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On the origin of the "cumulative semantic inhibition" effect

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We investigated whether the cumulative semantic inhibitio effect found by Howard, Nickels, Coltheart, and Cole-Virtue (2006) provides information about semantic representations. By applying more sensitive statistical analyses to the original dataset, we found a significant variation in the magnitude of the effect across categories. This variation cannot be explained by the naming speed of each category. In addition, using a sub-sample of the data, a second cumulative effect arouse for newly-defined supra-categories, over and above the effect of the original ones. We discuss these findings in terms of the representations that drive lexical access, and show that they favor featural or distributed hypotheses.

In a recent article, Howard et al. (2006) reported a remarkable observation concerning lexical access during speech production. They asked speakers to name pictures of common objects presented in a continuous series of trials. The sequence of trials had an underlying structure; the members of a given category were separated by a variable, yet carefully controlled, number of trials. Such design allowed contrasting semantic effects driven by the ordinal position of every response within the sequence of items from its category, from those driven by the distance (in trials) between related items.[1] The remarkable observation was that the ordinal position within the category had a very systematic effect, whereas the distance of the previous related item (measured in trials) did not affect performance. The relationship between ordinal position and average naming latency was reported to be linear. A unit increase in ordinal position lead to an average increase of 30 ms in naming latency (95 confidence interval ± 8.2 ms). As shown in their Figure 1, the average latency data plotted against ordinal position are remarkably aligned.

In the theoretical discussion of this phenomenon, Howard et al. (2006) focus on the cumulative property of the effect. These authors rightly highlight that none of the current models of lexical access in language production predicts this observation. They then construct a working model of word selection involving a process of priming and competitive selection which simulates the observed cumulative effect. The purpose of this article is not the cumulative nature of this effect. Rather, we focus on the relatively undiscussed structure of the semantic representations[2] (for a modelization of these findings that builds on error-driven learning, see Oppenheim, Dell, & Schwartz, 2007, 2009; see also Navarrete, Mahon, & Caramazza, 2008). Howard et al.'s (2006) computational model includes non-decomposed localist semantic representations for each item. A model variant including decomposed semantic features was also tested. These alternative semantic representations are motivated by previous general hypothesis adopted in models of language production and are not explored in detail. The analysis they present suggests that both the localist and the distributed models are equally supported by the experimental data.

Our main question is whether the cumulative inhibition effect can be used to constrain theories of semantic representation. As we will show, the data reported by Howard et al. (2006) are in fact inconsistent with localist categorical representations. Our analysis further show how this effect could be used to assess the structure of distributed representations.

Howard et al. (2006) used a total of 24 categories (listed in their appendix). The use of such a large number of ensures a high statistical power for the analysis in which the ordinal position and distance parameters are contrasted. It also leads to considerable diversity in the definitions, with categories ranging from rather general sets (e.g. *buildings* or *furniture*) to more specific ensembles (e.g. *computer equipment* or *farm animals*). Despite this diversity in the definition of categories, the reported semantic cumulative effect is re-

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[1] More specifically, each list comprised 120 items drawn from 24 different categories (*i.e.* 5 items per category), plus a set of 45 filler pictures. The items of a given category were separated by 2, 4, 6 or 8 trials; this arrangement was counterbalanced across participants and categories.

[2] For consistency with the terminology used in the original study, we will refer to the effect as cumulative *semantic* inhibition. A possible contribution of visual factors will be mentioned in the General Discussion.

markably strong in the analysis "by categories", suggesting that it is not driven by a subset of the materials.

Our investigation will pay special attention to the role played by these categories in the observation of the effect. We will proceed in two steps, in which we will answer the following related questions:

1. Is the magnitude of the effect similar across the 24 categories, or does it show a systematic variability?

2. Is the effect better understood in terms of categorical representations of these particular categories, or in terms of a by-product of some other representational structure?

To answer the first question, we reanalyzed Howard et al.'s (2006) original dataset using a more sensitive technique. To answer the second question, we extended this analysis with newly defined categories replacing the original ones. Our analyses were based on the mixed-effect modelling methodology (Bates, 2005) recently introduced in psycholinguistics (Baayen, 2007; Baayen, Davidson, & Bates, 2008). This technique relies on single trial data, rather than on averages by participant, by category, or by ordinal position. This methodological choice yields two distinct benefits. First, it avoids an important shortcoming of the statistical analyses reported in the original article. As the authors acknowledge, there is a potential confound between ordinal position in the category and trial position in the experiment. The analysis performed to address this issue runs a risk of circularity. The effect of trial position was estimated on the dataset and reinjected as a corrective parameter in the same dataset. This procedure may have distorted the results.

Second, the additional benefit of the new method is that it allows to model explicitly the fixed *vs.* random nature of the different effects under consideration. As is shown below, this enables more detailed and robust analyses than it is possible with the traditional analysis techniques.

Variability of the cumulative inhibition effect across categories

By focusing on single trial data we were able to test, in a single analysis, the potential contributions of the different order and distance parameters that characterize every trial of the experiment. Furthermore, this analysis enables the investigation of a question that was not addressed in the original study, namely possible systematic variations in the magnitude of the cumulative inhibition effect across categories.

Linear analysis of the dataset

We obtained the dataset used in the original study. This dataset comprised a total of 2568 trials (after the exclusion of filler trials, errors and responses identified as outliers). The individual naming latencies were log-transformed using the natural logarithm to reduce skewness and approach a normal distribution, then fitted to three linear mixed effect models with different combinations of fixed, random, and mixed effects. The predictors were added sequentially into these three models in the order in which they are mentionned below.

The first model, referred to as *Hh-model 1* for *Howard's hypothesis modelling*), was intended to test the same hypothesis as Howard et al. (2006), namely that there is a main linear effect of ordinal position in the category independent of the lag between related trials and of the position of the trials in the experiment. We defined as fixed effects the factors of theoretical interest, namely the *Ordinal position* in the category and the *Lag* between the current trial and the previous trial from the same category, as well as *Trial number* (i.e. the ordinal position in the experiment). In addition, to be able to handle trial-level data, participant and item identity were explicitly included as random effects in the model. As can be seen on the first row of Table 1, Ordinal position has a significant inhibitory effect, and no evidence is found for influences of Lag or Trial number. In *Hh-model 2* (second row of Table 1), the effect of Trial number was allowed to vary between participants (see Howard et al., 2006). This was done by including an interaction between the fixed effect of trial number and the random effect of participant (i.e., a mixed-effect). A formal comparison of *Hh-model 1* and *2* (namely, a log-likelihood test) shows a significant improvement in the model's fit ($\chi^2(1) = 13.6$, $p = .001$) while the estimates for the theoretically relevant predictors remain largely unaffected. Together, these results are fully concordant with those of Howard et al. (2006).

More interestingly, in the third model (*Hh-model 3*), we further estimated the cross-categorical variability of the linear cumulative semantic inhibition effect. To do so, we included *Categories* as an additional random effect, on top of participants and items. This new random effect has 24 levels under which the items are nested. We computed its main random effect, as well as its interaction with the inhibitory fixed effect of Ordinal position (i.e., a mixed-effect). The main effect estimates possible systematic contributions of the categories over and above the items that compose them. The interaction with Ordinal position provides an estimate of the systematic variation in the amount of cumulative semantic inhibition produced specifically by each category.

Table 1
Comparison of the fixed effects in linear mixed effect models of the log-transformed naming latency in the full dataset (2568 observations from 24 participants naming 120 items in 24 categories). β in log-scale.

Hh-model[a]		Fixed effect		
		Ordinal position	Lag	Trial number
	β	$3.81 \cdot 10^{-2}$	$5.18 \cdot 10^{-4}$	$2.26 \cdot 10^{-4}$
1	$t(2564)$	7.22	.20	1.55
	p	$< .001$	.84	.12
	β	$3.80 \cdot 10^{-2}$	$6.59 \cdot 10^{-4}$	$2.17 \cdot 10^{-4}$
2	$t(2564)$	7.25	.26	.97
	p	$< .001$	.80	.33
	β	$3.87 \cdot 10^{-2}$	$7.16 \cdot 10^{-4}$	$2.09 \cdot 10^{-4}$
3	$t(2564)$	5.51	.28	.94
	p	$< .001$	.78	.35

[a]Hh-model: Howard's hypothesis modelling.

The comparison of the models' estimates in Table 1 indi-

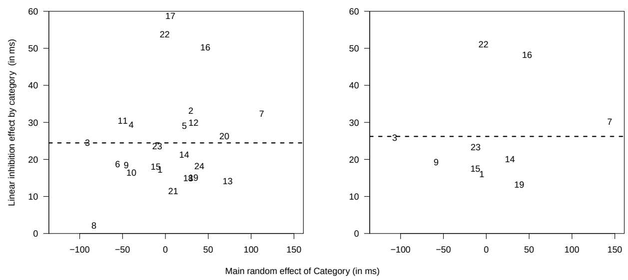

Figure 1. Estimates of the random intercept of *Category* (x-axis) and the mixed interaction between *Category* and *Ordinal position* (y-axis) for each of the original categories.Larger values in the x-axis indicate slower categories. Larger values in the y-axis indicate stronger coefficients for the linear semantic effect (*i.e.* stronger inhibition). Each data point is a category (see Appendix for details). *Left*: complete data set (Hh-model 2). *Right*: subset used in the second analysis (N-model 1). The magnitudes and relative orderings of these random effect estimates have been validated using a bootstrapping technique (N = 100; Efron, 1979)

cates that the magnitude and significance of the main linear semantic effect is largely unaffected by the inclusion of this new random factor. A formal comparison between models by means of a log-likelihood test shows a significant improvement of the model's fit, both from the inclusion of a variable intercept across categories ($\chi^2(1) = 13.0$, $p < .001$) and from a variable ordinal position effect across categories ($\chi^2(1) = 16.5$, $p < .001$). This indicates that, while it is true that there is a main inhibitory effect of the ordinal position within the category, valid on average for all categories, two additional factors not reported by Howard et al. (2006) need to be considered. On the one hand, there is a significant random effect of category, meaning that items in some categories are systematically faster than items in other categories. On the other hand, the amount of inhibition provided by each occurrence of an item within a category shows significant systematic variation across individual categories: Some categories produce consistently more inhibition than others.

To clarify this finding, the main random effect of Categories and its interaction with Ordinal position are plotted on the left panel of Figure 1. Three findings are noteworthy. First, the overall speed for each category presents a considerable degree of variability, which is estimated over and above item variability. Secondly, while all of the coefficients are positive, there is also a significant variability in the magnitude of the linear cumulative effect across categories. This indicates that every single category contributes to the cumulative inhibition effect (with the possible exception of category 8, *Body parts*). Finally, the main speed of a category is unrelated to its contribution to the semantic cumulative effect, with no evidence for a correlation between the two estimates (r = .15, $t(22)$ = .69, p = .49).

Discussion

The analysis we computed over the original dataset provides a confirmation of the observations made by Howard et al. (2006) on the basis of data averaged by participants, items and categories. They further show that the linear cumulative semantic inhibition effect is present for all the categories that were tested(with one possible exception). In other words, the cumulative semantic inhibition effect is in no way a consequence of the trial position of successive members of a category, or a consequence of averaging across a heterogeneous dataset. In addition, two new issues have arisen from our analyses. First, there is a systematic variation in the overall speeds of items belonging to different categories. Second, and more important, there is also a systematic variation in the strength of the cumulative semantic inhibition across categories. Finally, the overall speed with which the members of a category are named is unrelated to the strength of the cumulative inhibition shown by that category. Therefore we cannot conclude that the variability in the size of the cumulative effect is a mere consequence of variations in naming speed. One possible origin of the variation in cumulative inhibition effect across categories may be the relationships among the items that compose the categories. The theoretical interpretation of these findings will be addressed in more detail in the General Discussion. For now, these observations set the stage for a deeper exploration of the effect on a subset of the data.

Contrastive hypothesis about the cumulative inhibition effect

The second analysis we report investigates the representational status of some of the categories used in the original study. Our first analysis showed that all of these categories produce a sizeable cumulative inhibition effect. Does this mean the categories should be understood, in any strong sense, as representational categories in the speakers' cognitive system? Although a positive answer to that question would be rather surprising (e.g.*zoo* and *farm animals* were distinguished; *white goods* is a category in itself), the question is a useful anchor point for our rationale.

An inspection of the list of materials shows that at least 10 categories allow a natural regrouping in pairs of "co-categories" under a "supra-category" (Table 2). This property allows manipulating the structure of the categories used to analyze the data, and hence to provide answers to the question above. If two co-categories are representationally independent, then naming the members of one of them should not affect how the members of the other are named anymore than having named any other items. For example, the speed of naming of *farm animals* should be independent of whether *zoo animals* (or *buildings*) were named before or not. By contrast, if the items of co-categories share part of their representation, such influence should be apparent in the naming performance. In the latter case the relative contributions of supra- and co-category groupings might be clarified.

We report a series of analysis on a subset of the original data in which only the materials listed in Table 2 were in-

Table 2
Regrouping of a subset of the original items in supra-categories.

Co-categories	Members	Supra-cat.[a]	Motivation	N[b]
Farm animals	cow, donkey, horse, pig, sheep	Mammals	All are mammals	10
Zoo animals	gorilla, monkey, hippo, tiger, elephant			14
Clothes	bra, jacket, pyjamas, skirt, sock	Clothing	All items are worn	11
Headgear	beret, cap, crown, hat, helmet			13
Fish	eel, goldfish, shark, stingray, swordfish	Sea creatures	All live in the sea	14
Shellfish	crab, lobster, mussel, oyster, prawn			10
Computer equipment	computer, joystick, keyboard, mouse, printer	Electronic equipment	We watch TV on computers and we browse networks on TVs	13
Audio-visual	headphones, microphone, radio, speaker, TV			11
Fruits	apple, banana, lemon, pear, orange	F & V	Never dissociated in patients[c]	14
Vegetables	broccoli, carrot, cauliflower, onion, potato			10

[a] cat. = category
[b] N = participants (/24) that named that co-category before the other one
[c] Capitani, Laiacona, Mahon, and Caramazza (2003)

cluded. We proceed in three steps. First, we show that the original effect of interest is similarly present in the restricted dataset. Second, we show that having named the co-category earlier in the experiment affects naming latencies in a systematic fashion. Finally, we contrast two assumptions about the underlying representations that may cause the influence of co-categories on one another.

First step: Is the cumulative inhibition effect present in the restricted dataset?

The data from the ten categories of Table 2 were entered in a linear regression model very similar[3] to *Hh-model 3*. This model is summarized under *N-model 1* (for *New hypothesis modelling*) on Table 3. The linear inhibition effect driven by Ordinal position is also present in this restricted dataset, with an estimated size of the same order of magnitude than in the complete dataset. This conclusion is strengthened by an inspection of Figure 1, which shows that individual estimates of the inhibition effect for each of the categories in the restricted data set (right panel) are very similar to those obtained previously from the complete dataset (left panel). Here again there is a significant increase of the model's fit with the inclusion of a variable intercept across categories ($\chi^2(1) = 5.99$, $p = .014$) and a variable ordinal position effect ($\chi^2(1) = 5.08$, $p = .025$). The estimate of *N-model 1* for the Ordinal position effect is plotted in the leftmost panel of Figure 2.

In contrast to the full dataset analyses, trial position produced a significant effect in the restricted dataset of *N-model 1*. This result will be discussed below in relation to the manipulations concerning the relative position of co-categories. For the rest, the restricted dataset provides a robust and safe testing ground for the hypotheses stated above about the mutual influence of co-categories on the cumulative inhibition effect.

Second step: Is there a dependency between co-categories?

The pairs of co-categories summarized in Table 2 may, or may not, be sub-served by common representations. If two co-categories are independent, naming the items of one of them should be independent of whether the members of the co-category have been named before or not. By contrast, if two co-categories have a common underlying representation, then the category that is presented second should be slowed down by the previous naming of its co-category. We test this prediction by differentiating co-categories on the basis of the order in which they were named in the experiment. For this test to be possible, two precautions need to be taken.

First, the order in which categories were presented across participants has to be checked. The last column of Table 2 summarizes the relative position of each of the two co-categories. The order in which they were presented in the experimental lists is relatively well balanced across participants. Furthemrmore, in most cases, the two co-categories were non-overlapping in the stimulus sequence. Any effect observed for co-categories presented second can therefore be attributed to their position in the experimental list, rather than to the specifics of the items that compose them.

[3] The variables Lag between trials and Lag between co-categories were included in previous versions of the analysis. They never contributed significantly, and hence are omitted here for simplicity.

Table 3
Comparison of estimated parameters in various linear regression models of the log-transformed naming latency in the restricted dataset (1056 observations from 24 participants naming 50 items in 10 categories). β in log-scale

