Task-D: Collinear features and their effect on linear models

In [4]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
from sklearn.metrics import accuracy_score,roc_auc_score
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import SGDClassifier,SGDRegressor
from sklearn.model_selection import GridSearchCV
import seaborn as sns
import matplotlib.pyplot as plt
import random
from tqdm import tqdm
import math
import random
```

In [5]:

```
data = pd.read_csv('/content/drive/MyDrive/temp/Linear model/task_d.csv')
```

In [6]:

```
data.tail()
```

Out[6]:

	x	y	z	x*x	2*y	2*z+3*x*x	w	target
95	0.358663	-0.207835	0.928390	0.300024	-0.207835	0.382111	1.716476	1
96	0.358663	-0.417770	0.928390	0.300024	-0.417770	0.382111	1.841269	1
97	1.141771	-0.417770	0.997724	1.130131	-0.417770	1.137586	0.019860	1
98	-0.581066	-1.257507	0.096375	-0.604025	-1.257507	-0.531992	0.590582	1
99	0.358663	-0.627704	0.859055	0.300024	-0.627704	0.373740	-0.045364	1

In [11]:

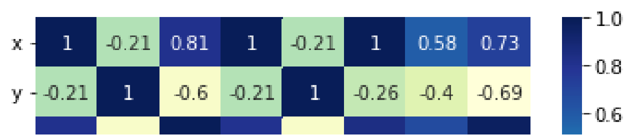
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

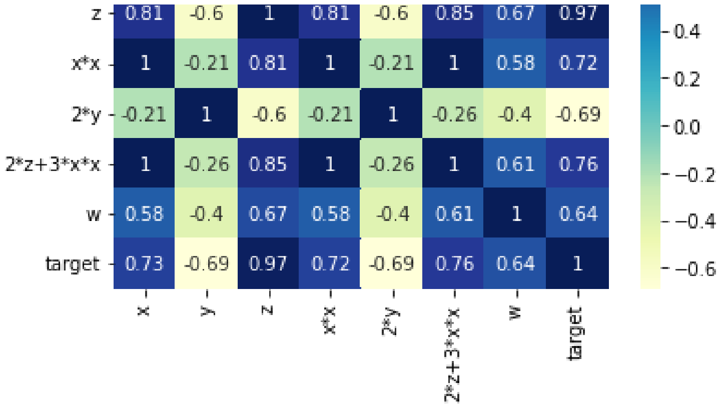
In [8]:

```
print(data.corr())
dataplot = sns.heatmap(data.corr(), cmap="YlGnBu", annot=True)
```

```
                  x         y         z  ...  2*z+3*x*x         w    target
x          1.000000 -0.205926  0.812458  ...   0.996252  0.583277  0.728290
y         -0.205926  1.000000 -0.602663  ...  -0.261123 -0.401790 -0.690684
z          0.812458 -0.602663  1.000000  ...   0.847163  0.674486  0.969990
x*x        0.997947 -0.209289  0.807137  ...   0.997457  0.583803  0.719570
2*y       -0.205926  1.000000 -0.602663  ...  -0.261123 -0.401790 -0.690684
2*z+3*x*x  0.996252 -0.261123  0.847163  ...   1.000000  0.606860  0.764729
w          0.583277 -0.401790  0.674486  ...   0.606860  1.000000  0.641750
target     0.728290 -0.690684  0.969990  ...   0.764729  0.641750  1.000000

[8 rows x 8 columns]
```





Doing perturbation test to check the presence of collinearity

> **Indented block**

Task: 1 Logistic Regression

```
1. Finding the Correlation between the features
    a. check the correlation between the features
    b. plot heat map of correlation matrix using seaborn heatmap
2. Finding the best model for the given data
    a. Train Logistic regression on data(X,Y) that we have created in the above cel
l
    b. Find the best hyper prameter alpha with hyper parameter tuning using k-fold
cross validation (grid search CV or
    random search CV make sure you choose the alpha in log space)
    c. Creat a new Logistic regression with the best alpha
    (search for how to get the best hyper parameter value), name the best model as
'best_model'

