

HW2__Regression

March 27, 2020

1 Final Results - Regression

- Without GridSearchCV
- LASSO Model
- Best parameters: {'alpha': 1}
- Cross-validation scores: 0.8842639367598525
- Train score: 0.9115
- Test score: 0.8752

- With GridSearchCV
- Linear Regression with Model Parameter - Lasso *GridSearchCV
- Best parameters: {'regressor': Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000, normalize=False, positive=False, precompute=False, random_state=0, selection='cyclic', tol=0.0001, warm_start=False)}
- Cross-validation scores: 0.8782561788110849
- Train score: 0.9115
- Test score: 0.8752

1.1 Data PreProcessing

```
[1]: from math import sqrt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LinearRegression
```

```

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt

pd.pandas.set_option('display.max_columns', None)
%matplotlib inline

```

1.1.1 Load Datasets

```

[2]: # load dataset
# your code here
data = pd.read_csv(r'C:\Users\nabhs\OneDrive\BUAN - Semester 2\BUAN 6341 - Applied Machine Learning\Datasets\houseprice.csv')

```

```

[3]: data.head()

```

```

[3]:   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape \
0    1         60      RL         65.0     8450   Pave   NaN     Reg
1    2         20      RL         80.0     9600   Pave   NaN     Reg
2    3         60      RL         68.0    11250   Pave   NaN     IR1
3    4         70      RL         60.0     9550   Pave   NaN     IR1
4    5         60      RL         84.0    14260   Pave   NaN     IR1

      LandContour Utilities LotConfig LandSlope Neighborhood Condition1 \
0          Lvl1   AllPub   Inside      Gtl      CollgCr      Norm
1          Lvl1   AllPub    FR2      Gtl      Veenker    Feedr
2          Lvl1   AllPub   Inside      Gtl      CollgCr      Norm
3          Lvl1   AllPub  Corner      Gtl      Crawfor      Norm
4          Lvl1   AllPub    FR2      Gtl      NoRidge      Norm

      Condition2 BldgType HouseStyle OverallQual OverallCond YearBuilt \
0          Norm    1Fam    2Story           7           5      2003
1          Norm    1Fam    1Story           6           8      1976
2          Norm    1Fam    2Story           7           5      2001
3          Norm    1Fam    2Story           7           5      1915
4          Norm    1Fam    2Story           8           5      2000

      YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType \
0          2003     Gable  CompShg   VinylSd   VinylSd    BrkFace
1          1976     Gable  CompShg   MetalSd   MetalSd      None
2          2002     Gable  CompShg   VinylSd   VinylSd    BrkFace
3          1970     Gable  CompShg    Wd Sdng    Wd Shng      None
4          2000     Gable  CompShg   VinylSd   VinylSd    BrkFace

      MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure \
0          196.0        Gd        TA        PConc        Gd        TA        No

```

1	0.0	TA	TA	CBlock	Gd	TA	Gd
2	162.0	Gd	TA	PConc	Gd	TA	Mn
3	0.0	TA	TA	BrkTil	TA	Gd	No
4	350.0	Gd	TA	PConc	Gd	TA	Av

	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	\
0	GLQ	706	Unf	0	150	856	
1	ALQ	978	Unf	0	284	1262	
2	GLQ	486	Unf	0	434	920	
3	ALQ	216	Unf	0	540	756	
4	GLQ	655	Unf	0	490	1145	

	Heating	HeatingQC	CentralAir	Electrical	1stFlrSF	2ndFlrSF	LowQualFinSF	\
0	GasA	Ex	Y	SBrkr	856	854	0	
1	GasA	Ex	Y	SBrkr	1262	0	0	
2	GasA	Ex	Y	SBrkr	920	866	0	
3	GasA	Gd	Y	SBrkr	961	756	0	
4	GasA	Ex	Y	SBrkr	1145	1053	0	

	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	\
0	1710	1	0	2	1	3	
1	1262	0	1	2	0	3	
2	1786	1	0	2	1	3	
3	1717	1	0	1	0	3	
4	2198	1	0	2	1	4	

	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	\
0	1	Gd	8	Typ	0	NaN	
1	1	TA	6	Typ	1	TA	
2	1	Gd	6	Typ	1	TA	
3	1	Gd	7	Typ	1	Gd	
4	1	Gd	9	Typ	1	TA	

	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual	\
0	Attchd	2003.0	RFn	2	548	TA	
1	Attchd	1976.0	RFn	2	460	TA	
2	Attchd	2001.0	RFn	2	608	TA	
3	Detchd	1998.0	Unf	3	642	TA	
4	Attchd	2000.0	RFn	3	836	TA	

	GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	\
0	TA	Y	0	61	0	0	
1	TA	Y	298	0	0	0	
2	TA	Y	0	42	0	0	
3	TA	Y	0	35	272	0	
4	TA	Y	192	84	0	0	

	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	\
0	0	0	NaN	NaN	NaN	0	2	2008	
1	0	0	NaN	NaN	NaN	0	5	2007	
2	0	0	NaN	NaN	NaN	0	9	2008	
3	0	0	NaN	NaN	NaN	0	2	2006	
4	0	0	NaN	NaN	NaN	0	12	2008	

	SaleType	SaleCondition	SalePrice
0	WD	Normal	208500
1	WD	Normal	181500
2	WD	Normal	223500
3	WD	Abnorml	140000
4	WD	Normal	250000

1.1.2 Types of variables

```
[4]: # we have an Id variable, that we should not use for predictions:
```

```
print('Number of House Id labels: ', len(data.Id.unique()))
print('Number of Houses in the Dataset: ', len(data))
```

Number of House Id labels: 1460

Number of Houses in the Dataset: 1460

Find categorical variables

```
[5]: # find categorical variables- hint data type = 'O'
```

```
categorical = [var for var in data.columns if data[var].dtype=='O']

print(f'There are {len(categorical)} categorical variables')
categorical
```

There are 43 categorical variables

```
[5]: ['MSZoning',
      'Street',
      'Alley',
      'LotShape',
      'LandContour',
      'Utilities',
      'LotConfig',
      'LandSlope',
      'Neighborhood',
      'Condition1',
      'Condition2',
      'BldgType',
      'HouseStyle',
```

```

'RoofStyle',
'RoofMatl',
'Exterior1st',
'Exterior2nd',
'MasVnrType',
'ExterQual',
'ExterCond',
'Foundation',
'BsmtQual',
'BsmtCond',
'BsmtExposure',
'BsmtFinType1',
'BsmtFinType2',
'Heating',
'HeatingQC',
'CentralAir',
'Electrical',
'KitchenQual',
'Functional',
'FireplaceQu',
'GarageType',
'GarageFinish',
'GarageQual',
'GarageCond',
'PavedDrive',
'PoolQC',
'Fence',
'MiscFeature',
'SaleType',
'SaleCondition']

