Activity Recognition by Using Neural Network in IoT Environment

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Introduction

- **Internet of Things (IoT)** is physical objects that are connected to the internet and collect and transfer data
- Used in many fields
  - Agriculture
  - Healthcare
  - Self-driving car
- Capability of future technological development

Motivation

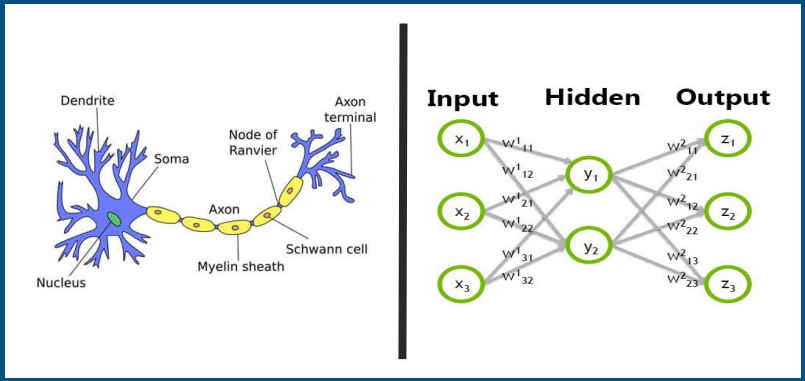
- Smart home (IoT environment) and sensors collect the data on human activity and assist a user by predicting desired behavior
  - Usual patterns -> configuring IoT environment
  - Unusual patterns -> Reminder
- Goal is to train and analyze the collected data by using neural network and predict desired behavior (Jiho Park et al.)

Outline

- Background
  - Neural Network Overview
    - Feedforward Neural Network (FNN)
    - Recurrent Neural Network (RNN)
      - Long Short-Term Memory (LSTM)
      - Gated Recurrent Units (GRU)
- Activity Recognition
- Test and Results
- Conclusion

Neural Networks Overview

- Artificial Neural Networks (ANN)
- Inspired by human brain
- Input layer, one or more hidden layers, and an output layer.
- Nodes or neurons
- Weights between layers



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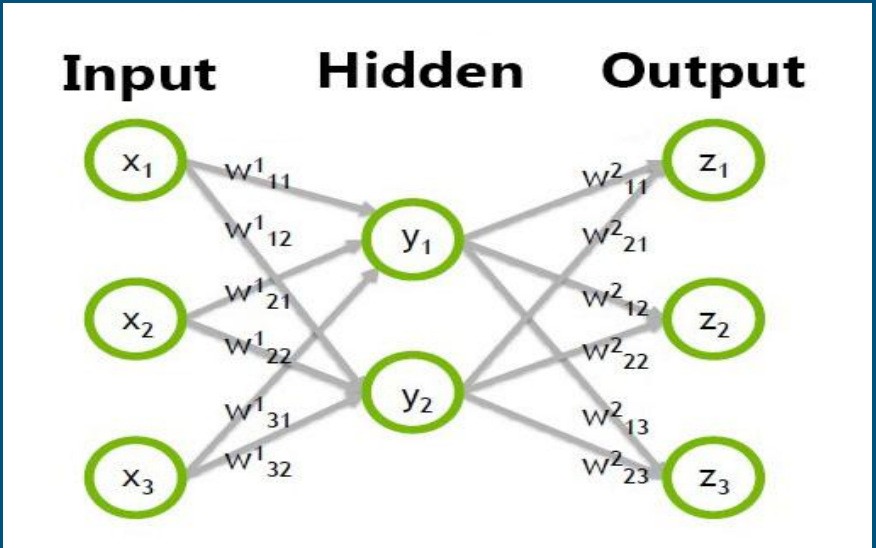
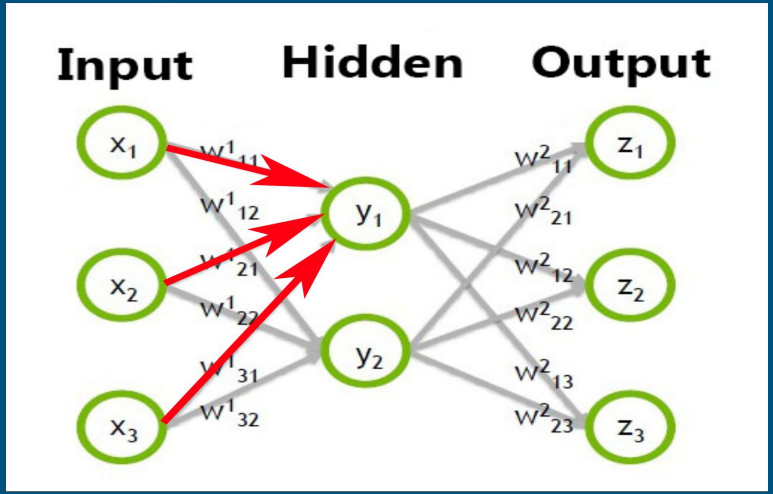
Feedforward Neural Network (FNN)

- Simplest type of ANN
- Connections between the nodes do not form a cycle
  - Only one direction



How FNN works

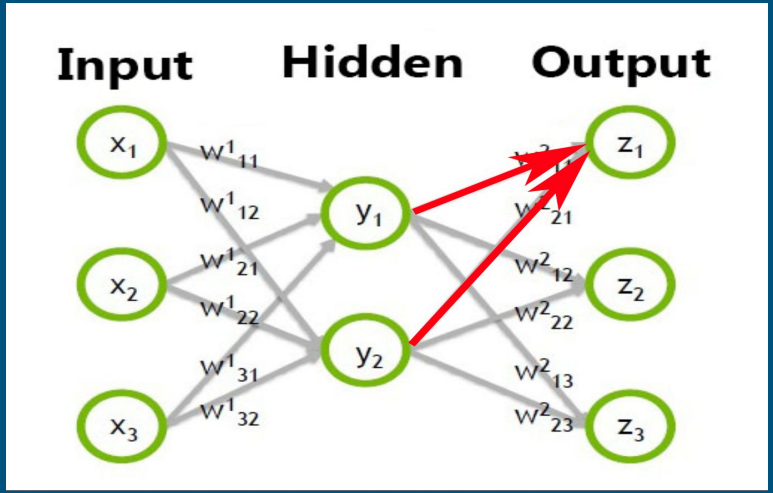
1. Multiply by weight
2. Sum up all the nodes values from the input layers
3. Perform conversion by activation function*



