

KalmanNN

June 14, 2021

```
[ ]: # standard imports\n",
import os
import random
import numpy as np

# work with data\n",
import pandas as pd
import h5py
import matplotlib.pyplot as plt
%matplotlib inline
from mpl_toolkits.mplot3d import Axes3D
import glob
from tqdm.auto import tqdm
from IPython.display import clear_output

# like numpy, only good + NN
import torch, torch.nn as nn
import torch.nn.functional as torch_nn_F
from torch.utils.data import DataLoader, Dataset, Subset
# import torchvision
# from torchvision import transforms
import time

# local
import utils

from scipy.linalg import block_diag

plt.rcParams[
    "figure.facecolor"
] = "w" # force white background on plots when using dark mode in JupyterLab

# Dark plots\n",
#plt.style.use('dark_background')\n",
```

```

TIME_STEP = 1
CLASSNAME = {0: 'ballistic', 1: 'hgv', 2: 'hcm'}
CLASSTYPE = {'ballistic': 0, 'hgv': 1, 'hcm': 2}

```

1 Prepare data

1.1 Load and examine data

```

[ ]: # Data reading function
def read_trajectories(path_to_file, look: bool = False):
    with h5py.File(path_to_file, 'r') as dset:
        for k, v in dset.attrs.items():
            print(f"{k}: {v}")

    dset = pd.HDFStore(path_to_file, 'r')
    if look:
        print(dset.info())
    return dset

```

1.2 Splitting the data

```

[ ]: def train_val_test_split(data, tts = (0.7, 0.1, 0.2), shuffle=False):
    '''Split data into train, validation and test sets according to `tts` tuple

    By default, tts = (train, val, test) = (0.7, 0.1, 0.2)
    '''
    assert sum(tts) == 1

    if shuffle:
        data = np.random.shuffle(data)

    h = len(data)
    train = data[:int(h * tts[0])]
    val = data[int(h * tts[0]) : int(h * np.round(tts[0] + tts[1], 4))]
    test = data[int(h * np.round(tts[0] + tts[1], 4)) : int(h * sum(tts))]

    return train, val, test

```

1.3 Invertible trajectory pre-processing transform

```

[ ]: class RelativeTrajectory():
    def __init__(self, df, diff=False, ref_point=30, check_point=100, config=None):
        if config == None:
            self.init0(df, diff, ref_point, check_point)
        else:

```

```

        self.init1(df, config)

def init0(self, df, diff=False, ref_point=30, check_point=100):

    self.diff = diff
    self.ref_point = ref_point

    data = np.array(df.drop('t', 1))
    assert data.shape[0] >= ref_point

    # Remember first state
    self.start_state = data[0].copy()

    # Make changes relative to the start state
    data -= self.start_state

    # Scale data to kilometers
    data /= 1000

    # Rotate coordinate system
    x = utils.normalize(data[-1, :3] - data[0, :3])           # X axis
    → along flight direction
    z = utils.orthogonal(x, data[ref_point, :3] - data[0, :3]) # Z axis
    → along upward (from Earth)
    y = np.cross(z, x)           # Y is a
    → cross product to form basis

    p = np.array([x, y, z]) # -> Relative CS axes in current frame
    p_prime = np.eye(3) # -> How they should be
    self.M = utils.get_transformation_matrix(p, p_prime)[:3, :3]

    # Perform rotation for coordinates
    data[:, :3] = data[:, :3].dot(self.M)
    # data[:, :3] = np.absolute(data[:, :3])

    self, data = self.abs(data, check_point)

    # Perform rotation for velocities
    if data.shape[1] > 3:
        data[:, 3:6] = data[:, 3:6].dot(self.M)

    ## Calculate angle of rotation: arctan(y_r / x_r), where r is ref_point
    self.theta = np.arctan(data[check_point][1] / data[check_point][0])

```

```

    ## Rotation matrix for XY plane around Z axis
    ## Perform rotation for coordinates
    data[:, :3] = self.rotate_Z(data[:, :3], -self.theta)

    self.first_diff_elem = None
    if diff:
        self.first_diff_elem = data[0].copy()
        data = np.diff(data, axis=0)

    self.data = data

def init1(self, data, config):
    self.data = data
    self.ref_point = config['ref_point']
    self.diff = config['diff']
    self.start_state = config['start_state']
    self.first_diff_elem = config['first_diff_elem']
    self.M = config['M']
    self.theta = config['theta']
    self.abs = config['abs']

def restore(self, columns, ts=1, config=None):

    assert ts > 0

    if config:
        self.set_info(config)

    # Restore diff data
    if self.diff:
        data = np.r_[np.expand_dims(self.first_diff_elem, 0), np.
→cumsum(self.data, axis=0)]
    else:
        data = self.data.copy()

    ## Rotation matrix for XY plane around Z axis
    ## Perform rotation for coordinates
    data[:, :3] = self.rotate_Z(data[:, :3], self.theta)

    data[:, :3] = data[:, :3] * self.abs[:3]

```

```

    # Perform rotation for coordinates
    data[:, 0:3] = data[:, 0:3].dot(np.linalg.inv(self.M))

    # Perform rotation for velocities
    if data.shape[1]>3:
        data[:, 3:6] = data[:, 3:6].dot(np.linalg.inv(self.M))

    # Scale data from km back to meters
    data *= 1000

    # Make changes absolute
    if data.shape[1]==3:
        data += self.start_state[:3]

    # Restore Pandas.DataFrame format
    t = np.arange(0, data.shape[0], ts)
    data = np.c_[data, t]
    data = pd.DataFrame(data, columns=columns)

    return data

    @staticmethod
    def rotate_Z(data, theta):
        """Rotate data around the Z axis using matrix R"""

        R = np.array([
            [np.cos(theta), -np.sin(theta), 0],
            [np.sin(theta),  np.cos(theta), 0],
            [          0,          0, 1]
        ])
        return data @ R.T

    @staticmethod
    def rotate_X(data, theta):
        """Rotate data around the X axis using matrix R"""

        R = np.array([
            [ 1,          0,          0],
            [ 0,  np.cos(theta), -np.sin(theta)],
            [ 0,  np.sin(theta),  np.cos(theta)]
        ])
        return data @ R

    @staticmethod
    def rotate_Y(data, theta):
        """Rotate data around the Y axis using matrix R"""

```

```

R = np.array([
    [ np.cos(theta), 0, np.sin(theta)],
    [      0, 1,      0],
    [-np.sin(theta), 0, np.cos(theta)]
])
return data @ R

def abs(self, data, check_point):
    self.abs = np.array([1,1,1])

    if (data[check_point][2] < 0):
        self.abs[2] = -1
        data[:, 2] = self.abs[2]*(data[:, 2])

    if (data[check_point][1] < 0):
        self.abs[1] = -1
        data[:, 1] = self.abs[1]*(data[:, 1])

    if (data[check_point][0] < 0):
        self.abs[0] = -1
        data[:, 0] = self.abs[0]*(data[:, 0])
    return self, data

@property
def info(self):
    return {
        'ref_point' : self.ref_point,
        'diff' : self.diff,
        'start_state' : self.start_state,
        'first_diff_elem' : self.first_diff_elem,
        'M' : self.M,
        'theta' : self.theta,
        'abs': self.abs
    }

@info.setter
def info(self, config):
    self.ref_point = config['ref_point']
    self.diff = config['diff']
    self.start_state = config['start_state']
    self.first_diff_elem = config['first_diff_elem']
    self.M = config['M']
    self.theta = config['theta']
    self.abs = config['abs']

```

1.4 Generation of datasets

```
[ ]: def max_min_len_coordinate(dset, keys):
    max_size = 0
    min_size = len(np.array(dset[keys[0]])[:,0])
    for key_k in keys:
        size = len(np.array(dset[key_k])[:,0])
        if size > max_size:
            max_size = size
            max_key = key_k
        if size < min_size:
            min_size = size
            min_key = key_k
    return (max_size, min_size, max_key, min_key)

def max_coordinate(dset, keys):
    max_size = [0,0,0]
    for key_k in keys:
        x = np.absolute(np.array(dset[key_k][0])).max(axis=0)
        for i in range(3):
            if x[i] > max_size[i]:
                max_size[i] = x[i]
    return max_size

[ ]: def get_strided_data_clust(dset, keys, variables=3, residuals=True, gt_size=8,
    ↪horizon=12, step=1, diff=False, verbose=False):
    '''Return list with parts of trajectories and their residuals.

    Arguments:
    dset -- h5py Data set with trajectory data
    keys -- keys for extracting data from `dset`

    Keyword arguments:
    variables -- (default: 3) how many variables to extract:
    3 for XYZ -- coordinates,
    6 for XYZUVW -- coordinates and speeds,
    7 for XYZUVWH -- coords, speeds and altitude

    residuals -- (default: True) if True, residuals of trajectory will
    be concatenated, such that, in case of 3 variables:
    [[X1, Y1, Z1], [X1, Y1, Z1, 0, 0, 0],
    [X2, Y2, Z2], --> [X2, Y2, Z2, X2-X1, Y2-Y1, Z2-Z1],
    [X3, Y3, Z3]] [X3, Y3, Z3, X3-X2, Y3-Y2, Z3-Z2]]

    gt_size -- how many trajectory points are to be observed
    horizon -- how many trajectory points are to be predicted
    step -- (default: 1)
```

```

        if 1, every row from the `dset` will be processed,
        if >1, some rows will be skipped accordingly.
    diff -- (default: False) toggle extract differentiated relative_
→trajectories
    '''

    assert variables in [3, 6, 7]

    # Create list with parts of trajectories,
    # each element has (gt_size+horizon) trajectory points
    data_seqs = []

    # Set of configs for each trajectory.
    configs = {}

    # List of trajectory indices
    # (to which trajectory this traj_elem belongs to)
    traj_ids = []

    # Collect trajectories, preprocess and
    # split them into trajectory parts
    for k in tqdm(range(len(keys)), disable=1-verbose, desc='Collecting strided_
→data'):
        # Get relative trajectory from the dataset
        rt = RelativeTrajectory(dset[keys[k]], diff=diff)
        configs[k] = rt.info # save for future restoration

        # Collect list of trajectory parts from `rt`
        # using time window [gt_size + horizon] and time shift `step`
        for i in range(1 + (rt.data.shape[0] - gt_size - horizon) // step):
            data_seqs.append([rt.data[i*step : i*step + gt_size + horizon, :
→variables]])
            traj_ids.append(k)

    data_norm_factor = np.array(max_coordinate(data_seqs,
→range(len(data_seqs)))) / 100
    data_seqs = np.array(data_seqs) / data_norm_factor
    data_seqs_noise = np.random.normal(data_seqs, random.randint(1,2)/2)

    # Collect all data seqs into one huge dataset
    # of shape [?, gt_size + horizon, variables]
    data_seqs_all = np.stack(data_seqs).squeeze()
    data_seqs_all_noise = np.stack(data_seqs_noise).squeeze()
    traj_ids_all = np.stack(traj_ids)

    # Calculate mean and std over all data

```

```

data_mean = data_seqs_all.mean((0, 1))
data_std = data_seqs_all.std((0, 1))
res_mean = np.zeros(variables)
res_std = np.ones(variables)

if residuals:
    # Compute and add columns with residuals
    # note that the first row should be zeros
    # (if we have 8 measurements, we only can have 7 residuals)
    res = np.concatenate((
        np.zeros((data_seqs_all.shape[0], 1, variables)),
        data_seqs_all[:, 1:, :] - data_seqs_all[:, :-1, :]
    ), 1)

    res_mean = res[:, 1:].mean((0, 1))
    res_std = res[:, 1:].std((0, 1))

    data_seqs_all = np.concatenate((data_seqs_all, res), 2)

stats = {
    'data_mean': data_mean,
    'data_std': data_std,
    'res_mean': res_mean,
    'res_std': res_std,
    'data_norm_factor': data_norm_factor
}

if verbose:
    with np.printoptions(precision=3):
        print(f'Total trajectory parts: {data_seqs_all.shape[0]}')
        print(f'Each: {gt_size} observed + {horizon} horizon =
→{gt_size+horizon} points in total')
        if residuals:
            print(f'Each point contains {int(data_seqs_all.shape[-1]/2)}
→variables and {int(data_seqs_all.shape[-1]/2)} residuals')
        else:
            print(f'Each point contains {data_seqs_all.shape[-1]}
→variables')

    print('Data mean:', stats['data_mean'],
          'Data std:', stats['data_std'],
          'Data normalization factor', stats['data_norm_factor'],
          sep='\n')
    if residuals:
        print('Residuals mean:', stats['res_mean'],
              'Residuals std:', stats['res_std'],
              sep='\n')

```

```

return (
    data_seqs_all.squeeze()[:, :gt_size], # src sequences
    data_seqs_all.squeeze()[:, gt_size:], # tgt sequences
    data_seqs_all_noise.squeeze()[:, :gt_size], # data_noise sequences
    configs,
    stats,
    traj_ids_all
)

```

```

[ ]: class TrajectoryDataset(torch.utils.data.Dataset):
    def __init__(self, data, name, variables=3, configs=None, stats=None):
        super().__init__()

        self.data = data
        self.name = name
        self.variables = variables
        self.configs = configs
        self.stats = stats

    def __len__(self):
        return self.data['data'].shape[0]

    def __getitem__(self, index):

        ret = {
            'data': torch.Tensor(self.data['data'][index]),
            'tgt': torch.Tensor(self.data['tgt'][index]),
            'data_noise': torch.Tensor(self.data['data_noise'][index]),
            'traj_id': self.data['traj_ids'][index],
        }

        return ret

```

```

[ ]: def create_dataset(dset, keys, name, variables=3, residuals=True, gt_size=8,
    ↪horizon=12, step=1, diff=False, train=True, scaler=None, verbose=False):
    """Create TrajectoryDataset for training NNs.

    Arguments:
        dset -- h5py dataset object
        keys -- list of strings: keys for extracting data from `dset`
        name -- name of the TrajectoryDataset

    Keyword arguments:
        variables -- (default: 3) how many variables to extract:
            3 for XYZ -- coordinates,
            6 for XYZUVW -- coordinates and speeds,
            7 for XYZUVWH -- coords, speeds and altitude

```

```

    residuals -- (default: True) if True, residuals of trajectory will
                be concatenated, such that, in case of 3 variables:
                [[X1, Y1, Z1],      [[X1, Y1, Z1,      0,      0,      0],
                [X2, Y2, Z2], --> [X2, Y2, Z2, X2-X1, Y2-Y1, Z2-Z1],
                [X3, Y3, Z3]]      [X3, Y3, Z3, X3-X2, Y3-Y2, Z3-Z2]]

    gt_size -- how many points are observed (model input)
    horizon -- how many points the model tries to predict into the future
    step -- stride step for data
    diff -- toggle differentiate trajectories
    train -- this data will be used for training
    scaler -- custom scaler, so data will have zero mean and unit variance
    verbose -- toggle print info to the terminal

Note:
    If `train == True`, the scaler will fit on the collected data and
    then returned as the TrajectoryDataset.scaler attribute

    If 'train == False', this function will look for scaler from the
    arguments, then use it to scale collected data for evaluation.
"""
if verbose:
    print(f"Loading dataset in {'train' if train else 'evaluation'} mode...
→")

inp, out, inp_noise, configs, stats, traj_ids = get_strided_data_clust(
    dset, keys, variables, residuals, gt_size, horizon, step, diff, verbose)

data = {
    'data': inp,
    'tgt': out,
    'data_noise': inp_noise,
    'traj_ids': traj_ids
}

return TrajectoryDataset(data, name, variables, configs, stats)

```

1.5 Recurrent Module

```

[ ]: # Our recurrent Module
class ModuleRNN(nn.Module):
    """
    Implement the scheme above as torch module
    torch style

    """
    def __init__(self, vect_dim=3, rnn_num_units=64):

```

```

super(self.__class__,self).__init__()

self.num_units = rnn_num_units
self.vect_dim = vect_dim

#         our linear layer
self.rnn_update = self.block(vect_dim, rnn_num_units)

self.rnn_forget = self.block(vect_dim, rnn_num_units)
self.rnn_save = self.block(vect_dim, rnn_num_units)
self.rnn_data_selection = self.block(vect_dim, rnn_num_units)
self.rnn_quick_overview = self.block(vect_dim, rnn_num_units)

self.rnn_prediction = self.predicted_block(rnn_num_units+vect_dim,
↪vect_dim)

def forward(self, new_data, flash_memory, short_term_memory,
↪long_term_memory, F):
    """
    This method computes  $h_{next}(x, h_{prev})$  and  $\log P(x_{next} | h_{next})$ 
    We'll call it repeatedly to produce the whole sequence.

    :param x: batch of character ids, containing vector of int64
    :param h_prev: previous rnn hidden states, containing matrix [batch,
↪rnn_num_units] of float32
    """

    memory = torch.cat([new_data, short_term_memory], dim=-1)

    forgetfulness = torch.sigmoid(self.rnn_forget(memory)) #forgetting
↪dataforgetting data
    conservation = torch.tanh(self.rnn_save(memory)) #the acquisition of
↪new data
    information = torch.sigmoid(self.rnn_data_selection(memory))

    long_term_memory = (forgetfulness * long_term_memory) + (information *
↪conservation)

    short_term_memory = torch.sigmoid(self.rnn_quick_overview(memory)) *
↪torch.tanh(long_term_memory)

    with torch.no_grad():
        flash_memory = self.predict_Kalman(F, flash_memory)
        flash_memory_grad = flash_memory[:,0::3]

```

```

        predicted_data = self.rnn_prediction(torch.cat([flash_memory_grad,
↳short_term_memory], dim=-1))

        with torch.no_grad():
            flash_memory[:,0::3] = predicted_data

        return predicted_data, flash_memory, short_term_memory, long_term_memory

    def initial_state(self, batch_size):
        """ return rnn state before it processes first input (aka h0) """
        return torch.zeros(batch_size, self.num_units, dtype=torch.float32,
↳requires_grad=True)

    def initial_state_old_data(self, batch_size):
        return torch.zeros(batch_size, self.vect_dim*3, dtype=torch.float32,
↳requires_grad=True)

    def block(self, in_f, out_f):
        return nn.Sequential(
            self.base_block(in_f + out_f, (in_f + 2 * out_f)//2),
            self.base_block((in_f + 2 * out_f)//2, out_f)
        )

    def base_block(self, in_f, out_f):
        return nn.Sequential(
            nn.Linear(in_f, out_f),
        )

    def predicted_block(self, in_f, out_f):
        return nn.Sequential(
            # nn.Dropout(0.2),
            nn.Linear(in_f, (in_f + out_f)//2),
            nn.Dropout(0.5),
            nn.Linear((in_f + out_f)//2, out_f),
        )

    def predict_Kalman(self, F, old_data):
        return torch.mm(F, old_data.transpose(0,1)).transpose(0,1)

```

```

[ ]: '''
RNN old
without kalman
'''
# Our recurrent Module

```

```

class ModuleRNN(nn.Module):
    """
    Implement the scheme above as torch module
    torch style

    """
    def __init__(self, vect_dim=3, rnn_num_units=64):
        super(self.__class__,self).__init__()
        self.num_units = rnn_num_units

#         our linear layer
        self.rnn_update = self.block(vect_dim, rnn_num_units)

        self.rnn_forget = self.block(vect_dim, rnn_num_units)
        self.rnn_save = self.block(vect_dim, rnn_num_units)
        self.rnn_data_selection = self.block(vect_dim, rnn_num_units)
        self.rnn_quick_overview = self.block(vect_dim, rnn_num_units)

        self.rnn_prediction = self.predicted_block(rnn_num_units, vect_dim)

    def forward(self, new_data, short_term_memory, long_term_memory):
        """
        This method computes  $h_{next}(x, h_{prev})$  and  $\log P(x_{next} | h_{next})$ 
        We'll call it repeatedly to produce the whole sequence.

        :param x: batch of character ids, containing vector of int64
        :param h_prev: previous rnn hidden states, containing matrix [batch,  $\hookrightarrow$ 
 $\hookrightarrow$  rnn_num_units] of float32
        """

        memory = torch.cat([new_data, short_term_memory], dim=-1)

        forgetfulness = torch.sigmoid(self.rnn_forget(memory)) #forgetting  $\hookrightarrow$ 
 $\hookrightarrow$  data forgetting data
        conservation = torch.tanh(self.rnn_save(memory)) #the acquisition of  $\hookrightarrow$ 
 $\hookrightarrow$  new data
        information = torch.sigmoid(self.rnn_data_selection(memory))

        long_term_memory = (forgetfulness * long_term_memory) + (information *  $\hookrightarrow$ 
 $\hookrightarrow$  conservation)

        short_term_memory = torch.sigmoid(self.rnn_quick_overview(memory)) *  $\hookrightarrow$ 
 $\hookrightarrow$  torch.tanh(long_term_memory)

```

```

        #compute logits for next character probs
        predicted_data = self.rnn_prediction(short_term_memory)

        return predicted_data, short_term_memory, long_term_memory

    def initial_state(self, batch_size):
        """ return rnn state before it processes first input (aka h0) """
        return torch.zeros(batch_size, self.num_units, requires_grad=True)

    def block(self, in_f, out_f):
        return nn.Sequential(
            self.base_block(in_f + out_f, (in_f + 2 * out_f)//2),
            self.base_block((in_f + 2 * out_f)//2, out_f)
        )

    def base_block(self, in_f, out_f):
        return nn.Sequential(
            nn.Linear(in_f, out_f),
        )

    def predicted_block(self, in_f, out_f):
        return nn.Sequential(
            nn.Linear(in_f, (in_f + out_f)//2),
            nn.Dropout(0.05),
            nn.Linear((in_f + out_f)//2, out_f),
        )

```

```

[ ]: def preKalman(vect_dim=3, time_step = 0.25):
    F = np.array([[1., time_step, time_step**2/2],
                  [0., 1.,      time_step      ],
                  [0., 0.,      1.              ]])

    if vect_dim==3:
        F = block_diag(F, F, F)
    elif vect_dim==2:
        F = block_diag(F, F)

    F = torch.from_numpy(F).type(torch.float32)

    return F

```

1.6 RNN Loop

```
[ ]: def rnn_loop(trjectories_rnn, batch_ix, device):
    """
    Computes log P(next_character) for all time-steps in names_ix
    :param names_ix: an int32 matrix of shape [batch, time], output of
    ↪to_matrix(names)
    """
    batch_size, max_length, vec_dim = batch_ix.size()

    short_term_memory = trajectories_rnn.initial_state(batch_size)
    long_term_memory = trajectories_rnn.initial_state(batch_size)

    flash_memory_copy = torch.zeros(batch_size, vec_dim*3, dtype=torch.float32)
    flash_memory = trajectories_rnn.initial_state_old_data(batch_size)

    flash_memory_copy[:,0::3] = batch_ix.transpose(0,1)[0]
    flash_memory = flash_memory_copy
    predictions = []

    F = preKalman(3, 0.1)

    for new_data in batch_ix.transpose(0,1):
        prediction, flash_memory, short_term_memory, long_term_memory =
    ↪trajectories_rnn(new_data, flash_memory.to(device), short_term_memory.
    ↪to(device), long_term_memory.to(device), F.to(device)) # <-- here we call
    ↪your one-step code
        predictions.append(prediction)

    return torch.stack(predictions, dim=1)
```

```
[ ]: '''
RNN old
without kalman
'''
def rnn_loop(trjectories_rnn, batch_ix, device):
    """
    Computes log P(next_character) for all time-steps in names_ix
    :param names_ix: an int32 matrix of shape [batch, time], output of
    ↪to_matrix(names)
    """
    batch_size, max_length, vec_dim = batch_ix.size()

    short_term_memory = trajectories_rnn.initial_state(batch_size)
    long_term_memory = trajectories_rnn.initial_state(batch_size)
    predictions = []
```

```

    for new_data in batch_ix.transpose(0,1):
        prediction, short_term_memory, long_term_memory =
→trajectories_rnn(new_data, short_term_memory.to(device), long_term_memory.
→to(device)) # <-- here we call your one-step code
        predictions.append(prediction)

    return torch.stack(predictions, dim=1)

```

1.7 The training loop

```

[ ]: def accuracy(x_pred, x_real, Discrepancy):
    delta = np.absolute(x_pred)-np.absolute(x_real)
    return np.sum(
        (np.absolute(delta/x_pred) <= Discrepancy)|
        (np.absolute(delta/x_real) <= Discrepancy))/ x_real.size

def print_epoc(train_loss, val_loss, train_accuracy, val_accuracy, epoc,
→EPOCH_NUM, lr, now_time, start_time):
    print(f'Epoch {epoc + 1} of {EPOCH_NUM} took {now_time - start_time:.3f}s')

    print('    training loss:', train_loss[-1],)
    print('    validation loss:', val_loss[-1])
    print('train accuracy:', train_accuracy[-1]*1000//1/10,'%')
    print('validation accuracy:', val_accuracy[-1]*1000//1/10,'%')
    if lr!=0:
        print('changed optimizer lr:', lr)
    # print(f"\t training loss: {train_loss[-1]:.9f}")
    # print(f"\t validation loss: {val_loss[-1]:.9f}")
    # print(f"\t validation accuracy: {val_accuracy[-1]:.3f}")
    plot_process(train_loss, val_loss, None, train_accuracy, val_accuracy, None)
    if len(train_loss)>5:
        plot_process(train_loss[-5:], val_loss[-5:], None, train_accuracy[-5:],
→val_accuracy[-5:], None)

```

```

[ ]: def traning_fun(trajectories_rnn, criterion, opt, train_dl, val_dl, train_loss,
→val_loss, train_accuracy, val_accuracy, Discrepancy, EPOCH_NUM, device, draw:
→bool = False):

    error = 0
    retraining = 0

    if (draw)&(len(train_loss)>0):
        for g in opt.param_groups:
            lr = g['lr']

```

```

        print_epoc(train_loss, val_loss, train_accuracy, val_accuracy, 0,
↪EPOCH_NUM, lr, time.time(), time.time())
        lr = 0

    for epoc in range(EPOCH_NUM):

        ep_train_loss = []
        ep_val_loss = []
        ep_train_accuracy = []
        ep_val_accuracy = []
        start_time = time.time()

        if ((epoc+1)%(EPOCH_NUM/4) == 0)&(EPOCH_NUM > 5):
            for g in opt.param_groups:
                g['lr'] = g['lr']/10
                lr = g['lr']

        trajectories_rnn.train(True) # enable dropout / batch_norm training
↪behavior
        for id_b, batch_total in enumerate(train_dl):
            opt.zero_grad()
            batch = batch_total['data_noise'].to(device, torch.float32)

            predictions = rnn_loop(trajectories_rnn, batch, device)

            # compute loss
            data_real = batch_total['data'].to(device, torch.float32)

            # print(predictions_logp.shape, actual_next_tokens.shape)
            loss = criterion(
                predictions.contiguous().view(-1),
                data_real.contiguous().view(-1)
            )
            ep_train_accuracy.append(accuracy(predictions.cpu().detach().
↪numpy(), data_real.cpu().detach().numpy().astype(float), Discrepancy))

            # train with backprop
            loss.backward()
            opt.step()

            ep_train_loss.append(loss.cpu().data.numpy())

        for id_b, batch_total in enumerate(train_dl):
            opt.zero_grad()
            batch = batch_total['data'].to(device, torch.float32)

```

```

predictions = rnn_loop(trajectories_rnn, batch, device)

# compute loss
data_real = batch_total['data'].to(device, torch.float32)

# print(predictions_logp.shape, actual_next_tokens.shape)
loss = criterion(
    predictions.contiguous().view(-1),
    data_real.contiguous().view(-1)
)
ep_train_accuracy.append(accuracy(predictions.cpu().detach().
→numpy(), data_real.cpu().detach().numpy().astype(float), Discrepancy))

# train with backprop
loss.backward()
opt.step()

ep_train_loss.append(loss.cpu().data.numpy())

trajectories_rnn.train(False) # enable dropout / batch_norm training_
→behavior
with torch.no_grad():
    for id_b, batch_total in enumerate(val_dl):

        batch = batch_total['data_noise'].to(device, torch.float32)

        predictions = rnn_loop(trajectories_rnn, batch, device)

        # compute loss
        data_real = batch_total['data'].to(device, torch.float32)

        # print(predictions_logp.shape, actual_next_tokens.shape)
        loss = criterion(
            predictions.contiguous().view(-1),
            data_real.contiguous().view(-1)
        )
        ep_val_loss.append(loss.cpu().data.numpy())
        ep_val_accuracy.append(accuracy(predictions.cpu().numpy(),
→data_real.cpu().numpy().astype(float), Discrepancy))

clear_output(True)

train_loss.append(np.mean(ep_train_loss))
val_loss.append(np.mean(ep_val_loss))
train_accuracy.append(np.mean(ep_train_accuracy))
val_accuracy.append(np.mean(ep_val_accuracy))

```

```

    if error > 0:
        print('Warning: the network is hard to learn.')
    if retraining>EPOC_NUM*3//10:
        print('Warning: the network is being retrained - overfitting.')
    if train_loss[0] < train_loss[-1]:
        error+=1
        assert error!=3, "RNN didn't converge!!!"
    else:
        if error>0:
            error-=1

    if train_loss[-1] < val_loss[-1]:
        retraining+=1
    else:
        if retraining>0:
            retraining-=1

    # print the results for this epoch:
    if draw:
        print_epoc(train_loss, val_loss, train_accuracy, val_accuracy,
        ↪epoc, EPOC_NUM, lr, time.time(), start_time)

    return trajectories_rnn, train_loss, val_loss, train_accuracy,
    ↪val_accuracy, opt

```

1.8 Test

```

[ ]: def print_test(test_loss, test_accuracy, iteration, iteration_num, now_time,
    ↪start_time):
    print(f'Iteration {iteration + 1} of {iteration_num} took {now_time -
    ↪start_time:.3f}s')

    print('    testing loss:', test_loss[-1],)
    print('testing accuracy:', test_accuracy[-1]*100//1/10,'%')
    plot_process(None, None, test_loss, None, None, test_accuracy)

```

```

[ ]: def testing_fun(trajectories_rnn, criterion, test_dl, test_loss, test_accuracy,
    ↪Discrepancy, device, draw: bool = False):

    start_time = time.time()
    iteration_num = len(test_dl)
    trajectories_rnn.train(False) # enable dropout / batch_norm training
    ↪behavior
    pack_predictions = []
    with torch.no_grad():

```

```

    for id_b, batch_total in enumerate(test_dl):

        start_time = time.time()

        batch = batch_total['data_noise'].to(device, torch.float32)

        predictions = rnn_loop(trjectories_rnn, batch, device)

        # compute loss
        data_real = batch_total['data'].to(device, torch.float32)

        # print(predictions_logp.shape, actual_next_tokens.shape)
        loss = criterion(
            predictions.contiguous().view(-1),
            data_real.contiguous().view(-1)
        )
        pack_predictions.append(predictions.cpu())
        test_loss.append(loss.cpu().data.numpy())
        test_accuracy.append(accuracy(predictions.cpu().numpy(), data_real.
→cpu().numpy().astype(float), Discrepancy))
        if draw:
            clear_output(True)
            print_test(test_loss, test_accuracy, id_b, iteration_num, time.
→time(), start_time)

    return pack_predictions, test_loss, test_accuracy

```

1.9 Drawing

```

[ ]: def plot_process(train_loss, val_loss, test_loss, train_accuracy, val_accuracy,
→test_accuracy):
    plt.title('Loss')
    plt.ylabel('Loss')
    plt.xlabel('Epoch/Iteration')
    if train_loss != None:
        plt.plot(train_loss, label='train')
    if val_loss != None:
        plt.plot(val_loss, label='validation')
    if test_loss != None:
        plt.plot(test_loss, label='test')
    plt.legend()
    plt.grid(True)
    plt.show()

    plt.title('Validation accuracy')
    plt.ylabel('Accuracy')

```

```

plt.xlabel('Epoch/Iteration')
if train_accuracy != None:
    plt.plot(train_accuracy, label='train accuracy', color='b')
if val_accuracy != None:
    plt.plot(val_accuracy, label='validation accuracy', color='r')
if test_accuracy != None:
    plt.plot(test_accuracy, label='test accuracy', color='r')
plt.legend()
plt.grid(True)
plt.show()

```

1.10 Save the model

```

[ ]: def save_checkpoint(checkpoint_path, model, optimizer):
    # state_dict: a Python dictionary object that:
    # - for a model, maps each layer to its parameter tensor;
    # - for an optimizer, contains info about the optimizer's states and
    ↪ hyperparameters used.
    state = {
        'state_dict': model.state_dict(),
        'optimizer' : optimizer.state_dict()}
    torch.save(state, checkpoint_path)
    print('model saved to %s' % checkpoint_path)

def load_checkpoint(checkpoint_path, model, optimizer):
    state = torch.load(checkpoint_path)
    model.load_state_dict(state['state_dict'])
    optimizer.load_state_dict(state['optimizer'])
    print('model loaded from %s' % checkpoint_path)

```

1.11 Pre Training

```

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

```

Mounted at /content/drive

```

[ ]: # reading
name_file_trajectories = '/content/drive/MyDrive/      /NN/2021-05-08-04-13.h5'
    ↪ '#/content/2021-05-08-04-13.h5'
try:
    dset = read_trajectories(name_file_trajectories)
except FileNotFoundError:
    assert "NO file!!!"

```

```

class_size: 1000
horizontal_noise: 1.0

```

```

radar: 1
radar_coord: [5172967.18425192 3489210.42312431 1317416.0454895 ]
radial_noise: 100
time_step: 1
vertical_noise: 1.0

```

```

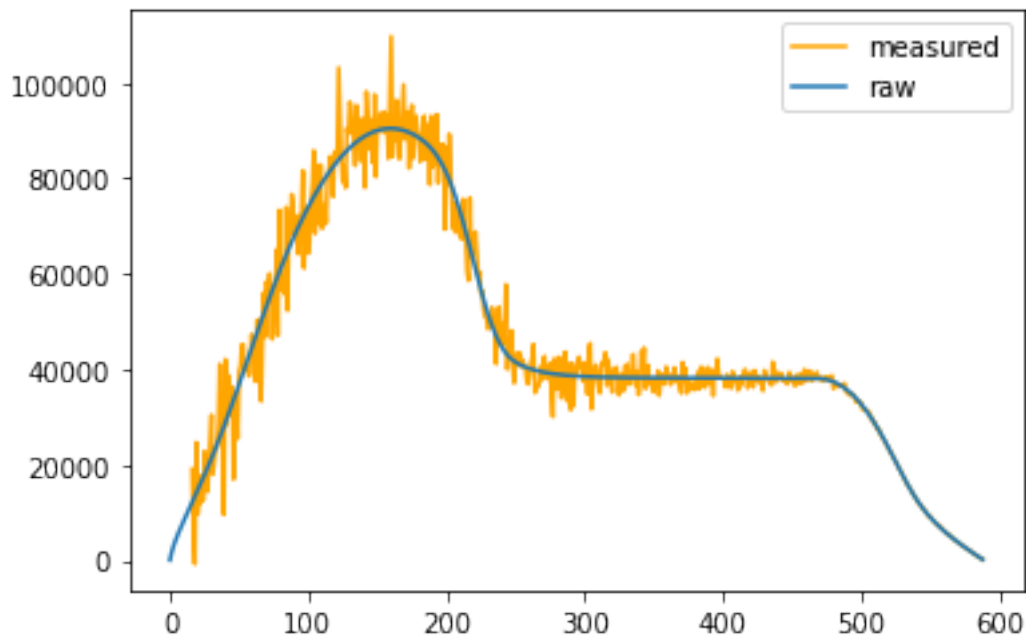
[ ]: %matplotlib inline
m = dset['/hgv/HGV_0/measured']
plt.plot(m.t, m.alt, c='orange', label='measured')
v = dset['/hgv/HGV_0/raw']
plt.plot(v.t, v.alt, label='raw')
plt.legend()

```

```

[ ]: <matplotlib.legend.Legend at 0x7f14cc5d6c90>

```



```

[ ]: # Train-val-test split data
data_keys = sorted([key for key in dset.keys() if ('raw' in key)&('hgv' in
→key)])
# Test data          = 20% of total keys
# Validation data    = 10% of total keys
# Train data         = 70% of total keys
train_keys, val_keys, test_keys = train_val_test_split(
    data_keys, (0.7, 0.1, 0.2), shuffle=False)

print(f'Train keys: {len(train_keys):>5} -> {len(train_keys)/len(data_keys) * 100}%')

```

```
print(f'Valid keys: {len(val_keys):>5} -> {len(val_keys)/len(data_keys) * 100}%')
print(f'Test keys: {len(test_keys):>5} -> {len(test_keys)/len(data_keys) * 100}%')
```

```
Train keys: 700 -> 70.0%
Valid keys: 100 -> 10.0%
Test keys: 200 -> 20.0%
```

```
[ ]: from sklearn.preprocessing import StandardScaler

# Calculate mean and variance over all training set
print('Calculating mean and variance over all training data...')
scaler = StandardScaler()
means = []
for train_key in tqdm(train_keys):
    traj = RelativeTrajectory(dset[train_key])
    means.append(traj.data.mean(axis=0))

scaler.fit(np.array(means))
```

Calculating mean and variance over all training data...

HBox(children=(FloatProgress(value=0.0, max=700.0), HTML(value='')))

```
[ ]: StandardScaler(copy=True, with_mean=True, with_std=True)
```

```
[ ]: print('Mean:')
pd.DataFrame([scaler.mean_], columns=dset[train_key].columns[:-1])
```

Mean:

```
[ ]:      coord_x  coord_y  coord_z  vel_x  vel_y  vel_z  alt
0  253.22097  3.510966  47.438657  0.74148  0.000255 -1.996948  45.0317
```

```
[ ]: print('Variance:')
pd.DataFrame([scaler.var_], columns=dset[train_key].columns[:-1])
```

Variance:

```
[ ]:      coord_x  coord_y  coord_z  vel_x  vel_y  vel_z  alt
0  2510.70446  14.488958  30.97313  0.010034  0.000007  2.148593e-07  28.243728
```

```
[ ]: # use GPU if available
device = torch.device("cuda") if torch.cuda.is_available() else torch.
      device("cpu")
```

```
device
```

```
[ ]: device(type='cuda')
```

```
[ ]: max_len_trajectory, min_len_trajectory, key_max, key_min =  
    ↪max_min_len_coordinate(dset, np.concatenate((train_keys, val_keys, ↪  
    ↪test_keys),axis=0))  
max_len_trajectory, min_len_trajectory, key_max, key_min
```

```
[ ]: (920, 495, '/hgv/HGV_736/raw', '/hgv/HGV_455/raw')
```

```
[ ]: BATCH_SIZE = 40#40  
BATCH_SIZE_TEST=BATCH_SIZE*1//5  
SET_LONG = min_len_trajectory  
VEC_DIM = 3  
MEM_RNN = SET_LONG*5#10  
EPOCH_NUM = 10
```

```
[ ]: train_keys = np.concatenate((train_keys, val_keys, test_keys),axis=0)
```

```
[ ]: train_data = create_dataset(  
    dset,  
    train_keys,  
    name='train',  
    gt_size=SET_LONG,  
    horizon=0,  
    step=SET_LONG,  
    variables=VEC_DIM,  
    residuals=False,  
    train=True,  
    verbose=True  
)  
val_data = create_dataset(  
    dset,  
    val_keys,  
    name='validation',  
    gt_size=SET_LONG,  
    horizon=0,  
    step=SET_LONG,  
    variables=VEC_DIM,  
    residuals=False,  
    train=False,  
    verbose=True  
)  
test_data = create_dataset(  
    dset,  
    test_keys,
```

```

    name='test',
    gt_size=SET_LONG,
    horizon=0,
    step=SET_LONG,
    variables=VEC_DIM,
    residuals=False,
    train=False,
    verbose=True
)

```

Loading dataset in train mode...

HBox(children=(FloatProgress(value=0.0, description='Collecting strided data', max=700.0, style=ProgressStyle()),

Total trajectory parts: 700

Each: 495 observed + 0 horizon = 495 points in total

Each point contains 3 variables

Data mean:

[37.277 -4.69 36.342]

Data std:

[26.749 9.138 21.85]

Data normalization factor

[4.729 0.26 1.55]

Loading dataset in evaluation mode...

HBox(children=(FloatProgress(value=0.0, description='Collecting strided data', style=ProgressStyle()),

Total trajectory parts: 100

Each: 495 observed + 0 horizon = 495 points in total

Each point contains 3 variables

Data mean:

[38.544 -5.034 36.394]

Data std:

[27.72 10.026 21.557]

Data normalization factor

[4.61 0.247 1.55]

Loading dataset in evaluation mode...

HBox(children=(FloatProgress(value=0.0, description='Collecting strided data', max=200.0, style=ProgressStyle()),

Total trajectory parts: 200

Each: 495 observed + 0 horizon = 495 points in total

Each point contains 3 variables

Data mean:

```
[36.334 -6.656 35.709]
Data std:
[26.01 12.24 21.829]
Data normalization factor
[4.829 0.207 1.558]
```

```
[ ]: array_err = []
```

```
[ ]: array_err = [1, 5, 8, 10, 16, 19, 23, 28, 30, 32, 38, 39, 47, 53, 54, 55, 57,
↪71, 84, 87, 91, 96, 97, 98, 99, 100, 102, 103, 106, 113, 115, 124, 129, 133,
↪140, 146, 155, 160, 166, 168, 184, 187, 188, 191, 195]
```

```
[ ]: for i in range(3):
      for k in array_err:
          train_data.data['data'] = np.append(train_data.data['data'], [test_data.
↪data['data'][k]], axis = 0)
          train_data.data['data_noise'] = np.append(train_data.
↪data['data_noise'], [test_data.data['data_noise'][k]], axis = 0)
          train_data.data['traj_ids'] = np.append(train_data.data['traj_ids'],
↪[test_data.data['traj_ids'][k]], axis = 0)
```

```
[ ]: train_dl = DataLoader(
    train_data,
    batch_size=BATCH_SIZE,
    shuffle=True, #try \n",
    num_workers=1) #num_workers=-2# use CPU"

val_dl = DataLoader(
    val_data,
    batch_size=BATCH_SIZE,
    shuffle=False, #try \n",
    num_workers=1) #num_workers=-2# use CPU"

test_dl = DataLoader(
    test_data,
    batch_size=BATCH_SIZE_TEST,
    shuffle=False, #try \n",
    num_workers=1) #num_workers=-2# use CPU"
```

1.12 Training

```
[ ]: trajectories_rnn = ModuleRNN(vect_dim=VEC_DIM, rnn_num_units=MEM_RNN)
```

```
[ ]: load_checkpoint('/content/drive/MyDrive/      /NN/trajectories_rnn11ep5mem.pth',
↪trajectories_rnn, opt)
```

model loaded from

```
/content/drive/MyDrive/      /NN/trajectories_rnn11ep5mem.pth
```

```
[ ]: trajectories_rnn.to(device, torch.float32)

criterion = nn.MSELoss() # nn.CrossEntropyLoss()
```

```
[ ]: opt = torch.optim.Adam(trajectories_rnn.parameters(), lr=1e-4, weight_decay=0.
    ↪1) # lr=1e-4
```

```
[ ]: train_loss = []
    val_loss = []
    train_accuracy = []
    val_accuracy = []
    test_loss = []
    test_accuracy = []

    Discrepancy = 0.05
```

```
[ ]: test_loss = []
    test_accuracy = []
```

```
[ ]: EPOCH_NUM = 6
```

```
[ ]: trajectories_rnn, train_loss, val_loss, train_accuracy, val_accuracy, opt = ↪
    ↪training_fun(trajectories_rnn, criterion, opt, train_dl, val_dl, train_loss, ↪
    ↪val_loss, train_accuracy, val_accuracy, Discrepancy, EPOCH_NUM, device, ↪
    ↪draw=True)
```

```
[ ]: save_checkpoint('trajectories_rnn5ep11mem.pth', trajectories_rnn, opt)
```

model saved to trajectories_rnn5ep11mem.pth

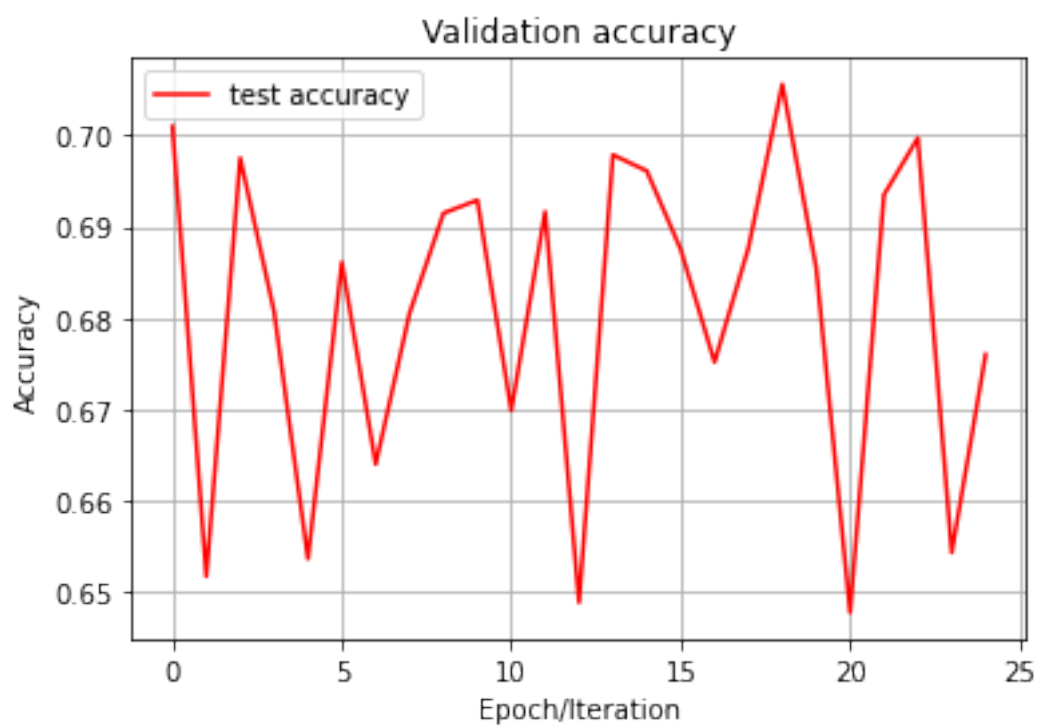
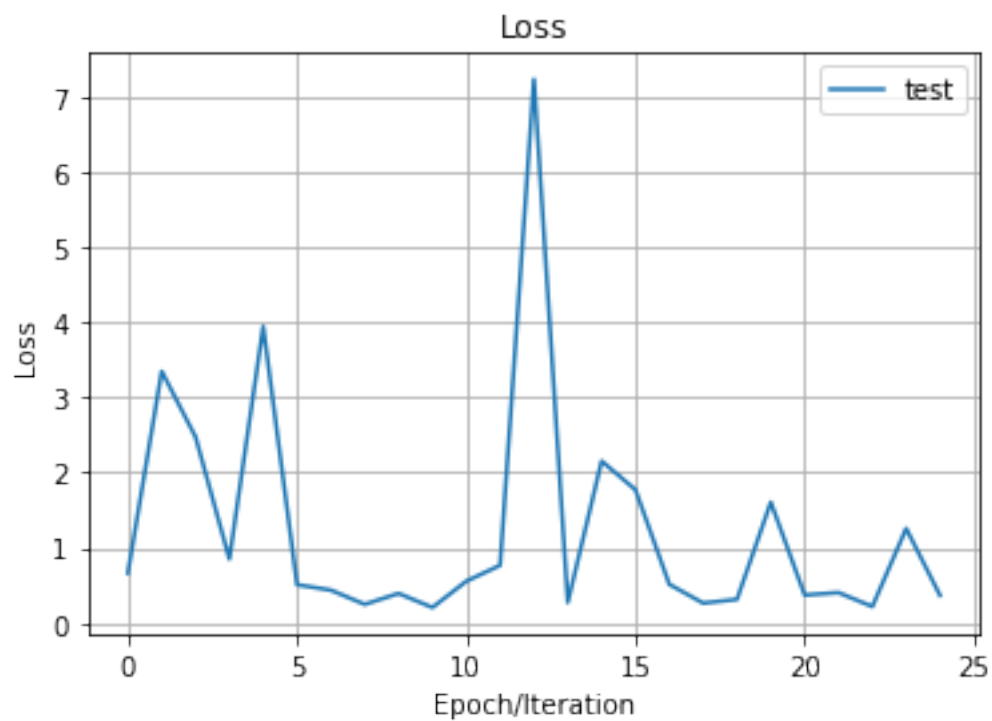
```
[ ]: Discrepancy = 0.05
    pack_predictions, test_loss, test_accuracy = testing_fun(trajectories_rnn, ↪
    ↪criterion, test_dl, test_loss, test_accuracy, Discrepancy, device, draw=True)
    print('mean test loss:', np.mean(test_loss))
    print('mean test accuracy:', np.mean(test_accuracy)*1000//1/10,'%')

    data_norm_factor = test_data.stats['data_norm_factor'][: ]
    for k in range(len(test_data.data['data'])):
        pack_predictions[k//BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST].
        ↪numpy()[:, :] *= data_norm_factor
```

Iteration 25 of 25 took 0.745s

testing loss: 0.36585286

testing accuracy: 67.6 %



```
mean test loss: 1.2452556
mean test accuracy: 68.0 %
```

```
[ ]: def plot_trajectory(data, label=''):
    # display some trajectories for visual representation
    fig = plt.figure(figsize=plt.figaspect(1))
    ax = fig.add_subplot(111, projection='3d')
    data = np.array(data)
    colors = np.arange(data.shape[0])

    # Plot:
    ax.scatter3D(data[:, 0], data[:, 1], data[:, 2], c=colors, cmap='plasma');
    ax.set_xlabel('X (106 m)')
    ax.set_ylabel('Y (106 m)')
    ax.set_zlabel('Z (106 m)')
    ax.set_title(CLASSNAME.get(label, label))

    plt.show()
```

Kalman

```
[ ]: def predict(x, P, F, Q, B, u):
    x = F @ x + B @ u
    P = F @ P @ F.T + Q
    return x, P

def update(x, P, z, R, H, size_coordinates):
    I = np.eye(3*size_coordinates)
    y = z - H @ x
    S = H @ P @ H.T + R
    S_1 = np.linalg.inv(S)
    K = P @ H.T @ S_1
    x = x + K @ y
    P = (I - K @ H) @ P
    return x, P

[ ]: def FilterKalman(trajectories, size_coordinates, time_step, Q_spectator_noise,
    ↪ coordinates_noise, B = None, U = None):
    assert size_coordinates in [1, 2, 3]

    dt = time_step

    R = np.eye(size_coordinates) * coordinates_noise**2 #covariance matrix of
    ↪ measurements
    if B == None:
        B = np.zeros(size_coordinates)
    if U == None:
```

```

u = np.zeros(size_coordinates)

Q = np.array([[dt**5/20, dt**4/8, dt**3/6],
              [dt**4/8, dt**3/3, dt**2/2],
              [dt**3/6, dt**2/2, dt]])
Q = Q * Q_spector_noise

F = np.array([[1., dt, dt**2/2],
              [0., 1., dt ],
              [0., 0., 1.  ]])

H = np.array([1., 0., 0.])

if size_coordinates==3:
    F = block_diag(F, F, F)
    Q = block_diag(Q, Q, Q)
    H = block_diag(H, H, H)
elif size_coordinates==2:
    F = block_diag(F, F)
    Q = block_diag(Q, Q)
    H = block_diag(H, H)

x = np.zeros(3*size_coordinates) #the initial prediction
P = np.eye(3*size_coordinates) * 500. #confidence in the initial prediction

trajectories_filter = []
trajectories_filter_x = []
trajectories_filter_P = []

for id_p, point in enumerate(trajectories):
    x, P = predict(x, P, F, Q, B, u)
    x, P = update(x, P, point, R, H, size_coordinates)
    trajectories_filter.append(x[0::3])
    trajectories_filter_P.append(P[0::3,0::3]@np.ones(size_coordinates))

return trajectories_filter, trajectories_filter_P

```

```

[ ]: Q_spector_noise = 100 #the density of the White noise / our trust in the filter
coordinates_noise = 5 #noise sqrt(dispersion) at the radius
size_coordinates = 3
time_step = 0.25

```

```

[ ]: data_trajectories_filter = []
data_trajectories_filter_P = []
km_to_metr = 1000

```

```

for id_b, batch_total in enumerate(test_dl):
    batch_trajectories_filter = []
    batch_data_trajectories_filter_P = []
    for id_t, trajectories in enumerate(batch_total['data_noise'].numpy()):
        traj, traj_P = FilterKalman(trajectories * data_norm_factor *
↪km_to_metr, size_coordinates, time_step, Q_spector_noise, coordinates_noise)
        batch_trajectories_filter.append(traj)
        batch_data_trajectories_filter_P.append(traj_P)
    data_trajectories_filter.append(batch_trajectories_filter)
    data_trajectories_filter_P.append(batch_data_trajectories_filter_P)
data_trajectories_filter=np.array(data_trajectories_filter)/km_to_metr

```

2 Research

```

[ ]: def MSE(data1, data2):
    data = data1 - data2
    data *= data
    return np.sum(data)/data.size

```

```

[ ]: len(test_data.data['data'])

```

```

[ ]: 200

```

```

[ ]: def Deviation(data_real, data_rnn, data_kalman, Discrepancy, BATCH_SIZE_TEST,
↪start, array_err):
    loss_rnn = []
    loss_kalman = []
    accuracy_rnn = []
    accuracy_kalman = []
    for k in range(len(data_real)):
        while k in array_err:
            k+=1

        loss_rnn.append(MSE(data_real[k][start:,:] * data_norm_factor,
↪data_rnn[k//BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST] .
↪numpy()[start:,:]))

        loss_kalman.append(MSE(data_real[k][start:,:] * data_norm_factor, np.
↪array(data_kalman[k//BATCH_SIZE_TEST][k-k//
↪BATCH_SIZE_TEST*BATCH_SIZE_TEST])[start:,:]))
        if (len(array_err) == 0):
            if (loss_rnn[len(loss_rnn)-1]>loss_kalman[len(loss_rnn)-1]):
                print(k)
            accuracy_rnn.append(accuracy(data_rnn[k//BATCH_SIZE_TEST][k-k//
↪BATCH_SIZE_TEST*BATCH_SIZE_TEST].numpy()[start:,:], data_real[k][start:,:] *
↪data_norm_factor, Discrepancy))

```

```

        accuracy_kalman.append(accuracy(np.array(data_kalman[k//
↪BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][start:,:],
↪data_real[k][start:,:] * data_norm_factor, Discrepancy))

plt.title('Validation accuracy')
plt.ylabel('Accuracy')
plt.xlabel('num trajectory')
plt.plot(accuracy_kalman, label='kalman accuracy', color = '#1f77b4')
plt.plot(accuracy_rnn, label='rnn accuracy', color = '#ff7f0e')
plt.legend()
plt.grid(True)
plt.show()

plt.title('Loss')
plt.ylabel('Loss')
plt.xlabel('num trajectory')
plt.plot(loss_rnn, label='rnn loss', color = '#ff7f0e')
plt.plot(loss_kalman, label='kalman loss', color = '#1f77b4')
plt.legend()
plt.grid(True)
plt.show()

return loss_rnn, loss_kalman, accuracy_rnn, accuracy_kalman

```

```

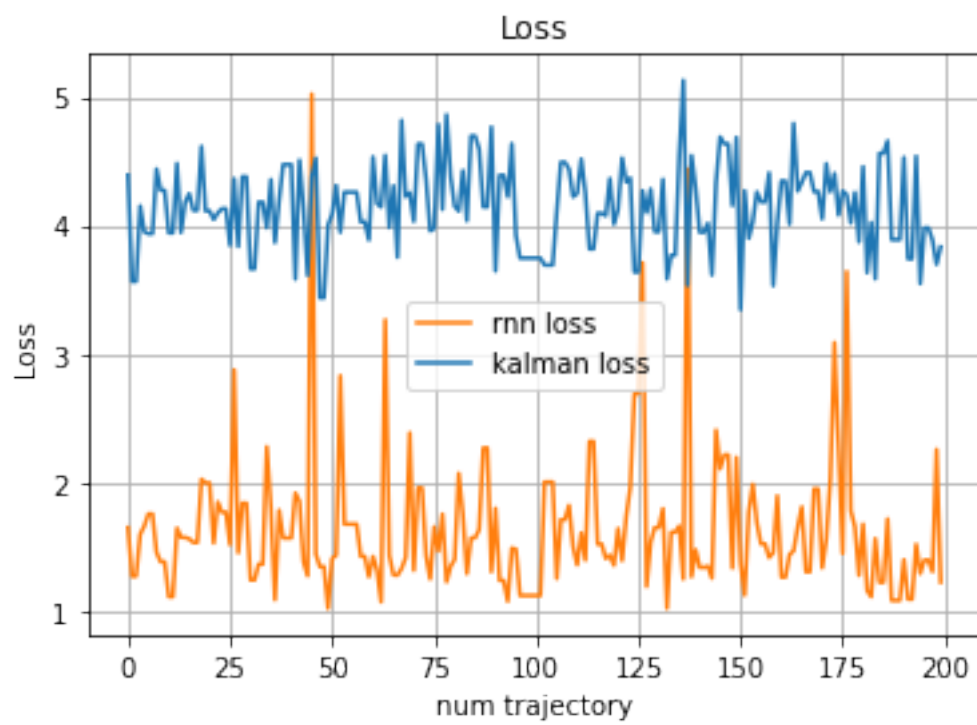
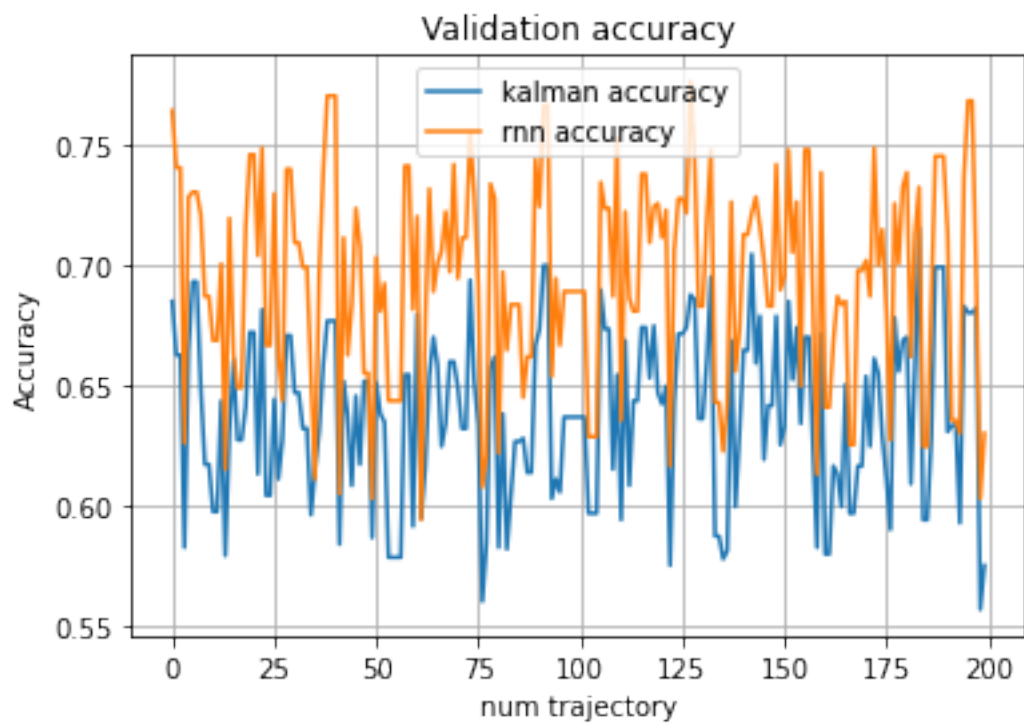
[ ]: start = 3
     k = 1

```

```

[ ]: loss_rnn, loss_kalman, accuracy_rnn, accuracy_kalman = Deviation(test_data.
↪data['data'], pack_predictions, data_trajectories_filter, Discrepancy,
↪BATCH_SIZE_TEST, start, array_err)
print('mean loss rnn', np.mean(loss_rnn))
print('mean loss kalman', np.mean(loss_kalman))
print('mean accuracy rnn', np.mean(accuracy_rnn)*100//1,'%')
print('mean accuracy kalman', np.mean(accuracy_kalman)*100//1,'%')

```



```

mean loss rnn 1.6379049723148813
mean loss kalman 4.14840735826588
mean accuracy rnn 69.0 %
mean accuracy kalman 63.0 %

```

```

[ ]: k = 2
loss_rnn_k = []
loss_kalman_k = []
losss_measurement = []
for i in range(len(test_data.data['data'][k])):
    loss_kalman_k.append([test_data.data['data'][k,i,0] * data_norm_factor[0]
↳-data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
↳BATCH_SIZE_TEST*BATCH_SIZE_TEST][i][0],
                        test_data.data['data'][k,i,1] * data_norm_factor[1]
↳-data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
↳BATCH_SIZE_TEST*BATCH_SIZE_TEST][i][1],
                        test_data.data['data'][k,i,2] * data_norm_factor[2]
↳-data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
↳BATCH_SIZE_TEST*BATCH_SIZE_TEST][i][2]])

    loss_rnn_k.append([test_data.data['data'][k,i,0] * data_norm_factor[0]
↳-pack_predictions[k//BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST] .
↳numpy()[i][0],
                        test_data.data['data'][k,i,1] * data_norm_factor[1]
↳-pack_predictions[k//BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST] .
↳numpy()[i][1],
                        test_data.data['data'][k,i,2] * data_norm_factor[2]
↳-pack_predictions[k//BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST] .
↳numpy()[i][2]])

    loss measurement.append([test_data.data['data'][k,i,0] *
↳data_norm_factor[0]-test_data.data['data_noise'][k,i,0] *
↳data_norm_factor[0],
                        test_data.data['data'][k,i,1] *
↳data_norm_factor[1]-test_data.data['data_noise'][k,i,1] *
↳data_norm_factor[1],
                        test_data.data['data'][k,i,2] *
↳data_norm_factor[2]-test_data.data['data_noise'][k,i,2] *
↳data_norm_factor[2]])
loss_kalman_k = np.absolute(np.array(loss_kalman_k))
loss_rnn_k = np.absolute(np.array(loss_rnn_k))
losss_measurement = np.absolute(np.array(losss_measurement))

```

```

[ ]: plt.ylabel('x')
plt.xlabel('t')
plt.plot(losss_measurement[:,0], label='loss measurement k(x)')
plt.plot(loss_kalman_k[:,0], label='loss kalman k(x)')
plt.legend()

```

```

plt.grid(True)
plt.show()

plt.ylabel('x')
plt.xlabel('t')
plt.plot(loss_measurement[:,0], label='loss measurement k(x)')
plt.plot(loss_rnn_k[:,0], label='loss rnn k(x)')
plt.legend()
plt.grid(True)
plt.show()

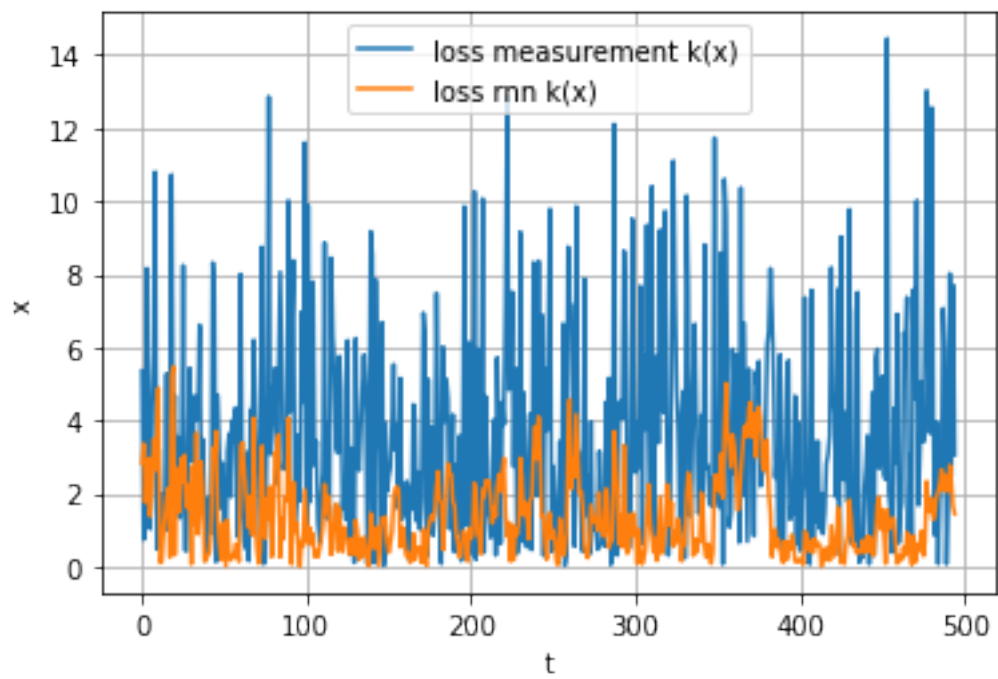
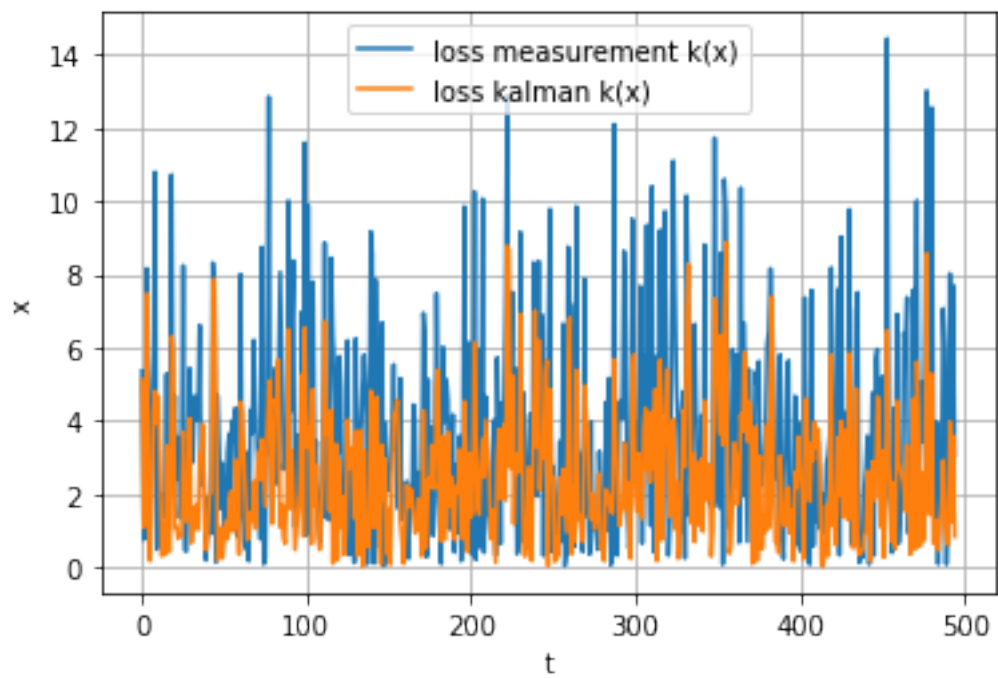
plt.ylabel('y')
plt.xlabel('t')
plt.plot(loss_measurement[:,1], label='loss measurement k(y)')
plt.plot(loss_kalman_k[:,1], label='loss kalman k(y)')
plt.legend()
plt.grid(True)
plt.show()

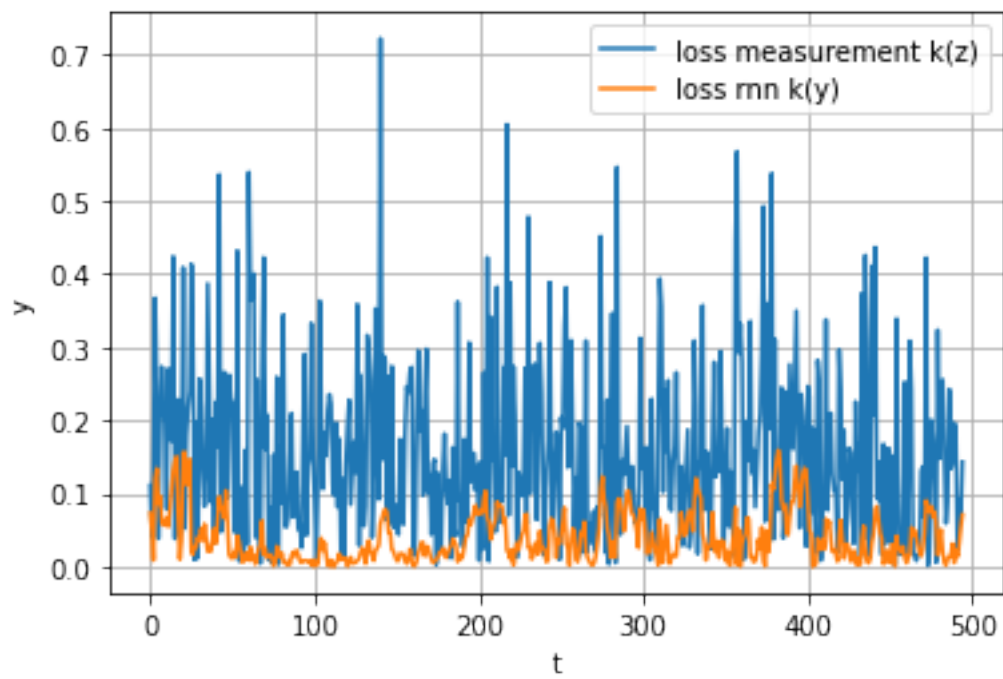
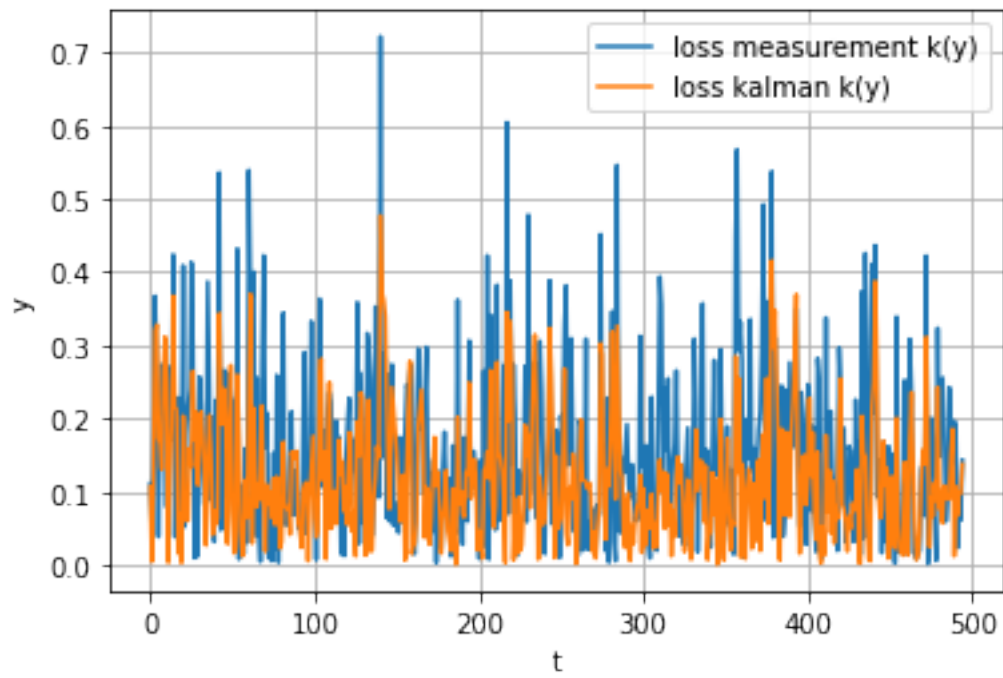
plt.ylabel('y')
plt.xlabel('t')
plt.plot(loss_measurement[:,1], label='loss measurement k(z)')
plt.plot(loss_rnn_k[:,1], label='loss rnn k(y)')
plt.legend()
plt.grid(True)
plt.show()

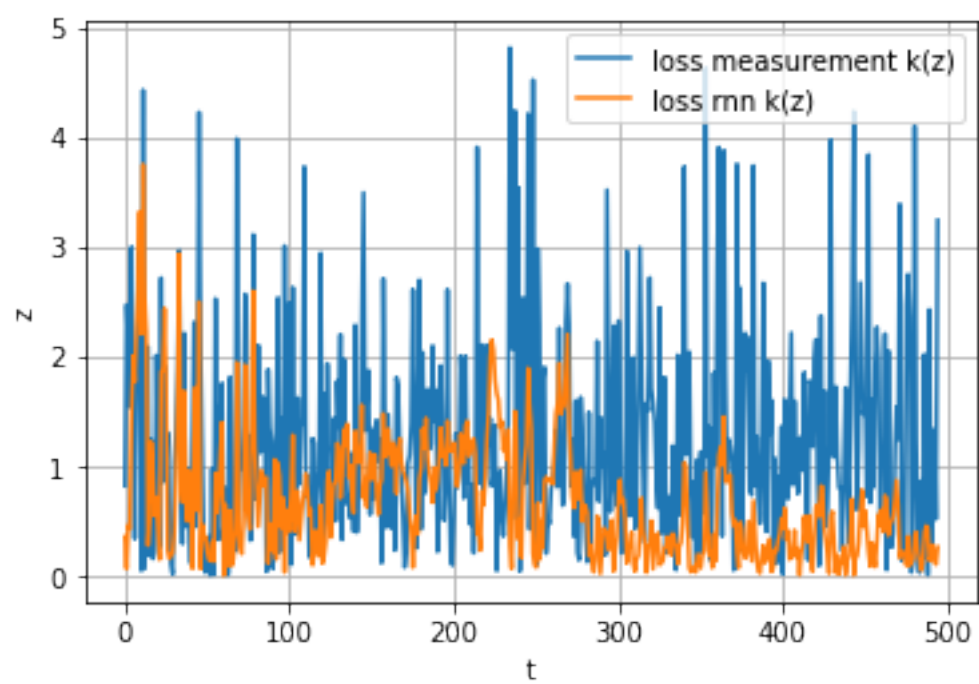
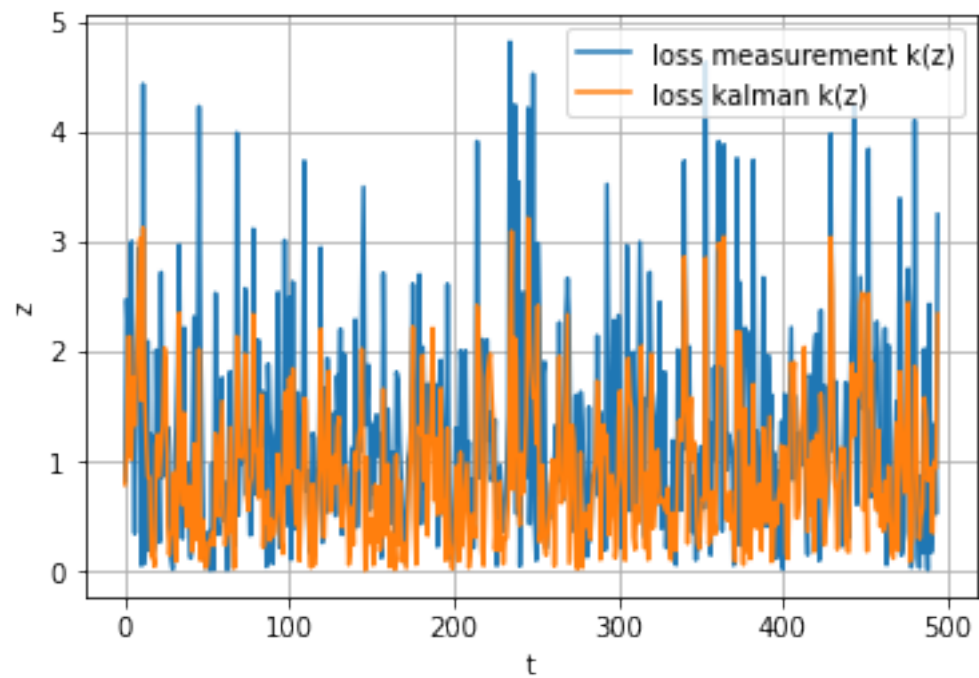
plt.ylabel('z')
plt.xlabel('t')
plt.plot(loss_measurement[:,2], label='loss measurement k(z)')
plt.plot(loss_kalman_k[:,2], label='loss kalman k(z)')
plt.legend()
plt.grid(True)
plt.show()

plt.ylabel('z')
plt.xlabel('t')
plt.plot(loss_measurement[:,2], label='loss measurement k(z)')
plt.plot(loss_rnn_k[:,2], label='loss rnn k(z)')
plt.legend()
plt.grid(True)
plt.show()

```







```
[ ]: a0 = start
      a1 = 0
```

```

a2 = 2
plt.ylabel('z')
plt.xlabel('x')
plt.scatter(test_data.data['data_noise'][k][a0:,a1] * data_norm_factor[a1],
    ↳test_data.data['data_noise'][k][a0:,a2] * data_norm_factor[a2],
    ↳label='data+noise', c='pink', s=6)
plt.plot(test_data.data['data'][k][a0:,a1] * data_norm_factor[a1], test_data.
    ↳data['data'][k][a0:,a2] * data_norm_factor[a2], label='data', color='black')
plt.plot(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a1], np.
    ↳array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a2], label='filter data Kalman',
    ↳color='green')
plt.plot(pack_predictions[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a1], pack_predictions[k//
    ↳BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a2],
    ↳label='filter data RNN', color='r')
plt.legend()
plt.grid(True)
plt.show()

a1 = 1
a2 = 2
plt.ylabel('z')
plt.xlabel('y')
plt.scatter(test_data.data['data_noise'][k][a0:,a1] * data_norm_factor[a1],
    ↳test_data.data['data_noise'][k][a0:,a2] * data_norm_factor[a2],
    ↳label='data+noise', c='pink', s=6)
plt.plot(test_data.data['data'][k][a0:,a1] * data_norm_factor[a1], test_data.
    ↳data['data'][k][a0:,a2] * data_norm_factor[a2], label='data', color='black')
plt.plot(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a1], np.
    ↳array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a2], label='filter data Kalman',
    ↳color='green')
plt.plot(pack_predictions[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a1], pack_predictions[k//
    ↳BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a2],
    ↳label='filter data RNN', color='r')
plt.legend()
plt.grid(True)
plt.show()

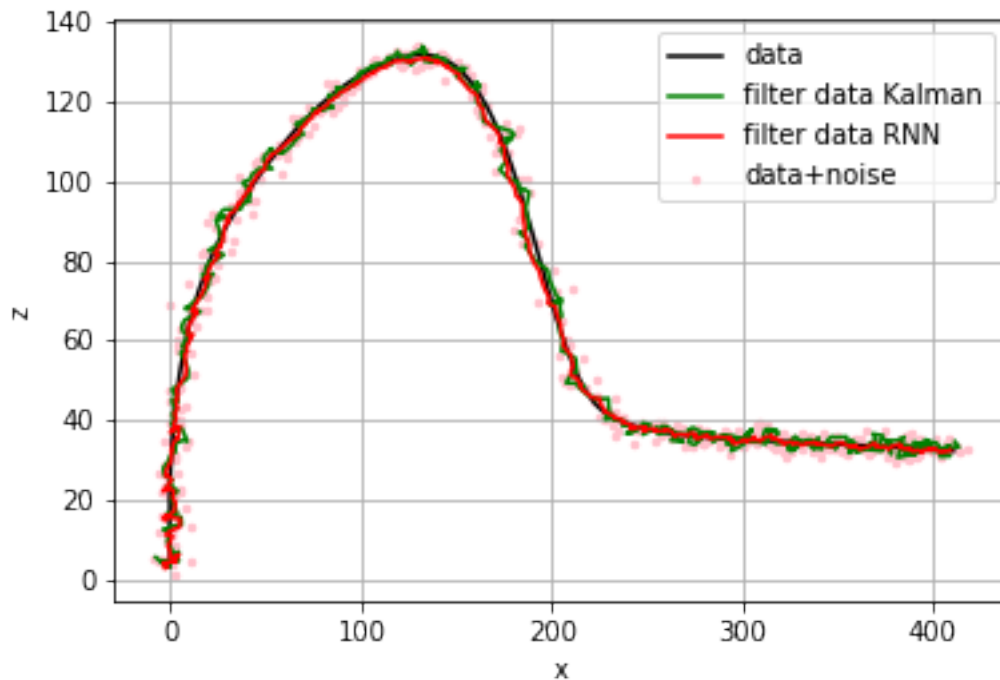
a1 = 0
a2 = 1
plt.ylabel('y')

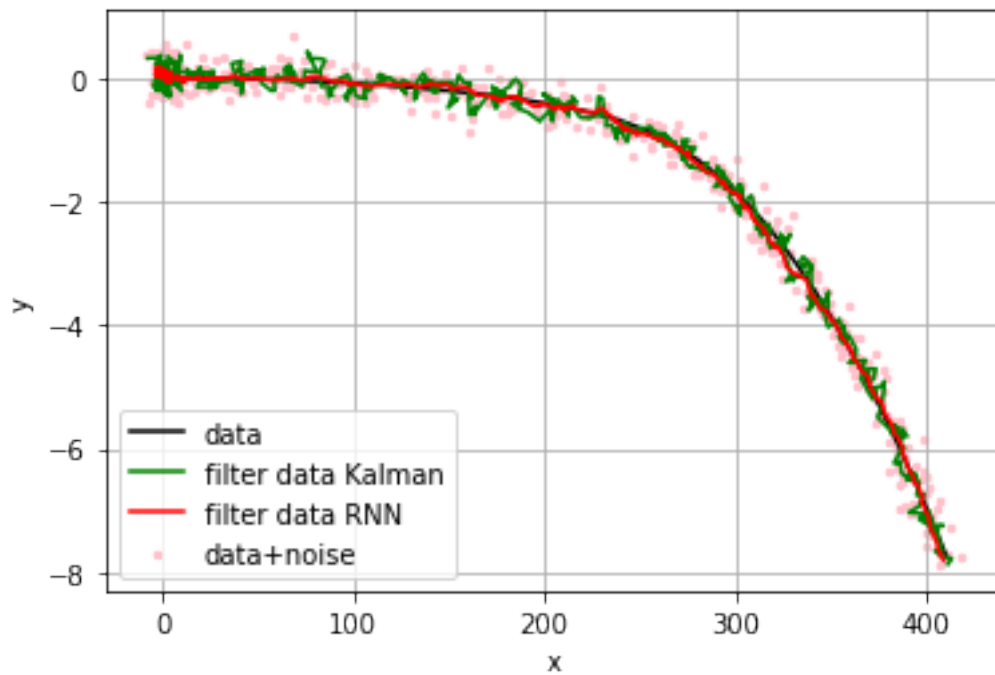
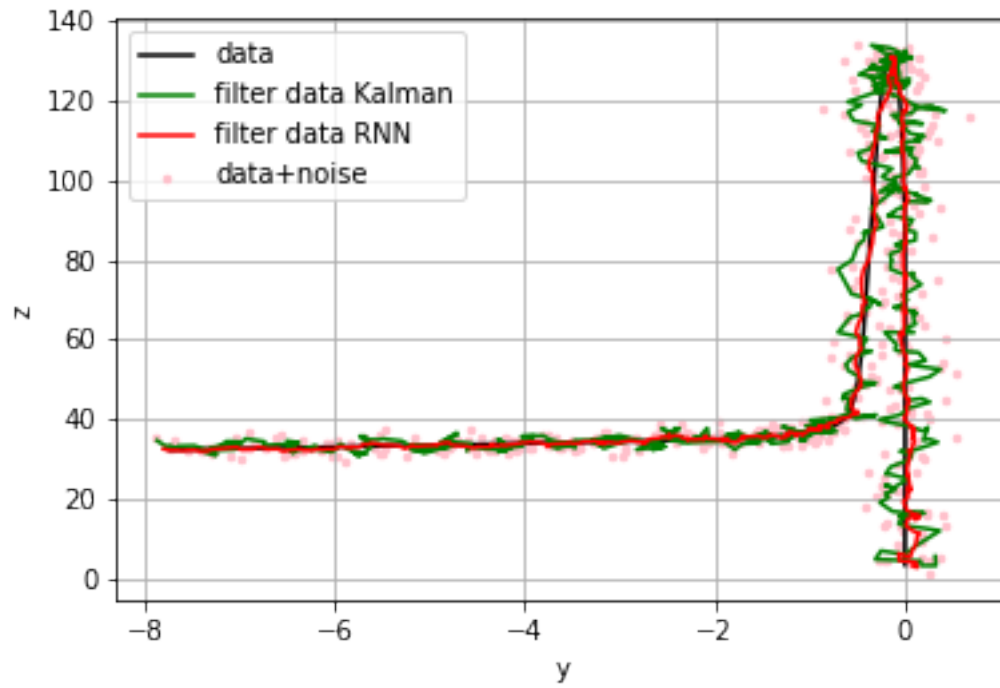
```

```

plt.xlabel('x')
plt.scatter(test_data.data['data_noise'][k][a0:,a1] * data_norm_factor[a1],
    ↳test_data.data['data_noise'][k][a0:,a2] * data_norm_factor[a2],
    ↳label='data+noise', c='pink', s=6)
plt.plot(test_data.data['data'][k][a0:,a1] * data_norm_factor[a1], test_data.
    ↳data['data'][k][a0:,a2] * data_norm_factor[a2], label='data', color='black')
plt.plot(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a1], np.
    ↳array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a2], label='filter data Kalman',
    ↳color='green')
plt.plot(pack_predictions[k//BATCH_SIZE_TEST][k-k//
    ↳BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a1], pack_predictions[k//
    ↳BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a2],
    ↳label='filter data RNN', color='r')
plt.legend()
plt.grid(True)
plt.show()

```





```
[ ]: plot_trajectory(test_data.data['data'][k][a0:,:] * data_norm_factor[:],  
    ↪ 'completed data')
```

```

plot_trajectory(test_data.data['data_noise'][k][a0:,:]* data_norm_factor[:],  

    ↪ 'data+noise')
plot_trajectory(pack_predictions[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,:], 'filter data RNN')
plot_trajectory(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,:], 'filter data Kalman')

```

```

[ ]: a0 = 3
a1 = 0
a2 = 2
plt.ylabel('z')
plt.xlabel('x')
for k in range(len(test_data.data['data'])//10):
    plt.plot(test_data.data['data'][k][a0:,a1], test_data.data['data'][k][a0:  

    ↪ ,a2], label='data', color='black')
    plt.scatter(test_data.data['data_noise'][k][a0:,a1], test_data.  

    ↪ data['data_noise'][k][a0:,a2], label='data+noise', c='pink', s=6)
#plt.plot(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a1], np.  

    ↪ array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a2], label='filter data Kalman',  

    ↪ color='green')
#plt.plot(pack_predictions[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a1], pack_predictions[k//  

    ↪ BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a2],  

    ↪ label='filter data RNN', color='r')
plt.legend()
plt.grid(True)
plt.show()

a1 = 1
a2 = 2
plt.ylabel('z')
plt.xlabel('y')
for k in range(len(test_data.data['data'])//10):
    plt.plot(test_data.data['data'][k][a0:,a1], test_data.data['data'][k][a0:  

    ↪ ,a2], label='data', color='black')
    plt.scatter(test_data.data['data_noise'][k][a0:,a1], test_data.  

    ↪ data['data_noise'][k][a0:,a2], label='data+noise', c='pink', s=6)
#plt.plot(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a1], np.  

    ↪ array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//  

    ↪ BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a2], label='filter data Kalman',  

    ↪ color='green')

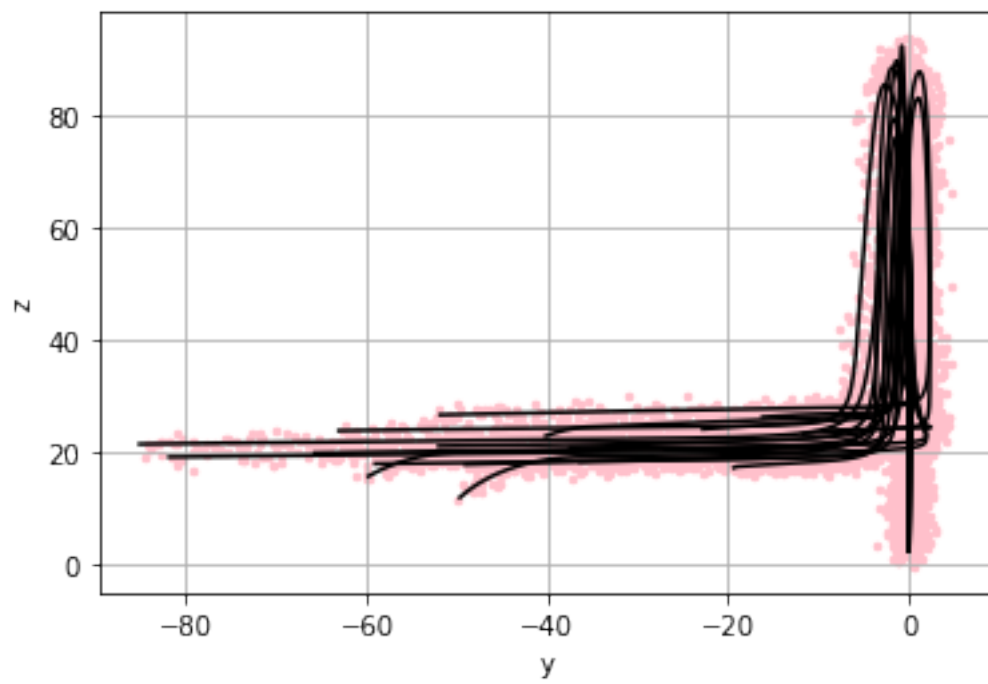
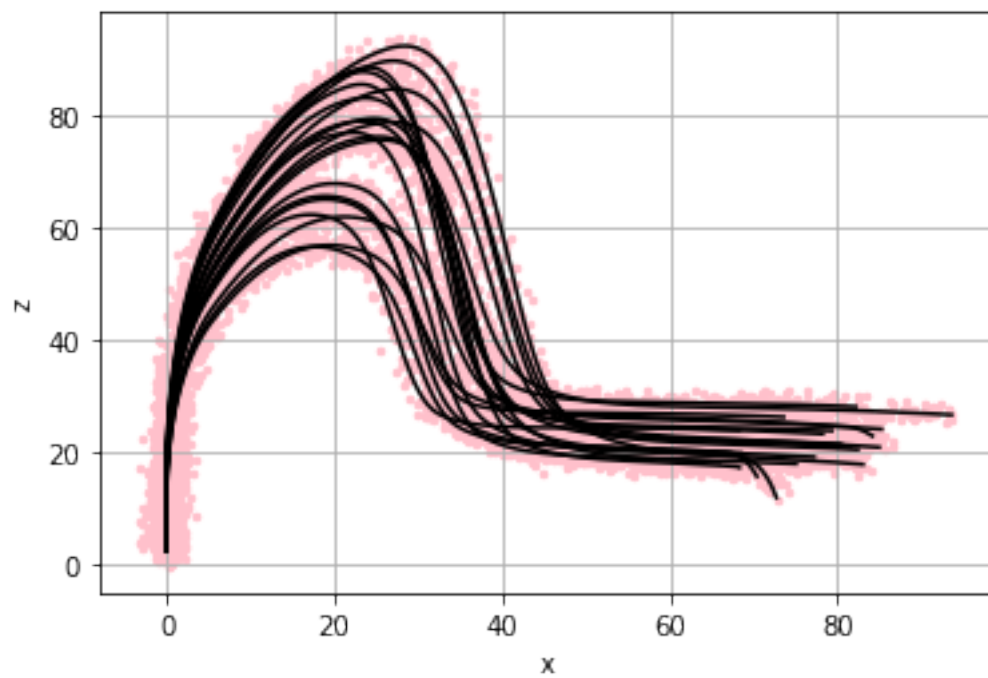
```

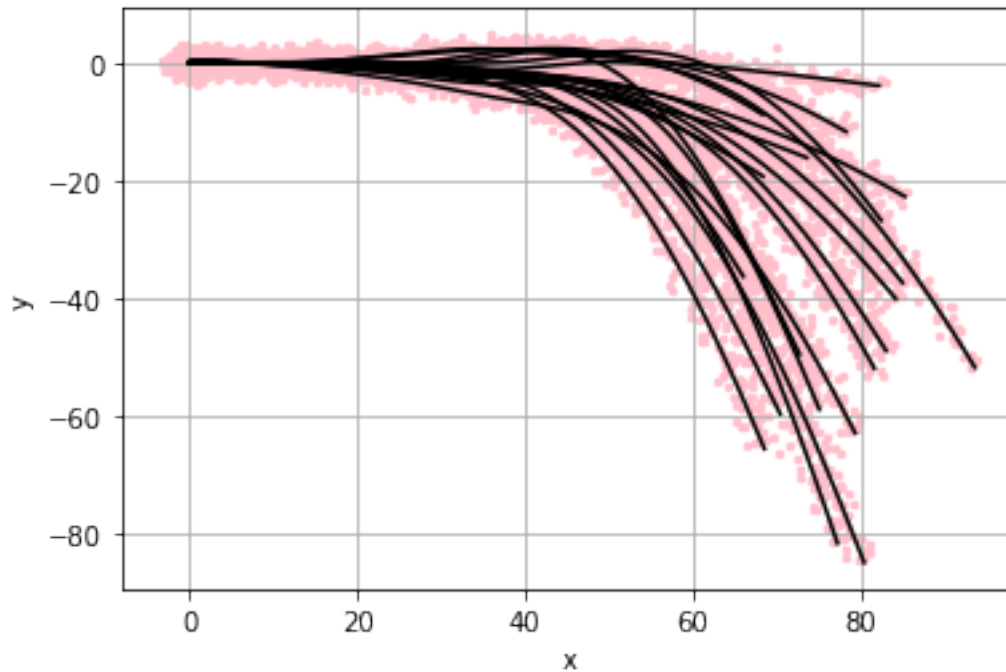
```

#plt.plot(pack_predictions[k//BATCH_SIZE_TEST][k-k//
→BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a1], pack_predictions[k//
→BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a2],
→label='filter data RNN', color='r')
#plt.legend()
plt.grid(True)
plt.show()

a1 = 0
a2 = 1
plt.ylabel('y')
plt.xlabel('x')
for k in range(len(test_data.data['data'])//10):
    plt.plot(test_data.data['data'][k][a0:,a1], test_data.data['data'][k][a0:
→,a2], label='data', color='black')
    plt.scatter(test_data.data['data_noise'][k][a0:,a1], test_data.
→data['data_noise'][k][a0:,a2], label='data+noise', c='pink', s=6)
#plt.plot(np.array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
→BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a1], np.
→array(data_trajectories_filter[k//BATCH_SIZE_TEST][k-k//
→BATCH_SIZE_TEST*BATCH_SIZE_TEST])[a0:,a2], label='filter data Kalman',
→color='green')
#plt.plot(pack_predictions[k//BATCH_SIZE_TEST][k-k//
→BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a1], pack_predictions[k//
→BATCH_SIZE_TEST][k-k//BATCH_SIZE_TEST*BATCH_SIZE_TEST][a0:,a2],
→label='filter data RNN', color='r')
#plt.legend()
plt.grid(True)
plt.show()

```





```
[ ]: a0 = 3
a1 = 0
a2 = 2
plt.ylabel('z')
plt.xlabel('x')
for k in range(len(test_keys)//2):
    key_k = test_keys[k]
    plt.plot(np.array(dset[key_k])[a0:,a1], np.array(dset[key_k])[a0:,a2],
             label='data', color='black')
plt.grid(True)
plt.show()

a1 = 1
a2 = 2
plt.ylabel('z')
plt.xlabel('y')
for k in range(len(test_keys)//2):
    key_k = test_keys[k]
    plt.plot(np.array(dset[key_k])[a0:,a1], np.array(dset[key_k])[a0:,a2],
             label='data', color='black')
plt.grid(True)
plt.show()

a1 = 0
```

```

a2 = 1
plt.ylabel('y')
plt.xlabel('x')
for k in range(len(test_keys)//2):
    key_k = test_keys[k]
    plt.plot(np.array(dset[key_k])[a0:,a1], np.array(dset[key_k])[a0:,a2],
    ↪label='data', color='black')
plt.grid(True)
plt.show()

```

```

[ ]: def return_RelativeTrajectory(data_RelativeTrajectory, name = 'data'):
    columns = ['coord_x', 'coord_y', 'coord_z', 't']
    for k in range(len(data_RelativeTrajectory.data[name])):
        data_RT = data_RelativeTrajectory.data[name][k]
        if k == 0:

            data_rnn = []
            pre_id = data_RelativeTrajectory.data['traj_ids'][k]
            orig= data_RT * data_RelativeTrajectory.stats['data_norm_factor'][:]
        else:
            if data_RelativeTrajectory.data['traj_ids'][k] == pre_id:
                orig= np.append(orig, data_RT * data_RelativeTrajectory.
    ↪stats['data_norm_factor'][:], axis = 0)
            else:
                pre_id = data_RelativeTrajectory.data['traj_ids'][k]
                rt = RelativeTrajectory(orig, config=data_RelativeTrajectory.
    ↪configs[k])
                data_rnn.append(rt.restore(columns))
                orig = data_RT * data_RelativeTrajectory.
    ↪stats['data_norm_factor'][:]
    return data_rnn

```

```

[ ]: data_rnn = return_RelativeTrajectory(test_data, name = 'data')#'data_noise'

```

```

[ ]: a0 = 3
a1 = 0
a2 = 2
plt.ylabel('z')
plt.xlabel('x')
for k in range(len(data_rnn)//2):
    plt.plot(np.array(data_rnn[k])[a0:,a1], np.array(data_rnn[k])[a0:,a2],
    ↪label='data', color='black')
plt.grid(True)
plt.show()

a1 = 1

```

```

a2 = 2
plt.ylabel('z')
plt.xlabel('y')
for k in range(len(data_rnn)//2):
    plt.plot(np.array(data_rnn[k])[a0:,a1], np.array(data_rnn[k])[a0:,a2],
    ↪label='data', color='black')
plt.grid(True)
plt.show()

a1 = 0
a2 = 1
plt.ylabel('y')
plt.xlabel('x')
for k in range(len(data_rnn)//2):
    plt.plot(np.array(data_rnn[k])[a0:,a1], np.array(data_rnn[k])[a0:,a2],
    ↪label='data', color='black')
plt.grid(True)
plt.show()

```

```

[ ]: def return_predictions(pack_predictions, data_RelativeTrajectory,
    ↪BATCH_SIZE_TEST, name = 'data'):
    columns = ['coord_x', 'coord_y', 'coord_z', 't']
    for k in range(len(data_RelativeTrajectory.data[name])):
        data_RT = np.array(pack_predictions[k//BATCH_SIZE_TEST][k-k//
    ↪BATCH_SIZE_TEST*BATCH_SIZE_TEST])
        if k == 0:

            data_rnn = []
            pre_id = data_RelativeTrajectory.data['traj_ids'][k]
            orig= data_RT * data_RelativeTrajectory.stats['data_norm_factor'][::]
        else:
            if data_RelativeTrajectory.data['traj_ids'][k] == pre_id:
                orig= np.append(orig, data_RT * data_RelativeTrajectory.
    ↪stats['data_norm_factor'][:, axis = 0])
            else:
                pre_id = data_RelativeTrajectory.data['traj_ids'][k]
                rt = RelativeTrajectory(orig, config=data_RelativeTrajectory.
    ↪configs[k])
                data_rnn.append(rt.restore(columns))
                orig = data_RT * data_RelativeTrajectory.
    ↪stats['data_norm_factor'][:, axis = 0])
        return data_rnn

[ ]: orig_pack_predictions = return_predictions(pack_predictions, test_data,
    ↪BATCH_SIZE_TEST, 'data')

```