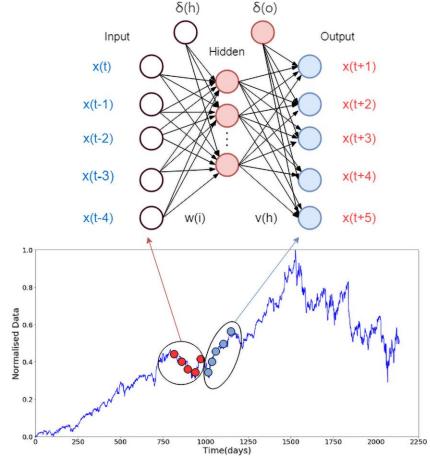
# Stock Market Prediction using Ensemble of Graph Theory, Machine Learning and Deep Learning Models

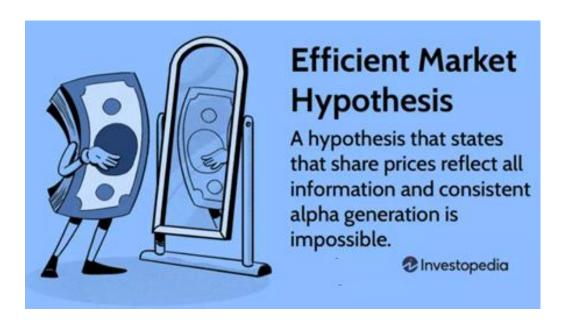
(2020, ACM: Pratik Patil, Ching-She, Katerina Potika, Marjan Orang)

### **Present my Implementation**

Sayed Ahmed



### The Problem

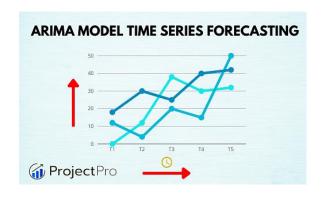


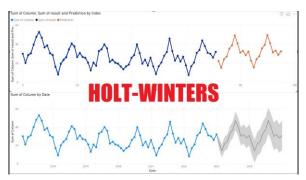
 "Opponents of EMH believe that it is possible to beat the market and that stocks can deviate from their fair market values." [2]

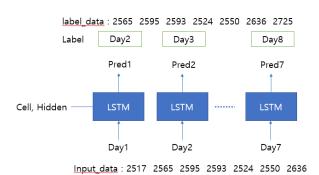
- We predict stocks using
  - Usually: Proper selection of
    - Stocks and Time Intervals
      - Statistics
      - Machine Learning

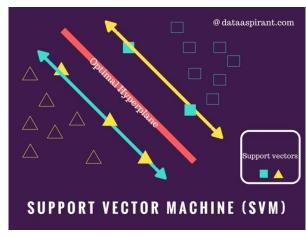
- This paper goes beyond and Uses
  - Spatio-Temporal Relationship
    - among stocks
  - Graph theory

### Related Work

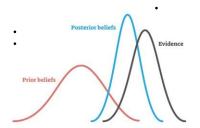




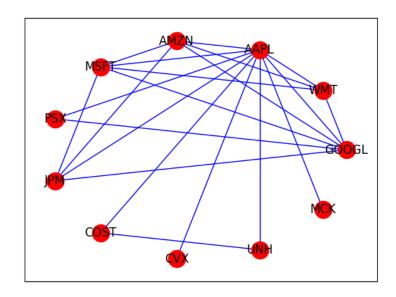


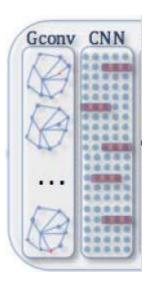


#### **BAYESIAN ANALYSIS**

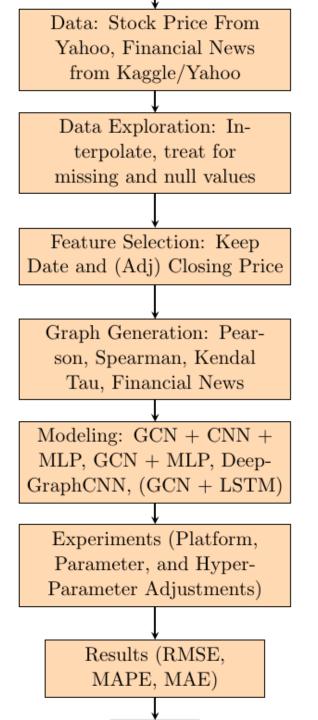


# **Graph Based**





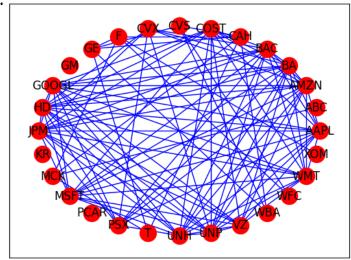
# Methodology



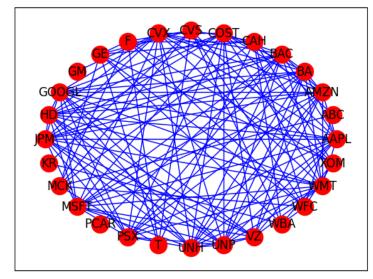
### **Dataset**

- Final
  - 30 (28) Stocks from
    - Fortune 500 companies
  - Stock Price Data
    - 1-day interval (2017-01 to 2019-12)
  - News dataset:
    - Yahoo News Articles
    - Couple Thousands ( > 15000)
- Another Dataset/Started with
  - From Kaggle
  - With Nasdaq, NYSE data

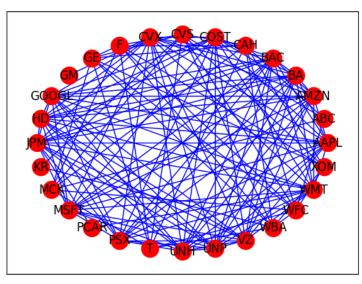
# Model Stocks into Graph



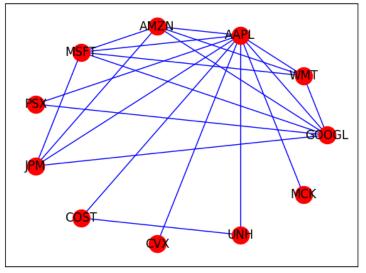
Pearson based



Kendal Tau based



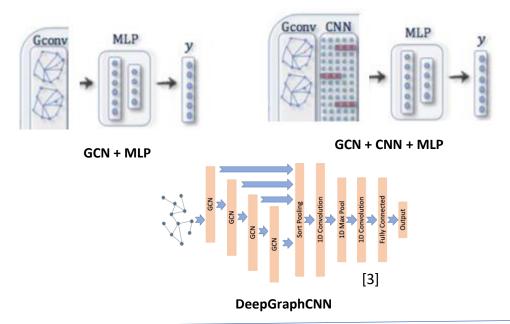
Spearman based

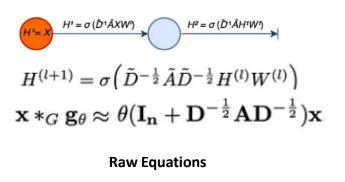


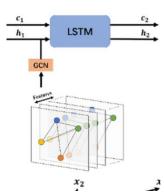
Financial News based

## **Models and Platforms**

### **Models**



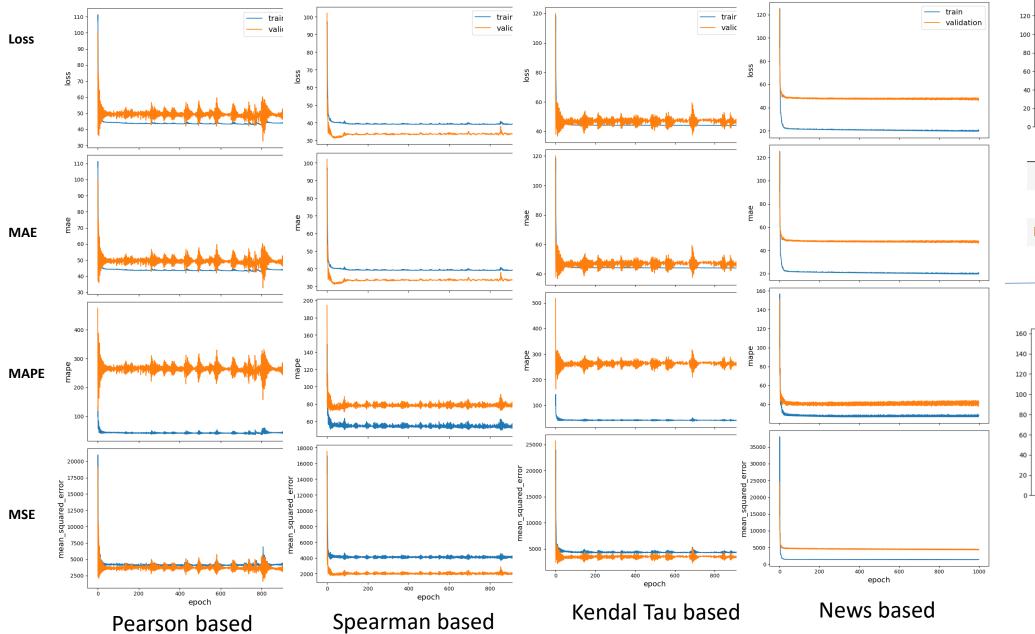


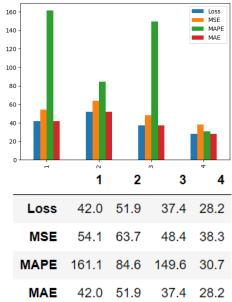


### **Platforms**

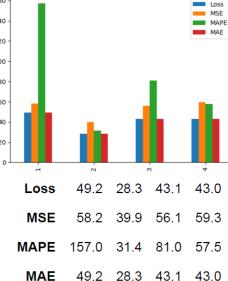
- CPU with 16 GB ram
- Intel Coe i7
- Jupyter Notebook
- Python
- Stellar Graph
- Networkx
- NLTK
- yFinance

### Results: 1st Case: GCN + MLP: Performance (1000 Epochs)



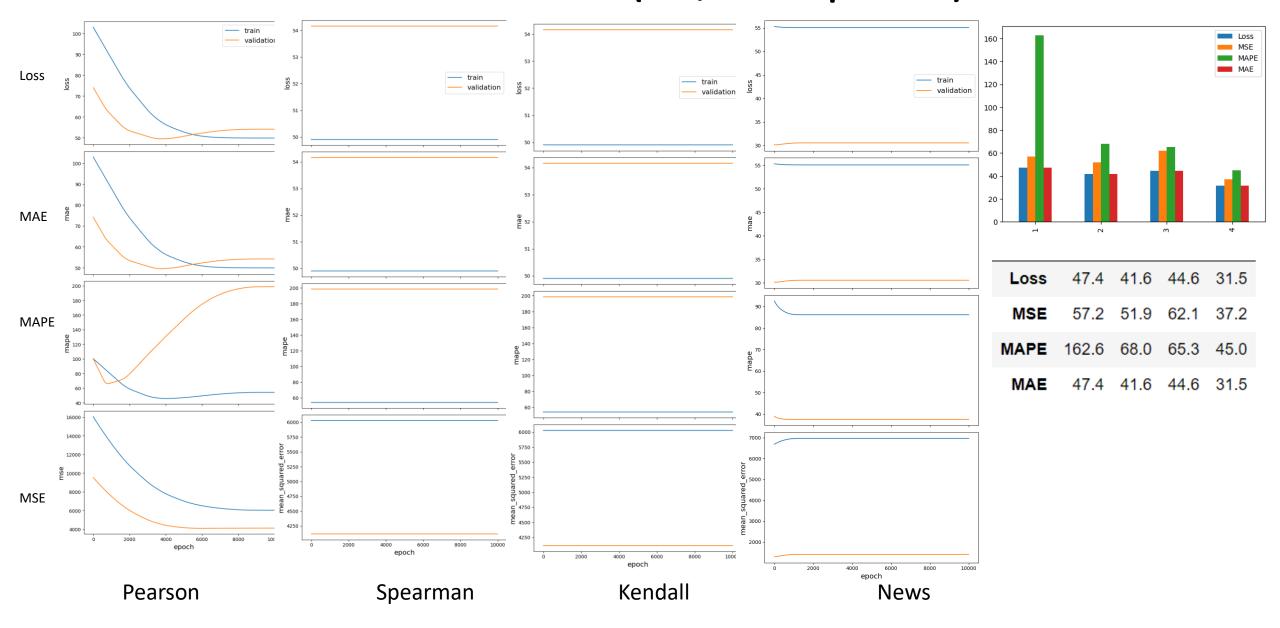




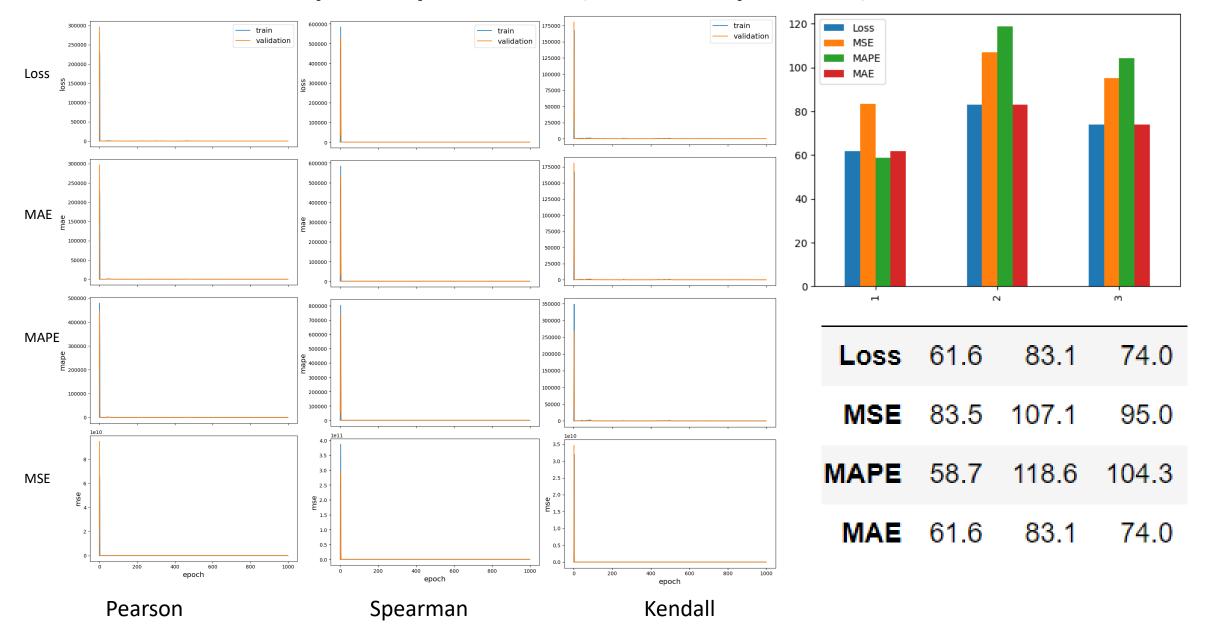


2<sup>nd</sup> Case: GCN + CNN + MLP (1000 Epochs) Mae Loss 39.8 72.6 34.6 64.3 Mape & \* 48.0 98.3 42.5 90.6 MAPE 66.7 57.6 89.7 40.4 MAE 39.8 72.6 34.6 64.3 Mse Loss Mae Mape 97.5 58.8 51.3 50.4 MSE 122.5 71.9 80.7 79.7 75.5 58.2 79.4 37.2 Mse MAPE 97.5 58.8 51.3 50.4 Kendall **Pearson** Spearman News

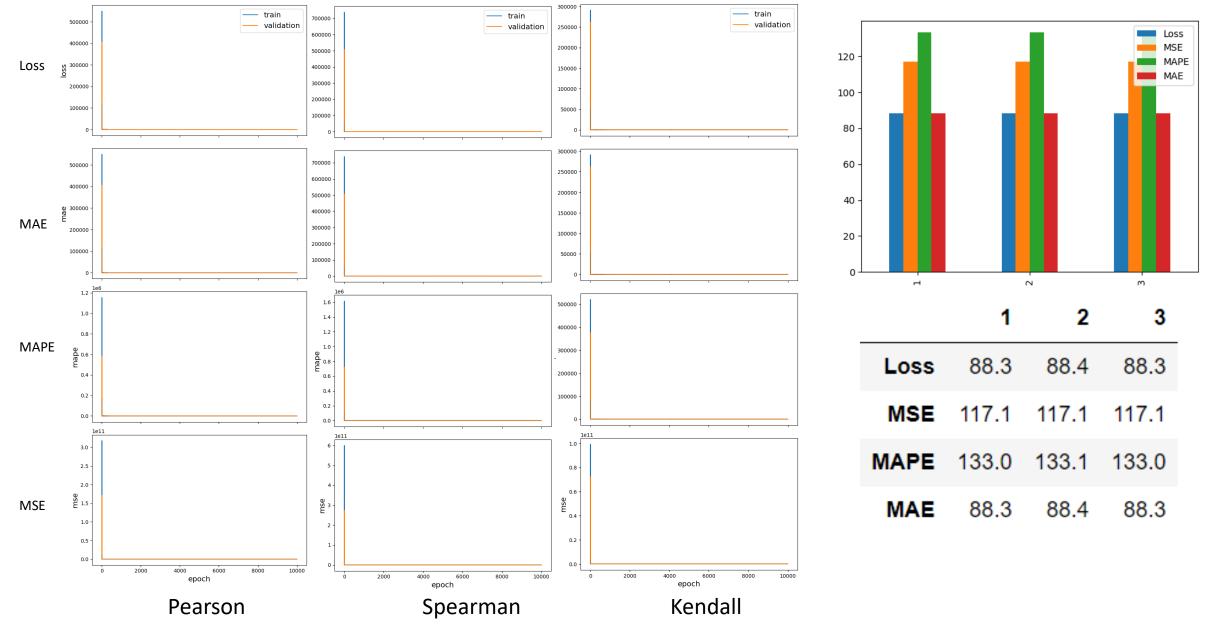
# 2<sup>nd</sup> Case: GCN + CNN + MLP (10,000 Epochs)



# 3<sup>rd</sup> Case: DeepGraphCNN (1000 Epochs)



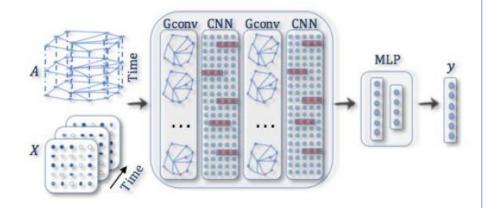
# 3<sup>rd</sup> Case: DeepGraphCNN (10, 000 Epochs)



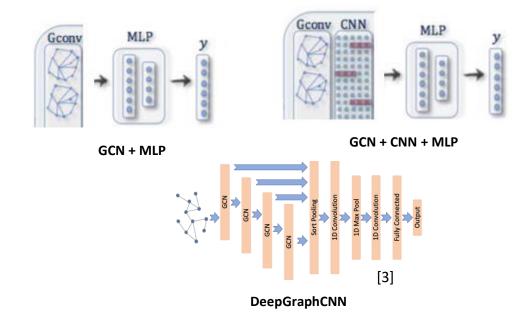
More Comparison: My Work with the Paper

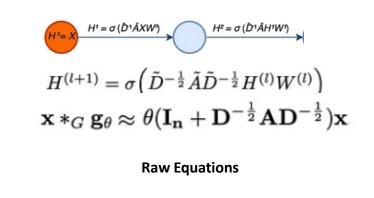
# **Compare Architectures**

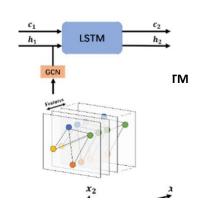
Paper



#### Mine







# Compare Performance Numbers (1000 Epochs)

Paper					Our Approaches											
-> Archi	(GCN + CNN)* + MLP			GCN + MLP			GCN + CNN + MLP				DeepGraph CNN					
	pea	spe	ken	news	pea	spe	ken	news	pea	spe	ken	news	pea	spe	ken	news
RMSE	12	12	10	9	<b>54.1</b>	63.7	48.4	38.3	122	71.9	80.7	79.7	83	107	95	
MAPE	15	5	4	4	161.1	84.6	149.6	30.7	75.5	<b>58.2</b>	79.4	37.2	58	118	104	
MAE	8	6	5	5	<b>42.0</b>	51.9	37.4	28.2	97.5	58.8	51.3	50.4	61	83	74	

Rank:

**RMSE**: News, Kendall, Pearson

MAPE: News, News, Spearman

MAE: News, Kendall, Pearson

Which Architecture is Better?

GCN + MLP

# Compare Performance Numbers (10, 000 Epochs)

Paper					Our Approaches											
-> Archi	(GCN + CNN)* + MLP				GCN + MLP			GCN + CNN + MLP				DeepGraph CNN				
	pea	spe	ken	news	pea	spe	ken	news	pea	spe	ken	news	pea	spe	ken	news
RMSE	12	12	10	9	58.2	39.9	56.1	59.3	57.2	<b>(51.9)</b>	62.1	37.2	117.1	117.1	117.1	
MAPE	15	5	4	4	157.0	31.4	81.0	<b>(57.5)</b>	162	68.0	65.3	45.0	133	133.1	133.0	
MAE	8	6	5	5	49.2	28.3	43.1	43.0	47.4	<u>41.6</u>	44.6	31.5	88.3	88.4	88.3	

Rank:

**RMSE**: News, Spearman, Spearman

MAPE: Spearman, News, News

MAE: Spearman, News, Spearman

#### Which Architecture is Better?

GCN + MLP although GCN + CNN + MLP – Very close/equivalent

Overall: 1000 Epochs are as good as 10,000 epochs

## Compare: Ranking or Performance

### Paper

- Causation: Financial News
- Kendall tau correlation (nonlinear)
- Spearman (nonlinear)
- Pearson (linear)

### Ours

Was hard to conclude.

- Causation
- Spearman
- Pearson/Kendall

# Challenges, Limitations and Future Work

### Challenges

- Exact Dataset
  - Finding or Generating
- Find and implement Exact Architecture
  - Not exact specific details
- Exact Platform to execute
- Adapting data for Deep Network
  - Esp. for different time steps

### Limitations of my work

- Implement exact architecture
- Execute and tune
  - to get the same or better performance
- News dataset

### Future Work

- Address the challenges and limitations mentioned
- Also, resolve Exploding Gradient
  - To reduce training complexity

### References

- [1] Pratik Patil, Ching-She, Katerina Potika, Marjan Orang Stock Market Prediction Using Ensemble of Graph Theory, Machine Learning and Deep Learning Models
- [2] Investopedia: Efficient Market Hypothesis (EMH): Definition and Critique. <a href="https://investopedia.com/terms/e/efficientmarkethypothesis.asp">https://investopedia.com/terms/e/efficientmarkethypothesis.asp</a>
- [3] Supervised graph classification with Deep Graph CNN https://stellargraph.readthedocs.io/en/latest/demos/graph-classification/dgcnn-graph-classification.html
- [4] **Graph Convolutional Networks (GCN) & Pooling** https://jonathanhui.medium.com/graph-convolutional-networks-gcn-pooling-839184205692

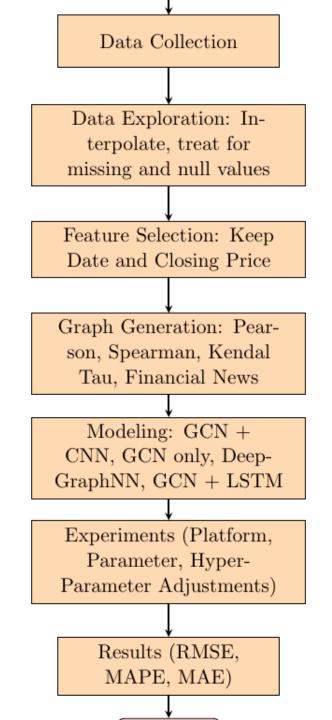
# I Hope that you Enjoyed the Presentation

If you have any **Questions**?

I will be happy to **answer** 

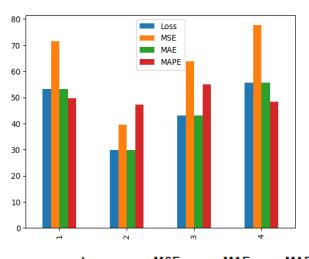
# Methodology

- Data Collection
- Data Exploration
  - find date range where data exist for all stocks under consideration
    - Remove out of date data
  - Still looked for NAN/NA
    - Replaced those with surrounding values (interpolate) (8 or 9)
    - Even NAN, dropped them (1 row)
    - 4301, 4292
  - Verified all stocks has equal number of values
  - Any Plotting/Unitary/Bi-Variate analysis
    - Scaling/normalization does not seem that I need (will see)
- Feature selection/engineering
  - Kept: Date, Ticker, Adjusted Close
    - For accuracy try the other close
- Graph Generation
- Model (Deep Learning Models)
  - GCN + CNN based stock price prediction
  - GCN only
  - DeepgraphNN
  - GCN + LSTM
- Experiments
- Results



2<sup>nd</sup> Case: GCN + CNN + MLP (1000 Epochs)

#### 15k Epochs



	Loss	MSE	MAL	MAPE
1	53.140034	71.558536	53.140034	49.651329
2	29.864273	39.612246	29.864273	47.168633
3	43.128960	63.828448	43.128960	54.905254
4	55.650585	77.589062	55.650585	48.469971