```

Find temporal variables

```

[6]: # make a list of the numerical variables first= Hint data type != 0
numerical = [var for var in data.columns if data[var].dtype!='O']

# list of variables that contain year information= Hint variable name has Yr
→ or
year_vars = [var for var in numerical if 'Yr' in var or 'Year' in var]

year_vars

```

```

[6]: ['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']

```

```

[7]: numerical

```

```
[7]: ['Id',
      'MSSubClass',
      'LotFrontage',
      'LotArea',
      'OverallQual',
      'OverallCond',
      'YearBuilt',
      'YearRemodAdd',
      'MasVnrArea',
      'BsmtFinSF1',
      'BsmtFinSF2',
      'BsmtUnfSF',
      'TotalBsmtSF',
      '1stFlrSF',
      '2ndFlrSF',
      'LowQualFinSF',
      'GrLivArea',
      'BsmtFullBath',
      'BsmtHalfBath',
      'FullBath',
      'HalfBath',
      'BedroomAbvGr',
      'KitchenAbvGr',
      'TotRmsAbvGrd',
      'Fireplaces',
      'GarageYrBlt',
      'GarageCars',
      'GarageArea',
      'WoodDeckSF',
      'OpenPorchSF',
      'EnclosedPorch',
      '3SsnPorch',
      'ScreenPorch',
      'PoolArea',
      'MiscVal',
      'MoSold',
      'YrSold',
      'SalePrice']
```

Find discrete variables To identify discrete variables- numerical variables with less than 20 unique values

```
[8]: # let's visualise the values of the discrete variables
discrete = [var for var in numerical if len(data[var].unique()) < 20 and var_
↪not in year_vars]

print(f'There are {len(discrete)} discrete variables')
```

```
discrete
```

There are 14 discrete variables

```
[8]: ['MSSubClass',  
      'OverallQual',  
      'OverallCond',  
      'BsmtFullBath',  
      'BsmtHalfBath',  
      'FullBath',  
      'HalfBath',  
      'BedroomAbvGr',  
      'KitchenAbvGr',  
      'TotRmsAbvGrd',  
      'Fireplaces',  
      'GarageCars',  
      'PoolArea',  
      'MoSold']
```

Continuous variables

```
[9]: # find continuous variables- hint numerical variables not in discrete and   
      ↪ year_years  
      # Also remove the Id variable and the target variable SalePrice  
      # which are both also numerical  
  
      continuous = [var for var in numerical if var not in discrete and var not in [  
          'Id', 'SalePrice'] and var not in year_vars]  
  
      print('There are {} numerical and continuous variables'.format(len(numerical)))  
      continuous
```

There are 38 numerical and continuous variables

```
[9]: ['LotFrontage',  
      'LotArea',  
      'MasVnrArea',  
      'BsmtFinSF1',  
      'BsmtFinSF2',  
      'BsmtUnfSF',  
      'TotalBsmtSF',  
      '1stFlrSF',  
      '2ndFlrSF',  
      'LowQualFinSF',  
      'GrLivArea',  
      'GarageArea',  
      'WoodDeckSF',  
      'OpenPorchSF',
```

```
'EnclosedPorch',
'3SsnPorch',
'ScreenPorch',
'MiscVal']
```

1.1.3 Separate train and test set

```
[10]: # Let's separate into train and test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(data.drop(['Id',
↳ 'SalePrice'], axis=1),

                                                    data['SalePrice'],
                                                    test_size=0.1,
                                                    random_state=0)

X_train.shape, X_test.shape
```

```
[10]: ((1314, 79), (146, 79))
```

Now we will move on and engineer the features of this dataset. The most important part for this course.

1.1.4 Craete New Variables

Replace 'YearBuilt', 'YearRemodAdd', 'GarageYrBlt with time elapsed since YrSold So YearBuilt = YrSold-YearBuilt.

Similarly transform 'YearRemodAdd', 'GarageYrBlt. After making transformation drop YrSold

```
[11]: X_train.head()
```

```
[11]:
```

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	\
930	20	RL	73.0	8925	Pave	NaN	IR1	
656	20	RL	72.0	10007	Pave	NaN	IR1	
45	120	RL	61.0	7658	Pave	NaN	Reg	
1348	20	RL	NaN	16196	Pave	NaN	IR3	
55	20	RL	100.0	10175	Pave	NaN	IR1	

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	\
930	HLS	AllPub	Inside	Gtl	Timber	Norm	
656	Lvl	AllPub	Inside	Gtl	NAMES	Norm	
45	Lvl	AllPub	Inside	Gtl	NridgHt	Norm	
1348	Low	AllPub	Inside	Gtl	SawyerW	Norm	
55	Lvl	AllPub	Inside	Gtl	NAMES	Norm	

	Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt	\
930	Norm	1Fam	1Story	8	5	2007	
656	Norm	1Fam	1Story	5	7	1959	

45	Norm	TwnhsE	1Story	9	5	2005
1348	Norm	1Fam	1Story	7	5	1998
55	Norm	1Fam	1Story	6	5	1964

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType	\
930	2007	Gable	CompShg	VinylSd	VinylSd	None	
656	2006	Gable	CompShg	HdBoard	HdBoard	BrkFace	
45	2005	Hip	CompShg	MetalSd	MetalSd	BrkFace	
1348	1998	Gable	CompShg	VinylSd	VinylSd	None	
55	1964	Gable	CompShg	HdBoard	Plywood	BrkFace	

	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	\
930	0.0	Gd	TA	PConc	Gd	TA	
656	54.0	Gd	TA	CBlock	TA	TA	
45	412.0	Ex	TA	PConc	Ex	TA	
1348	0.0	Gd	TA	PConc	Gd	TA	
55	272.0	TA	TA	CBlock	TA	TA	

	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
930	Av	GLQ	16	Unf	0	
656	No	ALQ	806	Unf	0	
45	No	GLQ	456	Unf	0	
1348	Gd	GLQ	1443	Unf	0	
55	No	BLQ	490	Unf	0	

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	Electrical	\
930	1450	1466	GasA	Ex	Y	SBrkr	
656	247	1053	GasA	Ex	Y	SBrkr	
45	1296	1752	GasA	Ex	Y	SBrkr	
1348	39	1482	GasA	Ex	Y	SBrkr	
55	935	1425	GasA	Gd	Y	SBrkr	

	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	\
930	1466	0	0	1466	0	0	
656	1053	0	0	1053	1	0	
45	1752	0	0	1752	1	0	
1348	1494	0	0	1494	1	0	
55	1425	0	0	1425	0	0	

