Vec2GC - A Graph Based Clustering Method for Text Representations

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ABSTRACT

NLP pipelines with limited or no labeled data, rely on unsupervised methods for document processing. Unsupervised approaches typically depend on clustering of terms or documents. In this paper, we introduce a novel clustering algorithm, Vec2GC (Vector to Graph Communities), an end-to-end pipeline to cluster terms or documents for any given text corpus. Our method uses community detection on a weighted graph of the terms or documents, created using text representation learning. Vec2GC clustering algorithm is a density based approach, that supports hierarchical clustering as well.

KEYWORDS
text clustering, embeddings, document clustering, graph clustering

1 INTRODUCTION

Dealing with large corpus of unlabeled domain specific documents is a common challenge faced in industrial NLP pipeline. Unsupervised algorithms like clustering are the first step in processing unlabeled corpus to get an overview of the data distribution. Visual exploration based on clustering and dimensionality reduction algorithms provide a good overview of data distribution. In this context, clustering and dimensionality reduction are important steps. Dimensionality reduction techniques like PCA [5], t-SNE [18] or UMAP [12] would map the document in embedding space to 2 dimensional space as shown in figure 1. Clustering algorithm would groups semantically similar documents or term together. Traditional cluster algorithm like k-Mean [9], k-medoids [16], DBSCAN [4] or HDBSCAN [11] with distance metric derived from Cosine Similarity [10] do not do a very good job on this.

We propose the Vec2GC, Vector To Graph Community, a clustering algorithm that converts the terms or documents in the vector embedding space [13] [7] to a graph and generate clusters based on Graph Community Detection algorithm.

2 LITERATURE SURVEY

Hossain and Angryk [6] represented text documents as hierarchical document-graphs to extract frequent subgraphs for generating sense-based document clusters. Wang et. al. [19] used vector representations of documents and run k-means clustering on them to understand general representation power of various embedding generation models. Angelov [1] proposed Top2Vec, which uses joint document and word semantic embedding to find topic vectors using HDBSCAN as clustering method to find dense regions in the embedding space. Saiyad et. al. [16] presented a survey covering major significant works on semantic document clustering based on latent semantic indexing, graph representations, ontology and lexical chains.

3 ALGORITHM DETAILS

Vec2GC converts the vector space embeddings of terms or documents to a graph and performs clustering on the constructed graph. The algorithm consists of two steps: construction of the graph and generation of clusters using Graph Community detection algorithm.

3.1 Graph Construction

For the graph construction, we consider each term or document embedding as a node. A node can be represented by $a$ and its embedding represented by $v_a$. And to construct the graph, we measure the cosine similarity of the embeddings, equation (1). An edge is drawn between two nodes if their cosine similarity is greater than a specific threshold $\theta$, which is a tuneable parameter in our algorithm.

$$cs(a, b) = \frac{v_a \cdot v_b}{\|v_a\| \|v_b\|}$$ (1)

The edge weight is determined by the cosine similarity value and is given by equation 2.
We define such nodes as Non Community nodes.

If we consider VecGC for term embeddings, we believe there are two reasons for a term to become a Non Community node. Either it appears in multiple contexts and does not have a strong similarity with any specific context or it is not close enough to a community to be included as member.

### 3.2 Graph Community Detection

We construct the graph with words or documents as nodes and edges between nodes with cosine similarity greater than $\theta$.

The Graph Community Detection algorithm considers only local neighborhood in community detection. If we consider documents in a corpus, the cosine similarity is a strong indicator of similarity between two documents, when cosine similarity is high ($>\theta$), it strongly indicates the two documents are semantically similar. However, when cosine similarity is low ($<\theta$), it indicates a dis-similarity between the two documents. And the strength of dis-similarity is not indicated by the value of the cosine similarity. A cosine similarity of 0.2 does not indicate a higher dis-similarity than cosine similarity of 0.4. Thus we eliminate the notion of dis-similarity by only connecting nodes which have a high degree of similarity. Thus, all pairs nodes with cosine similarity below the given threshold are ignored.

Though we discuss the idea of similarity and dis-similarity in the context of documents, the arguments extend equally well to terms represented by embeddings.

We apply a standard Graph Community Detection algorithm, **Parallel Louvian Method** [2] in determining the communities in the graph. We calculate the modularity index [14], given by equation 4, for each execution of the PLM algorithm.

$$Q = \frac{1}{2m} \sum_{a,b} W_{E,ab} \left( \frac{k_a k_b}{2m} \right) \delta(c_a, c_b)$$

We execute the Graph Community Detection algorithm recursively. The pseudo code of the recursive algorithm is shown in Algorithm 1.

### 3.3 Non Community Nodes

Note, not all nodes would be member of a community. There will be nodes that do not belong to any community. Nodes that are not connected or not well connected fail to be a member of a community. We define such nodes as Non Community nodes.

Algorithm 1: Recursive Graph Community Detection

```python
def GetCommunity(g, c_node, tree, mod_thresh, max_size):
    if mod_index < $\theta$modularity then
        tree.add_node(c_node)
        return
    foreach comm in c_list do
        if len(comm) > max_size then
            s_g = get_community_subgraph(comm)
            n_node = Node()
            tree.add_node(n_node)
            GetCommunity(s_g, n_node, tree, mod_thresh, max_size)
        else
            new_node = Node()
            tree.add_node(new_node)
```

with any specific context or it is not close enough to a community to be included as member.

### 4 EXPERIMENT

We perform extensive set of experiments and comparisons to show the advantage of Vec2GC as a clustering algorithm for documents or words in a text corpus. We consider 5 different text document datasets along with class information. The dataset details are as follows:

#### 4.1 Datasets

**4.1.1 20 newsgroups.** The 20 Newsgroups data set comprises of approximately 20,000 newsgroup documents, evenly distributed across 20 different newsgroups, each corresponding to a different topic.  

**4.1.2 AG News.** AG is a collection of more than 1 million news articles gathered from more than 2000 news sources by ComeToMyHead [5], which is an academic news search engine. The AG’s news topic classification dataset is developed by Xiang Zhang [3] from the above news articles collection, consisting of 127600 documents. It was first used as a text classification benchmark in the following paper [20].

**4.1.3 BBC Articles.** This dataset is a public dataset from the BBC, comprised of 2225 articles, each labeled under one of 5 categories: Business, Entertainment, Politics, Sport or Tech.  

**4.1.4 Stackoverflow QA.** This is a dataset of 16000 question and answers from the Stackoverflow website [4], labeled under 4 different categories of coding language - CSharp, JavaScript, Java, Python.  

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1 [http://qwone.com/~jason/20Newsgroups/](http://qwone.com/~jason/20Newsgroups/)
2 [http://groups.di.unipi.it/~gulli/AG_corpus_of_news_articles.html](http://groups.di.unipi.it/~gulli/AG_corpus_of_news_articles.html)
3 xiang.zhang@nyu.edu
4 [https://www.kaggle.com/c/learn-ai-bbc/data](https://www.kaggle.com/c/learn-ai-bbc/data)
5 [www.stackoverflow.com](http://www.stackoverflow.com)
6 [http://storage.googleapis.com/download.tensorflow.org/data/stack_overflow_16k.tar.gz](http://storage.googleapis.com/download.tensorflow.org/data/stack_overflow_16k.tar.gz)
4.1.5 **DBpedia.** DBpedia is a project aiming to extract structured content from the information created in Wikipedia. This dataset is extracted from the original DBpedia data that provides taxonomic, hierarchical categories or classes for 342,782 articles. There are 3 levels of classes, with 9, 70 and 219 classes respectively. \(^8\)

We use two different document embedding algorithms to generate document embeddings for all text datasets. The first algorithm that we use is Doc2Vec, which creates document embeddings using the distributed memory and distributed bag of words models from [7]. We also create document embeddings using Sentence-BERT [15]. It computes dense vector representations for documents, such that similar document embeddings are close in vector space using pretrained language models on transformer networks like BERT [3] / RoBERTa [8] / DistilBERT [17] etc. in its framework. For our experiment, we use stsb-distilbert-base\(^9\) pretrained model to generate document embeddings using Sentence-BERT.

To compare the effectiveness of our algorithm, we perform clustering on the document embeddings for each dataset using our proposed method Vec2GC, along with conventional document clustering methods HDBSCAN \([11]\) and KMedoids \([16]\). For KMedoids, we used an approach like KMeans++ as the medoid initialization method, which gives initial medoids which are more separated in vector space. For HDBSCAN, we used Excess of Mass algorithm as the cluster selection method to find the most persistent clusters. This gave use better result than Leaf method. HDBSCAN also creates a cluster labeled as -1, which contains noisy data points. We tuned the parameters of Vec2GC such that the number of data points in -1 cluster from HDSCAN matches approximately with the number of data points in the Non-Community Nodes community which we get as an output from Vec2GC, which also indicates noisy data points detected by Vec2GC, to maintain the experiments and comparisons unbiased.

4.2 **Results**

We perform cluster analysis with the results obtained from each of these methods. Cluster purity is a very commonly used metric in cluster analysis to measure how good the clusters are. It measures the extent to which clusters contain a single class, or Homogeneity [19]. Here, we calculate purity for each cluster. The number of data points from the most common class is counted for each cluster. e.g. If the total number of data points in a cluster C is 10, and the data points from the most common class in that cluster C is 8, then cluster C is said to have \((8/10) \times 100\% = 80\%\) cluster purity.

From the obtained \(N\) clusters from a clustering method on a given dataset, we calculate the numbers of clusters that have 50%, 70% and 90% purity, as \(M_1, M_2, M_3\) respectively. Then we calculate the fractions \(M_1/N, M_2/N, M_3/N\). From the outputs of each clustering method (Vec2GC, HDBSCAN and KMedoids) on all five datasets, these three values are calculated individually and put into Table 1 and Table 2. Table 1 results are from Doc2Vec document embeddings, where as Table 2 results contain from Sentence-BERT document embeddings. Best results are put in bold, second best results are underlined.

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\(^8\)https://en.wikipedia.org/wiki/DBpedia

\(^9\)https://www.kaggle.com/danofer/dbpedia-classes/version/1

\(^9\)https://huggingface.co/sentence-transformers/stsb-distilbert-base

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### Table 1: Comparison using Doc2Vec Embeddings

| Dataset   | Purity Value | Fraction of clusters @ k% purity (KMedoids) | Fraction of clusters @ k% purity (hdbscan) | Fraction of clusters @ k% purity (Vec2CG) |
|-----------|--------------|---------------------------------------------|--------------------------------------------|------------------------------------------|
| 20Newsgroup | 50%          | .53                                         | .76                                        | .89                                      |
|           | 70%          | .38                                         | .56                                        | .69                                      |
|           | 90%          | .07                                         | .20                                        | .39                                      |
| AG News   | 50%          | .98                                         | .98                                        | .99                                      |
|           | 70%          | .74                                         | .90                                        | .94                                      |
|           | 90%          | .20                                         | .63                                        | .80                                      |
| BBC Articles | 50%        | 1.0                                         | .99                                        | .99                                      |
|           | 70%          | .86                                         | .93                                        | .96                                      |
|           | 90%          | .50                                         | .70                                        | .83                                      |
| DBPedia   | 50%          | .84                                         | .90                                        | .93                                      |
|           | 70%          | .52                                         | .80                                        | .77                                      |
|           | 90%          | .24                                         | .54                                        | .53                                      |
| Stackoverflow | 50%        | .30                                         | .63                                        | .79                                      |
|           | 70%          | .14                                         | .35                                        | .46                                      |
|           | 90%          | .02                                         | .15                                        | .20                                      |

### Table 2: Comparison using Sentence-Transformer Embeddings (Using stsb-distilbert-base pretrained model)

| Dataset   | Purity Value | Fraction of clusters @ k% purity (KMedoids) | Fraction of clusters @ k% purity (hdbscan) | Fraction of clusters @ k% purity (Vec2CG) |
|-----------|--------------|---------------------------------------------|--------------------------------------------|------------------------------------------|
| 20Newsgroup | 50%          | .46                                         | .64                                        | .65                                      |
|           | 70%          | .27                                         | .64                                        | .50                                      |
|           | 90%          | .09                                         | .29                                        | .13                                      |
| AG News   | 50%          | .88                                         | .98                                        | .99                                      |
|           | 70%          | .66                                         | .90                                        | .90                                      |
|           | 90%          | .18                                         | .67                                        | .65                                      |
| BBC Articles | 50%        | 1.0                                         | .94                                        | .98                                      |
|           | 70%          | .85                                         | .74                                        | .84                                      |
|           | 90%          | .30                                         | .47                                        | .60                                      |
| DBPedia   | 50%          | .80                                         | .94                                        | .99                                      |
|           | 70%          | .54                                         | .88                                        | .88                                      |
|           | 90%          | .32                                         | .75                                        | .77                                      |
| Stackoverflow | 50%        | .13                                         | .28                                        | .34                                      |
|           | 70%          | .05                                         | .10                                        | .11                                      |
|           | 90%          | .01                                         | .01                                        | .02                                      |

As we can see from Table 1 and 2, for most of the datasets, Vec2GC clusters are the best with highest fraction of clusters with k% purities. HDBSCAN comes second best for majority of the datasets, where as KMedoids gives the poorest clusters, in terms of cluster purity. This clearly shows that Vec2GC outperforms the baseline clustering methods for all datasets used and produces better semantic clusters.

We can also use Vec2GC as a word clustering algorithm to generate clusters of words for a given text corpus. This can be very
helpful and an important step for topic modeling related frameworks. Tables 3-7 show few word clusters generated from each of the datasets from section 4 using Vec2GC algorithm.

Table 3: A few clusters generated from 20 Newsgroups dataset using Vec2GC

| Cluster No. | Cluster Data                                |
|-------------|---------------------------------------------|
| 1           | moral, objective, morality, absolute, subjective, immoral, morals, objectively |
| 2           | encryption, security, privacy, algorithm, secure, communications |
| 3           | ford, mustang, camaro, firebird, sporty, mustangs |
| 4           | france, sweden, italy, finland, switzerland, norway, australia |

Table 4: A few clusters generated from AG News dataset using Vec2GC

| Cluster No. | Cluster Data                                |
|-------------|---------------------------------------------|
| 1           | percent, third, quarter, reported, sales, profit, rose, strong, higher, earnings, fell, loss, demand |
| 2           | election, presidential, elections, vote, electronic, voters, machines, voting, voted, poll, candidates |
| 3           | music, apple, digital, ipod, mac, download, itunes, photo, songs, mp, photos |
| 4           | quarterback, nhl, wide, defensive, indianapolis, receiver, manning, tackle, colts, dan, linebacker |

Table 5: A few clusters generated from BBC Articles dataset using Vec2GC

| Cluster No. | Cluster Data                                |
|-------------|---------------------------------------------|
| 1           | airline, airlines, passengers, flights, jet, airways, carriers |
| 2           | lee, spider, comic, marvel, stan, comics |
| 3           | browser, firefox, ie, explorer, holes, mozilla |
| 4           | roddick, nadal, spaniard, volley, saves, tiebreak |

Table 6: A few clusters generated from Stackoverflow dataset using Vec2GC

| Cluster No. | Cluster Data                                |
|-------------|---------------------------------------------|
| 1           | width, style, px, height, top, background, center, css |
| 2           | import, io, throws, ioexception, from, bufferedreader, printstacktrace |
| 3           | anaconda, ch, tornado, notebook, jupyter |
| 4           | queue, priority, comparator, enqueue, priorityqueue, dequeue, prq |

Table 7: A few clusters generated from DBpedia dataset using Vec2GC

| Cluster No. | Cluster Data                                |
|-------------|---------------------------------------------|
| 1           | russia, soviet, moscow, oblast, petersburg, ivan, ussr, leningrad, belarus, vladimir |
| 2           | wings, monoplane, pilot, tail, conventional, fixed, configuration, gear, mounted |
| 3           | extinct, volcano, volcanic, ago, lava, fossil, stratovolcano, prehistoric, fossils, caldera |
| 4           | habitat, tropical, natural, forests, subtropical, loss, forest, threatened, moist, dry |

which are generally used in document clustering frameworks [16]. Our experiments demonstrate that for term or document embedding clustering, Vec2GC is a better clustering algorithm.

6 FUTURE WORKS

Currently we have shown the result of Vec2GC with respect to document clustering. However, this can be applied to terms as well. We will benchmark Vec2GC for clustering terms and compare it with existing clustering algorithms.

Combining terms and documents in a single vector space provides an opportunity to create Topic Modeling clusters. Similar to [1], we intend to apply Vec2GC clusters to identify Topics in a given corpus.

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