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

In [39]:
```
%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
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
```

In [40]:
```
data = pd.read_csv('task_d.csv')
```

In [41]:
```
data.head()
```

Out[41]:

	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 [42]:
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

In [43]:
```
data.head()
```

Out[43]:

	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 [44]:
```
data=data.drop('target', axis = 1)
```

In [45]:
```
data.head()
```

Out[45]:

	x	y	z	x*x	2*y	2*z+3*x*x	w
0	-0.581066	0.841837	-1.012978	-0.604025	0.841837	-0.665927	-0.536277
1	-0.894309	-0.207835	-1.012978	-0.883052	-0.207835	-0.917054	-0.522364
2	-1.207552	0.212034	-1.082312	-1.150918	0.212034	-1.166507	0.205738
3	-1.364174	0.002099	-0.943643	-1.280666	0.002099	-1.266540	-0.665720
4	-0.737687	1.051772	-1.012978	-0.744934	1.051772	-0.792746	-0.735054

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 cro
ss 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 'be
st_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_accura
cy'
    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
```

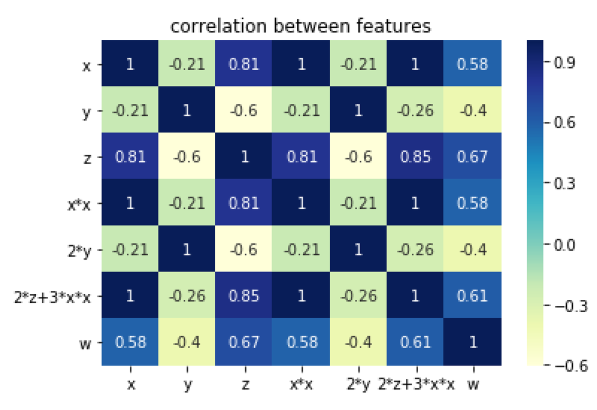
Task: 2 Linear SVM

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

Find correlation between features

In [46]:
```
##https://www.geeksforgeeks.org/how-to-create-a-seaborn-correlation-heatmap-in-python/
correlation=data.corr()
```

In [47]:
```
dataplot = sns.heatmap(correlation, cmap="YlGnBu", annot=True)
plt.title("correlation between features")
plt.show()
```



Finding the best model for the given data

In [48]:
```
##https://stackoverflow.com/questions/19018333/gridsearchcv-on-logisticregression-in-scikit-
learn
alpha=np.logspace(0.001,0.1,1,5,8)
A=alpha
#print(A)
param_grid = {'C': A }
model = LogisticRegression(random_state=42)
Search=GridSearchCV(model,param_grid , cv=5)
Search.fit(X,Y)
```

Out[48]:
```
GridSearchCV(cv=5, estimator=LogisticRegression(random_state=42),
             param_grid={'C': array([1.00208161])})
```

In [49]:
```
Search.best_params_
```

Out[49]:
```
{'C': 1.0020816050796328}
```

Getting the weights with the original data

In [50]:
```
best_model=LogisticRegression(C=1.0020816050796328,random_state=42)
best_model.fit(X,Y)
weight = best_model.coef_[0]
print("weight:",weight)
```

```
weight: [ 0.72329758 -0.90390578  1.68356004  0.66756968 -0.90390578  0.80407875
  0.50979515]
```

In [51]:
```
##https://www.codegrepper.com/code-examples/python/how+to+get+test+accuracy+in+logistic+regr
ession+model+in+python
from sklearn.metrics import accuracy_score
pred = best_model.predict(X)
best_model_accuracy=(accuracy_score(Y, pred))
print(best_model_accuracy)
```

```
1.0
```

Modifying original data

In [52]:
```
Xm = X+0.01
```

In [53]:
```
best_model.fit(Xm,Y)
```

Out[53]:
```
LogisticRegression(C=1.0020816050796328, random_state=42)
```

In [54]:
```
pred_mod = best_model.predict(Xm)
best_model_accuracy_edited = (accuracy_score(Y, pred_mod))
print(best_model_accuracy_edited)
```

```
1.0
```

In [55]:
```
weight_mod = best_model.coef_[0]
print("weight:",weight_mod)
```

```
weight: [ 0.72329329 -0.90390618  1.68356007  0.66757059 -0.90390618  0.80407955
  0.50979151]
```

Checking deviations in metric and weights

In [56]:
```
Acc_diff=(best_model_accuracy_edited-best_model_accuracy)
Acc_diff
```

Out[56]:
```
0.0
```

In [57]:
```
Wt_diff = weight - weight_mod
Wt_diff
```

Out[57]:
```
array([ 4.28394267e-06,  3.98921538e-07, -3.31293399e-08, -9.05736003e-07,
        3.98921538e-07, -8.00066609e-07,  3.63705858e-06])
```

In [58]:
```
percent_change=[]
for i in range(len(data.columns)):
    percent=100*(Wt_diff[i]/weight[i])
    percent_change.append(percent)
```

In [59]:
```
print(percent_change)
```

