ConvNet实验报告

18340052 何泽

一、要求

Train your best model

Try to get the best performance that you can on CIFAR-10 using a ConvNet. You can try some different parameters or add batch/layer normalization and dropout layer which are completed in annp/layers.py into your model for faster training.

Things you can try:

- Filter size: Different filters can extract different degree of image features
- Number of filter: Do more or fewer better ?
- Network architecture: The network above has two layers of trainable parameters. Can you do better with deeper network ? You can implement alternative architecture in the file annp/classifiers/cnn.py.

Expectation

At last, you should be expected to train a ConvNet that gets at least 60% accuracy on the validation set.

You should use the space below to experiment and train your network. The final cell should contain the training, validation and test set accuracies for your final trained network.

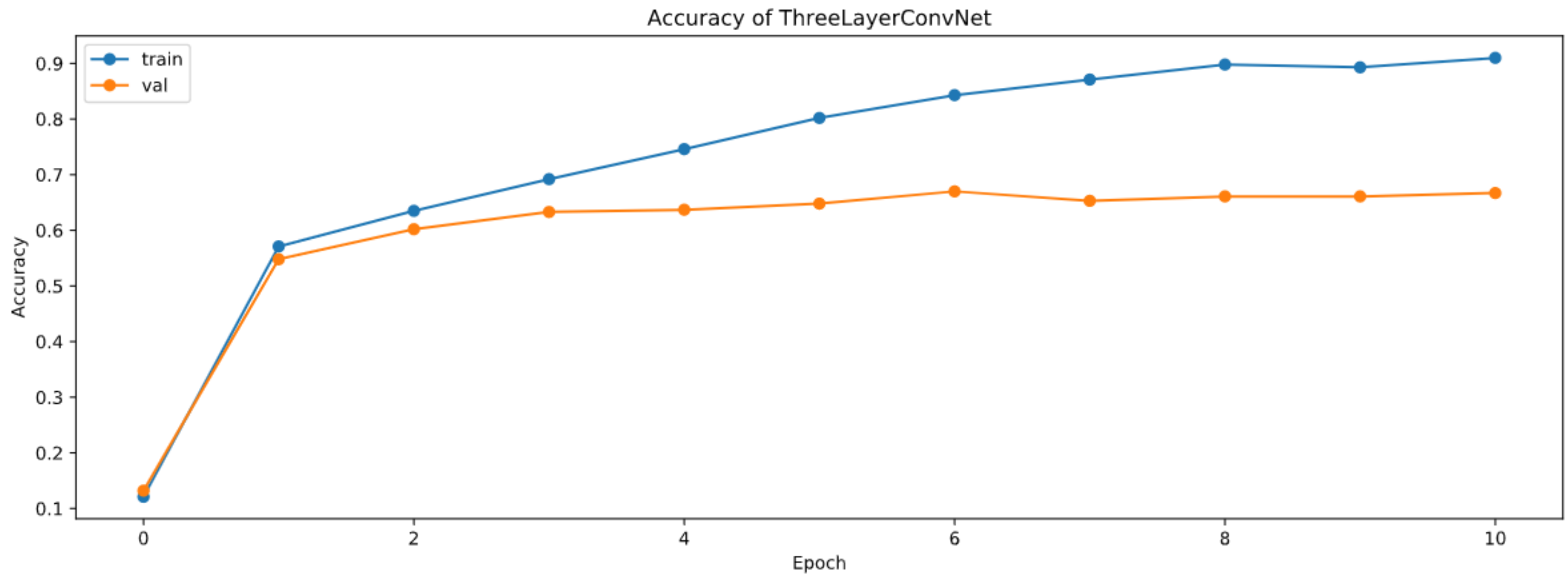
You should write a report about what you did, any additional features that you implemented and any visualizations or graphs on evaluating your network.

Attention

You should not be allowed to use any deep learning framework !!!

二、三层网络

首先，为了对比，我训练了上面已经实现过的三层网络，并将学习率由1e-3调小到1e-4，然后训练了10轮，可以看到结果如下：



在训练集上准确率最高83.91%，测试集上最高67%，此时其实已经达到了60%准确率的要求，不过接下来我将增加网络的层数，改变结构，并在之后的版本上讨论Filter size和filter大小的影响。

三、ConvNet

1. 模型架构

之前的三层网络结构是 `conv - relu - max pool - affine - relu - affine - softmax` ，我准备再加一层卷积层并将后一个纺射层删除，即更改之后的结构是这样的： `conv - relu - conv - relu - max pool - affine - relu - softmax` ，实现为 `cnn.py` 的 `ConvNet` 类。

2. 代码解读

和前面一样依然作用于(N,C,H,W)的minibatch，即N个图像，C条通道，长宽为H和W。

首先是一些初始化：

- 首先初始化参数并定义维度

```
self.params = {}
self.bn_params = {}
self.spatialbn_params = {}
self.use_bn = use_batchnorm
self.reg = reg
self.dtype = dtype
self.filter_size = filter_size
self.conv_layers = conv_layers
self.affine_layers = affine_layers
C,H,W = input_dim
```

```
F = filter_size
pad = (F-1)//2
pool_S = 2
H2,W2 = H,W
```

- 然后初始化卷积层的权重、偏置量和归一化的参数（γ 、β 以及平均值与方差）

```
for l in range(2*conv_layers):
    self.params['W%d' % (l+1)] = np.random.randn(num_filters,C,F,F) * weight_scale
    self.params['b%d' % (l+1)] = np.zeros(num_filters)
    C = num_filters
    if(l % 2 == 1 and l != 0):
        H2,W2 = [(H2+2*pad-F)//pool_S + 1, (W2+2*pad-F)//pool_S + 1]
        if(self.use_bn is True):
            self.params['gamma%d' % (l+1)] = np.ones(C)
            self.params['beta%d' % (l+1)] = np.zeros(C)
            self.spatialbn_params['running_mean'] = np.zeros(num_filters)
            self.spatialbn_params['running_var'] = np.zeros(num_filters)
```

- 和上面类似，接下来初始化纺射层的参数（权重、偏置量、γ 、β 以及平均值与方差）

```
if(affine_layers == 1):
    hidden_dims = [H2*W2*num_filters] + [hidden_dims] + [num_classes]
else:
    hidden_dims = [H2*W2*num_filters] + hidden_dims + [num_classes]

for l in range(affine_layers+1):
    self.params['W%d' % (l+2*conv_layers+1)] = np.random.randn(hidden_dims[l],hidden_dims[l+1]) * weight_scale
    self.params['b%d' % (l+2*conv_layers+1)] = np.zeros(hidden_dims[l+1])
    if(self.use_bn is True and l != affine_layers):
        self.params['gamma%d' % (l+2*conv_layers+1)] = np.ones(hidden_dims[l+1])
        self.params['beta%d' % (l+2*conv_layers+1)] = np.zeros(hidden_dims[l+1])
        self.bn_params['running_mean'] = np.zeros(hidden_dims[l+1])
        self.bn_params['running_var'] = np.zeros(hidden_dims[l+1])
```

- 然后将参数类型转变为浮点型：

```
for k, v in self.params.items():
    self.params[k] = v.astype(dtype)
```

接下来计算loss和梯度：

- 先对卷积层和池化层的前向传播的一些参数赋值

```
filter_size = self.filter_size
conv_param = {'stride': 1, 'pad': (filter_size - 1) / 2}
pool_param = {'pool_height': 2, 'pool_width': 2, 'stride': 2}
```

- 计算出前向传播的层数

```
total_layers = conv_layers+affine_layers+1
```

- 然后进行前向传播

```
for l in range(total_layers):
    # 卷积层
    if(l < conv_layers):
        conv_a, conv_cache[2*l+1] = conv_relu_forward(
            conv_a, self.params['W%d' % (2*l+1)], self.params['b%d' % (2*l+1)], conv_param)
        conv_a, conv_cache[2*l+2] = conv_relu_pool_forward(
            conv_a, self.params['W%d' % (2*l+2)], self.params['b%d' % (2*l+2)], conv_param, pool_param)
        if(l == conv_layers-1):
            fp_check = True
    # 纺射层
    else:
        if(fp_check is True):
            fp_check = False
            N,num_F,H,W = conv_a.shape
            fc_a = np.reshape(conv_a,(N,num_F*H*W))
        if(l == total_layers-1):
            scores, fc_cache[l] = affine_forward(
                fc_a, self.params['W%d' % (2*conv_layers+l-1)], self.params['b%d' % (2*conv_layers+l-1)])
        else:
            fc_a, fc_cache[l] = affine_forward(
                fc_a, self.params['W%d' % (2*conv_layers+l-1)], self.params['b%d' % (2*conv_layers+l-1)])
if y is None:
            return scores
```

- 使用softmax计算loss和delta_l

```
loss, delta_l = softmax_loss(scores,y)
```

- 然后反向传播

```
# 反向传播
for l in range(total_layers-1,-1,-1):
    # 纺射层
    if(l >= conv_layers):
        delta_l, grads['W%d' % (2*conv_layers+l-1)], grads['b%d' % (2*conv_layers+l-1)] = affine_backward(delta_l, fc_cache[l])
        if(l == conv_layers):
            delta_l = np.reshape(delta_l, (N,num_F,H,W))
    # 卷积层
    else:
        delta_l, grads['W%d' % (2*l+2)], grads['b%d' % (2*l+2)] = conv_relu_pool_backward(delta_l, conv_cache[2*l+2])
        delta_l, grads['W%d' % (2*l+1)], grads['b%d' % (2*l+1)] = conv_relu_backward(delta_l, conv_cache[2*l+1])
```

- 计算loss、grads

```
for l in range(total_layers):
    if(l < conv_layers):
        W1 = self.params['W%d' % (2*l+1)]
        W2 = self.params['W%d' % (2*l+2)]
        loss += 0.5*self.reg*(np.sum(W1*W1)+np.sum(W2*W2))
        grads['W%d' % (2*l+1)] += self.reg*W1
        grads['W%d' % (2*l+2)] += self.reg*W2
    else:
        W = self.params['W%d' % (2*conv_layers+l-1)]
        loss += 0.5*self.reg*np.sum(W*W)
        grads['W%d' % (2*conv_layers+l-1)] += self.reg*W

return loss, grads
```

以上便是我的ConvNet。

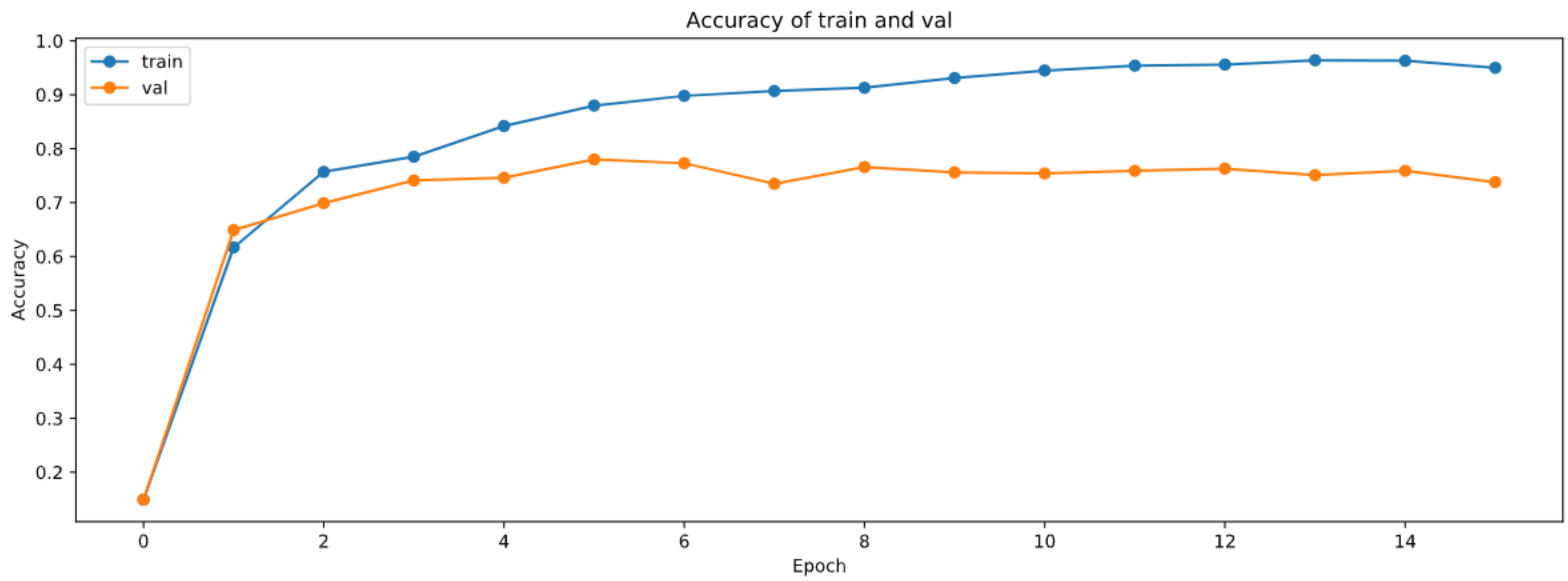
三、网络的训练

接下来便开始训练网络，对于学习率，我是先试了几个，最后决定在前面1e-4的基础上稍微调大一些，设为了0.00015；而lr_decay设为了0.99，也就是每过一轮学习率乘0.99。

而对于filter的大小和数量以及隐藏层的维度，我准备接下来设置不同的参数训练进而对比结果。

1. num_filters=96, filter_size=3, hidden_dims=2000

因为是第一次训练，所以我训练了较多轮（15轮），结果如下：

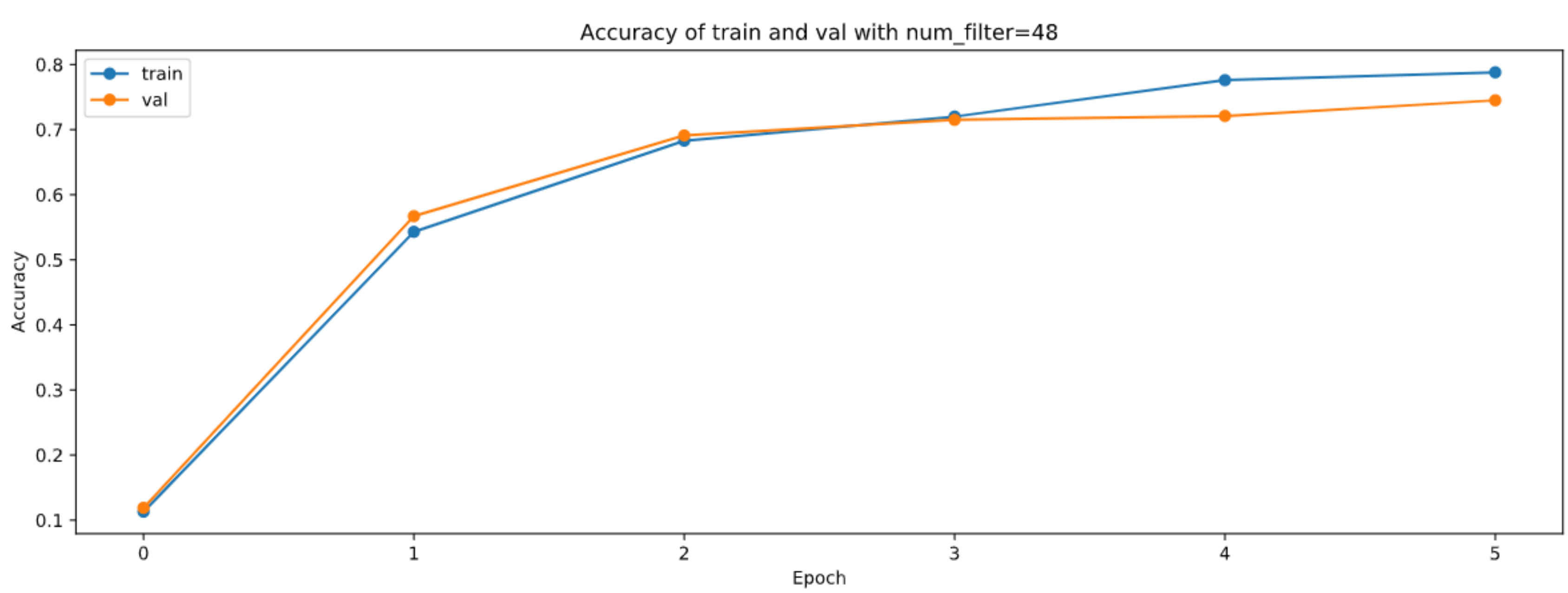


最终在训练集上准确率为87.91%，测试集上准确率为78%。**（提前说一下，这是最好的结果）**

同时可以看到在训练到第5、6轮左右的时候测试集上准确率达到最高，在这之后便出现了过拟合的情况，即虽然在训练集上准确率提高但是在测试集上的准确率不增反降，由于训练一轮比较久为了节省时间所以我决定后面的网络都只训练5轮。

2. num_filters=48 filter_size=3 hidden_dims=2000

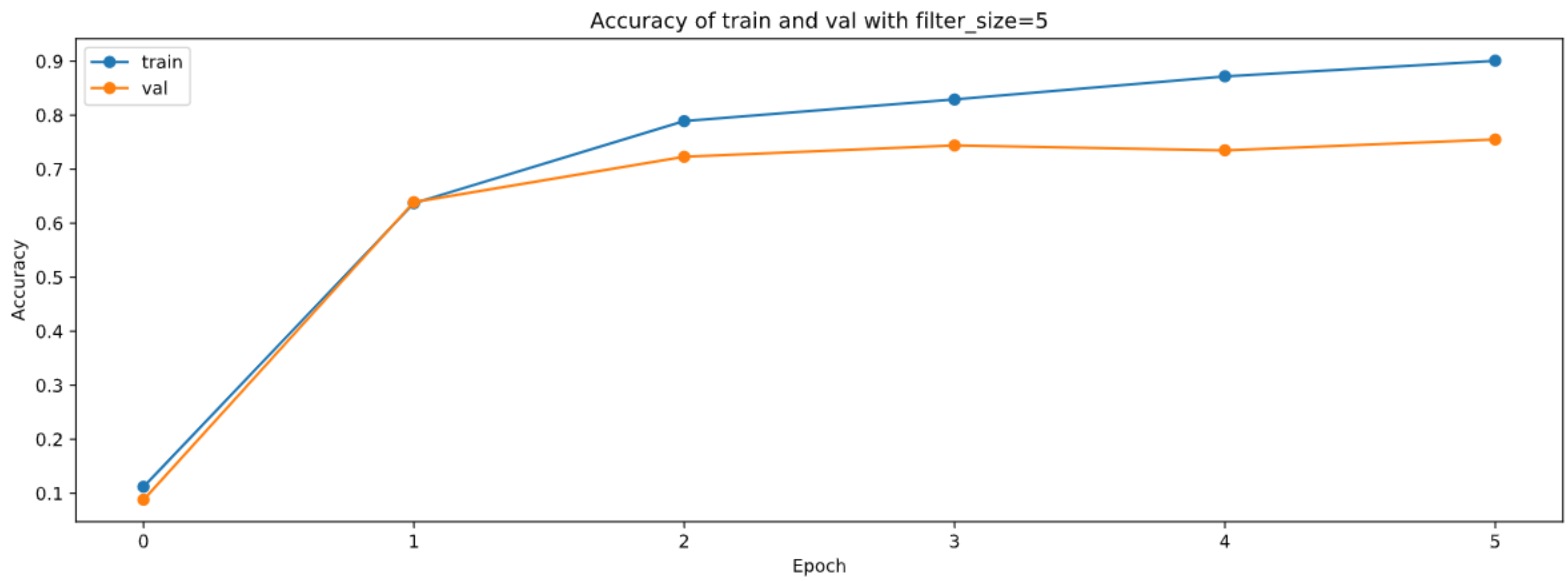
将filter的大小由96调小至48，其余不变，结果如下：



最终在训练集上准确率为79.37%，测试集上准确率为74.5%。

3. num_filters=96 filter_size=5 hidden_dims=2000

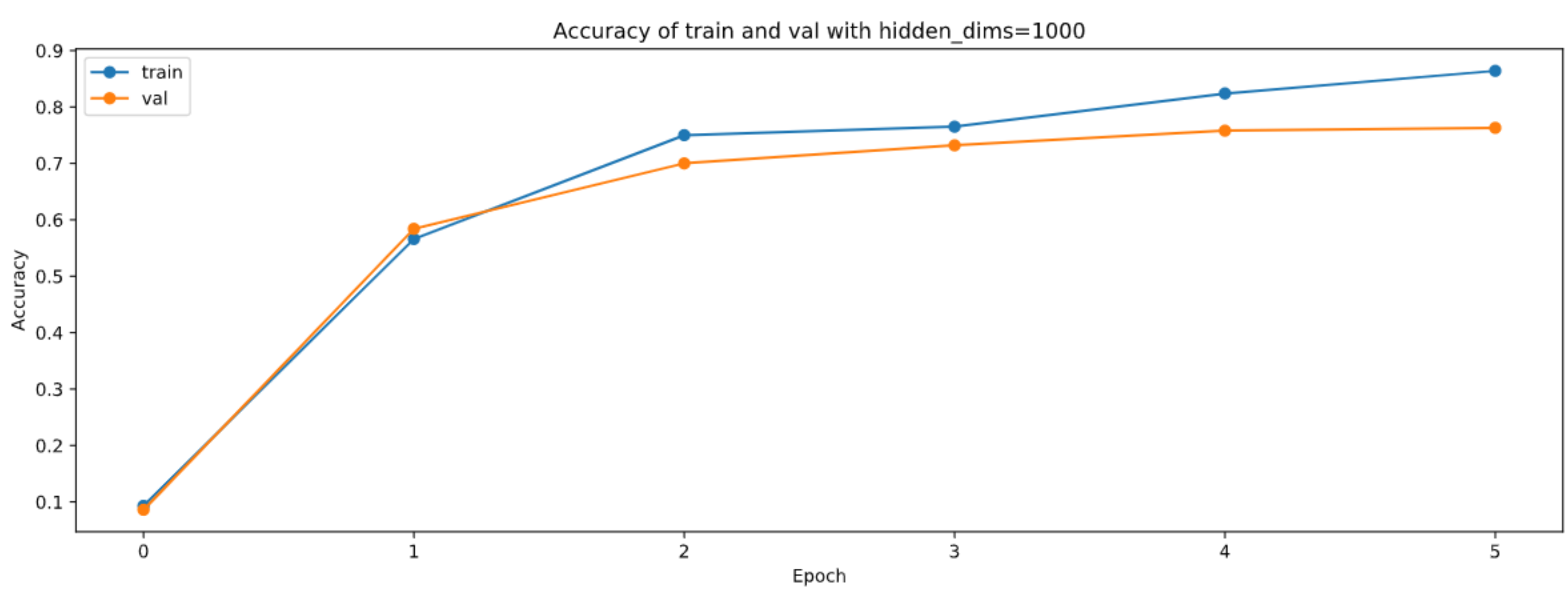
将filter_size由3增加至5，其余不变，结果如下：



最终在训练集上准确率为85.72%，测试集上准确率为76.3%。

4. num_filters=96 filter_size=3 hidden_dims=1000

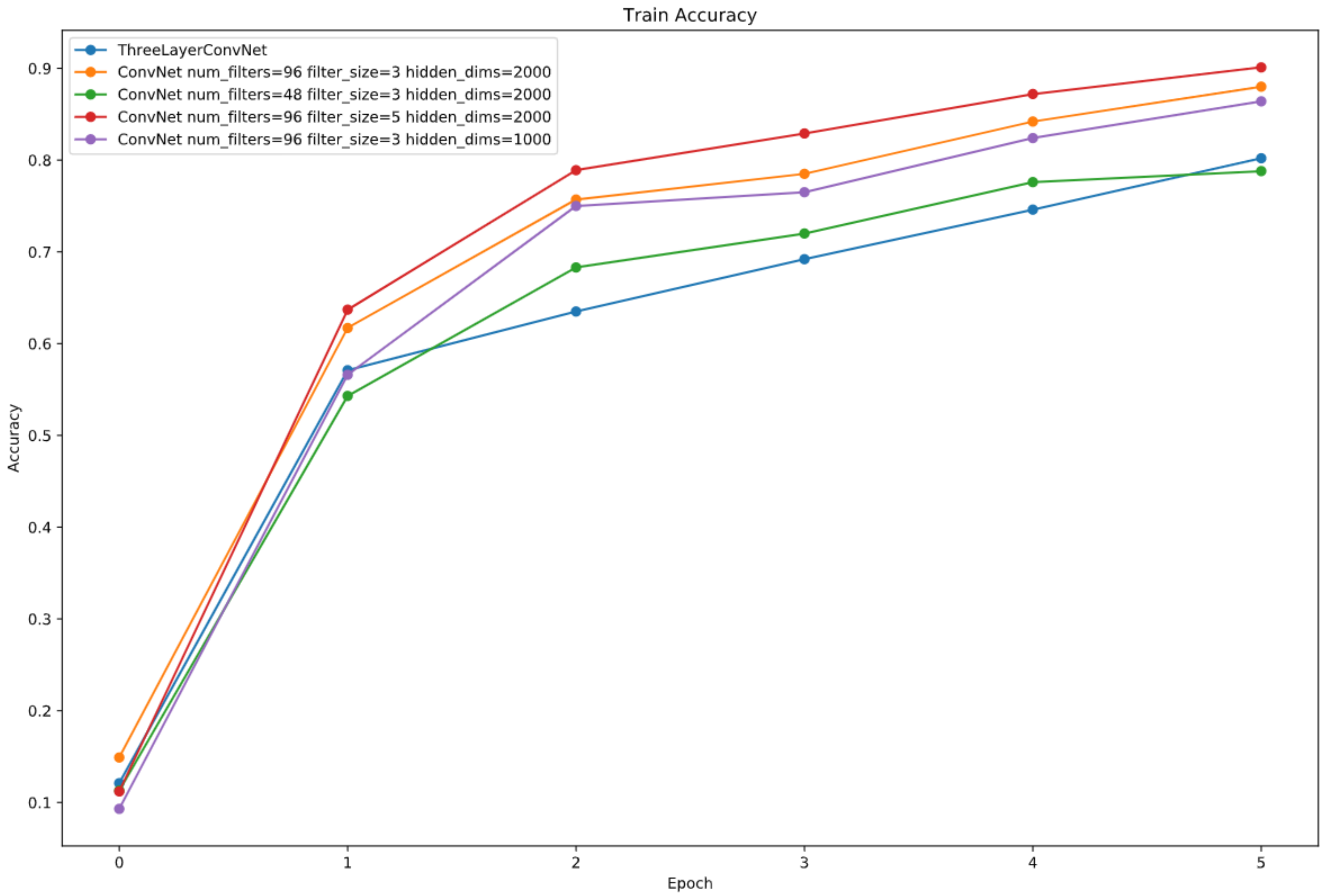
将隐藏层维度由2000×2000减小为1000×1000，其余不变，结果如下：



最终在训练集上准确率为86.4%，测试集上准确率为76.3%。

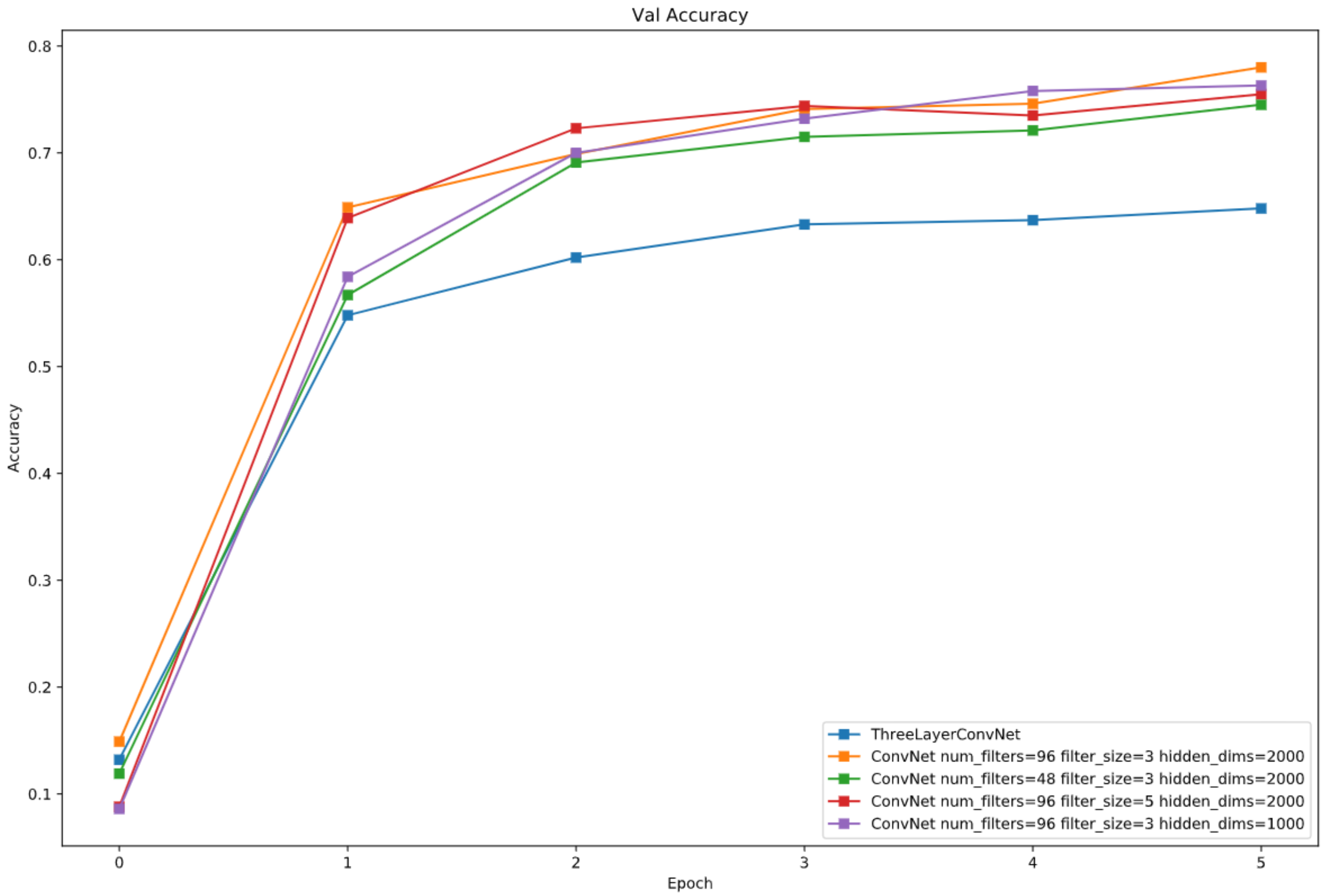
四、结果分析

将上面各参数的结果汇总，并将最开始的三层网络的训练结果也放进来作为对比，在训练集上对比如下：



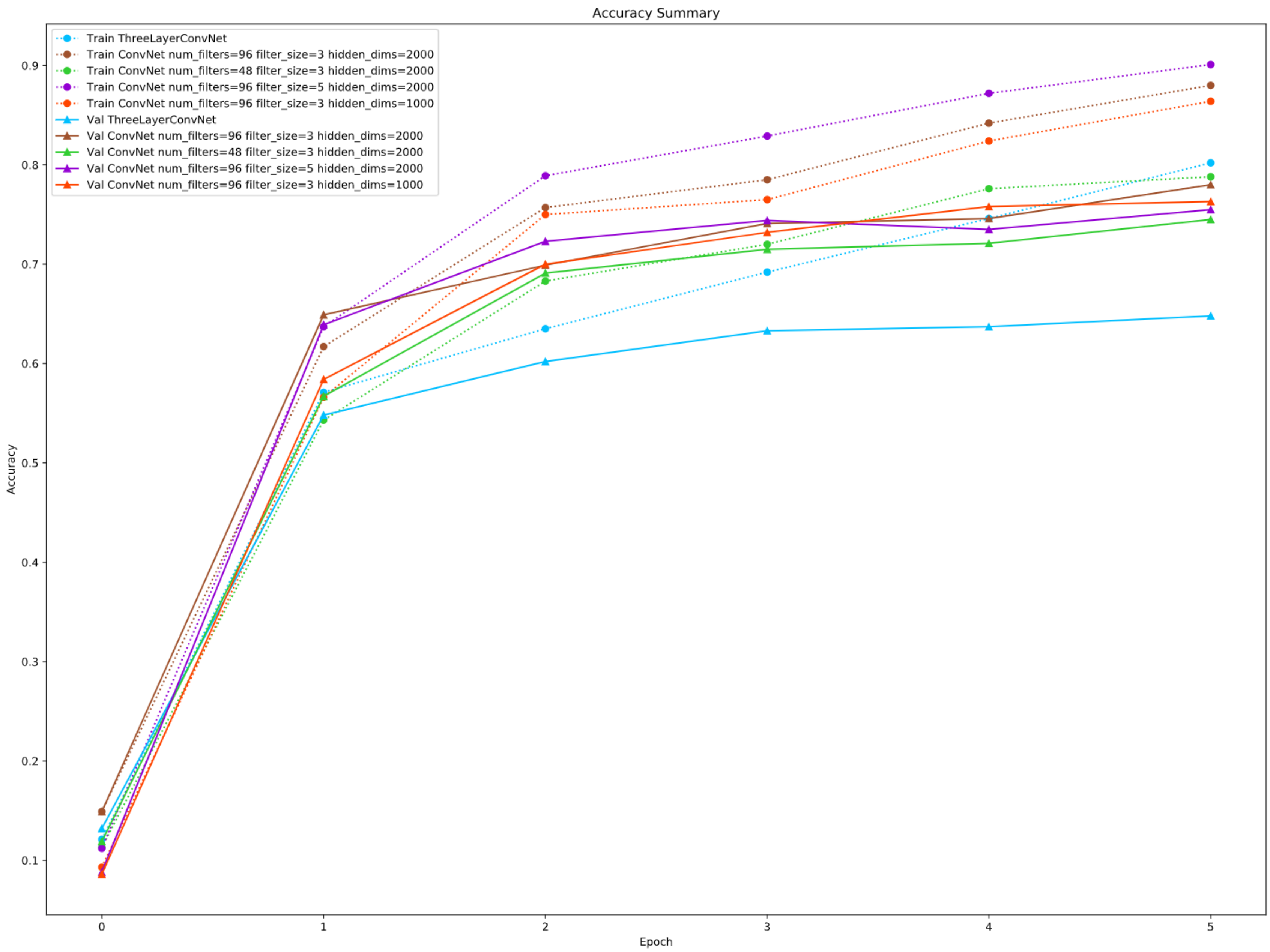
可以看出在训练集上，filter的大小、数量以及隐藏层维度都是越大效果越好，同时和三层网络的结构的差别并不是特别地大，甚至在第五轮的时候准确率超过了num_filters为48的情况。

在测试集上如下：



在测试集上三层网络和我的网络的结果就相差很多了，有着10%以上的准确率的差距，但是各参数的结果的差距就小了很多。

然后将以上结果全部汇总分析各参数的影响：



由此可以得出以下结论：

- 因为无论在训练集还是测试集上num_filters为48的效果都是最差的，所以filter的数量即num_filters的确是大一些比较好
- 对于filter_size，虽然为5的时候在训练集上表现最好但是在测试集上却只比num_filters为48的好，而且这也会增加训练时间但并不会获得一个更好的实验结果，所以filter_size并不是越大或越小就越好，要找一个合适的大小
- 对于隐藏层的维度大小同样为大一些比较好
- 另外，对比三层网络的结构提升的确比较大，测试集上的准确率由67%提升到了78%，说明 `conv - relu - conv - relu - max pool - affine - relu - softmax` 的结构的确要比 `conv - relu - max pool - affine - relu - affine - softmax` 的结构要好。

以上便是我对于网络架构与参数、实验结果的分析，在最好的参数下（num_filters=96, filter_size=3, hidden_dims=2000 即第一次训练的结果），在训练集上最高有87.91%的准确率，在测试集上有78%的准确率。