HeteGCN: Heterogeneous Graph Convolutional Networks for Text Classification

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ABSTRACT
We consider the problem of learning efficient and inductive graph convolutional networks for text classification with a large number of examples and features. Existing state-of-the-art graph embedding based methods such as predictive text embedding (PTE) and TextGCN have shortcomings in terms of predictive performance, scalability and inductive capability. To address these limitations, we propose a heterogeneous graph convolutional network (HeteGCN) modeling approach that unites the best aspects of PTE and TextGCN together. The main idea is to learn feature embeddings and derive document embeddings using a HeteGCN architecture with different graphs used across layers. We simplify TextGCN by dissecting into several HeteGCN models which (a) helps to study the usefulness of individual models and (b) offers flexibility in fusing learned embeddings from different models. In effect, the number of model parameters is reduced significantly, enabling faster training and improving performance in small labeled training set scenario. Our detailed experimental studies demonstrate the efficacy of the proposed approach.

CCS CONCEPTS
• Computing methodologies → Neural networks; Learning latent representations.

KEYWORDS
text classification, graph convolutional networks, heterogeneous networks, text embedding, word embedding

1 INTRODUCTION
Text classification has been an important class of machine learning problems for several decades with challenges arising from different dimensions including a large number of documents, features and labels, label sparsity, availability of unlabeled data and side information, training and inference speed, type of classification problem (binary, multi-class, multi-label). Many statistical models [1, 4, 11, 26] and machine learning techniques [9, 13, 16, 27] have been proposed to address these challenges.

Traditional document classification approaches use Bag-of-Words (BoW) sparse representation of documents [26] and contributed towards designing models for binary, multi-class and multi-label classification problems [4, 11, 16, 27] and speeding-up learning algorithms [9] for large scale applications. Semi-supervised learning methods [3, 11] became an important area of research with the availability of an extensive collection of unlabeled data (e.g., web pages). Furthermore, web pages and publications brought in rich information through link graphs enabling the use of auxiliary information. Development of new graph-based learning methodologies [18, 30] started with the goal of improving classifier model performance.

For nearly a decade, there has been a surge in the development of learning representation of text data using distributed representation models [15, 20, 23] and deep learning models (e.g., convolutional and recurrent neural networks). See [21] for a comprehensive review. These models achieve superior performance compared to traditional models and exploit large volume of available unlabeled data to learn word, sentence and document embeddings. The key idea is to learn better representation (embedding) for documents that help to get significantly improved performance using even off-the-shelf linear classifier models. Recently, there has been tremendous progress in learning embeddings for entities in relational graphs [6, 24, 31, 32] and designing graph convolutional and neural network models [14] that exploit rich relational information present among entities in the graph. Many variants of GCNs and GNNs [8, 14, 29, 34, 36] have been proposed and explored for solving classification and recommendation problems.

Our interest lies in learning text classifier models that make use of underlying relations among words and documents. In Predictive Text Embedding [31] modeling approach, a document corpus is viewed as a heterogeneous graph that encodes relationship among words, documents and labels. The method learns embeddings for words using unsupervised learning techniques using a large volume of unlabeled data and some labeled data. It derives document embedding using learned word embeddings and learns a simple linear classifier model for class prediction. Like PTE, TextGCN [36] uses a heterogeneous graph but learns a text classifier model with a graph convolutional network and it outperforms many popular neural network models [12, 17] and PTE on several benchmark datasets. PTE’s modelling approach is simple, efficient and inductive, but it suffers in performance compared to the complex, slow and transductive TextGCN. Therefore, we focus on designing a text classification modeling approach that unites the best aspects of PTE and TextGCN together.

A key contribution of this work is a proposal to compose different heterogeneous graph convolution networks (HeteGCN) with individual graphs used in TextGCN. Unlike traditional GCN and TextGCN, HeteGCN makes use of compatible graphs across layers. They are simple and efficient as the number of model parameters is reduced significantly, enabling faster training and better generalization performance when the number of labeled training examples are small. Our HeteGCN modeling approach helps to understand effectiveness of different HeteGCN model variants and their usefulness in different application scenarios (e.g., availability of
auxiliary information, compute and storage constrained settings). HeteGCN offers flexibility in designing networks with fusion and shared learning capabilities.

Following PTE, we suggest a simple idea of using learned feature embeddings from both TextGCN and HeteGCN for inductive inference. Our work also raises a few research questions from inductive inference perspective. Further, LIGHTGCN work talks about simplifying GCN for recommendation application [8]. We show how LIGHTGCN can be used for the text classification task as a competitive baseline for TextGCN.

We conduct a detailed experimental study on several benchmark datasets and compare HeteGCN with many state-of-the-art methods. HeteGCN outperforms these methods when the number of labeled training examples is small and gives as high as 2–8% improvement over TextGCN and PTE for several datasets. It provides competitive performance in transductive large labeled training data scenario. In inductive setting, we find that the idea of using only learned feature embeddings is quite effective and HeteGCN achieves significantly improved performance with 3–7% lifts on several datasets compared to TextGCN and PTE. Training time comparison shows that HeteGCN is faster than TextGCN by 2–9 times. Overall, we demonstrate how HeteGCN unites the best aspects of PTE and TextGCN by offering a high-performance text classification solution with lower model complexity, faster training and inductive capabilities.

The paper is organized as follows. We present notation, problem formulation and background for graph embedding methods in Sections 2 & 3, our approach in Section 4, experimental details and results in Section 5 followed by related work in Section 6. The paper ends with discussion on investigations and possible extensions in Section 7 followed by conclusion.

2 NOTATION AND PROBLEM FORMULATION

We introduce notation used throughout the paper. We use $x_i \in R^m$ to denote $m$-dimensional feature vector of $i^{th}$ example, $y_i \in \{1, \ldots, k\}$ to denote the corresponding binary representation of target class and $k$ to denote the number of classes. We use $X$ to denote the document-feature matrix of the entire corpus (where each row represents the feature vector of an example) and $L_{tr}$ to denote the set of labeled training examples. We use $F$ to denote a feature-feature relation matrix and $N$ to denote a document-document relation matrix. The relation matrices are either explicitly provided or implicitly constructed from $X$. We view each matrix as a graph (and vice-versa) with rows and columns representing nodes. For example, $X$ is a graph connecting document nodes and feature nodes with edge weights that may be set to TF-IDF scores. We use $v_i = \text{Emb}(d_i)$ ($i \in \{1, \ldots, n\}$) to denote the document embedding of the $i^{th}$ document and $u_j = \text{Emb}(f_j)$ to denote the embedding of the $j^{th}$ feature ($j \in \{1, \ldots, m\}$). The corresponding embedding matrices are denoted as $V$ and $U$ respectively. Finally, $I_p$ and $W$ denote the $n$ dimensional identity matrix and the network model weights respectively. We use $P$ to denote the class probability distribution of documents over $k$ classes. The terms document and example are used interchangeably. Similarly, we use feature and word interchangeably. In some privacy sensitive applications, only hashed feature identifiers are available and pre-trained word embeddings (e.g., Word2Vec) cannot be used.

Problem Formulation. We are given a document corpus ($X$) with a set of labeled and unlabeled examples. Additionally, we may have access to $F$ and $N$. Our goal is to learn feature embeddings ($U$) using simple and efficient graph convolutional networks and learn an inductive classifier model that makes use of document embeddings ($V$) computed using $U$ to predict the target class.

3 BACKGROUND AND MOTIVATION

Predictive Text Embedding (PTE). Tang et al. [31] proposed a semi-supervised embedding learning method that makes use of both labeled and unlabeled documents. They construct a heterogeneous text graph which is a composition of three graphs, document-word ($X$), word-word ($F$) and word-label ($L$). Note that $X$ and $F$ are available for the entire corpus and $L$ is constructed using only labeled training examples. The core idea is to learn shared word embeddings ($U$) by leveraging labeled information available through $L$ jointly with $X$ and $F$. The embedding of any document is computed as an average of the embeddings of words present in the document. Finally, a linear (Softmax) classifier model is learned by minimizing cross-entropy loss function with labeled training examples:

$$M(W) = - \sum_{i \in L_{tr}} \sum_{k} y_{i,k} \ln(p(y_{i,k}|v_i;W))$$

Note that the embeddings and classifier model are learned sequentially. PTE is efficient and has the inductive capability.

Graph Convolutional Network. Kipf et al. [14] proposed a semi-supervised learning method using graph convolutional networks. A graph convolutional network is a multi-layer network and each layer takes node embeddings ($E^{(l)}$) of the $l^{th}$ layer as input and produces either embeddings ($E^{(l+1)}$) for the $(l+1)^{th}$ layer or predictions for a given task (e.g., target class probability distribution) at the final layer. Formally, $E^{(l+1)} = g(A, E^{(l)}, W^{(l)})$ where $E^{(l)}$ and $W^{(l)}$ denote the embedding and weight matrices of the $l^{th}$ layer respectively, $g(\cdot)$ is a transformation function (e.g., ReLU or Softmax), and $E^{(0)}$ is the input feature matrix (e.g., $X$) or 1-hot encoding representation of nodes (i.e., $I_p$). $A$ denotes an adjacency matrix and is fixed across layers. Like PTE, the model weights $W$ are learned using only labeled training examples (see 1). However, GCN is only transductive, as embeddings for unseen documents cannot be computed during inference.