	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	KitchenQual	\
930	2	0	3	1	Gd	
656	1	1	3	1	Gd	
45	2	0	2	1	Ex	
1348	2	0	3	1	Gd	
55	2	0	3	1	TA	

TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType	GarageYrBlt	\
--------------	------------	------------	-------------	------------	-------------	---

930	7	Typ	0	NaN	Attchd	2007.0
656	5	Typ	0	NaN	Attchd	1959.0
45	6	Typ	1	Gd	Attchd	2005.0
1348	5	Typ	1	Fa	Attchd	1998.0
55	7	Typ	1	Gd	Attchd	1964.0

	GarageFinish	GarageCars	GarageArea	GarageQual	GarageCond	PavedDrive	\
930	Fin	3	610	TA	TA	Y	
656	RFn	1	312	TA	TA	Y	
45	RFn	2	576	TA	TA	Y	
1348	RFn	2	514	TA	TA	Y	
55	RFn	2	576	TA	TA	Y	

	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	\
930	100	18	0	0	0	
656	0	0	0	0	0	
45	196	82	0	0	0	
1348	402	25	0	0	0	
55	0	0	0	407	0	

	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	SaleType	\
930	0	NaN	NaN	NaN	0	7	2009	WD	
656	0	NaN	MnPrv	NaN	0	8	2008	WD	
45	0	NaN	NaN	NaN	0	2	2010	WD	
1348	0	NaN	NaN	NaN	0	8	2007	WD	
55	0	NaN	NaN	NaN	0	7	2008	WD	

	SaleCondition
930	Normal
656	Normal
45	Normal
1348	Normal
55	Normal

```
[12]: # function to calculate elapsed time

def elapsed_years(df, var):
    # capture difference between year variable and
    # year the house was sold

    df[var] = df['YrSold'] - df[var]
    return df
```

```
[13]: for var in ['YearBuilt', 'YearRemodAdd', 'GarageYrBlt']:
    X_train = elapsed_years(X_train, var)
    X_test = elapsed_years(X_test, var)
```

```
[14]: # drop YrSold
X_train.drop('YrSold', axis=1, inplace=True)
X_test.drop('YrSold', axis=1, inplace=True)

[15]: year_vars.remove('YrSold')

[16]: # capture the column names for use later in the notebook
final_columns = X_train.columns
final_columns

[16]: Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley',
          'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
          'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
          'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
          'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
          'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
          'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
          'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
          'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
          'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
          'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
          'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
          'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
          'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
          'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal',
          'MoSold', 'SaleType', 'SaleCondition'],
          dtype='object')
```

1.1.5 Feature Engineering Pipeline

```
[17]: # I will treat discrete variables as if they were categorical
# to treat discrete as categorical using Feature-engine
# we need to re-cast them as object

X_train[discrete] = X_train[discrete].astype('O')
X_test[discrete] = X_test[discrete].astype('O')

[18]: # import relevant modules for feature engineering
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from feature_engine import missing_data_imputers as mdi
from feature_engine import categorical_encoders as ce
from feature_engine.variable_transformers import YeoJohnsonTransformer
from sklearn.preprocessing import StandardScaler
from feature_engine.discretisers import DecisionTreeDiscretiser
```

```
[19]: house_preprocess = Pipeline([

    # missing data imputation
    ('missing_ind', mdi.AddNaNBinaryImputer(
        variables=['LotFrontage', 'MasVnrArea', 'GarageYrBlt'])),
    ('imputer_num', mdi.MeanMedianImputer(imputation_method='mean',
        variables=['LotFrontage',
↪ 'MasVnrArea', 'GarageYrBlt'])),
    ('imputer_cat', mdi.CategoricalVariableImputer(variables=categorical)),

    # categorical encoding
    ('rare_label_enc', ce.RareLabelCategoricalEncoder(
        tol=0.01, n_categories=6, variables=categorical+discrete)),
    ('categorical_enc', ce.MeanCategoricalEncoder(variables = categorical +
↪ discrete)),

    # Transforming Numerical Variables
    ('yjt', YeoJohnsonTransformer(variables = ['LotFrontage', 'MasVnrArea',
↪ 'GarageYrBlt'])),

    # discretisation and encoding
    ('treeDisc', DecisionTreeDiscretiser(cv=2,
↪ scoring='neg_mean_squared_error',
        regression=True,
        param_grid={'max_depth': [1,2,3,4,5,6]})),

    # feature Scaling
    ('scaler', StandardScaler()),

])
```

```
[20]: house_preprocess.fit(X_train,y_train)
```

```
[20]: Pipeline(memory=None,
    steps=[('missing_ind',
        AddNaNBinaryImputer(variables=['LotFrontage', 'MasVnrArea',
            'GarageYrBlt'])),
    ('imputer_num',
        MeanMedianImputer(imputation_method='mean',
            variables=['LotFrontage', 'MasVnrArea',
            'GarageYrBlt'])),
    ('imputer_cat',
        CategoricalVariableImputer(variables=['MSZoning', 'Street',
            'Alley', 'LotShape',
```

```

        'LandContour',
        'Utilities', '...'
        'Utilities', 'LotConfig',
        'LandSlope', 'Neighborhood',
        'Condition1', 'Condition2',
        'BldgType', 'HouseStyle',
        'OverallQual',
        'OverallCond', 'YearBuilt',
        'YearRemodAdd', 'RoofStyle',
        'RoofMatl', 'Exterior1st',
        'Exterior2nd', 'MasVnrType',
        'MasVnrArea', 'ExterQual',
        'ExterCond', 'Foundation',
        'BsmtQual', ...]),
        ('scaler',
         StandardScaler(copy=True, with_mean=True, with_std=True)]],
        verbose=False)

```

```

[21]: # Apply Transformations
X_train=house_preprocess.transform(X_train)
X_test=house_preprocess.transform(X_test)

```

1.2 DO NOT CHANGE STEPS BEFORE THIS POINT

1.3 Regression Models- Tune different models one by one

1.3.1 Linear Regression

```

[22]: # Train a linear regression model, report the coefficients and model_
      ↪performance

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

lr = LinearRegression().fit(X_train, y_train)
cv_scores = cross_val_score(lr, X_train, y_train)

```

C:\Users\nabhs\Anaconda3\lib\site-packages\sklearn\model_selection_split.py:1978: FutureWarning: The default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.

```
warnings.warn(CV_WARNING, FutureWarning)
```

Results

```

[23]: x_lrtrain= lr.predict(X_train)
      x_lrtest = lr.predict(X_test)

