

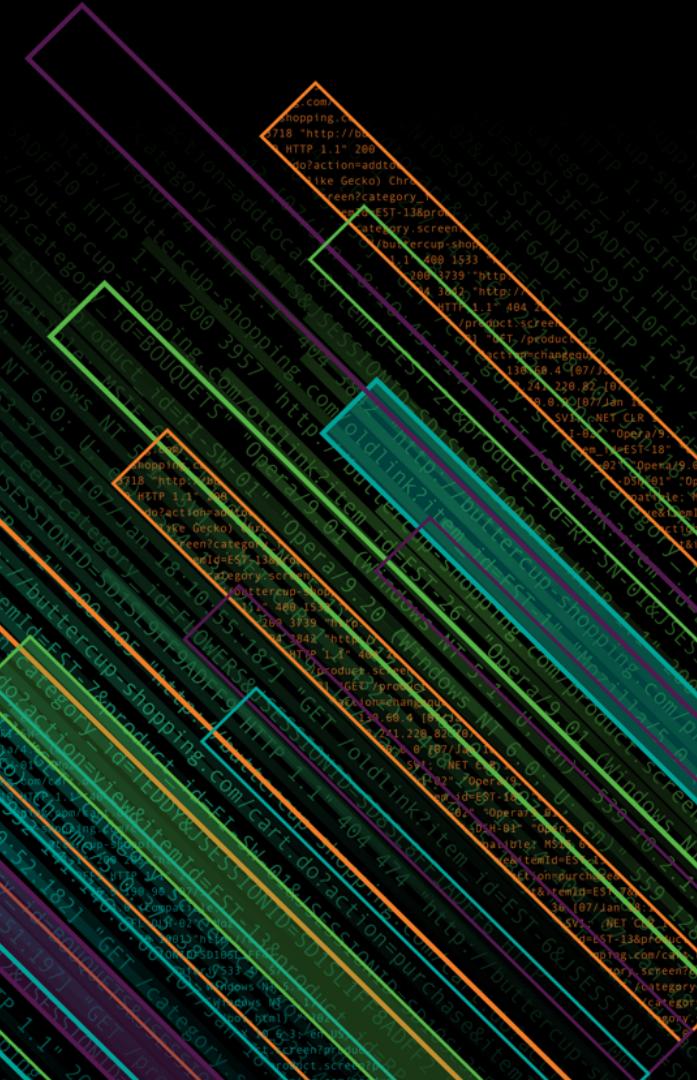


splunk>

Splunking for Fraud: Let the Machines Look for Unknowns

Matthew J Joseff, CFE | Minister of Reality, Sr. Security Specialist

September 6, 2018 | v3.0



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Hello World. Pleased To Meet You.



3 years @Splunk

- Over three decades in technology
- Sysadmin, Security, Fraud



Based in Central CT

- Raised overseas in the IC
- Relocating to Tokyo



Matthew Joseff, CFE



mjoseff@splunk.com



Training

- Psychology/Human behavior
- Product Management
- Certified Fraud Examiner



Hobbies

- Breaking & fixing things
- Film
- Politics





Time is our only
non-renewable
resource.

Compliance, Security, Fraud What's the difference?

