EDF: Ensemble, Distill, and Fuse for Easy Video Labeling

Giulio Zhou  
Carnegie Mellon University  
giuliozhou@cmu.edu

Subramanya R. Dulloor  
ThoughtSpot, inc.  
dulloor@thoughtspot.com

David G. Andersen  
Carnegie Mellon University  
dga@cs.cmu.edu

Michael Kaminsky  
Intel Labs  
michael.e.kaminsky@intel.com

Abstract

We present a way to rapidly bootstrap object detection on unseen videos using minimal human annotations. We accomplish this by combining two complementary sources of knowledge (one generic and the other specific) using bounding box merging and model distillation. The first (generic) knowledge source is obtained from ensembling pre-trained object detectors using a novel bounding box merging and confidence reweighting scheme. We make the observation that model distillation with data augmentation can train a specialized detector that outperforms the noisy labels it was trained on, and train a Student Network on the ensemble detections that obtains higher mAP than the ensemble itself. The second (specialized) knowledge source comes from training a detector (which we call the Supervised Labeler) on a labeled subset of the video to generate detections on the unlabeled portion. We demonstrate on two popular vehicular datasets that these techniques work to emit bounding boxes for all vehicles in the frame with higher mean average precision (mAP) than any of the reference networks used, and that the combination of ensembled and human-labeled data produces object detections that outperform either alone.

1. Introduction

Advancements in machine learning, and specifically deep learning, have brought image and video analysis nearly within the grasp of non-experts. Unfortunately, while applying off-the-shelf models produces impressive results, there remains a gap between the performance of a generic model and one that has been specialized for the specific domain of interest using fine-tuning or transfer learning [18]. Re-training a pre-trained model into a domain, of course, requires a sufficient quantity of labeled data [31], and producing accurate labels is costly and time-consuming, particularly when there are privacy or expertise constraints on the data.

In this paper, we present an approach for offline object detection in video that (1) obtains better results using pre-trained object detectors through a combination of model ensembling and distillation [8]; and (2) can incorporate small quantities of provided labels to increase accuracy. Notably, our approach does not attempt to create a better, general object detector; instead, it capitalizes on the redundancy and specificity of individual video streams to create a specialized, trained detector that empirically performs better on that specific video.

To do so, we present a new approach to ensembling object detections. Unlike classification, multiple object detectors may output non- or partially-overlapping bounding boxes, potentially different object categories, and different confidence values. Our merging strategy (Section 3) combines these factors into a single output bounding box whose behavior matches the intuitive expectations for an ensemble: When more models agree, the output has higher confidence; a single model disagreeing does not cause the location of the bounding box to be considered erroneous.

We then use the ensembled results (i.e., predicted labels on the video we are analyzing) to train a Student Network. Particularly when used with data augmentation, this Student Network is able to emit object detections (again on that video) that outperform the ensemble itself. We evaluate our technique on both a stationary video dataset (the DETRAC dataset, surveillance videos across multiple cameras in Beijing and Tianjin) and a first-person moving automotive dataset (KITTI, driving videos taken from the same car within the city of Karlsruhe). Our approach produces a mean average precision (mAP) that is 1.25 and 1.21x higher than the best performing member of the ensemble.
2. Background and Related Work

Object Detection: The object detection literature is extensive. Modern CNN object detection architectures integrate feature generation, proposal, and classification into a single pipeline, and generally fall into one of two categories: (a) single-stage architectures (such as SSD [14] and YOLO [21]) which directly predict the coordinates and class of bounding boxes, and (b) two-stage detectors (such as Faster R-CNN [22]) that refine proposals produced by a region proposal network. Single-stage detectors are less expensive, but also less accurate than their two-stage counterparts. Other work examines how to build more effective multi-scale convolutional feature hierarchies, such as Feature Pyramid Networks [12] (FPN). Our work uses the outputs of an ensemble of CNN-based object detectors trained on Microsoft COCO [13] to generate labels with which we fine-tune a compact single-stage object detector (MobileNet-SSD FPN).

Object detection in the video setting can leverage frame-to-frame flow estimates [32] or correlation and regression-based tracking [3] to detect objects more consistently across frames. For simplicity, we run and train only per-frame object detectors but could easily train student detectors that incorporate convolutional or flow features across frames.

Model Distillation trains a (typically smaller) student model to match the outputs of a teacher model [8]. Distillation for classification typically trains on a weighted average of hard labels and the teacher’s softmax outputs, often softened using a temperature \( T \) to \( \frac{\exp(y_i / T)}{\sum_j \exp(y_j / T)} \). Here, we train a specialized detector using model distillation, which aims to match the teacher’s bounding box confidences and coordinates on the dataset of interest. Our process for training a custom detector bears many similarities to techniques commonly used for model distillation, such as confidence-based loss reweighting [4] and treating the teacher’s outputs as soft targets [1]. The way that our work differs is in how we obtain labels: rather than simply using the detections of a single teacher detector, we use various forms of detector ensembling to generate better labels with more reliable confidence estimates.

Learning from Noisy Labels: One way to reduce the amount of human annotation needed to train accurate models do so is to build models that can learn from noisy labels, which can be generated more quickly and automatically than clean annotations. Approaches to learning from noisy labels generally fall into two categories [27]. The first aims to learn directly on the noisy labels, focusing on noise-robust algorithms and label cleaning procedures. The second approach is based on semi-supervised learning techniques that propagate labels from the clean part of a dataset onto the noisy or unlabeled portion.

Similar to our work, Tripathi et al. [26] train what they call a “pseudo-labeler” on a labeled subset of a video to generate bounding box labels on the unlabeled portion; this is an identical setup to our Supervised Labelers, only their labeled subset is an inherent part of their dataset. They use an RNN to smooth the generated bounding boxes using only high-level category labels and a smoothness constraint. They observe that the pseudo-labeler can sometimes produce erroneous labels, which causes their method to fail. Our Supervised Labelers suffer from a similar problem, which we overcome by counterbalancing their detections with ensemble detections that are more “generically” robust.

Misra et al. [17] iteratively train SVM-based detectors starting with a small collection bounding box labels. But because they did not have the benefit of using pre-trained detectors, they achieve a much lower mAP score. Snorkel [19] addresses the related problem of automating label generation for weakly supervised learning by combining many weak user-defined heuristics using a probabilistic model. Our work instead uses pre-trained object detectors to generate the initial set of noisy labels, and achieves high accuracy with minimal additional work. Because we start with pre-trained detectors as a starting point, we have a higher baseline for accuracy than much existing work.

Object Detector Ensembling: In single object detection, ensembling can be as simple as naively averaging the predictions from multiple detectors. OverFeat [24] uses a custom bounding box merging procedure to produce localization maps for a single object. In general, however, the single object assumption is not realistic for most real-world video. The authors of ResNet [7] provide a method for ensembling multiple object detectors (with the same Faster R-CNN architecture) that processes the union over all region proposals using an ensemble of per-region classifiers. This approach, however, requires that all the detectors have a region proposal mechanism and that they share the same architecture. YOLO [20] proposes a simple scheme whereby it screens the outputs of Fast-RCNN for false positives.

Minimizing the number of labels needed to analyze new video: Few-shot detection aims to adapt a detector to a target domain using few target domain examples. A recent approach [2] fine-tunes a detector using a small labeled subset of the data while using regularization to ensure that fine-tuned detector does not diverge too much from its starting checkpoint. Although this few-shot approach is appropriate for detection in images, it is limited by the small number of starting annotations. In contrast, the distillation approach used in this paper leverages the redundancy in video to, in effect, automatically augment the results of the initial detectors using additional unlabeled video.

Active learning is another technique to reduce human annotation costs by exploiting the inherent redundancy of
Video [28]. It attempts to sample a sparse set of keyframes for the user to label (based on some proxy for the complexity of scene and object appearance changes) and then perform interpolation on the annotated bounding boxes. The end goal, however, is to perfectly annotate all frames of a video, so label sampling occurs over fairly short time horizons, and thus requires a fairly substantial number of labels. However, active learning techniques for choosing which frames to label can complement our work.

**Video stream specialization:** Existing work [11, 9, 15] seeks to reduce the time to run expensive CNNs on video by learning cheap video-specific and camera view specific models. One shortcoming is that these systems are concerned only with matching the predictions of a reference CNN rather than improving ground truth accuracy. In addition, they often fail to show significant improvements for moving cameras. We believe that this area of research is complementary to our work and could reduce the overall run time of per-frame detectors where applicable (e.g. static video surveillance scenes).

### 3. Design

Figure 1 shows an overview of our approach. The top half of the figure shows the basic design, where we take a set of pre-trained object detectors and combine them into an ensemble. We use the ensemble to produce a new set of predictions on the target video, and use those predictions to train a Student Network. This part of the system assumes no access to ground truth labels. The bottom half of the figure shows how our system can incorporate a small number of human-provided ground truth labels to further improve the object detection results. We describe each part of the design below.

#### 3.1. An ensemble of pre-trained object detectors

Ensembling is a well-known technique to improve predictions, but most of the existing work focuses on image classification. Applying ensembling to object detection, however, introduces additional questions not answered by previous work, such as how to combine spatially-scoped bounding boxes, classifications, and confidences. We show that successfully combining the results from individual detectors can help overcome their individual biases and spurious failures; this section presents our design; the results are in Section 4.

To ensemble the object detectors, one must merge bounding boxes that may only partially overlap (or may not overlap at all) and produce a single ensemble output confidence, based on both the confidence of the individual ensemble members as well as the overlap between the predicted boxes.

**Merging bounding boxes:** Our ensemble consists of three pre-trained object detectors: Faster R-CNN, SSD FPN Resnet-50, and YOLOv2. We run each detector on every frame of the video. We then apply a greedy IOU-based merging strategy (illustrated in Figure 2) to merge the ensemble outputs into a discrete set of bounding boxes. This procedure is as follows:

1. **Match bounding boxes to their neighbor with highest IOU:** First, we compute the IOU between each detector’s bounding box and the boxes generated by the other detectors. Then, we remove boxes with IOU less than $IOU_{\text{thresh}}$ from consideration. Our evaluation, described below, uses a threshold of 0.7. For a given bounding box, its nearest neighbors are the overlapping bounding boxes for each of the other detectors with the highest $(IOU_{\text{thresh}})$. In our system, a bounding box could have between 0 and 2 nearest neighbors.

2. **Find “mutually nearest tuples”:** For each bounding box, create a tuple consisting of itself (acting as the “anchor”) and all of its nearest neighbors where the nearest neighbor relationship is mutual.

3. **Output merged bounding boxes:** Iterate through the mutually nearest tuples in descending order of cardinality (i.e., start with bounding boxes that have two mutually nearest neighbors). If none of its elements have been consumed, output merged bounding box and add elements to consumed set. Merge the boxes by averaging their coordinates and confidences.

4. **Remove overlapping boxes using non-maximal suppression (NMS):** NMS (using the same $IOU_{\text{thresh}}$ as Step 1) helps reduce unmerged false positives.

Because the pre-trained detectors we use already apply NMS with thresholds between 0.5 and 0.6, we set $IOU_{\text{thresh}}$ to a somewhat higher value (0.7) so that detections must have above-average overlap in order to be matched.

**Combining confidences:** The next step is to modify the bounding box confidences using detector consensus. Without further processing, simply averaging the detection confidences undervalues detections that have high agreement. Intuitively, having multiple detectors agree on a detection should make it more likely to be correct. To reflect this increased confidence, we modify a bounding box with average confidence $\bar{y}$ from $n$ detectors using the equation

$$\hat{y}^* = \bar{y}^{\frac{1}{n+\beta}}$$

where $\beta >= 1$. We are interested in how $n$ deviates from the “mean number of detections”; here, we do not modify...
Table 1. Increasing $\beta$ upweights triplet detections and downweights single detections, improving mAP.

| Setting         | KITTI  | DETRAC |
|-----------------|--------|--------|
| Ensemble (2-of-3) | 0.436  | 0.471  |
| Ensemble (1-of-3) | 0.401  | 0.419  |
| Reweighted Ensemble | 0.451  | 0.518  |

Table 2. Ensemble (2-of-3) simply drops all single unmatched detections. Ensemble (1-of-3) keeps all detections. Reweighting uses the detections from Ensemble (1-of-3).

the confidence of merged detections from two sources. Setting $\beta = 2$ squares the confidence for 1 detector (decreasing its confidence) and takes the square root for 3 detectors (increasing its confidence), while setting $\beta = 1$ ignores the ensemble agreement altogether. Increasing $\beta$ pushes detection confidences asymptotically closer to 0 and 1. In our experiments, we use $\beta = 3$, and we observe little change in confidences from setting $\beta > 3$. Table 1 shows how increasing $\beta$ increases mAP.

Distilling to a Student Network: To further improve detection accuracy, we use the ensemble outputs as detections to train a Student Network (Figure 1). We show in Section 4 that this Student Network outperforms the ensemble itself. The Student Network is initialized using a MobileNet-SSD object detector with a Feature Pyramid Network (FPN) base, pretrained on MS-COCO. This model is relatively lightweight compared to the ensemble detectors, which reduces its capacity to overfit. As shown in Figure 3, training a Student Network improves mAP (compared to the ensemble output) from 0.451 to 0.454 on KITTI and from 0.518 to 0.530 on DETRAC. Adding data augmentation (specifically, random cropping) further improves the mAP to 0.504 on KITTI and 0.554 on DETRAC.

The Student Network is trained on all of the video frames using the ensemble detections as its labels. We initially trained the Student Network using the noisy ensemble outputs as ground truth, but found that this resulted in poor accuracy. This approach failed because it treated high-confidence true positive detections as equal in importance to low-confidence false positives. We overcame this problem by adopting a technique from model distillation: treat these ensemble detections as “soft targets” and directly regress to their confidences using cross entropy loss. This target encourages the Student Network to match the ensemble confidences directly and leads to better generalization.

3.2. Incorporating human labels

The second part of our design allows the system to accommodate a small amount of labeled data. We use these ground truth labels to train a Supervised Labeler using transfer learning. Here, we define a single label as all of the bounding boxes in a given image. In our experiments, we use a variable, small fraction of the datasets ground-truth labels to train a Supervised Labeler, and in Section 4.2 evaluate the performance of the Student Network and the Super-
Performing well on this dataset requires detecting objects (car, truck, bus, van) have 594,555 bounding boxes in total. fps video across 60 videos from a collection of surveillance the only one that does not contain any vehicles. Techniques specific to stationary cameras). To simplify evaluate while the object is moving (which precludes the use of tech-niques under heavy occlusion and in changing lighting conditions is especially challenging because one must detect objects among the vehicle classes (car, truck, van). This dataset Karlsruhe, Germany. There are 31,790 bounding boxes video divided among 21 videos from a car driving through to the provided ground truth on the same video collection. We, therefore, conduct offline video analysis, we are not concerned with generalizing beyond the given video collection. We, therefore, conduct all of our experiments on the training set alone, and ignore the provided ground truth labels except in those experiments where we train a Supervised Labeler. The end goal is to produce detections on the given video collection that are close to the provided ground truth on the same video collection.

The KITTI training set consists of 8,008 frames of 10 fps video divided among 21 videos from a car driving through Karlsruhe, Germany. There are 31,790 bounding boxes among the vehicle classes (car, truck, van). This dataset is especially challenging because one must detect objects under heavy occlusion and in changing lighting conditions while the object is moving (which precludes the use of techniques specific to stationary cameras). To simplify evaluation, we remove video 0017, a short 145 frame video and the only one that does not contain any vehicles.

The DETRAC training set contains 83,791 frames of 25 fps video across 60 videos from a collection of surveillance cameras in Beijing and Tianjin. The four vehicle classes (car, truck, bus, van) have 594,555 bounding boxes in total. Performing well on this dataset requires detecting objects at multiple scales under occlusion as well as generalizing across multiple camera views under different weather conditions (i.e., sunny, cloudy, night, rainy).

Experiment Setup: We use the Tensorflow Object Detection API [10] as (a) the source of two pre-trained object detectors (Faster R-CNN and SSD FPN ResNet-50) and (b) a training platform for fine-tuning a MobileNet-SSD detector. We use a Keras implementation of YOLOv2 [30], which is based on the original DarkNet model.

We use mAP@0.5:0.95 (hereafter mAP) from COCO as our accuracy metric. This metric takes the average precision at all IOU thresholds between 0.5 and 0.95 spaced at increments of 0.05 and averages them. Throughout the paper, we define accuracy as the mAP achieved when evaluating detections obtained by processing a given dataset against the ground truth on that same dataset.

As described previously, we merge all vehicle categories (e.g., car, truck, bus, van) into a single vehicle superclass. We do so because the categories defined in KITTI and DETRAC do not overlap exactly with COCO vehicle classes—and even for categories with the same label name (e.g., car, truck), the labeling decisions in COCO are not necessarily consistent with the target datasets. For example, pickup trucks and similar car-truck hybrids may not be identically placed into the respective car or truck categories. Class confusion is a large source of error in object detection that we do not address in this paper. Rather, we focus on accurately detecting all vehicles so that users can partition classes as they choose after the fact.

We run the pre-trained detectors at the resolution that performs best for Faster-RCNN. For DETRAC, this is the original 960x540 resolution. For KITTI, this is 1920x600 (upscaled from the original resolution of 1242x375). We train Student Networks on both datasets at the original resolutions.

We trained our student detectors on Google Cloud Platform using Cloud TPUs. All training is performed at full (32 bit floating point) precision. Because TPUs do not support Non-Maximal Suppression, the only change from standard MobileNet-SSD training is that we do not use Online Hard Example Mining [25], which we found has little impact on results.

### 4. Evaluation

**Datasets:** We evaluate our system on two datasets: KITTI [5] and DETRAC [29]. Because we focus on offline video analysis, we are not concerned with generalizing beyond the given video collection. We, therefore, conduct all of our experiments on the training set alone, and ignore the provided ground truth labels except in those experiments where we train a Supervised Labeler. The end goal is to produce detections on the given video collection that are close to the provided ground truth on the same video collection. The KITTI training set consists of 8,008 frames of 10 fps video divided among 21 videos from a car driving through Karlsruhe, Germany. There are 31,790 bounding boxes among the vehicle classes (car, truck, van). This dataset is especially challenging because one must detect objects under heavy occlusion and in changing lighting conditions while the object is moving (which precludes the use of techniques specific to stationary cameras). To simplify evaluation, we remove video 0017, a short 145 frame video and the only one that does not contain any vehicles.

The DETRAC training set contains 83,791 frames of 25 fps video across 60 videos from a collection of surveillance cameras in Beijing and Tianjin. The four vehicle classes (car, truck, bus, van) have 594,555 bounding boxes in total. Performing well on this dataset requires detecting objects at multiple scales under occlusion as well as generalizing across multiple camera views under different weather conditions (i.e., sunny, cloudy, night, rainy).

| Detector          | KITTI | DETRAC |
|-------------------|-------|--------|
| Faster R-CNN      | 0.416 | 0.433  |
| SSD ResNet50 FPN  | 0.422 | 0.458  |
| YOLOv2            | 0.367 | 0.406  |
| Ensemble          | 0.451 | 0.518  |

Table 3. Pre-trained detector mAP scores.
Table 4. The Supervised Labeler uses 3% of labels from KITTI and 0.5% of labels from DETRAC.

| Settings               | KITTI | DETRAC |
|------------------------|-------|--------|
| Ensemble               | 0.451 | 0.518  |
| Mask R-CNN             | 0.440 | 0.517  |
| Supervised Labeler     | 0.625 | 0.693  |

Mask R-CNN Comparison: We also run Mask R-CNN [6], an expensive but more accurate model. Its accuracy is worse than either the supervised baseline or the performance of ensembling+distillation, but it does roughly match that of the reweighted ensemble alone (Table 4). We were computational resources abundant, one could use Mask R-CNN as part of a stronger ensemble baseline. Its high computational requirements suggest, however, that Mask R-CNN might be more effective as an “oracle” that the system could query for frames where the ensemble is less confident. We observe that Faster R-CNN, YOLOv2, and SSD ResNet-50 FPN run at 5.3, 16, and 6.4 FPS on a P100 GPU. Mask R-CNN runs at 1 FPS, which makes it 2.5 times the cost of the ensemble, and 1.7x the cost of running the ensemble followed by the distilled student. On the small DETRAC and KITTI datasets, the training cost of the student becomes dominant, but we hypothesize that for larger videos, the training can be done with a subset of ensemble-labeled frames (but necessarily defer exploring this future work for lack of a suitable fully labeled large video baseline).

4.2. Improved Accuracy Through Multi-Source Knowledge Distillation

Training a MobileNet-SSD FPN Student Network on ensemble detections with data augmentation improves mAP (compared to the ensemble) from 0.451 to 0.504 on KITTI and from 0.518 to 0.554 on DETRAC (Figure 4). There are several reasons why this may be the case. First, while the ensemble is run per-frame, the Student Network is trained on all of the frames before it has to make predictions about any of the frames, and therefore the training data from other frames can affect its prediction on some frame \( f \). Second, data augmentation in the form of random cropping helps prevent the Student Network from simply memorizing the data (the benefit of random cropping is examined in greater detail in Section 4.3). In addition, the similarity of nearby frames in video can also be thought of as performing implicit data augmentation.

Figure 5 shows that combining the Student Network detections with the Supervised Labeler detections greatly improves mAP in the low-label regime compared to Supervised Labeler alone. The Supervised Labelers trained on few labels perform poorly (compared to the ensemble) because traditional transfer learning requires a sizeable number of labels. However, the Supervised Labelers still perform fairly well on what may appear at first sight to be an astonishingly small number of labeled frames. It is important to recall that these are fully annotated frames with all objects labeled: The crossover points (at 3% of KITTI and 0.5% of DETRAC) of Figure 5 correspond to labeling 992 bounding boxes across 236 frames on KITTI; and 2,771 bounding boxes across 419 frames on DETRAC.
Figure 4. 2% and 5% of KITTI corresponds to labeling 157 and 393 frames. 0.2% and 1% of DETRAC corresponds to labeling 168 and 838 frames.

Lastly, we note that even when Supervised Labelers perform worse than or comparably to the Student Network, the fact that combining their detections significantly improves mAP suggests that they are at least modestly complementary sources of knowledge.

4.3. Ablation Studies

In this section, we examine the individual contributions of several key pieces of our work in greater detail. As shown in Figure 3, using data augmentation, Feature Pyramid Networks, and an ensemble teacher all help improve mAP.

The Effect of Data Augmentation: Using data augmentation was crucial to training both detectors to the desired level of accuracy. Without data augmentation, the Supervised Labeler frequently failed to converge, and its achieved accuracy was lower. The Student Network also benefited from data augmentation: Figure 3 shows that the Student Networks trained without data augmentation only obtain mAP scores that are slightly higher than the ensemble mAP, whereas applying data augmentation leads to a substantially improved mAP.

Feature Pyramid Networks vs. Standard MobileNet-SSD: It was also important to use a sufficiently accurate base student architecture. We initially used the standard MobileNet-SSD architecture, which (with data augmentation) was able to nearly match the accuracy of the ensemble from which it was trained. We found, however, that the MobileNet-SSD Student Network struggled with medium-sized occluded objects. The Feature Pyramid-based detector, which is better at recognizing objects at different scales [12], handled these cases better, while remaining sufficiently compact and fast.

Success Using a Single Teacher vs. An Ensemble: To understand whether our distillation technique is general enough to work with a single teacher, we train a Student Network using only the detections from Faster R-CNN. While the final mAP is lower than that of training a Student Network with an ensemble teacher (as expected), distillation from a single teacher improves mAP relative to that teacher to a similar degree as it does when using an ensemble teacher.

5. Discussion

Having a strong baseline detector. Our work assumes a sufficiently strong baseline for the domain in question. We use state-of-the-art, but fairly expensive object detectors on each frame of the video collection. Because we were able to use the Cloud TPUs for training the student, but not for
running inference, this step was, surprisingly, the longest part of our pipeline. We expect better results from running ensembles of improved detectors, which may be reasonable when taking advantage of optimized inference accelerators.

Our results show that the ensemble detectors trained on MS-COCO somewhat generalize to scenarios where objects have relatively similar size and aspect ratios. They are unlikely, however, to work on drone and aerial camera datasets. For most common video domains, we believe there should be a sufficient amount of labeled data that can be used to train a decent general-purpose detector.

When to label frames of a video: Given a fixed labeling budget $B$ significantly smaller than the total number of frames $N$, an ideal approach would be to acquire labels for a maximally diverse set of frames. In this paper, we do not address the question of how to choose the best $B$ frames to label. We simply label $B$ evenly spaced frames throughout a video and discuss how to choose $B$ based on how long objects persist in a video.

Given frequent-enough annotations, existing video annotation tools can track and interpolate object bounding boxes across frames. Using our uniform labeling approach, we can think of there being a minimum labeling interval where it becomes possible to recover the labels for all of the frames in the video. This “phase-transition” point is different for each video. We examine the median object durations in KITTI and DETRAC as a proxy for the rate of change, and find them to be 32 and 71 frames respectively. We thus choose (1/20=5%) and (1/50=2%) as the highest labeled baseline for each respective dataset.

Different detectors contribute different biases to the training: Each of the ensemble detectors is pre-trained on the same dataset yet each one contributes to the student’s accuracy because they have different biases. We were surprised by the degree to which the detectors varied. For instance, when running on KITTI, Faster R-CNN produced the most detections with high confidence, yet SSD ResNet-50 FPN was actually more accurate than Faster R-CNN. Our work treats all ensemble detectors equally and could be improved by examining the correlations between the ensemble members in greater detail. Right now, we require fairly strong ensemble detectors, but properly accounting for inter-detector correlations could enable us to construct larger ensembles of weaker detectors.

6. Future Work

Our core plans for future work are to incorporate additional video-derived constraints into improving the labels fed to the student network.

Manual inspection of mistakes made by the off-the-shelf detectors on a subset of frames in KITTI suggest that heavy occlusion is one of the major sources of error for the off-the-shelf detectors, and that our techniques help correct some of them. This suggests that approaches that can improve bounding box detection when an object is (often transiently, in video) occluded may provide a rich source of accuracy improvements.

One such source, which can also correct for transient detection failures, is to incorporate object tracking to boost the accuracy of object detections by the ensemble. Object tracking and metric learning associate detections across frames, smoothing out detector confidences over time. Previous work shows that slight modifications to a frame can have significant non-local impacts on object detection [23]. In video, this manifests as detections of the same object having unstable confidence and localization across frames (Figure 6 shows an example from the KITTI dataset). We believe that object tracking holds promise for improving detection confidence. Multiple Object Tracking (MOT) [16] and related challenges provide the basis for identifying objects with appearance constancy—those that maintain a similar appearance over time—to normalize the ensemble’s prediction confidence across the stream. Our preliminary approaches to do using off-the-shelf tracking methods (Kalman filters, correlation filters, and regression-based trackers) were thus far unsuccessful, but we plan to return to this approach in the future.

7. Conclusion

This paper presented a new method for using an ensemble of object detectors, together with in-domain distillation to a Student Network, that outperforms all members of the ensemble and the aggregate ensemble itself. The presented method can further be combined with small numbers of labeled training samples to increase accuracy above either the ensemble or Supervised Labeler. Despite using weaker detectors in its ensemble, the ensemble and student together outperform state of the art methods such as Mask R-CNN, resulting in a practical method for for unlabeled (or lightly-labeled) object detection on video.

References

[1] G. Chen, W. Choi, X. Yu, T. Han, and M. Chandraker. Learning efficient object detection models with knowledge distillation. In Advances in Neural Information Processing Systems, pages 742–751, 2017.

[2] H. Chen, Y. Wang, G. Wang, and Y. Qiao. Lstd: A low-shot transfer detector for object detection. arXiv preprint arXiv:1803.01529, 2018.

[3] C. Feichtenhofer, A. Pinz, and A. Zisserman. Detect to track and track to detect. In Proceedings of the IEEE International Conference on Computer Vision, pages 3038–3046, 2017.

[4] T. Furlanello, Z. C. Lipton, M. Tschannen, L. Itti, and A. Anandkumar. Born again neural networks. arXiv preprint arXiv:1805.04770, 2018.
Confidence discontinuities in the center of the pairwise cosine distance matrix.

Figure 6. Tracked car sequence exiting a highway in KITTI. There is a sharp drop in confidence at the halfway through the sequence (likely due to the rapidly changing surroundings) despite the car’s appearance remaining relatively consistent, as indicated by the lack of sharp discontinuities in the center of the pairwise cosine distance matrix.

[5] A. Geiger, P. Lenz, C. Stiller, and R. Urtasun. Vision meets robotics: The kitti dataset. The International Journal of Robotics Research, 32(11):1231–1237, 2013.
[6] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In Computer Vision (ICCV), 2017 IEEE International Conference on, pages 2980–2988. IEEE, 2017.
[7] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.
[8] G. Hinton, O. Vinyals, and J. Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.
[9] K. Hsieh, G. Ananthanarayanan, P. Bodik, P. Bahl, M. Philipose, P. B. Gibbons, and O. Mutlu. Focus: Querying large video datasets with low latency and low cost. arXiv preprint arXiv:1801.03493, 2018.
[10] 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.
[11] D. Kang, J. Emmons, F. Abuzaid, P. Bailis, and M. Zaharia. Noscope: optimizing neural network queries over video at scale. Proceedings of the VLDB Endowment, 10(11):1586–1597, 2017.
[12] T.-Y. Lin, P. Dollár, R. B. Girshick, K. He, B. Hariharan, and S. J. Belongie. Feature pyramid networks for object detection.
[13] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014.
[14] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C. Y. Fu, and A. C. Berg. Ssd: Single shot multibox detector. In European conference on computer vision, pages 21–37. Springer, 2016.
[15] Y. Lu, A. Chowdhery, S. Kandula, and S. Chaudhuri. Accelerating machine learning inference with probabilistic predicates. In Proceedings of the 2018 International Conference on Management of Data, pages 1493–1508. ACM, 2018.
[16] A. Milan, L. Leal-Taixé, I. Reid, S. Roth, and K. Schindler. Mot16: A benchmark for multi-object tracking. arXiv preprint arXiv:1603.00831, 2016.
[17] I. Misra, A. Shrivastava, and M. Hebert. Watch and learn: Semi-supervised learning for object detectors from video. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3593–3602, 2015.
[18] S. J. Pan and Q. Yang. A survey on transfer learning. IEEE Trans. on Knowl. and Data Eng., 2010.
[19] A. J. Ratner, S. H. Bach, H. R. Ehrenberg, and C. Ré. Snorkel: Fast training set generation for information extraction. In Proceedings of the 2017 ACM International Conference on Management of Data, pages 1683–1686. ACM, 2017.
[20] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi. You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 779–788, 2016.
[21] J. Redmon and A. Farhadi. Yolo9000: Better, faster, stronger. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 6517–6525. IEEE, 2017.
[22] S. Ren, K. He, R. Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems, pages 91–99, 2015.
[23] A. Rosenfeld, R. Zemel, and J. K. Tsotsos. The elephant in the room. arXiv preprint arXiv:1808.03305, 2018.
[24] P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, and Y. LeCun. Overfeat: Integrated recognition, localization and detection using convolutional networks. arXiv preprint arXiv:1312.6229, 2013.
[25] A. Shrivastava, A. Gupta, and R. Girshick. Training region-based object detectors with online hard example mining. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 761–769, 2016.
[26] S. Tripathi, Z. C. Lipton, S. Belongie, and T. Nguyen. Context matters: Refining object detection in video with recurrent neural networks. arXiv preprint arXiv:1607.04648, 2016.
[27] A. Veit, N. Alldrin, G. Chechik, I. Krasin, A. Gupta, and S. J. Belongie. Learning from noisy large-scale datasets with minimal supervision.
[28] C. Vondrick, D. Patterson, and D. Ramanan. Efficiently scaling up crowdsourced video annotation. *International Journal of Computer Vision*, 101(1):184–204, 2013.
[29] L. Wen, D. Du, Z. Cai, Z. Lei, M.-C. Chang, H. Qi, J. Lim, M.-H. Yang, and S. Lyu. Ua-detrac: A new benchmark and protocol for multi-object detection and tracking. *arXiv preprint arXiv:1511.04136*, 2015.
[30] Yad2k: Yet another darknet 2 keras. https://github.com/allanzelener/YAD2K, 2016.
[31] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson. How transferable are features in deep neural networks? *CoRR*, 2014.
[32] X. Zhu, Y. Wang, J. Dai, L. Yuan, and Y. Wei. Flow-guided feature aggregation for video object detection. In *Computer Vision (ICCV), 2017 IEEE International Conference on*, pages 408–417. IEEE, 2017.