```
[0.0005922794177936326, -4.413308829825735e-05, -1.967814583107191e-06, -0.000135676622944295
6, -4.413308826140982e-05, -9.950102624229029e-05, 0.0007134353067270253]
```

In [61]:
```
##https://www.skytowner.com/explore/numpy_argpartition_method
top_four = np.argpartition(percent_change,2)[-4:]
print(top_four)
Top_four=(data.columns[top_four])
print("top four ", list(reversed(Top_four)))
```

```
[0 4 2 6]
top four  ['w', 'z', '2*y', 'x']
```

Task2

In [62]:
```
alpha=np.logspace(0.001,0.1,1,5,8)
A=alpha
#print(A)
param_grid = {'C': A }
model_SVM = SVC(kernel="linear",random_state=42)
Search=GridSearchCV(model_SVM,param_grid , cv=5)
Search.fit(X,Y)
```

Out[62]:
```
GridSearchCV(cv=5, estimator=SVC(kernel='linear', random_state=42),
             param_grid={'C': array([1.00208161])})
```

In [63]:
```
Search.best_params_
```

Out[63]:
```
{'C': 1.0020816050796328}
```

In [64]:
```
best_model=SVC(kernel="linear",C=1.0020816050796328,random_state=42)
best_model.fit(X,Y)
weight = best_model.coef_[0]
print("weight:",weight)
```

```
weight: [ 0.42059793 -0.36090175  1.04442829  0.34263578 -0.36090175  0.43447147
  0.17056102]
```

In [65]:
```
from sklearn.metrics import accuracy_score
pred = best_model.predict(X)
best_model_accuracy=(accuracy_score(Y, pred))
print(best_model_accuracy)
```

```
1.0
```

In [66]:
```
Xm = X+0.01
best_model.fit(Xm,Y)
```

Out[66]:
```
SVC(C=1.0020816050796328, kernel='linear', random_state=42)
```

In [67]:
```
pred_mod = best_model.predict(Xm)
best_model_accuracy_edited = (accuracy_score(Y, pred_mod))
print(best_model_accuracy_edited)
```

```
1.0
```

In [72]:
```
weight_mod = best_model.coef_[0]
print("weight:",weight_mod)
```

```
weight: [ 0.42059794 -0.36090176  1.04442829  0.34263578 -0.36090176  0.43447147
  0.17056109]
```

In [73]:
```
Acc_diff=(best_model_accuracy_edited-best_model_accuracy)
Acc_diff
```

Out[73]:
```
0.0
```

In [74]:
```
Wt_diff = weight - weight_mod
Wt_diff
```

Out[74]:
```
array([-7.43466311e-09,  7.75015052e-09,  3.76124021e-10,  9.42294021e-11,
        7.75015041e-09,  1.30217614e-10, -6.79247945e-08])
```

In [75]:
```
percent_change=[]
for i in range(len(data.columns)):
    percent=100*(Wt_diff[i]/weight[i])
    percent_change.append(percent)

print(percent_change)
```

```
[-1.7676413861213756e-06, -2.1474405290860614e-06, 3.601243126721183e-08, 2.7501331521809104e
-08, -2.1474404983235887e-06, 2.9971499620355126e-08, -3.982433563470589e-05]
```

In [78]:
```
top_four = np.argpartition(percent_change,1)[-4:]
print(top_four)
Top_four=(data.columns[top_four])
print("top four ", list(reversed(Top_four)))
```

```
[3 4 5 0]
top four  ['x', '2*z+3*x*x', '2*y', 'x*x']
```

1.After perturbation test, since there is no significant change in the weights , there is less chance of collinearity.

2.The weights chnge in the order of e-06 to e-08

3.Some features are correlated with others.

4.percentage changes of Linear SVM [-1.7676413861213756e-06, -2.1474405290860614e-06, 3.601243126721183e-08, 2.7501331521809104e-08, -2.1474404983235887e-06, 2.9971499620355126e-08, -3.982433563470589e-05]

5.Top 4 features=['x', '2z+3xx', '2y', 'x*x']

6.percentage changes of logistic regression [0.0005922794177936326, -4.413308829825735e-05, -1.967814583107191e-06, -0.0001356766229442956, -4.413308826140982e-05, -9.950102624229029e-05, 0.0007134353067270253]

7.Top 4 features = ['w', 'z', '2*y', 'x']