Solve Big Problems with ML

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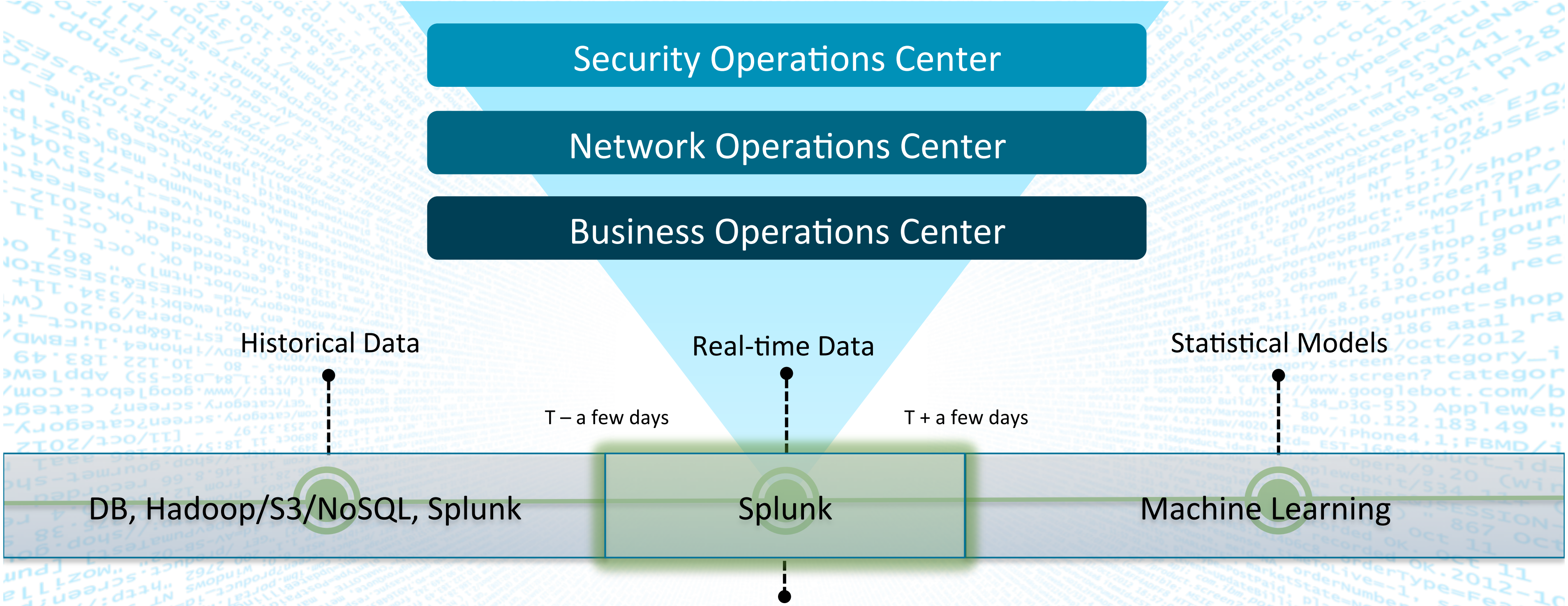
Abstract

- Sometimes problem-solving feels like fighting fires with no relief. Leverage machine learning to help solve the problem of problem solving. We will introduce general ML concepts & workflows, and guide you through the long slog of exploratory data analysis to figure out what relates to what. Then we'll walk you through how to develop a systematic architecture to leverage ML models and improve your team's problem-solving capabilities. We'll talk about big data architectures, how to fit models on historical data and apply them in real time. We will close with a demonstration of ML capabilities in Splunk.

Why do we need ML?



Security Operations Center

Network Operations Center

Business Operations Center

Historical Data

Real-time Data

Statistical Models

T – a few days

T + a few days

DB, Hadoop/S3/NoSQL, Splunk

Splunk

Machine Learning

Why is this so challenging using traditional methods?

- **DATA IS STILL IN MOTION**, still in a **BUSINESS PROCESS**.
- Enrich real-time **MACHINE DATA** with structured **HISTORICAL DATA**
- Make decisions **IN REAL TIME** using **ALL THE DATA**
- Combine **LEADING** and **LAGGING INDICATORS** (KPIs)

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Machine Learning Customer Success

TELUS
Network Optimization
Detect & Prevent Equipment Failure

NTT docomo
Security / Fraud Prevention

Telco
Prevent Cell Tower Failure
Optimize Repair Operations

Zillow®
Prioritize Website Issues
and Predict Root Cause

Entertainment Company
Predict Gaming Outages
Fraud Prevention

CONCANON™
INSIGHT ON DEMAND
Machine Learning Consulting Services

SCIANTA ANALYTICS
DEEP INSIGHT™
Analytics App built on ML Toolkit

Optimizing operations and business results

ML Toolkit Customer Use Cases

TELUS

Reduce customer service disruption with early identification of difficult-to-detect network incidents

Minimize cell tower degradation and downtime with improved issue detection sensitivity

Zillow®

Speed up website problem resolution by automatically ranking actions for support engineers

NTT docomo

Ensure mobile device security by detecting anomalies in ID authentication

Entertainment Company

Predict and avert potential gaming outage conditions with finer-grained detection

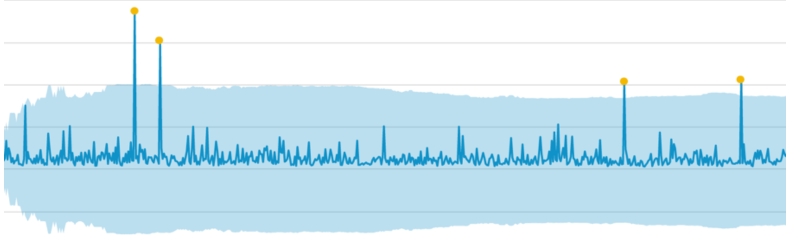
Prevent fraud by Identifying malicious accounts and suspicious activities

Telco

Improve uptime and lower costs by predicting/preventing cell tower failures and optimizing repair truck rolls

Detect Network Outliers

Reduced downtime + increased service availability = better customer satisfaction



ML Use Case

Monitor noise rise for 20,000+ cell towers to increase service and device availability, reduce MTTR

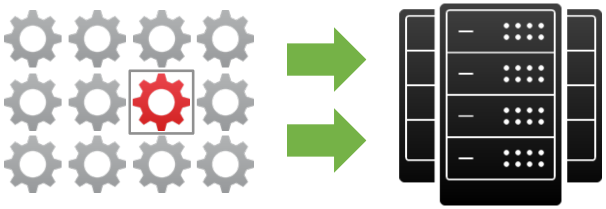
Technical overview

- A customized solution deployed in production based on outlier detection.
- Leverage previous month data and voting algorithms

"The ability to model complex systems and alert on deviations is where IT and security operations are headed … Splunk Machine Learning has given us a head start..."

Reliable website updates

Proactive website monitoring leads to reduced downtime



ML Use Case

- Very frequent code and config updates (1000+ daily) can cause site issues
- Find errors in server pools, then prioritize actions and predict root cause

Technical overview

- Custom outlier detection built using ML Toolkit Outlier assistant
- Built by Splunk Architect with no Data Science background

"Splunk ML helps us rapidly improve end-user experience by ranking issue severity which helps us determine root causes faster thus reducing MTTR and improving SLA

ML Use Cases

IT Ops: Predictive Maintenance

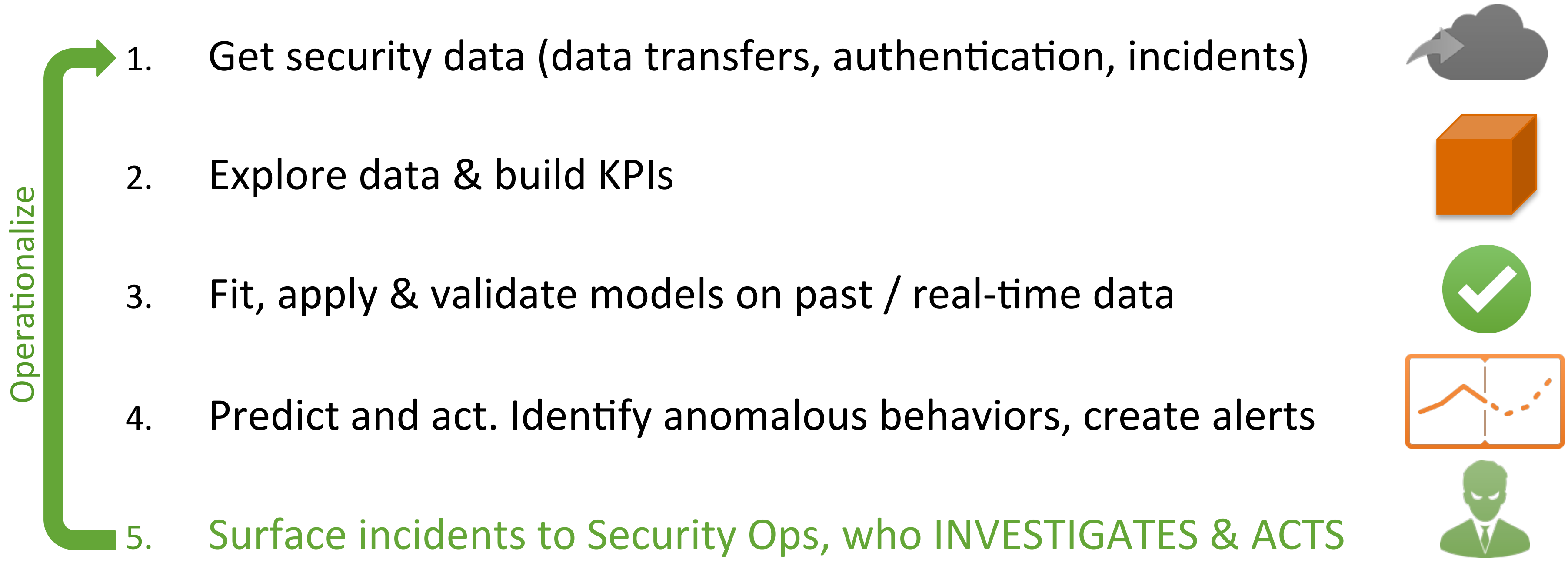
Problem: Network outages and truck rolls cause big time & money expense
Solution: Build predictive model to forecast outage scenarios, act pre-emptively & learn

Operationalize

1. Get resource usage data (CPU, latency, outage reports)
2. Explore data & build KPIs
3. Fit, apply & validate models on past / real-time data
4. Predict and act. Identify resource spikes, create alerts
5. Surface incidents to IT Ops, who INVESTIGATES & ACTS

Security: Find Insider Threats

Problem: Security breaches cause big time & money expense
Solution: Build predictive model to forecast threat scenarios, act pre-emptively & learn



1. Get security data (data transfers, authentication, incidents)
2. Explore data & build KPIs
3. Fit, apply & validate models on past / real-time data
4. Predict and act. Identify anomalous behaviors, create alerts
5. Surface incidents to Security Ops, who INVESTIGATES & ACTS

Business Analytics: Predict Customer Churn

Problem: Customer churn causes big time & money expense
Solution: Build predictive model to forecast possible churn, act pre-emptively & learn

Operationalize

1. Get customer data (set-top boxes, web logs, transaction history)
2. Explore data & build KPIs
3. Fit, apply & validate models on past / real-time data
4. Predict and act. Identify churning customers, create alerts
5. Surface incidents to Business Ops, who INVESTIGATES & ACTS

Summary: The ML Process

Problem: <Stuff in the world> causes big time & money expense
Solution: Build predictive model to forecast <possible incidents>, act pre-emptively & learn

Operationalize

1. Get all relevant data to problem
2. Explore data & build KPIs
3. Fit, apply & validate models on past / real-time data
4. Predict and act. Identify notable events, create alerts
5. Surface incidents to X Ops, who INVESTIGATES & ACTS

ML with Splunk

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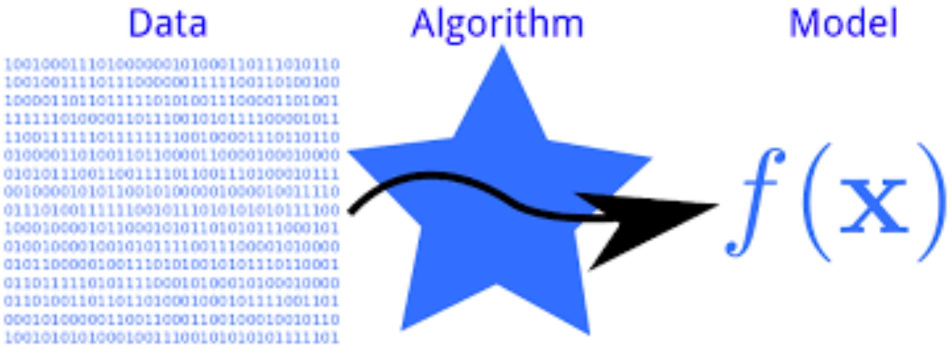
ML 101: What is it?

- Machine Learning (ML) is a process for generalizing from examples
  - Examples = example or "training" data
  - Generalizing = build "statistical models" to capture correlations
  - Process = ML is never done, you must keep validating & refitting models
- Simple ML workflow:
  - Explore data
  - FIT models based on data
  - APPLY models in production
  - Keep validating models



"All models are wrong, but some are useful."
- George Box

Building ML Apps

- An ML application is an app which uses ML to solve a business problem
- An algorithm is just one piece of a larger solution
- Example: Outage Forecasting app, with workflows, analytics & alerts
  - Personas: deliver insights to IT Ops
  - Data: all IT-relevant data (incl. tickets)
  - Analytics: compute KPIs from raw data ← 80% of work here
  - ML: correlate outages with traffic, latency, resource usage, etc.
- Keep in mind:
  - Who is this solution designed for? Does this solve their problem?
  - What data is needed? What KPIs do we have to monitor? Who builds KPIs?
  - How do we fit/apply models as part of the app? Who validates models?

Machine Learning and Advanced Analytics at Splunk

Splunk IT Service Intelligence™

Splunk User Behavior Analytics™

Purpose-built, turnkey-key analytics dedicated to managing IT services and security

Packaged Machine Learning

Easy to use ML integrated into standard day-to-day operations

splunk>enterprise

splunk>cloud

Integrated & custom analytics for any use case

Custom Machine Learning

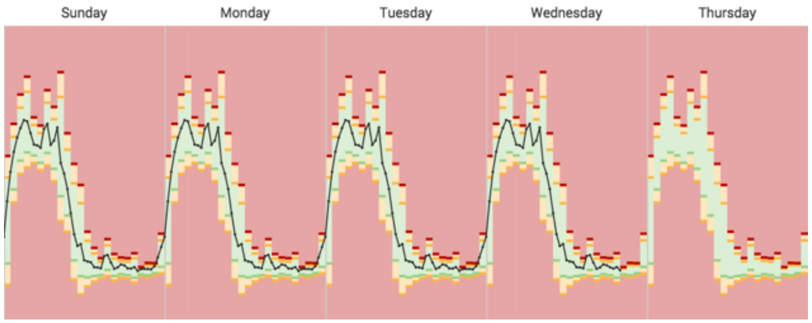
Predictive analytics tailored for a customer's specific environment and target use cases

From platform to packaged premium solutions

Machine Learning in Splunk ITSI

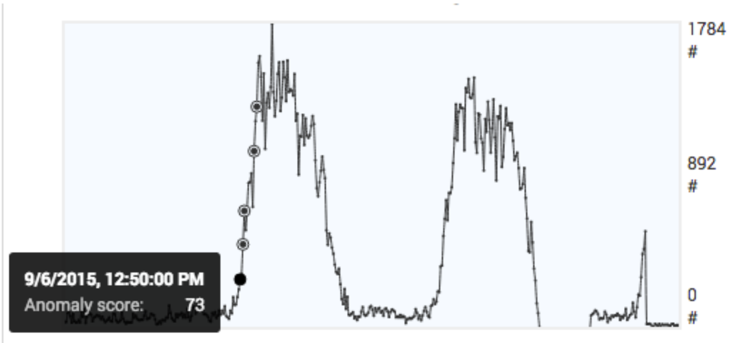
Adaptive Thresholding:

- Learn baselines & dynamic thresholds
- Alert & act on deviations
- Manage for 1000s of KPIs & entities
- Stdev/Avg, Quartile/Median, Range



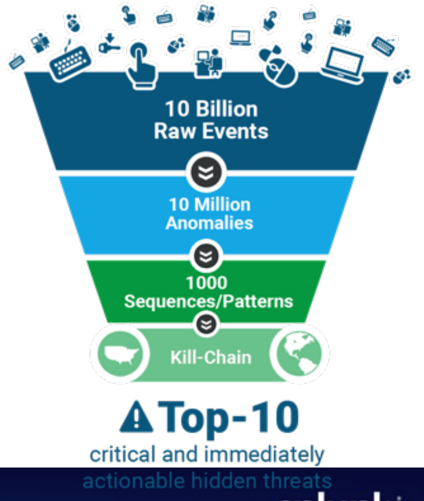
Anomaly Detection:

- Find "hiccups" in expected patterns
- Catches deviations beyond thresholds
- Uses advanced proprietary algorithm



Splunk User Behavior Analytics (UBA)

- Understand normal & anomalous behaviors for ALL users
- UBA detects Advanced Cyberattacks and Malicious Insider Threats
- Lots of ML under the hood:
  - Behavior Baselining & Modeling
  - Anomaly Detection (30+ models)
  - Advanced Threat Detection
- E.g., Data Exfil Threat:
  - "Saw this strange login & data transfer for user mpittman at 3am in China…"
  - Surface threat to SOC Analysts



10 Billion
Raw Events

10 Million
Anomalies

1000
Sequences/Patterns

Kill-Chain

Top-10
critical and immediately
actionable hidden threats

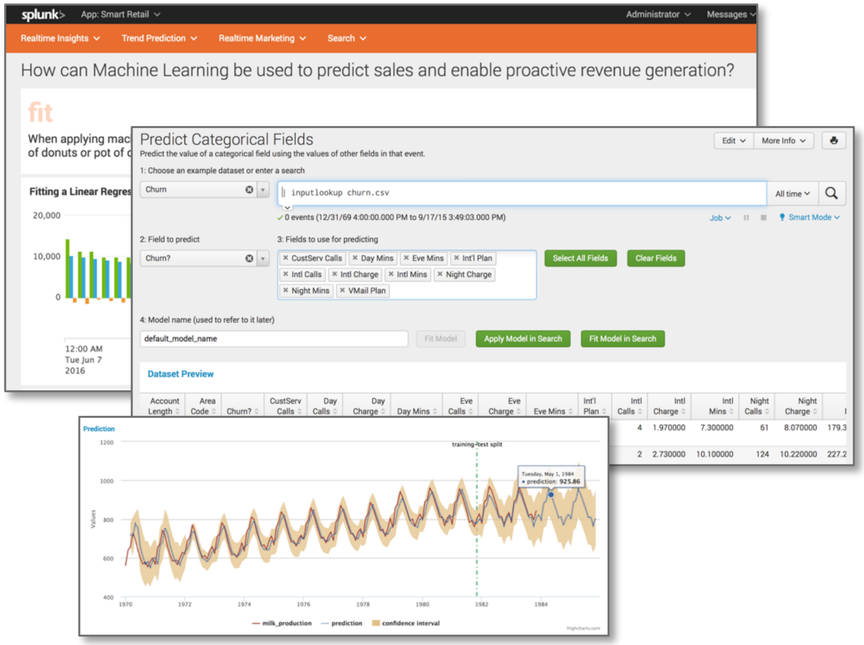
Splunk Machine Learning Toolkit

Assistants: Guide model building, testing & deployment for common objectives

Showcases: Interactive examples for typical IT, security, business, IoT use cases

SPL ML Commands: New commands to fit, test and operationalize models

Python for Scientific Computing Library: 300+ open source algorithms available for use



How can Machine Learning be used to predict sales and enable proactive revenue generation?

When applying mac
of donuts or pot of c

Predict Categorical Fields

Predict the value of a categorical field using the values of other fields in that event.

1: Choose an example dataset or enter a search

Churn

```
| inputlookup churn.csv
```

✓ 0 events (12/31/69 4:00:00.000 PM to 9/17/15 3:49:03.000 PM)

2: Field to predict

Churn?

3: Fields to use for predicting

CustServ Calls, Day Mins, Eve Mins, Int'l Plan, Intl Calls, Intl Charge, Intl Mins, Night Charge, Night Mins, VMail Plan

4: Model name (used to refer to it later)

default_model_name

Account Length	Area Code	Churn?	CustServ Calls	Day Calls	Day Charge	Day Mins	Eve Calls	Eve Charge	Eve Mins	Int'l Plan	Intl Calls	Intl Charge	Intl Mins	Night Calls	Night Charge	I
											4	1.970000	7.300000	61	8.070000	179.3
											2	2.730000	10.100000	124	10.220000	227.2

Tuesday, May 1, 1984
• prediction: 925.86

Build custom analytics for any use case

Building ML Apps

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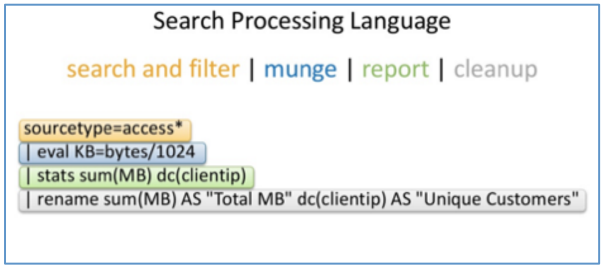
1. Where's the Data & Who Needs it?

- Prioritize & solve the big problems:
  - Cell tower or critical infrastructure failing
  - Hard-to-find, high-risk behaviors
- Use ALL data to help solve problems:
  - E.g., can't identify app crashes without app data
  - Enrich machine data with tickets, app data, DB, etc.

