Sentiment Analysis

1.1) Load & Combine Data

In [1]:
```
import pandas as pd  # for handling dataframes
import re  # for regular expressions
import numpy as np  # for numerical operations
from collections import Counter  # for counting words/n-grams
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS  # stopwords list

# --- Load Data from text files ---
# Each dataset has sentences and labels (0=negative, 1=positive)

df_yelp = pd.read_csv(
    './sentiment labelled sentences/yelp_labelled.txt',  # path to Yelp dataset
    names=['sentence', 'label'],  # column names
    sep='\t',  # tab-separated values
    encoding='utf-8'
)

df_amazon = pd.read_csv(
    './sentiment labelled sentences/amazon_cells_labelled.txt',  # Amazon reviews
    names=['sentence', 'label'],
    sep='\t',
    encoding='utf-8'
)

df_imdb = pd.read_csv(
    './sentiment labelled sentences/imdb_labelled.txt',  # IMDB reviews
    names=['sentence', 'label'],
    sep='\t',
    encoding='utf-8'
)

# Print dataset shapes to see how many rows/examples each has
print("Yelp:", df_yelp.shape)
print("Amazon:", df_amazon.shape)
print("IMDB:", df_imdb.shape)

# --- Combine all datasets into one dataframe ---
df_all = pd.concat([df_yelp, df_amazon, df_imdb], ignore_index=True)
print("Combined:", df_all.shape)  # check total number of examples

# Keep a copy of combined dataset for further processing
df = df_all.copy()
```

```
Yelp: (1000, 2)
Amazon: (1000, 2)
IMDB: (748, 2)
Combined: (2748, 2)
```

1.2) Explore Data

```
In [2]: # --- Tokenizer ---
        # This regex keeps words and contractions like "don't"
        _token_re = re.compile(r"[A-Za-z]+(?:'[A-Za-z]+)?")


        def tok(s):
            """Convert a sentence to a list of lowercase tokens/words."""
            if not isinstance(s, str):
                return []
            return _token_re.findall(s.lower())


        # --- Label distribution per dataset ---
        for name, d in [('Yelp', df_yelp), ('Amazon', df_amazon), ('IMDB', df_imdb)]:
            percent = (d['label']
                        .value_counts(normalize=True)  # get percentages
                        .sort_index() * 100).round(2)
            print(f"\n{name} label distribution (%):")
            print(percent)

        # --- Overview of combined dataset ---
        print("\nDataset shape:", df.shape)  # number of rows and columns
        print("Missing values:", df.isna().sum().to_dict())  # check for NaNs

        # --- Global label distribution ---
        counts = df['label'].value_counts().sort_index()  # counts of 0 and 1
        pct = (df['label'].value_counts(normalize=True).sort_index() * 100).round(2)  # per
        print("\nGlobal label distribution:")
        print(pd.DataFrame({'count': counts, 'percent': pct}))


        # --- Basic text statistics ---
        def stats(text):
            """Compute simple statistics for a sentence."""
            s = text if isinstance(text, str) else ""  # handle non-string entries
            t = tok(s)  # tokenize
            n = len(t)  # number of tokens
            return pd.Series({
                'char_len': len(s),  # number of characters
                'word_len': n,  # number of words
                'avg_word_len': (sum(len(x) for x in t) / n) if n else 0.0,  # average word
                'stop_ratio': sum(x in ENGLISH_STOP_WORDS for x in t) / (n or 1),  # fracti
                'ttr': len(set(t)) / (n or 1),  # type-token ratio (vocabulary richness)
            })


        # Apply stats to all sentences
        df_e = df['sentence'].apply(stats)
        # Combine label column with computed stats
        df_e = pd.concat([df[['label']], df_e], axis=1)

        print("\nOverall descriptors:")
        print(df_e.describe().round(3).T)  # summary statistics

        print("\nMean descriptors per label:")
        print(df_e.groupby('label').mean(numeric_only=True).round(3))  # average per sentim


        # --- N-Gram Extraction ---
        def top_ngrams(texts, n=1, k=10, drop_stop=True):
            """
            Extract top-k n-grams from a list of sentences.

            Args:
                texts: list of sentences
                n: size of n-gram (1=unigram, 2=bigram, etc.)
                k: top-k n-grams to return
                drop_stop: whether to remove stopwords
            Returns:
                DataFrame with top-k n-grams and counts
            """
            c = Counter()
            for s in texts:
                tokens = tok(s)
                if drop_stop:
                    tokens = [w for w in tokens if w not in ENGLISH_STOP_WORDS]
                grams = tokens if n == 1 else [
                    " ".join(tokens[i:i + n]) for i in range(len(tokens) - n + 1)
                ]
                c.update(grams)
            df_out = pd.DataFrame(c.most_common(k), columns=[f'{n}-gram', 'count'])
            return df_out


        print("\nTop Unigrams (all):")
        print(top_ngrams(df['sentence'], n=1, k=10))  # top 10 single words

        print("\nTop Bigrams (all):")
        print(top_ngrams(df['sentence'], n=2, k=10))  # top 10 two-word combinations

        # Top n-grams per label
        for lbl in sorted(df['label'].unique()):
            print(f"\nTop Unigrams (Label={lbl}):")
            print(top_ngrams(df[df['label'] == lbl]['sentence'], n=1, k=10))

            print(f"\nTop Bigrams (Label={lbl}):")
            print(top_ngrams(df[df['label'] == lbl]['sentence'], n=2, k=10))


        # --- Vocabulary Size ---
        def vocab_size(texts):
            """Compute the number of unique words in a list of sentences, excluding stopwor
            v = set()
            for s in texts:
                v.update([w for w in tok(s) if w not in ENGLISH_STOP_WORDS])
            return len(v)
```

```python
print("\nTotal vocabulary size (no stopwords):", vocab_size(df['sentence']))

print("\nVocabulary size per label:")
print(df.groupby('label')['sentence'].apply(vocab_size).to_frame('vocab_size'))
```

```
Yelp label distribution (%):
label
0    50.0
1    50.0
Name: proportion, dtype: float64

Amazon label distribution (%):
label
0    50.0
1    50.0
Name: proportion, dtype: float64

IMDB label distribution (%):
label
0    48.4
1    51.6
Name: proportion, dtype: float64

Dataset shape: (2748, 2)
Missing values: {'sentence': 0, 'label': 0}

Global label distribution:
       count  percent
label
0       1362    49.56
1       1386    50.44

Overall descriptors:
              count    mean      std  min     25%     50%     75%     max
label        2748.0   0.504    0.500  0.0   0.000   1.000   1.000     1.0
char_len     2748.0  71.620  204.405  7.0  32.000  55.000  87.000  8041.0
word_len     2748.0  12.896   33.489  0.0   6.000  10.000  16.000  1297.0
avg_word_len 2748.0   4.498    0.974  0.0   3.923   4.364   4.909    13.0
stop_ratio   2748.0   0.494    0.181  0.0   0.417   0.500   0.609     1.0
ttr          2748.0   0.956    0.073  0.0   0.917   1.000   1.000     1.0

Mean descriptors per label:
       char_len  word_len  avg_word_len  stop_ratio    ttr
label
0        74.437    13.467         4.462       0.515  0.955
1        68.852    12.334         4.533       0.474  0.956

Top Unigrams (all):
  1-gram  count
0   good    231
1  great    210
2  movie    181
3  phone    165
4   film    160
5   food    126
6   like    125
7   just    119
8  place    114
9   it's    114

Top Bigrams (all):
```

```
             2-gram  count
0        waste time     17
1       works great     17
2  customer service     15
3     sound quality     14
4       waste money     12
5       don't waste     11
6  highly recommend     11
7      battery life     11
8       don't think     10
9         i've seen     10

Top Unigrams (Label=0):
  1-gram  count
0    bad     96
1  movie     95
2  phone     78
3   film     71
4   just     69
5   like     67
6   food     66
7   time     62
8  don't     60
9   good     57

Top Bigrams (Label=0):
             2-gram  count
0        waste time     16
1  customer service     12
2       waste money     12
3       don't waste     11
4       don't think      8
5         i've seen      8
6         it's just      6
7      doesn't work      6
8         does work      6
9         don't buy      6

Top Unigrams (Label=1):
   1-gram  count
0   great    193
1    good    174
2    film     89
3   phone     87
4   movie     86
5    food     60
6  really     60
7    it's     60
8    best     59
9   place     58

Top Bigrams (Label=1):
             2-gram  count
0       works great     17
1  highly recommend     11
2     sound quality     10
```

```
3       great phone      9
4        great food      8
5       really good      8
6     great service      7
7       pretty good      7
8         food good      7
9      good quality      7

Total vocabulary size (no stopwords): 4903

Vocabulary size per label:
       vocab_size
label
0            3111
1            3079
```

2.1) Text Cleaning (Improved)

In [3]:
```python
import re  # regular expressions for text processing
import html  # for handling HTML entities

# --- Optional: Lemmatization using NLTK ---
use_lemmatize = True
try:
    import nltk
    from nltk.stem import WordNetLemmatizer

    # Check if NLTK data is downloaded
    nltk.data.find('corpora/wordnet')
    nltk.data.find('corpora/omw-1.4')
    _lemmatizer = WordNetLemmatizer()  # create lemmatizer
except Exception:
    # fallback to stemming if NLTK or wordnet not available
    use_lemmatize = False

from nltk.stem import PorterStemmer  # fallback stemmer

_stemmer = PorterStemmer()  # create stemmer instance

# --- Common English contractions ---
# This dictionary maps contractions to their expanded form
# e.g., "don't" -> "do not"
CONTRACTIONS = {
    "ain't": "am not", "aren't": "are not", "can't": "cannot", "can't've": "cannot
    "could've": "could have", "couldn't": "could not", "didn't": "did not", "doesn'
    "don't": "do not", "hadn't": "had not", "hasn't": "has not", "haven't": "have n
    "he's": "he is", "she's": "she is", "it's": "it is", "i'm": "i am", "i've": "i
    "i'd": "i would", "i'll": "i will", "isn't": "is not", "let's": "let us", "migh
    "mustn't": "must not", "shan't": "shall not", "shouldn't": "should not",
    "that's": "that is", "there's": "there is", "they're": "they are", "they've": "
    "we're": "we are", "we've": "we have", "we'll": "we will", "weren't": "were not
    "what's": "what is", "who's": "who is", "won't": "will not", "wouldn't": "would
    "you'd": "you would", "you'll": "you will", "you're": "you are", "y'all": "you
}
```

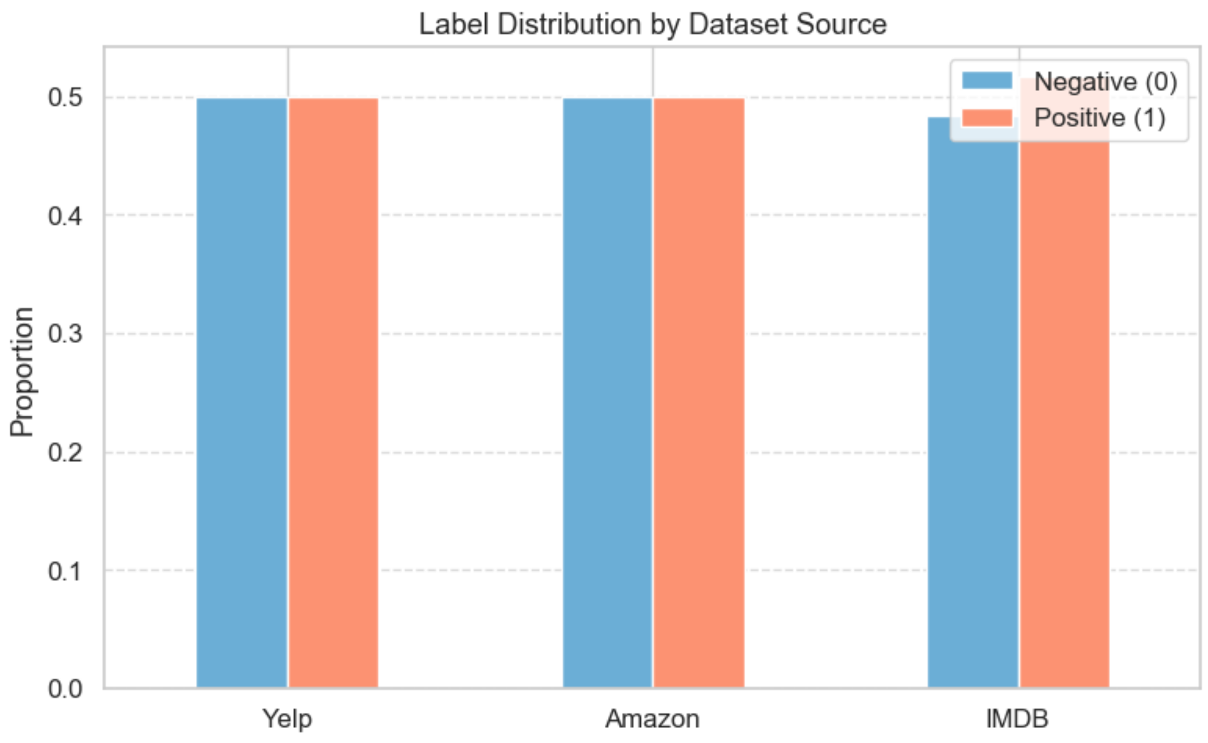
```python
# --- Regex patterns for cleaning ---
_url_re = re.compile(r"https?://\S+|www\.\S+", re.IGNORECASE)  # match URLs
_html_tag_re = re.compile(r"<[^>]+>")  # match HTML tags
_num_re = re.compile(r"\b\d+(?:[.,]\d+)?\b")  # match numbers
_punct_re = re.compile(r"[\.,!?:;\-\(\)\[\]\{\}\"\'`~\/_\\\|@#\$%\^&\*\+=><]+")  #
_token_re = re.compile(r"[A-Za-z]+(?:'[A-Za-z]+)?")  # keep words and contractions


# --- Core functions ---

def expand_contractions(text: str) -> str:
    """Expand common English contractions to full words."""
    if not isinstance(text, str):
        return ""  # return empty string if input is not text

    def repl(match):
        return CONTRACTIONS.get(match.group(0).lower(), match.group(0))  # replace

    # Create regex pattern from all contractions keys
    pattern = r"\b(" + "|".join(map(re.escape, CONTRACTIONS.keys())) + r")\b"
    return re.sub(pattern, repl, text, flags=re.IGNORECASE)  # apply replacement


def basic_clean(text: str) -> str:
    """Clean text: remove URLs, HTML tags, numbers, punctuation, lowercase."""
    if not isinstance(text, str):
        return ""
    s = html.unescape(text)  # convert HTML entities to normal text
    s = _url_re.sub(" ", s)  # remove URLs
    s = _html_tag_re.sub(" ", s)  # remove HTML tags
    s = expand_contractions(s)  # expand contractions
    s = _num_re.sub(" ", s)  # remove numbers
    s = _punct_re.sub(" ", s)  # remove punctuation
    s = s.lower()  # convert to lowercase
    s = re.sub(r"\s+", " ", s).strip()  # remove extra spaces
    return s


def tokenize(text: str):
    """Split text into list of words (tokens)."""
    return _token_re.findall(text)


def normalize_tokens(tokens):
    """Convert tokens to base form using lemmatization or stemming."""
    out = []
    for t in tokens:
        if use_lemmatize:
            try:
                out.append(_lemmatizer.lemmatize(t))  # lemmatize word
            except Exception:
                out.append(_stemmer.stem(t))  # fallback to stemming
        else:
            out.append(_stemmer.stem(t))  # stem if lemmatizer not available
    return out
```

```
def clean_text_pipeline(text: str, remove_stopwords=False):
    """
    Full text preprocessing pipeline.

    Args:
        text: raw sentence
        remove_stopwords: True to remove common English stopwords
    Returns:
        clean string, list of normalized tokens
    """
    clean_str = basic_clean(text)  # clean text
    tokens = tokenize(clean_str)  # tokenize
    if remove_stopwords:
        tokens = [t for t in tokens if t not in ENGLISH_STOP_WORDS]  # remove stopw
    tokens = normalize_tokens(tokens)  # lemmatize or stem
    return clean_str, tokens


# --- Apply cleaning to the dataset ---
# For deep learning, keep stopwords (important for negations like "not good")
df['clean_text'], df['tokens'] = zip(*df['sentence'].map(lambda x: clean_text_pipel

# --- Compute sentence length after cleaning ---
df['len_tokens'] = df['tokens'].apply(len)  # number of tokens per sentence

# --- Quick check of cleaned data ---
print(df[['sentence', 'clean_text', 'label', 'len_tokens']].head())  # show first 5
```

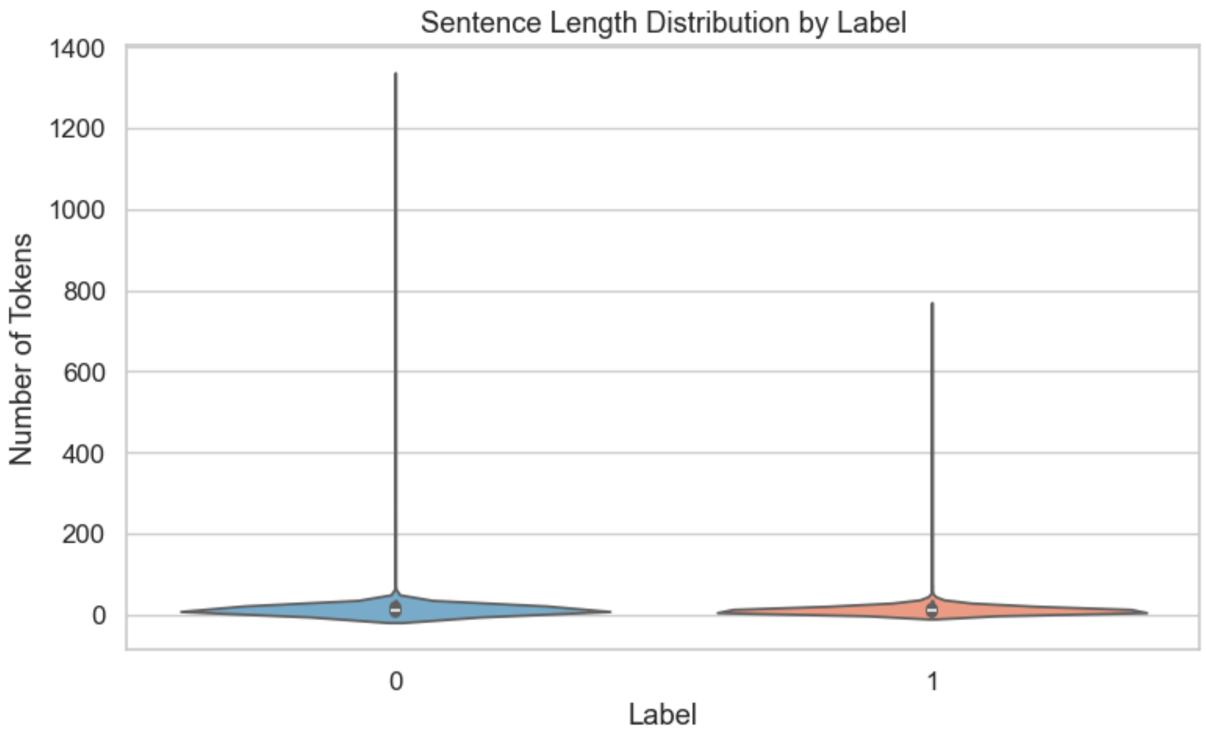
```
                                             sentence  \
0                            Wow... Loved this place.
1                                  Crust is not good.
2           Not tasty and the texture was just nasty.
3   Stopped by during the late May bank holiday of...
4   The selection on the menu was great and so wer...

                                           clean_text  label  len_tokens
0                                wow loved this place      1           4
1                                   crust is not good      0           4
2             not tasty and the texture was just nasty      0           8
3   stopped by during the late may bank holiday of...      1          15
4   the selection on the menu was great and so wer...      1          12
```

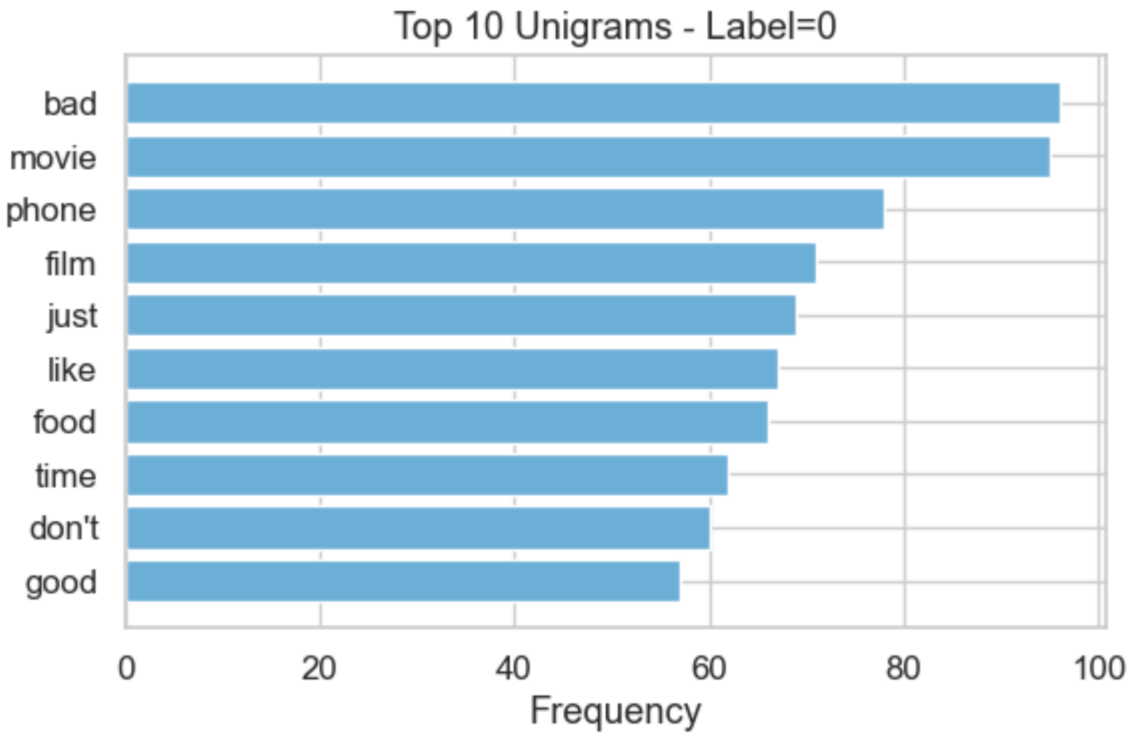
2.2) Exploratory Data Analysis (EDA) (Improved)

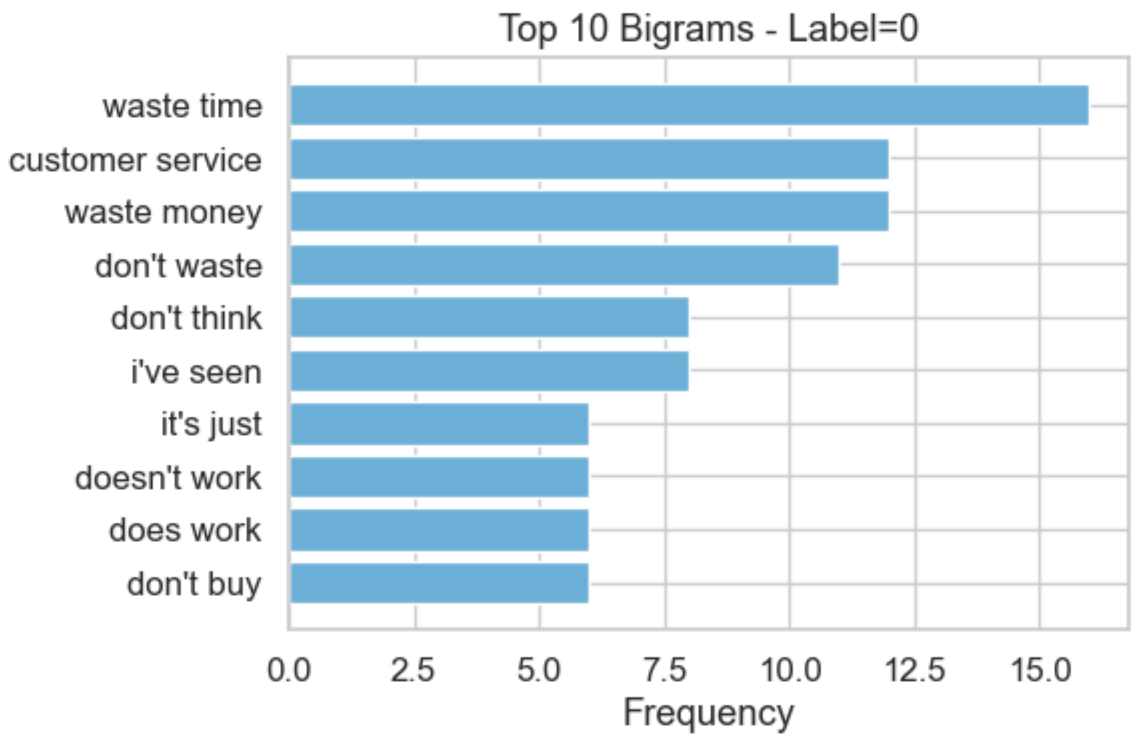
In [4]:
```
import matplotlib.pyplot as plt  # for plotting
import seaborn as sns  # for nicer statistical plots
from wordcloud import WordCloud  # for creating word clouds

# Set seaborn style for all plots (white background + muted colors + slightly large
sns.set(style="whitegrid", palette="muted", font_scale=1.1)

# --- Label distribution by source ---
# Create a DataFrame with proportion of each label per dataset
label_df = pd.DataFrame({
    'Yelp': df_yelp['label'].value_counts(normalize=True).sort_index(),
    'Amazon': df_amazon['label'].value_counts(normalize=True).sort_index(),
    'IMDB': df_imdb['label'].value_counts(normalize=True).sort_index()
}).T  # transpose so that datasets are rows
label_df.columns = ['Negative (0)', 'Positive (1)']  # rename columns

# Plot grouped bar chart
label_df.plot(kind='bar', figsize=(8,5), color=['#6baed6','#fc9272'])
plt.ylabel('Proportion')
plt.title('Label Distribution by Dataset Source')
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.7)  # horizontal grid lines
plt.tight_layout()
plt.show()

# --- Sentence length distribution by label ---
# Violin plot shows distribution and density of sentence lengths
plt.figure(figsize=(8,5))
sns.violinplot(x='label', y='len_tokens', data=df, palette=['#6baed6','#fc9272'])
plt.title('Sentence Length Distribution by Label')
plt.xlabel('Label')
plt.ylabel('Number of Tokens')
plt.tight_layout()
plt.show()

# --- Top N-grams per label (horizontal barplots) ---
def plot_top_ngrams_bar(texts, label_name, n=1, top_k=10, drop_stop=True):
    """Plot top-k unigrams or bigrams for a given label."""
    c = Counter()  # count occurrences
    for s in texts:
        tokens = tok(s)  # tokenize sentence
        if drop_stop:
            tokens = [w for w in tokens if w not in ENGLISH_STOP_WORDS]  # remove s
        grams = tokens if n == 1 else [
            " ".join(tokens[i:i+n]) for i in range(len(tokens)-n+1)  # create n-gra
        ]
        c.update(grams)  # update counts
    top = c.most_common(top_k)  # get top k n-grams
    if not top:
        return
    words, counts = zip(*top)
    plt.figure(figsize=(6,4))
    plt.barh(words[::-1], counts[::-1], color='#6baed6')  # horizontal bar plot
    plt.title(f'Top {top_k} {"Unigrams" if n==1 else "Bigrams"} - Label={label_name
    plt.xlabel('Frequency')
    plt.tight_layout()
    plt.show()

# Plot top unigrams and bigrams for each label
for lbl in sorted(df['label'].unique()):
    plot_top_ngrams_bar(df[df['label']==lbl]['sentence'], label_name=lbl, n=1, top_
    plot_top_ngrams_bar(df[df['label']==lbl]['sentence'], label_name=lbl, n=2, top_

# --- Vocabulary overlap (Venn diagram) ---
try:
    from matplotlib_venn import venn2
    # Get unique tokens per label (exclude stopwords)
    tokens_neg = set([t for toks in df[df['label']==0]['tokens'] for t in toks if t
    tokens_pos = set([t for toks in df[df['label']==1]['tokens'] for t in toks if t

    plt.figure(figsize=(6,6))
    venn2([tokens_neg, tokens_pos], set_labels=('Negative (0)', 'Positive (1)'),
          set_colors=('#fc9272','#6baed6'), alpha=0.7)
    plt.title('Vocabulary Overlap Between Labels')
    plt.show()
except Exception as e:
    print("Venn diagram could not be plotted:", e)

# --- Label distribution (overall) ---
label_counts = df['label'].value_counts().sort_index()
plt.figure(figsize=(6,4))
sns.barplot(x=label_counts.index, y=label_counts.values, palette=['#6baed6','#fc927
plt.title('Label Distribution', fontsize=14)
plt.xlabel('Label', fontsize=12)
plt.ylabel('Count', fontsize=12)
# Add counts on top of bars for clarity
for i, v in enumerate(label_counts.values):
    plt.text(i, v + max(label_counts.values)*0.01, str(v), ha='center', fontsize=10
plt.tight_layout()
plt.show()

# --- Word frequency plots ---
def plot_top_words(token_series, title, top_k=20, color="#74c476"):
    """Plot top-K words from tokenized series."""
    freq = Counter([t for tokens in token_series for t in tokens])  # count all tok
    top = freq.most_common(top_k)
    if top:
        words, counts = zip(*top)
        plt.figure(figsize=(12,5))
        sns.barplot(x=list(words), y=list(counts), palette=[color]*len(words))
        plt.xticks(rotation=45, ha='right')
        plt.title(title, fontsize=14)
        plt.ylabel('Frequency', fontsize=12)
        plt.xlabel('')
        plt.tight_layout()
        plt.show()
    else:
        print(f"No tokens available for {title}")

# Plot top words for all labels combined
plot_top_words(df['tokens'], 'Top Words (All Labels)', top_k=25, color="#74c476")

# Plot top words per label
label_colors = ['#6baed6','#fc9272']
for i, lbl in enumerate(sorted(df['label'].unique())):
    plot_top_words(df.loc[df['label']==lbl, 'tokens'], f'Top Words (Label={lbl})',

# --- Word clouds ---
for i, lbl in enumerate(sorted(df['label'].unique())):
    # Combine all tokens for label into single string
    text_blob = " ".join([" ".join(toks) for toks in df.loc[df['label']==lbl, 'toke
    if text_blob.strip():
        wc = WordCloud(
            width=900, height=450,
            background_color='white',
            colormap='Paired',  # color palette
            max_words=150,
            contour_color='black',
            contour_width=1
        ).generate(text_blob)
        plt.figure(figsize=(12,6))
        plt.imshow(wc, interpolation='bilinear')  # render word cloud
        plt.axis('off')
        plt.title(f'Word Cloud (Label={lbl})', fontsize=16)
        plt.tight_layout()
        plt.show()
    else:
        print(f"No tokens for label {lbl} to build word cloud")

# --- Sentence length histogram ---
plt.figure(figsize=(8,4))
sns.histplot(df['len_tokens'], bins=30, kde=True, color='#fc9272')  # histogram + K
plt.title('Sentence Length Distribution (Cleaned Tokens)', fontsize=14)
plt.xlabel('Number of Tokens', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.tight_layout()
plt.show()
```

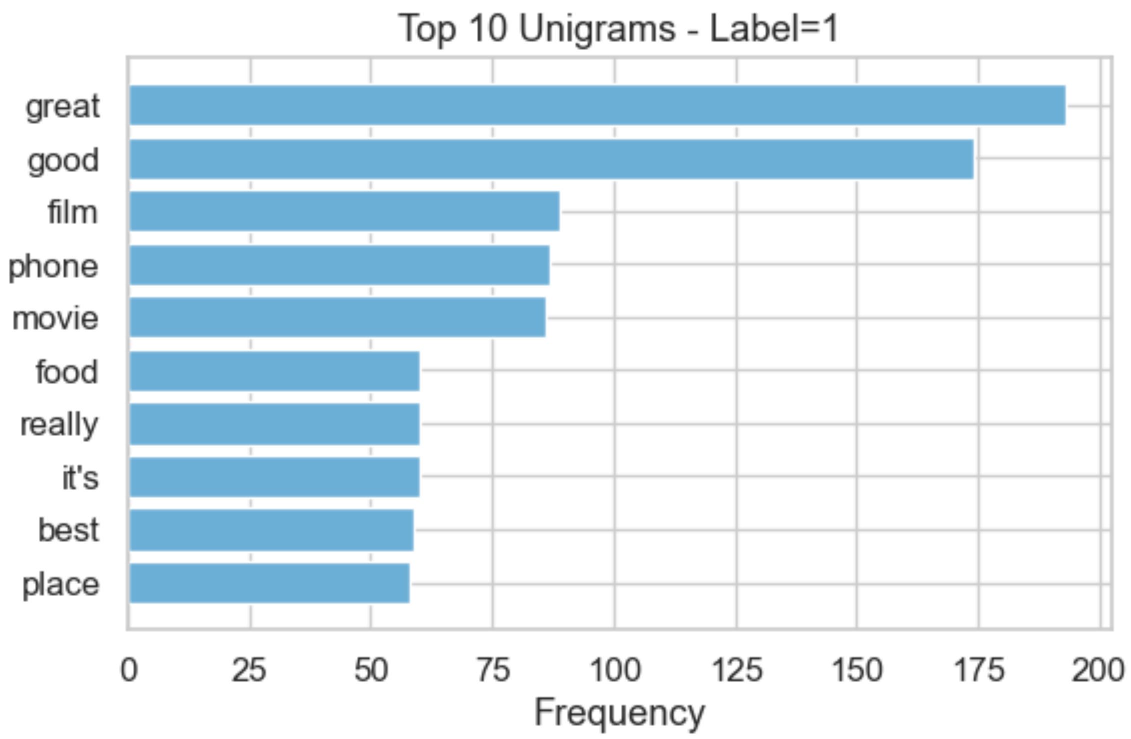


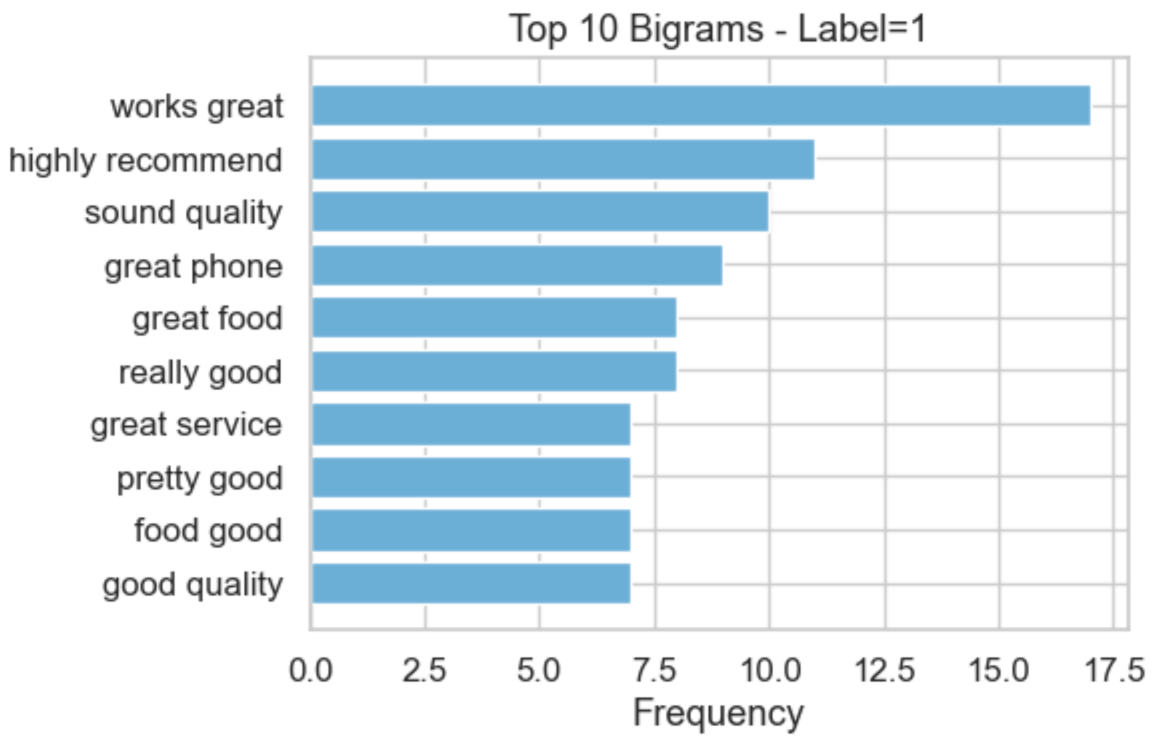
```
C:\Users\kayam\AppData\Local\Temp\ipykernel_10724\2476994674.py:29: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.violinplot(x='label', y='len_tokens', data=df, palette=['#6baed6','#fc9272'])
```

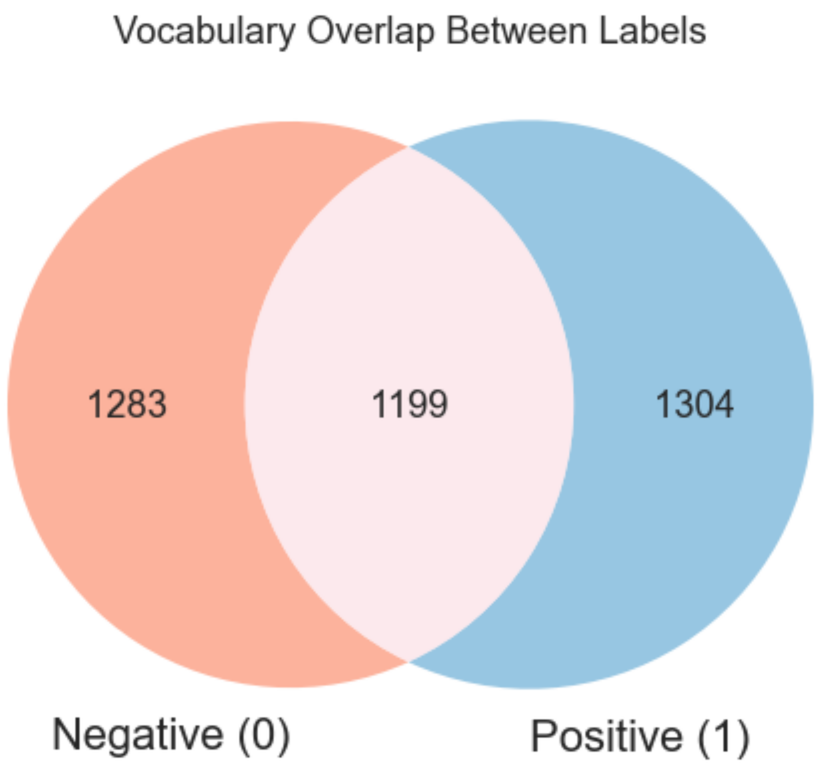

Sentence Length Distribution by Label
Number of Tokens
1400
1200
1000
800
600
400
200
0
0
1
Label


Top 10 Unigrams - Label=0
bad
movie
phone
film
just
like
food
time
don't
good
0
20
40
60
80
100
Frequency

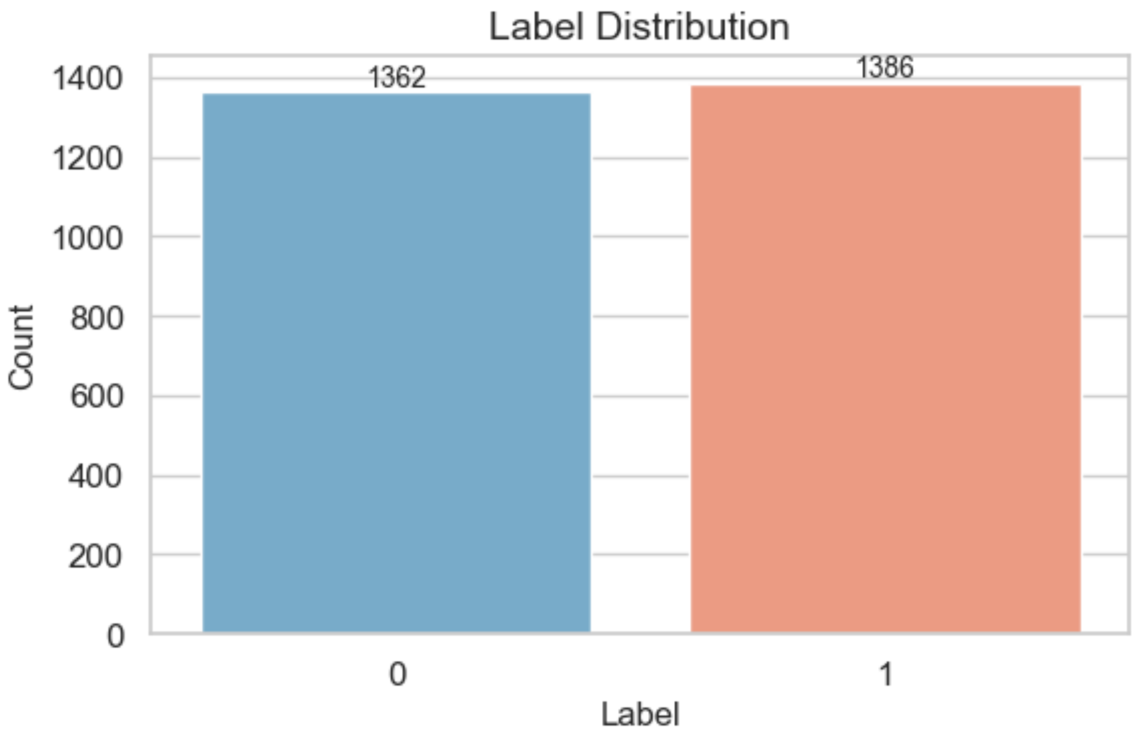

Top 10 Bigrams - Label=0
waste time
customer service
waste money
don't waste
don't think
i've seen
it's just
doesn't work
does work
don't buy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
Frequency


Top 10 Unigrams - Label=1
great
good
film
phone
movie
food
really
it's
best
place
0
25
50
75
100
125
150
175
200
Frequency

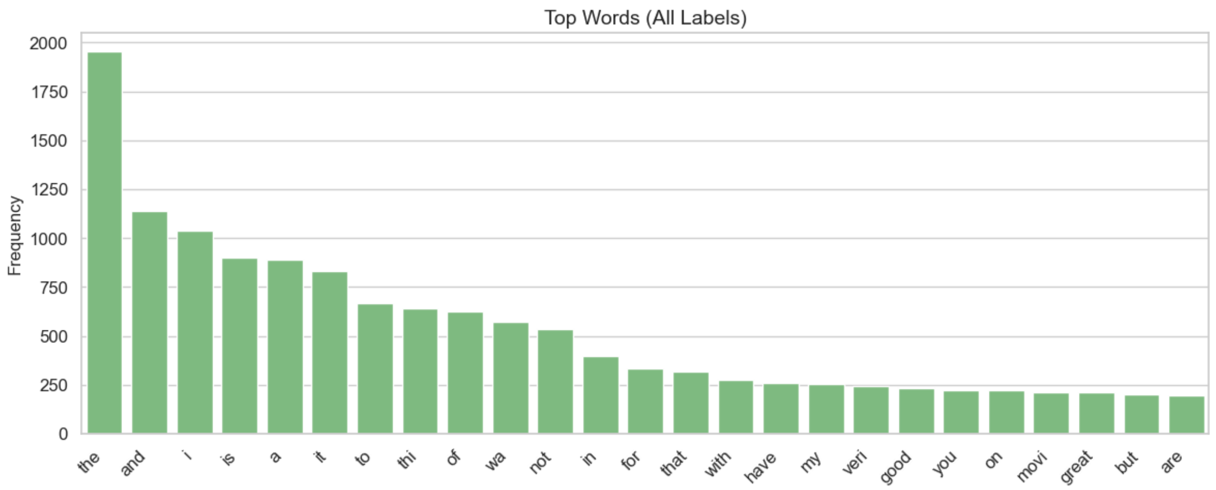




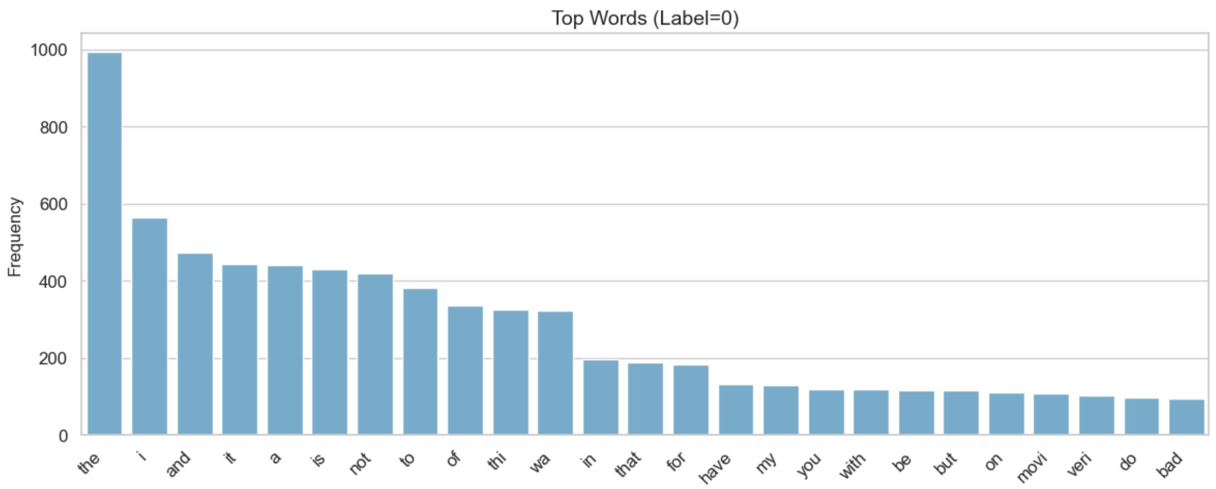
```
C:\Users\kayam\AppData\Local\Temp\ipykernel_10724\2476994674.py:83: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=label_counts.index, y=label_counts.values, palette=['#6baed6','#fc92
72'])
```



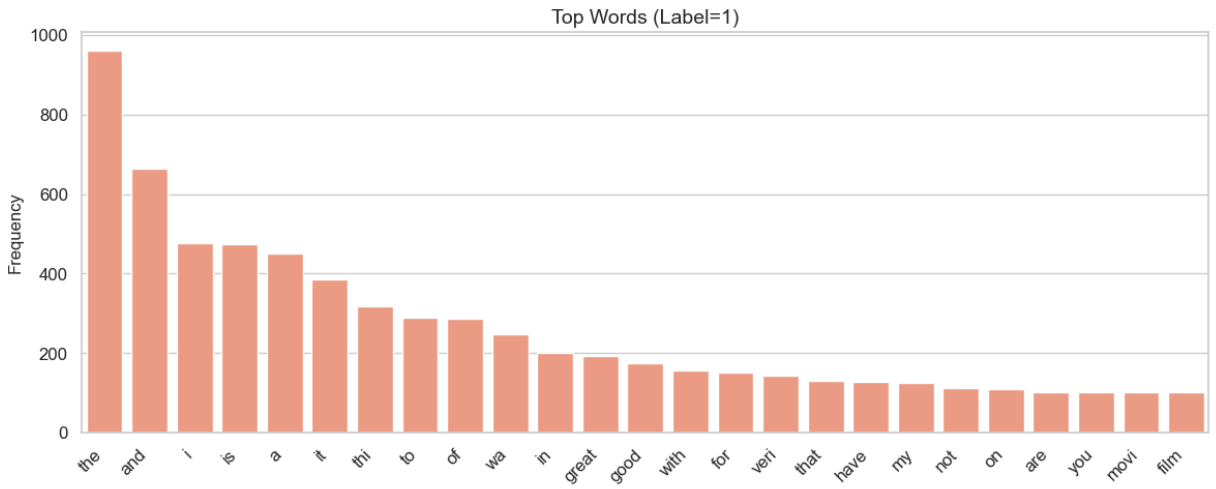
```
C:\Users\kayam\AppData\Local\Temp\ipykernel_10724\2476994674.py:101: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=list(words), y=list(counts), palette=[color]*len(words))
```

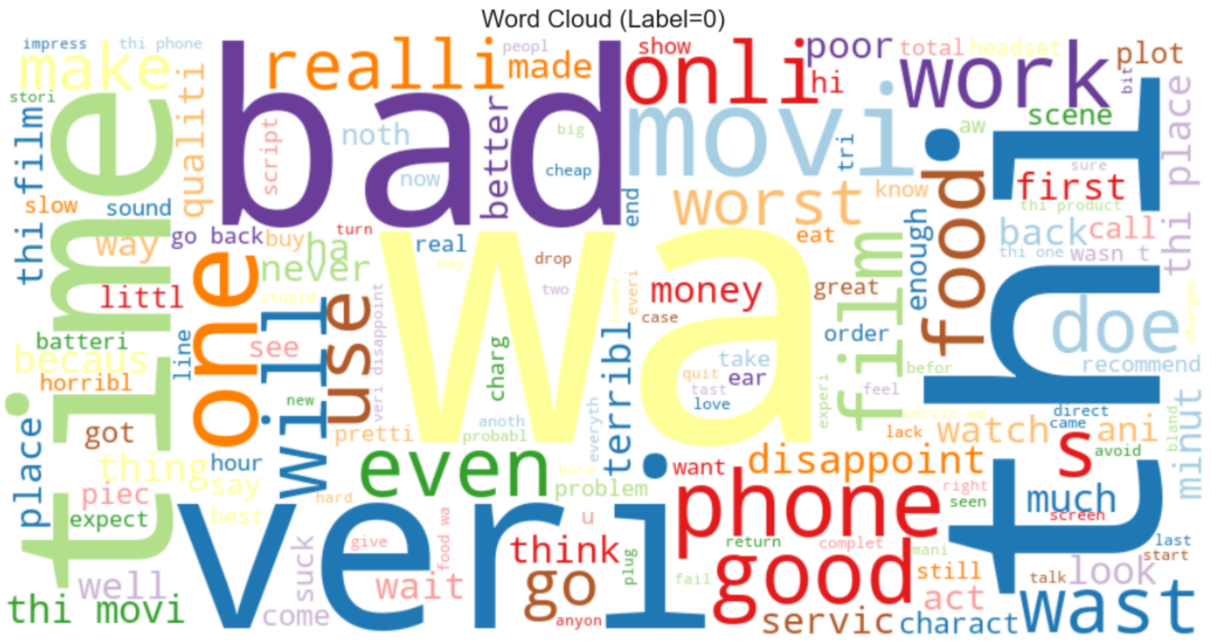


```
C:\Users\kayam\AppData\Local\Temp\ipykernel_10724\2476994674.py:101: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=list(words), y=list(counts), palette=[color]*len(words))
```

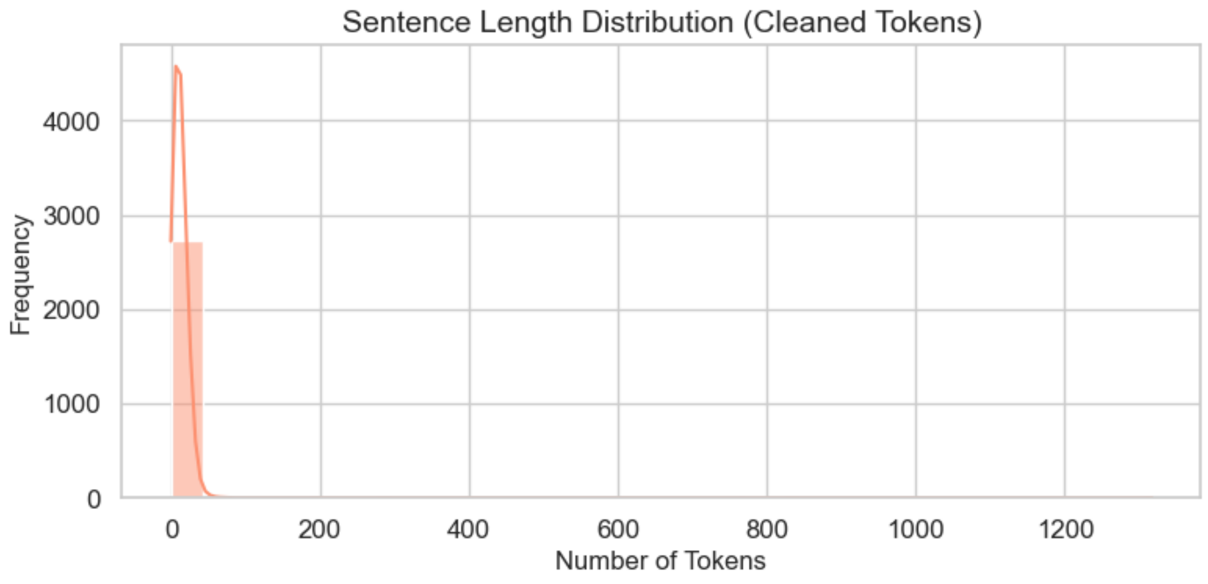


```
C:\Users\kayam\AppData\Local\Temp\ipykernel_10724\2476994674.py:101: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=list(words), y=list(counts), palette=[color]*len(words))
```





Word Cloud (Label=1)
wa
thi
good
great
well
movi
phone
love
veri
film
one
best
time
realli
work
price
servic
product
use
nice
excel



2.3) Train/Validation/Test Split (70/15/15) with CSV Save

In [5]:
```
from sklearn.model_selection import train_test_split  # for splitting data into tra

# Features (X) include original sentence, cleaned text, and token list
X = df[['sentence','clean_text','tokens']].copy()
# Labels (y) are the sentiment values (0 or 1), ensure integer type
y = df['label'].astype(int)

# --- First split: 70% train, 30% temporary (to be split into val/test) ---
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, stratify=y, random_state=42  # stratify ensures label dist
)

# --- Second split: split temp into 50% validation, 50% test (15% each overall) ---
```

```
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, stratify=y_temp, random_state=42
)

# --- Print shapes to confirm sizes ---
print("Shapes:")
print("Train:", X_train.shape, y_train.shape)
print("Validation:", X_val.shape, y_val.shape)
print("Test:", X_test.shape, y_test.shape)

import os

# Ensure that a folder exists to save CSVs
os.makedirs('./data/', exist_ok=True)

# --- Save train/val/test splits as CSV for reproducibility ---
X_train.join(y_train).to_csv('./data/train_split.csv', index=False)  # combine feat
X_val.join(y_val).to_csv('./data/val_split.csv', index=False)
X_test.join(y_test).to_csv('./data/test_split.csv', index=False)
print("Train/Val/Test splits saved to ./data/")
```

```
Shapes:
Train: (1923, 3) (1923,)
Validation: (412, 3) (412,)
Test: (413, 3) (413,)
Train/Val/Test splits saved to ./data/
```

3.1 TF-IDF features for classical ML

In [6]:

```
from sklearn.feature_extraction.text import TfidfVectorizer  # to convert text to n

# --- Custom stopwords list: remove default stopwords but keep negations (important
negations = {"not", "no", "never"}
custom_stopwords = list(ENGLISH_STOP_WORDS.difference(negations))

# Hyperparameters for TF-IDF
max_features = 5000  # maximum number of features to keep
ngram_range = (1, 2)  # include unigrams and bigrams

# Initialize TF-IDF vectorizer with custom settings
tfidf_vectorizer = TfidfVectorizer(
    max_features=max_features,
    ngram_range=ngram_range,
    stop_words=custom_stopwords
)

# Convert train/val/test cleaned text to string type
X_train_text = X_train['clean_text'].astype(str)
X_val_text   = X_val['clean_text'].astype(str)
X_test_text  = X_test['clean_text'].astype(str)

# Fit TF-IDF on training data, then transform val/test data
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train_text)
X_val_tfidf   = tfidf_vectorizer.transform(X_val_text)
X_test_tfidf  = tfidf_vectorizer.transform(X_test_text)
```

```
# Print shapes to confirm number of features and samples
print("TF-IDF shapes:")
print("Train:", X_train_tfidf.shape)
print("Val:  ", X_val_tfidf.shape)
print("Test: ", X_test_tfidf.shape)

import joblib
# Ensure folder exists to save trained models
os.makedirs('./models/', exist_ok=True)

# Save the fitted TF-IDF vectorizer for later use
joblib.dump(tfidf_vectorizer, './models/tfidf_vectorizer.pkl')
print("TF-IDF vectorizer saved to ./models/tfidf_vectorizer.pkl")
```

```
TF-IDF shapes:
Train: (1923, 5000)
Val:   (412, 5000)
Test:  (413, 5000)
TF-IDF vectorizer saved to ./models/tfidf_vectorizer.pkl
```

3.2 Tokenization and Padding for Deep Learning Model

In [7]:
```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# --- Hyperparameters for deep learning ---
max_words = 10000  # maximum number of words to keep in tokenizer (top most frequen
max_len = 100      # maximum sequence length for padding/truncating

# Convert token lists back to strings because Keras tokenizer expects raw text
X_train_text_dl = X_train['tokens'].apply(lambda toks: " ".join(toks))
X_val_text_dl   = X_val['tokens'].apply(lambda toks: " ".join(toks))
X_test_text_dl  = X_test['tokens'].apply(lambda toks: " ".join(toks))

# Initialize tokenizer, with special token for out-of-vocabulary words
tokenizer_dl = Tokenizer(num_words=max_words, oov_token="<OOV>")
tokenizer_dl.fit_on_texts(X_train_text_dl)  # fit tokenizer only on training data

# Convert text to sequences of integers
X_train_seq_dl = tokenizer_dl.texts_to_sequences(X_train_text_dl)
X_val_seq_dl   = tokenizer_dl.texts_to_sequences(X_val_text_dl)
X_test_seq_dl  = tokenizer_dl.texts_to_sequences(X_test_text_dl)

# Pad sequences to the same length for model input
# 'post' padding/truncating means extra zeros or truncation occur at the end
X_train_pad_dl = pad_sequences(X_train_seq_dl, maxlen=max_len, padding='post', trun
X_val_pad_dl   = pad_sequences(X_val_seq_dl,   maxlen=max_len, padding='post', trun
X_test_pad_dl  = pad_sequences(X_test_seq_dl,  maxlen=max_len, padding='post', trun

# Print shapes to confirm
print("Padded sequence shapes (DL):")
print("Train:", X_train_pad_dl.shape)
print("Val:  ", X_val_pad_dl.shape)
print("Test: ", X_test_pad_dl.shape)

# Save tokenizer information for embedding layers or future preprocessing
word_index_dl = tokenizer_dl.word_index  # dictionary mapping word -> index
print("Vocabulary size (DL):", len(word_index_dl))

# Save tokenizer object for reuse
joblib.dump(tokenizer_dl, './models/tokenizer_dl.pkl')
print("Tokenizer saved to ./models/tokenizer_dl.pkl")
```

```
Padded sequence shapes (DL):
Train: (1923, 100)
Val:   (412, 100)
Test:  (413, 100)
Vocabulary size (DL): 3390
Tokenizer saved to ./models/tokenizer_dl.pkl
```

4.1 Classical Model: Logistic Regression with TF-IDF (Improved, Namespaced)

In [8]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (classification_report, confusion_matrix, accuracy_scor
                             precision_recall_curve, auc)
import seaborn as sns

# --- Use pre-defined train/val/test labels for classical ML ---
y_train_cls = y_train
y_val_cls   = y_val
y_test_cls  = y_test

# --- Naive Bayes model: hyperparameter grid search ---
nb_params = {'alpha': [0.1, 0.5, 1.0, 2.0]}  # smoothing parameter
nb_grid_cls = GridSearchCV(MultinomialNB(), param_grid=nb_params, cv=5,
                           scoring='accuracy', n_jobs=-1)  # 5-fold CV
nb_grid_cls.fit(X_train_tfidf, y_train_cls)  # fit grid search on training TF-IDF f

# Print best parameters and CV accuracy for Naive Bayes
print("Best Naive Bayes params:", nb_grid_cls.best_params_)
print("Best CV accuracy (NB):", nb_grid_cls.best_score_)

# --- Logistic Regression model: hyperparameter grid search ---
log_params = {'C': [0.01, 0.1, 1, 10], 'solver': ['lbfgs', 'liblinear']}  # C: regu
log_grid_cls = GridSearchCV(LogisticRegression(max_iter=1000), param_grid=log_param
                            cv=5, scoring='accuracy', n_jobs=-1)
log_grid_cls.fit(X_train_tfidf, y_train_cls)

# Print best parameters and CV accuracy for Logistic Regression
print("Best Logistic Regression params:", log_grid_cls.best_params_)
print("Best CV accuracy (LogReg):", log_grid_cls.best_score_)

# --- Select the better model based on CV accuracy ---
if log_grid_cls.best_score_ >= nb_grid_cls.best_score_:
    best_model_cls = log_grid_cls.best_estimator_
    print("Selected model: Logistic Regression")
else:
    best_model_cls = nb_grid_cls.best_estimator_
    print("Selected model: Naive Bayes")
```

```
Best Naive Bayes params: {'alpha': 2.0}
Best CV accuracy (NB): 0.8211038961038961
Best Logistic Regression params: {'C': 1, 'solver': 'lbfgs'}
Best CV accuracy (LogReg): 0.8190219155844156
Selected model: Naive Bayes
```

4.2 Deep Learning Model: BiLSTM (Improved, Light Hyperparameter Search)

In [9]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Bidirectional, Dense, Dropout,
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.regularizers import l2

# ----------------------------
# Reproducibility: ensure consistent results
# ----------------------------
np.random.seed(42)        # for numpy operations
tf.random.set_seed(42)    # for TensorFlow operations

# ----------------------------
# Hyperparameter options (light search to save time)
# ----------------------------
embedding_dims_dl = [50, 100]       # size of word embeddings (2 options)
lstm_units_list_dl = [32]           # number of LSTM units (1 option to reduce load
dropout_rates_dl = [0.3]            # dropout rate after dense layer
spatial_dropouts_dl = [0.2]         # spatial dropout after embedding layer
batch_size_dl = 64                   # number of samples per batch
epochs_dl = 12                        # max epochs for training (reduce for speed)

# ----------------------------
# Labels as numpy arrays (required by Keras)
# ----------------------------
y_train_dl = np.array(y_train)
y_val_dl = np.array(y_val)
y_test_dl = np.array(y_test)

# ----------------------------
# Vocabulary size: limited by max_words and tokenizer
# ----------------------------
vocab_size_dl = min(max_words, len(word_index_dl) + 1)

# Variables to track best model during hyperparameter search
best_val_acc_dl = 0.0
best_model_dl = None
best_params_dl = {}

# ----------------------------
# Light hyperparameter search: nested loops
# ----------------------------
for embedding_dim_dl in embedding_dims_dl:
    for lstm_units_dl in lstm_units_list_dl:
        for dropout_rate_dl in dropout_rates_dl:
            for spatial_dropout_dl in spatial_dropouts_dl:

                # Print current hyperparameters
                print(
                    f"\nTraining BiLSTM (DL) with emb={embedding_dim_dl}, "
                    f"lstm={lstm_units_dl}, dropout={dropout_rate_dl}, spatial={spa
                )

                # ----------------------------
                # Build BiLSTM model
                # ----------------------------
                model_dl = Sequential([
                    # Embedding layer converts integer sequences to dense vectors
                    Embedding(
                        input_dim=vocab_size_dl,
                        output_dim=embedding_dim_dl,
                        input_length=max_len
                    ),
                    # SpatialDropout1D drops entire embedding dimensions to reduce
                    SpatialDropout1D(spatial_dropout_dl),
                    # Bidirectional LSTM layer
                    Bidirectional(LSTM(
                        lstm_units_dl,
                        return_sequences=False,     # last output only
                        dropout=0.3,               # dropout on input connections
                        recurrent_dropout=0.3,     # dropout on recurrent connectio
                        kernel_regularizer=l2(1e-4),       # L2 regularization on w
                        recurrent_regularizer=l2(1e-4)     # L2 regularization on r
                    )),
                    # Dense hidden layer
                    Dense(32, activation='relu', kernel_regularizer=l2(1e-4)),
                    Dropout(dropout_rate_dl),        # dropout for regularization
                    # Output layer for binary classification
                    Dense(1, activation='sigmoid')
                ])

                # ----------------------------
                # Compile model
                # ----------------------------
                model_dl.compile(
                    loss='binary_crossentropy',  # suitable for binary classificati
                    optimizer='adam',            # adaptive optimizer
                    metrics=['accuracy']         # track accuracy during training
                )

                # ----------------------------
                # Early stopping: stop if no improvement in validation loss
                # ----------------------------
                early_stop_dl = EarlyStopping(
                    monitor='val_loss',          # monitor validation loss
                    patience=2,                  # wait for 2 epochs before stoppin
                    restore_best_weights=True    # keep best weights
```

```python
                )

                # ----------------------------
                # Train model
                # ----------------------------
                history_dl = model_dl.fit(
                    X_train_pad_dl, y_train_dl,
                    validation_data=(X_val_pad_dl, y_val_dl),
                    epochs=epochs_dl,
                    batch_size=batch_size_dl,
                    callbacks=[early_stop_dl],  # apply early stopping
                    verbose=0                   # silent output
                )

                # ----------------------------
                # Track maximum validation accuracy
                # ----------------------------
                val_acc_dl = max(history_dl.history['val_accuracy'])
                print(f"Max val accuracy (DL): {val_acc_dl:.3f}")

                # ----------------------------
                # Keep best model and hyperparameters
                # ----------------------------
                if val_acc_dl > best_val_acc_dl:
                    best_val_acc_dl = val_acc_dl
                    best_model_dl = model_dl
                    best_params_dl = {
                        'embedding_dim': embedding_dim_dl,
                        'lstm_units': lstm_units_dl,
                        'dropout_rate': dropout_rate_dl,
                        'spatial_dropout': spatial_dropout_dl
                    }

# ----------------------------
# Print best hyperparameters and validation accuracy
# ----------------------------
print("\nBest hyperparameters found for DL model:")
print(best_params_dl)
print(f"Best Validation Accuracy (DL): {best_val_acc_dl:.3f}")

# ----------------------------
# Save best model to disk
# ----------------------------
os.makedirs('./models/', exist_ok=True)  # ensure folder exists
best_model_dl.save('./models/bilstm_model_best_dl.keras')
print("Best BiLSTM DL model saved to ./models/bilstm_model_best_dl.keras")
```

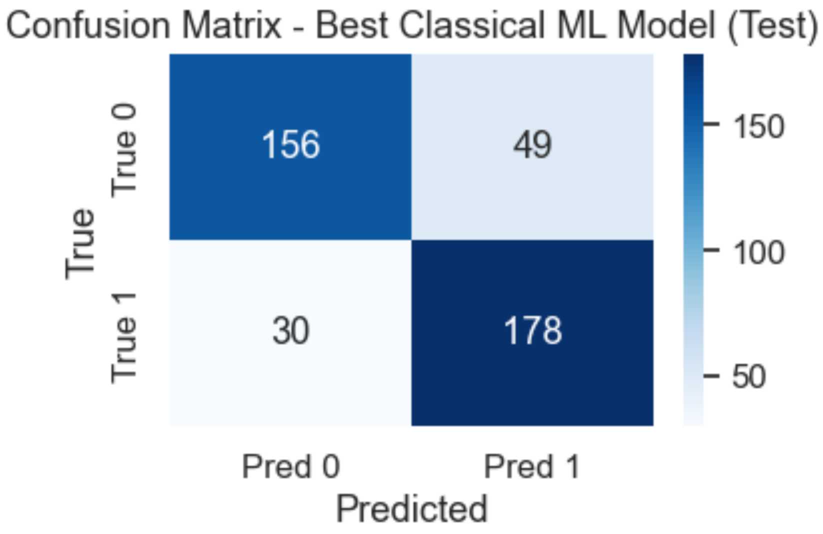
```
Training BiLSTM (DL) with emb=50, lstm=32, dropout=0.3, spatial=0.2
```

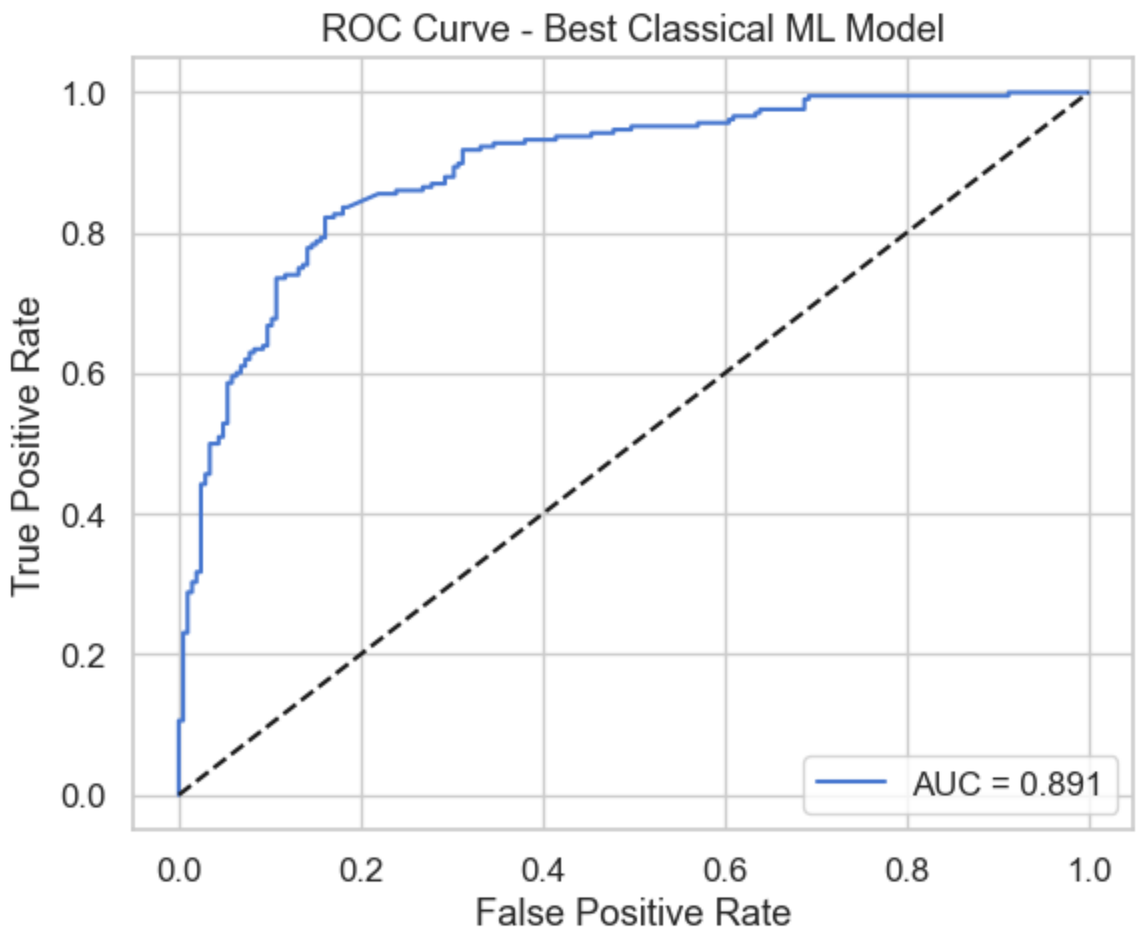
```
C:\Users\kayam\AppData\Local\Programs\Python\Python312\Lib\site-packages\keras\src\l
ayers\core\embedding.py:97: UserWarning: Argument `input_length` is deprecated. Just
remove it.
  warnings.warn(
Max val accuracy (DL): 0.833

Training BiLSTM (DL) with emb=100, lstm=32, dropout=0.3, spatial=0.2
Max val accuracy (DL): 0.825

Best hyperparameters found for DL model:
{'embedding_dim': 50, 'lstm_units': 32, 'dropout_rate': 0.3, 'spatial_dropout': 0.2}
Best Validation Accuracy (DL): 0.833
Best BiLSTM DL model saved to ./models/bilstm_model_best_dl.keras
```

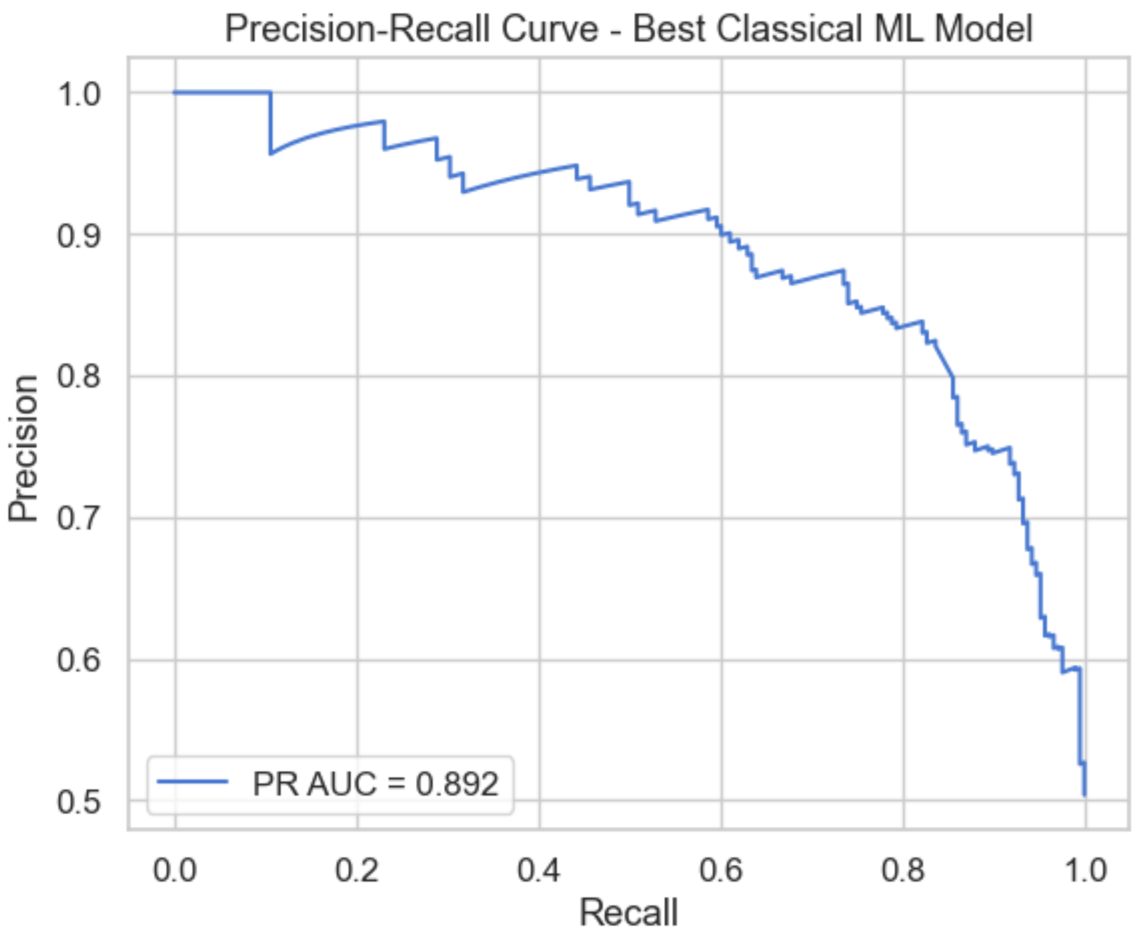
5.1 Plots - Classical Machine Learning Model

In [10]:
```python
# --- Evaluate on validation set ---
# Predict labels on validation set using the best classical ML model
y_val_pred_cls = best_model_cls.predict(X_val_tfidf)
print("Validation classification report CLASSICAL:")
# Print detailed metrics: precision, recall, f1-score for each class
print(classification_report(y_val_cls, y_val_pred_cls, digits=3))

# --- Evaluate on test set ---
# Predict labels on the test set
y_test_pred_cls = best_model_cls.predict(X_test_tfidf)
print("Test classification report CLASSICAL:")
# Show metrics on test set
print(classification_report(y_test_cls, y_test_pred_cls, digits=3))

# Compute overall test accuracy
test_acc_cls = accuracy_score(y_test_cls, y_test_pred_cls)
print(f"Test Accuracy (Classical ML): {test_acc_cls:.3f}")

# --- Confusion Matrix ---
# Confusion matrix: shows True vs Predicted counts
cm_cls = confusion_matrix(y_test_cls, y_test_pred_cls)
plt.figure(figsize=(4,3))
sns.heatmap(cm_cls, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Pred 0', 'Pred 1'],
            yticklabels=['True 0', 'True 1'])
plt.title('Confusion Matrix - Best Classical ML Model (Test)')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.tight_layout()
plt.show()

# --- ROC and PR Curves ---
# Get probability estimates for positive class
y_test_proba_cls = best_model_cls.predict_proba(X_test_tfidf)[:,1]

# ROC Curve
fpr_cls, tpr_cls, _ = roc_curve(y_test_cls, y_test_proba_cls)
roc_auc_cls = roc_auc_score(y_test_cls, y_test_proba_cls)

plt.figure(figsize=(6,5))
plt.plot(fpr_cls, tpr_cls, label=f'AUC = {roc_auc_cls:.3f}')
plt.plot([0,1], [0,1], 'k--')  # random classifier line
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Best Classical ML Model')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# Precision-Recall Curve
precision_cls, recall_cls, _ = precision_recall_curve(y_test_cls, y_test_proba_cls)
pr_auc_cls = auc(recall_cls, precision_cls)

plt.figure(figsize=(6,5))
plt.plot(recall_cls, precision_cls, label=f'PR AUC = {pr_auc_cls:.3f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve - Best Classical ML Model')
plt.legend(loc='lower left')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Top TF-IDF Features (Logistic Regression only) ---
# Only applicable if the model has coefficients (like Logistic Regression)
if hasattr(best_model_cls, 'coef_'):
    feature_names = tfidf_vectorizer.get_feature_names_out()
    coefs_cls = best_model_cls.coef_[0]
    # Top 10 positive features (most indicative of positive sentiment)
    top_pos_idx_cls = coefs_cls.argsort()[-10:][::-1]
    # Top 10 negative features (most indicative of negative sentiment)
    top_neg_idx_cls = coefs_cls.argsort()[:10]

    print("\nTop 10 Positive Features (words indicating positive sentiment):")
    for i in top_pos_idx_cls:
        print(f"{feature_names[i]}: {coefs_cls[i]:.3f}")

    print("\nTop 10 Negative Features (words indicating negative sentiment):")
    for i in top_neg_idx_cls:
        print(f"{feature_names[i]}: {coefs_cls[i]:.3f}")
```

```
Validation classification report CLASSICAL:
              precision    recall  f1-score   support

           0      0.782     0.828     0.805       204
           1      0.821     0.774     0.797       208

    accuracy                          0.801       412
   macro avg      0.802     0.801     0.801       412
weighted avg      0.802     0.801     0.801       412

Test classification report CLASSICAL:
              precision    recall  f1-score   support

           0      0.839     0.761     0.798       205
           1      0.784     0.856     0.818       208

    accuracy                          0.809       413
   macro avg      0.811     0.808     0.808       413
weighted avg      0.811     0.809     0.808       413

Test Accuracy (Classical ML): 0.809
```

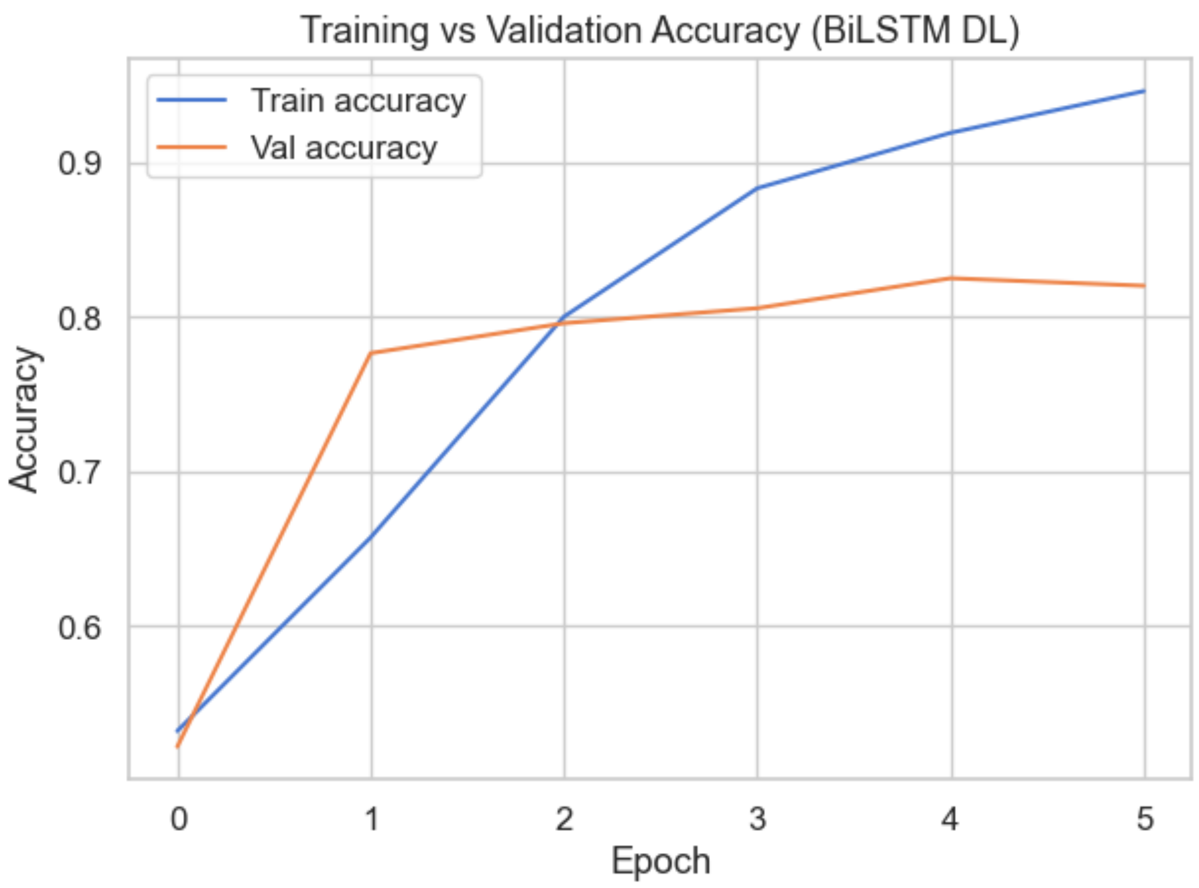


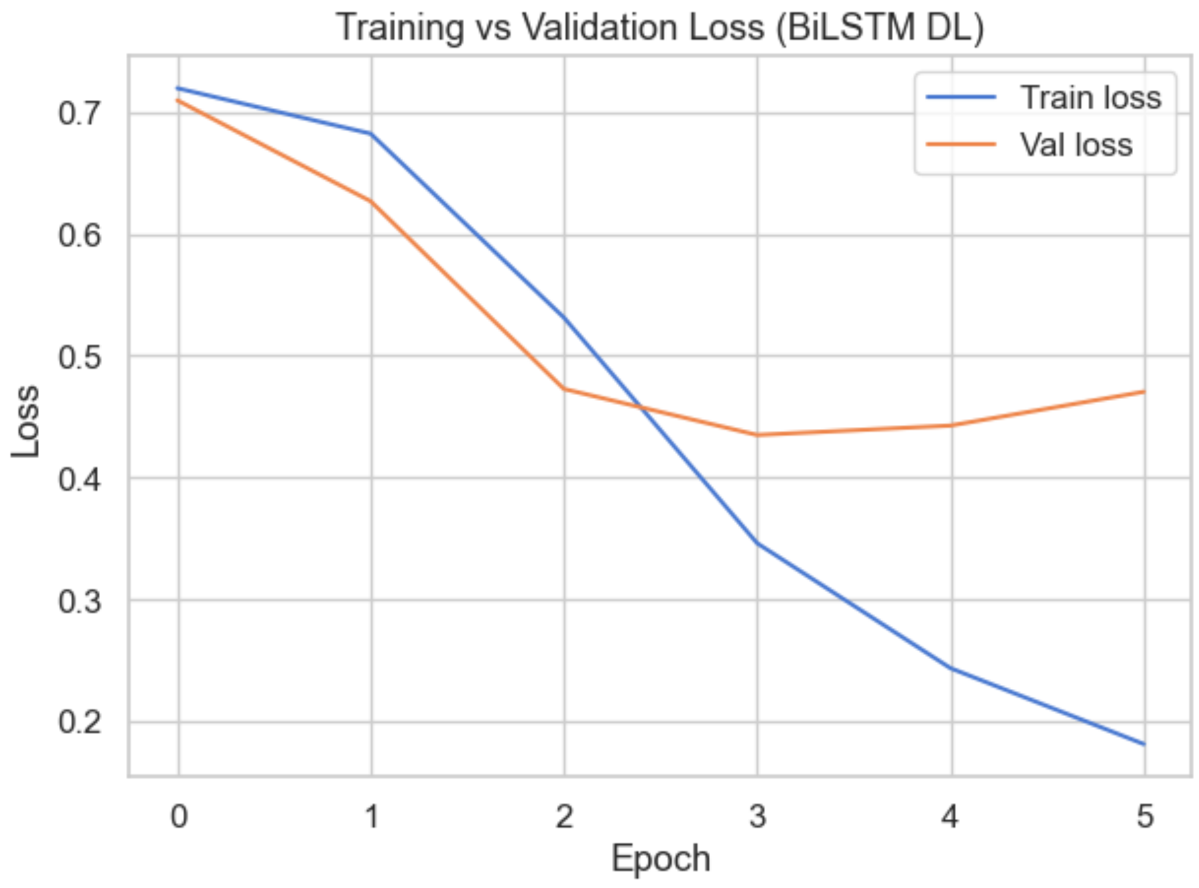

ROC Curve - Best Classical ML Model
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
AUC = 0.891



5.2 Plot Training Curves (DL)

In [11]:
```
# Accuracy Curve
# Plot training and validation accuracy over epochs for BiLSTM model
plt.figure()
plt.plot(history_dl.history['accuracy'], label='Train accuracy')
plt.plot(history_dl.history['val_accuracy'], label='Val accuracy')
plt.title('Training vs Validation Accuracy (BiLSTM DL)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Loss Curve
# Plot training and validation loss over epochs for BiLSTM model
plt.figure()
plt.plot(history_dl.history['loss'], label='Train loss')
plt.plot(history_dl.history['val_loss'], label='Val loss')
plt.title('Training vs Validation Loss (BiLSTM DL)')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



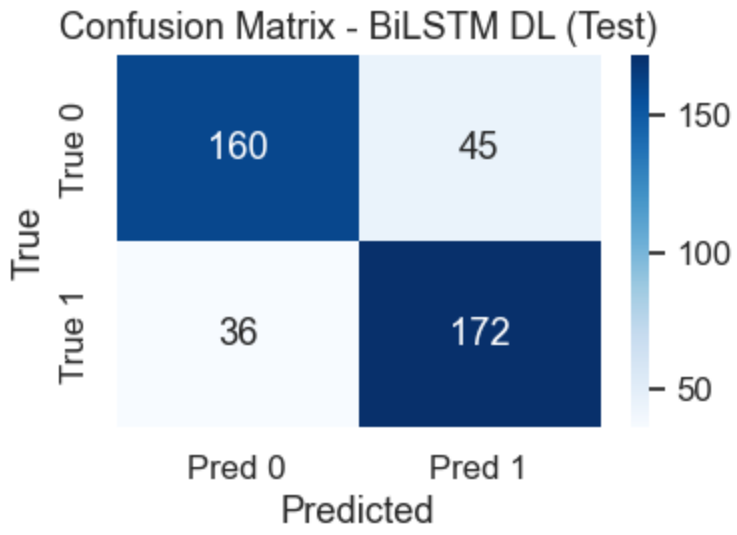


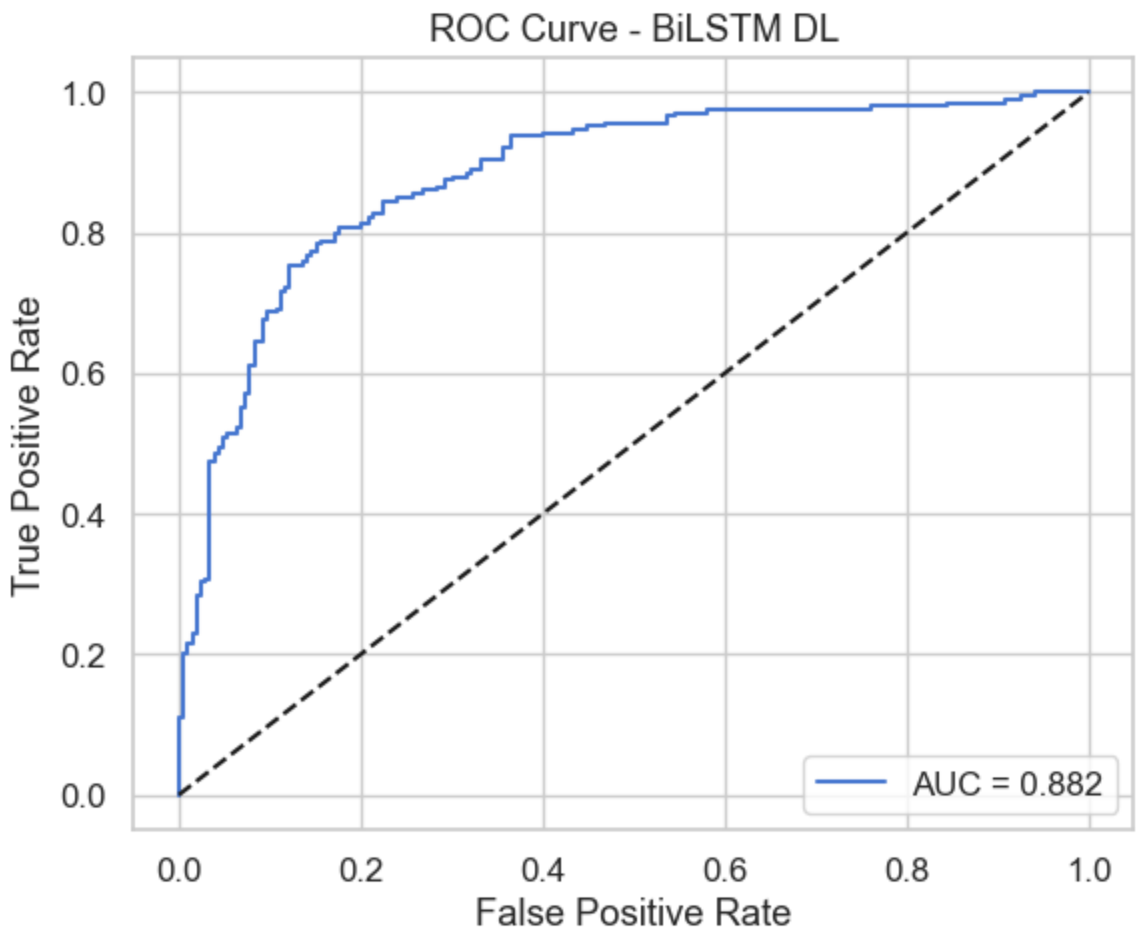
5.3 Evaluation on Test Set (DL)

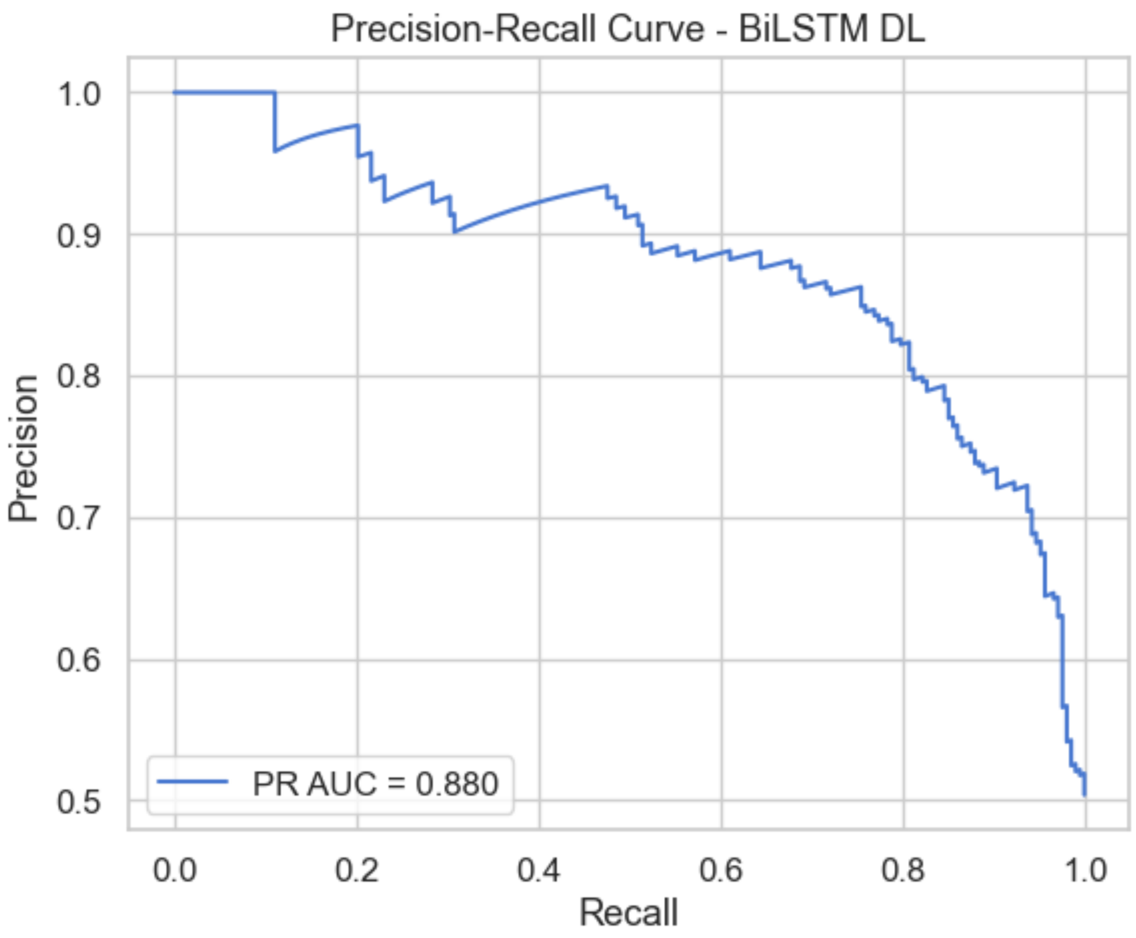
In [12]:
```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# --- Evaluate overall test loss and accuracy for BiLSTM DL model ---
test_loss_dl, test_acc_dl = best_model_dl.evaluate(X_test_pad_dl, y_test_dl, verbos
print(f"Test Loss (BiLSTM DL): {test_loss_dl:.3f}")
print(f"Test Accuracy (BiLSTM DL): {test_acc_dl:.3f}")

# --- Predicted probabilities & class labels ---
# Predict probabilities for the positive class (output of sigmoid)
y_test_proba_dl = best_model_dl.predict(X_test_pad_dl).ravel()
# Convert probabilities to binary labels (threshold = 0.5)
y_test_pred_dl = (y_test_proba_dl >= 0.5).astype(int)

# --- Classification report ---
# Show precision, recall, F1-score per class
print("\nClassification report (BiLSTM DL):")
print(classification_report(y_test_dl, y_test_pred_dl, digits=3))

# --- Confusion matrix ---
# Visualize True vs Predicted labels counts
cm_dl = confusion_matrix(y_test_dl, y_test_pred_dl)
plt.figure(figsize=(4,3))
sns.heatmap(cm_dl, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Pred 0', 'Pred 1'],
            yticklabels=['True 0', 'True 1'])
plt.title('Confusion Matrix - BiLSTM DL (Test)')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.tight_layout()
plt.show()

# --- Additional evaluation metrics ---
from sklearn.metrics import roc_curve, roc_auc_score, precision_recall_curve, auc,

# ROC Curve & AUC
fpr_dl, tpr_dl, _ = roc_curve(y_test_dl, y_test_proba_dl)
roc_auc_dl = roc_auc_score(y_test_dl, y_test_proba_dl)

plt.figure(figsize=(6,5))
plt.plot(fpr_dl, tpr_dl, label=f'AUC = {roc_auc_dl:.3f}')
plt.plot([0,1], [0,1], 'k--')  # diagonal = random classifier
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - BiLSTM DL')
plt.legend(loc='lower right')
plt.grid(True)
plt.tight_layout()
plt.show()

# Precision-Recall Curve & AUC
precision_dl_vals, recall_dl_vals, _ = precision_recall_curve(y_test_dl, y_test_pro
pr_auc_dl = auc(recall_dl_vals, precision_dl_vals)
```

```
plt.figure(figsize=(6,5))
plt.plot(recall_dl_vals, precision_dl_vals, label=f'PR AUC = {pr_auc_dl:.3f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve - BiLSTM DL')
plt.legend(loc='lower left')
plt.grid(True)
plt.tight_layout()
plt.show()

# --- Token Importance (Simple Interpretability Proxy) ---
# Extract embedding weights (word vectors) from first layer
embedding_layer_dl = best_model_dl.layers[0]
embedding_weights_dl = embedding_layer_dl.get_weights()[0]  # shape: (vocab_size, e

# Compute L2 norm for each word vector as a measure of "importance"
token_importance_dl = np.linalg.norm(embedding_weights_dl, axis=1)

# Reverse lookup: index → word
index_word_dl = {v: k for k, v in tokenizer_dl.word_index.items()}

# Top 10 most influential tokens based on L2 norm
top_tokens_idx_dl = token_importance_dl.argsort()[-10:][::-1]
top_tokens_dl = [index_word_dl.get(i, "<OOV>") for i in top_tokens_idx_dl]

print("\nTop 10 influential tokens (BiLSTM DL, L2 norm):")
for token, score in zip(top_tokens_dl, token_importance_dl[top_tokens_idx_dl]):
    print(f"{token}: {score:.3f}")

# --- Final Metrics (DL) ---
# Compute standard evaluation metrics
acc_dl = accuracy_score(y_test_dl, y_test_pred_dl)
prec_dl = precision_score(y_test_dl, y_test_pred_dl)
recall_dl = recall_score(y_test_dl, y_test_pred_dl)
f1_dl = f1_score(y_test_dl, y_test_pred_dl)

# Print final metrics
print(f"\nBiLSTM DL Test Accuracy: {acc_dl:.3f}")
print(f"BiLSTM DL Precision: {prec_dl:.3f}")
print(f"BiLSTM DL Recall: {recall_dl:.3f}")
print(f"BiLSTM DL F1-score: {f1_dl:.3f}")
```

```
Test Loss (BiLSTM DL): 0.452
Test Accuracy (BiLSTM DL): 0.804
13/13 ━━━━━━━━━━━━━━━━━━━━ 4s 158ms/step

Classification report (BiLSTM DL):
              precision    recall  f1-score   support

           0      0.816     0.780     0.798       205
           1      0.793     0.827     0.809       208

    accuracy                          0.804       413
   macro avg      0.804     0.804     0.804       413
weighted avg      0.804     0.804     0.804       413
```




ROC Curve - BiLSTM DL
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
AUC = 0.882



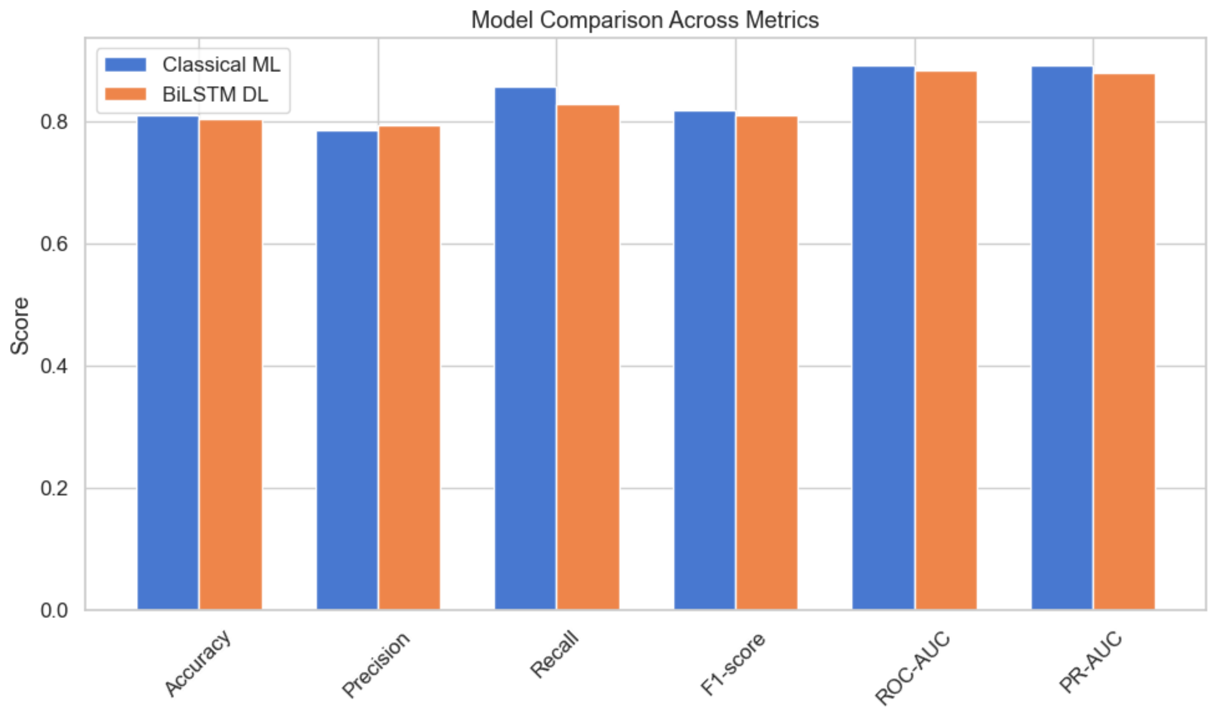
```
Top 10 influential tokens (BiLSTM DL, L2 norm):
great: 1.054
not: 0.839
disappoint: 0.749
excel: 0.717
love: 0.699
bad: 0.688
nice: 0.686
wast: 0.677
worst: 0.640
good: 0.640

BiLSTM DL Test Accuracy: 0.804
BiLSTM DL Precision: 0.793
BiLSTM DL Recall: 0.827
BiLSTM DL F1-score: 0.809
```

5.4 Combined Model Comparison

In [13]:
```
import pandas as pd
import matplotlib.pyplot as plt

# --- Collect Metrics for both models ---
# Create a dictionary to store key evaluation metrics for each model
metrics = {
    "Model": ["Classical ML", "BiLSTM DL"],  # Model names
    "Accuracy": [test_acc_cls, acc_dl],  # Overall accuracy on test set
    "Precision": [precision_score(y_test_cls, y_test_pred_cls),
                  prec_dl],  # How many predicted positives were correct
    "Recall": [recall_score(y_test_cls, y_test_pred_cls),
               recall_dl],  # How many true positives were captured
    "F1-score": [f1_score(y_test_cls, y_test_pred_cls),
                 f1_dl],  # Harmonic mean of precision & recall
    "ROC-AUC": [roc_auc_cls, roc_auc_dl],  # Area under ROC curve
    "PR-AUC": [pr_auc_cls, pr_auc_dl]  # Area under precision-recall curve
}

# Convert dictionary into a pandas DataFrame for easy tabular display
df_metrics = pd.DataFrame(metrics)
# This DataFrame will be printed and visualized in plots
```

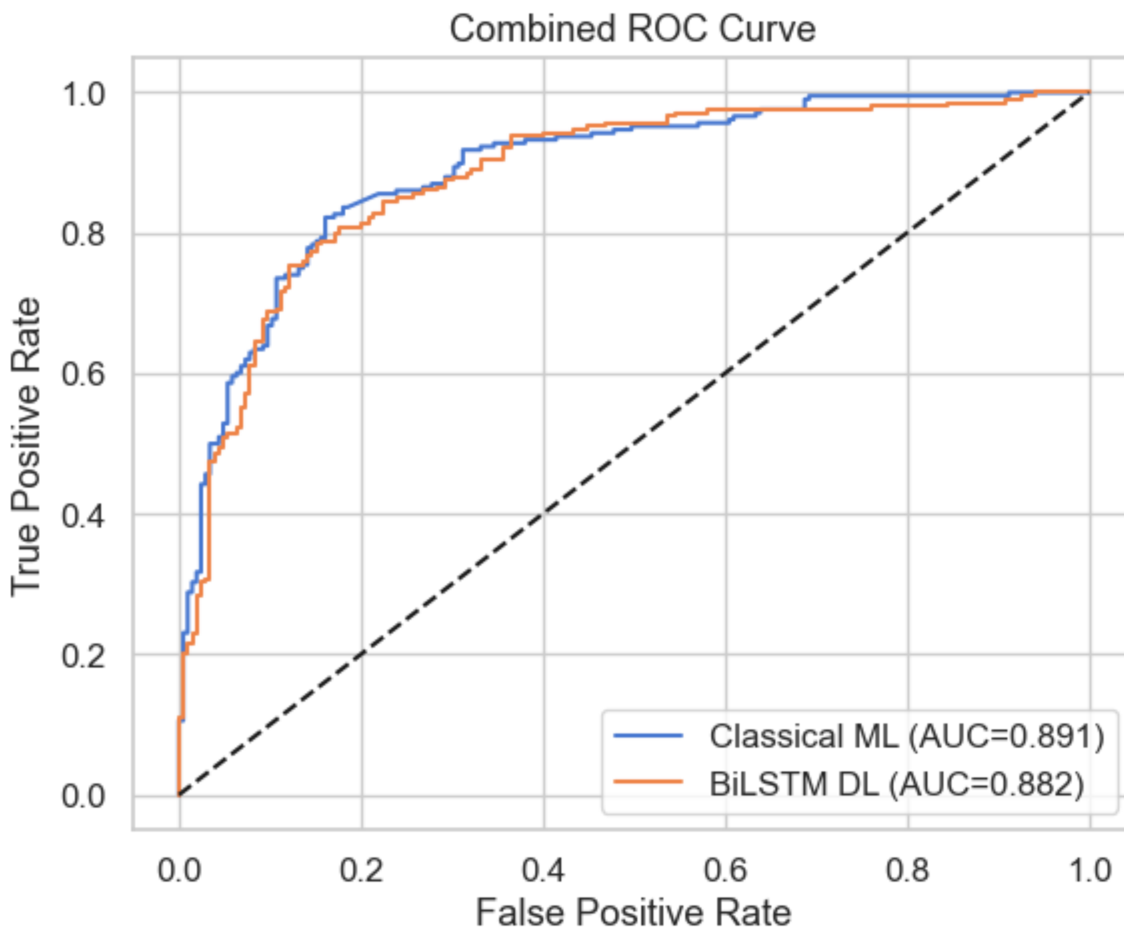
5.5 Bar Plot — Metric Comparison

In [14]:
```
plt.figure(figsize=(10,6))  # Set figure size

bar_width = 0.35  # Width of each bar
x = np.arange(len(df_metrics.columns[1:]))  # Positions on x-axis for metrics (excl

# Plot bars for Classical ML metrics (shifted left)
plt.bar(x - bar_width/2, df_metrics.iloc[0,1:], width=bar_width, label="Classical M
# Plot bars for BiLSTM DL metrics (shifted right)
plt.bar(x + bar_width/2, df_metrics.iloc[1,1:], width=bar_width, label="BiLSTM DL")

# Set x-axis tick labels as metric names
plt.xticks(x, df_metrics.columns[1:], rotation=45)
plt.ylabel("Score")  # Label y-axis
plt.title("Model Comparison Across Metrics")  # Add title
plt.legend()  # Show legend
plt.tight_layout()  # Adjust layout to fit everything
plt.grid(True, axis='y')  # Add horizontal grid lines for easier reading
plt.show()  # Display the plot
```



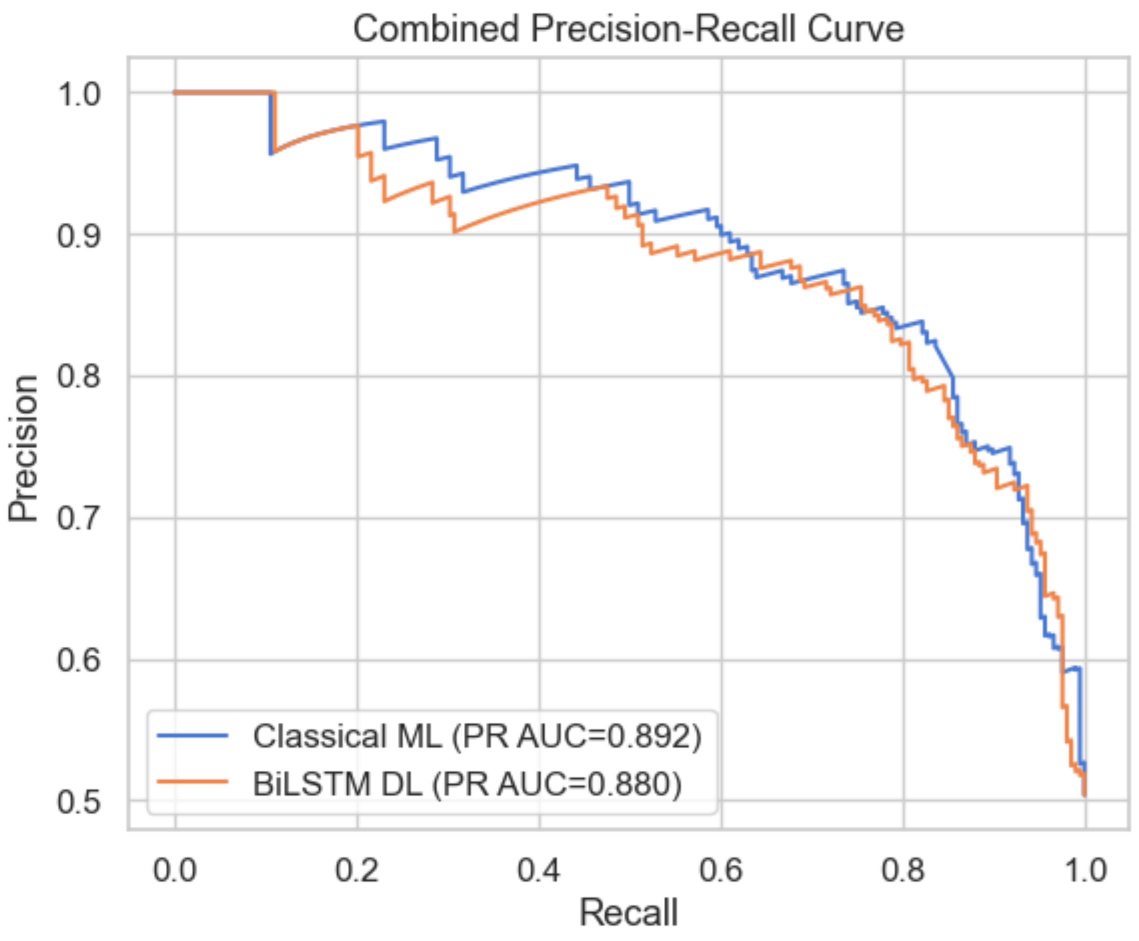
5.6 Combined ROC Curve

In [15]:
```
plt.figure(figsize=(6,5))

# Plot ROC curve for Classical ML
plt.plot(fpr_cls, tpr_cls, label=f"Classical ML (AUC={roc_auc_cls:.3f})")
# Plot ROC curve for BiLSTM DL
plt.plot(fpr_dl, tpr_dl, label=f"BiLSTM DL (AUC={roc_auc_dl:.3f})")
# Add diagonal line for random classifier reference
plt.plot([0,1], [0,1], 'k--')

# Labels and title
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Combined ROC Curve")
plt.grid(True)  # Add grid
plt.legend()  # Show legend
plt.tight_layout()
plt.show()
```



5.7 Combined Precision-Recall Curve

In [16]:
```python
plt.figure(figsize=(6,5))

# Plot Precision-Recall curve for Classical ML
plt.plot(recall_cls, precision_cls, label=f"Classical ML (PR AUC={pr_auc_cls:.3f})"
# Plot Precision-Recall curve for BiLSTM DL
plt.plot(recall_dl_vals, precision_dl_vals, label=f"BiLSTM DL (PR AUC={pr_auc_dl:.3

# Labels and title
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Combined Precision-Recall Curve")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



5.8 Final Summary

In [17]:
```
# Print a clear, final comparison table for both models
print("\n=== Final Model Comparison Summary ===")
print(df_metrics.to_string(index=False))

# Determine the best model based on F1-score (balances precision & recall)
best_model_name = df_metrics.loc[df_metrics['F1-score'].idxmax(), 'Model']
print(f"\nBest overall model based on F1-score: **{best_model_name}**")
```

```
=== Final Model Comparison Summary ===
       Model  Accuracy  Precision   Recall  F1-score  ROC-AUC   PR-AUC
Classical ML  0.808717   0.784141 0.855769  0.818391 0.891229 0.891547
   BiLSTM DL  0.803874   0.792627 0.826923  0.809412 0.882411 0.879646

Best overall model based on F1-score: **Classical ML**
```