Regression model

Relative location of CT slices on axial axis

The data are available at:

https://archive.ics.uci.edu/dataset/206/relative+location+of+ct+slices+on+axial+axis

The dataset consists of 384 features extracted from CT images. The class variable is numeric and denotes the relative location of the CT slice on the axial axis of the human body.

The data was retrieved from a set of 53500 CT images from 74 different patients (43 male, 31 female).

To exstract the data use the panda routines

```
import zipfile
import pandas as pd
# read the dataset using the compression zip
df =
pd.read csv('https://archive.ics.uci.edu/static/public/206/relative+lo
cation+of+ct+slices+on+axial+axis.zip',compression='zip')
# display dataset
print(df.head())
   patientId value0 value1 value2 value3
                                                value4
                                                        value5
                                                                 value6
value7
                 0.0
                          0.0
                                  0.0
                                           0.0
                                                   0.0
                                                            0.0
                                                                  -0.25
-0.25
           0
                                                                  -0.25
                 0.0
                          0.0
                                  0.0
                                           0.0
                                                   0.0
                                                            0.0
1
-0.25
           0
                 0.0
                          0.0
                                  0.0
                                           0.0
                                                   0.0
                                                            0.0
                                                                  -0.25
-0.25
                                                                  -0.25
3
           0
                  0.0
                          0.0
                                  0.0
                                           0.0
                                                   0.0
                                                            0.0
-0.25
           0
                  0.0
                          0.0
                                           0.0
                                                   0.0
                                                            0.0
                                                                  -0.25
                                  0.0
-0.25
   value8
                value375 value376 value377 value378
                                                           value379
value380 \
    -0.25
                    -0.25
                           0.980381
                                           0.0
                                                     0.0
                                                                0.0
0
0.0
    -0.25
                    -0.25 0.977008
                                           0.0
                                                     0.0
                                                                0.0
1
0.0
```

```
2
    -0.25
                    -0.25
                           0.977008
                                           0.0
                                                      0.0
                                                                 0.0
0.0
3
    -0.25
                    -0.25
                           0.977008
                                           0.0
                                                      0.0
                                                                 0.0
0.0
4
    -0.25
                    -0.25 0.976833
                                           0.0
                                                      0.0
                                                                 0.0
0.0
   value381
             value382
                        value383
                                   reference
0
                                   21.803851
        0.0
                 -0.25
                           -0.25
1
        0.0
                 -0.25
                           -0.25
                                   21.745726
2
        0.0
                 -0.25
                           -0.25
                                   21.687600
3
        0.0
                 -0.25
                           -0.25
                                   21.629474
4
        0.0
                 -0.25
                           -0.25 21.571348
[5 rows x 386 columns]
```

We transform the data to a matrix of shape 53500 x 386

```
Aall=df.to_numpy()
print(Aall.shape)

(53500, 386)
```

We add a column of all 1 and we organize the input data by dividing in test set and training set

```
from sklearn.model_selection import train_test_split
import numpy as np
#Add a column of ones at the beginning of the data matrix
Aall = np.column_stack([np.ones(Aall.shape[0]), Aall])
X = Aall
X=np.delete(X,386,1)
y = Aall[:,386]
```

Use the prepared data to solve the regression model with all the studied techniques. Can we use the normal equation and the QR factorization? If the answer is positive compare the condition numbers of the QR methods and the normal equations. What are the results?

Use the funcation scipy.linalg.lstsq and check if all the lapack drivers works. Compare the results changing the initial value cond. The results are the same? What about the execution time?

Analyze the singular values and check if it is possible to use a principal component regression procedure. Compute the solution using the singular value decomposition. Can you observe a relation in the chosen singular value and the value of cond of the routine lstsg?

Perform the same analysis by preprocessing the data in order to have data from a normal distribution with mean zero and compute the singular value decomposition on this matrix.

Check the performance of the method by computing the least square residual for the training set and the testset. The minimum and the maximum values of the predicted error for both, the training set and the testset.

Compute the multiple R-squared: R2_train = 1 - sum((y - yest)**2)/sum((y-mean(y))**2 where y are the value to predict and yest are the estimated values for the training set. Compute the value R2 test for the testset.

A value of R2 near one means that the constructed model is good.

Change the size of the training set and the testing set to 0.7% and 0.3% and repeat the previous steps.

Comment the obtained results.

Normal equation is a method to solve the linear regression problem. It is based on the following formula:

$$\theta = (X^T X)^{-1} X^T y$$

where θ is the vector of parameters, X is the matrix of input data, and y is the vector of output data. It is important to note that the matrix X^T X must be full rank, otherwise the inverse of X^T X does not exist, so the normal equation cannot be used.

```
def normalEquations(X train, y train, X test, y test):
    print("Rank of train data:
",np.linalg.matrix_rank(X_train.T@X_train))
   print("Shape of train data: ",(X_train.T @ X_train).shape)
    if np.linalg.matrix rank(X train.T@X train)==X train.shape[1]:
        theta=np.linalg.solve(X_train.T@X_train,X train.T@y train)
        y_train_pred=X_train@theta
        y train_pred = X_train @ theta
        residuals_train = y_train - y_train_pred
        print("Residuals for train set:
",np.linalg.norm(residuals train,2))
        print("Maximum error for train set:
",np.max(np.abs(residuals train)))
        print("Minimum error for train set:
",np.min(np.abs(residuals train)))
        R2 train = 1 - np.sum((y train -
y train pred)**2)/np.sum((y train - np.mean(y train))**2)
        print("R2 for train set: ",R2 train)
        y test pred = X test @ theta
        residuals_test = y_test - y_test_pred
        print("Residuals for test set:
",np.linalg.norm(residuals test,2))
        print("Maximum error for test set:
",np.max(np.abs(residuals test)))
        print("Minimum error for test set:
",np.min(np.abs(residuals test)))
        R2\_test = 1 - np.sum((y test -
y test pred)**2)/np.sum((y test - np.mean(y test))**2)
        print("R2 for test set: ",R2_test)
```

```
else:
    print("Matrix is singular")
```

The QR factorization can be used to solve the linear regression problem. It is based on the following formula:

$$X = QR$$

where X is the matrix of input data, Q is an orthogonal matrix, and R is an upper triangular matrix. The solution of the linear regression problem is given by:

$$\theta = R^{-1} Q^T y$$

When X is not full rank, we cannot use the QR factorization to solve the problem. We need to use the Pivot QR factorization, which is based on the following formula:

$$XP = \begin{pmatrix} Q_X & Q_X^- \end{pmatrix} \begin{pmatrix} R_1 & R_2 \\ 0 & 0 \end{pmatrix}$$

where P is a permutation matrix. The solution of the linear regression problem is given by:

$$\hat{\theta} = P \begin{pmatrix} R_1^{-1} Q_X^T y \\ 0 \end{pmatrix}.$$

```
import scipy.linalg as la
def QRsolver(X train, y train, X test, y test):
    rank=np.linalg.matrix rank(X train)
    #if rank not maximum
    if rank<X train.shape[1]:</pre>
        Q,R,P = la.qr(X_train, pivoting=True, mode='economic')
\#economic \rightarrow Q \text{ is } m \times k, R \text{ is } k \times n \text{ where } k=min(m,n)
         print("Condition number of QR factorization matrix:
",np.linalg.cond(R,2))
        #truncate R and Q to rank
        R trunc = R[:rank, :rank]
        Q_{trunc} = Q[:, :rank]
        QTb = Q trunc.T @ y_train
        theta permuted=np.zeros(X train.shape[1])
        theta permuted [:rank]= la.solve triangular(R trunc, QTb)
#store the solution in the first rank columns
        #restore original order
        theta = np.zeros_like(theta_permuted)
        theta[P] = theta_permuted #permute the elements of
theta_permuted to get the solution
    else:
        Q,R=la.qr(X train, mode='economic')
        R \text{ trunc} = R[:rank, :rank]
        Q \text{ trunc} = Q[:, :rank]
        QTb = Q trunc.T @ y train
```

```
theta = la.solve triangular(R trunc, QTb)
             y train pred = X train @ theta
              residuals_train = y_train - y_train_pred
              print("Residuals for train set:
",np.linalg.norm(residuals_train,2))
             print("Maximum error for train set:
",np.max(np.abs(residuals train)))
              print("Minimum error for train set:
",np.min(np.abs(residuals train)))
             R2 train = 1 - np.sum((y train -
y_train_pred)**2)/np.sum((y_train - np.mean(y_train))**2)
             print("R2 for train set: ",R2_train)
             y test pred = X test @ theta
              residuals_test = y_test - y_test_pred
             print("Residuals for test set: ",np.linalg.norm(residuals_test,2))
             print("Maximum error for test set:
",np.max(np.abs(residuals test)))
             print("Minimum error for test set:
",np.min(np.abs(residuals test)))
             R2\_test = 1 - np.sum((y\_test - y\_test\_pred)**2)/np.sum((y_test - y\_test\_pred)**2)/np.sum((y_test - y_test\_pred)**2)/np.sum((y_test - y_test\_pred)**2)/np.sum((y_test_pred)**2)/np.sum((y_test - y_test\_pred)**2)/np.sum((y_test - y_test\_pred)**2)
np.mean(y test))**2)
              print("R2 for test set: ",R2_test)
```

The Singular Value Decomposition (SVD) can also be used to solve the linear regression problem. It is based on the following formula:

$$X = U \Sigma V^T$$

where X is the matrix of input data, U is an orthogonal matrix, Σ is a rectangular, and V is an orthogonal matrix. The solution of the linear regression problem is given by:

$$theta=V_rD^{-1}U_r^Ty$$

where V_r is the matrix containing the first r columns of V, U_r is the matrix containing the first r columns of U, and D is the diagonal matrix containing the first r singular values, which are the non-zeros one

```
def SVDSolver(X_train, y_train, X_test, y_test):
    rank = np.linalg.matrix_rank(X_train)
    U, S, Vt = np.linalg.svd(X_train, full_matrices=False) #U and V
are of size m x k and n x k, k=min(m,n) when full_matrices=False
    print("Rank of X_train: ",rank)
    print("Number of non zero singular values: ",np.count_nonzero(S))
    #S contains all singular values. If we consider only the non zero
singular values, they should be equal to the rank of X_train. In this
case this is not true, probably due to numerical errors.
    # I will use later the PCR and Euckardt-Young theorem to remove
noise
```

```
# So let's consider the first r=rank(X train) singular values
    U r = U[:, :rank]
    V\bar{t} r = Vt[:rank, :]
    S r = np.diag(S)[:rank, :rank]
    S r inv = np.linalg.inv(S r)
    theta = Vt_r.T @ S_r_inv @ U_r.T @ y_train
    y train pred = X train @ theta
    residuals_train = y_train - y_train_pred
    print("Residuals for train set:
",np.linalg.norm(residuals_train,2))
    print("Maximum error for train set:
",np.max(np.abs(residuals train)))
    print("Minimum error for train set:
",np.min(np.abs(residuals_train)))
    R2_{train} = 1 - np.sum((y train -
y train pred)**2)/np.sum((y train - np.mean(y train))**2)
    print("R2 for train set: ",R2 train)
    y_test_pred = X_test @ theta
    residuals_test = y_test - y_test_pred
    print("Residuals for test set: ",np.linalg.norm(residuals test,2))
    print("Maximum error for test set:
",np.max(np.abs(residuals test)))
    print("Minimum error for test set:
",np.min(np.abs(residuals test)))
    R2 test = \frac{1}{1} - np.sum((y test - y test pred)**2)/np.sum((y test -
np.mean(y_test))**2)
    print("R2 for test set: ",R2_test)
```

The function scipy.linalg.lstsq is a method to solve the least squares problem. It uses different LAPACK drivers to solve the problem. The available drivers are:

gelsd:

Description: The gelsd driver solves the least squares problem using Singular
 Value Decomposition (SVD) and Divide-and-Conquer method.

