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

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T-Mobile has the America’s Largest 5G Network

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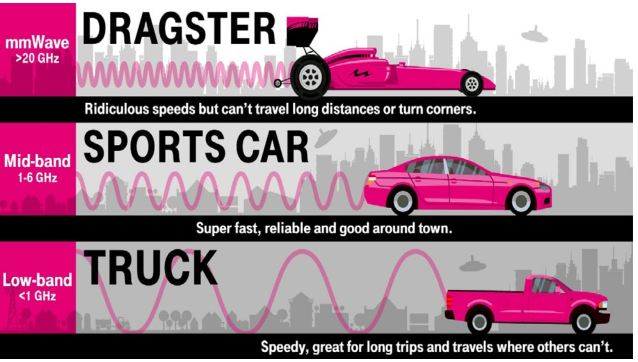

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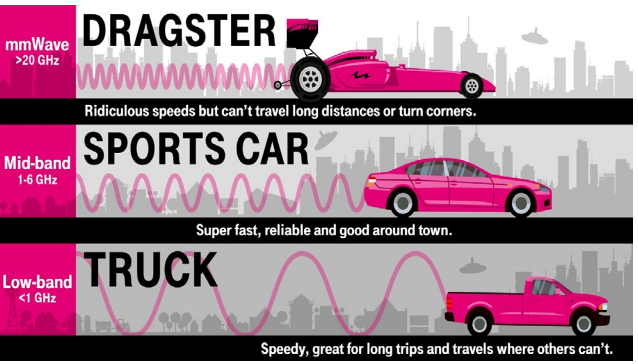

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Agenda

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

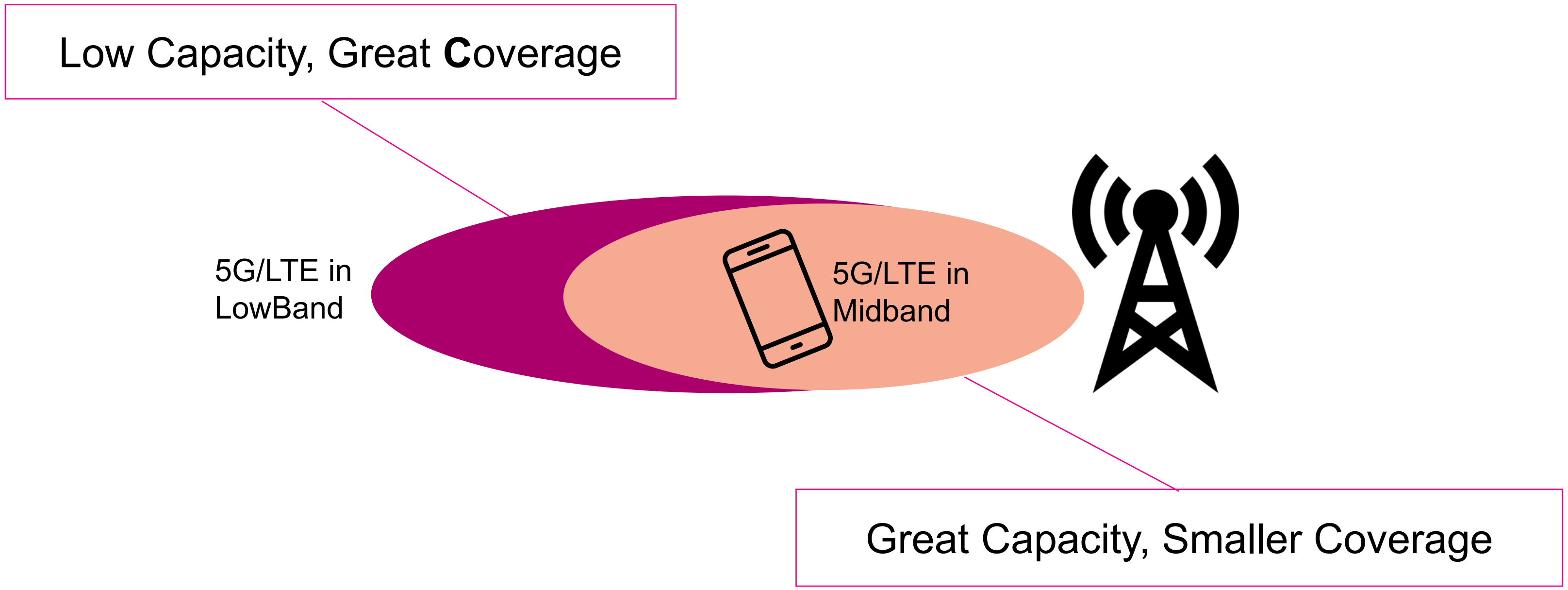
How do Subscribers Experience Our Network?

Coverage

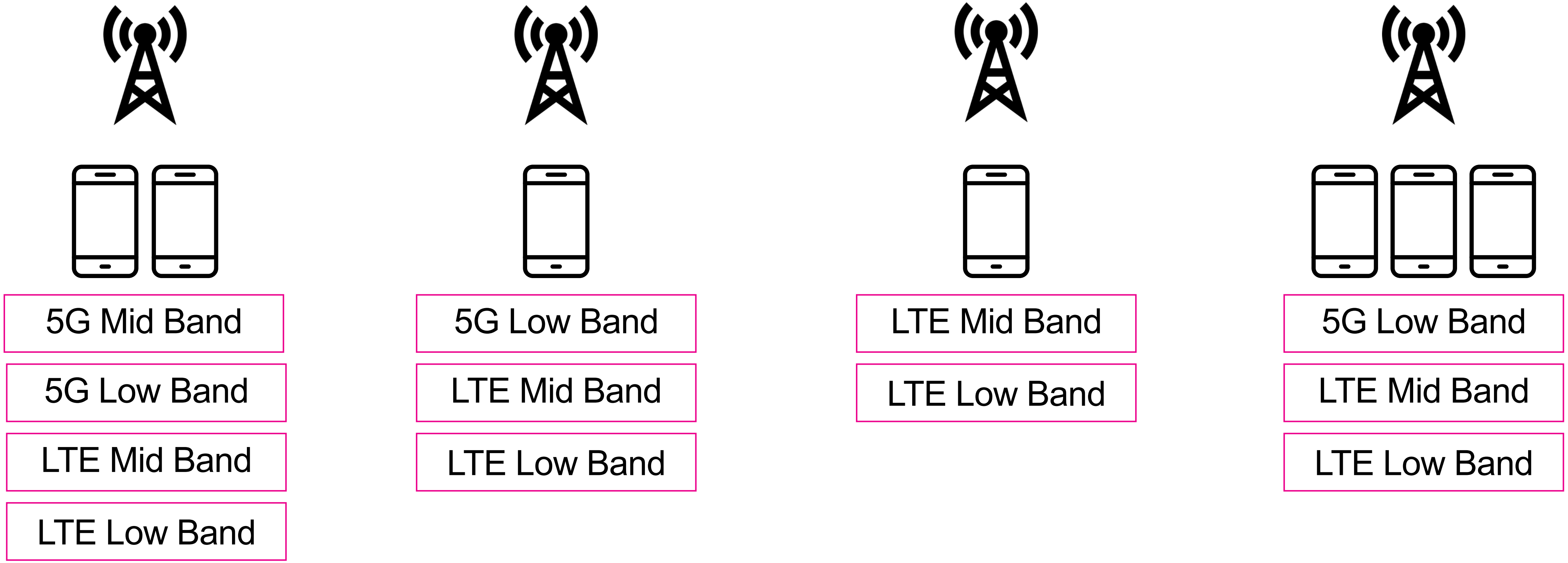
- Customer perceives as ‘bars’ on device

Capacity

- Customer perceives as ‘Speed’ on device

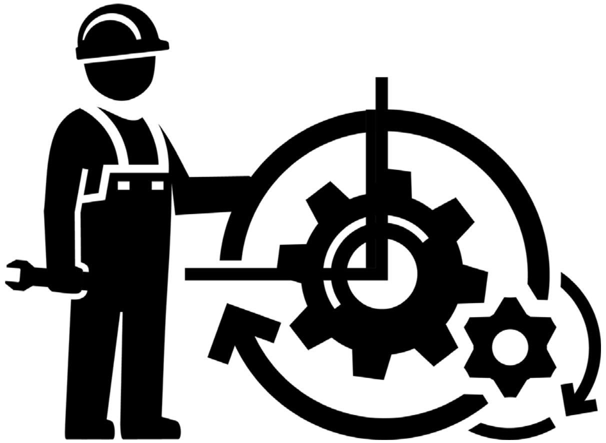


Layers in Cellular Networks



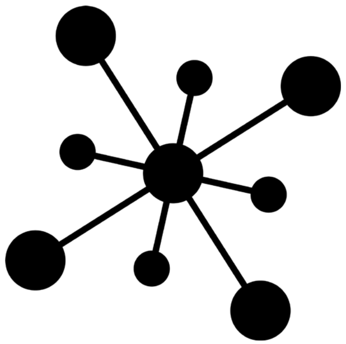
Layers can be deployed for either ‘signal’ and/or ‘speed’

Role of RF Engineers



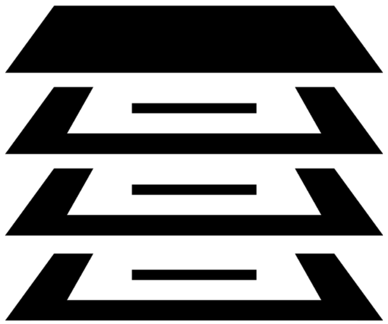
Analyze	Tune	Repeat
Data from 1000s of cell towers in network	100s of Configurable Network Parameters	Multiple iterations to reach optimal performance

Challenges in Managing Cellular Networks



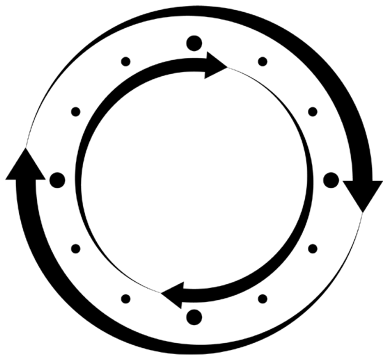
Network Complexity

Interworking of multiple layers



Data Nuggets

Huge dataset



Time Consuming

Manual process & tuning

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splunk>

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

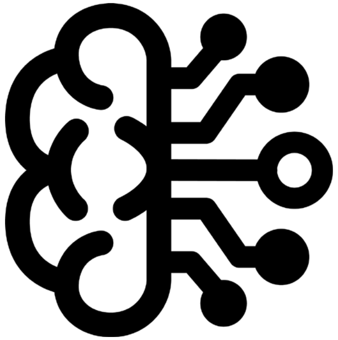
Machine Learning

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

Solution Journey

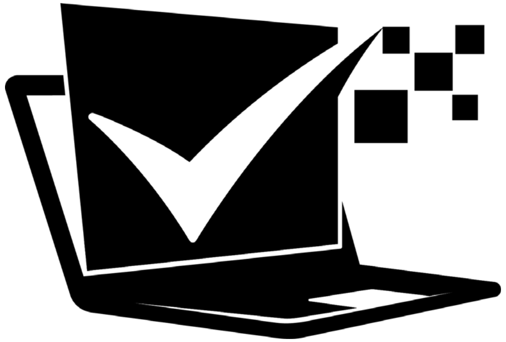
Feasibility Assessment

- 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

Cluster Details

cell	cluster	[redacted]	[redacted]	[redacted]	a1a2SearchThresholdRsrp	a1a2SearchThresholdRsrq	a2CriticalThresholdRsrp	a3offset_A3Inter	a3offset_A3Intra	a5Threshold1Rsrp_A3IFLB	a5Threshold1Rsrp_A5	a5Threshold1Rsrq	a5Threshold2Rsrp_A3IFLB
[redacted]	20	1.93	0.50	376	-108	-45	-130	40	40	-140	-106	-50	-110
[redacted]	20	1.34	0.50	209	-108	-45	-130	40	40	-140	-106	-50	-110
[redacted]	20	1.20	0.50	386	-108	-45	-130	40	40	-140	-106	-50	-110
[redacted]	20	1.17	0.50	94	-65	-45	-130	40	40	-140	-70	-50	-110
[redacted]	20	1.01	0.50	335	-65	-45	-130	40	40	-140	-70	-50	-110
[redacted]	20	0.93	0.50	377	-108	-45	-130	40	40	-140	-106	-50	-110
[redacted]	20	0.53	0.50	462	-108	-45	-130	40	40	-140	-106	-50	-110
[redacted]	20	0.50	0.50	128	-100	-45	-130	40	40	-140	-102	-50	-110

Data Analysis | Visualization Capabilities

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Cluster Details

cell	cluster	[redacted]	[redacted]	[redacted]	a1a2SearchThresholdRsrp	a1a2SearchThresholdRsrq	a2CriticalThresholdRsrp	a3offset_A3Inter	a3offset_A3Intra	a5Threshold1Rsrp_A3IFLB	a5Threshold1Rsrp_A5	a5Threshold1Rsrq	a5Threshold2Rsrp_A3IFLB
[redacted]	20	1.93	0.50	376	-108	-45	-130	40	40	-140	-106	-50	-110
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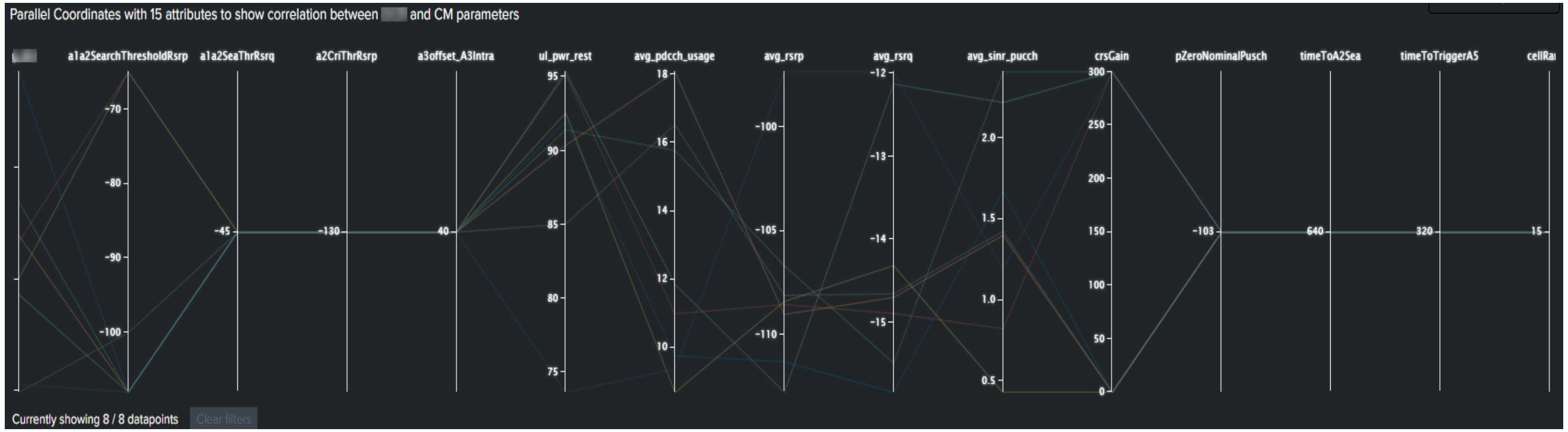
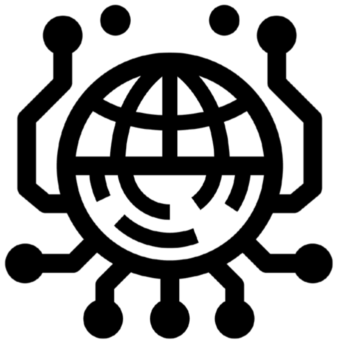
Leverage Charts

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

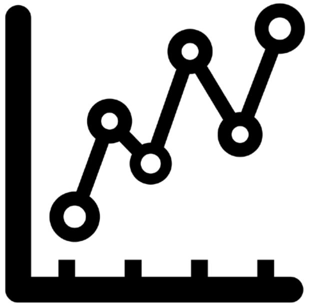


Machine Learning Algorithms



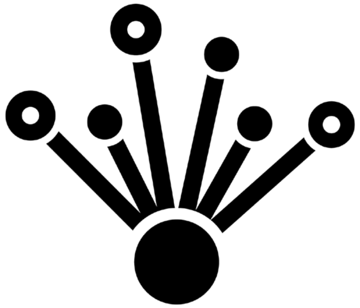
Preprocessing for Accuracy

- Feature Transformation
- Standard scaling



Anomaly Detection

- Density Function
- Persistent Trends



Clustering Using Features

- Cluster similar sectors
- Improved Accuracy

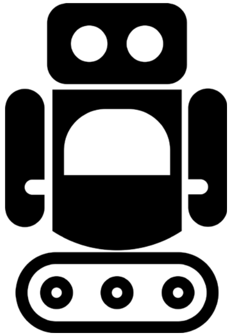
3) Benefits & Lessons

Trial Results, Benefits and Lessons Learned

Benefits of ML Based Layer Tuning

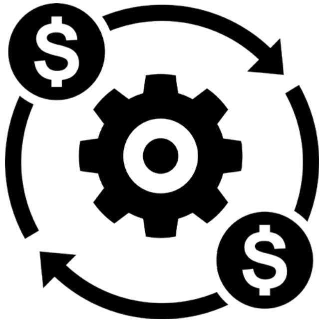
Happier Subscribers

Granular data-based tuning result in Speed improvements



Engineer Efficiency

Automated platform yields time savings for Engineers



Network Efficiency

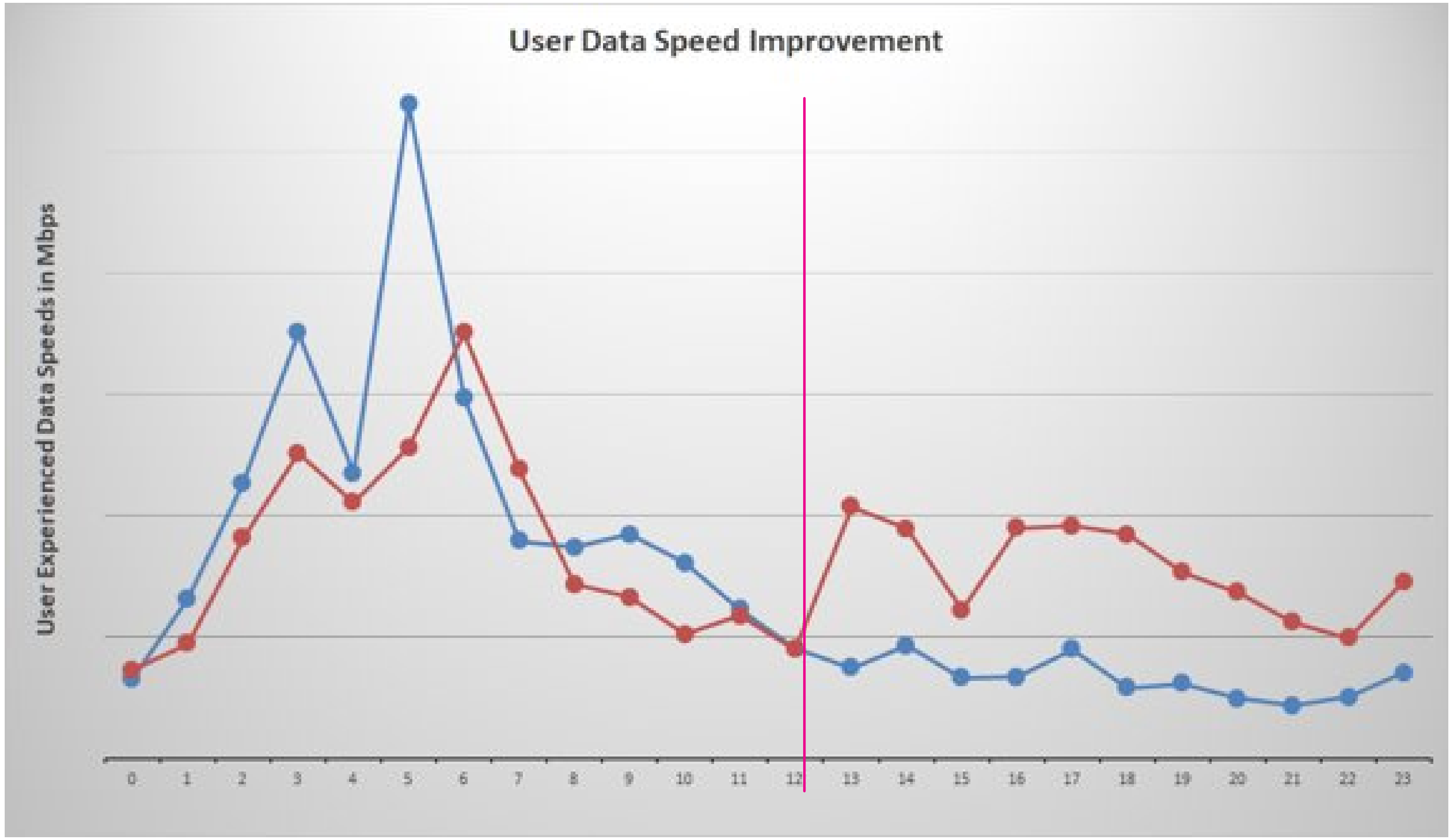
Utilize spectrum and network resources better

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

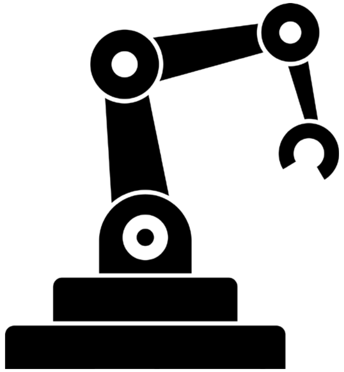
30 Minutes

Data Collection

Generate Insights

Anomaly Detection

Verification of Anomaly



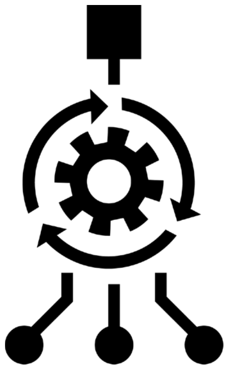
<5 Minutes

Setup Daily Report

Generate Report

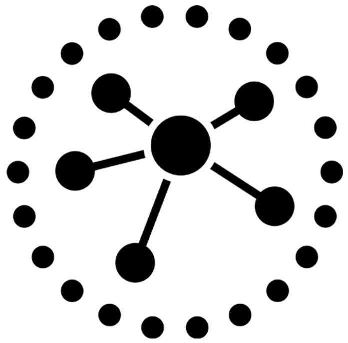
Visualize ML Results

Challenges Faced | Operational Issues



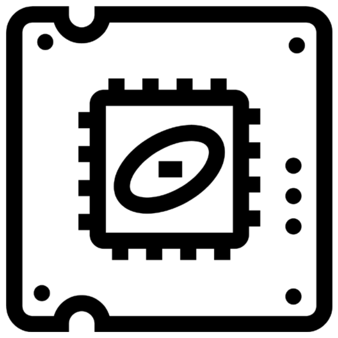
Anomalies

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



Configuration

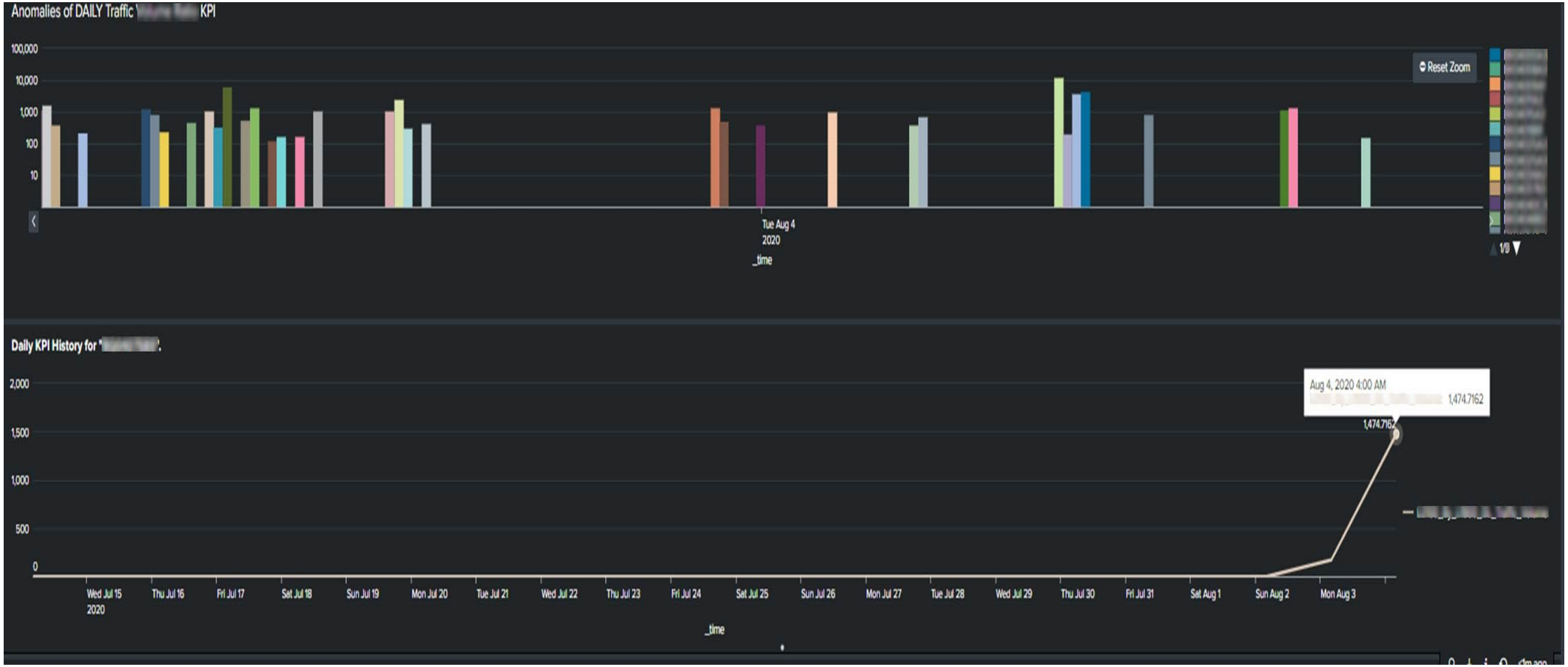
- Reduce Number of Models



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

Thank You

Please provide feedback via the

SESSION SURVEY