Exploring the Correlation Between Musicianship and Visual Categorization Skills through the SET Game

CS22B Final Project

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1. Abstract

This study probes the potential correlation between musicianship and visual categorization skills by employing a unique approach centered around the digital version of the game SET, originally a card game from the 1990s, which was recreated digitally for this research. The research posits that musicians, due to their regular engagement with musical compositions, may exhibit enhanced performance in tasks involving visual representation and categorization compared to non-musicians. This version of SET that I created challenges players to identify patterns in the cards within a constrained time frame of 5 minutes.

A diverse sample of college students, predominantly aged 18-24, participated in the study, providing a mix of musicians and non-musicians. Following their participation in the SET game, the students filled out a form capturing demographic information and, for musicians, details about their musical engagement. Initial observations suggest that musicians and individuals with strong visual categorization skills, regardless of their professional or personal background, performed well in the SET game.

The collected data is undergoing rigorous analysis using Python and various libraries to identify statistically significant trends and correlations and to validate the initial observations. Key findings include a statistically significant advantage for musicians over non-musicians in the SET game performance. There was a marginal but not statistically significant, better outcome for STEM students over non-STEM students. A slightly negative correlation was observed between the age of the participant and the SET game performance. A strong correlation was found between the GPA of the students and the sets they found, with a higher GPA correlating with a higher number of sets found. Lastly, a positive correlation was observed between the number of instruments a person can play and the number of sets they found. This research could provide valuable insights into the cognitive advantages conferred by musicianship and other activities involving visual categorization.

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2. Introduction

2.1 Background of the Project

This research project stems from an interest in exploring the relationship between musicianship and visual categorization skills using the card game SET as a cognitive testing ground. The inspiration for this study arose from recognizing the parallel between the complex visual representations found in musical compositions and the visual challenges presented by SET. For the last few years, I have often had the opportunity to teach my friends and family about this game, and to a warm reception; almost everyone enjoys the challenge of finding sets, and the competitive environment when playing with other people.
Many of my friends and family members are musicians, and I always thought that my musician friends had a distinct advantage to learning the game and thinking about things in a logical way. This study is guided by the hypothesis that cognitive skills developed through musical training may extend to improved performance in visually demanding tasks, as exemplified by the patterns encountered in the SET game.

2.2 Brief Overview of the SET Card Game

The game of SET was invented by population geneticist Marsha Jean Falco in 1974. She was studying epilepsy in German Shepherds, and began representing genetic data on the dogs by drawing symbols on cards and then searching for patterns in the data. After realizing the potential as a challenging puzzle, with encouragement from friends and family she developed and marketed the card game. Since then, SET has become a huge hit both inside and outside the mathematical community. Falco initially created the game as a teaching tool to help her students develop their pattern recognition skills. However, it soon became clear that SET had a broader appeal as a standalone card game. From then on, it became a family business to produce and distribute the card game.

The rules of the game are simple. Each card has four features: number, color, shape and filling. Each of these four features has three variants. As shows in Figure 1:

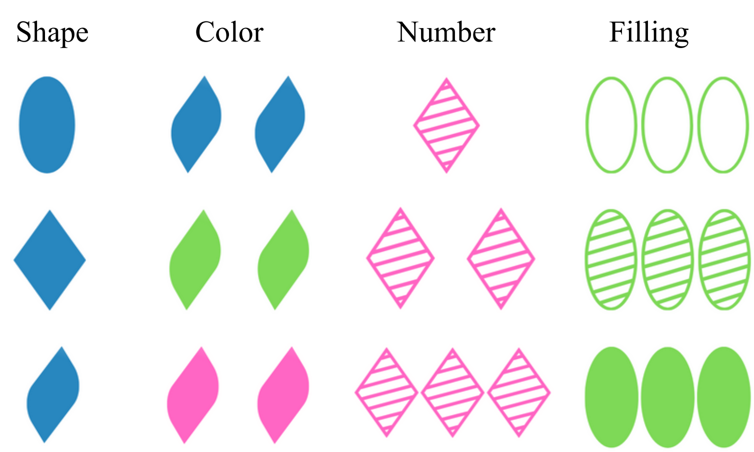

Figure 1: Displaying all features and variants of the cards.

The goal of the game is to make "sets." A set is comprised of three cards in which each of the four features are either all the same or all different. Specifically, each feature needs to be satisfied, all the same or all different, independently in order to form a valid set.

The other way of thinking about a these rules is by the "Golden Rule." The Golden Rule is: "if two are and one is not, then it is not a set." Specifically, if two cards share a feature in which the third card does not, it is not a set. This is essentially the opposite, or inverse, of what a set is. We will discuss this in more detail in section 3.2.

There are 81 different cards in the game of set, and it is a fairly simple Combinatorics problem. Each card has four features, and each feature has three variants. Which means we have $3 \cdot 3 \cdot 3 \cdot 3$ different possibilities, or $3^4 = 81$, different cards. A nice way to visualize this is with a Decision Tree as shown in Figure 2:

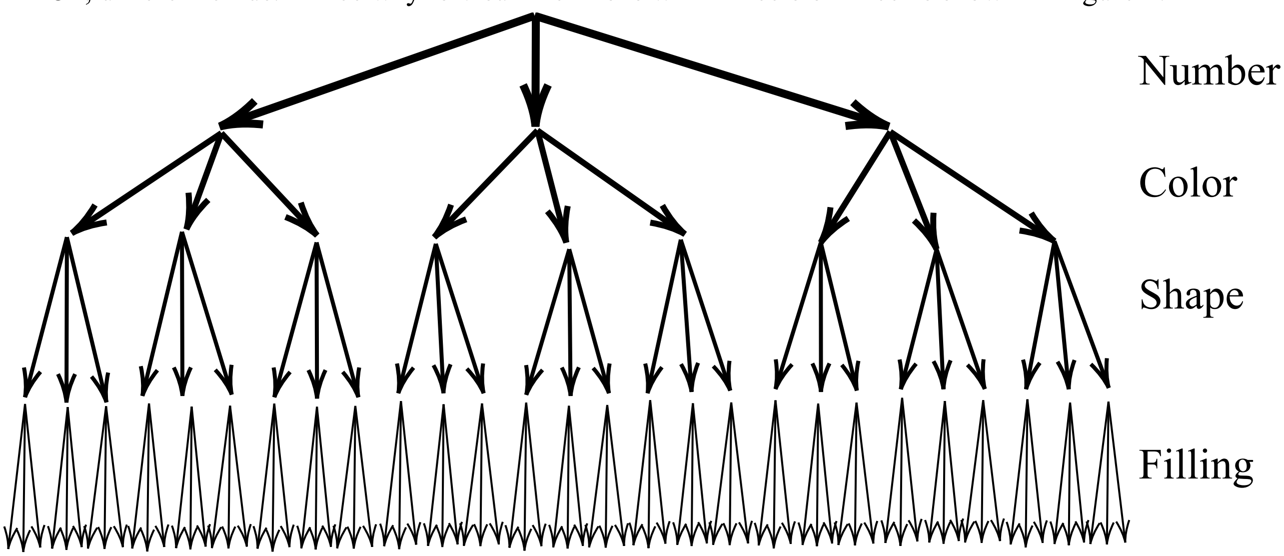

Figure 2: Decision Tree displaying the 81 possible cards.