2. gelsy:

Description: The gelsy driver solves the least squares problem using QR decomposition with column pivoting.

3. **gelss**:

Description: The gelss driver solves the least squares problem using Singular Value Decomposition (SVD).

Divide and conquer is an optimization technique used to compute the **Singular Value Decomposition (SVD)** more efficiently.

• Concept: Divide and conquer breaks down the SVD problem into smaller, more manageable subproblems. Instead of performing the full SVD computation at once, the

algorithm recursively divides the matrix into smaller parts and computes the decomposition in stages, merging results as it progresses.

```
import time
def lstsqSolver(X_train, y_train, X_test, y_test):
    conditions=[1e-1,1e-2,1e-4,1e-8,1e-12,1e-16]
    values={}
    for condition in conditions:
        #gelsd
        times=[]
        for i in range(5):
            start_time = time.time()
            theta gelsd = la.lstsq(X train,
y train, lapack driver='gelsd', cond=condition)[0] #we took [0] because
lstsq returns a tuple
            times.append(time.time()-start time)
        values['driver']='gelsd'
        values['condition']=condition
        values['AVGtime']=np.mean(times)
        y train pred = X train @ theta gelsd
        residuals_train = y_train - y_train_pred
        values['residuals train']=np.linalg.norm(residuals train,2)
        values['Min error
residuals train']=np.min(np.abs(residuals train))
        values['Max error
residuals_train']=np.max(np.abs(residuals_train))
        R2 train = 1 - np.sum((y train -
y_train_pred)**2)/np.sum((y_train - np.mean(y_train))**2)
        values['R2 train']=R2 train
        y test pred = X test @ theta gelsd
        residuals_test = y_test - y_test_pred
        values['residuals test']=np.linalg.norm(residuals test,2)
        values['Min error
residuals test']=np.min(np.abs(residuals test))
        values['Max error
residuals test']=np.max(np.abs(residuals test))
        R2\_test = 1 - np.sum((y\_test -
y_test_pred)**2)/np.sum((y_test - np.mean(y_test))**2)
        values['R2 test']=R2 test
        print(values)
        #gelss
        times=[]
        for i in range(5):
            start time = time.time()
            theta gelss = la.lstsg(X train,
y train, lapack driver='gelss', cond=condition)[0] #we took [0] because
lstsq returns a tuple
            times.append(time.time()-start time)
        values['driver']='gelss'
```

```
values['condition']=condition
        values['AVGtime']=np.mean(times)
        y_train_pred = X_train @ theta_gelss
        residuals_train = y_train - y_train_pred
        values['residuals train']=np.linalg.norm(residuals train,2)
        values['Min error
residuals train']=np.min(np.abs(residuals train))
        values['Max error
residuals train']=np.max(np.abs(residuals train))
        R2 train = 1 - np.sum((y train -
y train pred)**2)/np.sum((y train - np.mean(y train))**2)
        values['R2 train']=R2 train
        y_test_pred = X_test @ theta_gelss
        residuals test = y test - y test pred
        values['residuals_test']=np.linalg.norm(residuals_test,2)
        values['Min error
residuals test']=np.min(np.abs(residuals test))
        values['Max error
residuals test']=np.max(np.abs(residuals test))
        R\overline{2} test = 1 - np.sum((y_test -
y test pred)**2)/np.sum((y test - np.mean(y test))**2)
        values['R2 test']=\overline{R}2 test
        print(values)
        #gelsy
        times=[]
        for i in range(5):
            start_time = time.time()
            theta gelsy = la.lstsq(X train,
y train, lapack driver='gelsy', cond=condition)[0] #we took [0] because
lstsq returns a tuple
            times.append(time.time()-start time)
        values['driver']='gelsy'
        values['condition']=condition
        values['AVGtime']=np.mean(times)
        y train pred = X train @ theta gelsy
        residuals_train = y_train - y_train_pred
values['residuals_train']=np.linalg.norm(residuals_train,2)
        values['Min error
residuals_train']=np.min(np.abs(residuals_train))
        values['Max error
residuals train']=np.max(np.abs(residuals train))
        R2 train = 1 - np.sum((y train -
y_train_pred)**2)/np.sum((y_train - np.mean(y_train))**2)
        values['R2_train']=R2_train
        y_test_pred = X_test @ theta_gelsy
        residuals_test = y_test - y_test_pred
        values['residuals test']=np.linalg.norm(residuals test,2)
        values['Min error
residuals test']=np.min(np.abs(residuals test))
```

```
values['Max error
residuals_test']=np.max(np.abs(residuals_test))
    R2_test = 1 - np.sum((y_test -
y_test_pred)**2)/np.sum((y_test - np.mean(y_test))**2)
    values['R2_test']=R2_test
    print(values)
```

PCR can be used to solve the linear regression problem. It is based on the following formula:

$$X_k = U_k \Sigma_k V_k^T$$

where X_k is an approximation of the matrix of input data, U_k contains the first k columns of U, Σ_k contains the first k singular values, and V_k contains the first k columns of V.

The problem is to find the best value of k. There are several methods that we can use like:

1. **Mixed Error**: We can use the mixed error to find the best value of k. The criterion is based on the following formula:

$$\frac{\|X - X_k\|_2}{\|X\|_2 + 1} = \frac{\sigma_{k+1}}{\sigma_1 + 1} \le \text{tol}$$

When we find k+1 so that the criterion is satisfied, we can use k as the best value of k.

- 1. **Scree Plot**: We can use the scree plot to find the best value of k. The scree plot shows the singular values in decreasing order. We can find the best value of k by looking at the point where the curve starts to flatten.
- 2. **Cumulative Percentage of Variance**: We can use the cumulative percentage of variance to find the best value of k. The cumulative percentage of variance is given by:

$$\frac{\sum_{i=1}^{k} \sigma_i^2}{\sum_{i=1}^{r} \sigma_i^2} > \mathcal{L} p$$

where p is the percentage of variance that we want to explain between 0 and 1. When we find k so that the criterion is satisfied, we can use k as the best value of k.

```
import matplotlib.pyplot as plt
from kneed import KneeLocator

def PCRSolver(X_train, y_train, X_test, y_test):
    U, S, Vt = np.linalg.svd(X_train, full_matrices=False)
    #1: mixed error criterion
    tol=1e-6
    k=np.argmax(S/(S[0]+1)<tol)-1 #argmax returns the first
occurrence of the that satisfies the condition and this is k+1</pre>
```

```
print("k=",k," with mixed error criterion and tol=",tol)
    print("Sigma k=",S[k])
    U k = U[:, :k]
    Vt k = Vt[:k, :]
    S k = np.diag(S)[:k, :k]
    S k inv = np.linalg.inv(S k)
    theta = Vt k.T @ S k inv @ U k.T @ y train
    y train pred = X train @ theta
    residuals train = y train - y train pred
    print("Residuals for train set:
",np.linalg.norm(residuals_train,2))
    print("Maximum error for train set:
",np.max(np.abs(residuals_train)))
    print("Minimum error for train set:
",np.min(np.abs(residuals_train)))
    R2 train = 1 - np.sum((y train -
y train pred)**2)/np.sum((y train - np.mean(y train))**2)
    print("R2 for train set: ",R2_train)
    y test pred = X test @ theta
    residuals_test = y_test - y_test_pred
    print("Residuals for test set: ",np.linalg.norm(residuals_test,2))
    print("Maximum error for test set:
",np.max(np.abs(residuals test)))
    print("Minimum error for test set:
",np.min(np.abs(residuals test)))
    R2 test = \frac{1}{1} - np.sum((y test - y test pred)**2)/np.sum((y test -
np.mean(y test))**2)
    print("R2 for test set: ",R2 test)
    #2: Scree Plot
    k1 = KneeLocator(range(len(S)), S, curve='convex',
direction='decreasing')
    plt.plot(range(len(S)), S)
    plt.scatter(k1.elbow, S[k1.elbow], c='red', s=100, alpha=0.5)
    plt.xlabel('Singular value index')
    plt.ylabel('Singular value')
    plt.title('Scree plot')
    plt.legend(['Singular values', 'Elbow'])
    plt.show()
    k=k1.elbow
    print("k=",k," with Screep plot")
    print("Sigma_k=",S[k])
```

```
U k = U[:, :k]
         Vt k = Vt[:k, :]
         S k = np.diag(S)[:k, :k]
         S k inv = np.linalg.inv(S k)
         theta = Vt k.T @ S k inv @ U k.T @ y train
         y_train_pred = X_train @ theta
         residuals_train = y_train - y train pred
         print("Residuals for train set:
",np.linalg.norm(residuals train,2))
         print("Maximum error for train set:
",np.max(np.abs(residuals train)))
         print("Minimum error for train set:
",np.min(np.abs(residuals_train)))
         R2 train = 1 - np.sum((y train -
y_train_pred)**2)/np.sum((y_train - np.mean(y_train))**2)
         print("R2 for train set: ",R2 train)
         y_test_pred = X_test @ theta
          residuals_test = y_test - y_test_pred
         print("Residuals for test set: ",np.linalg.norm(residuals test,2))
         print("Maximum error for test set:
",np.max(np.abs(residuals_test)))
         print("Minimum error for test set:
",np.min(np.abs(residuals_test)))
         R2\_test = 1 - np.sum((y\_test - y\_test\_pred)**2)/np.sum((y\_test - y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum
np.mean(y test))**2)
         print("R2 for test set: ",R2 test)
         #3: Cumulative percentage of variance
         p=0.99
         total sum=np.sum(S**2)
         cumulative sum=np.cumsum(S^{**2})
         k=np.argmax((cumulative_sum/total sum)>p)
         print("k=",k,"with cumulative percentage of variance and p=",p)
         print("Sigma k=",S[k])
         U k = U[:, :k]
         Vt k = Vt[:k, :]
         S k = np.diag(S)[:k, :k]
         S k inv = np.linalg.inv(S k)
         theta = Vt_k.T @ S_k_inv @ U_k.T @ y_train
         y_train_pred = X_train @ theta
          residuals_train = y_train - y_train_pred
         print("Residuals for train set:
",np.linalg.norm(residuals_train,2))
         print("Maximum error for train set:
",np.max(np.abs(residuals train)))
         print("Minimum error for train set:
",np.min(np.abs(residuals_train)))
         R2\_train = 1 - np.sum((y\_train -
```

```
y_train_pred)**2)/np.sum((y_train - np.mean(y_train))**2)
    print("R2 for train set: ",R2 train)
    y test pred = X test @ theta
    residuals test = y test - y test pred
    print("Residuals for test set: ",np.linalg.norm(residuals test,2))
    print("Maximum error for test set:
",np.max(np.abs(residuals_test)))
    print("Minimum error for test set:
",np.min(np.abs(residuals_test)))
    R2 test = \frac{1}{1} - np.sum((y test - y test pred)**2)/np.sum((y test -
np.mean(y test))**2)
    print("R2 for test set: ",R2 test)
import numpy as np
from sklearn.model selection import train_test_split
X train, X test, y train, y test = train test split(
    Χ.
    у,
    train size = .9,
    test size = .1,
    random state = 5,
    shuffle = True
)
print("\nNORMAL EQUATIONS")
normalEquations(X train, y train, X test, y test)
print("\nQR SOLVER")
QRsolver(X_train, y_train, X_test, y_test)
print("\nSVD SOLVER")
SVDSolver(X train, y train, X test, y test)
print("\nLSTSQ SOLVER")
lstsqSolver(X_train, y_train, X_test, y_test)
print("\nPCR SOLVER")
PCRSolver(X train, y train, X test, y test)
NORMAL EQUATIONS
Rank of train data: 375
Shape of train data: (386, 386)
Matrix is singular
OR SOLVER
Condition number of QR factorization matrix: 2.4463550697566203e+32
Residuals for train set: 1798.3737270942406
Maximum error for train set: 49.47129163028276
Minimum error for train set: 1.4352963262354024e-12
R2 for train set: 0.8653831545119198
```

```
Residuals for test set: 613.1967475658972
Maximum error for test set: 46.98621458423358
Minimum error for test set:
                              0.0023313738117138882
R2 for test set: 0.8603214800189586
SVD SOLVER
Rank of X train: 375
Number of non zero singular values: 386
Residuals for train set: 1798.3737270942406
Maximum error for train set: 49.47129163028183
Minimum error for train set: 5.613287612504791e-13
R2 for train set: 0.8653831545119198
Residuals for test set: 613.1967475658979
Maximum error for test set: 46.98621458423264
Minimum error for test set:
                              0.0023313738110175564
R2 for test set: 0.8603214800189583
LSTSO SOLVER
{'driver': 'gelsd', 'condition': 0.1, 'AVGtime': 1.778600263595581,
'residuals train': 7079.003325567669, 'Min error residuals train':
0.00016317329873416497, 'Max error residuals train':
86.12879856814983, 'R2 train': -1.085853217608597, 'residuals test':
2361.142356336503, 'Min error residuals test': 0.0015384355100849234,
'Max error residuals test': 86.21332456608175, 'R2 test': -
1.0709722681710114}
{'driver': 'gelss', 'condition': 0.1, 'AVGtime': 1.7356050491333008,
'residuals_train': 7079.00332556767, 'Min error residuals train':
0.00016317329874482311, 'Max error residuals train':
86.12879856814982, 'R2_train': -1.085853217608597, 'residuals_test': 2361.142356336503, 'Min error residuals_test': 0.0015384355101133451,
'Max error residuals test': 86.21332456608174, 'R2 test': -
1.0709722681710114}
{'driver': 'gelsy', 'condition': 0.1, 'AVGtime': 2.619104099273682,
'residuals_train': 7079.030051187763, 'Min error residuals train':
0.001103681757442132, 'Max error residuals_train': 86.13955960940007,
'R2 train': -1.0858689672341675, 'residuals test': 2361.119587258657,
'Min error residuals test': 0.0034863125009110263, 'Max error
residuals test': 86.22408570665593, 'R2 test': -1.070932326571298}
{'driver': 'gelsd', 'condition': 0.01, 'AVGtime': 1.564098834991455, 'residuals_train': 2852.209177373248, 'Min error residuals_train':
0.0001833803512454324, 'Max error residuals train': 59.94903873041823,
'R2 train': 0.6613880686470945, 'residuals test': 947.1567219811014,
'Min error residuals test': 0.002341357849196868, 'Max error
residuals_test': 57.95973924838983, 'R2_test': 0.6667473351505734}
{'driver': 'gelss', 'condition': 0.01, 'AVGtime': 1.6477362155914306,
'residuals train': 2852.2091773732373, 'Min error residuals train':
0.00018338034929143987, 'Max error residuals train': 59.9490387304176,
'R2 train': 0.6613880686470971, 'residuals test': 947.1567219810992,
'Min error residuals test': 0.002341357847889469, 'Max error
```

```
residuals_test': 57.959739248389454, 'R2_test': 0.6667473351505749} {'driver': 'gelsy', 'condition': 0.01, 'AVGtime': 2.6249019622802736,
'residuals_train': 7079.030051187763, 'Min error residuals_train':
0.001103681757442132, 'Max error residuals train': 86.13955960940007,
'R2 train': -1.0858689672341675, 'residuals test': 2361.119587258657,
'Min error residuals test': 0.0034863125009\overline{1}10263, 'Max error
residuals test': 86.22408570665593, 'R2 test': -1.070932326571298}
{'driver': 'gelsd', 'condition': 0.0001, 'AVGtime':
1.5610857486724854, 'residuals_train': 1798.3994734141352, 'Min error
residuals train': 1.8338172878884507e-05, 'Max error residuals train':
49.47573432749514, 'R2 train': 0.8653793000147989, 'residuals test':
613.1715704956185, 'Min error residuals test': 0.0014430106109344365,
'Max error residuals test': 46.9891455047549, 'R2 test':
0.8603329498244735}
{'driver': 'gelss', 'condition': 0.0001, 'AVGtime': 1.6475080013275147, 'residuals_train': 1798.3994734141352, 'Min error
residuals train': 1.8338172111498352e-05, 'Max error residuals train':
49.475734327497754, 'R2_train': 0.8653793000147989, 'residuals test':
613.1715704956163, 'Min error residuals test': 0.0014430106120997266.
'Max error residuals test': 46.98914550475641, 'R2 test':
0.8603329498244745}
{'driver': 'gelsy', 'condition': 0.0001, 'AVGtime':
2.6496541023254396, 'residuals train': 1798.3882302496897, 'Min error
residuals_train': 8.989160991035305e-05, 'Max error residuals train':
49.47471047246335, 'R2 train': 0.8653809832425342, 'residuals test':
613.1948421789593, 'Min error residuals test': 0.0006585745238822938,
'Max error residuals test': 46.98724460469762, 'R2 test':
0.860322348064052}
{'driver': 'gelsd', 'condition': 1e-08, 'AVGtime': 1.5690276622772217,
'residuals train': 1798.3737270942404, 'Min error residuals train':
1.8260948309034575e-12, 'Max error residuals train':
49.47129163027922, 'R2_train': 0.8653831545119198, 'residuals test':
613.1967475659, 'Min error residuals test': 0.002331373807535897, 'Max
error residuals test': 46.986214584231135, 'R2_test':
0.8603214800189574}
{'driver': 'gelss', 'condition': 1e-08, 'AVGtime': 1.633497953414917,
'residuals train': 1798.3737270942404, 'Min error residuals train':
4.050093593832571e-13, 'Max error residuals train':
49.471291630281804, 'R2_train': 0.8653831545119198, 'residuals test':
613.1967475658978, 'Min error residuals test': 0.002331373811045978,
'Max error residuals test': 46.98621458423261, 'R2 test':
0.8603214800189584}
{'driver': 'gelsy', 'condition': 1e-08, 'AVGtime': 2.636412000656128,
'residuals_train': 1798.3737270942406, 'Min error residuals_train':
1.3287149158713873e-12, 'Max error residuals train':
49.471291630282785, 'R2_train': 0.8653831545119198, 'residuals_test':
613.1967475658972, 'Min error residuals test': 0.002331373811642834,
'Max error residuals test': 46.986214584233636, 'R2 test':
0.8603214800189586}
```

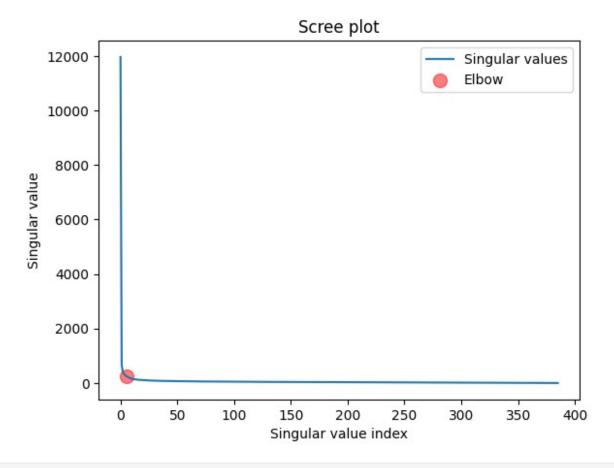
```
{'driver': 'gelsd', 'condition': 1e-12, 'AVGtime': 1.5784571647644043,
'residuals_train': 1798.3737270942404, 'Min error residuals train':
1.8260948309034575e-12, 'Max error residuals_train':
49.47129163027922, 'R2 train': 0.8653831545119198, 'residuals test':
613.1967475659, 'Min error residuals test': 0.002331373807535897, 'Max
error residuals test': 46.986214584231135, 'R2 test':
0.8603214800189574}
{'driver': 'gelss', 'condition': 1e-12, 'AVGtime': 1.6809359550476075,
'residuals_train': 1798.3737270942404, 'Min error residuals train':
4.050093593832571e-13, 'Max error residuals train':
49.471291630281804, 'R2_train': 0.8653831545119198, 'residuals test':
613.1967475658978, 'Min error residuals test': 0.002331373811045978,
'Max error residuals test': 46.98621458423261, 'R2 test':
0.8603214800189584}
{'driver': 'gelsy', 'condition': 1e-12, 'AVGtime': 2.6335572719573976,
'residuals_train': 1798.3737270942406, 'Min error residuals train':
1.3287149158713873e-12, 'Max error residuals train':
49.471291630282785, 'R2_train': 0.8653831545119198, 'residuals_test':
613.1967475658972, 'Min error residuals test': 0.002331373811642834,
'Max error residuals test': 46.986214584233636, 'R2 test':
0.8603214800189586}
{'driver': 'gelsd', 'condition': 1e-16, 'AVGtime': 1.6632410049438477,
'residuals_train': 1798.3737270942404, 'Min error residuals train':
1.8260948309034575e-12, 'Max error residuals train':
49.47129163027922, 'R2 train': 0.8653831545119198, 'residuals test':
613.1967475659, 'Min error residuals test': 0.002331373807535897, 'Max
error residuals test': 46.986214584231135, 'R2_test':
0.8603214800189574}
{'driver': 'gelss', 'condition': 1e-16, 'AVGtime': 1.7481321334838866,
'residuals train': 1798.3737270942404, 'Min error residuals train':
4.050093593832571e-13, 'Max error residuals train':
49.471291630281804, 'R2_train': 0.8653831545119198, 'residuals_test':
613.1967475658978, 'Min error residuals test': 0.002331373811045978,
'Max error residuals test': 46.98621458423261, 'R2 test':
0.8603214800189584}
{'driver': 'gelsy', 'condition': 1e-16, 'AVGtime': 2.6745798110961916,
'residuals_train': 1798.3737270942406, 'Min error residuals train':
1.3287149158713873e-12, 'Max error residuals train':
49.471291630282785, 'R2_train': 0.8653831545119198, 'residuals_test':
613.1967475658972, 'Min error residuals test': 0.002331373811642834,
'Max error residuals test': 46.986214584233636, 'R2 test':
0.8603214800189586}
PCR SOLVER
k= 374 with mixed error criterion and tol= 1e-06
Sigma k= 0.24235413263899452
Residuals for train set: 1798.3737432334817
Maximum error for train set: 49.47135129405567
Minimum error for train set: 8.885552780668604e-06
```

R2 for train set: 0.8653831520957216

Residuals for test set: 613.1967323323433 Maximum error for test set: 46.9862610598538

Minimum error for test set: 0.0023566596409949625

R2 for test set: 0.8603214869589831



k= 5 with Screep plot Sigma k= 250.9209568227013

Residuals for train set: 4314.872172761188 Maximum error for train set: 81.8056017452396 Minimum error for train set: 4.238081472607291e-05

R2 for train set: 0.22504697175187627 Residuals for test set: 1430.3535335393976 Maximum error for test set: 72.85619426228541 Minimum error for test set: 0.004824564473430826

R2 for test set: 0.23999451660000515

k= 1 with cumulative percentage of variance and p= 0.99

Sigma k= 688.74133812504

Residuals for train set: 7079.00332556767 Maximum error for train set: 86.12879856814982 Minimum error for train set: 0.00016317329874482311

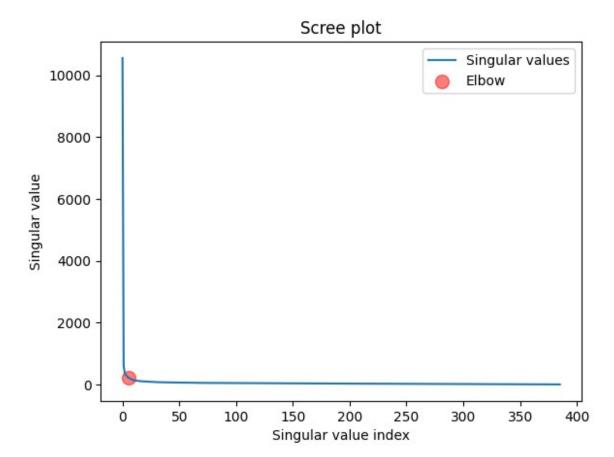
R2 for train set: -1.085853217608597

```
Residuals for test set: 2361.142356336503
Maximum error for test set: 86.21332456608174
Minimum error for test set:
                            0.0015384355101133451
R2 for test set: -1.0709722681710114
X train, X test, y train, y_test = train_test_split(
   у,
    train size = .7,
   test size = .3,
    random state = 5,
   shuffle = True
)
print("\nNORMAL EQUATIONS")
normalEquations(X_train, y_train, X_test, y_test)
print("\nQR SOLVER")
QRsolver(X train, y train, X test, y test)
print("\nSVD SOLVER")
SVDSolver(X_train, y_train, X_test, y_test)
print("\nLSTSQ SOLVER")
lstsqSolver(X_train, y_train, X_test, y_test)
print("\nPCR SOLVER")
PCRSolver(X train, y train, X test, y test)
NORMAL EQUATIONS
Rank of train data: 374
Shape of train data: (386, 386)
Matrix is singular
OR SOLVER
Condition number of QR factorization matrix: 2.4045944568960685e+32
Residuals for train set: 1581.8224079089453
Maximum error for train set: 49.31879889962844
Minimum error for train set: 3.197442310920451e-14
R2 for train set: 0.8663961504183206
Residuals for test set: 1056.7495138518016
Maximum error for test set: 46.86165824234786
Minimum error for test set: 0.0005819565929527926
R2 for test set: 0.8602025218438263
SVD SOLVER
Rank of X train: 374
Number of non zero singular values: 386
Residuals for train set: 1581.822407908945
Maximum error for train set: 49.31879889962739
Minimum error for train set: 4.973799150320701e-13
R2 for train set: 0.8663961504183206
Residuals for test set: 1056.7516844256186
```

```
Maximum error for test set: 46.86165824234698
Minimum error for test set:
                             0.0005819565922635661
R2 for test set: 0.8602019475524668
LSTSQ SOLVER
{'driver': 'gelsd', 'condition': 0.1, 'AVGtime': 1.46379656791687,
'residuals_train': 6242.025534840823, 'Min error residuals_train':
0.0017990607773157308, 'Max error residuals train': 86.14804612741862,
'R2_train': -1.080437181562219, 'residuals_test': 4089.558851795378,
'Min error residuals test': 0.0019065736120893462, 'Max error
residuals_test': 86.23257111283189, 'R2_test': -1.0936696064790175}
{'driver': 'gelss', 'condition': 0.1, 'AVGtime': 1.5929749488830567,
'residuals_train': 6242.025534840823, 'Min error residuals train':
0.001799060777251782, 'Max error residuals train': 86.14804612741861,
'R2 train': -1.080437181562219, 'residuals_test': 4089.558851795378,
'Min error residuals test': 0.0019065736121319787, 'Max error
residuals test': 86.23257111283188, 'R2 test': -1.0936696064790175}
{'driver': 'gelsy', 'condition': 0.1, 'AVGtime': 2.054758977890015,
'residuals train': 6242.048764526194, 'Min error residuals train':
0.00018963670160587753, 'Max error residuals train':
86.15872329147919, 'R2_train': -1.0804526662765381, 'residuals test':
4089.5916751438244, 'Min error residuals test': 0.005121768266448612,
'Max error residuals test': 86.24324837727318, 'R2 test': -
1.0937032147606436}
{'driver': 'gelsd', 'condition': 0.01, 'AVGtime': 1.317377233505249,
'residuals train': 2524.7404922403675, 'Min error residuals train':
0.0004900707692385708, 'Max error residuals train': 59.87019625700878,
'R2 train': 0.6596411749341676, 'residuals test': 1654.2352059891818,
'Min error residuals test': 0.0004001028437556897, 'Max error
residuals test': 59.98093166872872, 'R2 test': 0.6574296727962979}
{'driver': 'gelss', 'condition': 0.01, 'AVGtime': 1.6145201683044434,
'residuals_train': 2524.740492240369, 'Min error residuals train':
0.0004900707691106732, 'Max error residuals train':
59.870196257008764, 'R2 train': 0.6596411749341673, 'residuals test':
1654.2352059891825, 'Min error residuals test': 0.00040010284392622,
'Max error residuals_test': 59.98093166872871, 'R2 test':
0.6574296727962976}
{'driver': 'gelsy', 'condition': 0.01, 'AVGtime': 2.1120631217956545,
'residuals_train': 6242.048764526194, 'Min error residuals train':
0.00018963670160587753, 'Max error residuals train':
86.15872329147919, 'R2_train': -1.0804526662765381, 'residuals test':
4089.5916751438244, 'Min error residuals_test': 0.005121768266448612,
'Max error residuals test': 86.24324837727318, 'R2 test': -
1.0937032147606436}
{'driver': 'gelsd',
                    'condition': 0.0001, 'AVGtime':
1.3047335147857666, 'residuals train': 1581.8437697309062, 'Min error
residuals train': 0.0007629050405597582, 'Max error residuals train':
49.31676311501686, 'R2 train': 0.8663925418704774, 'residuals test':
1056.7598827874262, 'Min error residuals_test': 0.0005193352064569723,
```

```
'Max error residuals test': 46.859145978843486, 'R2 test':
0.8601997784157118}
{'driver': 'gelss', 'condition': 0.0001, 'AVGtime':
1.6330953598022462, 'residuals train': 1581.8437697309062, 'Min error
residuals train': 0.0007629050438566765, 'Max error residuals train':
49.31676311501602, 'R2_train': 0.8663925418704774, 'residuals_test':
1056.7598827874242, 'Min error residuals test': 0.0005193352055457012,
'Max error residuals test': 46.859145978843046, 'R2 test':
0.8601997784157124}
{'driver': 'gelsy', 'condition': 0.0001, 'AVGtime':
2.0623705863952635, 'residuals_train': 1581.8458133076267, 'Min error
residuals train': 0.00027573671723502, 'Max error residuals train':
49.314168214308275, 'R2_train': 0.866392196656528, 'residuals test':
1056.762181979197, 'Min error residuals_test': 0.0002701702831870989,
'Max error residuals_test': 46.858824935300504, 'R2_test':
0.8601991700885527}
{'driver': 'gelsd', 'condition': 1e-08, 'AVGtime': 1.2989150524139403,
'residuals_train': 1581.8224079089448, 'Min error residuals train':
6.231459792616079e-12, 'Max error residuals train':
49.318798899628355, 'R2 train': 0.8663961504183206, 'residuals test':
1056.7516844256204, 'Min error residuals test': 0.0005819565920646141,
'Max error residuals test': 46.8616582423474, 'R2 test':
0.8602019475524664}
{'driver': 'gelss', 'condition': 1e-08, 'AVGtime': 1.6138881206512452,
'residuals train': 1581.822407908945, 'Min error residuals train':
7.105427357601002e-14, 'Max error residuals train': 49.31879889962756,
'R2_train': 0.8663961504183206, 'residuals_test': 1056.7516844256186,
'Min error residuals test': 0.000581956592178301, 'Max error
residuals test': 46.86165824234698, 'R2 test': 0.8602019475524668}
{'driver': 'gelsy', 'condition': 1e-08, 'AVGtime': 2.0616582870483398,
'residuals train': 1581.822407908945, 'Min error residuals train':
1.1013412404281553e-13, 'Max error residuals_train':
49.31879889962847, 'R2_train': 0.8663961504183206, 'residuals test':
1056.7516844256193, 'Min error residuals_test': 0.0005819565928035786,
'Max error residuals test': 46.8616582423479, 'R2 test':
0.8602019475524667}
{'driver': 'gelsd', 'condition': 1e-12, 'AVGtime': 1.3123390674591064,
'residuals train': 1581.8224079089448, 'Min error residuals train':
6.231459792616079e-12, 'Max error residuals train':
49.318798899628355, 'R2 train': 0.8663961504183206, 'residuals test':
1056.7516844256204, 'Min error residuals test': 0.0005819565920646141,
'Max error residuals test': 46.8616582423474, 'R2 test':
0.8602019475524664}
{'driver': 'gelss', 'condition': 1e-12, 'AVGtime': 1.6143386840820313,
'residuals_train': 1581.822407908945, 'Min error residuals_train':
7.105427357601002e-14, 'Max error residuals_train': 49.31879889962756,
'R2 train': 0.8663961504183206, 'residuals test': 1056.7516844256186,
'Min error residuals test': 0.000581956592178301, 'Max error
residuals test': 46.86165824234698, 'R2 test': 0.8602019475524668}
```

```
{'driver': 'gelsy', 'condition': 1e-12, 'AVGtime': 2.0766768932342528,
'residuals train': 1581.822407908945, 'Min error residuals train':
1.1013412404281553e-13, 'Max error residuals_train':
49.31879889962847, 'R2_train': 0.8663961504183206, 'residuals_test':
1056.7516844256193, 'Min error residuals test': 0.0005819565928035786,
'Max error residuals test': 46.8616582423479, 'R2 test':
0.8602019475524667}
{'driver': 'gelsd', 'condition': 1e-16, 'AVGtime': 1.30711932182312,
'residuals_train': 1581.8224079089448, 'Min error residuals train':
6.231459792616079e-12, 'Max error residuals train':
49.318798899628355, 'R2 train': 0.8663961504183206, 'residuals test':
1056.7516844256204, 'Min error residuals test': 0.0005819565920646141,
'Max error residuals test': 46.8616582423474, 'R2 test':
0.8602019475524664}
{'driver': 'gelss', 'condition': 1e-16, 'AVGtime': 1.6059051990509032,
'residuals train': 1581.822407908945, 'Min error residuals train':
7.105427357601002e-14, 'Max error residuals train': 49.31879889962756,
'R2_train': 0.8663961504183206, 'residuals_test': 1056.7516844256186,
'Min error residuals test': 0.000581956592178301, 'Max error
residuals_test': 46.86165824234698, 'R2_test': 0.8602019475524668}
{'driver': 'gelsy', 'condition': 1e-16, 'AVGtime': 2.0868249893188477,
'residuals train': 1581.822407908945, 'Min error residuals train':
1.1013412404281553e-13, 'Max error residuals train':
49.31879889962847, 'R2_train': 0.86639615041\(\overline{8}\)3206, 'residuals_test': 1056.7516844256193, 'Min error residuals_test': 0.0005819565928035786,
'Max error residuals test': 46.8616582423479, 'R2 test':
0.8602019475524667}
PCR SOLVER
k= 373 with mixed error criterion and tol= 1e-06
Sigma k= 0.2419127715529588
Residuals for train set: 1581.8224258404935
Maximum error for train set: 49.31887428974955
Minimum error for train set: 1.0329512576845445e-05
R2 for train set: 0.8663961473892525
Residuals for test set: 1056.751680001771
Maximum error for test set: 46.861719477894866
Minimum error for test set: 0.0005178873795301797
R2 for test set: 0.8602019487229315
```



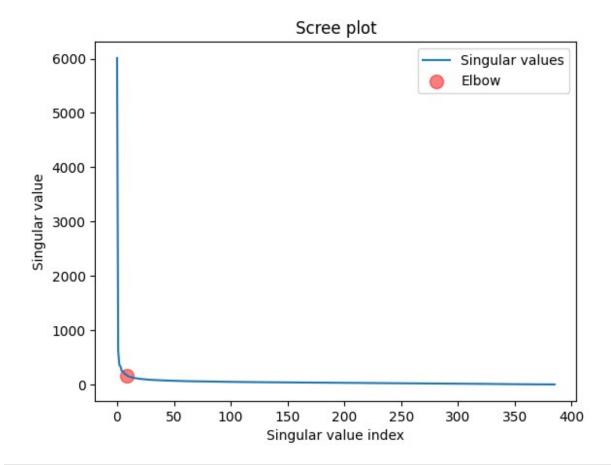
```
k= 5 with Screep plot
Sigma k= 221.56058987580698
Residuals for train set: 3827.891659917939
Maximum error for train set: 77.98276634172981
Minimum error for train set:
                              0.0007443352258604818
R2 for train set: 0.21761088436209697
Residuals for test set:
                        2501.375548893731
Maximum error for test set:
                             82.1296511792311
Minimum error for test set:
                             0.0006695430814858128
R2 for test set:
                  0.21672723822862605
k= 1 with cumulative percentage of variance and p= 0.99
Sigma k = 606.6409563436413
Residuals for train set: 6242.025534840823
Maximum error for train set: 86.14804612741864
Minimum error for train set:
                              0.0017990607773654688
R2 for train set: -1.080437181562219
Residuals for test set:
                        4089.558851795378
Maximum error for test set: 86.23257111283189
Minimum error for test set:
                             0.001906573612053819
R2 for test set: -1.093669606479018
X = X - np.mean(X, axis=0)
y=y-np.mean(y)
```

```
X train, X test, y train, y test = train test split(
   Χ,
   у,
    train size = .9,
   test size = .1,
    random state = 5,
    shuffle = True
)
print("\nNORMAL EQUATIONS")
normalEquations(X_train, y_train, X_test, y_test)
print("\nQR SOLVER")
QRsolver(X_train, y_train, X_test, y_test)
print("\nSVD SOLVER")
SVDSolver(X_train, y_train, X_test, y_test)
print("\nLSTSQ SOLVER")
lstsqSolver(X_train, y_train, X_test, y_test)
print("\nPCR SOLVER")
PCRSolver(X train, y train, X test, y test)
NORMAL EQUATIONS
Rank of train data: 374
Shape of train data: (386, 386)
Matrix is singular
OR SOLVER
Condition number of QR factorization matrix: inf
Residuals for train set: 1798.375168923055
Maximum error for train set: 49.48141087921306
Minimum error for train set: 0.00010451105330844257
R2 for train set: 0.8653829386563148
Residuals for test set: 613.1883250084952
Maximum error for test set: 46.99654288414338
Minimum error for test set:
                             0.0006169212601747631
R2 for test set: 0.8603253170982564
SVD SOLVER
Rank of X train: 374
Number of non zero singular values: 386
Residuals for train set: 1798.375168923055
Maximum error for train set: 49.48141087921296
Minimum error for train set:
                              0.00010451105312370146
R2 for train set: 0.8653829386563148
Residuals for test set: 613.1883250084953
Maximum error for test set: 46.99654288414334
Minimum error for test set:
                             0.0006169212603666097
R2 for test set: 0.8603253170982563
```

```
LSTSQ SOLVER
{'driver': 'gelsd', 'condition': 0.1, 'AVGtime': 1.7849128723144532,
'residuals train': 4755.570567097338, 'Min error residuals train':
0.000262427226318529, 'Max error residuals train': 50.36096798485837,
'R2 train': 0.05866377462668071, 'residuals test': 1587.9902364224715,
'Min error residuals test': 0.0012715306054857933, 'Max error
residuals test': 50.13814410503954, 'R2 test': 0.0632459161733121}
{'driver': 'gelss', 'condition': 0.1, 'AVGtime': 1.945432186126709, 'residuals_train': 4755.570567097334, 'Min error residuals_train':
0.0002624272262981009, 'Max error residuals train': 50.36096798485853,
'R2_train': 0.05866377462668182, 'residuals_test': 1587.9902364224702,
'Min error residuals test': 0.0012715306053419084, 'Max error
residuals_test': 50.1381441050397, 'R2_test': 0.06324591617331332}
{'driver': 'gelsy', 'condition': 0.1, 'AVGtime': 2.79490442276001, 'residuals_train': 4900.828826291249, 'Min error residuals_train':
0.0003575149926536292, 'Max error residuals train': 50.81533254000823,
'R2 train': 0.00027954336952462633, 'residuals test':
1640.5141987499783, 'Min error residuals_test': 0.0003739759662430009,
'Max error residuals test': 50.89981613229195, 'R2 test':
0.0002534215123161099}
{'driver': 'gelsd', 'condition': 0.01, 'AVGtime': 1.8146845340728759,
'residuals train': 2108.137325866397, 'Min error residuals train':
0.00013572860698474187, 'Max error residuals train':
50.161593481761926, 'R2 train': 0.815014662390456, 'residuals test':
703.1095775793399, 'Min error residuals test': 0.00036970048081386153,
'Max error residuals test': 45.97968388437563, 'R2 test':
0.8163563284379058}
{'driver': 'gelss', 'condition': 0.01, 'AVGtime': 2.1100863933563234,
'residuals_train': 2108.1373258663994, 'Min error residuals train':
0.00013572860682842247, 'Max error residuals train':
50.161593481763525, 'R2_train': 0.8150146623904556, 'residuals test':
703.1095775793397, 'Min error residuals_test': 0.00036970048049234094,
'Max error residuals test': 45.97968388437485, 'R2 test':
0.816356328437906}
{'driver': 'gelsy', 'condition': 0.01, 'AVGtime': 3.0165273666381838,
'residuals train': 2520.2405401243936, 'Min error residuals train':
7.746705687594613e-06, 'Max error residuals train': 47.27200080131459,
'R2 train': 0.7356231050963493, 'residuals_test': 838.5783311330284,
'Min error residuals test': 0.0005136025978078607, 'Max error
residuals test': 45.74035126344225, 'R2 test': 0.7387735121708896}
{'driver': 'gelsd', 'condition': 0.0001, 'AVGtime':
1.7419917583465576, 'residuals train': 1798.3820295191035, 'Min error
residuals train': 6.735755479780892e-05, 'Max error residuals train':
49.48069319797044, 'R2 train': 0.865381911556901, 'residuals test':
613.1889342656056, 'Min error residuals test': 0.0013570743457371748,
'Max error residuals_test': 46.995565748867016, 'R2_test':
0.8603250395396909}
{'driver': 'gelss', 'condition': 0.0001, 'AVGtime':
1.7329828262329101, 'residuals train': 1798.3820295191033, 'Min error
```

```
residuals train': 6.735755465214766e-05, 'Max error residuals train':
49.480693197970695, 'R2_train': 0.865381911556901, 'residuals test':
613.1889342656057, 'Min error residuals test': 0.0013570743452895329,
'Max error residuals test': 46.99556574886715, 'R2 test':
0.8603250395396908}
{'driver': 'gelsy', 'condition': 0.0001, 'AVGtime':
2.7779926300048827, 'residuals train': 1798.382051640633, 'Min error
residuals train': 0.00024318692035407707, 'Max error residuals train':
49.48074237739562, 'R2_train': 0.8653819082450819, 'residuals_test': 613.1877983373976, 'Min error residuals_test': 0.0014086055356834493,
'Max error residuals test': 46.99563332089457, 'R2 test':
0.8603255570329844}
{'driver': 'gelsd', 'condition': 1e-08, 'AVGtime': 1.7098489284515381,
'residuals_train': 1798.3751689230546, 'Min error residuals train':
0.00010451105293896035, 'Max error residuals train': 49.4814108792126,
'R2 train': 0.8653829386563148, 'residuals test': 613.1883250084949,
'Min error residuals_test': 0.000616921259741332, 'Max error
residuals_test': 46.996542884143025, 'R2_test': 0.8603253170982565}
{'driver': 'gelss', 'condition': 1e-08, 'AVGtime': 1.774636697769165,
'residuals train': 1798.375168923055, 'Min error residuals train':
0.00010451105289632778, 'Max error residuals train':
49.48141087921289, 'R2_train': 0.8653829386563148, 'residuals test':
613.1883250084951, 'Min error residuals test': 0.0006169212602671337,
'Max error residuals test': 46.99654288414318, 'R2 test':
0.8603253170982565}
{'driver': 'gelsy', 'condition': 1e-08, 'AVGtime': 2.7203440189361574,
'residuals_train': 1798.375168923055, 'Min error residuals_train':
0.00010451105330133714, 'Max error residuals train':
49.48141087921306, 'R2_train': 0.86538293865\(\overline{6}\)3147, 'residuals_test': 613.1883250084953, 'Min error residuals_test': 0.0006169212601605523,
'Max error residuals test': 46.99654288414338, 'R2 test':
0.8603253170982564}
{'driver': 'gelsd', 'condition': 1e-12, 'AVGtime': 1.6896587371826173,
'residuals train': 1798.3751689230546, 'Min error residuals train':
0.00010451105293896035, 'Max error residuals train': 49.4814108792126,
'R2 train': 0.8653829386563148, 'residuals test': 613.1883250084949,
'Min error residuals test': 0.000616921259741332, 'Max error
residuals test': 46.996542884143025, 'R2 test': 0.8603253170982565}
{'driver': 'gelss', 'condition': 1e-12, 'AVGtime': 1.7570572376251221,
'residuals train': 1798.375168923055, 'Min error residuals train':
0.00010451105289632778, 'Max error residuals train':
49.48141087921289, 'R2_train': 0.86538293865\(\overline{6}\)3148, 'residuals_test': 613.1883250084951, 'Min error residuals_test': 0.0006169212602671337,
'Max error residuals test': 46.99654288414318, 'R2 test':
0.8603253170982565}
{'driver': 'gelsy', 'condition': 1e-12, 'AVGtime': 2.7103029251098634,
'residuals train': 1798.375168923055, 'Min error residuals train':
0.00010451105330133714, 'Max error residuals train':
49.48141087921306, 'R2 train': 0.8653829386563147, 'residuals test':
```

```
613.1883250084953, 'Min error residuals test': 0.0006169212601605523,
'Max error residuals test': 46.99654288414338, 'R2 test':
0.8603253170982564}
{'driver': 'gelsd', 'condition': le-16, 'AVGtime': 1.669171190261841,
'residuals train': 1798.3751689230546, 'Min error residuals train':
0.00010451105293896035, 'Max error residuals train': 49.4814108792126,
'R2 train': 0.8653829386563148, 'residuals test': 613.1883250084949,
'Min error residuals test': 0.000616921259741332, 'Max error
residuals_test': 46.996542884143025, 'R2_test': 0.8603253170982565}
{'driver': 'gelss', 'condition': 1e-16, 'AVGtime': 1.7121876716613769,
'residuals train': 1798.375168923055, 'Min error residuals train':
0.00010451105289632778, 'Max error residuals_train':
49.48141087921289, 'R2_train': 0.8653829386563148, 'residuals_test': 613.1883250084951, 'Min error residuals_test': 0.0006169212602671337,
'Max error residuals test': 46.99654288414318, 'R2 test':
0.8603253170982565}
{'driver': 'gelsy', 'condition': 1e-16, 'AVGtime': 2.6775108337402345,
'residuals_train': 1798.375168923055, 'Min error residuals_train':
0.00010451105330133714, 'Max error residuals train':
49.48141087921306, 'R2 train': 0.8653829386563147, 'residuals test':
613.1883250084953, 'Min error residuals test': 0.0006169212601605523,
'Max error residuals test': 46.99654288414338, 'R2 test':
0.8603253170982564}
PCR SOLVER
k= 373 with mixed error criterion and tol= 1e-06
Sigma k = 0.24804292714425785
Residuals for train set: 1798.3765462771964
Maximum error for train set: 49.48194745002998
Minimum error for train set: 6.089655833818597e-05
R2 for train set: 0.865382732453025
Residuals for test set: 613.1881807499456
Maximum error for test set: 46.9969652643756
Minimum error for test set: 0.0002830075600641635
R2 for test set: 0.8603253828179187
```



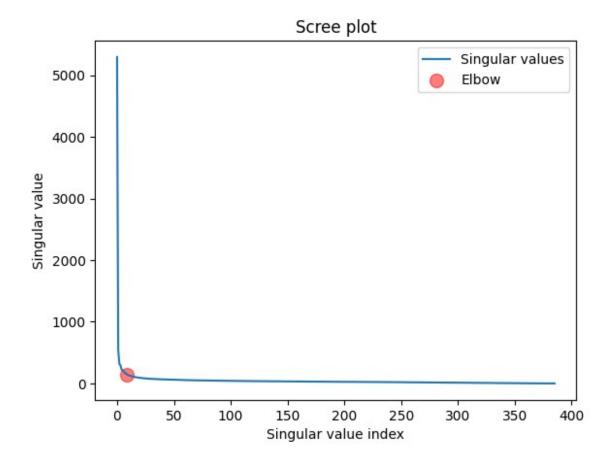
```
k= 9 with Screep plot
Sigma k = 160.0371010848383
Residuals for train set: 2834.123989129834
Maximum error for train set: 53.56869903518497
Minimum error for train set:
                              6.0258639919652524e-05
R2 for train set: 0.6656685720463946
Residuals for test set:
                         942.4515117574208
Maximum error for test set:
                            53.68821132157274
Minimum error for test set:
                            0.005007439769400435
R2 for test set:
                  0.6700501235002101
k= 46 with cumulative percentage of variance and p= 0.99
Sigma k = 69.20495430475549
Residuals for train set: 2135.767310283201
Maximum error for train set: 50.95697458632548
Minimum error for train set:
                              0.00013314212461068564
R2 for train set: 0.810133921331676
Residuals for test set: 709.0843727595702
Maximum error for test set: 48.38086047422813
Minimum error for test set:
                             0.001812555850200681
R2 for test set:
                 0.8132219797565957
```

```
X train, X test, y_train, y_test = train_test_split(
   Χ,
   у,
   train size = 0.7,
   test size = .3,
    random state = 5,
    shuffle = True
)
print("\nNORMAL EQUATIONS")
normalEquations(X_train, y_train, X_test, y_test)
print("\nQR SOLVER")
QRsolver(X train, y train, X test, y test)
print("\nSVD SOLVER")
SVDSolver(X_train, y_train, X_test, y_test)
print("\nLSTSQ SOLVER")
lstsqSolver(X train, y train, X test, y test)
print("\nPCR SOLVER")
PCRSolver(X_train, y_train, X_test, y_test)
NORMAL EQUATIONS
Rank of train data: 373
Shape of train data: (386, 386)
Matrix is singular
OR SOLVER
Condition number of QR factorization matrix:
Residuals for train set: 1581.8224079089448
Maximum error for train set: 49.31879889963359
Minimum error for train set: 3.1938895972416503e-12
R2 for train set: 0.8663961504183206
Residuals for test set: 24323.803995926748
Maximum error for test set: 17502.659908336667
Minimum error for test set: 0.0005819565969105156
R2 for test set: -73.06588457680839
SVD SOLVER
Rank of X train: 374
Number of non zero singular values: 386
Residuals for train set: 1581.8224079089446
Maximum error for train set: 49.318798899683344
Minimum error for train set: 3.9126035744629917e-11
R2 for train set: 0.8663961504183207
Residuals for test set: 24323.80398699717
Maximum error for test set: 17502.659901901887
Minimum error for test set: 0.0005819565577045438
R2 for test set: -73.06588452242733
LSTSQ SOLVER
```

```
{'driver': 'gelsd', 'condition': 0.1, 'AVGtime': 1.304492425918579,
'residuals train': 4199.813466862267, 'Min error residuals train':
0.0007778557055178048, 'Max error residuals train': 50.34528515106919,
'R2 train': 0.05818949864139089, 'residuals test': 2738.064978785508,
'Min error residuals test': 0.0017434290058133683, 'Max error
residuals test': 50.23110506691755, 'R2 test': 0.06148174467595835}
{'driver': 'gelss', 'condition': 0.1, 'AVGtime': 1.8272982120513916,
'residuals train': 4199.813466862264, 'Min error residuals train':
0.0007778557053468305, 'Max error residuals train': 50.34528515106909,
'R2 train': 0.05818949864139222, 'residuals test': 2738.0649787855064,
'Min error residuals test': 0.001743429005886199, 'Max error
residuals test': 50.23110506691745, 'R2 test': 0.061481744675960015}
{'driver': 'gelsy', 'condition': 0.1, 'AVGtime': 2.098579263687134, 'residuals_train': 4327.143540775084, 'Min error residuals_train':
0.003853264487539809, 'Max error residuals train': 50.77097759824818,
'R2 train': 0.0002161229312992452, 'residuals test':
2825.830505497923, 'Min error residuals test': 0.0005380666435376158,
'Max error residuals_test': 50.85546110958141, 'R2_test':
0.00035121616083677587}
{'driver': 'gelsd', 'condition': 0.01, 'AVGtime': 1.3862902164459228,
'residuals train': 1856.2978631758865, 'Min error residuals train':
5.694623258634124e-05, 'Max error residuals train': 50.37107954236377,
'R2 train': 0.816008036324967, 'residuals test': 1218.4421714493662,
'Min error residuals test': 0.00024393765594865613, 'Max error
residuals test': 49.1741317140975, 'R2_test': 0.8141489292378865}
{'driver': 'gelss', 'condition': 0.01, 'AVGtime': 1.7717936038970947,
'residuals_train': 1856.297863175887, 'Min error residuals train':
5.6946232447785405e-05, 'Max error residuals train':
50.37107954236397, 'R2_train': 0.8160080363249669, 'residuals_test': 1218.4421714493665, 'Min error residuals_test':
0.00024393765635100095, 'Max error residuals_test':
49.174131714097875, 'R2_test': 0.8141489292378865} {'driver': 'gelsy', 'condition': 0.01, 'AVGtime': 2.491049957275391,
'residuals train': 2262.0315035962994, 'Min error residuals train':
0.000878605419591949, 'Max error residuals train': 46.14311581758492,
'R2 train': 0.7267873377369896, 'residuals test': 1483.2331242384055,
'Min error residuals test': 0.0006409777382154758, 'Max error
residuals test': 45.62933976984492, 'R2 test': 0.7245935829332961}
{'driver': 'gelsd', 'condition': 0.0001, 'AVGtime':
1.4514110565185547, 'residuals train': 1581.830968104192, 'Min error
residuals train': 0.0010936828899694717, 'Max error residuals train':
49.30710240018327, 'R2_train': 0.866394704392361, 'residuals_test':
1056.7479613315134, 'Min error residuals test':
0.00040345495549054533, 'Max error residuals_test': 46.84894729577002,
'R2 test': 0.8602029326095919}
{'driver': 'gelss', 'condition': 0.0001, 'AVGtime':
2.0281887531280516, 'residuals train': 1581.8309681041917, 'Min error
residuals train': 0.0010936828900449669, 'Max error residuals train':
49.30710240018255, 'R2 train': 0.866394704392361, 'residuals test':
```

```
1056.7479613315134, 'Min error residuals test': 0.0004034549560731904,
'Max error residuals test': 46.84894729576919, 'R2 test':
0.8602029326095919}
{'driver': 'gelsy', 'condition': 0.0001, 'AVGtime': 2.345961332321167,
'residuals train': 1581.831004882127, 'Min error residuals train':
0.0003969291845997702, 'Max error residuals train': 49.307162353691,
'R2 train': 0.8663946981796531, 'residuals test': 1056.7484149362238,
'Min error residuals test': 0.00031059155839230357, 'Max error
residuals test': 46.84905600491508, 'R2_test': 0.8602028125949354}
{'driver': 'gelsd', 'condition': 1e-08, 'AVGtime': 1.5774375915527343,
'residuals train': 1581.822407908945, 'Min error residuals train':
1.5376144801848568e-11, 'Max error residuals train':
49.31879889962687, 'R2_train': 0.8663961504183207, 'residuals_test': 24323.803994354585, 'Min error residuals_test': 0.0005819566007279064,
'Max error residuals test': 17502.65990720368, 'R2 test': -
73.06588456723391}
{'driver': 'gelss', 'condition': 1e-08, 'AVGtime': 2.3048064708709717,
'residuals_train': 1581.8224079089453, 'Min error residuals_train':
1.0899725566559937e-11, 'Max error residuals train':
49.318798899612474, 'R2 train': 0.8663961504183206, 'residuals test':
24323.80399435412, 'Min error residuals test': 0.0005819566077427396,
'Max error residuals test': 17502.659907203324, 'R2 test': -
73.06588456723107}
{'driver': 'gelsy', 'condition': 1e-08, 'AVGtime': 2.5028640747070314,
'residuals train': 1581.822407908945, 'Min error residuals train':
3.5420555377640994e-12, 'Max error residuals train':
49.31879889963379, 'R2_train': 0.8663961504183206, 'residuals_test':
24323.803995927075, 'Min error residuals test': 0.0005819565974967134,
'Max error residuals test': 17502.659908336907, 'R2 test': -
73.06588457681035}
{'driver': 'gelsd', 'condition': 1e-12, 'AVGtime': 1.7076046466827393,
'residuals train': 1581.822407908945, 'Min error residuals_train':
1.5376144801848568e-11, 'Max error residuals_train':
49.31879889962687, 'R2_train': 0.8663961504183207, 'residuals_test': 24323.803994354585, 'Min error residuals_test': 0.0005819566007279064,
'Max error residuals test': 17502.65990720368, 'R2 test': -
73.06588456723391}
{'driver': 'gelss', 'condition': 1e-12, 'AVGtime': 2.104235792160034,
'residuals_train': 1581.8224079089453, 'Min error residuals train':
1.0899725566559937e-11, 'Max error residuals train':
49.318798899612474, 'R2_train': 0.8663961504183206, 'residuals_test':
24323.80399435412, 'Min error residuals test': 0.0005819566077427396,
'Max error residuals test': 17502.659907203324, 'R2_test': -
73.06588456723107}
{'driver': 'gelsy', 'condition': 1e-12, 'AVGtime': 2.6398069858551025,
'residuals train': 1581.822407908945, 'Min error residuals_train':
3.5420555377640994e-12, 'Max error residuals_train':
49.31879889963379, 'R2_train': 0.8663961504183206, 'residuals_test': 24323.803995927075, 'Min error residuals_test': 0.0005819565974967134,
```

```
'Max error residuals test': 17502.659908336907, 'R2_test': -
73.06588457681035}
{'driver': 'gelsd', 'condition': 1e-16, 'AVGtime': 1.639665460586548,
'residuals train': 1581.8230194231592, 'Min error residuals train':
0.0001049201432898883, 'Max error residuals train':
49.310829051343205, 'R2 train': 0.8663960471189004, 'residuals test':
20758.818481852188, 'Min error residuals test': 0.0010493647844036502,
'Max error residuals test': 14933.18677097949, 'R2 test': -
52.946153831635115}
{'driver': 'gelss', 'condition': 1e-16, 'AVGtime': 2.2896727085113526,
'residuals_train': 1581.8224079089453, 'Min error residuals_train':
1.0899725566559937e-11, 'Max error residuals train':
49.318798899612474, 'R2 train': 0.8663961504183206, 'residuals test':
24323.80399435412, 'Min error residuals test': 0.0005819566077427396,
'Max error residuals test': 17502.659907203324, 'R2_test': -
73.06588456723107}
{'driver': 'gelsy', 'condition': 1e-16, 'AVGtime': 2.146107482910156,
'residuals_train': 1581.822407908945, 'Min error residuals_train':
3.5420555377640994e-12, 'Max error residuals train':
49.31879889963379, 'R2_train': 0.8663961504183206, 'residuals_test': 24323.803995927075, 'Min error residuals_test': 0.0005819565974967134,
'Max error residuals test': 17502.659908336907, 'R2 test': -
73.06588457681035}
PCR SOLVER
k= 372 with mixed error criterion and tol= 1e-06
Sigma k = 0.24758868405284473
Residuals for train set: 1581.8256182319878
Maximum error for train set: 49.308567591462875
Minimum error for train set: 0.0008552917770172641
R2 for train set: 0.8663956081173012
Residuals for test set: 1056.745414663184
Maximum error for test set: 46.8505079503417
Minimum error for test set: 6.500971892187124e-05
R2 for test set: 0.8602036064057064
```



```
with Screep plot
k=9
Sigma k= 141.26352434443368
Residuals for train set: 2497.332145821892
Maximum error for train set: 53.68137331724654
Minimum error for train set:
                              0.0001362779641826961
R2 for train set:
                   0.6669908704885368
Residuals for test set:
                         1637.0185070544176
Maximum error for test set:
                             53.81545195900935
Minimum error for test set:
                             0.0005248476698405113
R2 for test set:
                  0.6645232691281926
k= 46 with cumulative percentage of variance and p= 0.99
Sigma k = 61.22165898458327
Residuals for train set:
                          1883.4871974261753
Maximum error for train set: 50.84759004578369
Minimum error for train set:
                              0.00034606460312680554
R2 for train set:
                   0.8105786750485895
Residuals for test set:
                         1233.3201425743985
Maximum error for test set:
                             51.03784522031048
Minimum error for test set:
                             0.0009238708125600681
                  0.8095824940245349
R2 for test set:
```

For a setted configuration of the training set and the testing set, we have the following results:

- 1. **Normal Equation**: The normal equation cannot be used because the matrix $X^T X$ is not full rank.
- 2. **QR Factorization**: The QR factorization cannot be used because the matrix X is not full rank, so we use the Pivot QR factorization.
- 3. **SVD**: The SVD can be used to solve the linear regression problem. SVD and QR factorization have almost the same results
- 4. **Scipy.linalg.lstsq**: We can notice that, decreasing the value of cond, the residual error decreases as the errors and R2. Regarding the execution time, we can notiche that in general the gelsy driver is slower than the other two. The execution time tends to increase with the decrease of the value of cond. At the beginning, gelsy performs worse than the other two, but as the value of cond decreases, the execution time of gelsy becomes closer to the other two drivers.
- 5. **PCR**: When the value of the last singular values increas, the error gets worse. This happens also for the cond number in ltsq

	Data	So	R2	R2						
Train	Centerin	lve	Trai	Tes	Res	Res	Max Err	Min Err	Max Err	Min Err
Set	g	r	n	t	Train	Test	Train	Train	Test	Test
90%	No	Q R	0.86 5	0.8 60	1798. 37	613. 19	49.47	1.43e-12	46.98	0.002
70%	No	Q R	0.86 6	0.8 60	1581. 82	105 6.74	49.31	3.19e-14	46.86	0.0006
90%	Yes	Q R	0.86 5	0.8 60	1798. 37	613. 18	49.48	0.0001	46.99	0.0006
70%	Yes	Q R	0.86 6	- 73. 06 5	1581. 82	243 23.8 0	49.31	3.19e-12	17502.6 5	0.0006

For the QR method, we can see that for the train set results are very similar, we have better result with less data in the training set with an improvement when the data is centered. For the test set we have better results with more data in the training set. The last configuration is the worst one, with a very high error in the test set.

Train Set	Data Centerin g	So lve r	R2 Trai n	R2 Tes t	Res Train	Res Test	Max Err Train	Min Err Train	Max Err Test	Min Err Test
90%	No	SV D	0.86 5	0.8 60	1798. 37	613. 19	49.47	5.61e-13	46.98	0.002
70%	No	SV D	0.86 6	0.8 60	1581. 82	105 6.74	49.31	3.19e-14	46.86	0.0006
90%	Yes	SV D	0.86 5	0.8 60	1798. 37	613. 18	49.48	0.0001	46.99	0.0006
70%	Yes	SV D	0.86 6	- 73. 06 5	1581. 82	243 23.8 0	49.31	3.19e-11	17502.6 5	0.0006

For the SVD method, we can see that for the train set results are very similar, we have better result with less data in the training set with an improvement when the data is centered. For the test set we have better results with more data in the training set. The last configuration is the worst one, with a very high error in the test set.

Tra in Set	Data Cente ring	S o l v e r	Condition	R2 Tr ai n	R 2 T e st	Re s Tra in	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	Si g m a _ k
90 %	No	P C R	mixed error criterion, tol=1e- 06	0. 86 5	0. 8 6 0	179 8.3 7	61 3.1 9	49.47	8.88e -06	46.9 8	0.00	0. 2 4 2
90 %	No	P C R	Scree plot	0. 22 5	0. 2 3 9	43 14. 87	14 30 .3 5	81.80	4.23e -05	72.8 5	0.00	2 5 0. 9 2
90 %	No	P C R	cumulative variance, p=0.99	- 1. 08 5	- 1. 0 7 0	70 79. 00	23 61 .1 4	86.12	0.00 01	86.21	0.00	6 8 8. 7 4
70 %	No	P C R	mixed error criterion, tol=1e- 06	0. 86 6	0. 8 6 0	15 81. 82	10 56 .7 5	49.31	1.03e -05	46.8 6	0.00 05	0. 2 4 1
70 %	No	P C R	Scree plot	0. 21 7	0. 21 6	38 27. 89	25 01 .3 7	77.98	0.00 07	82.12	0.00 06	2 21 .5 6
70 %	No	P C R	cumulative variance, p=0.99	- 1. 08 0	- 1. 0 9	62 42. 02	40 89 .5 5	86.14	0.001	86.2	0.00	6 0 6. 6 4
90 %	Yes	P C R	mixed error criterion, tol=1e- 06	0. 86 5	0. 8 6 0	179 8.3 7	61 3.1 8	49.48	6.08e -05	46.9 9	0.00 028	0. 2 4 8
90 %	Yes	P C R	Scree plot	0. 66 5	0. 6 7 0	28 34. 12	94 2. 45	53.56	6.02e -05	53.6 8	0.00 5	1 6 0. 0

Tra in Set	Data Cente ring	S o l v e r	Condition	R2 Tr ai n	R 2 T e st	Re s Tra in	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	Si g m a –
90 %	Yes	P C R	cumulative variance, p=0.99	0. 81 0	0. 8 1 3	213 5.7 6	70 9. 08	50.95	0.00 01	48.3 8	0.00 1	3 6 9. 2 0
70 %	Yes	P C R	mixed error criterion, tol=1e- 06	0. 86 6	0. 8 6 0	15 81. 82	10 56 .7 4	49.30	0.00 08	46.8 5	6.5e- 5	0. 2 4 7
70 %	Yes	P C R	Scree plot	0. 66 6	0. 6 6 4	24 97. 33	16 37 .0 81	53.68	0.00 01	53.81	0.00 05	1 4 1. 2 6
70 %	Yes	P C R	cumulative variance, p=0.99	0. 81 0	0. 8 0 9	18 83. 48	12 33 .3 2	50.84	0.00 03	51.0 3	0.00 09	6 1. 2 2

We can notice that in general the best criterion is the first one, of course because it takes more singular_values, so the approximation is better. When we center our data we get better results

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
90 %	No	LSTSQ (gelsd)	0.1	- 1.0 85 85	- 1. 07 09 7	707 9.0 033 3	23 61. 14 23 6	86.128 80	0.000 16	86.21 332	0.001 54	1.7 78 60
90 %	No	LSTSQ (gelsd)	0.0	0.6 61 39	0. 66 67 5	285 2.2 091 8	94 7.1 56 72	59.94 904	0.000 18	57.95 974	0.002 34	1. 56 41 0
90 %	No	LSTSQ (gelsd)	0.0 001	0.8 65 38	0. 86 03 3	179 8.3 994 7	61 3.1 715 7	49.47 573	0.000 02	46.98 915	0.001 44	1. 56 10 9

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
90 %	No	LSTSQ (gelsd)	1e- 08	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000 00	46.98 621	0.002 33	1. 56 90 3
90 %	No	LSTSQ (gelsd)	1e- 12	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	1. 57 84 6
90 %	No	LSTSQ (gelsd)	1e- 16	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	1. 66 32 4
70 %	No	LSTSQ (gelsd)	0.1	- 1.0 80 44	- 1. 09 36 7	624 2.0 255 3	40 89. 55 88 5	86.148 05	0.0017 9	86.23 257	0.001 91	1. 46 38 0
70 %	No	LSTSQ (gelsd)	0.0 1	0.6 59 64	0. 65 74 3	252 4.7 404 9	16 54. 23 521	59.87 020	0.000 49	59.98 093	0.000 40	1. 31 73 8
70 %	No	LSTSQ (gelsd)	0.0 001	0.8 66 39	0. 86 02 0	158 1.8 437 7	10 56. 75 98 8	49.316 76	0.000 76	46.85 915	0.000 52	1. 30 47 3
70 %	No	LSTSQ (gelsd)	1e- 08	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000	46.86 166	0.000 58	1.2 98 92
70 %	No	LSTSQ (gelsd)	1e- 12	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000	46.86 166	0.000 58	1. 31 23 4
70 %	No	LSTSQ (gelsd)	1e- 16	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000 00	46.86 166	0.000 58	1. 30 71 2
90 %	Yes	LSTSQ (gelsd)	0.1	0.0 58 66	0. 06 32	475 5.5 705	15 87. 99	50.36 097	0.000 26	50.13 814	0.001 27	1.7 84 91

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
90 %	Yes	LSTSQ (gelsd)	0.0	0.8 15 01	0. 81 63 6	210 8.13 733	4 70 3.1 09 58	50.161 59	0.000 14	45.97 968	0.000 37	1. 81 46 8
90 %	Yes	LSTSQ (gelsd)	0.0 001	0.8 65 38	0. 86 03 3	179 8.3 820 3	61 3.1 88 93	49.48 069	0.000 07	46.99 557	0.001 36	1.7 41 99
90 %	Yes	LSTSQ (gelsd)	1e- 08	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	1.7 09 85
90 %	Yes	LSTSQ (gelsd)	1e- 12	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	1. 68 96 6
90 %	Yes	LSTSQ (gelsd)	1e- 16	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	1. 66 91 7
70 %	Yes	LSTSQ (gelsd)	0.1	0.0 58 19	0. 06 14 8	419 9.8 134 7	27 38. 06 49 8	50.34 529	0.000 78	50.23 111	0.001 74	1. 30 44 9
70 %	Yes	LSTSQ (gelsd)	0.0	0.8 16 01	0. 81 41 5	185 6.2 978 6	121 8.4 42 17	50.371 08	0.000 06	49.17 413	0.000 24	1. 38 62 9
70 %	Yes	LSTSQ (gelsd)	0.0 001	0.8 66 39	0. 86 02 0	158 1.83 097	10 56. 74 79 6	49.30 710	0.001 09	46.84 895	0.000 40	1. 45 14 1
70 %	Yes	LSTSQ (gelsd)	1e- 08	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000 00	17502 .6599 1	0.000 58	1. 57 74 4

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
70 %	Yes	LSTSQ (gelsd)	1e- 12	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000 00	17502 .6599 1	0.000 58	1.7 07 60
70 %	Yes	LSTSQ (gelsd)	1e- 16	0.8 66 40	- 52 .9 46 15	158 1.82 302	20 75 8.8 18 48	49.310 83	0.000 10	14933 .1867 7	0.001 05	1. 63 96 7
90 %	No	LSTSQ (gelss)	0.1	- 1.0 85 85	- 1. 07 09 7	707 9.0 033 3	23 61. 14 23 6	86.128 80	0.000 16	86.21 332	0.001 54	1.7 35 61
90 %	No	LSTSQ (gelss)	0.0	0.6 61 39	0. 66 67 5	285 2.2 091 8	94 7.1 56 72	59.94 904	0.000 18	57.95 974	0.002 34	1. 64 77 4
90 %	No	LSTSQ (gelss)	0.0 001	0.8 65 38	0. 86 03 3	179 8.3 994 7	61 3.1 715 7	49.47 573	0.000 02	46.98 915	0.001 44	1. 64 75 1
90 %	No	LSTSQ (gelss)	1e- 08	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	1. 63 35 0
90 %	No	LSTSQ (gelss)	1e- 12	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	1. 68 09 4
90 %	No	LSTSQ (gelss)	1e- 16	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	1.7 48 13
70 %	No	LSTSQ (gelss)	0.1	- 1.0 80 44	- 1. 09 36 7	624 2.0 255 3	40 89. 55 88 5	86.148 05	0.0017 9	86.23 257	0.001 91	1. 59 29 7
70	No	LSTSQ	0.0	0.6	0.	252	16	59.87	0.000	59.98	0.000	1.

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
%		(gelss)	1	59 64	65 74 3	4.7 404 9	54. 23 521	020	49	093	40	61 45 2
70 %	No	LSTSQ (gelss)	0.0 001	0.8 66 39	0. 86 02 0	158 1.8 437 7	10 56. 75 98 8	49.316 76	0.000 76	46.85 915	0.000 52	1. 63 31 0
70 %	No	LSTSQ (gelss)	1e- 08	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000	46.86 166	0.000 58	1. 61 38 9
70 %	No	LSTSQ (gelss)	1e- 12	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000	46.86 166	0.000 58	1. 61 43 4
70 %	No	LSTSQ (gelss)	1e- 16	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000 00	46.86 166	0.000 58	1. 60 59 1
90 %	Yes	LSTSQ (gelss)	0.1	0.0 58 66	0. 06 32 5	475 5.5 705 7	15 87. 99 02 4	50.36 097	0.000 26	50.13 814	0.001 27	1. 94 54 3
90 %	Yes	LSTSQ (gelss)	0.0 1	0.8 15 01	0. 81 63 6	210 8.13 733	70 3.1 09 58	50.161 59	0.000 14	45.97 968	0.000 37	2.1 10 09
90 %	Yes	LSTSQ (gelss)	0.0 001	0.8 65 38	0. 86 03 3	179 8.3 820 3	61 3.1 88 93	49.48 069	0.000 07	46.99 557	0.001 36	1.7 32 98
90 %	Yes	LSTSQ (gelss)	1e- 08	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	1.7 74 64
90 %	Yes	LSTSQ (gelss)	1e- 12	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	1.7 57 06

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
90 %	Yes	LSTSQ (gelss)	1e- 16	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	1.7 12 19
70 %	Yes	LSTSQ (gelss)	0.1	0.0 58 19	0. 06 14 8	419 9.8 134 7	27 38. 06 49 8	50.34 529	0.000 78	50.23 111	0.001 74	1. 82 73 0
70 %	Yes	LSTSQ (gelss)	0.0	0.8 16 01	0. 81 41 5	185 6.2 978 6	121 8.4 42 17	50.371 08	0.000 06	49.17 413	0.000 24	1.7 71 79
70 %	Yes	LSTSQ (gelss)	0.0 001	0.8 66 39	0. 86 02 0	158 1.83 097	10 56. 74 79 6	49.30 710	0.001 09	46.84 895	0.000 40	2. 02 81 9
70 %	Yes	LSTSQ (gelss)	1e- 08	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000	17502 .6599 1	0.000 58	2. 30 48 1
70 %	Yes	LSTSQ (gelss)	1e- 12	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000	17502 .6599 1	0.000 58	2.1 0 42 4
70 %	Yes	LSTSQ (gelss)	1e- 16	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000	17502 .6599 1	0.000 58	2. 28 96 7
90 %	No	LSTSQ (gelsy)	0.1	- 1.0 85 87	- 1. 07 09 3	707 9.0 300 5	23 61. 119 59	86.139 56	0.0011 0	86.22 409	0.003 49	2. 61 91 0
90 %	No	LSTSQ (gelsy)	0.0 1	- 1.0 85	- 1. 07	707 9.0 300	23 61. 119	86.139 56	0.0011 0	86.22 409	0.003 49	2. 62 49

T:	Data		Car	DO	DO	Daa	Re	N4	N 4:	Mari	Min	A V
Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	Gt im e
				87	09 3	5	59					0
90 %	No	LSTSQ (gelsy)	0.0 001	0.8 65 38	0. 86 03 2	179 8.3 882 3	61 3.1 94 84	49.47 471	0.000 09	46.98 724	0.000 66	2. 64 96 5
90 %	No	LSTSQ (gelsy)	1e- 08	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	2. 63 64 1
90 %	No	LSTSQ (gelsy)	1e- 12	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	2. 63 35 6
90 %	No	LSTSQ (gelsy)	1e- 16	0.8 65 38	0. 86 03 2	179 8.3 737 3	61 3.1 96 75	49.471 29	0.000	46.98 621	0.002 33	2. 67 45 8
70 %	No	LSTSQ (gelsy)	0.1	- 1.0 80 45	- 1. 09 37 0	624 2.0 487 6	40 89. 59 16 8	86.158 72	0.000 19	86.24 325	0.005 12	2. 05 47 6
70 %	No	LSTSQ (gelsy)	0.0	- 1.0 80 45	- 1. 09 37 0	624 2.0 487 6	40 89. 59 16 8	86.158 72	0.000 19	86.24 325	0.005 12	2.1 12 06
70 %	No	LSTSQ (gelsy)	0.0 001	0.8 66 39	0. 86 02 0	158 1.8 458 1	10 56. 76 21 8	49.314 17	0.000 28	46.85 882	0.000 27	2. 06 23 7
70 %	No	LSTSQ (gelsy)	1e- 08	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000	46.86 166	0.000 58	2. 06 16 6
70 %	No	LSTSQ (gelsy)	1e- 12	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000	46.86 166	0.000 58	2. 07 66 8

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
70 %	No	LSTSQ (gelsy)	1e- 16	0.8 66 40	0. 86 02 0	158 1.82 241	10 56. 751 68	49.318 80	0.000 00	46.86 166	0.000 58	2. 08 68 2
90 %	Yes	LSTSQ (gelsy)	0.1	0.0 00 28	0. 0 0 02 5	490 0.8 288 3	16 40. 51 42 0	50.815 33	0.000 36	50.89 982	0.000 37	2. 79 49 0
90 %	Yes	LSTSQ (gelsy)	0.0	0.7 35 62	0. 73 87 7	252 0.2 405 4	83 8.5 78 33	47.272 00	0.000 01	45.74 035	0.000 51	3. 01 65 3
90 %	Yes	LSTSQ (gelsy)	0.0 001	0.8 65 38	0. 86 03 3	179 8.3 820 5	61 3.1 87 80	49.48 074	0.000 24	46.99 563	0.001 41	2. 77 79 9
90 %	Yes	LSTSQ (gelsy)	1e- 08	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	2. 72 03 4
90 %	Yes	LSTSQ (gelsy)	1e- 12	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	2. 71 03 0
90 %	Yes	LSTSQ (gelsy)	1e- 16	0.8 65 38	0. 86 03 3	179 8.3 751 7	61 3.1 88 33	49.481 41	0.000 10	46.99 654	0.000 62	2. 67 75 1
70 %	Yes	LSTSQ (gelsy)	0.1	0.0 00 22	0. 0 0 03 5	432 7.14 354	28 25. 83 05	50.770 98	0.003 85	50.85 546	0.000 54	2. 09 85 8
70 %	Yes	LSTSQ (gelsy)	0.0	0.7 26 79	0. 72 45 9	226 2.0 315 0	14 83. 23 312	46.143 12	0.000 88	45.62 934	0.000 64	2. 49 10 5
70 %	Yes	LSTSQ (gelsy)	0.0 001	0.8 66 39	0. 86 02	158 1.83 100	10 56. 74	49.30 716	0.000 40	46.84 906	0.000 31	2. 34 59

Trai n Set	Data Centeri ng	Solver	Con diti on	R2 Tra in	R2 Te st	Res Trai n	Re s Te st	Max Err Train	Min Err Train	Max Err Test	Min Err Test	A V Gt im e
					0		84 1					6
70 %	Yes	LSTSQ (gelsy)	1e- 08	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000	17502 .6599 1	0.000 58	2. 50 28 6
70 %	Yes	LSTSQ (gelsy)	1e- 12	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000	17502 .6599 1	0.000 58	2. 63 98 1
70 %	Yes	LSTSQ (gelsy)	1e- 16	0.8 66 40	- 73 .0 65 88	158 1.82 241	24 32 3.8 03 99	49.318 80	0.000	17502 .6599 1	0.000 58	2.1 46 11

- The gelsd driver performs poorly with a condition of 0.1, but improves with lower condition values.
- Data centering with a 70% training set leads to a catastrophic failure in generalization, especially with lower condition values. The 90% set is less affected.
- Lower condition values (e.g., 0.0001, 1e-08, 1e-12, 1e-16) generally provide the best results, with R² values close to those of QR and SVD with non-centered data.
- The gelsd driver is generally faster than gelss and gelsy.
- The gelss driver shows similar trends to gelsd regarding the impact of the condition parameter and data centering.
- gelsy is the slowest and does not offer any significant advantage in term of performance over gelsd or gelss.

When we center our data, we obtain similar results of PCA

Example

```
from sklearn.decomposition import PCA
n_components= 46
pca = PCA(n_components=n_components)
pca.fit(X_train)

#now use PCA to compute theta for the least squares problem
X_train_pca = pca.transform(X_train)
X_test_pca = pca.transform(X_test)
```

```
U, S, Vt = np.linalq.svd(X train pca, full matrices=False)
S = np.diag(S)
theta = Vt.T @ np.linalg.inv(S) @ U.T @ y train
y train pred = X train pca @ theta
residuals_train = y_train - y_train_pred
print("Residuals for train set: ",np.linalg.norm(residuals train,2))
print("Maximum error for train set: ",np.max(np.abs(residuals_train)))
print("Minimum error for train set: ",np.min(np.abs(residuals_train)))
R2 train = \frac{1}{n} - np.sum((y train - y train pred)**2)/np.sum((y train -
np.mean(y train))**2)
print("R2 for train set: ",R2 train)
y test pred = X test pca @ theta
residuals test = y test - y test pred
print("Residuals for test set: ",np.linalg.norm(residuals test,2))
print("Maximum error for test set: ",np.max(np.abs(residuals test)))
print("Minimum error for test set: ",np.min(np.abs(residuals_test)))
R2\_test = 1 - np.sum((y\_test - y\_test\_pred)**2)/np.sum((y\_test - y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**2)/np.sum((y\_test\_pred)**
np.mean(y test))**2)
print("R2 for test set: ",R2_test)
Residuals for train set: 1881.996070664596
Maximum error for train set: 50.27252631978616
Minimum error for train set:
                                                                                     0.00018055820469253803
R2 for train set: 0.8108784800073678
Residuals for test set: 1233.9720054889888
Maximum error for test set: 50.60630051087459
Minimum error for test set: 0.0003054529720927235
R2 for test set: 0.8093811530926048
```