Model Ideal

Load Libraries

```
library(glmnet) # create model
library(caret) # ml library
library(tidyverse) # common libraries
```

Load Data

```
df<-read.csv("rent-amount-clear-preprocesing.csv")
```

```
attach(df)
```

Split Data

```
set.seed(2018) # random state

training.ids<-createDataPartition(rent.amount,p=0.7,list = F)

train_data<-df[training.ids,] # select train data index
test_data<-df[-training.ids,] # select test data index
```

```
X_train<- train_data %>% select(-rent.amount)
X_train<-as.matrix(X_train)# transform to matrix
Y_train<-train_data$rent.amount


X_test<- test_data %>% select(-rent.amount)
X_test<-as.matrix(X_test) # transform to matrix
Y_test<-test_data$rent.amount
```

Model Creation

```
lm_ridge<-glmnet(x=X_train,y=Y_train,alpha = 0.1,lambda = 0.001)
```

We assign the same parameters of the best model, which we had previously estimated.

```
predict_model<-function(data){

  y_pred<-predict(lm_ridge,newx =data)
  y_pred<-as.vector(y_pred)
}
```

```
pred_train<-predict_model(X_train)
pred_test<-predict_model(X_test)
```

```
train_data<- train_data %>% mutate(predictions=pred_train)

test_data<- test_data %>% mutate(predictions=pred_test)
```

MSE

Measures the average error between the predicted value and the original.

Train

```
train_data %>% summarise(mse=RMSE(predictions,rent.amount))
```

mse
<dbl>
0.1915151

1 row

Test

```
test_data %>% summarise(mse=RMSE(predictions,rent.amount))
```

mse
<dbl>
0.2209271

1 row

R^2

It measures the degree of fit of the model. The higher the value, the better the model fit.

```
train_data %>% summarise(mse=R2(predictions,rent.amount))
```

mse
<dbl>
0.9392654

1 row

```
test_data %>% summarise(mse=R2(predictions,rent.amount))
```

mse
<dbl>
0.917652

1 row

Both metrics are very similar. Therefore, it indicates that our model is not overtrained. This means that the model is only good for the training data but it is unable to generalize with new data that it has never seen.

Exponential transformation

```
test_data<-test_data %>%

  mutate(rent.amount=exp(rent.amount)) %>%

  mutate(predictions=exp(predictions))
```

Let us remember that the rent.amount variable is in logarithmic scale and we perform the exponential transformation because it is its opposite operation.

Variable coefficients

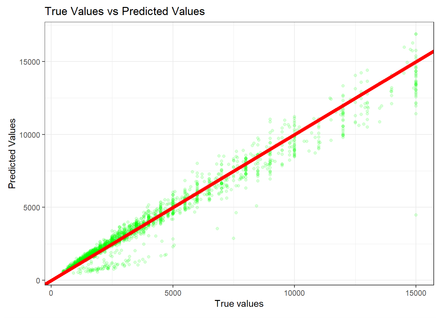
```
coef(lm_ridge)
```

```
## 10 x 1 sparse Matrix of class "dgCMatrix"
##                         s0
## (Intercept)     4.6666887400
## city            0.1171973949
## animal         -0.0003875935
## furniture       0.0928719962
## area            0.0502690908
## fire.insurance  0.8194256100
## rooms          -0.0041296755
## bathrooms       0.0293551434
## floor           0.0483440792
## parking.spaces  0.0118199662
```

We previously knew that the health insurance charge variable. It had a great relationship with respect to the rental price, which I assign the highest coefficient.

To the other complementary variables that add value, I minimize the weight of the coefficient as we had previously explained.

```
test_data %>%
  ggplot(aes(x=rent.amount,y=predictions))+
  geom_point(color="green",alpha=0.15) +
  geom_abline(intercept = 0,slope = 1,color="red",lwd=2) +
  theme_bw() +
  labs(title = "True Values vs Predicted Values",
       x="True values",y="Predicted Values")
```




```
test_data %>% select(rent.amount,predictions) %>% head(50)
```

rent.amount	predictions
<dbl>	<dbl>
7	5000	4575.1661
10	2900	2903.8756
11	720	834.6194
15	3950	4047.3172
17	3010	3235.3602
18	3500	3669.5282
19	7800	7235.7664
23	3500	3561.7759
27	6500	5464.5172
29	1800	1883.0248

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In most predictions, it gives predictions very close to the original value.

Save Model

```
saveRDS(lm_ridge,"lm_ridge_rent.RDS")
```