8D_LR_SVM

November 7, 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
```

0.1.1 Doing perturbation test to check the presence of collinearity

Task: 1 Logistic Regression

Task: 2 Linear SVM Do write the observations based on the results you get from the deviations of weights in both Logistic Regression and linear SVM

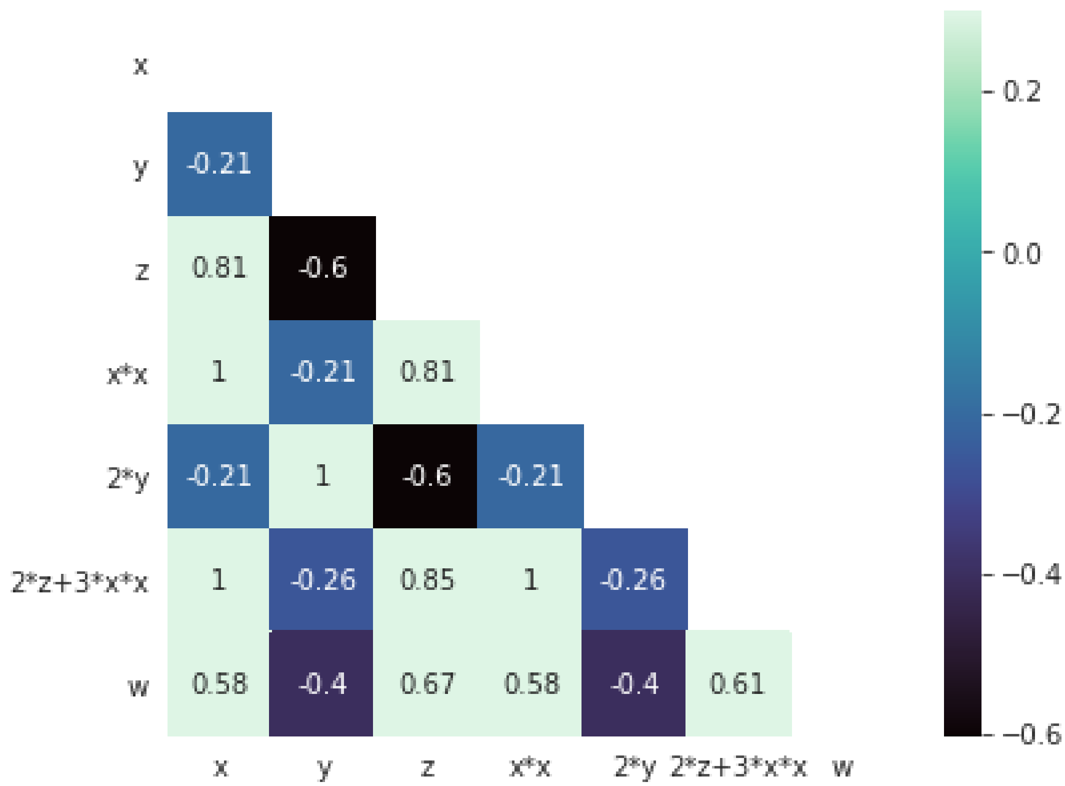
0.1.2 TASK1 : Logistic Regression

[5]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

alphas = np.logspace(-2, 1, 20).tolist()
```

[6]:
```python
corr = data.drop(['target'], axis=1).corr()
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

with sns.axes_style("white"):
    f, ax = plt.subplots(figsize=(7, 5))
    ax = sns.heatmap(corr, mask=mask, vmax=.3, square=True, cmap='mako',␣
↪annot=True)
```



[7]:
```python
LR = LogisticRegression(random_state=0)

parameters = {'C': alphas}
```

```
clf = GridSearchCV(LR, parameters, cv=5, scoring='accuracy')
clf = clf.fit(X, Y)
```

[8]:
```
clf.best_params_, clf.best_score_, clf.best_estimator_
```

[8]: ({'C': 0.01}, 1.0, LogisticRegression(C=0.01, random_state=0))

[9]:
```
best_model = LogisticRegression(random_state=0, C=0.01, max_iter=10)
best_model.fit(X, Y)
pred = best_model.predict(X)

print(accuracy_score(Y, pred))

print("Best-Weights : ", best_model.coef_)
```

```
1.0
Best-Weights :  [[ 0.16985876 -0.18662565  0.25913329  0.16588976 -0.18662565
0.18058804
   0.15042411]]
```

[10]:
```
# X_dash = X + e

noise = []
for i in range(X.shape[1]):
    noise.append(np.array([j*l for j in X[:,i] for l in np.random.
 ↪uniform(1*10**-2, 9*10**-2, 1)]))

X_dash = np.array(noise).reshape(100, 7)
```

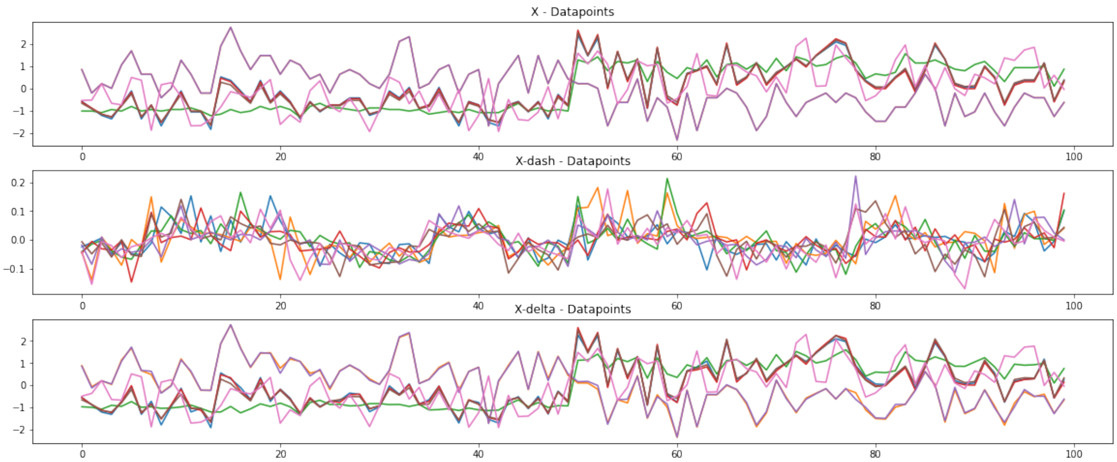
[11]:
```
fig = plt.figure(figsize=(20,8))

plt.subplot(3, 1, 1);
plt.plot(X);
plt.title("X - Datapoints")

plt.subplot(3, 1, 2);
plt.plot(X_dash);
plt.title("X-dash - Datapoints")

plt.subplot(3, 1, 3);
plt.plot(np.subtract(X, X_dash));
plt.title("X-delta - Datapoints")

fig.show()
```




```
[12]: best_model_edited = LogisticRegression(C=0.01, random_state=0, max_iter=10)
best_model_edited.fit(X_dash, Y)
pred = best_model_edited.predict(X)

print(accuracy_score(Y, pred))

print("Best-Model-Weights : \n", best_model.coef_, "\n")
print("Best-Model-Edited-Weights : \n", best_model_edited.coef_)
```

```
0.4
Best-Model-Weights :
 [[ 0.16985876 -0.18662565  0.25913329  0.16588976 -0.18662565  0.18058804
   0.15042411]]

Best-Model-Edited-Weights :
 [[-0.00114892  0.00963693  0.00171287  0.00204401  0.00385349  0.00291935
   0.00215612]]
```

```
[13]: print("Weight-Delta:")

top_4 = np.argsort(np.subtract(best_model.coef_, best_model_edited.coef_)).
 ↪flatten().tolist()

print("Top4 Affected features : ", [list(data.columns)[i] for i in␣
 ↪sorted(top_4, reverse=True)[:4]])
```

```
Weight-Delta:
Top4 Affected features :  ['w', '2*z+3*x*x', '2*y', 'x*x']
```

0.1.3 OBSERVATION :

1. Classifier overfits within 10 epochs, due to colinear features.

2. Weight-Delta clearly indicates, one features changes affects the colinear feature weights.

3. Top-4 Features are colinnear features.

0.1.4 TASK2 : Linear SVM

[14]:
```
from sklearn.svm import LinearSVC

LR = LinearSVC(random_state=0)

parameters = {'C': alphas}

clf = GridSearchCV(LR, parameters, cv=5, scoring='accuracy')

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

[15]:
```
clf.best_params_, clf.best_score_, clf.best_estimator_
```

[15]: ({'C': 0.01}, 1.0, LinearSVC(C=0.01, random_state=0))

[16]:
```
best_model = LinearSVC(random_state=0, C=0.01, max_iter=10)
best_model.fit(X, Y)
pred = best_model.predict(X)

print(accuracy_score(Y, pred))

print("Best-Weights : ", best_model.coef_)
```

```
1.0
Best-Weights :  [[ 0.13229866 -0.17891499  0.29999505  0.12253074 -0.17891499
0.14649785
   0.10743375]]
```

[17]:
```
# X_dash = X + e

noise = []
for i in range(X.shape[1]):
    noise.append(np.array([j*l for j in X[:,i] for l in np.random.
 ↪uniform(1*10**-2, 9*10**-2, 1)]))

