Project 2- Regression

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Source: random sample of 1734 houses taken from full Saratoga Housing Data (De Veaux) Number of Cases: 1734 Story: House prices and properties in New York. What properties of a house can predict its price? Can we use such a model to identify houses that are extraordinarily expensive or inexpensive?

Data Description,

1. price price (1000s of US dollars)
2. lotSize size of lot (square feet)
3. age age of house (years)
4. landValue value of land (1000s of US dollars)
5. livingArea living area (square feet)
6. pctCollege percent of neighborhood that graduated college
7. bedrooms number of bedrooms
8. firplaces number of fireplaces
9. bathrooms number of bathrooms (half bathrooms have no shower or tub)
10. rooms number of rooms
11. heating type of heating system
12. fuel fuel used for heating
13. sewer type of sewer system
14. waterfront whether property includes waterfront
15. newConstruction whether the property is a new construction
16. centralAir whether the house has central air

Pre-Processing of the dataset

Exploratory Data Analysis

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [ ]:

In [5]:
```
house=pd.read_csv("house.csv")
```

In [6]:
```
house.head()
```

Out[6]:

	Price	Lot.Size	Waterfront	Age	Land.Value	New.Construct	Central.Air	Fuel.Type	Heat.Type	Sewer.Type	Living.Area	Pct.College
0	311000	0.46	0	17.0	60500	0	1	Gas	Hot Water	Public	2762	63.0
1	182000	0.02	0	32.0	22500	0	0	Electric	Electric	Private	1753	35.0
2	297900	0.30	0	15.0	34000	0	1	Gas	Hot Air	Public	2288	64.0
3	210000	0.49	0	15.0	25000	0	0	Gas	Hot Air	NaN	1592	54.0
4	130000	0.16	0	36.0	54900	0	0	Gas	Hot Air	Public	1134	57.0

In [7]:
```
df=pd.DataFrame(house)
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1734 entries, 0 to 1733
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Price          1734 non-null   int64
 1   Lot.Size       1734 non-null   float64
 2   Waterfront     1734 non-null   int64
 3   Age            1713 non-null   float64
 4   Land.Value     1734 non-null   int64
 5   New.Construct  1734 non-null   int64
 6   Central.Air    1734 non-null   int64
 7   Fuel.Type      1734 non-null   object
 8   Heat.Type      1734 non-null   object
 9   Sewer.Type     1709 non-null   object
 10  Living.Area    1734 non-null   int64
 11  Pct.College    1712 non-null   float64
 12  Bedrooms       1734 non-null   int64
 13  Fireplaces     1724 non-null   float64
 14  Bathrooms      1734 non-null   float64
 15  Rooms          1720 non-null   float64
 16  Test           1734 non-null   int64
dtypes: float64(6), int64(8), object(3)
memory usage: 230.4+ KB
```

