RÉPUBLIQUE FRANÇAISE

Liberté
Égalité
Fraternité

Inria

FlowChronicle

Synthetic Network Flow Generation Through Pattern Set Mining

Joscha Cüppers[1]; Adrien Schoen[2]; Gregory Blanc[3]; **Pierre-François Gimenez**[2]

[1]CISPA, Germany; [2]Inria, France; [3]Telecom SudParis, France

Information system security

How to protect information system?

- Prevent the attack, detect it, and react
- Detection with Intrusion Detection System (EDR/NDR)

Information system security

How to protect information system?

- Prevent the attack, detect it, and react
- Detection with Intrusion Detection System (EDR/NDR)

Detection relies on observation

- System : OS and applications logs
- Network : network communications


```
2024-05-06T23:24:16.806598+02:00 stellar-sheep sshd[16039]: Failed password for pfg from 192.168.1.36 port 48650 ssh2
```

```
"ts": 1591367999.305988, "id.orig_h": "192.168.4.76", "id.resp_h": "192.168.4.1", "id.resp_p": 53, "proto": "udp", "service": "dns", "duration": 0.066851, "orig_bytes": 62, "resp_bytes": 141, "conn_state": "SF", "orig_pkts": 2, "orig_ip_bytes": 118, "resp_pkts": 2, "resp_ip_bytes": 197
```

Information system security

How to protect information system?

- Prevent the attack, detect it, and react
- Detection with Intrusion Detection System (EDR/NDR)

Detection relies on observation

- System : OS and applications logs
- Network : network communications

Main issues

- Detect APT attacks on long period of time
- Limit false positives
- Good quality data?


```
2024-05-
06T23:24:16.806598+02:00
stellar-sheep sshd[16039]:
Failed password for pfg from
192.168.1.36 port 48650 ssh2
```

```
"ts": 1591367999.305988,
"id.orig_h": "192.168.4.76",
"id.resp_h": "192.168.4.1",
"id.resp_p": 53, "proto":
"udp", "service":
"dns", "duration":
0.066851, "orig_bytes":
62, "resp_bytes":
141, "conn_state":
"SF", "orig_pkts":
2, "orig_ip_bytes":
118, "resp_pkts": 2,
"resp_ip_bytes": 197
```

The issue of data in security

Why do we need data?

- For evaluating security measures, most notably detection
- For using machine learning in cybersecurity

The issue of data in security

Why do we need data?

- For evaluating security measures, most notably detection
- For using machine learning in cybersecurity

Current state of datasets

- Public datasets are typically run in testbed with no real users
- They can suffer from mislabelling, network and attack configurations errors, etc.
- We cannot access private data due to confidentiality and privacy reasons

$\Rightarrow$ we cannot confidently evaluate intrusion detection systems because of this dubious quality

The issue of data in security

Why do we need data?

- For evaluating security measures, most notably detection
- For using machine learning in cybersecurity

Current state of datasets

- Public datasets are typically run in testbed with no real users
- They can suffer from mislabelling, network and attack configurations errors, etc.
- We cannot access private data due to confidentiality and privacy reasons

$\Rightarrow$ we cannot confidently evaluate intrusion detection systems because of this dubious quality

Our goal: **to use AI to generate synthetic network data**

Other applications of synthetic data

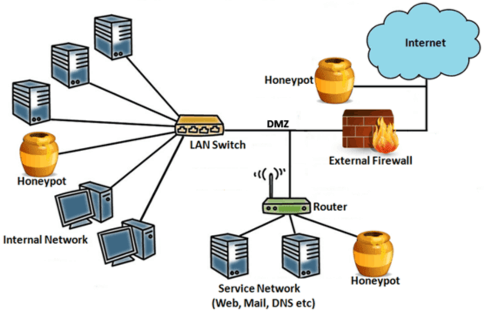
Cyber range realism

- Cyber ranges are emulated IT environments with vulnerabilities
- They are used to train red team (pentesters) and blue team (defenders)
- They are also useful in education and in CTF competitions
- Without realistic background network traffic, the scenario can become too easy

Other applications of synthetic data

Honeynets

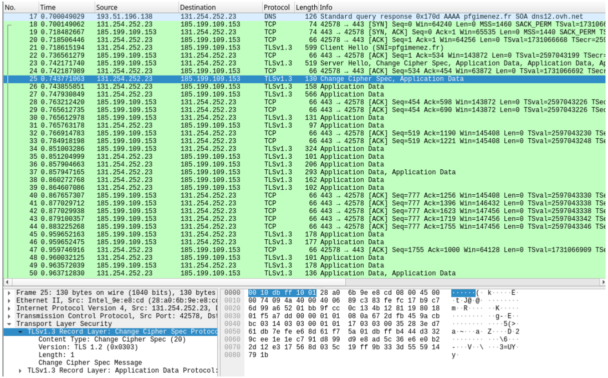
- Honeypots (and honeynets) are deliberately vulnerable (networks of) computers to attract and monitor attackers
- They must be attractive *but* contain nothing of value
- Honeypots and honeynets must be realistic so attackers (and their tools) generate traces
- Realistic network communications contribute to this realism



