

VS\_sup

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## Virtual screening for high affinity guests for synthetic supramolecular receptors

### Orginal literature

<https://doi.org/10.1039/C5SC00534E>

### Function used in this analysis

I don't have a R data science package(library) yet...

### Replication of our analysis in the manuscript using python

We load cleaned data from the supporting information

```
df = read.csv("tab_gold_wt.csv", header = TRUE)
```

### Run some exploratory data analysis

#### Data summary

```
summary(df)
```

```
##      Guest      Ligand_clash      Ligand_torsion      Part_buried
##  Min.   : 1   Min.   :0.00000   Min.   :0.0000   Min.   :-4.621
##  1st Qu.:18  1st Qu.:0.00000  1st Qu.:0.0000  1st Qu.:-3.046
##  Median :35  Median :0.00000  Median :0.0000  Median :-2.193
##  Mean   :35  Mean   :0.02582  Mean   :0.0650  Mean   :-2.027
##  3rd Qu.:52  3rd Qu.:0.00000  3rd Qu.:0.0016  3rd Qu.:-1.708
##  Max.   :69  Max.   :1.78130  Max.   :1.0855  Max.   : 8.908
##      Non.polar      Ligand_flexibility      logKexp
##  Min.   :-72.20   Min.   :0.0000   Min.   :-1.000
##  1st Qu.:-49.49  1st Qu.:0.0000  1st Qu. : 1.860
##  Median :-40.64  Median :0.0000  Median : 3.600
##  Mean   :-42.43  Mean   :0.7971  Mean   : 3.167
##  3rd Qu.:-34.32  3rd Qu.:1.0000  3rd Qu. : 4.300
##  Max.   :-22.77  Max.   :7.0000  Max.   : 8.000
```

we still have guest number the data frame we will remove it

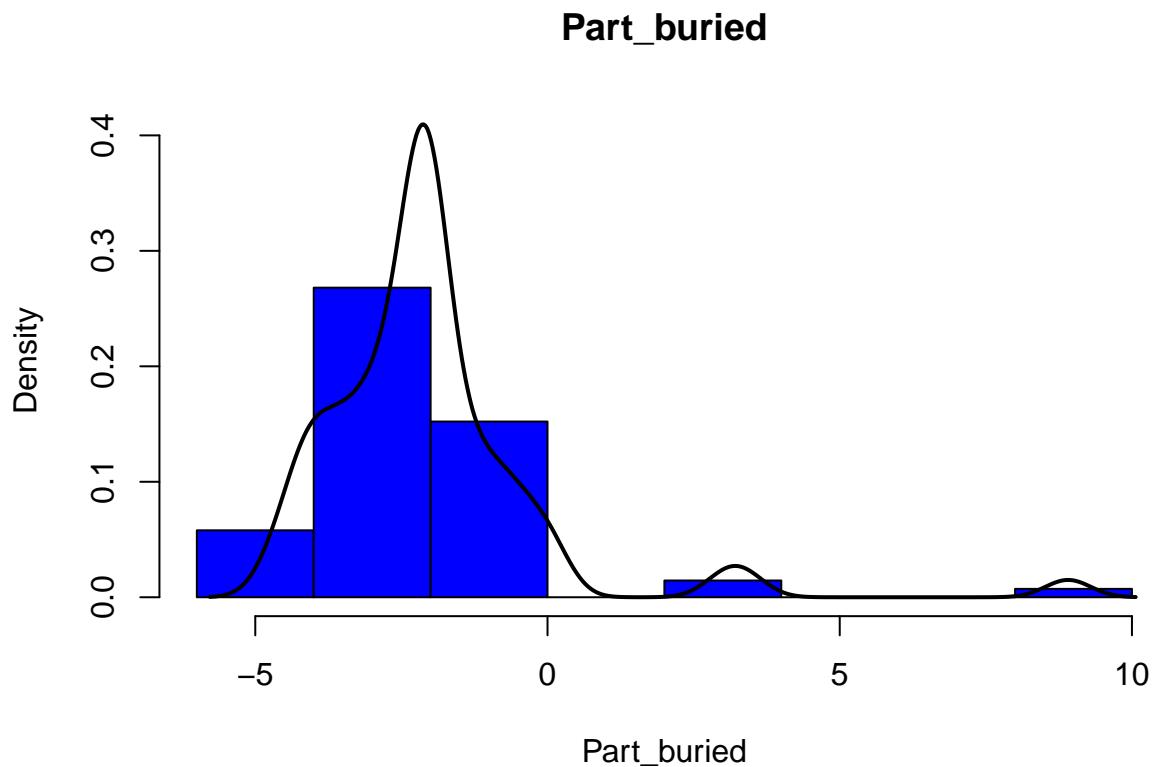
```
df <- df[ -c(1)]
summary(df)

##   Ligand_clash      Ligand_torsion     Part_buried      Non.polar
##   Min.   :0.00000   Min.   :0.00000   Min.   :-4.621   Min.   :-72.20
##   1st Qu.:0.00000  1st Qu.:0.00000  1st Qu.:-3.046  1st Qu.:-49.49
##   Median :0.00000  Median :0.00000  Median :-2.193  Median :-40.64
##   Mean   :0.02582  Mean   :0.0650   Mean   :-2.027  Mean   :-42.43
##   3rd Qu.:0.00000  3rd Qu.:0.0016  3rd Qu.:-1.708  3rd Qu.:-34.32
##   Max.   :1.78130  Max.   :1.0855   Max.   : 8.908  Max.   :-22.77
##   Ligand_flexibility    logKexp
##   Min.   :0.0000   Min.   :-1.000
##   1st Qu.:0.0000  1st Qu.: 1.860
##   Median :0.0000  Median : 3.600
##   Mean   :0.7971  Mean   : 3.167
##   3rd Qu.:1.0000  3rd Qu.: 4.300
##   Max.   :7.0000  Max.   : 8.000
```

