Graph Convolutional Networks based Word Embeddings

Shikhar Vashishth1*Prateek Yadav1*Manik Bhandari2*Piyush Rai3Chiranjib Bhattacharyya1Partha Talukdar1

¹ Indian Institute of Science

² Birla Institute of Technology and Science, Pilani
 ³ Indian Institute of Technology, Kanpur

{shikhar, prateekyadav, chiru, ppt}@iisc.ac.in

f2014088@pilani.bits-pilani.ac.in, piyush@cse.iitk.ac.in

Abstract

Recently, word embeddings have been widely adopted across several NLP applications. However, most word embedding methods solely rely on linear context and do not provide a framework for incorporating word relationships like hyper*nym*, *nmod* in a principled manner. In this paper, we propose WordGCN, a Graph Convolution based word representation learning approach which provides a framework for exploiting multiple types of word relationships. WordGCN operates at sentence as well as corpus level and allows to incorporate dependency parse based context in an efficient manner without increasing the vocabulary size. To the best of our knowledge, this is the first approach which effectively incorporates word relationships via Graph Convolutional Networks for learning word representations. Through extensive experiments on various intrinsic and extrinsic tasks, we demonstrate WordGCN's effectiveness over existing word embedding approaches. We make WordGCN's source code available to encourage reproducible research.

1 Introduction

Representing words as low dimensional real-valued vectors is an effective and widely adopted technique in NLP. Such representations capture semantic and syntactic properties of words based on their usage and allow them to generalize for unseen examples. Meaningful word embeddings have been shown to improve performance on several important tasks, such as named entity recognition (NER) (Bengio, Courville, and Vincent 2013), parsing (Socher et al. 2013), and part-of-speech (POS) tagging (Ma and Hovy 2016). Using word embeddings for initializing Deep Neural Networks has also been found to be quite effective (Collobert et al. 2011).

Most popular methods for learning word embeddings are based on the distributional hypothesis, which utilizes the co-occurrence of words for learning word representations (Mikolov et al. 2013; Pennington, Socher, and Manning 2014). More recently, this approach has been extended to include syntactic contexts (Levy and Goldberg 2014) derived from dependency parse of text. Higher order dependencies have also been exploited by (Komninos and Manandhar 2016; Li et al. 2018). Syntax-based embeddings encodes functional similarity (in place substitutable words) rather than topical similarity (topically related words) which provides an advantage on certain tasks like NER. However, current approaches incorporate syntactic context by severely expanding context vocabulary which limits their scalability on large corpora.

Incorporating relevant signals from semantic knowledge sources like WordNet (Miller 1995), FrameNet (Baker, Fillmore, and Lowe 1998), and Paraphrase Database (PPDB) (Pavlick et al. 2015) have been shown to improve the quality of word embeddings. Recent works utilize them by incorporating them in a neural language modeling objective function (Yu and Dredze 2014) or as a post-processing step (Faruqui et al. 2014; Mrkšić et al. 2016). Although, the existing approaches improve the quality of word embeddings, they ignore the directionality and types of word-relationships provided by these sources like *homonyms* and *hypernyms*.

Recently proposed, Graph Convolutional Networks (GCN) (Defferrard, Bresson, and Vandergheynst 2016; Kipf and Welling 2016) have been found to be quite effective at encoding structural information in graphs. GCNs have been successfully employed for several NLP tasks like machine translation (Bastings et al. 2017), semantic role labeling (Marcheggiani and Titov 2017), and event detection (Nguyen and Grishman 2018). Information from word co-occurrence and semantic knowledge sources can be modeled as edges in a graph with words as nodes. Such graphs can be effectively encoded using GCNs.

In this paper, we propose WordGCN, a novel Graph Convolution based method, which jointly utilizes word co-occurrence and information from semantic knowledge sources for learning word representation. Unlike prior works, WordGCN functions at both sentence as well as corpus level and provides a framework for incorporating multiple types of semantic knowledge while learning word representation, without expanding the word vocabulary. Our contributions can be summarized as follows:

1. We propose WordGCN, a novel Graph Convolution based method for learning word embeddings by encoding relationships between words on two levels – sentence level and corpus level.

^{*} contributed equally to this paper.

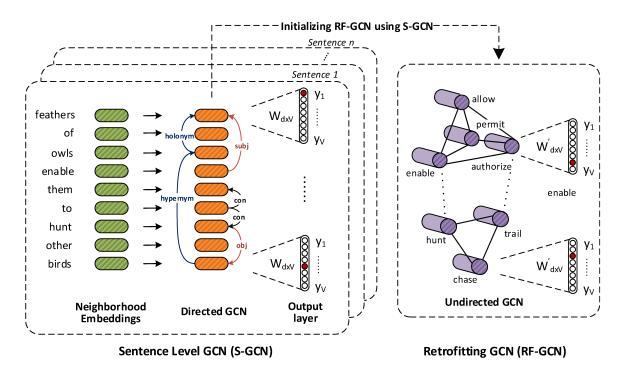


Figure 1: Overview of WordGCN. WordGCN utilizes sentence level word co-occurrence relationships and directed semantic information for learning word embeddings through S-GCN component. These are further improved by RF-GCN, which incorporates corpus level synonym relationships. Each word has two embeddings – neighborhood and target, for both components. W and W' consist of target embeddings of each word in the vocabulary which is used to compute the final softmax scores. Please refer Section 4 for details.

- 2. WordGCN allows to jointly utilize word co-occurrence and different types of semantic knowledge for learning word embeddings.
- 3. By experiments on multiple intrinsic and extrinsic tasks, we demonstrate WordGCN's effectiveness. The learned embeddings obtain substantial improvement over the previous state-of-the-art method across all the tasks.

