

# Hunting for Attack Chains in Event Streams

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# About the Presenters

## Ray Ruvinskiy

- Lead of the Detection Automation Team. Our team's job is to help our Security Analysts avoid the noise and zero in on the actionable.

## Jonathan Walsh

- Member of the Threat Operations and Analysis team. We utilize the tools provided by the Detection Automation Team to improve our threat detection.

# About Arctic Wolf Networks

What is a SOC?

Security Operations Centres (SOCs) deal with security issues on an organizational level.



# About Arctic Wolf Networks

SOC-as-a-Service

AWN CyberSOC manages the security detection for our customer, gathering data from deployed network sensors and logs from other security tools.

These logs are processed by our system and the output is provided to human experts to make decisions on.



# Alert on actionable data

Rising above the noise

Balance between being informative  
and being noisy

Focus on what the client needs to deal  
with immediately





Crying wolf may have been the boy's undoing, but the true irony was that the wolves were always lurking nearby.

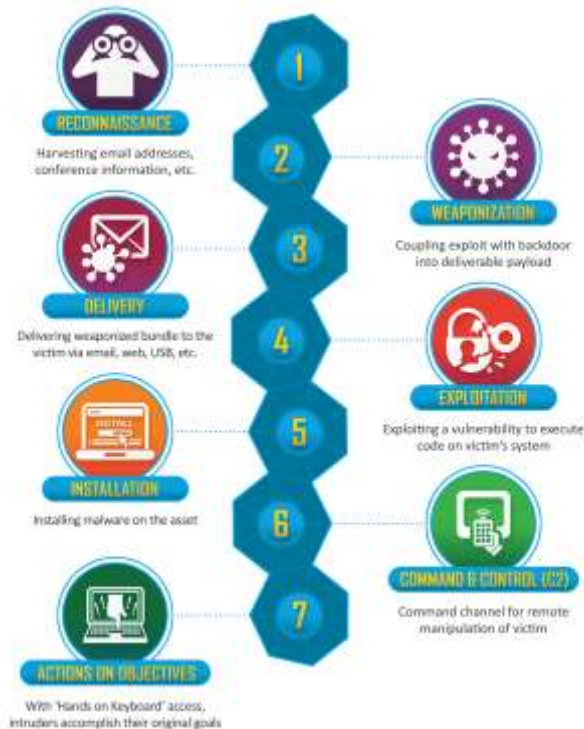
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**Wes Fesler**

American football player

# Lifecycle of an attack

Attributes shared by network breaches



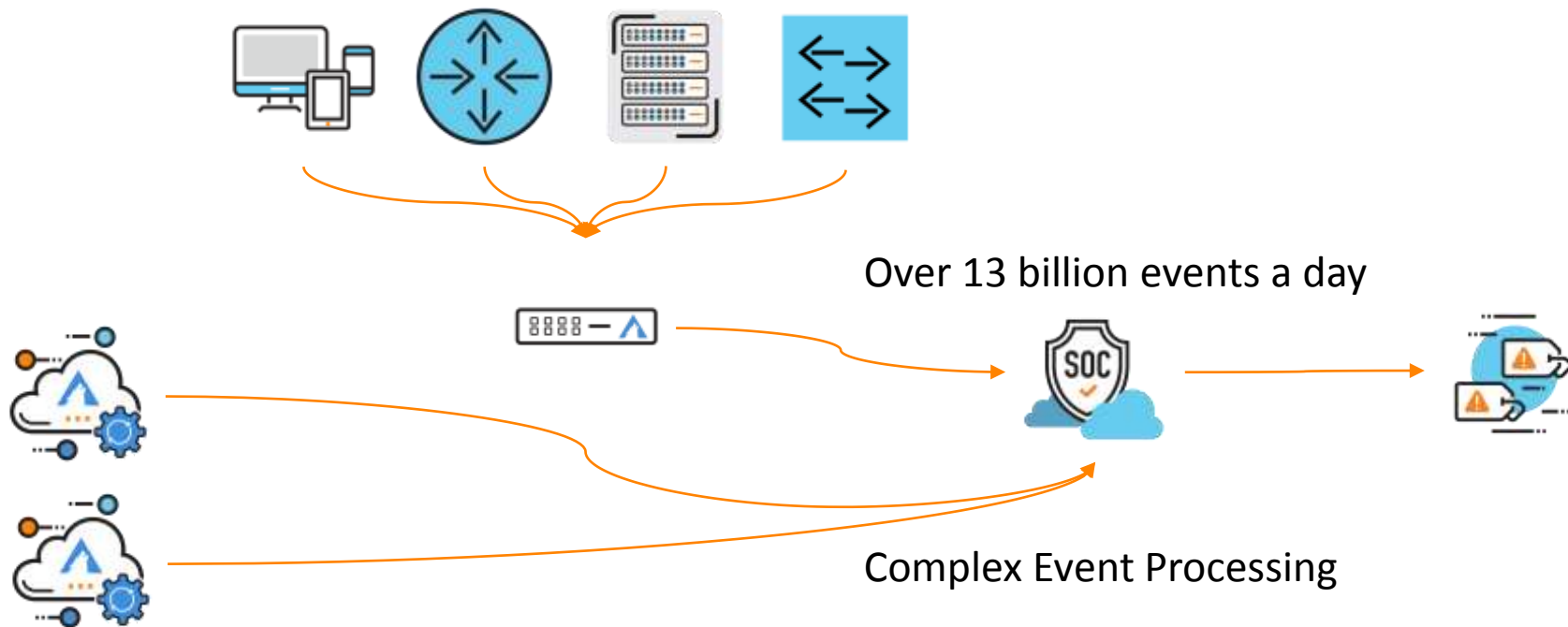
Source: <https://www.lockheedmartin.com/en-us/capabilities/cyber/cyber-kill-chain.html>

# Applying Attack Chain to WannaCry Outbreaks

- Reconnaissance – social networking
- Weaponization – build ransomware binary
- Deliver/exploit – spearphishing
- Command and control – encrypted backchannel
- Actions on Objectives – encryption and lateral movement

Indicators at each of these steps can be noisy and prone to false positives. Correlation of events focuses us on what is relevant.





# Why Flink?

Built for streaming  
Out-of-order events  
Scalability



# FlinkCEP

Our experience dates to 1.2.1

Difficulties with expressivity and scalability

- At the time, no counts

# Esper

Mature and expressive streaming CEP framework

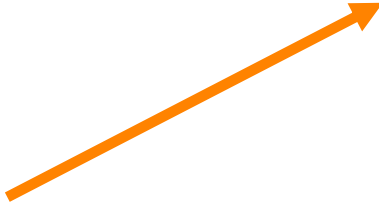
EPL – SQL-like Event Processing Language

# EPL

PsExec services created on at least 10 devices in 5 minutes

```
select ... from PsExecEvent#time(5 minutes)
#unique(target_ip)
#length_batch(10);
```

Typed event, with  
properties



Stream composition




Property in  
PsExecEvent



# EPL

Endpoint virus detection followed by network IDS exploit detection

```
select ... from pattern [  
    AntiVirusEvent -> IDSExploitEvent where timer:within(15 minutes)  
];
```



"followed by" operator

# EPL

A minimum number of login failures with no successes interspersed, then a success

```
create window LoginFailureWindow#time(5 minutes) as LoginEvent;
```

```
on LoginEvent(not login_success) as login_failure  
  merge LoginFailureWindow as failures  
  where login_failure.id = failures.id  
  when not matched then insert select *;
```

```
on LoginEvent(login_success) as login_success  
  select and delete ... from LoginFailureWindow as failures  
  having count(*) >= 10;
```

# Complex Event Processing with Flink and Esper

Putting it all together

A single, continuously-running Flink job



# Complex Event Processing with Flink and Esper

Putting it all together

Events are ingested

Source

Events are parsed and subjected to  
sanity filtering

FlatMap

Timestamp extraction, watermark  
assignment

TimestampExtractor

`SplitStream` used to create a  
stream per rule

Split

# Complex Event Processing with Flink and Esper

Putting it all together

Each of the per-rule streams  
aggressively filters events of interest  
and converts to `Tuples`

- Reduce per-event memory footprint as much as possible

keyBy rule-specific partition key to ensure  
unrelated events are processed in isolation

- e.g., for a login failure rule we key by  
customer ID and username

FlatMap

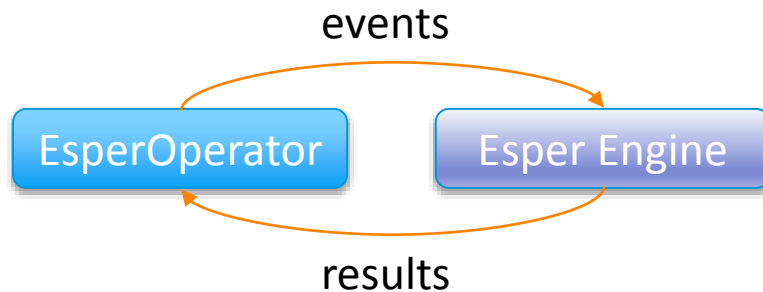
KeyBy

# Complex Event Processing with Flink and Esper

Putting it all together

## Esper operator

- Per-rule (potentially multi-statement) EPL that defines the logic
- Priority queue to order events by timestamp
  - Same as FlinkCEP
- Send tuples to Esper engine
- Register subscriber for results



# Complex Event Processing with Flink and Esper

Putting it all together

Esper operator output formatted as  
AWN events with a special type

These AWN events then undergo  
another filter pass where some are  
whitelisted depending on specific  
rules defined by Security Analysts

Events that survive this pass then  
brought to Security Analyst attention  
for investigation

EsperOperator

Escalation  
Service



# Flink/Esper at AWN

## AWS EMR (Elastic MapReduce)

- Managed Hadoop environment
- Easiest way to get started two years ago (Flink 1.2)

## Flink 1.4.2

### m5.2xlarge core nodes

- 8 virtual cores, 32 GB RAM
- 8 task slots per node

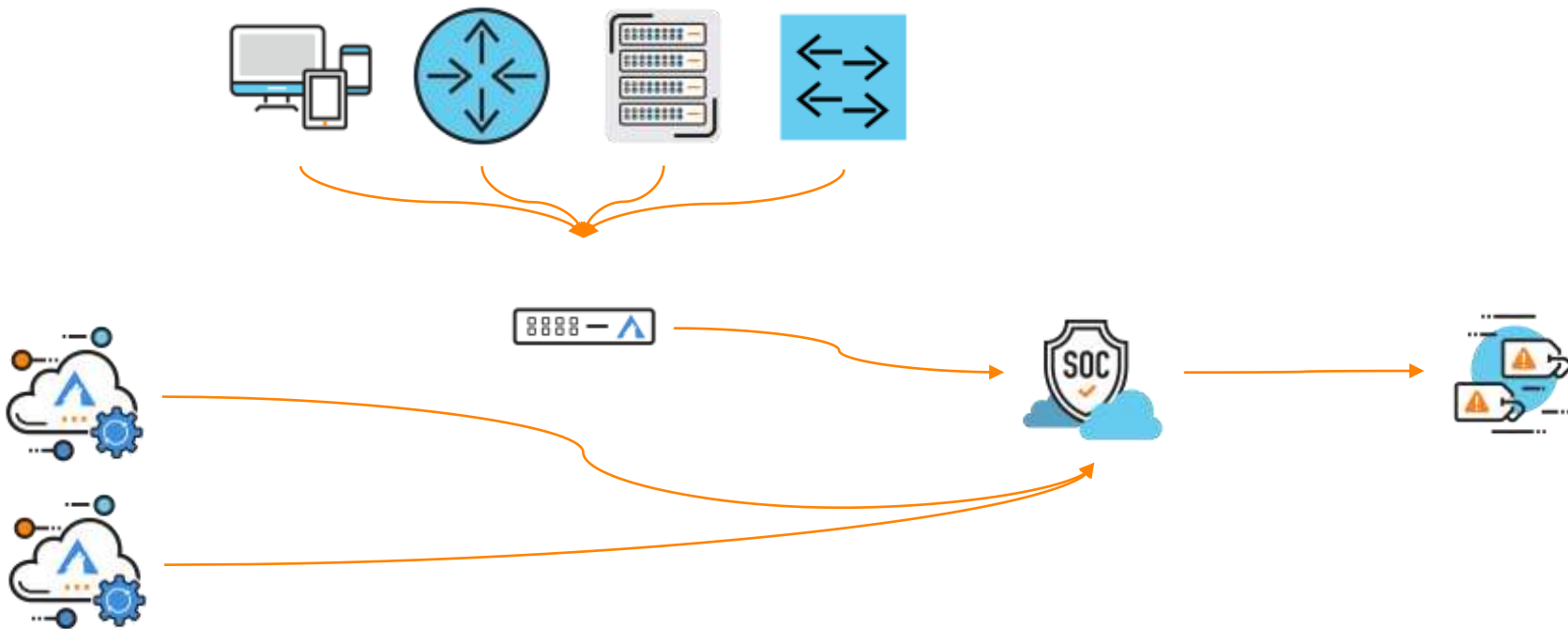
# Flink/Esper at AWN

Over 30 rules

Over 13 billion events a day passing through Flink

- But only a small subset is evaluated by the rules

6 m5.2xlarge instances



# Flow of Time Difficulties

Different data sources have different delays

- Events from cloud data sources (e.g., Office365) can in particular trickle in slowly

Time zone adjustments

- Normalize to UTC but *a lot* of data sources to keep track of



## In summary

Together, Flink's simple deployment patterns and scalability and Esper's powerful CEP engine enable us to pick out attack chains in streams of billions of events.

# Thank You

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For more information, visit us at: [www.arcticwolf.com](http://www.arcticwolf.com)



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