```

```

# check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, x_lrtrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_lrtrain))))
print('train r2: {}'.format(r2_score(y_train, x_lrtrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_lrtest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_lrtest))))
print('test r2: {}'.format(r2_score(y_test, x_lrtest)))

#print("Best parameters: {}".format(lr.best_params_))
print("Mean Cross-validation scores: {}".format(cv_scores))
print('Train score: {:.4f}'.format(lr.score(X_train, y_train)))
print('Test score: {:.4f}'.format(lr.score(X_test, y_test)))

```

```

train mse: 552937051.405446
train rmse: 23514.61357125492
train r2: 0.9114426745730106

test mse: 861097775.8563162
test rmse: 29344.467551078793
test r2: 0.8746968378820517
Mean Cross-validation scores: [ 8.76530743e-01 -7.34975702e+22  8.94769314e-01]
Train score: 0.9114
Test score: 0.8747

```

1.3.2 Ridge Regression

```

[24]: # Train a Ridge regression model, report the coefficients, the best parameters,
      ↪and model performance
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge
ridge = Ridge()

#define a list of parameters
#param_ridge = {'alpha':[0.001, 0.01, 0.1, 1, 10, 100] }
param_ridge = {'alpha':[1, 1e3, 1e4] }
grid_ridge = GridSearchCV(ridge, param_ridge, cv=10, return_train_score = True)
grid_ridge.fit(X_train, y_train)

```

```

[24]: GridSearchCV(cv=10, error_score='raise-deprecating',
                  estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True,
                                  max_iter=None, normalize=False, random_state=None,
                                  solver='auto', tol=0.001),
                  iid='warn', n_jobs=None,
                  param_grid={'alpha': [1, 1000.0, 10000.0]},
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=True,

```

```
scoring=None, verbose=0)
```

Results

```
[25]: x_gridtrain= grid_ridge.predict(X_train)
      x_gridtest = grid_ridge.predict(X_test)

      # check model performance:

      print('train mse: {}'.format(mean_squared_error(y_train, x_gridtrain)))
      print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_gridtrain))))
      print('train r2: {}'.format(r2_score(y_train, x_gridtrain)))
      print()
      print('test mse: {}'.format(mean_squared_error(y_test, x_gridtest)))
      print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_gridtest))))
      print('test r2: {}'.format(r2_score(y_test, x_gridtest)))

      print("Best parameters: {}".format(grid_ridge.best_params_))
      print("Cross-validation scores: {}".format(grid_ridge.best_score_))
      print('Train score: {:.4f}'.format(grid_ridge.score(X_train, y_train)))
      print('Test score: {:.4f}'.format(grid_ridge.score(X_test, y_test)))
```

```
train mse: 552540520.7585117
```

```
train rmse: 23506.1804800038
```

```
train r2: 0.911506182152134
```

```
test mse: 858035459.791463
```

```
test rmse: 29292.242314159957
```

```
test r2: 0.8751424526508844
```

```
Best parameters: {'alpha': 1}
```

```
Cross-validation scores: 0.8843013657740887
```

```
Train score: 0.9115
```

```
Test score: 0.8751
```

1.3.3 Lasso

```
[26]: # Train a Lasso regression model, report the coefficients, the best parameters,
      ↪and model performance

      # YOUR CODE HERE

      from sklearn.linear_model import Lasso
      lasso = Lasso(random_state=0)

      #define a list of parameters
      #param_lasso = {'alpha':[0.001, 0.01, 0.1, 1, 10, 100] }
      param_lasso = {'alpha':[1, 1e4, 1e5] }
```

```
grid_lasso = GridSearchCV(lasso, param_lasso, cv=10, return_train_score = True)
grid_lasso.fit(X_train, y_train)
```

```
[26]: GridSearchCV(cv=10, error_score='raise-deprecating',
                  estimator=Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
                                  max_iter=1000, normalize=False, positive=False,
                                  precompute=False, random_state=0,
                                  selection='cyclic', tol=0.0001, warm_start=False),
                  iid='warn', n_jobs=None,
                  param_grid={'alpha': [1, 10000.0, 100000.0]},
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
                  scoring=None, verbose=0)
```

Results

```
[27]: x_lassotrain= grid_lasso.predict(X_train)
x_lassotest = grid_lasso.predict(X_test)

# check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, x_lassotrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_lassotrain))))
print('train r2: {}'.format(r2_score(y_train, x_lassotrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_lassotest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_lassotest))))
print('test r2: {}'.format(r2_score(y_test, x_lassotest)))

print("Best parameters: {}".format(grid_lasso.best_params_))
print("Cross-validation scores: {}".format(grid_lasso.best_score_))
print('Train score: {:.4f}'.format(grid_lasso.score(X_train, y_train)))
print('Test score: {:.4f}'.format(grid_lasso.score(X_test, y_test)))
```

train mse: 552539222.3512008

train rmse: 23506.152861563733

train r2: 0.9115063901025299

test mse: 857849072.1153543

test rmse: 29289.060621934503

test r2: 0.87516957496597

Best parameters: {'alpha': 1}

Cross-validation scores: 0.8842639367598525

Train score: 0.9115

Test score: 0.8752

1.4 Linear Regression with SGD

```
[28]: from sklearn.linear_model import SGDRegressor
```

```
[29]: # create pipeline
reg_sgd_pipe = Pipeline([

    # feature Scaling
    ('scaler', MinMaxScaler()),
    # regression
    ('sgd_reg', SGDRegressor(max_iter=1000, tol = 1e-6))
])

param_sgd = {'sgd_reg__eta0':[0.01, 0.05, 0.1 ,0.5],
             'sgd_reg__penalty' :['l1','l2'],#lasso,ridge
             'sgd_reg__alpha' :[0.1,0.01,0.001] }

grid_linearsgd = GridSearchCV(reg_sgd_pipe,
                              param_sgd,cv=5,
                              n_jobs=-1,
                              return_train_score = True,
                              scoring='neg_mean_squared_error')

# let's fit the pipeline
grid_linearsgd.fit(X_train, y_train)

# let's get the predictions
X_train_preds = grid_linearsgd.predict(X_train)
X_test_preds = grid_linearsgd.predict(X_test)
```

C:\Users\nabhs\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:814: DeprecationWarning: The default of the `iid` parameter will change from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal.

DeprecationWarning)

1.4.1 Results

```
[30]: # check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, X_train_preds)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, X_train_preds))))
print('train r2: {}'.format(r2_score(y_train, X_train_preds)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, X_test_preds)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, X_test_preds))))
print('test r2: {}'.format(r2_score(y_test, X_test_preds)))
```

```

print("Best parameters: {}".format(grid_linearsgd.best_params_))
print('Train score: {:.4f}'.format(grid_linearsgd.score(X_train, y_train)))
print('Test score: {:.4f}'.format(grid_linearsgd.score(X_test, y_test)))

```

```

train mse: 606391235.6555519
train rmse: 24625.01239909438
train r2: 0.9028815561273599

```

```

test mse: 989766831.120983
test rmse: 31460.559930188512
test r2: 0.8559734827144475
Best parameters: {'sgd_reg__alpha': 0.001, 'sgd_reg__eta0': 0.05,
'sgd_reg__penalty': 'l1'}
Train score: -606391235.6556
Test score: -989766831.1210

```

1.5 Polynomial Regression

```

[31]: #apply polynomial regression in pipeline
#pipe_poly = make_pipeline(PolynomialFeatures(),MinMaxScaler(),
↳LinearRegression())
pipe_poly=Pipeline([
    ('polynomialfeatures', PolynomialFeatures()),
    ('scaler',MinMaxScaler()),
    ('norm_reg', LinearRegression())

])
#define a list of parameters
param_poly = {'polynomialfeatures__degree':range(1,3)}

grid_poly = GridSearchCV(pipe_poly, param_poly,cv=5, n_jobs=-1,
↳return_train_score = True,scoring='neg_mean_squared_error')

grid_poly.fit(X_train, y_train)

# let's get the predictions
X_train_preds = grid_poly.predict(X_train)
X_test_preds = grid_poly.predict(X_test)

```

C:\Users\nabhs\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:814: DeprecationWarning: The default of the `iid` parameter will change from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal.

DeprecationWarning)

1.5.1 Results

```
[32]: x_polytrain= grid_lasso.predict(X_train)
x_polytest = grid_lasso.predict(X_test)

# check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, x_polytrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_polytrain))))
print('train r2: {}'.format(r2_score(y_train, x_polytrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_polytest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_polytest))))
print('test r2: {}'.format(r2_score(y_test, x_polytest)))

print("Best parameters: {}".format(grid_poly.best_params_))
print("Cross-validation scores: {}".format(grid_poly.best_score_))
print('Train score: {:.4f}'.format(grid_poly.score(X_train, y_train)))
print('Test score: {:.4f}'.format(grid_poly.score(X_test, y_test)))
```

train mse: 552539222.3512008

train rmse: 23506.152861563733

train r2: 0.9115063901025299

test mse: 857849072.1153543

test rmse: 29289.060621934503

test r2: 0.87516957496597

Best parameters: {'polynomialfeatures__degree': 2}

Cross-validation scores: -6.118248744280687e+32

Train score: -27597.3189

Test score: -2148247783488639653001383903232.0000

```
[33]: print('train mse: {}'.format(mean_squared_error(y_train, X_train_preds)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, X_train_preds))))
print('train r2: {}'.format(r2_score(y_train, X_train_preds)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, X_test_preds)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, X_test_preds))))
print('test r2: {}'.format(r2_score(y_test, X_test_preds)))
```

train mse: 27597.318873668188

train rmse: 166.12440782036873

train r2: 0.9999955800669494

test mse: 2.1482477834886397e+30

test rmse: 1465690207202272.2

test r2: -3.126035716632908e+20

1.6 ElasticNet

```
[34]: from sklearn.linear_model import ElasticNet

elasticnet = ElasticNet().fit(X_train, y_train)

#define a list of parameters
param_elasticnet = {'alpha':[1, 1e4, 1e5],
                    'l1_ratio':[0.2,0.4,0.6,0.8]}

grid_elasticnet = GridSearchCV(elasticnet , param_elasticnet, cv=5,
    ↪return_train_score = True)
grid_elasticnet.fit(X_train, y_train)

x_elastictrain_predict = grid_elasticnet.predict(X_train)
x_elastictest_predict = grid_elasticnet.predict(X_test)

[35]: print('train mse: {}'.format(mean_squared_error(y_train,
    ↪x_elastictrain_predict)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train,
    ↪x_elastictrain_predict))))
print('train r2: {}'.format(r2_score(y_train, x_elastictrain_predict)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_elastictest_predict)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test,
    ↪x_elastictest_predict))))
print('test r2: {}'.format(r2_score(y_test, x_elastictest_predict)))
print()
print('Best parameters: ', grid_elasticnet.best_params_)
print('Best cross-validation score:', grid_elasticnet.score(X_test, y_test))
print("Training set score: {:.2f}".format(elasticnet.score(X_train, y_train)))
print("Test set score: {:.2f}".format(elasticnet.score(X_test, y_test)))
```

train mse: 580812656.1496782

train rmse: 24100.055106776796

train r2: 0.9069781717972707

test mse: 908630644.7418916

test rmse: 30143.500870699998

test r2: 0.8677800638026185

Best parameters: {'alpha': 1, 'l1_ratio': 0.8}

Best cross-validation score: 0.8677800638026185

Training set score: 0.90

Test set score: 0.85

1.7 Tune Multiple Models with one GridSearch

1.7.1 Model - Linear Regression with Model Parameter - Ridge *GridSearch

```
[36]: model_linear = Pipeline([("regressor", LinearRegression())])
```

```
[37]: model_parm_gd1 = [{ 'regressor': [Ridge()]}]
```

```
[38]: from sklearn import svm
grid_search_linear = GridSearchCV(svm.SVC(gamma='auto'),{
    'C':[30],
    'kernel':['linear']
},cv=5,return_train_score=False)
```

```
[39]: grid_search_linear = GridSearchCV(model_linear,model_parm_gd1)
```

```
[40]: grid_search_linear.fit(X_train,y_train)
```

C:\Users\nabhs\Anaconda3\lib\site-packages\sklearn\model_selection_split.py:1978: FutureWarning: The default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.

```
warnings.warn(CV_WARNING, FutureWarning)
```

```
[40]: GridSearchCV(cv='warn', error_score='raise-deprecating',
                  estimator=Pipeline(memory=None,
                                     steps=[('regressor',
                                             LinearRegression(copy_X=True,
                                                                fit_intercept=True,
                                                                n_jobs=None,
                                                                normalize=False))],
                                     verbose=False),
                  iid='warn', n_jobs=None,
                  param_grid=[{'regressor': [Ridge(alpha=1.0, copy_X=True,
                                                    fit_intercept=True, max_iter=None,
                                                    normalize=False,
                                                    random_state=None, solver='auto',
                                                    tol=0.001)]}],
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring=None, verbose=0)
```

Results

```
[41]: x_lrtrain= grid_search_linear.predict(X_train)
x_lrtest = grid_search_linear.predict(X_test)
```

```
# check model performance:
```

```

print('train mse: {}'.format(mean_squared_error(y_train, x_lrtrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_lrtrain))))
print('train r2: {}'.format(r2_score(y_train, x_lrtrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_lrtest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_lrtest))))
print('test r2: {}'.format(r2_score(y_test, x_lrtest)))
print()

print("Best parameters: {}".format(grid_search_linear.best_params_))
print("Cross-validation scores: {}".format(grid_search_linear.best_score_))
print('Train score: {:.4f}'.format(grid_search_linear.score(X_train, y_train)))
print('Test score: {:.4f}'.format(grid_search_linear.score(X_test, y_test)))

