WordEmbeddingsWithWord2Vec

December 25, 2023

1 Word Embeddings with Word2Vec

Being able to represent a word as a series of numerical values is essential to the large language modeling done using the transformer architecture. Word2Vec makes this possible extracting the word embeddings creating during the skip-gram or continuous bag-of-words(CBOW) process. More info can be found here. Adapted from Kaggle and TowardsDataScience. Written By: Da'Vel Johnson

[1]:
```
# Importing the Word2Vec module
import gensim.downloader as api
from gensim.models import Word2Vec
```

1.1 Training the Word2Vec model

[2]:
```
# Download a text corpus for training Word2Vec
corpus = api.load('text8')

# Train a Word2Vec model on the text corpus
#sg=0: Uses the CBOW architecture. sg=1: Uses the Skip-gram architecture.
model = Word2Vec(corpus, vector_size=100, window=5, min_count=5, workers=4,␣
 ↪epochs=5, sg=0)

# Save the trained model to a file
model.save("word2vec_model")

# Load the saved model
loaded_model = Word2Vec.load("word2vec_model")
```

1.1.1 How many words are in the corpus?

[3]:
```
# Flatten the list of lists into a single list of words
all_words = [word for sentence in corpus for word in sentence]

# Create a set of unique words
unique_words = set(all_words)

# Count the number of unique words
num_unique_words = len(unique_words)
```

```
print(f"Number of unique words in the text8 corpus: {num_unique_words}")
```

```
Number of unique words in the text8 corpus: 253854
```

1.2 Using the trained model

[4]:
```
# Find the vector representation of a word
word1='computer'
word2='laptop'
word_vector = loaded_model.wv[word1]

# Find the most similar words to a given word
similar_words = loaded_model.wv.most_similar(word1, topn=10)

# Find the similarity between two words
similarity = loaded_model.wv.similarity(word1, word2)

print("Vector representation of the word :", word1)
print(word_vector)

print("\nTop 10 most similar words to :", word1)
for word, score in similar_words:
    print(f"{word}: {score}")

print("\nSimilarity between ", word1 + " and " + word2)
print(similarity)
```

```
Vector representation of the word : computer
[-0.1696152   0.03977273 -1.6142509   0.80795836 -1.3488977  -1.9992895
  0.07614967  0.39692298 -0.8842152   0.5970802   1.4464766  -4.3852897
  0.46164048 -2.3159826  -3.4858932   0.70859474  0.76130426 -1.1508452
  1.1162137   0.03445475 -0.8702186  -1.4601638  -0.74114686 -1.1341766
 -0.01858072  0.09850959  1.3609     -0.36663023 -0.19098063  0.6380601
  1.1645826   1.7270626   0.8823621   1.7756115  -1.0360365   2.3361828
  0.86468875 -0.246082    0.30048078 -0.4279755  -2.04644    -1.1439999
  2.0315814   0.52497965  2.3341107  -0.18531676 -0.18521233  2.4032943
 -0.730989   -1.8627257   1.4713875   0.80163485  1.5171877  -3.3317647
 -1.6274753   0.32910073 -1.0830698  -2.228089   -1.2469157  -1.2434509
 -2.246893   -0.6814539   3.032343    1.0753156   0.1537342   0.8198287
  1.9957052   0.87849724  1.2810159   1.598118   -1.9588158   1.3699526
 -0.9967758   1.1140213   0.3165327   0.7611594   1.622918    1.1761311
 -3.5265074  -3.8231611  -1.0519999  -0.43476844  2.1806726   1.4339157
  0.42024964 -0.04400216 -2.1766722   1.9769117   2.09343    -0.12948199
 -1.2056701   2.4072082  -1.004069    1.3870637   2.0461462   2.263556
  0.11803816  1.6566203   1.8861741  -1.9534225 ]

Top 10 most similar words to : computer
```

```
computers: 0.7199147343635559
computing: 0.6983553171157837
programmer: 0.6778250336647034
mainframe: 0.6719053387641907
console: 0.6692198514938354
hardware: 0.6426659226417542
technology: 0.6381118893623352
networking: 0.6324590444564819
programmable: 0.6286059617996216
laptop: 0.6279082298278809

Similarity between  computer and laptop
0.6279082
```

1.2.1 Demonstrating word similarity

A classic example is to show that the word most similar to 'woman' + 'king' - 'man' is 'queen'. This is intuitive linguistically, but it's interesting to see this emerge mathematically.

[5]:
```python
#Woman + King - Man = Queen
loaded_model.wv.most_similar(positive=['woman','king'], negative=['man'], topn
↪= 10)
```

[5]:
```
[('queen', 0.6963896751403809),
 ('prince', 0.6523086428642273),
 ('throne', 0.6451753377914429),
 ('empress', 0.6381632685661316),
 ('princess', 0.6225873231887817),
 ('emperor', 0.6196994781494141),
 ('regent', 0.6025001406669617),
 ('daughter', 0.597307562828064),
 ('mary', 0.5865886211395264),
 ('son', 0.5853062272071838)]
```

Playing with more word similarity

[6]:
```python
word1='robot'
word2='human'
```

[7]:
```python
result = loaded_model.wv.most_similar(positive=[word1, word2], topn=10)
print("Word analogy result: ", word1 + " plus " + word2 + " = " + result[0][0])
```

```
Word analogy result:  robot plus human = sentient
```

[8]:
```python
print("\nTop 10 most similar words to ", word1 + " and " + word2)
for word, score in result:
    print(f"{word}: {score}")
```

```

Top 10 most similar words to  robot and human
```

```
sentient: 0.7057055830955505
humanoid: 0.6676562428474426
mutant: 0.6371280550956726
alien: 0.6275253295898438
animal: 0.6161515712738037
robots: 0.5867959260940552
robotic: 0.5852395296096802
humans: 0.5788995623588562
supernatural: 0.5704163312911987
beings: 0.5629681944847107
```

Sometimes you arrive at non intuative results.

[9]:
```python
result = loaded_model.wv.most_similar(positive=[word1], negative=[word2],␣
    ↪topn=10)
print("Word analogy result: ", word1 + " minus " + word2 + "= " + result[0][0])
print("\nTop 10 most similar words to ", word1 + " minus " + word2)
for word, score in result:
    print(f"{word}: {score}")
```

```
Word analogy result:  robot minus human= icarus

Top 10 most similar words to  robot minus human
icarus: 0.5767585039138794
wee: 0.5725619196891785
circus: 0.5677955150604248
gumby: 0.5618346333503723
boss: 0.5595255494117737
toting: 0.5552021861076355
kid: 0.5513733625411987
fawlty: 0.5473917126655579
slayer: 0.5422278046607971
hi: 0.5376124382019043
```

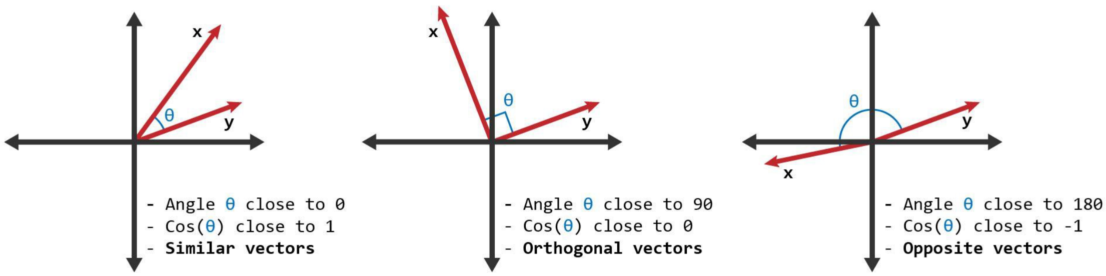
[10]:
```python
result = loaded_model.wv.most_similar(positive=[word1], topn=10)
print("Word analogy result: ", result[0][0])
print("\nTop 10 most similar words to your query:")
for word, score in result:
    print(f"{word}: {score}")
```

```
Word analogy result:  cyborg

Top 10 most similar words to your query:
cyborg: 0.7102828621864319
monster: 0.7012732028961182
killer: 0.6965927481651306
dalek: 0.6858187913894653
humanoid: 0.6793836951255798
wizard: 0.6763895153999329
```

```
robotic: 0.6740067601203918
rogue: 0.6690255403518677
vampire: 0.6664007306098938
superhero: 0.6518058776855469
```

1.2.2 Opposite words vectorally

Finding opposite words has a different meaning with word embeddings. It means going in the opposite direction in vector space.



[11]:
```python
def find_opposite_word(word, model, top_n=10):
    # Get the word vector for the given word
    word_vector = model.wv[word]

    # Negate the word vector
    opposite_vector = -word_vector

    # Find the most similar words to the opposite vector
    opposite_words = model.wv.similar_by_vector(opposite_vector)

    return opposite_words

word = 'up'
opposite_words = find_opposite_word(word, loaded_model)

print(f"Opposite words for '{word}':")
for w, similarity in opposite_words:
    print(f"{w} (similarity: {similarity})")
```

```
Opposite words for 'up':
landa (similarity: 0.32932358980178833)
carolus (similarity: 0.3000851273536682)
ganshof (similarity: 0.299647718667984)
faust (similarity: 0.2943476736545563)
lucis (similarity: 0.2943273186683655)
ren (similarity: 0.29378005862236023)
ayurveda (similarity: 0.292289137840271)
founder (similarity: 0.28902316093444824)
chomsky (similarity: 0.28655877709388733)
```

```
de (similarity: 0.2844894826412201)
```

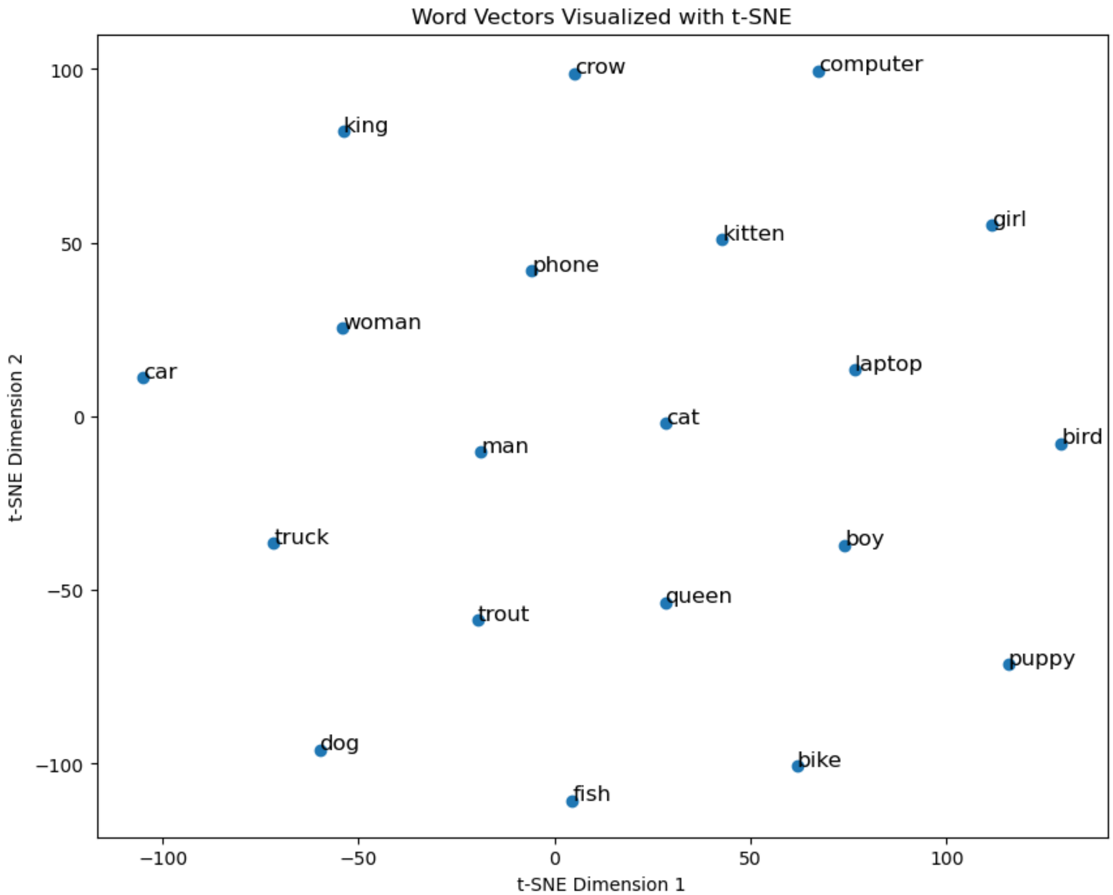
As a result, the outcomes nonsensical. Finding antonyms requires an understanding and encoding of context that Word2Vec is not designed to do.

1.2.3 Visualize Word Embeddings

Since words are being represented as vectors, this means they can be plotted using a dimension reduction algorithm called t-distributed Stochastic Neighbor Embedding (TSNE)

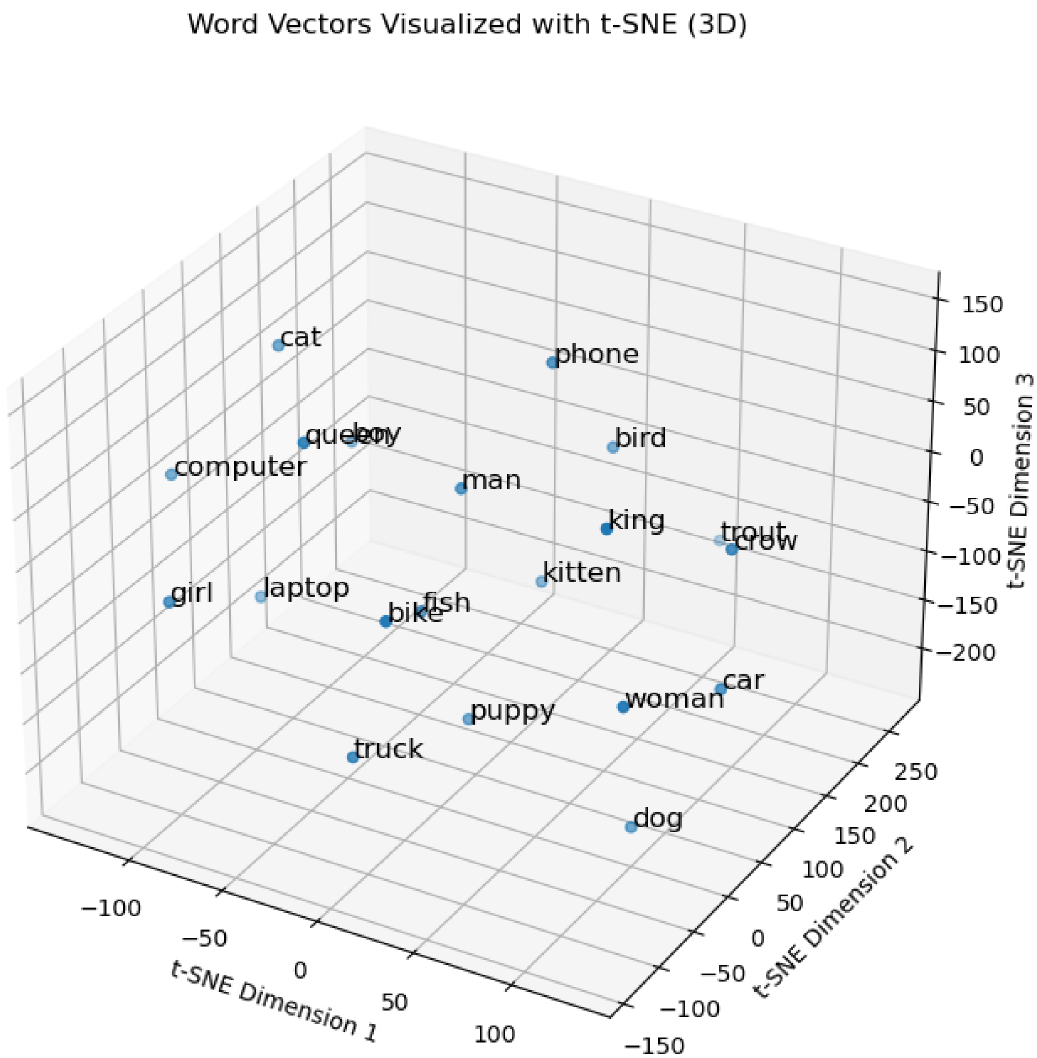
[15]:

```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE

# Select a set of words to visualize
words_to_visualize = ['king', 'queen', 'man', 'woman', 'trout',␣
 ↪'computer','phone', 'boy','girl', 'kitten','laptop', 'car', 'truck', 'bike',␣
 ↪'dog','puppy', 'cat', 'fish', 'bird', 'crow']

# Get the word vectors for the selected words
word_vectors = np.array([loaded_model.wv[word] for word in words_to_visualize])

# Perform t-SNE dimensionality reduction
tsne = TSNE(n_components=2, random_state=42, perplexity=len(words_to_visualize)␣
 ↪- 1)
word_vectors_2d = tsne.fit_transform(word_vectors)

# Create a scatter plot of the 2D word vectors
plt.figure(figsize=(10, 8))
plt.scatter(word_vectors_2d[:, 0], word_vectors_2d[:, 1])

# Add labels to the points
for i, word in enumerate(words_to_visualize):
    plt.annotate(word, (word_vectors_2d[i, 0], word_vectors_2d[i, 1]),␣
 ↪fontsize=12)

plt.xlabel('t-SNE Dimension 1')
plt.ylabel('t-SNE Dimension 2')
plt.title('Word Vectors Visualized with t-SNE')
plt.show()
```



[16]:
```
from mpl_toolkits.mplot3d import Axes3D

# Perform t-SNE dimensionality reduction
tsne = TSNE(n_components=3, random_state=42, perplexity=len(words_to_visualize)␣
↪- 1)
word_vectors_3d = tsne.fit_transform(word_vectors)

# Create a 3D scatter plot
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(word_vectors_3d[:, 0], word_vectors_3d[:, 1], word_vectors_3d[:, 2])

# Add labels to the points
for i, word in enumerate(words_to_visualize):
    ax.text(word_vectors_3d[i, 0], word_vectors_3d[i, 1], word_vectors_3d[i,␣
↪2], word, fontsize=12)

ax.set_xlabel('t-SNE Dimension 1')
```

```
ax.set_ylabel('t-SNE Dimension 2')
ax.set_zlabel('t-SNE Dimension 3')
plt.title('Word Vectors Visualized with t-SNE (3D)')
plt.show()
```



[14]:
```
from gensim import downloader as api

# Load the text8 corpus
corpus = api.load('text8')

# Flatten the list of lists into a single list of words
all_words = [word for sentence in corpus for word in sentence]
```

```python
# Create a set of unique words
unique_words = set(all_words)

# Count the number of unique words
num_unique_words = len(unique_words)

print(f"Number of unique words in the text8 corpus: {num_unique_words}")
```

```
Number of unique words in the text8 corpus: 253854
```

[ ]:

```python

```