8D_LR_SVM_Assignment

June 12, 2020

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

[1]:
```
%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
```

[2]:
```
data = pd.read_csv('task_d.csv')
```

[3]:
```
data.head()
```

[3]:
```
          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

   target
0       0
1       0
2       0
3       0
4       0
```

[4]:
```
X = data.drop(['target'], axis=1).values
Y = data['target'].values
```

[5]:
```
feature_names=list(data.columns)
feature_names.pop()
print(feature_names)
```

```
['x', 'y', 'z', 'x*x', '2*y', '2*z+3*x*x', 'w']
```

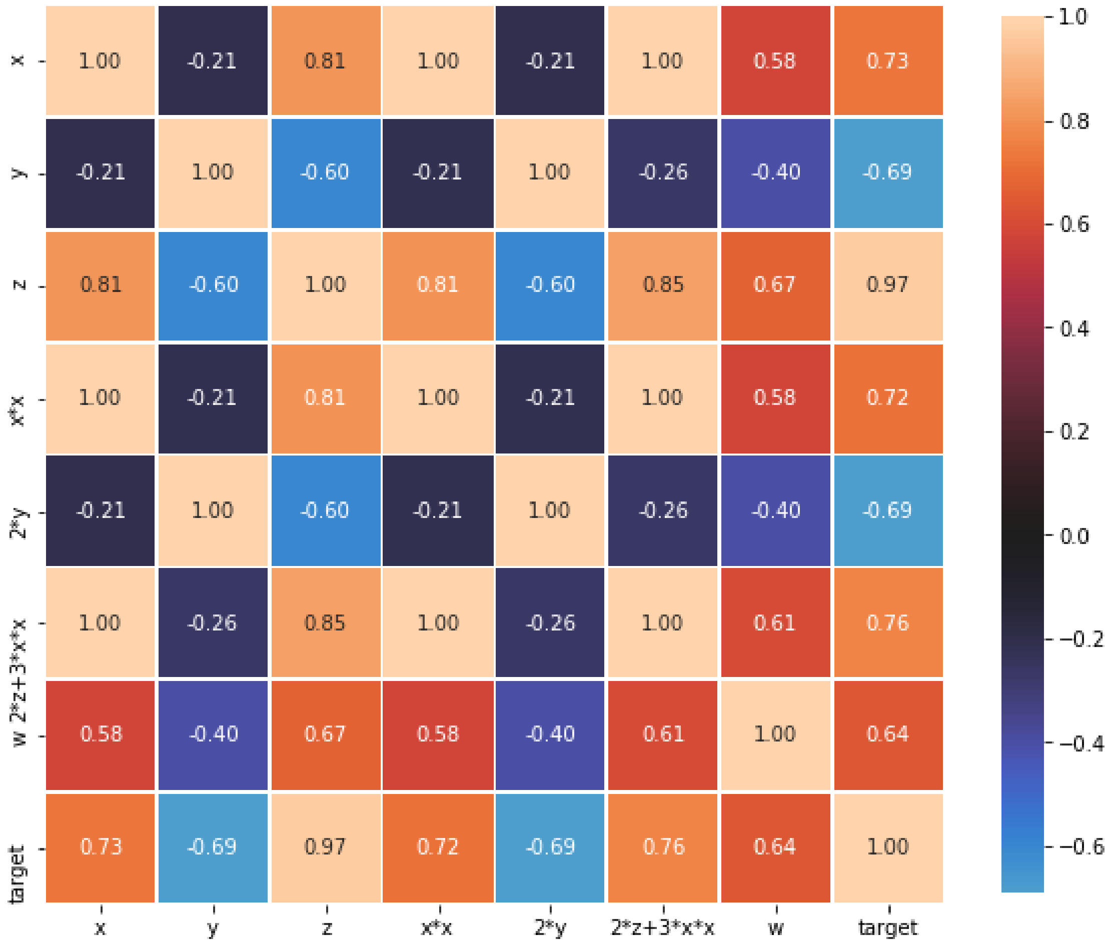
0.2 Finding the Correlation between the features

[6]:
```python
correlation=data.corr()
print(correlation)
```

```
                  x         y         z       x*x       2*y  2*z+3*x*x  \
x          1.000000 -0.205926  0.812458  0.997947 -0.205926   0.996252
y         -0.205926  1.000000 -0.602663 -0.209289  1.000000  -0.261123
z          0.812458 -0.602663  1.000000  0.807137 -0.602663   0.847163
x*x        0.997947 -0.209289  0.807137  1.000000 -0.209289   0.997457
2*y       -0.205926  1.000000 -0.602663 -0.209289  1.000000  -0.261123
2*z+3*x*x  0.996252 -0.261123  0.847163  0.997457 -0.261123   1.000000
w          0.583277 -0.401790  0.674486  0.583803 -0.401790   0.606860
target     0.728290 -0.690684  0.969990  0.719570 -0.690684   0.764729

                  w    target
x          0.583277  0.728290
y         -0.401790 -0.690684
z          0.674486  0.969990
x*x        0.583803  0.719570
2*y       -0.401790 -0.690684
2*z+3*x*x  0.606860  0.764729
w          1.000000  0.641750
target     0.641750  1.000000
```

[7]:
```python
fig,ax=plt.subplots(figsize=(10,10))
sns.heatmap(correlation,vmax=1.0,center=0,fmt='.2f',square=True,linewidths=.
 ↪5,annot=True,cbar_kws={"shrink": .80})
plt.show();
```



0.3 TASK 1 Logistic Regression

0.3.1 Finding the best model for the given data

[8]:
```
clf =SGDClassifier(loss='log',tol=1e-3,alpha=0.0001,eta0=0.
↪0001,learning_rate='constant')
clf.fit(X,Y)
```

[8]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0001,
              fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
              loss='log', max_iter=1000, n_iter_no_change=5, n_jobs=None,
              penalty='l2', power_t=0.5, random_state=None, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False)
```

[9]:
```
parameters={'alpha':np.logspace(-3,3,num=10)}
```

```
gscv= GridSearchCV(clf,parameters,cv= 10)
gscv.fit(X,Y)
```

[9]:
```
GridSearchCV(cv=10, error_score=nan,
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
                                     epsilon=0.1, eta0=0.0001,
                                     fit_intercept=True, l1_ratio=0.15,
                                     learning_rate='constant', loss='log',
                                     max_iter=1000, n_iter_no_change=5,
                                     n_jobs=None, penalty='l2', power_t=0.5,
                                     random_state=None, shuffle=True, tol=0.001,
                                     validation_fraction=0.1, verbose=0,
                                     warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'alpha': array([1.00000000e-03, 4.64158883e-03,
2.15443469e-02, 1.00000000e-01,
       4.64158883e-01, 2.15443469e+00, 1.00000000e+01, 4.64158883e+01,
       2.15443469e+02, 1.00000000e+03])},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

[10]:
```
bestalpha=gscv.best_params_['alpha']
print(bestalpha)
```

```
0.001
```

[11]:
```
best_model=SGDClassifier(loss='log',tol=1e-3,alpha=bestalpha,eta0=0.
 ↪0001,learning_rate='constant')
best_model.fit(X,Y)
```

[11]:
```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0001,
              fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
              loss='log', max_iter=1000, n_iter_no_change=5, n_jobs=None,
              penalty='l2', power_t=0.5, random_state=None, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False)
```

0.3.2 Getting the weights with the original data

[12]:
```
y_pred=best_model.predict(X)
print(y_pred)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

```
[13]: from sklearn.metrics import accuracy_score
      best_model_accuracy=accuracy_score(Y,y_pred)
      print(best_model_accuracy)
```

```
1.0
```

```
[14]: w=best_model.coef_
      print(w)
```

```
[[ 0.27545672 -0.29961614  0.41298518  0.26959946 -0.29961614  0.2925026
   0.24487388]]
```

0.3.3 Modifying original data

```
[15]: X_=X+0.01
```

```
[16]: best_model_edit=SGDClassifier(loss='log',tol=1e-3,alpha=bestalpha,eta0=0.
       ↪0001,learning_rate='constant')
      best_model_edit.fit(X_,Y)
```

```
[16]: SGDClassifier(alpha=0.001, average=False, class_weight=None,
                    early_stopping=False, epsilon=0.1, eta0=0.0001,
                    fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
                    loss='log', max_iter=1000, n_iter_no_change=5, n_jobs=None,
                    penalty='l2', power_t=0.5, random_state=None, shuffle=True,
                    tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False)
```

```
[17]: y_pred=best_model_edit.predict(X_)
      print(y_pred)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

```
[18]: from sklearn.metrics import accuracy_score
      best_model_accuracy_edit=accuracy_score(Y,y_pred)
      print(best_model_accuracy_edit)
```

```
1.0
```

```
[19]: w_edit=best_model_edit.coef_
      print(w_edit)
```

```
[[ 0.27557379 -0.29954096  0.41304048  0.26971998 -0.29954096  0.29261692
   0.24493493]]
```

0.3.4 Checking deviations in metric and weights

[20]:
```
accuracy_diff=best_model_accuracy_edit-best_model_accuracy
print(accuracy_diff)
```

```
0.0
```

[21]:
```
w_diff=np.absolute(w_edit-w)
print(w_diff)
```

```
[[1.17065233e-04 7.51832910e-05 5.52989908e-05 1.20524169e-04
  7.51832910e-05 1.14317116e-04 6.10451117e-05]]
```

[22]:
```
index=(np.argsort(w_diff)[0])[::-1][0:4]
print("top 4 features")
print(np.take(feature_names,index))
```

```
top 4 features
['x*x' 'x' '2*z+3*x*x' '2*y']
```

observations:

1.Accuracy of the model does not change before and after perturbation test 2.features are non collinear because weights before and after perturbation test doesnot change significantly. So,these weights can used for getting feature importance.

