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The Effects of Semantic Neighborhood Density on the Processing of Ambiguous Words

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by

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Graduate Program in Psychology

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Abstract

Semantic neighborhood density's effects on the processing of ambiguous words were examined in three lexical decision experiments. Semantic neighborhoods were defined in terms of semantic set size and connectivity in Experiment 1, and in terms of semantic set size in Experiments 2 and 3. In Experiment 1, set size, connectivity, and ambiguity were crossed. An ambiguity disadvantage was observed for large set, high connectivity words, and there was some suggestion of an ambiguity advantage for small set, high connectivity words. Experiments 2 and 3 held connectivity constant at a high level, and set size and ambiguity were crossed, with Experiment 3 using pseudohomophone nonwords. Neither experiment produced an ambiguity advantage. Participants responded faster to unambiguous words relative to ambiguous words, particularly for large set size words, essentially supporting Experiment 1's results. These results are discussed within a framework in which meaning-level competition can affect the recognition of semantically ambiguous words.

Keywords: Semantic neighborhood density, semantic ambiguity, lexical decision

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Introduction

There has been growing interest in the last few decades in how orthographic, phonological, and semantic information are stored and activated during word reading. One particular focus of this research has been examining how "neighborhood effects" influence the process of visual word recognition. For example, extensive work has been done on the effects of orthographic neighborhood size – defined as the set of words of the same length that differ from that word by only one letter, (e.g., *car* and *cot* are neighbors of *cat*) – on visual word recognition processes (e.g., Andrews, 1989, 1992; Coltheart, Davelaar, Jonasson, & Besner, 1977; Grainger, 1990; Grainger & Jacobs, 1996; Sears, Hino, & Lupker, 1995; Siakaluk, Sears, & Lupker, 2002). Likewise, phonological neighborhoods – words that differ by a single phoneme from a specific word – have also been extensively researched in an attempt to determine their role in word recognition (e.g., Vitevitch, 2007; Yates, 2005, 2009; Ziegler, Muneaux, & Grainger, 2003).

In contrast, relatively little research has been done on semantic neighborhood effects. As Buchanan, Westbury, and Burgess (2001) note, this dearth of research has stemmed in part from several challenges in defining what constitutes a semantic neighbor. Whereas researchers have reached some general consensus on reasonable definitions for what constitutes an orthographic or phonological neighbor, there is no obvious way to define a semantic neighbor, because words have many ways of being semantically related to each other. For example, an object-based view of semantics defines semantic similarity in terms of the similarity of the objects themselves, be it in terms of the amount of featural overlap shared by concepts (e.g., *cat* and *dog* are close semantic neighbors because they share many semantic features, such as having four legs, fur, and a tail), and/or in terms of being members of the same category of objects (e.g., McRae, Cree, Seidenberg, & McNorgan, 2005). In contrast, a language-based view of semantics classifies concepts as being semantically related on the basis of the statistical co-occurrence of the two concepts regardless of the properties shared by the two objects. According to such a view, *cat* and *dog* are near neighbors because they appear in similar contexts when large samples of language are analyzed (e.g., global co-occurrence; Burgess & Lund, 2000; Landauer & Dumais, 1997; Lund & Burgess, 1996), or because the words are commonly used adjacent to each other in everyday language (e.g., local co-occurrence; Nelson, McEvoy, & Schreiber, 1998), and concepts can be semantically similar regardless of any similarity the objects themselves share.

Certainly, it may be the case that the space of semantic neighborhoods incorporates properties of both object- and language-based semantics. As a result, semantic space would be both very large and highly variable in structure. At worst, this would mean that the semantic space can only be defined for any individual. More likely, however, while possessing a very large and variable structure, such a semantic space may share characteristics across individuals. For the purpose of the present thesis, it is assumed that while individual differences in semantics do exist, the structure of this space is guided by general principles that influence how the space is organized.

A central issue that the present research focuses on is the impact of a word's semantic neighborhood on the effects of semantic ambiguity. Semantically ambiguous words are those having more than one meaning. In languages such as English, ambiguity is a highly prominent feature of a person's everyday linguistic environment in that a large majority of words in the English language mean different things in different contexts. As such, ambiguity has been the subject of much research and debate within the psycholinguistic literature over the last several decades. Intuitively speaking, since ambiguity is such a ubiquitous feature of English, it would follow that such ambiguity would have an influence on the organization of a word's semantic space and, hence, on the process of visual word recognition. This idea is one that will be developed in greater detail below. First, however, I will begin by discussing research that has been done on both the effects of semantic neighborhood size and semantic ambiguity, as well as some of the theoretical explanations of both of these effects. Finally, the main focus of this thesis, the relationship between semantic ambiguity effects and semantic neighborhoods, will be discussed.

Previous Research on Semantic Neighborhood Effects

Early research on semantic neighborhood effects has shown that the size and density of semantic neighborhoods predict response times (RTs) in word recognition tasks. In the earliest study of semantic neighborhood effects in visual word recognition, Buchanan et al. (2001) quantified semantic space on the basis of Lund and Burgess's (1996) hyperspace analogue to language (HAL) model, a co-occurrence model of semantic memory. The HAL model constructs a high-dimensional semantic space from a co-occurrence matrix, created by analyzing a massive corpus of text. The model then encodes the contexts of word usage, as reflected in weighted co-occurrences. The semantic neighborhood of a word corresponds to a group of words that are close to it. A word's neighborhood size is quantified either as how many words are within a certain distance of the target word, or as the distance from the target word to a criterion number of words, such as the 20^{th} furthest word. The distance of neighbors around any particular word varies, and this variance reflects the variance in the word's "semantic density". Using this metric, Buchanan et al. found that words with denser neighborhoods produced faster response times in both lexical decision and word naming tasks. A subsequent study by Siakaluk, Buchanan, and Westbury (2003) replicated Buchanan et al.'s findings in a go/no-go semantic categorization task.

Buchanan et al. (2001) offered a feedback activation account for these types of effects based on the proposals of Balota, Ferraro, and Connor (1991). This account assumes that there are distinct sets of reciprocally connected units dedicated to processing phonological, orthographic, and semantic information. Activation of one of these sets of units subsequently influences processing in the other sets of units through feedback, and the nature of this activation determines the ease or difficulty of processing. A final assumption is that decisions in different tasks will be based on the processing of different sets of units. The orthographic units would be the locus of lexical decision making, the semantic units would be the locus of semantic categorizations, and the phonological units would be the locus in naming tasks. In lexical decision tasks, Buchanan et al. suggested that words with denser semantic neighborhoods are processed faster as a result of enhanced feedback activation from the semantic units to the orthographic units, causing the orthographic units to increase their activation more quickly.

Opposite Effects of Near and Distant Neighbors

Whereas earlier research on semantic neighborhood effects point to facilitative effects of semantic neighbors, more recent research offers a finer grained analysis of the effects of semantic neighbors on visual word recognition. Mirman and Magnuson (2008) suggested that neighbors can simultaneously have both facilitative and inhibitory effects, rather than having only one type of effect. They examined the independent effects of near and distant neighbors on semantic access using a concreteness judgment task. Near neighbors are words having high similarity, whereas distant neighbors have more moderate similarity. Their data showed opposite effects for near and distant neighbors: words with many near neighbors were recognized more slowly than words with few near neighbors, and words with many distant neighbors were recognized more quickly than words with few distant neighbors. Mirman (2011) has reported similar findings in word production tasks, finding higher semantic error rates for words with many near semantic neighbors, and fewer semantic errors for words with many distant semantic neighbors with aphasic patients, as well as with controls in a speeded picture-naming task.

Mirman and colleagues (Mirman, 2011; Mirman & Magnuson, 2008) argued that their opposite effects are explainable within an attractor dynamics framework. In attractor models of semantics (e.g., Cree, McRae, & McNorgan, 1999), attractors refer to stable states that correspond to a concept’s combination of features. In such models, processing gravitates towards the closest stable state or states, and is pulled more rapidly into a stable state as processing gets closer to an attractor. Since near semantic neighbors are close to the target attractor, their representations exert a pull just as processing is about to settle on the correct representation, slowing the approach towards the target attractor. Because distant neighbors are farther from the target, it is assumed that they would not induce such a high degree of competition. Further, because the distant neighbors outnumber near neighbors, Mirman and Magnuson suggested that the combination of small pulling effects from distant neighbors, pulling towards the vicinity of the target, facilitates movement towards the attractor, overwhelming any impact of near neighbors.

To test this account, Mirman and Magnuson (2008) analyzed simulations of another attractor dynamics model of semantic processing (O’Connor, Cree, & McRae, 2009). Consistent with the behavioral data that Mirman and Magnuson presented, they found that the attractor model demonstrated detrimental effects of near neighbors and facilitative effects of distant neighbors.

While the opposite effects of near and distant semantic neighbors have not been investigated as thoroughly as other neighborhood effects, the results of Mirman and colleagues

(Mirman, 2011; Mirman & Magnuson, 2008) provide important insights into the dynamics of semantic neighborhood effects. Recent research by Chen and Mirman (2012) has used a simple interactive activation and competition (IAC) framework to simulate facilitative-inhibitive effect reversals, and attempted to develop a unified account of the computational principles that govern whether neighbor effects will be facilitative or inhibitory. Their model exhibited opposite effects of near and distant semantic neighbors on word recognition and word production. In the word recognition task, the model was slower to settle when the target word had many near semantic neighbors, and was faster when the target had many distant semantic neighbors. Likewise, in their word production simulations, word activation was slower for words with many near semantic neighbors, and faster for words with many distant semantic neighbors. Overall, there was a general trend that determined whether neighbor effects were facilitative or inhibitory: strongly activated neighbors have a net inhibitory effect, while weakly active neighbors have a net facilitative effect.

The present experiments attempted to extend the investigation of how neighbors exert their effects in different circumstances. Of particular interest is examining whether semantic neighborhood dynamics exert an influence on the strength and direction of another semantic effect, specifically, semantic ambiguity, a semantic effect that has garnered much research interest over the past several decades.

Previous Research on Semantic Ambiguity

The first studies to examine the effects of semantic ambiguity on visual word recognition were conducted by Rubenstein and colleagues (Rubenstein, Garfield, & Millikan, 1970; Rubenstein, Lewis, & Rubenstein, 1971), who found that homographs (i.e., words with the same spelling but different meanings – ambiguous words) yielded faster RTs than nonhomographs in lexical decision tasks, which was later replicated by Jastrzembski (1981). However, these findings were criticized by Gernsbacher (1984), who argued that ambiguous words are typically more familiar than unambiguous words, and the faster response times for ambiguous words is merely caused by a confound with familiarity. Once word familiarity was taken into account, she found no effect of ambiguity. Since then, however, a number of studies have found a significant facilitative effect for ambiguous words (i.e., an *ambiguity advantage*) in lexical decision tasks (e.g., Hino & Lupker, 1996; Kellas, Ferraro, & Simpson, 1988; Millis & Button, 1989; Pexman & Lupker, 1999), and naming tasks (e.g., Lichacz, Herdman, LeFevre, & Baird, 1999; Hino, Lupker, & Pexman, 2002; Hino, Lupker, Sears, & Ogawa, 1998; Rodd, 2004; although see Borowsky & Masson, 1996, for contradictory results) after controlling for familiarity. In contrast, some studies have reported an *ambiguity disadvantage* when certain types of semantic categorization tasks are used (Hino et al., 2002), or in an auditory lexical decision task when the ambiguous stimuli used had multiple unrelated meanings (Rodd, Gaskell, & Marslen-Wilson, 2002, 2004). Given such inconsistencies, it is clear that understanding how readers deal with semantic ambiguity presents a special challenge in psycholinguistic research.

Hino and Lupker (1996) and Pexman and Lupker (1999) argued that the ambiguity advantage seen in lexical decision tasks can be explained in terms of the semantic feedback account that was discussed above (Balota et al., 1991). As with having large, dense semantic neighborhoods, words with multiple meanings are assumed to possess a more *enriched* semantic representation, and should thus produce enriched semantic feedback from the semantic level to the orthographic level.

To test this idea, Pexman and Lupker (1999) conducted two lexical decision experiments examining the effects of semantic ambiguity, homophony, and nonword foil type (pronounceable pseudowords vs. pseudohomophones). Pexman and Lupker argued that the homophony effect – the finding that homophones (e.g., *maid*) are responded to slower than nonhomophones – is also quite consistent with a feedback model's predictions. Homophones have one phonological code that would feed back activation to multiple orthographic codes (e.g., for *made* and *maid*), which would create competition at the orthographic level, ultimately slowing processing. Further, Pexman and Lupker predicted: a) that if a feedback mechanism can account for the effects of ambiguity and homophony, then the effects should co-occur in a lexical decision task; and b) they should both increase in size when pseudohomophones are used because using pseudohomophones should increase the activation necessary for a lexical representation to trigger a "word" response. The results of their experiments supported their predictions. These results provide support for a feedback account of the ambiguity advantage as well as the homophone disadvantage in lexical decision.

Parallel Distributed Processing (PDP) Approaches to Explaining Semantic Ambiguity

Other research has directly examined the ability of parallel distributed processing (PDP) models to account for the ambiguity advantage in lexical decision tasks, under the assumption that performance is based on the nature of semantic coding. In such models (e.g., Borowsky & Masson, 1996; Kawamoto, Farrar, & Kello, 1994; Plaut & McClelland, 1993; Plaut, McClelland, Seidenberg, & Patterson, 1996; Rodd et al., 2004; Seidenberg & McClelland, 1989; Van Orden, Pennington, & Stone, 1990), it is assumed that orthographic, phonological, and semantic information for a word are not captured by individual processing units, but by unique patterns of activation across sets of processing units representing these different domains. These units are assumed to share interconnections with each other, and as the learning process occurs, the sets of weights on these connections are adjusted in order to gradually produce an output (i.e., phonology or meaning) that is correctly associated with the orthographic input. Finally, it is assumed that the consistency of this input-output relationship determines the strength of association, which determines how quickly the model can settle on a correct output, and, as such, predict that the speed and efficiency of phonological and semantic coding depends on the nature of the orthographic-phonological and orthographic-semantic relationships of the words.

PDP models attempting to explain the ambiguity advantage in terms of semantic activation would seem to face some difficulty because ambiguous words must, by definition, have multiple different patterns of activation amongst the semantic units. Therefore, one would expect competition, which would prolong settling time. In fact, as Joordens and Besner (1994) have pointed out, such models do typically predict a processing time disadvantage for ambiguous words due to the settling process being more difficult for words with these one-to-many orthographic-semantic relationships; a prediction that is, of course, is inconsistent with the body of empirical research showing an ambiguity advantage.

Nevertheless, models have emerged that attempt to explain the ambiguity advantage specifically using PDP principles in constructing semantic representations. For example, Joordens and Besner (1994) found that learning ambiguous words led their model to fail to settle into one of the meaning patterns, and instead settled into a *blend* state in which there was a mixture of the two learned meaning patterns. However, by using the number of processing cycles to settle on *any* pattern in their simulations as a metric of lexical decision response latencies, they found an ambiguity advantage.