### Histogram with KDE line for clarity

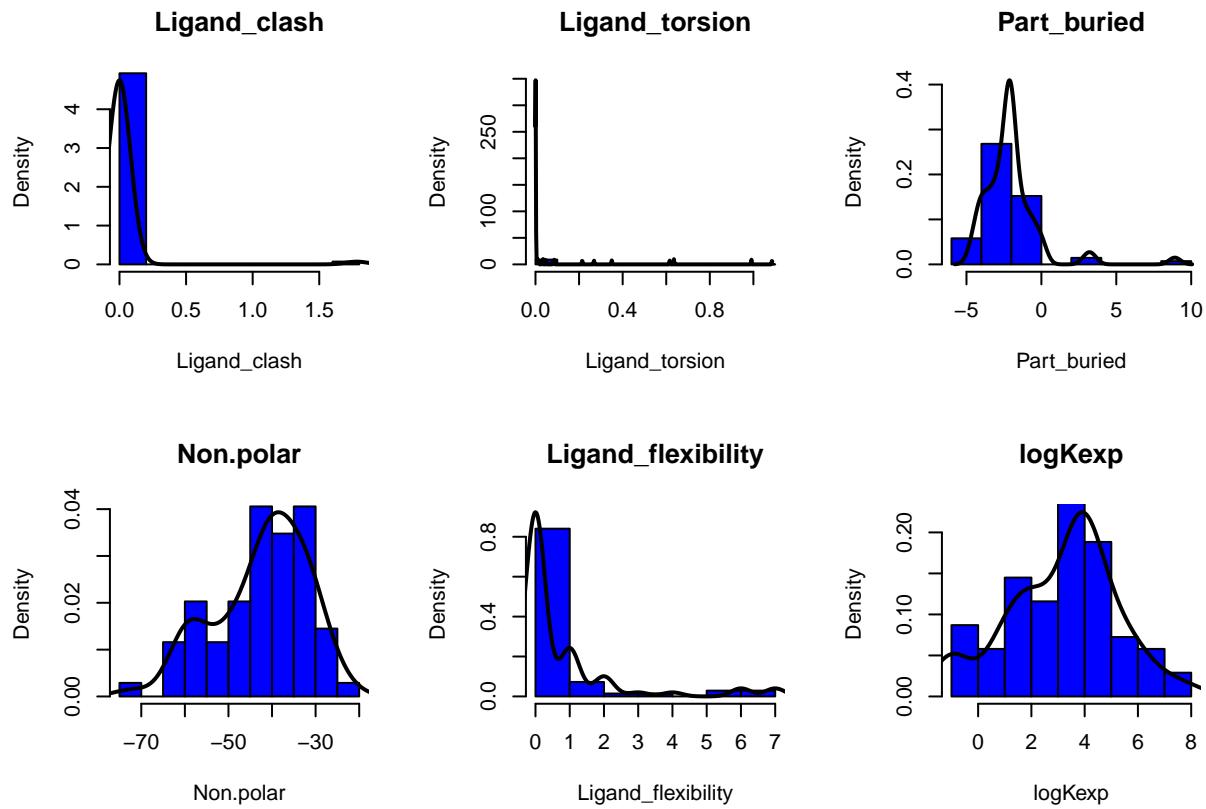
The histogram is in blue bars. The Kernel Density Estimation line is and estimation of the histogram represented as a continuous line and is shown as a black line.

```
hist_kde(df, "Part_buried")
```



Its helpful to plot all dataframe columns

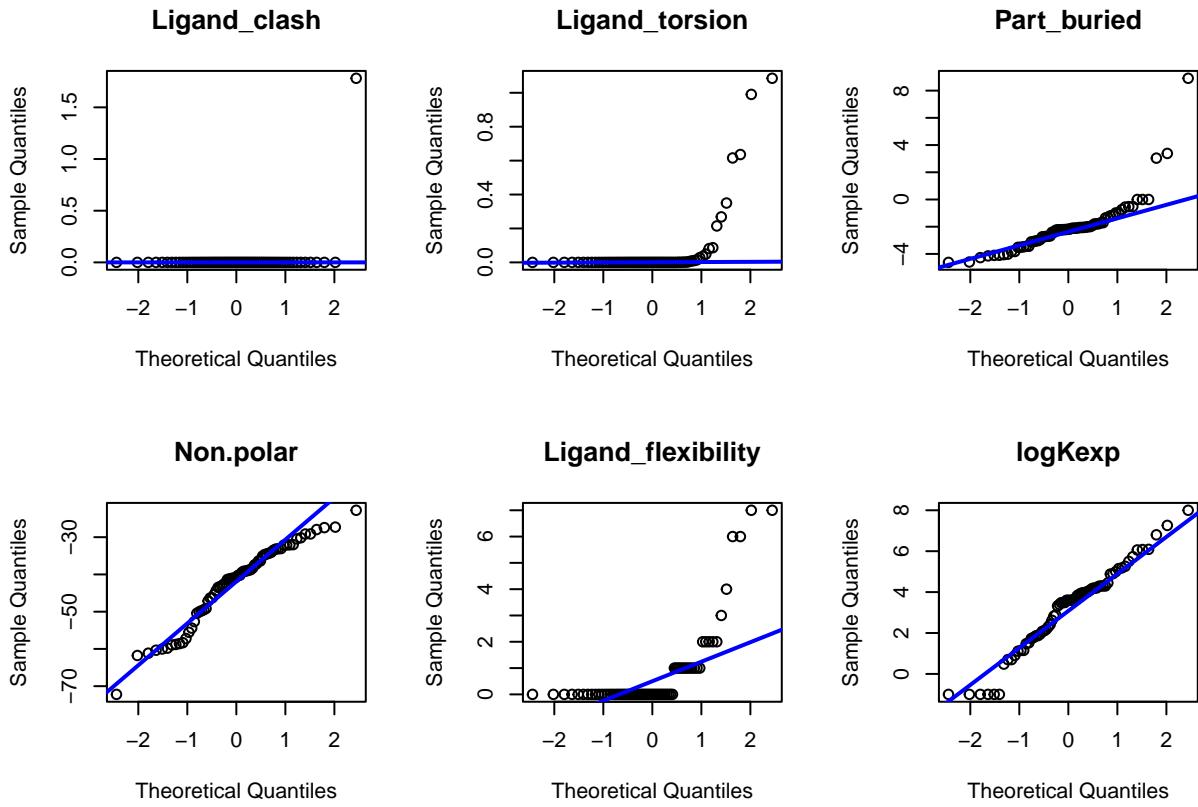
```
multi_plot(df, hist_kde)
```



### Quantile quantile plots

Our quantile quantile plots show us weather our data fits to a theoretical distribution

```
multi_plot(df, q_q_plot)
```



This is experimental data from 69 individual data points our team generated, so we don't really expect it to fit a normal distribution. We would expect the replicates of **logKexp** to fit a normal distribution and the error quoted in the manuscript is at 95% confidence.

### Correlation matrix heatmap

Over correlated molecular descriptor (GoldPLP functions) columns can cause problems with our regression models. Too many correlated models cause a misrepresentation of those molecular descriptors in our regression model.

```
cor_mat <- round(cor(df), 2)
head(cor_mat)
```

	Ligand_clash	Ligand_torsion	Part_buried	Non.polar
## Ligand_clash	1.00	-0.02	0.68	-0.19
## Ligand_torsion	-0.02	1.00	0.15	-0.24
## Part_buried	0.68	0.15	1.00	-0.61
## Non.polar	-0.19	-0.24	-0.61	1.00
## Ligand_flexibility	0.02	0.36	-0.01	-0.26
## logKexp	-0.25	-0.06	0.20	-0.46
## Ligand_flexibility	0.02	-0.25		
## Ligand_clash		0.36	-0.06	
## Ligand_torsion		-0.01	0.20	
## Part_buried			-0.26	-0.46
## Non.polar				

```

## Ligand_flexibility          1.00  -0.58
## logKexp                      -0.58   1.00

```

Reshape our dataframe

```

melted_cor_mat <- melt(cor_mat)
head(melted_cor_mat)

```

```

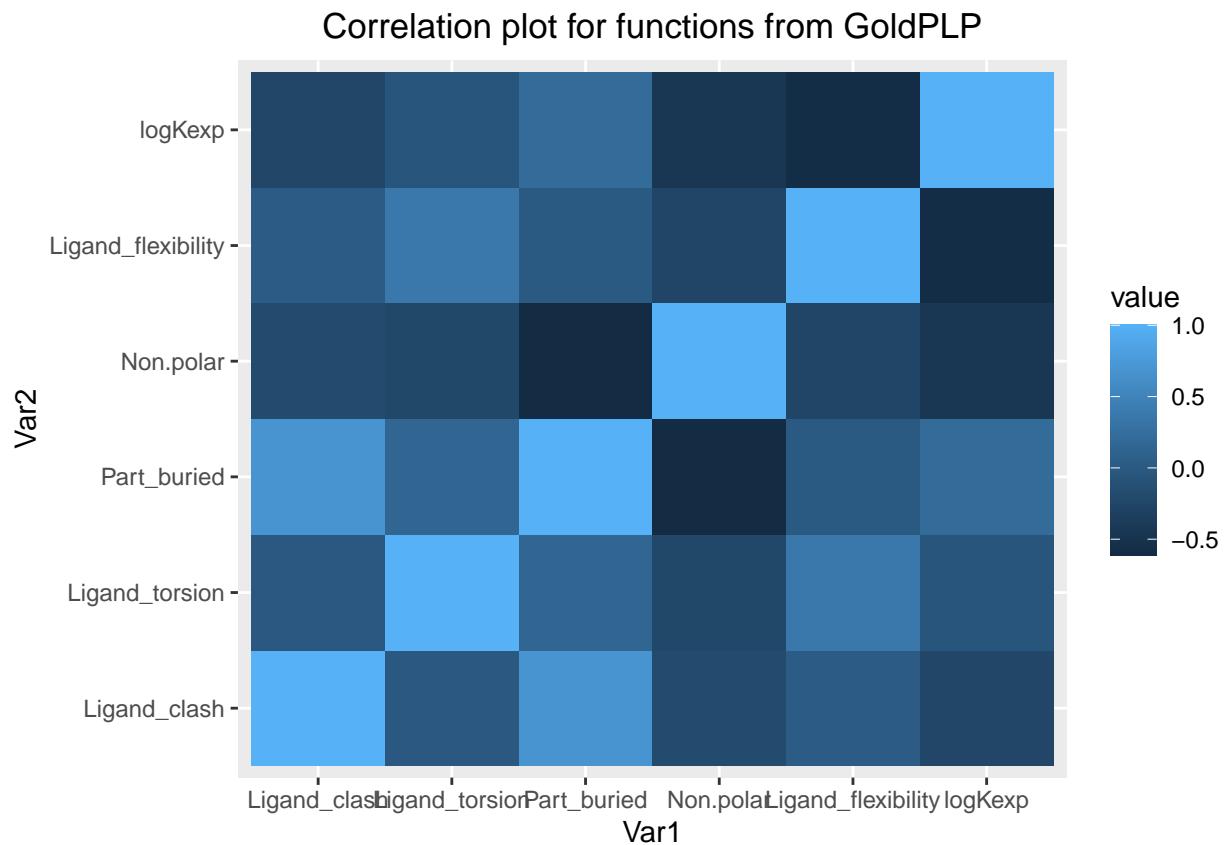
##           Var1      Var2 value
## 1    Ligand_clash Ligand_clash  1.00
## 2    Ligand_torsion Ligand_clash -0.02
## 3    Part_buried Ligand_clash  0.68
## 4    Non.polar Ligand_clash -0.19
## 5 Ligand_flexibility Ligand_clash  0.02
## 6        logKexp Ligand_clash -0.25

```

```

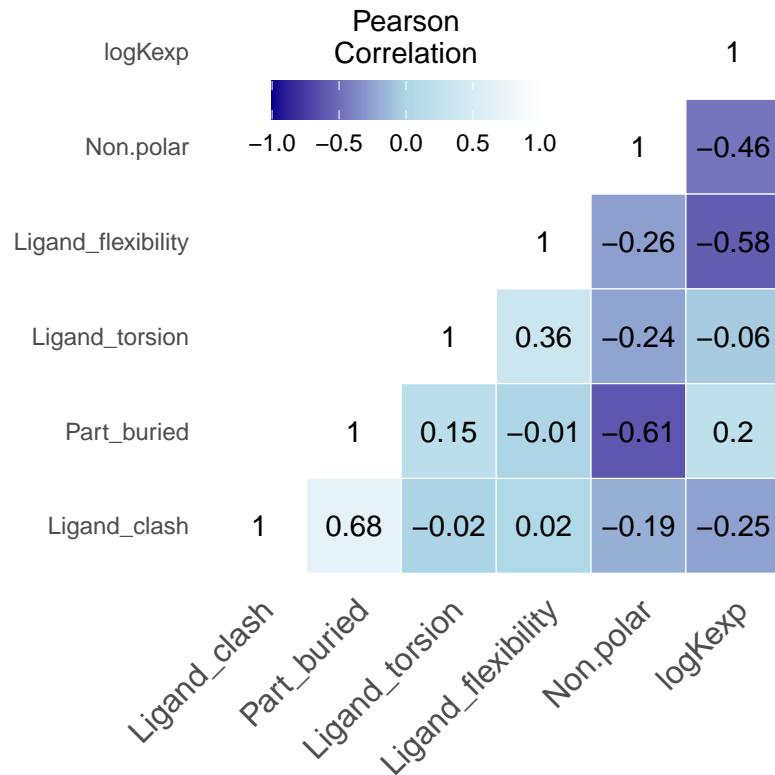
ggplot(data = melted_cor_mat, aes(x=Var1, y=Var2, fill=value)) +
  geom_tile() +
  ggtitle("Correlation plot for functions from GoldPLP") +
  theme(plot.title = element_text(hjust = 0.5))

```



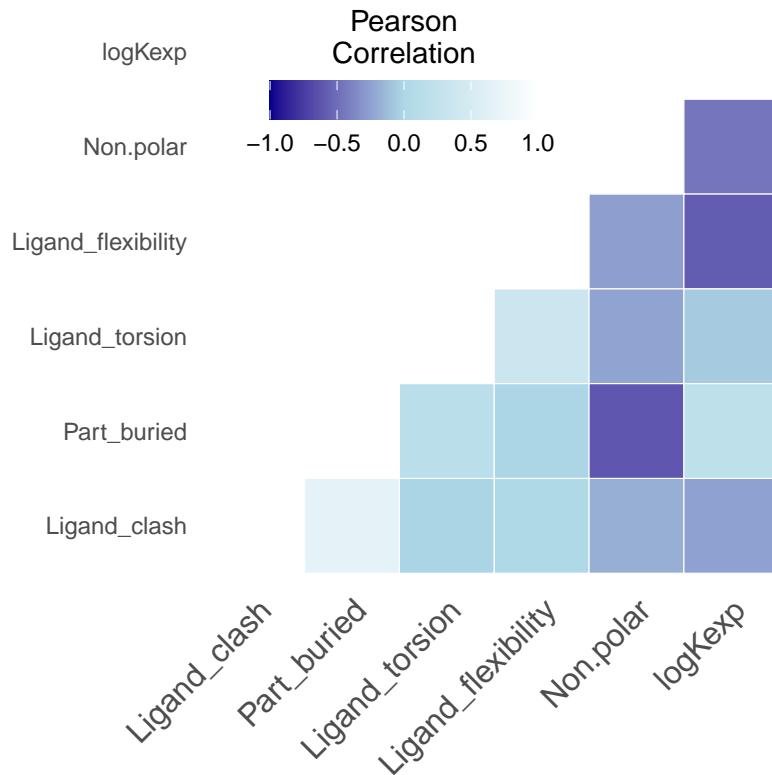
```
correl_mat_plot_2(df, "Correlation plot for functions from GoldPLP")
```

Correlation plot for functions from GoldPLP



```
correl_mat_plot_3(df, "Correlation plot for functions from GoldPLP")
```

## Correlation plot for functions from GoldPLP



You can make your correlation plot neater but they are not really pretty.

## Replication of our analysis in the manuscript using R

We take a set df cleaned and prepared in the python verson of this lecture.

### We load cleaned data from the supporting information

```
df_chemplp_score = read.csv("chemplp_score.csv", header = TRUE)
dim(df_chemplp_score)
```

```
## [1] 54 3
```

### Comparision of logKexp and ChemPLP\_Score for training set from the manuscript

```
corr_man = lm(ChemPLP_Score~logKexp, data = df_chemplp_score)

summary(corr_man)$r.squared
```

```
## [1] 0.01782835
```

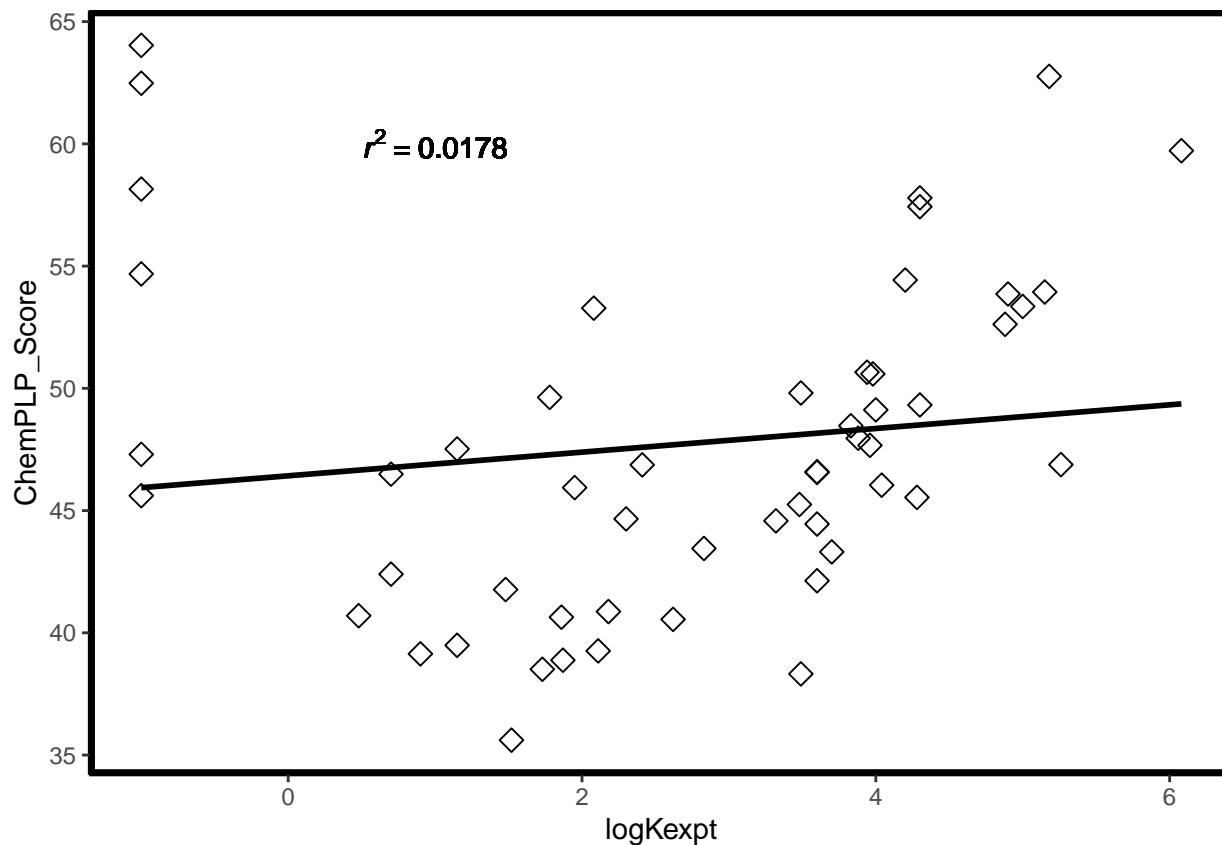
```

lm_rsq <- function(mod){
  m <- mod;
  rsq <- substitute(italic(r)^2~"="~r2,
    list(r2 = format(summary(m)$r.squared, digits = 3)))
  as.character(as.expression(rsq));
}

ggplot(data = df_chemplp_score, aes(x=logKexpt, y=ChemPLP_Score)) +
  geom_point(size=3, shape=23) +
  theme(axis.line = element_line(colour = "black"),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.border = element_rect(color = 'black',
                                      fill = NA,
                                      size = 2),
        panel.background = element_blank()) +
  geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
  geom_text(x = 1, y = 60, label = lm_rsq(corr_man), parse = TRUE)

## Warning: The 'size' argument of 'element_rect()' is deprecated as of ggplot2 3.4.0.
## i Please use the 'linewidth' argument instead.
## This warning is displayed once per session.
## Call 'lifecycle::last_lifecycle_warnings()' to see where this warning was
## generated.

