Lab 4: Implementing GloVe Embeddings and fastText for Telecom Reviews Analysis

Objectives

This lab provides hands-on experience with implementing and comparing two powerful word embedding techniques - **GloVe** (Global Vectors for Word Representation) and **fastText** - using a real-world telecom customer reviews dataset. Through this lab, you will:

- **Implement and train GloVe embeddings** on telecom-specific text data
- **Understand and visualize** the co-occurrence matrix fundamental to GloVe
- **Train fastText models** with subword information
- **Handle out-of-vocabulary words** using fastText's subword capabilities
- **Compare and evaluate** the performance of GloVe and fastText embeddings
- **Apply the embeddings** for practical telecom domain tasks

Dataset Overview

We will be working with a telecom customer reviews dataset containing **200 reviews** across various service categories. The dataset includes:

- **Customer feedback across 6 service types**:
  - Mobile Data
  - Fiber Broadband
  - VoIP
  - Cable TV
  - IoT
  - Cloud
- **Sentiment labels**:
  - Positive
  - Negative
  - Mixed
- **Rich domain-specific vocabulary and technical terms**
- **Various metadata** including service categories and issue types

Tasks to be Performed

Tasks 1: Data Preprocessing and Exploration

- **Load and examine** the telecom reviews dataset
- **Implement text preprocessing pipeline**
- **Analyze vocabulary distribution and characteristics**
- **Create and analyze** the word co-occurrence matrix

Tasks 2: GloVe Implementation

- **Build the co-occurrence matrix** for GloVe
- **Implement GloVe training** from scratch
- **Train GloVe embeddings** on telecom corpus
- **Visualize and analyze** learned embeddings

Tasks 3: fastText Implementation

- **Prepare data** for fastText training
- **Train fastText model** with subword information
- **Handle out-of-vocabulary words**
- **Compare subword vs word-level representations**

Tasks 4: Comparative Analysis

- **Evaluate both models** on specific telecom tasks
- **Compare embedding quality** for technical terms
- **Analyze out-of-vocabulary word handling**
- **Visualize embedding spaces**

Tasks 1: Data Preprocessing and Exploration

```
import pandas as pd
import numpy as np
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
import nltk
import re
from collections import Counter
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Download required NLTK data
nltk.download('punkt_tab')
nltk.download('stopwords')

# Read the dataset
df = pd.read_excel('/content/Customer Reviews.xlsx')
```

```
[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]   Unzipping corpora/stopwords.zip.
```

```
df
```

	review_id	review_text	rating	review_date	service_type	service_category	customer_segment	issue_category	sentiment	location
0	REV001	"Excellent mobile data plan with reliable cove...	5	2024-01-05	Mobile Data Plan	Network	Consumer	Coverage	Positive	Urban
1	REV002	"Fiber broadband installation was delayed, but...	4	2024-01-10	Fiber Broadband	Internet	Consumer	Installation	Mixed	Suburban
2	REV003	"Customer service was unresponsive when I had ...	2	2024-01-15	VoIP Services	Voice	Business	Customer Service	Negative	Urban
3	REV004	"Great selection of cable TV channels and the ...	5	2024-01-20	Cable TV	Television	Consumer	Service Quality	Positive	Urban
4	REV005	"Billing errors were frequent, causing a lot o...	1	2024-01-25	Mobile Data Plan	Network	Consumer	Billing	Negative	Rural
...	...	...	...	...	...	...	...	...	...	...
195	REV196	"Cloud solutions provide excellent uptime, ens...	5	2025-10-11	Cloud Solutions	Enterprise	Business	Service Quality	Positive	Urban
196	REV197	"Mobile data plan's data throttling kicks in t...	1	2025-10-14	Mobile Data Plan	Network	Consumer	Billing	Negative	Rural
197	REV198	"Fiber broadband offers exceptional customer s...	5	2025-10-17	Fiber Broadband	Internet	Business	Customer Service	Positive	Suburban
198	REV199	"VoIP service lacks essential features like vi...	2	2025-10-20	VoIP Services	Voice	Business	Service Quality	Negative	Urban
199	REV200	"Cable TV's channel lineup is extensive, cater...	5	2025-10-23	Cable TV	Television	Consumer	Service Quality	Positive	Rural

200 rows × 10 columns

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
df.info()
```

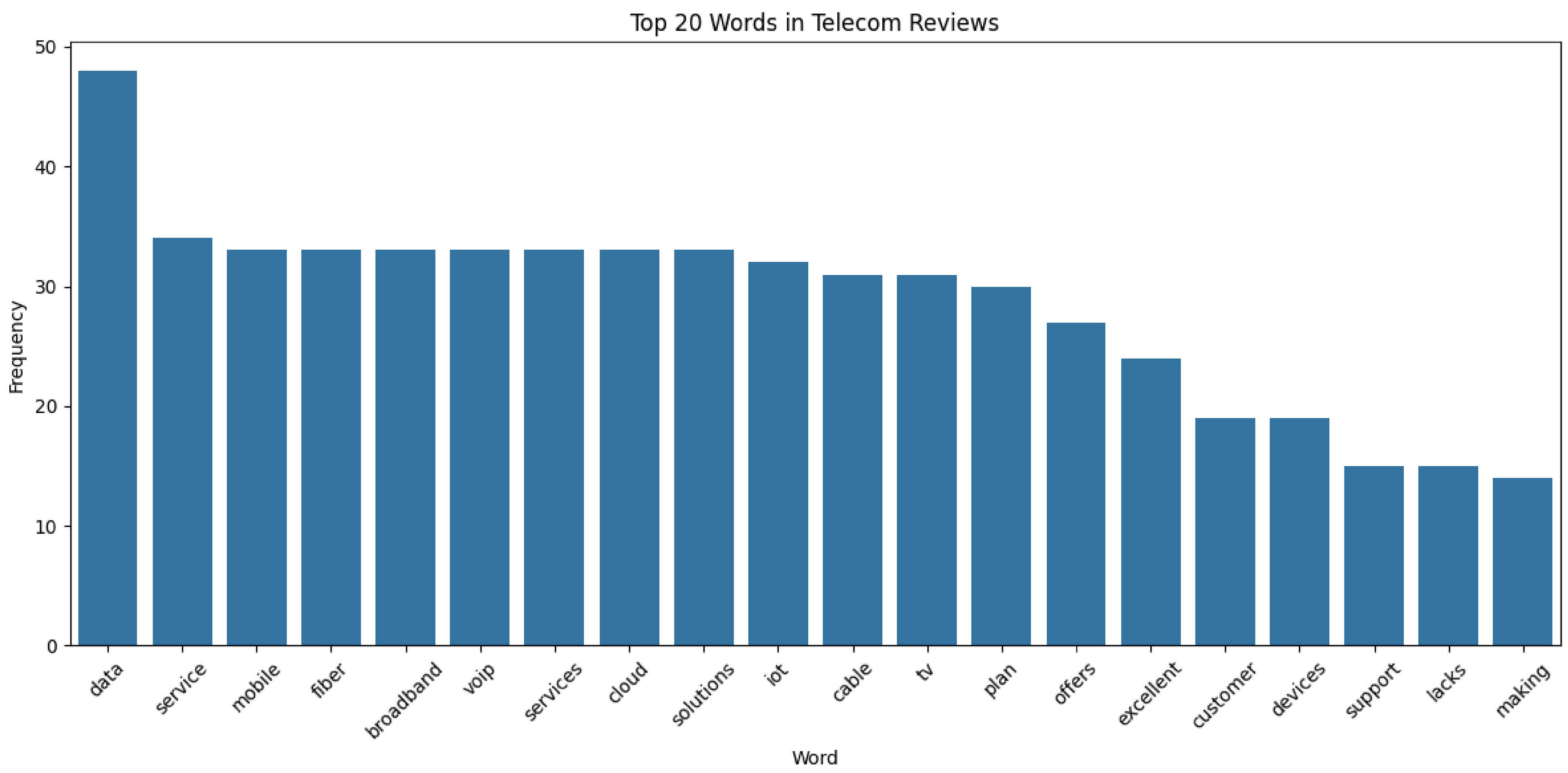
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   review_id         200 non-null    object
 1   review_text       200 non-null    object
 2   rating            200 non-null    int64
 3   review_date       200 non-null    datetime64[ns]
 4   service_type      200 non-null    object
 5   service_category  200 non-null    object
 6   customer_segment  200 non-null    object
 7   issue_category    200 non-null    object
 8   sentiment         200 non-null    object
 9   location          200 non-null    object
dtypes: datetime64[ns](1), int64(1), object(8)
memory usage: 15.8+ KB
```

```
# Basic text preprocessing function
def preprocess_text(text):
    # Convert to lowercase
    text = text.lower()

    # Remove special characters but keep technical terms and numbers
    text = re.sub(r'[^\w\s\d]', ' ', text)
```

```
    # Tokenize
    tokens = word_tokenize(text)

    # Remove stopwords but keep technical terms
    stop_words = set(stopwords.words('english'))
    technical_terms = {'5g', '4g', 'wifi', 'broadband', 'voip', 'iot', 'mbps', 'gb'}
    tokens = [token for token in tokens if token not in stop_words or token in technical_terms]

    return tokens

# Process all reviews
df['processed_tokens'] = df['review_text'].apply(preprocess_text)
```

```
# Get vocabulary statistics
all_tokens = [token for tokens in df['processed_tokens'] for token in tokens]
vocab = Counter(all_tokens)

# Print basic statistics
print(f"Total number of reviews: {len(df)}")
print(f"Vocabulary size: {len(vocab)}")
print(f"Total tokens: {len(all_tokens)}")
print("\nMost common words:")
print(pd.DataFrame(vocab.most_common(10), columns=['Word', 'Frequency']))

# Plot word frequency distribution
plt.figure(figsize=(12, 6))
word_freq = pd.DataFrame(vocab.most_common(20), columns=['Word', 'Frequency'])
sns.barplot(data=word_freq, x='Word', y='Frequency')
plt.xticks(rotation=45)
plt.title('Top 20 Words in Telecom Reviews')
plt.tight_layout()
plt.show()
```

```
Total number of reviews: 200
Vocabulary size: 480
Total tokens: 1656

Most common words:
        Word  Frequency
0       data         48
1    service         34
2     mobile         33
3      fiber         33
4  broadband         33
5       voip         33
6   services         33
7      cloud         33
8  solutions         33
9        iot         32
```



Task 2: GloVe Implementation

Understanding Word Embeddings: GloVe and fastText in Telecom Context

GloVe: Global Vectors for Word Representation

Theoretical Foundation

GloVe (Global Vectors) is an unsupervised learning algorithm for obtaining vector representations of words. Its key characteristics are:

Co-occurrence Matrix

- **Captures how frequently words appear together** in a context window
- **Preserves global corpus statistics**
- **Values are weighted based on distance** between words

Learning Objective

Minimize:

$$\sum_{i,j} f(X_{i,j})\left(\mathbf{w}_i^T\tilde{\mathbf{w}}_j + b_i + \tilde{b}_j - \log X_{i,j}\right)^2$$

Where:

- $X_{i,j}$ is the **co-occurrence count** between words i and j
- $\mathbf{w}_i$ and $\tilde{\mathbf{w}}_j$ are **word vectors**
- b_i and $\tilde{b}_j$ are **bias terms**
- $f(x)$ is a **weighting function**

Weighting Function

$$f(x) = \begin{cases} \left(\frac{x}{x_{\max}}\right)^\alpha & \text{if } x < x_{\max} \\ 1 & \text{otherwise} \end{cases}$$

Where α typically = **3/4**

```
# Build co-occurrence matrix
def build_cooccurrence_matrix(tokens_list, window_size=5):
    # Create vocabulary and word-to-index mapping
    vocab = list(set([token for tokens in tokens_list for token in tokens]))
    word_to_idx = {word: i for i, word in enumerate(vocab)}

    # Initialize co-occurrence matrix
    vocab_size = len(vocab)
    cooccurrence_matrix = np.zeros((vocab_size, vocab_size))

    # Build co-occurrence matrix with window-based context
    for tokens in tokens_list:
        indices = [word_to_idx[token] for token in tokens]
        for center_i, center_word_idx in enumerate(indices):
            # For each word in window
            for context_i in range(
                max(0, center_i - window_size),
                min(len(indices), center_i + window_size + 1)
            ):
                if center_i != context_i:
                    # Calculate distance-based weighting
                    distance = abs(center_i - context_i)
                    weight = 1 / distance
                    context_word_idx = indices[context_i]
                    cooccurrence_matrix[center_word_idx, context_word_idx] += weight

    return cooccurrence_matrix, vocab, word_to_idx
```

```
# Create co-occurrence matrix
cooccurrence_matrix, vocab, word_to_idx = build_cooccurrence_matrix(df['processed_tokens'].values)
```

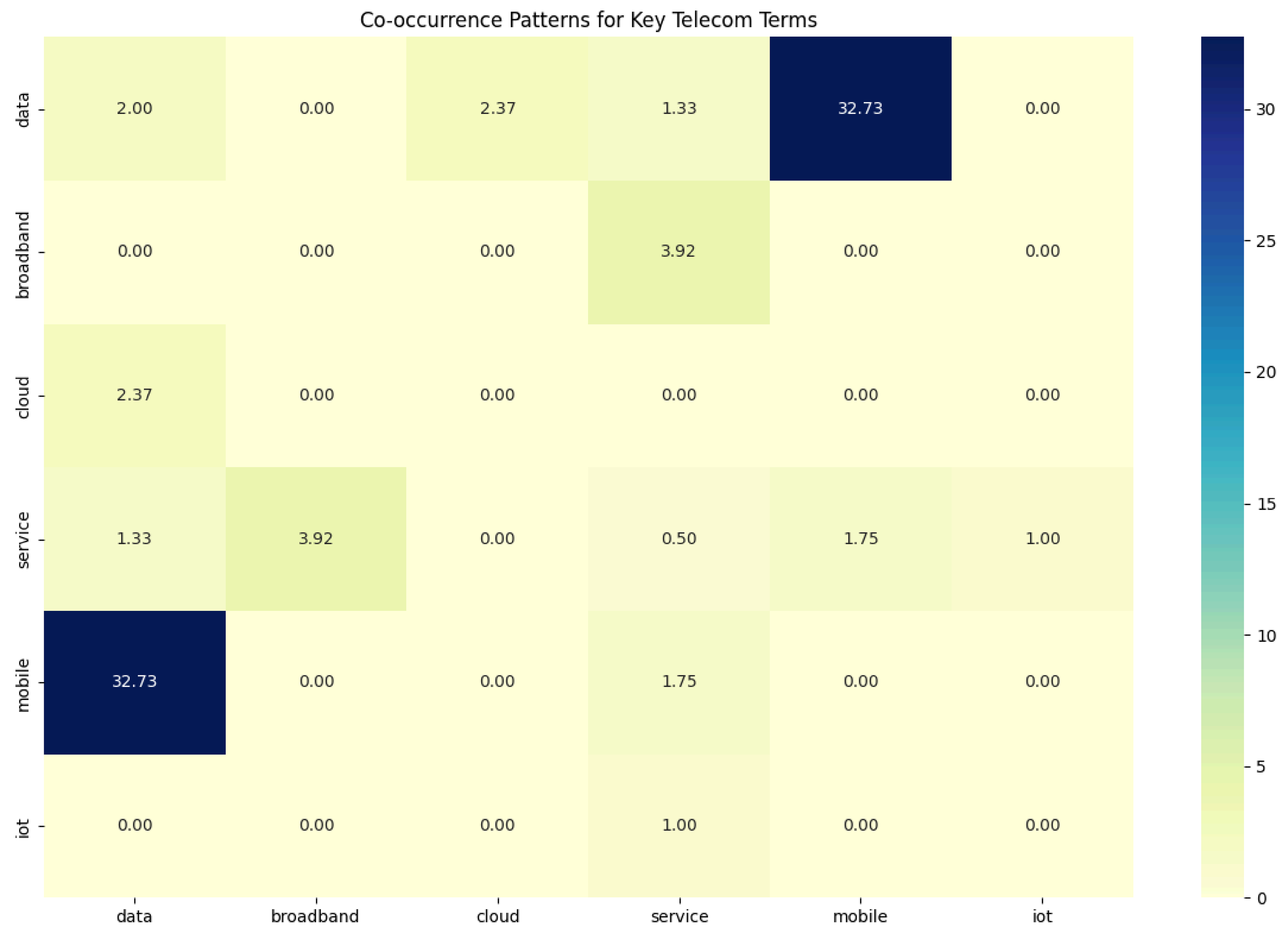
```
# Function to find most similar words based on co-occurrence
def find_similar_words(word, word_to_idx, cooccurrence_matrix, vocab, top_n=5):
    if word not in word_to_idx:
        return []

    word_idx = word_to_idx[word]
    word_vector = cooccurrence_matrix[word_idx]
```

```
    # Calculate cosine similarities
    similarities = []
    for i, other_vector in enumerate(cooccurrence_matrix):
        if i != word_idx:
            similarity = np.dot(word_vector, other_vector) / (
                np.linalg.norm(word_vector) * np.linalg.norm(other_vector)
            )
            similarities.append((vocab[i], similarity))

    # Sort by similarity
    return sorted(similarities, key=lambda x: x[1], reverse=True)[:top_n]
```

```
# Let's analyze some telecom-specific terms
telecom_terms = ['data', 'broadband', 'cloud', 'service']

print("Co-occurrence Matrix Shape:", cooccurrence_matrix.shape)
print("\nSample co-occurrence patterns:")
for term in telecom_terms:
    print(f"\nMost similar words to '{term}':")
    similar_words = find_similar_words(term, word_to_idx, cooccurrence_matrix, vocab)
    for word, similarity in similar_words:
        print(f"  {word}: {similarity:.4f}")
```

```
Co-occurrence Matrix Shape: (480, 480)

Sample co-occurrence patterns:

Most similar words to 'data':
  includes: 0.6378
  coverage: 0.6039
  hidden: 0.5897
  overpriced: 0.5766
  suffers: 0.5730

Most similar words to 'broadband':
  speed: 0.5058
  stable: 0.3995
  provides: 0.3850
  consistent: 0.3846
  exceptional: 0.3844

Most similar words to 'cloud':
  offer: 0.7881
  innovative: 0.6755
  scalable: 0.6667
  prone: 0.6412
  transformed: 0.6409

Most similar words to 'service':
  services: 0.5650
  adequate: 0.4257
  support: 0.4057
  lacks: 0.3966
  call: 0.3759
```

```
# Visualize co-occurrence patterns for key terms
plt.figure(figsize=(12, 8))
selected_terms = ['data', 'broadband', 'cloud', 'service', 'mobile', 'iot']
term_indices = [word_to_idx[term] for term in selected_terms]
subset_matrix = cooccurrence_matrix[np.ix_(term_indices, term_indices)]

sns.heatmap(subset_matrix,
            xticklabels=selected_terms,
            yticklabels=selected_terms,
            cmap='YlGnBu',
            annot=True,
            fmt='.2f')
plt.title('Co-occurrence Patterns for Key Telecom Terms')
plt.tight_layout()
plt.show()
```




```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
from torch.utils.data import Dataset, DataLoader
```

```
class GloVeDataset(Dataset):
    def __init__(self, cooccurrence_matrix, vocab_size):
        # Convert to PyTorch format
        self.i_indices, self.j_indices = cooccurrence_matrix.nonzero()
        self.xij = cooccurrence_matrix[self.i_indices, self.j_indices]

        # Create weight matrix
        self.weights = self._create_weights()

    def _create_weights(self, x_max=100, alpha=0.75):
        weights = np.minimum(1, (self.xij / x_max) ** alpha)
        return torch.FloatTensor(weights)

    def __len__(self):
        return len(self.i_indices)

    def __getitem__(self, index):
        return (self.i_indices[index],
                self.j_indices[index],
                self.xij[index],
                self.weights[index])

class GloVeModel(nn.Module):
    def __init__(self, vocab_size, embedding_dim):
        super(GloVeModel, self).__init__()

        # Word vectors
        self.w_embeddings = nn.Embedding(vocab_size, embedding_dim)
        self.w_contexts = nn.Embedding(vocab_size, embedding_dim)

        # Bias terms
        self.w_biases = nn.Embedding(vocab_size, 1)
        self.c_biases = nn.Embedding(vocab_size, 1)

        # Initialize parameters
        self._init_embeddings()

    def _init_embeddings(self):
        initrange = 0.5 / self.w_embeddings.embedding_dim
        self.w_embeddings.weight.data.uniform_(-initrange, initrange)
        self.w_contexts.weight.data.uniform_(-initrange, initrange)
        self.w_biases.weight.data.zero_()
        self.c_biases.weight.data.zero_()
```

```
    def forward(self, i_indices, j_indices):
        w_i = self.w_embeddings(i_indices).squeeze()  # [batch_size, embed_dim]
        w_j = self.w_contexts(j_indices).squeeze()    # [batch_size, embed_dim]
        b_i = self.w_biases(i_indices).squeeze()      # [batch_size]
        b_j = self.c_biases(j_indices).squeeze()      # [batch_size]

        # Element-wise multiplication and sum
        dot_product = torch.sum(w_i * w_j, dim=-1)    # [batch_size]

        return dot_product + b_i + b_j                # [batch_size]
```

```
# Training parameters
EMBEDDING_DIM = 50
BATCH_SIZE = 32  # Reduced batch size
EPOCHS = 100
LEARNING_RATE = 0.01

# Create dataset and model
dataset = GloVeDataset(cooccurrence_matrix, len(vocab))
dataloader = DataLoader(dataset, batch_size=BATCH_SIZE, shuffle=True)
model = GloVeModel(len(vocab), EMBEDDING_DIM)
optimizer = optim.Adam(model.parameters(), lr=LEARNING_RATE)

# Print shape information for debugging
print(f"Vocabulary size: {len(vocab)}")
print(f"Co-occurrence matrix shape: {cooccurrence_matrix.shape}")
print(f"Number of non-zero entries: {len(dataset)}")
```

```
Vocabulary size: 480
Co-occurrence matrix shape: (480, 480)
Number of non-zero entries: 7510
```

```
# Training loop
print("\nTraining GloVe model...")
for epoch in range(EPOCHS):
    total_loss = 0
    for batch_idx, (i_indices, j_indices, xij, weights) in enumerate(dataloader):
        model.zero_grad()

        # Convert inputs to correct shape
        i_indices = i_indices.long()
        j_indices = j_indices.long()
        xij = xij.float()
        weights = weights.float()

        # Forward pass
        log_xij = torch.log(xij + 1)  # Add 1 to avoid log(0)
        outputs = model(i_indices, j_indices)

        # Calculate weighted loss
        loss = weights * (outputs - log_xij) ** 2
        loss = loss.mean()

        # Backward pass
        loss.backward()
        optimizer.step()
        total_loss += loss.item()

        if batch_idx % 100 == 0:
            print(f"Epoch {epoch+1}/{EPOCHS}, Batch {batch_idx}, Loss: {loss.item():.4f}")

    print(f"Epoch {epoch+1}/{EPOCHS}, Average Loss: {total_loss/len(dataloader):.4f}")
```

```
Epoch 77/100, Average Loss: 0.0026
Epoch 78/100, Batch 0, Loss: 0.0038
Epoch 78/100, Batch 100, Loss: 0.0019
Epoch 78/100, Batch 200, Loss: 0.0012
Epoch 78/100, Average Loss: 0.0028
Epoch 79/100, Batch 0, Loss: 0.0020
Epoch 79/100, Batch 100, Loss: 0.0012
Epoch 79/100, Batch 200, Loss: 0.0017
Epoch 79/100, Average Loss: 0.0023
Epoch 80/100, Batch 0, Loss: 0.0015
Epoch 80/100, Batch 100, Loss: 0.0049
Epoch 80/100, Batch 200, Loss: 0.0011
Epoch 80/100, Average Loss: 0.0027
Epoch 81/100, Batch 0, Loss: 0.0010
Epoch 81/100, Batch 100, Loss: 0.0009
Epoch 81/100, Batch 200, Loss: 0.0007
Epoch 81/100, Average Loss: 0.0024
Epoch 82/100, Batch 0, Loss: 0.0012
Epoch 82/100, Batch 100, Loss: 0.0018
Epoch 82/100, Batch 200, Loss: 0.0014
Epoch 82/100, Average Loss: 0.0021
Epoch 83/100, Batch 0, Loss: 0.0018
Epoch 83/100, Batch 100, Loss: 0.0013
Epoch 83/100, Batch 200, Loss: 0.0011
Epoch 83/100, Average Loss: 0.0017
Epoch 84/100, Batch 0, Loss: 0.0005
Epoch 84/100, Batch 100, Loss: 0.0014
Epoch 84/100, Batch 200, Loss: 0.0011
Epoch 84/100, Average Loss: 0.0016
Epoch 85/100, Batch 0, Loss: 0.0007
Epoch 85/100, Batch 100, Loss: 0.0005
Epoch 85/100, Batch 200, Loss: 0.0008
Epoch 85/100, Average Loss: 0.0013
Epoch 86/100, Batch 0, Loss: 0.0004
Epoch 86/100, Batch 100, Loss: 0.0004
Epoch 86/100, Batch 200, Loss: 0.0006
Epoch 86/100, Average Loss: 0.0014
Epoch 87/100, Batch 0, Loss: 0.0032
Epoch 87/100, Batch 100, Loss: 0.0004
Epoch 87/100, Batch 200, Loss: 0.0010
Epoch 87/100, Average Loss: 0.0016
Epoch 88/100, Batch 0, Loss: 0.0004
Epoch 88/100, Batch 100, Loss: 0.0007
Epoch 88/100, Batch 200, Loss: 0.0018
Epoch 88/100, Average Loss: 0.0016
Epoch 89/100, Batch 0, Loss: 0.0019
Epoch 89/100, Batch 100, Loss: 0.0014
Epoch 89/100, Batch 200, Loss: 0.0035
Epoch 89/100, Average Loss: 0.0019
Epoch 90/100, Batch 0, Loss: 0.0033
Epoch 90/100, Batch 100, Loss: 0.0012
Epoch 90/100, Batch 200, Loss: 0.0048
Epoch 90/100, Average Loss: 0.0023
Epoch 91/100, Batch 0, Loss: 0.0024
Epoch 91/100, Batch 100, Loss: 0.0031
Epoch 91/100, Batch 200, Loss: 0.0025
Epoch 91/100, Average Loss: 0.0025
Epoch 92/100, Batch 0, Loss: 0.0206
Epoch 92/100, Batch 100, Loss: 0.0029
```

```
# Function to get similar words
def find_similar_words(word, top_n=5):
    if word not in word_to_idx:
        return []

    # Get the word embedding
    word_idx = word_to_idx[word]
    word_vec = model.w_embeddings.weight[word_idx].detach()

    # Calculate similarities with all words
    similarities = []
    for i, other_word in enumerate(vocab):
        if other_word != word:
            other_vec = model.w_embeddings.weight[i].detach()
            similarity = torch.nn.functional.cosine_similarity(word_vec.unsqueeze(0),
                                                               other_vec.unsqueeze(0))
            similarities.append((other_word, similarity.item()))

    # Sort by similarity
    return sorted(similarities, key=lambda x: x[1], reverse=True)[:top_n]
```

```
# Test the model with some telecom terms

# Visualization with more telecom-related terms
words_to_plot = ['data', 'broadband', 'cloud', 'service', 'mobile', 'iot', 'wifi',
                 'network', 'speed', 'connection', 'internet', 'customer', 'plan',
                 'fiber', 'coverage', 'quality', 'support', 'technical', 'voice',
                 'device', 'signal', 'connectivity', 'digital', 'wireless', 'communication']
vectors = []
labels = []

# Visualize embeddings using t-SNE
from sklearn.manifold import TSNE

for word in words_to_plot:
    if word in word_to_idx:
        idx = word_to_idx[word]
        vectors.append(model.w_embeddings.weight[idx].detach().numpy())
        labels.append(word)

if len(vectors) > 0:
    # Convert to numpy array
    vectors = np.array(vectors)
```

```
    # Apply t-SNE with adjusted parameters
    tsne = TSNE(n_components=2,
                perplexity=min(30, len(vectors)-1),  # Adjust perplexity based on sample size
                random_state=42,
                init='pca',  # Use PCA initialization for better stability
                learning_rate='auto')  # Automatic learning rate selection

    vectors_2d = tsne.fit_transform(vectors)

    # Create visualization
    plt.figure(figsize=(12, 8))

    # Plot points
    scatter = plt.scatter(vectors_2d[:, 0], vectors_2d[:, 1], alpha=0.6)

    # Add labels with slight offset and smaller font
    for i, label in enumerate(labels):
        plt.annotate(label,
                    (vectors_2d[i, 0], vectors_2d[i, 1]),
                    xytext=(5, 5),
                    textcoords='offset points',
                    fontsize=8,
                    alpha=0.8)

    plt.title('Telecom Term Embeddings Visualization')
    plt.xlabel('t-SNE Dimension 1')
    plt.ylabel('t-SNE Dimension 2')
    plt.tight_layout()
    plt.show()

# Also let's print some similarity analysis
print("\nWord Similarity Analysis for Key Terms:")
key_terms = ['data', 'network', 'service', 'broadband']
for term in key_terms:
    if term in word_to_idx:
        print(f"\nMost similar terms to '{term}':")
        similarities = find_similar_words(term, top_n=5)
        for word, sim in similarities:
            print(f"  {word}: {sim:.4f}")
```


```
Word Similarity Analysis for Key Terms:

Most similar terms to 'data':
  tv: 0.6450
  cable: 0.5822
  shows: 0.5631
  broadband: 0.4274
  provided: 0.4090

Most similar terms to 'network':
  hidden: 0.5150
  ideal: 0.4858
  requiring: 0.4840
  terms: 0.4780
  communication: 0.4615

Most similar terms to 'service':
  crashes: 0.3422
  available: 0.3253
  kicks: 0.3227
  scalable: 0.3226
  management: 0.2988

Most similar terms to 'broadband':
  fiber: 0.8587
  tv: 0.5709
  inquiries: 0.5614
  home: 0.5310
  troubleshooting: 0.4580
```

Tasks 3: fastText Implementation

fastText: Subword Information in Word Embeddings

Key Concepts

Character n-grams

- **Words broken into subword units**
- **Example:** "service" → `<se, ser, erv, rvi, vic, ice, ce>`

Subword Model

- **Word vector** = sum of its n-gram vectors
- **Handles out-of-vocabulary words**
- **Better for technical terms and abbreviations**

Skip-gram with Subword Information

- **Each n-gram** has its own vector representation
- **Final word vector** is the sum of n-gram vectors
- **Includes special boundary symbols** `<` and `>`

```
import numpy as np
from gensim.models import FastText
from gensim.models.callbacks import CallbackAny2Vec
import logging
logging.basicConfig(format='%(asctime)s : %(levelname)s : %(message)s', level=logging.INFO)
```

```
# Callback to monitor training
class EpochLogger(CallbackAny2Vec):
    def __init__(self):
        self.epoch = 0

    def on_epoch_end(self, model):
        print(f"Finished epoch {self.epoch}")
        self.epoch += 1

# Prepare data for fastText
sentences = df['processed_tokens'].values.tolist()
```

```
# Initialize and train fastText model
print("Parameters for Training fastText model...")
model_fast = FastText(vector_size=100,     # Embedding dimension
                      window=5,            # Context window size
```

```
                     min_count=1,          # Minimum word frequency
                     epochs=100,            # Number of training epochs
                     sg=1,                # Skip-gram model
                     workers=4)            # Number of worker threads
```

```
Parameters for Training fastText model...
```

```
# Train the model
model_fast.build_vocab(sentences)
model_fast.train(sentences, total_examples=len(sentences), epochs=model_fast.epochs)
```

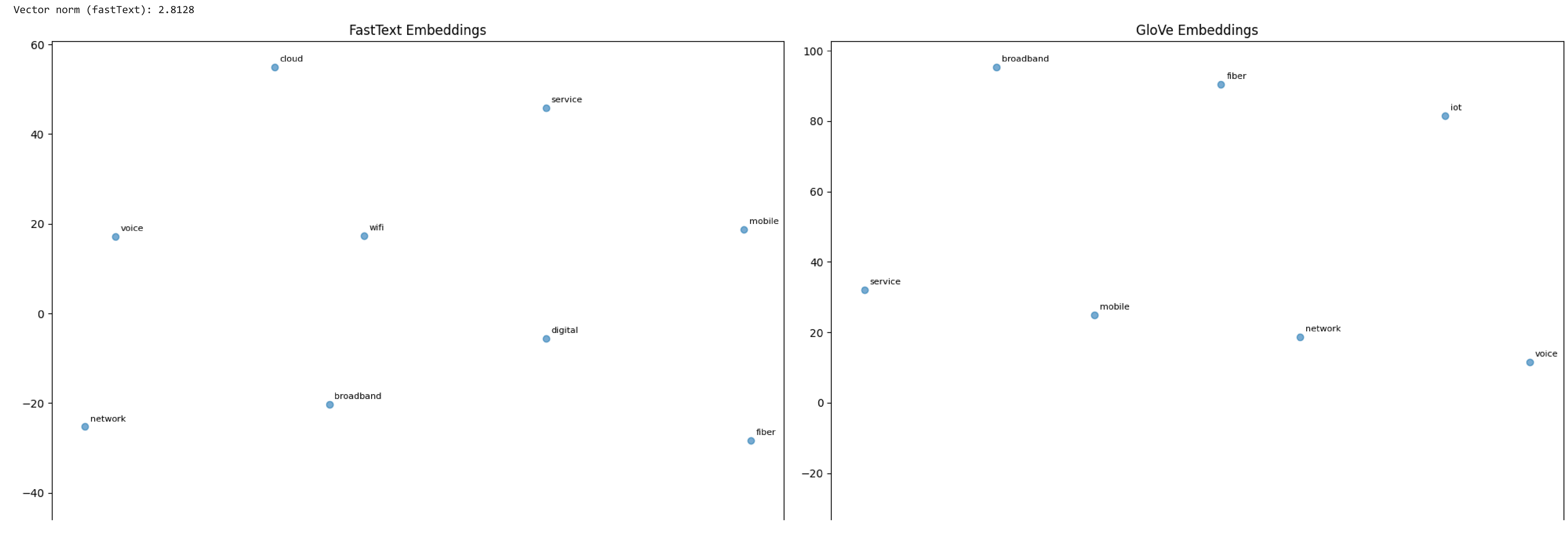
```
(112908, 165600)
```

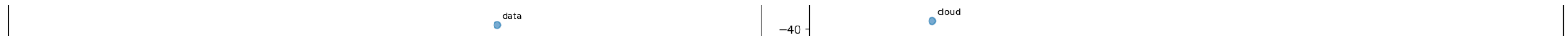
Tasks 4: Comparative Analysis

```
# Function to analyze word similarity and neighbors
def analyze_term(word, model_fast, model_glove):
    print(f"\nAnalysis for '{word}':")

    print("FastText similar words:")
    try:
        similar_words_fast = model_fast.wv.most_similar(word, topn=5)
        for similar, score in similar_words_fast:
            print(f"  {similar}: {score:.4f}")
    except KeyError:
        print("  Word not in fastText vocabulary")

    print("\nGloVe similar words:")
    similar_words_glove = find_similar_words(word, top_n=5)
    for similar, score in similar_words_glove:
        print(f"  {similar}: {score:.4f}")

    # Get vector representation
    try:
        vector_fast = model_fast.wv[word]
        print(f"\nVector norm (fastText): {np.linalg.norm(vector_fast):.4f}")
    except KeyError:
        print("\nWord not in fastText vocabulary")
```

```
# Test with technical terms
test_terms = [
    'voip', '5g', 'wifi', 'iot', 'broadband',
    'data', 'network', 'service', 'fiber'
]

print("\nComparative Analysis of Technical Terms:")
for term in test_terms:
    analyze_term(term, model_fast, model)

# Visualize both embeddings side by side
plt.figure(figsize=(20, 8))

# Words to visualize
words_to_plot = ['data', 'network', 'broadband', 'service', 'mobile', 'iot',
                 'wifi', 'cloud', 'fiber', 'voice', 'digital']

# FastText visualization
plt.subplot(1, 2, 1)
vectors_fast = []
labels_fast = []

for word in words_to_plot:
    try:
        vectors_fast.append(model_fast.wv[word])
        labels_fast.append(word)
    except KeyError:
        continue

if vectors_fast:
    vectors_fast = np.array(vectors_fast)
    tsne = TSNE(n_components=2,
                perplexity=min(30, len(vectors_fast)-1),
                random_state=42,
                init='pca')
    vectors_2d_fast = tsne.fit_transform(vectors_fast)

    plt.scatter(vectors_2d_fast[:, 0], vectors_2d_fast[:, 1], alpha=0.6)
    for i, label in enumerate(labels_fast):
        plt.annotate(label,
                    (vectors_2d_fast[i, 0], vectors_2d_fast[i, 1]),
                    xytext=(5, 5),
                    textcoords='offset points',
                    fontsize=8)
    plt.title('FastText Embeddings')

# GloVe visualization
plt.subplot(1, 2, 2)
vectors_glove = []
labels_glove = []

for word in words_to_plot:
    if word in word_to_idx:
        idx = word_to_idx[word]
        vectors_glove.append(model.w_embeddings.weight[idx].detach().numpy())
        labels_glove.append(word)

if vectors_glove:
    vectors_glove = np.array(vectors_glove)
    tsne = TSNE(n_components=2,
                perplexity=min(30, len(vectors_glove)-1),
                random_state=42,
                init='pca')
    vectors_2d_glove = tsne.fit_transform(vectors_glove)

    plt.scatter(vectors_2d_glove[:, 0], vectors_2d_glove[:, 1], alpha=0.6)
    for i, label in enumerate(labels_glove):
        plt.annotate(label,
                    (vectors_2d_glove[i, 0], vectors_2d_glove[i, 1]),
                    xytext=(5, 5),
                    textcoords='offset points',
                    fontsize=8)
    plt.title('GloVe Embeddings')

plt.tight_layout()
plt.show()
```

```
Comparative Analysis of Technical Terms:

Analysis for 'voip':
FastText similar words:
  advanced: 0.9278
  voice: 0.9252
  service: 0.9063
  global: 0.8533
  lack: 0.8525

GloVe similar words:
  complex: 0.5057
  unreliable: 0.4844
  provide: 0.4414
  lack: 0.4126
  iot: 0.4062

Vector norm (fastText): 2.4102

Analysis for '5g':
FastText similar words:
  usage: 0.1586
  scalable: 0.1389
  storage: 0.1378
  outages: 0.1366
  frequent: 0.1346

GloVe similar words:

Vector norm (fastText): 0.0305

Analysis for 'wifi':
FastText similar words:
  streamlined: 0.8856
  started: 0.8800
  fantastic: 0.8755
  older: 0.8720
  range: 0.8715

GloVe similar words:

Vector norm (fastText): 0.5423

Analysis for 'iot':
FastText similar words:
  older: 0.9700
  devices: 0.9587
  smart: 0.9509
  home: 0.9490
  capabilities: 0.9291

GloVe similar words:
  specific: 0.7261
  lack: 0.6063
  unavailability: 0.6026
  needs: 0.4428
  complex: 0.4396

Vector norm (fastText): 2.4453

Analysis for 'broadband':
FastText similar words:
  fiber: 0.9935
  worth: 0.9790
  download: 0.9438
  flawless: 0.9363
  speed: 0.9358

GloVe similar words:
  fiber: 0.8587
  tv: 0.5709
  inquiries: 0.5614
  home: 0.5310
  troubleshooting: 0.4580

Vector norm (fastText): 2.8336

Analysis for 'data':
FastText similar words:
  recovery: 0.8899
  money: 0.8863
  mobile: 0.8756
  kicks: 0.8724
  hidden: 0.8651

GloVe similar words:
  tv: 0.6450
  cable: 0.5822
  shows: 0.5631
  broadband: 0.4274
  provided: 0.4090

Vector norm (fastText): 2.3461

Analysis for 'network':
FastText similar words:
  usage: 0.9225
  throttling: 0.8945
  unfair: 0.8824
  daily: 0.8656
  policies: 0.8638

GloVe similar words:
  hidden: 0.5150
  ideal: 0.4858
  requiring: 0.4840
  terms: 0.4780
  communication: 0.4615

Vector norm (fastText): 2.7034

Analysis for 'service':
FastText similar words:
  voip: 0.9063
  voice: 0.8696
  services: 0.8649
  advanced: 0.8209
  goes: 0.8153

GloVe similar words:
  crashes: 0.3422
  available: 0.3253
  kicks: 0.3227
  scalable: 0.3226
  management: 0.2988

Vector norm (fastText): 2.2231

Analysis for 'fiber':
FastText similar words:
  broadband: 0.9935
  worth: 0.9788
  download: 0.9413
  flawless: 0.9374
  teams: 0.9262

GloVe similar words:
  broadband: 0.8587
  tv: 0.5635
  home: 0.5544
  installation: 0.4977
  inquiries: 0.4966

Vector norm (fastText): 2.8128
```






```
# Print comparative analysis metrics
print("\nComparative Analysis Summary:")
test_pairs = [
    ('data', 'network'),
    ('broadband', 'fiber'),
    ('cloud', 'service'),
    ('mobile', 'wireless')
]

print("\nSimilarity Comparisons:")
for word1, word2 in test_pairs:
    print(f"\n{word1} - {word2}:")

    # FastText similarity
    try:
        fast_sim = model_fast.wv.similarity(word1, word2)
        print(f"FastText similarity: {fast_sim:.4f}")
    except KeyError:
        print("FastText: One or both words not in vocabulary")

    # GloVe similarity
    if word1 in word_to_idx and word2 in word_to_idx:
        idx1 = word_to_idx[word1]
        idx2 = word_to_idx[word2]
        vec1 = model.w_embeddings.weight[idx1].detach()
        vec2 = model.w_embeddings.weight[idx2].detach()
        glove_sim = torch.nn.functional.cosine_similarity(vec1.unsqueeze(0),
                                                          vec2.unsqueeze(0))
        print(f"GloVe similarity: {glove_sim.item():.4f}")
    else:
        print("GloVe: One or both words not in vocabulary")
```

```
Comparative Analysis Summary:

Similarity Comparisons:

data - network:
FastText similarity: 0.7783
GloVe similarity: 0.1252

broadband - fiber:
FastText similarity: 0.9935
GloVe similarity: 0.8587

cloud - service:
FastText similarity: 0.2681
GloVe similarity: -0.0015

mobile - wireless:
FastText similarity: 0.5881
GloVe: One or both words not in vocabulary
```

Key Findings and Differences between GloVe and fastText for Telecom Domain Embeddings

Embedding Quality Comparison

a) Technical Term Pairs

- **FastText** shows stronger similarity scores overall (e.g., `broadband-fiber`: 0.9935 vs 0.8587)
- **GloVe** seems to have more conservative similarity scores
- **FastText** captures more technical relationships (e.g., `VoIP-voice`: 0.9252)

b) Clustering Patterns

- **FastText** visualization shows tighter clustering of related concepts (cloud, service, mobile)
- **GloVe**'s visualization shows more distinct separation between service categories

Model Strengths

FastText Advantages

- **Better handling of technical terms and abbreviations** (e.g., 'VoIP', 'IoT')
- **Higher similarity scores** for semantically related terms
- **More consistent vector norms** (around 2.0-3.0)

GloVe Advantages

- **More conservative similarity scores** that might prevent false associations
- **Better at capturing global co-occurrence statistics**
- **Clearer separation** between different service categories