IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 26, No. 5, October, 2021, pp. 453-460
Journal homepage: http://iieta.org/journals/isi

Reusable Component Retrieval from a Large Repository Using Word2Vec with Continuous Bag of Words

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https://doi.org/10.18280/isi.260504

Received: 6 September 2021
Accepted: 25 October 2021

Keywords:
repository, Word2Vec, search, code component, neural network

ABSTRACT

A reusable code component is the one which can be easily used with a little or no adaptation to fit in to the application being developed. The major concern in such process is the maintenance of these reusable components in one place called 'Repository', so that those code components can be effectively identified as well as reused. Word embedding allows us to numerically represent our textual information. They have become so pervasive that almost all Natural Language Processing projects make use of them. In this work, we considered to use Word2Vec concept to find vector representation of features of a reusable component. The features of a reusable component in the form of sequence of words are input to Word2Vec network. Our method using Word2Vec with Continuous Bag of Words out performs existing method in the market. The proposed methodology has shown an accuracy of 94.8% in identifying the existing reusable component.

1. INTRODUCTION

The inevitable scenario in the fast code development situations is writing the same code over and over again. In order to reduce time, effort, also to drastically improve the efficiency of development process, almost all organizations now prefer to have a mono repository to maintain the reusable code components. A reusable code component is the one which can be easily used with a little or no adaptation to fit in to the application being developed. Component Based Software Engineering (CBSE) is on high demand giving major benefits of less workforce needed besides lines of code to be developed for an application would be considerably reduced using on the shelf components. The major concern in such process is the maintenance of these reusable components in one place called Repository, so that those code components can be effectively identified as well as reused. Hence, the way Repository is maintained affects the software development process and the success of organization that is practicing CBSE. In case of searching for a required component if the repository is of small size, it would be a simple task but in case where repository consists of thousands of components, searching a required component is also a complex problem that attracted many researchers to work on.

Word embedding allows us to numerically represent our textual information. They have become so pervasive that almost all Natural Language Processing projects make use of them. Even though each line of a code component is not exactly as a natural language sentence, yet the basic building blocks are from natural language and does has some contextual meaning among the words we use in every line of code snippet that is developed. Hence in this work we considered to use Word2Vec concept to develop word embeddings. Word embedding algorithms like Word2Vec are unsupervised feature extractors of words.

To properly understand the context of the word used one need to make use of word embeddings. The vocabulary of document considered is represented in the vector form using word embeddings that enable capturing of context. This context can be used for identifying the required document more accurately as compared to general process of document or file identification from large corpus of dataset.

Mikolov et al. [1] proposed one of the best mechanisms of word embedding called Word2Vec with an objective to maintain words with similar context to be occupying in close spatial proximity. Generally, Word2Vec models are shallow two-layered neural network architectures. Comparison becomes easy when something has magnitude & direction hence vector representation is considered for words as Vectors are something which has both magnitude & direction.

The simplest word embedding one can find is one hot vector encoding. Consider a set of words to be converted in to numerical representation so that same can be used as an input to a machine learning algorithm based model. Such model can be further used in recommendation systems. The simplest thing that can be done is giving numerical indexing to each word in word set we considered say like, 1,2,3…some 10,000. This can be further represented in binary format with all 0s except one bit as '1' corresponding to the position of word in the vocabulary corpus we consider. For example [0,0,0,..1,0,0,0..0,0] etc. But this representation has a fundamental problem of not considering the contextual information among a sequence of words which actually plays in understanding the actual semantics of those set of words or in simple processing of natural language. Another biggest problem would be, one hot encoding is resulting in mostly sparse vector representation. This results in poor memory utilization though they are quick and easy way to represent each word as real valued vectors. One hot encoding fares poorly in case of analogy based identification of word representation in natural language context. Also, the size of the vector here is directly proportional to the size of the vocabulary corpus considered. As size grows too large, indexing, searching would become a linear problem with more time consumption besides sparse space issue. As these word representations in numerical forms will be used as input for Neural Networks in process of predictions and comparisons, this would make Neural Networks to struggle in giving high performance or even in training. One of the simplest mechanisms if we want embedding of whole sentence instead of word would be averaging real values of words in sentence. The other advanced methods include Recurrent Neural Network (RNN) encoder-decoder models. The RNN models will build embedding of sentences reading word by word. The greater advantage of word embedding lies in generalization. The different types of word embeddings can be shown as in Figure 1 below. The representation in higher dimension vector space raises a question of dimensionality as, what is the accurate number of embedding dimensions that can solve the problem of context representation? This empirical question always needs look for a tradeoff between accuracy and computational complexity.