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
Price             0
Lot.Size          0
Waterfront        0
Age              21
Land.Value        0
New.Construct     0
Central.Air       0
Fuel.Type         0
Heat.Type         0
Sewer.Type       25
Living.Area       0
Pct.College      22
Bedrooms          0
Fireplaces       10
Bathrooms         0
Rooms            14
Test              0
dtype: int64
```

In [10]:
```
df.describe()
```

Out[10]:

	Price	Lot.Size	Waterfront	Age	Land.Value	New.Construct	Central.Air	Living.Area	Pct.College	B
count	1734.000000	1734.000000	1734.000000	1713.000000	1734.000000	1734.000000	1734.000000	1734.000000	1712.000000	173
mean	211545.054210	0.500294	0.008651	28.201985	34536.228374	0.046713	0.366205	1752.630911	55.639019	
std	98553.809581	0.698201	0.092632	29.687785	34980.940615	0.211084	0.481905	620.224953	10.309385	
min	5000.000000	0.000000	0.000000	0.000000	200.000000	0.000000	0.000000	616.000000	20.000000	
25%	145000.000000	0.170000	0.000000	13.000000	15100.000000	0.000000	0.000000	1300.000000	52.000000	
50%	189700.000000	0.370000	0.000000	19.000000	25000.000000	0.000000	0.000000	1632.000000	57.000000	
75%	257289.500000	0.540000	0.000000	34.000000	40200.000000	0.000000	1.000000	2133.500000	64.000000	
max	775000.000000	12.200000	1.000000	225.000000	412600.000000	1.000000	1.000000	5228.000000	82.000000	

In [11]:
```
df.drop('Test',axis=1,inplace=True)
```

Imputing Null values in the dataset

In [12]:
```
df['Age']=df[['Age']].transform(lambda x: x.fillna(int(x.median())))
```

In [13]:
```
df['Sewer.Type'].unique()
```

Out[13]:
```
array(['Public', 'Private', nan, 'None/Unknown'], dtype=object)
```

In [14]:
```
df['Sewer.Type']=df[['Sewer.Type']].transform(lambda x: x.fillna('None/Unknown'))
```

In [15]:
```
df.describe()
```

Out[15]:

	Price	Lot.Size	Waterfront	Age	Land.Value	New.Construct	Central.Air	Living.Area	Pct.College	B
count	1734.000000	1734.000000	1734.000000	1734.000000	1734.000000	1734.000000	1734.000000	1734.000000	1712.000000	173
mean	211545.054210	0.500294	0.008651	28.090542	34536.228374	0.046713	0.366205	1752.630911	55.639019	
std	98553.809581	0.698201	0.092632	29.524534	34980.940615	0.211084	0.481905	620.224953	10.309385	
min	5000.000000	0.000000	0.000000	0.000000	200.000000	0.000000	0.000000	616.000000	20.000000	
25%	145000.000000	0.170000	0.000000	13.000000	15100.000000	0.000000	0.000000	1300.000000	52.000000	
50%	189700.000000	0.370000	0.000000	19.000000	25000.000000	0.000000	0.000000	1632.000000	57.000000	
75%	257289.500000	0.540000	0.000000	34.000000	40200.000000	0.000000	1.000000	2133.500000	64.000000	
max	775000.000000	12.200000	1.000000	225.000000	412600.000000	1.000000	1.000000	5228.000000	82.000000	

In [16]:
```
df['Pct.College']=df[['Pct.College']].transform(lambda x: x.fillna(int(x.median())))
```

In [17]:
```
df['Fireplaces']=df[['Fireplaces']].transform(lambda x: x.fillna(int(x.median())))
```

In [18]:
```
df['Rooms']=df[['Rooms']].transform(lambda x: x.fillna(x.median()))
```

In [19]:
```
df.isnull().sum()
```

Out[19]:
```
Price            0
Lot.Size         0
Waterfront       0
Age              0
Land.Value       0
New.Construct    0
Central.Air      0
Fuel.Type        0
Heat.Type        0
Sewer.Type       0
Living.Area      0
Pct.College      0
Bedrooms         0
Fireplaces       0
Bathrooms        0
Rooms            0
dtype: int64
```

In [20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1734 entries, 0 to 1733
Data columns (total 16 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Price          1734 non-null   int64
 1   Lot.Size       1734 non-null   float64
 2   Waterfront     1734 non-null   int64
 3   Age            1734 non-null   float64
 4   Land.Value     1734 non-null   int64
 5   New.Construct  1734 non-null   int64
 6   Central.Air    1734 non-null   int64
 7   Fuel.Type      1734 non-null   object
 8   Heat.Type      1734 non-null   object
 9   Sewer.Type     1734 non-null   object
 10  Living.Area    1734 non-null   int64
 11  Pct.College    1734 non-null   float64
 12  Bedrooms       1734 non-null   int64
 13  Fireplaces     1734 non-null   float64
 14  Bathrooms      1734 non-null   float64
 15  Rooms          1734 non-null   float64
dtypes: float64(6), int64(7), object(3)
memory usage: 216.9+ KB
```

In [21]:
```
df['Fuel.Type'].unique()
```

Out[21]:
```
array(['Gas', 'Electric', 'Oil', 'Unknown/Other', 'Wood', 'None', 'Solar'],
      dtype=object)
```

Using one hot encoding to convert categorical features to numerical features

In [22]:
```
cl=pd.get_dummies(df['Fuel.Type'],columns='Fuel.Type',prefix='Fuel')
df[cl.columns]= cl
df.drop(('Fuel.Type'),axis=1, inplace=True)
```

In [23]:
```
df['Heat.Type'].unique()
```

Out[23]:
```
array(['Hot Water', 'Electric', 'Hot Air', 'None'], dtype=object)
```

In [24]:
```
    cl=pd.get_dummies(df['Heat.Type'],columns='Heat.Type',prefix='Heat')
    df[cl.columns]= cl
    df.drop(('Heat.Type'),axis=1, inplace=True)
```

In [25]:
```
cl=pd.get_dummies(df['Sewer.Type'],columns='Sewer.Type',prefix='Sewer')
df[cl.columns]= cl
df.drop(('Sewer.Type'),axis=1, inplace=True)
```

In [26]:
```
df.shape
```

Out[26]:
```
(1734, 27)
```

Splitting the data into train and test sets

In [27]:
```
X=df.drop('Price',axis=1)
Y=df['Price']
```

In [28]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
```

In [29]:
```
X_train_org,X_test_org,Y_train,Y_test= train_test_split(X,Y,test_size=0.2, random_state=0)
```

In [30]:
```
scaler= MinMaxScaler()
scaler.fit(X_train_org)
X_train= scaler.transform(X_train_org)
X_test= scaler.transform(X_test_org)
print(X_train.shape)
```

```
(1387, 26)
```

Bagging Regressor with Decision Tree Regressor

In [31]:
```
from sklearn.ensemble import BaggingRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV

dt_clf = DecisionTreeRegressor(random_state=0)
bag_clf = BaggingRegressor(dt_clf, bootstrap=True, n_jobs=-1, random_state=0)
param_grid={'n_estimators':[50,100,150],'max_samples':[100,200,300]}
grid=GridSearchCV(bag_clf,param_grid,cv=5,return_train_score=True)
grid.fit(X_train, Y_train)
train=grid.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid.score(X_test,Y_test)))
```

```
Best Parameters: {'max_samples': 300, 'n_estimators': 100}
Train score: 0.7487440603707227
Test score: 0.6606910990744923
```

Bagging Regressor with Linear SVR

In [32]:
```
from sklearn.svm import SVR,LinearSVR
clf1=LinearSVR()
bag_clf1 = BaggingRegressor(clf1, bootstrap=True, n_jobs=-1, random_state=0)
param_grid={'n_estimators':[50,100,150],'max_samples':[100,200,300]}
grid1=GridSearchCV(bag_clf1,param_grid,cv=5,return_train_score=True)
grid1.fit(X_train, Y_train)
train=grid1.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid1.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid1.score(X_test,Y_test)))
```

```
Best Parameters: {'max_samples': 300, 'n_estimators': 50}
Train score: -4.41795945354148
Test score: -5.514295947492502
```

Pasting with Linear Regression

In [33]:
```
from sklearn.linear_model import LinearRegression
lr_clf = LinearRegression(copy_X= True, fit_intercept= False, normalize= True)
pas_clf = BaggingRegressor(lr_clf,bootstrap=False, n_jobs=-1, random_state=0)
param_grid={'n_estimators':[50,100,150],'max_samples':[100,200,300]}
grid2=GridSearchCV(pas_clf,param_grid,cv=5,return_train_score=True)
grid2.fit(X_train, Y_train)
train=grid2.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid2.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid2.score(X_test,Y_test)))
```

```
Best Parameters: {'max_samples': 300, 'n_estimators': 50}
Train score: 0.6531192708568357
Test score: 0.6558298304823773
```

Pasting with Ridge Regression

In [34]:
```
from sklearn.linear_model import Ridge
r_clf = Ridge(alpha= 0.1)
pas_clf1 = BaggingRegressor(r_clf,bootstrap=False, n_jobs=-1, random_state=0)
param_grid={'n_estimators':[50,100,150],'max_samples':[100,200,300]}
grid3=GridSearchCV(pas_clf1,param_grid,cv=5,return_train_score=True)
grid3.fit(X_train, Y_train)
train=grid3.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid3.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid3.score(X_test,Y_test)))
```

```
Best Parameters: {'max_samples': 300, 'n_estimators': 50}
Train score: 0.6508847478954797
Test score: 0.6586860199227791
```

Ada Boosting with Decision Tree Regressor

In [35]:
```
from sklearn.ensemble import AdaBoostRegressor
ada_clf = AdaBoostRegressor(DecisionTreeRegressor(max_depth=1), random_state=0)
param_grid={'n_estimators':[50,100,150],'learning_rate':[0.5,1]}
grid4=GridSearchCV(ada_clf,param_grid,cv=5,return_train_score=True)
grid4.fit(X_train, Y_train)
train=grid4.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid4.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid4.score(X_test,Y_test)))
```

```
Best Parameters: {'learning_rate': 0.5, 'n_estimators': 50}
Train score: 0.24405456901323372
Test score: 0.09041442379441822
```

Ada Boosting with Lasso Regression

In [36]:
```
from sklearn.linear_model import Lasso
ada_clf1 = AdaBoostRegressor(Lasso(alpha=10), random_state=0)
param_grid={'n_estimators':[50,100,150],'learning_rate':[0.5,1]}
grid5=GridSearchCV(ada_clf1,param_grid,cv=5,return_train_score=True)
grid5.fit(X_train, Y_train)
train=grid5.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid5.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid5.score(X_test,Y_test)))
```

```
Best Parameters: {'learning_rate': 1, 'n_estimators': 50}
Train score: 0.6090201881608291
Test score: 0.6190785936891614
```

Gradient Boosting Regressor

In [37]:
```
from  sklearn.ensemble import GradientBoostingRegressor

gbrt = GradientBoostingRegressor(max_depth=2, random_state=0)
param_grid={'n_estimators':[50,100,150],'learning_rate':[0.5,1]}
grid6=GridSearchCV(gbrt,param_grid,cv=5,return_train_score=True)
grid6.fit(X_train, Y_train)
train=grid6.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid6.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid6.score(X_test,Y_test)))
```

```
Best Parameters: {'learning_rate': 0.5, 'n_estimators': 50}
Train score: 0.8937514177117686
Test score: 0.5921138788581473
```

PCA with KNN Regression

In [38]:
```
from sklearn.decomposition import PCA
from sklearn.neighbors import KNeighborsRegressor
from sklearn.pipeline import Pipeline

clf = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("knn", KNeighborsRegressor())
    ])
param_grid5 = {'knn__n_neighbors': [3,5,7,10,19],'knn__weights': ['uniform','distance'],'knn__metric':
['euclidean','manhattan']}
grid7=GridSearchCV(clf,param_grid5,cv=3,return_train_score=True)
grid7.fit(X_train,Y_train)
train=grid7.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid7.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid7.score(X_test,Y_test)))
```

```
Best Parameters: {'knn__metric': 'manhattan', 'knn__n_neighbors': 19, 'knn__weights': 'distance'}
Train score: 0.7901379744999255
Test score: 0.5115595216235551
```

PCA with Linear Regression

In [39]:
```
clf1 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("lr", LinearRegression())
    ])
parameters = {'lr__fit_intercept':[True,False], 'lr__normalize':[True,False], 'lr__copy_X':[True, False
]}
grid8=GridSearchCV(clf1,parameters,cv=3,return_train_score=True)
grid8.fit(X_train,Y_train)
train=grid8.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid8.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid8.score(X_test,Y_test)))
```

