.conf18

splunk>
TransUn

TransUnion and a Time Traveling DeLorean

MTTR Fading Like Marty McFly

Steve Koelpin, TransUnion and Splunk Trust MVP Andrew Stein, Splunk Principal PM for Machine Learning Oct 2018

Forward-Looking Statements

During the course of this presentation, we may make forward-looking statements regarding future events or the expected performance of the company. We caution you that such statements reflect our current expectations and estimates based on factors currently known to us and that actual events or results could differ materially. For important factors that may cause actual results to differ from those contained in our forward-looking statements, please review our filings with the SEC.

The forward-looking statements made in this presentation are being made as of the time and date of its live presentation. If reviewed after its live presentation, this presentation may not contain current or accurate information. We do not assume any obligation to update any forward-looking statements we may make. In addition, any information about our roadmap outlines our general product direction and is subject to change at any time without notice. It is for informational purposes only and shall not be incorporated into any contract or other commitment. Splunk undertakes no obligation either to develop the features or functionality described or to include any such feature or functionality in a future release.

Splunk, Splunk>, Listen to Your Data, The Engine for Machine Data, Splunk Cloud, Splunk Light and SPL are trademarks and registered trademarks of Splunk Inc. in the United States and other countries. All other brand names, product names, or trademarks belong to their respective owners. © 2018 Splunk Inc. All rights reserved.



Steve Koelpin

Lead Splunk Engineer
Splunk Trust MVP
New Dad
Winner of the Splunk
Answers Karma Contest



Andrew Stein

Splunk Principal Product Manager, Machine Learning

- 18 years creating mathematically modeled solutions as a data scientist
- I spend 80% of time preparing data and 20% of time complaining about the need to prepare data



Agenda

- TransUnion and Splunk
- Why Use Machine Learning?
- TransUnion and ITSI
- TransUnion and ITSI + MLTK
 - How It Works
 - Training the Model
 - Applying the Model
- Challenges in Predictive Analytics
- Pro Tips
- Bring This to Your Organization



TransUnion and Splunk

Information for Good

TransUnion and Splunk

Hundreds of daily users

Several core Splunkers Casual users to certified consultants



TransUnion and Data

TransUnion is a BIG Data and Information Solutions Company

Founded as a Credit Bureau in 1968

We See Data Differently – Not for What it is – But for What it Can Help People Accomplish

This View – The Individuals for Whom we Steward and Protect Information

We Call this Information For Good





4.8 billion
data updates each month





74 offices





65,000

business

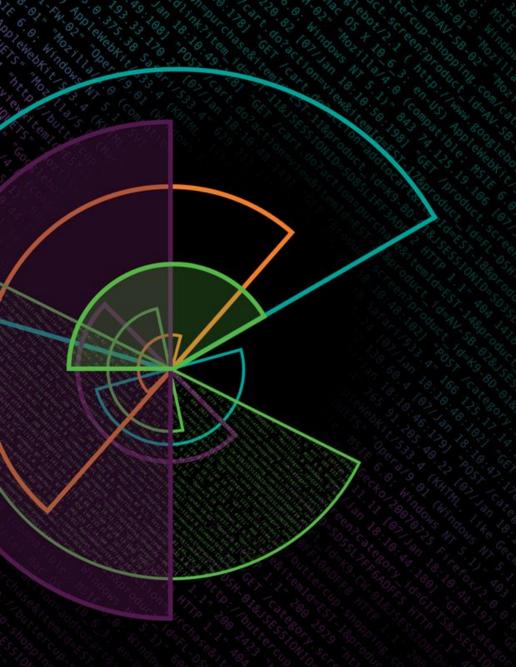




90,000 data sources

50+ petabytes of information



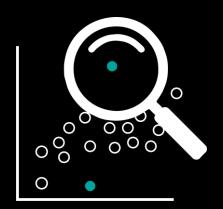


Why Use Machine Learning?