X_dash = np.array(noise).reshape(100, 7)
```

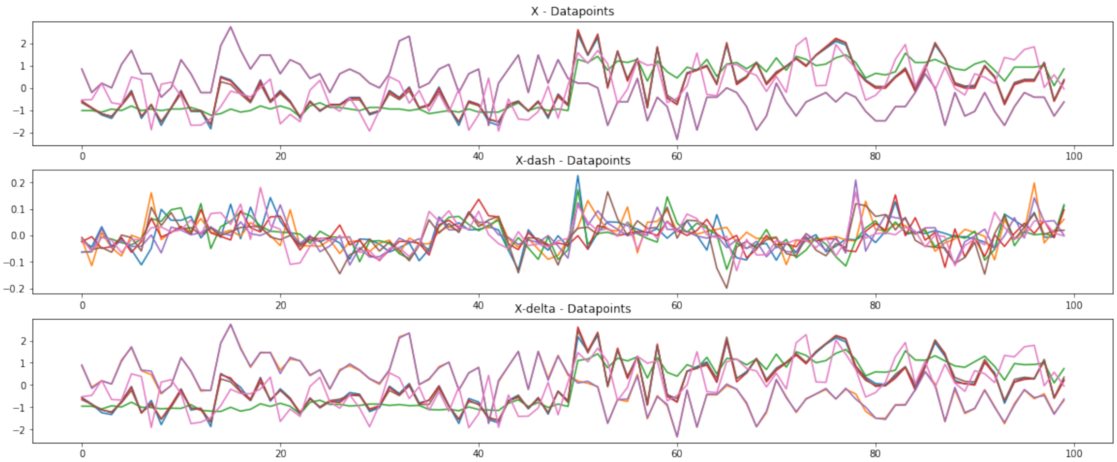
[18]:
```
fig = plt.figure(figsize=(20,8))

plt.subplot(3, 1, 1);
plt.plot(X);
plt.title("X - Datapoints")
```

```
plt.subplot(3, 1, 2);
plt.plot(X_dash);
plt.title("X-dash - Datapoints")

plt.subplot(3, 1, 3);
plt.plot(np.subtract(X, X_dash));
plt.title("X-delta - Datapoints")

fig.show()
```



[19]:
```
best_model_edited = LinearSVC(C=0.01, random_state=0, max_iter=10)
best_model_edited.fit(X_dash, Y)
pred = best_model_edited.predict(X)

print("Accuracy Score : ", accuracy_score(Y, pred), "\n")

print("Best-Model-Weights : \n", best_model.coef_, "\n")
print("Best-Model-Edited-Weights : \n", best_model_edited.coef_)
```

```
Accuracy Score :  0.32

Best-Model-Weights :
 [[ 0.13229866 -0.17891499  0.29999505  0.12253074 -0.17891499  0.14649785
   0.10743375]]

Best-Model-Edited-Weights :
 [[ 0.00884605  0.02191811 -0.00197535 -0.00238561  0.0201486   0.01031313
   0.00204918]]
```

[20]:
```
print("Weight-Delta:")
```

```
top_4 = np.argsort(np.subtract(best_model.coef_, best_model_edited.coef_)).
 ↪flatten().tolist()

print("Top4 Affected features : ", [list(data.columns)[i] for i in␣
 ↪sorted(top_4, reverse=True)[:4]])
```

```
Weight-Delta:
Top4 Affected features :  ['w', '2*z+3*x*x', '2*y', 'x*x']
```

0.1.5 OBSERVATION :

1. Classifier overfits within 10 epochs, due to colinear features.

2. Weight-Delta clearly indicates, independent features changes affects the corresponding colinear feature weights.

3. After introduced noise onto dataset, the Top-4 affected features are colinear features.