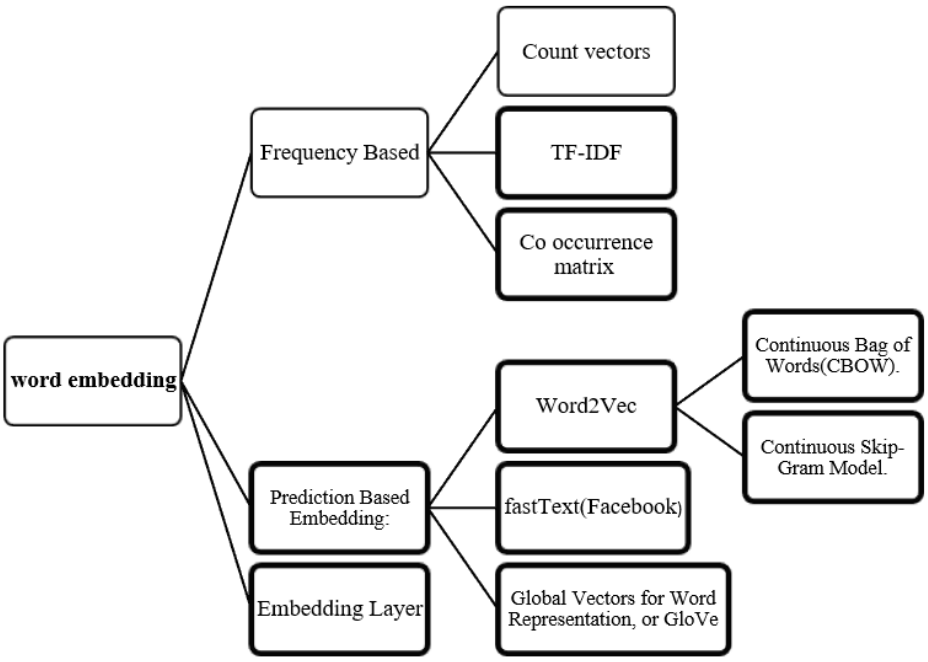

word embedding
Frequency Based
Count vectors
TF-IDF
Co occurrence matrix
Prediction Based Embedding:
Word2Vec
Continuous Bag of Words(CBOW).
Continuous Skip-Gram Model.
fastText(Facebook)
Global Vectors for Word Representation, or GloVe
Embedding Layer

Figure 1. Different types of word embeddings

There are two main differences between Bag of Words (BoW) or Term Frequency-Inverse Document Frequency (TF-IDF) in keeping with word embedding:

- BoW or TF-IDF creates one number per word while word embedding typically creates one vector per word.
- BoW or TF-IDF is good for classification documents as a whole, but word embedding is good for identifying contextual content.

2. RELATED WORK

New avenues are being open for machine learning to process source code with ever growing demand of open source repositories. Attention based neural machine transition using encoder- decoder architecture is used to select relevant paths while decoding by representing code as an Abstract Syntax Tree (AST) in the work done by Alon et al. [2] named as code2seq model. The developing of natural language sequences from the code snippets is very useful in retrieval, summarization or documentation of code snippets. They have worked on two aspects – code summarization and code captioning but did not test it on code retrieval. Shido et al. [3] in their work entitled “Automatic source code summarization with extended tree-LSTM” have successfully implemented multi-way tree Long Short Term Memory to handle a node that has arbitrary number of children and their order in ASTs simultaneously.

In the work of Hussian et al. [4], they developed a CODESEARCHNET corpus besides throwing open CODE SEARCH-NET CHALLANGE. The corpus they developed was based on different open source code works and contains around six million functions belonging to different programming languages like Ruby, Java, GO, JavaScript etc. The researchers make use of ‘joint vector representation’ for code search. A neural system is implemented using joint embeddings of code and queries. Contextualization of token embedding was achieved using Neural Bag of Words architecture. Any how the underlying searching mechanism is of Elastic search which performs traditional keyword based search but representing rare terms was a thing missing in their work. They do raise a question of, “can we have similar to BERT pre training methods of Natural Language Processing for the encoders considered in work?”

In the work done by Akbar and Kak [5], they concentrated on mechanisms to impose ordering constraints using logic of Markov Random Fields (MRF) on the embedded word representations. During source code retrieval, while matching order of words in an enquiry with words sequence in a file, exploitation of semantic word vector generated using word2vec is done. In the literature, we can find several BoW based source code retrieval methods [6-13]. Authors have also reported using word2vec for software search [14-17], The researchers considered Correct at r C@r with abbreviation occurring in top r ranked positions and Pearson Correlation score to evaluate their work using popular data sets of Eclipse and AspectJ.

Emphasizing on the issue of handling mismatch in code search/retrieval using deep learning with Word2Vec was done by Van Nguyen et al. [16], in which the researchers combined Word2Vec with Revised Vector Space model for better code retrieval (rVSM). rVSM computes the weight for a word based on a new term frequency-inverse document frequency (*tf-idf*) formula and a new scoring scheme among the vectors that takes documents' lengths into account. In their work they claim an API code example retrieval accuracy for rVSM + Word2Vec to be as 60.9 for top 5 recommended code snippets. We could get a better performance through our method than this for our data set as discussed in Results section at the end of this paper.

Sugatadasa et al. [18] have considered Legal Domain with 25000 legal cases collected from other research works, for document information retrieval. They proposed document embeddings system for legal domain based on TF-IDF with page ranking graph network and the same was used to train a neural network model in an incremental model. In the process they did not consider a specific legal case that is mentioned in another legal case a greater number of times, as it may be more significant for that case. By assigning weights to this most relevant case for the legal case under consideration more accurate interlinking is possible among the documents that may enhance the overall performance Li et al. [19] work on a structure driven method for information retrieval-based change impact analysis (SDM-CIA). This SDM CIA integrates both bag of words and word embedding models [20].

3. METHODOLOGY

Though the main purpose of word2vec can be seen in word prediction yet in our case it acts as a proxy to learn vector notations of words which will be further used to represent the features of a reusable component and a repository is build based on collection of these vector notations. The weights obtained after training, between Input Layer and Hidden Layer are the values we plan to use to represent feature set of a reusable component. The flow chart of our idea is depicted in Figure 2 below.

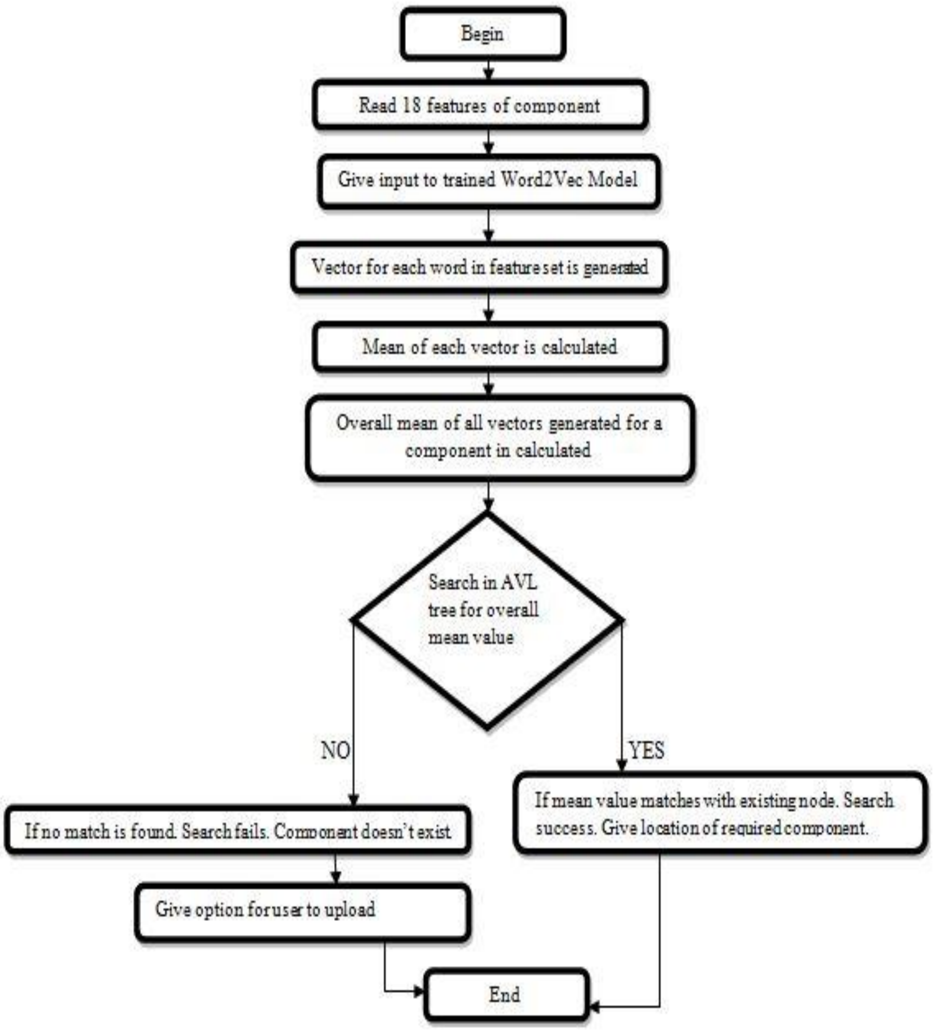

Begin
Read 18 features of component
Give input to trained Word2Vec Model
Vector for each word in feature set is generated
Mean of each vector is calculated
Overall mean of all vectors generated for a component in calculated
Search in AVL tree for overall mean value
NO
YES
If no match is found. Search fails. Component doesn't exist
If mean value matches with existing node. Search success. Give location of required component.
Give option for user to upload
End

Figure 2. The flow chart of methodology we followed

The algorithm followed in implementing this work is as shown below.

Algorithm 1_CR: Algorithm for component retrieval using Word2Vec-CBoW method (parameter1, parameter2.. .. parameter18):

Input: feature set consisting of 18 words, read from the user i.e. Parameter 1 to Parameter 18 as shown in parenthesis above.

Output: 1. If the component exists in Repository; it gives "component matches" message along with location of

```
component to retrieve.
    2. If the component doesn't exist in the Repository, it gives a "Not Found" or error message and gives an option for user to upload the component.
    Begin:
    Step1: Read $Fc_i \leftarrow \{f_1,f_2,f_3,f_4...f_{18}\}$;//18 features selected from GUI.
    Step 2: $M \leftarrow Fc_i$//Trained Word2Vec-CBoW Neural network model given with input
    Step 3: $wv_i \leftarrow M(f_i)$ where i=1,2,3,4...18;// vector for each word in feature set is generated
        $m_i \leftarrow mean(wv_i)$, where i=1,2,3,4...18;// mean for each vector of word is calculated
        $M_C \leftarrow (\Sigma_{i=1to\ 18} m_i)\ /18$;// overall mean of all vectors generated for all features of a component
    Step 4: Result = Search_AVL ($M_c$)// Searching for required component in AVL tree using Mc
    4a: If the mean value matches with any node value in AVL tree,
        Result $\leftarrow$ Component Matches, its Location.
    4b: If the mean value doesn't match with any node of AVL tree constructed during building of Repository,
        Result $\leftarrow$ Not Found
        Option to upload is given.
    End.
```

In the above algorithm, Fc_i stands for the 18 features set of a component being searched. This is given as input by the user during searching for a reusable component. M is the trained Word2Vec-CBoW Neural Network model for which this Fc_i is given as input. The model finds word vectors of each word in the feature set like wv_1,wv_2.... wvi. wv_{18}. The mean of each such generated word embedding vector is calculated in m_i and Average of all 18 means of all 18 features is calculated in M_c. This value in M_c is given as input for *search in AVL*tree developed during building of repository to check whether the component already exists or not. Let us try to understand the logic behind word embedding and how this algorithm works with an example as discussed here after in this section.

In embeddings, dense vectors are used to represent words where in these vectors are in fact projection of word in continuous vector space. For applying neural networks on text data, data pre-processing is to be done to generate equivalent integer of unique value. This unique integer is further mapped in to a specific dimension real valued vector by embedding. The unique integer can be generated in preprocessing of data using Tokenizer API of Keras. The Embedding layer results in a 2D vector with each word being embedded uniquely from input sequence. Which means the word is represented as two real valued components in vector.

The mathematics behind word2vec is simple to understand. It takes one hot encoding of a specific word having "1" corresponding to that word index and all remaining index as zero. By multiplying weight matrix generated from random seed and updated over iterations of training by this input vector we would be extracting word index's corresponding row. For example, considering a 4th word of a phrase [0 0 0 1] as shown below:

[0 0 0 **1**] * [24, 17, 6; 11, 8, 15; 16, 23, 43; **18, 9, 5**]=[18,9,5]

In case of word2vec being implemented using Keras or Tensorflow this math work is done by a special layer called as "Ebedding Layer". Consider the following 2 phrases simple training set for further understanding.

Happy to see you again; Hope to see you soon.

The above two phrases can be encoded by assigning a unique integer number based on order of appearance in training data set as [0, 1, 2, 3, 4]; [5, 1, 2, 3, 6]. The statement required for building embedding can be given as:

Embedding (7,2, input_length=5); where in 7 stands for number of unique words available in training set, the argument 2 indicates size of embedding vectors and the size of each input sequence is determined using argument input_length. The weights of embedding layer can be obtained after network is trained and for this example the size of matrix would be of 7X2. Let's consider the embeddings as shown below in Table 1:

Table 1. Word Embeddings (Sample)

Index	Embeddings
0	[1.2,3.1]
1	[0.4,4.1]
2	[1.0,3.1]
3	[0.3,2.1]
4	[2.3,1.5]
5	[0.9,1.7]
6	[5.6,2.4]

Accordingly, the second phrase in training can be represented as [[0.9,1.7], [0.4,4.1], [1.0,3.1], [0.3,2.1]].

For a given word say "soon", the index is 6 and resulting one hot encoding of [0,0,0,0,0,0,1], multiplying this 1X7 matrix with embedding matrix of 7X2 we get required 2-Dimensional embedding, which can be seen in this case as [5.6,2.4]. The weight matrix of embedding gets initialized with random values and then optimized over training phases. The one hot encoding dimension of a given word would be consistent with the embedding matrix as it is dependent on size of word corpus of considered training set.

In general, the Continuous Bag of Words (CBoW) model predicts a current word based on the context of words given within a specific window size. The window size indicates how many context words should be considered. The CBOW model of Word2Vec can be depicted as shown in Figure 3 below.

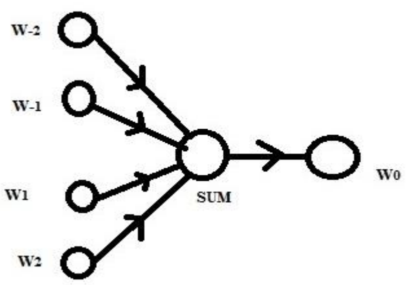


Figure 3. Simple representation of CBOW model of Word2Vec. W_{-2}, W_{-1}, W_1, W_2 are context words for word W_0

The underlying architecture of Word2Vec includes a Two-layer Neural Network for training that makes use of Back propagation algorithm. The Neural Network would have an Input Layer consisting of neurons in number equal to count of words in the vocabulary (V)followed by a Hidden Layer consisting of size equal to required dimensionality(N) of the resulting word vectors. The last layer would be an Output layer having neurons equal to input layer(V). The window size indicates the total words considered including center word for building context. In the above Figure 3, the window size considered is 5 for schematic purpose. The context window size considered for our work is 3 with vector dimensionality expected as 300. How we happened to fix with this 300 is explained in Results section below. The 300 means each word would be coded in to a vector size of 300 as shown in Figure 6 in following pages. The learning of parameters would be based on Backpropagation Algorithm and SoftMax activation function in output layer. The schematic representation of Neural Network model considered can be as shown in Figure 4 below. One hot encoding of word is considered as input with V dimensions that is equal to number of total words, which happens to be 18 in feature set. W_{VXN} represents Weight matrix between input layer and Hidden layer whereas W'_{NXV} represents weight matrix between hidden layer and output layer. As mentioned earlier that we use Word2Vec model as proxy as our concentration is on N dimension representation of word but not on the output layer.

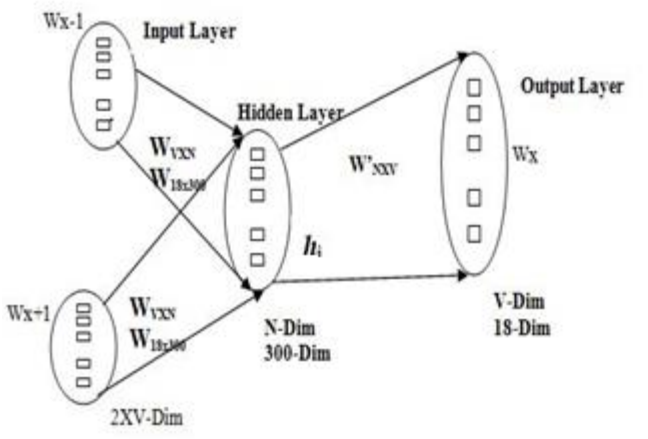


Figure 4. The schematic view of Neural Network considered in Word2Vec model we used with window size=3

The work was carried out by considering a data set of 40000 components. The feature vector of reusable component constitutes of following information:

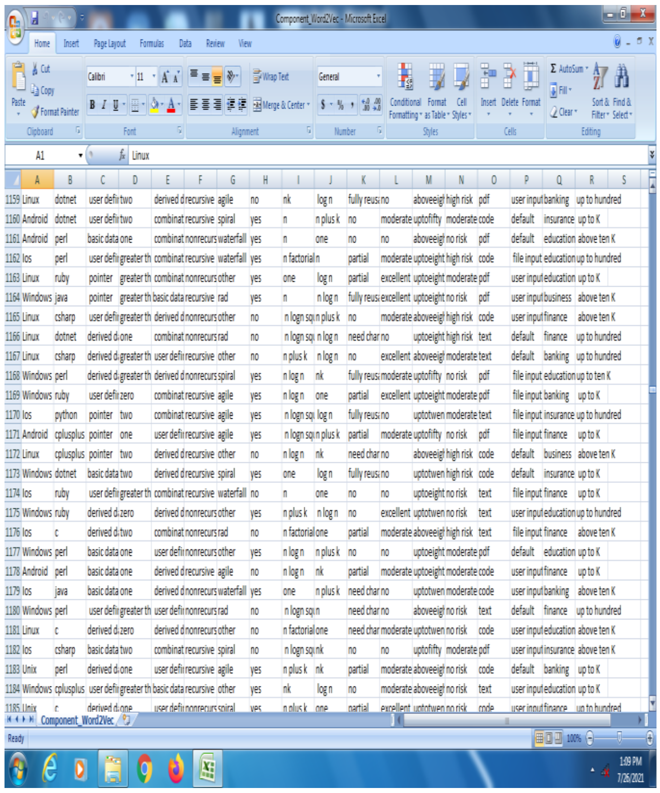
1.Operating System; 2. Programming Language; 3. Return Type; 4. No of Parameter 5. Type of Parameters; 6. Recursion; 7. Development Model; 8. Already Modified; 9. Time Complexity; 10. Space Complexity; 11. Reusability; 12. Well Documented; 13. Reliability; 14. Risk Factor; 15. Uploaded file type; 16. Data info; 17. Domain; 18. Lines of Code; 19. License; 20. Name of Program.

Each component is represented using a feature vector of 20 features set. For training purpose of Neural Network only 18 features were considered as "name of the program" (20th feature) and "licensing" (19th features) were not exactly contributing to identification of component very specifically. The feature vector is a collection of specific words which clearly distinguishes a code component. The considered 18 features are converted to vectors, which further will be given as input to neural network.

The following is a sample entry of one reusable component's feature set as given by a user, let's call it $\mathbf{F_c}$:

1.Linux; 2. Ruby; 3. Derived data type; 4. Zero; 5. User defined data type; 6. Non recursive; 7.RAD; 8. Yes; 9. Nlogn; 10. One; 11. Fully reusable; 12. Excellent; 13. Up to Eighty; 14. High risk; 15. Code; 16. File input; 17. Banking; 18. Up to hundred.

All the feature set of 40000 components considered is stored in a CSV file as shown in Figure 5 below, where each row indicates one component's feature vector. Using Word2Vec technique the vector representation of each word is identified and these values are averaged to find equivalent vector value of one row, which is equal to the vector value representation of one component. The components are represented as a single mean value of word vector generated for features considered. These mean values are stored in an AVL tree data structure at the time of creation of repository.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1159	Linux	dotnet	user defi	two	derived d	recursive	agile	no	nk	log n	fully reus	no	aboveeigh	high risk	pdf	user input	banking	up to hundred	
1160	Android	dotnet	user defi	two	combinat	recursive	spiral	yes	n	n plus k	no	moderate	uptofifty	moderate	code	default	insurance	up to K	
1161	Android	perl	basic data	one	combinat	nonrecurs	waterfall	yes	n	one	no	no	aboveeig	no risk	pdf	default	education	above ten K	
1162	Ios	perl	user defi	greater th	combinat	recursive	waterfall	yes	n factorial	n	partial	moderate	uptoeight	high risk	code	file input	education	up to hundred	
1163	Linux	ruby	pointer	greater th	combinat	nonrecurs	other	yes	one	log n	partial	excellent	uptoeight	moderate	pdf	user input	education	up to K	
1164	Windows	java	pointer	greater th	basic data	recursive	rad	yes	n	n log n	fully reus	excellent	uptoeight	no risk	pdf	user input	business	above ten K	
1165	Linux	csharp	user defi	greater th	derived d	nonrecurs	other	no	n logn sq	n plus k	no	moderate	aboveeig	high risk	code	user input	finance	above ten K	
1166	Linux	dotnet	derived d	one	combinat	nonrecurs	rad	no	n logn sq	n log n	need char	no	uptoeight	high risk	text	default	finance	up to hundred	
1167	Linux	csharp	derived d	greater th	user defi	recursive	other	no	n plus k	n log n	no	excellent	aboveeig	moderate	text	default	banking	up to hundred	
1168	Windows	perl	derived d	greater th	derived d	nonrecurs	spiral	yes	n log n	nk	fully reus	moderate	uptofifty	no risk	pdf	file input	education	up to ten K	
1169	Windows	ruby	user defi	zero	combinat	recursive	agile	yes	n log n	one	partial	excellent	uptoeight	moderate	pdf	file input	banking	up to K	
1170	Ios	python	pointer	two	combinat	recursive	agile	yes	n logn sq	log n	fully reus	no	uptotwen	moderate	text	file input	insurance	up to hundred	
1171	Android	cplusplus	pointer	one	user defi	recursive	agile	yes	n logn sq	n plus k	partial	moderate	uptofifty	no risk	pdf	file input	finance	up to K	
1172	Linux	cplusplus	pointer	two	derived d	recursive	other	no	n log n	nk	need char	no	aboveeig	high risk	code	default	business	above ten K	
1173	Windows	dotnet	basic data	two	derived d	recursive	spiral	yes	one	log n	fully reus	no	uptotwen	high risk	code	default	insurance	up to K	
1174	Ios	ruby	user defi	greater th	combinat	recursive	waterfall	no	n	one	no	no	uptoeight	no risk	text	file input	finance	up to K	
1175	Windows	ruby	derived d	zero	derived d	nonrecurs	other	yes	n plus k	n log n	no	excellent	uptotwen	no risk	text	user input	education	up to hundred	
1176	Ios	c	derived d	two	combinat	nonrecurs	rad	no	n factorial	one	partial	moderate	aboveeig	high risk	text	file input	finance	above ten K	
1177	Windows	perl	basic data	one	user defi	nonrecurs	other	yes	n log n	n plus k	no	no	uptoeight	moderate	pdf	default	education	up to K	
1178	Android	perl	basic data	one	derived d	recursive	agile	no	n log n	nk	partial	moderate	uptoeight	moderate	code	user input	finance	up to K	
1179	Ios	java	basic data	one	derived d	nonrecurs	waterfall	yes	one	n plus k	need char	no	uptotwen	moderate	code	user input	banking	above ten K	
1180	Windows	perl	user defi	greater th	user defi	nonrecurs	rad	no	n logn sq	n	need char	no	aboveeig	no risk	text	default	finance	up to hundred	
1181	Linux	c	derived d	zero	derived d	nonrecurs	other	no	n factorial	one	need char	moderate	uptotwen	no risk	code	user input	education	above ten K	
1182	Ios	csharp	basic data	two	combinat	recursive	spiral	no	n logn sq	nk	no	no	uptofifty	moderate	pdf	user input	insurance	above ten K	
1183	Unix	perl	derived d	one	user defi	recursive	agile	yes	n plus k	nk	partial	moderate	aboveeig	no risk	code	default	banking	up to K	
1184	Windows	cplusplus	user defi	greater th	basic data	recursive	other	yes	nk	log n	no	moderate	aboveeig	no risk	text	user input	education	up to K	
1185	Unix	c	derived d	one	user defi	nonrecurs	spiral	yes	n plus k	one	partial	excellent	uptotwen	no risk	code	user input	finance	up to hundred	

Figure 5. Snapshot of dataset used in csv file format for training

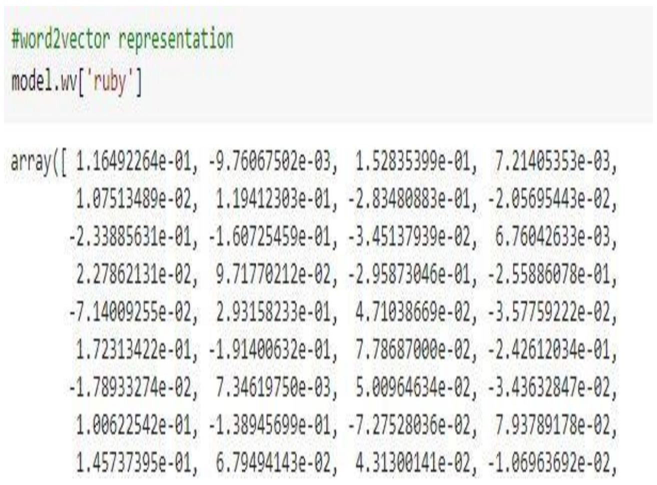
When the user wants to search for a specific component, the user is asked to select the features of the component he is looking for, from the dropdown list created for each feature element in the GUI that is created using Tkinter. This leaves no scope for user to enter random data. Thus, makes it easy to handle data avoiding any necessity of cleaning and all fields are made mandatory so that no null values are taken. The entered feature set is a collection of words so using the already trained model the average value of vector representation of this collection of words is considered. The resulting average value now indicates the vector value of the component being search. Using AVL tree this value is simply checked whether exists in the repository or not. If it is there it means the required component exists else it means, the required component being searched for is not available in the component repository. For the purpose of experimentation, we have collected many code components from different resources on line such as sourceforge.net, Github etc. sites and as our methodology is completely new it requires building own repository.

Let us consider for step 1 the input is given as shown in example earlier called as Fc for the algorithm 1 described above. This is fed as an input to the pre trained model M generating word vector of each feature.

1.Linux 2.Ruby 3.Derived data type 4.zero 5.User defined data type 6.Non recursive 7.RAD 8.Yes 9.Nlogn 10.One

11.Fully reusable 12.Excellent 13.Up to Eighty 14.High risk 15.Code 16.File input 17.Banking 18.Up to hundred.

The vector representation of a word indicating “Language” feature of a specific component as considered in Fc, which is “Ruby” was observed to be as shown in Figure 6 below:



```
#word2vector representation
model.wv['ruby']
```

```
array([ 1.16492264e-01, -9.76067502e-03,  1.52835399e-01,  7.21405353e-03,
        1.07513489e-02,  1.19412303e-01, -2.83480883e-01, -2.05695443e-02,
       -2.33885631e-01, -1.60725459e-01, -3.45137939e-02,  6.76042633e-03,
        2.27862131e-02,  9.71770212e-02, -2.95873046e-01, -2.55886078e-01,
       -7.14009255e-02,  2.93158233e-01,  4.71038669e-02, -3.57759222e-02,
        1.72313422e-01, -1.91400632e-01,  7.78687000e-02, -2.42612034e-01,
       -1.78933274e-02,  7.34619750e-03,  5.00964634e-02, -3.43632847e-02,
        1.00622542e-01, -1.38945699e-01, -7.27528036e-02,  7.93789178e-02,
        1.45737395e-01,  6.79494143e-02,  4.31300141e-02, -1.06963692e-02,
```

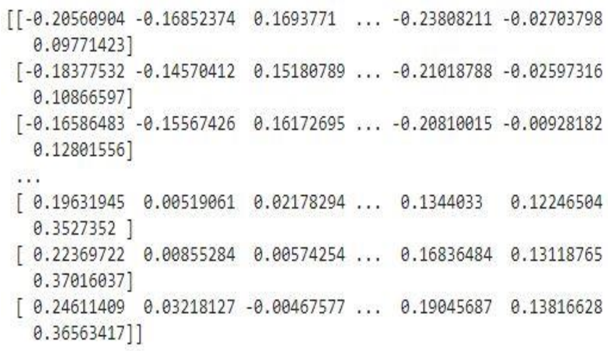
Figure 6. Sample 300-dimension vector generated for a Word of “ruby” indicating “Language” feature of a component
(Owing to space only a part of vector shown)

The values in the array in above figure indicate the 300 dimensions representation of word representing one feature of the component. This also signifies that we considered 300 neurons in the hidden layer of Word2Vec neural network. These hidden layer neurons are trained using back propagation algorithm. The authors of this work have done empirical study using size as 50,100,200,300,400 and the results obtained showed that when the size considered is 300 the model was giving better accuracy and hence, we stick on to 300-dimension vector representation.

Table 2 shows mean values obtained for the vector representation of each word in the feature set consisting of 18 features as shown in second column of table for the component being searched for. The mean value of all these 18 values is observed to be -0.007391004. This value now represents one reusable component.

The mean value of vector generated for all words of the feature set would be a value of -0.007391004. This becomes the first node in the AVL tree at the time of repository creation and further values of second, third components etc. would be inserted under the root node and height balancing of AVL tree happens. While searching, this value generated like -0.007391004 is then checked for its availability in the repository built using AVL tree. The Figure 7 represents word vectors generated for features of first component considered from training set as shown in Figure 5. The mean value of each vector generated for each feature is calculated and further mean value of all such 18 features is calculated as explained in step 2 and step 3 of algorithm 1 above. This final mean value becomes the representation of a single component. Figure 8 shows the mean value of each component that would be stored in AVL tree. Owing to space constrains only values of a few (10) components are being shown in Figure 8. This means 0.007711691 value now represents first component as shown in first row of CVS file in Figure 5 and 0.0077005713 represents second component from Figure 5 and so on.

Considering inserting of first 5 values from the above mean values in to the AVL tree, the generated AVL tree after height balancing looks as in Figure 9.

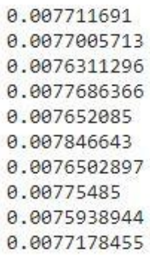


```
[[-0.20560904 -0.16852374  0.1693771  ... -0.23808211 -0.02703798
   0.09771423]
 [-0.18377532 -0.14570412  0.15180789 ... -0.21018788 -0.02597316
   0.10866597]
 [-0.16586483 -0.15567426  0.16172695 ... -0.20810015 -0.00928182
   0.12801556]
 ...
 [ 0.19631945  0.00519061  0.02178294 ...  0.1344033   0.12246504
   0.3527352 ]
 [ 0.22369722  0.00855284  0.00574254 ...  0.16836484  0.13118765
   0.37016037]
 [ 0.24611409  0.03218127 -0.00467577 ...  0.19045687  0.13816628
   0.36563417]]
```

Figure 7. Generated vector representation of features belonging to first component (Fc) from training set shown in Figure 5

Table 2. The table shows mean values of vectors generated by Word2Vec of each feature element for a component being searched for

Sl.No.	Feature	Sample Considered	Mean of Vector generated
Feature1	Operating System	Linux	-0.0068095303
Feature 2	Programming Language	Ruby	-0.006214711
Feature 3	Return Type	Derived data type	-0.0069797197
Feature 4	No.Of Parameters	zero	-0.0070498325
Feature 5	Type of Parameters	User defined data type	-0.007185216
Feature 6	Recursion	Non recursive	-0.0070020645
Feature 7	Development Model	RAD	-0.0056332634
Feature 8	Already Modified	Yes	-0.0066335257
Feature 9	Time Complexity	n log n	-0.0056920093
Feature 10	Space Complexity	One	-0.0058320006
Feature 11	Reusability	Fully reusable	-0.007200637
Feature 12	Well Documented	Excellent	-0.0071973926
Feature 13	Reliability	Up to Eighty	-0.00783842
Feature 14	Risk Factor	High risk	-0.008600807
Feature 15	Uploaded file type	Code	-0.008872024
Feature 16	Data info	File input	-0.009424939
Feature 17	Domain	Banking	-0.009272366
Feature 18	Lines of Code	Upto hundred	-0.009599611



```
0.007711691
0.0077005713
0.0076311296
0.0077686366
0.007652085
0.007846643
0.0076502897
0.00775485
0.0075938944
0.0077178455
```

Figure 8. Mean values calculated for word vectors of 10 components considered for training using CSV file as shown in Figure 5

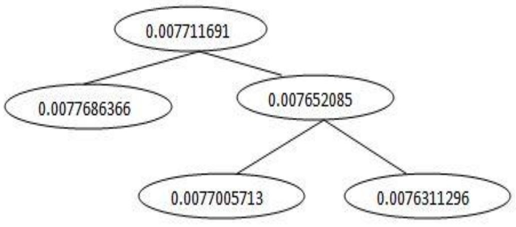


Figure 9. AVL Tree generated after insertion of mean values of vector representation for 5 components

While the tree is being generated or repository being built, in case if the mean value generated matches with any node value already inserted in the AVL tree, it would display as "Component Already Existing". For step 4 in algorithm above, while searching for component, if considered for an existing component, we get a message like "***Component matches***" and gives the location of component in system enabling easy retrieval. In case of non-existing component, it gives a "***Not Found***" message and also the option for uploading component is given to the user.

4. IMPLEMENTATION RESULTS AND DISCUSSIONS

The experiments were carried out with following specifications:

Total components Considered: 40000; Embedding Size: 300.

Table 3. The results of the experiments done using Word2Vec with CBOW

	Case 1	Case 2	Case 3
Components count	40000	40000	40000
Training Data	28000	32000	24000
Testing Data (Existing/Total)	8000/12000	5780/8000	12360/16000
True Positive	6820	4480	11190
False Positive	390	840	1240
True Negative	4560	2160	2900
False Negative	230	520	670
Precision	0.94	0.84	0.90
Recall	0.96	0.89	0.94
Accuracy	0.948	0.83	0.88

The Table 3 records Accuracy obtained with different experimentations done during this work. We considered 3 cases with different count of Existing components as 8000,5780,12360 respectively for a total testing component input of 12000,8000,16000 respectively as shown in Row 3-Testing Data, of Table 3. Accuracy of 0.948 or 94.8% is calculated as ratio of sum of True Positives and True negative to the total output samples i.e. (6820+4560)/12000 which is 11380/12000 resulting in 0.948.

Table 4 below shows comparison of accuracy as obtained by our method with other existing methods.

Table 4. Comparing results of experimentation with other existing methods

Sl.No	Model Used	Accuracy
1	Word2Vec [16]	29.5%
	rVSM	56.5%
	rVSM+Word2Vec	60.9%
2	Bag of words with count vectorizer [21]	86%
3.	Word2Vec using CBoW method (***Present research work***) ***from Table 3***.	**94.8%**

With the above table, it is clear that our method out performs existing method in the market as we are able to get an accuracy of 94.8% in best case making use of vector representation of words taken from Word2Vec model for our data set whereas the other researchers method using Word2Vec with Revised Vector Space model has achieved only 60.9% or 86% when researchers used Bag of words with count vectorizer.

5. CONCLUSIONS

In this paper, a novel approach of reusable component repository maintenance is reported. The work used AVL tree having nodes containing mean values of vector representation for component's features in building repository. The user chooses the features of the component searching for, from the drop down list of each feature constituents from the GUI. The words representing features are given as input to already trained neural network model developed using Word2Vec with CBoW method. The word vector for each word in feature set is generated and the mean of all word vectors as well as mean of whole feature set is calculated for that component. The AVL tree constructed while building Repository is searched for this mean value to check whether the component exists in the repository or not. If the mean value matches with any node value in AVL tree, it means component is present and the corresponding component matches message is given as an output along with the location of component to retrieve. The work was carried out on a data set of 40000 components' features. This work would be very much helpful for developers who need to code reliable large programs following component based software engineering process as by using the developed model, identifying a reusable component in large repository becomes easy. The work resulted in better performance with accuracy of 94.8% using Word2Vec with CBoW and AVL tree, as compared to existing proven mechanisms of component retrieval like rVSM, Bag of Words with vector quantization. The authors plan to refine this work by more emphasis on identifying number of parameters for representing a component by using PCA or other feature extracting mechanisms.

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