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

In [1]:
```
%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
from sklearn.model_selection import train_test_split
import tqdm
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn import svm
```

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]:
```
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 C
V 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

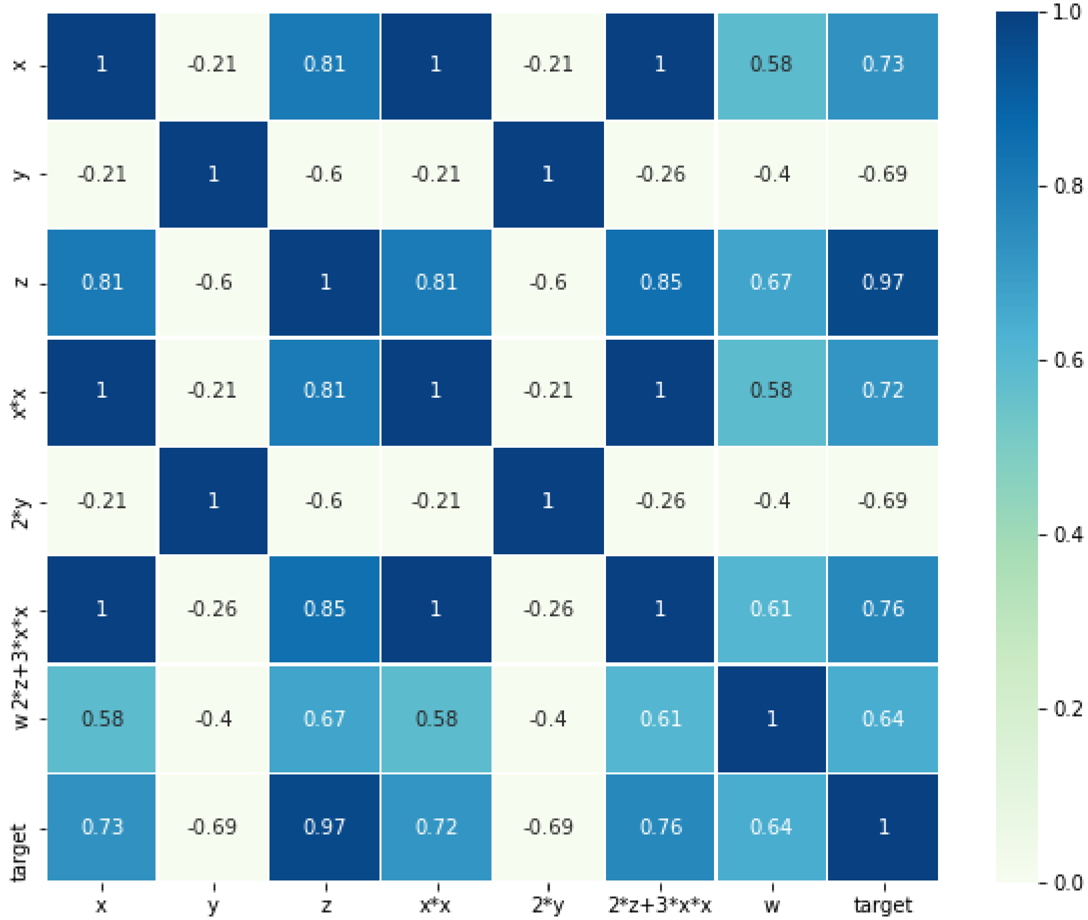
1. Finding the Correlation between the features

In [5]:
```
data = pd.read_csv('task_d.csv')
data.corr()
```

Out[5]:

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

In [6]:
```
fig, ax = plt.subplots(figsize=(10,8))
ax = sns.heatmap(data.corr(), vmin=0, vmax=1, annot=True, linewidth=0.2, cmap='GnBu')
```



2. Finding the best model for the given data

In [7]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, stratify=y)
```

In [8]:
```
C=[0.00001, 0.00005, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100, 500, 1000, 2500,
5000, 10000]
log_alphas = [np.log10(a) for a in C]

distributions = dict(C=log_alphas,
                     penalty=['l2', 'l1'])
model = LogisticRegression()

clf = RandomizedSearchCV(model, distributions, cv=3, scoring='roc_auc')

top_model = clf.fit(X_train, y_train)

print('Best Penalty:', top_model.best_estimator_.get_params()['penalty'])
print('Best C:', top_model.best_estimator_.get_params()['C'])
print('Best AUC score: ', clf.best_score_)
print('='*50)
```

```
Best Penalty: l2
Best C: 0.6989700043360189
Best AUC score:  1.0
==================================================
```

In [9]:
```
from sklearn.metrics import accuracy_score

best_model = LogisticRegression(C=3, penalty='l2', fit_intercept=True, class_weight='balanced')
best_model.fit(X_train, y_train)
```

Out[9]:
```
LogisticRegression(C=3, class_weight='balanced')
```

3. Getting the weights with the original data

In [10]:
```
y_pred = best_model.predict(X_test)
best_model_accuracy = accuracy_score(y_pred, y_test)
print('The accuracy for the best model: ', best_model_accuracy)
```

```
The accuracy for the best model:  1.0
```

In [11]:
```
print('The weights of the best model: ', best_model.coef_)
```

```
The weights of the best model:  [[ 0.82834244 -0.97474895  2.09849794  0.75211145 -0.97474895  0.93026347
   0.59702973]]
```

4. Modifying original data

In [12]:
```
for i in data.columns[0:-1]:
    data[i] = 0.01+data[i]
```

In [13]:
```
X = data.drop(['target'], axis=1).values
y = data['target'].values
```

In [14]:
```
X2_train, X2_test, y2_train, y2_test = train_test_split(X, y, test_size=0.33, stratify=y)
```

In [15]:
```
almost_best_model = LogisticRegression(C=3, penalty='l2', fit_intercept=True, class_weight='balanced')
almost_best_model.fit(X2_train, y2_train)
```

Out[15]:
```
LogisticRegression(C=3, class_weight='balanced')
```

In [16]:
```
y2_pred = almost_best_model.predict(X2_test)
almost_best_model_accuracy = accuracy_score(y2_pred, y2_test)
print('The accuracy for the almost best model: ', almost_best_model_accuracy)
```

```
The accuracy for the almost best model:  1.0
```

In [17]:
```
print('The weights of the almost best model: ', almost_best_model.coef_)
```

```
The weights of the almost best model:  [[ 0.88401202 -0.97966536  2.09261835  0.79299364 -0.97966536  0.9663
4706
   0.62534456]]
```

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
```

In [18]:
```
print('The differnce between both accuracies is: ', almost_best_model_accuracy - best_model_accuracy)
```

```
The differnce between both accuracies is:  0.0
```

In [19]:
```
weight_difference = abs(best_model.coef_ - almost_best_model.coef_)
print("The absolute change between each value of W and W': ", weight_difference)
```

```
The absolute change between each value of W and W':  [[0.05566958 0.00491641 0.0058796  0.04088219 0.0049164
1 0.03608359
  0.02831483]]
```

In [20]:
```
d = {}
for key, value in zip(data.columns[0:-1], weight_difference[0]):
    d.update({key:value})
```

In [21]:
```
sorted_weights = sorted(d.items(), key = lambda kv: kv[1])
print(sorted_weights[::-1])
```

```
[('x', 0.05566957545306406), ('x*x', 0.04088219060264964), ('2*z+3*x*x', 0.036083590993214454), ('w', 0.0283
1483316640615), ('z', 0.005879597915972923), ('2*y', 0.004916406885147939), ('y', 0.004916406885147939)]
```

In [22]:
```
print('Features with the highest change: ', sorted_weights[::-1])
```

```
Features with the highest change:  [('x', 0.05566957545306406), ('x*x', 0.04088219060264964), ('2*z+3*x*x',
0.036083590993214454), ('w', 0.02831483316640615), ('z', 0.005879597915972923), ('2*y', 0.00491640688514793
9), ('y', 0.004916406885147939)]
```

Task 2

1. Finding the Correlation between the features

In [23]:
```
print('The differnce between both accuracies is: ', almost_best_model_accuracy - best_model_accuracy)
```

```
The differnce between both accuracies is:  0.0
```

In [24]:
```
weight_difference = abs(best_model.coef_ - almost_best_model.coef_)
print("The absolute change between each value of W and W': ", weight_difference)
```

```
The absolute change between each value of W and W':  [[0.05566958 0.00491641 0.0058796  0.04088219 0.0049164
1 0.03608359
  0.02831483]]
```

In [25]:
```
lst = []
for key in sorted(d):
    lst.append("{0}: {1}".format(key, d[key]))
```

In [26]:
```
print('Features with the highest change: ', lst[::-1][0:4])
```

```
Features with the highest change:  ['z: 0.005879597915972923', 'y: 0.004916406885147939', 'x*x: 0.0408821906
0264964', 'x: 0.05566957545306406']
```

In [27]:
```
C=[0.00001, 0.00005, 0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100, 500, 1000, 2500,
5000, 10000]
log_alphas = [np.log10(a) for a in C]

distributions = dict(C=log_alphas,
                     kernel=['linear', 'rbf'])
model = svm.SVC()

clf = RandomizedSearchCV(model, distributions, cv=3, scoring='roc_auc')

top_model = clf.fit(X_train, y_train)

print('Best Penalty:', top_model.best_estimator_.get_params()['kernel'])
print('Best C:', top_model.best_estimator_.get_params()['C'])
print('Best AUC score: ', clf.best_score_)
print('='*50)
```

```
Best Penalty: rbf
Best C: 3.0
Best AUC score:  1.0
==================================================
```

In [28]:
```
from sklearn.metrics import accuracy_score

best_model = svm.SVC(C=0.69, kernel='linear', class_weight='balanced')
best_model.fit(X_train, y_train)
```

Out[28]:
```
SVC(C=0.69, class_weight='balanced', kernel='linear')
```

3. Getting the weights with the original data

In [29]:
```
y_pred = best_model.predict(X_test)
best_model_accuracy = accuracy_score(y_pred, y_test)
print('The accuracy for the best model: ', best_model_accuracy)
```

```
The accuracy for the best model:  1.0
```

In [30]:
```
print('The weights of the best model: ', best_model.coef_)
```

```
The weights of the best model:  [[ 0.35948583 -0.31718921  1.00906181  0.29499107 -0.31718921  0.38732092
   0.18617242]]
```

4. Modifying original data

In [31]:
```
for i in data.columns[0:-1]:
    data[i] = 0.01+data[i]
```

In [32]:
```
X = data.drop(['target'], axis=1).values
y = data['target'].values
```

In [33]:
```
X2_train, X2_test, y2_train, y2_test = train_test_split(X, y, test_size=0.33, stratify=y)
```

In [34]:
```
almost_best_model = LogisticRegression(C=3, penalty='l2', fit_intercept=True, class_weight='balanced')
almost_best_model.fit(X2_train, y2_train)
```

Out[34]:
```
LogisticRegression(C=3, class_weight='balanced')
```

In [35]:
```
y2_pred = almost_best_model.predict(X2_test)
almost_best_model_accuracy = accuracy_score(y2_pred, y2_test)
print('The accuracy for the almost best model: ', almost_best_model_accuracy)
```

```
The accuracy for the almost best model:  1.0
```

In [36]:
```
print('The weights of the almost best model: ', almost_best_model.coef_)
```

```
The weights of the almost best model:  [[ 0.85779172 -1.02560254  2.09590515  0.7625755  -1.02560254  0.9393
6702
   0.52986848]]
```

5 . Checking deviations in metric and weights

In [37]:
```
print('The differnce between both accuracies is: ', almost_best_model_accuracy - best_model_accuracy)
```

```
The differnce between both accuracies is:  0.0
```

In [38]:
```
weight_difference = abs(best_model.coef_ - almost_best_model.coef_)
print("The absolute change between each value of W and W': ", weight_difference)
```

```
The absolute change between each value of W and W':  [[0.49830589 0.70841333 1.08684333 0.46758443 0.7084133
3 0.5520461
  0.34369606]]
```

In [39]:
```
d = {}
for key, value in zip(data.columns[0:-1], weight_difference[0]):
    d.update({key:value})
```

In [40]:
```
sorted_weights = sorted(d.items(), key = lambda kv: kv[1])
```

In [41]:
```
print('Features with the highest change: ', sorted_weights[::-1])
```

```
Features with the highest change:  [('z', 1.0868433322235253), ('2*y', 0.7084133324669484), ('y', 0.708413332
4669484), ('2*z+3*x*x', 0.5520461020467411), ('x', 0.4983058910568803), ('x*x', 0.4675844294513532), ('w',
0.34369606151097093)]
```