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

In [1]:
```
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.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
import seaborn as sns
from prettytable import PrettyTable
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]:
```
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
```

Reference

https://online.stat.psu.edu/stat501/lesson/12/12.4

https://www.edupristine.com/blog/detecting-multicollinearity

Step 4: Review the Variance Inflation Factor.

A measure that is commonly available in software to help diagnose multicollinearity is the variance inflation factor (VIF).

Variance inflation factors (VIF) measures how much the variance of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related.

Use the following guidelines to interpret the VIF:

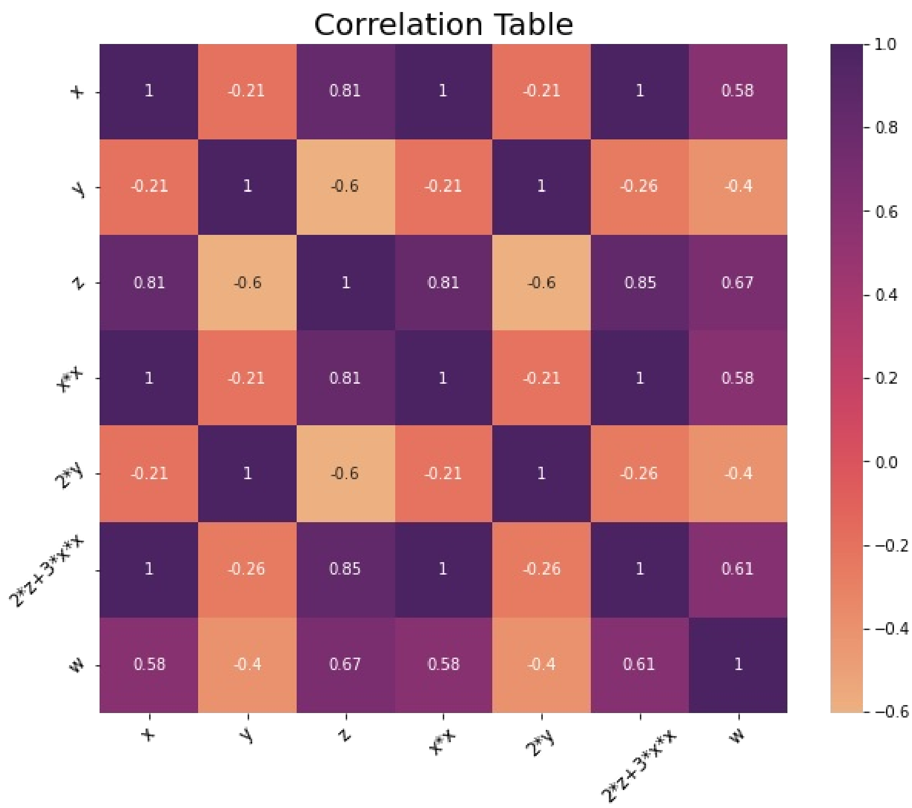
VIF	Status of predictors
VIF = 1	Not correlated
1 < VIF < 5	Moderately correlated
VIF > 5 to 10	Highly correlated

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 [5]:
```
# b. plot heat map of correlation matrix using seaborn heatmap
correlation = data.drop(['target'], axis=1).corr()

fig = plt.figure(figsize =(10,8))
fig = sns.heatmap(correlation, annot = True, fmt = '.2g', cmap = 'flare')
plt.title('Correlation Table', fontsize = 20)
plt.xticks(rotation = 45, fontsize = 12)
plt.yticks(rotation = 45, fontsize = 12)
plt.show()
```



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 [6]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html
# https://scikit-learn.org/stable/tutorial/statistical_inference/putting_together.html
# https://www.kaggle.com/funxexcel/p2-logistic-regression-hyperparameter-tuning

lr_model = LogisticRegression(max_iter = 100000, tol = 0.0001, penalty='l2')
param_grid = {'C': np.logspace(-4, 4, 5)}
model = GridSearchCV(lr_model, param_grid, n_jobs = -1, cv = 5)

model.fit(X, Y)

print(f'Best Parameters : {model.best_params_}')
# print(model.best_estimator_)

lr_best_C = model.best_params_['C']

best_model = LogisticRegression(max_iter = 100000, tol = 0.0001, penalty='l2', C = lr_best_C)
```

```
Best Parameters : {'C': 0.0001}
```

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 [7]:
```
best_model.fit(X, Y)

best_model_accuracy = best_model.score(X, Y)
print(f'Best model Avg. accuracy : {best_model_accuracy}')

best_weights = best_model.coef_
print(f"Best model wights W : {best_weights}")
```

```
Best model Avg. accuracy : 1.0
Best model wights W : [[ 0.0035963  -0.00341973  0.00479983  0.00355269 -0.00341973  0.00377695
   0.00316971]]
```

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 [8]:
```
# a. Add a noise(order of 10^-2) to each element of X
X_ = X + (10**-2)

# b. Train the same 'best_model' with data (X', Y)
best_model_noicy = LogisticRegression(max_iter = 100000, tol = 0.0001, penalty='l2', C = lr_best_C)
best_model_noicy.fit(X_, Y)

# c. Check the accuracy of the model 'best_model_accuracy_edited'
best_model_accuracy_edited = best_model_noicy.score(X_, Y)
print(f'Best model Avg. accuracy : {best_model_accuracy_edited}')

# d. Get the weights W' using best_model.coef_
best_model_noicy_weights = best_model_noicy.coef_
print(f"Best model wights W' : {best_model_noicy_weights}")
```

```
Best model Avg. accuracy : 1.0
Best model wights W' : [[ 0.00359617 -0.00341988  0.00480004  0.00355254 -0.00341988  0.00377683
   0.00316958]]
```

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 [9]:
```
# a. find the difference between 'best_model_accuracy_edited' and 'best_model_accuracy'
difference = best_model_accuracy_edited - best_model_accuracy
print(f"Difference between 'best_model_accuracy_edited' and 'best_model_accuracy' : {difference}")

# b. find the absolute change between each value of W and W' ==> |(W-W')|
abs_weight_difference = abs(best_weights - best_model_noicy_weights)
print(f'\nAbsolute weights differences : {abs_weight_difference}')

# c. print the top 4 features which have higher % change in weights compare to the other feature
abs_weight_diff_per  = abs_weight_difference*100
lr_top_4_feature = np.argsort(abs_weight_diff_per)[:,:4]

print(f'\nTop 4 Features indices are : {lr_top_4_feature[0]}')
print(f'\nCorresponding column names are : {[col for col in data.columns[lr_top_4_feature][0]]}')
```

```
Difference between 'best_model_accuracy_edited' and 'best_model_accuracy' : 0.0

Absolute weights differences : [[1.30431323e-07 1.45321783e-07 2.04625934e-07 1.53887588e-07
  1.45321783e-07 1.13731171e-07 1.22541126e-07]]

Top 4 Features indices are : [5 6 0 1]

Corresponding column names are : ['2*z+3*x*x', 'w', 'x', 'y']
```

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

1. Finding the best model for the given data

In [10]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html

svc_model = LinearSVC(max_iter = 100000, tol = 0.0001, penalty='l2')
param_grid = {'C': np.logspace(-4, 4, 5)}
scv_model = GridSearchCV(svc_model, param_grid, n_jobs = -1, cv = 5)

scv_model.fit(X, Y)

print(f'Best Parameters : {scv_model.best_params_}')
# print(model.best_estimator_)

svc_best_C = scv_model.best_params_['C']

svc_best_model = LogisticRegression(max_iter = 10000, tol = 0.0001, penalty='l2', C = svc_best_C)
```

```
Best Parameters : {'C': 0.0001}
```

1. Getting the weights with the original data

In [11]:
```
svc_best_model.fit(X, Y)

svc_best_model_accuracy = svc_best_model.score(X, Y)
print(f'Best model Avg. accuracy : {svc_best_model_accuracy}')

svc_best_weights = svc_best_model.coef_
print(f"Best model wights 'W' : {svc_best_weights}")
```

```
Best model Avg. accuracy : 1.0
Best model wights 'W' : [[ 0.0035963  -0.00341973  0.00479983  0.00355269 -0.00341973  0.00377695
   0.00316971]]
```

1. Modifying original data

In [12]:
```
# b. Train the same 'best model' with data (X', Y)
```

```
svc_best_model_noicy = LogisticRegression(max_iter = 100000, tol = 0.0001, penalty='l2', C = svc_best_C)
svc_best_model_noicy.fit(X_, Y)

# c. Check the accuracy of the model 'best_model_accuracy_edited'
svc_best_model_accuracy_edited = svc_best_model_noicy.score(X_, Y)
print(f'Best model Avg. accuracy : {svc_best_model_accuracy_edited}')

# d. Get the weights W' using best_model.coef_
scv_best_model_noicy_weights = svc_best_model_noicy.coef_
print(f"Best model wights 'W' : {scv_best_model_noicy_weights}")
```

```
Best model Avg. accuracy : 1.0
Best model wights 'W' : [[ 0.00359617 -0.00341988  0.00480004  0.00355254 -0.00341988  0.00377683
   0.00316958]]
```

1. Checking deviations in metric and weights

In [13]:

```
# a. find the difference between 'best_model_accuracy_edited' and 'best_model_accuracy'
difference_svc = svc_best_model_accuracy_edited - svc_best_model_accuracy
print(f"Difference between 'best_model_accuracy_edited' and 'best_model_accuracy' : {difference_svc}")

# b. find the absolute change between each value of W and W' ==> |(W-W')|
abs_svc_weight_difference = abs(svc_best_weights - scv_best_model_noicy_weights)
print(f'\nAbsolute weights differences : {abs_svc_weight_difference }')

# c. print the top 4 features which have higher % change in weights compare to the other feature
abs_svc_weight_diff_per  = abs_svc_weight_difference*100
svc_top_4_feature = np.argsort(abs_svc_weight_diff_per)[:,:4]

print(f'\nTop 4 Features indices are : {svc_top_4_feature[0]}')
print(f'\nCorresponding column names are : {[col for col in data.columns[svc_top_4_feature][0]]}')
```

```
Difference between 'best_model_accuracy_edited' and 'best_model_accuracy' : 0.0

Absolute weights differences : [[1.30431323e-07 1.45321783e-07 2.04625934e-07 1.53887588e-07
  1.45321783e-07 1.13731171e-07 1.22541126e-07]]

Top 4 Features indices are : [5 6 0 1]

Corresponding column names are : ['2*z+3*x*x', 'w', 'x', 'y']
```

In [14]:

```
p_table = PrettyTable()

p_table.field_names = ['', "Best 'C'",'Accuracy', 'Column Indices']
p_table.add_row(['Logistic regression', lr_best_C, best_model_accuracy, '-'])
p_table.add_row(['Logistic regression + Noice', lr_best_C, best_model_accuracy_edited, lr_top_4_feature[0]])
p_table.add_row(['Linear SVM', svc_best_C, svc_best_model_accuracy, '-'])
p_table.add_row(['Linear SVM + Noice', svc_best_C, svc_best_model_accuracy_edited, svc_top_4_feature[0]])
```

Observation

In [15]:

```
print(p_table)
```

```
+-----------------------------+----------+----------+----------------+
|                             | Best 'C' | Accuracy | Column Indices |
+-----------------------------+----------+----------+----------------+
|     Logistic regression     |  0.0001  |   1.0    |       -        |
| Logistic regression + Noice |  0.0001  |   1.0    |   [5 6 0 1]    |
|          Linear SVM         |  0.0001  |   1.0    |       -        |
|      Linear SVM + Noice     |  0.0001  |   1.0    |   [5 6 0 1]    |
+-----------------------------+----------+----------+----------------+
```

- Multi colinearity is not affecting the accuracy of the model dataset for both linear and SVM model.
- The noice have no impact on accuracy values

```
difference = best_model_accuracy_edited - best_model_accuracy
print(f"Difference between 'best_model_accuracy_edited' and 'best_model_accuracy' : {difference}")
>>> Difference between 'best_model_accuracy_edited' and 'best_model_accuracy' : 0.0
```

- By observing Top4 features with maximum abs percentage weights difference of original data and noisy data we can conclude that features having multi colinearity and high corelation is affected by outliers (added noise) and coefficient are changing for those features.

```
print(f'Top 4 Features indices are : {top_4_feature[0]}')
>>> Top 4 Features indices are : [5 6 0 1]
```

- Both linear and SVM model returns the same column names