2 Related Work

Word Embeddings: Recently, there has been a lot of interest in learning meaningful word representations. Neural language modeling (Bengio et al. 2003) based continuousbag-of-words (CBOW) and skip-gram (SG) models were proposed by (Mikolov et al. 2013). These models lead to representations with semantic regularities and perform well on similarity and analogy tasks without explicitly optimizing for them. The work is further extended by (Pennington, Socher, and Manning 2014), which explicitly impose structural constraints through their loss function via a matrix factorization approach based on words cooccurrence. Other formulations for learning word embeddings include multi-task learning (Collobert et al. 2011) and ranking frameworks (Ji et al. 2015).

Since then, there has been an interest in several different aspects of word representations. Maas et al.; Jastrzebski, Lesniak, and Czarnecki focus on learning task specific word representations. Alternate training of CBOW and SG models has been explored by (Song, Lee, and Xia 2017) while several other works explore the use of negative sampling to speed up training (Mikolov et al. 2013). In this work, we use a more recent approach – sampled softmax (Jean et al. 2015) to reduce training time.

Syntax-based Embeddings: Dependency parse context based word embedding are first introduced by (Levy and Goldberg 2014). This allows encoding syntactic relationships between words and gives advantage on tasks where functional similarity is more relevant than topical similarity. The inclusion of syntactic context was further extended through secondorder (Komninos and Manandhar 2016) and multi-order (Li et al. 2018) dependencies. However, in all the existing approaches either context or target vocabulary has to be severely increased for incorporating syntactic relationships. For instance, to learn representation for 220k words, the context vocabulary blows to 1.3 million in (Komninos and Manandhar 2016). In this paper, we attempt to address this drawback by exploiting advances in encoding graphical structures through Graph Convolution networks.

Graph Convolutional Networks: The first neural network model on graphs is proposed by (Scarselli et al. 2009). Graph Convolutional Networks are the generalization of Convolutional Neural Networks (CNN) to non-euclidean domains. Bruna et al. formulated the spectral and spatial construction of GCNs which is later improved by (Defferrard, Bresson, and Vandergheynst 2016) through an efficient localized filter approximation. First-order formulation of GCNs via a layer-wise propagation rule is proposed by (Kipf and Welling 2016). A detailed description of GCNs and their applications can be found in (Bronstein et al. 2017). GCNs have been shown to improve performance on semantic role la-(Marcheggiani and Titov 2017), beling event detec-(Nguyen and Grishman 2018), tion document timestamping (Vashishth et al. 2018), and machine translation (Bastings et al. 2017).

Incorporating semantic knowledge sources: There have been several methods which aim to incorporate semantic knowledge source like WordNet (Miller 1995) and PPDB (Pavlick et al. 2015) to improve the quality of word representations (Faruqui et al. 2014; Mrkšić et al. 2016; Alsuhaibani et al. 2018). Most approaches use pre-trained word embeddings and use the knowledge sources as a post-processing step. Our proposed method, WordGCN is capable of training word embeddings from scratch as well as incorporating semantic knowledge sources – both, during training or as a post processing step.

3 Background: Graph Convolutional Networks

Graph Convolutional Networks (GCNs) are an effective way to learn meaningful node representation based on node features and the graph structure. In this section, we will provide a brief overview of GCNs (Defferrard, Bresson, and Vandergheynst 2016; Kipf and Welling 2016) and its extension to directed labeled graphs.

3.1 GCN on Undirected Graphs:

Given $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{X})$, an undirected graph, where \mathcal{V} is the set of nodes, $\mathcal{E} = \{\{u, v\}: \text{ if } u \text{ and } v \text{ have an edge}\}$, is the set of undirected edges and $|\mathcal{V}| = n$. The input node features are denoted by $\mathcal{X} \in \mathbb{R}^{n \times d}$, where each row x_v is the representation of the node $v \in \mathcal{V}$. A single layer of GCN propagation as defined by (Kipf and Welling 2016) is

$$H^{k+1} = f(AH^k W^{k+1}),$$

where, $H^k \in \mathbb{R}^{n \times d}$ is the hidden representation of nodes after the k^{th} layer of GCN, $A \in \mathbb{R}^{n \times n}$ is the adjacency matrix of the graph, $W^k \in \mathbb{R}^{d \times d}$ is a set of learnable parameters and $f(\cdot)$ is the activation function. For the first layer, we initialize $H^0 := \mathcal{X}$. Alternatively, we can represent one layer of GCN as

$$h_v^{k+1} = f\left(\sum_{u \in \mathcal{N}(v)} W^{k+1} h_u^k + b^{k+1}\right), \quad \forall v \in \mathcal{V}.$$
 (1)

where $b^{k+1} \in \mathbb{R}^d$ is the bias, $\mathcal{N}_{\mathcal{G}}(v) = \{u : \{u, v\} \in \mathcal{E}\}\$ is the set of immediate neighbors of $v, h_u^k \in \mathbb{R}^d$ is hidden representation of node u in H_u^k .