```



```
#print(lm_rsq(corr_man))
```

Multivariate linear regression on the training set from the manuscript using eq. 2

Slice our data set

```
df_train <- df[1:54,]
df_test <- df[55:69,]
print("Dimensions of training set")
```

```
## [1] "Dimensions of training set"
```

```
print(dim(df_train))
```

```
## [1] 54 6
```

```
print("Dimensions of test set")
```

```
## [1] "Dimensions of test set"
```

```
print(dim(df_test))
```

```

## [1] 15 6

summary(df_train)

##   Ligand_clash    Ligand_torsion    Part_buried    Non.polar
##   Min. :0.00000   Min. :0.00000   Min. :-4.621   Min. :-60.02
##   1st Qu.:0.00000  1st Qu.:0.00000  1st Qu.:-3.078  1st Qu.:-45.14
##   Median :0.00000  Median :0.00000  Median :-2.224   Median :-39.06
##   Mean   :0.03299  Mean   :0.061415  Mean  :-2.349   Mean  :-39.97
##   3rd Qu.:0.00000  3rd Qu.:0.004375 3rd Qu.:-2.048  3rd Qu.:-33.13
##   Max.  :1.78130   Max.  :0.990400  Max.  : 8.908   Max.  :-22.77
##   Ligand_flexibility logKexp
##   Min. :0.0000   Min. :-1.000
##   1st Qu.:0.0000  1st Qu.: 1.573
##   Median :0.0000  Median : 3.400
##   Mean   :0.8704  Mean   : 2.688
##   3rd Qu.:1.0000  3rd Qu.: 3.995
##   Max.  :7.0000  Max.   : 6.080

eq2_lm = lm(logKexp~Ligand_clash + Ligand_torsion + Part_buried + Non.polar,data = df_train)
summary(eq2_lm)

##
## Call:
## lm(formula = logKexp ~ Ligand_clash + Ligand_torsion + Part_buried +
##     Non.polar, data = df_train)
##
## Residuals:
##      Min       1Q       Median      3Q      Max 
## -5.0396 -0.7326  0.6488  1.1804  2.1094 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  1.1812    2.0172   0.586   0.5609    
## Ligand_clash -4.2954    2.1439  -2.004   0.0507 .  
## Ligand_torsion -2.3586    1.4062  -1.677   0.0998 .  
## Part_buried    0.2338    0.3260   0.717   0.4767    
## Non.polar     -0.0586    0.0365  -1.605   0.1148    
## ---      
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.743 on 49 degrees of freedom
## Multiple R-squared:  0.1994, Adjusted R-squared:  0.134 
## F-statistic:  3.05 on 4 and 49 DF,  p-value: 0.02535

logKcalc = predict(eq2_lm, select(df_train,c(1:5)))

#print(logKcalc)

df_train["logKcalc"] = logKcalc

df_train["test"] = df_train["logKcalc"] - df_train["logKexp"]

```

```

#rmse_value <- sqrt(mean((df_train$logKexp] - df_train$logKcalc])^2))

library(caret)

## Loading required package: lattice

## 
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
## 
##     lift

rmse_value <- RMSE(df_train$logKcalc, df_train$logKexp)

print(rmse_value)

## [1] 1.659942

#print(df_train)

#install.packages("caret")
#library(caret)

#rmse_value <- RMSE(logKcalc, logKexp)

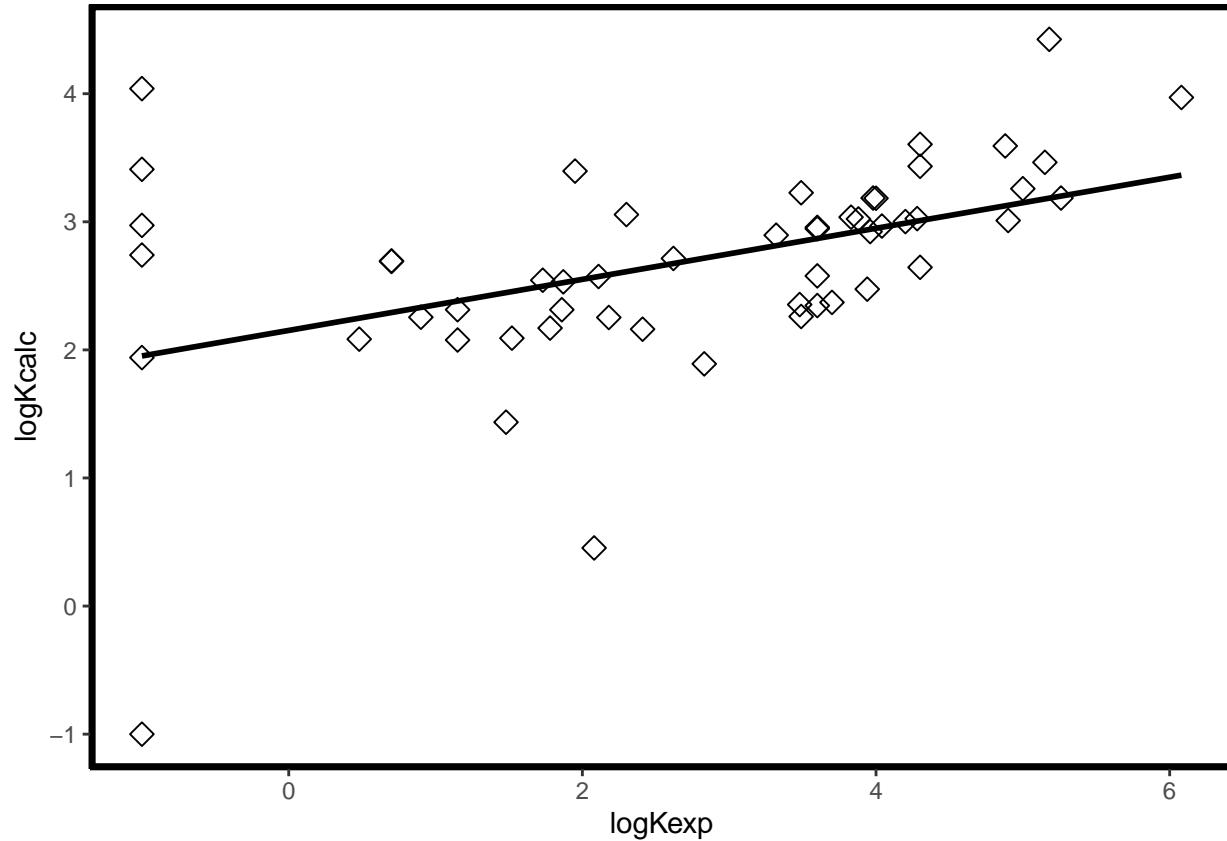
#print(df_train["logKexp"])

#rmse_value <- sqrt(mean((df_train["logKexp"] - df_train["logKcalc"])^2))

#print(rmse_value)

ggplot(data = df_train, aes(x=logKexp, y=logKcalc)) +
  geom_point(size=3, shape=23) +
  theme(axis.line = element_line(colour = "black"),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.border = element_rect(color = 'black',
                                     fill = NA,
                                     size = 2),
        panel.background = element_blank()) +
  geom_smooth(method = "lm", se=FALSE, color="black", formula = y ~ x) +
  geom_text(x = 1, y = -2, label = rmse_value, parse = TRUE)

```



```
paste("rmse = ", rmse_value)
```

```
## [1] "rmse = 1.65994233649364"
```