

# Melting Point Data

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## Introduction

Karthikeyan's article is proposing a new model, using a neural network to analyze compounds and predict the melting points of said compounds. What I had to do was analyze the data in order to find correlation and causality between 2D factors, and the compounds melting point. After finding basic correlations with pairwise plots, and regression plots, I was able to perform BIC analyses to find causation if there was any. I found that the 2D descriptors that I measured heavily affected the melting point with differences in BIC scores >100. The article uses p scores to find whether or not signs were statistically significant, whereas I can look at the BIC score. Overall it is interesting to see the different methods used between this deliverable and the article, and the fact that they can achieve similar results. ## Importing data and Library For this project I am using tidyverse, dplyr and reading melting point data from M. Karthikeyan.

```
library(tidyverse)
library(dplyr)
#
#Load mouse data
mp <- read.csv("dirtyMPdata.csv", header = TRUE)
```

## Cleaning data

To start I looked at the data demographics.

```
names(mp)
```

```
## [1] "i..structure" "mp" "rings" "heavy.atoms"
## [5] "single.bonds" "triple.bonds" "reactive" "molar.mass"
## [9] "refractivity" "formal.charge" "logP" "tpsa"
## [13] "dipole.moment" "energy" "density" "volume"
## [17] "PCA1" "PCA2"
```

```
dim(mp)
```

```
## [1] 4450 18
```

```
str(mp)
```

```
## 'data.frame':    4450 obs. of  18 variables:
## $ i..structure : chr  "O=C1Cc2ccccc21" "Clc1ccc(cc1)C1c2c(OC(N)=C1C#N)[nH][nH0]c2C(F)(F)F" "O=C(OC)C(=Cc1ccccc1)Cc1ccccc1" "FC(F)(F)c1[nH0]cc2ccccc2c1" ...
## $ mp : num  14 20.5 27.5 30.5 31 31.5 32 32.5 33 34 ...
## $ rings : int  6 11 12 10 6 6 6 5 12 12 ...
## $ heavy.atoms : int  9 23 19 14 12 14 12 10 16 14 ...
## $ single.bonds : int  9 20 22 10 16 19 14 12 21 16 ...
## $ triple.bonds : int  0 1 0 0 0 0 0 0 0 0 ...
## $ reactive : int  0 0 0 0 1 0 0 0 0 0 ...
## $ molar.mass : num  118 341 252 197 162 ...
## $ refractivity : num  3.56 7.73 7.8 4.73 4.65 ...
## $ formal.charge: int  0 0 0 0 0 0 0 0 0 0 ...
## $ logP : num  1.43 3.64 3.49 3.57 1.94 ...
## $ tpsa : num  17.1 87.7 26.3 12.9 26.3 ...
## $ dipole.moment: num  2.72 6.32 1.91 5.2 1.76 ...
## $ energy : num  -57.8 -189.1 -123.5 -119.7 -83.5 ...
## $ density : num  0.959 1.296 0.946 1.195 0.978 ...
## $ volume : num  123 263 267 165 166 ...
## $ PCA1 : num  15.55 1.92 2.98 11.03 10.97 ...
## $ PCA2 : num  1.622 0.502 2.723 1.826 -0.905 ...
```

```
sapply(mp, class)
```

```
## i..structure      mp      rings  heavy.atoms  single.bonds
## "character"      "numeric"  "integer"    "integer"    "integer"
## triple.bonds      reactive  molar.mass  refractivity  formal.charge
## "integer"        "integer"  "numeric"    "numeric"    "integer"
## logP              tpsa  dipole.moment  energy      density
## "numeric"        "numeric"  "numeric"    "numeric"    "numeric"
## volume            PCA1      PCA2
## "numeric"        "numeric"  "numeric"
```

```
head(mp)
```

```

##                                     i..structure   mp rings heavy.atoms
## 1                                     O=C1Cc2ccccc21 14.0      6          9
## 2 Clc1ccc(cc1)C1c2c(OC(N)=C1C#N)[nH][nH0]c2C(F)(F)F 20.5     11         23
## 3                                     O=C(OC)C(=Cc1ccccc1)Cc1ccccc1 27.5     12         19
## 4                                     FC(F)(F)c1[nH0]cc2ccccc2c1 30.5     10         14
## 5                                     O=C(OC1Cc2ccccc21)C 31.0      6          12
## 6                                     O=C(OC)C1=Cc2ccccc2C1C 31.5      6          14
##   single.bonds triple.bonds reactive molar.mass refractivity formal.charge
## 1           9           0           0      118.135      3.557232          0
## 2          20           1           0      340.692      7.729887          0
## 3          22           0           0      252.313      7.799344          0
## 4          10           0           0      197.159      4.729193          0
## 5          16           0           1      162.188      4.651153          0
## 6          19           0           0      188.226      5.533352          0
##   logP  tpsa dipole.moment      energy  density  volume  PCA1  PCA2
## 1 1.425370 17.07      2.722717 -57.76601 0.9589853 123.1875 15.5507 1.6219
## 2 3.637884 87.72      6.320718 -189.06262 1.2962539 262.8281 1.9216 0.5024
## 3 3.485670 26.30      1.911006 -123.45357 0.9463216 266.6250 2.9803 2.7226
## 4 3.565100 12.89      5.203625 -119.71445 1.1952425 164.9531 11.0316 1.8263
## 5 1.942370 26.30      1.759848 -83.47468 0.9782332 165.7969 10.9710 -0.9051
## 6 2.360100 26.30      2.046720 -95.11963 0.9741601 193.2188 8.9700 0.3246

```

tail(mp)

```

##                                     i..structure   mp rings
## 4445                                     N=1CCNC=1Cc1c(C)cc(cc1C)C(C)(C)C 131      6
## 4446                                     O=C(OC)C1C(0)CCC2CN3CCc4c5ccccc5[nH]c4C3CC21 234      9
## 4447                                     O=C1NC(=O)C(C)=CN1C10C(CO)C(N=[N+]=[N-])C1 106      0
## 4448                                     s1c2ccccc2cc1C(N(0)C(=O)N)C 157      9
## 4449 [S+2]([O-])([O-])(C)c1ccc(cc1)c1[nH0]c2[nH0](C=CC=C2)c1 242     11
## 4450 Clc1ccc2Sc3ccccc3C=C(OCCN(C)C)c2c1 90      12
##   heavy.atoms single.bonds triple.bonds reactive molar.mass refractivity
## 4445          18          37           0           0      245.390      7.652000
## 4446          26          46           0           1      355.458      9.993037
## 4447          19          28           0           1      267.245      6.299167
## 4448          16          18           0           1      236.295      6.457717
## 4449          19          20           0           0      272.328      7.474073
## 4450          22          30           0           0      332.875      9.547561
##   formal.charge  logP  tpsa dipole.moment      energy  density  volume
## 4445           1 1.22571 26.00      13.028417 -112.7691 0.8720617 281.3906
## 4446           1 1.32547 66.76       8.226915 -177.9712 1.0188236 348.8906
## 4447           0 0.22820 103.59      4.728840 -146.1079 1.1644663 229.5000
## 4448           0 2.82770 66.56       1.821058 -112.0673 1.0833784 218.1094
## 4449           0 2.45110 51.96       8.410813 -127.4689 1.0959562 248.4844
## 4450           1 3.26210 13.67      23.597216 -146.3722 1.0327710 322.3125
##   PCA1  PCA2
## 4445  2.2338 1.6217
## 4446 -3.7905 -1.1574
## 4447  2.7954 -7.6893
## 4448  5.4399 -3.3301
## 4449  3.0028 -0.5994
## 4450 -0.2923 4.3546

```

```
glimpse(mp)
```

```
## Rows: 4,450
## Columns: 18
## $ i..structure <chr> "O=C1Cc2ccccc21", "Clc1ccc(cc1)C1c2c(OC(N)=C1C#N)[nH]...
## $ mp <dbl> 14.0, 20.5, 27.5, 30.5, 31.0, 31.5, 32.0, 32.5, 33.0,...
## $ rings <int> 6, 11, 12, 10, 6, 6, 6, 5, 12, 12, 6, 14, 11, 6, 6, 6...
## $ heavy.atoms <int> 9, 23, 19, 14, 12, 14, 12, 10, 16, 14, 11, 22, 18, 12...
## $ single.bonds <int> 9, 20, 22, 10, 16, 19, 14, 12, 21, 16, 13, 26, 23, 17...
## $ triple.bonds <int> 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
## $ reactive <int> 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,...
## $ molar.mass <dbl> 118.135, 340.692, 252.313, 197.159, 162.188, 188.226,...
## $ refractivity <dbl> 3.557232, 7.729887, 7.799344, 4.729193, 4.651153, 5.5...
## $ formal.charge <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,...
## $ logP <dbl> 1.425370, 3.637884, 3.485670, 3.565100, 1.942370, 2.3...
## $ tpsa <dbl> 17.070000, 87.720001, 26.299999, 12.890000, 26.299999...
## $ dipole.moment <dbl> 2.7227166, 6.3207178, 1.9110060, 5.2036252, 1.7598478...
## $ energy <dbl> -57.76601, -189.06262, -123.45357, -119.71445, -83.47...
## $ density <dbl> 0.9589853, 1.2962539, 0.9463216, 1.1952425, 0.9782332...
## $ volume <dbl> 123.1875, 262.8281, 266.6250, 164.9531, 165.7969, 193...
## $ PCA1 <dbl> 15.5507, 1.9216, 2.9803, 11.0316, 10.9710, 8.9700, 10...
## $ PCA2 <dbl> 1.6219, 0.5024, 2.7226, 1.8263, -0.9051, 0.3246, 0.75...
```

```
summary(mp)
```

```
## i.structure          mp          rings          heavy.atoms
## Length:4450         Min.    : 14.0    Min.    : 0.000    Min.    : 6.00
## Class :character    1st Qu.:117.5    1st Qu.: 6.000    1st Qu.:17.00
## Mode  :character    Median :161.5    Median :11.000    Median :22.00
##                               Mean   :165.3    Mean   : 9.956    Mean   :22.24
##                               3rd Qu.:209.4    3rd Qu.:12.000    3rd Qu.:26.00
##                               Max.    :392.5    Max.    :36.000    Max.    :59.00
##
## single.bonds         triple.bonds         reactive         molar.mass
## Min.    : 4.00       Min.    :0.0000    Min.    :0.0000    Min.    : 84.08
## 1st Qu.: 19.00       1st Qu.:0.0000    1st Qu.:0.0000    1st Qu.:243.27
## Median : 24.00       Median :0.0000    Median :0.0000    Median :308.33
## Mean   : 28.24       Mean   :0.1058    Mean   :0.2209    Mean   :317.41
## 3rd Qu.: 33.00       3rd Qu.:0.0000    3rd Qu.:0.0000    3rd Qu.:375.38
## Max.    :119.00      Max.    :4.0000    Max.    :1.0000    Max.    :815.62
##
## refractivity         formal.charge         logP             tpsa
## Min.    : 1.992     Min.    :-3.00000    Min.    :-6.023    Min.    : 0.00
## 1st Qu.: 6.609     1st Qu.: 0.00000    1st Qu.: 2.106    1st Qu.: 38.33
## Median : 8.310     Median : 0.00000    Median : 3.221    Median : 61.07
## Mean   : 8.514     Mean   : 0.01236    Mean   : 3.337    Mean   : 67.50
## 3rd Qu.:10.179     3rd Qu.: 0.00000    3rd Qu.: 4.529    3rd Qu.: 88.06
## Max.    :19.354     Max.    : 2.00000    Max.    :12.780    Max.    :413.24
##
## dipole.moment        energy          density          volume
## Min.    : 0.000     Min.    : -489.00    Min.    :0.7945    Min.    : 78.89
## 1st Qu.: 2.375     1st Qu.: -186.18    1st Qu.:0.9812    1st Qu.:230.77
## Median : 3.811     Median : -150.42    Median :1.0540    Median :285.19
## Mean   : 5.210     Mean   : -157.51    Mean   :1.0804    Mean   :294.47
## 3rd Qu.: 5.633     3rd Qu.: -118.36    3rd Qu.:1.1432    3rd Qu.:349.31
## Max.    :248.303    Max.    : -44.35    Max.    :1.8956    Max.    :728.58
##                               NA's      :13
## PCA1                PCA2
## Min.    : -33.7975   Min.    : -19.9754
## 1st Qu.: -4.1177     1st Qu.: -2.8547
## Median : 0.6655      Median : 0.3189
## Mean   : 0.0000      Mean   : 0.0000
## 3rd Qu.: 4.6769      3rd Qu.: 3.2613
## Max.    : 17.3486    Max.    : 12.4899
##
```

Then I noticed that when the energy was missing the dipole moment was 0. So I changed the 0s to N/A's and replaced them.  
 ### Replacing N/As Then to check for missing data I ran each column under a na check that looks like the following

```
any(is.na(mp$structure))#F
```

```
## [1] FALSE
```

```
any(is.na(mp$mp))#F
```

```
## [1] FALSE
```

```
any(is.na(mp$strings))#F
```

```
## [1] FALSE
```

```
#ETC.....
```