```

```

train mse: 552540520.7585117
train rmse: 23506.1804800038
train r2: 0.911506182152134

```

```

test mse: 858035459.791463
test rmse: 29292.242314159957
test r2: 0.8751424526508844

```

```

Best parameters: {'regressor': Ridge(alpha=1.0, copy_X=True, fit_intercept=True,
normalizer=False, random_state=None, solver='auto', tol=0.001)}
Cross-validation scores: 0.8783595644720746
Train score: 0.9115
Test score: 0.8751

```

1.8 Linear Regression with Model Parameter - Lasso *GridSearchCV

```
[42]: model_linear2 = Pipeline([("regressor", LinearRegression())] )
```

```
[43]: model_parm_gd2 = [{ 'regressor': [Lasso(random_state=0)]]}
```

```
[44]: grid_search_linear2 = GridSearchCV(svm.SVC(gamma='auto'),{
    'C': [1,10,20,30],
    'kernel': ['polynomial']

},cv=5,return_train_score=False)
```

```
[45]: grid_search_linear2 = GridSearchCV(model_linear2,model_parm_gd2)
```

```
[46]: grid_search_linear2.fit(X_train,y_train)
```

C:\Users\nabhs\Anaconda3\lib\site-

packages\sklearn\model_selection_split.py:1978: FutureWarning: The default value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to silence this warning.

```
warnings.warn(CV_WARNING, FutureWarning)
```

```
[46]: GridSearchCV(cv='warn', error_score='raise-deprecating',
                  estimator=Pipeline(memory=None,
                                     steps=[('regressor',
                                             LinearRegression(copy_X=True,
                                                                fit_intercept=True,
                                                                n_jobs=None,
                                                                normalize=False))],
                                     verbose=False),
                  iid='warn', n_jobs=None,
                  param_grid=[{'regressor': [Lasso(alpha=1.0, copy_X=True,
                                                    fit_intercept=True, max_iter=1000,
                                                    normalize=False, positive=False,
                                                    precompute=False, random_state=0,
                                                    selection='cyclic', tol=0.0001,
                                                    warm_start=False)]}],
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring=None, verbose=0)
```

Results

```
[47]: x_lrtrain= grid_search_linear2.predict(X_train)
      x_lrtest = grid_search_linear2.predict(X_test)

      # check model performance:

      print('train mse: {}'.format(mean_squared_error(y_train, x_lrtrain)))
      print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_lrtrain))))
      print('train r2: {}'.format(r2_score(y_train, x_lrtrain)))
      print()
      print('test mse: {}'.format(mean_squared_error(y_test, x_lrtest)))
      print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_lrtest))))
      print('test r2: {}'.format(r2_score(y_test, x_lrtest)))
      print()
      print("Best parameters: {}".format(grid_search_linear2.best_params_))
      print("Cross-validation scores: {}".format(grid_search_linear2.best_score_))
      print('Train score: {:.4f}'.format(grid_search_linear2.score(X_train, y_train)))
      print('Test score: {:.4f}'.format(grid_search_linear2.score(X_test, y_test)))
```

```
train mse: 552539222.3512008
```

```
train rmse: 23506.152861563733
```

```
train r2: 0.9115063901025299
```

```
test mse: 857849072.1153543
```

```
test rmse: 29289.060621934503
test r2: 0.87516957496597
```

```
Best parameters: {'regressor': Lasso(alpha=1.0, copy_X=True, fit_intercept=True,
max_iter=1000,
    normalize=False, positive=False, precompute=False, random_state=0,
    selection='cyclic', tol=0.0001, warm_start=False)}
Cross-validation scores: 0.8782561788110849
Train score: 0.9115
Test score: 0.8752
```

1.9 Pipeline - RandomForest Regressor with Model Parameter - Linear Regression *GridSearchCV

```
[48]: from sklearn.ensemble import RandomForestRegressor
```

```
[49]: model_rf = Pipeline([('regressor', RandomForestRegressor(random_state = 42))])
```

```
[50]: model_parm_rf = [{ 'regressor': [LinearRegression()]}]
```

```
[51]: from sklearn import svm
```

```
[52]: grid_rf = GridSearchCV(svm.SVC(gamma='auto'),{
    'C':[30],
    'kernel':['linear']
},cv=5,return_train_score=False)
```

```
[53]: grid_rf = GridSearchCV(model_rf, model_parm_rf)
```

```
[54]: grid_rf.fit(X_train,y_train)
```

```
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\model_selection\_split.py:1978: FutureWarning: The default
value of cv will change from 3 to 5 in version 0.22. Specify it explicitly to
silence this warning.
```

```
warnings.warn(CV_WARNING, FutureWarning)
```

```
[54]: GridSearchCV(cv='warn', error_score='raise-deprecating',
    estimator=Pipeline(memory=None,
        steps=[('regressor',
            RandomForestRegressor(bootstrap=True,
                                criterion='mse',
                                max_depth=None,
                                max_features='auto',
                                max_leaf_nodes=None,
                                min_impurity_decrease=0.0,
```



```

min_impurity_split=None,
min_samples_leaf=1,
min_samples_split=2,
min_weight_fraction_leaf=0.0,
n_estimators='warn',

n_jobs=None,
oob_score=False,
random_state=42,
verbose=0,

warm_start=False))] ,

verbose=False),

iid='warn', n_jobs=None,
param_grid=[{'regressor': [LinearRegression(copy_X=True,
fit_intercept=True,
n_jobs=None,
normalize=False)]]],

pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
scoring=None, verbose=0)

```

```

[55]: x_rftrain= grid_rf.predict(X_train)
x_rftest = grid_rf.predict(X_test)

# check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, x_rftrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_rftrain))))
print('train r2: {}'.format(r2_score(y_train, x_rftrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_rftest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_rftest))))
print('test r2: {}'.format(r2_score(y_test, x_rftest)))

print("Best parameters: {}".format(grid_rf.best_params_))
print("Cross-validation scores: {}".format(grid_rf.best_score_))
print('Train score: {:.4f}'.format(grid_rf.score(X_train, y_train)))
print('Test score: {:.4f}'.format(grid_rf.score(X_test, y_test)))

```

```

train mse: 552937051.405446
train rmse: 23514.61357125492
train r2: 0.9114426745730106

