

CSC 730 Assignment 05

AD Bench

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Overview

The aim of this assignment is to:

- Install ADBench.
- Generate labels for the skewed-MNIST dataset with two least represented classes marked as anomalies.
- Select 2 supervised algorithms that are built into ADBench, and apply them to the data.
- Characterize the resulting performance.

Installing ADBench

ADBench was installed following the instructions provided on the git repo. I did require help from my classmates and the internet to get around the errors to get it installed properly.

Data Processing

The data was read in from the skewed-MNIST dataset. Labels were generated for this data to classify two lowest represented classes, which are 1 and 7, as anomalies. Then the data was shuffled and split into training and testing dataset. 80% of the data was used for training and the rest 20% was used for testing.

```
lbls = np.asarray([1 if i == 1 or i == 7 else 0 for i in y])

X_train = X[:9795, :]
y_train = lbls[:9795]
X_test = X[9795:, :]
y_test = lbls[9795:]
```

Figure 1: Creating Labels and Splitting Data

Algorithm 1 : XG Boost

I selected XG Boost as one of the two algorithms. Using ADBench the model was initialised and trained to fit the dataset created. The model predicted with an accuracy of around 99.6%. The implementation and results of run can be seen below.

```
model = supervised(seed=42, model_name='XGB') # initialization
model.fit(X_train, y_train) # fit
score = model.predict_score(X_test) # predict

preds_XGB = [1 if i > 0.5 else 0 for i in score]

cm = confusion_matrix(y_test, preds_XGB)
cm

array([[2439,  0],
       [  8,   2]], dtype=int64)

cm.trace() / np.sum(cm)

0.9967333605553287
```

Figure 2: XG Boost

Algorithm 1 : Cat Boost

Cat Boost was the other algorithm selected. Using ADBench the model was initialised and trained to fit the dataset created. The model predicted with an accuracy of around 99.6% as well. The implementation and results of run can be seen below.

```
model = supervised(seed=42, model_name='CatB') # initialization
model.fit(X_train, y_train) # fit
score = model.predict_score(X_test) # predict
```

```
140: learn: 0.0054402 total: 8.61s remaining: 52.3s
141: learn: 0.0054092 total: 8.67s remaining: 52.4s
142: learn: 0.0053814 total: 8.72s remaining: 52.3s
143: learn: 0.0053724 total: 8.78s remaining: 52.2s
144: learn: 0.0053142 total: 8.84s remaining: 52.1s
145: learn: 0.0052952 total: 8.9s remaining: 52s
146: learn: 0.0052199 total: 8.95s remaining: 51.9s
147: learn: 0.0051307 total: 9.01s remaining: 51.9s
148: learn: 0.0051074 total: 9.08s remaining: 51.8s
149: learn: 0.0050846 total: 9.13s remaining: 51.8s
150: learn: 0.0050693 total: 9.19s remaining: 51.7s
151: learn: 0.0049394 total: 9.25s remaining: 51.6s
152: learn: 0.0049149 total: 9.31s remaining: 51.5s
153: learn: 0.0048942 total: 9.36s remaining: 51.4s
154: learn: 0.0047809 total: 9.42s remaining: 51.4s
155: learn: 0.0047702 total: 9.48s remaining: 51.3s
156: learn: 0.0046719 total: 9.54s remaining: 51.2s
157: learn: 0.0045557 total: 9.6s remaining: 51.2s
158: learn: 0.0045202 total: 9.66s remaining: 51.1s
159: learn: 0.0045038 total: 9.71s remaining: 51s
```

```
preds_CatB = [1 if i > 0.5 else 0 for i in score]
```

```
cm = confusion_matrix(y_test, preds_CatB)
cm
```

```
array([[2439,  0],
       [  8,   2]], dtype=int64)
```

```
cm.trace() / np.sum(cm)
```

```
0.9967333605553287
```

Figure 3: Cat Boost

Conclusion

Both the models end up with a pretty high accuracy, but looking at the confusion matrices we can see that the models tend to predict everything as not an anomaly as doing so will lead to a higher accuracy.