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# Anomaly Detection

Advanced Techniques

2021



Yandex



EPFL



# Distance scores

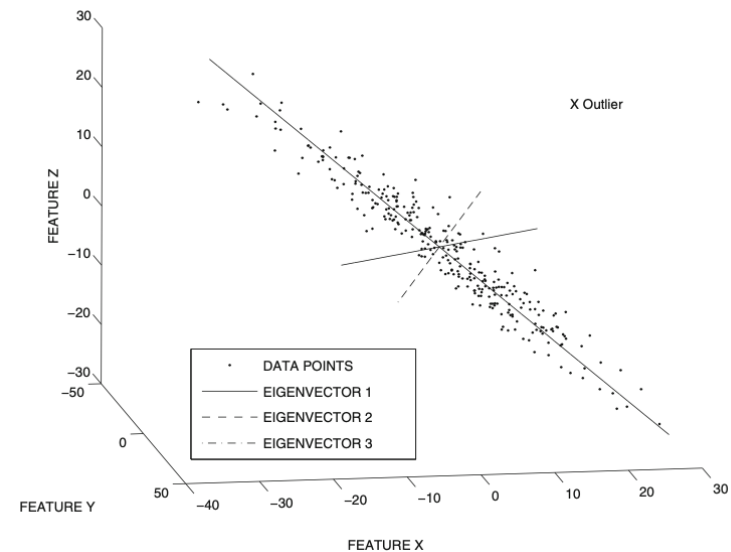


# Introduction

- ▶ we know that anomalies are rare and deviate from the populous "normal" class;
- ▶ "normal" class is usually concentrated in some area of feature space;
- ▶ can we use this property?

# Principle component analysis

- ▶ selects the k-dimensional hyperplane that minimizes the squared projection error over the remaining dimensions;
- ▶ all points can be projected to this hyperplane;
- ▶ a data point, which is far away from its projection is deemed as anomalous.
- ▶ anomaly score: normalized distance of the data point to the centroid of the sample along main components.



# PCA for anomaly detection: issues

- ▶ sensitivity to noise
  - in presence of multiple outliers PCA can have difficulties in determining the main component.
- ▶ normalization issues
  - in case of very different feature scale, the variation of one components can eclipse other variations.
- ▶ regularization Issues
  - not really stable for small datasets.

# Robust PCA

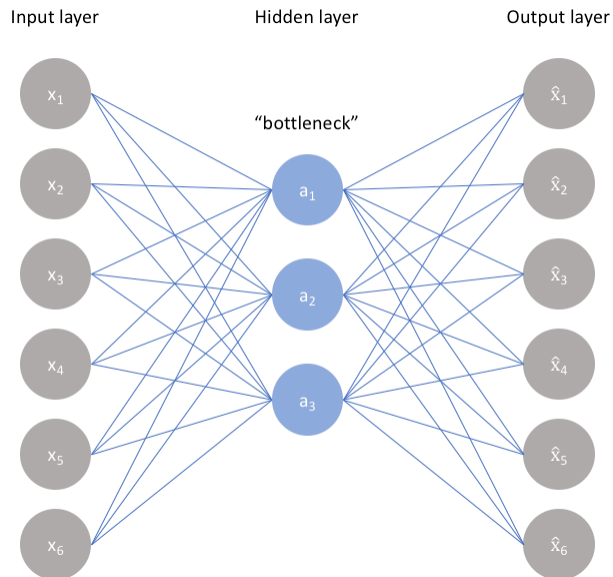
The presence of many outliers can be overcome by using Robust PCA analysis. The analysis seeks to separate low-rank trends from sparse outliers within a data matrix:

$$\mathbf{X} = \mathbf{L} + \mathbf{S}$$

The diagram illustrates the Robust PCA decomposition. It shows three matrices:  $\mathbf{X}$ ,  $\mathbf{L}$ , and  $\mathbf{S}$ . Matrix  $\mathbf{X}$  is labeled "Signal trajectory matrix" and contains a mix of colored squares (orange, green, yellow, blue) and pink squares. Matrix  $\mathbf{L}$  is labeled "Low-rank feature component" and contains only the colored squares in a structured, block-like arrangement. Matrix  $\mathbf{S}$  is labeled "Sparse strong background noise" and contains only the pink squares scattered across a light gray background. The equation  $\mathbf{X} = \mathbf{L} + \mathbf{S}$  is shown with an equals sign between  $\mathbf{X}$  and  $\mathbf{L}$ , and a plus sign between  $\mathbf{L}$  and  $\mathbf{S}$ .

