

# ML\_Group\_Project

2024-11-20

## Data Exploration

ADD SAMARA'S part

```
#cor(df_train[,-c(1,10)])
```

It is worth to note that “decane\_toluene” is not in the test data set

## Missing Data

Missing data was found in the ‘parentsspecies’ attribute. According to the definition of the ‘parentsspecies’ attribute, missing values imply a meaning. They are not missing randomly but due to difficulty in retrieving the ‘parentspecies’. Therefore, a new level was created as ‘Unknown’.

```
test_data$parentsspecies[test_data$parentspecies == ""] <- "Unknown"  
train_data$parentspecies[train_data$parentspecies == ""] <- "Unknown"
```

## Dummy model

A dummy model is a supervised learning model that gives the same constant output regardless of the values of the covariates. We first built a dummy model and calculated the training error and the cross validation error.

```
set.seed(123)  
dummy_model = glm(log_pSat_Pa ~ 1, data = train_data[,-1])  
dummy_cv_error_5 = cv.glm(train_data[,-1] , dummy_model , K = 10)$delta[1]  
dummy_error_train = mean((train_data$log_pSat_Pa - predict(dummy_model, train_data[,-1]))^2)
```

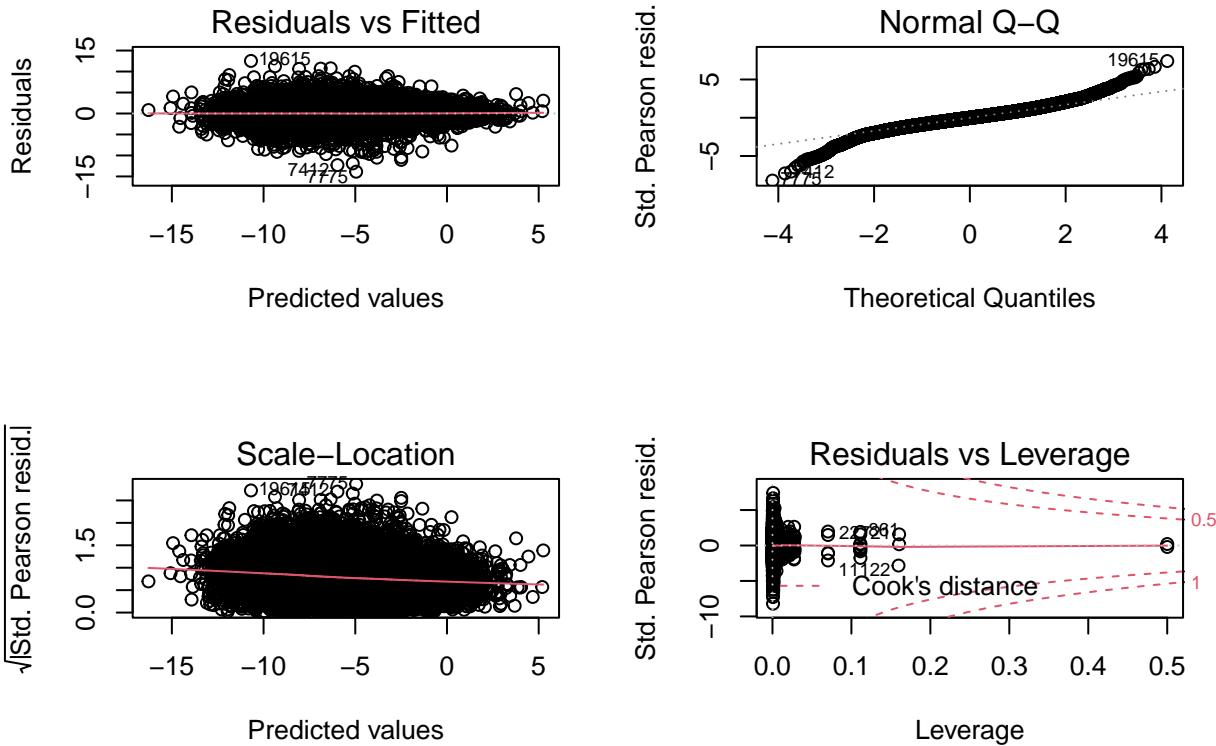
model	train	cv	kaggle_score
Dummy	9.735229	9.736679	-1e-04

