Iron Ore Quality Prediction

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Introduction

Flotation is a process in which pulp containing some mineral ore deposit is fed into a plant with some reagents such that at the end of the process, pure mineral is collected while all impurities stay in the plant.In this project, the mineral of interest is iron ore.The quality of iron ore in a mining flotation plant is determined by the amount of silica (SiO_2) in the ore concentrate; a higher silica amount is indicative of a more impure sample. In this project the objective is to use other variables from the plant to try and predict the silica content. This will be helpful in improving productivity as there is at least one hour that has to be waited before obtaining the silica content reading of each sample sent to the lab, and many samples are sent in a day,creating a lot of dead time. Prediction using machine learning would save this time. The R code used to create this report is found in the iron_ore_code.R file that goes with this report.

Dataset

The `data` dataset taken from kaggle contains 7 37 453 entries of 24 variables from an iron ore mining flotation plant. The variables are attributes of the plant like pulp density, pulp pH and flow rate, amount of iron and silica in the feed, flow rates of the reagents used in the plant. Below are the first six lines of the dataset.

```
##                  date X..Iron.Feed X..Silica.Feed Starch.Flow Amina.Flow
## 1 2017-03-10 01:00:00         55,2          16,98     3019,53    557,434
## 2 2017-03-10 01:00:00         55,2          16,98     3024,41    563,965
## 3 2017-03-10 01:00:00         55,2          16,98     3043,46    568,054
## 4 2017-03-10 01:00:00         55,2          16,98     3047,36    568,665
## 5 2017-03-10 01:00:00         55,2          16,98     3033,69    558,167
## 6 2017-03-10 01:00:00         55,2          16,98      3079,1    564,697
##   Ore.Pulp.Flow Ore.Pulp.pH Ore.Pulp.Density Flotation.Column.01.Air.Flow
## 1       395,713     10,0664             1,74                      249,214
## 2       397,383     10,0672             1,74                      249,719
## 3       399,668      10,068             1,74                      249,741
## 4       397,939     10,0689             1,74                      249,917
## 5       400,254     10,0697             1,74                      250,203
## 6       396,533     10,0705             1,74                       250,73
##   Flotation.Column.02.Air.Flow Flotation.Column.03.Air.Flow
## 1                      253,235                      250,576
## 2                      250,532                      250,862
## 3                      247,874                      250,313
## 4                      254,487                      250,049
## 5                      252,136                      249,895
## 6                      248,906                      249,521
##   Flotation.Column.04.Air.Flow Flotation.Column.05.Air.Flow
## 1                      295,096                        306,4
```

```
## 2                      295,096                       306,4
## 3                      295,096                       306,4
## 4                      295,096                       306,4
## 5                      295,096                       306,4
## 6                      295,096                       306,4
##   Flotation.Column.06.Air.Flow Flotation.Column.07.Air.Flow
## 1                      250,225                      250,884
## 2                      250,137                      248,994
## 3                      251,345                      248,071
## 4                      250,422                      251,147
## 5                      249,983                      248,928
## 6                      250,356                      251,873
##   Flotation.Column.01.Level Flotation.Column.02.Level Flotation.Column.03.Level
## 1                   457,396                   432,962                   424,954
## 2                   451,891                    429,56                   432,939
## 3                    451,24                   468,927                    434,61
## 4                   452,441                   458,165                   442,865
## 5                   452,441                     452,9                   450,523
## 6                   444,384                   443,269                   460,449
##   Flotation.Column.04.Level Flotation.Column.05.Level Flotation.Column.06.Level
## 1                   443,558                   502,255                    446,37
## 2                   448,086                   496,363                   445,922
## 3                   449,688                   484,411                   447,826
## 4                    446,21                   471,411                    437,69
## 5                    453,67                   462,598                   443,682
## 6                    439,92                   451,588                   433,539
##   Flotation.Column.07.Level X..Iron.Concentrate X..Silica.Concentrate
## 1                   523,344               66,91                  1,31
## 2                   498,075               66,91                  1,31
## 3                   458,567               66,91                  1,31
## 4                   427,669               66,91                  1,31
## 5                   425,679               66,91                  1,31
## 6                   425,458               66,91                  1,31
```

