8_D

Importing libraries

In [12]:
```
%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
from sklearn.metrics import accuracy_score
```

Reading the dataset

In [13]:
```
data = pd.read_csv('task_d.csv')
```

In [14]:
```
data.head()
```

Out[14]:

	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

	x	y	z	x*x	2*y	2*z+3*x*x	w	target
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 [15]:
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

1. Finding the Correlation between the features

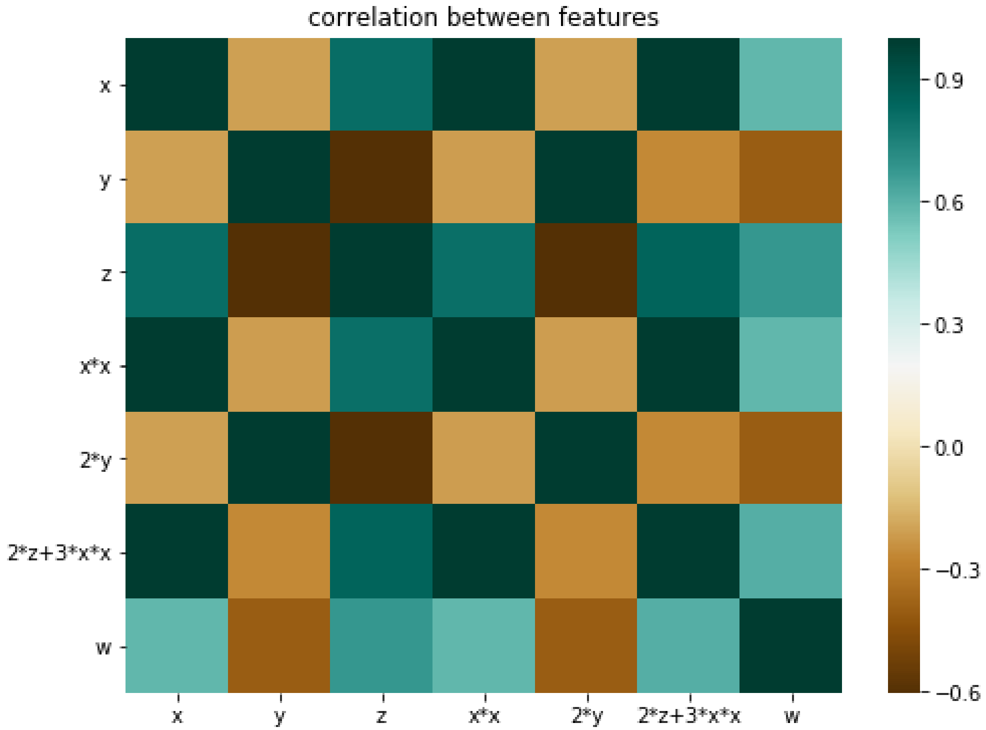
In [16]:
```
corr=data[data.columns[:-1]].corr()
corr
```

Out[16]:

	x	y	z	x*x	2*y	2*z+3*x*x	w
x	1.000000	-0.205926	0.812458	0.997947	-0.205926	0.996252	0.583277
y	-0.205926	1.000000	-0.602663	-0.209289	1.000000	-0.261123	-0.401790
z	0.812458	-0.602663	1.000000	0.807137	-0.602663	0.847163	0.674486
x*x	0.997947	-0.209289	0.807137	1.000000	-0.209289	0.997457	0.583803
2*y	-0.205926	1.000000	-0.602663	-0.209289	1.000000	-0.261123	-0.401790
2*z+3*x*x	0.996252	-0.261123	0.847163	0.997457	-0.261123	1.000000	0.606860
w	0.583277	-0.401790	0.674486	0.583803	-0.401790	0.606860	1.000000

In [17]:
```
plt.figure(figsize=(8,6))
plt.title("correlation between features")
sns.heatmap(corr, cmap="BrBG",
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24c2f177470>
```



