Anomalous Pattern and Systemic Error Detection in Radiation Portal Monitors via Robust Deep Autoencoders

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Introduction

- Radiation portal monitors are used across U.S. borders to detect dangerous radioactive materials
- With hundreds of sensors, sensor malfunctions in RPMs due to bias and noise are not uncommon
- Systemic malfunctions:
  - Barely affect classification accuracy
  - Hard to detect
  - Early identification is critical

Radiation Portal Monitors across U.S. Border

Motivation and Objectives

- ***Problems*** with current methods:
  - Distance and density based are less effective when detecting anomalous patterns in high dimensions
  - Clustering based approaches require extensive tuning and many need to make assumptions about the underlying data
  - PCA based approaches assume a linear projection of the data
- ***Objective***
  - Detect and flag anomalous patterns in data that may occur due to systemic errors
  - Maintain high detection accuracy while limiting false alarms

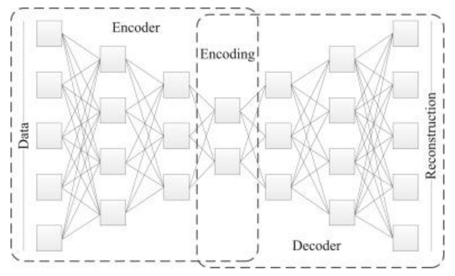
Approach

Scheme

1. **Train** a robust autoencoder on training data. The autoencoder should learn to effectively project normal data onto a lower dimensional subspace
2. **Reconstruct** test data points via this autoencoder network and calculate reconstruction error for these points
3. **Detect** significant changes in patterns of reconstruction error and flag anomalous behavior in data

Benefits

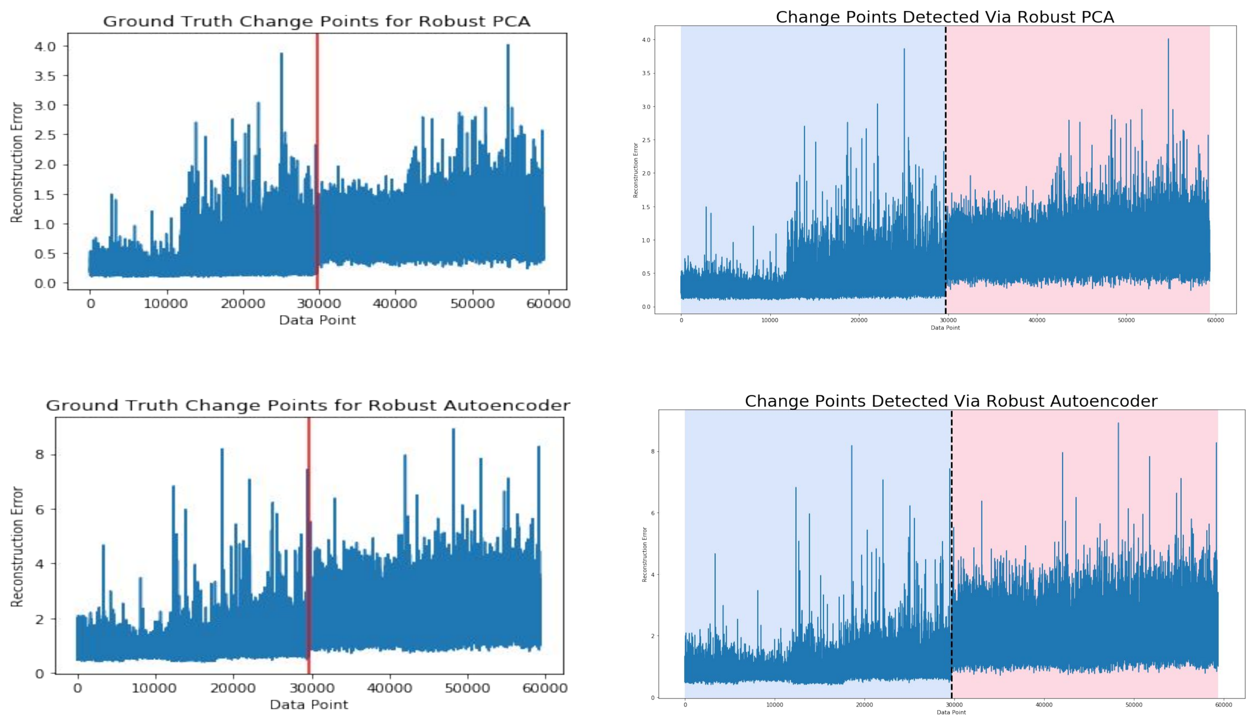
- Leverage complex relations present in data
- Not restricted to linear subspace
- Online or offline change point detection scheme



Autoencoder architecture

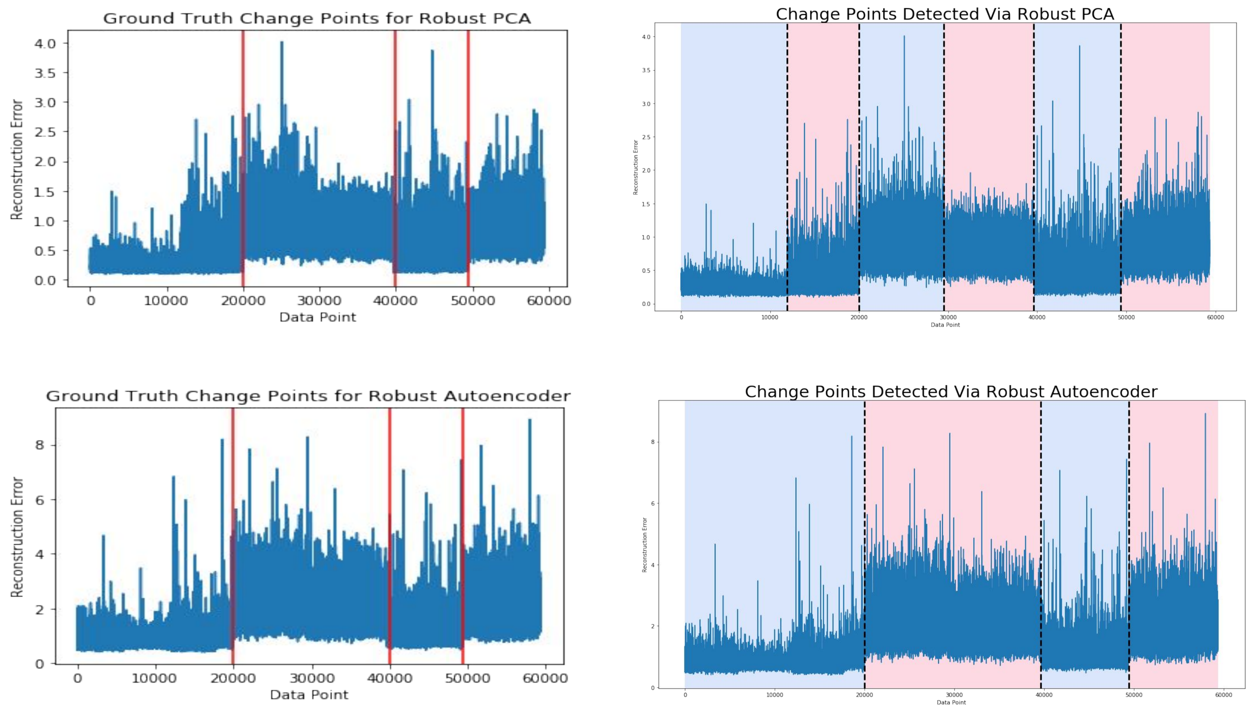
Experiments and Results

Detecting singular malfunction



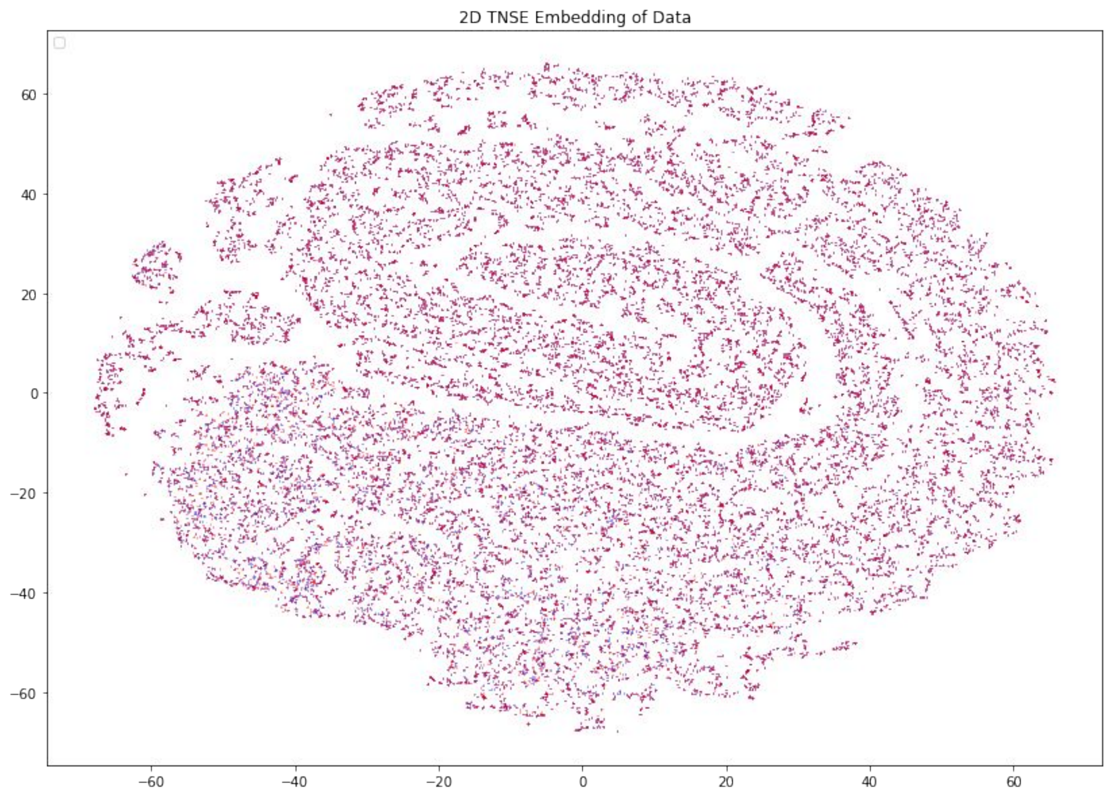
Both methods work effectively in this scenario

Detecting multiple malfunctions



PCA fails in this scenario unlike the autoencoder, highlighting a potential shortcoming of PCA

TSNE Embedding



Blue = Normal
Red = Anomalous

Conclusion

- These results illustrate potential issues PCA based techniques face: imbalanced representation of various classes
- Clustering based approaches such as ***TSNE may not capture subtle errors***
  - Another drawback: much harder to tune
- Autoencoders learn classes more equally, and so the line between “normal” and “anomalous” is better defined
- Using autoencoders + change point detection could provide a fast, online solution for real-time detection of systemic errors

Future Work

- Develop a more robust evaluation metric to numerically compare different methods
- Comprehensive testing with different kinds of noise and varying degrees of malfunctions
- Ensemble methods for detecting anomalous patterns

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