VAE-LSTM Joint Model for Time Series Prediction and Anomaly Detection

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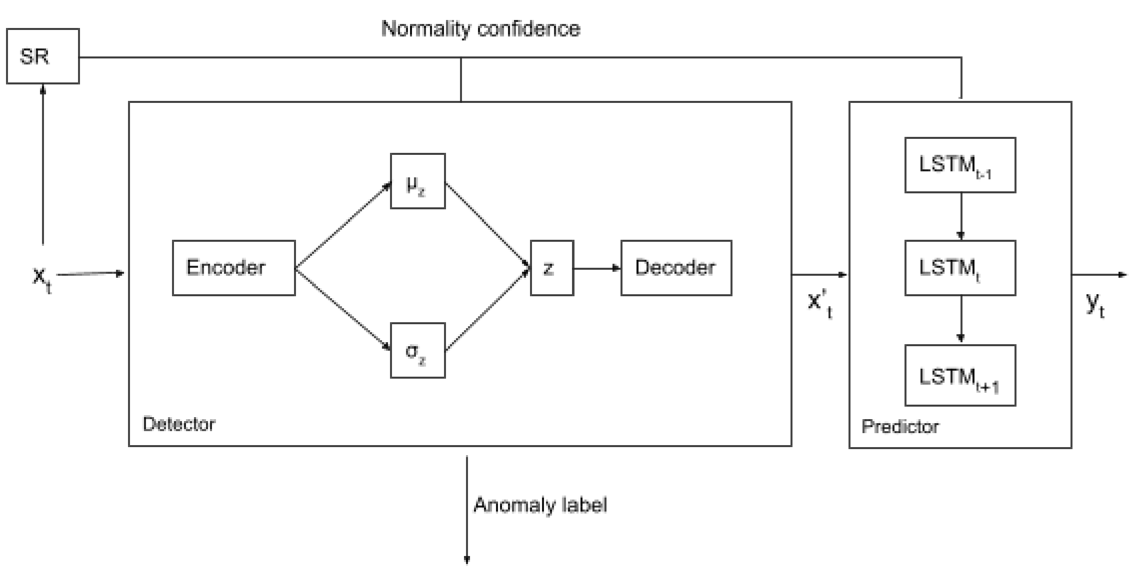
Abstract

In this paper, I will consider the problem of predicting time series values and detecting anomalies. To solve these problems, I use a joint model of variational autoencoder for anomaly detection and long short-term memory for prediction.

1. Introduction

The problem of detecting anomalies and predicting values arises in many areas from healthcare to monitoring IT systems. The difficulty in finding anomalies is the inability to collect a sufficient amount of tagged data. Therefore, using an unsupervised approach is a significant advantage.

The following model architecture is proposed.



The model consists of two main blocks: anomalies detector(VAE) and predictor(LSTM). The detector takes a vector of initial statuses x_1 ... x_t and reconstructs it into a vector x'_1 ... x'_t. The difference between x_t and x'_t is compared with a threshold value and forms an anomaly label. The reconstructed vector is fed to the LSTM input to predict the next value in the time window y_t. In addition, spectral residual analysis is used to produce the normality confidence weights for each status in each segment x_t

2. Dataset

The KPIs dataset is used for the experiment. The data was collected from some web services and computer systems. Web service KPIs consist of performance metrics, such as response time, web page visits, connection errors etc. Computer system KPIs consist of the health status of computers (servers, routers, switches), CPU utilization, memory utilization, disk I/O, network bandwidth etc. The dataset contains 28 timeseries, 22 of which consist of minute intervals, the rest of five minute intervals. For the experiment, I took time series with minute intervals.

3. Model

3.1. Data preprocessing

There is missing data in the time series. The data is cyclic with a period of 24 hours. This property is used to fill in missing values the same way as in [1]. If the missing interval is less than 7 minutes, linear interpolation along the interval boundaries is used to fill it. If the interval is larger than 7 minutes, linear interpolation is used for statuses that are +-24 hours apart from the missed one. Further, the data is standardized.

3.2. Normality Confidence Weighting

Spectral residual (SR) analysis is used to construct normality confidence weighting, which are further used as the weighting coefficients of the loss function of the model.

3.3. Anomaly detection

VAE is trained with loss function

$L_{VAE}(x_t) = \|w_n \circ (x_t - x'_t)\|^2_2 + \beta\, \hat{w}_n / 2\, (- \log \sigma^2_z + \mu^2_z + \sigma^2_z - 1)$

First term is the reconstruction loss and second is Kullback-Leibler divergence between true posterior distribution $p_\theta(z|x)$ and the approximate posterior distribution is assumed to follow a diagonal Gaussian distribution $q_\varphi(z|x) = N(\mu_z, \sigma^2_z \cdot I)$

w_n is the normality confidence of statuses in segment x_t (Eqn. 1) and $\hat{w}_n$ is the average over w_n

β is the hyper parameter to balance between first and second terms.

Due to the anomalies being a rare occurrence, the distribution of these statuses is different from those of the normal statuses and ideally anomalies are not reconstructed by the decoder. x_t is viewed as abnormal when the absolute error of x_t from x'_t is higher than threshold

3.4. Prediction

LSTM block is trained with loss function

$L_{LSTM}(x_t) = \hat{w}_n \|(x_{t+1} - y_t)\|^2_2$

3. Experiments

For the experiment, I took 4 versions of the models PAD, PAD-, AD, P-AD. PAD: predictor (LSTM) trained together with anomaly detector (VAE), taking into account normality confidence weighting. PAD - the same as in the previous case, but without use of the normality confidence weighting. AD is a predictor(VAE) only. P-AD separately trained predictor (LSTM) and anomaly detector (VAE).

The sliding window size is set to 256. Learning rate is set to 1-e3. The number of VAE z dimensions is set to 32. β is set 0.01, 0.1, 1. ƛ is set to 1 and 10. I divide the dataset into training, validation and testing sets, whose ratios are 50%, 5%, 45% respectively..

For the predictor I used MSE, RMSE, MAE metrics. F1, precision and recall with adjusted anomalies label's(with delay set to 7) are used for the detector. The results of calculations on the test dataset are presented in the tables below

	MSE	**RMSE**	**MAE**
PAD beta=0.01	0.104	0.260	0.173
PAD beta=0.1	0.116	0.277	0.191
PAD beta=1	0.979	0.962	0.787
PAD beta=10	0.982	0.961	0.785
PAD- beta=0.01	0.162	0.318	0.197
P-AD beta=0.01	0.102	0.258	0.171

	F1	Precision	Recall
PAD beta=0.01	0.653	0.722	0.595
PAD beta=0.1	0.579	0.526	0.644
PAD beta=1	0.454	0.591	0.368
PAD beta=10	0.421	0.560	0.337
PAD- beta=0.01	0.581	0.514	0.669
AD beta=0.01	0.224	0.962	0.12

4. Conclusion

The results of the experiment show that the joint training of models has a positive effect on the results of both tasks. The predictor, taking as input the reconstructed data from the VAE, gives the predictions robust to outliers in the original data. LSTM helps VAE to maintain the long term sequential patterns that are out of the VAE encoding window. SR boosts the performance of both VAE and LSTM.

References

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