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

```
%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
```

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

```
data.head()
```

```
          x         y         z       x*x       2*y  2*z+3*x*x
w  \
0 -0.581066  0.841837 -1.012978 -0.604025  0.841837  -0.665927 -
0.536277
1 -0.894309 -0.207835 -1.012978 -0.883052 -0.207835  -0.917054 -
0.522364
2 -1.207552  0.212034 -1.082312 -1.150918  0.212034  -1.166507
0.205738
3 -1.364174  0.002099 -0.943643 -1.280666  0.002099  -1.266540 -
0.665720
4 -0.737687  1.051772 -1.012978 -0.744934  1.051772  -0.792746 -
0.735054

   target
0       0
1       0
2       0
3       0
4       0
```

```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
feature_mapping =
{1:'x',2:'y',3:'z',4:'x*x',5:'2*y',6:'2*z+3*x*x',7:'w'}
```

```
print(X.shape)
print(Y.shape)
#print(X[1:10])
#print((X+100)[1:10])
```

```
(100, 7)
(100,)
```

Doing perturbation test to check the presence of collinearity

Task: 1 Logistic Regression

Task: 2 Linear SVM

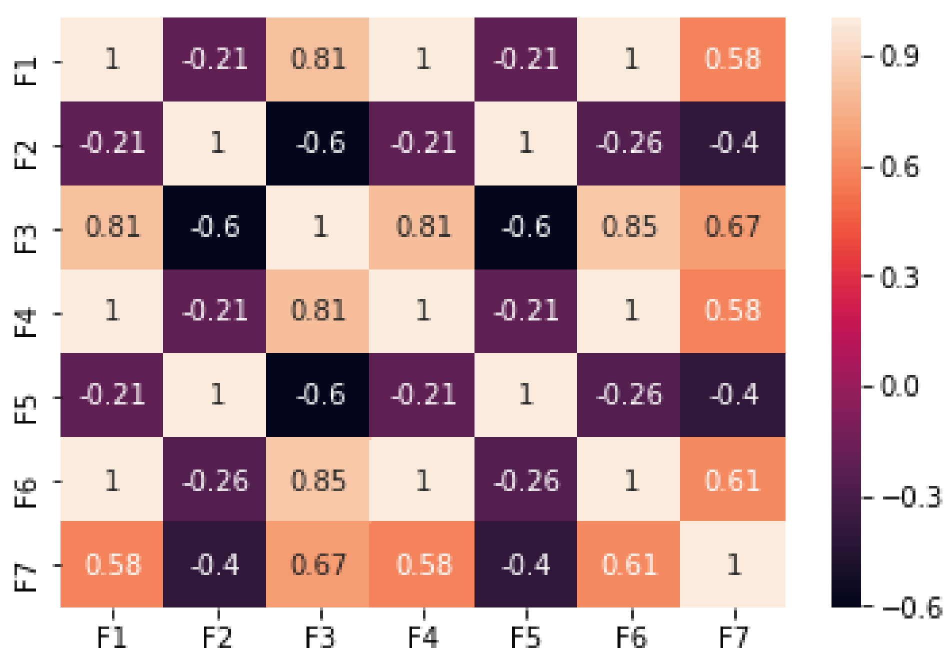
Do write the observations based on the results you get from the deviations of weights in both Logistic Regression and linear SVM

```
#Doing perturbation test to check the presence of collinearity
#Task: 1 Logistic Regression

#Finding the Correlation between the features via Pearson Correlation Cofficient
correlation_coef = np.corrcoef(X,rowvar=False)
#print(correlation_coef.shape)
#print(correlation_coef)

#Adding column names, row names for more readability
df =
pd.DataFrame(correlation_coef,columns=["F1","F2","F3","F4","F5","F6","F7"],index = ["F1","F2","F3","F4","F5","F6","F7"])
#print(df)
print("***************Heat Map of correlation between feature***********************")
ax =sns.heatmap(df,annot = True, xticklabels=True, yticklabels=True)
```

```
***************Heat Map of correlation between feature***********************
```



```
#Finding the best model for the given data
#Train Logistic regression on data(X,Y) that we have created in the
above cell
logistic_regression = SGDClassifier(loss='log',random_state = 20)
logistic_regression.fit(X,Y)

#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)
parameters = {'alpha':[0.0001,0.001,0.01,0.1,1, 10,100,1000,10000]}
clf = GridSearchCV(logistic_regression, parameters)
clf.fit(X,Y)
#print(clf.cv_results_)
print("********Best Estimator********")
best_alpha = clf.best_params_['alpha']
print(clf.best_estimator_)
print(clf.best_params_)
#print(clf.cv_results_)

#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'
best_model = SGDClassifier(loss = 'log',alpha =
best_alpha,random_state =20)
best_model.fit(X,Y)
```

```
********Best Estimator********
SGDClassifier(alpha=0.01, loss='log', random_state=20)
{'alpha': 0.01}

SGDClassifier(alpha=0.01, loss='log', random_state=20)
```

```
#Getting the weights with the original data
#Check the accuracy of the model 'best_model_accuracy'
class_weights = best_model.coef_[0]
best_model_accuracy = best_model.score(X,Y)
print("Best Model Accuracy: ", best_model_accuracy)

#Get the weights W using best_model.coef_
print("Best Model's Class Weights: ", class_weights)
```

```
Best Model Accuracy:  1.0
Best Model's Class Weights:  [ 0.726548   -0.89728841  1.72389953
0.66247604 -0.89728841  0.80436469
  0.50135355]
```

```
#Modifying original data
#Add a noise(order of 10^-2) to each element of X and get the new data
set X' (X' = X + e)
e = 0.01
```

```
print("X before Pertuberation:")
print(X[0:1])
X = X+e
print("X after Pertuberation:")
print(X[0:1])

#Train the same 'best_model' with data (X', Y)
best_model.fit(X,Y)

#Check the accuracy of the model 'best_model_accuracy_edited'
print("**********************************************************************
*****************************")
best_model_accuracy_edited = best_model.score(X,Y)
print("Best Model Accuracy After Pertuberation: ",
best_model_accuracy_edited)

#Get the weights W' using best_model.coef_
class_weights_edited = best_model.coef_[0]
print("Best Model's Class Weights: ", class_weights_edited)

X before Pertuberation:
[[-0.5810659   0.84183714 -1.01297765 -0.60402468  0.84183714 -
0.66592679
  -0.53627703]]
X after Pertuberation:
[[-0.5710659   0.85183714 -1.00297765 -0.59402468  0.85183714 -
0.65592679
  -0.52627703]]
**********************************************************************
*********************
Best Model Accuracy After Pertuberation:  1.0
Best Model's Class Weights:  [ 0.72665047 -0.89716276  1.72336461
0.66294523 -0.89716276  0.80469158
  0.50207115]

# Checking deviations in metric and weights
# find the difference between 'best_model_accuracy_edited' and
'best_model_accuracy'
accuracy_difference = (best_model_accuracy_edited-best_model_accuracy)
print("difference between 'best_model_accuracy_edited' and
'best_model_accuracy': ",accuracy_difference)

# find the absolute change between each value of W and W' ==> |(W-W')|
class_weigths_difference = abs(class_weights - class_weights_edited)
print("Absolute change between each value of W and W':
",class_weigths_difference)

# print the top 4 features which have higher % change in weights
compare to the other feature
class_weigths_difference_pct_logistic = abs((class_weights -
```

```
class_weights_edited) / class_weights)
print("class_weigths_difference_pct: ",
class_weigths_difference_pct_logistic)
#print(np.argsort(class_weigths_difference_pct))
print("**********************************************************************
********************************")
#print(np.argsort(class_weigths_difference_pct)[:2:-1])

print("Top 4 features which have higher % change in weights compare to
the other feature",[feature_mapping[i+1] for i in
(np.argsort(class_weigths_difference_pct_logistic)[:2:-1])])
```

```
difference between 'best_model_accuracy_edited' and
'best_model_accuracy':  0.0
Absolute change between each value of W and W':  [0.00010247
0.00012565 0.00053492 0.0004692  0.00012565 0.00032689
 0.0007176 ]
class_weigths_difference_pct:  [0.00014103 0.00014003 0.0003103
0.00070825 0.00014003 0.00040639
 0.00143133]
**********************************************************************
*************************
Top 4 features which have higher % change in weights compare to the
other feature ['w', 'x*x', '2*z+3*x*x', 'z']
```

```
#***************Perform Steps 2 to 5 with SVM******************
#Finding the best model for the given data
#Train svm on data(X,Y) that we have created in the above cell
svm = SGDClassifier(loss='hinge',random_state =20)
svm.fit(X,Y)

#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)
parameters = {'alpha':[0.0001,0.001,0.01,0.1,1, 10,100,1000,10000]}
clf = GridSearchCV(svm, parameters)
clf.fit(X,Y)
#print(clf.cv_results_)
print("********Best Estimator********")
best_alpha = clf.best_params_['alpha']
print(clf.best_estimator_)
print(clf.best_params_)
#print(clf.cv_results_)

#Creat a new svm with the best alpha (search for how to get the best
hyper parameter value), name the best model as 'best_model'
best_model = SGDClassifier(loss = 'log',alpha =
best_alpha,random_state = 20)
best_model.fit(X,Y)
```

```
********Best Estimator********
SGDClassifier(alpha=0.1, random_state=20)
{'alpha': 0.1}

SGDClassifier(alpha=0.1, loss='log', random_state=20)

#Getting the weights with the original data
#Check the accuracy of the model 'best_model_accuracy'
class_weights = best_model.coef_[0]
best_model_accuracy = best_model.score(X,Y)
print("Best Model Accuracy: ", best_model_accuracy)

#Get the weights W using best_model.coef_
print("Best Model's Class Weights: ", class_weights)

Best Model Accuracy:  1.0
Best Model's Class Weights:  [ 0.4078346  -0.52117395  0.79424456
0.38563394 -0.52117395  0.4429374
  0.34597669]

#Modifying original data
#Add a noise(order of 10^-2) to each element of X and get the new data
set X' (X' = X + e)
e = 0.01
print("X before Pertuberation:")
print(X[0:1])
X = X+e
print("X after Pertuberation:")
print(X[0:1])

#Train the same 'best_model' with data (X', Y)
best_model.fit(X,Y)

#Check the accuracy of the model 'best_model_accuracy_edited'
print("****************************************************************
*****************************")
best_model_accuracy_edited = best_model.score(X,Y)
print("Best Model Accuracy After Pertuberation: ",
best_model_accuracy_edited)

#Get the weights W' using best_model.coef_
class_weights_edited = best_model.coef_[0]
print("Best Model's Class Weights: ", class_weights_edited)

X before Pertuberation:
[[-0.5710659   0.85183714 -1.00297765 -0.59402468  0.85183714 -
0.65592679
  -0.52627703]]
X after Pertuberation:
[[-0.5610659   0.86183714 -0.99297765 -0.58402468  0.86183714 -
0.64592679
```

```
  -0.51627703]]
**********************************************************************
*********************
Best Model Accuracy After Pertuberation:  1.0
Best Model's Class Weights:  [ 0.40800789 -0.52064558  0.79465013
0.3858671  -0.52064558  0.44316916
  0.34658003]
```

```
# Checking deviations in metric and weights
# find the difference between 'best_model_accuracy_edited' and
'best_model_accuracy'
accuracy_difference = (best_model_accuracy_edited-best_model_accuracy)
print("difference between 'best_model_accuracy_edited' and
'best_model_accuracy': ",accuracy_difference)

# find the absolute change between each value of W and W' ==> |(W-W')|
class_weigths_difference = abs(class_weights - class_weights_edited)
print("Absolute change between each value of W and W':
",class_weigths_difference)

# print the top 4 features which have higher % change in weights
compare to the other feature
class_weigths_difference_pct_svm = abs((class_weights -
class_weights_edited) / class_weights)
print("class_weigths_difference_pct: ",
class_weigths_difference_pct_svm)
#print(np.argsort(class_weigths_difference_pct))
print("**********************************************************************
********************************")
#print(np.argsort(class_weigths_difference_pct)[:2:-1])

print("Top 4 features which have higher % change in weights compare to
the other feature",[feature_mapping[i+1] for i in
(np.argsort(class_weigths_difference_pct_svm)[:2:-1])])
```

```
difference between 'best_model_accuracy_edited' and
'best_model_accuracy':  0.0
Absolute change between each value of W and W':  [0.00017328
0.00052838 0.00040557 0.00023316 0.00052838 0.00023176
 0.00060334]
class_weigths_difference_pct:  [0.00042488 0.00101382 0.00051063
0.00060461 0.00101382 0.00052324
 0.00174387]
**********************************************************************
*************************
Top 4 features which have higher % change in weights compare to the
other feature ['w', '2*y', 'y', 'x*x']
```

```
 #Print the top 4 feature names explicitly having the highest
percentage change in both the tasks.
```

```
print("-"*70)
print("class_weigths_difference_pct via logistic: ",
class_weigths_difference_pct_logistic)
print("-"*70)
print("class_weigths_difference_pct via SVM: ",
class_weigths_difference_pct_svm)
print("No differnce in class_weigths_difference_pct via logistic and
SVM ")
print("-"*70)
print("Top 4 features which have higher % change in weights in both
cases [SVM] and [Logistic Regression]",[feature_mapping[i+1] for i in
(np.argsort(class_weigths_difference_pct_svm)[:2:-1])])
```

```
----------------------------------------------------------------------
class_weigths_difference_pct via logistic:  [0.00014103 0.00014003
0.0003103  0.00070825 0.00014003 0.00040639
 0.00143133]
----------------------------------------------------------------------
class_weigths_difference_pct via SVM:  [0.00042488 0.00101382
0.00051063 0.00060461 0.00101382 0.00052324
 0.00174387]
No differnce in class_weigths_difference_pct via logistic and SVM
----------------------------------------------------------------------
Top 4 features which have higher % change in weights in both cases
[SVM] and [Logistic Regression] ['w', '2*y', 'y', 'x*x']
```

Observation:

- Mean deviation of class weights for logistic regression: 0.1177683
- Mean deviation of class weights for SVM: 0.037347999
- Therefore, SVM has less deviation and more robust to pertuberation of train data.
- And, Feature 7 is more important in classification irrespective of algorithm selected.
- Top 4 features which have higher % change in weights in both cases [SVM] and [Logistic Regression] ['w', '2*y*', '*y*', '*x*x']