

How Much Do People Remember? Some Estimates of the Quantity of Learned Information in Long-term Memory

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How much information from experience does a normal adult remember? The "functional information content" of human memory was estimated in several ways. The methods depend on measured rates of input and loss from very long-term memory and on analyses of the informational demands of human memory-based performance. Estimates ranged around 10^9 bits. It is speculated that the flexible and creative retrieval of facts by humans is a function of a large ratio of "hardware" capacity to functional storage requirements.

HOW MUCH INFORMATION DOES AN ADULT HUMAN REMEMBER?

The question is interesting in its own right, and its answer may bear on important questions about the requirements and mechanisms of information storage in the brain and in artificial devices that are designed to perform similar tasks.

Some previous speculations regarding the size of human memory have been based on anatomical or neurophysiological facts. For example, the most commonly quoted figure, 10^{13} bits, is simply an old estimate of the number of synapses in the cortex. Another widely quoted number, 10^{20} , due to John Von Neumann (1958), represents the estimated sum of all neural impulses conducted in the brain in a lifetime. From the perspective of this paper, the chief deficiency of these approaches is not their obviously questionable assumptions (e.g., that synapses or impulses represent only one flip-flop bit, rather than multiple thresholds or interpulse interval values). What is wrong with such estimates is their level. Even if we knew that the wetware of the brain was capable of representing 10^{20} bits, we would have

I thank Patricia Grampsch and Joe Kruskal for mathematical advice at various stages of this work; Karim Jinnah, Sheila Borack, and Sam Glucksberg for collecting data; and many colleagues at Bell Labs and Bellcore, including, but not limited to, George Furnas, Dave Krantz, and Saul Sternberg, for helpful suggestions.

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no idea how much information gleaned from experience is actually encoded and later retrievable, because we know very little about how neural information is recorded or about how neural phenomena might be related to the information-maintaining capacity of the whole brain. We do not, for example, know how much neural capacity is used up in "internal affairs," "book-keeping," "data base management," or in overcoming the effects of noise, unreliability, and damage. The first requirement for an estimate of the functional content is to measure information maintenance in terms of the functioning system as a whole, rather than at the level of presumed components.

In what follows, I describe some attempts to estimate how much functional information is actually held in human memory. Several different methods of estimation will be described, all relying on direct data about the performance of intact adult humans learning and remembering in normal ways. The first approach follows Von Neumann in that it assumes that all information that is entered into long-term memory (but not all that is merely perceived) is kept permanently. For this approach, we need estimates of the rate at which information is added to memory. Data from two very different learning and retrieval tasks, reading recall and picture recognition memory, are described. The second approach adds the effects of forgetting. Again two representative sources of data are used, picture recognition and life-event date recall. The third approach guesses at the amount of remembered information needed to support the kinds of performance of which an adult human is capable.

Before describing the detailed estimates, a few general remarks and warnings are needed. First, this investigation required data on human memory formation, forgetting, and performance that could be converted into information-capacity terms. Psychologists have not usually measured performance in appropriate ways, the natural elements of knowledge for their purposes usually being facts or "chunks," which, unfortunately, do not have the necessary properties of measurement units. As a consequence, the transformation of available data into bit rates has sometimes required the formulation of new models. These models specify an abstract scheme by which the input might be coded in memory. Behavioral data are then used to estimate the information that must be transmitted from input to output in order for humans to do what they do. The amount of information transmitted from input to output with some delay is taken as the quantity of "functional information" that must have been kept in memory. I have tried to keep the models simple and to make them correspond as well as possible to what is known about the mechanisms of the behavior in question. In general, they provide a description of the form, "if the information were stored this way, it would require so many bits of memory." Second, the broad limits on the desired and attainable degree of accuracy in this kind of exercise need to be kept in mind. We currently have no firm knowledge of

even the plausible range for the size of human memory. It is this kind of estimate we seek. That is, we want to know whether human memory should be thought of as representing millions, billions, or millions of billions of bits. We need answers at this level of accuracy to think about such questions as: What sort of storage and retrieval capacities will computers need to mimic human performance? What sort of physical unit should we expect to constitute the elements of information storage in the brain: molecular parts, synaptic junctions, whole cells, or cell-circuits? What kinds of coding and storage methods are reasonable to postulate for the neural support of human capabilities? In modeling or mimicking human intelligence, what size of memory and what efficiencies of use should we imagine we are copying? How much would a robot need to know to match a person?

