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

In [2]:
```
%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 [4]:
```
data = pd.read_csv('task_d.csv')
```

In [5]:
```
data.head()
```

Out[5]:

	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 [6]:
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

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 creat
ed in the above cell
    b. Find the best hyper prameter alpha with hyper parameter t
uning using k-fold cross validation (grid search CV or         r
andom search CV make sure you choose the alpha in log space)
    c. Creat a new Logistic regression with the best alpha(searc
h 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_edit
ed'
    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_accuracy'
    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 we
ights 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

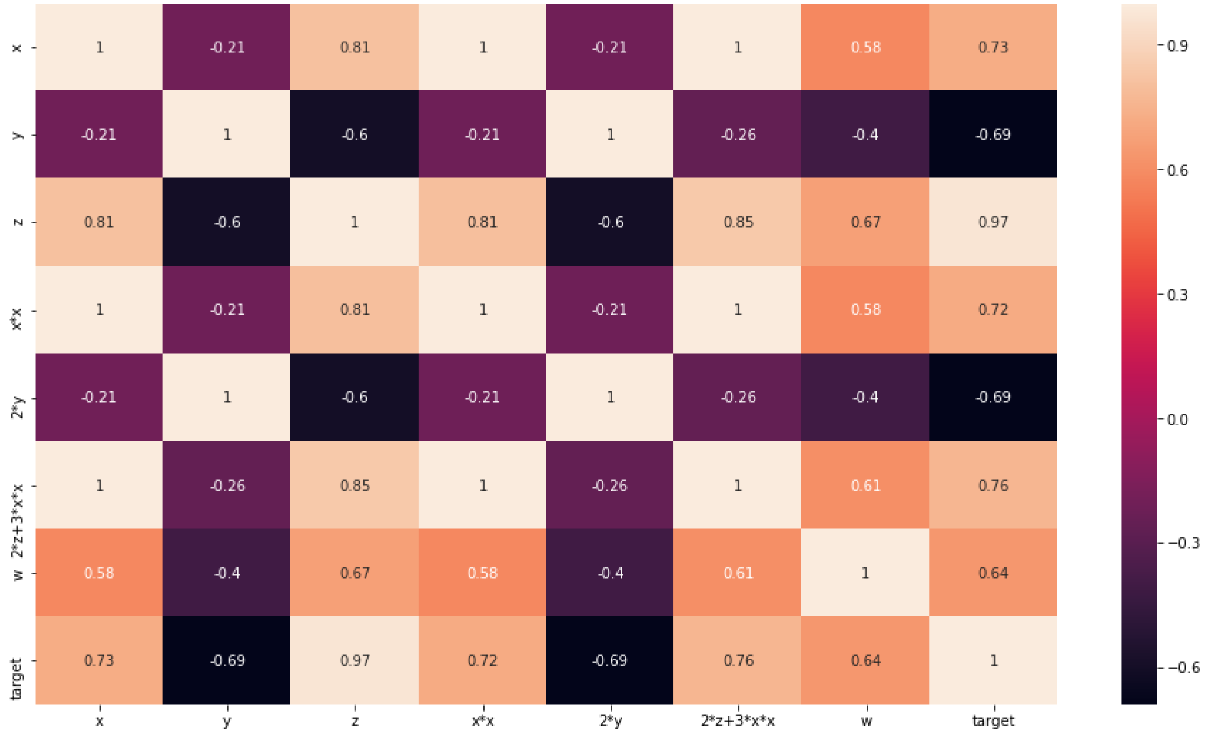
In [7]:
```
data.corr()
```

Out[7]:

	x	y	z	x*x	2*y	2*z+3*x*x	w	
x	1.000000	-0.205926	0.812458	0.997947	-0.205926	0.996252	0.583277	0.72
y	-0.205926	1.000000	-0.602663	-0.209289	1.000000	-0.261123	-0.401790	-0.6
z	0.812458	-0.602663	1.000000	0.807137	-0.602663	0.847163	0.674486	0.96
x*x	0.997947	-0.209289	0.807137	1.000000	-0.209289	0.997457	0.583803	0.7
2*y	-0.205926	1.000000	-0.602663	-0.209289	1.000000	-0.261123	-0.401790	-0.6
2*z+3*x*x	0.996252	-0.261123	0.847163	0.997457	-0.261123	1.000000	0.606860	0.76
w	0.583277	-0.401790	0.674486	0.583803	-0.401790	0.606860	1.000000	0.64
target	0.728290	-0.690684	0.969990	0.719570	-0.690684	0.764729	0.641750	1.00

In [8]:

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x1fba38d9cf8>



In [9]:
```
random_state=25
param_grid = {'alpha':[0.0001,0.01,1,100]}
log_reg = SGDClassifier(loss='log',random_state=42)
grid_search = GridSearchCV(log_reg,param_grid)
grid_search.fit(X,Y)
print(grid_search.best_params_)
```

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

In [10]:
```
best_model = SGDClassifier(loss='log', alpha=grid_search.best_params_[
'alpha'],random_state=42)
best_model
```

Out[10]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercep
```

```
t=True,
                  l1_ratio=0.15, learning_rate='optimal', loss='log', max_i
ter=1000,
                  n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.
5,
                  random_state=42, shuffle=True, tol=0.001, validation_frac
tion=0.1,
                  verbose=0, warm_start=False)
```

In [11]:

```
best_model.fit(X,Y)
prediction = best_model.predict(X)
accuracy = best_model.score(X,prediction)
weight = best_model.coef_
print("Accuracy:",accuracy)
print("weight:",weight)
```

```
Accuracy: 1.0
weight: [[ 0.71810131 -0.91776522  1.70700796  0.65857264 -0.91776522
0.79881225
   0.50168857]]
```

In [27]:

```
X_edited = X+1e-2
best_model.fit(X_edited,Y)
prediction = best_model.predict(X_edited)
best_model_accuracy_edited = best_model.score(X_edited,prediction)
w_edited = best_model.coef_
print(best_model_accuracy_edited)
print(w_edited)
```

```
1.0
[[ 0.7182315  -0.91798831  1.70612177  0.65888883 -0.91798831  0.799000
34
   0.50153083]]
```

In [32]:

```
print(best_model_accuracy_edited-accuracy)
print(abs(weight-w_edited))
```

```
0.0
[[0.00013019 0.00022309 0.00088619 0.00031619 0.00022309 0.00018809
```

```
0.00015774]]
```

In [36]:
```
top4_features = np.argsort(abs(weight-w_edited)[0])[::-1][:4]
print(data.columns[top4_features])
```

```
Index(['z', 'x*x', '2*y', 'y'], dtype='object')
```

TASK-2

In [37]:
```
random_state=25
param_grid = {'alpha':[0.0001,0.01,1,100]}
log_reg = SGDClassifier(loss='hinge',random_state=42)
grid_search = GridSearchCV(log_reg,param_grid)
grid_search.fit(X,Y)
print(grid_search.best_params_)
```

```
{'alpha': 0.0001}
```

In [38]:
```
best_model = SGDClassifier(loss='hinge', alpha=grid_search.best_params_
['alpha'],random_state=42)
best_model
```

Out[38]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercep
t=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty
='l2',
              power_t=0.5, random_state=42, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [39]:
```
best_model.fit(X,Y)
prediction = best_model.predict(X)
accuracy = best_model.score(X,prediction)
weight = best_model.coef_
print("Accuracy:",accuracy)
print("weight:",weight)
```

```
Accuracy: 1.0
weight: [[  7.21730153 -10.49088768  19.80601486   5.97954742 -10.49088
768
    7.77287118   7.53662906]]
```

In [40]:

```
X_edited = X+1e-2
best_model.fit(X_edited,Y)
prediction = best_model.predict(X_edited)
best_model_accuracy_edited = best_model.score(X_edited,prediction)
w_edited = best_model.coef_
print(best_model_accuracy_edited)
print(w_edited)
```

```
1.0
[[  7.27288796 -10.43530125  19.86160129   6.03513386 -10.43530125
    7.82845761   7.5922155 ]]
```

In [42]:

```
print(best_model_accuracy_edited-accuracy)
print(abs(weight-w_edited))
```

```
0.0
[[0.05558644 0.05558644 0.05558644 0.05558644 0.05558644 0.05558644
  0.05558644]]
```

In [43]:

```
top4_features = np.argsort(abs(weight-w_edited)[0])[::-1][:4]
print(data.columns[top4_features])
```

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

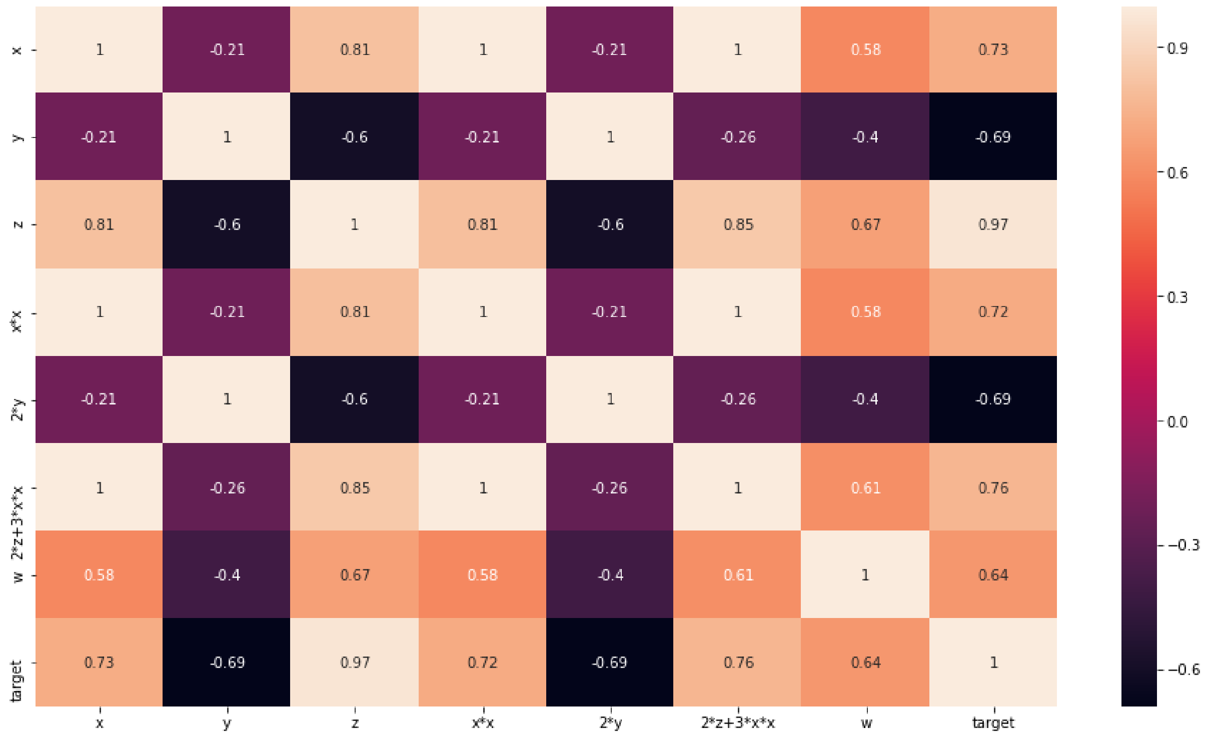
In [45]:

```
data_edited = pd.DataFrame(np.concatenate((X_edited,Y.reshape(100,1)),a
xis=1),columns=['x','y','z','x*x','2*y','2*z+3*x*x','w','target'])
#reference from https://indianaiproduction.com/seaborn-heatmap/
plt.figure(figsize=(16,9))

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

Out[45]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fba5d35b00>
```



x
y
z
x*x
2*y
2*z+3*x*x
w
target
1 -0.21 0.81 1 -0.21 1 0.58 0.73
-0.21 1 -0.6 -0.21 1 -0.26 -0.4 -0.69
0.81 -0.6 1 0.81 -0.6 0.85 0.67 0.97
1 -0.21 0.81 1 -0.21 1 0.58 0.72
-0.21 1 -0.6 -0.21 1 -0.26 -0.4 -0.69
1 -0.26 0.85 1 -0.26 1 0.61 0.76
0.58 -0.4 0.67 0.58 -0.4 0.61 1 0.64
0.73 -0.69 0.97 0.72 -0.69 0.76 0.64 1
0.9
0.6
0.3
0.0
−0.3
−0.6