

```
#knitr::opts_chunk$set(echo = TRUE, tidy.opts=list(width.cutoff=80), tidy=TRUE)
knitr::opts_chunk$set(echo = TRUE)
```

```
forbes<-read.table("Forbes.txt",header=T)
```

```
#forbes # displays datatable
```

```
attach(forbes)
```

```
## The following objects are masked from forbes (pos = 4):
```

```
##
```

```
## PRESS, TEMP
```

```
## The following objects are masked from forbes (pos = 28):
```

```
##
```

```
## PRESS, TEMP
```

```
n<-length(TEMP)
```

```
plot(TEMP,PRESS,pch=19,col="blue",xlab="Boiling point in degrees of  
↳ Fahrenheit",ylab="Pressure measurement",main="Scatter plot of Boiling point versus  
↳ Pressure")
```

```
fit<-lm(PRESS~TEMP) # least squares estimate
```

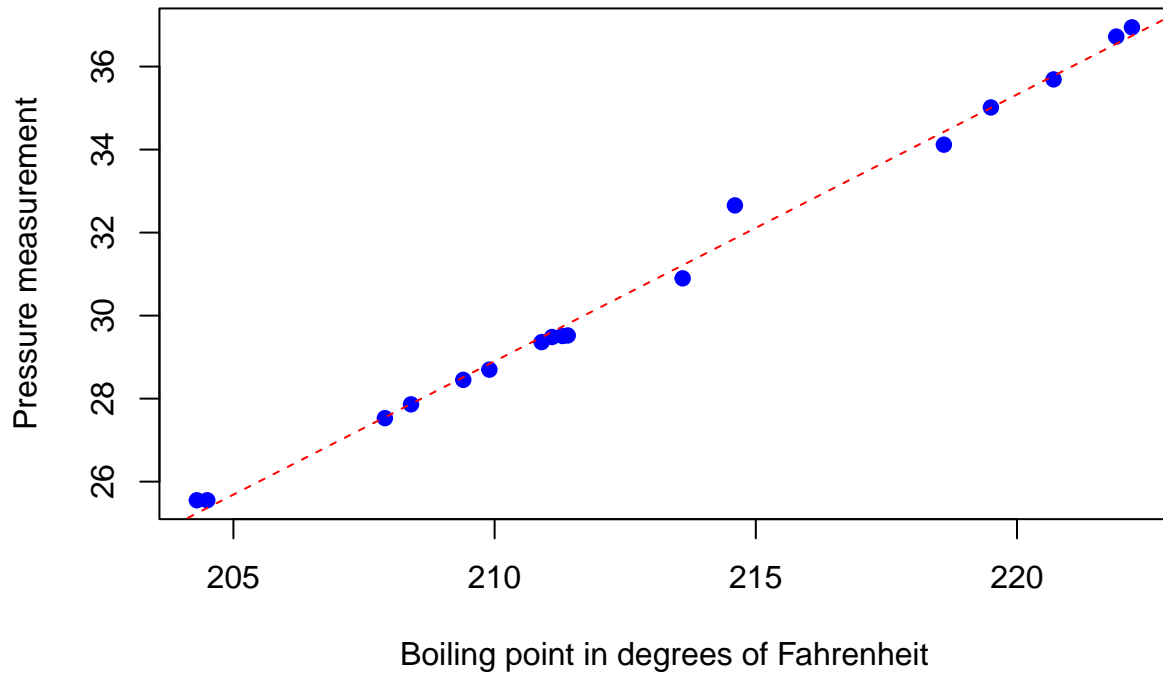
```
#summary(fit)
```

```
#fit$coef
```

```
#abline(a=fit$coef[1],b=fit$coef[2],lty=2,col="red")
```

```
abline(fit,lty=2,col="red")
```

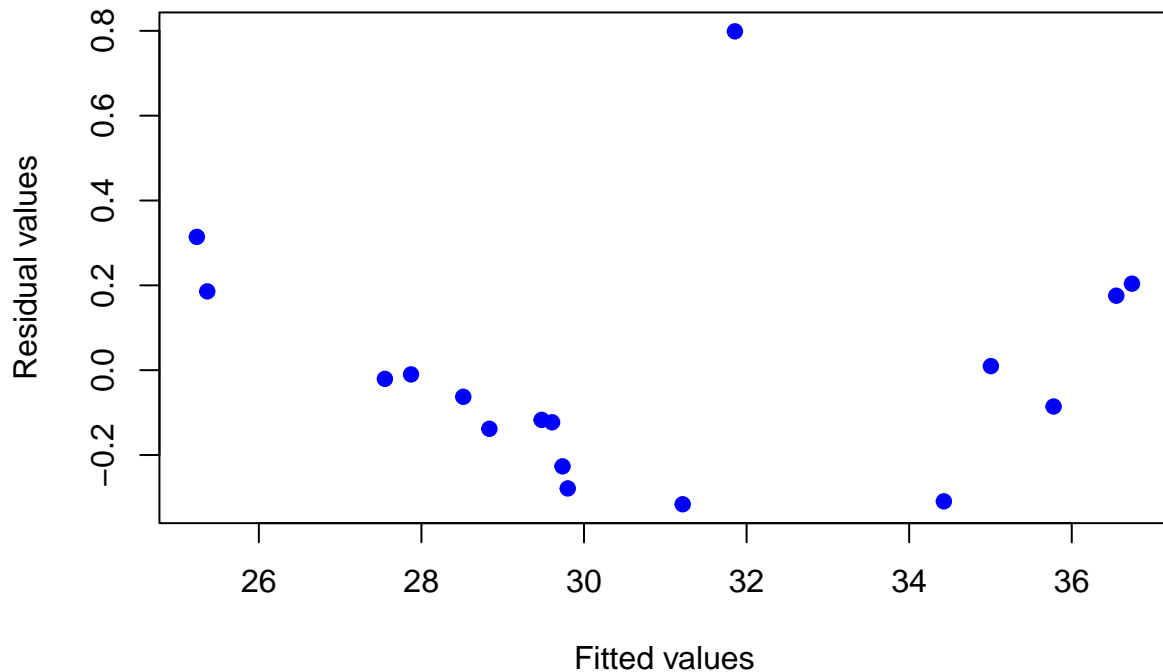
Scatter plot of Boiling point versus Pressure



```
#fit$fit
#fit$res

plot(fit$fit,fit$res,pch=19,col="blue",xlab="Fitted values",ylab="Residual
↪ values",main="Fitted vs. Residual values of PRESS vs. TEMP")
```

Fitted vs. Residual values of PRESS vs. TEMP



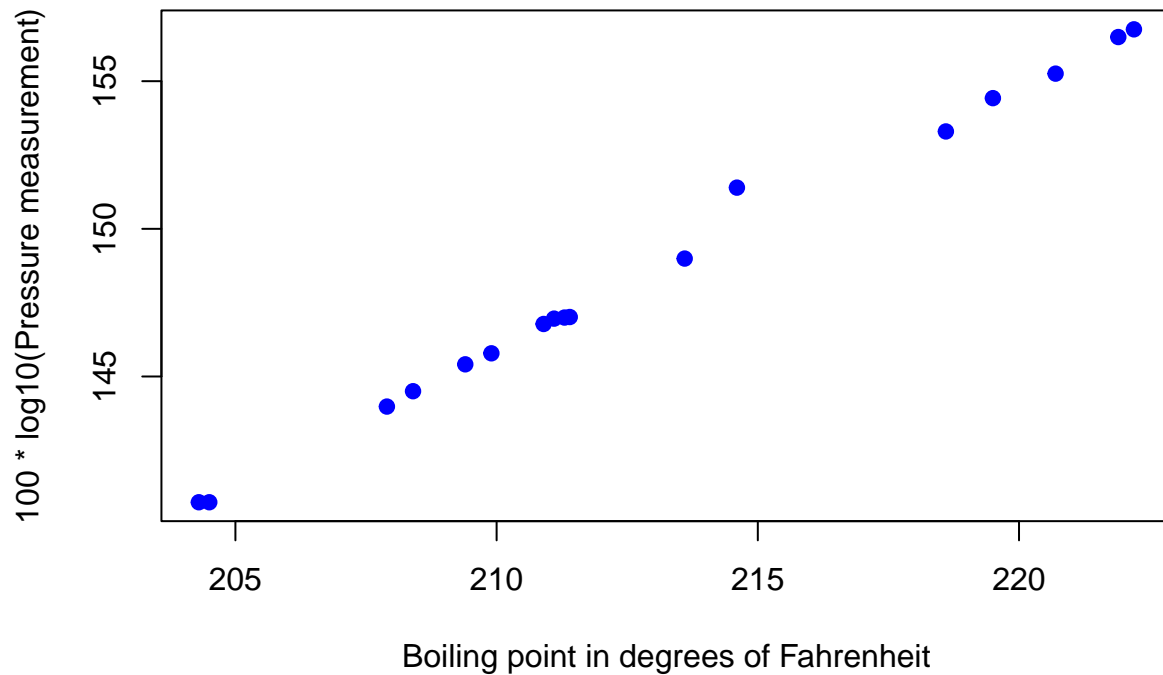
My observations for the residuals versus fitted values graph is that the data from Forbes.txt is fitted very well to a linear regression. This is because the residual values all seem to be less than ± 0.5 . This would mean that all the pressure measurements are within a range of ± 0.5 to their fitted value, which suggests that a linear regression is a very good fit for the data. There is only 1 outlier of the 17 data points which has a residual of ± 1.0 .

```
#PRESS2<-data.frame(PRESS)
PRESS_B=100*log10(PRESS)

#PRESS_B

plot(TEMP,PRESS_B,pch=19,col="blue",xlab="Boiling point in degrees of
  ↪ Fahrenheit",ylab="100 * log10(Pressure measurement)",main="Scatter plot of Boiling
  ↪ point versus 100 * log10(Pressure)")
```

Scatter plot of Boiling point versus $100 * \log_{10}(\text{Pressure})$



```
fit_C<-lm(PRESS_B~TEMP)
```

```
# Computed estimates of parameters:
```

```
fit_C$coef
```

```
## (Intercept)      TEMP
```

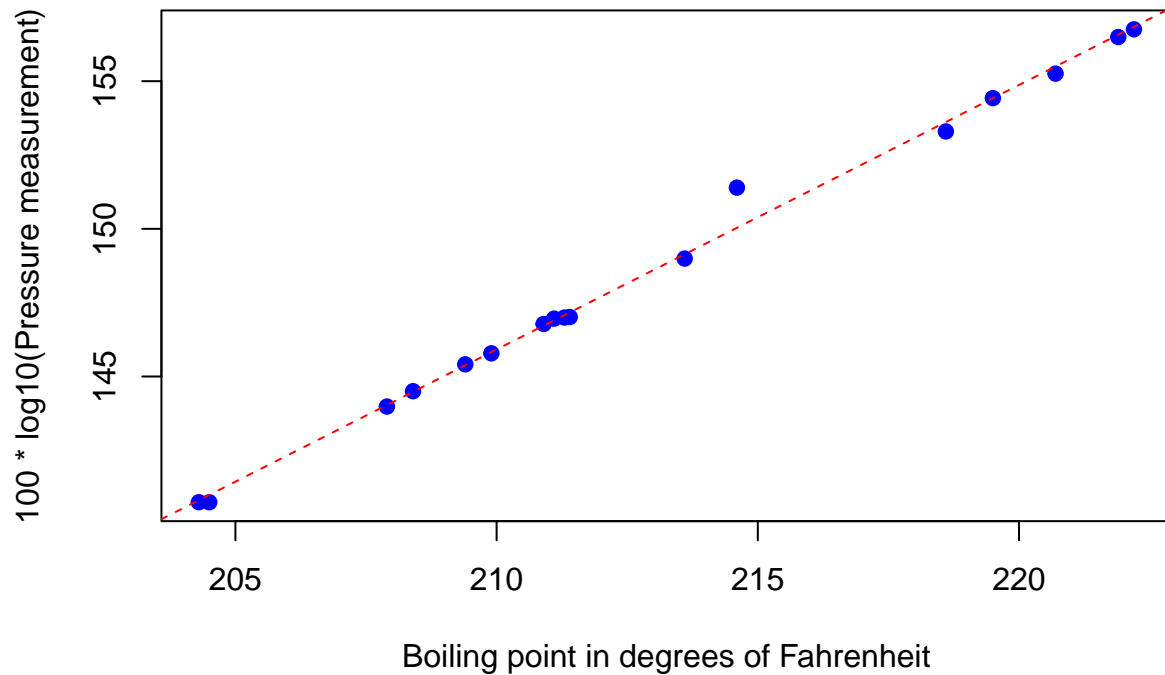
```
## -42.1641169    0.8956176
```

```
# Fitted line:
```

```
#  $\hat{Y}_i = 0.8956176 * X_i - 42.1641$ 
```

```
plot(TEMP,PRESS_B,pch=19,col="blue",xlab="Boiling point in degrees of  
  ↪ Fahrenheit",ylab="100 * log10(Pressure measurement)",main="Scatter plot of Boiling  
  ↪ point versus 100 * log10(Pressure)") # need to plot before adding fitted line  
abline(fit_C,lty=2,col="red")
```

Scatter plot of Boiling point versus $100 * \log_{10}(\text{Pressure})$



ANOVA Table:

```
anova(fit_C)
```

```
## Analysis of Variance Table
```

```
##
```

```
## Response: PRESS_B
```

```
##           Df Sum Sq Mean Sq F value    Pr(>F)
```

```
## TEMP         1  425.76    425.76   2961.6 < 2.2e-16 ***
```

```
## Residuals   15    2.16     0.14
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# R^2 = 1 - (RSS/TSS)
```

```
#RSS - residual sum of squares
```

```
RSS_C = sum(fit_C$res^2)
```

```
#TSS - total sum of squares
```

```
TSS_C = sum((PRESS_B - (sum(PRESS_B)/n))^2)
```

```
R_2 = 1 - (RSS_C/TSS_C)
```

```
# R^2:
```

```
R_2
```

```
## [1] 0.9949606
```

```

# b1 and b0 are estimators and have ^ hats

# fit_C$coef[2] = b1
# fit_C$coef[1] = b0

# CI = b +- t_(1-alpha/2,df=n-2) * standard_error(b)

# 95% Confidence interval for b1 and b0 of 100*log(PRESS) on TEMP

# 95% CI for b1
b1_95CI = c(fit_C$coef[2]-qt(1-0.05/2,n-2)*summary(fit_C)$coef[4],+
  ↪ fit_C$coef[2]+qt(1-0.05/2,n-2)*summary(fit_C)$coef[4])
b1_95CI

```

```

##      TEMP      TEMP
## 0.8605393 0.9306958

```

```

# 95% CI for b0

b0_95CI = c(fit_C$coef[1]-qt(1-0.05/2,n-2)*summary(fit_C)$coef[3],+
  ↪ fit_C$coef[1]+qt(1-0.05/2,n-2)*summary(fit_C)$coef[3])
b0_95CI

```

```

## (Intercept) (Intercept)
## -49.63670 -34.69153

```

```

# Fitted value at 200F for 100*log(PRESS)
x_E<-200
fit_C$coef[1]+fit_C$coef[2]*x_E

```

```

## (Intercept)
## 136.9594

```

```

# Prediction at 200F for 100*log(PRESS) at 99% prediction interval
newdata_E = data.frame(TEMP=200)
predict(fit_C, newdata_E, interval="predict", level = 0.99)

```

```

##      fit      lwr      upr
## 1 136.9594 135.6493 138.2695

```

```

# 99% CI for 100*log(PRESS) for the fitted value at 200F
predict(fit_C, newdata_E, interval="confidence", level = 0.99)

```

```

##      fit      lwr      upr
## 1 136.9594 136.2753 137.6435

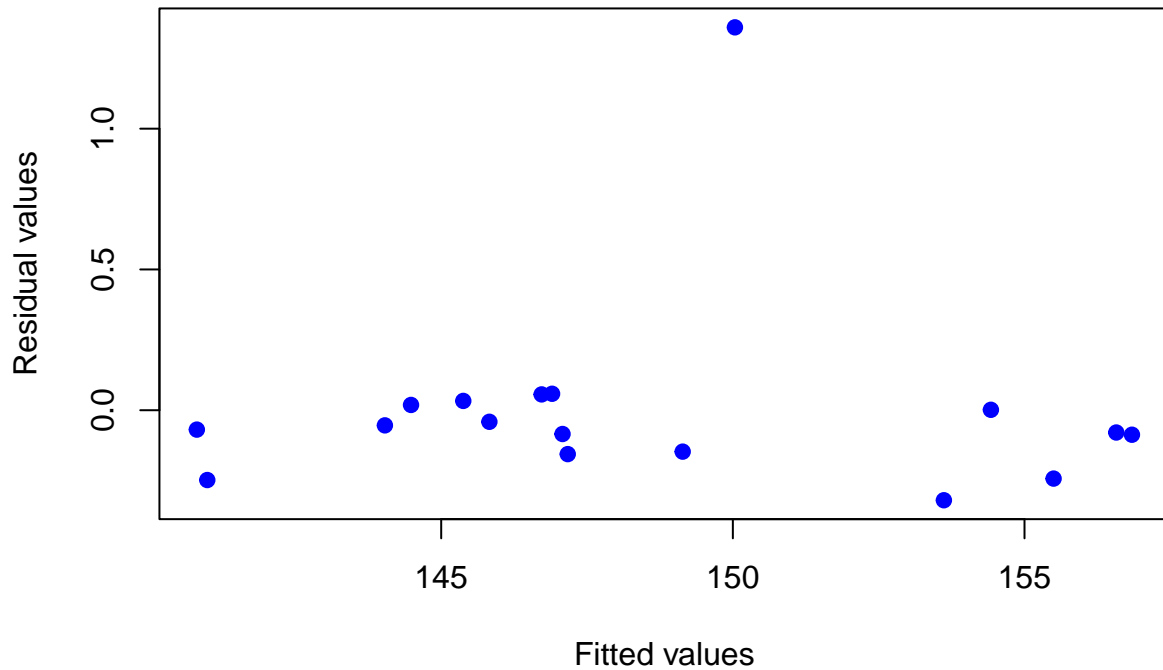
```

```

plot(fit_C$fit,fit_C$res,pch=19,col="blue",xlab="Fitted values",ylab="Residual
  ↪ values",main="Fitted vs. Residual values of 100*log(PRESS) vs. TEMP")

```

Fitted vs. Residual values of $100 \times \log(\text{PRESS})$ vs. TEMP



My conclusion is that the residuals versus fitted values is fitted extremely well; the
→ residual plot of $100 \times \log(\text{PRESS})$ vs. TEMP is a better fit than the residual plot of
→ PRESS vs. TEMP. All the residuals are mostly ± 0.25 , which is extremely well fitted.
→ The linear regression line will fit the data from $100 \times \log(\text{PRESS})$ vs. TEMP extremely
→ well. The only thing to note is the 1 outlier which has a residual of almost ± 1.5 .
→ This outlier is even more of an outlier than that from PRESS vs. TEMP, but overall,
→ the data from $100 \times \log(\text{PRESS})$ vs. TEMP is more fitted to the linear regression
→ (because there are 16 other points that were almost 2x more better fitted and the 1
→ outlier that is about 1.5x worse fitted).