# Assessing Adaptive Experimentation Techniques for Maximizing the Impact of Breathing Exercises on Academic Performance

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## Abstract

An experiment was conducted on a group of first year computer science students, to evaluate the effect of breathing exercises on academic performance. A written prompt, guiding participants through a focused breathing exercise, was presented to the students before they completed an online quiz question. Adaptive experimentation methods were used to sample if a student received the prompt or not, in order to evaluate the prompt's effect. It was found that the prompt showed a slightly positive impact on the probability of a student getting the answer correct. However, the difference between the reward for each arm was not statistically significant. Also, since this experiment was not conducted in a controlled environment we have no way of knowing if the breathing exercise was actually completed. This research also aimed to evaluate the performance of the 3 algorithms; Thompson Sampling, Uniform random, and TS-PostDiff, in terms of both statistical accuracy and total reward. Since the experiment showed no statistical difference between the two arms, a simulation was created to compare the algorithms' performance. It was found that TS-PostDiff was able to effectively balance achieving statistical accuracy and optimizing total reward.

## 1. Introduction and Objective

The purpose of this research was two fold; first, to explore the effect of breathing exercises on academic performance, and second, to explore the trade-off between total reward and statistical accuracy for various adaptive experimentation techniques.

Many studies have been done which validate the hypothesis that breathing exercises can immediately improve academic performance. A study done at the University of Malaysia Pahang, showed that providing engineering students with anxiety treatment, including breathing exercises, positively impacted their performance on a math exam and decreased their average heart rate [1]. Another study done at Tufts University, produced results that showed breathing exercises brought a marked improvement in the performance of the high-anxiety students relative to the low-anxiety students [2]. Based on the results from these studies, the following hypothesis was made; asking students to perform a breathing exercise prior to answering an online programming question will improve their chance of getting the question correct.

The TS-PostDiff algorithm was created with the goal of developing an algorithm that balanced and optimized the key benefits of two algorithms; Uniform Random Sampling and Thompson Sampling [3]. Uniform Random Sampling provides accurate statistical analysis of the sampled arms, because it samples from each arm with equal probability. However, Uniform Random Sampling does a poor job of maximizing total reward because it does not ever exploit the observed better arm. On the other end of the spectrum, Thompson sampling can provide a very high total reward because it can very accurately find and exploit an arm with high reward. However, Thompson sampling can often fail to accurately compute the true distributions of the arms, since it will neglect to sample initially lower scoring arms. TS-PostDiff combines these two methods by using Thompson Sampling unless the difference in the sampled posterior is less than some threshold c, in which Uniform Random sampling will be used. This allows the algorithm to use Uniform Random sampling more when the observed distributions are similar, and less when there is a clearly better arm. This research compares TS-PostDiff with both Uniform Random Sampling and Thompson Sampling (with beta bernoulli distributions), to measure the associated trade-off of statistical accuracy and total reward.

# 2. Related Work

Breathing exercises as a means to affect performance in short-term academic testing settings like exams, tests, and quizzes is an idea that researchers have scientifically studied in the past. Vitasari et al. [4] reported that in a study of twelve subjects being provided anxiety treatment (six sessions - two hours each) - breathing retreatment, relaxation and study coping skills - saw a statistically significant decrease in anxiety levels (measure using breath-per-minute) and a statistically insignificant increase in test scores. Gupta et al. [5] studied the effects of two therapeutic breathing interventions on the test performance of over a hundred student subjects in grade 3, reporting on the subjects in the treatment group having a higher attention span and attendance rates, staying on the assigned task for longer while having minimal referrals for behavioural issues.

In the same vein, we also found Brunyé et al. [6] detailing how when the effects of three short-term breathing exercises and a nutritional intervention (theanine consumption) were studied on subjects with math anxiety the breathing exercises increased rated calmness and improved performance in an arithmetic test amongst subjects with high math anxiety while the theanine consumption didn't. The effect of breathing exercises on anxiety and depression - two factors negatively correlated with academic performance - has been studied in the past. Here we had

Akinsola et al. [7] report that a combination of relaxation (via breathing exercises) and cognitive restructuring (restructuring attitudes towards exams, creating personal words and phrases to promote success in exams, visualizing success) led to significant improvement in test scores and a marked reduction in depression and anxiety. The subject groups here consisted of seventy-two students who had been identified as having relatively high anxiety scores.

While exploring Thompson Sampling (TS) based adaptive experimentation techniques, we have focussed on the results presented by Annonymous et al. [8] where a new algorithm (TS-PostDiff) has been proposed to address the issue of low statistical power that results from vanilla Thompson Sampling often suffer from. This is achieved using a combination of Thompson Sampling and Uniform Randomization leading to a better balance of reward, statistical analysis, and FPRs than epsilon-TS, along with more statistical power in the results generated.

# 3. Experimental Design

## 3.1. Prompt Design

To analyze the effect of breathing exercises on student performance a meaningful prompt was provided to students before answering the given homework question. The prompt given was as follows;

> *"It has been shown that breathing exercises can help immediately alleviate stress and increase academic performance. Take a few minutes now, to take 5 deep breaths, remembering to; tune into the feeling of the breath moving in and out of your body, focusing on the sensation of the breath moving past the nostrils; or alternatively, on the feeling of your belly expanding gently on each in-breath, and receding gently with each out-breath."*

This prompt was written, by building on the research done by Brunye et al. (2013), where they conducted breathing exercises with students prior to a math exam. During this experiment, students participated in various types of breathing exercises, including focused, unfocused and worry-based exercises. Their research showed that the focused breathing exercises, like the one detailed in our prompt, had the most success in both calming students measured by change in heart rate, and exam performance measured by grade [2]. Therefore, the exercise outlined in our prompt, was taken directly from Brunye et al. (2013)'s focused breathing experiment.

## 3.2. Policy Design

The experiment assigned participants to one of the three policies used (Uniform Random, Thompson Sampling, and TS-PostDiff) with equal probability. Meaning a third of the population were assigned using each policy. For the Uniform Random group, we expected to see the most accurately predicted distributions, with the lowest observed reward. For the Thompson sampling, we expected to see the highest reward, with the lowest accuracy for the worse arm's distribution. And lastly, we expected TS-PostDiff to provide an intermediary result on both total reward, and statistical accuracy. The results of these three policies are outlined in Section 4 Results.

*Table 1: Hyperparamertes for the designed policies*.

| Parameter | Uniform Random | Thompson Sampling | TS-PostDiff |
|---|---|---|---|
| **Allocation** | 33% | 33% | 34% |
| **Burnin** | - | 0 | 0 |
| **Batch Size** | - | 1 | 1 |
| **C** | - | - | 0.004 |

Table 1 shows the design of the hyperparameters for the policies. The burnin period is the number of data samples sampled using Uniform Random, before starting the adaptive algorithm (ie. Thompson sampling or TS-PostDiff). For both Thompson Sampling and TS-PostDiff this was set to 0, to effectively evaluate the base algorithm's performance. The batch size represents the number of samples to be observed before updating the distributions. This was set to 1 for both Thompson Sampling and TS-PostDiff, to achieve the most adaptive experiment possible. This was feasible since our data size was fairly small. Lastly the c value for TS-PostDiff was set to 0.004, which is significantly smaller than the values used in the experiments by the Web Con (2018) study [3]. This value was chosen because our hypothesis was that the distributions of the two arms would be fairly similar, and so we wanted the algorithm to still be able to effectively exploit the better arm.

It is important to note that in order to accurately assess these algorithms, the two distributions of our data must be independent, meaning the prompt has an effect on the reward. Otherwise the distributions of the two arms will be equivalent and all three policies will provide similar results.

## 3.3. Deployment Process

This experiment was run on a group of first year computer science students, at the University of Toronto Mississauga Campus. To deploy the experiment, we collaborated with the University of Toronto's Intelligent Adaptive (IAI) Intervention Research Lab. The IAI has developed an architecture for conducting A/B experimentation, crowdsourcing, real-time data analysis, and personalization, called "MOOClet". Our experiment was run using the MOOClet tool, through the following process;

1. A policy is selected (Uniform Random, Thompson Sampling, or TS_PostDiff) based on our policy design
2. The participant is assigned to an arm (prompt or no prompt) based on this policy
3. The observed reward (correctly answered or not) is recorded
4. The policies are updated based on this reward

The data collected through this process was analyzed against the hypothesis. The results of this analysis are detailed in section 4. Results.

The MOOClet tool is a web service that allows for adaptive A/B testing using machine learning, with flexibility to change algorithms over time. Through a webservice call to the MOOClet, with a specified policy and data store variable, we can generate a decision on which arm to choose. With each call, the MOOCLet also records the observed reward and updates the distributions. The great quality of the MOOClet solution is that the policy can easily be modified or even completely changed, at any point during the experiment. Though this wasn't necessary for this specific project.

# 4. Results

## 4.1. Effect of Prompt on Reward

Before comparing the policies, the overall results for the two arms are compared, to determine a baseline understanding of the data before comparing the results of the policies. Also, in this section the hypothesis that the prompt would have a positive effect on reward is investigated.

*Table 2: Average observed reward and sample size for the two arms, regardless of sampling policy*.

| Arm | Average Observed Reward | Number of Observations |
|---|---|---|
| 0 (No Prompt) | 0.215 | 793 |
| 1 (Prompt) | 0.230 | 781 |

Table 2 shows the overall average reward for the two arms. It is clear just by looking at these results that there is a possibility the prompt had little or no effect on the outcome because the observed rewards are very similar. Also, the arm with the larger observed reward, arm 1, has less observations assigned to it. This is odd, because intuitively the arm with the larger observed reward should have been exploited in both Thompson Sampling and TS-PostDiff. Therefore, to test if these two distributions are equivalent or not, a 2-sample t-test was performed.

*Table 3: Results of the two sample t-test on the distribution of reward for the two arms*

| Metric | Value |
|---|---|
| T-Statistic | -0.7066 |
| P-Value | 0.4798 |

Table 3 shows the results of the t-test. Since the p-value is significantly larger than the typical threshold of 0.05, we can not reject the null hypothesis that the distributions are equal. Therefore, it is likely that the prompt had little or no effect on reward.

## 4.2. Policy Results

Figure 1 shows the final observed distributions for the 3 designed policies, plotted as a function of the probability of reward. Table 4 shows the final observed distributions for each arm over the 3 policies.

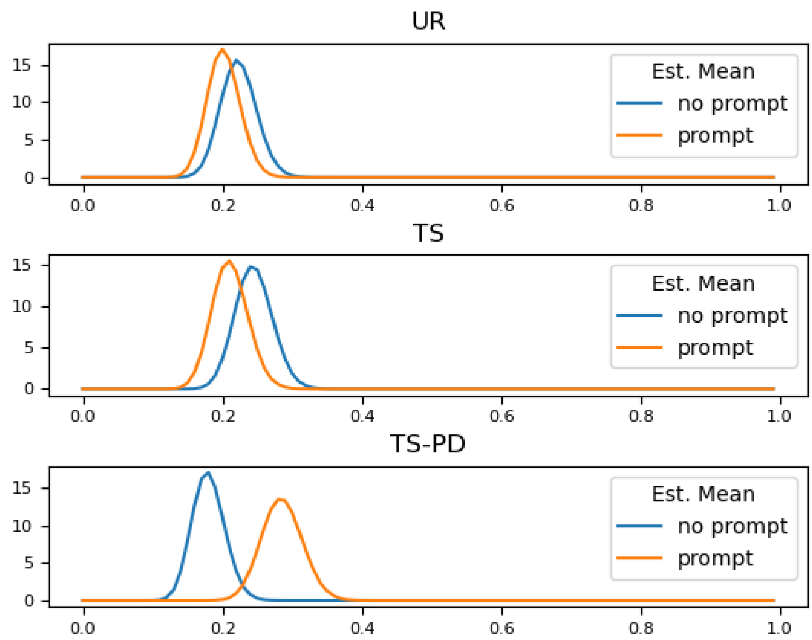


*Figure 1: The plotted final observed distributions for both arms over the three deployed policies*

*Table 4: Final observed distributions for both arms over each Policy*.

| Policy | Arm | Avg. Mean | Alpha | Beta | Support |
|---|---|---|---|---|---|
| UR | 0 | 0.2234 | 59 | 205 | 264 |
| UR | 1 | 0.2020 | 59 | 233 | 292 |
| TS | 0 | 0.2451 | 63 | 194 | 257 |
| TS | 1 | 0.2111 | 53 | 198 | 251 |
| TS-PD | 0 | 0.1801 | 49 | 223 | 272 |
| TS-PD | 1 | 0.2857 | 68 | 170 | 238 |

There are many inconsistencies with these results, compared to the expected results for each policy outlined in Section 3.2-Policy Design. Firstly, the TS-PostDiff predicted that arm 1 (promt) has a higher mean probability of reward, whereas the other two policies predicted arm 0 (no prompt) has a higher mean probability of reward. When we compare this to the baseline observed means for the two arms, we see that TS-PostDiff is technically more accurate than Uniform Random, which is not expected. Also, from this data it is clear that Thompson Sampling did not converge to exploiting one arm, since the supports for the two arms are very close to equal. These results further indicate the conclusion made from the t-test in section 4.1, that the distributions for the two arms are likely equivalent. Meaning, the prompt had little to no impact on the reward. Therefore, the performance of the 3 different policies cannot be meaningfully analyzed for this data.

## 4.3. Simulation Results

In section 4.1 and 4.2 it was shown that the observed data from the two arms likely came from the same distribution, making it very difficult to analyze the performance of the three policies. Therefore, a simulation was built to model the experiment, under the new assumption that the observed means of each arm were true and come from separate distributions. When running this simulation on the same sample size for each policy with the same hyperparameters, very different results were observed. Figure 2 shows the final observed distributions for the 3 simulated policies, plotted as a function of the probability of reward. Table 5 shows the final simulated distributions for each arm over the 3 policies.

*Figure 2: The plotted final simulated distributions for both arms over the three deployed policies*

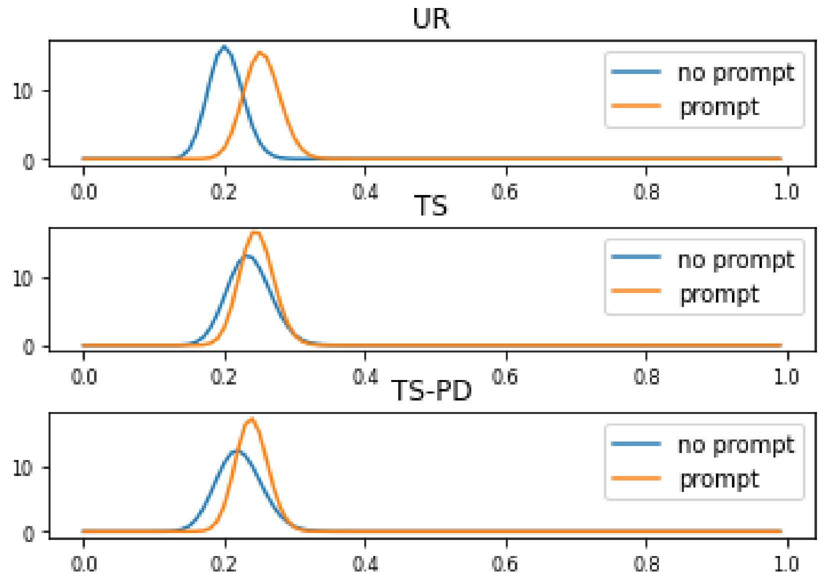


*Table 5: Final simulated distributions for both arms over each Policy*.

| Policy | Arm | Avg. Mean | Alpha | Beta | Support |
|---|---|---|---|---|---|
| UR | 0 | 0.2022 | 55 | 217 | 272 |
| UR | 1 | 0.2534 | 73 | 215 | 288 |
| TS | 0 | 0.2356 | 45 | 146 | 191 |
| TS | 1 | 0.2461 | 79 | 242 | 321 |
| TS-PD | 0 | 0.2216 | 37 | 130 | 167 |
| TS-PD | 1 | 0.2392 | 83 | 264 | 347 |

These results reflect the expected behaviour of the 3 algorithms. Both Thompson Sampling and TS-PostDiff exploited arm 1, which is the arm with the higher mean. Whereas, Uniform Random did not exploit either arm. The results also show that Uniform Random had the most accurate predicted mean of arm 0. This makes sense because Uniform Random sampled arm 0, the worse arm, more than the other two algorithms which exploited arm 1, the better arm. Table 6 shows the observed reward from each policy.

*Table 5: Final simulated reward for each Policy*.

| Policy | Average Reward |
|---|---|
| UR | 0.2266 |
| TS | 0.2401 |

| | |
|---|---|
| TS-PD | 0.2313 |

These results also match the expectation. Thompson sampling achieved the highest average reward, since it is best able to find and exploit the optimal arm. Uniform Random achieved the worst expected reward since it has no way to exploit either arm. Finally, TS-PostDiff achieved a total reward between that of Uniform random and Thompson Sampling, which was also expected.

# 5. Discussion

The analysis of the results for the experiment demonstrated that the prompt likely did not have a significant effect on the student's chance of getting the answer correct. To understand why our hypothesis did not hold true, we must consider the constraints of our experiment. The experiments that were analyzed in the introduction and related work sections, were conducted in a controlled live environment, where the participants were monitored and led through the breathing exercises by a professional. In contrast, during our experiment, the participants were remote and had the prompt presented in text. Because of this, it is very likely that many of the students did not participate in the breathing exercises or even read the prompt. Therefore, an extension to this research would be to add a confirmation to the prompt, for students to confirm if they completed the breathing exercise or not. Therefore, we would be able to analyze the effect on reward for the observations where it is confirmed the exercise was completed.

Since the data observed may have come from the same distribution, it is hard to analyze the performance of each policy. However, the simulated policies provided more meaningful results. It was shown that the TS-PostDiff algorithm was able to successfully balance the tradeoff between statistical accuracy and total reward, compared to uniform random and Thompson Sampling. Also, when the expected means of the arms are similar, TS-PostDIff balances this trade off better with a smaller c value. Since a larger c value would perform more similarly to Uniform Random.

## References


[1] A pilot study of pre- post anxiety treatment to improve academic performance for engineering students

[2] Learning to relax: Evaluating four brief interventions for overcoming the negative emotions accompanying math anxiety

[3] Algorithms for Adaptive Experiments that Trade-off Statistical Analysis with Reward: Adaptively Combining Uniform Random Assignment and Thompson Sampling

[4] A pilot study of pre- post anxiety treatment to improve academic performance for engineering students

[5] Academic Performance and Therapeutic Breathing

[6] Learning to relax: Evaluating four brief interventions for overcoming the negative emotions accompanying math anxiety

[7] Test Anxiety, Depression and Academic Performance: Assessment and Management Using Relaxation and Cognitive Restructuring Techniques

[8] Algorithms for Adaptive Experiments that Trade-off Statistical Analysis with Reward: Adaptively Combining Uniform Random Assignment and Thompson Sampling