



Data Science in Cybersecurity

ALLAN OGWANG



How Vectra applies data science for threat detection

Vectra uses AI to detect attackers in real time and enrich threat investigations with a conclusive chain of forensic evidence



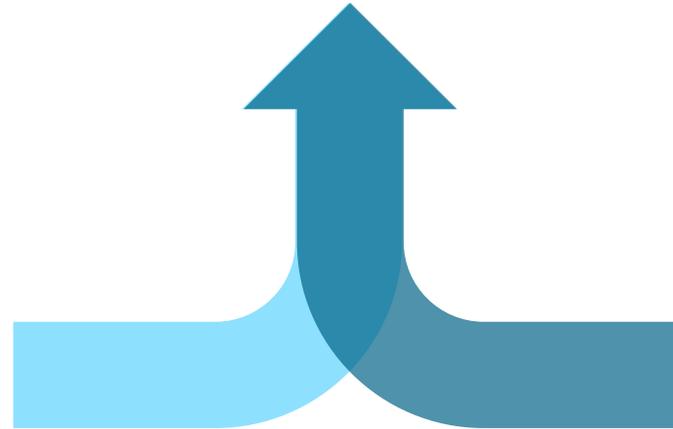
Attacker behaviors: unifying data science and security research

Attacker behavior models

- High-fidelity detection of things attackers must do
- No signatures: find known and unknown

Security Research

- Identify, prioritize, and characterize fundamental attacker behaviors
- Validate models



Data Science

- Determine best approach to identify behavior
- Develop and tune models



Who is Vectra AI?

- Vectra AI provides automated threat detection to expose hidden and unknown cyberattackers in a network.
- Apply artificial intelligence to seek out the fundamental threat behaviors that attackers simply can't avoid

Data Breach Tied to China Hits Millions

**Federal
Target**

By DAV
and JULIE P
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Equifax Attack Exposes Data Of 143 Million

*This article is by Tara Siegel
Bernard, Tiffany Hsu, Nicole Perl-
roth and Ron Lieber.*

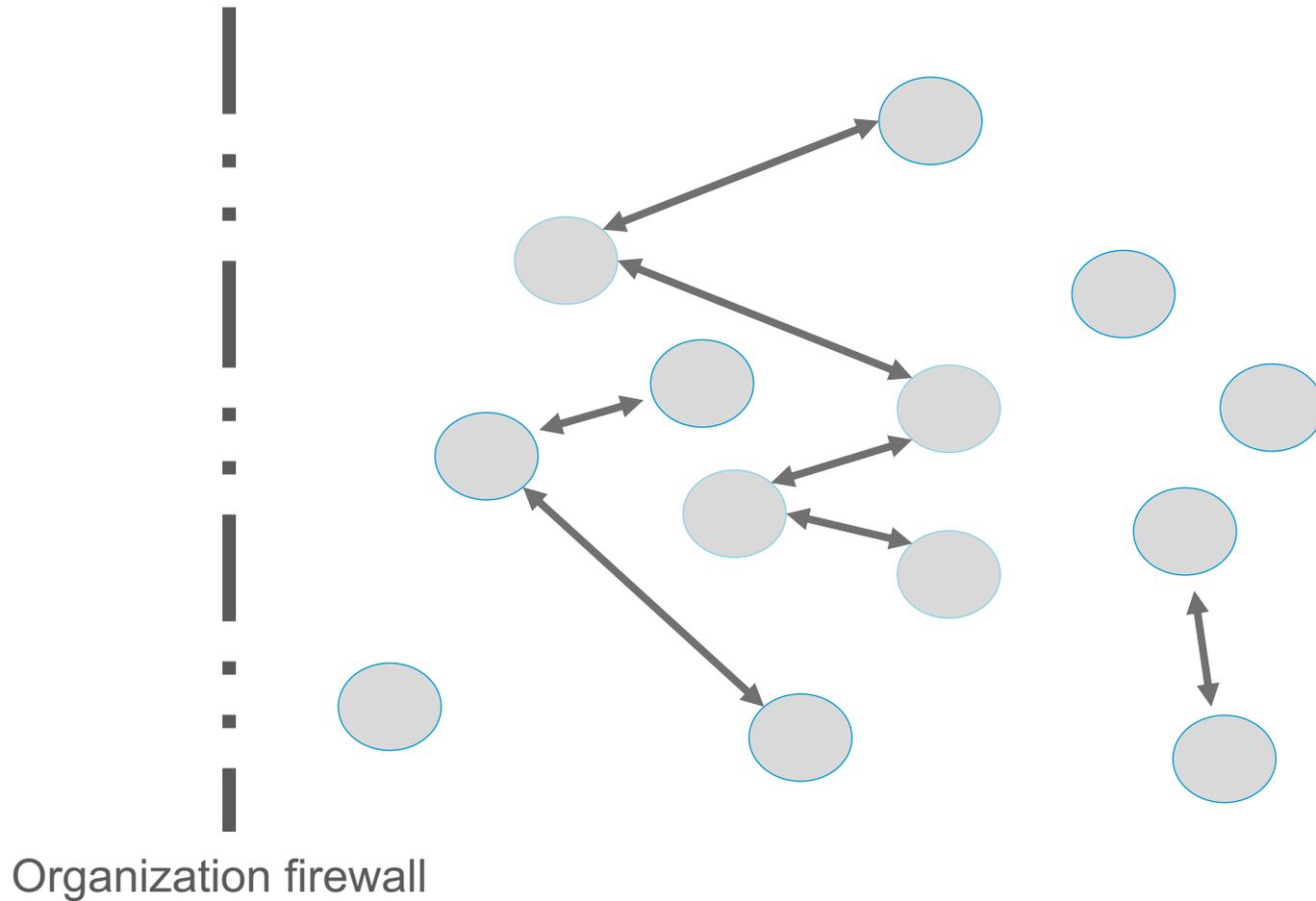
Equifax, one of the three major consumer credit reporting agencies, said on Thursday that hackers had gained access to company data that potentially compromised sensitive information for 143 million American consumers, including Social Security numbers and driver's license numbers.



Cyberthreats in an enterprise: An advanced attack



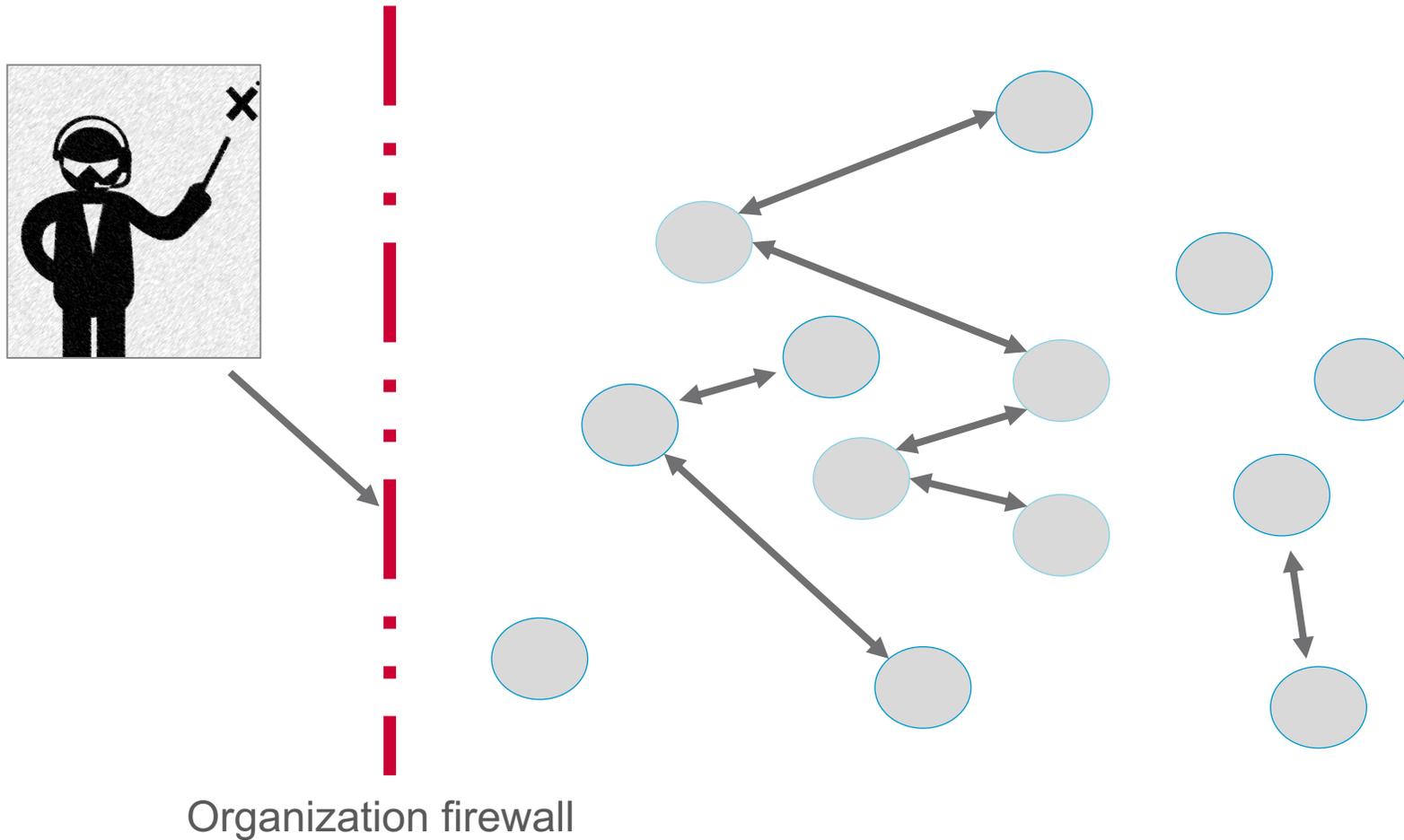
Enterprise networks



Firewall creates a separation between inside and outside of the network



Enterprise networks



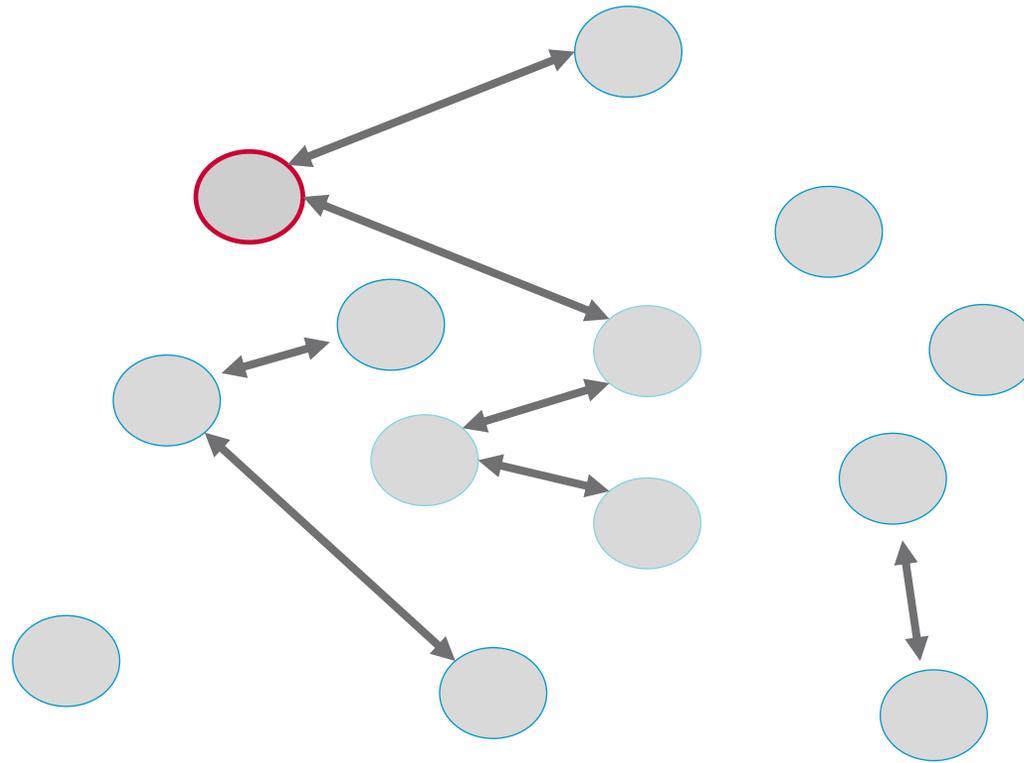
Firewall prevents an attacker from connecting to network computers



Advanced attack



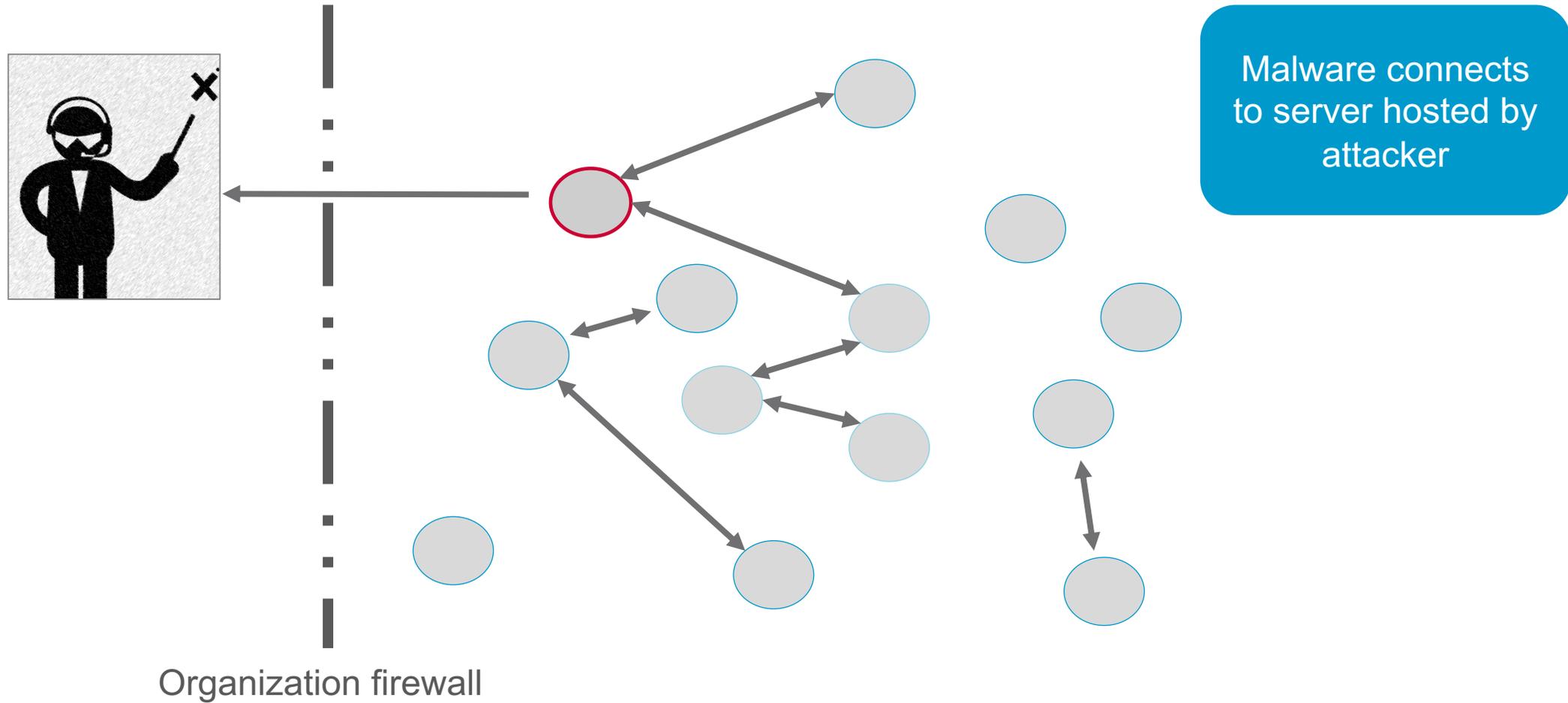
Organization firewall



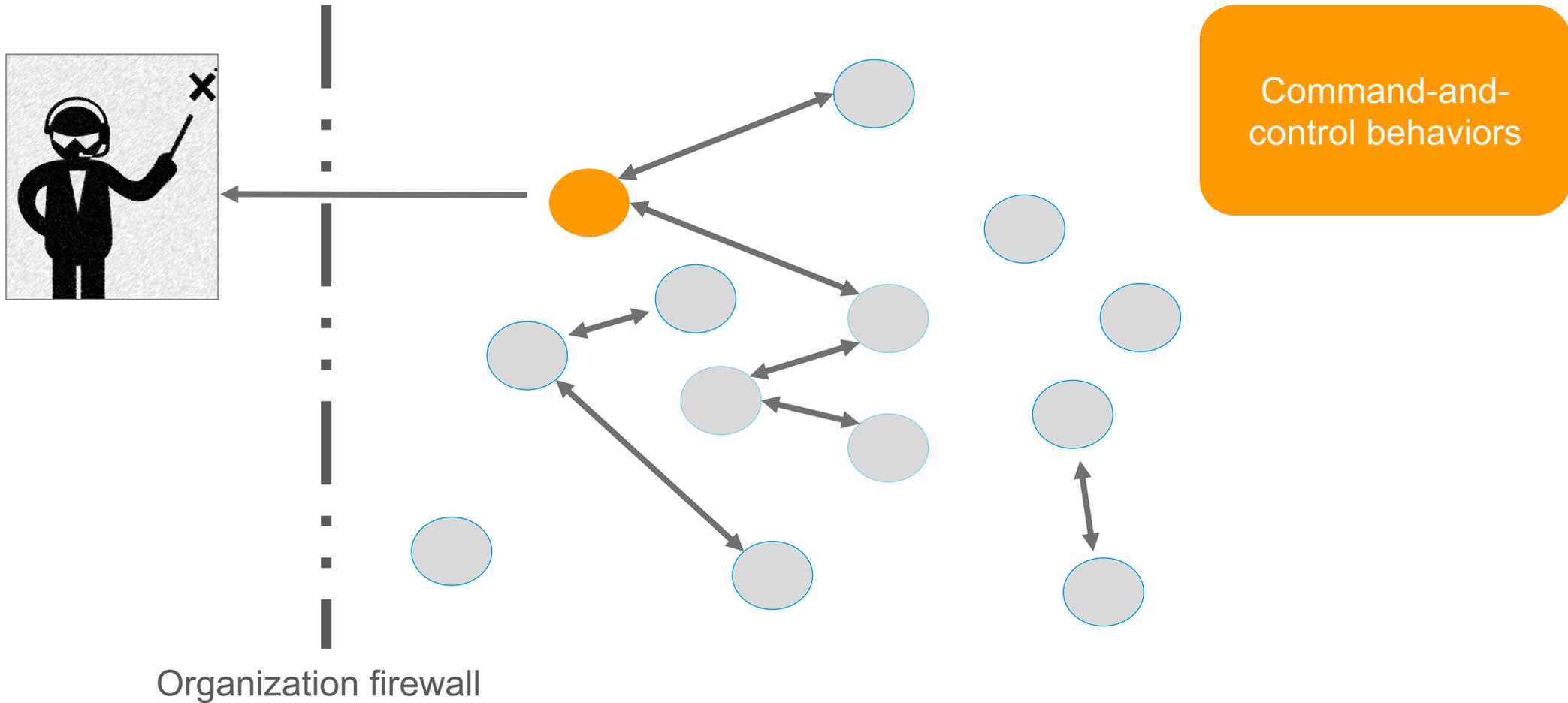
Infect with malware



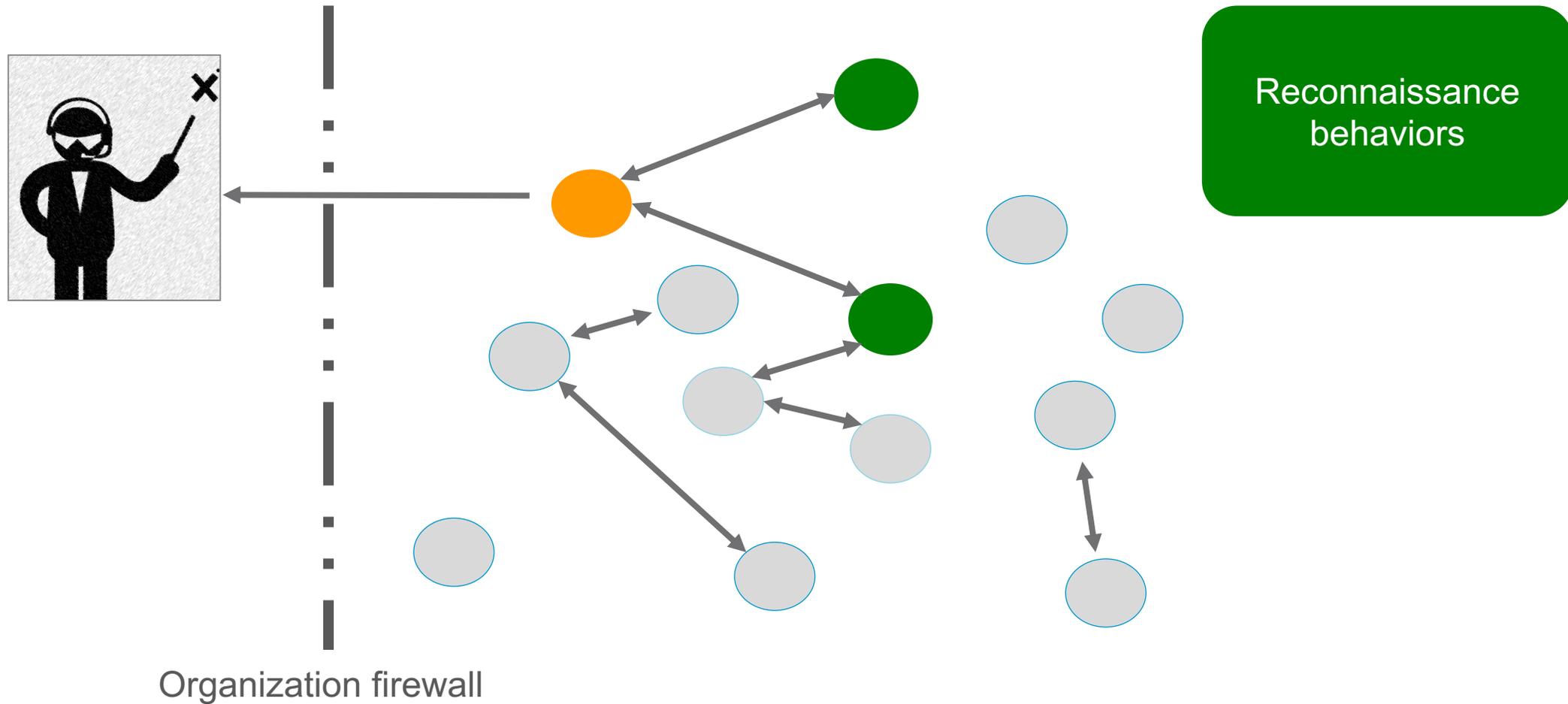
Advanced attack



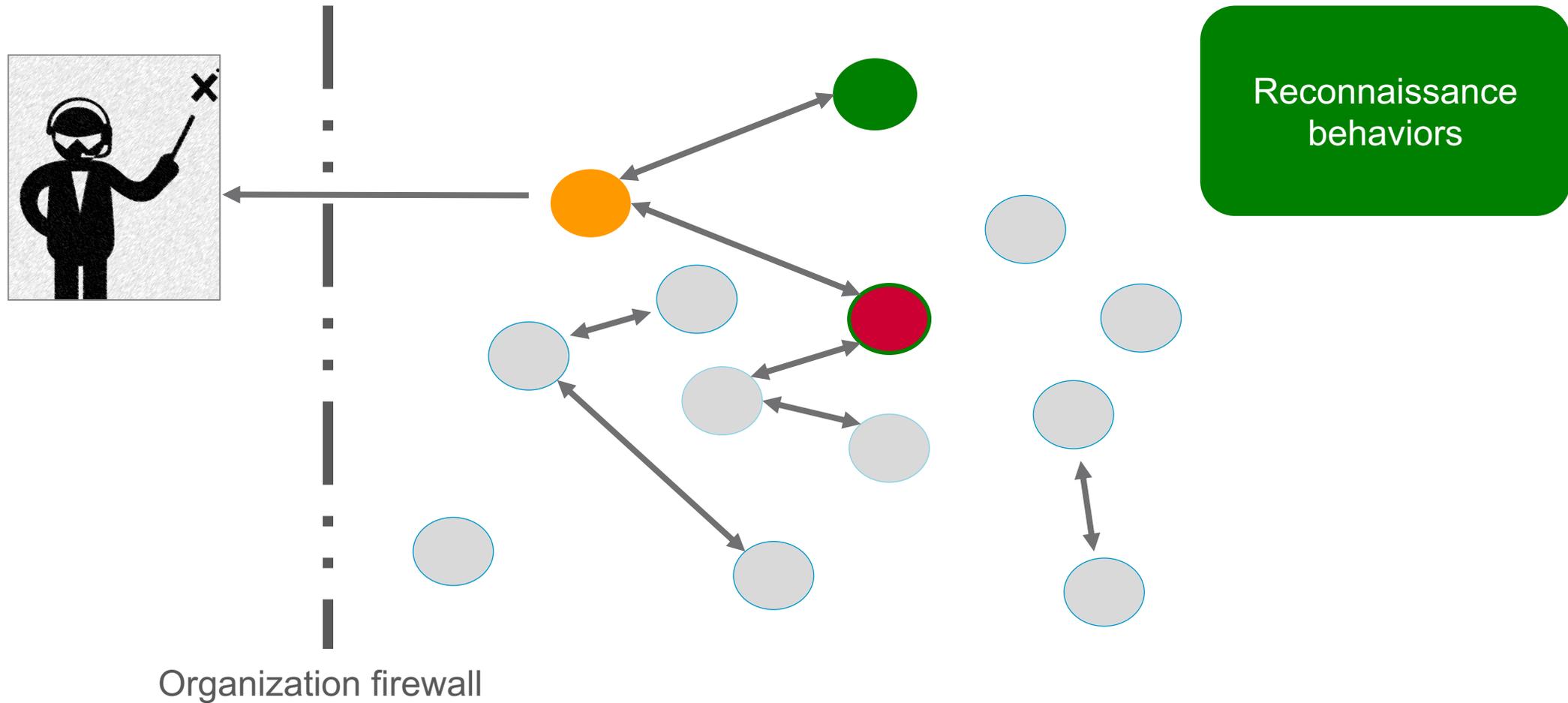
Advanced attack



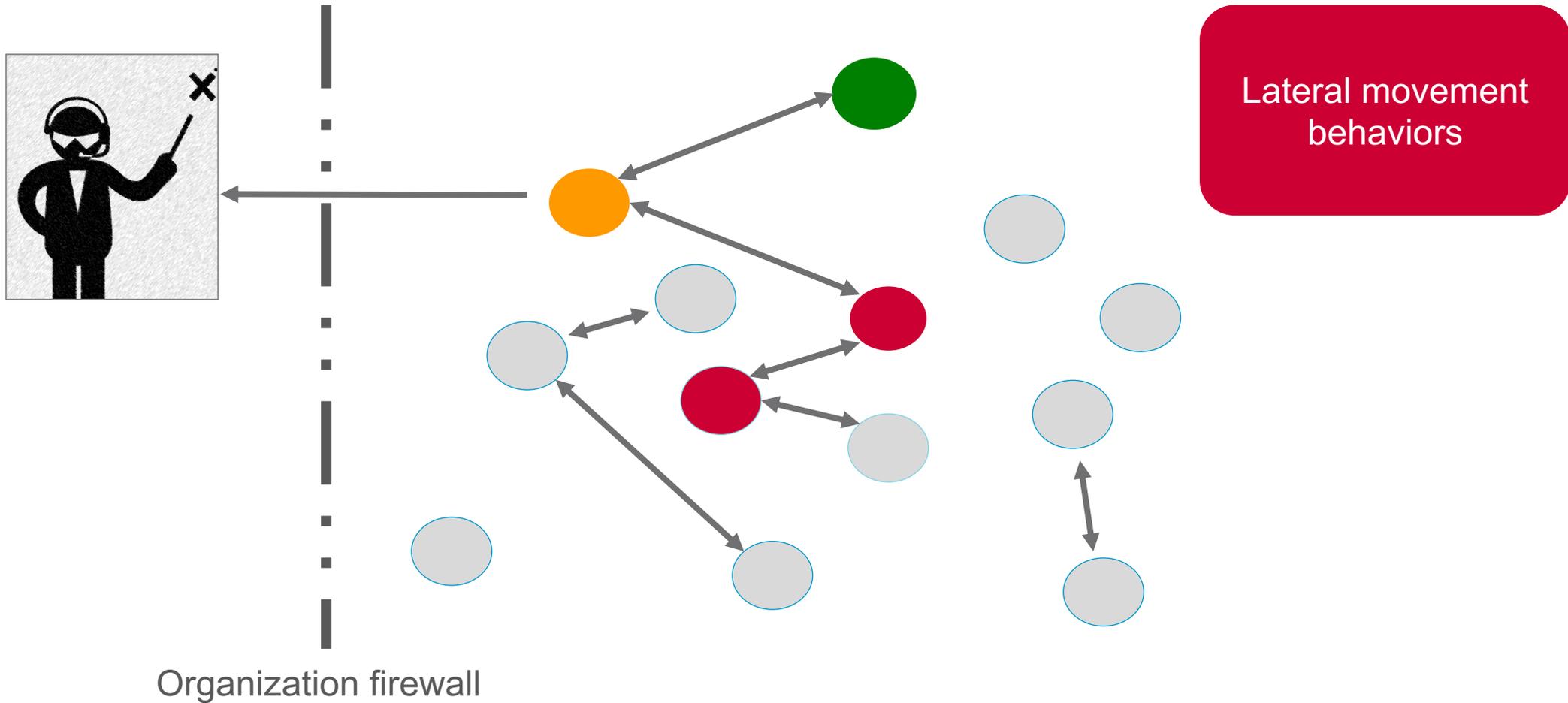
Advanced attack



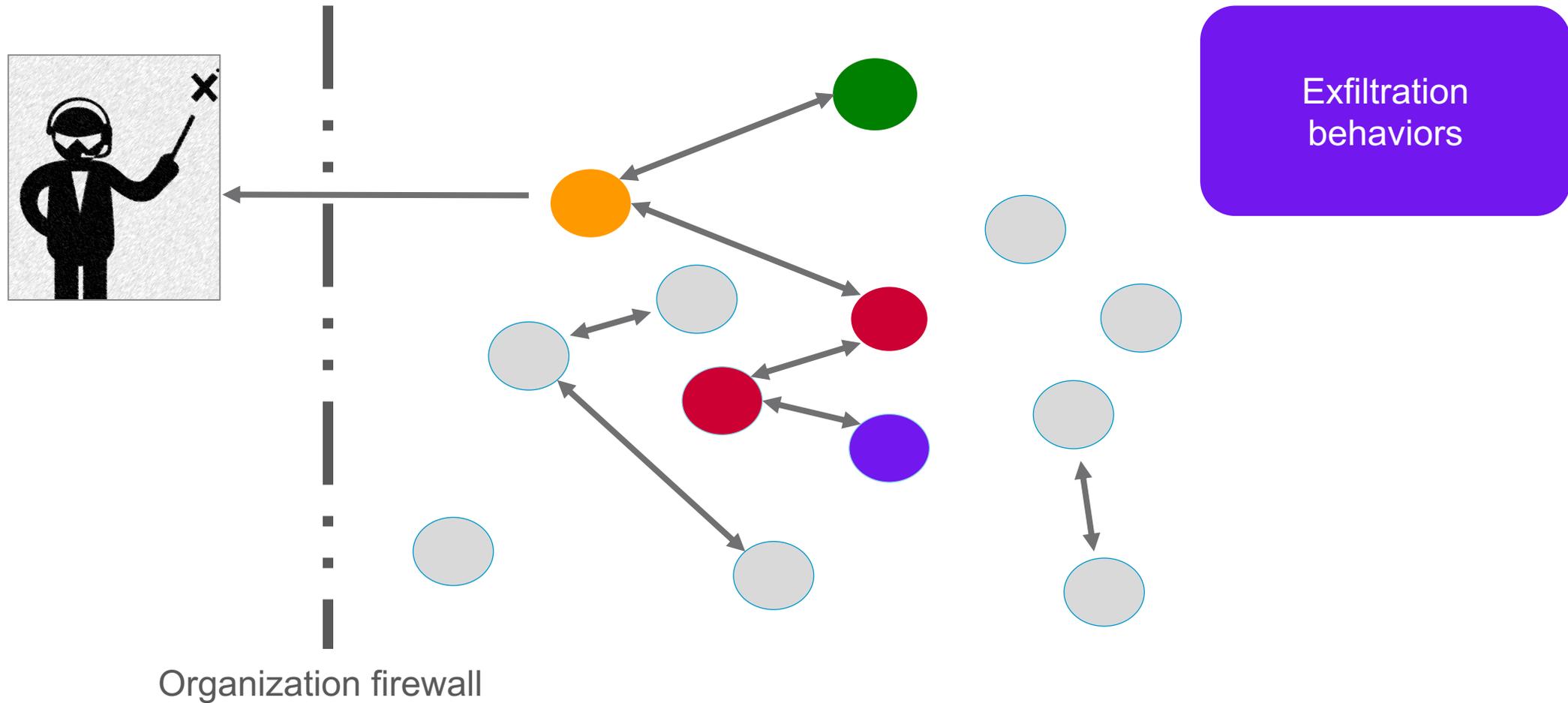
Advanced attack



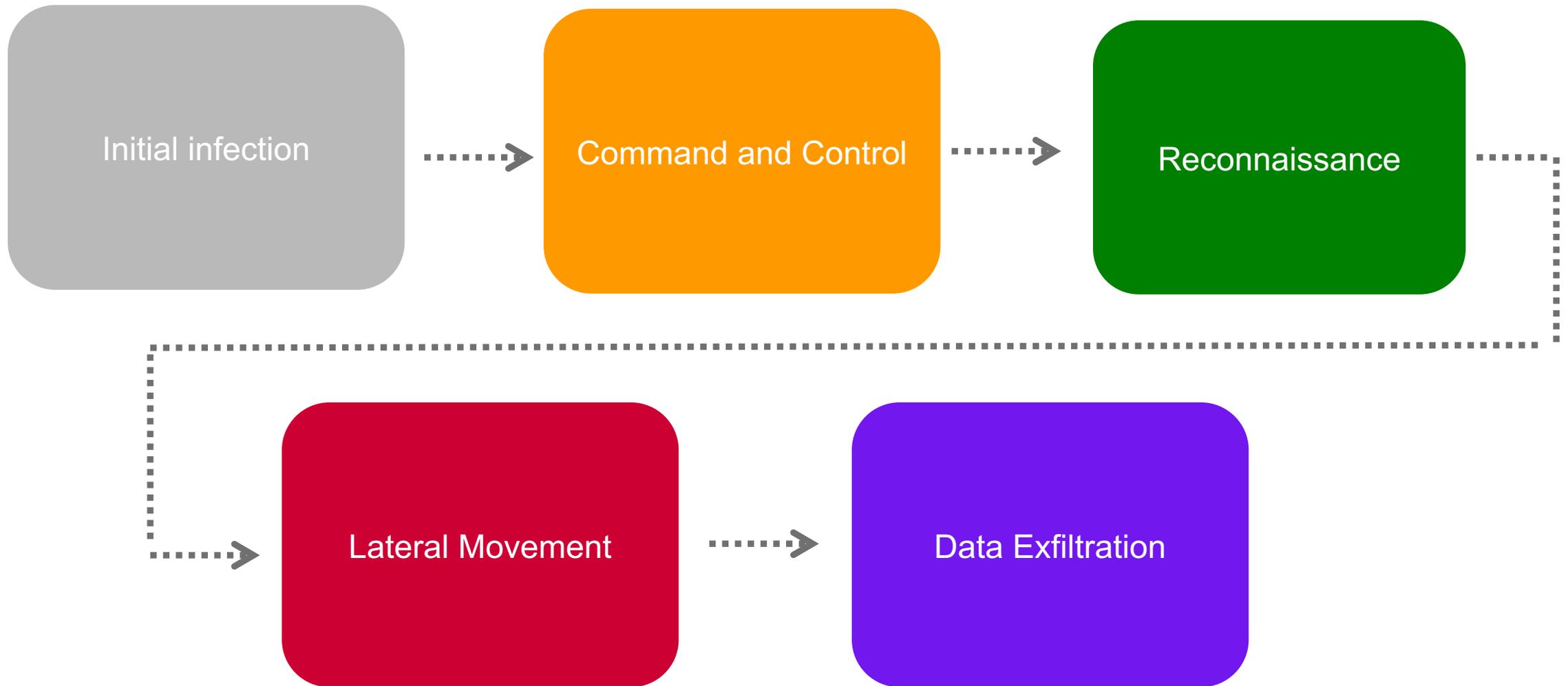
Advanced attack



Advanced attack



Progression of an attack



Attack



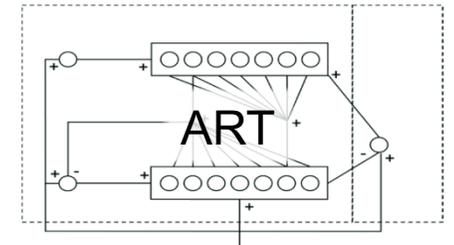
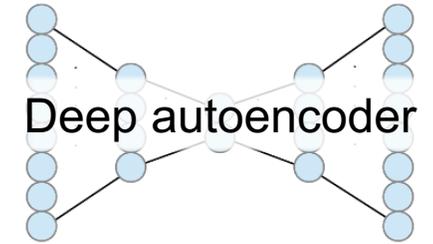
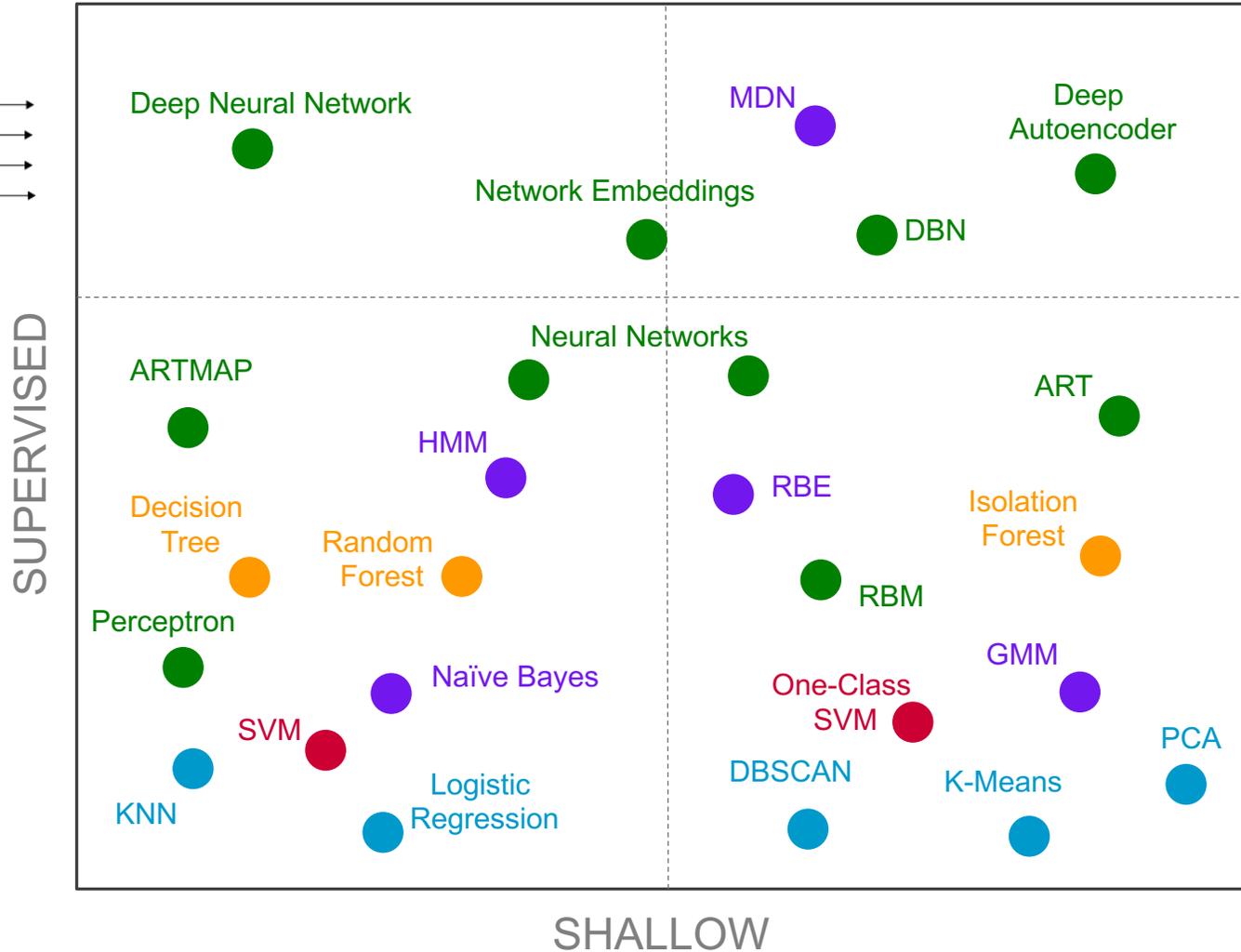
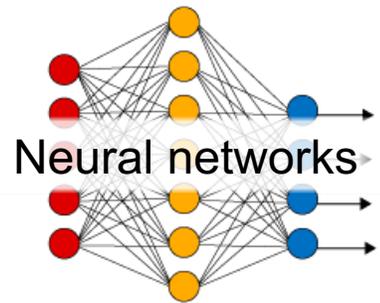
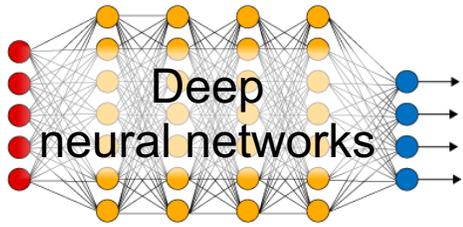
Data



Machine learning

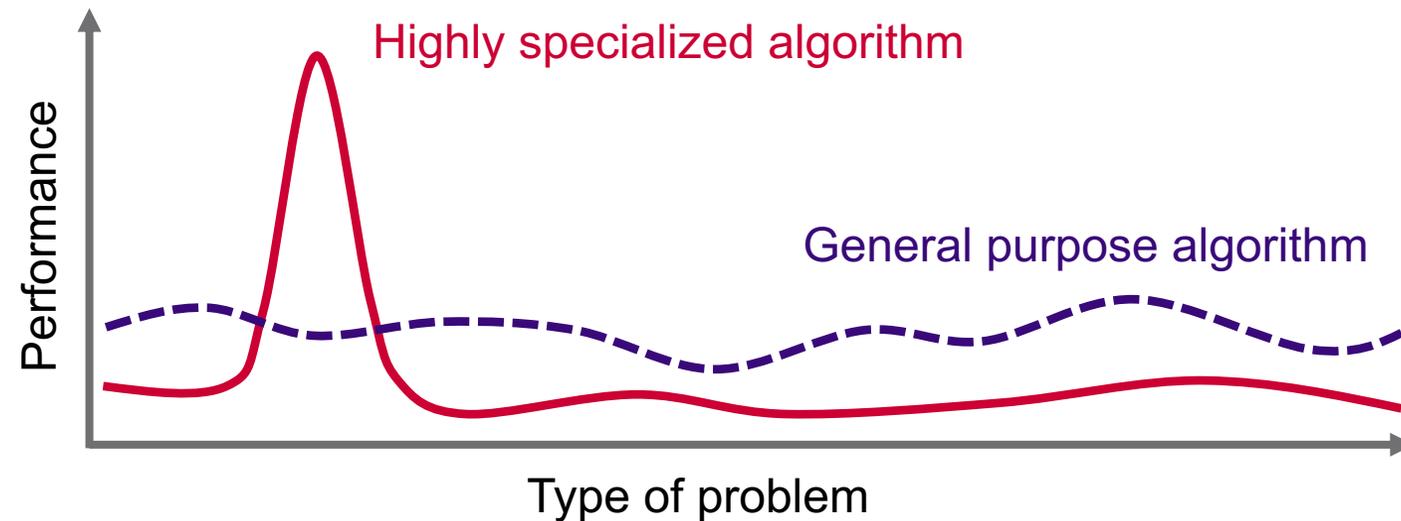


Different types of learning: Supervised vs. unsupervised

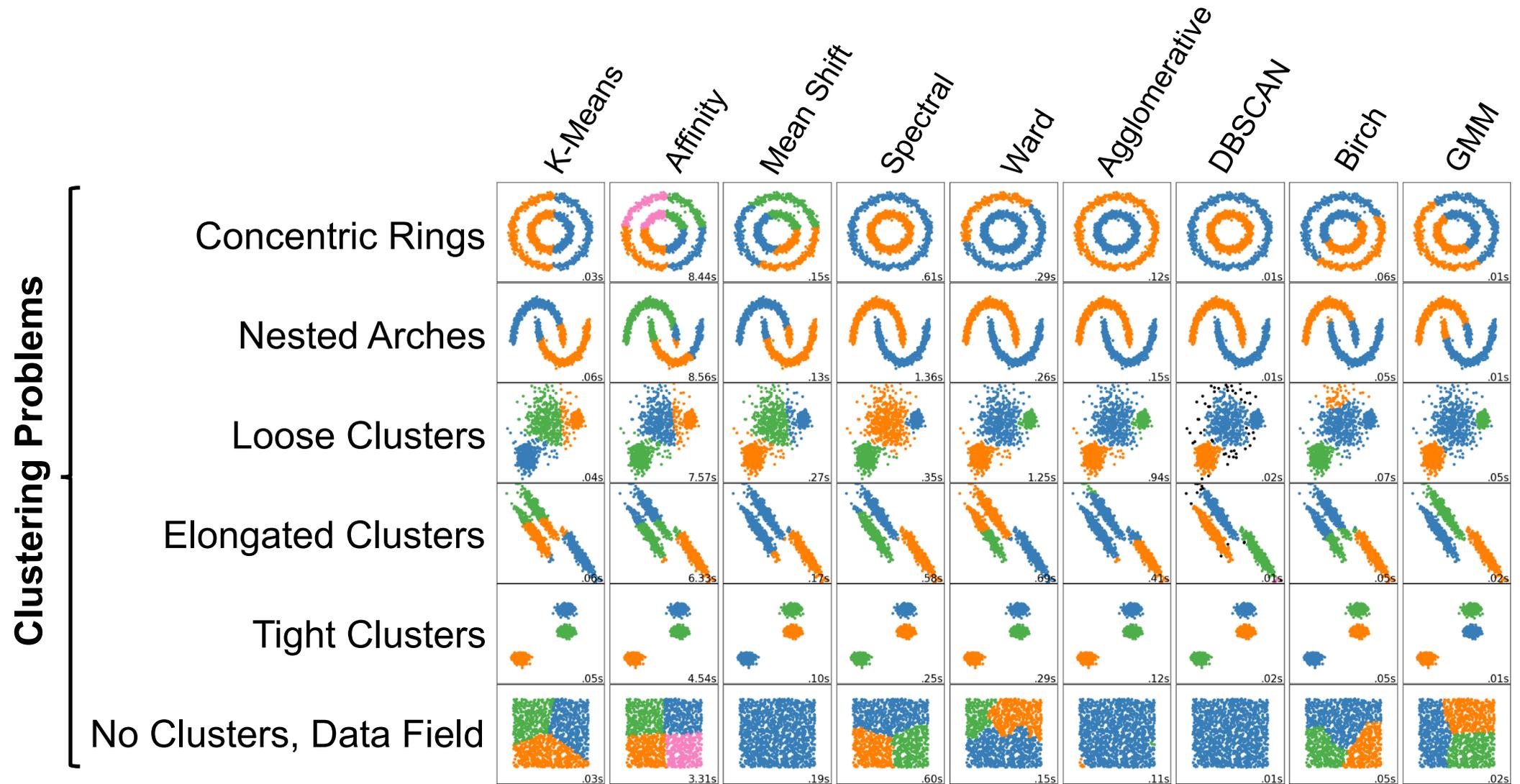


The “no-free-lunch” theorem

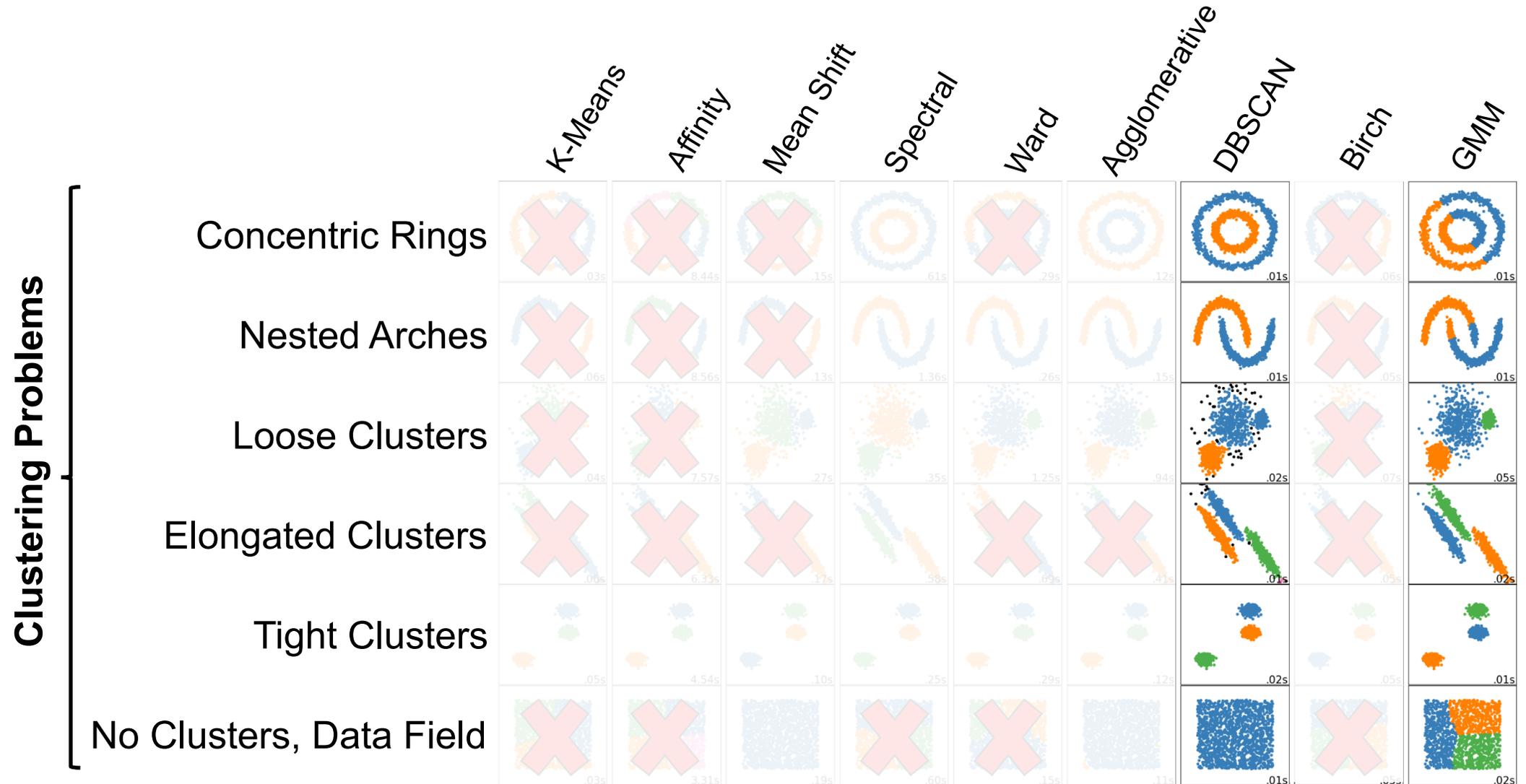
No single algorithm performs best for all problems



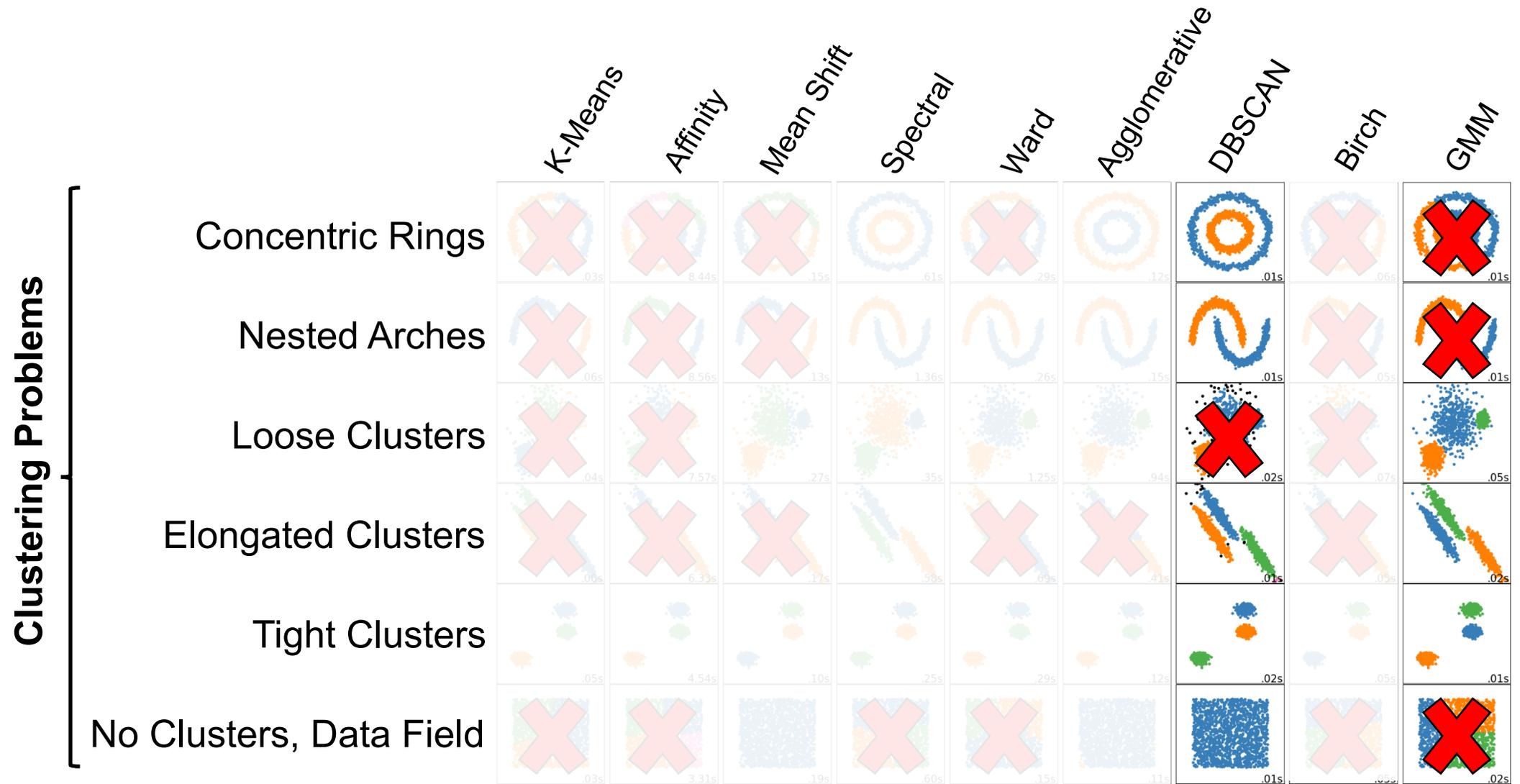
Choosing the right algorithm: Know your data



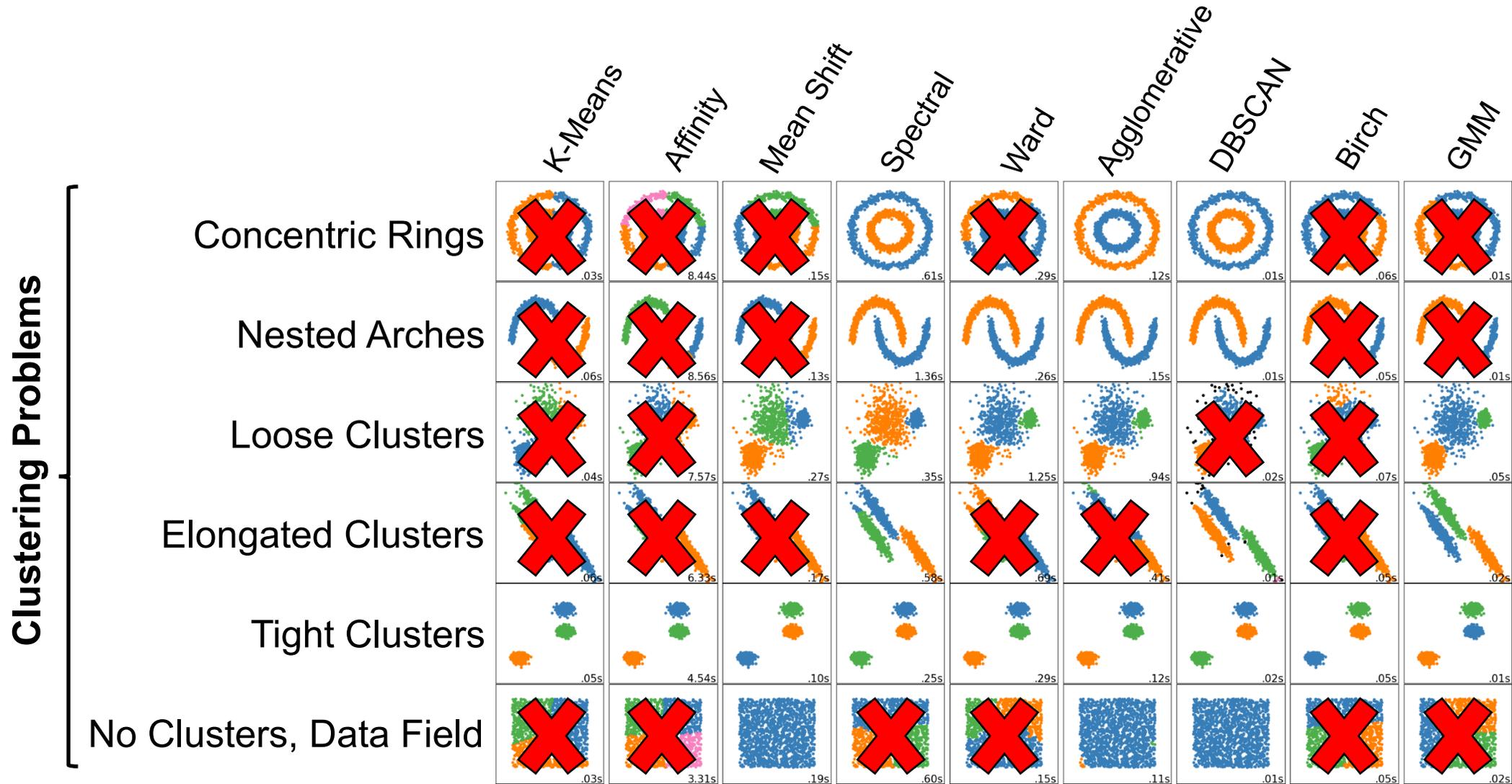
Choosing the right algorithm: Know your data



Choosing the right algorithm: Know your data



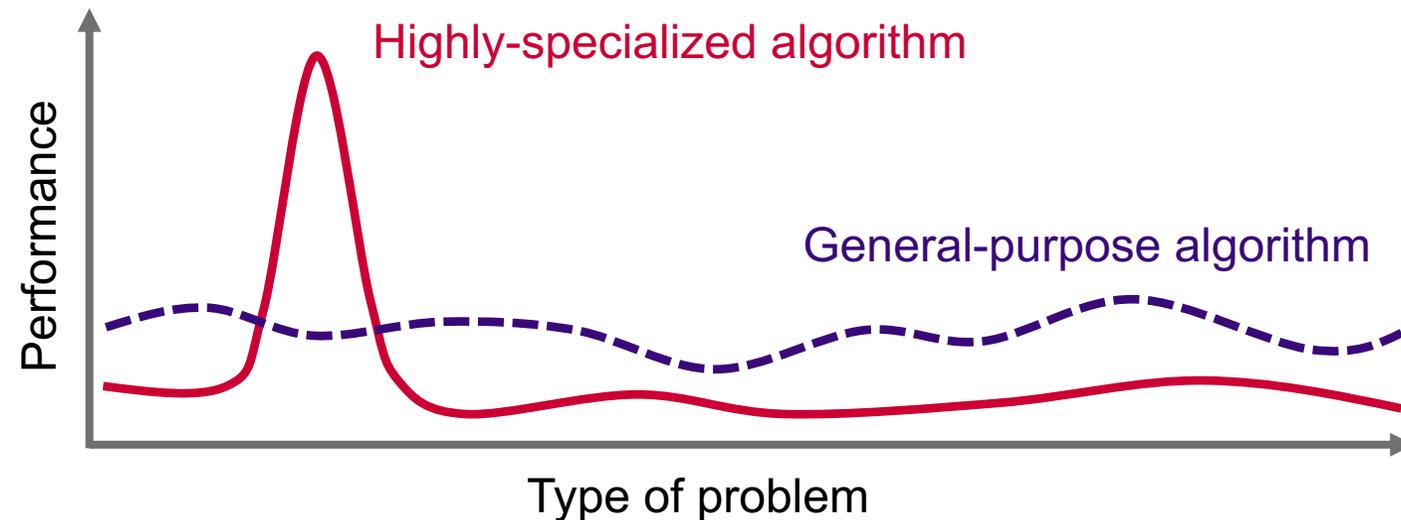
Choosing the right algorithm: Know your data



Choosing the right algorithm

No single algorithm performs best for all problems

Select the right option for your data and performance needs



Outline

- Metadata used for threat detection
- Approach to detection
 - Detecting Remote Access Trojans (RATs)
 - Signatures
 - Anomaly detection
 - Random forest
 - Deep learning
- Conclusions



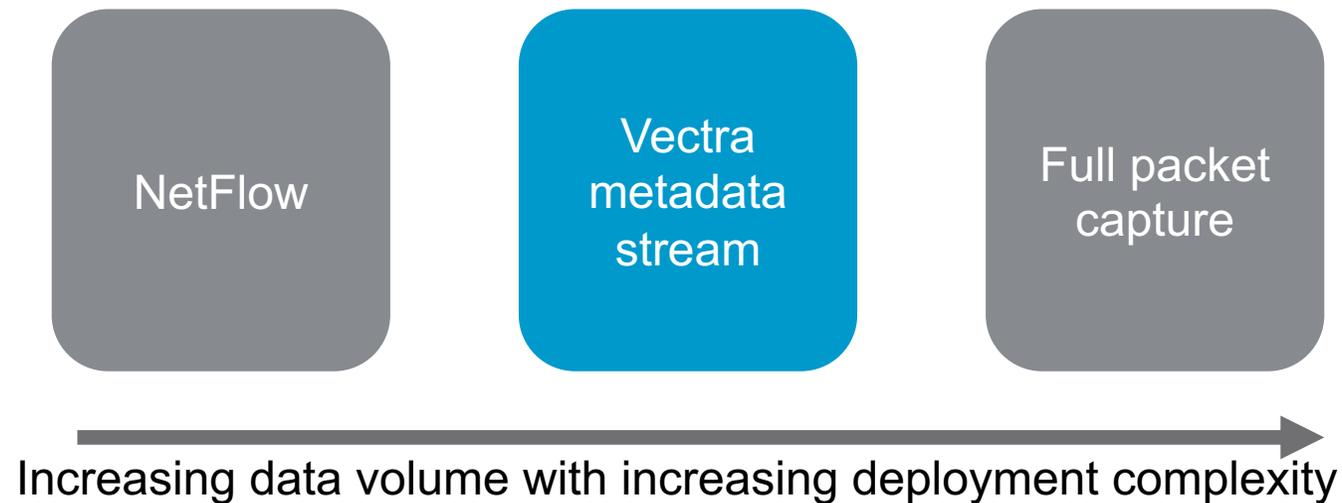
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Metadata hits the sweet spot for security applications

- Vectra metadata designed with attacker behavior in mind
- All detection models are based on Vectra metadata
 - Metadata includes bytes, protocols, domains, ips
 - Other advanced models are based off enhanced metadata



Example of enhanced metadata: Beaconing behavior

- Beaconing behavior is a common sign of a command and control channel
- Whether a host is beaconing must be inferred based on the host behavior
- By applying machine learning to this raw Vectra metadata we can identify beaconing behavior
- HTTP/S tunnel model was developed using this data to help identify command and control channels



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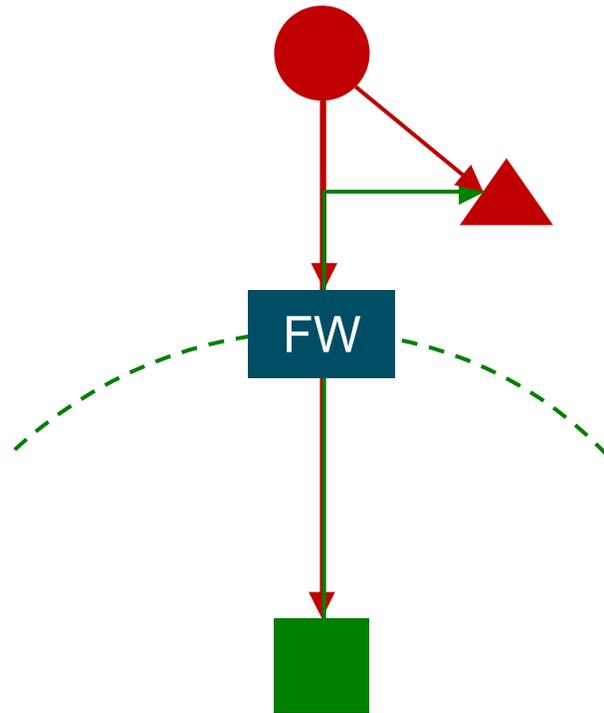


Remote Access Trojans (aka external remote access)

Attacker wants to establish manual control over asset inside the network

Firewalls block most inbound connection attempts

So compromised internal asset calls out to “meeting point” and attacker takes over



Examples

Blackshades

Poison Ivy

NOPEN (Shadow Brokers)

WebEx

TeamViewer



Network Signatures

- Based on known patterns flag known RATs
- Network
 - URLs, User Agents, Payloads, Domains, IP Addresses, etc

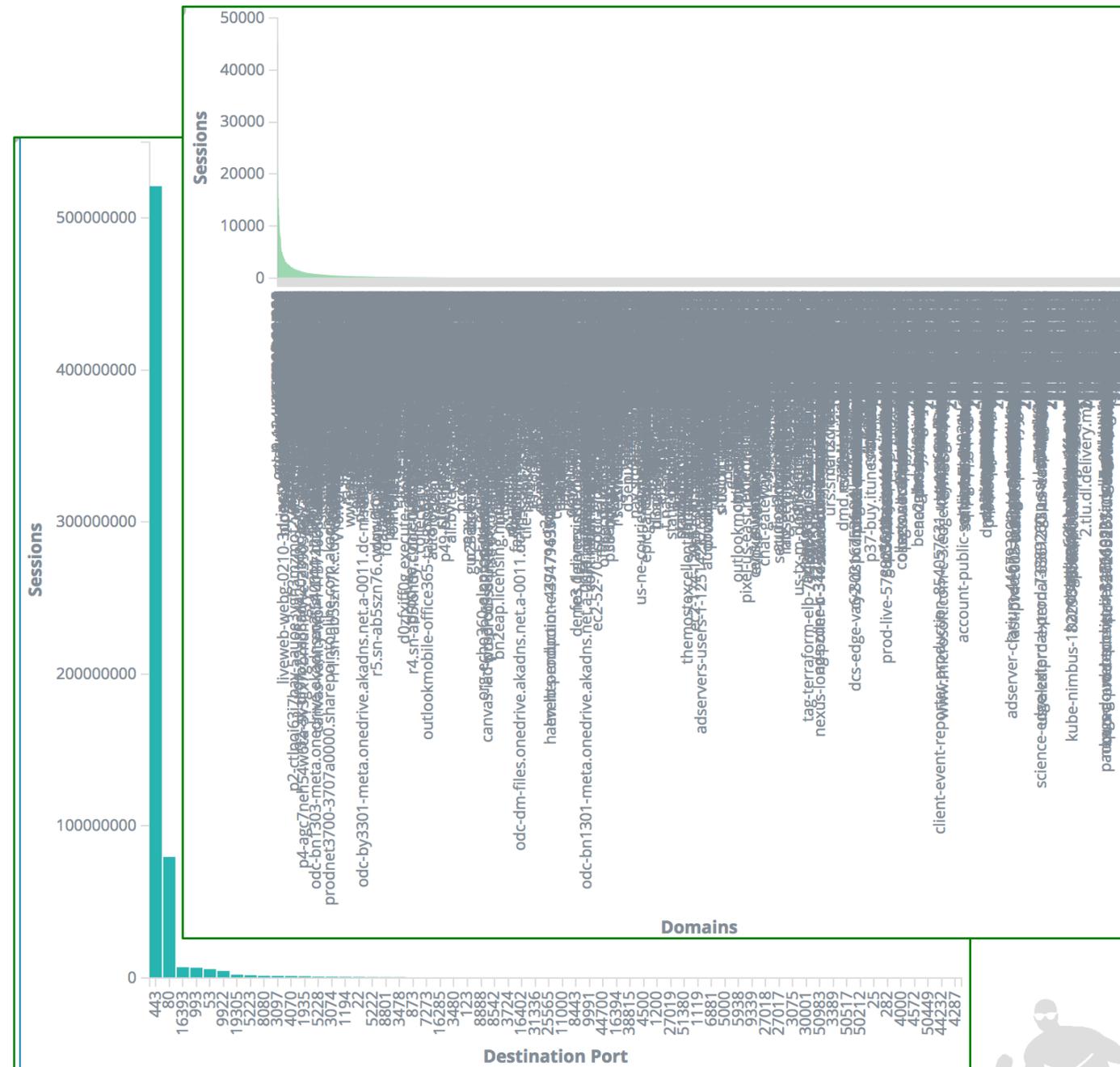
```
trojan.rules:alert tcp $HOME_NET any -> $EXTERNAL_NET any (msg:"ET TROJAN DarkComet-RAT server join acknowledgement";  
flow:to_server,established; dsize:12; content:"|39 34 41 35 41 44 30 41 45 46 36 39|"; flowbits:isset,ET.DarkCometJoin;  
reference:url,www.darkcometrat.com; reference:url,anubis.iseclab.org/?action=result&task_id=1a7326f61fef1ecb4ed4fbf3de3f3b8cb  
&format=txt; classtype:trojan-activity; sid:2013284; rev:3; metadata:created_at 2011_07_18, updated_at 2011_07_18;)
```

- Great for known threats
 - Easily bypassed with changes to the malware
 - Lags behind new changes in malware



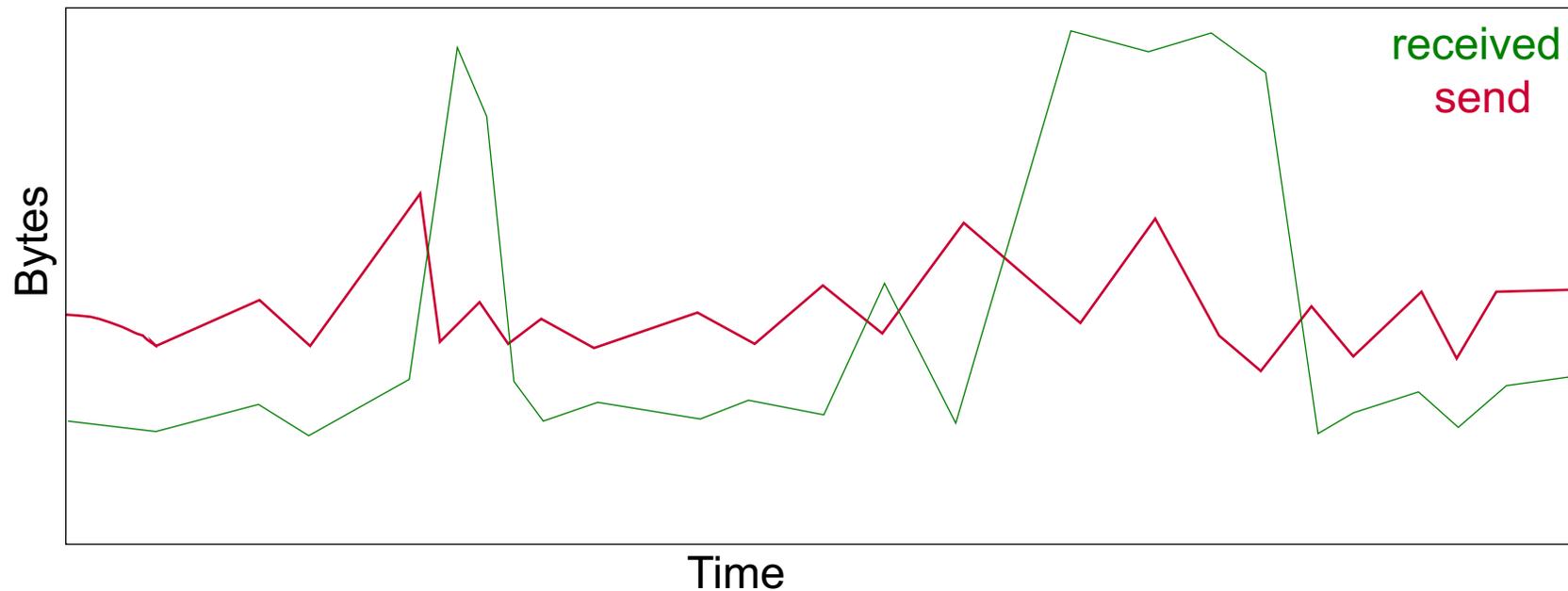
Anomaly detection

- Unsupervised
 - Assume a RAT
 - Uncommonly used port
 - Uncommon destination
 - Uncommon hour
- Everything is “uncommon”
- New ports everyday
- New domains everyday
- Time is not a great signal
- Will likely alert you to the event
 - But how do you find true event in this haystack?

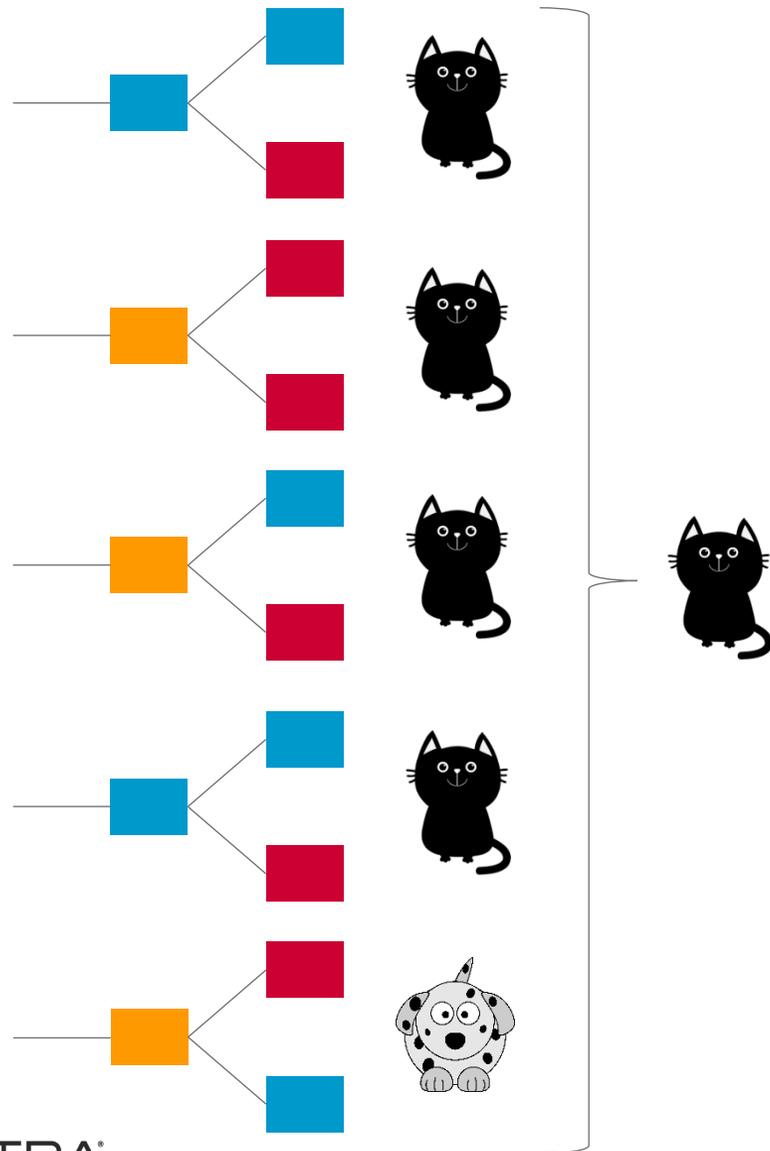


Data is king – How Vectra sees RATs

- A RAT is not static
 - All behavior happens in time
 - Commands are issued
 - Information is received
- Incremental flow between a RAT server and client host



Machine learning first pass – Random forest



- A random forest is a collection of decision trees
- Not likely a single perfect decision tree model
 - Randomly look at features
 - Randomly look at data
 - Build several models
- Each model votes
 - Every model does not need to be right
 - But more that vote more confidence in decision



Random forest for RATs

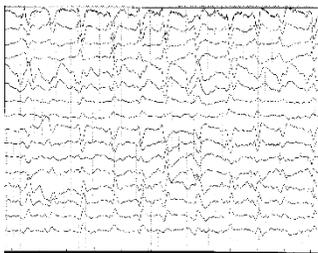
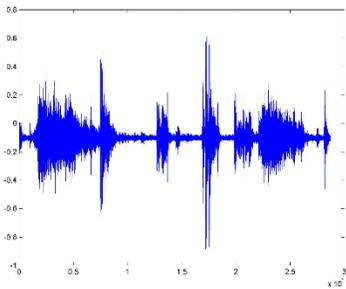
- Featurize the timeseries window – 20+ Features
 - Data and packet client / server ratios
 - Consistency of the client / server data
 - Frequency where the server breaks silence
 - Total session length
 - Entropy of the session
 - etc...
- Observe multiple windows and trigger on convergence
- Model provided value
 - Alerted on large % of known RATs but not all
 - Did not trigger on all known RAT behaviors
- Issues
 - Did not properly represent the temporal nature
 - One sequence impacts the next
 - Human driven features missed behaviors
 - Can guess and test but can never be sure



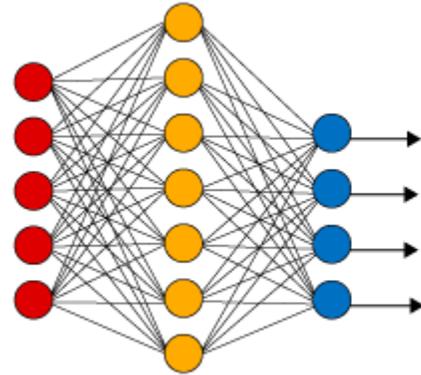
Deep learning

1 1 5 4 3
7 5 3 5 3
5 5 9 0 6
3 5 2 0 0

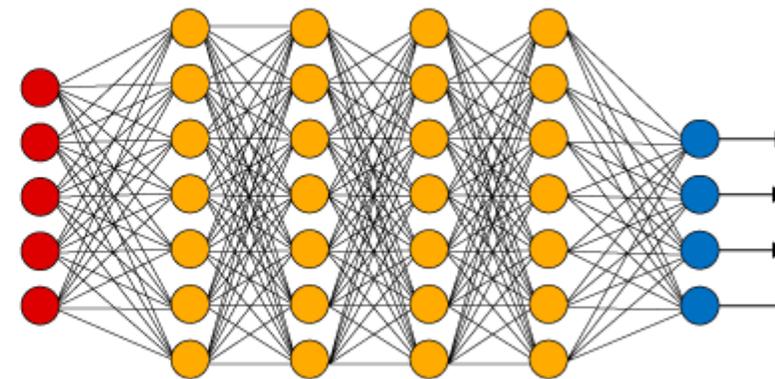
Digit labels
0,1,2,3,4,5,6,7,8,9



Simple Neural Network



Deep Learning Neural Network



Phonemes
dh, aw, s, ax, n, d, ...

● Input Layer ● Hidden Layer ● Output Layer

Mouse Movements
(right, left, up, down)

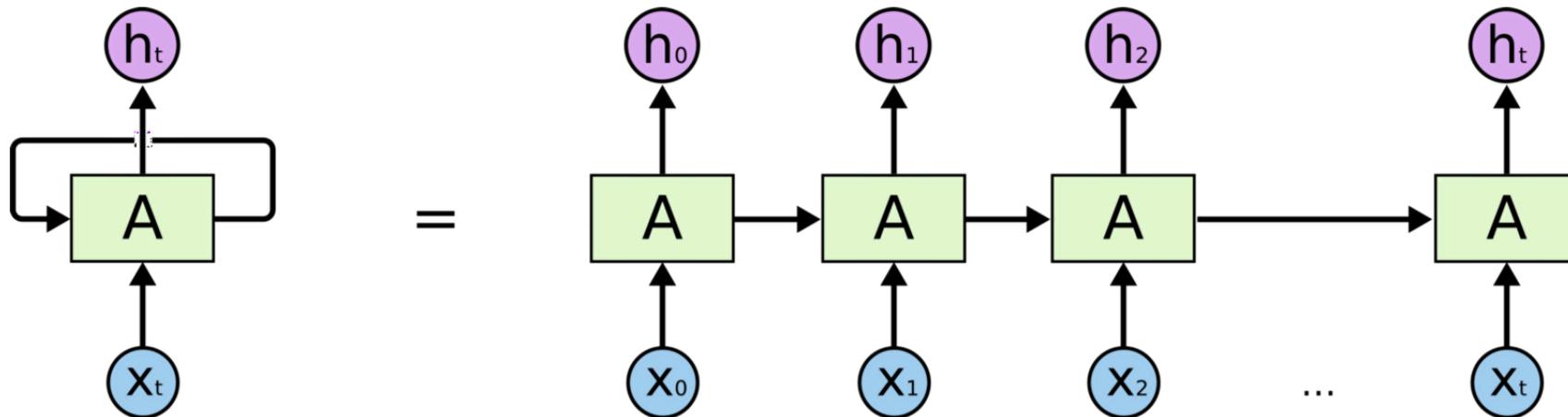


Deep learning:

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

- RNN

- Similar to feedforward NN
- Recurrent connections == Memory

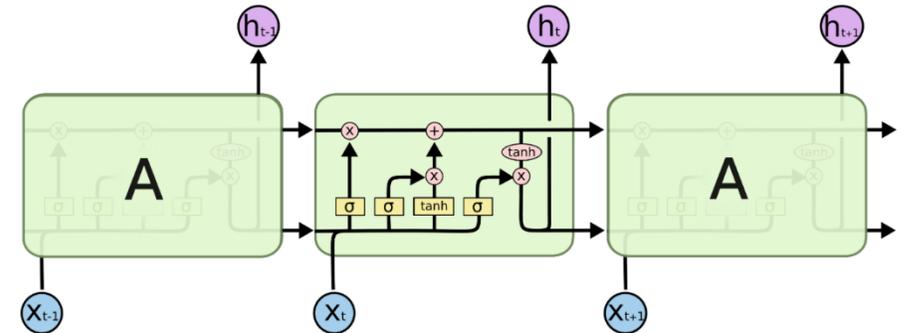


Deep Learning:

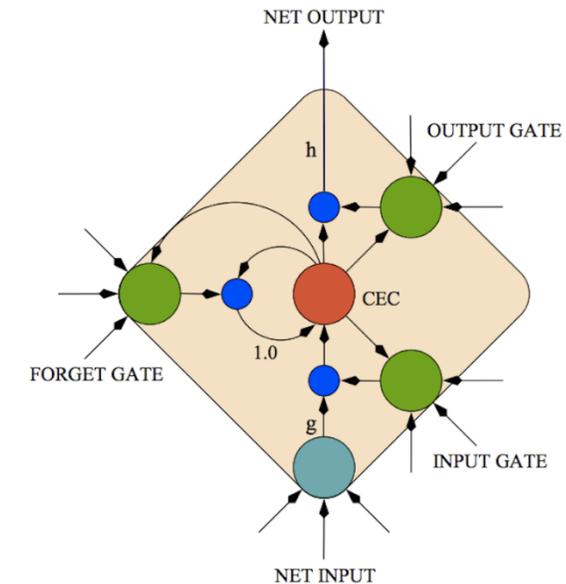
Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

• LSTM

- Similar to RNNs
- Replace simple neurons with LSTM blocks
- Prevents “vanishing gradient” problem
- Capable of learning long-range temporal dependencies



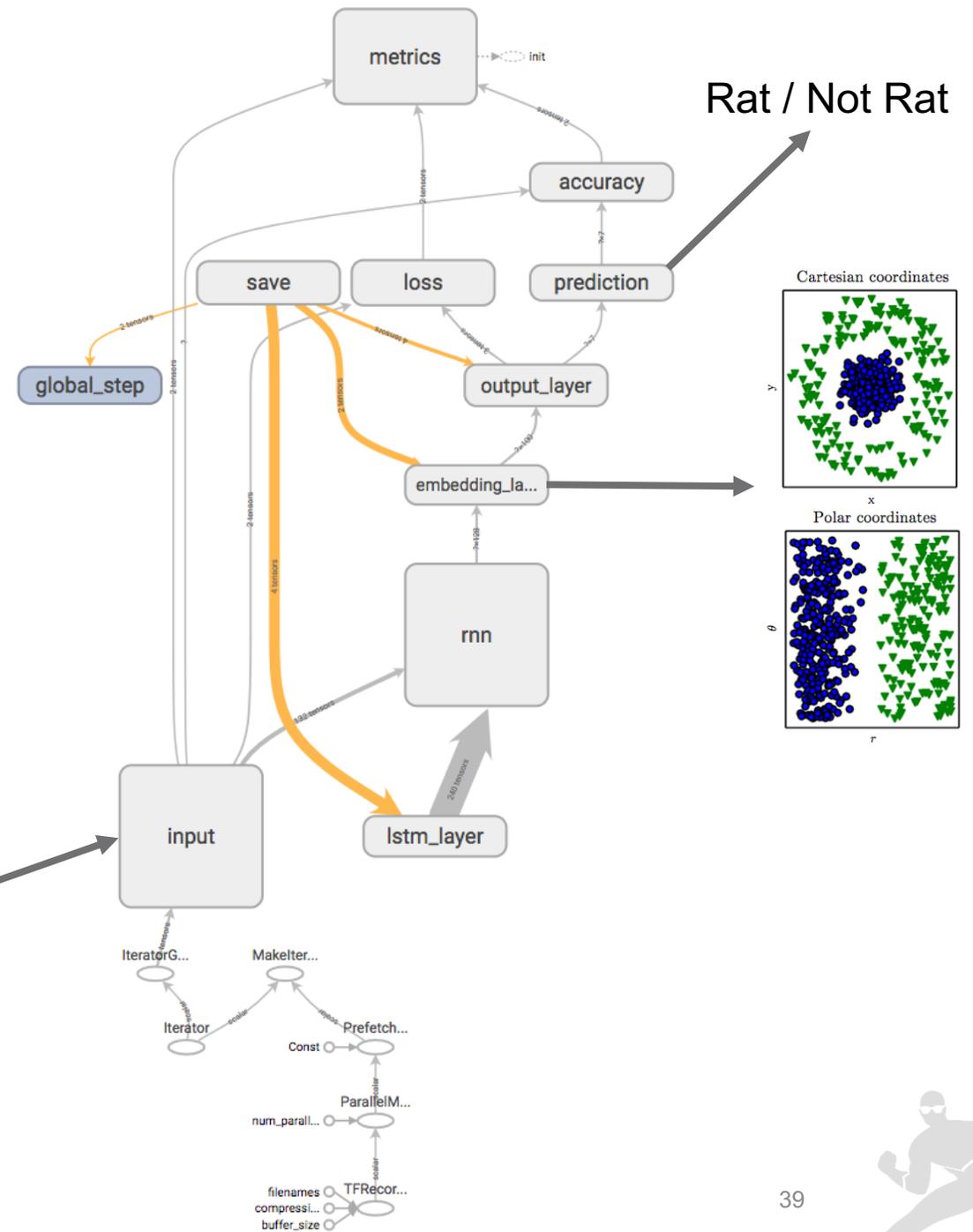
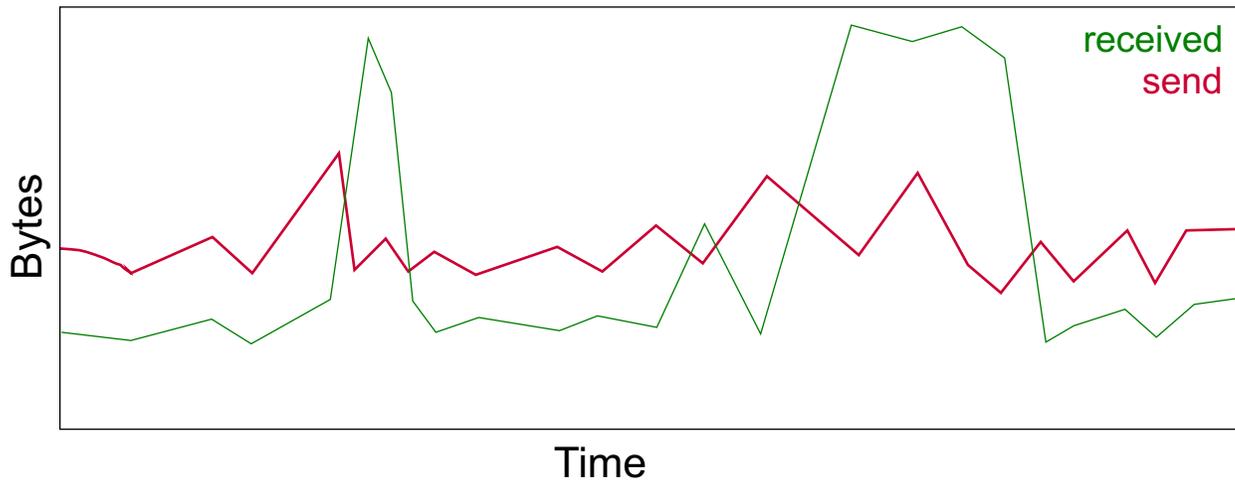
The repeating module in an LSTM contains four interacting layers.



Deep learning: Model training strategy

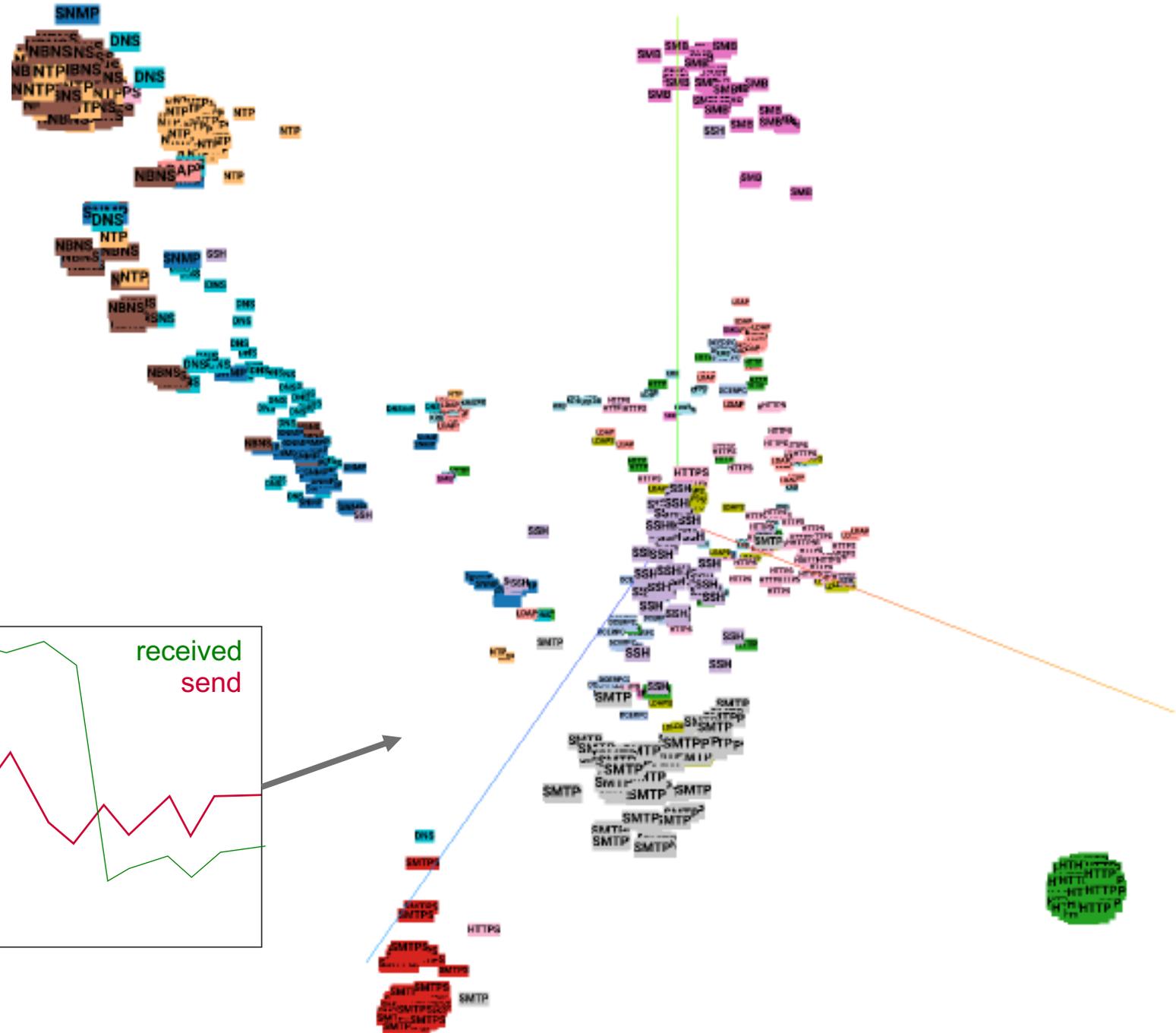
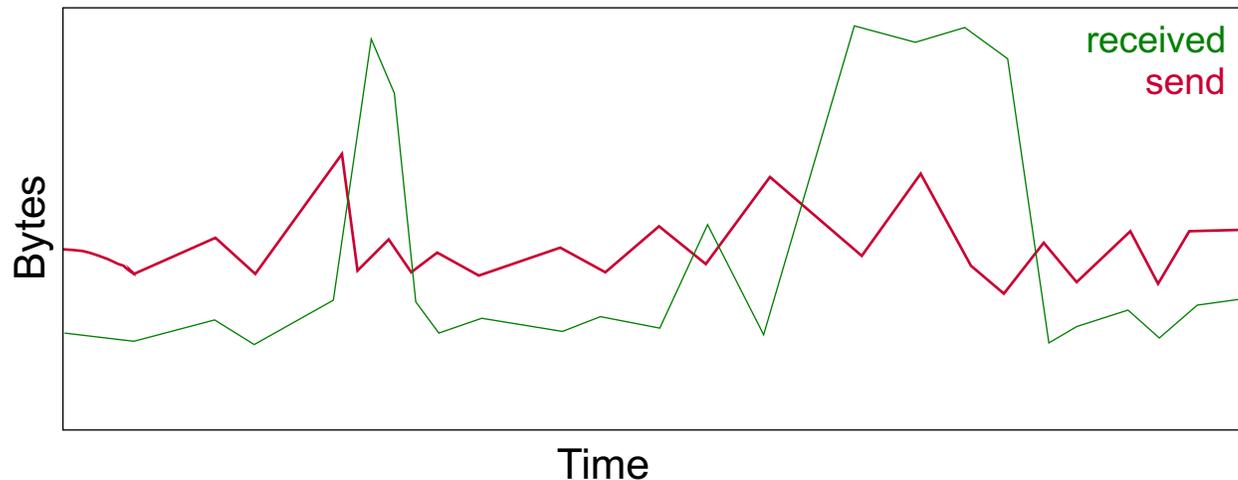
Model training

- Framework: TensorFlow
- Model: RNN (LSTM cell)
- Train on AWS w/ NVIDIA v100 GPUs



Deep learning: Learning representations

- Map input time-series to embedded representation
- Classify the embedding as RAT / not RAT
- Observe convergence in classification
- Report behavior



Host: IP-10.1.10.194
IP: 10.1.10.194
Source: Vectra X ?



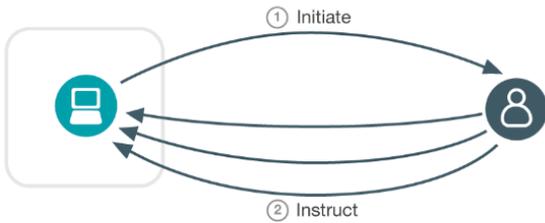
Actions PCAP Tag Note Assign Share

Threat 34 / Certainty 10 ?

Summary

Internal Host: IP-10.1.10.194
External Hosts: 54.186.246.98
Unique Ports: 1
Sessions: 1
Active Time: 0:16:50
Bytes Sent: 168.9 KB
Bytes Received: 77.6 KB

Infographic



Timeline (Sessions)



Recent Activity

EXTERNAL HOST	PORT	BYTES SENT	BYTES RECEIVED	FIRST SEEN	LAST SEEN
54.186.246.98 ec2-54-186-246-98.us-west-2.compute.amazonaws.com	tcp:22	168.9 KB	77.6 KB	Oct 29th 2018 16:07	Oct 29th 2018 16:24



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Know your model

- In security, the problems are various and complex; data are sometimes unavailable, sometimes imbalanced
- Many approaches are available, but not all will perform equally well
- No free lunch! Understand the problem and choose the right model
 - Supervised or unsupervised?
 - Classification or regression?
 - Temporal factors are crucial
- Data science is not just about math. Attackers can only be detected through conjunction of deep knowledge of machine learning and security

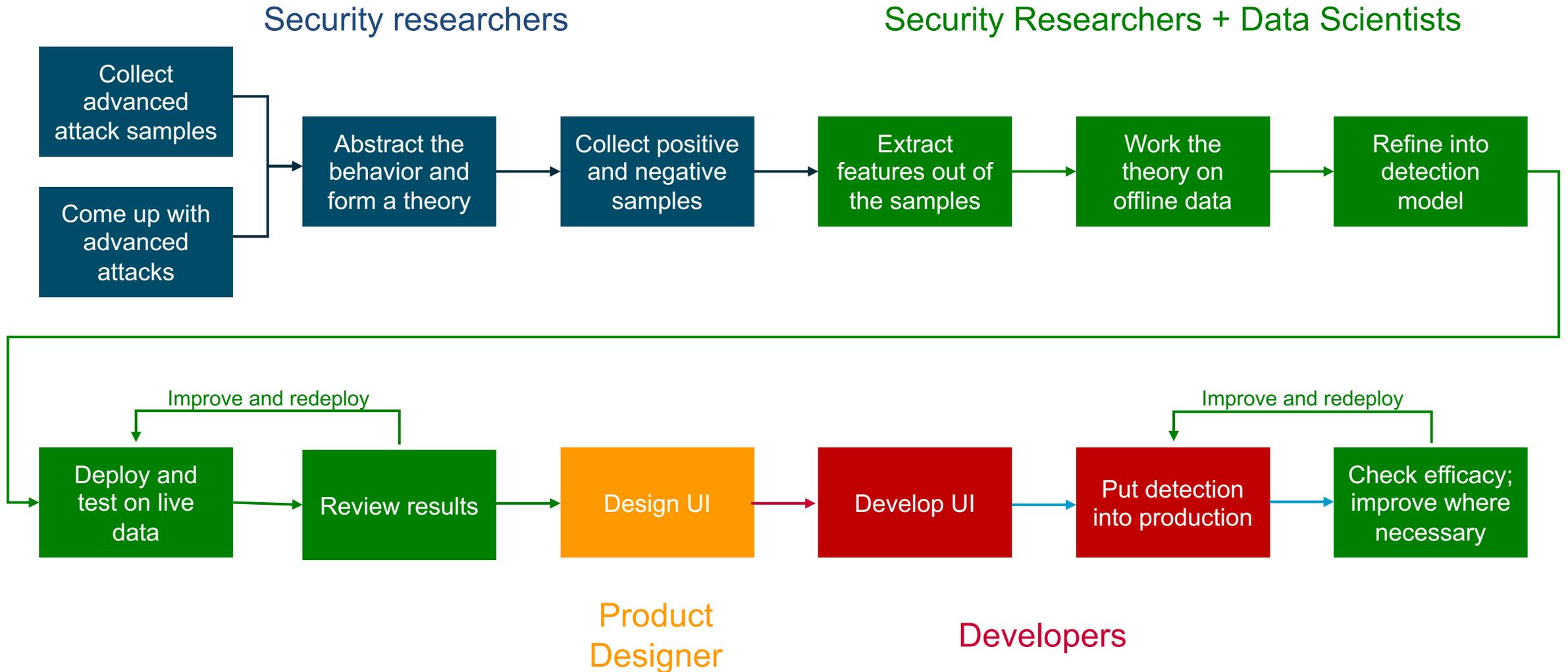


Data science – first as an art, then apply the science





Detection lifecycle



Model Development Philosophy – *Research to Production*

1. Report an advanced attack behavior
 - Methodology and data sources are irrelevant
2. Provides the relevant context to investigate
 - Necessary information for rapid validation
3. Improvable over time
 - Trackable efficacy
4. Minimal noise and high coverage
 - Meets initial recall and precision requirements