0.4 TASK 2 Linear SVM

0.4.1 Finding the best model for the given data

[23]:
```
clf =SGDClassifier(loss='hinge',tol=1e-3,alpha=0.0001,eta0=0.
↪0001,learning_rate='constant')
clf.fit(X,Y)
```

[23]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0001,
              fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
              loss='hinge', max_iter=1000, n_iter_no_change=5, n_jobs=None,
              penalty='l2', power_t=0.5, random_state=None, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False)
```

[24]:
```
parameters={'alpha':np.logspace(-3,3,num=10)}

gscv= GridSearchCV(clf,parameters,cv= 10)
gscv.fit(X,Y)
```

[24]:
```
GridSearchCV(cv=10, error_score=nan,
             estimator=SGDClassifier(alpha=0.0001, average=False,
                                     class_weight=None, early_stopping=False,
```

```
                                             epsilon=0.1, eta0=0.0001,
                                             fit_intercept=True, l1_ratio=0.15,
                                             learning_rate='constant', loss='hinge',
                                             max_iter=1000, n_iter_no_change=5,
                                             n_jobs=None, penalty='l2', power_t=0.5,
                                             random_state=None, shuffle=True, tol=0.001,
                                             validation_fraction=0.1, verbose=0,
                                             warm_start=False),
                   iid='deprecated', n_jobs=None,
                   param_grid={'alpha': array([1.00000000e-03, 4.64158883e-03,
2.15443469e-02, 1.00000000e-01,
       4.64158883e-01, 2.15443469e+00, 1.00000000e+01, 4.64158883e+01,
       2.15443469e+02, 1.00000000e+03])},
                   pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                   scoring=None, verbose=0)
```

[25]:
```
bestalpha=gscv.best_params_['alpha']
print(bestalpha)
```

```
0.001
```

[26]:
```
best_model=SGDClassifier(loss='hinge',tol=1e-3,alpha=bestalpha,eta0=0.
 ↪0001,learning_rate='constant')
best_model.fit(X,Y)
```

[26]:
```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0001,
              fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
              loss='hinge', max_iter=1000, n_iter_no_change=5, n_jobs=None,
              penalty='l2', power_t=0.5, random_state=None, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False)
```

0.4.2 Getting the weights with the original data

[27]:
```
y_pred=best_model.predict(X)
print(y_pred)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

[28]:
```
from sklearn.metrics import accuracy_score
best_model_accuracy=accuracy_score(Y,y_pred)
print(best_model_accuracy)
```

```
1.0
```

[29]:
```
w=best_model.coef_
print(w)
```

```
[[ 0.21169674 -0.27080862  0.3785204   0.20422448 -0.27080862  0.22950351
   0.18892872]]
```

0.4.3 Modifying original data

[30]:
```
X_=X+0.01
```

[31]:
```
best_model_edit=SGDClassifier(loss='hinge',tol=1e-3,alpha=bestalpha,eta0=0.
 ↪0001,learning_rate='constant')
best_model_edit.fit(X_,Y)
```

[31]:
```
SGDClassifier(alpha=0.001, average=False, class_weight=None,
              early_stopping=False, epsilon=0.1, eta0=0.0001,
              fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
              loss='hinge', max_iter=1000, n_iter_no_change=5, n_jobs=None,
              penalty='l2', power_t=0.5, random_state=None, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=0, warm_start=False)
```

[32]:
```
y_pred=best_model_edit.predict(X_)
print(y_pred)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

[33]:
```
from sklearn.metrics import accuracy_score
best_model_accuracy_edit=accuracy_score(Y,y_pred)
print(best_model_accuracy_edit)
```

```
1.0
```

[34]:
```
w_edit=best_model_edit.coef_
print(w_edit)
```

```
[[ 0.21194954 -0.26950828  0.37686423  0.20458215 -0.26950828  0.22962007
   0.18894916]]
```

0.4.4 Checking deviations in metric and weights

[35]:
```
accuracy_diff=best_model_accuracy_edit-best_model_accuracy
print(accuracy_diff)
```

```
0.0
```

[36]:
```
w_diff=np.absolute(w_edit-w)
print(w_diff)
```

```
[[2.52791281e-04 1.30034031e-03 1.65617163e-03 3.57671354e-04
  1.30034031e-03 1.16562140e-04 2.04405190e-05]]
```

[37]:
```
index=(np.argsort(w_diff)[0])[::-1][0:4]
print("top 4 features")
print(np.take(feature_names,index))
```

```
top 4 features
['z' '2*y' 'y' 'x*x']
```

observations:

1.Accuracy of the model does not change before and after perturbation test 2.features are non collinear because weights before and after perturbation test doesnot change significantly. So,these weights can used for getting feature importance.

[ ]:
```

```