Compliance



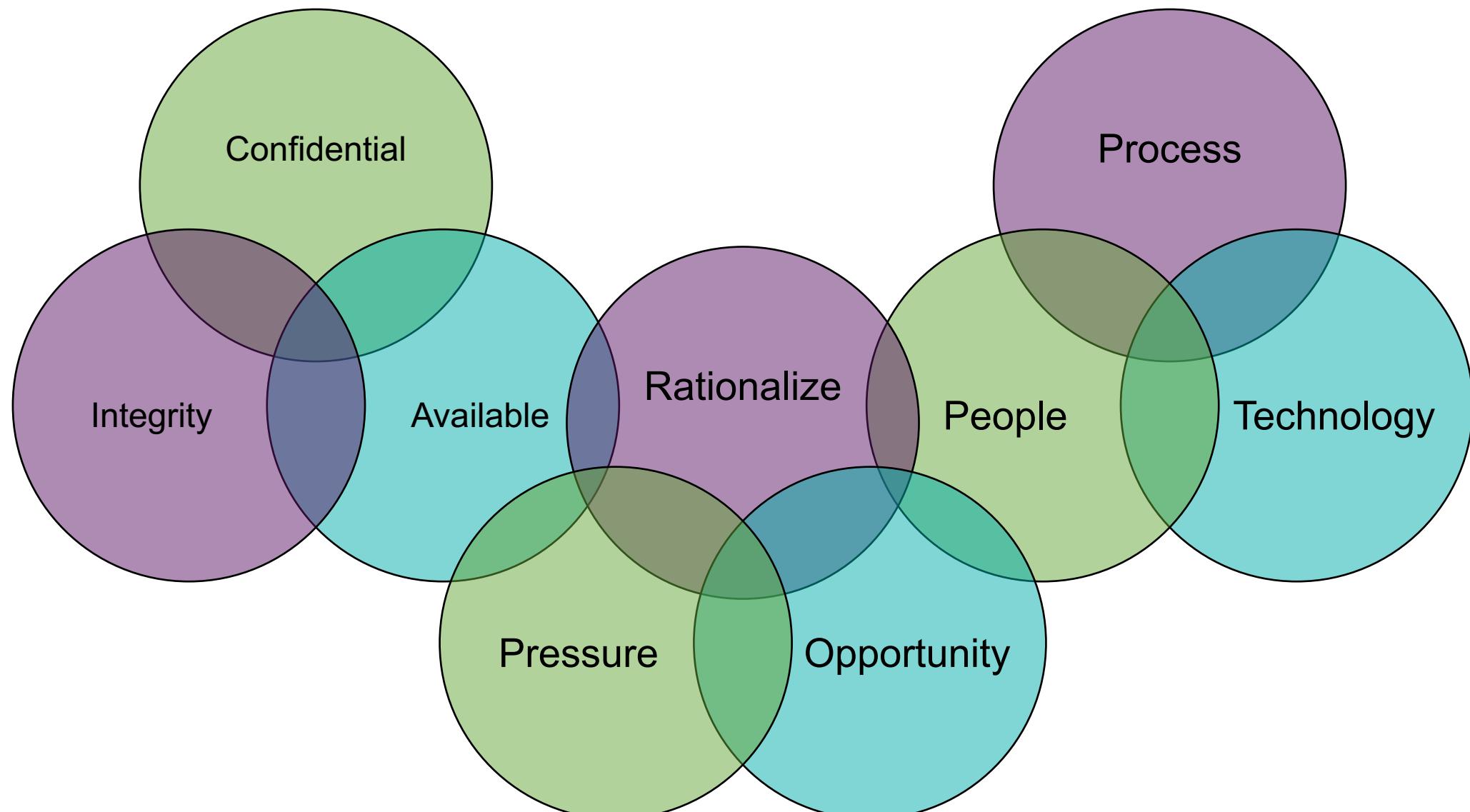
Security



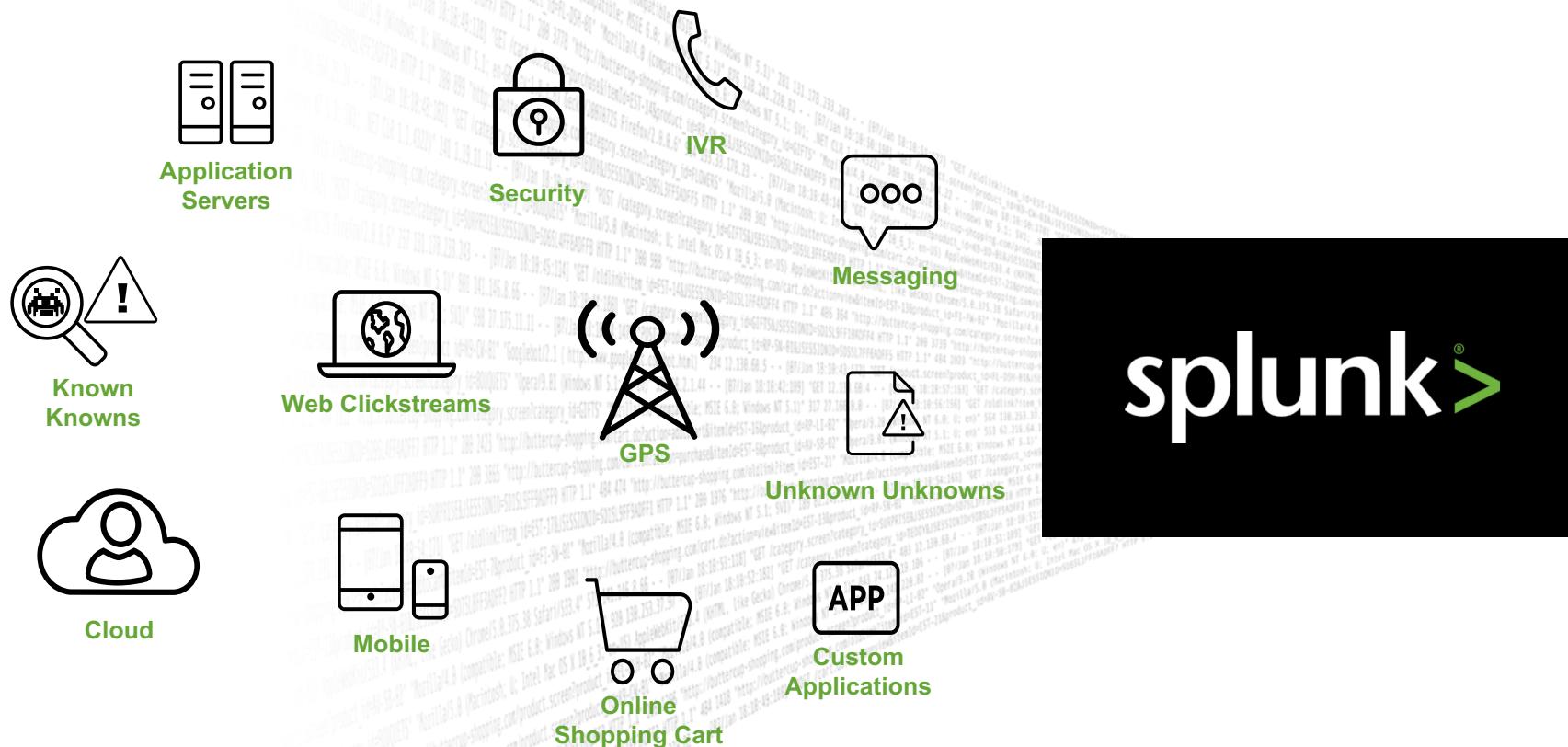
Fraud



Interrelated Components of Fraud



Turning Machine Data Into Answers



Challenges

Outliers & Anomalies

Account Take Over

Transactional Fraud

Behavioral Patterns

Abuse

Making machine data accessible, usable and valuable to everyone.

Agenda

Let's measure our Time

Approaches
To Fraud

Machine
Learning

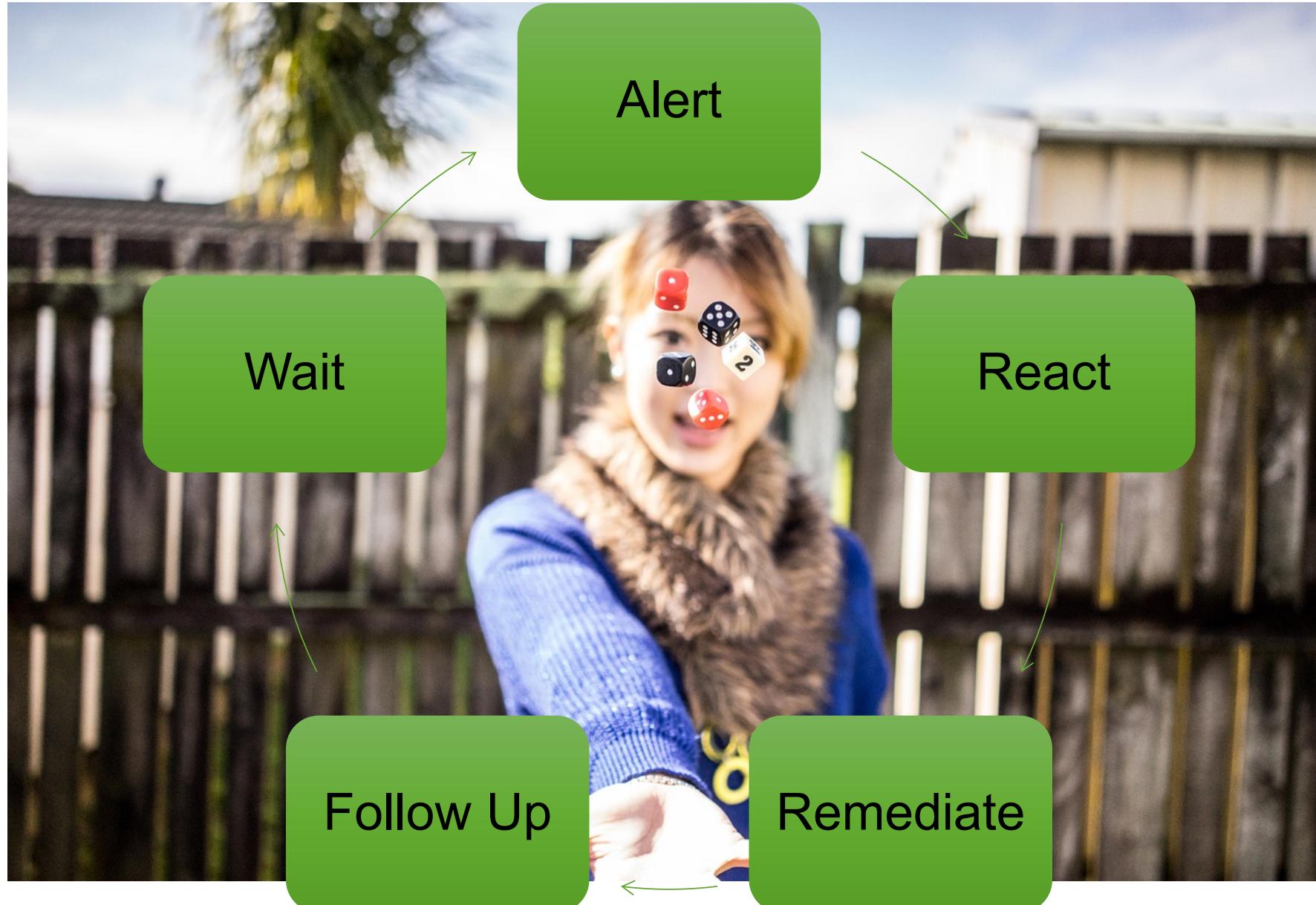
Now What?

Approaches To Fraud

Time is our only non-renewable resource



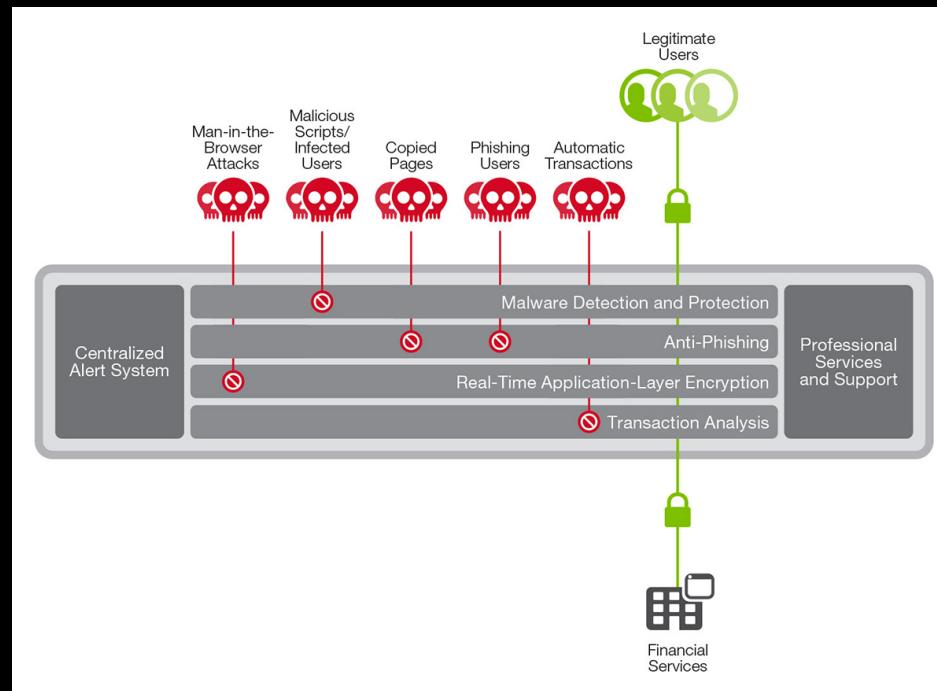
We Are Failing at Prioritization



Splunk: Anti-Fraud

Where we are best of breed

Web Fraud



Source: F5

Transactional

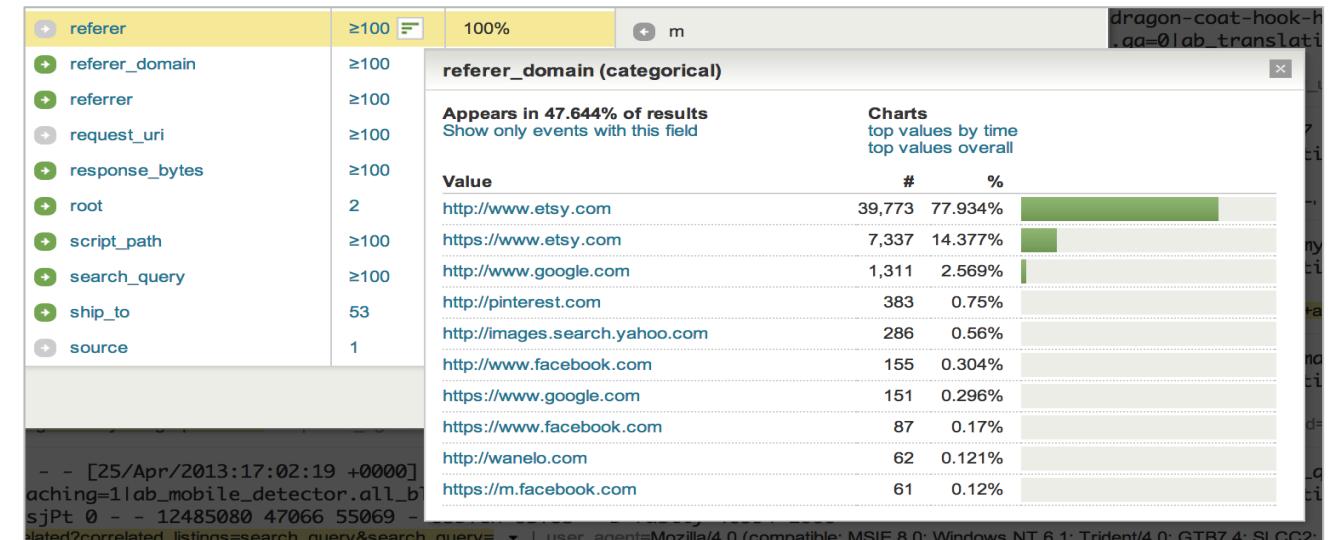
<u>Trans Date</u>	<u>Post Date</u>	<u>Type</u>	<u>Description</u>	<u>Expense Category</u>	<u>Amount</u>
11/24/2011	11/25/2011	Sale	EXXONMOBIL 97484687	Auto Related	\$57.31
11/24/2011	11/24/2011	Sale	MLK	Household	\$1,685.40
11/24/2011	11/24/2011	Sale	MLK	Household	\$818.41
11/24/2011	11/24/2011	Sale	MLK	Household	\$1,618.80
11/24/2011	11/24/2011	Sale	MLK	Household	\$1,085.30
11/24/2011	11/24/2011	Sale	MLK	Household	\$2,035.69
11/24/2011	11/24/2011	Sale	MLK	Household	\$1,618.80
11/24/2011	11/24/2011	Sale	MLK	Household	\$2,152.59
11/24/2011	11/24/2011	Sale	MLK	Household	\$1,085.30
11/24/2011	11/24/2011	Sale	MLK	Household	\$2,352.36
11/24/2011	11/24/2011	Sale	MLK	Household	\$1,618.80
11/24/2011	11/24/2011	Sale	MLK	Household	\$2,152.59

Needs of Anti-Fraud Teams

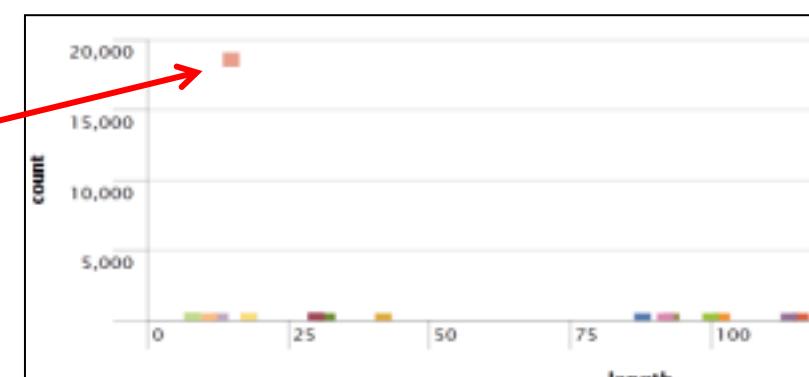


Need #1: Fraud Monitoring and Detection

- ▶ Advanced correlations
- ▶ Baseline & detect anomalies
- ▶ Deviations
- ▶ Real-time searches & alerts
- ▶ Automation

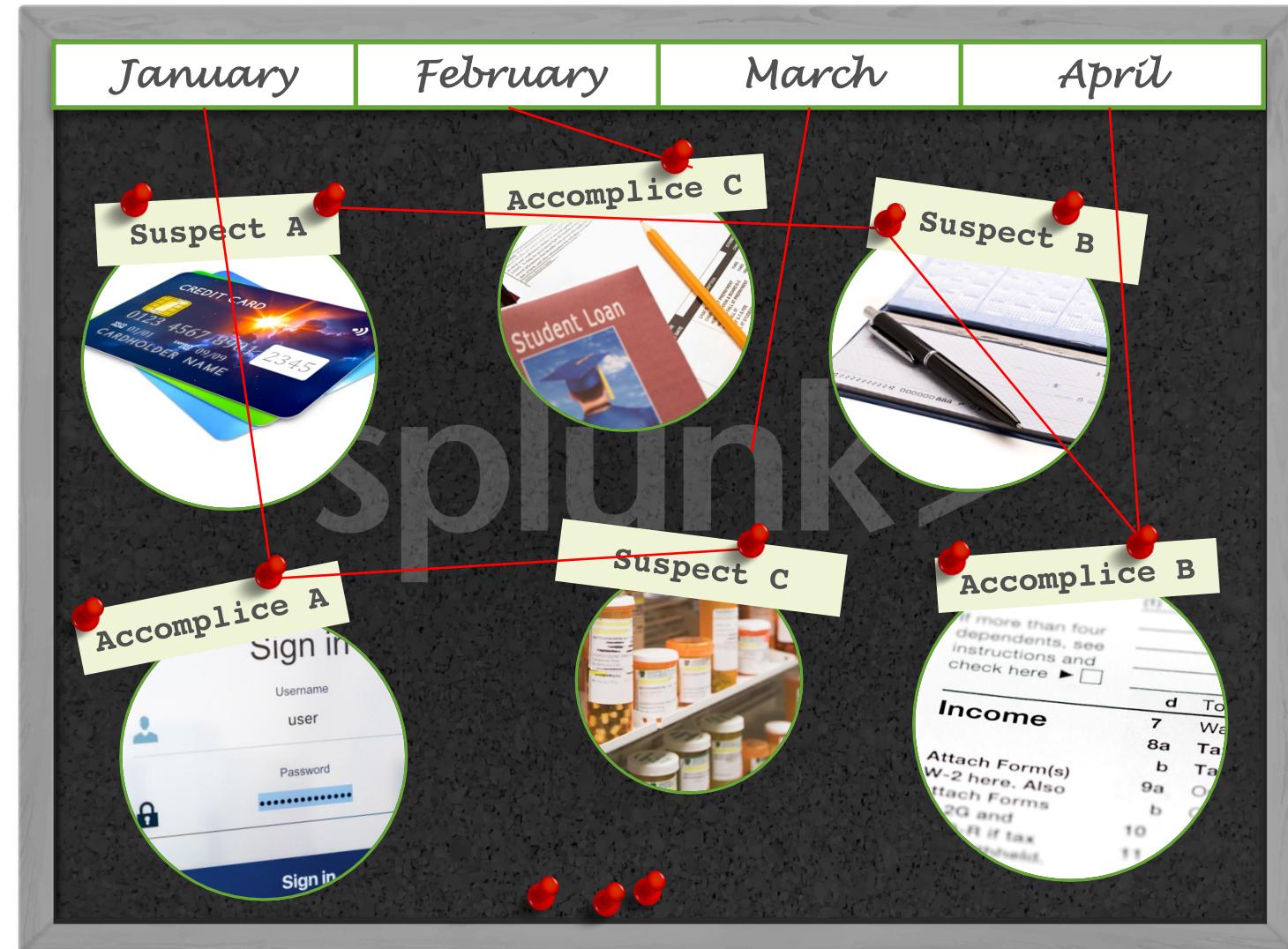


Spot outliers

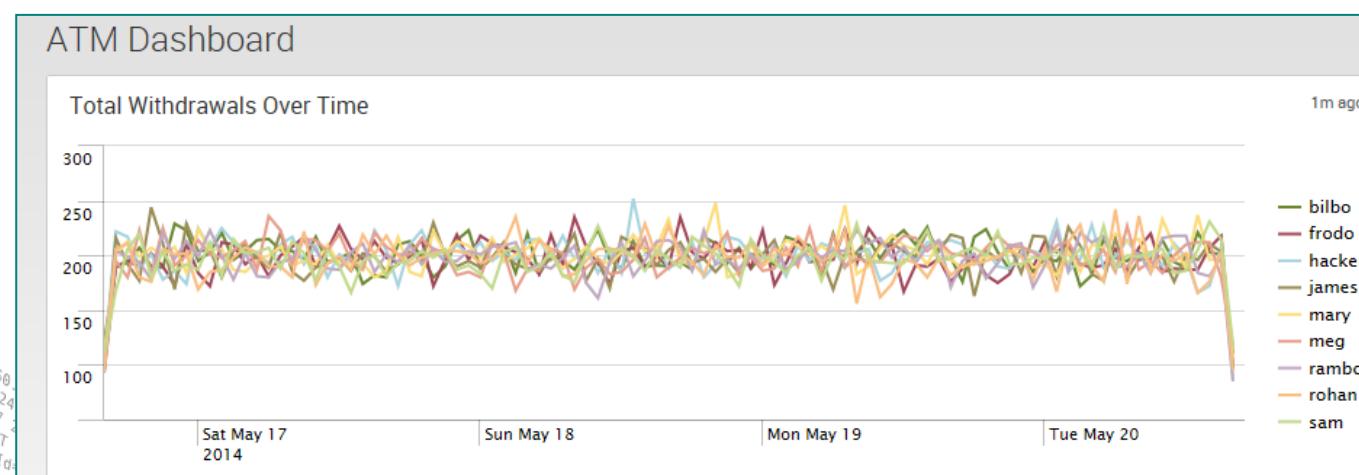
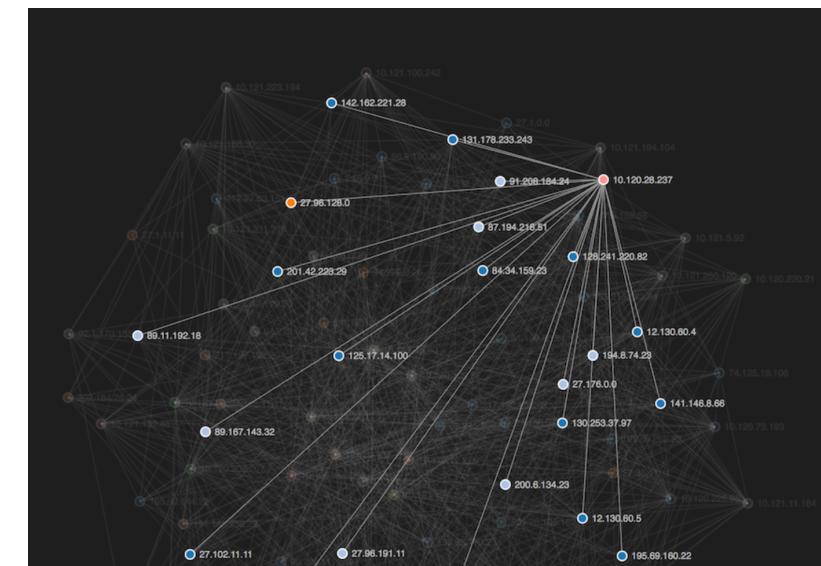
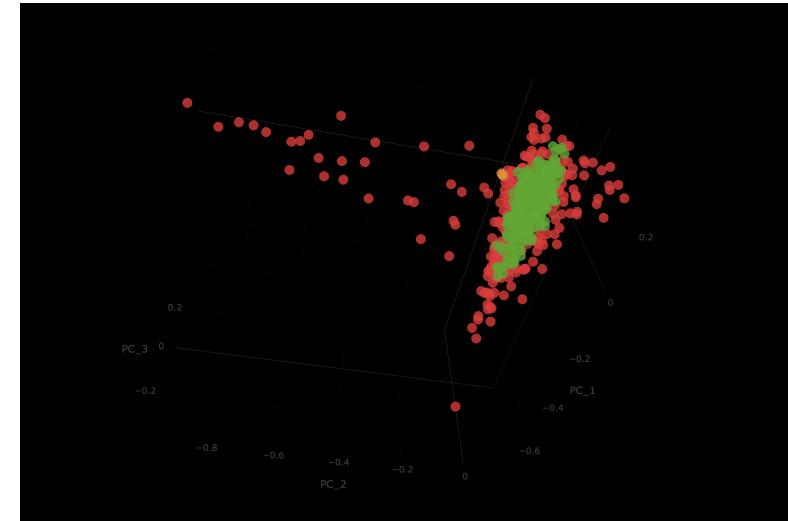


Need #2 – Fraud Investigations

- ▶ Pivot
- ▶ Patterns
- ▶ Past



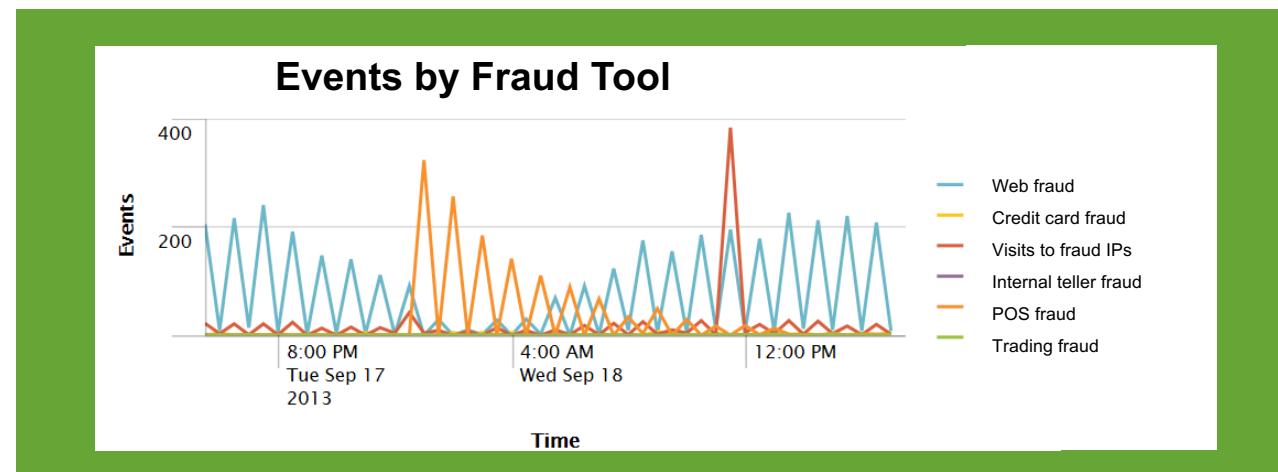
Need #3 – Fraud Analytics and Reporting



Need #4: Enhance Existing Fraud Tools

Sample Splunk Summary Index

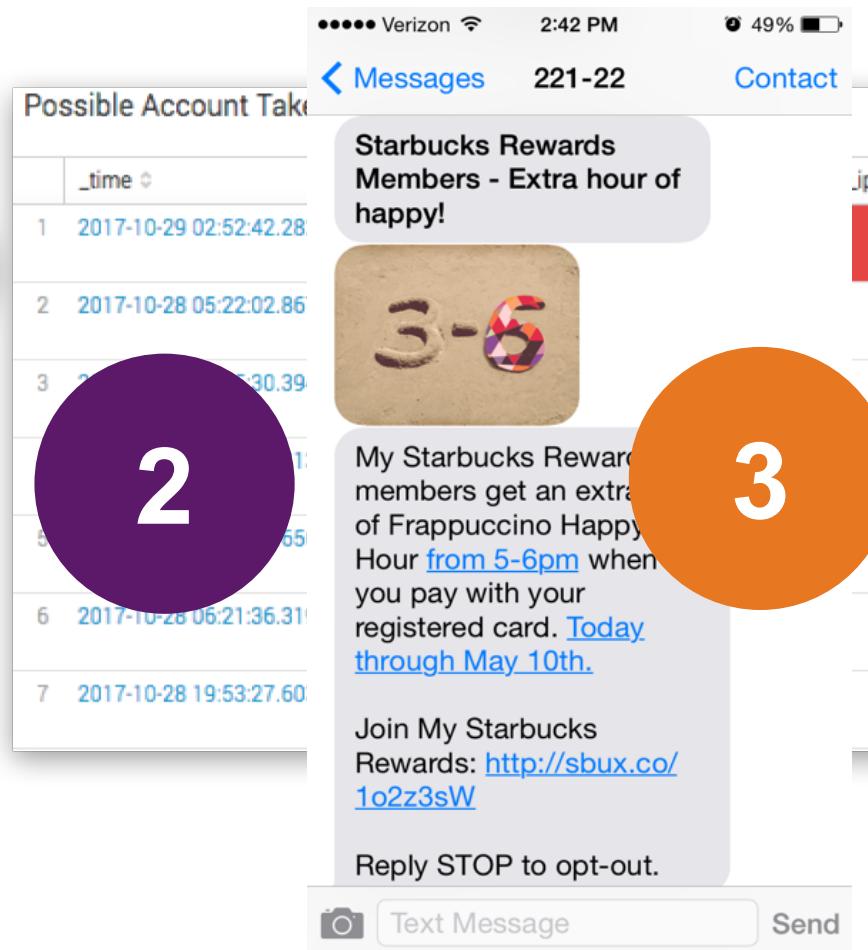
Session ID	Web fraud risk score	Credit card risk score	Threat Intel risk score	Splunk Total
1234567	0	2	0	2
7654321	6	9	15	30
1231789	1	2	0	3



