Encrypted Traffic Classification with Recurrent Neural Networks

GitHub: https://github.com/imaginebreake/RNNTraffic

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Overview

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3. Background
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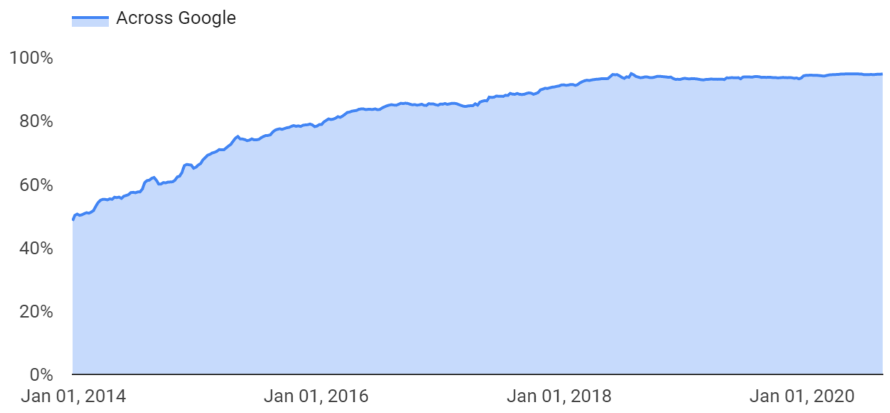
1 Introduction



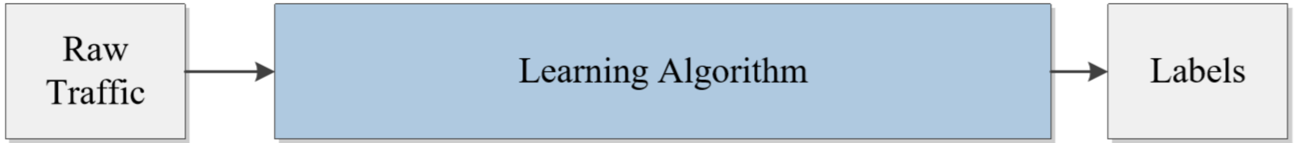
Encrypted traffic (HTTPS) across Google

- **The need for network traffic classification**
  - Malware traffic detection
  - Quality of service (QoS)
- **New change and challenge**
  - Application layer encryption: High percentage of encrypted traffic
  - Transport layer encryption: Big market size of VPN service
- **Current best approach – End-to-end 1D CNN model**
- **Our contributions**
  - 1D CNN model r**eproduction**
  - **RNN model** on VPN / Non-VPN binary classification
  - **RNN model** on detailed type classification (Email, Chat, P2P and Streaming)

2 Related Work

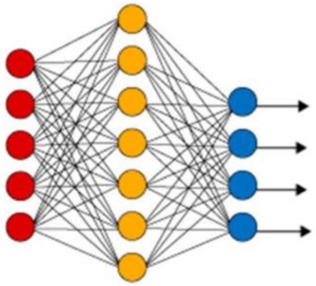
- Previous generation methods
  - Port-based methods
  - Deep packets inspection
  - Statistics methods
- **Neural network methods**
  - **End-to-end 1D CNN model**

a) Divide-and-conquer model

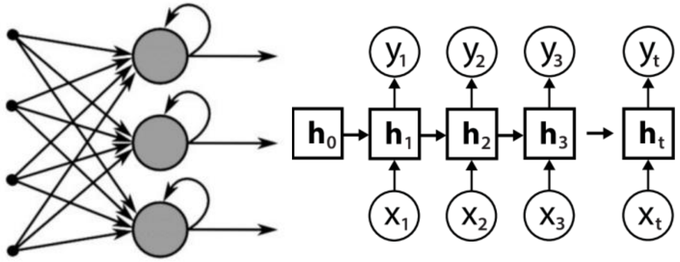


b) End-to-end learning model

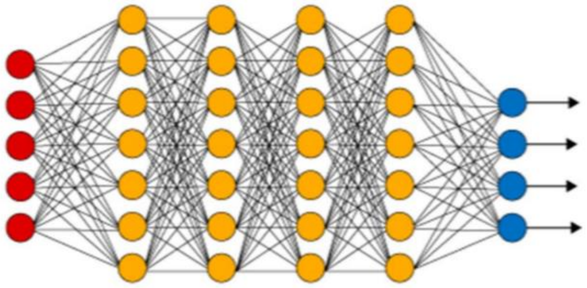
3 Background



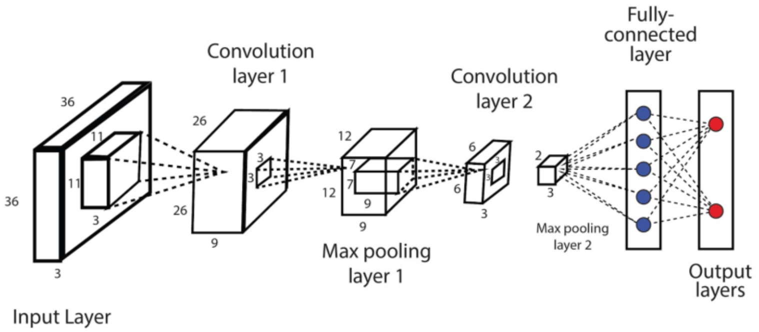
Neural Networks



Recurrent Neural Network (RNN)



Deep Neural Networks



Convolutional Neural Network (CNN)

4.1 Method - Data Processing

Network Traffic Captured **.pcap Files**

Here, large pcap files are splitted by SplitCap tool to each session.

Separate Sessions **small .pcap files**

Each session is read byte by byte as **raw 8-bit unsigned integers**. In this case, sessions larger than 1,500 bytes are **trimmed** to 1,500 bytes, and sessions smaller than 300 bytes are discarded, and the other sessions are **self-repeated** up to 1,500 bytes.

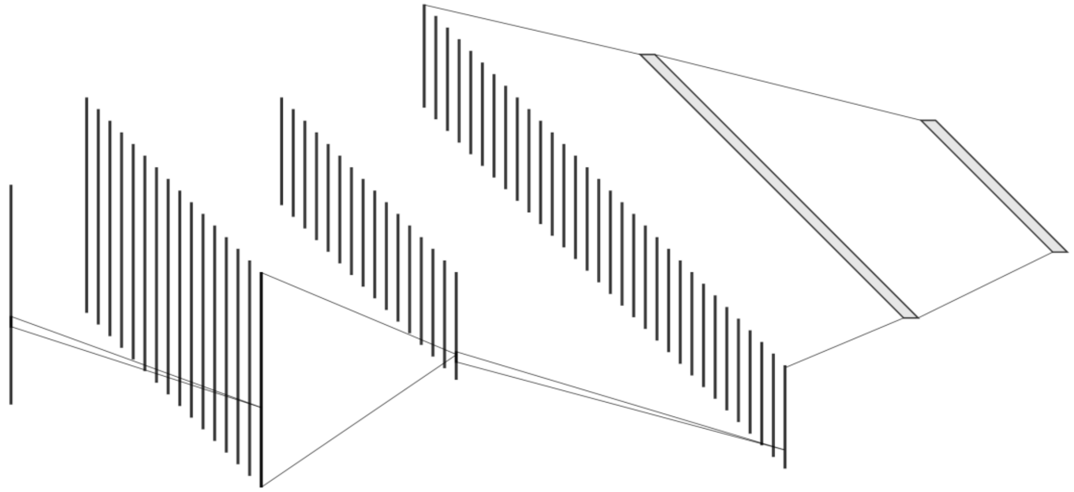
Normalised Sessions **.csv files**

4.2 Method - 1D CNN Model Reproduction

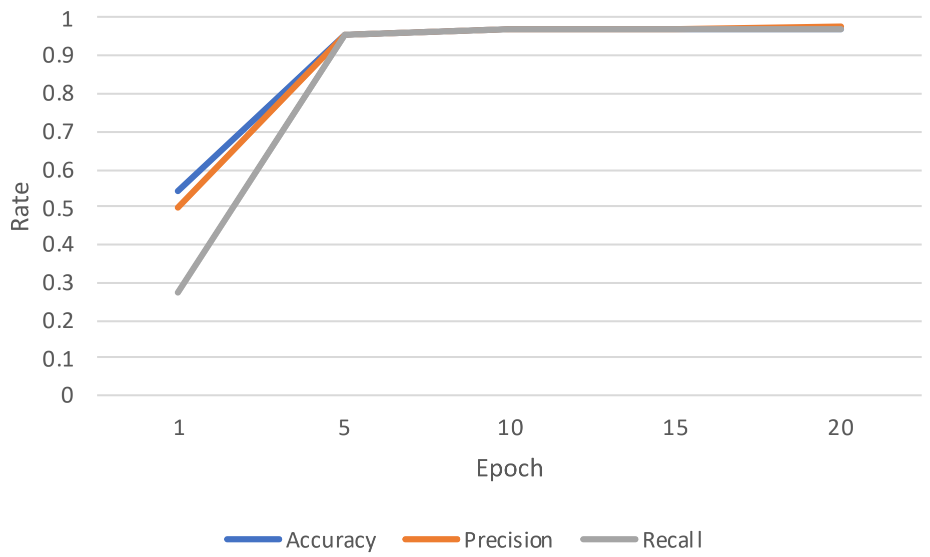
We reproduced the end-to-end 1D CNN model for binary non-VPN/VPN traffic classification.

All the network traffic data were split into 3 sets for training (80%, 5930 records), validation (10%, 741 records) and testing (10%, 742 records).

After 20 epochs of optimization, the model ended up with the validation result of: **97.30% Accuracy, 97.46% Precision, 97.22% Recall**.



Reproduced model architecture



Evaluation data on validation set during training

4.3 Method – RNN Model

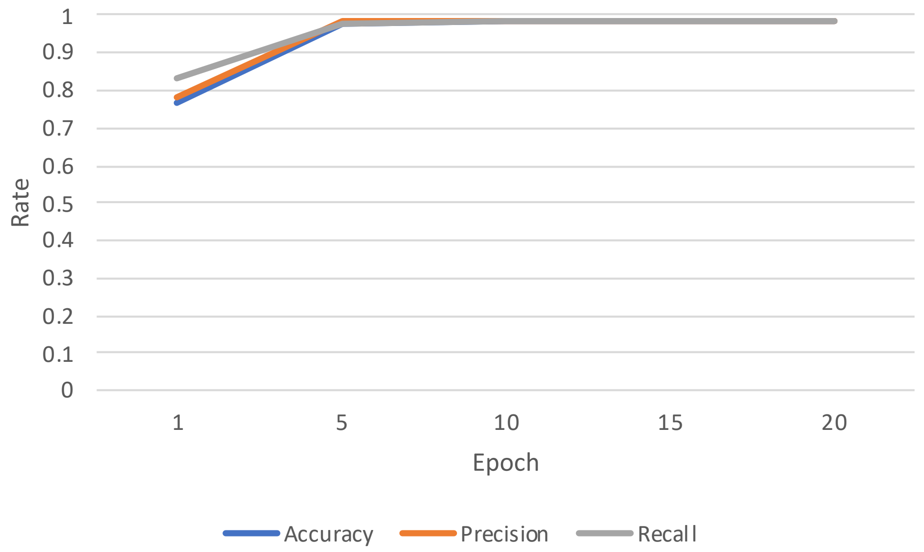
We proposed three brand new RNN models on different tasks. The train/validate/test dataset settings is same as the 1D CNN one. In practice, bidirectional LSTM neuron units are applied instead of simple RNN neuron units.

4.3.1 non-VPN/VPN Binary Classification

The RNN architecture is listed and the model ended up with the validation result of: **98.25% Accuracy, 98.38% Precision, 98.16% Recall**.

Layer number	Layer type	Input size	Output size	Comment
0	LSTM	1500	512 * 2	1 inner layer, bidirectional
1	Dense	1024	128	ReLU applied
2	Dense	128	2	
3	Log Softmax	2	2	

RNN Model for non-VPN/VPN Binary Classification



Evaluation data on validation set during training

4.3.2 Detailed Type of Traffic Classification on RNN Model

For this task, same RNN model for VPN traffic and non-VPN traffic were designed. And separate model is trained. The RNN architecture is listed.

The result of traffic type under VPN on validation set is: **95.21% Accuracy, 87.69% Precision, 92.88% Recall**.

The result of traffic type under non-VPN on validation set is: **83.38% Accuracy, 84.91% Precision, 85.08% Recall**.

Layer number	Layer type	Input size	Output size	Comment
0	LSTM	1500	512 * 2	1 inner layer, bidirectional
1	Dense	1024	128	ReLU applied
2	Dense	128	4	
3	Log Softmax	4	4	

RNN Model for Detailed Traffic Type Classification

5 Conclusion

- This paper has implemented the binary classification of VPN and non-VPN traffic based on **CNN model and RNN model**. And the results of both models were **considerably well** while the RNN model has performed slightly better than the CNN model.
- Then, in order to categorize the network traffic into four detailed types (i.e. Email, Chat, P2P and Streaming), **RNN model** has been applied on VPN traffic and non-VPN traffic respectively. The results of this classification were not as good as those of the binary classification between VPN and non-VPN traffic, but they were **also acceptable**.

Model	Accuracy	Precision	Recall
4.2	98.11%	98.24%	98.02%
4.3.1	98.25%	98.39%	98.15%
4.3.2 A	95.49%	89.11%	92.02%
4.3.2 B	86.88%	86.96%	87.83%

Results on evaluation of test set

6 Future work

Potential further advancement of this paper might be:

- More effective methods of data representation,
- Further tuning of hyperparameters of the models,
- Trying out other advanced machine learning methods,
- etc.

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Q & A

Thanks For Watching