Cleaning The Dataset

All variables except date are numeric, but are not written in the correct format, with commas making them character strings. The date variable is also not in the datetime type. Cleaning this dataset will just be about making all variables numeric and datetime for the date variable, and also renaming the long variable names to shorter versions that will be quicker to write.Hourly entries will also have to be aggregated, because as seen in the dataset, there are different readings of all the other variables for each 60 entries with the same silica content reading. This is because all those entries belong to a single batch of ore taken to the lab to obtain the silica content reading, that comes after one hour.These values will be combined and an average taken for each variable to correspond with each unique value of silica concentrate.Below are the first six lines of the cleaned dataset.

```
##                  date iron_feed silica_feed starch_flow amina_flow pulp_flow
## 1 2017-03-10 01:00:00      55.2       16.98    3162.625   578.7867  398.7534
## 2 2017-03-10 02:00:00      55.2       16.98    3133.256   537.2197  399.8718
## 3 2017-03-10 03:00:00      55.2       16.98    3479.483   591.9067  398.7638
## 4 2017-03-10 04:00:00      55.2       16.98    3228.036   593.1701  399.8670
## 5 2017-03-10 05:00:00      55.2       16.98    3327.281   619.7108  399.6151
## 6 2017-03-10 06:00:00      55.2       16.98    3405.162   621.8785  399.7493
```

```
##     pulp_ph pulp_density air_flow_1 air_flow_2 air_flow_3 air_flow_4 air_flow_5
## 1 10.113487     1.729558   251.1667   250.2261   250.1783    295.096      306.4
## 2 10.129742     1.667784   249.8806   250.2140   250.0333    295.096      306.4
## 3 10.048403     1.732711   250.1613   250.1042   250.0463    295.096      306.4
## 4  9.918614     1.731056   250.2088   250.2048   250.1209    295.096      306.4
## 5  9.746029     1.765879   249.9178   250.1605   250.0135    295.096      306.4
## 6  9.892237     1.765064   249.8983   250.1110   250.0754    295.096      306.4
##   air_flow_6 air_flow_7 column_level_1 column_level_2 column_level_3
## 1   251.2325   250.2082       450.3838       446.8918       450.4745
## 2   249.9095   249.8976       449.3734       450.2494       450.0812
## 3   250.2422   250.4842       449.9729       450.8687       450.9018
## 4   249.8251   250.1576       487.9407       491.4621       487.3872
## 5   250.2496   250.0786       549.0315       549.9832       549.4596
## 6   249.9425   250.1499       550.5996       549.9291       549.0892
##   column_level_4 column_level_5 column_level_6 column_level_7 iron_concentrate
## 1       449.9123       455.7922       464.3833       450.5327            66.91
## 2       450.3288       448.7230       455.5015       451.3877            67.06
## 3       451.1458       451.1342       459.9813       450.2967            66.97
## 4       494.5282       495.6640       502.7638       494.9399            66.75
## 5       549.9755       549.5125       560.6963       550.2718            66.63
## 6       549.6097       549.2207       561.0516       551.0908            66.85
##   silica_concentrate
## 1               1.31
## 2               1.11
## 3               1.27
## 4               1.36
## 5               1.34
## 6               1.15
```

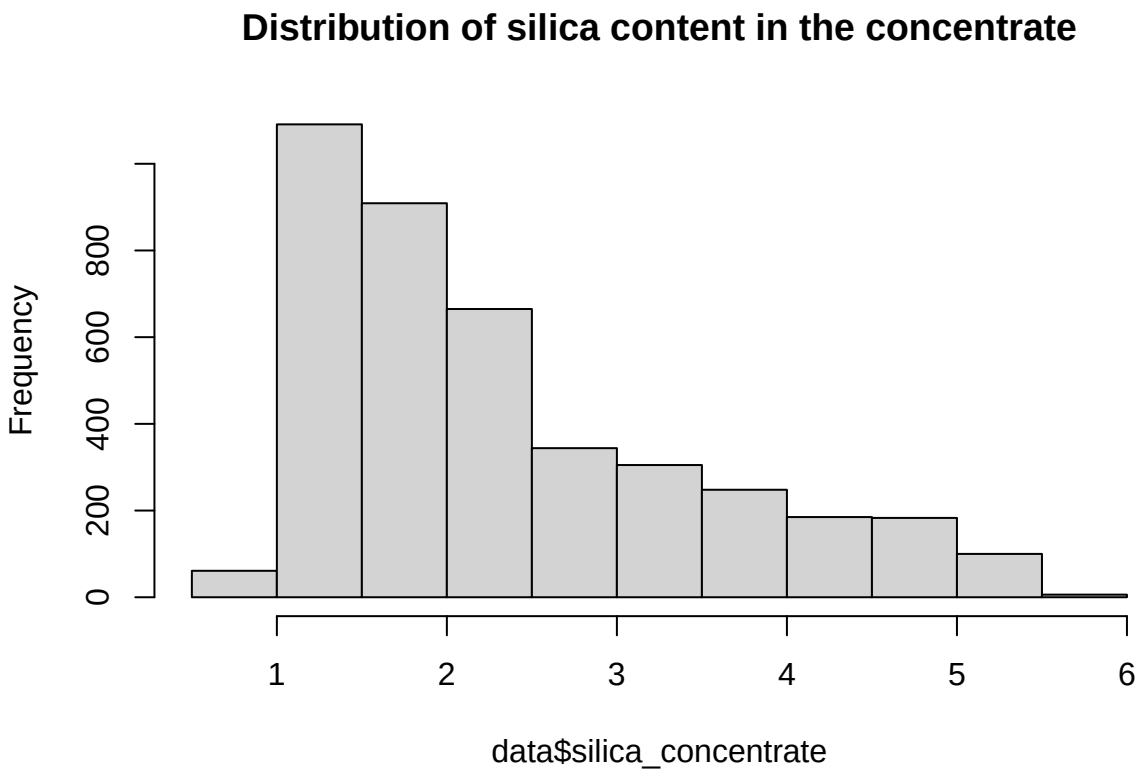
Exploratory Data Analysis

The first step is to check the summary statistics of each variable, to see how variable each one is. Then explore the distribution of the response variable, and then checking how it changes with time. This can be done by plotting silica content against time and observe whether or not there is an obvious pattern. The first plot is the distribution of silica content in the concentrate, is it changing at all and if yes how? The second plot shows silica content over the course of the three months in which these data were collected.

