

# ST502 Project

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## Part I

### Framingham Heart Study

The Framingham data set contains the diastolic blood pressure of 300 smokers and nonsmokers. For this study we will assume the following:

$$H_0: \mu_1 - \mu_2 = 0$$

$$H_A: \mu_1 - \mu_2 \neq 0$$

The null hypothesis being there is no difference in the blood pressure between smokers and non smokers. We believe that there is a difference and this paper will prove if we have enough evidence to reject the null hypothesis.

### Normality of Data

Plotting the density of total data (see Appendix I: Figure 1A), we can that it closely follows a normal distribution, Density plots of the split data exhibit similar forms (see Appendix I: Figure 1B). We can also calculate the kurtosis and the skew of the data, which are 3.812, 0.88 for kurtosis and skew respectively, and see that they are quite close to values typically found in normally distributed data. Additionally, the calculated values of sample standard deviation,  $\frac{IQR}{1.35}$ , and  $\frac{MAD}{0.675}$  are 22.89, 22.22, and 21.48. The similarities between the three values indicate that the data is not influenced by outliers. Therefore, we will assume the data and the subsequent split data to be normal.

### Statistical Analysis

In the first analysis we will be assuming equal variances, thereby allowing us to use pooled sample variance (see Appendix I: Equation 1).

The pooled sample variance of the data is 510 using a degree of freedom value 298. In this case, we reject the null hypothesis because the calculated p value, 0.0041, is smaller than the chosen  $\alpha$  value of 0.05. In terms of t values, our observed t value of -3.04 is smaller than the t value, -1.97 for a two sided  $\alpha$  of 0.05.

When computing the observed t value using the assumption that the population variances are not equivalent (variance smoker is 352.2 and variance nonsmoker is 562.1), a value of -2.9 is obtained. Comparing that the two sided  $\alpha$  of -1.98 with 158 degrees of freedom (as computed using the Satterthwaite Approximation see Appendix I: Equation 4). The observed t value is less than the chosen  $\alpha$  value of 0.05. In case, there is sufficient evidence to reject the null hypothesis in favor of the alternative.

The observed 95% confidence intervals are -15.08 to -3.23 for pooled sample variance and -15.4 to -2.91 for non pooled sample variance. It can be seen that 0 does not fall into the 95% confidence interval in either case. Therefore the null hypothesis can be rejected.

In all three case, there is sufficient evidence to reject the null hypothesis and to support the alternative at an  $\alpha$  level of 0.05.

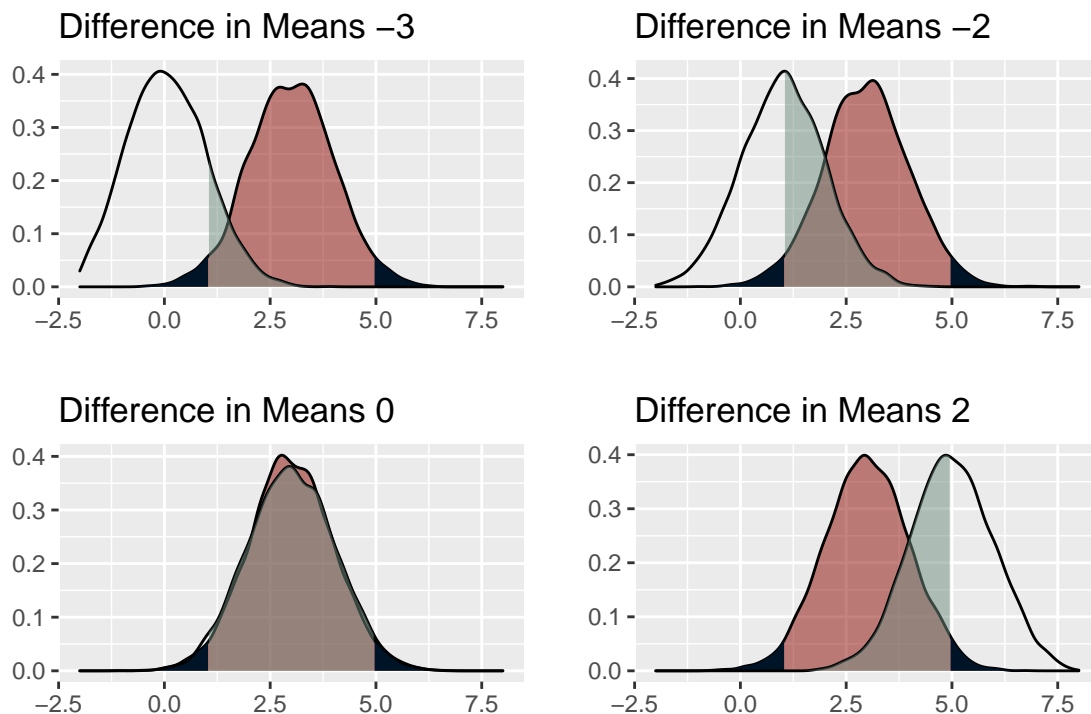
## Part II

### Introduction

In Part I we were able to see how hypothesis testing allowed to find enough evidence to challenge the “status quo” argument that smoking has no affect on the blood pressure of a person. What we found, through a number of robust statistical methods, that the difference in means, calculated to be 9.1577778, was significant to not have arisen by chance. That within an  $\alpha$  of 5%, we are confident that the two groups do exhibit measurable differences. In the following sections, we will explore, through simulated data, the concept of randomness in data and what steps we can take to mitigate that randomness. All simulated data will be generated using the built in `rnorm()` function in R.

### Power of Hypothesis Testing

It is important to briefly discuss the concept of power in hypothesis testing. Power describes the probability of not committing a Type II error, which is to not reject the null hypothesis when there was in actuality enough evidence to do so. The probability of a Type II error is represented by  $\beta$ . Power is the complement to that probability ( $1 - \beta$ ). The value of  $\beta$  is the portion of the alternate distribution that is within the null hypothesis non rejection region limits. Below are a number of plots to help depict this concept. In each of the plots the shaded red is the null distribution and its location stays constant (mean = 3). The dark red tails represent the rejection region of the null distribution. The outline distribution represents the “true” alternative distribution. Within that distribution is the shaded light blue region which is equal to  $\beta$ . It can be seen that as the difference between the two distributions shrinks the value of  $\beta$  increases and the power shrinks. Power reaches minimum and  $\beta$  reaches maximum when the two distributions are the same.



### Simulation Study

Below, various scenarios were simulated by creating 2 normally distributed data sets of various mean, variances, and sample sizes. Each scenario was repeated a thousand times. For each of those repeats a hypothesis

test was conducted and the number of times the null hypothesis was rejected was recorded. See Appendix III for results. All hypothesis testing was using pooled and unpooled variance, regardless of the actual values of variance.

The following table includes the values of each parameter used in the simulation:

Parameter	Possible Values
$\mu_0$	0, 4, 5, 6, 10
$\sigma_0^2$	1, 4, 9
$n_0$	10, 30, 70
$\mu_A$	5
$\sigma_A^2$	1
$n_A$	10, 30, 70

It was noted that the smaller difference between the alternative and null mean values were, the less likely the null hypothesis was rejected. Larger values of variance also reduced the number of rejected null hypothesis. In both cases, the more overlap between the two distributions, the less powerful the test. One way that can increase the power of the t-test is to increase the sample size. For a specific example, we can look at test cases #10 and #129. In both cases the distribution means were 6 and 5 for the null and alternative hypotheses respectively, along with variances of 1 for both distributions. The only difference between the two cases was the sample size ( $n_{10} = 10$  and  $n_{129} = 70$ ). This increase in sample size resulted in almost a 6 fold increase in power (169 vs 958 rejected nulls). Test cases 69 and 114 use different combinations of, but lower than 70, sample sizes than the aforementioned two. While they exhibited increased signs of power, they did not get as high as test case 129. It stands to reason that large variances and small deltas in mean can be mitigated by increasing the sample size accordingly.

## Appendix I: Equations and Figures

### Figures

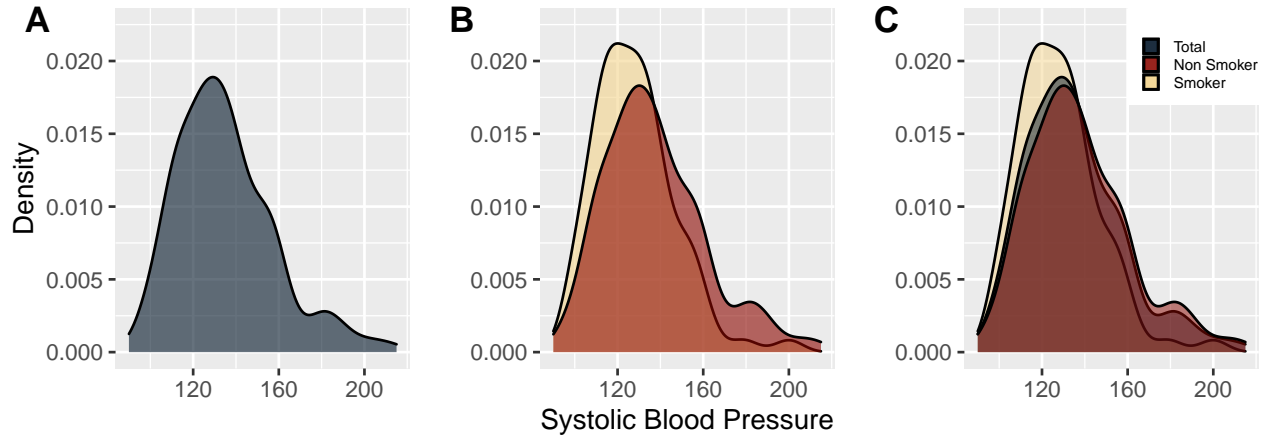


Figure 1: Data plots

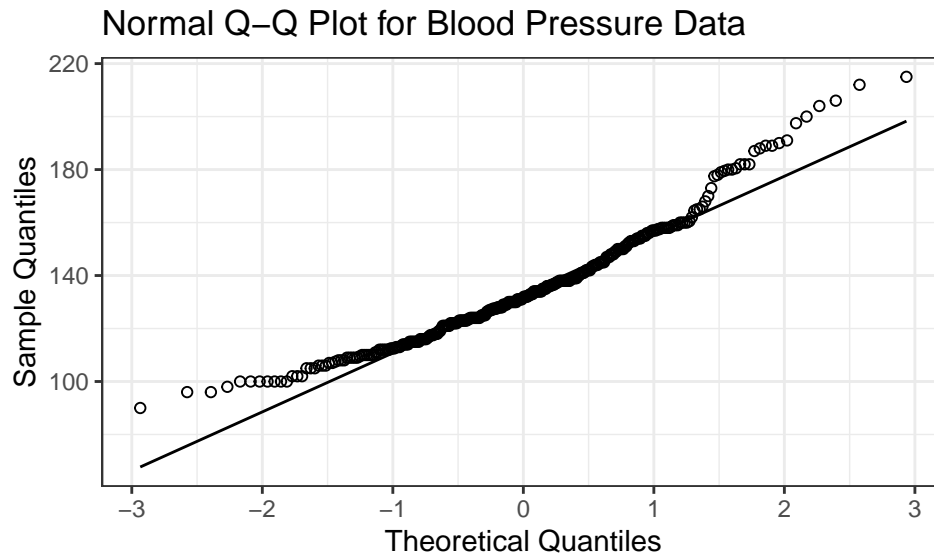


Figure 2: Q-Q Plot

### Equations:

Equation 1: Pooled Sample Variance:

$$S_p^2 = \frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}$$

**Equation 2: Observed T Statistic (pooled variance):**

$$t_{obs} = \frac{\mu_1 - \mu_2}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

**Equation 3: Observed T Statistic (distinct variance):**

$$t_{obs} = \frac{\mu_1 - \mu_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

**Equation 4: Satterthwaite Approximation:**

$$\nu = \frac{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2}{\frac{\left(\frac{S_1^2}{n_1}\right)^2}{n_1-1} + \frac{\left(\frac{S_2^2}{n_2}\right)^2}{n_2-1}}$$

