SF3: Machine Learning Project IIA

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Interim report

# Task 1

## Task 1.1

In this task, I wrote a function (start\_the\_cart) that plotted the 4 measures of cart dynamics over a specified number of steps. I was curious how the trajectories of the different cart dynamics (cart location, cart velocity, pole angle, pole velocity) will be affected by the initial conditions, so I incorporated that into the aforementioned function. Note that in this section, the cart dynamics will be represented in square brackets in this order:

[Cart location, Cart velocity, Pole angle, Pole velocity].

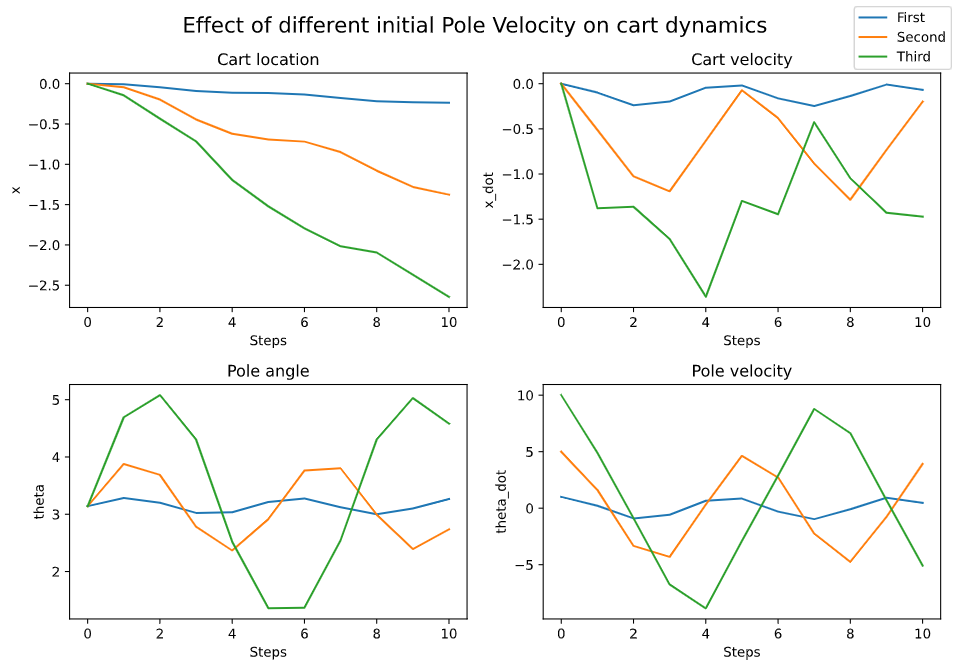


Figure 1. Cart dynamics (discreet) time evolution from a stable equilibrium. The different lines are different initial pole velocities.

Figure 1 shows how the cart behaves when at a stable equilibrium, [0,0,π,0], but the pole velocities are non-zero. The figure has the following initial conditions: First (blue) – [0,0,π,1]; Second (orange) - [0,0,π,5]; Third (green) - [0,0,π,10]. We see, as expected, the higher pole velocities lead to a larger change in cart location (supported by a higher cart velocity), and a large variation in pole angle. The function can also be called to vary a different variable, perhaps cart velocity. Note that the angle is not remapped. We see that in Figure 1, the pole angle never crosses 2π or 0, so I increased the initial conditions to [0,0,π,15]. This produced Figure 2, where we clearly see that multiple full rotations have occurred (from pole angle). Note that unlike Figure 1, the pole velocity is always positive as the pole never “falls back”.

