# Food Recipe Text Classification Using Graph Convolution Network

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## Introduction

Recipe text classification is used to categorize new recipe's based on the knowledge acquired from trained dataset. Here we utilized Graph Convolution Neural Networks to perform the text classification. Graph Convolution Networks are very effective in non euclidean domains where complex relationships and inter-dependency between the objects are represented as graph. Graph Convolution neural networks are used to classify Food recipe text into various categories (like vegetarian, meat etc...) and compare it with standard neural networks like LSTM.

## What is Graph Convolution Network?

To understand better on Graph Convolution Networks lets understand what is a graph. A graph represents the relations (edges) between a collection of entities (Vertex).

- **V** Vertex (or node) attributes e.g., node identity, number of neighbors
- **E** Edge (or link) attributes and directions e.g., edge identity, edge weight
- **U** Global (or master node) attributes e.g., number of nodes, longest path

GCN is semi-supervised learning on graph-structured data. It is based on an efficient variant of convolutional neural networks which operate directly on graphs[4]. The choice of convolutional architecture is motivated via a localized first-order approximation of spectral graph convolutions. The model scales linearly in the number of graph edges and learns hidden layer representations that encode both local graph structure and features of nodes. As for traditional CNN's, a GCN consists of several convolutional and pooling layers for feature extraction, followed by the final fully-connected layers.

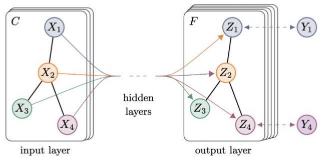


Figure 1. Graph Convolution Network[4]

A GCN [4] is a multilayer neural network that operates directly on a graph and induces embedding vectors of nodes based on properties of their neighborhoods. Formally, consider a graph G = (V, E), where V (|V | = n) and E are sets of nodes and edges, respectively. Every node is assumed to be connected to itself, i.e., (v, v) ? E for any v. Let X ? R n×m be a matrix containing all n nodes with their features, where m is the dimension of the feature vectors, each row xv ? R m is the feature vector for v. We introduce an adjacency matrix A of G and its degree matrix D, where Dii = P j Aij . The diagonal elements of A are set to 1 because of self-loops. GCN can capture information only about immediate neighbors with one layer of convolution[1].

## Recipe Text Data set

| | category | recipe | encoded |
|---|---|---|---|
| 0 | 0 | make a choice and proceed with recipe dependin... | [[2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, ... |
| 1 | 0 | mix all ingredients& boil for 2 1 / 2 hours , ... | [[35, 82, 83, 84, 85, 22, 86, 87, 14, 86, 88, ... |
| 2 | 0 | toast the fennel seeds and lightly crush them ... | [[121, 58, 122, 21, 5, 123, 124, 125, 126, 82,... |
| 3 | 0 | drain green chiles sprinkle cornstarch on shee... | [[136, 137, 138, 139, 140, 10, 141, 142, 143, ... |
| 4 | 0 | heat the oil or margarine in a soup pot and ad... | [[186, 58, 26, 18, 187, 105, 3, 188, 189, 5, 1... |

Figure 2. Recipe Text Dataset

1. **Data** we have utilized subset of food recipe data set[3] for training the neural network. we will be using only the category and recipe description for our classification task.As this dataset is huge with 250k entries, will be using equal distribution 5k recipe for our experiment.
2. **Pre-processing** Original dataset is prepossessed to fetch only the category and recipe text is con-catted to form a single continues string and special characters are removed before tokenized the text.

## Implementation

Two layer graph convolution neural network is used to train our dataset with model parameters as hidden layer one size is 330, hidden layer two size is 130,number of classes as 2, number of epochs is 1000 and learning rate of 0.011. Also we have split dataset in 80 vs 20 for training and test use. GCN is implemented based on [1] and below is the graph preparation and GCN approach.

1. **Nodes** in the text graph |V | is the number of documents (corpus size) plus the number of unique words (vocabulary size) in a corpus. We simply set feature matrix X = I as an identity matrix which means every word or document is represented as a one-hot vector as the input to Text GCN
2. **Edges** among nodes based on word occurrence in documents (document-word edges) and word co-occurrence in the whole corpus (word-word edges).The weight of the edge between a document node and a word node is the term frequency-inverse document frequency (TF-IDF) of the word in the document.
3. **co-occurance** point-wise mutual information (PMI), a popular measure for word associations, is used to calculate weights between two word nodes. A positive PMI value implies a high semantic correlation of words in a corpus, while a negative PMI value indicates little or no semantic correlation in the corpus.
4. **GCN** After building the text graph, we feed the graph into a simple two layer GCN as in the second layer node (word/document) embeddings have the same size as the labels set and are fed into a softmax classifier

## Results

The results graph show comparison between test accuracy vs train accuracy over the epochs for graph convolution network. compared to LSTM, GCN achieves higher validation accuracy.

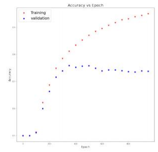


Figure 3. GCN train vs test accuracy

## Conclusion

For the recipe classification using GCN, we observed higher validation accuracy for GCN compared to LSTM network. Below table show the F1-score comparison between two. Also GCN can achieve better prediction accuracy even with smaller training dataset.

| Neural Network | weighted F1-score | Validation Accuracy |
|---|---|---|
| GCN | 0.74 | 0.74 |
| LSTM | 0.66 | 0.66 |

Table 1. A table caption.

## References

[1] Yao, Liang, Chengsheng Mao, and Yuan Luo. "Graph convolutional networks for text classification." Proceedings of the AAAI conference on artificial intelligence. Vol. 33. No. 01. 2019.
[2] Huang, L., Ma, D., Li, S., Zhang, X., Wang, H. (2019). Text level graph neural network for text classification.
[3] Food recipe Dataset https://www.kaggle.com/shuyangli94/food-com-recipes-and-user-interactions

[4] Kipf, Thomas N., and Max Welling. "Semi-supervised classification with graph convolutional networks." arXiv preprint arXiv:1609.02907 (2016).