EDI END SEMESTER ASSESSMENT SEM I 2024-25

Comparative Performance Analysis of GAN, LSTM, and GRU for Financial Time Series Forecasting

DIVISION: ET-C **GROUP_NUMBER: 4** **DATE: 27/11/2024**

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INTRODUCTION

Stock price prediction is an interesting and challenging topic and is a kind of time series forecasting. Many classic algorithms are used in time series forecasting, such as LSTM, GRU and GAN.

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Project goal:

- Compare the basic LSTM, GRU and GAN, and improve the model to get more accurate prediction.

Contribution:

- Input different features-- Compare the different models' performance Improve GAN by adjusting the loss function

PROBLEM STATEMENT

- To use GAN to predict the stock system can help improve the time series prediction.
- Utilize the GANs to see if it can perform better than traditional LSTM and GRU model, unlike the traditional GANs, the GAN model will be implemented with a RNN as a generator and a CNN as a discriminator.

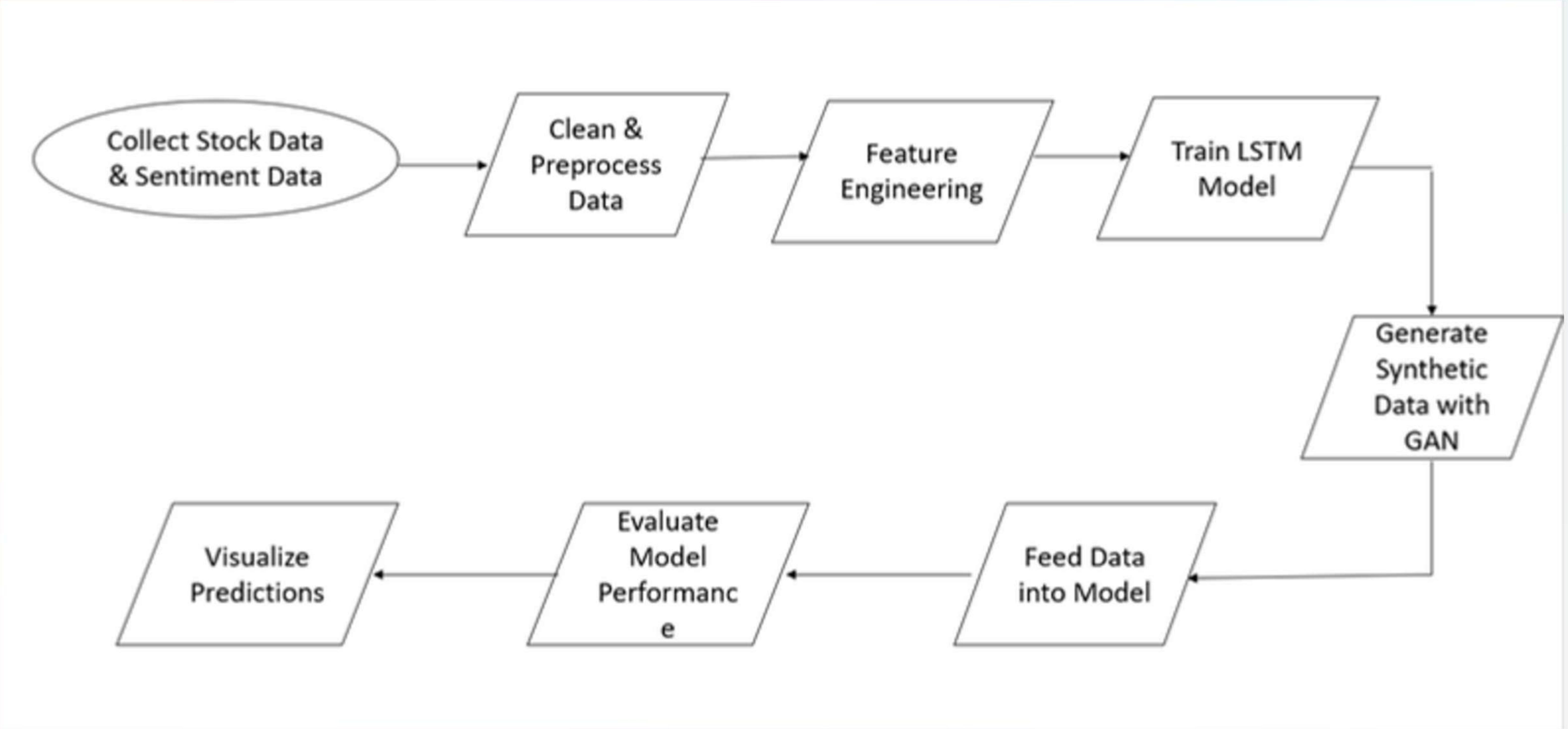
OBJECTIVE

- Compare Different methods like LSTM, GAN, GRU for time series forecasting
- Evaluate the Performance of each method

LITERATURE REVIEW

PAPER	AUTHOR	METHODOLOGY
STOCK PRICE MANIPULATION DETECTION USING GENERATIVE ADVERSARIAL NETWORKS	TEEMA LEANGARUN, POJ TANGAMCHIT, SUTTIPONG THAJCHAYAPONG	An unsupervised learning framework using GAN and LSTM networks to detect stock price manipulation, trained solely on normal trading data. The model effectively identifies anomaly behaviors, achieving 68.1% accuracy in detecting pump-and-dump schemes without requiring labeled manipulation data.
STOCKGAN: ENHANCING STOCK PRICE PREDICTION WITH GAN AND SENTIMENT ANALYSIS	MUSKAAN BHARDWAJ, ADITYA ROY, SAURABH BILGAIYAN	The optimization of LSTM models for stock price prediction in the Indian market, addressing challenges like noise, seasonality, and trends. It provides valuable insights into selecting LSTM hyperparameters and compares stateful and stateless models.

METHODOLOGY



Data Source

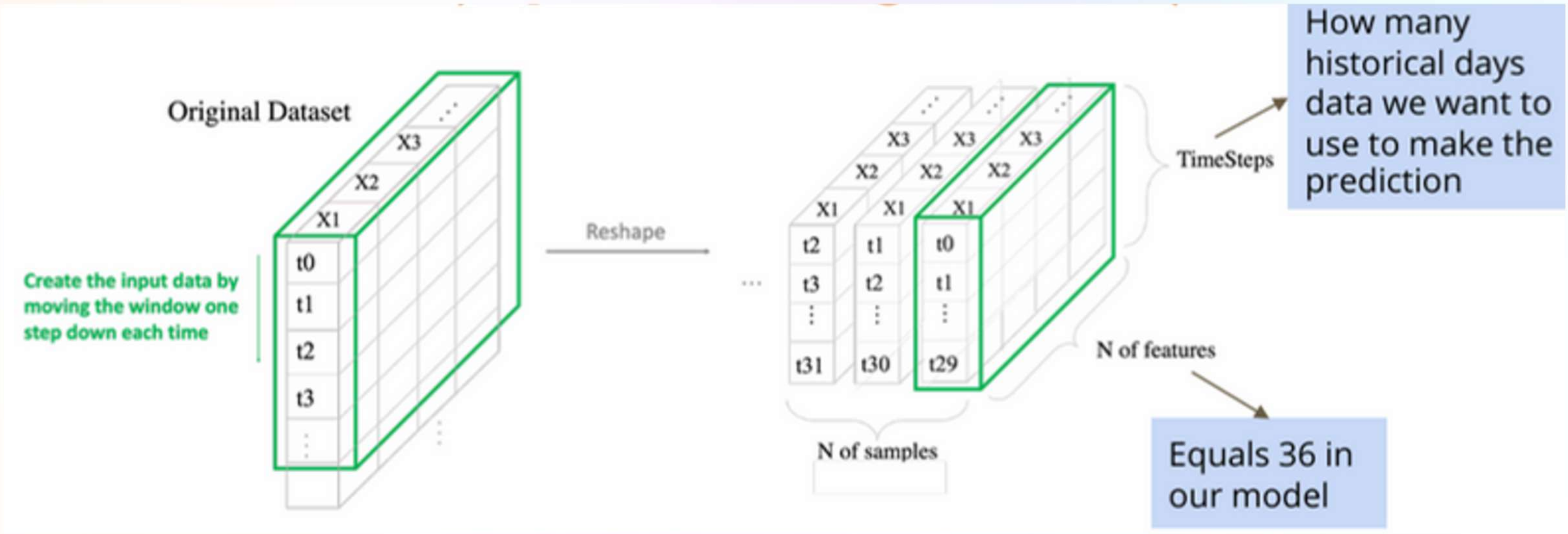
- Target(predicted stock price): Apple.Inc closing price.
- Feature:
    - 1. The stock price and stock index are from Yahoo Finance
    - 2. The dollar index is from Fred
    - 3. News sentiment data are scrapped from Seeking Alpha
    - 4. Calculated statistical data

Data Source

- Days: 2497
- Features: 36
- Train/Test split: 7： 3

Feature Name			
Open	Nikki225	Amazon	EMA
High	BSE SENSEX	Goolgle	logmomentum
Low	RUSSELL2000	Microsoft	absolute of 3 comp
Close	HENGSENG	MA7	angle of 3 comp
Volume	SSE	MA21	absolute of 6 comp
NASDAQ	CrudeOil	20SD	angle of 6 comp
NYSE	Gold	MACD	absolute of 9 comp
S&P500	VIX	upper	angle of 9 comp
FTSE100	USD index	Lower	News

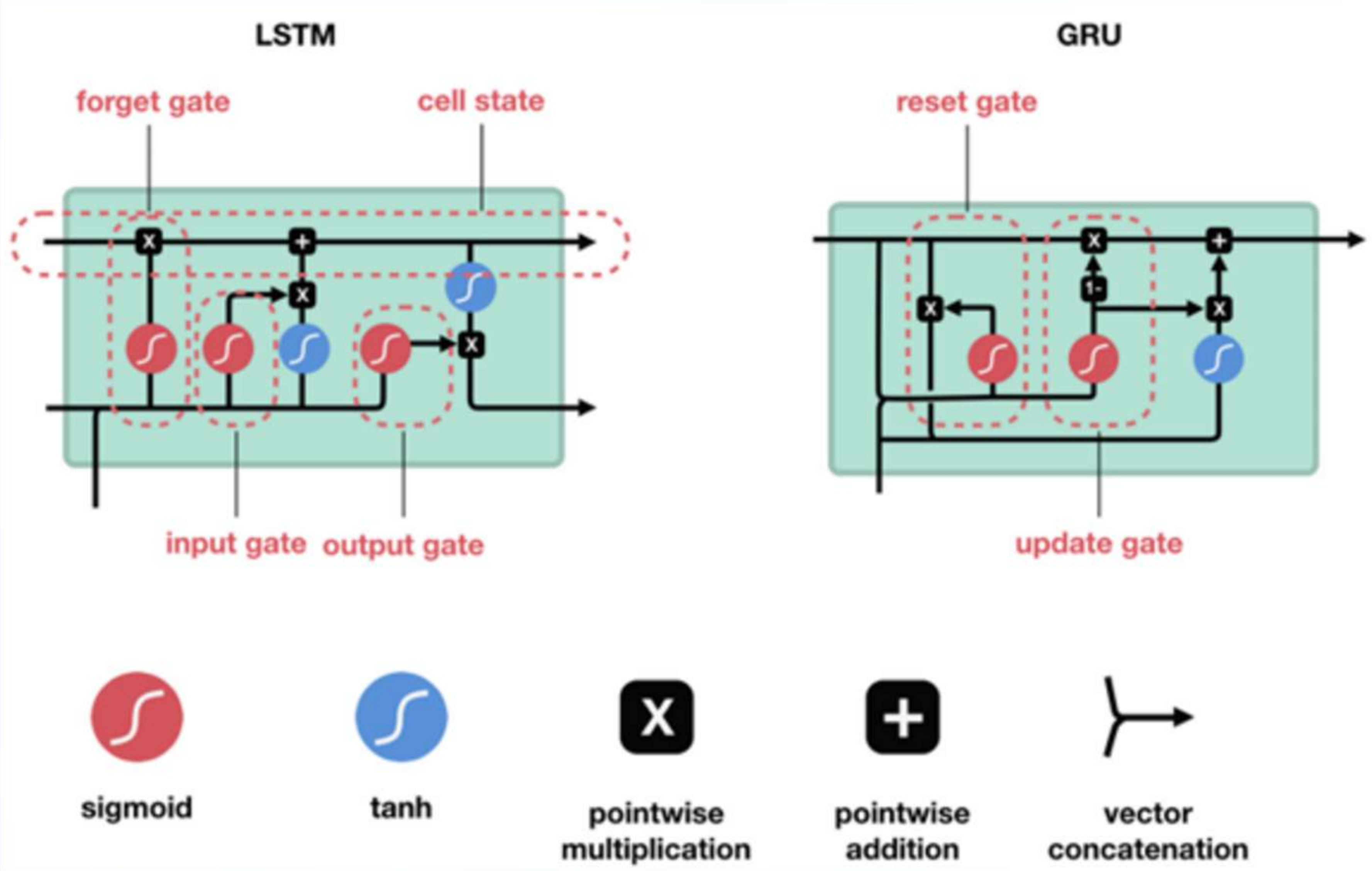
Data Structure(input data of generator)



- The original dataset is 2 dimensional, we need to reshape the data to 3 dimensions according to the timesteps

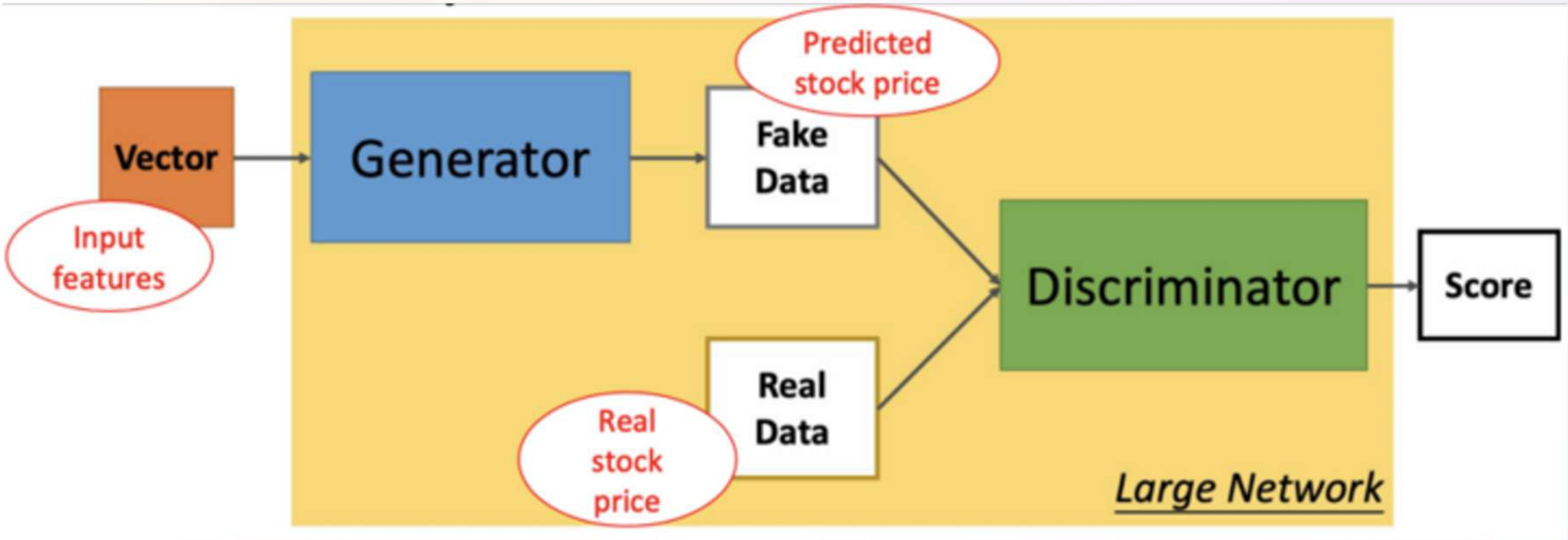
Model Theory (RNN)

- Structure:
  - LSTM(1997): Input, output and forget gate
  - GRU(2014): Reset and update gate



- Samepoints:
  - Prevent the vanishing gradient problem in traditaional RNN
  - Perform well on dealing with sequence of data
- Differentpoints:
  - LSTM has the cell state to store the memory, but GRU only has the hidden state
  - GRU train quick and has less parameters

Model Theory(Original GAN)



x:Input for generator
y:Real price from original data
G(x^i): Generated price (fake price)

- GAN basically made up of two competing neural network models
- The Generator generates fake data and tries to fool the Discriminator
- The Discriminator tries to distinguish between the real data and fakedata

Loss function of Descriminator:

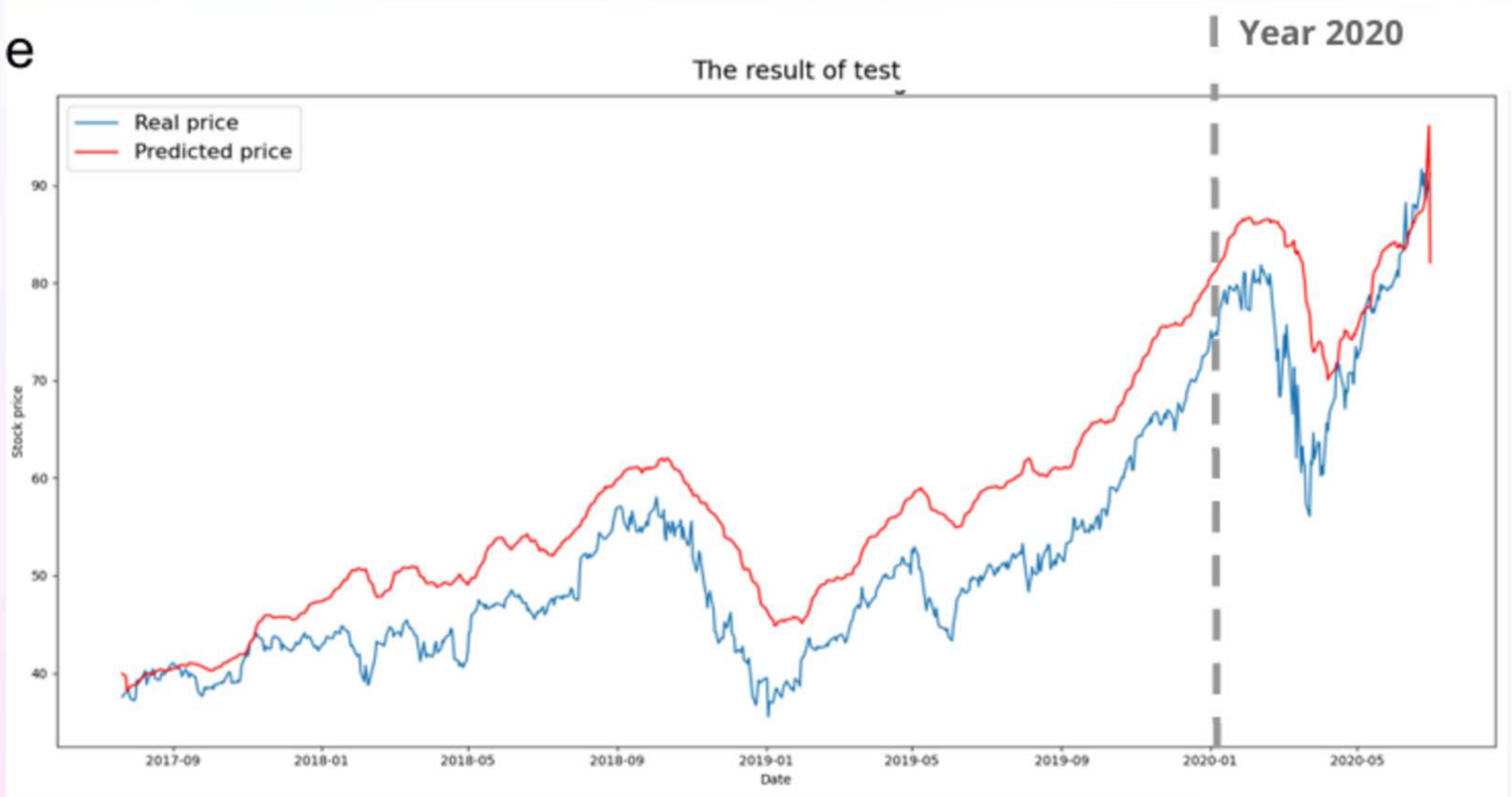
$$-\frac{1}{m}\sum_{i=1}^{m} log\ D(y^{i}) - \frac{1}{m}\sum_{i=1}^{m}(1 - log\ D(G(x^{i})))$$

Loss function of Generator:

$$-\frac{1}{m}\sum_{i=1}^{m}(log\ D(G(x^{i})))$$

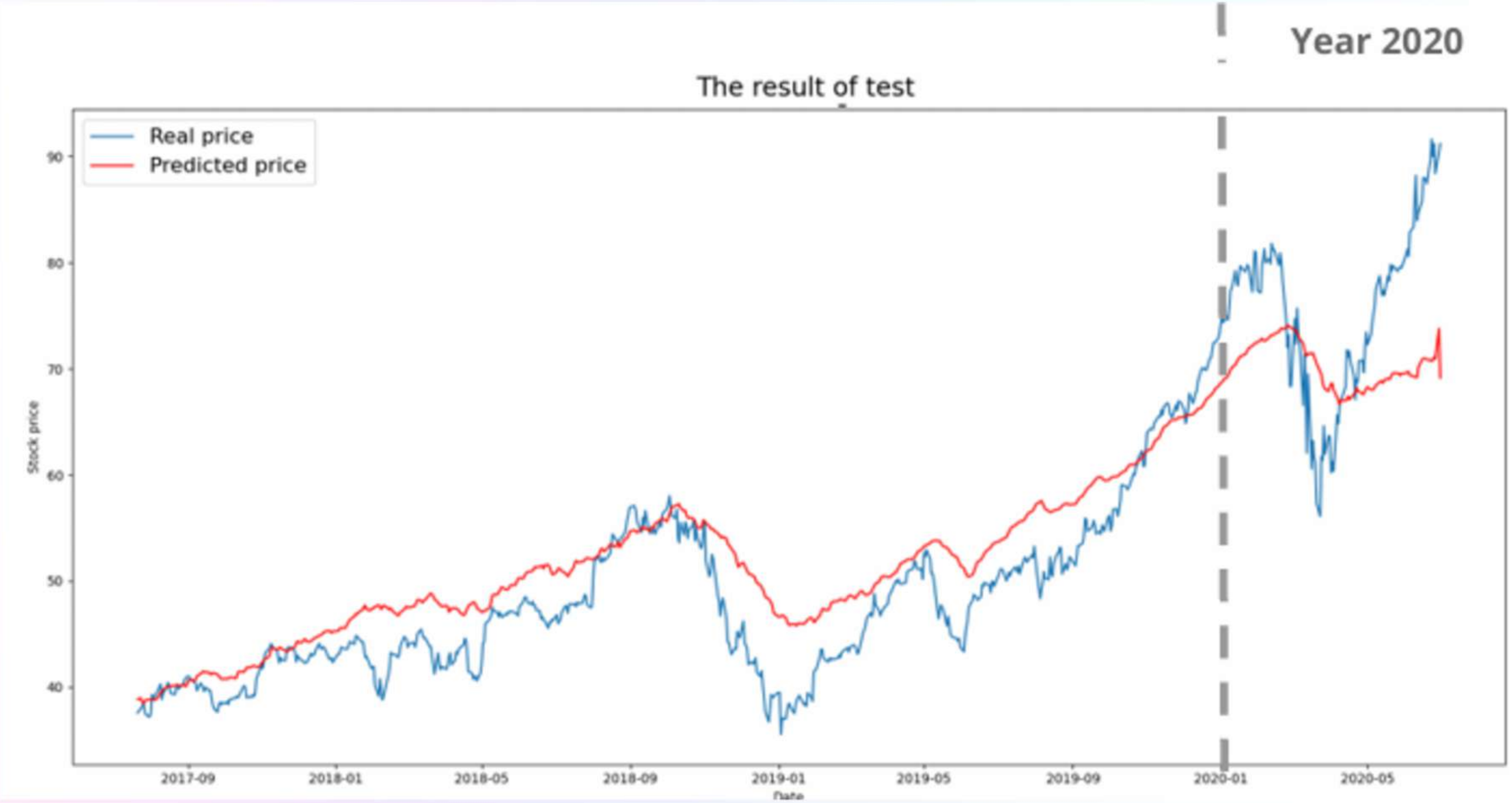
Experimental and Result (LSTM)

- Structure:
  - Bidirectional(LSTM) + Dense
- Hypermarameter:
  - Batch_size: 64
  - Epoch: 50
  - Learning _rate: 0.001
- RMSE(include 2020): 6.60
- RMSE(exclude 2020): 9.42



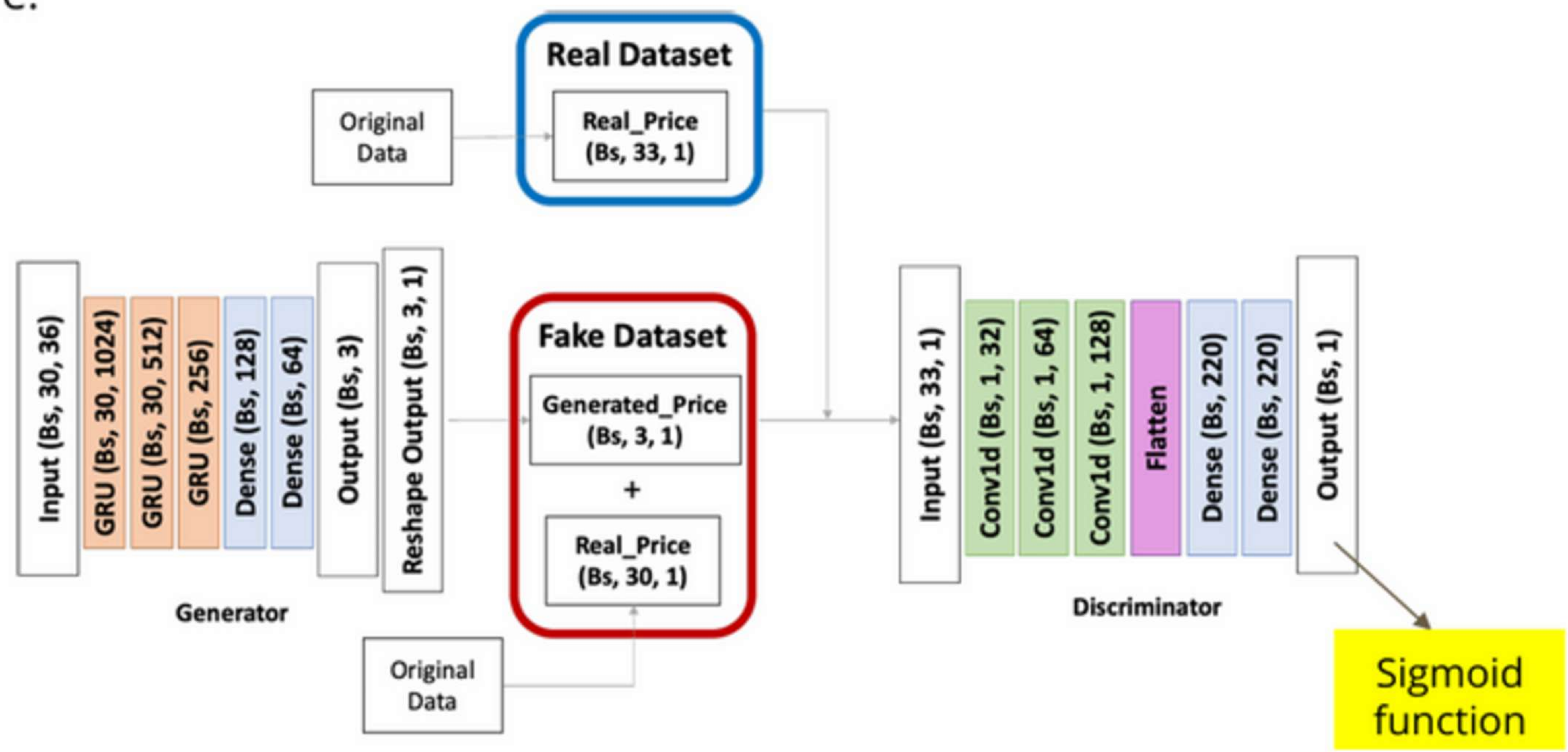
Experimental and Result (GRU)

- Structure:
  - GRU + GRU
- Hypermarameter:
  - Batch_size: 128
  - Epoch: 50
  - Learning _rate: 0.0001
- RMSE(include 2020): 5.33
- RMSE(exclude 2020): 4.08



Experimental and Result (Basic GAN))

- Structure:

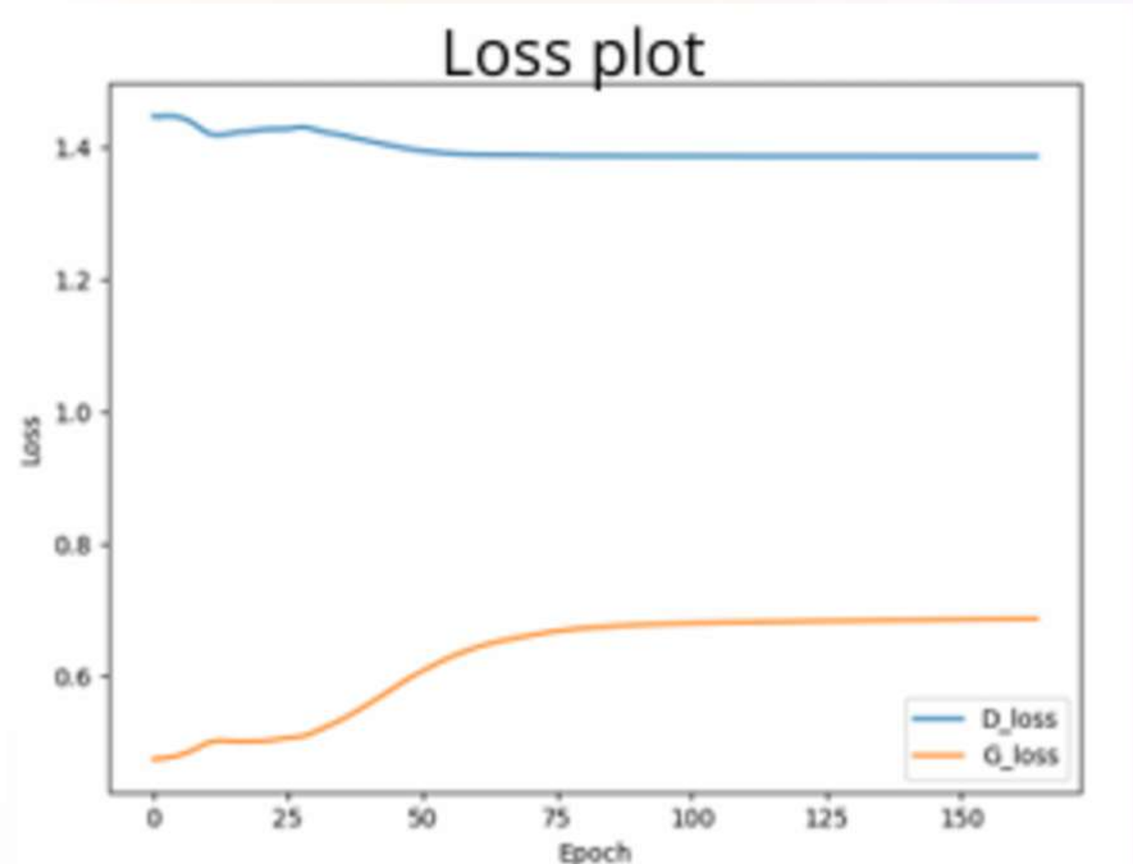


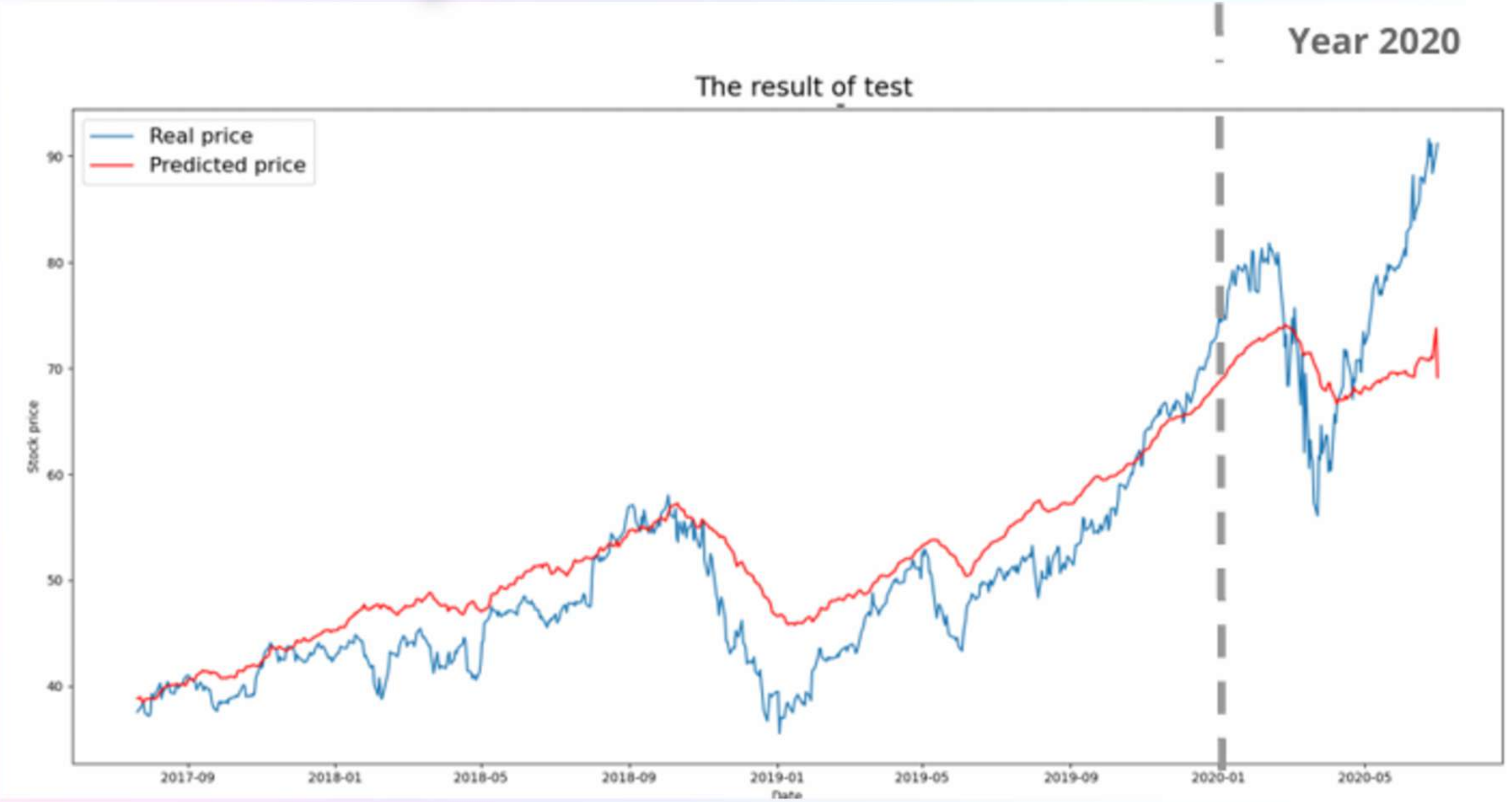
Experimental and Result (Basic GAN)

- Hypermarameter:
  - Batch_size: 128
  - Epoch: 165
  - Learning _rate: 0.00016

- RMSE(include 2020): 5.36

- RMSE(exclude 2020): 3.09





Evaluation

	LSTM	GRU	Basic GAN	WGAN-GP
RMSE of Training dataset	1.52	$\boxed{1.00}$	1.64	1.74
RMSE of Testing dataset (include 2020)	6.60	5.33	5.36	$\boxed{4.77}$
RMSE of Testing dataset (exclude 2020)	9.45	4.08	$\boxed{3.09}$	3.88

RESULTS

- **Effective Feature Engineering:** Created 19 features, such as momentum, moving averages, EMA, and Bollinger Bands, which improved model performance. Fourier Transform models delivered accurate predictions with low AIC and BIC values and close p-values.

- **LSTM Model Limitations:** LSTM models, whether using single or multiple features, did not achieve desired prediction accuracy. They are better suited for forecasting long-term price trends rather than short-term stock prices. Future efforts will focus on utilizing a larger dataset to enhance prediction accuracy.

Conclusion

- Compared the GAN model with the traditional models, the GAN model can help to improve the GRU model and LSTM model, both basic GAN and WGAN-GP perform better than traditional models.
- When there is an unexpected event like COVID-19, WGAN-GP performs better than basic GAN, but in normal periods, basic GAN performs better.
- GAN model including RNN is unstable, it is very difficult for these models to tune hyperparameters, without good parameters you may have bad results.

Reference

- K. Zhang, G. Zhong, J. Dong, S. Wang, and Y. Wang (2019), “Stock Market Prediction Based on Generative Adversarial Network,” Procedia Computer Science, vol. 147, pp. 400–406, 2019.
- Bhardwaj, Anjul, and Uday Pratap Singh. "An Empirical Study on: Time Series Forecasting of Amazon Stock Prices using Neural Networks LSTM and GAN models." In Proceedings of the 5th International Conference on Information Management & Machine Intelligence, pp. 1-10. 2023.
- Faraz, Mehrnaz, Hamid Khaloozadeh, and Milad Abbasi. "Stock market prediction-by-prediction based on autoencoder long short-term memory networks." In 2020 28th Iranian conference on electrical engineering (ICEE), pp. 1-5. IEEE, 2020.

THANK YOU