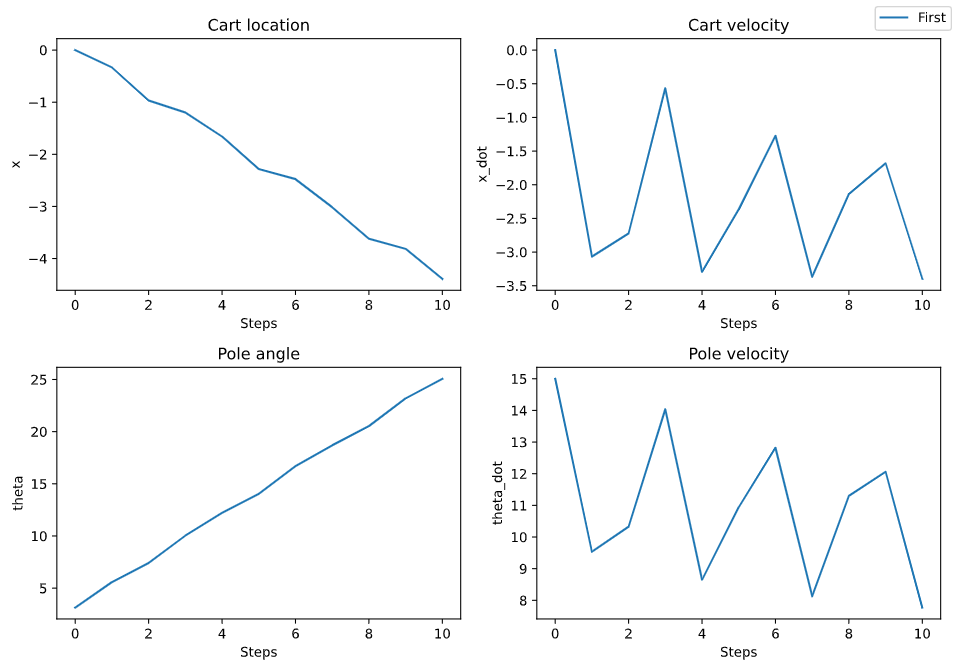


Figure 2. Cart dynamics after complete rotations of the pendulum.

## Task 1.2

I randomly initialized the starting conditions, [-0.24,-9.27,-1.07,9.09], and scanned over one variable at a time. I observed how the cart dynamics varied after one step with the (modified) initial conditions. Since one step didn’t cause a large change, the resulting plot was roughly linear. Figure 3 shows one of these plots, where I varied initial pole velocity.

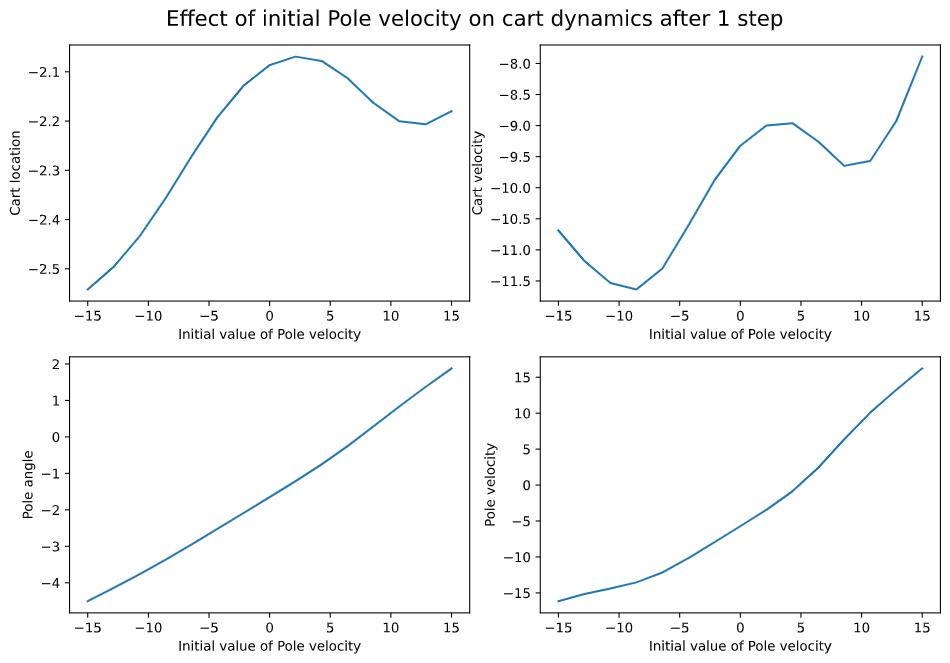


Figure 3. Cart dynamics after one step while varying initial pole velocity (and keeping other conditions constant).

We see the bottom-right graph in Figure 3 is roughly linear, as expected. To get a better idea of the effect of varying a single variable, we plot the *change* in cart dynamics after 1 step. Figure 4 shows a similar graph to Figure 3, but now the vertical axis displays the difference instead of the next value. We see that the dynamics depend non-linearly on the pole angle and velocity. We can also see that cart location doesn’t affect the next step (top left graph).

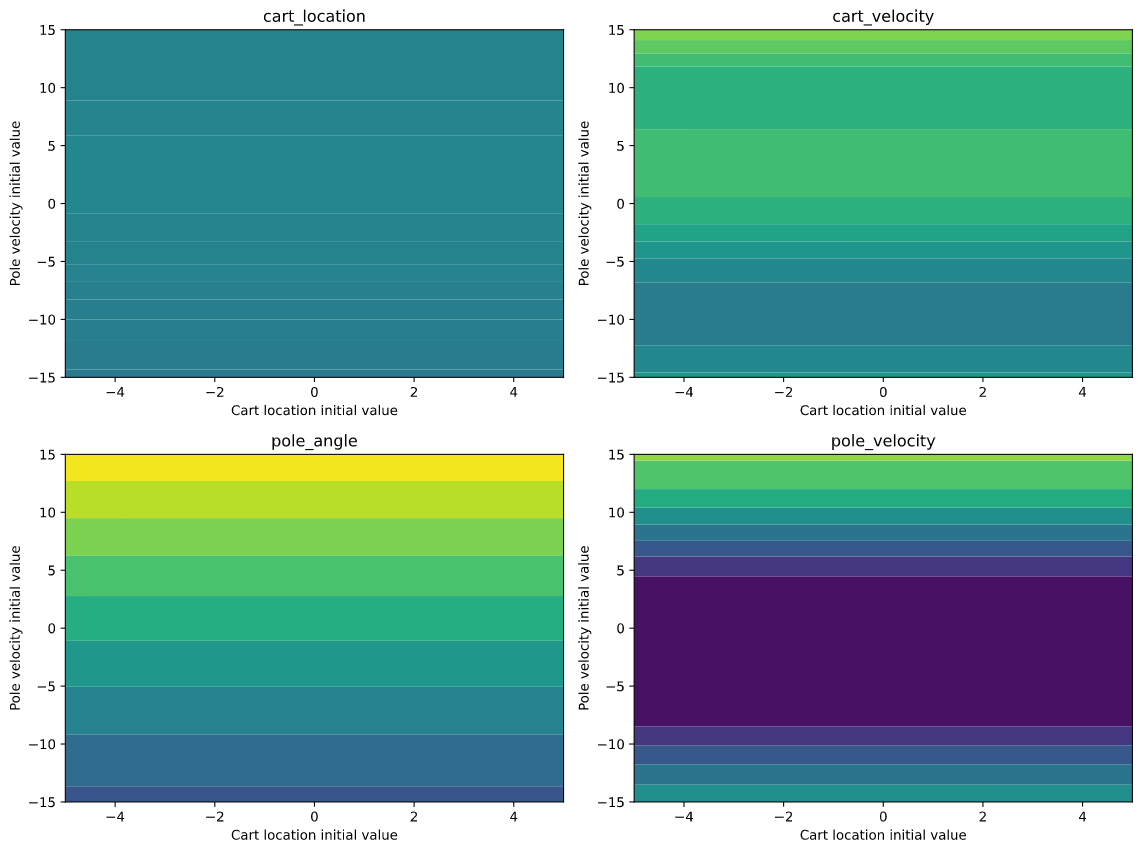


Figure 5. Contour plots displaying the change in cart dynamics with 2 changing initial variables – Cart location and Pole velocity.

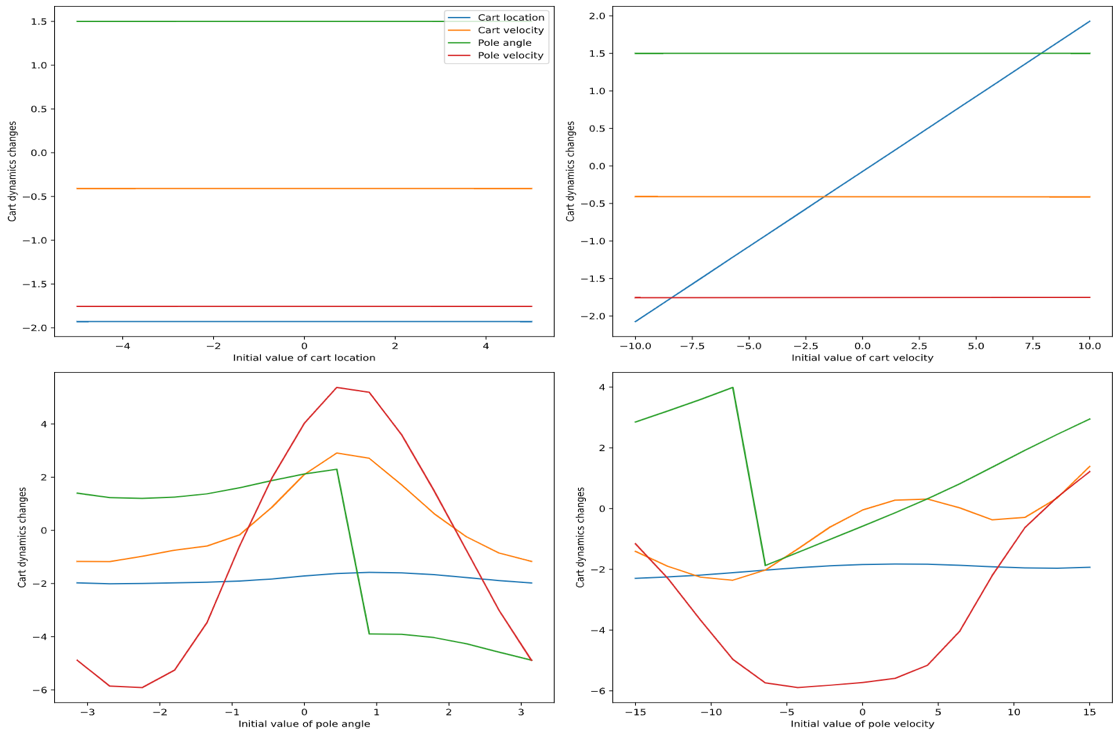


Figure 4. Change in cart dynamics after one step

Another interesting way to visualise these results is to scan over 2 variables (keeping others fixed) and observe the change in cart dynamics after 1 step, shown in Figures 5 and 6.

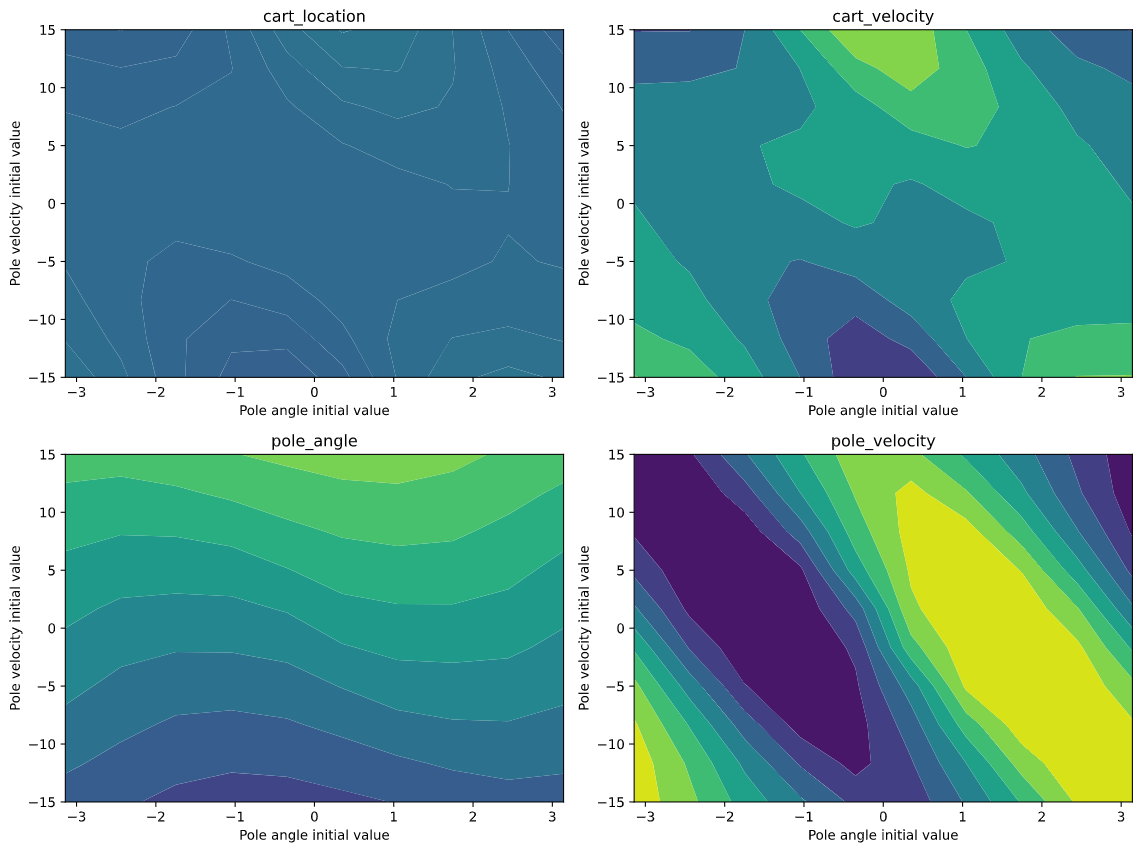


Figure 6. Contour plots displaying the change in cart dynamics with 2 changing initial variables – Pole angle and Pole velocity.

We see from the perfectly horizontal contour lines in Figure 5 that the cart location doesn’t affect the change to the next step. In my code, I have plotted all combinations of the 4 variables and in each one it is clear that cart location doesn’t have an effect. I have included Figure 6 here to display the fact that pole angle and pole velocity have a non-linear effect on the change in cart dynamics after 1 step.

## Task 1.3

To perform linear regression, I generated 500 (X) data points randomly and got 1-step change (Y) points by running the perform\_action function once. I split these (X,Y) pairs into a train and a test dataset. To perform linear regression, I tried 2 ways. Firstly, using the numpy pseudoinverse function, I obtained the optimal weights W, where:

Secondly, out of interest, I used the “sklearn” package to perform linear regression as well. The results were nearly identical and can be found in my code. Throughout this report I will be discussing the results of the first method.

In Figure 7a and 7b I have plotted the predictions after 1 step versus the real cart dynamics after 1 step. In Figure 7a, the closer the blue and yellow dots are, the better. In Figure 7b, the perfect predictor would give a straight line of gradient 1. Visually, we see that the linear regression results work relatively well for cart location, and to an extent, cart velocity too. However, scanning through the pole angle and velocity did not produce predictions close to the real values. This is evident visually through the bottom charts of Figures 7a and 7b, but I wanted to quantify that gap (since the axes have different scales). For this, I wrote the function “rmse\_calc” that calculates the root mean square error (RMSE) of each variable. The results were [0.12,1.06,1.83,2.79]. These figures confirm my visual observations. It is worth noting that due to the remap\_angle function, the range of pole angles is only [-π, π]. Hence, a RMSE of 1.83 is relatively large to that of 2.79 (pole velocity) when we consider the range of the scans. This explains why the pole velocity charts in Figures 7a and 7b seem better fit than those of pole angle, even though they have a higher RMSE.

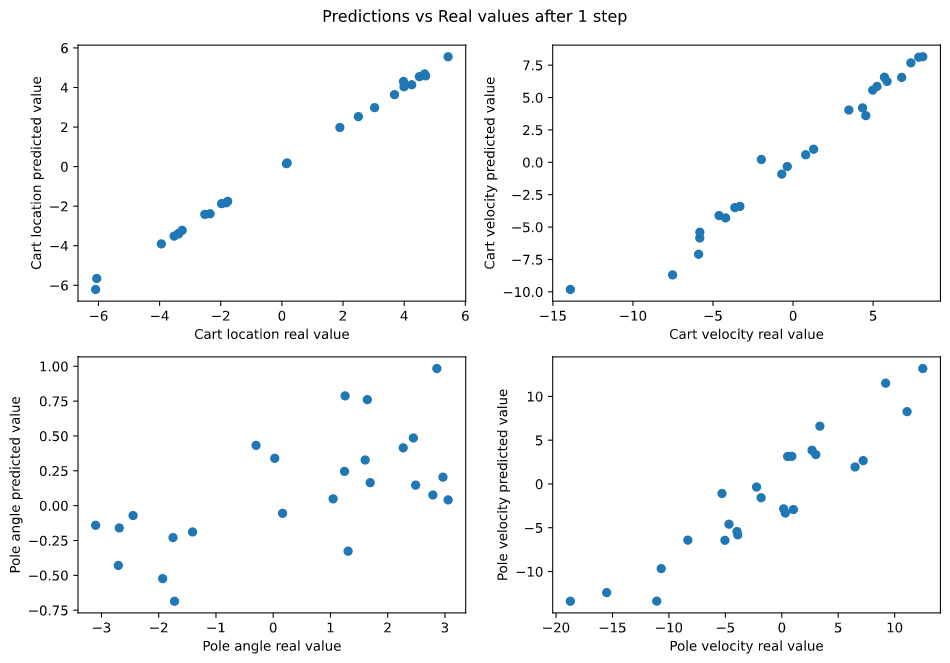
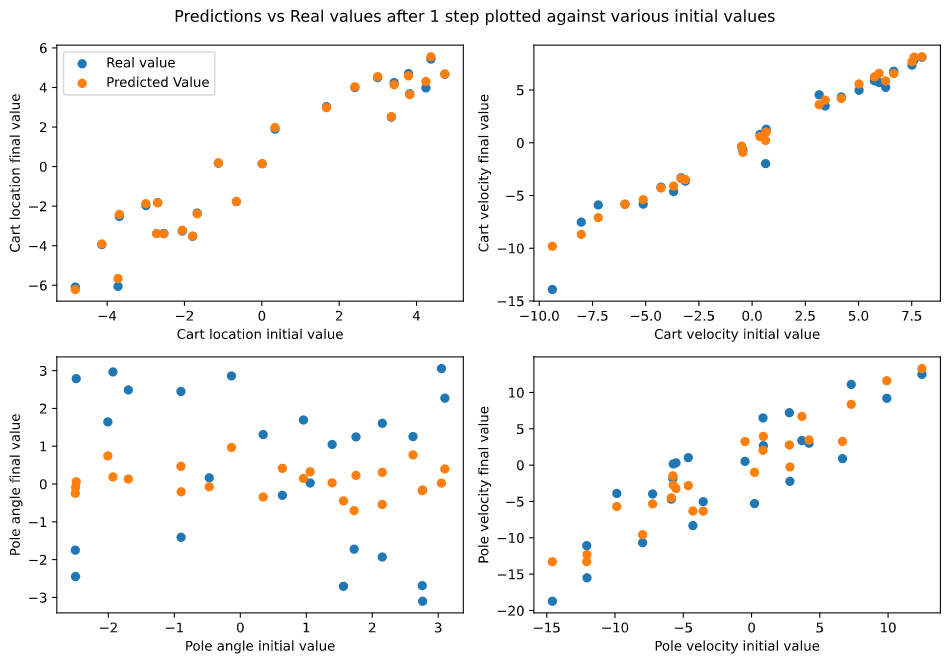


Figure 7a. Scanning through all variables on the x-axis and plotting the predicted vs real next values on the y-axis.

Figure 7b. The next real value on the x-axis and the next predicted value on the y-axis for all variables.

From Figure 8, we can see why cart location has such a small RMSE – as we vary any variable, the real cart velocity remains roughly linear, thus can be predicted by a linear model. The other 3 variables vary non-linearly over the scans, so can’t be predicted accurately by a linear model. In the top 2 graphs, there is an offset with the predictions, even though the real scans are linear. This might occur due to the non-linearity in the scans of the other variables. The non-linear contours for cart velocity, pole angle, and pole velocity in Task 1.2 support the results shown in Figure 8.

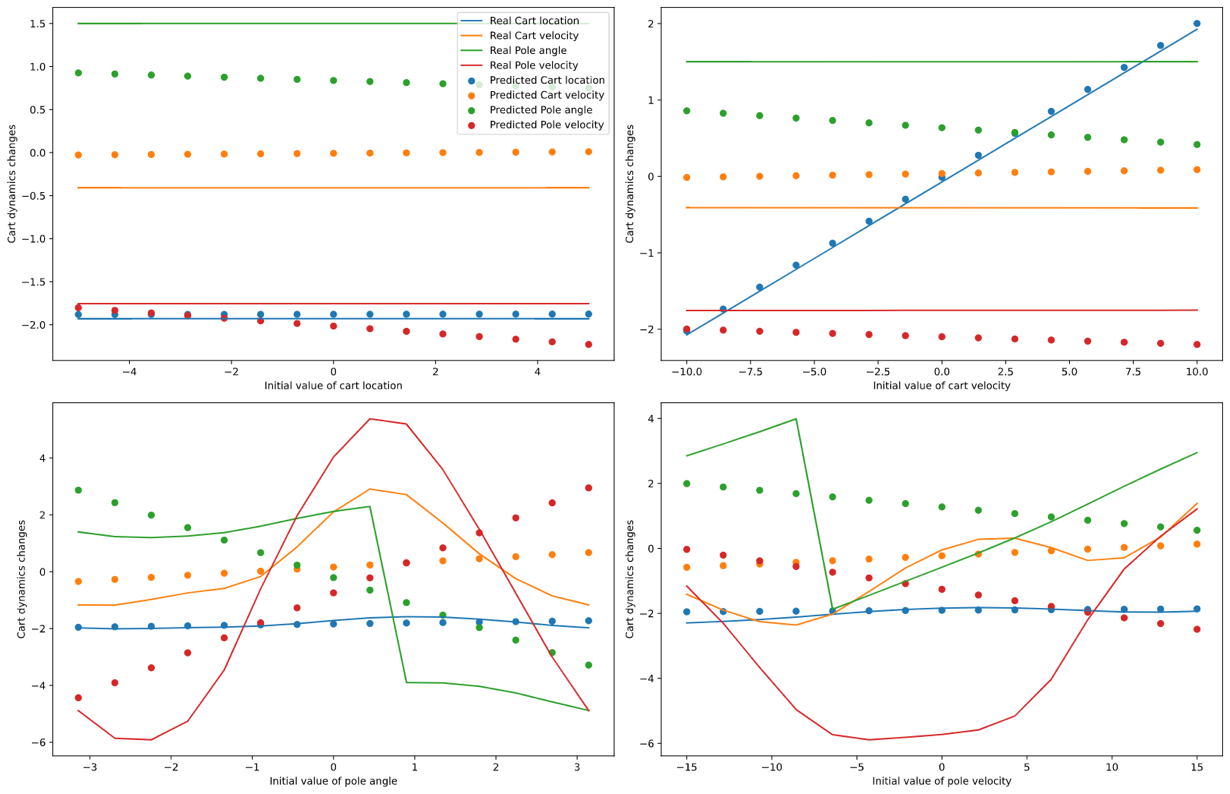


Figure 8. Predictions vs real cart dynamics after 1 step change, scanned over all variables.

## Task 1.4

To model how well the linear model predicts into the future, I decided to explore 2 paths. Firstly, I used real dynamics from the previous step to predict the next step - displayed in Figure 9. Secondly, I used the predicted value from the previous step to predict the next step, displayed in Figure 10.

We see from Figure 9 that the linear model performs well on cart location given the previous real dynamics (this is what we saw in Task 3, that the model performs well for 1 step). The cart velocity and pole velocity are also predicted well, but an obvious delay is noticeable. This might be the model registering the previous value and adjusting its prediction for the next step. The pole angle prediction is making small adjustments but is nowhere near the true value. That is understandable given the RMSE of 1.83 and the sudden changes between -π and π around the equilibrium.

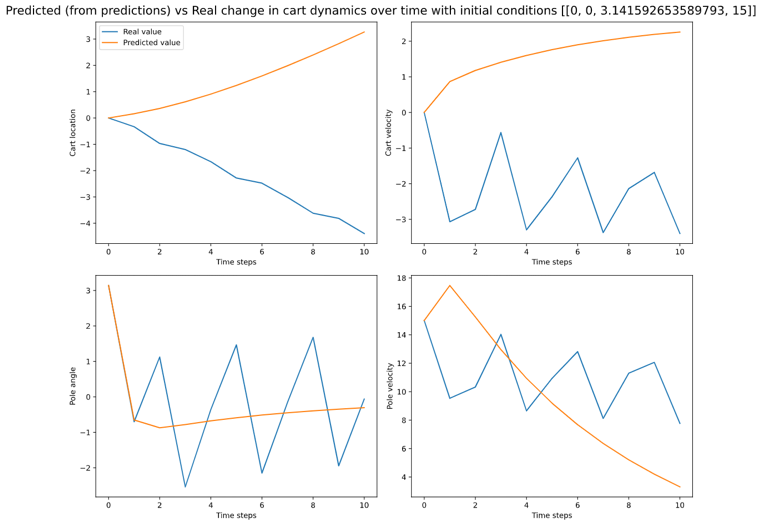
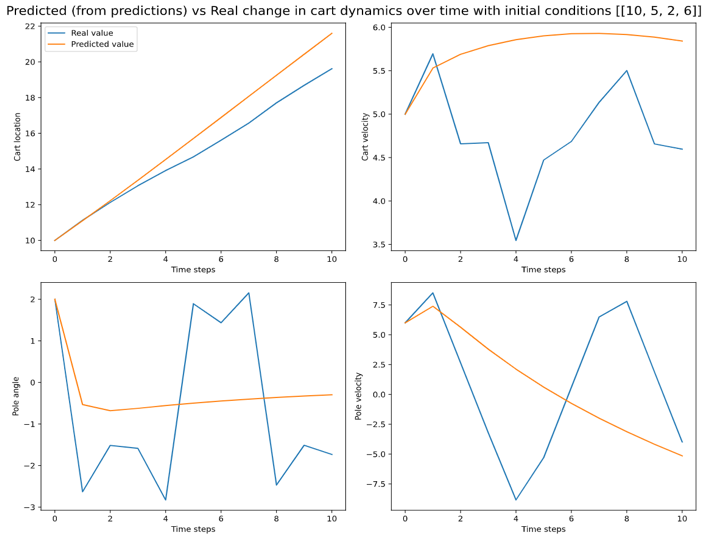


Figure 10a. Time forecasting using previous prediction. Initial conditions [10,5,2,6].

Figure 10b. Time forecasting using previous prediction. Initial conditions [0,0, π,15]. A full rotation of the pendulum.

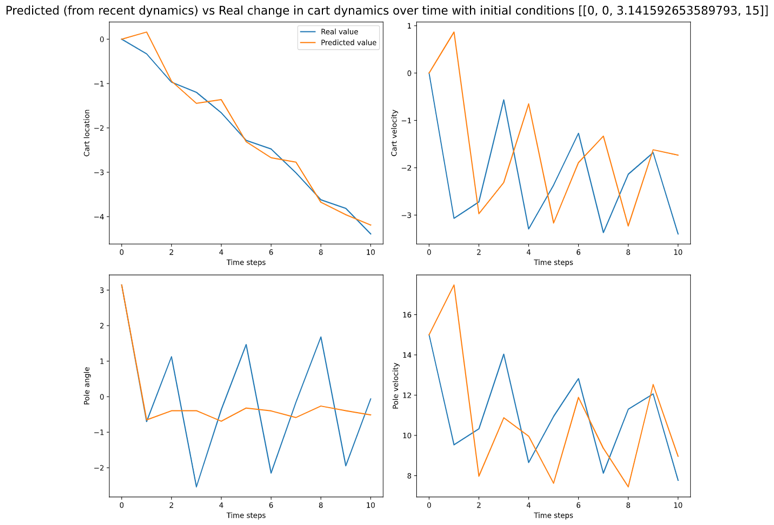
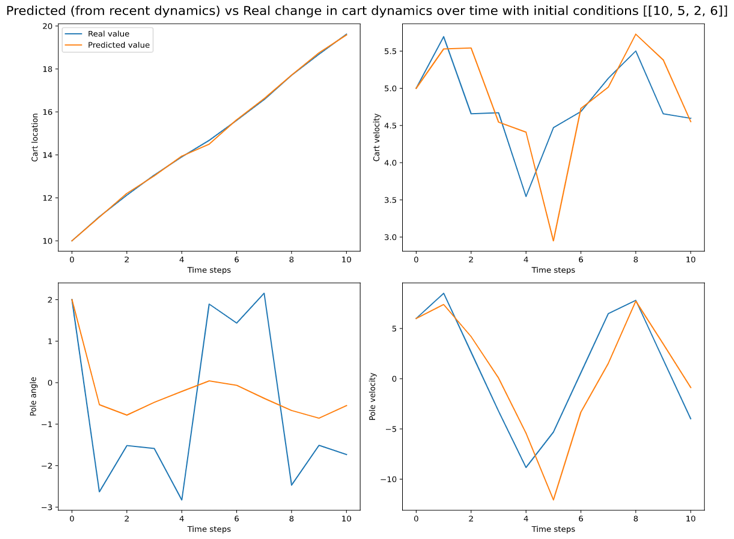


Figure 9a. Time forecasting using real change in dynamics. Initial conditions [10,5,2,6].

Figure 9b. Time forecasting using real change in dynamics. Initial conditions [0,0, π,15]. A full rotation of the pendulum.

The lines in Figure 10 are much smoother than those in Figure 9. This is expected since the model doesn’t receive any “correction” data, but just propagates the trend it started. In general, the predictions are worse after the first step, which is expected since our model was only trained on data after one step. More complex (non-linear) models could make the results better. Note that this model performs significantly worse in the case where the pendulum makes a full round.

If the angle was not remapped during the model training and prediction, the predictions diverge from the real dynamics. This is due to the fact that the equations of motion only contain θ in trigonometric functions. Hence, for the real dynamics, it won’t matter if the angle is remapped or not. For instance, a pole angle of 3π will result in the same next step as an angle of π. However, for a linear model, an angle of 3π is vastly different to π. Therefore, without remapping, the real dynamics and predictions will diverge; all the variables will diverge since pole angle affects all variables.