

Charlie meeting 27th June

Meeting

In this meeting, we talked about how I should change my ODE data generator to a SDE model by adding noise to the dynamics; i.e. by adding noise to every Euler discrete integration steps. We have also talked about using Laurent Series to represent the inverse term. We also talked about how to evaluate our metrics, by producing future predictions of the trajectory. Or else, I should use a latent Markov GP, using Kalman filter or particle filter model that accounts for the noise instead. After I have added the future prediction thing, I found the invariance kernel does not actually do that well in terms of prediction, it is barely different from the original one, but with much better marginal likelihood, is that a positive sign assuming it means that it has lower uncertainty. It is the same with low damping but with higher damping the predictive power is same but with lower marginal likelihood. For example, see the pendulum in large angle, it is not able to learn to turn around. Either way, they can both learn the invariance equation fine. For 2D, it is quite hard for the system to learn the correct invariance, it sort of does for 2D SHM but not really. A problem is the limit of the training datasets. Also the local invariance does not quite work well in paramertisation learning and it is a lot more stable with fixed grid. However, the knowledge of invariance in double pendulum does seem quite help to predict the trajectory. Maybe I should switch to leap frog too.