Exploration in Free Word Association Networks: Models and Experiment

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Abstract Free association is a task that requires a subject to express the first word to come to their mind when presented with a certain cue. It is a task which can be used to expose the basic mechanisms by which humans connect memories. In this work we have made use of a publicly available database of free associations to model the exploration of the averaged network of associations using a statistical and the ACT-R model. We performed, in addition, an online experiment asking participants to navigate the averaged network using their individual preferences for word associations. We have investigated the statistics of word repetitions in this guided association task. We find that the considered models mimic some of the statistical properties, viz the probability of word repetitions, the distance between repetitions and the distribution of association chain lengths, of the experiment, with the ACT-R model showing a particularly good fit to the experimental data for the more intricate properties as, for instance, the ratio of repetitions per length of association chains.

Keywords Associative Network · Semantic Network · Online Experiment · Memory Retrieval

1 Introduction

Semantic memory [14], which can be considered as a part of explicit memory, is responsible for the brain’s ability to memorize the meaning of words and concepts and also their mental representation, including their properties and functions and the relation to each other [25]. One possible tool to study semantic memory is the task of free association, where a subject is asked to
express the first word to come to mind related to some given cue. This task has a long history in psychology, dating back to the late 19th century [8]. It is an instance of verbal fluency tasks which are commonly used for the study of the structure of concept to concept associations within the network organization of semantic memory [9].

A range of distinct semantic memory models have been suggested over the years, beginning in the sixties’ and seventies’ models recording dictionary information [18]. It has been observed that priming effects, namely when a semantically related cue has been presented to the test person before, play a substantial role in memory retrieval and task performances [15, 20, 25], with prime and target possibly forming a compound object [24].

A range of lexigraphical and associative semantic databases have been collected over the years, like WordNet [16], the South Florida collection of free association, rhyme, and word fragment norms [17] and ConceptNet [12]. These word association networks typically exhibit small-world structures, with short average distances between words, together with strong local clustering [24, 11], a property shared with lexigraphical spaces obtained from word co-occurrences [13].

A comprehensive database of free associations, obtained from the participation of a large number of individuals (in the order of 6000), was made public by Nelson et al. [17]. This database, which we will denote as South Florida Free Associations, SFFA, in the following, can be considered an example of a semantic space [23]. The data essentially constitutes a weighted directed network, since both the forward and the backwards connectivity strength between all associatively related pairs of around 5000 words, the vertices of the network, are provided. These association strengths are averaged over all subjects taking place in compiling the database. Therefore, individual associative preference may differ from that of the SFFA database. In addition, external effects like the environment, the last happenings before the experiment, etc. are ignored by the database. Also native and non-native English speaker may have different associative preferences, depending on the respective countries of origin.

In this work, we use the SFFA database as a basis for a guided association task. In this task, the subjects (either human or simulated models) navigate the network of words obtained from the SFFA database by connecting words in a free association task. By comparing the statistical properties of word repetitions, as obtained by the the associations chains created by human subjects, with those of the models for semantic memory retrieval, we expect to deepen our understanding of which properties may be important for modelling semantic spreading [7] on associative nets. Our works may be embedded in the context of related studies employing the SFFA database, for which the Google page rank has been computed and compared to the experimental results of a lexical association task [10]. It is also possible to simulated stochastic cognitive navigation on the SFFA database in order to study possible mechanisms for information retrieval [3].
Our work on exploration of free association networks can be considered also in the general context of semantic language networks [22], with the structure and the dynamics of the respective network properties being studied intensively [4]. From the perspective of neurobiology an interesting question regards the relation to possible underlying neural network correlate for the association network studied here and its relation to functional brain networks in general [5]. We also remark in this context that the association network used for our study corresponds to that of adults, with the development of the human semantic network during childhood being an interesting but separate topic [2].

2 Methods

We set up an online experiment for a guided association task, attracting at total of 450 voluntary participants, mostly from the University of Frankfurt/Germany, the United Kingdom and the United States. The goal of the experiment was to study associative exploration on the SFFA network.

For the online experiment a randomly selected word from the SFFA, the cue, is presented to the subjects on the screen, along with a list of varying numbers of related words. The list of words presented are all linked to the cue with a strength higher than 5% in the SFFA. The subjects are instructed to select the word from the list that seems to them most related to the cue. Then the selected word is taken as the next cue and presented to the subject along with a new list of related words, extracted again from the SFFA. The subject can select one word, as in the previous step. The task repeats itself until the subject voluntarily decides to quit.

The sequence of words chosen by the participants is called a chain, and the set of the 1688 chains collected constitutes the data from which statistical properties of the free association task were derived.

2.1 Models

In order to evaluate comparatively the data collected from the online experiment we consider two models of memory retrieval. We use these models to generate exploration chains in the SFFA network and to compare the obtained simulated associative latching with the actual data obtained from the online experiment.

2.1.1 Mem model

The Mem model (for “Memory”) consist in a random exploration through the SFFA network. The exploration starts at a random node (a word) from the network and moves to the next one, which is selected randomly with a probability proportional to the association strength to the present node, as
given by the SFFA database. The process is followed until a node is reached for which no outgoing link is provided. In addition to this simple exploration, there is a limitation for repeated words. When the exploration would jump to a word which was already visited during the exploration (the word is already in the chain), it will be visited again only with a probability $c$. The word will therefore be ignored (at this step) with a probability $1 - c$, which means that if such word is the only outgoing link of the present node, the exploration will end with said probability $1 - c$.

The parameter $c$ is chosen in this work to the value $c = 0.08$, for which it reproduces the experimental results for the distance between repetitions as closely as possible.

Notice that this model represents a memoryless probabilistic model for the exploration of the word association network, in contrast to the one-step memory model represented by the ACT-R model shown in next section.

### 2.1.2 ACT-R model

Within the ACT-R model (Adaptive Control of Thought-Rational) one tries to model both the activity and the retrieval dynamics of previously acquired memories [1]. In the ACT-R model, a memory element $i$ has an activity $A_i(t)$, which is calculated as the sum of the base-level activity $B_i$ and an attentional weight $S_i$,

$$ A_i(t) = B_i(t) + S_i(t) . $$

The task attention term $S_i(t)$ is calculated as

$$ S_i(t) = \sum_j \omega_j(t) W_{ji} , $$

where $\omega_j(t)$ is the attentional weight of the elements that are part of the current task, and $W_{ji}$ are the strengths of the connections between element $j$ and $i$. For our purpose we have taken then $W_{ji}$ as the association strengths of to the SFFA database.

In our work, we have chosen to set $\omega_j(t) = 1$ if $j$ is the presently active memory (the node visited at previous the moment), and $\omega_j(t) = 0$ otherwise. Thus, in our version of the model, a word has a higher task attention $S_i(t)$ if it is strongly related to the last observed word.

The base level activation $B_i(t)$ in Eq. (1) of node $i$ is given by

$$ B_i(t) = \log \left( \sum_{k: t_k < t} \left( \frac{1}{t - t_k} \right)^d \right) , $$

where $t_k$ is the time of the $k$th last recall of the element $i$, and the exponent $d$ is a constant. Thus a given word has a high base activity level if it has been evoked many times lately.
Having defined the activity $A_i(t)$, the probability that an element $i$ is remembered at time $t$, viz the retrieval probability, is given by

$$P_i(t) = \frac{1}{1 + \exp\left[-\frac{(A_i(t) - \tau)}{s}\right]}$$

where $\tau$ is the activity threshold and $s$ is a parameter introduced to account for the effect of noise onto the activation levels \[1\]. A word $i$ is recalled with probability $P_i(t)$ and the averseness of a subject to repeat a word is given by $1 - P_i(t)$.

Finally, the exploration of the network follows the same procedure as in the Mem model. Being at site $j$ of the SFFA network a word $m$ is selected with probability $W_{mj}$ and accepted with probability $1 - P_m(t)$. If this word is accepted, than all $A_i(t)$, $B_i(t)$ and $S_i(t)$ are updated. If not, the procedure repeats until one word is selected out of the list of candidates linked to the current site $j$. The chain is terminated if all candidate sites are rejected.

For our simulations of this model, we have taken $d = 0.5$, $s = 0.4$, $\tau = 0.35 * s$, which is a fairly standard set of values \[1\]. A different set of values may be chosen to obtain a better fit to the experimental results. However, it is our intention maintain a range of values comparable with other studies in the literature.

3 Results

In Fig. 1, the probability distribution of chain lengths is shown in a normal-log representation, as well as the corresponding complementary cumulative distribution function (CCDF) in the inset. We observe an approximately exponential decay in the frequency of chain lengths for the experimental data as well as of both models. Also included in Fig. 1 are exponential fits, given by respective solid lines, evaluated using a maximum likelihood estimation (MLE) \[6, 26\], evaluated with the corresponding code from the GNU R software package \[19\].

The experimental data can be fitted well with a single exponential having an exponent $\lambda = -0.068(1)$. By chain length $\sim 50$ the number of data points is too low for reliable data analysis. The Mem model allows for larger chain length, having an exponent $\lambda = -0.03593(3)$.

For chain lengths of size smaller than $\sim 20$ elements, the ACT-R model follows closely the behavior of the experimental data, with an exponent $\lambda = -0.0400(1)$. There is a kink for chain lengths $\sim 20$, with larger chain length becoming progressively more unlikely for the ACT-R model. This decay for larger chain lengths can be fitted well by an exponential with an exponent $\lambda = -0.335(2)$. The theoretical models’ data has been obtained, for both the Mem and for the ACT-R model, using $10^6$ chains generated from random starting points on the SFFA network. It is hence interesting, that the ACT-R data show a substantial amount of scattering for small chain lengths.
Fig. 1 Probability to observe word association chains of length $l$, the vertical axis in log scale while the horizontal axis is linear. The data is obtained from the 1688 chains of the experimental data (red) and from $10^6$ chains generated by the Mem model (blue) as well as by the ACT-R model (yellow). The solid lines are respective exponential fits (see text for exponents). The inset shows the complementary cumulative distribution function of the same data, using the same representation.

The experimental data is scarce and noise for chain length $\sim 50$ and longer, as only very few subjects enjoyed engaging in the task as long. One may hence disregard, for further data analysis, all long chains. This would, however, involve setting a somewhat arbitrary cutoff. We have tested this procedure and found that the property of the experimental data remains essentially unaffected when keeping or removing long chains. We therefore opted, for simplicity, to present the results corresponding to the whole sample, including long chains.

In Fig. 2 we present the probability $p$ that a word is repeated one or more times, averaged over all chain lengths. Only the data involving five or less repetitions is significant, for the results of the online experiment. The subject would prefer to stop a chain altogether and try with a new cue, than go on once a large number of repetitions did occur. In this respect, we found that 19% of all chains in our experimental results end in a cycle. We observe that the behavior of the chainlength distribution remains unperturbed if these chains are not included.

The experimental results could, as a matter of principle, be approximated by a power law, but the small number of data points does not allow for any definite judgement. This behavior seems to be shared with the ACT-R models for the initial repetitions. However, when the complete trend for larger number of repetitions is analyzed, a seemingly concave curve in the log-log plot can be devised both for the Mem and for the ACT-R model. This behavior cannot be cross-checked with the experimental data, due to the lack of data for larger numbers of word repetitions. We also tried to fit the data for the Mem both...
Fig. 2 The probability of observing $r$ word repetitions, averaged over all chains lengths. The data is obtained from the 1688 chains of the online experiment (red) and from the $10^6$ chains generated by the ACT-R model (yellow) as well as by the Mem model (blue).

with a Gaussian and with a simple exponential decay, but both approximations are not convincing.

In Fig. 3 the distribution of distances between consecutive repetitions of the same word is presented. All three datasets presented, for the two models and for the experimental data, agree quite well up to repetition distances of $\approx 10$. However, for larger repetition distances, marked discrepancies are observed for both models, which exhibit concave behaviors. The experimental data can, suggestively, be approximated by a power-law with an exponent $\gamma = -1.9(1)$.

For the distribution of distances between repetitions, the Mem model reproduces the experimental results somewhat better. This is not a coincidence, as the free parameter of the Mem model, the repetition probability $c = 0.08$, has been selected to reproduce the experimental results for this property as closely as possible.

Although the decay of both models seem to fit relatively well the experimental data for small distances, they do not follow a similar law for the complete range. Due to the lack of enough data in the tail of the experimental distribution, we do not consider this as strong evidence to disregard either of the models.

An interesting result can be observed in Fig. 4 where we present the probability density $\rho$ to find a given ratio $r/l$ of word repetitions ($r$) per chain length ($l$). A word that occurs three times in a chain of length ten, to give an example, would contribute to the frequency $\rho(r/l)$ of chains having a ratio of $r/l = 3/10 = 0.3$. One observes a highly non-monotonic distribution of ratios $r/l$. Experimentally the maximal density is 0.5, which corresponds to a binary loop like warm-cold-warm-cold-... There are additional peaks at $r/l = 1/3$
Fig. 3 Log-log plot of the distribution of distances \( d_r \) between repetitions of a given word. The data is obtained from the \( 10^6 \) chains generated by the ACT-R model (yellow) and by the Mem model (blue), as well as from the 1688 chains of the online experiment (red). The solid line represents, for comparison, a power law decay with exponent \(-1.9\). The inset shows the complementary cumulative distribution functions of the same data, the solid line has in this case an exponent of \(-0.9\).

and \( r/l = 1/4 \), corresponding to word repetition loops of length three and four respectively. It is evident from Fig. 4 that the ACT-R model exhibits the same peaks as found by the online experiment with human subjects, with approximately similar amplitudes for the respective word repetition frequencies. This seems to be an indication that the ACT-R model is suited for predicting the human behavior in this guided association task. It may be also a hint that this distribution is strongly influenced by the inclusion of a memory, which the Mem model lacks.

Finally we present in Fig. 5 the distribution (as an histogram) of chain length, just as in Fig. 1 but retaining only word association chains with at least one repetition, which are mostly long chains. The human subjects tend to repeat words, on the average, substantially before both the Mem and the ACT-R model, which have have their distribution maxima at larger chains lengths. This result can be regarded as robust, despite the observation that the results from the online experiment is quite noisy. Note, however, that the substantial scattering of the ACT-R, which had been generated using \( 10^6 \) chain realizations, as for the other results.

4 Conclusion

Here we suggest, that online experiments for guided and related associative tasks may provide interesting databases for human association dynamics. The
The probability density $\rho$ to find a given ratio $r/l$ of $r$ repetitions of a word per chain length $l$, obtained from the 1688 chains of the experimental data (red) and from $10^6$ chains generated by the Mem model (blue) as well as by the ACT-R model (yellow). The peaks at $l/r = 2, 3, 4, \ldots$ correspond to associative loops of length $2, 3, 4, \ldots$.

The same data as in Fig. 4 but only for word association chains with a least one word occurring twice, with histogram bin size 10, and plotted in a normal-log representation.

drawback of online experiments is, to date, that there is no real control of how serious the individual subjects take the task, some participants may just play around randomly. There may be hence a certain fraction of non-characteristic subjects which may, as a matter of principle, be taken into account by considering models with two populations of participants. Our experimental database
is however not large enough for this type of analysis, for which a substantially larger number of participants would be necessary. We however believe that this first online experiment indicates that interesting data can be acquired. In particular we analyzed the distribution of the lengths of guided associative world chains and various features of word repetitions. We attempted to model the experimental results with cognitive models for human memory retrieval dynamics, finding, in general, good qualitative agreement.

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