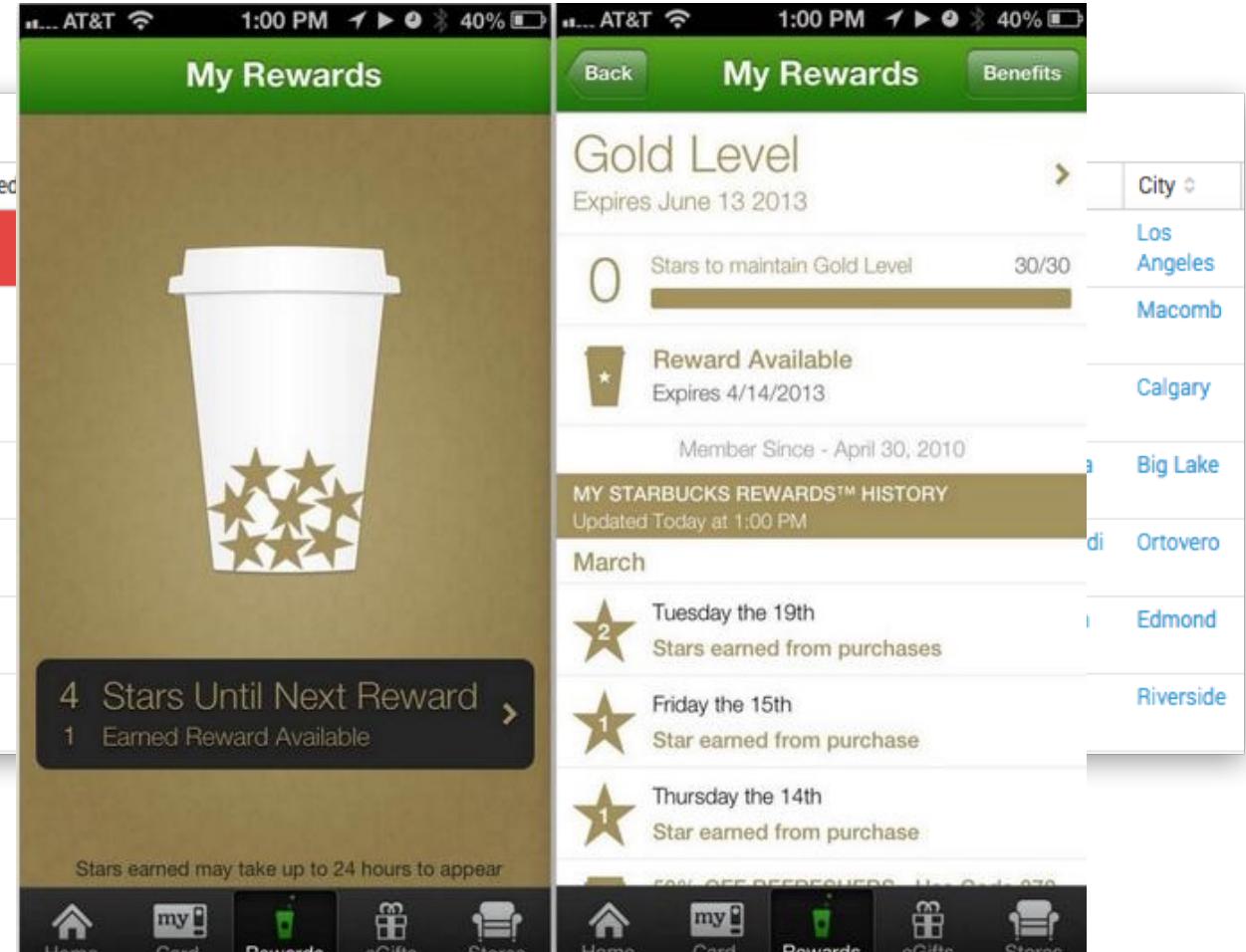
Account Takeover (ATO) Example

Monitor Logins from Unusual IPs/Locations

1



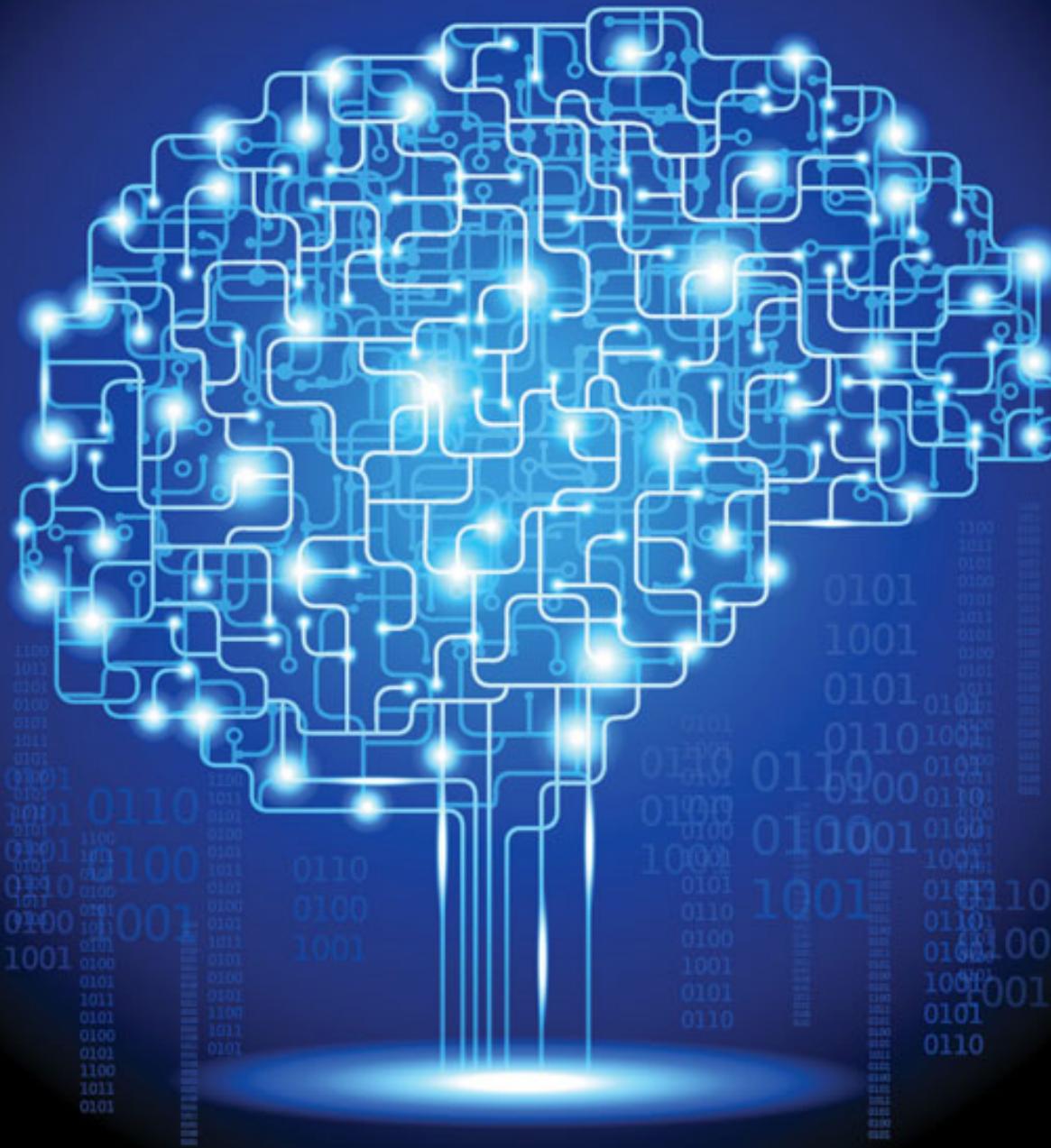
3



What is Machine Learning?

I, for one, welcome our ____ overlords.





Machine Learning

Automating analytical model building using algorithms that iteratively learn from data without requiring explicit programming

Evolution of Security Correlation, Advanced Analytics & ML



N-Dimensional Advanced – Data Science

- Shift from heavy manual tagging and rule building alone,
 - Machine learning and data science for UEBA
 - Enhances analyst capabilities to identify **unknown** threats



Multi-Dimensional – Analytics

- Hybrid model developed as adversaries circumvent basic correlation
 - Goal to reduce false positives
 - Thresholds and combinations of rules developed.
 - Behavioral models, statistics and patterns not signatures alone



Two-Dimensional – Correlation

- Regex/pattern-matching for strings
 - Used in anti-malware, IDS/IPS, DLP and basic/legacy SIEM
 - Use of string matching to search a binary file to identify type of threat
 - Enhanced capability to identify **previously known** threats and host enumeration



One-Dimensional – Correlation

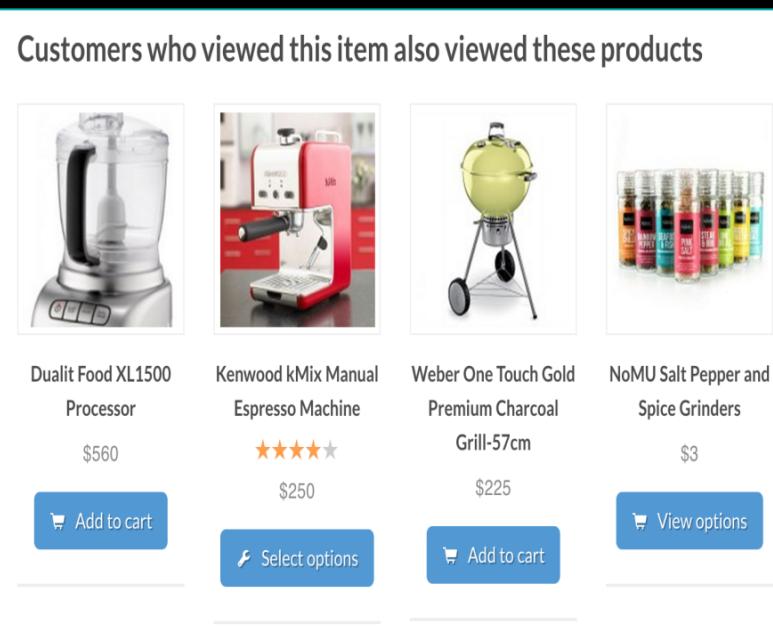
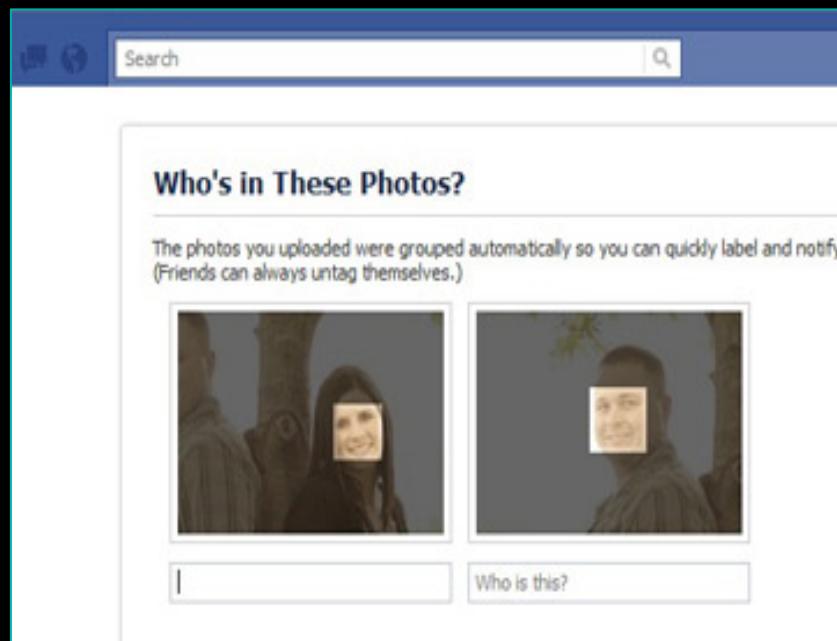
- Fast and efficient basic matching eg. domains IP addresses, user-agent, MD5 file hashes
 - Boolean operators to identify if signature is on a black/white list.
 - Common usage in most firewall and IDS tools

130, 68, 4
128, 241, 220, 82
1st, 317, 27, 160,
OWS NT 5.1; 5
itemId=EST-cup-shopping
://buttcup.com/Ca
to?action=purchase&
opping.com/Butt
10

Data Volume & Velocity

ML Examples IRL

It's everywhere



Solving Problems With Machine Learning

Anomaly Detection



- ▶ Past behavior
 - ▶ User vs Group
 - ▶ Unusual changes

Predictive Analytics



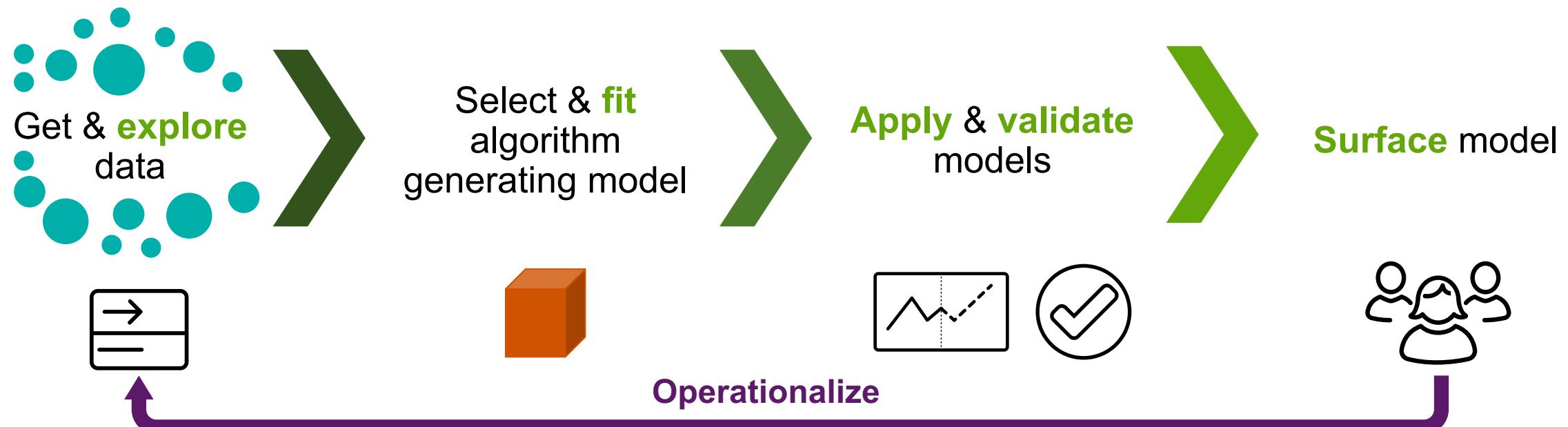
- ▶ Trend forecasting
 - ▶ Planning
 - ▶ Early warning

Clustering

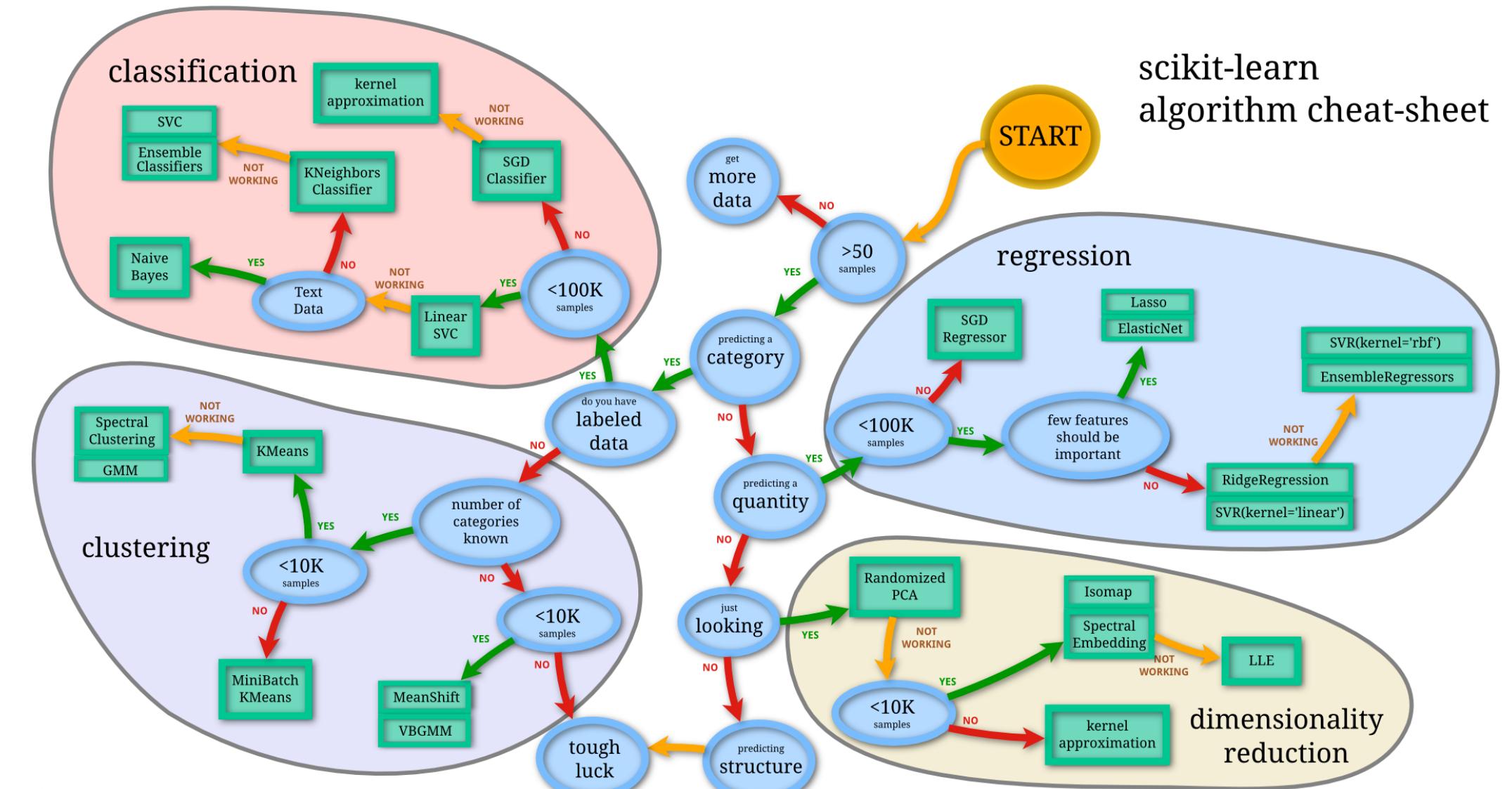


- ▶ Identify peer groups
 - ▶ Event correlation
 - ▶ Behavioral analytics

The ML Process



scikit-learn algorithm cheat-sheet



Back

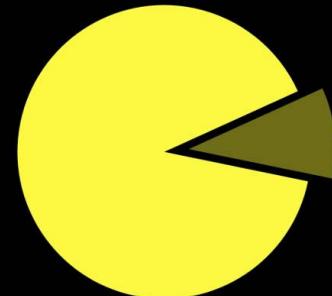
scikit
learn

Exploratory Data Analysis

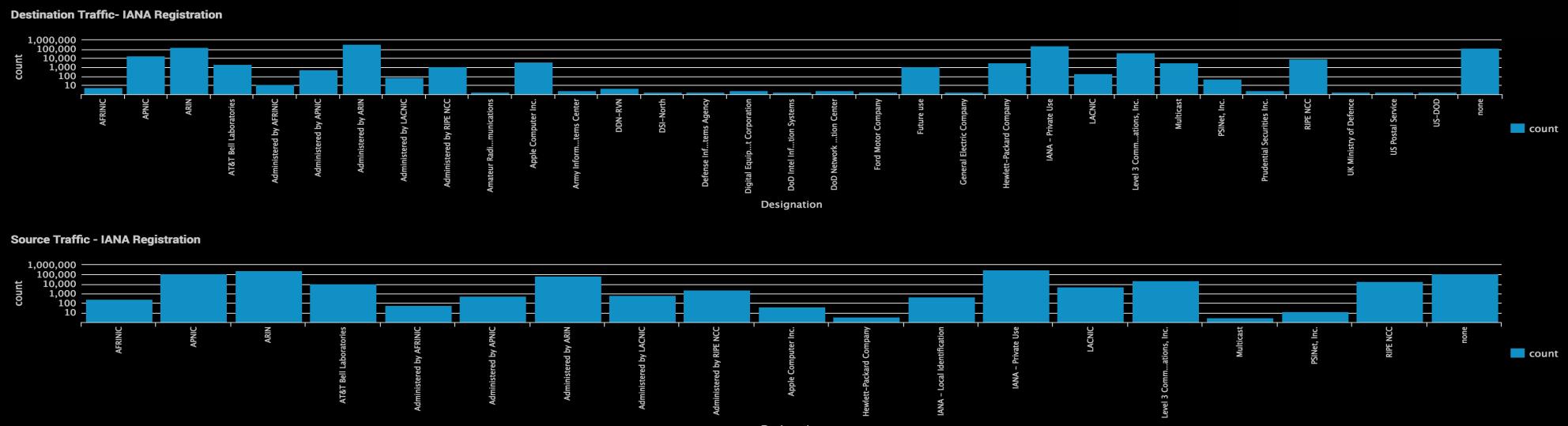
Utilizing the Splunk platform for data science

Visualization & Creating Context (EDA)

- ▶ **Visualization** is a powerful EDA tool
 - Not everything can be described as bits, bytes, plaintext or pie charts.
 - ▶ **Correlation** to add context to your data during the EDA process

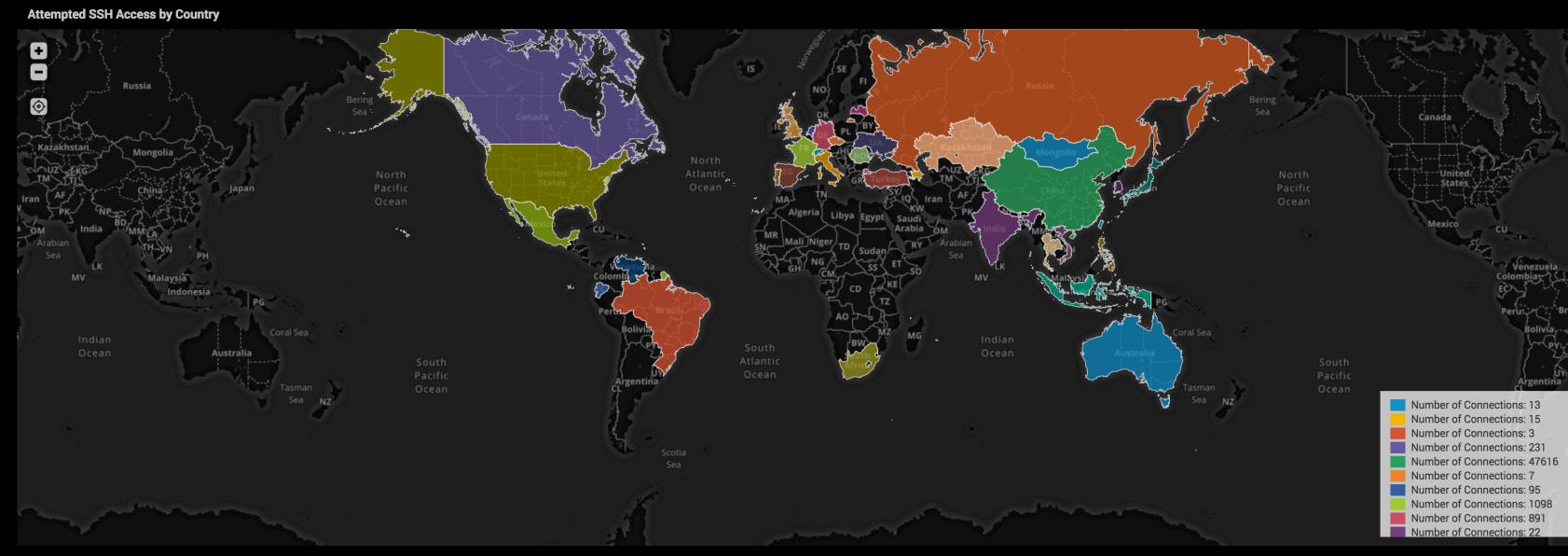


- PERCENTAGE OF PIE CHART RESEMBLING PAC MAN
- PERCENTAGE OF PIE CHART NOT RESEMBLING PAC MAN



Geographical EDA - Visualization

- ▶ Visualization useful for exploring multi-dimensional data
 - ▶ Tells a story about the data you can't describe in words
 - ▶ “Where are connections ‘originating’, and how often?”



Number of Connections: 47616

Patient Claims, Cost and Diagnosis Anomaly Investigator - 3D

Edit Export ...

Clustering Algorithm

KMeans k=18

Select time window

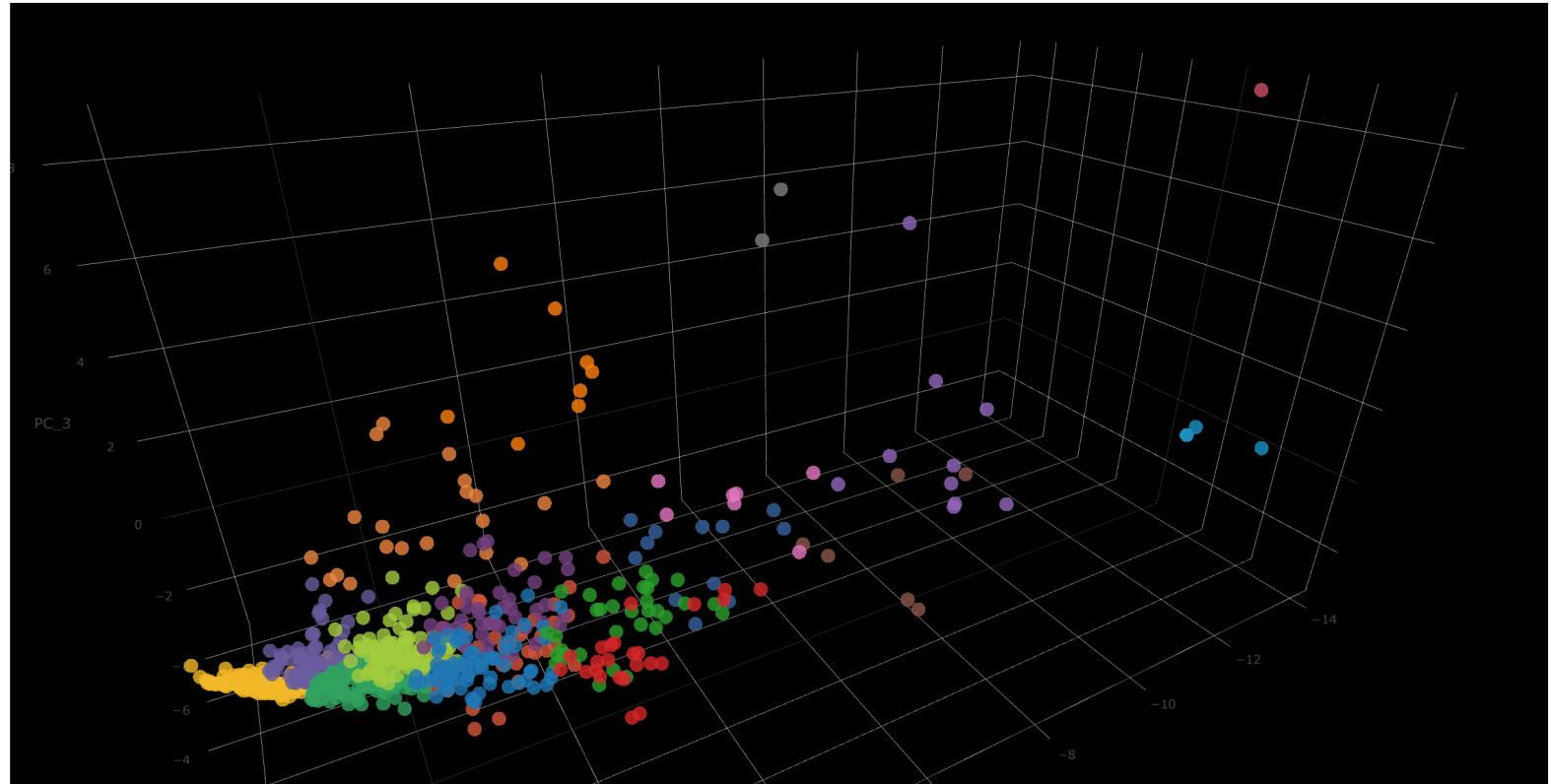
Last 7 days

Submit

Hide Filters

[Reset Dashboard](#)

Clustered Claims Data by: Total \$ amount paid out, Insurance \$ cost, Patient co-pay amount, Primary diagnosis codes used, Secondary diagnosis codes used, Drug codes used.



