

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

```
# Load dataset
df = pd.read_csv("Lab10_4_tSNE_Word_Dataset.csv")

# Display first few rows
print(df.head())

# Dataset shape
print("Dataset shape:", df.shape)
```

```
      word category
0      dog  animal
1      cat  animal
2     lion  animal
3    tiger  animal
4 elephant  animal
Dataset shape: (46, 2)
```

```
# Extract words
words = df.iloc[:, 0].values

# Extract embedding vectors
vectors = df.iloc[:, 1:].values

print("Total words:", len(words))
print("Vector dimension:", vectors.shape[1])

# Display one example vector
print("Example word:", words[0])
print("Example vector:", vectors[0])
```

```
Total words: 46
Vector dimension: 1
Example word: dog
Example vector: ['animal']
```

```
tsne = TSNE(
    n_components=1, # Changed from 2 to 1 because the input data has only 1 feature
    random_state=42,
    perplexity=10,
    # n_iter was renamed to max_iter in version 1.5. Using max_iter for future compatibility.
    max_iter=1000
)

# The 'vectors' variable currently contains string categories (e.g., 'animal', 'fruit').
# t-SNE requires numerical input. Convert the categorical strings to numerical labels.
# We'll use pandas.factorize to achieve this.

# Flatten the 2D array of strings to a 1D array for factorize, then reshape to (n_samples, 1)
numerical_vectors, _ = pd.factorize(vectors.flatten())
vectors_for_tsne = numerical_vectors.reshape(-1, 1)

vectors_2d = tsne.fit_transform(vectors_for_tsne)
```

```
tsne_df = pd.DataFrame({
    "Word": words,
    "X": vectors_2d[:, 0]
})

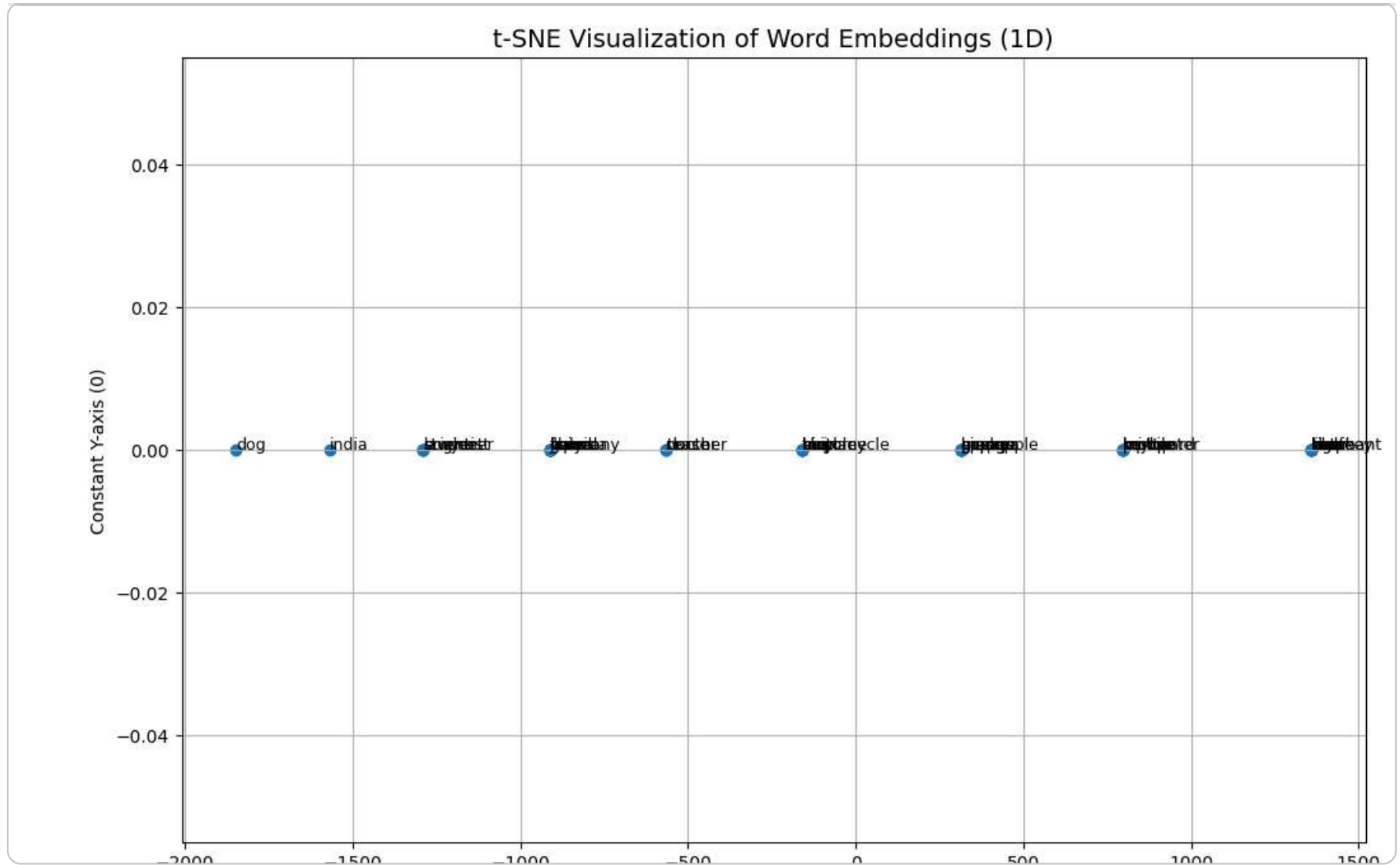
print(tsne_df.head())
```

	Word	X
0	dog	-1849.326294
1	cat	1359.462891
2	lion	1359.462891
3	tiger	1359.462891
4	elephant	1359.462891

```
plt.figure(figsize=(12, 8))
plt.scatter(tsne_df["X"], [0] * len(tsne_df)) # Plotting against 0 for the Y-axis

for i, word in enumerate(tsne_df["Word"]):
    plt.annotate(word, (tsne_df["X"][i], 0), fontsize=9) # Annotate also at Y=0

plt.title("t-SNE Visualization of Word Embeddings (1D)", fontsize=14)
plt.xlabel("Dimension 1")
plt.ylabel("Constant Y-axis (0)") # Adjusted label for Y-axis
plt.grid(True)
plt.show()
```



**T** **B** **I** **<>** **↔** **🖼** **”** **☰** **☷** **—** **ψ** **😊** **☰**

Close

LAB REPORT: The t-SNE visualization shows that semantically related words form visible clusters. Words belonging to similar categories such as animals, cities, or technology appear close together.

This indicates that word embeddings capture

LAB REPORT: The t-SNE visualization shows that semantically related words form visible clusters. Words belonging to similar categories such as animals, cities, or technology appear close together. This indicates that word

semantic relationships effectively.  
For example, related objects or concepts are positioned near each other in the 2-D space. Some words appear slightly distant despite being related due to dimensionality reduction loss. A few unrelated words appear close, which is a known limitation of t-SNE.  
Overall the visualization helps in understanding

embeddings capture semantic relationships effectively. For example, related objects or concepts are positioned near each other in the 2-D space. Some words appear slightly distant despite being related due to dimensionality reduction loss. A few unrelated words appear close, which