

MS-LSTM: a Multi-Scale LSTM Model for BGP Anomaly Detection

LyuJiuyang, Dec 21st, 2021.

Introduction

Info

Authors: Min Cheng, Qian Xu, Jianming Lv, Wenyin Liu, Qing Li, Jianping Wang. ICNP 2016

Code: <https://github.com/jayvischeng/MSLSTM> (Tensorflow).

Link: [MS-LSTM](#)

Target

Detecting anomalous Border Gateway Protocol traffic.

BGP: Border Gateway Protocol (边界网关协议), which is designed to exchange routing and reachability information among autonomous systems (AS) on the Internet. TCP layer. [Zhihu-Link](#)

Motivation

Existing solutions apply classic classifiers to make real-time decision based on **the traffic features of present moment**. However, due to the frequently happening burst and noise in dynamic Internet traffic, the decision based on short-term features is not reliable.

Contribution

- propose to adopt MS-LSTM, a multi-scale LSTM model, for BGP anomaly detection.
- show that applying optimal and time scale to the existing classification model in BGP anomaly detection can improve their performance by 10%.

Related Work

- Based on statistics pattern and signal processing techniques, where the anomalies are identified as correlated abrupt changes occurring in the underlying distribution.
- Rule-based method, which is applying Internet Routing Forensics (IRF) to classify anomalies.
- Machine-learning methods have been employed to build traffic classification models and predict anomaly.

Time Series Analysis

- Integrating the historical information into the classifier can make the decision more cautious and more accurate.
- In a larger time scale, the global trend of the time sequence is easier to be captured, but it becomes harder to sense a local change.

Methodology

Input: previous traffic features x_{t_1} , x_{t_2} , ..., x_{t_n} ,

Output: the current state of traffic $x_{t_{n+1}}$

Preprocessing

e , the size of window; p , the time scale.

$$S_n = x_{t_{n-e+1}}, x_{t_{n-e+2}}, \dots, x_{t_n}$$

$$S_n = (d_1, d_2, \dots, d_{e/p})$$

$$d_1 = 1/p (x_{t_{n-e+1}} + x_{t_{n-e+2}} + \dots + x_{t_{n-e+p}})$$

Model

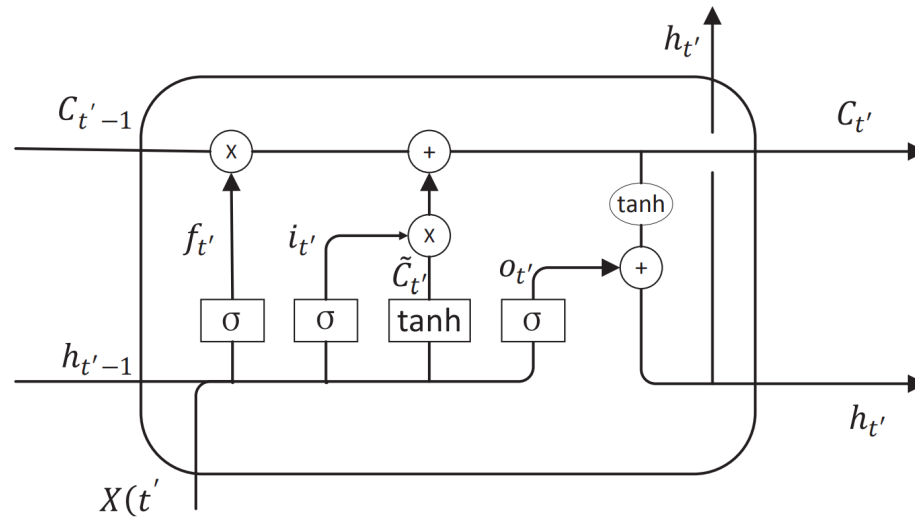


Figure 3: Structure of LSTM memory cell.

Step1: Throw away redundant old information.

$$f_t = \sigma(W_f \cdot [h_{t'-1}, X'_t] + b_f)$$

Step2: Store new useful information.

$$i_t = \sigma(W_i \cdot [h_{t'-1}, X'_t] + b_i)$$

$$\widetilde{C}'_t = \tanh((W_c \cdot [h_{t'-1}, X'_t] + b_c))$$

Step3: Update the cell state.

$$C_t = f_t * C'_t - 1 + i_t * \widetilde{C}'_t$$

Step4: Output for next memory cell.

$$o_t = \sigma(W_o \cdot [h_{t'-1}, X'_t] + b_o), h_t = o_t * \tanh(C'_t)$$

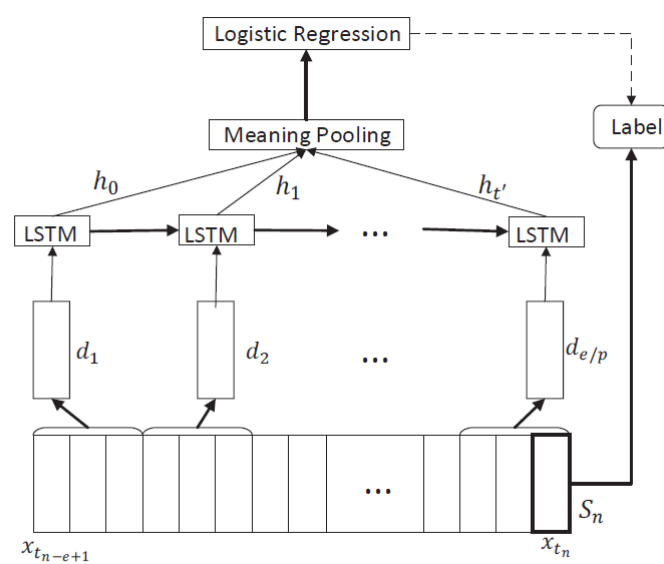


Figure 4: MS-LSTM classification model.

Experiment

Dataset: RIPE

Optimal window size: 40.

Optimal time scale: 8.

- The highlight of this article is using LSTM to detect anomalous BGP and time scale.