

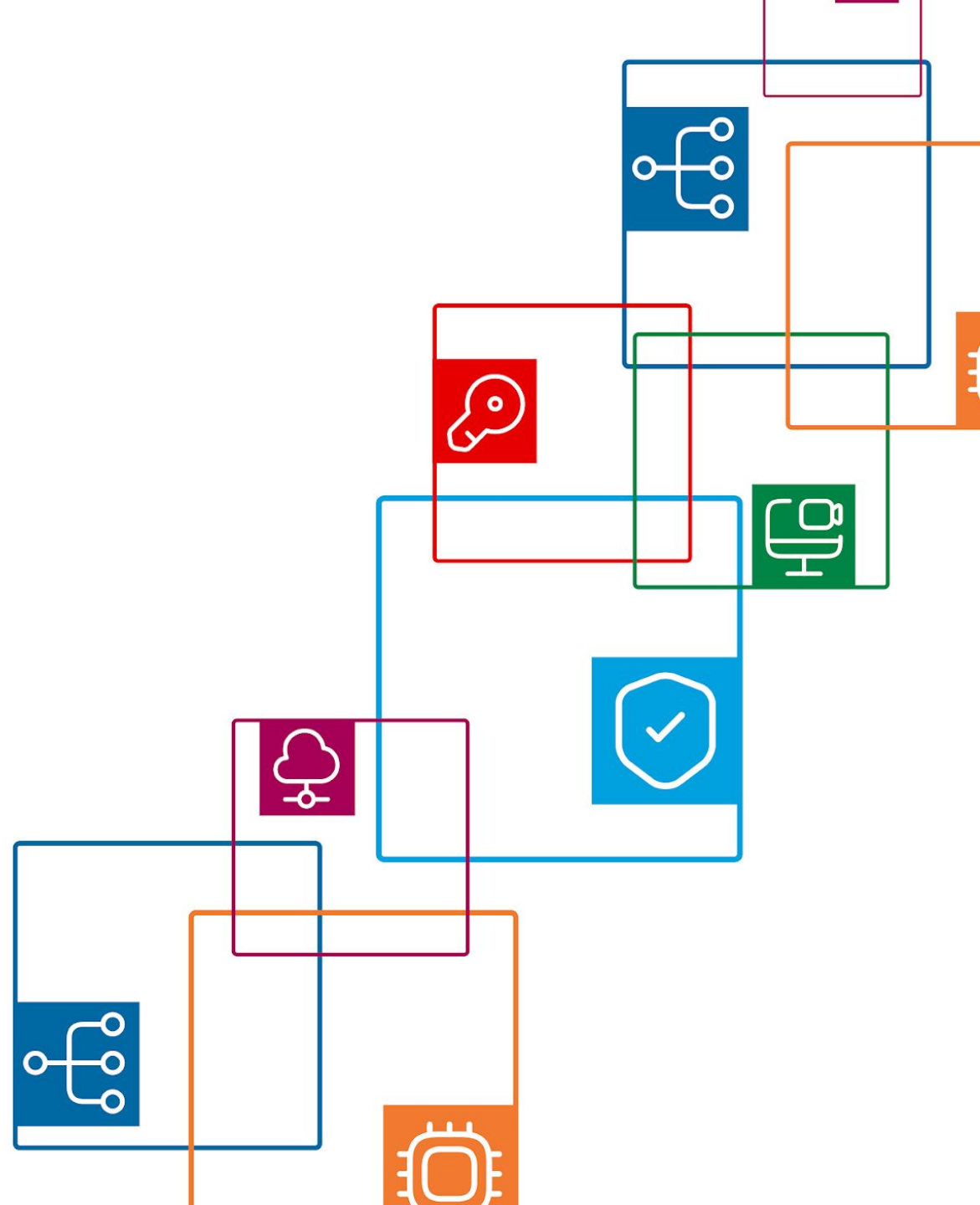


# Tour into Practical AI for Network Traffic Analysis

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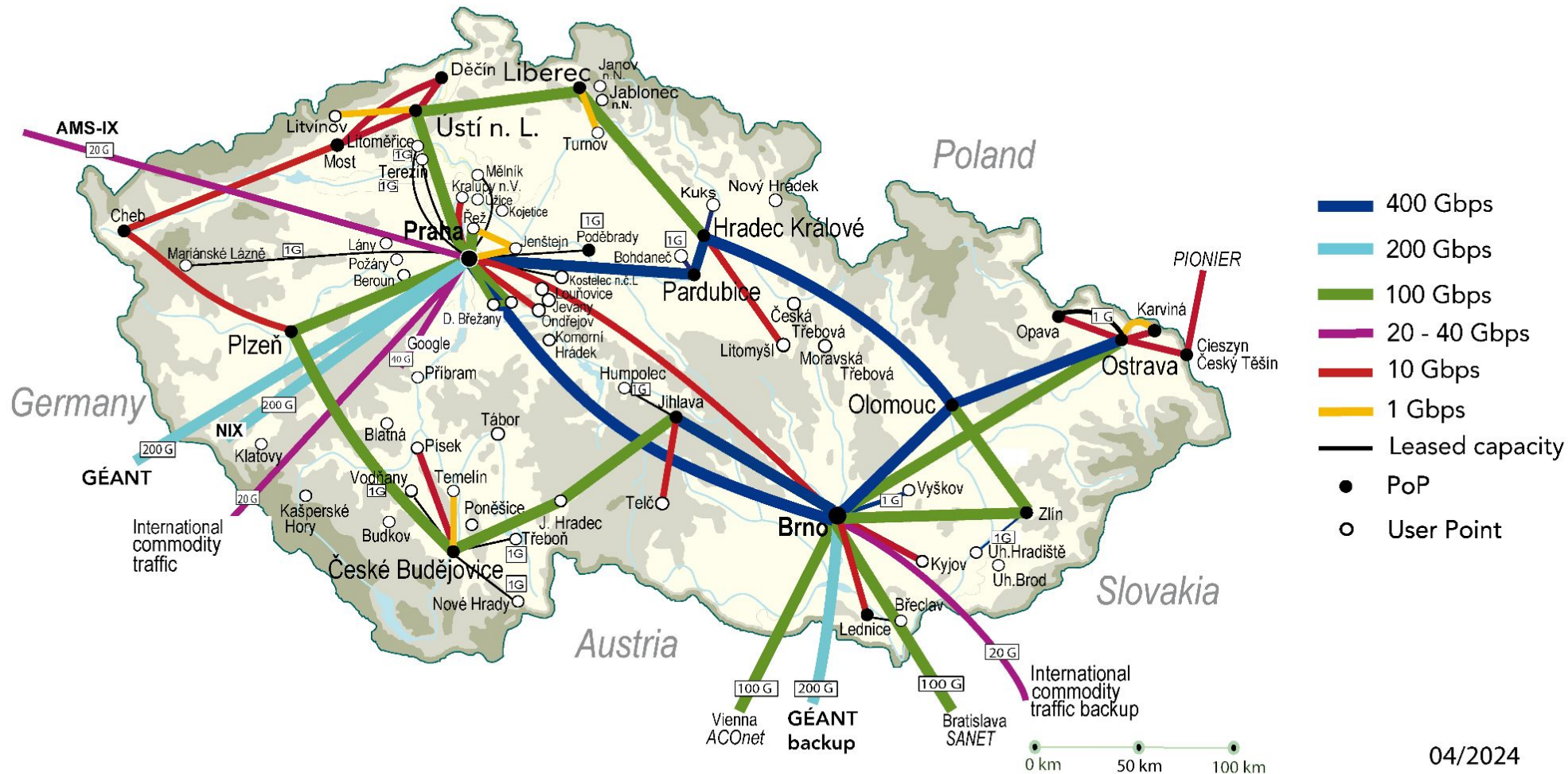


