Bayesian Updating in Experiment: Good News and Bad News in Small Feedback-Based Decision Problems

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Abstract

This paper explores small decision problems experimentally. Conducted is the current experiment in which agent's payoff distribution is limited to either high (favourable) distribution ("*Good News*") or low (unfavourable) distribution ("*Bad News*"). We conduct calibration of numerical optimal solution to search behaviour by Bayesian updating and agents' tendency in the laboratory experiment in small feedback-based problems. One assumption on an rational agent is that an agent is to behave to maximise his expected payoff. Results of the current experiment, however, show subjects' seemingly puzzled tendency inconsistent with the assumption above. The law of small numbers is observed in the experiment. The law of small numbers tells us that an agent will gather too little data and will overgeneralise from small samples to distributions. Agent's overgeneralisation of distribution may lead him to behave not to maximise expected payoff.

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1 Introduction

Nowadays there is some literature on exploring how an agent makes an optimal decision under uncertainty in terms of theoretical, empirical and experimental research. Experiments on decision making under uncertainty are useful because of the following reasons. One is that the experiments naturally give simultaneous observations of individual and aggregate activity, which are the best raw material for judging how individual errors are important for aggregate behaviour. (Kagel and Roth (1995)) Secondly, controlled experiments have a unique role to play in studies of the empirical validity of behaviour models under uncertainty because an experimenter can control, and thereby observe within the experimental environment, an agent's information about the distribution of payoffs, the length of their search horizons. Therefore, we will introduce our experiment on decision making under uncertainty, especially decision making in small feedback-based decision problems and will report results of the experiment.

This literature discusses an important subset of small decision problems in the light of the fact that many common activities in bygone days involve *small* decision problems. Early experiments on search under uncertainty, especially search in small feedback-based decisions were reported by Barron and Erev (2003) and Fujikawa and Oda (2004). It was in fact asserted by Barron and Erev that driving, for instance, requires repeated tasks and selections among routes, speeds and various other options. Although little time and effort is typically invested in these and similar small decisions, they can be consequential. They also asserted that the estimated cost of traffic accidents in the USA is more than 100 billion dollars a year, and many of the accidents are at least partially products of *ex-post* unwise decisions.

Barron and Erev (2003) stated that small feedback-based decision problems are quite distinct from "big description-based" decision problems studied in mainstream decision research, such as Kahneman and Tversky's (1979). Small feedback-based decision problems are defined as consequential decision problems but each single choice is not *very* important because the options available to subjects have similar expected values that may be quite small, so that *little* time and effort is typically invested in these problems. An agent in small feedback-based decision problems is supposed to make his decision many times *without* evaluating carefully the possible outcomes. On the contrary, mainstream research tends to focus on "big" decisions that are made based on a careful evaluation of the options available to the subjects. These decisions are naturally studied in a "description-based" paradigm as seen in a typical study, an example of which was performed by Kahneman and Tversky (1979) to test prospect theory, the popular and elegant summary of the main results obtained in studies of description-based decisions. In the typical study, the subjects are presented with a complete description of a non-trivial choice problem and are asked to make one selection among the possible outcomes.

Fujikawa and Oda (2004) conducted a search experiment in which subjects in small feedback-based decisions were not informed of prior information as to payoff distribution. Interesting but significant results were obtained from Fujikawa and Oda's search experiment. The results showed that search under uncertainty may be examined by the ambiguity model that examines how people make judgements under ambiguity, which results from having limited knowledge of the process that generates outcomes. Practical difficulties, however, arise in the search experiment with respect to calibrating agent's behaviour with applying Bayesian updating. We shall mention the importance of Bayesian updating in agents' sequential search process and the reason why we have had these difficulties in the search experiment in the following paragraphs.

The standard principles adopted in economics to model probability judgement under uncertainty are concepts of Bayes' rule, also known as Bayesian updating. It is common that

Bayesian agent's ultimate goal is to judge the likelihood of events by updating his (initial) subjective probabilities in the face of new evidence as a result of sequential search process.

With search experiments conducted by Fujikawa and Oda (2004), for instance, each (Bayesian) subject would have his initial subjective payoff distribution and its corresponding probability at the beginning of search. This is non-trivial description in exploring subject's behaviour in terms of Bayesian updating. There are, however, practical difficulties, not only in Fujikawa and Oda's search experiment but in many field experiments on search, that arise with respect to calibrating numerical solution to particular search problems by computer simulation with Bayesian updating. This is because each subject's prior subjective information and probabilities cannot be observed by the experimenter, which leads to difficulties in analysing subjects' search behaviour under uncertainty.

To overcome the difficulties above, we conducted the current experiment on small feedback-based decisions in a similar way as Cox and Oaxaca (2000). Cox and Oaxaca studied optimal job-search theory and conducted experiments in which agents' *initial* subjective wage-offer distribution was limited to either high ("Good News" in their scenario) or low distribution ("Bad News" in their scenario). Under their presumption that the agent's subjective *initial* distribution is given by either of the two distributions, it seems straightforward to anchor his subjective *initial* probability of payoff distribution he should face to 0.5 at the beginning of the search. Before conducting our experiment, it was our expectation that we could calibrate agent's posterior subjective probabilities of small feedback-based decisions with Bayes' rule by letting 0.5 be his subjective *initial* probability.

In spite of their well-polished research, what seems missing in Cox and Oaxaca's study is the calibration of each subject's job-search tendency and numerical solution to their search model by computer simulation with Bayesian updating. We will pursue this simulation in this literature with the help of mathematical software to investigate artificial agent's behaviour, which might be variable during given search period. In addition, the simulation discussed above is to be conducted since it is straightforward and significant to compare human agent's behaviour to artificial agent's behaviour.

The current experiments were conducted with the repetition of 400 rounds, while some famous experiments in mainstream decision research (e.g. Kahneman and Tversky (1979)) focused upon one-shot description-based decisions. The further reasons of conducting experiments with *repeated-play* conditions are as follows. One is that we should avoid causing biases among subjects' decision, say *the law of small numbers*. (Tversky and Kahneman (1971)) The law of small numbers posits that subjects may gather too little data and may overgeneralise from small past outcomes to distributions. It has been said that the subjects in economic applications will search too little and learn too quickly, compared to models of optimal sampling and inference. (Kagel and Roth (1995)) The second reason is that economic experiments typically use *stationary replication*, where the same task is repeated over and over, with fresh endowments in each period. Data from the last few periods of the experiment are typically used to draw conclusions about equilibrium behaviour outside the laboratory. (Camerer, Loewenstein, and Rabin (2004))

2 Bayesian updating

When the probabilities people judge are conditional, as in updating belief in X after learning M, they should follow the prescription of Bayes' rule:

$$P(X|M) = \frac{P(M|X)P(X)}{P(M)}$$

Consider the two choice problems, Problem A and Problem B. Let $\alpha, \beta > 0$, $p_1, p_2 \in [0,1]$, $\alpha p_1 > \beta$ and $\alpha p_2 < \beta$. In Problem A, two bingo cages are available: cage H from which a ball numbered α is drawn with probability p_1; cage L a ball numbered β with certainty. In Problem B, two bingo cages are available: cage H from which a ball numbered α is drawn with probability p_2; cage L a ball numbered β with certainty.

Problem A. Choose between:

H: α points with probability p_1 ; 0 otherwise

L: β points with certainty.

Problem B. Choose between:

H: α points with probability p_2 ; 0 otherwise

L: β points with certainty.

Suppose next that an individual is asked to join a game where he is asked to choose either H or L for 400 times but is not informed that an outcome in each trial comes from only Problem A. That is, he is not informed whether the actual alternatives to be chosen, H and L belong to Problem A or Problem B. It is also supposed that he can receive money corresponding to the number on the ball drawn. Meanwhile he may need to discover which of Problem A and B is the actual choice problem he is performing actually by trying out H or L for a maximum of 400 times.

We explore an analysis in this literature under the assumption that a rational agent should make his decision to maximise his expected payoff under uncertainty. This assumption asserts that one is willing to keep choosing H (L) after he has appeared to an actual choice problem to be Problem A (B).

Applying Bayes' rule to the situation above, we can obtain the following:

$$P(ProblemA|\alpha) = \frac{P(\alpha|ProblemA)P(ProblemA)}{P(\alpha|ProblemA)P(ProblemA) + P(\alpha|ProblemB)P(ProblemB)}$$

Introducing time periods to the above due to our repeated tasks, we can obtain:

$$P_{t+1}(ProblemA|x_{t+1}) = \begin{cases} \frac{P(\alpha|ProblemA)P_{t+1}(ProblemA)}{P(\alpha|ProblemA)P_{t+1}(ProblemA)+P(\alpha|ProblemB)P_{t+1}(ProblemB)}, & \text{if } x_{t+1} = \alpha; \\ \frac{P(0|ProblemA)P_{t+1}(ProblemA)}{P(0|ProblemA)P_{t+1}(ProblemA)+P(0|ProblemB)P_{t+1}(ProblemB)}, & \text{if } x_{t+1} = 0; \\ P_t(ProblemA), & \text{if } x_{t+1} = \beta, \end{cases}$$

where we denote x_t an outcome an individual receives at period t.

From tenets of Bayesian updating and an assumption on a rational agent, we realise following important hypothesises on an agent's behaviour. One is that an individual should choose an alternative L whenever $P_{t+1}(ProblemA|x_{t+1}) > 0.5$ in period t, which tells us that Problem A is more likely to be an actual choice problem he/she should perform. The second hypothesis is that an individual should choose an alternative R whenever $P_{t+1}(ProblemA|x_{t+1}) < 0.5$ in period t, which tells us that Problem B is more likely to be an actual choice problem he/she should perform.

3 Experimental design

We conducted two economic experiments, Experiment 1 and Experiment 2, at Kyoto Sangyo University Economic Experiment Laboratory (KEEL). Thirty-three undergraduates at Kyoto Sangyo University served as paid subjects in both experiments. Nobody had participated in previous search or small feedback-based decisions experiments. Both Experiment 1 and 2 were conducted under the condition that each subject was informed the exact number of rounds and sessions to be performed. At the conclusion of the experiments, subjects received monetary payoffs contingent upon their performance and no initial (showing up) fee was paid. The translation from points to monetary payoffs was according to the exchange rate: 1 point= 0.6 Yen (0.5 US cent).

Each experiment consisted of four sessions, each session consisted of 400 rounds (100 rounds only in session 1). The subjects' basic task at each round in Experiment 1 and 2 was a binary choice between L and R in the choice problem below. The alternative L yields x points with probability p_1, and 0 point with probability $(1 - p_1)$; the alternative R yields y points with probability p_2, and 0 point with probability $(1 - p_2)$.

Problem. Choose between:

L : x points with probability p_1 ; 0 otherwise

R : y points with probability p_2 ; 0 otherwise,

where $p_1,\ p_2 \in [0, 1],\ x > 0$ and $y > 0$.

The basic task was performed 400 times (with immediate feedback) in each of sessions.[1]

3.1 Experiment 1

Experiment 1 was conducted under the condition that subjects was presented with both dummy payoff distribution, which is a priori relatively high (*good news*), referred as Problem A and the actual payoff distribution, which is a priori relatively low (*bad news*), referred as Problem B, at the beginning of each of four sessions. However the subjects were not told which of the two problems was an actual choice problem to be performed in each session. The subjects were informed that each drawing of each session came from either Problem A or Problem B in each of 400 trials (100 trials only in session 1). Hence the subjects were expected to discover which of the two problems would generate each draw in each session since they were not informed that an actual choice problem was Problem B.

3.1.1 Session 1

Problem A (dummy choice problem). Choose between:

L: 6 points with probability 1

R: 5 points with probability 1

Problem B (actual choice problem). Choose between:

L: 4 points with probability 1

R: 3 points with probability 1

[1] See the instruction of the experiments in Appendix in detail.

3.1.2 Session 2

Problem A (dummy choice problem). Choose between:

L: 4 points with probability 0.9 ; 0 otherwise

R: 3 points with probability 1

Problem B (actual choice problem). Choose between:

L: 4 points with probability 0.8 ; 0 otherwise

R: 3 points with probability 1

3.1.3 Session 3

Problem A (dummy choice problem). Choose between:

L: 4 points with probability 0.3 ; 0 otherwise

R: 3 points with probability 0.25 ; 0 otherwise

Problem B (actual choice problem). Choose between:

L: 4 points with probability 0.2 ; 0 otherwise

R: 3 points with probability 0.25 ; 0 otherwise

3.1.4 Session 4

Problem A (dummy choice problem). Choose between:

L: 32 points with probability 0.2 ; 0 otherwise

R: 3 points with probability 1

Problem B (actual choice problem). Choose between:

L: 32 points with probability 0.1 ; 0 otherwise

R: 3 points with probability 1

3.2 Experiment 2

Experiment 2 was conducted under the condition that subjects was presented with both actual payoff distribution, which is a priori relatively high (*good news*), referred as Problem A and dummy payoff distribution, which is a priori relatively low (*bad news*), referred as Problem B, at the beginning of each of four sessions. As in Experiment 1, the subjects were not told which of the two problems was an actual choice problem to be performed in each session. The subjects were informed that each drawing of each session came from either Problem A or Problem B in each of 400 trials (100 trials only in session 1). Hence the subjects were expected to discover which of the two problems would generate each draw in each session since they were not informed that an actual choice problem was Problem A.

3.2.1 Session 1

Problem A (actual choice problem). Choose between:

L: 4 points with probability 1

R: 3 points with probability 1

Problem B (dummy choice problem)

L: 2 points with probability 1

R: 1 points with probability 1

3.2.2 Session 2

Problem A (actual choice problem). Choose between:

L: 4 points with probability 0.8 ; 0 otherwise

R: 3 points with probability 1

Problem B (dummy choice problem)

L: 4 points with probability 0.7 ; 0 otherwise

R: 3 points with probability 1

3.2.3 Session 3

Problem A (actual choice problem). Choose between:

L: 4 points with probability 0.2 ; 0 otherwise

R: 3 points with probability 0.25 ; 0 otherwise

Problem B (dummy choice problem). Choose between:

L: 4 points with probability 0.1 ; 0 otherwise

R: 3 points with probability 0.25 ; 0 otherwise

3.2.4 Session 4

Problem A (actual choice problem). Choose between:

L: 32 points with probability 0.1 ; 0 otherwise

R: 3 points with probability 1

Problem B (dummy choice problem). Choose between:

L: 32 points with probability 0.05 ; 0 otherwise

R: 3 points with probability 1

4 Results and Discussion

Table 1 shows the mean proportion of L choices in each experiment. Denoted by N is the number of subjects in each experiment. It is found from Table 1 that the *reversed* certainty effect might be observed in Experiment 1 and Experiment 2 since mean proportions of L choices in Problem 2 in both experiments were more than 0.5. In addition, we see that the proportion of L choices varied among the subjects. For example, a subject chose L 389 times in Problem 2, whereas another subject chose L only once in the same problem.

	Session 1	Session 2	Session 3	Session 4
Kahneman & Tversky (*N*=95)		0.2	0.65	
Barron & Erev (*N*=48)	0.9	0.63	0.51	0.24
Fujikawa & Oda (*N*=42)	0.72	0.48	0.55	0.22
Experiment 1 (*N*=33)	0.944	0.56	0.76	0.52
Experiment 2 (*N*=33)	0.94	0.54	0.5	0.46

Table 1: The mean proportion of L choices in each experiment

It is also found from Table 1 that the mean proportion of L choices in Experiment 1 was larger than that in Experiment 2 for all choice problems. The corresponding p-values are 0.491, 0.000, 0.319, 0.460 for Problem 1, 2, 3, 4 respectively.

4.1 Analysis

The law of small numbers was observed both in Experiment 1 and 2. The law of small numbers tells us that an agent will gather too little data and will overgeneralise from small samples to distributions. Agent's overgeneralisation of distribution may sometimes lead him to behave not to maximise expected payoff. In economic applications, each agent will search too little and learn too quickly, compared to models of optimal sampling and inference. (Kagel and Roth (1995)) Table 1 shows that subjects in Session 4 on Experiment 1, on the average, chose L only 208 times. One possible explanation of this is that the subjects might try L too little (only 208 times) and learn mistakenly too quickly that the alternative L had less expected payoff than R. Due to their mistaken learning, the subjects did choose R many times. Fujikawa and Oda (2004)'s search model insists that the probability that an agent can recognize correctly that the alternative L has higher expected payoff than R is quite small with only hundreds of trials. Their model clearly tells us that such probability does not exceed 0.98 until she tries L 10,000 times.

We classify subject's behaviour in Experiment 2 into the following three cases. Among those cases, we assume each subject requires $T \in [1, 400]$ periods to understand payoff structure correctly, that is, to realise that each outcome in Experiment 2 is drawn from Problem A.

4.1.1 Case I

First, we consider Case I in which a subject in session 4 chooses L for many times after search period T in case that his subjective posterior probability of Problem A obtained by Bayesian updating has remained greater than 0.5 after period T. One possible explanation of this is that the subject is willing to choose L for many times after period T since his subjective posterior probability of Problem A obtained by Bayesian updating has remained greater than 0.5 after period T. Also, assuming that rational agents should behave to maximise their expected payoff, the alternative L stochastically dominates R.

A subject, for instance, continued to choose L for many times in session 4 in Experiment 2 after the period $T = 48$. His subjective posterior probability of problem A from Bayesian updating in the session remained more than 0.5 after the period $T = 48$.

4.1.2 Case II

Next, we consider Case II in which a subject chooses R for many times after period T in case that his subjective probability of Problem A obtained by Bayesian updating has become greater than 0.5 after period T. One may consider the subject should be risk averse since he chooses L for many times after period T in spite of the fact that his subjective probability of Problem A from Bayesian updating has become greater than 0.5.

A subject, in fact, chose L for many times after the period $T = 32$ in session 4 in Experiment 2. His subjective probability of Problem A obtained by Bayesian updating in the session remained more than 0.5 after the period $T = 32$.

4.1.3 Case III

Lastly, we consider Case III in which a subject chooses R for many times after period T in case that his subjective probability of Problem A by Bayesian updating has become less than 0.5. This subject makes quite rational choice after period T assuming that rational agents should behave to maximise their expected payoff. An agent who believes an actual choice problem would be Problem B should choose R to maximise his expected payoff.

For example, a subject's subjective probability of problem A obtained by Bayesian updating in the session remained less than 0.5 after the period $T = 315$, and he continued to choose L after that period.

4.2 Methodologies

One insists that experiments on search under uncertainty or on small feedback-based decisions should be done with the condition that the choices and payoffs of others could be observable to each subject. In spite of that, current experiments were actually conducted in the setting that each subject was informed of no information as to the choices and payoffs of others. One reason of this is that in many *routine-learning* models, knowing the choices and payoffs of others is inessential since players are assumed to simply choose strategies that yielded high payoffs in the past. (Kagel and Roth (1995))

Another claims that the current experiments on small feedback-based decisions should be conducted under the condition that each subject is questioned in each trial which of the two possible problems (referred as Problem A and B in our scenario) is the actual one he faces in the experiment. This should be to the point at a rough glance but we have considered it inappropriate settings in the current experiments. Firstly, one considers it unreasonable setting

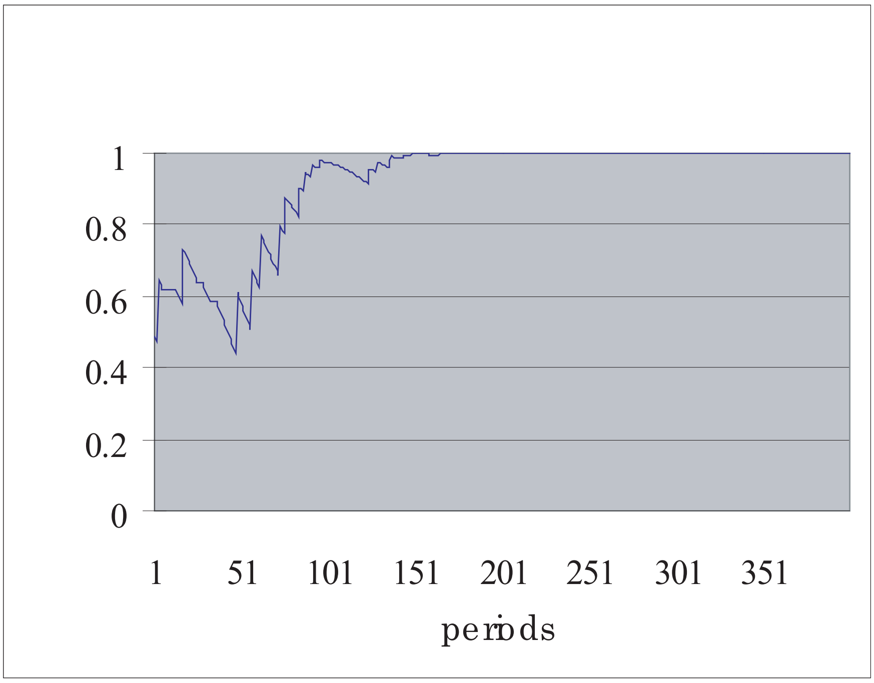

Figure 1: Subjective probability of Problem A for Case I

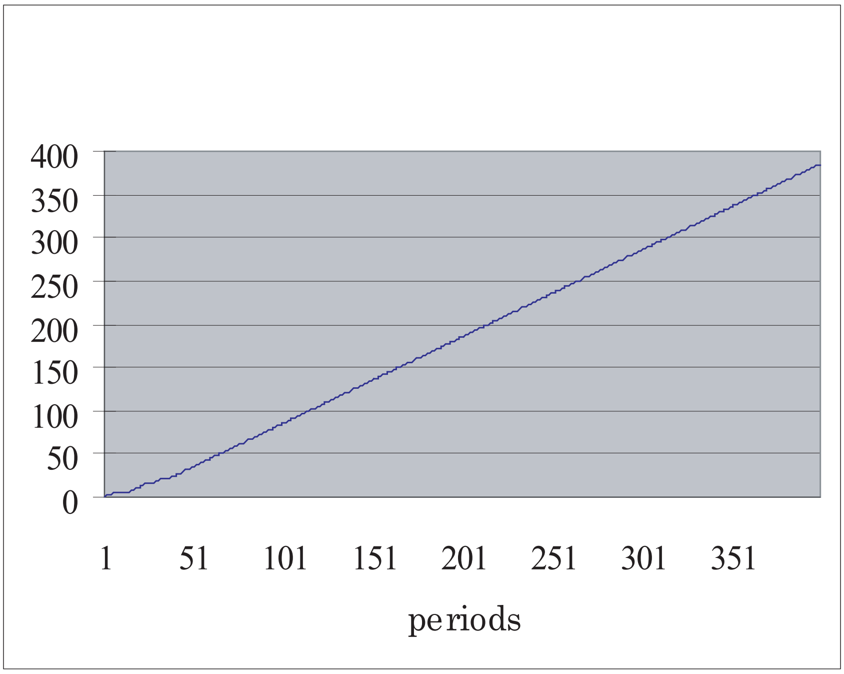

Figure 2: Cumulative number for L choices for Case I

Figure 3: Subjective probability of Problem A for Case II

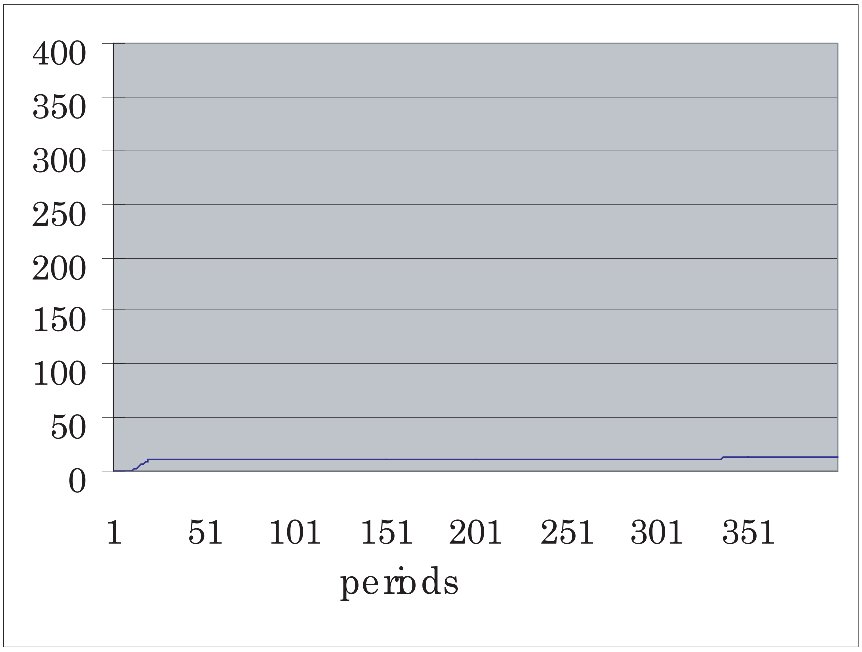

Figure 4: Cumulative number for L choices for Case II

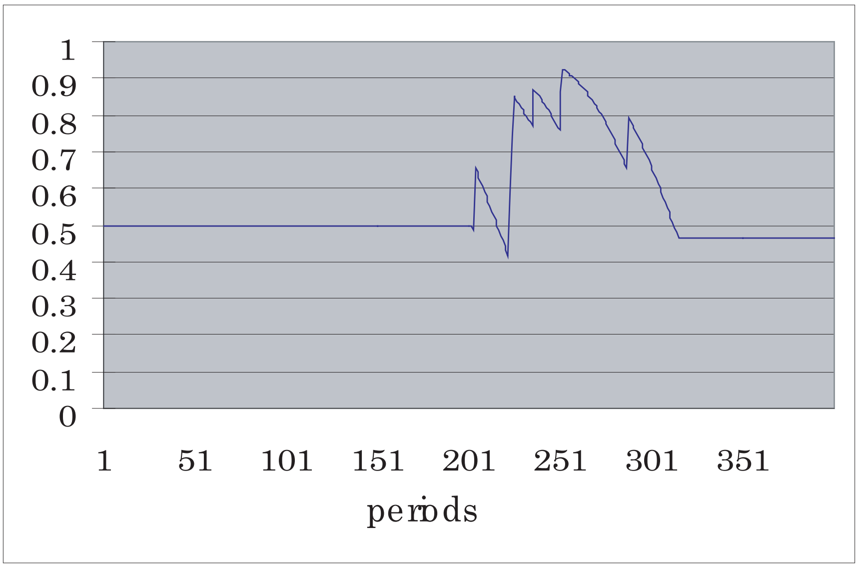

Figure 5: Subjective probability of Problem A for Case III

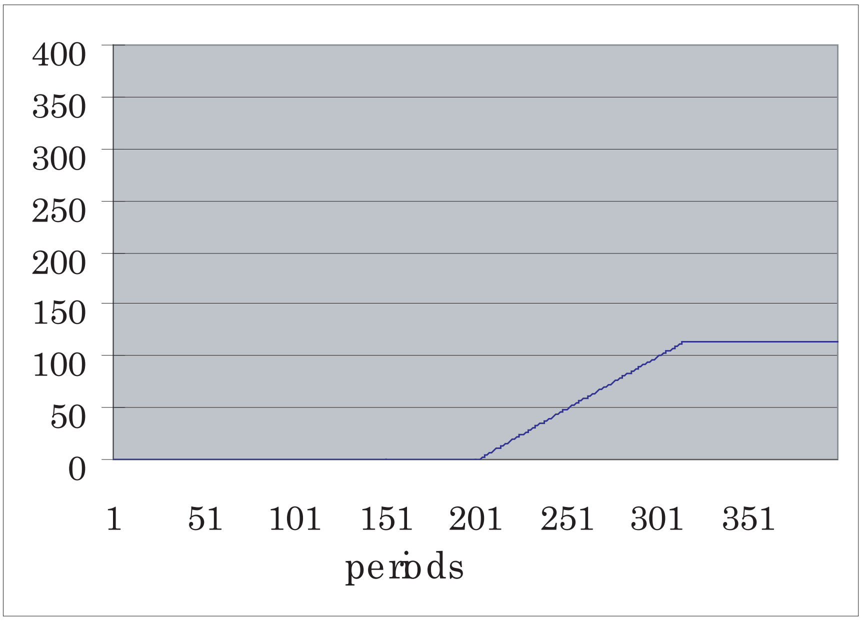

Figure 6: Cumulative number for L choices for Case III

for economics experiment that a subject is asked to answer repeated questions, which are not experimenter's primary concern and may affect subject's decision making either directly or indirectly. Recall that the primary concern of our small feedback-based decision experiment is not to ask which of the two choice problems the subject will consider to make his decision in each trial, but to observe what option the subject is willingly to choose to maximise his (monetary) payoff in the whole trials. Secondly, asking the subject either Problem A or B many times (for 1300 times in each experiment) will take him much time and effort and induce careful evaluation of the possible options in his small feedback-based decisions. As discussed above, although careful evaluation is needed for agents in "big" description-based decision experiment, we should avoid such careful evaluation in small feedback-based decision experiment. Lastly, the problem we have to consider is that the repeated questions in each trial are likely to influence subject's "adaptive learning" to be done to make his optimal decision.[2] Therefore, we conducted our small feedback-based decision experiments without asking subjects in each trial any other questions than those which are our primary attention.

5 Concluding remarks

Very few attempts have made upon reviewing econometric studies on individuals' search behaviour in small feedback-based decisions that use data from national economies. Yet it is straightforward to use search and choice models as maintained hypotheses for conducting econo-

[2]Immediate feedback may lead to "adaptive learning" that moves behaviour toward expected value maximization. Although Kahneman and Tversky's study (1979) of description-based decisions reveals robust deviations from maximization of expected values, the "adaptive learning" assertion implies higher maximization rates in feedback-based decisions. (See Barron and Erev (2003).)

metric estimation. Hence it is hoped that further research on this type of decision making in small feedback-based decisions would clarify the empirical validity of search theory itself.

The current research will be developed further by considering the following two questions to be clarified by econometric tests. Firstly, should an agent believe that the more he chooses an alternative L in 400 times, the more subjective probability of realising the actual payoff structure by Bayesian updating goes up? This type of question is likely to being clarified by investigating correlation an actual choice made in period t and a subjective probability in the next period $t+1$ obtained by Bayesian updating. Secondly, should an agent choose L in period t whenever subjective probability that the actual draw comes from Problem A in period t has become greater than the one in period $t-1$? One can account for the answer of this question by investigating correlation an actual choice made in period t and a subjective probability in the same period t calculated by Bayesian updating.

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Appendix A

Instruction

Introduction

Thank you very much for participating in this experiment. In this experiment you will be asked to play easy games and have to make decisions that will enable you to earn some points. At the end of the experiment, these points will be converted into cash at a fixed rate described in the following of the instruction.

Notice

- You may NOT leave the laboratory during the experiment.
- You may keep switching your portable phone off during the experiment.
- You must leave all items distributed by personnel in the laboratory.
- You may NOT touch a keyboard.
- Do NOT click on right.
- You may NOT attempt to tamper with a computer.

Failure to comply with administrator's directions can result in points you earned being cancelled and no money will be paid.

If you need an administrator

If at any time during the experiment you believe you have a problem with your computer or need an administrator for any reason, raise your hand.

Payment

At the conclusion of the experiment, points will be converted to monetary payoffs according to the exchange rate: 100points = 60 yen (about 56 US cents). The amount below 10 yen is rounded up.

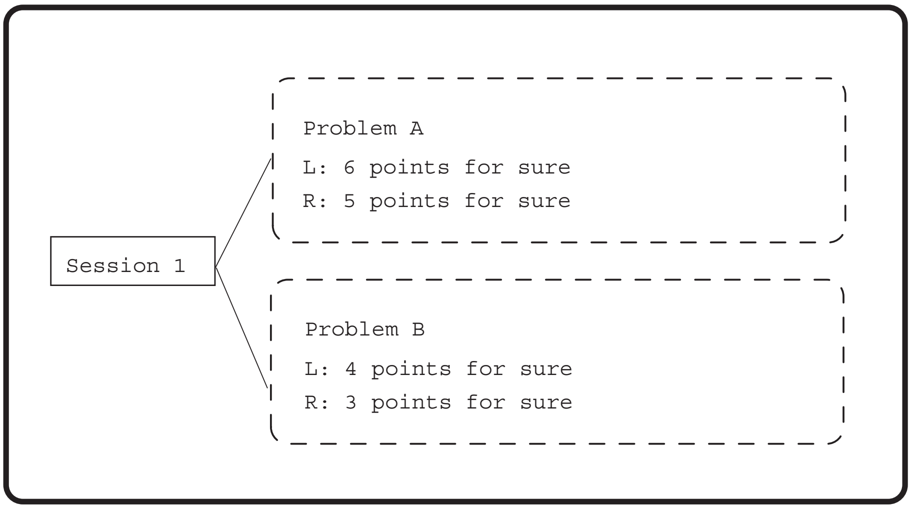
Procedure

In this experiment, you are asked to perform session 1, 2, 3 and 4 in order. Each session consists of two problems: Problem A and Problem B. The basic task in each problem is a binary choice between two options referred to as L and R. This basic task is performed 400 times (100 times in session 1) in each session.

At the beginning of each session, a computer determines which of the two choice problems is the actual choice problem you should perform throughout the session with particular probabilities. The outcome of the selection by the computer is not displayed. Once the computer determines the choice problem you should perform at the beginning of the current session, only the problem determined is performed throughout that session. For example, if the computer determines Problem A at the beginning of session 1, you perform only Problem A throughout session 1. On the other hand, if a computer determines Problem B at the beginning of session 1, you perform only Problem B throughout session 1.

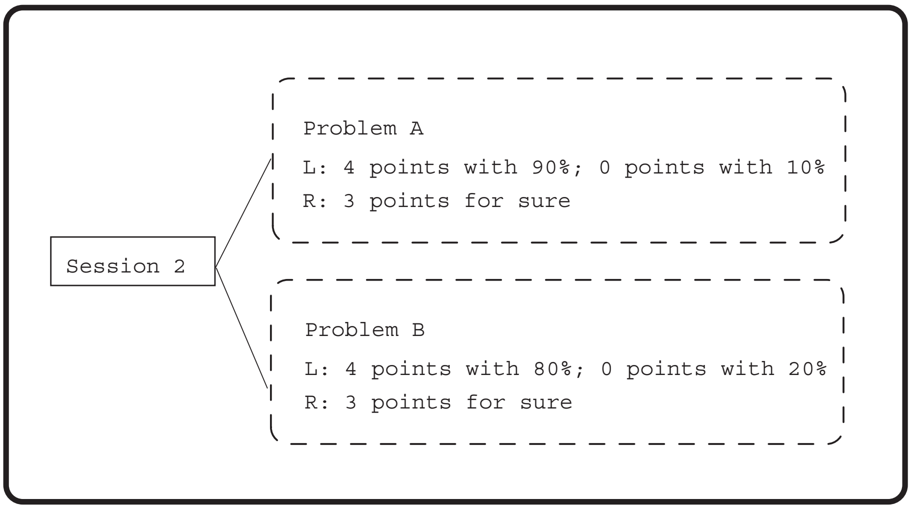
Payoff structure

Session 1



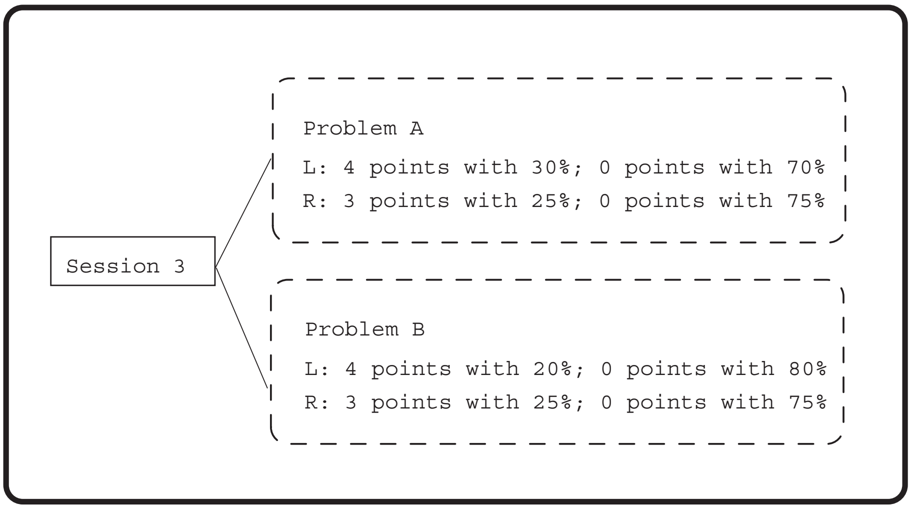
If Problem A (B) is determined by the computer at the beginning of session 1, you are asked to do Problem A (B) for 100 times in session 1. In Problem A (B), you can get 6 (4) points for sure by pressing “L” button and get 5 (3) points for sure by pressing “R” button in each trial.

Session 2



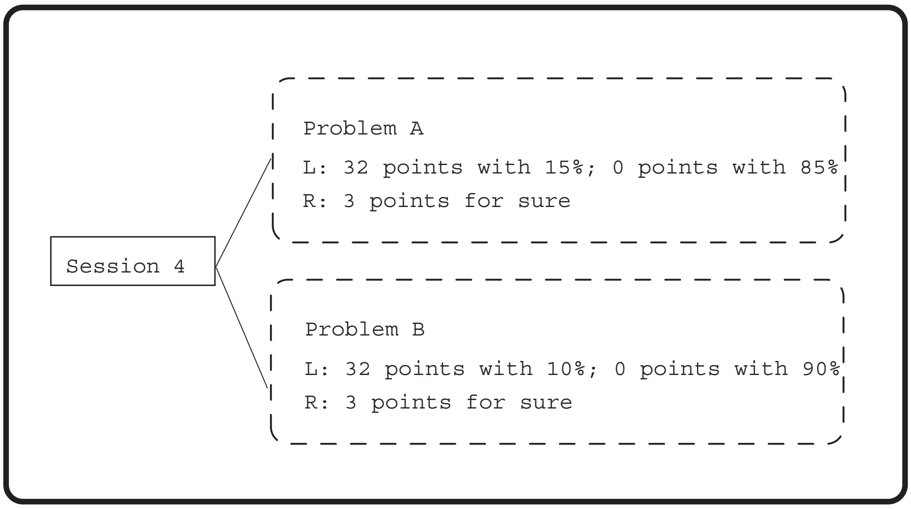
If Problem A (B) is determined by the computer at the beginning of session 2, you are asked to do Problem A (B) for 400 times in session 2. In Problem A (B), you can get 4 points with probability of 90% (80%) and 0 point with probability of 10% (20%) by pressing “L” button, and get 3 points for sure by pressing “R” button in each trial.

Session 3



If Problem A (B) is determined by the computer at the beginning of session 3, you are asked to do Problem A (B) for 400 times in session 3. In Problem A (B), you can get 4 points with probability of 30% (20%) and 0 point with probability of 70% (80%) by pressing “L” button, and get 3 points with probability of 25% and 0 point with probability of 75% by pressing “R” button in each trial.

Session 4



If Problem A (B) is determined by the computer at the beginning of session 4, you are asked to do Problem A (B) for 400 times in session 4. In Problem A (B), you can get 32 points with probability of 15% (10%) and 0 point with probability of 85% (90%) by pressing “L” button, and get 3 points for sure by pressing “R” button in each trial.

Experimental screen

Registration

Check that Figure 12 is displayed on your screen. (If it is not, please raise your hand.) Click on “►” or “◄” in order to equalize the number appeared on screen with your subject number then press “Correct”. Assuming that your subject number is I-19, press “Correct” in the Figure 13. After pressing “Correct”, you will see Figure 14 and you are about to begin the first session of experiment, session 1.

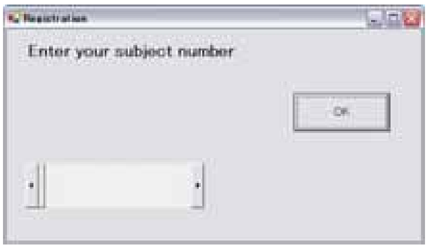


Figure 7:

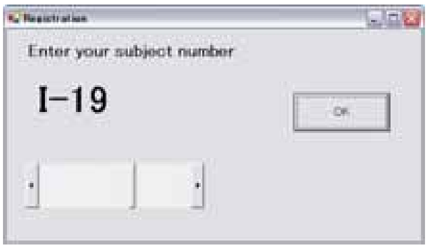


Figure 8:

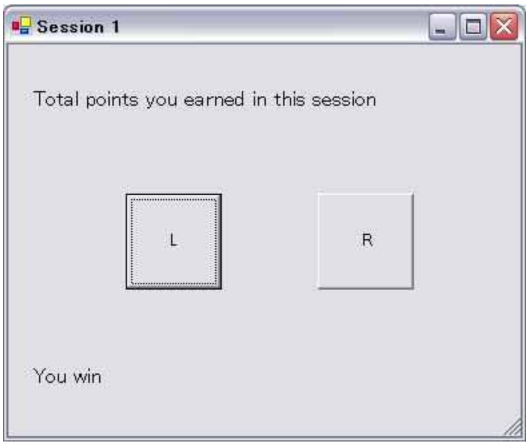


Figure 9:

Figure 10:

Figure 11:

Session

The experiment consists of four sessions, session 1, session 2, session 3 and session 4. Each session consists of 400 trials. (Only session 1 consists of 100 trials.) You are asked to choose either “L” or “R” button in each trial as seen in Figure 14. The points corresponding to selected button appear on the right side of “You win” and you can get it at that trial. Your score is not affected by other’s behavior. A series of these procedure above is done for 400 times (100 times in session 1) in each session. An update of an accumulating score is constantly displayed on the right side of “Total points earned in this session”. After completing each session, you will see the figure which tells you the end of the session. For example, Figure 15 appears when you finished session 1. And Figure 16 appears after pressing “OK” in Figure 15. Press “OK” and you can face Figure 14 again. Begin to play next session as in the first session you did.

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Do you have any questions? If yes, please raise your hand. If not, please begin experiment.

Appendix B

Instruction

A Introduction

Thank you very much for participating in this experiment. In this experiment you will be asked to play easy games and have to make decisions that will enable you to earn some points. At the end of the experiment, these points will be converted into cash at a fixed rate described in the following of the instruction.

Notice

- You may NOT leave the laboratory during the experiment.
- You may keep switching your portable phone off during the experiment.
- You must leave all items distributed by personnel in the laboratory.
- You may NOT touch a keyboard.
- Do NOT click on right.
- You may NOT attempt to tamper with a computer.

Failure to comply with administrator's directions can result in points you earned being cancelled and no money will be paid.

If you need an administrator

If at any time during the experiment you believe you have a problem with your computer or need an administrator for any reason, raise your hand.

Payment

At the conclusion of the experiment, points will be converted to monetary payoffs according to the exchange rate: 100points = 60 yen (about 56 US cents). The amount below 10 yen is rounded up.

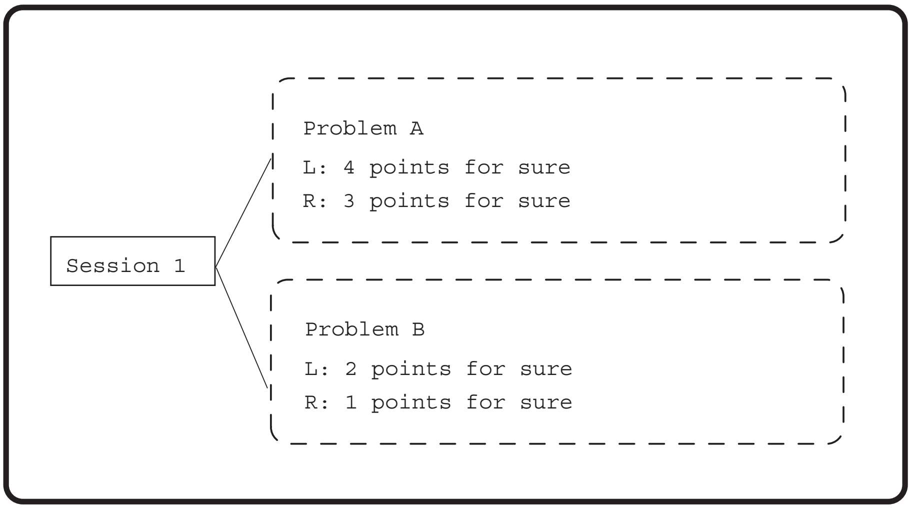
Procedure

In this experiment, you are asked to perform session 1, 2, 3 and 4 in order. Each session consists of two problems: Problem A and Problem B. The basic task in each problem is a binary choice between two options referred to as L and R. This basic task is performed 400 times (100 times in session 1) in each session.

At the beginning of each session, a computer determines which of the two choice problems is the actual choice problem you should perform throughout the session with particular probabilities. The outcome of the selection by the computer is not displayed. Once the computer determines the choice problem you should perform at the beginning of the current session, only the problem determined is performed throughout that session. For example, if the computer determines Problem A at the beginning of session 1, you perform only Problem A throughout session 1. On the other hand, if a computer determines Problem B at the beginning of session 1, you perform only Problem B throughout session 1.

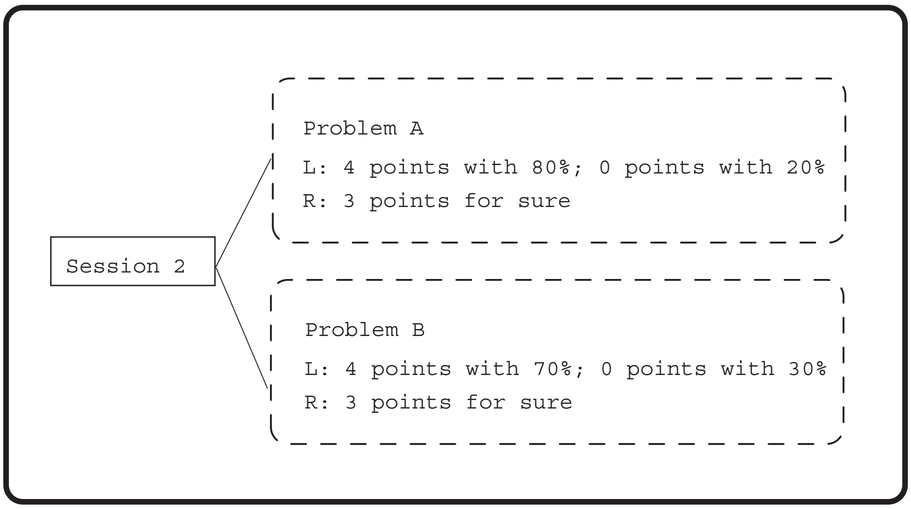
Payoff structure

Session 1



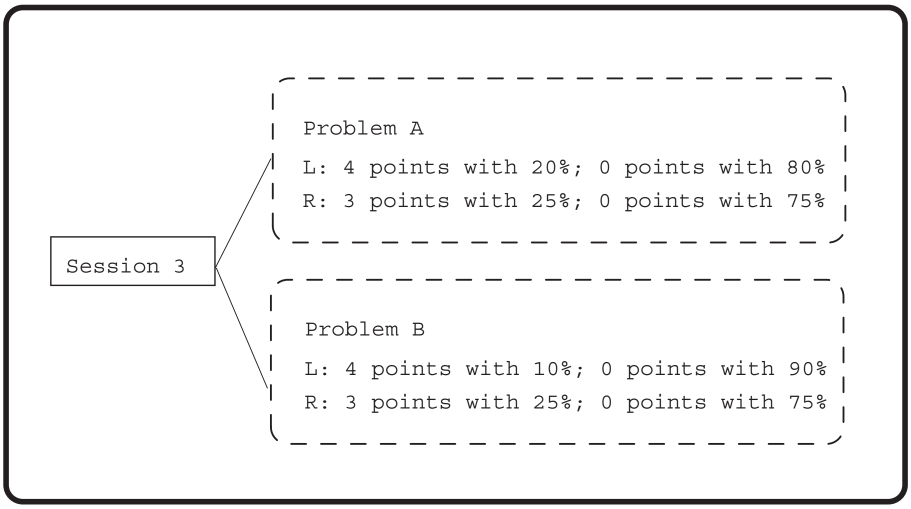
If Problem A (B) is determined by the computer at the beginning of session 1, you are asked to do Problem A (B) for 100 times in session 1. In Problem A (B), you can get 4 (2) points for sure by pressing “L” button and get 3 (1) points for sure by pressing “R” button in each trial.

Session 2



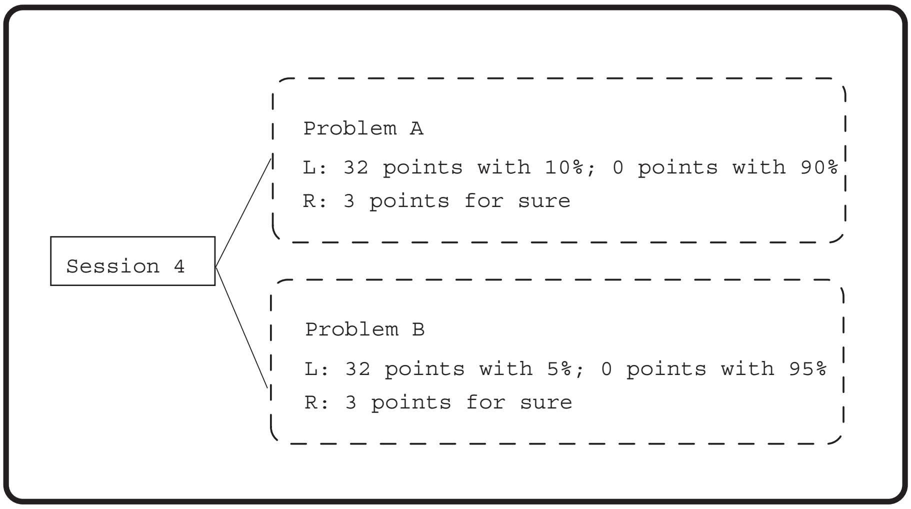
If Problem A (B) is determined by the computer at the beginning of session 2, you are asked to do Problem A (B) for 400 times in session 2. In Problem A (B), you can get 4 points with probability of 80% (70%) and 0 point with probability of 20% (30%) by pressing "L" button, and get 3 points for sure by pressing "R" button in each trial.

Session 3



If Problem A (B) is determined by the computer at the beginning of session 3, you are asked to do Problem A (B) for 400 times in session 3. In Problem A (B), you can get 4 points with probability of 20% (10%) and 0 point with probability of 80% (90%) by pressing "L" button, and get 3 points with probability of 25% and 0 point with probability of 75% by pressing "R" button in each trial.

Session 4



If Problem A (B) is determined by the computer at the beginning of session 4, you are asked to do Problem A (B) for 400 times in session 4. In Problem A (B), you can get 32 points with probability of 10% (5%) and 0 point with probability of 90% (95%) by pressing “L” button, and get 3 points for sure by pressing “R” button in each trial.

Experimental screen

Registration

Check that Figure 12 is displayed on your screen. (If it is not, please raise your hand.) Click on “►” or “◄” in order to equalize the number appeared on screen with your subject number then press “Correct”. Assuming that your subject number is I-19, press “Correct” in the Figure 13. After pressing “Correct”, you will see Figure 14 and you are about to begin the first session of experiment, session 1.

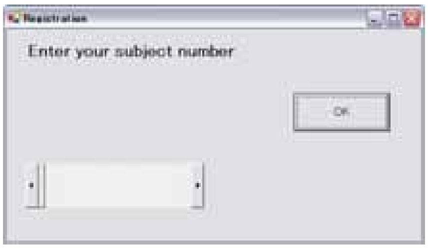


Figure 12:

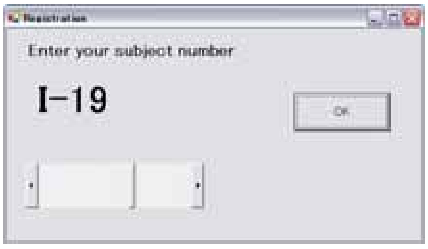


Figure 13:

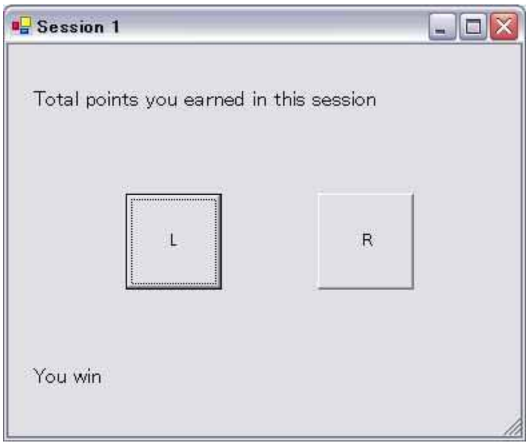


Figure 14:

Figure 15:

Figure 16:

Session

The experiment consists of four sessions, session 1, session 2, session 3 and session 4. Each session consists of 400 trials. (Only session 1 consists of 100 trials.) You are asked to choose either "L" or "R" button in each trial as seen in Figure 14. The points corresponding to selected button appear on the right side of "You win" and you can get it at that trial. Your score is not affected by other's behavior. A series of these procedure above is done for 400 times (100 times in session 1) in each session. An update of an accumulating score is constantly displayed on the right side of "Total points earned in this session". After completing each session, you will see the figure which tells you the end of the session. For example, Figure 15 appears when you finished session 1. And Figure 16 appears after pressing "OK" in Figure 15. Press "OK" and you can face Figure 14 again. Begin to play next session as in the first session you did.

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Do you have any questions? If yes, please raise your hand. If not, please begin experiment.