Name: Yash Waghumbare Div: **BE9-S9** Roll no: 43180 Title: Assignment 5: Implement the Continuous Bag of Words (CBOW) Model In [1]: #importing libraries from keras.preprocessing import text from keras.utils import np\_utils from keras.preprocessing import sequence from keras.utils import pad\_sequences import numpy as np import pandas as pd In [2]: #taking random sentences as data data = """Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks, convolutional dl\_data = data.split() In [3]: #tokenization tokenizer = text.Tokenizer() tokenizer.fit\_on\_texts(dl\_data) word2id = tokenizer.word\_index word2id['PAD'] = 0id2word = {v:k for k, v in word2id.items()} wids = [[word2id[w] for w in text.text\_to\_word\_sequence(doc)] for doc in dl\_data] vocab\_size = len(word2id)  $embed_size = 100$  $window_size = 2$ print('Vocabulary Size:', vocab\_size) print('Vocabulary Sample:', list(word2id.items())[:10]) Vocabulary Size: 75 Vocabulary Sample: [('learning', 1), ('deep', 2), ('networks', 3), ('neural', 4), ('and', 5), ('as', 6), ('of', 7), ('machine', 8), ('supervised', 9), ('have', 10)] In [4]: #generating (context word, target/label word) pairs def generate\_context\_word\_pairs(corpus, window\_size, vocab\_size): context\_length = window\_size\*2 for words in corpus: sentence\_length = len(words) for index, word in enumerate(words): context\_words = []  $label_word = []$ start = index - window\_size end = index + window\_size + 1 context\_words.append([words[i] for i in range(start, end) if 0 <= i < sentence\_length</pre> and i != index]) label\_word.append(word) x = pad\_sequences(context\_words, maxlen=context\_length) y = np\_utils.to\_categorical(label\_word, vocab\_size) yield (x, y) for x, y in generate\_context\_word\_pairs(corpus=wids, window\_size=window\_size, vocab\_size=vocab\_size): **if** 0 **not in** x[0]: # print('Context (X):', [id2word[w] for w in x[0]], '-> Target (Y):', id2word[np.argwhere(y[0])[0][0]]) **if** i == 10: break In [5]: #model building import keras.backend as K from keras.models import Sequential from keras.layers import Dense, Embedding, Lambda cbow = Sequential() cbow.add(Embedding(input\_dim=vocab\_size, output\_dim=embed\_size, input\_length=window\_size\*2)) cbow.add(Lambda(lambda x: K.mean(x, axis=1), output\_shape=(embed\_size,))) cbow.add(Dense(vocab\_size, activation='softmax')) cbow.compile(loss='categorical\_crossentropy', optimizer='rmsprop') print(cbow.summary()) # from IPython.display import SVG # from keras.utils.vis\_utils import model\_to\_dot # SVG(model\_to\_dot(cbow, show\_shapes=True, show\_layer\_names=False, rankdir='TB').create(prog='dot', format='svg')) Model: "sequential" Layer (type) Output Shape Param # \_\_\_\_\_\_ embedding (Embedding) (None, 4, 100) 7500 lambda (Lambda) (None, 100) 0 dense (Dense) (None, 75) 7575 \_\_\_\_\_\_ Total params: 15,075 Trainable params: 15,075 Non-trainable params: 0 None In [6]: for epoch in range(1, 6): loss = 0.for x, y in generate\_context\_word\_pairs(corpus=wids, window\_size=window\_size, vocab\_size=vocab\_size): i += 1 loss += cbow.train\_on\_batch(x, y) **if** i % 100000 == 0: print('Processed {} (context, word) pairs'.format(i)) print('Epoch:', epoch, '\tLoss:', loss) print() Epoch: 1 Loss: 434.40525007247925 Epoch: 2 Loss: 429.64614844322205 Epoch: 3 Loss: 426.254625082016 Epoch: 4 Loss: 422.88486409187317 Epoch: 5 Loss: 420.2294900417328 In [7]: weights = cbow.get\_weights()[0] weights = weights[1:] print(weights.shape) pd.DataFrame(weights, index=list(id2word.values())[1:]).head() (74, 100) Out[7]: 91 92 deep -0.028218 -0.005919 0.005274 -0.029521 -0.022013 -0.019620 0.027524 0.011648 0.025632 -0.008394 ... 0.014053 0.002022 -0.046732 0.045974 -0.040925 -0.039103 -0.005919 0. **networks** 0.004388 -0.018607 0.009451 0.030428 -0.031672 0.031915 0.055260 0.020617 -0.008885 -0.030407  $0.029352 \quad -0.036660 \quad 0.021049 \quad 0.003298 \quad -0.023420 \quad 0.046911 \quad -0.039212 \quad 0.010056$ 0.043364 -0.042134 ... -0.033033 neural 0.013651 -0.043134 -0.045682 0.017554 -0.042856 -0.025171 0.022546 0.006237 0.001115 -0.019212 0.003657 -0.048563 0.045061 -0.048979 0.004712 ... 0.002042 -0.031780 0.047122 0.016723 -0.014286 -0.018209 and  $0.041465 \quad -0.014640 \quad \dots \quad -0.038623 \quad 0.010498 \quad -0.013775 \quad 0.005803 \quad 0.013803 \quad -0.037896$ -0.013465 -0.035403 0.010038 0.037268 -0.045731 0.005324 -0.017414 -0.0052595 rows × 100 columns In [8]: from sklearn.metrics.pairwise import euclidean\_distances distance\_matrix = euclidean\_distances(weights) print(distance\_matrix.shape) similar\_words = {search\_term: [id2word[idx] for idx in distance\_matrix[word2id[search\_term]-1].argsort()[1:6]+1] for search\_term in ['deep']} similar\_words (74, 74)

{'deep': ['transformers', 'climate', 'convolutional', 'of', 'family']}