## OLS as a baseline model

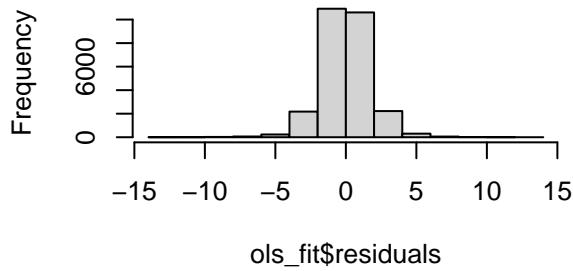
ten fold cross validation was done to get the cross validation error

```
set.seed(123)
ols_fit = glm(log_pSat_Pa ~ ., data = train_data[,-1])
cv_error_10 = cv.glm(train_data[,-1] , ols_fit , K = 10)$delta[1]
error_train = mean((train_data$log_pSat_Pa - predict(ols_fit, train_data[,-1]))^2)
```

## Plotting



**Histogram of ols\_fit\$residuals**



model	train	cv	kaggle_score
Dummy	9.735229	9.736679	-0.0001
ols	2.855265	2.862134	0.7163

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

Then we analyze the correlation between each column and the target, selecting columns with a correlation above 0.5 or 0.3, and then using these for the model prediction. However, even after trying these two methods, the prediction score didn't change,

## Lasso

Before moving to non-linear models we tried regularization using Lasso

“decane\_toluene” is not in the test data set. so it was handled in a way so that both train and test dataset has the same number of levels

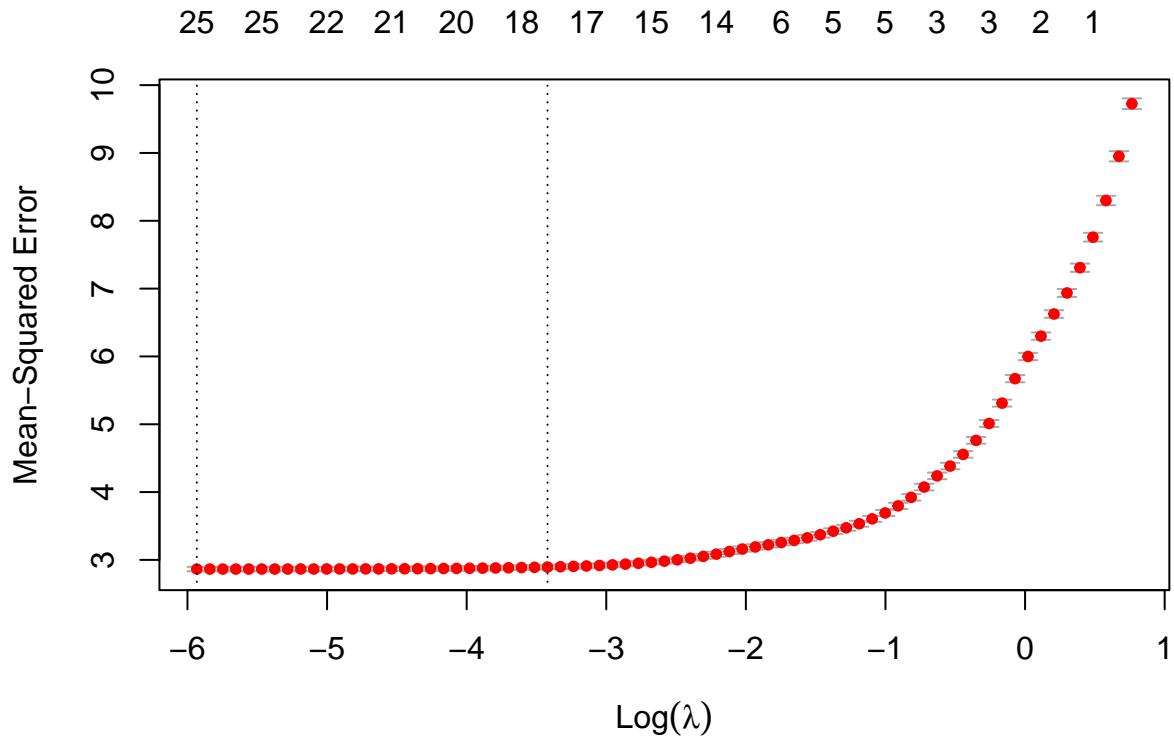
Level	Freq_train	Freq_test
apin	6165	1195
apin_decane	46	5
apin_decane_toluene	9	2
apin_toluene	37	5
decane	2218	381
decane_toluene	2	0
toluene	17950	3379
Unknown	210	33

