2. A brief pdf report with the following content:

i) State how you checked your analytic gradient computations and whether you think that your gradient computations were bug free.

```
Give evidence for these conclusions.
```

- 解：我的梯度实现遵循每一步的正确求解梯度过程：

Aggregated backward pass for a 2-layer neural network

1. Let
$$\mathbf{g} = -\frac{\mathbf{y}^T}{\mathbf{y}^T\mathbf{p}}\left(\text{diag}(\mathbf{p}) - \mathbf{p}\mathbf{p}^T\right)$$
2. Gradient of J w.r.t. second bias vector is the $1 \times c$ vector
$$\frac{\partial J}{\partial \mathbf{b}_2} = \mathbf{g}$$
3. Gradient of J w.r.t. second weight matrix W_2 is the $c \times m$ matrix
$$\frac{\partial J}{\partial W_2} = \mathbf{g}^T\mathbf{h}^T + 2\lambda W_2$$
4. Propagate the gradient vector $\mathbf{g}$ to the first layers
$$\mathbf{g} = \mathbf{g}W_2$$
$$\mathbf{g} = \mathbf{g}\ \text{diag}(\text{Ind}(\mathbf{s}_1 > 0)) \leftarrow \text{assuming ReLu activation}$$
5. Gradient of J w.r.t. the first bias vector is the $1 \times d$ vector
$$\frac{\partial J}{\partial \mathbf{b}_1} = \mathbf{g}$$
6. Gradient of J w.r.t. the first weight matrix W_1 is the $m \times d$ matrix
$$\frac{\partial J}{\partial W_1} = \mathbf{g}^T\mathbf{x}^T + 2\lambda W_1$$

在代码中的实现与上图手写的求解梯度过程可以一一对应，请注意下面代码中的注释说明了这一点：

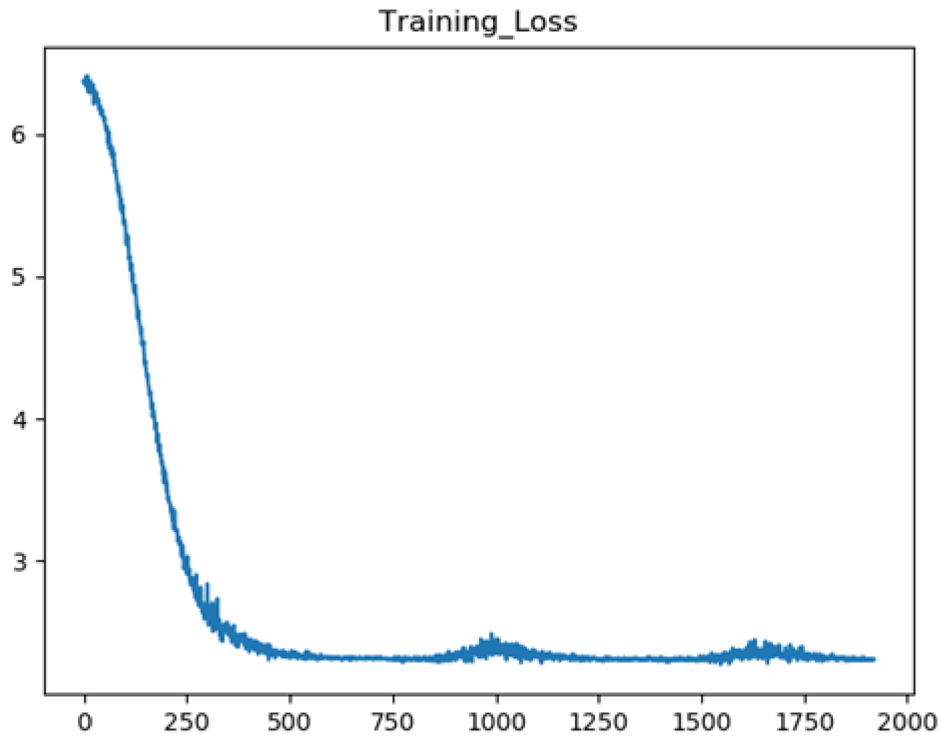
```python
def backward(self, X_, y_, outputs_, loss_):
    N, hdim = X_.shape[1], self.W2.shape[1]
    b1Grad, b2Grad, W1Grad, W2Grad = np.zeros((hdim, 1)), np.zeros((self.C, 1)), \
                                     np.zeros((hdim, self.D)), np.zeros((self.C, hdim))
    for i in range(N):
        x, y, p, h = X_[:, i], y_[:, i], outputs_[:, i], self.h[:, i]
        x, y, p, h = \
            np.expand_dims(x, axis=1), np.expand_dims(y, axis=1), np.expand_dims(p, axis=1), np.expand_dims(h, axis=1)
        pDiag = np.multiply(np.eye(p.shape[0]), p)
        # g: (1, C)
        # 这里对应第一步 g 的求解:
        g = -((y.T / (y.T @ p)) @ (pDiag - p @ p.T))
        # 这里对应第二步 \partial b 的求解:
        b2Grad += g.T
        # W2Grad: (C, hdim)
        # 这里对应第三步 \partial W_2 的求解:
        W2Grad += (g.T @ h.T)
        if (self.args.leaky_ReLU):
            h = np.where(h > 0, 1, 0.01)
```

```
        else:
            h = np.where(h > 0, 1, 0)
        # self.W2: (C, hdim)
        # g: (1, hdim)
        # 这里对应新的 g (更新步) 的求解:
        g = (g @ self.W2) @ np.multiply(np.eye(h.shape[0]), h)
        # 这里对应 \partial b_1 的求解:
        b1Grad += g.T
        # 这里对应 W_1 的求解:
        # W1Grad: (hdim, features)
        W1Grad += (g.T @ X.T)

    W1Grad, W2Grad = \
        2 * self.args.Lambda * self.W1 + W1Grad / N, 2 * self.args.Lambda * self.W2 + W2Grad / N
    b1Grad, b2Grad = \
        b1Grad / N, b2Grad / N

    # 更新 momentum 和对应的梯度:
    self.W1_momentum = self.W1_momentum * self.args.rho + self.eta * W1Grad
    self.W2_momentum = self.W2_momentum * self.args.rho + self.eta * W2Grad
    self.b1_momentum = self.b1_momentum * self.args.rho + self.eta * b1Grad
    self.b2_momentum = self.b2_momentum * self.args.rho + self.eta * b2Grad

    self.W1 -= self.W1_momentum
    self.b1 -= self.b1_momentum
    self.W2 -= self.W2_momentum
    self.b2 -= self.b2_momentum
```

在检查梯度计算的过程中，我保证每一步实现的方法(使用 `@` 算子)与PPT中手写求解的过程一一对应，保证每一层的计算结果都是正确的，这样就可以保证梯度的计算是正确的.

在实现代码的过程中也遇到了一些问题：比如因为 `*` 与 `@` 算子混淆导致的维度出错，不过很快被我发现并改正了.

ii) The curves for the training and validation loss/cost when using the cyclical learning rates with the default values, that is replicate figures 3 and 4. Also comment on the curves.



可以发现Training Loss整体是明显的下降趋势，因为这里只训练了5个epoch，对超参数的搜索也有限，否则Training loss还能降到更低.

iii) State the range of the values you searched for lambda, the number of cycles used for training during the coarse search and the hyper-parameter settings for the 3 best performing networks you trained.

iv) State the range of the values you searched for lambda, the number of cycles used for training during the ne search, and the hyper-parameter settings for the 3 best performing networks you trained.

在这里我设置了`decay_eta`参数对η进行搜索，`Lambda`的值也被设置成命令行参数方便调整. 训练epoch为6.

Coarse Search:

$$\eta = 0.01, 0.02, 0.03, 0.05, 0.1, 0.2, 0.5, 0.75;$$

$$\lambda = 0, 0.001, 0.005, 0.01, 0.25, 0.5, 0.75, 1$$

$$8 \times 8 = 64$$

如上，初始值有64种组合.

其中最优组合为:

$$\eta = 0.02, \lambda = 0.01$$

其中训练集上准确率为0.4803

v) For your best found lambda setting (according to performance on the validation set), train the network on all the training data (all the batch data), except for 1000 examples in a validation set, for $\sim$ 3 cycles. Plot the training and validation loss plots and then report the learnt network's performance on the test data.