- One part of the department:
  - 2 post-docs
  - 8 PhD students
  - 3 full time developers
  - uncountable number of students (~ 10)
- Main topics:
  - Development of tools and software
  - Dataset creation
  - Research of application of machine learning
  - Building of infrastructure for handling the data

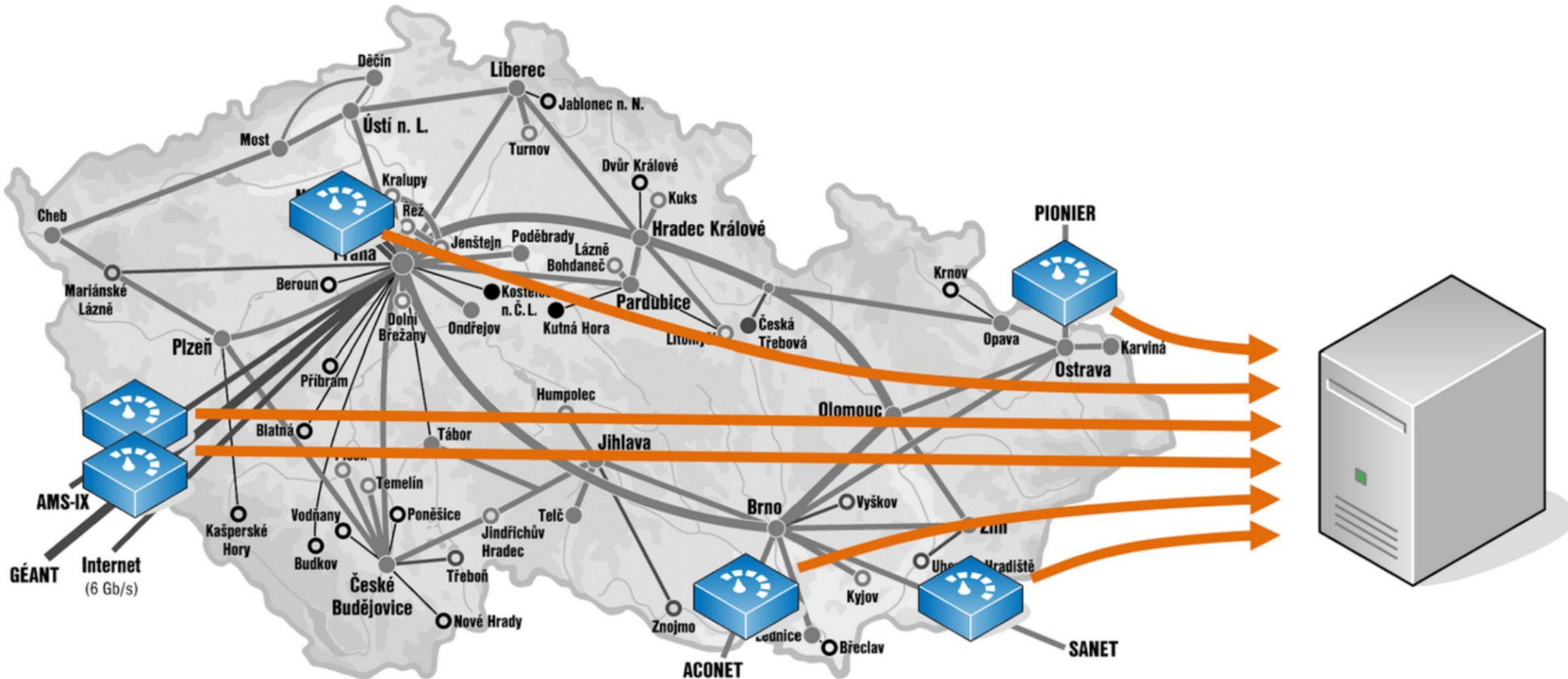


1. Infrastructure and software, visualization and LLM baby steps
