Setup

First wget https://s3.amazonaws.com... (removed due to copyright issues)

In each data fold, there is a raw data subfolder and a syn data subfolder, which represent the raw data collection without synchronisation but with high precise timestep, and the synchronised data but without high precise timestep.

In Google Colab



Here I also changed the Oxford Datasets, so I seperated the Oxford into 2 folders for train and test instead of putting the information in each folder.

Here is the header of the sensor file and ground truth file.

In each data fold, there is a raw data subfolder and a syn data subfolder, which represent the raw data collection without synchronisation but with high precise timestep, and the synchronised data but without high precise timestep.

Here is the header of the sensor file and ground truth file.

vicon (vi*.csv)

Time Header translation.x translation.y translation.z rotation.x rotation.y rotation.z rotation.w

Sensors (imu*.csv)

Time attitude_roll(radians) attitude_pitch(radians) attitude_yaw(radians) rotation_rate_x(radians/s) rotation_rate_y(radians/s) rotation_rate_z(radians/s) gravity_x(G) gravity_y(G) gravity_z(G) user_acc_x(G) user_acc_y(G) user_acc_y(G) magnetic_field_x(microteslas) magnetic_field_y(microteslas)

magnetic_field_z(microteslas)

Structure

In this folder

```
user@fedora ~/C/magnetic_localization (master)> ls data/Oxford\ Inertial\ (
data1/ data3/ data5/
                               Test.txt*
data2/ data4/ handheld.xlsx* Train.txt*
user@fedora ~/C/magnetic_localization (master)> ls data/0xford\ Inertial\ (
imu1.csv* imu4.csv* imu7.csv* vi3.csv* vi6.csv*
imu2.csv* imu5.csv* vi1.csv* vi4.csv* vi7.csv*
imu3.csv* imu6.csv* vi2.csv* vi5.csv*
user@fedora ~/C/magnetic_localization (master)> ls data/0xford\ Inertial\ (
imu1.csv* imu2.csv* imu3.csv* vi1.csv* vi2.csv* vi3.csv*
user@fedora ~/C/magnetic_localization (master)> ls data/0xford\ Inertial\ (
imu1.csv* imu3.csv* imu5.csv* vi2.csv* vi4.csv*
imu2.csv* imu4.csv* vi1.csv* vi3.csv* vi5.csv*
user@fedora ~/C/magnetic_localization (master)> ls data/0xford\ Inertial\ (
data1/ data3/ data5/
                               Test.txt*
data2/ data4/ handheld.xlsx* Train.txt*
user@fedora ~/C/magnetic_localization (master)> pwd
/home/user/Code/magnetic_localization
```

Also like each of them are the same length, so no need to sync the timesteps

```
user@fedora ~/C/magnetic_localization (master)> cat data/0xford\ Inertial\
  23446   23446   3282548
user@fedora ~/C/magnetic_localization (master)> cat data/0xford\ Inertial\
  23446   23446   1740520
```

Just fucking ignore the Time and Header

Some more Information

```
user@fedora ~/C/m/d/O/h/d/syn (master)> pwd
```

```
/home/user/Code/magnetic_localization/data/Oxford Inertial Odometry Datase
user@fedora \sim/C/m/d/0/h/d/syn (master)> ls
imu1.csv* imu4.csv* imu7.csv* vi3.csv* vi6.csv*
imu2.csv* imu5.csv* vi1.csv* vi4.csv* vi7.csv*
imu3.csv* imu6.csv* vi2.csv* vi5.csv*
user@fedora ~/C/m/d/0/h/d/syn (master)> cat imu1.csv |head -n 5
1.50E+11,0.003649,0.44925,-0.21255,0.036483,-0.029496,0.020632,0.003286,-0
1.50E+11,0.00305,0.44954,-0.21219,0.067307,-0.038284,0.029241,0.002747,-0.4
1.50E+11,0.002363,0.45003,-0.21184,0.076935,-0.039423,0.021788,0.002128,-0
1.50E+11,0.001778,0.45053,-0.21167,0.066339,-0.039321,0.006826,0.001601,-0
1.50E+11,0.001393,0.45086,-0.21171,0.037685,-0.030543,-0.010317,0.001253,-0
user@fedora ~/C/m/d/0/h/d/syn (master)> cat vil.csv |head -n 5
1.50E+11,12978,-1.2991,1.7212,1.1931,-0.21409,-0.012459,-0.097183,0.97189
1.50E+11,12979,-1.2993,1.7213,1.1932,-0.21473,-0.01237,-0.097239,0.97174
1.50E+11,12980,-1.2993,1.7213,1.1932,-0.21509,-0.012288,-0.097244,0.97166
1.50E+11,12981,-1.2994,1.7214,1.1933,-0.21526,-0.012291,-0.09738,0.97161
1.50E+11,12982,-1.2995,1.7213,1.1933,-0.21541,-0.012199,-0.097503,0.97157
```

Note: Use os list dir instead of hardcoding data folders

YOU MUST SPLIT DATA AT THE FILE LEVEL TO PREVENT LEAKAGE

TENSORBOARD Logs

Tensorboard logs shouldn't be put in Git, so I put them here

```
https://jimchen4214-public.s3.amazonaws.com/other/mag_tensorboard_logs/logs.zip https://jimchen4214-public.s3.amazonaws.com/other/mag_tensorboard_logs/lstm_logs.zip
```

Command to upload

```
zip -r logs.zip logs/
aws s3 cp logs.zip s3://jimchen4214-public/other/mag_tensorboard_logs/logs
```

Goal

Our goal is to predict the current x, y, z based on the previous all previous data(but not previous x, y, z)

Trying Vanilla LSTM without splitting windows

1. Suffers from distribution shift

```
X_train means:
mag_x: -0.46830051313300697
mag_y: -15.668869715403527
mag_z: -36.376663738555756
mag_total: 42.527113564066134
X_test means:
mag_x: -4.326749743812862
mag_y: -13.854210498185887
mag_z: -32.72580701915449
mag_total: 38.786503919304415
y_train means:
x: 0.12568006574318533
y: 0.023374721301369764
z: 1.176188457321701
y_test means:
x: 0.15600621631161352
y: 0.075468841401043
z: 1.1843440265075935
```

1. High variance

```
Epoch [0/49], Train MSE (denorm): 1.4946, Test MSE (denorm): 2.5259

Epoch [0/49], Train Loss: 0.3160

Epoch [1/49], Train MSE (denorm): 0.2647, Test MSE (denorm): 3.6559

Epoch [1/49], Train Loss: 0.2283

Epoch [2/49], Train MSE (denorm): 0.1589, Test MSE (denorm): 3.4956
```

Easy LSTM

So basically this is an intuitive file for LSTM, with minimal configurations and it can be trained 5 minutes on a CPU

We basically did a really simple thing, like feed everything into LSTM model (split data on the file level)

Improvements

Variance Too High

If we use the sliding window approach we can easily like make sure they don't overlap to make variance much smaller.

Sequence Too Short

If the sequence is too short then it performs poorly, improving the sequence length to 200 or 300 drastically improves the performance.

Handheld Training

As we can see it quickly reaches some benchmark(though not bad)

```
Total training samples: 6002
Total validation samples: 981
```

```
Total samples: 6983

Input shape: torch.Size([100, 15])

Target shape: torch.Size([3])

Number of training batches: 188

Number of validation batches: 31

Performing mean baseline evaluation...

Baseline Train Loss: 1.5063, Baseline Val Loss: 1.6076

Epoch [10/50], Train Loss: 0.5113, Val Loss: 0.5460

Epoch [15/50], Train Loss: 0.3930, Val Loss: 0.4855

Epoch [20/50], Train Loss: 0.3466, Val Loss: 0.3950

Epoch [25/50], Train Loss: 0.3294, Val Loss: 0.4008

Epoch [27/50], Train Loss: 0.3010, Val Loss: 0.3548
```

Tried it on Trolley

```
(mlenv) user@fedora ~/C/m/src (master)> python easy_lstm.py
Total training samples: 3880
Total validation samples: 376
Total samples: 4256
Input shape: torch.Size([100, 15])
Target shape: torch.Size([3])
Number of training batches: 122
Number of validation batches: 12
Performing mean baseline evaluation...
Baseline Train Loss: 1.6448, Baseline Val Loss: 1.4999
Epoch [5/50], Train Loss: 0.5197, Val Loss: 0.4581
Epoch [10/50], Train Loss: 0.5856, Val Loss: 0.4645
Epoch [15/50], Train Loss: 0.4282, Val Loss: 0.4330
Epoch [20/50], Train Loss: 0.4565, Val Loss: 0.4461
Epoch [25/50], Train Loss: 0.3967, Val Loss: 0.3775
Epoch [29/50], Train Loss: 0.3408, Val Loss: 0.3440
```

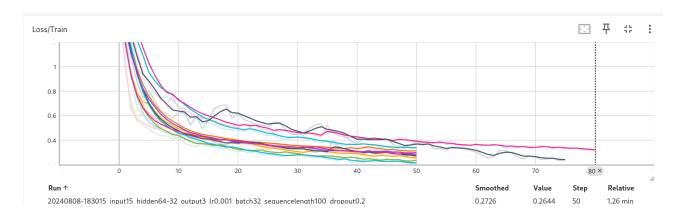
Finetuning

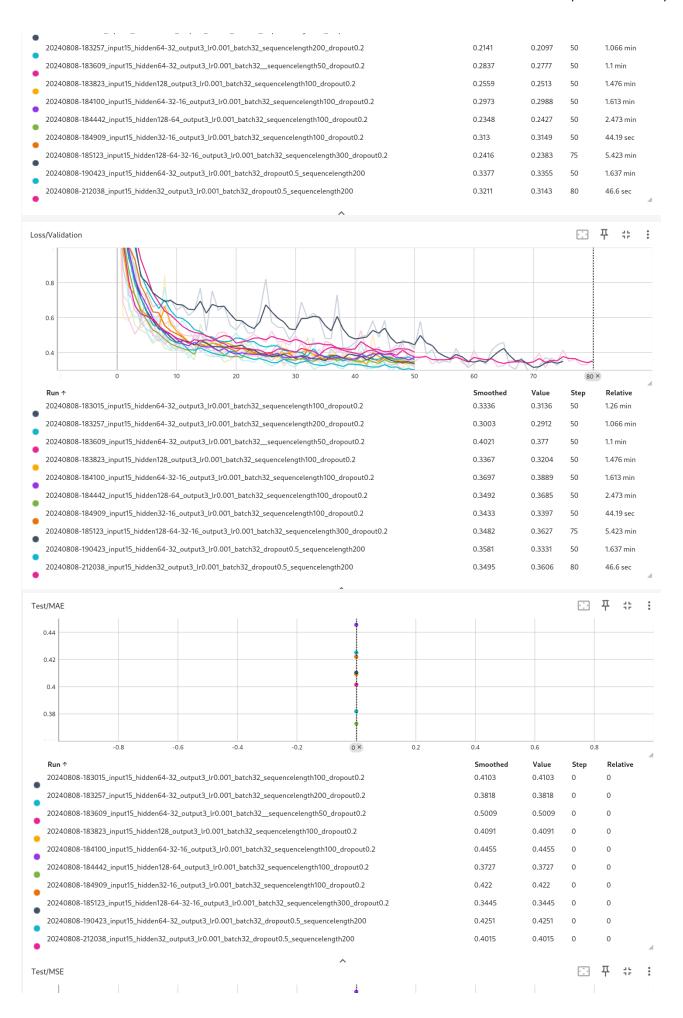
We need to finetune these

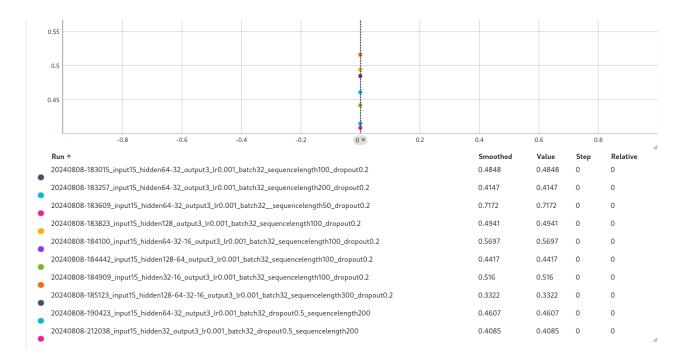
Basically I run these to test

```
# Basic configuration:
python lstm_train.py --sequence_length 100 --hidden_sizes 64 32 --num_epocl
# Longer sequence length
python lstm_train.py --sequence_length 200 --hidden_sizes 64 32 --num_epocl
# Shorter sequence length
python lstm_train.py --sequence_length 50 --hidden_sizes 64 32 --num_epoch
# Single layer LSTM
python lstm_train.py --sequence_length 100 --hidden_sizes 128 --num_epochs
# Three-layer LSTM
python lstm_train.py --sequence_length 100 --hidden_sizes 64 32 16 --num_e
# Larger hidden sizes
python lstm_train.py --sequence_length 100 --hidden_sizes 128 64 --num_epo
# Smaller hidden sizes
python lstm_train.py --sequence_length 100 --hidden_sizes 32 16 --num_epocl
# Complex configuration
python lstm_train.py --sequence_length 300 --hidden_sizes 128 64 32 16 --ni
##### With higher dropout #####
# Longer sequence length
python lstm_train.py --sequence_length 200 --hidden_sizes 64 32 --num_epocl
# Single layer LSTM
python lstm_train.py --sequence_length 200 --hidden_sizes 64 --num_epochs !
```

Tensorboard Results



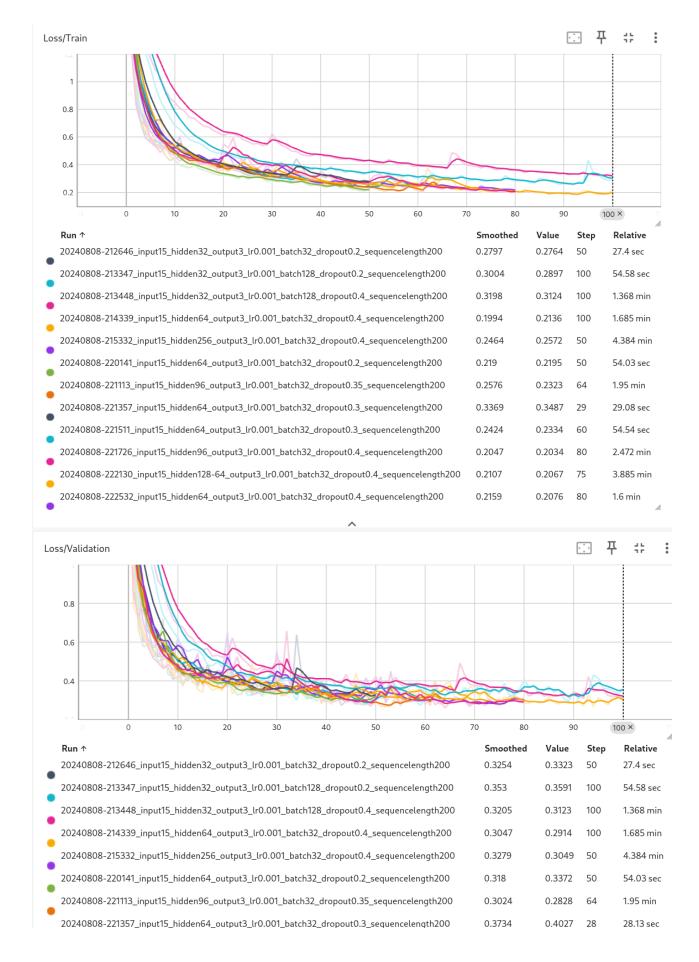


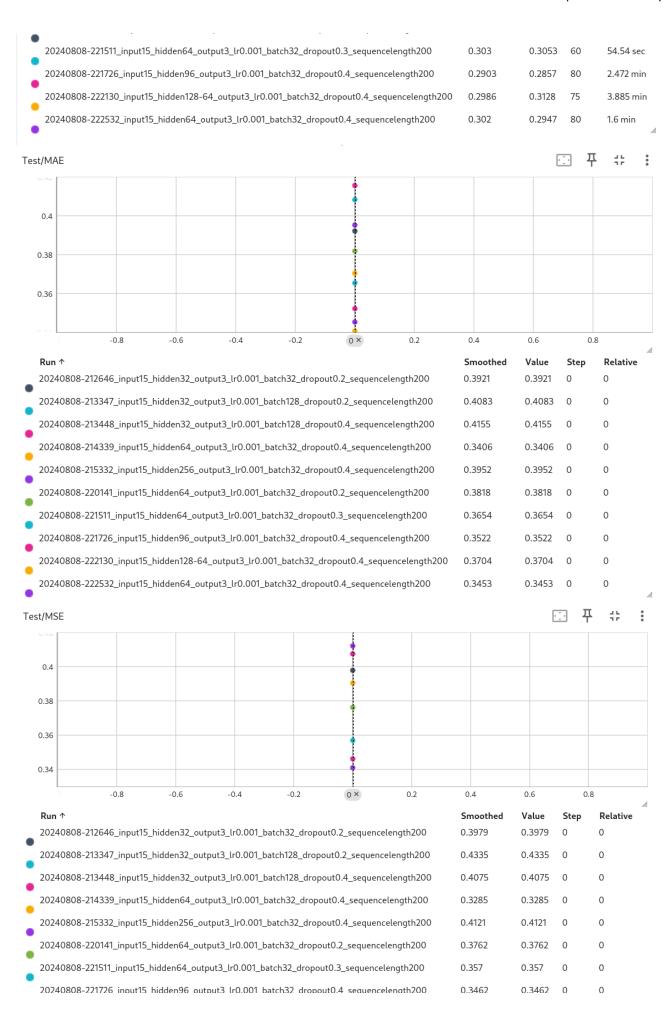


Some More Training and Finetuning

```
python lstm_train.py --sequence_length 200 --hidden_sizes 32 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 64 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 64 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 64 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 256 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 64 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 96 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 96 --num_epochs apython lstm_train.py --sequence_length 200 --hidden_sizes 128 64 --num_epochs apython lstm_train.py --sequence_length
```

Tensorboard Results





```
20240808-222130_input15_hidden128-64_output3_lr0.001_batch32_dropout0.4_sequencelength200 0.3904 0.3904 0 0 20240808-222532_input15_hidden64_output3_lr0.001_batch32_dropout0.4_sequencelength200 0.341 0.341 0 0
```

Extreme Long Seq Length

I also tried to increase the sequence length to 400, which resulted in

```
Overall Mean Squared Error: 0.2241
Overall Mean Absolute Error: 0.2934
```

So like I cannot get it much below 0.3 with this vanilla LSTM approach

Easy Transformer

Transformer is more complicated to implement than RNN, and thus very prune to mistakes. I am working hard to make sure no misconfigs happen (though it is very likely).

Run Some Configuarations

So basically run different configs to get an idea what happens

```
# Baseline configuration

python transformer_train.py --d_model 32 --nhead 2 --num_layers 1 --dim_fer

# Deeper model

python transformer_train.py --d_model 64 --nhead 4 --num_layers 2 --dim_fer

python transformer_train.py --d_model 64 --nhead 4 --num_layers 6 --dim_fer

# Wider model

python transformer_train.py --d_model 128 --nhead 8 --num_layers 2 --dim_fer

# Mean pooling

python transformer_train.py --d_model 64 --nhead 4 --num_layers 2 --dim_fer

# Return all positions
```

```
# Larger batch size
python transformer_train.py --d_model 64 --nhead 4 --num_layers 2 --dim_fed
# More training epochs
python transformer_train.py --d_model 64 --nhead 4 --num_layers 2 --dim_fed
# Higher dropout
python transformer_train.py --d_model 64 --nhead 4 --num_layers 3 --dim_fed
```