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

In [6]:
```
%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
```

In [7]:
```
data = pd.read_csv("C:\\Users\\Akashraj D S\\Downloads\\8_LinearModels-2021071
```

In [8]:
```
data.head()
```

Out[8]:

	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 [9]:
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

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 t
he above cell
    b. Find the best hyper prameter alpha with hyper parameter tuning u
sing 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 be
st 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 'be
st_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

Finding the Correlation between the features

In [10]:
```
correlation = data.corr()
```

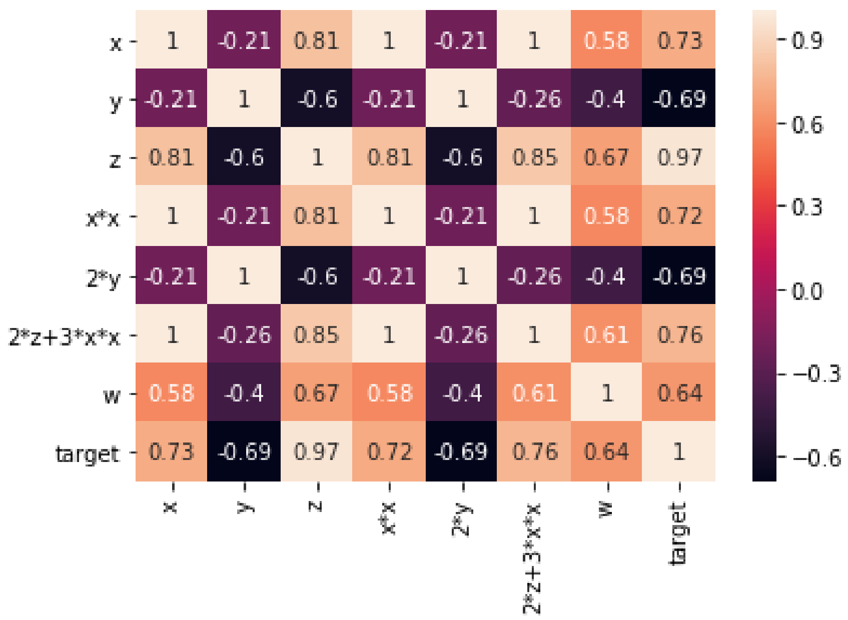
In [11]:
```
correlation
```

Out[11]:

	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 [12]:
```
sns.heatmap(correlation,annot=True)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x28b4d7b0408>



In [13]:
```
#Y and 2Y are highly correlated
#X and X*X are highly correlated
#2*Z+3*X*X is highly correlated with X and X*X
```

Logistic Regression

Finding the best model for given data

In [14]:
```
import numpy
alpha = numpy.logspace(0.001,1,5)
```

In [15]:
```
alpha
```

Out[15]:
```
array([ 1.00230524,  1.78135304,  3.16592046,  5.62665128, 10.        ])
```

In [16]:
```
params={'alpha':alpha}
clf=SGDClassifier(loss='log')
cross_val = GridSearchCV(estimator=clf,param_grid = params, cv=5)
cross_val.fit(X,Y)
```

Out[16]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
                                     epsilon=0.1, eta0=0.0, fit_intercept=Tru
e,
                                     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=0.00
1,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'alpha': array([ 1.00230524,  1.78135304,  3.1659204
6,  5.62665128, 10.        ])},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [17]:
```
pd.DataFrame(cross_val.cv_results_)
```

Out[17]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	param
0	0.002401	0.001854	0.000456	0.000456	1.00231	{'alpha 1.0023052380778996
1	0.001001	0.000002	0.000256	0.000392	1.78135	{'alpha 1.781353043008640
2	0.000601	0.000491	0.000401	0.000491	3.16592	{'alpha 3.165920463432237
3	0.000601	0.000491	0.000400	0.000490	5.62665	{'alpha 5.62665128067506
4	0.000738	0.000388	0.000198	0.000397	10	{'alpha': 10.0

In [18]:
```
best_model_lr = cross_val.best_estimator_
```

Getting the weights with original data

In [19]:
```python
best_model_lr.fit(X,Y)
```

Out[19]:
```
SGDClassifier(alpha=1.0023052380778996, 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=100
0,
              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 [20]:
```python
y_pred_lr = best_model_lr.predict(X)
```

In [21]:
```python
from sklearn.metrics import accuracy_score
best_model_accuracy = accuracy_score(Y,y_pred_lr)
best_model_accuracy
```

Out[21]:
```
0.99
```

In [22]:
```python
weights_without_noise = best_model_lr.coef_
```

Modifying original data

In [23]:
```python
X_dash = data.drop(['target'], axis=1)
X_dash = X_dash.add(0.01)
X_dash = X_dash.values
```