TextGCN. Yao et al.[36] proposed a text graph convolutional network (TextGCN) method by using the matrix:

$$A = \begin{bmatrix} F & X^T \\ X & 0 \end{bmatrix}$$

in GCN across layers. Note that it makes use of both word-word and document-word relational graphs excluding $N$ (which may not be explicitly available). With a two-layer network, document-document relations are inferred and used along with word embeddings to obtain document embeddings. TextGCN [36] achieved significantly improved accuracy performance over PTE. TextGCN does not make use of $L$, and the gain mainly comes from using GCN. Nevertheless, TextGCN has several limitations which we explain next.
Consider the first layer output of TextGCN. With A as given in (2), the feature and document embedding matrices are given by:

\[ U^{(1)} = g(FL_m W_u^{(0)} + X^T I_n W_v^{(0)}) , \quad V^{(1)} = g((FT)^T X^T V^{(1)} W_u^{(0)}) \]  

where 1-hot representation is used for features and documents. The subscripts in \( W_v^{(0)} \) and \( W_u^{(0)} \) denote embedding type in the first (aka input) layer. In other layers, we use the subscript in the weight matrix (e.g., \( W_v^{(1)} \)) to match the type of multiplicant (e.g., document embedding, \( XU \)).

We note that the number of model parameters is dependent on the number of features \( m \) and documents \( n \). This implies TextGCN is not suitable for large scale applications when \( n + m \) is very large with \( n \gg m \). Furthermore, when the number of labeled training examples is small, it is difficult to learn a large number of model parameters reliably, resulting in poor generalization. Next, learning document embedding using (2) makes TextGCN transductive.

Motivated by the success of PTE and TextGCN in semi-supervised text classification, yet recognizing their limitations, we focus on designing a graph convolutional network-based approach that brings the best capabilities of PTE (i.e., efficient training and inductive) and TextGCN (i.e., superior performance) together.

4 PROPOSED APPROACH

We present our main idea of constructing a novel heterogeneous graph convolutional network (HeteGCN) variants with individual graphs used in TextGCN. Decomposition of TextGCN into different HeteGCN models helps to understand the usefulness and importance of each model. HeteGCN modeling approach offers flexibility in fusing embeddings from different HeteGCN models with or without layer sharing possibilities. Furthermore, taking a cue from PTE, we suggest a simple method to make inference on unseen documents. Finally, we explain how HeteGCN and TextGCN can be simplified by removing intermediate non-linearity and transformations, as suggested in [35] and [8].

4.1 Heterogeneous Graph Convolutional Network (HeteGCN)

We start with the observation that feature embeddings \( U^{(1)} \) are computed using both word-word (F) and word-document (X) matrices (see \( U^{(1)} \) in Equation 3) in TextGCN. This happens mainly because of how A (see Equation 2) is used in GCN. Our proposal is to consider individual matrices F, X and \( X^T \) used in A separately, decompose the embedding computation operations and fuse the embeddings from different layer outputs if required. We illustrate our main idea of composing different HeteGCN models in Figure 1 using the following set of GCN layers:

- **F - ReLU GCN**: This layer has feature embeddings as both input and output. For example, with F in the first layer and 1-hot encoding for feature embeddings, we have: \( U_{F}^{(1)} = g(FL_m W_u^{(0)}) \) with the subscript F indicating the graph used and \( g(\cdot) \) = ReLU(\( \cdot \)).
- **TX - ReLU GCN**: This layer takes document embeddings as input and produces feature embeddings as output. We use the prefix T to denote the transpose operation in TX. An example is: \( U_{X}^{(2)} = g(XTV^{(1)}W_u^{(1)}) \).
- **X - ReLU GCN**: This layer takes feature embeddings as input and produces document embeddings as output. In this case, we may have the second layer as: \( V_{X}^{(2)} = g(XU^{(1)}W_v^{(1)}) \).
- **N - ReLU GCN**: This layer has document embeddings as both input and output. With N in the first layer and 1-hot encoding for document embeddings, we have: \( V_{N}^{(1)} = g(N_l W_v^{(0)}) \).
- **X - Softmax GCN**: This layer takes feature embeddings as input and produces probability distribution P of documents over classes as output: \( P_X = \text{Softmax}(XU^{(1)}W_v^{(1)}) \).
- **N - Softmax GCN**: This layer takes document embeddings as input and produces the output: \( P_N = \text{Softmax}(NV^{(1)}W_v^{(1)}) \).

The basic Softmax layer produces \( P_f \) as output. Note that neither PTE nor TextGCN makes use of N, while we allow the possibility of using N or any other graph (e.g., the word-label relational graph used in PTE) when available. We define a homogeneous layer as a layer that consumes and produces embeddings of the same entity type (e.g., features or documents). Similarly, a heterogeneous layer consumes embeddings of one entity type (e.g., feature) and produces embeddings of another entity type (e.g., document). Thus, F - ReLU GCN is a homogeneous layer and X - ReLU GCN is a heterogeneous layer.

4.2 HeteGCN Models, Complexity and Implications

Given the basic homogeneous or heterogeneous layers, the idea is to compose different HeteGCN models using compatible layers. We illustrate four HeteGCN models using Figure 1. In the top row (Figure 1(a)), we have a HeteGCN (F -> X) model where F and X are the graphs used in the first and second layer. The feature embeddings (1-hot representation at the input) and Softmax classifier model weights are learned using Equation 1. Unlike TextGCN, we only learn feature embeddings. Therefore, the model complexity is \( O(md + kd) \) with \( d \) and \( k \) denoting the feature embedding dimension and number of classes. Similarly, we have a HeteGCN (TX -> X) model (Figure 1(c)) where TX and X are the graphs used in consecutive layers and the document embeddings are learned and the model complexity is \( O(n d + kd) \). HeteGCN is heterogeneous in the sense of using different graphs across layers. This is different from traditional GCN and TextGCN. However, two consecutive layers have to be compatible in terms of output-input relation. For example, a F - ReLU GCN layer cannot be followed by a TX - ReLU GCN. This is because the first layer produces feature embeddings as outputs and the second layer consumes document embeddings as inputs.

We observe that the model size plays an important role from two perspectives. (1) It affects the training time and tuning with a large number of hyper-parameter configurations becomes difficult. (2) When the number of labeled examples is small, it is preferable to learn models with lesser number of parameters, so that good generalization performance is achievable. We note that TextGCN learns both feature embeddings and document embeddings. Therefore, its model complexity is \( O((n + m)d) \) where \( d \) is the embedding dimension, assuming the same dimension for features and documents.
Therefore, we may expect HetGCN models explained above to take lesser time to train and generalize well for small labeled training set scenario.

Besides model complexity, the generalization performance of each HetGCN network is dependent on the information available. For example, HetGCN (F – X) has rich side information (knowledge) available through F and may help to get significantly improved performance over HetGCN (X – TX – X) when the number of labeled examples are small. The main reason why we may expect such performance difference is that the quality of learned feature embeddings in the former model is highly likely to be better due to feature co-occurrence knowledge. On the other hand, this knowledge has to be implicitly learned by the first two layers to derive feature embeddings in the latter model; with a limited number of labeled examples. Similarly, HetGCN (F – X) may perform better than HetGCN (N – N) when the quality of F is better than N.

It is important to note that it may not be possible to experiment with models such as HetGCN (F – X) due to several practical reasons. While this model may prove to be very effective, it may not always be feasible because it assumes that F is accessible or can be explicitly computed and stored. However, F may not be accessible or cannot be pre-computed and stored when m is very large. Similarly, it may not be feasible to pre-compute N and store when n is very large. In such situations, we are constrained to use only models such as HetGCN (X – TX – X) or HetGCN (TX – X) with only available X.

Finally, we also note that our proposed approach is flexible. For example, we can learn a composite HetGCN model by fusing feature embedding outputs at the layers TX and F of two HetGCN (F – X) and HetGCN (TX – X) models and passing the fused embedding to an X - Softmax GCN as shown in the middle row (Figure 1(e)). This composite HetGCN model is equivalent to performing nonlinear operation on each of the terms in $U^{(1)}$ (see Equation 3) separately and passing to the classifier model layer. Another possibility is to compose a composite model where the output embedding of one layer (e.g., X - ReLU GCN) is passed to two subsequent layers (e.g., TX - ReLU GCN and N - ReLU GCN) layers enabling shared learning of the first layer.

4.3 Inductive Inference

We observe that PTE is inductive because the feature embeddings are pre-computed and used during inference on unseen documents using a Softmax GCN layer. Building upon this, our simple idea is to store the feature embeddings available at the appropriate layer outputs and make inference like PTE. For example, we store feature embeddings at the F layer for HetGCN (F – X) and store the fused embedding at an X - Softmax GCN as shown in the middle row (Figure 1(e)). This composite HetGCN model is equivalent to performing nonlinear operation on each of the terms in $U^{(1)}$ (see Equation 3) separately and passing to the classifier model layer. Another possibility is to compose a composite model where the output embedding of one layer (e.g., X - ReLU GCN) is passed to two subsequent layers (e.g., TX - ReLU GCN and N - ReLU GCN) layers enabling shared learning of the first layer.

Figure 1: HetGCN Architecture. (a),(b),(c) and (d) show networks starting from F, X, TX and N matrices, producing document embeddings, used to predict class probabilities. (e) and (f) show two possibilities of fusing feature and document embeddings coming from two different but compatible networks. $U^{(0)}_F$ and $V^{(0)}_N$ can be 1-hot representations of features and documents.
We note that the above method does not make TextGCN inductive in a strict sense because the way document embedding is inferred during testing and training is different, as no 1-hot document representations are available for test documents – the same holds for HeteGCN (TX − X). Conversely, the scenario is quite different for HeteGCN models with the first layer learning only the feature embeddings (e.g., F − X and X − TX − X). For these paths, it is possible to update F and X as learned model weights are used for inference on new documents. F and X may require updates because IDF factors or feature co-occurrence based F may change. However, the quality of inference with updated matrices will be dependent on the degree of changes and the sensitivity of the learned HeteGCN model with respect to the changes. More analysis and investigations are needed and are left as future work.

4.4 Simplifying HeteGCN and C-Light GCN (C-LightGCN) for classification

There has been some effort [8, 35] to simplify GCN model by understanding the usefulness of feature and nonlinear transformations. [35] presented some evidence that feature smoothing (i.e., AX) is the most important function in GCN and performance degradation due to removal of nonlinear activation is not much. These experiments were conducted using several benchmark datasets for a classification task. The simplified GCN classifier model turns out to be linear with a smoothed feature matrix (A−1X) fed as input where L denotes the number of GCN layers. The same idea can be used to simplify all HeteGCN models (i.e., removing non-linearity).

