TREND ANALYSIS WITH ESA

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Introducing the model

• How does it work?

Implementation details



INTRODUCING THE MODEL



Analytics with the Netwitness Suite

- The Netwitness Suite already provides a number of ways to analyze your data:
 - Investigation
 - Reports
 - Big Data
 - Parallel Coordinates
 - Alerts
 - Correlation
 - Data Science
- But can we do more?



Trend analysis and baselining

- Why not having trend analysis capabilities as well?
 - Common request among our users
 - Implicitly available in ESA but without a formalized implementation

- When does it help?
 - Whenever a significant change in the rate of given value could imply a security issue
 - Not all the threats can be identified in this way!



Baselining model requirements

- Generic enough to work with any meta key
- Plug & play
- Reusable across multiple rules
- Suitable for production
- Minimum performance impact
- Persistent across service restart/reboot



Common challenges

- To perform any statistical analysis, numbers are an obvious requirement
 - Have to be derived from the collected events first!
- A solid way to count the number of occurrences is key

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- Buffering in the ESA memory all the events with their meta for a long timeframe before applying any calculation would not scale
- A multi-stage approach is required to only store aggregated information in memory



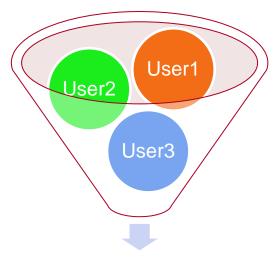
HOW DOES IT WORK?

(3)



How does it work

- For each value of a given meta key, we will sum the number of occurrences:
 - This is done every minute
 - Then aggregated every 5 minutes
 - Then aggregated every hour
 - Then aggregated every day
- For each hour and for each value, a baseline is created:
 - Mean
 - Standard Deviation

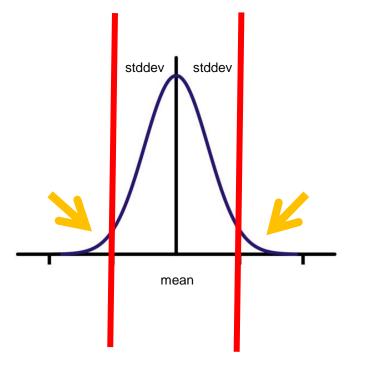


8am – 9am:

User1) mean=10; stddev = 2 User2) mean=23; stddev = 15 User3) mean=79; stddev = 5

How does it work (cont.)

- Each hour
 - for each meta key
 - for each meta value
 - the number of occurrences is compared with the baseline of that hour
 - An alert is generated if there is a significant deviation
 - By default if the number of events is more than mean+sttdev or less then mean-sttdev
- The same is done for each day



Trend analysis module in action

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		Name		Count	Severity	Last Detected				
		Baseline		8	Low	2016-02-16T09:00:0	0			
		11								_

Trend analysis module in action

							\times					
Baseline Test												
Description	Davide Basline Test Rule											
Time	2016-02-25T13:00:04										×	
Severity	Critical				Baseline							
# Of Events	77			Description								
Event Meta Events												
Date	Source	Time 2016-02-16T00:00:00										
Additional Meta					Severity Low # Of Events 100							
Deviation Event Count Meta Key	8.660254037844387 45 event_cat_name				Event Meta Date	Events	Source	Destination	Username	Alias Host		
Meta Value Timeframe	Policies.ACL.Added					ONaN-NaN-NaNTNaN						
Invalid date Additional Meta Average 304.0						ONaN-NaN-NaNTNaN						
						NaN-NaN-NaNTNa						
Average Deviation Event Count Meta Key Meta Value	247.51363598799966			average 12.0 deviation 5.291502622129181 eventCount 18 metaKey ip_src metaValue 192.168.1.145 timeframe day								
					ONaN-NaN-NaNTNaN							
12					ONaN-NaN-NaNTNaN							

Possible Use Cases

- What does a significant change in the rate of given value mean?
 - Do NOT use meta keys with too many unique values (e.g. ip.src) since would generate too many false positives
 - Focus on those with a few but significant unique values:
 - Browsers uncommon client may be associated with malicious codes
 - Country source/destination can help identifying attacks or potential data exfiltration
 - TLDs uncommon TLDs can be an indicator of something strange happening
 - Combine multiple meta keys together
 - E.g username and browser,

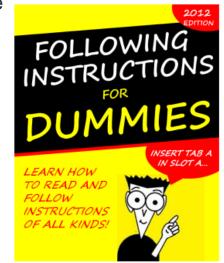
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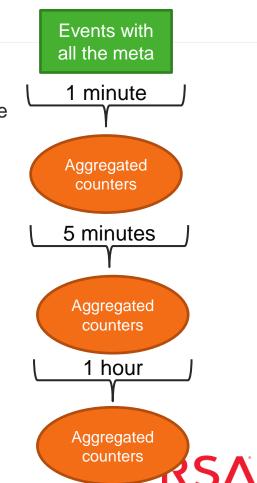
Implementing the model

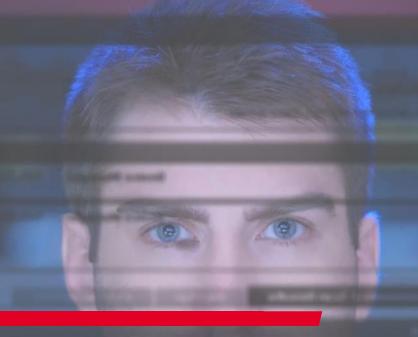
- 1. Create a new ESA Advanced rule and copy and paste the EPL code provided in the last slide
- 2. Append or customize the «baselineInput» statement(s) to feed the model with the meta key you want to monitor
- 3. Activate trial mode and enable the rule
- 4. Constantly monitor in H&W the amount of memory the rule is consuming
- 5. Review the results at the end of the learning phase and increase/decrease «anomalyStddevTimes» as needed
- The same approach can be leveraged in other custom rules whenever a very long timeframe has to be considered
- Combined keys can be monitored by concatenating them



Implementation overview

- Aggregation done in multiple steps:
 - Summarized data only is kept between each step to minimize performance impacts
- The baseline is created over the last 30 days:
 - Can be customized
 - Statistics are saved on disk to persist across reboot/restart
- Learning phase by default is 5 days:
 - Can be customized
 - This prevent alerting when no enough data is available
- Anomaly is by default mean +/- 3*sttdev
 - Can be customized







IMPLEMENTATION DETAILS

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Trend analysis EPL implementation summary

- 1. Create time-based contexts
- 2. Create data structures to store aggregated statistics
- 3. Create a data structure to store the baseline statistics
- 4. Every minute the values of a given meta key count are fed them into the baseline model
- 5. Every 5 minutes / 1 hour / 1 day the data is aggregated, always for each meta value
- 6. A baseline model is generated at the end of each hour and day
- 7. Every hour, compare the number of events for each meta value with the baseline created for the same hour during the previous days and generate an alert if an anomaly is detected
- 8. Every day, compare the number of events for each meta value with the baseline created during the previous days and generate an alert if an anomaly is detected

• Set the baseline model settings:

/* duration in days of the learning phase during which no alerts will be triggered */
CREATE VARIABLE integer learningPhaseInDays = 5;

/* the alert is triggered when the number of events is mean+/-anomalyStddevTimes*sttdev */
CREATE VARIABLE double anomalyStddevTimes = 3.0;

 Create time-based contexts within which the calculations are performed:

CREATE CONTEXT contextEvery1Minute INITIATED @now AND PATTERN [every timer:at(*, *, *, *, *)] TERMINATED AFTER 1 min;

CREATE CONTEXT contextEvery5Minutes INITIATED @now AND PATTERN [every timer:at(*/5, *, *, *, *,] TERMINATED AFTER 5 min;

CREATE CONTEXT contextEverylHour INITIATED @now AND PATTERN [every timer:at(0, *, *, *, *)] TERMINATED AFTER 1 hour;

CREATE CONTEXT contextEvery1Day INITIATED @now AND PATTERN [every timer:at(0, 0, *, *, *)] TERMINATED AFTER 1 day;

 Create data structures to store aggregated statistics lasting enough time to allow the sub-sequent data aggregation:

CREATE WINDOW baselineInput.win:time(5 minutes) (metaKey string, metaValue string, eventCount long);

```
CREATE WINDOW baselineEvery5MinutesData.win:time(60 minutes) (metaKey string, metaValue string, eventCount long);
```

```
@RSAPersist
CREATE WINDOW baselineEvery1HourData.win:time(30 days) (metaKey string, metaValue string,
eventCount long, timeframe string);
```

```
@RSAPersist
CREATE WINDOW baselineEvery1DayData.win:time(30 days) (metaKey string, metaValue string,
eventCount long, timeframe string);
```

```
@RSAPersist
```

CREATE WINDOW baseline.std:groupwin(metaKey, metaValue, timeframe).win:length(1)(metaKey string, metaValue string, timeframe string, average double, dev double);

• Every minute count the values of a given meta key and feed them into the model:

```
@Name('baselineInput1')
CONTEXT contextEvery1Minute
```

INSERT INTO baselineInput

SELECT 'event cat name' AS metaKey, event cat name AS metaValue, COUNT(*) AS eventCount

FROM Event (event cat name IS NOT NULL)

GROUP BY event cat name

OUTPUT snapshot WHEN TERMINATED;



• Every 5 minutes the data is aggregated, always for each meta value:

@Name('baselineAggregateEvery5Minutes')

CONTEXT contextEvery5Minutes

INSERT INTO baselineEvery5MinutesData

SELECT metaKey, metaValue, SUM(eventCount) AS eventCount

FROM baselineInput

GROUP BY metaKey, metaValue

OUTPUT snapshot WHEN TERMINATED;



• Every hour the data is aggregated again

@Name('baselineAggregateEvery1Hour')

CONTEXT contextEvery1Hour

INSERT INTO baselineEvery1HourData

```
SELECT metaKey, metaValue, SUM(eventCount) AS eventCount,
'hour '||current timestamp().get('hour').toString() AS timeframe
```

FROM baselineEvery5MinutesData

GROUP BY metaKey, metaValue

OUTPUT snapshot WHEN TERMINATED;

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• At the end of the day, aggregate once again the data:

@Name('baselineAggregateEvery1Day') CONTEXT contextEvery1Day

INSERT INTO baselineEvery1DayData

```
SELECT metaKey, metaValue, SUM(eventCount) AS eventCount, 'day' AS timeframe
```

FROM baselineEvery1HourData

GROUP BY metaKey, metaValue

OUTPUT snapshot WHEN TERMINATED;



• At the end of the hour, calculate and store the baseline model for the previous hour:

@Name('baselineGenerateByHour')

INSERT INTO baseline

SELECT metaKey, metaValue, timeframe, average, stddev AS dev

FROM baselineEvery1HourData.std:groupwin(metaKey,metaValue, timeframe).stat:uni(eventCount, metaKey,metaValue, timeframe)

GROUP BY metaKey, metaValue, timeframe

HAVING datapoints >= learningPhaseInDays;

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• Every hour, compare the number of events for each meta value with the baseline and generate an alert if an anomaly is detected:

@Name('baselineAlertByHour')

@RSAAlert(oneInSeconds=0)

CONTEXT contextEvery1Hour

SELECT baselineEvery1HourData.metaKey AS metaKey, baselineEvery1HourData.metaValue AS metaValue, baselineEvery1HourData.eventCount AS eventCount,

baselineEvery1HourData.timeframe AS timeframe, baseline.average AS average, baseline.dev
AS deviation

FROM baselineEvery1HourData, baseline

```
WHERE baselineEvery1HourData.metaKey = baseline.metaKey AND
baselineEvery1HourData.metaValue = baseline.metaValue AND baselineEvery1HourData.timeframe
= baseline.timeframe AND (baselineEvery1HourData.eventCount >
(baseline.average+anomalyStddevTimes*baseline.dev) OR baselineEvery1HourData.eventCount <
(baseline.average-anomalyStddevTimes*baseline.dev)) AND
'hour_'||current_timestamp().get('hour').toString() = baselineEvery1HourData.timeframe
OUTPUT snapshot WHEN TERMINATED;
```

• Every day compare the number of events for each meta value with the baseline and generate an alert if an anomaly is detected:

@Name('baselineAlertByDay')
@RSAAlert(oneInSeconds=0)
CONTEXT contextEvery1Day

SELECT baselineEvery1DayData.metaKey AS metaKey, baselineEvery1DayData.metaValue AS metaValue, baselineEvery1DayData.eventCount AS eventCount, baselineEvery1DayData.timeframe AS timeframe, baseline.average AS average, baseline.dev AS deviation

FROM baselineEvery1DayData, baseline

WHERE baselineEvery1DayData.metaKey = baseline.metaKey AND baselineEvery1DayData.metaValue = baseline.metaValue AND baselineEvery1DayData.timeframe = baseline.timeframe AND (baselineEvery1DayData.eventCount > (baseline.average+anomalyStddevTimes*baseline.dev) OR baselineEvery1DayData.eventCount < (baseline.average-anomalyStddevTimes*baseline.dev)) OUTPUT snapshot WHEN TERMINATED;

• Every day compare the number of events for each meta value with the baseline and generate an alert if an anomaly is detected:

@Name('baselineAlertByDay')
@RSAAlert(oneInSeconds=0)
CONTEXT contextEvery1Day

SELECT baselineEvery1DayData.metaKey AS metaKey, baselineEvery1DayData.metaValue AS metaValue, baselineEvery1DayData.eventCount AS eventCount, baselineEvery1DayData.timeframe AS timeframe, baseline.average AS average, baseline.dev AS deviation

FROM baselineEvery1DayData, baseline

WHERE baselineEvery1DayData.metaKey = baseline.metaKey AND baselineEvery1DayData.metaValue = baseline.metaValue AND baselineEvery1DayData.timeframe = baseline.timeframe AND (baselineEvery1DayData.eventCount > (baseline.average+anomalyStddevTimes*baseline.dev) OR baselineEvery1DayData.eventCount < (baseline.average-anomalyStddevTimes*baseline.dev)) OUTPUT snapshot WHEN TERMINATED;

Full implementation



baseline_v2.1.txt



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