In [24]:
```python
best_model_lr.fit(X_dash,Y)
```

Out[24]:
```
SGDClassifier(alpha=1.0023052380778996, 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=100
0,
              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 [25]:
```python
y_pred_lr_with_noise = best_model_lr.predict(X_dash)
```

In [26]:
```python
best_model_accuracy_edited = accuracy_score(Y,y_pred_lr_with_noise)
best_model_accuracy_edited
```

Out[26]:
```
1.0
```

In [27]:
```python
weights_with_noise = best_model_lr.coef_
```

Checking deviations in metric and weights

In [28]:
```
difference_accuracy = best_model_accuracy - best_model_accuracy_edited
difference_accuracy
```

Out[28]:
```
-0.010000000000000009
```

In [29]:
```
values = abs(weights_without_noise - weights_with_noise)
```

In [30]:
```
values
```

Out[30]:
```
array([[0.00385742, 0.00116328, 0.00032523, 0.00447727, 0.00116328,
        0.00407881, 0.00054663]])
```

In [31]:
```
keys = data.columns[0:len(data.columns)-1]
```

In [32]:
```
keys
```

Out[32]:
```
Index(['x', 'y', 'z', 'x*x', '2*y', '2*z+3*x*x', 'w'], dtype='object')
```

In [33]:
```
d={}
for i in range(0,len(values[0])):
    d[keys[i]]=values[0][i]
d
```

Out[33]:
```
{'x': 0.0038574172414173324,
 'y': 0.0011632779234296842,
 'z': 0.0003252314872647655,
 'x*x': 0.004477268693702935,
 '2*y': 0.0011632779234296842,
 '2*z+3*x*x': 0.004078808976586579,
 'w': 0.0005466275841054802}
```

In [34]:
```
sorted_by_feature = sorted(d.items(), key = lambda kv: kv[1], reverse=True)
```

In [35]:
```
sorted_by_feature
```

Out[35]:
```
[('x*x', 0.004477268693702935),
 ('2*z+3*x*x', 0.004078808976586579),
 ('x', 0.0038574172414173324),
 ('y', 0.0011632779234296842),
 ('2*y', 0.0011632779234296842),
 ('w', 0.0005466275841054802),
 ('z', 0.0003252314872647655)]
```

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SVM

Finding the best model for given data

In [36]:
```
import numpy
alpha_svm = numpy.logspace(0.001,1,5)
```

In [37]:
```
alpha
```

Out[37]:
```
array([ 1.00230524,  1.78135304,  3.16592046,  5.62665128, 10.        ])
```

In [38]:
```
params={'alpha':alpha}
clf=SGDClassifier(loss='hinge')
cross_val_svm = GridSearchCV(estimator=clf,param_grid = params, cv=5)
cross_val_svm.fit(X,Y)
```

Out[38]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
                                     epsilon=0.1, eta0=0.0, fit_intercept=Tru
e,
                                     l1_ratio=0.15, learning_rate='optimal',
                                     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=0.00
1,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='warn', n_jobs=None,
             param_grid={'alpha': array([ 1.00230524,  1.78135304,  3.1659204
6,  5.62665128, 10.        ])},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [39]:
```
pd.DataFrame(cross_val_svm.cv_results_)
```

Out[39]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha	param
0	0.001690	0.000588	0.000938	0.000539	1.00231	{'alpha 1.0023052380778996
1	0.001191	0.000394	0.000402	0.000493	1.78135	{'alpha 1.781353043008640
2	0.001648	0.000447	0.000056	0.000113	3.16592	{'alpha 3.165920463432237
3	0.001040	0.000077	0.000000	0.000000	5.62665	{'alpha 5.62665128067506
4	0.000600	0.000490	0.000210	0.000420	10	{'alpha': 10.0

In [40]:
```
best_model_svm = cross_val_svm.best_estimator_
```

Getting the weights with original data

In [41]:
```
best_model_svm.fit(X,Y)
```

Out[41]:
```
SGDClassifier(alpha=1.0023052380778996, 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=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 [42]:
```
y_pred_svm = best_model_svm.predict(X)
```

In [43]:
```
from sklearn.metrics import accuracy_score
best_model_accuracy_svm = accuracy_score(Y,y_pred_svm)
best_model_accuracy_svm
```

Out[43]:
```
1.0
```

In [44]:
```
weights_without_noise_svm = best_model_svm.coef_
```

Modifying original data

In [45]:
```
X_dash = data.drop(['target'], axis=1)
X_dash = X_dash.add(0.01)
X_dash_svm = X_dash.values
```

In [46]:
```
best_model_svm.fit(X_dash_svm,Y)
```

Out[46]:
```
SGDClassifier(alpha=1.0023052380778996, 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=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 [47]:
```
y_pred_svm_with_noise = best_model_svm.predict(X_dash_svm)
```

In [48]:
```
best_model_accuracy_svm_edited = accuracy_score(Y,y_pred_svm_with_noise)
best_model_accuracy_svm_edited
```

Out[48]:
```
1.0
```

In [49]:
```
weights_with_noise_svm = best_model_svm.coef_
```

Checking deviations in metric and weights

In [50]:
```
difference_accuracy_svm = best_model_accuracy_svm - best_model_accuracy_svm_edit
difference_accuracy_svm
```

Out[50]:
```
0.0
```

In [51]:
```
values_svm = abs(weights_without_noise_svm - weights_with_noise_svm)
```

In [52]:
```
d_svm={}
for i in range(0,len(values_svm[0])):
    d_svm[keys[i]]=values_svm[0][i]
d_svm
```

Out[52]:
```
{'x': 0.00085927662336438,
 'y': 0.0010573313722122002,
 'z': 0.00019098094162989243,
 'x*x': 0.0013565964789609142,
 '2*y': 0.0010573313722122002,
 '2*z+3*x*x': 0.0012425583672647234,
 'w': 0.0018825165417649 67}
```

In [53]:
```
sorted_by_feature_svm = sorted(d_svm.items(), key = lambda kv: kv[1], reverse=Tr
sorted_by_feature_svm
```

Out[53]:
```
[('w', 0.001882516541764967),
 ('x*x', 0.0013565964789609142),
 ('2*z+3*x*x', 0.0012425583672647234),
 ('y', 0.0010573313722122002),
 ('2*y', 0.0010573313722122002),
 ('x', 0.00085927662336438),
 ('z', 0.00019098094162989243)]
```

Observations

If the features are said to be non-collinear, there should not be any differences between them. In both LR and SVM, it shows difference between weights. So they are collinear

In [ ]:
```

```