Predicting Ultrafast Nonlinear Dynamics in Fibre Optics with a Neural Network

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2022.12

Contents

Introduction

Project Overview

- Topic: Nonlinear pulse propagation in optic-fibre - a typical case of nonlinear Schrodinger equation system (NLSE).
- Target: Predicting the propagation of pulses in optical fibre using Recurrent Neural Network (RNN).
- Method: Long Short Term Memory (LSTM) Network and Complex Gated Recurrent Unit (CGRU) Network.

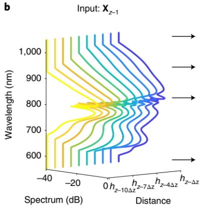

Figure: Predicting propagation of pulses

Introduction

Motivation of Using RNN in Nonlinear Schrodinger Equation (NLSE) System

Challenges for traditional numerical methods in studying nonlinear Schrodinger equatio (NLSE) system :

- Require extensive numerical simulations.
- Computationally demanding.
- Creates server bottleneck in using them in experiments in real time.

Motivation of using RNN to study NLSE system:

- Similar idea as traditional numerical methods - Use earlier intensity of a signal to predict temporal intensity at particular distance.
- Less computational burden after training.
- Better performance in real time application.

Solution 1

A solution using LSTM inspired by the work of L. Salmela et al[1].

[1] L. Salmela, et al., "Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent neural network," Nature Machine Learning Intelligence, 2021

Introduction

Motivation of Using Complex Representation of Pulses and Complex Neural Networks

Motivation of using complex time domain representation in pulse propagation prediction:

- Amplitude/Power representation suffers a potential loss of information.
- Complex representation provides complete information about spectra, power, and phase of the pulse.

Challenges of implementing complex neural networks:

- No existing libraries.
- Difficulty lies in implementing **complex operations**, especially in calculating complex gradients.
- Split complex approach. Real-valued non-linear activations are applied separately to the real and imaginary parts of the complex number.

Introduction

Motivation of Using Complex Recurrent Neural Network

Motivation of using Complex Gated Recurrent Unit (CGRU) Network:

- Use complex operation to **replace** the real number operation in a typical Gated Recurrent Unit (GRU) cell.
- GRU has a simpler structure comparing to LSTM.
- Easier to implement a complex version.

Solution 2

A solution using Complex Gated Recurrent Unit (CGRU) Network inspired by the work of M. Wolter and A. Yao[2].

[2] M. Wolter, et al., "Complex Gated Recurrent Neural Networks" , CoRR, abs/1806.08267, 2018.

Methodology

LSTM Solution

The LSTM model is composed of 3 functioning layers:

- 1 LSTM layer with 250 neuron
- 2 Dense layer with 250 neuron
- Input data is **real** number data (power/amplitude)

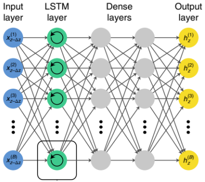

Figure: LSTM Model Structure

Methodology

Complex Gated Recurrent Unit (CGRU) Solution

A primitive CGRU model is composed of 1 layer:

- CGRU layer with 100 neuron
- Input data is **complex** number data (Complex time domain representation)

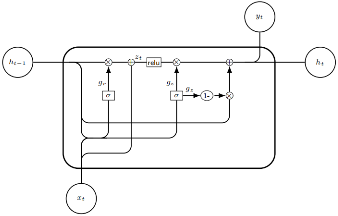

Figure: CGRU Cell Structure

Experiment

Data

Simulation generated time domain power data and complex time domain data is used for the two solution separately:

- 1300 different input pulses
- 101 steps of propagation along the optic fibre
- 101 (for power data)/512 (for complex data) sampling points per signal

Experiment

LSTM Results

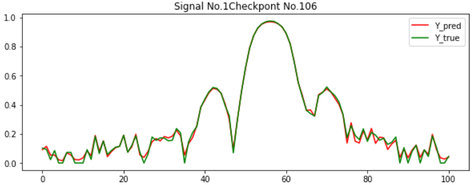

Figure: Example Prediction vs Truth Plot

TABLE II: Experiment Result on Dataset 1

Experiment Index	Optimizer	Window Size	learning Rate	Epochs	MSE (test)	MAE (test)
1_1_0	RMSprop	10	1e-4	5	8.2850e-05	0.0069
1_1_1	RMSprop	10	1e-4	10	6.7079e-05	0.0063
1_1_2	RMSprop	10	1e-4	20	5.3493e-05	0.0055
1_1_3(Early Stopping)	RMSprop	10	1e-4	29	5.9736e-05	0.0060
1_3_0	Adam	10	1e-4	10	4.7846e-05	0.0050
1_3_1	SGD	10	1e-4	10	0.0011	0.0196
1_5_0	RMSprop	15	1e-4	10	6.4968e-05	0.0060

Figure: LSTM Result

Experiment

Complex Gated Recurrent Unit (CGRU) Results

CGRU model has a less accurate prediction results comparing to LSTM, further study is needed to increase its performance.

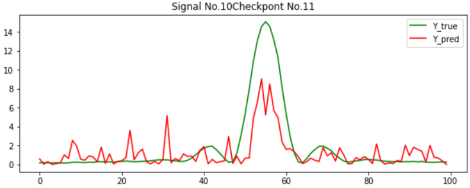

Figure: Example Prediction vs Truth Plot

Limitation

Possible reasons for the relatively poor performance of CGRU model:

- GRU has a simpler structure comparing to LSTM.
- Possible information loss in complex operations.
- Not enough data samples.
- Further tuning may be needed.

Conclusion

Using Recurrent Neural Network to predict pulse propagation in optic fibre proved to be a **feasible** solution:

- LSTM solution is **satisfactory** with regard to its prediction accuracy.
- CGRU solution points out a **feasible** and **promising** direction of future study using complex representation of pulses.

References

[1] L. Salmela, N. Tsipinakis, A. Foi, et al., “Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent neural network,” Nature Machine Learning Intelligence 3, 344–354 (2021).
[2] M. Wolter and A. Yao, “Complex Gated Recurrent Neural Networks” , CoRR, abs/1806.08267, 2018. [Online]. Available: http://arxiv.org/abs/1806.08267

Thank You!