



Towards automatic model specialization for edge video analytics

Daniel Rivas^{a,b,*}, Francesc Guim^c, Jordà Polo^a, Pubudu M. Silva^d, Josep Ll. Berral^a, David Carrera^a

^a Barcelona Supercomputing Center (BSC), C. Jordi Girona, 1-3, 08034, Barcelona, Spain

^b Universitat Politècnica de Catalunya (UPC), Campus Nord, Edif. D6, C. Jordi Girona, 1-3, 08034, Barcelona, Spain

^c Intel Corporation Iberia, Barcelona, Spain

^d Intel Corporation, Hillsboro, OR, USA



ARTICLE INFO

Article history:

Received 10 December 2021

Received in revised form 26 March 2022

Accepted 28 March 2022

Available online 1 April 2022

Keywords:

Model specialization

Computer vision

Edge cloud

Cova framework

Real-time video analytics

ABSTRACT

The number of cameras deployed to the edge of the network increases by the day, while emerging use cases, such as smart cities or autonomous driving, also grow to expect images to be analyzed in real-time by increasingly accurate and complex neural networks. Unfortunately, state-of-the-art accuracy comes at a computational cost rarely available in the edge cloud. At the same time, due to strict latency constraints and the vast amount of bandwidth edge cameras generate, we can no longer rely on offloading the task to a centralized cloud. Consequently, there is a need for a meeting point between the resource-constrained edge cloud and accurate real-time video analytics. If state-of-the-art models are too expensive to run on the edge, and lightweight models are not accurate enough for the use cases in the edge, one solution is to demand less from the lightweight model and specialize it in a narrower scope of the problem, a technique known as model specialization. By specializing a model to the context of a single camera, we can boost its accuracy while keeping its computational cost constant. However, this also involves one training per camera, which quickly becomes unfeasible unless the entire process is fully automated. In this paper, we present and evaluate COVA (Contextually Optimized Video Analytics), a framework to assist in the automatic specialization of models for video analytics in edge cloud cameras. COVA aims to automatically improve the accuracy of lightweight models by specializing them to the context to which they will be deployed. Moreover, we discuss and analyze each step involved in the process to understand the different trade-offs that each one entails. Using COVA, we demonstrate that the whole pipeline can be effectively automated by leveraging large neural networks used as *teachers* whose predictions are used to train and specialize lightweight neural networks. Results show that COVA can automatically improve pre-trained models by an average of 21% mAP on the different scenes of the VIRAT dataset.

© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The edge cloud aims to provide compute and storage resources closer to where the data is produced to filter the amount of data crossing the backhaul and alleviate it. Nevertheless, a geographically distributed edge cloud entails two characteristics whose implications are often undermined. First, different physical locations (at which resources are installed) involve different sets of constraints that ultimately impact the type and size of the resources that can be installed [1]. For example, a street cabinet might be limited to a handful of server-grade nodes, while a solar-powered node in a street pole might have to settle for an IoT gate

with a low-power processor. Regularly, resources become scarcer the closer we are to the edge of the network. Consequently, the more challenging yet more critical it becomes to leverage those resources efficiently.

Second, the workloads (i.e., services) and the distribution of the incoming requests are tightly coupled to the geographical area the edge location is serving. This relation has long been experienced and exploited in traditional CDNs (Content Delivery Networks). Several factors, such as the time of the day or local trends, shape users' access patterns to the different internet locations daily. CDNs leverage this information aiming to predict what users will access next and cache it near them. Together, the combination of scarce resources, workloads coupled to a geographical location, and any other outside-world data that might affect the workload makes the context of the edge deployment up.

Video analytics, powered by all kinds of DNNs (Deep Neural Networks), is already one of the prominent use cases being

* Corresponding author at: Barcelona Supercomputing Center (BSC), C. Jordi Girona, 1-3, 08034, Barcelona, Spain.

E-mail addresses: daniel.rivas@bsc.es (D. Rivas), francesc.guim@intel.com (F. Guim), jorda.polo@bsc.es (J. Polo), pubudu.m.silva@intel.com (P.M. Silva), josep.berral@bsc.es (J.Ll. Berral), david.carrera@bsc.es (D. Carrera).

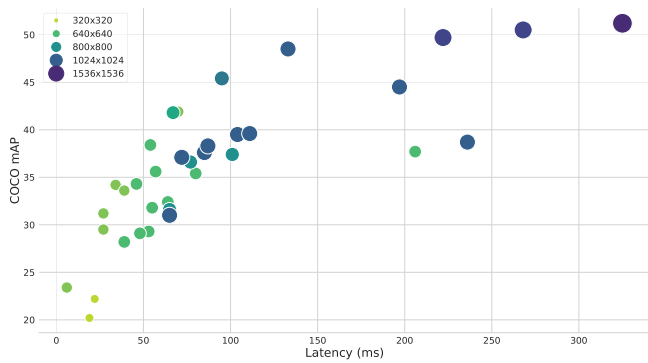


Fig. 1. Speed versus mAP (mean Average Precision) on the COCO for different object detection pre-trained models [6]. Bubble size represents the input size of the model.

executed at the edge [2]. At the same time, the edge has been appointed as a required actor and the primary accelerator for large-scale video analytics [3,4]. All over the world, cameras generate constant data streams whose contents remain largely disregarded unless a specific event triggers their review. Some of these events require immediate action (e.g., alert security if someone breaks in a store or open a barrier after a car approaches it upon checking credentials), while others involve bulk analysis (e.g., crowd counting at a fair or car counting for traffic analysis in smart cities). However, in both cases, action and information are taken at a local level. Therefore, images can be processed in the edge while only a fraction of the data (the results) must be sent back to centralized locations to be registered.

Moreover, there is a direct relationship between the accuracy of a trained neural network and the size of the network (i.e., number of trainable parameters). Unfortunately, bigger networks tend to have higher computational complexity than simpler ones, as depicted in Fig. 1. Ultimately, resource constraints on edge nodes set a limit to the size of the neural networks that execute and, thus, also to the accuracy they can achieve. State-of-the-art accuracy is usually out of the picture for the so-called *edge DNNs* and is only within reach of bigger neural networks. The difference between these two may imply orders of magnitude more trainable parameters, and the gap is only increasing with time [5]. At the same time, hardware acceleration becomes a must to provide anything near real-time performance. Altogether, these limitations pose a challenge for the edge cloud to postulate itself as a serious alternative to current data centers for video analytics unless the hardware installed is upgraded or the models deployed are greatly optimized.

One of the main reasons for bigger models to achieve higher accuracy is that the extra trainable parameters can be used to learn more robust high-level features that allow the model to generalize its predictions in new environments successfully. Simpler models may face difficulties in capturing the relationship between the input examples (i.e., images) and the target values (i.e., predictions), which is known as *underfitting*. However, it is essential to emphasize that simple or big are adjectives relative to the scope of the problem, and neural networks should be dimensioned according to the level of generality and complexity required for the task at hand. Otherwise, the *underfitting* we experience whenever we expect too much from a model may turn into *overfitting* when the network is big enough to memorize the training examples, which will translate into poor generalization on unseen examples.

Several popular challenges evaluate neural networks on specific datasets to tell how well a neural network architecture might perform. For example, ResNet152 scores 94.5% Top-1 accuracy

on the ImageNet [7] dataset, while a smaller edge model like a MobileNetV2 is limited to only 71% Top-1 accuracy on the same challenge [8]. However, challenges like ImageNet or COCO (Common Objects in Context) [9] are notoriously generalists, and models are required to distinguish a car from a toothbrush while also telling a *water snake* and a *vine snake* apart. Such diversity of objects is rarely captured by static cameras deployed to the edge. Just as a camera in the wild will hardly see many trucks, a camera controlling traffic at an urban intersection will not capture many wild animals. By narrowing down the diversity of objects to detect, simpler neural networks become available to be executed in the edge in real-time.

Nevertheless, the loss of generality brought about by the specialization of the model also implies that models are now potentially tight to a camera's context. Where we previously had a single model for the analysis of many cameras, we now potentially need one model per camera, each requiring its very own training process with properly annotated training examples. One training per camera quickly becomes unrealistic as the number of cameras grows, limiting the potential benefits of model specialization unless the process can be optimized and completely automated.

This paper presents COVA (Contextually Optimized Video Analytics), a framework to automate the specialization of models for real-time edge video analytics. Through it, COVA funnels the generality of big neural networks with state-of-the-art accuracy into specialized edge neural networks, resulting in models with high accuracy but on a narrowed scope. Our work is based on a simple observation: *static cameras do not move, but objects do*. At the same time, in the context of edge video analytics, we can safely assume that moving objects are equivalent to objects of interest, which allows us to leverage computer vision techniques to simplify the task. Moreover, we define the context of a camera as the set of invariant properties associated with its deployment location. For example, height or focal distance determine the perspective from which objects are seen. Similarly, the background and the environment (e.g., urban area, indoor, or nature) determine the type of objects that we can expect the camera to capture. Once the context of a camera is defined, automating the specialization of models can be vastly simplified.

The contributions of this paper are two-fold. On one hand, we present and evaluate COVA (Contextually Optimized Video Analytics), a framework to assist in the rapid deployment of tailored edge models for real-time video analytics. The pipeline in COVA is conceived to be highly modular and easily extensible to allow for different types of contextual analysis of the scenes. It supports TensorFlow [10] (training and inference) and OpenVINO [11] (inference only) and can run either local or on *Amazon Web Services* (AWS) and orchestrated from the edge. Moreover, source code is made publicly available [12]. On another hand, we present an extensive exploration and review of the different steps involved in the process of automating the specialization of models, including considerations and findings to be taken into account in case some of the pipeline stages are to be exchanged or extended. In COVA, we leverage automated specialization of edge models to boost their accuracy, showing that models with state-of-the-art accuracy (ground-truth) can generalize to new environments, that more specialization translates to higher accuracy when the scope of the problem is equally specialized, and examples automatically annotated by the ground-truth models can be effectively used to train edge models.

The rest of the paper is organized as follows: Section 2 revises the previous work and discusses the gaps that our work aims to fill. Section 3 breaks the problem of automating the specialization of models down, and provides the background to understand the challenges behind deploying accurate neural network models to the edge. Section 4 describes the COVA framework and

its components. Section 5 describes the methodology followed throughout the evaluation. Section 6 presents and discusses the experimental results. Finally, Section 7 presents the conclusions of our work, and introduces future lines of research opened by the COVA framework.

2. Related work

2.1. Edge video analytics

The edge cloud has been previously proposed as a key enabler of video analytics [13]. In some cases, the edge is considered the *only* realistic approach to meet the latency requirements needed for real-time video analytics [3], while maximizing QoE by minimizing the cost and flow of data between data centers and users [4]. However, the edge cloud presents as many opportunities as new challenges that will have to be properly addressed on any new edge deployment [13,14].

Within the context of edge video analytics, there have been lots of efforts focused on optimizing the data flow between edge devices and the data center. Authors in [15] propose an edge infrastructure with the pipeline for deep learning execution distributed across different points in the network (edge, in-transit, and cloud resources). Another optimization point consists of filtering what is sent to the data center. Authors in [16] present *FilterForward*, a system aimed to reduce bandwidth consumption and improve computational efficiency on constrained edge nodes by installing lightweight edge filters that backhaul only relevant video frames.

2.2. Model specialization

Model specialization is recurrently used as a mean to optimize the inference cost in scenarios where generality is known to be unnecessary. On the one hand, some approaches leverage specialization over time through online training. For example, authors in [17] identify short-term skews in the class distribution often present in day-to-day videos and exploit it by training models specialized for such distribution online. On the other end of the spectrum, authors in [18] propose *Once-for-All*, a neural network architecture that can be repurposed and deployed under diverse architectural configurations but is trained only once.

Moreover, model specialization in edge video analytics is core to various video query systems [19–22]. Such systems aim to answer queries about a video by analyzing its contents (e.g., return frames containing instances of a red car between two points in time). Authors in [19] are able to reduce the cost of running queries against a video by up to three orders of magnitude thanks to *NoScope*, a system that uses inference-optimized model search to find and train the optimal cascade of binary classifiers specialized for the video being queried. Authors in [20] propose the use of inexpensive specialized NN at ingest time (i.e., when images are captured) to filter the frames to be considered at query time. Nonetheless, these systems focus on the optimization of queries. Therefore, their main metric to optimize is the latency of a query (involving multiple inferences) and not that of a single inference. Consequently, such systems are subject to a different set of requirements and constraints than real-time edge video analytics.

2.3. Automatic training

Model specialization at large-scale can only be feasible if the process is automated. When the goal is to generate specialized models, previous works have focused on distilling previously acquired knowledge from complex and accurate models (teachers)

into simpler ones (students) [23]. Through distillation, the student model is trained by trying to mimic the output of the teacher model. On the one hand, distillation can be used to transfer the knowledge of the teacher model into the student. The resulting model can be seen as a simplified or compressed version of the original teacher model, which aims to retain its original accuracy with a reduced computational footprint [24]. On the other hand, distillation can be used to generate specialized models in cases where the problem to be solved by the student is a subset of the problem for which the teacher was trained. In such cases, the teacher model works as an oracle that is consulted to predict the labels of the training examples for the student [19,25]. In this paper, we focus on the latter to automatically specialize models for the context of each camera deployment.

Other works have focused on self-supervised learning. Authors in [26,27] demonstrate that such methods are able to outperform traditional methods for supervised training in terms of accuracy. However, while very promising, these methods rely on vast amounts of compute resources and tackle the problem from a completely different baseline than does not fit the requirements and restrictions of the edge cloud.

2.4. Spatio-temporal locality

When analyzing video feeds from static cameras or any other kind of video where the camera remains still, there is a piece of information that is key to guessing where interesting objects may lie: anything new in the scene. Vehicles, persons, birds, or anything moving is subject to be identified. Spatio-temporal information can tell us when something has moved within the range of view, and the region around the moving object can be used as the region of interest to start looking. Authors in [25] leverage the spatio-temporal locality captured by static cameras to drive the online training of a small specialized model, while authors in [28] propose a training mechanism in which temporal information is used to train a deep neural network at *instance level* (instead of pixel level) and successfully identify even occluded objects.

Beery et al. take this approach a little bit further with Context R-CNN [29] and propose a neural network that is divided into two stages: the first one is trained as a traditional R-CNN for object detection whose region proposals are used to train an LSTM. Stage 2 is an attention block that will consider the information of previous frames where detected objects have already appeared. The authors used video feeds from the span of more than one month to train the Context R-CNN. This method is able to correctly identify and detect objects even under challenging environmental conditions such as dense fog. However, authors in [30] make the observation that without sufficient data variability, models learn to focus on correlations in the background, which leads to poor generalization to new deployments. In this paper, we propose to take the previous observation and invert the variable to optimize. Instead of finding methods to generalize to new deployments, we propose to specialize models for each deployment using images from the same static camera. By removing the generalization as the goal, simple and lightweight architectures for object detection become available, which is a requirement to run real-time video analytics in resource-constrained nodes in the edge.

2.5. Comparison of existing approaches

As revised in this section, the previous work has come a long way when it comes to optimize edge cloud deployments and leverage an interplay with the centralized cloud (Section 2.1), to specialize neural network models and make them adapt to changes in the class distribution (Section 2.2), to automate the

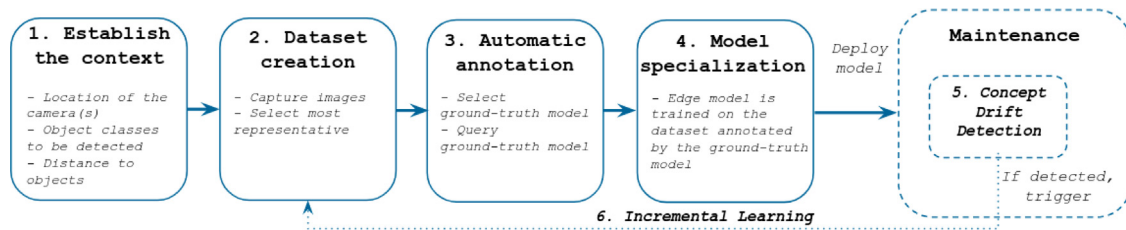


Fig. 2. Breakdown of the different steps involved in the automation of specializing models.

training of neural networks using larger models that work as *teachers* and distill their knowledge to smaller *student* networks (Section 2.3), and to leverage the spatio-temporal locality present in video feeds from static cameras to drive the training of specialized models and achieve higher accuracy (Section 2.4). However, to the best of our knowledge, there is no existing framework that combines advances in different fields to provide an end-to-end solution. Such framework is needed if the resource-constrained edge cloud is expected to take over real-time video analytics at large-scale. In this paper, we aim to close the gap existing in the literature and provide a solution that can enable accurate and real-time video analytics deployed at scale in the edge. Consequently, this paper presents and evaluates COVA, a framework to provide automatic specialization of models for real-time edge video analytics along with tools to ease the development of new custom video analytics applications. Moreover, COVA is envisioned with extensibility in mind and could be used in conjunction with some of the methods mentioned above to further increase accuracy or speed. To the best of our knowledge, no previous work provides the framework and tools here provided.

3. Problem breakdown

Convolutional Neural Networks (CNNs) are able to learn abstract high-level representations of the objects they are trained to detect. The rule of thumb is that assuming proper training, the bigger the network, the better it can learn high-level features to generalize with high accuracy on new data. However, the deployment of generalist CNNs with state-of-the-art accuracy raises three main difficulties:

- They require a vast amount of training examples and each one must be properly labeled with their respective ground-truth (e.g., object class and coordinates of the bounding box surrounding the object for detection problems).
- The training phase often takes hundreds, if not thousands, of hours, even with high-end accelerators (such as GPUs or TPUs).
- Complex models may provide good accuracy but are not suitable to be executed on resource-constrained edge nodes, while simpler models suitable for the edge achieve lower out-of-the-box accuracy that is often not enough for many use cases.

Thanks to automating the retrieval, selection and annotation of the training images (even if it results in an imperfect annotation) and tailoring or specializing lightweight models, we can provide high accuracy models with real-time performance that can be reliably trained within minutes (or less than an hour on CPU-only).

The end-to-end process of specializing models is composed of various steps, each with its own set of challenges. Therefore, the automation of the process with satisfactory results requires several considerations to be made. This section breaks the problem of model specialization down into its core parts to analyze

its challenges and considerations. Fig. 2 depicts the different steps involved in the process, as described in detail in the next subsections. Once images are captured by the camera, the most representative are selected to be annotated by the ground-truth model and be included in the training dataset. Following, the edge model is trained using the generated dataset. Once deployed, the model's accuracy can be monitored to trigger new training iterations if it falls below a certain threshold.

3.1. Static context from static cameras

Before we delve into the specifics of the problem and the solution we propose, we would like to highlight the main observation that makes everything possible: static cameras do not move. While this observation may seem obvious, it simplifies the problem and the solution to a great extent.

The training of object detection models requires a large number of diverse training examples. Object instances in the training dataset should appear in all their diversity (e.g., different colors, shapes, or perspectives). This diversity allows the neural network to learn high-level features inherent to the object class and invariant regardless of the specifics of the observed instance. In the end, diversity during training lets the model generalize. At the same time, a static camera is a camera whose position and orientation remain invariable throughout time. That is, it always points at the same scene using the same lens and from the same distance and point of view. Therefore, thanks to assuming static cameras, we are able to define the context of a camera and, then, tailor models for it.

A static camera thus allows the effective optimization of the pipeline by applying simple traditional computer vision techniques. Specifically, we make use of simple techniques for background subtraction with two purposes: (1) select for training and annotation only those frames where there was any meaningful change and (2) let the *ground-truth* model use the image resolution to its full extent by focusing on the changing parts.

3.2. Capture (relevant) training images

Each image annotated by the ground-truth model has a cost associated in terms of network bandwidth and compute power in the data center. However, not all images captured by a camera provide the same amount of new information (if any, at all). Video streams from static cameras tend to have a high degree of *temporal locality* as frame rates between 10 to 30 frames per second are standard for edge cameras. Such frame rates translate to new images being captured every 100 ms to as low as 30 ms. In most scenarios, nothing new happens within 30 ms, but simply increasing the time between frames does not guarantee that new objects enter the scene. Therefore, we should find the right set of images that will maximize the accuracy of the resultant edge model while minimizing the number of queries to the data center.

Luckily, we can exploit the temporal locality to easily detect changes or quantify similarity between consecutive frames. As the scene's background remains mostly still throughout time,

change can be detected by simply comparing frames and set a threshold to decide whether a frame should be considered or not. Relatively simple and inexpensive distance metrics, such as the Mean Squared Error (MSE), can be used to detect meaningful changes between frames [19], while other mechanisms, more robust but also more computationally expensive, rely on Siamese neural networks [31].

Furthermore, thanks to the same temporal locality, we can also leverage robust motion detection and background subtraction techniques. When working with static cameras, we can consider change to be caused by movement. Therefore, we can identify and isolate the regions of the scene that contain movement, i.e., regions of interest. For such purposes, different approaches with different accuracy-cost trade-offs are available, from those that make use of traditional computer vision techniques [32] to more modern neural networks [33].

COVA, as detailed in Section 4.1, makes use of traditional computer vision techniques to model the background and detect and extract the regions containing movement. These regions are regularly smaller than the full scene and can be compared against the same region in previous frames to quantify the level of similarity at a finer grain. Moreover, the extraction of such regions brings an unexpected benefit that, according to our results, boosts the accuracy of the annotations [34]. Nowadays, FullHD video (1920×1080 pixels), if not 4K (3840×2160 pixels), is widely used even among inexpensive cameras available on the market. However, neural networks are rarely deployed with an input resolution matching the camera's resolution, as the computational cost of their execution would become intractable. However, it does not appear to be a limitation on technology but rather a matter of diminishing returns. On the contrary, neural networks do not require large pixel densities to distinguish objects of different classes. An input size of $768 \times 768 \times 3$ (as the ground-truth model used throughout the paper) is above average, judging by what can be found in the literature [6], while $300 \times 300 \times 3$ pixels is a typical size for edge models (like the one used throughout the paper).

If we consider object detection in the outside world, small input sizes may indeed become a problem. In these scenarios, objects are captured from arbitrarily large distances, and the smaller objects quickly turn into a small set of indistinguishable pixels as the image is resized to the neural network's input size. In such cases, it is worth considering the image to its full extent. The same motion detection techniques we use to optimize the collection of images allow us to do this. Once motion is detected, COVA crops the bounding box containing all frame regions that changed with respect to the background model. Consequently, regions that did not add any information are discarded, and the model can focus on detecting whatever was that moved. For example, before passing the image to the ground-truth model, we have compressed the information captured by the camera between 3.5 and 14 times for FullHD and 4K images, respectively (or between 23 and 92 times for the edge model). As Fig. 3 shows, the average percentage of the frame's area containing motion in different scenarios is often a small fraction of the total area. According to the results, these regions represent as little as 3% of the scene's area.

3.3. Considerations on automatic annotation

The bigger models (potentially) have higher accuracy because they have more trainable parameters. When properly trained, the extra parameters can learn more and better features. These may come in the form of more layers, but the easiest way to increase accuracy (at the expense of computational cost) is to increase the input size [5]. A larger input size increases the

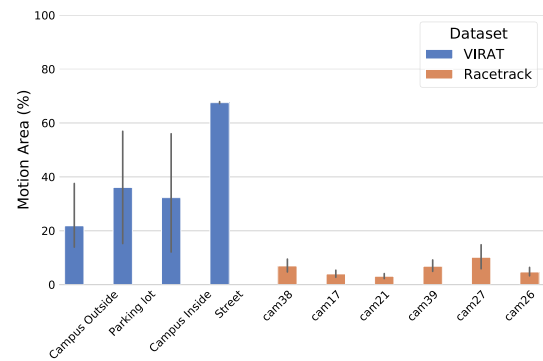


Fig. 3. Average percentage of the frame's area containing motion for different scenes. Frames from the Racetrack dataset have much smaller areas, as cars in the track can only drive through the asphalt and always follow the same paths. The VIRAT dataset contains scenes with up to 67% of the area covered by objects of interest, common in busy urban scenarios with objects appearing from multiple points.

amount of information that the network receives in the form of pixels and allows models to see objects bigger, meaning the network's receptive field takes more pixels into account which is particularly important when trying to detect small objects in the background.

Experiments show that mispredictions often come from the model's inability to distinguish the object from the background (i.e., while Top-1 or Top-5 recall might be good, the confidence is below the threshold to be considered) [20]. In other words, the model may correctly distinguish an object from other objects but not be sure whether the object is actually there. This phenomenon increases as the object gets smaller and becomes just a few pixels large, as showcased by the experiment depicted in Fig. 4. The figure shows the impact that the size of the input image has on the confidence of a model's predictions for different models trained on the same dataset. The input images belong to different frames captured from one scene of the Racetrack dataset, all containing a single car centered in the scene. For each frame, the region of interest (RoI) containing the car object is cropped in different sizes and fed to the model. Therefore, the car represents a smaller area of the model's input as we increase the RoI size. The experiment evaluates models with three different neural network architectures: SSD detector with MobileNet V2 feature extractor (left), SSD detector with ResNet101 feature extractor (center), and EfficientDet (right), which is also an SSD detect but with an EfficientNet feature extractor. The models are different pre-trained versions of these three neural network architectures that were trained and dimensioned with different input sizes. These results show that confidence drops as the object gets smaller with respect to the rest of the scene. There are two factors contributing to this effect. First, the model's input size. Intuitively, bigger input sizes have a larger receptive field and are, potentially, better at locating small objects. Second, the neural network architecture. While the more modest MobileNet achieves on-par confidence compared to the state-of-the-art EfficientDet when the car represents the largest part of the input image, its confidence quickly drops as the object becomes smaller regardless of its input size. On the contrary, the ResNet101 and the EfficientNet backbones seem to sustain their confidence as the object gets smaller. However, their confidences still drop for the larger RoI sizes, especially for the models with smaller input sizes.

Finally, the ground-truth model is assumed to be knowledgeable of the scope in which edge deployments will happen but is not required to be trained on images from those deployments. We build this assumption upon the observation that large models are

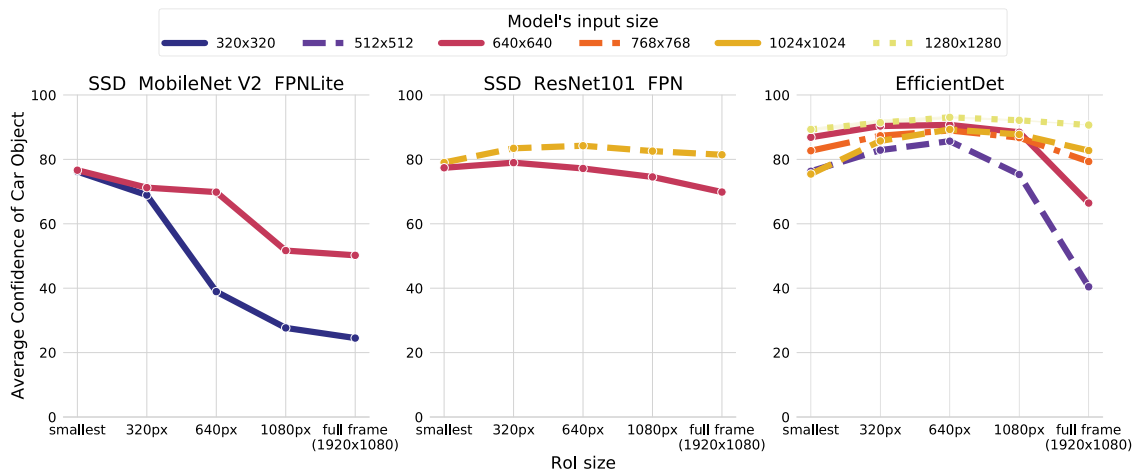


Fig. 4. Average confidence of car detections from three models with different input sizes and varying the size of the Region of Interest (Rol) passed as inputs. All Rols contain a car centered. *Smallest* refers to the smallest square Rol that contains the car object, i.e., the smallest bounding box with aspect ratio of 1 that contains the full car object. *Full Frame* refers to the full frame passed to the model as input at full resolution (1920×1080), i.e., as it was captured by the camera.

better at retaining features that allow them to generalize better. These models are therefore expected to correctly identify *most* of the objects from classes they have been trained to detect, even if these objects are seen from new perspectives and distances. This level of generalization is a characteristic that models small enough to run on edge devices do not share.

3.4. Model specialization

To deploy video analytics to multiple cameras (each one with its own context), we could take two main directions. On the one hand, we could run big and complex CNNs capable of generalizing and delivering high accuracy regardless of the cameras' context. This solution could work out-of-the-box if the model has already been trained to detect the same set (or a superset) of object classes as those we want to detect in the edge. Moreover, this solution would require a single training for multiple cameras. However, the reality is that edge deployments do not have the luxury to run such models whose compute requirements are rarely met at the edge. Accuracy comes at the price of high latency and low throughput, often below the minimum required to run real-time use cases. On the other hand, we can use lightweight neural networks but *specialize* them to each specific deployment and let them deliver their full potential on a narrower scope.

The edge cloud is limited on the size of the neural networks that can run. At the same time, this puts a limit on the level of accuracy that a model can achieve with respect to that in the state-of-the-art [8]. Hence, models deployed to the edge may face difficulties extrapolating their knowledge to detect objects in new environments. The specific lighting conditions, points of view, or focal distance of every deployment may impact the ability of small neural networks to extrapolate using previously learned features. One approach to mitigate the effects of lack of generalization from smaller models is called *model specialization*, which implies narrowing the scope of what the network has to learn and, thus, demanding less from it. In the context of edge video analytics, model specialization allows us to adapt a model for the specific context of each camera deployment. The specifics of a context may not be known beforehand but can be easily extracted once the camera has been deployed and begins to capture images.

Model specialization can be achieved through different means. One option is to train the network from scratch on a specialized dataset. However, the computational cost plus the number of

labeled training images required to train a network from scratch on a per-camera basis makes it unfeasible for rapid deployments. Nevertheless, different techniques, such as model distillation [35] or transfer learning, allow us to use previously learned knowledge and repurpose it faster while requiring fewer training images. In this paper, we focus on transfer learning to specialize pre-trained models on the specifics of each deployment. The knowledge of a pre-trained generic model with state-of-the-art accuracy, working as *teacher* or *ground-truth model*, is distilled into a specialized training dataset used to train the *student* or *edge model*.

Nonetheless, a neural network's predictions are as good as the dataset used to train the network, and transfer learning still requires properly labeled images to specialize models. A proper training dataset is essential to produce an accurate yet small model that can process images in real-time on constrained nodes.

3.5. Concept drift detection

Concept drift refers to a change in the statistical properties of the variable that a model tries to predict. In the context of edge deployments, concept drift could arise in different ways. For example, a camera in the wild would capture predominantly green backgrounds during spring that turn white during winter due to snow; a camera whose perspective changes substantially after it is relocated; a change in light conditions from day to night; or simply because the user is interested in new classes. A new training should be triggered to adapt the models to the new environment or contextual features in all these cases.

This said, concept drift detection is not trivial. Traditional approaches try to detect concept drift by performing statistical hypothesis testing on multivariate data [36], while more recent ones explicitly designed for neural networks propose the use of an oracle or teacher model that is consulted intermittently to assess the deployed model's accuracy [25] and drive the training rate whenever accuracy falls below a threshold.

Nonetheless, it is important to highlight how, in the context of static cameras, concept drift is highly coupled to the level of specialization of the deployed model. A highly-specialized model trained using only daytime examples may face difficulties in detecting the same objects during nighttime due to lighting variations. On the contrary, a model trained with all-day examples and big enough to retain the sufficient level of generality will not experience a concept drift as day turns to night. Consequently, prediction cascades can help mitigate the problems

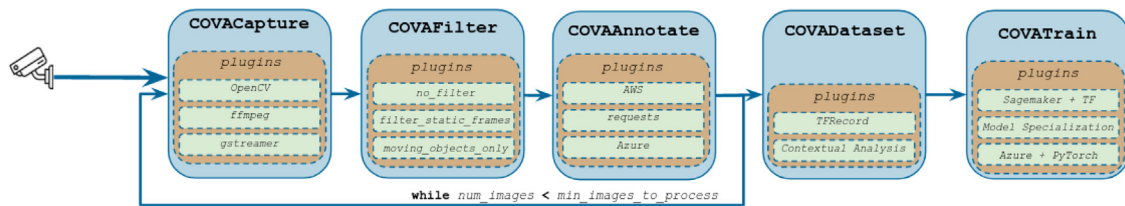


Fig. 5. Default pipeline in COVA for automatic specialization of models.

associated with concept drift without requiring retraining. In prediction cascades, multiple specialized models (either binary [19] or multi-label classifiers [37]) are sorted by decreasing level of specialization (or increasing level of accuracy and cost) and a model is only consulted if the previous one is not confident enough of its predictions. In the event of a short-term concept drift that cannot be absorbed by the more specialized models, prediction cascades use the more expensive models as fallback to ensure the accuracy of the predictions. However, in the event of a long-term concept drift, the specialized models will be rendered useless and counterproductive, as the cascade will keep consulting them even when they can no longer produce reliable predictions. Therefore, prediction cascades can mitigate the problem but do not solve it. As such, they are a better suited for query systems where the model search can consider the full video stream being queried.

3.6. Incremental learning

The detection of a concept drift irredeemably results in a new training of the model to adapt it to the new environment. This is especially true in ever-changing scenarios, like seasons in a forest, where we have to rely on *incremental learning* to train a model with whatever data is available at the time of the deployment and, as new examples appear, retrain the model using the newly captured examples. However, there is one crucial limitation: *catastrophic forgetting* [38], which refers to the tendency of neural networks to forget previously learned features entirely upon learning new ones. The straightforward solution is to train again using the entire dataset, i.e., include the newly captured examples into to the training dataset used during previous iterations. However, this can lead to an oversized dataset that can quickly become intractable for edge nodes, while older examples may not be significant anymore in the current environment. When the set of classes that are missing is known, another solution is to add generic instances for those classes (e.g., using online image search engines [39] or reusing a subset of the examples used during the training of the ground-truth model or other *students*). Nonetheless, previous work demonstrates that using knowledge distilling techniques [35] networks can retain most of the previously learned features, even if trained only on new classes of objects [40,41].

4. The COVA framework

COVA is a framework that automates the task of specializing neural network models for edge video analytics. As a framework, it aims to enable the rapid deployment of customized applications in resource-constrained edge nodes. As such, it has been implemented with customization and extensibility in mind.

COVA is made out of two main building blocks. On one side, it provides high-level structures to allow video analytics models to be tailored for a specific deployment in just a few lines of code. On the other side, it also provides multiple built-in methods to ease the extension and customization of the existing structures.

4.1. Framework architecture

The backbone component in the workflow of COVA is the pipeline (or *COVAPipeline*). A pipeline describes the sequence of steps involved in specializing a neural network model and how each step communicates with the next. Together, a sequence of steps conforms a pipeline. Fig. 5 depicts the default pipeline implemented in COVA entailing five steps. These are 1. capture images, 2. filter images, 3. annotate images, 4. create the dataset, and 5. training. The default pipeline iterates over steps 1–3 until enough images are available to continue. Then, step 4 generates the training dataset from the images and the annotations from the previous steps. Finally, the model is trained in step 5.

The potential of COVA relies on the high level of customization allowed by the pipeline architecture while keeping a simple structure within its core. Each step in the pipeline is implemented using a plugin architecture, allowing to easily extend or modify the default behavior. For example, the annotation step can be carried out using the built-in server exposing a REST API or the annotation plugin offloading the task to Amazon Web Services. Moreover, any step implementation (i.e., plugin) is interchangeable with any other implementation of the same step as long as their interfaces match what is described in the pipeline definition. Furthermore, it is possible to define different pipelines that use different stages and plugins and do so only through the configuration file, i.e., without any modification in the code.

4.2. Pipeline components

By default, COVA implements a pipeline with the five stages previously described. However, the pipeline itself can be extended or modified if another sequence of stages is needed. Nonetheless, we describe and focus on the default pipeline, its stages, and the built-in plugins.

COVACapture. Captures and decodes images from a stream (input) and returns decoded frames as an RGB matrix. COVA implements capture using OpenCV, which, in turn, accepts different backends such as Ffmpeg or GStreamer.

COVAFilter. Filters decoded frames (input) and returns a list of RGB matrices. Among the built-in filters, *no_filter* returns the same frame it received as input, i.e., does not apply any filtering; *filter_static_frames* returns either the same input frame or an empty list, depending on whether any movement was detected in the latest frame or not; *moving_objects_only* returns a list of the regions of the input frame where movement was detected.

COVAAnnotate. Annotates images. It receives filtered frames and returns the list of bounding boxes and labels of the objects detected on the input images. COVA implements two annotation methods: using the built-in REST API or using AWS. Both methods assume a ground-truth model trained on the target problem whose predictions are assumed to be ground-truths during training. Section 6 evaluates the impact of this assumption. This stage supports both TensorFlow and OpenVINO models.

COVADataset. Generates the training dataset from the filtered images and their respective annotations. The built-in plugin results in a TFRecord file as output (format used in TensorFlow


```

"capture": {
  "plugin": "VideoCapture",
  "args": {
    "stream": "rtmp://example.com/stream",
    "frameskip": 25,
    "deadline_max_images": 1000,
    "deadline_max_seconds": 3600
  }
},
"filter": {
  "plugin": "FilterStatic",
  "args": { "warmup_seconds": 10 }
},
"annotate": {
  "plugin": "AWSAnnotation",
  "args": {
    "aws_config": {
      "role": "$globals#aws_role",
      "instance_type": "ml.m4.xlarge"
    }
  }
},
"dataset": {
  "plugin": "AWSDataset",
  "args": {
    "valid_classes": [
      "car", "person", "motorcycle",
      "bicycle", "truck", "bus"],
    "min_score": 0.3
  }
},
"train": {
  "plugin": "TFTrainer",
  "args": {
    "checkpoint": "models/ssd-mobilenetv2/",
    "epochs": 1000,
    "layers_to_train": "box_regression"
  }
}

```

Fig. 6. Example of configuration file defining a COVA pipeline.

that stores data as a sequence of binary strings). However, the resulting dataset can be subject to different processes. Specifically, COVA implements a default dataset in which all annotations make it into the dataset (since filtering occurs in the Filter stage).

COVATrain. Trains a neural network using the previously generated training dataset. TensorFlow is the default library used. Built-in plugins support two flavors of training: standard TensorFlow and TensorFlow Object Detection API (used for training or fine-tuning object detection models). Both flavors can be executed either locally or using AWS. As output, this stage generates a specialized model (in TensorFlow's *SavedModel* format).

4.3. Pipeline configuration

COVA allows pipelines to be fully defined using a configuration file in JSON format. The configuration file allows users to dynamically define the plugins to be used on each pipeline stage and the parameters expected by each stage. Fig. 6 shows an example of a pipeline defined using a configuration file in JSON format. Custom plugins can be loaded in the configuration file using the *plugin_path* keyword. The set of parameters accepted by each plugin will ultimately depend on the specific plugin implementation. However, some of the most important ones include:

Target classes of objects. List of object classes for which the model will be specialized. The list of classes is the basis of model specialization for two reasons. On the one hand, the type of objects expected to be seen and detected in the scene is essential to define a camera's context. Limiting the classes of objects the model has to learn to identify helps specialize the resulting model, and the learning process can focus on those classes it will

eventually encounter. On the other hand, the precision of the ground-truth model gets a boost after we discard detections from classes that are unlikely to be seen in a specific context (e.g., a boat detected crossing a pedestrian crossing can be omitted or, at the very least, flagged to be double-checked). Only frames containing instances of one of the target classes are considered during the dataset's creation, while the rest are filtered out.

Training deadline. It is important to set a deadline to force the trigger of the training process in scenarios where there is no high influx of new objects of interest entering the scene. If the training is triggered by the deadline, results may not be optimal, but, at least, the model can start working while new images are being captured for a new training iteration.

Motion sensitiveness. If the filter plugin uses motion detection, it can be tweaked to be more or less sensitive to small changes in the frame. This parameter will highly depend on the characteristics of the scene. The smaller the objects we want to capture, the higher the sensitivity required to detect their movement. However, high sensitivity may incur an undesirably large number of frames being flagged with motion, as small variations can occur due to glitches, camera jitter, or the wind blowing on background objects.

Trainable Layers. If the training plugin uses a checkpoint of a pre-trained model, COVA allows defining the layers that are to be trained while the rest are frozen. We have tested three configurations: *unfrozen* (all weights are trainable), *box regression* (only the layers of the object detector head are trainable), and *top* (box regression plus the last few layers of the feature extractor). According to our experiments, the optimal configuration will highly depend on the size of the training dataset. With enough examples, *unfrozen* seems to yield the best results. However, *box regression* is the safest option and yields good results even with only tens of images, while *unfrozen* has a higher risk of overfitting with small datasets.

4.4. Built-in utilities

COVA also provides several built-in methods aimed at assisting with the development of new applications. Among all the utilities and auxiliary methods, we primarily focus on motion detection, as it is the basis of how COVA analyzes the scene to provide better results while reducing the amount of network bandwidth (as only a portion of the frame needs to be sent) and compute used (by reducing the amount of annotations required).

4.4.1. Motion detection

There is a myriad of existing methods to perform motion detection. Nonetheless, it involves many challenges (e.g., camera jitter or lighting variations), and, as a problem, it is far from being solved. There is not a *de-facto* approach that can handle all scenarios robustly, and different methods offer different trade-offs in terms of speed or accuracy. In COVA, we prioritized speed over accuracy when selecting the methods to implement for two reasons. First, the accuracy of these methods is usually evaluated using image quality metrics of the generated background or error metrics at the pixel level to compare the generated background to the ground-truth background. Second, COVA must run on resource-constrained Edge nodes and do it faster and more cost-effectively than the alternative: send whole frames over the network and process them in a centralized data center. Therefore, COVA implements two simple methods consisting of two steps or building blocks:

Background Modeling of the scene is the key step for motion detection to work effectively. Take an incorrect background of the scene, and any advantage from motion detection fades away, as every single frame could be incorrectly flagged as containing

changes. As previously mentioned, COVA assumes images from static cameras, which greatly simplifies the background modeling. Nonetheless, the optimal algorithm will still be highly dependent on the specific context in which the camera is placed. Therefore, COVA implements several methods. The first and simplest is to assume that the first frame captured is the background of the scene. This method works best when the scene is known to be empty of moving objects when the process starts, and the background is not subject to long-term changes. However, in many cases, this is not only false, but the definition of background can change over time (e.g., sunlight turning into darkness or objects left unattended for long periods, like parked cars). Therefore, background modeling works best when the background is computed over time. In this direction, COVA implements background modeling using a Mixture of Gaussians (MoGs) [42]. Our results have shown that this method yields robust results while being computationally inexpensive (i.e., on average, 2.7 ms on a single core of an Intel Xeon 4114). This is the method used by default.

Monitor the scene for any substantial changes. A simple subtraction operation will give us the pixel-to-pixel absolute difference between the current frame and the background model. Nonetheless, in real-world deployments, two consecutive frames will never be identical. Multiple factors will cause small pixel changes even with a static background and no objects moving.

On the one hand, digital camera sensors are imperfect and introduce tiny variations that cause pixel values to vary, even when the scene remains seemingly invariant. Applying a Gaussian blur to both the background and the current frame filters noise out when computing the pixel-to-pixel difference. Next, COVA applies a binary threshold to the computed difference to consider only those regions containing significant changes in the pixel intensity. After applying a *dilate* operation to fill in the holes over the result of the binary threshold, we obtain a mask with the changing regions in the frame. Finally, we compute the bounding boxes by finding the contours on the masked frame. A contour is a curve joining all the adjacent points along the boundary of a region of pixels with the same color or intensity.

On the other hand, small changes can still be undesirably (although not necessarily incorrectly) flagged as motion. There is no rule of thumb to determine how large a region must be to be considered a potential moving object, as it will highly depend on the specifics of the scene and the objects we want to detect. For example, in the *Racetrack* dataset, some cameras point directly to the track at a relatively short distance, and cars are seen big enough to consider only large regions as motion. However, other cameras have a broader view and capture cars and other objects from different distances, and, area-wise, a distant car might be indistinguishable from a leaf fluttered by the breeze from a nearby tree. Therefore, COVA considers a user-defined threshold that sets the minimum area for regions to be considered of interest.

Fig. 7 depicts an example of the process, where two cars are correctly detected as the only two objects moving in the scene. Each one of these operations is already implemented by OpenCV [43]. Altogether, they result in an inexpensive yet effective method for our purpose. Through them, motion detection takes orders of magnitude less time than computing a single inference on resource-constrained nodes. Therefore, it becomes ideal to be executed on resource-constrained nodes on a frame-by-frame basis to optimize the automatic annotation of images, which is indeed the most expensive single operation in the whole process.

4.4.2. Cloud-assisted edge deployments

As part of the Edge-Cloud interplay that COVA aims to leverage, some of the built-in plugins already implement the usage of Amazon Web Services. Specifically, S3 to upload images and SageMaker for the annotation and training stages. Moreover, COVA provides several auxiliary modules and utilities to integrate these services on new applications.



Fig. 7. (a) Two cars in the racetrack with bounding boxes around them, obtained after performing background subtraction on the frame. (b) Thanks to a static background, the task of separating moving objects from the background is largely simplified. The regions of interest after applying simple computer vision techniques are much smaller than the whole FullHD frame captured by the camera lens, which allows us to focus the attention closer to the objects and increase the accuracy of the ground-truth model. In an scenario like the racetrack of the image, motion detection alone is able to filter all empty frames out and only consider those with cars and minimize the annotation costs.

Table 1

Summary table of the model taxonomy with the different types of models considered throughout the paper.

Model	Variant	Trained/Specialized on
Ground-truth	Off-the-shelf	MS COCO
	Generic	Similar edge scenarios
Edge	Off-the-shelf	MS COCO
	Generic	Similar edge scenarios
	Specialized	Scene to be deployed

4.5. Source code availability

The entirety of the COVA project has been made publicly available in the project's repository [12] with an open license (Apache License 2.0) to encourage the community to use it, test it, and extend it. The repository includes the fully documented source code with detailed instructions on deploying it end-to-end and reproducing the experiments described in this paper.

COVA is implemented in Python. By default, its only requirements are OpenCV and TensorFlow, while CUDA can be used if available.

5. Methodology

In this section, we detail the methodology followed throughout the experiments whose results are presented and analyzed in Section 6.

5.1. Edge model taxonomy

The evaluation in Section 6 is carried out using two neural network architectures and three different versions of each one. Table 1 describes the model taxonomy used throughout the remainder of the paper. The *edge model* refers to the model that we aim to optimize (i.e., specialize) for its deployment to the edge. It is typically a lightweight model that can run at real-time performance on resource-constrained nodes. The *ground-truth model* refers to the model whose predictions are considered to be ground-truths while building the dataset to use during the training phase of the edge model. Edge and ground-truth are conceptual classifications for two models that play different roles within our proposed solution. Therefore, these do not refer to any specific neural network architectures, and any model can be used as either edge or ground-truth models. However, the ground-truth model is expected to be more accurate and more complex than the edge model. Otherwise, the latter would be a better choice to deploy to the edge.

Moreover, we define three different variants that refer to how the model was trained: *off-the-shelf*, generic, and specialized. Off-the-shelf (OTS) refers to the model pre-trained on the COCO dataset (Common Objects in Context) [9] without any further training nor tuning on any other context. It is easy to find most of the well-known neural network architectures already trained on this dataset. Generic and specialist variants are categories always relative to the model to deploy. Generic refers to a version of the model trained or fine-tuned on contexts similar to the deployment context. For example, if we want to deploy a model to control cars at a parking lot, a generic model could have been trained using images from other parking lots or urban areas with mostly cars. Specialized refers to a model that has been trained using images from the same edge camera of the deployment.

5.2. Datasets

Throughout this paper, we use two datasets to evaluate the different points of our approach.

- VIRAT Video Dataset [44]. Data collected in “*in natural scenes showing people performing normal actions in standard contexts, with uncontrolled, cluttered backgrounds*”. After filtering scenes that were not fully annotated, the dataset we used contains a total of 10 scenes from 10 different static cameras. We have grouped these 10 scenes into 4 contexts: *Campus Inside* for scenes 0000, 0001, and 0002; *Campus Outside* for scenes 0100, 0101, and 0102; *Parking Lot* for scenes 0401 and 0403; and *Street* for scenes 0501 and 0503. The name of these groups is descriptive of the context in which the images were captured.
- Racetrack. Custom dataset with footage captured during car training session in a racetrack. The dataset includes images from 6 static cameras placed in different spots along the track and captured at 12 different points in time. This dataset is not fully annotated, and we use it only for a meta-analysis of its characteristics. It is nonetheless interesting, as it gives the perspective of a use case in which cars are virtually the only moving objects crossing the field of vision of the cameras.

In the experiments presented in Section 6, we focus the evaluation on the VIRAT dataset, as we consider it to present enough diversity of scenes to be representative.

5.3. Evaluation metrics

In image classification, the two main metrics to evaluate a model are *precision* and *recall*. For a certain class of objects, precision will tell us how much we can trust that a given prediction has been correctly classified (i.e., the ratio of True Positives with respect to the total of predictions), while recall will tell us how much we can trust that images of a certain class are correctly classified (i.e., the ratio of True Positives with respect to the total number of *ground-truth* True Positives). However, the goal of object detection models is to find the bounding box coordinates of each detected object, and these coordinates are real numbers. Therefore, to classify a prediction as True or False Positive and Negatives, the Intersection over Union (IoU) tells us the ratio of overlap between the predicted box and the ground-truth. Then, a detection is considered a True Positive if the computed IoU is over a certain threshold and considered a False Positive otherwise.

Mean Average Precision (mAP): We use mAP (mean Average Precision) as the main metric to evaluate each version of the different models resulting from the experiments. Within object detection,

mAP has gained popularity as it is used in some of the most popular challenges in the field, such as PASCAL Visual Object Classes (VOC) [45] and MS Common Objects in Context (COCO) [9]. However, the details of how mAP is computed may vary from challenge to challenge. In this paper, we compute mAP as specified by the COCO challenge.

5.4. Experiment setup

The experiments explore the different considerations we have identified. The training configuration and most hyperparameters are fixed throughout the experiments and only the training images and their respective annotations vary from one experiment to another (i.e., scene or scenes from which images were captured and their annotations correspond to either ground-truth or automatic annotation). All the models used in the experiments take the same off-the-shelf edge model as starting point, which can be found in [46]. Therefore, most of the hyper-parameters are likewise shared with the off-the-shelf model. On the one hand, those related to the neural network remained untouched: mobilenetv2 feature extractor and SSD detection head for box regression, both with l2 regularization ($weight = 0.0004$) and *RELU6* as activation function.

However, some hyper-parameters related to training required to be tuned, considering the specifics of the experiment design. The relatively small number of training examples, although enough for transfer learning, forces us to take some precautions to prevent the neural network from forgetting valuable features. First, the training affects only the parameters on the box regression layers of the model, i.e., box regression layers are left unfrozen, while feature extraction layers are frozen. Additionally, the momentum optimizer ($momentum = 0.9$) uses a cosine decay learning rate with a relatively low initial value ($base = 0.001$). Moreover, we add a pipeline of pre-processing layers during training to leverage data augmentation using the following TensorFlow functions: *horizontal_flip*, *vertical_flip*, *rotation90*, *adjust_brightness*, *adjust_hue*, *adjust_saturation* (all preceded by the *random_* prefix), and *ssd_random_crop*. Finally, the batch size is set to 16 images and training stops after 5000 epochs.

5.5. Baseline off-the-shelf models

For the evaluation, we start from an edge and ground-truth *off-the-shelf* models. These models are publicly accessible from the TF Model Zoo [6] and have been pre-trained on the COCO (Common Objects in Context) dataset [9]. For the experiments, we have selected a MobileNetV2 feature extractor with a Single Shot Detector (SSD) detection head [46] with an input size of $300 \times 300 \times 3$ pixels as the *edge* model and an EfficientNet feature extractor with an SSD head [47] and an input size of $768 \times 768 \times 3$ pixels as our *ground-truth* model. The edge model was selected for being the smallest and fastest pre-trained model available with a while the ground-truth model was selected for being on the high-end of best performing models. The mAP of the models on the COCO dataset is 20.2% and 41.8%, for the edge and ground-truth models, respectively.

6. Results

We have broken down the process of automatic tuning of neural networks into different steps. Each step invariably brings a trade-off that we must understand before moving forward. The following experiments are designed to test the contributions and premises in which COVA is based. That is, that ground-truth models generalize better than smaller edge models, that model specialization can help boost accuracy of a model when evaluated on the same context it is expected to be deployed, and that ground-truth models can be effectively used to automatically specialize edge models.

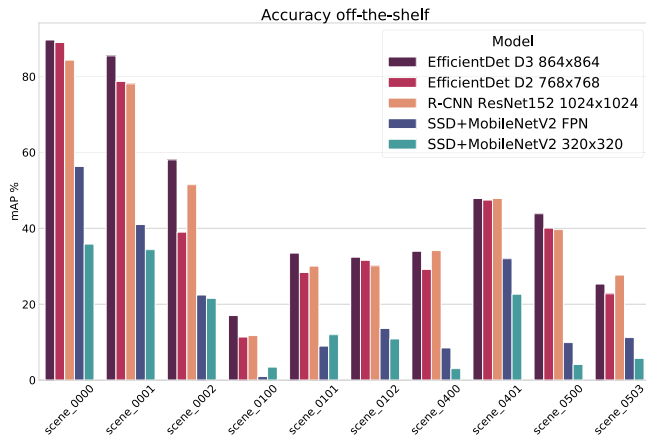


Fig. 8. Mean Average Precision of three ground-truth models and two edge models *off-the-shelf* evaluated on the VIRAT dataset. Breakdown by scene.

Table 2

Comparison of mean Average Precision on the COCO and VIRAT (average of all scenes) datasets for different *off-the-shelf* ground-truth and edge models.

Model	Category	COCO	VIRAT	Diff
EfficientDetD3	Ground-truth	45.4	46.7	+3%
EfficientDetD2	Ground-truth	41.8	41.7	-0.25%
R-CNN ResNet152	Ground-truth	39.6	43.5	+10%
SSD MobilenetV2-FPNLite	Edge	22.2	20.5	-8%
SSD MobilenetV2	Edge	20.2	15.4	-25%

6.1. Off-the-shelf generalization

Here we test the hypothesis that models expected to act as ground-truth models (i.e., complex models able to achieve state-of-the-art accuracy) generalize substantially better than their smaller and less compute-demanding counterparts, the edge models. For this, we consider three *off-the-shelf* ground-truth models and two *off-the-shelf* edge models and evaluate them on the VIRAT dataset, unknown to all models.

Table 2 shows the average mAP achieved by different ground-truth and edge models *off-the-shelf*, i.e., pre-trained on the COCO dataset. According to the evaluation, all three ground-truth models achieve similar or higher accuracy when evaluated on the different scenes of the VIRAT dataset compared to what they achieved on the dataset on which they were trained. On the contrary, both edge models struggle to generalize to the VIRAT dataset using their pre-trained knowledge and drop their accuracy between 8% and 25%, on average.

Fig. 8 zooms into the mAP of all models broken down by scene. Again, all ground-truth models consistently outperform the edge models on all scenes. The difference between ground-truth and edge models fluctuates between 2x and 18x, depending on the scene. On average, the ground-truth models outperform the edge models by a factor of 6x. These results highlight two things. First, the ground-truth models achieve significantly better accuracy than the smaller edge models, as expected. Second, ground-truth models seem to sustain their accuracy in new environments, implying a higher generalization level.

6.2. Generic vs. specialized

Here we test the hypothesis that a specialized model performs better than a generic model when evaluated on the same context of its deployment. For this, we evaluate the three versions of the edge model described in 5.1, which can be mapped to three levels

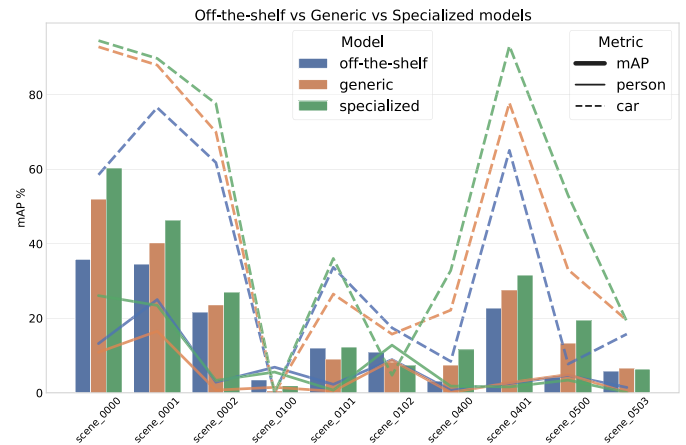


Fig. 9. Mean Average Precision of the generic edge model compared to the specialized edge model for the VIRAT dataset. Breakdown by scene. Bars show average mAP and lines and dotted lines show person and car AP, respectively.

of specialization (being *off-the-shelf* the less specialized, followed by *generic* and *specialized*). We define the *generic* edge model as a version of the edge model that has been fine-tuned using images from scenes similar to the one to which we want to deploy the model. That is, images from other cameras different than the one to evaluate but belonging to the same supercategory as used in Section 3 (i.e., Campus Outside, Campus Inside, Parking Lot, Street). Analogously, we define the *specialized* edge model as a version of the edge model that has been fine-tuned using images from the context to deploy. That is, the model is fine-tuned using images from a single camera. Nonetheless, images on the training and evaluation datasets are from videos captured at different times, i.e., a video is used for either training or evaluation dataset, but never in both.

Fig. 9 shows the mAP of the generic and the specialized edge models. On the one hand, the *off-the-shelf* models consistently underperform both generic and specialized models except on one scene. In scene 0102, the pre-trained model achieves 10% higher mAP than the generic and 15% higher than the specialized. Diving into the breakdown accuracy by object classes, the specialized achieves higher accuracy on person detection but still drops the average accuracy due to poor car detection. Upon closer inspection of the contents of the scene, we observed that the scene (supercategory *Campus Inside*) contains a single instance of a car, which was seemingly insufficient during training. On the other hand, the specialized model outperforms the generic model on every scene of the dataset (except, again, scene 0102) by a minimum of 2% and up to 87%, with an average improvement of 30%. These results prove how model specialization can help us achieve greater accuracy without altering the computational complexity of the model. However, they also highlight that special care should be taken in scenes where there is an imbalance on the class distribution of the objects captured.

6.3. Manual ground-truth vs. automatic annotation

Here, we test the hypothesis that ground-truth models can be effectively used to annotate images that will be used to train specialized edge models. For this, we evaluate the impact of automatic annotation on the resulting model's accuracy. The edge model is trained three times, each time with a different dataset containing the exact same set of training examples but whose annotations differ in each case. On the one hand, manual annotation, which is taken as the reference, as it is assumed to be perfect. On the other hand, automatic annotation in which predictions

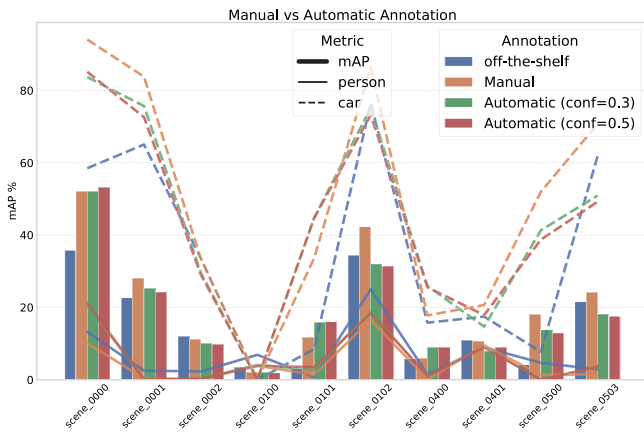


Fig. 10. Mean Average Precision of a specialized edge model after being trained on a manually annotated dataset vs. a dataset automatically annotated by the ground-truth model with thresholds of confidence of 0.3 and 0.5. Bars show average mAP, and lines and dotted lines show person and car AP, respectively.

from the ground-truth model are taken as ground-truths during training. Automatic annotation is evaluated with a minimum confidence threshold of 0.3 and 0.5. Therefore, predictions from the ground-truth model with lower confidence are discarded. Moreover, the ground-truth model is assumed to be trained on (or, at least, knowledgeable of) the classes of objects that will have to annotate and detect.

Fig. 10 shows the mean Average Precision of the specialized edge model using three datasets annotated differently: manual, automatic (conf = 0.3) and automatic (conf = 0.5). Compared to manual annotation, the automatic annotation yields similar results on some scenes while it lags behind on others. Automatic annotation seems to struggle in those scenes where smaller objects are predominant, as the ground-truth model fails to detect them with enough confidence to be included in the training dataset. Interestingly enough, automatic annotation outperforms manual annotation, which is supposed to be an upper bound, in three scenes, although not significantly. Overall, automatic annotation successfully outperforms the results of the off-the-shelf model and increases the mAP of all scenes in average by 21%. It is worth noting that varying the confidence threshold from 0.3 to 0.5 does not result in substantial differences. This seems to be due to the low number of False Positives introduced during the annotation of the dataset.

6.4. Discussion

The experimental results show the potential of model specialization within an automated training pipeline. At the same time, they also highlight the steps where more work is required or special care should be taken to build a more robust pipeline.

It is important to emphasize that the desired property for a model to be used as ground-truth is a high level of generalization. That is, a model able to sustain a certain level of accuracy when evaluated in previously unseen scenarios. State-of-the-art neural networks, like those used as ground-truth, can get *unreasonably* expensive to train. Consequently, generalization becomes the enabler of an automated training pipeline where a single ground-truth model is expected to specialize multiple edge models at large scale. In the first experiment we observe how, on top of a higher accuracy, ground-truth models are able to maintain or even increase their accuracy when evaluated on the different scenes of the VIRAT dataset, contrary to the edge models.

Moreover, specialized models have shown to consistently outperform their more generic counterparts, except on a single scene

where the reduced number of cars led to a high imbalance on the class distribution during training, causing the specialized model overspecialize the features of that class. This could be mitigated by adding generic instances to the specialization training dataset until more instances are captured from the deployed camera to trigger a new training.

Additionally, the quality of the models specialized using an automatically annotated dataset has shown, on average, an accuracy boost compared to off-the-shelf models. However, we have observed certain limitations that should be addressed to make the quality of the results more robust. We have found a relationship between the average object size in a scene and the accuracy obtained by these models, being accuracy higher the larger the average object. A closer look at the composition of the scenes where automatic annotation lacks significantly behind manual annotation hinted that the problem lies in the smaller objects being predominant in those scenes, like person instances captured from afar. Small objects are usually more difficult to detect for obvious reasons, and this translates to second-order errors, as the ground-truth model introduces annotation errors (mostly in the form of False Negatives by not detecting them). Thus, the edge model fails to detect them during inference due to size and deficient training. In this regard, we would like to highlight the importance of the main observation used to build COVA: *objects of interest move*. Before introducing motion detection and background subtraction to the pipeline, even the ground-truth models were unable to detect most of the regular-size objects in a common scene, as most objects would turn into just a few pixels after downsizing the image to the model's input size. Nonetheless, automatic annotation could benefit from an improved preprocessing of the images fed to the ground-truth models.

Moreover, we have observed some scenes in which the automatic annotation outperforms the manual annotation, which was supposed to be an upper limit. We believe this is due to a beneficial side-effect of distilled learning, as models are trained to mimic the behavior of another model (ground-truth). Consequently, the specialized model focuses, during training, on those objects that will be able to realistically identify after being deployed and disregard those that could not be identified even by the ground-truth model, which is expected to be significantly more capable than the specialized (edge) model. This effect has been already shown in the literature [23] and could be further exploited to increase accuracy or reduce training costs in COVA.

Finally, it is worth stating that the edge model used throughout the experiments, even if arguably small, accounts for the non-negligible amount of 4.5 billion trainable parameters. It uses a MobileNetV2 architecture that can achieve a considerable 72% accuracy on the notoriously generalist ImageNet and 19% mAP on COCO when coupled with a Single Shot Detector head for box regression. Such neural network architectures can be useful, especially if they have been pre-trained on a related problem (even if it is loosely related). They offer a reasonable level of generalization that makes it easier to adapt to new environments, all at a relatively low computational cost. However, we believe there is a margin to further specialize the models used while keeping the same accuracy. Nevertheless, it is important to highlight the challenges involved in specializing neural networks. The more specialized a model is, the harder it becomes to use it reliably under uncontrolled environments, as these effectively increase the number of possible inputs the model will observe and for which it cannot generalize. Analogously, the better the automated analysis of a camera's context, the better and faster concept drifts can be detected, i.e., detect whenever the scene's context evolves into something the model is not trained to recognize.

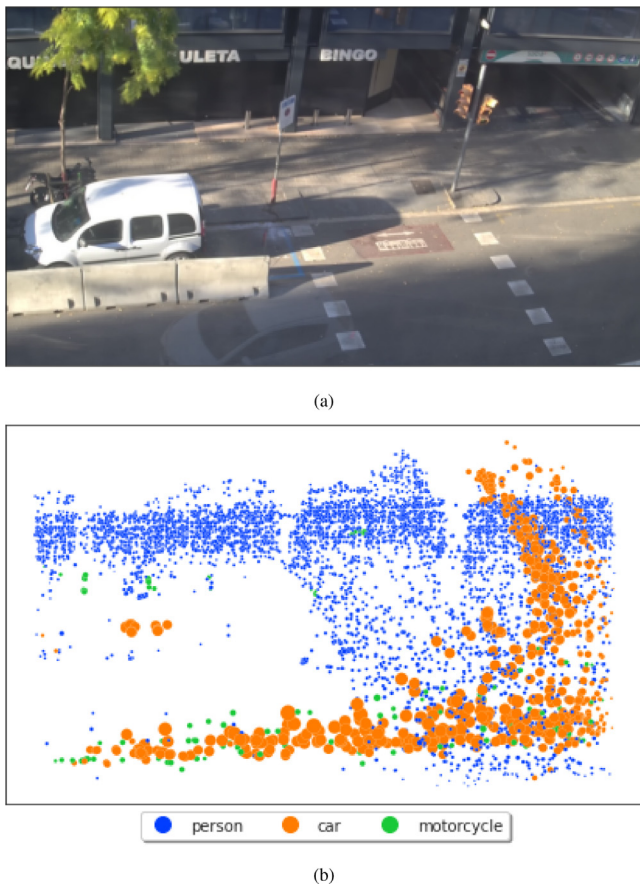


Fig. 11. (a) Image captured by a static camera on a street. (b) Position (within the scene) and size of the objects captured by the camera throughout a day. Coordinates represent the centroid of the object and the point size is relative to the object size as per its detected bounding box.

7. Conclusions and future work

In this paper, we have presented and evaluated COVA (Contextually Optimized Video Analytics), a framework that automates the process of model specialization to ease the deployments of real-time video analytics on resource-constrained edge nodes. COVA provides various high-level structures and tools that allow users to quickly define and customize the automated pipeline, resulting in object detection models specially tailored for their deployments.

COVA results from an extensive exploration and a subsequent analysis of the considerations to optimize the execution of models in resource-constrained edge nodes. We have successfully identified several key characteristics of edge video analytics that allowed us to efficiently and largely simplify the scope of the problem. For example, our results have shown that simple motion detection techniques can boost the accuracy of already trained models by allowing us to direct the inference to those parts of the frame that are moving.

Moreover, COVA allowed us to explore some of these considerations, which we hope can help pave the way for future improvements. We have shown how, in the case of static cameras, it is worth assuming a certain loss of generality to boost accuracy on the specific surroundings of the deployment. Specifically, results have shown that the edge model (MobileNetV2 with an SSD head for box regression) specialized for the context of a camera achieved between 2% and 87% higher accuracy than the same model trained using images from various cameras. At the same

time, results have shown how, using COVA, the specialization of the edge model for the context of specific cameras results in an increase of the *off-the-shelf* accuracy by an average of 21%, while keeping the computational cost constant, all through an automated process that uses a pre-trained model with state-of-the-art accuracy as teacher. From the same results, we have observed some beneficial side-effects of using automatic annotation, as the resulting model is trained to mimic the ground-truth model, which seem to improve the efficiency of training in some cases and yield higher accuracy than manual annotation. However, the ground-truth model seems to struggle to detect objects that are small with respect to the rest of the scene and, therefore, provides a sub-optimal annotation in scenes where such objects are predominant. Additionally, results also highlight that special care should be taken in scenes where there is a clear imbalance on the class distribution of the objects captured. In such cases, reusing examples captured by cameras in similar contexts can help mitigate the issue.

As future work, we intend to explore alternative methods to further exploit the context of a camera. The modular design of COVA and its components open the door to seamlessly introduce new contextual features into the analysis of the scene, during the stages of automatic annotation and generation of the training dataset. We expect these new features to drive the generation of inexpensive and highly-specialized models that can still achieve high accuracy. Towards this goal, we intend to explore the use of custom and highly specialized neural networks for image classification and rely on the same techniques already used for motion detection to leverage localization. These networks are orders of magnitude smaller than the one used as the edge model previously mentioned. As a result, they are unable to generalize even in the slightest. In contrast, several of these can be trained for each camera context due to their small size and be quickly re-trained as soon as a concept drift is detected.

We could argue that COVA leverages the context of a camera by exploiting the implicit inductive biases of convolutional neural networks, i.e., CNNs learn to consider the surroundings of an object and COVA uses during training images where objects are seen in the same context they will be when captured during inference. However, the context can offer much more than just visual information. For example, when considering static cameras within a given context, objects tend to follow pre-established paths unless an extraordinary event occurs. From the point of view of a street camera, cars drive following the driveway, while pedestrians walk mostly on the sides of the street and the crosswalk. Therefore, the coordinates of an object can be indicative of the type of object. Additionally, if the camera is placed in the middle of the street, cars and pedestrians get bigger or smaller as they get closer or further from the camera while following their paths. Consequently, the size of an object, along with its coordinates, can tell us its distance from the camera and, thus, be indicative of the type of object. Fig. 11 depicts an example of how the type of object is strongly related to its position and size within the scene where it is captured. In the example, pedestrians (blue) walk mainly on the sidewalk and the crosswalk. Similarly, cars (orange) and motorcycles (green) are mostly captured on the driveway or entering the parking lot. Pedestrians and cars can be seen together in the region of the crosswalk, but the fact that not many people are the size of a car helps discern between them. Therefore, we observe a strong relationship between the position and size of an object with the type of object. It is important to highlight that the distribution shown in Fig. 11(b) will vary even if the camera is only shifted in place, let alone moved to a different location. Therefore, these features can be considered part of a camera's context, and context is tightly coupled to its camera. It is precisely for this reason that the process of model specialization must be automated or, otherwise, it becomes unfeasible at scale.

CRedit authorship contribution statement

Daniel Rivas: Conceptualization, Investigation, Software, Writing – original draft, Writing – review and editing. **Francesc Guim:** Conceptualization, Validation, Funding acquisition. **Jordà Polo:** Methodology, Supervision. **Pubudu M. Silva:** Validation, Formal analysis. **Josep Ll. Berral:** Writing – review and editing. **David Carrera:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work has been partially supported by the Spanish Government (contract PID2019-107255GB) and by Generalitat de Catalunya, Spain (contract 2014-SGR-1051).

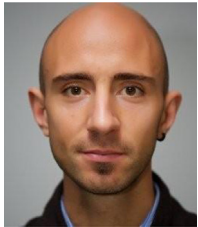
References

- [1] D. Rivas, F. Guim, J. Polo, D. Carrera, Performance characterization of video analytics workloads in heterogeneous edge infrastructures, *Concurr. Comput.: Pract. Exper.* (2021) e6317.
- [2] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, J. Zhang, Edge intelligence: Paving the last mile of artificial intelligence with edge computing, *Proc. IEEE* 107 (8) (2019) 1738–1762.
- [3] G. Ananthanarayanan, P. Bahl, P. Bodik, K. Chintalapudi, M. Philipose, L. Ravindranath, S. Sinha, Real-time video analytics: The killer app for edge computing, *Computer* 50 (10) (2017) 58–67.
- [4] K. Bilal, A. Erbad, Edge computing for interactive media and video streaming, in: 2017 Second International Conference on Fog and Mobile Edge Computing (FMEC), IEEE, 2017, pp. 68–73.
- [5] J. Huang, V. Rathod, C. Sun, M. Zhu, A. Korattikara, A. Fathi, I. Fischer, Z. Wojna, Y. Song, S. Guadarrama, et al., Speed/accuracy trade-offs for modern convolutional object detectors, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 7310–7311.
- [6] TensorFlow, TensorFlow 2 detection model zoo, 2021, https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/tf2_detection_zoo.md. [Accessed: 2021-11-10].
- [7] ImageNet large scale visual recognition challenge (ILSVRC), 2021, <http://image-net.org/challenges/LSVRC/>. [Accessed: 2021-11-10].
- [8] S. Bianco, R. Cadene, L. Celona, P. Napoletano, Benchmark analysis of representative deep neural network architectures, *IEEE Access* 6 (2018) 64270–64277.
- [9] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, C.L. Zitnick, Microsoft coco: Common objects in context, in: European Conference on Computer Vision, Springer, 2014, pp. 740–755.
- [10] TensorFlow, 2021, <https://www.tensorflow.org/>. [Accessed: 2021-11-10].
- [11] OpenVINO documentation, 2021, <https://docs.openvino.ai/latest/index.html>. [Accessed: 2021-11-10].
- [12] COVA - repository, 2021, <https://github.com/HiEST/cova-tuner>. [Accessed: 2021-11-20].
- [13] W. Shi, J. Cao, Q. Zhang, Y. Li, L. Xu, Edge computing: Vision and challenges, *IEEE Internet Things J.* 3 (5) (2016) 637–646.
- [14] D. Kang, P. Bailis, M. Zaharia, Challenges and opportunities in DNN-based video analytics: A demonstration of the blazeit video query engine, in: CIDR, 2019.
- [15] M. Ali, A. Anjum, M.U. Yaseen, A.R. Zamani, D. Balouek-Thomert, O. Rana, M. Parashar, Edge enhanced deep learning system for large-scale video stream analytics, in: 2018 IEEE 2nd International Conference on Fog and Edge Computing (ICFEC), IEEE, 2018, pp. 1–10.
- [16] C. Canel, T. Kim, G. Zhou, C. Li, H. Lim, D.G. Andersen, M. Kaminsky, S.R. Dulloor, Scaling video analytics on constrained edge nodes, 2019, arXiv preprint arXiv:1905.13536.
- [17] H. Shen, S. Han, M. Philipose, A. Krishnamurthy, Fast video classification via adaptive cascading of deep models, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 3646–3654.
- [18] H. Cai, C. Gan, T. Wang, Z. Zhang, S. Han, Once-for-all: Train one network and specialize it for efficient deployment, 2019, arXiv preprint arXiv:1908.09791.
- [19] D. Kang, J. Emmons, F. Abuzaid, P. Bailis, M. Zaharia, Noscope: optimizing neural network queries over video at scale, 2017, arXiv preprint arXiv:1703.02529.
- [20] K. Hsieh, G. Ananthanarayanan, P. Bodik, S. Venkataraman, P. Bahl, M. Philipose, P.B. Gibbons, O. Mutlu, Focus: Querying large video datasets with low latency and low cost, in: 13th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 18), 2018, pp. 269–286.
- [21] D. Kang, P. Bailis, M. Zaharia, Blazelt: Optimizing declarative aggregation and limit queries for neural network-based video analytics, 2019, arXiv:1805.01046.
- [22] C.-C. Hung, G. Ananthanarayanan, P. Bodik, L. Golubchik, M. Yu, P. Bahl, M. Philipose, Videoedge: Processing camera streams using hierarchical clusters, in: 2018 IEEE/ACM Symposium on Edge Computing (SEC), IEEE, 2018, pp. 115–131.
- [23] J. Gou, B. Yu, S.J. Maybank, D. Tao, Knowledge distillation: A survey, *Int. J. Comput. Vis.* 129 (6) (2021) 1789–1819.
- [24] A. Polino, R. Pascanu, D. Alistarh, Model compression via distillation and quantization, 2018, arXiv preprint arXiv:1802.05668.
- [25] R.T. Mullaipudi, S. Chen, K. Zhang, D. Ramanan, K. Fatahalian, Online model distillation for efficient video inference, in: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2019, pp. 3573–3582.
- [26] P. Goyal, M. Caron, B. Lefauveux, M. Xu, P. Wang, V. Pai, M. Singh, V. Liptchinsky, I. Misra, A. Joulin, P. Bojanowski, Self-supervised pretraining of visual features in the wild, 2021, arXiv:2103.01988.
- [27] S. Purushwalkam, A. Gupta, Demystifying contrastive self-supervised learning: Invariances, augmentations and dataset biases, 2020, arXiv:2007.13916.
- [28] S. Wang, Y. Zhou, J. Yan, Z. Deng, Fully motion-aware network for video object detection, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 542–557.
- [29] S. Beery, G. Wu, V. Rathod, R. Votel, J. Huang, Context R-CNN: Long term temporal context for per-camera object detection, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 13075–13085.
- [30] S. Beery, G. Van Horn, P. Perona, Recognition in terra incognita, in: Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 456–473.
- [31] R.C. Daudt, B. Le Saux, A. Boulch, Fully convolutional siamese networks for change detection, in: 2018 25th IEEE International Conference on Image Processing (ICIP), IEEE, 2018, pp. 4063–4067.
- [32] Y. Benezeth, P.-M. Jodoin, B. Emile, H. Laurent, C. Rosenberger, Comparative study of background subtraction algorithms, *J. Electron. Imaging* 19 (3) (2010) 033003.
- [33] T. Bouwmans, S. Javed, M. Sultana, S.K. Jung, Deep neural network concepts for background subtraction: A systematic review and comparative evaluation, *Neural Netw.* 117 (2019) 8–66.
- [34] D. Rivas, F. Guim, J. Polo, D. Carrera, Large-scale video analytics through object-level consolidation, 2021, arXiv preprint arXiv:2111.15451.
- [35] G. Hinton, O. Vinyals, J. Dean, Distilling the knowledge in a neural network, 2015, arXiv preprint arXiv:1503.02531.
- [36] A. Dries, U. Rückert, Adaptive concept drift detection, *Stat. Anal. Data Min.: ASA Data Sci. J.* 2 (5–6) (2009) 311–327.
- [37] X. Wang, Y. Luo, D. Crankshaw, A. Tumanov, F. Yu, J.E. Gonzalez, Idk cascades: Fast deep learning by learning not to overthink, 2017, arXiv preprint arXiv:1706.00885.
- [38] R.M. French, Catastrophic forgetting in connectionist networks, *Trends Cogn. Sci.* 3 (4) (1999) 128–135.
- [39] D. Li, S. Tasci, S. Ghosh, J. Zhu, J. Zhang, L. Heck, RILOD: near real-time incremental learning for object detection at the edge, in: Proceedings of the 4th ACM/IEEE Symposium on Edge Computing, 2019, pp. 113–126.
- [40] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A.A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska, et al., Overcoming catastrophic forgetting in neural networks, *Proc. Natl. Acad. Sci.* 114 (13) (2017) 3521–3526.
- [41] K. Shmelkov, C. Schmid, K. Alahari, Incremental learning of object detectors without catastrophic forgetting, in: Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 3400–3409.
- [42] C. Stauffer, W.E.L. Grimson, Adaptive background mixture models for real-time tracking, in: Proceedings. 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Cat. No. PR00149), Vol. 2, IEEE, 1999, pp. 246–252.
- [43] OpenCV: Tutorial background subtraction, 2021, https://docs.opencv.org/master/d1/dc5/tutorial_background_subtraction.html. [Accessed: 2021-11-10].
- [44] S. Oh, A. Hoogs, A. Perera, N. Cuntoor, C.-C. Chen, J.T. Lee, S. Mukherjee, J. Aggarwal, H. Lee, L. Davis, et al., A large-scale benchmark dataset for event recognition in surveillance video, in: CVPR 2011, IEEE, 2011, pp. 3153–3160.
- [45] M. Everingham, L. Van Gool, C.K. Williams, J. Winn, A. Zisserman, The pascal visual object classes (voc) challenge, *Int. J. Comput. Vis.* 88 (2) (2010) 303–338.
- [46] TensorFlow, SSD MobileNet V2 320x320 pre-trained model, 2021, http://download.tensorflow.org/models/object_detection/tf2/20200711/ssd_mobilenet_v2_320x320_coco17_tpu-8.tar.gz. [Accessed: 2021-11-10].

[47] TensorFlow, EfficientDet D2 768x768 pre-trained model, 2021, http://download.tensorflow.org/models/object_detection/tf2/20200711/efficientdet_d2_coco17_tpu-32.tar.gz. [Accessed: 2021-11-10].



Daniel Rivas received the degree in computer science in 2012, the M.Sc. degree in advanced computing in 2016, and pursues his Ph.D. at Universitat Politècnica de Catalunya (UPC) since 2017. He is a doctoral researcher working in applied machine learning on edge cloud environments at the Barcelona Supercomputing Center (BSC).



Francesc Guim received the M.Sc degree in computer architecture from University of Catalonia (UPC) in 2003 and his Ph.D. from the same university in 2008. In 2008, he joined Intel as CPU architect and since 2015 leads the Server Platform Architecture Europe, doing research on future Edge Cloud architectures.



Jordà Polo received an M.S. from the Technical University of Catalonia (UPC) in 2009, and a Ph.D. from the same university in 2014. He currently leads a team of Ph.D. students and postdocs at the Data-Centric Computing group at Barcelona Supercomputing Center (BSC), doing research in software-defined infrastructures and data-centric architectures, proposing new models and algorithms for placement of jobs and data in future data-centers.



machine/deep learning.

Pubudu Madhawa Silva received the B.Sc (Hons.) degree in electronics and telecommunication engineering from the University of Moratuwa, Colombo, Sri Lanka, in 2006, and the M.S. and Ph.D. degrees in electrical engineering and computer science from Northwestern University, Evanston, IL, USA, in 2010 and 2014, respectively. He joined Intel Corporation, Hillsboro, OR, USA, in 2014, where he is now an AI Architect. His research interests include tactile and multimodal interfaces, sensory substitution, perceptual models for multimedia processing, virtual/augmented reality and



for a scholar visit to IBM (2019). He is an IEEE member and ACM member.

Josep Ll. Berral received his Engineering degree in Informatics (2007), M.Sc. in Computer Architecture (2008), and Ph.D. on Computer Science (2013) at Universitat Politècnica de Catalunya (UPC). He is the leader of the “Data Centric Computing” research group at the Barcelona Supercomputing Center (BSC), working on applications of machine learning on datacenter and cloud environments. He has been awarded with a “Juan de la Cierv” research fellowship from the Spanish Ministry of Economy (2018–2019), and a mobility grant “José Castillejo” from the Spanish Ministry of Education



David Carrera received the MS degree at the Technical University of Catalonia (UPC) in 2002 and his Ph.D. from the same university in 2008. He is an associate professor at the Computer Architecture Department of the UPC. He is also the Head of the DataCentric Computing research group at the Barcelona Supercomputing Centre (BSC). He has participated in several EU-funded projects and been PI for several industrial projects and collaborations with IBM, Microsoft, and Cisco among others. In 2015 he was awarded an ERC Starting Grant, and in 2010 he received an IBM Faculty Award.