Anomaly Detection using Adversarial Generative Networks in Multivariate Time Series

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Anomaly detection in multivariate time series data is a technique for detecting unusual values or behaviors from a series of data points consisting of multiple variables obtained by continuously observing temporal changes in a particular phenomenon.
Capturing the signs of changes and anomalies in multivariate time series data is an essential task in all fields, and studies on its automation have been conducted.
Anomalies are generally classified into three types: point anomalies, in which observed values deviate significantly from the majority of data points; contextual anomalies, in which anomalies are peculiar in the specific context behind the observed values; and collective anomalies, in which individual data points are normal, but the behavior is peculiar when multiple consecutive data points are considered together.
Since point and contextual anomalies are relatively easy to detect by handling individual data points, many methods have been proposed.
On the other hand, with the recent development of measurement technology and the availability of large amounts of time series data, there is a growing motivation to detect collective anomalies peculiar to time series data.
Developing a model that captures the temporal dependence between observed data points is necessary to detect collective anomalies.

With the development of information technology, methods using deep learning have been proposed for anomaly detection in multivariate time series data.
In addition to anomaly detection for point and contextual anomalies, deep learning can handle complex multivariate and time series data and is expected to be applied to collective anomaly detection.
However, this method has challenges in detection accuracy for practical use, and there is room for improvement in detecting collective anomalies.

In this thesis, we propose anomaly detection models based on Generative Adversarial Networks (GANs), one of the deep learning models, for multivariate time series data combining RNN or Transformer.
GANs consist of a generator, which generates multidimensional data points from low-dimensional latent variables, and a discriminator, which judges whether a given data point is real.
These networks are learned through minimax optimization called adversarial training.
In the proposed model of this thesis, an encoder that compresses multidimensional data points into low-dimensional latent variables is introduced, and multidimensional data points are converted into

low-dimensional feature representations that retain important information, making it possible to detect anomalies in multidimensional data without lowering accuracy.

On the other hand, GANs cannot capture the temporal dependencies between data points in time series data.

The proposed model combines the encoder and generator of GANs with a new model called RNN or Transformer and learns the encoder, generator, and discriminator by adversarial training.

In the model combining GANs and Transformer, sparse attention is utilized as an attention mechanism to learn long-term temporal dependencies between data points, increasing the influence of strongly related data points in time series data and improving the accuracy of detecting anomalies over a long period.