Generative Adversarial Active Learning for Unsupervised Outlier Detection

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INTRODUCTION

OUTLIERS refer to the observations that have significantly different characteristics from the other data. Due to the critical and interesting insights they often provide, outlier detection technologies play important roles in various application domains. Such as the abnormal trajectory and moving object detection, fraud detection, emerging topic detection and medical information detection.

RELATED WORK

Here we briefly summarize some of the previous work on outlier detection, including the following three main approaches.

- Classic Outlier Detection Methods: Gaussian mixture model (GMM), kth nearest neighbor (kNN), local reachability density (LOF), fast angle-based outlier detection (FastABOD) and so on.
- AGPO-Based Outlier Detection Methods: One-Class Random Forests (OCRF), Active-Outlier method (AO) and so on.
- GAN-Based Outlier Detection Methods: convolutional generative adversarial network (AnoGAN) and our methods.

METHODOLOGY

Core idea: view the outlier detection as a binary classification problem

Given a data set, each data will have a label indicating normal/abnormal (normal=1, abnormal=0). Anomaly detection is about finding a boundary that separates the abnormal data from the normal data. The optimal bound can be obtained by minimizing this objective function as follows. The optimal boundary can be determined by minimizing the loss function L_ζ of $\zeta(x)$.

$$L_\zeta = -\sum_{i=1}^{n}(c_n y_i \log(\zeta(x_i)) + c_o(1-y_i)\log(1-\zeta(x_i)))$$

where C_0 and C_n are the misclassification costs of outlier. $\zeta(x) \in (0,1)$ is a scoring function.

Therefore, we can assume that the density around the abnormal data is lower than the density of the normal data. This is shown in the figure below.

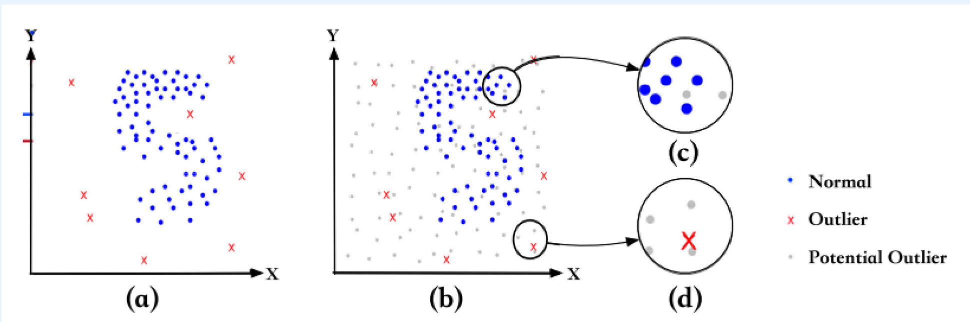

Figure 1. Illustration of the AGPO-based outlier detection mechanism.

$$\zeta(x|\rho(x) \geq \tau) \to 1,$$
$$\zeta(x|\rho(x) \leq \tau) \to 0,$$

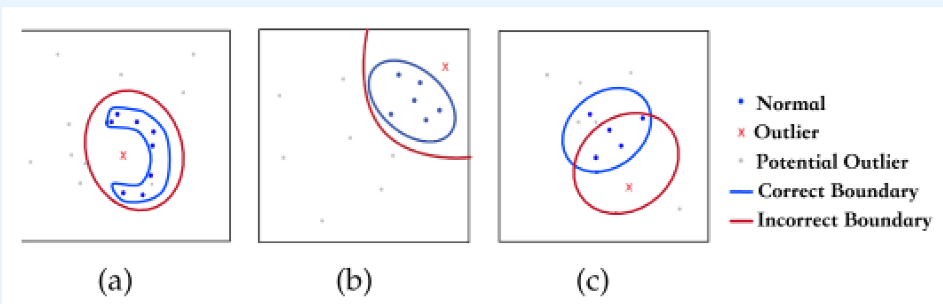

Figure 2. Illustration of the detection performance of the classifier $C(x)$ in three cross-sectional data drilled from high-dimensional datasets. The correct boundaries are shown with blue lines and incorrect boundaries with red lines.

$$L_C = -\frac{1}{2n}\sum_{i=1}^{2n}(y_i \log(C(x_i)) + (1-y_i)\log(1-C(x_i)))$$

Generative Adversarial Active Learning for Outlier Detection

Single-Objective Generative Adversarial Active Learning

$$\min_{\theta_g}\max_{\theta_d} V(D,G) = \mathbb{E}_{x\ p_{data}}[\log D(x)] + \mathbb{E}_{z\ p_z}[\log(1-D(x))]$$

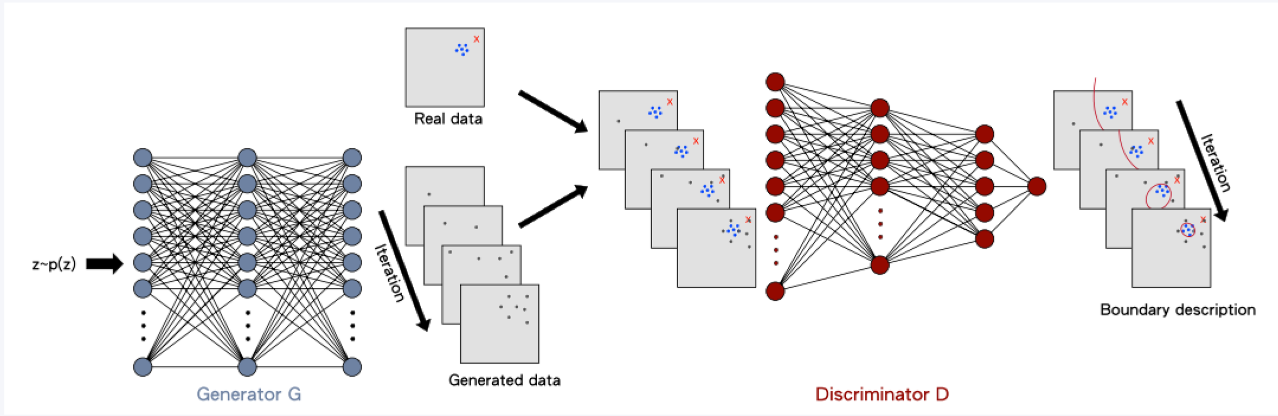

Figure 3. The detection process of SO-GAAL based outlier detection algorithm.

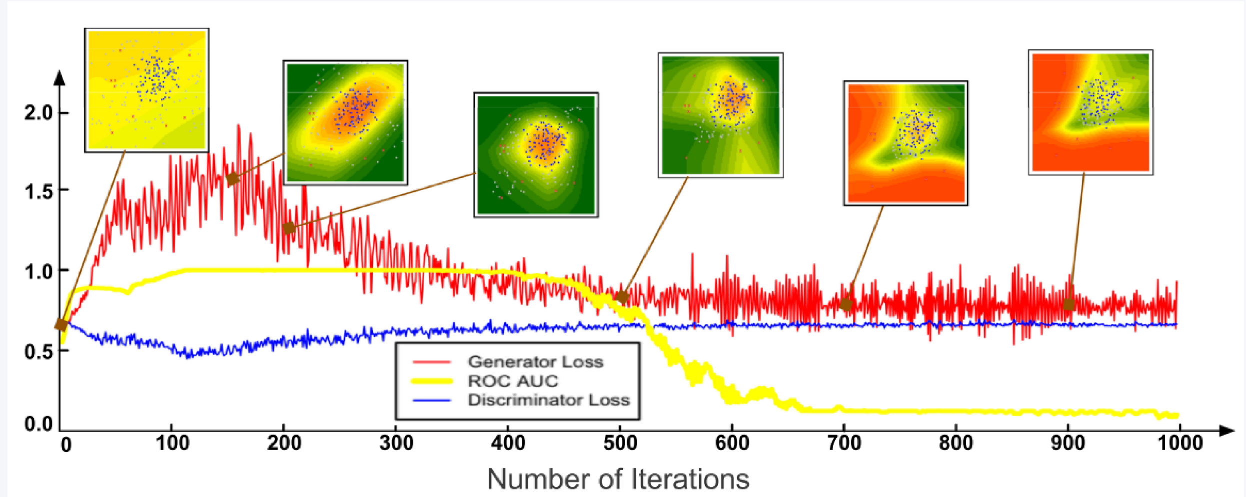

Figure 4. The optimization process of SO-GAAL based outlier detection.

Multiple-Objective Generative Adversarial Active Learning

$$\max_{\theta_d} V_D = \frac{1}{2n}\Big[\sum_{j=1}^{n}\log(D(x^{(j)})) + \sum_{i=1}^{k}\sum_{j=1}^{n_i}\log(1-D(G_i(z_i^{(j)})))\Big]$$

$$\min_{\theta_{g_i}} V_{G_i} = -\frac{1}{n}\sum_{j=1}^{n}[T_i\log(D(G_i(x^{(j)}))) + (1-T_i)\log(1-D(G_i(z_i^{(j)})))]$$

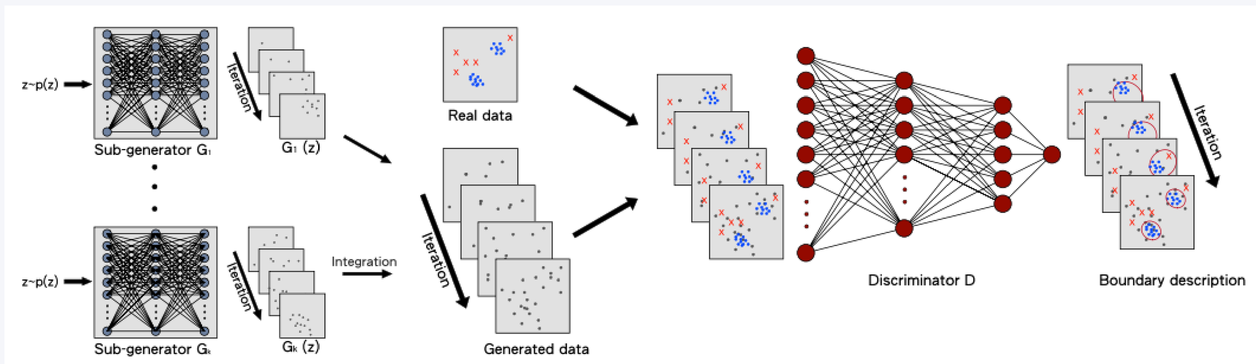

Figure 5. The detection process of MO-GAAL based outlier detection algorithm.

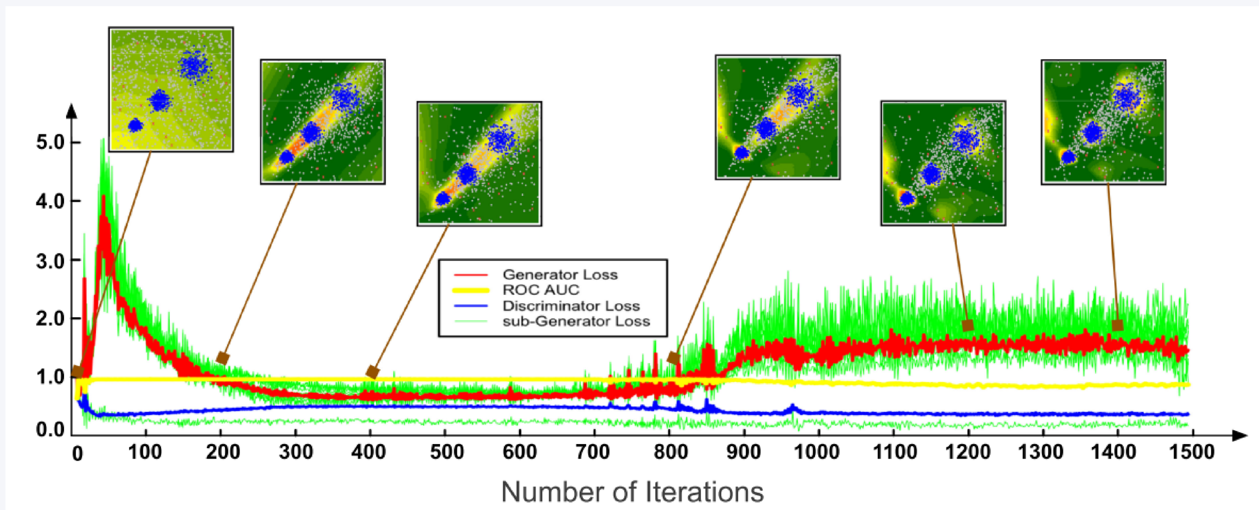

Figure 6. The optimization process of MO-GAAL based outlier detection.

RESULTS

Experimental results on real-world datasets are shown in Table 1. For each dataset, the best result is highlighted in bold. MO-GAAL achieves the highest accuracy on six of the fourteen datasets.

Table 1. Experimental Results of Outlier Detection Algorithms on Real-World Datasets.

Dataset	MO-GAAL	SO-GAAL	AGPO	AO	kNN	FastABOD	LOF	KDEOS	GMM	Parzen	OC-SVM	k-means
Pima	**0.758**	0.669	0.588	0.575	0.731	**0.758**	0.665	0.537	0.674	0.729	0.569	0.681
Shuttle	0.907	0.902	0.273	0.701	**0.989**	0.838	**0.989**	0.812	0.964	0.970	0.672	0.969
Stamps	0.908	0.654	**0.922**	0.791	0.901	0.733	0.740	0.546	0.856	0.896	0.705	0.877
PageBlocks	0.903	0.821	0.627	0.796	0.888	0.692	**0.926**	0.572	0.915	0.889	0.798	0.921
PenDigits	0.976	0.934	0.810	0.768	**0.985**	0.961	0.926	0.514	0.808	0.969	0.365	0.977
Annthyroid	**0.699**	0.607	0.465	0.586	0.649	0.623	0.674	0.604	0.546	0.586	0.560	0.595
Waveform	0.836	**0.841**	0.819	0.587	0.779	0.677	0.753	0.668	0.573	0.795	0.582	0.744
WDBC	**0.964**	0.033	0.947	0.946	0.923	0.939	0.912	0.553	0.908	0.938	0.025	0.919
Ionosphere	0.874	0.732	0.789	0.786	0.927	0.911	0.904	0.655	0.922	0.912	0.752	**0.929**
SpamBase	**0.627**	0.380	0.616	0.599	0.574	0.432	0.503	0.571	0.549	0.599	0.590	0.578
APS	0.966	0.947	0.740	0.872	**0.977**	na	0.865	0.785	0.790	na	0.537	0.972
Arrhythmia	**0.751**	0.729	0.743	0.636	**0.751**	0.742	0.737	0.539	0.473	**0.751**	0.707	0.746
HAR	0.972	0.971	0.882	0.842	0.964	0.442	0.965	0.647	0.012	0.962	**0.976**	0.969
p53Mutant	**0.727**	0.714	0.565	na	0.698	na	0.616	0.500	na	na	na	0.710
Average Ranks	2.58	7.42	6.83	8.17	3.67	6.83	5.83	10.17	7.17	4.50	9.33	4.83

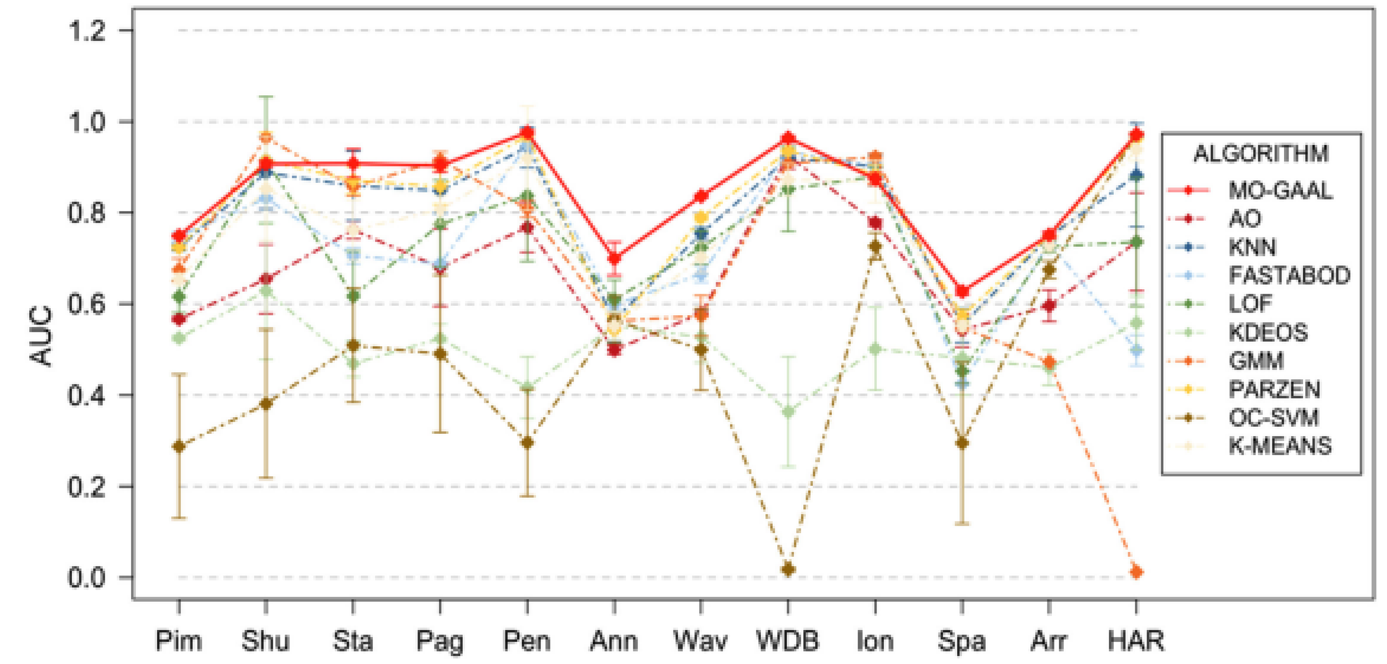

Figure 7. Performance fluctuations of different outlier detectors with different parameters.

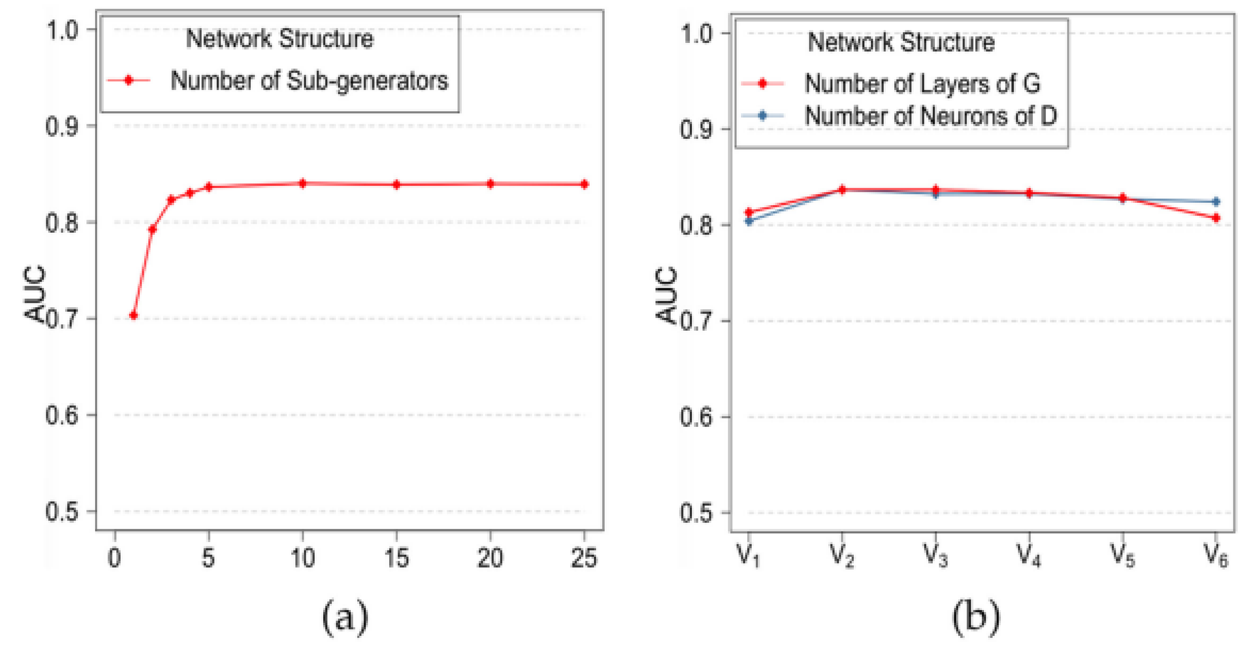

Figure 8. Experimental results of different network structures on real-world datasets.

CONCLUSIONS

- A novel outlier detection algorithm we proposes a novel outlier detection algorithm SOGAAL, which can directly generate informative potential outliers, to solve the lack of information caused by the curse of dimensionality
- Strong robustness MO-GAAL achieves the best average ranking on the real-world datasets, and shows strong robustness to varying parameters.