```
import torch
torch.cuda.is_available()
```

```
True
```

```
from google.colab import files
uploaded = files.upload()
```

Choose files text_corpus.txt

- **text_corpus.txt**(text/plain) - 131 bytes, last modified: 11/04/2025 - 100% done

```
Saving text_corpus.txt to text_corpus.txt
```

```
with open('text_corpus.txt', 'r') as f:
    text = f.read().lower()
print(text)
```

```
deep learning is amazing. machine learning is powerful. ai is the future.
computers can learn from data. data is crucial for ai.
```

```
import nltk
import string
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize

nltk.download('punkt')
nltk.download('punkt_tab')
nltk.download('stopwords')

stop_words = set(stopwords.words('english'))

tokens = word_tokenize(text)
tokens = [word for word in tokens if word not in stop_words and word not in string.punctuation]

print(tokens)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt_tab.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
['deep', 'learning', 'amazing', 'machine', 'learning', 'powerful', 'ai', 'future', 'computers', 'learn', 'data', 'data', 'crucial', 'ai'
```

```
vocab = sorted(set(tokens))
word2idx = {word: idx for idx, word in enumerate(vocab)}
idx2word = {idx: word for word, idx in word2idx.items()}

print("Vocab size:", len(vocab))
```

```
Vocab size: 11
```

```
def generate_skipgram_pairs(tokens, window_size=2):
    pairs = []
    for idx, target in enumerate(tokens):
        for offset in range(-window_size, window_size + 1):
            context_idx = idx + offset
            if context_idx >= 0 and context_idx < len(tokens) and context_idx != idx:
                pairs.append((target, tokens[context_idx]))
    return pairs

skipgram_pairs = generate_skipgram_pairs(tokens, window_size=2)
print(skipgram_pairs[:10])
```

```
[('deep', 'learning'), ('deep', 'amazing'), ('learning', 'deep'), ('learning', 'amazing'), ('learning', 'machine'), ('amazing', 'deep'),
```

```
import torch
import torch.nn as nn
import torch.nn.functional as F

class SkipGramModel(nn.Module):
    def __init__(self, vocab_size, embedding_dim):
        super(SkipGramModel, self).__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim)
        self.output_layer = nn.Linear(embedding_dim, vocab_size)

    def forward(self, input_word):
        embed = self.embeddings(input_word)
        out = self.output_layer(embed)
        return out
```

```
import random

embedding_dim = 10
learning_rate = 0.01
epochs = 100
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

model = SkipGramModel(len(vocab), embedding_dim).to(device)
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
loss_fn = nn.CrossEntropyLoss()

pairs_idx = [(word2idx[target], word2idx[context]) for target, context in skipgram_pairs]

for epoch in range(epochs):
    total_loss = 0
    random.shuffle(pairs_idx)
    for target_idx, context_idx in pairs_idx:
        input_tensor = torch.tensor([target_idx], dtype=torch.long).to(device)
        target_tensor = torch.tensor([context_idx], dtype=torch.long).to(device)

        optimizer.zero_grad()
        output = model(input_tensor)
        loss = loss_fn(output, target_tensor)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

    if (epoch + 1) % 10 == 0:
        print(f"Epoch {epoch+1}/{epochs}, Loss: {total_loss:.4f}")
```

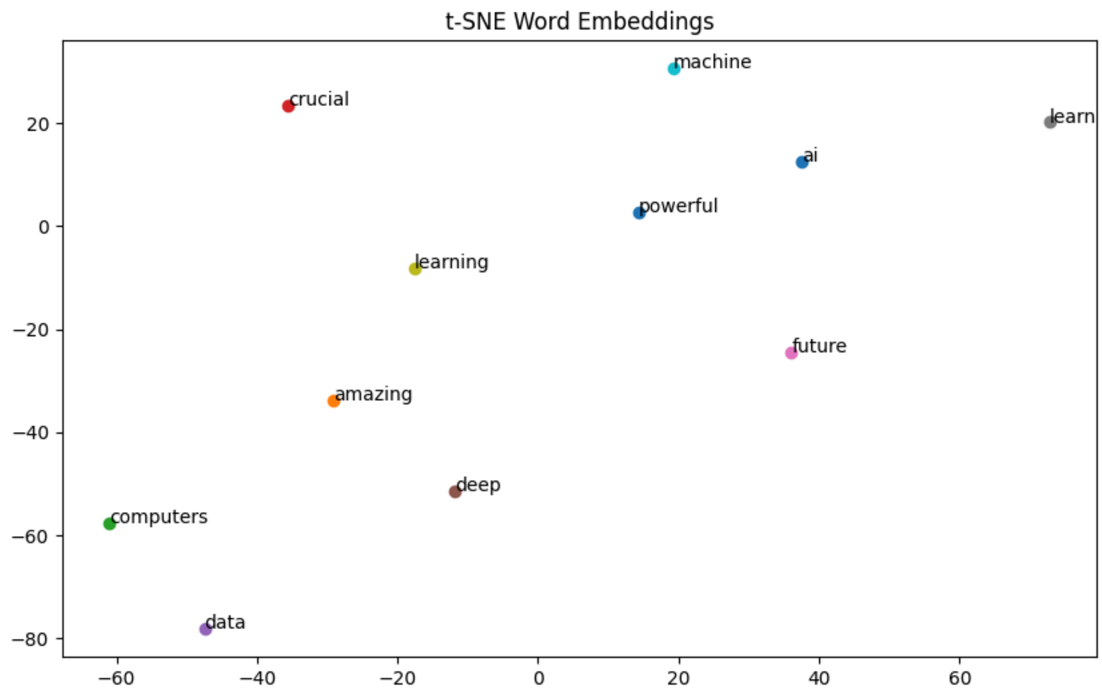
```
Epoch 10/100, Loss: 107.1393
Epoch 20/100, Loss: 98.4845
Epoch 30/100, Loss: 92.3397
Epoch 40/100, Loss: 87.3514
Epoch 50/100, Loss: 83.4436
Epoch 60/100, Loss: 80.4566
Epoch 70/100, Loss: 78.1629
Epoch 80/100, Loss: 76.3460
Epoch 90/100, Loss: 74.9522
Epoch 100/100, Loss: 73.8833
```

```
embeddings = model.embeddings.weight.data.cpu().numpy()
```

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

# Set perplexity to a value less than the number of samples (len(vocab))
tsne = TSNE(n_components=2, random_state=0, perplexity=5)
reduced_embeddings = tsne.fit_transform(embeddings)

plt.figure(figsize=(10, 6))
for i, word in enumerate(vocab):
    x, y = reduced_embeddings[i]
    plt.scatter(x, y)
    plt.annotate(word, (x, y))
plt.title("t-SNE Word Embeddings")
plt.show()
```



NOW WORKING FOR CBOW TASK 5

```
def generate_cbow_pairs(tokens, window_size=2):
    pairs = []
    for idx in range(window_size, len(tokens) - window_size):
        context = [tokens[i] for i in range(idx - window_size, idx + window_size + 1) if i != idx]
        target = tokens[idx]
        pairs.append((context, target))
    return pairs

cbow_pairs = generate_cbow_pairs(tokens, window_size=2)
print(cbow_pairs[:5])
```

```
[(['deep', 'learning', 'machine', 'learning'], 'amazing'), (['learning', 'amazing', 'learning', 'powerful'], 'machine'), (['amazing', '
```

```
cbow_pairs_idx = [([word2idx[w] for w in context], word2idx[target]) for context, target in cbow_pairs]
```

```
class CBOWModel(nn.Module):
    def __init__(self, vocab_size, embedding_dim):
        super(CBOWModel, self).__init__()
        self.embeddings = nn.Embedding(vocab_size, embedding_dim)
        self.linear = nn.Linear(embedding_dim, vocab_size)

    def forward(self, context_idxs):
        embeds = self.embeddings(context_idxs)
        hidden = embeds.mean(dim=0).view(1, -1)
        out = self.linear(hidden)
        return out



embedding_dim = 10
cbow_model = CBOWModel(len(vocab), embedding_dim).to(device)
optimizer = torch.optim.SGD(cbow_model.parameters(), lr=0.01)
loss_fn = nn.CrossEntropyLoss()

epochs = 100

for epoch in range(epochs):
    total_loss = 0
    random.shuffle(cbow_pairs_idx)
    for context_idxs, target_idx in cbow_pairs_idx:
```

```
        context_tensor = torch.tensor(context_idxs, dtype=torch.long).to(device)
        target_tensor = torch.tensor([target_idx], dtype=torch.long).to(device)

        optimizer.zero_grad()
        output = cbow_model(context_tensor)
        loss = loss_fn(output, target_tensor)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()

    if (epoch+1) % 10 == 0:
        print(f"Epoch {epoch+1}, Loss: {total_loss:.4f}")
```

```
Epoch 10, Loss: 21.3407
Epoch 20, Loss: 19.6235
Epoch 30, Loss: 18.1152
Epoch 40, Loss: 16.7568
Epoch 50, Loss: 15.5145
Epoch 60, Loss: 14.3690
Epoch 70, Loss: 13.3094
Epoch 80, Loss: 12.3279
Epoch 90, Loss: 11.4197
Epoch 100, Loss: 10.5800
```

```
cbow_embeddings = cbow_model.embeddings.weight.data.cpu().numpy()
```

WORD ANALOGY:

```
import numpy as np

def find_analogy(word_a, word_b, word_c, embeddings, word2idx, idx2word):
    vec_a = embeddings[word2idx[word_a]]
    vec_b = embeddings[word2idx[word_b]]
    vec_c = embeddings[word2idx[word_c]]

    target_vec = vec_b - vec_a + vec_c

    similarities = []
    for i in range(len(embeddings)):
        similarity = np.dot(target_vec, embeddings[i]) / (np.linalg.norm(target_vec) * np.linalg.norm(embeddings[i]))
        similarities.append((idx2word[i], similarity))

    similarities = sorted(similarities, key=lambda x: -x[1])
    for word, score in similarities[:5]:
        print(f"{word}: {score:.4f}")

find_analogy("machine", "learning", "data", cbow_embeddings, word2idx, idx2word)
```

```
data: 0.5273
powerful: 0.4352
learning: 0.3566
learn: 0.2367
computers: 0.1792
```

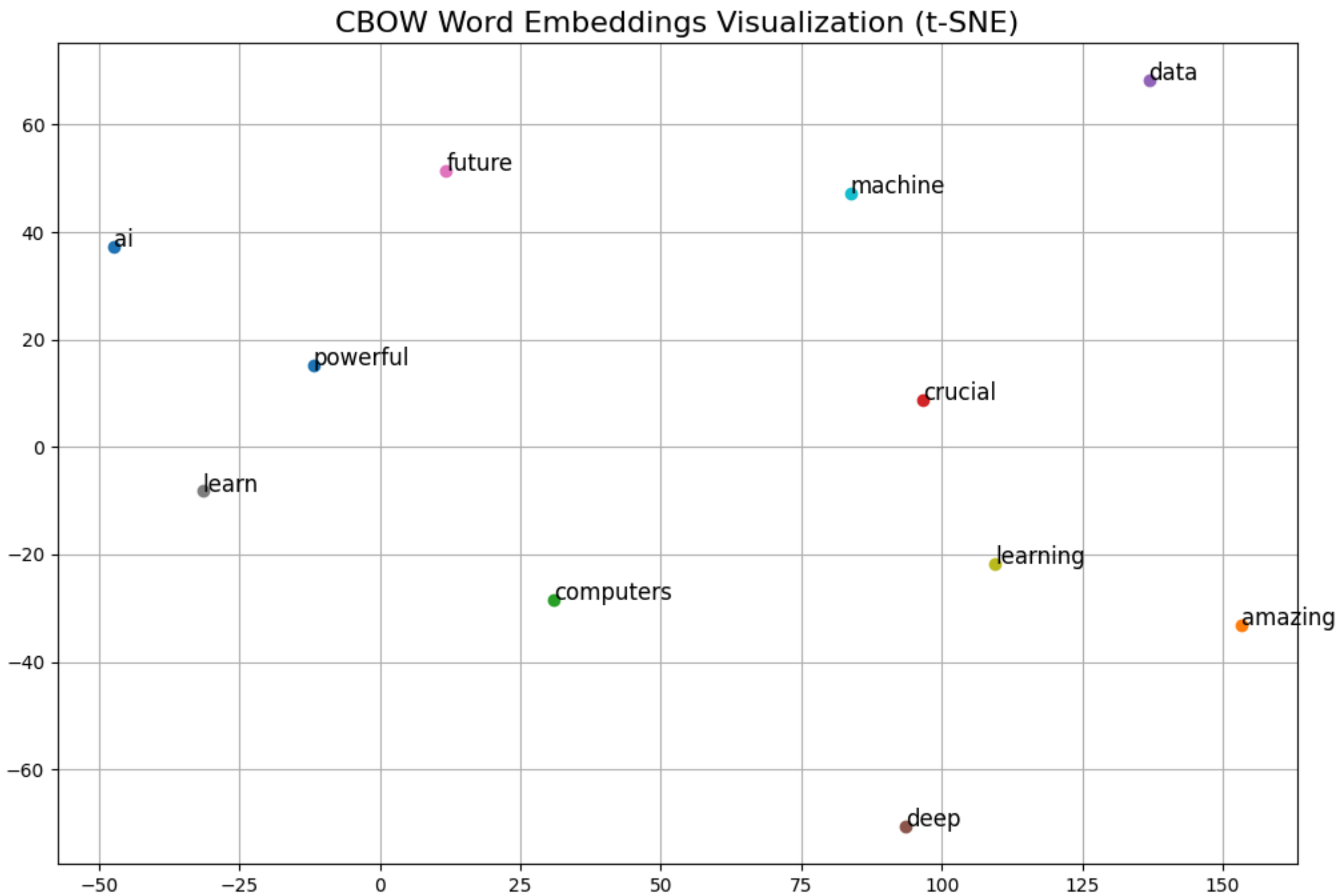
```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
```

```
tsne = TSNE(n_components=2, random_state=42, perplexity=3)
cbow_2d = tsne.fit_transform(cbow_embeddings)
```

```
plt.figure(figsize=(12, 8))
for i, label in enumerate(word2idx.keys()):
    x, y = cbow_2d[i, 0], cbow_2d[i, 1]
    plt.scatter(x, y)
    plt.annotate(label, (x, y), fontsize=12)

plt.title("CBOW Word Embeddings Visualization (t-SNE)", fontsize=16)
plt.grid(True)
```

```
plt.show()
```


CBOW Word Embeddings Visualization (t-SNE)
data
future
machine
ai
powerful
crucial
learn
learning
computers
amazing
deep
60
40
20
0
−20
−40
−60
−50
−25
0
25
50
75
100
125
150