INPUT RATES AND ESTIMATES BASED ON A NO-LOSS ASSUMPTION

If we assume that all information that enters long-term memory is permanently stored and we can get an estimate of the average rate at which information is gained, we can cumulate over a normal lifetime to obtain an estimate of how much information the adult memory might contain. Of course, the physical memory could have capacity to hold many times the information gained in a single lifetime, but, to repeat, we are interested here in realized functional "holdings" rather than potential maximum capacity (by analogy, how many books the library has, not how much shelf space.) We want the rate at which information is added to memory, in the sense that it can be retrieved after some delay. That is, we seek estimates for what is sometimes called long-term memory rather than short-term memory. Most information that is perceived is only retrievable for a short time, on the order of a minute, if it is not properly rehearsed or repeated. Moreover, these short-lived memories contain only relatively small amounts of information. We are interested here in lasting memories, those that cumulate to form the bulk of what an adult knows.

In order to estimate the rate at which information is added to long-lasting memory, I have made the simplifying assumption that the input rate is roughly constant. This implies a kind of conservation-of-learning principle: If one isn't learning one thing, one is learning an equal amount about something else. For example, a person obtains information both from the surroundings and from intentional study, but I will assume that the devotion of attention to one source will reduce, approximately equally, the gain from others. Thus, the average rate of accumulation of new information is assumed approximately equal to the measured rate for a single absorbing task. I have examined several sources of data that yield information measures for concentrated input. Two that seem reasonably typical of normal experience and for which relatively reliable data are available will be de-

scribed in detail. These are for concentrated reading and for recognition of pictured scenes.

Long-Term Memory Input From Concentrated Reading

Good readers typically read moderately difficult material at about 200 words per min. At this rate, a reader who is stopped and asked questions about contents will recall gist and recognize changes in wording of text read a few minutes earlier with high accuracy. However, not all of this information is newly learned. Given a text like this, if words are deleted at random, a reader can guess approximately half from context and previous knowledge. Thus, the new information available in the text is roughly an average of one bit per word. But not all of what is read is remembered. I recently estimated the amount transmitted through long-term memory in the following way. Two hundred and four Bellcore employees, local homemakers, and Princeton undergraduates read paragraphs of moderate difficulty. After another 1.5 min of reading, they were asked to fill in randomly deleted words either from the text they had just read or from equivalent (counterbalanced) paragraphs that they had never seen. The average proportions correct were .63 and .48, respectively. Thus, the new information transferred through long-term memory was equivalent to $\log_2 (.63/.48)$, or about 0.4 bits per word read. The participants read an average of 180 words per min, for an input rate to long-term memory of about 1.2 bits per second (b/s).

Note that the measurement method in this case makes no assumptions about what kinds of knowledge or what mental representations “contain” the maintained information. We need only assume that whatever the new representation—perceptual pattern traces, spellings, semantic features, facts, propositions, improved comprehension of gist, and the like—the information it represents is reflected in increased likelihood of correctly restoring the original word. The method is likewise indifferent to the physical form in which the information is stored.

This estimated input rate of just over 1 b/s may strike the reader as remarkably low. I will shortly describe other, similar estimates from very different sources. But to increase the intuitiveness of the order of magnitude, consider the following. Suppose one remembered every word as a verbatim record, as if it were stored on a digital disk. How many bits would be required for each word? This depends on how many different words a person can discriminate and code, because the pattern standing for a word must distinguish it from all other words the person could have read and remembered.

Robert S. Moyer and I once estimated this number by sampling 1,000 entries randomly from a large unabridged dictionary and testing Stanford undergraduates about their meaning. By reinflating to the size of the full

dictionary and taking rough account of the number of words that can be understood by reconstruction from common roots, we estimated that the average student knew around 100,000 words. To distinguish any of 100,000 words from any other requires a code of about 17 bits. (A compression trick like Huffman coding, in which frequent symbols are given shorter codes, might reduce the average code length by about one-half for normal English text.) If a text were stored in a phonetic or alphabetic code instead of as word identities, 30 to 50 bits would be needed for each word. Thus, literal storage would correspond to input rates of about 50 to 150 b/s. But this ignores semantic and syntactic redundancy, the fact that little of the knowledge in what is read is new to the reader, and the certainty that only a fraction of what is new is remembered. Thus, that the actual ratio of newly stored and retrievable information to nominal information in text is as little as 1/40 or even 1/100 does not seem at all implausible.

The first line of Table 1 shows that a rate of 1.2 b/s for 16 hr per day (there is little evidence of learning during sleep) for a lifetime of 70 years yields $(1.2 \times 1.5 \times 10^9 \text{ sec}) = 1.8 \times 10^9$ bits, for a first estimate of the total amount of information a person might remember.

