Anomaly Detection from Sensor Data

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Msc Machine Learning and Data Mining (MLDM)
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January 13th, 2020

Introduction

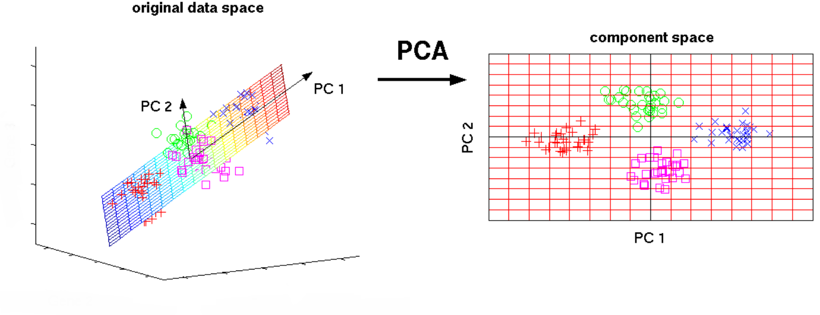
Problem Context: Similar to previous pitch:

- Training: 1677 sequences, All normal !
- Validation: 600 sequences
- Test: ~ 2000 sequences
- Each sequence ~ 60000 points

Goal: Use this data to learn the true representation of normal samples and use it to detect Abnormalities.

Challenges

- Large feature vectors ~ 60 k
- No Labels in training
- Learn the true representation of Normal
- Anomalies in the final test data different from validation.
- When an anomaly is detected on one flight, all sequences of this flight are labelled as abnormal
- ,,,

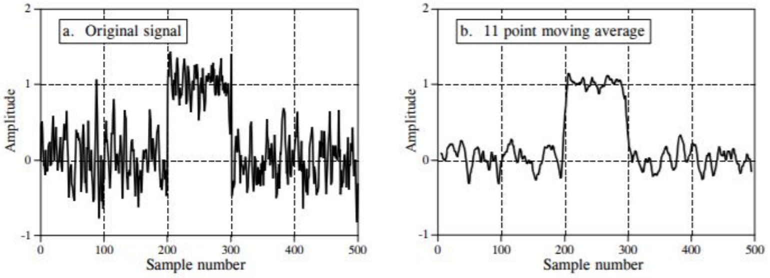


Effectively reduces the dimension. BUT, Loses temporal information and it is Linear

Solutions: Large Dimensionality

- **Moving Average**: Sliding window that consider the average of each window as a representative.

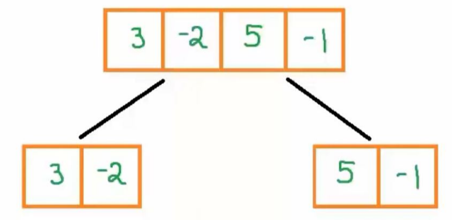
- Window of size 1000 (one second) $\Rightarrow$ the new signal of size 60.



Effectively reduces the dimension. BUT, Choosing window size is tricky and average suffers from compensation

Solutions: Large Dimensionality

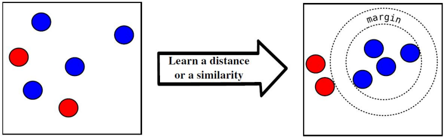
- **Creating new dataset**: Splitting each sequence into K new sub sequences and treat each one as a new dataset instance
- ⇒ Increase dataset size, Decrease feature vectors.
- ⇒ Less prone to overfitting.
- K = 12 ⇒ each sample will give 12 new instances, each of size 5000



Effectively reduces the dimension and give more samples.
BUT, needs to tune K and extra processing when classifying

Solutions: Large Dimensionality, Learn Representation

- **Metric Learning**: Learn a metric that assigns small (resp. large) distance to pairs of examples that are semantically similar (resp. dissimilar)[1].
- Lower Dimension
- Better Representation
- Needs some Label !
- Linear, but could be Kernelized !



Results

Rank	Team	University	F1-Score	Precision	Recall	Method
2	The-h-star	Universite Jean Monnet Saint Etienne	0.99	0.98	1.0	Metric Learning
40	The-h-star	Universite Jean Monnet Saint Etienne	0.93	1.0	0.88	Autoencoders + OCSVM + Splitting
80	The-h-star	Universite Jean Monnet Saint Etienne	0.89	1.0	0.80	PCA + OCSVM

Table 1: Ranking at Nov. 29, 2019

Conclusion

- Anomaly detection could be very tricky
- Dimensionality Reduction highly impact model performance and accuracy
- Metric Learning is effective tool to learn better data representation, but needs labels
- Autoencoders also effective to learn better representation (No need for labels)