RNN

> 2013551 雷贺奥

实验要求

- 掌握RNN原理
- 学会使用PyTorch搭建循环神经网络来训练名字识别
- 学会使用PyTorch搭建LSTM网络来训练名字识别

原始版本RNN

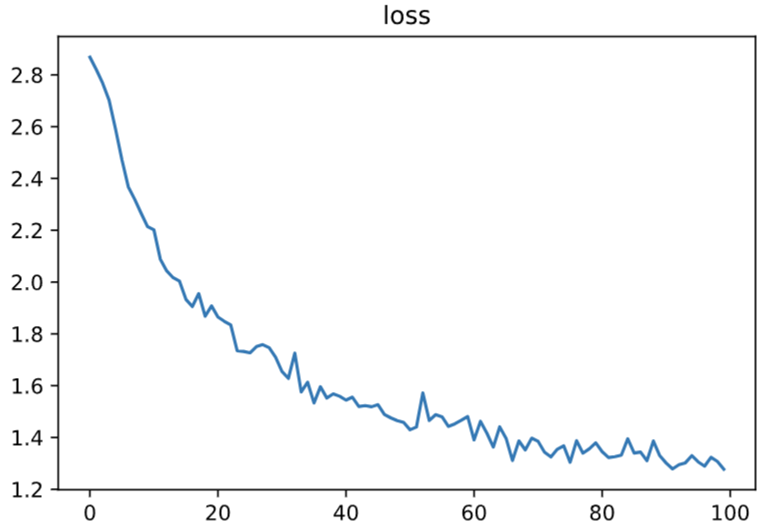
网络结构

```
class RNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(RNN, self).__init__()
        self.hidden_size = hidden_size
        self.i2h = nn.Linear(input_size + hidden_size, hidden_size)
        self.i2o = nn.Linear(input_size + hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, input, hidden):
        combined = torch.cat((input, hidden), 1)
        hidden = self.i2h(combined)
        output = self.i2o(combined)
        output = self.softmax(output)
        return output, hidden

    def initHidden(self):
        return torch.zeros(1, self.hidden_size)
```

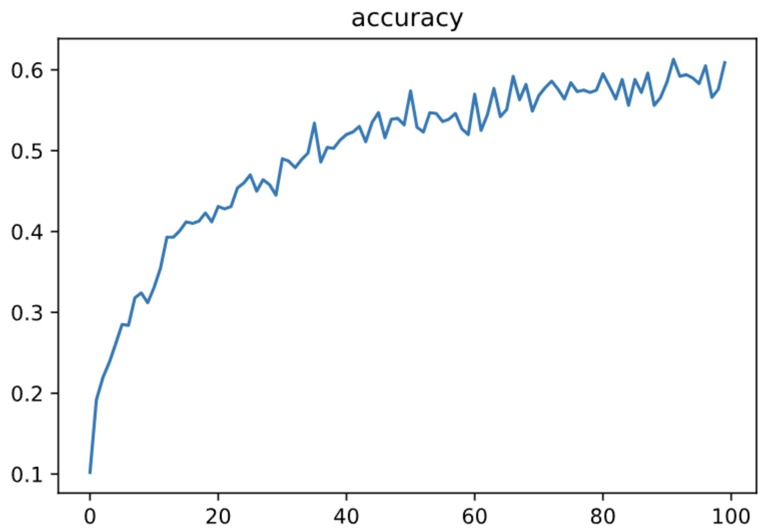
使用print()函数打印网络结构的结果如下：

```
RNN(
  (i2h): Linear(in_features=185, out_features=128, bias=True)
  (i2o): Linear(in_features=185, out_features=18, bias=True)
  (softmax): LogSoftmax(dim=1)
)
```

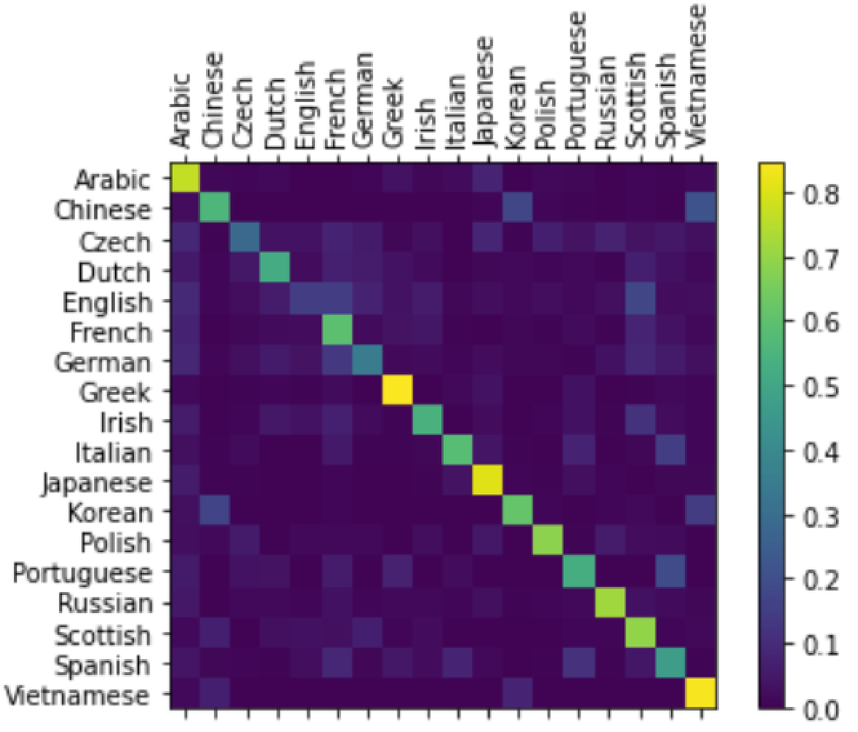
loss图



准确度图



预测矩阵图



可以看出，对角线十分清晰，预测效果良好。

Lstm 库

网络结构

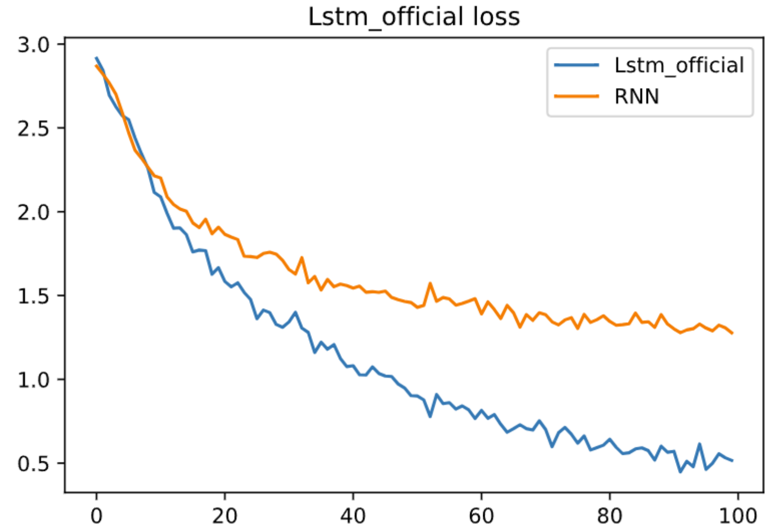
作者先使用pytorch提供的Lstm库，**在最后一段展示自己手写的Lstm网络。**

```
class Lstm_official(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(Lstm_official,self).__init__()
        self.lstm=nn.LSTM(input_size,hidden_size,2)
        self.linear=nn.Sequential(
            nn.Linear(hidden_size,output_size),
            nn.LogSoftmax(dim=1)
        )
    def forward(self,input):
        x,(h_n,c_n)=self.lstm(input)
        # 只使用最后一次的输出
        x=self.linear(x[-1])
        return x
```

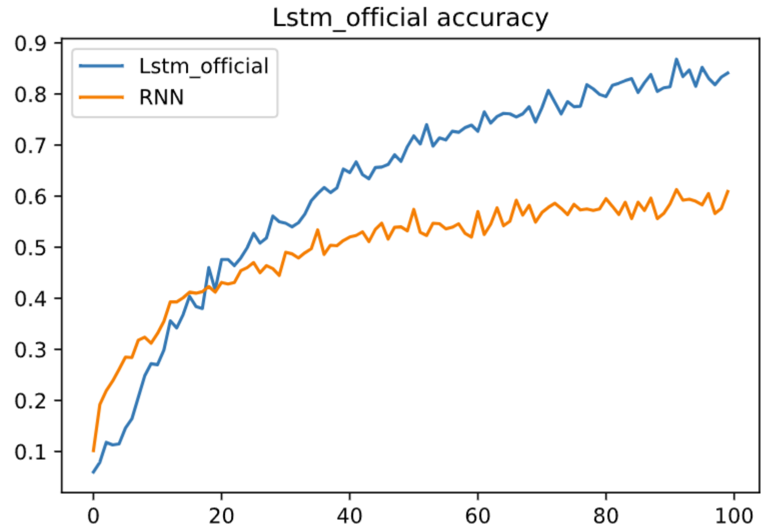
使用print()函数打印网络结构的结果如下：

```
Lstm_official(
  (lstm): LSTM(57, 128, num_layers=2)
  (linear): Sequential(
    (0): Linear(in_features=128, out_features=18, bias=True)
    (1): LogSoftmax(dim=1)
  )
)
```

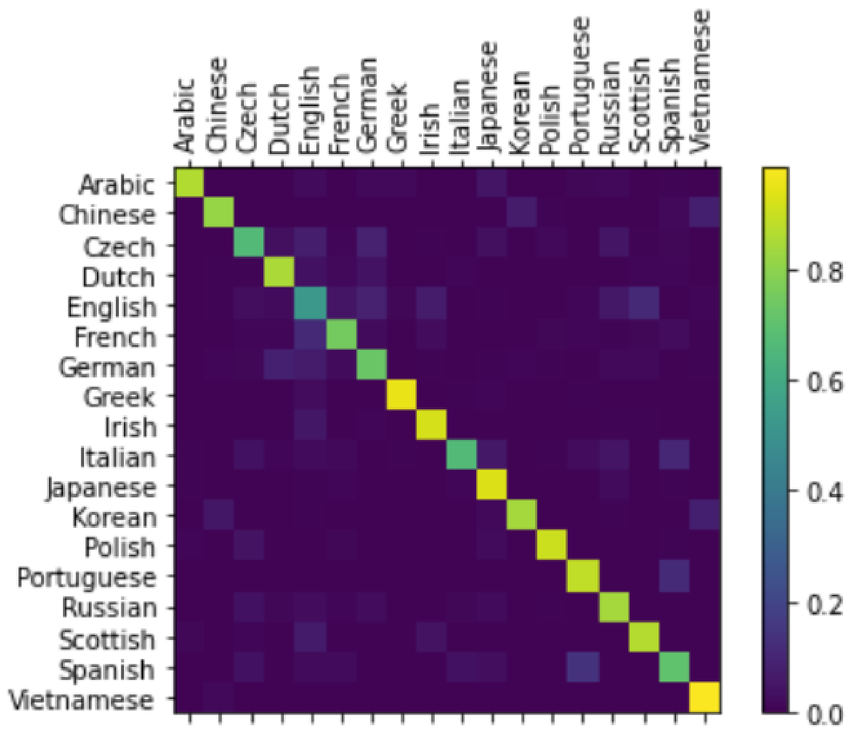
loss图



准确度



预测矩阵图



Lstm 优于RNN的原因

RNN在处理的Sequence长度很长时会产生梯度爆炸或消失，所以循环神经网络（RNN）实际上只能学习到短期的依赖关系。下面证明产生梯度爆炸或消失的原因：（**来源：智能计算系统课程PPT**）

损失函数对W的偏导为:

$$\frac{\partial L}{\partial W}=\sum_{t=1}^{\tau}\frac{\partial L^{(t)}}{\partial W}=\sum_{t=1}^{\tau}\sum_{k=1}^{t}\frac{\partial L^{(t)}}{\partial \hat{\boldsymbol{y}}^{(t)}}\frac{\partial \hat{\boldsymbol{y}}^{(t)}}{\partial \boldsymbol{o}^{(t)}}\frac{\partial \boldsymbol{o}^{(t)}}{\partial \boldsymbol{h}^{(t)}}\frac{\partial \boldsymbol{h}^{(t)}}{\partial \boldsymbol{h}^{(k)}}\frac{\partial \boldsymbol{h}^{(k)}}{\partial W}$$

因为:

$$\frac{\partial \boldsymbol{h}^{(t)}}{\partial \boldsymbol{h}^{(k)}}=\prod_{i=k+1}^{t}\frac{\partial \boldsymbol{h}^{(i)}}{\partial \boldsymbol{h}^{(i-1)}}$$

根据推导可知序列损失函数对U和W的偏导为:

$$\begin{aligned}\frac{\partial L}{\partial W}&=\sum_t\sum_{k=1}^{k=t}\frac{\partial L^{(t)}}{\partial \hat{\boldsymbol{y}}^{(t)}}\frac{\partial \hat{\boldsymbol{y}}^{(t)}}{\partial \boldsymbol{o}^{(t)}}\frac{\partial \boldsymbol{o}^{(t)}}{\partial \boldsymbol{h}^{(t)}}\left(\prod_{i=k+1}^{t}W^{\top}\operatorname{diag}\left(1-\left(\boldsymbol{h}^{(i)}\right)^2\right)\right)\frac{\partial \boldsymbol{h}^{(k)}}{\partial W}\\ \frac{\partial L}{\partial U}&=\sum_t\sum_{k=1}^{k=t}\frac{\partial L^{(t)}}{\partial \hat{\boldsymbol{y}}^{(t)}}\frac{\partial \hat{\boldsymbol{y}}^{(t)}}{\partial \boldsymbol{o}^{(t)}}\frac{\partial \boldsymbol{o}^{(t)}}{\partial \boldsymbol{h}^{(t)}}\left(\prod_{i=k+1}^{t}W^{\top}\operatorname{diag}\left(1-\left(\boldsymbol{h}^{(i)}\right)^2\right)\right)\frac{\partial \boldsymbol{h}^{(k)}}{\partial U}\end{aligned}$$

令 $\gamma=\left\|\prod_{i=k+1}^{t}W^{\top}\operatorname{diag}\left(1-\left(\boldsymbol{h}^{(i)}\right)^2\right)\right\|_2$

当Sequence长度很长时，$t>>k$，就会产生爆炸或消失。

$$r\begin{cases}\to\infty,\ \frac{\partial L}{\partial U}\to\infty,\ \frac{\partial L}{\partial W}\to\infty\\ \to 0,\ \frac{\partial L}{\partial W}\to 0,\ \frac{\partial L}{\partial U}\to 0\end{cases}$$

。。。。。。。以后再写

自己实现的Lstm

网络结构

作者自己实现的为两层Lstm，在myLstm中嵌套两个myLstmbase。

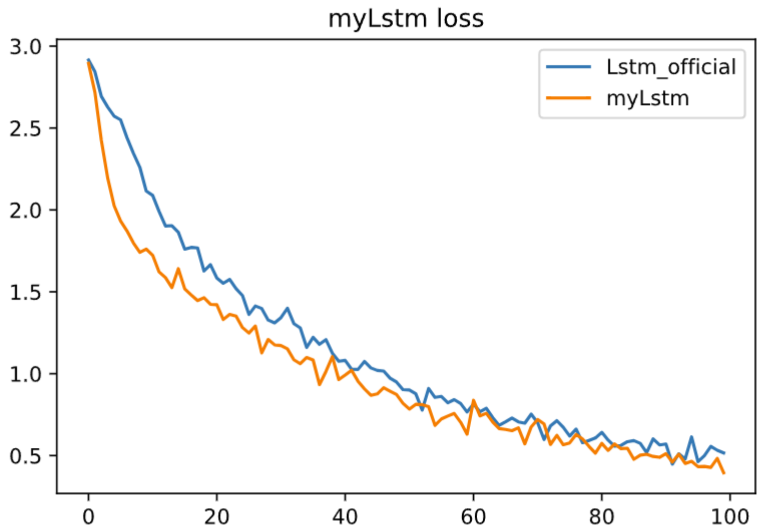
```
class myLstmbase(nn.Module):
    def __init__(self,input_sz,hidden_sz):
        super().__init__()
        self.input_size=input_sz
        self.hidden_size=hidden_sz
        #输入参数
        self.U_i=nn.Parameter(torch.Tensor(input_sz,hidden_sz))
        self.V_i = nn.Parameter(torch.Tensor(hidden_sz,hidden_sz))
        self.b_i = nn.Parameter(torch.Tensor(hidden_sz))

        #遗忘门参数
        self.U_f = nn.Parameter(torch.Tensor(input_sz, hidden_sz))
        self.V_f = nn.Parameter(torch.Tensor(hidden_sz, hidden_sz))
        self.b_f = nn.Parameter(torch.Tensor(hidden_sz))

        #记忆门参数
        self.U_c = nn.Parameter(torch.Tensor(input_sz, hidden_sz))
        self.V_c = nn.Parameter(torch.Tensor(hidden_sz, hidden_sz))
```

```
        self.b_c = nn.Parameter(torch.Tensor(hidden_sz))

        #输出门参数
        self.U_o = nn.Parameter(torch.Tensor(input_sz, hidden_sz))
        self.V_o = nn.Parameter(torch.Tensor(hidden_sz, hidden_sz))
        self.b_o = nn.Parameter(torch.Tensor(hidden_sz))

        self.init_weights()

    # 初始化，采用正态分布
    def init_weights(self):
        stdv = 1.0 / math.sqrt(self.hidden_size)
        for weight in self.parameters():
            weight.data.uniform_(-stdv, stdv)
    # 前向
    def forward(self,x,h_t,c_t):
        bs,seq_size = x.size()
        #计算
        x_t = x
        i_t = torch.sigmoid(x_t @ self.U_i + h_t @ self.V_i + self.b_i)
        f_t = torch.sigmoid(x_t @ self.U_f + h_t @ self.V_f + self.b_f)
        g_t = torch.tanh(x_t @ self.U_c + h_t @ self.V_c + self.b_c)
        o_t = torch.sigmoid(x_t @ self.U_o + h_t @ self.V_o + self.b_o)
        c_t = f_t * c_t + i_t * g_t
        h_t = o_t * torch.tanh(c_t)

        hidden_seq=h_t
        return hidden_seq, (h_t, c_t)

# 两层lstm
class myLstm(nn.Module):
    def __init__(self,input_sz,hidden_sz,output_size):
        super().__init__()
        self.input_size=input_sz
        self.hidden_size=hidden_sz
        # 第一层lstm
        self.lstm1 = myLstmbase(input_sz,hidden_sz)
        # 第二层lstm
        self.lstm2 = myLstmbase(input_sz,hidden_sz)
        # linear
        self.linear=nn.Sequential(
            nn.Linear(hidden_sz,output_size),
            nn.LogSoftmax(dim=1)
        )
    def forward(self,x,h_t,c_t):
        # layer1
        hidden_seq,(temp_h_t,temp_c_t) = self.lstm1(x,h_t,c_t)
        # layer2
        hidden_seq,(temp_h_t,temp_c_t) = self.lstm2(x,temp_h_t,temp_c_t)
        # result
        result = self.linear(hidden_seq)
        return result,(temp_h_t,temp_c_t)
```

使用print()打印网络结构

```
myLstm(
  (lstm1): myLstmbase()
  (lstm2): myLstmbase()
  (linear): Sequential(
    (0): Linear(in_features=128, out_features=18, bias=True)
    (1): LogSoftmax(dim=1)
  )
)
```

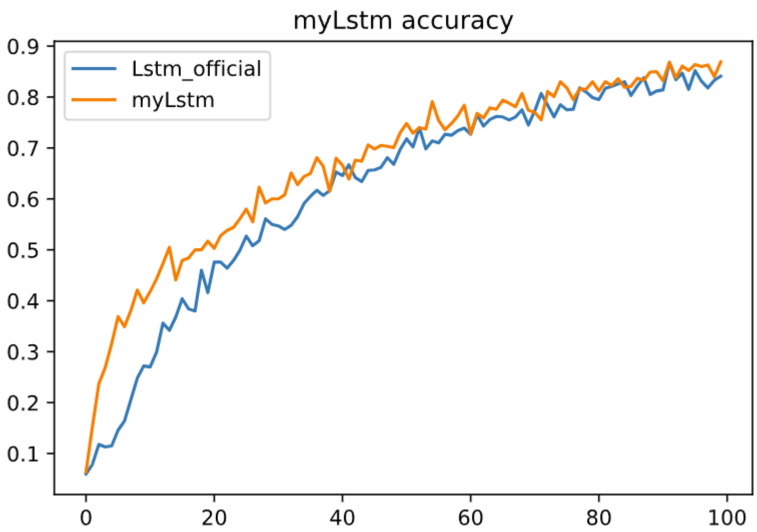
loss图



从图中可以看出，自己实现的Lstm与调库实现的Lstm的Loss曲线趋势基本相同，最终，自己实现的lstm甚至优于调库实现的Lstm。

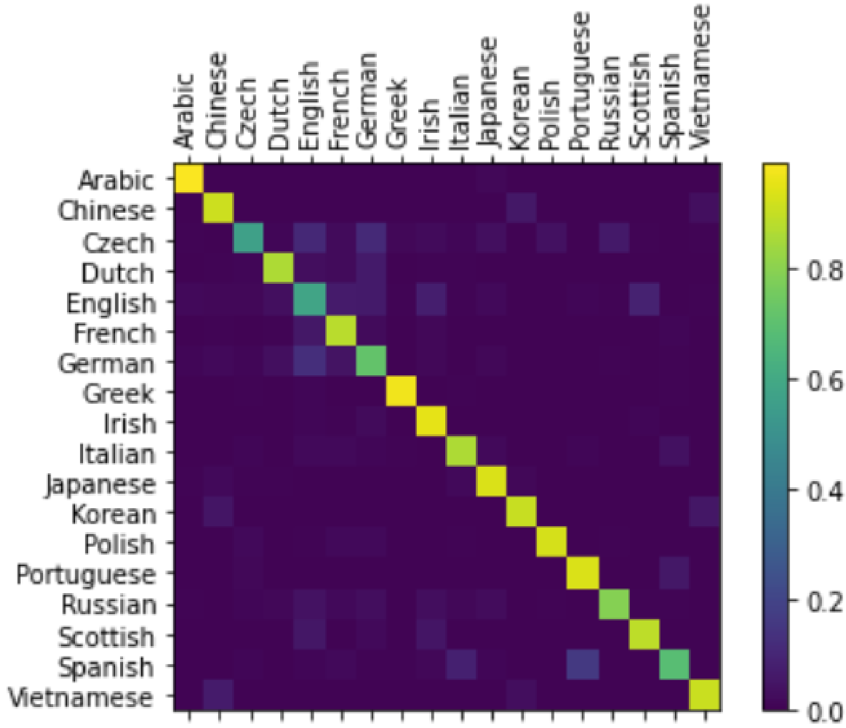
但是，自己实现的Lstm训练时间很长，远大于调库实现的Lstm。

准确度



从图中可以看出，自己实现的Lstm与调库实现的Lstm的accuracy曲线趋势基本相同，最终，自己实现的lstm甚至优于调库实现的Lstm。

预测矩阵图



Arabic
Chinese
Czech
Dutch
English
French
German
Greek
Irish
Italian
Japanese
Korean
Polish
Portuguese
Russian
Scottish
Spanish
Vietnamese
0.8
0.6
0.4
0.2
0.0