```

```

test mse: 861097775.8563162
test rmse: 29344.467551078793
test r2: 0.8746968378820517
Best parameters: {'regressor': LinearRegression(copy_X=True, fit_intercept=True,
n_jobs=None, normalize=False)}
Cross-validation scores: -2.449919008266954e+22

```

Train score: 0.9114
Test score: 0.8747

1.10 KNN Regressor

```
[56]: from sklearn.neighbors import KNeighborsRegressor
      from sklearn.pipeline import make_pipeline
      from sklearn.preprocessing import MinMaxScaler
      knnreg = KNeighborsRegressor().fit(X_train, y_train)
      print("Training set score: {:.2f}".format(knnreg.score(X_train, y_train)))
      print("Test set score: {:.2f}".format(knnreg.score(X_test, y_test)))
```

Training set score: 0.88
Test set score: 0.59

```
[57]: pipe_knn = make_pipeline(MinMaxScaler(), KNeighborsRegressor())
      knnreg = pipe_knn.fit(X_train, y_train)
      print("Training set score: {:.2f}".format(knnreg.score(X_train, y_train)))
      print("Test set score: {:.2f}".format(knnreg.score(X_test, y_test)))
```

Training set score: 0.86
Test set score: 0.71

```
[58]: from sklearn.model_selection import GridSearchCV

      pipe_knn=Pipeline([
          ('scaler',MinMaxScaler()),
          ('knnreg', KNeighborsRegressor())
      ])
      # define a list of parameters
      #param_knn = {'n_neighbors': [5, 10, 15, 20, 25, 30]}
      param_knn = {'knnreg__n_neighbors': range(1,25)}

      #apply grid search
      grid_knn = GridSearchCV(pipe_knn, param_knn, cv=5, return_train_score=True)
      grid_knn.fit(X_train, y_train)
```

```
[58]: GridSearchCV(cv=5, error_score='raise-deprecating',
                  estimator=Pipeline(memory=None,
                                     steps=[('scaler',
                                             MinMaxScaler(copy=True,
                                                            feature_range=(0, 1))),
                                             ('knnreg',
                                              KNeighborsRegressor(algorithm='auto',
                                                                  leaf_size=30,
                                                                  metric='minkowski',
                                                                  metric_params=None,
```

```

n_jobs=None,
n_neighbors=5, p=2,
weights='uniform'))],
verbose=False),
iid='warn', n_jobs=None,
param_grid={'knnreg__n_neighbors': range(1, 25)},
pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
scoring=None, verbose=0)

```

1.10.1 Results

```

[59]: x_knntrain= grid_knn.predict(X_train)
x_knntrain = grid_knn.predict(X_train)

# check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, x_knntrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_knntrain))))
print('train r2: {}'.format(r2_score(y_train, x_knntrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_knntrain)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_knntrain))))
print('test r2: {}'.format(r2_score(y_test, x_knntrain)))
print()
print('train score: ', grid_knn.score(X_train, y_train))
print('test score: ', grid_knn.score(X_test, y_test))

#find best parameters
print('Best parameters: ', grid_knn.best_params_)
print('Best cross-validation score:', grid_knn.best_score_)

```

```

train mse: 926540858.0310757
train rmse: 30439.13366098115
train r2: 0.8516070137143069

```

```

test mse: 1657648286.6700912
test rmse: 40714.227079364915
test r2: 0.7587863099604379

```

```

train score: 0.8516070137143069
test score: 0.7587863099604379
Best parameters: {'knnreg__n_neighbors': 6}
Best cross-validation score: 0.7858788323709909

```

1.11 ElasticNet with GridSearch

```
[60]: elasticnet = ElasticNet()

#define a list of parameters
param_elasticnet = {'alpha':[0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10],
                    ↪'l1_ratio':[0.2,0.4,0.6,0.8]}

grid_elasticnet = GridSearchCV(elasticnet , param_elasticnet, cv=5,
                                ↪return_train_score = True)
grid_elasticnet.fit(X_train, y_train)

grid_elasticnet_train_score = grid_elasticnet.score(X_train, y_train)
grid_elasticnet_test_score = grid_elasticnet.score(X_test, y_test)
```

```
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 275261918430.7595, tolerance: 657118734.8147435
positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 270472843507.742, tolerance: 655974723.0327224
positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269415475236.1935, tolerance: 635955900.9288123
positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 293367949607.249, tolerance: 642749145.1567798
positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 299702168310.0032, tolerance: 689033704.679551
positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 275132322643.92615, tolerance: 657118734.8147435
positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
```

```

Duality gap: 270265546612.78378, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269359988115.02875, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 293114639456.2878, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 299461621874.3815, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 274876218400.22867, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269853488069.79288, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269250900786.1243, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 292610782725.36975, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 298983659623.677, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 274113520713.21634, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-

```

```

packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 268620977582.17148, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 268927308309.11826, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 291102803101.93744, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 297554322499.26166, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 275285371342.0834, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 270500219669.26224, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269455263299.4938, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 293390700602.9906, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 299724423882.7319, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 275126170208.67175, tolerance: 657118734.8147435

```

```

    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 270267583340.30392, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269382447458.56412, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 293109101936.22723, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 299452447939.0266, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 274841772404.84204, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269830678356.61826, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269256329279.5095, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 292577554374.5457, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 298943887810.3167, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:

```

Objective did not converge. You might want to increase the number of iterations.
Duality gap: 274051946790.85733, tolerance: 657118734.8147435
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 268573717281.67993, tolerance: 655974723.0327224
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 268915978578.34824, tolerance: 635955900.9288123
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 291042350452.3709, tolerance: 642749145.1567798
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 297484634292.5844, tolerance: 689033704.679551
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 274840164312.18774, tolerance: 657118734.8147435
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 270621725492.51758, tolerance: 655974723.0327224
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269731153808.08066, tolerance: 635955900.9288123
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 293432778873.37506, tolerance: 642749145.1567798
positive)

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 299665315171.12964, tolerance: 689033704.679551
positive)


```

C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 274320207459.15918, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 270089455409.16162, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269461868093.74542, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 292811730158.3288, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 299004317909.24976, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 273940590197.94852, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269428587209.82605, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 269193156672.4067, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 292033002979.416, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.

```

```

Duality gap: 298242533193.7177, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 273151756027.88977, tolerance: 657118734.8147435
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 267998525106.42767, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 268738473819.79742, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 290312550120.06335, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 296613343354.8944, tolerance: 689033704.679551
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 221086170647.84283, tolerance: 655974723.0327224
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 204650042677.63684, tolerance: 635955900.9288123
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 232586340970.15808, tolerance: 642749145.1567798
    positive)
C:\Users\nabhs\Anaconda3\lib\site-
packages\sklearn\linear_model\coordinate_descent.py:475: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 186705495812.65787, tolerance: 689033704.679551
    positive)

```

1.11.1 Results

```
[61]: # let's get the predictions
x_elastictrain= grid_elasticnet.predict(X_train)
x_elastictest = grid_elasticnet.predict(X_test)

# check model performance:

print('train mse: {}'.format(mean_squared_error(y_train, x_elastictrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train,
↳x_elastictrain))))
print('train r2: {}'.format(r2_score(y_train, x_elastictrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_elastictest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_elastictest))))
print('test r2: {}'.format(r2_score(y_test, x_elastictest)))

print('Training set score: ', grid_elasticnet_train_score)
print('Test score: ', grid_elasticnet_test_score)

#find best parameters
print('Best parameters: ', grid_elasticnet.best_params_)
print('Best cross-validation score:', grid_elasticnet.best_score_)
```

```
train mse: 560460520.2398213
train rmse: 23674.04739878294
train r2: 0.9102377304004107
```

```
test mse: 872749277.5992303
test rmse: 29542.33026691074
test r2: 0.8730013625797748
Training set score: 0.9102377304004107
Test score: 0.8730013625797748
Best parameters: {'alpha': 0.1, 'l1_ratio': 0.2}
Best cross-validation score: 0.8840622166107981
```

1.12 Decision Tree Regression

```
[62]: from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
decisiontree = DecisionTreeRegressor(random_state = 0)

param_DTree = {"max_depth": range(1,30),
               "max_leaf_nodes": range(2,20),
               "min_samples_split":range(2,30)}

grid_dtree = GridSearchCV(decisiontree,param_DTree,cv=5)
```

```
grid_dtrees.fit(X_train,y_train)
```

```
[62]: GridSearchCV(cv=5, error_score='raise-deprecating',
                  estimator=DecisionTreeRegressor(criterion='mse', max_depth=None,
                                                  max_features=None,
                                                  max_leaf_nodes=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  presort=False, random_state=0,
                                                  splitter='best'),
                  iid='warn', n_jobs=None,
                  param_grid={'max_depth': range(1, 30),
                              'max_leaf_nodes': range(2, 20),
                              'min_samples_split': range(2, 30)},
                  pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                  scoring=None, verbose=0)
```

```
[63]: # let's get the predictions
x_dtreetrain= grid_dtrees.predict(X_train)
x_dtreetest = grid_dtrees.predict(X_test)

print('train mse: {}'.format(mean_squared_error(y_train, x_dtreetrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_dtreetrain))))
print('train r2: {}'.format(r2_score(y_train, x_dtreetrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_dtreetest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_dtreetest))))
print('test r2: {}'.format(r2_score(y_test, x_dtreetest)))
print()
print('Best parameters: ', grid_dtrees.best_params_)
print("Accuracy on training set: {:.4f}".format(grid_dtrees.score(X_train,
    ↪y_train)))
print("Accuracy on test set: {:.3f}".format(grid_dtrees.score(X_test, y_test)))
```

```
train mse: 1105977258.816959
train rmse: 33256.23638984061
train r2: 0.8228688278802175
```

```
test mse: 1548654925.2624905
test rmse: 39352.953196202325
test r2: 0.7746465446714791
```

```
Best parameters: {'max_depth': 6, 'max_leaf_nodes': 19, 'min_samples_split': 29}
```

Accuracy on training set: 0.8229
Accuracy on test set: 0.775

1.13 SVM

```
[64]: from sklearn.svm import SVC
svc_kernel = SVC()

#define a list of parameters
param_svc_kernel = [{'C': [1,10,100,1000,10000],
                        'gamma':['auto'],
                        'kernel':['rbf']},
                    {'C': [1,10,100,1000,10000],
                        'gamma':['auto'],
                        'kernel':['poly']},
                    {'C': [1,10,100,1000,10000],
                        'gamma':['auto'],
                        'kernel':['sigmoid',]}]

#apply grid search
grid_svc_kernel = GridSearchCV(svc_kernel, param_svc_kernel, cv=5, n_jobs=2)
grid_svc_kernel.fit(X_train, y_train)
```

C:\Users\nabhs\Anaconda3\lib\site-packages\sklearn\model_selection_split.py:657: Warning: The least populated class in y has only 1 members, which is too few. The minimum number of members in any class cannot be less than n_splits=5.

% (min_groups, self.n_splits)), Warning)

C:\Users\nabhs\Anaconda3\lib\site-packages\sklearn\model_selection_search.py:814: DeprecationWarning: The default of the `iid` parameter will change from True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal.

DeprecationWarning)

```
[64]: GridSearchCV(cv=5, error_score='raise-deprecating',
                  estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
                                decision_function_shape='ovr', degree=3,
                                gamma='auto_deprecated', kernel='rbf', max_iter=-1,
                                probability=False, random_state=None, shrinking=True,
                                tol=0.001, verbose=False),
                  iid='warn', n_jobs=2,
                  param_grid=[{'C': [1, 10, 100, 1000, 10000], 'gamma': ['auto'],
                                'kernel': ['rbf']},
                              {'C': [1, 10, 100, 1000, 10000], 'gamma': ['auto'],
                                'kernel': ['poly']},
                              {'C': [1, 10, 100, 1000, 10000], 'gamma': ['auto'],
```

```

        'kernel': ['sigmoid']]],
    pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
    scoring=None, verbose=0)

```

1.13.1 Results

```

[65]: # let's get the predictions
x_svctrain= grid_svc_kernel.predict(X_train)
x_svctest = grid_svc_kernel.predict(X_test)

print('train mse: {}'.format(mean_squared_error(y_train, x_svctrain)))
print('train rmse: {}'.format(sqrt(mean_squared_error(y_train, x_svctrain))))
print('train r2: {}'.format(r2_score(y_train, x_svctrain)))
print()
print('test mse: {}'.format(mean_squared_error(y_test, x_svctest)))
print('test rmse: {}'.format(sqrt(mean_squared_error(y_test, x_svctest))))
print('test r2: {}'.format(r2_score(y_test, x_svctest)))
print()
print('Best parameters: ', grid_svc_kernel.best_params_)
print('train score: ', grid_svc_kernel.score(X_train, y_train))
print('test score: ', grid_svc_kernel.score(X_test, y_test))

```

```

train mse: 2439782937.844749
train rmse: 49394.15894460345
train r2: 0.609249097978234

```

```

test mse: 3425485845.3767123
test rmse: 58527.650263586635
test r2: 0.501538361553501

```

```

Best parameters: {'C': 1, 'gamma': 'auto', 'kernel': 'poly'}
train score: 0.3082191780821918
test score: 0.3082191780821918

```

[]:

[]: