Vehicle and Pedestrian detection for autonomous cars

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Abstract

Autonomous vehicles are gaining traction and have the potential to transform the transport sector. However, the safety of passengers and other road users is paramount. Real-time pedestrian and vehicle detection is a vital safety factor for self-driving cars. When a model is trained on a training dataset and a new class of objects is introduced, the model must be trained on the entire dataset. We can save time, though, by implementing incremental learning on object detection algorithms. Incremental learning approaches, such as knowledge distilling and keeping a few exemplars from previous classes, have been proposed to retain knowledge obtained in previous classes. When the training data is unbalanced, distinguishing between a growing number of visually identical classes becomes especially difficult. We present a simple and practical solution to the data imbalance problem. We discovered that the final completely connected layer had a large bias towards the new classes, which may be adjusted using a linear model. Our approach performs admirably on larger and smaller datasets.

1. Introduction

Natural learning systems are essentially incremental, with new knowledge being learned constantly over time while current knowledge is maintained. Many real-world computer vision applications necessitate incremental learning capabilities. A facial recognition system, for example, should be able to add new people without forgetting the faces it has already learned. However, most deep learning techniques suffer from catastrophic forgetting , which results in severe performance deterioration when previous data is not accessible. As the world moves towards automation, autonomous vehicles are becoming more popular. Every day, a large amount of data is generated that machine learning models must learn. Firstly, knowledge distillation will be used to improve model performance on old data using only a few examples from old data, and then the bias of the final FC layer towards new classes is corrected. This prejudice towards new classes is rectified utilising a bias correction technique that helps to relieve the problem of significant bias towards new classes. The challenging issue is for large number new classes due to coupling of two factors.First, the training data are unbalanced. Secondly, as the number of classes increases, it is more likely to have visually similar classes

2. Project Objective

The main objective of this project is to develop a robust and accurate pedestrian and vehicle detection system that can operate in real-time.Specifically, the project will aim to:

- Identify pedestrians and vehicles in real-time
- Improve the performance of model on old data when new data is learnt
- Knowledge Distillation will be applied to predict old classes accuratley
- Implement a very efficient method of bias correction to reduce the bias towards new classes after model's learning on new data

3. Literature Review

We reviewed the paper "Large Scale Incremental Learning" [1] and they suggested a new strategy in this research to handle the imbalance issue in incremental learning, which is crucial as the number of classes grows high.First, We performed knowledge distillation and then using this paper we validated their hypothesis that the classifier layer (the final fully connected layer) is biased towards the new classes, which have significantly more training data than the old classifications. This paper also depicted that using a linear model with a limited validation set can effectively correct this bias. Their method has excellent results on two large datasets with 1,000+ classes (ImageNet ILSVRC 2012 and MS-Celeb-1M), outperforming the state-of-the-art by a large margin (11.1 percent on ImageNet ILSVRC 2012 and 13.2 percent on MS-Celeb-1M).

4. Datasets used in Training

4.1. Mnist Data set for Incremental Learning

We have used mnist digits dataset to perform incremental learning. We dataset has very concise classes and easy to work with it. We Prepared dataloader for 0-5 digits and 6-7 digits using pytorch. 0-5 digits were old classes and 6-7 digits were new classes. We prepared another dataset that consisted of some examplars, in this case 20 samples from each class of 0-5 digits and all 6-7 classes. Similary for Bias correction we prepared a validation data set which was subtracted from training set.

4.2. Coco-Dataset

We will perform incremental on yolov5 as well with cocodataset. We have prepare data from the fiftyone webiste which is the open source toolkit for building high-quality datasets. We created a list of desired classes and then applied a filter over the coco2017 dataset. We used only test dataset due to storage issue and processing capability and then converted it into train,validation and test parts.

5. Methodology and Results

We will implemet the concept of incremental learning on yolo architecture. First, we will experiment with the MNIST dataset for incremental learning. I'll walk you through our process step by step. First, we created our own architecture, which serves as our baseline model. We employed two models: one is the teacher model, and the other is a deep clone of the teacher model called student model with two extra logits. The teacher model is trained on the MNIST dataset, which has digits ranging from 0 to 5. The student model is then trained on a dataset including digits 6 and 7 as well as equal examplers from 0-5 classes which are very less than 6 and 7 digits classes.

5.1. Results on direct learning new classes

We observed 98 percent accuracy from the baseline model on a dataset of 0-5 digits, but when we tested this data with the student model, we saw a decline in accuracy to 67percent on 0-5 data. We got a very good accuracy of 99 percent on 6,7 digits. In this situation, we can see that when we directly train a teacher model (baseline model) on a fresh dataset with only a few examples from the previous dataset, its performance on the previous data diminishes.

5.2. Proposed Distillation Loss Method

Then we used the distillation loss notion, taking two models, teacher and student, where student is a duplicate of the teacher model. In this case, we employed two losses: distillation loss derived from the teacher and student models, and cross entropy loss estimated from the student model prediction and the original data. We used expected output from the instructor model and predicted output from the student model in the distillation loss concept. Then, on both outputs, we used temperature scaling to smooth the resulting probability. The smoother the distribution, the higher the temperature value. A lower temperature value produces sharper and more confident distributions. After applying temperature scaling to the output of the teacher model, we use the SoftMax to transform the logits to probabilities. The goal of soft teacher targets is to collect information from the teaching model. Then, during the distillation concept, log SoftMax is applied to soft student outputs to assure conformity with soft target output. Total loss is computed by combining distillation loss and cross entropy loss with alpha as the weightage parameter for both losses.

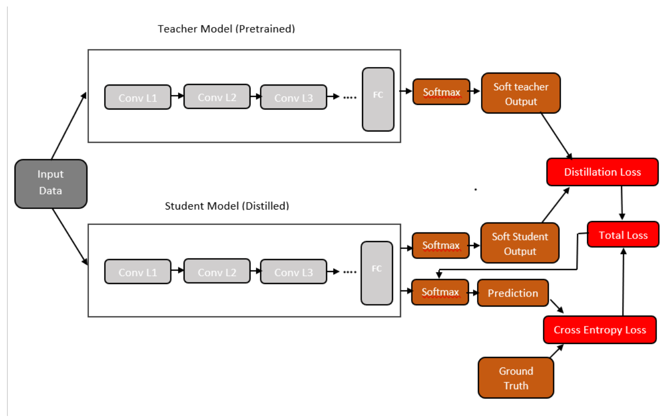

Figure 1. Diagram of the baseline solution using distillation. It contains two losses: the distilling loss on old classes and the softmax cross-entropy loss on all old and new classes.

5.3. Results after Distillation

Our research results revealed that the application of knowledge distillation, a sophisticated machine learning technique, led to a substantial increase in the model's accuracy. Initially, we were operating with a baseline accuracy of 65 percent on our combined test dataset. This figure, while respectable, indicated room for significant improvement in our model's performance. The incorporation of knowledge distillation methods into our experimental procedure proved to be a key decision in this context.

Upon implementation of knowledge distillation, the accuracy metric experienced a noteworthy boost, escalating to an impressive 88 percent on the same combined test dataset. This technique, which essentially translates the specialist knowledge of a sophisticated model into a format comprehensible to a less complex model, greatly improved the performance of our model. The increase of 23 percentage points is not a minor increment by any means. It strongly suggests that knowledge distillation has the potential to be a game-changer in terms of model accuracy.

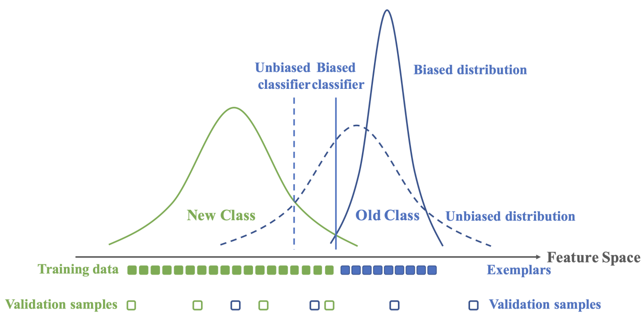

Figure 2. Diagram of bias correction. Since the number of exemplars from old classes is small, they have narrow distributions on the feature space. This causes the learned classifier to prefer new classes. Validation samples, not involved in training feature representation, may better reflect the unbiased distribution of both old and new classes in the feature space. Thus, we can use the validation samples to correct the bias

5.4. Proposed Bias Correction Method

In this particular case study, our primary approach hinges on leveraging the most recent model that has been trained using the concept of distillation loss. This particular technique forms the bedrock of our methodology, aimed at maximizing the efficiency and accuracy of our model. As a part of this process, we're incorporating an additional fully connected (FC) layer towards the end, specifically designed to rectify any biases that may have developed towards the new classes during the training phase.

Our strategy involves passing the logits of the old classes in their original form without any modifications, ensuring the continuity of their initial accuracy. However, when it comes to the new classes, we're implementing the alpha and beta factors to adjust for bias. This two-factor adjustment process helps to ensure that our model maintains a balanced approach when dealing with both old and new classes.

Considering that our model is already trained, we're opting to freeze all the convolutional and FC layers, thus preventing any changes to their weights during the backpropagation stage. This decision contributes to maintaining the stability of our model and preserving the learning that has already occurred. The newly added bias correction layer is the only exception to this rule, as it will be updated during the training stage. This layer is responsible for learning the alpha and beta values, crucial for adjusting the bias towards new classes.

Finally, our methodology includes the training of this model on validation data. This step is instrumental in the refinement of the alpha and beta parameters so that any bias towards new classes can be reduced effectively. It ensures that the accuracy of the model, both for the old and new classes, is maintained consistently. This strategy illustrates our commitment to creating a model that can handle multiple classes of data without favoring one over the other, resulting in balanced and accurate results.

5.5. Results after Bias Layer correction

Our study employed a bias correction method applied to a model previously trained using distillation loss, and the findings shed light on the effects of this technique. One of the most significant observations was an impressive increase in accuracy for the combined dataset. Originally, our model had an accuracy of 87% on this dataset. However, with the application of the bias correction method, this accuracy rose remarkably to 97%. This considerable increase indicates a successful refinement in the model's ability to generalize across diverse data points, signifying that the bias towards older classes was effectively reduced.

However, the analysis of the data related specifically to digits 6 and 7 revealed a slight decrease in accuracy following the implementation of the bias correction method. The initial model boasted an accuracy of 99%, but this figure dropped to 96% after applying bias correction. Although this might initially seem like a drawback, it's essential to recognize that this decrease represents a reduction in overfitting towards these specific classes. Consequently, the model's performance is expected to be more balanced across various classes of data, instead of leaning heavily towards the classes represented by the digits 6 and 7.

In summary, our observations indicate that the bias correction method has contributed to an overall improvement in the model's performance on a broader dataset while ensuring a more uniform performance across different classes. These results reinforce the importance of bias correction in machine learning models, demonstrating its efficacy in reducing class-specific bias and improving overall model performance.

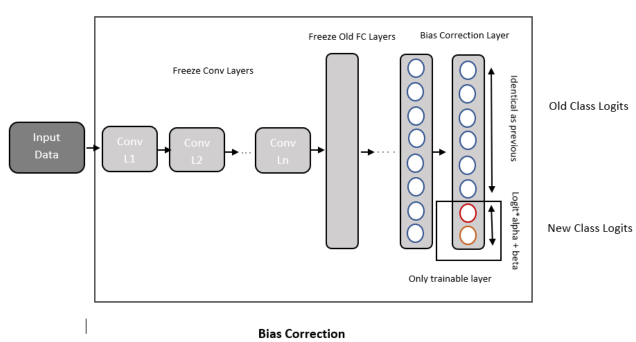

Figure 3. bias layer correction

6. Results

The results of our study were deduced through the implementation of a confusion matrix, a critical tool in machine learning for understanding the performance of classification models. One of the key observations from the confusion matrix is that the instances of misclassified data points have progressively moved towards the diagonal with each step in our experiment. This pattern indicates an improvement in the model's predictive capabilities. The data points lying on the diagonal of the confusion matrix represent correctly classified instances. As the wrongly predicted classes are moving towards this diagonal, it signifies that the number of correct predictions is increasing, reducing the misclassifications. Notably, this incremental improvement in prediction accuracy has led to a significant overall increase in our model's performance. At the commencement of our study, the model exhibited an accuracy of 66%. However, through the application of the techniques of knowledge distillation and bias correction, and the stepwise enhancements observed in the confusion matrix, we were able to elevate this metric to an impressive 97.4%. Overall, the inference from the confusion matrix and the corresponding increase in accuracy demonstrate the successful application of our methodologies in this study. This significant rise in accuracy underscores the efficacy of the knowledge distillation and bias correction methods in improving the performance of the model, leading us towards our goal of achieving a more balanced and accurate classification model.

- This is the result of predictions after the model learnt on new classes with a few examplars from previous classes. Accuracy = 68.7%

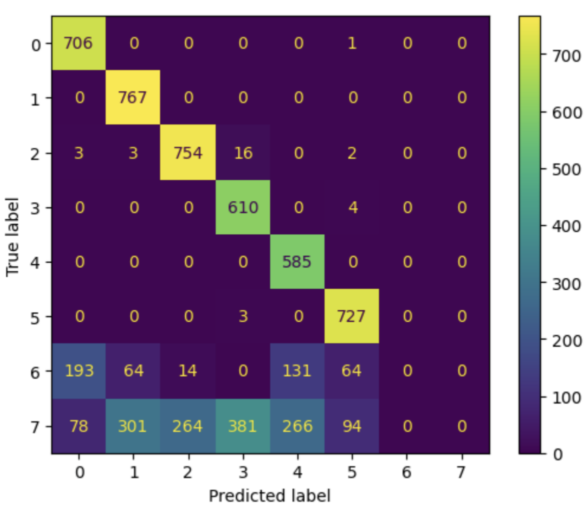

Figure 4. predicted labels before implementation of knowledge distillation and bias layer correction

- This is the result of predictions after the model learnt on new classes with a few examplars from previous classes. Accuracy = 85.7%

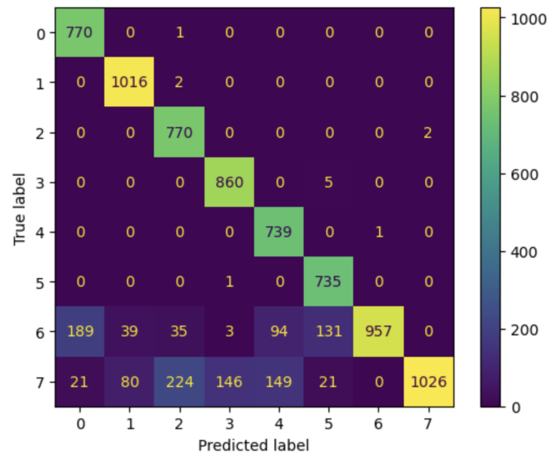

Figure 5. predicted labels after implementation of knowledge distillation

- This is the result of predictions after the model learnt on new classes with a few examplars from previous classes. Accuracy = 97.1%

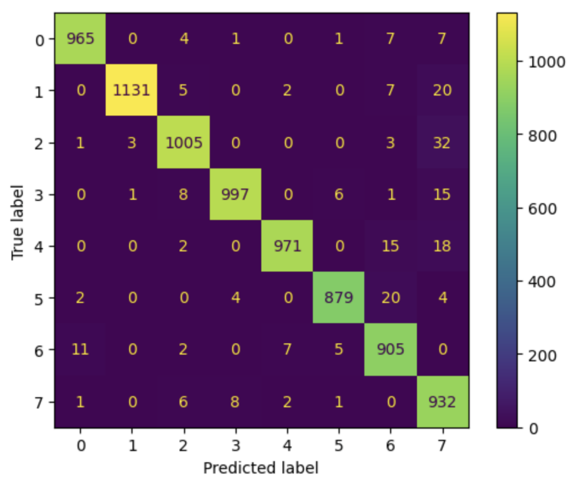

Figure 6. predicted labels after implementation of knowledge distillation and bias layer correction

7. Conclusion

In conclusion, our exploration into the application of incremental learning using distillation and bias layer correction on MNIST digits has produced promising results. We found that these techniques can significantly improve the flexibility of our model while maintaining high accuracy levels.

Through the use of distillation, we were able to impart the knowledge of the fully trained model into a new model during each incremental learning step. This process efficiently prevented catastrophic forgetting, preserving vital knowledge from prior stages of training. Furthermore, the bias layer correction method enhanced the model's capability to learn new classes without detrimentally affecting its performance on the previous classes. This was especially useful when updating the model with additional classes or new data.

Nevertheless, this study is not without its limitations. The computational requirements associated with these methods are a substantial consideration. Moreover, while we have achieved commendable results on the MNIST dataset, further testing is required on larger and more complex datasets to determine the methods' robustness and scalability.

Our results point to a future where continuous learning systems can be both effective and efficient, adjusting to new data in an ever-changing environment. It offers a promising avenue of exploration for machine learning applications, from real-time data analysis to adaptive personal assistance systems, and beyond. Future work should focus on further optimization of these techniques and their application in diverse, real-world scenarios.

References

[1] Yue Wu, Yinpeng Chen, Lijuan Wang, Yuancheng Ye, Zicheng Liu, Yandong Guo, and Yun Fu. Large scale incremental learning, 2019. 1