Network data example

Network data

- Raw data consist of packets, regrouped in conversation
- Cybersecurity analysis typically rely on network flow records that describe conversations statistically
- This is the kind of data we want to generate




```
ts,proto,src_ip,dst_ip,dst_port,fwd_packets,bwd_packets,fwd_bytes,bwd_bytes
1730800143,TCP,131.254.252.23,216.58.213.78,443,33,41,5988,1950
```

Just use an LLM!

State of the part

- Several approaches have been tried to generate network flows or pcap: VAE, GAN, LLMs
- The results are not very good:
- A significant portion of generated data do not comply with network protocols
- Generated data do not reflect the diversity of the original data
- The models are not explainable
- More generally, the dependencies are not well replicated

Just use an LLM!

State of the part

- Several approaches have been tried to generate network flows or pcap: VAE, GAN, LLMs
- The results are not very good:
  - A significant portion of generated data do not comply with network protocols
  - Generated data do not reflect the diversity of the original data
  - The models are not explainable
  - More generally, the dependencies are not well replicated

Dependencies

- Intra-flow dependency
  - the port depends on the destination IP
  - the number of packets depends on the application protocol
- Inter-flow dependency:
  - DNS query then HTTP(S)
  - IMAP request then HTTP(S)

Contribution: FlowChronicle

Intuition

Network data have a specific structure

- They are many interleaved and uncorrelated flows
- They are many hard constraints (HTTP is not over UDP, DNS port is 53, etc.)
- The inter-flow dependencies are not arbitrary:
  - $A \rightarrow B$, and then $A \rightarrow C$ can happen (for example: DNS request and then an HTTP request)
  - $A \rightarrow B$, and then $B \rightarrow C$ can happen (for example: request to a Website, that then contacts the database)
  - $A \rightarrow B$, and then $C \rightarrow A$ cannot happen: C cannot coordinate with A

With FlowChronicle, we identify *flow patterns* that are constrained with basic networking expert knowledge and are explainable

Contribution: FlowChronicle

FlowChronicle: A Novel Approach

- **Pattern Language**
  - Captures intra-flow and inter-flow dependencies
  - Summarizes data with non-redundant patterns
- **Data Generation**
  - Produces realistic traffic respecting protocols
  - Preserves temporal dependencies
- **Interpretability**
  - Patterns are interpretable and auditable

Intro

What is a pattern?

Frequently occurring substructure in data

Pattern Mining

- Define the set of possible patterns, named the ”pattern language”
- Find a small set of patterns that best describes the data
- More precisely, we use the patterns to compress the data: higher the compression, better the patterns

Pattern description

Pattern language

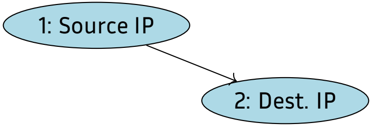
Each pattern has two parts: a partially defined flow, and a Bayesian network

- Fixed values are defined in the partial flow
- the distribution of Free variables is defined in the Bayesian network
- Reused variables are always equal to some Free variable

Partial flows

Source IP	Dest. IP	Dest. Port
β_A	8.8.8.8	53
A	β	80

Bayesian Network



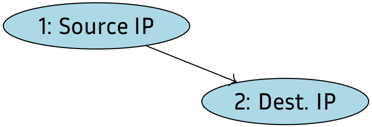
In reality there are more columns!

Pattern description

Partial flows

Source IP	Dest. IP	Dest. Port
β_A	8.8.8.8	53
A	β	80

Bayesian Network



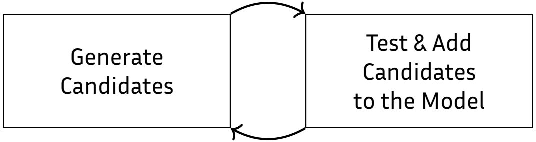
Example

- Here, there are two flows
- The first flow is contacting 8.8.8.8 on port 53 (DNS). The source IP is random
- The second flow has the same source IP as the first flow, and is contacting a destination IP that is random and depends on the first source IP, on port 80 (HTTP)

