Introducing the idea of sustained query exposure in the context of language vocabulary learning

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Abstract

This paper introduces a basic pool-sink vocabulary model and describes how it supports the idea of sustained query exposure. This idea translates into a concrete visualization which has been designed in an attempt to improve the learning process by extending and facilitating the interaction between user and query objects.

1 Introduction

Most of what we learn is forgotten after a short period of time. Considering the amount of largely redundant data with which our cognitive apparatus is continuously bombarded, this tendency to forget is a blessing and deserves being ranked as a chief adaptation against information overload. This ability becomes a curse, however, whenever there is a need for selective long-term memorization. As was first described mathematically by the German psychologist Ebbinghaus, recall ability decreases at an exponential rate [4], a relationship that has been validated ever since (see for example [1] and [3]). The majority of methods devised to overcome this degradation are based on either of two learning paradigms, namely associative learning and what may be called staggered learning. The second of the above-mentioned techniques and the one this report is concerned with, staggered learning, is based on the observation that each time a periodical review takes place of the information to be learnt, recall ability does not only jump to its initial level but, more importantly, the rate of subsequent decay decreases such that retention is ensured for progressively longer intervals [2].

The positive effect of staggered learning on recall ability can be enhanced by excluding from reviews those items which the student has successfully recalled during previous reviews. Depending on the exact criteria that an item needs to satisfy in order to be ranked as *learnt*, there exist a few software systems of varying degree of sophistication providing support for selective, staggered learning of foreign language vocabularies (see for example [6] which is based on a card-board predecessor [5]). Queries that are answered incorrectly are typically put back into the system to be used in a subsequent review. It is common to all these systems that such queries disappear from the user's sight, which may be regarded as a relict from the card-board era. We here advocate an approach which we shall refer to as sustained query exposure and which consists in displaying every query previously answered incorrectly in the periphery of the user interface until that query is posed again and answered correctly. By thus keeping incorrect queries visually accessible following their explicit exposure, further interaction between user and data becomes possible, allowing the query to "sink in" further. With the principal focus being on the current query, the interaction between the user and peripheral objects takes a much more passive and less focussed form, much like the perception of an afterimage that diffusely persists on the retina after the visual stimulus has disappeared.

This visualization is built around a language learning model which has the desirable property that the number of incorrectly answered queries held back for a subsequent review is kept relatively constant (sink size constancy).

The report is organized in two parts. The first part introduces the underlying model, in particular the method used to achieve sink size constancy, and discusses performance measures that can be derived from it. The second part provides a description of the visualization.

2 The pool-sink model

The system presented here is based on a simple pool-sink learning model as depicted in Figure 1. The words used as queries are verbs of the Spanish language and initially reside in a pool. The pool is accessed to obtain a new query with probability p. If the query is answered correctly, it is marked as successfully learnt and excluded from the learning session. If the answer is incorrect, the query enters a sink which is accessed during each round with probability $q = 1 - p$. We can thus distinguish between two kinds of queries which we shall refer to as type A (pool) and type B (sink) queries.

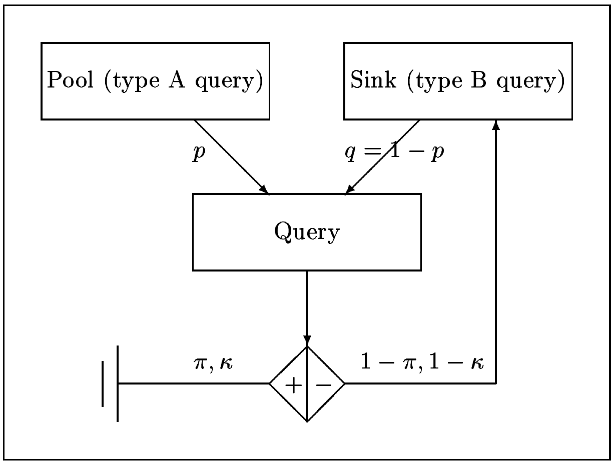

Figure 1: Basic training model. Queries are either drawn from the pool (new query) or from a sink (holding queries which were answered incorrectly). The variables determining the word flow through the system are the probabilities p, q, π and κ (see text for details).

