

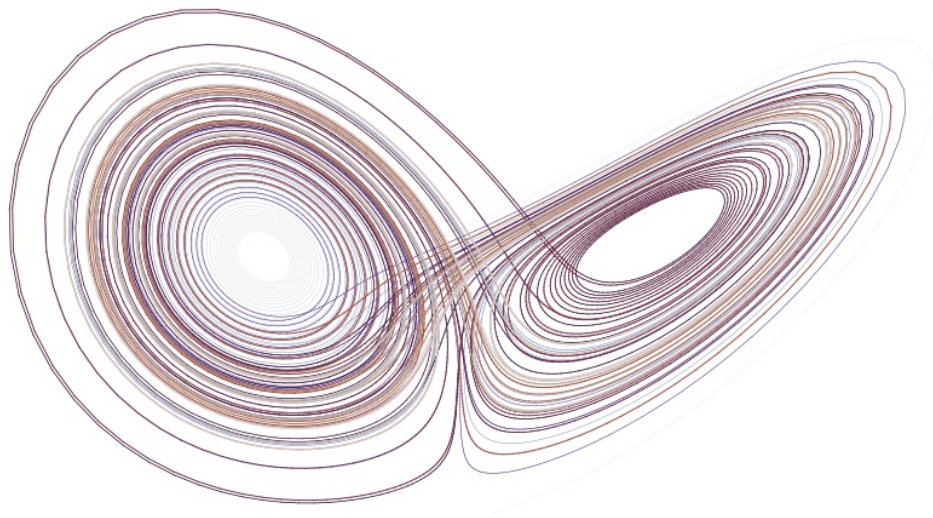
Supervisor: Thomas Lennartson

Program: Natural Sciences Program

School: Procivitas Privata Gymnasium Malmö

Which Neural Network Architecture is Optimal for Predicting Chaotic Dynamics?

A comparative study between LSTM RNN, Transformers and Echo State Networks regarding their capacity to predict the Lorenz 63 system.



Sebastian M.D.

March 2024

Abstract

This study seeks to identify the neural network architecture that showcases most potential at predicting chaotic dynamics, by comparing LSTM Recurrent Neural Networks (LSTM RNN), Echo State Networks (ESN), and the Transformers architecture. Using the Lorenz 63 system as a standard model for chaotic systems, this research evaluates each architecture's ability to capture chaotic behavior over time based on their Mean Squared Error (MSE). The architectures are implemented and optimized in Python with the help of libraries such as PyTorch for RNNs and Transformers, and ReservoirPy for ESNs. Initial results indicate that while all architectures are capable of learning the patterns present in chaotic systems, there are notable differences in performance. The ESN shows a slight advantage over Transformers in predicting the Lorenz attractor shape and trajectory. The Transformers model, however, demonstrates a stronger and more stable prediction during the initial phases compared to the ESN model. The LSTM RNN model performs significantly worse than both the ESN and Transformers models. This study provides insights into the practical application of neural network models for chaotic system prediction and suggests directions for future research.

Contents

1	Introduction	4
2	Theory	4
2.1	The Lorenz System	4
2.2	Neural Networks	5
2.3	RNNs	6
2.4	Transformers	8
2.5	Reservoir Computing and Echo State Networks	9
3	Method	11
3.1	Generating Data	11
3.2	Setting up the LSTM RNN	12
3.3	Setting up the Transformers Model	13
3.4	Setting up the RC-ESN	13
3.5	Hyperparameter optimization process	13
4	Results	15
4.1	Lorenz attractor	15
4.2	Trajectory	15
4.3	MSE	15
5	Discussion	15
5.1	Conclusion	17
A	Code snippets	18
B	Figures	24

1 Introduction

A chaotic system is a dynamical system that is highly sensitive to initial conditions, leading to long-term unpredictability despite its deterministic nature. Chaotic systems are found in many natural phenomena, such as weather, water flows, and planetary orbits. Traditionally chaotic systems have been modeled using numerical methods, however papers such as [Chattopadhyay et al., 2020] have tried to apply neural network models instead. Neural networks are computing systems that mimic the brain to learn from data and recognize patterns without explicit instructions. Results have shown that neural networks, specifically ESN, can be promising in capturing chaotic dynamics. The goal of this study is to further explore the application of neural networks by also testing out the Transformers architecture as introduced by Google in their research paper [Vaswani et al., 2017] and compare it to the LSTM RNN and ESN architectures. The networks will be judged on their MSE over time and their ability to capture the Lorenz 63 system’s chaotic patterns. The objective is to determine which of these architectures prove most effective in predicting chaotic systems.

2 Theory

2.1 The Lorenz System

The original Lorenz system is a set of three differential equations. It is one of the earliest and most studied examples of systems that exhibit chaotic behavior. It is defined by the following equations:

$$\frac{dx}{dt} = \sigma(y - x) \tag{1}$$

$$\frac{dy}{dt} = x(\rho - z) - y \tag{2}$$

$$\frac{dz}{dt} = xy - \beta z \tag{3}$$

where x , y , and z make up the system’s positional state with respect to time t , and σ , ρ , and β are parameters. Typically, the values $\sigma = 10$, $\rho = 28$, and $\beta = \frac{8}{3}$ are used.

The Lorenz system is known for its butterfly-shaped attractor, which is a set of points the system, regardless of the starting condition, always end up at. The attractor is visualized in Figure 1.

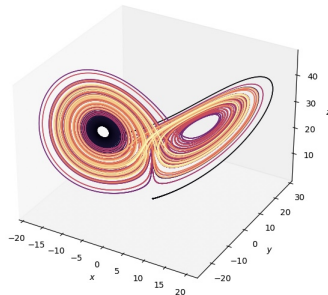


Figure 1: The Lorenz attractor for $\sigma = 10$, $\rho = 28$, and $\beta = \frac{8}{3}$. Generated with the RK4 method for 100 time units

2.2 Neural Networks

Neural networks are a type of machine learning model that are inspired by the structure of the human brain. They are composed of layers with interconnected nodes, which represent neurons, that process input data and produce an output. These nodes are usually connected to each other with linear transformations called weights (W) and biases (b). The weights and biases are the parameters of the network that initially are randomly initialized and are optimized during the training process.

At the heart of neural networks is the feedforward computation that passes the data from one layer x to the next y as follows:

$$y = f(Wx + b)$$

where y is the output, W is the weights matrix, x is the input vector, b is the bias vector, and f is the activation function, typically the ReLU(rectified linear unit) function is used. The ReLU function is defined as:

$$\text{ReLU}(z) = \max(0, z)$$

Which maps all positive inputs to themselves while negative inputs are mapped to zero. The ReLU activation function introduces non-linearity to the model, which is critical for capturing complex behavior. Another popular activation function is the hyperbolic tangent or tanh, which squashes the input values to be within the range -1 and 1 :

$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

This allows tanh to output values that have mean zero, which can make learning for the subsequent layers slightly easier. Another activation function commonly used for the output layer is the sigmoid function. The sigmoid function maps the input values to a range between 0 and 1 , interpreted as probabilities:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

Due to its shape, the sigmoid function is suitable for binary outputs and is useful when a probabilistic interpretation is desired for the output neuron. However, for multiclass classification tasks, the softmax activation function is commonly used instead. It maps the input vector to a probability distribution:

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

Here K is the length or dimensionality of the input z vector. The softmax function ensures that the sum of the probabilities of all z_i elements is 1 , which is great for a probabilistic interpretation.

