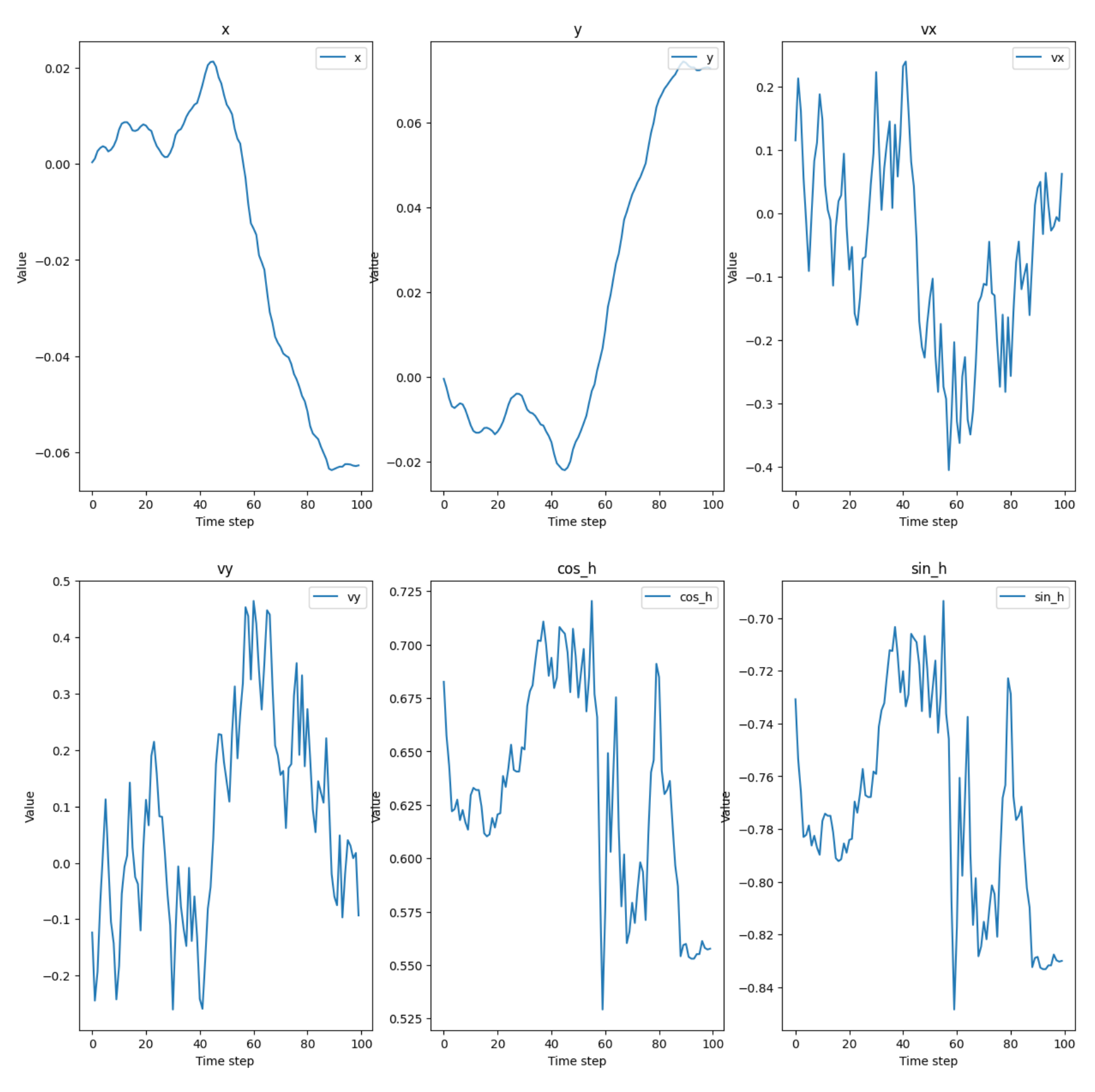
Generated at Fri Feb 16 01:12:27 2024.

Source at https://jupyterhub-dev.cheme.cmu.edu/user/tungyuh@andrew.cmu.edu/lab/tree/s24-06642/tungyuh_P2.ipynb.

Ans 1.1

Run one episode with random actions. Check the observation dictionary returned by the environment. Store the observations (states) and rewards over time! What is your target state (desired goal) s∗? What is your final state sn at the 100-th time step? Plot the values of all the states over time!

Ans



Final state at 100th time step : [-0.06271608 0.0729472 0.06265756 -0.09325798 0.55768866 -0.83005022]

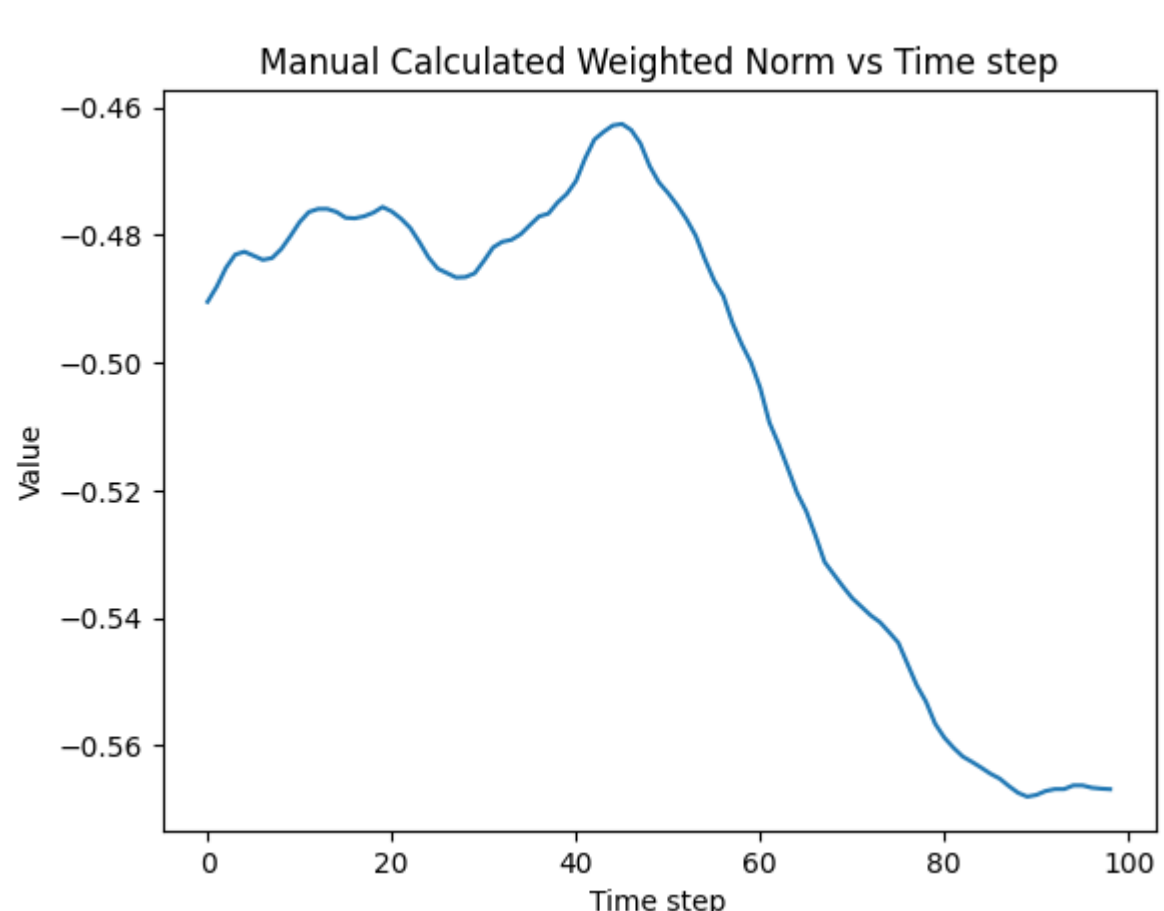
Desired state : [1.800000e-01 -1.400000e-01 0.000000e+00 0.000000e+00 6.123234e-17 -1.000000e+00]

Ans 1.2

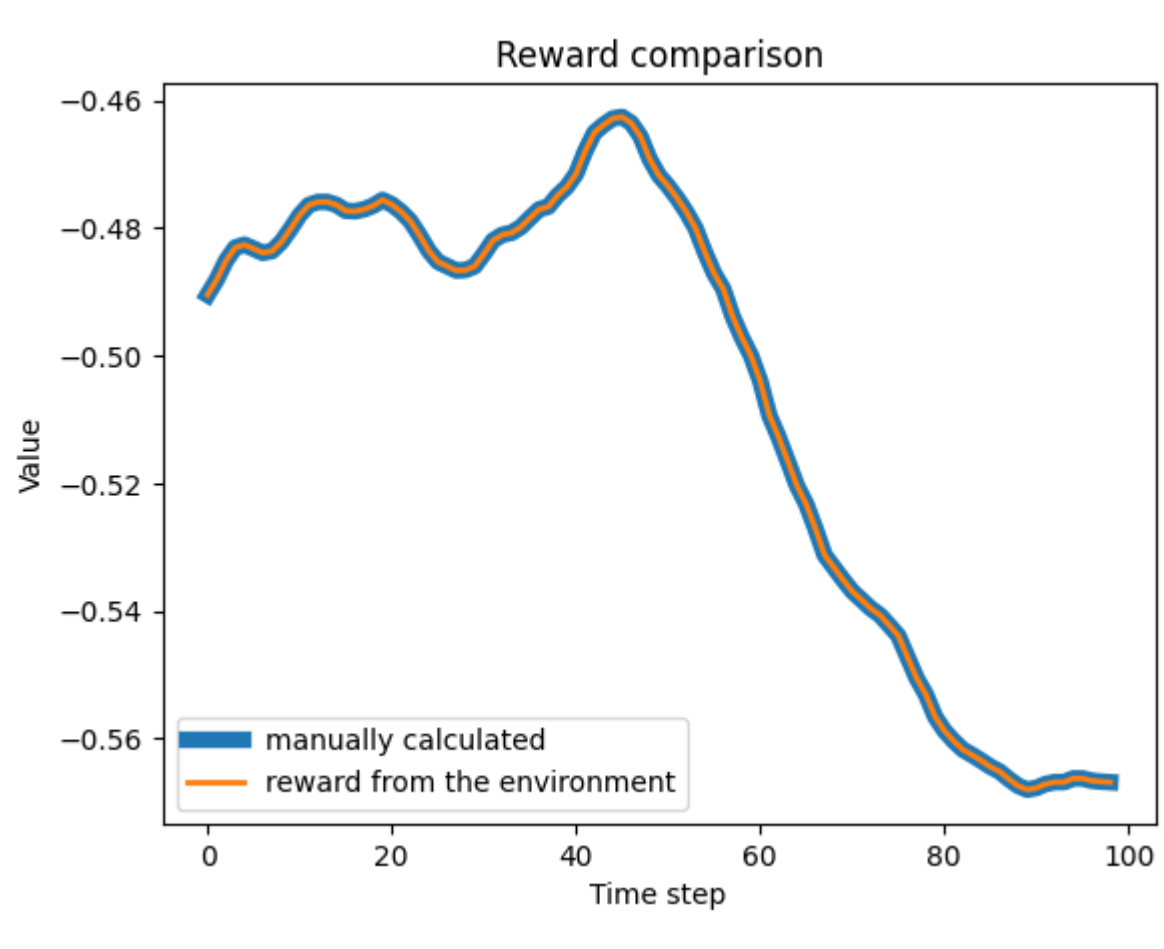
Calculate the reward of the environment manually. The reward rt is defined as the negative of the weighted Euclidean norm of |st −s∗|. That is, for some weight β = [β(1),··· ,β(d)],

where d is the dimension of the state variables and β = [1,0.3,0,0,0.02,0.02]. (Hint: Compare your manual calculation with the environment reward to check if you are correct!)

Manual Calculated Weigthed norm



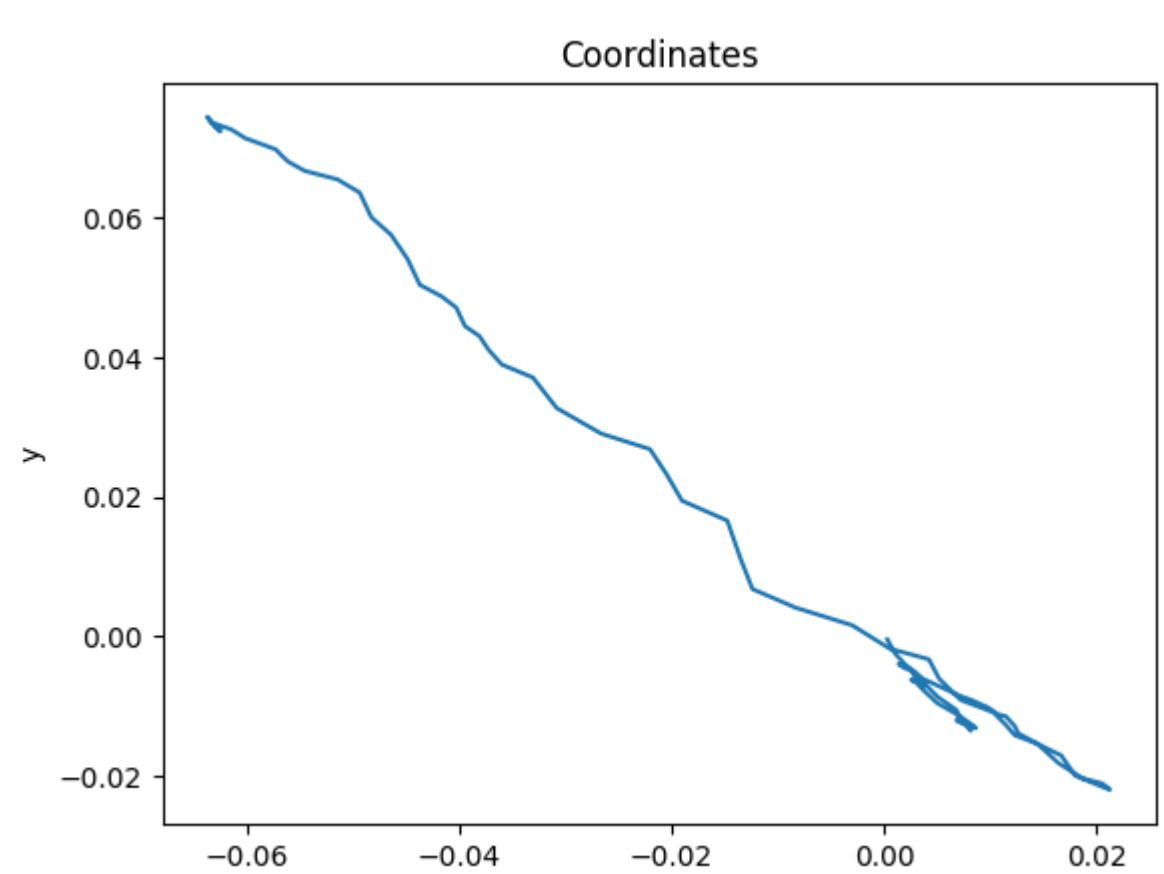
Comparison



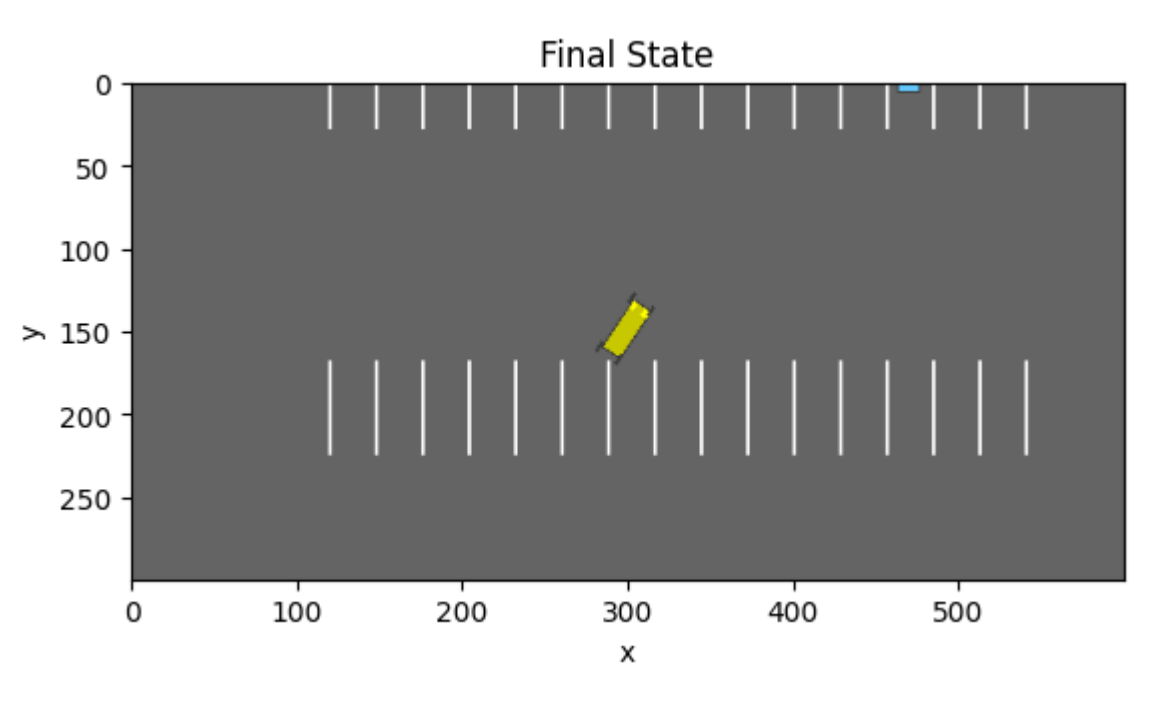
Ans 1.3

Plot the positions (x and y coordinate) of the vehicle! What is the reward at the final time step in the episode? Show the rendered image of the environment at the final time step in the episode!

Coordinates



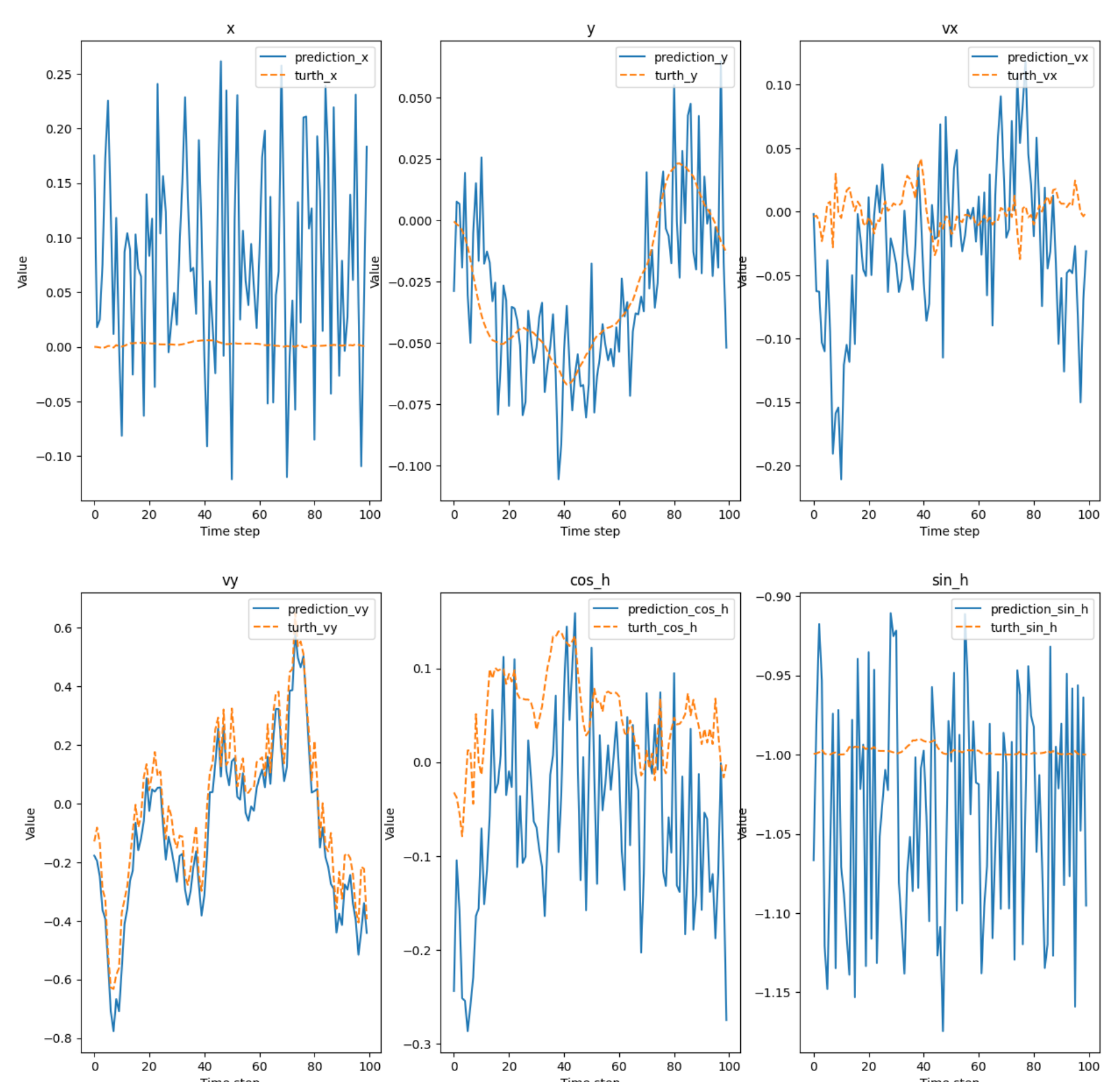
Final State



Ans 2.1

Construct a NN model with one hidden layer with random initialization (the structure is given in the Colab notebook). Implement the forward pass. Perform one run of episode and plot the untrained NN predictions and the true values of all the states over time!

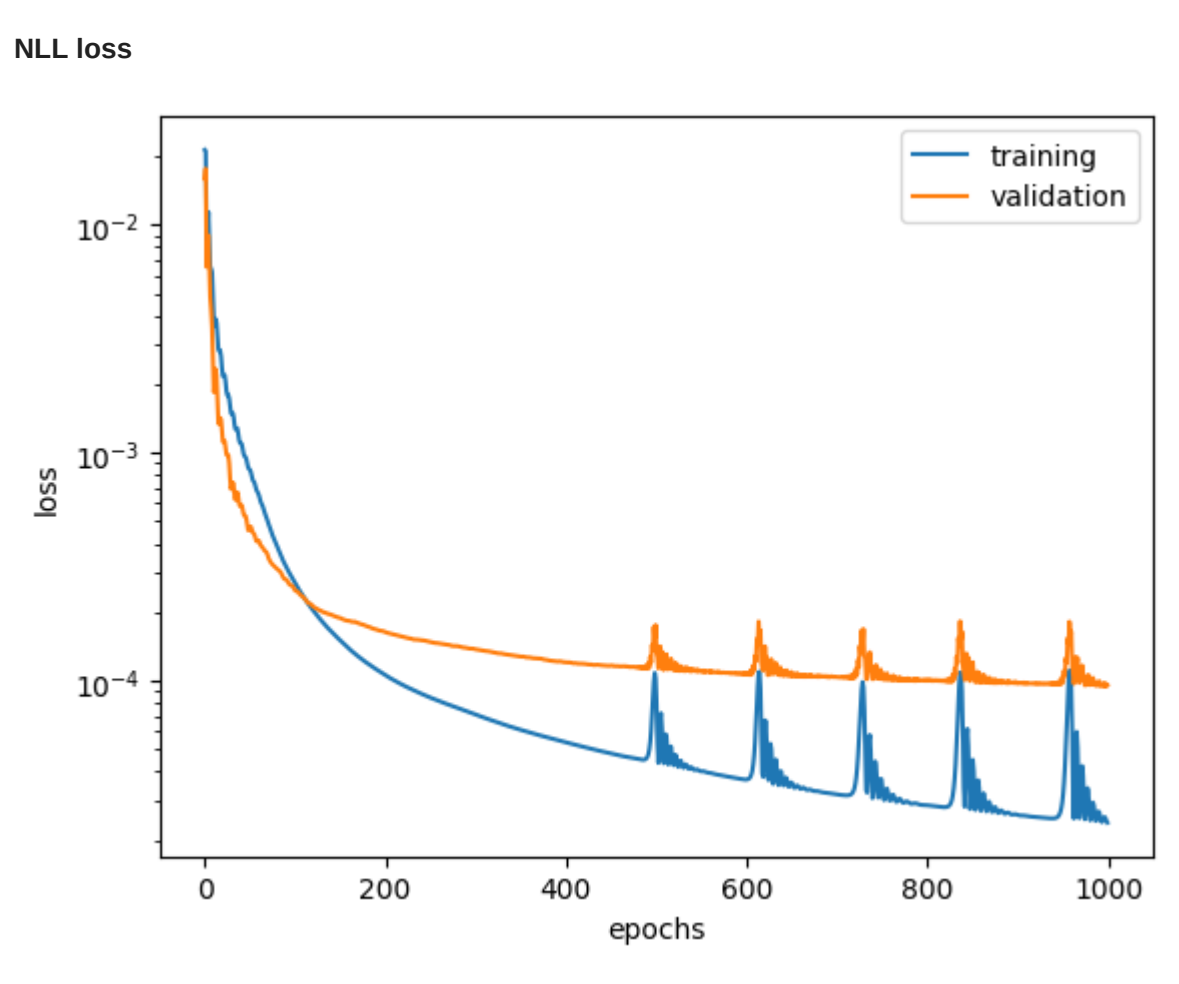
Untrained NN Predictions



Ans 2.2

Create a batch of experiences dataset D with n = 2000 using the provided function. Train a NN model that consists of one hidden layer with 128 nodes and ReLU activation (the structure is already provided in the Colab notebook). Use this dataset with training and validation ratio 70%-30% using Adam optimizer with learning rate 0.01 and training epoch 1,000. Plot the MSE loss for training and validation set!

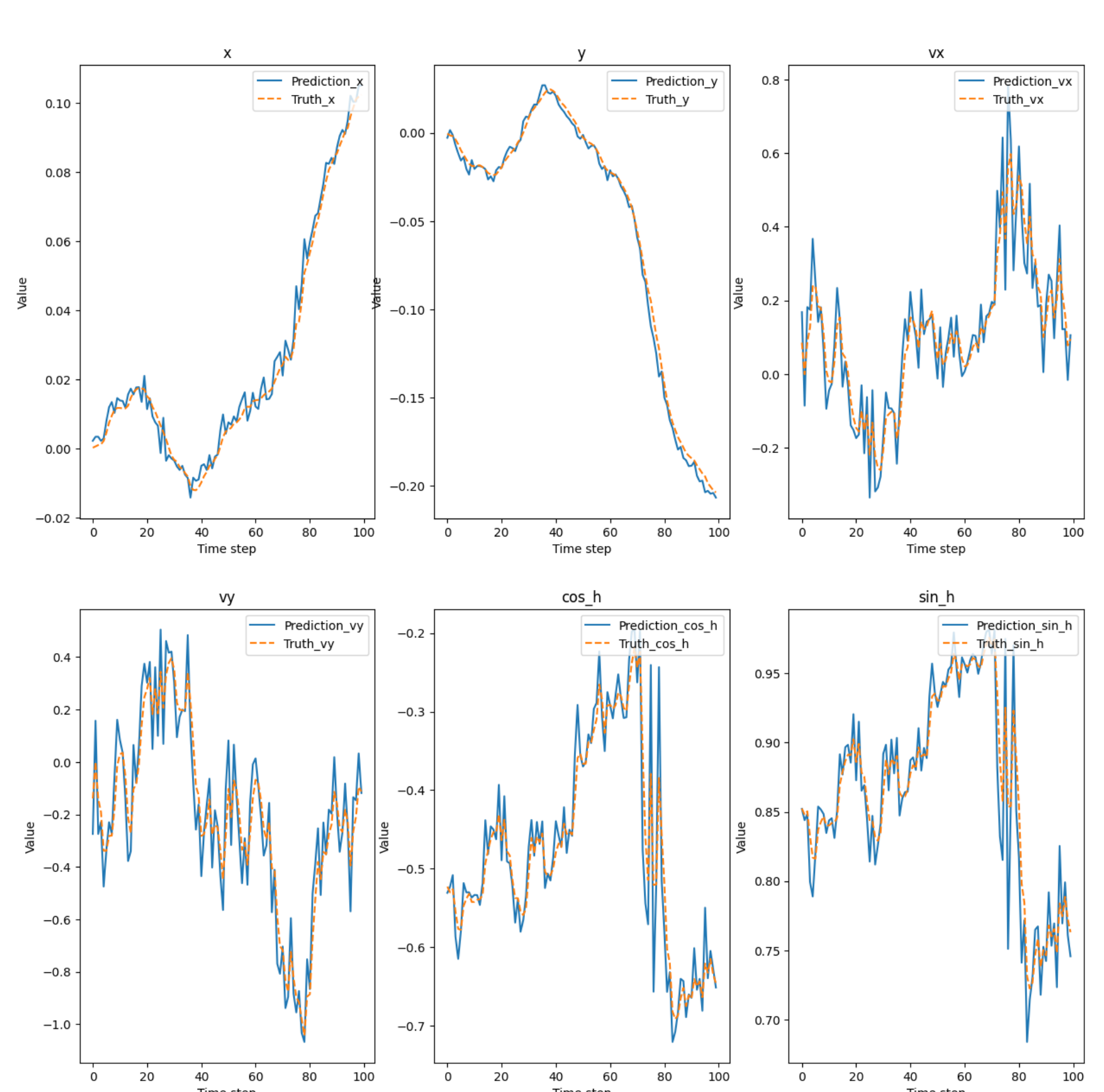
NLL loss



Ans 2.3

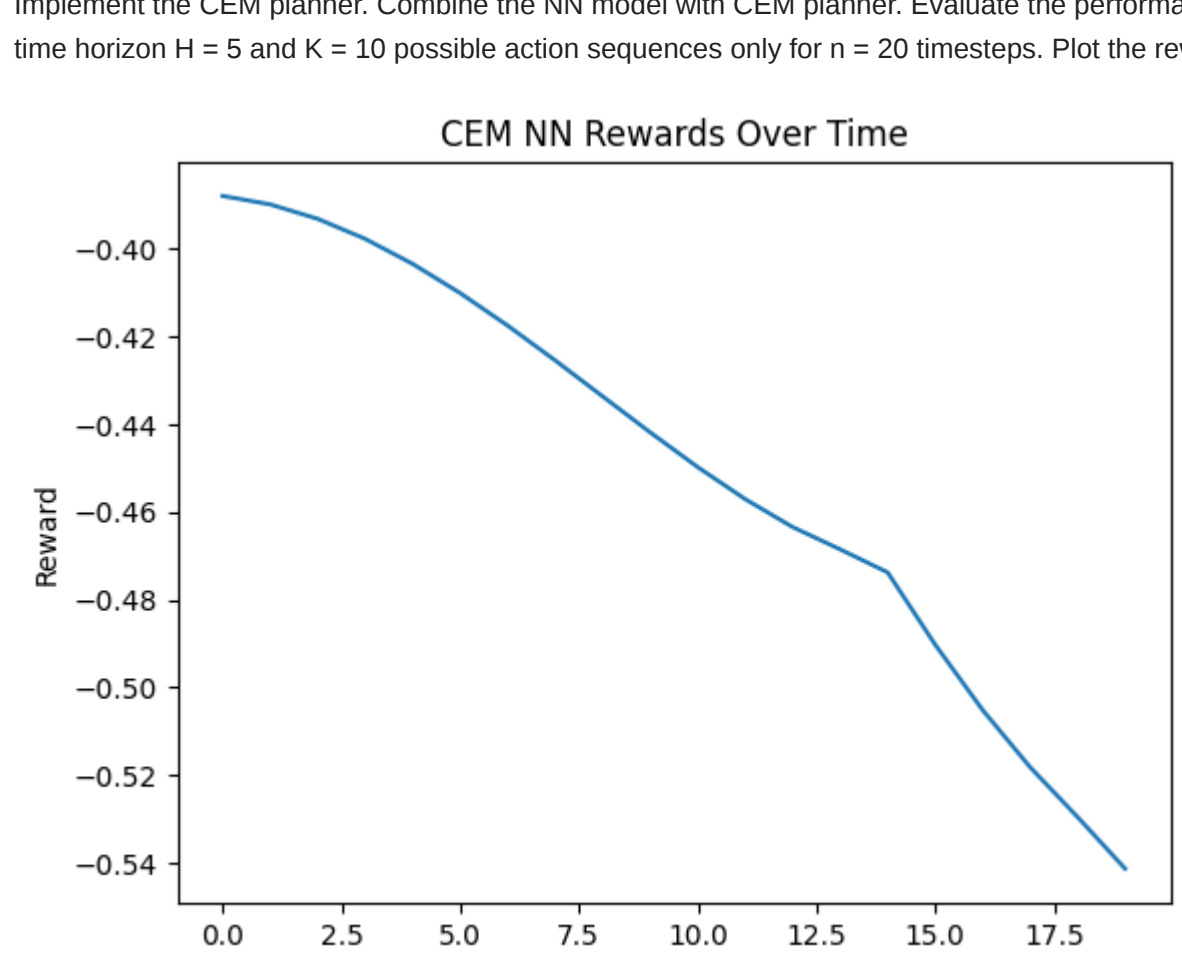
Perform one run of episode again and plot the trained NN predictions and the true values of all the states over time!

Trained NN Predictions



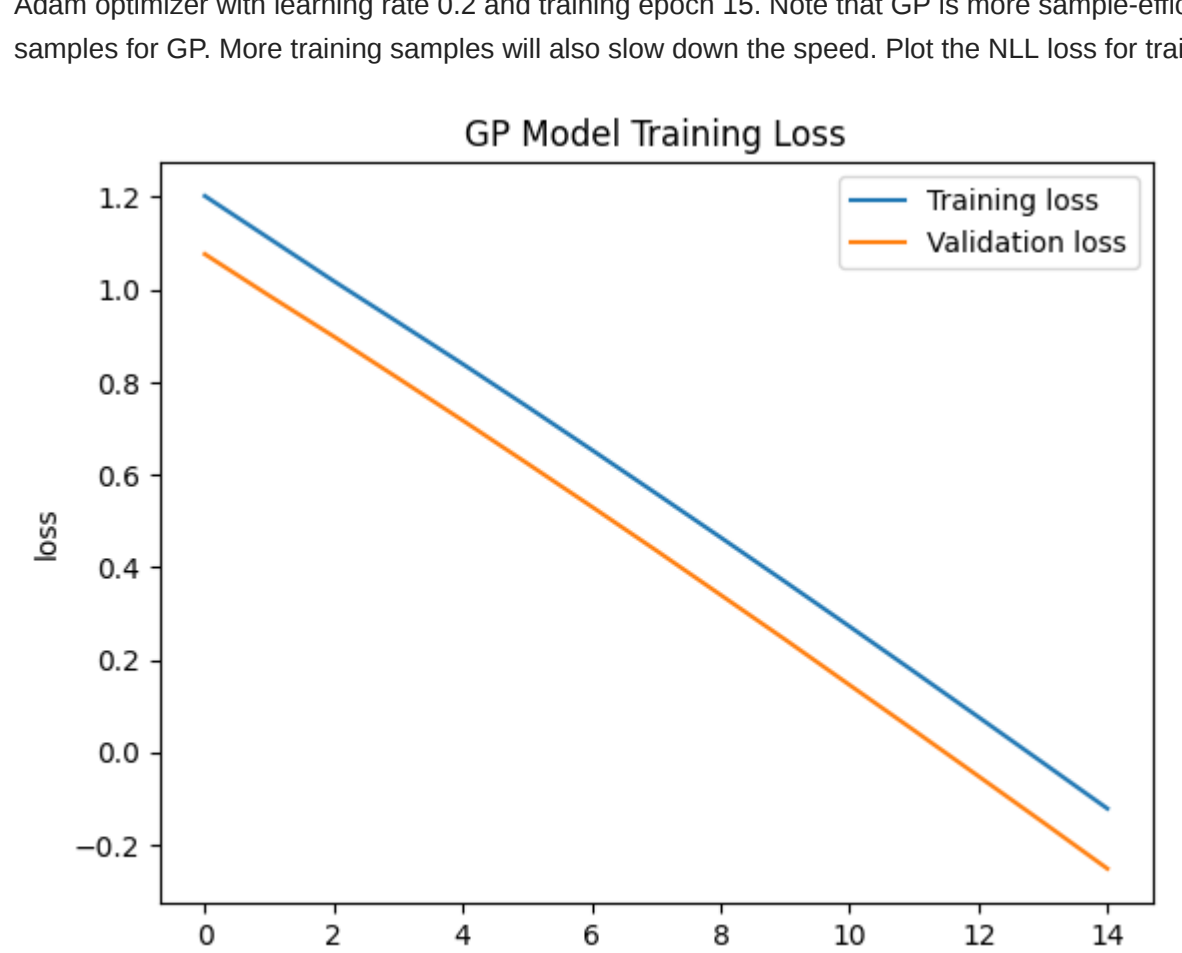
Ans 2.4

Implement the CEM planner. Combine the NN model with CEM planner. Evaluate the performance of your model when planning using a time horizon H = 5 and K = 10 possible action sequences only for n = 20 timesteps. Plot the rewards over time!



Ans 3.1

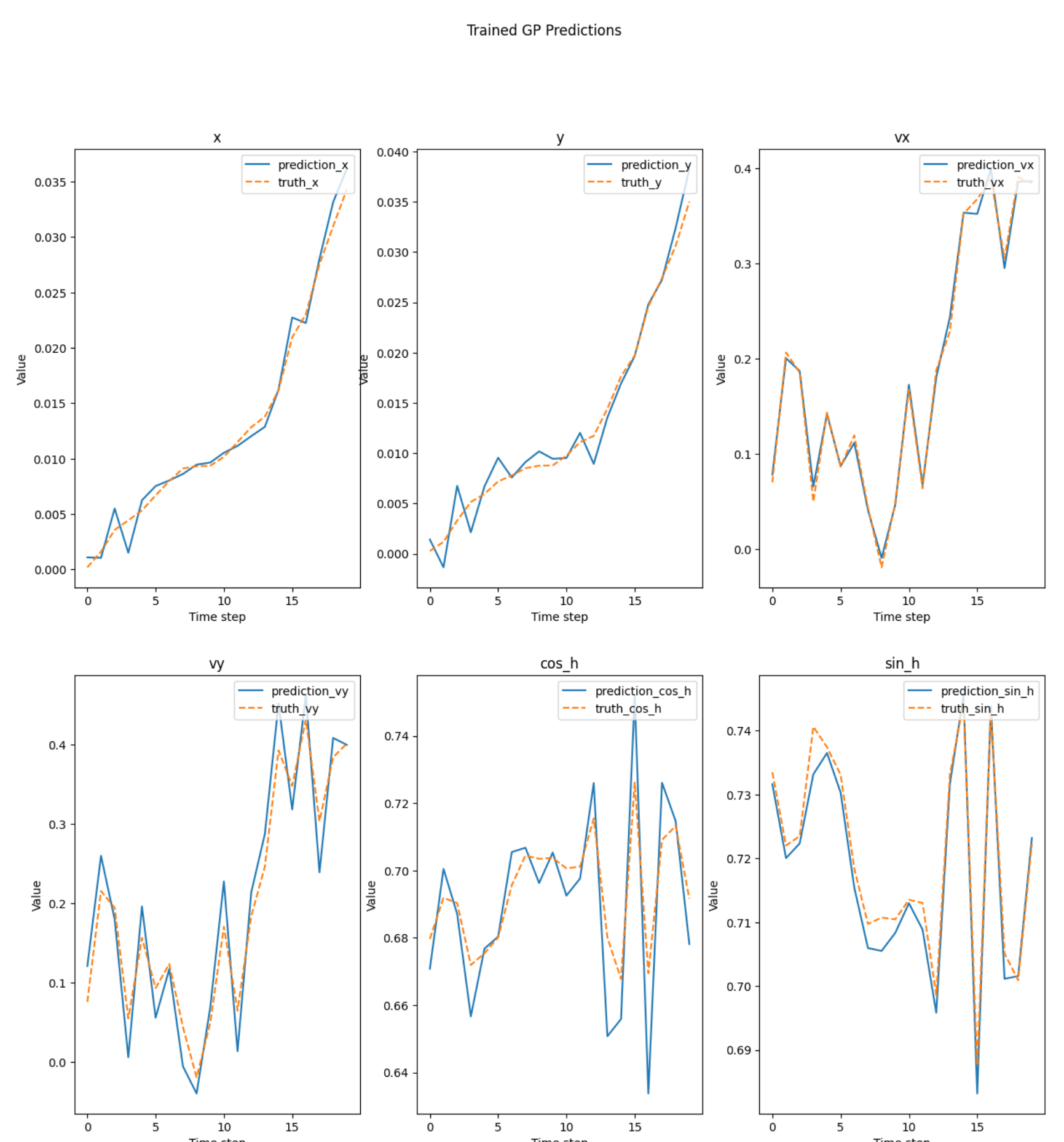
Construct and train the provided GP model. Train the model using dataset D from 2.2 with training and validation ratio 20%-80% using Adam optimizer with learning rate 0.2 and training epoch 15. Note that GP is more sample-efficient than NN, so we need fewer training samples for GP. More training samples will also slow down the speed. Plot the NLL loss for training and validation set!



Ans 3.2

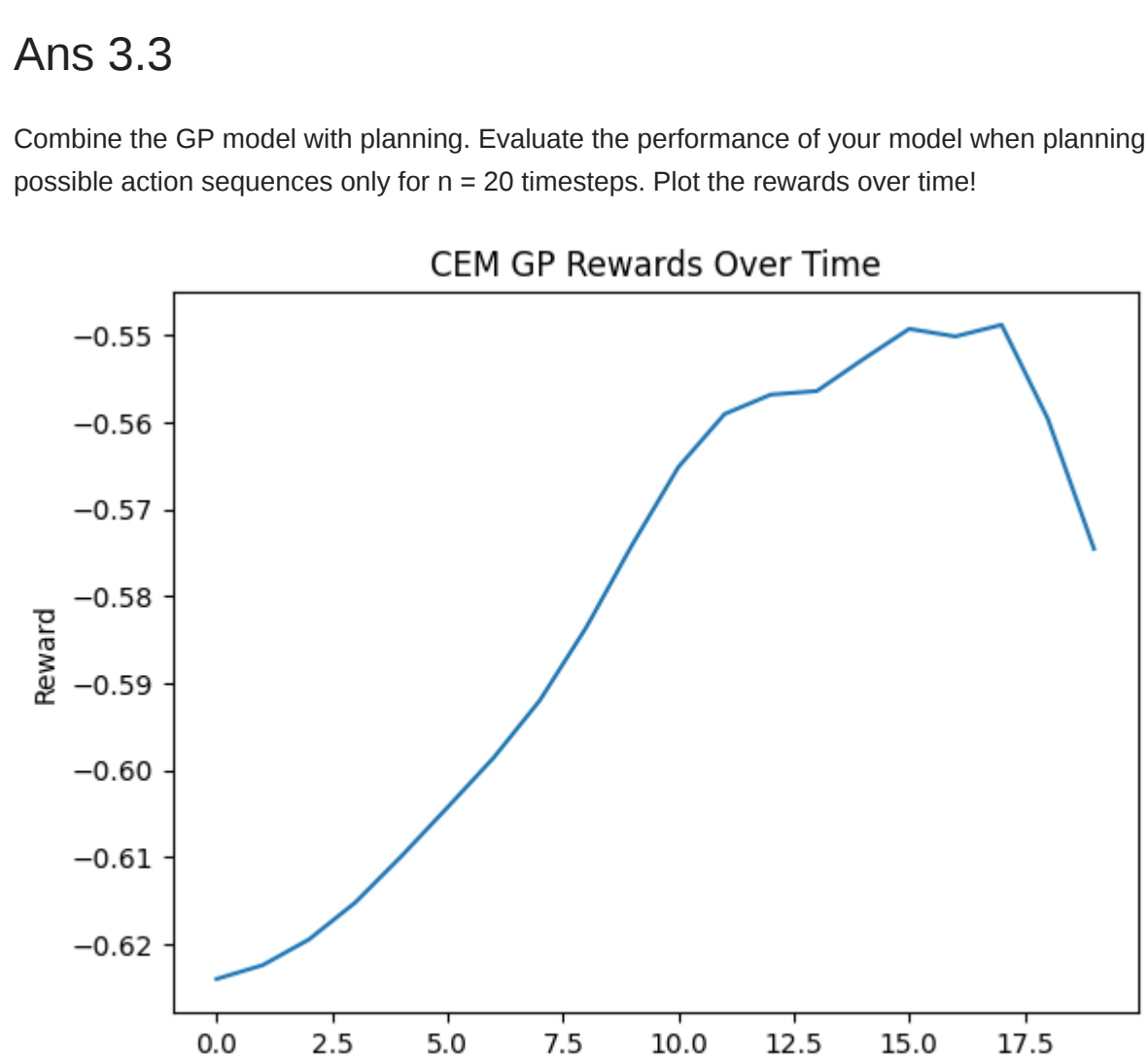
Perform one run of episode again for only n = 20 timesteps and plot the trained GP predictions and the true values of all the states over time!

Trained GP Predictions



Ans 3.3

Combine the GP model with planning. Evaluate the performance of your model when planning using a time horizon H = 5 and K = 10 possible action sequences only for n = 20 timesteps. Plot the rewards over time!



Ans 3.4

Compare NN and GP with the following metrics: final reward, prediction error, and computation time!

Ans

Final reward of NN with CEM: -0.5413685236403645

Final reward of GP with CEM: -0.5745496406173378

Neural network prediction error: 0.004192639607936144

Neural network computation time: 0.30714941024780273

Gaussian process prediction error: 0.00031115300953388214

Gaussian process computation time: 95.67181277275085

%run ~/s24-06642/s24.py %pdf

In [1]:
```
%run ~/s24-06642/s24.py
%pdf
```

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