The Impact of Feedback Semantics in Visual Word Recognition: Number of Features Effects in Lexical Decision and Naming Tasks

Penny M. Pexman (pexman@ucalgary.ca)
Department of Psychology, University of Calgary
2500 University Drive NW, Calgary AB, T2N 1N4

Stephen J. Lupker (lupker@julian.uwo.ca)
Department of Psychology, The University of Western Ontario
London, ON, Canada, N6A 5C2

Yasushi Hino (hino@sccs.chukyo-u.ac.jp)
Department of Psychology, Chukyo University
101-2 Yagotohonmachi, Showaku, Nagoya, Aichi 466-8666, Japan

Abstract

The notion of feedback activation from semantics to both orthography and phonology has recently been used to explain certain semantic effects in visual word recognition, including polysemous effects (Hino & Lupker, 1996; Pexman & Lupker, 1999) and synonym effects (Pecher, in press). In the present research we tested an account based on feedback activation by investigating a new semantic effect: number of features (NOF). Words with high NOF (e.g., LION) should activate richer semantic representations than words with low NOF (e.g., LIME). Richer semantic representations should facilitate lexical decision task (LDT) and naming task performance via feedback activation to orthographic and phonological representations. The predicted facilitory NOF effects were observed in both LDT and naming.

Introduction

Although the average speaker or reader of English seldom notices it, the English language is actually quite ambiguous in its usage. For example, many English words are "polysemous", in that they have multiple meanings (e.g., BANK). Thus, deriving the intended meaning requires the use of context. These polysemous words have been a useful tool in psycholinguistic research since they allow researchers the opportunity to study the impact of semantic ambiguity on word recognition and reading.

There is now considerable evidence that semantic ambiguity produces a processing advantage in lexical decision tasks (LDT) and naming tasks. That is, responding in those tasks is usually faster to polysemous than nonpolysemous words (Borowsky & Masson, 1996; Gottlob, Goldinger, Stone, & Van Orden, 1999; Hino & Lupker, 1996; Hino, Lupker, Sears, & Ogawa, 1998; Jastrzembski, 1981; Jastrzembski & Stanners, 1975; Kellas, Ferraro, & Simpson, 1988; Lichace, Herdman, LeFevre, & Baird, 1999; Millis & Button, 1989; Pexman & Lupker, 1999; Rubenstein, Garfield, & Milikan, 1970). This effect has proven difficult to explain for current models of word recognition. For example, Joordens and Besner (1994) attempted to simulate polysemous effects using two PDP models but found that neither model was successful. The problem is that polysemous involves a one-to-many mapping between orthography and semantics and, thus, polysemous words should create competition in the semantic units. Because Joordens and Besner assumed that lexical decision performance depends on the settling time in the semantic units, the inevitable result was that this competition hindered, rather than facilitated, performance. That is, according to this and similar models, polysemous should produce a processing disadvantage in LDTs (for related discussions see Besner & Joordens, 1995; Kawamoto, Farrar, & Kello, 1994; Borowsky & Masson, 1996; Piercey & Joordens, 2000; Rueckl, 1995).

As Hino and Lupker (1996) argued, however, it is possible to explain polysemous effects within a PDP framework if slightly different assumptions are made. Following Balota, Ferraro, and Connor's (1991) basic argument, Hino and Lupker assumed that semantic activation feeds back to the orthographic units. That is, when a target word is presented, there is initially activation of an orthographic representation for that word. Very quickly, there is also activation of a semantic representation for the target word (and also activation of a phonological representation). The semantic representation then increases the activation of the orthographic (and phonological) representation via feedback connections. Because polysemous words (e.g., BANK) have a more extensive semantic representation than nonpolysemous words, polysemous words would produce more semantic activation than nonpolysemous words. Hence, the feedback activation from semantics to orthography should be stronger for polysemous words than for nonpolysemous words. As a result, the activation in the orthographic units for polysemous words should increase more rapidly than that for nonpolysemous words. Assuming that lexical decision responses are mainly based on orthographic activation, the expectation is that LDT responses should be faster for
polysemous than for nonpolysemous words, as is typically observed.

