Demystifying Dropout

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Outline

1 Motivation

2 Forward and Backward Dropout
   - Definition
   - Observations

3 Augmented Dropout
   - Augmented Dropout
   - Results
Motivation

1. Dropout is a popular technique to alleviate overfitting.
2. What is the underlying reason for its performance gain?
   - Feature augmentation, Regularization
3. **Dropdown happens in both the forward and backward pass**
   - Forward pass: feature augmentation
   - Backward pass: noisy gradient
   - Which pass accounts for performance gain of dropout?
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forward dropout randomly drops features in the forward pass but it does not drop features and backpropagated errors in the backward pass.

- **Forward pass**
  \[
  z^{(l+1)} = W_l(h^{(l)} \odot \epsilon^{(l)}) + b^{(l)},
  \]
  \[
  h^{(l+1)} = f_l(z^{(l+1)}).
  \]

- **Backward pass**
  \[
  \frac{\partial J}{\partial W(l)} = \delta^{(l+1)} h^{(l)T},
  \]
  \[
  \delta^{(l)} \triangleq \frac{\partial J}{\partial z^{(l)}} = (W^{(l)}T \delta^{(l+1)}) \odot f'_l(z^{(l)}).
  \]
Backward Dropout

Backward dropout keeps all features in the forward pass while drops features and propagated errors as the standard dropout in the back-ward pass.

- **Forward pass**
  \[
  z^{(l+1)} = W^l h^{(l)} + b^{(l)}, \\
  h^{(l+1)} = f_l(z^{(l+1)}).
  \] (3)

- **Backward pass**
  \[
  \frac{\partial J}{\partial W^{(l)}} = \delta^{(l+1)}(h^{(l)} \circ \epsilon^{(l)})^T, \\
  \delta^{(l)} \triangleq \frac{\partial J}{\partial z^{(l)}} = ((W^{(l)} \delta^{(l+1)}) \circ f'_l(z^{(l)})) \circ \epsilon^{(l)}.
  \] (4)
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Table: The test accuracy of ConvNet-Quick for CIFAR10

<table>
<thead>
<tr>
<th>Dropout Ratio</th>
<th>0.3</th>
<th>0.2</th>
<th>0.1</th>
<th>0.05</th>
<th>0.01</th>
<th>0.005</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plain</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.7579</td>
<td></td>
</tr>
<tr>
<td>Standard Dropout</td>
<td>0.7523</td>
<td>0.7617</td>
<td>0.7657</td>
<td>0.7647</td>
<td>0.7626</td>
<td>0.7608</td>
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<tr>
<td>Forward Dropout</td>
<td>0.6908</td>
<td>0.7211</td>
<td>0.7482</td>
<td>0.7627</td>
<td>0.7612</td>
<td>0.7578</td>
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<tr>
<td>Backward Dropout</td>
<td>0.7433</td>
<td>0.7557</td>
<td>0.7585</td>
<td>0.7593</td>
<td>0.7583</td>
<td>0.7599</td>
</tr>
</tbody>
</table>

Table: The test accuracy of ResNet-20 for CIFAR10

<table>
<thead>
<tr>
<th>Dropout Ratio</th>
<th>0.3</th>
<th>0.2</th>
<th>0.1</th>
<th>0.05</th>
<th>0.01</th>
<th>0.005</th>
</tr>
</thead>
<tbody>
<tr>
<td>Plain</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.9143</td>
<td></td>
</tr>
<tr>
<td>Standard Dropout</td>
<td>0.9163</td>
<td>0.9176</td>
<td>0.9193</td>
<td>0.9174</td>
<td>0.9141</td>
<td>0.9154</td>
</tr>
<tr>
<td>Forward Dropout</td>
<td>0.9007</td>
<td>0.9093</td>
<td>0.9169</td>
<td>0.9171</td>
<td>0.9141</td>
<td>0.9142</td>
</tr>
<tr>
<td>Backward Dropout</td>
<td>0.9109</td>
<td>0.9130</td>
<td>0.9140</td>
<td>0.9142</td>
<td>0.9147</td>
<td>0.9146</td>
</tr>
</tbody>
</table>
When the dropout ratio is large ($p = 0.2$), the training loss of the forward dropout are much larger than those of other methods. In other words, when $p$ is large, due to interrupting features heavily, the forward dropout can increase the model bias and cause underfitting. As a result, it degrades the performance of the plain network. As for the standard dropout, although it employs the same dropout ratio with the forward dropout, yet its loss and accuracy are better than those of the forward dropout. The possible reason is the implicit regularization of the noisy gradient in the backward pass, which is helpful to escape local minima. When it comes to the backward dropout, although it can arrive at a smaller training loss compared with the standard dropout, it cannot outperform the standard one. The possible reason is that there is no data augmentation in the forward pass as the standard dropout. Hence, its generalization performance is worse than the standard dropout.
When the dropout ratio becomes moderately small ($p = 0.05$), the training loss of the forward and backward dropout approach to that of the standard dropout, and their accuracy is a little better than that of the plain network. Thus, the data augmentation in the forward and the noisy gradient in the backward pass caused by the mild noise are helpful to improve the generalization performance. Additionally, the forward dropout outperforms the backward one. In other words, mild noise is more helpful in the forward pass.

When the dropout ratio is very small ($p = 0.005$), it is intuitive that the forward dropout has little effect on the performance of the plain deep neural networks. Surprisingly, the backward dropout has better performance than the plain network, which means that the noisy gradient caused by the small noise in the backward pass contributes to improving the generalization performance.
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Augmented Dropout

Based on aforementioned observations, we propose the augmented dropout, which employs different dropout strategy for two passes.

- **Forward pass**

  \[
  \hat{h}^{(l)}_{\text{forward}} = h^{(l)} \odot \epsilon^{(l)}_{\text{forward}}, \\
  z^{(l+1)} = W_l \hat{h}^{(l)}_{\text{forward}} + b^{(l)}, \\
  h^{(l+1)} = f_l(z^{(l+1)}),
  \]

- **Backward pass**

  \[
  \hat{h}^{(l)}_{\text{backward}} = h^{(l)} \odot \epsilon^{(l)}_{\text{backward}}, \\
  \frac{\partial J}{\partial W^{(l)}} = \delta^{(l+1)} \hat{h}^{(l)}_{\text{backward}}^T, \\
  \delta^{(l)} \triangleq \frac{\partial J}{\partial z^{(l)}} = (W^{(l)}^T \delta^{(l+1)}) \odot (f'_l(z^{(l)}) \odot \epsilon^{(l)}_{\text{backward}}),
  \]
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## Results

**Table:** The test accuracy of ConvNet-Quick

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Standard</th>
<th></th>
<th>Augmented</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dropout Ratio</td>
<td>Acc</td>
<td>Acc</td>
<td>Dropout Ratio</td>
</tr>
<tr>
<td>SVHN</td>
<td>0.1</td>
<td>0.9240</td>
<td>0.9248</td>
<td>0.1/0.0002</td>
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<tr>
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<td>0.2</td>
<td>0.9231</td>
<td>0.9258</td>
<td>0.2/0.0002</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.9249</td>
<td>0.9250</td>
<td>0.3/0.0002</td>
</tr>
<tr>
<td>CIFAR10</td>
<td>0.1</td>
<td>0.7657</td>
<td>0.7674</td>
<td>0.1/0.0002</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.7617</td>
<td>0.7655</td>
<td>0.2/0.0002</td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>0.7523</td>
<td>0.7606</td>
<td>0.3/0.0002</td>
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</tbody>
</table>
### Table: The test accuracy of ResNet-20

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Standard Dropout Ratio</th>
<th>Standard Acc</th>
<th>Augmented Acc</th>
<th>Augmented Dropout Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.1</td>
<td>0.9618</td>
<td>0.9627</td>
<td>0.1/0.0002</td>
</tr>
<tr>
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<td>0.9626</td>
<td>0.9648</td>
<td>0.2/0.0002</td>
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<td>0.3</td>
<td>0.9655</td>
<td>0.9667</td>
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<tr>
<td>SVHN</td>
<td>0.1</td>
<td>0.9193</td>
<td>0.9196</td>
<td>0.1/0.0001</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>0.9176</td>
<td>0.9195</td>
<td>0.2/0.0001</td>
</tr>
<tr>
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<td>0.9163</td>
<td>0.9177</td>
<td>0.3/0.0001</td>
</tr>
<tr>
<td>CIFAR10</td>
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<tr>
<td>CIFAR100</td>
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Thank You