TABLE 1
Estimates of Amount of Information Held in Human Memory

Source of Parameters	Method of Estimate	Input Rate (b/s)	Loss Rate (b/b/s)	Total (bits)
1. Concentrated reading	70-year linear cumulation	1.2		1.8×10^9
2. Picture recognition	70-year linear cumulation	2.3		3.4×10^9
3. Central values	asymptotic net gain over 70 years	2.0	10^{-9}	2.0×10^9 1.4×10^9
4. Word knowledge	semantic nets $\times 15$ domains			0.5×10^9

Input Rates for Recognition Memory of Pictures and Other Material

A second input rate estimate was obtained from data from several published experiments on recognition memory for pictures. In a method introduced by Nickerson (1965) and refined by Shepard (1967), people are shown pictures, one at a time, sampled at random from a large pool. Later they are shown pairs of pictures, one from the previously examined set and another from the same pool but not previously seen. They make their best guess as to which of the two they have seen before. Accuracy is quite high; for example Shepard's subject were correct on 97% of their choices when they had seen 612 pictures.

To turn this kind of performance measure into an estimate of required information capacity, we need a model. The following one describes the data quite well. Assume that each picture as seen is transformed into a b bit

code, perhaps representing a description of some of the features of the picture that can be perceptually analyzed. There are, consequently, a total of 2^n codes available. At time of test each picture in the pair is coded, and its code compared with all the codes previously stored to represent pictures seen during the inspection series. Because recognition is virtually perfect immediately after a single picture is presented, and because we are assuming no loss, the model supposes that the perception of every old picture leads to a code that matches one stored in memory. Therefore, an error occurs only if the new picture in a test pair happens to be coded the same as one of the previously seen pictures. When this occurs, both pictures appear to be old, and the subject must guess. Accuracy, therefore, is determined by the likelihood that a new picture is coded in the same way as some old picture. Now, suppose that pictures are optimally coded, in that each code is as likely as any other. Recall that in the experimental method, pictures are chosen randomly from a large pool, so any picture is as likely to be chosen as any other. Therefore, the likelihood that a newly chosen picture will have a code not assigned to any previously seen picture is given by the expression

$$p(\text{new code}) = \left[1 - \frac{1}{2^n}\right]^n, \quad (1)$$

where n is the number of pictures initially shown.

If the model is correct, the relation between the number of pictures shown in an inspection series and the proportion correctly identified will yield a constant number of bits for the code. Some data obtained by Lionel Standing (1973) using some 11,000 slides of scenes, faces, and other mundane subjects, provide an interesting set of data for this purpose.

As shown in Table 2, the bits required for coding, according to the model expressed in Equation 1, are remarkably constant for inspection series of 10 to 1,000 pictures. A central value for these data is roughly 10 bits per pic-

TABLE 2
Information required for recognition memory of sets of pictures.
Data are from Standing (1973).
The information requirements were estimated according to a model described in the text.

Number of Pictures Originally Shown	Proportion of New-old Pairs Correctly Judged	Code Bits Required
20	.99	10.0
40	.96	8.7
100	.95	9.9
200	.92	10.1
400	.86	10.2
1,000	.88	11.9
4,000	.81	13.0
10,000	.83	14.6

ture. But another factor must be taken into account. Standing tested these subjects two days after seeing the pictures and, despite our working assumption of no loss, their performance was demonstrably (Nickerson, 1968; Shepard, 1967; Standing, 1973) degraded by the delay. At this point we want an estimate of the amount retained after about a minute or two, that is when the influence of short-term memory has been lost, and long-term memory first "consolidated." Data collected at different delay times by Shepard (1967) and others (see Table 3) suggest adjusting the estimate upwards to approximately 14 bits per picture initially stored in long-term memory.

Similar experiments have been done with words, both visually and auditorily presented, short passages of music, sentences, and nonsense syllables. Comparable estimates of coding requirements for these items and for other data on picture memory are shown in Table 3. The similarity of the values is striking.

TABLE 3
Estimates of information required for recognition memory for various kinds of materials
(in bits).

