbian learning. *Neural Computation*, 6(1), 100-126.

Pavlenko, A., & Malt, B. C. (2010). Kitchen Russian: Cross-linguistic differences and first-language object naming by Russian–English bilinguals. *Bilingualism: Language and Cognition*, 14(01), 19–45.

Shook, A., & Marian, V. (2013). The bilingual language interaction network for comprehension of speech. *Bilingualism: Language and Cognition*, 16(2).

Sirosh, J., & Miikkulainen, R. (1994). Self-organizing feature maps with lateral connections: modeling ocular dominance. In M. C. Mozer and P. Smolensky and D. S. Touretzky and J. L. Elman and A. S. Weigend (eds.) *Proceedings of the 1993 Connectionist Models Summer School* (CMSS-93, Boulder, CO), 31-38. Hillsdale, NJ: Erlbaum.

Wierzbicka, A. (1992). *Semantics, culture, and cognition*. Oxford: Oxford University Press

Wolff, P., & Ventura, T. (2009). When Russians learn English: How the semantics of causation may change. *Bilingualism: Language and Cognition*, 12(02), 153.

Zhao, X., & Li, P. (2013). Simulating cross-language priming with a dynamic computational model of the lexicon. *Bilingualism: Language and Cognition*, 16(2), 288–303.

Zinszer, B. D., Malt, B. C., Ameel, E., & Li, P. (2014). Native-likeness in second language lexical categorization reflects individual language history and linguistic community norms. *Frontiers in psychology*, 5(October), 1203. doi:10.3389/fpsyg.2014.01203