An alternative way to explain the ambiguity advantage within a distributed representational framework has been to assume that actual performance in lexical decision tasks is based mainly on orthographic processing, rather than semantic coding. For example, Kawamoto et al. (1994) assumed that simulating a lexical decision task required the orthographic units, rather than the meaning units, to settle on a stable pattern of activation. They simulated the ambiguity advantage in lexical decision tasks using a recurrent PDP network that used a least mean square learning algorithm. When presented with ambiguous words, instead of modifying the weights between orthographic and meaning units, their model strengthened the connection weights between orthographic units. Using the number of cycles required for settling in the orthographic module as a metric for performance in lexical decision, Kawamoto et al. found that orthographic units settled more quickly for ambiguous words because the connection weights between orthographic units had been strengthened in compensation for the weaker associations between orthographic and semantic units.

The Issue of the Relatedness of the Multiple Meanings

An additional issue that researchers have investigated concerning the ambiguity effect has been the relatedness of the meanings of ambiguous words (Azuma & Van Orden, 1997; Rodd et al., 2002, 2004). Azuma and Van Orden factorially manipulated the relatedness of meanings (ROM) and the number of meanings (NOM) possessed by their ambiguous words in lexical decision tasks. Their results indicated that, while NOM was not a reliable predictor of latencies, a significant main effect of ROM was found when pseudohomophone nonwords were used. Given these findings, Azuma and Van Orden argued that the relatedness among meanings can influence lexical decision times.

This approach was extended by Rodd et al. (2002). The large majority of studies examining semantic ambiguity have not distinguished between what are regarded as the two types of ambiguous words, referred to as *homonyms* and *polysemes*. Rodd et al. suggested that such distinctions are crucial. Homonyms refer to words with multiple unrelated meanings, as in *bark*, or *bank*, whereas polysemes refer to words with a variety of different senses, such as *twist*. The crux of their argument was that, while having multiple word senses would produce an ambiguity advantage, having multiple unrelated meanings would induce meaning-level competition that would delay word recognition, consistent with what a PDP model might predict. To test this prediction, Rodd et al. manipulated the type of ambiguity by referring to the dictionary entries of words to classify words as having either multiple meanings or multiple senses. Consistent with this idea, Rodd et al. reported an ambiguity advantage for words with multiple senses when pseudohomophones were used in a visual lexical decision task and an ambiguity disadvantage for words with unrelated meanings in an auditory lexical decision task.

Subsequently, Rodd et al. (2004) implemented a connectionist model to simulate these findings. The simulations that they reported showed that words with multiple, unrelated meanings such as *bark* demonstrated an ambiguity disadvantage, while words with multiple senses demonstrated an ambiguity advantage. They explained these effects in terms of the principles of attractor dynamics. They suggested that the ambiguity disadvantage occurs in words with multiple meanings because these separate meanings correspond to separate attractor basins in different regions of semantic space, resulting in a blend state during early activation that the system must move away from before it can properly settle into one of the different meanings. In contrast, the semantic representations of words with multiple senses correspond to highly overlapping regions of semantic space. As a result, there is a larger area of semantic space that corresponds to the meaning of these words, and this broader attractor basin aids the system in settling, at least initially.

Support for Rodd et al.'s (2002, 2004) argument has been mixed. Some studies have successfully replicated the polysemy advantage/homonymy disadvantage (e.g., Beretta, Fiorentino, & Poeppel, 2005; Klepousniotou & Baum, 2007) using Rodd et al.'s (2002) stimuli, while others have found equivalent ambiguity advantages for both polysemes and homonyms in lexical decision tasks (e.g., Hino, Pexman, & Lupker, 2006; Hino, Kusunose, & Lupker, 2010; Klein & Murphy, 2001, 2002). For example, Hino et al. (2006) examined the relatedness of meaning effect using lexical decision and semantic categorization tasks with Katakana-written ambiguous words. Hino et al. obtained relatedness of meaning ratings of ambiguous words to find words that could be classified as homonyms (i.e., essentially unrelated meanings) or polysemous (generally related meanings). The result of their lexical decision experiment was that there was no difference between homonyms and polysemes in their lexical decision latencies, finding an equivalent ambiguity advantage for the two types of ambiguous words. These results were replicated by Hino et al. (2010), who found equivalent ambiguity advantages for polysemes and homonyms using both Katakana and Kanji words and nonwords.

Semantic Neighborhoods and Ambiguity

Given the abundance of evidence contrary to the claims of any PDP models that try to explain ambiguity effects in terms of settling at the semantic level, semantic ambiguity continues to present a major challenge for any PDP account of semantics. At the same time, however, the results from ambiguity experiments have not been entirely consistent with other models either. One possible explanation is that there has been little consideration of how ambiguous words interact within the constraints of their semantic space. Indeed, as noted before, some theorists (e.g., Buchanan et al., 2001) have suggested that semantic neighborhood effects are highly similar to ambiguity effects, in that both concepts involve multiple items being simultaneously activated at the semantic level. Further, it is likely that semantic ambiguity is represented in some way within semantic neighborhoods. For example, consider words with two very distinct meanings, such as *bark*. *Bark* occurs in some contexts when referring to the outer layer of a tree, and in other contexts when referring to the sound that a dog makes. Such words will likely have semantic neighbors related to both of these senses. At present, there appears to be only one study that has examined semantic neighborhood effects on the processing of ambiguous words, Locker, Simpson, and Yates (2003).

Locker et al. (2003) argued that it should be possible to induce semantic-level competition between the multiple meanings of an ambiguous word if the magnitude of activation of the different meanings is increased. Words with more meanings, they surmised, would have richer representations in semantic memory, and would be more strongly activated. Such strong activation, they argued, may also cause the multiple meanings to interfere with each other. Such competition would reduce the strength of semantic feedback, or cause the feedback to be inconsistent. As such, Locker et al. predicted that an ambiguity advantage would more likely be observed when the meaning-level activation for secondary meanings is weak.

Locker et al. (2003) tested this idea by using two semantic neighborhood metrics to estimate of the strength of activation of the meanings of an ambiguous word. Specifically, they used *semantic set size* and *network connectivity*, derived from Nelson et al.'s (1998) free association norms, as their measure of semantic neighborhood density/meaning activation. The semantic set size in Nelson et al.'s norms is derived from presenting participants a list of words and recording a single response that is meaningfully related to each target. The number of responses across participants comprises the word's set. For example, according to these norms, the word *dog* has a set containing the words *cat*, *animal*, *puppy*, *friend*, and *house*, and thus has a set size of five. At the same time, there are two associative connections among *dog*'s neighbors (the word *animal* is related to both *cat* and *house*). Connectivity is defined as the number of associative connections within the neighborhood divided by the total neighborhood size. Since *dog* has a set size of five, and there are two associative connections within *dog*'s neighborhood, *dog* would have a connectivity of .40.

In their most relevant experiment, Locker et al. (2003) manipulated ambiguity (ambiguous or unambiguous), semantic set size (large or small), and neighborhood connectivity (high or low). Since Locker et al. predicted that the ambiguity advantage would only arise when meaning-level activation is relatively weak, they predicted that an ambiguity advantage would be most likely to arise when the semantic set size was small and neighborhood connectivity was low. These predictions were borne out, as an ambiguity advantage only arose for words with low connectivity and small set sizes. Locker et al.'s results can be found in Table 1.

Locker et al.'s (2003) results suggest that semantic neighbors may have some influence over the strength and direction of other semantic effects. However, although Locker et al.'s results suggest that semantic neighbors influence the strength and direction of the ambiguity effect, they also raise a number of questions about the nature of ambiguity effects. Thus, the main purpose of the present investigation was to expand on previous work done by Locker et al. and Mirman and colleagues (Chen & Mirman, 2012; Mirman, 2011; Mirman & Magnuson, 2008). The studies reported below were designed to investigate how the organization of semantic neighborhoods influences the strength and direction of the ambiguity effect, and whether the inconsistencies in the literature on the ambiguity advantage can be accounted for in light of semantic neighborhood dynamics.

Experiment 1

Experiment 1 was an attempt to replicate the results of Locker et al.'s (2003) Experiment 1 using both their stimuli (10 in each cell of their design) and an equal number of new stimuli in each cell of the design. The essential purpose of Experiment 1 was to evaluate Locker et al.'s claim that the ambiguity advantage was restricted to small set size, low connectivity words (i.e., it was an attempt to replicate their three-way interaction). Their argument, again, is that if increasing the scope of activation by manipulating connectivity reflects an increase in competition, an ambiguity advantage should be observed when the scope of activation is particularly low, specifically when the neighborhood set size is small and connectivity is relatively low. Conversely, in cases where the scope of activation is extremely high, as when the neighborhood size is large and the semantic connectivity is high, the greater scope of semantic activation could be detrimental to the processing efficiency of semantically ambiguous words. If increasing the scope of activation of the multiple meanings of an ambiguous word results in greater semantic-level competition, one possibility is that there would be an inhibitory effect for those ambiguous words. Locker et al. did not find this result, instead finding a small (~11 ms) ambiguity advantage, yet the English Lexicon Project (ELP; Balota, Yap, Cortese, et al., 2007) produced a sizable (~26 ms) inhibitory effect for ambiguous words with large set sizes and high connectivity for Locker et al.'s stimuli. The ELP database results for Locker et al.'s stimuli are shown in Table 2. Given the results from the ELP database, one might even expect that ambiguous words with large, highly interconnected semantic neighborhoods will produce an inhibitory effect.

Beyond the results in that cell, however, there are also other reasons to wonder about the stability of Locker et al.'s (2003) results. First, the results produced by the ELP database (Balota et al., 2007) for Locker et al.'s Experiment 1 stimuli failed to replicate Locker et al.'s pattern concerning the ambiguity advantage. Although there was evidence in the ELP database suggesting an ambiguity advantage for small set, low connectivity words, the largest ambiguity advantage was for words with small set sizes and high connectivity. In addition, there is the simple fact that the ambiguity advantage has been replicated many times over the past several decades (e.g., Hino & Lupker, 1996; Kellas et al., 1988; Millis & Button, 1989; Pexman & Lupker, 1999), and it seems unlikely that those researchers would have, just by chance, selected only ambiguous words with small semantic set sizes and low connectivity. Therefore, it is far from clear that Locker et al.'s findings will successfully replicate, and that it may be the case that the advantage for ambiguous words may be more widespread than their results suggest.

Method

Participants. Participants were 52 undergraduate psychology students at the University of Western Ontario, who participated in this study for course credit, or were compensated monetarily. The data from 10 participants were excluded from the experiment on the basis of excessive error rates (>15% for word stimuli, or >20% for nonword stimuli). Thus, the analyses reported are based on the data from 42 participants. All participants had normal or corrected-to-normal vision, and all were native English speakers.

Stimuli. For the word trials, a 160-word list formed by crossing semantic ambiguity (ambiguous or unambiguous), set size (large or small) and connectivity (high or low) was used. All of the words included in this study can be found in the University of South Florida Word Association, Rhyme, and Word Fragment Norms (Nelson et al., 1998). Half of the word stimuli used in this study were used in Locker et al.'s (2003) Experiment 1, and the other half were selected from previous studies based on normative data (e.g., Twilley, Dixon, Taylor, & Clark, 1994). Consistent with Locker et al., words with a number of associates greater than 15 were classified as large set (M = 19.26), whereas words with associates numbering 14 or fewer were classified as small set (M = 9.31). Similarly, high-connectivity words had 1.5 connections or greater (*M* = 2.20), whereas low-connectivity words all had fewer than 1.5 connections (*M* = 0.85). All word types were equated in terms of length, CELEX frequency, and orthographic neighborhood size using N-watch (Davis, 2005), and concreteness using the MRC psycholinguistic database (Coltheart, 1981). Additionally, data on the age of acquisition (AoA) of all the word stimuli using norms developed by Kuperman, Stadtagen-Gonzalez, and Brysbaert (2012) were collected. AoA is known to be a strong predictor of performance on a variety of linguistic tasks (e.g., Catling, Dent, & Williamson, 2008; Catling & Johnston, 2005, 2006; Coltheart, Laxon, & Keating, 1988; Cortese & Schock, 2013; Johnston & Barry, 2005) and it had not been equated by Locker et al. As a result, it was not possible to equate the words fully on AoA in our set of stimuli as well, a problem that was addressed by doing an analysis of covariance (ANCOVA). The stimulus characteristics for each condition are shown in Table 3. The stimuli are shown in Appendix A. In addition, 160 orthographically legal nonwords were used, which were equated with the word stimuli in terms of length and orthographic neighborhood size. An additional 5 words and 5 nonwords that did not appear in the experimental trials were presented as practice trials for each participant.

Procedure. Stimuli were presented on a LG Flatron W2242TQ-BF LCD monitor. Recording of response latencies and accuracy was controlled using DMDX software (Forster & Forster, 2003). At the beginning of each trial, a fixation stimulus (#####) appeared in the middle of the screen for 750 ms. The stimulus was then removed, and a word or nonword was presented in uppercase letters. The target remained on the screen until the participant responded. Lexical decisions were made by pressing the / key for words and the *z* key for nonwords. Presentation of trials was randomized for each participant.

Results and Discussion

Mean lexical decision latencies and error rates for both participants and items were submitted to a 2 (semantic ambiguity: ambiguous vs. unambiguous) x 2 (semantic set size: large vs. small) x 2 (connectivity: high vs. low) repeated-measures analysis of variance (ANOVA) based on subjects, and a between-word ANOVA based on items. Outliers were defined as latencies shorter than 250 ms or longer than 1,500 ms and were removed from all analyses. Five word stimuli and 5 nonword stimuli were also excluded from the analyses due to excessive error rates (>15% for word stimuli, or >20% for nonword stimuli). For the item analysis, AoA was treated as a covariate. Mean response latencies and error percentages for each word condition in the subject analysis are reported in Table 4 (without AoA as a covariate), and Table 5 contains the means from the item analysis with the covariate. As can be seen, the impact of treating AoA as a covariate on the pattern of results was minimal. Additionally, we calculated mean RTs for all of the word stimuli using the English Lexicon Project database (ELP; Balota et al., 2007). Table 6 provides the mean response latencies and error percentages based on those data.

There were no significant main effects in the latency analyses. The interaction between ambiguity and semantic set size approached significance in the subject analysis, but was not significant in the item analysis, $F_1(1, 41) = 3.62$, $p < .10$, $F(1, 145) = 1.55$, $p < .30$. The interaction between set size and connectivity was highly significant in the subject analysis, but not in the item analysis, $F_1(1, 41) = 10.79$, $p < .005$, $F_2(1, 145) = 1.05$, $p < .50$. Finally, a significant three-way interaction was found between ambiguity, semantic set size, and connectivity in both analyses, $F_1(1, 41) = 15.83$, $p < .001$, $F_2(1, 145) = 5.28$, $p < .05$.

Simple main effects analyses were undertaken to determine which cells show a significant ambiguity effect. It was found that that unambiguous words with large set sizes and high connectivity (M = 611) were processed significantly faster than their ambiguous counterparts (M = 639) in both the subjects and item analyses, $F_1(1, 41) = 18.65$, $p < .001$, $F_2(1, 145) = 6.46$, $p < .05$. No other differences reached significance (all Fs < 2.7).