3.2 GCN on Directed Labeled Graphs:

Given a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{X})$, with \mathcal{V} and \mathcal{X} as defined in section 3.1 and the set \mathcal{E} contains directed labeled edges, where an edge from node u to node v with label l_{uv} is denoted by (u, v, l_{uv}) . The set $\mathcal{N}_{\mathcal{G}}(v) = \{(u, l_{uv}) : (u, v, l_{uv}) \in \mathcal{E}\}$ is the *labeled in-neighborhood* set containing tuples of all nodes u from which there is an edge to v, along with their edge labels. As the information need not always propagate only along the direction of the edge, following (Marcheggiani and Titov 2017), we append \mathcal{E} by inverse edges (v, u, l_{uv}^{-1}) and self-loop edges (v, v, l_{loop}) . The embedding of a node v after k^{th} GCN layer is thus given by:

$$h_v^{k+1} = f\left(\sum_{(u,l_{uv})\in\mathcal{N}_{\mathcal{G}}(v)} \left(W_{l_{uv}}^k \cdot h_u^k + b_{l_{uv}}^k\right)\right).$$

where, $W_{l_{uv}}^k \in \mathbb{R}^{d \times d}$ and $b_{l_{uv}} \in \mathbb{R}^d$ are learnable model parameters.

3.3 Edge Label Gating Mechanism:

For a given task, all the edge labels might not be equally important and might sometimes be erroneous. To address this issue, we employ edge-wise gating (Marcheggiani and Titov 2017; Bastings et al. 2017) in directed labeled GCNs. For each node v, we assign a relevance score $g_{l_{uv}}^k \in \mathbb{R}$ to all the edges incident on it. The score is computed independently for each layer as:

$$g_{l_{uv}}^k = \sigma\left((\hat{W}_{l_{uv}}^k)^\top \cdot h_u^k + \hat{b}_{l_{uv}}^k \right), \tag{2}$$

where $\hat{W}_{l_{uv}}^k \in \mathbb{R}^d$ and $\hat{b}_{l_{uv}}^k \in \mathbb{R}$ are trainable parameters and $\sigma(\cdot)$ here is the sigmoid function. The updated GCN propagation rule for the k^{th} layer can be written as

$$h_v^{k+1} = f\left(\sum_{(u,l_{uv})\in\mathcal{N}_{\mathcal{G}}(v)} g_{l_{uv}}^k \times \left(W_{l_{uv}}^k \cdot h_u^k + b_{l_{uv}}^k\right)\right).$$
(3)

4 WordGCN Overview

The task of learning word representations in unsupervised setting can be formulated as follows: given a text corpus, the aim is to learn a d-dimensional embedding for each word in the vocabulary. For each sentence, we construct a directed labeled sentence graph, with the set of words as nodes and edges denoting word relationships. For instance, as shown in Figure 1, in the sentence "Feathers of owls enable them to hunt other birds.", the asymmetric relation, obj between hunt and birds is represented through a directed labeled edge. For utilizing corpus level information like synonym, which is inherently symmetric in nature, we construct an undirected labeled graph with the set of nodes as the entire word vocabulary. For example, the synonym relation between hunt and chase is represented as an undirected labeled edge. Given the two types of graphs, WordGCN employs directed (Marcheggiani and Titov 2017) and undirected GCNs (Defferrard, Bresson, and Vandergheynst 2016; Kipf and Welling 2016) for learning word representation. We briefly describe the components of WordGCN below.

- Sentence Level GCN (S-GCN) learns word embeddings by capturing global co-occurrence properties of words in the corpus, available via context and dependency edges. It also allows to incorporate other types of directed word relationships during training.
- **Retrofitting GCN (RF-GCN)** further refines embeddings learned by S-GCN by incorporating corpus level information from semantic knowledge sources.

5 WordGCN Details

In this section, we describe the components of WordGCN in detail. WordGCN utilizes word relationships at sentence and corpus level based on their inherent nature. Unlike prior works (Levy and Goldberg 2014; Komninos and Manandhar 2016) which increase vocabulary size to incorporate word relationships and multi order dependencies, S-GCN incorporates this in a principled manner using edge labeled GCNs. We hypothesize that this allows us to better capture semantic and syntactic properties of words. We validate our hypothesis in Section 7. Since a word has different semantic properties depending upon whether it appears as a target or neighboring word, we keep two embeddings, namely target and neighborhood embeddings for each word similar to (Mikolov et al. 2013).

5.1 Sentence Level GCN (S-GCN):

Sentence graph construction:

For each sentence $s = (w_1, w_2, \ldots, w_n)$, we construct a directed labeled sentence graph $\mathcal{G}_s = (\mathcal{V}_s, \mathcal{E}_s)$, where $\mathcal{V}_s = \{w_1, w_2, \ldots, w_n\}$, the set of words in s and \mathcal{E}_s denotes directed word relationships. In WordGCN, linear context, dependency parse based context and directed WordNet relations are utilized as described below.

• Linear context edges: Since a word in similar context has similar meaning (Harris 1954; Rumelhart, Hinton, and Williams 1988), for each word w_i in s, we construct incoming edges from words lying in its k-length context window. The obtained edges, \mathcal{E}_{con} can be defined as

$$\mathcal{E}_{con} = \{ (w_{i+j}, w_i, l_{con}) : j \in [-k, k] \cap \mathbb{I} \setminus \{0\}, \forall i \in [n] \}.$$

where, l_{con} is the label corresponding to linear context edges, $[n] = \{1, 2, ..., n\}$ and \mathbb{I} is the set of integers.

• Dependency context edges: For each sentence s, we obtain dependency parse graph (\mathcal{G}_d^s) extracted using Stanford CoreNLP parser (Manning et al. 2014). Prior works (Levy and Goldberg 2014; Komninos and Manandhar 2016), utilize dependency parse information by concatenating words with edge labels. This severely increases the word vocabulary limiting their applicability on large corpora. In WordGCN, we incorporate this information much more efficiently

by directly including dependency edges in the sentence graph as defined below.

$$\mathcal{E}_{deps} = \{ (w_j, w_i, l_{ji}^d) : (w_j, l_{ji}^d) \in \mathcal{N}_{\mathcal{G}_d^s}(w_i), \forall i \in [n] \},\$$

where, $\mathcal{N}_{\mathcal{G}_d^s}(w_i)$ is the *labeled in-neighborhood* set of w_i w.r.t graph \mathcal{G}_d^s .

• WordNet Edges: WordNet (Miller 1995), a large lexical database of English, provides several types of symmetric and asymmetric words relations which have been used to improve word embeddings (Faruqui et al. 2014; Alsuhaibani et al. 2018). In WordGCN, we utilize relations – hypernym, hyponym, holonym, and meronym in S-GCN via \mathcal{E}_{wnet} as defined below.

$$\mathcal{E}_{wnet} = \{ (w_j, w_i, l_{ji}^w) : (w_j, l_{ji}^w) \in \mathcal{N}_{\mathcal{G}_w}(w_i), \forall i \in [n] \},\$$

where, \mathcal{G}_w is the directed WordNet relationship graph between words as provided by (Alsuhaibani et al. 2018).

In WordGCN, the edge set \mathcal{E}_s of sentence graph, \mathcal{G}_s is defined as

$$\mathcal{E}_s = \mathcal{E}_{con} \cup \mathcal{E}_{deps} \cup \mathcal{E}_{wnet}.$$

For the experiments in this paper, we have used \mathcal{E}_s as defined above. However, it can be further extended based on the availability of other directed word relations.

Directed Graph Convolution:

On the obtained sentence graph \mathcal{G}_s , we employ directed GCN (Marcheggiani and Titov 2017) as defined in Section 3.2. Similar to CBOW model (Mikolov et al. 2013), we prevent a word from occuring in its own context by removing self-loops from \mathcal{E}_s . Since some of the edges obtained from automatically constructed dependency parse graph can be erroneous, we perform edge-wise gating (Section 3.3) to give importance to relevant edges and suppress the noisy ones. The k^{th} layer update rule used for updating embeddings of word w_i is defined as

$$h_i^{k+1} = f\left(\sum_{(w_j, l_{ji}) \in \mathcal{N}_{\mathcal{G}_s}(w_i)} g_{l_{ji}}^k \times \left(W_{l_{ji}}^k \cdot h_j^k + b_{l_{ji}}^k\right)\right).$$

where, $\mathcal{N}_{\mathcal{G}_s}(w_i)$ denotes the *labeled in-neighborhood* set of w_i in \mathcal{G}_s and $g_{l_{j_i}}^k$ is the gating value for the edge (j, i, l_{j_i}) . The updated embeddings are then used to calculate loss as describe in Section 5.3.

5.2 Retrofitting GCN (RF-GCN):

Graph construction:

Incorporating semantic knowledge in word embeddings has been shown to improve their quality (Faruqui et al. 2014; Alsuhaibani et al. 2018). In WordGCN, we use synonym information from Paraphrase Database (PPDB) (Pavlick et al. 2015) and WordNet. Inspired by (Faruqui et al. 2014), we preserve the information learned via S-GCN by initializing target and neighborhood embeddings of RF-GCN by embeddings from S-GCN. For each synonym cluster, we construct an undirected labeled complete graph $\mathcal{G}_u = (\mathcal{V}_u, \mathcal{E}_u)$, where \mathcal{V}_u is the set of words in the synonym cluster, \mathcal{E}_u is the edge list consisting of all possible pairs as defined below.

$$\mathcal{E}_u = \{(\{w_i, w_j\}, l_{i \sim j}) : i \le j \le |\mathcal{V}_u|, \forall w_i, w_j \in \mathcal{V}_u\}$$

where, $l_{i\sim j}$ is the label of the undirected edge between iand j which can be either l_{ppdb} or l_{wnet} corresponding to PPDB or WordNet synonym word relationship. The above constructed graph, can be extended for other symmetric semantic relationships like *antonym*. In this paper, we focus only on *synonym* relationship.

Undirected Graph Convolution:

On the constructed undirected graph \mathcal{G}_u , we employ GCN formulation proposed by (Kipf and Welling 2016) defined in Section 3.1. Unlike S-GCN, we do not include edge-wise gating as the used semantic knowledge sources are not noisy. The embedding of word w_i at k^{th} layer is updated as

$$h_{i}^{k+1} = \sigma \left(\sum_{(w_{j}, l_{i \sim j}) \in \mathcal{N}_{\mathcal{G}_{u}}(w_{i})} W_{l_{i \sim j}}^{k+1} h_{j}^{k} + b_{l_{i \sim j}}^{k+1} \right)$$

where, $\mathcal{N}_{\mathcal{G}_u}(w_i) = \{(w_j, l_{i\sim j}), \dots\}$ is the tuple containing neighbors of w_i along with their labels. $W_{l_{i\sim j}}^{k+1}$ and $b_{l_{i\sim j}}^{k+1}$ are label specific trainable model parameters. The updated embeddings are then used to calculate loss as describe in Section 5.3.

5.3 Training Loss

Given the embedding of each word from GCN, the training objective of WordGCN is to predict the target word given its neighbors in the graph. Formally, we wish to maximize E defined as

$$E = \sum_{t=1}^{|V|} \log P(w_t | w_1^t, w_2^t \dots w_{N_t}^t).$$

where, w_t is the target word and $w_1^t, w_2^t \dots w_{N_t}^t$ are its neighbors in the graph. The log probability E is calculated using the softmax function.

$$E = \sum_{t=1}^{|V|} \left(v_{w_t}^T h_t - \log \sum_{i=1}^{|V|} \exp(v_{w_i}^T h_t) \right)$$
(4)

where, h_t is the GCN output for the target word w_t and v_{w_t} is its target embedding.

The second term in Equation 4 is computationally expensive as the summation needs to be taken over the entire vocabulary. This can be overcome using several approximations like noise-contrastive estimation (Gutmann and Hyvärinen 2012) and hierarchical versions of softmax (Morin and Bengio 2005; Mnih and Hinton). In WordGCN, we use sampled-softmax (Jean et al. 2015), a recently proposed efficient way of estimating softmax when the size of vocabulary is very large.

6 Experimental Setup

6.1 Dataset and Training

In our experiments, we use March 2018 English dump of Wikipedia¹ for training the models. After discarding too long and too short sentences, we get an average sentence length of nearly 20 words. The corpus consists of 57 million sentences with 1.1 billion tokens and 1 billion syntactic dependencies extracted using Stanford CoreNLP (Manning et al. 2014).

6.2 Baselines

For evaluating WordGCN, we compare against the following baselines:

- Word2vec is continuous-bag-of-words model originally proposed by (Mikolov et al. 2013).
- **GloVe** (Pennington, Socher, and Manning 2014), a logbilinear regression model which leverages global cooccurrence statistics of corpus.
- **Deps** (Levy and Goldberg 2014) is a modification of skipgram model which uses dependency context in place of window based context.
- EXT (Komninos and Manandhar 2016) is an extension of (Levy and Goldberg 2014) model which utilizes second-order dependency context features.
- **Retro-fitting** (Faruqui et al. 2014) is a post-processing procedure which uses similarity constraints from semnatic knowledge sources.
- Counter-fitting (Mrkšić et al. 2016), a method for injecting linguisitic constraints for improving word embeddings.
- **WordGCN** is the method proposed in this paper. Please refer Section 4 for more details.

6.3 Evaluation method:

To evaluate the effectiveness of WordGCN, we compare it against the baselines on the following intrinsic and extrinsic benchmark tasks:

Word Similarity is the task of evalucloseness ating semantic between words. Following (Komninos and Manandhar 2016; Pennington, Socher, and Manning 2014), we evaluate WordGCN on various word similarity datasets WS353S. WS353R (Finkelstein et al. 2001), MTurk (Radinsky et al.), RG65. and MEN (Bruni, Tran, and Baroni 2014).

Concept Categorization involves grouping nominal concepts into natural categories. For instance, *tiger* and *elephant* should belong to *mammal* class. In our experiments, we evalute on AP (Almuhareb 2006), Battig (Baroni and Lenci 2010), BLESS (Baroni and Lenci 2011), ESSLI datasets.

Analogy captures relational similarity between two pairs of words. Given pairs of words a, a^* and b, b^* , the task is to measure the degree to which semantic relation between a

¹https://dumps.wikimedia.org/enwiki/20180301/

	Similarity				Categorization			Analogy		
Method	WS353S	WS353R	MTurk	RG65	MEN	AP	Battig	BLESS	ESSLI	SemEval2012
Word2vec	69.4	44.0	62.2	57.1	68.5	62.9	44.1	67.4	55.6	18.9
GloVe	68.4	44.9	61.6	56.2	67.6	58.0	40.1	68.2	59.3	16.6
Deps	71.5	42.5	58.7	67.5	58.0	65.4	44.1	68.0	55.6	22.2
EXT	68.1	42.2	61.7	61.0	63.1	52.7	34.3	69.5	62.2	19.0
WordGCN(-Sem) WordGCN	74.5 80.3	42.8 49.2	62.9 62.9	75.5 79.3	66.8 70.2	62.4 70.9	44.2 44.6	70.5 73.0	64.4 75.6	18.9 22.5

Table 1: Evaluation on three intrinsic tasks: word similarity (spearman correlation), concept categorization (cluster purity), and word analogy (spearman correlation). WordGCN(-Sem) denotes WordGCN without using any information from semantic knowledge sources. Overall, WordGCN either outperforms or performs competitively compared to other existing approaches. Please refer to Section 7.1 for more details.

and a^* is similar to that between b and b^* . We demonstrate results on *SemEval2012* dataset.

Question Classification is the problem of categorizing questions into different types. We use TREC dataset (Li and Roth 2006) which comprises of six question types.

News Categorization involves identifying category of a given document. Following (Faruqui et al. 2014), we use document belonging to *Computers:IBM* and *Computers:Mac* from 20 Newsgroup dataset and model it as a binary classification task.

Named Entity Recognition (NER) is a task to locate and classify entity mentions into persons, organization, location and miscellaneous category. We use the NeuralNER model (Dernoncourt, Lee, and Szolovits 2017) to train and test on CoNLL-2003 dataset (Tjong Kim Sang and De Meulder).

Part-of-speech (POS) tagging aims at associating each word a unique tag describing its syntactic role. For evaluating word embeddings we use (Reimers and Gurevych 2017), to train and test on Penn Treebank POS dataset as done by (Lee, He, and Zettlemoyer).

Co-reference Resolution (CR) involves identifying all expressions that refer to the same entity in the text. To inspect the effect of embeddings, we use (Lee, He, and Zettlemoyer) on CoNLL-2012 shared task (Pradhan et al.) dataset.

6.4 Hyperparameters

Our vocabulary consists of top 150k words based on their frequency in the corpus. We observe similar trends for (50, 100, 300, 600) dimensional embeddings and have reported results for 100 dimensional embeddings. We used Adam optimizer (Kingma and Ba 2014) with learning rate of 0.001. Following (Mikolov et al. 2013), subsampling is used with threshold parameter t being 10^{-4} . Window size of 3 is used for obtaining linear context. The target and neighborhood embeddings are initialized randomly using Xavier initialization (Glorot and Bengio 2010). In GCN, ReLU is used as the activation function.

7 Results

In this section, we attempt to answer the following questions:

- Q1. Does WordGCN learn more meaningful word embedding than existing approaches? (Section 7.1 and 7.5)
- Q2. How effective is WordGCN's embeddings on downstream tasks? (Section 7.2)
- Q3. What is the effect of ablating different components on WordGCN's performance? (Section 7.3)
- Q4. Does WordGCN efficiently capture information from sematic knowledge sources? (Section 7.4)

7.1 Intrinsic Evaluation

Evaluation results on intrinsic tasks are summarized in Table 1. For fair comparison, we also report performance of WordGCN without using information from semantic knowledge sources, denoted by WordGCN(-Sem). Overall, we find that our proposed method, WordGCN outperforms or performs competitive to the existing word embedding approaches on most of the datasets. Linear context based approaches like Word2vec and GloVe outperforms others on WS353R dataset as their embeddings capture more of topical similarity rather than functional similarity. This is consistent with the observation reported in (Levy and Goldberg 2014). On incorporating signals from semantic knowledge sources (WordNet and PPDB), there is significant improvement in performance across all the tasks.

7.2 Extrinsic Evaluation

In this section, we evaluate the performance of different word embedding approaches on the downstream tasks as defined in Section 6.3. Experimental results are summarized in Table 2. Similar to Section 7.1, we also evaluate the semantic knowledge deficient version of WordGCN. Overall, we find that in four out of five tasks, WordGCN outperforms existing word embedding approaches. Incorporating semantic knowledge drastically helps in improving performance on all the downstream tasks.

7.3 Ablation Results

For demonstrating the efficacy of WordGCN in incorporating different directed and undirected information, we evaluate the performance of different ablated versions of WordGCN. The results are summarized in Figure 2. We observe a substantial increase in performance across all the

Method	TREC	News Cat.	NER	POS	NCR
Word2vec	90.4	66.8	85.8	94.4	70.7
GloVe	89.6	68.7	83.9	92.1	69.9
Deps	93.6	65.5	75.6	91.0	69.9
EXT	89.6	64.0	82.3	93.9	70.5
WordGCN(-Sem)	92.0	67.7	86.2	93.9	70.4
WordGCN	94.4	70.1	86.2	94.4	71.2

Table 2: Evaluation on extrinsic tasks: question classification, news categorization, named entity recognition, parts-of-speech tagging, and neural co-reference resolution. WordGCN outperforms all existing approaches on four out of five tasks. Refer Section 7.2 for details.

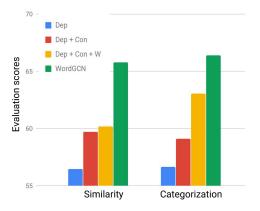


Figure 2: Average scores on similarity and categorization tasks. Similar trends are observed on analogy task. *Dep* stands for only dependency based context in WordGCN. Similarly *Con* and *W* stand for linear context and WordNet information respectively. Refer Section 7.3 for details.

tasks on including dependency context and information from semantic knowledge sources.

7.4 Evaluating incorporation of undirected semantic knowledge

The RF-GCN component can also be used as a standalone model to fine tune pre-trained embeddings from other models by incorporating corpus level semantic knowledge. To evaluate the effectiveness of RF-GCN, we compare it against Retro-fitting (Faruqui et al. 2014) and Counterfitting (Mrkšić et al. 2016) (Section 6.2). The results are summarized in Table 3. We report average score on similarity task, however, we observe similar trends across all other tasks. We find that RF-GCN performs comparable or outperforms the baselines in almost all of the settings.

7.5 Qualitative Results

In this seciton we analyze some qualitative properties of WordGCN embeddings. As shown in Table 4, WordGCN is able to capture multiple senses of the same word. For instance, we find that for most embedding methods, closest word to *bank* are banking related terms like *citibank*, *invest*-

Method	Retro-fitting	Counter-fitting	RF-GCN
Word2vec	67.5	64.2	65.4
GloVe	64.5	59.9	64.6
Deps	56.5	54.0	61.4
EXT	58.0	54.4	61.8
WordGCN(-Sem)	59.22	62.36	65.5

Table 3: Comparison of average similarity scores of RF-GCN against other methods on incorporating semantic knowledge in pre-trained embeddings. Refer to Section 7.4 for details.

ment whereas WordGCN is also able to capture the other sense of *bank* i.e. *riverbank*. For the word *grave*, we find WordGCN captures its sense as a part of *graveyard* (topical similarity) and also captures its other meaning i.e. to be *serious* (functional similarity). This shows that WordGCN captures multiple, diverse connotations of a word as well as functional and topical similarities.

Target	Word2vec	GloVe	Deps	WordGCN
bank	hsbc	banking	brokerage	citibank
	citibank	investment	mortgage	banking
	lloyds	finance	banking	riverbank
grave	graveyard	burial	tomb	tomb
	gravestone	graves	mausoleum	graveyard
	tomb	tomb	headstone	serious
bow	prow	barrel	hoist	prow
	oar	nose	paddle	stoop
	rudder	deck	nose	bend
current	changing	present	previous	currently
	existing	new	actual	existing
	original	change	thermal	voltage

Table 4: Comparison of words close to the target word according to different word embedding methods

8 Conclusion

In this paper, we propose WordGCN, a graph convolution based approach for learning word representation. WordGCN can utilize multiple types of word relationships such as linear context, syntactic context, hypernym, meronym and synonym in a principled manner, through a single model. To the best of our knowledge, this is the first model to use graph convolution for this task. Through extensive experiment on various intrinsic and extrinsic tasks, we evaluate the effectiveness of WordGCN and find that it outperforms existing word embedding approaches. We also find that WordGCN is able to capture multiple connotations of a word in the learned embeddings. We make WordGCN's source code available to encourage reproducible research.

References

[Almuhareb 2006] Almuhareb, A. 2006. Attributes in lexical acquisition.

- [Alsuhaibani et al. 2018] Alsuhaibani, M.; Bollegala, D.; Maehara, T.; and Kawarabayashi, K.-i. 2018. Jointly learning word embeddings using a corpus and a knowledge base. *PLOS ONE* 13(3):1– 26.
- [Baker, Fillmore, and Lowe 1998] Baker, C. F.; Fillmore, C. J.; and Lowe, J. B. 1998. The berkeley framenet project. In *ACL*, ACL '98, 86–90. Stroudsburg, PA, USA: ACL.
- [Baroni and Lenci 2010] Baroni, M., and Lenci, A. 2010. Distributional memory: A general framework for corpus-based semantics. *Comput. Linguist.* 36(4):673–721.
- [Baroni and Lenci 2011] Baroni, M., and Lenci, A. 2011. How we blessed distributional semantic evaluation. In *GEMS*, GEMS '11, 1–10. Stroudsburg, PA, USA: ACL.
- [Bastings et al. 2017] Bastings, J.; Titov, I.; Aziz, W.; Marcheggiani, D.; and Simaan, K. 2017. Graph convolutional encoders for syntax-aware neural machine translation. In *EMNLP*, 1957–1967. ACL.
- [Bengio et al. 2003] Bengio, Y.; Ducharme, R.; Vincent, P.; and Janvin, C. 2003. A neural probabilistic language model. *JMLR* 3:1137–1155.
- [Bengio, Courville, and Vincent 2013] Bengio, Y.; Courville, A.; and Vincent, P. 2013. Representation learning: A review and new perspectives. *IEEE TPAMI* 35(8):1798–1828.
- [Bronstein et al. 2017] Bronstein, M. M.; Bruna, J.; LeCun, Y.; Szlam, A.; and Vandergheynst, P. 2017. Geometric deep learning: Going beyond euclidean data. *IEEE Signal Processing Magazine* 34(4):18–42.
- [Bruna et al. 2013] Bruna, J.; Zaremba, W.; Szlam, A.; and LeCun, Y. 2013. Spectral networks and locally connected networks on graphs. *CoRR* abs/1312.6203.
- [Bruni, Tran, and Baroni 2014] Bruni, E.; Tran, N. K.; and Baroni, M. 2014. Multimodal distributional semantics. *J. Artif. Int. Res.* 49(1):1–47.
- [Collobert et al. 2011] Collobert, R.; Weston, J.; Bottou, L.; Karlen, M.; Kavukcuoglu, K.; and Kuksa, P. 2011. Natural language processing (almost) from scratch. *JMLR* 12:2493–2537.
- [Defferrard, Bresson, and Vandergheynst 2016] Defferrard, M.; Bresson, X.; and Vandergheynst, P. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. *CoRR* abs/1606.09375.
- [Dernoncourt, Lee, and Szolovits 2017] Dernoncourt, F.; Lee, J. Y.; and Szolovits, P. 2017. NeuroNER: an easy-to-use program for named-entity recognition based on neural networks. *EMNLP*.
- [Faruqui et al. 2014] Faruqui, M.; Dodge, J.; Jauhar, S. K.; Dyer, C.; Hovy, E. H.; and Smith, N. A. 2014. Retrofitting word vectors to semantic lexicons. *CoRR* abs/1411.4166.
- [Finkelstein et al. 2001] Finkelstein, L.; Gabrilovich, E.; Matias, Y.; Rivlin, E.; Solan, Z.; Wolfman, G.; and Ruppin, E. 2001. Placing search in context: The concept revisited. In *WWW 2001*.
- [Glorot and Bengio 2010] Glorot, X., and Bengio, Y. 2010. Understanding the difficulty of training deep feedforward neural networks. In *AISTATS*.
- [Gutmann and Hyvärinen 2012] Gutmann, M. U., and Hyvärinen, A. 2012. Noise-contrastive estimation of unnormalized statistical models, with applications to natural image statistics. *J. Mach. Learn. Res.* 13(1):307–361.
- [Harris 1954] Harris, Z. S. 1954. Distributional structure. WORD.
- [Jastrzebski, Lesniak, and Czarnecki] Jastrzebski, S.; Lesniak, D.; and Czarnecki, W. M. How to evaluate word embeddings?

on importance of data efficiency and simple supervised tasks. abs/1702.02170.

- [Jean et al. 2015] Jean, S.; Cho, K.; Memisevic, R.; and Bengio, Y. 2015. On using very large target vocabulary for neural machine translation. In *IJCNLP*, 1–10. ACL.
- [Ji et al. 2015] Ji, S.; Yun, H.; Yanardag, P.; Matsushima, S.; and Vishwanathan, S. V. N. 2015. Wordrank: Learning word embeddings via robust ranking. *CoRR* abs/1506.02761.
- [Kingma and Ba 2014] Kingma, D., and Ba, J. 2014. Adam: A method for stochastic optimization.
- [Kipf and Welling 2016] Kipf, T. N., and Welling, M. 2016. Semisupervised classification with graph convolutional networks. *CoRR* abs/1609.02907.
- [Komninos and Manandhar 2016] Komninos, A., and Manandhar, S. 2016. Dependency based embeddings for sentence classification tasks.
- [Lee, He, and Zettlemoyer] Lee, K.; He, L.; and Zettlemoyer, L. Higher-order coreference resolution with coarse-to-fine inference. In *NAACL 2018*.
- [Levy and Goldberg 2014] Levy, O., and Goldberg, Y. 2014. Dependency-based word embeddings. In *ACL*, 302–308. ACL.
- [Li and Roth 2006] Li, X., and Roth, D. 2006. Learning question classifiers: The role of semantic information. *NLE* 12(3):229–249.
- [Li et al. 2018] Li, C.; Li, J.; Song, Y.; and Lin, Z. 2018. Training and evaluating improved dependency-based word embeddings. In *AAAI*.
- [Ma and Hovy 2016] Ma, X., and Hovy, E. H. 2016. End-toend sequence labeling via bi-directional lstm-cnns-crf. *CoRR* abs/1603.01354.
- [Maas et al. 2011] Maas, A. L.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning word vectors for sentiment analysis. In ACL, HLT '11, 142–150. Stroudsburg, PA, USA: ACL.
- [Manning et al. 2014] Manning, C. D.; Surdeanu, M.; Bauer, J.; Finkel, J.; Bethard, S. J.; and McClosky, D. 2014. The Stanford CoreNLP natural language processing toolkit. In *ACL*, 55–60.
- [Marcheggiani and Titov 2017] Marcheggiani, D., and Titov, I. 2017. Encoding sentences with graph convolutional networks for semantic role labeling. In *EMNLP*, 1506–1515. ACL.
- [Mikolov et al. 2013] Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In *Proceedings of the 26th International Conference on Neural Information Processing Systems Volume 2*, NIPS'13, 3111–3119. USA: Curran Associates Inc.
- [Miller 1995] Miller, G. A. 1995. Wordnet: A lexical database for english. *Commun. ACM* 38(11):39–41.
- [Mnih and Hinton] Mnih, A., and Hinton, G. A scalable hierarchical distributed language model. In *NIPS*, NIPS'08.
- [Morin and Bengio 2005] Morin, F., and Bengio, Y. 2005. Hierarchical probabilistic neural network language model. In *AISTATS*.
- [Mrkšić et al. 2016] Mrkšić, N.; Ó Séaghdha, D.; Thomson, B.; Gašić, M.; Rojas-Barahona, L. M.; Su, P.-H.; Vandyke, D.; Wen, T.-H.; and Young, S. 2016. Counter-fitting word vectors to linguistic constraints. In *ACL*, 142–148. ACL.
- [Nguyen and Grishman 2018] Nguyen, T., and Grishman, R. 2018. Graph convolutional networks with argument-aware pooling for event detection.
- [Pavlick et al. 2015] Pavlick, E.; Rastogi, P.; Ganitkevitch, J.; Van Durme, B.; and Callison-Burch, C. 2015. Ppdb 2.0: Better paraphrase ranking, fine-grained entailment relations, word embeddings, and style classification. In ACL, 425–430. ACL.

- [Pennington, Socher, and Manning 2014] Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In *EMNLP*, 1532–1543.
- [Pradhan et al.] Pradhan, S.; Moschitti, A.; Xue, N.; Uryupina, O.; and Zhang, Y. Conll-2012 shared task: Modeling multilingual unrestricted coreference in ontonotes. In *EMNLP-CONLL*, CoNLL '12.
- [Radinsky et al.] Radinsky, K.; Agichtein, E.; Gabrilovich, E.; and Markovitch, S. A word at a time: Computing word relatedness using temporal semantic analysis. In *WWW 2011*.
- [Reimers and Gurevych 2017] Reimers, N., and Gurevych, I. 2017. Reporting Score Distributions Makes a Difference: Performance Study of LSTM-networks for Sequence Tagging. In *EMNLP*, 338– 348.
- [Rumelhart, Hinton, and Williams 1988] Rumelhart, D. E.; Hinton, G. E.; and Williams, R. J. 1988. Neurocomputing: Foundations of research. Cambridge, MA, USA: MIT Press. chapter Learning Representations by Back-propagating Errors, 696–699.
- [Scarselli et al. 2009] Scarselli, F.; Gori, M.; Tsoi, A. C.; Hagenbuchner, M.; and Monfardini, G. 2009. The graph neural network model. *IEEE Transactions on Neural Networks* 20(1):61–80.
- [Socher et al. 2013] Socher, R.; Bauer, J.; Manning, C. D.; and Ng, A. Y. 2013. Parsing With Compositional Vector Grammars. In *ACL*.
- [Song, Lee, and Xia 2017] Song, Y.; Lee, C.-J.; and Xia, F. 2017. Learning word representations with regularization from prior knowledge. In *CONLL 2017*.
- [Tjong Kim Sang and De Meulder] Tjong Kim Sang, E. F., and De Meulder, F. Introduction to the conll-2003 shared task: Language-independent named entity recognition. In *HLT-NAACL*, CONLL '03.
- [Vashishth et al. 2018] Vashishth, S.; Dasgupta, S. S.; Ray, S. N.; and Talukdar, P. 2018. Dating documents using graph convolution networks. In *ACL*, 1605–1615. ACL.
- [Yu and Dredze 2014] Yu, M., and Dredze, M. 2014. Improving lexical embeddings with semantic knowledge. In *ACL*, 545–550. ACL.