Pictures

Unselected pictures

- 10.0-14.6 (Standing, 1973; 20 to 10,000 tested after 2 days)
- 12.9 (Standing, 1973; 200 tested after 1 hr)
- 12.0 (Nickerson, 1968; 200 tested after 1 day)
- 13.1 (Shepard, 1967; 612 tested after 0.5 hr)

Vivid pictures

- 11.9-13.0 (Standing, 1973; 20 to 1000 tested after 2 days)

Words, visual

- 11.0 (Shepard, 1968; 540 tested after 0.5 hr)
- 6.5-11.0 (Standing, 1973; 20 to 1000 tested after 2 days)
- 11.5 (Standing, 1973; 200 tested after 1 hr)

Words, auditory

- 11.7 (Standing, 1973; 200 tested after 1 hr)

Sentences

- 11.3 (Shepard, 1968; 612 tested after 0.5 hr)

Nonsense syllables

- 10.2 (Standing, 1973; 200 tested after 1 hr)

Music segments

- 11.4 (Standing, 1973; 200 tested after 1 hr)
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For an input rate for pictures we also need to know how long it takes to encode each one. Standing performed most of his experiments with a 5.6-seconds-per-picture presentation rate, which is close to the 5.9-second average chosen by Shepard's self-paced subjects. If 6 seconds per picture is taken to be a normal absorbing learning rate, then an estimated memory input rate of about 2.3 b/s is obtained. This corresponds to a lifetime no-loss accumulation of about 3.4×10^9 bits, as shown in line 2 of Table 1.¹

Note that the estimated number of bits initially stored for words and nonsense syllables is only a little lower than that for pictures, despite the fact that they have very different learning rates by ordinary measures. Results from recognition experiments with a variety of other materials are shown in Table 3. The implied input rates to long-term memory are quite consistent. Isolated words, at 6 sec and 12 bits per word, would give about 2 b/s, as would nonsense syllables and music. Whole-sentence recognition yields a similar b/s rate, and assuming sentences to average about seven words, matches the per-word rate based on recall of missing words from continuous text. This invariance over measurement methods and materials lends some credibility to the working hypothesis of conservation of memory input.² The similarity of estimates derived from methods based on cued recall and those based on forced-choice recognition is especially encouraging to the information-theoretic approach to input measurement, because these two indicants are usually considered to mark the extremes of sensitivity for assessments of retention in human memory.

¹ Potter and Levy (1969), using artificial means of rapid presentation of short strings of pictures, have achieved higher input rates. For example, at three pictures per sec, their subjects had false positive and hit rates of around .03 and .48 respectively, that is, $.48/.03 = 4$ bits per picture, or 12 b/s. Three per second is about the maximum rate of natural eye fixations. However, these experiments used quite short retention intervals, sometimes well under 1 minute. It is worth noting that the total time rule (Bugelski, 1962), which holds to a first approximation across a wide range of conditions (see, e.g., Baddeley, 1976), states that long-term memory formation rate is independent of presentation rate.

² The estimates given here are, in general, the simplest and most central of several tried. In some cases, additional considerations lead to either higher or lower rates, but not by large factors. For example, the picture-coding estimate is questionable on two grounds, one leading to overestimate, the other to underestimate. The assumption of equally frequent independent codes is likely to be unrealistic, even for a "functional" capacity measurement, because it is unlikely that features can be found that equalize the likelihood of every code for the scenes actually encountered in life. In a somewhat more complicated model, I assumed that picture codes were distributed across pictures in the way words are distributed in English usage, instead of the uniform distribution assumed here, and found that a code length approximately one-third again as long would be required to support the kind of performance observed. On the other hand, a more efficient coding scheme, for example, a Huffman code, would reduce the average requirement by representing relatively frequent patterns (or features) as relatively shorter bit patterns, as is done to some extent, for example, in the alphabetic representation of words.

ESTIMATES BASED ON BOTH INPUT AND LOSS RATES

At the functional level it is clearly not true that all information that is entered is retained. People do forget. By measuring forgetting rates appropriately, estimates of functional memory size that take into account both input and loss can be made. Suppose we have both a constant input rate I , and a constant loss rate L , where I is the number of bits added to memory per unit time, and L is the likelihood that any previously added bit is altered during any unit time period. Then the resultant growth in total number of stored bits, T , remaining unaltered at a time t , is given by

$$T = \frac{I}{L} (1 - e^{-Lt}) \quad (2)$$

Note that as t grows, the value of T monotonically approaches I/L , which must be the maximum quantity. There are two ways to combine input and loss rates. One is to follow the first approach and calculate the information cumulated over a particular time period, e.g., 70 years. The other is to use just the asymptotic value, I/L .

The latter method corresponds to an interesting special interpretation that requires that loss be measured in a particular manner, and the discussion will be simplified by considering it first. This interpretation allows I/L to be seen not just as an infinitely distant equilibrium point at which gain equals loss, but as an estimate of total potential capacity at any fixed time of measurement. It is based on a particular model of the nature of very long-term loss from human memory that is somewhat unusual (its relation to some current theories will be touched on later). The model assumes that the cause of most of the forgetting going on at any point in time, that is, the forgetting that occurs over years, is the result of overwriting or masking of old information by new. It also assumes there is a certain fixed amount of storage capacity, that is, writable bits, available. Each newly learned bit occupies one of these loci, either filling a previously unused one or "overwriting" one previously occupied. "Loci" at which new information is written are distributed in the same way as those of old information, that is, there is no systematic allocation of new information to previously unused portions of memory. (For a rough computer analogy, think of hash coding or Hopfield net storage.) Then the likelihood of a particular bit being overwritten in any time period is given by the ratio of the number of bits entered in that period to the total capacity. Note that even if certain regions of memory were specialized for certain kinds of information, so that only similar kinds of information overwrote each other, the same relation would hold on the average. Moreover, it would be reasonable for the system to allocate capacity proportionally to demand so that different kinds of information would suffer similar degradation rates.

To estimate capacity in this model, or directly by Equation 2, a measure is needed of the rate at which an average bit of previously stored information is lost. So far, I have been able to obtain useful loss rates for only two sorts of material, the best one for picture-recognition memory over 1 year, the other for recollection of dates over a 3-month period.

Loss-Rate Estimates for Picture Memory

A loss-rate estimate was obtained from an experiment by Nickerson (1968), who had subjects return and make recognition judgments about pictures seen between 1 day and 1 year previously. Nickerson did not use exactly the same procedure as the studies quoted above. Instead, he presented the pictures one at a time and asked for judgments of "old" or "new." Most of the change in performance over the year was due to an increase in miss errors, that is, occasions on which an old picture was erroneously judged to be new. These data can be generated by the same process as modeled above, as follows. The number of codes used for the 200 pictures in the learning phase is a small fraction of the total code space available in 14 bits. Thus, change of any one bit of the corresponding stored pattern would almost always cause a failure of the code for an "old" picture to match any previously coded test picture, thus a "miss" error. Using our earlier estimates of the number of bits needed to represent each picture we can solve for the probability that any one bit was changed in any 1 second, the loss rate we need.

However, the rate of forgetting shown in Figure 1 is not uniform; forgetting is much more rapid during the first month than thereafter. This is a typical result in human memory research.

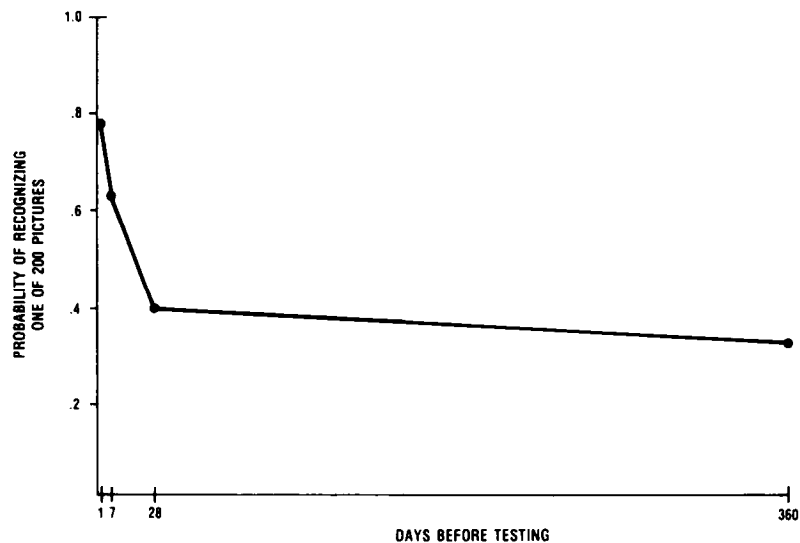


Figure 1. Loss of picture recognition memory over a year (data from Nickerson, 1968)

It is the loss rate represented by the very long-term portion that we want, because we are interested in the rate at which the average bit in memory is changed, and, of course, the vast majority of information known at any one point in time has been known for a long time. The estimated long-term picture-memory loss rate is approximately 6.5×10^{-10} bits per bit per sec (b/b/s).

Loss-Rate Estimates for Date Memory

So far, I have been unable to find quantitative data on memory loss for any other material for periods greater than 4 months. However, in order to judge the generality of the value obtained for picture-recognition memory, it is desirable to compare forgetting rates for this kind of information to those for some very different material. Luckily for this purpose, Thompson (1982) collected data on people's memory for dates on which unique personal events occurred during a period of 3 months, and Shepard (1967) tested small numbers of subjects on his picture memory task at 3, 7, and 120 days. To make the comparison, we need first to derive a loss estimate for the date-memory situation.

