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.metrics import accuracy_score
import math
```

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]:

```
feature_labels = list(data.columns[:-1])
```

In [5]:

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

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, random_state=
0)
```

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-fo
ld 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

Corelation of features

In [6]:

```
corr = data.corr()
print(corr)
```

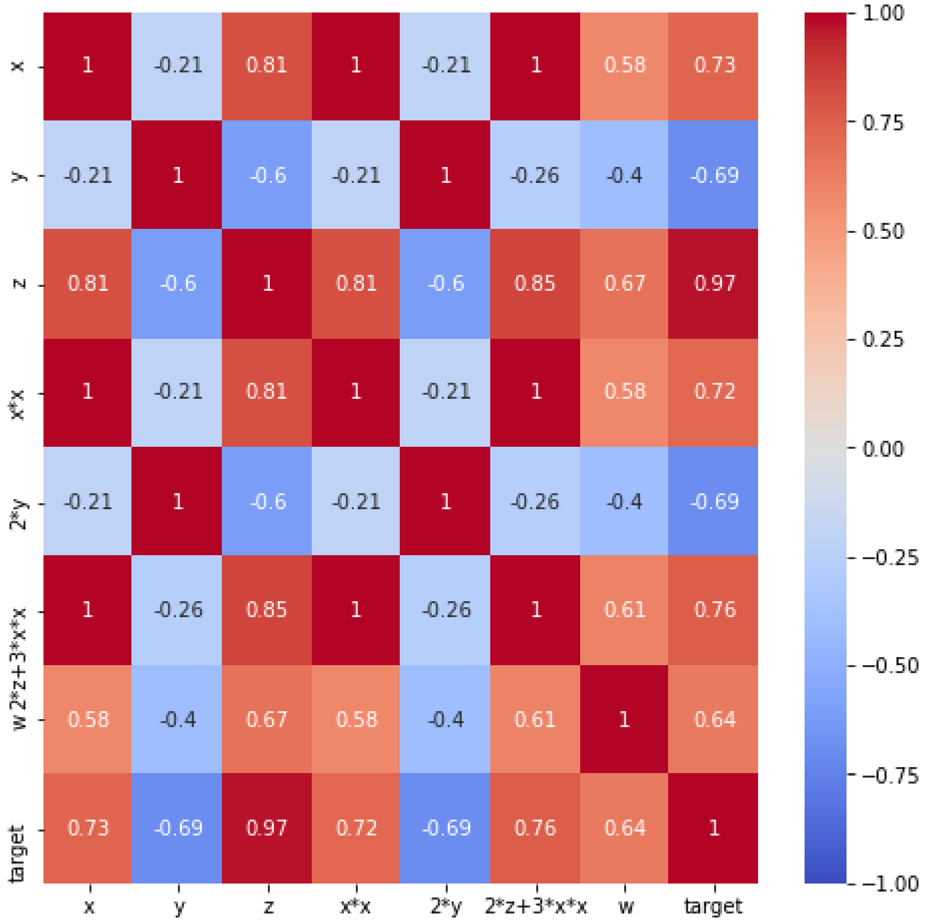
```
                  x         y         z  ...  2*z+3*x*x         w    targe
t
x          1.000000 -0.205926  0.812458  ...   0.996252  0.583277  0.72829
0
y         -0.205926  1.000000 -0.602663  ...  -0.261123 -0.401790 -0.69068
4
z          0.812458 -0.602663  1.000000  ...   0.847163  0.674486  0.96999
0
x*x        0.997947 -0.209289  0.807137  ...   0.997457  0.583803  0.71957
0
2*y       -0.205926  1.000000 -0.602663  ...  -0.261123 -0.401790 -0.69068
4
2*z+3*x*x  0.996252 -0.261123  0.847163  ...   1.000000  0.606860  0.76472
9
w          0.583277 -0.401790  0.674486  ...   0.606860  1.000000  0.64175
0
target     0.728290 -0.690684  0.969990  ...   0.764729  0.641750  1.00000
0

[8 rows x 8 columns]
```

In [7]:

```
fig, ax = plt.subplots(figsize=(8,8))         # Sample figsize in inches
sns.heatmap(data.corr(),annot= True,vmin=-1, vmax=1, center= 0,cmap= 'coolwarm', ax =ax
)
```

Out[7]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f25d648a9e8>



Task 1 : Logistic Regression

Finding the best model for the given data

In [8]:

```
# alphas = list(np.logspace(1,4,num=10))
alphas = [0.0001,0.001,0.09,0.01,0.1,1,50,100,1000]
param = {"alpha" : alphas}

hyp = GridSearchCV(SGDClassifier(loss="log"), param_grid=param,cv=5)
hyp.fit(X_train,y_train)
```

Out[8]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=Fal
se,
                                     epsilon=0.1, eta0=0.0, fit_intercept=
True,
                                     l1_ratio=0.15, learning_rate='optima
l',
                                     loss='log', max_iter=1000,
                                     n_iter_no_change=5, n_jobs=None,
                                     penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True, tol=
0.001,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'alpha': [0.0001, 0.001, 0.09, 0.01, 0.1, 1, 50,
100,
                                   1000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring=None, verbose=0)
```

In [9]:

```
print("Best value of alpha: " ,hyp.best_params_)
```

```
Best value of alpha:  {'alpha': 0.001}
```

In [10]:

```
best_model = SGDClassifier(loss = "log",alpha = 0.001)
```

Getting the weights with the original data

In [11]:

```
best_model.fit(X_train,y_train)
```

Out[11]:

```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=T
rue,
              l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter
=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.5,
              random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [12]:

```
# best_model_accuracy = accuracy_score(Y,best_model.predict(X))
# best_model_coef_ = best_model.coef_[0]
best_model_accuracy = accuracy_score(y_test,best_model.predict(X_test))
```

In [13]:

```
print("Model Weights :",best_model.coef_[0])
best_model_weights = best_model.coef_[0]
```

```
Model Weights : [ 2.06224354 -1.83122882  4.06319327  1.74237383 -1.831228
82  2.05871072
  0.74369364]
```

Modifying original data

In [14]:

```
print(np.random.rand(1)/100)
```

```
[0.00121151]
```

In [15]:

```
# X_d = [x+ (np.random.rand(1)/100) for]
X_mod = np.zeros_like(X_train)
for i in range(len(X_train)):
  for j in range(len(X_train[0])):
    X_mod[i][j] =  X_train[i][j] + (np.random.rand(1))
```

In [16]:

```
best_model.fit(X_mod,y_train)
```

Out[16]:

```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=T
rue,
              l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter
=1000,
              n_iter_no_change=5, n_jobs=None, penalty='l2', power_t=0.5,
              random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [17]:

```
best_model_edited_accuracy = accuracy_score(y_test,best_model.predict(X_test))
```

In [18]:

```
print("Model Weights :",best_model.coef_[0])
best_model_edited_weights= best_model.coef_[0]
```

```
Model Weights : [ 2.24095847 -3.2652303   4.86136624  1.42795158 -2.566159
5   2.37436443
  0.13434754]
```

Compare weights

In [19]:

```
# Difference in accuracy
print("Difference in accuracy : ",best_model_accuracy - best_model_edited_accuracy)
```

```
Difference in accuracy :  0.0
```

In [20]:

```
# absolute change in weights
print("Change in weights: ",np.abs(best_model_weights-best_model_edited_weights))
```

```
Change in weights:  [0.17871493 1.43400148 0.79817297 0.31442225 0.7349306
8 0.31565371
 0.6093461 ]
```

In [21]:

```
# top 4 features which have higher % change in weights
print(best_model_weights)
print(best_model_edited_weights)
```

```
[ 2.06224354 -1.83122882  4.06319327  1.74237383 -1.83122882  2.05871072
  0.74369364]
[ 2.24095847 -3.2652303   4.86136624  1.42795158 -2.5661595   2.37436443
  0.13434754]
```

In [22]:

```
# calculate percent change
percent_change = [ (np.abs(a-b)/np.abs(a))*100  for a,b in zip(best_model_weights,best_
model_edited_weights)]
percent_sort = np.argsort(percent_change)
top_4 = percent_sort[::-1][:4]
```

In [23]:

```
print("The top 4 features which had highest % change:")
for idx in top_4:
  print("%s with %.3f%% change"%(feature_labels[idx],percent_change[idx]))
```

```
The top 4 features which had highest % change:
w with 81.935% change
y with 78.308% change
2*y with 40.133% change
z with 19.644% change
```

Task 2 : Linear SVM

In [24]:

```
# alphas = list(np.logspace(1,4,num=10))
alphas = [0.0001,0.001,0.09,0.01,0.1,1,50,100,1000]
param = {"alpha" : alphas}

hyp_svm = GridSearchCV(SGDClassifier(loss="hinge"), param_grid=param,cv=5)
hyp_svm.fit(X_train,y_train)
```

Out[24]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=Fal
se,
                                     epsilon=0.1, eta0=0.0, fit_intercept=
True,
                                     l1_ratio=0.15, learning_rate='optima
l',
                                     loss='hinge', max_iter=1000,
                                     n_iter_no_change=5, n_jobs=None,
                                     penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True, tol=
0.001,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'alpha': [0.0001, 0.001, 0.09, 0.01, 0.1, 1, 50,
100,
                                   1000]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring=None, verbose=0)
```

In [25]:

```
print("Best value of alpha: " ,hyp_svm.best_params_)
```

```
Best value of alpha:  {'alpha': 0.09}
```

In [26]:

```
best_model_svm = SGDClassifier(loss = "hinge",alpha = 0.001)
```

Getting the weights with the original data

In [27]:

```
best_model_svm.fit(X_train,y_train)
```

Out[27]:

```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=T
rue,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='l
2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [28]:

```
# best_model_accuracy = accuracy_score(Y,best_model.predict(X))
# best_model_coef_ = best_model.coef_[0]
best_model_accuracy_svm = accuracy_score(y_test,best_model.predict(X_test))
```

In [29]:

```
print("Model Weights :",best_model_svm.coef_[0])
best_model_weights_svm = best_model_svm.coef_[0]
```

```
Model Weights : [ 3.7080206  -3.89749944  6.05389537  3.64225674 -3.897499
44  4.0089647
  0.13523995]
```

Modifying original data

In [30]:

```
# X_d = [x+ (np.random.rand(1)/100) for]
X_mod = np.zeros_like(X_train)
for i in range(len(X_train)):
  for j in range(len(X_train[0])):
    X_mod[i][j] =  X_train[i][j] + (np.random.rand(1))
```

In [31]:

```
best_model_svm.fit(X_mod,y_train)
```

Out[31]:

```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=T
rue,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge',
              max_iter=1000, n_iter_no_change=5, n_jobs=None, penalty='l
2',
              power_t=0.5, random_state=None, shuffle=True, tol=0.001,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [32]:

```
best_model_edited_accuracy_svm = accuracy_score(y_test,best_model_svm.predict(X_test))
```

In [33]:

```
print("Model Weights :",best_model_svm.coef_[0])
best_model_edited_weights_svm= best_model_svm.coef_[0]
```

```
Model Weights : [ 2.78976581 -2.03102938  4.53088393  3.07773338 -4.321406
72  3.39711635
  3.06039283]
```

Compare weights

In [34]:

```
# Difference in accuracy
print("Difference in accuracy : ",best_model_accuracy - best_model_edited_accuracy)
```

```
Difference in accuracy :  0.0
```

In [35]:

```
# absolute change in weights
print("Change in weights: ",np.abs(best_model_weights_svm-best_model_edited_weights))
```

```
Change in weights:  [1.46706213e+00 6.32269146e-01 1.19252913e+00 2.214305
16e+00
 1.33133994e+00 1.63460027e+00 8.92413656e-04]
```

In [36]:

```
# top 4 features which have higher % change in weights
print(best_model_weights_svm)
print(best_model_edited_weights_svm)
```

```
[ 3.7080206  -3.89749944  6.05389537  3.64225674 -3.89749944  4.0089647
  0.13523995]
[ 2.78976581 -2.03102938  4.53088393  3.07773338 -4.32140672  3.39711635
  3.06039283]
```

In [37]:

```
# calculate percent change
percent_change_svm = [ (np.abs(a-b)/np.abs(a))*100  for a,b in zip(best_model_weights_s
vm,best_model_edited_weights_svm)]
percent_sort_svm = np.argsort(percent_change_svm)
top_4_svm = percent_sort_svm[::-1][:4]
```

In [38]:

```
print("The top 4 features which had highest % change:")
for idx in top_4_svm:
  print("%s with %.3f%% change"%(feature_labels[idx],percent_change_svm[idx]))
```

```
The top 4 features which had highest % change:
w with 2162.935% change
y with 47.889% change
z with 25.158% change
x with 24.764% change
```

In [38]:

```

```

Observations

- We get the highest percentage deviation of weights for these features in case of SVM

Feature	Percentage Change
w	91.322%
z	63.757%
x*x	57.470%
y	28.886%

- We get the highest percentage deviation of weights for these features in case of Logistic Regression

Feature	Percentage Change
w	66.564%
y	45.096%
z	29.705%
2*y	27.908%

- In both cases feature 'w' had highest percentage deviation, which is a result of presence of multicolinearity
- If incase we would have picked 'w' as the most important or least important feature during training and ignored the presence of colinearity, then even if our dataset changed a little our previous obsercation about 'w' would be totally wrong as it can change by 91% in case of SVM as we observed in our experiment.

- In both the algorithms, we can say that the weight values change drastically even when a small change appears in the dataset which confirms that the data contains colinearity and hence we cant use the weights obtained for getting the feature importances.

In [38]:

```

```