minimal_mpc_with_cnode_dynamics

May 20, 2020

this code is dedicated to model based reinforcement learning with Neural Ordinary Differential equations as a function approximator for the dynamics model. the code is accomodated for addition of control actions in a forked repo. the envs and mpc controller is taken from pytorch mpc

0.1 imports

[0]:
```
!pip install mpc
!pip install noise
!pip install torch==1.4 torchvision==0.4.1
```

[0]:
```
!git clone https://github.com/karim174/torchdiffeq.git
```

[0]:
```
!cd torchdiffeq && pip install -e .
```

[0]:
```
import logging
import math
import time
import noise
import numpy as np
import pandas as pd

import torch
import torch.nn as nn
import torch.autograd
from torch.autograd import Function, Variable
from torch.nn.parameter import Parameter
import torch.nn.functional as F


from mpc import mpc
from mpc import util
from mpc.mpc import QuadCost, LinDx, GradMethods
from mpc.env_dx import pendulum, cartpole


%matplotlib inline
import os
import glob
```

```python
import io
import base64
from IPython.display import HTML
from IPython import display as ipythondisplay
import matplotlib.pyplot as plt

import random
import tempfile
import time
from tqdm import tqdm

from torchdiffeq.torchdiffeq import odeint_adjoint as odeint


use_cuda = True
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

[0]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

[0]:
```python
# Create a custom logger
base_file = '/content/drive/My Drive/CNODE-VAE/experiments/exp1'
logging.basicConfig(
    level=logging.INFO,
    format='%(asctime)s - %(name)s - %(levelname)s - %(message)s',
    handlers=[
        logging.FileHandler(base_file+"training_hist.log"),
        logging.StreamHandler()
    ]
)
logger = logging.getLogger('logger')
```

[0]:
```python
TRAIN_EPOCH = 15#100 #150

TIMESTEPS = 10  # T
LQR_ITER = 50
ACTION_LOW = -2.0
ACTION_HIGH = 2.0
SPEED_LOW = -8.0
SPEED_HIGH = 8.0

nx = 3 #changed to 2 theta and dtheta instead of sins and cosines
nu = 1
```

0.2 Network

[0]:
```
class code(nn.Module):

   def __init__(self, feature_dim=3, activation = nn.Tanh(), hidden_dim = 64,␣
↪ctrl_dim=1):
       super(code, self).__init__()


       self.net = nn.Sequential(
           nn.Linear(feature_dim+ctrl_dim, hidden_dim),
           activation,
           nn.Linear(hidden_dim, hidden_dim),
           activation,
           nn.Linear(hidden_dim, hidden_dim),
           nn.ELU(),
           nn.Linear(hidden_dim, hidden_dim),
           activation,
           nn.Linear(hidden_dim, hidden_dim),
           activation,
           nn.Linear(hidden_dim, feature_dim)
       )
       self.ctrl_dim = ctrl_dim
       if ctrl_dim:
         self.control_sequences = lambda x: torch.zeros(ctrl_dim)

       for m in self.net.modules():
           if isinstance(m, nn.Linear):
             if activation == nn.Tanh() :
               nn.init.xavier_uniform_(m.weight, gain=1.0)
             else:nn.init.normal_(m.weight, mean=0, std=np.sqrt(2/m.
↪in_features))
             nn.init.constant_(m.bias, val=0)

   def forward(self, t, y):

     if self.ctrl_dim:
       with torch.no_grad():

         if t.is_cuda:
           t_c = t.cpu()
           c = self.control_sequences(t_c.clone().detach().numpy())


         else:
           c = self.control_sequences(t.clone().detach().numpy())
```

```
        if not torch.is_tensor(c):
          c = torch.from_numpy(c)


        if len(c.shape) == 1:
          c = torch.ones_like(y[:, 0][..., None]) * c #replaced from zeros

        c =c.to(t)
        if t.requires_grad:
          c.requires_grad_()
      y_cat=torch.cat([y,c], axis = 1)
      return self.net(y_cat)
    return self.net(y)
```

0.3 Utility

[0]:
```
def get_batch_with_ctrl(XU):
    s = torch.from_numpy(np.random.choice(np.arange(XU.shape[0] - batch_time,␣
 ↪dtype=np.int64), batch_size, replace=True))
    ep = torch.from_numpy(np.random.choice(XU.shape[1], batch_size,␣
 ↪replace=True))
    batch_y0 = XU[s,ep,:nx]   # (M, D)
    t = torch.linspace(0., T*dt, T)
    batch_t = t[:batch_time]   # (T)
    batch_u = torch.stack([XU[s + i, ep, nx:] for i in range(batch_time)],␣
 ↪dim=0)   # (T, M, D)
    batch_y = torch.stack([XU[s + i, ep, :nx] for i in range(batch_time)],␣
 ↪dim=0)   # (T, M, D)
    return batch_y0, batch_t, batch_y, batch_u
```

[0]:
```
def tuning():
  n_ep = random.choice([2500, 3000, 4000, 5000])
  batch_size = random.choice([32, 64, 128, 256, 512])
  T = random.choice([250, 500, 750])
  batch_time = random.choice([16, 32, 64, 128])
  optimizer = random.choice(['RMSprop', 'Adam', 'AdamW'])
  activation = random.choice([nn.ReLU(), nn.LeakyReLU(), nn.ELU(), nn.Tanh()])
  hidden_dim = random.choice([32, 64, 128])
  steps_per_epoch = (n_ep * T) / (batch_time*batch_size) #ADDED (KARIM)␣
 ↪*batch_size
  control_option = random.choice(['single act diff scale', 'diff all'])
  Act_per_batch = random.choice([5, 10])
  # nets = ['net1', 'net2']
  return [n_ep, batch_size, T, batch_time,
          activation, hidden_dim, optimizer, steps_per_epoch,
          control_option, Act_per_batch]
```

[0]:
```python
class RunningAverageMeter(object):
    """Computes and stores the average and current value"""

    def __init__(self, momentum=0.99):
        self.momentum = momentum
        self.reset()

    def reset(self):
        self.val = None
        self.avg = 0

    def update(self, val):
        if self.val is None:
            self.avg = val
        else:
            self.avg = self.avg * self.momentum + val * (1 - self.momentum)
        self.val = val
```

[0]:
```python
def to_np(x):
    if type(x) is np.ndarray:
      return x
    #print(type(x))
    return x.detach().cpu().numpy()

def angle_normalize(x):
    return (((x + np.pi) % (2 * np.pi)) - np.pi)

def save_checkpoint(state, filename=base_file+'/checkpoint6.pth.tar'):
    """Save checkpoint if a new best is achieved"""

    torch.save(state, filename)  # save checkpoint
```

[0]:
```python
class normalizer():

  def __init__(self, orig_scale, target_scale):
    self.orig_scale = orig_scale
    self.tar_scale = target_scale

  def normalize(self, x):
    if  torch.is_tensor(self.orig_scale) and torch.is_tensor(self.tar_scale):
      self.orig_scale = self.orig_scale.to(x)
      self.tar_scale = self.tar_scale.to(x)
    ft_min = self.orig_scale[0]
    ft_max = self.orig_scale[1]
    rng = (self.tar_scale[1]-self.tar_scale[0])
    tar_min = self.tar_scale[0]
    x_norm = rng*(x-ft_min)/(ft_max-ft_min)+tar_min
```

```
        return x_norm

    def denorm(self, x):
        if  torch.is_tensor(self.orig_scale) and torch.is_tensor(self.tar_scale):
          self.orig_scale = self.orig_scale.to(x)
          self.tar_scale = self.tar_scale.to(x)
        ft_min = self.tar_scale[0]
        ft_max = self.tar_scale[1]
        rng = (self.orig_scale[1]-self.orig_scale[0])
        tar_min = self.orig_scale[0]

        x_norm = rng*(x-ft_min)/(ft_max-ft_min)+tar_min
        return x_norm
```

[0]:
```
def add_line(legend):
    from matplotlib.lines import Line2D
    ax = legend.axes
    #cmap = plt.cm.binary
    custom_line = Line2D([0], [0], color='k', lw=2, linestyle = '--', label =␣
 ↪'predicted')
    handles, labels = ax.get_legend_handles_labels()
    handles.append(custom_line)
    labels.append("predicted")
    ax.legend(handles=handles, labels=labels)

def plot_trajectories(obs=None, times=None, trajs=None, save=None, figsize=(16,␣
 ↪8), freq = 1):
    #print(obs[0].shape, times[0].shape, trajs[0].shape )
    fig, ax = plt.subplots(freq, 1, figsize = (figsize[0], freq*figsize[1]))  #␣
 ↪Create a figure and an axes.
    ax = ax if (type(ax) is tuple) or isinstance(ax, np.ndarray)  else (ax,)

    if obs is not None:
        if times is None:
            times = [None] * len(obs)
        for o, t in zip(obs, times):
            o, t = to_np(o), to_np(t)
            freq_o = min(freq, o.shape[1] )
            for b_i in range(freq):
                ax[b_i].plot(t, o[:,b_i, 0], 'g-', label='costheta') # Plot␣
 ↪some data on the axes.
                ax[b_i].plot(t, o[:,b_i, 1], 'b-', label='sintheta')  # Plot␣
 ↪some data on the axes.
                ax[b_i].plot(t, o[:,b_i, 2], 'r-', label='omega')  # Plot some␣
 ↪data on the axes.
                ax[b_i].set_xlabel('time')  # Add an x-label to the axes.
```

```
                ax[b_i].set_ylabel('states')  # Add a y-label to the axes.
                ax[b_i].set_title("Progression of states with time")  # Add a␣
↪title to the axes.
                ax[b_i].legend()  # Add a legend.
                #plt.plot(t, o[:,b_i, 0], 'g-', t, o[:, b_i, 1], 'b-', t, o[:,␣
↪b_i, 2], 'r-')



    if trajs is not None:
        for z, t in zip(trajs, times):
            z = to_np(z)
            freq_o = min(freq, z.shape[1] )

            for b_i in range(freq):
              ax[b_i].plot(t, z[:,b_i, 0], 'g--');  # Plot some data on the␣
↪axes.
              ax[b_i].plot(t, z[:,b_i, 1], 'b--');  # Plot some data on the␣
↪axes.
              ax[b_i].plot(t, z[:,b_i, 2], 'r--');  # Plot some data on the␣
↪axes.
              add_line(ax[b_i].legend())
              #ax[b_i].legend(handlelength=3)  # Add a legend.
              #plt.plot(t, z[:, b_i, 0], 'g--', t, z[:, b_i, 1], 'b--', t, z[:,␣
↪b_i, 2], 'r--')
              #plt.set_xlabel('time')  # Add an x-label to the axes.
              #plt.set_ylabel('states')  # Add a y-label to the axes.
              #plt.set_title("Progression of states with time")  # Add a title␣
↪to the axes.
              #plt.legend()  # Add a legend.

        if save is not None:
            plt.savefig(save)
    plt.show()
```

[0]:

```
def control_action(T, batch_size, ctrl_dim, boundary_scale, option = {'single␣
↪act diff scale'}, act_per_batch = None):
  #the SU_MS corresponds to having the same action but with different scales
  # the su corresponds to single control action for all
  act_per_batch = batch_size if act_per_batch is None else act_per_batch
  world = np.zeros((batch_size,T))
  #scales_order = np.arange(0,2,1,  dtype=float)[np.newaxis, ...]
  #scales_mag = np.arange(0.1,1, 0.1, dtype=float)[..., np.newaxis]
  #scales = (10**(scales_order)*scales_mag).flatten()
  scales = np.concatenate([np.arange(2,30, 1, dtype=float), np.arange(30,150,␣
↪3, dtype=float), np.arange(150,400, 20, dtype=float)]) #1,80
```

```
  #print(scales)
  #scales = np.arange(-20,100,5)

  if option == 'single act diff scale':

    for b in range(act_per_batch):
      scale = np.random.choice(scales)
      octaves = np.random.choice(2)+1
      lacunarcity = np.random.choice(2)+1
      for t in range(T):
        world[b,t] = noise.pnoise1(t/scale, octaves=octaves, persistence=0.5,␣
↪lacunarity=lacunarcity, repeat=T, base=0) #2


  elif option == 'diff all':
    # this should be tested
    for g in range(batch_size//act_per_batch):
      scale = np.random.choice(scales)
      octaves = np.random.choice(2)+1
      lacunarcity = np.random.choice(2)+1
      for t in range(T*act_per_batch):
        #print(g*(act_per_batch),  + t//T)
        world[g*(act_per_batch) + t//T, t%T] = noise.pnoise1(t/scale,␣
↪octaves=octaves, persistence=0.5, lacunarity=lacunarcity, base=0)

  # add boundries to the world instead of action from -1 to 1
  max_perep = np.amax(world,axis=-1)[..., np.newaxis]
  min_perep = np.amin(world, axis = -1)[..., np.newaxis]
  #print(np.unique(max_perep), np.unique(min_perep))
  world = 2*boundary_scale*(world-min_perep)/
↪(max_perep-min_perep)-boundary_scale

  return world
```

[0]:
```
def validate_model(func, T):
  #given the ode function validate it on new data
  val_bs = 600
  u = np.zeros((val_bs,T))
  scales = np.arange(2, 20, 0.5)

  for b in range(val_bs):
    scale = np.random.choice(scales)
    for t in range(T, 2*T):
      u[b,t-T] = noise.pnoise1(t/scale, octaves=2, persistence=0.5,␣
↪lacunarity=2.0, repeat=2*T, base=0)
  true_u = u.T
  time_t = np.arange(T)
```

```python
  #plt.plot(time_t , true_u[:,20])
  # bootstrap network with random actions
  params = torch.tensor((10., 1., 1.))
  dx = pendulum.PendulumDx(params, simple=True)

  states_ds = []
  ctrl_ds = []
  x_init = reset_env(val_bs).double()
  tensor_true_u = torch.from_numpy(true_u).double()
  for t in tqdm(range(T)):
      x = dx(x_init, tensor_true_u[t].view(-1,1))
      states_ds.append(x_init)
      action = torch.clamp(tensor_true_u[t], ACTION_LOW, ACTION_HIGH)
      x[...,-1] = torch.clamp(x[...,-1], SPEED_LOW, SPEED_HIGH)
      ctrl_ds.append(action)
      x_init = x
  states_ds = torch.stack(states_ds)
  ctrl_ds = torch.stack(ctrl_ds).view(T,val_bs,1)
  val_data = torch.cat((states_ds, ctrl_ds), dim = -1)
  val_data = norm.normalize(val_data)
  with torch.no_grad():
    y_tot = val_data[:T//4, :, :nx].cuda()
    y0_tot = val_data[0, :, :nx].cuda()
    c_tot = val_data[:T//4, :, nx:].cuda()
    t_tot = torch.linspace(0., T*dt//4, T//4).to(c_tot).cuda()
    func = func.double().cuda()
    pred_y_t = odeint(func, y0_tot.double(), t_tot.double(), c_tot.double(),␣
↪method = 'euler')
    qq = to_np(pred_y_t)
    loss_all = torch.mean(torch.sqrt(((pred_y_t - y_tot)/2)**2))
    loss_part = torch.mean(torch.sqrt(((pred_y_t[:10] - y_tot[:10])/2)**2))
    plot_trajectories([to_np(y_tot[:10])], [to_np(t_tot[:10])],␣
↪[to_np(pred_y_t[:10])])
    plot_trajectories([to_np(y_tot)], [to_np(t_tot)], [to_np(pred_y_t)])
    #plot_trajectories([to_np(y_tot[:10])], [to_np(t_tot[:10])],␣
↪[to_np(pred_y_t[:10])])
    print('Total Loss {:.6f}, {:.6f}'.format(loss_all, loss_part))
```

[0]:
```python
#sep test

def uniform(shape, low, high):
    r = high-low

    return torch.rand(shape)*r+low
```

```
def reset_env(n_env = 1,Low = torch.tensor([-np.pi, -2.5]), High = torch.
↪tensor([np.pi, 2.5])):

    state = uniform((n_env, nx-1), Low, High)
    return torch.stack((torch.cos(state[:,0]), torch.sin(state[:,0]), state[:
↪,1]), dim=-1)
```

0.4 setting up hyperparameters and getting control

[0]:
```
dataset = None
normalized = True
mse = True
add_aux = True

if mse and normalized:
  loss_f = lambda pred_y, batch_y: torch.mean((pred_y - batch_y)**2)
  logger.info(f'Loss type: mse, ')

elif not mse and normalized:
  loss_f = lambda pred_y, batch_y: torch.mean(torch.abs(pred_y - batch_y))
  logger.info(f'Loss type: not mse, ')

elif mse and not normalized:
  loss_f = lambda pred_y, batch_y: torch.mean(((pred_y - batch_y)*torch.
↪tensor([8, 8, 1]).cuda())**2)
  logger.info(f'Loss type: mse, ')

else:
  loss_f = lambda pred_y, batch_y: torch.mean(torch.abs(pred_y - batch_y)*torch.
↪tensor([8, 8, 1]).cuda())
  logger.info(f'Loss type: not mse, ')


logger.info(f'add_aux: {add_aux}, normalized:, {normalized} \n')
```

[0]:
```
single_u  = False
n_episodes, batch_size, T, batch_time, activation, hidden_dim, optim,␣
↪steps_per_epoch, control_option, act_per_batch = tuning()
logger.info(f'n_episodes {n_episodes} batch_size {batch_size} T {T} batch_time␣
↪{batch_time} activation {activation} hidden_dim {hidden_dim} optim {optim}␣
↪steps_per_epoch {steps_per_epoch} control_option {control_option}␣
↪act_per_batch {act_per_batch}')
logger.info('\n')
dt = 0.05
T = 500
```

```
batch_size = 512
batch_time = 20 #16
n_episodes = 40000 #3000 #remove
hidden_dim = 32
activation = nn.Tanh()
optim = 'adamW'
control_option = 'diff all'
act_per_batch = 200
steps_per_epoch = n_episodes*T//(batch_size*batch_time)
t = torch.linspace(0., T*dt, T)
print( 'n_episodes', n_episodes,'batch_size' , batch_size,'T' , T, 'batch_time'␣
↪, batch_time, 'activation' , activation, 'hidden_dim' , hidden_dim,
            'optim', optim, 'steps_per_epoch', steps_per_epoch,␣
↪'control_option', control_option, 'act_per_batch', act_per_batch)
```

0.5 Training

[0]:
```
class true_dynamics(torch.nn.Module):
      def forward(self, state, action):
          cos_th = state[:, 0].view(-1, 1)
          sin_th = state[:, 1].view(-1, 1)
          thdot = state[:, 2].view(-1, 1)
          th = torch.atan2(sin_th, cos_th)

          g = 10
          m = 1
          l = 1
          dt = 0.05

          u = action
          u = torch.clamp(u, -2, 2)

          newthdot = thdot + (-3 * g / (2 * l) * -(sin_th) + 3. / (m * l ** 2)␣
↪* u) * dt
          newth = th + newthdot * dt
          newthdot = torch.clamp(newthdot, -8, 8)

          state = torch.cat((torch.cos(newth),torch.sin(newth), newthdot),␣
↪dim=1)
          return state
```

[0]:
```
true_u = control_action(T, n_episodes, 1, 2, option = control_option,␣
↪act_per_batch=act_per_batch)

true_u=true_u.T
true_dyn = true_dynamics()
```

[0]:
```
from tqdm import tqdm

params = torch.tensor((10., 1., 1.))
dx = pendulum.PendulumDx(params, simple=True)

states_ds = []
ctrl_ds = []
x_init = reset_env(n_episodes).double()
tensor_true_u = torch.from_numpy(true_u).double()

for t in tqdm(range(T)):
    #print(x_int.shape, true_u.shape)

    x = dx(x_init, tensor_true_u[t].view(-1,1))
    states_ds.append(x_init)
    action = torch.clamp(tensor_true_u[t], ACTION_LOW, ACTION_HIGH)
    x[...,-1] = torch.clamp(x[...,-1], SPEED_LOW, SPEED_HIGH)
    ctrl_ds.append(action)
    x_init = x
states_ds = torch.stack(states_ds)
ctrl_ds = torch.stack(ctrl_ds).view(T,n_episodes,1)
print(states_ds.shape, ctrl_ds.shape)
new_data = torch.cat((states_ds, ctrl_ds), dim = -1)
```

[0]:
```
u_init = None
render = True
run_iter = 500
time_meter = RunningAverageMeter(0.97)
loss_meter = RunningAverageMeter(0.97)

ft_high = np.array([1, 1, SPEED_HIGH, ACTION_HIGH])

ft_low  = ft_high*-1
norm=normalizer([ft_low, ft_high], [-1,1])
```

[0]:
```
def train(new_data, activation, hidden_dim, optim, steps_per_epoch, norm,␣
 ↪old_dataset= True, save_data=False):
    global dataset
    global func #added

    if not torch.is_tensor(new_data):
        new_data = torch.from_numpy(new_data)
        # print(new_data.shape,'2')

    # preprocess data
    # clamp actions
```

```
    new_data[:,:, -1] = torch.clamp(new_data[:,:, -1], -ACTION_HIGH,␣
↪ACTION_HIGH)
    new_data = norm.normalize(new_data)


    # append data to whole dataset
    if dataset is None:
        dataset = new_data




    else:
      if old_dataset==False:
        dataset= new_data
      else:
        dataset = torch.cat((dataset, new_data), dim=0)


    if save_data==True:
      dataset_df=pd.DataFrame(dataset, columns =␣
↪['Time_steps,episodes,states&actions'])
      dataset_df.to_csv(base_file+'dataset.csv', index = False) #saved in video␣
↪folder




    # train on the whole dataset (assume small enough we can train on all␣
↪together)
    XU = new_data.detach()

    if use_cuda:
      # func = net(activation = activation, hidden_dim = hidden_dim, ctrl_dim=1)
      func = func.cuda()

    if optim == 'RMSprop':
      #play with the values of mommentum and weight decay
      optimizer = torch.optim.RMSprop(func.parameters(), lr=1e-3, alpha=0.99,␣
↪eps=1e-08, weight_decay=0, momentum=0, centered=False)

    elif optim == 'Adam':
      #play with the values of mommentum and weight decay
      optimizer = torch.optim.Adam(func.parameters(), betas=(0.9, 0.999),␣
↪lr=3e-3)

    else:
      #play with the values of mommentum and weight decay
```

```
    optimizer = torch.optim.AdamW(func.parameters(), lr=0.001)

  time_meter = RunningAverageMeter(0.97)
  loss_meter = RunningAverageMeter(0.97)

  for epoch in range(TRAIN_EPOCH):
      for i in range(int(steps_per_epoch)):

        optimizer.zero_grad()

        batch_y0, batch_t, batch_y, batch_u = get_batch_with_ctrl(XU)

        if use_cuda:
            batch_y0, batch_t, batch_y, batch_u = batch_y0.cuda(), batch_t.
↪cuda(), batch_y.cuda(), batch_u.cuda()

        pred_y = odeint(func, batch_y0.float(), batch_t.float(), batch_u.
↪float(), method = 'euler')

        loss = loss_f(pred_y, batch_y)

        if add_aux:
          loss_aux = 0.001* torch.mean(torch.abs(pred_y[:,:,0]**2 + pred_y[:,:
↪,1]**2 -1))
          loss = loss+loss_aux

        loss.backward()
        optimizer.step()
        logger.info("iter %d epoch %d loss %f \n", i, epoch, loss.mean().
↪item())
        #logger.info('\n')

        print("iter: ",i, "epoch: ", epoch, "loss: ", loss.mean().item())
      save_checkpoint({
      'epoch': epoch + 1,
      'state_dict': func.state_dict(),
      })

      with torch.no_grad():
          time_horizon = 64
          y_tot = XU[:time_horizon, :, :nx].cuda()
          y0_tot = XU[0, :, :nx].cuda()
          c_tot = XU[:time_horizon, :, nx:].cuda()
          t_tot = torch.linspace(0., time_horizon*dt, time_horizon).to(c_tot)
          pred_y_t = odeint(func, y0_tot.float(), t_tot.float(), c_tot.
↪float(), method = 'euler')
          loss_all = torch.mean(torch.abs(pred_y_t - y_tot))
```

```
            print('Iter {:04d} | Total Loss {:.6f}'.format(epoch, loss_all))
            plot_trajectories([to_np(batch_y)], [to_np(batch_t)],␣
 ↪[to_np(pred_y)])
            plot_trajectories([to_np(y_tot)], [to_np(t_tot)], [to_np(pred_y_t)])
```

[0]:
```
dataset = None
func = code(activation = activation, hidden_dim = hidden_dim, ctrl_dim=1)
```

[0]:
```
TRAIN_EPOCH = 18
train(new_data, activation, hidden_dim, optim, steps_per_epoch, norm)␣
 ↪#boot_strap ==0 init state data
logger.info("bootstrapping finished")
```

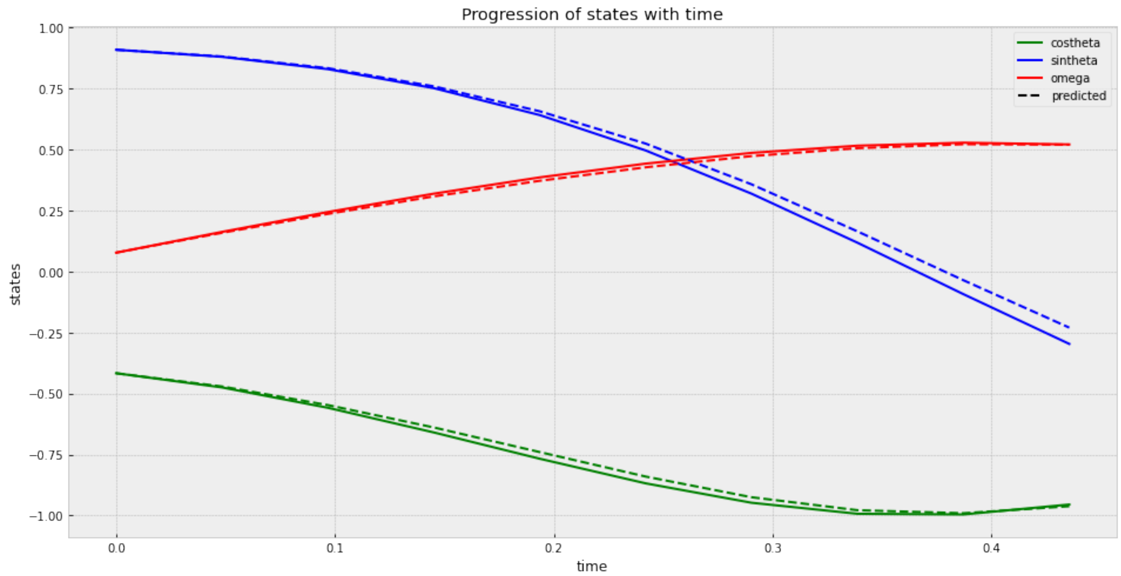
0.6 Loading and validating model

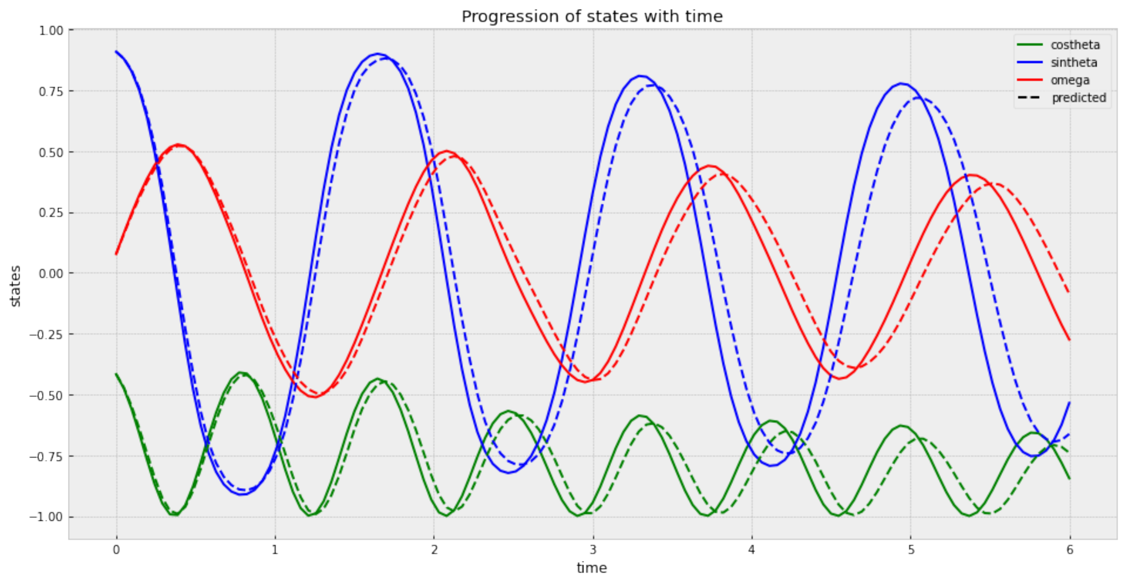
[0]:
```
from collections import OrderedDict
if use_cuda:
    checkpoint = torch.load('/content/drive/My Drive/checkpoint6.pth.tar')
else:
    # Load GPU model on CPU
    checkpoint = torch.load('/content/drive/My Drive/checkpoint6.pth.tar',
                            map_location=lambda storage,
                            loc: storage)
start_epoch = checkpoint['epoch']
weights = OrderedDict( (key.replace('net.', ''), value) for key, value in␣
 ↪checkpoint['state_dict'].items())
func = code(activation = activation, hidden_dim = hidden_dim, ctrl_dim=1)
func.net.load_state_dict(weights)
#print("=> loaded checkpoint '{}' (trained for {} epochs)".
 ↪format(resume_weights, checkpoint['epoch']))
```

[0]:
```
<All keys matched successfully>
```

[0]:
```
ft_high = np.array([1, 1, SPEED_HIGH, ACTION_HIGH])

ft_low  = ft_high*-1
norm=normalizer([ft_low, ft_high], [-1,1])
validate_model(func, T)
```

```
100%|      | 500/500 [00:00<00:00, 3153.78it/s]
```






```
Total Loss 0.074281, 0.005471
```

1 MPC with C-NODE

[0]:
```
class PendulumDynamics(torch.nn.Module):
    def __init__(self, diff_eq, norm, dt):
        super(PendulumDynamics, self).__init__()
        self.diff_eq = diff_eq.cpu().double() #net
```

```
        self.norm =  torch.from_numpy(np.array([1., 1.  , 8., 2.]))#norm
        self.dt = dt

    def forward(self, state, perturbed_action):
        # the state in here is in theta, dtheta and should be converted

        if state.dim() is 1 or perturbed_action.dim() is 1:
            state= state.view(1, -1)
            u = perturbed_action.view(1, -1)

        if perturbed_action.shape[1] > 1:
            u = perturbed_action[:, 0].view(-1, 1)

        u = torch.clamp(perturbed_action, ACTION_LOW, ACTION_HIGH).to(state)

        xu = torch.cat((state, u), dim = -1)
        xu_norm = xu/self.norm.to(xu) #self.norm.normalize(xu_conv)
        func = self.diff_eq.double().net

        next_state_norm = xu_norm[:,:nx] + func(xu_norm)*self.dt
        next_state = next_state_norm*self.norm[:-1].to(xu) #self.norm.
↪denorm(next_xu_conv_norm)

        return next_state
```

[0]:
```
class true_dynamics(torch.nn.Module):
      def forward(self, state, action):
          th = state[:, 0].view(-1, 1)
          thdot = state[:, 1].view(-1, 1)

          g = 10
          m = 1
          l = 1
          dt = 0.05

          u = action
          u = torch.clamp(u, -2, 2)

          newthdot = thdot + (-3 * g / (2 * l) * torch.sin(th + np.pi) + 3. /␣
↪(m * l ** 2) * u) * dt
          newth = th + newthdot * dt
          newthdot = torch.clamp(newthdot, -8, 8)

          state = torch.cat((angle_normalize(newth), newthdot), dim=1)
          return state
```

[0]:

```
params = torch.tensor((10., 1., 1.))
dx = pendulum.PendulumDx(params, simple=True)

n_batch, T, mpc_T = 9, 100, 24
th = uniform(n_batch, (3/4)* np.pi, 1.25*np.pi)
thdot = uniform(n_batch, -1., 1.)
x_init = torch.stack((torch.cos(th), torch.sin(th), thdot), dim=1).double()
u_init = None
time_meter = RunningAverageMeter(0.97)
loss_meter = RunningAverageMeter(0.97)

dynamics = PendulumDynamics(func,norm,dt)
plot = False
```

[0]:

```
states_list = []
```

[0]:

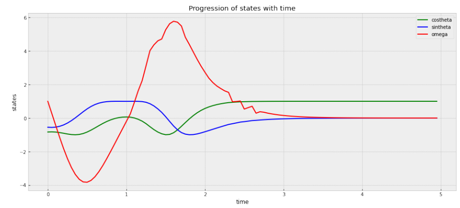
```
import warnings
x = x_init
u_init = None

# The cost terms for the swingup task can be alternatively obtained
# for this pendulum environment with:
# q, p = dx.get_true_obj()


goal_weights = torch.Tensor((1., 1., 0.1))
goal_state = torch.Tensor((1., 0. ,0.))
ctrl_penalty = 0.001
q = torch.cat((
    goal_weights,
    ctrl_penalty*torch.ones(dx.n_ctrl)
))
px = -torch.sqrt(goal_weights)*goal_state
p = torch.cat((px, torch.zeros(dx.n_ctrl)))
Q = torch.diag(q).unsqueeze(0).unsqueeze(0).repeat(
    mpc_T, n_batch, 1, 1
).double()
p = p.unsqueeze(0).repeat(mpc_T, n_batch, 1).double()

t_dir = tempfile.mkdtemp()
print('Tmp dir: {}'.format(t_dir))
with warnings.catch_warnings():
    warnings.filterwarnings("ignore",category=UserWarning)
    for t in tqdm(range(100)):
        nominal_states, nominal_actions, nominal_objs = mpc.MPC(
            dx.n_state, dx.n_ctrl, mpc_T,
            u_init=u_init,
```

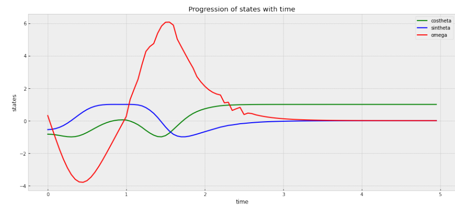
```
            u_lower=dx.lower, u_upper=dx.upper,
            lqr_iter=50,
            verbose=0,
            exit_unconverged=False,
            detach_unconverged=False,
            linesearch_decay=dx.linesearch_decay,
            max_linesearch_iter=dx.max_linesearch_iter,
            grad_method=GradMethods.AUTO_DIFF,
            eps=1e-2,
        )(x.double(), QuadCost(Q, p), dynamics)
        #print(nominal_objs[0])
        x_nop = util.get_traj(mpc_T, nominal_actions, x_init=x.double(),␣
↪dynamics= dx)
        tt = torch.arange(mpc_T)*0.05
        #print(x_nop.shape, nominal_states.shape)
        if plot:
          plot_trajectories([to_np(x_nop)], [to_np(tt)],␣
↪[to_np(nominal_states)])

        next_action = nominal_actions[0]
        u_init = torch.cat((nominal_actions[1:], torch.zeros(1, n_batch, dx.
↪n_ctrl).double()), dim=0)
        u_init[-2] = u_init[-3]
        states_list.append(x)
        x = dx(x, next_action)

        n_row, n_col = 3, 3
        fig, axs = plt.subplots(n_row, n_col, figsize=(3*n_col,3*n_row))
        axs = axs.reshape(-1)
        for i in range(n_batch):
            dx.get_frame(x[i], ax=axs[i])
            axs[i].get_xaxis().set_visible(False)
            axs[i].get_yaxis().set_visible(False)
        fig.tight_layout()
        fig.savefig(os.path.join(t_dir, '{:03d}.png'.format(t)))
        plt.close(fig)
```

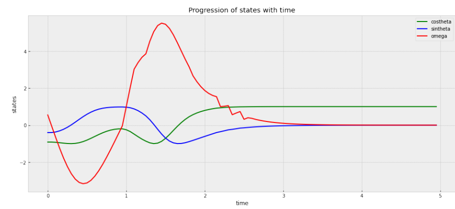
```
  0%|          | 0/100 [00:00<?, ?it/s]

Tmp dir: /tmp/tmpn_66hzl6

100%|      | 100/100 [05:12<00:00,  3.12s/it]
```

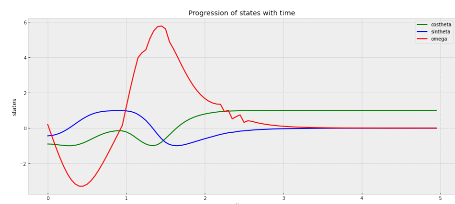
This plot involves the progression of actual states of the pendulum with time

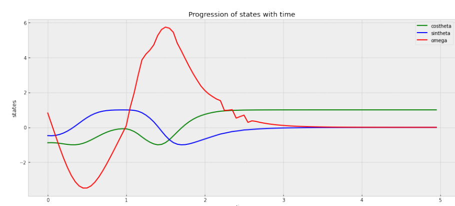
[0]:
```
plot_trajectories([to_np(torch.stack(states_list))], [to_np(torch.arange(100)*0.
↪05)], freq = 9)
```

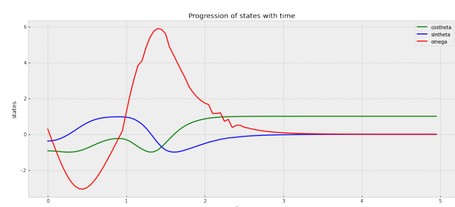

Progression of states with time
costheta
sintheta
omega
states
time

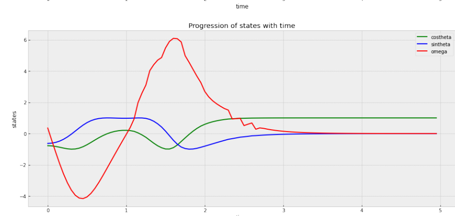

Progression of states with time
costheta
sintheta
omega
states
time

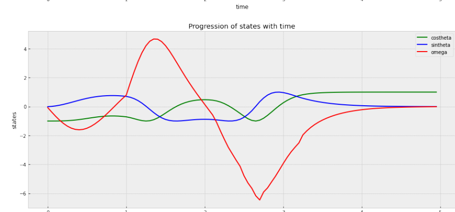

Progression of states with time
costheta
sintheta
omega
states
time

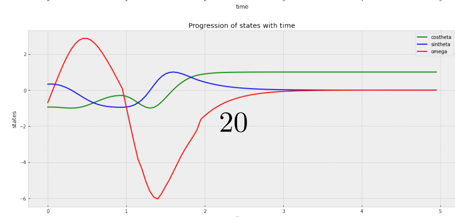

Progression of states with time
costheta
sintheta
omega
states
time


Progression of states with time
costheta
sintheta
omega
states
time


Progression of states with time
costheta
sintheta
omega
states
time


Progression of states with time
costheta
sintheta
omega
states
time


Progression of states with time
costheta
sintheta
omega
states
time


Progression of states with time
costheta
sintheta
omega
states
time

[0]:
```
vid_fname = 'pendulum-{}.mp4'.format('swingup')

if os.path.exists(vid_fname):
    os.remove(vid_fname)

cmd = 'ffmpeg -r 16 -f image2 -i {}/%03d.png -vcodec libx264 -crf 25  -pix_fmt␣
 ↪yuv420p {}'.format(
    t_dir, vid_fname
)
os.system(cmd)
print('Saving video to: {}'.format(vid_fname))
```

```
Saving video to: pendulum-swingup.mp4
```

[0]:
```
video = io.open(vid_fname, 'r+b').read()
encoded = base64.b64encode(video)
HTML(data='''<video alt="test" controls>
                <source src="data:video/mp4;base64,{0}" type="video/mp4" />
             </video>'''.format(encoded.decode('ascii')))
```