The explanation for polysemous effects in naming tasks is similar. For polysemous words, there would be considerable semantic activation, which would then help activate the phonological (as well as the orthographic) units. This semantic activation of phonological units could happen two ways: via feedforward connections for orthography-semantics-phonology linkages, and also via feedback connections for orthography-phonology-semantics-phonology linkages. In a naming task, it is assumed that responses are based on activation in the phonological units. Polysemous words would receive more phonological activation (via semantics), which would lead to a processing advantage in the naming task. Thus, according to Hino and Lupker (1996), polysemous effects in both tasks can be readily explained within a fully-interactive, PDP-type model of word recognition if feedback activation is assumed to play an important role in the process.

Note that certain models of word recognition do assume an important role for feedback connections. For example, Van Orden and Goldinger (1994; see also Stone, Vanhoy & Van Orden, 1997) argued for a system that incorporated both feedforward and feedback activation between sets of processing units. Additionally, in Seidenberg and McClelland’s (1989) PDP model, feedback connections were proposed, although they were never implemented. Feedback connections from semantic to orthographic units were also included in some of Plaut and Shallice’s (1993) simulations. Thus, models of this sort would be quite consistent with the existence of polysemous effects.

What should also be noted is that polysemous effects are not the only effects in the word recognition literature consistent with Hino and Lupker’s (1996) feedback activation account. For example, Pexman, Lupker, and Jared (2001) argued that a feedback activation explanation, involving feedback from the phonological to the orthographic units, was required in order to explain homophone effects. Homophones are words like MAID and MADE for which multiple spellings (and meanings) correspond to a single phonological representation. As had been typically reported (e.g., Rubenstein, Lewis, & Rubenstein, 1971), homophones produced longer lexical decision response latencies than control words in Pexman et al.’s experiments. These homophone effects were most apparent for low frequency homophones with high frequency homophone mates, and were larger in LDT when pseudohomophones (e.g., BRANE) were used as foils (as compared to pseudoword foils, e.g., PRANE).

In terms of the feedback activation account, homophone effects are assumed to be caused by a single phonological representation activating two orthographic representations (Pexman et al., 2001) while polysemous effects are presumed to be caused by multiple semantic representations activating a single orthographic representation (Hino & Lupker, 1996). That is, in spite of the fact that these two effects go in opposite directions, they are both presumed to be due to the basic architecture of the word recognition system (rather than being due to specific strategies). Pexman and Lupker (1999) argued that, if this account is correct, the two effects should occur simultaneously (i.e., in the same trial block) and both effects should be larger whenever there is increased opportunity for feedback to affect processing (i.e., when pseudohomophone foils are used). As predicted, Pexman and Lupker found that polysemous and homophone effects co-occurred and both were significantly larger with pseudohomophone foils than with pseudoword foils, supporting the feedback activation account.

One additional result that is consistent with Hino and Lupker’s (1996) account comes from Pecher’s (in press) examination of a different semantic factor: number of synonyms. Whereas polysemous words involve a many-to-one feedback mapping from the semantic units to the orthographic units (which helps increase the activation of the appropriate orthographic units), words with synonyms involve a one-to-many feedback mapping from the semantic units to the orthographic units. Thus, the feedback activation for a word with synonyms would tend to be dispersed to different orthographic representations, which should produce competition at the orthographic level. As a result, in contrast to the processing advantage created by polysemous words with synonyms should be at a processing disadvantage. Pecher reported that responses were slower for words with synonyms (e.g., JAIL) than for words without synonyms (e.g., MILK) in both LDT and naming, and explained these results in terms of feedback processes.

The purpose of present paper was to provide a new examination of the feedback activation account. Polysemous words, like BANK, have a number of different, relatively distinct, meanings. Thus, according to the feedback activation account, these words create considerable semantic activation and, hence, more feedback activation for the orthographic and phonological units, producing faster responding. A similar situation should arise with any words that create relatively more semantic activation, regardless of whether that activation corresponds to several distinct meanings. In order to examine this prediction, we investigated the effect of number of features in LDTs and naming tasks.