```
Best Parameters: {'lr__copy_X': True, 'lr__fit_intercept': True, 'lr__normalize': False}
Train score: -1.77331920117229
Test score: 0.47853450608838277
```

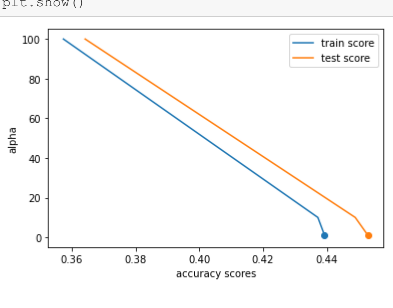
PCA with Ridge Regression

In [40]:
```
clf2 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("rid", Ridge())
    ])
parameters1={'rid__alpha':[0.1,1,10,100]}
grid9=GridSearchCV(clf2,parameters1,cv=3,return_train_score=True)
grid9.fit(X_train,Y_train)
train=grid9.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid9.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid9.score(X_test,Y_test)))
```

```
Best Parameters: {'rid__alpha': 1}
Train score: 0.4297418518317177
Test score: 0.4790003887649017
```

In [41]:
```
alpha = [0.1,1,10,100]
means = grid9.cv_results_['mean_test_score']
for i in alpha:
    if i==grid9.best_params_['rid__alpha']:
        ind=alpha.index(i)

plt.plot(means,alpha,label="train score")
plt.plot(train,alpha,label="test score")
plt.scatter(means[ind],alpha[ind])
plt.scatter(train[ind],alpha[ind])
plt.xlabel("accuracy scores")
plt.ylabel("alpha")
plt.legend(loc="upper right")
plt.show()
```



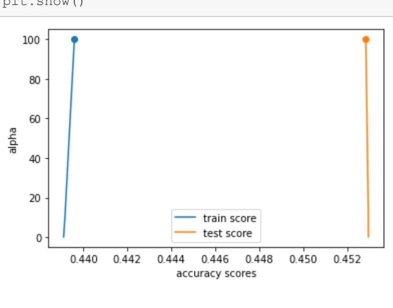
PCA with Lasso Regression

In [42]:
```
clf3 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("las", Lasso())
    ])
parameters2={'las__alpha':[0.1,1,10,100]}
grid10=GridSearchCV(clf3,parameters2,cv=3,return_train_score=True)
grid10.fit(X_train,Y_train)
train=grid10.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid10.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid10.score(X_test,Y_test)))
```

```
Best Parameters: {'las__alpha': 100}
Train score: 0.45293533576760786
Test score: 0.47961120989591877
```

In [43]:
```
alpha = [0.1,1,10,100]
means = grid10.cv_results_['mean_test_score']
for i in alpha:
    if i==grid10.best_params_['las__alpha']:
        ind=alpha.index(i)

plt.plot(means,alpha,label="train score")
plt.plot(train,alpha,label="test score")
plt.scatter(means[ind],alpha[ind])
plt.scatter(train[ind],alpha[ind])
plt.xlabel("accuracy scores")
plt.ylabel("alpha")
plt.legend(loc="best")
plt.show()
```



PCA with Polynomial Regression

In [44]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
pipe = make_pipeline(
    PolynomialFeatures(),
    Ridge())
clf4 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("poly", pipe)
    ])
parameters2={'poly__polynomialfeatures__degree':[1,2,3],'poly__ridge__alpha':[0.1,1,10,100]}
grid11=GridSearchCV(clf4,parameters2,cv=3,return_train_score=True)
grid11.fit(X_train,Y_train)
train=grid11.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid11.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid11.score(X_test,Y_test)))
```

```
Best Parameters: {'poly__polynomialfeatures__degree': 2, 'poly__ridge__alpha': 0.1}
Train score: 0.48880303409367004
Test score: 0.5345631769573334
```

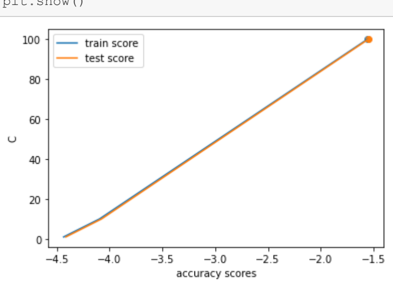
PCA with Linear SVR

In [45]:
```
clf5 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("lsvr", LinearSVR())
    ])
parameters2={'lsvr__C':[1,10,100]}
grid12=GridSearchCV(clf5,parameters2,cv=3,return_train_score=True)
grid12.fit(X_train,Y_train)
train=grid12.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid12.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid12.score(X_test,Y_test)))
```

```
Best Parameters: {'lsvr__C': 100}
Train score: -3.346103335379727
Test score: -0.991896257558669
```