In the error analyses, the main effect of connectivity approached significance in the subject analysis, $F_1(1, 41) = 3.18$, $p < .10$, but not in the item analysis $F_2(1, 145) = 2.62$, $p = .11$, as high connectivity words had slightly lower error rates overall. A two-way interaction between ambiguity and semantic set size was found in both analyses, $F_1(1, 41) = 8.10$, $p < .01$, $F_2(1, 145) = 4.22$, $p < .05$. A two-way interaction was also found between ambiguity and connectivity, $F_1(1, 41) = 5.69$, $p < .05$, $F_2(1, 145) = 9.54$, $p < .005$. Finally, the three-way interaction between ambiguity, semantic set size, and connectivity approached significance in the subject analysis, but did not in the item analysis, $F_1(1, 41) = 3.72$, $p < .10$, $F_2(1, 145) = 1.65$, $p = .20$.

Simple main effects analyses showed that ambiguous words with small set sizes and high connectivity (M = 1.63%) produced significantly fewer errors than unambiguous words with small set sizes and high connectivity (M = 5.24%) in both analyses, $F_1(1, 41) = 15.55$, $p < .001$, $F(1, 145) = 14.72$, $p < .001$. No other differences reached significance (all Fs < 2.5).

The results from Experiment 1 failed to produce an overall advantage for ambiguous words over their unambiguous counterparts, although, as in the Locker et al. (2003) experiment, it did produce a three-way interaction between ambiguity, set size, and connectivity. This interaction, however, was not the same interaction Locker et al. reported. Locker et al. found an ambiguity advantage for words with small semantic set sizes and low connectivity. Such was not the case in the present experiment, in which the ambiguous words in this condition were processed about 9 ms slower than the unambiguous words. Instead, in the present experiment, no cell showed a significant ambiguity advantage in the RT analysis, while the large set size, high connectivity condition produced an ambiguity disadvantage. What should be noted, of course, is that, according to Locker et al.'s analysis, this condition is the most likely to produce an ambiguity disadvantage due to the strong activation of neighbors that should arise for those words. That is, in cases when the scope of semantic activation is very high, as in when words have large, highly interconnected neighborhoods, there would be greater competition at the semantic level, which would potentially result in inhibition. The results of Experiment 1 are, therefore, at least somewhat consistent with Locker et al.'s notions.

What, of course, is somewhat surprising is that there was no ambiguity advantage in any condition, a result that appears to contradict a long line of research (e.g., Hino & Lupker, 1996; Kellas et al., 1988; Millis & Button, 1989; Pexman, Hino, & Lupker, 2004; Pexman & Lupker, 1999) and a result that is also inconsistent with the means for all the stimuli used here based on the ELP database. Specifically, there were large ambiguity advantages in the small set size, high connectivity (42 ms) and small set size, low connectivity (24 ms) conditions (with the latter one being the one in which Locker et al. found an ambiguity advantage). The former of these conditions did show some evidence of an ambiguity advantage in the RT (10 ms) and in the error (1.63%) analyses, while the latter, as noted, did not. Equally importantly, the one cell with a significant ambiguity effect in the present experiment, the large set size, high connectivity condition, showed only a small (8 ms) ambiguity disadvantage in the ELP database, in contrast to the 28 ms difference reported here.

In an effort to examine the data patterns more fully, separate analyses were done of the stimuli Locker et al. (2003) used and the ones added for Experiment 1. For the stimuli derived from Locker et al., mean RTs and error percentages can be found in Table 7. As noted, mean RTs and error rates from the ELP database for Locker's stimuli can be found in Table 2. For the new stimuli, mean RTs and error rates can be found in Table 8. For reference, Table 9 contains the means from the ELP database for the new stimuli.

Analysis of Locker et al.'s (2003) Stimuli

For data from the stimuli used by Locker et al. (2003), the main effect of set size was significant in the subject analysis, $F_1(1, 41) = 7.12$, $p < .05$, but not in the item analysis, $F_2(1, 67) = 2.59$, $p < .15$, as words with large set sizes had faster latencies than words with small set sizes. None of the other main effects were significant. A two-way interaction between set size and connectivity was significant in the subject analysis, $F_1(1, 41) = 9.53$, $p < .004$, but was not in the item analysis, $F_2(1, 67) < 1$, $p > .30$. Most importantly, the three-way interaction between ambiguity, set size, and connectivity was significant in both analyses, $F_1(1, 41) = 12.67$, $p = .001$, $F_2(1, 67) = 4.93$, $p < .05$.

A simple main effects analysis found that ambiguous words with small set sizes and low connectivity ($M = 637$) were processed more slowly than their unambiguous counterparts ($M = 614$) in the subject analysis, $F_1(1, 41) = 7.13$, $p < .05$, and this difference was marginally significant in the item analysis, $F_2(1, 67) = 2.75$, $p = .10$. This contrast is, of course, the one contrast in which Locker et al. (2003) found a significant ambiguity advantage. Finally, the contrast between ambiguous words with small set sizes and high connectivity ($M = 628$) and their unambiguous counterparts ($M = 650$) was significant in the subject analysis, $F_1(1, 41) = 4.18$, $p < .05$, but not in item analysis, $F(1, 67) = 1.97$, $p < .20$. As in the overall data set, there was an ambiguity disadvantage in the large semantic set size, high connectivity condition, however, this 14 ms effect was not significant in either analysis, $F_1(1, 41) = 2.43$, $p < .15$, $F_2 < 1$.

The error analysis produced no significant effect of set size in the subject analysis, $F_1(1, 41) = 1.90$, $p < .20$, but the set size effect was marginally significant in the item analysis, F_2(1,

67) = 2.91, $p < .10$, with large set size words producing marginally fewer errors than small set size words. A two-way interaction between ambiguity and set size was significant in the subject analysis, $F_1(1, 41) = 4.33$, $p < .05$, but not in the item analysis, $F_2(1, 67) = 1.46$, $p < .30$. A two-way interaction between ambiguity and connectivity was marginally significant in the subject analysis, $F_1(1, 41) = 3.08$, $p < .10$, and was statistically significant in the item analysis, $F(1, 67) = 6.25$, $p < .05$.

A simple main effects analysis showed that ambiguous words with small set sizes and high connectivity (*M* = 1.85%) produced significantly fewer errors than unambiguous words with small set sizes and high connectivity (*M* = 5.00%) in both analyses $F_1(1, 41) = 4.90$, $p < .05$, $F_2(1, 67) = 5.87$, $p < .05$. No other differences reached significance (all $F_S < 2.5$).

Analysis of the Added Stimuli

For data from the new stimuli, the main effect of ambiguity was significant in the subject analysis, $F_1(1, 41) = 4.07$, $p = .05$, but not in the item analysis $F_2(1, 69) = 1.07$, $p > .30$, as unambiguous words were responded to slightly faster than ambiguous words. No other main effect approached significance. A two-way interaction between ambiguity and set size was significant in the subject analysis, $F_1(1, 41) = 4.37$, $p < .05$, and approached significance in the item analysis $F_2(1, 69) = 3.05$, $p < .10$. A two-way interaction between ambiguity and connectivity was also found to be significant in the subject analysis, $F_1(1, 41) = 10.32$, $p < .005$, and approached significance in the item analysis $F_2(1, 69) = 3.29$, $p < .10$. Finally, the three-way interaction between ambiguity, connectivity, and semantic set size was significant in the subject analysis, but was not in the item analysis, $F_1(1, 41) = 4.14$, $p < .05$, $F_2(1, 69) = 1.04$, $p > .15$.

A simple main effects analysis showed that ambiguous words with large semantic set sizes and high connectivity (*M* = 656) were processed significantly more slowly than their unambiguous counterparts (*M* = 613) in both analyses, $F_1(1, 41) = 15.87$, $p < .001$, $F_2(1, 69) = 7.78$, $p < .01$. No other differences reached significance (all *Fs* < 1.0).

In the error analysis, the main effect of ambiguity was significant in the subject analysis, $F_1(1, 41) = 5.35$, $p < .05$, and approached significance in the item analysis, $F_2(1, 69) = 3.31$, $p < .10$, as ambiguous words produced fewer errors than unambiguous words. The main effect of connectivity was significant in both analyses, $F_1(1, 41) = 5.77$, $p < .05$, $F_2(1, 69) = 5.20$, $p < .05$, as words with low connectivity produced fewer errors than words with high connectivity. The two-way interaction between ambiguity and set size approached significance in the subject analysis, $F_1(1, 41) = 3.09$, $p < .10$, but not in the item analysis, $F_2(1, 69) = 2.44$, $p < .15$. The two-way interaction between ambiguity and connectivity was significant in the subject analysis, $F_1(1, 41) = 4.59$, $p < .05$, and approached significance in the item analysis, $F_2(1, 69) = 3.74$, $p < .10$.

A simple main effects analysis showed that with small set sizes and high connectivity, ambiguous words (*M* = 1.43%) produced significantly fewer errors than unambiguous words (*M* = 5.48%) in both analyses, $F_1(1, 41) = 15.57$, $p < .001$, $F_2(1, 69) = 8.80$, $p < .005$. No other differences reached significance (all *F*s < 1.5).

Experiment 1: Overall

From this examination of this data, several notable patterns emerge. First, the results from this experiment consistently showed that ambiguous words in the large set size, high connectivity condition were responded to more slowly than their unambiguous counterparts. Virtually all of the analyses showed this pattern to some degree. Second, whereas Locker et al. (2003) reported that the ambiguity advantage only manifested itself in the small set size, low connectivity condition, the results of Experiment 1, as well as the ELP database, do not support this empirical conclusion. Instead, the one condition that most consistently produced at least some hint of an ambiguity advantage both in the experimental data and in the ELP database (in terms of both latency and error rates) was the small set size, high connectivity condition.

These results suggest that although the explanation put forth by Locker et al. (2003) may have some grain of truth to it, it is far from accurate. Locker et al. argued that the processing of ambiguous words would benefit the most when the scope of activation of the word's meanings is minimized. That is, facilitation of processing is optimized when the scope of activation of a word's disparate meanings is low. As a result, they argued that the ambiguity advantage would be observed for words with weak meaning-level activation, and therefore, the ambiguity advantage should occur in the small set, low connectivity condition. However, Experiment 1 found an ambiguity disadvantage in this condition, and the effect was, in fact, strongest with Locker's own stimuli. Second, as was stated previously, the ELP database consistently showed the strongest ambiguity advantage in the small set size, high connectivity condition, rather than the small set size, low connectivity condition.

Where Locker et al.'s (2003) analysis was somewhat successful was in the large set size, high connectivity condition data. This analysis suggested that stronger semantic activation may result in more competition during processing. Because this condition showed clear evidence of an ambiguity disadvantage, that result from Experiment 1 provides at least some support for Locker et al.'s position. That is, the strong inhibitory effect in the large semantic set size, high connectivity condition is what one could predict if we assumed that the semantic-level competition was strong enough to nullify any beneficial effect of ambiguity. This result also bears some similarities to the results of Mirman and colleagues' (Chen & Mirman, 2012; Mirman, 2011; Mirman & Magnuson, 2008), who found an inhibitory effect of having many near neighbors, and a facilitory effect of having many distant neighbors. While the methods of defining and measuring semantic neighbors differ between this study and theirs, it is not impossible that Mirman and colleagues' findings reflect a principle that applies essentially independently of how semantic neighborhood density is measured.

Number of Meanings and Number of Senses Analysis

Before proceeding, one issue that should be addressed is whether the effects observed in Experiment 1 can be explained in terms of differences in the number of meanings or number of senses of the ambiguous words that we used. Paralleling what was done by Locker et al. (2003) in selecting their stimuli, we did not attempt to determine whether the numbers of polysemes and homonyms were equated across conditions. Thus, it is possible that there were differences along these lines. To address this issue, data on the number of meanings (NOM) and number of senses (NOS) of each word used in this experiment were acquired using entries in the Online Wordsmyth English Dictionary-Thesaurus (Parks, Ray, & Bland, 1998), just as Rodd et al. did. The overall NOM and NOS characteristics for all words in Experiment 1 can be found in Table 3. For reference, the NOM and NOS characteristics for the words that Locker used can be found in Table 10, and the NOM and NOS characteristics for the new word stimuli can be found in Table 11.

When we compared the number of Wordsmyth entries for ambiguous and unambiguous words, ambiguous words (M = 1.62) had a significantly greater number of Wordsmyth entries than unambiguous words (M = 1.08), $F(1, 147) = 26.44$, $p < .001$. The only condition in which ambiguous and unambiguous words did not differ significantly in number of Wordsmyth entries was the large set size, low connectivity condition, $F(1,147) = 2.35$, $p > .10$. Despite not controlling for Wordsmyth entries, ambiguous words were well-differentiated from unambiguous words in their number of entries. Furthermore, the number of Wordsmyth entries differed very little across conditions. The only notable difference was between ambiguous words with low connectivity, and small versus large sets. Ambiguous words with small set sizes and low connectivity (M = 1.83) had the highest number of entries of all the conditions.

Ambiguous and unambiguous words also differed significantly in the number of Wordsmyth senses as well. Ambiguous words (M = 9.89) had a significantly greater number of Wordsmyth senses than unambiguous words (M = 5.13), $F(1, 147) = 38.20$, $p < .001$. There was also a main effect of semantic set size, $F(1, 147) = 5.95$, $p < .018$, as words with large semantic set sizes (M = 8.44) had significantly more Wordsmyth senses than words with small semantic set sizes (M = 6.48). Finally, there was a significant main effect of connectivity, $F(1, 147) = 5.95$, $p < .05$, as words with low connectivity (M = 8.36) had a significantly greater number of Wordsmyth senses than words with high connectivity (M = 6.58).

Although there were differences between the number of senses for large set size words versus small set size words, and high and low connectivity words, these differences could not explain the present results, as they went in the wrong direction. It is very apparent that having a greater number of senses did not produce any significant benefit for the ambiguous words in the large set size, low connectivity condition, or the small set size, low connectivity condition (which had the greatest number of senses of any condition in this experiment). This analysis suggests that there are other factors at work that led to the ambiguity disadvantage in the large set, high connectivity condition than differences in number of meanings and number of senses.

Experiment 2

From the first experiment and the ELP database, it appears that, if there is an ambiguity advantage it is most likely to be found in cases where the semantic set size of the word is small and the interconnectivity of its neighbors is high. Conversely, the condition in which the target has a large semantic neighborhood and high connectivity, a situation in which representations would be most likely to compete with one another, we find the best evidence of an ambiguity disadvantage. These results do, however, raise a couple of questions. First, why was there so little evidence of any ambiguity advantage? That is, while the ELP database showed a sizable ambiguity advantage in the small set size condition with the stimuli used in Experiment 1, Experiment 1 still did not produce any noticeable differences between ambiguous and unambiguous words in these conditions. Before investing too much in a theoretical interpretation of the present data, it would seem to be a good idea to search again for the condition(s) producing the classic ambiguity advantage. A second question is why there was a clear ambiguity disadvantage in one condition when there is virtually no evidence of such an effect in the literature? It would, therefore, be important to attempt to replicate the ambiguity disadvantage that was found in the large set size, high connectivity condition.

One clear weakness of Experiment 1 was that, following Locker et al. (2003), the maximum cutoff criterion for small set words (14) was very close to the minimum cutoff criterion for the large set size words (15). Likewise, the distinction between high and low connectivity words was also somewhat minimal, meaning that neither manipulation was as strong as it could have been. That is, the problem is that both groups would then contain words with semantic neighborhood characteristics similar to words in the other group. For example, the minimum cutoff point for high connectivity was 1.5, whereas low connectivity words had a maximum cutoff of 1.5. As a result, under these criteria, a word with a set size of 14 and a connectivity of 1.49 could be included as a small set size, low connectivity word, whereas a word with a set size of 15 and a connectivity of 1.50 would be included in the large semantic set size, high connectivity condition. While most words in the two groups were not this close to each other, it is still clear that both manipulations could have been stronger. Thus, Experiment 2 was an attempt to re-examine the central issues here with new participants, items, and a stronger manipulation of set size.

Whereas Experiment 1 included semantic ambiguity, semantic set size, and connectivity as independent variables, the results of Experiment 1, as well as the results from the ELP database, suggest that the facilitation and inhibition based on ambiguous words is likely to be strongest in the high connectivity condition, contrary to the previous findings reported by Locker et al. (2003). The primary focus of this experiment was, therefore, high connectivity words. As a result, connectivity was discarded as an independent variable, and was instead held constant, so that all stimuli in Experiment 2 had high connectivity. If large, highly interconnected neighborhoods are more detrimental to the processing of ambiguous words, there should be an ambiguity disadvantage in the large set size condition. Further, if an ambiguity advantage were to arise, the results of Experiment 1 suggest that it should be in the condition with small set sizes.

Method

Participants. Participants were 95 undergraduate psychology students at the University of Western Ontario, who participated in the study for course credit. The data from 25 participants were excluded from the experiment on the basis of excessive error rates (>15% for word stimuli, or >20% for nonword stimuli). Thus, the analyses reported are based on the data from 70 participants. All participants had normal or corrected-to-normal vision, and all were native English speakers.

Stimuli. The stimuli were four sets of 25 words formed by crossing ambiguity (ambiguous or unambiguous) with semantic set size (large or small). As in Experiment 1, all of the stimuli can be found in the University of South Florida Word Association, Rhyme, and Word Fragment Norms (Nelson et al., 1998). Words with a number of associates greater than 15 were classified as having large set sizes (*M* = 20.46), and words with a number of associates less than 12 were classified as having small set sizes (*M* = 9.52). All stimuli had a connectivity of at least 1.30 (*M* = 2.05). All word types were equated in terms of length, CELEX frequency (Baayen, Piepenbrock, & Gulikers, 1995), orthographic neighborhood size, and concreteness using the MRC psycholinguistic database (Coltheart, 2007). As in Experiment 1, AoAs of all the word stimuli were collected using the Kuperman et al. (2012) norms. The stimulus characteristics are shown in Table 12. The stimuli are shown in Appendix B. In addition, 100 orthographically legal nonwords were used, which were equated with the target words in terms of length and orthographic neighborhood size. An additional 5 words and 5 nonwords that did not appear in the experimental trials were presented as practice trials for each participant.

Procedure. The procedure was identical to that used in Experiment 1. Stimulus presentation and recording of response latencies and accuracy were controlled by an LG Flatron W2242TQ-BF LCD monitor using DMDX software (Forster & Forster, 2003). At the beginning of each trial, a fixation stimulus (#####) appeared in the middle of the screen for 750 ms. The fixation stimulus was then removed, and a word or nonword was presented in uppercase letters. The target remained on the screen until the participant responded. Lexical decisions were made by pressing the */* key for words and the *z* key for nonwords. Presentation of trials was randomized for each participant.

Results and Discussion

Mean lexical decision latencies and error rates for both participants and items were submitted to a 2 (semantic ambiguity: ambiguous vs. unambiguous) x 2 (semantic set size: large vs. small) repeated-measures ANOVA for subjects, and a between-word ANOVA for items. Outliers were defined as latencies shorter than 250 ms or longer than 1,500 ms. Four word stimuli and six nonword stimuli were excluded from the analysis due to excessive error rates (>15% for word stimuli, or >20% for nonword stimuli). As in Experiment 1, AoA was treated as a covariate in the item analysis. Mean response latencies and error percentages for each word condition from the subject analysis are reported in Table 13 (without AoA as a covariate), and from the item analysis in Table 14 with AoA as a covariate. As with Experiment 1, however, treating AoA as a covariate did not impact the results. As in Experiment 1, we also calculated mean RTs for all of the conditions using the ELP database (Balota et al., 2007). Results from the ELP database can be found in Table 15.

Analysis of the response latencies produced a significant effect for ambiguity in the subject analysis, although this effect was not significant in the item analysis, $F_1(1, 69) = 8.74$, $p < .005$, $F_2(1, 91) = 2.34$, $p < .15$. Overall, ambiguous words were processed more slowly than unambiguous words. The two-way interaction between ambiguity and semantic set size approached significance in the subject analysis, $F_1(1, 69) = 3.32$, $p = .07$, but not in the item analysis, $F_2(1, 91) = 1.00$, $p > .30$. A simple main effects analysis found that unambiguous words with large set sizes ($M = 647$) had faster latencies than ambiguous words with large set sizes ($M = 661$), which was significant in the subject analysis, $F_1(1, 69) = 9.48$, $p < .005$, but not in the item analysis, $F_2(1, 91) = 1.02$, $p > .30$. The difference for small set words was not significant, $F_1(1, 69) = 2.62$, $p = .11$, $F_2 < 1$.

Once again, the results of Experiment 2 failed to produce any significant advantage for ambiguous words over unambiguous words. Across both experiments, however, the one observation that has remained constant is an ambiguity disadvantage when the word has many semantic neighbors. This effect bears a strong similarity to the inhibitory effect of having many near neighbors, as found in studies by Mirman and colleagues (Chen & Mirman, 2012; Mirman, 2011; Mirman & Magnuson, 2008), as well the findings of Nelson, Bennett, Gee, Schreiber, & McKinney (1993) and Storkel and Adlof (2009). According to Mirman's attractor-based account, near semantic neighbors exert an inhibitory effect because they act as competing attractors that the model must successfully move through in order to reach the target attractor. Despite differences in how near semantic neighbors were defined here as opposed by Mirman and colleagues, the results of Experiments 1 and 2 do appear to be consistent with an explanation in which one assumes that large, highly interconnected sets of semantic neighbors behave in the same manner as near semantic neighbors function in Mirman's analyses. That is, it is possible that large, highly interconnected sets of semantic neighbors act as competing attractors that slow the process of settling on a target attractor.

However, once again, the question emerges as to why there was absolutely no evidence of any ambiguity advantage in the small set size condition. As was mentioned previously, Experiment 1 used a more lenient cutoff for set size and connectivity, which may have compromised the results. However, the results of Experiment 2 showed that making the criteria more conservative made little difference in the outcome. Thus, the previous concerns about the results of Experiment 1 being influenced by the cutoffs used for our semantic measures would appear to be irrelevant.

Before drawing any further conclusions, we made one last attempt to find a condition that would produce an ambiguity advantage. One possible reason why we failed to find an ambiguity advantage was that the nonwords used here did not make the task sufficiently difficult. A number of studies have suggested that using more word-like nonwords, in particular, pseudohomophones, leads to larger semantic effects in lexical decision tasks (e.g., Azuma & Van Orden, 1997; Peman & Lupker, 1999; Locker et al., 2003; Rodd et al., 2002; Van Orden & Goldinger, 1994). As noted, pseudohomophones are nonwords that are pronounced the same as actual words (e.g., *brane*, *kat*). Indeed, Rodd et al. only found a significant effect for their number of senses manipulation when they used pseudohomophones as nonwords. As Pexman and Lupker (1999) argued, pseudohomophones make lexical decisions more difficult, forcing participants to set a higher threshold for activation when making those decisions. As a result, Pexman and Lupker predicted and found that the effects of ambiguity would be of greater magnitude when pseudohomophones are used. This possibility was explored in Experiment 3.

Experiment 3

Experiment 3 was a replication of Experiment 2 with pseudohomophone nonwords. That is, as in Experiment 2, only words with high connectivity were used, and semantic set size and ambiguity were manipulated. The stimuli were basically the same as in Experiment 2; however, the word stimuli that were problematic for participants, as well as a few others in order to balance the conditions, were removed. If sparser semantic neighborhoods aid the semantic processing of ambiguous words, then an ambiguity advantage should emerge in the small set size condition. With respect to the large set size condition, if dense, highly interconnected semantic neighborhoods have an inhibitory effect on semantic processing, then ambiguous words with large set sizes should still be more difficult than unambiguous words.

Method

Participants. Participants were 69 undergraduate psychology students at the University of Western Ontario, who participated in this study either for course credit, or were compensated for monetarily. The data from 15 participants were excluded from the experiment on the basis of excessive error rates (>15% for word stimuli, >30% for pseudohomophone stimuli). Since pseudohomophones are assumed to make the task more difficult, the error rate cutoff point was higher than in previous experiments. Thus, the analyses reported are based on the data from 54 participants. All participants had normal or corrected-to-normal vision, and all were native English speakers.

Stimuli. The word stimuli consisted of four sets of 20 words formed by crossing ambiguity (ambiguous or unambiguous) with semantic set size (large or small). As with the previous experiments, all of the stimuli can be found in the University of South Florida Word Association, Rhyme, and Word Fragment Norms (Nelson et al., 1998). Words with a number of associates greater than 15 were classified as having large set sizes ($M = 20.42$), while words with a number of associates less than or equal to 14 were classified as having small sets ($M = 9.78$). A one-way ANOVA found that this difference was statistically significant, $F(1, 76) = 305.06$, $p = .001$. However, there was a small but statistically significant difference in the set sizes of ambiguous versus unambiguous words with small set sizes. Ambiguous words ($M = 10.6$) had significantly larger set sizes than unambiguous words ($M = 8.95$), $F(1, 38) = 4.62$, $p < .05$. Controlling for many different variables resulted in not being able to balance all of the conditions on semantic set size, which will have to be considered a limitation of this experiment. Finally, ambiguous words with large set sizes ($M = 20.3$) did not differ significantly from unambiguous words with large set sizes ($M = 20.35$) in terms set size, $F(1, 36) < 1.0$.

Words with a connectivity above 1.3 were used in this experiment ($M = 2.04$). There was no significant difference between the connectivity of ambiguous words ($M = 2.04$) and unambiguous words ($M = 2.05$), $F(1, 77) < 1$, $p > .90$. All word types were equated in terms of length, CELEX frequency, orthographic neighborhood size, and concreteness. As in Experiments

1 and 2, data on the AoA of all word stimuli were collected using the Kuperman et al. (2012) norms. The stimulus characteristics are shown in Table 16. The stimuli are shown in Appendix B. In addition, 80 pseudohomophones were used, which were equated with the target words in terms of length.

Procedure. The procedure was identical to the one used in Experiments 1 and 2. Stimulus presentation and recording of response latencies and accuracy were controlled by an LG Flatron W2242TQ-BF LCD monitor using DMDX software. At the beginning of each trial, a fixation stimulus (#####) appeared in the middle of the screen for 750 ms. The fixation stimulus was then removed, and a word or nonword was presented in uppercase letters. The target remained on the screen until the participant responded. Lexical decisions were made by pressing the / key for words and the *z* key for nonwords. Presentation of trials was randomized for each participant.

Results and Discussion

Mean lexical decision latencies and error rates were submitted to a 2 (semantic ambiguity: ambiguous vs. unambiguous) x 2 (semantic set size: large vs. small) repeated-measures ANOVA based on subjects, and a between-word ANOVA based on items. Outliers were defined as latencies shorter than 250 ms or larger than 1500 ms. Two word stimuli and four pseudohomophones were excluded from the analysis due to having excessive error rates (>15% for word stimuli, or >30% for pseudohomophones). As with previous experiments, AoA was treated as a covariate in the item analysis. Mean response latencies and error percentages for the subject analysis can be found in Table 17 (without AoA as a covariate), and for the item analysis in Table 18 with AoA as a covariate. Once again, using AoA as a covariate made little difference in the pattern of means. For reference, means from the ELP database are contained in Table 19, however, it should be noted that the comparison to these data is severely compromised because the ELP data are not collected when using pseudohomophones as nonwords.

Analysis of the response latencies showed that the main effect of set size was significant in the subject analysis, $F_1(1, 53) = 7.50$, $p < .01$, and approached significance in the item analysis $F_2(1, 73) = 3.66$, $p = .06$, as words with small semantic set sizes ($M = 644$) were processed significantly faster than words with large semantic set sizes ($M = 656$). The main effect of ambiguity was statistically significant in the subject analysis, but not in the item analysis when AoA was treated as a covariate, $F_1(1, 53) = 4.51$, $p < .05$, $F_2 < 1$. Overall, ambiguous words were responded to more slowly than unambiguous words. No significant interaction was found (all *F*s < 1.0).

Like Experiments 1 and 2, Experiment 3 failed to produce any significant advantage for ambiguous words over unambiguous words in the small set size condition. However, despite this experiment's failure to produce any ambiguity advantage, once again, the pattern of the data showed an ambiguity disadvantage which was slightly larger when words have large set sizes than when they have small set sizes. The overall results across these three experiments, therefore, suggest one main conclusion, that the processing of ambiguous words is less efficient when they possess large, highly interconnected networks of semantic neighbors.

GENERAL DISCUSSION

The focus of the present research was the influences of semantic neighborhoods on the processing of ambiguous words. Locker et al. (2003) reported that the ambiguity advantage that has typically appeared in the literature (e.g., Hino & Lupker, 1996; Kellas et al., 1988; Millis & Button, 1989; Pexman & Lupker, 1999) was confined to situations where the ambiguous words had small, sparsely connected semantic neighborhoods. Locker et al. argued that the ambiguity advantage in small, sparsely connected neighborhoods was the result of minimizing semantic-level competition. When ambiguous words reside in large, dense neighborhoods, the large amount of semantic activation from having many highly interconnected neighbors would produce a higher degree of competition at the semantic level, causing semantic feedback to the orthographic level to become weakened or inconsistent. Experiment 1 was an attempt to replicate Locker et al.'s findings in a lexical decision task using a larger number of stimuli. Ambiguity, semantic set size, and network connectivity were manipulated in the same manner as done by Locker et al. This manipulation produced a sizable (~28 ms) ambiguity disadvantage when the words had large, densely interconnected neighborhoods. Unlike the findings reported by Locker et al., there was no ambiguity advantage in the small set size, low connectivity condition.

To examine the data in a more complete manner, the stimuli that Locker et al. (2003) used, and the stimuli that were added for Experiment 1 were analyzed separately. With Locker et al.'s stimuli, it was found that ambiguous words with small set sizes and low connectivity, which was the condition in which Locker et al. found an ambiguity advantage, produced a sizable (~23 ms) ambiguity *disadvantage*, contrary to Locker et al.'s findings. Instead, the largest ambiguity advantage found was for words with small set sizes and high connectivity, which were faster (~22 ms), and produced significantly fewer errors than unambiguous words in this condition. These latter results were also consistent with the data from the English Lexicon Project, which produced a large (~38 ms) ambiguity advantage for words with small, highly interconnected semantic neighborhoods. Although the ELP database did show a 20 ms advantage for Locker et al.'s ambiguous words in the small set size low connectivity condition, the fact that the results of Experiment 1 did not do so, and that both Experiment 1 and the ELP produced ambiguity advantages for Locker et al.'s words in cells other than the small set size, low connectivity condition with Locker et al.'s own stimuli gives us strong reason to doubt the stability of their original results.