2. Dataset and tools
3. Is field in crisis?

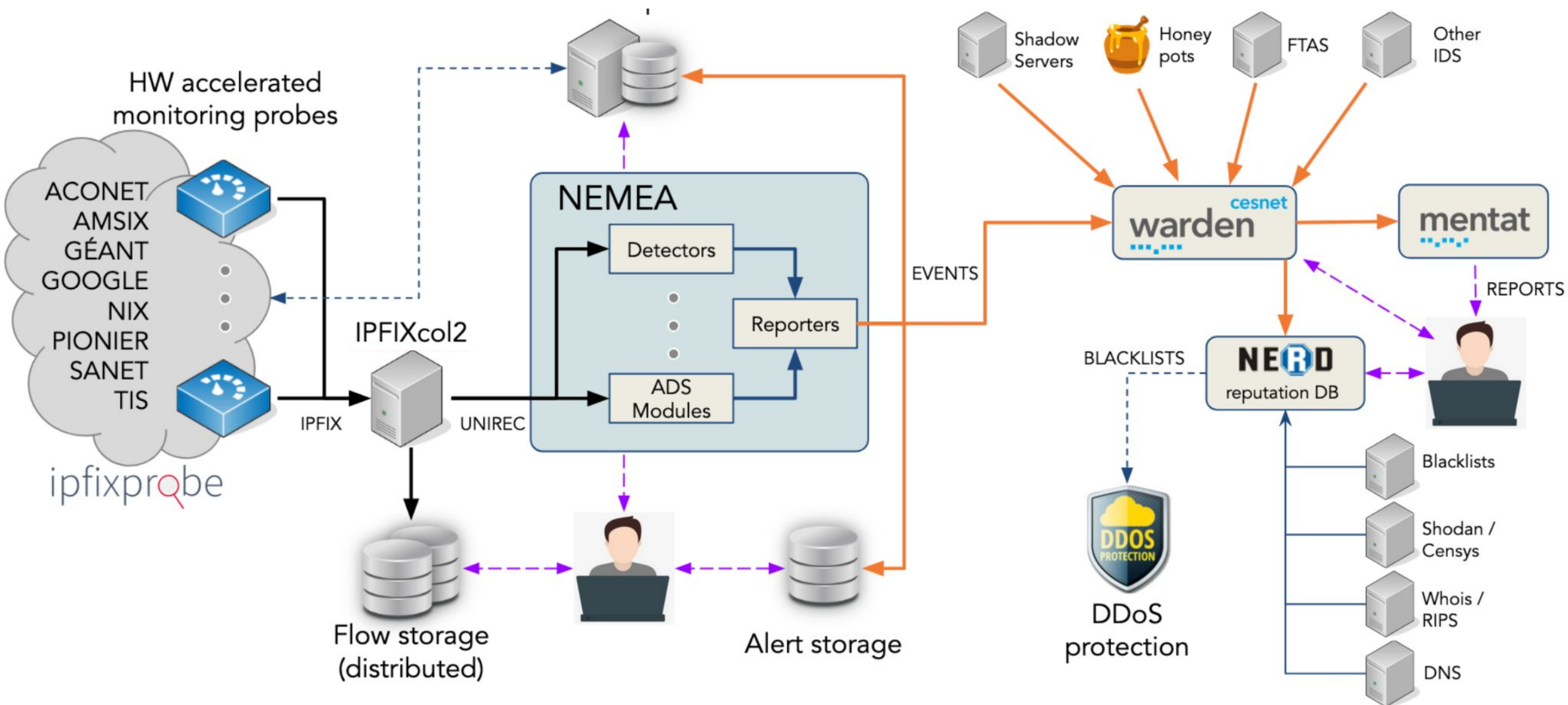




# Probes



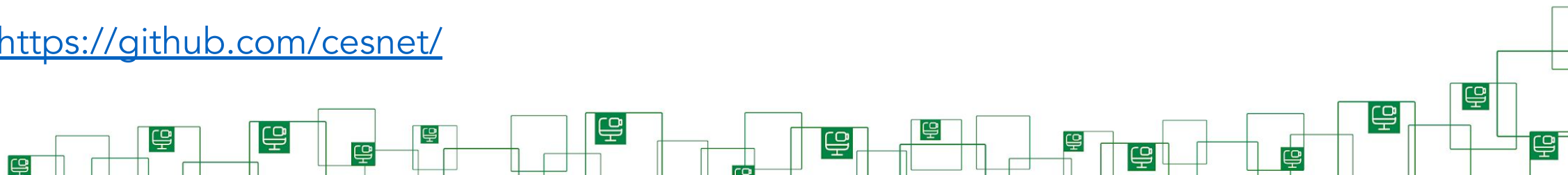
# Traffic monitoring and analysis



## Production-ready, established tools

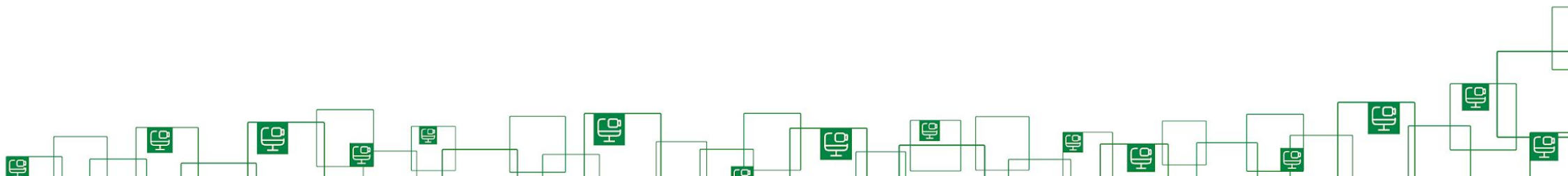
- ipfixprobe – modular and powerful flow exporter
- IPFIXcol2 – flow collector, supports IPFIX, NetFlow v5/v9
- NEMEA – modules based framework for data stream analysis

<https://github.com/cesnet/>

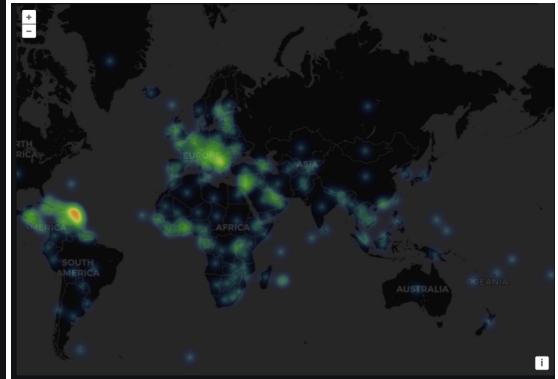
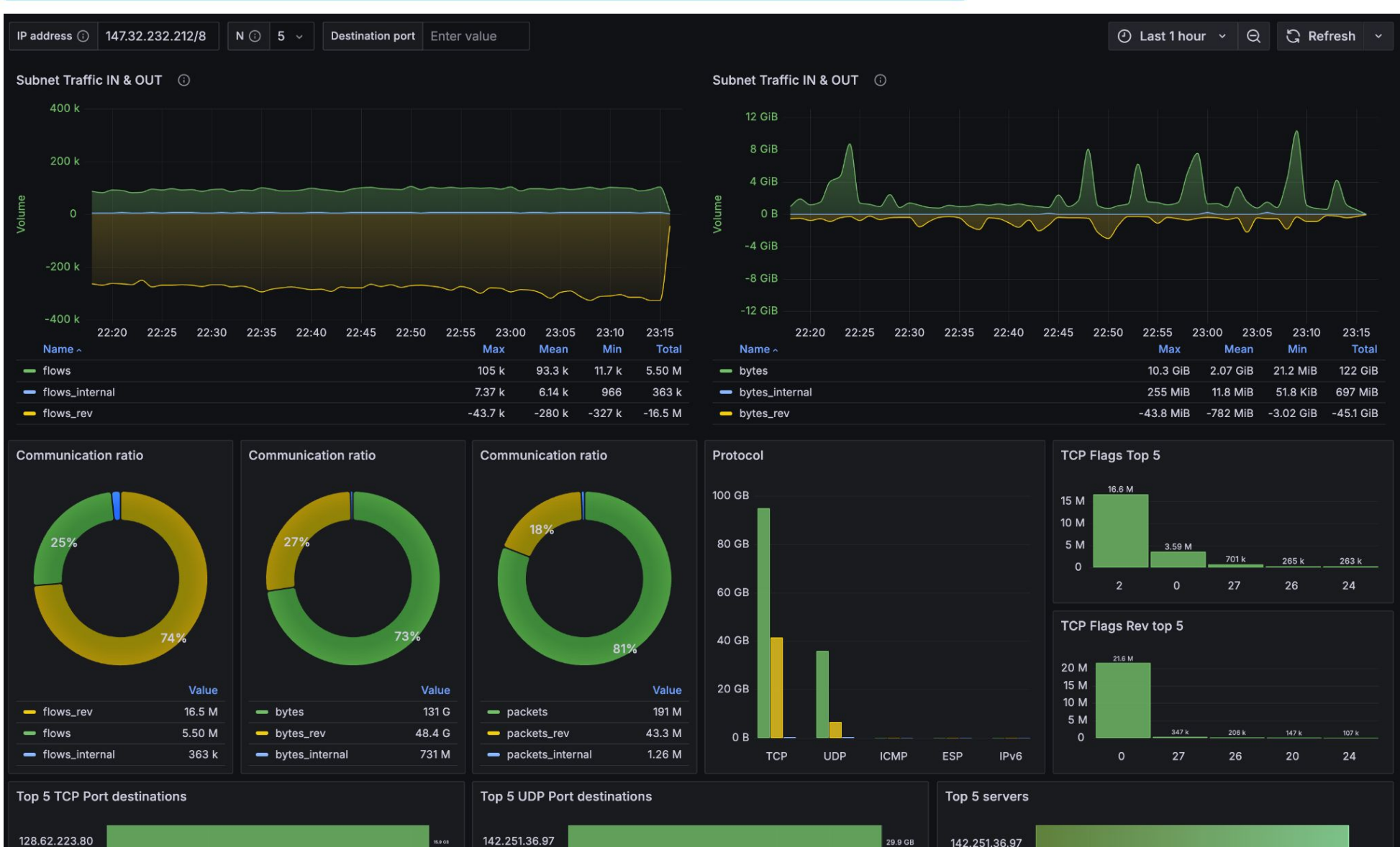


