Project 1 Q1-Q14

January 23, 2026

1 Project 1 Part 1: News article classification with TF-IDF, GloVe, and LLM embeddings

Note: use conda activate ece219

[1]:
```
import pandas as pd
df = pd.read_csv('Project1-ClassificationDataset.csv')
```

1.1 Question 1 -Dataset Examination

Let's examine the dataset to see how many rows (samples) and columns (features) are present in the dataset.

[2]:
```
count_rows, count_columns = df.shape
print(f"{count_rows} rows, {count_columns} columns")
```

```
3476 rows, 8 columns
```

[3]:
```
df.head(5)
```

[3]:

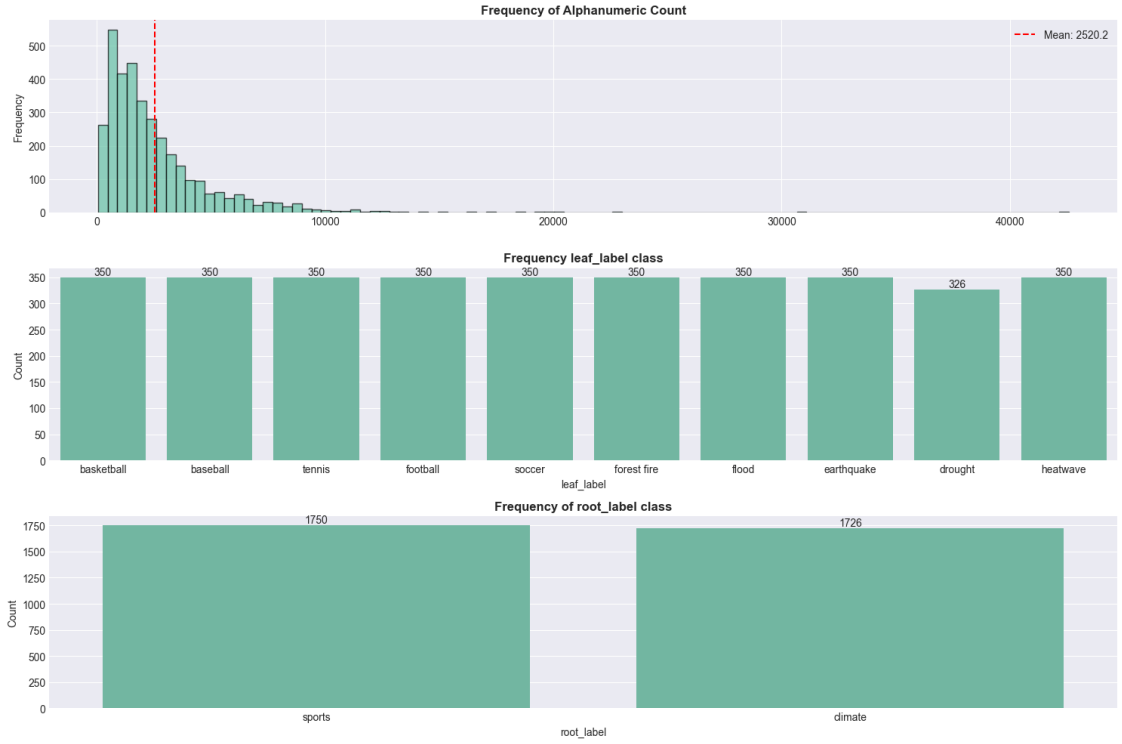
	full_text	summary	keywords
0	'Personalize Your NBA App Experience for the '…	'Personalize Your NBA App Experience for the '…	['original', 'content', 'live', 'slate', 'game…
1	'Mike Will attends the Pre-GRAMMY Gala and GRA…	'Mike WiLL Made-It has secured a partnership w…	['lead', 'espn', 'nbas', 'madeit', 'nba', 'lat…
2	'The Golden State Warriors are struggling to f…	'The Golden State Warriors are struggling to f…	['insider', 'york', 'thing', 'nbc', 'tag', 'nb…
3	'On Nov. 28, the NBA and Nike will collaborate…	'On Nov. 28, the NBA and Nike will collaborate…	['watch', 'telecast', 'ultimate', 'membership'…
4	'The NBA announced additions and innovations t…	'The NBA announced additions and innovations t…	

```
4  ['experience', 'bring', 'media', 'crennan', 'n…

                publish_date                                  authors  \
0                        NaN                  ['Official Release']
1  2023-10-18 16:22:29+00:00                      ['Marc Griffin']
2                        NaN                                    []
3                        NaN                  ['Official Release']
4  2023-10-17 12:00:17+00:00  ['Chris Novak', 'About Chris Novak']

                                                 url  leaf_label root_label
0  https://www.nba.com/news/nba-app-new-features-…  basketball     sports
1  https://www.vibe.com/news/entertainment/mike-w…  basketball     sports
2       https://www.nbcnewyork.com/tag/featured-nba/  basketball     sports
3  https://www.nba.com/news/watch-nba-games-ultim…  basketball     sports
4  https://awfulannouncing.com/tech/nba-app-2023-…  basketball     sports
```

Now I'll plot 3 histograms on (a) The total number of alpha-numeric characters per data point (row) in the feature full text: i.e count on the x-axis and frequency on the y-axis; (b) The column leaf label – class on the x-axis; (c) The column root label – class on the x-axis.

[4]:
```
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("Set2")

# histograms
fig, axes = plt.subplots(3, 1, figsize=(15, 10))

# alphanumeric chars
df["count_alnum"] = df["full_text"].str.count(r"[A-Za-z0-9]")
axes[0].set_title('Frequency of Alphanumeric Count', fontsize=12,␣
 ↪fontweight='bold')
axes[0].hist(df["count_alnum"], bins=100, edgecolor='black', alpha=0.7)
axes[0].axvline(df['count_alnum'].mean(), color='red', linestyle='--',
                    label=f'Mean: {df["count_alnum"].mean():.1f}')
axes[0].set_ylabel('Frequency')
axes[0].legend()

#column leaf_label
sns.countplot(data=df, x='leaf_label', ax=axes[1])
axes[1].set_title('Frequency leaf_label class', fontsize=12, fontweight='bold')
for container in axes[1].containers:
    axes[1].bar_label(container)
axes[1].set_ylabel('Count')

#column root_label
sns.countplot(data=df, x='root_label', ax=axes[2])
```

```
axes[2].set_title('Frequency of root_label class', fontsize=12,␣
 ↪fontweight='bold')
for container in axes[2].containers:
    axes[2].bar_label(container)
axes[2].set_ylabel('Count')

plt.tight_layout()
plt.show()


print(f"More statistics on alphanumeric character count:")
print(f"Mean: {df['count_alnum'].mean():.0f}")
print(f"Median: {df['count_alnum'].median():.0f}")
print(f"Std Dev: {df['count_alnum'].std():.0f}")
print(f"Min: {df['count_alnum'].min():.0f}")
print(f"Max: {df['count_alnum'].max():.0f}")
```




```
More statistics on alphanumeric character count:
Mean: 2520
Median: 1807
Std Dev: 2454
Min: 42
Max: 42580
```

1.1.1 Initial Qualitative Analysis

Our dataset contains news articles that fall under one of two root_labels: sports or climate. There are 1750 sports articles and 1725 climate articles. The articles are additionally tagged with a leaf label that further categorizes the article. For each leaf_label class present in the dataset, there are 350 articles, with the exception of "drought" which only has 326 articles. So notably, "drought" is less represented in the dataset than the other leaf_labels. By extension, "climate" is less represented than the other root label "sports". Lastly, the distribution of alphanumeric length of articles is right-skewed, meaning the articles are relatively short. The mean count of alphanumeric characters in articles is 2520.

1.2 Question 2 - Number of Training / Testing Samples

Let's split the data and report the number of training and testing samples.

[5]:
```
import numpy as np
import random
np.random.seed(42)
random.seed(42)
```

[6]:
```
from sklearn.model_selection import train_test_split
train, test = train_test_split(
df[["full_text", "root_label", "leaf_label"]],
test_size=0.2
)
print(f"{train.shape[0]} training samples, {test.shape[0]} testing samples")
```

```
2780 training samples, 696 testing samples
```

1.3 Question 3 - Extracting Features

Now we will clean / tokenize / lemmatize the data and create a pipeline

[7]:
```
import re
def clean(text):
    text = re.sub(r'^https?:\/\/.*[\r\n]*', '', text, flags=re.MULTILINE)
    texter = re.sub(r"<br />", " ", text)
    texter = re.sub(r"&quot;", "\"",texter)
    texter = re.sub('&#39;', "\"", texter)
    texter = re.sub('\n', " ", texter)
    texter = re.sub(' u '," you ", texter)
    texter = re.sub('`',"", texter)
    texter = re.sub(' +', ' ', texter)
    texter = re.sub(r"(!)\1+", r"!", texter)
    texter = re.sub(r"(\?)\1+", r"?", texter)
    texter = re.sub('&amp;', 'and', texter)
    texter = re.sub('\r', ' ',texter)
    clean = re.compile('<.*?>')
    texter = texter.encode('ascii', 'ignore').decode('ascii')
```

```
    texter = re.sub(clean, '', texter)
    if texter == "":
        texter = ""
    return texter
```

[8]:
```
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn.pipeline import Pipeline
from nltk.stem import WordNetLemmatizer, PorterStemmer
from nltk.corpus import wordnet
from nltk import pos_tag, word_tokenize

import nltk
#needed for WordNetLemmatizer and pos_tag
nltk.download('wordnet')
nltk.download('averaged_perceptron_tagger')
nltk.download('averaged_perceptron_tagger_eng')
nltk.download('omw-1.4')
nltk.download('punkt')
nltk.download('punkt_tab')

def get_wordnet_pos(tag):
    # Converts Penn Treebank tags to WordNet.
    morphy_tag = {'NN':'n', 'JJ':'a',
                  'VB':'v', 'RB':'r'}
    try:
        return morphy_tag[penntag[:2]]
    except:
        return 'n'

# lemmatizer tokenizer
class LemmaTokenizer:
    def __init__(self):
        self.lemmatizer = WordNetLemmatizer()

    def __call__(self, doc):
        tokens = word_tokenize(doc.lower())
        tokens = [t for t in tokens if re.match(r'\b[^\d\W]+\b', t)]
        pos_tags = pos_tag(tokens)
        return [self.lemmatizer.lemmatize(token, get_wordnet_pos(tag)) for␣
 ↪token, tag in pos_tags]

# stemming tokenizer
class StemTokenizer:
    def __init__(self):
        self.stemmer = PorterStemmer()

    def __call__(self, doc):
```

```
        tokens = word_tokenize(doc.lower())
        tokens = [t for t in tokens if re.match(r'\b[^\d\W]+\b', t)]
        return [self.stemmer.stem(token) for token in tokens]

train['full_text_cleaned'] = train["full_text"].apply(clean)
test['full_text_cleaned'] = test["full_text"].apply(clean)

#stemming pipeline + results
print("Stemming:")
tfidf_pipeline_stem = Pipeline([
    ('count', CountVectorizer(
        tokenizer=StemTokenizer(),
        stop_words='english',
        min_df=3
    )),
    ('tfidf', TfidfTransformer())
])

#fit/ transform
train_tfidf_stem = tfidf_pipeline_stem.fit_transform(train['full_text_cleaned'])
test_tfidf_stem = tfidf_pipeline_stem.transform(test['full_text_cleaned'])

print(f"Train TF-IDF Stemming shape: {train_tfidf_stem.shape}")
print(f"Test TF-IDF Stemming shape: {test_tfidf_stem.shape}")
print(f"Vocab size Stemming: {len(tfidf_pipeline_stem.named_steps['count'].
 ↪vocabulary_)}")



#Lemmatization pipeline + results
print("Lemmatizing:")
tfidf_pipeline_lemma = Pipeline([
    ('count', CountVectorizer(
        tokenizer=LemmaTokenizer(),
        stop_words='english',
        min_df=3
    )),
    ('tfidf', TfidfTransformer())
])

#fit/ transform
train_tfidf_lemma = tfidf_pipeline_lemma.
 ↪fit_transform(train['full_text_cleaned'])
test_tfidf_lemma = tfidf_pipeline_lemma.transform(test['full_text_cleaned'])


print(f"Train TF-IDF Lemmatizing shape: {train_tfidf_lemma.shape}")
```

```
print(f"Test TF-IDF Lemmatizing shape: {test_tfidf_lemma.shape}")
print(f"Vocab size Lemmatizing: {len(tfidf_pipeline_lemma.named_steps['count'].
 ↪vocabulary_)}")
```

```
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package omw-1.4 to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package omw-1.4 is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package punkt_tab to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package punkt_tab is already up-to-date!
```

Stemming:

```
C:\Users\jilli\.conda\envs\ece219\lib\site-
packages\sklearn\feature_extraction\text.py:517: UserWarning: The parameter
'token_pattern' will not be used since 'tokenizer' is not None'
  warnings.warn(
C:\Users\jilli\.conda\envs\ece219\lib\site-
packages\sklearn\feature_extraction\text.py:402: UserWarning: Your stop_words
may be inconsistent with your preprocessing. Tokenizing the stop words generated
tokens ['abov', 'afterward', 'alon', 'alreadi', 'alway', 'ani', 'anoth',
'anyon', 'anyth', 'anywher', 'becam', 'becaus', 'becom', 'befor', 'besid',
'cri', 'describ', 'dure', 'els', 'elsewher', 'empti', 'everi', 'everyon',
'everyth', 'everywher', 'fifti', 'formerli', 'forti', 'ha', 'henc', 'hereaft',
'herebi', 'hi', 'howev', 'hundr', 'inde', 'latterli', 'mani', 'meanwhil',
'moreov', 'mostli', 'nobodi', 'noon', 'noth', 'nowher', 'onc', 'onli',
'otherwis', 'ourselv', 'perhap', 'pleas', 'seriou', 'sever', 'sinc', 'sincer',
'sixti', 'someon', 'someth', 'sometim', 'somewher', 'themselv', 'thenc',
'thereaft', 'therebi', 'therefor', 'thi', 'thu', 'togeth', 'twelv', 'twenti',
'veri', 'wa', 'whatev', 'whenc', 'whenev', 'wherea', 'whereaft', 'wherebi',
'wherev', 'whi', 'yourselv'] not in stop_words.
  warnings.warn(
```

```
Train TF-IDF Stemming shape: (2780, 11999)
Test TF-IDF Stemming shape: (696, 11999)
```

```
Vocab size Stemming: 11999
Lemmatizing:

C:\Users\jilli\.conda\envs\ece219\lib\site-
packages\sklearn\feature_extraction\text.py:402: UserWarning: Your stop_words
may be inconsistent with your preprocessing. Tokenizing the stop words generated
tokens ['ha', 'u', 'wa'] not in stop_words.
  warnings.warn(

Train TF-IDF Lemmatizing shape: (2780, 15306)
Test TF-IDF Lemmatizing shape: (696, 15306)
Vocab size Lemmatizing: 15306
```

1. What are the pros and cons of lemmatization versus stemming? How do these processes affect the dictionary size? - Stemming uses simple rules to chop off word endings so its simpler to implement but can result in errors (for example "organ", "organizational", and "organic" would all become "organ" resulting in merging the representation of seperate concepts, so it is less accurate in practice. Lemmatization on the other hand uses vocab analysis, so concepts like "organ", "organizational", and "organic" are kept seperate because when combined with their part-of-speech tag, they'll have different dictionary entries and are recognized as distinct words with different meanings. However the vocab analysis makes the method slower and more computationally intense since this requires POS-tagging and dictionary lookups. Lemmatization also results in larger dictionaries.

2. min df means minimum document frequency. How does varying min df change the TF-IDF matrix? - min_df is the minimum document frequency. If set to 3 this means the word must appear in at least 3 documents. If we increase this value (say set to 10) we will get a smaller vocab size (fewer columns in the TF-IDF matrix). If we decrease this value (say set to 1) we will get a larger vocab size (more columns in the TF-IDF matrix). In general, increasing this value can remove rare words and reduce noise but can also cause information loss if set too high. Decreasing this value will keep more rare words, increase noise and can lead to the model learning overly-specific-to-one-document vocabulary (overfitting).

3. Should I remove stopwords before or after lemmatizing? Should I remove punctuations before or after lemmatizing? Should I remove numbers before or after lemmatizing? Hint: Recall that the full sentence is input into the Lemmatizer and the lemmatizer is tagging the position of every word based on the sentence structure. - Do all of these removals after lemmatizing. Lemmatization needs the full sentence context (including stopwords, punctuation, and numbers) to have the best chance of lemmatizing correctly. Removing this context can result in incorrect lemmatization because the POS tagger may not be able to determin what POS a word is.

4. Report the shape of the TF-IDF-processed train and test matrices. The number of rows should match the results of Question 2. The number of columns should roughly be in the order of k $\times$103. This dimension will vary depending on your exact method of cleaning and lemmatizing and that is okay. - This is printed above. Vocab size is ~11k for stemmed matrices and ~15k for the lemmatized matrices.

1.4 Question 4 - GloVE Paper

Below are answers to questions about the GloVE paper https://nlp.stanford.edu/pubs/glove.pdf

a. Why are GLoVE embeddings trained on the ratio of co-occurrence probabilities rather than the probabilities themselves? By training on co-occurence probabilities, GloVE captures captures semantic relationships. In particular, it captures what is discriminative about word-word relationships. (e.g., the ratio P(solid|ice)/P(solid|steam) is large because "solid" relates to ice but not steam and the raw probabilities P(solid|ice) and P(solid|steam) in isolation don't reveal this contrast.

b. In the two sentences: "James is running in the park." and "James is running for the presidency.", would GLoVE embeddings return the same vector for the word running in both cases? Why or why not? Yes, because GloVE has one embedding per word, not per word occurrence. This embedding is learned from global co-occurence statistics across the entire training corpus. During training, if the word "running" appeared, it would use the same vector even if the context is different!

c. What do you expect for the values of, ||GLoVE["left"] - GLoVE["right"]||2, ||GLoVE["wife"] - GLoVE["husband"]||2 and ||GLoVE["wife"] - GLoVE["orange"]||2 ? Compare these values. "left" and "right" would appear in similar contexts, as would "wife" and "husband", so we would expect ||GLoVE["left"] - GLoVE["right"]|| and ||GLoVE["wife"] - GLoVE["husband"]|| would be very small (close to 0). Alternatively, ||GLoVE["wife"] - GLoVE["orange"]|| would be large because "wife" and "orange" do not occur in similar contexts.

d. Given a word, would you rather stem or lemmatize the word before mapping it to its GLoVE embedding? You would rather do lemmatization before mapping it to its glove embedding if using a pretrained GloVE model. Since stemming returns word stems instead of real words, and GloVe embeddings are trained on real word forms, it makes sense to prefer lemmatization as lemmatization maps a word to its canonical dictionary form which is more likely to exist as-is in the GloVe vocabulary. If training a GloVE model from scratch you could use stemming, but there are downsides to this approach as well: since stemming merges unrelated word forms, this introduces semantic notise into the co-occurance probabilities that GloVe relies on.

1.5 Question 5 - GLoVE Feature Construction Pipeline

Below is a description of the pipeline I'm using:

1. Preprocessing: Uses full_text_cleaned (pre-cleaned text from previous question), tokenizes, lowercases, and lemmatizes using WordNet lemmatizer with POS tagging. Stopwords and non-alphabetic tokens are removed.

2. Word Vector Lookup: For each preprocessed token, retrieve its corresponding 300-dimensional GloVe vector from the pretrained glove.6B.300d embeddings. I choose to just skip any out-of-vocab words (OOV).

3. Normalization: Each word vector is L2-normalized to unit length.

4. Aggregation: The document embedding is computed as the arithmetic mean of all normalized word vectors in the document. This produces a single 300-dimensional vector per document.

Note: Documents with no in-vocabulary words receive a zero vector.

[9]:
```
embeddings_dict = {}
dimension_of_glove = 300
with open("glove/glove.6B.300d.txt", 'r', encoding='utf-8') as f:
```

```
    for line in f:
        values = line.split()
        word = values[0]
        vector = np.asarray(values[1:], "float32")
        embeddings_dict[word] = vector
```

1.5.1 Pipeline Implementation

[10]:
```
import numpy as np
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
import nltk

nltk.download('stopwords')

class GloVeEmbedder:
    def __init__(self, embeddings_dict):
        self.embeddings_dict = embeddings_dict
        self.stop_words = set(stopwords.words('english'))
        self.lemmatizer = WordNetLemmatizer()
        self.embedding_dim = len(next(iter(embeddings_dict.values())))

    def preprocess(self, text):
        #tokenize, lemmtize, filter out nonalphanumeric
        tokens = word_tokenize(text.lower())
        pos_tags = pos_tag(tokens)
        #lemmatize
        lemmatized = [
            self.lemmatizer.lemmatize(token, get_wordnet_pos(tag))
            for token, tag in pos_tags
        ]
        filtered = [
            word for word in lemmatized
            if word.isalpha() and
               len(word) > 1 and
               (word not in self.stop_words)
        ]
        return filtered

    def embed_doc(self, text):
        #Convert a document to embedding vector
        tokens = self.preprocess(text)
        word_vectors = []
        oov_count = 0

        for token in tokens:
            if token in self.embeddings_dict:
```

```
                vec = self.embeddings_dict[token]
                word_vectors.append(vec)
            else:
                oov_count += 1

        # if no valid words
        if len(word_vectors) == 0:
            print(f"WARNING: Document with no valid words. Sample tokens:␣
 ↪{tokens[:5]}")
            return np.zeros(self.embedding_dim), 1.0

        #get word vectors and normalize + avg
        word_vectors = np.array(word_vectors)
        word_vectors = normalize(word_vectors, axis=1, norm='l2')
        doc_embedding = np.mean(word_vectors, axis=0)

        #find OOV rate
        total_tokens = len(tokens)
        oov_rate = oov_count / total_tokens if total_tokens > 0 else 0
        return doc_embedding, oov_rate

    def transform(self, documents):
        #Transform list of documents to embedding matrix
        embeddings = []
        oov_rates = []

        for i, doc in enumerate(documents):
            emb, oov = self.embed_doc(doc)
            embeddings.append(emb)
            oov_rates.append(oov)
        return np.array(embeddings), np.array(oov_rates)


print("Creating doc embedder...")
embedder = GloVeEmbedder(
    embeddings_dict=embeddings_dict,
)

#transform train and test
print("Transforming training documents...")
train_glove_emb, train_oov_rates = embedder.
 ↪transform(train['full_text_cleaned'])

print("Transforming test documents...")
test_glove_emb, test_oov_rates = embedder.transform(test['full_text_cleaned'])

#Part(b): Report results
```

```
print(f"\nTrain GloVe embeddings shape: {train_glove_emb.shape}")
print(f"Test GloVe embeddings shape: {test_glove_emb.shape}")
print(f"\nAverage OOV rate (train): {np.mean(train_oov_rates):.2%}")
print(f"Average OOV rate (test): {np.mean(test_oov_rates):.2%}")
print(f"Median OOV rate (train): {np.median(train_oov_rates):.2%}")
print(f"Median OOV rate (test): {np.median(test_oov_rates):.2%}")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!

Creating doc embedder…
Transforming training documents…
Transforming test documents…

Train GloVe embeddings shape: (2780, 300)
Test GloVe embeddings shape: (696, 300)

Average OOV rate (train): 1.34%
Average OOV rate (test): 1.38%
Median OOV rate (train): 0.89%
Median OOV rate (test): 0.97%
```

1.6 Question 6 Using LLM Encoder Embeddings

Below is my code that uses a pretrained model "all-MiniLM-L6-v2" to compute vector embeddings. I had trouble running the LLM helper code for this part and got something similar to work that imports SentenceTransformer library explicitly. The code uses SentenceTransformers encode() method to get the embeddings which does truncation by default, however, I have increased the max_seq_length to be 512 to make it better suited to this task. My justification for using the truncation method is that most key information in a news article can usually be found at the beginning of the article. I think the first few sentences of an article will be enough for a classifier to be able to tell whether the article is about climate or sports. Additionally, this method is simpler to implement.

[11]:
```
from sentence_transformers import SentenceTransformer
import torch
from tqdm import tqdm

MODEL_NAME = "all-MiniLM-L6-v2"

print("Loading model...")
device = "cuda" if torch.cuda.is_available() else "cpu"
model = SentenceTransformer(MODEL_NAME, device=device)
print(f"Model loaded on this device: {device}")

def encode_texts(texts, batch_size=32):
```

```
#utilize sentence-transformers library to encode texts (truncation method used␣
↪automatically)
    model.max_seq_length = 512  # Set truncation max_se_length to 512
    print(f"Encoding {len(texts)} documents...")
    embeddings = model.encode(
        texts,
        batch_size=batch_size,
        show_progress_bar=True,
        convert_to_numpy=True
    )
    return torch.from_numpy(embeddings)

print("encoding training set")
train_transformer = encode_texts(train['full_text_cleaned'].tolist())
print("encoding test set")
test_transformer = encode_texts(test['full_text_cleaned'].tolist())

print(f"\nTransformer Train shape: {train_transformer.shape}")
print(f"Transformer Test shape: {test_transformer.shape}")
print(f"Embedding dimension: {train_transformer.shape[1]}")
```

```
Loading model…
Model loaded on this device: cuda
encoding training set
Encoding 2780 documents…
```

```
Batches:   0%|          | 0/87 [00:00<?, ?it/s]
```

```
encoding test set
Encoding 696 documents…
```

```
Batches:   0%|          | 0/22 [00:00<?, ?it/s]
```

```
Transformer Train shape: torch.Size([2780, 384])
Transformer Test shape: torch.Size([696, 384])
Embedding dimension: 384
```

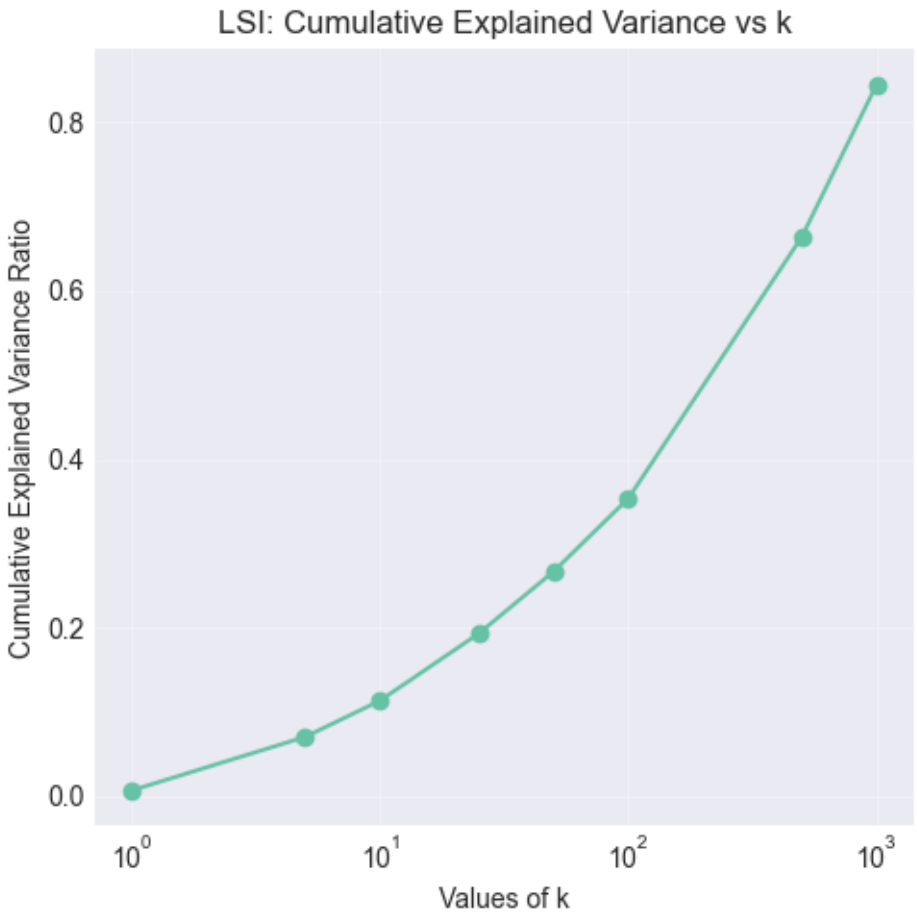
1.7 Question 7 - Dimensionality Reduction

In this section I fit annd LSI and NMF model on the training TF-IDF matrix and compare.

[12]:
```
from sklearn.decomposition import TruncatedSVD
import numpy as np

k_vals = [1, 5, 10, 25, 50, 100, 500, 1000]
cumulative_variances = []

for k in k_vals:
    print(f"Fitting for k = {k}")
```

```
    svd = TruncatedSVD(n_components=k, random_state=0)
    svd.fit(train_tfidf_lemma)
    if k == 25:
        svd25 = svd
        lsi_tfidf_lemma_train = svd.transform(train_tfidf_lemma)
        lsi_tfidf_lemma_test = svd.transform(test_tfidf_lemma)
    cumulative_var = np.sum(svd.explained_variance_ratio_)
    cumulative_variances.append(cumulative_var)

plt.figure(figsize=(5,5))
plt.plot(k_vals, cumulative_variances, marker='o')
plt.xlabel('Values of k')
plt.ylabel('Cumulative Explained Variance Ratio')
plt.title('LSI: Cumulative Explained Variance vs k')
plt.grid(True, alpha=0.3)
plt.xscale('log')
plt.tight_layout()
plt.show()

print(f"\nLSI TFIDF Train shape: {lsi_tfidf_lemma_train.shape}")
print(f"\nLSI TFIDF Test shape: {lsi_tfidf_lemma_test.shape}")
```

```
Fitting for k = 1
Fitting for k = 5
Fitting for k = 10
Fitting for k = 25
Fitting for k = 50
Fitting for k = 100
Fitting for k = 500
Fitting for k = 1000
```




```
LSI TFIDF Train shape: (2780, 25)

LSI TFIDF Test shape: (696, 25)
```

[13]:
```
from sklearn.decomposition import NMF

nmf25 = NMF(n_components=25, init='random', random_state=0)
nmf_tfidf_lemma_train = nmf25.fit_transform(train_tfidf_lemma)
nmf_tfidf_lemma_test = nmf25.transform(test_tfidf_lemma)

print(f"\nNMF TFIDF Train shape: {nmf_tfidf_lemma_train.shape}")
print(f"\nNMF TFIDF Test shape: {nmf_tfidf_lemma_test.shape}")
```

```
NMF TFIDF Train shape: (2780, 25)

NMF TFIDF Test shape: (696, 25)
```

[14]:
```
# compute reconstruction MSE
n, m = train_tfidf_lemma.shape

#Lsi
X_lsi = svd25.inverse_transform(lsi_tfidf_lemma_train)
mse_lsi = np.sum((train_tfidf_lemma.toarray() - X_lsi)**2) / (n * m)

# NMF
X_nmf = nmf25.inverse_transform(nmf_tfidf_lemma_train)
mse_nmf = np.sum((train_tfidf_lemma.toarray() - X_nmf)**2) / (n * m)

print(f"LSI Reconstruction MSE: {mse_lsi:.10f}")
print(f"NMF Reconstruction MSE: {mse_nmf:.10f}")
```

```
LSI Reconstruction MSE: 0.0000511210
NMF Reconstruction MSE: 0.0000515816
```

The LSI method has a lower reconstruction error. This is due to how SVD minimizes squared reconstruction error with no constraints. NMF, on the other hand, has a non-negativity constraint that makes it unable to reach the same optimal solution.

1.8 Question 8 - Comparing Hard Margin vs Soft Margin linear SVMs

I train linear SVMs (hard margin, soft margin, and extra hard margin) and compare their performance

[15]:
```
from sklearn.svm import LinearSVC
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, roc_curve, auc)

y_train = train['root_label']
y_test = test['root_label']

def train_svm(x_train, y_train, x_test, y_test, gamma):
    c = 1.0 / gamma
    svm = LinearSVC(loss='hinge',C=c, random_state = 42, max_iter = 10000)
    svm.fit(x_train, y_train)
    y_pred = svm.predict(x_test)
    #for ROC curve get decision scores
    y_scores = svm.decision_function(x_test)

    #metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, pos_label='sports')
    recall = recall_score(y_test, y_pred, pos_label='sports')
    f1 = f1_score(y_test, y_pred, pos_label='sports')

    conf_matrix = confusion_matrix(y_test, y_pred)
```

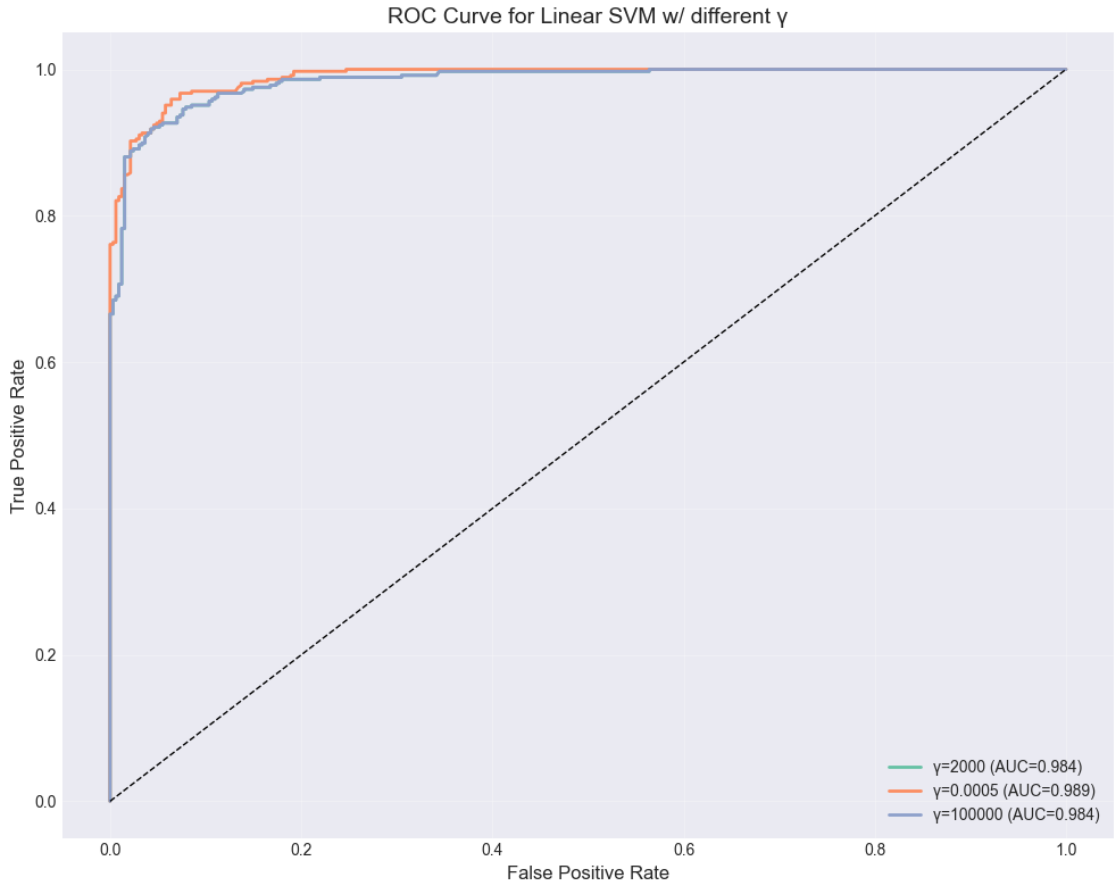
```
    print(f"\nResults for SVM where:   = {gamma} (C = {c})")
    print(f"Accuracy:  {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall:    {recall:.4f}")
    print(f"F1-Score:  {f1:.4f}")
    print(f"Confusion Matrix:")
    print(conf_matrix)

    return {
        'y_pred': y_pred,
        'y_scores': y_scores,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'confusion_matrix': conf_matrix,
        'gamma': gamma,
        'C': c
    }

def plot_roc_curve(results_list, y_test, title):
    plt.figure(figsize=(10, 8))
    if isinstance(y_test.iloc[0], str):
        y_test_binary = (y_test == 'sports').astype(int)
    else:
        y_test_binary = y_test

    for result in results_list:
        # Compute ROC curve
        fpr, tpr, thresholds = roc_curve(y_test_binary, result['y_scores'])
        roc_auc = auc(fpr, tpr)

        # Plot
        label = f" ={result['gamma']} (AUC={roc_auc:.3f})"
        plt.plot(fpr, tpr, linewidth=2, label=label)

    # Plot diagonal
    plt.plot([0, 1], [0, 1], 'k--', linewidth=1)

    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(title, fontsize=14)
    plt.legend(loc='lower right', fontsize=10)
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()
```

[16]:
```
#Using LSI Tfidf data (where k = 25)
results_hard = train_svm(lsi_tfidf_lemma_train, y_train, lsi_tfidf_lemma_test,␣
 ↪y_test, gamma=2000)

results_soft = train_svm(lsi_tfidf_lemma_train, y_train, lsi_tfidf_lemma_test,␣
 ↪y_test, gamma=0.0005)

results_extra_hard = train_svm(lsi_tfidf_lemma_train, y_train,␣
 ↪lsi_tfidf_lemma_test, y_test, gamma=100000)

plot_roc_curve([results_hard, results_soft, results_extra_hard], y_test, "ROC␣
 ↪Curve for Linear SVM w/ different  ")
```

```
Results for SVM where:   = 2000 (C = 0.0005)
Accuracy:  0.8391
Precision: 0.9885
Recall:    0.7038
F1-Score:  0.8222
Confusion Matrix:
[[325   3]
 [109 259]]
```

```
C:\Users\jilli\.conda\envs\ece219\lib\site-packages\sklearn\svm\_base.py:1250:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  warnings.warn(
```

```
Results for SVM where:   = 0.0005 (C = 2000.0)
Accuracy:  0.9411
Precision: 0.9504
Recall:    0.9375
F1-Score:  0.9439
Confusion Matrix:
[[310  18]
 [ 23 345]]

Results for SVM where:   = 100000 (C = 1e-05)
Accuracy:  0.8391
Precision: 0.9885
Recall:    0.7038
F1-Score:  0.8222
Confusion Matrix:
[[325   3]
 [109 259]]
```



1.8.1 Analysis

For the hard margin SVM (= 2000), the confusion matrix tells us that the model is very careful about predicting the "sports" label. It only predicts the "sports" label when it is 100% certain, so it misses a lot of sports articles (109 missed). For the soft margin SVM (= 0.0005), the model is able to make predictions when its less certain, so finds almost all sports articles with a few mistakes (misses 18 climate articles and finds 345/368 sports articles). For the extra hard margin SVM (= 1000000), the confusion matrix is identical to the hard margin svm (= 2000). The margin is too hard to make the data fit any better than it does at (= 2000).

Note that this analysis reflects in the F1 score. Soft margin SVM has the highest F1 score and therefore performs best.

In conclusion, there is a trade off between hard and soft margin SVMs. Hard margin SVMs are very precise but miss a lot of true positives. Soft margin svms have a more balanced performance on this dataset, it takes some extra risk to catch more cases of sports, which works well for this scenario of classifying news articles. The hard margin svm would be better to use if it was very costly to make false positives.

Does the ROC curve reflect the performance of the soft-margin SVM? Why? The ROC curve I plotted shows that all three models have similar AUC values (with the soft margin svm AUC

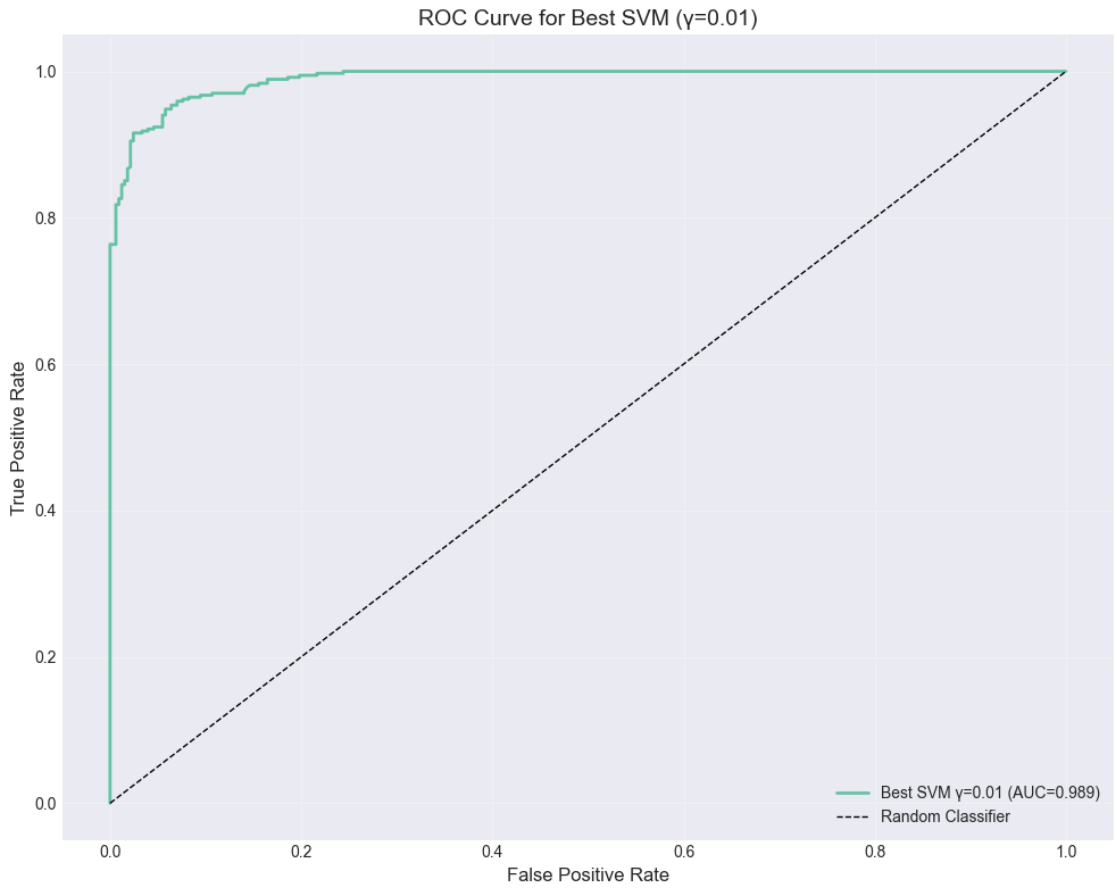
value being only slightly higher). From what I've learned about ROC curves during this project, AUC is the probability that the model ranks a random positive example higher than a random negative example. What this means is that all 3 models have excellent discrimination capabilities. However, there are some considerations to be made here as the ROC curve alone doesn't fully capture the practical performance differences. The key insight is that ROC curves show potential performance across all thresholds (varying the decision boundary), while the confusion matrices show actual performance at the chosen threshold (default decision boundary is 0). So, when we created the confusion matrix we are able to see that, given the default threshold, the soft margin svm operates at a better point on its ROC curve: it achieves good recall (93%) while maintaining good precision (95%), whereas the hard margin SVM operates very very conservatively, achieving good precision (99%) but only (70%) recall.

[17]:
```
from sklearn.model_selection import cross_val_score, KFold
from sklearn.exceptions import ConvergenceWarning
import warnings

warnings.filterwarnings('ignore', category=ConvergenceWarning)

# Define gamma range: {10^k|-3<=k<=6,k in Z}
gamma_range = [10**k for k in range(-3, 7)]

print("Testing gamma values with 5-fold CV...")

best_gamma = None
best_cv_acc = 0
cv_accuracies = []

# Set up 5-fold CV
kfold = KFold(n_splits=5, shuffle=True, random_state=42)

#try all the choices of gamma
for gamma in gamma_range:
    C = 1.0 / gamma
    svm = LinearSVC(loss='hinge', C=C, random_state=42)

    # Get CV scores
    cv_scores = cross_val_score(svm, lsi_tfidf_lemma_train, y_train, cv=kfold,␣
 ↪scoring='accuracy')
    mean_acc = cv_scores.mean()
    cv_accuracies.append(mean_acc)
    print(f"  = {gamma:8.1e} | CV Accuracy: {mean_acc:.4f}")

    if mean_acc > best_cv_acc:
        best_cv_acc = mean_acc
        best_gamma = gamma
print(f"Found the best   = {best_gamma} with CV Accuracy = {best_cv_acc:.4f}")
```

```
# train final model with best gamma and evaluate on test Set

print(f"\nTraining final model with   = {best_gamma}...")
C_best = 1.0 / best_gamma
svm_best = LinearSVC(loss='hinge', C=C_best, max_iter=1000, random_state=42,␣
 ↪dual='auto')
svm_best.fit(lsi_tfidf_lemma_train, y_train)
y_pred = svm_best.predict(lsi_tfidf_lemma_test)
y_scores = svm_best.decision_function(lsi_tfidf_lemma_test)

# Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, pos_label='sports')
recall = recall_score(y_test, y_pred, pos_label='sports')
f1 = f1_score(y_test, y_pred, pos_label='sports')
cm = confusion_matrix(y_test, y_pred)
print(f"\nTest Set Results:")
print(f"Accuracy:  {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall:    {recall:.4f}")
print(f"F1-Score:  {f1:.4f}")
print(f"\nConfusion Matrix:")
print(cm)

#Convert labels to binary
y_test_binary = (y_test == 'sports').astype(int)

#Calculate ROC
fpr, tpr, thresholds = roc_curve(y_test_binary, y_scores)
roc_auc = auc(fpr, tpr)

#Plot
plt.figure(figsize=(10, 8))
plt.plot(fpr, tpr, linewidth=2, label=f'Best SVM  ={best_gamma} (AUC={roc_auc:.
 ↪3f})')
plt.plot([0, 1], [0, 1], 'k--', linewidth=1, label='Random Classifier')
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title(f'ROC Curve for Best SVM ( ={best_gamma})', fontsize=14)
plt.legend(loc='lower right', fontsize=10)
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```

```
Testing gamma values with 5-fold CV…
  =  1.0e-03 | CV Accuracy: 0.9392
```

```
  =  1.0e-02 | CV Accuracy: 0.9496
  =  1.0e-01 | CV Accuracy: 0.9442
  =  1.0e+00 | CV Accuracy: 0.9388
  =  1.0e+01 | CV Accuracy: 0.9212
  =  1.0e+02 | CV Accuracy: 0.7626
  =  1.0e+03 | CV Accuracy: 0.7068
  =  1.0e+04 | CV Accuracy: 0.7068
  =  1.0e+05 | CV Accuracy: 0.7068
  =  1.0e+06 | CV Accuracy: 0.7068
Found the best   = 0.01 with CV Accuracy = 0.9496

Training final model with   = 0.01…

Test Set Results:
Accuracy:  0.9454
Precision: 0.9484
Recall:    0.9484
F1-Score:  0.9484

Confusion Matrix:
[[309  19]
 [ 19 349]]
```



1.9 Question 9 - Evaluate a Logistic Classifier

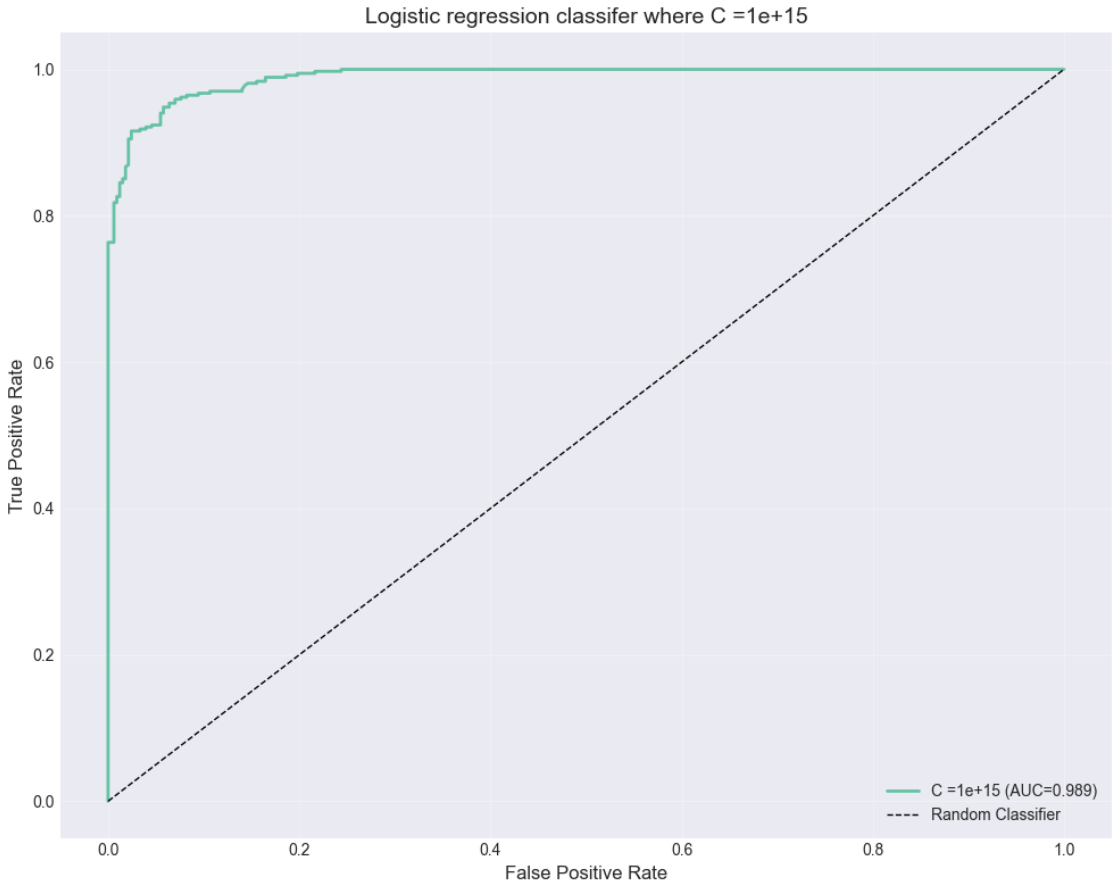
In this section I train and evaluate a logistic classifier, finding the optimal regularization coefficient

[18]:
```
from sklearn.linear_model import LogisticRegression

# we can set a very large C value to approximate no regularization (sklearn␣
 ↪docs)
def train_clf(x_train, y_train, x_test, y_test, c):
    clf = LogisticRegression(C=c, max_iter=1000, random_state=42)
    clf.fit(lsi_tfidf_lemma_train, y_train)
    y_pred = clf.predict(x_test)
    #for ROC curve
    y_scores = clf.predict_proba(x_test)[:, 1]

    #metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, pos_label='sports')
    recall = recall_score(y_test, y_pred, pos_label='sports')
    f1 = f1_score(y_test, y_pred, pos_label='sports')

    conf_matrix = confusion_matrix(y_test, y_pred)

    print(f"\nResults for CLF w/ C - 1e15 (approx no regularization)")
    print(f"Accuracy:  {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall:    {recall:.4f}")
    print(f"F1-Score:  {f1:.4f}")
    print(f"Confusion Matrix:")
    print(conf_matrix)

    return {
        'y_pred': y_pred,
        'y_scores': y_scores,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'confusion_matrix': conf_matrix,
        'C': c
    }
```

[19]:
```
results_clf = train_clf(lsi_tfidf_lemma_train, y_train, lsi_tfidf_lemma_test,␣
 ↪y_test, c=1e15) #very large c
```

```
#Plot
plt.figure(figsize=(10, 8))
plt.plot(fpr, tpr, linewidth=2, label=f'C ={results_clf["C"]:.0e} (AUC={roc_auc:
 ↪.3f})')
plt.plot([0, 1], [0, 1], 'k--', linewidth=1, label='Random Classifier')
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title(f'Logistic regression classifer where C ={results_clf["C"]:.0e}',␣
 ↪fontsize=14)
plt.legend(loc='lower right', fontsize=10)
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```

```
Results for CLF w/ C - 1e15 (approx no regularization)
Accuracy:  0.9454
Precision: 0.9484
Recall:    0.9484
F1-Score:  0.9484
Confusion Matrix:
[[309  19]
 [ 19 349]]
```



[20]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, roc_curve, auc)

def train_and_evaluate_logreg(X_train, y_train, X_test, y_test, penalty='l2',
                              C_range=None, kfold=None):
    #train and eval logistic regression with cross-validation.
    print(f"Using {penalty.upper()} Regularization")
    if C_range is None:
        C_range = [10**k for k in range(-5, 6)]
    if kfold is None:
        kfold = KFold(n_splits=5, shuffle=True, random_state=42)
    solver = 'liblinear' if penalty == 'l1' else 'lbfgs'
    best_C = None
    best_cv_acc = 0
    cv_accuracies = []

    # Cross-validation to find best C
    for C in C_range:
```

```
        logreg = LogisticRegression(
            penalty=penalty,
            C=C,
            solver=solver,
            max_iter=1000,
            random_state=42
        )

        cv_scores = cross_val_score(
            logreg, X_train, y_train,
            cv=kfold, scoring='accuracy'
        )
        mean_acc = cv_scores.mean()
        cv_accuracies.append(mean_acc)

        print(f"C = {C:8.1e} | CV Accuracy: {mean_acc:.4f}")

        if mean_acc > best_cv_acc:
            best_cv_acc = mean_acc
            best_C = C

    print(f"\nBest C for {penalty.upper()} = {best_C} with CV Accuracy =␣
↪{best_cv_acc:.4f}")

    # Train final model with best C
    print(f"\nTraining final {penalty.upper()} model with C = {best_C}...")
    logreg_best = LogisticRegression(
        penalty=penalty,
        C=best_C,
        solver=solver,
        max_iter=1000,
        random_state=42
    )
    logreg_best.fit(X_train, y_train)

    #get predict
    y_pred = logreg_best.predict(X_test)

    #like decision_function for SVM
    y_scores = logreg_best.predict_proba(X_test)[:, 1]

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, pos_label='sports')
    recall = recall_score(y_test, y_pred, pos_label='sports')
    f1 = f1_score(y_test, y_pred, pos_label='sports')
    cm = confusion_matrix(y_test, y_pred)
```

```
    print(f"\n{penalty.upper()} Test Set Results:")
    print(f"Accuracy:  {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall:    {recall:.4f}")
    print(f"F1-Score:  {f1:.4f}")
    print(f"\nConfusion Matrix:")
    print(cm)

    return {
        'penalty': penalty,
        'best_C': best_C,
        'cv_accuracy': best_cv_acc,
        'cv_accuracies': cv_accuracies,
        'y_pred': y_pred,
        'y_scores': y_scores,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'confusion_matrix': cm,
        'model': logreg_best
    }

C_range = [10**k for k in range(-5, 6)]
kfold = KFold(n_splits=5, shuffle=True, random_state=42)

print("Training No Regularization model...")
clf_no_reg = LogisticRegression(C=1e15, max_iter=1000, random_state=42)
clf_no_reg.fit(lsi_tfidf_lemma_train, y_train)
y_pred_no_reg = clf_no_reg.predict(lsi_tfidf_lemma_test)
y_scores_no_reg = clf_no_reg.predict_proba(lsi_tfidf_lemma_test)[:, 1]

# Calculate metrics for no reg
accuracy_no_reg = accuracy_score(y_test, y_pred_no_reg)
precision_no_reg = precision_score(y_test, y_pred_no_reg, pos_label='sports')
recall_no_reg = recall_score(y_test, y_pred_no_reg, pos_label='sports')
f1_no_reg = f1_score(y_test, y_pred_no_reg, pos_label='sports')
cm_no_reg = confusion_matrix(y_test, y_pred_no_reg)

print(f"\nNo Regularization Test Set Results:")
print(f"Accuracy:  {accuracy_no_reg:.4f}")
print(f"Precision: {precision_no_reg:.4f}")
print(f"Recall:    {recall_no_reg:.4f}")
print(f"F1-Score:  {f1_no_reg:.4f}")
print(f"\nConfusion Matrix:")
print(cm_no_reg)
```

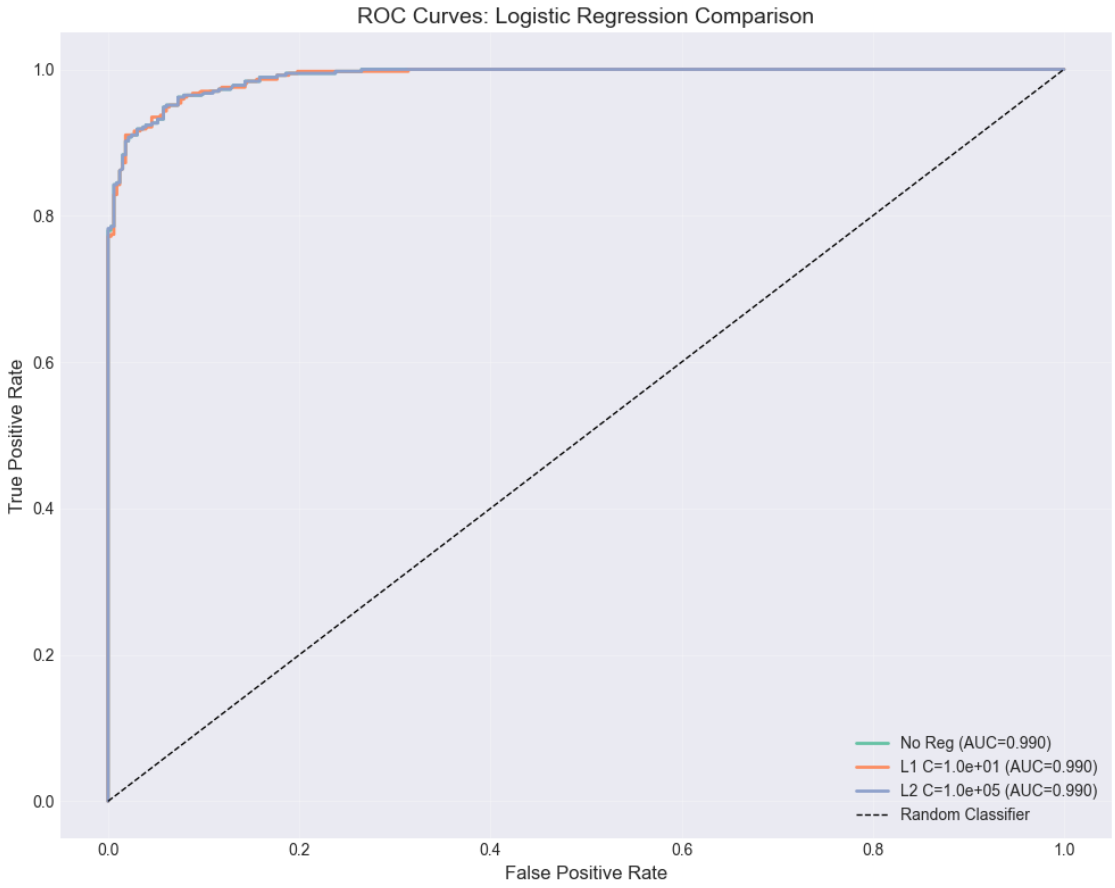
```
results_no_reg = {
    'penalty': 'none',
    'best_C': 1e15,
    'y_scores': y_scores_no_reg,
    'accuracy': accuracy_no_reg,
    'precision': precision_no_reg,
    'recall': recall_no_reg,
    'f1': f1_no_reg,
    'gamma': 1e-15
}

print("\n")

# Train L1 and L2 models
results_l1 = train_and_evaluate_logreg(
    lsi_tfidf_lemma_train, y_train,
    lsi_tfidf_lemma_test, y_test,
    penalty='l1',
    C_range=C_range,
    kfold=kfold
)
results_l1['gamma'] = 1.0 / results_l1['best_C']

print("\n")

results_l2 = train_and_evaluate_logreg(
    lsi_tfidf_lemma_train, y_train,
    lsi_tfidf_lemma_test, y_test,
    penalty='l2',
    C_range=C_range,
    kfold=kfold
)
results_l2['gamma'] = 1.0 / results_l2['best_C']

#Make Comparison table
print("Comparing: No Reg vs L1 vs L2")
print(f"{'Metric':<15} {'No Reg':<12} {'L1':<12} {'L2':<12}")
print("-" * 50)
print(f"{'Best C':<15} {'1e10':<12} {results_l1['best_C']:<12.1e}␣
 ↪{results_l2['best_C']:<12.1e}")
print(f"{'Accuracy':<15} {results_no_reg['accuracy']:<12.4f}␣
 ↪{results_l1['accuracy']:<12.4f} {results_l2['accuracy']:<12.4f}")
print(f"{'Precision':<15} {results_no_reg['precision']:<12.4f}␣
 ↪{results_l1['precision']:<12.4f} {results_l2['precision']:<12.4f}")
print(f"{'Recall':<15} {results_no_reg['recall']:<12.4f} {results_l1['recall']:
 ↪<12.4f} {results_l2['recall']:<12.4f}")
```

```
print(f"{'F1-Score':<15} {results_no_reg['f1']:<12.4f} {results_l1['f1']:<12.
 ↪4f} {results_l2['f1']:<12.4f}")

#ROC Curves
def plot_roc_curve_logreg(results_list, y_test, title):
    plt.figure(figsize=(10, 8))

    if isinstance(y_test.iloc[0], str):
        y_test_binary = (y_test == 'sports').astype(int)
    else:
        y_test_binary = y_test

    for result in results_list:
        # Compute ROC curve
        fpr, tpr, thresholds = roc_curve(y_test_binary, result['y_scores'])
        roc_auc = auc(fpr, tpr)
        if result['penalty'] == 'none':
            label = f"No Reg (AUC={roc_auc:.3f})"
        else:
            label = f"{result['penalty'].upper()} C={result['best_C']:.1e}␣
 ↪(AUC={roc_auc:.3f})"

        plt.plot(fpr, tpr, linewidth=2, label=label)

    # Plot diagonal
    plt.plot([0, 1], [0, 1], 'k--', linewidth=1, label='Random Classifier')

    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(title, fontsize=14)
    plt.legend(loc='lower right', fontsize=10)
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()

# Plot all three
plot_roc_curve_logreg(
    [results_no_reg, results_l1, results_l2],
    y_test,
    'ROC Curves: Logistic Regression Comparison'
)
```

```
Training No Regularization model…

No Regularization Test Set Results:
Accuracy:  0.9454
Precision: 0.9484
```

```
Recall:    0.9484
F1-Score:  0.9484

Confusion Matrix:
[[309  19]
 [ 19 349]]


Using L1 Regularization
C =  1.0e-05 | CV Accuracy: 0.5029
C =  1.0e-04 | CV Accuracy: 0.5029
C =  1.0e-03 | CV Accuracy: 0.5029
C =  1.0e-02 | CV Accuracy: 0.5029
C =  1.0e-01 | CV Accuracy: 0.9252
C =  1.0e+00 | CV Accuracy: 0.9363
C =  1.0e+01 | CV Accuracy: 0.9486
C =  1.0e+02 | CV Accuracy: 0.9486
C =  1.0e+03 | CV Accuracy: 0.9486
C =  1.0e+04 | CV Accuracy: 0.9486
C =  1.0e+05 | CV Accuracy: 0.9486

Best C for L1 = 10 with CV Accuracy = 0.9486

Training final L1 model with C = 10…

L1 Test Set Results:
Accuracy:  0.9440
Precision: 0.9458
Recall:    0.9484
F1-Score:  0.9471

Confusion Matrix:
[[308  20]
 [ 19 349]]


Using L2 Regularization
C =  1.0e-05 | CV Accuracy: 0.4698
C =  1.0e-04 | CV Accuracy: 0.4712
C =  1.0e-03 | CV Accuracy: 0.6277
C =  1.0e-02 | CV Accuracy: 0.9029
C =  1.0e-01 | CV Accuracy: 0.9306
C =  1.0e+00 | CV Accuracy: 0.9363
C =  1.0e+01 | CV Accuracy: 0.9403
C =  1.0e+02 | CV Accuracy: 0.9475
C =  1.0e+03 | CV Accuracy: 0.9493
C =  1.0e+04 | CV Accuracy: 0.9493
C =  1.0e+05 | CV Accuracy: 0.9496
```

```
Best C for L2 = 100000 with CV Accuracy = 0.9496

Training final L2 model with C = 100000…

L2 Test Set Results:
Accuracy:  0.9454
Precision: 0.9484
Recall:    0.9484
F1-Score:  0.9484

Confusion Matrix:
[[309  19]
 [ 19 349]]
Comparing: No Reg vs L1 vs L2
Metric          No Reg       L1           L2
--------------------------------------------------
Best C          1e10         1.0e+01      1.0e+05
Accuracy        0.9454       0.9440       0.9454
Precision       0.9484       0.9458       0.9484
Recall          0.9484       0.9484       0.9484
F1-Score        0.9484       0.9471       0.9484
```



[21]:
```
# Get coefficients from each model
coef_no_reg = clf_no_reg.coef_[0]
coef_l1 = results_l1['model'].coef_[0]
coef_l2 = results_l2['model'].coef_[0]

# Analyze coefficient properties
print(f"{'Model':<12} {'Non-zero':<12} {'Max':<12} {'L2 Norm':<12}")
print("-" * 60)
print(f"{'No Reg':<12} {np.sum(coef_no_reg != 0):<12} {np.max(np.
  ↪abs(coef_no_reg)):<12.4f} {np.linalg.norm(coef_no_reg):<12.4f}")
print(f"{'L1':<12} {np.sum(coef_l1 != 0):<12} {np.max(np.abs(coef_l1)):<12.4f}␣
  ↪{np.linalg.norm(coef_l1):<12.4f}")
print(f"{'L2':<12} {np.sum(coef_l2 != 0):<12} {np.max(np.abs(coef_l2)):<12.4f}␣
  ↪{np.linalg.norm(coef_l2):<12.4f}")
```

```
Model        Non-zero     Max          L2 Norm
------------------------------------------------------------
No Reg       25           44.7638      88.1104
L1           21           44.1342      77.7897
L2           25           44.7416      88.0698
```

1.9.1 Analysis

- No regularization model: Very weak regularization allows the model to fit training data closely. Possibly prone to overfitting but performance is strong on this test set. (accuracy 0.9454)
- L1 Regularization: Optimial C is low (C=10). Lower C means stronger regularization, but model has slightly lower test accuracy (0.9440).
- L2 Regularization: Optimal C is high (C=100000). Higher C means weaker regularization. Nearly identical performance to no regularization (accuracy 0.9454).

As regularization strength increases (C decreases), we see a U-shaped error curve: -No (Very weak) regularization (C=1e15): slight risk of overfitting but still performs well -Moderate regularization (C=10-100,000): optimal performance -Very strong regularization (C=0.0001): underfitting / low accuracy

How are the learned coefficients affected?

The learned coefficients show: - No reg (C=1e15) results in L2 Norm of 88.11 and maximum coefficient magnitude 44.76 - L1 regularization (C=10) results in L2 norm 88.06 and maximum coefficient magnitude 44.13 - L2 regularization (C=10,000) produces similar L2 norm 88.06 and maximum magnitude 44.74 to the unregularized model - On this test, L1 has 21/25 nozero coefficients while No Reg and L2 have 25/25 non-zero coefficients

This page helped me understand L1 vs L2 regularization conceptually. Both L1 and L2 regularization address the multicollinearity problem (where two or more independent variables are highly correlated) differently. L1 can potentially result in some coefficients going to 0 resulting in a sparse

vector if that is desired. Because of this, it can also be used as a feature selection method if you have to limit how many features you can use. Note that, in the coefficient table I printed, L1 is the only regularization method with some 0 coefficients. L2 regularization helps with multicollinearity by keeping all variables but putting constraints on the coefficient norm but does not frequently fully zero out coefficients. Note that, in our data L2 has no zero coefficients and also has smalled L2 norm. Importantly, L2 regularization can estimate a coefficient for each feature even if there are more features than observations.

SVM vs Logistic Regression: Decision Boundary Differences Both logistic regression and linear SVM find a linear decision boundary to separate classes, but they optimize different objectives. Logistic regression minimizes log-loss (cross-entropy) and cares about all data points. Meanwhile, linear SVM minimizes hinge loss and focuses primarily on maximizing the margin between classes, caring mainly about support vectors near the decision boundary and ignoring points far from the margin. In this project, the best SVM and the Logistic Regression models achieved similar performance accuracy. This suggests our data is linearly seperable. The small differences in accuracy (<1%) are not statistically signifigant.

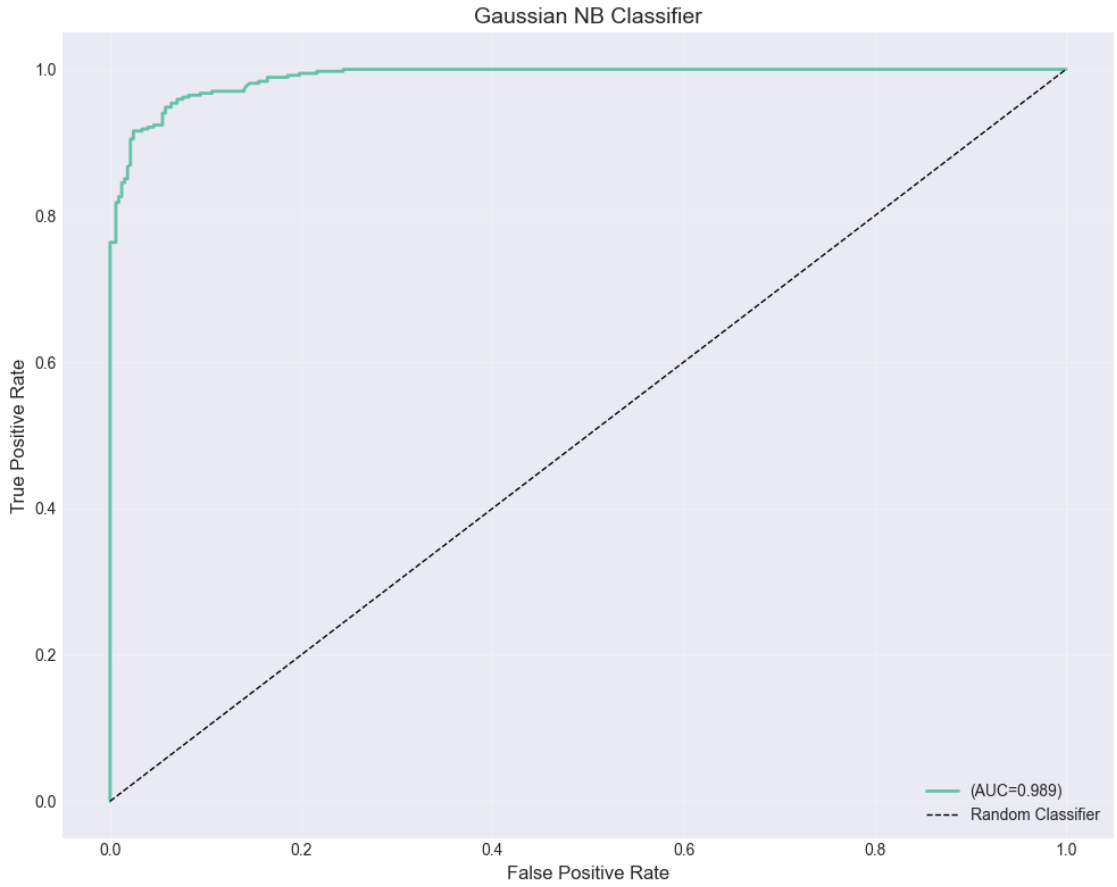
1.10 Question 10 - Naive Bayes

In this section I train and evaluate a GaussianNB classifier.

[22]:
```
from sklearn.naive_bayes import GaussianNB

def train_gnb(x_train, y_train, x_test, y_test):
    #train gaussian nb classifier
    gnb = GaussianNB()
    gnb.fit(lsi_tfidf_lemma_train, y_train)
    y_pred = gnb.predict(x_test)
    #for ROC curve
    y_scores = gnb.predict_proba(x_test)[:, 1]

    #metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, pos_label='sports')
    recall = recall_score(y_test, y_pred, pos_label='sports')
    f1 = f1_score(y_test, y_pred, pos_label='sports')

    conf_matrix = confusion_matrix(y_test, y_pred)

    print(f"\nResults for Gaussian NB Classifier")
    print(f"Accuracy:  {accuracy:.4f}")
    print(f"Precision: {precision:.4f}")
    print(f"Recall:    {recall:.4f}")
    print(f"F1-Score:  {f1:.4f}")
    print(f"Confusion Matrix:")
    print(conf_matrix)

    return {
```

```
        'y_pred': y_pred,
        'y_scores': y_scores,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'confusion_matrix': conf_matrix,
    }

results_gnb = train_gnb(lsi_tfidf_lemma_train, y_train, lsi_tfidf_lemma_test,␣
 ↪y_test)

#Plot
plt.figure(figsize=(10, 8))
plt.plot(fpr, tpr, linewidth=2, label=f'(AUC={roc_auc:.3f})')
plt.plot([0, 1], [0, 1], 'k--', linewidth=1, label='Random Classifier')
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title(f'Gaussian NB Classifier', fontsize=14)
plt.legend(loc='lower right', fontsize=10)
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```

```
Results for Gaussian NB Classifier
Accuracy:  0.9052
Precision: 0.8665
Recall:    0.9701
F1-Score:  0.9154
Confusion Matrix:
[[273  55]
 [ 11 357]]
```



1.11 Question 11 - Grid Search

In this section, I use grid search to find the best model and the best hyperparmeters.

[23]:
```
from sklearn.model_selection import GridSearchCV
# used to cache results
from tempfile import mkdtemp
from shutil import rmtree
from joblib import Memory
import os
import pickle
# print(__doc__)

warnings.filterwarnings('ignore', message='Your stop_words may be inconsistent')
warnings.filterwarnings('ignore', message='The parameter \'token_pattern\' will␣
 ↪not be used')
# Define pickle file path
PICKLE_FILE = 'gridsearch_results.pkl'
cachedir = mkdtemp()
```

```
memory = Memory(location=cachedir, verbose=0)
MIN_DF_OPTIONS = [2,5]
TOKENIZER_OPTIONS = [StemTokenizer(), LemmaTokenizer()]
N_FEATURES_OPTIONS = [5,30,100]
C_OPTIONS = [0.1, 1, 10]
pipeline = Pipeline([
    ('vect', CountVectorizer(
        tokenizer=StemTokenizer(),
        stop_words='english',
        min_df=2
    )),
    ('tfidf', TfidfTransformer()),
    ('reduce_dim', TruncatedSVD(random_state=0)),
    ('clf', GaussianNB()),
],
memory=memory
)
# Check if pickle file exists
if os.path.exists(PICKLE_FILE):
    print(f"Loading existing GridSearch results from {PICKLE_FILE}...")
    with open(PICKLE_FILE, 'rb') as f:
        grid = pickle.load(f)
    print("GridSearch results loaded successfully!")

else:
    print("No existing results found. Running GridSearch...")
    param_grid = [
        {
            'vect__tokenizer': TOKENIZER_OPTIONS, # 2 choices
            'vect__min_df': MIN_DF_OPTIONS, # 2 choices
            'reduce_dim': [TruncatedSVD(), NMF()], # 2 choices
            'reduce_dim__n_components': N_FEATURES_OPTIONS, # 3 choices
            'clf': [LinearSVC()], # 1 choice
            'clf__C': [100] # b/c best gamma was 0.01 and C=1.0/gamma
            # 9 choices
        },
        {
            'vect__tokenizer': TOKENIZER_OPTIONS, # 2 choices
            'vect__min_df': MIN_DF_OPTIONS, # 2 choices
            'reduce_dim': [TruncatedSVD(), NMF()], # 2 choices
            'reduce_dim__n_components': N_FEATURES_OPTIONS, # 3 choices
            'clf': [LogisticRegression(solver='liblinear')], # 1 choice
            'clf__penalty': ["l1"], # 1 choice
            'clf__C': [10] #1 choice of best regularization from before
            # 9 choices
        },
        {
```

```
            'vect__tokenizer': TOKENIZER_OPTIONS, # 2 choices
            'vect__min_df': MIN_DF_OPTIONS, # 2 choices
            'reduce_dim': [TruncatedSVD(), NMF()], # 2 choices
            'reduce_dim__n_components': N_FEATURES_OPTIONS, # 3 choices
            'clf': [LogisticRegression(solver= 'lbfgs')], # 1 choice
            'clf__penalty': ["l2"], # 1 choice
            'clf__C': [100000] #1 choice of best regularization from before
            # 9 choices
        },
        {
            'vect__tokenizer': TOKENIZER_OPTIONS, # 2 choices
            'vect__min_df': MIN_DF_OPTIONS, # 2 choices
            'reduce_dim': [TruncatedSVD(), NMF()], # 2 choices
            'reduce_dim__n_components': N_FEATURES_OPTIONS, # 3 choices
            'clf': [GaussianNB()]
            # 9 choices
        },
    ]
    print("Starting GridSearch (this may take a while)...")
    grid = GridSearchCV(pipeline, cv=5, n_jobs=1, param_grid=param_grid,␣
↪scoring='accuracy', verbose=1) #verbose to get prints
    grid.fit(train['full_text_cleaned'], train['root_label']) #using cleaned␣
↪data from earlier
    print(f"\nSaving GridSearch results to {PICKLE_FILE}...")
    with open(PICKLE_FILE, 'wb') as f:
        pickle.dump(grid, f)
    print("Results saved successfully!")
    rmtree(cachedir)
```

```
Loading existing GridSearch results from gridsearch_results.pkl…
GridSearch results loaded successfully!
```

[24]:
```
# Get top 5 combinations from CV
results_df = pd.DataFrame(grid.cv_results_)
top_5 = results_df['rank_test_score'].nlargest(5, keep='first').index
print("\nTop 5 Combinations (from CV)")
for i, idx in enumerate(top_5, 1):
    params = results_df.loc[idx, 'params']
    cv_score = results_df.loc[idx, 'mean_test_score']

    print(f"\nCombination {i}")
    print(f"Parameters: {params}")
    print(f"CV Accuracy: {cv_score:.4f}")

    model = pipeline.set_params(**params)
    model.fit(train['full_text_cleaned'], train['root_label'])
    y_pred = model.predict(test['full_text_cleaned'])
```

```
    print(f"\nTest Set Performance:")
    print(f"Accuracy: {accuracy_score(test['root_label'], y_pred):.4f}")
    print(f"Precision: {precision_score(test['root_label'], y_pred,␣
↪pos_label='sports'):.4f}")
    print(f"Recall: {recall_score(test['root_label'], y_pred,␣
↪pos_label='sports'):.4f}")
    print(f"F1-Score: {f1_score(test['root_label'], y_pred, pos_label='sports'):
↪.4f}")
```

```
Top 5 Combinations (from CV)

Combination 1
Parameters: {'clf': GaussianNB(), 'reduce_dim': TruncatedSVD(),
'reduce_dim__n_components': 5, 'vect__min_df': 2, 'vect__tokenizer':
<__main__.LemmaTokenizer object at 0x00000282DEE97F40>}
CV Accuracy: 0.8478

Test Set Performance:
Accuracy: 0.8190
Precision: 0.7500
Recall: 0.9864
F1-Score: 0.8521

Combination 2
Parameters: {'clf': GaussianNB(), 'reduce_dim': TruncatedSVD(n_components=5),
'reduce_dim__n_components': 5, 'vect__min_df': 5, 'vect__tokenizer':
<__main__.LemmaTokenizer object at 0x00000282DEE97F40>}
CV Accuracy: 0.8683

Test Set Performance:
Accuracy: 0.8448
Precision: 0.7790
Recall: 0.9864
F1-Score: 0.8705

Combination 3
Parameters: {'clf': GaussianNB(), 'reduce_dim': TruncatedSVD(n_components=5),
'reduce_dim__n_components': 5, 'vect__min_df': 2, 'vect__tokenizer':
<__main__.StemTokenizer object at 0x00000282DEE97AC0>}
CV Accuracy: 0.8784

Test Set Performance:
Accuracy: 0.8563
Precision: 0.7939
Recall: 0.9837
```

```
F1-Score: 0.8786

Combination 4
Parameters: {'clf': GaussianNB(), 'reduce_dim': TruncatedSVD(n_components=5),
'reduce_dim__n_components': 30, 'vect__min_df': 2, 'vect__tokenizer':
<__main__.LemmaTokenizer object at 0x00000282DEE97F40>}
CV Accuracy: 0.8910

Test Set Performance:
Accuracy: 0.9023
Precision: 0.8606
Recall: 0.9728
F1-Score: 0.9133

Combination 5
Parameters: {'clf': GaussianNB(), 'reduce_dim': TruncatedSVD(n_components=30),
'reduce_dim__n_components': 5, 'vect__min_df': 5, 'vect__tokenizer':
<__main__.StemTokenizer object at 0x00000282DEE97AC0>}
CV Accuracy: 0.8921

Test Set Performance:
Accuracy: 0.8779
Precision: 0.8209
Recall: 0.9837
F1-Score: 0.8949
```

1.12 Question 12 - Comparing TF-IDF and Pretrained Embeddings

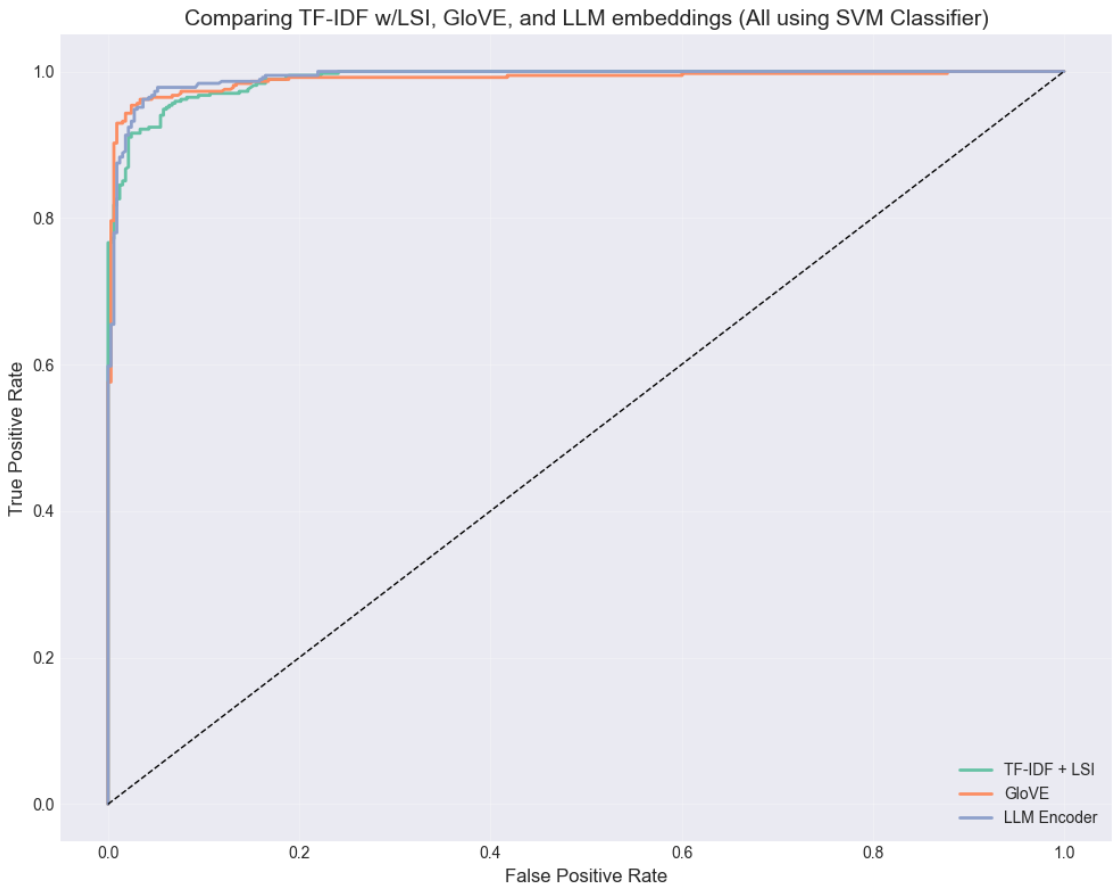
Now I will compare whether TF-IDF or pretrained embeddings perform better when the classifier is fixed.

[25]:
```
#Make use of previosuly saved lsi_tdidf, glove_emb, and transformer matrices.
#Train and test an SVM classifier on them to compare. Hold gamma at 0.01 to␣
 ↪"keep it fixed"
print("\nTF-IDF + LSI:")
results_svm_tfidf_lsi = train_svm(lsi_tfidf_lemma_train, y_train,␣
 ↪lsi_tfidf_lemma_test, y_test, gamma=0.01)
print("\nGlove:")
results_svm_glove = train_svm(train_glove_emb, y_train, test_glove_emb, y_test,␣
 ↪gamma=0.01)
print("\nLLM:")
results_svm_transformer = train_svm(train_transformer, y_train,␣
 ↪test_transformer, y_test, gamma=0.01)

def compare_embed_roc_curve(results_list, label_list, y_test, title):
    plt.figure(figsize=(10, 8))
    if isinstance(y_test.iloc[0], str):
```

```
        y_test_binary = (y_test == 'sports').astype(int)
    else:
        y_test_binary = y_test

    for i in range(len(results_list)):
        # Compute ROC curve
        fpr, tpr, thresholds = roc_curve(y_test_binary,␣
 ↪results_list[i]['y_scores'])
        roc_auc = auc(fpr, tpr)

        # Plot
        label = label_list[i]
        plt.plot(fpr, tpr, linewidth=2, label=label)

    # Plot diagonal
    plt.plot([0, 1], [0, 1], 'k--', linewidth=1)

    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(title, fontsize=14)
    plt.legend(loc='lower right', fontsize=10)
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.show()

labels = ["TF-IDF + LSI", "GloVE", "LLM Encoder"]
plot_title = "Comparing TF-IDF w/LSI, GloVE, and LLM embeddings (All using SVM␣
 ↪Classifier)"
compare_embed_roc_curve([results_svm_tfidf_lsi, results_svm_glove,␣
 ↪results_svm_transformer], labels, y_test, plot_title)
```

```
TF-IDF + LSI:

Results for SVM where:   = 0.01 (C = 100.0)
Accuracy:  0.9454
Precision: 0.9484
Recall:    0.9484
F1-Score:  0.9484
Confusion Matrix:
[[309  19]
 [ 19 349]]

Glove:

Results for SVM where:   = 0.01 (C = 100.0)
Accuracy:  0.9612
```

```
Precision: 0.9776
Recall:    0.9484
F1-Score:  0.9628
Confusion Matrix:
[[320   8]
 [ 19 349]]

LLM:

Results for SVM where:   = 0.01 (C = 100.0)
Accuracy:  0.9583
Precision: 0.9748
Recall:    0.9457
F1-Score:  0.9600
Confusion Matrix:
[[319   9]
 [ 20 348]]
```



1.12.1 Interpretation

GloVe performs best (96.12% accuracy), followed closely by LLM (95.83%), with TF-IDF + LSI trailing slightly (94.54%). However, these differences are relatively small (only ~1.6% separating best from worst).

Most notably, GloVE and LLM have a smaller false positive rate. TF-IDF has 19 false psoitives while GloVe has 8 and LLM has 9. (All three methods have similar false negative rates).

Glove achieves a better false positive rate than TF-IDF because GloVe captures word co-occurrence patterns that help it differentiate sports terminology from climate terminology. The average Glove OOV rate was 1.34% (from Q5), which is low, so we know GloVE was able to leverage its pretrained semantic knowledge when developing the embeddings.

LLM performs similarly to GloVE, which suggests that for this simple binary classification task, word level semantic knowledge is as effective as the LLM's contextual understanding. Since the two topics in this class have pretty different vocabularies (sports: "football", "touchdown", "dunk" and climate: "rain", "storm", "flooding"), its likely that contextualization does not bring as much improvement. Contextualization might make more of a difference if there was more overlap in the vocabularies or other kinds of ambiguity.

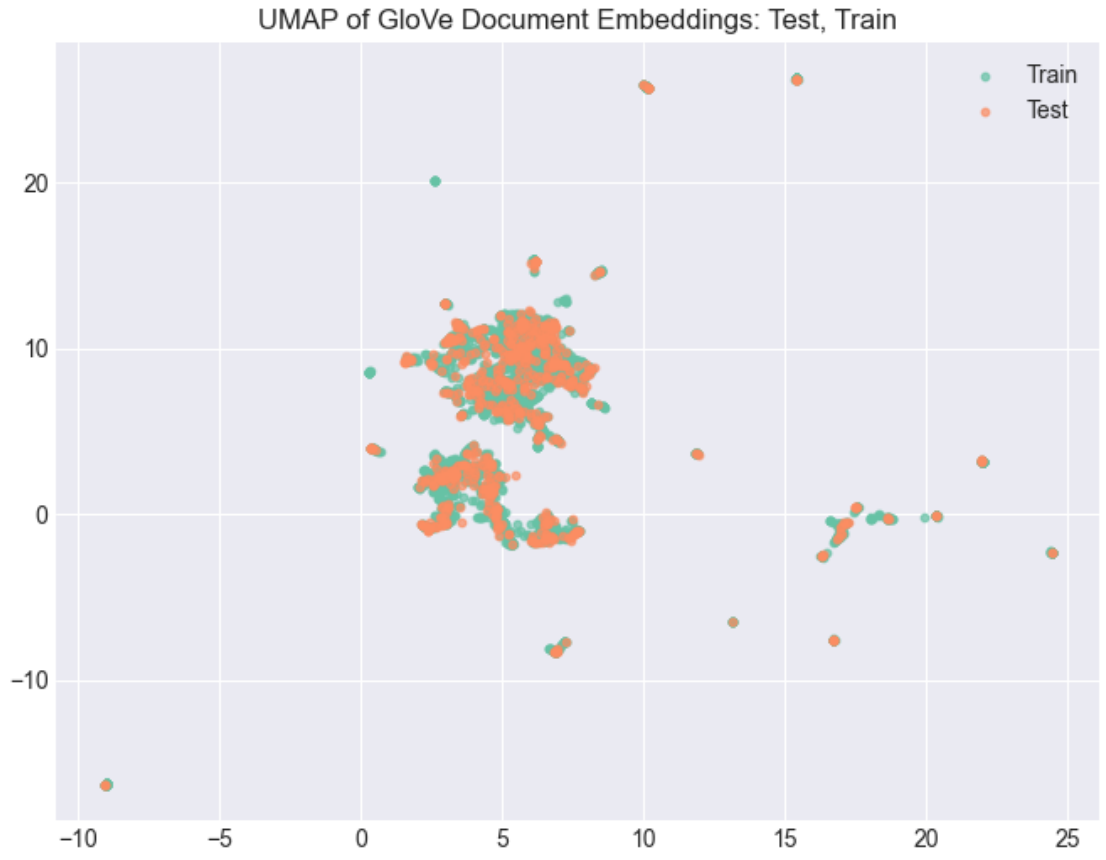
1.13 Question 13 - Comparing UMAP Visualization

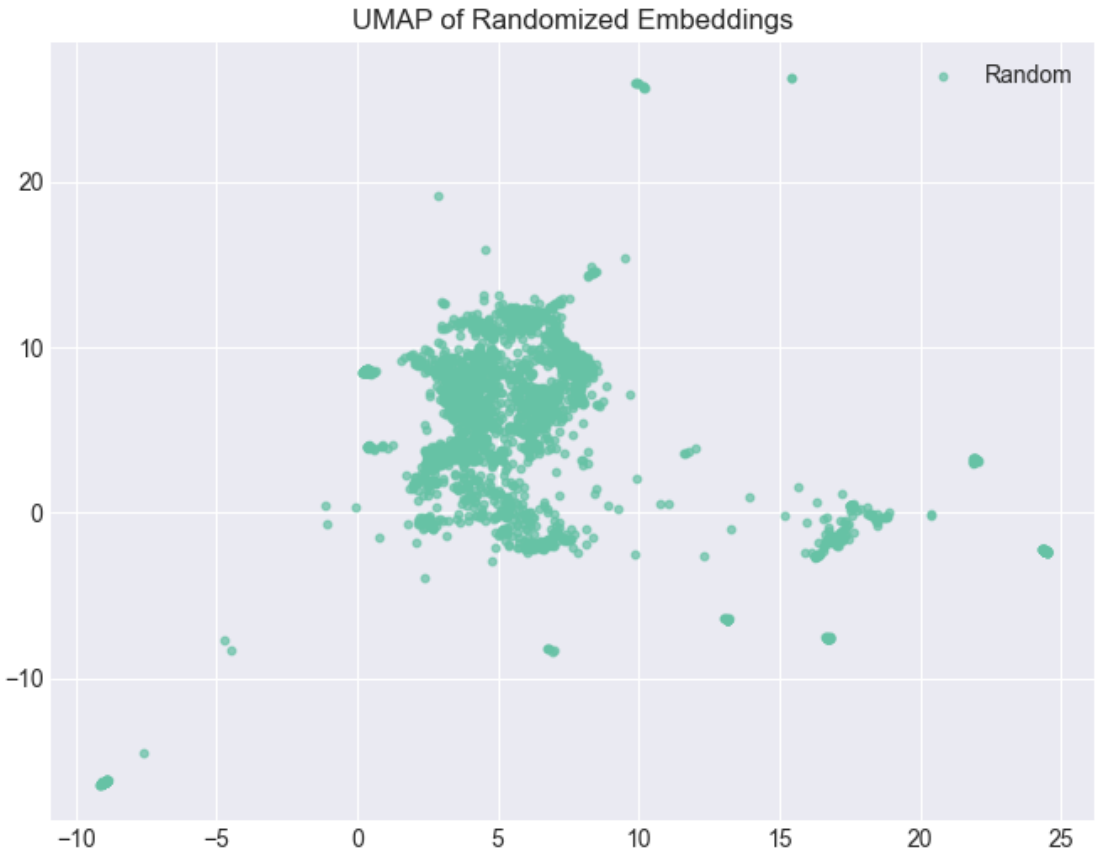
I will leverage UMAP in order to compare a 2D representation of GLoVE document embeddings vs random embeddings

[26]:
```
import umap
#use umap to represent vectors in 2d
reducer = umap.UMAP(
    n_neighbors=15,
    min_dist=0.1,
    n_components=2,
    metric="cosine",
    random_state=42
)

train_2d_umap = reducer.fit_transform(train_glove_emb)
test_2d_umap = reducer.transform(test_glove_emb)

rng = np.random.default_rng(42)
random_emb = rng.normal(
    loc=0.0,
    scale=1.0,
    size=(2780, 300)
)
random_2d_umap = reducer.transform(random_emb)

plt.figure(figsize=(8, 6))
plt.scatter(train_2d_umap[:, 0], train_2d_umap[:, 1], s=10, label="Train",␣
 ↪alpha=0.7)
```

```
plt.scatter(test_2d_umap[:, 0], test_2d_umap[:, 1], s=10, label="Test", alpha=0.
  ↪7)
plt.legend()
plt.title("UMAP of GloVe Document Embeddings: Test, Train")

plt.figure(figsize=(8, 6))
plt.scatter(random_2d_umap[:, 0], random_2d_umap[:, 1], s=10, alpha=0.7,␣
  ↪label="Random")
plt.legend()
plt.title("UMAP of Randomized Embeddings")
plt.show()
```

```
C:\Users\jilli\.conda\envs\ece219\lib\site-packages\umap\umap_.py:1952:
UserWarning: n_jobs value 1 overridden to 1 by setting random_state. Use no seed
for parallelism.
  warn(
```





Above, we see that the randomized embeddings graph has a similar shape to the Glove Document Embeddings graph, but the Glove Document Embeddings graph has approximately 3 clusters that are more obvious/ tightly-formed than the randomized embeddings, which only has two loosely-formed clusters.

1.14 Question 14 - Multiclass Classification

Now we move to a multiclass classification problem where I aim to learn classifiers for the 10 classes in leaf_label.

[27]:
```
from sklearn.multiclass import OneVsOneClassifier
from sklearn.multiclass import OneVsRestClassifier


def train_multiclass_nb(nb, x_train, y_train, x_test, y_test):
    nb.fit(x_train, y_train)
    y_pred = nb.predict(x_test)
    y_scores = nb.predict_proba(x_test)

    #metrics with macro averaging
```

```
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='macro')
    recall = recall_score(y_test, y_pred, average='macro')
    f1 = f1_score(y_test, y_pred, average='macro')

    #confusion matrix
    label_order = ["basketball", "baseball", "tennis", "football", "soccer",
                   "forest fire", "flood", "earthquake", "drought", "heatwave"]
    labels_in_data = [label for label in label_order if label in y_test.values]

    conf_matrix = confusion_matrix(y_test, y_pred, labels=labels_in_data)

    print(f"\nResults for Gaussian NB Classifier (Multiclass)")
    print(f"Accuracy:  {accuracy:.4f}")
    print(f"Precision (macro): {precision:.4f}")
    print(f"Recall (macro):    {recall:.4f}")
    print(f"F1-Score (macro):  {f1:.4f}")
    print(f"Confusion Matrix (10x10):")
    print(conf_matrix)

    return {
        'y_pred': y_pred,
        'y_scores': y_scores,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'confusion_matrix': conf_matrix,
    }


def train_svm_ovo(wrap_classifier, x_train, y_train, x_test, y_test, gamma,␣
 ↪balance = False):
    c = 1.0 / gamma
    if balance:
        base_svm = LinearSVC(loss='hinge', class_weight='balanced', C=c,␣
 ↪random_state=42, max_iter=10000)
    else:
        base_svm = LinearSVC(loss='hinge', C=c, random_state=42, max_iter=10000)
    if wrap_classifier == "OVO":
        svm_with_wrapper = OneVsOneClassifier(base_svm)
    else:
        svm_with_wrapper = OneVsRestClassifier(base_svm)
    svm_with_wrapper.fit(x_train, y_train)

    y_pred = svm_with_wrapper.predict(x_test)
    y_scores = svm_with_wrapper.decision_function(x_test)
```

```
    # Metrics with macro averaging for multiclass
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='macro')
    recall = recall_score(y_test, y_pred, average='macro')
    f1 = f1_score(y_test, y_pred, average='macro')

    #confusion matrix
    label_order = ["basketball", "baseball", "tennis", "football", "soccer",
                   "forest fire", "flood", "earthquake", "drought", "heatwave"]
    labels_in_data = [label for label in label_order if label in y_test.values]

    conf_matrix = confusion_matrix(y_test, y_pred, labels=labels_in_data)

    print(f"\nResults for SVM {wrap_classifier} where:   = {gamma} (C = {c})")
    print(f"Accuracy:  {accuracy:.4f}")
    print(f"Precision (macro): {precision:.4f}")
    print(f"Recall (macro):    {recall:.4f}")
    print(f"F1-Score (macro):  {f1:.4f}")
    print(f"Confusion Matrix ({len(labels_in_data)}x{len(labels_in_data)}):")
    print(conf_matrix)

    return {
        'y_pred': y_pred,
        'y_scores': y_scores,
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1': f1,
        'confusion_matrix': conf_matrix,
        'gamma': gamma,
        'C': c,
        'labels': labels_in_data
    }
```

[28]:
```
#Using GaussianNB as Tf-IDF+LSI, Glove, and Transformer embeddings are dense
y_train_multi = train["leaf_label"]
y_test_multi = test["leaf_label"]
print("\n*****************************")
print("USING TF-IDF + LSI WITH k=25")
print("*****************************")
multi_nb=train_multiclass_nb(GaussianNB(), lsi_tfidf_lemma_train,␣
 ↪y_train_multi, lsi_tfidf_lemma_test, y_test_multi)
multi_svm_ovo=train_svm_ovo("OVO", lsi_tfidf_lemma_train, y_train_multi,␣
 ↪lsi_tfidf_lemma_test, y_test_multi, gamma=0.01)
multi_svm_ovo=train_svm_ovo("OVR", lsi_tfidf_lemma_train, y_train_multi,␣
 ↪lsi_tfidf_lemma_test, y_test_multi, gamma=0.01)
```

```
print("\n*****************************")
print("USING GLOVE EMBEDDINGS")
print("*****************************")
multi_nb=train_multiclass_nb(GaussianNB(), train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi)
multi_svm_ovo=train_svm_ovo("OVO", train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi, gamma=0.01)
multi_svm_ovo=train_svm_ovo("OVR", train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi, gamma=0.01)
print("\n*****************************")
print("USING LLM EMBEDDINGS")
print("*****************************")
multi_nb=train_multiclass_nb(GaussianNB(), train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi)
multi_svm_ovo=train_svm_ovo("OVO", train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi, gamma=0.01)
multi_svm_ovo=train_svm_ovo("OVR", train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi, gamma=0.01)
```

```
*****************************
USING TF-IDF + LSI WITH k=25
*****************************

Results for Gaussian NB Classifier (Multiclass)
Accuracy:  0.6566
Precision (macro): 0.7045
Recall (macro):    0.6605
F1-Score (macro):  0.6709
Confusion Matrix (10x10):
[[70  9 10  1  0  0  0  0  0  0]
 [ 1 37 29  2  0  0  2  0  0  4]
 [ 0  6 57  1  3  0  2  0  0  0]
 [ 0  6  4 49  1  0  0  0  0  1]
 [ 0  5  9  3 55  0  0  0  0  1]
 [ 0  4  9  0  1 20  0  0  6 33]
 [ 0  0  1  0  0  5 55  0  0  5]
 [ 0  1  9  0  0  0  0 43  0  1]
 [ 0  1  3  0  0  1  0  0 54  9]
 [ 0  3 12  0  0 30  3  0  2 17]]

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.7471
Precision (macro): 0.7558
Recall (macro):    0.7491
F1-Score (macro):  0.7509
Confusion Matrix (10x10):
```

```
[[82  4  4  0  0  0  0  0  0  0]
 [ 2 58  6  1  0  4  1  0  0  3]
 [ 0 11 52  0  3  1  1  0  0  1]
 [ 0  2  0 57  2  0  0  0  0  0]
 [ 0  2  7  1 63  0  0  0  0  0]
 [ 0  1  3  0  0 18  0  2  4 45]
 [ 0  1  0  0  0  4 60  0  0  1]
 [ 0  2  2  0  0  0  0 48  0  2]
 [ 0  2  0  0  0  0  0  1 60  5]
 [ 0  3  5  0  0 32  3  0  2 22]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.7428
Precision (macro): 0.7359
Recall (macro):    0.7455
F1-Score (macro):  0.7388
Confusion Matrix (10x10):
[[82  2  1  2  0  3  0  0  0  0]
 [ 5 53  2  2  2  4  3  0  3  1]
 [ 0  7 44  0  7  8  2  0  0  1]
 [ 0  1  0 58  1  1  0  0  0  0]
 [ 0  2  1  2 65  2  0  0  0  1]
 [ 0  3  5  0  2 23  1  1  9 29]
 [ 0  1  0  0  0  0 64  0  1  0]
 [ 0  0  0  1  0  1  0 49  1  2]
 [ 0  2  0  0  0  2  0  0 61  3]
 [ 1  5  5  1  1 28  2  1  5 18]]

****************************
USING GLOVE EMBEDDINGS
****************************

Results for Gaussian NB Classifier (Multiclass)
Accuracy:  0.6494
Precision (macro): 0.6589
Recall (macro):    0.6499
F1-Score (macro):  0.6498
Confusion Matrix (10x10):
[[76  2  7  3  0  2  0  0  0  0]
 [12 46  6  0  2  6  1  0  0  2]
 [ 5  8 42  0  9  3  0  0  0  2]
 [ 5  2  3 47  3  1  0  0  0  0]
 [ 4  7  5  3 54  0  0  0  0  0]
 [ 0  2  7  0  0 15  6  0 17 26]
 [ 0  3  0  0  0  3 52  0  5  3]
 [ 0  3  4  0  0  3  0 42  0  2]
 [ 0  1  2  0  0  3  1  0 58  3]
 [ 0  5  8  0  0 22  3  0  9 20]]
```

```
Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.7399
Precision (macro): 0.7540
Recall (macro):    0.7403
F1-Score (macro):  0.7465
Confusion Matrix (10x10):
[[84  0  2  2  1  1  0  0  0  0]
 [ 2 57  4  3  1  3  2  0  1  2]
 [ 2  6 56  0  0  2  2  0  0  1]
 [ 1  1  0 56  2  0  0  1  0  0]
 [ 0  2  2  4 65  0  0  0  0  0]
 [ 0  1  0  0  0 17  0  1  4 50]
 [ 0  1  0  0  0  3 59  0  2  1]
 [ 0  1  0  0  1  2  1 47  0  2]
 [ 0  2  1  0  0  2  1  0 57  5]
 [ 0  1  0  0  0 46  1  1  1 17]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.7644
Precision (macro): 0.7472
Recall (macro):    0.7652
F1-Score (macro):  0.7550
Confusion Matrix (10x10):
[[87  0  0  2  0  0  1  0  0  0]
 [ 1 60  5  3  0  0  2  2  2  0]
 [ 3  5 57  1  0  1  0  1  0  1]
 [ 2  0  0 58  1  0  0  0  0  0]
 [ 0  3  3  3 64  0  0  0  0  0]
 [ 0  3  0  0  3 24  0  2  5 36]
 [ 0  2  1  0  0  0 59  1  2  1]
 [ 0  1  0  0  1  0  0 52  0  0]
 [ 0  1  0  0  0  2  1  0 62  2]
 [ 0  2  0  1  2 48  1  3  1  9]]

**************************
USING LLM EMBEDDINGS
**************************

Results for Gaussian NB Classifier (Multiclass)
Accuracy:  0.7126
Precision (macro): 0.7341
Recall (macro):    0.7119
F1-Score (macro):  0.7206
Confusion Matrix (10x10):
[[80  2  6  1  1  0  0  0  0  0]
 [ 1 59  1  3  0  4  1  0  1  5]
 [ 0 11 50  0  3  2  1  0  0  2]
```

```
 [ 0  2  1 55  3  0  0  0  0  0]
 [ 1  5  3  2 62  0  0  0  0  0]
 [ 0  3  2  0  1 19  1  0  3 44]
 [ 0  1  0  0  0  3 56  0  3  3]
 [ 0  1  4  0  1  0  0 43  0  5]
 [ 0  3  0  1  0  1  1  0 56  6]
 [ 0  3  3  0  1 41  2  0  1 16]]

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.7083
Precision (macro): 0.7222
Recall (macro):    0.7106
F1-Score (macro):  0.7151
Confusion Matrix (10x10):
[[83  0  2  3  1  1  0  0  0  0]
 [ 0 60  2  3  2  4  1  0  0  3]
 [ 0  6 52  1  6  0  2  1  0  1]
 [ 0  2  1 56  1  0  0  1  0  0]
 [ 1  2  2  7 60  0  0  0  0  1]
 [ 0  0  0  0  0  4  1  0  4 64]
 [ 0  1  0  0  0  3 58  0  1  3]
 [ 0  0  0  0  2  1  0 50  0  1]
 [ 0  1  0  1  0  2  0  0 62  2]
 [ 0  1  0  0  0 53  2  0  3  8]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.6940
Precision (macro): 0.6978
Recall (macro):    0.6958
F1-Score (macro):  0.6957
Confusion Matrix (10x10):
[[85  0  1  2  0  1  0  1  0  0]
 [ 1 55  8  4  2  2  1  0  0  2]
 [ 4  7 47  0  7  1  1  0  1  1]
 [ 1  1  0 57  0  1  0  1  0  0]
 [ 2  3  2  7 55  0  0  0  1  3]
 [ 0  0  0  0  2 11  2  0  4 54]
 [ 0  1  1  0  0  3 56  2  2  1]
 [ 0  0  2  0  1  1  0 50  0  0]
 [ 0  1  0  1  1  2  1  0 61  1]
 [ 0  0  2  0  1 54  1  0  3  6]]
```

1.14.1 Analysising Confusion Matrix

The confusion matrixes show a strong diagonal (correct predictions), indicating good performance. Glove SVM OVR actually has the best accuracy (0.76). However, there is a pattern that exists across all models showing a confusion between "Heatwave" (Class 9) and "Forest Fire" (Class 5) classes. Articles that talk about heatwaves might also be talking about widfire risk or use terms

that overlap between the two classes like “dry”, “hot”, or “emergency”. Since the confusion exists in both directions (forest fire is miscclassified as heatwave and heatwave is missclassified as forest fire) these two topics are basically the ssame thing in the models view. Some minor confusion also occurs between some sports classes (like baseball and tennis getting mixed up slightly).

One important thing to note is that there is not a lot of cross-category confusion between sports leaf labels and climate leaf labels. We can see this because the top right and bottom left corners of the matrix are basically all close to 0.

In the next part, I will merge the forest fire and heatwave labels and recompute the confusion matrices

1.14.2 Merging labels

[29]:
```
def merge_labels(y, merge_mapping):
    y_copy = y.copy()
    for old_label, new_label in merge_mapping.items():
        y_copy = y_copy.replace(old_label, new_label)
    return y_copy

merge_mapping = {
    'forest fire': 'heat_or_fire',
    'heatwave': 'heat_or_fire'
}

y_train_multi = merge_labels(train["leaf_label"],merge_mapping)
y_test_multi = merge_labels(test["leaf_label"], merge_mapping)
print("\n*****************************")
print("USING TF-IDF + LSI WITH k=25")
print("*****************************")
multi_nb=train_multiclass_nb(GaussianNB(), lsi_tfidf_lemma_train,␣
 ↪y_train_multi, lsi_tfidf_lemma_test, y_test_multi)
multi_svm_ovo=train_svm_ovo("OVO", lsi_tfidf_lemma_train, y_train_multi,␣
 ↪lsi_tfidf_lemma_test, y_test_multi, gamma=0.01)
multi_svm_ovo=train_svm_ovo("OVR", lsi_tfidf_lemma_train, y_train_multi,␣
 ↪lsi_tfidf_lemma_test, y_test_multi, gamma=0.01)
print("\n*****************************")
print("USING GLOVE EMBEDDINGS")
print("*****************************")
multi_nb=train_multiclass_nb(GaussianNB(), train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi)
multi_svm_ovo=train_svm_ovo("OVO", train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi, gamma=0.01)
multi_svm_ovo=train_svm_ovo("OVR", train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi, gamma=0.01)
print("\n*****************************")
print("USING LLM EMBEDDINGS")
print("*****************************")
```

```
multi_nb=train_multiclass_nb(GaussianNB(), train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi)
multi_svm_ovo=train_svm_ovo("OVO", train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi, gamma=0.01)
multi_svm_ovo=train_svm_ovo("OVR", train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi, gamma=0.01)
```

```
****************************
USING TF-IDF + LSI WITH k=25
****************************

Results for Gaussian NB Classifier (Multiclass)
Accuracy:  0.7471
Precision (macro): 0.8024
Recall (macro):    0.7547
F1-Score (macro):  0.7664
Confusion Matrix (10x10):
[[70  9 10  1  0  0  0  0]
 [ 1 37 28  2  0  2  0  0]
 [ 0  6 57  1  3  2  0  0]
 [ 0  6  4 49  1  0  0  0]
 [ 0  5  9  3 55  0  0  0]
 [ 0  0  1  0  0 55  0  0]
 [ 0  1  9  0  0  0 43  0]
 [ 0  1  3  0  0  0  0 54]]

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.8563
Precision (macro): 0.8770
Recall (macro):    0.8527
F1-Score (macro):  0.8635
Confusion Matrix (8x8):
[[82  4  3  0  0  0  0  0]
 [ 2 57  5  1  0  0  0  0]
 [ 0  9 46  0  3  1  0  0]
 [ 0  2  0 57  2  0  0  0]
 [ 0  2  7  1 63  0  0  0]
 [ 0  0  0  0  0 59  0  0]
 [ 0  1  1  0  0  0 47  0]
 [ 0  1  0  0  0  0  0 60]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.8549
Precision (macro): 0.8636
Recall (macro):    0.8531
F1-Score (macro):  0.8559
```

```
Confusion Matrix (8x8):
[[82  2  1  2  0  0  1  2]
 [ 5 54  2  2  2  1  0  1]
 [ 1  8 43  0  8  1  1  0]
 [ 1  1  0 57  1  0  0  0]
 [ 0  2  3  2 66  0  0  0]
 [ 0  1  0  0  0 61  0  0]
 [ 1  0  0  1  0  0 49  0]
 [ 0  1  0  0  0  0  1 59]]

****************************
USING GLOVE EMBEDDINGS
****************************

Results for Gaussian NB Classifier (Multiclass)
Accuracy:  0.7155
Precision (macro): 0.7422
Recall (macro):    0.7296
F1-Score (macro):  0.7303
Confusion Matrix (10x10):
[[76  2  7  3  0  0  0  0]
 [12 46  6  0  2  1  0  0]
 [ 5  8 42  0  9  0  0  0]
 [ 5  2  3 47  3  0  0  0]
 [ 4  7  5  3 54  0  0  0]
 [ 0  3  0  0  0 52  0  5]
 [ 0  3  5  0  0  0 42  0]
 [ 0  3  2  0  0  1  0 57]]

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.8736
Precision (macro): 0.8795
Recall (macro):    0.8672
F1-Score (macro):  0.8726
Confusion Matrix (8x8):
[[84  0  2  2  1  0  0  0]
 [ 2 58  4  3  1  2  0  1]
 [ 2  6 56  0  0  2  0  0]
 [ 1  0  0 56  2  0  1  0]
 [ 0  2  2  4 65  0  0  0]
 [ 0  1  0  0  0 56  0  2]
 [ 0  1  0  0  1  1 47  0]
 [ 0  2  1  0  0  1  0 57]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.8779
Precision (macro): 0.8835
Recall (macro):    0.8770
```

```
F1-Score (macro):  0.8795
Confusion Matrix (8x8):
[[86  0  0  2  0  1  0  0]
 [ 1 58  5  3  0  2  0  1]
 [ 3  5 56  0  0  0  2  0]
 [ 2  0  0 58  1  0  0  0]
 [ 0  3  3  2 64  0  0  0]
 [ 0  2  1  0  0 58  0  0]
 [ 0  1  0  0  1  0 49  0]
 [ 0  0  0  0  0  1  0 58]]

****************************
USING LLM EMBEDDINGS
****************************

Results for Gaussian NB Classifier (Multiclass)
Accuracy:  0.8305
Precision (macro): 0.8471
Recall (macro):    0.8284
F1-Score (macro):  0.8354
Confusion Matrix (10x10):
[[80  2  6  1  1  0  0  0]
 [ 1 59  1  3  0  1  0  1]
 [ 0 11 50  0  3  1  0  0]
 [ 0  2  1 55  3  0  0  0]
 [ 1  5  3  2 62  0  0  0]
 [ 0  1  0  0  0 56  0  3]
 [ 0  1  4  0  1  0 43  0]
 [ 0  3  0  1  0  1  0 56]]

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.8707
Precision (macro): 0.8736
Recall (macro):    0.8671
F1-Score (macro):  0.8688
Confusion Matrix (8x8):
[[83  0  2  3  1  0  0  0]
 [ 0 59  3  3  2  1  0  0]
 [ 0  6 50  1  6  3  1  0]
 [ 0  2  1 56  1  0  1  0]
 [ 1  2  2  7 60  0  0  0]
 [ 0  1  0  0  0 57  0  2]
 [ 0  0  0  0  2  0 50  0]
 [ 0  1  0  1  0  0  0 63]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.8477
Precision (macro): 0.8504
```

```
Recall (macro):    0.8425
F1-Score (macro):  0.8449
Confusion Matrix (8x8):
[[84  0  1  2  0  0  1  0]
 [ 1 55  6  4  2  1  0  0]
 [ 4  7 47  0  8  1  0  1]
 [ 1  2  0 57  0  0  1  0]
 [ 2  3  3  7 54  0  0  1]
 [ 0  1  0  0  0 57  0  2]
 [ 0  0  1  0  1  0 49  0]
 [ 0  1  0  1  1  1  0 60]]
```

Merging the "forest fire" and "heatwave" labels into a single "fire_heat_events" class produces large performance differences! After merging, accuracy improved by 11-16 percentage points across all embedding methods. The best-performing model, GloVe embeddings with SVM OvR, improved from 76.44% to 87.79% accuracy (+11.35 points), while LLM embeddings with SVM OvO saw the largest gain from 70.83% to 87.07% (+16.24 points). The merged "heat_or_fire" class is now almost-perfectly classified, with minimal confusion to other categories. This demonstrates that these two event types share overlapping vocabulary and contextual patterns in news coverage. The improvements generalized across all classifiers (Naive Bayes, SVM OvO, and SVM OvR), which indicates that the merge addressed a fundamental limitation in the label granularity rather than a model-specific weakness.

Now let's test whether balancing the classes has any affect for the SVM OVO and SVM OVR classifiers

1.14.3 Class Imbalance

[30]:
```
print("\n*****************************")
print("USING TF-IDF + LSI WITH k=25")
print("*****************************")
multi_svm_ovo=train_svm_ovo("OVO", lsi_tfidf_lemma_train, y_train_multi,␣
 ↪lsi_tfidf_lemma_test, y_test_multi, gamma=0.01, balance = True)
multi_svm_ovo=train_svm_ovo("OVR", lsi_tfidf_lemma_train, y_train_multi,␣
 ↪lsi_tfidf_lemma_test, y_test_multi, gamma=0.01, balance = True)
print("\n*****************************")
print("USING GLOVE EMBEDDINGS")
print("*****************************")
multi_svm_ovo=train_svm_ovo("OVO", train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi, gamma=0.01, balance = True)
multi_svm_ovo=train_svm_ovo("OVR", train_glove_emb, y_train_multi,␣
 ↪test_glove_emb, y_test_multi, gamma=0.01, balance = True)
print("\n*****************************")
print("USING LLM EMBEDDINGS")
print("*****************************")
multi_svm_ovo=train_svm_ovo("OVO", train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi, gamma=0.01, balance = True)
```

```
multi_svm_ovo=train_svm_ovo("OVR", train_transformer, y_train_multi,␣
 ↪test_transformer, y_test_multi, gamma=0.01, balance = True)
```

```
**************************
USING TF-IDF + LSI WITH k=25
**************************

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.8563
Precision (macro): 0.8671
Recall (macro):    0.8615
F1-Score (macro):  0.8627
Confusion Matrix (8x8):
[[82  4  4  0  0  0  0  0]
 [ 2 58  6  1  0  1  0  0]
 [ 0 14 51  0  3  1  0  0]
 [ 0  2  0 57  2  0  0  0]
 [ 0  2  7  1 63  0  0  0]
 [ 0  1  0  0  0 62  0  0]
 [ 0  3  2  0  0  0 48  0]
 [ 0  2  0  0  0  0  1 60]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.8491
Precision (macro): 0.8551
Recall (macro):    0.8576
F1-Score (macro):  0.8550
Confusion Matrix (8x8):
[[82  3  3  2  0  0  0  0]
 [ 3 56  4  2  1  3  0  1]
 [ 0  8 51  0  8  1  0  0]
 [ 0  1  0 58  2  0  0  0]
 [ 0  2  4  1 66  0  0  0]
 [ 0  1  0  0  0 61  0  0]
 [ 0  3  2  0  1  0 48  0]
 [ 0  3  1  0  0  0  0 59]]

**************************
USING GLOVE EMBEDDINGS
**************************

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.8764
Precision (macro): 0.8782
Recall (macro):    0.8727
F1-Score (macro):  0.8750
Confusion Matrix (8x8):
```

```
[[85  0  1  2  1  0  0  0]
 [ 2 58  4  3  1  3  0  1]
 [ 2  6 56  0  0  2  0  0]
 [ 1  0  0 56  2  0  1  0]
 [ 0  2  2  4 65  0  0  0]
 [ 0  1  0  0  0 57  0  3]
 [ 0  1  0  0  1  1 47  0]
 [ 0  2  0  0  0  1  0 60]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.8807
Precision (macro): 0.8874
Recall (macro):    0.8759
F1-Score (macro):  0.8807
Confusion Matrix (8x8):
[[86  0  0  2  0  1  0  0]
 [ 0 60  5  3  0  1  0  0]
 [ 1  8 55  0  1  1  0  1]
 [ 1  0  0 57  1  0  1  0]
 [ 0  2  2  4 64  0  0  0]
 [ 0  2  0  0  0 56  0  3]
 [ 0  0  0  0  2  0 48  0]
 [ 0  1  1  0  0  1  0 59]]

****************************
USING LLM EMBEDDINGS
****************************

Results for SVM OVO where:   = 0.01 (C = 100.0)
Accuracy:  0.8721
Precision (macro): 0.8750
Recall (macro):    0.8694
F1-Score (macro):  0.8705
Confusion Matrix (8x8):
[[83  0  2  3  1  0  0  0]
 [ 0 60  2  3  2  1  0  0]
 [ 0  6 51  1  5  3  1  1]
 [ 0  2  1 56  1  0  1  0]
 [ 1  2  2  7 60  0  0  0]
 [ 0  1  0  0  0 57  0  2]
 [ 0  0  0  0  1  0 50  1]
 [ 0  1  0  1  0  0  0 63]]

Results for SVM OVR where:   = 0.01 (C = 100.0)
Accuracy:  0.8534
Precision (macro): 0.8572
Recall (macro):    0.8463
F1-Score (macro):  0.8500
```

```
Confusion Matrix (8x8):
[[83  1  2  2  0  0  0  0]
 [ 1 56  4  3  2  1  2  0]
 [ 4  8 46  0  8  1  0  1]
 [ 1  1  0 57  1  0  1  0]
 [ 3  2  3  6 54  0  0  1]
 [ 0  1  0  0  0 56  0  2]
 [ 0  1  0  0  1  0 50  0]
 [ 0  2  0  0  1  0  0 61]]
```

The results of applying class_weight = "balance" show minimal accuracy changes (~0.6% change), indicating that class imbalance was not a significant factor in the merged 9-class dataset. OvR models showed slightly more sensitivity to class weighting than OvO. OvR's one-vs-all formulation is more likely to be affected by class imbalance, so this makes sense. To call out one instance: on LLM embeddings OvR accuracy improved from 84.77% to 85.34% (+0.57%), while OvO changed from 87.07% to 87.21% (+0.14%). In general, the F1 scores increased by 0.3-0.5 points, which suggests that class weighting creates some improvements in minority class performance without harming overall accuracy. This contrasts sharply with the dramatic 11-16% improvements from merging forest fire and heatwave, so the earlier less-than-ideal performance was caused moreso by the label confusion.

[ ]:

Project 1 Part 2 Q15-Q17

January 23, 2026

0.1 Question 15 - PAWS Benchmark, Data Inspection + GLoVE

In this section, I investigate the PAWS dataset, compute Jaccard similarity between the sentences, and train a logistic regression classifier using pretrained GLoVE embeddings

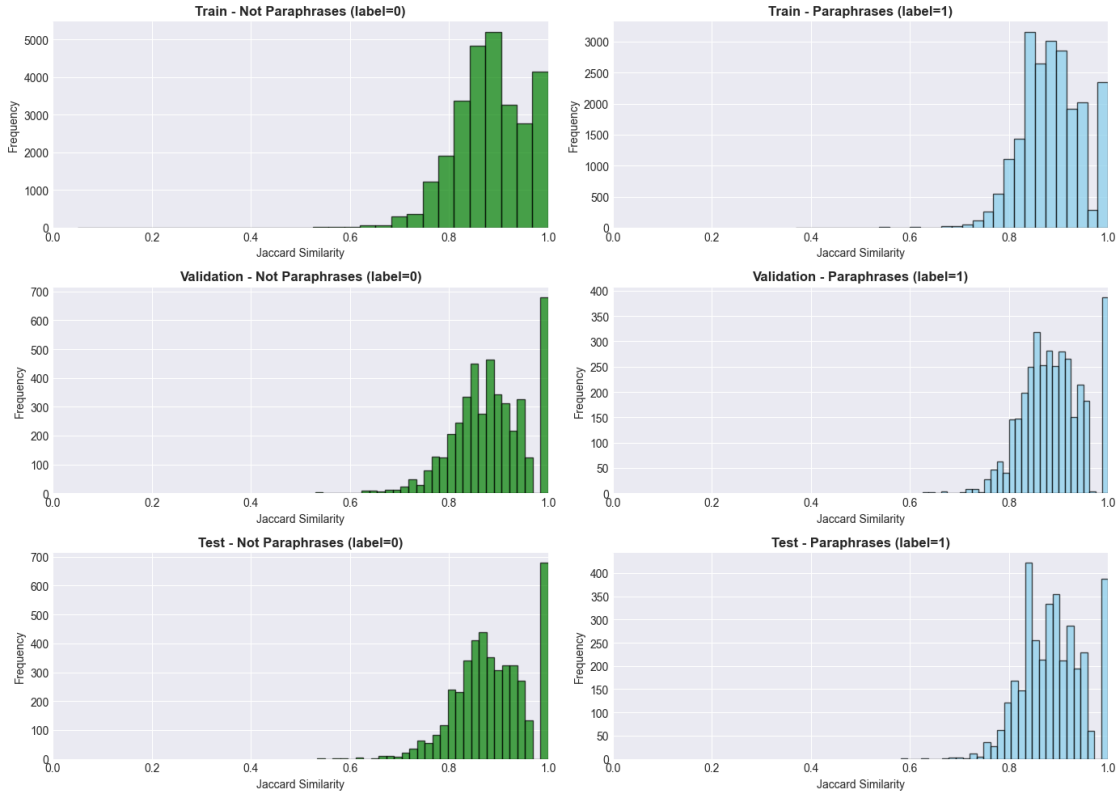
[1]:
```
from datasets import load_dataset
ds = load_dataset("paws","labeled_final")
```

[2]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("Set2")

def jaccard_similarity(example):
    tokens1 = set(example['sentence1'].lower().split())
    tokens2 = set(example['sentence2'].lower().split())

    #Compute intersection + Union
    intersection = tokens1.intersection(tokens2)
    union = tokens1.union(tokens2)

    if len(union) == 0:
        jaccard = 0.0
    else:
        jaccard=len(intersection) / len(union)
    return {'jaccard_similarity': jaccard}

train_data = ds['train'].map(jaccard_similarity)
validation_data = ds['validation'].map(jaccard_similarity)
test_data = ds['test'].map(jaccard_similarity)
datas = {"train": train_data, "validation" : validation_data, "test": test_data}

fig, axes = plt.subplots(3, 2, figsize=(14, 10))

for i, (split_name, split_data) in enumerate(datas.items()):
    n_examples = len(split_data)
```

```
    # Label distribution
    labels = split_data['label']
    n_paraphrase = sum(labels)
    n_not_paraphrase = len(labels) - n_paraphrase

    print(f"\nSplit: {split_name}, Total examples: {n_examples}")
    print(f"Paraphrases: {n_paraphrase} ({(n_paraphrase/n_examples)*100:.4f}%)")
    print(f"Not paraphrases: {n_not_paraphrase} ({(n_not_paraphrase/
↪n_examples)*100:.4f}%)")

    #get jaccard
    jaccard_scores = np.array(split_data['jaccard_similarity'])
    labels_array = np.array(split_data['label'])
    jaccard_label_0 = jaccard_scores[labels_array == 0]
    jaccard_label_1 = jaccard_scores[labels_array == 1]

    # Histogram for label = 0 (Not paraphrases)
    axes[i, 0].hist(jaccard_label_0, bins=30, edgecolor='black', alpha=0.7,␣
↪color='green')
    axes[i, 0].set_title(f'{split_name.capitalize()} - Not Paraphrases␣
↪(label=0)',
                         fontsize=12, fontweight='bold')
    axes[i, 0].set_xlabel('Jaccard Similarity')
    axes[i, 0].set_ylabel('Frequency')
    axes[i, 0].set_xlim(0, 1)

    # Histogram for label = 1 (Paraphrases)
    axes[i, 1].hist(jaccard_label_1, bins=30, edgecolor='black', alpha=0.7,␣
↪color='skyblue')
    axes[i, 1].set_title(f'{split_name.capitalize()} - Paraphrases (label=1)',
                         fontsize=12, fontweight='bold')
    axes[i, 1].set_xlabel('Jaccard Similarity')
    axes[i, 1].set_ylabel('Frequency')
    axes[i, 1].set_xlim(0, 1)

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

```
Split: train, Total examples: 49401
Paraphrases: 21829 (44.1874%)
Not paraphrases: 27572 (55.8126%)

Split: validation, Total examples: 8000
Paraphrases: 3539 (44.2375%)
Not paraphrases: 4461 (55.7625%)
```

```
Split: test, Total examples: 8000
Paraphrases: 3536 (44.2000%)
Not paraphrases: 4464 (55.8000%)
```



[3]:
```python
#get some examples
print("Dataset Examples")
print("\nExample of Paraphrase (label 0)")
for i, example in enumerate(train_data):
    if example['jaccard_similarity'] > 0.9 and example['label'] == 0:
        print(f"Sentence 1: {example['sentence1']}")
        print(f"Sentence 2: {example['sentence2']}")
        print(f"Jaccard: {example['jaccard_similarity']:.3f}")
        if i >= 0:
            break

print("\nExample of Not Paraphrase (label 1)")
for i, example in enumerate(train_data):
    if example['jaccard_similarity'] > 0.9 and example['label'] == 1:
        print(f"Sentence 1: {example['sentence1']}")
        print(f"Sentence 2: {example['sentence2']}")
        print(f"Jaccard: {example['jaccard_similarity']:.3f}")
        if i >= 0:
```

```
            break
```

```
Dataset Examples

Example of Paraphrase (label 0)
Sentence 1: There are also specific discussions , public profile debates and
project discussions .
Sentence 2: There are also public discussions , profile specific discussions ,
and project discussions .
Jaccard: 0.917

Example of Not Paraphrase (label 1)
Sentence 1: The NBA season of 1975 -- 76 was the 30th season of the National
Basketball Association .
Sentence 2: The 1975 -- 76 season of the National Basketball Association was the
30th season of the NBA .
Jaccard: 1.000
```

0.1.1 Analysis

For all splits we can see Jaccard similarity is very high. Centered around 0.9. This means that many of the words present in sentence 1 are also present in sentence 2. So, if we use a bag of words model, it will be very hard to use this model to classify. Note that the PAWS dataset contains many sentence pairs that share almost identical words but differ in meaning due to word order changes as well as sentences with same words and same meanings. We need a model that uses word context to classify, not just whether words are present in both sentences.

0.1.2 Using GloVE Embeddings and Classifying using Logistic Regression

[4]:
```
embeddings_dict = {}
dimension_of_glove = 300
with open("glove/glove.6B.300d.txt", 'r', encoding='utf-8') as f:
    for line in f:
        values = line.split()
        word = values[0]
        vector = np.asarray(values[1:], "float32")
        embeddings_dict[word] = vector
```

[5]:
```
import numpy as np
from nltk.corpus import stopwords
from sklearn.preprocessing import normalize
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
from nltk import pos_tag, word_tokenize
import nltk

nltk.download('stopwords')
def get_wordnet_pos(tag):
```

```
    # Converts Penn Treebank tags to WordNet.
    morphy_tag = {'NN':'n', 'JJ':'a',
                  'VB':'v', 'RB':'r'}
    try:
        return morphy_tag[penntag[:2]]
    except:
        return 'n'

class GloVeEmbedder:
    def __init__(self, embeddings_dict):
        self.embeddings_dict = embeddings_dict
        self.stop_words = set(stopwords.words('english'))
        self.lemmatizer = WordNetLemmatizer()
        self.embedding_dim = len(next(iter(embeddings_dict.values())))

    def preprocess(self, text):
        #tokenize, lemmtize, filter out nonalphanumeric
        tokens = word_tokenize(text.lower())
        pos_tags = pos_tag(tokens)
        #lemmatize
        lemmatized = [
            self.lemmatizer.lemmatize(token, get_wordnet_pos(tag))
            for token, tag in pos_tags
        ]

        #remove stopwords, non-alphabetic, single characters
        filtered = [
            word for word in lemmatized
            if word.isalpha() and
               len(word) > 1 and
               (word not in self.stop_words)
        ]

        return filtered

    def embed_doc(self, text):
        #Convert a document to embedding vector
        tokens = self.preprocess(text)
        word_vectors = []
        oov_count = 0

        for token in tokens:
            if token in self.embeddings_dict:
                vec = self.embeddings_dict[token]
                word_vectors.append(vec)
            else:
                oov_count += 1
```

```
        # if no valid words
        if len(word_vectors) == 0:
            print(f"WARNING: Document with no valid words. Sample tokens:␣
 ↪{tokens[:5]}")
            return np.zeros(self.embedding_dim), 1.0

        #get word vectors and normalize + avg
        word_vectors = np.array(word_vectors)
        word_vectors = normalize(word_vectors, axis=1, norm='l2')
        doc_embedding = np.mean(word_vectors, axis=0)

        #find OOV rate
        total_tokens = len(tokens)
        oov_rate = oov_count / total_tokens if total_tokens > 0 else 0
        return doc_embedding, oov_rate

    def transform(self, documents):
        #Transform list of documents to embedding matrix
        embeddings = []
        oov_rates = []

        for i, doc in enumerate(documents):
            emb, oov = self.embed_doc(doc)
            embeddings.append(emb)
            oov_rates.append(oov)
        return np.array(embeddings), np.array(oov_rates)

def construct_features(embed1, embed2):
    u = embed1
    v = embed2
    uv_abs = np.abs(u-v)
    uv_product = u * v
    return np.concatenate([u,v,uv_abs,uv_product], axis = 1)

print("Creating doc embedder...")
embedder = GloVeEmbedder(
    embeddings_dict=embeddings_dict,
)

train_data = ds['train'].map(jaccard_similarity)
validation_data = ds['validation'].map(jaccard_similarity)
test_data = ds['test'].map(jaccard_similarity)

#transform train test valid
print("Transforming training documents...")
```

```
train_sent1_glove_emb, train_oov_rates = embedder.
 ↪transform(train_data["sentence1"])
train_sent2_glove_emb, train_oov_rates = embedder.
 ↪transform(train_data["sentence2"])

print("Transforming validation documents...")
valid_sent1_glove_emb, train_oov_rates = embedder.
 ↪transform(validation_data["sentence1"])
valid_sent2_glove_emb, train_oov_rates = embedder.
 ↪transform(validation_data["sentence2"])

print("Transforming test documents...")
test_sent1_glove_emb, train_oov_rates = embedder.
 ↪transform(test_data["sentence1"])
test_sent2_glove_emb, train_oov_rates = embedder.
 ↪transform(test_data["sentence2"])

print("Constructing pair features for training...")
glove_X_train = construct_features(train_sent1_glove_emb, train_sent2_glove_emb)
y_train = np.array(train_data['label'])

print("Constructing pair features for validation...")
glove_X_valid = construct_features(valid_sent1_glove_emb, valid_sent2_glove_emb)
y_valid = np.array(validation_data['label'])

print("Constructing pair features for test...")
glove_X_test = construct_features(test_sent1_glove_emb, test_sent2_glove_emb)
y_test = np.array(test_data['label'])

print(f"Feature shape: {glove_X_train.shape}")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\jilli\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!

Creating doc embedder…
Transforming training documents…
Transforming validation documents…
Transforming test documents…
Constructing pair features for training…
Constructing pair features for validation…
Constructing pair features for test…
Feature shape: (49401, 1200)
```

For the GloVe baseline, I chose Logistic Regression with L2 regularization and investigated a choice of C. This choice is justified by the nature of our feature construction: all 1,200 dimensions are derived from meaningful GloVe word embeddings through concatenation operations. Unlike sparse bag-of-words features where many dimensions may be irrelevant, these features are all informative.

L2 regularization is more appropriate than L1 in this setting because it shrinks coefficients without eliminating features entirely, allowing the model to leverage information from all dimensions. I investigate several choices of C and report the best models test accuracy and f1.

[6]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, roc_curve, auc)
import time
import numpy as np

best_c = 0.1
best_acc = 0
best_model = None
for c in [0.01, 0.1, 1.0, 10.0]:
    print(f"\nTesting C: {c}")
    model = LogisticRegression(
        penalty='l2',
        C=c,
        solver='lbfgs',
        max_iter=1000,
        random_state=42
    )
    model.fit(glove_X_train, y_train)
    # Evaluate on validation set
    y_val_pred = model.predict(glove_X_valid)
    val_acc = accuracy_score(y_valid, y_val_pred)
    val_f1 = f1_score(y_valid, y_val_pred)
    cm = confusion_matrix(y_valid, y_val_pred)
    print(f"Accuracy:  {val_acc:.4f}")
    print(f"F1 Score:  {val_f1:.4f}")
    print(f"\nConfusion Matrix:")
    print(cm)
    if val_acc > best_acc:
        best_c = c
        best_acc = val_acc
        best_model = model

print("Training the best model...")
    #train best model
final_glove_model = LogisticRegression(
    penalty='l2',
    C=best_c,
    solver='lbfgs',
    max_iter=1000,
    random_state=42
)
```

```
best_glove_model = final_glove_model.fit(glove_X_train, y_train)
start_time = time.time()
y_pred = final_glove_model.predict(glove_X_test)
end_time = time.time()
glove_model_time = end_time - start_time
# Evaluate of best model on test set
test_acc = accuracy_score(y_test, y_pred)
test_f1 = f1_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
print(f"\nBest Model C:  {best_c}")
print(f"Inference time (1000 pairs): {(glove_model_time / len(glove_X_test)) *␣
 ↪1000:.4f} seconds")
print(f"Best Model Accuracy:  {test_acc:.4f}")
print(f"Best Model F1 Score:  {test_f1:.4f}")
print(f"Best Model Confusion Matrix:")
print(cm)
print("\n")

glove_encoder_results = {
    'test_accuracy': test_acc,
    'test_f1': test_f1,
    'confusion_matrix': cm,
    'inference_time_per_1000': (glove_model_time / len(glove_X_test)) * 1000
}
```

```
Testing C: 0.01
Accuracy:  0.5576
F1 Score:  0.0000

Confusion Matrix:
[[4461    0]
 [3539    0]]

Testing C: 0.1
Accuracy:  0.5571
F1 Score:  0.1096

Confusion Matrix:
[[4239  222]
 [3321  218]]

Testing C: 1.0
Accuracy:  0.5615
F1 Score:  0.2002

Confusion Matrix:
[[4053  408]
```

```
 [3100  439]]

Testing C: 10.0
Accuracy:  0.5596
F1 Score:  0.2506

Confusion Matrix:
[[3888  573]
 [2950  589]]
Training the best model…

Best Model C:  1.0
Inference time (1000 pairs): 0.0051 seconds
Best Model Accuracy:  0.5526
Best Model F1 Score:  0.2174
Best Model Confusion Matrix:
[[3924  540]
 [3039  497]]
```

This results in a poor F1 score of 0.13 for the best model. Note that based on the confusion matrix, we can tell that the model is almost always predicting "not paraphrase" (class 0). Since GloVE is context-blind, it is not expected to do well on this dataset. I will investigate other methods in the next parts.

0.2 Question 16 - Transformer Approaches on PAWS: Bi-encoder vs Cross-encoder

In this section, I investigate using transformers on PAWS. I use two methods of encoding, bi-encoding and cross-encoding, and evaluate their performance

0.2.1 Using the Bi-encoder

[7]:
```python
from sentence_transformers import SentenceTransformer
import torch
from tqdm import tqdm

MODEL_NAME = "all-MiniLM-L6-v2"

print("Loading model...")
device = "cuda" if torch.cuda.is_available() else "cpu"
bi_encoder_model = SentenceTransformer(MODEL_NAME, device=device)
print(f"Model loaded on this device: {device}")

def bi_encoder(sent1, sent2, batch_size=32):
#utilize sentence-transformers library to encode texts (truncation method used␣
 ↪automatically)
```

```
    bi_encoder_model.max_seq_length = 512  # Set truncation max_se_length to 512
    print(f"Encoding {len(sent1)} documents...")
    embeddings_sent1 = bi_encoder_model.encode(
        sent1,
        batch_size=batch_size,
        show_progress_bar=True,
        convert_to_numpy=True
    )
    embeddings_sent2 = bi_encoder_model.encode(
        sent2,
        batch_size=batch_size,
        show_progress_bar=True,
        convert_to_numpy=True
    )
    embeddings = construct_features(embeddings_sent1, embeddings_sent2)
    return torch.from_numpy(embeddings)

#transform train test valid
print("Transforming training documents...")
train_llm_emb = bi_encoder(train_data["sentence1"], train_data["sentence2"])
print("Transforming validation documents...")
validation_llm_emb = bi_encoder(validation_data["sentence1"],␣
 ↪validation_data["sentence2"])
print("Transforming test documents...")
test_llm_emb = bi_encoder(test_data["sentence1"], test_data["sentence2"])
print(f"\nTransformer Train shape: {train_llm_emb.shape}")
print(f"Transformer Test shape: {train_llm_emb.shape}")
print(f"Embedding dimension: {train_llm_emb.shape[1]}")
```

```
Loading model…
Model loaded on this device: cuda
Transforming training documents…
Encoding 49401 documents…
Batches:   0%|          | 0/1544 [00:00<?, ?it/s]
Batches:   0%|          | 0/1544 [00:00<?, ?it/s]
Transforming validation documents…
Encoding 8000 documents…
Batches:   0%|          | 0/250 [00:00<?, ?it/s]
Batches:   0%|          | 0/250 [00:00<?, ?it/s]
Transforming test documents…
Encoding 8000 documents…
Batches:   0%|          | 0/250 [00:00<?, ?it/s]
Batches:   0%|          | 0/250 [00:00<?, ?it/s]
```

```
Transformer Train shape: torch.Size([49401, 1536])
Transformer Test shape: torch.Size([49401, 1536])
Embedding dimension: 1536
```

[8]:
```python
# Prepare data
X_train = train_llm_emb
y_train = np.array(train_data["label"])

X_val = validation_llm_emb
y_val = np.array(validation_data["label"])

X_test = test_llm_emb
y_test = np.array(test_data["label"])

#Hyperparameter tuning on validation set
print("Tune hyperparameters on validation set")
best_c = 0.1
best_val_acc = 0
best_model = None
```

```
Tune hyperparameters on validation set
```

[9]:
```python
C_values = [0.001, 0.01, 0.1, 1.0, 10.0, 100.0]

for c in C_values:
    print(f"\nTesting C: {c}")
    lr_model = LogisticRegression(
        penalty='l2',
        C=c,
        solver='lbfgs',
        max_iter=1000,
        random_state=42
    )
    lr_model.fit(X_train, y_train)

    # Evaluate on validation set
    y_val_pred = lr_model.predict(X_val)
    val_acc = accuracy_score(y_val, y_val_pred)
    val_f1 = f1_score(y_val, y_val_pred)

    print(f"Validation Accuracy: {val_acc:.4f}")
    print(f"Validation F1 Score: {val_f1:.4f}")

    # Track best model based on validation accuracy
    if val_acc > best_val_acc:
        best_c = c
        best_val_acc = val_acc
```

```
        best_model = lr_model

print(f"\nBest Model: C = {best_c}")
print(f"Best Validation Accuracy: {best_val_acc:.4f}")

# Final evaluation on test set with best model
print("Final eval on test set")

start_time = time.time()
y_test_pred = best_model.predict(X_test)
end_time = time.time()
inference_time = end_time - start_time

test_acc = accuracy_score(y_test, y_test_pred)
test_f1 = f1_score(y_test, y_test_pred)
cm = confusion_matrix(y_test, y_test_pred)

print(f"Best C value: {best_c}")
print(f"Inference time (1000 pairs): {(inference_time / len(X_test)) * 1000:.
 ↪4f} seconds")
print(f"Test Accuracy: {test_acc:.4f}")
print(f"Test F1 Score: {test_f1:.4f}")
print(f"\nConfusion Matrix:")
print(cm)

bi_encoder_results = {
    'test_accuracy': test_acc,
    'test_f1': test_f1,
    'confusion_matrix': cm,
    'inference_time_per_1000': (inference_time / len(X_test)) * 1000
}

final_bi_enc_model = best_model
```

```
Testing C: 0.001
Validation Accuracy: 0.5576
Validation F1 Score: 0.0000

Testing C: 0.01
Validation Accuracy: 0.5984
Validation F1 Score: 0.3366

Testing C: 0.1
Validation Accuracy: 0.6071
Validation F1 Score: 0.4820

Testing C: 1.0
```

```
Validation Accuracy: 0.6218
Validation F1 Score: 0.5232

Testing C: 10.0
Validation Accuracy: 0.6214
Validation F1 Score: 0.5431

Testing C: 100.0
Validation Accuracy: 0.6109
Validation F1 Score: 0.5393

Best Model: C = 1.0
Best Validation Accuracy: 0.6218
Final eval on test set
Best C value: 1.0
Inference time (1000 pairs): 0.0065 seconds
Test Accuracy: 0.6180
Test F1 Score: 0.5268

Confusion Matrix:
[[3243 1221]
 [1835 1701]]
```

0.2.2 Interpretation

We can see that Bi-encoder performs much better than GloVe. This is because, GloVe assigns a single fixed vector to each word regardless of context. The word "run" gets the same embedding whether it means "run a 5k" or "run for president". When you get GloVe vectors for a sentence, you're getting static, context-free representations. Meanwhile, the bi-encoder uses self-attention to create contextual embeddings. Each token's representation depends on all other tokens in the sentence, resulting in the same word getting different representations depending on the surrounding words. Therefore, the bi-encoder has contextual understanding that gives it the advantage here.

Additionally the pre-training for each method plays a role here. GLoVE was trained on co-occurence stats from a specific text corpus (about 6B tokens). Meanwhile the bi-encoder leverages an LLM that was pretrained on a MASSIVE corpus (100B+ tokens). Also LLMs are often pretrained for specific objectgives including next sentence prediciton and sentence pair classification so the model already has some idea of what can make sentences seem "similar".

0.2.3 Using the Cross-Encoder

[10]:
```python
from transformers import AutoTokenizer, AutoModelForSequenceClassification,␣
↪TrainingArguments, Trainer
from datasets import Dataset
import torch

model_name = "distilbert-base-uncased"
device = "cuda" if torch.cuda.is_available() else "cpu"
```

```
tokenizer = AutoTokenizer.from_pretrained(model_name)
cross_encoder_model = AutoModelForSequenceClassification.from_pretrained(
    model_name,
    num_labels=2
).to(device)
print(f"Model loaded on: {device}")

def prepare_dataset(data, tokenizer, max_length=512):
    def tokenize_function(examples):
        return tokenizer(
            examples["sentence1"],
            examples["sentence2"],
            truncation=True,
            padding="max_length",
            max_length=max_length,
        )
    columns_to_remove = [col for col in data.column_names if col != 'label']
    # Apply tokenization
    tokenized_dataset = data.map(
        tokenize_function,
        batched=True,
        remove_columns=columns_to_remove
    )

    if 'label' in tokenized_dataset.column_names:
        tokenized_dataset = tokenized_dataset.rename_column('label', 'labels')
    return tokenized_dataset

print("Preparing training dataset...")
cross_train_dataset = prepare_dataset(train_data, tokenizer)
print("Preparing validation dataset...")
cross_val_dataset = prepare_dataset(validation_data, tokenizer)
print("Preparing testing dataset...")
cross_test_dataset = prepare_dataset(test_data, tokenizer)

print(f"\nDataset sizes:")
print(f"Train: {len(cross_train_dataset)}")
print(f"Validation: {len(cross_val_dataset)}")
print(f"Test: {len(cross_test_dataset)}")

# what columns does this give us?
print(f"\nTrain dataset columns: {cross_train_dataset.column_names}")
```

```
Some weights of DistilBertForSequenceClassification were not initialized from
the model checkpoint at distilbert-base-uncased and are newly initialized:
['classifier.bias', 'classifier.weight', 'pre_classifier.bias',
'pre_classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it
```

```
for predictions and inference.

Model loaded on: cuda
Preparing training dataset…
Preparing validation dataset…
Preparing testing dataset…

Dataset sizes:
Train: 49401
Validation: 8000
Test: 8000

Train dataset columns: ['labels', 'input_ids', 'attention_mask']
```

[11]:
```python
from transformers import AutoTokenizer, AutoModelForSequenceClassification,␣
 ↪TrainingArguments, Trainer
import json
import os

def compute_metrics(eval_pred):
    logits, labels = eval_pred
    predictions = np.argmax(logits, axis=-1)

    acc = accuracy_score(labels, predictions)
    f1 = f1_score(labels, predictions)

    return {
        'accuracy': acc,
        'f1': f1
    }

SAVED_MODEL_DIR = "./saved_cross_encoder_best_model"
FORCE_RETRAIN = False  # Set to True to force retraining

# Check if we have a saved model
if os.path.exists(SAVED_MODEL_DIR) and not FORCE_RETRAIN:
    print("!!!LOADING PREVIOUSLY TRAINED MODEL")
    print(f"Found saved model at: {SAVED_MODEL_DIR}")
    print("skipping training...")
    best_model = AutoModelForSequenceClassification.
 ↪from_pretrained(SAVED_MODEL_DIR).to(device)

    # Load the saved results
    import json
    with open(os.path.join(SAVED_MODEL_DIR, "cross_enc_training_results.json"),␣
 ↪"r") as f:
        saved_results = json.load(f)
```

```
    best_lr = saved_results['best_lr']
    best_val_acc = saved_results['best_val_acc']

    print(f"Best learning rate: {best_lr}")
    print(f"Best validation accuracy: {best_val_acc:.4f}")

else:
    print("!!!NO SAVED MODEL FOUND. TRAINING FROM SCRATCH")

    # Hyperparameter tuning
    learning_rates = [5e-5, 2e-5]
    best_val_acc = 0
    best_lr = None
    best_model = None
    best_trainer = None

    print("Tuning the cross-encoders hyperparameters")
    for lr in learning_rates:
        print(f"Training with Learning Rate: {lr}")

        model = AutoModelForSequenceClassification.from_pretrained(
            model_name,
            num_labels=2
        ).to(device)

        # Verify model is on GPU
        print(f"Model device: {next(model.parameters()).device}")

        #training args
        training_args = TrainingArguments(
            output_dir=f"./cross_encoder_results_lr_{lr}",
            num_train_epochs=2,
            per_device_train_batch_size=16,
            per_device_eval_batch_size=32,
            learning_rate=lr,
            eval_strategy="epoch",
            save_strategy="epoch",
            load_best_model_at_end=True,
            metric_for_best_model="accuracy",
            seed=42,
            no_cuda=False,
        )

        #trainer
        trainer = Trainer(
            model=cross_encoder_model,
            args=training_args,
```

```
            train_dataset=cross_train_dataset,
            eval_dataset=cross_val_dataset,
            compute_metrics=compute_metrics,
        )

        # Train
        print("Starting training...")
        trainer.train()

        # Eval
        print("\nEvaluating on validation set...")
        val_results = trainer.evaluate()
        val_acc = val_results['eval_accuracy']
        val_f1 = val_results['eval_f1']

        print(f"\nValidation Results:")
        print(f"  Accuracy: {val_acc:.4f}")
        print(f"  F1 Score: {val_f1:.4f}")

        if val_acc > best_val_acc:
            best_val_acc = val_acc
            best_lr = lr
            best_model = trainer.model
            best_trainer = trainer

    print(f"Fount the best model.")
    print(f"Best Learning Rate: {best_lr}")
    print(f"Best Validation Accuracy: {best_val_acc:.4f}")

    #save best model
    print("Saving best model for future use...")
    best_model.save_pretrained(SAVED_MODEL_DIR)
    tokenizer.save_pretrained(SAVED_MODEL_DIR)  # Save tokenizer too

    #save training
    training_results = {
        'best_lr': best_lr,
        'best_val_acc': best_val_acc,
    }
    with open(os.path.join(SAVED_MODEL_DIR, "cross_enc_training_results.json"),␣
↪"w") as f:
        json.dump(training_results, f, indent=2)
    print(f"Model saved to: {SAVED_MODEL_DIR}")

print("Final evaluation on the test set with best model...")

#best model on GPU
```

```
best_model = best_model.to(device)
print(f"Best model device: {next(best_model.parameters()).device}")

final_trainer = Trainer(
    model=best_model,
    args=TrainingArguments(
        output_dir="./cross_encoder_final_results",
        per_device_eval_batch_size=32,
        no_cuda=False,
    ),
    compute_metrics=compute_metrics,
)

# Get predictions and time it :)
start_time = time.time()
predictions = final_trainer.predict(cross_test_dataset)
end_time = time.time()
inference_time = end_time - start_time

y_pred = np.argmax(predictions.predictions, axis=-1)
y_test = np.array(cross_test_dataset['labels'])

# Metrics
test_acc = accuracy_score(y_test, y_pred)
test_f1 = f1_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)

#results
print(f"Final Test Results")
print(f"Best learning rate: {best_lr}")
print(f"Total inference time: {inference_time:.2f} seconds")
print(f"Inference time per 1000 pairs: {(inference_time /␣
 ↪len(cross_test_dataset)) * 1000:.4f} seconds")
print(f"\nTest Accuracy: {test_acc:.4f}")
print(f"Test F1 Score: {test_f1:.4f}")
print(f"\nConfusion Matrix:")
print(cm)

# Save results for comparison in part (d)
cross_encoder_results = {
    'best_lr': best_lr,
    'test_accuracy': test_acc,
    'test_f1': test_f1,
    'confusion_matrix': cm,
    'inference_time_per_1000': (inference_time / len(cross_test_dataset)) * 1000
}
```

```
final_cross_encoder_model = best_model
final_cross_encoder_trainer = final_trainer
```

```
!!!LOADING PREVIOUSLY TRAINED MODEL
Found saved model at: ./saved_cross_encoder_best_model
skipping training…
Best learning rate: 2e-05
Best validation accuracy: 0.8824
Final evaluation on the test set with best model…
Best model device: cuda:0
```

```
<IPython.core.display.HTML object>
```

```
Final Test Results
Best learning rate: 2e-05
Total inference time: 51.96 seconds
Inference time per 1000 pairs: 6.4946 seconds

Test Accuracy: 0.8759
Test F1 Score: 0.8645

Confusion Matrix:
[[3838  626]
 [ 367 3169]]
```

[12]:
```
# Analyze results
print(f"{'Encoder':<16} {'Test Accuracy':<16} {'Test F1':<12} {'Inference Time␣
 ↪(per 1k pairs)':<12}")
print("-" * 75)
print(f"{'GLoVe':<16} {glove_encoder_results['test_accuracy']:<16.4f}␣
 ↪{glove_encoder_results['test_f1']:<12.4f}␣
 ↪{glove_encoder_results['inference_time_per_1000']:<12.4f}")
print(f"{'Bi-encoder':<16} {bi_encoder_results['test_accuracy']:<16.4f}␣
 ↪{bi_encoder_results['test_f1']:<12.4f}␣
 ↪{bi_encoder_results['inference_time_per_1000']:<12.4f}")
print(f"{'Cross-encoder':<16} {cross_encoder_results['test_accuracy']:<16.4f}␣
 ↪{cross_encoder_results['test_f1']:<12.4f}␣
 ↪{cross_encoder_results['inference_time_per_1000']:<12.4f}")
```

```
Encoder          Test Accuracy    Test F1      Inference Time (per 1k pairs)
---------------------------------------------------------------------------
GLoVe            0.5526           0.2174       0.0051
Bi-encoder       0.6180           0.5268       0.0065
Cross-encoder    0.8759           0.8645       6.4946
```

0.2.4 Analysis

As you can see GLoVE performs the worst (F1 = 0.21), Bi-encoder is next (F1 = 0.52), and Cross-encoder performs best (F1 = 0.86). Note that while cross-encoder performs signifigantly better than

the Bi-encoder, it also has a longer inference time of ~6.6 seconds per 1000 pairs. The cross-encoder performs best because the sentences are fed into the encoder together. Self attention operates across both sentences simulaneously, allowing the model to compare specific phrases between the two sentences. Additionally, the model is fine-tuned end-to-end on PAWS training data with the actual paraphrase classification objective, which helps its performance signifigantly.

0.3 Question 17 - Prompt-based Paraphrase Classification with Qwen

Below I construct a Qwen/Qwen2.5-3B-Instruct model with decoding parameters: - max_new_tokens=32 - Maximum length of generated response - num_beams=1 - No beam search (greedy decoding) - do_sample=False - Deterministic generation (no sampling)

I perform both zero-shot and few-shot prompting and compare the outputs.

[16]:
```
import torch
from transformers import AutoModelForCausalLM, AutoTokenizer
import pandas as pd
from tqdm import tqdm

model_name = "Qwen/Qwen2.5-3B-Instruct"
MAX_NEW_TOKENS = 32

# Check GPU availability
if torch.cuda.is_available():
    print("Will be using GPU!")
else:
    print("GPU is NOT available. Running on CPU (this will be slow).")
print()

print("Loading model...")
tokenizer = AutoTokenizer.from_pretrained(model_name, trust_remote_code=True)

if tokenizer.pad_token is None:
    tokenizer.pad_token = tokenizer.eos_token
tokenizer.padding_side = 'left'

qwen_model = AutoModelForCausalLM.from_pretrained(
    model_name,
    torch_dtype=torch.float16 if torch.cuda.is_available() else torch.float32,
    device_map="auto",
    trust_remote_code=True
)

print("Model loaded successfully!")
print()

def create_balanced_subset(dataset, n_samples=200):
    # Get equal samples from each class, combine and shuffle
```

```
    df = pd.DataFrame(dataset)
    n_per_class = n_samples // 2
    paraphrase_samples = df[df['label'] == 1].sample(n=n_per_class,␣
 ↪random_state=42)
    not_paraphrase_samples = df[df['label'] == 0].sample(n=n_per_class,␣
 ↪random_state=42)
    subset = pd.concat([paraphrase_samples, not_paraphrase_samples])
    subset = subset.sample(frac=1, random_state=42).reset_index(drop=True)
    return subset

def create_prompt(sentence1, sentence2, examples=None):
    if examples is None:
        prompt = f"""Decide if these sentences are paraphrases. Respond with␣
 ↪only "paraphrase" or "not paraphrase".

Sentence 1: {sentence1}
Sentence 2: {sentence2}
Answer:"""
    else:
        prompt = "Decide if these sentences are paraphrases. Respond with only␣
 ↪\"paraphrase\" or \"not paraphrase\".\n\n"

        for s1, s2, label in examples:
            label_text = label if isinstance(label, str) else ("paraphrase" if␣
 ↪label == 1 else "not paraphrase")
            prompt += f"Sentence 1: {s1}\nSentence 2: {s2}\nAnswer:␣
 ↪{label_text}\n\n"
        prompt += f"Sentence 1: {sentence1}\nSentence 2: {sentence2}\nAnswer:"

    return prompt

def paraphrase_checker(sentence_pairs, fewshot_examples=None, batch_size=8):
    #check if paraphrase in batches
    results = []
    total_batches = (len(sentence_pairs) + batch_size - 1) // batch_size

    for i in tqdm(range(0, len(sentence_pairs), batch_size), desc="Processing␣
 ↪batches", total=total_batches):
        batch = sentence_pairs[i:i+batch_size]
        prompts = []

        for s1, s2 in batch:
            prompt = create_prompt(s1, s2, examples=fewshot_examples)
            all_messages = [{"role": "user", "content": prompt}]
            text = tokenizer.apply_chat_template(all_messages, tokenize=False,␣
 ↪add_generation_prompt=True)
```

```
            prompts.append(text)


        input_for_model = tokenizer(
            prompts,
            return_tensors="pt",
            padding=True,
            truncation=True,
            max_length=2048
        ).to(qwen_model.device)

        with torch.no_grad():
            outputs = qwen_model.generate(
                **input_for_model,
                max_new_tokens=MAX_NEW_TOKENS,
                num_beams=1,
                do_sample=False,
                pad_token_id=tokenizer.pad_token_id
            )

        for j, output in enumerate(outputs):
            response = tokenizer.decode(output[input_for_model['input_ids'].
 ↪shape[1]:], skip_special_tokens=True)
            results.append(response.strip())

    return results

def get_label(text):
    if "not paraphrase" in text.lower() or "not a paraphrase" in text.lower():
        return 0
    elif "paraphrase" in text.lower():
        return 1
    else:
        return 1

def get_fewshot_examples(train_data, n_examples=6):
    # Get examples from each class
    train_df = pd.DataFrame(train_data)
    n_per_class = n_examples // 2
    paraphrases = train_df[train_df['label'] == 1].sample(n=n_per_class,␣
 ↪random_state=42)
    not_paraphrases = train_df[train_df['label'] == 0].sample(n=n_per_class,␣
 ↪random_state=42)

    examples = []
    para_list = list(paraphrases.iterrows())
    not_para_list = list(not_paraphrases.iterrows())
```

```
    for i in range(n_per_class):
        # Add a paraphrase example
        _, row = para_list[i]
        examples.append((row['sentence1'], row['sentence2'], 'paraphrase'))

        # Add a not paraphrase example
        _, row = not_para_list[i]
        examples.append((row['sentence1'], row['sentence2'], 'not paraphrase'))

    return examples

print("Creating balanced 200-sample subset...")
test_subset = create_balanced_subset(test_data, n_samples=200)

print(f"\nFirst few examples:")
print(test_subset[['sentence1', 'sentence2', 'label']].head())

# Prepare sentence pairs for batch processing
sentence_pairs = list(zip(test_subset['sentence1'], test_subset['sentence2']))
true_labels = test_subset['label'].tolist()

print(f"\nPrepared {len(sentence_pairs)} sentence pairs for evaluation")
print()


# zero shot
print("Running zero shot inference...")
test_prompt = create_prompt(sentence_pairs[0][0], sentence_pairs[0][1])
print("\n")
print("SAMPLE ZERO-SHOT PROMPT:")
print(test_prompt)
print("\n")
start_zero = time.time()
out = paraphrase_checker(sentence_pairs, batch_size=8)
predictions = [get_label(output) for output in out]
end_zero = time.time()
zero_shot_time = end_zero - start_zero

# Calculate metrics
zero_shot_accuracy = accuracy_score(true_labels, predictions)
zero_shot_f1 = f1_score(true_labels, predictions)
zero_shot_cm = confusion_matrix(true_labels, predictions)

print(f"\nZero Shot Test Results")
print(f"Test Accuracy: {zero_shot_accuracy:.4f}")
print(f"Test F1 Score: {zero_shot_f1:.4f}")
```

```
print(f"\nConfusion Matrix:")
print(zero_shot_cm)
print()

# few shot
print("Running few shot inference...")
examples = get_fewshot_examples(train_data, 6)
test_prompt = create_prompt(sentence_pairs[0][0], sentence_pairs[0][1],␣
 ↪examples)
print("\n")
print("SAMPLE FEW-SHOT PROMPT:")
print(test_prompt)
print("\n")
start_few = time.time()
out = paraphrase_checker(sentence_pairs, batch_size=8,␣
 ↪fewshot_examples=examples)
end_few = time.time()
few_shot_time = end_few - start_few
predictions = [get_label(output) for output in out]

few_shot_accuracy = accuracy_score(true_labels, predictions)
few_shot_f1 = f1_score(true_labels, predictions)
few_shot_cm = confusion_matrix(true_labels, predictions)

print(f"\nFewShot Test Results")
print(f"Test Accuracy: {few_shot_accuracy:.4f}")
print(f"Test F1 Score: {few_shot_f1:.4f}")
print(f"\nConfusion Matrix:")
print(few_shot_cm)
```

```
Will be using GPU!

Loading model…

Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]

Some parameters are on the meta device because they were offloaded to the cpu.

Model loaded successfully!

Creating balanced 200-sample subset…

First few examples:
                                            sentence1  \
0  The first formal description of the Vietnamese…
1  The brewery produces eight standard beers and …
2  Bhavani , Ajay , & Hari lied to police that La…
3  The next A4 segment will connect Štip ( A3 jun…
4  Hamilton Ventura has won the South America Gam…
```

```
                                          sentence2  label
0  The first formal description of the Vietnamese…      1
1  The brewery produces eight standard beers and …      1
2  Bhavani , Ajay and Hari lied to the police tha…      1
3  The next A4 segment will connect Štip ( A3 jun…      0
4  The Álvarez won the South America Games agains…      0

Prepared 200 sentence pairs for evaluation

Running zero shot inference…


SAMPLE ZERO-SHOT PROMPT:
Decide if these sentences are paraphrases. Respond with only "paraphrase" or
"not paraphrase".

Sentence 1: The first formal description of the Vietnamese green fink was
carried out in 1926 by the American ornithologist Jean Théodore Delacour under
the binomial name `` Hypacanthis monguilloti '' .
Sentence 2: The first formal description of the Vietnamese greenfinch was by the
American ornithologist Jean Théodore Delacour in 1926 under the binomial name ``
Hypacanthis monguilloti '' .
Answer:



Processing batches:
100%|                                  | 25/25
[00:42<00:00,  1.68s/it]


Zero Shot Test Results
Test Accuracy: 0.8300
Test F1 Score: 0.8283

Confusion Matrix:
[[84 16]
 [18 82]]

Running few shot inference…


SAMPLE FEW-SHOT PROMPT:
Decide if these sentences are paraphrases. Respond with only "paraphrase" or
"not paraphrase".

Sentence 1: William died in 1859 and Elizabeth died the following year .
Sentence 2: In 1859 , William and Elizabeth died the following year .
```

```
Answer: paraphrase

Sentence 1: St Francis Inter College , Aligarh Road , is one of the best and
most renowned schools in Hathras .
Sentence 2: St Francis Inter College , Hathras Road , is one of the best and
most renowned schools in Aligarh .
Answer: not paraphrase

Sentence 1: The leaves are generally 1.5-4 mm wide and 0.2-0.7 mm long .
Sentence 2: The leaves are typically 1.5-4 mm wide and 0.2-0.7 mm long .
Answer: paraphrase

Sentence 1: Swarthmore is represented at the General Assembly of Pennsylvania as
the PA 161st Legislative District and the PA 26th Senate District .
Sentence 2: Swarthmore is represented in the Pennsylvania General Assembly as
the PA 26th Legislative District and the PA 161st Senate District .
Answer: not paraphrase

Sentence 1: Drummer Wayne Bennett left the band in June 2007 and was replaced by
Ben Timony .
Sentence 2: In June 2007 , drummer Wayne Bennett left the band and was replaced
by Ben Timony .
Answer: paraphrase

Sentence 1: The show was initiated by Peter Weil , produced by Barraclough Carey
Productions .
Sentence 2: The show was produced by Peter Weil and initiated by Barraclough
Carey Productions .
Answer: not paraphrase

Sentence 1: The first formal description of the Vietnamese green fink was
carried out in 1926 by the American ornithologist Jean Théodore Delacour under
the binomial name `` Hypacanthis monguilloti '' .
Sentence 2: The first formal description of the Vietnamese greenfinch was by the
American ornithologist Jean Théodore Delacour in 1926 under the binomial name ``
Hypacanthis monguilloti '' .
Answer:


Processing batches:
100%|                                   | 25/25
[00:59<00:00,  2.39s/it]


FewShot Test Results
Test Accuracy: 0.6800
Test F1 Score: 0.5362
```

```
Confusion Matrix:
[[99  1]
 [63 37]]
```

0.3.1 On Zero-Shot Outperforming Few-Shot

The zero-shot approach achieved higher accuracy (0.83) compared to few-shot (0.68), which might be attributed to several factors. First, the PAWS dataset is specifically designed as an adversarial benchmark where sentence pairs often share high lexical similarity but differ in meaning due to subtle differences. The randomly sampled few-shot examples may have inadvertently introduced a conservative prediction bias. The confusion matrix shows the model predicted "not paraphrase" for 63 out of 100 true paraphrases. The few-shot examples contain cases where small differences (such as "Aligarh Road" vs "Hathras Road") indicated non-paraphrases, which might lead the model to over-generalize this pattern and reject paraphrases with any minor variation. In contrast, the zero-shot approach relied solely on the model's pre-trained understanding of paraphrasing, which appears to work better for the PAWS task.

[18]:
```
test_200_subset = test_subset
true_labels_200 = test_200_subset['label'].tolist()

# Testing with GloVE on 200 samples
print("\n1. Evaluating GLoVe...")
sent1_glove_200, _ = embedder.transform(test_200_subset["sentence1"])
sent2_glove_200, _ = embedder.transform(test_200_subset["sentence2"])
glove_X_200 = construct_features(sent1_glove_200, sent2_glove_200)

start_time = time.time()
glove_pred_200 = best_glove_model.predict(glove_X_200)
glove_time_200 = time.time() - start_time

glove_acc_200 = accuracy_score(true_labels_200, glove_pred_200)
glove_f1_200 = f1_score(true_labels_200, glove_pred_200)
glove_cm_200 = confusion_matrix(true_labels_200, glove_pred_200)

print(f"Accuracy: {glove_acc_200:.4f}, F1: {glove_f1_200:.4f}, Time:␣
 ↪{glove_time_200:.4f}s")

# Testing with bi-encoder on 200 samples
print("\n2. Evaluating Bi-encoder...")
bi_X_200 = bi_encoder(
    test_200_subset["sentence1"].tolist(),
    test_200_subset["sentence2"].tolist(),
    batch_size=32
)

start_time = time.time()
```

```
bi_pred_200 = final_bi_enc_model.predict(bi_X_200)
bi_time_200 = time.time() - start_time

bi_acc_200 = accuracy_score(true_labels_200, bi_pred_200)
bi_f1_200 = f1_score(true_labels_200, bi_pred_200)
bi_cm_200 = confusion_matrix(true_labels_200, bi_pred_200)

print(f"Accuracy: {bi_acc_200:.4f}, F1: {bi_f1_200:.4f}, Time: {bi_time_200:.
 ↪4f}s")

# Testing with cross-encoder on 200 samples
print("\n3. Evaluating Cross-encoder...")
from datasets import Dataset as HFDataset

# Create dataset for the 200 samples (same format as before)
cross_200_dict = {
    'sentence1': test_200_subset['sentence1'].tolist(),
    'sentence2': test_200_subset['sentence2'].tolist(),
    'labels': test_200_subset['label'].tolist()
}
cross_200_dataset = HFDataset.from_dict(cross_200_dict)

# Tokenize using the same prepare_dataset function from before
cross_tokenizer_200 = AutoTokenizer.from_pretrained(SAVED_MODEL_DIR)
cross_200_tokenized = prepare_dataset(cross_200_dataset, cross_tokenizer_200)

# Use the saved trainer to predict
start_time = time.time()
predictions_200 = final_cross_encoder_trainer.predict(cross_200_tokenized)
cross_time_200 = time.time() - start_time

cross_pred_200 = np.argmax(predictions_200.predictions, axis=-1)

cross_acc_200 = accuracy_score(true_labels_200, cross_pred_200)
cross_f1_200 = f1_score(true_labels_200, cross_pred_200)
cross_cm_200 = confusion_matrix(true_labels_200, cross_pred_200)

print(f"Accuracy: {cross_acc_200:.4f}, F1: {cross_f1_200:.4f}, Time:␣
 ↪{cross_time_200:.4f}s")

print("\n")
print("COMPARING ALL MODELS ON 200 SAMPLES (BELOW)")
print("\n")

comparison_df = pd.DataFrame({
    'Model': ['GLoVe + LR', 'Bi-encoder + LR', 'Cross-encoder + LR', 'Qwen␣
 ↪(0-shot)', 'Qwen (few-shot)'],
```

```
    'Accuracy': [glove_acc_200, bi_acc_200, cross_acc_200, zero_shot_accuracy,␣
 ↪few_shot_accuracy],
    'F1 Score': [glove_f1_200, bi_f1_200, cross_f1_200, zero_shot_f1,␣
 ↪few_shot_f1],
    'Time (s)': [glove_time_200, bi_time_200, cross_time_200, zero_shot_time,␣
 ↪few_shot_time]
})

print(comparison_df.to_string(index=False))
```

```
1. Evaluating GLoVe…
Accuracy: 0.5050, F1: 0.2205, Time: 0.0015s

2. Evaluating Bi-encoder…
Encoding 200 documents…
Batches:   0%|          | 0/7 [00:00<?, ?it/s]
Batches:   0%|          | 0/7 [00:00<?, ?it/s]
Accuracy: 0.6000, F1: 0.5652, Time: 0.0020s

3. Evaluating Cross-encoder…
Map:   0%|          | 0/200 [00:00<?, ? examples/s]
<IPython.core.display.HTML object>
Accuracy: 0.8850, F1: 0.8844, Time: 11.5390s


COMPARING ALL MODELS ON 200 SAMPLES (BELOW)


             Model  Accuracy  F1 Score  Time (s)
        GLoVe + LR     0.505  0.220472  0.001499
   Bi-encoder + LR     0.600  0.565217  0.002004
Cross-encoder + LR     0.885  0.884422 11.539000
     Qwen (0-shot)     0.830  0.828283 42.062804
   Qwen (few-shot)     0.680  0.536232 59.849457
```

0.4 Evaluation of all models on PAWS:

Based on these results, Cross-encoder + LR had the best Accuracy / f1 score out of all models. It performed better than Qwen, likely because it had been fine-tuned on PAWS data, and it was able to learn how to solve this adversarial task of paraphrase detection. Additionally the cross-attention between the two sentences lets the model compare phrases between sentences which gives it an advantage over models like GloVE and Bi-encoder. Qwen zero-shot also performed well, likely because, as an LLM it would have been pre-trained on similar tasks. Unexpectedly, Qwen few-shot performed worse than Qwen zero-shot, probably because the few-shot examples that were

provided led to the model becoming overly conservative (as discussed previously). Additionally Qwen few-shot had the longest inference time (perhaps due to the length of the prompt). As expected, Bi-encoder + LR and GloVE had the worst F1 and Accuracy scores but the shortest inference times.

In my opinion, Cross-encoder + LR, is the best model for this task. With an F1 and Accuracy scores at 0.88, it achieves good performance on the PAWS dataset. Additionally, its inference time of 11 seconds is suitable for this task.

[ ]: