Salka

A Deep Learning Toolkit for Unsupervised Anomaly Detection in Computer Networks

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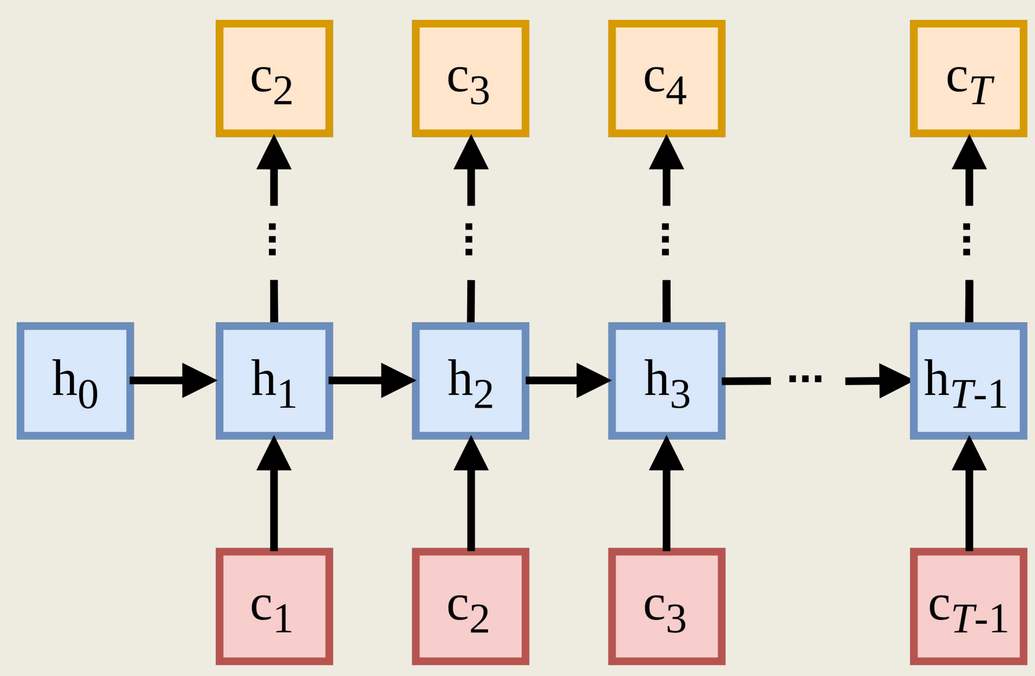
Introduction

Motivation: Computer network logs are large, difficult to comb through to detect anomalous, potentially malicious activity.

Goal: Reduce the burden incurred by security analysts by developing an easy–to–use, free, and open–source anomaly detection system to identify suspicious activity and filter these events for analysts.

Approach: Apply recent innovations in unsupervised deep learning to develop effective anomaly detection models.



Recurrent neural network language model.
Based on event model proposed in [1]. Model uses recurrent connections between hidden representations of tokens to infer the next token at each position in an event log line. Optionally supports bidirectional connections and residual connections between recurrent layers.

Methods

- Based on [1], we make use of deep learning to train *unsupervised language models* for anomaly detection.
  - Idea: learn probability of sentence as product of probabilities of each word given all previous words:

$$P(W) = \prod_{t=1}^{T} P(c_t \mid c_1, c_2, \dots, c_{t-1})$$

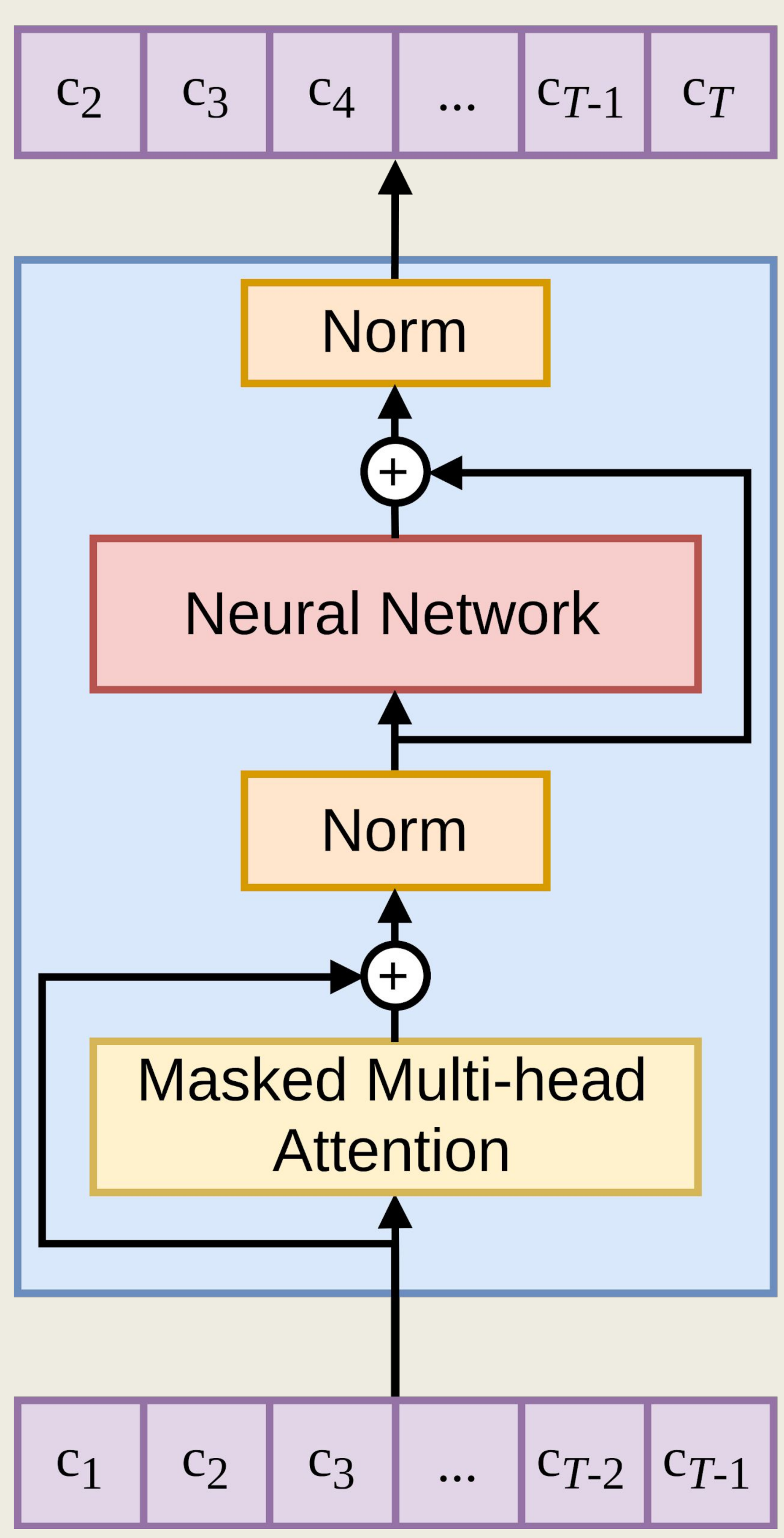
  - Models are trained to minimize cross–entropy between predicted and expected words:

$$H(c_t, \hat{c}_t) = -\sum_i c_{t,i} \log \hat{c}_{t,i}$$

  - If model fails to reconstruct event tokens incrementally, event incurs high loss.
  - This loss can be used to score and rank events by their anomalousness.
  - Models are trained incrementally and asynchronously:

```
while w < number of time windows in log:
   train on data from window w
   evaluate on data from window w + 1
   w = w + 1
```

- We further extend this framework with recent innovations in deep learning and language modeling.



Transformer decoder language model.
Based on model proposed in [2], extended by [3, 4]. Model uses masked self–attention heads and a position–wise neural network to infer tokens in an event log line. Includes residual connections and layer normalization for increased training stability. Figure derived from [3].

References

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[6] Sennrich, Rico, Barry Haddow, and Alexandra Birch. "Neural machine translation of rare words with subword units." *arXiv preprint arXiv:1508.07909* (2015).
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Features

Models

- Recurrent neural network:
  - As in [1], model uses recurrent connections across time steps.
  - Supports different types of RNN cells and bidirectional recurrent connections.
- Transformer decoder:
  - Non–recurrent, attention–based architecture based on [2].
  - OpenAI's GPT/GPT–2 [3,4] models have demonstrated excellent language modeling capabilities.
- Both models support weight tying of token embeddings and residual connections.

All models are developed using PyTorch [5].

Data Processing

- Support for character– and word–level log line tokenization, as well as byte–pair encoding [6].
- Parses and featurizes CSV logs on–the–fly.
- Can buffer large CSV logs by arbitrary time windows for asynchronous training.
- Easily configured using a YAML file.

Analysis

- Event scores are GZIP–compressed for easy storage and transfer.
- Toolkit will soon include analysis tools for ranking and flagging events based on user and network score statistics.

This toolkit is open source and available for free at `github.com/eskomski/salka`

Future Work

- Extend recurrent model to include attention mechanisms as in [7].
- Evaluate models on different datasets.
- Incorporate user and network metadata into model training data.
- Add simple analysis tools.
- Include more model variants.

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