

## Question 1:

Our approach to the **validation** method was to vary the ratio (or split) of the **train subset** to the **test subset** (of the training data), in a sense causing the ratio to become a hyperparameter of the model, while fixing the ratio of the **test** subset to the **validation** subset to exactly 50% (0.5). For each train subset-to-test subset ratio [0.2, 0.3, 0.5], the (simple) **Ordinary Least Squares** model was trained on the “train + validation” subsets (**model selection**). The model that yielded the lowest RSE was then used on the **test** subset (**model assessment**).

Displayed below and tabularized are sample scores from an instance of running validation on the training dataset.

```
Simple Linear Regression
x_train_sub: 160, y_train_sub: 160
x_val_sub: 320, y_val_sub: 320
Validation:
RSE_val_sub: 10.437398373022999
RSquare_val_sub: 0.6173016047616007
-----
x_train_sub: 240, y_train_sub: 240
x_val_sub: 280, y_val_sub: 280
Validation:
RSE_val_sub: 10.555812882473376
RSquare_val_sub: 0.5890871793136658
-----
x_train_sub: 400, y_train_sub: 400
x_val_sub: 200, y_val_sub: 200
Validation:
RSE_val_sub: 10.647141688182703
RSquare_val_sub: 0.5925505876774707
-----
x_train_sub: 480, y_train_sub: 480
x_test_sub: 320, y_test_sub: 320

Test:
RSE_test_sub: 10.399987291453957
RSquare_test_sub: 0.6406625212834421
```

train : validation : test	RSE	R <sup>2</sup>
0.2 : 0.4 : 0.4	10.4374	0.6173
0.3 : 0.35 : 0.35	10.5558	0.5891
0.5 : 0.25 : 0.25	10.6471	0.5926

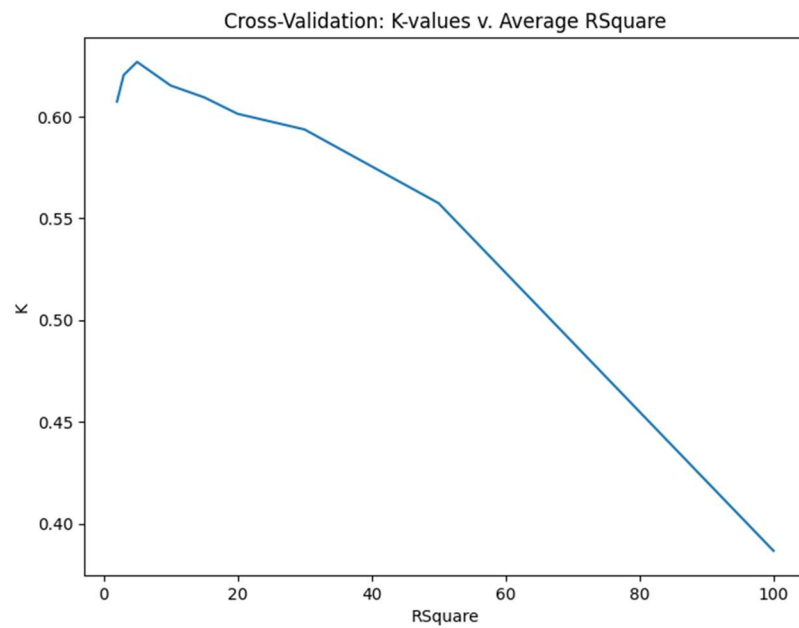
*Figure 1 – Sample results of validation*

For **cross-validation**, **model selection** was carried out by varying the hyper-parameter K, the number of folds created from the training dataset, and consequently the number of samples held out from training the model at a given moment. The average RSE and  $R^2$  values of the model's performance for each K were calculated. Subsequently, the model with the lowest RSE (optimal hyper-parameters) was fit on the entire training dataset and run on the test set to evaluate its performance (**model assessment**).

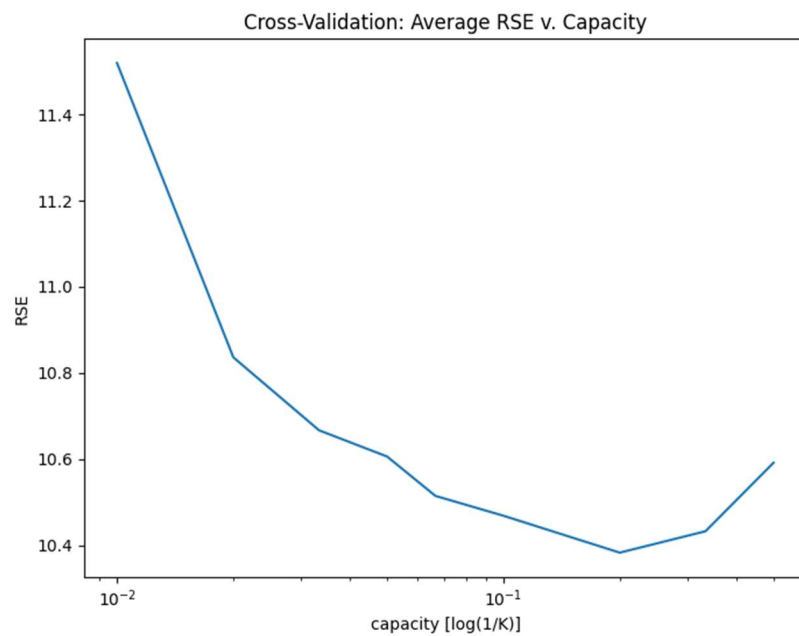
```
Simple Linear Regression : [K=2]
Cross Validation(n_splits=2):
RSE_cv_fold: 10.591530975350555
RSquare_cv_fold: 0.607473200454563
=====
Simple Linear Regression : [K=3]
Cross Validation(n_splits=3):
RSE_cv_fold: 10.432356065853336
RSquare_cv_fold: 0.6205865700222323
=====
Simple Linear Regression : [K=5]
Cross Validation(n_splits=5):
RSE_cv_fold: 10.382679026538245
RSquare_cv_fold: 0.6268905748544279
=====
Simple Linear Regression : [K=10]
Cross Validation(n_splits=10):
RSE_cv_fold: 10.4683512131033
RSquare_cv_fold: 0.615260325225556
=====
Simple Linear Regression : [K=15]
Cross Validation(n_splits=15):
RSE_cv_fold: 10.514479535044872
RSquare_cv_fold: 0.6094834518910771
=====
Simple Linear Regression : [K=20]
Cross Validation(n_splits=20):
RSE_cv_fold: 10.605818795201769
RSquare_cv_fold: 0.6014191871018241
=====
Simple Linear Regression : [K=30]
Cross Validation(n_splits=30):
RSE_cv_fold: 10.666731981667208
RSquare_cv_fold: 0.5936544396949841
=====
Simple Linear Regression : [K=50]
Cross Validation(n_splits=50):
RSE_cv_fold: 10.836096600621138
RSquare_cv_fold: 0.5574515576671456
=====
Simple Linear Regression : [K=100]
Cross Validation(n_splits=100):
RSE_cv_fold: 11.519408984614506
RSquare_cv_fold: 0.38673367020132643
=====
RSE_cv_test: 9.638450941285175
RSquare_cv_test: 0.5953110867026103
```

K	RSE	$R^2$
2	10.5915	0.6075
3	10.4324	0.6206
5	10.3827	0.6269
10	10.4684	0.6153
15	10.5145	0.6095
20	10.6058	0.6014
30	10.6667	0.5937
50	10.8361	0.5575
100	11.5194	0.3867

*Figure 2 – Sample results of cross-validation*



**Figure 3 – K-values v. Average  $R^2$  (cross-validation)**



**Figure 4 – Average RSE v. Capacity (cross-validation)**

In Figure 3, as expected, the  $R^2$  peaks around K-values of 3, 5, 10 and worsens as K increases; knowing that **smaller** values of K are preferred for cross-validation when the size of the dataset, N, is **large(r)**. Conversely, in Figure 4, the RSE decreases as the capacity increases.

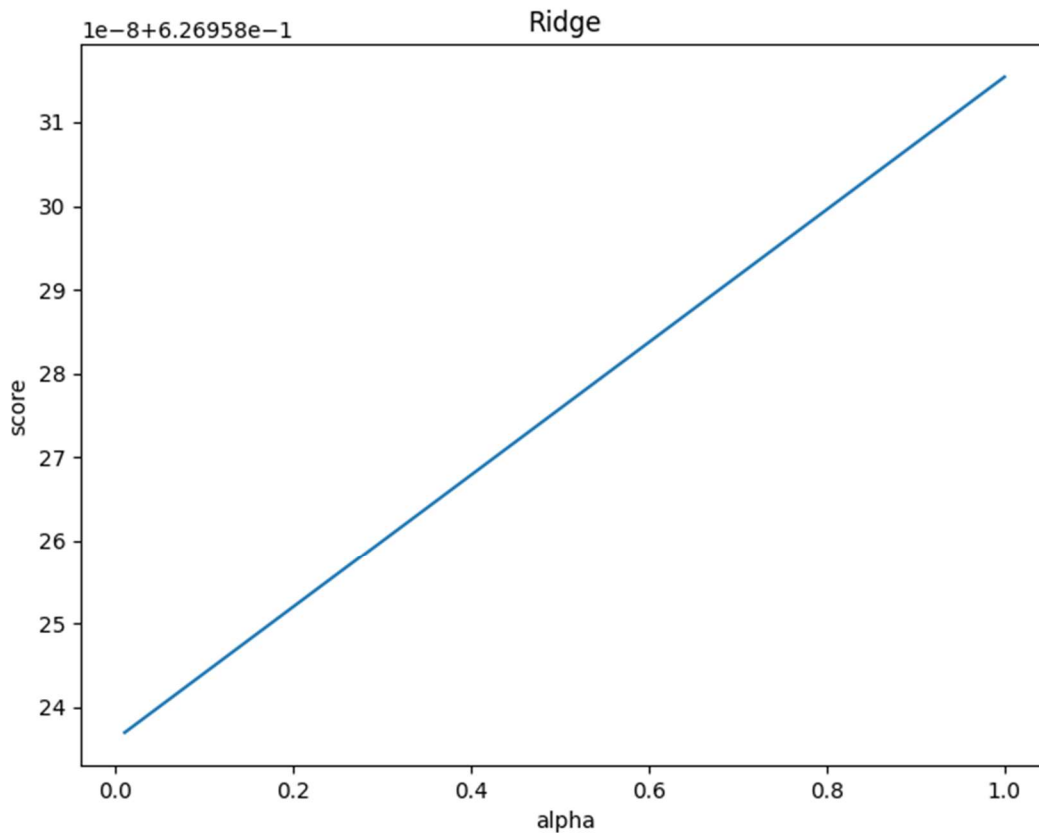
From the same run of validation, and cross-validation, below are the results of the model assessment; for validation, running the optimal model obtained from training on “**train + validation**” subsets on the **test** subset (of the training dataset), and for cross-validation, running the optimal model obtained, from the various K-values, on the actual **test** dataset.

Method	RSE	$R^2$
Validation	10.4000	0.6406
Cross-Validation	9.6385	0.5953

***Figure 5 – Comparison of assessment of Validation and Cross-Validation methods***

As observed above, the performance of the optimal model using the validation method on the “**test**” subset of the training data surpasses the performance of the optimal model obtained using K-fold cross-validation on the actual (blind) test dataset.

## Question 2:



**Figure 6 – alpha values v. scores of Ridge Regression Model**

Ridge Regression - alpha=1  
RSE: 9.638450768270868  
RSquare: 0.5953111012312874

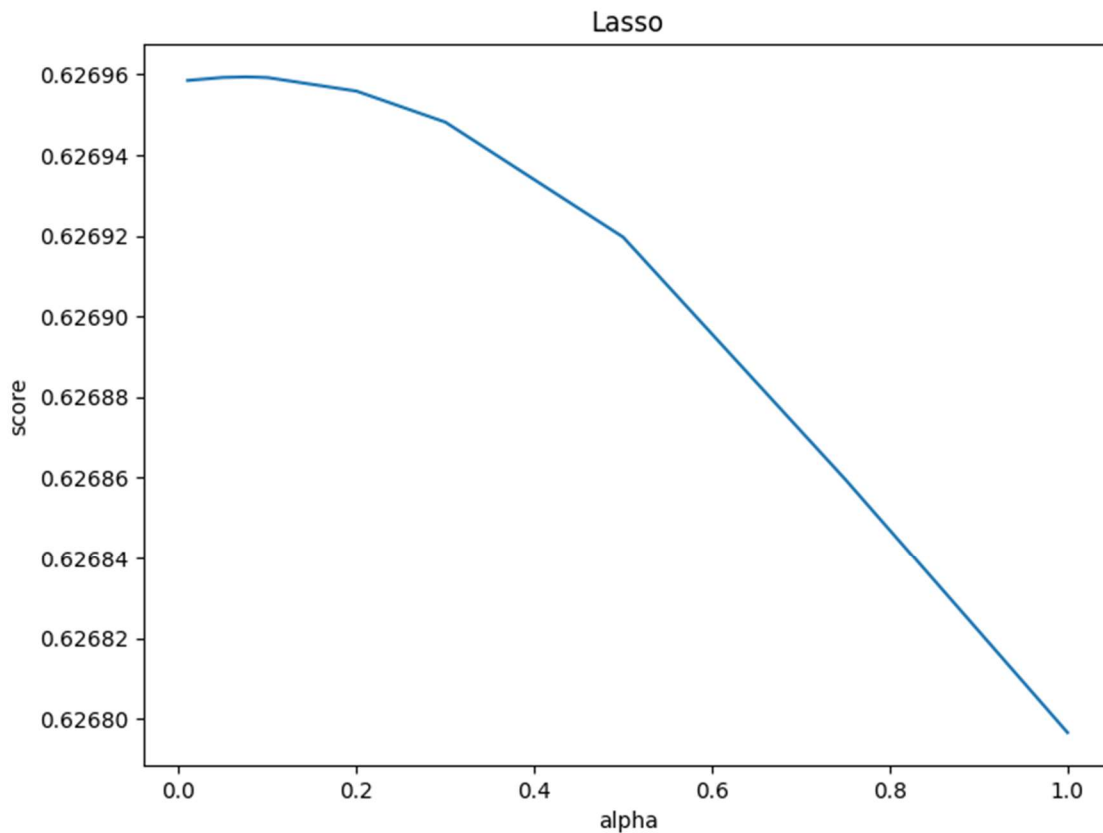
Method	RSE	R <sup>2</sup>
Simple OLE Validation	10.4000	0.6406
Simple OLE Cross-Validation	9.6385	0.5953
Ridge Regression	9.6385	0.5953

**Figure 7 – Comparison of assessment of Simple OLE and Ridge Regression**

As observed in Figure 6, the model performance of the Ridge Regressor is directly proportional to the alpha hyper-parameters, with the performance peaking at the highest alpha value during cross-validation.

Comparing the RSE and R<sup>2</sup> values of the Ridge Regressor using the optimal alpha value of 1, we observed approximately (to 4 d.p.) the same performance as the Simple OLE (cross-validation), but slightly worse than the Simple OLE validation (**NOTE:** Simple OLE validation was not on the actual test dataset, but on test subset of training dataset).

### Question 3:



**Figure 8 – alpha values v. scores of Lasso Regression Model**

```
Lasso Regression - alpha=0.075  
RSE: 9.639263910631346  
RSquare: 0.5952428156581796
```

Method	RSE	R <sup>2</sup>
Simple OLE Validation	10.4000	0.6406
Simple OLE Cross-Validation	9.6385	0.5953
Ridge Regression	9.6385	0.5953
Lasso Regression	9.6393	0.5952

**Figure 9 – Comparison of assessment of Simple OLE and Ridge Regression**

As observed in Figure 8, in contrast to the Ridge Regressor, the model performance of the Lasso Regressor is inversely proportional to the alpha hyper-parameters, and actually peaks somewhere around the lowest alpha value (expected based on how it optimizes the objective function).

Comparing the RSE and  $R^2$  values of the Lasso Regressor using the optimal alpha value of 0.075, we observed an extremely miniscule decrement in model performance to the Simple OLE and the Ridge Regressor.