Thompson (1982) had college roommates record events that happened to each other on Mondays to Thursdays over a semester. At the end of the term they were shown the descriptions and asked to guess the date on which the event occurred. Perfect recall would have required a little less than 6 bits of information to be transmitted through long-term memory for each date.

Note that, again, no assumption need be made about the form in which the information is stored. For example, there is no reason to suppose that a literal "time stamp" is involved; information about the relative times of various events, anchor dates, and so forth might serve as well to incorporate the needed information.

Once again, it is the rate of very long-term information loss that is desired. Unfortunately, the best we can do with these data is to consider the portion of forgetting between 24 and 84 days. In this period the proportion of correct dates declined from .24 to .12, a loss of 1 bit per date, or about 5×10^{-8} b/b/s of an initial 6-bit code.

Shepard (1967) gives data for picture recognition tests at 7 and 120 days on four subjects each. The estimated loss rate during this interval is about 4×10^{-9} b/b/s. The difference in the estimates from picture recognition and date memory is uncomfortably large, but still small enough to justify selecting a value for the sort of broad approximation desired. Two considerations favor using a value close to the slow extreme of the estimates: First, the average surviving memory of an adult is certainly much older than the oldest memories on which the estimates were made, and the loss rate appears to decline with time; second, slower decaying memories will tend to dominate faster in the distribution of survivors. Thus, a modest adjustment of the

7×10^{-10} value for very long-term picture memory to, say, 10^{-9} seems reasonable as a first approximation to the rate at which the average bit held in memory decays.

Before we actually obtain new size estimates, a few more words on the interpretation of forgetting rates are in order. First, let us continue to pursue the assumption that memory has a fixed maximum capacity, and that long-term loss is caused by new information replacing old. Received wisdom in the psychology of memory is that all or most long-term forgetting is due to interference, to confusion or conflict between one fact and previously or subsequently learned similar facts. The replacement idea used here need not be interpreted as literal overwriting. For what we have done, the addition, after the learning of an item, of other items that make it unavailable by some process like competition would serve the same function in reducing the likelihood of remembering. All we need for present purposes is the assumption that the rate at which information is made unusable is proportional to the rate at which other information is added. To a reasonable approximation, this is what work on interference in human memory suggests.

However, using the ratio of input to loss to estimate total capacity by the overwrite model requires that it be current input that causes forgetting, not previous input. Therefore, for this purpose the very long-term portion of the forgetting curve must be assumed to reflect only retroactive, not proactive interference. This is a plausible hypothesis, on current evidence, if not an established fact. (In the next approach, integrating net gain, this assumption will not be needed.)

If we take 2 b/s as the typical input rate, and 10^{-9} b/b/s as the typical loss rate, the total capacity, according to the overwrite model, is then about 2×10^9 bits. Next let us now turn to the theory-free estimation method implied by Equation 2. Here we are simply interested in how rapidly information is being gained and lost by memory. No explicit model of how memory is stored, retrieved, or forgotten is required, nor is an assumption of fixed capacity. The shape of the curve and its asymptotic limit, I/L results only from the assumption that loss occurs on a per-bit stored basis, that is, the more that has been stored, the more is being lost.

The reader may wish to note how the discussion to this point can rationalize what may have been an apparent contradiction between the first two approaches, the assumption of no loss and constant accumulation versus the assumption of destruction of old by new. Although obviously these both cannot be exactly true, they nevertheless provide somewhat independent estimates. In the overwrite model the difference is merely a feature of the storage process, a question of whether new information selectively utilizes previously unoccupied space or unselectively overwrites old information. If, instead of overwriting, one were to assume that all once-known information is preserved and that forgetting is only a matter of unavailability, then the first approach estimates the total stored and the second the amount retrievable.

