```
import torch
import torch.nn as nn
from torch.autograd import Variable

import os
import numpy as np
from torch.optim import Adam
from torch.utils.data import DataLoader

from dataset import FlowDataset
```

```
In [2] class FlowLSTM(nn.Module):
            def __init__(self, input_size, hidden_size, num_layers, dropout):
                 super(FlowLSTM, self).__init__()
                # build your model here
                # your input should be of dim (batch_size, seq_len, input_size)
                # your output should be of dim (batch size, seq len, input size) as well
                # since you are predicting velocity of next step given previous one
                # feel free to add functions in the class if needed
                 self.input size = input size
                 self.hidden size = hidden size
                 self.num_layers = num_layers
                 self.dropout = dropout
                if self.num layers > 1:
                     self.dropout = dropout
                else:
                     self.dropout = 0.0
                # define the LSTM layer
                 self.lstm = nn.LSTM(
                     input_size = self.input_size,
                     hidden_size = self.hidden_size,
                     num_layers = self.num_layers,
                     batch_first=True,
                     dropout=self.dropout
                 )
                # define the output layer
                 self.dense = nn.Linear(self.hidden_size,self.input_size)
            # initialize hidden state as
            def initial hidden state(self,batch):
                 return Variable(torch.zeros(self.num layers,batch,self.hidden size))
            # forward pass through LSTM layer
            def forward(self, x):
                 input: x of dim (batch_size, 19, 17)
                # define your feedforward pass
                batch = x.shape[0]
                h_0 = self.initial_hidden_state(batch)
                h_1 = self.initial_hidden_state(batch)
                 out, \underline{\phantom{}} = self.lstm(x, (h_0, h_1))
                 out = self.dense(out)
                 return out
            # forward pass through LSTM layer for testing
            def test(self, x):
                 1.1.1
                 input: x of dim (batch_size, 17)
                # define your feedforward pass
                 pred = torch.empty(x.shape[0], 19, x.shape[1])
                 pred[:,0,:] = x
                 for i in range(1, pred.shape[1]):
                                                   ۱ . ۱ . ۱ . ۱ . ۱ . ۱ . ۱ . ۱
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```
return pred
```

```
return pred
In [3]: # from lstm import FlowLSTM
        def main():
            # check if cuda available
            device = 'cuda:0' if torch.cuda.is_available() else 'cpu'
            # define dataset and dataloader
            train_dataset = FlowDataset(mode='train')
            test_dataset = FlowDataset(mode='test')
            train_loader = DataLoader(dataset=train_dataset, batch_size=32, shuffle=True, num_wo
            test_loader = DataLoader(dataset=test_dataset, batch_size=16, shuffle=False, num_wor
            # hyper-parameters
            num_epochs = 45
            lr = 0.0008
            input_size = 17 # do not change input size
            hidden_size = 128
            num layers = 6
            dropout = 0.2
            model = FlowLSTM(
                input_size=input_size,
                hidden_size=hidden_size,
                num_layers=num_layers,
                dropout=dropout
            ).to(device)
            # define your LSTM loss function here
            loss_func = nn.MSELoss()
            # define optimizer for lstm model
            optim = Adam(model.parameters(), lr=lr)
            loss_list = []
            for epoch in range(num_epochs):
                for n_batch, (in_batch, label) in enumerate(train_loader):
                    in_batch, label = in_batch.to(device), label.to(device)
                    # train LSTM
                    out = model(in batch)
                    # calculate LSTM loss
                    loss = loss_func(out, label)
                    optim.zero_grad()
                    loss.backward()
                    optim.step()
                    # print loss while training
                    loss_list.append(loss.item())
                    if (n batch + 1) % 200 == 0:
                        print("Epoch: [{}/{}], Batch: {}, Loss: {}".format(
                             epoch+1, num_epochs, n_batch+1, loss.item()))
            # test trained LSTM model
            l1_{err}, l2_{err} = 0, 0
            l1_loss = nn.L1Loss()
            l2_loss = nn.MSELoss()
```

```
mode(.eva()
            with torch.no_grad():
                for n_batch, (in_batch, label) in enumerate(test_loader):
                    in_batch, label = in_batch.to(device), label.to(device)
                    pred = model.test(in_batch)
                    l1_err += l1_loss(pred, label).item()
                    l2 err += l2 loss(pred, label).item()
            print("Test L1 error:", l1_err)
            print("Test L2 error:", l2_err)
            # visualize the prediction comparing to the ground truth
            if device == 'cpu':
                pred = pred.detach().numpy()[0,:,:]
                label = label.detach().numpy()[0,:,:]
            else:
                pred = pred.detach().cpu().numpy()[0,:,:]
                label = label.detach().cpu().numpy()[0,:,:]
            r = []
            num_points = 17
            interval = 1./num_points
            x = int(num points/2)
            for j in range(-x,x+1):
                r.append(interval*j)
            from matplotlib import pyplot as plt
            plt.figure()
            for i in range(1, len(pred)):
                c = (i/(num points+1), 1-i/(num points+1), 0.5)
                plt.plot(pred[i], r, label='t = %s' %(i), c=c)
            plt.xlabel('velocity [m/s]')
            plt.ylabel('r [m]')
            plt.legend(bbox_to_anchor=(1,1),fontsize='x-small')
            plt.show()
            plt.figure()
            for i in range(1, len(label)):
                c = (i/(num_points+1), 1-i/(num_points+1), 0.5)
                plt.plot(label[i], r, label='t = %s' %(i), c=c)
            plt.xlabel('velocity [m/s]')
            plt.ylabel('r [m]')
            plt.legend(bbox_to_anchor=(1,1),fontsize='x-small')
            plt.show()
            plt.plot(loss_list)
            plt.title("Loss vs iterations")
            plt.xlabel("Iteration")
In [4]: if __name__ == "__main__":
            main()
```

```
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Epoch: [36/45], Batch: 1200, Loss: 6.573502986384483e-08
Epoch: [37/45], Batch: 200, Loss: 6.964386756180829e-08
Epoch: [37/45], Batch: 400, Loss: 9.050972948898561e-08
Epoch: [37/45], Batch: 600, Loss: 7.402248058951955e-08
Epoch: [37/45], Batch: 800, Loss: 1.0235408609560182e-07
Epoch: [37/45], Batch: 1000, Loss: 1.4620408705923182e-07
Epoch: [37/45], Batch: 1200, Loss: 1.1216319961704357e-07
Epoch: [38/45], Batch: 200, Loss: 7.666930201821742e-08
Epoch: [38/45], Batch: 400, Loss: 7.043615823931759e-08
Epoch: [38/45], Batch: 600, Loss: 8.204606416484239e-08
Epoch: [38/45], Batch: 800, Loss: 9.027765202063165e-08
Epoch: [38/45], Batch: 1000, Loss: 7.183575689850841e-08
Epoch: [38/45], Batch: 1200, Loss: 8.00329829075963e-08
Epoch: [39/45], Batch: 200, Loss: 5.323461849116029e-08
Epoch: [39/45], Batch: 400, Loss: 5.137565040058689e-08
Epoch: [39/45], Batch: 600, Loss: 7.603181728654818e-08
Epoch: [39/45], Batch: 800, Loss: 1.816945456312169e-07
Epoch: [39/45], Batch: 1000, Loss: 8.928530093044174e-08
Epoch: [39/45], Batch: 1200, Loss: 9.657969712861814e-08
Epoch: [40/45], Batch: 200, Loss: 1.005958552013908e-07
Epoch: [40/45], Batch: 400, Loss: 1.6576400696521887e-07
Epoch: [40/45], Batch: 600, Loss: 1.442032271370408e-07
Epoch: [40/45], Batch: 800, Loss: 7.859640049900918e-08
Epoch: [40/45], Batch: 1000, Loss: 9.472785222897073e-08
Epoch: [40/45], Batch: 1200, Loss: 5.7033481937196484e-08
Epoch: [41/45], Batch: 200, Loss: 9.656254462697689e-08
Epoch: [41/45], Batch: 400, Loss: 8.711996457577698e-08
Epoch: [41/45], Batch: 600, Loss: 5.7156455568474485e-08
Epoch: [41/45], Batch: 800, Loss: 7.279953706529341e-08
Epoch: [41/45], Batch: 1000, Loss: 7.954677272437038e-08
Epoch: [41/45], Batch: 1200, Loss: 1.1135262667494317e-07
Epoch: [42/45], Batch: 200, Loss: 5.514426959507546e-08
Epoch: [42/45], Batch: 400, Loss: 4.13181311387234e-08
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Epoch: [42/45], Batch: 600, Loss: 6.670732943803159e-08 Epoch: [42/45], Batch: 800, Loss: 1.1253098364250036e-07 Epoch: [42/45], Batch: 1000, Loss: 1.1357283113966332e-07 Epoch: [42/45], Batch: 1200, Loss: 6.257906903783805e-08 Epoch: [43/45], Batch: 200, Loss: 1.1900504404138701e-07 Epoch: [43/45], Batch: 400, Loss: 7.35422247544193e-08 Epoch: [43/45], Batch: 600, Loss: 2.970030550386582e-07 Epoch: [43/45], Batch: 800, Loss: 8.526841099865123e-08 Epoch: [43/45], Batch: 1000, Loss: 9.009828261241637e-08 Epoch: [43/45], Batch: 1200, Loss: 1.0789925397602929e-07 Epoch: [44/45], Batch: 200, Loss: 4.517924523383954e-08 Epoch: [44/45], Batch: 400, Loss: 8.079925351012207e-08 Epoch: [44/45], Batch: 600, Loss: 1.0159882180005297e-07 Epoch: [44/45], Batch: 800, Loss: 5.457639318251495e-08 Epoch: [44/45], Batch: 1000, Loss: 1.156581248551447e-07 Epoch: [44/45], Batch: 1200, Loss: 4.4154425893339067e-08 Epoch: [45/45], Batch: 200, Loss: 8.871925416542581e-08 Epoch: [45/45], Batch: 400, Loss: 5.5569088885931706e-08 Epoch: [45/45], Batch: 600, Loss: 1.6741935837671917e-07 Epoch: [45/45], Batch: 800, Loss: 6.097327087672966e-08 Epoch: [45/45], Batch: 1000, Loss: 1.7409195152140455e-07 Epoch: [45/45], Batch: 1200, Loss: 8.593719513783071e-08

Test L1 error: 93.60745577514172 Test L2 error: 798.8346153497696





