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Augment your Security Monitoring Use Cases with MLTK's Machine Learning

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Splunk .conf19, Las Vegas, Oct 24th 2019

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EAGLE DataCenter

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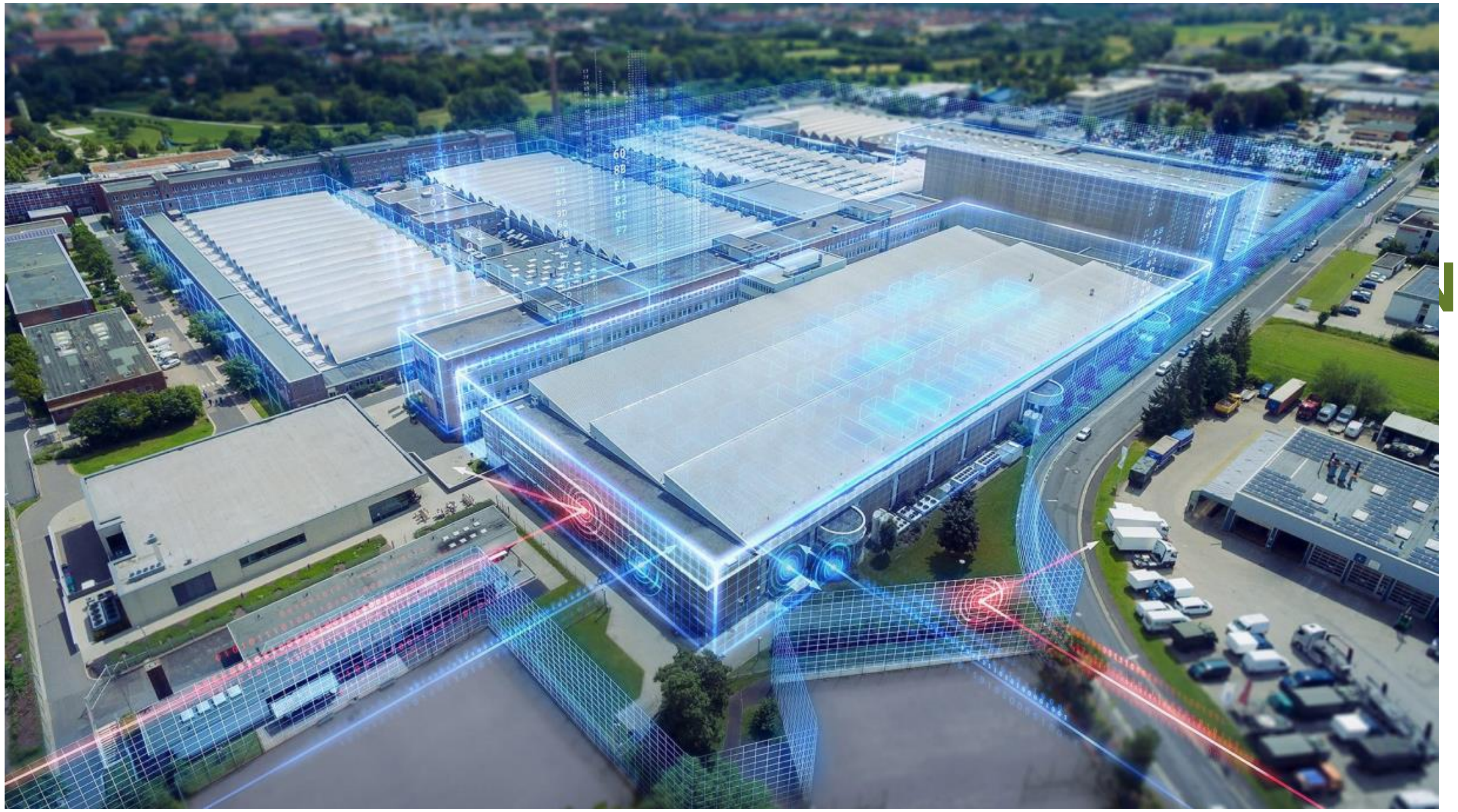

Since 12 years
In 4 locations
8 Petabytes storage
Net-zero carbon footprint

Splunk at EAGLE:
IT Ops and Security
70 indexes
3,200 data sources
210 data types

Agenda

- Intro
- Machine Learning Concepts
- Use Cases
  - Find Changes in Proxy Communication
  - Identify System Compromises
  - Baseline Privileged Account Behavior
- Wrap up, Q&A

Machine Learning for Security Monitoring: The Project

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Project setup

- Started Q1 2019
- Project staff of four
- Intention:
  - Can we extend SecMon with ML, to:
  - Baseline the data center, analyze behaviors?
  - Find security relevant patterns?

Project Team

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Markus
IT Sec deepwaters

Michael
ML concepts and fundamentals

Philipp
ML project & science coach

Oliver
Splunk> that!

Machine Learning Concepts

Typical Machine Learning Scenarios

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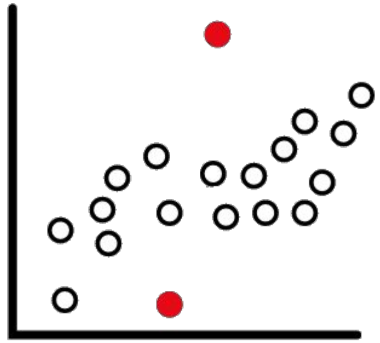
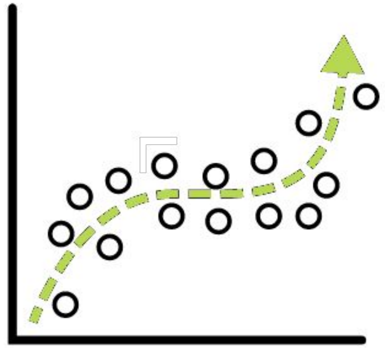
Anomaly detection



Deviation from past behavior

Proxy Communication

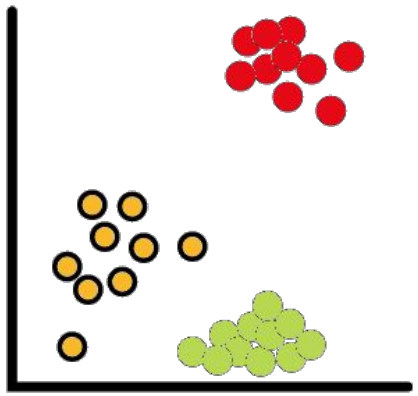
Predictive Analytics



Classify malware communication

Identify System Compromises

Clustering



Behavioral Analytics

Protect Privileged Accounts

Machine Learning Project Timeline

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Frame the Problem

E.g. Detect Anomalous Proxy Traffic

Get, explore and prepare data. Add context.

