Anomaly Detection in Imbalanced Problems

- Deep Learning Project -

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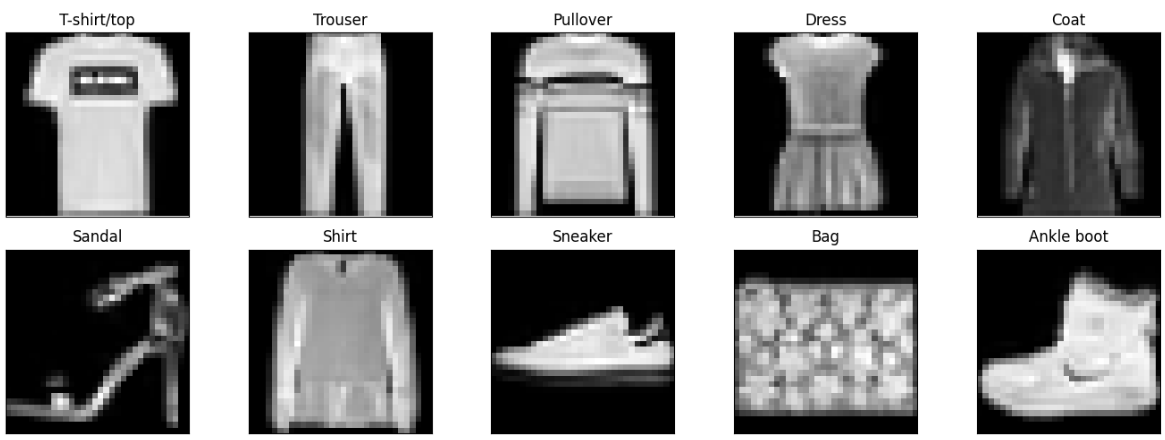
Introduction

1.1 Project Overview

The report which follows is the result of the project of the course of Deep Learning. The aim of this work was focused on the Anomaly Detection in Imbalance Problems, dealing with gap of samples and classes distributions, based on the paper: [1] *GAN-based Anomaly Detection in Imbalance Problems*. In particular this work implement the SOTA architecture explored in the paper's research and 2 more baseline to compare the results.

1.2 Dataset

The Dataset used is the FashionMNIST [2] , a dataset of Zalando's article images of 10 classes, with a total of 60,000 train samples and 10,000 test samples. Each sample is a 28x28 grayscale images (784 px) containing only 1 class. The dataset in particular is balanced, in training and test set.



Dataset

1.3 Data Augmentation

For the training was applied some Data Augmentation techniques to the FashionMNIST dataset, in particular the images were vertically and horizontally flipped, randomly cropped 0~2 pixels from the boundary, randomly rotated of 90, 180, or 270 degrees and resized to 32x32 dimension.

1.4 Preprocessing and Unbalance

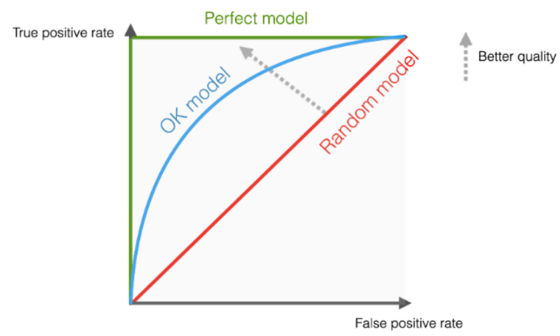
The dataset in the proposed implementation is loaded by using a specific realized class called *AnomalyDetectionDataModule*, which load the dataset and provide the training and test dataloaders. The DataModule is realized in a flexible way, allowing to perform a training/test also only on a subset of the available data in order to perform tests. Furthermore the model will need to deal with the imbalance problems typical of anomaly detection.

Class imbalance is a well known problem in Anomaly Detection, for which, usually, there is a class disparity between the normal and the anomal class. For this specific task with the FashionMNIST, each class is once considered as the 'normal class' at time, and the remaining 9 as 'anomal class', in this way, 10 experiments are performed and the resulting score is the mean among all. Due to samples availability this division lead to an unbalanced situation, to deal with this problem is performed a *sampling* from each class recognized as 'anomal' in order to get the same number of the 2 classes, both now with 6000 samples in the total training.

Furthermore, if the data are sampled randomly, without considering their particular distribution, the resulting dataset won't be balanced in the distribution and representation of starting dataset. To solve this condition was applied a *k-means clustering* approach, in order to sample the same number of data within each cluster of each group, now then considering the distribution of the samples. This is obtained by using the *kmeans_sampling* function in the DataModule, which performs both the k-means clustering and sampling according to these requirements.

1.5 Metric

In order to evaluate the performance of the models on the dataset, the main metric was the Area Under the Receiver-Operating Characteristics (ROCAUC) [3]. This metric, indicating the area under the ROC curve, sums up how well a model is able to produce relative scores to discriminate between positive or negative instances, which in our case is represented by the normal and anomalous samples of interest. This is possible because the plot allows the to visualize the tradeoff between the classifier's sensitivity and specificity. It ranges from 0 (bad) to 1 (perfect), and 0.5 indicates the performance of random guessing.



ROC AUC score

1.6 Limitations

For the implementation was used *pytorch lightning* and all the train and test phases were performed by using the hardware resources provided by the free version of Google Colab. Unfortunately the free version of Google Colab has some limitation in computational power and resource disponibility. These limitations have negatively impacted the overall performances of the work reducing the possible training. The Google Colab policy indeed, after some hours of use, will progressively limit the resources provided to the user, not allowing to perform the same training showed in the paper.

Models

2.1 Baseline 1: Random Guessing

The first choosen model as baseline is a random guessing type. The architecture is simple and straightforward, At each sample provided the model will randomly generate an output in the range [0,1], randomly guessing between the *normal* and *anomal class.*

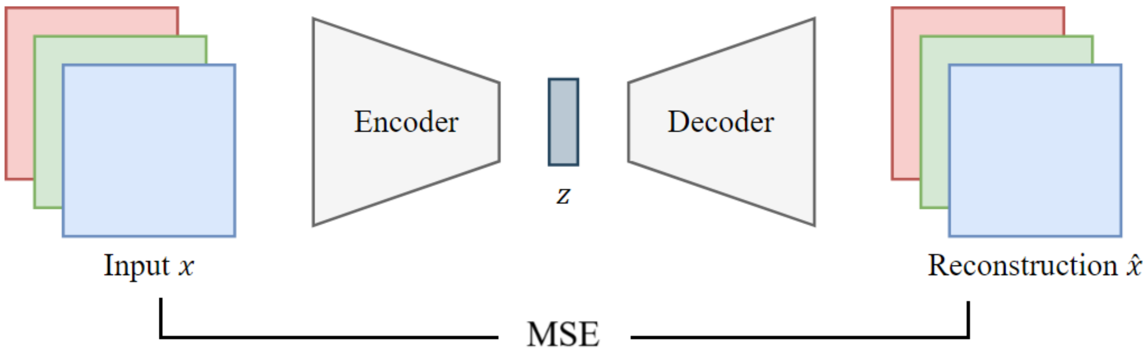
Due to it's intrinsic nature, this approach didn't need any training, ad can be directly performed the test on the testset. As expected the resulting AUROC is on the test set was of 0.5 .

2.2 Baseline 2: Autoencoder

The Autoencoder is often a popular choice for anomaly detection tasks. It consists of 2 main parts:

- *Encoder* = Map the input in a lower-dimensional latent space representation, in this case consists of 2 convolutional layers;

- *Decoder* = Map from the lower-dimensional latent space trying to reconstruct the original data.



For the training was only provided the *'normal class'*, and trained the model by trying to reduce the reconstruction error by minimizing the MSE (Mean Square Error) between input and output.
The model was trained for 15 epochs, with $lr = 0.0001$ with the Adam optimizer, and $batch\_size = 1$ to have comparable results with the sota architecture. The resulting AUROC = 0.77 .