Cross validation to obtain the best lambda(tuning parameter)

best lambda obtained was 0.002651092

Plot

```
plot(cvfit)
```



WE can use lasso as a variable selection method

```
## <sparse>[ <logic> ]: .M.sub.i.logical() maybe inefficient
```

	x
(Intercept)	6.2437263
MW	-0.0026108
NumOfAtoms	0.0000000
NumOfC	-0.7950384
NumOfO	-0.0008376
NumOfN	0.0000000
NumHBondDonors	-1.7561728
NumOfConf	-0.0022532
NumOfConfUsed	-0.0000226
parentspeciesapin	0.0000000
parentspeciesapin_decane	-0.4952347
parentspeciesapin_decane_toluene	0.0766192
parentspeciesapin_toluene	-0.2154127
parentspeciesdecane	-0.8308856
parentspeciesdecane_toluene	-0.4904175
parentspeciestoluene	0.0000000
parentspeciesUnknown	-0.8785030
C.C..non.aromatic.	-0.8968921
C.C.C.O.in.non.aromatic.ring	0.0000000

	x
hydroxyl..alkyl.	0.0000000
aldehyde	-0.2922533
ketone	0.0637678
carboxylic.acid	-1.0328902
ester	-0.2404483
ether..alicyclic.	-0.6441586
nitrate	0.0000000

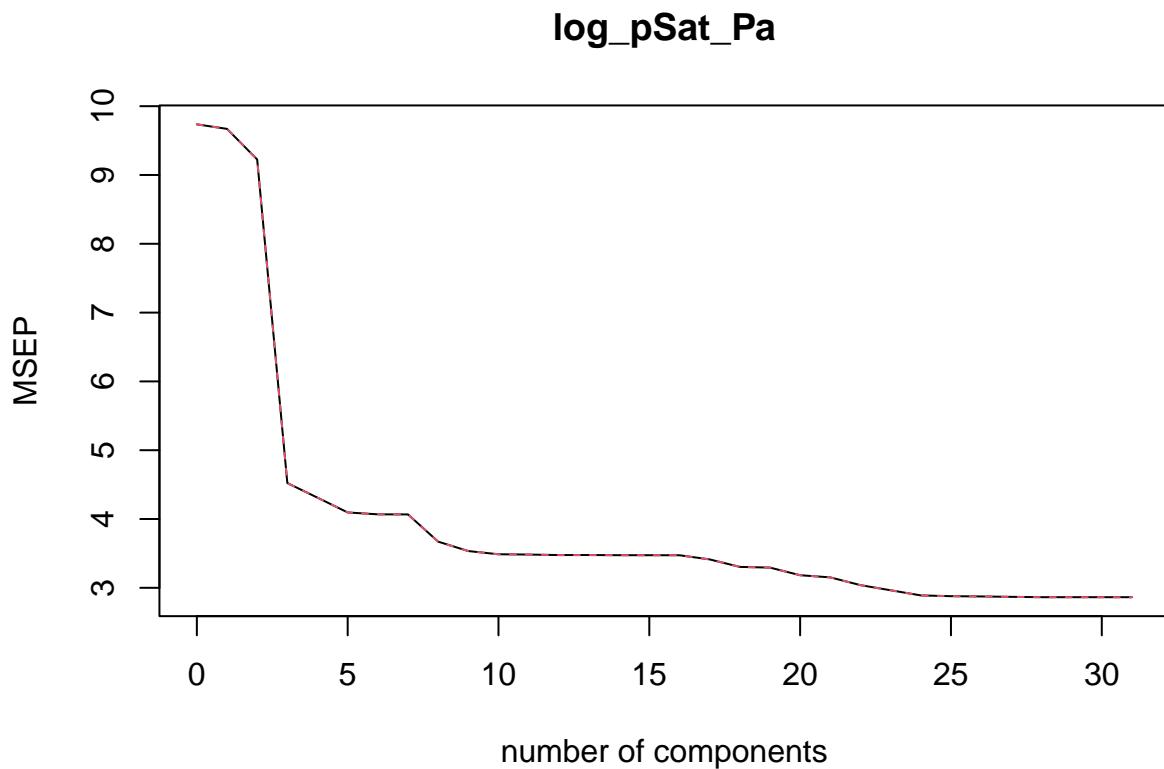
model	train	cv	kaggle_score
Dummy	9.735229	9.736679	-0.0001
ols	2.855265	2.862134	0.7163
Lasso	3.780056	2.857745	0.7160

## PCR

```
set.seed(9)
pcr_fit = pcr(log_pSat_Pa ~ ., data = train_data[,-1], scale = TRUE, validation = "CV")

#summary(pcr_fit)

validationplot(pcr_fit, val.type = "MSEP")
```



## Regression tree

```

set.seed(123)
rt_model = rpart(log_pSat_Pa ~ ., data = train_data[,-1])

printcp(rt_model)

##
## Regression tree:
## rpart(formula = log_pSat_Pa ~ ., data = train_data[, -1])
##
## Variables actually used in tree construction:
## [1] NumHBondDonors    NumOfAtoms      NumOfC
##
## Root node error: 259317/26637 = 9.7352
##
## n= 26637
##
##          CP nsplit rel error  xerror      xstd
## 1 0.322456      0    1.00000 1.00005 0.0091677
## 2 0.089325      1    0.67754 0.67761 0.0064662
## 3 0.042422      2    0.58822 0.58833 0.0058630

```

```

## 4 0.037709      3  0.54580 0.54598 0.0054090
## 5 0.037317      4  0.50809 0.51173 0.0053037
## 6 0.016344      5  0.47077 0.47100 0.0050751
## 7 0.012279      6  0.45443 0.45468 0.0049913
## 8 0.011859      7  0.44215 0.44525 0.0049292
## 9 0.010000      8  0.43029 0.43158 0.0048350

error_train_rt = mean((train_data$log_pSat_Pa - predict(rt_model, train_data[,-1]))^2)
error_train_rt

```

```
## [1] 4.188949
```

High testing error

Tree pruning check . I think this is wrong cp = 0.01

```

Pruned_rt = prune(rt_model, cp = 0.01)

error_val_rt = mean((train_data$log_pSat_Pa - predict(Pruned_rt, train_data[,-1]))^2)
error_val_rt

```

```
## [1] 4.188949
```

## Boosting

gradient Boosting by coco : Kaggle Score:0.7485

```

y_train <- train_data$log_pSat_Pa
x_train <- model.matrix(log_pSat_Pa ~ . - 1, data = train_data[,-1])

dtrain <- xgb.DMatrix(data = x_train, label = y_train)
#dtest <- xgb.DMatrix(data = as.matrix(X_test))

params <- list(
  booster = "gbtree",
  objective = "reg:squarederror",
  eta = 0.1,
  max_depth = 6,
  subsample = 0.8,
  colsample_bytree = 0.8
)

xgb_model <- xgb.train(
  params = params,
  data = dtrain,
  nrounds = 100,
  watchlist = list(train = dtrain),
  verbose = 1
)

```

I cannot run this

```
grid <- expand.grid(
  nrounds = c(100, 200),
  max_depth = c(3, 6, 9),
  eta = c(0.01, 0.1, 0.2),
  gamma = c(0, 1, 5),
  colsample_bytree = c(0.7, 0.8, 1),
  min_child_weight = c(1, 3, 5),
  subsample = c(0.7, 0.8, 1)
)

control <- trainControl(
  method = "cv",
  number = 5,
  verboseIter = TRUE
)

xgb_tuned <- train(
  x = x_train, y = y_train,
  method = "xgbTree",
  trControl = control,
  tuneGrid = grid
)

print(xgb_tuned$bestTune)

x_test <- model.matrix(~ . - 1, data = test_data[,-1])
y_hat = predict(xgb_tuned, newdata = x_test)
ID = test_data$ID
TARGET = as.vector(y_hat)
df = data.frame(ID, TARGET)
write.csv(df[, c("ID", "TARGET")], "dummy_submission.csv", row.names = FALSE)
```

## Random forest (Kaggle score: 0.7440)

Default mtry is P/3, Here p = 24

Have to try with P = 8

Kaggle score: 0.7440

```
set.seed(123)

bag.rf = randomForest(log_pSat_Pa ~ ., data = train_data[,-1], mtry = 5, importance = TRUE)

yhat.bag = predict(bag.rf , newdata = test_data[,-1])

importance(bag.rf)
```

	%IncMSE	IncNodePurity
Mw	45.897727	12795.57215
NumOfAtoms	41.912149	17391.89092
NumOfC	69.995928	15087.04646
NumOfO	49.467413	6320.67865
NumOfN	25.628846	5277.43812
NumHBondDonors	79.439765	67922.64607
NumOfConf	55.789496	41825.99036
NumOfConfUsed	64.000651	12644.26327
parentspecies	36.420462	3064.42500
C.C..non.aromatic.	54.002075	2389.86048
C.C.C.O.in.non.aromatic.ring	12.587809	243.31435
hydroxyl..alkyl.	32.789366	8853.75687
aldehyde	53.453905	3019.51319
ketone	55.952484	4482.04815
carboxylic.acid	48.594367	11361.55240
ester	36.431927	1739.50999
ether..alicyclic.	44.172666	1569.99315
nitrate	34.873295	2493.70582
nitro	25.110952	1215.78542
aromatic.hydroxyl	5.418516	69.27385
carbonylperoxynitrate	50.057204	7195.35574
peroxide	56.805588	1857.80184
hydroperoxide	28.198106	6782.46597
carbonylperoxyacid	33.511581	3311.32168
nitroester	12.733955	211.22329

## SVR

Selected features from lasso is used : Removed “NumOfAtoms” , “NumOfN”,“C.C.C.O.in.non.aromatic.ring”,“hydroxyl..alkyl.” , “nitrate”

```
library(e1071)
library(caret)

y_train <- train_data$log_pSat_Pa

x_train <- model.matrix(~ . - 1, data = train_data[,-c(1,2,4,7,13,14,20)])

svm_model <- svm(
  x = x_train, y = y_train,
  type = "eps-regression",
  kernel = "radial",
  cost = 1,
  gamma = 1 / ncol(x_train)
)

x_test <- model.matrix(~ . - 1, data = test_data[,-c(1,2,6,12,13,19)])
y_hat = predict(svm_model,newdata = x_test)
ID = test_data$ID
```

```
TARGET = as.vector(y_hat)
df = data.frame(ID, TARGET)
write.csv(df[, c("ID", "TARGET")], "dummy_submission.csv", row.names = FALSE)
```

Kaggle score: 0.5195