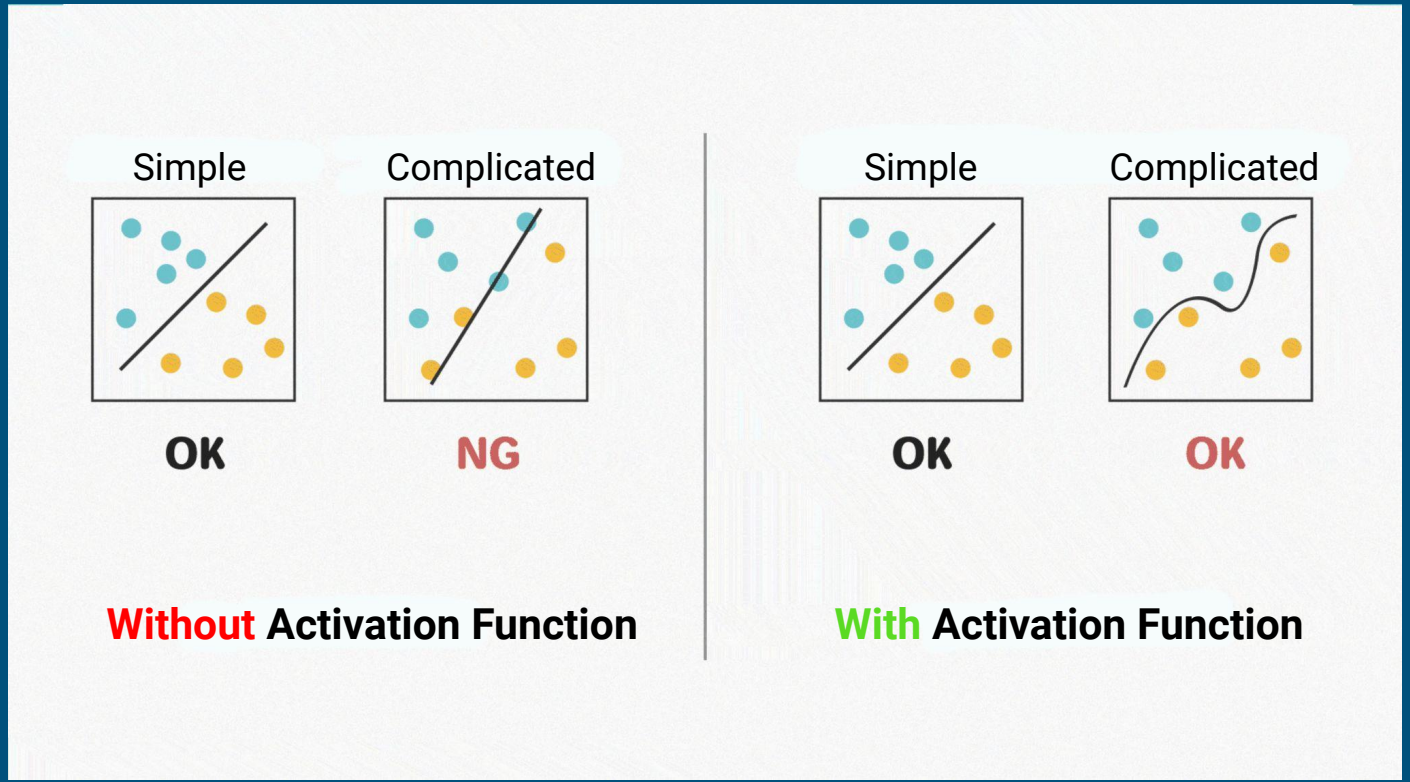
How FNN works

1. Multiply by weight
2. Sum up all the nodes values from the input layers
3. Perform conversion by activation function*

* Non-linear function that determines the output value



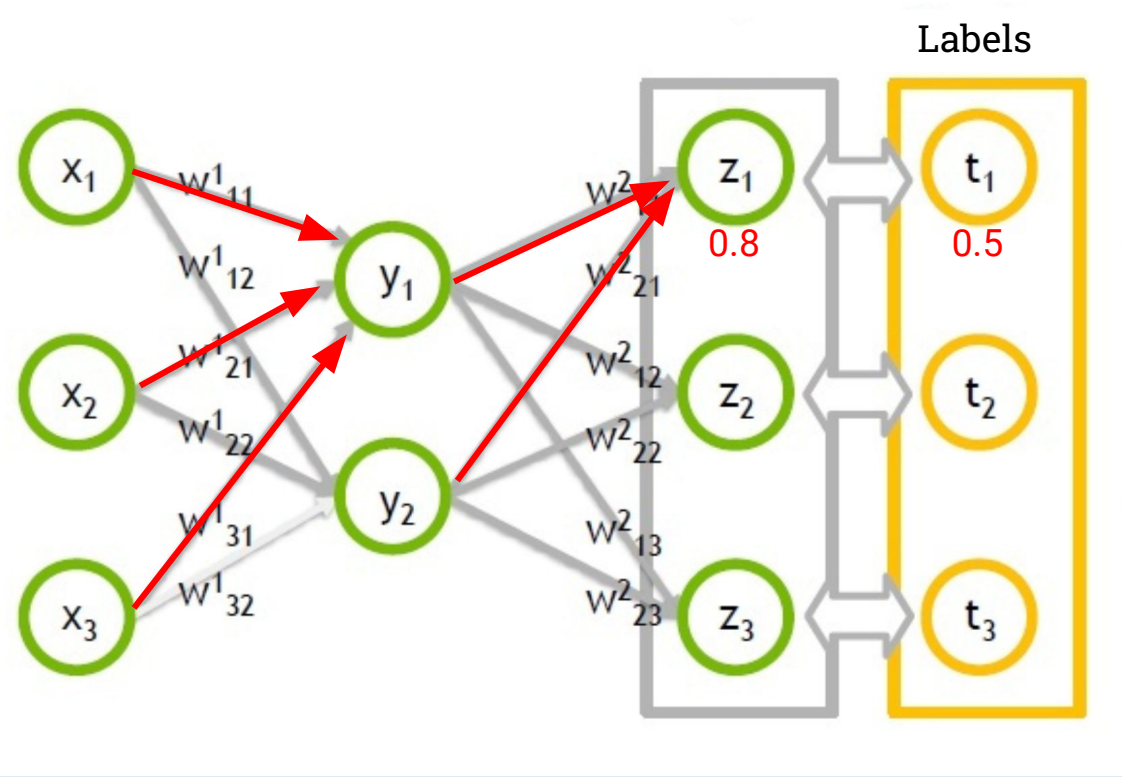
Activation Function



Training Neural Network

- Training Neural Network is important for performance with high accuracy
- Supervised learning
  - A neural network is a type of machine learning model
    - Usually used in supervised learning
  - Giving the answer in advance.
  - Need labeled set of data

Neural Network Training



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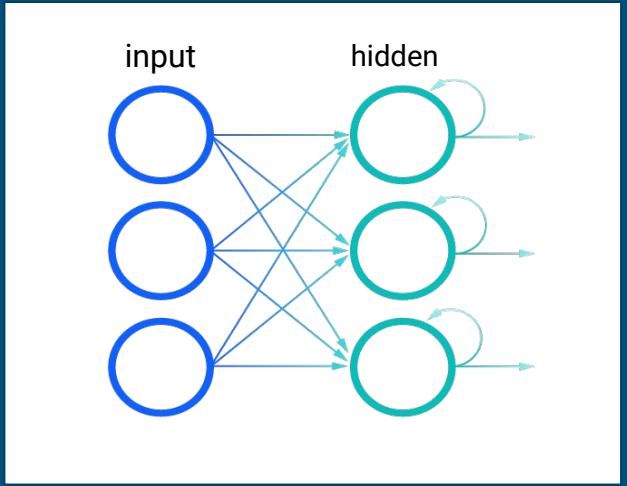
Recurrent Neural Network (RNN)

- Class of ANN
- Derived from FNN
- Internal cycle
- Input is sequential
- Use their internal memory
  - Capable of predicting sequential data
    - Suitable for pattern recognition



The Issue of RNN: **Short-Term Memory**

Cannot carry information when a sequence is long

Solution

Long Short-Term Memory
(LSTM)
and
Gated Recurrent Units
(GRU)

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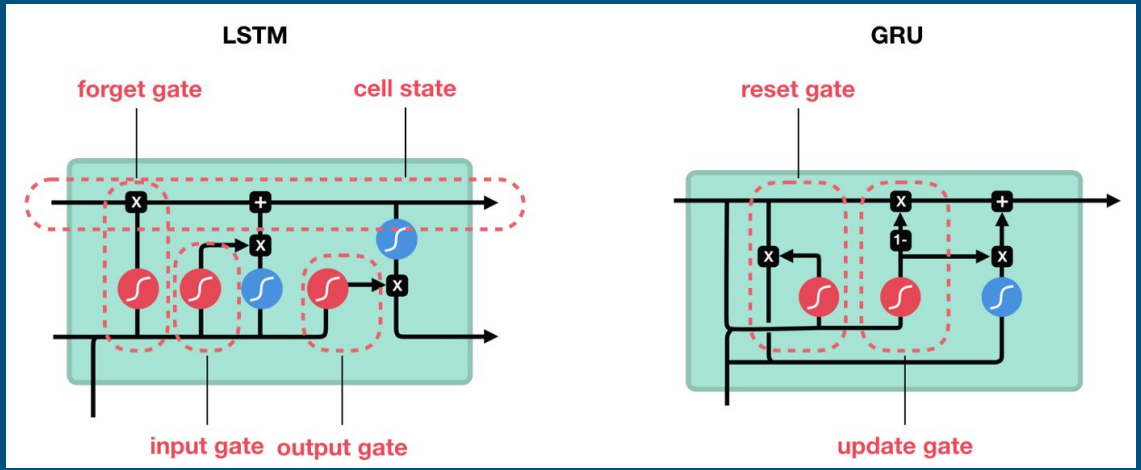
Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)

- Internal mechanism: Gates (2020)
  - Learns which data is important to keep or discard
  - Passes relevant information to make prediction



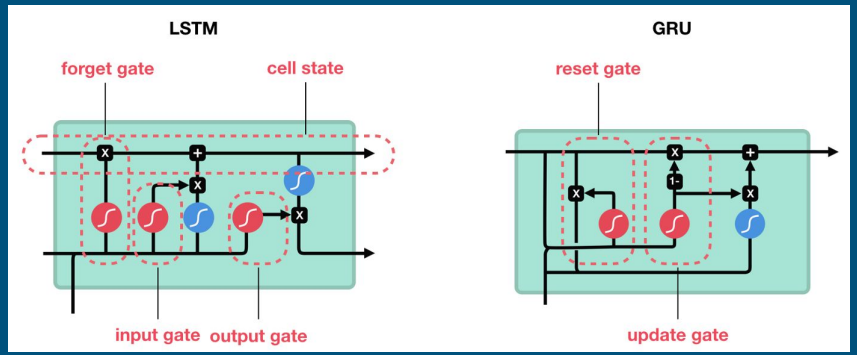
Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)

LSTM

- Cell state
  - Various gates that transfer relative information
- Forget Gate
  - Decides what information should be kept or discarded
- Input Gate
  - Updates the cell state
- Output Gate
  - Decides what the next hidden state should be

GRU

- Reset Gate
  - Decides which information should be kept or not
- Update Gate
  - Another gate to decide how much past information to throw away



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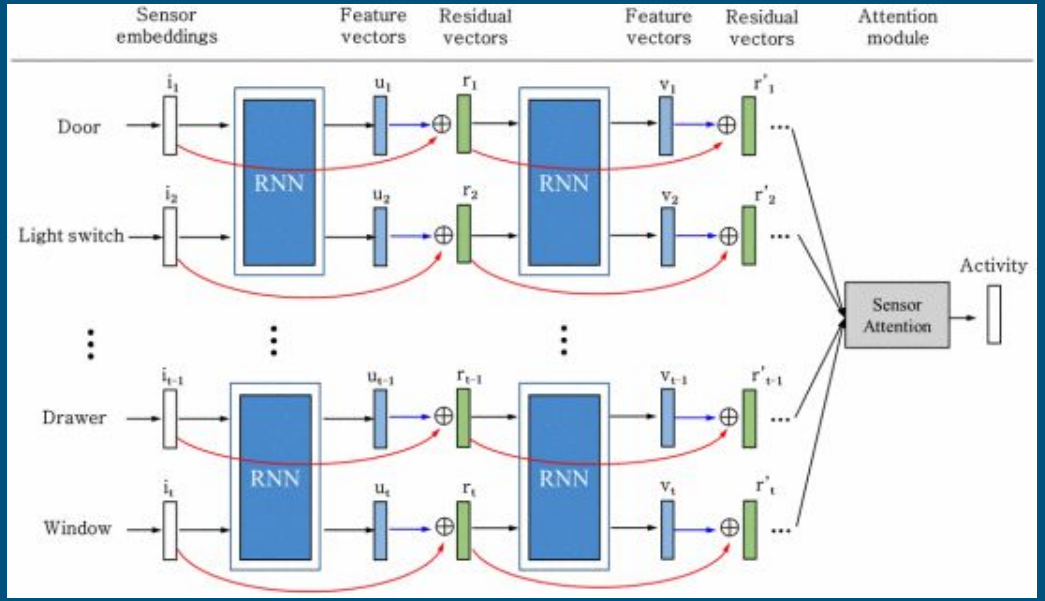
Activity Recognition: Approach

Residual-RNN

- Sensor embedding
  - Sensor-id
- RNN
  - Gates
- Feature vectors
  - Sensor-time label
- Residual vectors
  - Short-term memory
- Attention module
  - Soft attention
    - Probability Distribution



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Test and Results: Datasets

- Data from MIT laboratory (2 weeks)
- One resident (user) in apartment
- Sensors were installed in objects
  - Activated when the machine works or a movement is detected
- 295 activities, 76 sensors, and 2,823 detected activation

Activity name	Toileting	Preparing dinner	Doing laundry
Date	2003-03-28	2003-03-28	2003-03-29
Start time	12:30:56	19:44:07	15:43:11
End time	12:31:20	19:53:47	15:51:18
Sensor 1	Light switch	Cabinet	Door
Sensor 2	Toilet flush	Refrigerator	Washing machine
…			
Sensor n	Cabinet	Oven	Exhaust fan

Test

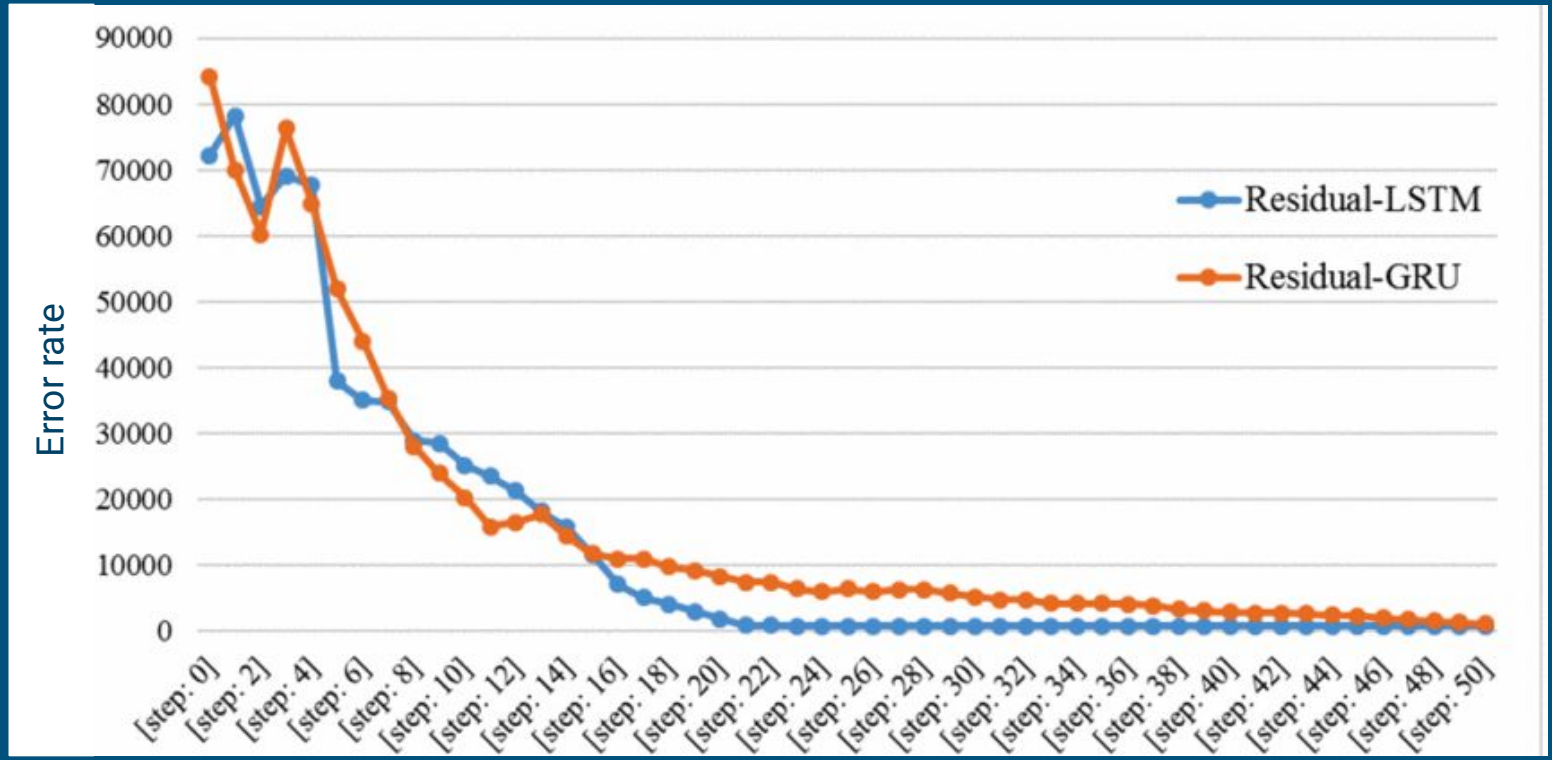
- Randomly split dataset into
  - **Training set** (50%)
    - Used for training the development model
  - **Validation set** (25%)
    - Used to tune the classifier's hyperparameters
  - **Test set** (25%)
    - Used to check the accuracy of the model
- Root Mean Square Error (RMSE)
  - Evaluates how far the prediction and the value are
- Get mean test errors by repeating 20 times

Result

Table of accuracy on test data

Model	10%	20%	30%	40%	50%	60%	70%	80%	90%
ANN	0.6802	0.6713	0.6708	0.6714	0.6738	0.7028	0.7076	0.7132	0.7121
LSTM	0.6803	0.6847	0.6890	0.6937	0.6982	0.7030	0.7075	0.7121	0.7120
GRU	0.6799	0.6842	0.6887	0.6932	0.6976	0.7023	0.7069	0.7115	0.7117
Residual-LSTM	**0.8720**	**0.8777**	**0.8827**	**0.8880**	**0.8930**	**0.8971**	**0.9013**	**0.9049**	**0.9085**
Residual-GRU	0.8652	0.8216	0.8516	0.8652	0.8652	0.8885	0.8812	0.9000	0.8952

Results


Error rate
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
Residual-LSTM
Residual-GRU
[step: 0]
[step: 2]
[step: 4]
[step: 6]
[step: 8]
[step: 10]
[step: 12]
[step: 14]
[step: 16]
[step: 18]
[step: 20]
[step: 22]
[step: 24]
[step: 26]
[step: 28]
[step: 30]
[step: 32]
[step: 34]
[step: 36]
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[step: 40]
[step: 42]
[step: 44]
[step: 46]
[step: 48]
[step: 50]

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Conclusion

- Park et al. developed activity recognition in an IoT environment with Residual-RNN and compared to other networks
- Park et al. successfully train and analyze the data by using neural networks
- Residual-RNN performs better with high accuracy than other networks

Acknowledgements

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References

- J. Park, K. Jang and S. -B. Yang, "Deep neural networks for activity recognition with multi-sensor data in a smart home," 2018 IEEE 4th World Forum on Internet of Things (WF-IoT), 2018, pp. 155-160, doi: 10.1109/WF-IoT.2018.8355147.
- Phi, M. (2020, June 28). *Illustrated guide to LSTM's and GRU's: A step by step explanation*. Medium. Retrieved April 14, 2022, from https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

Questions?