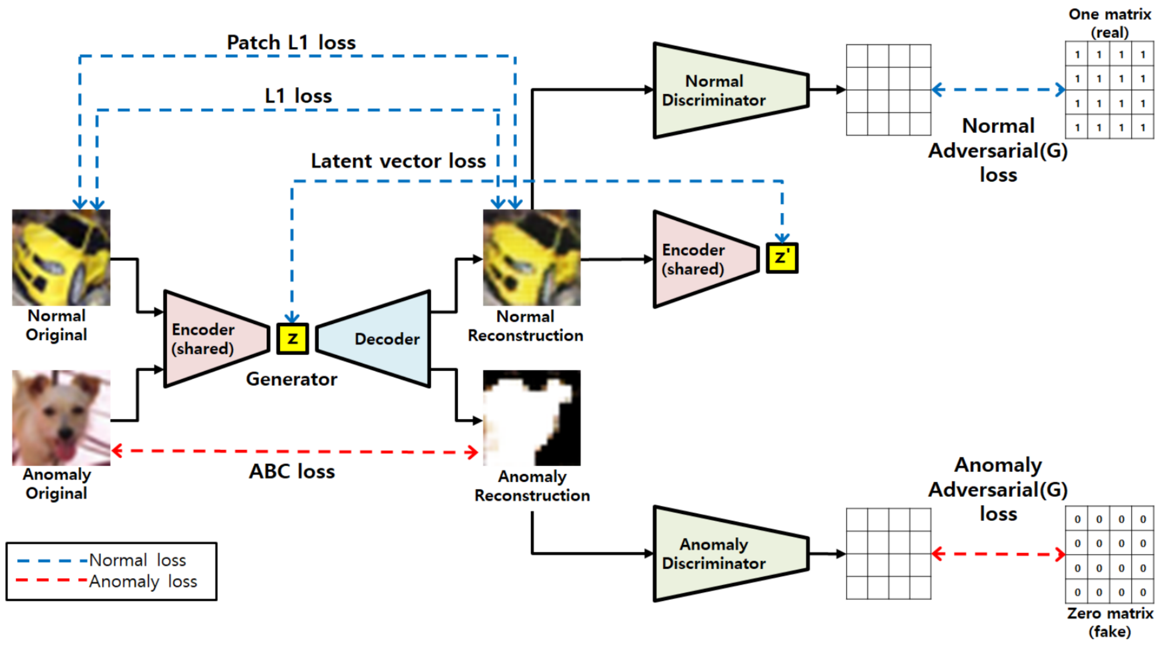
2.3 Baseline 3: GAN-based

This represent the GAN-based anomaly detection model, the state-of-art for the Benchmark datasets for the AUROC(%) presented in the paper. The network architecture is based on a GAN structure, consisting of a generator and a discriminator.

- *Generator* = It is a modified U-Net [4] structure, in the form of an autoencoder. It consists of four *4x4* convolutions with stride 2, then followed by 4 transposed *4x4* transposed convolutions;

- *Discriminator* = The discriminator is a more simple convolutional network, consisting of three *4x4* convoluitiond with stride 2 then followed by two *4x4* convolutions with stride 1.

During the training phase 2 Discriminator are used to separately process the input data when the class is the normal or anomal. While the Generator is trained to output 1 from normal data and 0 from anomaly. In this way the model will learn to minimize reconstruction error when normal data is provided to Generator, while will try to maximize the reconstruction error when input is anomal.



As in the paper, for the training where used 6 types of loss functions to train the generator and 2 for the discriminators (1 for each), used and combined with a weighted summation as in the research mentioned. The double discriminator allow to solve the discriminator distributional bias, because the generator will be trained to output 1 from normal data and 0 from anomaly, while, if it was trained with only 1 discriminator, the model will be trained to only classify well normal images.

The model was trained for 20 epochs with Adam optimizer, a batch size of 1, a learning rate of 0,002 , getting AUROC = 0.90 averaged.

Conclusions

Thanks to the following table we can summarize the behaviour and the performance of the models explored so far in the report.

Model	**AUROC**
Random Guessing	0.5
Autoencoder	0.771
GAN	0.904

Table 3.1: Comparison of Models

- The Random Guessing is by far the worst model among the three, representing the minimum baseline performances expected according to the AUROC metric.
- The Autoencoder on the other hand resulted in a really fast training, in particular if compared with the GAN. Due to the intrinsic nature of the approach, the model will always try to reconstruct in output the image provided as input, even the anomaly one, so the performances are linked to the reconstruction error which sometimes give good results even with an anomal sample.
- The GAN, in the end, resulted in a really slower training, due to the presence of 3 structures, but as expected, this approach provided the highest perfromances. This result is linked to the behaviour of the model which, when provided an anomal samples, will badly reconstruct on porpouse, limiting the mis-classifications between normal and anomal, due to the reconstruction error like in the Autoencoder.

Bibliography

[1] Junbong Kim, Kwanghee Jeong, Hyomin Choi, and Kisung Seo (2020). *GAN-based Anomaly Detection in Imbalance Problems*.

[2] FashionMNIST dataset. *https://github.com/zalandoresearch/fashion-mnist*.

[3] Area Under the Receiver-Operating Characteristics. *https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_auc_score.html*.

[4] Ronneberger, Fischer, Brox. U-net: Convolutional networks for biomedical image segmentation. In: International Conference on Medical image computing and computer-assisted intervention. pp. 234–241. Springer (2015)*https://arxiv.org/abs/1505.04597*.