Task: 1 Logistic Regression

In [18]:
```
alpha =  np.logspace(-5, 8, 10)
print(alpha)
param_grid={'C':alpha}
logreg = LogisticRegression()
```

```
[1.00000000e-05 2.78255940e-04 7.74263683e-03 2.15443469e-01
 5.99484250e+00 1.66810054e+02 4.64158883e+03 1.29154967e+05
 3.59381366e+06 1.00000000e+08]
```

2. Finding the best model for the given data

In [19]:
```
logreg = GridSearchCV(logreg, param_grid, cv=5)
```

In [20]:
```
logreg.fit(X,Y)
```

Out[20]:
```
GridSearchCV(cv=5, error_score='raise',
       estimator=LogisticRegression(C=1.0, class_weight=None, dual=Fals
e, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'C': array([1.00000e-05, 2.78256e-04, 7.74264e-03,
2.15443e-01, 5.99484e+00,
       1.66810e+02, 4.64159e+03, 1.29155e+05, 3.59381e+06, 1.00000e+0
8])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [21]:
```
logreg.best_params_
```

Out[21]:
```
{'C': 1e-05}
```

3. Getting the weights with the original data

In [22]:
```
best_model=LogisticRegression(C=1e-05)
```

In [23]:
```
best_model.fit(X,Y)
```

Out[23]:
```
LogisticRegression(C=1e-05, class_weight=None, dual=False, fit_intercep
t=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False)
```

In [24]:
```
predictions = best_model.predict(X)
```

In [25]:
```
accu=accuracy_score(Y, predictions)
print(accuracy_score(Y, predictions))
```

```
1.0
```

In [26]:
```
wei=best_model.coef_[0]
print(best_model.coef_)
```

```
[[ 0.00036369 -0.000345    0.00048449  0.00035933 -0.000345    0.000381
89
   0.00032048]]
```

4. Modifying original data

In [29]:
```
X_NEW=X+.01 # ADDING NOISE
```

In [30]:
```
updated_model=best_model.fit(X_NEW,Y)
```

In [31]:
```
prediction = best_model.predict(X_NEW)
```

In [32]:
```
new_accu=accuracy_score(Y, prediction)
print(accuracy_score(Y, prediction))
```

```
1.0
```

In [33]:
```
w_new=updated_model.coef_
w_new
```

Out[33]:
```
array([[ 0.00036369, -0.000345  ,  0.00048449,  0.00035933, -0.000345
,
         0.00038189,  0.00032048]])
```

5. Checking deviations in metric and weights

In [34]:
```
print(new_accu-accu)
```

```
0.0
```

In [35]:
```
difference=abs((wei-w_new))[0]
print(difference)
```

```
[3.04620171e-11 3.04801046e-11 3.04930581e-11 3.04600787e-11
 3.04801046e-11 3.04634312e-11 3.04687841e-11]
```

In [36]:
```
n=len(data.columns)-1
percentage_change=[]
for i in range (n):                          # calulating the percentage chang
e in weight
    cp=(difference[i]/wei[i])*100
    percentage_change.append(cp)
```

In [37]:
```
columns=list(data.columns.values)
indices=sorted(range(len(percentage_change)), key=lambda i: percentage_
change[i])[-4:]
print("the top 4 features which have higher % change in weights ")
for j in indices:
    print(columns[j])
```

```
the top 4 features which have higher % change in weights
2*z+3*x*x
x
x*x
w
```

Task: 2 Linear SVM

2. Finding the best model for the given data

In [38]:
```
alpha =  np.logspace(-5, 8, 10)
print(alpha)
param_grid={'C':alpha}
svm = SVC(kernel="linear")
```

```
[1.00000000e-05 2.78255940e-04 7.74263683e-03 2.15443469e-01
 5.99484250e+00 1.66810054e+02 4.64158883e+03 1.29154967e+05
 3.59381366e+06 1.00000000e+08]
```

In [39]:
```
model = GridSearchCV(svm, param_grid, cv=5)
```

In [40]:
```
model.fit(X,Y)
```

Out[40]:
```
GridSearchCV(cv=5, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.
0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='linea
r',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'C': array([1.00000e-05, 2.78256e-04, 7.74264e-03,
2.15443e-01, 5.99484e+00,
       1.66810e+02, 4.64159e+03, 1.29155e+05, 3.59381e+06, 1.00000e+0
8])},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [41]:
```
model.best_params_
```

Out[41]:
```
{'C': 0.007742636826811269}
```

3. Getting the weights with the original data

In [42]:
```
best_model=SVC(kernel='linear',C=0.007742636826811269)
```

In [43]:
```
best_model.fit(X,Y)
```

Out[43]:
```
SVC(C=0.007742636826811269, cache_size=200, class_weight=None, coef0=0.
0,
  decision_function_shape='ovr', degree=3, gamma='auto', kernel='linea
r',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [44]:
```
predictions = best_model.predict(X)
accu=accuracy_score(Y, predictions)
print(accuracy_score(Y, predictions))
```

```
1.0
```

In [45]:
```
wei=best_model.coef_[0]
print(best_model.coef_)
```

```
[[ 0.16056222 -0.20788705  0.32826166  0.14998082 -0.20788705  0.174615
87
   0.13401176]]
```

4. Modifying original data

In [46]:
```
X_NEW=X+.01
```

In [47]:
```
updated_model=best_model.fit(X_NEW,Y)
```

In [48]:
```
prediction = best_model.predict(X_NEW)
```

In [49]:
```
new_accu=accuracy_score(Y, prediction)
print(accuracy_score(Y, prediction))
```

```
1.0
```

In [50]:
```
w_new=updated_model.coef_
```

In [51]:
```
w_new
```

Out[51]:
```
array([[ 0.16049457, -0.20810298,  0.32832289,  0.14997999, -0.2081029
8,
         0.17462251,  0.13395324]])
```

5. Checking deviations in metric and weights

In [52]:
```
print(new_accu-accu)
```

```
0.0
```

In [53]:
```
difference=(k-w_new)[0]
print(difference)
```

```
-----------------------------------------------------------------------
----
NameError                                 Traceback (most recent call l
ast)
<ipython-input-53-633cf4288d5c> in <module>()
----> 1 difference=(k-w_new)[0]
      2 print(difference)

NameError: name 'k' is not defined
```

In [ ]:
```
n=len(data.columns)-1
percentage_change=[]
for i in range (n):                       # calulating the percentage chang
e in weight
    cp=(difference[i]/wei[i])*100
    percentage_change.append(cp)
```

In [54]:
```
columns=list(data.columns.values)
indices=sorted(range(len(percentage_change)), key=lambda i: percentage_
change[i])[-4:]
print("the top 4 features which have higher % change in weights ")
```

```
for j in indices:
    print(columns[j])
```

```
the top 4 features which have higher % change in weights
2*z+3*x*x
x
x*x
w
```

Observations

- FROM CORRELATION MATRIX WE CAN SEE THAT SOME FEATURES ARE HIGLY CORRELATED.
- AFTER DONE THE PERTURBATION TEST ON BOTH SVM AND LR, WEIGHT HAVE ONLY SMALL (VERY SMALL) CHANGE.
- SINCE NO ANY DRASTIC CHANGE WEIGHT WE CAN CONCLUDE THAT THERE IS NO COLLINEARITY BETWEEN FEATURES BASED ON PERTURBATION TEST.
- THE TOP 4 FEATURES WCHICH HAVE HIGHER % CHANGE IN WEIGHTS ARE FEATURES WHICH HIGHLY CORRELATED WITH OTHER FEATURES. (UNDERSTAND FROM CORRELATION MATRIX)