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Embracing Service Delivery Changes with Machine Learning

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Agenda

1 The Change Imperative

2 Techniques

- Change-Driven Segmentation
- Change Scoring

3 Operationalization

- Example

The Change Imperative

"I feel the need for speed"

- More services than ever before
- More devices than ever before
- More complex network than ever before

- More changes than ever before

- Subscribers expect change at internet speed & the business is pushing to meet that expectation

Embrace Change – Don't Fear It

"There are many different types of change and all need to be taken into account to be able to establish potential root causes for any given incident.

Among the most important types of change are code changes, data changes, workload changes and infrastructure topology changes.

While not all performance incidents can be traced to such changes, Gartner estimates that approximately 85% of all performance incidents can be so traced."*

Will Cappelli

Research VP, Gartner

Key is systematically identifying subscriber-related changes & evaluating them

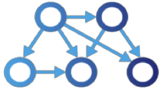
* "Causal Analysis Makes Availability and Performance Data Actionable", Gartner Report, 7 Oct 2015

Change-Driven Segmentation

Divide subscribers into subscriber segments with identical changes

Example subscriber-related attributes

- CPE & Aggregation Device Attributes
  - Make/model software version of any CPE; config file
  - Make/model software version of CMTS/CCAP/DPoE System, Remote Phy, etc.
- Topology Attributes



  - Fiber node (node split, fiber deep), Aggregation Device split/change
  - Video controller, email server, etc. – don’t need full connectivity just subscriber association
- Billing/Service Attributes

  - Billing system, speed tier, All IP, etc. even changes intended to be transparent

Change Time Variation

Align like changes relative to the time of the change itself

- Treat the date of the change as t0
- Evaluate based on scoring before and after t0
    - e.g. t0 +/-1 day, +/- 2 days,+/- 7 days, etc. much like looking at new sub tenancy

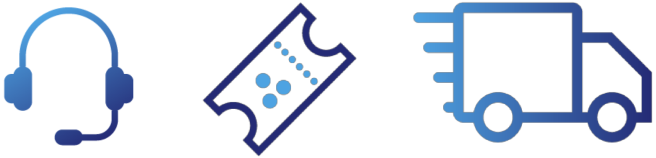
- Some changes may yield obvious & dramatic impacts
- Other change impacts may be more subtle
    - Sample size (i.e. size of the changed subscriber segment) may need to be/grow large enough to identify statistically significant before/after deviations

Scoring Changes

Direct Measures

Ultimate goal generally to evaluate impact on subscriber QoE

- Technical Support Call Rate (Agent Handled)
- Customer Reported Trouble Ticket Rate
- Scheduled Truck Roll Rate



Downside of these care-drive direct measures is customer impacted

- Scoring based on predictive measures of QoE preferable

Scoring Changes

Predictive/Indirect Measures – The Legacy Method

Lots of service- & network-layer telemetry data available

But at what level do these measures start to impact the delivered service?

- e.g. corrected codewords – clearly indicate a problem but at what level does it impact QoE?

Old way of determining “right” level of service/network telemetry impacting subs

Convene a bunch of RF experts, choose a region, gather a lot of data and “do a study”

- Output of the study – thresholds for SNR, CER, etc. for subscriber “in spec”

Limitations

- Generally performed infrequently, on a subset of the network
- Expensive & time consuming – doesn’t keep up with changes to user behavior & apps

Scoring Changes

Predictive/Indirect Measures – The Machine Learning Way

Key to determining when telemetry/other data is predictive of QoE impacts – Machine Learning

- Automatic feature selection used to determine which service/network measures are most predictive of direct QoE measures
- Historic service-/network-telemetry data for these measures are utilized to train the model
- Current service-/network-telemetry measures (aka “features”) input to model to evaluate how predictive data is of poor QoE measures
  - The output of the model is the “score”
  - Time-series telemetry data before & after the change yields a time series of scores
  - Trend of before/after scores can be compared or representative score calculated
- Model automatically retrained periodically to keep up with changes in user behavior & apps

Operationalization

Too many changes to manually review trends

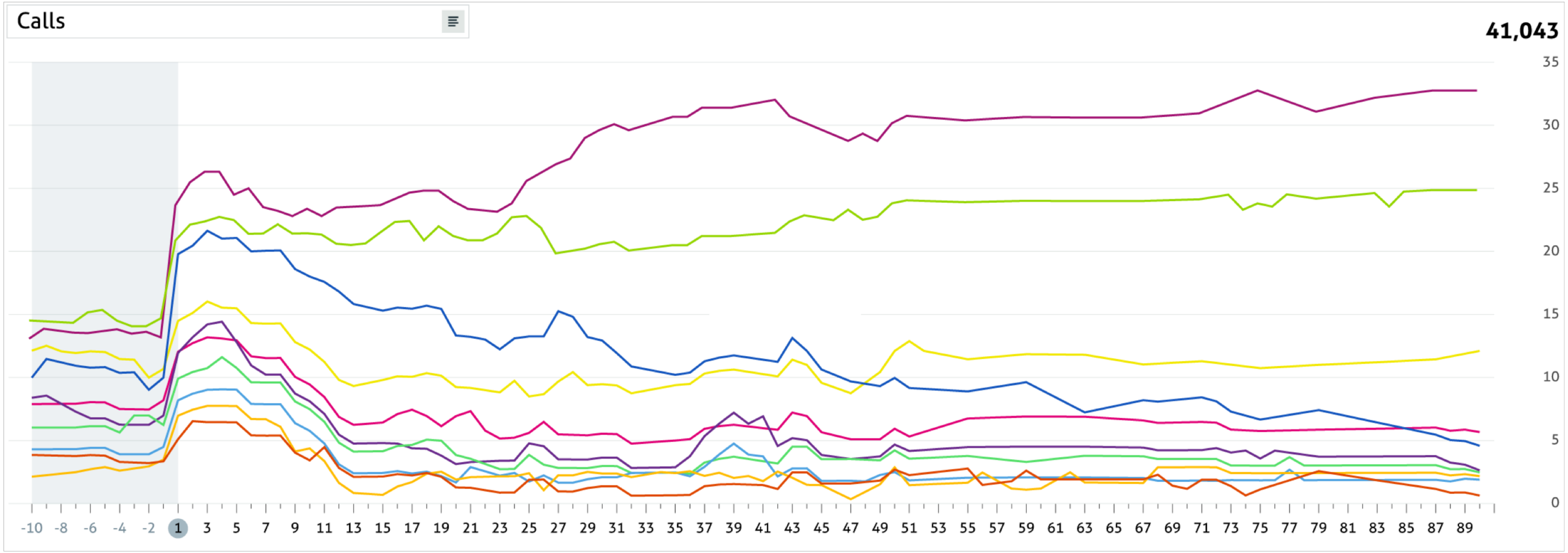
- Need a summary score for different time periods
- Automatically identify changes which negatively impact QoE

Big data, machine learning & streaming analytics are key

- Lots of service & network attributes on per sub basis critical for change-driven segmentation
- Scoring relies on direct and predictive measures of QoE requiring historic & current data
- Machine learning critical for getting ahead of calls & ensuring current QoE sensitivity

Doing this at scale is non-trivial

Example Before/After Scores on Change-Driven Segments



Customers demanding change at faster pace

- When you change things stuff breaks
- No lab can fully replicate production

Operators can embrace change with right tools in place

- Change-Driven Subscriber Segmentation
- Machine-Learning Driven Change Scoring

Need for analytics

- Big data, machine learning & streaming analytics are key to realizing this vision
- Not quite rocket science, but very difficult to do at scale

Thank You!

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