Collect and consolidate all relevant heterogeneous data into a dataset to start modelling work + consider adding context information (labels)

Explore and tune models

Unsupervised approaches first
Supervised approaches second
Labels from context info, third

Launch and Operationalize

Put the models live on framed problem data scope and collect findings

Present and Validate

Interface results, interpret findings. Challenge the model with simulated attacks / anomalous behavior

Use Case 1:
Proxy Communication

Use Case One: Proxy Communication
Idea, Concept, Results

Idea: Can we **profile system communications** outbound via webproxy and **detect changes** in behavior to ultimately **find unwanted outliers**?

Concept

- Collect eight features (each by Source IP) onto summary index.
- One DensityFunction per feature. **| fit** every night.
- **| apply** density models in intervals. Historize by again collecting onto summary index.
- Dashboard visualizes findings, guides investigation workflow.

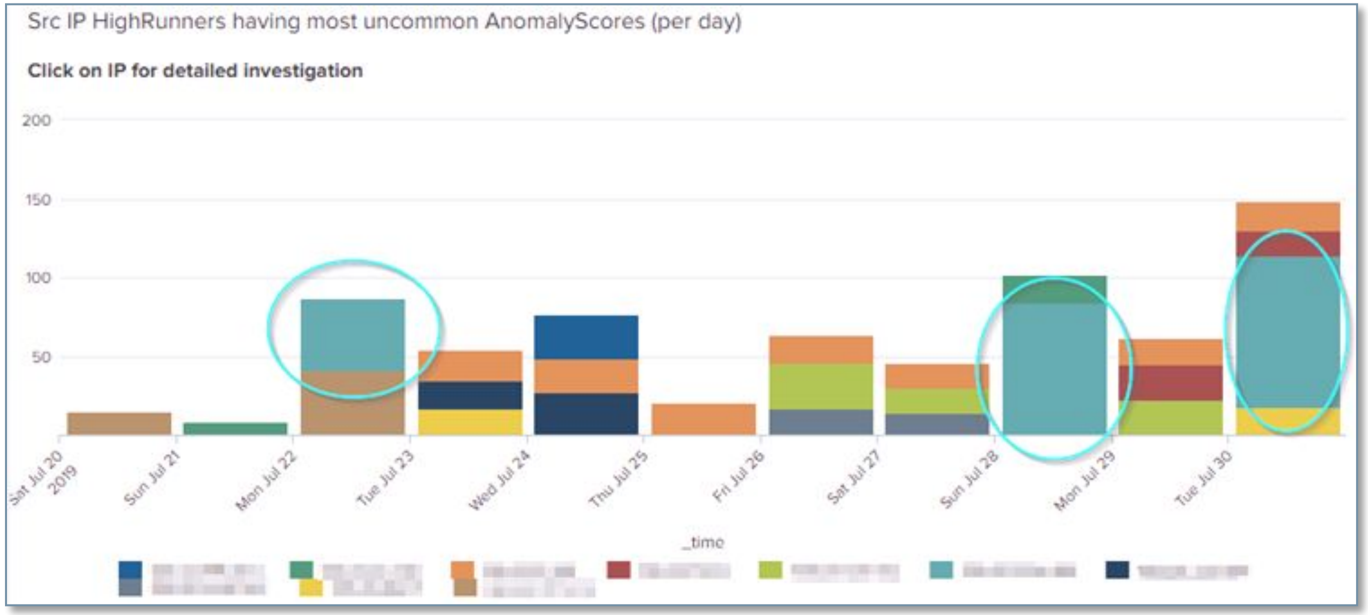
Results

- Changes are reliably reported.
- Findings are consolidated into meta alarms (aka “change of change”).
- Change caused by unwanted software (HTTP tunneling of SSH traffic) correctly detected.

Use Case One: Proxy Communication
Detected Malware Communication

Detect the Unwanted: HTTP tunneling of SSH traffic

- Meta Alert:
  Triggers on first change,
  then change of change.



- Alerted on outlying characteristics:

Anomaly Details for [illegible] (displaying all events having outliers)

_time	src_ip	outlierValue_newUserAgents	anomaly_score	outlier_newUserAgent	outlier_dcDstNetloc	outlier_countConns	outlier_sumBytesIn	outlier_sumBytesOut
2019-07-22 14:00	[illegible]	curl/7.60.0	6.0	1	1.0	1.0	1.0	1.0

Use Case One: Proxy Communication
Concept Building Blocks: SPL-Foo

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Three scheduled Searches:

Search #1: Base Collector and SummaryFiller

- Create eight feature fields (dcDstIp, dcDstNetloc, dcCategories, categories, dcUserAgent, UserAgents, sumBytesIn, sumBytesOut), splitted by _time (1h) and src_ip
- Collect onto summary index.

Search #2: Training / Model Fitter

- Train one DensityFunction per feature.
- Full **| fit** every night.

Search #3: Alert Generator, Delta Fields Generator and SummaryFiller

- AlertGen: Find outliers by **| apply** 'ing density models over latest timeslice (every few hours).
- DeltaFieldsGen: Also cover last month of data to generate additional feature “newUserAgent”, via **| streamstats** implementing a historybrain.
- Collecting again onto summary index, to historize and make available for dashboard.

Use Case One: Proxy Communication Concept Building Blocks: Scheduling the ML System

Dashboarding

Alerting

index=summary_alarming

Search #2 | fit DensityFunction into M

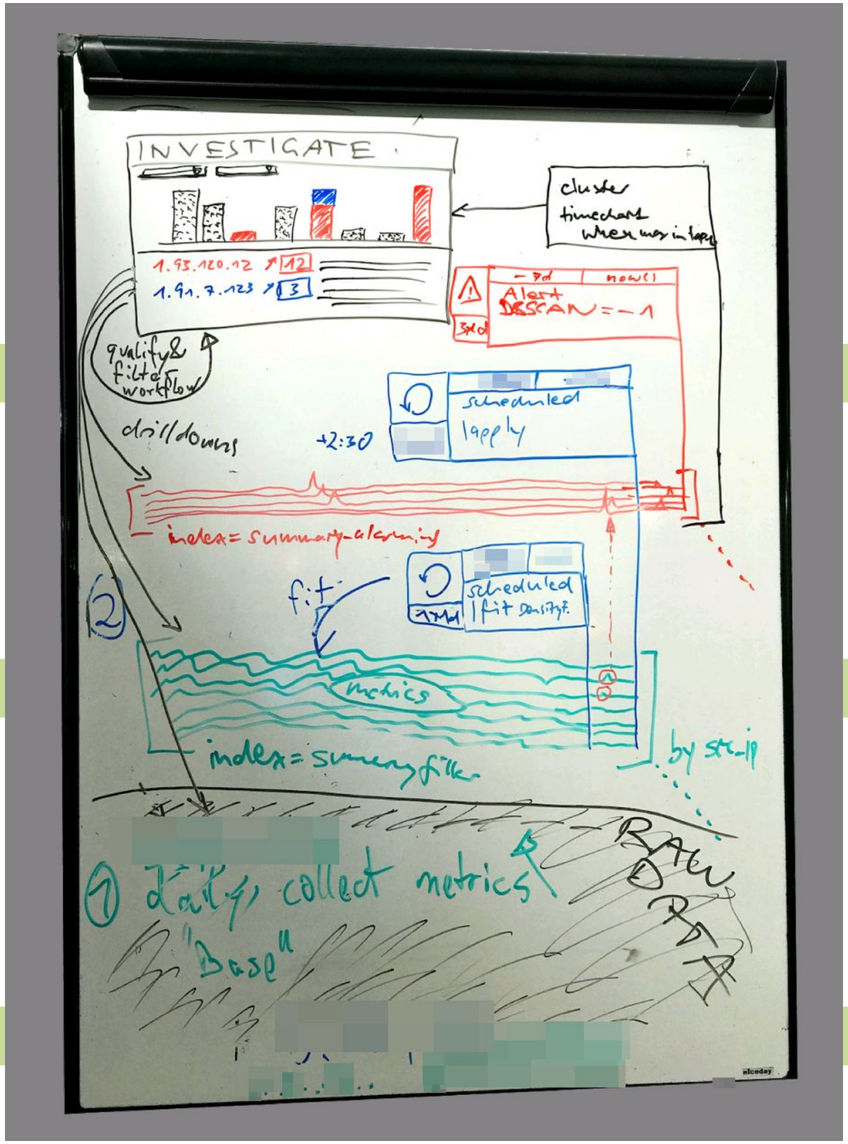
Search #3 | apply M

index=summary_filler

```
GET /oldlink?item_id=EST-26&JSESSIONID=SD5SL9FF1ADFF3 HTTP 1.1" 200 1318 "http://buttercup-shop
chase&itemId=EST-26&product_id=K9-CW-01" "Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV
GET /oldlink?item_id=EST-26&JSESSIONID=SD5SL9FF1ADFF3 HTTP 1.1" 200 1318 "http://buttercup-shop
chase&itemId=EST-26&product_id=K9-CW-01" "Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV
GET /oldlink?item_id=EST-26&JSESSIONID=SD5SL9FF1ADFF3 HTTP 1.1" 200 1318 "http://buttercup-shop
chase&itemId=EST-26&product_id=K9-CW-01" "Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV
GET /oldlink?item_id=EST-26&JSESSIONID=SD5SL9FF1ADFF3 HTTP 1.1" 200 1318 "http://buttercup-shop
chase&itemId=EST-26&product_id=K9-CW-01" "Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.1; SV
```

Search #1

index=_raw



Use Case One: Proxy Communication
SPL-Foo: Search #1 Base Collector and SummaryFiller

| stats instead of | timechart to not zero-flood

Retain multivalues by tokenizing

PCR: Producer-Consumer Ratio

Write features

Scheduled to run every few hours

```
| bin _time span=1h
| stats count as countConns, dc(r_ip) as dcDstIp, dc(ut_netloc) as
    dcDstNetloc, dc(cs_categories) as dcCategories, values(cs_categories) as
    categories, dc(viruses) as dcViruses, dc(UserAgent) as dcUserAgent,
    values(UserAgent) as UserAgents, sum(bytes_in) as sumBytesIn, sum
    (bytes_out) as sumBytesOut by _time, src_ip, sc_filter_result
| eval categoriesZipped=mvjoin(categories, `tok`), UserAgentsZipped=mvjoin
    (UserAgents, `tok`)
| fields - categories, UserAgents
| eval pcr=(sumBytesOut-sumBytesIn)
| collect testmode=false addtime=true index=[redacted]
    marker="search_name
    =[redacted]"
    sourcetype=stash source
    ="[redacted]"
```

Earliest time [redacted]@h

Time specifiers: y, mon, d, h, m, s Learn More

Latest time [redacted]@h

Time specifiers: y, mon, d, h, m, s Learn More

	_time	src_ip	countConns	dcDstIp	dcDstNetloc	dcCategories	categoriesZipped	dcViruses	dcUserAgent	UserAgentsZipped	sumBytesIn	sumBytesOut	pcr
1	2019-07-31 07:00	[redacted]	1	1	1	1	[redacted]	0	1	[redacted]	7994	1697	-6297
2	2019-07-31 07:00	[redacted]	362	1	1	1	[redacted]	0	3	[redacted]	68864188	4465611	-64398577
3	2019-07-31 07:00	[redacted]	2	1	1	1	[redacted]	0	1	[redacted]	2031	583	-1448
4	2019-07-31 07:00	[redacted]	3	1	1	1	[redacted]	0	1	[redacted]	3065	877	-2188

Use Case One: Proxy Communication
SPL-Foo: Search #2 Training / Model Fitter

Fit all eight Density Functions, one by one

Ensure learning starts late, after grace period of 2 days.

```
| eval UserAgents=split(UserAgentsZipped, `tok`), categories=split
    (categoriesZipped, `tok`)
| table _time, src_ip, sc_filter_result, countConns, dcDstIp, dcDstNetloc,
    dcCategories, categories, dcViruses, dcUserAgent, UserAgents, sumBytesIn,
    sumBytesOut, pcr
| search sc_filter_result=observed
| fit DensityFunction countConns by "src_ip" into app:Mdl
```

Earliest time: -90d@d

Time specifiers: y, mon, d, h, m, s Learn More

Latest time: -2d@d

Time specifiers: y, mon, d, h, m, s Learn More

Runs once per day, nightly.

