Assignment 4

Q1. Implement the normal equation (closed form) regression for the Boston housing dataset. The dataset description can be found here. The target feature is variable no. 14, 'MEDV', and the input variables are the remaining 13 variables.

Answer:

I implemented the closed form solution for calculating parameters $W = (X^{T}X)^{-1} X^{T}Y$

```
def linear_regressor_closed_form(X,Y):
    return (np.linalg.pinv(np.matmul(X.T,X))@X.T@Y)
```

Q1a.Divide the dataset into training and testing using an 80:20 split ratio.

Answer:

```
shape of split data : train data and labels of training dataset: (404, 13) (404,)
shape of test data and labels (102, 13) (102,)
```

Q1b.Perform Linear regression for all features and compute the RMSE for training as well as the testing set. (Note: There is no need to perform k-fold cross-validation for this part.)

Answer:

```
error on 80 percent dataset in case 1 and on entire dataset for question2 4.534460410890986
```

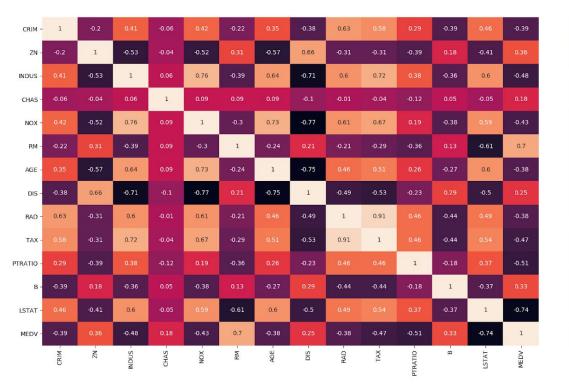
Common message as I have implemented a reusable function. Above is rmse for degree1 using all features.

Test set RMSE:

```
test set error when using all 13 features is 5.376194557068185
```

Q.1c Select the feature named 'LSTAT' for polynomial regression.

Answer: From the correlation matrix it is evident that LSTAT and RM are highly correlated with target variable MEDV. RM is positively correlated and LSTAT is negatively correlated.



0.6

0.3

- 0.0

-0.3

However RM and LSTAT are also correlated with each other. We choose Istat here by picking the corresponding column from dataframe.

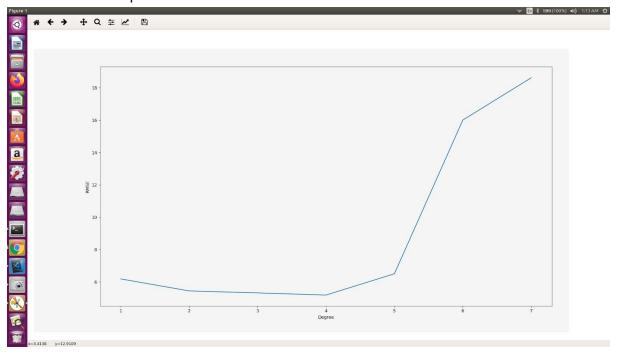
Q1d. K-fold-cross validation:

```
def k fold_cross_validation(data, k, labels):
    divided_data = np.array_split(data, k)
    labels = np.array_split(labels, k)
    train_errors = []
    val_errors = []
    for i in range(k):
        #copy to avoid mutation of original data
        data_for_fold = divided_data.copy()
        validation_data = divided_data[]
        validation_labels = labels[i]
        train_labels = labels.copy()
        del data_for_fold[i]
        del train_labels[i]
        print((np.concatenate(train_labels).shape))
        train_data_for_fold = np.concatenate( data_for_fold, axis=0)
        weights_estimated = linear_regressor_closed_form(train_data_for_fold, np.concatenate(train_labels))
        predictions_train = predict(train_data_for_fold, weights_estimated)
        train_error = RMSE_error(np.concatenate(train_labels), predictions_train)
        print("train_error in 5_fold_cross_validation", train_error)
        predictions_val = predict(validation_data, weights_estimated)
        val_error = RMSE_error(validation_labels, predictions_val)
        val_error = RMSE_error(validation_labels, predictions_val)
        val_errors.append(val_error)
        print("val_error in 5_fold_cross_validation", val_error)
        return_train_errors, val_errors
```

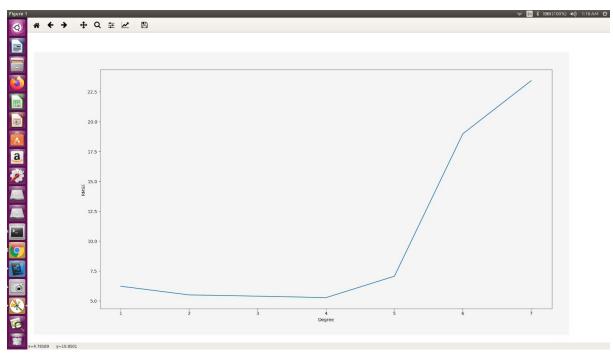
Q1e
Performing k-fold cross validation for different degrees of polynomial:
Sample output: (not exhaustive).

Q1f.
Computing RMSE and mean of RMSE for different degrees(1,2,3,4,5,6,7 etc.) and plotting it:

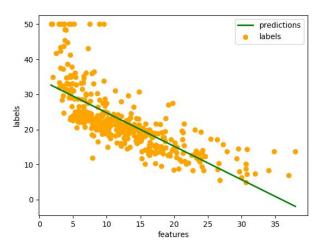
Train mean RMSE plot:



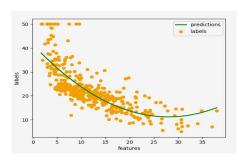
Validation Mean RMSE plot:



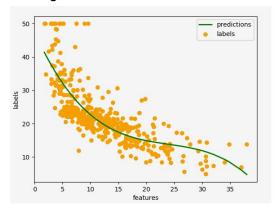
Fitted line plots for degree 1:



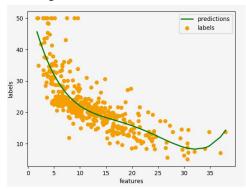
For degree 2:



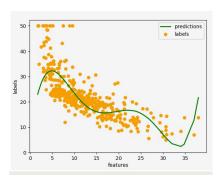
For degree 3:



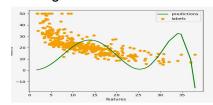
For degree 4:



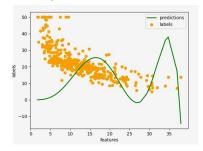
For degree 5:



For degree 6:



For degree 7:



Q1g.
Choosing degree of polynomial with lowest mean validation RMSE, and performing regression on training set and test set :

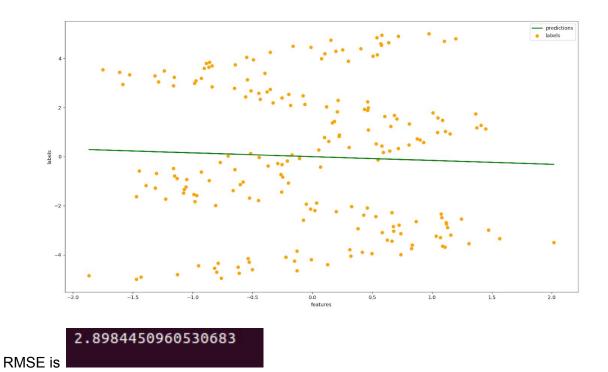
```
min_degree 4
best degree is 4 and validation error is 5.274042824968437

RMSE on 80 percent train dataset for best degree is 5.197111228704988

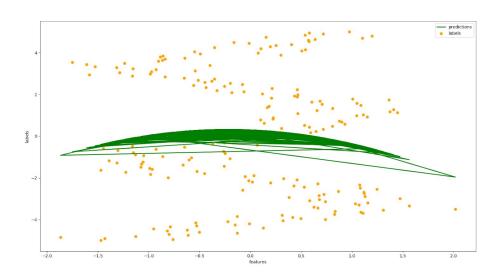
RMSE on 20 percent test dataset for best degree is 5.513721075111767
```

Q2 A and B

Fitted line for degree1:

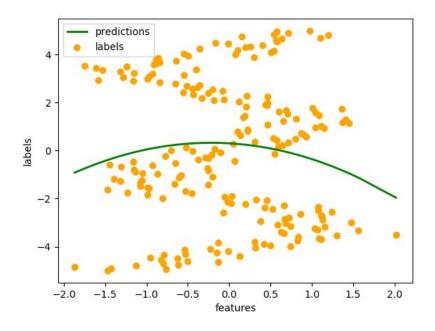


For degree 2:



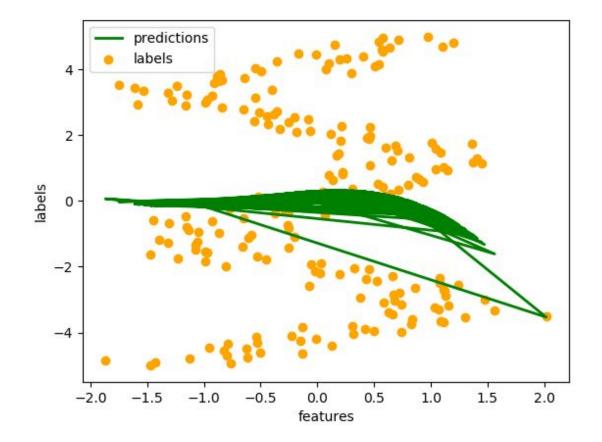
I could take the average line for a more clear plot but wanted to illustrate the default plot and fitted model.Or i could sort x values before line plot

After sorting X values the plot we get is

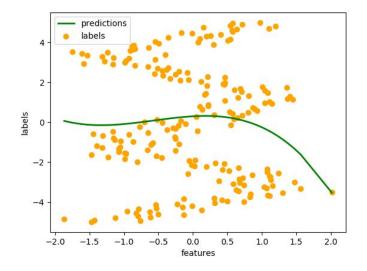


RMSE for degree2: 2.88000505198886

For degree 4: Before sorting for line plot :

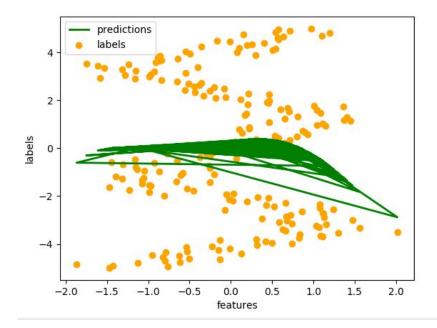


After sorting for line plot:

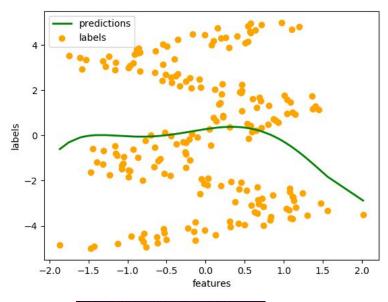


2.8726896919751668 RMSE is:

For degree 5: Before sorting:

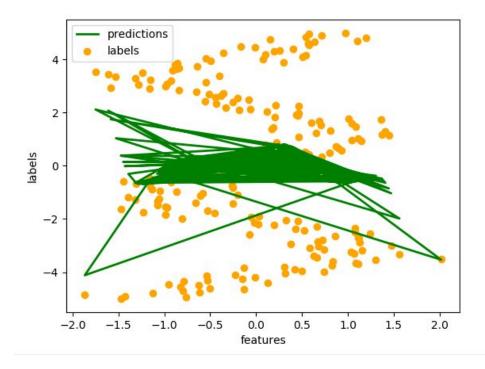


After sorting for line plot:

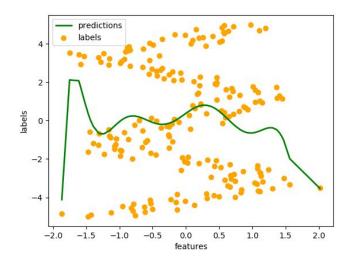


2.870418058719128

RMSE is: For degree 10:Before sorting

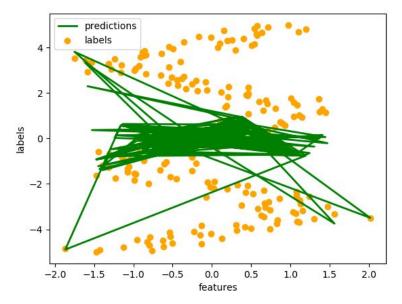


After sorting for line plot:

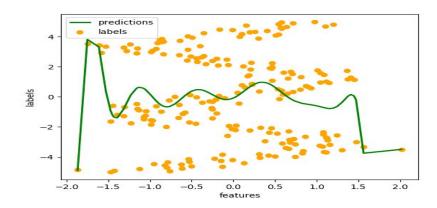


2.8293330859285635 RMSE is

For degree 15: Before sorting:

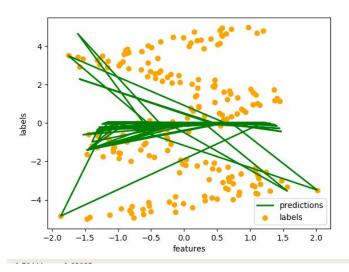


After sorting line plot becomes:

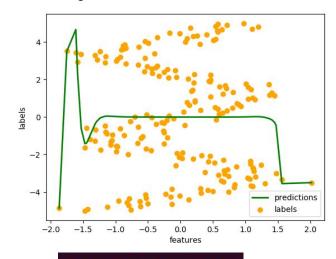


RMSE:

For degree 30: Before sorting



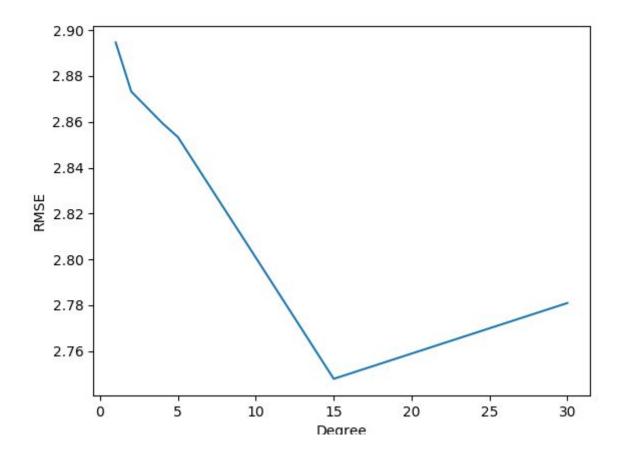
After sorting:



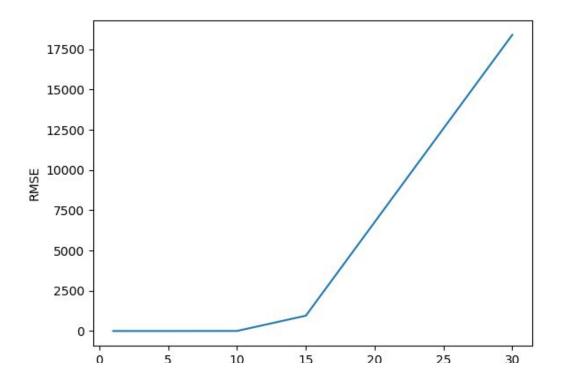
RMSE:

2.8162022462288094

RMSE plot for different degrees



Mean RMSE plot of val set when performing k-fold cross validation is



Sample RMSE during cross validations (only for degree 5 and 10 screenshot is given for brevity but was performed for all degrees as seen in above plot)

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valerror in 5 fold cross validation 2.88339701384613547
valerror in 5 fold cross validation 3.208483763535113
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