In the stimuli that this experiment introduced, ambiguous words with large set sizes and high connectivity produced a very large (~43 ms) ambiguity disadvantage. It should be noted that this effect was not found in the ELP database. However, for these new stimuli, once again, the ELP data produced a very large (~46 ms) ambiguity advantage in the small set size, high connectivity condition.

Overall, the aggregate results of Experiment 1 and the ELP database suggest that the processing of ambiguous words is facilitated by having smaller semantic neighborhoods. However, contrary to the results of Locker et al. (2003), Experiment 1 showed that ambiguous words are easier to respond to when the neighborhoods in which they reside are highly interconnected, rather than when the neighborhoods are sparsely interconnected, which Locker et al. suggested should reduce semantic-level competition and aid in the speed of processing of words with multiple meanings. Such a finding may indicate that the conditions that help give rise to the ambiguity advantage may not be as restrictive as Locker et al. suggested. Furthermore, while Locker et al. never showed an ambiguity advantage, they argued that increasing the scope of activation of the multiple meanings of an ambiguous word may cause the multiple meanings to interfere with each other as a result of weakened or inconsistent feedback. If increasing the scope of activation of the multiple meanings of an ambiguous word does, in fact, result in the multiple meanings interfering with each other, as Locker et al. suggest, then one prediction that can be made from this position is that large semantic neighborhoods, and high connectivity words may produce an ambiguity disadvantage. This type of prediction would seem to be supported by both the results of Experiment 1 and the results from the ELP database.

Experiment 2 was an attempt to replicate the findings of Experiment 1 using stricter cutoff criteria for set size and connectivity. Since the best evidence for an ambiguity effect was produced by high connectivity words, only high connectivity words were used, and the only factors were ambiguity and the set sizes of the words. Paralleling Experiment 1’s results, Experiment 2 did not produce a significant advantage for ambiguous words over unambiguous words. Both small set size and large set size ambiguous words were processed more slowly than unambiguous words, although this difference was not significant in the item analysis. There was also a hint of an interaction between ambiguity and set size as large set size ambiguous words produced slightly stronger inhibition (~19 ms) than ambiguous words with small set sizes (~7 ms), however, this interaction was only marginally significant in the subject analysis, and was nonsignificant in the item analysis.

In a final attempt to find optimal conditions for demonstrating the classical ambiguity advantage, Experiment 3 used pseudohomophones as nonwords in order to increase the difficulty of the task. Since a number of studies have found that using pseudohomophones produces larger semantic effects in lexical decision tasks (e.g., Azuma & Van Orden, 1997; Pexman & Lupker, 1999; Locker et al., 2003; Rodd et al., 2002; Van Orden & Goldinger, 1994), it was predicted that using pseudohomophones would give us the best chance to produce an ambiguity advantage. This expectation was not borne out, however. Paralleling the findings of Experiment 2, ambiguous words were processed slower than unambiguous words.

Clearly, the results of three experiments leave a number of questions unanswered. The most central one would seem to be why wasn’t there any evidence of an ambiguity advantage in any of the experiments, when clear ambiguity advantages have been reported in so many other experiments (e.g., Hino & Lupker, 1996; Kellas et al., 1988; Millis & Button, 1989; Pexman &

Lupker, 1999). In the remainder of this thesis, possible reasons why this effect did not appear will be discussed.

Potential Interactions between Ambiguity and Age of Acquisition

One possible reason for the lack of an ambiguity advantage may have been that the words were not properly balanced for Age of Acquisition (AoA). As mentioned previously, AoA is known to be a strong predictor of response times, as early-acquired words are generally recognized faster (e.g., Catling et al., 2008; Catling & Johnston, 2005, 2006; Coltheart et al., 1988; Cortese & Schock, 2013; Johnston & Barry, 2005). Therefore, one possibility mentioned earlier was that, because the words were not selected in a way that allowed AoA to be equated, AoA could have been confounded with one of the relevant factors. This type of explanation is, however, ruled out by the fact that the item ANCOVA, in which AoA was the covariate, produced results that were virtually equivalent to those in the subject ANOVA, in which AoA was not a covariate in all experiments. Nonetheless, when considering the overall issue of the general pattern of data, the specific AoAs used in the present experiments may have had some effect on our ability to observe ambiguity effects.

More concretely, it is entirely possible that the multiple meanings of early-acquired ambiguous words are represented differently in semantic memory than those for late-acquired ambiguous words, and this difference in representation may result in different performances for early- and late-acquired ambiguous words in word recognition tasks. For early AoA words like *duck*, *mad*, and *plate*, for example, it may be the case that one of the meanings of the word was acquired at a very early age, while other meanings of the word were gradually acquired over the process of aging. On the other hand, late AoA words such as *fuse*, *grave*, and *temple* would presumably acquire all their meanings much later and, presumably, at about the same time. Early acquisition of a word's first meaning may result in a more ingrained representation of that meaning in semantic memory, providing a more stable basis upon which new meanings can be gradually added without inducing semantic competition. Acquiring the first meaning of a word at a later age, on the other hand, may result in a less stable representation in semantic memory upon which to add other meanings, which may eliminate any benefit of having multiple meanings, as semantic-level competition between the multiple meanings of these words may be greater.

To test these ideas, results for early AoA and late AoA stimuli were separately analyzed for all of the experiments based on a median split of the AoA values for all the words in that experiment (using the AoA values as reported by Kuperman et al., 2012). The median AoA was 5.84 in Experiment 1, 5.62 in Experiment 2, and 5.44 in Experiment 3. The mean RTs and error rates for the early AoA words from Experiment 1 can be found in Table 20. The mean RTs and error rates for the late AoA words from Experiment 1 can be found in Table 21. For Experiment 2, the mean RTs and error rates for early AoA words can be found in Table 22, and the RTs and error rates for late AoA words can be found in Table 23. Finally, for Experiment 3, the RTs and error rates for early AoA words can be found in Table 24, and the late AoA RTs and error rates can be found in Table 25.

Although the ambiguity effects are reported for all conditions in Experiment 1, to allow a direct comparison to the effects in the other two experiments, the focus in Experiment 1 will only be on the high-connectivity conditions. Interestingly, for late AoA words, there was evidence of an overall disadvantage, with the effect being stronger for words with large semantic sets (31 ms). That result is consistent with the hypothesis advanced above. For early AoA words, there was no evidence of an overall advantage, although there was evidence of an interaction with semantic set size. Specifically, there was a 26 ms advantage for ambiguous words in the small set size (high connectivity) condition, and a 25 ms ambiguity *disadvantage* in the large set size, high connectivity condition. One could also argue that this pattern is generally consistent with the above hypothesis.

Unfortunately, the pattern from Experiment 2 was even less clear. For late AoA words, there was, again, some evidence of an ambiguity disadvantage. However, for early AoA words there was no evidence of an ambiguity advantage for either large or small semantic set words.

In Experiment 3, the pattern was also not particularly supportive of the hypothesis. For late AoA words, the overall ambiguity disadvantage was quite small, although it was again stronger for the large set words (in fact, there was a small advantage for the small set words). For the early AoA words, there was an overall null effect. Further, although there was some evidence of an interaction, the interaction pattern was exactly the opposite of that observed in Experiment 1. That is, it was the large set words that showed some evidence of an ambiguity advantage.

Overall, therefore, while it does seem to be the case that late AoA words, particularly those with large semantic sets, are more likely to show an ambiguity disadvantage, there does not seem to be a set of words that generally produced an ambiguity advantage. The results of Experiment 1 seemed to suggest that an ambiguity advantage would most likely be obtained when the words have an early AoA and a small semantic set; Experiment 2 showed very little evidence of an ambiguity advantage at all. Experiment 3 showed some evidence of an ambiguity advantage for the early AoA words, but the words showing that advantage were those in the large set size condition. At best, the results are inconsistent. If the ambiguity advantage is most likely to be produced by early-acquired ambiguous words, then why was there no hint of an ambiguity advantage in Experiment 2, and why did Experiment 3 produce an ambiguity advantage for early AoA words only in the large set condition?

The contrast between Experiments 2 and 3 is especially puzzling. Essentially the same words were used in the two experiments. Therefore, one would have imagined that the results would have been more similar than they were. The only possible explanation at this point would seem to be based on the fact that the nonwords in Experiment 3 were pseudohomophones, although there is no obvious mechanism why pseudohomophones would have had the effect that was observed here.

There has been research that has shown that pseudohomophones typically magnify the effects of both ambiguity (Pexman & Lupker, 1999) and semantic set size (e.g., Yates et al., 2003).The data on this topic are, however, not extensive. One way to investigate the impact of pseudohomophones would be to run a series of experiments in which ambiguity, semantic set size, and nonword type (e.g., orthographically legal nonwords vs. pseudohomophones) are manipulated. The first experiment could use only words with early AoAs, and the second experiment could use only words with late AoAs. If this argument were correct, such an experiment would find an ambiguity advantage for small set size words with early AoAs when orthographically legal pseudowords are used, and an ambiguity advantage for large set size words at with early AoAs when pseudohomophones are used. For late AoA words, this argument would predict that no ambiguity advantage should be observed when orthographically legal pseudowords are used. Instead, there should be an ambiguity disadvantage in the large set size condition. However, such an experiment has not yet been carried out, and until such an experiment is done, the impact of pseudohomophones and how it might interact with AoA remains unclear.

Number of Meanings and Number of Senses Revisited

Another possible explanation for the lack of an ambiguity advantage across the three experiments is that the ambiguous words were simply not ambiguous enough to produce an ambiguity advantage. That is, perhaps Rodd et al. (2002) are correct, and it is ambiguity in terms of the number of senses rather than the number of meanings that matters and these ambiguous words do not have enough senses (or had too many meanings, which can, according to Rodd et al., lead to inhibition). To examine the ambiguous words used in Experiments 2 and 3, the number of meanings (NOM) and number of senses (NOS) for each word were calculated from the Online Wordsmyth English Dictionary-Thesaurus (Parks et al., 1998). (A similar analysis based on the words from Experiment 1 was reported earlier). The mean NOM and NOS for words from Experiment 2 can be found in Table 12. The mean NOM and NOS for words from Experiment 3 can be found in Table 16.

As can be seen in Table 12, ambiguous words with small set sizes did not differ from unambiguous words by much in terms of the number of Wordsmyth entries (i.e., NOMs), but had a greater number of Wordsmyth senses (i.e., NOSs). On the other hand, ambiguous words with large set sizes had a larger number of Wordsmyth entries and senses, although unambiguous words with large set sizes still had quite a few senses (~6) on average. As noted, the stimuli used in Experiment 3 did not differ that much from those in Experiment 2 since Experiment 3 used very much the same set of words that were used in Experiment 2. Once again, ambiguous words with small set sizes did not differ from unambiguous words with small set sizes in terms of number of Wordsmyth entries, but differed in terms of number of Wordsmyth senses. Once again, ambiguous words with large set sizes had a larger number of Wordsmyth entries and senses, although unambiguous words still had quite a few senses (~6) on average.

Paralleling Experiment 1, it does appear that Experiments 2 and 3 used ambiguous stimuli that were differentiated from unambiguous stimuli in terms of number of Wordsmyth senses. As Rodd et al., (2002) argued, words with many senses should be faster to process than words with fewer senses, because such words should aid in the process of settling at the semantic level, and produce enriched feedback to the orthographic level. Words with many different meanings, however, should be processed more slowly, as the multiple meanings compete, and slow down settling. However, if having many senses benefits ambiguous words, and having many meanings inhibits processing, one would have expected a clear ambiguity advantage, at least in the small set size condition in Experiments 2 and 3. Ambiguous words in this condition did not differ significantly from unambiguous words in number of Wordsmyth meanings (hence, inhibition from multiple meanings would have played essentially no role in the ambiguous-unambiguous contrast), and they clearly had a greater number of Wordsmyth senses than their unambiguous counterparts. If there truly is a benefit for having many senses, and a detriment for having many meanings, then the small set size condition in Experiments 2 and 3 would have been the optimal condition to produce the ambiguity advantage. However, no such benefit was found in this condition. In contrast, the large set ambiguous words did differ somewhat from their unambiguous counterparts in terms of number of meanings, which could at least partly explain their inability to produce an ambiguity advantage. Therefore, if one wished to maintain Rodd et al.'s (2002) position, the only claim one could still make is that, even though these ambiguous words did differ from their unambiguous counterparts in terms of number of senses, the average NOS for ambiguous words used in these experiments was still simply not large enough (compared to other experiments that found a benefit for words with many senses, e.g., Rodd et al., 2002) to produce an effect.

Along those lines, one thing to note, however, is that there are a number of problems with using the number of dictionary senses as a measure of the number of senses. For one, it is often unclear what the criteria are for what constitutes a separate sense and a separate meaning, and the differentiation is often highly arbitrary. For example, the word *coast* has once sense that refers to "the land or area next to the ocean; seashore", and another sense that refers to "the region of a country or continent that lies along an ocean". Are these truly different senses? Often, there are very few differences between the definition of one sense and another. Second, if having many senses is a form of semantic ambiguity, why have studies such as Rodd et al.'s used words that they classify as unambiguous when the words have many senses? For example, Locker et al. (2003) classified the word *grind* as an ambiguous word when it has one Wordsmyth meaning, and 12 Wordsmyth senses, but classified the word *burn* as unambiguous, when the word has one Wordsmyth meaning, and 14 Wordsmyth senses. If anything, *burn* is more ambiguous than *grind* if dictionary senses are to be trusted, but one was arbitrarily classified as ambiguous, and the other unambiguous. Thus, using dictionary senses can often blur the line between what is an ambiguous word and what is an unambiguous word. If the experiments reported in this thesis had used the number of senses as a criterion for what constitutes an ambiguous word versus an unambiguous word, then unambiguous words would be words with only one Wordsmyth entry, and one or only a few Wordsmyth senses, a kind of word that is very few in number. The important point is just that it could be the case that a simple difference in the way that ambiguity was operationally defined and manipulated could have, in fact, had a large impact on the results of experiments looking for an ambiguity effect, a point that will need to be kept in mind when selecting both ambiguous and unambiguous words in future research.

Recent work in computational modelling may offer a potential solution to this problem. Recently, Hoffman, Ralph, and Rogers (2013) have developed a computational approach to measuring semantic ambiguity, called *semantic diversity* (SD), which uses lexical co-occurrence data. Their measure considers all of the contexts that a word can appear in, and the similarity between these contexts is computed. Words that appear in very diverse linguistic contexts (e.g., *part*) are what would be considered high-SD, and would be considered highly ambiguous. Words that occur in only a restricted range of contexts (e.g., *coronary*) are considered low-SD, and would be considered less ambiguous. This measure correlates moderately with number of senses (r = 0.41), yet words with few senses can vary in their SD values significantly. Potentially, therefore, this measure might be an appropriately sensitive measure of the relatedness of a word's meanings. In future research, such a measure could be effectively used to study the ambiguity advantage, and may eventually help research move beyond using dictionary meanings and senses as a measure of ambiguity.

The Inhibition of Ambiguous Words: Are Neighbors to Blame?

