

Using Splunk ML to Optimize T-Mobile 5G for Better Throughput

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T-Mobile
has the
America's
Largest 5G
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DRAGSTER
mmWave
>20 GHz
Ridiculous speeds but can't travel long distances or turn corners.

SPORTS CAR
Mid-band
1-6 GHz
Super fast, reliable and good around town.

TRUCK
Low-band
<1 GHz
Speedy, great for long trips and travels where others can't.

5G FLEET

MMW X-WING
FAST SHORT RANGE FIGHTER

MID BAND Y-WING
MID RANGE FIGHTER-BOMBER

LOW BAND MON CALAMARI CRUISER
LONG RANGE TRANSPORTER

LIVE

BREAKING NEWS

LAYER CAKE SEEN IN MANHATTAN

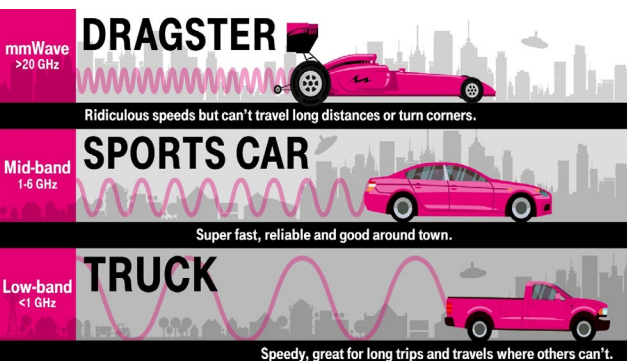
INNOCENT BYSTANDER: "I DIDN'T THINK THEY COULD PULL IT OFF"



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Agenda

1) Spectrum Bands

Business Challenges in Subscriber Management
Complexity for Radio Frequency Engineers

2) Solution Overview

Data Analysis Techniques
Machine Learning Algorithms

3) Benefits and Lessons Learned

Success in NY Trial
Challenges Addressed



1) Spectrum Bands

What are Bands or Layers? How to overcome challenges and complexities for happy subscribers

Efficient Use of Layers for Happy Subscribers



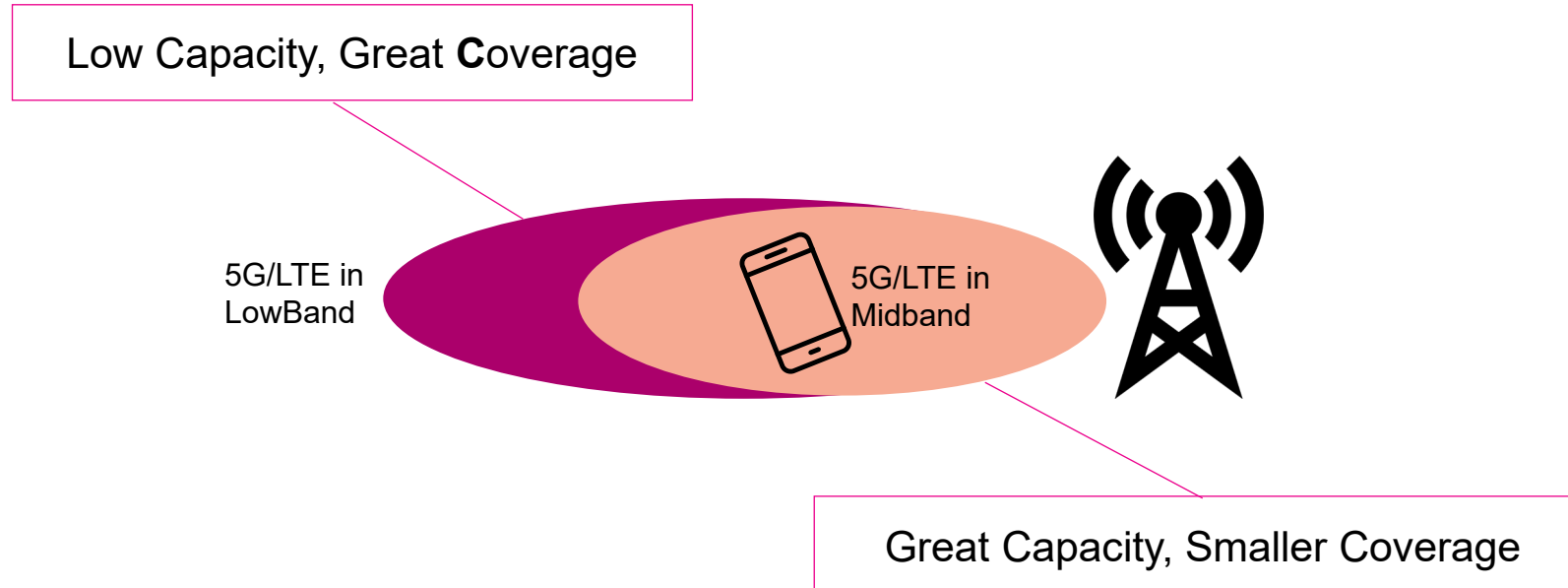
How do Subscribers Experience Our Network?

Coverage

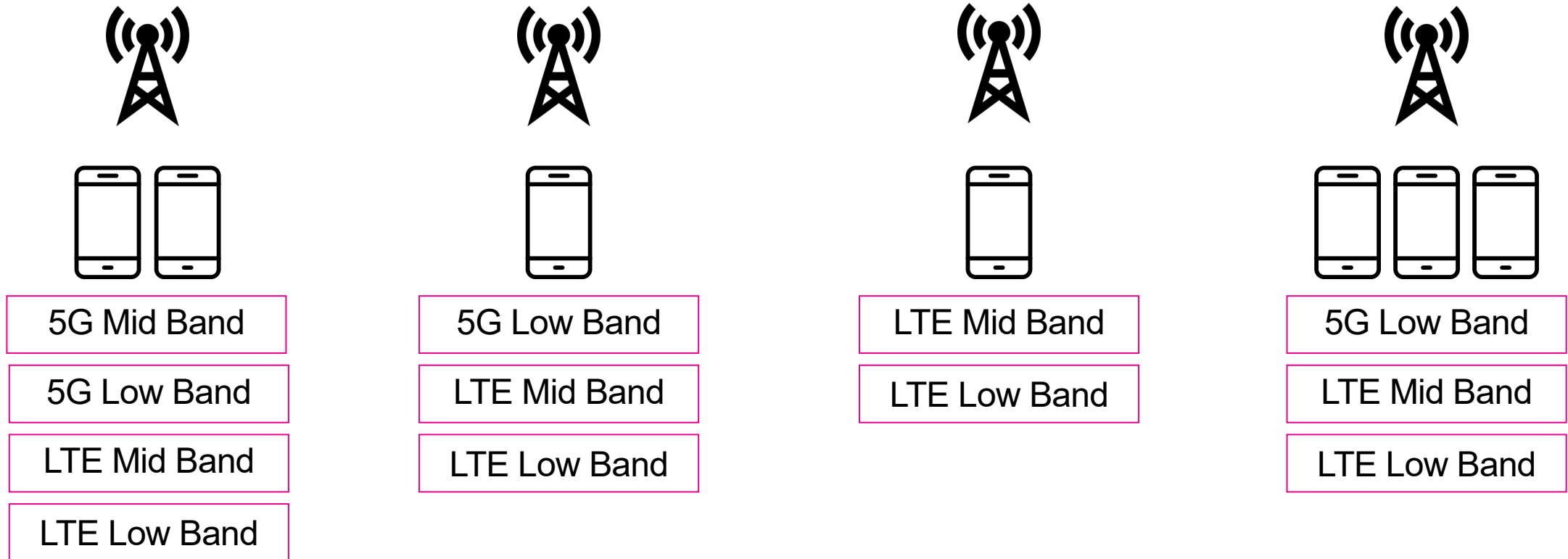
- Customer perceives as 'bars' on device

Capacity

- Customer perceives as 'Speed' on device

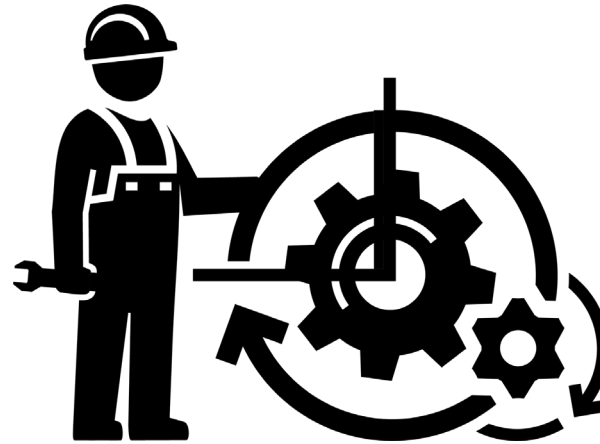


Layers in Cellular Networks



Layers can be deployed for either ‘signal’ and/or ‘speed’

Role of RF Engineers



Analyze

Data from 1000s of
cell towers in network

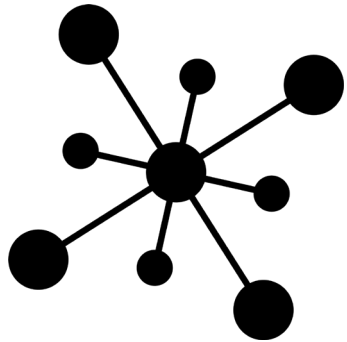
Tune

100s of Configurable
Network Parameters

Repeat

Multiple iterations to reach
optimal performance

Challenges in Managing Cellular Networks



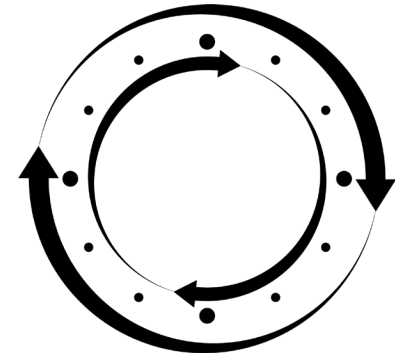
Network Complexity

Interworking of multiple layers



Data Nuggets

Huge dataset



Time Consuming

Manual process & tuning



2) Solution Journey

Overview of Data Analysis Techniques,
Visualization and ML Capabilities

Solution Journey



Feasibility Assessment

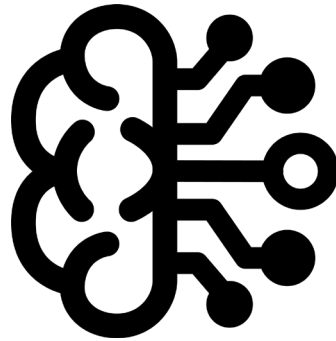
- Enable Data Analysis
 - Visualization
- Identify Features
 - SME Validation

Solution Journey



Feasibility Assessment

- Enable Data Analysis
 - Visualization
- Identify Features
 - SME Validation



Machine Learning

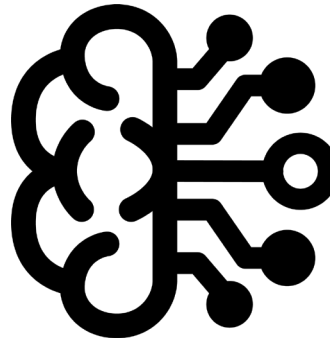
- Anomaly Detection
 - Actionable Insights
- Clustering
 - Tune CM parameters

Solution Journey



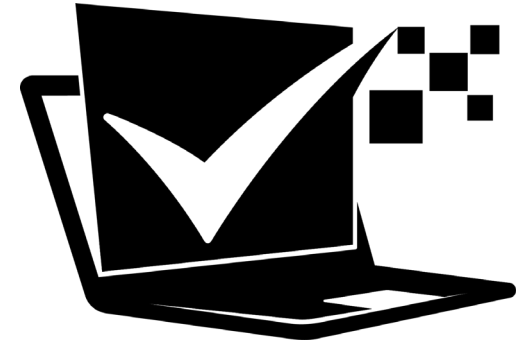
Feasibility Assessment

- Enable Data Analysis
 - Visualization
- Identify Features
 - SME Validation



Machine Learning

- Anomaly Detection
 - Actionable Insights
- Clustering
 - Tune CM parameters



Validation & Testing

- Validation
 - Iterative Feedback
- Trial
 - New York City

Data Analysis | Visualization Capabilities

Easier Analysis

- Gather relevant data (Performance and Configuration Management data) into Splunk

cell	cluster				a1a2SearchThresholdRsrp	a1a2SearchThresholdRsrq	a2CriticalThresholdRsrp	a3offset_A3Inter	a3offset_A3Intra	a5Threshold1Rsrp_A3IFLB	a5Threshold1Rsrp_A5	a5Threshold1Rsrq	a5Threshold2Rsrp_A3IFLB
	20	1.93	0.50	376	-108	-45	-130	40	40	-140	-106	-50	-110
	20	1.34	0.50	289	-108	-45	-130	40	40	-140	-106	-50	-110
	20	1.20	0.50	386	-108	-45	-130	40	40	-140	-106	-50	-110
	20	1.17	0.50	94	-65	-45	-130	40	40	-140	-70	-50	-110
	20	1.01	0.50	335	-65	-45	-130	40	40	-140	-70	-50	-110
	20	0.93	0.50	377	-108	-45	-130	40	40	-140	-106	-50	-110
	20	0.53	0.50	462	-108	-45	-130	40	40	-140	-106	-50	-110
	20	0.50	0.50	128	-100	-45	-130	40	40	-140	-102	-50	-110

Data Analysis | Visualization Capabilities

Easier Analysis

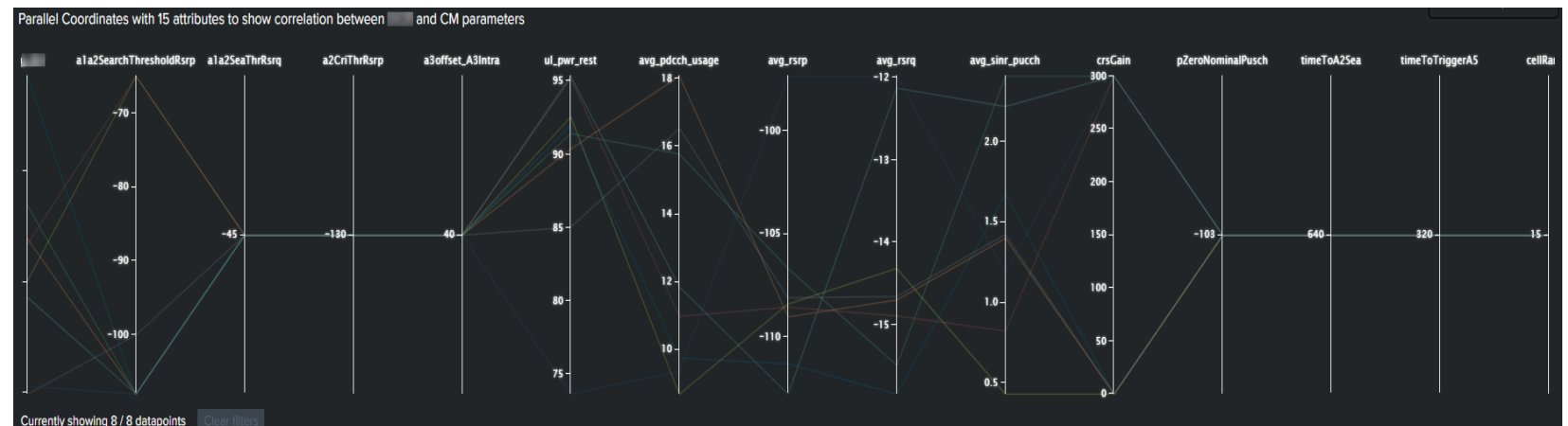
- Gather relevant data (Performance and Configuration Management data) into Splunk

Cluster Details

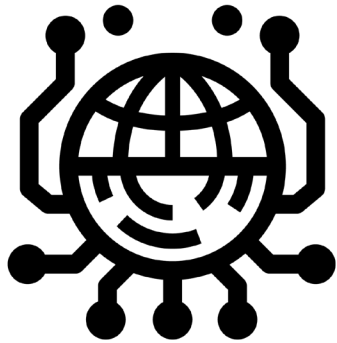
cell	cluster				a1a2SearchThresholdRsrp	a1a2SearchThresholdRsrq	a2CriticalThresholdRsrp	a3offset_A3Inter	a3offset_A3Intra	a5Threshold1Rsrp_A3IFLB	a5Threshold1Rsrp_A5	a5Threshold1Rsrq	a5Threshold2Rsrp_A3IFLB
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	20	0.50	0.50	128	-100	-45	-130	40	40	-140	-102	-50	-110

Leverage Charts

- Parallel Coordinates for impact analysis and finding tunable Configuration Management features

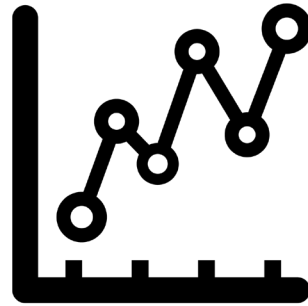


Machine Learning Algorithms



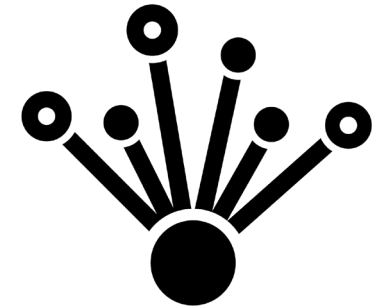
Preprocessing for Accuracy

- Feature Transformation
- Standard scaling



Anomaly Detection

- Density Function
- Persistent Trends



Clustering Using Features

- Cluster similar sectors
- Improved Accuracy



3) Benefits & Lessons

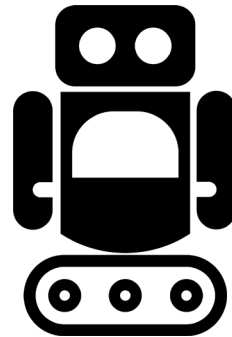
Trial Results, Benefits and Lessons Learned

Benefits of ML Based Layer Tuning



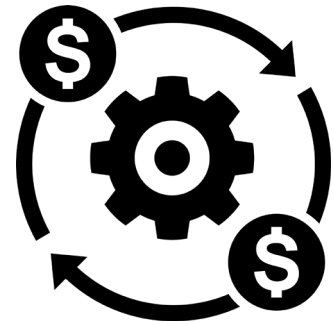
Happier Subscribers

Granular data-based tuning result
in Speed improvements



Engineer Efficiency

Automated platform yields
time savings for Engineers



Network Efficiency

Utilize spectrum and
network resources better

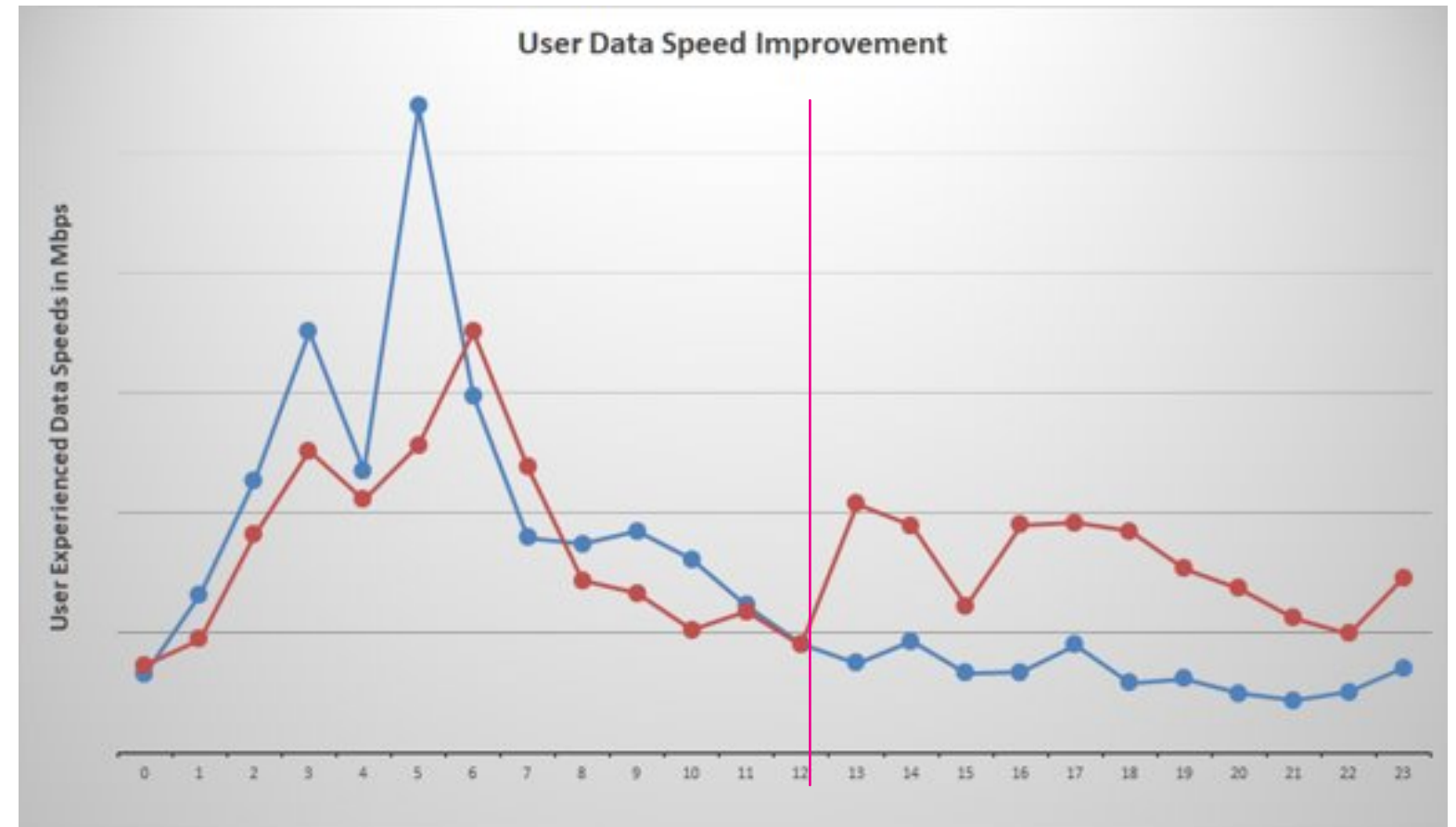


Improved Subscriber Experience

Changes made on real cell site based on Anomaly Detected yielded over 80% improvement in Data speeds in a busy NYC area

Success Scenario

Real life example of Network Improvement with Splunk MLTK



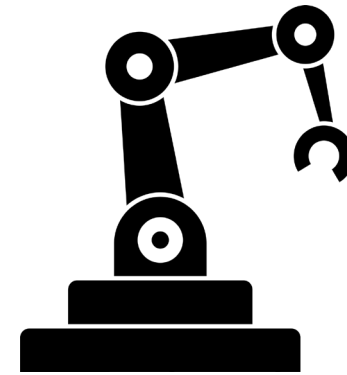
Automated Reports vs. Manual Tuning

Real life example of time-savings with Splunk MLTK platform



30 Minutes

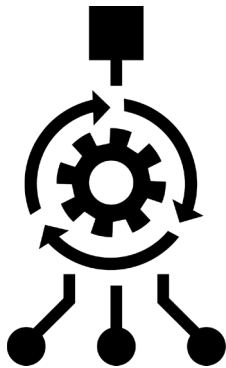
Data Collection
Generate Insights
Anomaly Detection
Verification of Anomaly



<5 Minutes

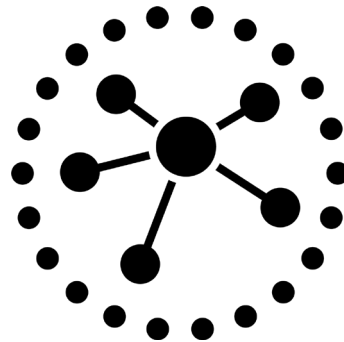
Setup Daily Report
Generate Report
Visualize ML Results

Challenges Faced | Operational Issues



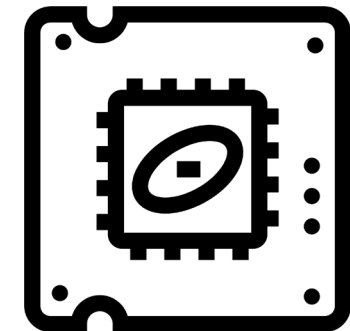
Anomalies

- Avoid noise
 - Persistent trends
- Time to Validate
 - Drilldown



Configuration

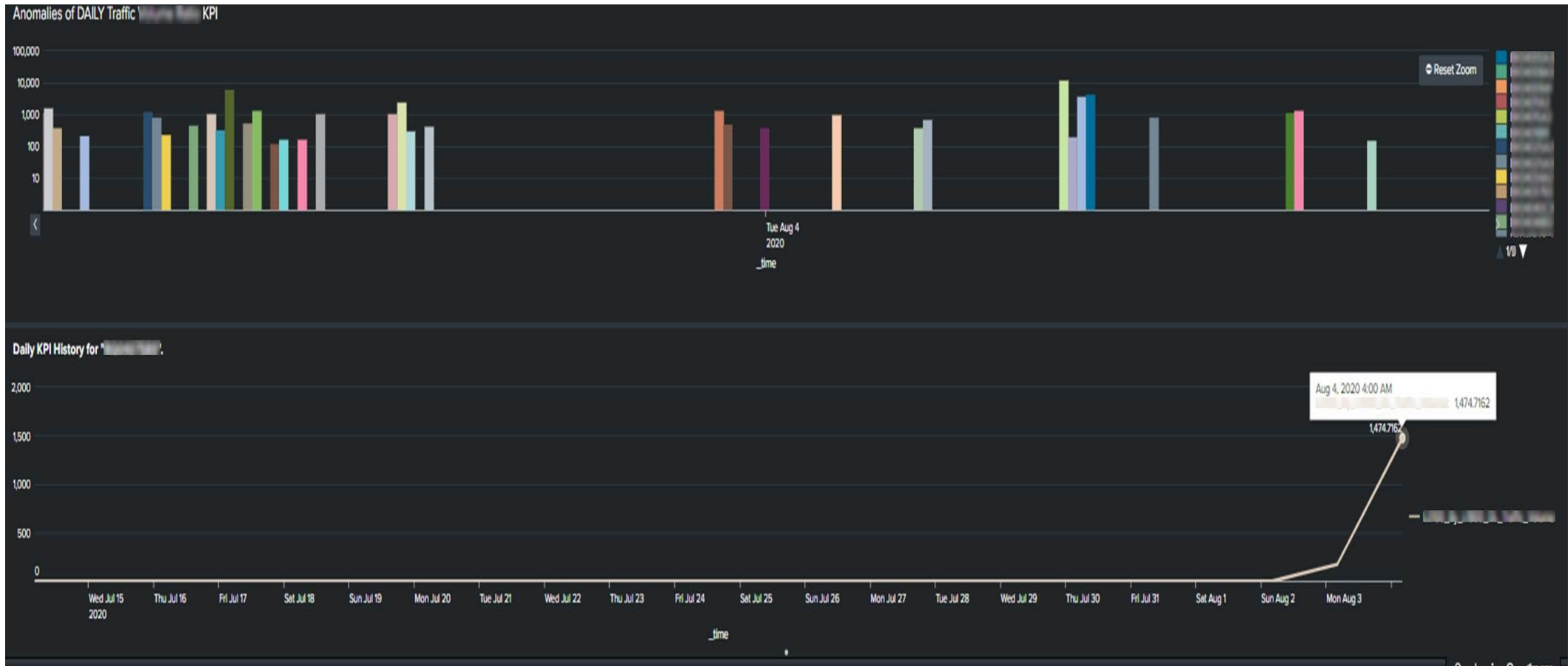
- Reduce Number of Models



Sizing

- Memory Limits
 - Algorithm
 - Splunk Instance

Actionable Anomalies | Key to Solution Accuracy



Easier Validation | Drilldown and Reduce Time to Validate



DensityFunction | Persistent Downward Trends

```
| mvexpand BoundaryRanges | rex field=BoundaryRanges
"(?<lower_bound>.+):( ?<upper_bound>.+):( ?<pct_of_boundary_region>.+)"
| eval BoundaryRangeType=case(lower_bound=="-
Infinity", "lower", upper_bound=="Infinity", "upper", isnum(lower_bound) AND
isnum(upper_bound), "middle")
| eval OutlierInBoundaryRange=case(BoundaryRangeType=="lower" AND
parameter2 < upper_bound, 1, BoundaryRangeType=="upper" AND parameter2 >
lower_bound, 1, parameter2 > lower_bound AND parameter2 < upper_bound, 1,
1=1, 0)
| where OutlierInBoundaryRange>0 AND BoundaryRangeType="lower"
... | streamstats count time_window=3d by object | where _time >=
relative_time(now(), "-2d@d") AND count>0
```

DensityFunction | Reduce Number of Models

```
| table _time, object, parameter1, parameter2
| eval metric_names=mvappend(" parameter1 "," parameter2 "),
metric_values=mvappend(parameter1, parameter2),
name_value=mvzip(metric_names,metric_values,";")
| fields _time object name_value
| mvexpand name_value
| rex field=name_value "(?<metric_name>[^;]+);(?<metric_value>.+)"
| fields - name_value
| fit DensityFunction metric_value by "object,metric_name" threshold=0.02
```

Key Takeaways

1

Pursue Incremental Data Analysis via Visualization

2

Actionable Anomalies are Key to Solution Accuracy

3

Cross-functional team collaboration is vital for success

