A spreading activation model of a discrete free association task

Vencislav Popov (vencislav.popov@gmail.com)
Department of Cognitive Science and Psychology,
New Bulgarian University, 21 Montevideo Street
Sofia 1618, Bulgaria

Introduction

Researchers in psycholinguistics often assume that the frequency with which an associate is given to a cue in a discrete free association task ("What is the first word that comes to your mind in response to the word ROBIN"?) by a group of participants, reflects the association strength in the mental lexicon of each individual (Nelson, McEvoy, & Schreiber, 2004). Based on this assumption they use these group-level production frequencies to control experimental stimuli or to define experimental condition.

It is also assumed that associates are produced by spreading activation from the cue to its targets as a function of their association strength and that the pattern of association strength is roughly the same for all speakers of a language. Two questions are warranted: (1) How does the cognitive system choose a response among the activated associates, so that it produces a different response each time, while maintaining the overall frequency pattern? (2) Why do people produce different associates if they share the same associative network?

I present a simple model that explains how the same associative network might give rise to different responses, whose frequencies approximate the underlying individual association strengths. The model serves mainly as a proof-of-concept that frequencies obtained by group experiments can be used to infer individual association strength. It does not, however, aim to be a general model of semantic memory, nor does it aim to model any other experimental effects at this time.

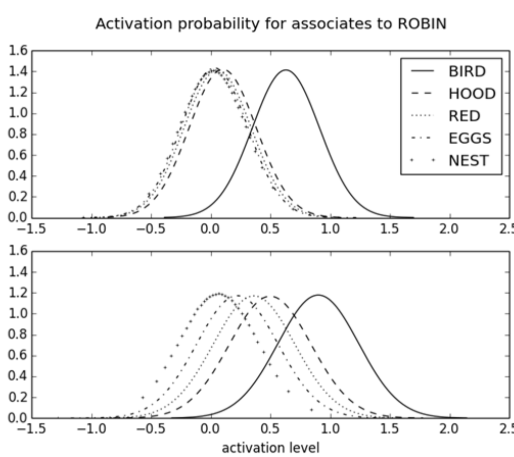

Figure 1. The probability of activation of each associate of the cue "ROBIN" in simulation 1 (a) with SD of the noise input 0.28 and in simulation 2 (b) with SD of the noise input 0.34

The free association model

In the model concepts are represented as single units, and the connection weights between them represent their association strength. If a cue is activated it spreads activation multiplied by the corresponding connection weight to all of its associates. Gaussian random error $\sim \mathrm{N}\left(0,\, \sigma^2\right)$, which represents random input from the rest of the system, is added to the input of each associate. The most active node is selected as a response to the task. Predicted production frequencies are obtained by running the model N times and dividing the count of all unique responses by N and all runs of the model are independent of each other.

Evaluation of the model

The model was evaluated with the root mean square error of the prediction frequencies,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(freq_{observed,i} - freq_{predicted,i}\right)^2}{N}}$$

Goals of the simulations

Since the observed frequencies are interpreted to reflect connection strengths, then the connection strengths must be a function of those observed frequencies. The simulations had two goals: 1) to estimate the connection weight parameters from observed production frequencies ($w_{i,c} = f(FSG)$) and 2) to estimate the noise distribution in a way that would minimize the residuals of the predicted and the observed production frequencies.

FSG corpus

Data for the observed FSG was obtained from the **University of South Florida Free Association Norms**, a database of association norms for 5019 cue words (Nelson et al. 2004). Each cue was presented to a mean of 149 (SD = 15) people, who gave a single response to each of about 100-120 cues. The database is freely accessible at http://w3.usf.edu/FreeAssociation/

Simulations

Simulations 1 and 2

Simulations 1 and 2 tested which of two functions of the observed frequencies when used as connection weights and what dispersion of the noise would lead to a better

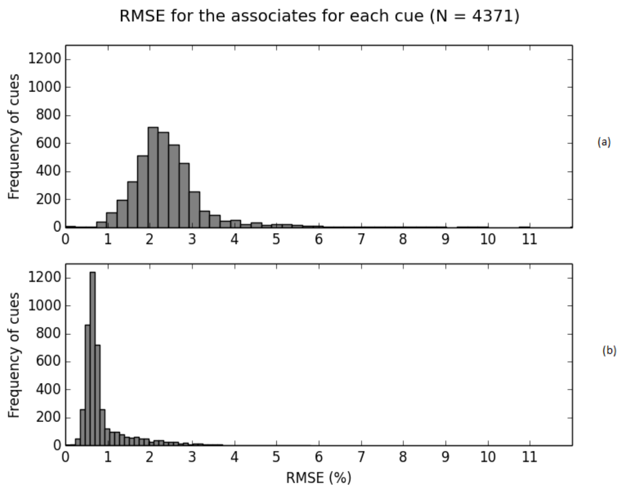

Figure 2. Frequencies of different RMSE levels for 4371 different cues for simulation 3 (a) and simulation 4 (b)

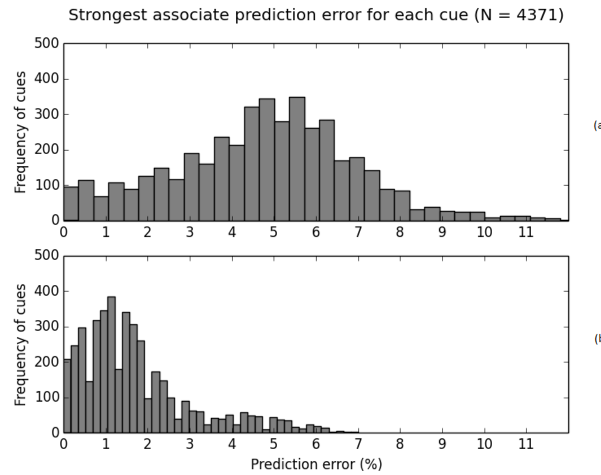

Figure 3. Frequencies of different prediction error of the strongest associate levels for 4371 different cues for simulation 3 (a) and simulation 4 (b)

approximation of the data. Simulation 1 tested the hypothesis that the individual connection weights are equal to the group-level production frequencies. Simulation 2 tests a model in which the connection strength in the mental lexicon is a logarithmic function of the observed production frequencies:

$$\frac{\log_{10}\left(freq_{observed,i}\ *\ 100\right)}{2}$$

Both simulations were run sequentially for 10000 times for each standard deviations of the noise input for all values from 0 to 1 with a step of 0.01. Both simulations fitted this parameter on the same subset of 10 randomly chosen cue words: 'TOMBSTONE', 'DOZEN', 'FEDERAL', 'REQUEST', 'BODY', 'LIFE', 'ROBBER', 'READ', 'WHISTLE', 'UNIVERSE'.

Results. Simulation 2 provided a much better fit of the data. Overall, in simulation 1, the RMSE was lowest when the noise standard deviation was equal to 0.28. In that case the predicted value of the model differed from the observed production frequencies by 2.4%, and the predicted value of the strongest associate – by 3.78%.

In simulation 2, when the weight of the connection between the cue and its associates is set to be equal to a logarithm of the observable production frequencies, the production frequencies of the model are closest to the observable production frequencies when the standard deviation of the noise input is equal to 0.34. The predicted frequencies of the model differ from the observed production frequencies by 0.72%, and the predicted value of the strongest associate – by 1.29%

Figure 1 presents a possible explanation for why the log transformation is more effective – it spreads the activation distributions of each associate further apart, which makes them more distinct.

Simulations 3 and 4

Both model 1 and model 2 were run on all standardized 4371 cues with SD of the noise input equal 0.28 and 0.34 respectively.

Results. Model 1 predicted the observed frequencies for the all 4371 cues with a 2.35% error rate. The model predicted the frequency of the strongest associate with a 5.24% prediction error. However, model 2 was again an even better predictor of the data for all 4371 cues – 99.15% overall successful prediction and 97.29% prediction success for the strongest associate. Also, the variance of the prediction error for all words (figure 2), and for the first associate (figure 3) was much smaller for model 2, compared to model 1, which makes its prediction much more reliable.

Discussion

This model provides a mechanism that can simulate the observable production frequencies of associates in a free association experiment with 0.85% prediction error, when activation is modeled as the spreading activation through a network in which the association strength is a logarithmic function of the observed production frequencies plus a Gaussian noise with a SD = 0.34. Importantly, this possibly validates the use of group-level production frequencies to estimate association strength between words in the individual lexicon. In this way it validates FSG's use in creating experimental conditions and its use as a control variable in psycholinguistics.

References

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments, & Computers*, *36*(3), 402–407.