Given a predicted value \hat{y}_i and a true value y_i a cost function is used to measure the degree of error in the prediction. Commonly used for regression-based tasks is the MSE function, which is defined by:

$$C = \frac{1}{2n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where C is the cost, n is the number of samples, y_i is the true value, and \hat{y}_i is the predicted value.

During the training process, optimization strategies such as stochastic gradient descent (SGD) are used. The gradient of the cost function is computed with respect to the weights in a process called backpropagation, and is used to adjust the weights in the direction that minimizes the cost:

$$W_{\text{new}} = W_{\text{old}} - \eta \nabla C$$

where W_{new} and W_{old} are the values of the weights after and before the update, respectively, ∇C is the gradient of the cost function with respect to the weights, and η is the learning rate.

Via processes like SGD, the network can compute a gradient to slowly shift the parameters and minimize the error of the network's predictions. Over time the network can generalize and learn the underlying patterns of the data to make accurate predictions on unseen data.

2.3 RNNs

A Recurrent Neural Network (RNN) is a type of neural network architecture designed to recognize patterns in sequential data. What makes the RNN architecture special is that it's composed of a train of nodes, called cells, each connected to the next, where all the cells share the same trainable weights and biases. Each node in the train has its own hidden state that is used when computing the next output. When the input vector is fed to the first cell of the train, it creates an output and then the hidden state is updated and passed along to the next cell. The hidden state makes it so the next cell can 'remember' the previous data input. The RNN is governed by these equations:

$$h^{(t)} = \tanh(W h^{(t-1)} + U x^{(t)} + b_h) \quad (4)$$

$$y^{(t)} = \text{softmax}(V h^{(t)} + b_y) \quad (5)$$

Here $h^{(t)}$ is the hidden state at timestep t , and $y^{(t)}$ the equivalent output at that timestep. The weights W , U and V and the biases b_h and b_y are trainable parameters of the network and they are the same for all cells. These equations highlight the recurrent nature of the RNN, as the computation of the hidden state at time t depends on the previous state at $t - 1$. This is what allows the network to maintain a form of memory over time. See Figure 2 for a visual representation of the RNN architecture, where $o^{(t)}$ represents $y^{(t)}$ before softmax.

However, RNNs have a significant limitation in that they often struggle to learn long term dependencies, since during backpropagation, the gradients are propagated through the same weights matrix multiple times, which especially when dealing with long sequences can lead to the vanishing and exploding gradient problem where the gradients either becomes extremely small or extremely big. Long Short-Term Memory (LSTM) networks aim to solve this problem. The LSTM network is a modification of the RNN that introduces a second hidden state, called the cell state. It is governed by these equations:

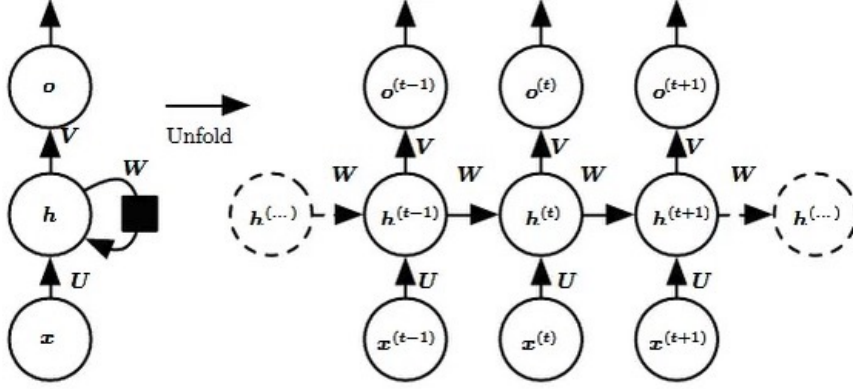


Figure 2: An architecture of a recurrent neural network (adapted from [Goodfellow et al., 2016]).

$$a^{(t)} = Wh^{(t-1)} + Ux^{(t)} + b_h \quad (6)$$

Now $a^{(t)}$ is used to compute four gates, i , f , o , and g with different biases and activation functions:

$$i^{(t)} = \sigma(a^{(t)} + b_i) \quad (7)$$

$$f^{(t)} = \sigma(a^{(t)} + b_f) \quad (8)$$

$$o^{(t)} = \sigma(a^{(t)} + b_o) \quad (9)$$

$$g^{(t)} = \tanh(a^{(t)} + b_g) \quad (10)$$

The gates are used to compute the next cell state, where the f gate decides how much to 'remember' or 'forget' from the previous cell state, and the i and g gates together decide how much new information to write.

$$C^{(t)} = f^{(t)} \odot C^{(t-1)} + i^{(t)} \odot g^{(t)} \quad (11)$$

The o gate then determines how much of the cell state to output to the next hidden state.

$$h^{(t)} = o^{(t)} \odot \tanh(C^{(t)}) \quad (12)$$

Usually the output vector equals the hidden state in an LSTM.

$$y^{(t)} = h^{(t)} \quad (13)$$

Figure 3 showcases an LSTM cell, notice the red arrows which show the gradient flow. Because the hadamard product is used instead of matrix multiplication and the gates can vary between cells, gradient flow becomes more stable, which allows the network to learn long-term dependencies without an exploding or vanishing gradient.

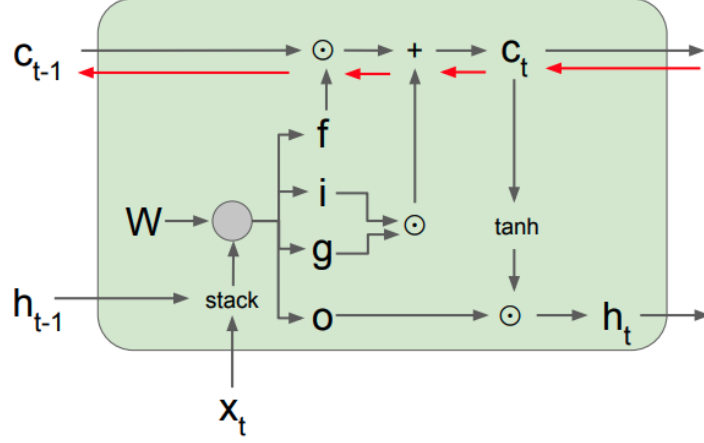


Figure 3: Diagram of LSTM cell (adapted from [Justin Johnsson and Yeung, 2017])

2.4 Transformers

Transformers is a type of neural network architecture that was introduced in the paper "Attention is all you need" [Vaswani et al., 2017]. Unlike RNNs, Transformers do not process the data in sequence, instead, they process the entire sequence at once. Transformers transform the data into an embedding layer where the positions are encoded into the data vectors themselves which allows for parallelization.

The key element in Transformers is the self-attention mechanism. In self-attention, each token in the input sequence is transformed with trainable weights into three vectors, a query vector Q , a key vector K and a value vector V . The query vector represents what a given token is looking for, the key vector what the token offers, whilst the value vector is the information the token contains.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V$$

The self-attention mechanism takes the dot product between the keys and queries of the tokens, divides it by the square root of the key dimension (to prevent too small gradients) and then applies softmax to create a weights matrix. The weights matrix is used to determine how much each token in the sequence should contribute to the value vector of another token. For example, let the tokens be words in a sentence. In the sentence "The cat sat on the mat", the word "cat" would have a high affinity for the word "mat" (a query vector looking for the object of the sentence) and a low affinity for the word "the". This mechanism allows the network to learn the relationships between the tokens in the sequence. Usually, a specific form of attention is used, called causal attention or masked attention. In masked attention each output position is only allowed to attend to earlier positions in the input or output sequence, effectively preventing the model from using future information to make its predictions.

The self-attention mechanism is usually applied multiple times on the same tokens in parallel. This is called multi-head attention where each "head" has its own self attention mechanism with its own parameters. For each head i , separate trainable transformations are applied to produce new Q^i , K^i , and V^i .

$$\text{head}_i = \text{Attention}(Q^i, K^i, V^i)$$

The results of each head are then concatenated and then linearly transformed to create the final output of the multi-head layer.

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O$$

where W^O is also a trainable weight matrix.

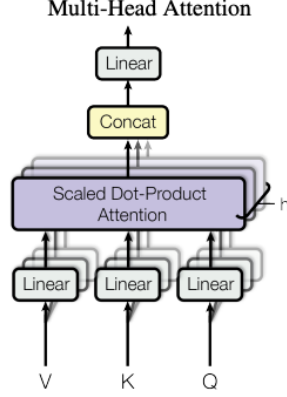


Figure 4: Multi-Head Attention mechaism (adapted from [Vaswani et al., 2017])

The multi-head layer is paired with a position-wise feed-forward network(FFN). The FFN applies two trainable linear transformations with a ReLU activation in between:

$$\text{FFN}(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2$$

The FFN layer allows the network to learn more complex representations of the data. The multi-head layer and FFN layer is usually repeated in blocks to form the transformer network. Between the layers goes a residual connection called LayerNorm. Each time a multi-head or an FFN layer has made a computation, the result is added to the original input and normalized through the LayerNorm:

$$\text{LayerNorm}(x + \text{Sublayer}(x))$$

where $\text{Sublayer}(x)$ is the function implemented by the multi-head or FFN layer and x is the original input. This residual connection and normalization make the gradient flow more stable through the network.

For a complete view of the Transformers architecture, see Figure 12 in Appendix B.

2.5 Reservoir Computing and Echo State Networks

Reservoir Computing (RC) is a variant of RNNs that has proven particularly effective in predicting chaotic systems. The fundamental principle behind reservoir computing is that only a part of the network is trained, while the rest of the network remains unchanged during training. This approach significantly reduces the computational cost of training RNNs and overcomes some of the issues related to gradient-based learning in traditional RNNs, such as vanishing and exploding gradients.

Echo State Networks (ESNs) are a particularly well-known implementation of reservoir computing. ESNs consist of a sparsely connected and randomly generated reservoir. The dynamics of the reservoir can be described by:

$$x^{(t)} = \tanh(\mathbf{W}x^{(t-1)} + \mathbf{W}_{\text{in}}u^{(t)} + \mathbf{W}_{\text{fb}}y^{(t-1)} + b), \quad (14)$$

where $x^{(t)}$ is the state vector of the reservoir at time t , $u^{(t)}$ is the input vector, \mathbf{W} is the reservoir weight matrix, \mathbf{W}_{in} is the input weight matrix, and \mathbf{W}_{fb} represents connections feeding back previous output. These matrices are randomly generated and not trained. Output is then computed as:

$$y^{(t)} = \mathbf{W}_{\text{out}}x^{(t)}, \quad (15)$$

where $y^{(t)}$ is the output vector, and \mathbf{W}_{out} is the output weight matrix, which is trained.

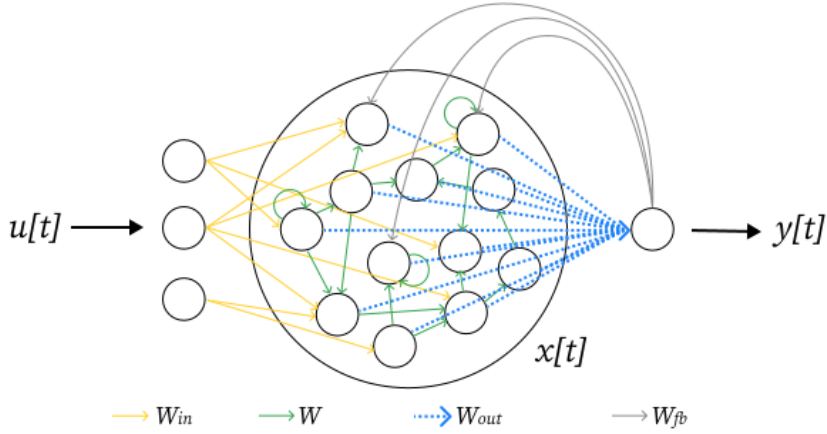


Figure 5: Echo State Network architecture (adapted from [Hinaut and Trouvain, 2021]).

The reservoir serves to project the input into a higher-dimensional space where the different parts of the input sequence become more linearly separable. Training only occurs in a readout layer, which is typically a linear model that is adjusted to map the reservoir states to the desired output. Reservoirs in ESNs also possess a "fading memory", enabling them to handle input sequences with varying time scales. This property allows ESNs to maintain the context of earlier inputs while also adapting quickly to recent changes in the input stream.

Training an ESN involves collecting the states of the reservoir for a known input sequence, then using a supervised learning technique, such as ridge regression, to determine \mathbf{W}_{out} such that the error between the predicted output $y^{(t)}$ and the actual target output $\hat{y}^{(t)}$ is minimized. This can be expressed as the following optimization problem:

$$\mathbf{W}_{\text{out}} = \arg \min_{\mathbf{W}_{\text{out}}} \left\{ \sum_{t=1}^n (\hat{y}^{(t)} - y^{(t)})^2 + \lambda \|\mathbf{W}_{\text{out}}\|_F^2 \right\}, \quad (16)$$

Here the squared Frobenius norm $\|\mathbf{W}_{\text{out}}\|_F^2$ of the is used, which is equivalent to the sum of all squared matrix entries, n is the number of training samples, and λ is the regularization parameter that controls the trade-off between fitting the training data and keeping the weights small to avoid overfitting. Notice that this is MSE with an added regularization term.

3 Method

The code is written in Python and uses the PyTorch library for implementation of the Transformers and LSTM RNN models as well as the ReservoirPy library for the implementation of the ESN model. The project is publicly available on GitHub at: <https://github.com/SebCodesTheWeb/lorents-net> ([Delgado, 2024])

3.1 Generating Data

The training data is processed via the RK4 method which is implemented in Appendix A, Listing 1.

The data is then created in the `generate_dataset.py` module.

```
1 from lorenz import RK4
2 import pandas as pd
3 import numpy as np
4 from constants import seed_nbr, dt, chunk_len
5
6 np.random.seed(seed_nbr)
7
8 total_data_points = 1e6
9 nbr_chunks = int(total_data_points // chunk_len)
10
11 pos = [17.67715816276679, 12.931379185960404, 43.91404334248268]
12
13 dataset = []
14 dataset.append({
15     't': 0,
16     'x': pos[0],
17     'y': pos[1],
18     'z': pos[2],
19 })
20
21 for i, _ in enumerate(nbr_chunks):
22     for j in range(chunk_len):
23         elapsedTime = j * dt + dt
24         pos = RK4(pos, dt)
25         x, y, z = pos
26         dataset.append({
27             't': elapsedTime,
28             'x': x,
29             'y': y,
30             'z': z
31         })
```

In this code the constants are $dt = 0.04$, $seed_nbr = 0$ and $chunk_len = 10$ (100 was used for Transformers and 2 for ESN). These values for dt and $chunk_len$ have after some trial and error proven effective in generating good data to train the models on. The code generates 1 million datapoints of the Lorenz system with the initial position [17.67715816276679, 12.931379185960404, 43.91404334248268], which was arbitrarily chosen.

```
1 dataset = pd.DataFrame(dataset)
2
3 dataset.to_csv('lorenz-sequences_raw.csv', index=False)
4
5 # Z-score normalization
6 numerical_cols = ['x', 'y', 'z']
7 dataset[numerical_cols] = (
8     dataset[numerical_cols] - dataset[numerical_cols].mean()
```

```

9
10 ) / dataset[numerical_cols].std()
11
12 dataset.to_csv('lorenz-sequences.csv', index=False)

```

The dataset is then normalized using Z-score normalization to improve gradient flow, which is critical. The raw unnormalized data is saved in a separate csv file to later on move the model predictions out of normalized space with inverse Z-score normalization (Listing 4).

Afterwards it is split into training, validation and testing sets in the `get_training_data.py` module (Listing 2).

3.2 Setting up the LSTM RNN

The `LSTM_RNN` class defines a LSTM RNN network based on PyTorch's `nn.Module` in Listing 3

The model is then instantiated like this:

```

1 from get_training_data import x_train, y_train
2 from lstm_rnn import LSTM_RNN
3 from torch import nn
4 from torch.utils.data import DataLoader, TensorDataset
5 import torch.optim as optim
6 import torch
7 from torch.optim.lr_scheduler import ExponentialLR
8 import optuna
9 from device import device as default_device
10
11 def train_rnn_lstm(
12     hidden_size=32,
13     num_layers=1,
14     learning_rate=0.0005,
15     batch_size=32,
16     epochs=5,
17     gamma=0.8,
18     trial = None,
19     device=default_device,
20 ):
21     x_train_device = x_train.to(device)
22     y_train_device = y_train.to(device)
23
24     train_data = TensorDataset(x_train_device, y_train_device)
25     train_dataloader = DataLoader(train_data, batch_size=batch_size)
26
27     input_size = x_train_device.shape[2]
28     output_size = y_train_device.shape[1]
29     model = LSTM_RNN(input_size, hidden_size, output_size, num_layers, device).
30         to(device)
31
32     loss_fn = nn.MSELoss()
33     optimizer = optim.Adam(model.parameters(), lr=learning_rate)
34     scheduler = ExponentialLR(optimizer, gamma=gamma)

```

It uses MSE loss function and the Adam optimizer. It also uses an exponentially decaying learning step scheduler, which has proven great for managing learning rate with many training epochs.

The RNN network is later on iterated over each batch of the training data and the loss is calculated and backpropagated through the network to update the weights. (Listing 5)

3.3 Setting up the Transformers Model

The transformers class is written with PyTorch TransformerEncoder and TransformerEncoder-Layer classes and is defined in transformer.py (Listing 6) with positional encoding implemented in the PositionalEncoding class in Listing 7.

The model is then trained in a similar fashion to the LSTM RNN model and uses the same training loop.

3.4 Setting up the RC-ESN

The echo state network was implemented with reservoirpy, a library for reservoir computing in Python in reservoir.py written in Listing 8

3.5 Hyperparameter optimization process

Firstly a new loss function was defined in true_loss.py (Listing 9) to evaluate the models on unseen data. This was done via generating a new random path with the RK4 method and then comparing the model's predictions to the actual path. The average MSE error was then computed to evaluate the model's performance.

The hyperparameters of the Transformers and LSTM RNN networks were then optimized using the optuna library implementation of the Tree-structured Parzen Estimator(TPE) algorithm.

```
1 import optuna
2 import torch
3 from train_transformer import train_transformer
4 from train_network import train_rnn_lstm
5 from true_loss import evaluate_model
6 import csv
7 from device import device as default_device
8
9 model_type = "Transformer"
10
11 def objective(trial):
12     learning_rate = trial.suggest_float("learning_rate", 1e-5, 1e-2)
13     batch_size = trial.suggest_categorical("batch_size", [4, 8, 16, 32, 64, 128, 256])
14     gpu_id = trial.number % 4
15     device = torch.device(
16         f"cuda:{gpu_id}" if torch.cuda.is_available() else default_device
17     )
18
19     if model_type == "Transformer":
20         model_hyperparams = {
21             "hidden_dim": trial.suggest_categorical(
22                 "hidden_dim", [256, 512, 768, 1024]
23             ),
24             "nhead": trial.suggest_int("nhead", 1, 2),
25             "num_layers": trial.suggest_int("num_layers", 1, 4),
26             "learning_rate": learning_rate,
27             "batch_size": batch_size,
28             "d_model": trial.suggest_categorical("d_model", [64, 128, 256, 512])
29         },
30         "dropout": trial.suggest_float("dropout", 0, 0.4),
31         "epochs": 5,
32         "trial": trial,
33         "device": device,
34     }
```

```

35     model = train_transformer(**model_hyperparams)
36     val_loss = evaluate_model(model, device)
37     return val_loss
38
39     elif model_type == "RNN_LSTM":
40         model_hyperparams = {
41             "hidden_size": trial.suggest_categorical(
42                 "hidden_size", [32, 64, 128, 256, 512]
43             ),
44             "num_layers": trial.suggest_int("num_layers", 1, 3),
45             "learning_rate": learning_rate,
46             "batch_size": batch_size,
47             "epochs": 5,
48             "gamma": trial.suggest_float("gamma", 0.7, 1),
49             "trial": trial,
50             "device": device,
51         }
52
53         model = train_rnn_lstm(**model_hyperparams)
54         val_loss = evaluate_model(model, device)
55         return val_loss
56
57
58 # Optuna study
59 pruner = optuna.pruners.MedianPruner()
60 study = optuna.create_study(
61     direction="minimize", pruner=pruner, storage="sqlite:///lorenz_study.db"
62 )
63 study.optimize(
64     objective, n_trials=100, n_jobs=4, show_progress_bar=True
65 ) # n_jobs is number of parallel jobs(one per gpu available)

```

It was parallelized to run on four Nvidia GPUs and took use of pruning to preemptively end unpromising trials. Once the best combination of hyperparameters was found the networks was retrained over more epochs for optimal results. The optimization took place over 100 trials and was trained on four RTX 4090s.

The ESN was on the hand manually optimized by trial and error, as the reservoirpy library does not support optuna as good as PyTorch. In the end the following optimal hyperparameters were found and used in the final test:

ESN:

- reservoir size: 1000
- leakage rate: 0.5
- spectral radius: 0.9
- ridge parameter: $2.5 \cdot 10^{-6}$
- inp_seq_len: 1

Transformers:

- hidden_dim: 256
- nhead: 2
- num_layers: 2
- learning_rate: 0.00257
- batch_size: 64
- d_model: 64
- dropout: 0.02078
- epochs: 30
- inp_seq_len: 49

LSTM RNN:

- hidden_size: 32
- num_layers: 1
- learning_rate: 0.0005
- batch_size: 32
- epochs: 10
- gamma: 0.8
- inp_seq_len: 9

The models were then evaluated by predicting 500 time steps and comparing the predictions to the testing data set. To evaluate the models, their Lorenz attractor shape, trajectory and MSE was plotted.

4 Results

4.1 Lorenz attractor

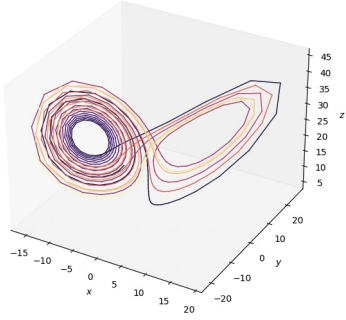


Figure 6: LSTM RNN

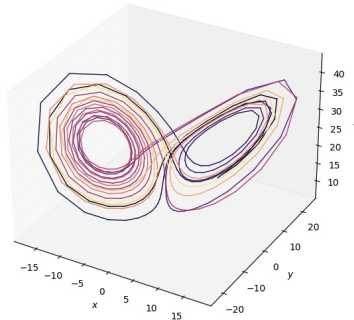


Figure 7: ESN

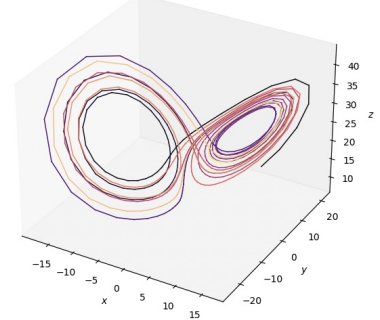


Figure 8: Transformers

4.2 Trajectory

View figures 9, 10 and 11.

4.3 MSE

The average MSE for the LSTM RNN was 50.1579.

The average MSE for the ESN was 48.7797.

The average MSE for the Transformers network was 29.1590.

For a more detailed overview of MSE over time view figures 13, 14 and 15 in Appendix B.

5 Discussion

Looking at figures 6, 7 and 8, it is clear that all models have learned the Lorenz patterns and thereby the underlying dynamics of the system. They all generated attractors of similar scale with two wings centering around two focal points. They differ slightly, however, and when comparing the figures, it is hard to tell which of the models has captured the best attractor shape (see figure 1). The Transformers model seems to have the most accurate angle between the two wings, but the left wing radius should be smaller and the outer right wing radius should be bigger. The ESN has more accurate outer wing radii, but the LSTM RNN seems to have more accurate inner wing radii. Overall, however, it seems like the ESN network has the most accurate Lorenz attractor shape.

The results from the trajectory plots are clear. In figure 9, the LSTM RNN path seems to deviate from the true path around timestep 40-50, which is confirmed by figure 13 where the MSE could be seen spiking. The MSE then goes down for a bit, showing that the LSTM RNN has learned the pattern of the Lorenz attractor but not with great accuracy.

Viewing figure 10, the ESN seems to diverge from the true path around timestep 60-100, which also is confirmed by figure 14 showcasing some big up and down spikes. The MSE seems to vary a lot, which shows that the ESN has not learned the Lorenz system's trajectory very accurately, but has learned the overall pattern and can follow it for a while.

Looking at figure 11, the Transformers model seems to follow the true path very well up till timestep 100-120. This is confirmed by figure 15 where the MSE is very low and stable untill

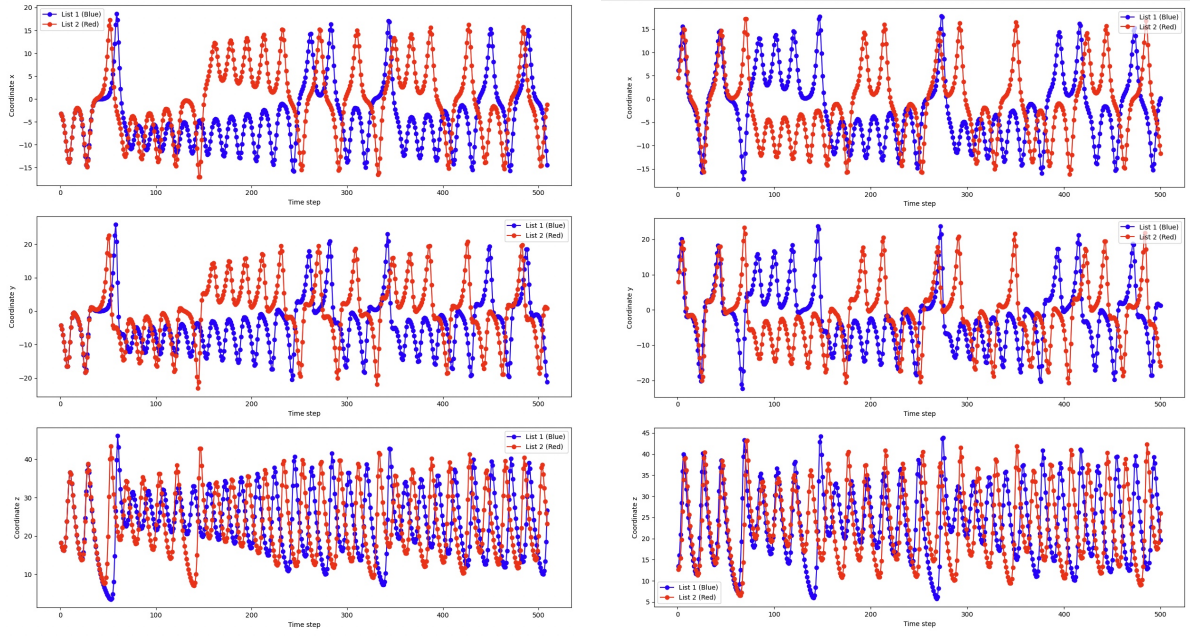


Figure 9: LSTM RNN path (true path is red, model path is blue)

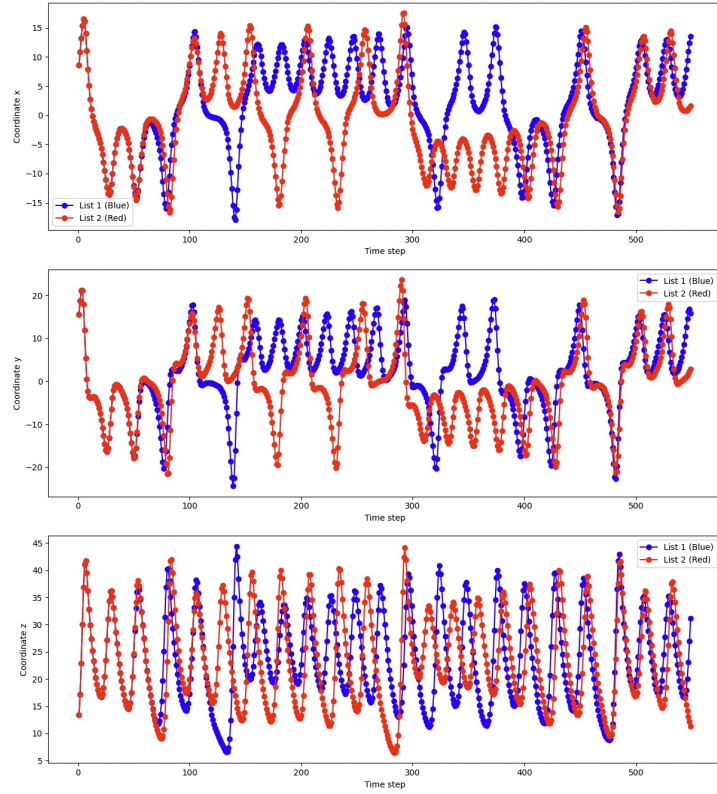


Figure 11: Transformers path(true path is red, model path is blue)

slightly after timestep 100. The Transformers model also appears to hop back on track around timestep 400 and follow the true path accurately for another 100 timesteps.

Keeping in mind that the ESN has a *inp_seq_len* of 1, the LSTM RNN a *inp_seq_len* of 9, and the Transformers model a *inp_seq_len* of 49, the ESN could hold an accurate prediction for about 70-80 timesteps. The LSTM RNN could hold an accurate prediction for about 30-40 timesteps. And the Transformers model could hold an accurate prediction for about 60 timesteps with a small bounce back where it held a good prediction for about another 100 more timesteps. Overall, the Transformers model had the lowest MSE.

5.1 Conclusion

The results are a bit mixed but it seems clear that the LSTM RNN was the worst performing model. It had the highest MSE, could hold a prediction for only 30-40 timesteps and did not have a very impressive Lorenz attractor. The ESN had an accurate Lorenz attractor and could hold the initial prediction the longest, but the Transformers model had much lower MSE without much shorter initial prediction accuracy. The difference does not seem significant enough to make a data-driven conclusion, but seeing as less efforts was spent optimizing the ESN model and it has in other literature shown great capabilities in predicting chaotic systems ([Chattopadhyay et al., 2020]), it seems reasonable to assume the ESN has a slight edge over the Transformers model, although a small one. Hence the results of this study show that the ESN seems to be the best neural network architecture for predicting chaotic systems, tightly followed by the Transformers model and LSTM RNN last.

The results show that the Transformers architecture has an impressive capacity to capture chaotic dynamics, similar to the level of an ESN, whilst the LSTM RNN is not as well suited towards capturing chaotic dynamics. For future research the NVAR reservoir computing variant could be explored, as it in other literature([Gauthier et al., 2021]) has shown great promise. Other hyperparameters of the ESN such as noise could be explored for further optimization, which was not attempted in this study. Regarding the Transformers architecture, different positional embeddings could be used, and the variations of the self attention mechanism like sparse attention could be investigated. With further research it may be possible to conclusively state the peak potential of the Transformers and ESN models in predicting chaotic systems.

Appendix

A Code snippets

```
1 import numpy as np
2
3 sigma = 10
4 rho = 28
5 beta = 8/3
6
7 def get_derivative(pos_vector):
8     x, y, z = pos_vector
9
10    dx_dt = sigma*(y-x)
11    dy_dt = x*(rho-z)-y
12    dz_dt = x*y - beta*z
13
14    return np.array([dx_dt, dy_dt, dz_dt])
15
16 def RK4(pos_vector, dt):
17     k1 = dt * get_derivative(pos_vector)
18     k2 = dt * get_derivative(pos_vector + k1/2)
19     k3 = dt * get_derivative(pos_vector+ k2/2)
20     k4 = dt * get_derivative(pos_vector + k3)
21
22    return pos_vector + (k1 + 2*k2 + 2*k3 + k4) / 6
```

Listing 1: RK4 implementation

```
1 import pandas as pd
2 import torch
3 import numpy as np
4 from constants import (
5     inp_seq_len,
6     val_ratio,
7     seed_nbr,
8 )
9
10 dataset = pd.read_csv("lorentz-sequences.csv")
11 data_tensor = torch.tensor(dataset[["x", "y", "z"]].values, dtype=torch.float32)
12
13 test_set = data_tensor[-10000:].numpy().tolist()
14 data_tensor = data_tensor[:-10000]
15
16
17 def create_seq(data):
18     seq = []
19     for i in range(0, len(data) - inp_seq_len, inp_seq_len):
20         input = data[i : i + inp_seq_len]
21         label = data[i + inp_seq_len]
22         # Given input sequence, predict the next value(label)
23         seq.append((input, label))
24     return seq
25
26
27 data_seq = create_seq(data_tensor)
28
29
30 def manual_split(data, val_ratio, seed):
31     np.random.seed(seed)
32     num_examples = len(data)
33     val_size = int(num_examples * val_ratio)
```

```

34     shuffled_indices = np.random.permutation(num_examples)
35     val_indices = shuffled_indices[:val_size]
36     train_indices = shuffled_indices[val_size:]
37
38
39     train_data = [data[i] for i in train_indices]
40     val_data = [data[i] for i in val_indices]
41
42     return train_data, val_data
43
44
45 inout_seq_train, inout_seq_val = manual_split(data_seq, val_ratio, seed_nbr)
46
47 # item[0] is input sequence, item[1] is label
48 x_train = torch.stack([item[0] for item in inout_seq_train])
49 y_train = torch.stack([item[1] for item in inout_seq_train])
50 x_val = torch.stack([item[0] for item in inout_seq_val])
51 y_val = torch.stack([item[1] for item in inout_seq_val])

```

Listing 2: get_training_data.py

The function splits the training data into a list of separate, trainable sequences, where each individual sequence has a label(the next value to predict) associated with it. These data sequences are later split into a training and validation sets with a 85/15 ratio. The validation set will be used to optimize the hyperparameters of the models. Notice also that the last 10000 data points were split off for a final testing set.

```

1 import torch
2 import torch.nn as nn
3 from device import device as default_device
4
5 class LSTM_RNN(nn.Module):
6     def __init__(self, input_size, hidden_size, output_size, num_layers=1,
7         device=default_device):
8         """
9         input_size: input feature size, in this case 3 for the Lorenz system
10        output_size: output feature size, in this case 3 for the Lorenz system
11        hidden_size: number of hidden units in the LSTM
12        """
13        super(LSTM_RNN, self).__init__()
14        self.hidden_size = hidden_size
15        self.num_layers = num_layers
16
17        self.lstm = nn.LSTM(
18            input_size, hidden_size, num_layers=num_layers, batch_first=True
19        )
20        self.output_activation = nn.Linear(hidden_size, output_size)
21        self.device = device
22
23    def forward(self, inputSeq):
24        # inputSeq shape [batch_size, seq_len, feature_size]
25        batch_size = inputSeq.size(0)
26        state = self.init_state(batch_size)
27        lstm_out, _ = self.lstm(inputSeq, state)
28
29        # Select the last point in the sequence
30        prediction = self.output_activation(lstm_out[:, -1, :])
31
32        return prediction
33
34    def init_state(self, batch_size):

```

```

34     # Initializing the hidden and cell states for the LSTM based on the
    batch size
35     state = (
36         torch.zeros(self.num_layers, batch_size, self.hidden_size).to(self.
        device),
37         torch.zeros(self.num_layers, batch_size, self.hidden_size).to(self.
        device),
38     )
39     return state

```

Listing 3: LSTM RNN implementation

`input_size` is the dimensionality of the input vector(in this case three for the x, y and z values). The constructor initializes the LSTM layer and output activation layer. The `forward` method is passing the input through the `torch.nn.LSTM` cell and the activation layer to compute the output. The `init_state` method initializes the LSTM's internal state with zeros for each new batch.

```

1 import pandas as pd
2
3 dataset = pd.read_csv("lorenz-sequences_raw.csv")
4
5 mean_x, std_x = dataset["x"].mean(), dataset["x"].std()
6 mean_y, std_y = dataset["y"].mean(), dataset["y"].std()
7 mean_z, std_z = dataset["z"].mean(), dataset["z"].std()
8
9
10 def get_unnormalized_prediction(predictions: list):
11     unnormalized_predictions = [
12         [(x * std_x) + mean_x, (y * std_y) + mean_y, (z * std_z) + mean_z]
13         for x, y, z in predictions
14     ]
15
16     return unnormalized_predictions

```

Listing 4: inverse normalization

```

1 def train(dataloader, model, loss_fn, optimizer):
2     size = len(dataloader.dataset)
3     num_batches = len(dataloader)
4     model.train()
5     running_loss = 0.0
6
7     for batch_nbr, (seq, label) in enumerate(dataloader):
8         seq, label = seq.to(device), label.to(device)
9         label = label.squeeze(1) # Remove the extra middle dimension, in this
        case label shape is [batch_size, 1, feature_size]
10        prediction = model(seq)
11        loss = loss_fn(prediction, label)
12
13        optimizer.zero_grad()
14        loss.backward()
15        optimizer.step()
16
17        running_loss += loss.item()
18        if batch_nbr % 100 == 0:
19            current = batch_nbr * len(seq)
20            print(f"loss: {loss:>7f}    [{current:>5d}/{size:>5d}]")
21
22    running_loss /= num_batches
23    print(f"Average loss for epoch: {running_loss:>7f}")

```

```

24     return running_loss
25
26 for t in range(epochs):
27     print(f"epoch {t + 1} \n-----")
28     train(train_dataloader, model, loss_fn, optimizer)
29     if trial is not None:
30         trial.report(loss, t)
31         if trial.should_prune():
32             raise optuna.exceptions.TrialPruned()
33
34     scheduler.step()
35 print("Done")
36 torch.save(model.state_dict(), 'lstm_rnn_lorenz.path')

```

Listing 5: Training loop

The training loop iterates over the dataset, feeding batches of data to the model, calculating the loss, and updating the model parameters through backpropagation. Finally after five epochs, the model's parameters are saved.

```

1 import math
2 import torch
3 from torch import nn, Tensor
4 from torch.nn import TransformerEncoder, TransformerEncoderLayer
5
6 class TransformerModel(nn.Module):
7     def __init__(self, ntoken: int, d_model: int, nhead: int, d_hid: int,
8         nlayers: int, dropout: float = 0.5):
9         """
10         ntoken: The size of the vocabulary (total number of unique tokens).
11         d_model: The dimensionality of the token embeddings (the size of the
12         vectors that represent each token).
13         nhead: The number of attention heads in the multi-head attention
14         mechanisms.
15         d_hid: The dimensionality of the feedforward network model in the
16         transformer encoder.
17         nlayers: The number of sub-encoder-layers in the transformer encoder.
18         dropout: The dropout rate, a regularization technique to prevent
19         overfitting.
20
21         """
22         super().__init__()
23         self.model_type = 'Transformer'
24         self.pos_encoder = PositionalEncoding(d_model, dropout)
25         encoder_layers = TransformerEncoderLayer(d_model, nhead, d_hid, dropout,
26         batch_first=True)
27         self.transformer_encoder = TransformerEncoder(encoder_layers, nlayers)
28         ##Use linear layer instead of traidional embedding layer due to
29         continous data
30         self.input_linear = nn.Linear(3, d_model)
31         self.d_model = d_model
32         self.output_linear = nn.Linear(d_model, 3)
33
34         self.init_weights()
35
36     def init_weights(self) -> None:
37         initrange = 0.1
38         self.input_linear.weight.data.uniform_(-initrange, initrange)
39         self.input_linear.bias.data.zero_()
40         self.output_linear.bias.data.zero_()
41         self.output_linear.weight.data.uniform_(-initrange, initrange)

```

```

36
37 def forward(self, src: Tensor) -> Tensor:
38     """
39     Arguments:
40         src: Tensor, shape '[seq_len, batch_size]'
41         src_mask: Tensor, shape '[seq_len, seq_len]'
42
43     Returns:
44         output Tensor of shape '[seq_len, batch_size, ntoken]'
45     """
46     src = self.input_linear(src) * math.sqrt(self.d_model)
47     src = self.pos_encoder(src)
48     output = self.transformer_encoder(src)
49     output = self.output_linear(output)
50     return output

```

Listing 6: Transformer implementation

The input is first passed through a linear layer to transform the input data into the `d_model` dimensionality. The input is then passed through a positional encoding layer to add information about the position of the tokens in the sequence. The output is then passed through the transformer encoder and then through a linear layer to transform the output back to the original dimensionality. The positional encoding is defined as:

```

1 class PositionalEncoding(nn.Module):
2     def __init__(self, d_model: int, dropout: float = 0.1, max_len: int = 5000):
3         super().__init__()
4         self.dropout = nn.Dropout(p=dropout)
5
6         position = torch.arange(max_len).unsqueeze(1)
7         div_term = torch.exp(torch.arange(0, d_model, 2) * (-math.log(10000.0) /
8         d_model))
9         pe = torch.zeros(max_len, 1, d_model)
10        pe[:, 0, 0::2] = torch.sin(position * div_term)
11        pe[:, 0, 1::2] = torch.cos(position * div_term)
12        self.register_buffer('pe', pe)
13
14    def forward(self, x) :
15        """
16        Arguments:
17            x: Tensor, shape '[seq_len, batch_size, embedding_dim]'
18        """
19        x = x + self.pe[:x.size(0)]
20        return self.dropout(x)

```

Listing 7: Positional encoding implementation

The `PositionalEncoding` module in this code leverages sine and cosine functions to generate a sequence of positional encoding vectors up a maximum length of 5000. Even indices are used with sine and odd indices with cosine to give each vector a unique sequence position. Upon forward pass the positional encoding are added to the input vectors and then passed through a dropout layer to prevent overfitting.

```

1 import reservoirpy as rpy
2 from constants import seed_nbr, dt
3 from reservoirpy.nodes import Reservoir, Ridge
4 import matplotlib.pyplot as plt
5 import numpy as np
6 from unnormalize_data import get_unnormalized_prediction
7 import json
8 import pandas as pd

```

```

9
10 rpy.verbosity(999)
11 rpy.set_seed(seed_nbr)
12
13 train_time = 10.
14 test_time = 20.
15 warm_time = 5.
16
17 train_steps = round(train_time / dt)
18 test_steps = round(test_time / dt)
19 warm_steps = round(warm_time / dt)
20
21 n_timesteps = train_steps + test_steps + warm_steps
22
23 dataset = pd.read_csv("lorentz-sequences.csv")
24 X = dataset[["x", "y", "z"]].values
25
26 reservoir = Reservoir(1000, lr=0.5, sr=0.9)
27 readout = Ridge(3, ridge=2.5e-6)
28 esn_model = reservoir >> readout
29
30 X_train = X[:train_steps + warm_steps -1]
31 Y_train = X[1:train_steps + warm_steps] - X[:train_steps + warm_steps -1]
32
33 model = esn_model.fit(X_train, Y_train, warmup=warm_steps)

```

Listing 8: ESN implementation

The ESN is structured with a Reservoir node and a Ridge regression readout, connected sequentially to construct the model. Training data is prepared by segmenting the input array and generating target output through shifting forward by one step (in this case *inp_seq_len* is 1). Lastly, the model fitting process is carried out, adjusting output weights matrix.

```

1 import numpy as np
2 import torch
3 from constants import inp_seq_len, dt, seed_nbr
4 from lorenz import RK4
5 from mse import calculate_aggregate_mse
6 from unnormalize_data import get_unnormalized_prediction
7 from device import device as default_device
8
9 np.random.seed(seed_nbr)
10
11
12 def validate_long_term(nbrIter, init_input_seq, model, device):
13     predicted_path = [*init_input_seq]
14     for _ in range(nbrIter):
15         input_seq = np.array(predicted_path[-inp_seq_len:])
16         input_seq_tensor = (
17             torch.tensor(input_seq, dtype=torch.float32).unsqueeze(0).to(device)
18         )
19         with torch.no_grad():
20             next_pos = model(input_seq_tensor)
21
22         next_pos = next_pos.cpu().numpy().reshape(-1)
23         predicted_path.append(next_pos)
24
25     true_path = [*init_input_seq]
26     for _ in range(nbrIter):
27         true_path.append(RK4(np.array(true_path[-1]), dt).tolist())
28
29     unnormalized_path = true_path[:inp_seq_len] + get_unnormalized_prediction(

```

```

30     predicted_path[inp_seq_len:]
31 )
32
33 total = 0
34 for i in range(3):
35     list_a = [x[i] for x in true_path[inp_seq_len:]]
36     list_b = [x[i] for x in unnormalized_path[inp_seq_len:]]
37     mse_loss_ag = calculate_aggregate_mse(list_a, list_b)
38     total += mse_loss_ag
39 total /= 3
40
41 return total
42
43
44 init_seq = [np.random.rand(3)]
45 for _ in range(inp_seq_len - 1):
46     next_pos = RK4(np.array(init_seq[-1]), dt)
47     init_seq.append(next_pos.tolist())
48
49
50 def evaluate_model(model, device=default_device):
51     loss = validate_long_term(
52         1000,
53         init_seq,
54         model,
55         device,
56     )
57     print(f"Validation loss: {loss}")
58     return loss

```

Listing 9: true_loss.py

B Figures

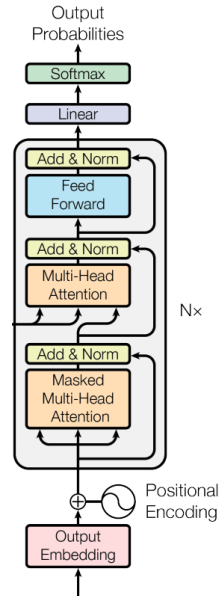


Figure 12: Transformers decoder architecture, (adapted from [Vaswani et al., 2017])

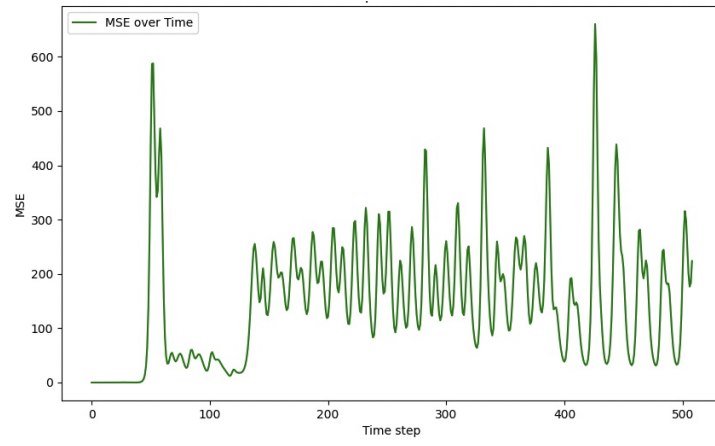


Figure 13: RNN MSE

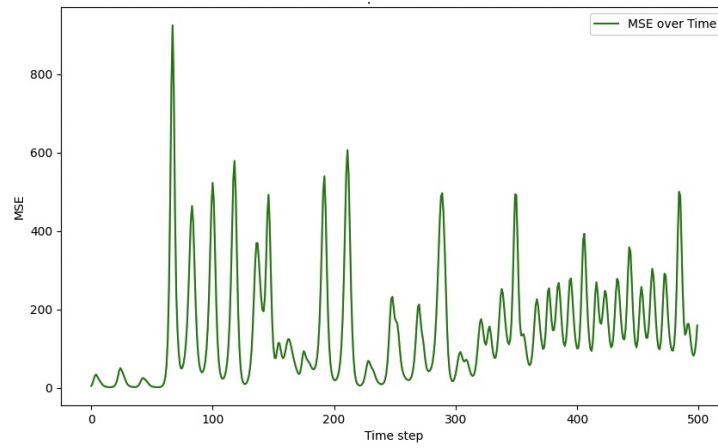


Figure 14: ESN MSE

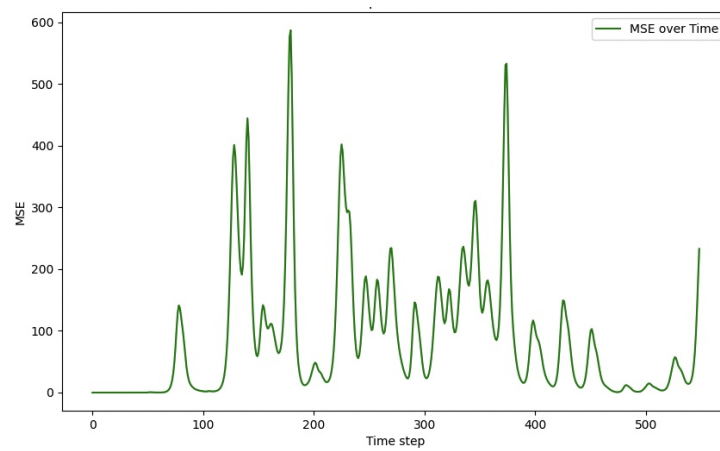


Figure 15: Transformers MSE

References

- [Chattopadhyay et al., 2020] Chattopadhyay, A., Hassanzadeh, P., and Subramanian, D. (2020). Data-driven predictions of a multiscale lorenz 96 chaotic system using machine-learning methods: reservoir computing, artificial neural network, and long short-term memory network. *Nonlinear Processes in Geophysics*, 27(3):373–389.
- [Delgado, 2024] Delgado, S. (2024). lorenz-net. <https://github.com/SebCodesTheWeb/lorenz-net>.
- [Gauthier et al., 2021] Gauthier, D. J., Bollt, E., Griffith, A., and Barbosa, W. A. S. (2021). Next generation reservoir computing. *Nature Communications*, 12(1):5564.
- [Goodfellow et al., 2016] Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*. MIT Press. <https://www.deeplearningbook.org/contents/rnn.html>.
- [Hinaut and Trouvain, 2021] Hinaut, X. and Trouvain, N. (2021). Reservoirpy documentation. https://reservoirpy.readthedocs.io/en/latest/user_guide/quickstart.html.
- [Justin Johnsson and Yeung, 2017] Justin Johnsson, F.-F. L. and Yeung, S. (2017). Lecture 10 — recurrent neural networks. <https://www.youtube.com/watch?v=6niqTuYFZLQ>.
- [Vaswani et al., 2017] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need. *CoRR*, abs/1706.03762.