Assignment 1

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Exercise 1

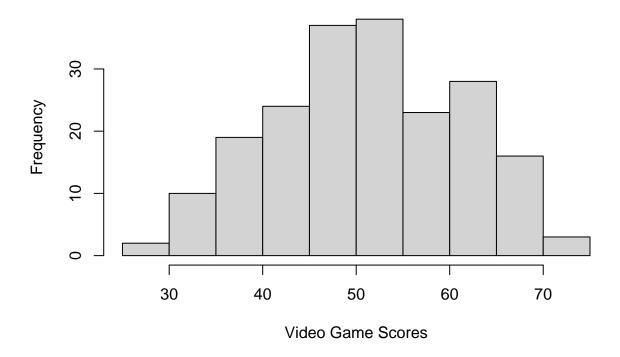
a) Relevant plots and normality assessment:

We will create a histogram and a Q-Q plot of the sample of video game scores to visually assess normality.

```
# Load the data
data <- read.csv("Ice_cream.csv")

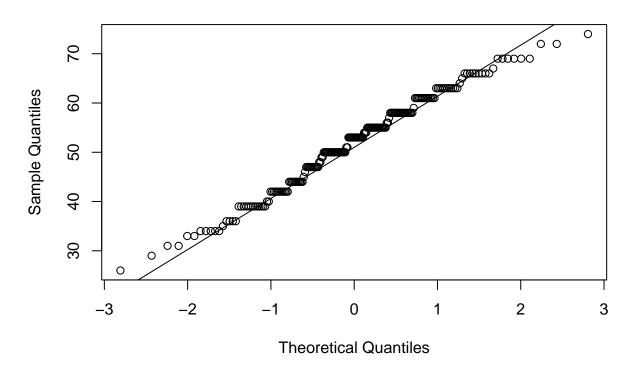
# Plot histogram
hist(data$video, main="Histogram of Video Game Scores", xlab="Video Game Scores")</pre>
```

Histogram of Video Game Scores



```
# Plot Q-Q plot
qqnorm(data$video)
qqline(data$video)
```

Normal Q-Q Plot



After examining the plots, we can comment on the normality of the video game scores.

Constructing a bounded 97%-CI for μ :

```
# Calculate the mean and standard deviation of the sample
sample_mean <- mean(data$video)
sample_sd <- sd(data$video)

# Calculate the margin of error
margin_of_error <- qt(0.985, df = length(data$video) - 1) * (sample_sd / sqrt(length(data$video)
# Construct the CI
lower_bound <- sample_mean - margin_of_error
upper_bound <- sample_mean + margin_of_error</pre>
```

Sample size needed for a 97%-CI with a maximum length of 3:

```
# Calculate the required sample size
required_sample_size <- (qt(0.985, df = 199) * sample_sd / 3) ^ 2</pre>
```

Bootstrap 97%-CI for μ :

```
# Bootstrap function
bootstrap_mean <- function(data, sample_size) {
  bootstrap_samples <- replicate(10000, mean(sample(data, sample_size, replace = TRUE)))
  ci_lower <- quantile(bootstrap_samples, 0.015)
  ci_upper <- quantile(bootstrap_samples, 0.985)
  return(c(ci_lower, ci_upper))
}

# Apply bootstrap function
bootstrap_ci <- bootstrap_mean(data$video, length(data$video))</pre>
```

b) T-test to verify mean score:

```
# Perform t-test
t_test <- t.test(data$video, mu = 50, alternative = "greater")

# Print t-test results and explanation of CI
print(t_test)</pre>
```

Explanation of CI: The CI in the output represents the 95% confidence interval for the difference between the sample mean and the hypothesized mean (μ_0). If the entire interval is above μ_0 , it suggests evidence for the alternative hypothesis.

c) Sign test and test based on ranks:

```
# Perform sign test
sign_test <- binom.test(sum(data$video > 50), length(data$video), p = 0.5, alternative = "great"
# Perform Wilcoxon signed-rank test
wilcox_test <- wilcox.test(data$video, mu = 50, alternative = "greater")
# Test for fraction of scores less than 42
binom_test <- binom.test(sum(data$video < 42), length(data$video), p = 0.25, alternative = "lest")</pre>
```

d) Bootstrap test with test statistic T:

```
# Bootstrap test function
bootstrap_test <- function(data, num_samples) {
   bootstrap_samples <- replicate(num_samples, min(sample(data, length(data), replace = TRUE)))
   p_value <- mean(bootstrap_samples < min(data) | bootstrap_samples > 100)
   return(p_value)
}

# Apply bootstrap test
p_value <- bootstrap_test(data$video, 10000)

# Apply Kolmogorov-Smirnov test
ks_test <- ks.test(data$video, "pnorm", mean = 50, sd = 10)

## Warning in ks.test.default(data$video, "pnorm", mean = 50, sd = 10): ties
## should not be present for the Kolmogorov-Smirnov test</pre>
```

e) Tests for male and female students:

```
# Separate scores for male and female students
male_scores <- data$video[data$female == 0]
female_scores <- data$video[data$female == 1]

# Perform two-sample t-test
t_test_gender <- t.test(male_scores, female_scores, alternative = "greater")

# Perform Mann-Whitney test
mannwhitney_test <- wilcox.test(male_scores, female_scores, alternative = "greater")

# Perform Kolmogorov-Smirnov test
ks_test_gender <- ks.test(male_scores, female_scores)</pre>
```

f) Correlation and comparison between video game and puzzle scores:

```
# Investigate correlation
correlation <- cor(data$video, data$puzzle)

# Test if puzzle scores are higher than video game scores
wilcox_test_puzzle <- wilcox.test(data$puzzle, data$video, alternative = "greater")</pre>
```