Several methods of finding the decomposition exist.

# Autoencoders



Two parts of the network:

- ▶ encoder  $h = f(x)$ ;
- ▶ decoder  $r = g(h)$

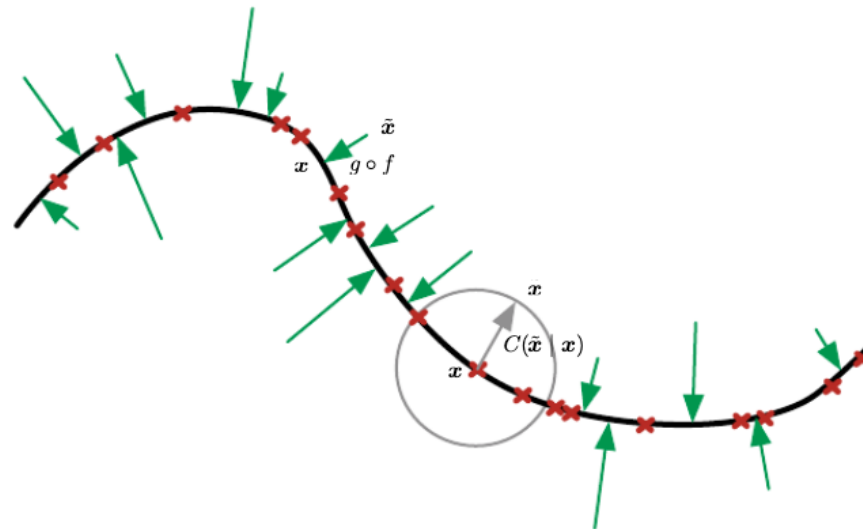
Generally, we want to find a transformation

$$g(f(x)) = x$$

The approach can be made more flexible than PCA transform.

# AE: learning manifold

In fact, we learn a manifold, where normal class is situated:



We can keep the same anomaly score as in PCA case.

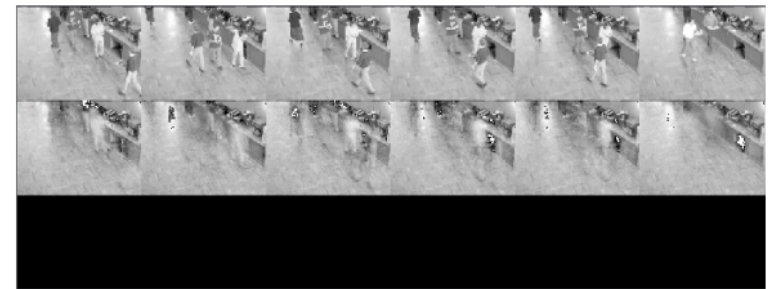


# Robust Autoencoder

- ▶ same problem as in the PCA case;
- ▶ same regularisation using sparse matrix  $S$ ;
- ▶ can be learned iteratively;
- ▶ different architectures possible.



(a) RCAE.



(b) RPCA.

# Variational Autoencoders

- ▶ "normal" manifold can be created with probabilistic model;
- ▶ anomaly score remains distance based but we can sample from "normal" distribution several events and average the distance.

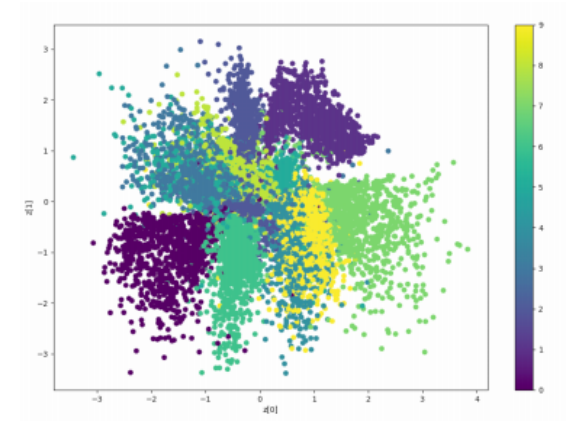


Figure 2.11: 2D plot of (variationally)autoencoded digits.

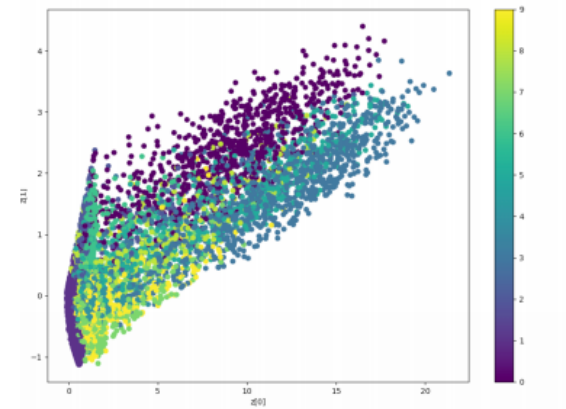


Figure 2.12: 2D plot of autoencoded digits.

