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# The Effect of Bayesian Feedback on Learning in an Odds Estimation Task

MICHAEL L. DONNELL AND WESLEY M. DU CHARME

*Rice University*

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Numerous studies have compared human and optimal uncertainty revision, but few have considered learning and transfer effects. The present study provided subjects with 60 feedback trials in an odds revision task using normal distribution data generators. Learning and transfer were tested by comparing pretraining and posttraining odds estimates for data generators differing in diagnosticity (higher and lower) and kind (binomial) from those used in training. Subjects showed rapid learning and a moderate amount of transfer. What subjects seem to do after training is to increase their initially too small odds by some factor related to the perceived diagnosticity of the data generators. The fact that transfer of training is so closely tied to the actual stimuli used during feedback poses problems for training operators of real world diagnostic systems.

Although numerous studies have been conducted comparing human and optimal uncertainty revision, few have considered the topic of learning, and none has looked for direct transfer effects. Slovic and Lichtenstein (1971) have cited Bayesian researchers' notable disinterest in the topic of learning: "they usually treat learning as a confounding to be avoided" (p. 93). A rare exception to Slovic and Lichtenstein's observation is an experiment by Martin and Gettys (1969), which, among other things, examined the effects of Bayesian probability feedback on subjective probability estimates. One group of subjects in their experiment saw samples of data produced by one of three multinomial data generators, estimated the posterior probability for each data generator, and then were informed of the Bayesian posterior probability distribution, i.e., the one specified by the optimal model, Bayes' theorem. No evidence of learning was found within the first 50 trials or over an additional 150 trials, but the overall performance of this group was significantly closer to optimal than that of another group that received feedback only about which data generator had produced the data. Martin and Gettys tentatively concluded that learning took place very rapidly either during five pre-experimental trials with feedback or very early in the experimental trials.

Fleming (1970) also gave a group of subjects correct posterior probability feedback in a multinomial task. He found that essentially all learning took place within the first 20 trials, thus supporting Martin and Gettys' conclusions. Neither Fleming nor Martin and Gettys looked for transfer effects in their experiment, but an experiment by Strub (1968) demonstrated that some factor related to experience does show positive transfer to an uncertainty revision task. Strub asked two groups of subjects, one relatively maive and the other very experienced, to revise probabilities about which of two binomial data generators had produced sequences of data. The naive subjects had served in one previous probability estimation task, but the experienced subjects had been in several previous experiments and had received approximately 114 hours of lectures, demonstrations, problem-solving sessions, and on-the-job training in a probabilistic information-processing system. The probability estimates of the experienced subjects were significantly more optimal than those of the naive subjects, but it is not possible to tell which experiential factors are the crucial ones.

The three studies discussed so far show that learning and transfer can take place in uncertainty revision, but the necessary conditions for success are not at all clear. Establishing such conditions is of interest for both theoretical and applied reasons. The most consistent finding in the area of uncertainty revision is that humans are conservative, i.e., the amount of uncertainty they express changes more slowly than the optimal model dictates. It has been suggested that such conservatism may be due to a response bias or lack of familiarity with the response scales used (Du Charme, 1970). If this is the case, then training with one such scale should lead to more optimal performance, and furthermore the training should transfer to other conditions in which the same scale is used. From a more applied standpoint Edwards has suggested and tested (Edwards, Phillips, Hays, & Goodman, 1968) an information-processing system in which humans provide some form of probabilistic input to a computer for processing. Clearly in applications of such a system it will be crucial to know to what extent human operators can be trained to provide accurate probabilistic inputs.

The present experiment was undertaken to provide data bearing on the issue of learning and transfer in uncertainty revision tasks. Odds responses were used as measures of uncertainty, and several pairs of normal distributions, differing in average diagnosticity, were used to generate stimuli. After making odds estimates in all conditions, subjects were given Bayesian odds feedback in one condition, and then transfer of learning was tested in the remaining conditions.

## METHOD

### *Stimuli*

Four different pairs of normal distributions were used as data generators. Each pair represented one $d'$ condition; $d'$ is used as a convenient measure of expected diagnosticity and is defined exactly as in the Theory of Signal Detection. The distributions were composed of the lengths of fish of fictitious species, and each species was identified only by an arbitrary letter of the alphabet. These are the same stimuli used in an experiment by Du Charme (1970); Table 1 lists the relevant characteristics of each pair of distributions.

Feedback was given in the condition of intermediate diagnosticity, $d' = 2.0$. As Table 1 shows, there were two distribution pairs with a $d'$ of 2.0; half the subjects worked with one of these, AB, and the other half with GH. Although Du Charme (1970) found comparable performance for the AB and GH pairs, they were both included in the present experiment to help elucidate the effects of feedback, since it was not known which aspects of the stimulus distribution would be most salient. Numerous two-datum samples were generated for each pair of species, and relevant aspects of the sampling distribution were controlled here as they were in Du Charme (1970).

Two data samples, one from each of two binomial population pairs, were also included as stimuli to test further the transfer of learning. One binomial pair consisted of a population of 55 red poker chips and 45 blue ones, and another a population of 45 red chips and 55 blue ones. The sample from this binomial pair was four blue chips, which has a combined likelihood of 2.22 corresponding roughly to the likelihood of an observation at the mean of the EF distributions. The other binomial pair

TABLE 1
DISTRIBUTION CHARACTERISTICS

| Distribution | *M* | *SD* | $d'$ | Likelihood of an observation at the mean |
|---|---|---|---|---|
| A | 32.5 | 3.25 | 2.0 | 7.4 |
| B | 26 | 3.25 | | |
| C | 44 | 3.25 | 2.76 | 46.3 |
| D | 35 | 3.25 | | |
| E | 56.5 | 6.5 | 1.0 | 1.6 |
| F | 50 | 6.5 | | |
| G | 73 | 6.5 | 2.0 | 7.4 |
| H | 60 | 6.5 | | |

Note: Means are given in centimeters.

consisted of populations of 88 red–12 blue and 12 red–88 blue chips. The sample from this pair was two red chips, which has a combined likelihood of 55, roughly corresponding to the likelihood of an observation at the mean of the CD distributions.

*Subjects*

Twenty-four paid Rice University male undergraduates served individually as subjects.

*Apparatus*

A board scaled in units of 0.5 cm was fastened horizontally to the edge of a table and used to display the distributions. One of four removable graphs was displayed immediately below the scale. The four graphs displayed histograms or frequency distributions for each of the four pairs of species. Each graph showed a random sample of 100 from each species. At the appropriate times two additional charts were displayed, representing the two pairs of binomial populations. These were simply two columns colored in red and blue according to the proportions of red and blue poker chips in the populations, e.g., 55% red–45% blue and 45% red–55% blue. The stimuli were presented, and subjects wrote their responses, on slips of paper. During the feedback phase the stimuli were presented on $3 \times 5$ index cards; after the subject responded, he turned the card over to observe the correct response printed on the back.

*Procedure*

The experiment was divided into three phases. In Phase 1 the subjects received training on the characteristics of the stimuli and on the nature of the odds responses they were to make. They then made estimates in all three $d'$ conditions and for the two binomial samples. In Phase 2 they made estimates and received feedback in the $d' = 2.0$ condition, and in Phase 3 they made estimates in the remaining two $d'$ conditions and for the binomial samples. One group of 12 subjects worked with species pairs AB, CD, and EF, and the other 12 subjects worked with GH, CD, and EF.

*Phase 1.* For each subject the three $d'$ conditions were presented in one of the six possible orders. Prior to each $d'$ condition subjects saw defining samples of 50 fish lengths for each of the two species. They made two estimates of the mean for each sample, halfway through the presentation and again at the end. The average discrepancy of the final estimates was less than 0.5 cm. After the defining samples had been given, the histograms containing 100 fish lengths were displayed. The subjects were told that graphs contained, for each species, the 50 lengths from the defining sample plus an additional 50 random samples. They were cautioned that although the underlying population of lengths undoubtedly looked something like the histograms, the two were by no means the same. In particular it was pointed out to the subjects that if no fish of a specific length turned up in the random sample of 100, it did not necessarily follow that there were no fish of that length in the population.

After seeing the defining samples the subjects were informed that one of the two species of fish under consideration had been chosen by tossing a fair coin and that two lengths had been randomly sampled from the chosen population. After seeing the two lengths displayed, the subjects gave odds estimates as to which of the two species had been sampled. They made 30 such estimates, after which the histograms for that species pair were removed, and the procedure was repeated for the second and third $d'$ conditions. In the final segment of Phase 1, subjects were shown the charts representing the binomial populations and asked to make more odds estimates. In the case of the 55–45 populations, they were asked whether the predominantly red or the predominantly blue population would be more likely to yield a sequence of four blue poker chips and what the odds were favoring their choice. For the 88–12 population they were asked the same question about a sample of two red poker chips.

*Phase 2.* The subjects were told that an optimal model existed from which the correct odds responses could be obtained for each data sample. The subjects made estimates as they had in Phase 1, but after each estimate they were told what the correct odds were. They received 60 feedback trials of this sort in the $d' = 2.0$ condition (using the AB pair for half the subjects and the GH pair for the other half). The appropriate histograms were displayed throughout training. Their instructions for this phase included the following key points: (a) they were to use the feedback to calibrate their own feelings of uncertainty; (b) they were not to use the feedback information to work out a formula telling them how to respond; (c) they were not to try to learn what odds went with what particular fish lengths; and (d) to emphasize these points, they would be asked to make estimates again in the other conditions without feedback, and a $10 prize would be given to the subject whose odds estimates were then closest to optimal.

*Phase 3.* Transfer of training was tested by having subjects estimate odds again for the same 30 data samples for species pairs CD and EF and for the same two binomial samples as in phase one.

## RESULTS

Since the experiment was concerned with the effects of training, the first step was to see whether any learning took place before training. The 30 pretraining trials in each $d'$ condition were broken into three blocks of 10 trials each, and results for the first and last block were examined. For all analyses mean log odds were first calculated for each subject for each block of trials, and then a mean over subjects for each block was determined. (All results reported are for both groups combined; no significant differences were found between the groups on any analysis.) The 99% confidence intervals for the first and third blocks of trials for each condition, $d' = 1.0$, $d' = 2.0$, and $d' = 2.76$, overlapped in each condition, indicating no significant learning took place prior to training.

The next logical step is to see whether training was successful. Figure 1 plots the mean log odds for each block of 10 trials during the 60-trial training phase of the experiment. The point at the lower left shows the mean log odds for the 30 pretraining trials in the $d' = 2.0$ condition. The dashed line indicates the Bayesian log odds, and the vertical bars represent the 99% confidence intervals (these and all other confidence intervals are based on the $t$ value for 23 *df* (see Hays, 1973, p. 399). Clearly learning occurs and occurs relatively rapidly. The subjects show marked improvement in the first block of 10 feedback trials, are optimal by the second block, and remain optimal throughout training except for the last block where the Bayesian log odds is 0.04 higher than the upper confidence limit.

Figure 2 shows the effects, and transfer, of training. The three $d'$ conditions are spaced along the abscissa in terms of the log likelihood ratio of an observation at the mean of each distribution pair, and the ordinate gives the mean log estimated odds over subjects. Vertical bars again mark the 99% confidence intervals, and the triangles represent the average Bayesian log odds for the actual stimuli (samples of two fish lengths) used in each condition. The "after" training point for the

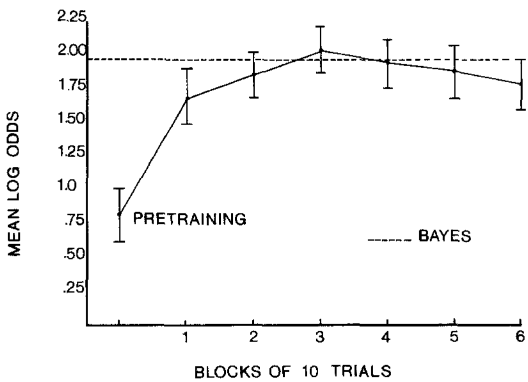


FIG. 1. Mean log odds over 60 feedback trials. Mean log odds are taken over all subjects and averaged in blocks of 10 trials. Vertical lines represent 99% confidence intervals. Point at lower left plots pretraining trials.

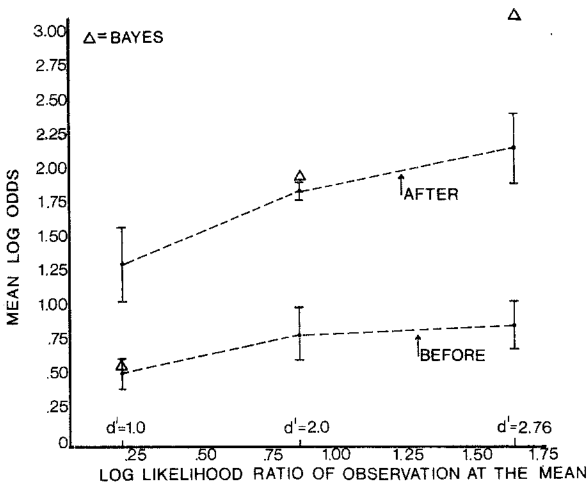


FIG. 2. Mean log odds before and after training as a function of the logarithm of the likelihood of an observation at the mean of each distribution pair. Vertical lines represent 99% confidence intervals and triangles indicate the Bayesian values.

$d' = 2.0$ condition was computed over the last 30 trials of the training phase. The figure illustrates that although training was successful, transfer of training was not complete. The effect of training was to change the subjects' estimates from optimal to extreme in the $d' = 1.0$ condition and from very conservative to significantly less conservative (but still not Bayesian) in the $d' = 2.76$ condition.

Roughly the same transfer effect generalizes to the binomial samples as shown in Fig 3. For the 55–45 sample, corresponding to the $d' = 1.0$ condition, subjects were Bayesian before training and extreme after.

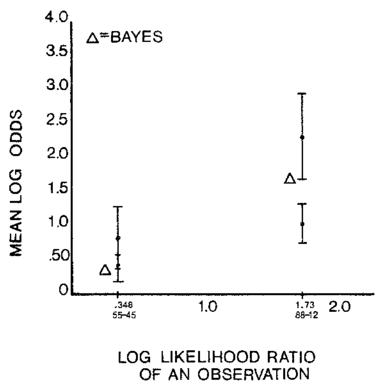


FIG. 3. Mean log odds for the binomial samples as a function of the logarithm of the likelihood of a single binomial observation. Triangles (displaced to the left for clarity) represent Bayesian values, and vertical lines indicate 99% confidence intervals.

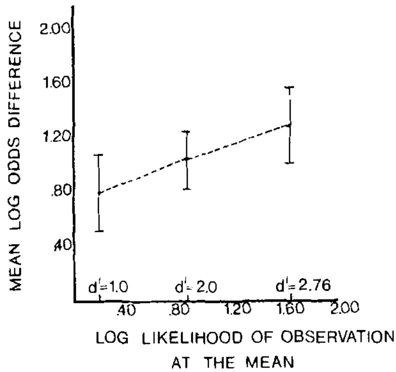


FIG. 4. Mean log odds difference (posttraining–pretraining) as a function of the logarithm of the likelihood of an observation at the mean of each distribution pair. Vertical lines represent 99% confidence intervals.

With the 88–12 sample, corresponding to the $d' = 2.76$ condition, the subjects were initially conservative but became significantly less conservative, and, in fact, extreme after training.

Since both Figs. 2 and 3 show some transfer of training, it is reasonable to speculate about what is being learned during training. One possibility suggested by a cursory examination of Fig. 2 is that the training trials simply teach subjects to increase their odds responses by some fixed multiplicative constant. A fixed multiplicative constant would show up as a constant difference, across conditions, between pretraining and posttraining log odds. Figure 4 shows that this difference does not seem to be constant across conditions, although the overlap of the 99% confidence intervals does not make it possible to reject this hypothesis.

## DISCUSSION

One of the most interesting of the present findings is the rapid rate of learning shown by the subjects. They are essentially optimal by the 20th feedback trial and are vastly improved after only 10 trials. This finding tends to confirm Martin and Gettys' speculation about why their feedback group showed no learning effect; all the learning may well have taken place in the first block of 50 trials. Later in training the present experiment shows an evident decrease in performance. Some informal feedback from the subjects indicates that the decrease may be due to boredom or fatigue in the latter stages of training.

Figure 4 indicates that the subjects seem to be doing more than just increasing their odds estimates by some constant factor regardless of condition. To be optimal, however, the subjects should not have changed their estimates in the $d' = 1.0$ condition at all and should have multiplied by a factor of about 180 in the $d' = 2.76$ condition. They obviously did not learn to attach numbers accurately, in this case odds, to their feelings of uncertainty. Thus, conservatism does not seem to be merely a problem of learning the response scale. What the subjects do seemed to have learned is to adjust their odds estimates by a multiplicative constant, which is a monotonically increasing function of $d'$ or diagnosticity.

In conclusion it can be stated that the subjects in this experiment seemed to learn two things from the feedback given them: first, that their naive odds estimates were too small, and, second, that the amount by which their naive odds estimates should be changed was a function of the diagnosticity of the data generators. It may be that more prolonged training with a greater variety of data generators would have led to a more precise learning of the response scale. This is a topic for further research. The fact that transfer seems to be tied to the particular stimuli used, although not unreasonable, is somewhat discouraging from an applied point of view. What it indicates is that training programs for human uncertainty estimators in real-world information-processing systems will be successful only to the degree that the stimuli used for training are similar to those that the systems actually will process.

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