## AS.3

Q1:

1. ##------Q1------##

mydata<-read.csv('Sediment.csv')

#1-----scatterplot matrices-----#install.packages('GGally')

library(GGally)

pairs(mydata)

corelationship<-cor(mydata,method='pearson')

write.xlsx(corelationship,file = 'cor.xlsx')

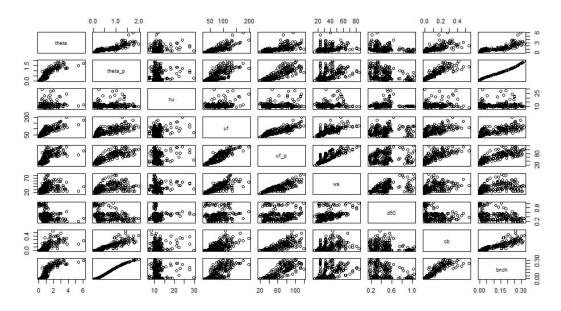


Fig.1 scatterplot matrices

#### Tab.1 correlation of all variables

	theta	theta_p	nu	uf	uf_p	WS	d50	cb	bnch
theta	1	0.8459082	0. 152097	0. 782360	0.660920	0. 278248	-0. 282756	0.7109135	0. 8286713
		58	888	562	907	71	202	52	33
theta	0.8459082	1	0. 075677	0. 698698	0.835765	0. 443326	-0. 289941	0.8936768	0.9961893
_p	58	1	581	532	443	319	362	34	52
2011	0. 1520978	0. 0756775	1	0. 266900	0. 175539	0. 133498	0.0711901	0. 1517867	0. 0866866
nu	88	81	1	973	725	763	41	53	35
uf	0. 7823605	0. 6986985	0. 266900	1	0.866942	0. 742154	0. 1997312	0. 6279347	0. 6941653
uı	62	32	973		743	315	91	3	54
	0.6609209	0.8357654	0. 175539	0.866942	1	0.846940	0. 1449141	0. 7840808	0.8462475
uf_p	07	43	725	743	1	99	23	45	62
ws	0. 2782487	0. 4433263	0. 133498	0. 742154	0.846940	1	0.4556866	0. 4301430	0.4617698
	1	19	763	315	99	1	58	66	29
d50	-0. 282756	-0. 289941	0. 071190	0. 199731	0. 144914	0. 455686	1	-0. 231695	-0. 270209

	202	362	141	291	123	658		236	813
ah	0.7109135	0. 8936768	0. 151786	0. 627934	0. 784080	0. 430143	-0. 231695	1	0.8977457
cb	52	34	753	73	845	066	236	1	69
bnch	0.8286713	0. 9961893	0.086686	0.694165	0.846247	0.461769	-0. 270209	0.8977457	1
	33	52	635	354	562	829	813	69	1

As we can see, theta\_p has the largest correlation with theta.

```
2.
```

```
#2------linear model------
library(UsingR)
plot(mydata$theta_p,mydata$theta)
modelize<-lm(mydata$theta~mydata$theta_p)
abline(Im(mydata$theta~mydata$theta_p))
Im_r<- simple.Im(mydata$theta_p,mydata$theta)
simple.Im(mydata$theta_p,mydata$theta,show.ci = T)
summary(Im_r)
```

mathematical equation of this model is y=1.54x+0.18;

the proportion of predictor and response variable is R square which is 0.7156;

## 3.

```
residual_mydata<-resid(lm_r)
summary(residual_mydata)
qqnorm(residual_mydata)</pre>
```

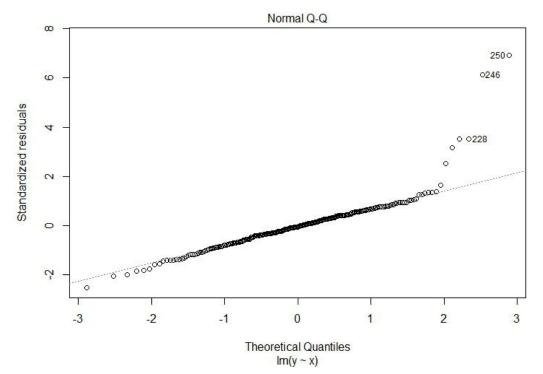


Fig.2. residual distribution

From this figure, the residuals distribution approximately approach to normal distribution and it validates our model.