3. Getting the weights with the original data
    a. train the 'best_model' with X, Y
    b. Check the accuracy of the model 'best_model_accuracy'
    c. Get the weights W using best_model.coef_

4. Modifying original data
    a. Add a noise(order of 10^-2) to each element of X
    and get the new data set X' (X' = X + e)
    b. Train the same 'best_model' with data (X', Y)
    c. Check the accuracy of the model 'best_model_accuracy_edited'
    d. Get the weights W' using best_model.coef_

5.  Checking deviations in metric and weights
    a. find the difference between 'best_model_accuracy_edited' and 'best_model_acc
uracy'
    b. find the absolute change between each value of W and W' ==> |(W-W')|
    c. print the top 4 features which have higher % change in weights
    compare to the other feature
```

Task: 2 Linear SVM

```
1. Do the same steps (2, 3, 4, 5) we have done in the above task 1.
```

Do write the observations based on the results you get from the deviations of weights in both Logistic Regression and linear SVM

In [16]:

```
def RandomSearchCV(x,y, params, folds):
 trainscores = [] #list to store train score for each value of k
 testscores = [] #list to store test score for each value of k
 for k in tqdm(params):

  trainscores_folds = [] #list to store train score for each fold
  testscores_folds = [] #list to store test score for each fold
  for j in range(0, folds):
     # check this out: https://stackoverflow.com/a/9755548/4084039
     #train_indices = randomly_select_60_percent_indices_in_range_from_1_to_len(x_train)
     #test_indices = list(set(list(range(1, len(x_train)))) - set(train_indices))
     list1=[*range(1,len(x)+1)]# list of all indices in x
     list2=np.array(list1)# converting it to np array
     splited_array=np.array_split(list2,folds) #splitting x to in f folds
     test_indice =splited_array[j]
     train_indice=list(set(list(range(1,len(x)+1))) - set(test_indice))#getting index fo
r all points of train
     test_indices=[x -1 for x in test_indice ] #subtracting each index by one as origina
l index of x start with 0
     train_indices=[x -1 for x in train_indice ]#subtracting each index by one asorigina
l index of x start with 0
     # selecting the data points based on the train_indices and test_indices
     X_train = x[train_indices]
     Y_train = y[train_indices]
     X_test = x[test_indices]
     Y_test = y[test_indices]
     c = k
     classifier=SGDClassifier(loss='log',penalty='l2', alpha=c, l1_ratio=0.15,
                              fit_intercept=True, max_iter=1000, tol=0.001, shuffle=Tr
ue,
                              verbose=0, epsilon=0.1, n_jobs=None, random_state=None,
                              learning_rate='optimal', eta0=0.0, power_t=0.5, early_st
opping=False,
                              validation_fraction=0.1, n_iter_no_change=5, class_weigh
t=None,
                              warm_start=False, average=False)
     classifier.fit(X_train,Y_train)
     Y_predicted = classifier.predict(X_test)#predict y of X_test

     testscores_folds.append(accuracy_score(Y_test, Y_predicted))
     Y_predicted = classifier.predict(X_train)#predict y of X_train
     trainscores_folds.append(accuracy_score(Y_train, Y_predicted))
  trainscores.append(np.mean(np.array(trainscores_folds)))
  testscores.append(np.mean(np.array(testscores_folds)))
 return trainscores,testscores
#model = LogisticRegression() #define classifier
#list3=[*range(1,1000)]
#param=random.sample(list3,10) #generating 10 random number betwwn 1 to 50
param=[0.000001,0.00001,0.0001,0.001,0.1,1,10,100,1000]
param1=[]
for i in param:
    tmp=math.log(i)
    param1.append(tmp)

params=[param.sort()]

folds = 4
trainscores,testscores = RandomSearchCV(X, Y, param, folds)


plt.plot(param1,trainscores, 'o-',label='train cruve')
plt.plot(param1,testscores,'o-', label='test cruve')
plt.title('Hyper-parameter VS accuracy plot')
plt.legend()
plt.show()

bestmodel=SGDClassifier(loss='log',penalty='l2', alpha=10, l1_ratio=0.15,
                              fit_intercept=True, max_iter=1000, tol=0.001, shuffle=Tr
ue,
```

