Anomaly Detection for Time Series Data using VAE-LSTM Model

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***Abstract*—Here is a abstract...**

***Index Terms*—Here are some keywords...**

I. Introduction

This is an introduction...

II. Methodology

Anomaly detection is represented by measuring the reconstruction error from a given deep learning model. For this system, a VAE and LSTM hybrid model is used for finding a latent space with a known distribution and capturing temporal information over time series data. This data is presented in a windowed fashion to locate anomalies within a given window. Evaluation of the anomaly detection will be measured using the harmonic mean of precision and recall (F1 score).

A. Preprocessing

The nature of the data used for this detection system does not need to be specific, but it does require being time series data. With a given window size, a sliding window will sample the original signal, and the VAE input and output will be equivalent to the size of the window.

As this data does not need to be labeled, it does need to be clean of noise or anomalies. This is due to the model learning the clean distribution of the data, and after training, the poor reconstruction of a signal will indicate the possibility of an anomaly.

B. Variational Autoencoder

An autoencoder structure establishes a method for compressing information into a dense latent space. This space is not unique as the original signal can be encoded into a large number of different latent spaces. The VAE addresses this non-regularization issue of the latent space by forcing the space to follow a specific distribution [**?**]. For most VAEs, this distribution is a normal distribution, and the output of the encoder will be a prediction of mean and standard deviation. Once the distribution of the latent space is known, a sampling will be performed to create a latent vector for the input of the decoder. When the latent space distribution is well formed, the output of the decoder aims to reconstruct the original signal as best as possible.

As the autoencoder represents encoder and decoder models, these structures can be created in a variety of ways. For this project, both will be presented by 1-dimensional convolutional layers with a leaky ReLU activation function and batch normalization. The number of samples per window will decrease while depth increases for every layer in the encoder structure. At the end of the encoder, the samples and depth are flattened and passed to linear layers to condense to the final latent space mean and standard deviation values. Samples from the normal distribution will be given to a decoder that is identical to the encoder, but with transpose convolutional layers to increase the size and decrease the depth. Padding for each layer is forced to maintain a consistence linear decrease in number of samples.

C. Long Short-Term Memory

Here is the LSTM...

D. VAE-LSTM Model Training

Here is the VAE-LSTM model training...

E. Anomaly Detection

Here is the anomaly detection...

F. Evaluation Metrics

Here are the evaluation metrics...

III. Experiments

Here are the experiments...

A. Inertial Measurement Unit Dataset

Here is the dataset...

B. Synthesized Photoplethysmography Dataset

Here is the dataset...

C. Electric Vehicle Drive Cycle Dataset

Here is the dataset...

IV. Results

Here are the results...

A. Inertial Measurement Unit

Here is the dataset...

B. Synthesized Photoplethysmography

Here is the dataset...

C. Electric Vehicle Drive Cycle

Here is the dataset...

V. Conclusion

Here is a conclusion...

A. Future Work

Here is some future work...

Acknowledgment

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Contributions

Randall Fowler developed the models, evaluation methods, and experimented with the IMU dataset. Conor King experimented with the synthesized PPG dataset. Ajay Suresh experimented with the EV drive cycle dataset. All authors contributed to the writing of the paper.

References

[1] Citation 1
[2] Citation 2
[3] Citation 3
[4] Citation 4
[5] Citation 5