# 4. theta<-mydata\$theta theta\_p<-mydata\$theta\_p pre\_theta<- data.frame(theta\_p=c(0.1,0.2,0.3,0.4,0.5,0.6,0.7)) prediction<-predict(lm(theta~theta\_p),pre\_theta) write.xlsx(prediction,file = 'prediction.xlsx')

#### Tab.2 prediction of theta

	1	2	3	4	5	6	7
X	0. 339027387	0. 493439283	0. 647851178	0.802263073	0. 956674969	1.111086864	1. 265498759

#### Q2:

```
1.
    ##1-----split the data into 2 data sets-----
my_data<-read.csv('Sediment.csv')
dim(my_data)
index<- sample(1:nrow(my_data),size = round(0.3*nrow(my_data)))
test_data<- my_data[index,]
train_data<-my_data[-index,]
2.
multi_model<- lm(train_data$theta~train_data$theta_p+train_data$uf+train_data$uf_p)
plot(multi_model)
summary(multi_model)
coef(multi_model)
coef(summary(multi_model))
write.xlsx(coef(multi_model),file = 'coef.xlsx')</pre>
```

#### Tab.3 coefficients of regression

	(Intercept)	train_data\$theta_p	train_data\$uf	train_data\$uf_p
X	-0. 185736	1. 972069	0. 029421	-0.038886

#### 3.

```
theta<-train_data$theta
theta_p<-train_data$theta_p
uf<-train_data$uf
uf_p<-train_data$uf_p
predict_data<-predict(lm(theta~theta_p+uf+uf_p),test_data)
write.xlsx(predict_data,file = 'prediction_data.xlsx')
```

### Tab.4 prediction of theta in multiple regression model

order	х
102	0. 93159172
122	2. 241143277
228	0.713006117
169	0. 373286967

107	0.700005671
187	0.789085671
230	1. 073375584
161	0. 63761097
217	0. 788662343
72	1.630723901
33	1. 089343053
248	0. 55437153
18	0. 410191328
47	1.065920476
66	1.521104313
126	1. 389524098
32	0. 338707449
68	3. 160124662
45	0. 379485709
50	0. 796046996
202	0. 871159131
129	2. 043002139
116	1. 213646647
151	2. 865762558
105	0. 63709957
256	0. 425930596
106	1. 104875906
212	3. 451311706
23	0. 279320299
81	0. 183973668
82	0. 02511623
55	1. 500502726
215	1. 046310074
188	0. 577261285
98	0. 331947446
54	0. 714899531
14	1.27116902
232	0.541869708
132	0.857455792
90	0. 143885471
210	0. 932284923
164	1. 151940831
70	3. 148491918
197	1. 200954938

138	0.456487604
206	0.620126898
34	0.802896417
140	0. 48424187
238	0. 889696975
3	1.762053099
172	0.841540474
239	1.032272124

predict\_data<-as.data.frame(predict\_data)</pre>

X<-seq(1:length(predict\_data\$predict\_data))

theta\_test<-as.data.frame(test\_data\$theta)

data\_new<-cbind(theta\_test,predict\_data)</pre>

data\_new\$order<-X

data\_new<-melt(data\_new,id='order')

ggplot(model,aes(order,theta))+geom\_line(aes(color=source,group=source))+ggtitle('comparison of predict data and observed data')

# comparison of predict data and observed data

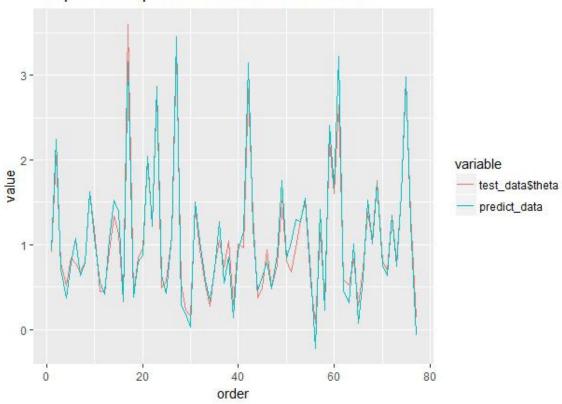


Fig.3 model validation