In [46]:
```
C=[1,10,100]
means = grid12.cv_results_['mean_test_score']
for i in C:
    if i==grid12.best_params_['lsvr__C']:
        ind=C.index(i)

plt.plot(means,C,label="train score")
plt.plot(train,C,label="test score")
plt.scatter(means[ind],C[ind])
plt.scatter(train[ind],C[ind])
plt.xlabel("accuracy scores")
plt.ylabel("C")
plt.legend(loc="best")
plt.show()
```



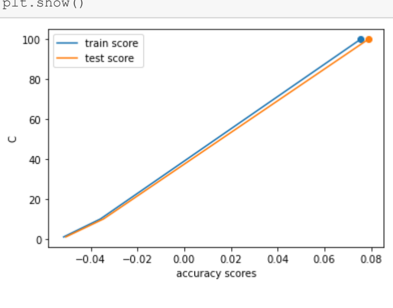
PCA with SVR with linear kernel

In [47]:
```
clf6 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("lsvrk", SVR(kernel='linear'))
    ])
parameters2={'lsvrk__C':[1,10,100]}
grid13=GridSearchCV(clf6,parameters2,cv=3,return_train_score=True)
grid13.fit(X_train,Y_train)
train=grid13.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid13.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid13.score(X_test,Y_test)))
```

```
Best Parameters: {'lsvrk__C': 100}
Train score: -0.002119218205083586
Test score: 0.17142848967891244
```

In [48]:
```
C=[1,10,100]
means = grid13.cv_results_['mean_test_score']
for i in C:
    if i==grid13.best_params_['lsvrk__C']:
        ind=C.index(i)

plt.plot(means,C,label="train score")
plt.plot(train,C,label="test score")
plt.scatter(means[ind],C[ind])
plt.scatter(train[ind],C[ind])
plt.xlabel("accuracy scores")
plt.ylabel("C")
plt.legend(loc="best")
plt.show()
```



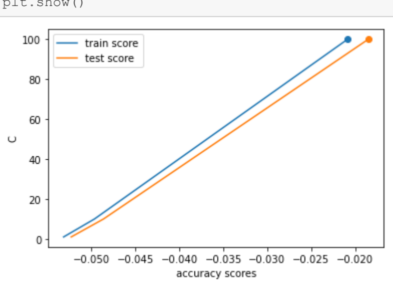
PCA with SVR with rbf kernel

In [49]:
```
clf7 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("rsvrk", SVR(kernel='rbf',C=100,gamma=1))
    ])
parameters2={"rsvrk__C":[1,10,100]}
grid14=GridSearchCV(clf7,parameters2,cv=3,return_train_score=True)
grid14.fit(X_train,Y_train)
train=grid14.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid14.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid14.score(X_test,Y_test)))
```

```
Best Parameters: {'rsvrk__C': 100}
Train score: -0.0398004685114283
Test score: 0.035388336351242056
```

In [50]:
```
C=[1,10,100]
means = grid14.cv_results_['mean_test_score']
for i in C:
    if i==grid14.best_params_['rsvrk__C']:
        ind=C.index(i)

plt.plot(means,C,label="train score")
plt.plot(train,C,label="test score")
plt.scatter(means[ind],C[ind])
plt.scatter(train[ind],C[ind])
plt.xlabel("accuracy scores")
plt.ylabel("C")
plt.legend(loc="best")
plt.show()
```



