on word with least error,

stab iguas va stembr lación bind

shore in land to string

model architecture: WI Swap o The CBOW model architecture is as shown above The model tries to predict the target surrounding words. Consider the same sentence as above 'Its a pleasant day'. The model convert this sentence into word pairs in form. Weith these word pairs, the model tries to predict the target word considered context words. of we have 4 context words used for predicting one target word the ilp layer will be in the form of four IXW ip rectors. Finally IXN layer where element wise summation is performed and off is obtained. Implementation of CBOW model: · emport libraries and read dataset. . For the implementation · Cremerate june that weate meindow sizes and pairi of touget woods.

Build neural network ou sample dater.

Ep No.5 it worlds. These can be used for text recognition, onverti nes and

```
DL_LabExp_5 - Jupyter Notebook
     In [1]: import matplotlib.pyplot as plt
                                                                                            53
              import seaborn as sns
              import matplotlib as mpl
              import matplotlib.pylab as pylab
              import numpy as np
     In [2]: import re
    In [3]: sentences = """We are about to study the idea of a computational process.
             Computational processes are abstract beings that inhabit computers.
             As they evolve, processes manipulate other abstract things called data.
             The evolution of a process is directed by a pattern of rules
             called a program. People create programs to direct processes. In effect,
             we conjure the spirits of the computer with our spells."""
    In [4]: sentences = re.sub('[^A-Za-z0-9]+', ' ', sentences)
   In [5]: sentences = re.sub(r'(?:^| )\w(?:$| )', ' ', sentences).strip()
   In [6]: sentences = sentences.lower()
   In [7]: |words = sentences.split()
            vocab = set(words)
  In [8]: vocab_size = len(vocab)
            embed_dim = 10
            context_size = 2
  In [9]: word_to_ix = {word: i for i, word in enumerate(vocab)}
           ix_to_word = {i: word for i, word in enumerate(vocab)}
 In [10]: data = []
           for i in range(2, len(words) - 2):
               context = [words[i - 2], words[i - 1], words[i + 1], words[i + 2]]
               target = words[i]
               data.append((context, target))
           print(data[:5])
          [(['we', 'are', 'to', 'study'], 'about'), (['are', 'about', 'study', 'the'], 'to'), (['about', 'to', 'the', 'idea'], 'study'), (['to', 'study', 'idea', 'of'],
           'the'), (['study', 'the', 'of', 'computational'], 'idea')]
In [11]: embeddings = np.random.random_sample((vocab_size, embed_dim))
In [12]: def linear(m, theta):
              w = theta
              return m.dot(w)
```

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```

```
e_x = np.exp(x - np.max(x))
 In [13]: def log_softmax(x):
              return np.log(e_x / e_x.sum())
              out = logs[range(len(targets)), targets]
 In [14]: def NLLLoss(logs, targets):
              return -out.sum()/len(out)
In [15]: def log_softmax_crossentropy_with_logits(logits, target):
              out = np.zeros_like(logits)
              out[np.arange(len(logits)), target] = 1
              softmax = np.exp(logits) / np.exp(logits).sum(axis=-1,keepdims=True)
              return (- out + softmax) / logits.shape[0]
In [16]: |def forward(context_idxs, theta):
              m = embeddings[context_idxs].reshape(1, -1)
              n = linear(m, theta)
              o = log_softmax(n)
              return m, n, o
In [17]: def backward(preds, theta, target_idxs):
              m, n, o = preds
             dlog = log_softmax_crossentropy_with_logits(n, target_idxs)
              return dw
In [18]: def optimize(theta, grad, lr=0.03):
             theta -= grad * lr
             return theta
In [19]: theta = np.random.uniform(-1, 1, (2 * context_size * embed_dim, vocab_size))
```

```
In [20]: epoch_losses = {}

for epoch in range(80):

losses = []

for context, target in data:
    context_idxs = np.array([word_to_ix[w] for w in context])

target_idxs = np.array([word_to_ix[target]])

target_idxs = np.array([word_to_ix[target]])

losses.append(loss)

grad = backward(preds, theta, target_idxs)

theta = optimize(theta, grad, lr=0.03)
```

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```

```
In [21]: ix = np.arange(0,80)
         fig.suptitle('Epoch/Losses', fontsize=20)
         plt.plot(ix,[epoch_losses[i][0] for i in ix])
         plt.xlabel('Epochs', fontsize=12)
         plt.ylabel('Losses', fontsize=12)
```

In

out

In

Out[21]: Text(0, 0.5, 'Losses')

## Epoch/Losses 3.5 3.0 2.5 2.0 1.5 1.0 0.5 0 10 20 30 40 50 60 70 80 **Epochs**

```
In [22]: def predict(words):
             context_idxs = np.array([word_to_ix[w] for w in words])
             preds = forward(context_idxs, theta)
             word = ix_to_word[np.argmax(preds[-1])]
             return word
In [23]: predict(['we', 'are', 'to', 'study'])
Out[23]: 'about'
```

```
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                                                                                   57
   In [24]: def accuracy():
                                            DL_LabExp_5 - Jupyter Notebook
                wrong = 0
                for context, target in data:
                    if(predict(context) != target):
                return (1 - (wrong / len(data)))
  In [25]: accuracy()
  out[25]: 1.0
  In [26]: predict(['processes', 'manipulate', 'things', 'study'])
   In [ ]:
```