Problems Machine Learning Solves

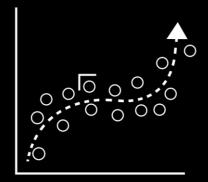
Getting Answers From Your Data

Anomaly Detection



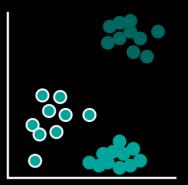
- Deviation from past behavior
- Deviation from peers
- Unusual changes in features
- ITSI MAD Anomaly Detection

Predictive Analytics



- Predicting ServiceHealthScore
- Predicting churn
- Predicting events
- Trend forecasting
- Detecting influencing entities
- Imminent outage prediction
- ITSI Predictive Analytics

Clustering

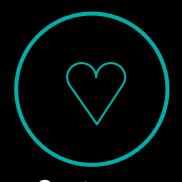


- Identify peer groups
- Event correlation
- Reduce alert noise
- Behavioral analytics
- ITSI Event Analytics

The Cost of an Incident



Line of Revenue



Customer Satisfaction



Brand Reputation



*According to "Damage Control: The Impact of Critical IT Incidents"

https://www.splunk.com/en_us/form/damage-control-the-impact-of-critical-it-incidents.html



Reduce Your Technical Debt with Machine Learning



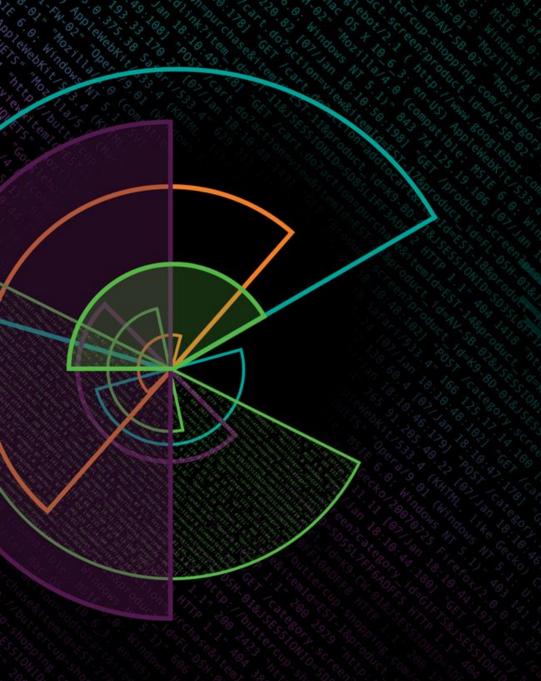
Correlate dozens of KPIs against data in the past



No more tribal Knowledge



Have machine learning do the leg work

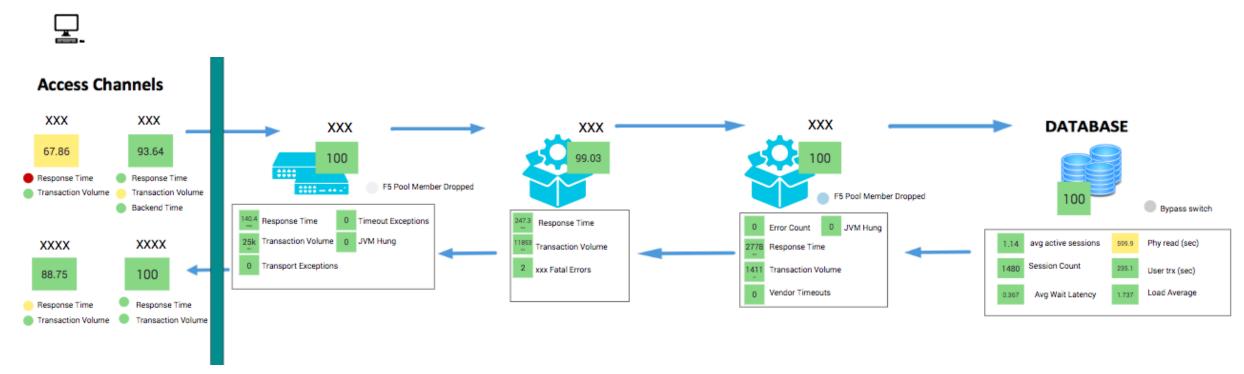


TransUnion and ITSI

IT Service Intelligence

TransUnion and ITSI

Glass Table View of Application Pipeline



*Updates every 1 minute



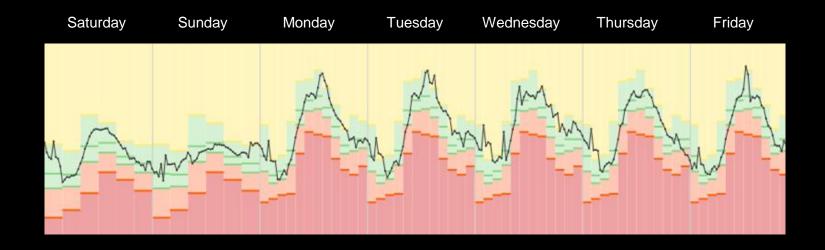
What Was the Investment to Build the Solution?

MOST TIME-CONSUMING TASKS

 Understanding effective KPIs

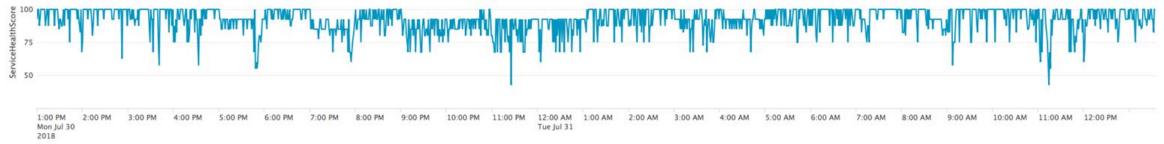
Getting information from other BUs

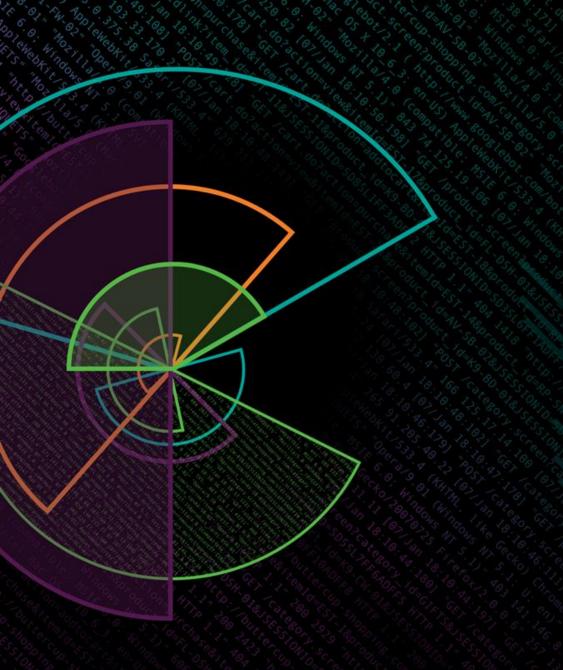
Developing a workflow Applying thresholds



How Does ITSI Tie Into Predicting Incidents?

- ITSI gives us the ability to take multiple KPIs and tie them into a single health score
- Apply adaptive thresholding to cyclic-type data patterns
- Faster time to value



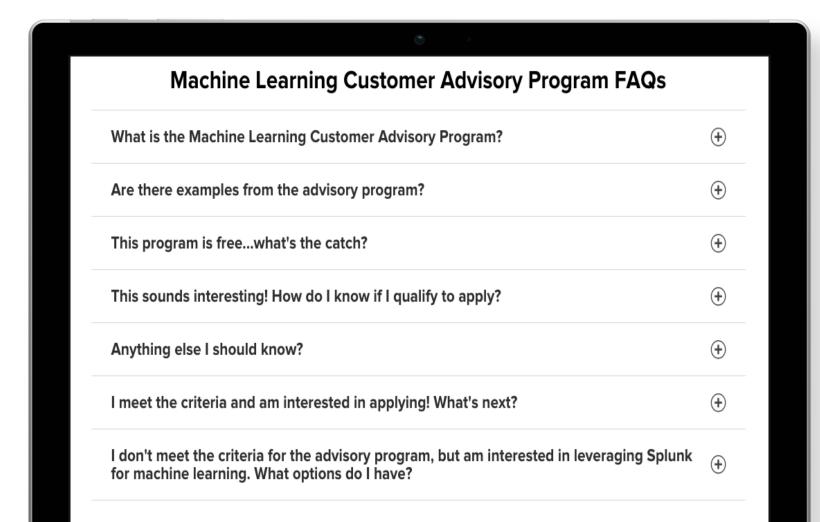


TransUnion and the MLTK

Splunk Advisory Program

What Is the ML Advisory Program?

Provides customers with Splunk data science resources to help operationalize a specific ML use case



- Early access to new and enhanced MLTK features
- Opportunity to shape the development of the product
- Assistance in operationalizing a production-quality ML model



ML Advisory Customers













/product-scteegory_id=GIFTS&JSESSIONID=SD1SL4FF18ADFF18 HTTP 1.1 "AD-1, /product-scteeg/product_id=FL-DSH-01&JSESSIONID=SD55L7FF6ADF9 HTTP 1.1 200 1318 /product-scteegy-scteegy-scteegy-screen/category-scteegy-scteegy-scteegy-scteegy-scteegy-scteegy-sci







TransUnion and Machine Learning

Anomaly Detection



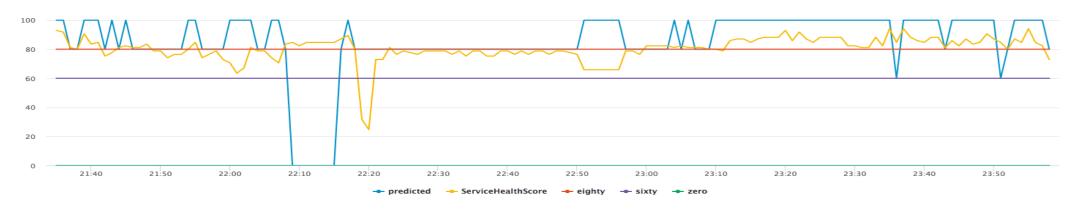
TransUnion and Machine Learning

Predictive Analytics

NORMAL DAY



NON-NORMAL DAY





Investment to Build the Solution

Three months

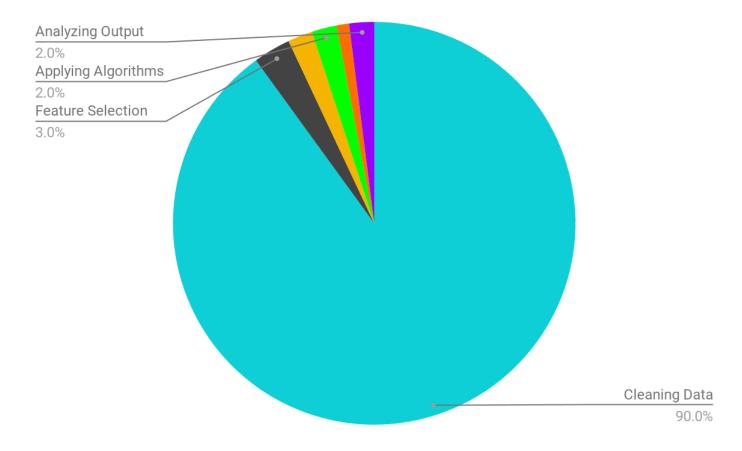
MOST TIME-CONSUMING TASKS:

Obtaining clean quality data

Identifying features

Backfilling service health score

Time Percentage





How Much Effort Does ITSI Save You?

Time + Effort for One Use Case

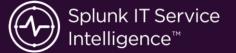
Just MLTK



ITSI + MLTK



ITSI 4.0



- Two engagements with the Splunk ML Advisory Program
- 100+ hours of work over
 3 months
- 10+ hours of Webex
- Multiple business rules

- Leveraged the ITSI and Sophisticated Machine Learning Blog
- 30 hours + 1 hour
 Webex
- Everything else was customizing

- ITSI 4.0 now includes this as a turn key feature
- Saves a TON of time getting to an outcome

How It Works

Predictive Analytics



Types of Incidents Two Incident Types

Steady-State Incidents



An Incident Due to a Change



Predictive Analytics Explained

Create a ServiceHealthScoreFromFuture: Read the Blog

```
bin _time span=1m
stats min(<FEATURES>) by _time
eval ServiceHealthScore=(<FEATURES>)/17
reverse
streamstats window=10 current=f first(ServiceHealthScore) as ServiceHealthScoreFromFuture
reverse
timechart span=1m <FEATURES>
 eval ServiceHealthFutureState=case(ServiceHealthScoreFromFuture>80, "Green", ServiceHealthScoreFromFuture>60, "Yellow", ServiceHealthScoreFromFuture>40, "Orange"
    ,ServiceHealthScoreFromFuture>0, "Red")
|fit RandomForestClassifier ServiceHealthFutureState from <FEATURES> into Steve_RF_Model_v8
```

https://www.splunk.com/blog/2017/08/28/itsi-and-sophisticated-machine-learning.html

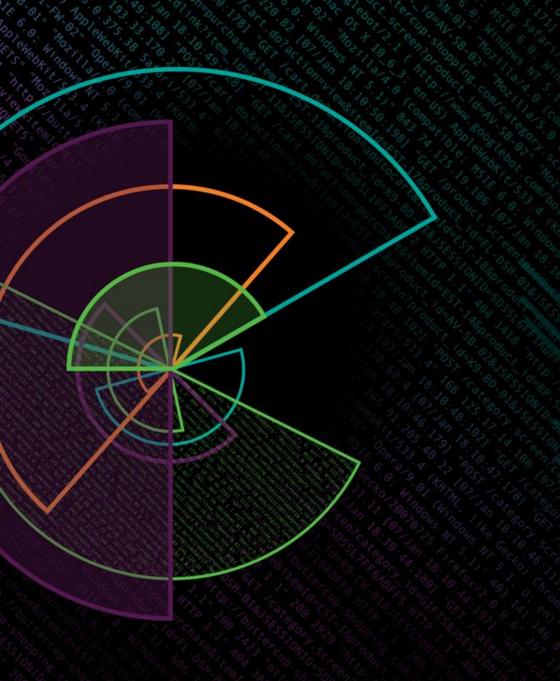


Predictive Analytics Explained

Create a ServiceHealthScore From the Future

- Determine which features have a tight mathematical relationship with the ServiceHealthScore
 - Use the ITSI deep dive view to identify which KPIs started to degrade before the incident occurs
 - Strong leading indicators make excellent features which improve accuracy





Training the Model

Predictive Analytics

Grandfather Paradox: Don't Use the Future to Predict the Future

Don't use ServiceHealthScore from the future as your predictor







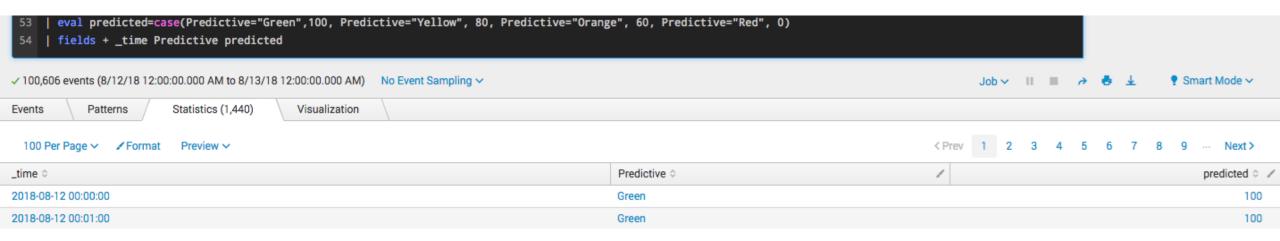
Applying the Model

The Analysis

Predictive Analytics

The Analysis

Change those string values to numeric for easy visualization



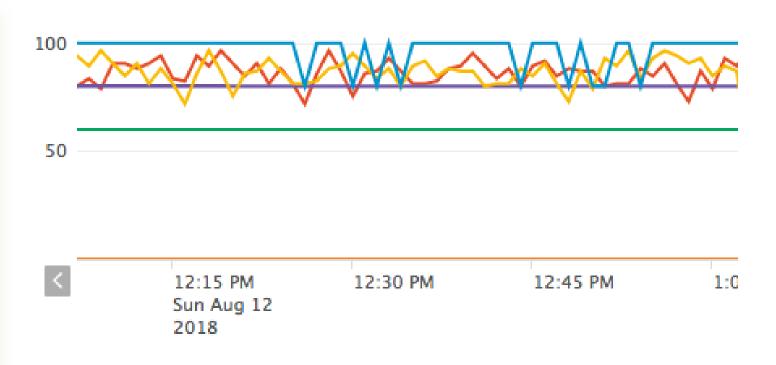


Predictive Analytics

The Analysis

Add boundary lines for easy identification

```
eval eighty=80
eval sixty=60
eval zero=0
```



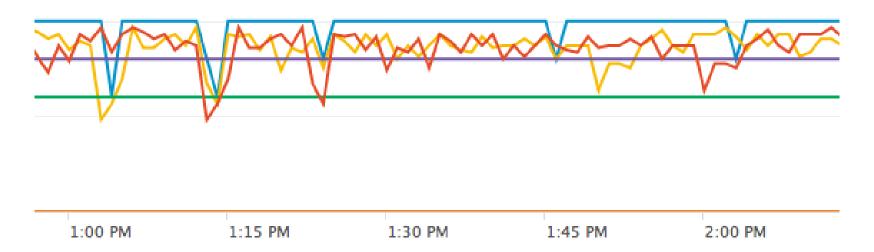


Predictive Analytics

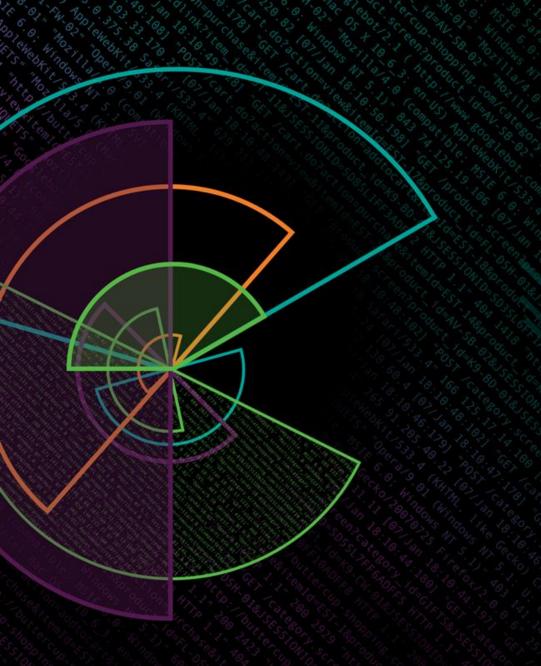
The Analysis

Test against ServiceHealthScoreFromFuture rather than ServiceHealthScore so you don't have to offset the times in your head

timechart span=1m min(predicted) AS predicted min(ServiceHealthScoreFromFuture) AS ServiceHealthScoreFromFuture







Challenges In Predictive Analytics

Challenges



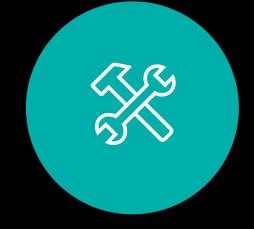
Challenges We Faced



Lots of quality data needed



Slow search speed for large amounts of data



Any minor changes to a KPI requires a new backfill



Dirty data is bad

— use adaptive
thresholding
wisely



Challenges: Accuracy

DIALING IN THE ACCURACY AND FILTERING OUT THE NOISE

- THIS CAN BE SOLVED BY
 - Training on a larger set of data
 - Ensuring clean quality data
 - Visually exploring the data



Challenges

Backfilling the ServiceHealthScore

Any time you add or modify a KPI, it does not retroactively change the ServiceHealthScore

Change a KPI and you must wait 30 days before having enough quality data to train on

Add a KPI to a service — you must wait to get more runtime until that KPI shows its mathematical relationship with the ServiceHealthScore

Why not just create a new service with existing/new KPIs and backfill?

ServiceHealthScore Does Not Backfill



Challenges: Custom Predictive Analytics

Backfilling the ServiceHealthScore Through SPL

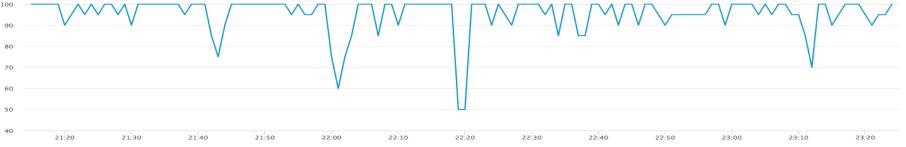
```
index=itsi_summary

| val Volume=case(kpiid="a3c0cc8213e6120c25eca484" AND serviceid="1ad210ad-329d-4bba-8c31-fc6c878cb608", 'alert_severity')
| eval Response_Time=case(kpiid="1e75e8ee4a395fc86ced70c3" AND serviceid="1ad210ad-329d-4bba-8c31-fc6c878cb608", 'alert_severity')
| eval Errors=case(kpiid="1e75e8ee4a395fc86ced70c3" AND serviceid="1ad210ad-329d-4bba-8c31-fc6c878cb608", 'alert_severity')
| eval Vendor_Timeouts=case(kpiid="b726f6de942dc7a4ce7842eb" AND serviceid="1ad210ad-329d-4bba-8c31-fc6c878cb608", 'alert_severity')

| eval vendor_Timeouts=case(kpiid="b726f6de942dc7a4ce7842eb" AND serviceid="1ad210ad-329d-4bba-8c31-fc6c878cb608", 'alert_severity')

| eval severity_Errors=case(Errors="normal", 100, Errors="low", 80, Errors="medium", 60, Errors="critical", 0)
| eval severity_Vendor_Timeouts=case(Vendor_Timeouts="normal", 100, Vendor_Timeouts="low", 80, Vendor_Timeouts="medium", 60, Vendor_Timeouts="high", 40, Vendor_Timeouts="critical", 0)
| eval severity_Response_Time=case(Response_Time="normal", 100, Response_Time="low", 80, Response_Time="medium", 60, Response_Time="high", 40, Response_Time="critical", 0)
| eval severity_Volume=case(Volume="normal", 100, Volume="low", 80, Volume="medium", 60, Volume="critical", 0)
```

_time 0	ServiceHealthScore 🗘 🖊	severity_Errors 🌣 🖊	severity_Vendor_Timeouts 0	severity_Response_Time \(\times \)	severity_Volume 🗘 🗸
2018-08-11 22:15:00	100	100	100	100	100
2018-08-11 22:16:00	100	100	100	100	100
2018-08-11 22:17:00	100	100	100	100	100
2018-08-11 22:18:00	100	100	100	100	100
2018-08-11 22:19:00	50	0	100	0	100
2018-08-11 22:20:00	50	0	100	0	100
2018-08-11 22:21:00	100	100	100	100	100
2018-08-11 22:22:00	100	100	100	100	100
2018-08-11 22:23:00	100	100	100	100	100
2018-08-11 22:24:00	90	100	100	60	100



Pro Tips

Predictive Analytics

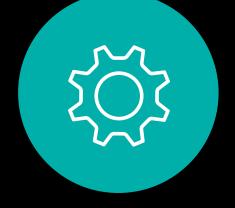


Customer ML Tips and Tricks

Pro Tips From the Splunk Trust



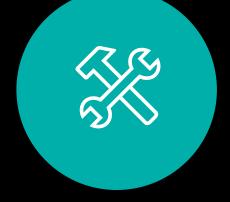
Version each model you create



Make sure your Service Health Score is aligned with known incidents



Ensure thresholds are set properly in ITSI



Validate that regular expressions are capturing correct values



Make your KPIs as granular as possible



Bring This to Your Organization

Where Do I Start?

How to Get Started With Custom Predictive Analytics











Use ITSI to build a top-level view of your most critical services to understand the input variables needed.

Aggregate indicators into a single Service Health Score.

Use these KPIs to train your models.

Select several KPIs with good runtime and create a backfilled Service Health Score.

Align that Service Health Score against known incidents to test effectiveness.

Train a model and experiment with different algorithms.

Use the MLTK to get feedback about the models you train.

Understand the difference between algorithms.

Use the Service Health Score calculation and search for a score lower than 60%.

Run this over the last six months to pinpoint your larger incidents with day and time.

Create a report so you can use it to go back and identify incidents.

Test your models against known incidents.





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