Use Case One: Proxy Communication
SPL-Foo: Search #3 AlertGen, DeltaFieldsGen and SmryFillr

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Run longer for historybrain

Earliest time: -[illegible]d@d
Time specif
Latest time: -2h@h

```
| table _time, src_ip, sc_filter_result, countConns, dcDstIp, dcDstNetloc,
  dcCategories, categories, dcViruses, dcUserAgent, UserAgents, sumBytesI
  sumBytesOut, pcr
| rename UserAgents as UserAgent
| sort 0 _time
| streamstats window=[illegible] current=t global=f count as countUserAgent by
  src_ip, sc_filter_result, UserAgent
| eval outlier_newUserAgent = if(countUserAgent == 1, 1, 0)
| eval outlierValue_newUserAgent = if(outlier_newUserAgent == 1, UserAgent,
  null())
```

Historybrain: Find new values

```
| addinfo
| eval secsInHour=60*60
| eval timeRemainder=info_max_time % secsInHour
| eval timeMaxSnappedHour=info_max_time - timeRemainder
| eval myEarliest=timeMaxSnappedHour - 8*secsInHour
| eval myLatest=timeMaxSnappedHour
| where _time >= myEarliest AND _time < myLatest
| fields - secsInHour, timeRemainder, timeMaxSnappedHour
```

Throw away events which were only needed for historybrain

```
| apply [illegible]Mdl[illegible]sumBytesIn threshold=0.005
| rename IsOutlier(sumBytesIn) as outlier_sumBytesIn
| apply [illegible]Mdl[illegible]sumBytesOut threshold=0.005
| rename IsOutlier(sumBytesOut) as outlier_sumBytesOut
| eval version=11
| eval categoriesZipped=mvjoin(categories, `tok`), UserAgentsZipped=mvjoin
  (UserAgents, `tok`), outlierValue_newUserAgentZipped=mvjoin
  (outlierValue_newUserAgent, `tok`)
| fields - categories, UserAgents, outlierValue_newUserAgent
| collect testmode=false addtime=true index=[illegible]
  marker="search_name
```

Apply to get outliers.
Versionize.
Collect to historize.

Use Case One: Proxy Communication Investigation Workflow

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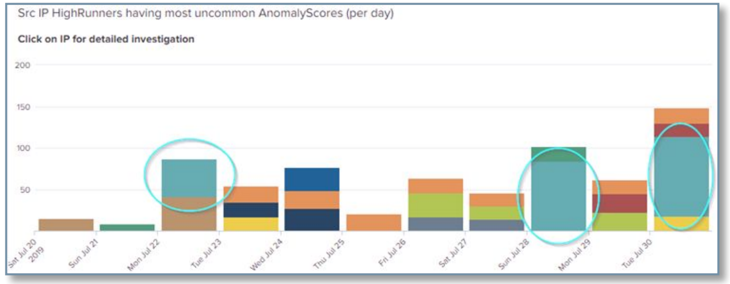
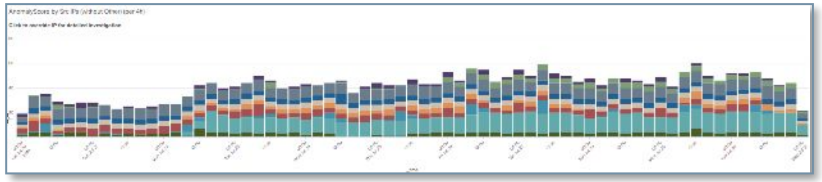
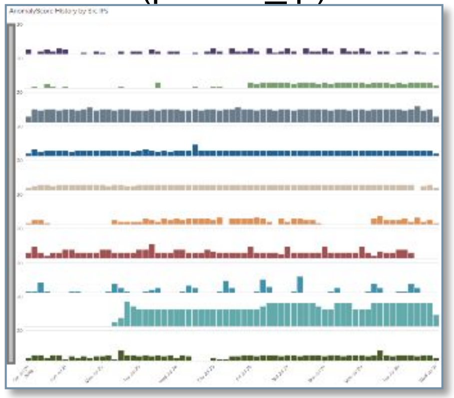
1. Derivate Alerts: Act on these

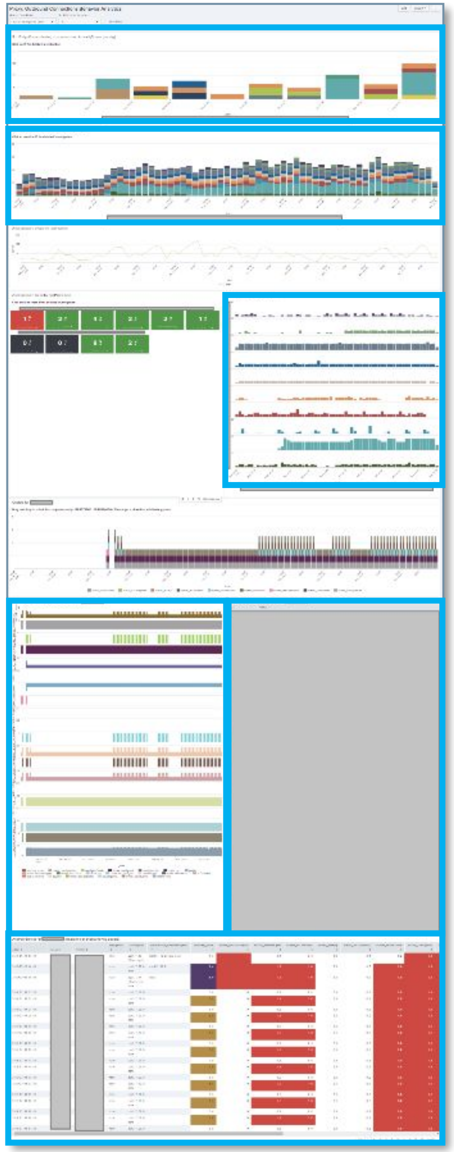


2. Deriving from sum(outliers) (=scoring) per src_ip

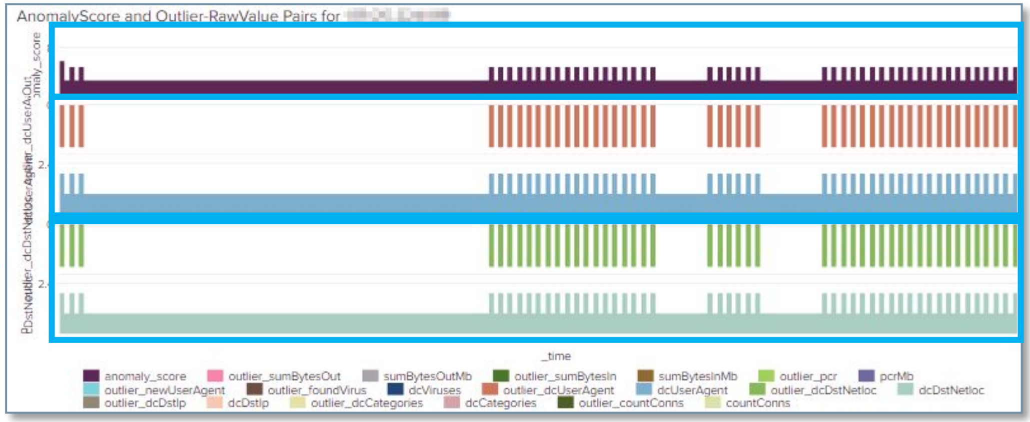


3. See anomaly_score trend (per src_ip)

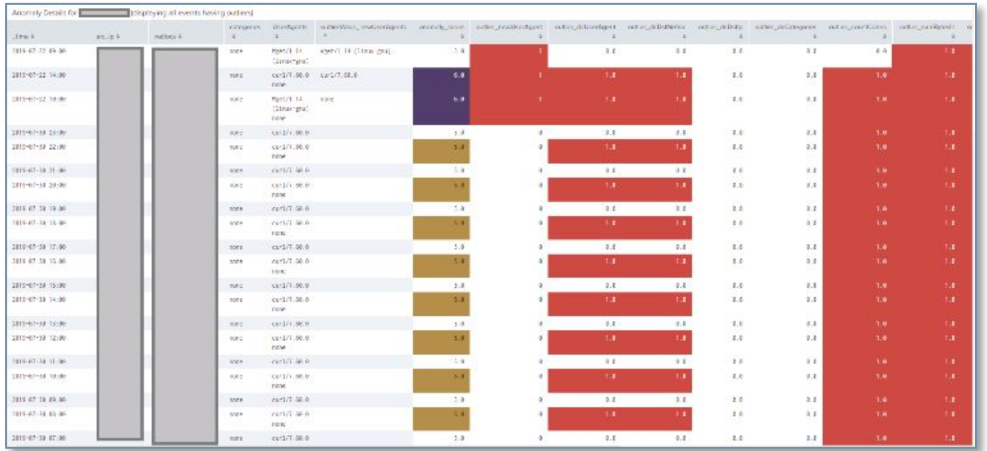




4. Drilldown on specific src_ip: Check outliers by visually presenting base values and its delta



5. Drilldown on specific src_ip: Check raw values



Use Case 2: Identifying System Compromises

Use Case Two: Webserver Monitoring
Identify compromises by their behavior

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Idea

- Can we use MLTK to ease alert fatigue?
- Instead of further evolving attack signatures:

 Let's find signals that **identify successful compromises**

  - A hacked webserver will change its behavior. How?
    - Files written where they should not, e.g. Webshell
    - Webpage or DB table modified
    - OS Command executed, e.g. cmd.exe
    - …

Concept

  - Use Windows logs (standard and sysmon) to generate features:
    - *[Webserver: File Written into Webroot by Webserver Worker Process Classic SPL]*
    - *[All Systems: Lsass CrossProcs Classic SPL]*
    - Webserver: Suspicious commands started by webserver worker process ML
    - ...

Use Case Two: Webserver Monitoring
Find Suspicious Commands started by W3Worker Process

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Observations

- How can we find unusual command from w3wp.exe?
  - **“unsual” can be tricky, CommandLines have a high variance (e.g. date/time parameter).**
- Instead, how about suspicious commands? But not every process binary is bad
  - **Need to consider whole CommandLine.**
- A single command may not be significant enough
  - **Need to consider multiple commands, their sequence.**

Concept

- Define a list of suspicious words to extract matches from the CommandLine
- Collect extracted matches into bag of words pattern of suspicious sequences
- Classify malicious sequences:
  - **| fit TFIDF** from bag of words
  - Classify with **| fit LogisticRegression** from a set of positive examples
- Identify malicious sequences with a supervised learning approach
- Maintain lookup of positive examples to train and refine the model over time and adapt to new situations

Use Case Two: Webserver Monitoring
Find Suspicious Commands

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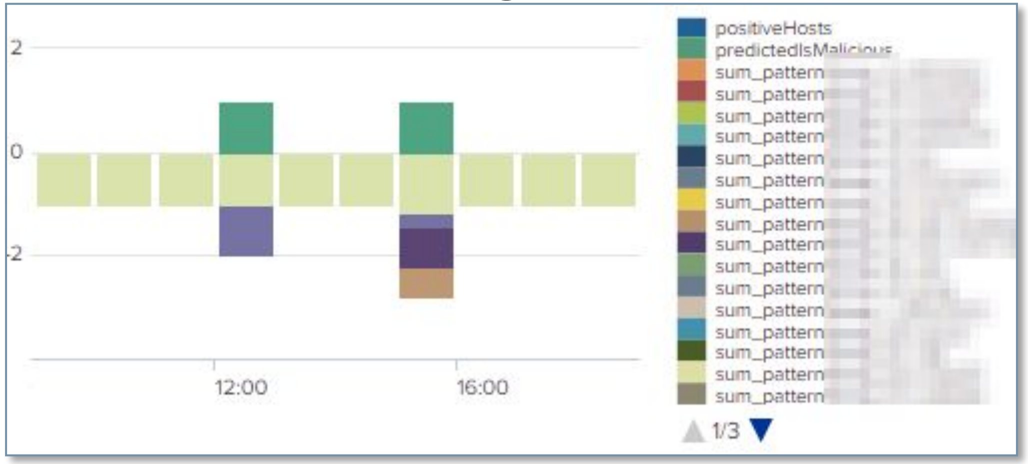
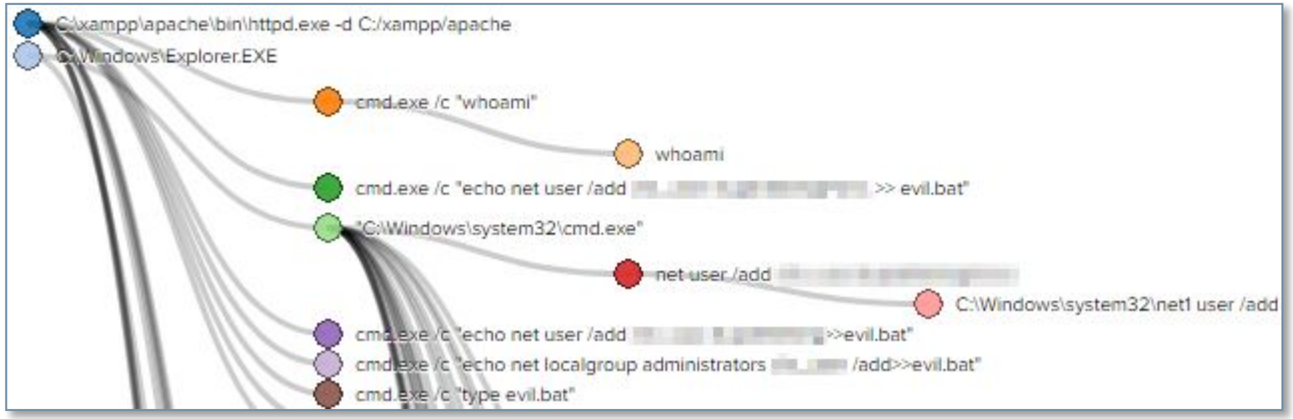
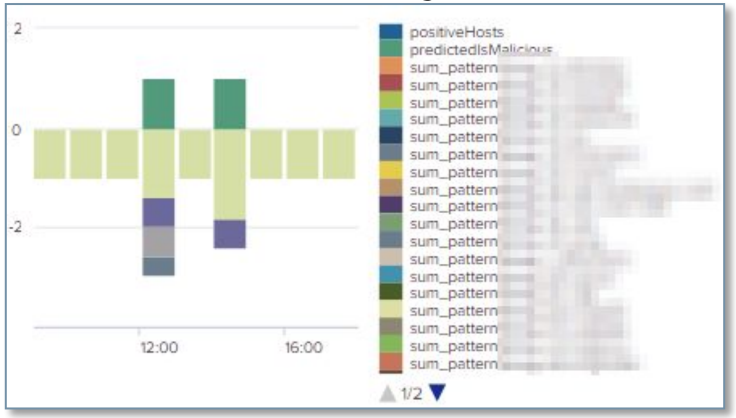
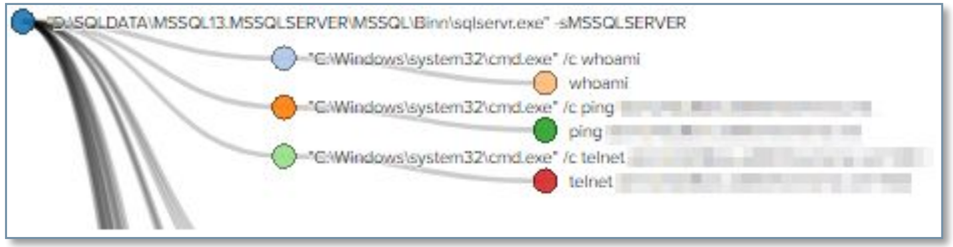
Apache webshell usage





SQL Server CmdInjection





Use Case 3:
Baseline Privileged Account Behavior

Use Case Three: Baseline Privileged Account Behavior
Idea, Concept, Gain

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Idea: Can we **profile Windows admin logon sessions** and **detect changes** in behavior to ultimately **find suspicious outliers**?

Concept

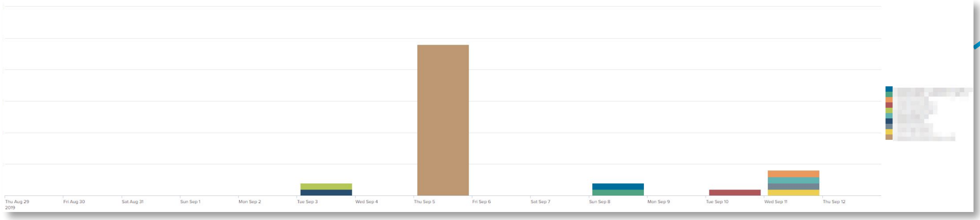
- Collect features describing Windows admin logon sessions onto summary index
- Cluster training data (last [30;1[days) using **| fit XMeans** models every night. One model each for focusing on source (ip address), session (behavior) and target (host)
- **| apply** models each day to testing data (last day). Historize by collecting onto summary index.
- Detect anomalies based on changes in cluster_distances (**| fit** DensityFunctions and **| outputlookup** percXX statistics) and cluster memberships (**| outputlookup** account to cluster relations)
- Dashboard visualizes findings and guides investigation workflow.

