

Graph Convolutional Networks with Knowledge Graph for Myers-Briggs Type Indicator

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Abstract: The order of vertices in a graph is very important because the graph is oriented. Or the vertices are not important because they are not oriented. The graph of data is a heterogeneous polydigraph, called a directed vertex set, with many edges between any two vertices. Information is created by establishing real-world relationships between graphics and objects. This study was conducted to improve machine learning performance by proposing a theoretical model for the data used and creating a graph convolutional network (GCN) model for training the data. Data are created from a low-dimensional (latent) space, but can only be observed in a high-dimensional (observation) space. The results of these studies may not always yield the same results because they were not measured on the same person, were unreliable, or the results obtained did not provide consistent results. MBTI tests may change at any time. It is obtained according to the result of a person's mood. This MBTI method is often considered weak and unscientific, so it must be tested with 200 iterations on the GCN. The resulting GCN scores are 89.8% accuracy and 2.78 Test Loss.

1 INTRODUCTION

MBTI (Myers-Briggs Type Indicator) gives a simple description in a manner psychometric about type personality. Although characterization is short This is Possibly useful in some context apply (in predicting style behavior characteristics individual, intellectual, and interpersonal), exists limitations to the psychometric clear instrument (Albrecht et al.,). The MBTI is a system-type personality that divides people into 16 types of different personalities of 4 parts: Introversion (I) - Extroversion (E), Intuition (N) - Feeling (S), Thinking (T) - Feeling (F), Judging (J) - Perceiving (P), (You can read more carry on about What meaning here).

For example, someone with more introversion, intuition, thinking, and perception is called an INTP inside the MBTI system, and there are Lots of component-based modeling personality or describe preference or the person's behavior based on appointment (Altuner and Kilimci,).

This is one tests the most popular personality in the world. This is used For business, online, fun, research, and more. A simple Google search will disclose all method different that has been used to test from time to time. Can be said that testing This Still very up to date its use worldwide. From the corner

view scientific or psychological based on Carl Jung's work on function cognitive, that is Jungian typology. This is a model of eight functions, thought processes, or methods to think differently that has been suggested for is inside the mind. Work This has changed become some system with different personalities for facilitating it, the most popular Of course just is the MBTI (Hogan et al.,). recently, its usage/validity questioned because, among other things, it doesn't can dependable in experiments around. However, it has still become a very tool useful in many fields, and the goals of this data set are to determine if there is a possible pattern recognized in type and style writing certain and, more general, for test validity test moment analysis, predict, or classify behavior

2 METHODOLOGY

The vertices in a graph is very important so that the graph is directed, or the vertices of the graph are not important, so they are not directed. The knowledge graph is a heterogeneous multidigraph which is called a sequence of directed vertices and has many edges between the two nodes. A knowledge is created by making a real relationship between graphics and objects. The knowledge graph (KG), also known as

a database, representation structured from describing facts and gathering description entity related, related, and description semantics entity. Difference between a database and a Knowledge graph with a scheme other defined as structured, homogeneous, and stable, making data graph can be scaled. KG's advantage is a more good representation of the heterogeneous object using room integrated to connect it (Liemena et al.,).

At the actual data graph moment, this tends not to be a complete and necessary inference engine in predicting the links between entities available in KG and the complete missing facts. Classification connection or inference from available KG data called Link Divination. An example of what it looks like is shown in Figure 1 (Rajabi and Etmnani,).

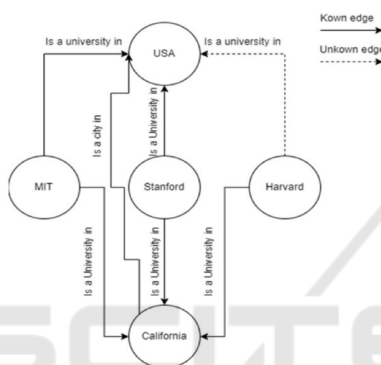


Figure 1: Sample KG Two Nodes.

Study This is done to help increase Machine Learning performance with propose a theoretical model for the data used and building a Graph Convolutional Network (GCN) model for train data. Data is created from room dimension low (latent) but only can observe in dimensional (observational) space high (Ramezani et al.,). This means that data is real depending on many small factors, however, stretched in a manner artificial to appear to depend on a lot of factors. GCN only see room data observation and create prediction more accurately based on the data used. Data used though simple will but no trivial matter (Elhammadi and B,). The GCN model in research This is as follows:

3 RESULTS AND DISCUSSIONS

This research requires experimental data to be tested on the GCN method regarding the MBTI so that later it can be implemented in the MBTI. This is an experimental method using data obtained from Kaggle. The data has been analyzed so that it has column types to identify. Analyzed data in which the final column is

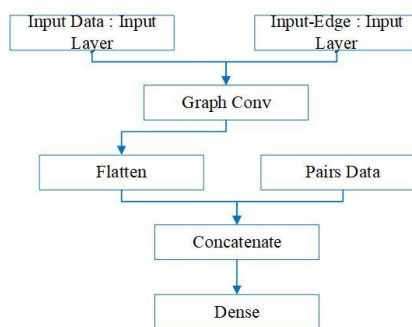


Figure 2: GCN Models.

considered the target, and the other columns are the attributes. The shared datasets become training sets, validation sets, and test sets.

3.1 Testing

Data has been analyzed to have a type column for identification. Moment analyzes data, column final is treated as target and column other will be enforced as input field. Shared dataset into training data, validation sets, and testing data (Wang et al.,). The following is the data table used.

The dataset used in the work consists of tagged tweets. One of 16 MBTI types. These tags are a combination of four letters. Each character matches. The first or second character of four MBTI class characteristics. The dataset consists of 8660 rows. Distribution of MBTIs. The characteristics of each class (8600 lines) are as follows.

- a. Introversion (I) : 6664
- b. Extroversion (E): 1996
- c. Recognition: 7466
- d. Intuition (N): 1194
- e. Think (T): 4685
- f. Feeling (F) : 3975
- g. Judging (J): 5231
- h. Perceiving (F) : 3429.

GCN has data representation of chart usually use adjacency matrix and use the feature as input. Feature This is used as a property of the nodes on the graph and presented become numbers. Feature This made example of many groups that have social networks that become rejected measuring patience from some people. Matrix feature This is a 2-dimensional shape. On-line matrix feature i.e. a vector of similar features with knot graph, from facet size on each knot. On the column, the matrix will be the same with features certain can understand nodes and their graphs.

For example, in research this does testing against the Myers-Briggs Indicator personality namely:

- a. Extraversion vs. Introversion
- b. Feel vs. Intuition
- c. Thinking vs. Feel
- d. Assess vs. Perceive

3.2 Test Results

This research requires experimental data to be tested on the GCN regarding the Myers-Briggs Type Indicator so that later it can be implemented in users of social networks. This is an experimental method using data obtained from Kaggle (Yani and Krisnadi,). So that it can be simulated to see the achievement of searching for the highest accuracy and can be used in a psychological test that is designed to measure a person's purely psychological basic preferences. The resulting achievement was successful in obtaining the highest value from the epoch experiment carried out in the analysis process. The table below will be shown the results of data analysis from epochs 1 to 200. Comparison of results Among target networks (0 and 1). More clear information could be seen in the table under this:

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 7614)	0	[]
dropout_1 (Dropout)	(None, 7614)	0	['input_1[0][0]']
input_2 (InputLayer)	(None, 7614)	0	[]
gcn_conv_1 (GCNConv)	(None, 16)	121824	['dropout_1[0]'], ['input_2[0][0]']
dropout_2 (Dropout)	(None, 16)	0	['gcn_conv_1[0][0]']
gcn_conv_2 (GCNConv)	(None, 16)	256	['dropout_2[0][0]'], ['input_2[0][0]']

Total params: 122,888
Trainable params: 122,888
Non-trainable params: 0

Figure 3: GCN Process.

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Epoch 1/200: 21.26/step - loss: 118.246490908.0000 - acc: 0.0000 - val_loss: 432.027112048.0000 - val_acc: 0.0000
Epoch 2/200: 19.1886/step - loss: 100.0110810707614.0000 - acc: 0.0000 - val_loss: 324.0233107378.0000 - val_acc: 0.0000
Epoch 3/200: 19.9886/step - loss: 157.946772924261.0000 - acc: 0.0000 - val_loss: 132.046681054.0000 - val_acc: 0.0000
Epoch 4/200: 19.7786/step - loss: 133.0232938381.0000 - acc: 0.0000 - val_loss: 208.2222079905.0000 - val_acc: 0.1193
Epoch 5/200: 19.6886/step - loss: 106.0221421041.0000 - acc: 0.1070 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 6/200: 19.6886/step - loss: 0.9022 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 7/200: 19.6886/step - loss: 0.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 8/200: 19.7276/step - loss: 1.8408 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 9/200: 19.8766/step - loss: 1.8402 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 10/200: 19.8766/step - loss: 2.8252 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 11/200: 19.7866/step - loss: 2.7998 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 12/200: 19.7866/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 13/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 14/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 15/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 16/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 17/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 18/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 19/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Epoch 20/200: 19.8766/step - loss: 2.7922 - acc: 0.0000 - val_loss: 2.7074 - val_acc: 0.0000
Total loss: 2.78251042399248
Total accuracy: 0.00001204814168
    
```

Figure 4: Epoch Test.

This research was conducted to design a personality test myers-briggs type indicator (mbti) using the knowledge graph method and predict personality.

4 CONCLUSIONS

In the results study, This No can produce always results same, because No measure from One the same



Figure 5: KG of Myers-Briggs Type Indicator.

individual, and no have reliability or the resulting results No get consistent results. The MBTI test is also available depending on the results atmosphere heart someone who can capricious any time. the MBTI is a frequent method considered weak and not scientific, then need exists testing to use GCN with iterations as many as 200. Results obtained with the GCN evaluation are 89% accuracy produced and the test loss is 2.78. Result of knowledge graph in p reference third focus in study How method in making the decision. Someone decides in a manner objective or based on a hunch, a (T) if decide in a manner objective, and an (F) if weigh everything with consider circumstances personal. Because someone's objective and biased preferences logic (T) is not mean they have no feelings. only Because somebody's own preference this (F) feeling No means they No think about something. The last preference is determination style alive, this will evaluate according to the information data filled out, for the group becomes someone who plans or is flexible.

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