Analysis of Koopman Operator using Deep Neural Networks

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Presentation Overview

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Introduction

- To understand very complex function like brain, climate change or financial market, robotics, manufacturing system, autonomous vehicles and transportation networks etc.
- To understand very complex functions, data driven techniques are better than basic principle driven equations.
- Based on data driven, koopman operator is very efficient technique to study the non-linear dynamical systems in controls.

 Koopman operator is an efficient method to represent nonlinear dynamical system in terms of linear dynamical system.

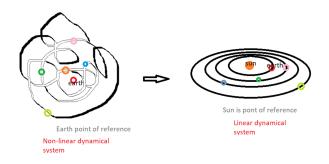


Figure: Change of reference



Frame title - Problems and Solutions

- Often equations are unknown or partially known.
 Model discovery with mechine learning.
- Nonlinear dynamics are still poorly understood.
 Coordinate transformations to linearize dynamics.
- High dimensionality often obscures dynamics.
 patterns exists facilitating reduction.

Frame title - Relevant Literature

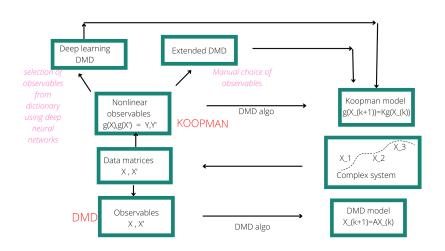


Figure: Comparison among DMD,EDMD,deepDMD

DMD algo

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• Step 1: X = U \sum V
Step 2: A = X'X^{\dagger}
Step 3: \tilde{A}W = W \wedge
Step 4: \Phi = X'V \sum_{i=1}^{N} W
Output: x = \sum_{i=1}^{n} b_i \phi_i \exp(\lambda_i t)
Where.
W=Eigenvectors
∧=Eigenvalues
A=Linear model of dynamical system
\phi=Eigen vectors of A
x=modes
if A=billion by billion matrix
then \tilde{A}= few hundred by hundred order matrix from which we
can easily get eigen values and eigen vectors
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 As we know that in dynamic mode decomposition we do not have flexible choice of dictionary of observables, while in extended dynamic mode decomposition user can manually select observables from dictionary [2,6]. In deepDMD, selection of observables possible by deep neural network hence this method has advantage over EDMD.

Problem Statement

• The purpose of this project is to learn the deep neural network representaion of koopman operator so that linear estimation prediction, control and analysis of non-linear dynamical system using koopman operator can be done.

Frame Title - Proposed Solution

- Koopman operator theory tells that any non-linear dynamical system can be transformed into infinite dimensional linear operator.
- Because of infinite dimensional linear operator, it is not easy to find relevant eigen values and modes. Extended DMD is the method for finding such eigen values and modes.
- But in extended DMD there is need to define the observables by user, which is a big challenge .To address this challenge, deepDMD method uses auto-encoder network

Frame Title - Expected Outcomes

- In this project, i will simulate deep dynamic mode decomposition(deepDMD) for training koopman operators from data.
- I will try to tune deep neural networks so that it can be used to generate more efficient dictionaries, to obtain an accurate estimate of koopman operator.

Frame title - Deliverables

UP-Till	Tasks
1 st evaluation (Sem-3, Aug 2022)	Literature survey
2 nd evaluation (Sem-3, Nov 2022)	Literature survey, DMD algo simulation and work on data set.
1 st evaluation (Sem-4, Feb 2023)	Simulation of deep dynamic mode decomposition for higher dimensional dynamic system .
2 nd /Final evaluation (Sem-4, May 2023)	I will try to find more efficient dictionaries by tuning it's hyper parameters and Final report preparation .

^{*} Tentative

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QUESTIONS

THANK YOU