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

In [117…

```
%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 LogisticRegression
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import GridSearchCV
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn import metrics
```

In [69]:

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

In [70]:

```
data.head()
```

Out[70]:

	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 [71]:

```
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
created in the above cell
    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_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
weights
    compare to the other feature
```

Task: 2 Linear SVM

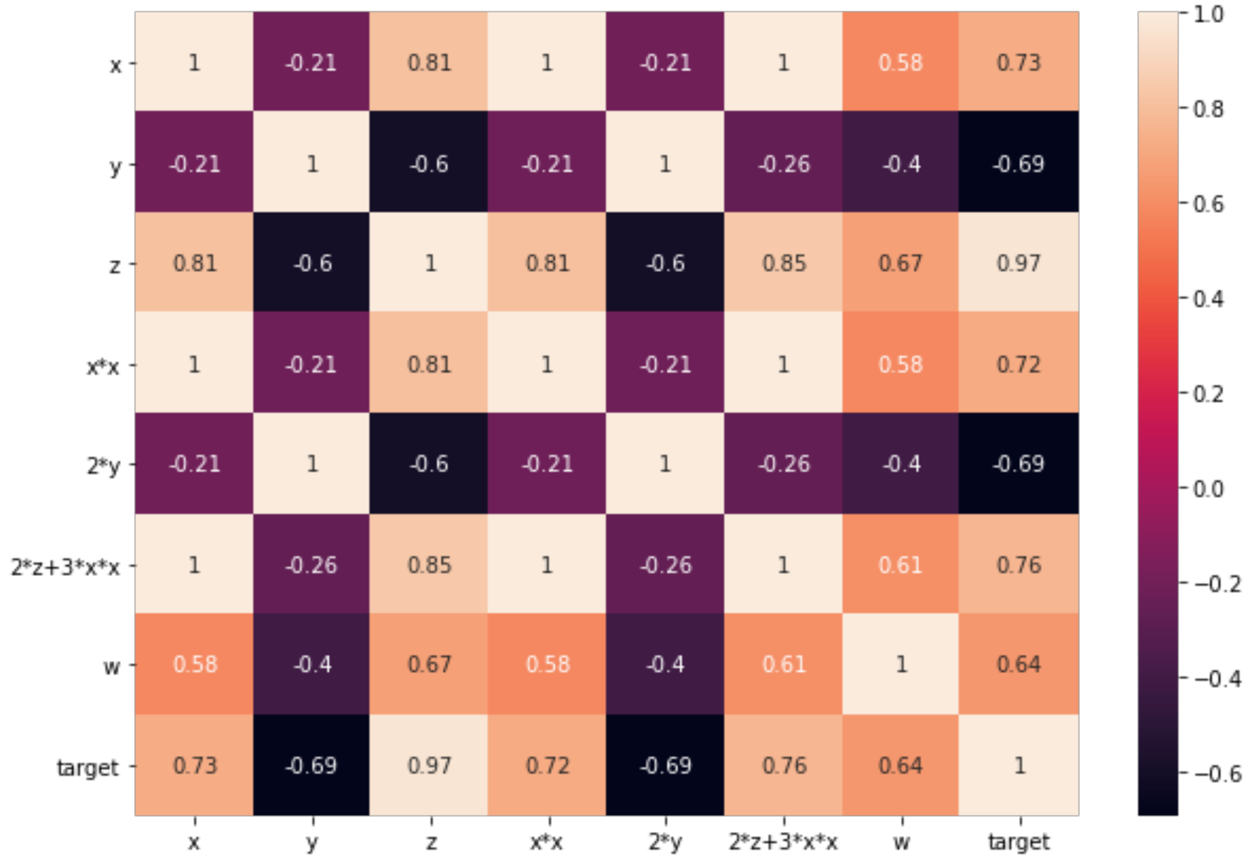
```
1. Do the same steps (2, 3, 4, 5) we have done in the above
task 1.
```

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

Task - 1

In [59]:
```python
fig, ax = plt.subplots(figsize=(10,7))
sns.heatmap(data.corr(), annot = True, ax=ax)
```

Out[59]: <AxesSubplot:>



In [60]:
```
model = LogisticRegression()
penalty = ['l1','l2']
C = np.logspace(1,8,num=5)
alpha = dict(C=C, penalty = penalty)
clf = GridSearchCV(model, alpha, cv=5, verbose=0)
temp = clf.fit(X,Y)
print("Best alpha:", temp.best_estimator_.get_params()['C'])
print("Best score:", temp.best_score_)
```

```
Best alpha: 10.0
Best score: 1.0
```

In [61]:
```
best_model = LogisticRegression(penalty='l2', C=10)
```

In [80]:
```
best_model.fit(X,Y)
```

Out[80]: LogisticRegression(C=10)

In [119…
```
y_pred = best_model.predict(X)
best_model_accuracy = best_model.score(X, y_pred)
print("Accuracy:",best_model_accuracy)
```

```
Accuracy: 1.0
```

In [82]:
```
W = best_model.coef_
print(W)
```

```
[[ 1.10390355 -1.31307824  2.97742302  0.97952119 -1.31307824  1.24104888
   0.65549702]]
```

In [73]:
```
X1 = X + 0.01
```

In [84]:
```
best_model.fit(X1,Y)
y_pred1 = best_model.predict(X1)
best_model_accuracy_edited = best_model.score(X1, y_pred1)
print(best_model_accuracy_edited)
W1 = best_model.coef_
print(W1)
```

```
1.0
[[ 1.10392869 -1.31306492  2.97744834  0.97946819 -1.31306492  1.24100273
   0.65559227]]
```

In [85]:
```
best_model_accuracy_edited - best_model_accuracy
```

Out[85]:
```
0.0
```

In [87]:
```
diff_in_weights = abs(W1-W)
print(diff_in_weights)
```

```
[[2.51415473e-05 1.33256522e-05 2.53241049e-05 5.30064630e-05
  1.33256522e-05 4.61560009e-05 9.52478348e-05]]
```

In [142…
```
feature_names = data.drop(['target'], axis=1).columns.tolist()
```

In [112…
```
top_ind_pos=np.argsort(diff_in_weights[0])[::-1][:4]
top_features=np.take(feature_names,top_ind_pos)
print(top_features)
```

```
['w' 'x*x' '2*z+3*x*x' 'z']
```

Observation:

- In heatmap image, the number tells correlation between each and every feature.
- The darker the color is, the least there is correlation between the features. The colors help in visualizing in a better way
- Using logspace for alpha, and l2 regularization, we get the accuracy of 1 and some weights assigned to the features.
- When noise of order of 10^-2 is added to data, the accuracy remains same.
- However, there is a slight difference visible in weights.
- ['w' 'x*x' '2*z+3*x*x' 'z'] are the features with higher difference in the weights before and after noise is added.

Task - 2 (Linear SVM)

In [133…
```
clf = svm.SVC(kernel='linear', C=1)
clf.fit(X,Y)
y_pred_svm = clf.predict(X)
```

In [139…

```
clf_accuracy = metrics.accuracy_score(Y, y_pred_svm)
print("Accuracy:",clf_accuracy)
```

```
Accuracy: 1.0
```

In [135…

```
print(clf.coef_)
W2 = clf.coef_
# [[ 1.10390355 -1.31307824  2.97742302  0.97952119 -1.31307824  1.2410488
#    0.65549702]]
```

```
[[ 0.42059793 -0.36090175  1.04442829  0.34263578 -0.36090175  0.43447147
   0.17056102]]
```

In [136…

```
clf.fit(X1,Y)
y_pred2 = clf.predict(X1)
clf_accuracy_edited = clf.score(X1, y_pred2)
print(clf_accuracy_edited)
W3 = clf.coef_
print(W3)
```

```
1.0
[[ 0.42059794 -0.36090176  1.04442829  0.34263578 -0.36090176  0.43447147
   0.17056109]]
```

In [140…

```
clf_accuracy_edited - clf_accuracy
```

Out[140…

```
0.0
```

In [144…

```
diff_in_weights_svm = abs(W2-W3)
print(diff_in_weights_svm)
```

```
[[7.43466255e-09 7.75015030e-09 3.76125131e-10 9.42298461e-11
  7.75015030e-09 1.30218003e-10 6.79247940e-08]]
```

In [145…

```
top_ind_pos=np.argsort(diff_in_weights_svm[0])[::-1][:4]
top_features_svm=np.take(feature_names,top_ind_pos)
print(top_features_svm)
```

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

Observation:

- Using logspace for alpha, and l2 regularization, we get the accuracy of 1 and some weights assigned to the features.
- When noise of order of 10^-2 is added to data, the accuracy remains same.
- However, there is a slight difference visible in weights.
- ['w' 'xx' '2z+3xx' 'z'] are the features with higher difference in the weights before and after noise is added.