I discovered that the only column with missing data was the energy column. So, I replaced the missing values with the mean of the column using the following code.

```
mp$energy <- ifelse(is.na(mp$energy), mean(mp$energy, na.rm=TRUE), mp$energy)
mp$dipole.moment[mp$dipole.moment == 0] <- NA
mp$dipole.moment <- ifelse(is.na(mp$energy), mean(mp$energy, na.rm = TRUE), mp$energy)
```

## New table

I needed to somewhat replicate table one from the reading, which I noticed contained data from the summary command. I created an empty table with arbitrary values to start with.

```
table1data <- data.frame(A= numeric(0), B= numeric(0)) #Creating a data frame with arbitrary numbers so i can easily add things
table1data[1:6,] <- c(5,23) #filling in spots so I can add
```

Next I added the summary statistics from each column I needed. But first I created a list of names that would become the column titles.

```
names<- c("Min", "1 Quartile", "2 Quartile", "Mean", " 3 Quartile", 'Max') #Will be thre names for the columns
#
table1data <- mutate(table1data, row = names) #Actually adding what I need
table1data <- mutate(table1data, Melting_Point_C = summary(mp$mp))
table1data <- mutate(table1data, Molecular_weight =summary(mp$molar.mass))
table1data <- mutate(table1data, Num_heavy_atoms=summary(mp$heavy.atoms))
table1data <- mutate(table1data, SlogP=summary(mp$logP))
table1data <- mutate(table1data, Molar_refractivity=summary(mp$refractivity))
table1data <- mutate(table1data, dipole_moment=summary(mp$dipole.moment))
```

Finally I got rid of the two 'dummy' rows, A and B.

```
table1data$A <- NULL
table1data$B <-NULL
```

This is the new data set:

```
table1data
```

##	row	Melting_Point_C	Molecular_weight	Num_heavy_atoms	SlogP
## 1	Min	14.0000	84.0780	6.00000	-6.023260
## 2	1 Quartile	117.5000	243.2710	17.00000	2.106125
## 3	2 Quartile	161.5000	308.3345	22.00000	3.220600
## 4	Mean	165.2896	317.4089	22.23506	3.337355
## 5	3 Quartile	209.3750	375.3785	26.00000	4.529044
## 6	Max	392.5000	815.6210	59.00000	12.780020

##	Molar_refractivity	dipole_moment
## 1	1.992427	-488.9954
## 2	6.608528	-186.1653
## 3	8.309703	-150.6026
## 4	8.514301	-157.5131
## 5	10.179192	-118.4209
## 6	19.353979	-44.3485

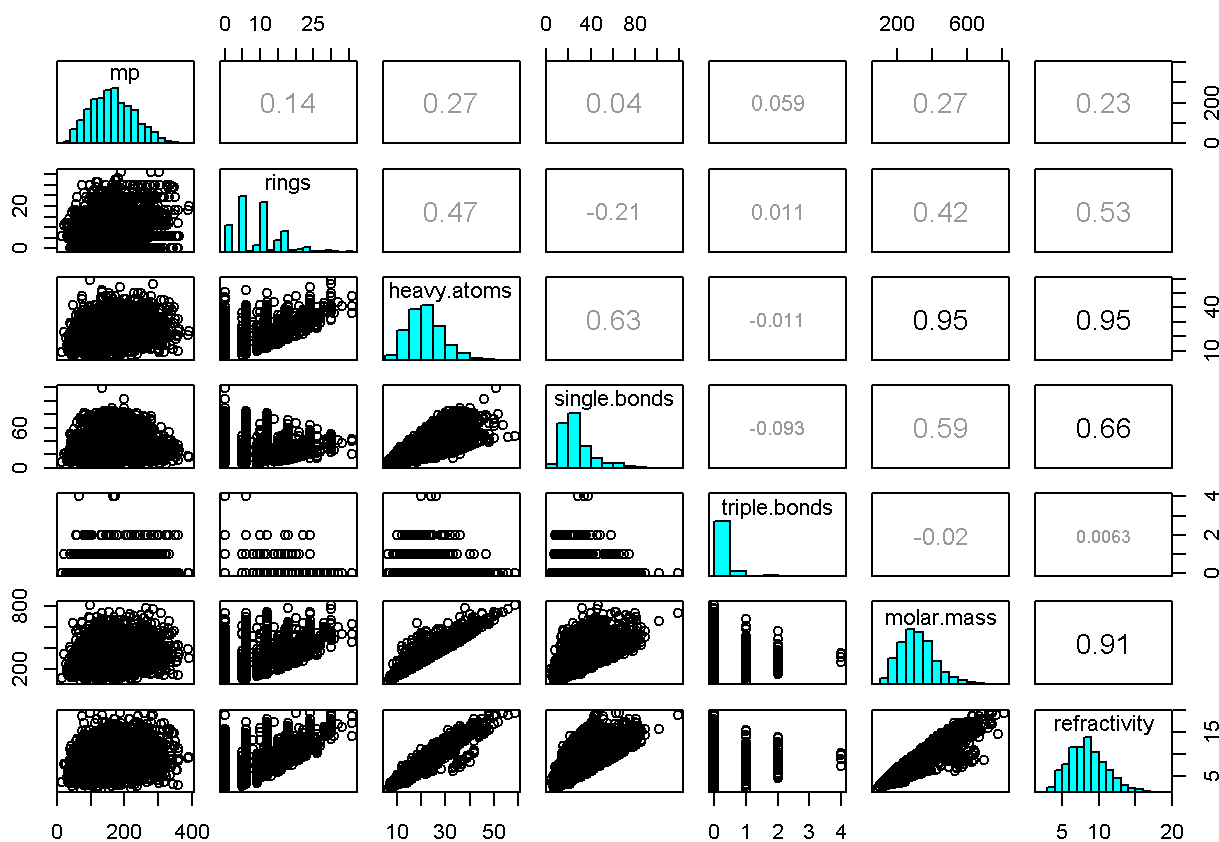
## Analysis

To start my analysis I always like to do some pairwise plots to just get a grasp on the data. With this many columns one pairwise plot is too big so I split the data in half and just did two pairwise plots.

```

numerics1 <-mp[,c(2:6,8:9)] #small first half
numerics2 <-mp[,c(11:18)] #second half
pairs(numerics1,upper.panel = panel.cor,diag.panel=panel.hist)

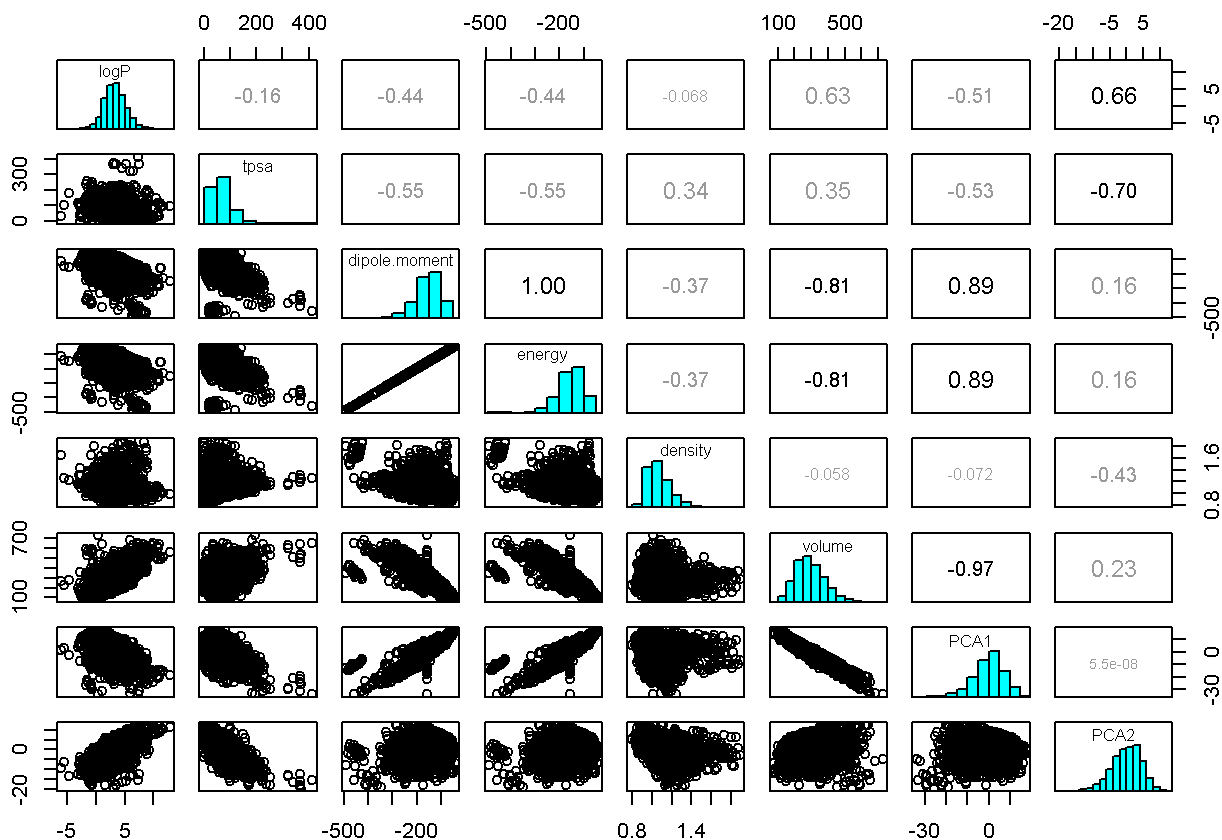
```



```

pairs(numerics2,upper.panel = panel.cor,diag.panel=panel.hist)

```



## Linear regressions

Next I needed to do some linear regressions of the three 2D descriptors. I first did melting point and the dformal charge of the compound and found that the charge has a negative correlation with the melting point.

```
mpxcharge <- lm(mp$mp~mp$formal.charge) #comparing melting point and formal charge
mpxcharge
```

```
##
## Call:
## lm(formula = mp$mp ~ mp$formal.charge)
##
## Coefficients:
##      (Intercept)  mp$formal.charge
##           165.57             -22.46
```

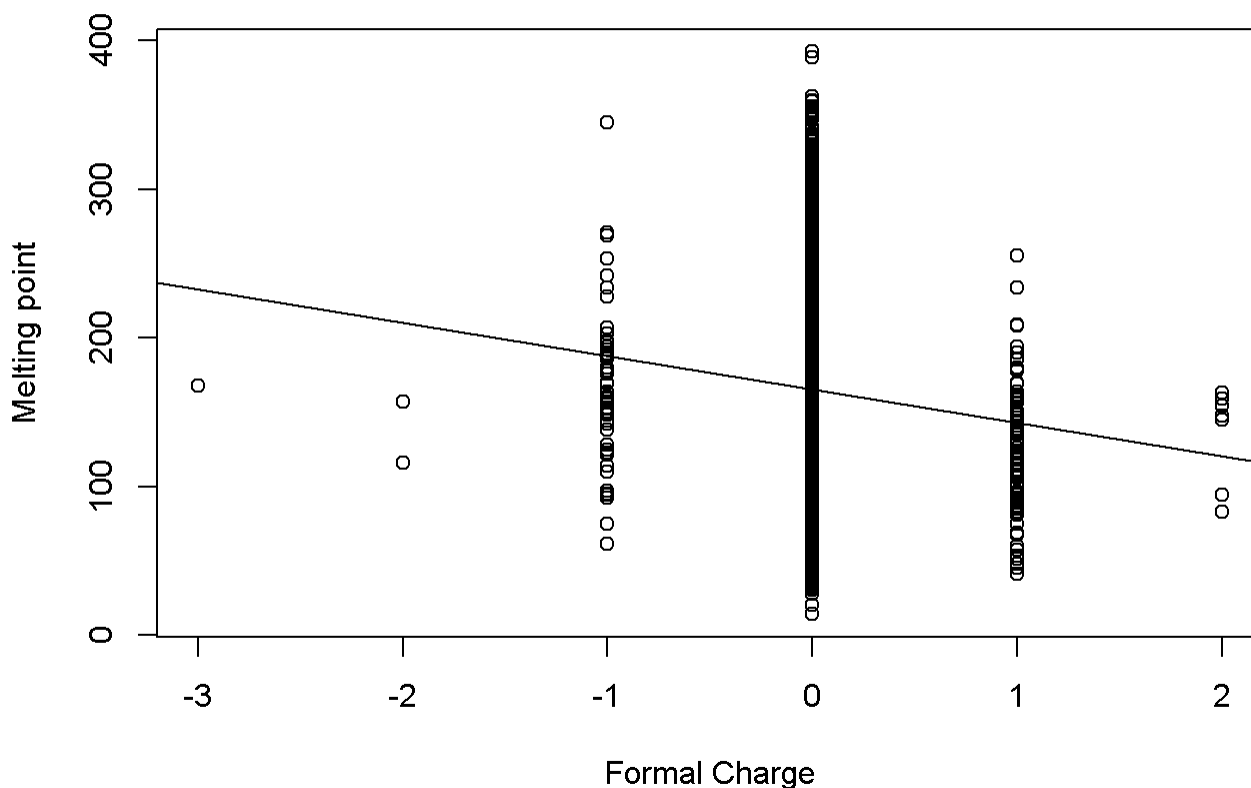
```
summary(mpxcharge)
```



```
##
## Call:
## lm(formula = mp$mp ~ mp$formal.charge)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -151.567  -47.567   -3.567   43.933  226.933
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    165.5672     0.9602 172.430 < 2e-16 ***
## mp$formal.charge -22.4622     4.5180  -4.972 6.89e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 63.94 on 4448 degrees of freedom
## Multiple R-squared:  0.005526,    Adjusted R-squared:  0.005303
## F-statistic: 24.72 on 1 and 4448 DF,  p-value: 6.885e-07
```

```
plot(mp$mp~mp$formal.charge, main = "Plot of Melting Point vs formal Charge",      #doing an actual plot
      xlab = "Formal Charge", ylab = "Melting point")
abline(mpxcharge)
```