2.3 Purpose of the Digital Card Game

The digital adaptation of the SET card game for this research project was strategically designed to enhance control over random variables, a pragmatic necessity identified from the project's inception. By choosing a to create the game on my laptop, a portable platform, it made things easier to standardize the testing environment, effectively minimizing the potential impact of random variables found in traditional, in-person card game setups. This decision substantially decreases variations in physical card handling, environmental conditions, and other external factors that could introduce unpredictability and compromise the study's integrity. The overarching objective was always to minimize randomness and reduce the likelihood of unexpected outcomes. Ensuring a consistent and controlled testing environment from the outset, the digital platform significantly contributes to the precision and reliability of the research findings. This approach fosters a fair and equitable testing ground for participants from diverse backgrounds, aligning seamlessly with the primary goal of minimizing the influence of random variables on the study's outcomes.

2.4 Significance of the Study

This project has been an exciting opportunity to delve into the fascinating intricacies of the human brain and it's adaptability. From my findings we can make some abstract inferences that scientists have been eluding to throughout history in many different ways. We can think of the brain as a muscle, for the brain to be good at anything we must exercise it and train it in different ways. Scientists have long been interested in studying a child in adolescence because their brain is working through phases of development. This is similar to the rest of the body in puberty, where each year serving as a metrics for change which can provide inferences across populations.

There is vast amounts of research from the psychological to biological reasoning why children think and act the way they do and it has been well documented that specific areas of the brain become hyper activated during specific tasks. Several research papers have concluded cognitive demand, or amplitude, when performing tasks like problem solving evoke a similar response from the brain when we are solving a new mathematical equation, and learning a new language. Similarly, the part of the brain that is active when we elicit an emotion response to something is active when we are viewing art, reading a book, or having a meaningful conversation. So as we can see, we can activate the same parts of our brain with different tasks.

This is exactly what I wanted to study. We can think of the brain as a muscle; a musician who has trained and practiced music, either currently or in their adolescence, would have the portion of their brain that is associated with pattern recognition, more proficient and better conditioned for performing similar tasks in a different setting. The same way a weight lifter can lift heavier objects than a laymen because their muscles are more conditioned to lift heavy objects. In the experiment, we can force people to activate parts of their brain, by giving them a game, that theoretically should stimulate their frontal lobe in a similar way that music stimulates the forntal lobe.

By analyzing these MRI scans in Figure 3, we can see the specific areas that are activated in the musician's brain are the Frontal lobe, the Motor cortex, and the Auditory cortex when they are actively playing music. From looking at the research in more detail, we can derive that the three main areas are working together, which is reasonable to believe given that the motor functions of a musician are directly related to their auditory receptors that tell the musician things like pitch, tonality and timbre.

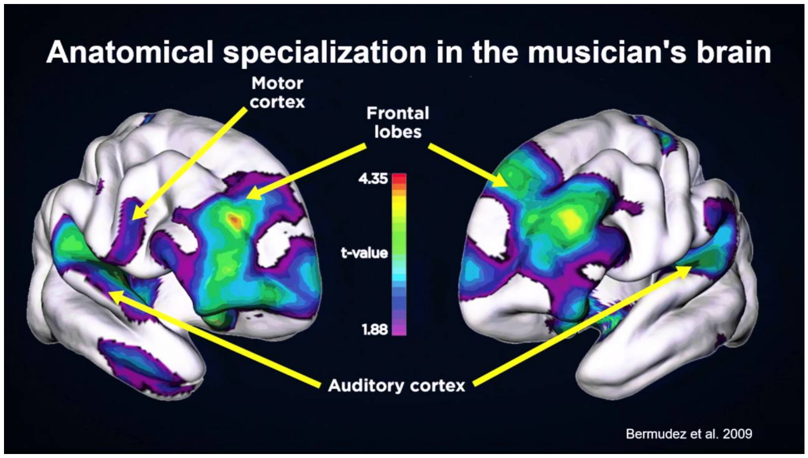

Figure 3: Anatomical specialization in the musician's brain.

One of the main function of the Frontal Lobe, among it's many "jobs," is to help with problem solving. More specifically this area of the brain is involved in a range of higher cognitive functions, including problem solving, planning, decision-making, and controlling emotional responses. There is a research paper from the University of Grenada that highlights musicians being better at decision-making and problem-solving, in figure 4 we can see an image from their research that shows the musician's brain activity activated when preforming problem solving task. As follows the main parts of the brain utilized in problem solving are very near to the other components that help with sensory processing. The frontal cortex is also involved in working memory, which is essential for holding and manipulating information in the mind over short periods of time. This is crucial for problem solving as it allows us to keep track of different elements of a problem and test potential solutions.

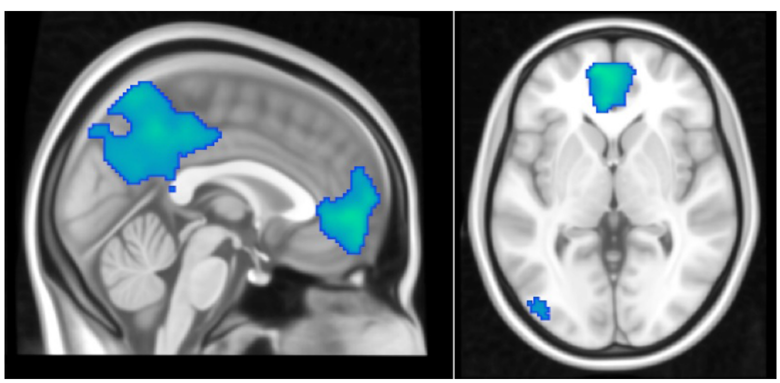

Figure 4: Active sites of the musician's brain when problem solving

To help prove my hypothesis, I wanted to kill as many birds as possible with one stone, by giving my participants the opportunity to learn a game that specifically activates the areas of the brain that I am interested in, I wanted to see if there was a specific connection between a person's history as a musician, and their ability to preform better than non musicians in the SET game.

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3. Development of the Digital Card Game

3.1 Overview of the Game Creation

In section 2.3, I talked about the purpose of the digital card game, and now it is time to dive into some code and the process of the game's creation. The goal before I started creating the game itself, was to develop the logic in a way that I could easily apply techniques we learned in class and in our assignments. I wanted to develop an algorithm to emulate the logic and rules present in the original card game, while catering to an audience that has predominantly never played the game before. This meant deciding where to be flexible and realistic with my approach to the development, knowing there was a limited time and I set myself a lofty goal of collecting as many people as possible.

A few notes on the differences between the version in which my participants played and the original card game.

- The card game has 81 cards and so does mine, but each card is randomized in my emulation and thus allows for duplicate cards, which in turn makes it slightly easier for new players. While the physical card game does not allow for "replacement," and it is entirely possible in my version, it brings the total number of unique sets to 1161, 81 more than the original card game of 1080.
- When playing the original, the board starts with 12 cards, and it is entirely possible for there to be no sets on the board. In that case, when each player decides there are no sets on the board, they add more and more cards until someone finds a set. To mitigate the frustration new players often feel when they can't find any sets, I added a refresh button which can quickly give them a new board of entirely randomized cards. This caters to my sample because it makes it easier for the participants to not get stuck for too long and find "easier" sets faster.
  - It is mathematically possible to have up to 20 cards on the board at a given time with no valid sets; as soon as the 21st card enters the board, there is a 100% chance there is at least one set on the board. This is a fascinating mathematical problem in the field of affine geometry, known as "the cap set problem," which is the problem of finding the size of the largest possible cap set, as a function of n. Cap sets may be defined more generally as subsets of finite affine or projective spaces with no three in line, where these objects are simply called caps.
- The card game is not usually played with a timer. It is usually played as a competition between two or more people to see who can find more sets. The added timer creates an extra layer of intangible variables, pressure. People often perform worse at a given task when there is added pressure to do well. Several of my participants expressed to me they "hated" being under a time constraint, and felt they would have preformed better without such form of torture.

An integral part of the creation of the game was the design of the cards. The cards did not exist in a convenient digital medium before this experiment, and so, I created all 81 cards by hand. This gave me the chance to develop a nomenclature within the naming scheme of each card that corresponds with logic in the game. The nomenclature I created is displayed below:

Number	1	2	3
	1	2	3
Color	blue	green	pink
	1	2	3
Shape	oval	rhombus	squiggle
	1	2	3
Filling	□	▧	■
	1	2	3

Using this, I could systematically assign logic to the name of each card. Each name would be a series of 4 numbers depending on which branch of the decision tree we go down. In figure 5, we have an example of an isolated branch in our tree to select the card with the name `'3213'`.

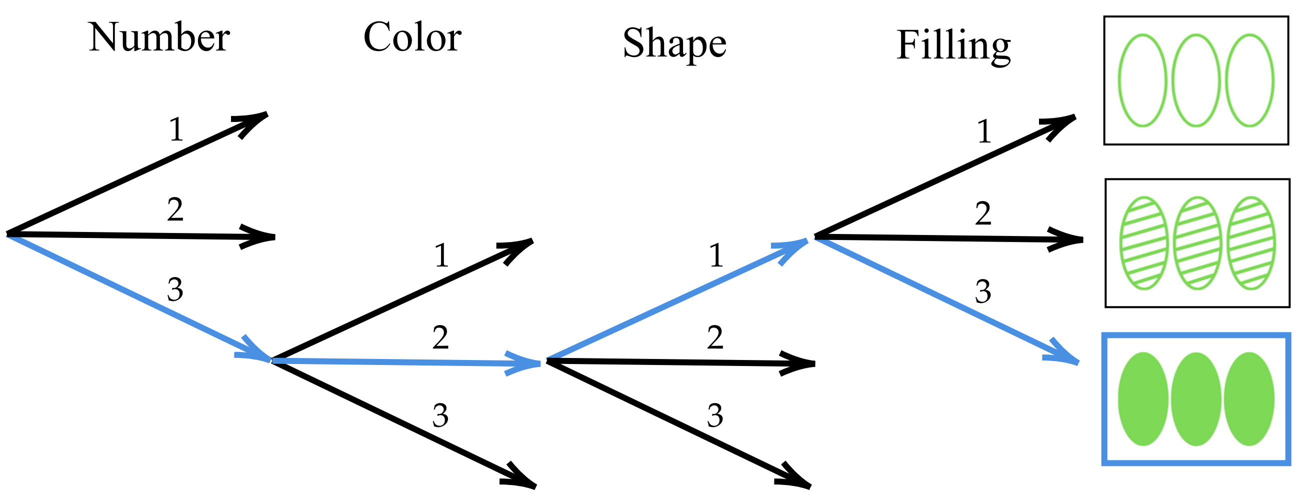

Figure 5: Decision Tree example with logic.

The game itself was created with the GUI library, tkinter. In short, I created a grid of buttons, and various other elements like the timer, the console box, play button, refresh button and a set counter to keep track of the number of sets found. I used functional programming for each element, so that I could easily call functions from button clicks and keep the code clean and modular. The white box at the bottom of figure 6 is the console box, which sends information to the user, like reasons their guess was incorrect or validation that their guess was correct. I needed to adjust and customized the logic behind the buttons, which have different relief attributes, like "sunken" when the button is pushed down, and "groove" when the button is in it's default raised state. I developed logic to allow the user to select and deselect buttons, but when the user selects a third card, the program runs the logic to check if the three cards make a set. The refresh button does exactly what it describes, and provides a function for the play button to call; when the game begins, the cards "shuffle," the set counter gets reset, and the timer begins. The last thing I added to the final version of the game was sound, I wanted to have a reward for finding a set and an alert to let me know when the game was over.

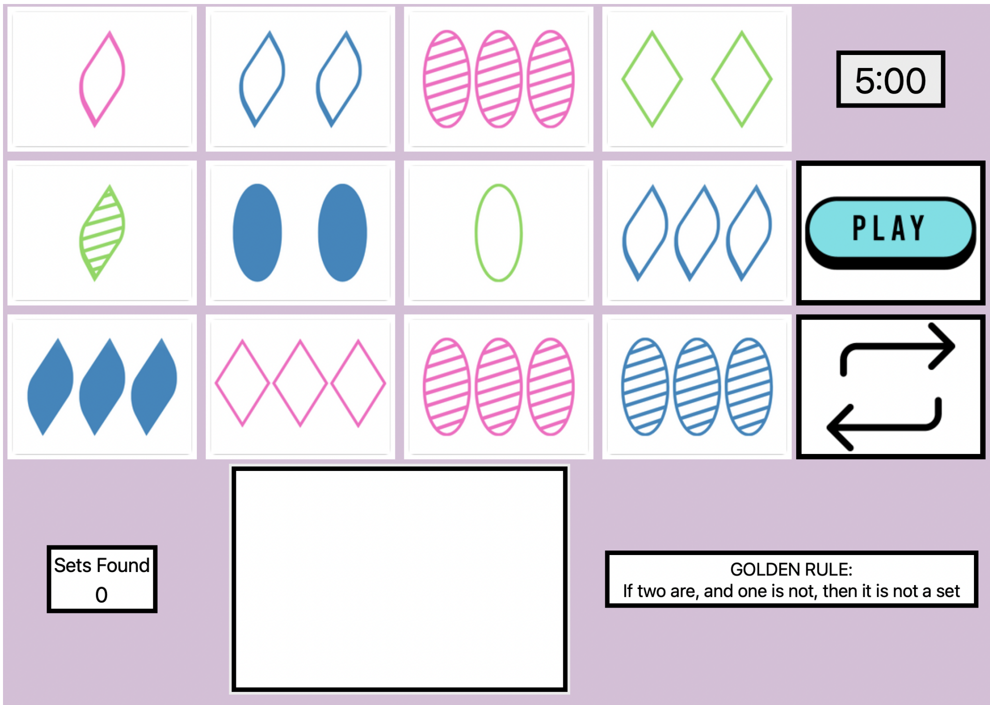

Figure 6: The game itself

3.2 Logic and Algorithms Used

After a user selects three cards the names of the three cards are added to a new list called image_names. Here's a few examples of some valid sets, in a list format:

```
Image names: ['1112', '1212', '1312']
Image names: ['2333', '3123', '1213']
Image names: ['2323', '2223', '2123']
Image names: ['3211', '3232', '3223']
Image names: ['1112', '2122', '3132']
```

At first, I thought it would be very difficult to check for all the possibilities, and develop an algorithm to find solutions. It proved to be much easier to check for what is not a set, than to check for what "is" a set. The golden rule is, if two are and one is not, then it is not a set. To do this we are checking the i'th element in our list of image names and counting the number of instances each element appears. If two elements are the same and one is different, then it is not a set. For example, `['1313', '2333', '3333']`, this is not a set because, in the 3rd position we have two instances of the number 3, and one which is not, i.e. two cards share a similar feature and one does not. From here, we check the position of the element in the and display the message where his or her error is in finding the set. In this example, two cards have the same shape.
Here's a few more examples of not sets:

`['3121', '2311', '1131']`, two cards have the same color.
`['1123', '1133', '2113']`, two cards have the same number.
`['2211', '2111', '2312']`, two cards have the same filling.

```python
# Initialize a flag to indicate whether a set was found
is_set = True

# Check each position in the strings
for i in range(4):
    # Get the i-th character of each string
    elements = [name[i] for name in image_names]
    # Count how many times each element appears
    counts = [elements.count(e) for e in elements]
    # If two elements are the same and one is different, print a message and set the flag to False
    if counts.count(2) > 0:
        is_set = False
```

Figure 7: Checking for not a set

If in fact we do find a set, we replace the cards, play the sound, and add to our set counter.

3.3 Challenges Encountered and Solutions

One of the major challenges I faced when programming the game was developing it for both Mac and Windows system architecture. When I originally programmed the game, it was on a Windows desktop running an X64 processor, but when I brought the game to my laptop a Macbook Air running on Apple's M2 system architecture, there were a few problems with the game. Logically, everything was working perfectly, but visually, there were some side effects for attempting to make it cross platform.

After a substantial amount of research I realized my easiest solution was to have two versions of the script, one for Windows and one for Mac.

Collecting data was an incredibly laborious task, with each person taking between 10 and 20 minutes to collect a single data point, and with a grand total of 125 participants, the whole process was both eye opening and humbling.

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4. Methodology

4.1 Data Collection Procedures

For over a month, I would walk up to random students and ask them help me with my research project. When they were willing and able, I sat down with them, either individually or in small groups, and explained the rules of the game and how to think about solutions logically. I provided them plenty of time to practice, enough so they would feel comfortable playing the game on their own. For those who needed extra explanations and extra examples, I always provided them. After the game was over, the participants filled out a google form, in which they answered questions that I will discuss in further detail in section 5. From this sample, we can make inferences about the general population of the school.

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5. Participants

The sample exclusively consists of students, which implies that any inferences drawn about the larger population will reflect the demographics of the student body.

5.1 Demographic Information

The primary question I asked every participant is: "Do you consider yourself a musician?" or "Did you play in instrument growing up?" This separates our sample into separate populations. Depending on whether or not they answered Yes or No to the first question, the musicians get to answer a few extra questions to help break down my data further into separate cohorts of musicians. I wanted to know how frequently each musician played, to find out if the dedicated musicians who play every day would have an advantage over people who grew up playing music but had since quit, or not played for over a year. On the quantitative side, I was curious to see if the number of instruments a person could play confidently would result in a positive trend in the data. And finally, I wanted to know the last time the musicians read sheet music.

Everyone, both non musicians and musicians, answered the following questions:

- Age
- Major
  - This enables me to categorize individuals into STEM and non-STEM cohorts.
- GPA

Now that I had a mixture of categorical and numerical data, I had the tools to make a proper data analysis.

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6. Categorical and Numerical Data Analysis

6.1 Overview of Categorical and Numerical Data Collected

The following is a list of comparisons conducted in the study:

- Distribution of sets found by musicians and non-musicians.
- Relationship between age and number of sets.
- Distribution of ages in the sample compared to the distribution of ages of SJSU.
- Relationship between GPA and number of sets found.
- Average number of sets for each frequency level for musicians depending on the amount they practice.
- Average number of sets for each last played level for musicians depending on the last time they read sheet music.
- Relationship between instruments played and number of sets.
- Average number of sets for each major (count >= 4).

All of the graphs were created with Seaborn and MatPlotLib.

6.2 Data Analysis of Musician vs. Non-Musician Performance

Figure 8 depicts the distribution of sets found by musicians compared to non musicians. It's important to note that each of our samples is normally distributed, allowing for interpretation using Gaussian statistical methods. This will be crucial for our analysis and will be discussed in further detail in section 7.

Details:

- Musicians: Mean = 5.02, Standard Deviation = 3.18
- Non-Musicians: Mean = 3.51, Standard Deviation = 2.20
- I have: 58 musicians
- I have: 67 non musicians
- Average of both musicians and non musicians: 4.21

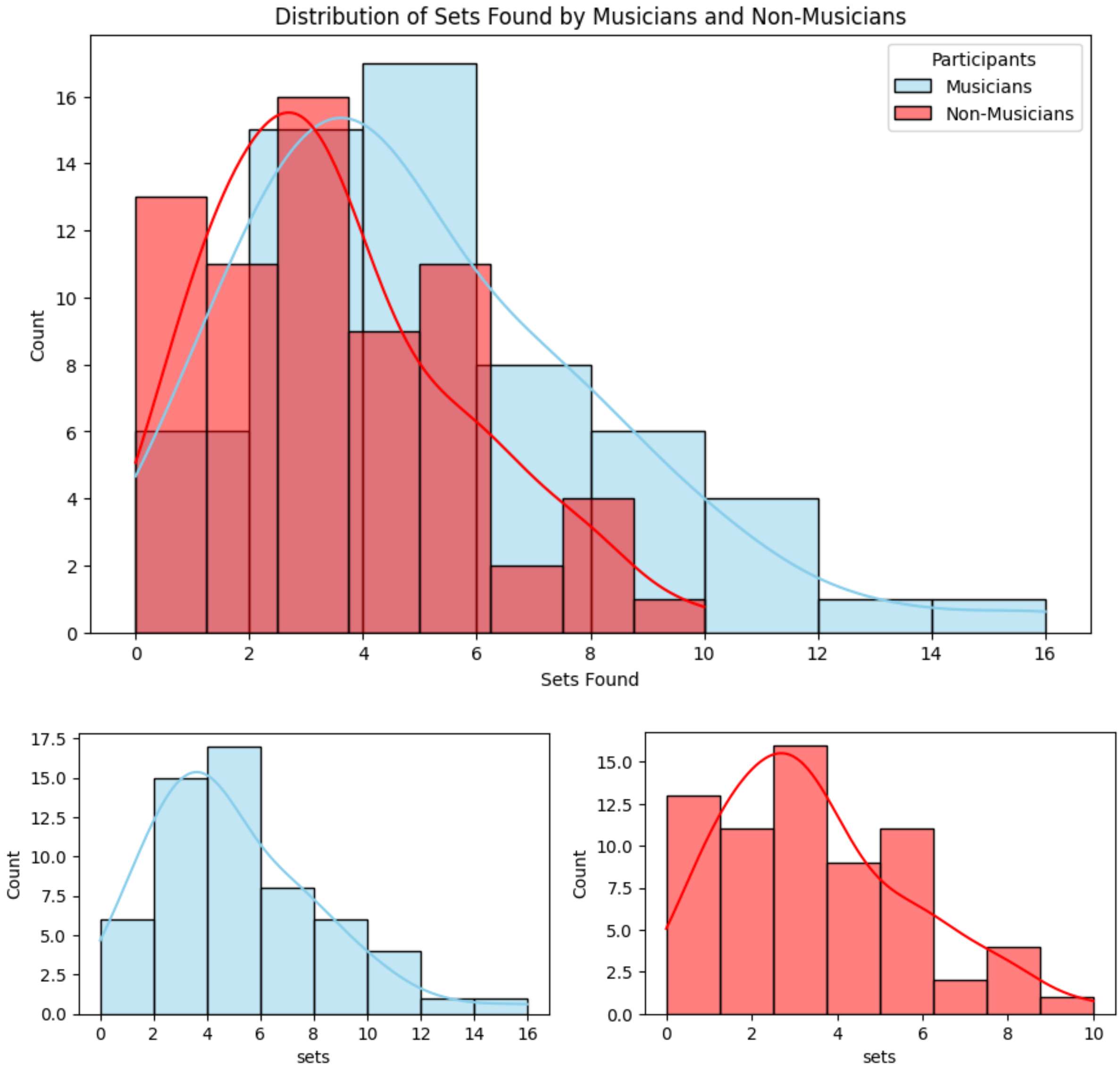

Figure 8: Distribution of sets found by musicians and non-musicians

6.3 Analysis of STEM vs Non STEM Students

In Figure 9, two distinct distributions of the number of sets found are illustrated, with the cohorts divided into STEM (Science, Technology, Engineering, and Mathematics) students on the left and non-STEM students on the right. It is important to note that while our STEM students are normally distributed, our non STEM students are not. This does not mean we are unable to test the confidence, but because it will break some other assumptions outlined in section 7.1, we cannot interpret the results of these statistical tests with the same level of scrutiny.

Details

- STEM students: Mean = 4.38, Standard Deviation = 2.86
- Non STEM students: Mean = 3.17, Standard Deviation = 2.14

- Total of 107 STEM students
- Total of 18 Non STEM Students

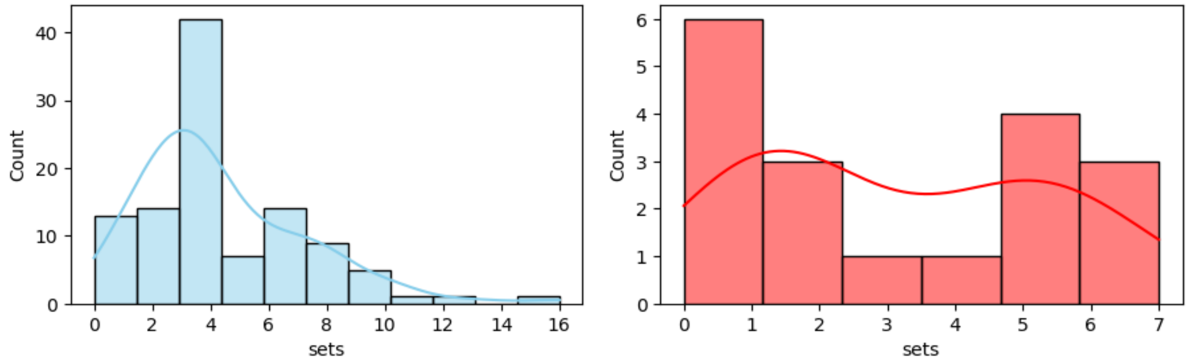

Figure 9: Comparing STEM students [left] to non STEM students [right]

6.4 Patterns and Trends Observed

Figure 10 depicts the relationship between age and number of sets. There is a discernible but weak negative correlation, suggesting that as individuals age, they tend to find fewer sets, although this relationship is observed with low confidence.

Details:

- Oldest: 41.0
- Youngest: 18.0
- Average age: 21.70

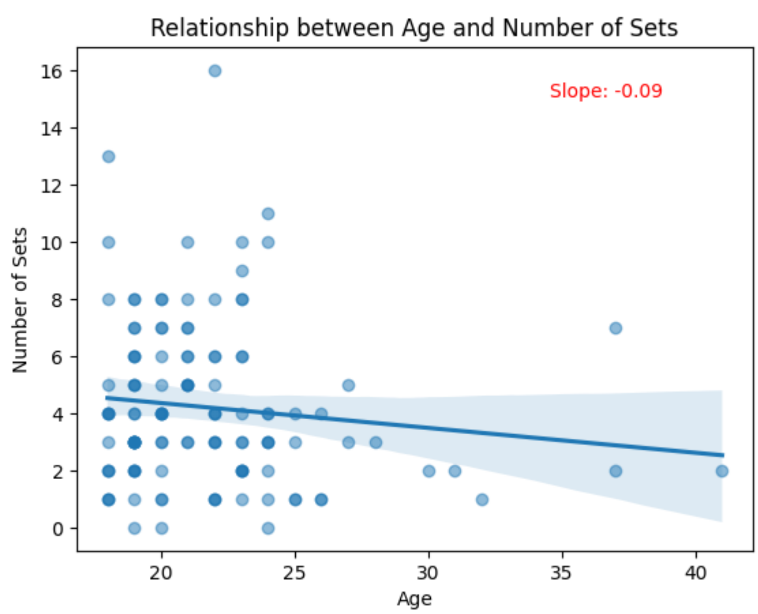

Figure 10: Relationship between age and number of sets.

In Figure 11, a comparison is presented between the age distribution in the sample and the age distribution at SJSU. This is crucial for ensuring the accuracy of our representation of the general population when making statistical inferences based on this data. It is also important to note that the data on the x-axis is binned differently in each graph.

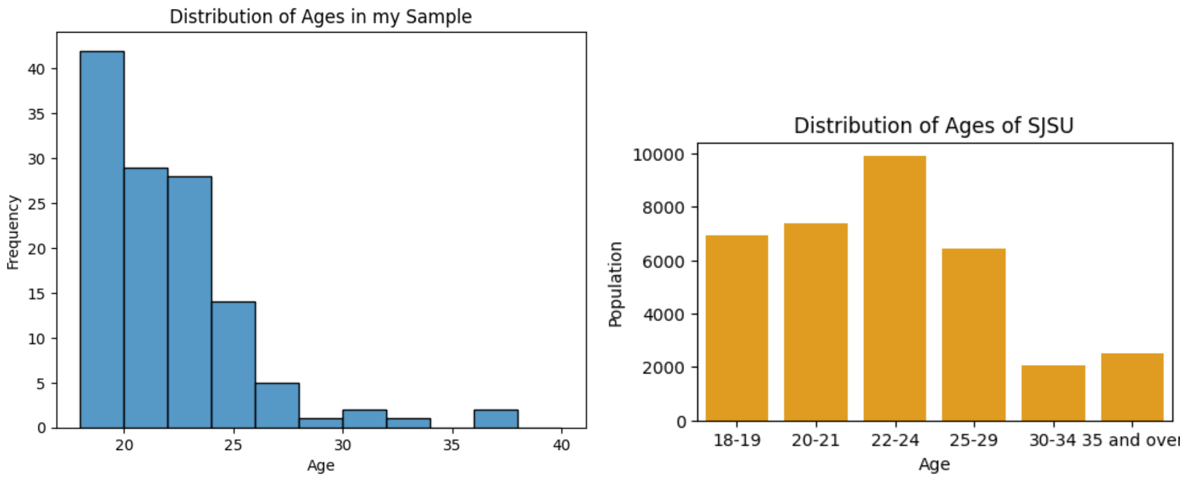

Figure 11: Distribution of ages in sample [left] and distribution of ages at SJSU [right]

Figure 12 illustrates the relationship between GPA and the number of sets found. A marginal but discernible positive trend is evident, indicating that participants with higher GPAs tend to find more sets.
Details:

- Highest GPA: 4.0
- Lowest GPA: 2.0
- Average GPA: 3.47

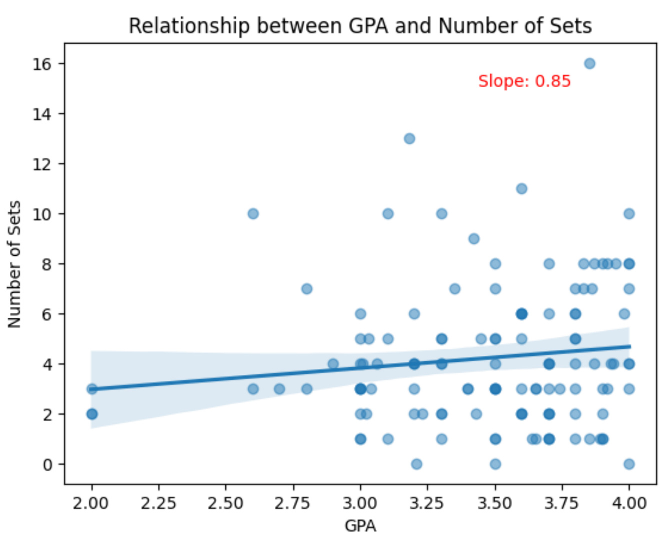

Figure 12: The relationship between GPA and number of sets found.

In Figure 13, the average number of sets for each frequency level for musicians is depicted based on their practice amount. While no statistical correlation is observed, it is noteworthy that musicians who practice a few times a month tend to, on average, find more sets than their counterparts.

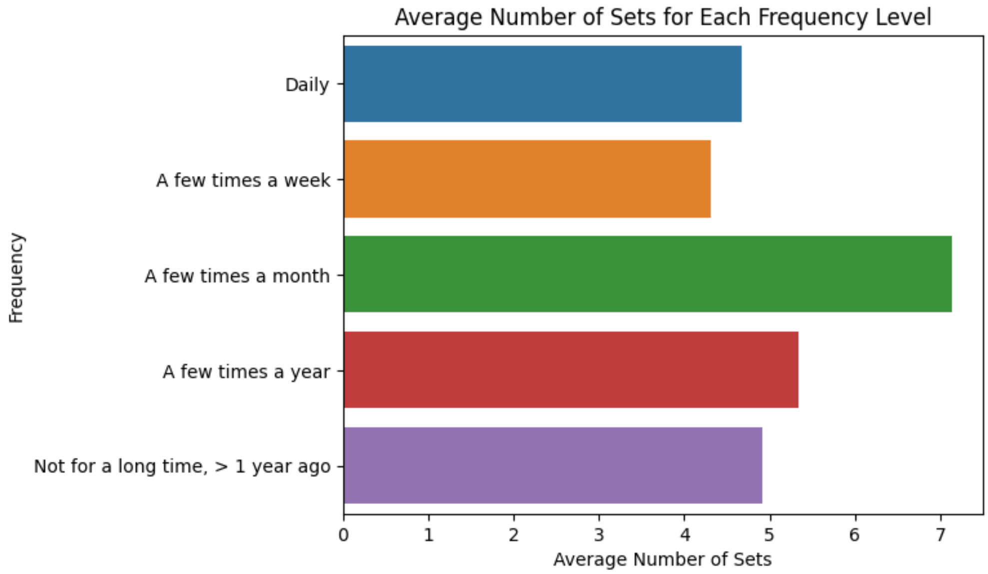

Figure 13: Average number of sets for each frequency level: amount they practice.

In Figure 14, the average number of sets for each frequency level for musicians is depicted based on the last time they read sheet music. Similar to Figure 13, Figure 14 shows that as long as the musician reads sheet music a few times a month, they are more likely to find more sets than their counterparts. Also noteworthy is the relatively normal distribution across the board, and surprisingly if the person had read sheet music on the same day that they participated in my experiment, they score lower than any of their counterparts.

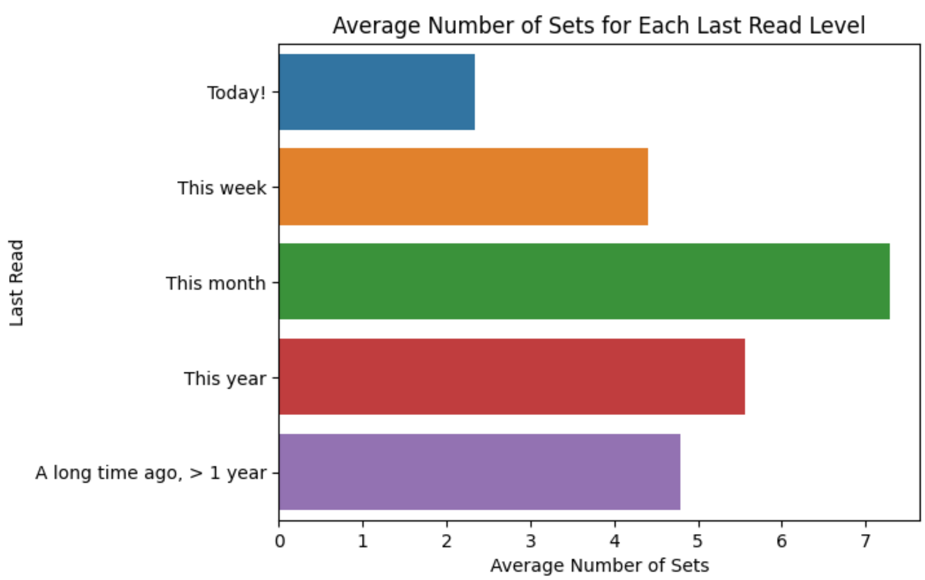

Figure 14: Average number of sets for each frequency level: last time they read sheet music.

In Figure 15, the average number of sets is illustrated based on the participants' majors, with a minimum of 4 individuals per major. Our analysis draws from section 6.3, revealing that the average score of STEM students surpasses that of non-STEM students, psychology, aligning with the findings presented below. Notably, a substantial disparity is observed between software engineers and computer scientists, despite their comparable representation in terms of participant numbers. On the Y axis labels, we have the name of the major, the number of participants, and their average sets.

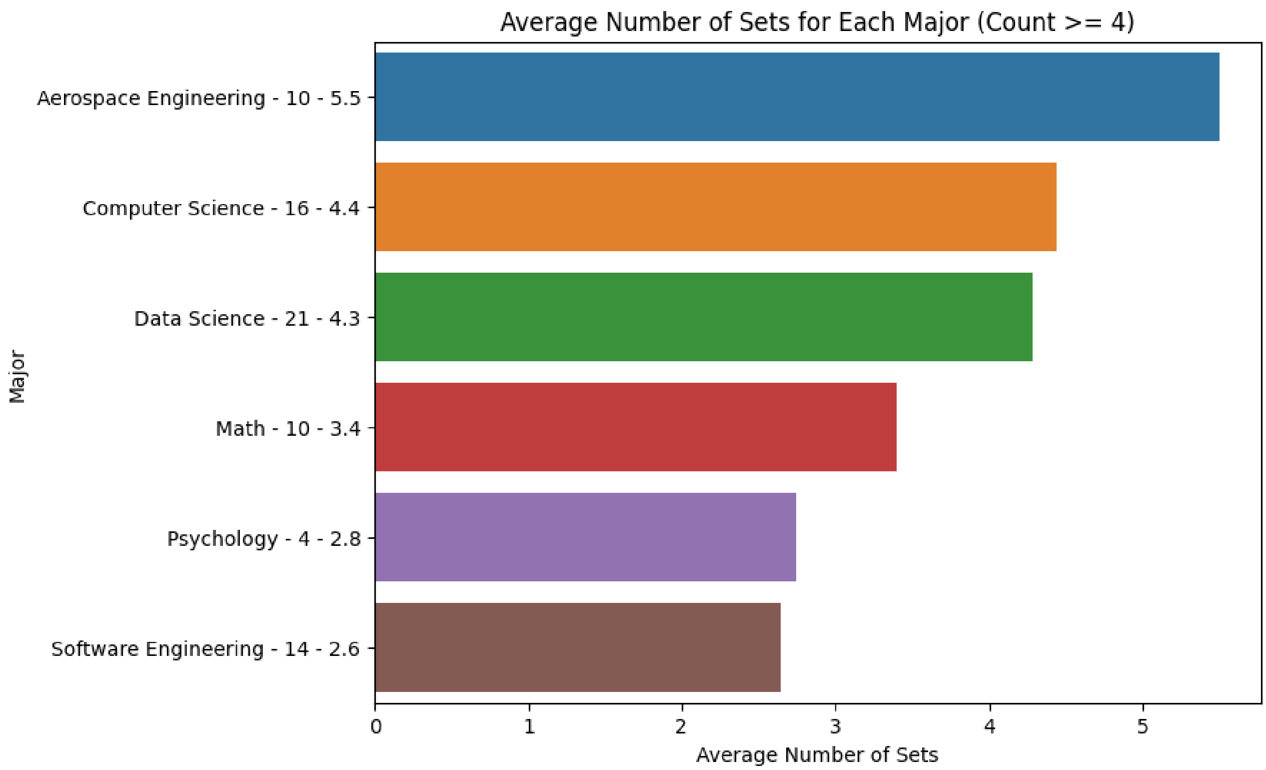

Figure 15: Average Number of sets for Majors with at least 4 participants.

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7 Hypothesis Testing

7.1 Description of Statistical Tests Used

In section 2.4, I outlined the premise of the research, and the overarching questions I wanted to answer. I was curious to investigate whether there exists a distinct correlation between an individual's background as a musician and their proficiency in performing better than non-musicians in the SET game. The nature of this question calls for statistical tests to create inferences based on two samples.

When performing z-tests and constructing confidence intervals for the difference between two population means, the assumption of normality is important. Here's why:

1. Central Limit Theorem: The CLT states that if you have a population with mean μ and standard deviation σ and take sufficiently large random samples from the population with replacement, then the distribution of the sample means will be approximately normally distributed. This will hold true regardless of whether the source population is normal or skewed, provided the sample size is sufficiently large (usually $n > 30$).

2. Z-tests: Z-tests are parametric tests that are based on the standard normal distribution. They assume that the populations from which the samples are drawn are normal. However, due to the CLT, if the sample sizes are large enough, the sampling distribution of the mean will approach normality, even if the underlying population distribution is not normal.

3. Confidence Intervals: When constructing confidence intervals for the difference between two means, the assumption of normality allows us to use the properties of the normal distribution to calculate the interval. Again, if the sample sizes are large enough, the sampling distribution of the mean will be approximately normal due to the CLT.

So, while the distribution of each individual sample does not necessarily need to be normally distributed, the distribution of the sample means does.

- $X_1, X_2, \cdots, X_m$ is a random sample from a distribution with mean μ_1 and variance ${\sigma_1}^2$
- $Y_1, Y_2, \cdots, Y_n$ is a random sample from a distribution with mean μ_2 and variance ${\sigma_2}^2$
- The X and Y samples are independent of one another.
- The expected value of $\overline{X} - \overline{Y}$ is $\mu_1 - \mu_2$, so $\overline{X} - \overline{Y}$ is an unbiased estimator of $\mu_1 - \mu_2$. The standard deviation of $\overline{X} - \overline{Y}$ is:

$$\sigma_{\overline{X}-\overline{Y}} = \sqrt{\frac{{\sigma_1}^2}{m} + \frac{{\sigma_2}^2}{n}}$$

The purpose of the null hypothesis is to provide a benchmark against which the alternative hypothesis is tested.

If the data provide sufficient evidence to reject the null hypothesis in favor of the alternative hypothesis, it suggests that there is a statistically significant effect or difference between the populations. If not, we fail to reject the null hypothesis, which means that we do not have enough evidence to conclude that there is a significant effect or difference. However, failing to reject the null hypothesis does not prove it to be true. It simply means that the data do not provide strong enough evidence against it. Mathematically represented:

$$H_o : \mu_1 - \mu_2 = \Delta_o$$

We will use a Null Hypothesis H_0
μ_1 to represent the population mean of our musicians, and
μ_2 to represent the population mean of our non musicians.

Null hypothesis: $H_o : \mu_1 - \mu_2 = \Delta_0$

Test Statistic Value: $z = \dfrac{\bar{x} - \bar{y} - \Delta_0}{\sqrt{\dfrac{{\sigma_1}^2}{m} + \dfrac{{\sigma_2}^2}{n}}}$

Alternative Hypothesis: $H_a : \mu_1 - \mu_2 \neq \Delta_0$

Rejection Region for Level α Test: either $z \geq z_{\alpha/2}$ or $z \leq z_{\alpha/2}$ (two tailed)

P-value: $2(1 - \Phi(|z|)$

Where Φ is the cumulative distribution function of the standard normal distribution.

7.2 Formulation and application of a zTest and Confidence Intervals

The analysis of a random sample consisting of $m = 58$ specimens of musicians with an average sets found of $\bar{x} = 5.02$. A second random sample of $n = 67$ specimens of non musicians with an average sets found of $\bar{y} = 3.51$. This is assuming, that the two samples are normally distributed with $\sigma_1 = 3.18$ and $\sigma_2 = 2.20$. Does the data indicate that the corresponding true average sets μ_1 and μ_2 are different? We will test at a significance level of $\alpha = .05$.

1. The parameter of interest is $\mu_1 - \mu_2$, the difference being between the true average number of sets found for musicians and non musicians.
2. The null hypothesis is $H_o : \mu_1 - \mu_2 = \Delta_0$
3. The alternative hypothesis is $H_a : \mu_1 - \mu_2 \neq \Delta_0$; if H_a is true, then μ_1 and μ_2 are different.
4. With $\Delta_0 = 0$, the test statistic value is

$$z = \frac{\overline{x} - \overline{y}}{\sqrt{\frac{{\sigma_1}^2}{m} + \frac{{\sigma_2}^2}{n}}}$$

5. The inequality in H_a implies that the test is two-tailed. For $\alpha = .05,\ \alpha/2 = .025$, and $z_{\alpha/2} = z_{.025} = 1.96,\ H_0$ will be rejected if $z \geq 1.96$ or if $z \leq -1.96$.

6. Substituting $m = 58,\ \overline{x} = 5.02,\ {\sigma_1}^2 = 3.18^2,\ n = 67,\ \overline{y} = 3.51$ and, ${\sigma_2}^2 = 2.20^2$ into the formula for z yields

$$z = \frac{5.02 - 3.51}{\sqrt{\frac{3.18^2}{58} + \frac{2.20^2}{67}}} = \frac{1.51}{.496} = 3.04$$

That is, the observed value of $\overline{x} - \overline{y}$ is more than 3 standard deviations above the what would be expected were H_0 true.

7. Since $3.04\ >\ 1.96$, z does fall in the upper tail of the rejected region. $H_0$is therefore rejected at the level $\alpha = .05$ in favor of the conclusion that $\mu_1 \neq \mu_2$. The sample data strongly suggests that the true average sets found for musicians differs from that of non musicians. The P-value for this two-tailed test is $2(1 - \Phi(3.04)) \approx\ 0.0023657814$, so H_0 should be rejected at a significance level much higher than $\alpha = .05$.

This in fact holds up to $\alpha = .0048$. Not bad.

7.3 STEM vs Non STEM

We can do a similar test for our two populations of STEM students and non STEM students, but there is a problem I will highlight later. If we take the same assumption, that STEM students uniquely stand above non STEM students, thus our Alternative Hypothesis is $\mu_1 - \mu_2 \neq \Delta_0$. We can perform the exact same test following the same assumptions we defined in section 7.1.

Setting $\alpha = .05$, we have a rejection region of $-1.96 \geq z \geq 1.96$, and plugging in everything the same way we did for our musicians hypothesis testing in 7.2. We find that we can also reject the null hypothesis, by finding a text statistic value $z = 2.6425$, and furthermore a P-value of 0.0082906. This, would mean we can reject our null hypothesis in favor of our alternative hypothesis that $\mu_1 \neq \mu_2$. However, there is a problem with the population parameters that breaks one of our initial assumptions.

These calculations assume that the populations are normally distributed or that the sample sizes are large enough for the Central Limit Theorem to apply. Since one of the samples is quite small $(n = 18)$, these assumptions may not be met, and the results should be interpreted with caution.

7.4 Interpretation of Results

For testing between musicians and non musicians:

Based on our calculations in 7.3, we are able to confirm with statistical confidence that musicians are indeed different from non musicians. By preforming a $zTest$ and comparing this to a confidence interval with with a high enough α, we were able to reject our null hypothesis that the two samples are equivalent and thus show not significant difference between them.

For testing between STEM students and non STEM students:

While our conditions pass our $zTest$ and display a high level of confidence in favor of our alternative hypothesis, which would enable our STEM stem students to statistically differentiate themselves from the non STEM students, we break the initial assumptions of these tests which in this case relies on the Central Limit Theorem as stated in 7.1. Thus, we cannot interpret these tests with with any degree of confidence.

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8. Discussion

8.1 Comparison with Initial Hypotheses

From section 2.3, I outlined exactly what I wanted to study. I was interested in whether there exists a noticeable link between a person's experience as a musician, including their musical background, how frequently they practice, how many instruments they play, and their capacity to excel in playing the SET game, as well as a whole host of other categorical and numerical statistics when compared to individuals who do not have a musical background. Following the data analysis in section 6 and the hypothesis testing in section 7, we were successfully able to differentiate our samples of musicians and non musicians.

8.2 Implications of the Study

The connection between music and math has long been studied throughout history, each discipline is encompassed in logical thinking and understanding patterns. Music theory involves understanding fractions, ratios and proportions, which in an abstract way is similar to many fundamental concepts in math. It has also long been studied the exposure to music and musical training in a child's brain can have a positive impact on their development of the child's brain. Learning to play an instrument or engaging with music at a young age can help improve cognitive skills, including memory, attention, and spatial-temporal skills. Music can also aid in the development of language and reasoning skills, as it involves the processing of different sounds and patterns, which are essential for language development and problem-solving. The keys to healthy development as a child extend well into the individuals future. I was eager to encourage my fellow students to think innovatively and revitalize the processes related to problem-solving they may have been familiar with as a child.

8.3 Future Directions

- I am working on developing a version 2 of the game that can better emulate the original card game, as well as developing game modes to keep it exciting.
- I would love to incorporate artificial intelligence into my project at some point. To train a computer how to play the game would be a great opportunity to incorporate a player vs computer simulation like in online versions of Chess.

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9. Conclusion

9.1 Summary of Key Findings

The data analysis reveals several noteworthy trends. On average, musicians outperform non-musicians in finding sets. There's a weak negative correlation between age and set-finding, suggesting a tendency for older individuals to find fewer sets, although this observation carries low confidence. Moreover, a marginal positive trend indicates that individuals with higher GPAs are more likely to find sets. Taken with a grain of salt, STEM students demonstrate a higher average score compared to their non-STEM counterparts.

Based on the information and the data analysis conducted, we can assert with greater confidence the applicability of our findings to the wider population of SJSU students. As our sample population closely mirrors the broader student body at SJSU, we anticipate that the trends we have identified will persist.

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10. References

2.2 Brief Overview of the SET Card Game

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2.4 Significance of the Study

Paddock, Catharine. “Listening and reading evoke almost identical brain activity” 22 Aug. 2019, www.medicalnewstoday.com/articles/326140. Accessed 1 Dec. 2023.

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Figure 3: Anatomical specialization in the musician's brain.

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Figure 4: Active sites of the musician's brain when problem solving

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Grochow, Joshua A. “New applications of the polynomial method: The cap set conjecture and beyond” 15 Nov. 2018, www.ams.org/journals/bull/2019-56-01/S0273-0979-2018-01648-0/www.ams.org/journals/bull/2019-56-01/S0273-0979-2018-01648-0/S0273-0979-2018-01648-0.pdf. Accessed 2 Dec. 2023.

Figure 11: Distribution of ages in sample [left] and distribution of ages at SJSU [right]

“San Jose State University Diversity: Racial Demographics & Other Stats” 1 May 2022, www.collegefactual.com/colleges/san-jose-state-university/student-life/diversity/. Accessed 30 Nov. 2023.

7.2 Formulation and application of a zTest and Confidence Intervals

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11. Appendices

11.1 Additional Material and Raw data

The pythons script that I used in tandem with the Spyder IDE can be retrieved from the public github repository here:

https://github.com/ryanfernald/SET-game

An ipynb file is also available in the github repository, for use in Google Colab to see the breakdown and creation of the charts and data processing.

Link to raw data csv:

https://raw.githubusercontent.com/ryanfernald/SET-game/main/SETProject%20Responces%20-%20Form%20Responses%201.csv

Link to the google form I used to collect data:

https://docs.google.com/forms/d/e/1FAIpQLSdxR_sjjJg1_j7tB-slRl1-6LBbDB2Mv8JCI6wLUSINhYDUiQ/viewform

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