“Deep Learning for Anomaly Detection”

Paper Implemented:-

VELC: A New Variational AutoEncoder Based Model for Time Series Anomaly Detection

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Introduction to the problem

Anomaly Detection : To find different patterns in the data which often contain important information, and these patterns are not caused by random deviations.

Challenges in Anomaly Detection :

- Abnormal data are usually unbalanced
- Characteristics of anomalous data may be unknown

Task : A time series anomaly detection based on VAE with re-Encoder and Latent Constraint network, named as VELC. This model adds a re-encoder in the architecture of VAE to obtain new latent vectors, and this more complex architecture can optimize the reconstruction error both in the original space and latent space to accurately model the normal samples.

Related Work

To account for this challenge, lots of unsupervised anomaly detection methods based on deep learning model are designed.

1. "Malhotra, P., Vig, L., Shro, G., Agarwal, P.: Long Short Term Memory Networks for Anomaly Detection in Time Series p. 6 (2015)"used the distribution of the prediction errors of LSTMs to compute anomaly scores.
2. "Sabokrou, M., Fathy, M., Hoseini, M., Klette, R.: Real-time anomaly detection and localization in crowded scenes. In: Proceedings of the IEEE conference on computer vision and pattern recognition workshops. pp. 56{62 (2015)" trained an autoencoder using the normal data and detects anomalies using the output of the model's hidden layer and the SSIM feature of the test samples.
3. "Bayer, J., Osendorfer, C.: Learning stochastic recurrent networks. Eprint Arxiv (2015)" used the variational inference and RNNs to model time series data and introduced stochastic recurrent networks (STORNs), which were subsequently applied to anomaly detection in robot time series data.

Method proposed to solve the problem

Author proposed a novel time series anomaly detection based on **VAE with re-Encoder and Latent Constraint network(VELC)**.

The aim of the proposed model work is to detect the anomalies of a time series based on the reconstruction error of generative model.

The model is trained with normal data, it means that the model will have relatively small reconstruction errors for normal data, but large reconstruction errors for abnormal data.

VELC Model has 4 parts

1. **VAE Encoder**
2. **VAE Decoder**
3. **Re-Encoder**
4. **Constraint Network**

VAE Encoder, Decoder and Re-Encoder uses Bidirectional LSTM.

Architecture of VELC

Purpose of Re-Encoder : VAE with Re-Encoder will have more parameters and complex model structure. Thus model can extract more features.

Purpose of Constraint Network : Constraint Network is added after sampling latent variables to limit the model's ability to reconstruct abnormal data

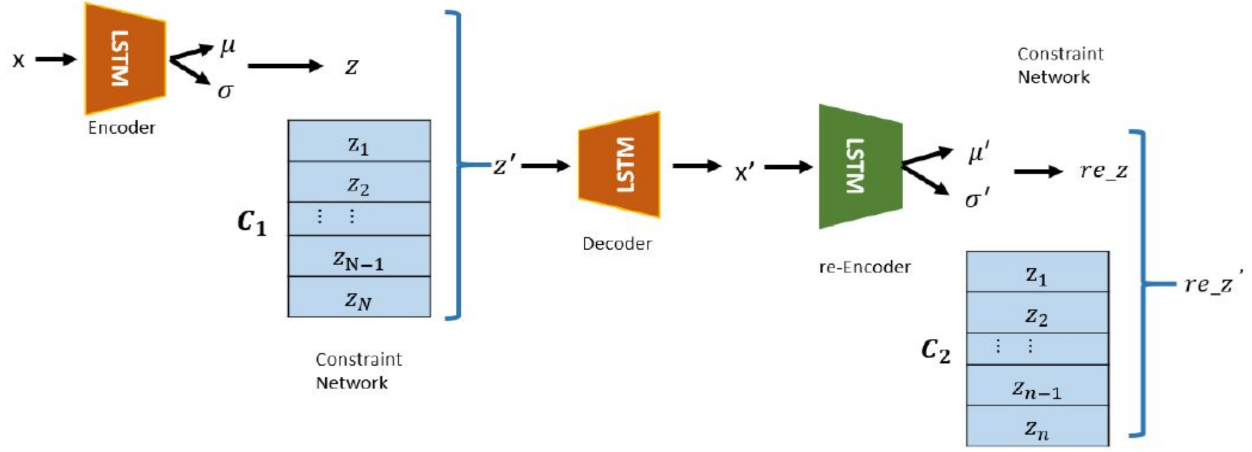


Fig. 1. The network structure of VELC. Two orange blocks are the encoder and decoder layer of VAE, the green block is the re-Encoder layer and the blue part is the constraint network.

Loss Function and Anomaly Score

For the entire model, the loss function can be described as:

$$L_{VELC} = \underbrace{L_{rec\_x} + L_{KL\_1}}_{\text{VAE Losses}} + \underbrace{L_{lat} + L_{KL\_2}}_{\text{Losses due to constraint networks and re-encoder}}$$

The new anomaly score is defined as follows:

$$A(x_i) = \alpha \left\| x - x' \right\|_1 + \beta \left\| z' - re\_z' \right\|_1$$, where $\alpha + \beta = 1$

Datasets to be used

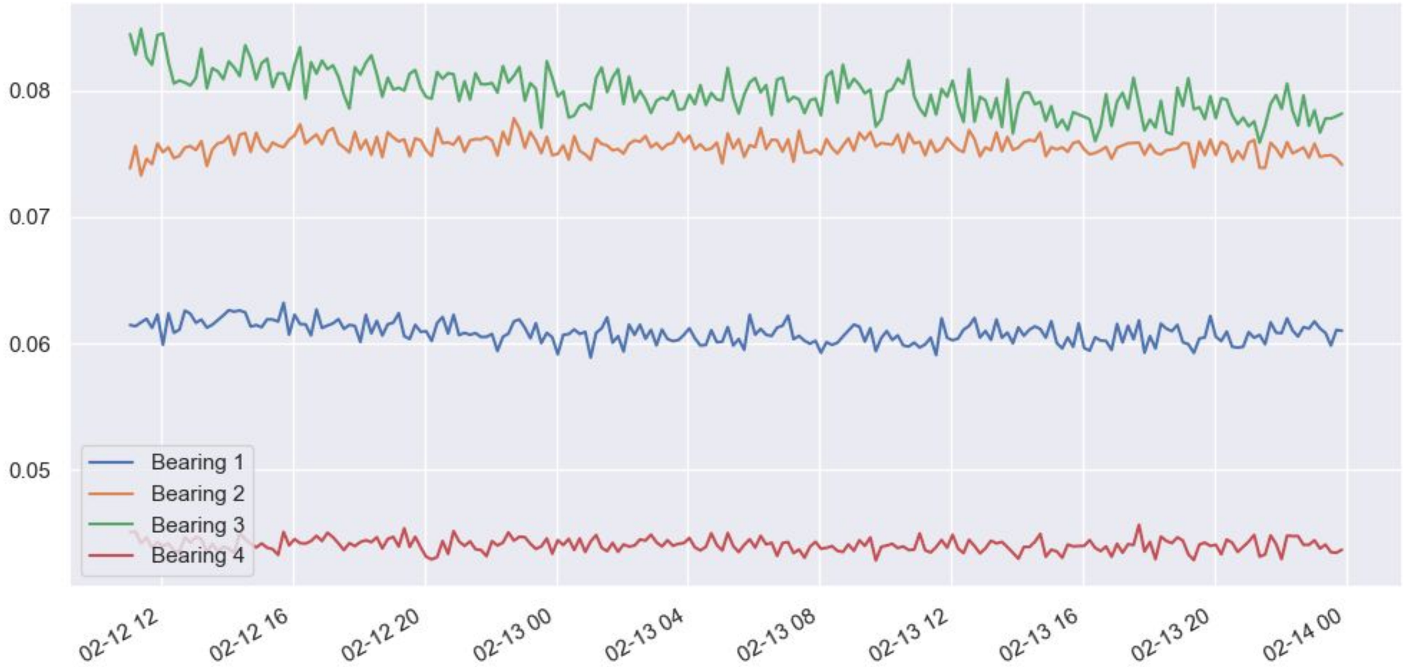
- The data was generated by the NSF I/UCR Center for Intelligent Maintenance Systems (IMS –www.imscenter.net) with support from Rexnord Corp. in Milwaukee, WI.

- The data set describes a test-to-failure experiment. It consists of individual files that are 1-second vibration signal snapshots recorded at specific intervals. Each file consists of 20,480 points with the sampling rate set at 20 kHz.

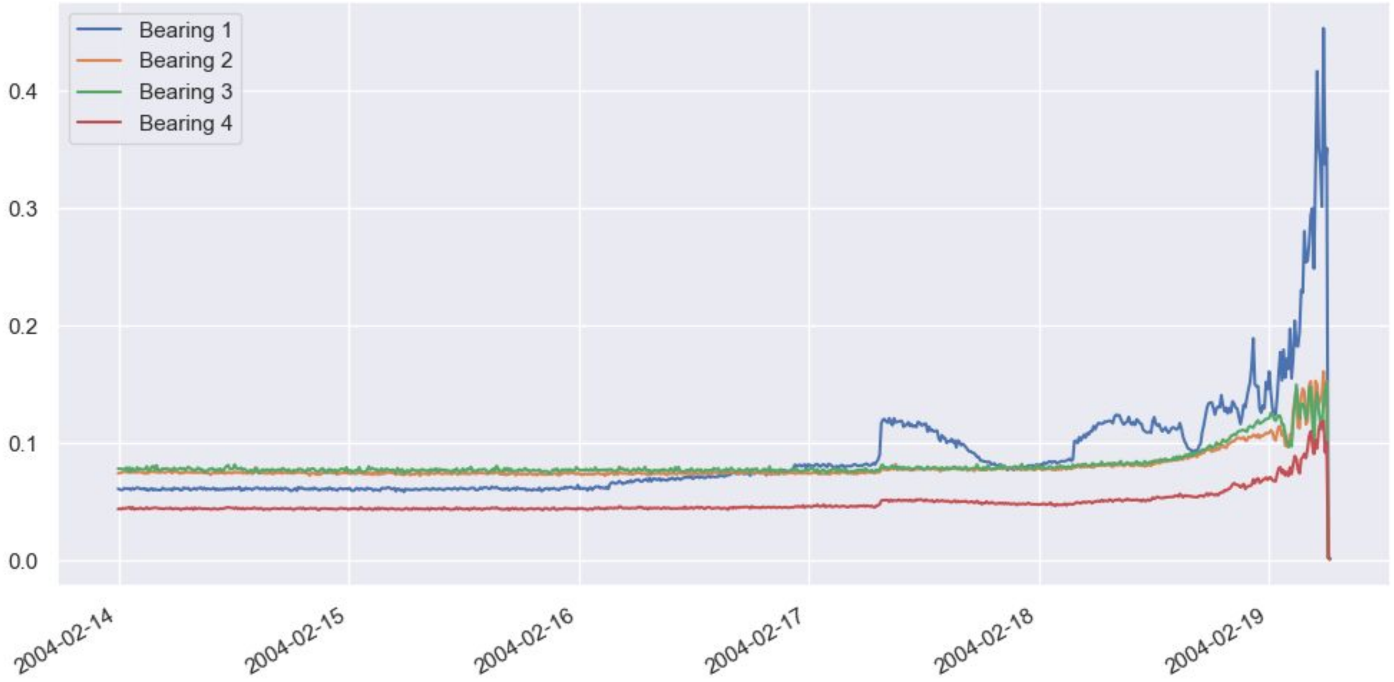
- An assumption is that gear degradation occur gradually over time, so we use one datapoint every 10 minutes in the following analysis. Each 10 minute datapoint is aggregated by using the mean absolute value of the vibration recordings. We use the data from the 2nd Gear failure test only, further we merge together everything in a single dataframe. Each datapoint has the readings of four bearings.

- Dataset is downloadable at: https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/

Training data Insights



Test data Insights



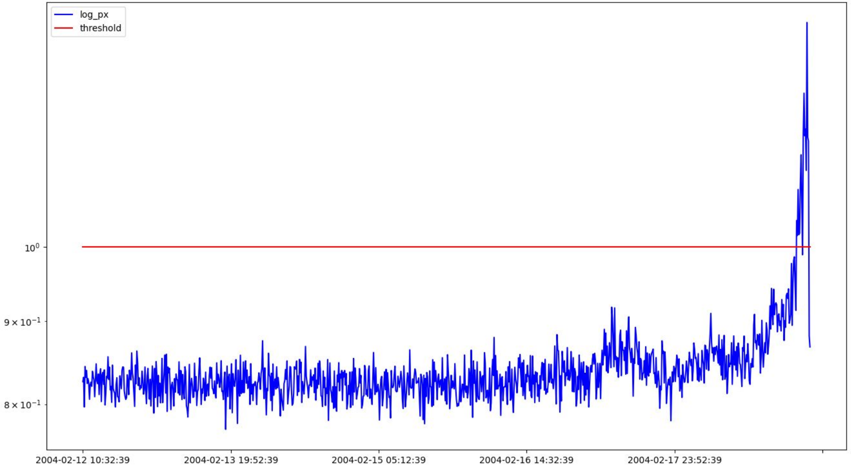
Model1- Simple LSTM-VAE

1. LSTM-VAE is a reconstruction-based anomaly detection model, which consists of a pair of encoder and decoder.
2. The encoder is comprised of a LSTM network and two linear neural networks to estimate the mean and co-variance of the latent variable z.
3. The decoder has similar structure with a LSTM network and two linear neural networks to estimate the mean and co-variance of the reconstructed variable x_hat.
4. The anomaly detection is based on so-called anomaly score, which is defined as the log-likelihood of an input observation respect with the reconstructed mean and co-variance.
5. The model is trained with normal data, it means that the model will have relatively small reconstruction errors for normal data, but large reconstruction errors for abnormal data.

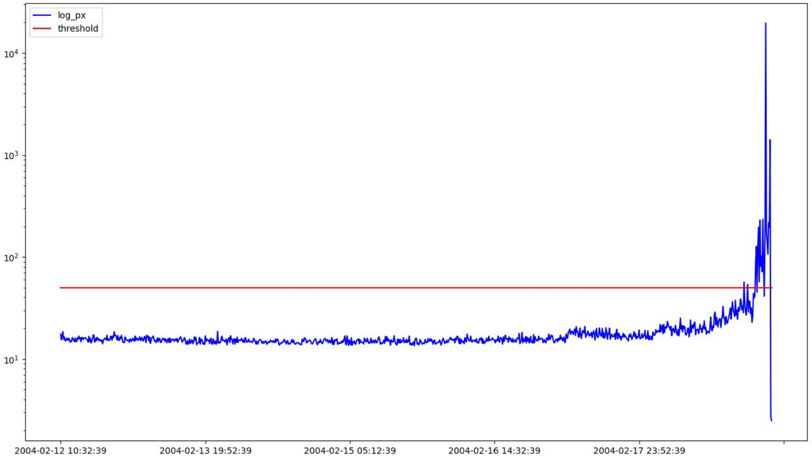
Model2- VELC

1. This is also a time series anomaly detection based on VAE with re-Encoder and Latent Constraint network, named as VELC.
2. This model adds a re-encoder in the architecture of VAE to obtain new latent vectors, and this more complex architecture can optimize the reconstruction error both in the original space and latent space to accurately model the normal samples.
3. Besides, it can compute the anomaly score both in the two feature spaces (original space and the latent space), which has higher accuracy than only in the original space.
4. The model is trained with normal data, it means that the model will have relatively small reconstruction errors for normal data, but large reconstruction errors for abnormal data.

Results: log_px plot



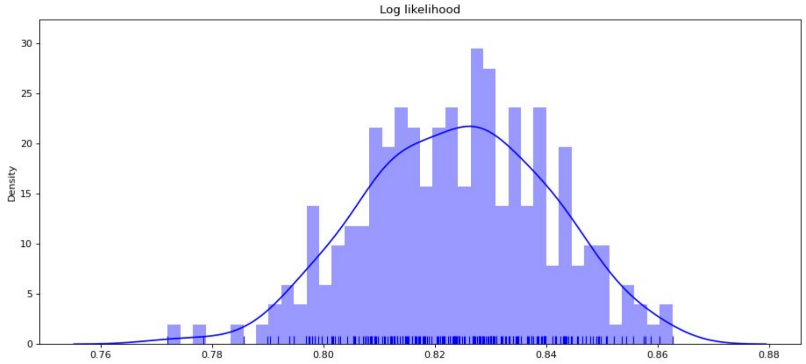
Anomaly from log_px with threshold 1 for VAE LSTM



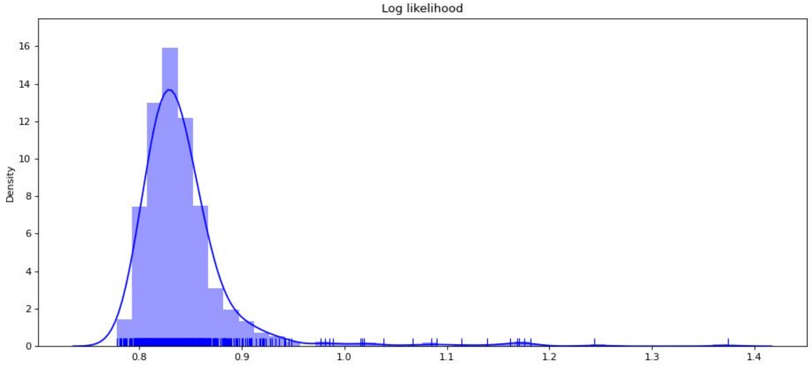
Anomaly from log_px with threshold 50 for VELC

Results: log likelihood

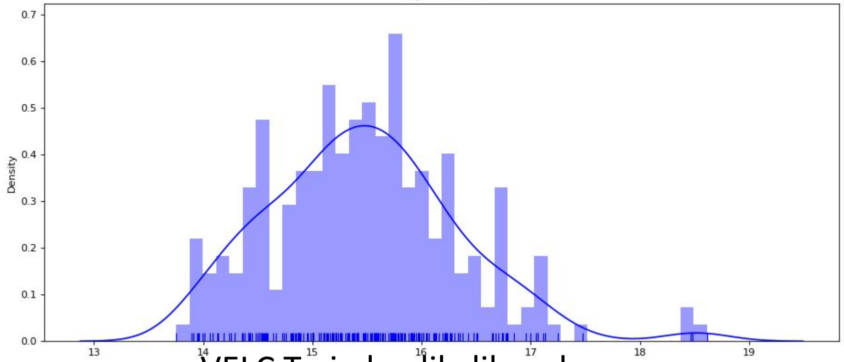
Train VS Test Log likelihood



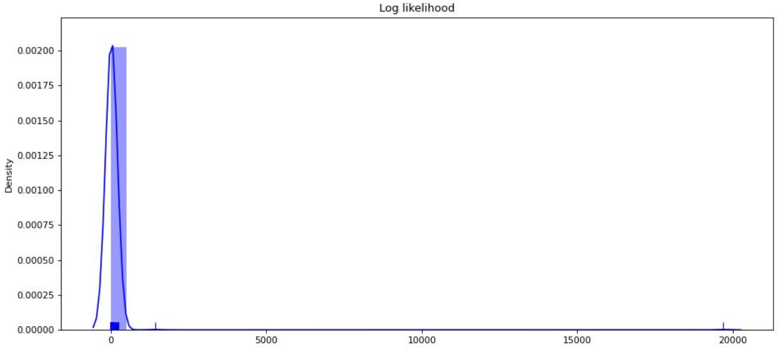
VAE LSTM Train log likelihood



VAE LSTM Test log likelihood



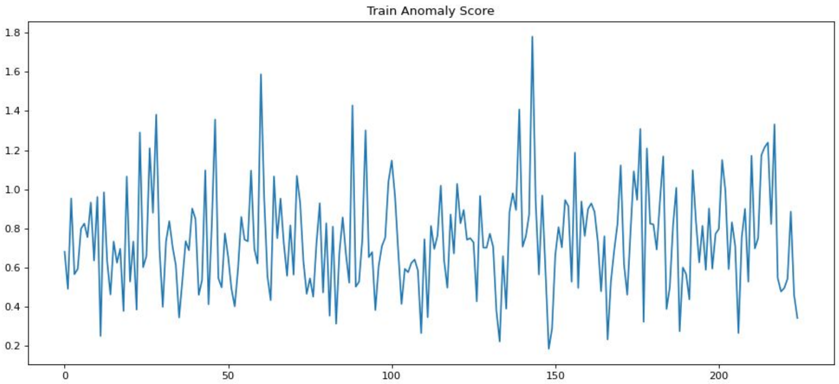
VELC Train log likelihood



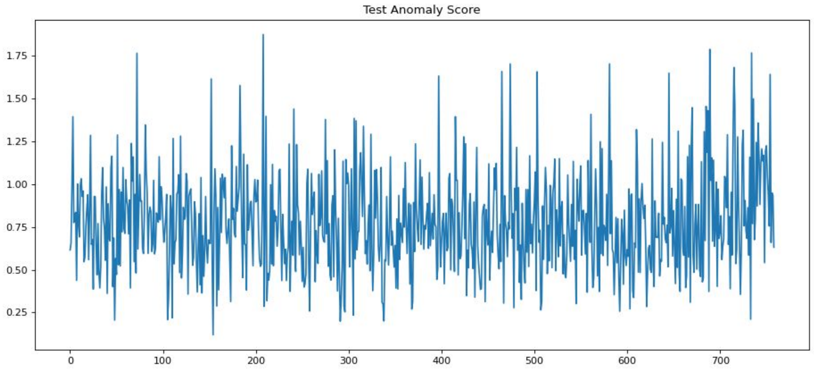
VELC Test log likelihood

Results: Anomaly Score for VELC

Train VS Test Anomaly Score



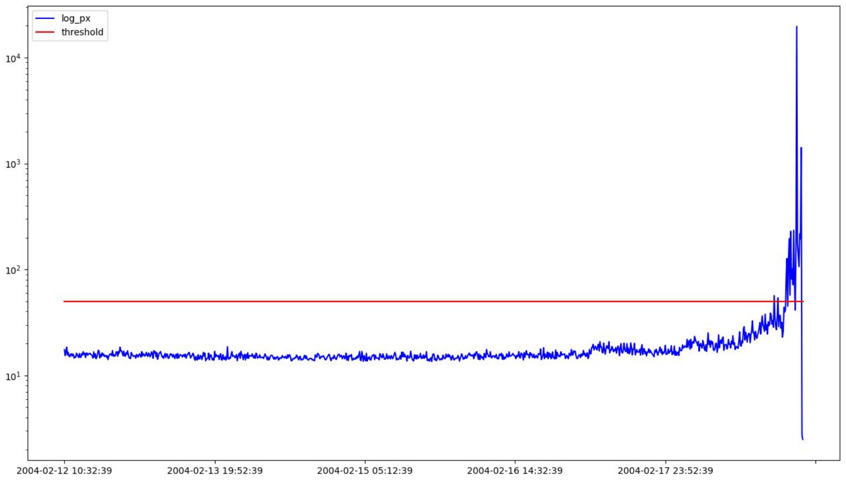
VELC Train Anomaly Score



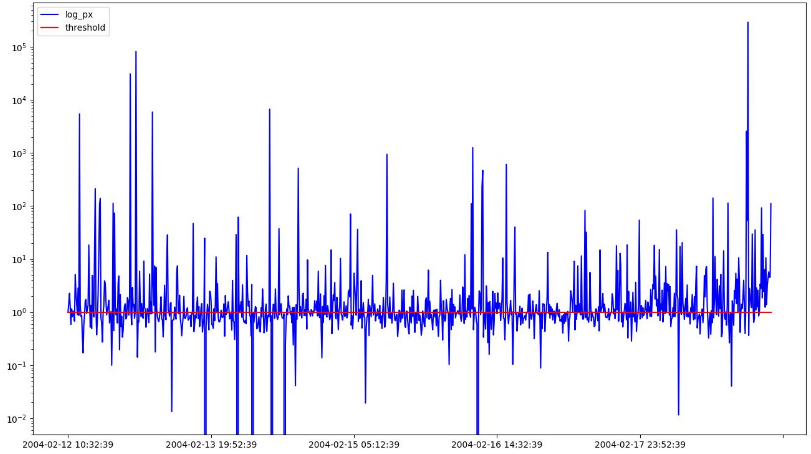
VELC Test Anomaly Score

Importance of Constraint Network

log_px plot



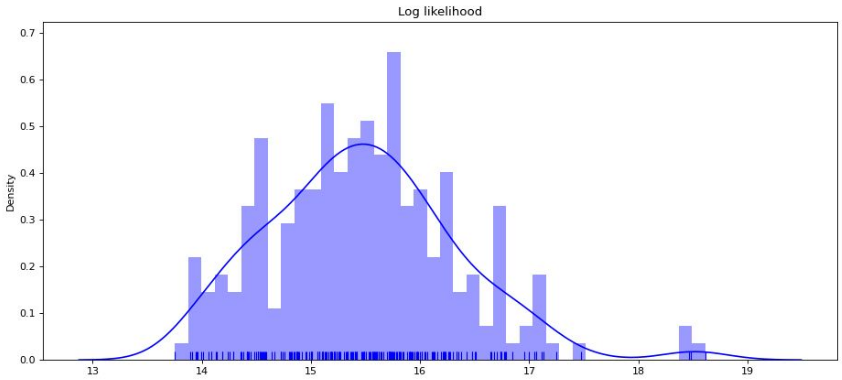
VELC with constraint Network



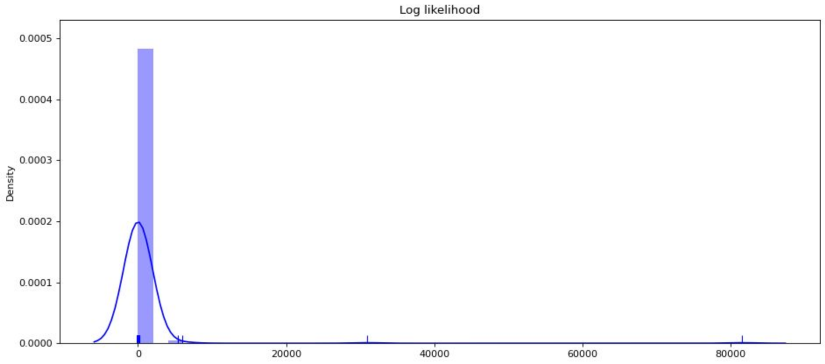
VELC without constraint Network

Importance of Constraint Network

Log likelihood plot



VELC with constraint Network



VELC without constraint Network

Work Distribution

Apoorva Agarwal, 203050018

- Implementation of Constraint Network and Anomaly Score

Vikrant Sharma, 203050035

- Data Preprocessing, Encoder and Decoder Implementation

Anurag Kumar Karn, 203050006

- Worked on Data preprocessing and Sampling Layers

Himanshu Gupta, 17d100016

- Implementation of Loss Function and Constraint Network

Conclusion

- We design an unsupervised deep learning anomaly detection method named VELC.
- The model uses VAE with re-Encoder and constraint network to model the normal time series.
- Through extensive experiments, VELC is better than VAE LSTM for this task. As Loss from VAE LSTM is 8.4789 but from VELC is 6.9267. Also It is able to predict more anomalies.
- Constraint Network is important in VELC network as it restricts the network from generating anomaly distribution.

Implementation

Implementation is available at Github Link

References

Paper Link - https://arxiv.org/abs/1907.01702

Citation - @misc{zhang2020velc,
    title={VELC: A New Variational AutoEncoder Based Model for Time Series Anomaly Detection},
    author={Chunkai Zhang and Shaocong Li and Hongye Zhang and Yingyang Chen},
    year={2020},
    eprint={1907.01702},
    archivePrefix={arXiv},
    primaryClass={cs.LG}
}

https://github.com/shaohua0116/VAE-Tensorflow

https://towardsdatascience.com/machine-learning-for-anomaly-detection-and-condition-monitoring-d4614e7de770

https://towardsdatascience.com/how-to-use-machine-learning-for-anomaly-detection-and-condition-monitoring-6742f82900d7

https://towardsdatascience.com/variational-autoencoders-as-generative-models-with-keras-e0c79415a7eb