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

```
%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, LogisticRegression
from sklearn.model_selection import GridSearchCV
import seaborn as sns
sns.set()
import matplotlib.pyplot as plt
```

```
#Mounting Google drive folder
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive/My Drive/Appliedai colab/Assignment 8 - Linear models/
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.a

Enter your authorization code:
··········
Mounted at /content/drive
/content/drive/My Drive/Appliedai colab/Assignment 8 - Linear models
```

```
data = pd.read_csv('task_d.csv')
```

```
data.head()
```

| | 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 |

```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          rand
    c. Creat a new Logistic regression with the best alpha(search for how to get the best hyper parameter value), name the best mod

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**

# 1. Finding the Correlation between the features

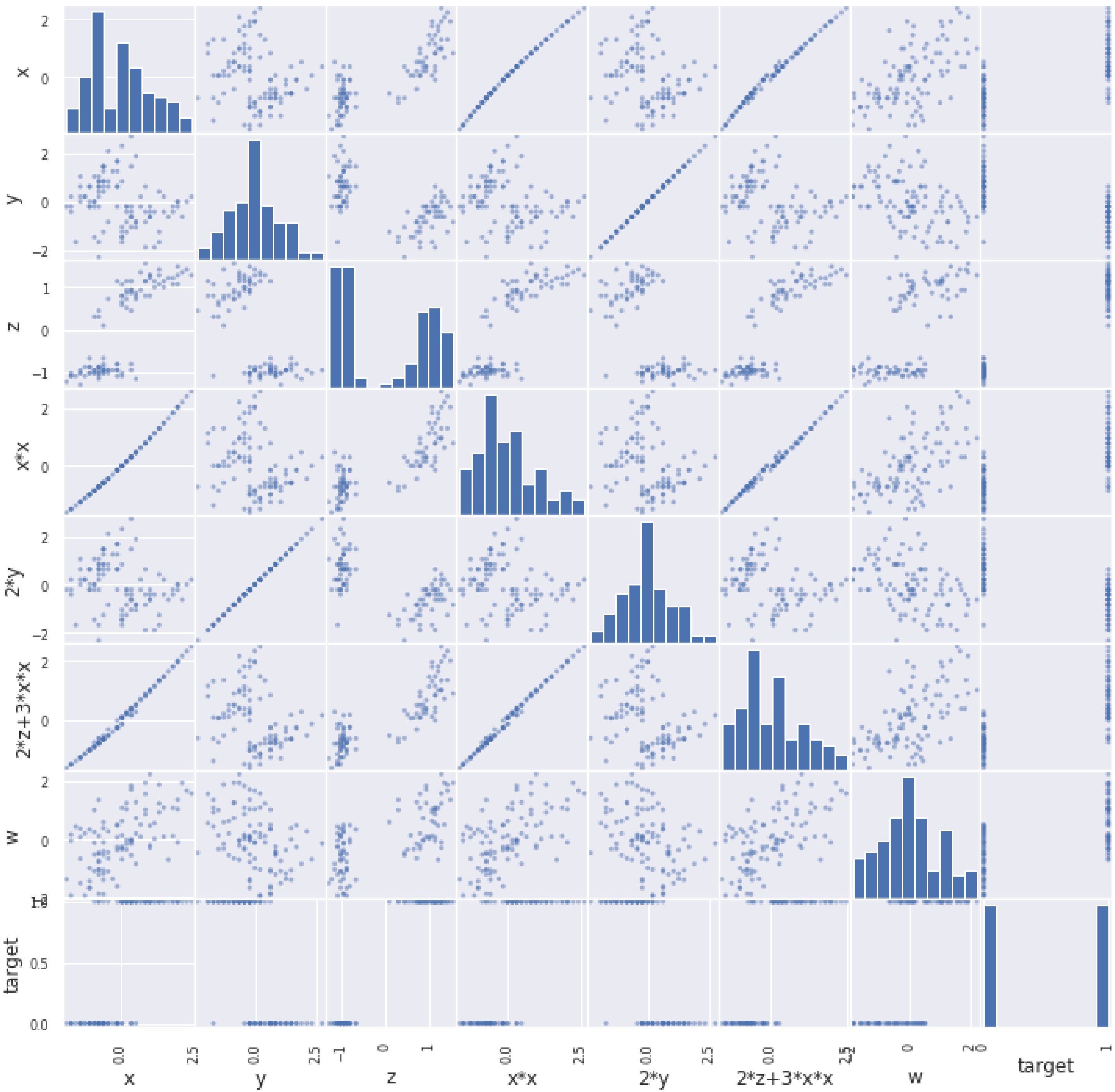
## a. check the correlation between the features

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

| | 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 |

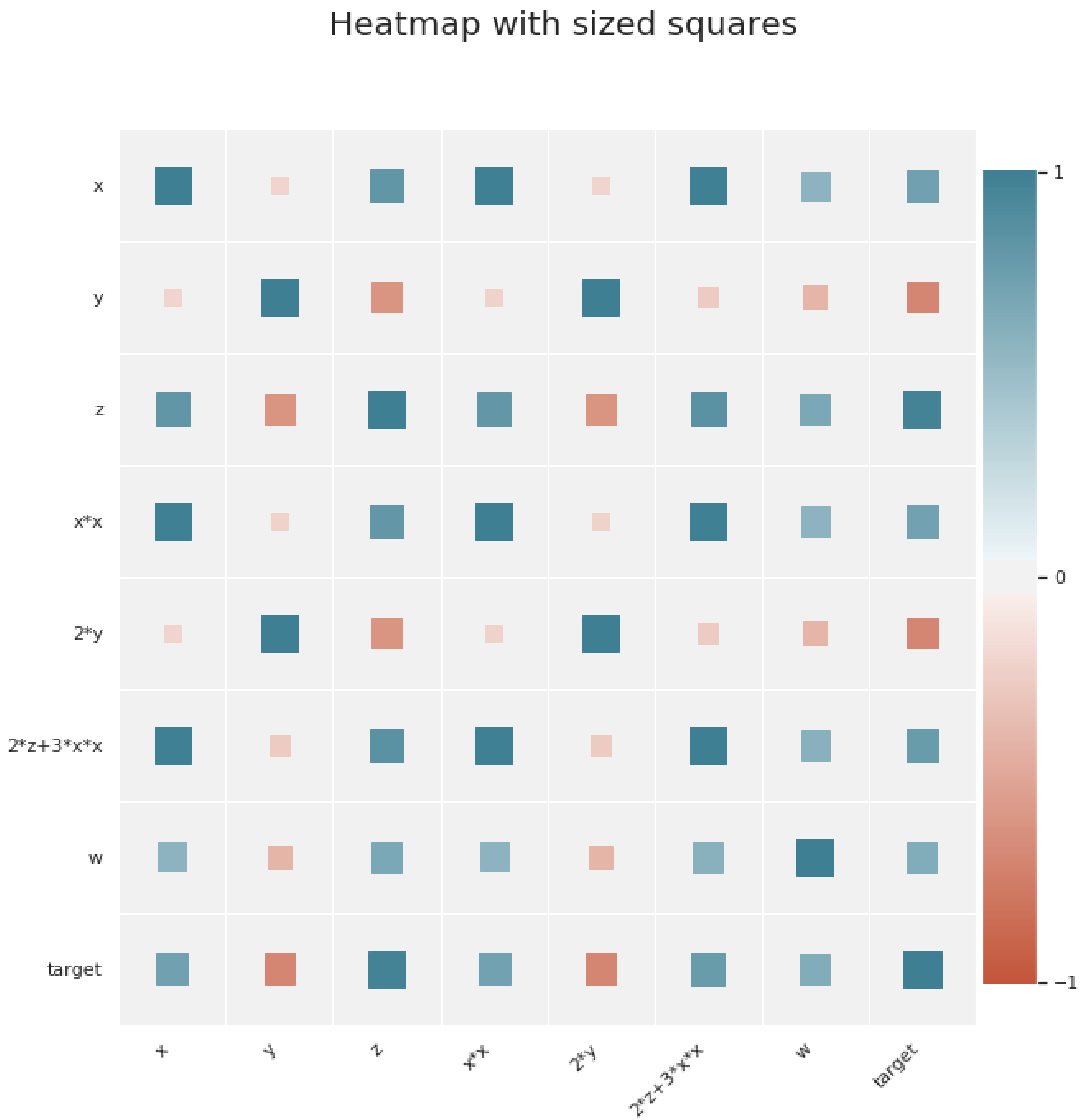
## b. plot heat map of correlation matrix using seaborn heatmap

