Improved Training for Self-Training

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Abstract
It is well known that for some tasks, labeled data sets may be hard to gather. Therefore, we wished to tackle here the problem of having insufficient training data. We examined learning methods from unlabeled data after an initial training on a limited labeled data set. The suggested approach can be used as an online learning method on the unlabeled test set. In the general classification task, whenever we predict a label with high enough confidence, we treat it as a true label and train the data accordingly. For the semantic segmentation task, a classic example for an expensive data labeling process, we do so pixel-wise. Our suggested approaches were applied on the MNIST data-set as a proof of concept for a vision classification task and on the ADE20K data-set in order to tackle the semi-supervised semantic segmentation problem.

Introduction
We examine here a semi-supervised approach for training a classifier given a limited training data set. This approach can be used on top of any boosting and data augmentation methods, improving the obtained results. After finishing the training stage of any classification method, it is possible to continue the learning process of the classifier on-line, based on the unlabeled test samples it is asked to classify: whenever the classifier encounters a sample on which the certainty that the classification is correct is high, this sample will be kept for a second semi-supervised training stage - tailored with the label the classifier had predicted for it. For example, if an MNIST classifier declared that a certain test picture is very likely to be the number 3, this picture is adjusted with this label and can be used as a training picture, for adjusting the weights of the classifier. It is most reasonable to use this approach when the amount of unlabeled data is much greater than the labeled data. An example for this situation is the on-line stage of a classifier, in which the training data is fully exploited, but the unlabeled test data keeps coming. Another common task which suffers from insufficient labeled data, but has almost unbounded test data - or potentially unlabeled train data, is the semantic segmentation. The key concept our technique relies on is the ability to know when to trust a networks prediction. In classification tasks (segmentation included) the standard method for extracting a confidence-measure is by looking at the softmax layer probabilities. Unfortunately, networks tend to be over-confident in that sense and not informative enough. We therefore applied maximal entropy regularization as recently suggested in [18], which penalizes the network whenever the softmax-probabilities are too concentrated in one class. Evidently, even when we know how to measure a networks confidence in its predictions, a crucial challenge remains - setting a confidence-threshold by which to decide whether to trust those prediction or not. The trade-off is clear - a low threshold will result in a high false-positive (FP) rate which will cause the network to train on wrong samples; a high threshold will result in a low true-positive (TP) rate which will mean that not enough additional data is obtained to make a difference. We therefore turned to additional methods that help asses if a prediction is trustworthy: 1. Using MC-dropout as another way to represent a networks uncertainty [6] by running the same network multiple times on a given sample with some dropout $< 1$ value and thus obtaining a distribution over the networks predictions and 2. Bagging of two networks - even when the networks have exactly the same architecture, the random initialization of the weights and the fact that the training is stochastic due to dropout layers are enough to ensure that the networks will yield different results on the borderline cases. That is, if they agree on a prediction - the chances of it being correct are much greater.

Previous Works
Semantic Segmentation
The semantic Segmentation task gives a pixel-wise labeling for a given picture. Many applications on the rise are based on image segmentation. Common examples are the autonomous driving, indoor navigation and even medical radiology diagnostics [12]. The end-to-end fully convolution network [13] is the base of many recent successful ap-
proaches for this task [8] [4].

Semi Supervised Learning

Self Training The approach of self-training was first represented by Nigam et. al. [17] and was show that it can be interpreted as an instance of the Classification Expectation Maximization algorithm [1]. It was independently discovered by ourselves, after not recognizing an acquaintance who stop putting makeup all-together. Only after doing a decent portion of the work here we have discovered that this approach was already suggested.

Semi Supervised Semantic Segmentation Previous works have approached the Semi-supervised Semantic Segmentation task by trying to label the unknown pixels of an image based on the known pixels of the same image, using graph-cuts, random walks, geodesic shortest path, geodesic star convexity and topological constraints. Successfully boosting these approaches was demonstrated in [25]. Another successfully semi-supervised semantic segmentation have harnessed GANs for increasing the success rates after the initial training on the full training set. Here we suggest a general top down approach with the potential of ultimately achieving the results of fully supervised methods by itself or by applying together with any other pre-suggested methods.

Semi Supervised MNIST Classification Implementing the self-train method harnessing Denoising Auto-Encoder and Dropout [11] on the visible layer in order to avoid overfitting to the train set [14] have achieved the best known results for the self-train method on MNIST data-set so far. In our work, we have manage to out-preform that implementation by 7%. Additional approaches for the semi-supervised task on MNIST include:

Generative Adversarial Networks [21] have been successfully used in order to achieve close to state-of-the-art results using a data-set containing only 10 samples for each of the ten classes. On the other hand, our approach is simpler and dose not require hand picking the train set. The unsupervised Ladder Networks technique [24] was successfully harnessed for semi-supervised classification [21] with success on the MNIST task as well; a comparison can be found in the result section. Another successful technique for contending with insufficient labeled data is the augmentation method, usually used for vision tasks. The method examined in this work can be used in top of augmentation even after the later was exploit to its fullest; in addition, the method examined here can be efficiently used for multiclass classification tasks outside the area of computer-vision.

Methods

The general self-learner approach is first to train a classifier on a small labeled data set, and later classify samples from a pool of unlabeled data. If a prediction is likely to be certain, the sample is associated with the predicted label and set together in a batch on which further training is executed. This step repeats until the unlabeled data has ended then the whole procedure repeats itself on the whole database, until convergence.

We have examined several techniques to choose the unlabeled samples on which further training will be preformed:
(1) certainty above a "hard coded" threshold;
(2) agreement of several classifiers;
(3) agreement of multiple output of the same classifier, executed with MC-dropout;
(4) credible interval of the MC-dropout-based prediction, for estimating how sure is the model on the prediction.

Networks

For each data set we used a different appropriate architecture. For MNIST, we have used a network constructed of two layers of convolution filters followed by a fully connected layer, then dropout, another fully connected layer and a softmax classification head. When sampling the same network was used, dropout on the second convolution layer was applied as well, implementing the MC-Dropout technique. This technique was suggested as a valid method [23] for achieving the Maximum a Posterior estimation, as opposed to achieving the Maximum Likelihood estimator. The efficiency of this approach was widely demonstrated [7] [5] [6]. For segmentation, we have used the fully convolution network, based on the VGG architecture [22], which have shown to achieves fair results [15].

MNIST

The limited data set was chosen to be of sizes 100, 150, 300 and 1000.

Threshold Confidence threshold of the softmax score was found empirically. Samples that were predicted to came from a certain class with a probability higher than this threshold would be used for the self learning step. For any threshold with any regularization coefficient examined - both positives [18] and negative [9], up to probability of 0.999, to many false positives had been predicted with enough confidence and this approached failed to work.

Ensemble Method Ensemble methods is a natural approach for lowering the rate of the false-positives predictions. Implementation of this technique for the image classification task was done by training two networks with different parameters and consider a sample for the second-stage training if the two networks have agreed on the prediction of that sample. Harsher criterion was suggested as well, including a constraint that each of the voters predictions will be higher then a certain probability. Even when using a confidence value of 50%, only a scarce set of examples have
achieved the criteria. The first network was train with learning rate of $10^{-6}$ and with regularization parameter of 1, while the second with $10^{-6}$ and 0.1 respectfully. Results can be seen in Table 0 and Table 1.

**Dropout Consensus** In this work we propose two ways for estimating when a network is confident in it’s classification outcome, besides the strait forward threshold prediction. The first is a consensus among all of the outcomes among MC-Dropout iterations; the second is using Confidence Interval on this outcome. Majority-Vote was considered as well, but neglected. Even though Majority-Vote was shown to be efficient [13], it’s efficiency is maximal when the voters are negatively depend on each other - which is not the situation here. In addition, in order to minimize false positives, consensus vote is more effective. A constraint of predicting the class with probability above a threshold of 95% was added for improving the minimization of false-positives predictions. We have applied the classification task with consensus of both 80 and 25 voters. Results are presented in table 2.

**Dropout Confidence Interval** In order to increase the true positives predictions the model would be train on while keeping a low rate of false positives, a confidence interval on the prediction of the network was examined as well. Usually, confidence interval is used as a mean to estimate a parameter, when considered as a random variable - under the Bayesian paradigm. The output of the network is an estimation of the probability that the sample belongs to each of the examined classes. From these, we can look on the network outcome as parameters for the Multinomial distribution and construct a confidence interval for their values. From the central limit theorem, we can assume that the average of each parameter is coming form distribution that can be approximated to the normal distribution. We can use the t-distribution in order to construct the confidence interval for the average of the parameters, as the true variances of the averages are not known. Since the average is an unbiased estimator to the expectation and the parameter equals to its expectation in the Multinomial distribution, these intervals are valid for the estimation of the probabilities that the sample belongs to each of the classes.

For applying this method, the classifier learned from samples for which the lower value of the interval was higher then 0.95. As a trade-off between the running time and accuracy, we have used 80 MC-Dropout iteration. The Credible interval was the common 95% one.

For getting even better results, the threshold of the lower value was initially set to 0.98 and then slowly decreased all the way to 0.9. By that, the network first trained on the example it was most sure of and only later handling with the less obvious examples.

When the TP is 1, but very low positives - it is still not working as well; when using the SD, it recovered - as opposed to the other technique;

**Semantic Segmentation**

Unfortunately, the Self-Training approach on semantic segmentation did not provide good results. The data-set on which we experimented is ADE20K described in [26], which consists of 20,000 training examples and a validation set of 2000 images. While segmentation models are evaluated with mIoU score, their training is done using pixel-wise cross-entropy loss. Our model, FCN [15] is not different. Therefore, the viability of the self-training method should be decided by a pixel-wise accuracy score, since having a low FP rate and high TP rate is crucial to our method. In the MNIST experiments, we saw that the method fails when starting with a model whose accuracy is below 70%. Using FCN trained on 10,000 samples, we could only reach pixel-accuracy of 55%, which is far below what is needed. Potentially, it was possible to increase the pixel-accuracy by training on a larger data-set, but experimenting with initially training with even up to 80 percent of the original training set gave similar results; nevertheless, this would have been resulted in a much smaller unlabeled data on which the self learning model could have been trained.

**Results**

For each experiment, we first ran 40 epochs over the labeled train data; then continued with 40 epochs over the unlabeled one. After each such iteration on the unlabeled data we went over the labeled data once more, for one epoch. In this section we present the labeled data size, the initial test accuracy after training on merely the labeled data only, the test accuracy after the entire training session (best acc), the true positive rate among the positives (TP ) and the Positive rate (P) which is the rate of the unlabeled data that was classified as a labeled and was train on. In the cases of using only one network for the TP criteria, decreasing value of the regularization coefficient $\lambda$ was used, from one to zero. That was suggested in [9] as increasing the $\lambda$ value when using the minimize entropy regularization. Using positive value of 1 for $\lambda$, punishing on over confidence, and gradually decreasing this value all the way to -1, aiming to direct the classifier to be more sure in its predictions gave similar results to the case in which $\lambda$ was decreased only up to 0. We have used Dropout value of 50% for both the training stage and the decision criteria.

Results for using consensus with two networks:

First, notice that the results are comparable, regardless of the entropy regularization. This is somewhat expected since this regularization is applied in order to influence the networks own certainty about its predictions. On this approach
the networks confidence was not considered into account when deciding rather or not to trust the predictions. It was simply examined if the two networks agreed. Another thing to note is that label set of only 100 samples is not enough for this approach; more specifically, initial accuracy of 70% in the network predictions was to low for this technique. With that said, even a slight improvement (a 0.74 accuracy) lead to a much better TP rate and therefore to an improvement in the second stage of the training. Finally, a well known phenomena can be observed here - reaching a 0.95-0.97 accuracy was only at 0.85, but an accuracy of 0.99 remained outside of our reach even when starting with an initial 0.92 accuracy. For passing this glass ceiling, more accurate decision criteria is needed.

In table 3, we present the results when running the predictions with 25 Dropout voters. A lower number of voters increase the likelihood of agreement among the voters.

We can see that the self training approach based on the Dropout-consensus is quite sensitive to the initial training stage and could not maintain satisfying results from a very small labeled data set. For the Dropout Confidence Interval method, we got great results even with training size=100. Therefore, there was no need for larger labeled sets. Based on this training set, the initial accuracy was 73%; after 100

epochs finished with 95.94% (TP=99%, P=87.6%). Applying the deteriorating confidence threshold (together with gradually decrease in the regularization coefficient, from 1 all the way down to −0.5) yield slightly better accuracy of 96.58% with (TP=98.7%, P=92.8%). The higher percentage of positives can be explained by the lower threshold at the end of the training stage. Table 5 contains the comparison with other semi-supervised classification methods on the MNIST data-set

In table 5, we present the results where obtained when the confidence interval was converged towards a local minimum. To explain why superior results where obtained when the confidence interval was considered, we take a closer look at the true-positives ("TP") and total positives ("P") rates. Obviously, each sample that is labeled as Positive under the consensus & above threshold criteria, will be labeled as positive under the Dropout Confidence Interval criteria. On the other hand, the Dropout Confidence Interval criteria classifies much more samples
as Positive, and judging by the TP percentage, most of them are TP. Therefore, compared to the other examined criteria, the Dropout Confidence Interval manage to trains on more samples (while keeping a low rate of false positives), which increase the generalization power of the classifier. When using an initial random labeled training set of 80, the initial rate of successful predictions of the classifier was 67%. In this case, the classifier failed to recover from the low TP rate. This suggests a lower bound on the initial accuracy when using the self-train approach on semi-supervised vision tasks.

**Discussion**

We examined here the intuitive and flexible approach of self-training as a semi-supervised approach for computer vision tasks. The main contributions of this work are (1) demonstrating how to effectively use the well studied self-training method, by harnessing Bayesian techniques (2) Suggesting an empirical limitation of this method, including a lower bound on the preliminary success rate and data set size when implementing the self-training or C-EM method on multi-class classification image tasks. Unfortunately, the segmentation network we have used did not achieved this bound and we weren’t yet succeeded to show positive results on the semi-supervised semantic segmentation task with limited data set. The reason for failing to implement the self-learning approach on the semantic segmentation task is likely to be insufficient preliminary success rate. Hence, it is reasonable that the self-trained method will work for semantic segmentation as well, given a better initial weights of newer model architecture. Another approach that will probably work is first train the model over all of the available labeled set, and then continue the self-trained step over another data-set similar to the labeled. Examples for this kind of data-set are other segmentation data-sets and the CIFAR data-set. One last thing to additionally explore is the preforming of the network when evaluated using MC-Dropout, meaning taking the mean among several runs of the network on a test sample.

**Future work**

Following the conclusions, much work can be done to follow up. Focusing on the segmentation task, the confidence threshold should probably not be a fixed number. It should vary for each pixel, based on nearby pixels, and should change based on classes appearances. If we had more time, this is the probable directions we would take. Interesting work can be done by harnessing the recent advances in low-shot visual recognition to the challenging semi-supervised semantic segmentation task. In addition, harnessing sophisticated techniques for coping with biased prediction, especially in segmentation, can be of great use when trying to learn from a minimal random data-set. Another interesting work that can be done using the self-training method is unsupervised classification, in similar to K-means. The advantage of the self-train method over k-means is its wider approach, which can come into practice by consideration of higher statistical moments then the first one - in C-EM, for example, and more generally, by learning the underlying representation of the class in an implicit manner, which can eventually be more accurate. Maintaining effective choosing of class seeds, as described in k-means++ and it’s following works, can result in an adequate unsupervised discriminator, especially when using the Entropy minimization regularization.

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