Our goal is to learn ("mine") such patterns

Mining process

Basic Idea - Two Steps:



Candidate generation

Extending existing pattern with attribute:

Existing Pattern:

Flow	Src IP	Dst IP	Port
1	β_A	8.8.8.8	53
2	A		443

New Pattern Candidate:

Flow	Src IP	Dst IP	Port
1	β_A	8.8.8.8	53
2	A		443
3			3306

Candidate generation

Extending existing pattern with attribute:

Existing Pattern:

Flow	Src IP	Dst IP	Port
1	β_A	8.8.8.8	53
2	A		443

New Pattern Candidate:

Flow	Src IP	Dst IP	Port
1	β_A	8.8.8.8	53
2	A		443
3			3306

Merging existing patterns:

Existing Patterns:

Flow	Src IP	Dst IP	Port
1	β_A	8.8.8.8	53
2	A		443

Flow	Src IP	Dst IP	Port
1		8.8.8.8	53

New Pattern Candidate:

Flow	Src IP	Dst IP	Port
1	β_A	8.8.8.8	53
2	A		443
3		8.8.8.8	53

Dataset cover

Model — Pattern and Bayesian Network:

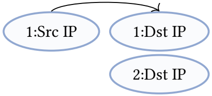
ϵ :

$[\ \beta\ \ \beta\ \ \beta\ ]$

p :

$[\ \beta_A\ \ \beta\ \ 993\ ]$

$[\ A\ \ \beta\ \ 80\ ]$



q

$[\ \beta_A\ \ 8.8.8.8\ \ 53\ ]$

$[\ A\ \ \beta_B\ \ 443\ ]$

$[\ B\ \ \beta\ \ 3306\ ]$

Data and Pattern Windows:

Time	Src IP	Dst IP	Port
12	134.96.235.78	142.251.36.5	993
56	134.96.235.129	8.8.8.8	53
89	134.96.235.78	212.21.165.114	80
113	134.96.235.129	198.95.26.96	443
145	198.95.26.96	198.95.28.30	3306
156	134.96.235.78	134.96.234.5	21
178	134.96.235.36	185.15.59.224	993
206	134.96.235.36	128.93.162.83	80

Loss function: $L(M) + L(D|M)$

Loss function: $L(M) + L(D|M)$

Length of Model:

$$L(M) = L_{\mathbb{N}}(|M|) + \sum_{p \in M} L(p)$$

Length of one pattern:

$$L(p) = L_{\mathbb{N}}(|p|) + \left(\sum_{j=1}^{|p|} L(X[j]|p) \right) + L(BN_p)$$

Loss function: $L(M) + L(D|M)$

Length of Model:

$$L(M) = L_{\mathbb{N}}(|M|) + \sum_{p \in M} L(p)$$

Length of one pattern:

$$L(p) = L_{\mathbb{N}}(|p|) + \left(\sum_{j=1}^{|p|} L(X[j]|p) \right) + L(BN_p)$$

Length of data given the model:

$$L(D \mid M) = \sum_{p \in M} (L_{\mathbb{N}}(|W_p|) + L(W_p))$$

where:

$$L(W_p) = \sum_{i=1}^{|W_p|} \left(L(t_1 \text{ of } w_i) + \sum_{k=2}^{|p|} L(t_k \text{of } w_i \mid t_{i-1}) \right) - \log(Pr(w_i|BN_p, \{w_j|j < i\}))$$

Generating network flows from a model

Key Steps

Select patterns sample patterns from the model.

Generate timestamp of the first flow sample a timestamp from the timestamp distribution.

Generate delays between the flows sample a delay from the delay distribution.

Fill values in the following order

- Fixed cells: Predefined values.
- Free cells: Sampled from the Bayesian network.
- Reuse cells: Context-based values.

Data quality evaluation

Hard to evaluate

- No standard metrics
- Evaluation often partial

Proposition

A set of evaluating metrics:

Realism : could the data actually exist?

Diversity : do we generate the diversity of behavior from the training set?

Novelty : can the generator create data absent from the training set?

Compliance : do the generated data comply with the technical specifications?