```
                                        verbose=0, epsilon=0.1, n_jobs=None, random_state=None,
                                        learning_rate='optimal', eta0=0.0, power_t=0.5, early_st
opping=False,
                                        validation_fraction=0.1, n_iter_no_change=5, class_weigh
t=None,
                                        warm_start=False, average=False)
bestmodel.fit(X,Y)
Y_predicted = bestmodel.predict(X) #predict y of X_test
best_model_accuracy=accuracy_score(Y, Y_predicted)
bestmodelcoef=bestmodel.coef_
print("best_model_accuracy=",best_model_accuracy)
print("feature weights=",bestmodelcoef)

X_=X+random.randrange(1,10)*0.01
bestmodel.fit(X_,Y)
Y_predicted = bestmodel.predict(X) #predict y of X_test
best_model_accuracy_edited=accuracy_score(Y, Y_predicted)
bestmodelcoef_edited=bestmodel.coef_
print("best_model_accuracy_edited=",best_model_accuracy_edited)
print("feature weights_edited=",bestmodelcoef_edited)

differene_between_accuracy=best_model_accuracy_edited-best_model_accuracy
print("differene_between_accuracy=",differene_between_accuracy)
list3=[abs(i-j) for i,j in zip(bestmodelcoef,bestmodelcoef_edited)]
print(list3)
list4=list3[0]
list4=np.array(list4)
print("abs_change_in_weights=",list4)
print(np.argsort(list4))
list_sorted=np.argsort(list4)[::-1]
print("sorted index according to abs weights=",list_sorted)
col_list=data.columns
print(col_list)
top4_feature_change=[]
for i in list_sorted[0:4]:
    top4_feature_change.append(col_list[i])
print("top4_feature_change",top4_feature_change)
```

```
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```
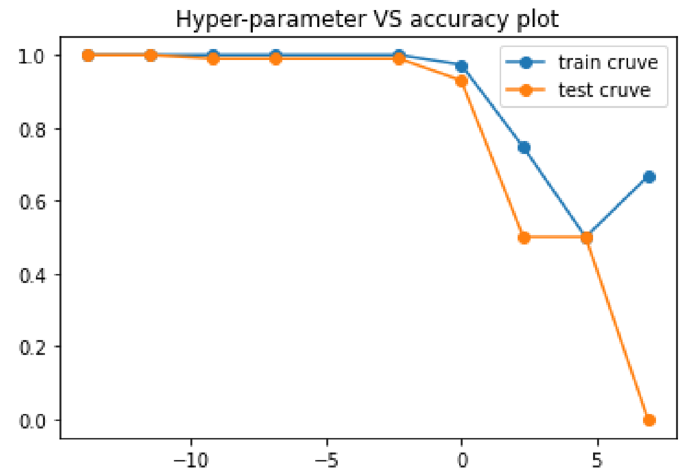




```
best_model_accuracy= 0.52
feature weights= [[ 0.03244351 -0.03153831  0.0440694   0.03200811 -0.03153831  0.0341281
9
   0.02862859]]
best_model_accuracy_edited= 0.51
feature weights_edited= [[ 0.03187996 -0.0322185   0.04350955  0.03144423 -0.0322185   0.
03356671
   0.02805848]]
differene_between_accuracy= -0.010000000000000009
[array([0.00056355, 0.00068019, 0.00055985, 0.00056389, 0.00068019,
       0.00056148, 0.00057011])]
abs_change_in_weights= [0.00056355 0.00068019 0.00055985 0.00056389 0.00068019 0.00056148
 0.00057011]
[2 5 0 3 6 1 4]
sorted index according to abs weights= [4 1 6 3 0 5 2]
Index(['x', 'y', 'z', 'x*x', '2*y', '2*z+3*x*x', 'w', 'target'], dtype='object')
```

