

# PRACTICAL ASSESMENT



## ACTIVITY 1

# Python Implementation of Word Embeddings using word2vec

## **Requirements**

- Personal computer/laptop
- ➢ Google Collab

### **Procedure**

1. Import Necessary Libraries

```
[1] # Import necessary Libraries
from gensim.models import Word2Vec
from nltk.tokenize import word_tokenize
from nltk import download
```

download("punkt")

2. Download Required NLTK Data

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Unzipping tokenizers/punkt.zip.
True
```

### Define Example Sentences

```
[2] # Example sentences

sentences = [

"Natural Language Processing is fun.",

"Language models are improving every day."

]
```

#### Tokenize Sentences

```
# Tokenize sentences
tokenized_sentences = [word_tokenize(sentence.lower()) for sentence in sentences]
tokenized_sentences

[['natural', 'language', 'processing', 'is', 'fun', '.'],
['language', 'models', 'are', 'improving', 'every', 'day', '.']]
```

#### Train the Word2Vec Model

```
# Train the Word2Vec model
model = Word2Vec(sentences=tokenized_sentences, vector_size=5, window=5, min_count=1, workers=4, sg=0)
# Here sg=0 means the model will use Continuous bag of words architecture and if sg=1 then it will use Skip-gram Model
# Get word vectors
word_vectors = model.wv
print("Word Vector for 'language':", word_vectors['language'])

Word Vector for 'language': [-0.14233617 0.12917745 0.17945977 -0.10030856 -0.07526743]
```

## ACTIVITY 2

# Python Implementation of Word Embeddings using GloVe

## Requirements

- Personal computer/laptop
- ➢ Google Collab

## **Procedure**

Import the Gensim downloader

```
√ [2] import gensim.downloader as api
```

 Load the pre-trained GloVe model with 50 dimensions and Check the dimensions of a sample word vector (e.g., 'language')

- Load the pre-trained GloVe model with 100 dimensions
- Check the dimensions of a sample word vector (e.g., 'language')

```
[ ] # Load the pre-trained GloVe model with 100 dimensions
glove_vectors_100d = api.load("glove-wiki-gigaword-100")
print("Dimensions of 100d GloVe vector:", len(glove_vectors_100d['language']))
```

- Load the pre-trained GloVe model with 200 dimensions
- Check the dimensions of a sample word vector

```
[ ] #*Load*the*pre-trained*GloVe*model*with*200*dimensions
glove_vectors_200d*=*api.load("glove-wiki-gigaword-200")
print("Dimensions*of*200d*GloVe*vector:",*len(glove_vectors_200d['language']))
```

- Load the pre-trained GloVe model with 300 dimensions
- Check the dimensions of a sample word vector

```
[ ] #-Load the pre-trained GloVe model with 300 dimensions
glove_vectors_300d = api.load("glove-wiki-gigaword-300")
print("Dimensions of 300d GloVe vector:", len(glove_vectors_300d['language']))
```

# ACTIVITY 3

# Python Implementation of Word Embeddings using Fasttext

## <u>Requirements</u>

- > Personal computer/laptop
- ➤ Google Collab

## **Procedure**

Importing Necessary Libraries

```
[1] # Import necessary libarries
from gensim.models import FastText
from nltk.tokenize import word_tokenize
from nltk import download
```

#### Downloading NLTK Data

```
# Download required NLTK data
download('punkt')
```

#### **Example Sentences**

```
# Example sentences
sentences = [
    "Natural Language Processing is fun.",
    "Language models are improving every day."
]
```

#### **Tokenizing Sentences**

```
# Tokenize sentences
tokenized_sentences = [word_tokenize(sentence.lower()) for sentence in sentences]
```

#### Training the FastText Model

```
# Train the FastText model
model = FastText(sentences=tokenized_sentences, vector_size=5, window=5, min_count=1, workers=4, sg=1)
# Get word vectors
word_vectors = model.wv
print("Word Vector for 'language':", word_vectors['language'])
# Get vector for an OOV word
print("Word Vector for 'NLPfun':", word_vectors['nlpfun'])
Word Vector for 'language': [-0.00461428  0.01921903 -0.00035116 -0.00750383 -0.02619313]
Word Vector for 'NLPfun': [ 0.01152632  0.00589536 -0.01608402 -0.00613909  0.00409522]
```

output the word vectors for 'language' and 'NLPfun'. The FastText model's ability to handle OOV words through subword information is one of its key strengths, making it robust for a variety of natural language processing tasks.