hw2: report

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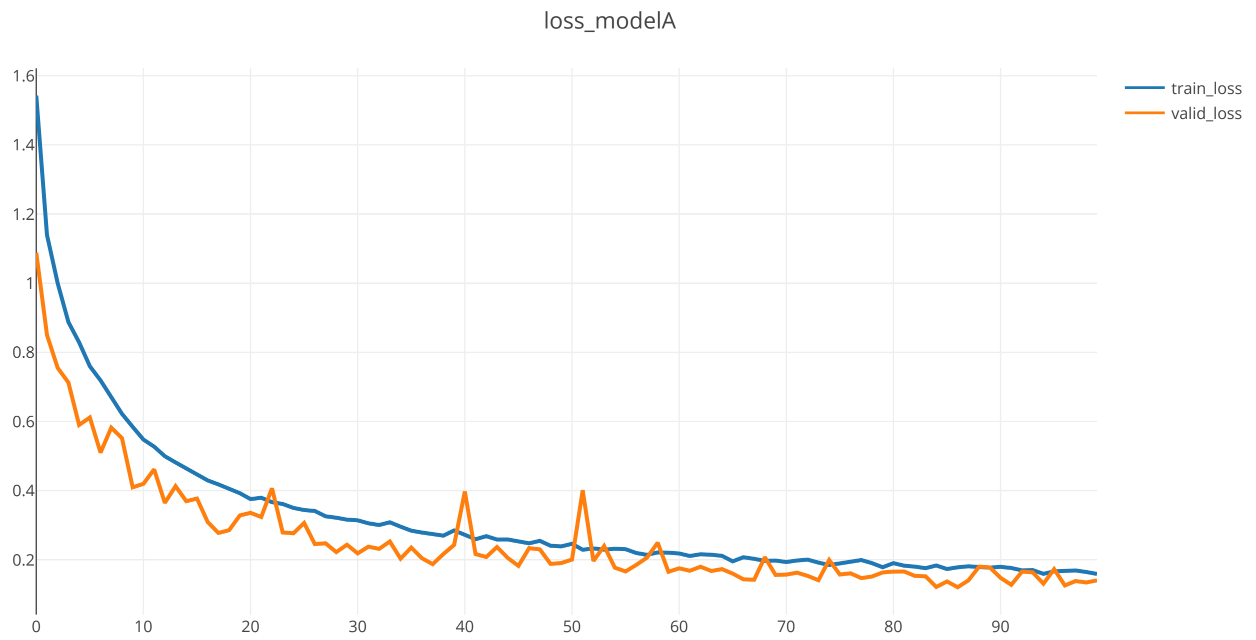
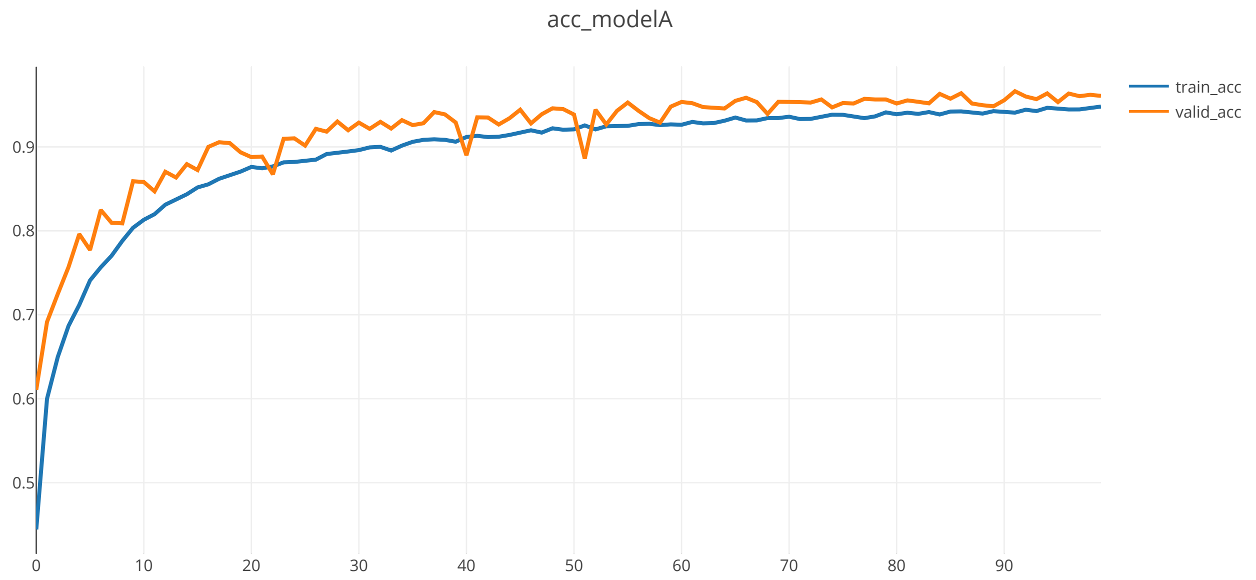
Task A: Large-Scale Learning

1. Training and test curves [10pts]

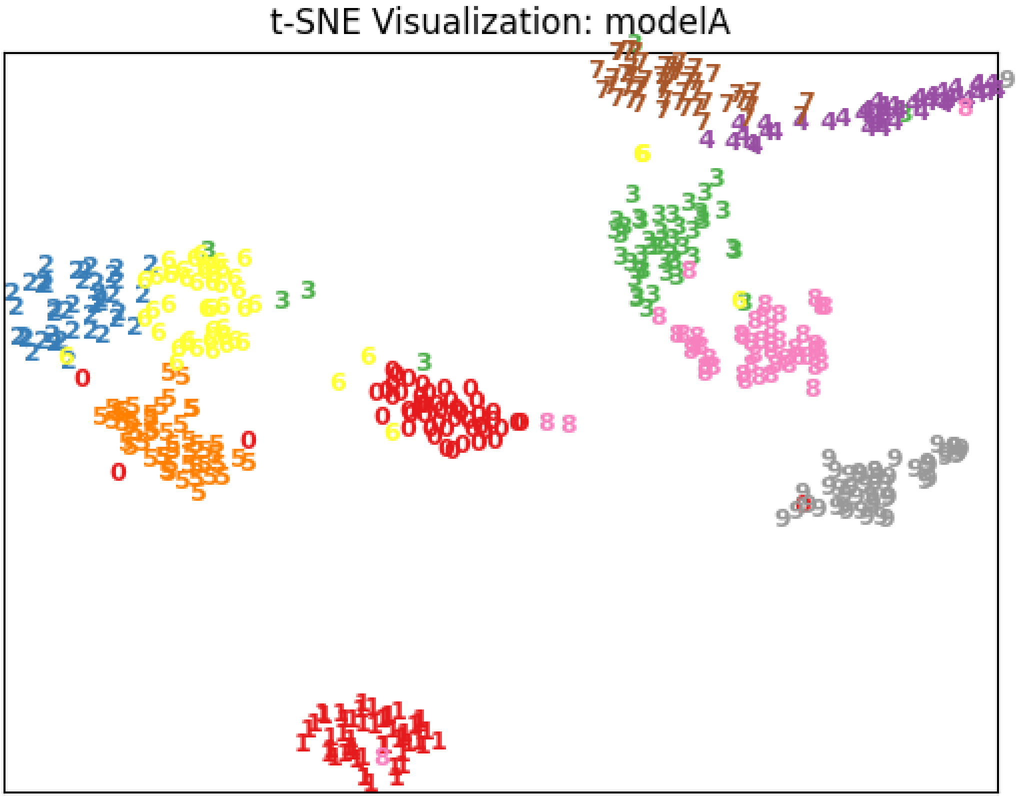
Use Visdom to visualize training and test curves. Model A (ResNet50) achieves **94.80%** accuracy on the **large-scale training** set and **96.63%** accuracy on the **test** set. The training and test curves are as follows:





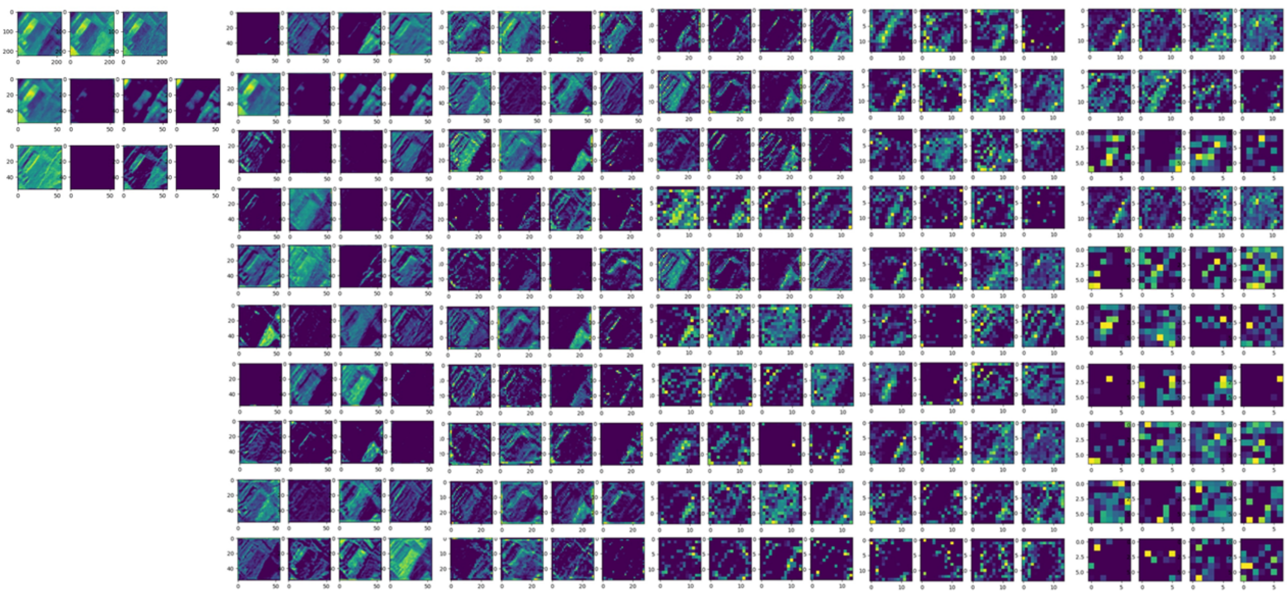
2. t-SNE Visualization [10pts]

Visualize the features before the last fully-connected layer using **t-SNE**. Select **500** pictures from the test set (**50 pictures per category**), and the tSNE distribution diagram of the **label** is as follows:



3. conv Visualization [10pts]

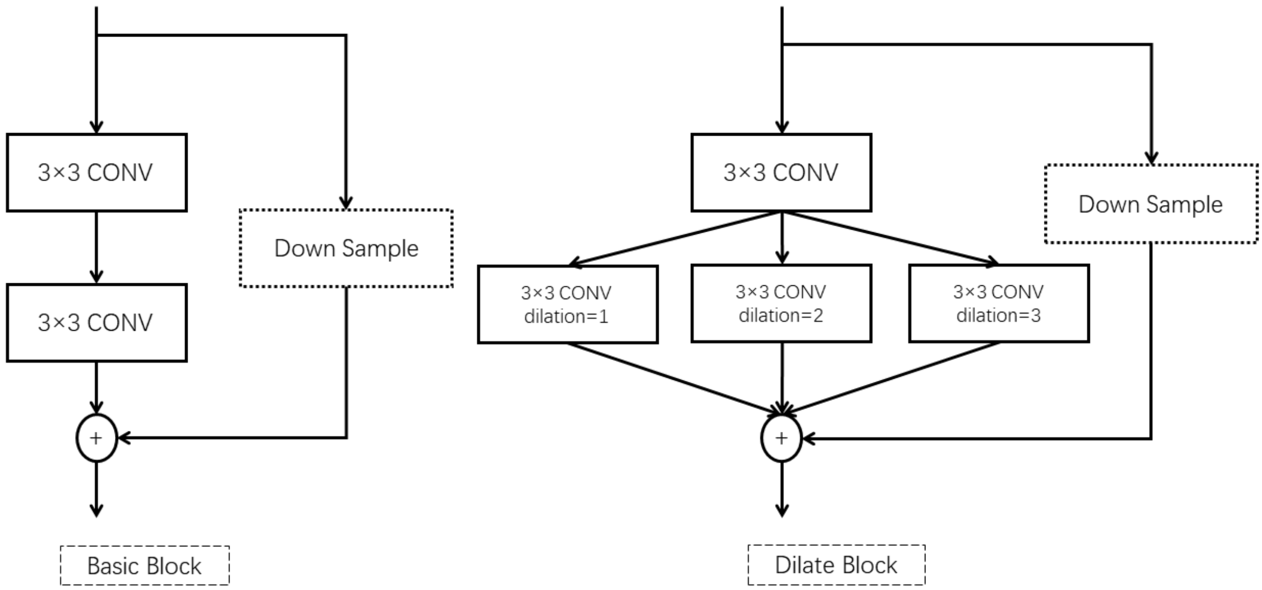
Use `AnnualCrop_11.jpg` in the test set to visualize the convolutional layer features of model A (display up to 4 images). According to the order from top to bottom and left to right (the first one in the upper left corner is the input), the results are as follows:



Task B: Medium-Scale Learning

Inspired by the dilated convolution [1], my model B will use 3 convolution kernels with different dilation rates to replace part of the convolutional layer of resNet (replace `BasicBlock` with `DilateBlock` in the code), as shown in the figure below. The following experiments will focus on these aspects:

- Different number of layers
  - 18 & 34
- Different replacement (using dilate module in different layers)
  - [0,0,1,1] means layer1 and layer2 use `BasicBlock`, layer3 and layer4 use `DilateBlock`
- Data augmentation
  - RandomVerticalFlip、RandomHorizontalFlip
  - CenterCrop、RandomResizedCrop
- Learning rate strategy
  - Adam



1. Training and test curves [10pts]

Sorry for not having enough time to go through all possible situations. The summary results are shown in the table below.

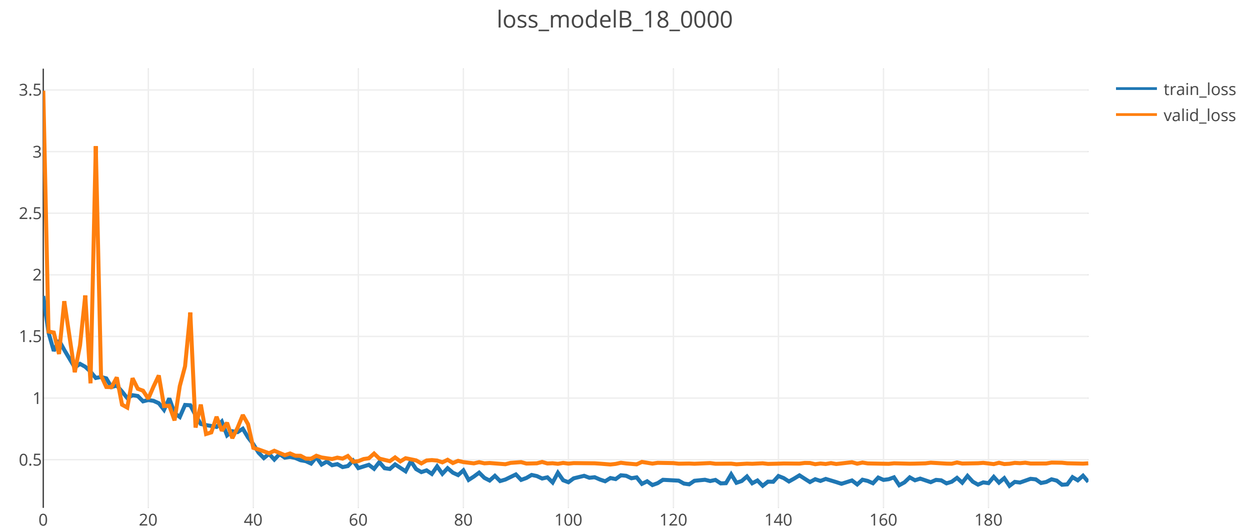
Model	Training Accuracy	Test Accuracy
DilateNet18[0,0,0,0] (ResNet18)	**90.60%**	**86.01%**
DilateNet18[0,0,0,1]	91.60%	86.56%
DilateNet18[0,0,1,1]	**94.50%**	**87.76%**
DilateNet18[1,1,1,1]	92.90%	87.13%
DilateNet34[0,0,1,1]	89.50%	84.59%

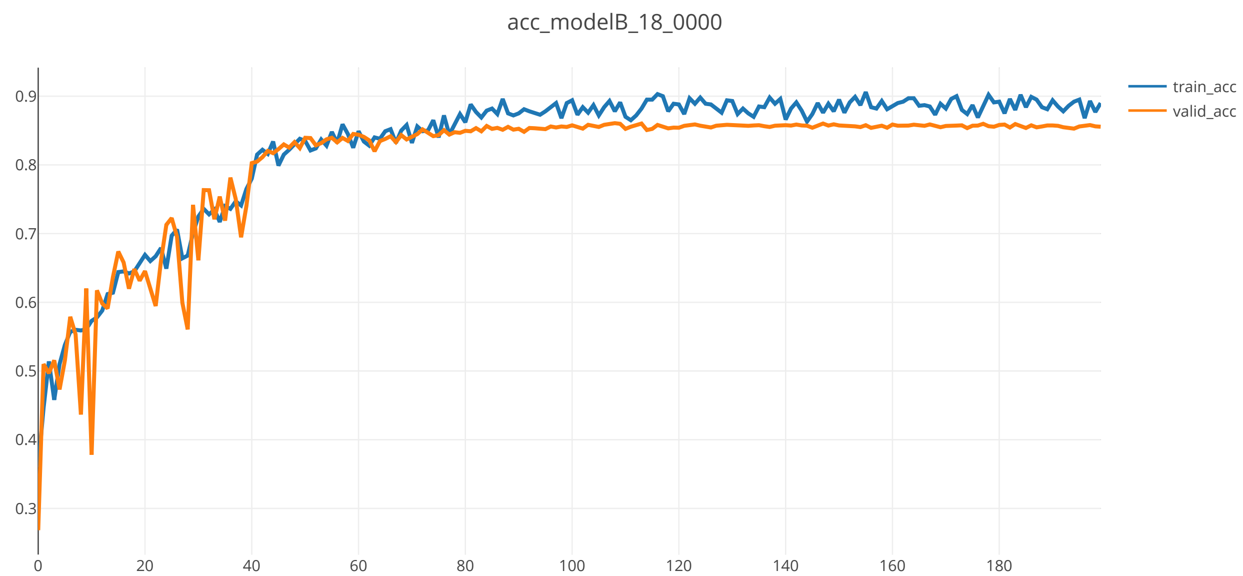
Result analysis:

- Compared with the model (DilateNet18[0,0,0,0]) that does not use `DilateBlock`, the accuracy of the DilateNet18[0,0,1,1] is improved (training accuracy: 90.60% to 94.50%, test accuracy: 86.01% to 87.76%).
- Comparing DilateNet18[0,0,1,1] and DilateNet34[0,0,1,1], the depth of the model does not necessarily have a positive effect on the accuracy
- Different replacements have an impact on accuracy. In the limited experimental results, [0,0,1,1] is the best.

1.1. DilateNet18 [0,0,0,0] (ResNet18)

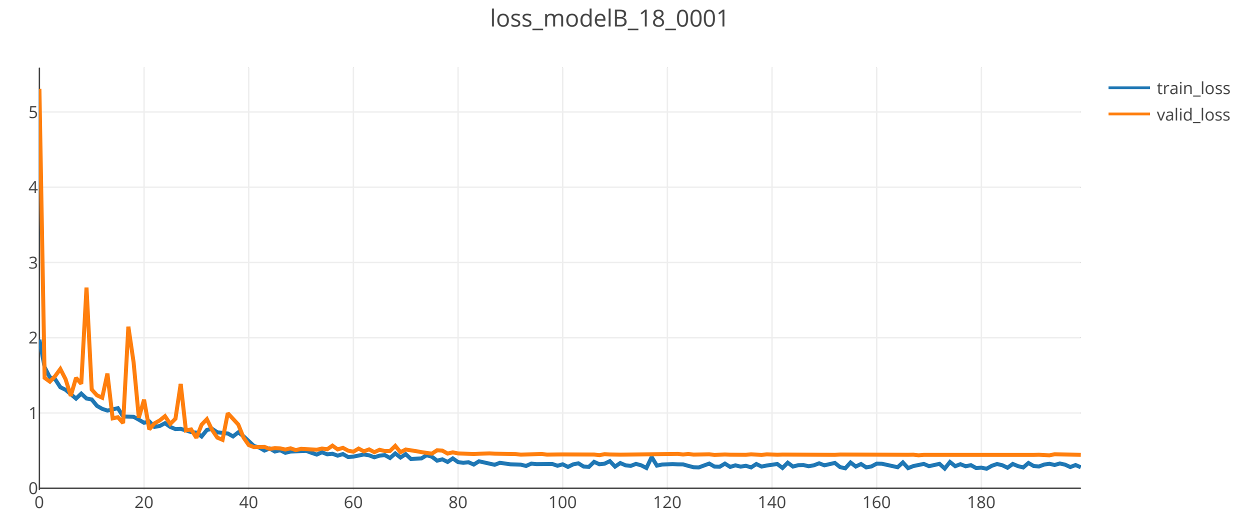
Use Visdom to visualize training and test curves. Model B (**DilateNet18 [0,0,0,0] (ResNet18)**) achieves **90.60%** accuracy on the **medium-scale training** set and **86.01%** accuracy on the **test** set. The training and test curves are as follows:

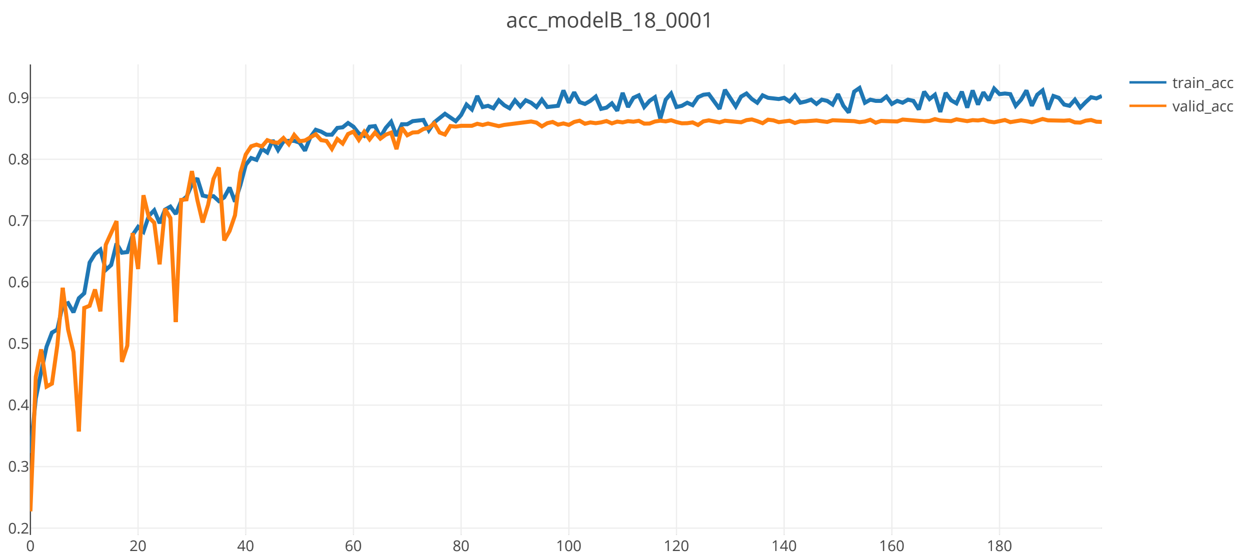




1.2. DilateNet18 [0,0,0,1]

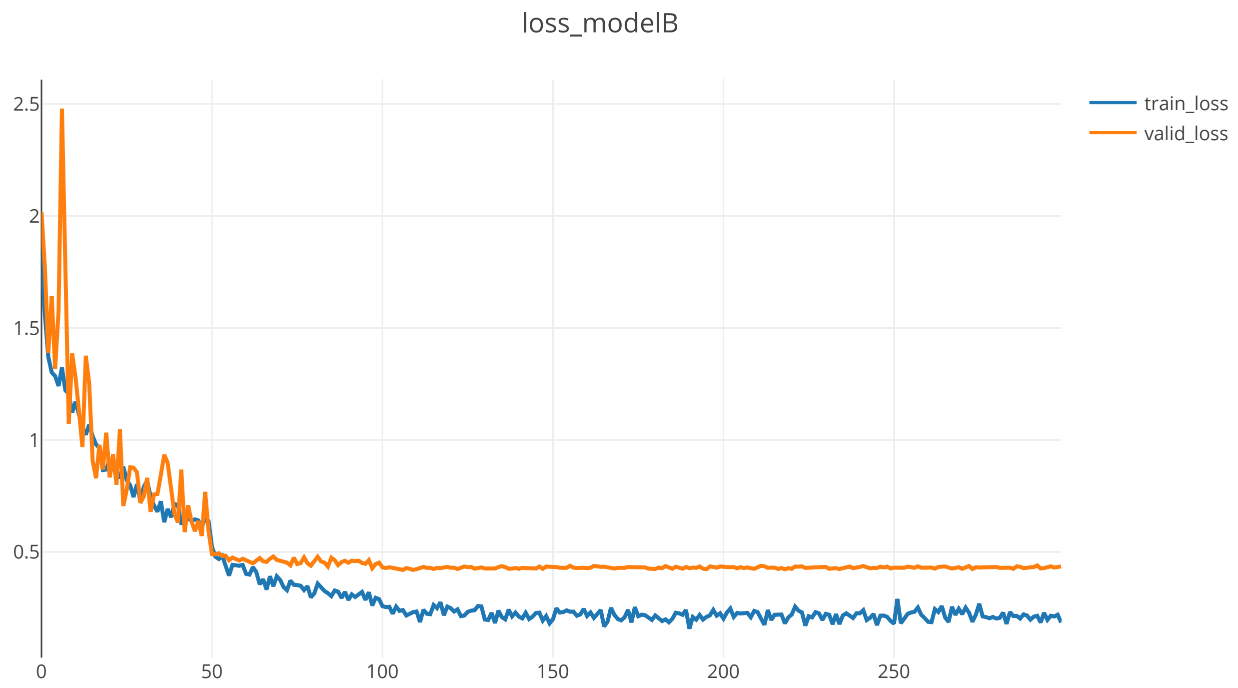
Use Visdom to visualize training and test curves. Model B (**DilateNet18[0,0,0,1]**) achieves **91.60%** accuracy on the **medium-scale training** set and **86.56%** accuracy on the **test** set. The training and test curves are as follows:

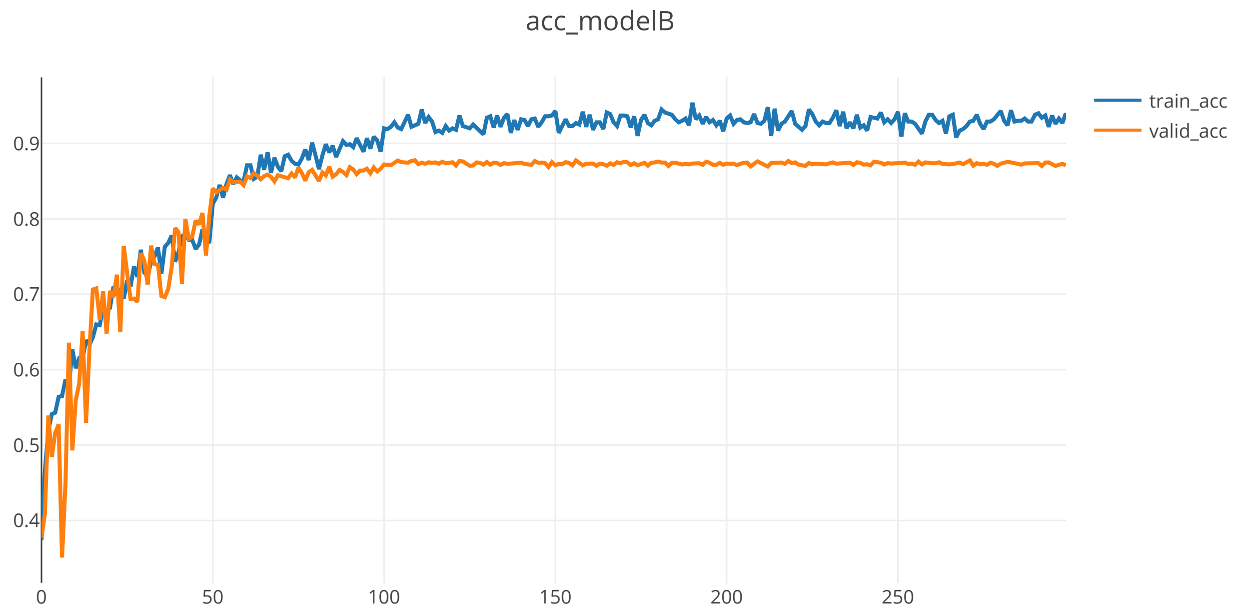




1.3. DilateNet18 [0,0,1,1]

Use Visdom to visualize training and test curves. Model B (**DilateNet18[0,0,1,1]**) achieves **94.50%** accuracy on the **medium-scale training** set and **87.76%** accuracy on the **test** set. The training and test curves are as follows:

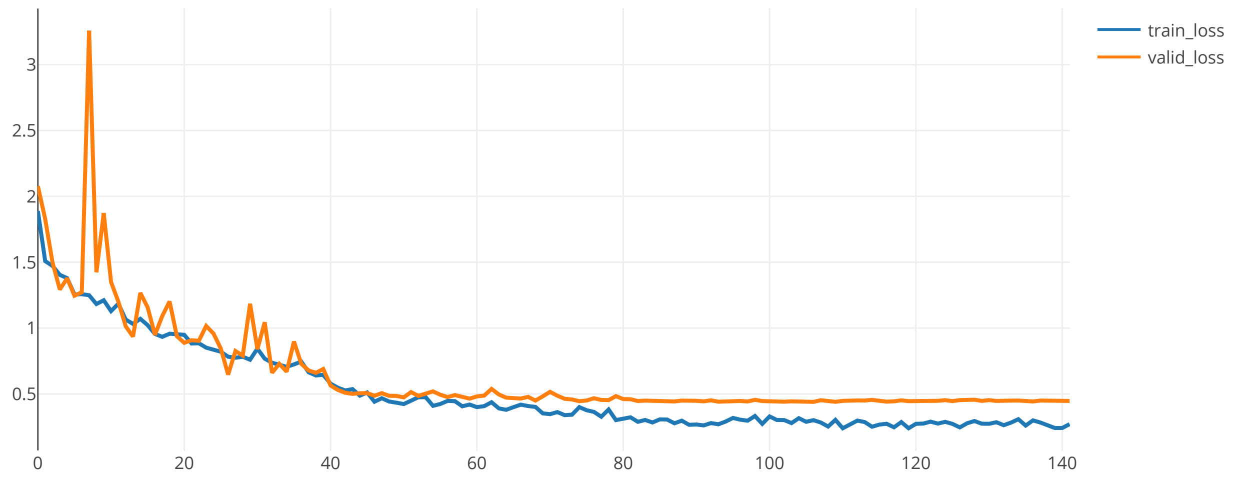




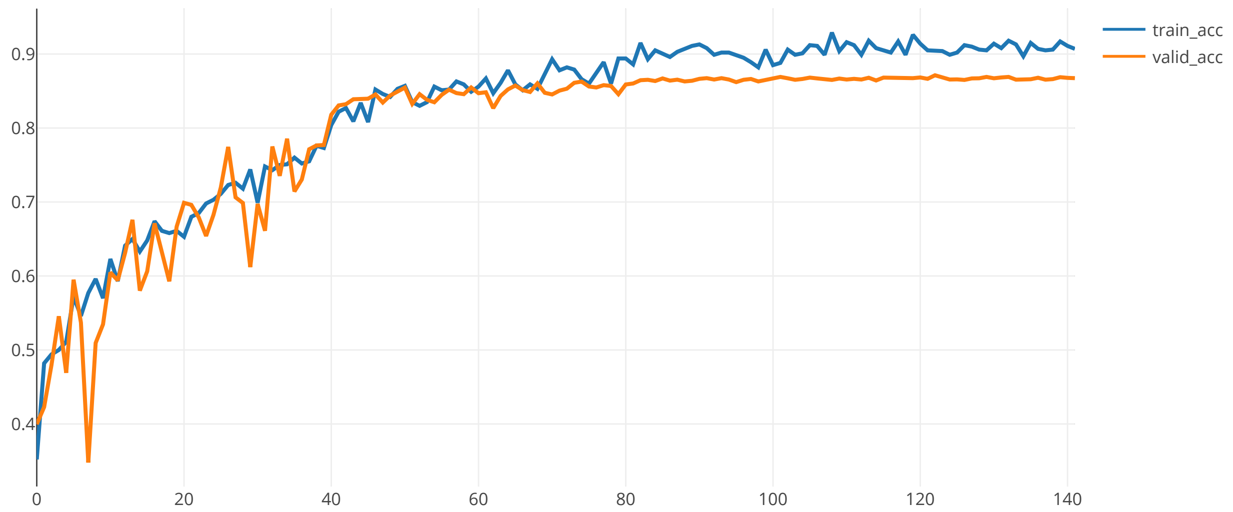
1.4. DilateNet18 [1,1,1,1]

Use Visdom to visualize training and test curves. Model B (**DilateNet18[1,1,1,1]**) achieves **92.90%** accuracy on the **medium-scale training** set and **87.13%** accuracy on the **test** set. The training and test curves are as follows:

loss_modelB_18_1111

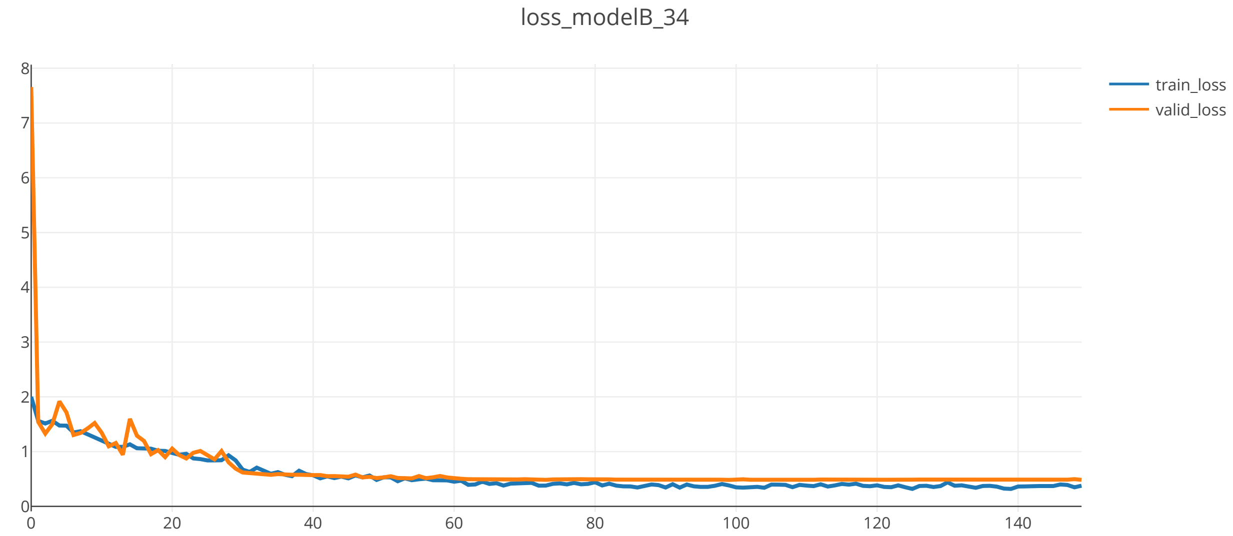


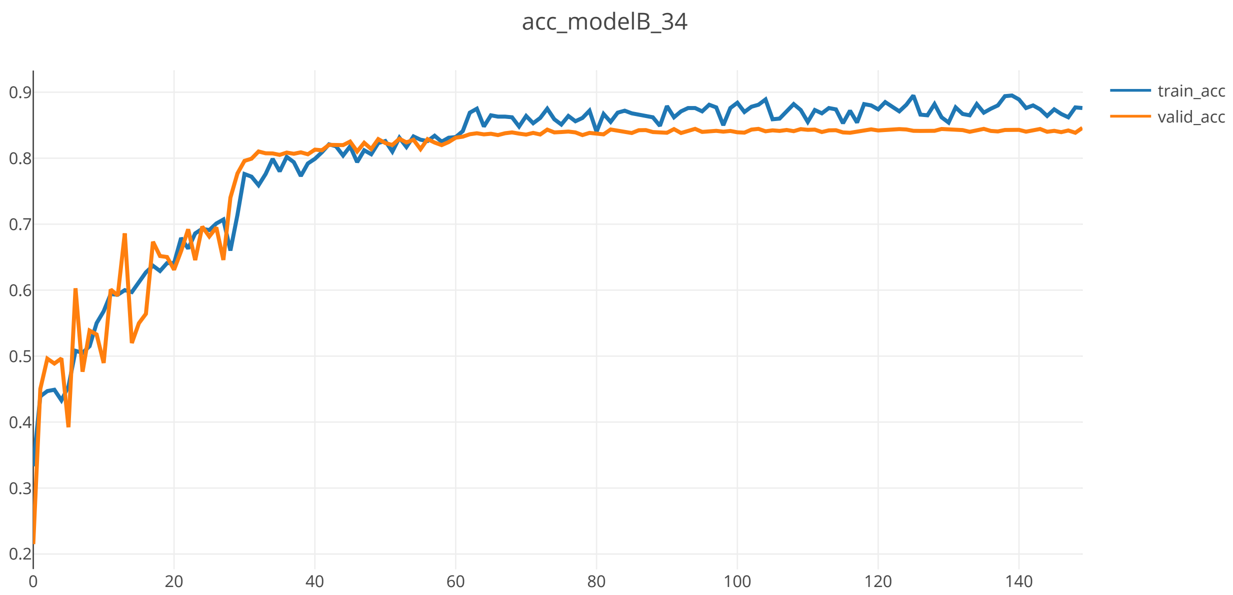
acc_modelB_18_1111



1.5. DilateNet34 [0,0,1,1]

Use Visdom to visualize training and test curves. Model B (**DilateNet18[0,0,1,1]**) achieves **89.50%** accuracy on the **medium-scale training** set and **84.59%** accuracy on the **test** set. The training and test curves are as follows:





2. Data augmentation and learning rate strategy [10pts]

Sorry for not having enough time to go through all possible situations. Using **`RandomHorizontalFlip`** and **`RandomResizedCrop`**, the result of Model B is as 1.3 (DilateNet18 [0,0,1,1]). In addition, all experiments in 1 used **`Adam optimizer`** with **`MultiStepLR`**.

The following experiments will all use DilateNet18 [0,0,1,1]. The summary results are shown in the table below.

Data Augmentation	Learning Rate Strategy	Training accuracy	Test accuracy
RandomHorizontalFlip + RandomResizedCrop	Adam + MultiStepLR	94.50%	87.76%
RandomVerticalFlip + RandomResizedCrop	Adam + MultiStepLR	93.40%	86.72%
RandomHorizontalFlip + CenterCrop	Adam + MultiStepLR	100.00%	44.30%

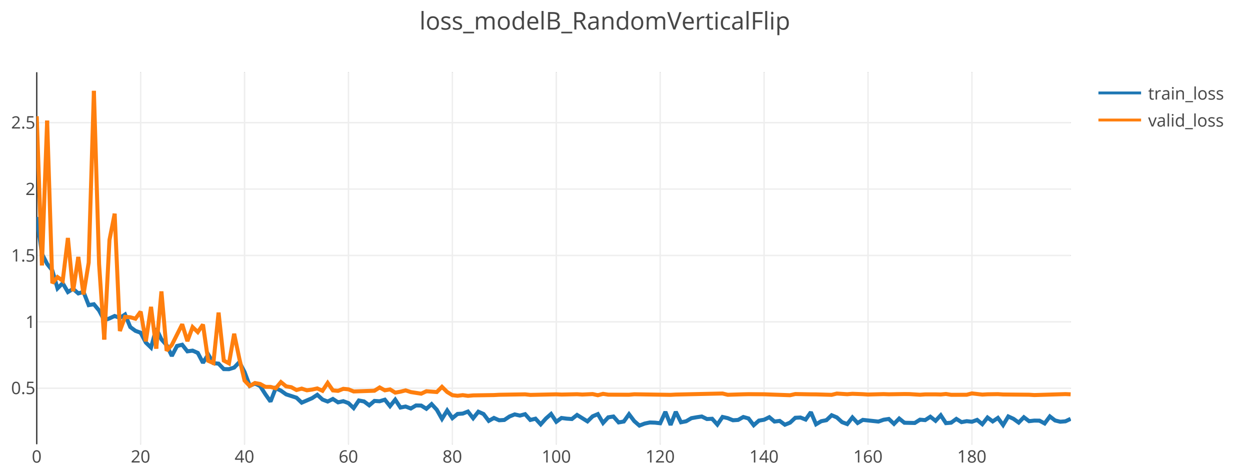
Data Augmentation	Learning Rate Strategy	Training accuracy	Test accuracy
RandomHorizontalFlip + RandomResizedCrop	SGD + None	92.60%	84.83%

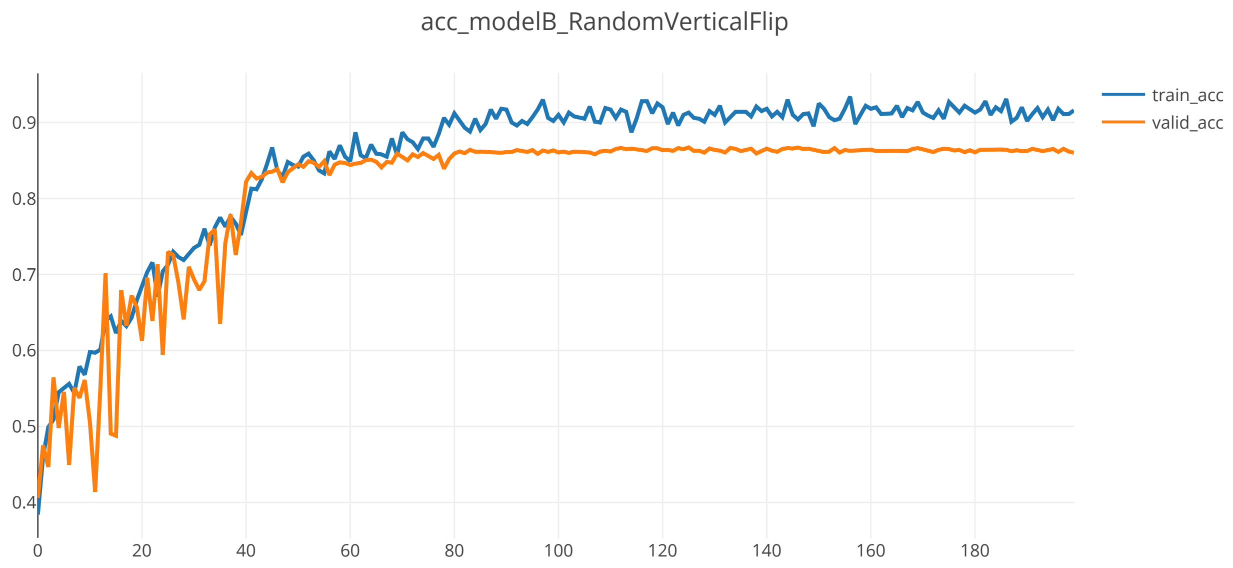
Result analysis:

- Data augmentation method
  - In the limited experimental results, RandomHorizontalFlip + RandomResizedCrop provided by the start code is the best.
  - The results of training with CenterCrop are very poor
- Learning Rate Strategy
  - In the limited experimental results, Adam + MultiStepLR improves the accuracy of the model.

2.1. RandomVerticalFlip

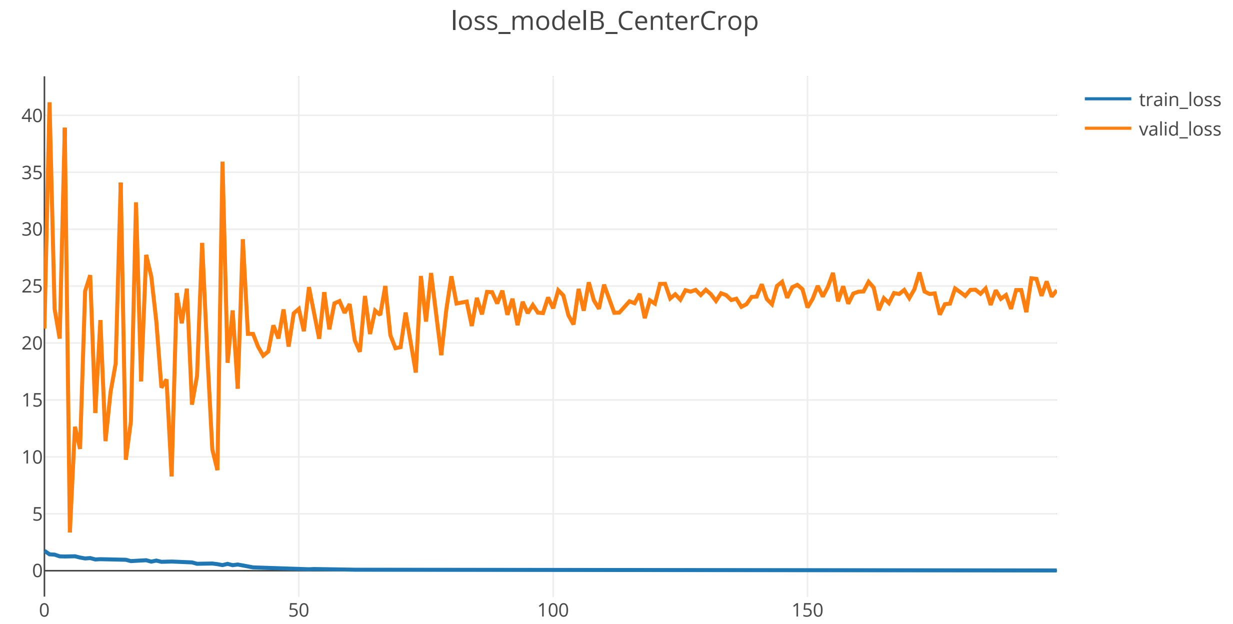
Use Visdom to visualize training and test curves. Using `RandomVerticalFlip`, Model B achieves **93.40%** accuracy on the **medium-scale training** set and **86.72%** accuracy on the **test** set. The training and test curves are as follows:

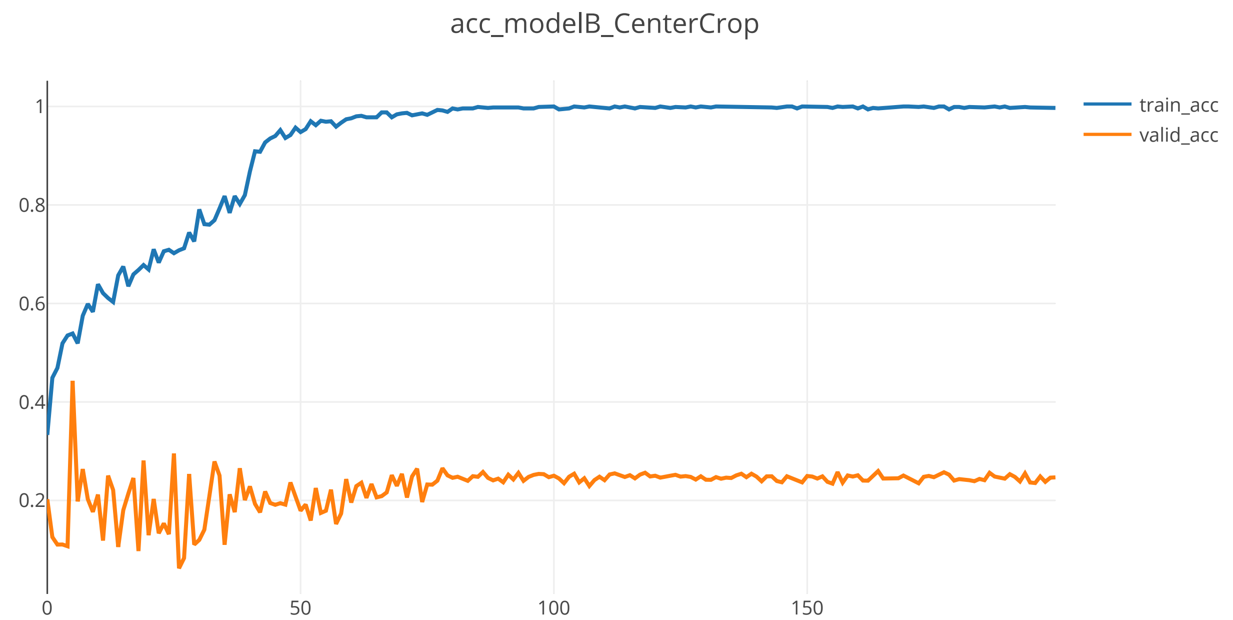




2.2. CenterCrop

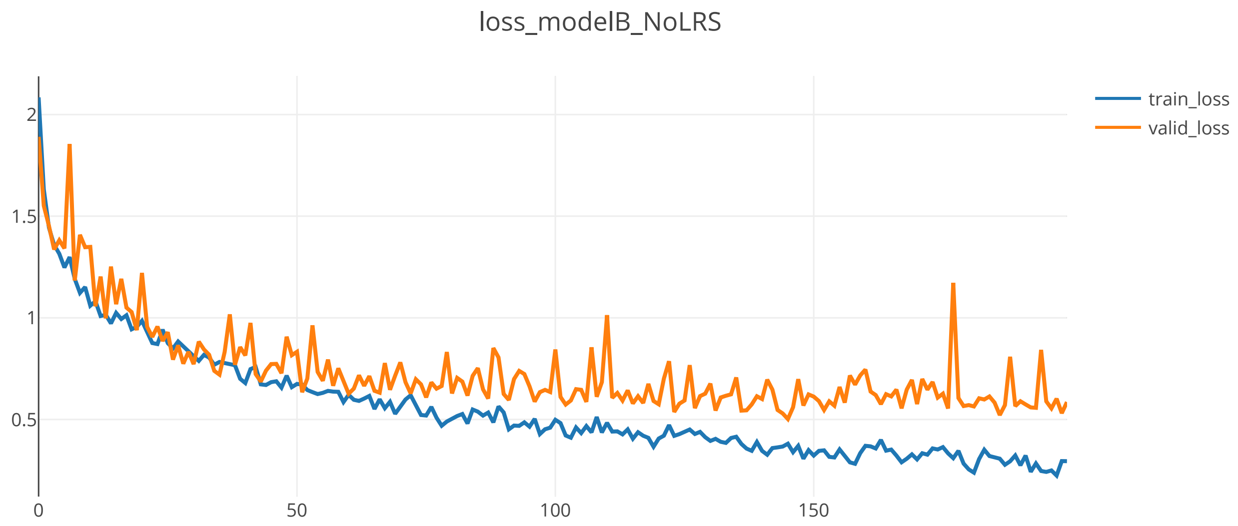
Use Visdom to visualize training and test curves. Using `CenterCrop`, Model B achieves **100.00%** accuracy on the **medium-scale training** set and **44.30%** accuracy on the **test** set. The training and test curves are as follows:

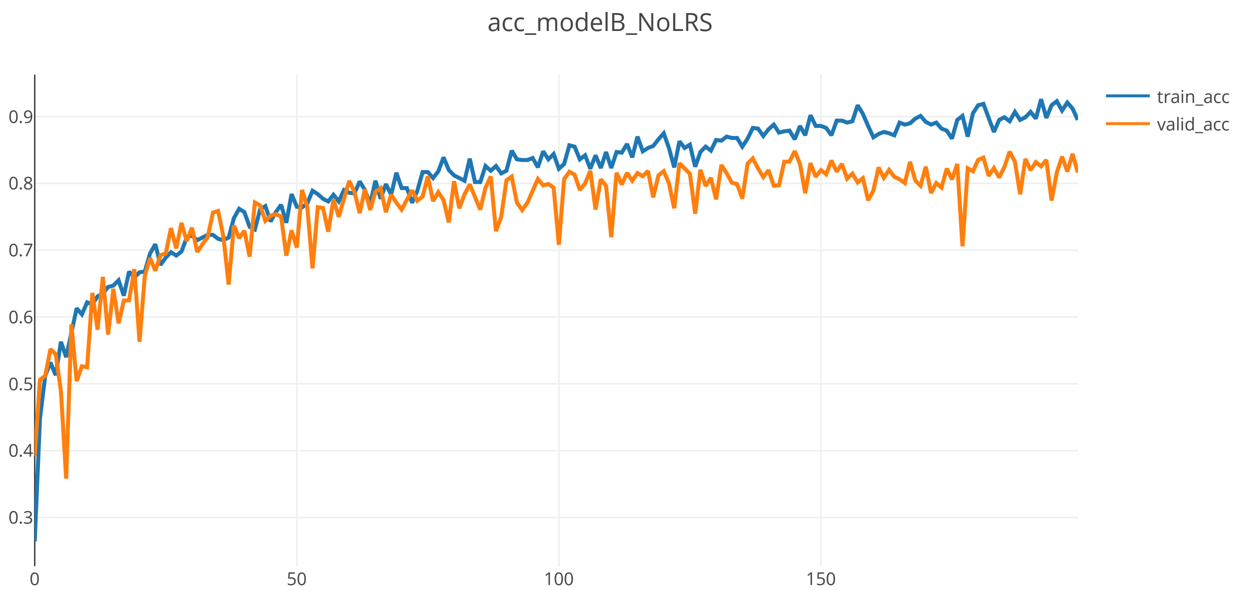




2.3. No Learning Rate Strategy

Use Visdom to visualize training and test curves. Using `CenterCrop`, Model B achieves **92.60%** accuracy on the **medium-scale training** set and **84.83%** accuracy on the **test** set. The training and test curves are as follows:





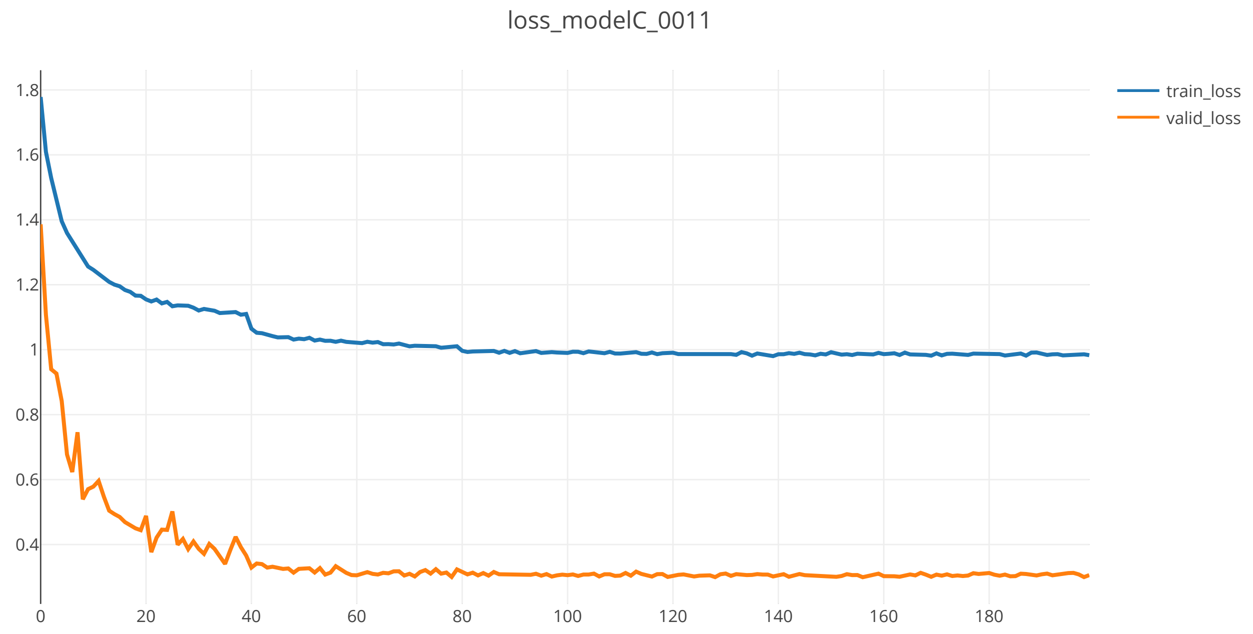
Task C: Weakly-Supervised Learning

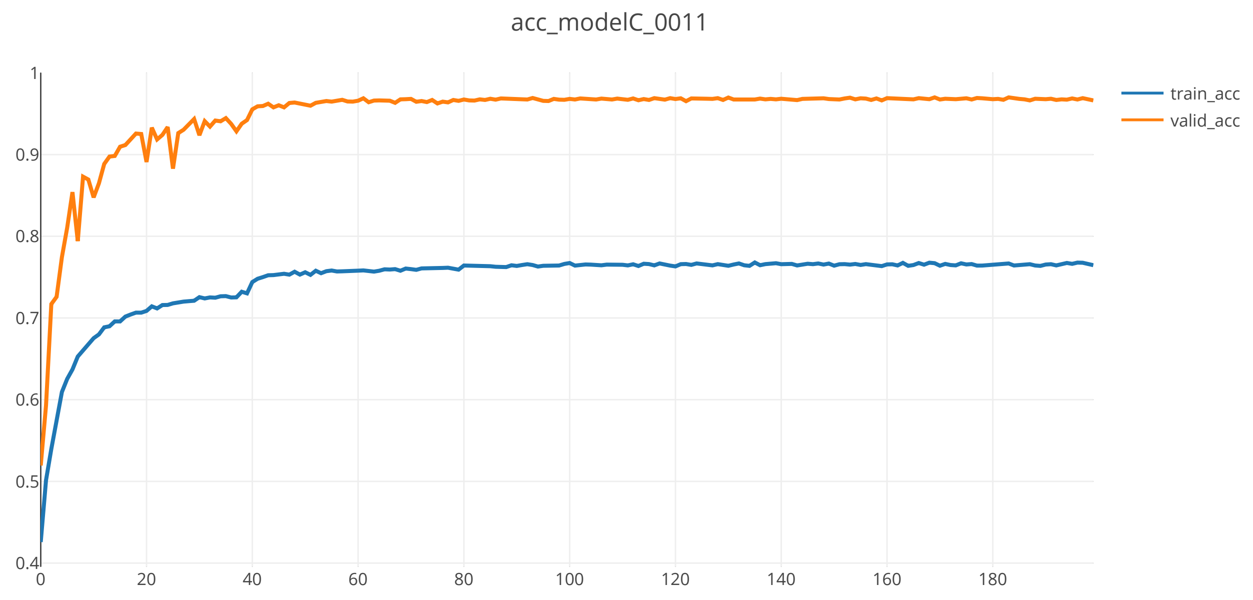
In order to verify the universality of model B, I still use DilateNet18[0,0,1,1] as my model C for Weakly-Supervised Learning. Experimental results show that the accuracy of the model on the test set in Weakly-Supervised Learning is as high as 95.98%. Besides, I used **Kaiming Normal** for weight initialization. The following experiments all use RandomHorizontalFlip+RandomResizedCrop and Adam+MultiStepLR for training and will focus on these aspects:

- Compare with DilateNet18[0,0,0,0] (ResNet18) to verify the effectiveness of dilated convolution.
- Use Kaiming Normal or not.

1. Training and test curves [20pts]

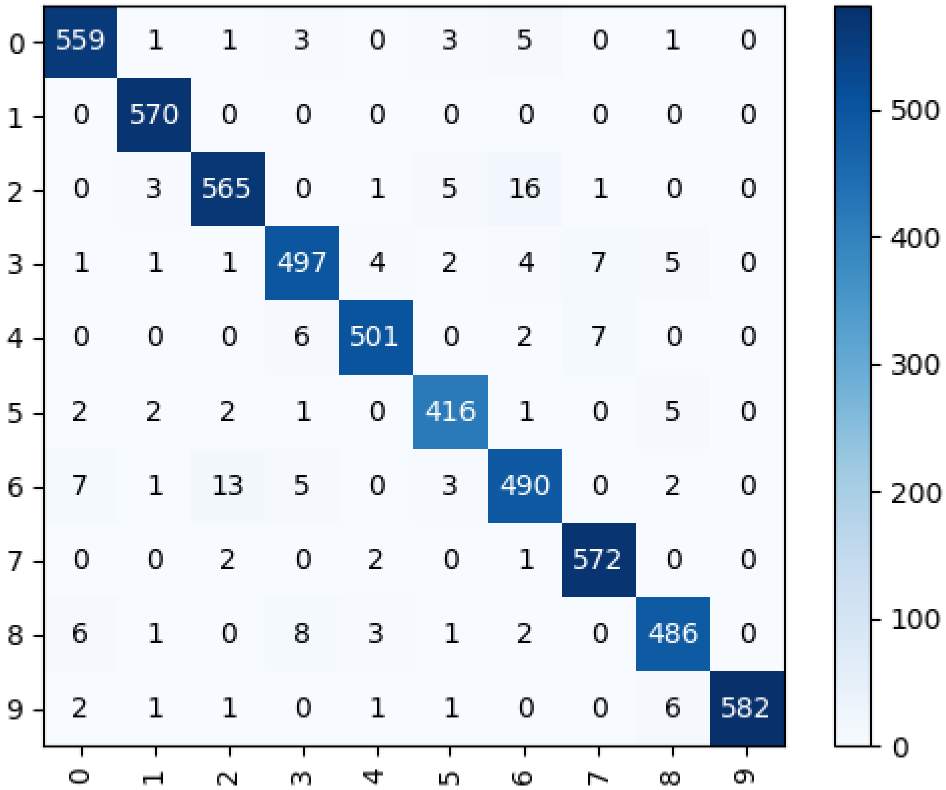
Use Visdom to visualize training and test curves. Model C (DilateNet18[0,0,1,1]) achieves **76.80%** accuracy on the **weakly-supervised training** set and **97.00%** accuracy on the **test** set. The training and test curves are as follows:





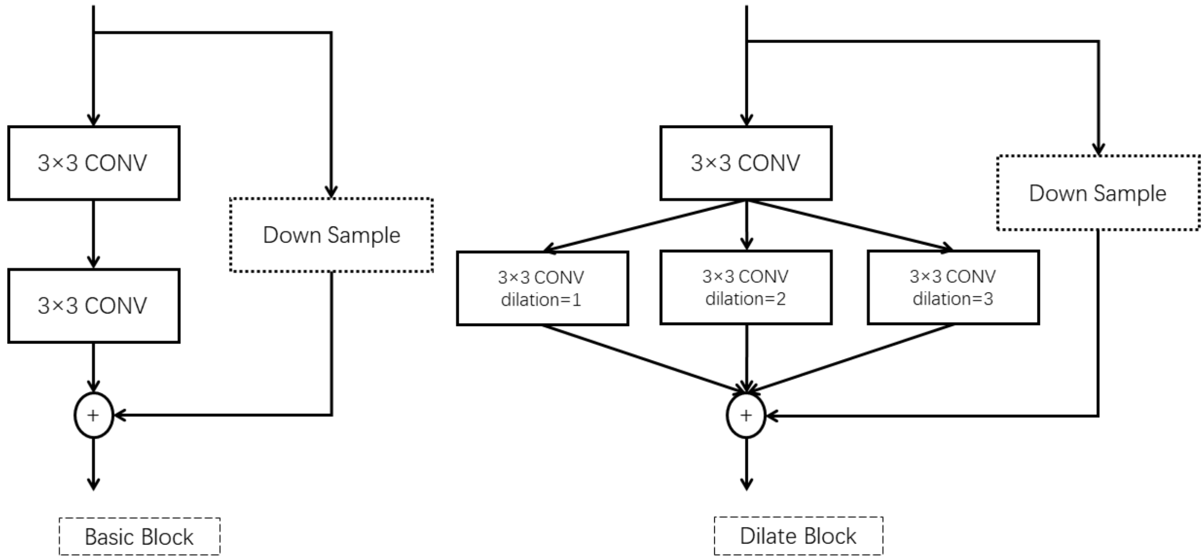
2. Confusion matrix [10pts]

The confusion matrix of model C on test set is as follows:



3. Extra techniques to improve [20pts]

1. Use 3 convolution kernels with different **dilation rates** to replace part of the convolutional layer of resNet



- As shown in the figure above, using 3 convolution kernels with different dilation rates to share the same input, not only does not bring input loss, but because of the 3 different receptive fields, the effective information of the input is increased.

2. Used **Kaiming Normal** for weight initialization

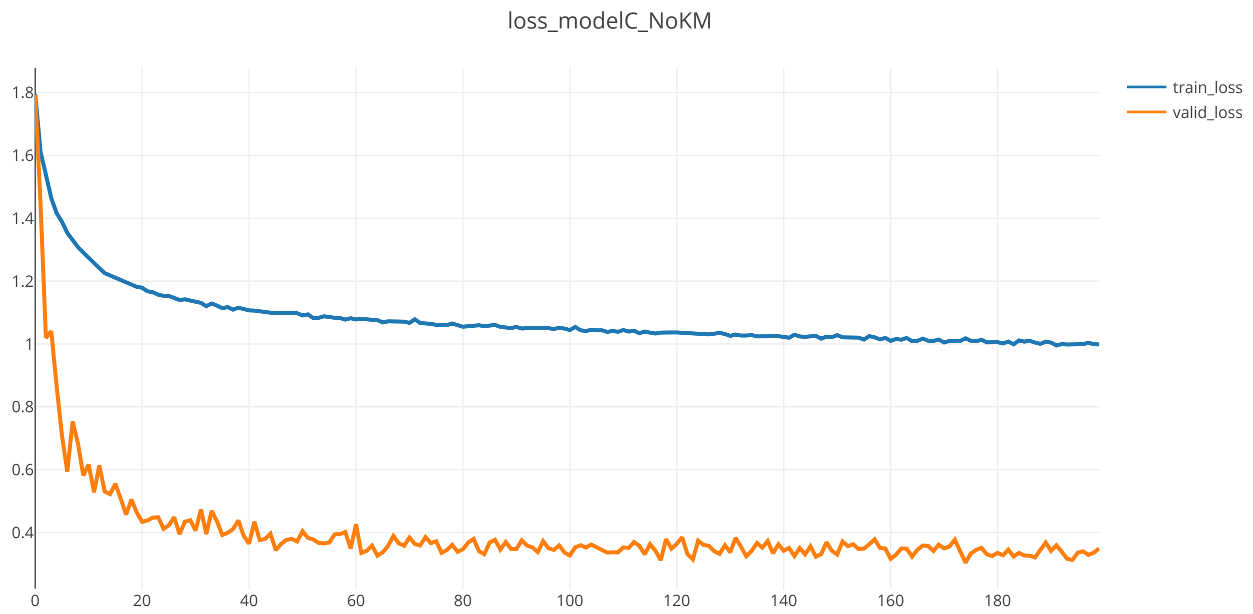
- For the effectiveness of Kaiming Initialization, please refer to Reference [2]. For more details, please refer to section 2.2 of the paper.

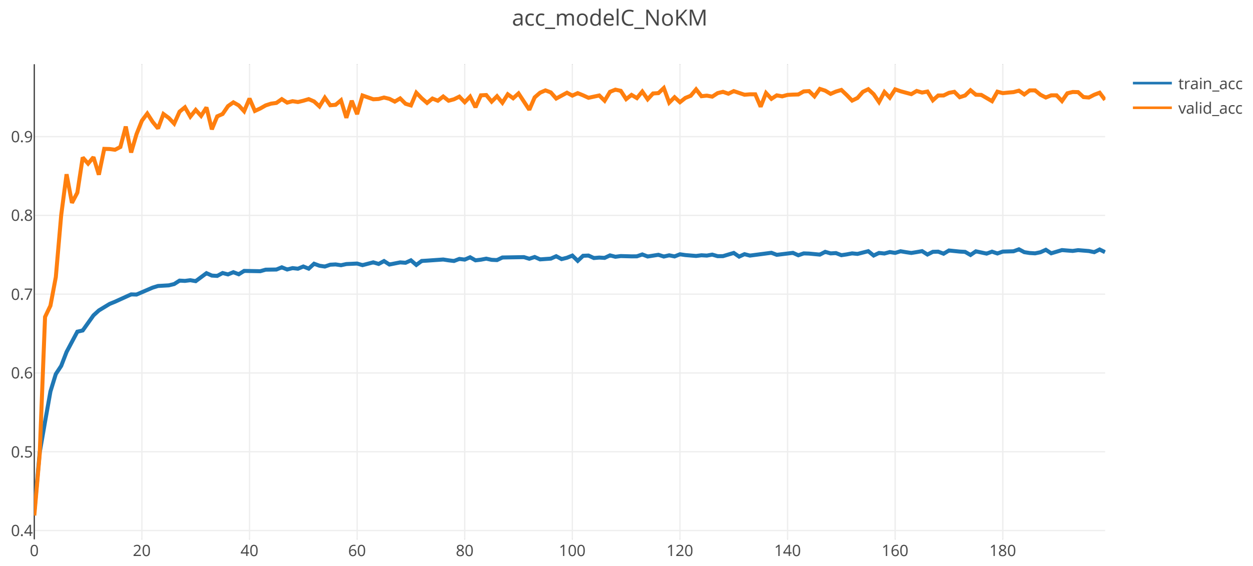
I used the above two techniques to improve the model C. The summary results are shown in the table below.

Extra Techniques	Training accuracy	Test accuracy
Dilate+Kaiming Normal	76.80%	**97.00%**
Dilate (no kaiming)	76.39%	96.81%
Kaiming Normal (no dilate)	75.69%	96.17%

3.1 No Kaiming

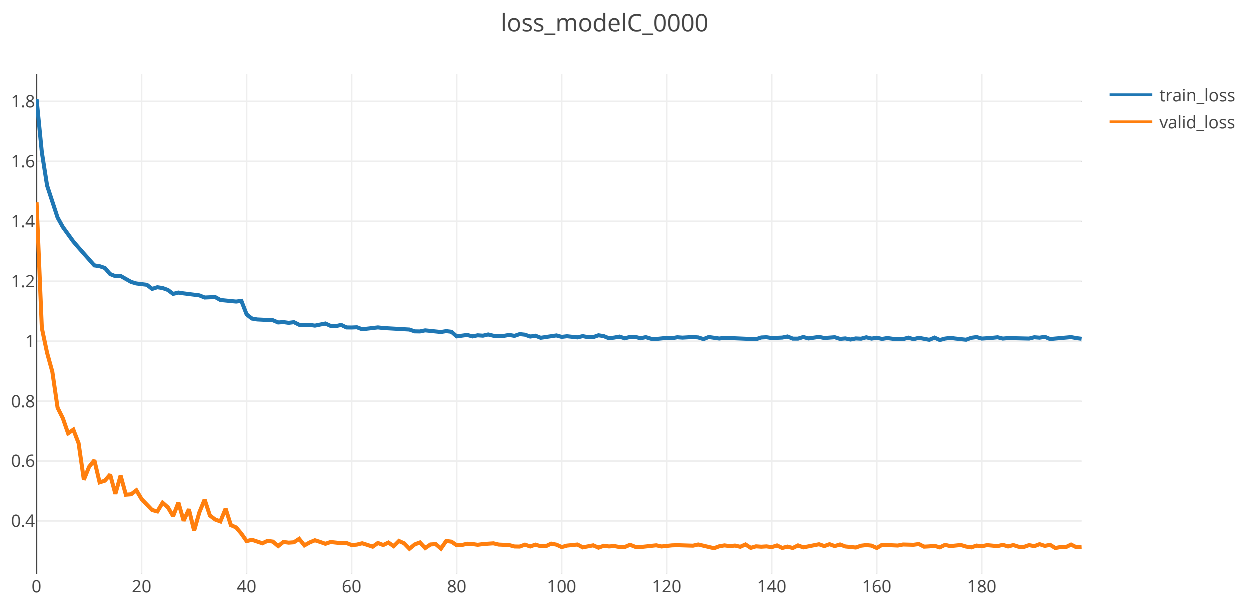
Use Visdom to visualize training and test curves. Model C (DilateNet18[0,0,1,1]) **without** Kaiming Normal achieves **76.39%** accuracy on the **weakly-supervised training** set and **96.81%** accuracy on the **test** set. The training and test curves are as follows:

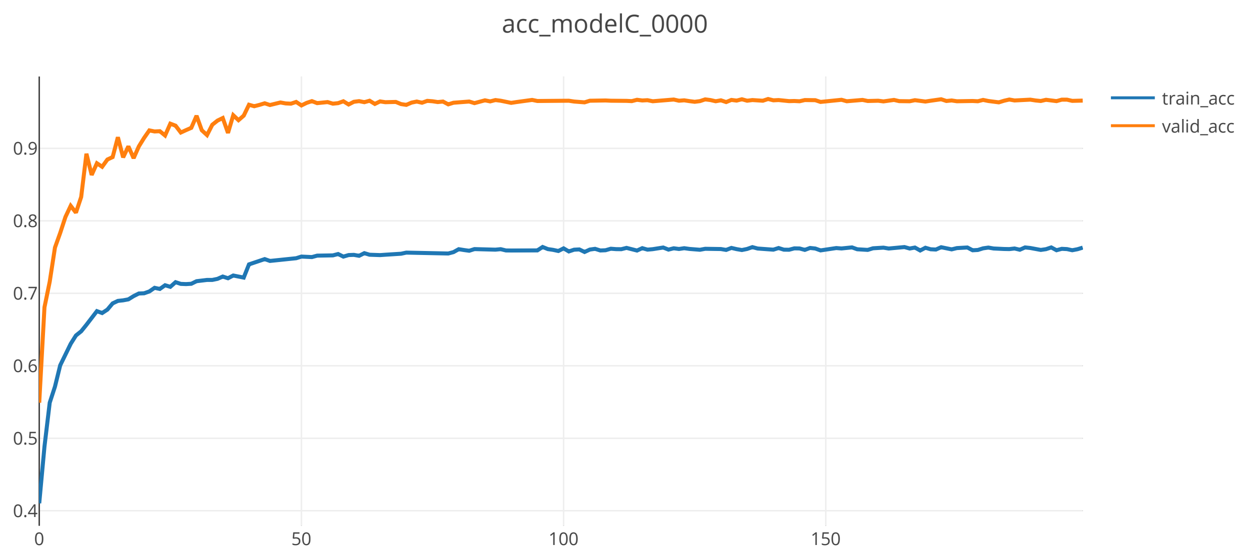




3.2 No Dilate

Use Visdom to visualize training and test curves. DilateNet18[0,0,0,0] (ResNet18) **with** Kaiming Normal achieves **75.69%** accuracy on the **weakly-supervised training** set and **96.17%** accuracy on the **test** set. The training and test curves are as follows:





references

[1] Wang, Panqu, et al. "Understanding convolution for semantic segmentation." *2018 IEEE winter conference on applications of computer vision (WACV)*. IEEE, 2018.

[2] He, Kaiming, et al. "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification." *Proceedings of the IEEE international conference on computer vision*. 2015.