DEEP LEARNING 4
NETWORK TRAFFIC PREDICTION

INTRODUCTION

- **Network traffic prediction** is a form of time-series forecasting that allows operators to manage networks more efficiently.
- Accurate traffic prediction **can improve a network's performance**, in areas such as congestion management, resource distribution and volume alerts.
- Most neural network models find it difficult to learn long-range temporal relationships in a dataset, however, Long short-term memory **(LSTM) models can capture the long and short-term trends in network traffic data.**
- This project implemented **three LSTM models for traffic prediction on the SANReN**. SANReN is a country-wide network of education and research institutions in South Africa.

RESEARCH QUESTIONS

Considering that both prediction accuracy and computational cost were important in model selection, the following research questions were set out:

- How does the SANREN traffic data vary with time and day **in relation to the South African university calendar?**
- What is the **computational cost** of different LSTM architectures, given a required level of accuracy in predicting future traffic flows on the SANREN?
- Which of the LSTM models, Bidirectional, Simple or Stacked, **provides the highest accuracy when predicting future SANREN traffic data**, subject to network constraints?

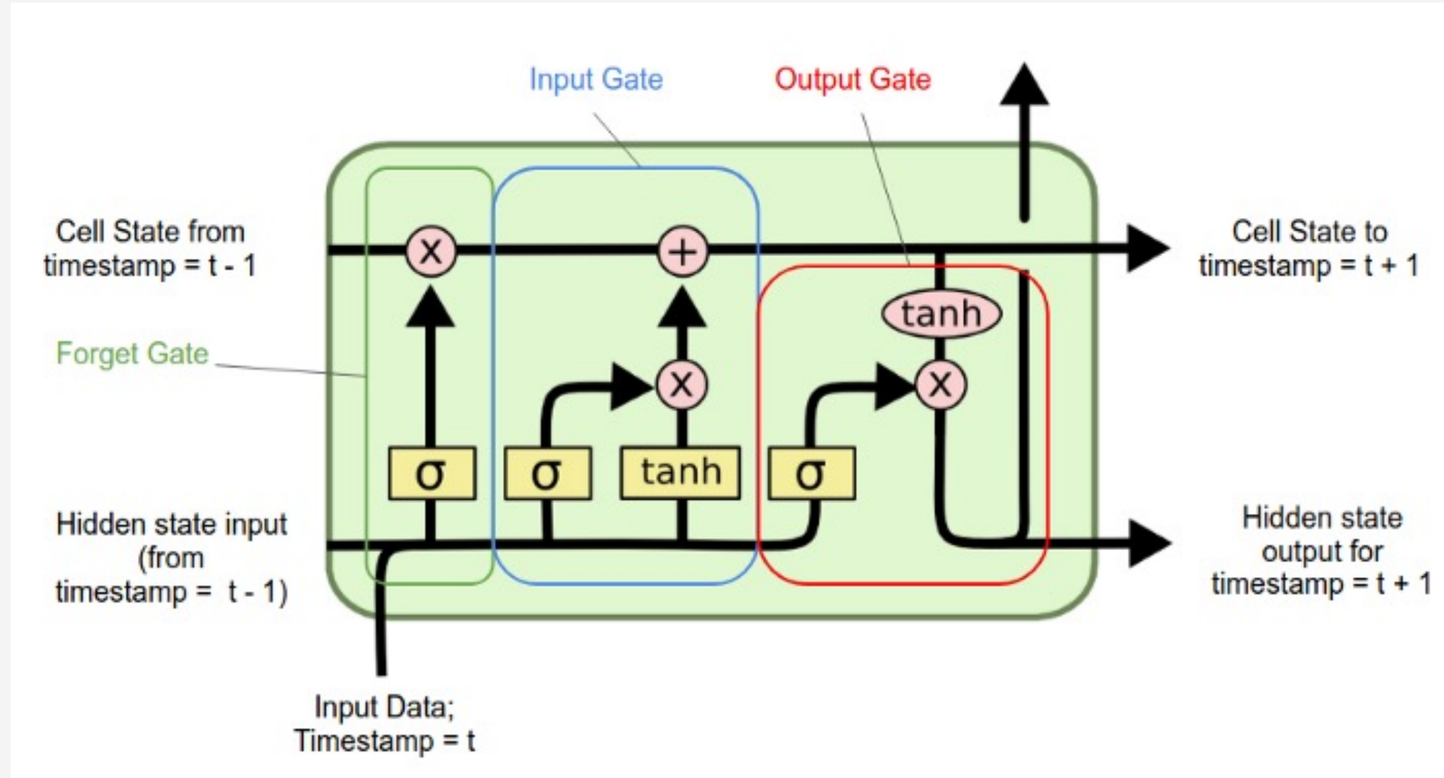
RESULTS

- The results show that **the stacked LSTM is the most accurate model**. It had the best MSE by 40% and the highest R^2 by 23%.
- However, **it also takes the longest to train** – nearly double the simpler models.
- Prediction accuracy for all models increased with sample size - at the **cost of an increased training time.**
- **The bidirectional LSTM is the least accurate predictor** and does not justify its additional complexity.
- The preliminary statistical analysis also determined that **there is no obvious pattern linking SANReN network traffic flows with the university calendar.**

CONCLUSIONS

- The **stacked LSTM is the recommended model for the SANReN network traffic prediction use case.**
- By using the stacked LSTM as a network traffic predictor, SANReN **will be able to implement measures to manage network congestion and network resources.**
- However, **given a complexity constraint**, the simple LSTM's accuracy may be an adequate network traffic predictor on a low resource network.
- The positive skew in the sample resulted in none of the models being able to model **the volatility of the short-term burst flows.**

LSTM DESIGN AND DEVELOPMENT

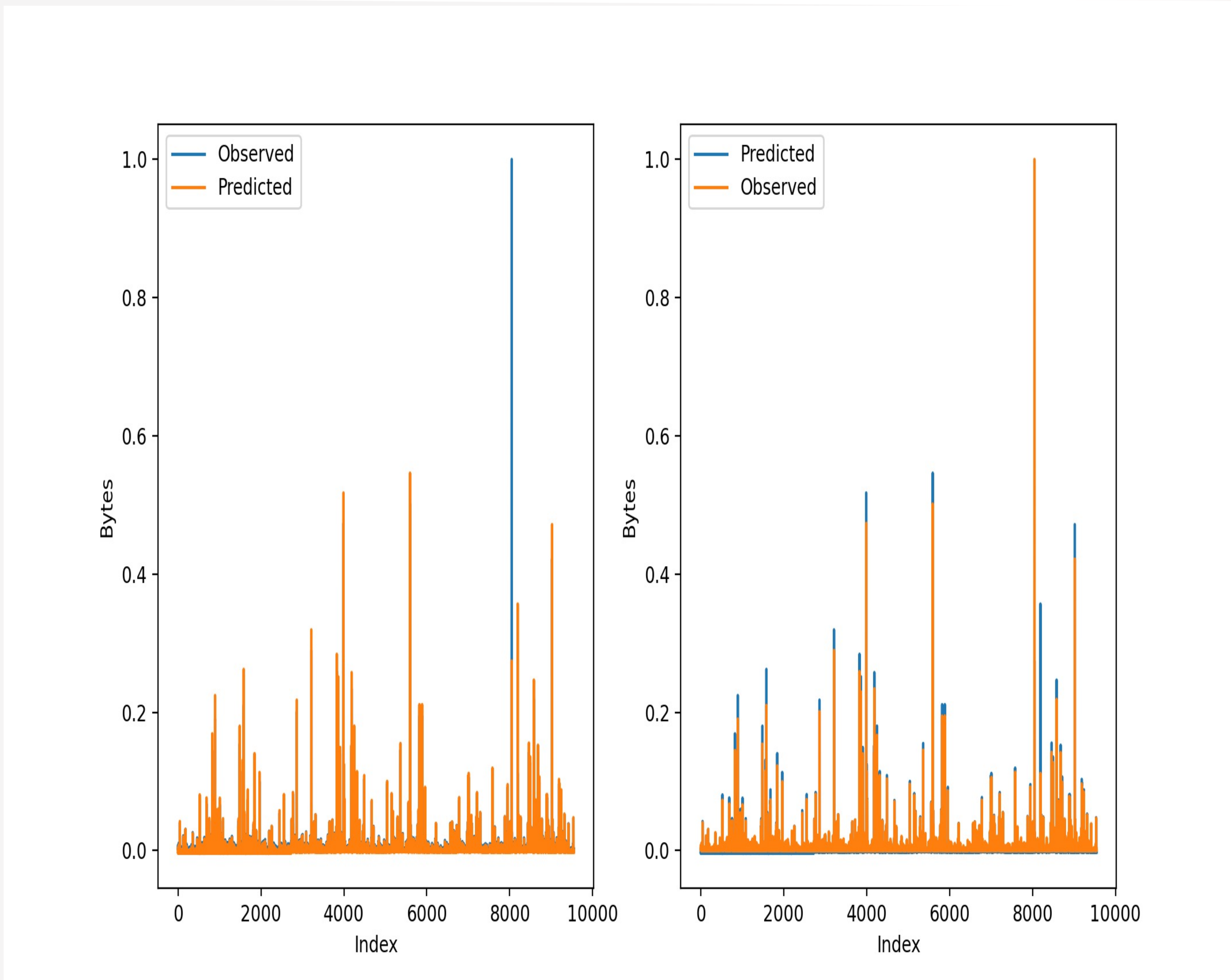


An example of a LSTM Cell and its gates. Input is received from the previous cell and passes through the forget gates, where values deemed unimportant are dropped. Eventually new values are sent to the next cell through the output gate.

The LSTM models were implemented in Python using the Keras. Each model was optimised as a predictor using a hyperparameter grid search. The three LSTM models' architectures are:

- A **simple LSTM**, also known as a vanilla LSTM, is an LSTM with a single hidden layer.
- A **bidirectional LSTM** involves duplicating the first recurrent layer in the network. It then provides a reversed copy of the input sequence to the reversed layer.
- A **stacked LSTM** is a simple LSTM with multiple LSTM layers. Rather than producing a scalar output, the LSTM layer will provide a sequence output to the LSTM layer below it.

Model	MAE	MSE	R^2	Training (s)
Bidirectional	0.0078	0.00013	0.55	306.60
Simple	0.0063	0.00010	0.65	**293.67**
Stacked	**0.0029**	**0.00006**	**0.80**	591.20



Predicted vs observed bytes using the stacked LSTM

UNIVERSITY OF CAPE TOWN - DEPARTMENT OF COMPUTER SCIENCE
Justin Myerson – MYRJUS002@MYUCT.AC.ZA
Antony Fleischer – FLSANT005@MYUCT.AC.ZA
Supervisor: Dr. Josiah Chavula