Besides our in-house software, we use

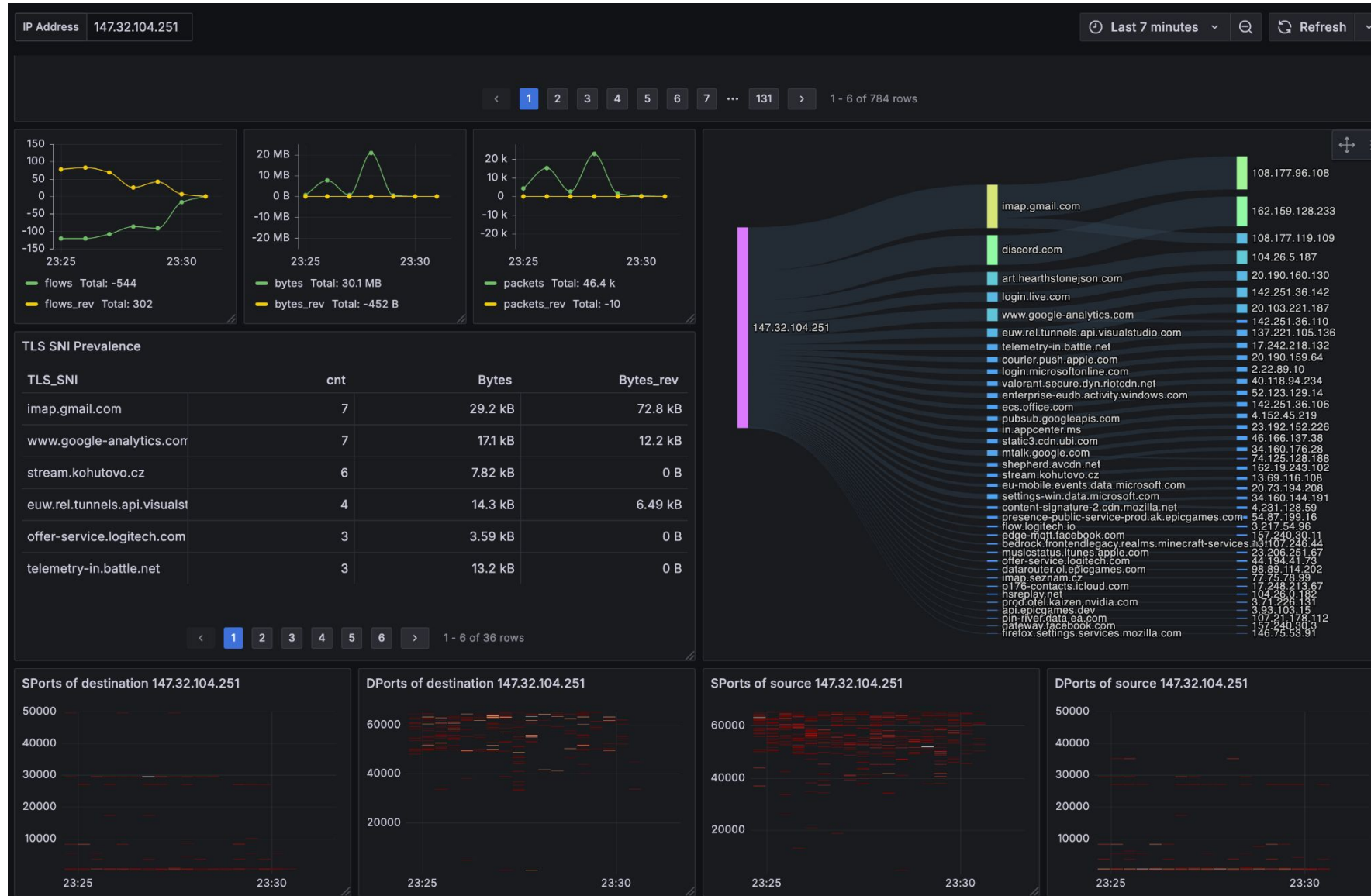
- Nix and NixOS for reproducible and fast deploying (we replaced Ansible)
- Clickhouse as analytical database
- Grafana for visualization



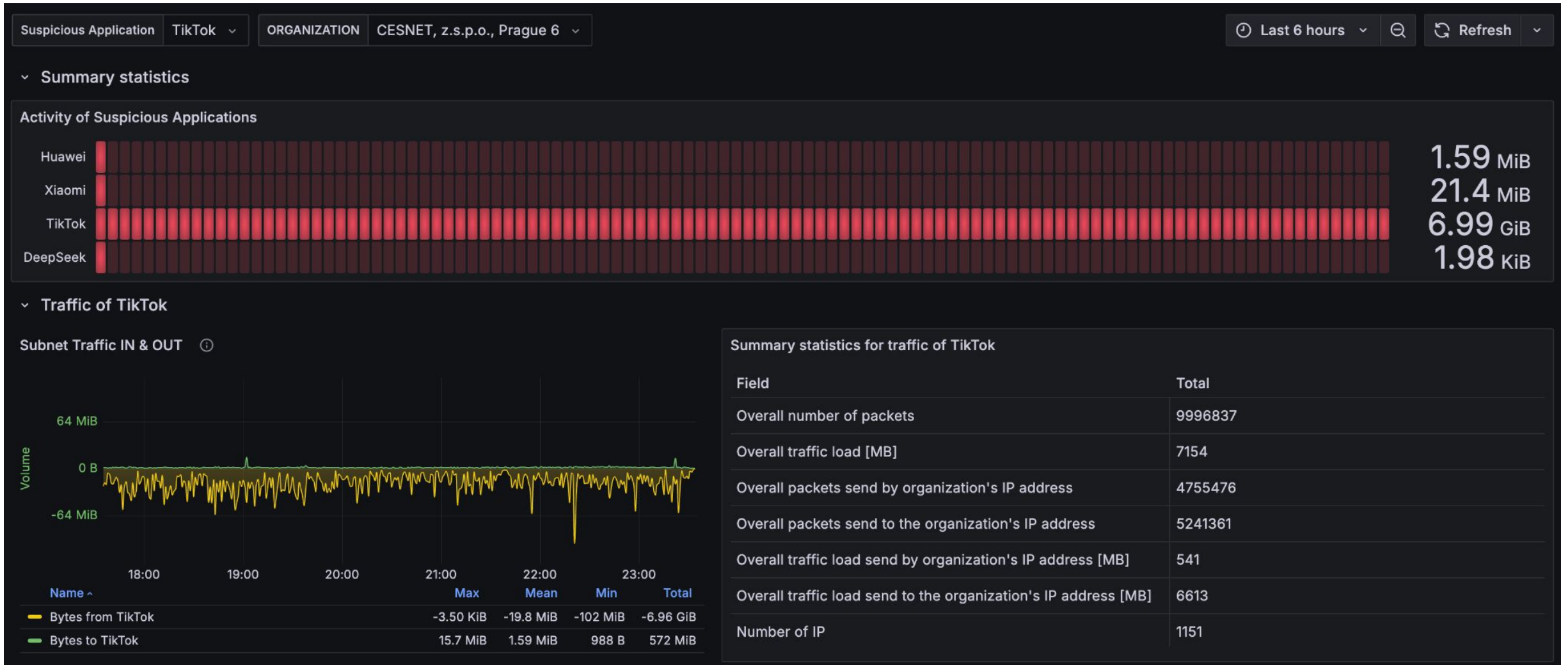
# Degustation of our tech stack



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We try to use LLM agent that reads the dashboards and reports to superior, i.e.:

**Daily SOC Report – 2025-10-08**

Network activity remained within normal limits. No major anomalies or security events detected overnight.

Inbound and outbound traffic volumes were balanced ( $\approx 55\%$  /  $43\%$ ), dominated by TCP ( $\approx 90\%$ ) with minor UDP activity. Top talkers and ports matched expected operational behavior.

The “Decrypto” detection module reported no critical findings or suspicious flows. Geolocation map shows usual communication patterns—mainly Western Europe and North America—with no unexpected hotspots.

**Action:** No escalation required. Continue regular monitoring and verify top hosts if traffic growth persists.

Or:

## Daily SOC Report – 2025-10-08

A volumetric anomaly was detected between 02:15–03:00 UTC, indicating a possible DDoS attack targeting internal web services. Inbound traffic spiked to over **8× the daily average**, primarily consisting of **UDP** and **TCP SYN** packets.

Geolocation analysis shows that over **70 % of the malicious traffic** originated from IP ranges registered in Russia, with smaller portions from Ukraine and Belarus. The top destination was **147.32.1.10 (public web endpoint)**, receiving sustained requests on ports **80** and **443**.

Firewall counters confirmed **packet drops and connection resets** consistent with rate-limiting behavior. No data exfiltration or lateral movement observed.

**Action:** Incident escalated to L2 for correlation and mitigation. Recommend reviewing upstream filtering rules and updating threat intelligence lists.

## LLM as SOC member:

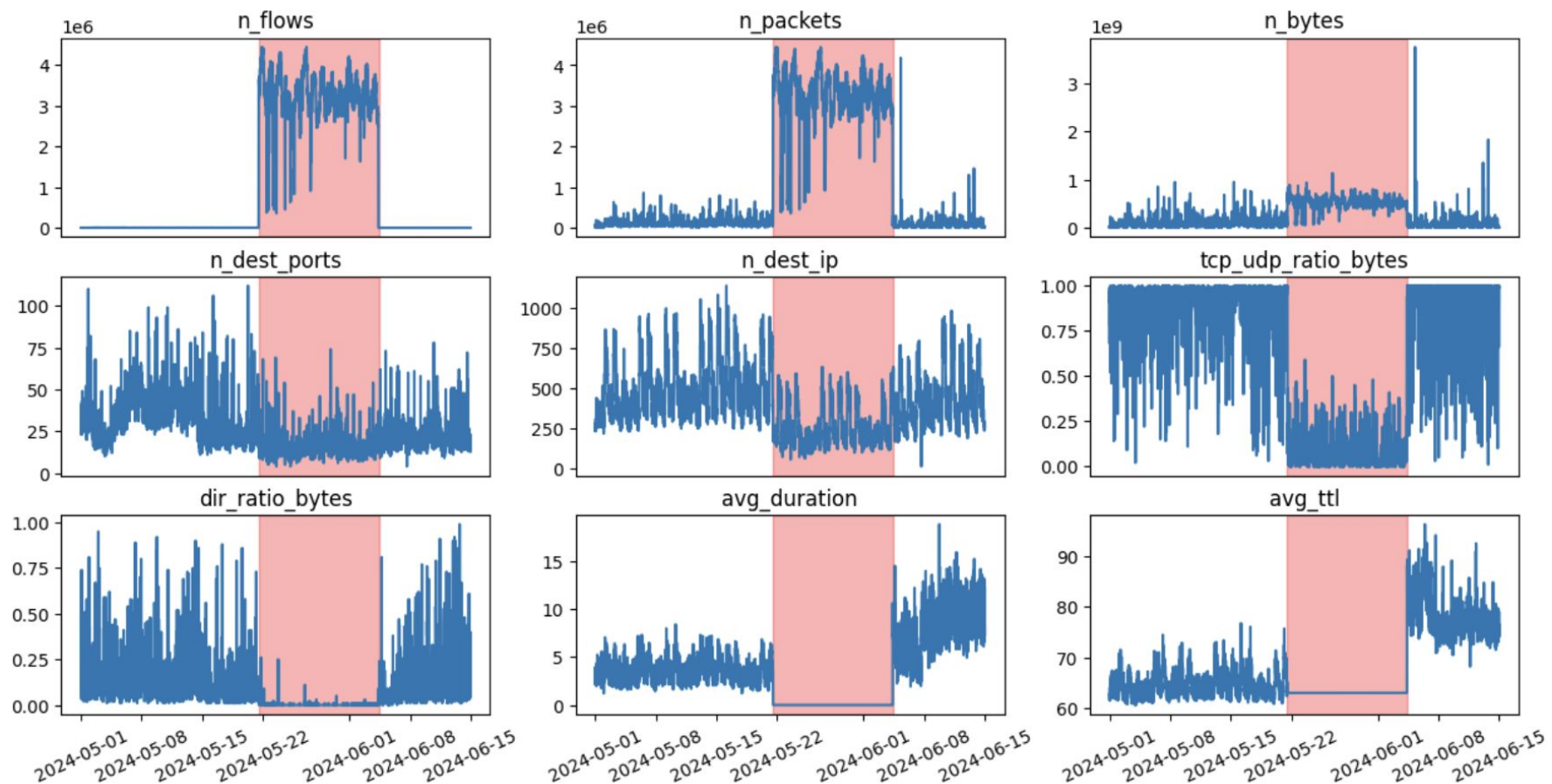
**Label:** Potential DDoS

**Priority:** critical

**Confidence:** High

**Explanation:** Significant spikes in multiple metrics suggest a coordinated traffic anomaly.

**Suggested Action:** Immediately investigate the source IPs and traffic patterns; implement rate limiting if confirmed as an attack.

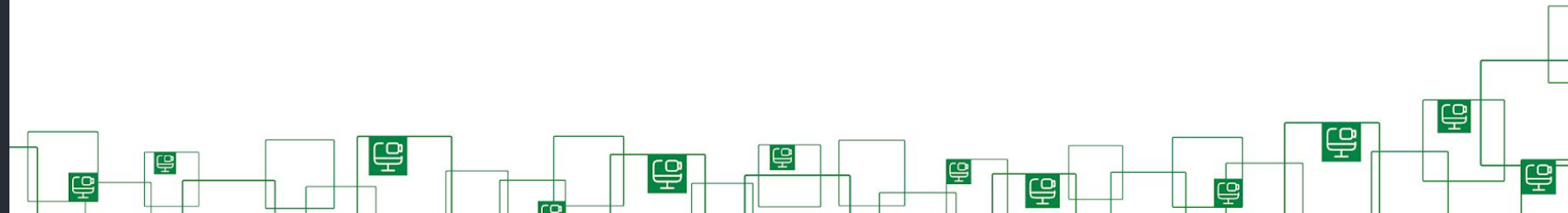


## CESNET-DataZoo & CESNET-TsZoo

- Tools for working with large REAL traffic data in simple way
- CESNET-TLS-Year22 and CESNET-TimeSeries24 published in Nature Scientific Data journal
- QUIC services dataset
- WIP: Curating new benchmark datasets from outside

```
from cesnet_datazoo.datasets import CESNET_QUIC22
from cesnet_datazoo.config import DatasetConfig, AppSelection

dataset = CESNET_QUIC22("/datasets/CESNET-QUIC22/", size="XS")
dataset_config = DatasetConfig(
    dataset=dataset,
    apps_selection=AppSelection.ALL_KNOWN,
    train_period_name="W-2022-44",
    test_period_name="W-2022-45",
)
dataset.set_dataset_config_and_initialize(dataset_config)
train_dataframe = dataset.get_train_df()
val_dataframe = dataset.get_val_df()
test_dataframe = dataset.get_test_df()
```



- Contemporary research often uses complex, deep learning models
- Papers published in 2025 only...:

network traffic classification "deep learning"

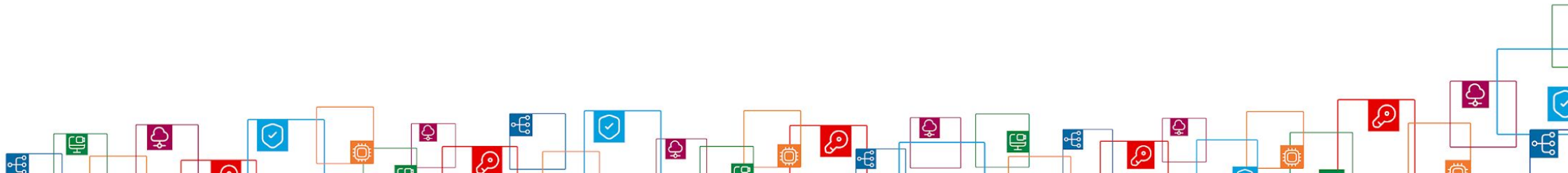


About 16 900 results (0,14 sec)

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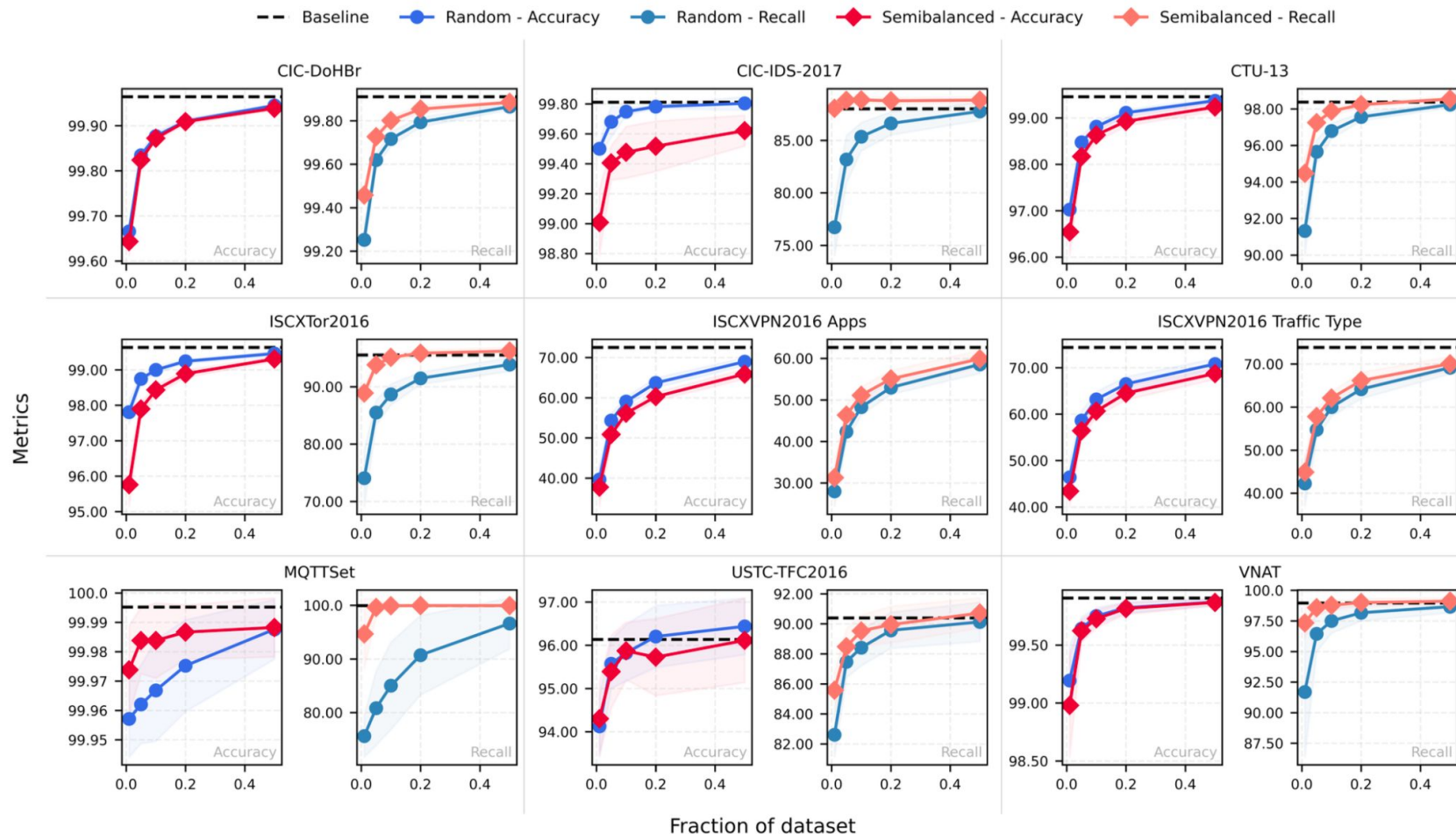
- Contemporary research often uses complex, deep learning models
- Our study shows simple 1-NN (one nearest neighbour) using sequence of 10 first packets only can achieve the similar performance
- The model is not genius, it is data redundancy in benchmark datasets
- The reported progress in field is overestimated



# Findings

Even when we heavily sample the dataset, the results are still quite ok

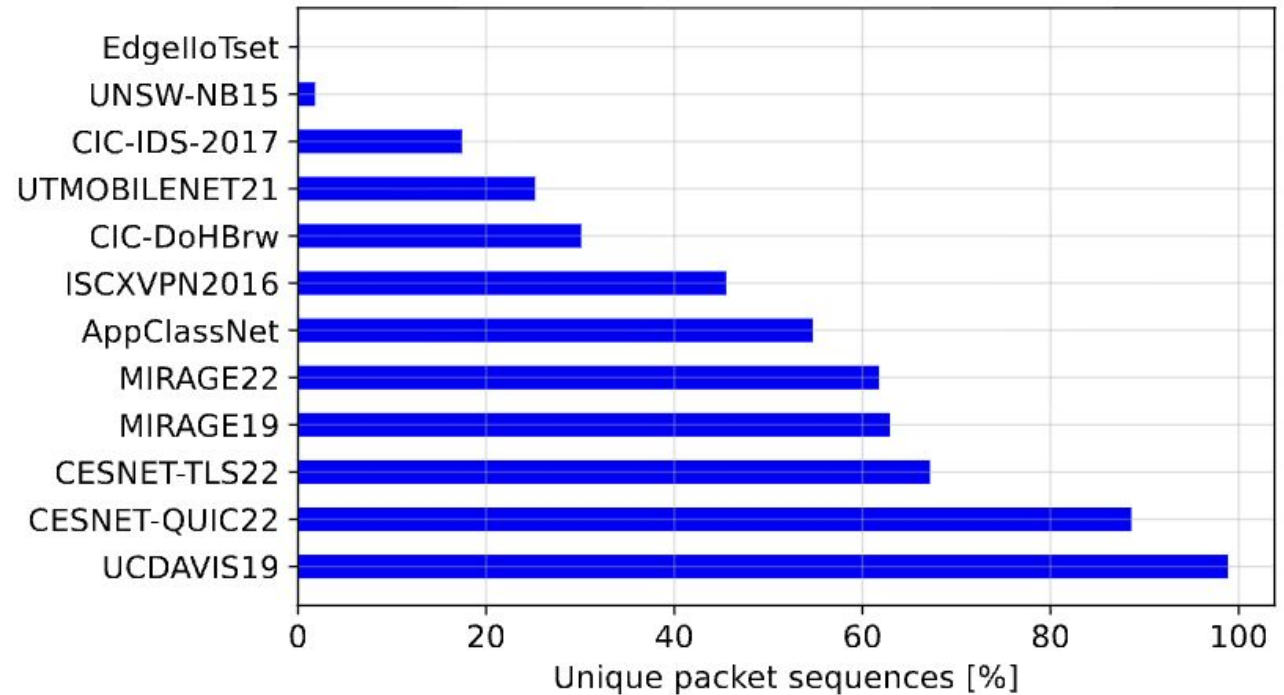
We see the same phenomenon for all major community favorit datasets



Fraction of redundant sequences are relatively high

Models just memorize samples

That is why 1-NN model just works



# Comparison

Dataset	Task	SOTA Accuracy [%]	Baseline Accuracy [%]	$\Delta$ Accuracy [pp]
ISCXTor2016 [10]	tor, non-tor	100.00 $\pm$ 0.01 [11]	99.63 $\pm$ 0.02	-0.37 $\pm$ 0.02
USTC-TFC2016 [12]	10 mal., 1 benign	98.30 [13]	96.14 $\pm$ 0.64	-2.16 $\pm$ 0.64
VNAT [14]	vpn, non-vpn	98.03 [15]	99.91 $\pm$ 0.01	1.88 $\pm$ 0.01
CTU-13 [3]	mal., benign	99.30 [16]	99.46 $\pm$ 0.08	0.16 $\pm$ 0.08
MQTTSet [17]	4 mal., 1 benign	99.90 [18]	100.00 $\pm$ 0.01	0.10 $\pm$ 0.01
ISCXVPN2016 App [1]	17 benign svc.	79.92 $\pm$ 1.31 [19]	72.54 $\pm$ 1.05	-7.38 $\pm$ 1.68
ISCXVPN2016 Traffic [1]	6 benign types	81.71 $\pm$ 1.26 [19]	74.39 $\pm$ 1.35	-7.32 $\pm$ 1.85
CIC-DoHBr [20]	mal., benign	99.99 [21]	99.96 $\pm$ 0.00	-0.03 $\pm$ 0.00
CIC-IDS-2017 [2]	7 mal., 1 benign	95.79 [22]	99.81 $\pm$ 0.02	4.02 $\pm$ 0.02

- We should focus less on building bigger models and more on building better, more diverse datasets that truly reflect the complexity of real network traffic
- Let's create redundancy-aware benchmarks
- Is traffic analysis in crisis?

Based on papers:

<https://ieeexplore.ieee.org/abstract/document/11096965>

<https://arxiv.org/pdf/2506.08655>