We do not consider privacy yet

Experimental protocol

Training data

We use the CIDDS 001 dataset: train on one week of traffic and generate one week of traffic

Baselines

We compare FlowChronicle with:

- Bayesian networks
- Variational autoencoders
- GAN
- Transformers
- ”Reference”

Reference

Actual data from the same dataset to simulate the best generative method

Non-temporal Evaluation

	Density	CMD	PCD	EMD	JSD	Coverage	DKC	MD	Rank
	Real. ↑	*Real.* ↓	*Real.* ↓	*Real./Div.* ↓	*Real./Div.* ↓	*Div.* ↑	*Comp.* ↓	*Nov.* =	*Average Ranking*
Reference	**0.69**	**0.06**	**1.38**	**0.00**	**0.15**	**0.59**	**0.00**	**6.71**	-
IndependentBN	0.24	0.22	2.74	*0.11*	0.27	0.38	0.05	5.47	5.25
SequenceBN	0.30	0.13	2.18	0.08	0.21	0.44	0.02	5.51	3.875
TVAE	0.49	0.18	1.84	0.01	0.30	0.33	0.07	5.17	4.125
CTGAN	0.56	0.15	1.60	0.01	0.15	0.51	*0.11*	5.70	3.0
E-WGAN-GP	*0.02*	0.34	*3.63*	0.02	0.38	*0.02*	0.07	4.66	7.0
NetShare	0.32	0.28	**1.47**	0.03	0.36	0.22	0.05	3.82	5.25
Transformer	**0.62**	*0.78*	3.62	**0.00**	*0.55*	0.03	0.05	*3.75*	*5.375*
FlowChronicle	0.41	**0.03**	2.06	0.02	**0.10**	**0.59**	**0.02**	**5.87**	**2.125**

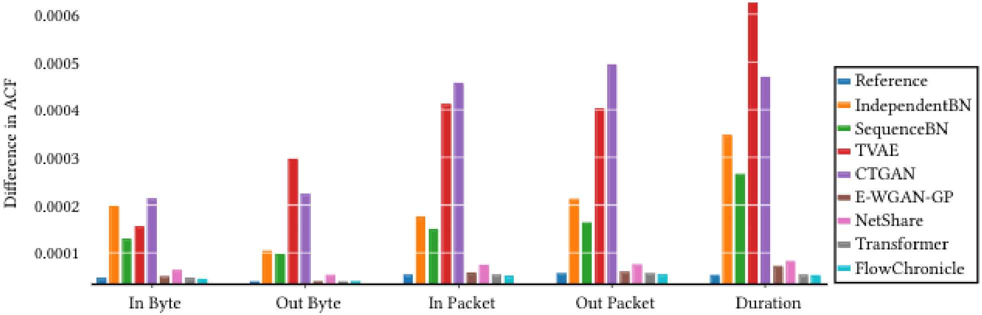
FlowChronicle produces overall the best traffic among the generative methods

Temporal Dependencies: Numerical Features

Difference in Autocorrelation Functions

- Autocorrelation function: correlation between the value of a feature and the value of this feature at other timestamps
- Evaluation: difference between autocorrelation of training data and synthetic data for each feature
- Lower is better

Temporal Dependencies: Numerical Features

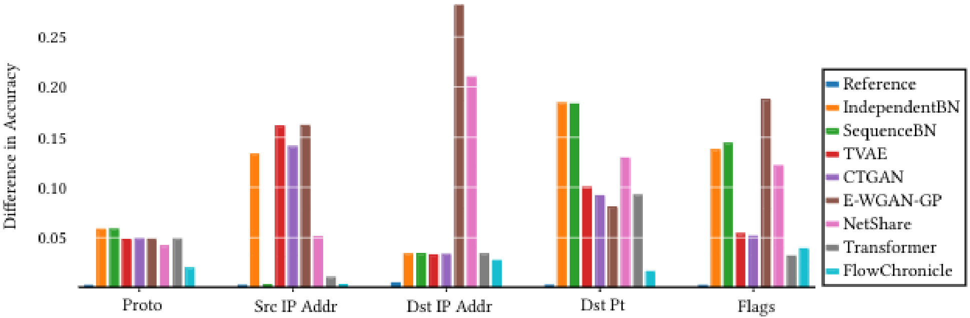


Temporal Dependencies: Categorical Features

Difference in the accuracy of LSTM autoregressive models

- Train an LSTM to predict the value of a feature
  - Input: Previous value of the feature $\rightarrow$ autoregressive task
- Difference of accuracy between two LSTMs on real data:
  - First LSTM trained on the Training Dataset
  - Second LSTM trained on the Synthetic Dataset
- Lower is better

Temporal Dependencies: Categorical Features



Conclusion

The need of data

- Good quality data is of utmost importance for security system evaluation and for cyber ranges and honeypots realism
- One way to achieve such quality is through generative AI

Contributions of FlowChronicle

- Innovative pattern set mining approach for synthetic network traffic generation
- Maintains both flow quality and temporal dependencies
- High performances: outperforms other generative models
- Auditable patterns: enables explainable and adaptable generation

Future works

We are building upon FlowChronicle for pcap generation