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A Decision Tree Approach to Customer Surveys

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***Abstract*—Many companies assess performance by using customer feedback surveys. A primary purpose for such surveys is to generate actionable insights to improve the company's areas of weaknesses. Asking too few questions in the survey does not provide sufficient information for root cause analysis. On the other hand, one can also ask a series of more detailed questions which will force the customer to provide specific insights. However, customers are unlikely to complete such detailed surveys and many parts of the survey may be of little interest to them anyway. Suppose instead, we focus on requesting feedback for a small number of pain points of the customer using a hierarchical decision tree approach. By doing this we can provide a more focused, smaller set of questions for that individual, based on their branching choices. This would provide the level of detail needed to determine weak points in the company. We address this problem and outline a hierarchical decision tree approach for determining such a survey, also known as a computer adaptive survey (CAS). Computer adaptive surveys have been shown to be a great tool for root cause analysis. Our approach adds to CAS by providing a relative performance score for measuring customer experience across similar companies and over time. Furthermore, we ensure that responses to the survey are appropriately weighted in order to reduce bias. In addition, we describe the procedure of updating survey questions in the future based on historical survey responses and propose how incentives can be provided to increase participation in such a way that the customer benefits only by providing quality data. In this paper we illustrate the approach using data from the telecommunications industry and compare customer experience results for two different cellular providers.**

***Index Terms*—Root Cause Analysis, Computer Adaptive Survey, Customer Experience, Decision Tree, Incentives**

I. Introduction

Customer experience is one of the key perspectives used to measure company performance in the telecommunications industry [1], [2]. Certain metrics such as Net Promoter Score (NPS), Customer Satisfaction Score (CSAT) and Customer Effort Score (CES) have been used to assess overall customer experience in the context of customer loyalty and customer satisfaction. However, these metrics by themselves cannot be adequately used to identify specific weaknesses of customer experience, and thus actionable insights offered by such indicators are limited.

Another approach to analyzing customer experience is to acknowledge customer touch points. These are instances when the customer interacts with the company and its products and services throughout the customer journey [3]. Note that customers interact with, and are therefore only interested in, a selected set of touch points. This varies from customer to customer; for example, some customers may prefer to report issues to a call center rather than visiting a store or outlet. While some studies allow for the assessment of several specific touch points and hence drill down to specific areas of weaknesses, the utilized questionnaires do not allow customers to choose whichever touch points matter to them. Rather, customers are encouraged to answer all questions even though they may only be interested in a select few. This introduces a lot of noise in the data collected and makes it difficult to assess the true importance of the factors being measured.

Surveys should have a large sample size while reducing non-response bias. Traditional questionnaires used in customer experience surveys target a few major touch points in a broad and vague manner. This is typically an attempt to maintain simplicity and efficiency in the survey design, so as to boost response rate and response quality [4], [5], [6]. However, asking a short number of questions may be insufficient to capture the scope of customer touch points or satisfaction attributes. Hence, root cause analysis of customer satisfaction cannot be extracted from these types of surveys.

Alternatively, questionnaires may address many specific touch points in a linear survey design. However, the survey now becomes too long and complicated, resulting in a reduced response rate and a decline in data quality. We argue that both approaches have flaws that may be overcome by employing a hierarchical survey design for measuring customer experience, and we illustrate the advantages and flexibility of the proposed approach.

Consider, for example, a generic company that sells and delivers certain products. They may be concerned with issues facing the customer with respect to their service, the cost of their products and possibly the range and availability of the products they offer. A survey with questions on each of these aspects can be developed but most customers will probably only be concerned with about one or two aspects and so the addition of the other questions is a burden. Suppose, as we do in Fig. 1, we ask preliminary questions and allow the customer to focus on a single topic and then rate their experience on that topic. In this case the customer answers two questions and provides a single rating. In the traditional survey the customer would have to provide ratings for six questions and many of these may be of little concern. In general, if a traditional survey has N questions and we provide binary splits in the decision tree then the number of questions that would have to be answered using a decision tree would be $\mathcal{O}(\log N)$.

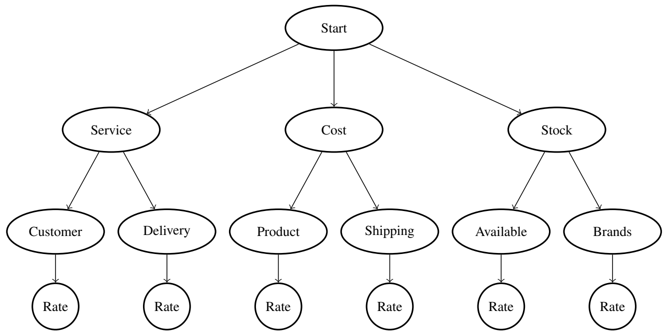

Fig. 1. Sample decision tree survey for a generic company.

The value provided by this research allows for better identification of specific pain points which will offer explanations for the root cause of customer satisfaction, since customers can choose to respond to their items of concern. The hierarchical decision tree approach used to achieve this (referred to as a computer adaptive survey) has already been shown to be effective when compared to traditional surveys [7]. However, our approach additionally reduces bias in responses. Some respondents will give more responses than others but we want all respondents to have the same impact in the survey. We therefore weight by the inverse of the number of nonzero responses that the user provides. We can then come up with a relative performance metric that captures customer experience holistically. Another benefit of our method is that the telecommunications service provider can implement a continuous improvement strategy by updating the prioritization of touch points once different weak and strong points are identified from surveys over time. Finally, we suggest a practical incentive which will simultaneously boost response rate and response quality. This incentive consists of informing respondents that their most negative pain points will be targeted once the survey illuminates these points, and this will encourage the respondents to highlight their views in a transparent manner, as necessary.

II. Related Work and Contributions

The quantification and measurement of customer experience via surveys and questionnaires have received much attention in previous literature [8], [9]. However, causal factors using such measurements have rarely been emphasized. For example, the NPS measure can be utilized as a customer loyalty indicator but it does not provide an explanation for root cause [10].

Machine learning and statistical techniques for identifying important factors that influence customer experience have been applied on telecommunications customer survey data. As examples, these include genetic algorithm, multiple regression, confirmatory factor analysis, structural equation modelling and supervised classification techniques [11], [12], [13], [14]. Nonetheless, there is usually a lack of clear and accurate association between the customer experience metric and the customer attributes which are supposed to provide root cause explanation [11].

Studies suggest that there is a need for a holistic and dynamic view across multiple touch points that change over time. For example, a positive overall experience may be reported by the customer but specific aspects within that experience may be in competition with each other where positive aspects overshadow the negative aspects [15]. There is hence a need to disaggregate customer experience into more granular aspects to get a comprehensive view and evaluate all aspects as a unified experience [3]. Furthermore, it is suggested that touch points to be improved should be mapped out from the customer's perspective and not only from the company's perspective [16]. Through the use of text mining, [16] developed a model to help identify and monitor pain points, which also aided in the early detection of potentially 'vulnerable' customers that were typically labelled as highly satisfied. This also led to the identification of the root causes of this vulnerability.

Reference [7] employed the same hierarchical decision tree approach proposed in this paper to investigate root cause of customer dissatisfaction at cafés. They showed that this survey, referred to as a computer adaptive survey (CAS), allowed for deeper understanding of root cause when compared to the assessment of online reviews. They outlined the numerous advantages of CAS (as also discussed in this paper), such as the ability to include a large number of questions without respondent fatigue and for which the respondent can focus on a narrow set of salient questions only. Additionally, whereas traditional surveys cannot handle complex correlations between items in a survey, there is an implicit dependent variable (customer satisfaction) which is captured in the data but which the survey does not ask, and there are structured and defined correlations throughout the hierarchical levels.

With further detail, high correlations are expected between a parent and one child in CAS. For instance, if a respondent is dissatisfied with a service, there must be at least one sub-dimension of service they are dissatisfied with (example service quality). However, due to orthogonality of sub-dimensions across the same level in the hierarchy, low correlations between sub-dimensions are expected. For instance, if a respondent is dissatisfied with the efficiency of a service it does not necessarily mean they are dissatisfied with the quality of service [7]. Our approach adds to CAS by appropriately weighting responses, producing a relative performance metric, suggesting an appropriate incentive and updating the survey over time. These aspects of our approach will be discussed in later sections.

Finally, the concept of offering incentives to increase customer participation in surveys has also been studied. For example, [17] discuss the positive impacts on response rate by using incentives in web-based surveys. While it may be logical to assume that respondents would simply rush through the survey to earn an offered incentive, there is little evidence to suggest that the provision of incentives decreases response quality [18]. Response quality is generally measured by item non-response but this may not be an adequate indicator of the true response quality. In order to mitigate any risk of obtaining careless responses, we prescribe a non-monetary, conditional incentive that will boost both response rate and quality.

III. Decision Tree Survey Framework

We use a hierarchical structure to define the potential pain points of customers. This idea is illustrated by the sample computer adaptive survey diagram in Fig. 1. At the first level, there is a set of touch-points which are represented by services and products that the company offers. At the second level, we have attributes to offer root cause explanation, represented by typical issues faced when subscribing to such services or purchasing such products. The third level consists of a scoring system for the topic dictated by a combination of the previous two levels. One chooses an integer from -3 to $+3$ with -3 indicating a very negative view, $+3$ a very positive view and 0 being the default value indicating no opinion.

Our objectives are to reduce the number of questions that a customer must answer, as well as to reduce the number of options for each question. We do this by providing an appropriate set of items at each level. We will later outline a process for updating the items to better match the needs of the customer population. Customers are asked to complete at least one sequence of questions which will require a few clicks (one for the choice at each level and one for the score of the choice). After completing some feature information and at least one sequence of questions they can submit or they can, if they wish, complete more choices. Therefore an individual can focus on a single annoying pain point or beneficial attribute of the company and quickly complete the survey, or they can complete multiple entries if they so desire. In the latter case we reduce the weighting of their scores so all customers have similar impact on the survey results. One can then use the responses to answer various questions such as which aspects of the company are viewed favourably and which aspects are not viewed favourably. We demonstrate the approach in more detail through an actual survey.

IV. Description of the Conducted Survey

We demonstrate the approach with an example for cellular providers. We first collect information of the respondent including gender, age bracket, email address (used as a unique identifier), their cellular provider (denoted by cellular provider A (CP-A) and cellular provider B (CP-B)), their subscription type (postpaid or prepaid) and their monthly payment for service (suitably grouped). As this is a pilot study and we did not utilize customer information from the cellular providers, we propose that the collection of this information would be different for cellular providers collecting information from their own customers. The cellular providers can access each respondent's demographics through an existing customer database and the survey would simply require a phone number, account number or unique identifier from each customer. Next, we present the service or function that is of concern and for each of these services we present a set of attributes. Each attribute of concern must then be ranked on a scale from -3 to $+3$. A respondent must complete at least one attribute from at least one service in order to have their survey considered. All unanswered options are set at their default value of 0.

The services and attributes used in this survey have been thoroughly researched and are derived from previous voice of the customer (VoC) surveys used by a cellular provider, customer satisfaction (CSAT) questionnaires and other sources based on similar questionnaire designs from previous work described in section II (see for example [12], [13]).

All services and attributes outlined in our questionnaire, along with corresponding tags, are listed in Table I. We group between four to six (second level) attributes from the questions within each (first level) service and this would enable the respondent to view at least four (second level) attributes and therefore make (third level) responses.

We recommend adopting the aforementioned approach for building the initial survey since we would like to enable the respondent to answer a balanced set of related questions on areas that are of primary concern to them to truly identify sources of concern. The statistics of the collected data are provided in Tables II and III. The terms $N, \tilde{Q}, C_i$ and R_j are described in section V-A.

V. Analysis of Survey Results

The collected data provides an array of useful information for the cellular providers. We describe how we extract pertinent information and apply various analyses on the collected data.

A. Performance Metric Definition

We first compute a single metric that provides a global picture of the perceived success or failure of a provider. We mathematically derive this metric from the customer experience attributes (see (3) and (4)). For convenience, let us denote the questions asked by Q (i.e. A1, A2, A3, A4, A5, B1, ..., N4, N5) indexed by j. The number of responses to question j is denoted by R_j. We use x_{ij} to denote the score provided by customer i to question j. We denote the number of respondents for a provider by N. We would like to derive a metric that represents the consensus view of the provider.

Since we want each respondent to have the same impact on the survey and some respondents provide more responses than others, we weight scores of a user by the inverse of the number of responses that user provides. In our analysis, we only consider questions for which we received at least one response. For convenience let $\tilde{Q}$ denote the set of questions with at least one response so that $\tilde{Q} = \{j : (j \in Q) \wedge (R_j > 1)\}$. For such questions, we compute the average score of topic j as

$$F_j = \frac{1}{3N} \sum_{i=1}^{N} \frac{x_{ij}}{C_i} \tag{1}$$

where

$$C_i = \sum_{j \in \tilde{Q}} 1 - \delta_{x_{ij},0} \tag{2}$$

is the number of questions for which customer i provided a score and δ is the Kronecker Delta function (i.e. $\delta_{x_{ij},0} = 1$

TABLE I
SERVICES AND ATTRIBUTES OF SURVEY

Service or Function	Attribute	Tag
(A) Purchase/Activation of Phone at an Outlet	Amount of time taken for the purchase process	A1
	Ease of purchasing a mobile phone	A2
	Variety of products to choose from	A3
	Time taken to activate phone after purchase	A4
	Value for money on the purchase of the product	A5
(B) Quality of Phone Purchased at an Outlet	Ease of using features	B1
	Phone stands up to my everyday use	B2
	Battery life	B3
	Phone meets technological expectations	B4
(C) Billing Information Payments (postpaid)	Timeliness of receiving bills	C1
	Accuracy of bills	C2
	Layout/legibility of bills	C3
	Sufficient information is provided to justify bill charges	C4
	Ease of paying bills online/with the mobile app	C5
	Ease of paying bills at cellular provider's outlets/affiliates	C6
(D) Topping Up (prepaid customers)	Convenience of buying phone cards	D1
	Convenience of using phone cards	D2
	Availability of phone cards in the dollar amounts I want	D3
	Layout/legibility of instructions on phone cards	D4
	Ease of topping up online/with the mobile app	D5
(E) Mobile Data Quality/Plans	Download and upload speeds	E1
	Reliability of data connection	E2
	Access to data plans that suit my lifestyle	E3
	Ease of activating/switching from one data plan to another plan	E4
	Value for money on what I spend on data	E5
(F) Local Calling Quality/Plans	Ability to connect (make and receive calls)	F1
	Reliability of connection (calls do not drop)	F2
	Quality of calls (clarity and volume of calls)	F3
	Access to voice plans (to local destinations) that suit my lifestyle	F4
	Ease of switching from one local voice plan to another plan	F5
	Value for money on what I spend on talk/minutes	F6
(G) International Calling Quality/Plans	Ability to connect (make and receive calls)	G1
	Reliability of connection (calls do not drop)	G2
	Quality of calls (clarity and volume of calls)	G3
	Access to international voice plans that suit my lifestyle	G4
	Ease of activating/switching from one voice plan to another plan	G5
	Value for money on what I spend on talk/minutes	G6
(H) Roaming Quality/Plans	Ability to connect when overseas	H1
	Reliability of connection when roaming	H2
	Quality of connection when roaming	H3
	Access to roaming plans that suit my lifestyle	H4
	Ease of switching from one roaming plan to another plan	H5
	Value for money on what I spend on roaming	H6
(I) SMS Text Messaging Quality/Plans	Text message notifications from cellular provider	I1
	Reliability of sending/receiving text messages	I2
	Access to SMS text messaging plans that suit my lifestyle	I3
	Ease of switching from one SMS text messaging plan to another plan	I4
	Value for money on what I spend on SMS text messaging	I5
(J) Reporting Issues Queries to Outlets	Time spent not being attended to throughout the reporting process	J1
	Convenience of accessing customer service outlets/affiliates	J2
	Representatives' courteousness/willingness to help	J3
	Representatives' knowledge/understanding of my needs	J4
	Accuracy of information received	J5
(K) Reporting Issues Queries to Call Centres	Time taken for my call/online request to be answered	K1
	Representatives' courteousness/willingness to help	K2
	Representatives' knowledge/understanding of my needs	K3
	Representatives' ability to communicate clearly	K4
	Accuracy of information received	K5
(L) Resolution of Reported Issues/Queries	Issues/queries were resolved after being reported	L1
	Status updates on resolutions of issues/queries	L2
	Timeliness of resolving issues/queries after being reported	L3
	No recurrence of the same issues/queries	L4
	Rebate policy	L5
(M) Cellular Provider's Image	Cellular provider's innovation/creativity	M1
	Cellular provider's care for its customers	M2
	Cellular provider's fulfilment of corporate social responsibility	M3
	Cellular provider is a brand I trust	M4
(N) Provider's Promotions Incentives/Advertisements	Seasonal promotions/incentives suited for my lifestyle	N1
	Suitable incentives (emergency credit/bonus credit/credit transfers)?	N2
	Effectiveness of advertisements for promotions/plans	N3
	Frequency of advertisements for promotions/products/plans	N4
	Access to more information of products/plans/promotions/incentives	N5

TABLE II
RESPONSE STATISTICS FOR CP-A

Feature	N	$\lvert\tilde{Q}\rvert$	Average C_i	Average R_j
CP-A	40	53	5.325	4.019
Male	21	42	5.048	2.524
Female	19	39	5.632	2.846
Postpaid	9	16	4.778	2.688
Prepaid	31	52	5.484	3.365
0-17 Years Old	1	2	2	1
18-24 Years Old	16	40	5.875	2.425
25-34 Years Old	18	44	5.667	2.364
35-44 Years Old	3	9	3	1
45-54 Years Old	0	0	N/A	N/A
55-64 Years Old	2	6	3	1
65-99 Years Old	0	0	N/A	N/A
$0-$50	18	41	4.833	2.171
$50-$100	5	19	5	1.316
$100-$150	0	0	N/A	N/A
$150-$200	3	8	4	1.5
$200-$250	4	25	9	1.48
$250-$300	4	16	5.5	1.5
$300-$350	1	7	7	1
$350-$400	5	15	4.8	1.6
$400-$1000	0	0	N/A	N/A

TABLE III
RESPONSE STATISTICS FOR CP-B

Feature	N	$\lvert\tilde{Q}\rvert$	Average C_i	Average R_j
CP-B	90	70	6.078	7.814
Male	43	64	5.349	3.594
Female	47	66	6.745	4.803
Postpaid	25	48	6.76	3.521
Prepaid	65	69	5.815	5.478
0-17 Years Old	1	2	2	1
18-24 Years Old	24	43	6.042	3.372
25-34 Years Old	40	63	6.45	4.095
35-44 Years Old	13	27	4.923	2.370
45-54 Years Old	5	29	7.2	1.241
55-64 Years Old	5	29	6.2	1.069
65-99 Years Old	2	6	5.5	1.833
$0-$50	27	50	5.741	3.1
$50-$100	11	39	7.364	2.077
$100-$150	4	17	4.5	1.059
$150-$200	4	16	7	1.75
$200-$250	19	48	5.737	2.271
$250-$300	4	13	5.5	1.692
$300-$350	5	24	7.2	1.5
$350-$400	9	19	4.889	2.316
$400-$1000	7	36	7.714	1.5

if $x_{ij} = 0$, and 0 otherwise). Note that this prevents a single customer from providing a significant bias to the results. The overall score for the provider is then given by

$$S = \frac{1}{3N} \sum_{j \in \tilde{Q}} \sum_{i=1}^{N} \frac{x_{ij}}{C_i} = \sum_{j \in \tilde{Q}} F_j \tag{3}$$

Note that we divided by 3 so that $-1 \leq S \leq 1$. When this metric is evaluated, we obtain 0.069 for CP-A and 0.036 for CP-B. Although both cellular providers have a positive score, CP-A is viewed more favourably than CP-B.

Another factor we may want to consider is the monthly payments made by a respondent. We can provide a heavier weighting to those who pay more for their service since a loss of such customers results in heavier losses to the provider. Let P_i denote the amount paid per month by user i. We define $\kappa_i \equiv \left\lceil \frac{P_i}{50} \right\rceil$ and so for every additional $50 spent, the value of κ goes up by one unit. We will weight each user's score by this value. The resulting expense-based metric is given by

$$S_E = \left(\frac{1}{\sum_{i=1}^{N} \kappa_i} \right) \frac{1}{3} \sum_{j \in \tilde{Q}} \sum_{i=1}^{N} \frac{\kappa_i x_{ij}}{C_i} \tag{4}$$

Dividing by the sum of the κ_i values ensures that $-1 \leq S_E \leq 1$. Computing this metric for the two providers we obtain 0.172 for CP-A and -0.070 for CP-B, and hence CP-B is viewed even less favourably by their high paying customers due to their negative score.

Note that S and S_E are not absolute scores for company performance but they merely track customer experience over time in a relative manner. Hence a value close to zero does not necessarily indicate poor performance but any value greater than zero implies general customer satisfaction when considering all touch points as a whole. The above metrics will have a clear and defined association with the customer service attributes that offer root cause explanation, in contrast to traditional metrics such as NPS. For instance, if the cellular provider wishes to determine the driving factors that influence NPS, attributes that have high correlation with the NPS score may be used for analysis. Nevertheless, correlations may be weak with unclear relationships. This limitation is resolved if our metric is employed. Our metric also removes the shortcoming of having to conduct regression, confirmatory factor analysis, etc. to pinpoint relationships between the customer experience metric and the customer experience attributes.

B. Determination of Weak and Strong Points

In this section we determine the areas of weakness and the areas of strength for the providers. For each question j we compute the average weighted score F_j using (1). Note that this metric captures two aspects of the question: its popularity (i.e. how many people responded) and the average score over those who responded. If few people responded then the value will be close to zero (because most of the scores will be zero). If many people responded but some were positive and some were negative in their feedback then the metric will also be

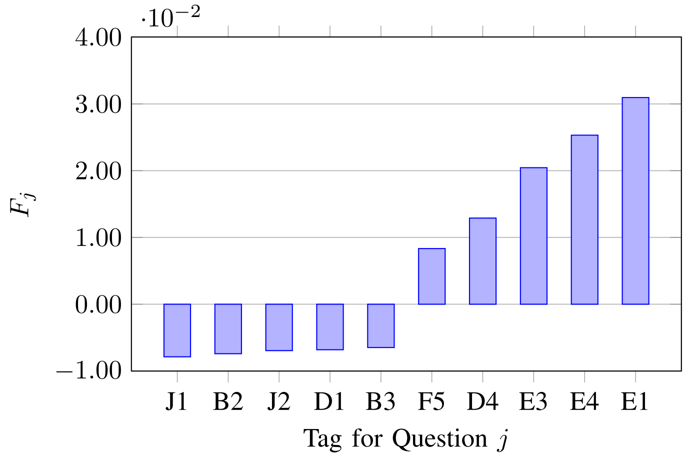

Fig. 2. Best and worst average question scores for CP-A.

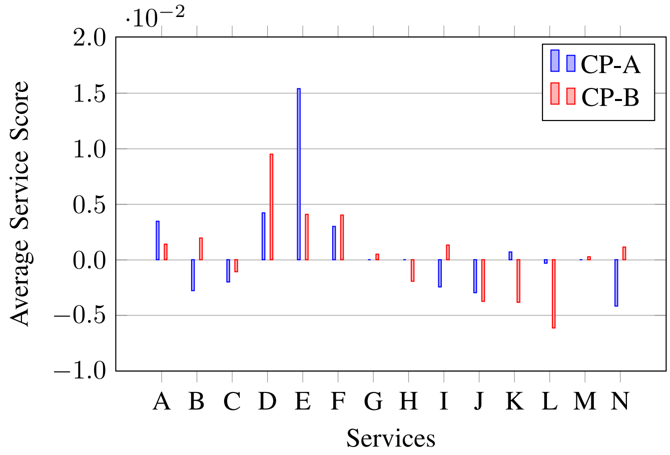

Fig. 4. Comparison of function scores for providers.

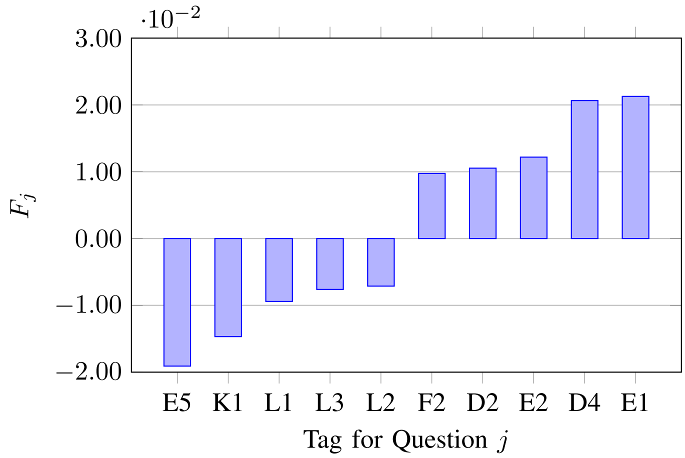

Fig. 3. Best and worst average question scores for CP-B.

close to zero. We can therefore rank questions based on this metric to determine which ones are favourable and which are not. We plot this metric for the five worst and five best scored questions for CP-A in Fig. 2 and for CP-B in Fig. 3. We can also determine the performance as a function of services. We do this by considering all questions within the service with at least one response and by averaging over their F_j scores. Due to the relatively small sample size of the study, results may not accurately represent the true views of the customer population for CP-A and CP-B. However, some interesting insights can still be demonstrated from this pilot study. These results are included in Fig. 4 and allows for comparisons of the two service providers to be drawn across the variety of services.

VI. Providing Incentives

People are sometimes reluctant to complete surveys since there is typically no incentive to do so. On the other hand, if an incentive is provided then customers may simply perform a quick, haphazard completion of the survey in order to get the incentive but without putting sufficient thought into their responses. The quality of the data then becomes questionable. We suggest the following incentive. For the most negatively scored topic(s) overall, we will prioritize addressing specific subsets of customer groups (by location, type of plan, etc.) that provide the most negative scores. In this way the only incentive for the customer is faster response times to their major pain point and so naturally they would like this priority applied to the topic that pains them the most.

As an illustration, let us consider CP-B. We recall that the attribute with the worst score outlined in Fig. 3 is the E5 tag (Value for money on what I spend on data). We can now consider all respondents that have filled out the survey and have given this attribute a negative score. Through unique identifiers, the cellular provider can utilize their customer database and align information for these respondents to the attributes. For the E5 tag, we will consider the data plan of each respondent as a means of obtaining subsets of the customer group that has given negative E5 scores. We can then pinpoint which data plans require revision by identifying the plan with the worst weighted score. The weighted score for respondent i and question j is computed as $\frac{x_{ij}}{C_i}$. The weighted score for specific characteristics would be the sum of the weighted scores of respondents that share the same characteristics.

We do not have the specific data plan for each respondent so we will examine the combination of prepaid/postpaid plan and monthly subscription. We calculated the summary statistics of the respondent characteristics for respondents who have given negative E5 scores. The cellular provider should focus on improving the data plans that give the worst weighted E5 scores. In this case the top three characteristics with the worst scores were: prepaid plans with a \$0-\$50 monthly subscription, prepaid plans with a \$200-\$250 monthly subscription, and prepaid plans with a \$50-\$100 monthly subscription. These characteristics have negative E5 weighted summaries of -2.6964, -1.6583 and -0.9214 respectively. The cellular provider should therefore seek to target these three customer characteristics to increase value in these plans.

VII. Updating Survey Questions and Responses

We advocate that the survey remains accessible to all subscribers of each cellular provider at all times and reminders of the survey updates/modifications be sent at regular time intervals to customers. Questions should be reviewed once a sufficient inflow of new responses is attained. For instance, attributes can be reviewed after every 1000 responses or after every additional 1% of the customer base's responses.

Note that certain topics may be of interest at one point in time but once the company improves in that area the topic may no longer be of interest and so customers will stop choosing that item. We therefore need to identify and remove such items. On the other hand, another item may suddenly have increased in interest and it would be better to split that item into two new items (either at the service level or question level) to be better able to identify the root cause of the issue. Resources are expended by the cellular provider to fix the issues highlighted, so the overall satisfaction score will gradually increase over time. However, new problems or issues will arise, and the overall satisfaction score will begin to trend downward once more. The objective of the cellular provider will therefore be the optimization of the overall satisfaction score (ideally keeping it positive), based on resource constraints.

We first determine the popularity index of each question, which is the ratio of the number of responses to the question and the total number of responses. If this index is sufficiently small then we remove this question from the survey. Similarly if this index is sufficiently large then we expand the survey to more accurately cover the issues surrounding the question in concern. Let us illustrate this approach for CP-B. In Fig. 5 we plot the 8 least popular and 5 most popular questions for the cellular provider. Using thresholds of less than 2 responses per question and the 5 most popular questions, we decide to remove question tags G5, H5, I4, N4 and all question tags in M (cellular provider's image), and expand on all question tags in E (mobile data quality/plans). Since we obtain high popularity indices for question tags in mobile data quality/plans (E), we can expand on this topic by splitting the (first level) service into two services, namely mobile data quality (E_a) and mobile data plans/pricing (E_b). E_a may be tagged with attributes E_a^1, E_a^2 and E_a^3, where E_a^1 denotes download and upload speeds, E_a^2 denotes ability to connect to data wherever I go, and E_a^3 denotes stability/consistency of data connection during use. Meanwhile, E_b may be tagged with attributes E_b^1, E_b^2 and E_b^3, where E_b^1 denotes access to data plans that suit my lifestyle, E_b^2 denotes ease of activating/switching from one data plan to another plan, and E_b^3 denotes value for money on what I spend on data. Future surveys will therefore result in more balanced responses and hence better coverage of the areas of concern.

The survey will be open to customers indefinitely, and as a result, we need to adopt a mechanism of removing outdated responses so that they will not influence the current perception of the company. Customers that complete the survey multiple times will only have their most recent submission retained for analyses. We assume that customer perspectives on pain points

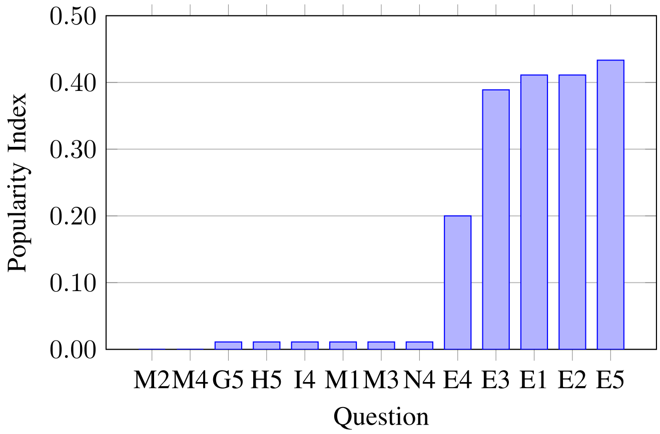

Fig. 5. Least and most popular questions for CP-B.

will change for those who have benefited from the incentives of the survey (see section VI). Thus, we can remove their survey submissions from the database and ask them to submit new responses. This will shed light on pain points that were overlooked or were not important at the time, and will aid in establishing a continuous improvement scheme.

VIII. Conclusions and Future Work

We proposed a new method of measuring customer experience for root cause. Using a computer adaptive survey (CAS) framework, we can drill down to specific pain points in customer experience. Furthermore, simplicity and brevity of the survey are maintained since customers are encouraged to answer only the questions that impact them and ignore the rest. Thus, the measurement of customer experience is not blanketed or generalized by noisy data since touch points are identified by the customers themselves. This is due to a highly streamlined and personalized survey that meets the needs of individual customer journeys. Overall satisfaction score is not only weighted more heavily on topics that are popular and are of greater interest, but also weighted by the customer's number of responses so as to limit the potential bias provided by a single customer. This survey also allows for the determination of weak and strong touch points, and the subsequent addition or removal of topics and respondent submissions based on the changing relevance of certain topics over time. Finally, a suitable non-monetary incentive for the survey was outlined and can be used to encourage higher response rate and quality. Note that the proposal outlined is simply a proof of concept done using a pilot survey. Future work should involve carrying out larger-scale surveys over time to examine the scoring functions and features that may be used to tune the questionnaire. Changes in customer experience scores over time, as well as the effectiveness of removal and splitting of questions in the survey can hence be thoroughly examined.

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