## Appendix II: Part I Results

Data Mean: 134.935

Data Sample Variance: 524.0852258

Smoker Mean: 128.0666667

Smoker Variance: 352.2117117

Nonsmoker Mean: 137.2244444

Nonsmoker Variance: 562.1447123

Difference in mean: -9.1577778

Pooled Sample Variance: 510.0136987

Nonpooled Sample Variance: 9.9936838

CI Pooled: -15.08, -3.23

CI Nonpooled: -15.4, -2.91

### Appendix III: Part II Results

Test Case	$\mu_1$	$\sigma_1^2$	$n_1$	$\mu_2$	$\sigma_2^2$	$n_2$	Test Results Unpooled	Test Results Pooled	Difference in Mean
1	0	1	10	5	1	10	1000	1000	-5
2	4	1	10	5	1	10	590	562	-1
3	5	1	10	5	1	10	58	39	0
4	6	1	10	5	1	10	535	546	1
5	10	1	10	5	1	10	1000	1000	5
6	0	4	10	5	1	10	1000	1000	-5
7	4	4	10	5	1	10	288	259	-1
8	5	4	10	5	1	10	45	55	0
9	6	4	10	5	1	10	286	265	1
10	10	4	10	5	1	10	1000	1000	5
11	0	9	10	5	1	10	996	995	-5
12	4	9	10	5	1	10	143	156	-1
13	5	9	10	5	1	10	59	50	0
14	6	9	10	5	1	10	156	200	1
15	10	9	10	5	1	10	992	999	5
16	0	1	30	5	1	10	1000	1000	-5
17	4	1	30	5	1	10	781	776	-1
18	5	1	30	5	1	10	58	52	0
19	6	1	30	5	1	10	767	740	1
20	10	1	30	5	1	10	1000	1000	5
21	0	4	30	5	1	10	1000	1000	-5
22	4	4	30	5	1	10	278	260	-1
23	5	4	30	5	1	10	10	6	0
24	6	4	30	5	1	10	274	281	1
25	10	4	30	5	1	10	1000	1000	5
26	0	9	30	5	1	10	1000	1000	-5
27	4	9	30	5	1	10	84	82	-1
28	5	9	30	5	1	10	5	3	0
29	6	9	30	5	1	10	81	87	1
30	10	9	30	5	1	10	1000	1000	5
31	0	1	70	5	1	10	1000	1000	-5
32	4	1	70	5	1	10	831	812	-1
33	5	1	70	5	1	10	61	54	0
34	6	1	70	5	1	10	848	842	1
35	10	1	70	5	1	10	1000	1000	5
36	0	4	70	5	1	10	1000	1000	-5
37	4	4	70	5	1	10	240	242	-1
38	5	4	70	5	1	10	3	4	0
39	6	4	70	5	1	10	257	244	1
40	10	4	70	5	1	10	1000	1000	5
41	0	9	70	5	1	10	1000	1000	-5
42	4	9	70	5	1	10	36	29	-1
43	5	9	70	5	1	10	0	1	0
44	6	9	70	5	1	10	39	31	1
45	10	9	70	5	1	10	1000	1000	5
46	0	1	10	5	1	30	1000	1000	-5
47	4	1	10	5	1	30	784	734	-1
48	5	1	10	5	1	30	48	53	0
49	6	1	10	5	1	30	768	753	1



Test Case	$\mu_1$	$\sigma_1^2$	$n_1$	$\mu_2$	$\sigma_2^2$	$n_2$	Test Results Unpooled	Test Results Pooled	Difference in Mean
50	10	1	10	5	1	30	1000	1000	5
51	0	4	10	5	1	30	1000	1000	-5
52	4	4	10	5	1	30	549	534	-1
53	5	4	10	5	1	30	148	161	0
54	6	4	10	5	1	30	531	523	1
55	10	4	10	5	1	30	1000	1000	5
56	0	9	10	5	1	30	1000	1000	-5
57	4	9	10	5	1	30	421	417	-1
58	5	9	10	5	1	30	220	203	0
59	6	9	10	5	1	30	414	404	1
60	10	9	10	5	1	30	1000	1000	5
61	0	1	30	5	1	30	1000	1000	-5
62	4	1	30	5	1	30	968	968	-1
63	5	1	30	5	1	30	62	46	0
64	6	1	30	5	1	30	967	963	1
65	10	1	30	5	1	30	1000	1000	5
66	0	4	30	5	1	30	1000	1000	-5
67	4	4	30	5	1	30	664	696	-1
68	5	4	30	5	1	30	65	65	0
69	6	4	30	5	1	30	687	665	1
70	10	4	30	5	1	30	1000	1000	5
71	0	9	30	5	1	30	1000	1000	-5
72	4	9	30	5	1	30	403	383	-1
73	5	9	30	5	1	30	55	56	0
74	6	9	30	5	1	30	387	397	1
75	10	9	30	5	1	30	1000	1000	5
76	0	1	70	5	1	30	1000	1000	-5
77	4	1	70	5	1	30	995	997	-1
78	5	1	70	5	1	30	42	42	0
79	6	1	70	5	1	30	998	994	1
80	10	1	70	5	1	30	1000	1000	5
81	0	4	70	5	1	30	1000	1000	-5
82	4	4	70	5	1	30	765	763	-1
83	5	4	70	5	1	30	11	8	0
84	6	4	70	5	1	30	783	764	1
85	10	4	70	5	1	30	1000	1000	5
86	0	9	70	5	1	30	1000	1000	-5
87	4	9	70	5	1	30	392	396	-1
88	5	9	70	5	1	30	4	7	0
89	6	9	70	5	1	30	376	422	1
90	10	9	70	5	1	30	1000	1000	5
91	0	1	10	5	1	70	1000	1000	-5
92	4	1	10	5	1	70	832	825	-1
93	5	1	10	5	1	70	45	47	0
94	6	1	10	5	1	70	836	838	1
95	10	1	10	5	1	70	1000	1000	5
96	0	4	10	5	1	70	1000	1000	-5
97	4	4	10	5	1	70	627	628	-1
98	5	4	10	5	1	70	243	242	0
99	6	4	10	5	1	70	665	623	1
100	10	4	10	5	1	70	1000	1000	5

Test Case	$\mu_1$	$\sigma_1^2$	$n_1$	$\mu_2$	$\sigma_2^2$	$n_2$	Test Results Unpooled	Test Results Pooled	Difference in Mean
101	0	9	10	5	1	70	1000	1000	-5
102	4	9	10	5	1	70	542	544	-1
103	5	9	10	5	1	70	353	323	0
104	6	9	10	5	1	70	531	544	1
105	10	9	10	5	1	70	1000	1000	5
106	0	1	30	5	1	70	1000	1000	-5
107	4	1	30	5	1	70	993	993	-1
108	5	1	30	5	1	70	42	47	0
109	6	1	30	5	1	70	997	991	1
110	10	1	30	5	1	70	1000	1000	5
111	0	4	30	5	1	70	1000	1000	-5
112	4	4	30	5	1	70	856	872	-1
113	5	4	30	5	1	70	125	121	0
114	6	4	30	5	1	70	853	872	1
115	10	4	30	5	1	70	1000	1000	5
116	0	9	30	5	1	70	1000	1000	-5
117	4	9	30	5	1	70	618	655	-1
118	5	9	30	5	1	70	165	186	0
119	6	9	30	5	1	70	650	639	1
120	10	9	30	5	1	70	1000	1000	5
121	0	1	70	5	1	70	1000	1000	-5
122	4	1	70	5	1	70	1000	1000	-1
123	5	1	70	5	1	70	58	45	0
124	6	1	70	5	1	70	999	1000	1
125	10	1	70	5	1	70	1000	1000	5
126	0	4	70	5	1	70	1000	1000	-5
127	4	4	70	5	1	70	959	969	-1
128	5	4	70	5	1	70	46	53	0
129	6	4	70	5	1	70	952	948	1
130	10	4	70	5	1	70	1000	1000	5
131	0	9	70	5	1	70	1000	1000	-5
132	4	9	70	5	1	70	747	738	-1
133	5	9	70	5	1	70	53	57	0
134	6	9	70	5	1	70	766	732	1
135	10	9	70	5	1	70	1000	1000	5

## Appendix IV: Code

```
knitr::opts_chunk$set(echo = TRUE)

#Use required packages
library(tidyverse) #for plots and data manipulation
library(cowplot) #aligning plots
library(gridExtra)
library(scales)

df_data <- read_csv("framingham_data.csv") # Read in data
df_data$index <- seq(nrow(df_data)) # Add an index column

#df_data %>% summary # Summarize Data

# Split data into smoker and nonsmoker
df_smoker <- df_data %>% filter(currentSmoker == 1)
df_nonsmoker <- df_data %>% filter(currentSmoker == 0)

#Create a sample variance function to ensure proper calculation
sample_variance <- function(x, sampling = TRUE){
  if (sampling == TRUE){
    sum((x - mean(x))^2) / (length(x) - 1)
  } else if(sampling == FALSE) {
    sum((x - mean(x))^2) / (length(x))
  }
}

#Create pooled sample variance function
f_pooled_variance <- function(x, y){
  ((length(x) - 1) * sample_variance(x) +
   (length(y) - 1) * sample_variance(y)) /
  (length(x) + length(y) - 2)
}

# Skewness function
skew_function <- function(x){
  mean((x - mean(x))^3) / sqrt(sample_variance(x))^3
}

# kurtosis function
kurt_function <- function(x){
  mean((x - mean(x))^4) / sqrt(sample_variance(x))^4
}

# Create a Satterthwaite Approximation Function

satterth <- function(s1, s2, n1, n2){
  term1 <- s1/n1
  term2 <- s2/n2
  nu <- (term1 + term2)^2 / ((term1^2/(n1 - 1)) + (term2^2/(n2 - 1)))
  return(floor(nu))
}
```

```

#Plot and compare split data

#options(repr.plot.width = 6, repr.plot.height = 4, repr.plot.res = 150)

plot_colors <- c("#001427", "#708d81", "#f4d58d", "#bf0603", "#8d0801")
y_limits <- c(0, 0.0225)

total_data <- ggplot(df_data) + geom_density(aes(sysBP),
                                             fill = plot_colors[1],
                                             alpha = 0.6) +
  ylim(y_limits) + ylab("Density") + xlab("")

sep_data <- ggplot() + geom_density(data = df_smoker, aes(sysBP),
                                   fill = plot_colors[3], alpha = 0.6) +
  geom_density(data = df_nonsmoker, aes(sysBP),
               fill = plot_colors[5], alpha = 0.6) +
  ylim(y_limits) + ylab("") + xlab("Systolic Blood Pressure")

plot_3 <- ggplot() + geom_density(data = df_smoker, aes(sysBP),
                                  fill = plot_colors[3]), alpha = 0.5) +
  geom_density(data = df_data, aes(sysBP),
               fill = plot_colors[1]), alpha = 0.5) +
  geom_density(data = df_nonsmoker, aes(sysBP),
               fill = plot_colors[5]), alpha = 0.5) +
  ylim(y_limits) + ylab("") + xlab("") +
  scale_fill_manual("",
                    values = plot_colors[c(1, 5, 3)],
                    labels = c("Total", "Non Smoker", "Smoker")) +
  theme(legend.position = c(0.8, 0.9),
        legend.text = element_text(size = 6),
        legend.key.height = unit(0.25, 'cm'),
        legend.key.width = unit(0.25, 'cm'))

#plot_grid(total_data, sep_data, plot_3, align = 'vh',
           #hjust = -1, nrow = 2, ncol = 2)

data_kurtosis <- kurt_function(df_data$sysBP)
data_skew <- skew_function(df_data$sysBP)
data_IQR <- as.numeric(quantile(df_data$sysBP, probs = 0.75)) -
  as.numeric(quantile(df_data$sysBP, probs = 0.25))
data_MAD <- median(abs(df_data$sysBP - median(df_data$sysBP)))
data_samVar <- sample_variance(df_data$sysBP)

eIQR <- data_IQR / 1.35
eMAD <- data_MAD / 0.675

# Q-Q Plot

data_qqplot <-
  ggplot(df_data, aes(sample = sysBP)) +
  stat_qq(shape = 1) + stat_qq_line() +
  ggtitle("Normal Q-Q Plot for Blood Pressure Data") +
  xlab("Theoretical Quantiles") +