Detected Anomalies:

	PC_1 (x) ◊	PC_2 (y) ◊	PC_3 (z) ◊	cluster ◊	ENROLID ◊	TOTCOST ◊	copaytot ◊	ingtot ◊	netpaytot ◊	num_drug ◊	num_dx ◊	num_proc ◊
1	-13.9460300716	1.23333181943	8.66409981836	10(1 elements)	853532301	175370.98	778.15	9067.79	165525.04	10	17	72
2	-7.28332188576	-6.80316072015	4.81332180042	7(2 elements)	884268802	55297.46	638.34	24346.42	30312.7	22	23	32
3	-8.20940917125	-8.55247798253	5.66966119146	7(2 elements)	2059938602	61514.4	606.31	27938.93	32969.16	39	13	30
4	-13.1334643037	2.24187114206	0.225561438913	13(4 elements)	1064879704	91184.11	56.89	6551.5	84575.72	62	46	141
5	-11.8554131149	6.11646101014	1.87965286941	13(4 elements)	25433641701	109547.29	150.89	730.97	108665.43	15	50	145
6	-12.3691516297	0.24177114206	0.22556114206	10(1 elements)	1664979704	194.11	56.89	6551.5	21575.79	60	16	141

“Machine Generated Data is a Definitive Record of Human-to-Machine and Machine-to-Machine Interaction”

Data defines reality

Now What?

**"We are the music makers,
And we are the dreamers of dreams"**



Collect & Normalize Inventory, Standards, and Data



Assets

Do you balance your checkbook?



- ▶ Device ID (MAC)
- ▶ Ecosystem
- ▶ Data Driven
- ▶ Risk Based Approach

Take Inventory

More than just assets

Access Points

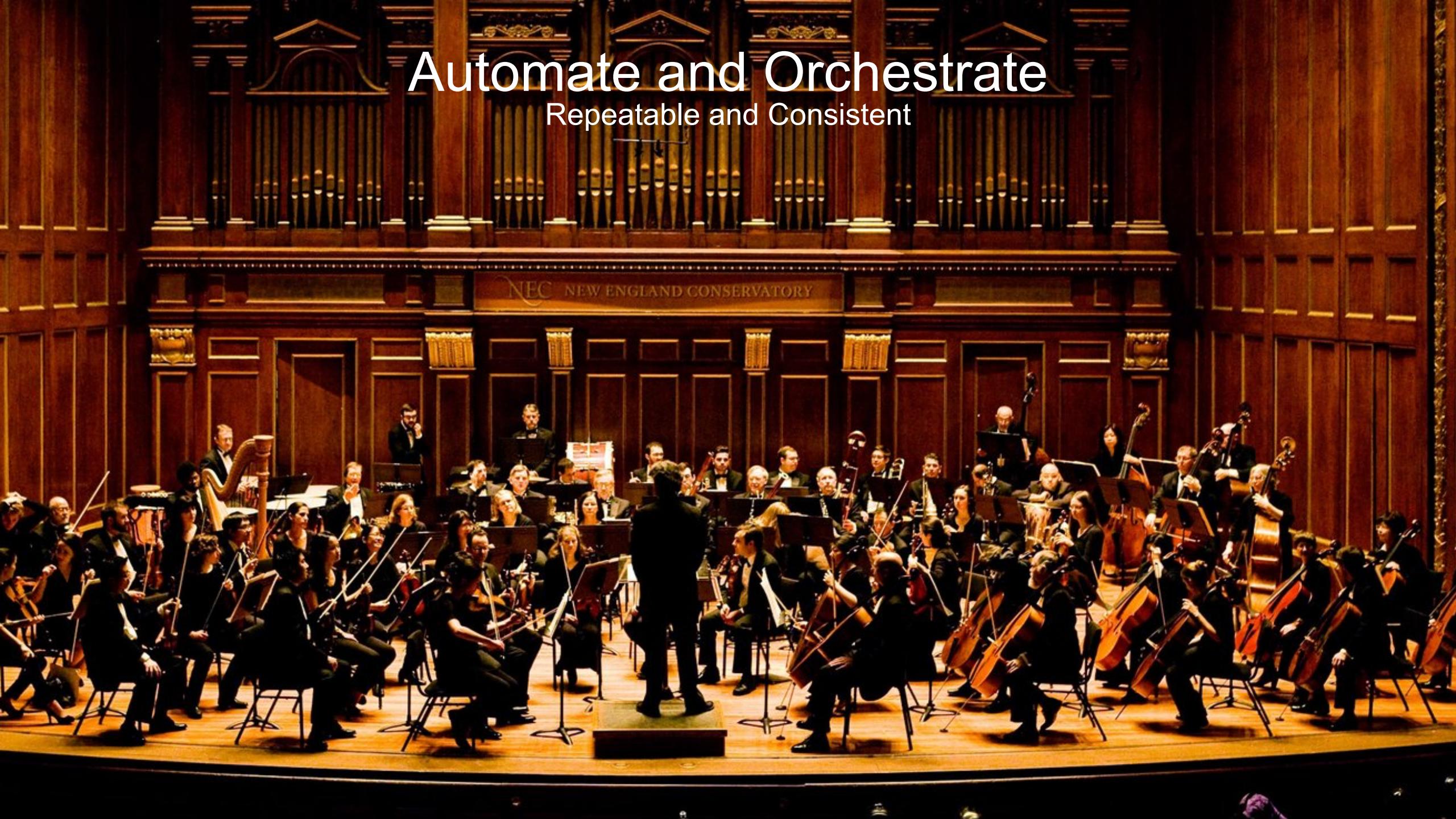


Egress/Ingress Data





Enrich
Context and Impact



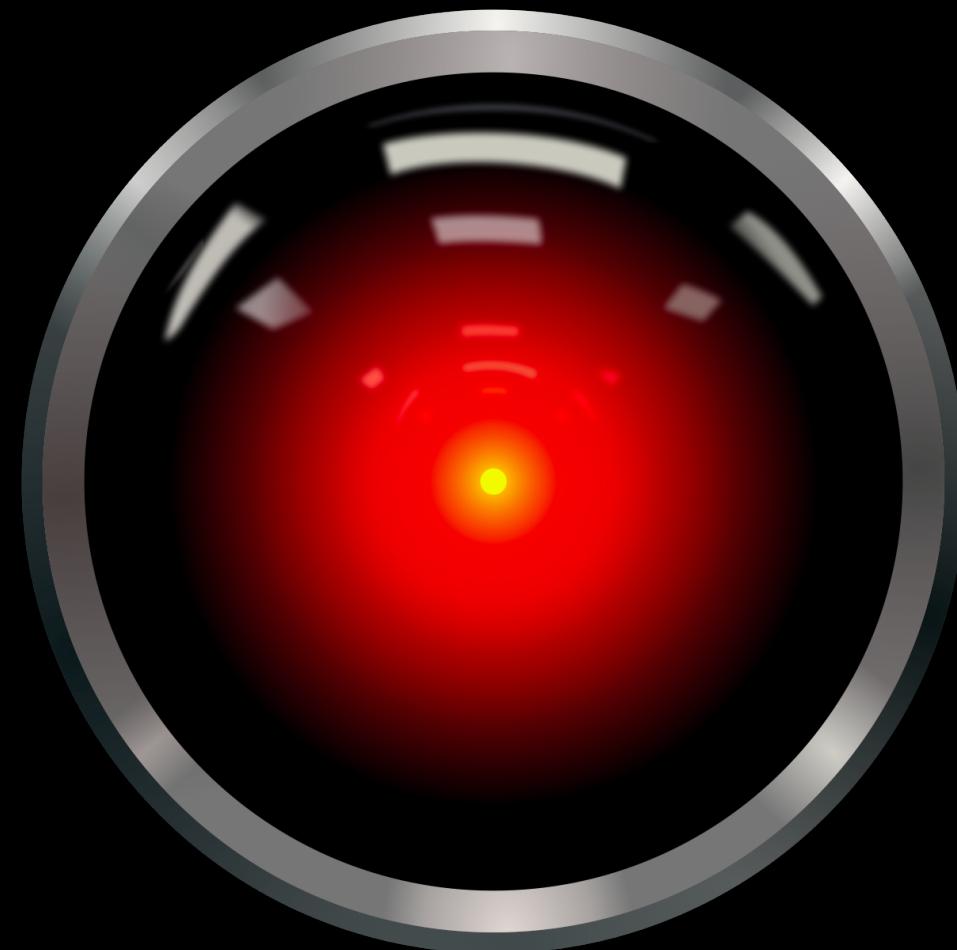
Automate and Orchestrate

Repeatable and Consistent

Machine Learning

10 Print "hello"

20 Go to 10



What Does a “Clean” Network Look Like?

“Machine Generated Data is a Definitive Record of Human-to-Machine and Machine-to-Machine Interaction”

Data defines reality

Splunk Demo

Presented by Mathew J Joseff

Thank you

mjoseff@splunk.com

Don't forget to rate this session
in the .conf18 mobile app

