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Short Communication

Language production is facilitated by semantic richness but inhibited by semantic density: Evidence from picture naming

Milena Rabovsky [a,*], Daniel J. Schad [b], Rasha Abdel Rahman [a]

[a] Department of Psychology, Humboldt-Universität zu Berlin, Germany
[b] Charité, Universitätsmedizin Berlin, Germany

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ABSTRACT

Communicating meaningful messages is the ultimate goal of language production. Yet, verbal messages can differ widely in the complexity and richness of their semantic content, and such differences should strongly modulate conceptual and lexical encoding processes during speech planning. However, despite the crucial role of semantic content in language production, the influence of this variability is currently unclear. Here, we investigate influences of the number of associated semantic features and intercorrelational feature density on language production during picture naming. While the number of semantic features facilitated naming, intercorrelational feature density inhibited naming. Both effects follow naturally from the assumption of conceptual facilitation and simultaneous lexical competition. They are difficult to accommodate with language production theories dismissing lexical competition.

1. Introduction

Language production ultimately aims to convey meaning. However, even at the level of single words verbal messages differ widely in the richness of their semantic representations and in the density of the regions they inhabit in semantic space. For instance, verbal concepts can transport a relatively high or low number of semantic features associated with them, and they can co-activate a relatively big or small number of related meaning alternatives. Given the key role of meaning in language production, such differences in the semantic richness or density of verbal messages should strongly modulate conceptual and lexical encoding processes. The aim of the present study was to describe how speech planning is shaped by the richness and density of the planned message.

In language comprehension research semantic richness has often been quantified by the number of semantic features (NOF; e.g. mouse – *is small*, *has four legs*, etc.) associated with a concept based on empirical semantic feature production norms (McRae, Cree, Seidenberg, & McNorgan, 2005), yielding facilitatory effects in different comprehension tasks such as lexical decisions, semantic categorizations, and self-paced reading (e.g., Pexman, Holyk, & Monfils, 2003; Pexman, Lupker, & Hino, 2002; Rabovsky, Sommer, & Abdel Rahman, 2012a, 2012b). In contrast, semantic factors in language production research are often investigated by manipulating the contexts in which identical messages are produced, rather than contrasting item-inherent attributes of different utterances (but see Bormann, 2011). For instance, the simultaneous presentation of a semantically related distractor word accompanying a to-be named picture in the picture–word interference (PWI) paradigm (e.g., Glaser & Glaser, 1989; La Heij, 1988; Lupker, 1979; Schriefers, Meyer, & Levelt, 1990), a semantically homogeneous composition of objects in the semantic blocking paradigm (Belke, Meyer, & Damian, 2005; Damian, Vigliocco, & Levelt, 2001; Kroll & Stewart, 1994), or the previous experience of naming objects from the same semantic category (Howard, Nickels, Coltheart, & Cole-Virtue, 2006) slows down naming times compared to unrelated distractor and block conditions. Facilitative influences of semantic context have also been observed (e.g., Abdel Rahman & Melinger, 2007; Alario, Segui, & Ferrand, 2000; Costa, Alario, & Caramazza, 2005; La Heij, Dirkx, & Kramer, 1990). Most production theories share the assumption that semantic contexts can induce facilitative priming of the target at the conceptual (Abdel Rahman & Melinger, 2009b; Costa et al., 2005) or lexical level (Mahon, Costa, Peterson, Vargas, & Caramazza, 2007), resulting in faster activation of the target concept and its lexical

* Corresponding author at: Department of Psychology, Stanford University, 450 Serra Mall, Stanford, CA 94305, USA.
E-mail address: rabovsky@stanford.edu (M. Rabovsky).

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representation. However, they are at variance concerning why interference overrides facilitation in some situations but not in others. Specifically, there is an active debate as to whether lexical selection is competitive, as traditionally assumed (Abdel Rahman & Melinger, 2009a, 2009b; Hantsch & Maedebach, 2013; Jescheniak, Matushanskaya, Mädebach, & Müller, 2014; Jescheniak, Schriefers, & Lemhöfer, 2014; Levelt, Roelofs, & Meyer, 1999; Roelofs, Piai, & Schriefers, 2013a, 2013b; Starreveld, La Heij, & Verdonschot, 2013) or whether interference effects are due to alternative mechanisms (Costa et al., 2005; Finkbeiner & Caramazza, 2006; Janssen, 2013; Mahon & Caramazza, 2009; Mahon et al., 2007; Navarrete & Mahon, 2013).

The swinging lexical network proposal as a variant of competitive models assumes that semantic contexts cause conceptual priming and lexical competition simultaneously, and that the trade-off between conceptual facilitation and lexical competition crucially depends on whether an interrelated lexical cohort of sufficient size is activated (Abdel Rahman & Melinger, 2009b; Melinger & Abdel Rahman, 2012). This account was formulated to explain semantic context effects of opposite polarity, as observed, e.g., for categorically vs. associatively related distractors (Alario et al., 2000; La Heij et al., 1990). When target and distractor are members of the same category (e.g. dog, cat), they spread converging activation to further category members through shared semantic features so that a cohort of interrelated lexical nodes is co-activated and competes for selection, resulting in one-to-many competition, and therefore inducing substantial interference effects that outweigh semantic priming. On the other hand, when target and distractor are associatively related (e.g. bee, honey), their activation does not converge on semantic features that are shared by additional concepts so that they do not jointly activate other related concepts. Instead, both the target and the distractor separately activate other mutually unrelated concepts so that their activation diverges and eventually dissipates. Thus, only the target and distractor are highly activated, resulting in one-to-one competition which does not override conceptual priming.

Concerning semantic richness effects, an increasing NOF associated with the message should induce facilitatory effects similar to conceptual priming, with higher activation levels of concepts associated with many as compared to few semantic features (see Rabovsky & McRae, 2014; simulation 3). Stronger semantic activation specifically related to the to-be-named concept should result in enhanced activation flow to the corresponding lexical representation, inducing faster lexical selection and naming. This may be accompanied by the simultaneous activation of a bigger number of co-activated lexical competitors – those that share the semantic features with the target. However, while lexical co-activation should not be strong enough to outweigh direct conceptual facilitation due to semantic feature activation, a related variable, the density of semantic space, should reflect lexical cohort activation and competition more directly. This variable, the intercorrelational feature density, also provided in the feature norms by McRae et al. (2005), indicates the degree to which a concept's features are intercorrelated. Specifically, McRae et al. constructed a matrix where each element corresponds to the production frequency of a specific feature for a specific concept, and then calculated pairwise correlations between the resulting feature vectors for features that appeared in at least three concepts. Then the percentage of shared variance between each pair of a concept's features (for pairs sharing at least 6.5% of their variance) was summed. Concepts with high intercorrelational density inhabit denser regions of semantic space, and their activation results in stronger partial co-activation of other concepts through the intercorrelated features.

There is currently no evidence concerning influences of neither NOF nor intercorrelational density in language production. Here we assume that concepts with high intercorrelational density should co-activate cohorts of interrelated lexical competitors because highly correlated feature clusters often characterize groups of closely interrelated concepts (e.g. *has wings*, *can fly*, *has a beak*, etc. or *has four legs*, *has fur*, *has a tail*, etc.). As noted above, within the swinging lexical network, the activation of lexical cohorts should result in enhanced lexical competition, which should be reflected in sizeable interference effects that outweigh any possible facilitation induced by conceptual co-activation.

To summarize, in the present study we investigate how language production is shaped by message-inherent semantic attributes that have thus far gained little attention. We focused on the semantic richness and density of verbal messages. An increasing NOF associated with a concept should facilitate the formulation of the message at the conceptual level, and the density of the message in semantic space should cause the activation of an interrelated competitive cohort at the lexical level, resulting in semantic interference.

Please note that here, in contrast to most studies on semantic context effects, the target utterances necessarily differ between conditions, posing potential problems in terms of confounding variables. One common strategy to avoid these problems is to compare groups of stimuli that differ in the variables of interest (e.g., high vs. low NOF) but are closely matched on potentially confounding variables. However, dichotomizing continuous variables can result in a substantial loss of statistical power due to reducing the amount of experimental variance. Furthermore, the excessive matching of other variables required by this dichotomization strategy can result in the selection of unusual materials (Hauk, Davis, Ford, Pulvermuller, & Marslen-Wilson, 2006). Therefore, we used all the 541 object concepts from McRae et al.'s (2005) norms with richness and density continuously varying in the stimulus set, and analyzed naming responses with linear mixed models (Baayen, Davidson, & Bates, 2008) which allow for statistical control of potential confounds.

2. Material and methods

2.1. Participants

16 native German speakers (13 women) with mean age of 25 (range = 19–38) took part in our study. They reported normal or corrected-to-normal visual acuity, gave written informed consent prior to participation and received either course credit or monetary compensation (7 €/h) for participation.

2.2. Materials and procedure

Stimuli were grayscale photographs of the 541 concrete object concepts from the feature production norms by McRae et al. (2005) which were scaled to 3.5 $\times$ 3.5 cm and presented on a light blue background. To increase the number of correct responses for response time analyses, half of the participants ($n = 8$) were shown the object pictures and their correct German names (translated from the feature norms by McRae et al., 2005) in a familiarization block prior to the experiment proper where each picture/name pair was shown for 2 s. To control for potential influences of this procedure on the experimental effects, the other participant group ($n = 8$) was not familiarized with the pictures. For the main experiment, participants were instructed to name the pictures as correct (familiarization group) or as intuitive and specific (group without familiarization) as possible. Each trial began with a fixation cross displayed for 0.5 s. Then a picture was presented until a response was given or for maximally 4 s. The 541 pictures were presented in different random order for each participant. Naming latencies were registered with a voice key and response accuracy was assessed by the experimenter using four categories: (1) experimental error, (2) wrong response, (3) almost correct response, e.g. a synonym, or (4) correct response.

3. Results

We used (generalized) linear mixed models (GLMMs) implemented in the packages lme4 (Bates, Maechler, Bolker, & Walker, 2014) and lmerTest (Kuznetsova, Brockhoff, & Christensen, 2015) in R (www.r-project.org) to analyze influences of NOF (including taxonomic features) and intercorrelational density (square-root transformed to reduce the influence of outliers) on response times (recoded as 1/RT [s] to adhere to normal distribution assumptions, via a LMM) and binary error rates (via a logistic GLMM). We also included prior familiarization with the stimuli as a between subject factor, as well as its interactions with NOF and intercorrelational density. Moreover, we added crossed random effects for subjects and items, with random item intercepts and random item slopes for the familiarization factor, and random subject intercepts and random subject slopes for the number of semantic features and intercorrelational density. In addition, we controlled for influences of familiarity, number of orthographic neighbors, and lexical frequency by including these variables as fixed effects in the (G) LMMs so that their influences on the variance in performance could be attributed to them and subtracted from the estimates of the influences of the number of features and density (in analogy to multiple regression). For the reported analyses, responses were considered as correct when they received a score of 3 (almost correct) or 4 (correct) in the above described categories. However, the result pattern did not change when changing the criterion to considering only category 4 responses as correct.

Results showed facilitative influences of semantic richness, with significantly faster response times ($b = 0.012$, $SE = 0.0025$; $t_{(252)} = 4.8$; $p < .001$) and lower error rates ($b = 0.153$; $SE = 0.025$; $z = 6.0$; $p < .001$) for words associated with many semantic features (see Figs. 1 and 2, left). On the other hand, we found high intercorrelational density to reduce response speed ($b = -0.021$; $SE = 0.0062$; $t_{(273)} = -3.4$; $p < .001$) and accuracy ($b = -0.432$; $SE = 0.064$; $z = -6.7$; $p < .001$; see Figs. 1 and 2, right). Prior familiarization increased accuracy ($b = 0.689$; $SE = 0.238$; $z = 2.9$; $p < .01$). There was no influence of familiarization on response speed ($p = .45$), but an interaction between familiarization and NOF ($b = -0.0051$; $SE = 0.0024$; $t_{(24)} = -2.11$; $p < .05$) indicating that the influence of NOF on response speed was somewhat weaker for those participants that had been familiarized with the stimuli

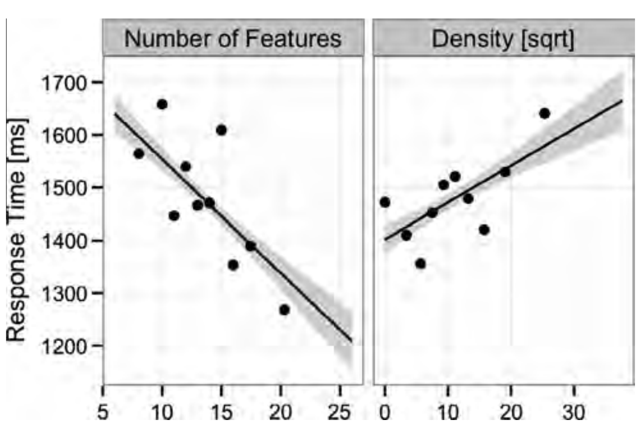

Fig. 1. Response time as a function of the number of features (left) and intercorrelational density (right), depicted as independently computed linear regression lines with 95% point-wise confidence intervals. Points indicate average response times for 10 essentially equal-sized (quantile-based) bins.

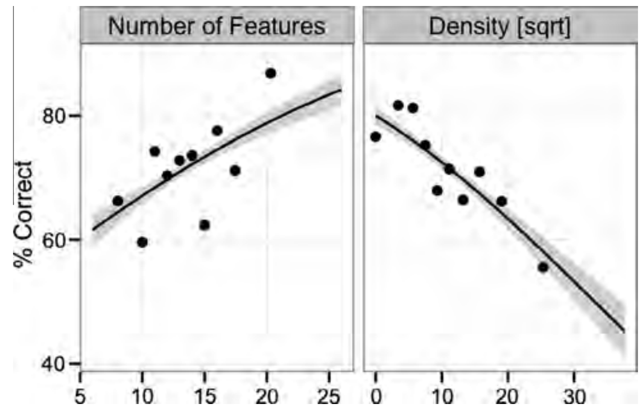

Fig. 2. Accuracy as a function of the number of features (left) and intercorrelational density (right), depicted as independently computed logistic regression lines with 95% point-wise confidence intervals. Points indicate average accuracies for 10 essentially equal-sized (quantile-based) bins.

($b = 0.0089$; $SE = 0.0027$; $t_{(71)} = 3.3$; $p < .01$) than for those without familiarization ($b = 0.014$; $SE = 0.0028$; $t_{(105)} = 5.0$; $p < .001$).

As can be seen in Table 1, there were relatively high correlations between some predictor variables. The problem with high collinearity is that obtained effects can be unstable. To address this issue, we thus examined the stability of the effects across subjects. A high NOF increased accuracy for all 16 subjects (significant for 15 out of 16 subjects even in individual subject analyses), and high intercorrelational density decreased accuracy for all 16 subjects (significant for 14). Responses were faster for a higher NOF in 15 out of 16 subjects (significant in 10) and responses were slower for higher intercorrelational density in 14 out of 16 subjects (significant in 4). Thus, the results are very stable despite the correlations. In addition, we calculated the variance inflation factor (VIF) which indicates the inflation of the standard errors associated with a particular beta weight that is due to multicollinearity. The VIF was 1.32 for the number of features and 1.30 for intercorrelational density which is well below the VIF values of 5 or 10 which have been recommended as acceptable maximum levels (Hair, Anderson, Tatham, & Black, 1995; Rogerson, 2001).

As visual complexity might be confounded with the variables of interest, we ran additional control analyses. Specifically, we obtained a subjective measure (visual complexity ratings on a five-point scale from an online rating study with 42 participants) and an objective measure, namely compressed file size, i.e. zip (Donderi, 2006a, 2006b), and separately included these variables as additional fixed effects in the analyses described above. While both measures of visual complexity made naming slower and more error-prone ($ps < .05$), the pattern of results for NOF and intercorrelational density did not change ($ps < .01$).

4. Discussion

The present study provides first evidence that the richness and density of semantic representations (based on McRae et al., 2005) modulates language production. While naming times and accuracy reflect facilitated production of semantically rich messages that are associated with many semantic attributes, naming is slower and more error-prone for concepts with high intercorrelational feature density, presumably reflecting that intercorrelated features co-activate a bigger number of competitors – an inter-related cohort – at the lexical level.

As described in Section 1, a higher NOF presumably enhances activation at the conceptual level, increasing activation flow to the corresponding lexical representation and thus facilitating the

Table 1
Correlations between predictor variables. NOF, number of features; Density, intercorrelational density; Fam, familiarity; Freq, frequency, ON, number of orthographic neighbors; Vis_sub, subjective visual complexity (rating); Vis_obj, objective visual complexity (zip file size); Distinct, mean feature distinctiveness.

	NOF	Density	Fam	Freq	ON	Vis_sub	Vis_obj
NOF							
Density	0.48***						
Fam	0.02	−0.02					
Freq	0.11	−0.03	0.40***				
ON	0.09	0.02	0.05	0.43***			
Vis_sub	0.04	0.13	−0.03	0.01	−0.06		
Vis_obj	−0.01	0.00	0.01	0.04	0.03	0.47***	
Distinct	−0.01	−0.53***	0.14*	0.15*	−0.05	−0.02	0.07

*** $p < .001$.
* $p < .05$.

naming response. In contrast, possible inhibitory consequences of the activation of many semantic features that might be shared by a number of related concepts should be weak. This latter aspect was investigated with another variable, the intercorrelational feature density, that should reflect the co-activation of inter-related lexical cohorts more directly. Specifically, the swinging lexical network proposal (Abdel Rahman & Melinger, 2009b) assumes that inhibitory influences induced by lexical competition will override any possible facilitation at the conceptual level when a lexical cohort of sufficient size is activated. As highly correlated feature clusters typically characterize groups of interrelated concepts, items with high intercorrelational density should activate lexical cohorts that mutually increase their activation, resulting in one-to-many competition and therefore substantial interference which outweighs facilitative influences at the semantic level. Thus, the swinging lexical network proposal directly predicts the obtained pattern of facilitatory and inhibitory influences of the number of semantic features and their density in semantic space, because the activation induced by a high NOF should be primarily related to the to-be-named concept while high intercorrelational density should primarily reflect the sharing of activation across concepts and competing lexical nodes. On the other hand, it is currently not clear how the present findings would be explained by language production theories dismissing lexical competition that were formulated to account for effects of word distractors (Mahon et al., 2007).

The influences of distinctive versus correlated features have been discussed by Tyler and Moss (2001) in the context of category-specific semantic brain activation and neuropsychological impairments. Distinctive features are very diagnostic for specific concepts such as *moos* for cow. Thus, because the activation of distinctive features is related to given concepts in a highly specific manner, distinctiveness is conceptually opposed to intercorrelational density and should induce opposite, i.e., facilitatory effects, in language production. When including mean feature distinctiveness (calculated as the inverse of the number of concepts in which a specific feature occurs, averaged across all features in a concept; cf. McRae et al., 2005) as additional factor in the analyses, distinctiveness was not significant ($ps > .22$), while the opposed effects of NOF and intercorrelational density remained significant ($ps < .05$). The lack of influences of distinctiveness was most probably due to the inherent contrariness to intercorrelational density as also indicated by their high negative correlation (−.53), so that there may be no unique variance explained by this additional variable. Indeed, when excluding intercorrelational density from the analyses, we obtained the expected facilitating influence of distinctiveness in both accuracy and RTs ($ps < .05$).

To summarize the present study investigated how language production is shaped by message-inherent attributes of semantic richness and density that have thus far gained little attention. We found facilitative influences of the richness of verbal message contents, operationalized as the number of associated features, and inhibitory influences for messages that inhabit denser regions in semantic space, operationalized as intercorrelational feature density. These findings demonstrate that the richness and density of semantic representations play an important role in semantic–lexical planning stages during language production that deserves more attention.

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