2.1 Fixed sink capacity

The sink is assigned a fixed capacity and the word flow through the system is regulated with the aim of keeping the level close to this capacity. This system constraint is desirable not only for the purpose of visualization. For staggered learning to be effective, the user ought not to be exposed to a type B query until some time after the first encounter (time until second exposure = TSE). This requirement of a minimum TSE can be met by ensuring that a certain number of queries may enter the sink before they are retrieved. It is not desirable, however, to allow the unlimited accumulation of queries as this would lead to an unacceptable prolongation of the TSE, hence the need for an upper bound. By keeping the sink level at a constant height, a competent user with a low rate of new queries entering the sink, pressure on the sink is low and TSE will be long. For a less competent user, pressure on the sink is higher and queries are retrieved more frequently resulting in a shorter TSE. Hence, imposing a fixed sink capacity and making full use of this capacity has the sensible implication that the TSE increases with the competency level of the user.

The system variable that regulates the flux through the system is the probability of a query being drawn from the pool, which we denote by p. The external variables impinging on the flow characteristics and on which we have little influence relate to the performance of the user. Specifically, they are the probabilities of the user correctly answering a query of type A and B, respectively. Let us denote these probabilities by π and κ as in Figure 1. These three variables p, π and κ provide a complete description of the system. Our aim is to achieve a dynamic equilibrium of the system with the sink level remaining stable and the rate of inflow of new queries being balanced by an equal rate of outflow of correctly answered queries. Let s_i be the sink level at time i. With p, π and κ as defined above, the state of the sink at time $i + 1$ is

$$\begin{aligned} s_{i+1} &= s_i + p(1-\pi) - (1-p)\kappa \\ &= s_i + p(1-\pi+\kappa) - \kappa \end{aligned}$$

At equilibrium we have $s_i = s_{i+1}$ and thus

$$p(1-\pi+\kappa) - \kappa = 0$$

and

$$p = \frac{\kappa}{1-\pi+\kappa} \tag{1}$$

As the user performs better on either type of query (increase in κ or π), the probability p of presenting a fresh query in the next round increases. To ensure that the system reaches the equilibrium in the first place and finds back to it when displaced as a result of variation in κ and π we note that

$$s_{i+n} = s_i + np(1-\pi+\kappa) - n\kappa$$

To reach the capacity after d steps, we have

$$s_{i+d} = s_i + dp(1-\pi+\kappa) - n\kappa = c$$

and thus

$$p = \frac{c - s_i}{d - d\pi + d\kappa}$$

The more the current state lies below the capacity the greater is thus the influx of new queries.

The values of the two variables π and κ are recomputed during each round from the last 20 queries of each type.

2.2 Measuring performance

From this model, we can derive a simple and reliable performance measure, which is the value of the variable p. The higher p the greater the proportion of queries answered correctly. It follows from the sink capacity constraint and directly from equation 1 that

$p = 1$ implies that all queries are of type A and are answered correctly ($\pi = 1$), while $p = 0$ implies that all queries are of type B and are answered incorrectly ($\kappa = 0$). p varies during any one particular session owing to user/query specific variations in κ and π. The mean value of p over all queries during one session thus provides an estimate of overall performance while the variance in p is an indicator of the extent of inter-query consistency in performance. The variations in p, π and κ during a typical learning session are depicted in Figure 2.

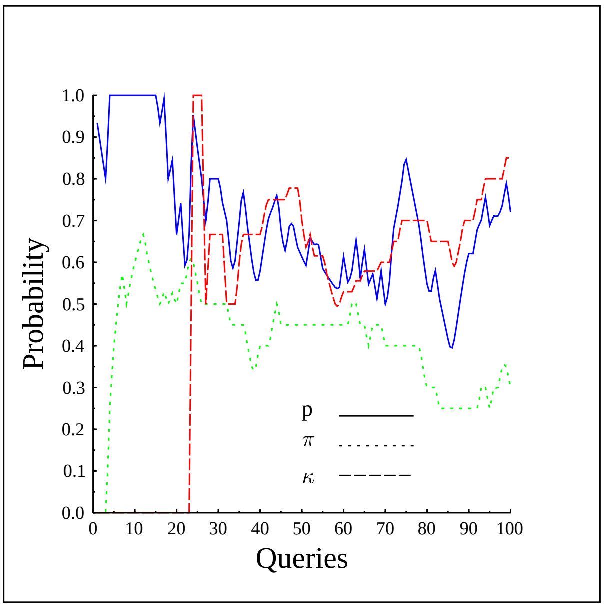

Figure 2: A typical learning session over 100 queries. Initially, a query is likely to come from the pool (p is high) so as to fill the sink. As the sink approaches its capacity (Figure 3), p decreases.

Figure 3 illustrates how continuous adjustment of p helps to keep the sink level within narrow bounds around the sink capacity ($c = 14$).

3 Sink visualization

With the sink level thus being kept relatively constant, the stage is now set for a visualization of the sink content.

The center of the display accommodates three text fields to display a query, enter a reply and inform the user about correctness and possible alternatives. Incorrectly answered queries are displayed as spheres on a concentric circle around this center as shown in the screenshot of Figure 4. The query string is printed across each sphere and for aesthetic purposes, the radii of the query spheres vary with query length.

To increase interaction between the user and the periphery, each query is assigned an electric charge,

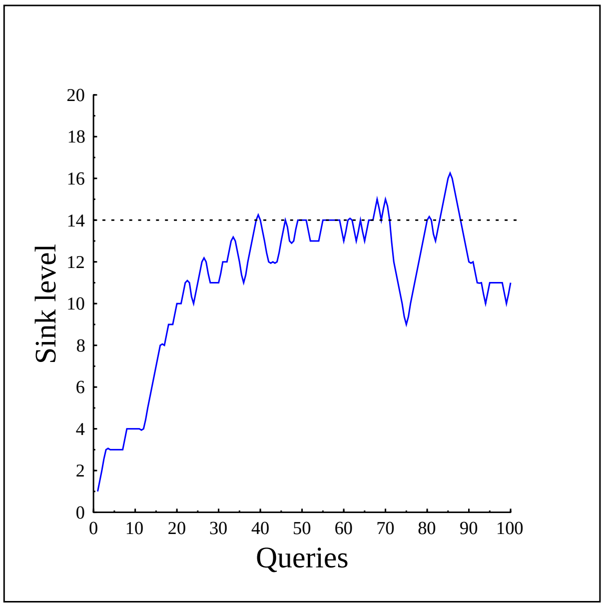

Figure 3: Sink level constancy is achieved by continuously updating the probability p of a query being obtained from the pool, taking into account variations in performance (π and κ).

with the charge depending on query length and thus the radius of the sphere. Spheres repel each other and whenever a new query is taken up into or leaves the set, the new set of queries are allowed to find a stable arrangement subject to the laws of electromagnetism. The movement towards equilibrium is recorded and displayed as a short animation sequence of one to two seconds after which the user is provided with a new query. In addition to thus drawing the user's attention towards the periphery and thereby facilitating interaction between user and incorrectly answered queries, it also gives the user a form of immediate visual feedback.

If the current query was obtained from the sink and is again answered incorrectly, the set remains unchanged and no animation sequence will be shown. Instead, the colour of the respective query sphere will turn darker as shown in Figure 4.

4 Outlook

This paper introduces the idea of sustained query exposure and suggests a possible way of how to use it to enhance the effectiveness of a staggered learning model. At this stage, we identify comparative evaluation as a chief desideratum to determine the precise scope of this form of passive knowledge consolidation.

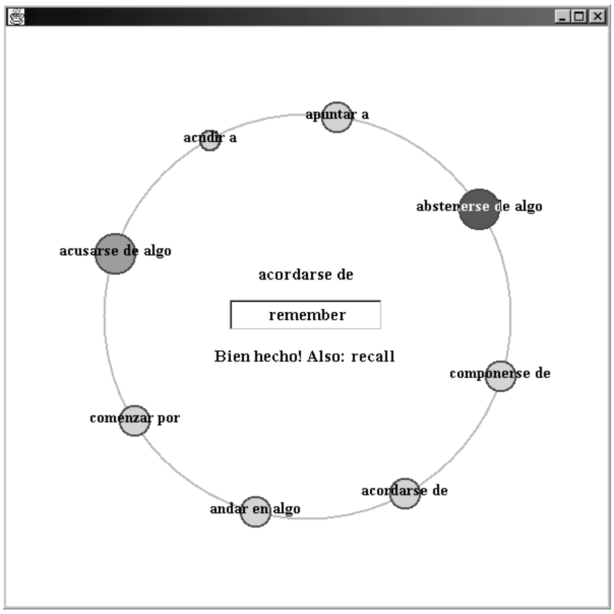

Figure 4: User interface and sink visualization. Animation and colour changes are included to facilitate interaction between user and periphery. See text for details.

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