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Composite Quality Metric KPIs: A General Framework for Interpretable Composite Metrics

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Overview

We propose an approach for constructing a composite metric for measuring product quality that is correlated with bottom-line KPIs.

Traditionally, companies may track several individual metrics related to the performance of a product. However, product owners need to know if moving such individual KPIs (quality levers) would move the needle on a bottom-line metrics.

Any customer impacting initiative to improve the product experience seeks to answer the question:

- *Did the initiative move the needle on a bottom-line KPI or not?*

Moving the needle on a bottom-line KPI can be difficult to do. On the other hand, moving the needle on individual KPIs that are quality levers begs the question:

- *What link do these individual KPIs have with the high level KPI, if any?*
- *What is the relative importance of the individual KPIs?*

Our Approach:	*Our approach is to move the needle on a **composite quality metric** constructed from individual KPIs, composite components, which are product levers that can be influenced by the product owners. The construction of the individual KPIs and their relative influence (weights) can be chosen such that the composite metric is predictive/correlated with the bottom-line metric.*

Approach

We propose an approach for constructing a composite metric for measuring product quality that is correlated with bottom-line KPIs.

Composite Quality Metric

Our approach is a general framework for creating an interpretable composite quality metric that takes the following form:

$$CQM = \left[\frac{w_1 C_1 + w_2 C_2 + w_3 C_3 + \cdots + w_n C_n}{8 * (w_1 + w_2 + w_3 + \cdots + w_n)}\right] * A_1 * \cdots * A_m$$

- $CQM\ stands\ for\ composite\ quality\ metric$
- $C_i\ is\ the\ i^{th}\ component\ of\ the\ composite\ metric\ with\ possible\ values\ (8,5,3,2,1)$
- $w_i\ is\ the\ weight\ assigned\ to\ the\ i^{th}\ component$
- $A_j\ is\ the\ j^{th}\ binary\ filter\ with\ possible\ values\ (0,1)$

Metric Construction Steps

1. **Bucketing Metric Components**
   The components or individual KPIs, C_i, are discretized on a Fibonacci scale 8, 5, 3, 2, 1 such that a score of 8 can be interpreted as best, 3 as bad and 1 as worst experience.
2. **Optimize Weights**
   The weights for the components, w_i, are selected via numerical method such that correlation with bottom-line KPI is measured for each weight combination.
3. **Model Selection**
   The weight combination with the best correlation and non-skewed distribution can be selected as optimal.

Approach – Metric Components and Binary Filters

The composite quality metric is comprised of component metrics C_i and binary filters A_j.

Composite Quality Metric Components and Binary Filters

$$CQM = \left[\frac{w_1 C_1 + w_2 C_2 + w_3 C_3 + \cdots + w_n C_n}{8 * (w_1 + w_2 + w_3 + \cdots + w_n)}\right] * A_1 * \cdots * A_m$$

Component Metrics

- C_i is the i^{th} component of the composite metric with possible values (8,5,3,2,1)
- Component metrics are lower level KPIs that can act as product levers that can be influenced by the product owners and are related to a bottom-line KPI
  - *For example, to track quality of experience across a hybrid-MVNO network, metrics such as received signal strength, latency, throughput and link speed etc. are metrics that can be improved upon and are related to customer experience*

Binary Filters

- A_j is the j^{th} binary filter with possible values (0,1)
- The binary filter terms allow for a pass/no pass gate for the CQM depending on success of critical events for acceptable customer experience.
  - *For example, in a search quality metric, if the page fails to load or search API itself fails then we would want the score to be zero. Alternatively, if there is no page load failure and no search API failure then the metric is allowed to "pass" and would receive a score as per the first term in equation 1.*

Approach – Bucketing Metric Components

The individual KPI components are discretized such that the highest score can be interpreted as the best, and the lowest score as the worst experience.

Bucketing Approach

Our bucketing approach is to discretize the components or individual KPIs, C_i, on a Fibonacci scale 8, 5, 3, 2, 1 such that a score of 8 can be interpreted as best, 3 as bad and 1 as worst experience.

- *Our choice of the Fibonacci scale is used to result in a larger reduction in metric from the best quality bucket to second best and so forth*

Equal partitioning into fifths based on the 20th, 40th, 60th and 80th percentile can be used as thresholds to get roughly equal proportion of distribution in five buckets.

- Bucket 8: greater than 80th percentile (interpreted as the best experience)
- Bucket 5: 80th – 60th percentile
- Bucket 3: 60th – 40th percentile
- Bucket 2: 40th – 20th percentile
- Bucket 1: below 20th percentile (interpreted as the worst experience)

Advantages:

✓ *Product owners can get a sense of the gradation of the customer experience in a simple and consistent fashion across metrics on different scales*

✓ *Robustness to outliers: Outliers are bounded in the highest/lowest buckets*

✓ *Underlying changes can occur and be accounted for in the buckets without changing the overall metric construction*

Approach – Optimize Weights and Model Selection

Optimal weights are selected by benchmarking the Composite Quality Metric against a bottom-line KPI.

Optimize Weights	**Optimal weights are selected by benchmarking the Composite Quality Metric against a bottom-line KPI for several combination of the component weights.** 1) For each combination of weights, calculate the CQM as shown on slide 3 2) Calculate the average of the bottom-line KPI for 5 or 10 equal buckets of the CQM score 3) Fit a simple linear regression between the average values of the bottom-line KPI (Y) and buckets of the CQM score (X) 4) The combination with best R2 and non-skewed distribution of CQM scores is selected as optimal. If an optimal combination is found, then as we move from a lower bucket of score to higher bucket, we should see higher bottom-line KPI values
Regression Analysis	**We also perform a basic regression analysis where we regress the individual components post bucketing as regressors against the bottom-line KPI.** • This helps us understand which components are significant prior to running the optimization. • We can possibly eliminate the non-significant components or substitute for a different component.
Model Selection and Validation	**The final metric is selected to optimize the weights of the Composite Quality Metric against a bottom-line KPI.** • As we move from a lower bucket CQM scores to higher buckets, the optimal combination results in higher bottom-line KPI values. We also want to see a non-skewed distribution of scores. • We also validate against out of sample data to ensure the relationship holds for more data and longer timeframes. This gives us confidence that the metric is not overfit and validates well on data that the model has not seen/trained with.

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Thank You!

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