



Real-time abnormal light curve detection based on a Gated Recurrent Unit network

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Introduction

In the development of astronomy, time domain astronomy has become an important development direction. It is based on high-resolution observations to anticipate, discover and study of extreme, rare astronomical phenomena in the universe that are related to cutting-edge astrophysics. GWAC (the Ground-based Wide-angle Camera array) is part of the SVOM (Space Variable Objects Monitor) of Sino-French cooperation. GWAC is exposed every 15 seconds and can get millions of light curves throughout the day. At present, abnormal light curves are detected from massive datasets, which creates fatigue for astronomers, thus increasing the probability of misjudgment. Therefore, it is imperative to study faster and more effective abnormal light curve detection.

Data and Data preprocessing

The original light curve observation signal is easily polluted by light, and the range of observations in the normal light curve is relatively large. In order to speed up the model training, we first normalize the original observation data and scale the range of the original observations to [0,1]. Figure 1 shows the raw observation data and the results of the data processing, where Figure 1(a) is the raw observation light curve data, and Figure 1(b) is the normalized light curve data.

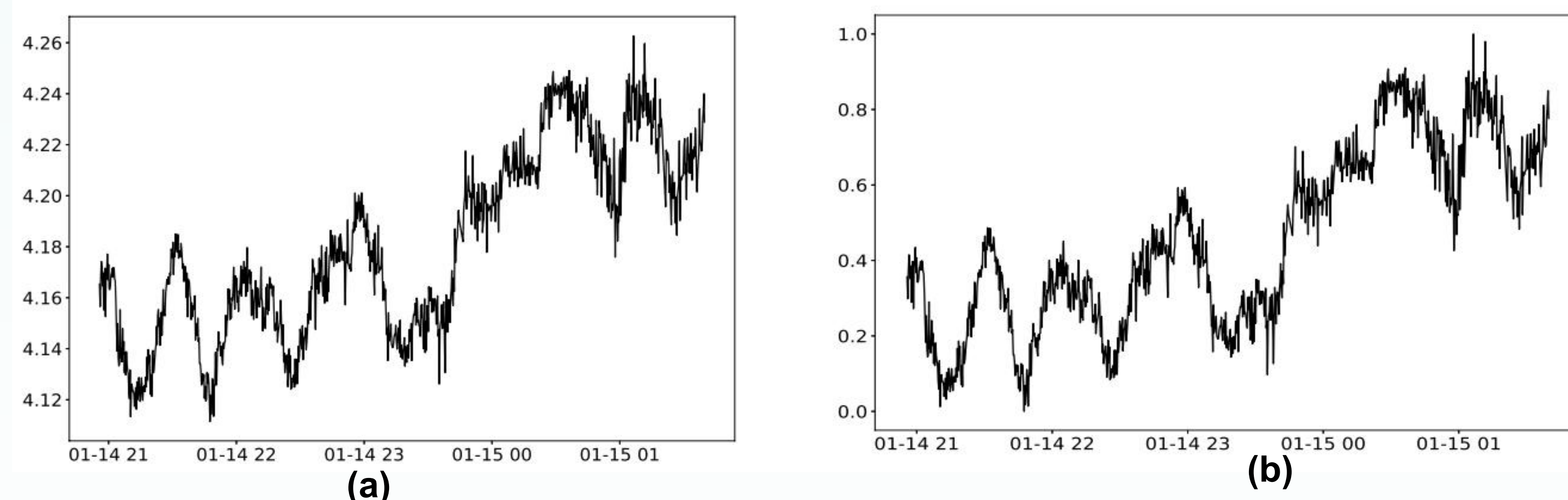


Fig. 1 Raw observation light curve data and normalized light curve data. (a) Raw observation light curve data. (b) Normalized light curve data.

Model Structure

We proposed the GRU for the Warning of Abnormal Light Curve (GRUWALC) model of abnormal light curves based on a GRU algorithm. The network structure is based on the GRU model design, and the structure of GRUWALC is shown in Figure 2. The network structure includes an input layer, two GRU layers, a fully connected layer, and an output layer. The input data is the acquired light curve, and the output is the model to predict the output value of the light curve at the next moment.

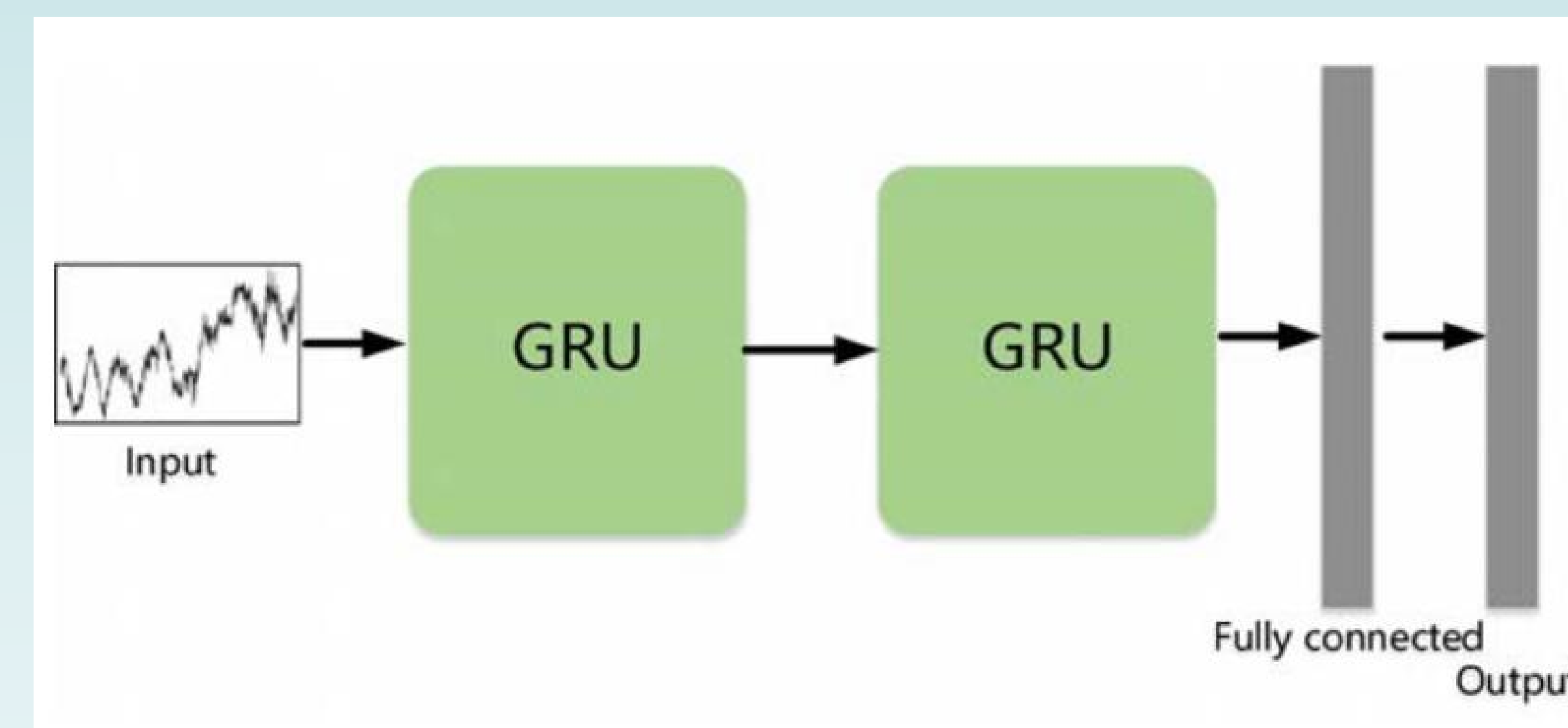


Fig. 2 GRUWALC network structure. Include input layer, two GRU layers, full connection layer and output layer.

EXPERIMENTAL ANALYSIS

Figure 3(a) presents the prediction results of the GRUWALC model proposed in this paper. The abscissa indicates the time of data acquisition, and the ordinate represents the result of normalization of the observed data. The blue line is the real data, and the orange line is the prediction result obtained by GRUWALC according to the training data.

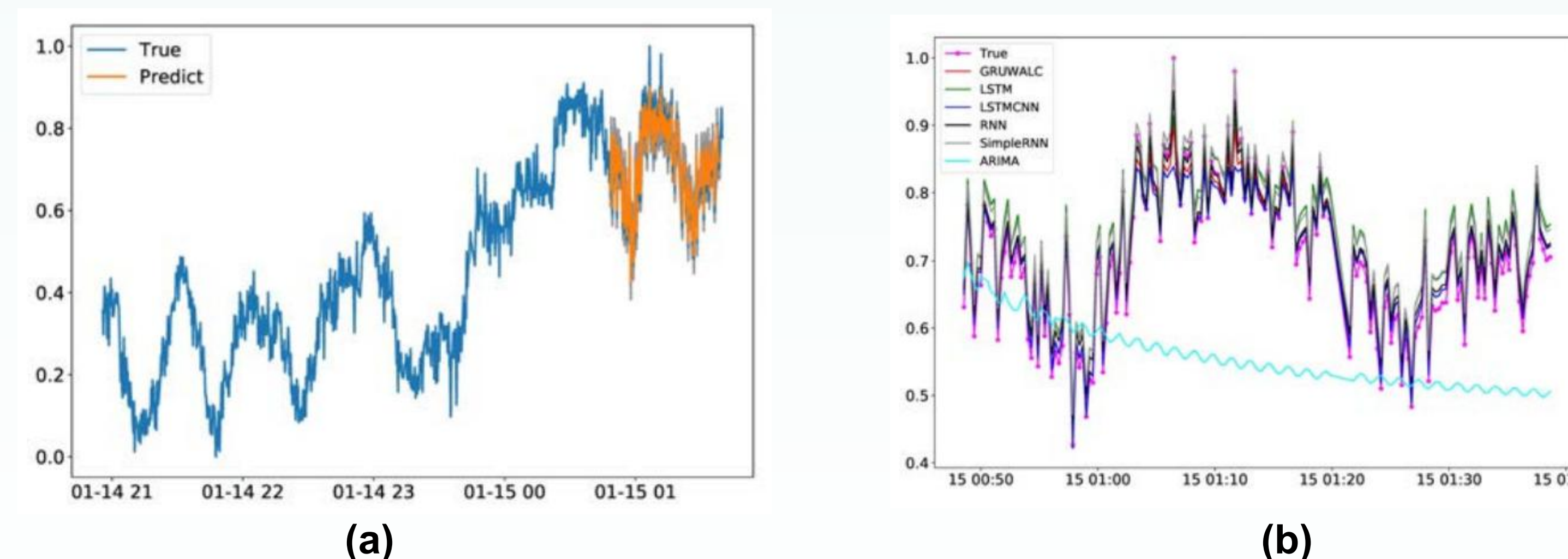


Fig. 3 (a) GRUWALC model prediction results. (b) Comparison of the prediction results of different algorithms.

This paper compares the prediction performance of different algorithms on the light curve. The prediction results of different algorithms are shown in Figure 3(b). The abscissa indicates the time at which the data was acquired, the ordinate indicates the normalized observation value. True indicates the actual observation.

We calculate the false alarm rate. The false alarm rates we get on the same test set according to different algorithms are shown in Table 1. According to the false alarm rate results, the thresholds for anomaly detection we selected are different, and the false alarm rate is different. Generally, the larger the threshold, the lower the false alarm rate obtained on the normal light curve data set. Therefore, if the algorithm fits better, that is, the smaller the difference between the predicted value and the true value of the model, the false alarm rate is lower under the same abnormal threshold.

Table 1 Comparison of False Alarm Rates of Different Algorithms

| Threshold | GRUWALC | LSTM | LSTMCNN | SimpleRNN | RNN | ARIMA | 0.6557 | 1.0928 |
|-----------|---------|--------|---------|-----------|--------|--------|----------|----------|
| 0.0988 | 0 | 0 | 0.0007 | 0 | 0 | 0.0257 | - | - |
| 0.0368 | 0.0019 | 0.0519 | 0.0051 | 0.0396 | 0.0027 | 0.0488 | - | - |
| 0.0345 | 0.0027 | 0.0531 | 0.0055 | 0.0440 | 0.0079 | 0.0503 | - | - |
| 0.0307 | 0.0035 | 0.0551 | 0.0059 | 0.0500 | 0.0142 | 0.0523 | - | - |
| 0.0304 | 0.0043 | 0.0551 | 0.0063 | 0.0500 | 0.0146 | 0.0531 | - | - |
| 0.0279 | 0.0051 | 0.0567 | 0.0075 | 0.0535 | 0.0218 | 0.0551 | - | - |
| 0.6557 | 0 | 0 | 0 | 0 | 0 | 0 | 0.066667 | - |
| 1.0928 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0.066667 |

Conclusion

In view of the high real-time light curve demands in time domain astronomy, this paper proposes a GRU-based real-time early warning model GRUWALC. The innovations of this paper mainly include two points. First, the GRU is introduced as a fitting model in the light curve prediction process for the first time; second, according to the established fitting model, the threshold for abnormal warning is set. By comparing the actual observation value and the model prediction value at the next moment, it is judged whether the observation value at the next moment is an abnormal value.