```
pd.plotting.scatter_matrix(data, figsize=(12, 12))
plt.show()
```


x
y
z
x*x
2*y
2*z+3*x*x
w
target

```
#https://www.geeksforgeeks.org/download-anything-to-google-drive-using-google-colab/
path = '/content/drive/My Drive/Appliedai colab/Assignment 8 - Linear models/'
import requests
file_url = "https://raw.githubusercontent.com/drazenz/heatmap/master/heatmap.py"

r = requests.get(file_url, stream = True)

with open(path+"heatmap.py", "wb") as file:
    for block in r.iter_content(chunk_size = 1024):
         if block:
             file.write(block)
```

```
#https://towardsdatascience.com/better-heatmaps-and-correlation-matrix-plots-in-python-41445d0f2bec
#https://github.com/drazenz/heatmap/blob/master/heatmap.py

from heatmap import heatmap, corrplot

plt.figure(figsize=(10, 10)).suptitle('Heatmap with sized squares', fontsize=20);
corrplot(corr)
```



Heatmap with sized squares
x
y
z
x*x
2*y
2*z+3*x*x
w
target
x
y
z
x*x
2*y
2*z+3*x*x
w
target
1
0
−1

# 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

```
clf = LogisticRegression().fit(X, Y)
```

## 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)

```
parameters = {'C':[0.001, 0.01, 0.1, 1, 10, 100], 'solver':["newton-cg", "lbfgs", "liblinear", "sag", "saga"]}
lr = LogisticRegression()
clf = GridSearchCV(lr, parameters, cv=5, n_jobs = -1, verbose = 2)
clf.fit(X, Y)
clf.best_estimator_
```

```
Fitting 5 folds for each of 30 candidates, totalling 150 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done 126 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done 150 out of 150 | elapsed:    1.7s finished
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='newton-cg', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
pd.DataFrame(clf.cv_results_).head()
```

| | mean_fit_time | std_fit_time | mean_score_time | std_score_time | param_C | param_solver | params | split0_test_score | split1_test_ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.004715 | 0.000987 | 0.000491 | 0.000057 | 0.001 | newton-cg | {'C': 0.001, 'solver': 'newton-cg'} | 1.0 | |
| **1** | 0.007045 | 0.004496 | 0.000432 | 0.000048 | 0.001 | lbfgs | {'C': 0.001, 'solver': 'lbfgs'} | 1.0 | |
| **2** | 0.000757 | 0.000156 | 0.000397 | 0.000026 | 0.001 | liblinear | {'C': 0.001, 'solver': 'liblinear'} | 1.0 | |
| **3** | 0.001411 | 0.000189 | 0.000791 | 0.000813 | 0.001 | sag | {'C': 0.001, 'solver': 'sag'} | 1.0 | |
| **4** | 0.001396 | 0.000122 | 0.000405 | 0.000029 | 0.001 | saga | {'C': 0.001, 'solver': 'saga'} | 1.0 | |

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 = LogisticRegression(C = 0.001, penalty = 'l2', solver = 'newton-cg')
```

# 3. Getting the weights with the original data

## a. train the 'best_model' with X, Y

```
best_model.fit(X, Y)
```

```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='newton-cg', tol=0.0001, verbose=0,
                   warm_start=False)
```

## b. Check the accuracy of the model 'best_model_accuracy'

```
best_model_accuracy = best_model.score(X, Y)
```

## c. Get the weights W using best_model.coef_

```
W = 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)

```
X.shape
```

```
(100, 7)
```

```
# creating a noise with the same dimension as the dataset (100,7)
```

```
# source - https://stackoverflow.com/a/46093600/9292995
noise = np.random.normal(0.01, 0.01, [100,7])
```

```
X_noise = X + noise
```

### b. Train the same 'best_model' with data (X', Y)

```
best_model.fit(X_noise, Y)
```

```
LogisticRegression(C=0.001, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='newton-cg', tol=0.0001, verbose=0,
                   warm_start=False)
```

### c. Check the accuracy of the model 'best_model_accuracy_edited'

```
best_model_accuracy_edited = best_model.score(X_noise,Y)
```

### d. Get the weights W' using best_model.coef_

```
W_noise = best_model.coef_
```

## 5. Checking deviations in metric and weights

### a. find the difference between 'best_model_accuracy_edited' and 'best_model_accuracy'

```
best_model_accuracy_edited - best_model_accuracy
```

```
0.0
```

## b. find the absolute change between each value of W and W' ==> |(W-W')|

```
abs(W - W_noise)
```

```
array([[8.96288255e-05, 8.94807891e-05, 4.66496288e-05, 1.19166451e-05,
        9.25985964e-05, 1.01621256e-05, 4.11553437e-05]])
```

## c. print the top 4 features which have higher % change in weights compare to the other feature

```
weight_change = abs(W - W_noise)
top_4_weights = -np.sort(-abs(weight_change))[0][0:4] #source - https://stackoverflow.com/a/55496638/9292995
```

```
weight_list = weight_change.tolist()[0]
print("top 4 features which have higher % change in weights compare to the other feature:")
for i in top_4_weights:
  print('feature',weight_list.index(i)+1)
```

```
top 4 features which have higher % change in weights compare to the other feature:
feature 5
feature 1
feature 2
feature 3
```