```

```

ylab("Sample Quantiles")

# Common values for analysis

alpha <- 0.05

mu_smoker <- mean(df_smoker$sysBP)
var_smoker <- sample_variance(df_smoker$sysBP)
n_smoker <- length(df_smoker$sysBP)

mu_nonsmoker <- mean(df_nonsmoker$sysBP)
var_nonsmoker <- sample_variance(df_nonsmoker$sysBP)
n_nonsmoker <- length(df_nonsmoker$sysBP)

# Two Sample T-test - Pooled Sample Variance - P-value

dof_1 <- (n_smoker + n_nonsmoker - 2)

p_sample_var_1 <- f_pooled_variance(df_smoker$sysBP,
                                   df_nonsmoker$sysBP)

t_obs_1 <- (mu_smoker - mu_nonsmoker) / (sqrt(p_sample_var_1) * sqrt(1/n_smoker + 1/n_nonsmoker))

t_stat_1 <- qt(alpha / 2, dof_1)

p_value_obs_1 <- dt(t_obs_1, dof_1)

#Two Sample T-test - Difference Variance Sample Variance - P-value

dof_2 <- satterth(var_smoker, var_nonsmoker, n_smoker, n_nonsmoker)

np_sample_var_2 <- (var_nonsmoker/n_smoker + var_nonsmoker/n_nonsmoker)

t_obs_2 <- (mu_smoker - mu_nonsmoker) / (sqrt(var_nonsmoker/n_smoker + var_nonsmoker/n_nonsmoker))

t_stat_2 <- qt(alpha / 2, dof_2)

p_value_obs_2 <- dt(t_obs_2, dof_2)

# Confidence Limits

diff_mu <- mu_smoker - mu_nonsmoker

#Pooled Sample variance

CL_pooled <- t_stat_1 * (sqrt(p_sample_var_1/n_smoker + p_sample_var_1/n_nonsmoker))

#Non pooled Sample variance

CL_nonpooled <- t_stat_2 * (sqrt(var_nonsmoker/n_smoker + var_nonsmoker/n_nonsmoker))

CI_pooled <- round(c(diff_mu + CL_pooled, diff_mu - CL_pooled), 2)

```

```

CI_nonpooled <- round(c(diff_mu + CL_nonpooled, diff_mu - CL_nonpooled), 2)

#Part II
#Introduction

options(repr.plot.width = 12, repr.plot.height = 5, repr.plot.res = 150)
set.seed(100)

null_mean <- 3
alt_means <- c(0, 1, 3, 5)
plot_list <- list()

#plot_colors <- c("#072ac8", "#1e96fc", "#a2d6f9", "#fcf300", "#ffc600")

for(i in 1:length(alt_means)){

  sim1 <- rnorm(5000, null_mean, sqrt(1))
  sim2 <- rnorm(5000, alt_means[i], sqrt(1))

  alpha1 <- qnorm(0.025, null_mean, sqrt(1))
  alpha2 <- qnorm(0.975, null_mean, sqrt(1))

  df_set <- tibble("H0" = sim1, "HA" = sim2)

  title_string <- sprintf("Difference in Means %i", (alt_means[i] - null_mean))

  plot_list[[i]] <-
    ggplot(data = df_set) + geom_density(aes(H0), alpha = 0.5, fill = plot_colors[5]) +
      geom_area(
        aes(x = stage(H0, after_scale = oob_censor(x, c(-Inf, alpha1)
          )
        ),
        stat = "density", fill = plot_colors[1]
      ) +
      geom_area(
        aes(x = stage(H0, after_scale = oob_censor(x, c(alpha2, Inf)
          )
        ),
        stat = "density", fill = plot_colors[1]
      ) +
      geom_density(aes(HA), alpha = 0.5) +
      geom_area(
        aes(x = stage(HA, after_scale = oob_censor(x, c(alpha1, alpha2)
          )
        ),
        stat = "density", fill = plot_colors[2], alpha = 0.5
      ) +
      xlim(-2, 8) + xlab("") + ylab("") + ggtitle(title_string)
}

```

```

    }

do.call(grid.arrange, plot_list)
#Part II
set.seed(1)

alpha <- 0.05

test_function <- function (x, y, pooled = FALSE){

  mu_1 <- mean(x)
  var_1 <- sample_variance(x, sampling = TRUE)

  mu_2 <- mean(y)
  var_2 <- sample_variance(y, sampling = TRUE)

  #Calculate the pooled sample variance
  pooled_sample <- ((length(x) - 1) * var_1 +
                    (length(y) - 1) * var_2) / (length(x) + length(y) - 2)

  #calculate the observed t statistic
  if (pooled == TRUE){

    cal_sigma <- (sqrt(pooled_sample/length(x) + pooled_sample/length(y)))

    ttest <- (mu_1 - mu_2) / cal_sigma
    dof <- length(x) + length(y) - 2 #Determine degrees of freedom

  } else {

    cal_sigma <- (sqrt(var_1/length(x) + var_2/length(y)))

    ttest <- (mu_1 - mu_2) / cal_sigma
    dof <- satterth(var_1, var_2, length(x), length(y))
  }

  # Determine whether or not the null hypothesis
  # can be rejected (1 = rejected, 0 = not rejected)
  verdict <- !between(ttest, qt(alpha / 2, dof), qt(1 - alpha / 2, dof))

  #Return calculated values
  return(c(mu_1, var_1, mu_2, var_2, ttest, cal_sigma, dof, verdict))
}

mu1 <- c(0, 4, 5, 6, 10)
var1 <- c(1, 4, 9)
n1 <- c(10, 30, 70)

mu2 <- 5
var2 <- 1
n2 <- c(10, 30, 70)

```

```

sim_test <- function(x_mu, x_var, x_n, y_mu, y_var, y_n, pooled = TRUE){

  sim_data_results <- matrix(rep(0, 8), ncol = 8)

  for (i in 1:1000){

    sim_set1 <- rnorm(x_n, x_mu, sqrt(x_var))
    sim_set2 <- rnorm(y_n, y_mu, sqrt(y_var))

    sim_data_results <- rbind(sim_data_results,
                              test_function(sim_set1, sim_set2, pooled))

    #print(sim_data_results)
  }

  df_sim_data <- data.frame(sim_data_results[2 : nrow(sim_data_results),])
  colnames(df_sim_data) = c("Null Mean", "Null Variance", "Alternate Mean",
                           "Alternate Variance", "T statistic",
                           "Calculated Variance", "DoF", "Null Reject")

  return(df_sim_data)
}

# HA: mean = 5, var = 1
df_combo <- expand.grid(mu1, var1, n1, mu2, var2, n2)
df_combo2 <- tibble(cbind(1:nrow(df_combo), df_combo,
                          matrix(rep(0, 2 * nrow(df_combo)), ncol = 2)))
colnames(df_combo2) <- c("Test_Case", "mu1", "var1", "n1", "mu2", "var2",
                        "n2", "Test_Results_up", "Test_Results_po")

test_results <- list()
test_results2 <- list()

for (i in 1:nrow(df_combo)){
  test_results[[i]] <- do.call(sim_test, as.list(as.numeric(df_combo[i,])))
  test_results2[[i]] <- do.call(sim_test, as.list(as.numeric(c(df_combo[i,], pooled = TRUE))))
  df_combo2[i, 8] <- sum(as.data.frame(test_results[i]),[8])
  df_combo2[i, 9] <- sum(as.data.frame(test_results2[i]),[8])
}

df_combo2 <- df_combo2 %>% mutate(diff = mu1 - mu2)
#df_combo2 %>% head()
# Plotting
options(repr.plot.width = 6, repr.plot.height = 4, repr.plot.res = 150)

plot_grid(total_data, sep_data, plot_3, align = 'vh',
          hjust = -1, nrow = 1, ncol = 3, labels = c("A", "B", "C"))
data_qqplot + theme_bw()
knitr::kable(df_combo2, col.names = c("Test Case",
                                       "$\\mu_1$",
                                       "$\\sigma_1^2$",
                                       "$n_1$",
                                       "$\\mu_2$",
                                       "$\\sigma_2^2$",

```



```
        "$n_2$",  
        "Test Results Unpooled",  
        "Test Results Pooled",  
        "Difference in Mean"),  
    escape = FALSE)
```