			Fixed effects				
Step	N-model[a]		Position of…			Ordinal within…	
			trial	start of cat.[b]	co-cat.	cat.	supra-cat.
1^{st}	1	β	$5.88 \cdot 10^{-4}$			$4.28 \cdot 10^{-2}$	
		$t(1053)$	2.48			4.13	
		p	.013			<.001	
2^{nd}	2	β	$-1.22 \cdot 10^{-4}$	$2.28 \cdot 10^{-4}$	$6.47 \cdot 10^{-2}$	$4.73 \cdot 10^{-2}$	
		$t(1051)$	-.05	.10	2.56	3.07	
		p	.96	.92	<.01	< .01	
	3	β			$7.00 \cdot 10^{-2}$	$4.68 \cdot 10^{-2}$	
		$t(1053)$			3.56	4.49	
		p			<.001	<.001	
3^{rd}	4	β	$7.68 \cdot 10^{-5}$			$3.07 \cdot 10^{-2}$	$1.38 \cdot 10^{-2}$
		$t(1052)$	.25			2.61	2.54
		p	.80			<.01	.01
	5	β				$3.02 \cdot 10^{-2}$	$1.47 \cdot 10^{-2}$
		$t(1053)$				2.61	3.55
		p				<.001	<.001

[a] New hypothesis modelling
[b] cat. = category

Secondly, the absolute position of each co-category within each experimental list has to be controlled. Obviously, the second co-category will always be presented later in the experiment. If there is a systematic variation of performance with trial position (see, for example, the suggestive effect of trial position in *N-model 1* above), it should be taken into account when interpreting relative category position. This was done by considering three related predictors. The first one, used previously, was the position of the trials in the list. The second predictor measured the absolute position of the category within the experimental list. It is defined as a constant number for all the members of a co-category, namely the trial number of the first item of the category. Finally, we introduced the critical predictor capturing the relative position of twp co-categories, with values 1 (*vs.* 0) when the co-category had (*vs.* had not) been named before. We also included the predictor of theoretical interest, ordinal position within the co-category.

N-model 2 shows that the effect of ordinal position within the category was significant. More importantly, the relative position of the co-category had a strong and significant effect, whereas the absolute position of the trial, or the absolute position of the category were not significant. This result indicates that the relative position of the co-category is indeed the best predictor of naming latencies, better than trial position or category position. A secondary analysis clarifies that this result is not due to trial position being a less efficient predictor than category relative position. We re-paired the co-categories randomly in 5 pairs 2000 times. Of those, 257 sample lists contained unrelated co-category pairs only. For these 257 samples, we estimated the effect of trial position vs. relative position given the new pairings. Trial position produced a significant effect ($t > 1.65, p < .05$) for 73% of the samples; "unrelated" category relative position was significant for only 7.4% of the samples, and in all cases the estimated relative position effect went in the opposite direction (second category faster) to what we observed in *N-model 2* with properly related pairs.

This finding also clarifies why trial position may have been significant in the restricted dataset (*N-model 1*) and not in the complete dataset (e.g. *Hh-model 2*). The restricted dataset includes only categories whose second occurrence is slowed down by their previously presented co-category. By contrast, the complete dataset includes many categories that did not have a co-category named earlier.

Summing up, this second analysis reveals a clear dependency between co-categories which is not due to the absolute position of the trials in the experiment, and which is observed over and above the effect of ordinal position within category. This is summarized in *N-model 3*, where only significant variables were included. The occurrence of the second co-category is slower than the first one, by an order of magnitude that is similar to the effect of ordinal position within category. It should be noted that the variable magnitude of the cumulative inhibition effect does not reach significance in these two models. Whether this is a mere consequence of the reduction in power of the analysis or a reflection of a theoretically meaningful observation remains an open question.

A very simple explanation for the dependency between co-categories would state that co-categories are in fact one single category, namely the supra-category listed in Table 2. In this view, going from the end of one co-category (e.g. 5^{th}

farm animal) to the beginning of its co-category (e.g. 1^{st} *zoo animal*) is equivalent to increasing by one the ordinal position of the item in the corresponding supra-category. If this were an appropriate description of the data, then the cumulative inhibition effect should make trials at the beginning of the second co-category be slower than trials at the end of the first co-category. A quick approximating test of this hypothesis (dataset size = 215 trials) shows, if anything, the opposite pattern. The 1^{st} trial of the 2^{nd} co-category is *faster* than the 5^{th} trial of the 1^{st} co-category ($t(212) = -2.15$, $p = .033$), irrespective of their inter-trial lag ($t(212) < 1$). This finding suggests that the effect of relative position of co-categories may be more than a simple accumulation of inhibition within a supra-category.

Third step: Are co-categories better described as a single encompassing category?

In this third step, we test more formally whether the two co-categories can be functionally reduced to a single supra-category. This account makes a clear prediction. Ordinal position within the supra-category (range: 1 – 10) should produce a significant effect that should absorb the effect of ordinal position within the (original) category (range: 1 – 5). A representation of the prediction of such a model is plotted on the rightmost panel of Figure 2. Alternatively, the slowing down of the co-category occurring second may not be due to the items belonging to a single category. The underlying representation of items that share a single feature or property within and across co-categories may be responsible for the effect. An example of such a feature for the co-categories *farm* and *zoo animals* could be *four-limbed animal* or *mammal*. This alternative account also makes a clear prediction. Ordinal position within the supra-category (range: 1 – 10) should produce a significant effect *in addition to* the previously reported effect of ordinal position within the (original) category (range: 1 – 5).

These alternative predictions were tested in *N-models 4* and *5* reported in Table 3. The estimates of *N-model 4* show that *both* the ordinal position within the supra-category and the ordinal position within the original category have independent significant inhibitory effects. The effect of supra-category cannot be ascribed to trial position, which was also included in the model. *N-model 5* reports the estimates when only the significant variables are considered in the model[4]. The combined estimated effects of ordinal position within co-category and ordinal positions within supra-category are plotted in the right-center panel of Figure 2. In summary, this third step establishes that the ordinal position within the supra-category has a significant inhibitory effect over and above a significant effect of ordinal position within the (original) category.

Discussion

The analysis of single trial data using linear mixed-effects models has equipped us with sufficient statistical power to analyze a subset of the original data with models similar to those used for the complete dataset. These analysis are based on the plausible pairings of categories summarized in Table 2. They indicate that, at least for the items under consideration, the semantic cumulative inhibition effect is not restricted within categories.

The plots on the left and right panels of Figure 2 illustrate the cumulative inhibition effect for models that consider a single level of category (respectively: when the only the co-category or only the supra-category levels are considered). The middle panel plots the model where the dependency between co-categories is captured by both predictors. Our analyses enable us discarding both single category models in terms of their predictive accuracy. The predictions are significantly better when both representational levels are considered.

Notice that statistics alone are not sufficient to disentangle the two models where co-categories depend on one another (namely, the 2^{nd} and 3^{rd} steps Table 3), as they both produce equally good predictions for this dataset. One way to resolve this issue would be to consider a hypothetical experiment where co-categories would be intermixed. The definition and predictions of the model with two ordinal factors at the two levels are straightforward, and our interpretation of the results described above leads to a distinct prediction. The middle panel of Figure 3 should be the better description of the results, over and above the left and right panels. The prediction depicted in this panel is an ordinal inhibition effect between items of any co-category *plus* an ordinal inhibition effect of different magnitude between successive trials belonging to two different co-categories. In contrast, defining which co-category comes first when co-categories are intermixed in the experiment would require additional assumptions. For this reason, the model with two ordinal factors may be preferred. Pending further evidence, however, we will simply draw the important conclusion that the dependency between co-categories is not reductible to supra-category.

General discussion

The cumulative inhibition effect reported by Howard et al. (2006) is present across categories. This confirms the robustness of their finding when random variation is explicitly taken into account, and the relative contibutions of ordinal position in the category and trial position in the experiment are considered simultaneously. On top of this, our analyses have added some facts that were not previously considered. We found a significant variation in the magnitude of the cumulative effect. This variation is independent of the variation in overall speed across categories. In the restricted dataset, a further cumulative effect was found for newly-defined supra-categories, over and above the original ordinal position effect within co-categories. These depper analysis and new findings allow contrasting theories of semantic representation, to better understand the involvement of these representations in lexical access.

From a methodological perspective, our analyses argue in favour of using single-trial information, instead of averaging

[4] As was the case in step two, the variable magnitude of the cumulative inhibition effect does not reach significance in this analysis

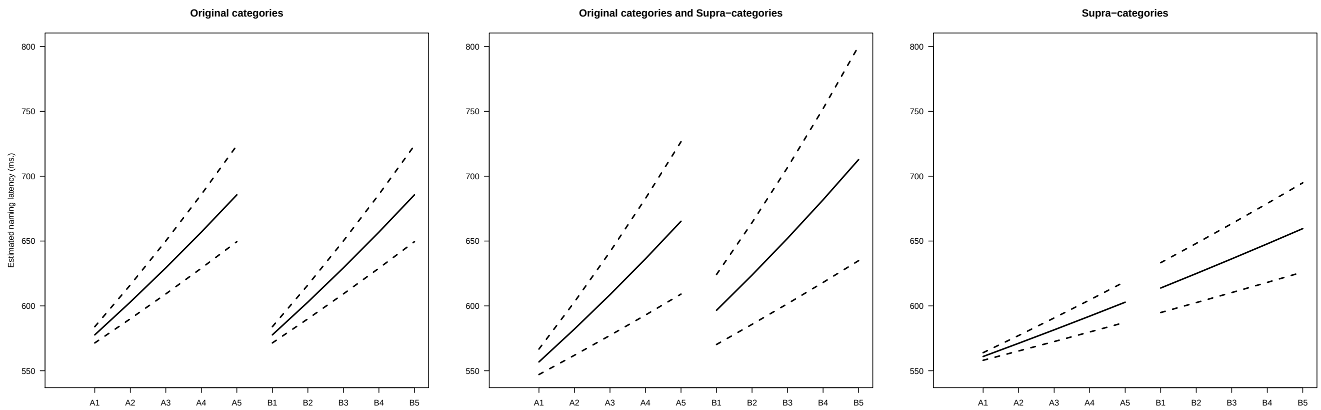

Figure 2. Estimated performance, with standard errors, for the members of two co-categories (A and B) in different models instantiating different hypothesis. A rationale for choosing among models is described in the General Discussion.*Left*: both co-categories are independent; their ordinal positions produce independent significant effects (N-model 1). *Center*: the co-categories depend on one another; both the ordinal position in the original categories and in the supra-category produce independent significant effects (N-model 5). *Right*: the co-categories are in fact a single supra-category; only ordinal position within the supra-category produces a significant effect (model not reported).

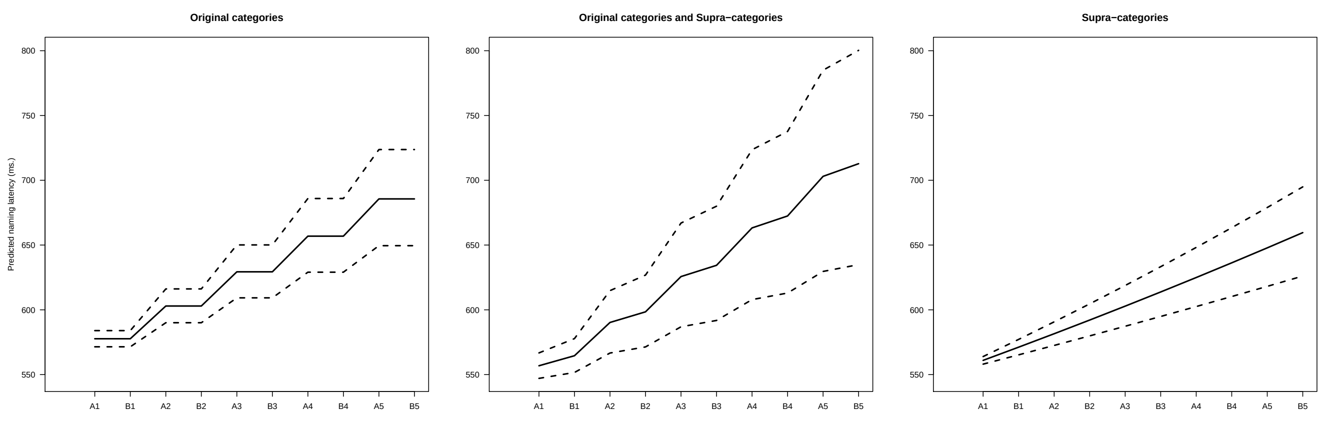

Figure 3. Predicted performance, with standard errors, for the members of two co-categories (A and B) interleaved in the experimental lists, for different models instantiating different hypothesis. *Left*: both co-categories are independent. *Center*: the co-categories depend on one another such that both the ordinal position in the original categories and in the supra-category produce independent significant effects. *Right*: the co-categories are in fact a single supra-category such that only ordinal position within the supra-category produces a significant effect.

performance across levels. This is especially true in the case at hand, where non counter-balanceable absolute and relative positions of individual trials have to be taken into consideration simultaneously to understand the data. Thus, our first conclusion is methodological. We have shown how the mixed effect methodology that Baayen et al. (2008) introduced for language comprehension studies provides a powerful tool also for language production studies.

From a theoretical perspective, the results of our analyses enrich the conclusions of Howard et al. (2006) in several ways. The first important observation is the significantly variable inhibition effect across categories. The fact that it is unrelated to overall speed indicates that this variation does not reflect a mere performance effect. One plausible explanation for this variation may come from some intrinsic property(ies) of the categories in question. Our analysis was conducted *post-hoc*, hence such properties were not manipulated explicitely. However several dimensions come to mind, which have been previously proposed to characterize diffferentialy the relationships between members of different categories: *structural similarity* across the members of a category (Humphreys, Riddoch, & Quinlan, 1988); *degree of correlation* of features accross the category (Caramazza, Hillis, Rapp, & Romani, 1990; McRae, de Sa, & Seidenberg, 1997; Moss, Tyler, & Taylor, 2007); *semantic distance* within and accross categories (Vigliocco, Vinson, Lewis, &

Garrett, 2004), etc. Testing the link between one or several of these dimensions to the amount of sematic cumulative inhibition would provide useful tool for contrasting these hypothesis. In previous research, the effect of semantic distance has been tested with other picture naming paradigms. Some authors have reported worse performance when the target and context words were semantically closer (Vigliocco, Vinson, Damian, & Levelt, 2002). Others, however, have observed that reducing semantic distance (or typicallity) had no effect (Lupker, 1979) or a facilitatory effect (Mahon, Costa, Peterson, Vargas, & Caramazza, 2007). Further *ad-hoc* studies using the simple picture naming task employed by (Howard et al., 2006) may contribute to clarify the relative contributions of these parameters, and their role in the cumulative inhibition effect.

The second important observation is the fact that more than one grouping parameter (i.e. "category") is needed to account for the performance. As shown by our second analysis, a categorical representation of the items that relies solely on one level of abstraction – be it the level of co-categories, or the level of supra-categories – would not capture the whole pattern of cumulative inhibition. This fact supports a hierarchical representation in which individual items belong to more than one semantic (or structural) nesting level. It excludes strict localist hypothesis, such as those implemented in the working model proposed by Howard et al. (2006), or other versions. It may not exclude, however, more sophisticated implementations of localist representations whose connexion weights or numbers code for properties elsewhere termed features (e.g., Page, 2000). In these cases, the difference between localist and distributed representations is not straightforward. For instance, Moss et al. (2007) and Vigliocco and Vinson (2007) note that most proposals now favour featural or distributed representations in one way or another (Lambon Ralph, McClelland, Patterson, Galton, & Hodges, 2001; McClelland & Rogers, 2003; McRae et al., 1997). This being said, the analysis we report was constrained by the categories available in the original study, yielding only two nesting levels that were statistically tractable. Yet this was sufficient to indicate that the cumulative inhibition effect is a useful tool for testing the structure of the representational network involved in lexical access. Testing if more than two levels of abstraction ultimately modulate performance, should contribute to clarify the hierarchical organization the representations driving lexical access.

One final point should be raised about the nature of the cumulative inhibition effect. Following Howard et al. (2006), we have modelled the effect with linear predictors (we did not observe any non-linear components reaching significance). The positive correlation between mean response times and the corresponding variance across conditions makes it impossible to model the data as arising from a linear additive model. It is for this reason that we log-transformed prior to analysis. Note that this transformation implies a non-linear, non-additive effect in the natural scale. This would seem to contrast with the original finding of a linear additive trend. The limited range of variation of the observed values makes these two alternatives virtually indistinguishable (the range in the log-transformed data was $[5.53, 7.58]$). However, we would expect to observe deviations from linearity in datasets with wider ranges of ordinal category positions (i.e., above 5). In other words, a linear effect of magnitude 26 ms may become unrealistic for item groupings comprising ten or more items. The apparently linear effect may prove to be non-linear after all.

In conclusion, we report an investigation of the cumulative semantic inhibition effect reported by Howard et al. (2006). Where these authors reported a single regression line, we showed that a richness of systematic variations can be observed and, more importantly, predicted. These are better understood in terms of featural or distributed representations driving lexical access. Our analysis further shows how these variations and predictions can be fruitfully used to confront current theories of semantic representation on quatitative basis.

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Appendix
Names of the original categories

1	Zoo animals	9	Clothes	17	White goods
2	Birds	10	Tableware	18	Reptiles and amphibians
3	Fruits	11	Furniture	19	Vegetables
4	Musical instruments	12	Bugs	20	Buildings
5	Tools	13	House parts	21	Celestial phenomena
6	Transport	14	Computer equipement	22	Headgear
7	Fish	15	Farm animals	23	Audio-visual
8	Body parts	16	Shellfish	24	Landscape features

[a] The numbers are those used on Figure 1. For details on the category members see Howard et al. (2006)