While none of the experiments in this thesis successfully produced the classic ambiguity advantage, one result that was consistently found was an ambiguity disadvantage, particularly when the words had large, highly interconnected semantic neighborhoods. While other studies have demonstrated an ambiguity disadvantage (e.g., Rodd et al., 2002), these studies never examined how semantic neighborhoods affect the processing of ambiguous words. Therefore, the present experiments appear to be the first to find an ambiguity disadvantage when words with large, highly interconnected semantic neighborhoods are used. The question becomes, why did this disadvantage occur? As Locker et al. (2003) argued, increasing the scope of activation of the multiple meanings of an ambiguous word may increase the effects of competition by inducing greater interference between the multiple meanings of ambiguous words. While Locker et al. never reported, nor predicted, an ambiguity disadvantage for their large set, high connectivity words, their argument does suggest that increasing the scope of activation of the multiple meanings of an ambiguous word would increase the amount of semantic-level competition, resulting in an ambiguity disadvantage. The results reported in this thesis, particularly in Experiment 1, do appear to support this idea.

This type of pattern is, of course, also consistent with Mirman and colleagues' (e.g., Chen & Mirman, 2012; Mirman, 2011; Mirman & Magnuson, 2008) results showing that words with many near semantic neighbors were processed more slowly, and words with many distant semantic neighbors are processed more quickly. These types of results do imply that there is processing inhibition for ambiguous words when they have many, highly interconnected semantic neighbors due to the representations for those highly interconnected semantic neighbors competing with each other during word recognition. If a word has more than one meaning (i.e., ambiguous words), then this problem may become more complicated because ambiguous words will have neighbors that reflect the multiple different uses of the word. For example, the word *bat* would have neighbors that are related to the furry winged mammal (e.g., *wings*, *vampire*, *Dracula*), as well as neighbors related to baseball (e.g., *ball, pitcher, helmet*). Ambiguous words with large, dense semantic neighborhoods would therefore have many neighbors for both meanings of the word, producing a discordant neighborhood in which the neighbors are not even related to the same concept.

This conclusion has, of course, taken us a considerable distance from our original question, which was, what are the circumstances that produce an ambiguity advantage? Nonetheless, they do at least indicate that there may be specific types of ambiguous words which clearly will not produce an ambiguity advantage, as they are, in fact, processed more slowly than unambiguous words. Therefore, those types of words should certainly be avoided if one wishes to study the ambiguity advantage. As a number of studies have unsuccessfully attempted to reproduce the ambiguity advantage in lexical decision (e.g., Borowsky & Masson, 1996), it is possible that the results of such studies were influenced by having too many ambiguous words with large, highly interconnected semantic neighborhoods. Of course, numerous studies have successfully produced an ambiguity advantage without controlling for set size and connectivity (e.g., Hino & Lupker, 1996; Kellas et al., 1988; Millis & Button, 1989; Rubenstein et al,. 1970; Pexman & Lupker, 1999), so a confound with set size and connectivity seems unlikely to be the sole cause of not being able to produce an ambiguity advantage. Clearly, the question of how ambiguous words are represented and processed is one that remains to be fully answered.

How Much Do Semantics Matter in Lexical Decision Tasks?

While the present experiments have produced evidence that there are circumstances which will produce an ambiguity disadvantage, as discussed, evidence for a facilitative effect of ambiguity and set sizes was scarce. Given that so many other studies have reported an ambiguity advantage (e.g., Beretta et al., 2005; Klepousnioutou & Baum, 2007; Hino & Lupker, 1996; Kellas et al., 1988; Locker et al., 2003; Millis & Button, 1989; Pexman & Lupker, 1999), and a number of other studies have found that semantic richness facilitates lexical decision (e.g., Buchanan et al., 2001; Duñabeitia, Avilés, & Carreiras, 2008; Hargreaves & Pexman, 2014; Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007; Pexman, Hargreaves, Siakaluk, Bodner, & Pope, 2008; Pexman, Holyk, & Monfils, 2003), it does appear that semantics has a clear impact on lexical decision making. However, one might question whether the extant literature is actually overstating that case.

How does one make a lexical decision? A number of researchers (e.g., Kawamoto et al., 1994; Pexman & Hargreaves, 2014; Pexman, Lupker, & Hino, 2002) have assumed that responses in lexical decision tasks are not primarily based on access to meaning. For example, the model that Kawamoto et al. proposed assumed that lexical decision performance is primarily based on the activation of orthographic units, an assumption shared by other models (e.g., Balota et al., 1991; Hino & Lupker, 1996) of lexical decision making. These models all assume that semantics influences lexical decision times only via top-down feedback from the semantic level to the orthographic level, where the decision-making process is thought to take place. Essentially, semantic contributions to lexical decision have typically been thought to be indirect due to the fact that the task demands do not require access to meaning. Thus, from a theoretical perspective, it's perhaps surprising that semantics would play much of a role in making a lexical decision.

A second point to consider is that although some studies looking directly at the impact of certain semantic variables, while showing effects of those variables, have also found that certain effects are limited in scope, and are selectively modulated by task-specific demands. For example, Pexman et al. (2008) compared three measures of semantic richness – number of semantic neighbors, number of features, and contextual dispersion (i.e., a measure of the distribution of a word's occurrence across different content areas) – on their ability to predict response times and error variance in lexical decision and semantic categorization tasks, and found that while number of features and contextual dispersion accounted for unique variance in both tasks, the number of semantic neighbors of a word only accounted for unique variance in their lexical decision task. In a follow-up study, Yap, Tan, Pexman, and Hargreaves (2011) examined the effects of number of senses and number of associates on lexical decision, speeded pronunciation, and semantic classification performance. Paralleling Pexman et al.'s results, Yap et al. found that while number of features and contexts consistently facilitated word recognition, the effects of semantic neighborhood density, number of associates, and number of senses were not as robust. In fact, the effect of number of senses was only marginal in the lexical decision task in their experiment. In yet another study on semantic richness, Yap, Pexman, Wellsby, Hargreaves, and Huff (2012) examined the impact of number of features, number of senses, semantic neighborhood density, imageability, and body-object interaction using five visual word recognition tasks: standard lexical decision, go/no-go lexical decision, speeded pronunciation, progressive demasking, and semantic classification. Once again, although semantic richness effects were observed in all tasks, there was also evidence of task-specificity. Most relevant to this discussion, the effect of number of senses was not significant in the standard lexical decision task. In fact, the number of senses was only found to be significant in their go/no-go lexical decision task.

More recent data on this topic comes from Hargreaves and Pexman (2014), who examined the time course of various semantic richness effects (specifically, number of senses, the average radius of co-occurrence (ARC), imageability, number of features, and body-object interaction ratings) in visual word recognition using a signal-to-respond (STR) paradigm with a lexical decision and a semantic categorization task. Their results showed that while none of the semantic richness effects were significant overall, certain measures of semantic richness were found to be more significant at specific STR durations. For example, when the STR duration increased from 200 to 400 ms in their study, there was an increase in the size of imageability effects in lexical decision. Most importantly, the results showed an early influence of number of senses in the semantic categorization task, but failed to produce any evidence that number of senses had any impact on lexical decision performance at any STR duration. For that matter, this study failed to show any early effect of semantic richness in lexical decision. The lack of early semantic richness effects in lexical decision may suggest that semantic effects emerge at a later stage.

A recent study by Yap and Seow (2013) has also come to a similar conclusion. Yap and Seow conducted an ex-Gaussian analysis of the effects of emotional valence in a lexical decision task, and they observed that valence effects were caused by both distributional shifting and an impact on the slow tail of the distribution. These findings suggest that the valence effects, and perhaps other semantic richness effects in lexical decision, may be produced, at least to some extent, by a later, post-lexical phase in which semantic activation can more directly affect decision making.

Overall, while previous research has shown that semantics certainly can exert a small influence on lexical decision tasks (e.g., Pexman et al., 2008; Yap et al., 2011, 2012), the point of this literature review is to note these effects are not always obtained in lexical decision tasks, with some semantic variables (e.g., number of features, imageability) being more robust than others (e.g., number of associates, number of senses). Further, even large-scale studies that have reported significant effects of semantic variables in lexical decision (e.g., Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004) showed only a modest correlation between semantic variables and response times in lexical decision tasks. The evidence for semantic effects in lexical decision tasks is, perhaps, less convincing than one might imagine. Therefore, it may not be overly surprising that the present experiments were unable to produce a clear ambiguity advantage or a clear advantage for words with large set sizes.

Conclusions

The present experiments were an attempt to examine the conclusions of Locker et al. (2003), who showed that the ambiguity advantage that has frequently been reported in the literature (e.g., Hino & Lupker, 1996; Kellas et al., 1988; Millis & Button, 1989; Pexman & Lupker, 1999; Rubenstein et al., 1970) was restricted to words with small, sparsely connected semantic neighborhoods. The present experiments showed no evidence of an ambiguity advantage for words with small, sparsely connected neighborhoods. The only evidence of an ambiguity advantage was found for words with small set sizes and high connectivity in Experiment 1; a result which was also found in the English Lexicon Project database (Balota et al., 2007). These findings were not successfully replicated in the subsequent experiments, however, suggesting that at least part of Locker et al.'s conclusions was incorrect.

What these experiments have also shown that there may be specific circumstances in which ambiguous words are processed more slowly than unambiguous words. Namely, when ambiguous words have large, highly interconnected neighborhoods, those words seem to be responded to more slowly than their unambiguous counterparts. These findings parallel the findings of other studies that suggest that near semantic neighbors act as competitors, and having a large number of near neighbors produces an inhibitory effect on visual word recognition (e.g., Chen & Mirman, 2012; Mirman, 2011; Mirman & Magnuson, 2008), with these types of results further suggesting that the characteristics of an ambiguous word's semantic neighborhood may act as a constraining factor on their processing. These types of results can be considered to be at least somewhat supportive of Locker et al.'s (2003) basic argument.

Even these inhibition effects were small and inconsistent, however. Given that other studies have found only a modest effect of ambiguity and semantic set size in lexical decision tasks (e.g., Hargreaves & Pexman, 2014; Pexman et al., 2008; Yap et al., 2011, 2012), and large-scale studies have found only modest correlations between semantic variables and response times in lexical decision (Balota et al., 2004), an additional conclusion that the present data suggest is that the role that semantics plays in lexical decision may be smaller than one may have come to believe. It may, therefore, be beneficial in future research examining ambiguous words to use tasks that are more inherently semantic (e.g., semantic categorization). Such tasks would likely provide a more effective tool for understanding the issues surrounding the processing and representation of multiple meaning words in semantic memory.

References

Andrews, S. (1989). Frequency and neighborhood effects on lexical access: Activation or search? *Journal of Experimental Psychology: Learning, Memory, & Cognition, 15*(5), 802-814. doi:10.1037/0278-7393.15.5.802

Andrews, S. (1992). Frequency and neighborhood effects on lexical access: Lexical similarity or orthographic redundancy? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18*(2), 234-254. doi:10.1037/0278-7393.18.2.234

Azuma, T., & Van Orden, G.C. (1997). Why safe is better than fast: The relatedness of a word's meaning affects lexical decision times. *Journal of Memory and Language, 36*(4), 484-504. doi:10.1006/jmla.1997.2502

Balota, D.A., Cortese, M.J., Sergent-Marshall, S.D., Spieler, D.H., & Yap, M.J. (2004). Visual word recognition of single-syllable words. *Journal of Experimental Psychology: General, 133*(2), 283-316. doi:10.1037/0096-3445.133.2.283

Balota, D.A., Ferraro, F.R., & Connor, L.T. (1991). On the early influence of meaning in word recognition: A review of the literature. In D.A. Balota, F.R. Ferraro, & L.T. Connor (Eds.), *The psychology of word meanings* (pp. 187-222). Hillsdale, NJ: Erlbaum.

Balota, D.A., Yap, M.J., Cortese, M.J., Hutchinson, K.A., Kessler, B., Loftis, B.,…&Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods, 39,* 445-459.

Beretta, A., Fiorentino, R., & Poeppel, D. (2005). The effects of homonymy and polysemy on lexical access: An MEG study. *Cognitive Brain Research, 24*(1), 57-65. doi:10.1016/j.cogbrainres.2004.12.006

Borowsky, R., & Masson, M.E.J. (1996). Semantic ambiguity effects in word identification. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22*(1), 63-85. doi:10.1037/0278-7393.22.1.63

Buchanan, L., Westbury, C., & Burgess, C. (2001). Characterizing semantic space: Neighborhood effects in word recognition. *Psychonomic Bulletin & Review, 8*(3), 531-544. doi:10.3758/BF03196189

Burgess, C., & Lund, K. (2000). The dynamics of meaning in memory. In E. Dietrich & A.B. Markman (Eds.), *Cognitive dynamics: Conceptual and representational change in humans and machines* (pp. 117-156). Mahwah, NJ: Erlbaum.

Catling, J.C., Dent, K., & Williamson, S. (2008). Age of acquisition, not word frequency affects object recognition: Evidence from the effects of visual degradation. *Acta Psychologica, 129*(1), 130-137. doi:10.1016/j.actpsy.2008.05.005

Catling, J.C., & Johnston, R.A. (2005). Age of acquisition effects on word generation. *European Journal of Cognitive Psychology, 17*(2), 161-177. doi:10.1080/09541440440000078

Catling, J.C., & Johnston, R.A. (2006). Effects of age of acquisition on priming and picture naming. *The Quarterly Journal of Experimental Psychology, 59*(8), 1443-1453. doi:10.1080/17470210500214291

Chen, Q., & Mirman, D. (2012). Competition and cooperation among similar representations: Toward a unified account of facilitative and inhibitory effects of lexical neighbors. *Psychological Review, 119*(2), 417-430. doi:10.1037/a0027175

Coltheart, M. (1981). The MRC psycholinguistic database. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology, 33*(4), 497-505. Doi:10.1080/15640748108400805

Coltheart, M., Davelaar, E., Jonasson, J.F., & Besner, D. (1977). Access to the internal lexicon. In S. Dornic (Ed.), *Attention & Performance VI* (pp. 535-555). Hillsdale, NJ: Erlbaum.

Coltheart, V., Laxon, V.J., & Keating, C. (1988). Effects of word imageability and age of acquisition on children's reading. *British Journal of Psychology, 79*(1), 1-12. doi:10.1111/j/2044-8295.1988.tb02270.x

Cortese, M.J., & Schock, J. (2013). Imageability and age of acquisition effects in disyllabic word recognition. *The Quarterly Journal of Experimental Psychology, 66*(5), 946-972.

Cree, G.S., McRae, K., & McNorgan, C. (1999). An attractor model of lexical conceptual processing: Simulating semantic priming. *Cognitive Science, 23*(3), 371-414. doi:10.1016/S0364-0213(99)00005-1

Davis, C.J. (2005). N-Watch: A program for deriving neighborhood size and other psycholinguistic statistics. *Behavior Research Methods, 37*(1), 65-70. doi:10.3758/BF03206399

Duñabeitia, J.A., Avilés, A., & Carreiras, M. (2008). NoA's ark: Influence of the number of associates on visual word recognition. *Psychonomic Bulletin & Review, 15*, 1072-1077. doi:10.3758/PBR.15.6.1072

Forster, K.I., & Forster, J.C. (2003). DMDX: A windows display program with millisecond accuracy. *Behavior Researh Methods, Instruments & Computers, 35*, 116-124.

Gernsbacher, M.A. (1984). Resolving 20 years of inconsistent interactions between lexical familiarity and orthography, concreteness, and polysemy. *Journal of Experimental Psychology: General, 113*(2), 256-281. doi:10.1037/0096-3445.113.2.256

Grainger, J. (1990). Word frequency and neighborhood frequency effects in lexical decision and naming. *Journal of Memory and Language, 29*(2), 228-244. doi:10.1016/0749-596X(90)90074-A

Grainger, J., & Jacobs, A.M. (1996). Orthographic processing in visual word recognition: A multiple readout model. *Psychological Review, 103,* 518-565.

Hargreaves, I.S., & Pexman, P.M. (2014). Get rich quick: The signal to respond procedure reveals the time course of semantic richness effects during visual word recognition. *Cognition, 131*(2), 216-242. doi:10.1016/j.cognition/2014.01.001

Hino, Y., Kusunose, Y., & Lupker, S.J. (2010). The relatedness-of-meaning effect for ambiguous words in lexical-decision tasks: When does relatedness matter? *Canadian Journal of Experimental Psychology, 64*(3), 180-196. doi:10.1037/a0020475

Hino, Y., & Lupker, S.J. (1996). Effects of polysemy in lexical decision and naming: An alternative to lexical access accounts. *Journal of Experimental Psychology: Human Perception and Performance, 22*(6), 1331-1356.

Hino, Y., Lupker, S.J., & Pexman, P.M. (2002). Ambiguity and synonymy effects in lexical decision, naming, and semantic categorization tasks: Interactions between orthography, phonology, and semantics. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*(4), 686-713. doi:10.1037/0278-7393.28.4.686

Hino, Y., Lupker, S.J., Sears, C.R., & Ogawa, T. (1998). The effects of polysemy for Japanese katakana words. *Reading and Writing: An Interdisciplinary Journal, 10,* 395-424. doi:10.1023/A:1008060924384

Hino, Y., Pexman, P.M., & Lupker, S.J. (2006). Ambiguity and relatedness effects in semantic tasks: Are they due to semantic coding? *Journal of Memory and Language, 55,* 247-273. doi:10.1016/j.jml.2006.04.001

Hoffman, P., Ralph, M.A.L., & Rogers, T.T. (2013). Semantic diversity: A measure of semantic ambiguity based on variability in the contextual usage of words. *Behavior Research Methods, 45*(3), 718-730. doi:10.3758/s13428-012-0278-x

Jastrzembski, J.E., (1981). Multiple meanings, number of related meanings, frequency of occurrence, and the lexicon. *Cognitive Psychology, 13*(2), 278-305. doi:10.1016/0010-0285(91)90011-6

Johnston, R.A., & Barry, C. (2005). Age of acquisition effects in the semantic processing of pictures. *Memory & Cognition, 33*(5), 905-912. doi:10.3758/BF03193084

Joordens, S., & Besner, D. (1994). When banking on meaning is not (yet) money in the bank: Explorations in connectionist modeling. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20,* 1051-1062. doi:10.1037/0278-7393.20.5.1051

Kawamoto, A.H., Farrar, W.T., & Kello, C.T. (1994). When two meanings are better than one: Modeling the ambiguity advantage using a recurrent distributed network. *Journal of Experimental Psychology: Human Perception and Performance, 20*(6), 1233-1247. doi:10.1037/0096-1523.20.6.1233

Kellas, G., Ferraro, F.R., & Simpson, G.B. (1988). Lexical ambiguity and the timecourse of attentional allocation in word recognition. *Journal of Experimental Psychology: Human Perception and Performance, 14*(4), 601-609.

Klein, D.E., & Murphy, G.L. (2001). The representation of polysemous words. *Journal of Memory and Language, 45*(2), 259-282. doi:10.1006/jmla.2001.2779

Klein, D.E., & Murphy, G.L. (2002). Paper has been my ruin: Conceptual relations of polysemous senses. *Journal of Memory and Language*, *47*(4), 548-570. doi:10.1016/S0749-596X(02)00020-7

Klepousniotou, E., & Baum, S.R. (2007). Disambiguating the ambiguity advantage effect in word recognition: An advantage for polysemous but not homonymous words. *Journal of Neurolinguistics, 20*(1), 1-24. doi:10.1016/j.jneuroling.2006.02.001

Kuperman, V., Stadthagen-Gonzalez, H., & Brysbaert, M. (2012). Age-of-acquisition ratings for 30,000 English words. *Behavior Research Methods, 44*(4), 978-990. doi:10.3758/s13428-012-0210-4

Landauer, T.K., & Dumais, S.T. (1997). A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, *104*(2), 211-240. doi:10.1037/0033-295X.104.2.211

Lichacz, F.M., Herdman, C.M., LeFevre, J., & Baird, B. (1999). Polysemy effects in word naming. *Canadian Journal of Experimental Psychology, 53*, 189-193. doi:10.1037/h0087309

Locker, L., Simpson, G.B., & Yates, M. (2003). Semantic neighborhood effects on the recognition of ambiguous words. *Memory & Cognition, 31*(4), 505-515. doi:10.3758/BF03196092

Lund, K., & Burgess, C. (1996). Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments & Computers, 28*(2), 203-208. doi:10.3758/BF03204766

McRae, K., Cree, G.S., Seidenberg, M.S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods, 37*(4), 547-559. doi:10.3758/BF03192726

Millis, M.L., & Button, S.B. (1989). The effect of polysemy on lexical decision time: Now you see it, now you don't. *Memory & Cognition, 17*(2), 141-147.

Mirman, D. (2011). Effects of near and distant semantic neighbors on word production. *Cognitive, Affective & Behavioral Neuroscience, 11*(1), 32-43. doi:10.3758/s13415-010-0009-7

Mirman, D., & Magnuson, J.S. (2008). Attractor dynamics and semantic neighborhood density: Processing is slowed by near neighbors and speeded by distant neighbors. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 34*(1), 65-79. doi:10.1037/0278-7393.34.1.65

Nelson, D.L., Bennett, D.J., Gee, N.R., Schreiber, T.A., & McKinney, V.M. (1993). Implicit memory: Effects of network size and interconnectivity on cued recall. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 19,* 747-764.

Nelson, D.L., McEvoy, C.L., & Schreiber, T.A. (1998). The University of South Florida word association, rhyme and word fragment norms. http://w3.usf.edu/FreeAssociation/

O'Connor, C.M., Cree, G.S., & McRae, K. (2009). Conceptual hierarchies in a flat attractor network: Dynamics of learning and computations. *Cognitive Science, 33*(4), 665-708. doi:10.1111/j.1551-6079.2009.01024.x

Parks, R., Ray, J., & Bland, S. (1998). *Wordsmyth English dictionary-thesaurus*. University of Chicago. http://www.wordsmyth.net

Pexman, P.M., Hargreaves, I.S., Edwards, J.D., Henry, L.C., & Goodyear, B.G. (2007). The neural consequences of semantic richness: When more comes to mind, less activation is observed. *Psychological Science, 18*(5), 401-406. doi:10.1111/j.1467-9280.2007.01913.x

Pexman, P.M., Hargreaves, I.S., Siakaluk, P.D., Bodner, G.E., & Pope, J. (2008). There are many ways to be rich: Effects of three measures of semantic richness on visual word recognition. *Psychonomic Bulletin & Review, 15*(1), 161-167. doi:10.3758/PBR.15.1.161

Pexman, P.M., Hino, Y., & Lupker, S.J. (2004). Semantic ambiguity and the process of generating meaning from print. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30*(6), 1252-1270. doi:10.1037/0278-7393.30.6.1252

Pexman, P.M., Holyk, G.G., & Monfils, M.-H. (2003). Number-of-features effects and semantic processing. *Memory & Cognition, 31*(6), 842-855. doi:10.3758/BF03196439

Pexman, P.M., & Lupker, S.J. (1999). Ambiguity and visual word recognition: Can feedback explain both homophone and polysemy effects? *Canadian Journal of Experimental Psychology, 53,* 323-334. doi:10.1037/h0087320

Pexman, P.M., Lupker, S.J., & Hino, Y. (2002). The impact of feedback semantics in visual word recognition: Number-of-feature effects in lexical decision and naming tasks. *Psychonomic Bulletin & Review, 9*(3), 542-549. doi:10.3758/BF03196311

Plaut, D.C., & McClelland, J.L. (1993). Generalization with componential attractors: Word and nonword reading in an attractor network. *Proceedings of the 15th Annual Conference of the Cognitive Science Society* (pp. 824-829). Hillsdale, NJ: Erlbaum.

Plaut, D.C., McClelland, J.L., Seidenberg, M.S., & Patterson, K. (1996). Understanding normal and impaired word reading: Computational principles in quasi-regular domains. *Psychological Review, 103*(1), 56-115. doi:10.1037/0033-295X.103.1.56

Rodd, J.M. (2004). The effect of semantic ambiguity on reading aloud: A twist in the tale. *Psychonomic Bulletin & Review, 11*(3), 440-445.

Rodd, J.M., Gaskell, M.G., & Marslen-Wilson, W.D. (2002). Making sense of semantic ambiguity: Semantic competition in lexical access. *Journal of Memory and Language, 46,* 245-266. doi:10.1006/jmla.2001.2810

Rodd, J.M., Gaskell, M.G., & Marslen-Wilson, W.D. (2004). Modelling the effects of semantic ambiguity in word recognition. *Cognitive Science, 28*(1), 89-104. doi:10.1016/j.cogsci.2003.08.002

Rubenstein, H., Garfield, L., & Millikan, J.A. (1970). Homographic entries in the internal lexicon. *Journal of Verbal Learning and Verbal Behavior, 9,* 487-494.

Rubenstein, H., Lewis, S.S., & Rubenstein, M.A. (1971). Homographic entries in the internal lexicon: Effects of systematicity and relative frequency of meanings. *Journal of Verbal Learning and Verbal Behavior, 10*(1), 57-62. doi:10.1016/S0022-5371(71)80094-4

Sears, C.R., Hino, Y., & Lupker, S.J. (1995). Neighborhood size and neighborhood frequency effects in word recognition. *Journal of Experimental Psychology: Human Perception and Performance, 21,* 876-900. doi:10.1037/0096-1523.21.4.876

Seidenberg, M.S., & McClelland, J.L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review, 96*(4), 523-568. doi:10.1037/0033-295X.96.4.523

Siakaluk, P.D., Buchanan, L., & Westbury, C. (2003). The effect of semantic distance in yes/no and go/no-go semantic categorization tasks. *Memory and Cognition, 31*(1), 100-113. doi:10.3758/BF03196086

Siakaluk, P.D., Sears, C.R., & Lupker, S.J. (2002). Orthographic neighborhood effects in lexical decision: The effects of nonword orthographic neighborhood size. *Journal of Experimental Psychology: Human Perception and Performance, 28,* 661-681. doi:10.1037/0096-1523.28.3.661

Van Orden, G.C., Pennington, B.F., & Stone, G.O. (1990). Word identification in reading and the promise of subsymbolic psycholinguistics. *Psychological Review, 97*(4), 488-522. doi:10.1037/0033-295X.97.4.488

Vitevitch, M.S. (2007). The spread of phonological neighborhood influences spoken word recognition. *Memory & Cognition, 35*(1), 166-175. doi:10.3758/BF03195952

Yap, M.J., Pexman, P.M., Wellsby, M., Hargreaves, I.S., & Huff, M.J. (2012). An abundance of riches: Cross-task comparisons of semantic richness effects in visual word recognition. *Frontiers in Human Neuroscience, 6,* 1-10. doi:10.3399/fnhum.2012.00072

Yap, M.J., & Seow, C.S. (2014). The influence of emotion on lexical processing: Insights from RT distributional analysis. *Psychonomic Bulletin & Review, 21*(2), 526-533. Doi:10.3758/s13423-013-0525-x

Yap, M.J., Tan, S.E., Pexman, P.M., & Hargreaves, I.S. (2011). Is more always better? Effects of semantic richness on lexical decision, speeded pronunciation, and semantic classification. *Psychonomic Bulletin & Review, 18*(4), 742-750. doi:10.3758/s13423-011-0092-y

Yates, M. (2005). Phonological neighbors speed visual word processing: Evidence from multiple tasks. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31*(6), 1385-1397. doi:10.1037/0278-7393.31.6.1385

Yates, M. (2009). Phonological neighbourhood spread facilitates lexical decisions. *The Quarterly Journal of Experimental Psychology, 62*(7), 1304-1314. doi:10.1080/17470210902725746

Ziegler, J.C., Muneaux, M., & Grainger, J. (2003). Neighborhood effects in auditory word recognition: Phonological competition and orthographic facilitation. *Journal of Memory and Language, 48,* 779-793. doi:10.1016/S0749-596X(03)00006-8

Table 1 - *Mean Response Times (RTs) and Error Rates from Locker, Simpson, & Yates (2003), Experiment 1*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	576	74	4	585	70	4
Unambiguous	587	45	2	577	69	4
Ambiguity Effect	+11		-2%	+8		+0%
Small						
Ambiguous	611	88	7	604	72	6
Unambiguous	609	70	10	627	75	12
Ambiguity Effect	-2		+3%	+23***‡		+6%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$; ‡ significant by subjects only.

Table 2 - *Mean Response Times (RTs) and Error Rates from Experiment 1 – Locker et al.'s (2003) stimuli – English Lexicon Project Database*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	621	33	4.50	591	35	1.50
Unambiguous	595	29	2.10	602	34	2.10
Ambiguity Effect	-26		-2.40%	+11		+0.60%
Small						
Ambiguous	600	44	2.00	604	43	1.50
Unambiguous	638	43	3.30	624	44	2.10
Ambiguity Effect	+38		+1.30%	+20		+1.60%

Table 3 - *Stimulus Characteristics from Experiment 1*

	Ambiguous				Unambiguous			
Semantic Set	Small		Large		Small		Large	
Connectivity	Low	High	Low	High	Low	High	Low	High
CELEX	39.40	39.00	38.33	36.96	24.23	39.16	24.77	31.82
Set Size	8.22	9.84	19.95	19.75	7.90	8.75	19.70	18.84
Connectivity	0.61	2.09	0.85	2.27	0.70	2.41	0.95	2.25
Concreteness	524.50	524.21	496.26	560.40	525.37	557.75	521.39	492.07
N	7.50	6.37	7.63	7.10	7.40	6.00	7.15	5.47
Length	4.67	4.63	4.58	4.85	4.50	4.35	4.75	4.47
NOM	1.83	1.58	1.47	1.60	1.00	1.05	1.30	1.10
NOS	10.17	7.63	12.16	9.65	4.60	3.95	7.20	5.05
AoA	5.84	6.40	5.82	5.86	5.67	6.12	6.37	6.12

Note: N = orthographic neighborhood size; NOM = number of meanings; NOS = Number of senses; AoA = Age of Acquisition.

Table 4 - *Mean Response Times (RTs) and Error Rates for Experiment 1 – Subject Analysis*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	639	94	3.38	627	82	2.88
Unambiguous	611	91	3.10	636	84	1.67
Ambiguity Effect	-28***		+0.28%	+9		-1.21%
Small						
Ambiguous	632	82	1.63	630	93	3.18
Unambiguous	642	90	5.24	621	79	2.62
Ambiguity Effect	+10		+3.61%***	-9		-0.56%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 5 - *Mean Response Times (RTs) and Error Rates for Experiment 1 – With Covariate*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	639	43	3.10	626	35	2.88
Unambiguous	611	29	3.57	633	29	1.67
Ambiguity Effect	-28*		+0.47%	+7		-1.21%
Small						
Ambiguous	632	45	1.63	630	31	3.18
Unambiguous	642	36	5.24	621	45	2.62
Ambiguity Effect	+10		+3.61%***	-9		-0.56%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 6 - *Mean Response Times (RTs) and Error Rates for Experiment 1 – English Lexicon Project*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	617	45	3.15	599	40	1.80
Unambiguous	609	46	2.85	608	29	2.40
Ambiguity Effect	-8		-0.30%	+9		-0.60%
Small						
Ambiguous	605	41	2.25	602	40	2.25
Unambiguous	647	40	2.10	626	42	3.00
Ambiguity Effect	+42		-0.15%	+24		+0.75%

Table 7 - *Mean Response Times (RTs) and Error Rates from Experiment 1 – Locker et al.'s (2003) stimuli*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	622	44	2.62	617	39	3.33
Unambiguous	607	37	2.38	627	29	1.67
Ambiguity Effect	-15		-0.53%	+10		-1.66%
Small						
Ambiguous	628	48	1.85	637	39	4.76
Unambiguous	650	34	5.00	614	35	2.86
Ambiguity Effect	+22*‡		+3.15%*	-23*‡		-1.90%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$; ‡ significant by subjects only.

Table 8 - *Mean Response Times (RTs) and Error Rates from Experiment 1 – New Stimuli*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	656	37	3.57	635	31	2.38
Unambiguous	613	16	4.76	640	29	1.67
Ambiguity Effect	-43***		+1.19%	+5		-0.71%
Small						
Ambiguous	635	44	1.43	624	23	1.90
Unambiguous	633	37	5.48	628	53	2.38
Ambiguity Effect	-2		+4.05%***	+4		+0.48%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$; ‡ significant by subjects only.

Table 9 - *Mean Response Times (RTs) and Error Rates from Experiment 1 – New Stimuli – English Lexicon Project Database*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	613	57	1.80	607	46	1.67
Unambiguous	624	58	3.33	615	23	2.70
Ambiguity Effect	+11		+1.53%	+8		+1.03%
Small						
Ambiguous	609	41	2.10	600	39	2.40
Unambiguous	655	38	0.90	629	40	3.90
Ambiguity Effect	+46		-1.20%	+29		+1.50%

Table 10 - *Number of Meanings (NOM) and Number of Senses (NOS) from Experiment 1-Locker et al. (2003) stimuli*

	High Connectivity		Low Connectivity	
Semantic Set	NOM	NOS	NOM	NOS
Large				
Ambiguous	1.20	9.10	1.70	13.70
Unambiguous	1.20	4.80	1.20	7.20
Small				
Ambiguous	1.22	6.44	1.88	10.62
Unambiguous	1.00	4.30	1.00	4.80

Table 11 - *Number of Meanings (NOM) and Number of Senses from Experiment 1- New Stimuli*

	High Connectivity		Low Connectivity	
Semantic Set	NOM	NOS	NOM	NOS
Large				
Ambiguous	2.00	10.20	1.22	10.44
Unambiguous	1.00	5.33	1.10	6.60
Small				
Ambiguous	1.90	8.70	1.80	9.80
Unambiguous	1.10	3.60	1.00	4.40

Table 12 - *Stimulus Characteristics from Experiment 2*

	Ambiguous		Unambiguous	
Semantic Set	Small	Large	Small	Large
CELEX	25.26	23.50	21.96	20.27
Set Size	10.21	20.68	9.13	20.21
Connectivity	2.02	2.00	2.07	2.08
Concreteness	533.25	536.92	538.70	545.83
N	7.17	7.52	7.56	5.88
Length	4.67	4.60	4.35	4.50
NOM	1.38	1.84	1.22	1.21
NOS	6.62	8.60	3.48	6.04
AoA	6.38	6.35	5.78	5.22

Note: N = orthographic neighborhood size; NOM = number of meanings; NOS = Number of senses; AoA = Age of Acquisition.

Table 13 - *Mean Response Times (RTs) and Error Rates from Experiment 2 – Subject Analysis*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	663	93	2.98	667	100	2.86
Unambiguous	656	90	3.35	649	88	2.32
Ambiguity Effect	-7		+0.37%	-18**		-0.54%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 14 - *Mean Response Times (RTs) and Error Rates from Experiment 2 – Item Analysis*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	661	48	2.98	666	47	2.86
Unambiguous	654	39	3.35	647	35	2.32
Ambiguity Effect	-7		+0.37%	-19		-0.54%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 15 - *Mean Response Times (RTs) and Error Rates from Experiment 2 – English Lexicon Project Database*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	625	48	3.12	621	51	3.12
Unambiguous	611	33	2.87	608	27	2.38
Ambiguity Effect	-14		+0.37%	-13		-0.54%

Table 16 - *Stimulus Characteristics from Experiment 3*

	Ambiguous		Unambiguous	
Semantic Set	Small	Large	Small	Large
CELEX	28.70	25.60	23.77	19.60
Set Size	10.60	20.50	8.95	20.35
Connectivity	2.08	2.00	2.04	2.06
Concreteness	527.40	538.61	538.35	562.05
N	7.85	9.33	7.75	6.45
Word Length	4.45	4.22	4.30	4.35
NOM	1.35	2.00	1.20	1.25
NOS	7.20	9.17	3.40	6.05
AoA	6.04	6.20	5.69	4.90

Note: N = orthographic neighborhood size; NOM = number of meanings; NOS = Number of senses; AoA = Age of Acquisition.

Table 17 - *Mean Response Times (RTs) and Error Rates from Experiment 3- Subject Analysis*

	Large			Small		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	668	98	2.59	650	81	2.06
Unambiguous	655	89	2.59	646	80	2.22
Ambiguity Effect	-13		+0.0%	-4		+0.16%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 18 - *Mean Response Times (RTs) and Error Rates from Experiment 3- With Covariate*

	Large			Small		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	667	50	2.10	649	35	2.64
Unambiguous	654	47	2.26	645	42	2.64
Ambiguity Effect	-13		+0.37%	-4		+0.0%

Note: † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 19 - *Mean Response Times (RTs) and Error Rates from Experiment 3- English Lexicon Project Database*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	618	40	2.85	608	45	3.00
Unambiguous	609	30	2.70	607	29	2.25
Ambiguity Effect	-9		-0.15%	-1		-0.75%

Table 20 - *Experiment 1 Results – Early AoA words (AoA < 5.84)*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	628	43	2.62	613	30	2.86
Unambiguous	603	32	3.97	636	32	1.43
Ambiguity Effect	-25		+1.35%	+23		-1.43%
Small						
Ambiguous	602	20	1.59	622	40	3.44
Unambiguous	628	18	3.27	620	44	2.78
Ambiguity Effect	+26		+1.68%	-2		-0.66%

Table 21 - *Experiment 1 Results – Late AoA words (AoA > 5.84)*

	High Connectivity			Low Connectivity		
Semantic Set	RT	*SD*	Error	RT	*SD*	Error
Large						
Ambiguous	650	42	3.57	636	35	3.74
Unambiguous	619	23	3.17	631	27	1.90
Ambiguity Effect	-31		-0.40%	-5		-1.84%
Small						
Ambiguous	662	47	1.59	637	18	2.91
Unambiguous	650	36	6.55	624	48	2.38
Ambiguity Effect	-12		+4.96%	-13		-0.53%

Table 22 - *Experiment 2 Results- Early AoA Words (AoA < 5.62)*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	634	30	2.14	648	29	2.14
Unambiguous	638	35	3.25	638	32	1.43
Ambiguity Effect	+4		+1.11%	-10		-0.71%

Table 23 - *Experiment 2 Results - Late AoA Words (AoA > 5.62)*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	680	51	3.57	682	56	3.52
Unambiguous	668	38	3.45	662	38	3.81
Ambiguity Effect	-12		-0.12%	-20		+0.29%

Table 24 - *Experiment 3 Results- Early AoA Words (AoA < 5.44)*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	635	42	3.14	636	45	1.62
Unambiguous	614	21	2.08	651	51	2.18
Ambiguity Effect	-21		-1.06%	+15		-0.56%

Table 25 - *Experiment 3 Results- Late AoA Words (AoA > 5.44)*

	Small			Large		
Stimuli	*RT*	*SD*	Error	*RT*	*SD*	Error
Ambiguous	660	28	2.23	686	48	2.40
Unambiguous	676	22	3.21	659	31	2.42
Ambiguity Effect	+16		-0.98%	-27		+0.02%

APPENDIX A

Materials used in Experiment 1

Large Semantic Set		Small Semantic Set	
High Connectivity	Low Connectivity	High Connectivity	Low Connectivity
Ambiguous			
Coast	Roll	Pen	Racket
Axe	Base	Meal	Bark
Drink	Pit	Sketch	Brush
Suit	Ticket	Ship	Cap
Toy	Grind	Sight	Calf*
Yellow	Blow	Bitter	Bank
Brass	Plain	Odd	Slip
Mate	Booth	Leaf	Cloud
Train	Tip	Suds*	Hound
Seal	Match	Stew	Perch
Sink	Pass	Pupil	Beam*
Swallow	Date	Purse	Draft
Grave	Tie	Shot	Switch
Diamond	Park	Temple	Rose
Iron	Card*	Coach	Rock
Cross	Trace	Spring	Count
Port	Chest	Shop	Bridge
Uniform	Craft	Article	Root
Speaker	Sentence	Kid	Palm
Bat	Fence	Stem	Novel
Unambiguous			
Burn	Vanity	Slim	Alter
Movie	Wire	Gem	Lamp
Pie	Zone	Youth	Profit
Vote	Maid	Pond	Dune
Pants	Rack	Vest	Pail
Farmer	Hole	Cab	Cone
Pink	Tube	Dinner	Link
Lab	Dragon	Shout	Itch
Damp	Dare	Huge	Win
Myth	Tree	Chill	Dog
Herb	Hay	Couch	Pencil
Cheat	String	Cent	Shoe
Potato	Drill	Task	Oak
Grow	Tiger	Bacon	Hat
Destroy	Clay	Goose	Mustard
Travel	Goat	Cattle	Jump
Poet	Gang	Ape	Beard
Bus	Launch	Dusk	Trout
Wool	Leather	Cab	Cattle
Pig*	Machine	Bloom	Scared

APPENDIX B

Materials used in Experiment 2

Large Semantic Set		Small Semantic Set	
Ambiguous	Unambiguous	Ambiguous	Unambiguous
Agency	Accident	Bitter	Bath
Bat	Boss	Cardinal	Brook
Block	Burn	Coin	Cash
Chicken	Carpet	Cool	Cow
Coast	Clam	Dough	Cube
Crab	Cloth	Film	Devil
Drug	Cookie	Foil	Dinner
Duck	Dirt	Fork	Jelly
Fan	Flute	Hearing	Lens
Fuse	Fog	Hog	Lung
Grave	Grape	Incense	Mall
Mark	Ham	Jam	Mist
Mate	Pie	Mad	Moss
Mole	Rain	Mug	Mule
Pig	Reward	Nickel	Navy
Rash	Scar	Organ	Oven
Rim	Shark	Pen	Planet
Seal	Soap	Plate	Pork
Speaker	Soul	Pupil	Salary
Suit	Stain	Ship	Shout
Swallow	Vote	Temple	Stove
Tense	Wolf	Text	Vest
Treat	Worm	Trip	Zoo
Tube	Bury*	Wound	Meal*
Uniform	Frog*	Suds*	Surf*

APPENDIX C

Materials used in Experiment 3

Large Semantic Set		Small Semantic Set	
Ambiguous	Unambiguous	Ambiguous	Unambiguous
Bat	Boss	Bitter	Bath
Block	Burn	Coin	Brook
Coast	Carpet	Cool	Cash
Crab	Cloth	Dough	Cow
Drug	Cookie	Film	Cube
Duck	Dirt	Foil	Devil
Fan	Fog	Fork	Dinner
Grave	Frog	Hearing	Jelly
Mark	Grape	Jam	Lens
Mate	Ham	Mad	Lung
Mole	Pie	Mug	Mall
Pig	Rain	Nickel	Mist
Rim	Reward	Organ	Moss
Seal	Scar	Pen	Navy
Suit	Shark	Plate	Oven
Tense	Soap	Ship	Planet
Treat	Stain	Temple	Pork
Uniform	Vote	Text	Shout
Fuse*	Wolf	Trip	Stove
Rash*	Worm	Wound	Zoo

Curriculum Vitae

McPhedran, Mark

EDUCATION

B.A. Psychology, Honours with Thesis
University of Windsor
September 2007 – June 2011
Honours Thesis: *Effects of Semantic Neighborhood Density on the Processing of Ambiguous and Unambiguous Words*
Supervisor: Dr. Lori Buchanan

GPA: 11.67
Major: 12.08

MSc. Psychology, Cognition & Perception
University of Western Ontario (UWO)
September 2012 – August 2014
Master's Thesis: *The Effects of Semantic Neighborhood Density on the Processing of Ambiguous Words*
Supervisor: Dr. Stephen Lupker

Academic Average: 85.5%

PhD. Psychology, Cognition & Perception
University of Western Ontario (UWO)
September 2014 – Present
Supervisor: Dr. Stephen Lupker

GRANTS, HONOURS, & SCHOLARSHIPS

2012-Present	Western Graduate Research Scholarship (WGRS)
2010-2011	President's Honour Roll
2009-2011	Dean's Honour Roll, Faculty of Arts & Social Sciences

EMPLOYMENT HISTORY

McDonald's Canada
April 2005 – September 2012
Worked as a basic crew member for seven years. My duties involved maintaining the lobby and the outside lot, stocking up supplies in the morning for lunch, and every now and then, working in the kitchen.

University of Western Ontario

Teaching Assistant
September 2012 – Present
My duties involve helping to proctor exams, working with Scantron data and marking, and holding office hours for my students to go over the coursework and exams, as well as answer any of their questions.

VOLUNTEER EXPERIENCE

Lose the Training Wheels
Spotter
August 2009, 2010
As part of a week-long program at the end of August, I was involved in a bike program that sought to teach people with disabilities to ride a two wheel bicycle in order to empower them towards becoming independent riders. My duties involved acting as a spotter for the riders, and helping to ensure that they were safe, while gradually teaching them to ride a two-wheeler.

Canadian Mental Health Association, Windsor-Essex County Branch (CMHA-WECB)
Volunteer Researcher
June – September 2011
Duties involved analyzing large bodies of clinical data for the CMHA Windsor-Essex branch as part of an evaluation of the effectiveness of their program at meeting the complex needs of their clients.

PRESENTATIONS

McPhedran, M., & Buchanan, L. (April, 2011). Effects of Semantic Neighborhood Density on the Processing of Ambiguous and Unambiguous Words. Paper presented at the Ontario Psychology Undergraduate Thesis Conference at the University of Guelph, Guelph, ON.

RESEARCH INTERESTS

- Semantic memory and lexical processing
- Visual word recognition, reading, and general psycholinguistic processes
- Synaesthesia and infant brain development