PCA with SVR with poly kernel

In [51]:
```
clf8 = Pipeline([
        ("pca", PCA(n_components=0.95)),
        ("psvrk", SVR(kernel='poly',C=100,degree=1))
    ])
parameters2={"psvrk__C":[1,10,100],"psvrk__degree":[1,2,3]}
grid15=GridSearchCV(clf8,parameters2,cv=3,return_train_score=True)
grid15.fit(X_train,Y_train)
train=grid15.cv_results_['mean_train_score']
print("Best Parameters: {}".format(grid15.best_params_))
print("Train score: {}".format(train.mean()))
print("Test score: {}".format(grid15.score(X_test,Y_test)))
```

```
Best Parameters: {'psvrk__C': 100, 'psvrk__degree': 1}
Train score: -0.03178802902280424
Test score: 0.11069774264206667
```

Scores of algorithms without PCA

Algorithm	Train Score	Test Score
K Nearest Neighbors	0.8181343712446223	0.5205609403529093
Linear Regression	0.04153727818031039	0.6417044300454586
Ridge	0.5341996581775573	0.6393481813161475
Lasso	0.6500176212701751	0.6393673931000765
Polynomial Regression	0.7733110614843973	0.6394886200845961
Linear SVR	-3.4619045155145174	-0.04573055192465872
SVR with linear kernel	-0.02695011195869257	0.07780976167175584
SVR with RBF kernel	-0.050443497989496405	-0.024432118052453922
SVR with poly kernel	-0.05245133029911933	-0.04702764160139896

Scores of algorithms with PCA

Algorithm	Train Score	Test Score
K Nearest Neighbors	0.7901379744999255	0.5115595216235556
Linear Regression	-1.77331920117229	0.4790003887649018
Ridge	0.42974185183171765	0.47858382881137123
Lasso	0.45293533576760786	0.47961120989591893
Polynomial Regression	0.48880303409367	0.5345631769573314
Linear SVR	-3.3461885678307914	-0.9913613571268671
SVR with linear kernel	-0.0021192182050836	0.17142848967891244
SVR with RBF kernel	-0.0398004685114283	0.035388336351242056
SVR with poly kernel	-0.04996824692728004	0.01129763243823756

For this dataset and the above computation, the PCA scores show improvement in accuracy scores of the model when executing algorithms with Kernel trick which lacked when running the same algorithms without PCA

Deep Learning model for Regression

In [52]:
```
import tensorflow as tf
from tensorflow import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasClassifier
```

In [55]:
```
X_train.shape
```

Out[55]:
```
(1387, 26)
```

In [56]:

```python
# Step 1: Build the model
model1 = Sequential()
#Input leyer
model1.add(Dense(126, input_dim = 26, activation = 'relu'))
#Hidden layer
model1.add(Dense(50, activation = 'relu'))
model1.add(Dense(25, activation = 'relu'))
#Output layer
model1.add(Dense(1, kernel_initializer='normal'))

# Step 2: Build the computational graph - compile
model1.compile(loss = 'mean_absolute_error', optimizer = 'adam', metrics = ['mean_absolute_error'])

# Step 3: Train the model
model1.fit(X_train, Y_train, epochs = 30, batch_size = 50)
scores = model1.evaluate(X_test, Y_test)
print("\n%s: %.2f%%" % (model1.metrics_names[1], scores[1]*100))

from sklearn.metrics import r2_score, recall_score, precision_score
```

```
Epoch 1/30
28/28 [==============================] - 0s 550us/step - loss: 213556.3906 - mean_absolute_error: 213
556.3906
Epoch 2/30
28/28 [==============================] - 0s 534us/step - loss: 213550.1250 - mean_absolute_error: 213
550.1250
Epoch 3/30
28/28 [==============================] - 0s 534us/step - loss: 213506.8906 - mean_absolute_error: 213
506.8906
Epoch 4/30
28/28 [==============================] - 0s 570us/step - loss: 213315.4375 - mean_absolute_error: 213
315.4375
Epoch 5/30
28/28 [==============================] - 0s 534us/step - loss: 212715.8750 - mean_absolute_error: 212
715.8750
Epoch 6/30
28/28 [==============================] - 0s 605us/step - loss: 211262.2656 - mean_absolute_error: 211
262.2656
Epoch 7/30
28/28 [==============================] - 0s 570us/step - loss: 208291.8594 - mean_absolute_error: 208
291.8594
Epoch 8/30
28/28 [==============================] - 0s 570us/step - loss: 202960.6562 - mean_absolute_error: 202
960.6562
Epoch 9/30
28/28 [==============================] - 0s 570us/step - loss: 194221.8594 - mean_absolute_error: 194
221.8594
Epoch 10/30
28/28 [==============================] - 0s 499us/step - loss: 180815.0469 - mean_absolute_error: 180
815.0469
Epoch 11/30
28/28 [==============================] - 0s 534us/step - loss: 161352.8750 - mean_absolute_error: 161
352.8750
Epoch 12/30
28/28 [==============================] - 0s 570us/step - loss: 134579.2188 - mean_absolute_error: 134
579.2188
Epoch 13/30
28/28 [==============================] - 0s 534us/step - loss: 101147.7422 - mean_absolute_error: 101
147.7422
Epoch 14/30
28/28 [==============================] - 0s 534us/step - loss: 71393.4375 - mean_absolute_error: 7139
3.4375
Epoch 15/30
28/28 [==============================] - 0s 570us/step - loss: 59262.0977 - mean_absolute_error: 5926
2.0977
Epoch 16/30
28/28 [==============================] - 0s 570us/step - loss: 57635.1797 - mean_absolute_error: 5763
5.1797
Epoch 17/30
28/28 [==============================] - 0s 534us/step - loss: 57333.2773 - mean_absolute_error: 5733
3.2773
Epoch 18/30
28/28 [==============================] - 0s 605us/step - loss: 57088.3594 - mean_absolute_error: 5708
8.3594
Epoch 19/30
28/28 [==============================] - 0s 570us/step - loss: 56872.6289 - mean_absolute_error: 5687
2.6289
Epoch 20/30
28/28 [==============================] - 0s 570us/step - loss: 56655.1914 - mean_absolute_error: 5665
5.1914
Epoch 21/30
28/28 [==============================] - 0s 499us/step - loss: 56440.2383 - mean_absolute_error: 5644
0.2383
Epoch 22/30
28/28 [==============================] - 0s 534us/step - loss: 56219.3320 - mean_absolute_error: 5621
9.3320
Epoch 23/30
28/28 [==============================] - 0s 534us/step - loss: 56037.3594 - mean_absolute_error: 5603
7.3594
Epoch 24/30
28/28 [==============================] - 0s 570us/step - loss: 55812.3086 - mean_absolute_error: 5581
2.3086
Epoch 25/30
28/28 [==============================] - 0s 570us/step - loss: 55634.8047 - mean_absolute_error: 5563
4.8047
Epoch 26/30
28/28 [==============================] - 0s 499us/step - loss: 55446.2578 - mean_absolute_error: 5544
6.2578
Epoch 27/30
28/28 [==============================] - 0s 534us/step - loss: 55287.0039 - mean_absolute_error: 5528
7.0039
Epoch 28/30
28/28 [==============================] - 0s 534us/step - loss: 55093.4844 - mean_absolute_error: 5509
3.4844
Epoch 29/30
28/28 [==============================] - 0s 534us/step - loss: 54943.8438 - mean_absolute_error: 5494
3.8438
Epoch 30/30
28/28 [==============================] - 0s 570us/step - loss: 54770.2305 - mean_absolute_error: 5477
0.2383
11/11 [==============================] - 0s 545us/step - loss: 49416.7773 - mean_absolute_error: 4941
6.7773

mean_absolute_error: 4941677.73%
```

In [57]:

```python
Y_train_predict = model1.predict(X_train)
Y_test_predict = model1.predict(X_test)

print('Train score: {:.2f}'.format(r2_score(Y_train, Y_train_predict)))
print('Test score: {:.2f}'.format(r2_score(Y_test, Y_test_predict)))
```

```
Train score: 0.37
Test score: 0.45
```

In [ ]: