# On Design of Problem Token Questions in Quality of Experience Surveys

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Abstract-User surveys for Quality of Experience (QoE) are a critical source of information. In addition to the common "star rating" used to estimate Mean Opinion Score (MOS), more detailed survey questions (problem tokens) about specific areas provide valuable insight into the factors impacting QoE. This paper explores two aspects of the problem token questionnaire design. First, we study the bias introduced by fixed question order, and second, we study the challenge of selecting a subset of questions to keep the token set small. Based on 900,000 calls gathered using a randomized controlled experiment from a live system, we find that the order bias can be significantly reduced by randomizing the display order of tokens. The difference in response rate varies based on token position and display design. It is worth noting that the users respond to the randomized-order variant at levels that are comparable to the fixed-order variant. The effective selection of a subset of token questions is achieved by extracting tokens that provide the highest information gain over user ratings. This selection is known to be in the class of NP-hard problems. We apply a well-known greedy submodular maximization method on our dataset to capture 94% of the information using just 30% of the questions.

Index Terms—QoE; Survey design; VoIP; data analysis

#### I. Introduction

Several Internet telephony applications employ end-of-call user surveys to gather data on in-call QoE [1]. In addition to the five star rating (MOS [2]), the percentage of calls rated 1 or 2 (poor call rate, or PCR) is often tracked as a measure of media quality. Previous studies have shown the value of combining PCR with an additional problem token questionnaire (PTQ) to gather detailed insights [3]. The UI design of the PTQ used in this study is provided in [3].

The range of questions used to capture these detailed problem areas has been studied in depth [4], [5]. However, to the best of our knowledge, the impact of presentation order on response rate has not been studied in a live, deployed system. Our work is motivated by the practical challenges faced in analyzing questionnaire data. For example, our analysis showed that the contribution of one-way audio (one side can hear, but the other side cannot) to PCR dwarfed the other areas by a factor of two on mobile platforms. Further investigation, showed that the most important factor for this gap was the display order of questions. The 'no sound' token was placed at the top, and users were 40% more likely to select this area purely due to its position in the survey. While one-way audio remains one of the top problem areas, we found that after randomization of the order, other impediments such as audio distortion and poor image quality occurred at comparable levels.

In mobile environments, the screen size is limited, so if designers want to avoid using a scrollbar, the number of questions needs to be kept small. The key question is how to minimize the number of questions, while maximizing their power in explaining PCR. Moreover, studies have shown the benefit of shortening surveys (without losing information) for improving response rate and improved data quality [6]. Identifying this subset of questions belongs to a class of NP-hard problems [7]. In order to solve this, we follow the lead of Krause et al., leveraging the fact that information gain is a submodular function, and can be optimized using provable greedy approaches [8], [9]. As shown in Section IV, this approach maps well to the our problem. The main contributions of this paper are:

- Results of a large scale randomized, controlled experiment in a live VoIP system to show the bias introduced by fixed order questions.
- Provide an efficient solution to select a subset of tokens that maximizes information and minimizes correlation.

### II. RELATED WORK

There is a rich area of research and practice in general survey design, validation and question order [10], [11]. Factor analysis is commonly employed to analyze surveys with the number of factors being smaller than the number of questions. [12]. There are many standards for subjective audio and video quality surveys, such as the ITU standards [13], [4], [5]. In this paper, our goal is not to replace these surveys, but instead to improve their utility by providing recommendations for presentation order, and a methodology to select a subset of informative questions. The selection of a subset of correlated random variables for maximizing the information gain has been studied in detail [8], [9] - this paper focuses on the application of these methods for QoE problem area surveys.

# III. IMPACT OF QUESTION DISPLAY ORDER

We study the impact of question order on our PTQ using a randomized controlled experiment. The control population was shown the original questionnaire with fixed token order. For video calls, the audio tokens were always shown on the left while the video tokens were always shown on the right. The treatment population was shown the questions in randomized order. For video calls in the treatment population, the position of the audio and video panels (left/right) were selected at random. The details of the experiment are below:

TABLE I: The difference in overall response rate in tokens between control group and treatment group

Population	Relative Delta	p-value
Audio-only	-1.38%	0.072
Video	-1.62%	0.001

- One-to-one calls that included both audio-only and video VoIP calls on desktop platforms.
- The control and treatment group each contained 450,000 calls spanning over 100,000 unique users.

The experiment aimed to answer the following questions:

- 1) Is there a change in the percentage of questionnaire responses?
- 2) What is the change in response rate of the individual audio and video tokens?

We present all results using relative measures due to commercial confidentiality.

# A. Overall Questionnaire Response Rate

We wanted to understand if randomizing the questions impacts the overall response rate of the PTQ. A user is said to respond to a PTQ if any token selection is made. We considered audio-only and video population. The differences in overall token response rate between the control group and the treatment group for these segments is shown in Table I. From a statistical perspective, there is no change in the percentage of responders in the audio population, but there is a change in the video population at the 99% significance level (i.e. p-value < 0.01). However, we find that the relative difference of 1.6% for video surveys is small enough that the benefits (Section III-B) of the randomized questionnaire outweigh the minor reduction in response rate.

# B. Response Rate of Individual Questions

The difference in response rates of individual tokens between the fixed order and randomized order for video, desktop tokens is shown in Table II. Negative sign (red) indicates that the response rate went down whereas a positive sign (green) indicates the response rate went up. Although a change in the response rate was expected, there are some significant insights from these results:

- 1) The response rate of the top token is dramatically impacted for audio and video tokens. The decrease in response rate between the two variants is greater than 20%. This shows the propensity for selecting the top token.
- 2) For audio, the response rates of the top four tokens decreased dramatically, However, for video the response rates of the bottom four tokens increased. This shows that panel position (left, right) impacts response rate.

The impact of panel position is even more pronounced in mobile environments. In mobile, we found the average response rate for tokens that require users to scroll was 49% lower. These results motivate the need for showing a small set of informative tokens to ensure that we do not lose the users attention while responding to the questionnaire.

TABLE II: The difference in response rate of individual tokens for fixed vs. randomized display order in video desktop calls.

Audio problem Token	Relative delta	p-value
I could not hear any sound	-26.7%	$\leq 2e^{-29}$
The other side could not hear any sound	-12.5%	$2e^{-23}$
I heard echo in the call	-12.7%	$6e^{-24}$
I heard noise in the call	-9.5%	$3e^{-18}$
Volume was low	-3.8%	0.01
The call ended unexpectedly	-2.4%	0.10
Speech was not natural or sounded distorted	+3.6%	0.00
We kept interrupting each other	-1.7%	0.22
Video problem Token	Relative delta	p-value
I could not see any video	-20.4%	$\leq 2e^{-29}$
The other side could not see my video	-1.9%	0.39
Image quality was poor	-2.2%	0.06
Video kept freezing	+10.1%	$3e^{-16}$
Video stopped unexpectedly	+28.0%	$4e^{-45}$
The other side was too dark	+25.2%	$8e^{-21}$
Video was ahead or behind audio	+25.2%	$5e^{-39}$

#### IV. TOKEN SUBSET SELECTION

The question we are trying to address is the following: Given a limited budget of questions, k, is there a systematic process of selecting the questions to maximize information? In this paper, we propose the selection of tokens by applying the algorithm described by Nushi et al. [9]. An overview of this approach is provided next.

A. Information Gain and Submodular Function Optimization Information gain (IG) captures the amount of information shared between two random variables. Mathematically, IG between variables PC and T, is defined as IG[PC;T] = $H[PC] - H[PC \mid T]$ ; where H represents the entropy (uncertainty) of a random variable. It should be clear that IG has the property of monotonicity [14]. We can easily see that for any two sets of random variables,  $T_1, T_2 : T_1 \subset$  $T_2, IG[PC; T_1] \ge IG[PC; T_2]$ . Building on the monotonicity property and borrowing notation from [4], IG also has a diminishing returns property. The incremental information gain obtained by adding a new element to a subset is higher than the incremental information gain obtained by adding a new element to its superset. Mathematically, if we consider two set of token variables  $T_1, T_2$  from the universe of problem tokens, T, such that  $T_1 \subset T_2 \subset T$ , and we consider a token  $e: e \notin T_1$  and  $e \notin T_2$  then the principle of diminishing returns property is shown in the equation below:

$$IG[PC; \{T_1 \cup \{e\}\}] - IG[PC; T_1] \ge IG[PC; \{T_2 \cup \{e\}\}] - IG[PC; T_2]$$
(1)

In other words, the marginal benefit of reducing the uncertainty in PCR by adding a new token to a smaller set is higher than any superset. This property is known as submodularity. [8] Krause et al. show that interaction effects (e.g., mutual exclusion) between variables can result in IG to not be strictly submodular. However, we do not see such interaction effects for our token dataset, and therefore no violation of submodularity of information gain.

The optimization of submodular functions is a known NP-hard problem, Nemhauser et al. [3, 4] provide a greedy algorithm to solve this problem that is 63% of the computationally

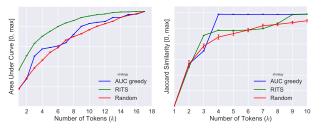


Fig. 1: Relative AUC performance of different strategies in selecting tokens is shown on left while Jaccard similarity scores are shown on right. Note: Scales removed for confidentiality.

expensive and exhaustive solution. The algorithm is iterative and fairly straightforward: In iteration 0, we start with an empty set,  $T_0$ . At every iteration i, we add the token, t, that maximizes the discrete derivative of information gain and set  $T_i$  is constructed using the equation:

$$T_i = T_{i-1} \cup \arg\max_t IG[PC; (T_{i-1} \cup t)]$$
 (2)

where  $t \in T \setminus T_{i-1}$  and  $IG[PC; (T_{i-1} \cup t)]$  represents the information gain of PC by jointly considering the tokens  $(T_{i-1} \cup t)$  for all candidate tokens t. Note that iteration 1 picks the token that provides the highest univariate information gain. In subsequent iterations, this method selects tokens that provide the information not already captured by the existing token set. By design, this results in selection of the least correlated tokens at every iteration. We view this method of selecting tokens as maximizing the return of information for tokens shown (hereafter referred to as RITS).

#### B. Evaluation of RITS

Data gathered from the treatment (randomized PTQ) population of the experiment was used for evaluation. The RITS method was evaluated using the following quantitative metrics:

- 1) AUC: Area under an ROC curve; [15]
- 2) JS: Jaccard Similarity Coefficient [15]

While AUC measures the ability of the token set to discriminate between a good call and a poor call, Jaccard similarity measures the pair-wise degree of overlap between the tokens. The ideal token set has an AUC close to 1 and a JS score of 0. Uncorrelatedness (i.e. a low JS score) is important when breaking down an overall quality metric into distinct factors. For a given token count, k, we studied and compared the performance of RITS with the following approaches:

- 1) Random: Select a random subset of tokens.
- AUC-Greedy: Select tokens sorted in descending order of their univariate AUC.

In our evaluation, we used the random forest implementation from the Python scikit-learn library [16] to obtain the classification boundary with default settings. The error bars were obtained using 100 independent runs of train/test splits.

# C. Results using RITS

The AUC and JS scores of the different token subset selection strategies are shown in Figure 1. Note that we represent the scale in terms of the maximum values obtained for our

dataset, and hide the labels for corporate confidentiality. This allows for relative comparison between the selection strategies. The RITS method significantly outperforms AUC-greedy and random method for all k in-terms of the AUC criterion. The shape of the RITS curve highlights the "Diminishing" returns property. The RITS method also has significantly lower JS score compared to the AUC greedy method for k>4. This is because RITS is designed to find the tokens that provide information that is not already covered by the existing set of tokens. Since the AUC-greedy method does not consider correlation, it performs poorly on the Jaccard similarity measure. Using the RITS method, the first five tokens capture 94% of the total information content in our dataset.

#### V. SUMMARY

In this paper, we studied two aspects of the problem token questionnaire design for VoIP applications - display order and token subset selection. Based on over 900,000 calls gathered from a randomized controlled experiment in a live system, we showed that there is a strong bias in response rate due to the presentation order of questions. The most dramatic impact is experienced by the top-most token. In mobile environments, scrolling can lead to a reduction in response rate by as much as 49%. Motivated by these observations, we studied the problem of selecting a subset of tokens that maximize information while minimizing correlation. We achieved this by mapping it to the problem of submodularity maximization studied in the machine learning community. By doing so, we were able to retain 94% of the information using just 30% of the questions. Finally, we would like to emphasize that these methods and results can vastly benefit the media community as they significantly improve the quality of data gathered from any QoE survey.

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