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

In [11]:
```python
%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 [12]:
```python
data = pd.read_csv('task_d.csv')
```

In [29]:
```python
data.head()
```

Out[29]:

	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 [30]:
```python
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 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

TASK 1. LOGISTIC REGRESSION.

1. **Finding the Correlation between the features**

   a. check the correlation between the features

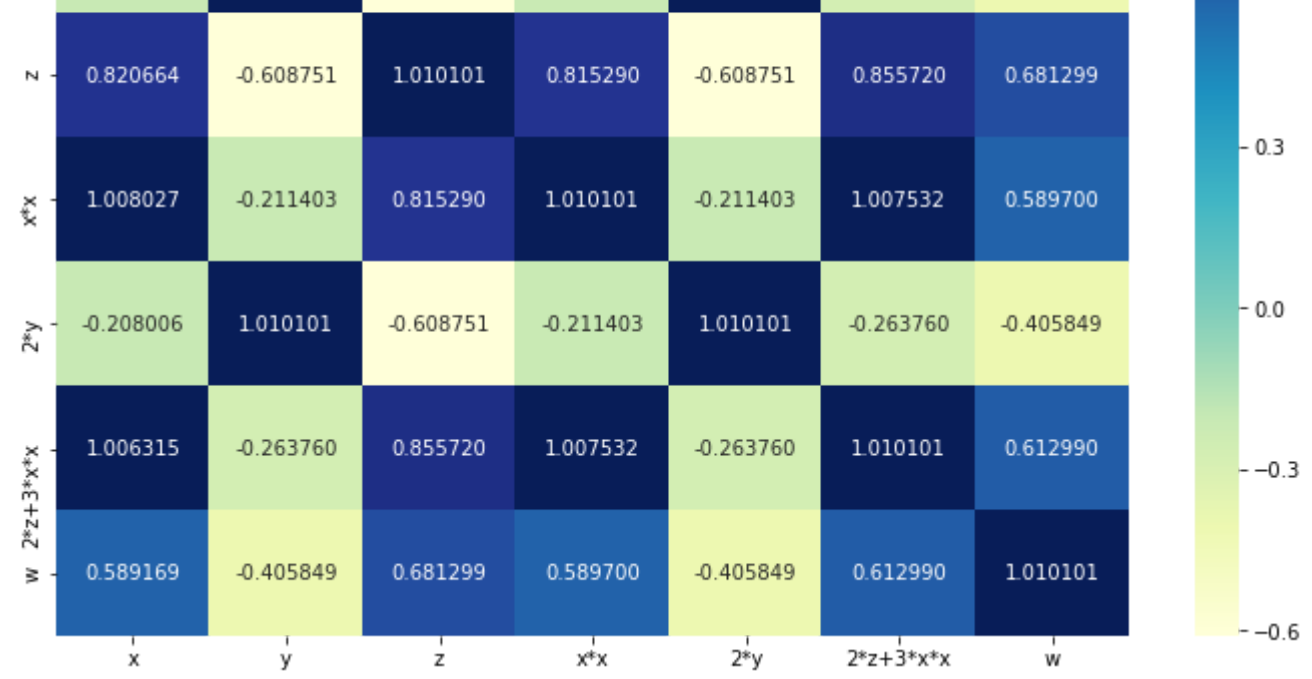
   b. plot heat map of correlation matrix using seaborn heatmap

In [33]:
```python
X_df = data.drop(['target'], axis=1)
covariance = pd.DataFrame(X_df.cov())
```

In [65]:
```python
plt.figure(figsize=(12,8))
sns.heatmap(covariance, annot=True, fmt="f", cmap="YlGnBu")
plt.plot()


'''
spearman_cov = data.corr(method='spearman')
plt.figure(figsize=(12,8))
sns.heatmap(spearman_cov, annot=True, fmt="f", cmap="YlGnBu")
plt.plot()
'''
```

Out[65]: '\nspearman_cov = data.corr(method=\'spearman\')\nplt.figure(figsize=(12,8))\nsns.heatmap(spearman_cov, annot=True, fmt="f", cmap="YlGnBu")\nplt.plot()\n'



1. **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

In [66]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn import metrics


X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.33, stratify = Y)


lr = LogisticRegression()


alphas = np.logspace(-2,3,10, endpoint=True, dtype='float')
param_grid = {'penalty':['l1','l2'],
              'C': np.logspace(-2,3,10, endpoint=True, dtype='float')
             }

clf = GridSearchCV(lr, param_grid=param_grid, cv=3)

clf.fit(X_train,y_train)


print("Best Parameters Are: ",clf.best_params_)
```

```
Best Parameters Are:  {'C': 0.03593813663804628, 'penalty': 'l2'}
```

In [67]:
```python
best_model = clf.best_estimator_
best_model
```

Out[67]: LogisticRegression(C=0.03593813663804628)

1. **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*

In [68]:
```python
best_model.fit(X_train,y_train)

y_pred = best_model.predict(X_test)

best_model_accuracy = metrics.accuracy_score(y_test, y_pred)
best_model_accuracy
```

Out[68]: 1.0

In [69]:
```python
weights = best_model.coef_
weights
```

Out[69]:
```
array([[ 0.25141997, -0.31088651,  0.40387112,  0.24372977, -0.31088651,
         0.26811928,  0.21457786]])
```

1. **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*

In [70]:
```python
err = np.random.uniform(0.01, 0.099)

X_dash = X + err
X_train, X_test, y_train, y_test = train_test_split(X_dash, Y, test_size = 0.33, stratify = Y)


best_model.fit(X_train,y_train)
y_pred = best_model.predict(X_test)
```

In [71]:
```python
best_model_accuracy_edited = metrics.accuracy_score(y_test, y_pred)
best_model_accuracy_edited
```

Out[71]: 1.0

In [72]:
```python
weights_edited = best_model.coef_
weights_edited
```

Out[72]:
```
array([[ 0.25906313, -0.30290895,  0.42063307,  0.25242117, -0.30290895,
         0.27796531,  0.20266497]])
```

1. **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

In [73]:
```python
best_model_accuracy_edited - best_model_accuracy
```

Out[73]: 0.0

In [74]:
```python
weight_change = weights - weights_edited
```

In [75]:
```python
import math
def absolute_val(vector):
    for i in vector:
        sq_sum = 0
        for j in i:
            sq_value = math.pow(j,2)
            sq_sum += sq_value
        abs_val = math.sqrt(sq_sum)
    return abs_val
```

In [76]:
```python
absolute_val(weight_change)
```

Out[76]: 0.02794755165503969

In [77]:
```python
features = data.drop('target', axis = 1)
features_names = features.columns
features_names = pd.DataFrame(features_names)
```

In [78]:
```python
features = data.drop('target', axis = 1)
features_names = pd.DataFrame(features.columns)

weights_df = pd.DataFrame(weights).T
weights_df['weights_edited'] = pd.DataFrame(weights_edited).T
weights_df.columns = ['weights', 'weights_edited']
weights_df['change'] = np.round((weights_df.weights - weights_df.weights_edited), 6)
weights_df['%change'] = np.round(((weights_df.weights - weights_df.weights_edited)/weights_df.weights)*100, 6)
weights_df = pd.merge(weights_df, features_names, left_index=True, right_index=True)
weights_df.columns = ['weights', 'weights_edited', 'change', '%change', 'feature']

weights_df['Rank'] = weights_df['%change'].rank(ascending=True)
weights_df = weights_df[['feature', 'weights','weights_edited','change','%change','Rank']]
weights_df
```

Out[78]:

	feature	weights	weights_edited	change	%change	Rank
0	x	0.251420	0.259063	-0.007643	-3.039998	4.0
1	y	-0.310887	-0.302909	-0.007978	2.566070	5.5
2	z	0.403871	0.420633	-0.016762	-4.150322	1.0
3	x*x	0.243730	0.252421	-0.008691	-3.565998	3.0
4	2*y	-0.310887	-0.302909	-0.007978	2.566070	5.5
5	2*z+3*x*x	0.268119	0.277965	-0.009846	-3.672257	2.0
6	w	0.214578	0.202665	0.011913	5.551778	7.0

Top features with highrst percentege change are:

In [49]:
```python
top_features = weights_df.nlargest(4, 'Rank')
top_features
```

Out[49]:

	feature	weights	weights_edited	change	%change	Rank
3	x*x	0.145937	0.138740	0.007197	4.931467	7.0
0	x	0.147764	0.140835	0.006929	4.689193	6.0
5	2*z+3*x*x	0.155488	0.148769	0.006719	4.321027	5.0
2	z	0.199976	0.197976	0.002000	1.000136	4.0

In [50]:
```python
print("Top features with highest percentege change are: {}".format(list(top_features.feature)))
```

```
Top features with highest percentege change are: ['x*x', 'x', '2*z+3*x*x', 'z']
```

OBSERVATIONS:

- From Covariance Matrix, it can be observed that some of the features are highly corelated as their corelation value is high. Example (y & 2y), (z, 2*z+3xx) (X*X, X) etc.
- After performing perbutation test top features with highest percentege change are: ['*xx', 'x', '2*z+3*xx*', 'z']. Which indicates that these features are collinear/multilinear.
- As we can expressed these features in terms of other in linear fashion i.e. we can establish linear relationship between these features. E.g. X*X is a square of X, their weights can be arbitairly changed hence we cannot used their weights directly as a feature inportance, therefore other methods such as "Forward Selection Method" can be recommendated in order to decide feature importance.

Task: 2 Linear SVM

1. Do the same steps (2, 3, 4, 5) we have done in the above task 1.

In [51]:
```python
from sklearn.svm import SVC

clf_svm = SVC(kernel='linear')
```

In [52]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.33, stratify = Y)


clf_svm = SVC(kernel='linear')


alphas = np.logspace(-2,3,10, endpoint=True, dtype='float')
param_grid = {'C': np.logspace(-2,3,10, endpoint=True, dtype='float')}

clf = GridSearchCV(clf_svm, param_grid=param_grid, cv=3)
clf.fit(X_train,y_train)

clf.best_params_

print("Best Parameters Are: ",clf.best_params_)
```

```
Best Parameters Are:  {'C': 0.01}
```

In [53]:
```python
best_model = clf.best_estimator_
best_model
```

Out[53]: SVC(C=0.01, kernel='linear')

In [54]:
```python
best_model.fit(X_train,y_train)

y_pred = best_model.predict(X_test)

best_model_accuracy = metrics.accuracy_score(y_test, y_pred)
best_model_accuracy
```

Out[54]: 1.0

In [55]:
```python
weights = best_model.coef_
weights
```

Out[55]:
```
array([[ 0.16146101, -0.20573303,  0.32174795,  0.15223195, -0.20573303,
         0.1758555 ,  0.1151547 ]])
```

In [56]:
```python
err = np.random.uniform(0.01, 0.099)

X_dash = X + err
X_train, X_test, y_train, y_test = train_test_split(X_dash, Y, test_size = 0.33, stratify = Y)


best_model.fit(X_train,y_train)
y_pred = best_model.predict(X_test)
```

In [57]:
```python
best_model_accuracy_edited = metrics.accuracy_score(y_test, y_pred)
best_model_accuracy_edited
```

Out[57]: 1.0

In [58]:
```python
weights_edited = best_model.coef_
weights_edited
```

Out[58]:
```
array([[ 0.16073594, -0.19641163,  0.31423158,  0.15059397, -0.19641163,
         0.17347383,  0.14159515]])
```

In [59]:
```python
best_model_accuracy_edited - best_model_accuracy
```

Out[59]: 0.0

In [60]:
```python
weight_change = weights - weights_edited
```

In [61]:
```python
absolute_val(weight_change)
```

Out[61]: 0.030630891044908456

In [62]:
```python
features = data.drop('target', axis = 1)
features_names = pd.DataFrame(features.columns)

weights_df = pd.DataFrame(weights).T
weights_df['weights_edited'] = pd.DataFrame(weights_edited).T
weights_df.columns = ['weights', 'weights_edited']
weights_df['change'] = np.round((weights_df.weights - weights_df.weights_edited), 6)
weights_df['%change'] = np.round(((weights_df.weights - weights_df.weights_edited)/weights_df.weights)*100, 6)
weights_df = pd.merge(weights_df, features_names, left_index=True, right_index=True)
weights_df.columns = ['weights', 'weights_edited', 'change', '%change', 'feature']

weights_df['Rank'] = weights_df['%change'].rank(ascending=True)
weights_df = weights_df[['feature', 'weights','weights_edited','change','%change','Rank']]
weights_df
```

Out[62]:

	feature	weights	weights_edited	change	%change	Rank
0	x	0.161461	0.160736	0.000725	0.449068	2.0
1	y	-0.205733	-0.196412	-0.009321	4.530824	6.5
2	z	0.321748	0.314232	0.007516	2.336107	5.0
3	x*x	0.152232	0.150594	0.001638	1.075977	3.0
4	2*y	-0.205733	-0.196412	-0.009321	4.530824	6.5
5	2*z+3*x*x	0.175855	0.173474	0.002382	1.354332	4.0
6	w	0.115155	0.141595	-0.026440	-22.960810	1.0

In [63]:
```python
top_features = weights_df.nlargest(4, 'Rank')
top_features
```

Out[63]:

	feature	weights	weights_edited	change	%change	Rank
1	y	-0.205733	-0.196412	-0.009321	4.530824	6.5
4	2*y	-0.205733	-0.196412	-0.009321	4.530824	6.5
2	z	0.321748	0.314232	0.007516	2.336107	5.0
5	2*z+3*x*x	0.175855	0.173474	0.002382	1.354332	4.0

In [64]:
```python
print("Top features with highest percentege change are: {}".format(list(top_features.feature)))
```

```
Top features with highest percentege change are: ['y', '2*y', 'z', '2*z+3*x*x']
```

OBSERVATIONS:

- From Covariance Matrix, it can be observed that some of the features are highly corelated as their corelation value is high. Example (y & 2y), (z, 2*z+3xx) (X*X, X) etc.
- After performing perbutation test top features with highest percentege change are: ['y', '2*y', 'z', '2*z+3*xx']. Which indicates that these features are collinear/multilinear.
- As we can expressed these features in terms of other in linear fashion i.e. we can establish linear relationship between these features. E.g. X*X is a square of X, their weights can be arbitairly changed hence we cannot used their weights directly as a feature inportance, therefore other methods such as "Forward Selection Method" can be recommendated in order to decide feature importance.
