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A latest anomaly detection method of device

Interpretable, Multidimensional, Multimodal Anomaly Detection with Negative Sampling for Detection of Device Failure

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Outline

1. Introduction
2. Existing Anomaly detection methods
3. Studied model
4. Anomaly interpretation
5. Discussion
6. Conclusion and outlooks

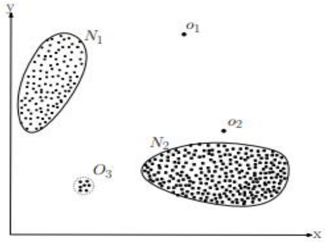
1. Introduction

Data streams

- Data arrives in real time
- Data is unlabeled
- Data are always Complex
  - Multidimensional
  - Correlated
  - Multimodal

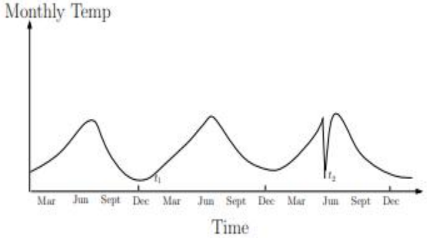
make anomaly detection harder

Anomalies



Point anomaly

Contextual anomaly



Problem solving

Unsupervised learning

Define anomalies types

- Point/Contextual
- 1-dim / N-dim

…

→

Find anomalies

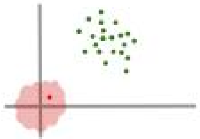
→

Analyze the cause of anomalies

- identify the root cause
- choose an appropriate fix

2. Existing Anomaly detection methods

Few/no failure labels challenge supervised approaches



One-class Classifiers

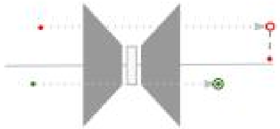
Learn a transformation to separate the observed points from the origin.

- One-Class SVM (2001)
- Deep SVDD (2018)

Density-Based

Anomalous points occur in low-density regions

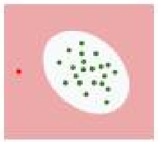
- Local Outlier Factor (2000)
- Isolation Forest (2009) and Ext. Isolation Forest (2018)



Autoencoders and Generative Models

Anomalies have larger reconstruction errors than Normal points

- AnoGAN (2017)
- GANomaly (2018)
- DAE-DBC (2018)



Negative Sampling Methods

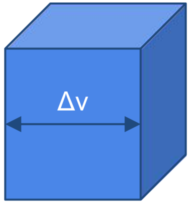
Explicitly define negative space for anomalies.

- Neg Selection Algorithms (NSA) (2002)
- Neg Sampling Classifiers (**this work**)

source: https://papertalk.org/papertalks/5618#similar_papers

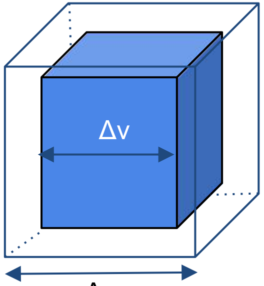
Negative sampling algorithm in AD

Normal hypercube: V



Δu = Δv ± δ

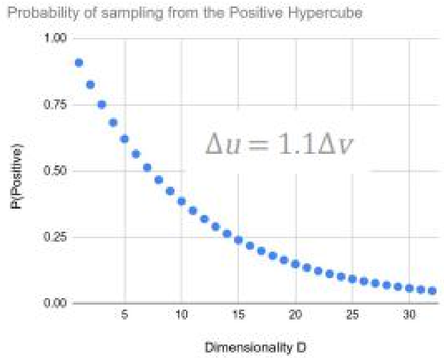
Anomaly hypercube: U



$$FPR = \frac{Vol(V)}{Vol(U)}$$

$$\lim_{D \to \infty} \prod_{d}^{D} \frac{\Delta v_d}{\Delta u_d} = 0$$

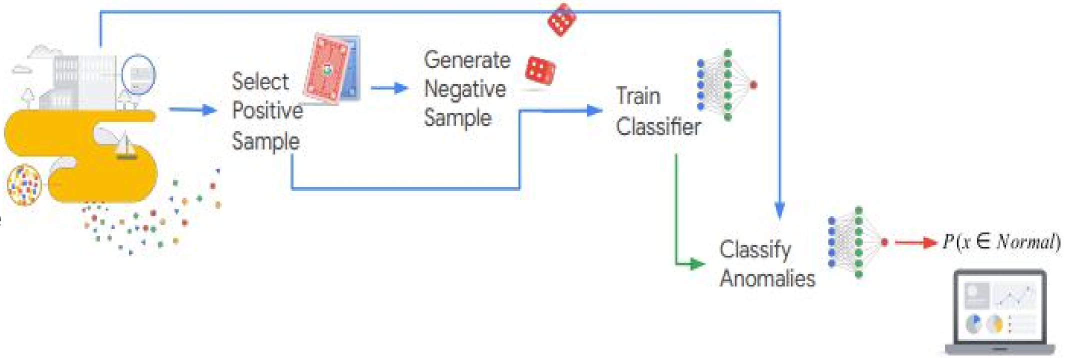
$$\Delta u_d > \Delta v_d$$



source: https://papertalk.org/papertalks/5618#similar_papers

Negative Sampling Method

- Use Negative Sampling algorithm to find positive and negative training sets
- Train the model with positive and negative samples



Studied Models

DATA SET	SIZE	DIM	ANOMALY
FOREST COVER (FC)	286,048	10	2,747 (0.9%)
SHUTTLE (SH)	49,097	9	3,511 (7%)
MAMMOGRAPHY (MM)	11,183	6	260 (2.3%)
MULCROSS (MC)	262,144	4	26,214 (10%)
SATELLITE (SA)	6,435	36	2,036 (32%)
SMART BUILDINGS (SB)	60,425	7	1,921 (3.2%)

Implemented classifiers

- Random Forest(**NSRF**)
- Neural Network(**NSNN**)

Evaluation metric

- AUC

	OCSVM	DSVDD	ISO	EIF	NSRF	NSNN
FC	53±20	69±7	85±4	**93±1**	80±2	86±4
SH	93±0	88±9	**96±1**	91±1	**93±7**	**96±5**
MM	71±7	78±6	77±2	**86±2**	**85±4**	84±2
MC	90±0	54±17	88±0	66±4	94±1	**99±1**
SA	51±1	62±3	67±2	**71±3**	65±4	**73±3**
SB	76±1	60±7	71±7	80±4	**95±1**	93±1

Anomaly interpretation

Integrated Gradients

- Baseline set U* from positive sample U

$$U^{*} \subset U : \forall_{u \in U^{*}} F(x) \approx 1$$

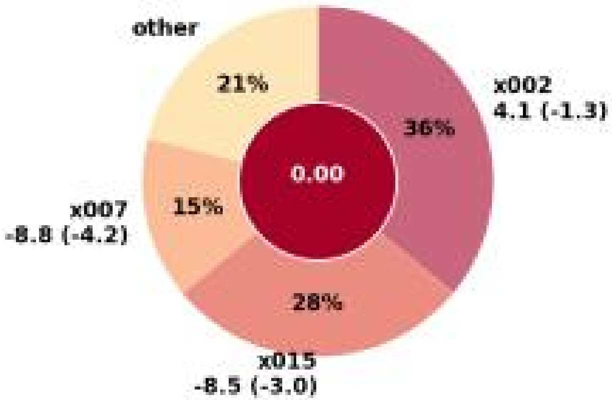
- Choose the closest u* to the data x

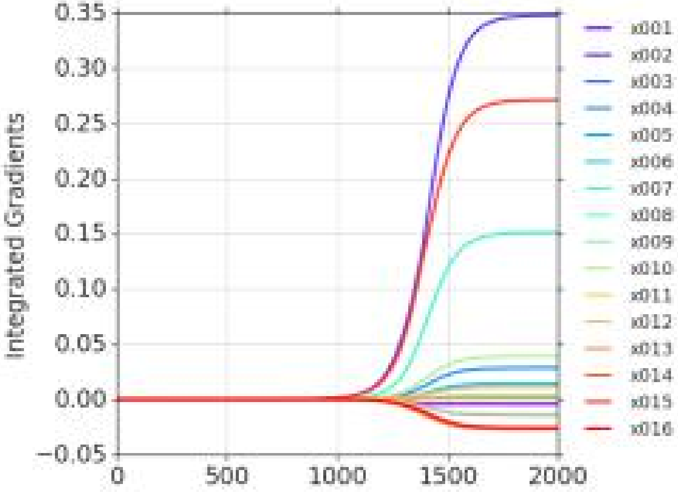
$$u^{*} = argmin_{u \in U^{*}} \{dist(x, u)\}$$

- Calculate the contribution of each dimension

$$B_d(x) \equiv (u_d^{*} - x_d) \times \int_{\alpha=0}^{1} \frac{\partial F(x + \alpha \times (u^{*} - x))}{\partial x_d} d\alpha$$

$$\sum_{d \in D} B_d(x) \approx 1$$


other
21%
x002
4.1 (-1.3)
36%
0.00
x007
-8.8 (-4.2)
15%
28%
x015
-8.5 (-3.0)


Integrated Gradients
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−0.05
0
500
1000
1500
2000
x001
x002
x003
x004
x005
x006
x007
x008
x009
x010
x011
x012
x013
x014
x015
x016

Application: Smart Buildings

Smart Buildings Fault Detection and Diagnostics (FDD) project

- 145 buildings at Google
- over 15,000 power and climate control devices
- Over 44% TP in real usage in 2019

Discussion

Pros

- Simple method with good effect
- Handling multidimensional and multi-modal data
- Help technicians understand anomalies

Cons

- High FP rate in low dimensional data
- Only for point anomalies
- Choose baseline set

Reference

Sipple, J. 2020. Interpretable, Multidimensional, Multimodal Anomaly Detection with Negative Sampling for Detection of Device Failure. In Proceedings of the 37th International Conference on Machine Learning (ICML 20).

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Thanks for listening!

Any questions?