Semantic features are attributes or characteristics that describe the meaning of a word. For instance, for the word LAMP, its semantic features might include such things as “is bright”, “has light bulbs”, “produces heat”, “has a shade”, etc. The notion that word meanings can be represented by semantic features has been controversial (e.g., Keil, 1989; Medin, 1989; Rips, 1989). That is, concept representations seem to involve much more than feature information; including such things as general world knowledge about relations between features, and heuristics like essentialism (the notion that things like lamps have “essences”). McRae, de Sa, and Seidenberg (1997; see also McRae, Clee, Westmacott, & de Sa, 1999) suggested, however, that featural representations do play an important role at least the initial computation of word meaning. Based on the feedback activation account, it would be predicted that words with many features would produce
more semantic activation and, hence, more feedback to the orthographic and phonological units than words with few features. Thus, in LDTs and naming tasks, faster responding should be observed for words with a large number of features than for words with a small number of features.

The suggestion that word recognition may be faster for words with more semantic activation, or "richer" semantic representations, is not a new one. In previous research, effects of concreteness and/or imageability have been examined (e.g., Cortese, Simpson, & Woolsey, 1997; de Groot, 1989; James, 1975; Strain & Herdman, 1999; Strain, Patterson, & Seidenberg, 1995; Zevin & Balota, 2000), with results tending to show faster responding in LDTs and naming tasks for concrete or imageable words than for abstract words. It has been argued, in fact, that highly imageable or concrete words have richer semantic representations because they activate more semantic features than abstract words (Jones, 1985; Plaut & Shallice, 1993). According to the feedback activation account, however, activation of a larger number of semantic features should facilitate word recognition even when all of the stimuli are highly imageable. That is, even if all of the target words are concrete nouns, if some words activate more semantic features than others do, they should produce more rapid responding in word recognition tasks. Thus, there should be number of features (NOF) effects when concreteness and imageability have been controlled.

In this research we tested these predictions. Experiments 1A and 1B were LDTs, and 1C was a naming task.

Method

Participants
The participants in these experiments were undergraduate students at the University of Calgary. There were 40 participants in Experiment 1A, 38 in Experiment 1B, and 35 in Experiment 1C.

Stimuli
Words The word stimuli for Experiments 1A, 1B, and 1C, were selected from norms provided by Ken McRae (see McRae & Cree, in press). The McRae norms were collected by asking participants to list features for a large number of concrete nouns. Two sets of words were created: one set consisted of 25 words with low NOF and the other set consisted of 25 words with high NOF. These sets were matched on several dimensions. The mean values on these dimensions, for the selected sets of words, are listed in Table 1.

Foil s There were 60 pseudowords presented in Experiment 1A and 60 pseudohomophones presented in Experiment 1B.

Procedure
On each trial, a letter string was presented in the centre of a 17-inch Sony Trinitron monitor controlled by a Macintosh G3 and presented using PsyScope (Cohen, MacWhinney, Flatt, & Provost, 1993). In Experiments 1A and 1B, lexical-decision responses were made by pressing either the left button (labeled NONWORD) or the right button (labeled WORD) on a PsyScope response box. In Experiment 1C, naming responses were made into a microphone attached to a PsyScope response box.

Table 1: Mean Characteristics for Word Stimuli

<table>
<thead>
<tr>
<th>Word characteristic</th>
<th>Low NOF words</th>
<th>High NOF words</th>
<th>Difference test (df=48)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of features</td>
<td>12.00</td>
<td>20.40</td>
<td>-18.05**</td>
</tr>
<tr>
<td>Kucera &amp; Francis</td>
<td>10.80</td>
<td>14.32</td>
<td>&lt;1</td>
</tr>
<tr>
<td>(1967) frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subjective</td>
<td>3.84</td>
<td>3.97</td>
<td>&lt;1</td>
</tr>
<tr>
<td>Familiarity</td>
<td>1.68</td>
<td>1.07</td>
<td>&lt;1</td>
</tr>
<tr>
<td>Number of meanings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Word length</td>
<td>6.28</td>
<td>5.52</td>
<td>1.65</td>
</tr>
<tr>
<td>Number of syllables</td>
<td>1.80</td>
<td>1.56</td>
<td>1.25</td>
</tr>
<tr>
<td>Orthographic</td>
<td>3.00</td>
<td>3.64</td>
<td>&lt;1</td>
</tr>
<tr>
<td>Neighborhood size</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

** p < .001

Experiment 1A – Results and Discussion
For this experiment, mean response latencies and mean error percentages are presented in Table 2. In all experiments, data were analyzed with subjects (E1 or E1) and, separately, items (E2 or E2) treated as random factors.

For high NOF words, response latencies were faster and there were fewer response errors (compared to responses for low NOF words) and, thus, there were significant NOF effects in both the latency analysis (t(91) = 2.95, p < .005, SE = 3.13; t(48) = 1.40, p = .16, SE = 15.30), and in the error analysis (t(91) = 2.66, p < .01, SE = 7.92; t(48) = 1.17, p = .25, SE = 1.88).

The results of Experiment 1A demonstrated that participants could more easily make word/nonword decisions for high NOF words than for low NOF words. According to the feedback activation account, this advantage was due to the additional semantic activation created by high NOF words. This additional semantic activation provided stronger feedback to the orthographic representation for the word presented, enhancing the activation of its orthographic units and speeding responding. In order to examine this NOF effect further, we used pseudohomophones as foils in Experiment 1B. According to the feedback activation account, these foils make lexical decisions more difficult because they require participants to set a higher criterion for orthographic activation. This leads to longer response times for both words and foils and increases the opportunity for feedback activation to affect responding. Thus, if the NOF effect is due to feedback activation from semantics to orthography, the effect should be larger in Experiment 1B.
Table 2: Mean Lexical Decision Latencies and Mean Error Percentages for Experiments 1A and 1B

<table>
<thead>
<tr>
<th>Stimulus type</th>
<th>Experiment 1A (pseudoword foils)</th>
<th>Experiment 1B (pseudohomophone foils)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RT</td>
<td>Error %</td>
</tr>
<tr>
<td>High NOF word</td>
<td>525</td>
<td>2.9</td>
</tr>
<tr>
<td>Low NOF word</td>
<td>541</td>
<td>5.0</td>
</tr>
<tr>
<td>Foil</td>
<td>602</td>
<td>4.0</td>
</tr>
</tbody>
</table>

**p < .01

Experiment 1B – Results and Discussion
For this experiment, mean response latencies and mean error percentages are presented in Table 2.

As in Experiment 1A, response latencies were faster and there were fewer response errors for high NOF words, and so there was a significant NOF effect in the latency analyses (t(137) = 5.01, p < .001, SE = 7.28; t(48) = 2.01, p = .05, SE = 21.30), and in the error analysis (t(137) = 2.98, p < .005, SE = 0.78; t(48) = 1.18, p = .24, SE = 1.95).

In Experiment 1C we tested an additional prediction of the feedback activation account: because semantic activation also facilitates the activation of phonological units, high NOF words should also produce faster naming latencies.

Experiment 1C – Results and Discussion
For this experiment, mean naming latencies and mean error percentages are presented in Table 3.

Table 3: Mean Naming Latencies and Mean Error Percentages for Experiment 1C

<table>
<thead>
<tr>
<th>Stimulus type</th>
<th>RT</th>
<th>Error %</th>
<th>RT effect</th>
<th>Error effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>High NOF word</td>
<td>525</td>
<td>0.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low NOF word</td>
<td>555</td>
<td>1.4</td>
<td>-30**</td>
<td>-1.1*</td>
</tr>
</tbody>
</table>

*p < .05, **p < .01

For high NOF words, naming latencies were faster and there were fewer response errors, so there was a significant NOF effect in the latency analyses (t(34) = 10.36, p < .001, SE = 2.96; t(48) = 2.09, p < .05, SE = 16.38), and in the error analysis (t(34) = 2.33, p < .05, SE = 0.45; t(48) = 1.41, p = .16, SE = 0.83).

Again, responses were faster for words with high NOF. This suggests that semantic activation also provides strong feedback to the phonological units, facilitating naming responses.

Our 2 sets of words were not perfectly matched; there were slight differences between sets on several dimensions. To ensure that these differences were not the source of the observed effects, we conducted regression analyses. These analyses showed significant, unique effects of NOF for response latencies and response errors in Experiment 1A, response latencies (but not errors) in Experiment 1B, and naming latencies (but not naming errors) in Experiment 1C.

General Discussion
The present results demonstrate the influence of a previously unexamined semantic variable on visual word recognition. In the past, effects have been reported for concreteness and imageability (e.g., Cortese, Simpson, & Woolsey, 1997; de Groot, 1989; James, 1975; Strain & Herdman, 1999; Strain, Patterson, & Seidenberg, 1995; Zevin & Balota, 2000), and for polysemy (e.g., Borowsky & Masson, 1996; Gottlob et al., 1999; Hino & Lupker, 1996; Hino et al., 1998; Jastrzembski, 1981; Jastrzembski & Stanners, 1975; Kellas et al., 1988; Lichacz et al., 1999; Millis & Button, 1989; Pexman & Lupker, 1999; Rubenstein et al., 1970). The number of features effects reported here are independent of these effects. Our word stimuli were all concrete nouns, and were all nonpolysemous, differing only in terms of how many features participants ascribed to those words. Thus, our results provide support for the claim that it is the “richness” of a semantic representation that facilitates word recognition regardless of how that richness is created.

We have argued here that the NOF effects observed in our LDT and naming experiments (as well as a number of other semantic effects) support Hino and Lupker’s (1996) feedback activation account. A key issue to address is to what extent other models of semantic effects, in particular, polysemy effects, could explain our NOF effects.

Alternative Explanations
Kawamoto et al. (1994) reported a successful simulation of polysemy effects in LDT using a model in which it was assumed that: (a) lexical decision performance is mainly based on activation of the orthographic units and (b) as a result of learning with their particular error-correction algorithm, weights for connections between orthographic units were enacted differently for polysemous and nonpolysemous words. Polysemy was captured in the model by having two different semantic patterns linked to a
single orthographic pattern. This inconsistent orthographic-to-semantic mapping created weaker connections between orthography and semantics. As a result, connections among orthographic units became more important in producing the appropriate orthographic activation for polysemous targets. In contrast, for nonpolysemous targets, semantic activation played a major role in producing the appropriate level of orthographic activation.

With respect to NOF effects, however, there would seem to be no reason why the number of features would affect the strength of either orthographic-to-semantic mappings or the connections among orthographic units. Neither our low nor high NOF words involved any orthographic-to-semantic inconsistencies. Thus, the model would have no obvious way to explain a NOF effect.

Borowsky and Masson (1996) successfully simulated their polysemous effects with a model in which it was assumed that lexical decisions are made on the basis of the "familiarity for a letter string's orthography and meaning" (p. 76). The model was a Hopfield network, and familiarity was assumed to be represented by the summed energy within the orthographic and meaning modules, with this energy reflecting the extent to which the network had settled into a basin of attraction. Energy was higher for polysemous words than for nonpolysemous words, due to proximity. That is, in the model, all the meaning-level units were initially set to +1 or −1 in a random fashion. Each unit was then updated until the network moved into a correct pattern. The distance (or the number of units to be changed) from the initial pattern to the correct pattern was probabilistically smaller when there were two correct patterns of activation (i.e., for polysemous words) than when there was only one correct pattern (i.e., for nonpolysemous words). Thus, the network moved into a basin of attraction more quickly for polysemous words than for nonpolysemous words, explaining the polysemy effect observed in LDT.

With respect to NOF effects, regardless of how many features a word has, it has only a single correct pattern of semantic activation. Thus, words with many features would not benefit from proximity like polysemous words do. Therefore, as with Kawamoto et al.,'s (1994) model, this model would have no obvious way of explaining NOF effects.

It is possible that either of these models could be modified in a way that would allow them to explain NOF effects in LDT. In neither case, however, would the models provide as parsimonious an account as that provided by the feedback activation account. Further, in both cases, new assumptions would be needed to explain NOF effects in naming.

The results of the present experiments provide evidence that LDT and naming performance is faster for words with rich semantic representations, where richness is defined in terms of the number of semantic features activated. These effects suggest that word recognition performance will best explained by fully-interactive models involving both feedforward and feedback activation.

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References