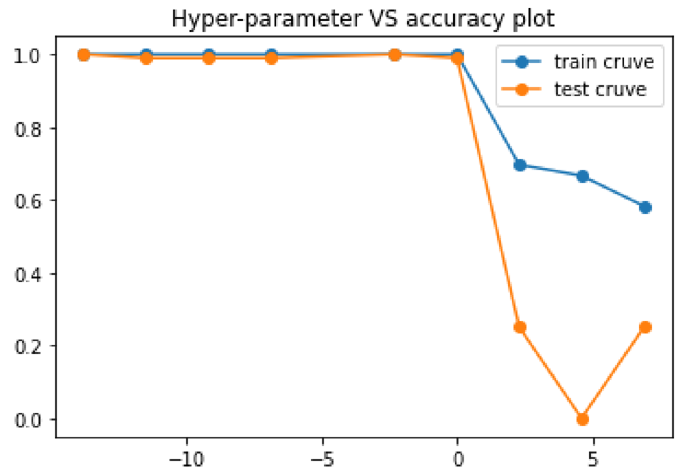
```
top4_feature_change ['2*y', 'y', 'w', 'x*x']
```

In [20]:

```
def RandomSearchCV(x,y, params, folds):
 trainscores = [] #list to store train score for each value of k
 testscores = [] #list to store test score for each value of k
 for k in tqdm(params):

  trainscores_folds = [] #list to store train score for each fold
  testscores_folds = [] #list to store test score for each fold
  for j in range(0, folds):
     # check this out: https://stackoverflow.com/a/9755548/4084039
     #train_indices = randomly_select_60_percent_indices_in_range_from_1_to_len(x_train)
     #test_indices = list(set(list(range(1, len(x_train)))) - set(train_indices))
     list1=[*range(1,len(x)+1)]# list of all indices in x
     list2=np.array(list1)# converting it to np array
     splited_array=np.array_split(list2,folds) #splitting x to in f folds
     test_indice =splited_array[j]
     train_indice=list(set(list(range(1,len(x)+1))) - set(test_indice))#getting index fo
r all points of train
     test_indices=[x -1 for x in test_indice ] #subtracting each index by one as origina
l index of x start with 0
     train_indices=[x -1 for x in train_indice ]#subtracting each index by one asorigina
l index of x start with 0
     # selecting the data points based on the train_indices and test_indices
     X_train = x[train_indices]
     Y_train = y[train_indices]
     X_test = x[test_indices]
     Y_test = y[test_indices]
     c = k
     classifier=SGDClassifier(loss='hinge',penalty='l2', alpha=c, l1_ratio=0.15,
                              fit_intercept=True, max_iter=1000, tol=0.001, shuffle=Tr
ue,
                              verbose=0, epsilon=0.1, n_jobs=None, random_state=None,
                              learning_rate='optimal', eta0=0.0, power_t=0.5, early_st
opping=False,
                              validation_fraction=0.1, n_iter_no_change=5, class_weigh
t=None,
                              warm_start=False, average=False)
     classifier.fit(X_train,Y_train)
     Y_predicted = classifier.predict(X_test) #predict y of X_test

     testscores_folds.append(accuracy_score(Y_test, Y_predicted))
     Y_predicted = classifier.predict(X_train) #predict y of X_train
     trainscores_folds.append(accuracy_score(Y_train, Y_predicted))
  trainscores.append(np.mean(np.array(trainscores_folds)))
  testscores.append(np.mean(np.array(testscores_folds)))
 return trainscores,testscores
#model = LogisticRegression() #define classifier
#list3=[*range(1,1000)]
#param=random.sample(list3,10) #generating 10 random number betwwn 1 to 50
param=[0.000001,0.00001,0.0001,0.001,0.1,1,10,100,1000]
param1=[]
for i in param:
    tmp=math.log(i)
    param1.append(tmp)

params=[param.sort()]

folds = 4
trainscores,testscores = RandomSearchCV(X, Y, param, folds)

plt.plot(param1,trainscores, 'o-',label='train cruve')
plt.plot(param1,testscores,'o-', label='test cruve')
plt.title('Hyper-parameter VS accuracy plot')
plt.legend()
plt.show()

