

# Deep Learning Part 1

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**Abstract**—This document contains a summary of what has been implemented and validated in the first part of the Deep Learning Project "Quality of Experience Prediction Trends for Live Video Streaming Events".

**Index Terms**—Deep Learning, QoE, buffer-ms, viewer-type

## I. INTRODUCTION

Live video streaming has become a mainstay as an essential communication solution for large enterprises. Fortune-500 companies<sup>1</sup> organize live video streaming events for several purposes, such as training employees, announcing product releases, and so on. Accounting for the high value of live video streaming services, companies invest a significant amount of their annual budgets. Therefore, large enterprises expect the viewers that participated in the event to receive highquality video, while being fully engaged. However, in the real-world setting there are several factors hindering the video quality and user engagement, for example, the bandwidth limitations when several employees attend an event simultaneously at several offices, the time when the event is scheduled, and so on. In the first part of the project we perform data analysis to extract valuable insights from the dataset.

## II. PRE-PROCESSING

To begin with, we search for Nan values and we observe that the data set does not contain any. Then, we look over the type of the data and we observe that all of them are numerical.

## III. FIRST Q&A

For this task we create figures that depict the QoE trend over time (month) for each customer. We selected 21 customers, because they represent the 95% of the entries. We observe that in the most cases the QoE is high (0.950 - 1.000).

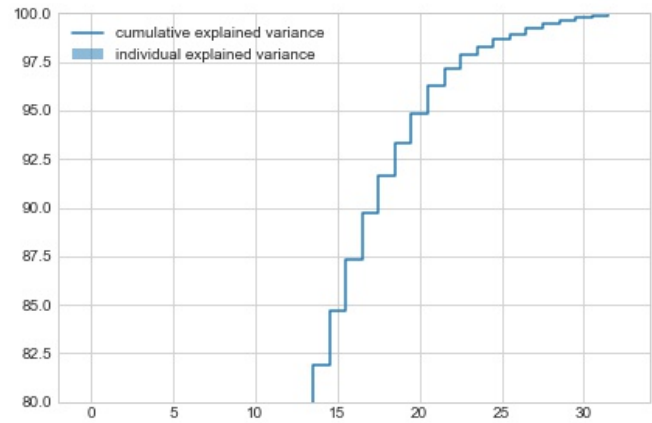


Fig. 1.

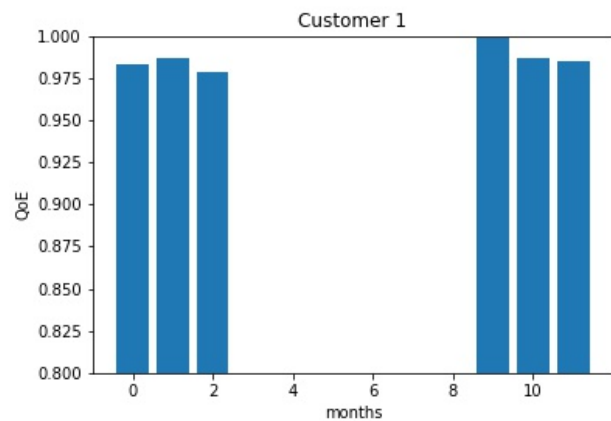


Fig. 2.



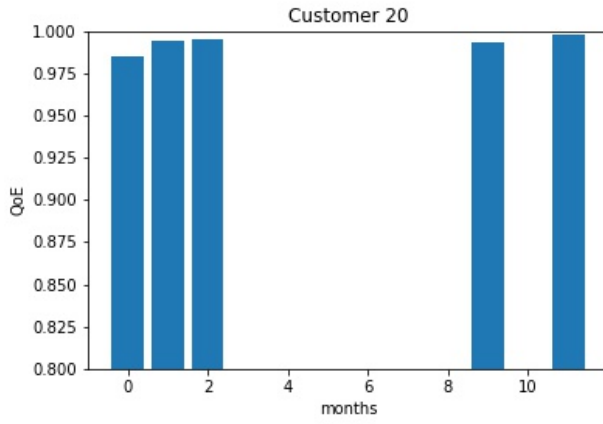


Fig. 4.

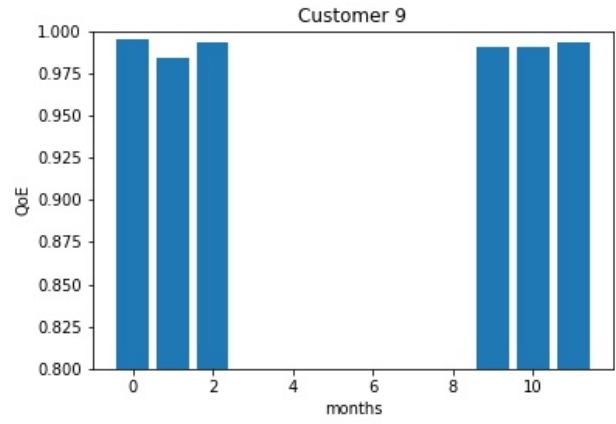


Fig. 7.

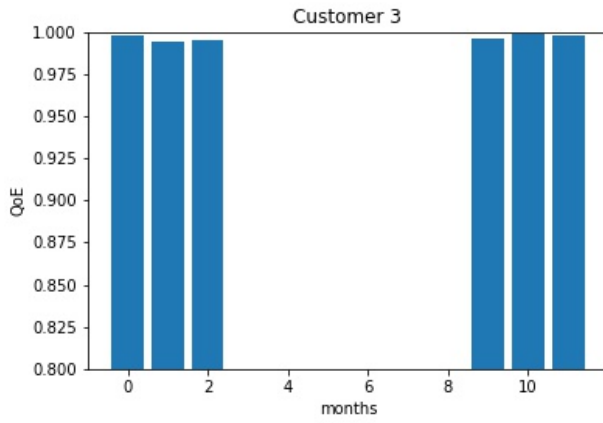


Fig. 5.

#### IV. SECOND Q&A

For this question, we discretize "buffer-ms" to 5 different levels (0 is Excellent, 1 is Good, 2 is Average, 3 is Poor and 4 is Bad). Then we plot the new discretized values (Buffering severity) over time (month) for each customer. For the x-axis we stored only the months that contain data. From the figures we conclude that the value of the Discretize buffer is mainly 0 , because there were only a few entries with a high buffer-ms.

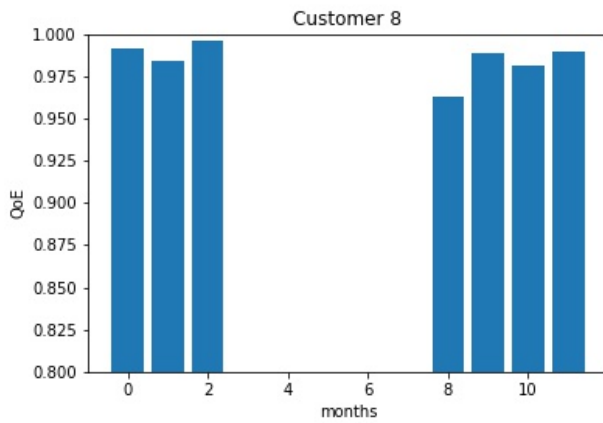


Fig. 6.

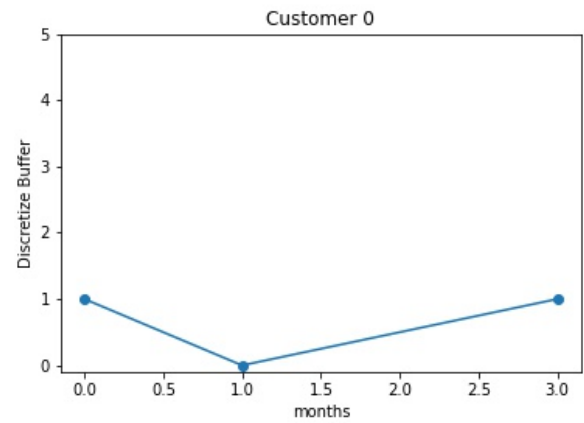


Fig. 8.

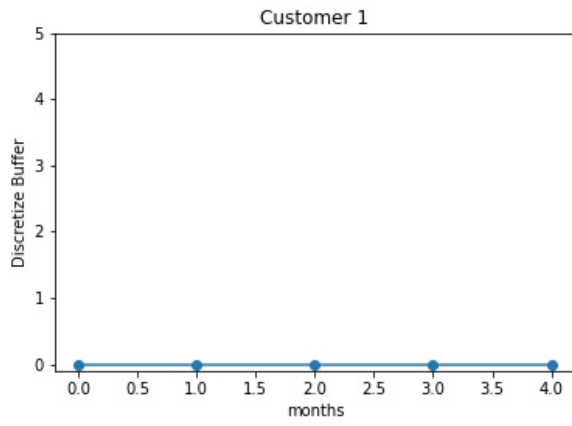


Fig. 9.

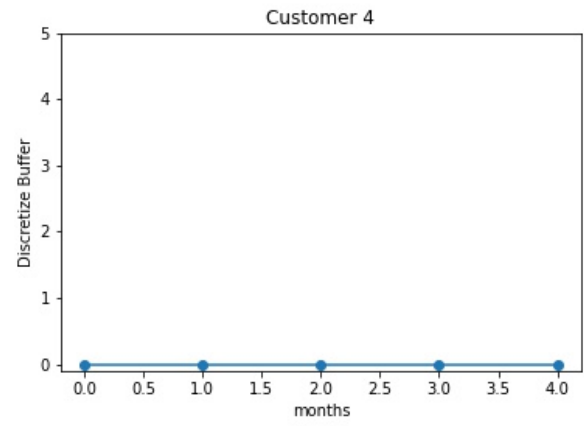


Fig. 12. s

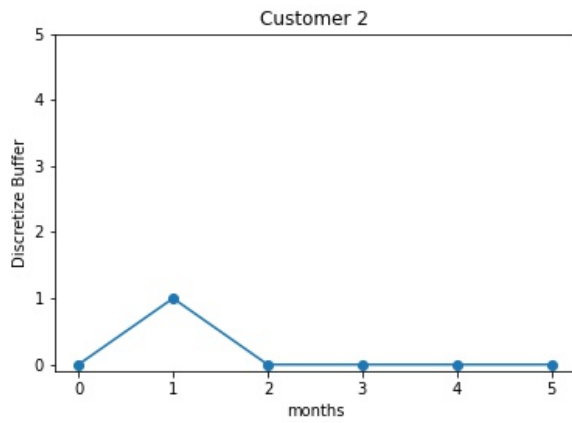


Fig. 10.

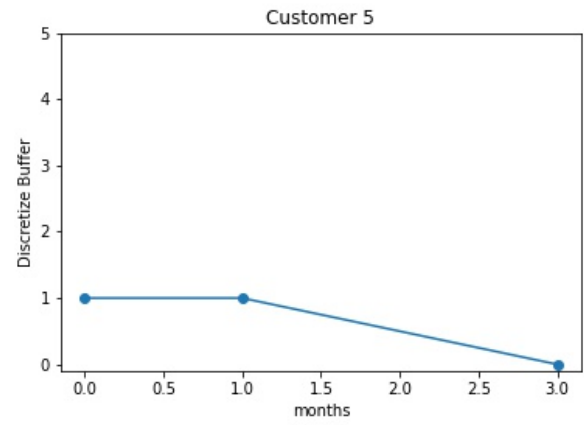


Fig. 13.

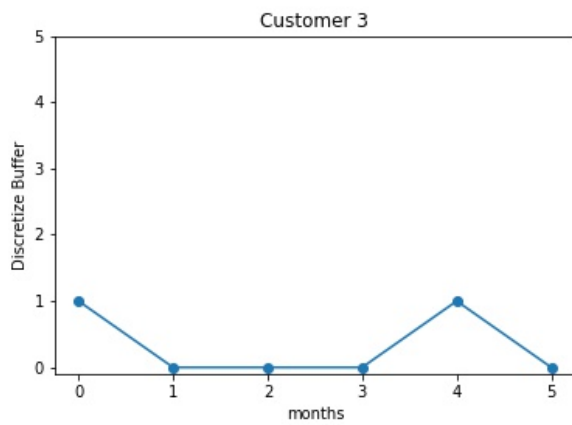


Fig. 11.

## V. THIRD Q&A

For this question, we depict the number of viewers over time that experience the QoE level. Similar to above, we to discretize the QoE values to 5 different levels (0 is Bad, 1 is Poor, 2 is Average, 3 is Good and 4 is Excellent). As expected, most viewers experience QoE level 4 (Excellent).

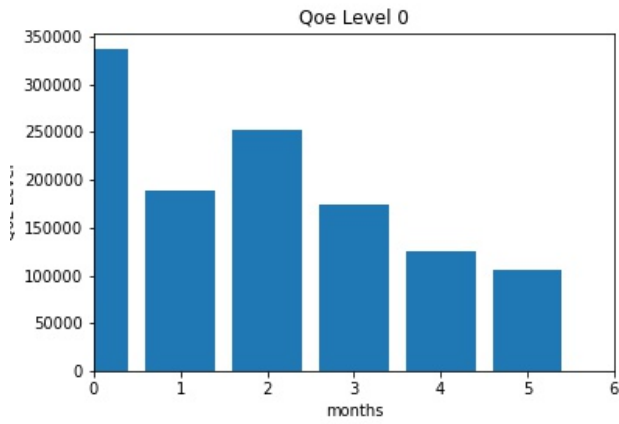


Fig. 14.

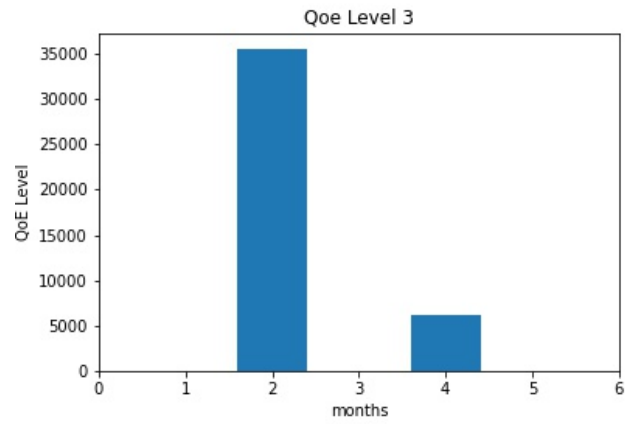


Fig. 17.

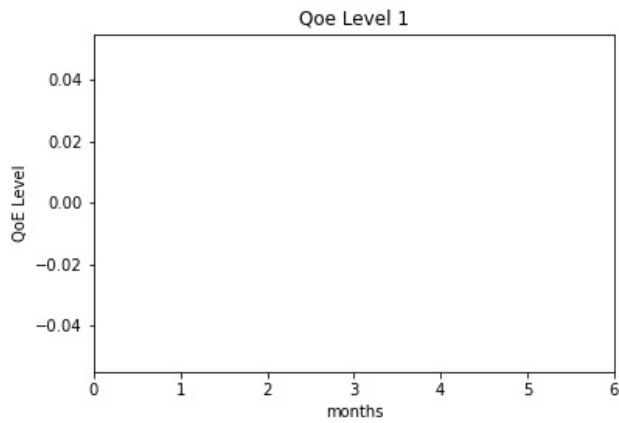


Fig. 15.

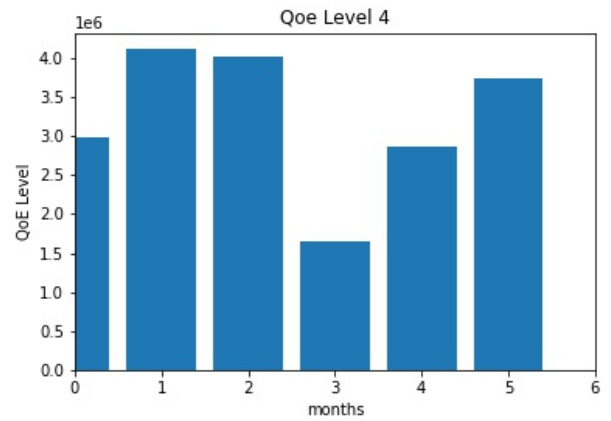


Fig. 18.

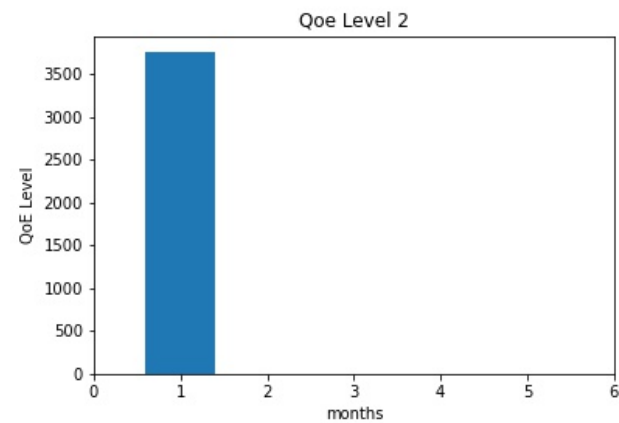


Fig. 16.

## VI. FOURTH Q&A

In this task, we plot the QoE trend over time for each customer and the viewers' location type. Green colour represents "work from office" and the blue colour represents "work from home". After we created the figures we observed that the people who worked from office have higher QoE than those who worked from home.

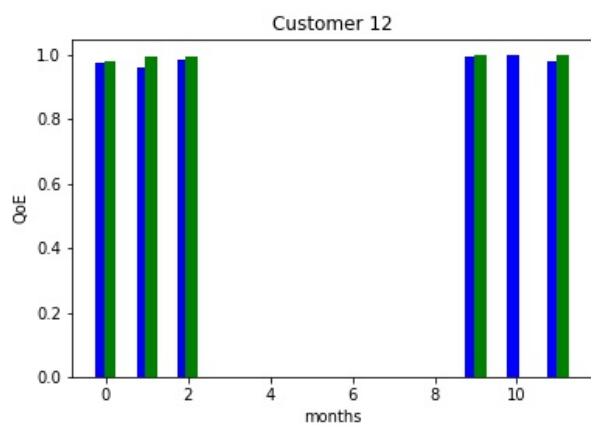


Fig. 19.

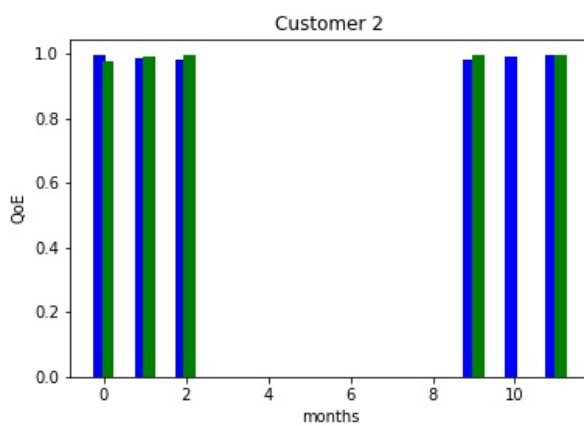


Fig. 22.

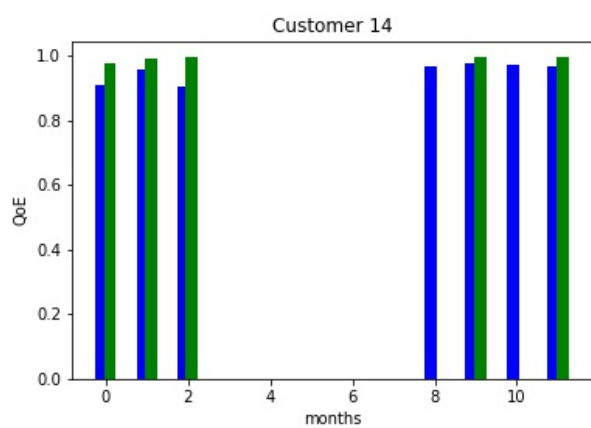


Fig. 20.

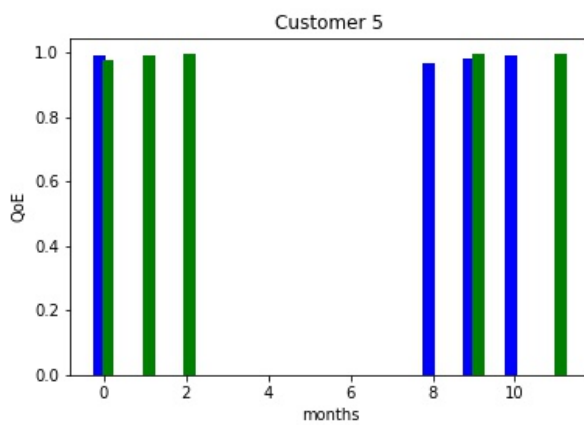


Fig. 23.

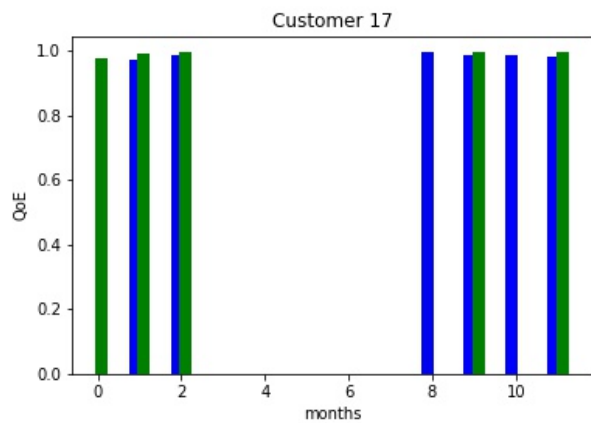


Fig. 21.

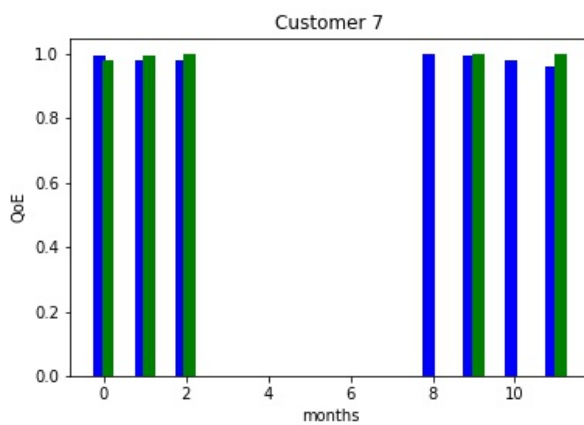


Fig. 24.