# Recap

- ▶ Linear methods are quite powerful for anomaly detection.
- ▶ Most of the analysis is done in the latent space.
- ▶ Issues:
  - data need to be correlated and not heavily clustered;
  - might be overfit;
  - lacks interpretability.

# Probability Scores



# Generative modeling

- ▶ Some generative modeling produce explicit estimate of probability of sample:
  - Variational autoencoders.
  - Flow-based models.
- ▶ Can we use it to find anomaly?



Figure: N. Schucher

# Constructing Score Function

- ▶ direct probability is overly optimistic for anomalous samples (tail problem!);
- ▶ one can try to construct a different probability-based measure:
  - Watanabe-Akaike Information Criterion;
  - use in-batch dependencies.
- ▶ empirically these approaches work better.

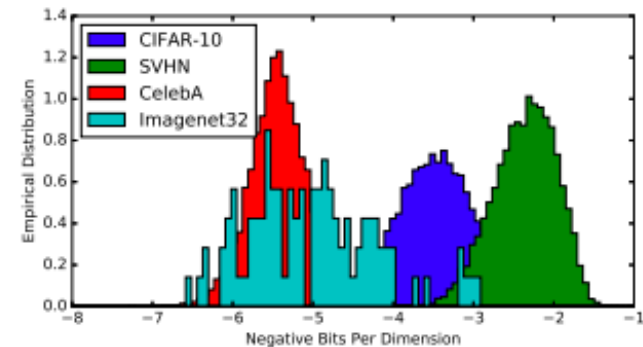


Figure 1. Density estimation models are not robust to OoD inputs. A GLOW model (Kingma & Dhariwal, 2018) trained on CIFAR-10 assigns much higher likelihoods to samples from SVHN than samples from CIFAR-10. .

H. Choi, WAIC, but Why. Generative Ensembles for Robust Anomaly Detection

# Advanced Ideas



# $(1 + \varepsilon)$ -class classification

## Two-class classification:

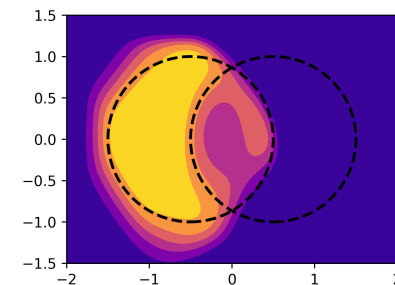
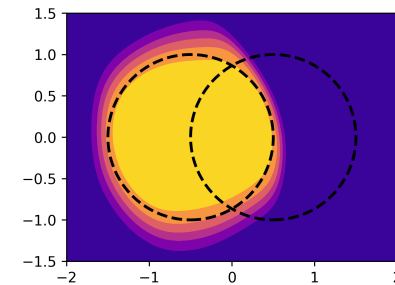
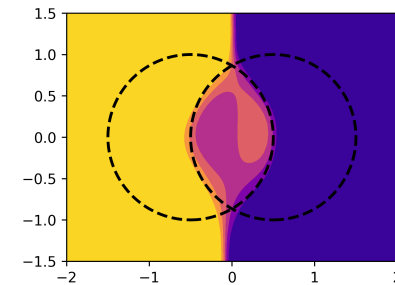
- ▶ undefined in empty regions;
- ▶ recovers proper probabilities;

## One-class classification:

- ▶ defined everywhere;
- ▶ ignores negative class;

## $(1 + \varepsilon)$ -class classification:

- ▶ shifts two-class solution towards a one-class solution;





# Approach Classification

Numerous approaches have been developed:

- ▶ Extreme value analysis (Z-score).
- ▶ Probabilistic and statistical models (Generative models).
- ▶ Linear models (Principle Component Analysis)/
- ▶ Proximity-based models (Clustering)
- ▶ Information theoretic models (Minimal Description Analysis).
- ▶ High-dimensional outlier detection (isolation forest).

Methods can be combined into sequential and independent ensembles.

C. Aggarwal, Outlier Analysis

# Summary

- ▶ Anomaly detection problem attracts a lot attention both from researchers and practitioners communities.
- ▶ Method should be selected based on the problem to be analysed.
- ▶ Many recent development in this area.