In [1]:
```
import gensim
from gensim.models import Word2Vec

# Sample sentences for training
sentences = [
    ["I", "love", "natural", "language", "processing"],
    ["Word2Vec", "is", "a", "great", "tool"],
    ["Machine", "learning", "is", "fun"],
]

# Train the Word2Vec model
model = Word2Vec(sentences, vector_size=100, window=5, min_count=1, sg=1)

# Get the vector for a word
vector = model.wv['language']
print("Vector for 'language':", vector)

# Find similar words
similar_words = model.wv.most_similar('language', topn=5)
print("Words similar to 'language':", similar_words)
```

```
Vector for 'language': [-0.00515624 -0.00666834 -0.00777684  0.00831073 -0.001982
34 -0.00685496
 -0.00415439  0.00514413 -0.00286914 -0.00374966  0.00162143 -0.00277629
 -0.00158436  0.00107449 -0.00297794  0.00851928  0.00391094 -0.00995886
  0.0062596  -0.00675425  0.00076943  0.00440423 -0.00510337 -0.00211067
  0.00809548 -0.00424379 -0.00763626  0.00925791 -0.0021555  -0.00471943
  0.0085708   0.00428334  0.00432484  0.00928451 -0.00845308  0.00525532
  0.00203935  0.00418828  0.0016979   0.00446413  0.00448629  0.00610452
 -0.0032021  -0.00457573 -0.00042652  0.00253373 -0.00326317  0.00605772
  0.00415413  0.00776459  0.00256927  0.00811668 -0.00138721  0.00807793
  0.00371702 -0.00804732 -0.00393361 -0.00247188  0.00489304 -0.00087216
 -0.00283091  0.00783371  0.0093229  -0.00161493 -0.00515925 -0.00470176
 -0.00484605 -0.00960283  0.00137202 -0.00422492  0.00252671  0.00561448
 -0.00406591 -0.00959658  0.0015467  -0.00670012  0.00249517 -0.00378063
  0.00707842  0.00064022  0.00356094 -0.00273913 -0.00171055  0.00765279
  0.00140768 -0.00585045 -0.0078345   0.00123269  0.00645463  0.00555635
 -0.00897705  0.00859216  0.00404698  0.00746961  0.00974633 -0.00728958
 -0.00903996  0.005836    0.00939121  0.00350693]
Words similar to 'language': [('is', 0.21617141366004944), ('processing', 0.04468
920826911926), ('natural', 0.015034784562885761), ('a', 0.0019510718993842602),
('learning', -0.03283996880054474)]
```

In [2]:
```
import gensim
from gensim.models import Word2Vec

# Sample sentences for training
sentences = [
    ["I", "love", "natural", "language", "processing"],
    ["Word2Vec", "is", "a", "great", "tool"],
    ["Machine", "learning", "is", "fun"],
    ["Natural", "language", "processing", "is", "awesome"]
]

# CBOW Model
cbow_model = Word2Vec(sentences, vector_size=100, window=2, min_count=1, sg=0)

# Skip-gram Model
skipgram_model = Word2Vec(sentences, vector_size=100, window=2, min_count=1, sg=
```

```python
# Example: Getting the vector for a word
word = "language"
cbow_vector = cbow_model.wv[word]
skipgram_vector = skipgram_model.wv[word]

print(f"CBOW Vector for '{word}':", cbow_vector)
print(f"Skip-gram Vector for '{word}':", skipgram_vector)

# Example: Finding similar words
cbow_similar_words = cbow_model.wv.most_similar(word, topn=5)
skipgram_similar_words = skipgram_model.wv.most_similar(word, topn=5)

print(f"CBOW - Words similar to '{word}':", cbow_similar_words)
print(f"Skip-gram - Words similar to '{word}':", skipgram_similar_words)
```

```
CBOW Vector for 'language': [ 9.4794443e-05  3.0776660e-03 -6.8129268e-03 -1.3756
783e-03
  7.6698321e-03  7.3483307e-03 -3.6729362e-03  2.6408839e-03
 -8.3165076e-03  6.2072724e-03 -4.6391813e-03 -3.1636052e-03
  9.3106655e-03  8.7376230e-04  7.4904198e-03 -6.0752141e-03
  5.1592872e-03  9.9243205e-03 -8.4574828e-03 -5.1340456e-03
 -7.0650815e-03 -4.8629697e-03 -3.7796097e-03 -8.5361497e-03
  7.9556443e-03 -4.8439130e-03  8.4241610e-03  5.2615325e-03
 -6.5502375e-03  3.9581223e-03  5.4700365e-03 -7.4268035e-03
 -7.4072029e-03 -2.4764745e-03 -8.6256117e-03 -1.5829162e-03
 -4.0474746e-04  3.3000517e-03  1.4428297e-03 -8.8208629e-04
 -5.5940356e-03  1.7293066e-03 -8.9629035e-04  6.7937491e-03
  3.9739395e-03  4.5298305e-03  1.4351519e-03 -2.7006667e-03
 -4.3665408e-03 -1.0332628e-03  1.4375091e-03 -2.6469158e-03
 -7.0722066e-03 -7.8058685e-03 -9.1226082e-03 -5.9341355e-03
 -1.8468037e-03 -4.3235817e-03 -6.4619821e-03 -3.7178723e-03
  4.2904112e-03 -3.7397402e-03  8.3768284e-03  1.5343785e-03
 -7.2409823e-03  9.4339680e-03  7.6326625e-03  5.4943082e-03
 -6.8490817e-03  5.8238246e-03  4.0079155e-03  5.1836823e-03
  4.2568049e-03  1.9397212e-03 -3.1705969e-03  8.3537176e-03
  9.6112443e-03  3.7936033e-03 -2.8369424e-03  6.7305832e-06
  1.2181988e-03 -8.4593873e-03 -8.2249697e-03 -2.3308117e-04
  1.2385092e-03 -5.7431920e-03 -4.7247363e-03 -7.3465765e-03
  8.3276192e-03  1.2043064e-04 -4.5089805e-03  5.7007410e-03
  9.1796070e-03 -4.1010864e-03  7.9633193e-03  5.3759255e-03
  5.8792117e-03  5.1329390e-04  8.2118409e-03 -7.0186048e-03]
Skip-gram Vector for 'language': [ 9.42478000e-05  3.07589723e-03 -6.81467308e-03
-1.37446506e-03
  7.66968913e-03  7.34756188e-03 -3.67422565e-03  2.64107878e-03
 -8.31711013e-03  6.20709499e-03 -4.63969819e-03 -3.16430302e-03
  9.31042060e-03  8.73924117e-04  7.48968776e-03 -6.07334916e-03
  5.15946327e-03  9.92259663e-03 -8.45542643e-03 -5.13521628e-03
 -7.06540514e-03 -4.86227963e-03 -3.78140691e-03 -8.53707641e-03
  7.95734860e-03 -4.84467065e-03  8.42242502e-03  5.26282424e-03
 -6.55034464e-03  3.95740150e-03  5.47204912e-03 -7.42573338e-03
 -7.40648946e-03 -2.47416925e-03 -8.62730667e-03 -1.58222113e-03
 -4.05228348e-04  3.30146588e-03  1.44360668e-03 -8.81455548e-04
 -5.59283607e-03  1.72997033e-03 -8.96777317e-04  6.79324893e-03
  3.97348078e-03  4.53017978e-03  1.43477262e-03 -2.69988249e-03
 -4.36586002e-03 -1.03212311e-03  1.43821072e-03 -2.64558522e-03
 -7.07180146e-03 -7.80386291e-03 -9.12202150e-03 -5.93545521e-03
 -1.84791500e-03 -4.32417588e-03 -6.46110671e-03 -3.71831306e-03
  4.28991020e-03 -3.73849226e-03  8.37847777e-03  1.53453019e-03
 -7.24213943e-03  9.43322573e-03  7.63178896e-03  5.49173821e-03
 -6.84854668e-03  5.82335703e-03  4.00784146e-03  5.18454844e-03
  4.25614510e-03  1.93787215e-03 -3.17041040e-03  8.35264847e-03
  9.61161498e-03  3.79254599e-03 -2.83515733e-03  7.22470668e-06
  1.21920742e-03 -8.46034940e-03 -8.22578371e-03 -2.32077524e-04
  1.23913167e-03 -5.74427750e-03 -4.72703110e-03 -7.34633533e-03
  8.32915492e-03  1.21630226e-04 -4.51042084e-03  5.70245273e-03
  9.18024499e-03 -4.09950921e-03  7.96421152e-03  5.37427003e-03
  5.87765872e-03  5.15150023e-04  8.21374636e-03 -7.01800501e-03]
CBOW - Words similar to 'language': [('tool', 0.1991048902273178), ('Word2Vec',
0.17271503806114197), ('Natural', 0.170233353972435), ('learning', 0.145952597260
47516), ('fun', 0.06409329921007156)]
Skip-gram - Words similar to 'language': [('tool', 0.19910898804664612), ('Word2V
ec', 0.17269527912139893), ('Natural', 0.17020359635353088), ('learning', 0.14597
59771823883), ('fun', 0.06406981498003006)]
```

In [ ]: