Assignment 3: Neuroscience of Decision Making PSY 3/507 (Monsoon 2023)

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Instructions: Please write your own responses and do not copy or lift text/code from any source (including the paper). If you are referring to credible external sources other than the attached paper for your answers, please cite those sources (within the body of text and the provide a reference list at the end) in the APA citation format (https://www.mendeley.com/guides/apa-citation-guide). Word limits given are indicative and less than the indicated numbers may also be used.

Please download this MS word question-cum-response template to TYPE your answers and feel free to add sheets as required. Convert this document to a PDF and rename the file: name_roll no. **before submitting. Please note that answers in this template only will be evaluated and hand-written or scanned answer sheets will not be evaluated.**

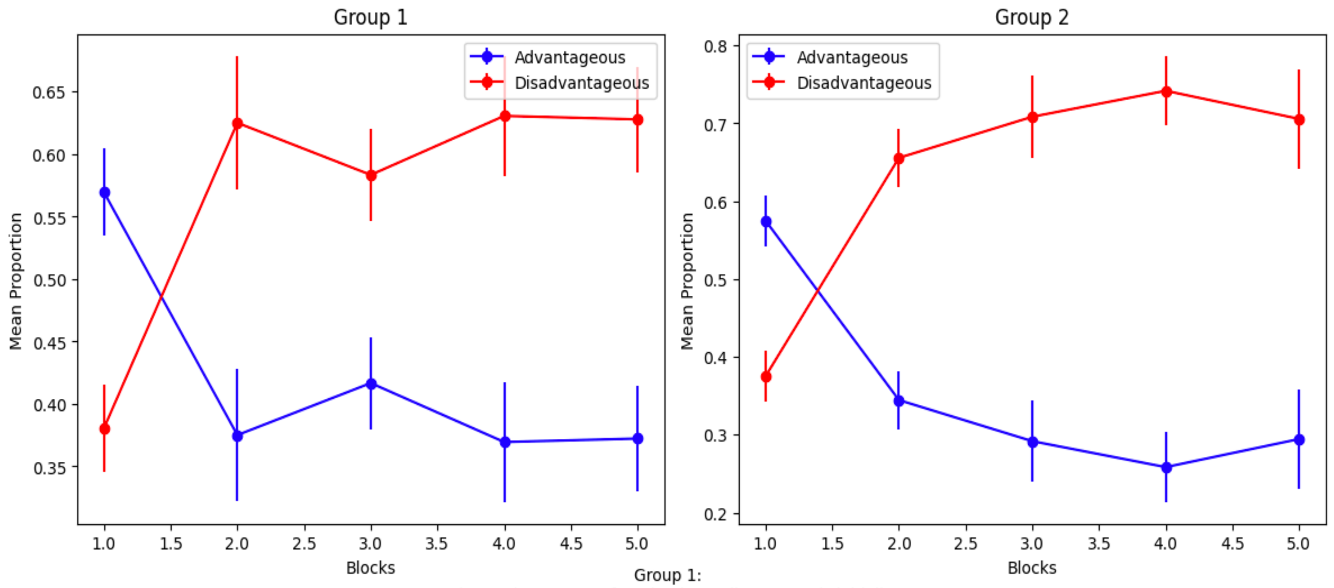
[Strict deadline for submission: 20.11.2023 Mondday 10.00 PM]

Q1)
Fill the following form https://forms.gle/LrYmKgXJSfFcFJyGA

Q2)
Two independent groups of participants (19 each) performed an Iowa Gambling task. Their data are named Data1 and Data2 respectively. Each sheet in the attached excel file (NDM_Assignment3) contains data of one group. Each row represents one participant and each column represents one trial. There are a total of 4 decks and 100 trials. Decks 1 and 2 yield immediate and steady rewards, but they are also characterised by unpredictable occasional losses that can result in negative long-term outcomes. Decks 3 and 4 offer relatively lower and steady immediate rewards, accompanied by even lower and less unpredictable occasional losses, leading to favourable long-term outcomes. Solve the following.

Insert a figure (wherever required) and paste the MATLAB/Python/R code for the same. All figures should be properly labelled and MUST have accompanying captions to provide all information necessary to interpret the figures

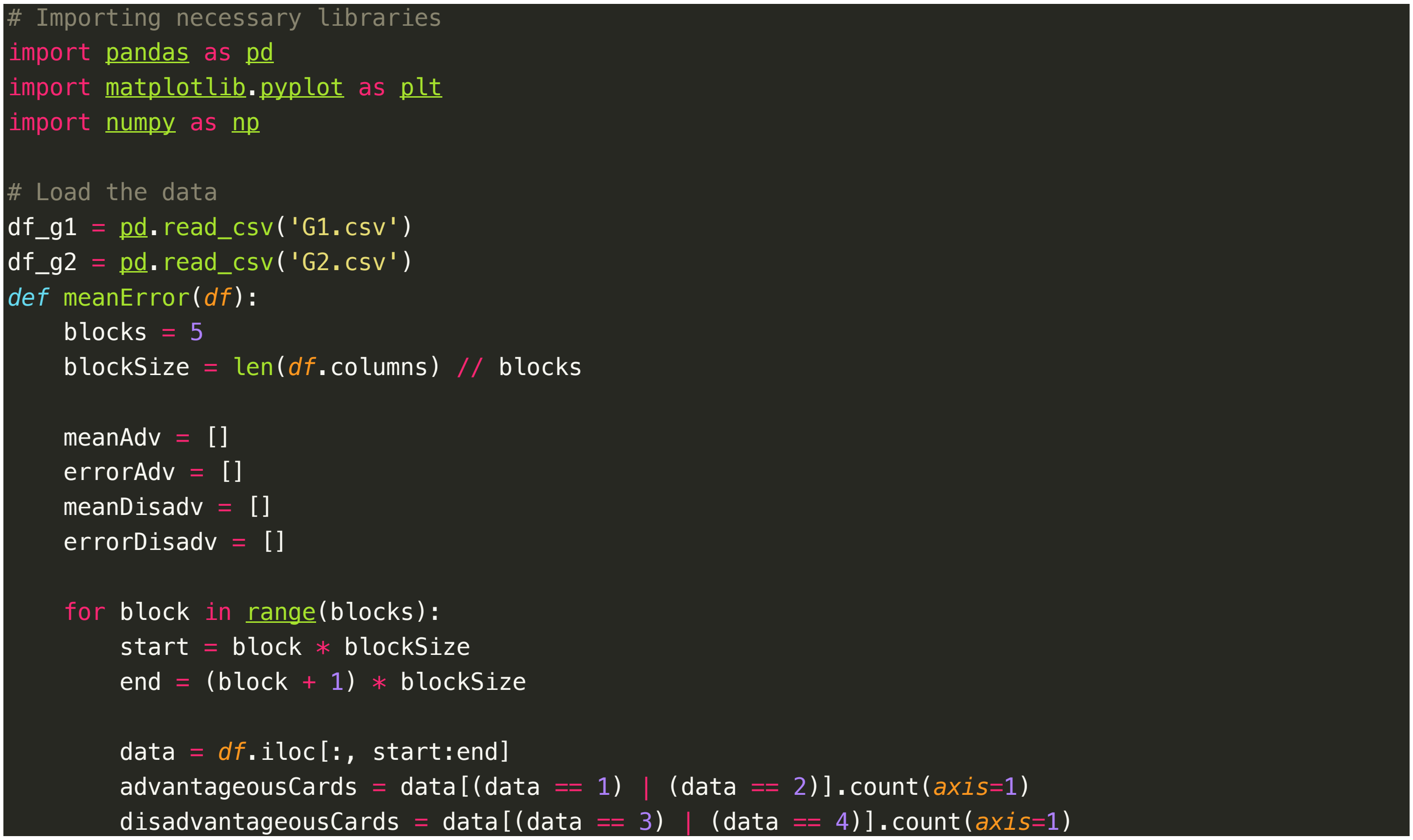
A. **Divide the trials into five equal sized blocks and then calculate the mean proportion (across participants) of advantageous cards and disadvantageous cards selected by the participants. Create two subplots as part of a single figure. Each subplot should depict the mean proportions across 5 blocks for each independent group using line and marker plots. Mark advantageous cards with blue colour and disadvantageous cards with red colour. Include standard errors of the mean as error bars at each marker location in both subplots. Interpret the figures in the context of affective decision making. [7+3 points]**



Group 1:
- Fluctuating pattern, favoring immediate rewards initially.
- Shift to advantageous cards by block 2, indicating learning.
- Decrease in advantageous selections in blocks 3 and 4.
- Increase in block 5 suggests strategy adjustment.

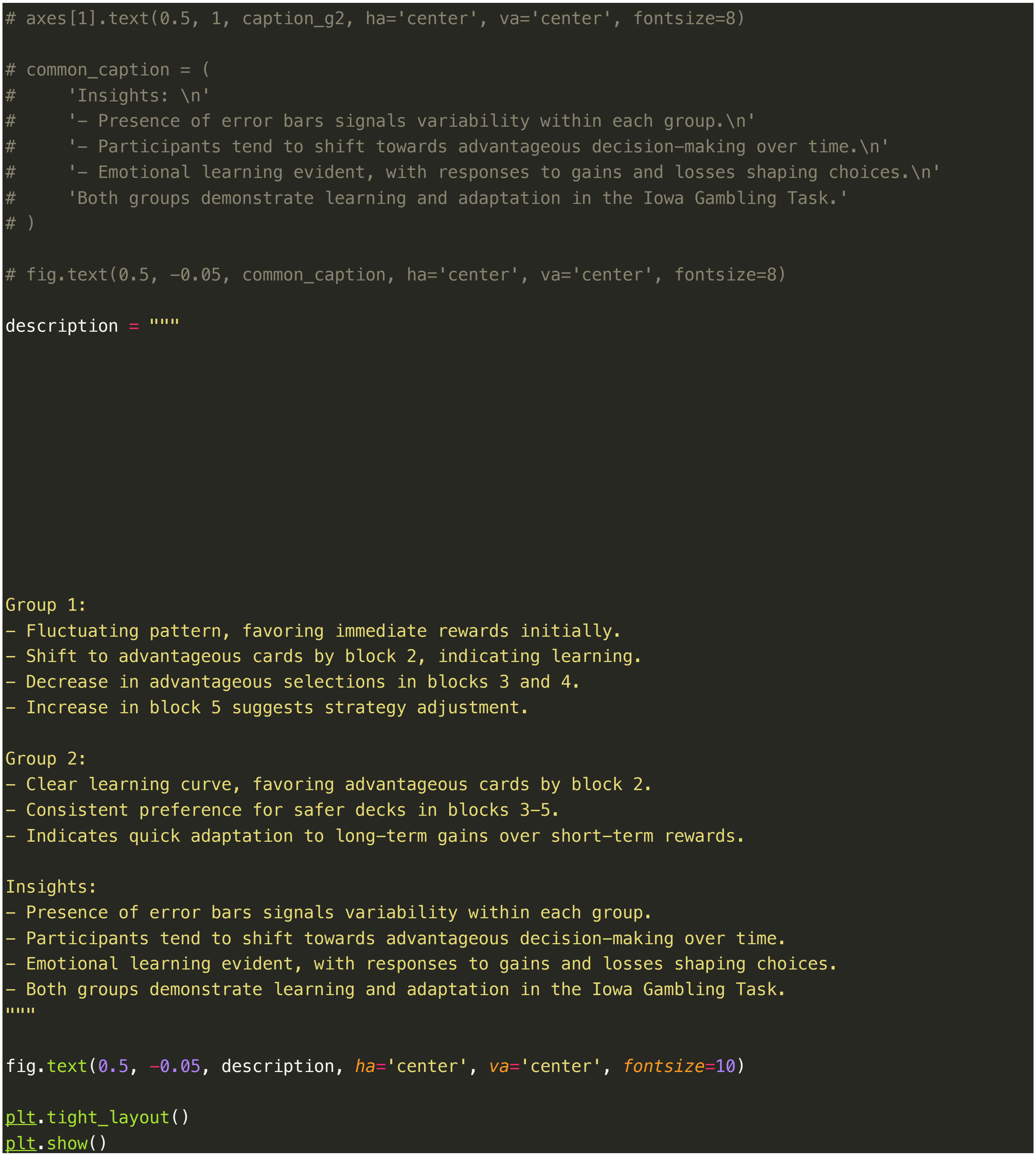
Group 2:
- Clear learning curve, favoring advantageous cards by block 2.
- Consistent preference for safer decks in blocks 3-5.
- Indicates quick adaptation to long-term gains over short-term rewards.

Insights:
- Presence of error bars signals variability within each group.
- Participants tend to shift towards advantageous decision-making over time.
- Emotional learning evident, with responses to gains and losses shaping choices.
- Both groups demonstrate learning and adaptation in the Iowa Gambling Task.



```
# Importing necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Load the data
df_g1 = pd.read_csv('G1.csv')
df_g2 = pd.read_csv('G2.csv')
def meanError(df):
    blocks = 5
    blockSize = len(df.columns) // blocks

    meanAdv = []
    errorAdv = []
    meanDisadv = []
    errorDisadv = []

    for block in range(blocks):
        start = block * blockSize
        end = (block + 1) * blockSize

        data = df.iloc[:, start:end]
        advantageousCards = data[(data == 1) | (data == 2)].count(axis=1)
        disadvantageousCards = data[(data == 3) | (data == 4)].count(axis=1)
```

```python
        meanAdv.append(advantageousCards.mean() / blockSize)
        errorAdv.append(advantageousCards.sem() / blockSize)
        meanDisadv.append(disadvantageousCards.mean() / blockSize)
        errorDisadv.append(disadvantageousCards.sem() / blockSize)

    return meanAdv, errorAdv, meanDisadv, errorDisadv

# Calculate means and errors for both groups
means_adv_g1, errors_adv_g1, means_disadv_g1, errors_disadv_g1 = meanError(df_g1)
means_adv_g2, errors_adv_g2, means_disadv_g2, errors_disadv_g2 = meanError(df_g2)

# Plotting
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))

# Group 1 subplot
axes[0].errorbar(range(1, 6), means_adv_g1, yerr=errors_adv_g1, marker='o', linestyle='-', color='blue', label='Advantageous')
axes[0].errorbar(range(1, 6), means_disadv_g1, yerr=errors_disadv_g1, marker='o', linestyle='-', color='red', label='Disadvantageous')
axes[0].set_title('Group 1')
axes[0].set_xlabel('Blocks')
axes[0].set_ylabel('Mean Proportion')
axes[0].legend()

# caption_g1 = """
# **Group 1 Insights:**
# - Fluctuating pattern, favoring immediate rewards initially.
# - Shift to advantageous cards by block 2, indicating learning.
# - Decrease in advantageous selections in blocks 3 and 4.
# - Increase in block 5 suggests strategy adjustment.
# """
# axes[0].text(0.5, -1, caption_g1, ha='center', va='center', fontsize=8)

# Group 2 subplot
axes[1].errorbar(range(1, 6), means_adv_g2, yerr=errors_adv_g2, marker='o', linestyle='-', color='blue', label='Advantageous')
axes[1].errorbar(range(1, 6), means_disadv_g2, yerr=errors_disadv_g2, marker='o', linestyle='-', color='red', label='Disadvantageous')
axes[1].set_title('Group 2')
axes[1].set_xlabel('Blocks')
axes[1].set_ylabel('Mean Proportion')
axes[1].legend()

# caption_g2 = """
# **Group 2 Insights:**
# - Clear learning curve, favoring advantageous cards by block 2.
# - Consistent preference for safer decks in blocks 3-5.
# - Indicates quick adaptation to long-term gains over short-term rewards.
# """
```



```python
# axes[1].text(0.5, 1, caption_g2, ha='center', va='center', fontsize=8)

# common_caption = (
#     'Insights: \n'
#     '- Presence of error bars signals variability within each group.\n'
#     '- Participants tend to shift towards advantageous decision-making over time.\n'
#     '- Emotional learning evident, with responses to gains and losses shaping choices.\n'
#     'Both groups demonstrate learning and adaptation in the Iowa Gambling Task.'
# )

# fig.text(0.5, -0.05, common_caption, ha='center', va='center', fontsize=8)

description = """










Group 1:
- Fluctuating pattern, favoring immediate rewards initially.
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Group 2:
- Clear learning curve, favoring advantageous cards by block 2.
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Insights:
- Presence of error bars signals variability within each group.
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- Emotional learning evident, with responses to gains and losses shaping choices.
- Both groups demonstrate learning and adaptation in the Iowa Gambling Task.
"""

fig.text(0.5, -0.05, description, ha='center', va='center', fontsize=10)

plt.tight_layout()
plt.show()
```
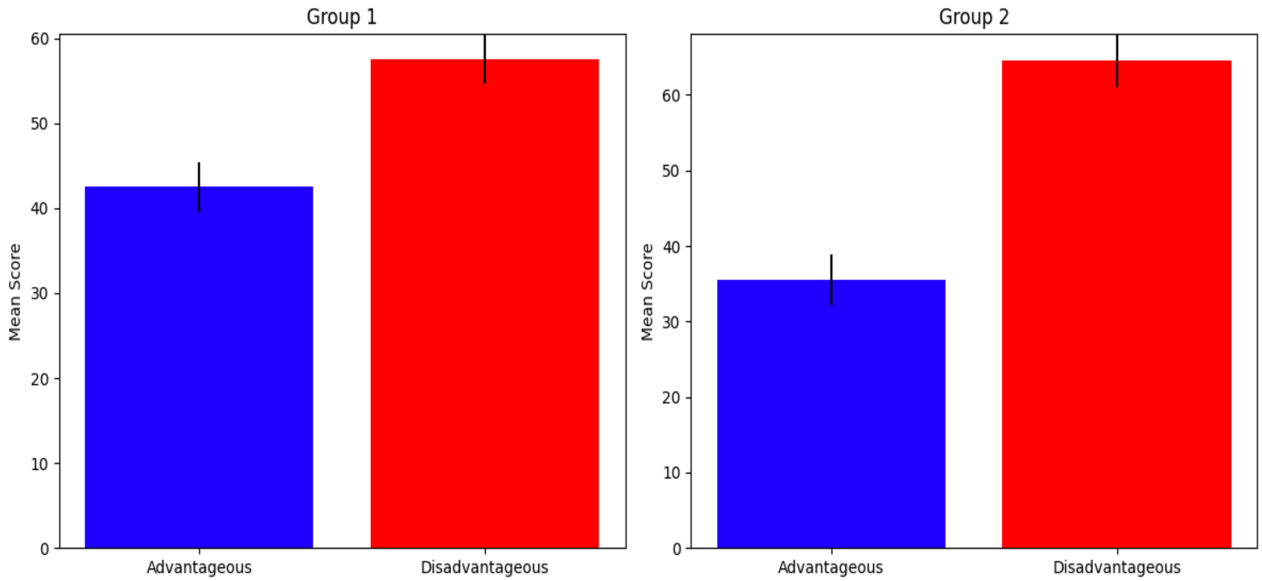
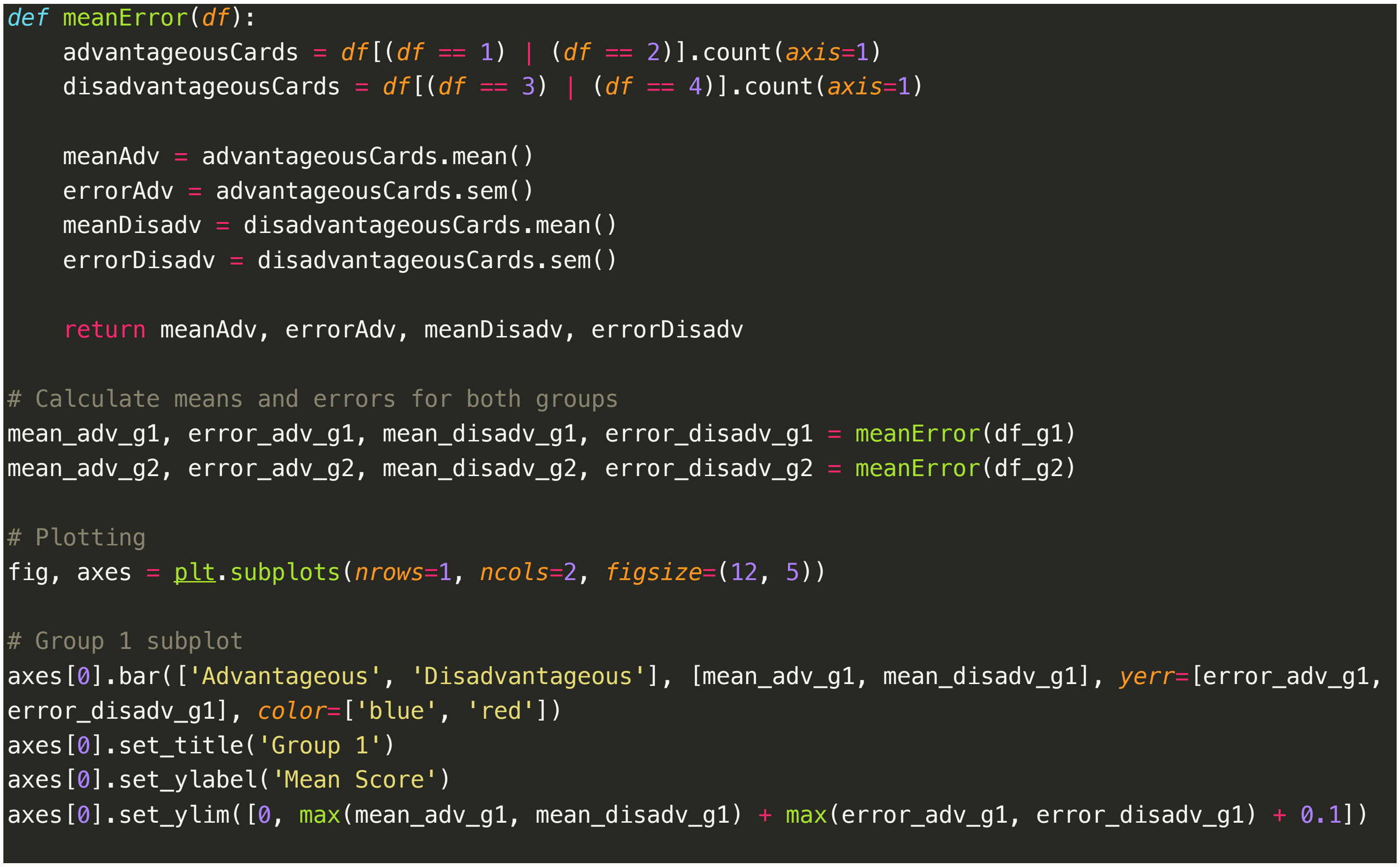

B. **Plot bar diagrams with error bars to show the net mean score/count/selections (across participants; across advantageous vs disadvantageous cards respectively) and standard error of the mean of advantageous cards versus disadvantageous cards selected by participants of both groups.**
[5 points]



Caption: Mean scores and standard errors of advantageous and disadvantageous cards selected by participants of both groups.



```python
def meanError(df):
    advantageousCards = df[(df == 1) | (df == 2)].count(axis=1)
    disadvantageousCards = df[(df == 3) | (df == 4)].count(axis=1)

    meanAdv = advantageousCards.mean()
    errorAdv = advantageousCards.sem()
    meanDisadv = disadvantageousCards.mean()
    errorDisadv = disadvantageousCards.sem()

    return meanAdv, errorAdv, meanDisadv, errorDisadv

# Calculate means and errors for both groups
mean_adv_g1, error_adv_g1, mean_disadv_g1, error_disadv_g1 = meanError(df_g1)
mean_adv_g2, error_adv_g2, mean_disadv_g2, error_disadv_g2 = meanError(df_g2)

# Plotting
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(12, 5))

# Group 1 subplot
axes[0].bar(['Advantageous', 'Disadvantageous'], [mean_adv_g1, mean_disadv_g1], yerr=[error_adv_g1, error_disadv_g1], color=['blue', 'red'])
axes[0].set_title('Group 1')
axes[0].set_ylabel('Mean Score')
axes[0].set_ylim([0, max(mean_adv_g1, mean_disadv_g1) + max(error_adv_g1, error_disadv_g1) + 0.1])
```

```
# Group 2 subplot
axes[1].bar(['Advantageous', 'Disadvantageous'], [mean_adv_g2, mean_disadv_g2], yerr=[error_adv_g2,
error_disadv_g2], color=['blue', 'red'])
axes[1].set_title('Group 2')
axes[1].set_ylabel('Mean Score')
axes[1].set_ylim([0, max(mean_adv_g2, mean_disadv_g2) + max(error_adv_g2, error_disadv_g2) + 0.1])

# Adding caption
fig.text(0.5, -0.05, 'Caption: Mean scores and standard errors of advantageous and disadvantageous
cards selected by participants of both groups.', ha='center')

plt.tight_layout()
plt.show()
```

C. Carry out a statistical test to find if the means of the two different groups (calculated in partB) from data1 and data2 differ from one another. Calculate the confidence interval and effect size and report the results along with p-values, test statistics, and degrees of freedom.

Interpret the results of the statistical test with regards to the decision making ability of the participants in the two groups citing the key brain region(s) that might be linked to the performance of both groups in the task.

[3+2 points]

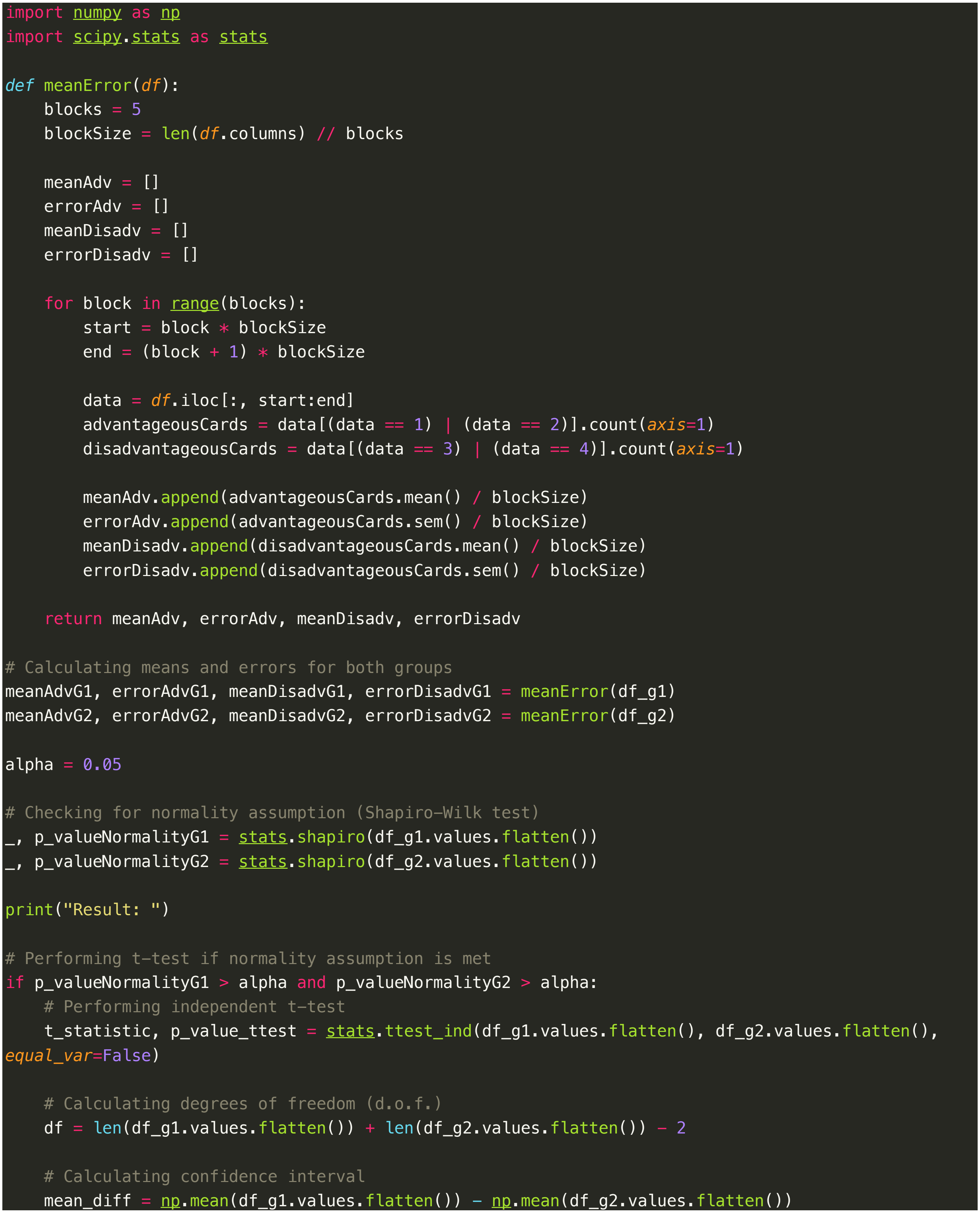
(Hint: If the data in each of the two groups follow a more or less normal distribution, use a parametric test for testing the difference of two independent group means. Otherwise, use a suitable non-parametric counterpart of the parametric test.)

Result:
Mann-Whitney U test results:
p-value: 0.691533448276711
U-statistic: 1792010.0

The Mann-Whitney U test results indicate that there is no significant difference between the two groups in terms of the decision-making ability. The p-value of 0.6915 is greater than the common significance level of 0.05, suggesting that we do not have enough evidence to reject the null hypothesis that there is no difference between the groups.

Interpretation:

- **The Mann-Whitney U test did not find a statistically significant difference in decision-making performance between the two groups. This suggests that, based on the Iowa Gambling Task, the decision-making abilities of Group 1 and Group 2 are similar.**
- **The lack of a significant difference implies that both groups may exhibit comparable strategies or patterns in their choices during the task.**



```python
import numpy as np
import scipy.stats as stats

def meanError(df):
    blocks = 5
    blockSize = len(df.columns) // blocks

    meanAdv = []
    errorAdv = []
    meanDisadv = []
    errorDisadv = []

    for block in range(blocks):
        start = block * blockSize
        end = (block + 1) * blockSize

        data = df.iloc[:, start:end]
        advantageousCards = data[(data == 1) | (data == 2)].count(axis=1)
        disadvantageousCards = data[(data == 3) | (data == 4)].count(axis=1)

        meanAdv.append(advantageousCards.mean() / blockSize)
        errorAdv.append(advantageousCards.sem() / blockSize)
        meanDisadv.append(disadvantageousCards.mean() / blockSize)
        errorDisadv.append(disadvantageousCards.sem() / blockSize)

    return meanAdv, errorAdv, meanDisadv, errorDisadv

# Calculating means and errors for both groups
meanAdvG1, errorAdvG1, meanDisadvG1, errorDisadvG1 = meanError(df_g1)
meanAdvG2, errorAdvG2, meanDisadvG2, errorDisadvG2 = meanError(df_g2)

alpha = 0.05

# Checking for normality assumption (Shapiro-Wilk test)
_, p_valueNormalityG1 = stats.shapiro(df_g1.values.flatten())
_, p_valueNormalityG2 = stats.shapiro(df_g2.values.flatten())

print("Result: ")

# Performing t-test if normality assumption is met
if p_valueNormalityG1 > alpha and p_valueNormalityG2 > alpha:
    # Performing independent t-test
    t_statistic, p_value_ttest = stats.ttest_ind(df_g1.values.flatten(), df_g2.values.flatten(),
equal_var=False)

    # Calculating degrees of freedom (d.o.f.)
    df = len(df_g1.values.flatten()) + len(df_g2.values.flatten()) - 2

    # Calculating confidence interval
    mean_diff = np.mean(df_g1.values.flatten()) - np.mean(df_g2.values.flatten())
    std_pooled = np.sqrt(((len(df_g1.values.flatten()) - 1) * np.std(df_g1.values.flatten(),
ddof=1)**2 + (len(df_g2.values.flatten()) - 1) * np.std(df_g2.values.flatten(), ddof=1)**2) /
(len(df_g1.values.flatten()) + len(df_g2.values.flatten()) - 2))
    margin_of_error = stats.t.ppf(1 - alpha / 2, df) * std_pooled * np.sqrt(1 /
len(df_g1.values.flatten()) + 1 / len(df_g2.values.flatten()))
    confidence_interval = (mean_diff - margin_of_error, mean_diff + margin_of_error)

    # Calculating effect size (Cohen's d)
    pooled_std = np.sqrt((np.std(df_g1.values.flatten(), ddof=1)**2 +
np.std(df_g2.values.flatten(), ddof=1)**2) / 2)
    effect_size = mean_diff / pooled_std

    # Printing results
    print(f"Independent t-test results:")
    print(f"t-statistic: {t_statistic}")
    print(f"p-value: {p_value_ttest}")
    print(f"Degrees of freedom: {df}")
    print(f"95% Confidence Interval for the Difference of Means: {confidence_interval}")
    print(f"Effect Size (Cohen's d): {effect_size}")

else:
    # Performing Mann-Whitney U test
    u_statistic, p_value_mannwhitney = stats.mannwhitneyu(df_g1.values.flatten(),
df_g2.values.flatten())

    # Printing results
    print(f"Mann-Whitney U test results:")
    print(f"p-value: {p_value_mannwhitney}")
    print(f"U-statistic: {u_statistic}")
```