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

In [9]:

```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import GridSearchCV
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:

```
data = pd.read_csv('task_d.csv')
```

In [3]:

```
data.head()
```

Out[3]:

	x	y	z	x*x	2*y	2*z+3*x*x	w	target
0	-0.581066	0.841837	-1.012978	-0.604025	0.841837	-0.665927	-0.536277	0
1	-0.894309	-0.207835	-1.012978	-0.883052	-0.207835	-0.917054	-0.522364	0
2	-1.207552	0.212034	-1.082312	-1.150918	0.212034	-1.166507	0.205738	0
3	-1.364174	0.002099	-0.943643	-1.280666	0.002099	-1.266540	-0.665720	0
4	-0.737687	1.051772	-1.012978	-0.744934	1.051772	-0.792746	-0.735054	0

In [4]:

```
X1 = data.drop(['target'],axis=1)
Y1 = data['target']
X = data.drop(['target'], axis=1).values
Y = data['target'].values
print(data['target'].nunique())
```

```
2
```

In [5]:

```
Y = Y.reshape(-1,1)
print(X.shape,Y.shape)
```

```
(100, 7) (100, 1)
```

Doing perturbation test to check the presence of collinearity

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
```

```
1
    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

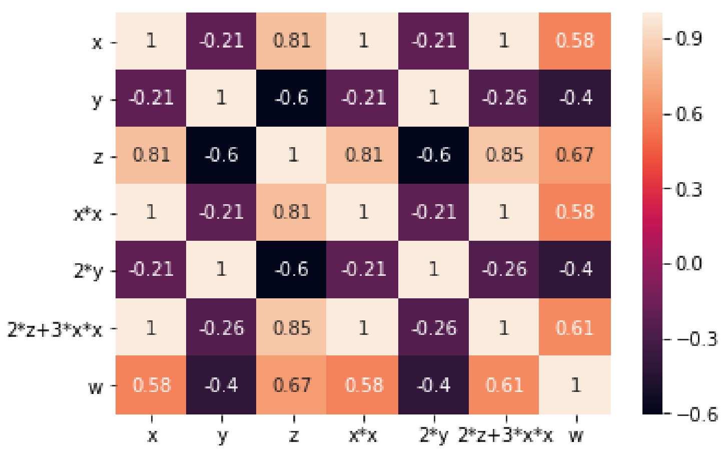
In [6]:

```
#heat map for correlation of the data

sns.heatmap(X1.corr(), annot = True)
```

Out[6]:

<matplotlib.axes._subplots.AxesSubplot at 0x220d01a4f28>



In [7]:

```
from sklearn.model_selection import train_test_split

X_train,X_test,Y_train,Y_test = train_test_split(X,Y,stratify =Y ,test_size = 0.33)
```

In [10]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.h
tml
#https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.SGDClassifier.htm
l

params = {'alpha': [0.001,0.01,0.1,10,100,1000]}
k = 4

clf = SGDClassifier(loss = 'log')
clf1 = GridSearchCV(clf,param_grid = params,cv = k)
clf1.fit(X_train,Y_train)
```

Out[10]:

```
GridSearchCV(cv=4, error_score=nan,
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
                                     epsilon=0.1, eta0=0.0, fit_intercept=True,
                                     l1_ratio=0.15, learning_rate='optimal',
                                     loss='log', max_iter=1000,
                                     n_iter_no_change=5, n_jobs=None,
                                     penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True, tol=0.001,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'alpha': [0.001, 0.01, 0.1, 10, 100, 1000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [11]:

```
clf1.best_params_
```

Out[11]:

```
{'alpha': 0.01}
```

In [12]:

```
#Random search
from scipy.stats import uniform
from sklearn.model_selection import RandomizedSearchCV

params1 = {'alpha' : uniform(loc = 0,scale = 1000)}
clf2 = RandomizedSearchCV(clf,param_distributions = params1,cv = k)
clf2.fit(X_train,Y_train)
```

Out[12]:

```
RandomizedSearchCV(cv=4, error_score=nan,
                   estimator=SGDClassifier(alpha=0.0001, average=False,
                                           class_weight=None,
                                           early_stopping=False, epsilon=0.1,
                                           eta0=0.0, fit_intercept=True,
                                           l1_ratio=0.15,
                                           learning_rate='optimal', loss='log',
                                           max_iter=1000, n_iter_no_change=5,
                                           n_jobs=None, penalty='l2',
                                           power_t=0.5, random_state=None,
                                           shuffle=True, tol=0.001,
                                           validation_fraction=0.1, verbose=0,
                                           warm_start=False),
                   iid='deprecated', n_iter=10, n_jobs=None,
                   param_distributions={'alpha': <scipy.stats._distn_infrastructure.rv_fr
ozen object at 0x00000220D05416A0>},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=0)
```

In [13]:

```
clf2.best_params_
```

Out[13]:

```
{'alpha': 313.27027369267824}
```

In [14]:

```
#here we are going with alpha value of 0.01 from GridSearchCV

best_model = SGDClassifier(loss = 'log',alpha = 0.01)
best_model.fit(X_train,Y_train)
Y_pred = best_model.predict(X_test)
```

In [15]:

```
W1 = best_model.coef_
W1
```

Out[15]:

```
array([[ 0.81866815, -0.81859759,  1.67756118,  0.76693894, -0.81859759,
         0.89278774,  0.47178502]])
```

In [16]:

```
X_train+=0.01
best_model = SGDClassifier(loss = 'log',alpha = 0.01)
best_model.fit(X_train,Y_train)
Y_pred = best_model.predict(X_test)
```

In [17]:

```
W2 = best_model.coef_
W2
```

Out[17]:

```
array([[ 0.83391226, -0.82777966,  1.61416753,  0.82238252, -0.82777966,
         0.93508036,  0.43592482]])
```

In [18]:

```
W = abs(W1-W2)
lst2 = sum(W)
sum_val = sum(sum(W))
sum_val

lst3 = list((lst2/sum_val)*100)
lst3
```

Out[18]:

```
[6.610674431305179,
 3.9818475774162456,
 27.49094431024543,
 24.04336122100457,
 3.9818475774162456,
 18.3403859822041,
 15.550938900408227]
```

In [19]:

```
lst1 = list(data.columns)
lst1
```

Out[19]:

```
['x', 'y', 'z', 'x*x', '2*y', '2*z+3*x*x', 'w', 'target']
```

In [20]:

```
hash_table = dict(zip(lst3,lst1))
```

```
hash_table = dict(zip(lst3,lst1))
hash_table
```

Out[20]:

```
{6.610674431305179: 'x',
 3.9818475774162456: '2*y',
 27.49094431024543: 'z',
 24.04336122100457: 'x*x',
 18.3403859822041: '2*z+3*x*x',
 15.550938900408227: 'w'}
```

In [23]:

```
#top four features
top_feature = sorted(lst3)
for i in range(4):
    print(hash_table[top_feature[i]])
```

```
2*y
2*y
x
w
```

OBSERVATIONS The above features are least in collinearity, therefore these four features are considered to be the top features among all.