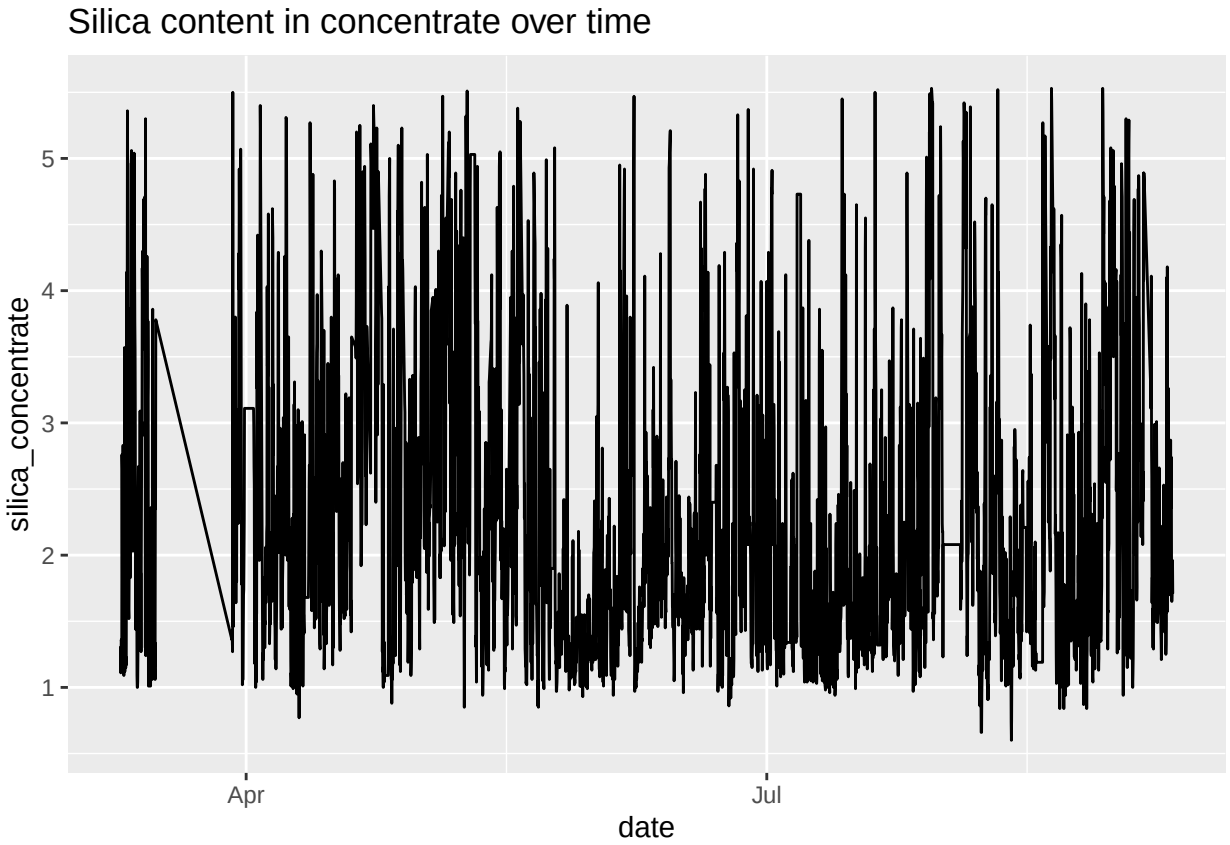
```
##       date                          iron_feed      silica_feed
##  Min.   :2017-03-10 01:00:00.00   Min.   :42.74   Min.   : 1.31
##  1st Qu.:2017-05-04 23:00:00.00   1st Qu.:52.67   1st Qu.: 8.94
##  Median :2017-06-16 15:00:00.00   Median :56.08   Median :13.85
##  Mean   :2017-06-16 03:26:05.82   Mean   :56.29   Mean   :14.65
##  3rd Qu.:2017-07-29 07:00:00.00   3rd Qu.:59.72   3rd Qu.:19.60
##  Max.   :2017-09-09 23:00:00.00   Max.   :65.78   Max.   :33.40
##   starch_flow        amina_flow      pulp_flow        pulp_ph
##  Min.   :  54.59   Min.   :242.9   Min.   :376.8   Min.   : 8.753
##  1st Qu.:2168.97   1st Qu.:436.0   1st Qu.:398.9   1st Qu.: 9.541
##  Median :2908.34   Median :502.5   Median :399.8   Median : 9.796
##  Mean   :2869.14   Mean   :488.1   Mean   :397.6   Mean   : 9.768
##  3rd Qu.:3528.73   3rd Qu.:549.5   3rd Qu.:400.6   3rd Qu.:10.031
##  Max.   :6270.16   Max.   :737.0   Max.   :418.1   Max.   :10.807
##   pulp_density     air_flow_1      air_flow_2      air_flow_3
##  Min.   :1.520   Min.   :175.9   Min.   :178.2   Min.   :177.2
```

```
##  1st Qu.:1.651   1st Qu.:250.1   1st Qu.:250.1   1st Qu.:250.1
##  Median :1.696   Median :299.8   Median :299.5   Median :299.9
##  Mean   :1.680   Mean   :280.2   Mean   :277.2   Mean   :281.1
##  3rd Qu.:1.722   3rd Qu.:300.0   3rd Qu.:300.0   3rd Qu.:299.9
##  Max.   :1.832   Max.   :312.3   Max.   :309.9   Max.   :302.8
##    air_flow_4      air_flow_5      air_flow_6      air_flow_7
##  Min.   :293.3   Min.   :287.1   Min.   :196.5   Min.   :199.7
##  1st Qu.:299.7   1st Qu.:299.7   1st Qu.:268.7   1st Qu.:283.2
##  Median :299.9   Median :299.9   Median :299.9   Median :299.9
##  Mean   :299.4   Mean   :299.9   Mean   :292.1   Mean   :290.8
##  3rd Qu.:300.0   3rd Qu.:300.1   3rd Qu.:300.1   3rd Qu.:300.1
##  Max.   :305.6   Max.   :307.0   Max.   :355.0   Max.   :351.3
##  column_level_1  column_level_2  column_level_3  column_level_4
##  Min.   :181.9   Min.   :224.9   Min.   :135.2   Min.   :165.7
##  1st Qu.:416.5   1st Qu.:449.2   1st Qu.:405.4   1st Qu.:351.5
##  Median :499.6   Median :499.8   Median :499.6   Median :401.3
##  Mean   :520.2   Mean   :522.6   Mean   :531.4   Mean   :420.3
##  3rd Qu.:599.7   3rd Qu.:599.3   3rd Qu.:600.2   3rd Qu.:496.2
##  Max.   :859.0   Max.   :827.8   Max.   :884.8   Max.   :675.6
##  column_level_5  column_level_6  column_level_7  iron_concentrate
##  Min.   :214.7   Min.   :203.7   Min.   :185.1   Min.   :62.05
##  1st Qu.:351.0   1st Qu.:354.1   1st Qu.:350.9   1st Qu.:64.37
##  Median :401.1   Median :407.5   Median :401.0   Median :65.21
##  Mean   :425.3   Mean   :429.9   Mean   :421.0   Mean   :65.05
##  3rd Qu.:497.8   3rd Qu.:497.8   3rd Qu.:462.3   3rd Qu.:65.86
##  Max.   :674.1   Max.   :698.5   Max.   :655.5   Max.   :68.01
##  silica_concentrate
##  Min.   :0.600
##  1st Qu.:1.440
##  Median :2.000
##  Mean   :2.327
##  3rd Qu.:3.010
##  Max.   :5.530
```

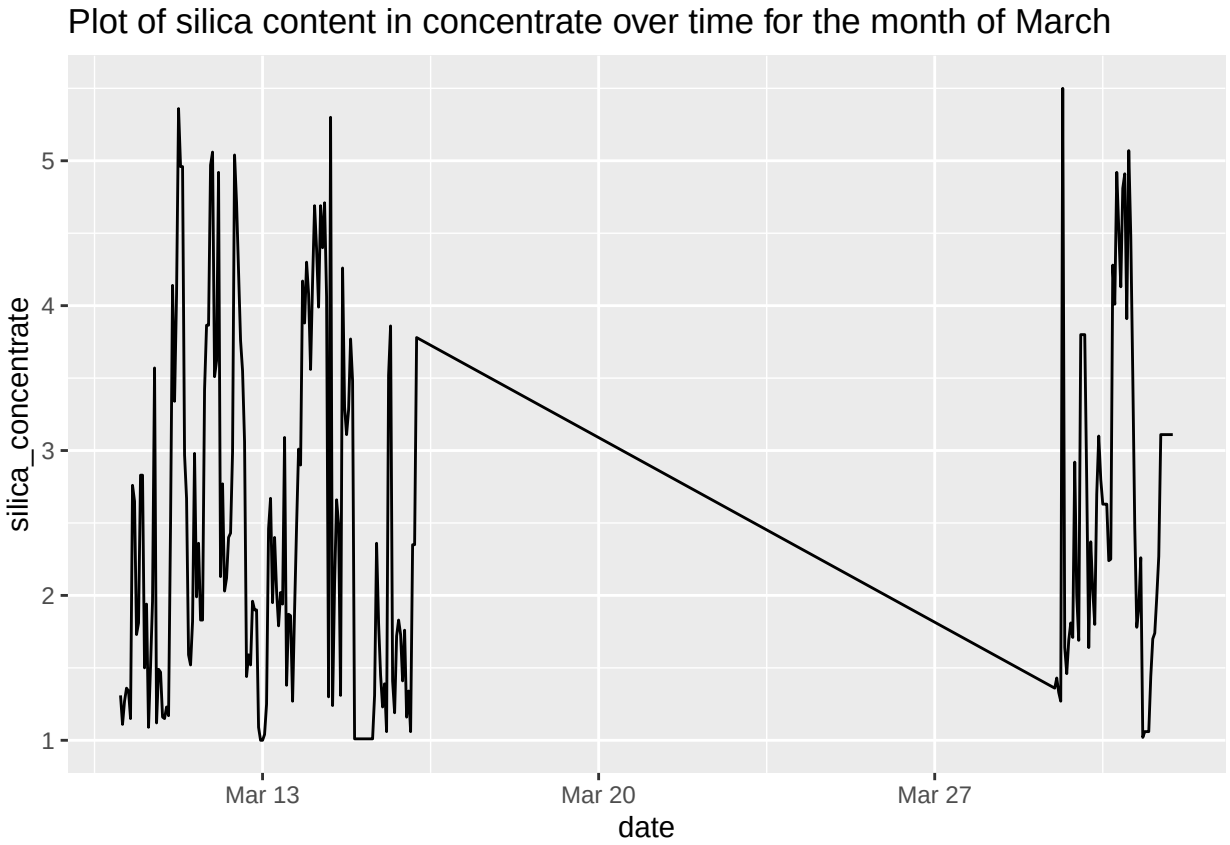
The summary shows that although almost all these variables are in the same order of magnitude, they are not exactly the same. The numbers are similar. Starch flow is the only variable in which the minimum is in the different order of magnitude from the rest of the other numbers.



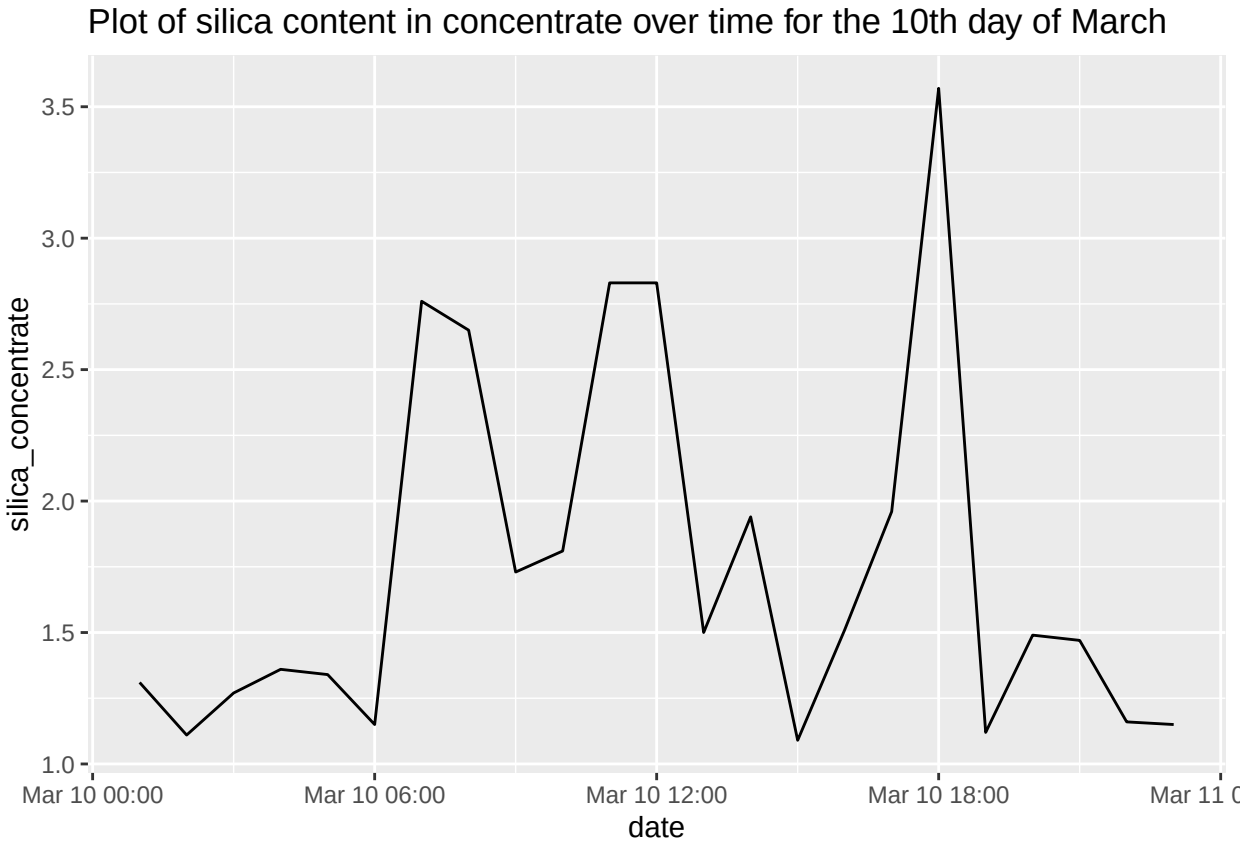
It can be seen that the distribution of the response variable is highly variable.

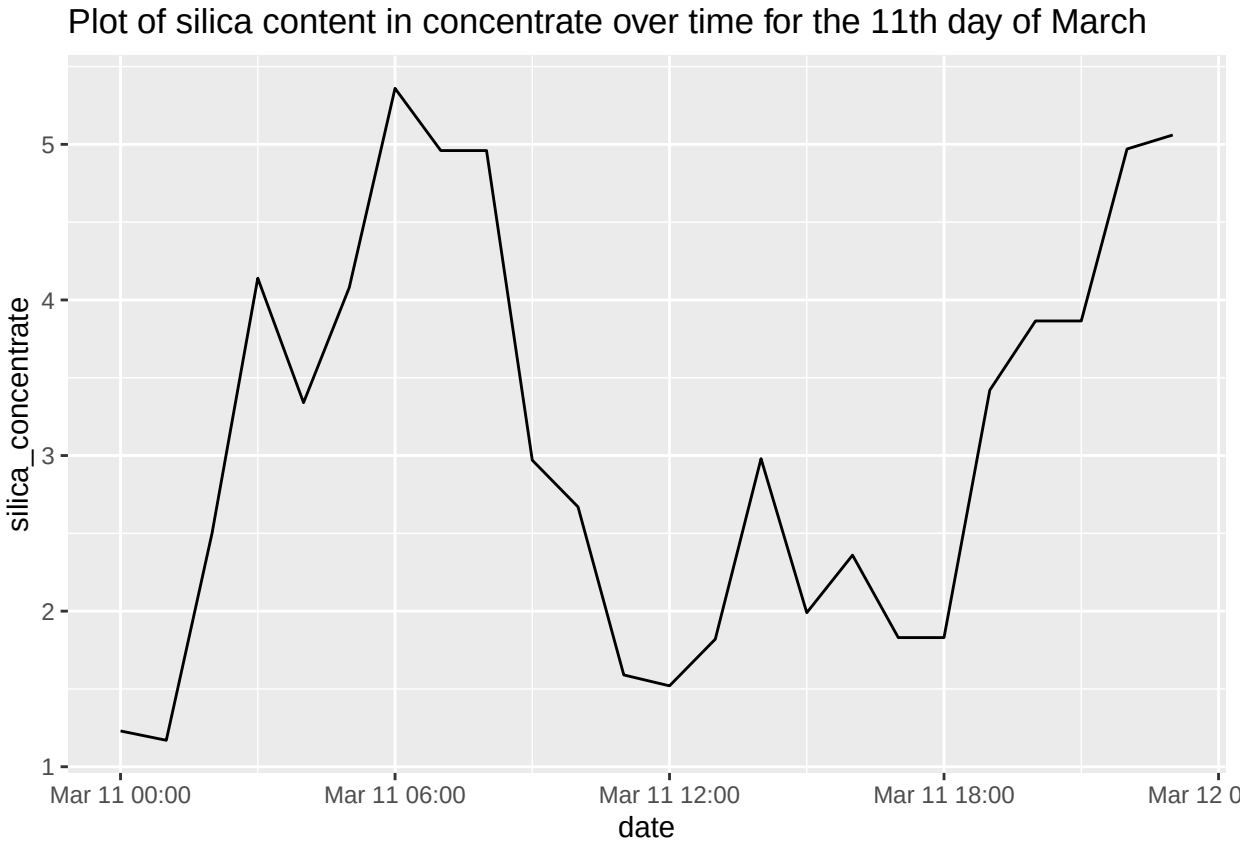


Looking at this plot shows that there is no clear pattern between the response variable and time in the whole of these three months.Maybe zooming in on just one month will be clearer :

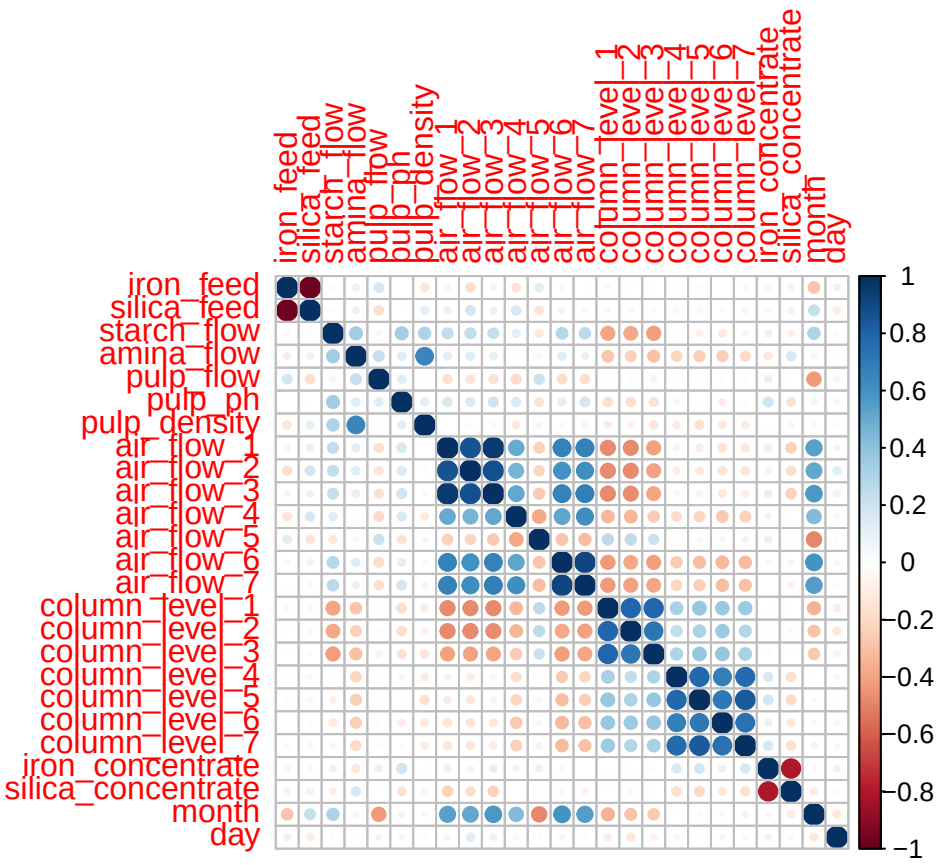


There still is no clear pattern. Below I check by a single day, will pick two random days to see if there is any relationship between silica content and say time of day.


Plot of silica content in concentrate over time for the 10th day of March
silica_concentrate
3.5
3.0
2.5
2.0
1.5
1.0
Mar 10 00:00
Mar 10 06:00
Mar 10 12:00
Mar 10 18:00
date



Both plots show that there is no obvious pattern. Next I move on to checking if all these variables are correlated with the response variable and with one another.This is in the correlation plot below:



The only variable that is clearly strongly correlated with the response variable as seen from the plot is iron concentrate, which is the amount of iron in the concentrate. It is a negative correlation and it makes sense because the more iron there is the less contaminant there will be and vice versa. All the variables do not seem to individually have a direct correlation with the response variable, but there are some variables that positively or negatively, correlated with one another.

Building A Predictive Model

Since all of the variables except date, in the dataset are numeric, the first option algorithm to explore is linear regression. The dataset is split into the training and test sets, and then a model is trained using linear regression and its performance tested on the test set. Because it has already been seen that many of the variables are correlated with one another, it is likely that the model will not fit the data with high efficiency due to the redundance in the features. Therefore, principal component analysis will be used to reduce the dimensions in the features and see whether or not the model fit will improve. Below is the summary of the model run with linear regression:

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3.05853 -0.39769 -0.03191  0.36265  2.33681
##
## Coefficients:
```

```
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       7.445e+02  5.287e+02   1.408 0.159172
## date             -4.661e-07  3.569e-07  -1.306 0.191688
## iron_feed        -2.122e-03  1.035e-02  -0.205 0.837468
## silica_feed       1.287e-02  7.587e-03   1.696 0.089973 .
## starch_flow      -6.466e-06  1.575e-05  -0.410 0.681491
## amina_flow        1.102e-03  2.065e-04   5.337 1.01e-07 ***
## pulp_flow         7.456e-04  1.658e-03   0.450 0.652982
## pulp_ph           1.716e-02  3.534e-02   0.486 0.627270
## pulp_density     -2.167e-01  2.583e-01  -0.839 0.401546
## air_flow_1       -4.626e-03  1.479e-03  -3.128 0.001775 **
## air_flow_2       -2.995e-03  8.744e-04  -3.426 0.000621 ***
## air_flow_3        1.136e-03  1.642e-03   0.692 0.489094
## air_flow_4       -2.083e-03  6.507e-03  -0.320 0.748945
## air_flow_5        5.048e-03  4.105e-03   1.230 0.218897
## air_flow_6        3.844e-04  1.035e-03   0.371 0.710411
## air_flow_7        2.547e-03  1.133e-03   2.248 0.024615 *
## column_level_1   -4.941e-04  1.854e-04  -2.665 0.007735 **
## column_level_2   -1.499e-04  1.722e-04  -0.871 0.383828
## column_level_3   -3.869e-07  1.412e-04  -0.003 0.997813
## column_level_4   -1.048e-04  2.555e-04  -0.410 0.681719
## column_level_5   -2.380e-05  3.055e-04  -0.078 0.937891
## column_level_6   -2.229e-04  2.395e-04  -0.931 0.351982
## column_level_7    2.979e-04  3.097e-04   0.962 0.336128
## iron_concentrate -7.982e-01  1.087e-02 -73.438  < 2e-16 ***
## month             1.143e+00  9.417e-01   1.214 0.225008
## day               4.324e-02  3.075e-02   1.406 0.159747
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6308 on 3250 degrees of freedom
## Multiple R-squared:  0.6895, Adjusted R-squared:  0.6871
## F-statistic: 288.6 on 25 and 3250 DF,  p-value: < 2.2e-16
```

As anticipated, the model does not fit the data well enough, the adjusted R-squared value is 0.6871, so there might still be room for improvement. BUt first the model is tested on test data to see its performance on new data. Below is the RMSE value obtained from comparing predictions on the test set with real values:

```
## [1] 0.6143063
```

This RMSE value, 0.61 is almost equal to the minimim value of this variable in the dataset, it is a big error that the model makes when trying to predict. Maybe applying pca will bring it down. Below is the summary of model fit after applying pca:

```
## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5    PC6     PC7
## Standard deviation     2.6341 1.8483 1.54072 1.43414 1.24837 1.1336 1.08018
## Proportion of Variance 0.2775 0.1367 0.09495 0.08227 0.06234 0.0514 0.04667
## Cumulative Proportion  0.2775 0.4142 0.50914 0.59141 0.65375 0.7052 0.75182
##                           PC8     PC9    PC10    PC11    PC12    PC13    PC14
## Standard deviation     0.99261 0.93657 0.84308 0.79394 0.71872 0.64511 0.56774
## Proportion of Variance 0.03941 0.03509 0.02843 0.02521 0.02066 0.01665 0.01289
## Cumulative Proportion  0.79123 0.82632 0.85475 0.87996 0.90062 0.91727 0.93016
```

```
##                            PC15    PC16    PC17    PC18    PC19    PC20    PC21
## Standard deviation     0.54341 0.50216 0.49677 0.45738 0.42678 0.40593 0.38187
## Proportion of Variance 0.01181 0.01009 0.00987 0.00837 0.00729 0.00659 0.00583
## Cumulative Proportion  0.94198 0.95206 0.96193 0.97030 0.97759 0.98418 0.99001
##                            PC22    PC23   PC24    PC25
## Standard deviation     0.35570 0.26215 0.1800 0.14861
## Proportion of Variance 0.00506 0.00275 0.0013 0.00088
## Cumulative Proportion  0.99507 0.99782 0.9991 1.00000
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.56545 -0.19537  0.01189  0.19806  1.23198
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept)  2.327561   0.005701  408.259  < 2e-16 ***
## PC1          0.030802   0.002165   14.229  < 2e-16 ***
## PC2          0.287542   0.003085   93.208  < 2e-16 ***
## PC3          0.310894   0.003701   84.005  < 2e-16 ***
## PC4         -0.023537   0.003976   -5.920 3.56e-09 ***
## PC5         -0.578237   0.004568 -126.596  < 2e-16 ***
## PC6         -0.168639   0.005030  -33.527  < 2e-16 ***
## PC7          0.101148   0.005279   19.161  < 2e-16 ***
## PC8          0.201552   0.005744   35.086  < 2e-16 ***
## PC9         -0.026557   0.006088   -4.362 1.33e-05 ***
## PC10        -0.196808   0.006763  -29.099  < 2e-16 ***
## PC11         0.056181   0.007182    7.822 6.94e-15 ***
## PC12         0.030186   0.007934    3.805 0.000145 ***
## PC13         0.101358   0.008839   11.467  < 2e-16 ***
## PC14        -0.016569   0.010043   -1.650 0.099103 .
## PC15         0.068952   0.010493    6.571 5.79e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3263 on 3260 degrees of freedom
## Multiple R-squared:  0.9166, Adjusted R-squared:  0.9163
## F-statistic:  2390 on 15 and 3260 DF,  p-value: < 2.2e-16
```

The results show that the adjusted R-squared is now 0.92, a big improvement from a linear regression without pca. They also show that after 15 principal components, 95% of the variance in the data has already been accounted for, so the dimensions can definately be reduced. Below we check how the linear regression model after reducing the dimensions using pca performs on new data by checking the RMSE value returned.

```
## [1] 0.3232659
```

The RMSE value for the liner regression model after first performing pca is now 0.32, almost half of that without pca.

Conclusion and further work

The linear regression model build here fits the data fairly well and predicts the target variable on new data with fairly good accuracy too.It makes an error of about 0.32 units when predicting the silica content in the concentrate. However, it is unknown whether or not this error is acceptable for this specific plant, because no further information is given regarding this flotation process. What margin of error can be acceptable for them? And what are the implications of making an error? More information is needed to better understand the process and this could be achieved by talking with the people concerned, about the process. With more information available then maybe more algorithms may be deployed to build a model with even better prediction accuracy.