Real-time Video Analytics at the Edge Using Collaboration Among Nodes

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Abstract

Machine learning has been applied in different aspect of networking. However, the focus of this review is particularly narrowed down to new opportunities of collaborative machine learning foe video analytics at the edge. With dropping camera prices and increasing accuracy of deep neural networks, we see an explosive growth of video-analytics applications. Driven by drastic fall in camera cost and organizations are deploying cameras in dense for different applications. Processing video feeds from such large deployments, however, requires a considerable investment in compute hardware or cloud resources. Due to the high demand for computation and storage resources, Deep Neural Networks, the core mechanisms in video analytics, are often deployed in the cloud. However, this approach introduces several key issues that we discuss some in this paper and discuss possible solutions to address such issues.

Machine learning has been applied in different aspect of networking [10], [12]–[15] [17] [21] [22] [23]. However, the focus of this review is particularly narrowed down to new opportunities of collaborative machine learning foe video analytics at the edge. With dropping camera prices and increasing accuracy of deep neural networks (DNNs), we see an explosive growth of video-analytics applications [2], [4] and deployments of large camera networks [1]. Driven by drastic fall in camera cost and the recent advances in computer vision-based video inference, organizations are deploying cameras in dense for different applications ranging from monitoring industrial or agricultural sites to retail planning. Processing video feeds from such large deployments, however, requires a considerable investment in compute hardware or cloud resources. Due to the high demand for computation and storage resources, DNNs, the core mechanisms in video analytics, are often deployed in the cloud. Therefore, nowadays, video analytics is typically done using a cloud-centered approach where data is passed to a central processor with high computational power. However, this approach introduces several key issues. In particular, executing DNNs inference in the cloud, especially for real-time video analysis, often results in high bandwidth consumption, higher latency, reliability issues, and privacy concerns. Therefore, the high computation and storage requirements of DNNs disrupt their usefulness for local video processing applications in low-cost devices. Hence, it is infeasible to deploy current DNNs into many devices with low-cost, low-power processors. This report is based on surveying the current opportunities for faster yet more reliable video analytics at the edge. Pasandi et al [18] introduce the opportunities of collaborative video analytics among cameras in large setting. In the following, we summaries the challenges and opportunities that they have highlighted.

Smarter Models

Cameras installed in different regions can collaborate among each other to build a smarter model. Such paradigm of allowing cameras to be trained using their local data and then sharing knowledge of the built models between relevant cameras only will enable us to have smarter customized models, lower latency, less communication overhead, less power consumption, all while ensuring privacy [18].

Enhancing Accuracy

Enhancing accuracy can happen at both training or inference step when multiple camera which have dense deployment can share their input feed together. FOr example, a camera with a low resolution can use the feed from a camera with high resolution to improve either its training or inference precision and recall.

Near Real-time Analytics

Authors in [5] introduce the real time video analytics at the edge as the killer application for edge computing. Edge-based video analytics have a diverse set of applications at the edge [8], [26]. In [19], [20] authors show that when cameras collaborate among each other they can significantly reduce the frame sampling rate which saves more than half of the bandwidth and computation time.

Saving Resources

Different applications could use the same set of publicly available vision models. This suggests one can share models, as well as data, between applications that perform the same tasks. For instance, instead of loading/unloading DNN models frequently, it is better to leave the models loaded on specific cameras and route the data to these locations. As mentioned in [18], when multiple camera collaborate together they can offload part of their task to the idle proximity cameras, or they could run the same models in parallel which enables recourse saving.

Privacy

If the models trained on private data are shared among users or with the service provider in the clear, the privacy of each user in the training may be violated by other users who may be honest-but-curious (i.e. honest in performing the operations, but also attempting to learn information about other users by analysing the received information [3]) or by an honest-but-curious service provider during training or prediction [7], [11]. Most of the current privacy-aware video streaming approaches involve denaturing, which means the content of images or video frames is modified based on a guided privacy policy [25]. In collaborative setting privacy can be achieved by defining policies in which cameras that capture sensitive information will perform locally certain stages of the inference pipeline that contain those sensitive data. Although some of the information might be kept locally, enabling these cameras to work collaboratively will help their local observations to enhance the overall accuracy of the desired model [18].

Sharing Computational State

When cameras are collaborating in a setting with significant spatial-temporal correlation, they could share the input of their DNN pipline to run less complex models. As an example, when the task is person detection, a camera that detects the person first, can share its model's 0 to ith layer with the proximity cameras to start their training/inference step from $i+1$ to nth layer.

Edge-based data analytics systems

There have been several attempts to provide system abstractions of edge compute resources [16]. Some are general-purpose solutions [6] or focus on edge servers, so they are not exactly suitable to explore the opportunities unique to camera clustering and video analytics. Recent works that has examined different issues in edge video analytics in isolation include video data storage [24], model management [9], and sensor network [27]. However, they lack an integrative collaborative effort towards video analytics.

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