Introduction

Kaggle Natural Language Processing with Disaster Tweets

Competition Description

Twitter has become an important communication channel in times of emergency. The ubiquitousness of smartphones enables people to announce an emergency they're observing in real-time. Because of this, more agencies are interested in programatically monitoring Twitter (i.e. disaster relief organizations and news agencies) (Addison Howard).

Problem

The challenge problem involves using Natural Language Processing (NLP) to classify tweets as either real disasters (labeled as '1') or not real disasters (labeled as '0'). This is a binary classification task where NLP techniques are crucial for understanding and extracting meaningful information from the unstructured text data (tweets).

This project will attempt to solve the problem using LSTM.

LSTMs are well-suited for disaster tweet classification because they effectively capture sequential patterns and dependencies in short text data, such as tweets, which often contain critical disaster-related keywords in specific orders. Their ability to retain context over sequences makes them adept at understanding the semantic meaning of phrases like "#earthquake alert" or "flood warning." LSTMs can also handle variable-length inputs (via padding), accommodating the diverse lengths of tweets while preserving important information. Additionally, their robustness to noise, when paired with proper preprocessing, allows them to focus on relevant signals in messy social media text, improving binary classification performance.

Data Description

The training dataset (train_df) consists of 7,613 entries and 5 columns. Each entry includes an id, a keyword (a string, though 61 entries are missing), a location (a string, with a substantial 2,533 missing entries), the text of the tweet (a string), and the target (an integer indicating whether the tweet is about a real disaster, with no missing values). Similarly, the test dataset (test_df) contains 3,263 entries and 4 columns. It also includes id, keyword (with 26 missing entries), location (with 1,105 missing entries), and text. The crucial difference is the absence of the target column in the test set, as this is the variable to be predicted. Both datasets have missing values in the keyword and location columns, with location having a more significant proportion of missing data.

Addison Howard, devrishi, Phil Culliton, and Yufeng Guo. Natural Language Processing with Disaster Tweets. https://kaggle.com/competitions/nlp-getting-started, 2019. Kaggle.

Inputs

In [216…

```
import os
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from sklearn.preprocessing import LabelEncoder
from Levenshtein import distance
from collections import defaultdict

import re
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, LSTM, Dense, Concatena
from sklearn.metrics import confusion_matrix, classification_report, f1_scor
import tensorflow as tf
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
import random

from sklearn.model_selection import ParameterGrid
```

In [217…

```
data_path = './nlp-getting-started/'
for file in os.listdir(data_path):
    if file[:5]=='train':
        train_df = pd.read_csv(data_path+file)
    elif file[:4]=='test':
        test_df = pd.read_csv(data_path+file)
```

EDA

In [218…

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   id        7613 non-null   int64 
 1   keyword   7552 non-null   object
 2   location  5080 non-null   object
 3   text      7613 non-null   object
 4   target    7613 non-null   int64 
dtypes: int64(2), object(3)
memory usage: 297.5+ KB
```

In [219…

```
train_df.head()
```

Out[219]:

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1

In [220…

```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   id        3263 non-null   int64 
 1   keyword   3237 non-null   object
 2   location  2158 non-null   object
 3   text      3263 non-null   object
dtypes: int64(1), object(3)
memory usage: 102.1+ KB
```

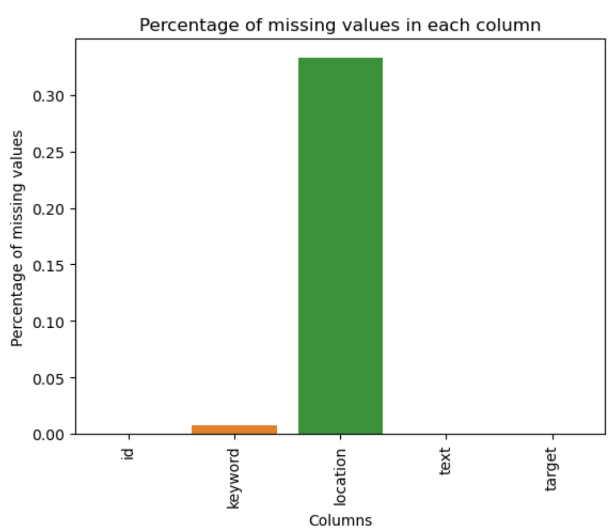
Missing Values

In [221…

```
plt.title('Percentage of missing values in each column')
sns.barplot((train_df.isnull().sum()/len(train_df)).reset_index(), x = 'inde
plt.xticks(rotation=90)
plt.xlabel('Columns')
plt.ylabel('Percentage of missing values')
```

Out[221]:

```
Text(0, 0.5, 'Percentage of missing values')
```

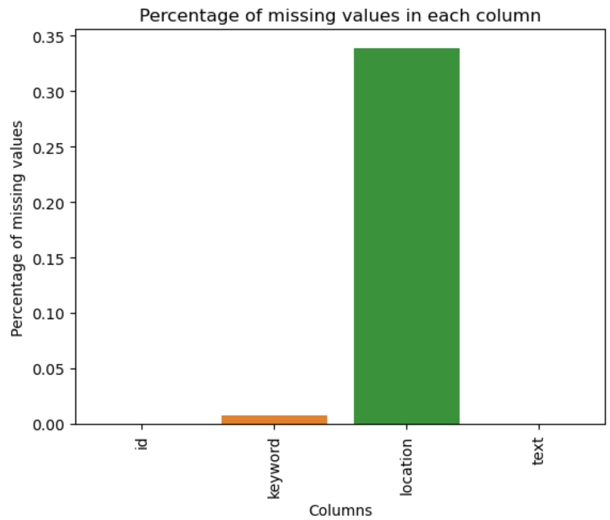


In [222…

```
plt.title('Percentage of missing values in each column')
sns.barplot((test_df.isnull().sum()/len(test_df)).reset_index(), x = 'index'
plt.xticks(rotation=90)
plt.xlabel('Columns')
plt.ylabel('Percentage of missing values')
```

Out[222]:

```
Text(0, 0.5, 'Percentage of missing values')
```



As expected from the data description, keyword and location contain missing values. location has over 30% missing values. These missing values will be imputed below.

Data Preprocessing

Imputing Missing Values

In [223…
```
print('Unique keywords:', train_df['keyword'].nunique())
```

```
Unique keywords: 221
```

- Given the limited missing keywords, simply dropping rows might be too aggressive.
- nokeyword will be used to impute the missing values in the keyword column.

In [224…
```
train_df['keyword'] = train_df['keyword'].fillna('nokeyword')
test_df['keyword'] = test_df['keyword'].fillna('nokeyword')
```

In [225…
```
print('Unique locations:', train_df['location'].nunique())
```

```
Unique locations: 3341
```

- While over 30% of the location values are missing, there are still over 3K unique locations.
- unknownlocation will be used to fill in the missing values.

In [226…
```
train_df['location'] = train_df['location'].fillna('unknownlocation')
test_df['location'] = test_df['location'].fillna('unknownlocation')
```

Standardization

- Keywords

In [227…
```
test_df['keyword'].unique()
```

```
Out[227]: array(['nokeyword', 'ablaze', 'accident', 'aftershock',
       'airplane%20accident', 'ambulance', 'annihilated', 'annihilation',
       'apocalypse', 'armageddon', 'army', 'arson', 'arsonist', 'attack',
       'attacked', 'avalanche', 'battle', 'bioterror', 'bioterrorism',
       'blaze', 'blazing', 'bleeding', 'blew%20up', 'blight', 'blizzard',
       'blood', 'bloody', 'blown%20up', 'body%20bag', 'body%20bagging',
       'body%20bags', 'bomb', 'bombed', 'bombing', 'bridge%20collapse',
       'buildings%20burning', 'buildings%20on%20fire', 'burned',
       'burning', 'burning%20buildings', 'bush%20fires', 'casualties',
       'casualty', 'catastrophe', 'catastrophic', 'chemical%20emergency',
       'cliff%20fall', 'collapse', 'collapsed', 'collide', 'collided',
       'collision', 'crash', 'crashed', 'crush', 'crushed', 'curfew',
       'cyclone', 'damage', 'danger', 'dead', 'death', 'deaths', 'debris',
       'deluge', 'deluged', 'demolish', 'demolished', 'demolition',
       'derail', 'derailed', 'derailment', 'desolate', 'desolation',
       'destroy', 'destroyed', 'destruction', 'detonate', 'detonation',
       'devastated', 'devastation', 'disaster', 'displaced', 'drought',
       'drown', 'drowned', 'drowning', 'dust%20storm', 'earthquake',
       'electrocute', 'electrocuted', 'emergency', 'emergency%20plan',
       'emergency%20services', 'engulfed', 'epicentre', 'evacuate',
       'evacuated', 'evacuation', 'explode', 'exploded', 'explosion',
       'eyewitness', 'famine', 'fatal', 'fatalities', 'fatality', 'fear',
       'fire', 'fire%20truck', 'first%20responders', 'flames',
       'flattened', 'flood', 'flooding', 'floods', 'forest%20fire',
       'forest%20fires', 'hail', 'hailstorm', 'harm', 'hazard',
       'hazardous', 'heat%20wave', 'hellfire', 'hijack', 'hijacker',
       'hijacking', 'hostage', 'hostages', 'hurricane', 'injured',
       'injuries', 'injury', 'inundated', 'inundation', 'landslide',
       'lava', 'lightning', 'loud%20bang', 'mass%20murder',
       'mass%20murderer', 'massacre', 'mayhem', 'meltdown', 'military',
       'mudslide', 'natural%20disaster', 'nuclear%20disaster',
       'nuclear%20reactor', 'obliterate', 'obliterated', 'obliteration',
       'oil%20spill', 'outbreak', 'pandemonium', 'panic', 'panicking',
       'police', 'quarantine', 'quarantined', 'radiation%20emergency',
       'rainstorm', 'razed', 'refugees', 'rescue', 'rescued', 'rescuers',
       'riot', 'rioting', 'rubble', 'ruin', 'sandstorm', 'screamed',
       'screaming', 'screams', 'seismic', 'sinkhole', 'sinking', 'siren',
       'sirens', 'smoke', 'snowstorm', 'storm', 'stretcher',
       'structural%20failure', 'suicide%20bomb', 'suicide%20bomber',
       'suicide%20bombing', 'sunk', 'survive', 'survived', 'survivors',
       'terrorism', 'terrorist', 'threat', 'thunder', 'thunderstorm',
       'tornado', 'tragedy', 'trapped', 'trauma', 'traumatised',
       'trouble', 'tsunami', 'twister', 'typhoon', 'upheaval',
       'violent%20storm', 'volcano', 'war%20zone', 'weapon', 'weapons',
       'whirlwind', 'wild%20fires', 'wildfire', 'windstorm', 'wounded',
       'wounds', 'wreck', 'wreckage', 'wrecked'], dtype=object)
```

The keyword column appears to be cleaned. There does appear to be very simillar words (ex. weapon and weapons, wild fires and wildfire). This will be standardized to contain the most frequent version.

