CONTROLLING EXPLORATION IMPROVES TRAINING FOR DEEP NEURAL NETWORKS

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Abstract. Stochastic optimization methods are widely used for training of deep neural networks. However, it is still a challenging research problem to achieve effective training by using stochastic optimization methods. This is due to the difficulties in finding good parameters on a loss function that have many saddle points. In this paper, we propose a stochastic optimization method called STDProp for effective training of deep neural networks. Its key idea is to effectively explore parameters on a complex surface of a loss function. We additionally develop momentum version of STDProp. While our approaches are easy to implement with high memory efficiency, it is more effective than other practical stochastic optimization methods for deep neural networks.

1. Introduction

Stochastic Gradient Descent (SGD) \cite{1} is one of the basic stochastic optimization methods. Since SGD can empirically train deep neural networks with high memory efficiency by using mini-batches of training data, SGD and its follow-up methods are widely used in Deep Learning community. Although SGD achieves a measure of success, the effective training of deep neural networks is still difficult problem. This is because there are many saddle points on a loss function of deep neural networks as pointed out in \cite{2}. If SGD approaches to a saddle point from a positive curvature, gradients tend to turn to the saddle point. In addition, since gradients have small values on the saddle point, SGD slowly progresses near saddle points. As a result, it is important to effectively handle saddle points on the function of deep neural networks for finding good parameters.

In the field of bayesian inference, exploration is a simple approach that uses randomness for finding good parameters on complex functions (see Markov Chain Monte Carlo \cite{3}, Sequential Monte Carlo \cite{4}, stochastic EM \cite{5} and Monte Carlo EM \cite{6}). This approach achieves good results even if the function is complex such as posterior distributions of complex models that have saddle points. Since the randomness allows the exploration to move toward non-optimal direction, it can avoid or escape from saddle points. The theoretical and empirical results of the approach suggest that we can effectively find good parameters on functions that have saddle points by using randomness.

Although the idea of using randomness is simple, few researches have used randomness to training of deep neural networks. \cite{7} integrates noises as randomness for training of very deep neural networks. Their idea is to add Gaussian noises...
into first order gradients. The results suggest that the Gaussian noise realizes active exploration of parameters and achieves effective training of very deep neural networks. However, this approach does not consider noises on first order gradients derived from mini-batch setting. Since SGD usually uses mini-batches as inputs for training of deep neural networks, first order gradients have noises as a result of changing mini-batches in each iteration. Although the noises of mini-batches are expected to have the effect of exploration, the effect is not taken into account in the previous approach. As the result, the previous approach fails to control the activity of exploration.

In this paper, we propose a stochastic optimization method called STDProp. The key idea is to adaptively control the activity of exploration by using variances of past first order gradients. This realizes constant activities to the exploration in each iteration. As the result, our approach effectively explores parameters on complex functions. In addition, we develop momentum version of STDProp. While our approaches are easy to implement with high memory efficiency, it is more effective than other practical stochastic optimization methods for deep neural networks.

2. Preliminary

In this section, we briefly review the background of this paper. Section 2.1 describes SGD [1], which is a basic algorithm in stochastic optimization such as mini-batch setting. Section 2.2 reviews SGD with Gaussian noises [7] which is a baseline method of this paper.

2.1. Stochastic Gradient Descent. Many training algorithms aim at minimizing the loss function $f(\theta)$ with respect to the parameter vector, $\theta$. SGD is a popular training algorithm for the mini-batch setting. To minimize $f(\theta)$, SGD iteratively updates $\theta$ with a mini-batch of samples as following:

$$\theta_{i,t} = \theta_{i,t-1} - \alpha \nabla f (\theta_{i,t-1}; x_{t-1})$$

where $\alpha$ is the learning rate, $\theta_{i,t}$ is the $i$-th element of the parameter vector at time $t$, $x_{t-1}$ is a sample or mini-batch at time $t - 1$, and $\nabla f (\theta_{i,t-1}; x_{t-1})$ is the first order gradient with respect to the $i$-th parameter given by $x_{t-1}$. SGD applies Equation (2.1) to each sample or mini-batch. Since SGD only uses a part of the data for computing gradients $\nabla f (\theta_{i,t-1}; x_{t-1})$, it entails noises on first order gradients $\nabla f (\theta_{i,t-1}; x_{t-1})$ as a result of changing $x_{t-1}$ in each training iteration.

2.2. Adding gradient noise. In the field of traditional neural networks, it is a popular approach to add noises to first order gradient $\nabla f (\theta_{i,t-1}; x_{t-1})$ in training the models [8]. On the other hand, in the field of recent deep neural networks, no researches have proposed to add gradient noise except for [7]. They achieved active exploration of parameters by adding gradient noises in training of deep neural networks. Since exploration and exploitation are trade-off, the approach reduces the activity of exploitation that progresses to optimal directions. However, it can effectively find good parameters on complex functions when we provide the good balance of exploration and exploitation. This is because we can escape saddle points or local minima by the exploration that uses randomness. The updating...
rule of their approach is as follows:

\begin{align}
\text{(2.2) } n_t & \sim N(0, \sigma_t^2) \\
\text{(2.3) } g_{i,t} & = \nabla f(\theta_{i,t-1}; x_{t-1}) + n_t \\
\text{(2.4) } \theta_{i,t} & = \theta_{i,t-1} - \alpha g_{i,t}
\end{align}

where $N(0, \sigma_t^2)$ is Gaussian noise that has mean 0 and variance $\sigma_t^2$. $\sigma_t^2$ is annealed as $\sigma_t^2 = \frac{\eta}{1+t\gamma}$ with $\eta$ selected from $\{0.01, 0.3, 1.0\}$ and $\gamma = 0.55$. $\sigma_t^2$ controls the activity of exploration. The approach is simple but effective for training very deep neural networks without overfitting. Since the Gaussian noise realizes active exploration, we can obtain good parameters even if we do not use special initialization such as initialization for deep rectifier networks [9]. However, the approach cannot decrease the activity of exploration even if the first order gradients have large noises derived from mini-batches.

3. Proposed Method

3.1. Problem of adding gradient noise. As described in Section 2.1, the first order gradients of SGD have the noises of mini-batches. These noises could have the effect of exploration the same as the previous approach of Section 2.2. However, the previous approach does not consider these noises of mini-batches. We show that the previous approach is problematic because it does not consider the noises. In order to consider the noises, we assume a Gaussian distribution on the first order gradients as:

\begin{equation}
\nabla f(\theta_{i,t-1}; x_{t-1}) \sim N(\bar{g}_{i,t}, c_{i,t}^2)
\end{equation}

where $\bar{g}_{i,t}$ is a latent true gradient and $c_{i,t}^2$ is a variance of observed first order gradients $\nabla f(\theta_{i,t-1}; x_{t-1})$. This assumption is also used in [10]. $c_{i,t}^2$ represents the variance of noises by mini-batches. In other words, we can interpret the variance $c_{i,t}^2$ as the activity of exploration the same as $\sigma_t^2$ of Section 2.2. By considering two Gaussian distributions of Equation (2.2) and (3.1), we can derive a Gaussian distribution of $g_{i,t}$ of Equation (2.3) as:

\begin{equation}
g_{i,t} \sim N(\bar{g}_{i,t}, \sigma_t^2 + c_{i,t}^2)
\end{equation}

We use following major rule in Equation (3.2): if $X_1 \sim N(m_1, \sigma_1^2)$ and $X_2 \sim N(m_2, \sigma_2^2)$, then $X_1 + X_2 \sim N(m_1 + m_2, \sigma_1^2 + \sigma_2^2)$. In the previous approach of Section 2.2 $\sigma_t^2$ controls the activity of exploration. However, in practice, the activity of exploration depends on $\sigma_t^2 + c_{i,t}^2$ of Equation (3.2). The previous approach only adds $\sigma_t^2$ to $c_{i,t}^2$; it only increases the activity of exploration. Even if SGD has too large activity of exploration for large $c_{i,t}^2$, the previous approach cannot reduce the activity because of $0 \leq \sigma_t^2$. In this case, SGD cannot effectively perform the exploitation because the exploration and exploitation are trade-off. Therefore, we should decrease the activity of exploration when the activity is too large.

3.2. Idea: variance control by affine transformation of gradients. Section 3.1 revealed that it is difficult to decrease the activity of exploration by adding gradient noise even if the noises of mini-batches give enough activity of exploration for large $c_{i,t}^2$. In order to effectively decrease and increase the activity, our approach
3.3. Algorithm. The online version of our approach described in Section 3.2 is the following simple algorithm:

\[
\begin{align*}
\mu_{i,t} &= \gamma \mu_{i,t-1} + (1 - \gamma) \nabla f(\theta_{i,t-1}; x_{t-1}) \\
\epsilon^2_{i,t} &= \epsilon^2_{i,t-1} + \gamma (1 - \gamma)(\nabla f(\theta_{i,t-1}; x_{t-1}) - \mu_{i,t-1})^2 \\
\theta_{i,t} &= \theta_{i,t-1} - \alpha \frac{\nabla f(\theta_{i,t-1}; x_{t-1})}{\sqrt{\epsilon^2_{i,t}}} 
\end{align*}
\]

where \(\mu_{i,t}\) is the moving average of first order gradients for \(i\)-th parameter at time \(t\) and \(\gamma\) is the hyperparameter of the decay rate for the moving average that has \(\gamma \in [0, 1]\). \(\epsilon^2_{i,t}\) is the exponentially moving variance of first order gradients for \(i\)-th parameter at time \(t\). We use \(\gamma\) in Equation (3.4) as the decay rate of the exponentially moving variance. Equation (3.6) is online updating rule for the variance \(\epsilon^2_{i,t}\). \(\mu_{i,t}\) and \(\epsilon^2_{i,t}\) are initialized as \(\mu_{i,1} = \nabla f(\theta_{i,0}; x_0)\) and \(\epsilon^2_{i,1} = 0\). \(\epsilon\) is a small positive value for stable computation. We call above algorithm STDProp because Equation (3.7) includes Standard Deviation \(\sqrt{\epsilon^2_{i,t}}\). We finally use \(\alpha \frac{\nabla f(\theta_{i,t-1}; x_{t-1})}{\sqrt{\epsilon^2_{i,t}}}\) for updating parameters in Equation (3.7). The same as Section 3.2, this quantity follows

\[
\alpha \frac{\nabla f(\theta_{i,t-1}; x_{t-1})}{\sqrt{\epsilon^2_{i,t}}} \sim N\left(\frac{\alpha \mu_{i,t}}{\sqrt{\epsilon^2_{i,t}}}, \alpha^2\right).
\]

The equation ignores a small positive value \(\epsilon\). Section 3.2 shows that the variance is only kept to 1. However, Equation (3.8) shows that we can control this variance other than 1 by changing learning rate \(\alpha\).
3.4. **Momentum version of STDProp.** We develop momentum version of STDProp. It is a popular approach to use momentum for efficient training of deep neural networks. Although there are some variants of momentum, we use moving average of first order gradients as a momentum the same as Adam [12]. This is because STDProp computes the moving average by Equation (3.5). We can reuse this moving average as the momentum. Momentum version of STDProp only changes Equation (3.7) as following:

\[
\theta_{i,t} = \theta_{i,t-1} - \alpha \frac{\mu_{i,t}}{\sqrt{c_{i,t}^2 + \epsilon}}.
\]

(3.9)

We can remove the bias for the moving average the same as [12].

In terms of memory consumption and computational cost, our approaches are more efficient than typical second order methods. If the number of parameters is \(N\), the typical second order methods need \(O(N^2)\) for memory consumption because we have to preserve the matrix of second order gradients. In addition, if the second order methods compute the inverse matrix, it requires \(O(N^3)\) for the computational cost. On the other hand, our approach needs \(O(N)\) for memory consumption because the moving average and variance are the same size as the number of parameters \(N\). In addition, it only computes the inverse of \(\sqrt{c_{i,t}^2}\) that needs \(O(N)\). Since our algorithms need \(O(N)\) for memory consumption and computational cost, it is suitable for the training of deep neural networks that have large number of parameters.

4. Experiments

We performed experiments to evaluate the effectiveness of our approaches for saddle points. Deep neural networks of many parameters have many saddle points on a loss function that lead to difficulties for the training of deep neural networks. Therefore, we investigated the performance of our approaches for most challenging setting by using deep fully-connected networks that typically have more parameters than Convolutional Neural Networks [13]. In the experiments, we compared our approaches to SGD of Section 2.1 and SGD with gradient noise of Section 2.2. In what follows, Noisy SGD represents the approach of SGD with gradient noise.

4.1. **Very deep fully-connected networks.** We investigated the effectiveness of our approaches. If our approaches effectively get away from saddle points by exploration, our approach improves the accuracy and efficiency comparing to other methods.

In this section, we conducted experiment by following the paper of Noisy SGD [7]. We used very deep fully-connected network with 20 hidden layers, 50 hidden units and ReLU activation functions. We used MNIST dataset for the 10-class classification task of images. The training criterion was negative log likelihood. The mini-batch size was 128. We tried two types of initialization for parameters. The first one is a variant of Simple Init that initializes parameters from a Gaussian with mean 0 and standard deviation 0.01 [7]. The second one is the initialization for deep rectifier networks by He et al. [14]. Since Simple Init does not consider the architecture of networks, it needs many training iterations or is difficult to converge the training [15]. On the other hand, since He et al. consider the property of ReLU activation and initializes parameters to avoid reducing or magnifying the magnitude of signals in deep rectifier networks, it achieves efficient training of deep rectifier...
Table 1. Average, Best and Worst test accuracy percentage for MNIST in very deep fully-connected networks. We train the model for each setting 10 times. STDPpropM represents STDPprop with momentum.

| Method  | α     | γ     | Ave. | Best | Worst | Ave. | Best | Worst |
|---------|-------|-------|------|------|-------|------|------|-------|
| SGD     | 0.1   | -     | 11.35| 11.35| 11.35 | 91.8 | 92.27| 91.53 |
|         | 0.01  | -     | 11.35| 11.35| 11.35 | 78.633| 83.27| 74.77 |
|         | 0.001 | -     | 11.35| 11.35| 11.35 | 45.717| 51.92| 35.41 |
| Noisy SGD | 0.1   | -     | 84.064| 85.44| 82.95 | 82.277| 85.78| 69.68 |
|         | 0.01  | -     | 10.604| 11.35| 9.58 | 82.435| 83.28| 81.1 |
|         | 0.001 | -     | 10.515| 11.35| 10.1 | 49.084| 50.98| 40.24 |
| STDPprop | 0.1   | 0.9   | 10.1 | 10.1 | 10.1 | 10.1 | 10.1 | 10.1 |
|         | 0.01  | 0.9   | 10.066| 10.28| 9.58 | 10.28 | 10.28| 10.28 |
|         | 0.001 | 0.9   | 92.153| 96.17| 86.27 | 94.643| 95.68| 92.36 |
| STDPpropM | 0.1   | 0.9   | 9.58 | 9.58 | 9.58 | 9.58 | 9.58 | 9.58 |
|         | 0.01  | 0.9   | 17.541| 74.31| 10.3 | 12.693| 28.5| 9.82 |
|         | 0.001 | 0.9   | 96.35 | 96.8 | 94.98 | 94.774| 95.24| 93.8 |
|         | 0.001 | 0.9   | 96.839| 97.02| 96.82 | 96.425| 96.84| 96.29 |

networks. Therefore, the initialization by He et al. achieves higher accuracy than Simple Init. However, if we can effectively explore parameters, we achieve high accuracy in few iterations even if we use Simple Init as the initialization. We tried constant learning rate $\alpha = 0.1$, $\alpha = 0.01$ and $\alpha = 0.001$ for all methods. We set hyper parameter $\eta = 0.01$ for Noisy SGD the same setting in [7]. We tried hyper parameter $\gamma = 0.9$ and $\gamma = 0.99$ for STDPprop and its momentum version. We removed initialization bias for the moving averages by using technique of [12]. The number of epochs was 50. We tried 10 runs for each above settings. Table 1 is the summary of results. They show averages, best, worst of test accuracies for each setting.

As shown in Table 1, if we use Simple Init as the initialization, it is difficult to realize effective training. SGD and Noisy SGD could not reach the accuracy of 90 percent with all settings while our approaches reach higher accuracies more than 90 percent with $\alpha = 0.001$. In the setting of Simple Init, SGD could not achieve effective training with all settings while Noisy SGD improved the accuracy with $\alpha = 0.1$. Similar results have been reported in [7]. It shows that Noisy SGD can train the model even if we use Simple Init. This is because Noisy SGD can achieve more active exploration than SGD. However, Noisy SGD cannot control the activity of exploration as described in Section 5.1. On the other hand, since STDPprop and its momentum version control the activity of exploration, the training is more effective than Noisy SGD. Our approaches with $\alpha = 0.001$ obviously improved the accuracy for more than 10 percent than the best accuracy of Noisy SGD with $\alpha = 0.1$. Since
Table 2. Test accuracy percentage for different sizes of mini-batches in very deep fully-connected networks. We used the hyperparameters that achieve high accuracies in Table 1. \(b\) represents the size of mini-batch.

| Method    | \(\alpha\) | \(\gamma\) | \(b = 32\) | \(b = 64\) | \(b = 128\) |
|-----------|-------------|-------------|------------|------------|------------|
| SGD       | 0.1         | -           | 91.8       | 94.41      | 11.35      |
| Noisy SGD | 0.01        | -           | 89.77      | 82.435     | 93.52      |
| STDProp   | 0.001       | 0.99        | **97.129** | **96.83**  | **96.72**  |

our approaches can effectively explore parameters, it can find good parameters even if the initialization is not so effective.

If we use the initialization by He et al., all methods achieved higher accuracies than Simple Init. Specifically, SGD achieved high accuracy with large learning rate \(\alpha = 0.1\) because it gives fast progress for the training. However, Noisy SGD gave lower accuracy than SGD with \(\alpha = 0.1\). This is because Noisy SGD had too large activity of exploration. As described in Section 3.1 we represent the activity of exploration as \(\sigma^2_t + c^2_{i,t}\). Although large learning rate such as \(\alpha = 0.1\) gives large \(c^2_{i,t}\), Noisy SGD only increases the activity of exploration by adding \(\sigma^2_t\). Since exploration and exploitation are trade-off, the activity of exploitation is very low for Noisy SGD with large learning rate such as \(\alpha = 0.1\). Therefore, Noisy SGD could not achieve higher accuracy than SGD with large learning rate \(\alpha = 0.1\). As shown in Table 1, Noisy SGD can improve the accuracy with the initialization by He et al. when \(\alpha = 0.01\) and \(\alpha = 0.001\). However, the worst accuracy of Noisy SGD is not so high if \(\alpha = 0.1\); it is 69.68 percent. This is because Noisy SGD fails to control the activity of exploration. On the other hand, since STDProp and its momentum version keep constant activity of exploration by Equation (3.8), we can realize stable training of deep neural networks. In fact, STDProp and its momentum version achieved the accuracy over 90 percent with \(\alpha = 0.001\) in the worst case. The results also suggest that our approaches are sensitive for learning rate \(\alpha\). This is because square of learning rate \(\alpha^2\) equals to variance of Equation (3.8) in our approaches. Since the variance corresponds to the activity of exploration, the learning rate directly controls the activity of exploration in our approach. However, since most stochastic gradient methods typically tune the learning rate, the tuning cost of our approaches is same as other most stochastic gradient methods.

Table 1 indicates that SGD is very sensitive for initialization. If we set \(\alpha = 0.1\), Noisy SGD achieves more stable training for initialization than SGD; this is the same result as reported in [7]. In addition, Noisy SGD achieves high accuracies in both initializations when \(\alpha = 0.1\). However, STDProp and its momentum version achieve more higher accuracies than Noisy SGD regardless of initialization when \(\alpha = 0.001\). In addition, our approaches with \(\alpha = 0.001\) are more stable than Noisy SGD with \(\alpha = 0.1\); difference between best and worst accuracies is smaller than that of other methods. As the result, our approaches achieve more effective and stable training than SGD and Noisy SGD by controlling the activity of exploration.

4.2. Sensitivity for size of mini-batch. We investigated the sensitivity of STDProp to the size of mini-batch. In the mini-batch setting, we compute a first order gradient as an average of first order gradients in each mini-batch. Therefore, we
Table 3. Test accuracies for 5 layered neural networks. $b$ represents the size of mini-batch.

| Method      | $\alpha$ | $\gamma$ | $b$ | Accuracy |
|-------------|----------|----------|-----|----------|
| SGD         | 0.1      | -        | 64  | 91.01    |
| Noisy SGD   | 0.01     | -        | 32  | 93.16    |
| STDProp     | 0.001    | 0.99     | 64  | 96.99    |

can reduce the noise on the first order gradients per mini-batch by increasing size of mini-batch. On the other hand, if we use small size of mini-batch, the first order gradients increase the noise. Therefore, we give large variance $c^2_{i,t}$ of the noise by using small size of mini-batch. Since our approaches can keep $c^2_{i,t}$ constant, the performance will not decline even if we use small size of mini-batch.

The same as Section 4.1, we used deep fully-connected network with 20 hidden layers, 50 hidden units and ReLU activation functions. We used MNIST dataset. The training criterion was negative log likelihood. We tried the initialization for deep rectifier networks the same as Section 4.1. We tried 128, 64 and 32 for size of mini-batch. We set $\alpha = 0.001$ and $\gamma = 0.99$ for STDProp, $\alpha = 0.01$ for Noisy SGD and $\alpha = 0.1$ for SGD because these settings achieved high average accuracies in Section 4.1.

Table 2 shows the test accuracies for each methods. SGD slowly progresses for mini-batch size of 32 because the gradients have large noise when we use small size of mini-batch. Interestingly, our results show that Noisy SGD increases accuracies as it uses the small size of mini-batch. Since the effectiveness of Noisy SGD highly depends on the size of mini-batch, we also have to tune the size of mini-batch other than learning rate $\alpha$ when we use Noisy SGD. This is because Noisy SGD cannot consider the noise by mini-batches. On the other hand, since STDProp keeps the variance $c^2_{i,t}$ of the noise constant, it can achieve high accuracy regardless of mini-batch sizes as shown in Table 2. Since STDProp can effectively train deep neural networks even if the size of mini-batch is small, it can be used on devices with scant memory.

4.3. Fully-connected networks. [7] shows that Noisy SGD cannot effectively train neural networks with small number of layers. We show that our approach successfully performs the training for such neural networks.

We used fully-connected network with 5 hidden layers, 50 hidden units and ReLU activation functions. We used MNIST dataset. The training criterion was negative log likelihood. We tried the initialization for deep rectifier networks the same as Section 4.1. We set $\alpha = 0.001$ and $\gamma = 0.99$ for STDProp, $\alpha = 0.01$ for Noisy SGD and $\alpha = 0.1$ for SGD. We set the size of mini-batch 64 for SGD and STDProp, and 32 for Noisy SGD. These setting achieves high accuracies for each methods in Section 4.2.

Table 3 shows the results. STDProp improved the accuracy from the result of Table 2 while other methods did not. [10] suggests that the depth of neural networks affects the landscape of the function. This indicates that we should control the activity of exploration to fit the depth. Since Noisy SGD fails to control the activity of exploration, the effectiveness of Noisy SGD depends on the depth. On the other hand, since STDProp keeps the activity of exploration regardless of the
depth for neural networks, it can effectively train neural networks even if the number of layers is small.

5. Related works

Although our updating rules are inspired from randomness, there are similar updating rules in other fields. Topmoumoute Online Natural Gradient Algorithm (TONGA) [10] is a stochastic gradient descent to reduce generalization error. The approach assumes Gaussian distribution on gradients the same as ours. It derives a posterior distribution by using the Gaussian distribution as a prior distribution of gradients. The updating rule divides gradients by variance-covariance matrix of gradients while ours divides the gradients by standard deviation of gradients. However, since deep neural networks have large number of parameters, the variance-covariance matrix has large size. This incurs large memory consumption. If the number of parameters is \( N \), the order of the memory consumption is \( O(N^2) \). In addition, TONGA costs \( O(N^3) \) time for computing inverse matrix of the variance-covariance matrix. On the other hand, the memory consumption and computational costs of STDProp are \( O(N) \). Although [10] proposed the diagonal block approximation of TONGA for large model, the computational cost is still high for the training of deep neural networks.

In the field of adaptive learning rate algorithms, AdaGrad [17] is a popular adaptive learning rate algorithm for convex optimization. Although it is motivated from efficient training for sparse high dimensional data, the updating rule is similar to our approaches. It divides learning rate by average of magnitudes over past gradients. Adam [12] is the latest developed algorithm with momentum based on AdaGrad. The updating rule divides learning rate by moving average of magnitudes over past gradients. However, above algorithms are developed to provide good convergence rates for the convex setting while the training of deep neural networks is non-convex setting. A heuristic variant of RMSProp [18] uses the variance of gradients with different formula to ours although typical RMSProp uses the magnitude [19]. However, [18] shows no intuitive or theoretical explanation of this heuristics for adapting learning rate. Our idea of controlling exploration explains why we use the variance, not the magnitude. It can give a novel interpretation to adaptive learning rate algorithms such as [18].

6. Conclusion

We propose STDProp and its momentum version for effective training of deep neural networks. Our approach controls the activity of exploration for finding good parameters on functions that have many saddle points. Our experimental results show that STDProp effectively achieves high accuracies. Since STDProp controls the noises of mini-batches, it achieves high accuracies even if we use small size of mini-batch. In addition, since STDProp keeps the activity of exploration constant, it can effectively train neural networks regardless of the number of layers.

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