



# COMP4332 Group 4 : **Project 1, Project 2**

CHAN Chun Hin, CHAN Long Ki,  
LEE Seungho, WAN Nga Chi

# PROJECT 1

## Sentiment Analysis Report

### DATA PREPROCESSING

#### Biased Data set

- Biased Towards positive and neutral rating  
→ Poor testing accuracy and F1 Score

Not applied stopwords(nltk library) filtering: Not for sentiment analysis

Possible Ratings	Possible words in reviews
1	Very not good
2	Not good
3	Not so good
4	Good
5	Very good

Stopword Filtering



After Stopword Filtering
Good
Good
Good
Good
Good

# CNN MODEL (Selected Model)

## WHY?

→ Effectiveness in handling text input

Employed a kernel size of 1, 2, and 3 to extract unigram, bigram, and trigram

→ Further N-grams not useful  
(Can capture fewer words)

Used softmax function for output layer

→ Adam Optimizer for multi-label classification

## The Model Layout:

Model: "model_9"			
Layer (type)	Output Shape	Param #	Connected to
input_10 (InputLayer)	[(None, 100)]	0	[]
embedding_9 (Embedding)	(None, 100, 100)	454600	['input_10[0][0]']
conv1d_27 (Conv1D)	(None, 100, 100)	10100	['embedding_9[0][0]']
conv1d_28 (Conv1D)	(None, 99, 100)	20100	['embedding_9[0][0]']
conv1d_29 (Conv1D)	(None, 98, 100)	30100	['embedding_9[0][0]']
activation_37 (Activation)	(None, 100, 100)	0	['conv1d_27[0][0]']
activation_38 (Activation)	(None, 99, 100)	0	['conv1d_28[0][0]']
activation_39 (Activation)	(None, 98, 100)	0	['conv1d_29[0][0]']
max_pooling1d_27 (MaxPooling1D)	(None, 1, 100)	0	['activation_37[0][0]']
max_pooling1d_28 (MaxPooling1D)	(None, 1, 100)	0	['activation_38[0][0]']
max_pooling1d_29 (MaxPooling1D)	(None, 1, 100)	0	['activation_39[0][0]']
flatten_27 (Flatten)	(None, 100)	0	['max_pooling1d_27[0][0]']
flatten_28 (Flatten)	(None, 100)	0	['max_pooling1d_28[0][0]']
flatten_29 (Flatten)	(None, 100)	0	['max_pooling1d_29[0][0]']
concatenate_9 (Concatenate)	(None, 300)	0	['flatten_27[0][0]', 'flatten_28[0][0]', 'flatten_29[0][0]']
dropout_9 (Dropout)	(None, 300)	0	['concatenate_9[0][0]']
dense_19 (Dense)	(None, 100)	30100	['dropout_9[0][0]']
activation_40 (Activation)	(None, 100)	0	['dense_19[0][0]']
dense_20 (Dense)	(None, 5)	505	['activation_40[0][0]']
Total params: 545505 (2.08 MB)			
Trainable params: 545505 (2.08 MB)			
Non-trainable params: 0 (0.00 Byte)			

# CNN MODEL (Selected Model)

Tested under different kernel configurations and stopwords filtering conditions

## Key Observations:

- Retaining stopwords appears to slightly improve model accuracy
- Increasing the complexity of the model does not enhance the performance
- Configuration [1, 2, 3] without stopwords filtering showed the best overall performance

Performance result

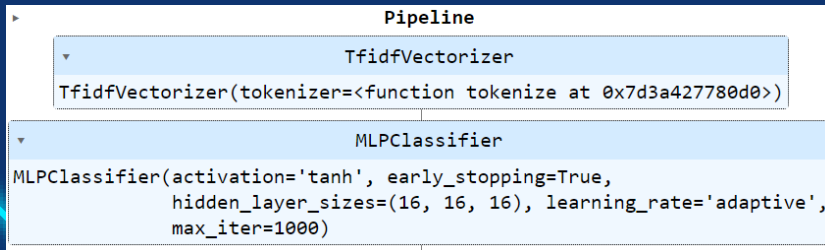
CNN kernel size (input condition)	Accuracy	Precision	Recall	F1
[1, 2, 3] (input without stopwords filtering)	0.543	0.524	0.514	0.514
[1, 2, 3] (input with stopwords filtering)	0.524	0.503	0.491	0.493
[1, 2, 3, 4] (input without stopwords filtering)	0.536	0.519	0.506	0.511

# ALTERNATIVE MODELS

Developed to utilize multi – layer perception

## MLP Model A:

Data preprocessing: TF-IDF  
Architecture:



## MLP Model B:

Data preprocessing: NLP (TF-IDF)  
Architecture:

Model: "model_3"			
Layer (type)	Output Shape	Param #	Trainable
dense1 (Dense)	(None, 64)	822784	Y
dense2 (Dense)	(None, 32)	2080	Y
dropout1 (Dropout)	(None, 32)	0	Y
batch_norm1 (BatchNormaliz ation)	(None, 32)	128	Y
dense3 (Dense)	(None, 20)	660	Y
dropout2 (Dropout)	(None, 20)	0	Y
dense4 (Dense)	(None, 16)	336	Y
dense5 (Dense)	(None, 5)	85	Y
Total params: 826073 (3.15 MB)			
Trainable params: 826009 (3.15 MB)			
Non-trainable params: 64 (256.00 Byte)			

# MLP MODEL VALIDATION

Model A Outperformed Model B

- Use of TfidfVectorizer() substantially enhanced model performance

Model Complexity Not Correlated with Performance

- Model B had more layers and hidden units, and advanced technique  
→ Simpler architecture is more effective for the sentiment analysis task

MLP Model	Accuracy	Precision	Recall	F1
Model A	0.535	0.43	0.48	0.45
Model B	0.469	0.37	0.43	0.39

# CONCLUSION of Project 1

- CNN model with varying kernel sizes showed competitive validation accuracy.
- MLP Models' Insights:
  - Investigated the role of `TfidfVectorizer()` in enhancing MLP models' accuracy.
  - Identified that simpler MLP models outperformed more complex ones.
- Key Takeaways for Future Research:
  - The effectiveness of model simplicity and `TfidfVectorizer()` warrants further exploration.
  - Project findings contribute to the knowledge base for sentiment analysis advancements.

# PROJECT 2

## Social Network Mining Report

### DeepWalk Model: Setup

- DeepWalk model from iterations 1 to 10

```
node dim: 5, num_walks: 20, walk_length: 20 building a DeepWalk model... number of walks: 1455900 average walk length: 20.0000 training time: 286.5846 valid auc: 0.5183
node dim: 15, num_walks: 20, walk_length: 20 building a DeepWalk model... number of walks: 1455900 average walk length: 20.0000 training time: 286.3902 valid auc: 0.6086
node dim: 5, num_walks: 30, walk_length: 15 building a DeepWalk model... number of walks: 2183850 average walk length: 15.0000 training time: 326.7124 valid auc: 0.5138
node dim: 15, num_walks: 25, walk_length: 10 building a DeepWalk model... number of walks: 1819875 average walk length: 10.0000 training time: 199.4453 valid auc: 0.6215
node dim: 10, num_walks: 15, walk_length: 15 building a DeepWalk model... number of walks: 1091925 average walk length: 15.0000 training time: 165.1049 valid auc: 0.5701
```

```
node dim: 10, num_walks: 5, walk_length: 5 building a DeepWalk model... number of walks: 363975 average walk length: 5.0000 training time: 24.8419 valid auc: 0.5976
node dim: 15, num_walks: 10, walk_length: 20 building a DeepWalk model... number of walks: 727950 average walk length: 20.0000 training time: 145.0097 valid auc: 0.6248
node dim: 5, num_walks: 25, walk_length: 25 building a DeepWalk model... number of walks: 1819875 average walk length: 25.0000 training time: 424.9159 valid auc: 0.5156
node dim: 25, num_walks: 20, walk_length: 25 building a DeepWalk model... number of walks: 1455900 average walk length: 25.0000 training time: 357.8886 valid auc: 0.6845
node dim: 5, num_walks: 25, walk_length: 10 building a DeepWalk model... number of walks: 1819875 average walk length: 10.0000 training time: 195.2348 valid auc: 0.5195
```

- The output of this model:

Best valid AUC achieved	0.68452011
Corresponding node_dim	25
Corresponding num_walks	20
Corresponding walk_length	25



# DEEPWALK Model

## Parameter Settings Explored

Explored 10 different parameter settings:

- Node Dimension (node\_dim\_combination): [5, 10, 15, 20, 25]
- Number of Walks (num\_walks\_combination): [5, 10, 15, 20, 25, 30]
- Walk Length (walk\_length\_combination): [5, 10, 15, 20, 25, 30, 35]

## Validation AUC Observations

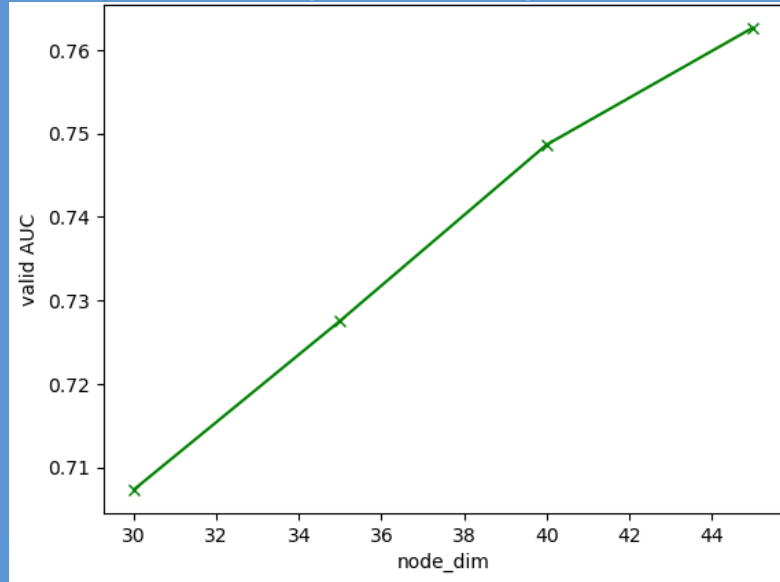
- Parameters to boost the Node2Vec model's validation AUC.

Parameter	Details	Observations of Validation AUC
Node Dimension	- 1 <sup>st</sup> : 25 (Validation AUC = 0.6845) 2 <sup>nd</sup> : 15 (Validation AUC = 0.6215)	Increasing node dimension by 10 raised validation AUC by 0.06.
Number of Walks and Walk Length	Both parameters should be at least 20	Using similar parameter values increases learning and AUC.
Range of Number of Walks	Range: 1450000 to 1820000	Maintain within the walk range yields a validation AUC of 0.65 to 0.70.

# FURTHER INVESTIGATION

- Increasing node dimension improves validation AUC in the DeepWalk model.
- Higher dimensions capture more complex network relationships, enhancing model understanding and performance.
- A graph shows rising validation AUC with larger node dimensions, aiding tasks like link prediction and node classification.

Performance of DeepWalk of valid AUC against node\_dim (with num\_walk = 25 and walk\_length = 25 being fixed)



# Node2Vec Model: Setup

## Node2Vec Model from iteration 1 to 20

```
node dim: 30, num_walks: 20, walk_length: 15, p: 0.08, q: 0.10 building a node2vec model... number of walks: 1605000 average walk length: 15.0000 training time: 197.2796
valid auc: 0.7657

node dim: 35, num_walks: 20, walk_length: 15, p: 1.00, q: 4.00 building a node2vec model... number of walks: 1605000 average walk length: 25.0000 training time: 140.1327
valid auc: 0.7339

node dim: 35, num_walks: 25, walk_length: 20, p: 0.30, q: 0.10 building a node2vec model... number of walks: 1803675 average walk length: 20.0000 training time: 169.3929
valid auc: 0.7324

node dim: 30, num_walks: 35, walk_length: 20, p: 1.00, q: 0.10 building a node2vec model... number of walks: 2547025 average walk length: 20.0000 training time: 205.1954
valid auc: 0.7000

node dim: 35, num_walks: 35, walk_length: 15, p: 1.00, q: 2.00 building a node2vec model... number of walks: 1803625 average walk length: 15.0000 training time: 176.3383
valid auc: 0.7438

node dim: 25, num_walks: 30, walk_length: 10, p: 0.50, q: 0.25 building a node2vec model... number of walks: 2183850 average walk length: 10.0000 training time: 96.1815
valid auc: 0.6958

node dim: 20, num_walks: 30, walk_length: 15, p: 1.00, q: 0.00 building a node2vec model... number of walks: 2183850 average walk length: 15.0000 training time: 133.1057
valid auc: 0.6560

node dim: 30, num_walks: 25, walk_length: 25, p: 1.00, q: 3.00 building a node2vec model... number of walks: 1803675 average walk length: 25.0000 training time: 179.0917
valid auc: 0.7000

node dim: 25, num_walks: 15, walk_length: 30, p: 1.20, q: 0.25 building a node2vec model... number of walks: 1803625 average walk length: 30.0000 training time: 127.3184
valid auc: 0.6877

node dim: 35, num_walks: 10, walk_length: 20, p: 1.00, q: 0.10 building a node2vec model... number of walks: 727950 average walk length: 20.0000 training time: 62.4368
valid auc: 0.7400
```

```
node dim: 30, num_walks: 15, walk_length: 10, p: 0.75, q: 0.10 building a node2vec model... number of walks: 1803625 average walk length: 10.0000 training time: 50.1803
valid auc: 0.7278

node dim: 25, num_walks: 10, walk_length: 25, p: 0.20, q: 0.10 building a node2vec model... number of walks: 727950 average walk length: 25.0000 training time: 72.3105
valid auc: 0.6911

node dim: 25, num_walks: 15, walk_length: 30, p: 2.00, q: 0.10 building a node2vec model... number of walks: 1803625 average walk length: 30.0000 training time: 111.0017
valid auc: 0.7304

node dim: 30, num_walks: 35, walk_length: 20, p: 2.00, q: 0.00 building a node2vec model... number of walks: 2547025 average walk length: 20.0000 training time: 205.6805
valid auc: 0.7000

node dim: 30, num_walks: 15, walk_length: 30, p: 0.25, q: 0.10 building a node2vec model... number of walks: 1803625 average walk length: 30.0000 training time: 143.7900
valid auc: 0.6487

node dim: 30, num_walks: 35, walk_length: 20, p: 1.00, q: 1.00 building a node2vec model... number of walks: 2547025 average walk length: 20.0000 training time: 204.8301
valid auc: 0.7000

node dim: 35, num_walks: 15, walk_length: 30, p: 1.00, q: 1.00 building a node2vec model... number of walks: 1803625 average walk length: 30.0000 training time: 90.4020
valid auc: 0.7468

node dim: 30, num_walks: 15, walk_length: 30, p: 0.40, q: 0.10 building a node2vec model... number of walks: 1803625 average walk length: 30.0000 training time: 128.4028
valid auc: 0.7000

node dim: 25, num_walks: 25, walk_length: 15, p: 0.50, q: 0.50 building a node2vec model... number of walks: 1803675 average walk length: 15.0000 training time: 114.0015
valid auc: 0.6893

node dim: 25, num_walks: 10, walk_length: 25, p: 1.00, q: 0.10 building a node2vec model... number of walks: 2183850 average walk length: 25.0000 training time: 211.1804
valid auc: 0.7203
```

The output of this  
model:

Best valid AUC achieved	0.7464476625
Corresponding node_dim	35
Corresponding num_walks	15
Corresponding walk_length	10
Corresponding p	1.6
Corresponding q	1.6

# PARAMETER SETTINGS

Explored 20 different parameter for the Node2Vec model:

Parameter	Values
Node Dimension	20, 25, 30, 35
Number of Walks	10, 15, 20, 25, 30, 35
Walk Length	10, 15, 20, 25, 30, 35
p (p_combination)	0.1, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6, 0.7, 0.75, 0.8, 0.9, 1.2, 1.4, 1.6, 1.8, 2, 3, 4
q (q_combination)	0.1, 0.2, 0.25, 0.3, 0.4, 0.5, 0.6, 0.7, 0.75, 0.8, 0.9, 1.2, 1.4, 1.6, 1.8, 2, 3, 4

# VALIDATION AUC Observations

Observed the following major phenomena:

- After evaluating various settings, we selected the best-performing Node2Vec model based on key observations from the training results.

Parameter	Observation and Impact on Validation AUC	Selected Value
Node Dimension	Highest validation AUC achieved with a node dimension of 35, indicating that increasing the node dimension increases AUC.	35
Number of Walks	Approximately 1100000 walks needed for a validation AUC of ~0.74, fewer than required in the DeepWalk model for similar AUC.	1,100,000
Walk Length	Effective walk length for higher validation AUC in the Node2Vec model is around 35, similar to the DeepWalk model.	35
p and q Parameters	No consistent pattern observed in the impact of p and q on validation AUC; their effectiveness depends on network specifics.	p: 0.5, q: 0.5

# FURTHER INVESTIGATION

- Node Dimension: Best at 250; higher dimensions don't improve AUC.
- Parameters p and q: Optimal below 1 to balance exploration-exploitation.
- Walks and Length: Moderate values recommended; high values cause overfitting.

Outputs of different models

node_dim	num_walks	walk_length	p	q	valid auc achieved
50	15	15	0.5	0.5	0.78810
100	15	15	0.5	0.5	0.83343
150	15	15	0.5	0.5	0.84520
200	15	15	0.5	0.5	0.84581
200	100	100	0.5	0.5	0.58102
<b>250</b>	<b>15</b>	<b>15</b>	<b>0.5</b>	<b>0.5</b>	<b>0.84691</b>
300	15	15	0.5	0.5	0.84548
500	15	15	0.5	0.5	0.84510

# CONCLUSION of Project 2

- Key Parameters:
  - Node Dimension: Increasing dimension improves validation AUC.
  - Number of Walks and Walk Length: Adequate numbers and lengths are crucial for effective model learning.
- Optimal Node2Vec Settings:
  - Node Dimension: 250;
  - Walks: 1,091,925
  - Walk Length: 15;
  - p and q: 0.5 each
- The best settings may vary based on the network's unique characteristics
- Future Steps:
  - Test these models on different social networks.
  - Explore advanced techniques like GCNs and GraphSAGE for improved performance.

The background is a dark blue field with glowing cyan lines that resemble circuit traces or data paths. These lines are arranged in a symmetrical, vertical pattern on both sides of the center, with some segments being dashed and others solid. The overall aesthetic is high-tech and digital.

**THANKS!**

**Q&A**