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

In [1]:
```python
%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
```

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

In [3]:
```python
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]:
```python
data.columns
```

Out[4]:
```
Index(['x', 'y', 'z', 'x*x', '2*y', '2*z+3*x*x', 'w', 'target'], dtype='object')
```

In [5]:
```python
features = data.columns[:-1]
print(features)
```

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

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

In [7]:
```python
X.shape
```

Out[7]:
```
(100, 7)
```

In [8]:
```python
np.unique(Y)
```

Out[8]:
```
array([0, 1], dtype=int64)
```

In [9]:
```python
X.ndim
```

Out[9]:
```
2
```

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

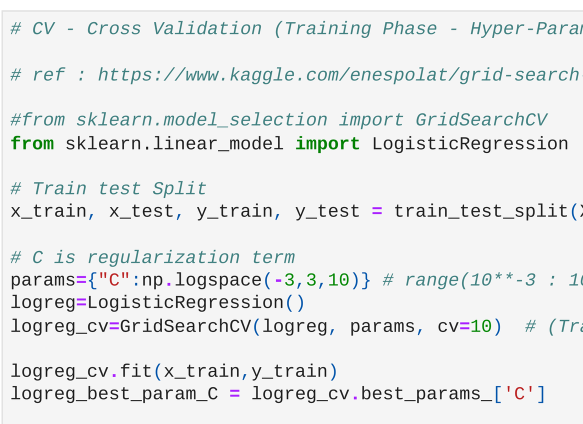
1. Finding the Correlation between the features

In [10]:
```python
# 1. Correlation (heat Map)

# a. check the correlation between the features
XData = data.drop(['target'], axis=1)

# b. plot heat map of correlation matrix using seaborn heatmap
sns.heatmap(XData.corr(), cmap="Blues", annot=True)
```

Out[10]:
```
<AxesSubplot:>
```



Logistic Regression

2. Finding the best model (ie Hyper-Param) for the given data

In [12]:
```python
# CV - Cross Validation (Training Phase - Hyper-Param Decision Time) (Model)

# ref : https://www.kaggle.com/enespolat/grid-search-with-logistic-regression

#from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

# Train test Split
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.3)

# C is regularization term
params={"C":np.logspace(-3,3,10)} # range(10**-3 : 10**3, 10)
logreg=LogisticRegression()
logreg_cv=GridSearchCV(logreg, params, cv=10)  # (Train-Test) Splitting Strategy = 10 Fold (ie Internal)

logreg_cv.fit(x_train,y_train)
logreg_best_param_C = logreg_cv.best_params_['C']

print("tuned hpyerparameters :(C) ",logreg_best_param_C)
print("accuracy :",logreg_cv.best_score_)
```

```
tuned hpyerparameters :(C)  0.004641588833612777
accuracy : 1.0
```

In [13]:
```python
# Target Variables Y := (Unique vals)
logreg_cv.classes_
```

Out[13]:
```
array([0, 1], dtype=int64)
```

In [18]:
```python
# Candidate params := Params (used whilst training)
cand_params = logreg_cv.cv_results_['params']
cand_params
```

Out[18]:
```
[{'C': 0.001},
 {'C': 0.004641588833612777},
 {'C': 0.021544346900318832},
 {'C': 0.1},
 {'C': 0.46415888336127775},
 {'C': 2.154434690031882},
 {'C': 10.0},
 {'C': 46.41588833612773},
 {'C': 215.44346900318823},
 {'C': 1000.0}]
```

In [19]:
```python
# Best Params Value position for param := 'C'
selected_param_idx = logreg_cv.best_index_
selected_param_idx, cand_params[selected_param_idx]
```

Out[19]:
```
(1, {'C': 0.004641588833612777})
```

In [20]:
```python
# Total features that were accounted whilst doing this Grid Search (for Logistic Regression)
feat_cnt = logreg_cv.n_features_in_
print(feat_cnt)
```

```
7
```

3. Getting Weights with Original Data

In [21]:
```python
# Best Model (Weights + Score)
best_model = LogisticRegression(C=logreg_best_param_C)
# Train
best_model.fit(x_train,y_train)
# Test (CV) -> Accuracy
best_score = best_model.score(x_test, y_test)

# Weight
best_weight = best_model.coef_.ravel()

print("Best Score ", best_score)
print("Best Weights ", best_weight)
```

```
Best Score  1.0
Best Weights  [ 0.0831106  -0.08739952  0.11976474  0.08098865 -0.08739952  0.08734999
  0.07534088]
```

4. Modifying the Original Data

In [22]:
```python
# 4. Modifying the Original Data
noise = 10**-2
X_m = X + noise

# Train test Split
x_train, x_test, y_train, y_test=train_test_split(X_m,Y,test_size=0.3)

# Train
best_model.fit(x_train,y_train)

# Test (CV) -> Accuracy
best_score_edited = best_model.score(x_test, y_test)

# ! NOTE :- You need to ravel/flatten ie convert the nd-array into single dimen array just like List to work efficiently late
# Weight
best_weight_edited = best_model.coef_.ravel()

print("Best Score ", best_score_edited)
print("Best Weights ", best_weight_edited)
```

```
Best Score  1.0
Best Weights  [ 0.0873578  -0.08296713  0.12143508  0.08634661 -0.08296713  0.09237386
  0.07136226]
```

> ! NOTE :- You need to ravel/flatten ie convert the nd-array into single dimen array just like List to work efficiently late

In [24]:
```python
# Adding Noise (ie Matrix + Scaler) // Sample Check
a = np.array([[1,2], [3,4]])
a + 4
```

Out[24]:
```
array([[5, 6],
       [7, 8]])
```

5. Checking Deviations in Metrics & Weights

In [25]:
```python
# 5. Checking Deviations in Metrics & Weights

import heapq

# 1.
diff_score = abs(best_score - best_score_edited)
print('Score Difference :- ', diff_score)

# 2.
diff_weights = np.abs(best_weight - best_weight_edited)
print('Weights Difference :- ', diff_weights)

# 3.
diff_weights_percent = diff_weights / best_weight
print('Diff Weight Percent :- ', diff_weights_percent)
largest_idxs = heapq.nlargest(4, range(len(diff_weights_percent)), diff_weights_percent.__getitem__)
print('Largest Indexes :-', largest_idxs)
top_features = [features[i] for i in largest_idxs]
print('Top 4 features that have higher % change in Weights :- ', top_features)
```

```
Score Difference :-  0.0
Weights Difference :-  [0.00424721 0.0044324  0.00167034 0.00535796 0.0044324  0.00502388
 0.00397862]
Diff Weight Percent :-  [ 0.05110306 -0.0507142   0.01394681  0.06615693 -0.0507142   0.05751434
  0.05280819]
Largest Indexes :- [3, 5, 6, 0]
Top 4 features that have higher % change in Weights :-  ['x*x', '2*z+3*x*x', 'w', 'x']
```

In [26]:
```python
# def perturbation_test(model, params):
#     '''To check presence of Collinearity'''
#     # Train test Split
#     x_train, x_test, y_train, y_test=train_test_split(X,Y,test_size=0.3)

#     #params={"C":np.logspace(-3,3,10)} # 10
#     model=LogisticRegression()
#     logreg_cv=GridSearchCV(logreg,params,cv=10)  # Splitting Strategy = 10 Fold

#     logreg_cv.fit(x_train,y_train)

#     logreg_best_param_C = logreg_cv.best_params_['C']

#     print("tuned hpyerparameters :(best parameters) ",logreg_best_param_C)
#     print("accuracy :",logreg_cv.best_score_)
```

In [ ]:

SVM (Linear)

2. Finding the best model (ie Hyper-Param) for the given data

In [35]:
```python
# CV - Cross Validation (Training Phase - Hyper-Param Decision Time) (Model)

# ref : https://www.kaggle.com/enespolat/grid-search-with-logistic-regression

#from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

# Train test Split
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.3)

# C is regularization term
params={"C":np.logspace(-3,3,10)} # range(10**-3 : 10**3, 10)
model=SVC(kernel='linear')
model_cv=GridSearchCV(model, params, cv=10)  # (Train-Test) Splitting Strategy = 10 Fold (ie Internal)

model_cv.fit(x_train,y_train)
best_param_C = model_cv.best_params_['C']

print("tuned hpyerparameters :(C) ",best_param_C)
print("accuracy :",model_cv.best_score_)
```

```
tuned hpyerparameters :(C)  0.004641588833612777
accuracy : 1.0
```

In [36]:
```python
# Target Variables Y := (Unique vals)
model_cv.classes_
```

Out[36]:
```
array([0, 1], dtype=int64)
```

In [37]:
```python
# Candidate params := Params (used whilst training)
cand_params = model_cv.cv_results_['params']
cand_params
```

Out[37]:
```
[{'C': 0.001},
 {'C': 0.004641588833612777},
 {'C': 0.021544346900318832},
 {'C': 0.1},
 {'C': 0.46415888336127775},
 {'C': 2.154434690031882},
 {'C': 10.0},
 {'C': 46.41588833612773},
 {'C': 215.44346900318823},
 {'C': 1000.0}]
```

In [38]:
```python
# Best Params Value position for param := 'C'
selected_param_idx = model_cv.best_index_
selected_param_idx, cand_params[selected_param_idx]
```

Out[38]:
```
(1, {'C': 0.004641588833612777})
```

In [39]:
```python
# Total features that were accounted whilst doing this Grid Search (for Logistic Regression)
feat_cnt = model_cv.n_features_in_
print(feat_cnt)
```

```
7
```

3. Getting Weights with Original Data

In [40]:
```python
# Best Model (Weights + Score)
best_model = SVC(C=best_param_C, kernel='linear')
# Train
best_model.fit(x_train,y_train)
# Test (CV) -> Accuracy
best_score = best_model.score(x_test, y_test)

# Weight
best_weight = best_model.coef_.ravel()

print("Best Score ", best_score)
print("Best Weights ", best_weight)
```

```
Best Score  1.0
Best Weights  [ 0.14219866 -0.13512138  0.23301992  0.1383527  -0.13512138  0.15265171
  0.10999079]
```

4. Modifying the Original Data

In [41]:
```python
# 4. Modifying the Original Data
noise = 10**-2
X_m = X + noise

# Train test Split
x_train, x_test, y_train, y_test=train_test_split(X_m,Y,test_size=0.3)

# Train
best_model.fit(x_train,y_train)

# Test (CV) -> Accuracy
best_score_edited = best_model.score(x_test, y_test)

# ! NOTE :- You need to ravel/flatten ie convert the nd-array into single dimen array just like List to work efficiently late
# Weight
best_weight_edited = best_model.coef_.ravel()

print("Best Score ", best_score_edited)
print("Best Weights ", best_weight_edited)
```

```
Best Score  1.0
Best Weights  [ 0.12074683 -0.16857629  0.22225544  0.11542463 -0.16857629  0.13071661
  0.13800882]
```

> ! NOTE :- You need to ravel/flatten ie convert the nd-array into single dimen array just like List to work efficiently late

5. Checking Deviations in Metrics & Weights

In [42]:
```python
# 5. Checking Deviations in Metrics & Weights

import heapq

# 1.
diff_score = abs(best_score - best_score_edited)
print('Score Difference :- ', diff_score)

# 2.
diff_weights = np.abs(best_weight - best_weight_edited)
print('Weights Difference :- ', diff_weights)

# 3.
diff_weights_percent = diff_weights / best_weight
print('Diff Weight Percent :- ', diff_weights_percent)
largest_idxs = heapq.nlargest(4, range(len(diff_weights_percent)), diff_weights_percent.__getitem__)
print('Largest Indexes :-', largest_idxs)
top_features = [features[i] for i in largest_idxs]
print('Top 4 features that have higher % change in Weights :- ', top_features)
```

```
Score Difference :-  0.0
Weights Difference :-  [0.02145183 0.0334549  0.01076448 0.02292808 0.0334549  0.0219351
 0.02801804]
Diff Weight Percent :-  [ 0.15085816 -0.24759148  0.04619553  0.16572194 -0.24759148  0.14369378
  0.25473077]
Largest Indexes :- [6, 3, 0, 5]
Top 4 features that have higher % change in Weights :-  ['w', 'x*x', 'x', '2*z+3*x*x']
```

Observations

Logistic Regression helps to spot out the correlated feature via perturbation test, more nearly compare to SVM(linear) because the top most feature deviated in case of Logistic Regression is `x*x` while for SVM is `w`
Now `x*x` is highly correlated to `x`, clearly

In [ ]: