CART- A Statistical Model for Predicting QoE using Machine Learning in Smartphones

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Abstract— The proliferation of fast, cheap, and ubiquitous network access, in particular on mobile devices, has significantly changed the way user’s access online benefits on an everyday premise. Alongside the expanded accessibility of a dependably on Internet, new advancements, for example, LTE have empowered the utilization of a wide range of administrations, with stringent necessities regarding system execution and limit requests. We consider different QoE appraisal models in view of administered machine learning strategies, which are proficient to foresee the QoE experienced by the end client of well-known cell phone applications (e.g., YouTube and Facebook), utilizing as info the inactive in-device estimations. In this extraordinary issue, we investigate the connection between the Quality of Service (QoS) that administrators screen and oversee and the Quality of Experience (QoE) that the clients really get. Utilizing a rich QoE dataset got from field trials in operational cell systems, we benchmark the execution of various machine learning based indicators, and build a choice tree based model which is able to foresee the per-client general understanding and administration worthiness with a win rate of 91% and 98% separately. To the best of our knowledge, this is the initial proposal using end-user, in-device passive measurements and machine learning models to predict the QoE of smartphone users in operational cellular networks.

Keywords—QoE, Machine Learning, End-device Measurements, Mobile Apps.

1. Introduction

More than 75% of all mobile network traffic will be consumed and generated by smartphones, by 2020. In this paper, to get a distributed Quality we present a set of monitoring tools and machine learning models to enable distributed Quality of Experience (QoE) monitoring and prediction, relying exclusively on in-device passive measurements. In-device network and traffic monitoring provides highly valuable information to network operators, as measurements are taken as close as possible to the end user, shedding light into particular phenomena not observable from traditional, in-network monitoring. Using end-devices as vantage points becomes especially attractive in current traffic encryption context, as end-to-end encryption is rapidly growing– especially due to the massive adoption of HTTPS, obfuscating network traffic analysis.

1.1 QoE Challenges in Cellular Networks

- A constrained ghostly data transmission to be shared, causes impedance.
- Communication joins are time shifting, recurrence specific channels.
- Packet deferrals and Application nerves causes’ client an irritating background.
- Error rate of wireless channel is higher due to mobility, interference from other media, multi-path fading. So mobile hosts may experience different channel rates in the same or different cells.
- Different applications have different requirements for bandwidth, delay, jitter, delay.
The most common approach to evaluate the performance of networks and services from a QoE perspective is to conduct experiments in the lab [2],[4]. Their key benefits rely on the full controllability on the evaluation process. Nevertheless, experiments in the lab normally introduce differences as compared to field studies [5], as they might overlook important QoE-relevant features such as contextual information, device usability, or user preferences. Field trials would therefore result in better, more representative evaluations, to the cost of higher complexity in acquiring and processing the results.

We study the QoE of popular apps in smartphones (YouTube, Facebook, and Google Maps), combining passive traffic QoS measurements collected directly in smartphones with crowd sourced QoE feedbacks provided by the end user in a field trial. While we are completely mindful that exact QoE estimation requires estimations gathered at numerous levels of the correspondences stack – including system, application and end-client layers, we adopt a handy strategy and give models to delineate activity QoS measurements to QoE straightforwardly.

We do as such to boost the use of bland system activity estimations which can be gathered in cell phones, independently of the particular application. Application level checking is for the most part more bulky, as few out of every odd application gives APIs to get to significant measurements, and much of the time, gadget root get to must be allowed to perform estimations profoundly into the application, obstructing huge scale detached observing.

Utilizing the individual cell phones and information contracts of the field trial members, the field trail keeps running in genuine operational cell systems. We built up a portion of the instruments, for example, aloof checking apparatus (to quantify the movement of the field trial members at their end gadgets) and a QOE-input application (which accumulates client encounter information in a group sourced design). Machine learning (ML) innovation is utilized as a part of this paper.

1.2 Machine Learning

It is a subfield of most interesting topic on artificial intellectual competence. The goal of machine adjusting generally is to understand the structure of data and fit that data into models that can be fathomed and utilized by people. Notwithstanding the way that machine learning is a field inside programming building, it differs from customary computational procedures. In customary enlisting, figuring are sets of unequivocally changed bearings used by PCs to figure or issue appreciate. Machine learning computations rather mull over PCs to get ready on data information sources and use quantifiable examination remembering the ultimate objective to yield regards that fall inside a specific range. Thusly, machine learning supports PCs in building models from test data with a particular ultimate objective to motorize fundamental initiative structures in light of data inputs.

Optical character acknowledgment (OCR) innovation changes over pictures of content into versatile kind. Proposal motors, fueled by machine learning, recommend what films or network shows to watch next in view of client inclinations. Self-driving autos that depend on machine figuring out how to explore may soon be accessible to shopper’s. Machine learning is a ceaselessly creating field. Along these lines, there are a few contemplations to remember as you work with machine learning approaches', or break down the effect of machine learning forms.

1.3 Supervised Learning

In managed taking in, the PC is furnished with case inputs that are named with their coveted yields. The reason for this strategy is for the calculation to have the capacity to "learn" by contrasting its genuine yield and the "instructed" yields to discover blunders, and alter the model likewise. Directed adapting hence utilizes examples to anticipate mark esteems on extra unlabeled information.
For instance, with regulated taking in, a calculation might be nourished information with pictures of sharks named as fish and pictures of seas marked as water. By being prepared on this information, the managed learning calculation ought to have the capacity to later recognize unlabeled shark pictures as fish and unlabeled sea pictures as water. A typical utilize instance of managed learning is to utilize recorded information to foresee factually likely future occasions. It might utilize recorded securities exchange data to envision up and coming changes, or be utilized to sift through spam messages. In directed learning, labeled photographs of pooches can be utilized as info information to arrange untagged photographs of puppies.

1.4 Unsupervised Learning

In unsupervised learning, data is unlabeled, so the learning count is left to find shared qualities among its data. As unlabeled data are richer than stamped data, machine learning methodologies that energize unsupervised learning are particularly gainful. The goal of unsupervised learning may be as immediate as finding covered plans inside a dataset, in any case it may in like manner have a goal of feature acknowledging, which empowers the computational machine to normally discover the depictions that are required to arrange unrefined data.

Unsupervised learning is conventionally used for esteem based data. You may have an extensive dataset of clients and their buys, yet as a human you will probably not have the capacity to understand what comparative qualities can be drawn from client profiles and their kinds of buys. With this information sustained into an unsupervised learning calculation, it might be resolved that ladies of a particular age extend who purchase unscented cleansers are probably going to be pregnant, and along these lines an advertising effort identified with pregnancy and child items can be centered to this gathering of spectators in order to fabricate their number of purchases.

Without being told a "right" answer, unsupervised learning strategies can look at complex data that is more expansive and obviously unimportant remembering the ultimate objective to form it in possibly huge ways. Unsupervised learning is consistently used for quirk acknowledgment including for false MasterCard purchases, and recommender structures that endorse what things to buy straightaway. In unsupervised learning, untagged photographs of canines can be utilized as information for the calculation to discover similarities and arrange pooch photographs together.

Utilizing the gathered estimations, we prepare a few directed ML models to anticipate the QOE experienced by the end client of these apps. ML gives a promising other option to QOE expectation and appraisal in light of the consolidated investigation of different movement descriptors or highlights.

The rest of the paper is as per the following:

1. Overviews the related work, concentrating on the particular instance of cell phones.
2. Portrays the field trial setup, the instruments created to quantify QoS-and QoE-related measurements toward the end-gadgets, and the machine-learning models utilized as indicators. Sec.
3. Gives a concise outline on the field trial estimations, and spotlights on the assessment of the forecast execution acquired by various ML-based models, including an investigation of the pertinence of the distinctive info includes on quality expectation.
4. Finishes up this work.
2. Related Work

The investigation of the QoE for present day online applications as the ones we focus in this paper has a considerable rundown of new and late references [9]. Because of its fame, the particular instance of YouTube QoE merits specific consideration. Past papers [10]– [13] have demonstrated that stalling’s, starting playback postponements and quality switches are the most essential KPIs for versatile gushing YouTube QoE. A complete review on versatile video gushing QoE is given in [14].

Concerning observing investigations in cell systems and cell phones, there is a varying rundown of instruments to gauge organize execution: In [18], [19] creators presented YoMoApp, an application to latently screen YouTube QoE-related highlights in cell phones. In [20] creators depict an on-line checking framework for YouTube QoE in cell systems utilizing as a part of system estimations as it were. QoE Doctor [21] measures portable application QoE, utilizing dynamic estimations at both application and system layers.

Other comparative papers contemplate Web QoE in cell systems [22], and video [23]. Near our work, creators in [24] propose a way to deal with assess versatile applications QoE utilizing inactive in-organize estimations and machine-learning models mapping QoE to QoE. The principle distinction to our approach is the use of in-organize estimations, in opposition to in-gadget ones.

While the lion's share of these papers just spotlight on QoE-applicable target measurements, for example, re-buffering, page stack times and collaboration latencies, they do not have an immediate reference to client criticism, e.g., Mean Opinion Scores. Here we take input from genuine clients and gather organize estimations to give an all-encompassing point of view to the issue of QoE observing in cell phones. This paper expands over past work on QoE for cell systems [7], [8]. Specifically, we consider a machine-learning based point of view to the issue of QoE expectation and appraisal, which isn't done in [7], [8].

2.1. Mobile QoE in The Field

The field trial occurred in Vienna in 2015; 30 clients furnished with their own particular gadgets associated with their favored cell administrators assessed the three applications as a major aspect of their typical day by day Internet movement. Members were told to perform free errands for each application. For YouTube, they were asked for to observe short (around 2 minutes in length) HD YouTube recordings. For Face book, they were asked for to get to the application, and perus both the course of events and some photograph collections of a phony client. For Gmaps, they needed to peruse maps of various urban areas utilizing the satellite-perspective of the Google maps application.

| Metric ID | Metric Name                  | Units | Example         |
|-----------|------------------------------|-------|-----------------|
| 1         | device id (IMEI)             |       | 39266604497251678 |
| 2         | flow start time              | s     | 16200825688     |
| 3         | flow direction (up/down)     |       | download        |
| 4         | flow duration                | s     | 19724           |
| 5         | flow size                    | KB    | 40410100        |
| 6         | avg flow throughput          | kbps  | 315793          |
| 7         | max flow throughput          | kbps  | 432015          |
| 8         | app (Android API) package    |       | welcome winger  |
| 9         | signal strength              | dB    | -101            |
| 10        | operator (MCC/MNC)           |       | 2594            |
| 11        | cell id                      |       | 19818           |
| 12        | cell location (latitude)     | deg   | 43.183333,15.5  |
| 13        | lat                          |       | 51E             |
QoE criticism was accounted for every session through a modified QoE crowd sourcing application, for an aggregate traverse of two weeks. In this paper we just spotlight on the general experience announced by members and the administration worthiness, however the QoE criticism gave incorporates more data that we intend to assess later on. The general experience is appraised by a discrete, 5-levels ACR Mean Opinion Score (MOS) scale [2], extending from "terrible" (i.e., MOS = 1) to "phenomenal" (i.e., MOS = 5). Worthiness is a twofold input, expressing whether the client would keep utilizing the application under the comparing conditions or not. Applications arrange activity was latently observed and broke down at their gadgets with the apparatuses portrayed straightaway. Members additionally showed their area at the season of the test (e.g., underground, auto, home, road, and so on.).

3. Proposed System

In this proposed framework utilizes a ML based on QoE indicator. This QoE Model uses a choice tree calculation known as Classification And Relapse Trees (CART) calculation used to distinguish the factual model that has greatest exactness for foreseeing the estimation of a straight outward variable from a dataset comprising of clear cut and persistent factors.

CART classification algorithm characterizes the occurrences (Data) by more than once apportioning the info space, to fabricate a tree whose hubs are as unadulterated as could reasonably be expected. Truck calculation utilizes choice tree based approach which are straightforward yet quick and powerful. Considering the order speed is a foremost resource when thinking in expansive scale checking situations, and choice trees are notable for their speed.

Classification Trees

Where the objective variable is all out and the tree is utilized to distinguish the "class" inside which an objective variable would likely fall into that and the same is shown in Figure 1.

Regression Trees

Where the objective variable is nonstop and tree is utilized to foresee it's esteem and shown in Figure 2.
The CART calculation is organized as a succession of inquiries, the responses to which figure out what the following inquiry, if any ought to be. The consequence of these inquiries is a tree like structure where the closures are terminal hubs and soon thereafter there are no more inquiries. The principle components of CART (and any choice tree calculation as in Figure 3) are:

1. Rules for part information at a hub in view of the estimation of one variable;
2. Stopping standards for choosing when a branch is terminal and can be part no more; and
3. Finally, an expectation for the objective variable in every terminal hub.

Dataset Metrics Collection

Keeping in mind the end goal to quantify Quality of Experience of Face book, Google Maps and YouTube, the detached QoS estimations for every individual Application should be gathered, sorted out, and detailed.
Passive Metrics

The detached approach watch the activity as it cruises by. These Metrics are then handled by an instrument known as Sniffer, they are incorporated with the client’s gadgets (Mobile Phones) and the measurements are embedded into a dataset. A dataset from Data. World – A non-benefit Organization is utilized as a part of the proposed demonstrate.

| Metric Name            | Units | Sample Data                   |
|------------------------|-------|-------------------------------|
| Device id (IMEI)       |       | 3264784534                    |
| Flow Start Time        |       | 11:02:55 (HH:MM:SS)           |
| Flow End Time          |       | 11:03:50 (HH:MM:SS)           |
| Flow Duration          | Seconds | 60                            |
| Flow Size              | KB    | 1255                          |
| Avg Flow Throughput    | KBPS  | 404100                        |
| Max Flow Throughput    | KBPS  | 4563214                       |
| App (API)              |       | Com.android.browser           |
| Signal Strength        | dBm  | -71                           |
| Operator               |       | MC123                         |
| Cell id                |       | 32165                         |
| Cell Location          | Deg   | (20.5937° N, 78.9623° E)     |

4. Result and Discussions

This session gives a clear on how we assess the QOE and QOS with the basic errors we have collected. So here we have collected data from World-A organization and classified into 10 codes on the basis of the different classifications. We can randomly chose any data on the basis of the error codes and send the problem to the developer. Once if there is a solution there itself we can rectify it directly or otherwise the main admin would upload the fix and then the error gets rectified. The error is chosen from the data and the social application used, the id and the error code is noted were shown in Figure 4 and Figure 5.
Figure 4: Choosing the error from the data collected and report sent to the developer.

![Image of choosing error from data](image1)

Figure 5: The developer uploads the fix for the problem and the error gets rectified.

![Image of developer uploading fix](image2)

5. Conclusion

In this paper, the problem of QoE monitoring, assessment and prediction in cellular networks, relying on in-smartphone QoS Passive traffic measurements are addressed. Using a rich dataset derived from a field study by a non-profit organization ‘Data. World’ is applied as part of the demonstration of this proposed methodology. We have trained different QoE prediction models based on supervised machine learning technique CART. The final selected model is based on decision trees, which are very attractive for large scale QoE/QoS assessment scenarios, not only because of their excellent performance but also due to their prediction speed.

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