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LAB-3 Report: Implementation and Visualization of Word2Vec Embeddings

This lab demonstrates the process of generating semantic word embeddings from a text corpus using the Word2Vec algorithm.

The objective is to represent words as dense vectors in a continuous vector space where semantically similar words are positioned close to one another.

The implementation utilizes several key Python libraries for natural language processing and data science:

- **Gensim**: Used for training the Word2Vec model and managing word vectors.
- **NLTK**: Employed for text preprocessing and tokenization.
- **Scikit-Learn**: Utilized for Principal Component Analysis (PCA) to reduce vector dimensions.
- **Matplotlib**: Used to generate the final 2D visualization of the word space.

The input data consists of a sample corpus focusing on Natural Language Processing (NLP) concepts. Before training, the text undergoes the following transformations:

Normalization: Converting all text to lowercase to ensure consistency.

Tokenization: Utilizing NLTK's word_tokenize to split sentences into individual word units (tokens).

```

▶ !pip install gensim scikit-learn matplotlib
from gensim.models import Word2Vec
from nltk.tokenize import word_tokenize
import nltk

nltk.download('punkt')
nltk.download('punkt_tab') # Added to download the missing resource

# Sample corpus
corpus = [
    "Natural language processing is a fascinating field",
    "Word embeddings capture semantic meanings",
    "NLP is used in chatbots and virtual assistants",
    "Word2Vec is a powerful tool for creating word embeddings"
]

# Tokenize sentences
tokenized_corpus = [word_tokenize(sentence.lower()) for sentence in corpus]
print(tokenized_corpus)

# Train Word2Vec model
model = Word2Vec(sentences=tokenized_corpus, vector_size=100, window=5, min_count=1, workers=4)

# Save the model
model.save("word2vec.model")

model = Word2Vec.load("word2vec.model")

# Get vectors for a subset of words
words = list(model.wv.index_to_key)[:10] # Select the first 10 words
print(words)
word_vectors = [model.wv[word] for word in words]
print(word_vectors)

```

Because 100-dimensional vectors cannot be visualized directly, the project applies **Principal Component Analysis (PCA)**. This mathematical technique reduces the vectors to 2 components while preserving as much variance as possible, allowing the words to be plotted on a 2D grid.

```

|
from sklearn.decomposition import PCA

# Apply PCA for dimensionality reduction
pca = PCA(n_components=2)
pca_result = pca.fit_transform(word_vectors)

import matplotlib.pyplot as plt

# Plot the words in 2D space
plt.figure(figsize=(10, 5))
plt.scatter(pca_result[:, 0], pca_result[:, 1])

# Annotate the points with the words
for i, word in enumerate(words):
    plt.annotate(word, xy=(pca_result[i, 0], pca_result[i, 1]))

plt.title("2D Visualization of Word Embeddings")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.grid(True)
plt.show()

```

Results and Analysis

The output demonstrates the model's ability to extract specific vectors for tokens like "is," "embeddings," and "word2vec".

- **Vector Output:** The model generates precise floating-point arrays for every word in the vocabulary.
 - **Graphical Representation:** The PCA plot visualizes the spatial relationship between terms, providing a map of how the model has learned the "meaning" of the input text.

```
Installing collected packages: gensim
Successfully installed gensim-4.4.0
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data] Unzipping tokenizers/punkt_tab.zip.
[!] nltk.download('punkt') is a 'fascinating' ['field'], ['word'], ['embeddings'], ['capture'], ['semantic'], ['meanings'], ['nip'], ['is'], ['used'], ['in'], ['chatbots'], ['and'], ['virtual'], ['assistants'], ['word2vec'], ['is'], ['a'], ['powerful'], ['is'], ['embeddings'], ['word'], ['is'], ['reading'], ['for'], ['text'], ['powerful'], ['word2vec'], ['assistants']
[!] [1]: 2.48732e-03, -1.38991e-03, -0.056563e-03, -0.013234e-03,
-0.304126e-03, -7.118421e-03, 0.4591165e-03, 8.9739806e-03,
-0.0517558e-03, -3.7653943e-03, 7.3820921e-03, 1.0518163e-03,
-4.5345500e-03, 6.5530594e-03, -4.8587834e-03, -1.8163866e-03,
2.877921e-03, 9.028728e-04, -8.2870843e-03, -9.4514126e-03,
7.3109688e-03, 5.0799019e-03, 6.7580262e-03, 6.6012913e-04,
0.5430810e-03, -0.1000000e+00, -0.0000000e+00, 5.1610000e-03,
-7.5215344e-03, -3.9357766e-03, -7.5177767e-03, -3.1125604e-04,
9.5384931e-03, -7.3194429e-03, -2.3347498e-03, -1.9366210e-03,
8.0779372e-03, -5.9318673e-03, 4.1685435e-05, -4.7525410e-03,
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-3.4098470e-05, 2.9744051e-04, -7.6616611e-03, 9.6138850e-03,
-4.3094245e-05, -0.0000000e+00, 1.0000000e+00, -0.0000000e+00,
-1.1370016e-03, 8.2416082e-03, 8.0053188e-03, -4.4610669e-03,
4.5164647e-03, -6.7853210e-03, -3.4573362e-03, 3.9908008e-03,
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-1.5084570e-03, 2.4713580e-03, -8.8901544e-04, 5.5368468e-03,
-2.7449303e-03, 2.2591040e-03, 5.4555875e-03, 8.3476352e-03,
-1.4524100e-03, 9.2081940e-03, 4.3700617e-03, 5.7318116e-04,
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-8.5941557e-04, 2.8728236e-03, 5.4084234e-03, -5.0977875e-03,
-2.0833232e-03, 3.0565345e-03, -2.0655333e-03, 2.0523301e-03
```

