This thesis investigates the application of Physics-Informed Neural Networks to address stiff linear and non-linear Ordinary Differential Equations. Physics-Informed Neural Networks integrate governing equations into neural network structures via automatic differentiation. The stiffness is a mathematical property of Ordinary Differential Equations that introduce difficulty to encode the solution during training. Behaviors such as rapid transient phases can be particularly challenging to encode.

We extend previous methodologies to tackle stiffness with a novel transfer learning-based approach. The approach consists in learning a multi-head architecture in a non-stiff regime and transferring it to a stiff regime without the need for retraining. The present approach is compared to both vanilla Physics-Informed Neural Networks and numerical methods, such as RK45 and Radau methods, on two linear and one non-linear Ordinary Differential Equation examples.

Our analysis indicates that transfer learning from a less rigid regime can be used to compute a more stiff solution, reducing the complications associated with training in stiff systems. Transfer learning on the Duffing equation from a Stiffness Ratio of less than 100 to a regime where the Stiffness Ratio is greater than 5000 has been achieved, while maintaining an average absolute error of less than $10^{-3}$. The approach provides competitive computational efficiency, especially when modifying initial conditions or force functions within a stiff domain. It is 70 times faster for linear problems and 4 times faster for non-linear problems than using the Radau method.

However, challenges persist in transferring to very stiff regimes to far from the training one. and handling all from of non-linear equations. Further research directions include enhancing the model's capacity to train in stiffer domains, aiming to address these limitations and broaden the applicability of the proposed methodology.