Lecture 5: Reproducibility and Replication I
Modeling Social Data, Spring 2019
Columbia University

February 22, 2019

Notes from pa2492

1 Introduction

This lecture is about evaluating a research results. The main evaluation questions that one should ask are the following

1. Was the research done and reported honestly / correctly?
2. Is the result real or an artifact of the data / analysis?
3. Will it hold up over time?
4. How robust is the result to small changes?
5. How important / useful is the finding?

2 Reproducibility and Replicability

We usually take the optimistic view that most researchers who publish their results are honest. However,some exceptions were reported, although few, in social science Literature available here.

The two main criteria for evaluating credibility of a research is the reproducibility and replicability of the results. Reproducibility is the ability to independently verify the exact results using the same data and the same analysis. This is improving with better software engineering practices among researchers like

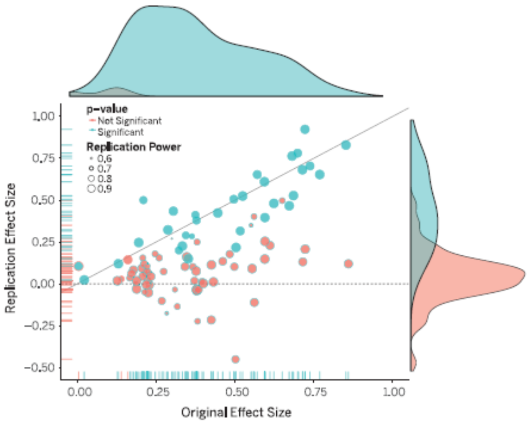
- Literate programming(Jupyter,Rmarkdown)
- Automated build scripts
- Containers(Docker,Code Ocean)

The well renowned journals like NIPS started to encourage researchers by attaching acknowledgement badges on their published papers as shown in Figure 1.

Figure 1: NIPS Badges

Replicability is the question of whether the result holds up with new data under the same analysis. Since it's easy to be fooled by randomness, and Noise can dominate signal in small datasets and asking too many questions of the data can lead to overfitting. Open science collaboration conducted replications of 100 experimental and correlation studies and deduced that 97 percent had significant results, but 36 percent had statistically significant results, 47 percent of original effect sizes were in the 95 percent confidence interval of the replication effect size. This leads to a Crisis where one has to believe half of what he reads.

Figure 2 depicts the original study effect size versus replication effect size.



Original study effect size versus replication effect size (correlation coefficients). Diagonal line represents replication effect size equal to original effect size. Dotted line represents replication effect size of 0. Points below the dotted line were effects in the opposite direction of the original. Density plots are separated by significant (blue) and nonsignificant (red) effects.

Figure 2: Original study effect size vs replication effect size.

3 Role of Statistics

Then, we talked in class through three quizes about the role of statistics specifically the hypothesis testing, p-values, statistical significance, confidence intervals and effect sizes. We draw the below conclusion on the these quizes:

1. Quiz 1 : One should choose Treatment A , even if it is with small numbers of participants , because following the below formula:

$$\sigma_{se} = \sigma_{sd}/\sqrt{N} \tag{1}$$

Under the same uncertainty about the mean (standard error) , the lower the N in the denominator of equation 1, the lower the standard deviation (numerator of equation 1), as shown in Figure 3.

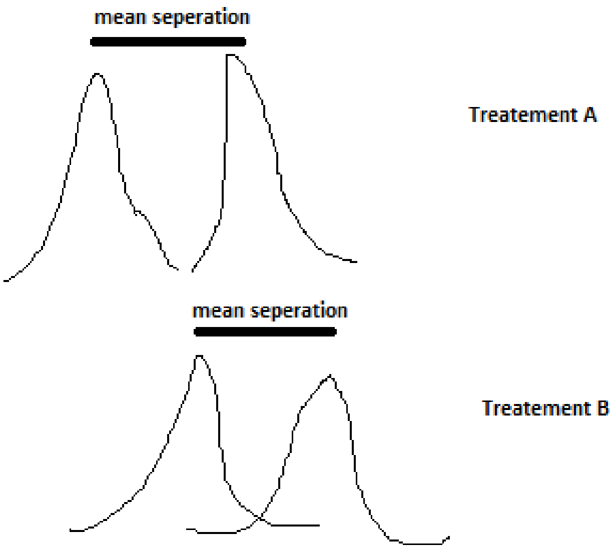


Figure 3: Effect size

2. Quiz 2 : All answers are false, the p-value given here is not a sufficient indicator of the null hypothesis, experimental hypothesis.

3. Quiz 3: Conclusion to draw here is one should not fool people with better visualization as it could be the case in Figure 4.

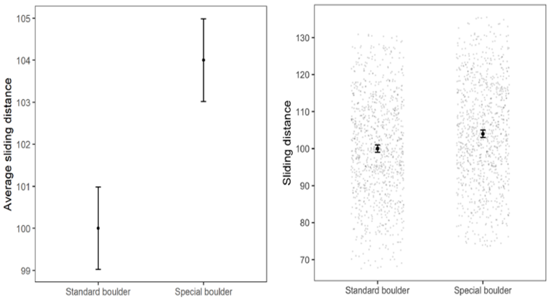


Figure 4: Left: Bad visualization Right: Correct visualization

4 Some Statistics Thoughts...

We cannot prove theories are right.Sometimes we can find contradictions to prove things false.Most often we have to settle for ruling things that are unlikely. How unlikely are my results in a boring world?

Assuming boring world (H0 is true) Imaging running study many times in a boring world as shown in Figure 5. Look at distribution of outcomes (test statistics) from repetition in a boring world. (Figure 6) . Compare outcome (100 flips) from actual world to this distribution. For instance, if actual outcome is 0.61 , as shown in Figure 7, It is unlikely that we live in a boring world and thus one could reject the Null H0. However, if actual outcome is 0.52, as shown in Figure 8 one cannot reject the Null. And thus the world could be boring.

As a conclusion :

1. One need to put a threshold on the p-value

2. Need to quantify Unlikeliness.

P-value tells you probability of data you saw given that you are in a boring world. (Null H0 is True)

$$p(D/H_0True) \tag{2}$$

You have to decide for p-value on a threshold alpha below which you reject boring world.

$$\alpha \tag{3}$$

Alpha is false positive rate and the convention value is 0.05 (1 in 20)

$$\alpha = p(rejectH_0/H_0true) \tag{4}$$

But what about

$$p(rejectH_0/H_0false) \tag{5}$$

- Assume exciting world where effect exists (H0 is false)

- Run a study in exciting world many times, execute test and look how often to reject the Null as in Figure 9.Convention: Want power about 80

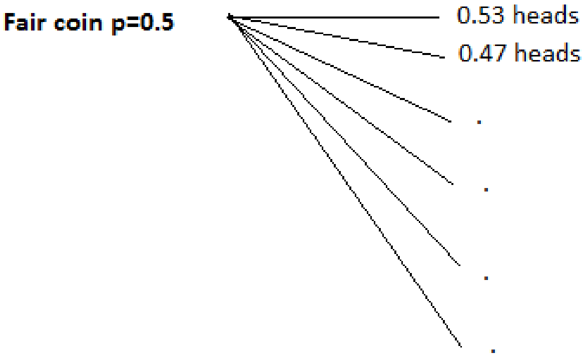


Figure 5: Boring world (H0 is true)

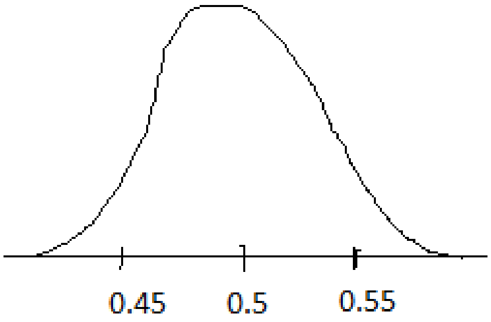


Figure 6: Distribution of outcomes from repetition in a boring world

Notes from sl3946

1 Introduction

1.1 Motivation for the lecture:

- Currently,we are seeing lots of issues with reproducibility and replication in Social Science academia, as well as in astronomy and the life sciences.
- This seems to happen because professors would get tenure from shiny results, so they occasionally had dubious approaches to achieve these results.
- Up until now we (students) have only been producing results, now we are going to look at analyzing/critiquing results to hopefully get rid of bad science and only get good scientific papers published.

1.2 Key Questions to consider in evaluation research:

- Was the research done and reported honestly/correctly?
- Is the result "real" or an artifact of the data?

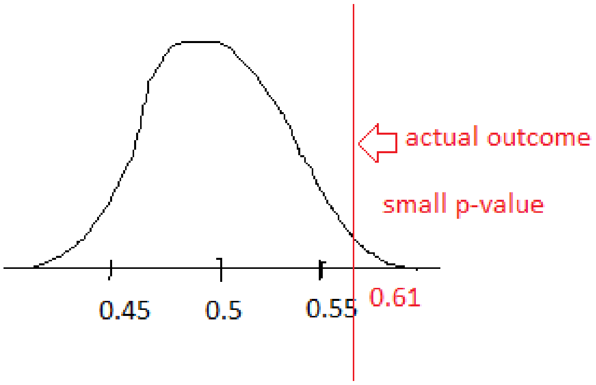


Figure 7: Reject the Null H0

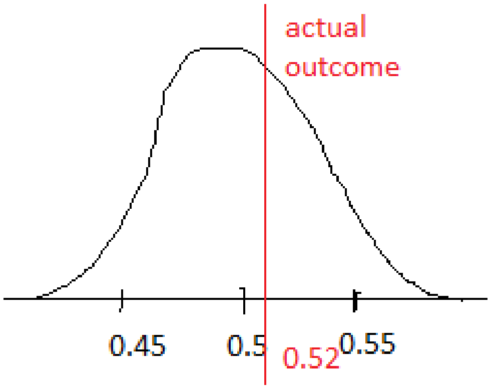


Figure 8: Cannot Reject the Null H0

- Will it hold up over time?
- How robust is the result to small changes?
- How important/useful is the finding?

2 Honesty

Was the data reported and collected honestly: Well take the optimistic view point that most researches are honest, and mistakes are due to stupidity, but that is not always the case.

2.1 When Contact Changes Minds: A Social Science Example of honesty failing

2.1.1 The experiment

- Ask question: Can a single conversation change peoples belief on gay marriage
- Someone knocks on your door to talk to you about talking gay rights (might present yourself as straight/gay whether you are or not)

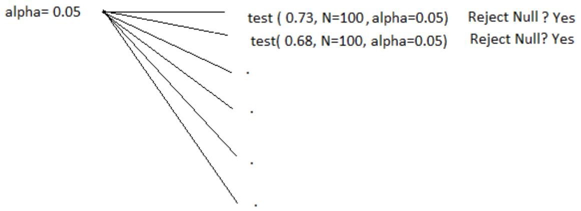

alpha= 0.05
test (0.73, N=100, alpha=0.05) Reject Null ? Yes
test(0.68, N=100, alpha=0.05) Reject Null? Yes

Figure 9: Study run in an exciting world with alpha=0.05

- This conversation changes your view in the moment. Furthermore if the person who knocked on the door said they were gay, the results were more persistent
- The idea was that this meant that more people could knock on doors to shift public perception

2.1.2 Questioning of Results and Reproducibility

- Irregularities in LaCour (2014) showed that the results were pretty dubious
- Looked at public opinion polls that were so different from the papers results
- But they thought question was interesting so they went to analyze it with transgender
- Found that conversations decreased transphobia at a greater rate and that the results persisted for 3 months, regardless if canvasser was trans or not.

3 Reproducibility

Can you independently verify the exact results using the same data and the same analysis

3.1 Though a low bar, most research doesnt currently pass this test

- Data or code arent available/complete
- Code is difficult to run/understand
- Complex software dependencies
- Full reproducibility is not part of the current pipeline. Due to dependencies or code being complex even if its given to you its tough run

3.2 This is improving with better software engineering practices among researchers

- Literate programming (Jupyter, Rmarkdown)
- Automated build scripts (Makefiles)
- Containers (Docker, Code Ocean)
- Currently, the ACM (association for computing machinery which is main CS society) puts badges on papers if example code is provided and is functional to use.

3.3 Practical Constraints that make this not a hard rule

- Open AI last week published a better language model that can be misused so they only published a fraction of their research.
- For example: Private company wants to publish paper that used a 50k GPU etc, doesnt want to give out their own private repository and not everyone has access to this GPU
- Jake cant publish the Twitter data that he worked with due to privacy concerns as well as general data access decision by Twitter
- A practical taxonomy of reproducibility for ML research is a paper from 2018 by UW professor and Kaggle team. They analyzed the NIPS conference (where 6k submissions only 700 accepted) only 40% of accepted papers provided links to work

4 Replicability

4.1 Will the result hold up with new data but the same analysis?

- Its easy to be fooled by randomness
  - For example seeing that sending people to the door to talk about gay rights changes peoples opinions.
  - You get results and it seems that there is an effect, but not persist because youre just looking at noise.
  - Small datasets of size of 50 are common in political science, which can make it especially difficult to draw conclusions
- Noise can dominate signal in small datasets
- Asking too many questions of the data can lead to overfitting
  - For example you keep y the same, but you add more and more xs to see how they impact y and eventually find a perfectly predictive model but it might not hold up
  - Tangential relationship to bias-variance trade off
  - XKCD election replicability comic

4.2 Replicability Crisis Example

- People at open science in Virginia (Brian Nozick) wanted to redo 100 different psych experiments to check to see if the results were replicable. They conducted 100 psych experiments
- Results
  - Replication effects were half the magnitude of original effects
  - 97% of original studies had statistically significant results, while in this study 36% of replicated studies had statistically significant results
  - Only 47% of original results were within the 95% confidence interval
  - The effect size versus replication shows how the independent variable effect size was rarely as strong as stated. In fact some times the effect size was negative when reported positive.
    - Effect size indicates the difference in mean of two distributions, ie the impact of a drug on health compared to that of placebo on health
- There is a clear crisis going on that suggests that you should basically believe about half of what you read for some scientific journals
  - Jake believes its more bad science rather than malevolence
  - World is struggling with bad science/bad statistics, so lets relearn statistics

5 Statistics Quiz

5.1 Question 1

5.1.1 Question:

- Treatment A was found to improve health over a placebo by 10 points on average (with standard error of 5 points) in a study with N = 100 participants.
- Treatment A was found to improve health over a placebo by 10 points on average (with standard error of 5 points) in a study with N = 1,000 participants.
- Which treatment would you prefer?

5.1.2 Answer:

$\sigma_{SE} = \frac{\sigma_{SD}}{\sqrt{n}}$ where σ_{SE} = the uncertainty about the mean, σ_{SD} = deviation in the population, and n = the sample size.

Clearly the difference is that treatment A has a smaller standard deviation than B therefore it has a bigger effect size. Thus **Treatment A is preferred over B**.

5.2 Question 2

5.2.1 Questions:

Suppose you have a treatment that you suspect may alter performance on a certain task. You compare the means of your control and experimental groups (say, 20 subjects in each sample). Furthermore, suppose you use a simple independent means t-test and your result is significant (t= 2.7, df = 18, p=0.01). Which of the following are true?

- You have absolutely disproved the null hypothesis (i.e., there is no difference between the population means).
- You have found the probability of the null hypothesis being true.
- You have absolutely proved your experimental hypothesis (that there is a difference between the population means).
- You can deduce the probability of the experimental hypothesis being true.
- You know, if you decide to reject the null hypothesis, the probability that you are making the wrong decision.
- You have a reliable experimental finding in the sense that if, hypothetically, the experiment were repeated a great number times, you would obtain a significant result on 99% of occasions.

5.2.2 Answers:

All false. See p-value notes in section 6

5.3 Question 3

A data visualization question that is based on the estimation of the probability of special boulder sliding further than a normal boulder based on some information from 1000 slides.

Key notes: Second visualization lowers people's confidence but still not the true result of 57%.

6 Understanding Statistics terms to better understand results

6.1 Key Ideas:

- Hypothesis testing?
- P-values?
- Statistical significance?
- Confidence intervals?
- Effect sizes?

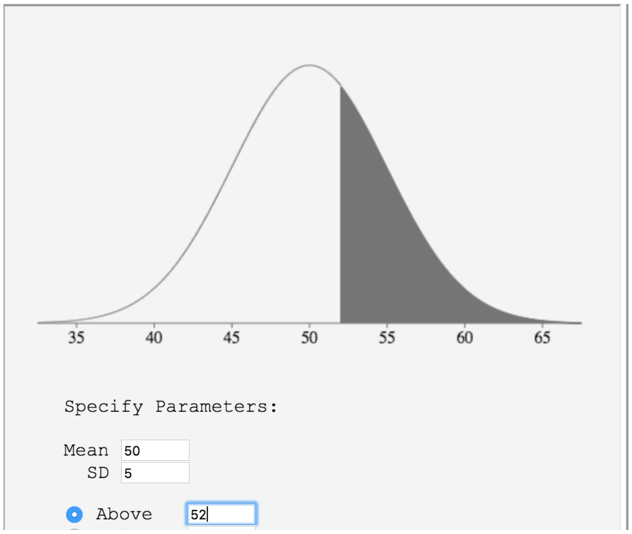
6.2 Understanding P-Values

Assume a boring world where H_0 is true and that we have a fair coin with $p = 0.50$.

Imagine a running many trials of an experiment (where one experiment is flipping the coin 100 times). You might get $\hat{p_0} = 0.53$ or 0.47 for example.

If you look at a distribution of the outcomes from the repetition of trials in the boring world you're likely to get a normal distribution with the mean of $\hat{p_0} = 0.50$.

Compare the outcome from one real world experiment (ie 100 flips) to the distribution from the boring world.



Specify Parameters:

Mean 50
SD 5

● Above 52

Figure 10: In this case the real world experiment had 52 head's tosses. Based on a normal distribution, the dark shaded area indicates the chance that you achieve 52 heads if $\hat{p_0} = 0.50$. In this case it is 0.34

The p-value essential tells you the probability of seeing the data that you saw in the single test trial given that you're in a boring world (H_0 is true). Mathematically this means $p(\text{Data} \mid H_0 = \text{true})$.

Ideally before you run the experiment you decide on a p-value threshold below which reject the hypothesis of being in a boring world. This is known as α or the false positive rate. Traditionally this is known to be 0.05, ie you expect to see 1 in 20 false positives. Another way to express is alpha is $\alpha = p(\text{reject } H_0 \mid H_0 = \text{true})$.

But what about $p($reject $H_0 \mid H_0 =$ false) or the idea of power. It measures how likely is it that I reject a boring world when it is not a boring world? We want this to be high. If you want the value to big even when $H_0 false$ for small differences from boring world, ie if think boring world is false when $\hat{p_0} = 0.52$ then you need a realtively huge sample size.

Notes from sc4401

1 Motivation

This lecture deals with challenges related to reproduciblity and replicability of scientific studies. The later part of the lecture gives an introduction to statistics and the correct way to interpret statistics.
While evaluating research results as a consumer, it is important to think critically about the study and formulate an informed opinion about whether or not the study can be believed. Here are a few questions to ask regarding the study:

1. Was the research honest?
2. How important is the result of the research?
3. How robust is the result to small changes?
4. Will the result of the research stand the test of time?
5. Is the result real or was the data manipulated in order to obtain this result?

For the rest of the lecture, we will assume that researchers are honest, although there is clear evidence which suggests the contrary.[1]

2 Reproducibility

A study is said to be reproducible if the same results are obtained as those mentioned in the study upon conducting an individual experiment using the same data and same analysis. There are several challenges related to reproducibility:

1. Data and code are not available publicly most of the time. Speifically, getting data from private companies to recreate ML/AI experiments is difficult since all the data and infrastructure will be needed. It becomes more problematic when something like reinforcement learning needs to be verified.
2. Sometimes, even when the code is available, it is difficult to understand it, which makes it difficult to run the code.
3. A major reason for this difficulty in running the code stems from the complex software dependencies of the programs.

However, recent efforts by researchers in the form of better software engineering practices is improving the situation:

1. Literate Programming
2. Automated Build Scripts
3. Containers

3 Replicability

Replicability seeks to answer the question: Will the result hold up with new data but the same analysis?
Real-life datasets tend to be very small and noise can dominate signal in small datasets. Even in the case of large-datasets, asking enough questions leads to overfitting.
For example. consider an experiment wherein every classroom in Columbia is split into two sides and the number of IPhones owned by each side of each classroom is counted. Eventually, a conclusion can be drawn that the

[1] https://en.wikipedia.org/wiki/List_of_scientific_misconduct_incidents

side of the room has an effect on IPhone ownership (even though this is clearly false). A different version of the same experiment is to take one very big classroom and conduct the same experiment on that big classroom. It is possible to find a feature which perfectly classifies this particular classroom but will not work for other classrooms. An open science collaboration based in Virginia re-conducted 100 psychological experiments to check for replicability. The results of this study can be summarised as follows:

1. Out of the 97% studies which reported significant results, only 36% reported statistically significant results.
2. Only 47% of the original results were in the 95% confidence interval.
3. In short, this study concluded that only half of what we read can be trusted.

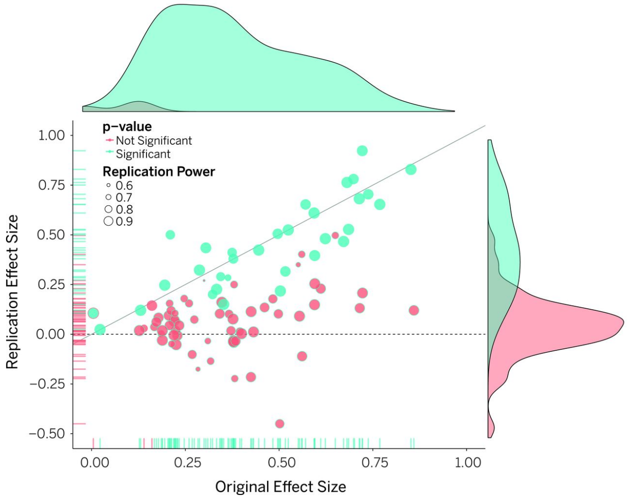


Figure 11: Original study effect size vs replication effect size

Figure 11 is the result of the above mentioned experiment. The blue points along the diagonal represent perfect replicability. However, as can be seen in the figure 11, there are far more red points than blue points and some experiments even resulted in negative correlation (replication study results directly contradict original study results).

4 Statistics Quiz

The answers and key take-aways of the quiz are as follows:

1. Treatment A is preferred over Treatment B. To understand this answer, we must first understand the definition of standard error and how it relates to the sample size:

   $$\sigma_{se} = \frac{\sigma_{sd}}{\sqrt{n}} \tag{6}$$

   In the equation above, σ_{sd} refers to the standard deviation in the population, n refers to the sample size and $sigma_{se}$ refers to the standard deviation of the sampling distribution. In simple words, this equation tells us how uncertain we are about the mean. Therefore, though the mean separation is same in both the treatments, the population in Treatment A must have had lesser variance than that in Treatment B. If we plot out the effects of the placebo treatment and the effects of both Treatments A and B, the graph would look something like Figure 12. This graph clearly tells us that in some cases, the placebo performs better than Treatment B but this is never the case in Treatment A.

2. All the statements are false. The reasons should become clear after reviewing the definition of p-value.

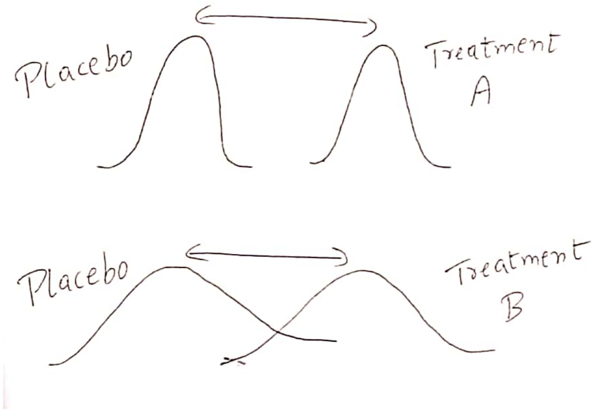


Figure 12: Treatment A vs Treatment B

3. The key take-away from this question is that data-visualisation can be used to mislead the readers and we should be wary of such attempts. The actual answer of the second part of this question is 57% but the professor says that most people are willing to bet good money that the special boulder would slide farther than the normal one with a probability of upwards of 65%.

5 Review of Statistics

- We cannot prove that theories are correct easily.
- Sometimes. we can find contradictions to prove things false.
- However, most of the time, we have to settle for ruling things out as "unlikely".
- We ask the question, "How unlikely are my results in a boring world?" (We will work with the assumption that when the null hypothesis H_0 is true, the world is boring)
- In practice, assume boring world (H_0 is true)

For example, let us consider the experiment wherein we toss a coin and try to find out if it is unbiased. For this experiment, we first take a fair coin (boring world) and toss it multiple times (say 100 times). We repeat this experiment (tossing a fair coin 100 times) multiple times and obtain the probabilities for each experiment. We can expect to see values like $p_0 = 0.52$, $p_0 = 0.48$ etc. However, when we plot these probabilities, we should obtain a normal distribution with the mean at around $p_0 = 0.5$. This normal distribution should look like the first figure in Figure 13 We now take the actual coin which we wanted to test and toss it 100 times. We now plot the resulting probability in the normal distribution obtained from the boring world. If the resulting p-value is small, like the second figure in Figure 13, we reject the null hypothesis and conclude that the coin is biased. This is because the result we observed did not conform to the result we should have observed if our world was boring (if the coin was fair). However, if the resulting p-value is large, like the third figure in Figure 13, then we conclude that our world is boring and declare that the coin is fair.

Therefore, the p-value tells us the probability of data we observed we given that we are in a boring world (null hypothesis H_0 is true).

We also have to decide a threshold for the p-value below which we reject the boring world. This threshold is called the false positive rate α. The convention is to pick $\alpha = 0.05$.

Power is defined as the probability of rejecting the null hypothesis H_0 given that it is false. In order to estimate this probability, we conduct the opposite experiment, i.e we assume an exciting world and run the experiment multiple times. Then, we compute the number of times we reject the null hypothesis and this results in Power. In order to correctly detect even small changes, i.e to be able to reject a boring world even with $p = 0.52$, we need huge sample size.

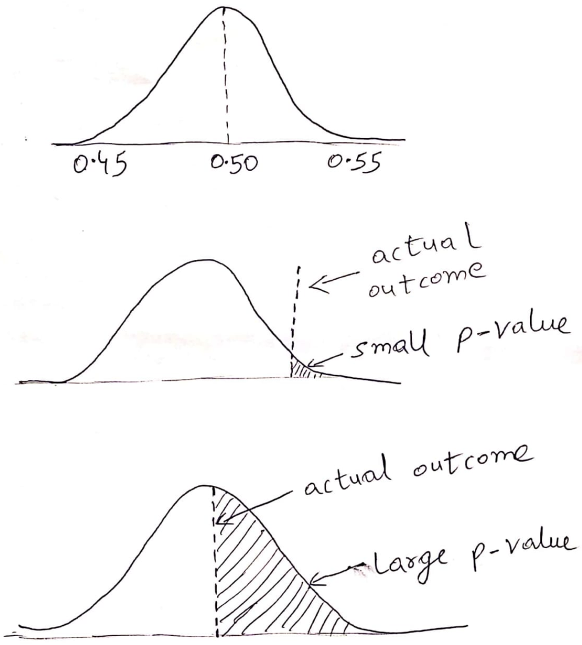


Figure 13: Coin Toss Experiment