REFRAMING UNSUPERVISED MACHINE CONDITION MONITORING AS A SUPERVISED CLASSIFICATION TASK WITH OUTLIER-EXPOSED BINARY CLASSIFIERS

Technical Report

Paul Primus

Institute of Computational Perception (CP-JKU)
Johannes Kepler University, Austria

ABSTRACT

Although Machine Condition Monitoring is mostly treated as an unsupervised classification task, we reframe it is as a binary classification task, where the goal is to distinguish between the normal machine sounds and any other arbitrary sound. To be more specific, we train binary classifiers to distinguish between recordings of the machine of interest and recordings of random other machines. Our proposed method dramatically improves upon the provided Auto Encoder baseline results across all machine types and IDs.

Index Terms— Unsupervised Anomaly Detection, Outlier-Exposed Classifiers, Machine Condition Monitoring, DCASE2020

1. INTRODUCTION

- anomaly detection as a problem class
- explain the difficulty of obtaining anomalous samples - mostly because destroying stuff that works is expensive and anomalies are scarce.
- one instance of this problem is *Machine Condition Monitoring*

2. RELATED WORK

- Taxonomy of Anomaly Detection Methods (TODO: find a survey paper)
- Challenge Baseline Paper [1]
- Very complicated MCM approach [2]
- AUC, pAUC [3]
- AUC Loss Equation [2]
- Rethinking Assumptions in Anomaly Detection [4]

3. OUTLIER-EXPOSED CLASSIFIERS

Using random outliers somehow improves classification results – still not sure why. Anyhow, we investigate under which conditions we can use outlier exposed classifiers for unsupervised MCM.

An outlier expose-classifier is a binary classifier trained in a one-vs-everything fashion.

4. EXPERIMENTS

4.1. Experimental Setup

4.1.1. Dataset & Pre-Processing

DataSets

- ToyADMOS [1]
- MIMII [5]

Same pre-processing as baseline:

4.1.2. Network Architecture

[6]

4.1.3. Training

4.2. Results

Baseline [3]
Fancy table or bar plot containing test results on development set for all submissions.

5. CONCLUSION

not fancy post processing no machine-type specific feature engineering no-ensembling
OEC *easily* beat the unsupervised baseline.

6. REFERENCES

[1] Y. Koizumi, S. Saito, H. Uematsu, N. Harada, and K. Imoto, "ToyADMOS: A dataset of miniature-machine operating sounds for anomalous sound detection," in *Proceedings of IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (WASPAA)*, November 2019, pp. 308–312. [Online]. Available: https://ieeexplore.ieee.org/document/8937164

[2] Y. Koizumi, S. Saito, H. Uematsu, Y. Kawachi, and N. Harada, "Unsupervised detection of anomalous sound based on deep learning and the neyman-pearson lemma," *IEEE ACM Trans. Audio Speech Lang. Process.*, vol. 27, no. 1, pp. 212–224, 2019. [Online]. Available: https://doi.org/10.1109/TASLP.2018.2877258

[3] Y. Koizumi, Y. Kawaguchi, K. Imoto, T. Nakamura, Y. Nikaido, R. Tanabe, H. Purohit, K. Suefusa, T. Endo, M. Yasuda, and N. Harada, "Description and discussion on DCASE2020 challenge task2: Unsupervised anomalous sound detection for machine condition monitoring," in *arXiv e-prints: 2006.05822*, June 2020, pp. 1–4. [Online]. Available: https://arxiv.org/abs/2006.05822

[4] L. Ruff, R. A. Vandermeulen, B. J. Franks, K. Müller, and M. Kloft, "Rethinking assumptions in deep anomaly detection," *CoRR*, vol. abs/2006.00339, 2020. [Online]. Available: https://arxiv.org/abs/2006.00339

[5] H. Purohit, R. Tanabe, T. Ichige, T. Endo, Y. Nikaido, K. Suefusa, and Y. Kawaguchi, "MIMII Dataset: Sound dataset for malfunctioning industrial machine investigation and inspection," in *Proceedings of the Detection and Classification of Acoustic Scenes and Events 2019 Workshop (DCASE2019)*, November 2019, pp. 209–213. [Online]. Available: http://dcase.community/documents/workshop2019/proceedings/DCASE2019Workshop_Purohit_21.pdf

[6] K. Koutini, H. Eghbal-zadeh, and G. Widmer, "Receptive-field-regularized CNN variants for acoustic scene classification," *CoRR*, vol. abs/1909.02859, 2019. [Online]. Available: http://arxiv.org/abs/1909.02859