Using a similar idea, LightGCN [8] proposed to learn embeddings for users and items (starting with 1-hot representation) for recommendation problems and demonstrated that dropping both nonlinear and feature transformation operations does not degrade performance much. The resultant model is linear and a weighted linear combiner model was suggested to fuse embeddings of different layers (i.e., V = \sum_{l=1}^{L} a_l V(l)) where V(l) = A(l)U(l) and the weights are tuned by treating them as hyper-parameters. Like TextGCN, LightGCN uses A (see Equation 2) with X representing the user-item interaction matrix but without F. One simple idea is to extend LightGCN for the text classification problem by using only off-diagonal block matrices (i.e., X) in A (ref. Equation 2). It is straightforward to derive expression for V. It turns out that each document embedding is (n + m) dimensional with contributions coming from both document-document and document-feature relations. The C-LightGCN classification model is interesting and useful because it can be interpreted as a simplified TextGCN model and compared against simplified HeteGCN models.

5 EXPERIMENTS

We conducted several experiments to bring out different aspects of the proposed approach in comparison with the baselines and state-of-the-art graph embedding methods and answer several research questions related to network architecture.

5.1 Experimental Setup

5.1.1 Datasets. We consider five benchmark datasets for our experiments. 20NG consists of long text documents, categorized into 20 newsgroups. MR consists of movie reviews classified into positive and negative sentiments. R8 and R52 consist of documents that appear on Reuters-21578 newswire grouped into 8 and 52 categories, respectively. Ohsumed consists of medical abstracts, which are categorized into 23 cardiovascular diseases.

5.1.2 Dataset Preparation. For consistency, we prepare the datasets in an identical setup as described in TextGCN [36]. We leveraged the code1 provided by the authors to prepare the dataset. Each of the raw text is cleaned and tokenized. Stop words and low-frequency words (less than 5 occurrences) are removed in 20NG, R8, R52, and Ohsumed except for MR, as they are short text. The statistics of the pre-processed datasets are detailed in Table 1.

Large Labeled Data. We use the standard train/test split. 10% of the train documents were randomly sampled to form the val set.

Small Labeled Data. We do a stratified sampling (1%, 5%, 10% and 20%) of the above training documents to form small labeled sets. Additionally, we enforce that smaller labeled training documents are included in the higher labeled training set for consistency. This is repeated 5 times to create 5 splits for each label percent. We use the val/test split as above.

5.1.3 Graph Construction. F is a word-word Pointwise Mutual Information (PMI) graph. X is a document-word Term Frequency-Inverse Document Frequency (TF-IDF) graph. Refer [36] for further details. N is a document-document nearest neighbor graph constructed from X with top 25 neighbours obtained using cosine similarity score. PMI and IDF are computed over all the documents in the transductive setting while only train documents are used to estimate in the inductive setting. Unseen words are removed from the validation and test documents.

5.1.4 Methods of comparison. We compared the methods given below and all models were trained by minimizing the cross-entropy loss function (1). Methods that learn embeddings are set to learn embeddings of size 200 for consistency.

LR: We trained Logistic Regression classifier on the TF-IDF transformed word vectors. We tuned hyper-parameter \( C (L_2\text{-regularization}) \) over \([1e-5, 1e5]\) in powers of 10 on the validation set.

PTE: PTE [31] learns words’ embeddings, generates text embedding from word embeddings and then utilizes them to train a logistic regression model. We used the code provided by the authors2 to learn the embeddings with following parameters: \( w = 5 \), \( \text{min count} = 0 \), and \( \text{negative samples} = 5 \). A logistic regression model was trained with these embeddings using LIBLINEAR [7] where the regularization parameter was swept over \([1e-4, 1e4]\) in powers of 10. The parameter was tuned on the validation set.

TextGCN: We used the code provided by the authors3 to set up the experiments. Apart from the best configuration suggested by the authors, we swept learning rate over \([1e-1, 1e-3]\) in powers of 10, weight decay over \([1e-2, 1e-4]\) in logarithmic steps and dropout over \([0, 0.75]\) in steps of 0.25.

C-LightGCN: LightGCN [8] adapted to classification problems (Section 4.4) is trained with the aggregation of adjacency matrices \( A, A^2, \) and \( A^3 \). The relevant rows of aggregated adjacency matrix are treated as document features, and a Logistic classifier is trained from

1https://github.com/yao8839836/text_gcn
2https://github.com/mnqu/PTE
3https://github.com/yao8839836/text_gcn
Table 1: Dataset Statistics [36]

| Dataset  | Words | Docs | Train Docs | Test Docs | Classes | Avg. Length |
|----------|-------|------|------------|-----------|---------|-------------|
| 20NG     | 42,757| 18,846| 11,314     | 7,532     | 20      | 221.26      |
| MR       | 18,764| 10,662| 7,108      | 3,554     | 2       | 20.39       |
| R8       | 7,688 | 7,674 | 5,485      | 2,189     | 8       | 65.72       |
| R52      | 8,892 | 9,100 | 6,532      | 2,568     | 52      | 69.82       |
| Ohsumed  | 14,157| 7,400 | 3,357      | 4,043     | 23      | 135.82      |

5.1.5 Evaluation Metrics. We evaluated the performance of all classifier models using Micro-F1 and Macro-F1 scores [19]. We use model accuracy (Micro-F1) evaluated on a held-out validation set to select the best model from various hyper-parameter configurations.

5.2 Large Labeled Data Scenario

We present results obtained from our experiments on five benchmark datasets in Table 2. We observe that thorough tuning of hyper-parameters gives us better performance for LR, PTE and TextGCN models than compared to performance reported in [36]. For nonlinear models (i.e., GCN, TextGCN and HeteGCN), we repeated experiments for 5 different seeds and report average performance. In [36], TextGCN gave competitive or better performance compared to many models. For this reason, we only compare the performance of our models with TextGCN. The proposed HeteGCN (F − X) model achieves similar or slightly better performance compared to TextGCN on all datasets, suggesting more complex TextGCN is unnecessary. The HeteGCN (TX − X) model gives only slightly inferior performance on four datasets (20NG, MR, R8 and R52) compared to TextGCN. The main reason is that models other than HeteGCN (F − X) do not have direct access to the word-word relational information and this information is learned only through labeled training examples. HeteGCN (X − N) and GCN models give similar performance and their inferior performance is due to the quality of N. We found the document - document matrix to be noisy in the sense that more documents belonging to different classes are connected. Finally, LightGCN performs reasonably well on 20NG, MR and R8 but is inferior to TextGCN and we believe this is due to over-smoothing with higher powers of A and a lack of nonlinear transformation. We found that LightGCN is sensitive to hyper-parameter tuning. We also conducted experiments with simplified HeteGCN models (i.e., removing non-linearity) and observed performance closer to that of HeteGCN models.

5.3 Small Labeled Training Data Scenario

We report our results from small labeled training data scenario specific experiment in Figure 2. We see that HeteGCN (F − X) performs significantly better than TextGCN and other models in almost all datasets and varying percentage of labeled data. The performance gains are in the range of 2 − 8%. The superior performance of HeteGCN (F − X) can be attributed to: (1) learning with lesser number of model parameters, (2) using F information and (3) neighborhood aggregation and non-linear transformation advantages of GCN. We find that the performance gap reduces as the percentage labeled data increases in several cases. GCN and LightGCN perform better compared to PTE on MR and R8. PTE performed reasonably well only in 20NG. Note that we show only HeteGCN (F − X) results and do not include results obtained from other HeteGCN models to make Figure 2 clutter-free. However, the observations made on other HeteGCN models in Table 2 with respect to rest of the models (i.e., TextGCN, PTE, etc.) nearly hold even in this scenario. We also observed that the performance of HeteGCN (X − TX − X) model is close to TextGCN (within 1%) when the percentage of labeled examples is very small (i.e., 1% and 5%). Thus, HeteGCN (X − TX − X) model is a useful alternative to TextGCN (X − TX) when (1) there are memory and compute constraints related to F and (2) we have very small labeled set. We also conducted experiments with HeteGCN (F − X) model with PTE embeddings fed as input. This model has lower model complexity (O(d^2 + kd)) and gave performance lift of (2 − 4%) on 20NG and MR datasets for 1% and 5% cases.

5.4 Inductive Experimental Study

We conducted this experiment on large labeled data and performed inference using the inductive inference method explained in Section 4.3. Results in Table 3 show that this method is effective and useful even for TextGCN. We find that HeteGCN (F − X) generalizes significantly better achieving (3−7%) lifts on all datasets (except MR) compared to TextGCN and outperforms PTE on all datasets. We find that HeteGCN (X − TX − X) gives 1−3% improvement on all datasets over TextGCN except 20NG and is a useful alternative to HeteGCN (F − X), as explained earlier. PTE gives surprisingly...
much lower performance than LR for e.g. in MR. We observed that as we increased the embedding dimension size in PTE, it tends to reach towards LR performance, suggesting that direct factorization of co-occurrence matrix may lead to a loss in information and that convolutional models are better from that perspective.

5.5 Timing Comparison
We made training time comparisons on the various HeteGCN variants and TextGCN. All the analysis was done on a machine with Intel Xeon 2.60GHz processor, 112 GB RAM, Ubuntu 16.04 OS, python 3.5 and tensorflow 1.14 (CPU). We are reporting average time taken for an epoch on 20NG and Ohsumed in Table 4. We observe that we get ~1.5x speed up by using HeteGCN (F – X), ~6x speed up by using HeteGCN (X – TX – X) and ~9x speed up using HeteGCN (TX – X). Similar speedups were observed for other datasets as well. The obtained speedups are proportional to the sparsity of the graphs involved (F is denser than X).

5.6 Visualization of learned embeddings
In this subsection, we discuss the effectiveness of the learned word representation. We, first, provide a tSNE [33] transformed document representations computed from the HeteGCN trained on R8-1% labeled dataset in Figure 3 and compare it against those from TextGCN, PTE and GCN. Two things to note: (1) the majority classes (cyan and violet) are much better separated in HeteGCN (F – X) embeddings than other models, (2) the minority classes get quite scattered in TextGCN and GCN models, and although PTE does somewhat better, HeteGCN (F – X) shows significantly better clustering of these points even in the 1% labeled setting. We also qualitatively analyse word embeddings by training a logistic regression model on aggregated training document embeddings and predicting words’ labels using word embeddings. We show top-10 words with the highest probabilities for few a classes in 20NG 1% labeled dataset in Table 5. We note that the top-10 words are interpretable even under low-labeled setting.

6 RELATED WORK
Traditional text classification models [1] and neural models [21] discussed in Section 1 require large amount of labeled data and/or pre-trained embeddings. In practice, large labeled data is not always available. Also, raw text information might be inaccessible due to privacy concerns making it infeasible to associate any pre-trained embeddings with this data. In such cases, the various models discussed in Section 1 cannot work effectively.

PTE [31] addresses these problems by learning word representations from given data by constructing a heterogeneous graph of documents, words and labels. It can be shown that PTE factorizes a joint heterogeneous graph to learn word representations [25]. Note that utilizing unlabeled data to improve models, and using graphs to improve performance in the low labeled setting has been studied significantly [2, 5, 22]. PTE builds on these ideas to learn better representations, while earlier models focused on improving classifier performance.

TextGCN [36] combines ideas from PTE with Graph Convolutional Network (GCN) to give better performance. GCN [14] has shown excellent performance on text classification datasets. However, it assumes access to a graph structure among documents like

Figure 2: Test Micro-F1 on the text classification task plotted by varying training data sizes. The training data sizes are varied in steps of 1%, 5%, 10% and 20%.
Figure 3: TSNE Plots of 20NG document embeddings obtained from the following 4 models: (a) HeteGCN (F-X); (b) TextGCN; (c) PTE; and (d) GCN.

### Table 2: Test Micro and Macro F1 scores on the text classification task in the large labeled setting. Models with random initializations were run with 5 different seeds, and standard deviations are reported for them in bracket wherever applicable.

| Dataset | Method       | Micro F1 | Macro F1 |
|---------|--------------|----------|----------|
| 20NG    | LR           | 84.76    | 84.09    |
|         | PTE          | 84.37    | 83.70    |
|         | GCN          | 76.32 (0.15) | 76.07 (0.14) |
|         | LightGCN     | 82.98    | 81.27    |
|         | TextGCN      | 85.86 (0.13) | 85.30 (0.12) |
|         | HeteGCN (F × X)| 87.15 (0.15) | 86.59 (0.16) |
|         | HeteGCN (X × TX – X)| 84.39 (0.15) | 83.86 (0.13) |
|         | HeteGCN (TX – X)   | 84.18 (0.07) | 83.71 (0.06) |
|         | HeteGCN (TX × N)   | 76.22 (0.14) | 75.99 (0.13) |
| MR      | LR           | 77.01    | 77.91    |
|         | PTE          | 71.07    | 71.06    |
|         | GCN          | 74.13 (1.29) | 74.12 (1.30) |
|         | LightGCN     | 75.55    | 75.55    |
|         | TextGCN      | 77.03 (0.10) | 77.02 (0.10) |
|         | HeteGCN (F × X)| 76.71 (0.33) | 76.71 (0.33) |
|         | HeteGCN (X × TX – X)| 75.48 (0.30) | 75.46 (0.32) |
|         | HeteGCN (TX – X)   | 75.21 (0.37) | 75.20 (0.37) |
|         | HeteGCN (TX × N)   | 74.23 (0.82) | 74.20 (0.84) |
| R8      | LR           | 97.26    | 93.32    |
|         | PTE          | 94.66    | 86.91    |
|         | GCN          | 94.10 (0.57) | 85.29 (0.83) |
|         | LightGCN     | 96.21    | 88.95    |
|         | TextGCN      | 96.65 (0.21) | 87.39 (1.71) |
|         | HeteGCN (F × X)| 97.24 (0.51) | 92.95 (2.01) |
|         | HeteGCN (X × TX – X)| 97.09 (0.15) | 90.99 (1.08) |
|         | HeteGCN (TX – X)   | 96.98 (0.21) | 91.84 (1.46) |
|         | HeteGCN (TX × N)   | 94.39 (0.18) | 86.14 (0.28) |
| R52     | LR           | 93.38    | 68.20    |
|         | PTE          | 90.65    | 59.21    |
|         | GCN          | 90.41 (0.54) | 61.77 (2.07) |
|         | LightGCN     | 92.37    | 69.29    |
|         | TextGCN      | 93.80 (0.09) | 68.62 (0.84) |
|         | HeteGCN (F × X)| 94.35 (0.25) | 68.42 (1.76) |
|         | HeteGCN (X × TX – X)| 92.05 (0.41) | 52.75 (2.41) |
|         | HeteGCN (TX – X)   | 92.87 (0.60) | 57.69 (5.67) |
|         | HeteGCN (TX × N)   | 91.93 (0.11) | 64.61 (2.05) |
| Ohsumed | LR           | 65.87    | 53.77    |
|         | PTE          | 60.00    | 53.67    |
|         | GCN          | 62.23 (0.32) | 54.87 (0.44) |
|         | LightGCN     | 65.84    | 59.23    |
|         | TextGCN      | 68.11 (0.19) | 60.61 (0.22) |
|         | HeteGCN (F × X)| 68.11 (0.70) | 60.62 (1.54) |
|         | HeteGCN (X × TX – X)| 61.44 (1.31) | 48.23 (4.17) |
|         | HeteGCN (TX – X)   | 66.14 (0.45) | 58.52 (2.31) |
|         | HeteGCN (TX × N)   | 62.46 (0.20) | 54.59 (0.36) |

| Dataset | Method       | Micro F1 | Macro F1 |
|---------|--------------|----------|----------|
| 20NG    | LR           | 83.70    | 83.31    |
|         | PTE          | 81.61 (0.09) | 80.91 (0.08) |
|         | TextGCN      | 80.88 (0.54) | 80.47 (0.48) |
|         | HeteGCN (F × X)| 84.59 (0.14) | 83.95 (0.12) |
|         | HeteGCN (X × TX – X)| 79.83 (0.54) | 79.13 (0.57) |
| MR      | LR           | 76.28    | 76.28    |
|         | PTE          | 68.78 (0.18) | 68.76 (0.18) |
|         | TextGCN      | 74.60 (0.43) | 74.55 (0.48) |
|         | HeteGCN (F × X)| 75.62 (0.26) | 75.62 (0.26) |
|         | HeteGCN (X × TX – X)| 75.15 (0.31) | 75.15 (0.31) |
| R8      | LR           | 93.33    | 82.19    |
|         | PTE          | 92.73 (0.14) | 82.94 (0.45) |
|         | TextGCN      | 94.00 (0.40) | 78.29 (0.59) |
|         | HeteGCN (F × X)| 97.17 (0.33) | 92.33 (0.86) |
|         | HeteGCN (X × TX – X)| 96.32 (0.60) | 89.32 (1.08) |
| R52     | LR           | 90.65    | 62.53    |
|         | PTE          | 87.97 (0.12) | 53.10 (0.65) |
|         | TextGCN      | 89.39 (0.38) | 47.30 (2.09) |
|         | HeteGCN (F × X)| 93.89 (0.45) | 66.53 (4.06) |
|         | HeteGCN (X × TX – X)| 91.39 (0.42) | 51.31 (2.57) |
| Ohsumed | LR           | 61.14    | 54.89    |
|         | PTE          | 56.93 (0.12) | 47.51 (0.45) |
|         | TextGCN      | 56.32 (1.36) | 36.74 (1.50) |
|         | HeteGCN (F × X)| 63.79 (0.80) | 50.17 (2.33) |
|         | HeteGCN (X × TX – X)| 59.12 (1.46) | 41.76 (3.01) |

Table 3: Test Micro and Macro F1 scores on the text classification task in inductive setting. Models with random initializations were run with 5 different seeds, and standard deviations are reported for them in bracket wherever applicable.

### Table 4: Average Per Epoch Time: HeteGCN, TextGCN

| Dataset | Avg. Time (s) | 20NG | Ohsumed |
|---------|---------------|------|---------|
| HeteGCN (F × X)| 4.23 | 1.99 |
| HeteGCN (X × TX – X)| 0.78 | 0.18 |
| TextGCN | 6.86 | 1.70 |

citation networks to provide a boost in performance. Such graphs may not always be available. TextGCN, like PTE, constructs a heterogeneous graph of documents and words (excluding labels) and uses it along with GCN. Unlike PTE, TextGCN jointly learns word representations and classifier together, thereby getting good performance. However, TextGCN has three issues: (1) it cannot scale to large datasets, (2) it force-fits a heterogeneous graph in GCN defined for homogeneous graph, (3) it is transductive without a natural inductive formulation. Our proposed approach solves all
HeteGCN: Heterogeneous Graph Convolutional Networks for Text Classification

| comp.graphics | sci.space | sci.med | rec.autos |
|---------------|-----------|---------|-----------|
| graphics      | space     | cancer  | car       |
| image         | moon      | disease | cars      |
| display       | shuttle   | doctor  | engine    |
| routines      | orbit     | patients| rear      |
| animation     | nasa      | treatment| ford      |
| 3d            | mission   | infection| dodge     |
| vga           | spacecraft| drug    | honda     |
| polygon       | launch    | medical  | gt        |
| processing    | earth     | clinical | models    |
| files         |          |         | tires      |

Table 5: Top-10 words per class in 20NG as computed using embeddings trained on 1% labeled data.

Finally, we also demonstrated how inductive inference is made with HeteGCN and TextGCN models.

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