# LSTM-based Encoder-Decoder for Multi-sensor Anomaly Detection

Pankaj Malhotra, Anusha Ramakrishnan, Gaurangi Anand, Lovekesh Vig,
Puneet Agarwal, and Gautam Shroff

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Seonyoung Kim

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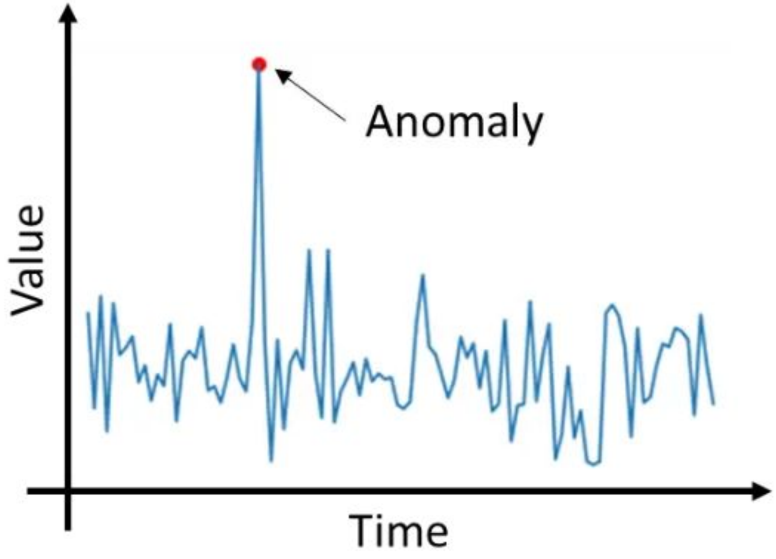
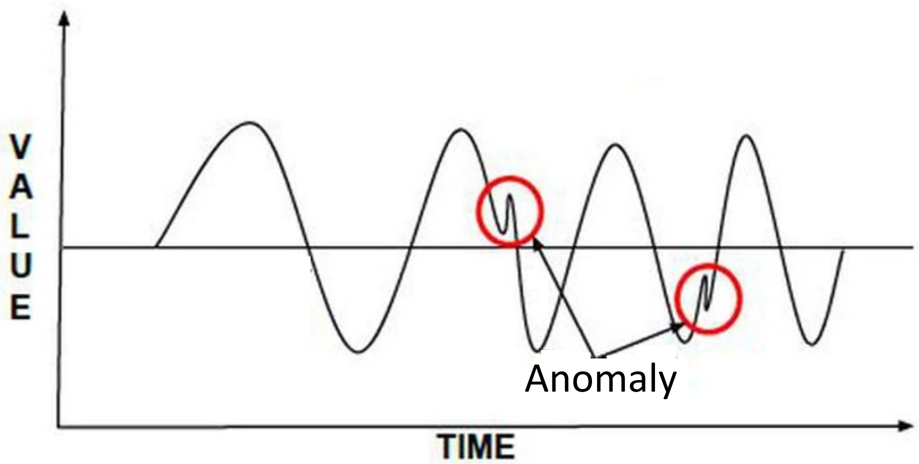
# Introduction

- Mechanical devices are instrumented with numerous sensors to capture the behavior and health of the machine

- Anomaly Detection
  - the process of identifying unexpected items or events in data sets, which differ from the normal data

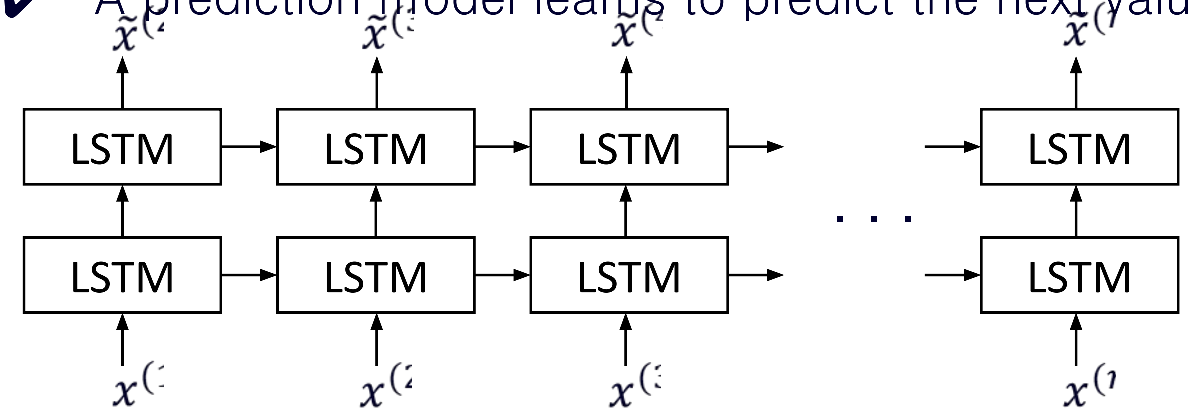


# Related Work and Motivations

- Traditional techniques monitoring anomalies use statistical measures to detect changes in the underlying distribution
  - Exponentially weighted moving average (EWMA), SVR

- Long Short Term Memory Networks for Anomaly Detection in Time Series [4]
  - Stacked LSTM based prediction model
    - ✔ A prediction model learns to predict the next values



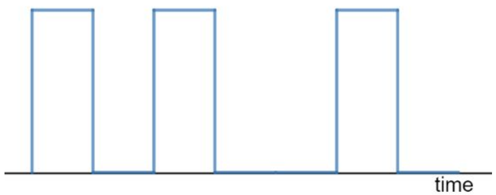

$A\ time\ series\ X = \{x^{(1)}, x^{(2)}, \dots, x^{(L)}\}\ of length\ L$

$x^{(i)} \in R^m :\ an\ m - dimensinal\ vector\ of\ readings\ for\ m\ variables\ at\ time\ instance\ t_i$

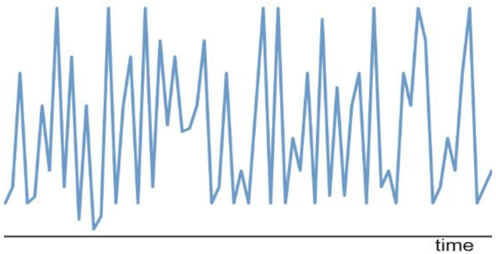
$\tilde{x}^{(i)} :\ the\ predicted\ value\ of x^{(i)}$

# Related Work and Motivations

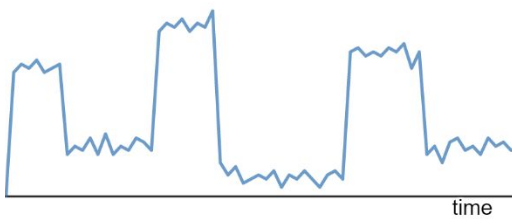
- Predictable & Unpredictable time-series
  - control variable : variable which are not captured by sensor and it can be simple or changes frequently in certain range
  - result = predictable time series or unpredictable time-series




Readings for a control variable with two states




Readings for a control variable that changes frequently




Predictable time-series

?

Unpredictable time-series

- Detecting anomalies with control variable that changes frequently becomes challenging using traditional approaches based on prediction models

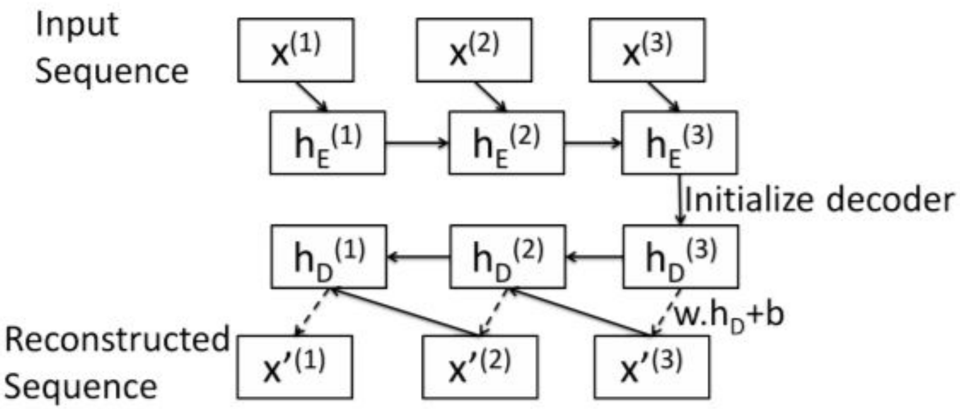
# Proposed method: EncDec-AD

- Solve the problem of the prediction model for anomaly detection
  - Predictable & Unpredictable problem
  - Uses autoencoder-based method to detect the anomalies

- Overview
  - Train LSTM Encoder-Decoder model
    1. **the LSTM Encoder learns a fixed length vector representation of the normal time-series data**
    2. **the LSTM Decoder uses this representation to reconstruct the time-series**
  - Compute likelihood of anomaly
    - ✔ With trained model, compute likelihood of anomaly of time-series data

# Proposed method: EncDec-AD

- LSTM Encoder-Decoder as reconstruction model




✓ $a\ time\ series\ X = \{x^{(1)}, x^{(2)}, \dots, x^{(L)}\}\ of\ length\ L$

✓ $x^{(i)} \in R^m$ : $an\ m-dimensinal\ vector\ of\ readings\ for\ m\ variables\ at\ time\ instance\ t_i$

✓ $h_E^{(i)} \in R^c$ : $the\ hidden\ state\ of\ encoder\ at\ time\ t_i\ for\ each\ i \in \{1,2,\dots,L\},$
$where\ c\ is\ the\ number\ of\ LSTM\ units\ in\ the\ hidden\ layer\ of\ the\ encoder$

✓ $h_D^{(i)} \in R^c$ : $the\ hidden\ state\ of\ decoder\ at\ time\ t_i\ for\ each\ i \in \{1,2,\dots,L\},$
$where\ c\ is\ the\ number\ of\ LSTM\ units\ in\ the\ hidden\ layer\ of\ the\ decoder$

✓ $w$ : $weight\ matrix$

✓ $b$ : $bias$

- The model is trained to minimize the objective function:

$$\sum_{X \in s_N} \sum_{i=1}^{L} \left\| x^{(i)} - x'^{(i)} \right\|^2$$

✓ $s_N$ : set of normal training sequences

# Proposed method: EncDec-AD

- Computing likelihood of anomaly(1/3)
  - Divide the normal time-series into four sets of time-series
    - ✓ $s_N$ : $set\ of\ normal\ training\ sequences$
    - ✓ $v_{N1}$ : $set\ of\ normal\ validation\ sequences\_1$
    - ✓ $v_{N2}$ : $set\ of\ normal\ validation\ sequences\_2$
    - ✓ $t_N$ : $set\ of\ normal\ test\ sequences$

  - Divide the anomalous time-series into two set of time-series
    - ✓ $v_A$ : $set\ of\ anomalous\ validation\ sequences$
    - ✓ $t_A$ : $set\ of\ anomalous\ test\ sequences$

# Proposed method: EncDec-AD

- Computing likelihood of anomaly(2/3)
  - The set of sequence $s_N$ is used to learn the LSTM encoder-decoder reconstruction model
  - The reconstruction error vector at time $t_i$
    - ✓ $The\ error\ vector\ e^{(i)} = \left|x^{(i)} - x'^{(i)}\right|$
  - The error vectors for the points in the sequences in $v_{N1}$ are used to estimate a Normal distribution $N(\mu, \Sigma)$ using Maximum Likelihood Estimation
    - ✓ Given $v_{N1}\ set\ \{x^{(1)}, x^{(2)}, \ldots, x^{(m)}\}$
    - ✓ $\mu = \frac{1}{m}\sum_{i=1}^{m} x^{(i)}$
    - ✓ $\Sigma = \frac{1}{m}\sum_{i=1}^{m}(x^{(i)} - \mu)(x^{(i)} - \mu)^T$

# Proposed method: EncDec-AD

- Computing likelihood of anomaly(3/3)
  - The anomaly score
    - ✓ For any point $x^{(i)}$
    - ✓ $a^{(i)} = \left(e^{(i)} - \mu\right)^T \Sigma^{-1} \left(e^{(i)} - \mu\right)$
    - ✓ If $a^{(i)} > \tau$, a point in a sequence can be predicted → "anomalous"
    - ✓ Otherwise, a point in a sequence can be predicted → "normal"

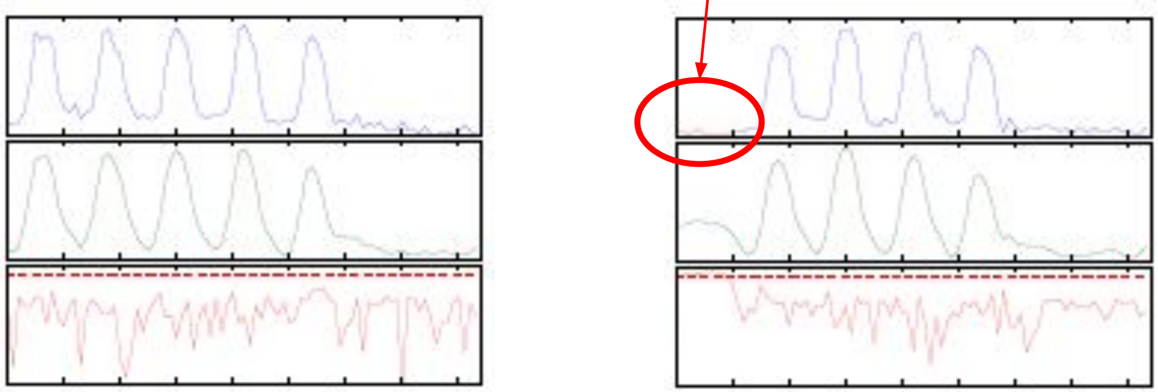
  - The $v_{N2}$ and $v_A$ are used to learn $\tau$ by maximizing $F_\beta - score$
    - ✓ $F_\beta = (1 + \beta^2) \times P \times \frac{R}{\beta^2 P + R}$
    - ✓ $P : precision$
    - ✓ $R : recall$

# Experiments

- Dataset
  - Power demand
    - ✔ One univariate time-series with 35,040 readings for power demand recorded over a period of one year
    - ✔ Length of sequence = 84
  - Space shuttle
    - ✔ Periodic sequences with 1000 points per cycle, and 15 such cycles
    - ✔ Length of sequence = 1500
  - Engine data
    - ✔ Reading for 12 sensors such as coolant temperature, torque, accelerator etc.
    - ✔ Consider two different applications of the engine : Engine-P, Engine-NP
    - ✔ Engine-P has a discrete external control with two states : 'high' and 'low' → "predictable"
    - ✔ Engine-NP has any value within a certain range and changes very frequently → "unpredictable"
    - ✔ Length of sequence = 30
  - ECG
    - ✔ Quasi-periodic time-series
    - ✔ Contains one anomaly corresponding to a pre-ventricular contraction
    - ✔ Length of sequence = 208

# Experiments

Anomaly

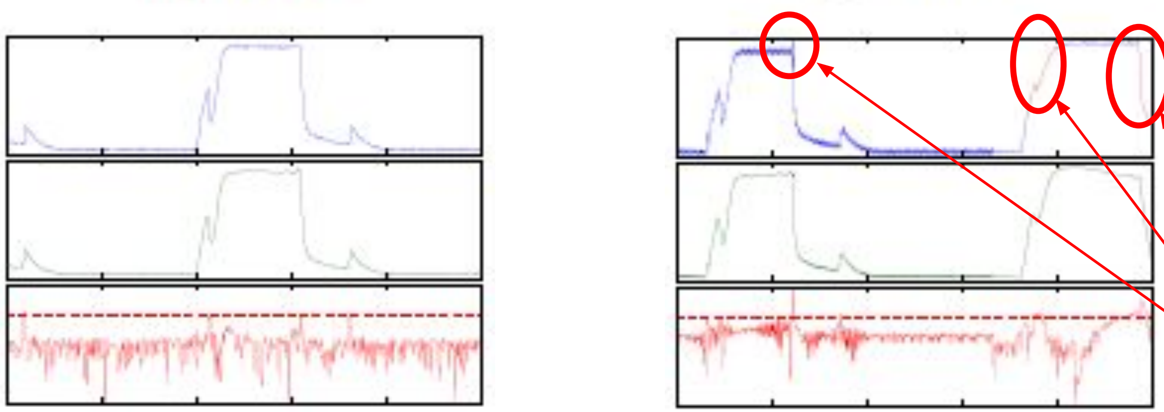


(a) Power-N (b) Power-A

Original Sequences(first row, blue color)

Reconstructed sequences(second row, green color)

Anomaly scores(third row, red color)

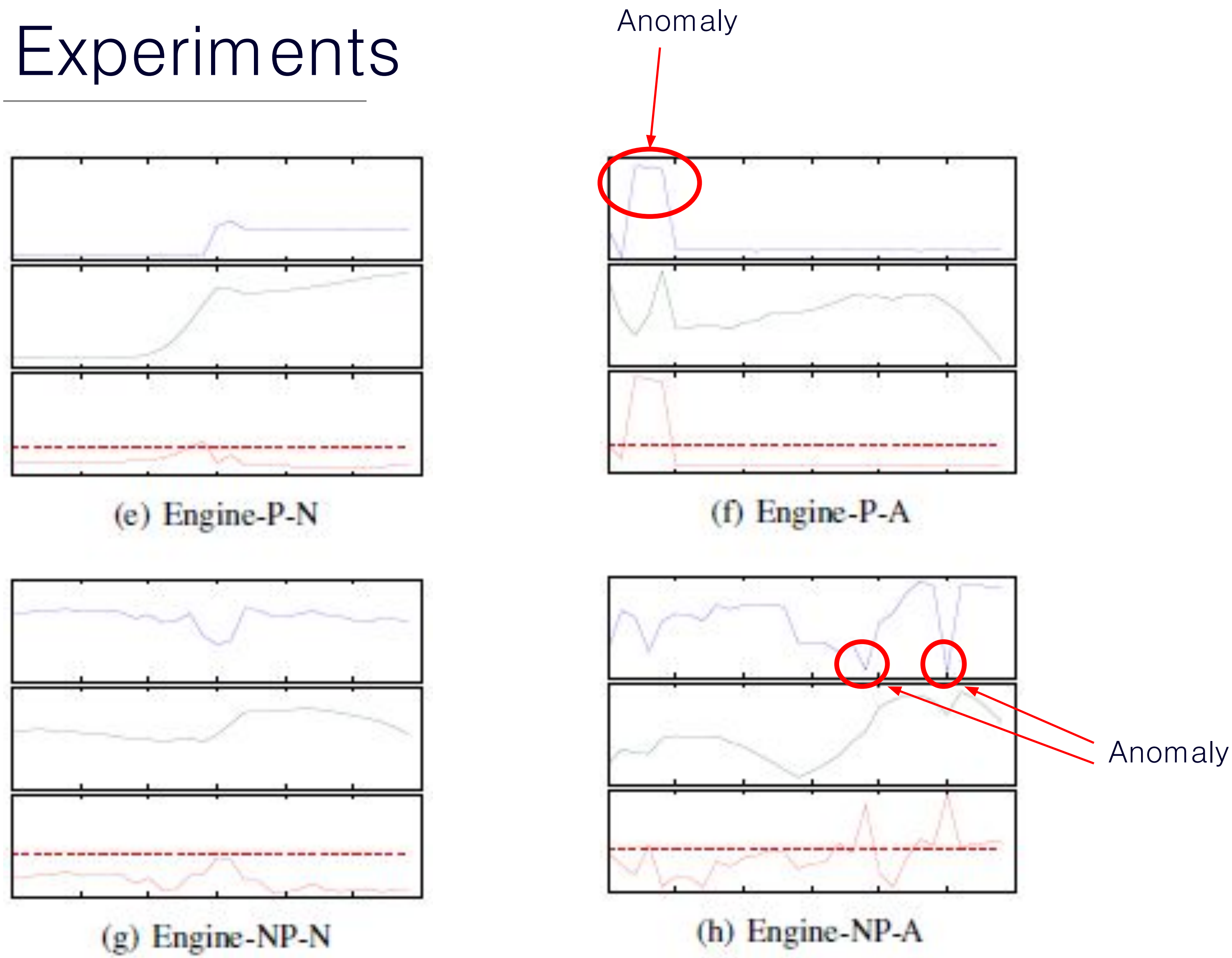


Anomaly

(c) Space Shuttle-N (d) Space Shuttle-A

Normal Anomalous

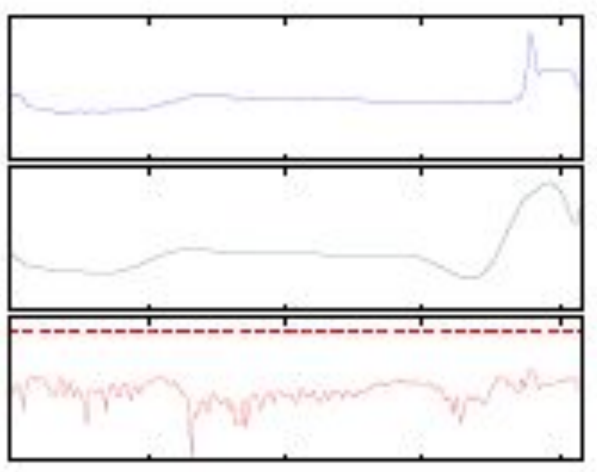
# Experiments



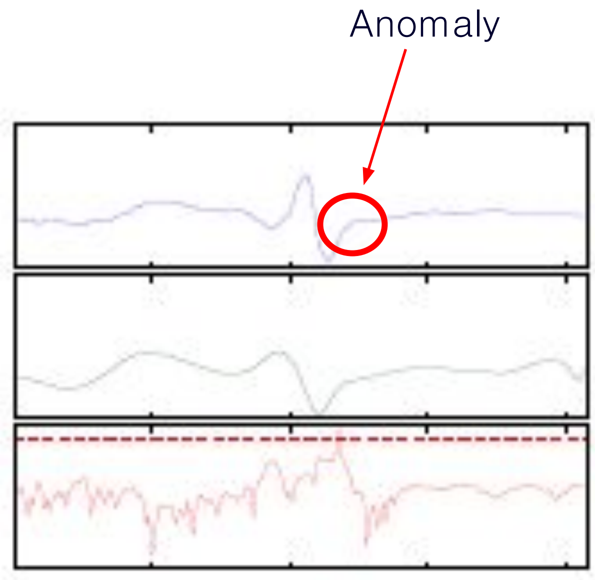

Normal

Anomalous

# Experiments



(i) ECG-N




(j) ECG-A

# Observation

| Datasets | L | c | $\beta$ | P | R | $F_\beta$-score | TPR/FPR |
|---|---|---|---|---|---|---|---|
| Power Demand | 84 | 40 | 0.1 | 0.92 | 0.04 | 0.77 | 33.0 |
| Space Shuttle | 500 | 50 | 0.05 | 0.83 | 0.08 | 0.81 | 4.9 |
| Engine-P | 30 | 40 | 0.05 | 0.94 | 0.02 | 0.82 | 13.8 |
| Engine-NP | 30 | 90 | 0.05 | 1.0 | 0.01 | 0.83 | $\infty$ |
| ECG | 208 | 45 | 0.05 | 1.0 | 0.005 | 0.65 | $\infty$ |

- ✓ $L$ : *Length of sequence*
- ✓ $c$ : *the number of LSTM units in the hidden layer of encoder and decoder*
- ✓ $\beta$ : *the value of* $\beta$ *in* $F_\beta - score$
- ✓ $P$ : *Precision*
- ✓ $TPR$ : *Ture Positive Rates*
- ✓ $FPR$ : *False Positive Rates*

- The positive likelihood ratio(TPR/FPR) > 1 for all the datasets
  - The probability of reporting an anomaly in anomalous region is much higher than the probability of reporting an anomaly in normal region.

- For periodic time-series, we experiment with varying window lengths
  - Being able to detect anomalies in all scenarios

- Compare to LSTM-AD[3], this method gives better results for Engine-NP where the sequence are not predictable

# Conclusion

- This paper proposes EncDec-AD for anomaly detection in multi-sensor time-series
- EncDec-AD first learns a LSTM-based Encoder-Decoder model to reconstruct values of normal time-series
- Then, EncDec-AD computes anomaly score of each time step by calculating the likelihood value with reconstruction error vectors
- Experimental results show that EncDec-AD detects anomalies in not only predictable time-series but also unpredictable time-series data

# References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# Thank you