Results

- Three types of anomalies detected: Source, Target and Session Metadata
- Enables detection of credential theft, malicious account usage (e.g. lateral movement), …
- Differentiation between local and global outliers: New accounts trigger only global alerts

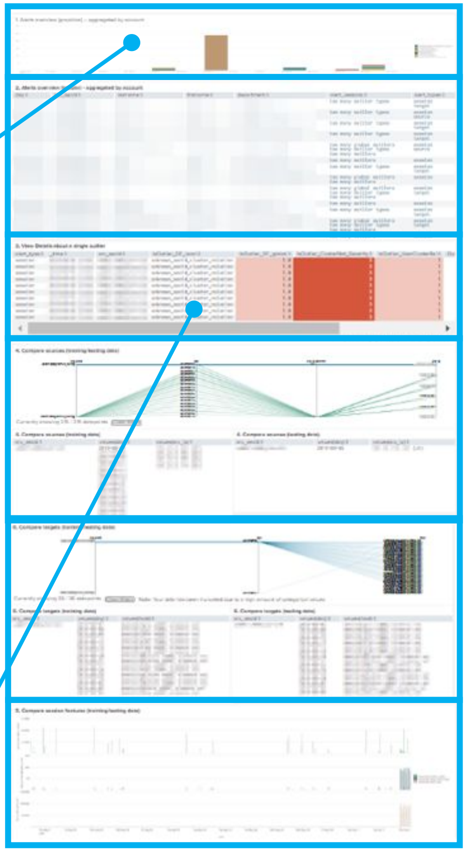
Use Case Three: Baseline Privileged Account Behavior Investigation Workflow

1. Alerts overview (graphical)



2. Alerts overview (tabular)

day	src_secid	lastname	firstname	department	alert_reasons	alert_types
2019-09-05	[illegible]	[illegible]	[illegible]	[illegible]	too many global outliers too many outlier types too many outliers	session target
2019-09-05	[illegible]	[illegible]	[illegible]	[illegible]	too many outlier types	session target
2019-09-05	[illegible]	[illegible]	[illegible]	[illegible]	too many outlier types	session target
2019-09-	[illegible]	[illegible]	[illegible]	[illegible]	too many outliers	session

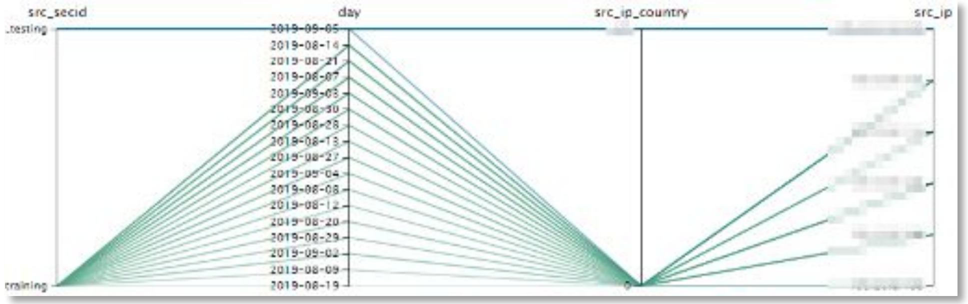


3. Drilldown on Alert: View Details

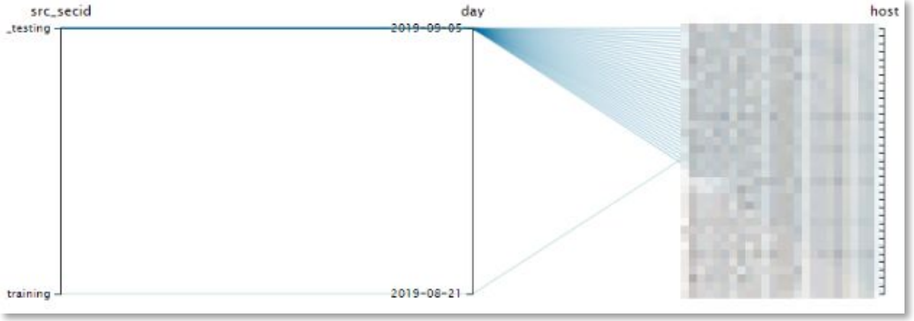
alert_type	_time	src_secid	IsOutlier_DF_local	IsOutlier_DF_global
session	2019-09-05 23:00	[illegible]	unknown_secid_cluster_relation	1.0
session	2019-09-05 23:00	[illegible]	unknown_s	
session	2019-09-05 23:00	[illegible]	unknown_s	
session	2019-09-05 23:00	[illegible]	unknown s	

IsOutlier_ClusterStat_Severity	IsOutlier_UserClusterRel
3	1
3	1
3	1
3	1

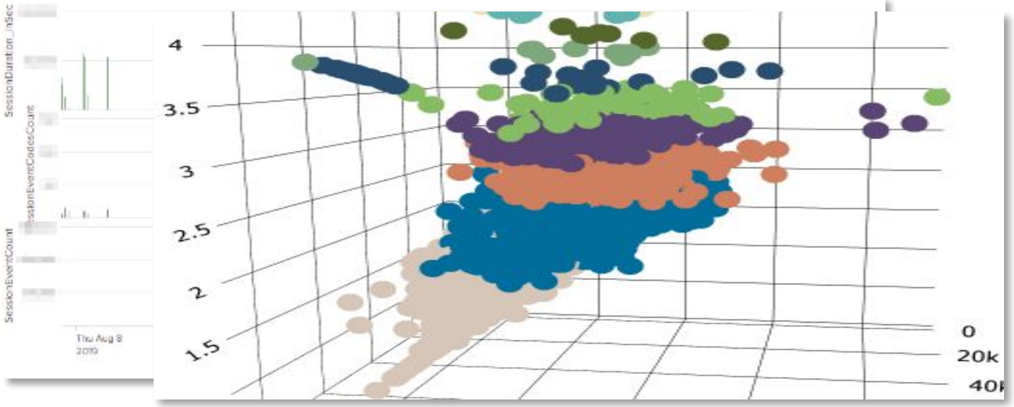
4. Compare sources



5. Compare targets



6. Compare session features



Graphs Special

Graphs Special: Consider Relations Between Use Cases

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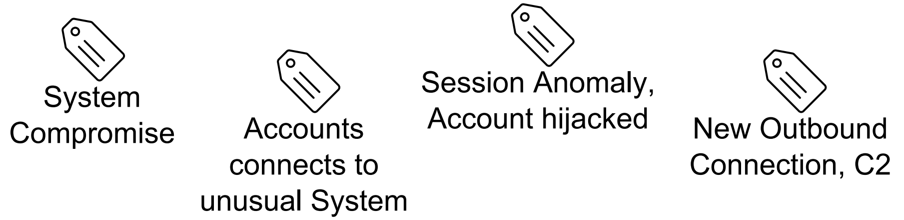
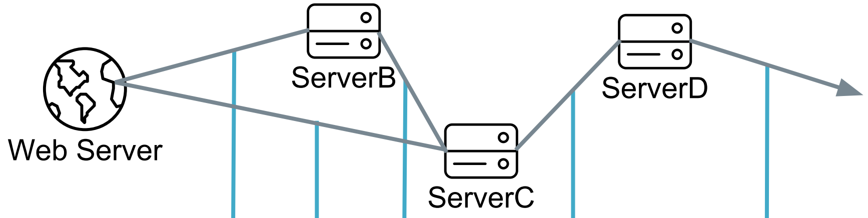
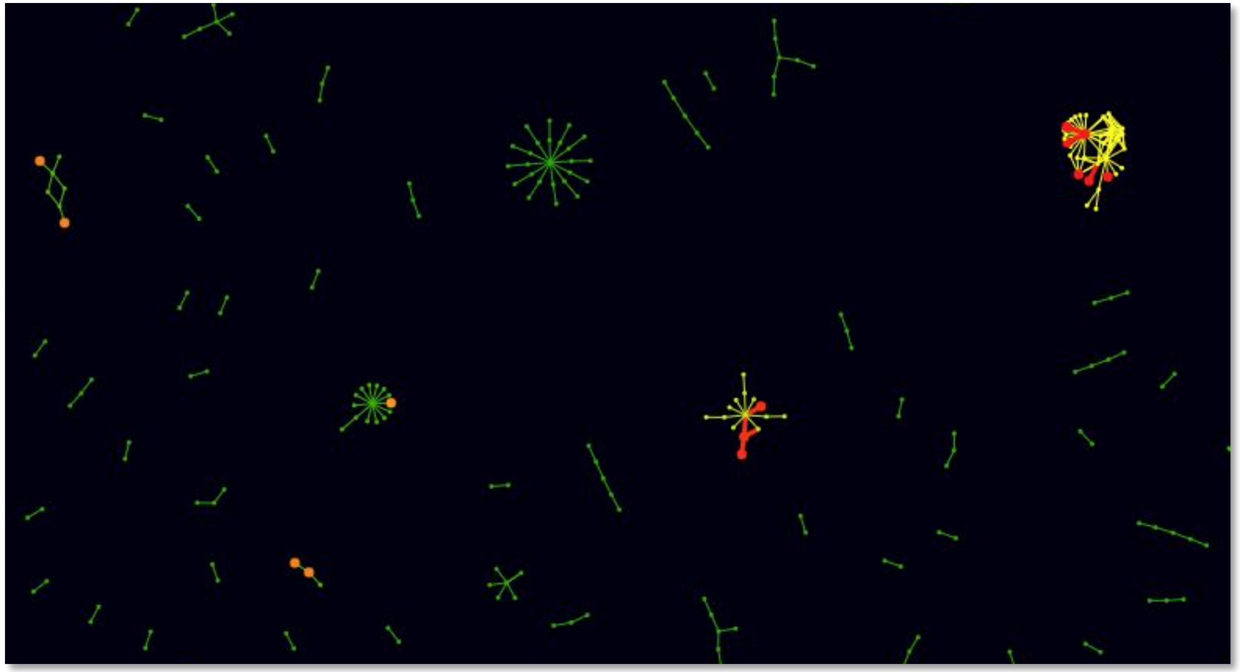
Scenario: Compromise, C2. Gives these Anomalies:



Relate e.g. via Accounts' Connections. Find ConnectedComponents in the Graph:





```
`comment("relate via Connections using ConnectedComponents")`
| eval FromSys = FromSystem + ":" + ConnectionId
| eval ToSys = ToSystem + ":" + ConnectionId
| graph algo=WeaklyConnectedComponents linkSrc=FromSys linkTgt=ToSys outfield=componentId
```

FromSys	ToSys
WebServer	ServerB
WebServer	ServerC
ServerC	ServerD
ServerB	ServerC

Calculate AnomalyScore per System, Connection and per ConnectedComponents. Map Score to Color:

```
| eventstats sum(objAnomalyScore) as componentAnomalyScore by componentId
| `bilinearinterpolatecolorgradient(objAnomalyScore, componentAnomalyScore, ..., outcolor)`
```

Wrap Up

Summary, Key Benefits and Takeaways

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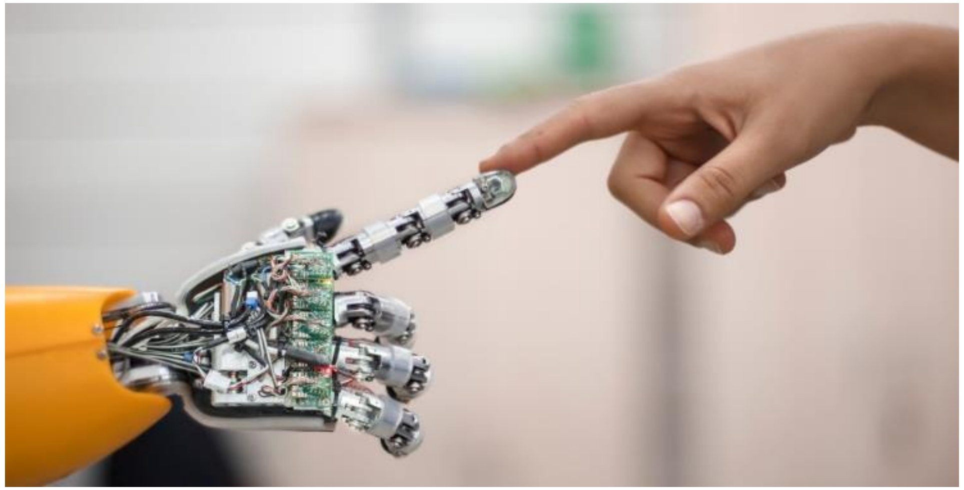
Key Benefits

- New SecMon capabilities:
  - 20 Mio Console Cmds classified every day by machine
  - Pattern analytics of core infrastructure components: Communications, compromises, privileged accounts
- Efficiency gained: Smoother day-to-day ops, more time for use case development.



Takeaways

- Classic SPL is here to stay
- ML vastly expands SecMon capabilities:
  - Allows to look at the “grey” between the black&white
  - Enables feature-rich use cases
  - Easy tuning
- New data insights may impact project plan. Stay flexible.

Thank you!
Q&A

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