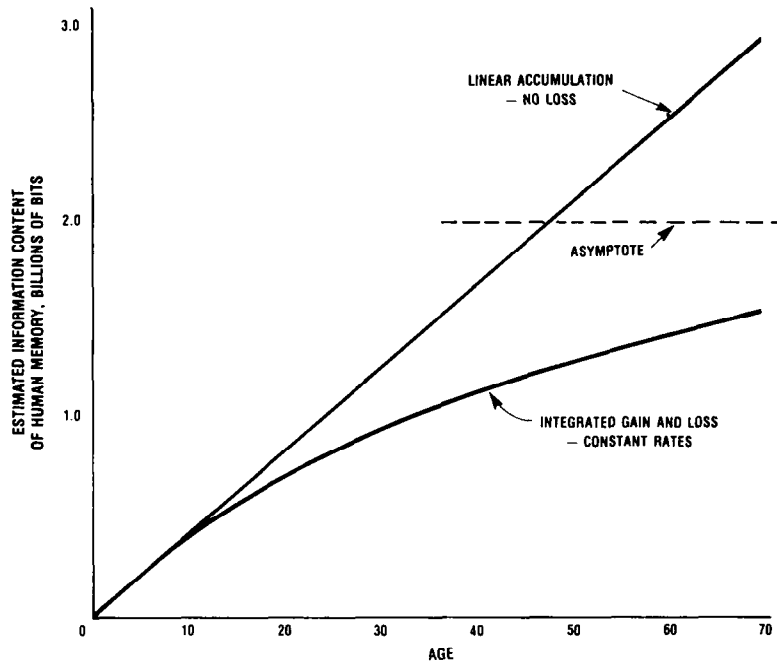


Figure 2. Estimated cumulative learned information in human memory as a function of age

Figure 2 shows both quantities as a function of age, based on the assumed input and loss rates of 2 b/s and 10^{-9} b/b/s. By midlife a person has about 10^9 bits of information accessible, according to this approximation, and by age 70, about 1.4×10^9 bits. If there were no loss, the analogous quantities would be around 1.5×10^9 and 3.0×10^9 , respectively. Thus, the difference between loss and no-loss assumptions, and between asymptotic or total capacity versus 70-year accumulation estimates, turns out to be relatively minor.

METHOD 3, PERFORMANCE REQUIREMENTS

A final approach to size estimation is to look at the information-using activities of an adult human and try to make a guess at the amount of stored information needed for their support. I've made such an estimate, and, although it is not very compelling by itself, it strengthens the intuition that the other estimates are in a reasonable range.

The performance estimate considers memory to be a library of information sources. One such information source is a "dictionary," a collection of the knowledge one has about words. We noted above that a well-educated adult can identify about 10^5 word meanings. What does it mean to know enough about a word to categorize it correctly or to read it usefully? At pre-

sent, there is no rigorous answer to this question, so I have made the following approximation. I sampled entries randomly from a dictionary and chose those that I knew according to the same criteria Moyer and I had used to get the 10^9 word-vocabulary estimate. I then looked to see how many words in the definition given in the dictionary I needed to know in order to reconstruct an intuitive match to my knowledge about that word. That is, I imagined constructing the portion of a semantic net that would connect the dictionary entry for a word to some number of words in the text of its definition, so as to represent just about as much as I know. I found I needed an average of about 12 content words per entry. To have a link to a word requires storing, in one way or another—for example, as some kind of a network structure or pointer—an address for the word. Because there are 10^9 different words that might be addressed, the information required for such an address is about 17 bits. My imaginary networks used only a limited number of relations, for example, “isa,” “part of,” “very similar to,” and the like as have some analyses and simulations of human word knowledge (e.g., Anderson & Bower, 1973; Rumelhart, Lindsey, & Norman, 1972; Moore & Newell, 1974.) Allotting 6 bits of label information to each of 12 arcs to represent my semantic knowledge of the average word that I can read with comprehension, and adding 70 bits for spelling, pronunciation, grammatical marks, and the like gives $12 \times (17 + 6) + 70 = 346$ bits per word, for a total of 3.5×10^7 bits to store the knowledge in my mental dictionary. Now, the English lexicon is one of my largest domains of knowledge, but there are others. I probably know a similar amount about geography, history, and politics, about music, art, nature, and science, other equal amounts about my vocation, my avocations, my domestic life, my own life history, places I’ve been, people I’ve known, my motor skills, and so forth. If I give myself credit for 15 domains of knowledge as large on average as what I know about words in English, the total “library” would contain around 0.5×10^9 bits.

Compared to the other approaches, this last is obviously a much wilder guess. But it does serve to indicate something of the expected amount of information an adult human memory needs to hold. For example, it would seem implausible to either divide or multiply it by much more than 10.

SUMMARY, CONCLUSIONS, AND REMARKS

Several different methods for estimating the approximate functional content of adult human memory have been tried. Estimates were obtained of the rate at which information is entered into, and lost from, long-term memory. These estimates were then used in three ways to arrive at total capacity estimates. One way assumed that information is accumulated linearly throughout life, yielding an estimate of 1.5×10^9 bits for a 35-year-old person. Second,

the estimate was made more realistic by taking into account loss rates, reducing the amount of retrievable information held by mid-life to around 10^9 bits. Third, the question of how much knowledge an adult needs to support knowledge-based behavior was considered. A guess of about 0.5×10^9 , based largely on estimates derived from word knowledge, was hazarded.

