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

In [316…

```
%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.metrics import accuracy_score
```

In [317…

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

In [318…

```
data.head()
```

Out[318…

	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 [319…

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

feature_lst = list(data.columns.values)
print(feature_lst)
```

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

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.
```

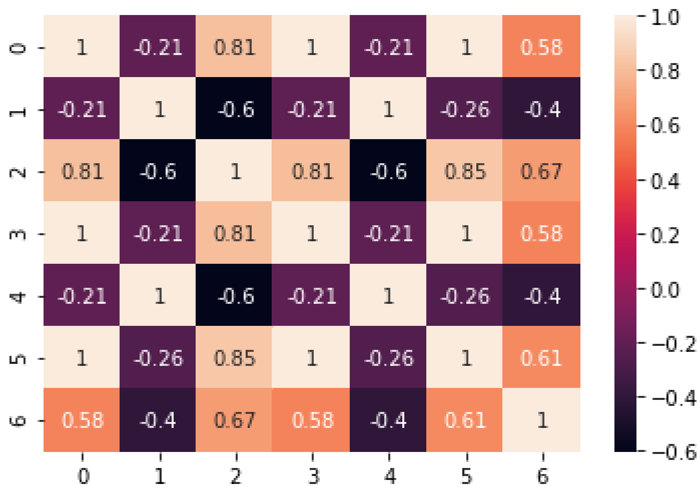
Do write the observations based on the results you get from the deviations of weights in both Logistic Regression and linear SVM

In [320…

```
df = pd.DataFrame(X)
#https://heartbeat.fritz.ai/seaborn-heatmaps-13-ways-to-customize-correlation-matrix-vi
sns.heatmap(df.corr() , annot = True)
```

Out[320…

```
<AxesSubplot:>
```



Logistic Regression

In [321…

```
log_res = SGDClassifier(loss = 'log')
```

```
params = {'alpha':[0.0001,0.001,0.01,0.1,1,10,100,1000]}
clf = GridSearchCV(log_res , params ,cv =3)
clf.fit(X,Y)

clf.best_params_
```

Out[321…

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

In [322…

```
best_model = SGDClassifier(loss = 'log' , alpha = 0.0001)
best_model.fit(X,Y)

best_model_accuracy = accuracy_score(Y , best_model.predict(X) )
w = best_model.coef_
print(best_model_accuracy , w)
```

```
1.0 [[  6.98723076 -11.06945882  17.99357874   6.48311605 -11.06945882
    8.00726825   1.36777686]]
```

In [323…

```
X_new= X + 0.01

best_model.fit (X_new , Y)

best_model_accuracy_edited = accuracy_score(Y ,best_model.predict(X_new))
w_dash = best_model.coef_
print(best_model_accuracy_edited  , w_dash)
```

```
1.0 [[ 3.18915299 -2.74640032  5.70732449  3.12942582 -2.74640032  3.50515689
   5.48731939]]
```

In [324…

```
acc_diff = best_model_accuracy_edited - best_model_accuracy
w_diff = w_dash - w
w_per = np.absolute(((w_dash - w)/w_dash)*100).flatten()

print("Accuracy Difference : " , acc_diff,"\n")
print("Difference in weights (w' - w) : \n",w_diff)
print("\nPercentage difference in weights : \n",w_per)

idx_top_4 = w_per.argsort()[-4:][::-1]

features = []
for i in idx_top_4:
    features.append(feature_lst[i])

print("\nTop 4 features by percentage change : ",features)
```

```
Accuracy Difference :  0.0

Difference in weights (w' - w) :
 [[ -3.79807777   8.3230585  -12.28625425  -3.35369023   8.3230585
   -4.50211136   4.11954253]]

Percentage difference in weights :
 [119.09362078 303.05336202 215.27169648 107.16631185 303.05336202
 128.44250609  75.07386101]

Top 4 features by percentage change :  ['2*y', 'y', 'z', '2*z+3*x*x']
```

Observations :

1. By adding a small noise in the data , the weights change by a significant percentage.

Linear SVM

In [326...
```
lr_svm = SGDClassifier(loss = 'hinge')
params = {'alpha':[0.0001,0.001,0.01,0.1,1,10,100,1000]}
clf = GridSearchCV(lr_svm , params ,cv =3)
clf.fit(X,Y)

clf.best_params_
```

Out[326...
```
{'alpha': 0.001}
```

In [327...
```
best_model = SGDClassifier(loss = 'hinge' , alpha = 0.001)
best_model.fit(X,Y)

best_model_accuracy = accuracy_score(Y , best_model.predict(X) )
w = best_model.coef_
print(best_model_accuracy , w)
```

```
1.0 [[ 2.78294456 -2.86831039  6.70391776  2.19749391 -2.86831039  2.7871434
   1.16471531]]
```

In [381...
```
X_new= X + 0.01

best_model.fit (X_new , Y)

best_model_accuracy_edited = accuracy_score(Y ,best_model.predict(X_new))
w_dash = best_model.coef_
print(best_model_accuracy_edited  , w_dash)
```

```
1.0 [[ 2.56392579 -1.66217536  4.86577501  2.30428622 -1.66217536  2.66109795
   1.31261022]]
```

In [382...
```
acc_diff = best_model_accuracy_edited - best_model_accuracy
w_diff = w_dash - w
w_per = np.absolute(((w_dash - w)/w_dash)*100).flatten()

print("Accuracy Difference : " , acc_diff,"\n")
print("Difference in weights (w' - w) : \n",w_diff)
print("\nPercentage difference in weights : \n",w_per)

idx_top_4 = w_per.argsort()[-4:][::-1]

features = []
for i in idx_top_4:
    features.append(feature_lst[i])

print("\nTop 4 features by percentage change : ",features)
```

```
Accuracy Difference :  0.0

Difference in weights (w' - w) :
 [[-0.21901878  1.20613503 -1.83814275  0.10679231  1.20613503 -0.12604545
   0.14789491]]

Percentage difference in weights :
 [ 8.54232123 72.56364553 37.77697779  4.63450703 72.56364553  4.73659561
 11.26723752]

Top 4 features by percentage change :  ['2*y', 'y', 'z', 'w']
```

Observations :

1. By adding a small noise in the data , the weights change by a lower percentage as compared to logistic regression.