Weight-averaged consistency targets improve semi-supervised deep learning results

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Abstract

The recently proposed temporal ensembling has achieved state-of-the-art results in several semi-supervised learning benchmarks. It maintains an exponential moving average of label predictions on each training example, and penalizes predictions that are inconsistent with this target. However, because the targets change only once per epoch, temporal ensembling becomes unwieldy when using large datasets. To overcome this problem, we propose a method that averages model weights instead of label predictions. As an additional benefit, the method improves test accuracy and enables training with fewer labels than earlier methods. We report state-of-the-art results on semi-supervised SVHN, reducing the error rate from 5.12% to 4.41% with 500 labels, and achieving 5.39% error rate with 250 labels. By using extra unlabeled data, we reduce the error rate to 2.76% on 500-label SVHN.

1. Introduction

Deep learning has seen tremendous success in areas such as image and speech recognition. In order to learn useful abstractions, deep learning models require a large number of parameters, thus making them prone to over-fitting. Moreover, adding high-quality labels to training data manually is often expensive. Therefore, it is desirable to use regularization methods that exploit unlabeled data effectively to reduce over-fitting in semi-supervised learning.

When a percept is changed slightly, a human typically still considers it to be the same object. Correspondingly, a classification model should favor functions which give a consistent output for similar data points. One approach for achieving this is to add noise to the input of the model. To enable the model to learn more abstract invariances, the noise may be added to intermediate representations, an insight that has motivated many regularization techniques, such as Dropout (Srivastava et al., 2014) and Adversarial Training (Goodfellow et al., 2014b). Rather than minimizing the classification cost at the zero-dimensional data points of the input space, the regularized model minimizes the cost on a manifold around each data point, thus pushing decision boundaries away from the labeled data points (Figure 1a).

Since the classification cost is undefined for unlabeled examples, the noise regularization by itself does not aid in semi-supervised learning. To overcome this, techniques such as Virtual Adversarial Training (Miyato et al., 2015) and Γ model (Rasmus et al., 2015) evaluate each data point with and without noise, and then apply a consistency cost between the two predictions. In this case, the model assumes a dual role as a teacher and a student. As a student, it learns as before; as a teacher, it generates targets, which are then used by itself as a student for learning. Since the targets are inevitably biased towards the model itself, it is important to balance these two roles carefully. If too much weight is given to the generated targets, the cost of inconsistency outweighs that of misclassification, preventing the learning of new information. In effect, the model suffers from confirmation bias (Figure 1b), a hazard that can be mitigated by improving the quality of the targets.

In general, the softmax output of a model does not provide a good Bayesian approximation outside training data. This can be alleviated without additional training by adding noise to the model (Gal & Ghahramani, 2016) at inference time. Consequently, a noisy teacher can yield targets with smaller bias (Figure 1c). This approach has been used recently by Laine & Aila (2016) in their Π model and by (Sajjadi et al., 2016) in a similar technique. Both of them have reported significant improvements over previous state-of-the-art methods on several semi-supervised benchmarks. However, this approach increases the variance of the generated targets, limiting its usefulness.

To reduce the variance, Laine & Aila (2016) have proposed temporal ensembling. With this method, targets are computed from an exponential moving average (EMA) of the

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Preliminary work. Under review by the International Conference on Machine Learning (ICML).
Weight-averaged consistency targets

Figure 1. A sketch with two labeled examples (large black dots) and one unlabeled example (vertical line), demonstrating how the choice of unlabeled targets (blue circles) affects the fitted function (gray curve). For the clarity of illustration, we consider a regression task, although consistency regularization may be more suited for classification tasks. (a) A model trained with noisy labeled data (small dots) learns to give consistent predictions around labeled data points. (b) Consistency to noise around unlabeled examples provides additional smoothing. For the clarity of illustration, the teacher model (blue curve) is first fitted to the labeled examples, and then left unchanged during the training of the student model. Also for clarity, we will omit the small dots in figures c and d. (c) Noise on the teacher model reduces the bias of the targets without additional training. The expected direction of stochastic gradient descent is towards the mean (large blue circle) of individual noisy targets (small blue circles). (d) An ensemble of models gives an even better expected target.

2. Weight-averaged consistency targets

To overcome the limitations of temporal ensembling, we propose weight-averaged consistency targets. Averaging model weights over training steps tends to give better validation cost than using the final weights directly (Polyak & Juditsky, 1992). We can take advantage of this during training to construct better targets. Instead of sharing the weights with the student model, the teacher model uses the EMA weights of the student model. Now it can aggregate information after every step instead of every epoch. The larger the dataset, the longer the span of the updates, and in the case of on-line learning, it is unclear how temporal ensembling can be used at all.

We define the consistency cost \( J(\theta) \) as the expected distance between the prediction of the student model (with weights \( \theta \) and noise \( \eta \)) and the expected prediction of the teacher model (with weights \( \theta' \) and noise \( \eta' \)).

\[
J(\theta) = \mathbb{E}_{x, \eta', \eta} \left[ \| f(x, \theta', \eta') - f(x, \theta, \eta) \|^2 \right]
\]

With regards to optimization, the teacher model parameters \( \theta' \) are treated as constants. Similarly to Laine & Aila (2016), we use mean square error as the distance metric.\(^1\) Noise can take many forms. In the experiments we will describe in the following section, we applied three types of noise: random translations of input images, Gaussian noise on the input layer, and dropout applied within the network.

We can approximate the cost in stochastic gradient descent by sampling noise \( \eta \) at each training step. Whereas the \( \Pi \) model uses \( \theta' = \theta \), and temporal ensembling approximates good \( f(x, \theta', \eta) \) with a weighted average of successive predictions, we define \( \theta'_t \) at training step \( t \) as the EMA of successive \( \theta \) weights:

\[
\theta'_t = \alpha \theta'_{t-1} + (1 - \alpha) \theta_t
\]

where \( \alpha \) is a smoothing coefficient hyperparameter.

3. Related work

In addition to dropout and adversarial noise, several other types of noise have been shown to regularize intermediate representations effectively. Dropconnect (Wan et al., 2013) generalizes dropout by zeroing individual weights instead of activations. Stochastic depth (Huang et al., 2016) drops entire layers of residual networks. Swapout (Singh et al., 2016) generalizes dropout and stochastic depth into a common method.

\(^1\)We also ran experiments with cross-entropy but saw no improvement in results.
Weight-averaged consistency targets

The idea of a teacher model training a student is related to model compression (Bucilu et al., 2006) and distillation (Hinton et al., 2015). The knowledge of a complicated model can be transferred to a simpler model by training the simpler model with the softmax outputs of the complicated model. The softmax outputs contain more information about the task than the one-hot outputs, and the requirement of representing this knowledge regularizes the simpler model. Besides its use in model compression, distillation can be used to harden trained models against adversarial attacks (Papernot et al., 2015). The difference between distillation and consistency regularization is that distillation is performed after training whereas consistency regularization is performed on training time.

Consistency regularization can be seen as a form of label propagation. Training samples that resemble each other are more likely to belong to the same class. Label propagation takes advantage of this assumption by pushing label information from each example to examples that are near it according to some metric (Zhu & Ghahramani, 2002). Weston et al. (2012) have showed that label propagation can also be applied in deep learning models. However, ordinary label propagation requires a predefined distance metric in the input space. In contrast, consistency targets employ a learned distance metric implied by the abstract representations of the model. As the model learns new features, the distance metric changes to accommodate these features. Therefore, consistency targets guide learning in two ways. On the one hand they spread the labels according to the current distance metric, and on the other hand, they aid the network learn a better distance metric.

4. Experiments

To test our hypothesis, we first replicated the Π model of Laine & Aila (2016) in TensorFlow (Abadi et al., 2015) as our baseline. We used the same architecture and hyperparameters as Laine & Aila (2016), except we used batch normalization instead of weight normalization. Probably because of this change, our baseline results were slightly worse than the results reported by Laine & Aila (2016). We then modified the baseline model to use weight-averaged consistency targets. We retained the Π model hyperparameters and applied $\alpha = 0.999$ as the EMA coefficient for teacher weight updates. The details of the model architecture are described in Appendix A.

In the development phase of our work, we separated 10% of training data into a validation set. We removed most of the labels from the remaining training data, retaining an equal number of labels from each class. We retained labels

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2We will publish the TensorFlow source code of our model in the near future.
in the validation set to enable exploration of the results. In the final evaluation phase we used the entire training set, including the validation set but with labels removed.3

4.1. SVHN

We ran experiments using the Street View House Numbers (SVHN) benchmark (Netzer et al., 2011). Each example in the dataset is a close-up of a house number, and the task is to recognize the digit in the middle of the image. SVHN consists of 73257 primary training samples, 531131 extra training samples, and 26032 test samples in 32x32 pixel RGB format.

Following standard practice in semi-supervised learning research, we trained the network with only the primary training data. From Table 1 we can see that the use of weight-averaged consistency targets improves the test accuracy over earlier methods on semi-supervised tasks. Figure 3 shows the training curves.

4.2. CIFAR-10

We also ran experiments using the CIFAR-10 (Krizhevsky, 2009) dataset. The training set consists of 50000 images belonging to ten different classes. The task is to recognize the class of each image. We ran the experiments using the same architecture and hyperparameters as for SVHN. Table 2 shows the results. Weight-averaged consistency targets improve results over our baseline II model, and yield similar results as II model and Temporal ensembling by Laine & Aila (2016).

Why do we see large improvements on SVHN but not on CIFAR-10? The answer may relate to the amount of training data and the difficulty of the classification task. Compared to SVHN, CIFAR has a similar amount of data, but represents more varied concepts. Consequently, mastering CIFAR requires learning more features and balancing the use of features carefully. From another point of view, the true data manifold on CIFAR presumably contains many nooks and crannies that may not be well-presented in the training data. Weight-averaged consistency targets help fill gaps in data more robustly than earlier methods, but do not necessarily help in uncovering new features. In the presence of sufficient data, weight-averaged consistency targets help the model learn useful generalizations, but when data is lacking, it cannot help the model perform better.

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Table 1. Error rate percentage on SVHN over 10 runs. The extra training data of SVHN was not used in these runs. Unlike temporal ensembling (TE), weight-averaged consistency (WAC) is applicable to on-line learning.

| Model                  | On-line compatible | 250 labels  | 500 labels  | 1000 labels | All labels\(^a\) |
|------------------------|--------------------|-------------|-------------|-------------|-----------------|
| Supervised-only        | yes                | 42.65 ± 2.68| 22.08 ± 0.73| 14.46 ± 0.71| 2.81 ± 0.07    |
| Improved GAN\(^b\)     | yes                | 18.44 ± 4.8 | 8.11 ± 1.3  |             |                 |
| II model\(^c\)         | yes                | 6.65 ± 0.53 | 4.82 ± 0.17 | 2.54 ± 0.04 |                 |
| TE\(^d\)               | no                 | 5.12 ± 0.13 | 4.42 ± 0.16 | 2.74 ± 0.06 |                 |
| II model (ours)        | yes                | 16.59 ± 2.20| 8.52 ± 0.40 | 5.97 ± 0.28 | 2.66 ± 0.07    |
| WAC (ours)             | yes                | 5.39 ± 0.39 | 4.41 ± 0.26 | 4.02 ± 0.19 | 2.64 ± 0.05    |

\(^a\) 4 runs \quad \(^b\) Salimans et al. (2016) \quad \(^c\) Laine & Aila (2016)

Table 2. Error rate percentage on CIFAR-10 over 10 runs.

| Model                  | 1000 labels  | 2000 labels | 4000 labels | All labels\(^a\) |
|------------------------|--------------|-------------|-------------|-----------------|
| Supervised-only\(^e\) | 35.56 ± 1.59 | 7.33 ± 0.04 |             |                 |
| Improved GAN\(^b\)     | 18.63 ± 2.32 |             |             |                 |
| II model\(^f\)         | 12.36 ± 0.31 | 5.56 ± 0.10 |             |                 |
| TE\(^d\)               | 12.16 ± 0.31 | 5.60 ± 0.10 |             |                 |
| II model (ours)        | 34.88 ± 2.49 | 20.17 ± 0.66| 14.24 ± 0.38| 5.78 ± 0.16    |
| WAC (ours)             | 23.64 ± 1.14 | 16.23 ± 0.43| 12.31 ± 0.28| 5.56 ± 0.03    |

\(^a\) 4 runs \quad \(^b\) Salimans et al. (2016) \quad \(^c\) Laine & Aila (2016)
Weight-averaged consistency targets

Figure 3. Classification cost (top) and error (bottom) of weight-averaged consistency and our baseline Π model on SVHN. The training cost shown is the average training cost over the epoch. The validation cost is the cost at the end of the epoch. In the semi-supervised tasks the student model adapts quickly to the teacher model, resulting in smaller test error.

4.3. SVHN with extra unlabeled data

We suggested that our method scales well to large datasets and on-line learning. In addition, the SVHN and CIFAR results indicate that weight-averaged consistency targets use unlabeled examples efficiently. Therefore, we wanted to test whether we have reached the limits of our approach. In order to do so, we returned to SVHN, and included some of the extra 531131 examples in the training data.

We picked 500 samples from the primary training set to be used as labeled training examples. We used the rest of the primary training set together with the extra training set as unlabeled examples. We ran experiments with weight-averaged consistency targets and our baseline Π model, and used either 0, 100000 or 500000 extra examples. Table 3 shows the results.

Table 3. Error percentage on SVHN with 500 labels over 5 runs. The training set is augmented with varying amount of unlabeled data from the extra training set.

| Model    | 0 extra | 100k extra | 500k extra |
|----------|---------|------------|------------|
| Π model  | 8.52 ± 0.40 | 6.46 ± 0.48 | 5.60 ± 0.32 |
| WAC      | 4.41 ± 0.26  | 3.19 ± 0.23  | 2.76 ± 0.23  |

* 10 runs

5. Discussion

Improvements in semi-supervised learning bring essential benefits. A powerful semi-supervised method enables training with fewer or lower-quality labels than before, and produces a higher test accuracy with a given training set. These merits produce tangible value in the creation of machine learning applications. Labeling of examples becomes quicker and less expensive. Consequently, the entire process of development from obtaining training data to producing a useful machine learning application is faster. Finally, entirely new applications become possible. In many domains humans do not know the correct label for all data points, thus rendering perfect manual labeling impossible. By giving humans more leeway regarding the number and quality of labels, some of these application areas will become feasibly solvable.

Recently, temporal ensembling and other forms of consistency regularization have shown their strength in semi-supervised learning. In this paper, we propose using consistency targets from a weight-averaged teacher model. Unlike temporal ensembling, the method works with large datasets and on-line learning. Our experiments on SVHN and CIFAR suggest that it improves the speed of learning and the classification accuracy of the trained network.
We believe that the ideas of this work can be applied and improved in many ways. Consistency targets can be combined with other semi-supervised methods. The value of teacher-generated information can likely be utilized in a more sophisticated manner. And the general principle of improving teacher predictions to improve the training results can suggest new techniques that bring additional benefits.

Weight-averaged consistency targets improve the training signal at the top of the network. They guide the model to find better representations on its upper layers, but not necessarily on the lower layers. A convolutional network is a natural match for the consistency targets, because the convolutions are strongly regularized by themselves. In other tasks and models, the consistency targets may need help from other regularizers. Recently, semi-supervised learning results have improved tremendously with the help of Variational auto-encoders (Kingma & Welling, 2013; Rezende et al., 2014), Generative adversarial networks (Goodfellow et al., 2014a; Salimans et al., 2016), and other methods. Combining consistency targets with these other methods will in all likelihood produce good results in a diverse set of tasks. As an example, consider Ladder networks (Rasmus et al., 2015). Whereas consistency targets apply to the top layer, the denoising cost of the ladder applies to the bottom layer. A combination of consistency targets and the ladder would yield a stronger signal to all the layers of the network.

The value of information provided by the teacher model changes during training. At the beginning of training, the student should not trust the teacher at all. Following Laine & Aila (2016), we tackle this complication with a ramp up of the consistency cost, whereas Sajjadi et al. (2016) use a mutual-exclusivity loss. Although these techniques solve the immediate problem, they account for the value of information only indirectly. Approximating and exploiting the value of teacher-generated information in a principled way remains an open problem.

The success of consistency regularization depends on the quality of the teacher-generated targets. If the targets can be improved, they should be. Weight-averaged consistency targets represent one way to exploit this principle. Additional techniques can likely be used to create even better targets and to attain an even higher classification accuracy.

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Weight-averaged consistency targets

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We used AdamOptimizer (Kingma & Ba, 2014) for training. We used parameters \( \beta_1 = 0.9, \beta_2 = 0.999, \) and \( \varepsilon = 10^{-8} \), except we ramped down \( \beta_1 \) to 0 during the last 50 epochs of training.\(^4\) We ramped up learning rate from 0 to 0.003 during the first 80 epochs, and ramped it back down to 0 during the last 50 epochs.\(^5\) We trained the model for 300 epochs.

The above-mentioned ramps of consistency cost, learning rate, and \( \beta_2 \) were performed using a sigmoid function. The function was \( e^{-5(1-x)^2} \) for ramp-ups and \( 1 - e^{-12.5x^2} \) for ramp-downs, where \( x \in [0, 1] \).\(^6\)

The teacher model parameters were updated after each training step using an EMA with \( \alpha = 0.999 \). The baseline II model was identical, but with \( \alpha = 0 \).

### A.1. SVHN with extra unlabeled data

In the SVHN experiments with extra training examples (the results in 100k and 500k columns in Table 3), we made changes to the setup described above to accommodate the varying and larger amount of data.

We used 1 labeled example and 99 unlabeled examples in each mini-batch. After all 500 labeled examples had been used, they were shuffled and reused. Similarly, after all unlabeled examples had been used, they were shuffled and reused.\(^7\)

We ramped up the learning rate and consistency coefficient during the first 40000 training steps. We ramped down the learning rate and \( \beta_2 \) parameter during the last 80000 steps on II model runs. We did not apply ramp-downs on the weight-averaged consistency model runs. We trained the network for 350000 steps when using 100k extra examples and for 500000 steps when using 500k extra examples.\(^8\)

### A. Model structure

As the basis of our experiments, we replicated the II model of Laine & Aila (2016). For the convenience of implementation, we deviated from the original architecture by using batch normalization (Ioffe & Szegedy, 2015) instead of weight normalization (Salimans & Kingma, 2016). We also used the same hyperparameters and trained the networks in the same way as Laine & Aila (2016).

Table 4 describes the architecture of the convolutional network. Leaky ReLu (Maas et al., 2013) with \( \alpha = 0.1 \) was used as the nonlinearity after each convolutional layer.

We used cross-entropy between the student softmax output and the one-hot label as the classification cost, and a mean square error between the student and teacher softmax outputs as the consistency cost. The total cost is the weighted sum of these two costs. We ramped up the coefficient of consistency cost from 0 to 100.0 during the first 80 epochs of training, and then kept it constant at 100.0.

We used mini-batch size 100 in all the experiments. In the CIFAR experiments and in the SVHN experiments without extra training data, we treated labeled and unlabeled data uniformly when forming mini-batches. After all training data had been used, they were shuffled and reused.

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\(^4\)This was an unintentional deviation from Laine & Aila (2016). They ramped down \( \beta_1 \) to 0.5. The effect is whether the gradient momentum at the end of the training considers approximately the two latests gradients or just the latest gradient.

\(^5\)At the end of the training the averaging of weights has approximately the same effect as learning-rate ramp-down. Therefore the ramp-downs can be removed from our model without decrease in performance. However, they improve the results of the II model and we decided to retain them for easier comparison.

\(^6\)In our experiments, linear ramps performed just as well.

\(^7\)We saw evidence that stratifying the number of labeled examples this way reduces gradient noise and improves results in other settings too. Using 10 or more labeled examples per mini-batch improves results even further with the right selection of hyperparameters. In the end we decided to use the simpler mini-batching strategy in the other experiments for comparability with earlier work.

\(^8\)We saw evidence that the test accuracy of weight-averaged consistency model would have kept improving if we had continued training beyond 500000 steps.

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Table 4. The convolutional network architecture we used in the experiments.

| Layer                | Hyperparameters                          |
|----------------------|------------------------------------------|
| Input                | 32 × 32 RGB image                        |
| Translation          | Randomly \( \{\Delta x, \Delta y\} \sim [-2, 2] \) |
| Horizontal flip\(^a\) | Randomly \( p = 0.5 \)                   |
| Gaussian noise       | \( \sigma = 0.15 \)                       |
| Convolutional        | 128 filters, 3 × 3, same padding         |
| Convolutional        | 128 filters, 3 × 3, same padding         |
| Convolutional        | 128 filters, 3 × 3, same padding         |
| Pooling              | Maxpool 2 × 2                            |
| Dropout              | \( p = 0.5 \)                            |
| Convolutional        | 256 filters, 3 × 3, same padding         |
| Convolutional        | 256 filters, 3 × 3, same padding         |
| Convolutional        | 256 filters, 3 × 3, same padding         |
| Pooling              | Maxpool 2 × 2                            |
| Dropout              | \( p = 0.5 \)                            |
| Convolutional        | 512 filters, 3 × 3, valid padding        |
| Convolutional        | 256 filters, 1 × 1, same padding         |
| Convolutional        | 128 filters, 1 × 1, same padding         |
| Pooling              | Average pool (6 × 6 → 1 × 1 pixels)      |
| Softmax              | Fully connected 128 → 10                 |

\(^a\)Not applied on SVHN experiments