Thus, the estimates all point toward a functional learned memory content of around a billion bits for a mature person. The consistency of the numbers is reassuring. But, before drawing implications from this estimate, it will be useful to develop some idea of its overall degree of accuracy and of its proper interpretation. In my judgment, the input-rate estimates are probably realistic within a factor of five in either direction. Several different data sources and memory-assessment procedures gave similar results. They all could be a little low because the measurement methods could fail to reflect all the stored information, for example, a reader might acquire pragmatic knowledge that is unrelated to that used to restore missing words, or because some additional information from the environment leaks in even when one is concentrating on a difficult task. On the other hand, the input estimates may be somewhat high because the concentrated learning during a laboratory session is faster than usual. In a similar vein, I have tried many variations on the models and assumptions without producing order-of-magnitude changes in the input-rate estimates. The loss-rate estimate is more questionable. It is based on only a single experiment and some bolstering data from two others. Moreover, the decay rate seems to get smaller with time in a way that is not currently well understood or modeled. However, the overall estimate is not extremely sensitive to the value of the decay rate. For example, substituting loss rates of 10^{-8} and 10^{-10} , which are 10 times faster and slower, respectively, than the the best-guess value, yields 35-year accumulation estimates of 0.2×10^9 and 1.4×10^9 .

One way to interpret these estimates is to think about what capacity a computer system would need to maintain and retrieve the information that people do. The main estimation techniques used here correspond roughly to inputting data either in text or in digitized pictures, later trying to retrieve information about the input, and describing the system's functional memory holdings by the amount of information transmitted from input to output. For such a measurement to make sense, it is obviously important that the input and retrieval methods be those by which the system is normally used. In the memory experiments analyzed here, the input methods are normal for humans. The retrieval tests are somewhat contrived, but, as noted, span the sensitivity range for such tests while giving consistent estimates. One of the salient features of humans, as compared with computers, as information-conserving systems, is that humans can retrieve information based on experience in a wide variety of different ways. More will be said on this point, shortly.

Let us now consider briefly how a functional memory-size estimate such as those obtained here might be related to the hardware-memory capacity of a computer system. Generally, a database system for textual material will require two or three times as much memory as is represented in the input text, depending on what kind of queries it will serve with what speed. The extra memory is used for the store and search routines and for additional representations of the input, such as hash tables or inverted files, that make retrieval faster and more flexible. If one were to build a system to recognize previously seen pictures, it might also have an elaborate preprocessor that extracted geometric features for coding. Like store and search routines, the preprocessor would probably be a common facility used for all input received through a particular channel. Such components entail a constant overhead in memory capacity, as compared to hash tables, inverted files, and the like, which grow at varying rates with the amount of information that is stored. The intention here is not to develop a serious computer model of human memory, but only to draw the analogy sufficiently to point out some of the differences between functional- and component-level descriptions of memory size. In particular, it should be clear that there is not a one-to-one correspondence between the amount of functional memory and the component capacity needed in its support. The more complex the analysis and transformation of the input, the more degradation protected the storage, the more flexible the retrieval, the less efficient the storage and processing methods, the larger the underlying capacity may be. We know that humans perform more powerful perceptual analyses in both visual and auditory mode than we know how to accomplish with machines, and that they are capable of many feats of associative memory based on content and context that are equally mysterious.

With these considerations in mind, some broad implications of the functional memory estimates for humans can be suggested. The numbers of bits are much lower than the number of synapses in the brain, and close to current physical memory capacities of electronic computers. What should be concluded from these last two comparisons? If we assume synaptic storage and suppose that each synapse corresponds to from 2 to 10 bits of storage and the brain of from 10^{12} to 10^{14} relevant synapses, then it would seem that the underlying physical storage devices are capable of a thousand to a million times the capacity manifest in learned behavior. Computer systems are now being built with many billion bit hardware memories, but are not yet nearly able to mimic the associative memory powers of our "billion" bit functional capacity. An attractive speculation from these juxtaposed observations is that the brain uses an enormous amount of extra capacity to do things that we have not yet learned how to do with computers. A number of theories of human memory have postulated the use of massive redundancy as a means for obtaining such properties as content and context addressability,

sensitivity to frequency of experience, resistance to physical damage, and the like (e.g., Landauer, 1975; Hopfield, 1982; Ackley, Hinton, & Sejnowski, 1985). Possibly we should not be looking for models and mechanisms that produce storage economies (e.g., Collins & Quillian, 1972), but rather ones in which marvels are produced by profligate use of capacity.

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