bestmodel=SGDClassifier(loss='hinge',penalty='l2', alpha=10, l1_ratio=0.15,
                              fit_intercept=True, max_iter=1000, tol=0.001, shuffle=Tr
```

```
ue,
                                   verbose=0, epsilon=0.1, n_jobs=None, random_state=None,
                                   learning_rate='optimal', eta0=0.0, power_t=0.5, early_st
opping=False,
                                   validation_fraction=0.1, n_iter_no_change=5, class_weigh
t=None,
                                   warm_start=False, average=False)
bestmodel.fit(X,Y)
Y_predicted = bestmodel.predict(X) #predict y of X_test
best_model_accuracy=accuracy_score(Y, Y_predicted)
bestmodelcoef=bestmodel.coef_
print("best_model_accuracy=",best_model_accuracy)
print("feature weights=",bestmodelcoef)

X_=X+random.randrange(1,10)*0.01
bestmodel.fit(X_,Y)
Y_predicted = bestmodel.predict(X) #predict y of X_test
best_model_accuracy_edited=accuracy_score(Y, Y_predicted)
bestmodelcoef_edited=bestmodel.coef_
print("best_model_accuracy_edited=",best_model_accuracy_edited)
print("feature weights_edited=",bestmodelcoef_edited)

differene_between_accuracy=best_model_accuracy_edited-best_model_accuracy
print("differene_between_accuracy=",differene_between_accuracy)
list3=[abs(i-j) for i,j in zip(bestmodelcoef,bestmodelcoef_edited)]
print(list3)
list4=list3[0]
list4=np.array(list4)
print("abs_change_in_weights=",list4)
print(np.argsort(list4))
list_sorted=np.argsort(list4)[::-1]
print("sorted index according to abs weights=",list_sorted)
col_list=data.columns
print(col_list)
top4_feature_change=[]
for i in list_sorted[0:4]:
    top4_feature_change.append(col_list[i])
print("top4_feature_change",top4_feature_change)
```

```
100%|██████████| 9/9 [00:00<00:00, 220.21it/s]
```




```
best_model_accuracy= 0.63
feature weights= [[ 0.06749926 -0.06755077  0.09295556  0.06704618 -0.06755077  0.0715649
1
   0.05872509]]
best_model_accuracy_edited= 0.61
feature weights_edited= [[ 0.06717658 -0.0661877   0.0924363   0.06671768 -0.0661877   0.
07120013
   0.05817939]]
differene_between_accuracy= -0.020000000000000018
[array([0.00032268, 0.00136307, 0.00051926, 0.0003285 , 0.00136307,
       0.00036478, 0.0005457 ])]
abs_change_in_weights= [0.00032268 0.00136307 0.00051926 0.0003285  0.00136307 0.00036478
 0.0005457 ]
[0 3 5 2 6 1 4]
sorted index according to abs weights= [4 1 6 2 5 3 0]
```

```
Index(['x', 'y', 'z', 'x*x', '2*y', '2*z+3*x*x', 'w', 'target'], dtype='object')
top4_feature_change ['2*y', 'y', 'w', 'z']
```

OBSERVATION

1.In linear regression model after adding error to the features,we do not see much change in weights after pertubation.

2.In LR, absolute changes in weights are approx 10^-3

3.accuracy of the model also decreased a little bit .

4.In SVM also feature wieghts do not change much after pertubation, so features are not collinear .

5.accuracy score difference is also less.

6.we can conclude that when feature weights drastically after pertubation ,then the feature whose weights changed are collinear feature.