INTRODUCTION :

1. Your topic, in context: what does your reader need to know to understand your thesis dissertation?

state the general topic and give some background provide a review of the literature related to the topic

Deep learning/Neural Networks introduction, example of application

NIPS2012\_c399862d: ImageNet Classification

7780460 : object detection

NIPS2017\_3f5ee243: Natural language processing

Deep learning has emerged as a powerful paradigm in machine learning, characterized using neural networks with multiple layers to learn intricate representations of data. In recent years, deep learning has revolutionized various fields; computer vision \cite{NIPS2012\_c399862d}, image classification \cite{7780460} or natural language processing \cite{NIPS2017\_3f5ee243}. These applications showcase the transformative potential of deep learning in handling diverse and complex data.

PINNS introduction, example of application

Introduced in 1998, neural networks for solving differential equations paved the way for today’s Physics-Informed Neural Networks (PINNs) Lagaris et al. \cite{712178}, NeuroDiffEq \cite{ Chen2020} and DeepXDE \cite{ lu2021deepxde} are two popular software programs that employ PINNs. These networks embed governing equations into the neural network architecture by minimizing the residual loss function using automatic differentiation. These models have demonstrated impressive outcomes in addressing physical problems, including the Navier-Stokes equation \cite{JIN2021109951}, the Schrödinger equation \cite{shah2022physicsinformed}, and problems in kinetic chemistry \cite{doi:10.2514/6.2021-1139}.

712178: Lagaris PINNs

JIN2021109951: Navier stokes

shah2022physicsinformed: Schrodinger equation

# doi:10.2514/6.2021-1139: chemistry kinetics

Stiff Introduction, example of application

Book: Overview of stiff problem

Robertson: Roberston equation in chemical kinetics

Vdp : electrical enngiinering

Stiff problems in numerical simulations presents significant difficulties due to their diverse timescales. The challenge is exacerbated by the fact that the stiffness of an equation lacks a precise mathematical definition, adding complexity to the evaluation process. Hairer, Ernst, and Wanner offer a comprehensive exploration of numerical methods for tackling stiff problems in their book \cite{book}, shedding light on the intricate nature of the issue. Stiff equations manifest in various domains such as chemical kinetics \cite{Robeston} and electrical engineering \cite{vdp}, further emphasizing the ubiquity of these challenges. Dahlquist noted in 1985 “Around 1960, things became completely different and everyone became aware that the world was full of stiff problems” \cite{Dahlquist}.

However, these advancements nessecite toujours de retrain le model si on change un peu le regime de stiffness ou des parametre de l’equation

1. Your focus and scope: what specific aspect of the topic will you address? The relevance of your research: how does your work fit into existing studies on your topic?

define the terms and scope of the topic

Cette these s’interresse à la resolution de problem stiff avec des PINNS. Despite the successful demonstration of PINN in many of the above works, \ref{wang2020understanding } investigated a fundamental mode of failure of PINN that is related to stiffness. It was suggested that the stiffness could lead to gradient pathologies and ill-conditioned optimization problems, which leads to the failure of stochastic gradient descent based optimization. Stiffness problem seems hard to optimize using the Vanilla PINNs Arcitecture. The publication \ref{ baty2023solving }, introduce very simple recipes to improve the training process in cases where only prior knowledge learn stiffness and \ref{ Ji\_2021} employ Quasi-Steady-State-Assumptions (QSSA) to reduce the stiffness of the ODE systems. But this advance always require to train the model when a new prio condution is known. On the other hand \{desai2022oneshot} present a framework for transfer learning PINNs that results in one-shot inference for linear systems ordinary differential equations. This means that highly accurate solutions to many unknown differential equations can be obtained instantaneously without retraining an entire network. A non-linear generalization is present in ref{ lei2023oneshot}. This idea of this thesis is two adapt these methods to stiff problem and try to competed in term of computational time with numerical methods for some stiff problem.

This thesis focuses on addressing stiff problem resolutions using Physics-Informed Neural Networks (PINNs). Despite the successful application of PINNs in various studies, Wang et al. (2020) \cite{wang2020understanding} delved into a fundamental failure mode associated with stiffness. The investigation revealed that stiffness could induce gradient pathologies and pose challenges in optimization, leading to the inefficacy of stochastic gradient descent-based optimization. Optimizing stiffness problems proves challenging within the conventional PINNs architecture.

Baty et al. (2023) \cite{baty2023solving} introduced straightforward approaches to enhance training when only prior knowledge addresses stiffness, while Ji et al. (2021) \cite{Ji\_2021} utilized Quasi-Steady-State Assumptions (QSSA) to mitigate stiffness in ODE systems. However, these advancements necessitate retraining when new prior conditions are identified. Conversely, Desai et al. (2022) \cite{desai2022oneshot} proposed a transfer learning framework for PINNs, enabling one-shot inference for linear systems of ordinary differential equations. This implies that highly accurate solutions for numerous unknown differential equations can be obtained instantaneously without retraining the entire network. A nonlinear extension of this one-shot approach is presented by Lei et al. (2023) \cite{lei2023oneshot}.

PINNs applied to Stiff problem Us Transfer learning way

outline the current situation

-> some example try to change the architecture to handle the stiffness.

wang2020understanding: fail to learn in a stiff domain investigated a fundamental mode of failure of PINN that is related to numerical stiffness leading to unbalanced back-propagated gradients between the loss function of initial/boundary conditions and the loss function of residuals of the differential equations during model training. It was suggested that the stiffness could lead to gradient pathologies and ill-conditioned optimization problems, which leads to the failure of stochastic gradient descent based optimization

baty2023solving: very simple recipes to improve the training process in cases where only prior knowledge learn stiffness

Ji\_2021: ODEs simplification in definition of the odes

-> Us Transfer learning way:

desai2022oneshot: we present a general framework for transfer learning PINNs that results in one-shot inference for linear systems of both ordinary and partial differential equations. This means that highly accurate solutions to many unknown differential equations can be obtained instantaneously without retraining an entire network

lei2023oneshot: non linear generalization

evaluate the current situation (advantages/ disadvantages) and identify the gap

-> competed in term of computational time with numerical methods for some problem

1. Your questions and objectives: what does your research aim to find out, and how?

state the research problem/ questions

The primary objective of this thesis is to adapt these methodologies to address stiff problems and strive to compete with numerical methods in terms of both computational efficiency and accuracy for select stiff problems.

Try transfer leaning to stiff problem and address a solution to stiffness with PINN

state the research aims and/or research objectives

Evaluate methods compare with vanilla PINNs and numerical methods

1. An overview of your structure: what does each section contribute to the overall aim?

La structure de la these sera la suivante, la premiere partie introduira les notions mathematics qui seront utilisé ; les ordinaty differential equation, la notion de Stifness ainsi que les Physics informed neural networks.

La seconde introduira la training preocedure de nos model avec la definition de la loss fonction utilisé, le choix de l’architecture du model ainsi que l setu de training .

Ensuite la troisième et quatrième présenterons les methods ainsi que les résultats sur les ODE lineaire et non linear respectivement.

Suivra un partie de discussions des résultats et de leur impluications