**Plot of Melting Point vs formal Charge**



```
mpxcharge$coefficients
```

```
##      (Intercept) mp$formal.charge
##      165.56722      -22.46217
```

```
mpxchargefit <- mpxcharge$fitted.values #Just to take a look
#melting point has a negative correlation with formal charge
```

Next I did melting point and volume and found there to be a positive correlation.

```
#Doing mp and volume
mpxvol <- lm(mp$mp~mp$volume) #comparing melting point and formal charge
mpxvol
```

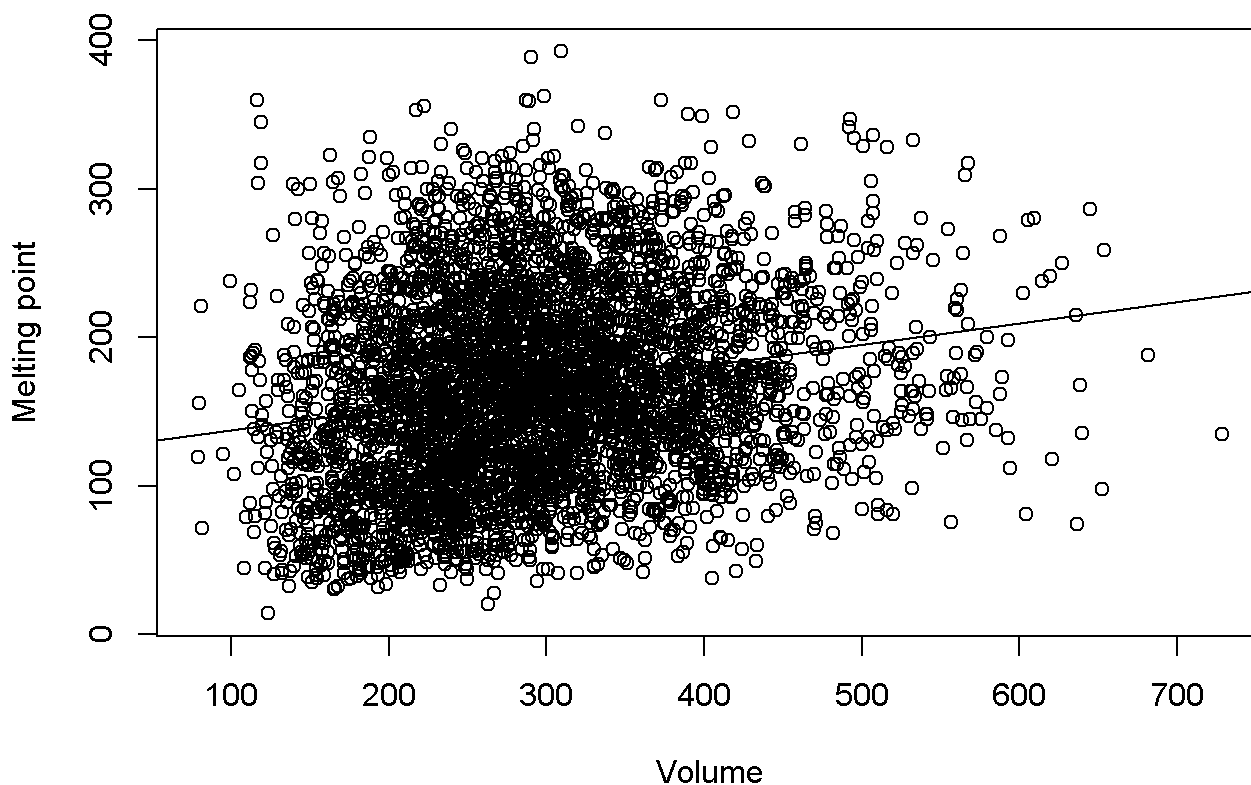
```
##
## Call:
## lm(formula = mp$mp ~ mp$volume)
##
## Coefficients:
## (Intercept)      mp$volume
##      122.9602         0.1437
```

```
summary(mpxvol)
```

```
##
## Call:
## lm(formula = mp$mp ~ mp$volume)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -143.177  -47.840   -5.304   42.298  225.089
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 122.96017    3.18370   38.62  <2e-16 ***
## mp$volume    0.14375    0.01033   13.92  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 62.77 on 4448 degrees of freedom
## Multiple R-squared:  0.04173,    Adjusted R-squared:  0.04151
## F-statistic: 193.7 on 1 and 4448 DF,  p-value: < 2.2e-16
```

```
plot(mp$mp~mp$volume, main = "Plot of Melting Point vs volume",      #doing an actual plot
      xlab = "Volume", ylab = "Melting point")
abline(mpxvol)
```

Plot of Melting Point vs volume



```
mpxvol$coefficients
```

```
## (Intercept)    mp$volume  
## 122.9601674    0.1437456
```

```
mpxvolfit <- mpxvol$fitted.values  
#There is a positive correlation between melting point and volume
```

And finally I did refractivity and melting point and found, again, a positive correlation.

```
#Now doing refractivity and melting point  
mpxref <- lm(mp$mp~mp$refractivity) #comparing melting point and formal charge  
mpxref
```

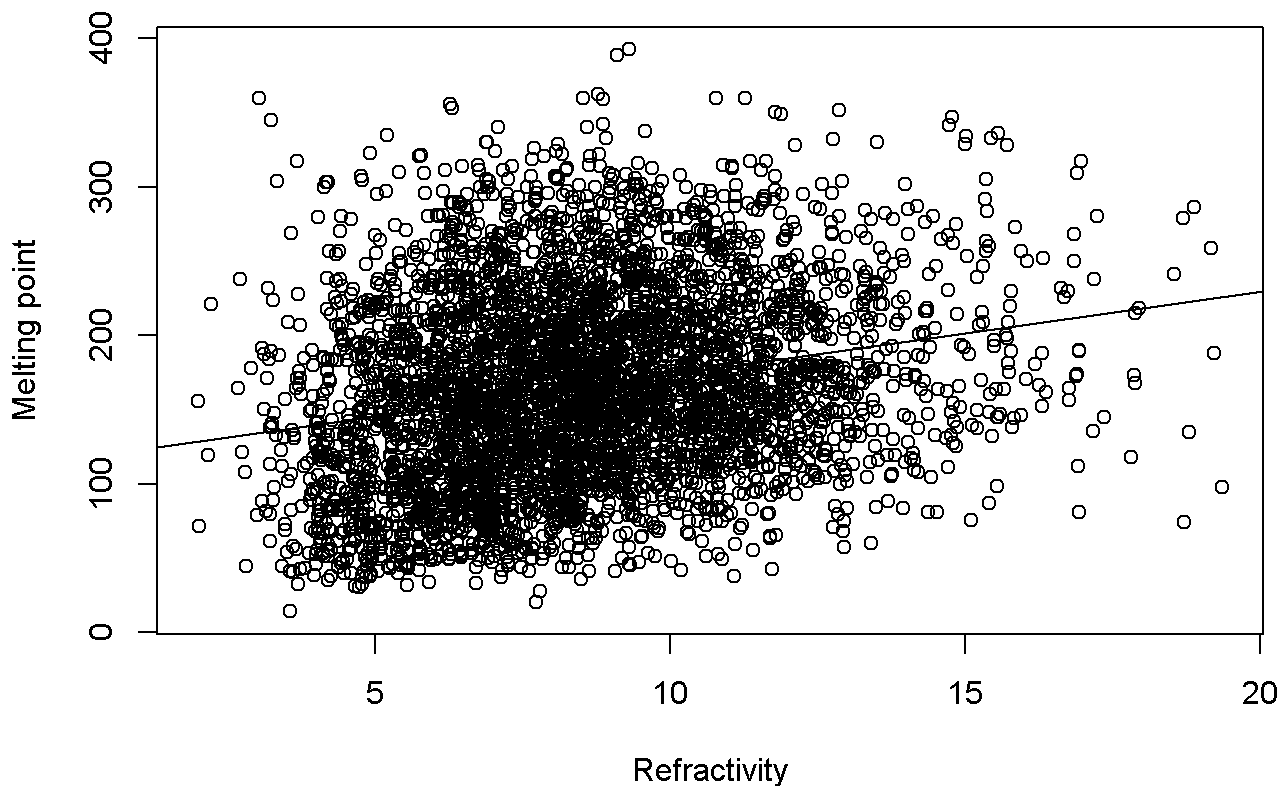
```
##  
## Call:  
## lm(formula = mp$mp ~ mp$refractivity)  
##  
## Coefficients:  
##      (Intercept)  mp$refractivity  
##      117.474      5.616
```

```
summary(mpxref)
```

```
##
## Call:
## lm(formula = mp$mp ~ mp$refractivity)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -148.530  -47.402   -5.525   41.857  225.477
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    117.4745     3.1181   37.67  <2e-16 ***
## mp$refractivity     5.6159     0.3494   16.07  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 62.34 on 4448 degrees of freedom
## Multiple R-squared:  0.05489,    Adjusted R-squared:  0.05468
## F-statistic: 258.4 on 1 and 4448 DF,  p-value: < 2.2e-16
```

```
plot(mp$mp~mp$refractivity, main = "Plot of Melting Point vs Refractivity",      #doing an actual
1 plot
      xlab = "Refractivity", ylab = "Melting point")
abline(mpxref)
```

**Plot of Melting Point vs Refractivity**



```
mpxref$coefficients
```

```
## (Intercept) mp$refractivity
## 117.474495 5.615857
```

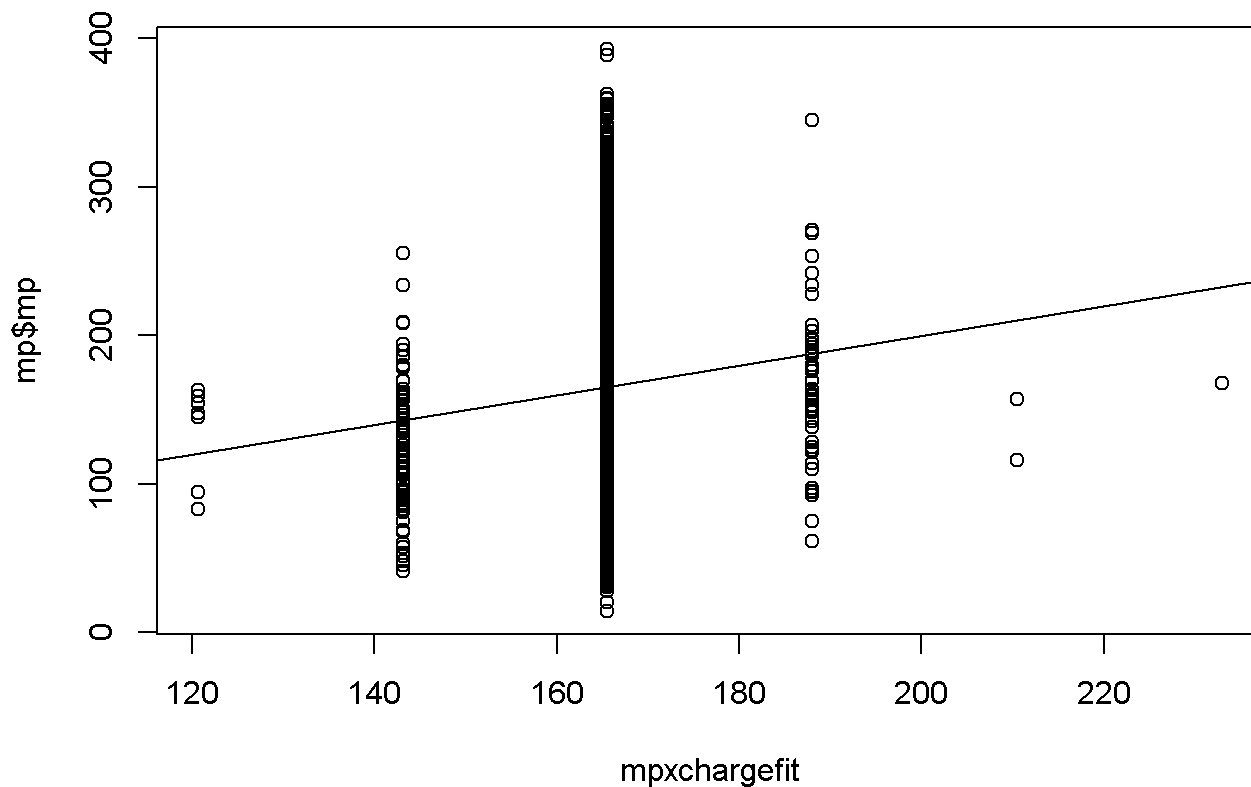
```
mpxreffit <- mpxref$fitted.values
```

*#There is a positive correlation between refractivity and melting point*

## Expirimental vs predicted

Next I had to do a plot of the expirimental (from the data) values and the predicted (fitted) values from the regressions I had done. First I did charge and melting point

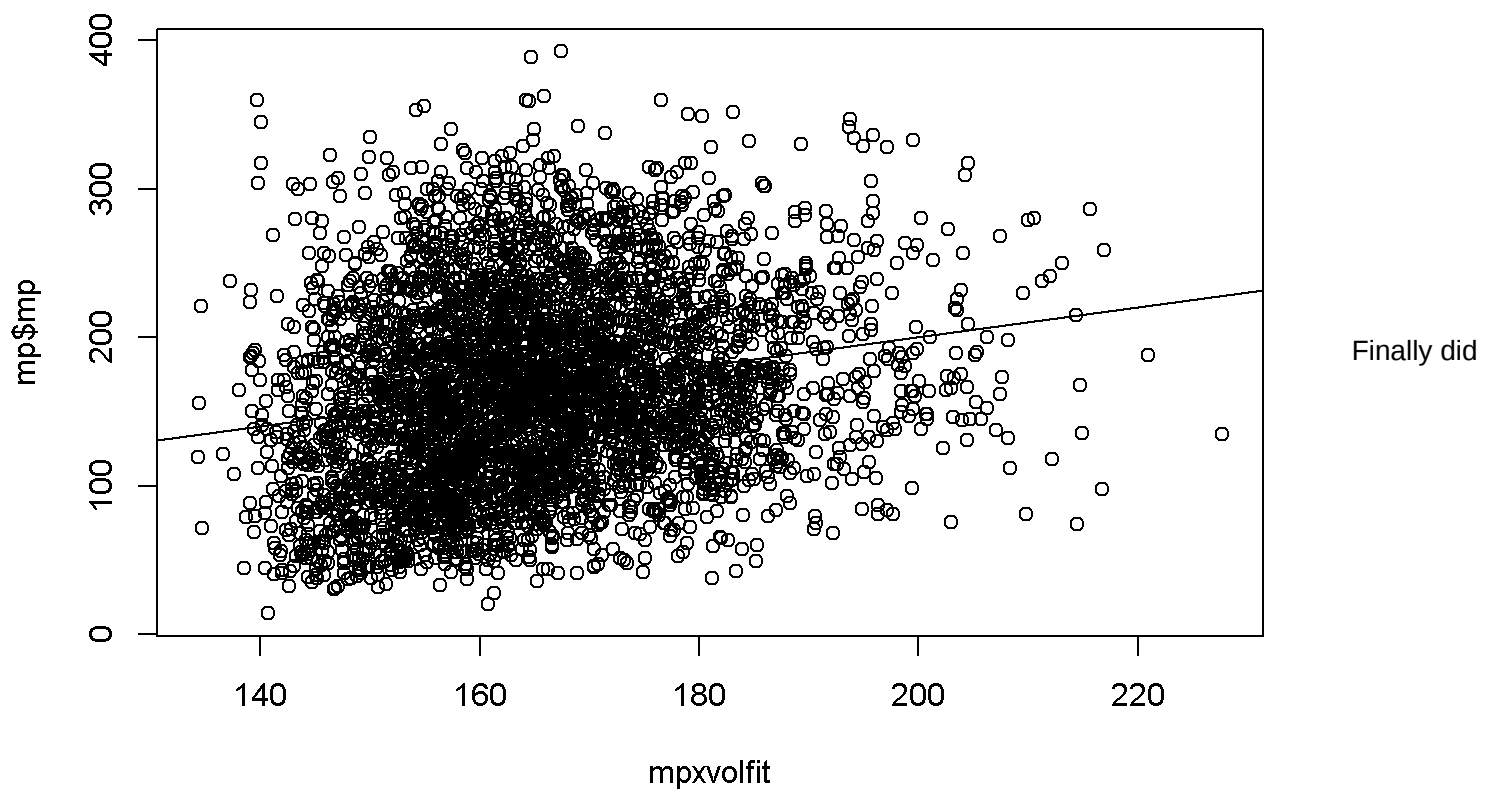
```
#charge and mp
mpmpchargefit <- lm(mp$mp~mpxchargefit)
plot(mp$mp~mpxchargefit)
abline(mpmpchargefit)
```



Then I did

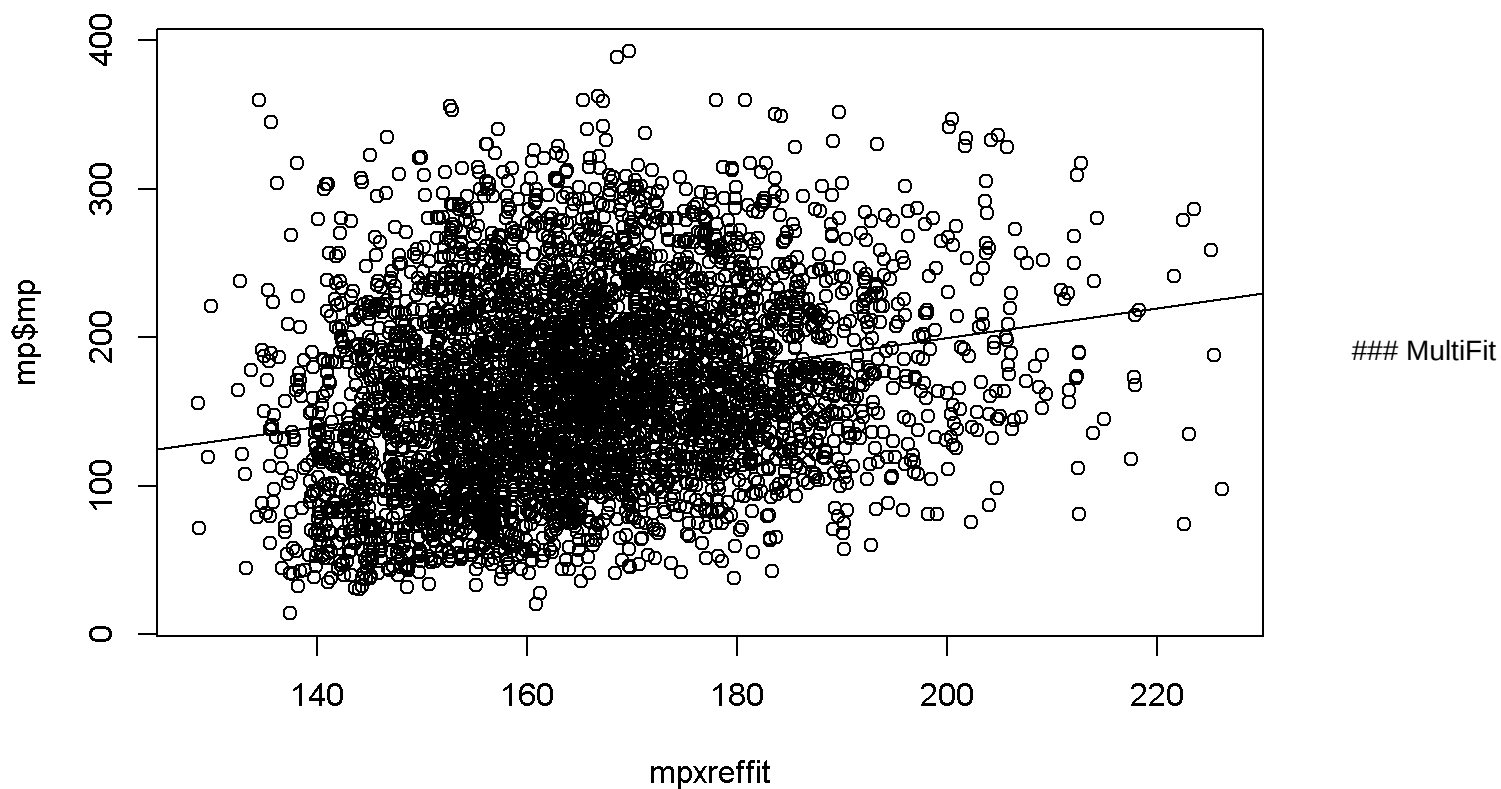
volume and melting point.

```
#mp/volume
mpmpvolfit <- lm(mp$mp~mpxvolfit)
plot(mp$mp~mpxvolfit)
abline(mpmpvolfit)
```



refractivity and melting point.

```
#And finally refractivity  
mpmpreflfit <- lm(mp$mp~mpxreffit)  
plot(mp$mp~mpxreffit)  
abline(mpmpreflfit)
```



Regression Next I did a multifit regression to look at how all of those correlate to melting point.

```
#Multiple linear regression
multifit <- lm(mp$mp~mp$formal.charge+mp$volume+mp$refractivity)
multifit
```

```
##
## Call:
## lm(formula = mp$mp ~ mp$formal.charge + mp$volume + mp$refractivity)
##
## Coefficients:
##      (Intercept)  mp$formal.charge      mp$volume  mp$refractivity
##      123.0117      -22.7805      -0.7187       29.8553
```

```
summary(multifit)
```

```
##
## Call:
## lm(formula = mp$mp ~ mp$formal.charge + mp$volume + mp$refractivity)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -151.529  -46.495   -5.889   42.009  230.036
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    123.01167     3.10703   39.591 < 2e-16 ***
## mp$formal.charge -22.78054     4.33599   -5.254 1.56e-07 ***
## mp$volume        -0.71869     0.06285  -11.435 < 2e-16 ***
## mp$refractivity   29.85526     2.14004   13.951 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 61.22 on 4446 degrees of freedom
## Multiple R-squared:  0.0888, Adjusted R-squared:  0.08818
## F-statistic: 144.4 on 3 and 4446 DF, p-value: < 2.2e-16
```

## BIC Analysis

Now to look at causation I performed a BIC analysis on melting point in reference to volume, and meltingpoint in reference to refractivity, with refractivity first.

```
#BIC analysis
#Does refractivity have an affect on Melting point?
refmel<-lm(mp$mp~mp$refractivity) #Comparing here to look at the summary
summary(refmel)
```

```
##
## Call:
## lm(formula = mp$mp ~ mp$refractivity)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -148.530  -47.402   -5.525   41.857  225.477
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    117.4745     3.1181   37.67 <2e-16 ***
## mp$refractivity   5.6159     0.3494   16.07 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 62.34 on 4448 degrees of freedom
## Multiple R-squared:  0.05489, Adjusted R-squared:  0.05468
## F-statistic: 258.4 on 1 and 4448 DF, p-value: < 2.2e-16
```

```
BIC(lm(mp$mp~1)) #Comparing to one
```



```
## [1] 49674.4
```

```
BIC(lm(mp$mp~mp$refractivity)) #looking at difference
```

```
## [1] 49431.56
```

```
#YES
```

There was an obvious difference that was greater than 10. So refractivity truly does affect the melting point of the compounds.

```
#Does volume have an affect on melting point  
volmel<-lm(mp$mp~mp$volume) #Comparing here to look at the summary  
summary(volmel)
```

```
##  
## Call:  
## lm(formula = mp$mp ~ mp$volume)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -143.177  -47.840   -5.304   42.298  225.089   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept) 122.96017     3.18370   38.62  <2e-16 ***  
## mp$volume    0.14375     0.01033   13.92  <2e-16 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Residual standard error: 62.77 on 4448 degrees of freedom  
## Multiple R-squared:  0.04173,    Adjusted R-squared:  0.04151   
## F-statistic: 193.7 on 1 and 4448 DF,  p-value: < 2.2e-16
```

```
BIC(lm(mp$mp~1)) #Comparing to one
```

```
## [1] 49674.4
```

```
BIC(lm(mp$mp~mp$volume)) #looking at difference
```

```
## [1] 49493.12
```

```
#Yes
```

Just like refractivity, volume also affects the melting point.

## Reference

For reference I used the article General Melting Point Prediction Based on a Diverse Compound Data Set and Artificial Neural Networks by M. Karthikeyan.