```
In [228…
train_df['keyword'] = train_df['keyword'].str.replace('%20', '', regex=False
test_df['keyword'] = test_df['keyword'].str.replace('%20', '', regex=False)
```

```
In [229…
all_keywords_series = pd.concat([test_df['keyword'], train_df['keyword']], a
unique_keywords = all_keywords_series.unique()

keyword_counts = all_keywords_series.value_counts()
# Define similarity threshold
SIMILARITY_THRESHOLD = 0.80 # 80% similarity

canonical_map = {word: word for word in unique_keywords}
# Keep track of which words have already been processed into a group
processed_words = set()
sorted_unique_keywords = keyword_counts.index.tolist()

print(f"\nFinding similar keywords (similarity > {SIMILARITY_THRESHOLD*100}%
for i, word1 in enumerate(sorted_unique_keywords):
    if word1 in processed_words:
        continue # Already part of a group

    # This will be the canonical form for the current group
    # Initially, it's the word itself, but might change if a more frequent w
    current_canonical = word1
    group_members = [word1] # Words that are similar to word1 (including wor

    for j, word2 in enumerate(sorted_unique_keywords):
        if i >= j: # Avoid comparing a word to itself or duplicating pairs (
            continue
        if word2 in processed_words: # If word2 is already grouped, skip
            continue

        len1 = len(word1)
        len2 = len(word2)
        max_len = max(len1, len2)

        # Calculate Levenshtein distance
        lev_dist = distance(word1, word2)

        # Calculate similarity percentage
        similarity = (1 - (lev_dist / max_len)) if max_len > 0 else 1.0

        if similarity > SIMILARITY_THRESHOLD:
            # If word2 is similar to word1, add it to the group
            group_members.append(word2)

    # If a group of similar words was found (more than just word1 itself)
    if len(group_members) > 1:
        # Find the most frequent word within this group to be the canonical
        # `key=keyword_counts.get` ensures we use the actual counts for sort
        canonical_form = max(group_members, key=keyword_counts.get)

        print(f"  Group found. Canonical: '{canonical_form}' (Count: {keywor
        print(f"  Members: {group_members}")

        # Update the canonical map for all members of this group
        for member_word in group_members:
            canonical_map[member_word] = canonical_form
            processed_words.add(member_word)
```

```
Finding similar keywords (similarity > 80.0%):
  Group found. Canonical: 'massmurder' (Count: 50)
  Members: ['massmurder', 'massmurderer']
  Group found. Canonical: 'obliterate' (Count: 50)
  Members: ['obliterate', 'obliterated']
  Group found. Canonical: 'quarantine' (Count: 50)
  Members: ['quarantine', 'quarantined']
  Group found. Canonical: 'ablaze' (Count: 50)
  Members: ['ablaze', 'blaze']
  Group found. Canonical: 'flood' (Count: 50)
  Members: ['flood', 'floods']
  Group found. Canonical: 'forestfires' (Count: 50)
  Members: ['forestfires', 'forestfire']
  Group found. Canonical: 'hostage' (Count: 50)
  Members: ['hostage', 'hostages']
  Group found. Canonical: 'rescued' (Count: 50)
  Members: ['rescued', 'rescue']
  Group found. Canonical: 'terrorism' (Count: 50)
  Members: ['terrorism', 'terrorist']
  Group found. Canonical: 'weapon' (Count: 50)
  Members: ['weapon', 'weapons']
  Group found. Canonical: 'wildfires' (Count: 50)
  Members: ['wildfires', 'wildfire']
  Group found. Canonical: 'survived' (Count: 50)
  Members: ['survived', 'survive']
  Group found. Canonical: 'siren' (Count: 50)
  Members: ['siren', 'sirens']
  Group found. Canonical: 'suicidebomb' (Count: 50)
  Members: ['suicidebomb', 'suicidebomber']
  Group found. Canonical: 'bodybags' (Count: 50)
  Members: ['bodybags', 'bodybag']
  Group found. Canonical: 'catastrophe' (Count: 50)
  Members: ['catastrophe', 'catastrophic']
  Group found. Canonical: 'collapse' (Count: 50)
  Members: ['collapse', 'collapsed']
  Group found. Canonical: 'collide' (Count: 50)
  Members: ['collide', 'collided']
  Group found. Canonical: 'crashed' (Count: 50)
  Members: ['crashed', 'crushed']
  Group found. Canonical: 'bloody' (Count: 50)
  Members: ['bloody', 'blood']
  Group found. Canonical: 'electrocute' (Count: 50)
  Members: ['electrocute', 'electrocuted']
  Group found. Canonical: 'evacuate' (Count: 50)
  Members: ['evacuate', 'evacuated']
  Group found. Canonical: 'explode' (Count: 50)
  Members: ['explode', 'exploded']
  Group found. Canonical: 'death' (Count: 50)
  Members: ['death', 'deaths']
  Group found. Canonical: 'deluge' (Count: 50)
  Members: ['deluge', 'deluged']
```

In [230…

```
train_df['keyword'] = train_df['keyword'].map(canonical_map)
test_df['keyword'] = test_df['keyword'].map(canonical_map)
```

- Location
    - Just like the keyword column, both locations from test AND train datasets will be used prevent the out of vocabulary error.

In [231…

```
train_df[train_df['location']!='unknownlocation']['location'].value_counts()
```

Out[231]:

```
USA                  104
New York              71
United States         50
London                45
Canada                29
Nigeria               28
UK                    27
Los Angeles, CA       26
India                 24
Mumbai                22
Washington, DC        21
Kenya                 20
Worldwide             19
Australia             18
Chicago, IL           18
California            17
Everywhere            15
New York, NY          15
California, USA       15
Florida               14
San Francisco         14
United Kingdom        14
Los Angeles           13
Indonesia             13
Washington, D.C.      13
Name: location, dtype: int64
```

In [232…

```
train_df[train_df['location']!='unknownlocation']['location'].value_counts()
```

Out[232]:
```
japon                            1
Phoenix, Arizona, USA            1
Malibu/SantaFe/Winning!          1
Bozeman, Montana                 1
McLean, VA                       1
Killa Hill, CO                   1
new york, ny                     1
Pawnee                           1
South Florida                    1
Dhaka, Bangladsh                 1
London, Greater London, UK       1
Positive 852                     1
Ashford, Kent, United Kingdom    1
Edinburgh, Scotland              1
Paris (France)                   1
Hammersmith, London              1
San Diego, Calif.                1
Kansas City, Mo.                 1
VCU                              1
Ealing, London                   1
Anywhere I like                  1
I ACCEPT SONG REQUESTS           1
USA, North Dakota                1
Norwalk, CT                      1
highlands&slands scotland        1
Name: location, dtype: int64
```

The location column is a bit more tricky to clean than the keyword. There does not appear to have been a standard format (ex. City, State, Country) used in this column, and there appears to even be erroneous locations like "I ACCEPT SONG REQUESTS".

In [233…
```
train_df['location'] = train_df['location'].str.lower().str.strip()
test_df['location'] = test_df['location'].str.lower().str.strip()
```

In [234…
```
all_locations_series = pd.concat([test_df['location'], train_df['location']]
single_loc_counts = all_locations_series.str.split(',').explode().str.strip(
```

The location column will be standardized by checking each component of a comma-seperated location against the counts of single locations. The component that has the highest count will be kept, however, if a single count is less than 5, it will be replaced with 'unknownlocation'.

In [235…
```
def clean_location(loc):
    # Handle missing, empty, or comma-only locations
    if pd.isna(loc) or not loc or loc.strip() == ",":
        return "unknownlocation"

    # Split at comma
    parts = [part.strip() for part in loc.split(",") if part.strip()]

    # Handle empty parts
    if not parts:
        return "unknownlocation"

    # Single-part or multi-part: Check counts
    for part in parts:
        if single_loc_counts.get(part, 0) >= 5:
            # For multi-part, pick part with highest count if >=5
            if len(parts) > 1:
                max_part = max(parts, key=lambda x: single_loc_counts.get(x,
                if single_loc_counts.get(max_part, 0) >= 5:
                    return max_part
            # For single-part, return if count >=5
            else:
                return parts[0]

    # No part has count >=5
    return "unknownlocation"
```

In [236…
```
# Apply cleaning
train_df['location'] = train_df['location'].apply(clean_location)
test_df['location'] = test_df['location'].apply(clean_location)
```

Lastly, we will remove any punctuations.

In [237…
```
train_df['location'] = train_df['location'].str.replace('[^\w\s]','', regex
test_df['location'] = test_df['location'].str.replace('[^\w\s]','', regex =

train_df['location'] = train_df['location'].replace('', 'unknownlocation')
test_df['location'] = test_df['location'].replace('', 'unknownlocation')
```

In [238…
```
train_df['location'].nunique()
```

Out[238]:
```
247
```

Feature encoding

- the keyword and lcoation column will become a categorical variable (1-n)
- keyword and location from train AND test will be used to fit the LabelEncoder to ensure no out of vabulary errors.
- Note: This is NOT suitable for real-world scenarios where truly new words might appear in future data.
    - The alternative would be to handle unknown words through transformation into an unknown ID + constant retraining to ensure limited unknown IDs.

In [239…
```
train_keywords = train_df['keyword'].unique()
test_keywords = test_df['keyword'].unique()
all_keywords = np.unique(np.concatenate((train_keywords, test_keywords), axi

le = LabelEncoder()
le.fit(all_keywords)

# Transform both train and test keywords
train_keywords_encoded = le.transform(train_keywords)
test_keywords_encoded = le.transform(test_keywords)

# Create a mapping of keywords to their encoded labels
train_df['keyword_encoded'] = le.transform(train_df['keyword'])
test_df['keyword_encoded'] = le.transform(test_df['keyword'])

keyword_mapping = {label: keyword for keyword, label in zip(le.classes_, le.
sorted_mapping = sorted(keyword_mapping.items(), key=lambda item: item[1])
print(sorted_mapping[:10])
```

```
[(0, 'ablaze'), (1, 'accident'), (2, 'aftershock'), (3, 'airplaneaccident'),
(4, 'ambulance'), (5, 'annihilated'), (6, 'annihilation'), (7, 'apocalyps
e'), (8, 'armageddon'), (9, 'army')]
```

In [240…
```
train_locations = train_df['location'].unique()
test_locations = test_df['location'].unique()
all_locations = np.unique(np.concatenate((train_locations, test_locations),

le = LabelEncoder()
le.fit(all_locations)

# Transform both train and test locations
train_locations_encoded = le.transform(train_locations)
test_locations_encoded = le.transform(test_locations)

# Create a mapping of locations to their encoded labels
train_df['location_encoded'] = le.transform(train_df['location'])
test_df['location_encoded'] = le.transform(test_df['location'])

location_mapping = {label: location for location, label in zip(le.classes_,
sorted_mapping = sorted(location_mapping.items(), key=lambda item: item[1])
print(sorted_mapping[:10])
```

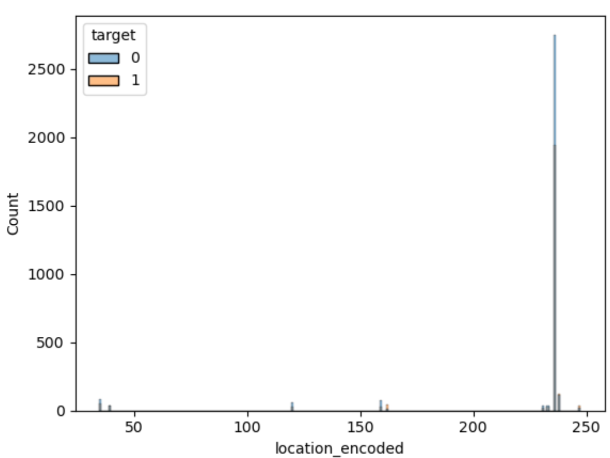
```
[(0, '304'), (1, 'abuja'), (2, 'adelaide'), (3, 'africa'), (4, 'ak'), (5, 'a
l'), (6, 'alabama'), (7, 'alaska'), (8, 'alberta'), (9, 'alexandria')]
```

Top keywords and locations per label

In [241…
```
train_df['location_encoded'] = pd.Categorical(train_df['location_encoded'])
train_df['keyword_encoded'] = pd.Categorical(train_df['keyword_encoded'])

test_df['location_encoded'] = pd.Categorical(test_df['location_encoded'])
test_df['keyword_encoded'] = pd.Categorical(test_df['keyword_encoded'])
```

In [242…
```
sns.histplot(train_df[train_df['location_encoded'].isin(train_df['location_e
             x = 'location_encoded', hue = 'target')
```

Out[242]:
```
<Axes: xlabel='location_encoded', ylabel='Count'>
```



In [243…
```
top_10_locations = pd.concat([train_df[(train_df['target']==0)&(train_df['lc
train_df[(train_df['target']==1)&(train_df['location_encoded']!= 'unknownloc
top_10_locations.columns = ['location_target_0', 'count_0', 'location_target
top_10_locations
```

Out[243]:

	location_target_0	count_0	location_target_1	count_1
0	236	2750	236	1941
1	238	115	238	119
2	35	80	35	51
3	159	74	162	42
4	120	57	39	36
5	233	35	91	33
6	39	34	247	32
7	231	34	120	31
8	61	31	159	29
9	66	30	235	28

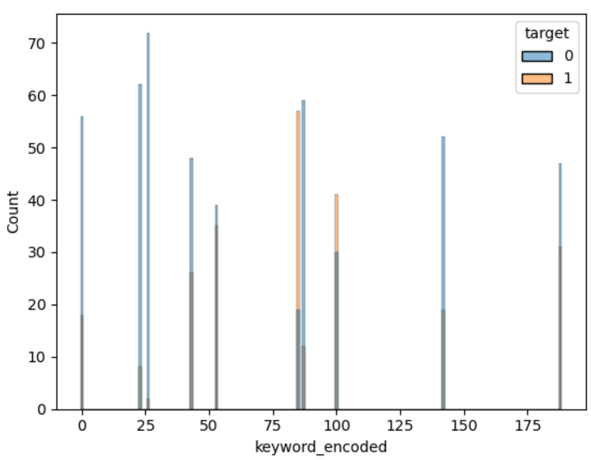
Unsurprisingly, the location feature has a decent amount of overlap within the top 10. From this, and the number of missing values, we hypothesize that this feature does not have strong predictive power.

In [244…

```
sns.histplot(train_df[train_df['keyword_encoded'].isin(train_df['keyword_enc
                x = 'keyword_encoded', hue = 'target')
```

Out[244]:

```
<Axes: xlabel='keyword_encoded', ylabel='Count'>
```



In [245…

```
top_10_keywords = pd.concat([train_df[(train_df['target']==0)&(train_df['key
train_df[(train_df['target']==1)&(train_df['keyword_encoded']!= 'unknownloca
top_10_keywords.columns = ['keyword_target_0', 'count_0', 'keyword_target_1'
top_10_keywords
```

Out[245]:

	keyword_target_0	count_0	keyword_target_1	count_1
0	26	72	166	62
1	23	62	85	57
2	87	59	190	56
3	160	57	171	47
4	55	56	125	47
5	0	56	113	42
6	134	54	102	42
7	142	52	131	42
8	79	52	100	41
9	169	50	137	39

Unliked the location feature, the keyword feature shows a decent amount of seperation between labels. From this, we can hypothesize that the keyword feature has decent predictive power.

In [246…
```
train_cat = train_df[['location_encoded','keyword_encoded']].values
test_cat = test_df[['location_encoded','keyword_encoded']].values
```

NLP on text field

- Tokenizer will be used on the train set with OOV to handle out of vocabulary words
- Remove url and mentions
- Keep hashtags to help with disaster event identification
- Preserve stop words to help with context in short tweets
- Robust to emoji and special charecters and normalizes for tokenization

In [247…
```
def preprocess_text(text):
    if pd.isna(text):
        return ""
    # Lowercase
    text = text.lower()
    # Remove URLs (replace with 'url' or '')
    text = re.sub(r'http\S+|www\S+|https\S+', '', text, flags=re.MULTILINE)
    # Remove @mentions
    text = re.sub(r'@\w+', '', text)
    # Remove excessive punctuation, keep hashtags and basic punctuation
    text = re.sub(r'[^\w\s#]', '', text)
    # Normalize whitespace
    text = re.sub(r'\s+', ' ', text).strip()
    return text
```

In [248…
```
train_df['text_cleaned'] = train_df['text'].apply(preprocess_text)
```

In [249…
```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(train_df['text_cleaned'])
total_vocab_size = len(tokenizer.word_index) + 1  # +1 for padding token
```

In [250…
```
total_vocab_size
```

Out[250]:
```
15873
```

In [251…
```
print(train_df['text_cleaned'].str.split().str.len().mean())
```

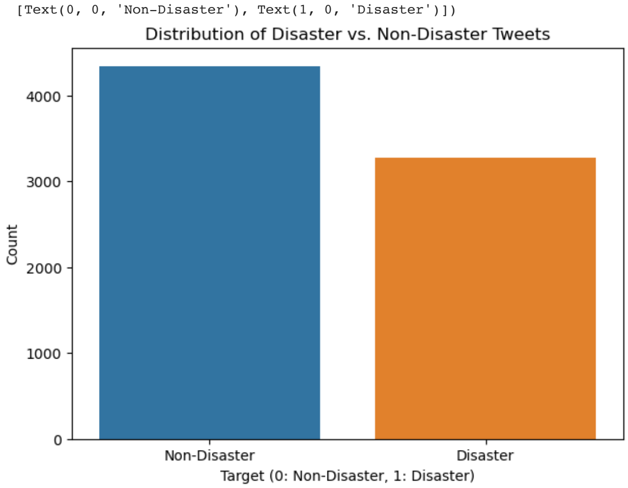
```
13.680546433731775
```

In [252…
```
max_words = 5000  # Vocabulary size (top 5000 words)
max_len = 30      # Maximum sequence length (tweets are short)

tokenizer = Tokenizer(num_words=max_words, oov_token='<OOV>')
tokenizer.fit_on_texts(train_df['text_cleaned'])
train_sequences = tokenizer.texts_to_sequences(train_df['text_cleaned'])
train_padded = pad_sequences(train_sequences, maxlen=max_len, padding='post'


test_df['text_cleaned'] = test_df['text'].apply(preprocess_text)
test_sequences = tokenizer.texts_to_sequences(test_df['text_cleaned'])
test_padded = pad_sequences(test_sequences, maxlen=max_len, padding='post',
```

Label Distribution

In [253…
```
plt.figure(figsize=(7, 5))
sns.countplot(data=train_df, x='target')
plt.title('Distribution of Disaster vs. Non-Disaster Tweets')
plt.xlabel('Target (0: Non-Disaster, 1: Disaster)')
plt.ylabel('Count')
plt.xticks([0, 1], ['Non-Disaster', 'Disaster'])
```

Out[253]:
```
([<matplotlib.axis.XTick at 0x7fb4f9bafe20>,
  <matplotlib.axis.XTick at 0x7fb4f9baff10>],
 [Text(0, 0, 'Non-Disaster'), Text(1, 0, 'Disaster')])
```



Surprisingly, the labels are evenly distributed. This allows for simple training data architecture without more complicated synthetic training sets (ex. SMOTE, over or under sampling)

Model Architecture

LSTM

- Well suited for sequential patterns and dependencies in short text data
    - words in specific order could be important in tweets
- Ability to retain context over sequences to better understand semantic meaning of phrases
- Padding allows for variable length inputs

Base Model

- Multi-input text sequence + dense branch
- embedding layer of 64 dimension
- LSTM 32 layer (tanh activation) for padded text
- Dense layer 16 for categorical features
- Single sigmoid output
- Adam optimizer, binary cross entropy loss, and accuracy metric
- Early stopping 5 (epochs 50)
- batch size 64

In [254…

```
print('''
Custom F1 score function that could be used:
class F1Score(tf.keras.metrics.Metric):
    def __init__(self, name='f1_score', **kwargs):
        super().__init__(name=name, **kwargs)
        self.precision = tf.keras.metrics.Precision()
        self.recall = tf.keras.metrics.Recall()

    def update_state(self, y_true, y_pred, sample_weight=None):
        y_pred = tf.cast(y_pred > 0.5, tf.float32)  # Binary predictions
        self.precision.update_state(y_true, y_pred, sample_weight)
        self.recall.update_state(y_true, y_pred, sample_weight)

    def result(self):
        p = self.precision.result()
        r = self.recall.result()
        return 2 * ((p * r) / (p + r + tf.keras.backend.epsilon()))

    def reset_state(self):
        self.precision.reset_state()
        self.recall.reset_state()
''')
```

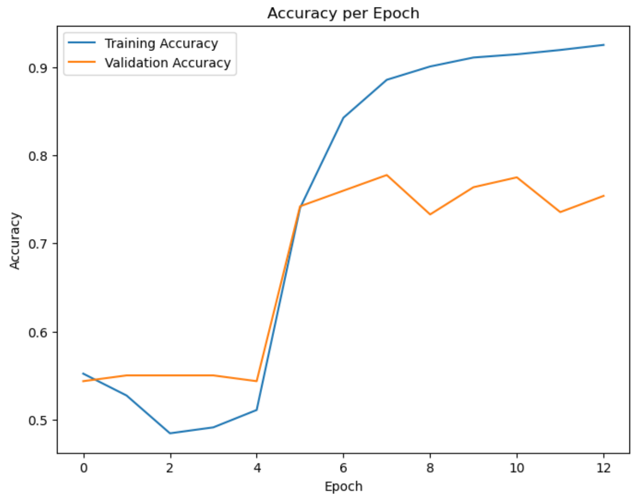

```
Custom F1 score function that could be used:
class F1Score(tf.keras.metrics.Metric):
    def __init__(self, name='f1_score', **kwargs):
        super().__init__(name=name, **kwargs)
        self.precision = tf.keras.metrics.Precision()
        self.recall = tf.keras.metrics.Recall()

    def update_state(self, y_true, y_pred, sample_weight=None):
        y_pred = tf.cast(y_pred > 0.5, tf.float32)  # Binary predictions
        self.precision.update_state(y_true, y_pred, sample_weight)
        self.recall.update_state(y_true, y_pred, sample_weight)

    def result(self):
        p = self.precision.result()
        r = self.recall.result()
        return 2 * ((p * r) / (p + r + tf.keras.backend.epsilon()))

    def reset_state(self):
        self.precision.reset_state()
        self.recall.reset_state()
```

In [255…
```
text_input = Input(shape=(max_len,), name='text_input')
text_embed = Embedding(max_words, 64, input_length=max_len)(text_input)
text_lstm = LSTM(32)(text_embed)
cat_input = Input(shape=(train_cat.shape[1],), name='cat_input')
cat_dense = Dense(16, activation='relu')(cat_input)
combined = Concatenate()([text_lstm, cat_dense])
output = Dense(16, activation='relu')(combined)
output = Dense(1, activation='sigmoid')(output)
model = Model(inputs=[text_input, cat_input], outputs=output)
model.compile(
    optimizer='adam',
    loss='binary_crossentropy',
    #metrics=['accuracy', F1Score()]
    metrics = 'accuracy'
)

early_stopping = EarlyStopping(
    #monitor='val_f1_score',
    monitor='val_accuracy',
    mode='max',
    patience=5,
    restore_best_weights=True,
    verbose=0
)
checkpoint = ModelCheckpoint(
    'best_model',
    #monitor='val_f1_score',
    monitor = 'val_accuracy',
    mode='max',
    save_best_only=True,
    verbose=0
)

history = model.fit(
    [train_padded, train_cat],
    train_df['target'].values,
    epochs=50,
    batch_size=64,
    validation_split=0.2,
    callbacks=[early_stopping, checkpoint],
    verbose=1,
    shuffle = False
)
```

```
Epoch 1/50
94/96 [============================>.] - ETA: 0s - loss: 6.6486 - accuracy:
0.5537INFO:tensorflow:Assets written to: best_model/assets
INFO:tensorflow:Assets written to: best_model/assets
96/96 [==============================] - 9s 63ms/step - loss: 6.5799 - accur
acy: 0.5522 - val_loss: 1.1453 - val_accuracy: 0.5437
Epoch 2/50
95/96 [============================>.] - ETA: 0s - loss: 1.2818 - accuracy:
0.5275INFO:tensorflow:Assets written to: best_model/assets
INFO:tensorflow:Assets written to: best_model/assets


96/96 [==============================] - 6s 64ms/step - loss: 1.2812 - accur
acy: 0.5274 - val_loss: 0.9786 - val_accuracy: 0.5502
Epoch 3/50
96/96 [==============================] - 2s 18ms/step - loss: 0.9861 - accur
acy: 0.4846 - val_loss: 0.9459 - val_accuracy: 0.5502
Epoch 4/50
96/96 [==============================] - 2s 21ms/step - loss: 0.9126 - accur
acy: 0.4913 - val_loss: 0.8490 - val_accuracy: 0.5502
Epoch 5/50
96/96 [==============================] - 2s 23ms/step - loss: 0.8537 - accur
acy: 0.5110 - val_loss: 0.7641 - val_accuracy: 0.5437
Epoch 6/50
96/96 [==============================] - ETA: 0s - loss: 0.5970 - accuracy:
0.7401INFO:tensorflow:Assets written to: best_model/assets
INFO:tensorflow:Assets written to: best_model/assets
96/96 [==============================] - 5s 54ms/step - loss: 0.5970 - accur
acy: 0.7401 - val_loss: 0.5860 - val_accuracy: 0.7420
Epoch 7/50
96/96 [==============================] - ETA: 0s - loss: 0.4236 - accuracy:
0.8424INFO:tensorflow:Assets written to: best_model/assets
INFO:tensorflow:Assets written to: best_model/assets
96/96 [==============================] - 5s 55ms/step - loss: 0.4236 - accur
acy: 0.8424 - val_loss: 0.5507 - val_accuracy: 0.7597
Epoch 8/50
93/96 [===========================>..] - ETA: 0s - loss: 0.3408 - accuracy:
0.8852INFO:tensorflow:Assets written to: best_model/assets
INFO:tensorflow:Assets written to: best_model/assets
96/96 [==============================] - 5s 55ms/step - loss: 0.3398 - accur
acy: 0.8854 - val_loss: 0.5387 - val_accuracy: 0.7774
Epoch 9/50
Epoch 9/50
96/96 [==============================] - 2s 18ms/step - loss: 0.3168 - accur
acy: 0.9005 - val_loss: 0.6281 - val_accuracy: 0.7328
Epoch 10/50
96/96 [==============================] - 2s 21ms/step - loss: 0.3069 - accur
acy: 0.9107 - val_loss: 0.6247 - val_accuracy: 0.7636
Epoch 11/50
96/96 [==============================] - 2s 19ms/step - loss: 0.3073 - accur
acy: 0.9143 - val_loss: 0.7208 - val_accuracy: 0.7748
Epoch 12/50
96/96 [==============================] - 2s 21ms/step - loss: 0.2797 - accur
acy: 0.9192 - val_loss: 0.9125 - val_accuracy: 0.7354
Epoch 13/50
96/96 [==============================] - 2s 20ms/step - loss: 0.2877 - accur
acy: 0.9250 - val_loss: 0.6847 - val_accuracy: 0.7538
```

In [256…
```
plt.figure(figsize=(8, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

Out[256]:
```
<matplotlib.legend.Legend at 0x7fb4e4584d00>
```



In [257…

```
n_samples = len(train_df)
val_size = int(0.2 * n_samples)
train_size = n_samples - val_size

train_indices = np.arange(train_size)
val_indices = np.arange(train_size, n_samples)

train_padded_split = train_padded[train_indices]
train_cat_split = train_cat[train_indices]
train_labels = train_df['target'].values[train_indices]

val_padded_split = train_padded[val_indices]
val_cat_split = train_cat[val_indices]
val_labels = train_df['target'].values[val_indices]

train_preds = (model.predict([train_padded_split, train_cat_split]) > 0.5).a
val_preds = (model.predict([val_padded_split, val_cat_split]) > 0.5).astype(

print("\nTraining Confusion Matrix:")
print(confusion_matrix(train_labels, train_preds))
print("\nTraining Classification Report:")
print(classification_report(train_labels, train_preds, target_names=['Non-Di

print("\nValidation Confusion Matrix:")
print(confusion_matrix(val_labels, val_preds))
print("\nValidation Classification Report:")
print(classification_report(val_labels, val_preds, target_names=['Non-Disast

train_metrics = {
    'F1': f1_score(train_labels, train_preds),
    'Accuracy': accuracy_score(train_labels, train_preds),
    'Precision': precision_score(train_labels, train_preds),
    'Recall': recall_score(train_labels, train_preds)
}
val_metrics = {
    'F1': f1_score(val_labels, val_preds),
    'Accuracy': accuracy_score(val_labels, val_preds),
    'Precision': precision_score(val_labels, val_preds),
    'Recall': recall_score(val_labels, val_preds)
}

print("\nTraining Metrics:")
for metric, value in train_metrics.items():
    print(f"{metric}: {value:.4f}")

print("\nValidation Metrics:")
for metric, value in val_metrics.items():
    print(f"{metric}: {value:.4f}")
```

```
191/191 [==============================] - 1s 4ms/step
48/48 [==============================] - 0s 5ms/step

Training Confusion Matrix:
[[3422  107]
 [ 550 2012]]

Training Classification Report:
              precision    recall  f1-score   support

Non-Disaster       0.86      0.97      0.91      3529
    Disaster       0.95      0.79      0.86      2562

    accuracy                           0.89      6091
   macro avg       0.91      0.88      0.89      6091
weighted avg       0.90      0.89      0.89      6091


Validation Confusion Matrix:
[[719  94]
 [245 464]]

Validation Classification Report:
              precision    recall  f1-score   support

Non-Disaster       0.75      0.88      0.81       813
    Disaster       0.83      0.65      0.73       709

    accuracy                           0.78      1522
   macro avg       0.79      0.77      0.77      1522
weighted avg       0.79      0.78      0.77      1522


Training Metrics:
F1: 0.8596
Accuracy: 0.8921
Precision: 0.9495
Recall: 0.7853

Validation Metrics:
F1: 0.7324
Accuracy: 0.7773
Precision: 0.8315
Recall: 0.6544
```

The base model is struggling with some overfitting, seen by the learning curves and the gap (~8%) in f1 score between training and validation. Some potential reasons for overfitting:

- relatively small data set
- lack of sufficient regularization (no drop out of L2)
- lack of class weights

However, the gap does not appear to be too large. A gridsearch will now be conducted to try and improve val f1 score.

GridSearch

- Batch Size: 32, 64
- Embedding Dimension: 32, 64
- Learning Rate: .001, .0005, .0001

In [264…

```python
param_grid = {
    'batch_size': [32, 64],
    'embedding_dim': [32, 64],
    'learning_rate': [0.001, 0.0005, 0.0001],
}
```

In [265…

```python
results_df = pd.DataFrame(columns=[
    'batch_size', 'embedding_dim', 'learning_rate',
    'train_f1', 'train_accuracy', 'train_precision', 'train_recall',
    'val_f1', 'val_accuracy', 'val_precision', 'val_recall', 'f1_gap'
])

# Grid search
best_val_f1 = 0.0
best_params = None
best_model_path = 'best_model_grid'
best_history = None

for params in ParameterGrid(param_grid):
    print(f"\nTesting parameters: {params}")

    # Model architecture
    text_input = Input(shape=(max_len,), name='text_input')
    text_embed = Embedding(max_words, params['embedding_dim'], input_length=
    text_lstm = LSTM(32)(text_embed)
    cat_input = Input(shape=(train_cat.shape[1],), name='cat_input')
    cat_dense = Dense(16, activation='relu')(cat_input)
    combined = Concatenate()([text_lstm, cat_dense])
    output = Dense(16, activation='relu')(combined)
    output = Dense(1, activation='sigmoid')(output)
    model = Model(inputs=[text_input, cat_input], outputs=output)

    # Compile model
```

```python
    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=params['learning_ra
        loss='binary_crossentropy',
        metrics='accuracy'
    )

    # Callbacks
    early_stopping = EarlyStopping(
        monitor='val_accuracy',
        mode='max',
        patience=5,
        restore_best_weights=True,
        verbose=0
    )
    checkpoint = ModelCheckpoint(
        f"model_{params['batch_size']}_{params['embedding_dim']}_{params['le
        monitor='val_accuracy',
        mode='max',
        save_best_only=True,
        verbose=0
    )

    # Train model
    history = model.fit(
        [train_padded, train_cat],
        train_df['target'].values,
        epochs=50,
        batch_size=params['batch_size'],
        validation_split=0.2,
        callbacks=[early_stopping, checkpoint],
        shuffle=False,
        verbose=1
    )
    n_samples = len(train_df)
    val_size = int(0.2 * n_samples)
    train_size = n_samples - val_size
    train_indices = np.arange(train_size)
    val_indices = np.arange(train_size, n_samples)
    train_padded_split = train_padded[train_indices]
    train_cat_split = train_cat[train_indices]
    train_labels = train_df['target'].values[train_indices]
    val_padded_split = train_padded[val_indices]
    val_cat_split = train_cat[val_indices]
    val_labels = train_df['target'].values[val_indices]

    train_preds = (model.predict([train_padded_split, train_cat_split]) > 0.
    val_preds = (model.predict([val_padded_split, val_cat_split]) > 0.5).ast

    train_f1 = f1_score(train_labels, train_preds)
    train_accuracy = accuracy_score(train_labels, train_preds)
    train_precision = precision_score(train_labels, train_preds)
    train_recall = recall_score(train_labels, train_preds)
    val_f1 = f1_score(val_labels, val_preds)
    val_accuracy = accuracy_score(val_labels, val_preds)
    val_precision = precision_score(val_labels, val_preds)
    val_recall = recall_score(val_labels, val_preds)
    f1_gap = train_f1 - val_f1

    # Store results
    results_df = pd.concat([results_df, pd.DataFrame([{
        'batch_size': params['batch_size'],
        'embedding_dim': params['embedding_dim'],
        'learning_rate': params['learning_rate'],
        'train_f1': train_f1,
        'train_accuracy': train_accuracy,
        'train_precision': train_precision,
        'train_recall': train_recall,
        'val_f1': val_f1,
        'val_accuracy': val_accuracy,
        'val_precision': val_precision,
        'val_recall': val_recall,
        'f1_gap': f1_gap
    }])], ignore_index=True)

    print(f"Training F1: {train_f1:.4f}, Validation F1: {val_f1:.4f}, F1 Gap

    if val_f1 > best_val_f1:
        best_val_f1 = val_f1
        best_params = params
        best_history = history
        model.save(best_model_path)
```

```
Testing parameters: {'batch_size': 32, 'embedding_dim': 32, 'learning_rate':
0.001}
Epoch 1/50
190/191 [============================>.] - ETA: 0s - loss: 0.8191 - accurac
y: 0.5118INFO:tensorflow:Assets written to: model_32_32_0.001/assets
INFO:tensorflow:Assets written to: model_32_32_0.001/assets
191/191 [==============================] - 17s 63ms/step - loss: 0.8196 - ac
curacy: 0.5118 - val_loss: 1.2730 - val_accuracy: 0.5345
Epoch 2/50
191/191 [==============================] - ETA: 0s - loss: 0.7079 - accurac
y: 0.6542INFO:tensorflow:Assets written to: model_32_32_0.001/assets
INFO:tensorflow:Assets written to: model_32_32_0.001/assets
191/191 [==============================] - 12s 63ms/step - loss: 0.7079 - ac
curacy: 0.6542 - val_loss: 0.6644 - val_accuracy: 0.7308
Epoch 3/50
190/191 [============================>.] - ETA: 0s - loss: 0.4637 - accurac
y: 0.8061INFO:tensorflow:Assets written to: model_32_32_0.001/assets
INFO:tensorflow:Assets written to: model_32_32_0.001/assets
```

```
191/191 [==============================] - 11s 58ms/step - loss: 0.4631 - ac
curacy: 0.8064 - val_loss: 0.6458 - val_accuracy: 0.7886
Epoch 4/50
191/191 [==============================] - 3s 17ms/step - loss: 0.3679 - acc
uracy: 0.8655 - val_loss: 0.6411 - val_accuracy: 0.7649
Epoch 5/50
191/191 [==============================] - 4s 19ms/step - loss: 0.3724 - acc
uracy: 0.8654 - val_loss: 0.7050 - val_accuracy: 0.7557
Epoch 6/50
191/191 [==============================] - 3s 17ms/step - loss: 0.3008 - acc
uracy: 0.8985 - val_loss: 0.6328 - val_accuracy: 0.7741
Epoch 7/50
191/191 [==============================] - 4s 19ms/step - loss: 0.2624 - acc
uracy: 0.9204 - val_loss: 0.6907 - val_accuracy: 0.7695
Epoch 8/50
191/191 [==============================] - 3s 18ms/step - loss: 0.2667 - acc
uracy: 0.9230 - val_loss: 0.6933 - val_accuracy: 0.7656
191/191 [==============================] - 1s 5ms/step
48/48 [==============================] - 0s 5ms/step
Training F1: 0.8074, Validation F1: 0.7424, F1 Gap: 0.0650
INFO:tensorflow:Assets written to: best_model_grid/assets
INFO:tensorflow:Assets written to: best_model_grid/assets
Testing parameters: {'batch_size': 32, 'embedding_dim': 32, 'learning_rate':
0.0005}
Epoch 1/50
191/191 [==============================] - ETA: 0s - loss: 0.8209 - accurac
y: 0.5067INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
191/191 [==============================] - 11s 43ms/step - loss: 0.8209 - ac
curacy: 0.5067 - val_loss: 0.9706 - val_accuracy: 0.5332
Epoch 2/50
190/191 [============================>.] - ETA: 0s - loss: 0.9024 - accurac
y: 0.4852INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
191/191 [==============================] - 7s 38ms/step - loss: 0.9022 - acc
uracy: 0.4852 - val_loss: 0.9018 - val_accuracy: 0.5345
Epoch 3/50
190/191 [============================>.] - ETA: 0s - loss: 0.6926 - accurac
y: 0.6831INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
191/191 [==============================] - 7s 35ms/step - loss: 0.6917 - acc
uracy: 0.6836 - val_loss: 0.5192 - val_accuracy: 0.7722
Epoch 4/50
190/191 [============================>.] - ETA: 0s - loss: 0.4148 - accurac
y: 0.8342INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
INFO:tensorflow:Assets written to: model_32_32_0.0005/assets
```

```
191/191 [==============================] - 7s 37ms/step - loss: 0.4143 - acc
uracy: 0.8345 - val_loss: 0.5190 - val_accuracy: 0.7768
Epoch 5/50
191/191 [==============================] - 3s 18ms/step - loss: 0.3251 - acc
uracy: 0.8806 - val_loss: 0.7813 - val_accuracy: 0.7360
Epoch 6/50
191/191 [==============================] - 3s 18ms/step - loss: 0.2975 - acc
uracy: 0.8939 - val_loss: 0.6355 - val_accuracy: 0.7505
Epoch 7/50
191/191 [==============================] - 3s 18ms/step - loss: 0.2663 - acc
uracy: 0.9074 - val_loss: 0.5957 - val_accuracy: 0.7702
Epoch 8/50
191/191 [==============================] - 3s 17ms/step - loss: 0.2459 - acc
uracy: 0.9154 - val_loss: 0.6479 - val_accuracy: 0.7722
Epoch 9/50
191/191 [==============================] - 3s 17ms/step - loss: 0.2098 - acc
uracy: 0.9315 - val_loss: 0.6795 - val_accuracy: 0.7748
191/191 [==============================] - 1s 5ms/step
48/48 [==============================] - 0s 6ms/step
Training F1: 0.8486, Validation F1: 0.7580, F1 Gap: 0.0906
INFO:tensorflow:Assets written to: best_model_grid/assets
INFO:tensorflow:Assets written to: best_model_grid/assets
Testing parameters: {'batch_size': 32, 'embedding_dim': 32, 'learning_rate':
0.0001}
Epoch 1/50
191/191 [==============================] - ETA: 0s - loss: 5.2527 - accurac
y: 0.5562INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 10s 36ms/step - loss: 5.2527 - ac
curacy: 0.5562 - val_loss: 0.9185 - val_accuracy: 0.4747
Epoch 2/50
189/191 [============================>.] - ETA: 0s - loss: 1.8541 - accurac
y: 0.5263INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 8s 42ms/step - loss: 1.8465 - acc
uracy: 0.5259 - val_loss: 0.7635 - val_accuracy: 0.5213
Epoch 3/50
190/191 [============================>.] - ETA: 0s - loss: 1.3190 - accurac
y: 0.5038INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 7s 36ms/step - loss: 1.3181 - acc
uracy: 0.5038 - val_loss: 0.7402 - val_accuracy: 0.5279
Epoch 4/50
189/191 [============================>.] - ETA: 0s - loss: 1.0303 - accurac
y: 0.5103INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 7s 36ms/step - loss: 1.0283 - acc
uracy: 0.5092 - val_loss: 0.7234 - val_accuracy: 0.5345
Epoch 5/50
191/191 [==============================] - 3s 17ms/step - loss: 0.8573 - acc
uracy: 0.5381 - val_loss: 0.7274 - val_accuracy: 0.5345
Epoch 6/50
190/191 [============================>.] - ETA: 0s - loss: 0.7734 - accurac
y: 0.5345INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
```

```
191/191 [==============================] - 7s 35ms/step - loss: 0.7733 - acc
uracy: 0.5345 - val_loss: 0.7318 - val_accuracy: 0.5351
Epoch 7/50
190/191 [============================>.] - ETA: 0s - loss: 0.7278 - accurac
y: 0.5521INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 7s 36ms/step - loss: 0.7277 - acc
uracy: 0.5522 - val_loss: 0.7220 - val_accuracy: 0.5437
Epoch 8/50
190/191 [============================>.] - ETA: 0s - loss: 0.5840 - accurac
y: 0.7113INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 8s 41ms/step - loss: 0.5834 - acc
uracy: 0.7118 - val_loss: 0.5241 - val_accuracy: 0.7623
Epoch 9/50
188/191 [============================>.] - ETA: 0s - loss: 0.4257 - accurac
y: 0.8290INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 7s 37ms/step - loss: 0.4250 - acc
uracy: 0.8294 - val_loss: 0.5102 - val_accuracy: 0.7689
Epoch 10/50
189/191 [============================>.] - ETA: 0s - loss: 0.3745 - accurac
y: 0.8590INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
INFO:tensorflow:Assets written to: model_32_32_0.0001/assets
191/191 [==============================] - 7s 35ms/step - loss: 0.3735 - acc
uracy: 0.8594 - val_loss: 0.5135 - val_accuracy: 0.7728
Epoch 11/50
191/191 [==============================] - 3s 17ms/step - loss: 0.3358 - acc
uracy: 0.8770 - val_loss: 0.5272 - val_accuracy: 0.7728
Epoch 12/50
191/191 [==============================] - 4s 19ms/step - loss: 0.3050 - acc
uracy: 0.8923 - val_loss: 0.5551 - val_accuracy: 0.7630
Epoch 13/50
191/191 [==============================] - 3s 17ms/step - loss: 0.2758 - acc
uracy: 0.9067 - val_loss: 0.5704 - val_accuracy: 0.7663
Epoch 14/50
191/191 [==============================] - 3s 18ms/step - loss: 0.2553 - acc
uracy: 0.9186 - val_loss: 0.6135 - val_accuracy: 0.7571
Epoch 15/50
191/191 [==============================] - 4s 20ms/step - loss: 0.2432 - acc
uracy: 0.9223 - val_loss: 0.6405 - val_accuracy: 0.7603
191/191 [==============================] - 1s 5ms/step
48/48 [==============================] - 1s 10ms/step
Training F1: 0.8444, Validation F1: 0.7422, F1 Gap: 0.1023

Testing parameters: {'batch_size': 32, 'embedding_dim': 64, 'learning_rate':
0.001}
Epoch 1/50
190/191 [============================>.] - ETA: 0s - loss: 1.0403 - accurac
y: 0.5437INFO:tensorflow:Assets written to: model_32_64_0.001/assets
INFO:tensorflow:Assets written to: model_32_64_0.001/assets
```

```
191/191 [==============================] - 11s 42ms/step - loss: 1.0406 - ac
curacy: 0.5437 - val_loss: 0.9878 - val_accuracy: 0.5522
Epoch 2/50
191/191 [==============================] - 4s 20ms/step - loss: 0.7348 - acc
uracy: 0.5179 - val_loss: 0.8290 - val_accuracy: 0.5391
Epoch 3/50
191/191 [==============================] - 4s 20ms/step - loss: 0.7138 - acc
uracy: 0.5381 - val_loss: 0.7687 - val_accuracy: 0.5391
Epoch 4/50
191/191 [==============================] - ETA: 0s - loss: 0.6974 - accurac
y: 0.5658INFO:tensorflow:Assets written to: model_32_64_0.001/assets
INFO:tensorflow:Assets written to: model_32_64_0.001/assets
191/191 [==============================] - 7s 38ms/step - loss: 0.6974 - acc
uracy: 0.5658 - val_loss: 0.7870 - val_accuracy: 0.6080
Epoch 5/50
191/191 [==============================] - 4s 19ms/step - loss: 0.6820 - acc
uracy: 0.5913 - val_loss: 0.8548 - val_accuracy: 0.5456
Epoch 6/50
190/191 [============================>.] - ETA: 0s - loss: 0.6561 - accurac
y: 0.6367INFO:tensorflow:Assets written to: model_32_64_0.001/assets
INFO:tensorflow:Assets written to: model_32_64_0.001/assets
191/191 [==============================] - 8s 44ms/step - loss: 0.6560 - acc
uracy: 0.6369 - val_loss: 0.6800 - val_accuracy: 0.6251
Epoch 7/50
189/191 [============================>.] - ETA: 0s - loss: 0.5911 - accurac
y: 0.7206INFO:tensorflow:Assets written to: model_32_64_0.001/assets
INFO:tensorflow:Assets written to: model_32_64_0.001/assets
191/191 [==============================] - 8s 44ms/step - loss: 0.5899 - acc
uracy: 0.7218 - val_loss: 0.6608 - val_accuracy: 0.6934
Epoch 8/50
191/191 [==============================] - 4s 19ms/step - loss: 0.5812 - acc
uracy: 0.7343 - val_loss: 0.7301 - val_accuracy: 0.6087
Epoch 9/50
191/191 [==============================] - 4s 22ms/step - loss: 0.5737 - acc
uracy: 0.7314 - val_loss: 0.7199 - val_accuracy: 0.6034
Epoch 10/50
191/191 [==============================] - 4s 22ms/step - loss: 0.5579 - acc
uracy: 0.7450 - val_loss: 0.7212 - val_accuracy: 0.6100
Epoch 11/50
191/191 [==============================] - 5s 24ms/step - loss: 0.5484 - acc
uracy: 0.7511 - val_loss: 0.6888 - val_accuracy: 0.6376
Epoch 12/50
191/191 [==============================] - 4s 20ms/step - loss: 0.5427 - acc
uracy: 0.7557 - val_loss: 0.6977 - val_accuracy: 0.6284
191/191 [==============================] - 2s 6ms/step
48/48 [==============================] - 0s 6ms/step
Training F1: 0.7287, Validation F1: 0.6905, F1 Gap: 0.0382

Testing parameters: {'batch_size': 32, 'embedding_dim': 64, 'learning_rate':
0.0005}
Epoch 1/50
190/191 [============================>.] - ETA: 0s - loss: 1.7723 - accurac
y: 0.5207INFO:tensorflow:Assets written to: model_32_64_0.0005/assets
INFO:tensorflow:Assets written to: model_32_64_0.0005/assets
```

```
191/191 [==============================] - 11s 43ms/step - loss: 1.7709 - ac
curacy: 0.5207 - val_loss: 0.9222 - val_accuracy: 0.5345
Epoch 2/50
191/191 [==============================] - 4s 21ms/step - loss: 0.9682 - acc
uracy: 0.4897 - val_loss: 0.9711 - val_accuracy: 0.5345
Epoch 3/50
190/191 [============================>.] - ETA: 0s - loss: 0.7599 - accurac
y: 0.6408INFO:tensorflow:Assets written to: model_32_64_0.0005/assets
INFO:tensorflow:Assets written to: model_32_64_0.0005/assets
191/191 [==============================] - 8s 40ms/step - loss: 0.7590 - acc
uracy: 0.6414 - val_loss: 0.5344 - val_accuracy: 0.7774
Epoch 4/50
189/191 [============================>.] - ETA: 0s - loss: 0.4623 - accurac
y: 0.8261INFO:tensorflow:Assets written to: model_32_64_0.0005/assets
INFO:tensorflow:Assets written to: model_32_64_0.0005/assets
191/191 [==============================] - 8s 39ms/step - loss: 0.4611 - acc
uracy: 0.8264 - val_loss: 0.4854 - val_accuracy: 0.7899
Epoch 5/50
191/191 [==============================] - 4s 20ms/step - loss: 0.3428 - acc
uracy: 0.8722 - val_loss: 0.6233 - val_accuracy: 0.7544
Epoch 6/50
191/191 [==============================] - 4s 22ms/step - loss: 0.2993 - acc
uracy: 0.8990 - val_loss: 0.6299 - val_accuracy: 0.7722
Epoch 7/50
191/191 [==============================] - 4s 20ms/step - loss: 0.2811 - acc
uracy: 0.9097 - val_loss: 0.7116 - val_accuracy: 0.7879
Epoch 8/50
191/191 [==============================] - 4s 18ms/step - loss: 0.2425 - acc
uracy: 0.9279 - val_loss: 0.6243 - val_accuracy: 0.7807
Epoch 9/50
191/191 [==============================] - 4s 22ms/step - loss: 0.2050 - acc
uracy: 0.9384 - val_loss: 0.6379 - val_accuracy: 0.7643
191/191 [==============================] - 2s 6ms/step
48/48 [==============================] - 0s 5ms/step
Training F1: 0.8205, Validation F1: 0.7647, F1 Gap: 0.0558
INFO:tensorflow:Assets written to: best_model_grid/assets
INFO:tensorflow:Assets written to: best_model_grid/assets
Testing parameters: {'batch_size': 32, 'embedding_dim': 64, 'learning_rate':
0.0001}
Epoch 1/50
189/191 [============================>.] - ETA: 0s - loss: 24.3697 - accurac
y: 0.4190INFO:tensorflow:Assets written to: model_32_64_0.0001/assets
INFO:tensorflow:Assets written to: model_32_64_0.0001/assets
191/191 [==============================] - 13s 41ms/step - loss: 24.2547 - a
ccuracy: 0.4205 - val_loss: 10.8648 - val_accuracy: 0.4767
Epoch 2/50
189/191 [============================>.] - ETA: 0s - loss: 9.1986 - accurac
y: 0.4418INFO:tensorflow:Assets written to: model_32_64_0.0001/assets
INFO:tensorflow:Assets written to: model_32_64_0.0001/assets
191/191 [==============================] - 8s 41ms/step - loss: 9.1525 - acc
uracy: 0.4412 - val_loss: 2.4059 - val_accuracy: 0.5502
Epoch 3/50
190/191 [============================>.] - ETA: 0s - loss: 2.4705 - accurac
y: 0.4944INFO:tensorflow:Assets written to: model_32_64_0.0001/assets
INFO:tensorflow:Assets written to: model_32_64_0.0001/assets
191/191 [==============================] - 8s 41ms/step - loss: 2.4685 - acc
uracy: 0.4944 - val_loss: 0.9556 - val_accuracy: 0.5548
Epoch 4/50
191/191 [==============================] - 4s 20ms/step - loss: 1.5063 - acc
uracy: 0.4898 - val_loss: 0.9027 - val_accuracy: 0.4754
Epoch 5/50
191/191 [==============================] - 4s 21ms/step - loss: 1.0489 - acc
uracy: 0.5031 - val_loss: 0.8728 - val_accuracy: 0.5121
Epoch 6/50
191/191 [==============================] - 4s 20ms/step - loss: 0.9167 - acc
uracy: 0.5046 - val_loss: 0.8552 - val_accuracy: 0.5115
Epoch 7/50
191/191 [==============================] - 4s 20ms/step - loss: 0.8634 - acc
uracy: 0.5064 - val_loss: 0.8432 - val_accuracy: 0.5076
Epoch 8/50
191/191 [==============================] - 4s 20ms/step - loss: 0.8341 - acc
uracy: 0.5103 - val_loss: 0.8348 - val_accuracy: 0.5062
191/191 [==============================] - 2s 5ms/step
48/48 [==============================] - 0s 6ms/step
Training F1: 0.5355, Validation F1: 0.1008, F1 Gap: 0.4347

Testing parameters: {'batch_size': 64, 'embedding_dim': 32, 'learning_rate':
0.001}
Epoch 1/50
95/96 [============================>.] - ETA: 0s - loss: 3.6597 - accuracy:
0.5373INFO:tensorflow:Assets written to: model_64_32_0.001/assets
INFO:tensorflow:Assets written to: model_64_32_0.001/assets
96/96 [==============================] - 9s 61ms/step - loss: 3.6548 - accur
acy: 0.5374 - val_loss: 0.7558 - val_accuracy: 0.5476
Epoch 2/50
96/96 [==============================] - ETA: 0s - loss: 1.2960 - accuracy:
0.5120INFO:tensorflow:Assets written to: model_64_32_0.001/assets
INFO:tensorflow:Assets written to: model_64_32_0.001/assets
96/96 [==============================] - 7s 74ms/step - loss: 1.2960 - accur
acy: 0.5120 - val_loss: 0.7663 - val_accuracy: 0.5522
Epoch 3/50
96/96 [==============================] - 2s 21ms/step - loss: 1.1186 - accur
acy: 0.4998 - val_loss: 0.7231 - val_accuracy: 0.5502
Epoch 4/50
96/96 [==============================] - 2s 20ms/step - loss: 1.0019 - accur
acy: 0.5222 - val_loss: 0.7087 - val_accuracy: 0.5279
Epoch 5/50
96/96 [==============================] - 2s 20ms/step - loss: 0.9225 - accur
acy: 0.5199 - val_loss: 0.7199 - val_accuracy: 0.5279
Epoch 6/50
94/96 [============================>.] - ETA: 0s - loss: 0.8638 - accuracy:
0.5349INFO:tensorflow:Assets written to: model_64_32_0.001/assets
INFO:tensorflow:Assets written to: model_64_32_0.001/assets
96/96 [==============================] - 6s 66ms/step - loss: 0.8601 - accur
acy: 0.5373 - val_loss: 0.6908 - val_accuracy: 0.6218
Epoch 7/50
93/96 [============================>.] - ETA: 0s - loss: 0.6536 - accuracy:
0.6803INFO:tensorflow:Assets written to: model_64_32_0.001/assets
INFO:tensorflow:Assets written to: model_64_32_0.001/assets
```

```
96/96 [==============================] - 5s 56ms/step - loss: 0.6486 - accur
acy: 0.6841 - val_loss: 0.6377 - val_accuracy: 0.6986
Epoch 8/50
93/96 [============================>.] - ETA: 0s - loss: 0.5356 - accuracy:
0.7762INFO:tensorflow:Assets written to: model_64_32_0.001/assets
INFO:tensorflow:Assets written to: model_64_32_0.001/assets
96/96 [==============================] - 6s 62ms/step - loss: 0.5318 - accur
acy: 0.7785 - val_loss: 0.5684 - val_accuracy: 0.7387
Epoch 9/50
96/96 [==============================] - 2s 22ms/step - loss: 0.4476 - accur
acy: 0.8215 - val_loss: 0.5861 - val_accuracy: 0.7380
Epoch 10/50
93/96 [============================>.] - ETA: 0s - loss: 0.3629 - accuracy:
0.8589INFO:tensorflow:Assets written to: model_64_32_0.001/assets
INFO:tensorflow:Assets written to: model_64_32_0.001/assets
96/96 [==============================] - 6s 62ms/step - loss: 0.3607 - accur
acy: 0.8599 - val_loss: 0.5853 - val_accuracy: 0.7610
Epoch 11/50
96/96 [==============================] - 2s 21ms/step - loss: 0.3068 - accur
acy: 0.8980 - val_loss: 0.5717 - val_accuracy: 0.7590
Epoch 12/50
96/96 [==============================] - 2s 26ms/step - loss: 0.2950 - accur
acy: 0.9069 - val_loss: 0.6904 - val_accuracy: 0.7459
Epoch 13/50
96/96 [==============================] - 2s 23ms/step - loss: 0.2645 - accur
acy: 0.9161 - val_loss: 0.6215 - val_accuracy: 0.7433
Epoch 14/50
96/96 [==============================] - 2s 23ms/step - loss: 0.2491 - accur
acy: 0.9230 - val_loss: 0.7295 - val_accuracy: 0.7374
Epoch 15/50
96/96 [==============================] - 2s 20ms/step - loss: 0.2284 - accur
acy: 0.9351 - val_loss: 0.8070 - val_accuracy: 0.7367
191/191 [==============================] - 1s 5ms/step
48/48 [==============================] - 0s 4ms/step
Training F1: 0.8585, Validation F1: 0.7301, F1 Gap: 0.1284

Testing parameters: {'batch_size': 64, 'embedding_dim': 32, 'learning_rate':
0.0005}
Epoch 1/50
96/96 [==============================] - ETA: 0s - loss: 0.7704 - accuracy:
0.5158INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
96/96 [==============================] - 9s 70ms/step - loss: 0.7704 - accur
acy: 0.5158 - val_loss: 0.7574 - val_accuracy: 0.5443
Epoch 2/50
96/96 [==============================] - 2s 18ms/step - loss: 0.7651 - accur
acy: 0.5087 - val_loss: 0.7288 - val_accuracy: 0.5443
Epoch 3/50
96/96 [==============================] - 2s 23ms/step - loss: 0.7986 - accur
acy: 0.4890 - val_loss: 0.7168 - val_accuracy: 0.5430
Epoch 4/50
96/96 [==============================] - 2s 23ms/step - loss: 0.7604 - accur
acy: 0.5085 - val_loss: 0.7157 - val_accuracy: 0.5437
Epoch 5/50
95/96 [============================>.] - ETA: 0s - loss: 0.6780 - accuracy:
0.6130INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
96/96 [==============================] - 7s 77ms/step - loss: 0.6775 - accur
acy: 0.6136 - val_loss: 0.5711 - val_accuracy: 0.7426
Epoch 6/50
95/96 [============================>.] - ETA: 0s - loss: 0.4856 - accuracy:
0.8039INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
96/96 [==============================] - 6s 63ms/step - loss: 0.4851 - accur
acy: 0.8043 - val_loss: 0.5275 - val_accuracy: 0.7676
Epoch 7/50
96/96 [==============================] - 2s 19ms/step - loss: 0.3985 - accur
acy: 0.8493 - val_loss: 0.5810 - val_accuracy: 0.7649
Epoch 8/50
95/96 [============================>.] - ETA: 0s - loss: 0.3363 - accuracy:
0.8873INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
INFO:tensorflow:Assets written to: model_64_32_0.0005/assets
96/96 [==============================] - 6s 59ms/step - loss: 0.3361 - accur
acy: 0.8874 - val_loss: 0.5461 - val_accuracy: 0.7748
Epoch 9/50
96/96 [==============================] - 2s 23ms/step - loss: 0.3154 - accur
acy: 0.9002 - val_loss: 0.7027 - val_accuracy: 0.7511
Epoch 10/50
96/96 [==============================] - 2s 23ms/step - loss: 0.3100 - accur
acy: 0.8993 - val_loss: 0.6480 - val_accuracy: 0.7511
Epoch 11/50
96/96 [==============================] - 2s 23ms/step - loss: 0.2774 - accur
acy: 0.9149 - val_loss: 0.7119 - val_accuracy: 0.7301
Epoch 12/50
96/96 [==============================] - 2s 23ms/step - loss: 0.2974 - accur
acy: 0.9115 - val_loss: 0.7719 - val_accuracy: 0.7150
Epoch 13/50
96/96 [==============================] - 2s 24ms/step - loss: 0.2862 - accur
acy: 0.9149 - val_loss: 0.7552 - val_accuracy: 0.7111
191/191 [==============================] - 1s 5ms/step
48/48 [==============================] - 0s 6ms/step
Training F1: 0.8246, Validation F1: 0.7431, F1 Gap: 0.0815

Testing parameters: {'batch_size': 64, 'embedding_dim': 32, 'learning_rate':
0.0001}
Epoch 1/50
95/96 [============================>.] - ETA: 0s - loss: 15.5218 - accuracy:
0.4206INFO:tensorflow:Assets written to: model_64_32_0.0001/assets
INFO:tensorflow:Assets written to: model_64_32_0.0001/assets
96/96 [==============================] - 10s 70ms/step - loss: 15.5155 - acc
uracy: 0.4207 - val_loss: 11.7111 - val_accuracy: 0.4655
Epoch 2/50
96/96 [==============================] - 2s 19ms/step - loss: 9.9525 - accur
acy: 0.4207 - val_loss: 4.4910 - val_accuracy: 0.4649
Epoch 3/50
96/96 [==============================] - ETA: 0s - loss: 5.0028 - accuracy:
0.4325INFO:tensorflow:Assets written to: model_64_32_0.0001/assets
INFO:tensorflow:Assets written to: model_64_32_0.0001/assets
```

```
96/96 [==============================] - 6s 60ms/step - loss: 5.0028 - accur
acy: 0.4325 - val_loss: 2.4407 - val_accuracy: 0.5410
Epoch 4/50
96/96 [==============================] - 2s 22ms/step - loss: 2.9000 - accur
acy: 0.4650 - val_loss: 3.3069 - val_accuracy: 0.5240
Epoch 5/50
96/96 [==============================] - 2s 22ms/step - loss: 2.0538 - accur
acy: 0.4719 - val_loss: 2.9034 - val_accuracy: 0.5253
Epoch 6/50
96/96 [==============================] - 2s 23ms/step - loss: 1.6149 - accur
acy: 0.4768 - val_loss: 2.3412 - val_accuracy: 0.5272
Epoch 7/50
96/96 [==============================] - 2s 24ms/step - loss: 1.3419 - accur
acy: 0.4837 - val_loss: 1.7706 - val_accuracy: 0.5259
Epoch 8/50
96/96 [==============================] - 2s 25ms/step - loss: 1.1500 - accur
acy: 0.4936 - val_loss: 1.4479 - val_accuracy: 0.5279
191/191 [==============================] - 2s 5ms/step
48/48 [==============================] - 0s 5ms/step
Training F1: 0.5604, Validation F1: 0.2410, F1 Gap: 0.3193

Testing parameters: {'batch_size': 64, 'embedding_dim': 64, 'learning_rate':
0.001}
Epoch 1/50
95/96 [============================>.] - ETA: 0s - loss: 0.8558 - accuracy:
0.4885INFO:tensorflow:Assets written to: model_64_64_0.001/assets
INFO:tensorflow:Assets written to: model_64_64_0.001/assets
96/96 [==============================] - 11s 82ms/step - loss: 0.8554 - accu
racy: 0.4887 - val_loss: 0.7419 - val_accuracy: 0.5220
Epoch 2/50
96/96 [==============================] - ETA: 0s - loss: 0.8494 - accuracy:
0.5335INFO:tensorflow:Assets written to: model_64_64_0.001/assets
INFO:tensorflow:Assets written to: model_64_64_0.001/assets
96/96 [==============================] - 6s 60ms/step - loss: 0.8494 - accur
acy: 0.5335 - val_loss: 0.7519 - val_accuracy: 0.5378
Epoch 3/50
95/96 [============================>.] - ETA: 0s - loss: 0.6520 - accuracy:
0.6400INFO:tensorflow:Assets written to: model_64_64_0.001/assets
INFO:tensorflow:Assets written to: model_64_64_0.001/assets
96/96 [==============================] - 6s 65ms/step - loss: 0.6511 - accur
acy: 0.6406 - val_loss: 0.5543 - val_accuracy: 0.7590
Epoch 4/50
96/96 [==============================] - ETA: 0s - loss: 0.4839 - accuracy:
0.8031INFO:tensorflow:Assets written to: model_64_64_0.001/assets
INFO:tensorflow:Assets written to: model_64_64_0.001/assets
```

```
96/96 [==============================] - 6s 60ms/step - loss: 0.4839 - accur
acy: 0.8031 - val_loss: 0.4871 - val_accuracy: 0.7932
Epoch 5/50
96/96 [==============================] - 2s 21ms/step - loss: 0.4015 - accur
acy: 0.8644 - val_loss: 0.5381 - val_accuracy: 0.7892
Epoch 6/50
96/96 [==============================] - 2s 23ms/step - loss: 0.3497 - accur
acy: 0.8910 - val_loss: 0.7334 - val_accuracy: 0.7689
Epoch 7/50
96/96 [==============================] - 3s 27ms/step - loss: 0.3296 - accur
acy: 0.8951 - val_loss: 0.7358 - val_accuracy: 0.7334
Epoch 8/50
96/96 [==============================] - 2s 24ms/step - loss: 0.3089 - accur
acy: 0.8993 - val_loss: 0.7443 - val_accuracy: 0.7728
Epoch 9/50
96/96 [==============================] - 2s 25ms/step - loss: 0.3110 - accur
acy: 0.9062 - val_loss: 0.8066 - val_accuracy: 0.7761
191/191 [==============================] - 2s 5ms/step
48/48 [==============================] - 0s 6ms/step
Training F1: 0.8096, Validation F1: 0.7498, F1 Gap: 0.0598

Testing parameters: {'batch_size': 64, 'embedding_dim': 64, 'learning_rate':
0.0005}
Epoch 1/50
95/96 [============================>.] - ETA: 0s - loss: 2.1974 - accuracy:
0.5492INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
96/96 [==============================] - 10s 69ms/step - loss: 2.1952 - accu
racy: 0.5491 - val_loss: 0.7841 - val_accuracy: 0.5351
Epoch 2/50
93/96 [============================>.] - ETA: 0s - loss: 0.7452 - accuracy:
0.5375INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
96/96 [==============================] - 8s 79ms/step - loss: 0.7446 - accur
acy: 0.5325 - val_loss: 0.7313 - val_accuracy: 0.5364
Epoch 3/50
96/96 [==============================] - ETA: 0s - loss: 0.7184 - accuracy:
0.5259INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
96/96 [==============================] - 6s 62ms/step - loss: 0.7184 - accur
acy: 0.5259 - val_loss: 0.6852 - val_accuracy: 0.5824
Epoch 4/50
94/96 [============================>.] - ETA: 0s - loss: 0.5149 - accuracy:
0.7753INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
INFO:tensorflow:Assets written to: model_64_64_0.0005/assets
```

```
96/96 [==============================] - 6s 67ms/step - loss: 0.5134 - accur
acy: 0.7765 - val_loss: 0.4884 - val_accuracy: 0.7840
Epoch 5/50
96/96 [==============================] - 2s 23ms/step - loss: 0.3680 - accur
acy: 0.8589 - val_loss: 0.5553 - val_accuracy: 0.7577
Epoch 6/50
96/96 [==============================] - 2s 22ms/step - loss: 0.3134 - accur
acy: 0.8867 - val_loss: 0.8362 - val_accuracy: 0.7209
Epoch 7/50
96/96 [==============================] - 2s 25ms/step - loss: 0.3374 - accur
acy: 0.8798 - val_loss: 0.5495 - val_accuracy: 0.7774
Epoch 8/50
96/96 [==============================] - 2s 22ms/step - loss: 0.2775 - accur
acy: 0.9085 - val_loss: 0.6626 - val_accuracy: 0.7728
Epoch 9/50
96/96 [==============================] - 2s 26ms/step - loss: 0.2417 - accur
acy: 0.9274 - val_loss: 0.6891 - val_accuracy: 0.7708
191/191 [==============================] - 2s 6ms/step
48/48 [==============================] - 0s 5ms/step
Training F1: 0.8311, Validation F1: 0.7543, F1 Gap: 0.0768

Testing parameters: {'batch_size': 64, 'embedding_dim': 64, 'learning_rate':
0.0001}
Epoch 1/50
95/96 [============================>.] - ETA: 0s - loss: 4.9208 - accuracy:
0.5694INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 11s 72ms/step - loss: 4.9144 - accu
racy: 0.5696 - val_loss: 2.8589 - val_accuracy: 0.5056
Epoch 2/50
96/96 [==============================] - 2s 21ms/step - loss: 2.4967 - accur
acy: 0.5346 - val_loss: 2.7083 - val_accuracy: 0.4524
Epoch 3/50
96/96 [==============================] - 3s 27ms/step - loss: 1.9199 - accur
acy: 0.5427 - val_loss: 2.1847 - val_accuracy: 0.4767
Epoch 4/50
95/96 [============================>.] - ETA: 0s - loss: 1.5837 - accuracy:
0.5373INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 6s 61ms/step - loss: 1.5819 - accur
acy: 0.5376 - val_loss: 1.8507 - val_accuracy: 0.5167
Epoch 5/50
96/96 [==============================] - 2s 23ms/step - loss: 1.3023 - accur
acy: 0.5522 - val_loss: 1.5987 - val_accuracy: 0.5135
Epoch 6/50
93/96 [============================>.] - ETA: 0s - loss: 1.0951 - accuracy:
0.5403INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 7s 76ms/step - loss: 1.0911 - accur
acy: 0.5427 - val_loss: 1.3901 - val_accuracy: 0.5246
Epoch 7/50
94/96 [============================>.] - ETA: 0s - loss: 0.9434 - accuracy:
0.5269INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets


96/96 [==============================] - 6s 64ms/step - loss: 0.9442 - accur
acy: 0.5264 - val_loss: 1.2147 - val_accuracy: 0.5253
Epoch 8/50
96/96 [==============================] - 2s 21ms/step - loss: 0.8449 - accur
acy: 0.5274 - val_loss: 1.0699 - val_accuracy: 0.5246
Epoch 9/50
94/96 [============================>.] - ETA: 0s - loss: 0.7783 - accuracy:
0.5308INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 6s 62ms/step - loss: 0.7795 - accur
acy: 0.5299 - val_loss: 0.9541 - val_accuracy: 0.5299
Epoch 10/50
96/96 [==============================] - 2s 24ms/step - loss: 0.7370 - accur
acy: 0.5389 - val_loss: 0.8670 - val_accuracy: 0.5253
Epoch 11/50
96/96 [==============================] - 2s 23ms/step - loss: 0.7087 - accur
acy: 0.5404 - val_loss: 0.8015 - val_accuracy: 0.5266
Epoch 12/50
94/96 [============================>.] - ETA: 0s - loss: 0.6346 - accuracy:
0.6365INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 6s 64ms/step - loss: 0.6330 - accur
acy: 0.6388 - val_loss: 0.6116 - val_accuracy: 0.7157
Epoch 13/50
96/96 [==============================] - ETA: 0s - loss: 0.4596 - accuracy:
0.8110INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 6s 67ms/step - loss: 0.4596 - accur
acy: 0.8110 - val_loss: 0.5534 - val_accuracy: 0.7557
Epoch 14/50
93/96 [============================>.] - ETA: 0s - loss: 0.4036 - accuracy:
0.8459INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 6s 60ms/step - loss: 0.4021 - accur
acy: 0.8471 - val_loss: 0.5450 - val_accuracy: 0.7577
Epoch 15/50
93/96 [============================>.] - ETA: 0s - loss: 0.3665 - accuracy:
0.8691INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 8s 81ms/step - loss: 0.3653 - accur
acy: 0.8700 - val_loss: 0.5567 - val_accuracy: 0.7623
Epoch 16/50
94/96 [============================>.] - ETA: 0s - loss: 0.3381 - accuracy:
0.8831INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
```

```
96/96 [==============================] - 6s 61ms/step - loss: 0.3376 - accur
acy: 0.8834 - val_loss: 0.5598 - val_accuracy: 0.7656
Epoch 17/50
96/96 [==============================] - 2s 23ms/step - loss: 0.3132 - accur
acy: 0.8934 - val_loss: 0.5683 - val_accuracy: 0.7636
Epoch 18/50
96/96 [==============================] - 2s 24ms/step - loss: 0.2908 - accur
acy: 0.9048 - val_loss: 0.5811 - val_accuracy: 0.7649
Epoch 19/50
96/96 [==============================] - 3s 27ms/step - loss: 0.2692 - accur
acy: 0.9153 - val_loss: 0.6022 - val_accuracy: 0.7649
Epoch 20/50
96/96 [==============================] - ETA: 0s - loss: 0.2552 - accuracy:
0.9202INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 7s 69ms/step - loss: 0.2552 - accur
acy: 0.9202 - val_loss: 0.6036 - val_accuracy: 0.7676
Epoch 21/50
96/96 [==============================] - 2s 22ms/step - loss: 0.2501 - accur
acy: 0.9232 - val_loss: 0.6372 - val_accuracy: 0.7630
Epoch 22/50
96/96 [==============================] - 2s 23ms/step - loss: 0.2410 - accur
acy: 0.9266 - val_loss: 0.6702 - val_accuracy: 0.7617
Epoch 23/50
96/96 [==============================] - ETA: 0s - loss: 0.2320 - accuracy:
0.9312INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 7s 69ms/step - loss: 0.2320 - accur
acy: 0.9312 - val_loss: 0.6358 - val_accuracy: 0.7781
Epoch 24/50
96/96 [==============================] - ETA: 0s - loss: 0.2357 - accuracy:
0.9274INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
INFO:tensorflow:Assets written to: model_64_64_0.0001/assets
96/96 [==============================] - 6s 66ms/step - loss: 0.2357 - accur
acy: 0.9274 - val_loss: 0.6275 - val_accuracy: 0.7859
Epoch 25/50
Epoch 25/50
96/96 [==============================] - 2s 23ms/step - loss: 0.2342 - accur
acy: 0.9276 - val_loss: 0.6433 - val_accuracy: 0.7794
Epoch 26/50
96/96 [==============================] - 2s 21ms/step - loss: 0.2364 - accur
acy: 0.9248 - val_loss: 0.6472 - val_accuracy: 0.7814
Epoch 27/50
96/96 [==============================] - 3s 27ms/step - loss: 0.2169 - accur
acy: 0.9350 - val_loss: 0.6646 - val_accuracy: 0.7754
Epoch 28/50
96/96 [==============================] - 2s 24ms/step - loss: 0.2020 - accur
acy: 0.9424 - val_loss: 0.6993 - val_accuracy: 0.7663
Epoch 29/50
96/96 [==============================] - 3s 26ms/step - loss: 0.1943 - accur
acy: 0.9461 - val_loss: 0.7164 - val_accuracy: 0.7682
191/191 [==============================] - 2s 5ms/step
48/48 [==============================] - 0s 5ms/step
Training F1: 0.8958, Validation F1: 0.7429, F1 Gap: 0.1529
```

In [266…

```
results_df
```

Out[266]:

	batch_size	embedding_dim	learning_rate	train_f1	train_accuracy	train_precision	t
0	32	32	0.0010	0.807381	0.859465	0.953241	
1	32	32	0.0005	0.848598	0.880315	0.906791	
2	32	32	0.0001	0.844436	0.873091	0.871624	
3	32	64	0.0010	0.728679	0.763914	0.705259	
4	32	64	0.0005	0.820524	0.867345	0.952062	
5	32	64	0.0001	0.535464	0.455919	0.417760	
6	64	32	0.0010	0.858491	0.881793	0.864608	
7	64	32	0.0005	0.824609	0.871286	0.965933	
8	64	32	0.0001	0.560391	0.439501	0.418140	
9	64	64	0.0010	0.809575	0.855032	0.904578	
10	64	64	0.0005	0.831070	0.861107	0.850777	
11	64	64	0.0001	0.895842	0.918568	0.969545	

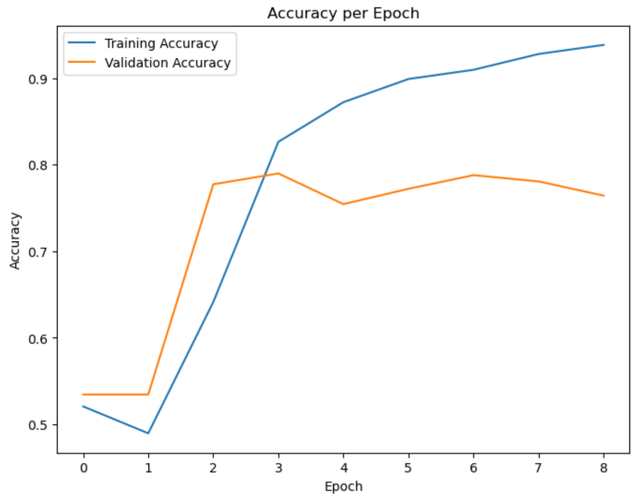
In [267…

```
# Print best results
print(f"\nBest Parameters: {best_params}")
print(f"Best Validation F1: {best_val_f1:.4f}")

plt.figure(figsize=(8, 6))
plt.plot(best_history.history['accuracy'], label='Training Accuracy')
plt.plot(best_history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

```
Best Parameters: {'batch_size': 32, 'embedding_dim': 64, 'learning_rate': 0.
0005}
Best Validation F1: 0.7647
```

Out[267]:

```
<matplotlib.legend.Legend at 0x7fb50791a260>
```



Best Model Performance: The model with embedding_dim=64, lstm_units=32, and learning_rate=0.0005 achieved the highest validation F1 score of 0.7647, demonstrating strong performance on unseen data. It also has a low F1 gap of 0.05582 between training and validation F1, indicating strong generalization. This model's validation accuracy (0.7898), precision (0.7988), and recall (0.7334) are all among the top performances.

Generalization and Stability: The best model's small F1 gap highlights its ability to avoid overfitting, unlike models with higher gaps (e.g., 0.1529 for embedding_dim=64, lstm_units=64, learning_rate=0.0001). Models with lower learning rates (0.0005, 0.0001) generally show better generalization, but some (e.g., embedding_dim=64, lstm_units=32, learning_rate=0.0001) underperform on validation F1 (0.2410), likely due to insufficient training.

What Went Well: The grid search effectively identified a balanced model with embedding_dim=64 and lstm_units=32, which consistently outperformed larger architectures in validation F1. Lower learning rates (0.0005) struck a good balance between convergence speed and stability, as seen in the best model's metrics. The use of early stopping prevented overfitting, particularly for models with smaller F1 gaps.

Areas for Improvement: Adding dropout layers (e.g., 0.2–0.3 after LSTM or Dense layers) could further reduce overfitting in models with larger F1 gaps (e.g., 0.1284 for embedding_dim=64, lstm_units=32, learning_rate=0.0010). Increasing early stopping patience (e.g., from 5 to 10) for lower learning rates (0.0001) might allow better convergence, as some models (e.g., embedding_dim=64, lstm_units=64, learning_rate=0.0001) show high training F1 (0.8958) but poor validation F1 (0.7429). Experimenting with larger LSTM units (e.g., 128) or additional Dense layers could enhance feature extraction, particularly for complex patterns, but should be paired with regularization to maintain generalization.

Predictions

In [268…

```
model = tf.keras.models.load_model('best_model_grid')
```

In [269…

```
predictions = model.predict([test_padded, test_cat])
predictions = (predictions > 0.5).astype(int)  # Convert probabilities to 0/

test_df['target'] = predictions
test_df[['id', 'target']].to_csv('submission.csv', index=False)
```

```
102/102 [==============================] - 1s 5ms/step
```

In [ ]: