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
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
import seaborn as sns
import matplotlib.pyplot as plt
```

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]:
```
data.shape
```

Out[4]:
```
(100, 8)
```

In [5]:
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

In [6]:
```
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.25,random_sta
te=16)
```

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 cel
l
    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 th
e 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_acc
uracy'
    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 th
e 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 Logistic Regression

1. Finding the Correlation between the features

In [7]:
```
# a. check the correlation between the features

data.corr()
```

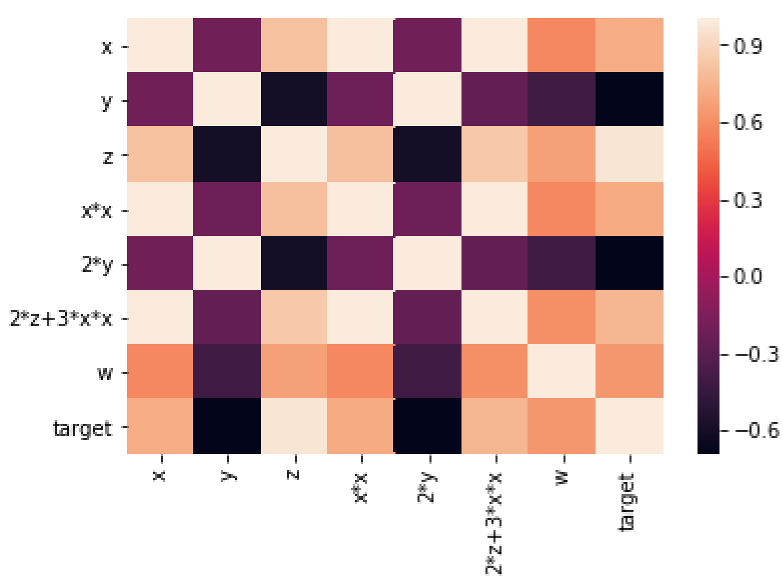
Out[7]:

	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 [8]:
```
# b. plot heat map of correlation matrix using seaborn heatmap

sns.heatmap(data.corr())
```

Out[8]: `<matplotlib.axes._subplots.AxesSubplot at 0xc22da20>`



2. Finding the best model for the given data

In [9]:
```
# a. Train Logistic regression on data(X,Y) that we have created in the above
 cell

cfg = SGDClassifier(loss='log')
cfg.fit(X_train,Y_train)
```

Out[9]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [10]:
```
# b. Find the best hyper prameter alpha with hyper parameter tuning using k-fo
ld cross validation

tuned_para = [{'alpha':[10**-4,10**-2,10**0,10**2,10**4]}]
model = GridSearchCV(SGDClassifier(loss='log',random_state = 1),tuned_para)
model.fit(X_train,Y_train)
print(model.best_estimator_)
```

```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=1, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [11]:
```
# 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'

best_model = SGDClassifier(loss='log',alpha=0.01)
```

3. Getting the weights with the original data

In [12]:
```
# a. train the 'best_model' with X, Y

best_model.fit(X_train,Y_train)
```

Out[12]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [13]:
```
# b. Check the accuracy of the model 'best_model_accuracy'

best_model_accuracy = best_model.score(X_test,Y_test)
print(best_model_accuracy)
```

```
1.0
```

In [14]:
```
# c. Get the weights W using best_model.coef_
W = best_model.coef_
print(W)
```

```
[[ 0.71392077 -0.84989874  1.83835164  0.63333854 -0.84989874  0.79195873
   0.47601577]]
```

4. Modifying original data

In [15]:
```
# a. Add a noise(order of 10^-2) to each element of X and get the new data set X' (X' = X + e)

X_train_new = X_train+0.01
```

In [16]:
```
# b. Train the same 'best_model' with data (X', Y)
best_model.fit(X_train_new,Y_train)
```

Out[16]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='log', max_iter=None,
              n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=None,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [17]:
```
# c. Check the accuracy of the model 'best_model_accuracy_edited'
best_model_accuracy_edited = best_model.score(X_test,Y_test)
print(best_model_accuracy_edited)
```

```
1.0
```

In [18]:
```
# d. Get the weights W' using best_model.coef_
W_error = best_model.coef_
print(W_error)
```

```
[[ 0.75015978 -0.88687805  1.70383348  0.69805751 -0.88687805  0.83399534
   0.47021967]]
```

5. Checking deviations in metric and weights

In [19]:
```
# a. find the difference between 'best_model_accuracy_edited' and 'best_model_
accuracy'
print(best_model_accuracy - best_model_accuracy_edited)
```

```
0.0
```

In [20]:
```
# b. find the absolute change between each value of W and W' ==> |(W-W')|
W_change = abs(W-W_error)
print(W_change)
```

```
[[0.03623901 0.03697931 0.13451815 0.06471897 0.03697931 0.0420366
  0.0057961 ]]
```

In [21]:
```
# c. print the top 4 features which have higher % change in weights compare to
the other feature
feat = list(data.columns)
percent_values = list((W_change*100/abs(W))[0])
values = sorted(zip(feat,percent_values),key = lambda x: x[1],reverse = True)
# print(values)
i = 0
print('Top 4 features which have higher % change in weights compare to the oth
er feature')
for x,y in enumerate(values):
    if i<4:
        print(y)
    i+=1
```

```
Top 4 features which have higher % change in weights compare to the other fea
ture
('x*x', 10.21870045461081)
('z', 7.317324378945202)
('2*z+3*x*x', 5.307928468448101)
('x', 5.076054953800743)
```

Task: 2 Linear SVM

2. Finding the best model for the given data

In [22]:
```
# a. Train Logistic regression on data(X,Y) that we have created in the above
 cell

cfg = SGDClassifier(loss='hinge')
cfg.fit(X_train,Y_train)
```

Out[22]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
              n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=None, shuffle=True, tol=None,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [23]:
```
# b. Find the best hyper prameter alpha with hyper parameter tuning using k-fo
ld cross validation

tuned_para = [{'alpha':[10**-4,10**-2,10**0,10**2,10**4]}]
model = GridSearchCV(SGDClassifier(loss='hinge',random_state = 1),tuned_para)
model.fit(X_train,Y_train)
print(model.best_estimator_)
```

```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=1, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [24]:
```
# 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'

best_model = SGDClassifier(loss='hinge',alpha=0.01,random_state = 1)
```

3. Getting the weights with the original data

In [25]:
```
# a. train the 'best_model' with X, Y

best_model.fit(X_train,Y_train)
```

Out[25]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
       power_t=0.5, random_state=1, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [26]:
```
# b. Check the accuracy of the model 'best_model_accuracy'

best_model_accuracy = best_model.score(X_test,Y_test)
print(best_model_accuracy)
```

```
1.0
```

In [27]:
```
# c. Get the weights W using best_model.coef_
W = best_model.coef_
print(W)
```

```
[[ 0.45215365 -0.51807836  1.48045548  0.42888775 -0.51807836  0.56474155
   0.32196128]]
```

4. Modifying original data

In [28]:
```
# a. Add a noise(order of 10^-2) to each element of X and get the new data set
X' (X' = X + e)

X_train_new = X_train+0.01
```

In [29]:
```
# b. Train the same 'best_model' with data (X', Y)
best_model.fit(X_train_new,Y_train)
```

Out[29]:
```
SGDClassifier(alpha=0.01, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
              l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=None,
              n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l2',
              power_t=0.5, random_state=1, shuffle=True, tol=None,
              validation_fraction=0.1, verbose=0, warm_start=False)
```

In [30]:
```
# c. Check the accuracy of the model 'best_model_accuracy_edited'
best_model_accuracy_edited = best_model.score(X_test,Y_test)
print(best_model_accuracy_edited)
```

```
1.0
```

In [31]:
```
# d. Get the weights W' using best_model.coef_
W_error = best_model.coef_
print(W_error)
```

```
[[ 0.73126318 -0.78528992  1.97252728  0.69455317 -0.78528992  0.86340519
   0.24176932]]
```

5. Checking deviations in metric and weights

In [32]:
```
# a. find the difference between 'best_model_accuracy_edited' and 'best_model_
accuracy'
print(best_model_accuracy - best_model_accuracy_edited)
```

```
0.0
```

In [33]:
```
# b. find the absolute change between each value of W and W' ==> |(W-W')|
W_change = abs(W-W_error)
print(W_change)
```

```
[[0.27910953 0.26721156 0.4920718  0.26566542 0.26721156 0.29866364
  0.08019196]]
```

In [34]:
```
# c. print the top 4 features which have higher % change in weights compare to
the other feature
feat = list(data.columns)
percent_values = list((W_change*100/abs(W))[0])
values = sorted(zip(feat,percent_values),key = lambda x: x[1],reverse = True)
print(values)
i = 0
print('Top 4 features which have higher % change in weights compare to the oth
er feature')
for x,y in enumerate(values):
    if i<4:
        print(y)
    i+=1
```

```
[('x*x', 61.94287977806593), ('x', 61.72891086334997), ('2*z+3*x*x', 52.88501
2958777835), ('y', 51.57744005458996), ('2*y', 51.57744005458996), ('z', 33.2
3786540840495), ('w', 24.90733150080833)]
Top 4 features which have higher % change in weights compare to the other fea
ture
('x*x', 61.94287977806593)
('x', 61.72891086334997)
('2*z+3*x*x', 52.885012958777835)
('y', 51.57744005458996)
```