hw0_ipyn

January 18, 2023

0.1 1.2

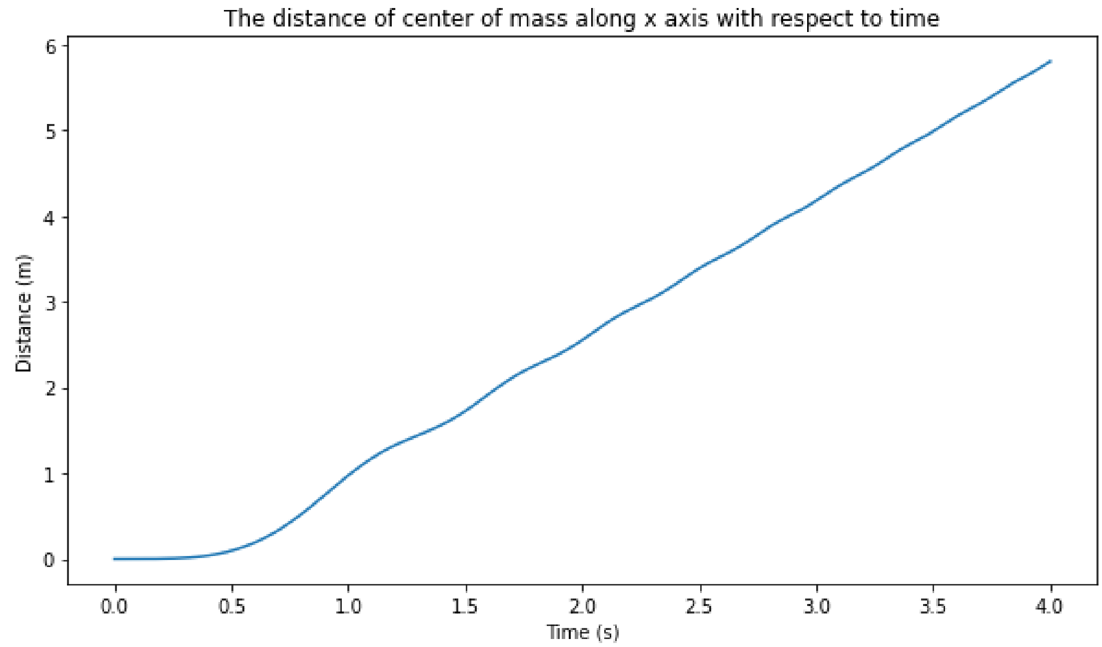
[ ]:
```python
import os
import numpy as np
import open3d as o3d
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.nn.parallel
import torch.utils.data
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import TensorDataset, DataLoader
```

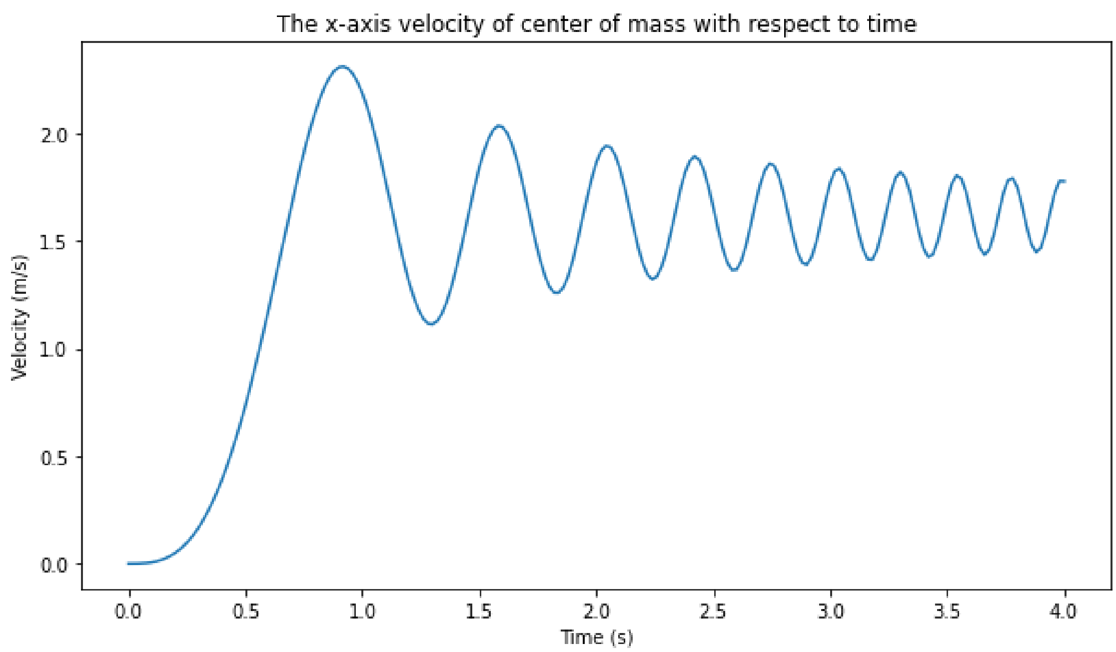
[ ]:
```python
class RK4():
    def __init__(self,t=4,x0=0,v0=0,h=0.02,x_axis=True) -> None:
        self.x0 = x0
        self.v0 = v0
        self.t = t
        self.h = h
        self.is_x = x_axis
        self.res = self.RungeKutta4()
    def f1(self,x,v,t):
        return v
    def f2(self,x,v,t):
        if self.is_x:
            return 5*np.sin((6*5*np.sqrt(0.5**2+4/4)*np.sin(np.arctan2(2*0.
 ↪5,2))/2**2)*t**2)
        else:
            return 5*np.cos((6*5*np.sqrt(0.5**2+4/4)*np.sin(np.arctan2(2*0.
 ↪5,2))/2**2)*t**2)
    def RungeKutta4(self):
        h = self.h
        n = int(self.t/self.h)
        V = np.zeros( n+ 1)
        T = np.zeros(n + 1)
        X = np.zeros(n + 1)
        X[0], V[0] = self.x0, self.v0
```

```python
        for i in range(n):
          k1_v = h*self.f2(X[i],V[i],T[i])
          k1_x = h*self.f1(X[i],V[i],T[i])
          k2_v = h*self.f2(X[i]+0.5*k1_x,V[i]+0.5*k1_v,T[i]+0.5*h)
          k2_x = h*self.f1(X[i]+0.5*k1_x,V[i]+0.5*k1_v,T[i]+0.5*h)
          k3_v = h*self.f2(X[i]+0.5*k2_x,V[i]+0.5*k2_v,T[i]+0.5*h)
          k3_x = h*self.f1(X[i]+0.5*k2_x,V[i]+0.5*k2_v,T[i]+0.5*h)
          k4_v = h*self.f2(X[i]+k3_x,V[i]+k3_v,T[i]+h)
          k4_x = h*self.f1(X[i]+k3_x,V[i]+k3_v,T[i]+h)
          X[i+1] = X[i] + (k1_x + 2*k2_x + 2*k3_x + k4_x)/6
          V[i+1] = V[i] + (k1_v + 2*k2_v + 2*k3_v + k4_v)/6
          T[i+1] = T[i] + h
        return (T,X,V)
```

[ ]:

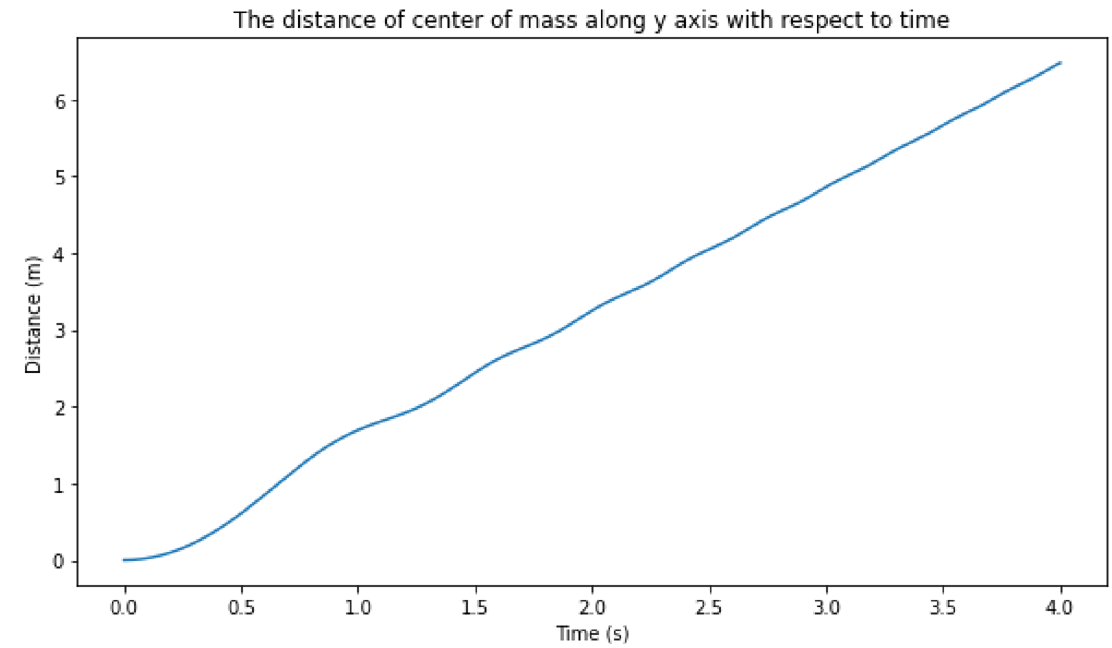
```python
x_axis = RK4()
t_x, dist_x, vel_x = x_axis.res
fig, (ax1,ax2) =plt.subplots(2,1,figsize=(10,12))
ax1.plot(t_x,dist_x)
ax1.set(xlabel='Time (s)', ylabel='Distance (m)',title='The distance of center␣
 ↪of mass along x axis with respect to time')
ax2.plot(t_x, vel_x)
ax2.set(xlabel='Time (s)', ylabel='Velocity (m/s)',title='The x-axis velocity␣
 ↪of center of mass with respect to time')
plt.savefig("1_2_x.png")
```

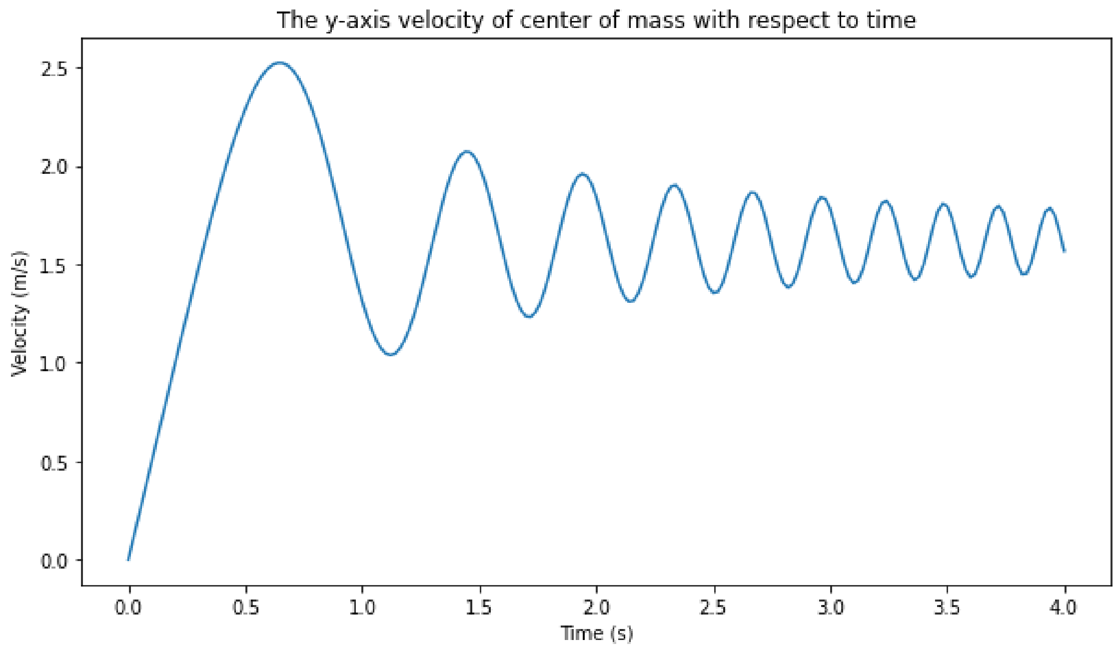




[ ]:
```
y_axis = RK4(x_axis=False)
t_y, dist_y, vel_y = y_axis.res
fig, (ax1,ax2) =plt.subplots(2,1,figsize=(10,12))
ax1.plot(t_y,dist_y)
ax1.set(xlabel='Time (s)', ylabel='Distance (m)',title='The distance of center␣
↪of mass along y axis with respect to time')
ax2.plot(t_y, vel_y)
```

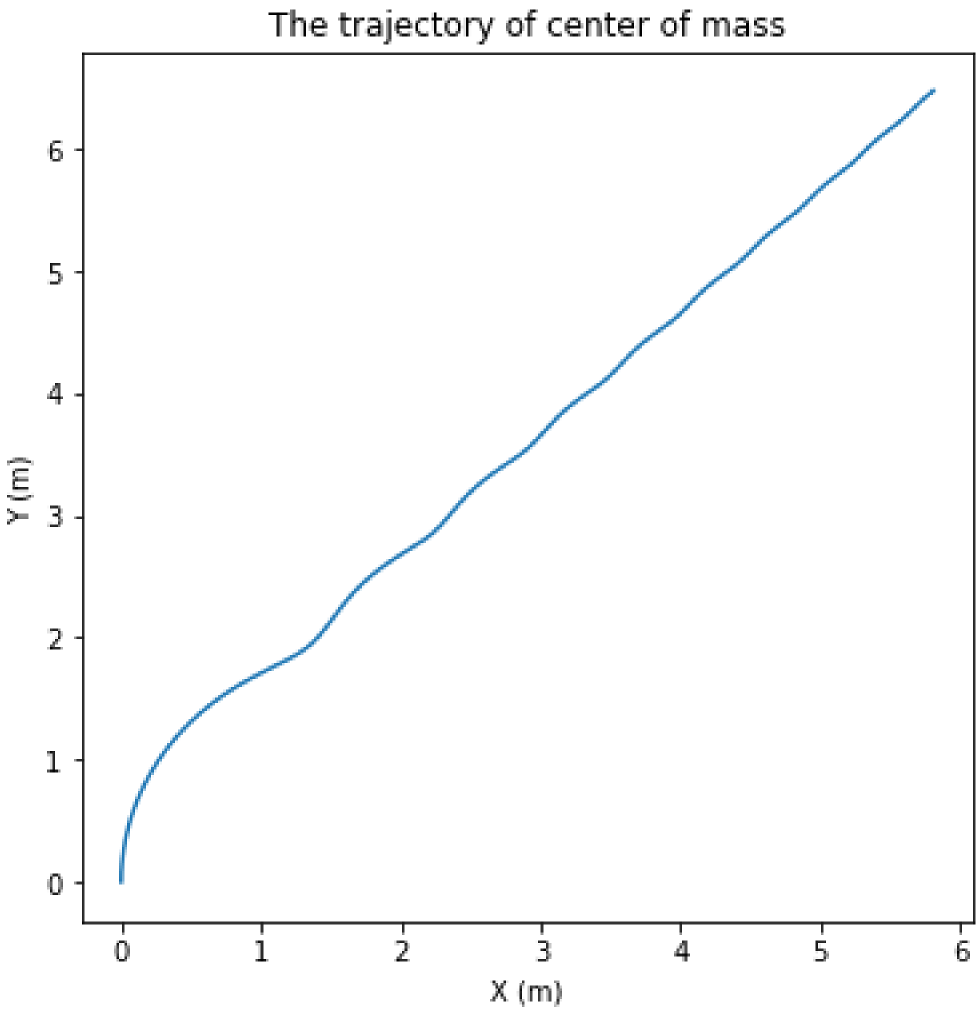
```
ax2.set(xlabel='Time (s)', ylabel='Velocity (m/s)',title='The y-axis velocity␣
  ↪of center of mass with respect to time')
plt.savefig("1_2_y.png")
```





0.2 1.3

[ ]:
```
fig, ax = plt.subplots(figsize=(6,6))
ax.plot(dist_x,dist_y)
ax.set(xlabel='X (m)', ylabel='Y (m)',title='The trajectory of center of mass')
plt.savefig("1_3_1.png")
```

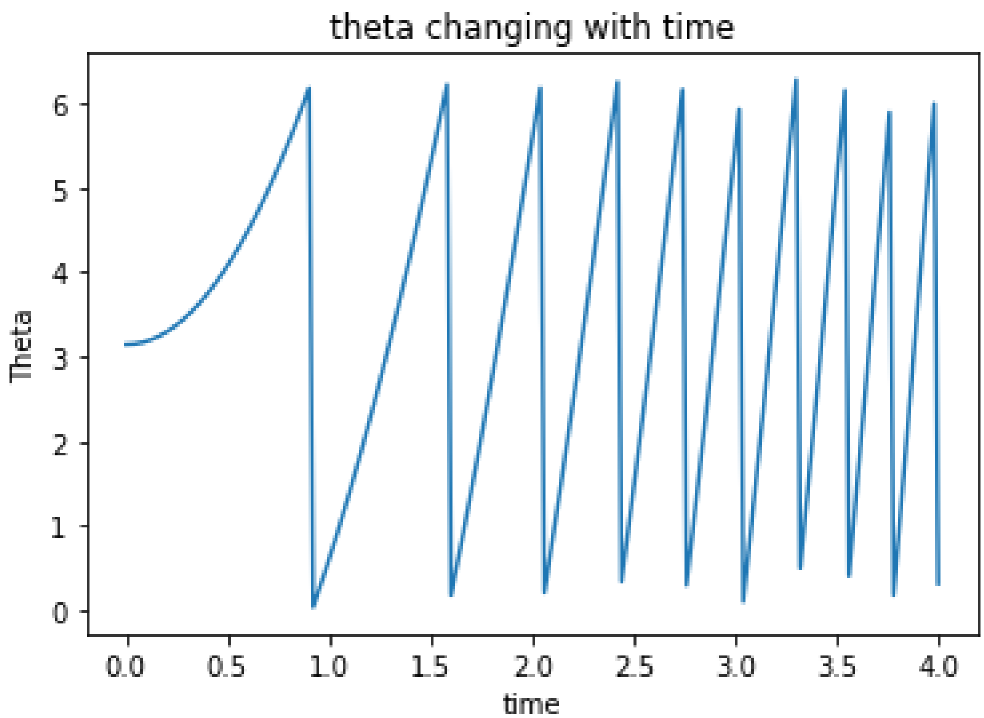


[ ]:
```
def theta(t,h):
    T = np.arange(0,t+h,h)
    return (6*5*np.sqrt(0.5**2+4/4)*np.sin(np.arctan2(2*0.5,2))/2**2)*T**2
def convert_to_range(theta):
    theta = np.arctan2(np.sin(theta),np.cos(theta))
    # for i in range(len(theta)):
    #     if theta[i] <0:
    #         theta[i] = 2*np.pi-np.abs(theta[i])
    # return theta
```

```
    return np.pi+theta
fig, ax = plt.subplots()
ax.plot(t_x,convert_to_range(theta(4,0.02)))
ax.set(xlabel="time",ylabel="Theta",title="theta changing with time")
# plt.savefig("1_3_2.png")
```

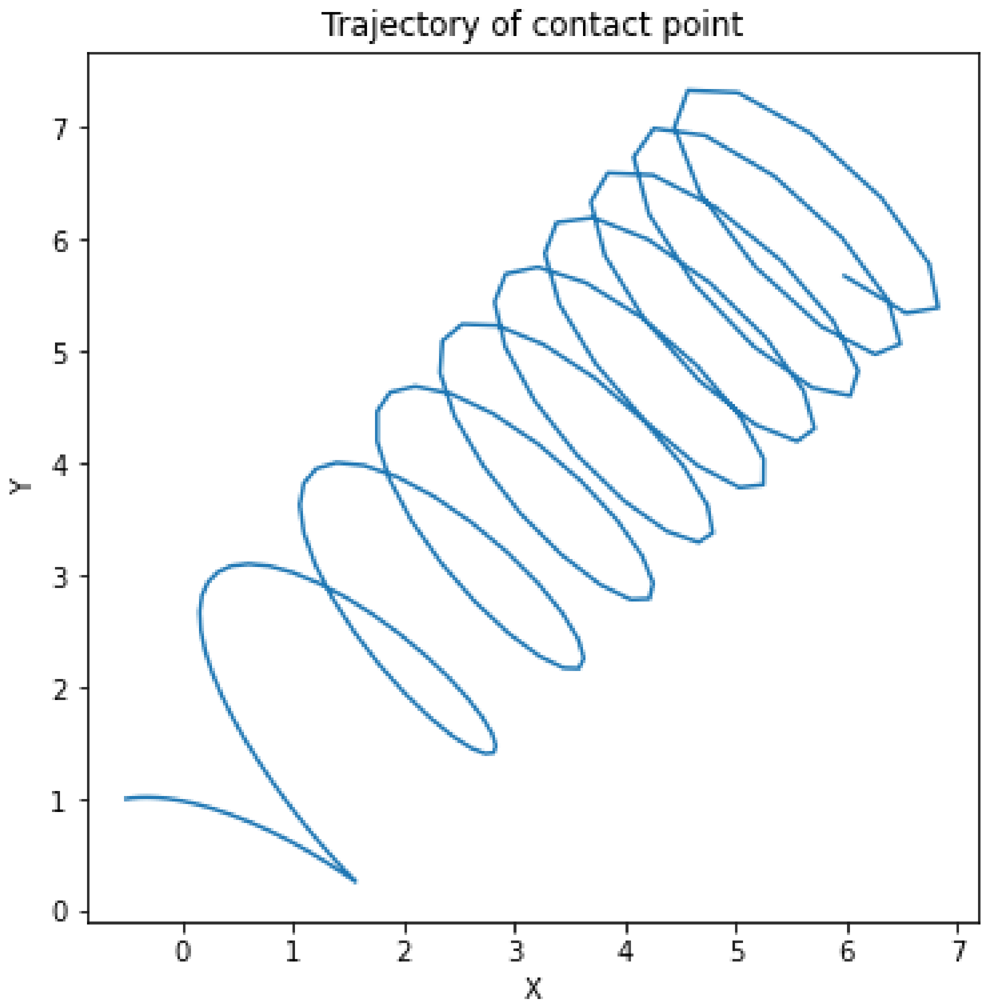
[ ]:

```
[Text(0.5, 0, 'time'),
 Text(0, 0.5, 'Theta'),
 Text(0.5, 1.0, 'theta changing with time')]
```



[ ]:

```
def trajectory(theta, dist_x, dist_y):
    L = 0.5
    D = 2
    X = -L*np.cos(theta) + D/2*np.sin(theta) + dist_x
    Y = -L*np.sin(theta) + D/2*np.cos(theta) + dist_y
    return X,Y
p_x,p_y = trajectory(theta(4,0.02), dist_x, dist_y)
fig, ax = plt.subplots(figsize=(6,6))
ax.plot(p_x,p_y)
ax.set(xlabel="X",ylabel="Y",title="Trajectory of contact point")
plt.savefig("1_3_3.png")
```




```
[ ]: print(dist_x[-1],dist_y[-1])
     print(p_x[-1],p_y[-1])
```

```
5.806979164419252 6.47741357390244
5.978375033524605 5.677405904038397
```

0.3 2.4

```
[ ]: npz = np.load("../../datasets/HW0_P1.npz")
     A = npz['A']
     b = npz['b']
     eps = npz['eps']
```

```
[ ]: def NewtonDescent(A,b,eps,lm=0.01,iters=1000):
         m,n = A.shape
         b = b.reshape(-1,1)
```

```
    x = np.random.rand(n,1)
    while(iters):
        if x.T@x<=eps:
            break
        x -= lm*(A.T)@(A@x-b)

        iters-=1
    print(x,iters)
    return x
min_x = NewtonDescent(A,b,eps)
```

```
[[ 0.10597233]
 [-0.13801678]
 [ 0.06598404]
 [ 0.07737474]
 [ 0.04011135]
 [ 0.0619423 ]
 [-0.18518747]
 [ 0.0468657 ]
 [ 0.33576678]
 [-0.1358843 ]
 [ 0.06463118]
 [-0.01992169]
 [-0.02817568]
 [-0.11036813]
 [-0.02259481]
 [-0.13755223]
 [ 0.22503204]
 [-0.18310344]
 [-0.18922506]
 [ 0.03619719]
 [ 0.10916455]
 [ 0.12787252]
 [-0.11483603]
 [-0.02349693]
 [ 0.03448602]
 [-0.25984269]
 [-0.16783084]
 [-0.08355302]
 [ 0.17950976]
 [-0.24833825]] 0
```

0.4 3

[ ]:
```
if torch.cuda.is_available():
    device = torch.device('cuda')
    print("use device:",device)
```

use device: cuda

[ ]:
```python
def pts_loader(path,NUM=1000,MAX_N = 2907):
    # pts_loader provides a load() method to read data from .pts files of
    # point clouds
    #
    # ---------------------------------------------------------
    # pts_loader
    # Licensed under The MIT License [see LICENSE.md for details]
    # Copyright (C) 2017 Samuel Albanie
    # ---------------------------------------------------------

    """takes as input the path to a .pts and returns a list of
        tuples of floats containing the points in in the form:
        [(x_0, y_0, z_0),
         (x_1, y_1, z_1),
         ...
         (x_n, y_n, z_n)]"""
    pts = np.zeros((NUM,MAX_N,3))
    dir_list = os.listdir(path)
    j=0
    for i in dir_list:
        file_path = path+i
        with open(file_path) as f:
            rows = [rows.strip() for rows in f]

        coords_set = [point.split() for point in rows]

        """Convert entries from lists of strings to tuples of floats"""
        points = [tuple([float(point) for point in coords]) for coords in␣
↪coords_set]
        points = np.array(points)
        pts[j,:points.shape[0],:] = points
        j+=1
    return pts
```

[ ]:
```python
def label_loader(path,MAX_N=2907):
    labels = np.zeros((1000,MAX_N))
    dir_list = os.listdir(path)
    j=0
    for i in dir_list:
        file_path = path+i
        with open(file_path) as f:
            rows = [rows.strip() for rows in f]
            labels[j,:len(rows)]=rows
        j+=1
    return labels
```

[ ]:
```
class PointNetSeg(nn.Module):
    def __init__(self,k) -> None:
        super(PointNetSeg,self).__init__()
        self.m = k
        self.conv1 = torch.nn.Conv1d(in_channels = 3, out_channels=␣
 ↪64,kernel_size= 1)
        self.conv21 = torch.nn.Conv1d(64, 128, 1)
        self.conv22 = torch.nn.Conv1d(128, 1024, 1)
        self.conv31 = torch.nn.Conv1d(1088,512,1)
        self.conv32 = torch.nn.Conv1d(512,256,1)
        self.conv33 = torch.nn.Conv1d(256,128,1)
        self.conv4 = torch.nn.Conv1d(128,self.m,1)

        self.bn1 = nn.BatchNorm1d(num_features = 64)
        self.bn21 = nn.BatchNorm1d(128)
        self.bn22 = nn.BatchNorm1d(1024)
        self.bn31 = nn.BatchNorm1d(512)
        self.bn32 = nn.BatchNorm1d(256)
        self.bn33 = nn.BatchNorm1d(128)

    def forward(self,x):
        # x shape is batch, channels, num of pts
        batchsize, n_chanel, n_pts = x.size()
        x = F.relu(self.bn1(self.conv1(x)))
        ptsfeats = x
        x = F.relu(self.bn21(self.conv21(x)))
        x = self.bn22(self.conv22(x))
        x = torch.max(x,dim =2,keepdim=True)[0]
        x = x.view(-1,1024,1).repeat(1,1,n_pts)
        x = torch.cat((ptsfeats,x),1)
        x = F.relu(self.bn31(self.conv31(x)))
        x = F.relu(self.bn32(self.conv32(x)))
        x = F.relu(self.bn33(self.conv33(x)))
        x = self.conv4(x)
        x = x.transpose(2,1).contiguous()
        x = F.log_softmax(x.view(-1,self.m),dim=-1)
        x = x.view(batchsize,n_pts,self.m)
        return x
```

[ ]:
```
batch_size = 250
num_segms = 5 #0,1,2,3,4  (0 is for padding)
learn_rate = 0.001
num_train = 1000
num_test = 6
num_epochs = 20
num_classes = 5
```

```
num_batch = int(num_train/batch_size)
n_pts=2907
```

[ ]:
```
train_pts_path = '../../datasets/train/pts/'
train_label_path = '../../datasets/train/label/'
test_path = '../../datasets/test/'
train_pts = pts_loader(train_pts_path)
train_labels = label_loader(train_label_path)
train_pts.shape, train_labels.shape #(1000, 2907, 3), (1000, 2907)
```

[ ]:
```
((1000, 2907, 3), (1000, 2907))
```

[ ]:
```
train_datasets = TensorDataset(torch.Tensor(train_pts),torch.
 ↪Tensor(train_labels))
train_dataloader = DataLoader(train_datasets,batch_size=batch_size)
```

[ ]:
```
pointNetClassifier = PointNetSeg(k=num_classes)
optimizer = optim.Adam(pointNetClassifier.parameters(),lr=learn_rate)
scheduler = optim.lr_scheduler.StepLR(optimizer, step_size=20, gamma=0.5)
pointNetClassifier.to(device)
```

[ ]:
```
PointNetSeg(
  (conv1): Conv1d(3, 64, kernel_size=(1,), stride=(1,))
  (conv21): Conv1d(64, 128, kernel_size=(1,), stride=(1,))
  (conv22): Conv1d(128, 1024, kernel_size=(1,), stride=(1,))
  (conv31): Conv1d(1088, 512, kernel_size=(1,), stride=(1,))
  (conv32): Conv1d(512, 256, kernel_size=(1,), stride=(1,))
  (conv33): Conv1d(256, 128, kernel_size=(1,), stride=(1,))
  (conv4): Conv1d(128, 5, kernel_size=(1,), stride=(1,))
  (bn1): BatchNorm1d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (bn21): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (bn22): BatchNorm1d(1024, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (bn31): BatchNorm1d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (bn32): BatchNorm1d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (bn33): BatchNorm1d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
)
```

[ ]:
```
temp_preds,temp_target,temp_loss,temp_choice,temp_correct = 0,0,0,0,0
```

[ ]:
```
for epoch in range(num_epochs):
    for batch_i, (points,target) in enumerate(train_dataloader,0):
```

```
        points = points.transpose(2,1)
        target = target.type(torch.LongTensor)
        points, target = points.to(device), target.to(device)
        target = target.view(-1,1)[:,0]
        optimizer.zero_grad()
        segmenter = pointNetClassifier.train()
        preds = segmenter(points)
        preds = preds.view(-1,num_classes)
        loss = F.nll_loss(preds,target)
        loss.backward()
        optimizer.step()
        pred_choice = preds.data.max(1)[1]
        # pred_choice = preds.max(1)[1]
        # pred_choice = pred_choice.type(torch.LongTensor).contiguous()
        # loss = F.nll_loss(pred_choice.cpu(),target.cpu())
        pred_correct = pred_choice.eq(target.data).cpu().sum()
        print('[epoch {}: {}/{}] train loss: {} accuracy: {}'.
↪format(epoch+1,batch_i+1,num_batch,loss.item(),pred_correct.item()/
↪float(batch_size*n_pts)))
        temp_preds,temp_target,temp_loss,temp_choice,temp_correct =␣
↪preds,target,loss,pred_choice,pred_correct
    scheduler.step()
```

```
[epoch 1: 1/4] train loss: 1.7102280855178833 accuracy: 0.1724485724114207
[epoch 1: 2/4] train loss: 1.376878023147583 accuracy: 0.4825208118335053
[epoch 1: 3/4] train loss: 1.141352653503418 accuracy: 0.595296869625043
[epoch 1: 4/4] train loss: 0.9598174095153809 accuracy: 0.7257117303061575
[epoch 2: 1/4] train loss: 0.8643354177474976 accuracy: 0.7679752321981425
[epoch 2: 2/4] train loss: 0.7950428128242493 accuracy: 0.787562435500516
[epoch 2: 3/4] train loss: 0.7384516596794128 accuracy: 0.7954275885792914
[epoch 2: 4/4] train loss: 0.6863488554954529 accuracy: 0.8082518059855521
[epoch 3: 1/4] train loss: 0.6519809365272522 accuracy: 0.8133319573443413
[epoch 3: 2/4] train loss: 0.6195282936096191 accuracy: 0.8241238390092879
[epoch 3: 3/4] train loss: 0.5976731777191162 accuracy: 0.8177860337117303
[epoch 3: 4/4] train loss: 0.5551645755767822 accuracy: 0.8283040935672514
[epoch 4: 1/4] train loss: 0.5337951183319092 accuracy: 0.832656346749226
[epoch 4: 2/4] train loss: 0.5052109360694885 accuracy: 0.8403894048847609
[epoch 4: 3/4] train loss: 0.49070408940315247 accuracy: 0.8452466460268317
[epoch 4: 4/4] train loss: 0.4563632309436798 accuracy: 0.8540144478844169
[epoch 5: 1/4] train loss: 0.44680413603782654 accuracy: 0.8616374269005848
[epoch 5: 2/4] train loss: 0.4200718402862549 accuracy: 0.8763384932920537
[epoch 5: 3/4] train loss: 0.41594934463500977 accuracy: 0.8752074303405573
[epoch 5: 4/4] train loss: 0.38076522946357727 accuracy: 0.8916339869281046
[epoch 6: 1/4] train loss: 0.3819567561149597 accuracy: 0.8898809769521844
[epoch 6: 2/4] train loss: 0.35605093836784363 accuracy: 0.9008393532851737
[epoch 6: 3/4] train loss: 0.3561458885669708 accuracy: 0.8966522187822498
```

```
[epoch 6: 4/4] train loss: 0.32443132996559143 accuracy: 0.9068083935328517
[epoch 7: 1/4] train loss: 0.332579642534256 accuracy: 0.900343997248022
[epoch 7: 2/4] train loss: 0.3106917440891266 accuracy: 0.9123288613691091
[epoch 7: 3/4] train loss: 0.3176509737968445 accuracy: 0.9070588235294118
[epoch 7: 4/4] train loss: 0.28719136118888855 accuracy: 0.9189597523219815
[epoch 8: 1/4] train loss: 0.2994996905326843 accuracy: 0.9107464740282077
[epoch 8: 2/4] train loss: 0.27967512607574463 accuracy: 0.9186088751289989
[epoch 8: 3/4] train loss: 0.28939273953437805 accuracy: 0.9127939456484349
[epoch 8: 4/4] train loss: 0.26187145709991455 accuracy: 0.9241541107671138
[epoch 9: 1/4] train loss: 0.2747644782066345 accuracy: 0.9165283797729619
[epoch 9: 2/4] train loss: 0.2575845718383789 accuracy: 0.922485036119711
[epoch 9: 3/4] train loss: 0.2663111388683319 accuracy: 0.917312693498452
[epoch 9: 4/4] train loss: 0.24634245038032532 accuracy: 0.9253223254213966
[epoch 10: 1/4] train loss: 0.25376632809638977 accuracy: 0.921062263501892
[epoch 10: 2/4] train loss: 0.24785155057907104 accuracy: 0.9209618163054696
[epoch 10: 3/4] train loss: 0.248787522315979 accuracy: 0.9216649466804265
[epoch 10: 4/4] train loss: 0.23619896173477173 accuracy: 0.9270299277605779
[epoch 11: 1/4] train loss: 0.2431413233280182 accuracy: 0.9237715858273133
[epoch 11: 2/4] train loss: 0.23138085007667542 accuracy: 0.927577571379429
[epoch 11: 3/4] train loss: 0.25022974610328674 accuracy: 0.9180915032679738
[epoch 11: 4/4] train loss: 0.21855002641677856 accuracy: 0.9296745786033712
[epoch 12: 1/4] train loss: 0.24946525692939758 accuracy: 0.9183983488132095
[epoch 12: 2/4] train loss: 0.2287818342447281 accuracy: 0.9251420708634331
[epoch 12: 3/4] train loss: 0.2343924194574356 accuracy: 0.9238775369797042
[epoch 12: 4/4] train loss: 0.23226425051689148 accuracy: 0.9233340213278294
[epoch 13: 1/4] train loss: 0.2316998690366745 accuracy: 0.9223680770553836
[epoch 13: 2/4] train loss: 0.21844130754470825 accuracy: 0.9279201926384589
[epoch 13: 3/4] train loss: 0.23571431636810303 accuracy: 0.9228730650154798
[epoch 13: 4/4] train loss: 0.21168392896652222 accuracy: 0.9285806673546612
[epoch 14: 1/4] train loss: 0.21400554478168488 accuracy: 0.9310409356725147
[epoch 14: 2/4] train loss: 0.20139609277248383 accuracy: 0.9339428964568284
[epoch 14: 3/4] train loss: 0.22088417410850525 accuracy: 0.9254158926728586
[epoch 14: 4/4] train loss: 0.1979270577430725 accuracy: 0.9340846233230135
[epoch 15: 1/4] train loss: 0.20548658072948456 accuracy: 0.9323412452700378
[epoch 15: 2/4] train loss: 0.20325139164924622 accuracy: 0.9296374269005848
[epoch 15: 3/4] train loss: 0.20709969103336334 accuracy: 0.9326659786721706
[epoch 15: 4/4] train loss: 0.1890232414007187 accuracy: 0.9370691434468524
[epoch 16: 1/4] train loss: 0.1998663991689682 accuracy: 0.9326136910904713
[epoch 16: 2/4] train loss: 0.18694177269935608 accuracy: 0.937047127622979
[epoch 16: 3/4] train loss: 0.1997421532869339 accuracy: 0.9325242518059855
[epoch 16: 4/4] train loss: 0.17993324995040894 accuracy: 0.9432074303405573
[epoch 17: 1/4] train loss: 0.18936733901500702 accuracy: 0.937938768489852
[epoch 17: 2/4] train loss: 0.180886372923851 accuracy: 0.9400591675266597
[epoch 17: 3/4] train loss: 0.18928217887878418 accuracy: 0.9353849329205366
[epoch 17: 4/4] train loss: 0.17465868592262268 accuracy: 0.9410663914688683
[epoch 18: 1/4] train loss: 0.1849082112312317 accuracy: 0.9376828345373237
[epoch 18: 2/4] train loss: 0.18052130937576294 accuracy: 0.9411186790505676
[epoch 18: 3/4] train loss: 0.18477386236190796 accuracy: 0.9386198830409357
```

```
[epoch 18: 4/4] train loss: 0.17008733749389648 accuracy: 0.9444045407636739
[epoch 19: 1/4] train loss: 0.17924588918685913 accuracy: 0.9402999656002752
[epoch 19: 2/4] train loss: 0.17309044301509857 accuracy: 0.9404169246646027
[epoch 19: 3/4] train loss: 0.18025416135787964 accuracy: 0.9378108015135879
[epoch 19: 4/4] train loss: 0.16566695272922516 accuracy: 0.943858273133815
[epoch 20: 1/4] train loss: 0.174861341714859 accuracy: 0.9406921224630203
[epoch 20: 2/4] train loss: 0.1625606119632721 accuracy: 0.9458685930512556
[epoch 20: 3/4] train loss: 0.17861561477184296 accuracy: 0.9390767113863089
[epoch 20: 4/4] train loss: 0.16066481173038483 accuracy: 0.9464107327141383
```

[ ]:
```
temp_preds,temp_target,temp_loss,temp_choice,temp_correct
```

[ ]:
```
(tensor([[-7.0616, -5.3301, -3.2657, -2.2919, -0.1566],
         [-7.0449, -5.2358, -4.8028, -1.9945, -0.1631],
         [-7.1161, -5.2106, -5.9520, -2.6999, -0.0791],
         …,
         [-0.0400, -5.9683, -6.1495, -6.8602, -3.3961],
         [-0.0400, -5.9683, -6.1495, -6.8602, -3.3961],
         [-0.0400, -5.9683, -6.1495, -6.8602, -3.3961]], device='cuda:0',
        grad_fn=<ViewBackward0>),
 tensor([4, 4, 4,  …, 0, 0, 0], device='cuda:0'),
 tensor(0.1607, device='cuda:0', grad_fn=<NllLossBackward0>),
 tensor([4, 4, 4,  …, 0, 0, 0], device='cuda:0'),
 tensor(687804))
```

[ ]:
```
def test_loader(path):
    path_list = os.listdir(path)
    pt = []
    for i in path_list:
        with open(path+i) as f:
            rows = [rows.strip() for rows in f]
        coords_set = [point.split() for point in rows]
        points = [tuple([float(point) for point in coords]) for coords in␣
 ↪coords_set]
        pt.append(np.array(points))
    return pt
test_path = '../../datasets/test/'
test_pts = test_loader(test_path)
```

[ ]:
```
test_path = '../../datasets/test/'
test_pts = pts_loader(test_path,NUM=6,MAX_N=2821)
test_i = test_pts.copy()
test_i = np.transpose(test_i,(0,2,1))
test_i = torch.tensor(test_i)
test_i = test_i.to(device,dtype=torch.float)
segmenter = pointNetClassifier.eval()
pred = segmenter(test_i)
```

```
pred_choice = pred.data.max(2)[1]
pred_final = pred_choice.cpu().data.numpy().astype('int')
```

[ ]:
```
pred_final.shape, test_pts.shape
```

[ ]: ((6, 2821), (6, 2821, 3))

[ ]:
```
red = [1,0,0]
green = [0,1,0]
blue = [0,0,1]
purple = [0.62,0.125,0.94]
white = [1,1,1]
def showopen3d(pts, c):
    pointcloud = o3d.geometry.PointCloud()
    pointcloud.points = o3d.utility.Vector3dVector(pts)
    pointcloud.colors = o3d.utility.Vector3dVector(c)
    o3d.visualization.draw_geometries([pointcloud])
for i in range(pred_final.shape[0]):
    plane = test_pts[i]
    segments = pred_final[i]
    colors = np.zeros(plane.shape)
    for i in range(plane.shape[0]):
        if segments[i] ==0:
            colors[i] = white
        elif segments[i] == 1:
            colors[i] = red
        elif segments[i] == 2:
            colors[i] = green
        elif segments[i] == 3:
            colors[i] = blue
        elif segments[i] == 4:
            colors[i] = purple
    showopen3d(plane,colors)
```

[ ]:
```
#1-4 indicates arm, back, leg, and seat
#0 padding no color
#1 arm red
#2 back green
#3 leg blue
#4seat purple rgb=0.62,0.125,0.94
```