- Find the stakeholders:
  - Who owns these problems?
  - Who will invest in you to build a solution?
- Solutions not science projects:
  - If it's mission-critical, treat it as such (Dev -> QA -> Prod)
  - Prototype: build simple MVPs, show value, iterate

2. Explore Data & Prototype in Splunk

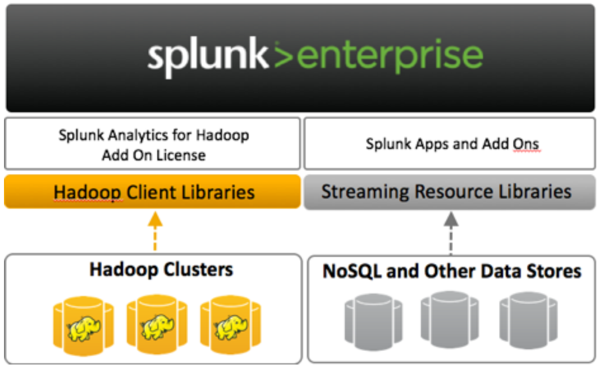
- Data Science is 80% Data Exploration – Build KPIs!!
- Is the data in Splunk?
  - Munge it in Splunk
  - ML prototype in Splunk
  - Model analysis/validation: Splunk + other tools
  - Operationalize in Splunk
- Data not in Splunk? Why not?
  - 1000+ Splunk apps & add-ons
  - Get DB data using DB Connect
  - Get Hadoop data using Hadoop Connect
  - Get NoSQL data using Splunk apps/add-ons



Search Processing Language

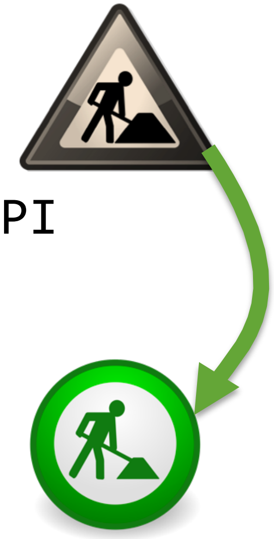
search and filter | munge | report | cleanup

```
sourcetype=access*
| eval KB=bytes/1024
| stats sum(MB) dc(clientip)
| rename sum(MB) AS "Total MB" dc(clientip) AS "Unique Customers"
```


splunk>enterprise
Splunk Analytics for Hadoop Add On License
Splunk Apps and Add Ons
Hadoop Client Libraries
Streaming Resource Libraries
Hadoop Clusters
NoSQL and Other Data Stores

3. Fit, Apply & Validate Models

- **ML SPL** – New grammar for doing ML in Splunk
- **`fit`** – fit models based on training data
  - *`[training data]`* `|` **`fit`** `LinearRegression costly_KPI from feature1 feature2 feature3 into my_model`
- **`apply`** – apply models on testing and production data
  - *`[testing/production data]`* `|` **`apply`** `my_model`
- **Validate Your Model** (The Hard Part)
  - Why hard? Because statistics is hard! Also: model error ≠ real world risk.
  - Analyze residuals, mean-square error, goodness of fit, cross-validate, etc.
  - Take Splunk's Analytics & Data Science Education course

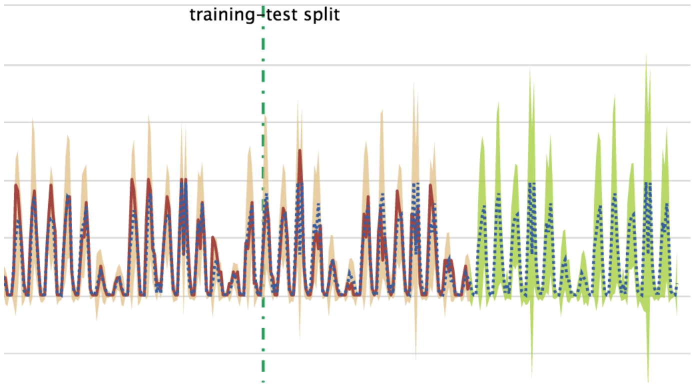


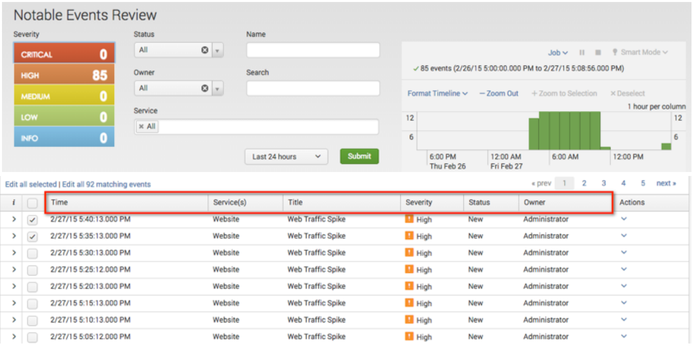
LOTS of new algorithms in ML Toolkit v2.0

- ARIMA
- SGDClassifier
- SGDRegressor
- DecisionTreeClassifier
- DecisionTreeRegressor
- AdaBoostRegressor
- BernoulliNB
- Birch
- DBSCAN
- ElasticNet
- FieldSelector
- GaussianNB
- KMeans
- KernelPCA
- KernelRidge
- Lasso
- LinearRegression
- LogisticRegression
- OneClassSVM
- PCA
- RandomForestClassifier
- RandomForestRegressor
- Ridge
- SVM
- SpectralClustering
- TFIDF
- StandardScaler

4. Predict & Act

- Forecast KPIs & predict notable events
  - When will my system have a critical error?
  - In which service or process?
  - What's the probable root cause?
- How will people act on predictions?
  - Is this a Sev 1/2/3 event? Who responds?
  - Deliver via Notable Events or dashboard?
  - Human response or automated response?
- How do you improve the models?
  - Iterate, add more data, extract more features
  - Keep track of true/false positives





Notable Events Review

Severity

CRITICAL	0
HIGH	85
MEDIUM	0
LOW	0
INFO	0

Status: All

Owner: All

Service: × All

Name:

Search:

Last 24 hours

✓ 85 events (2/26/15 5:00:00.000 PM to 2/27/15 5:08:56.000 PM)

Edit all selected | Edit all 92 matching events

« prev 1 2 3 4 5 next »

i	□	Time	Service(s)	Title	Severity	Status	Owner	Actions
›	☑	2/27/15 5:40:13.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	☑	2/27/15 5:35:13.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	□	2/27/15 5:30:13.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	□	2/27/15 5:25:12.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	□	2/27/15 5:20:13.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	□	2/27/15 5:15:13.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	□	2/27/15 5:10:13.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄
›	□	2/27/15 5:05:12.000 PM	Website	Web Traffic Spike	! High	New	Administrator	⌄

5. Operationalize Your Models

- Operationalizing closes the loop of the ML Process:

Operationalize

1. Get data
2. Explore data & fit models
3. Apply & validate models
4. Forecast KPIs & events
5. Surface incidents to Ops team

- When you deliver the outcome, keep track of the response
  - Human-generated response (detailed journal logs, etc)
  - Machine-generated response (workflow actions, etc)
  - External knowledge (closed tickets data, DB records, etc)
- Then operationalize: feed back Ops analysis to data inputs, repeat
- Lots of hard work & stats, but lots of value will come out.

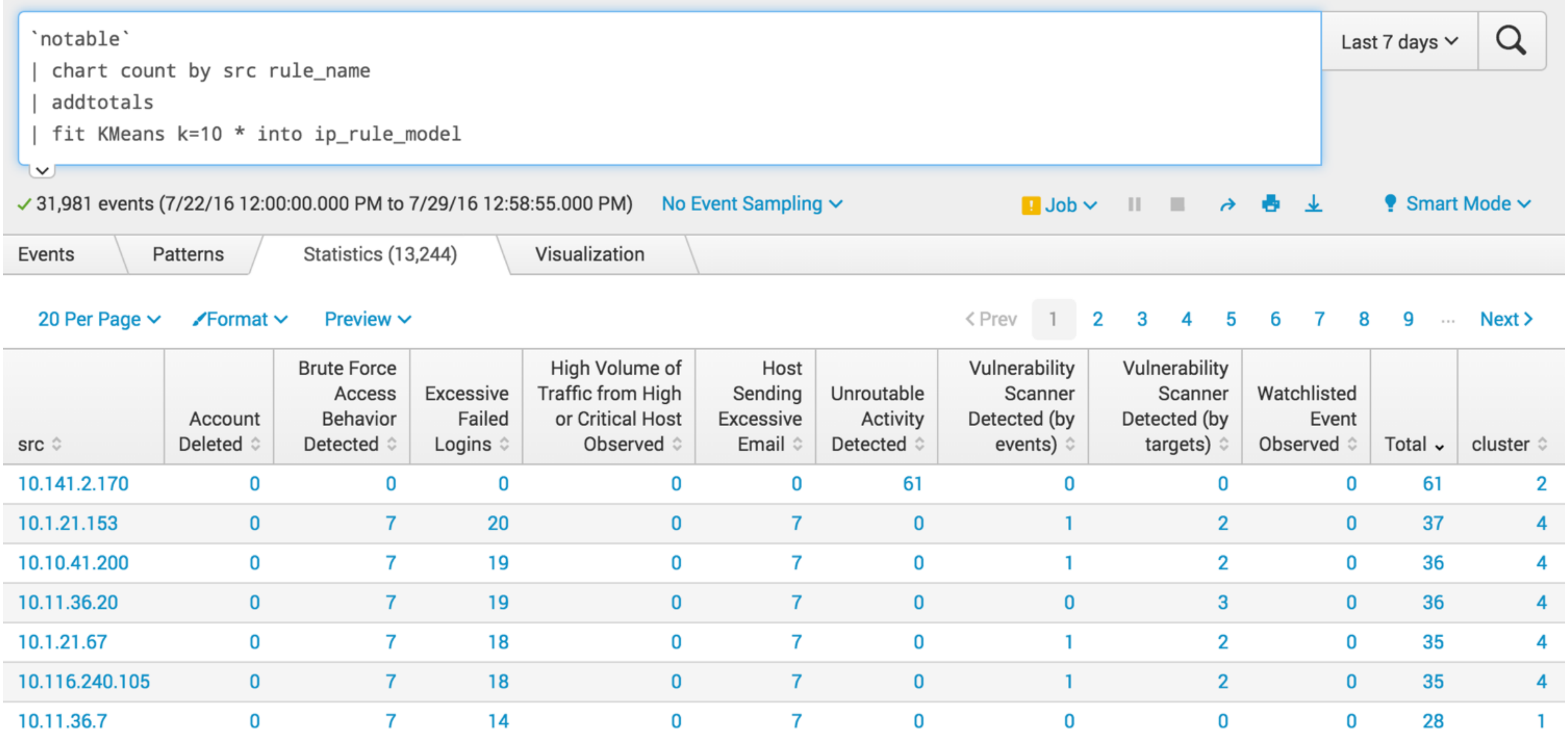
Show me the ML!

Example ML Architectures

- Example 1: Build models on Enterprise Security alerts
  - Data comes from: Splunk + ES indexes (index=notable, index=risk)
  - Fit workflow: fit models based on user/entity behavior
  - Apply workflow: apply model scores as part of correlation search
  - Who validates: SOC content developers
  - Action/Outcome: Deliver alerts to SOC analysts, reduce false positives & alert volume

- Example 2: Build models across clickstream + transaction data
  - Data comes from: Splunk + DB/Hadoop/NoSQL
  - Fit workflow: fit models based on customer behavior & actions
  - Apply workflow: apply model scores as part of regular jobs
  - Who validates: Business analysts + Splunk power users
  - Action/Outcome: Target qualified marketing leads, reduce customer churn

Example 1: Cluster IPs based on Security Alerts

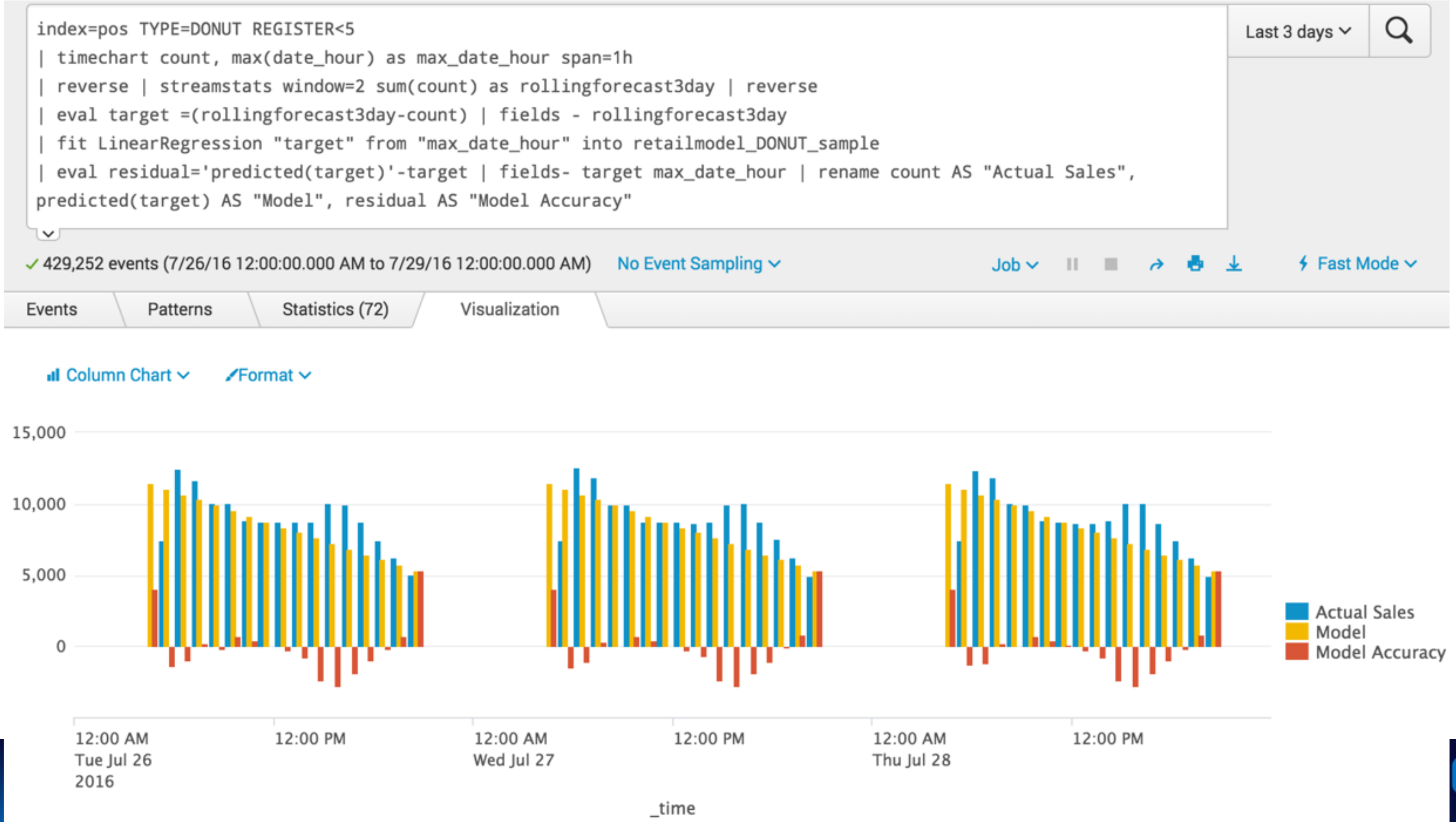


```
`notable`
| chart count by src rule_name
| addtotals
| fit KMeans k=10 * into ip_rule_model
```

✓ 31,981 events (7/22/16 12:00:00.000 PM to 7/29/16 12:58:55.000 PM)

src	Account Deleted	Brute Force Access Behavior Detected	Excessive Failed Logins	High Volume of Traffic from High or Critical Host Observed	Host Sending Excessive Email	Unroutable Activity Detected	Vulnerability Scanner Detected (by events)	Vulnerability Scanner Detected (by targets)	Watchlisted Event Observed	Total	cluster
10.141.2.170	0	0	0	0	0	61	0	0	0	61	2
10.1.21.153	0	7	20	0	7	0	1	2	0	37	4
10.10.41.200	0	7	19	0	7	0	1	2	0	36	4
10.11.36.20	0	7	19	0	7	0	0	3	0	36	4
10.1.21.67	0	7	18	0	7	0	1	2	0	35	4
10.116.240.105	0	7	18	0	7	0	1	2	0	35	4
10.11.36.7	0	7	14	0	7	0	0	0	0	28	1

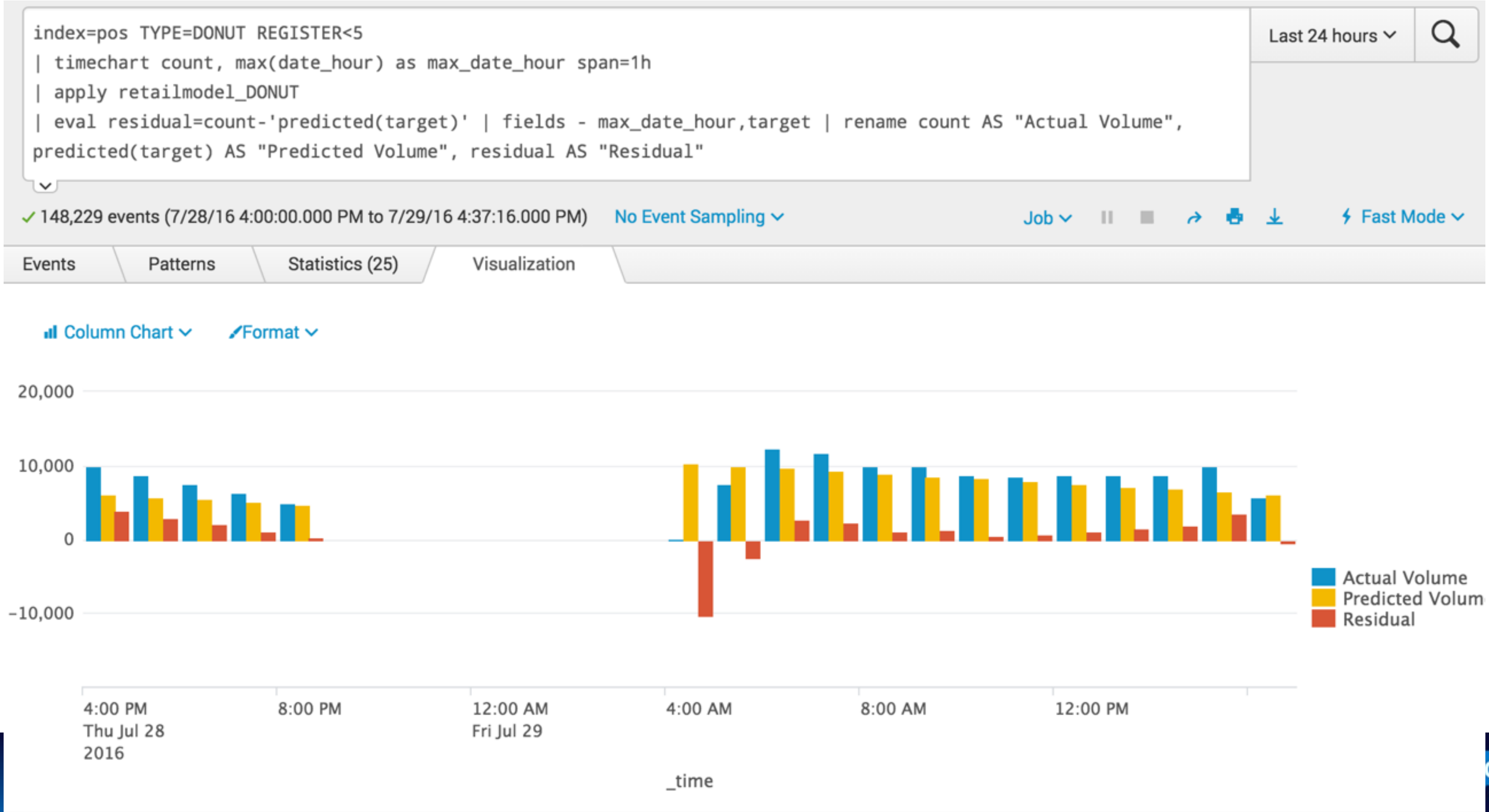
Example 2: Fit Regression Model on Sales Data



```
index=pos TYPE=DONUT REGISTER<5
| timechart count, max(date_hour) as max_date_hour span=1h
| reverse | streamstats window=2 sum(count) as rollingforecast3day | reverse
| eval target =(rollingforecast3day-count) | fields - rollingforecast3day
| fit LinearRegression "target" from "max_date_hour" into retailmodel_DONUT_sample
| eval residual='predicted(target)'-target | fields- target max_date_hour | rename count AS "Actual Sales",
predicted(target) AS "Model", residual AS "Model Accuracy"
```

✓ 429,252 events (7/26/16 12:00:00.000 AM to 7/29/16 12:00:00.000 AM)

Example 2: Apply Regression Model on Sales Data



```
index=pos TYPE=DONUT REGISTER<5
| timechart count, max(date_hour) as max_date_hour span=1h
| apply retailmodel_DONUT
| eval residual=count-'predicted(target)' | fields - max_date_hour,target | rename count AS "Actual Volume",
predicted(target) AS "Predicted Volume", residual AS "Residual"
```

✓ 148,229 events (7/28/16 4:00:00.000 PM to 7/29/16 4:37:16.000 PM)

Next Steps with Splunk ML

- **Reach out to your Tech Team! We can help architect ML solutions.**
- ITSI: surface anomalous alerts & outliers, better root-cause analysis
  - Free ITSI Cloud Sandbox! http://splunk.force.com/SplunkCloud?prdType=ITSI
- UBA: track anomalous behaviors, surface live threats
- ML Toolkit for building your own ML solutions
  - Completely free! http://tiny.cc/splunkmlapp
- Other cool ML talks:
  - When Recommendation Systems Go Bad
  - Hidden Biases in Machine Learning and Big Data
- Join the ML Early Adopter Program!
  - mlprogram@splunk.com