

Import Required Packages

```
In [1]: import pandas as pd
import numpy as np
import tensorflow as tf

import matplotlib.pyplot as plt
import seaborn as sns

import random

from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical # pip install git+https://github.com/tensorflow/addons.git
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, Bidirectional, LSTM, TimeDistributed, Dense
from tensorflow_addons.layers import CRF
from tensorflow_addons.optimizers import AdamW
from tensorflow_addons.losses import SigmoidFocalCrossEntropy

from gensim.models import Word2Vec
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

2024-12-27 13:51:53.452705: I tensorflow/core/util/port.cc:111] oneDNN custom operations are on. You may see slightly different numerical results due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-12-27 13:51:53.474128: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not find cuda drivers on your machine, GPU will not be used.
2024-12-27 13:51:53.581189: E tensorflow/compiler/xla/stream_executor/cuda/cuda_dnn.cc:9342] Unable to register cuDNN factory: Attempting to register factory for plugin cuDNN when one has already been registered
2024-12-27 13:51:53.581228: E tensorflow/compiler/xla/stream_executor/cuda/cuda_fft.cc:609] Unable to register cuFFT factory: Attempting to register factory for plugin cuFFT when one has already been registered
2024-12-27 13:51:53.581856: E tensorflow/compiler/xla/stream_executor/cuda/cuda_blas.cc:1518] Unable to register cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
2024-12-27 13:51:53.629783: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could not find cuda drivers on your machine, GPU will not be used.
2024-12-27 13:51:53.630643: I tensorflow/core/platform/cpu_feature_guard.cc:182] This TensorFlow binary is optimized to use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX512F AVX512_VNNI FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
2024-12-27 13:51:54.433810: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find TensorRT
/home/varun/Documents/MS/Business Cases/Twitter NER NLP/.twitter_venv/lib/python3.11/site-packages/tensorflow_addons/utils/tfa_eol_msg.py:23: UserWarning:

TensorFlow Addons (TFA) has ended development and introduction of new features.
TFA has entered a minimal maintenance and release mode until a planned end of life in May 2024.
Please modify downstream libraries to take dependencies from other repositories in our TensorFlow community (e.g. Keras, Keras-CV, and Keras-NLP).

For more information see: <https://github.com/tensorflow/addons/issues/2807>

```
warnings.warn(
```

Define the Problem Statement and perform Exploratory Data Analysis

Definition of Problem

Implement Named Entity Recognition (NER) for automatic content tagging and analysis. This initiative is intended to overcome the limitations of relying on user-generated hashtags, which can be inconsistent, inaccurate, or absent. The dataset is annotated with 10 fine-grained NER categories: person, geo-location, company, facility, product, music artist, movie, sports team, TV show, and other.

```
In [2]: # Check if TensorFlow is built with CUDA support
if tf.test.is_built_with_cuda():
    print("TensorFlow is built with CUDA support.")
else:
    print("TensorFlow is not built with CUDA support.")

# Check if a GPU is available and visible
if tf.config.list_physical_devices('GPU'):
    print("CUDA is available.")
else:
    print("CUDA is not available.")
```

TensorFlow is built with CUDA support.
CUDA is not available.

2024-12-27 13:51:57.046539: E tensorflow/compiler/xla/stream_executor/cuda/cuda_driver.cc:268] failed call to cuInit: CUDA_ERROR_UNKNOWN: unknown error
2024-12-27 13:51:57.046561: I tensorflow/compiler/xla/stream_executor/cuda/cuda_diagnostics.cc:168] retrieving CUDA diagnostic information for host: varun
2024-12-27 13:51:57.046565: I tensorflow/compiler/xla/stream_executor/cuda/cuda_diagnostics.cc:175] hostname: varun
2024-12-27 13:51:57.046707: I tensorflow/compiler/xla/stream_executor/cuda/cuda_diagnostics.cc:199] libcuda reported version is: 550.120.0
2024-12-27 13:51:57.046719: I tensorflow/compiler/xla/stream_executor/cuda/cuda_diagnostics.cc:203] kernel reported version is: 550.120.0
2024-12-27 13:51:57.046722: I tensorflow/compiler/xla/stream_executor/cuda/cuda_diagnostics.cc:309] kernel version seems to match DS0: 550.120.0

```
In [3]: # Hyperparams if GPU is available
if tf.test.is_gpu_available():
    BATCH_SIZE = 512 # Number of examples used in each iteration
    EPOCHS = 5 # Number of passes through entire dataset
    MAX_LEN = 75 # Max length of review (in words)
    EMBEDDING = 40 # Dimension of word embedding vector

# Hyperparams for CPU training
else:
    BATCH_SIZE = 32
    EPOCHS = 5
    MAX_LEN = 75
    EMBEDDING = 20
```

WARNING:tensorflow:From /tmp/ipykernel_220578/2737541736.py:2: is_gpu_available (from tensorflow.python.framework.test_util) is deprecated and will be removed in a future version.
Instructions for updating:
Use `tf.config.list_physical_devices('GPU')` instead.

```
In [4]: BATCH_SIZE

Out[4]: 32
```

Data Preprocessing

Data Cleaning and Formatting

```
In [5]: def read_conll(file_path):
    sentences = []
    sentence = []

    with open(file_path, 'r') as file:
        for line in file:
            line = line.strip()

            if line:
                token, tag = line.split('\t')
                sentence.append((token, tag))
            else:
                if sentence:
                    sentences.append(sentence)
                    sentence = []
```

```
        return sentences
```

```
In [6]: file_path = "dataset/wnut 16.txt.conll"
data = read_conll(file_path)

data[0]
```

```
Out[6]: [('@SammieLynnsMom', '0'),
        ('@tg10781', '0'),
        ('they', '0'),
        ('will', '0'),
        ('be', '0'),
        ('all', '0'),
        ('done', '0'),
        ('by', '0'),
        ('Sunday', '0'),
        ('trust', '0'),
        ('me', '0'),
        ('*wink*', '0')]
```

```
In [7]: len(data)
```

```
Out[7]: 2393
```

Data Transformation for NER

```
In [8]: # Convert to a DataFrame if needed
df = pd.DataFrame([(token, tag) for value in data for token, tag in value], columns=['Token', 'Tag'])
print(df.head())
```

	Token	Tag
0	@SammieLynnsMom	0
1	@tg10781	0
2	they	0
3	will	0
4	be	0

EDA

```
In [9]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46462 entries, 0 to 46461
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ---
 0   Token   46462 non-null     object
 1   Tag     46462 non-null     object
dtypes: object(2)
memory usage: 726.1+ KB
```

```
In [10]: df.shape
```

```
Out[10]: (46462, 2)
```

```
In [11]: print("Number of sentences: ", len(data))

Number of sentences:  2393
```

```
In [12]: print("Number of labels", df["Tag"].nunique())

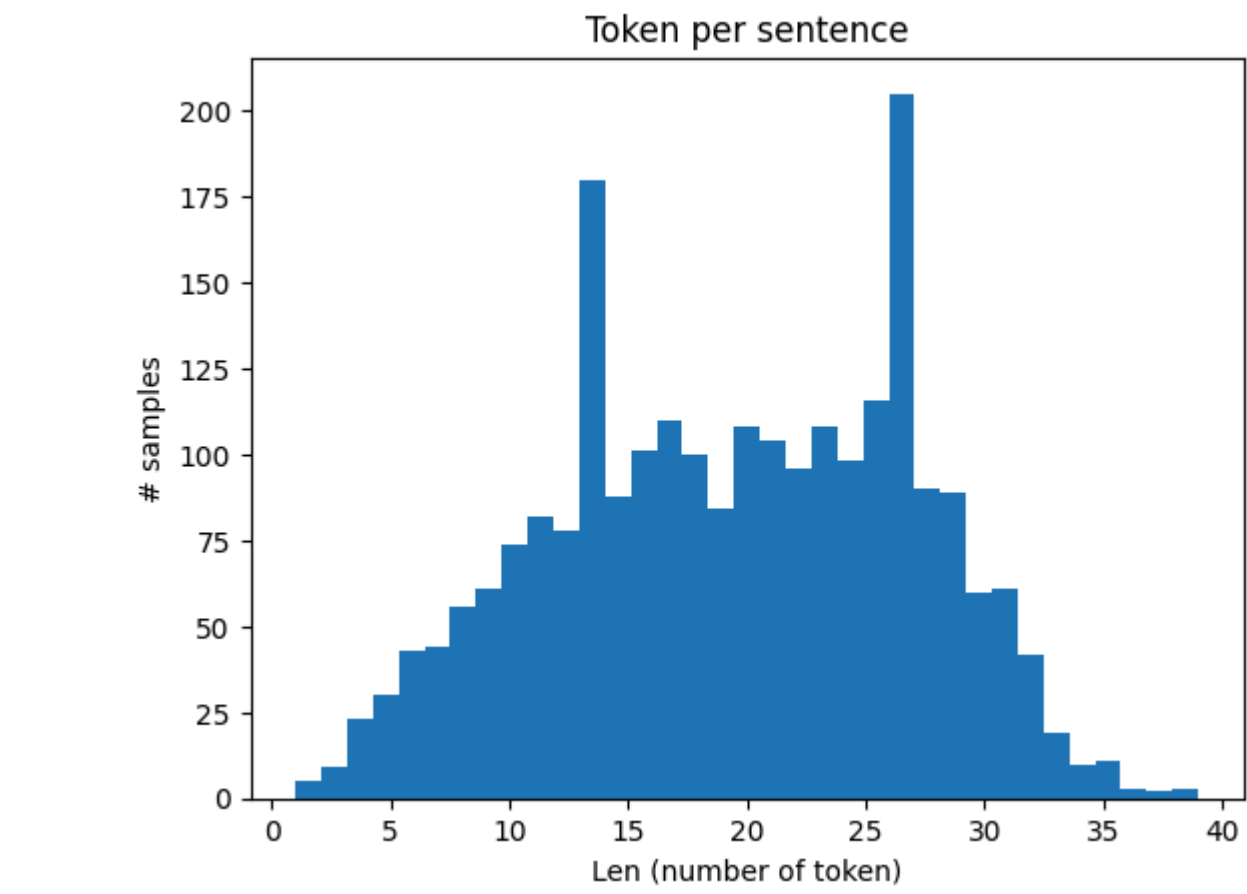
Number of labels 21
```

```
In [13]: print("Frequency of labels", df["Tag"].value_counts())

Frequency of labels Tag
0                44000
B-person          449
I-other           320
B-geo-loc         276
B-other           225
I-person          215
B-company         171
I-facility        105
B-facility        104
B-product          97
I-product          80
I-musicartist      61
B-musicartist      55
B-sportsteam       51
I-geo-loc          49
I-movie            46
I-company          36
B-movie            34
B-tvshow           34
I-tvshow           31
I-sportsteam       23
Name: count, dtype: int64
```

```
In [14]: senteces_length = [len(s) for s in data]
```

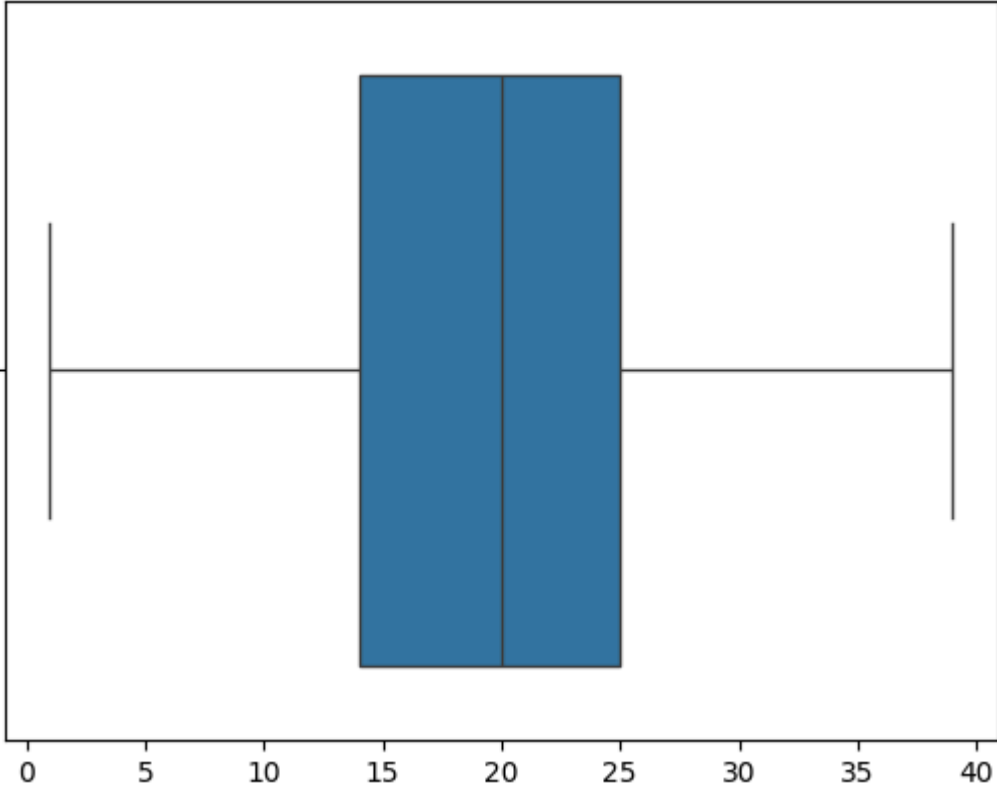
```
In [15]: # Plot sentence by lenght
plt.hist(senteces_length, bins=35)
plt.title('Token per sentence')
plt.xlabel('Len (number of token)')
plt.ylabel('# samples')
plt.show()
```



From the histogram, we can see most of the sentences have around **15 to 30 tokens** . Tokens can we referred as words ignoring punctuation marks.

```
In [16]: sns.boxplot(x = senteces_length)
```

Out[16]: <Axes: >



Handling Sparse Data

```
In [17]: df.head()
```

Out[17]:

	Token	Tag
0	@SammieLynnsMom	O
1	@tg10781	O
2	they	O
3	will	O
4	be	O

```
In [18]: df.Tag.value_counts()
```

Out[18]:

Tag	
0	44000
B-person	449
I-other	320
B-geo-loc	276
B-other	225
I-person	215
B-company	171
I-facility	105
B-facility	104
B-product	97
I-product	80
I-musicartist	61
B-musicartist	55
B-sportsteam	51
I-geo-loc	49
I-movie	46
I-company	36
B-movie	34
B-tvshow	34
I-tvshow	31
I-sportsteam	23
Name: count, dtype: int64	

```
In [19]: df["entity"] = df["Tag"].apply(lambda x : x.split("-")[-1] if len(x.split("-")) > 1 else "")
```

```
In [20]: df.entity.value_counts()
```

Out[20]:

entity	
	44000
person	664
other	545
loc	325
facility	209
company	207
product	177
musicartist	116
movie	80
sportsteam	74
tvshow	65
Name: count, dtype: int64	

```
In [21]: lowcount_labels = df.entity.value_counts().iloc[3:].reset_index().entity.tolist()
```

```
In [22]: for ele in data[:5]:
    print(ele)
```

```
[('@SammieLynnsMom', '0'), ('@tg10781', '0'), ('they', '0'), ('will', '0'), ('be', '0'), ('all', '0'), ('done', '0'), ('by', '0'), ('Sunday', '0'), ('trust', '0'), ('me', '0'), ('*wink*', '0'))]
[['Made', '0'), ('it', '0'), ('back', '0'), ('home', '0'), ('to', '0'), ('GA', 'B-geo-loc'), ('.', '0'), ('It', '0'), ('sucks', '0'), ('not', '0'), ('to', '0'), ('be', '0'), ('at', '0'), ('Disney', 'B-facility'), ('world', 'I-facility'), ('', '0'), ('but', '0'), ('its', '0'), ('good', '0'), ('to', '0'), ('be', '0'), ('home', '0'), ('.', '0'), ('T ime', '0'), ('to', '0'), ('start', '0'), ('planning', '0'), ('the', '0'), ('next', '0'), ('Disney', 'B-facility'), ('World', 'I-facility'), ('trip', '0'), ('.', '0')]
[('', '0'), ('Breaking', 'B-movie'), ('Dawn', 'I-movie'), ('', '0'), ('Returns', '0'), ('to', '0'), ('Vancouver', 'B-geo-loc'), ('on', '0'), ('January', '0'), ('11th', '0'), ('http://bit.ly/dbDMs8', '0')]
[['@ls_n', '0'), ('perhaps', '0'), ('', '0'), ('but', '0'), ('folks', '0'), ('may', '0'), ('find', '0'), ('something', '0'), ('in', '0'), ('the', '0'), ('gallery', '0'), ('th at', '0'), ('is', '0'), ('helpful', '0'), ('in', '0'), ('their', '0'), ('day-to-day', '0'), ('work', '0'), ('as', '0'), ('well', '0'), ('.', '0'), ('Even', '0'), ('just', '0'), ('to', '0'), ('use', '0'), ('it', '0'), ('.', '0')]
[('@Carr0t', '0'), ('aye', '0'), ('been', '0'), ('tonight', '0'), ('-', '0'), ('excellent', '0')]
```

Oversampling

```
In [23]: # oversampled_data = data

In [24]: oversampling = {}
         for label in lowcount_labels:
             oversampling[label] = []
         for sentence in data:
             for word, label in sentence:
                 if label.split("-")[-1] in df.entity.value_counts().iloc[3:].reset_index().entity.tolist():
                     oversampling[label.split("-")[-1]].append(sentence)
                 break

In [25]: for key, value in oversampling.items():
         print(key, len(value))

loc 174
facility 77
company 135
product 65
musicartist 35
movie 24
sportsteam 37
tvshow 29

In [26]: len(data)

Out[26]: 2393

In [27]: oversampled_data = data + random.choices(oversampling["loc"], k=200)
         oversampled_data += random.choices(oversampling["facility"], k=300)
         oversampled_data += random.choices(oversampling["company"], k=300)
         oversampled_data += random.choices(oversampling["product"], k=400)
         oversampled_data += random.choices(oversampling["musicartist"], k=400)
         oversampled_data += random.choices(oversampling["movie"], k=500)
         oversampled_data += random.choices(oversampling["sportsteam"], k=500)
         oversampled_data += random.choices(oversampling["tvshow"], k=500)

In [28]: len(oversampled_data)

Out[28]: 5493
```

Tokenization and Encoding:

```
In [29]: df.head()

Out[29]:
   Token Tag entity
0  @SammieLynnsMom  O
1      @tg10781  O
2         they  O
3         will  O
4          be  O

In [30]: df["Token"].value_counts()

Out[30]: Token
.          1524
,           914
the         876
to           824
I           762
...
shaped         1
hole           1
Def            1
tune           1
@ihatequotes   1
Name: count, Length: 10585, dtype: int64

In [31]: words = list(set(df["Token"].values))
         print("Number of unique words in the dataset: ", len(words))

Number of unique words in the dataset:  10585

In [32]: df["Tag"].value_counts()

Out[32]: Tag
0          44000
B-person    449
I-other     320
B-geo-loc   276
B-other     225
I-person    215
B-company   171
I-facility  105
B-facility  104
B-product   97
I-product   80
I-musicartist  61
B-musicartist  55
B-sportsteam  51
I-geo-loc    49
I-movie      46
I-company    36
B-movie      34
B-tvshow     34
I-tvshow     31
I-sportsteam  23
Name: count, dtype: int64

In [33]: tags = list(set(df["Tag"].values))
         print("Number of Labels: ", len(tags))

Number of Labels:  21

In [34]: tags
```

```
Out[34]: ['I-sportsteam',
'I-geo-loc',
'I-musicartist',
'B-tvshow',
'B-geo-loc',
'I-other',
'I-product',
'I-company',
'B-product',
'B-other',
'B-person',
'I-tvshow',
'I-facility',
'B-movie',
'0',
'I-movie',
'I-person',
'B-facility',
'B-company',
'B-musicartist',
'B-sportsteam']
```

Indexing my words and labels to consider them as Tokens

```
In [35]: word2idx = {w:i+2 for i,w in enumerate(words)}
word2idx["UNK"] = 1
word2idx["PAD"] = 0

tag2idx = {t:i+2 for i,t in enumerate(tags)}
tag2idx["PAD"] = 0
tag2idx["UNK"] = 1

print("The word doctor is identified by the index: {}".format(word2idx["doctor"]))
print("The labels B-movie(which defines Movie Enitities at the Bengining) is identified by the index: {}".format(tag2idx["B-movie"]))
```

The word doctor is identified by the index: 333
The labels B-movie(which defines Movie Enitities at the Bengining) is identified by the index: 15

```
In [36]: tag2idx
```

```
Out[36]: {'I-sportsteam': 2,
'I-geo-loc': 3,
'I-musicartist': 4,
'B-tvshow': 5,
'B-geo-loc': 6,
'I-other': 7,
'I-product': 8,
'I-company': 9,
'B-product': 10,
'B-other': 11,
'B-person': 12,
'I-tvshow': 13,
'I-facility': 14,
'B-movie': 15,
'0': 16,
'I-movie': 17,
'I-person': 18,
'B-facility': 19,
'B-company': 20,
'B-musicartist': 21,
'B-sportsteam': 22,
'PAD': 0,
'UNK': 1}
```

Training: Data Creation

```
In [37]: oversampled_data[0]
```

```
Out[37]: [('@SammiLynnsMom', '0'),
('@tg10781', '0'),
('they', '0'),
('will', '0'),
('be', '0'),
('all', '0'),
('done', '0'),
('by', '0'),
('Sunday', '0'),
('trust', '0'),
('me', '0'),
('*wink*', '0')]
```

```
In [38]: X = [[word2idx[ele[0]] for ele in sentence] for sentence in oversampled_data]
```

```
# pad the sequences, to have same length
X = pad_sequences(
    maxlen = MAX_LEN,
    sequences = X,
    padding = "post",
    value = word2idx["PAD"]
)

print('Raw Sample:\n ', ' '.join([w[0] for w in oversampled_data[0]]))
print('\n ')
print('After processing, sample:\n', X[0])
```

Raw Sample:
@SammiLynnsMom @tg10781 they will be all done by Sunday trust me *wink*

After processing, sample:

[8977	6739	116	330	6322	8426	5093	722	7062	9595	2997	147	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0]									

```
In [39]: # Convert my Tag/Label to tag_index
y = [[tag2idx[ele[1]] for ele in sentence] for sentence in oversampled_data]
```

```
# Padding each label to have same length
y = pad_sequences(
    maxlen = MAX_LEN,
    sequences = y,
    padding = "post",
    value = tag2idx["PAD"]
)

print('Raw Label:\n ', ' '.join([w[1] for w in oversampled_data[0]]))
print('\n ')
print('After processing, labels:\n', y[0])
```


After processing, labels:

```
[16 16 16 16 16 16 16 16 16 16 16 16 0 0 0 0 0 0 0 0 0 0 0 0  
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
 0 0 0]
```

```
# One-Hot encode
y = [to_categorical(i, num_classes=23) for i in y] # n_tags+1(PAD)

from sklearn.model_selection import train_test_split
X_tr, X_te, y_tr, y_te = train_test_split(X, y, test_size=0.1)

y_tr = np.array(y_tr)
y_te = np.array(y_te)
```

```
Out[41]: (4943, 4943)
```

```
Out[42]: array([[ 228,   858, 3814, 3138, 6898, 9446, 8950, 7873, 2240, 1387, 5679,  
                3610, 5343, 7477, 9446,    0,    0,    0,    0,    0,    0,    0],  
               [ 0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,  
                0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0],  
               [ 0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,  
                0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0],  
               [ 0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,  
                0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0],  
               [ 0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0,  
                0,    0,    0,    0,    0,    0,    0,    0,    0,    0,    0]])
```

```
Out[43]: array([[0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                ...,
                [1., 0., 0., ..., 0., 0., 0.],
                [1., 0., 0., ..., 0., 0., 0.],
                [1., 0., 0., ..., 0., 0., 0.]]) dtype=float32)
```

Training LSTM + CRF Models with Embeddings

```
In [44]: def build_model(max_len=75, input_dim=len(words)+2, crf_embedding_dim=200): # 10585 vocab size
# Model definition
input_layer = Input(shape=(max_len,), name='input_layer')

# Embedding layer
embeddings = Embedding(
    input_dim=input_dim,
    output_dim=embedding_dim,
    input_length=max_len,
    mask_zero=True
)(input_layer)

# BiLSTM layers
lstm_output = Bidirectional(LSTM(units=50, return_sequences=True))(embeddings)
lstm_output = Bidirectional(LSTM(units=50, return_sequences=True))(lstm_output)

# Dense layer
dense_output = TimeDistributed(Dense(23, activation="relu"))(lstm_output)

# CRF layer
crf = CRF(23, name='crf') # 21 classes
predicted_sequence, potentials, sequence_length, crf_kernel = crf(dense_output)

# Build the model
model = Model(inputs=input_layer, outputs=potentials, name = "Twitter_NER_V1")

# Compile the model
model.compile(
    optimizer=AdamW(weight_decay=0.001, learning_rate=0.001),
    loss=SigmoidFocalCrossEntropy(), # Use CRF-specific loss
    # loss = custom_loss,
    metrics=["accuracy"] # Optional: Use CRF accuracy
)

return model

# Build and compile the model
model = build_model()

# Checkpointing
save_model = tf.keras.callbacks.ModelCheckpoint(filepath='twitter_ner_crf.weights.h5',
    monitor='val_loss',
    save_weights_only=True,
    save_best_only=True,
    verbose=1
)

# Early stopping
es = tf.keras.callbacks.EarlyStopping(monitor='val_loss', verbose=1, patience=10)

callbacks = [save_model, es]

model.summary()
```

Model: "Twitter_NER_V1"

Layer (type)	Output Shape	Param #
=====		
input_layer (InputLayer)	[(None, 75)]	0
embedding (Embedding)	(None, 75, 200)	2117400
bidirectional (Bidirectional)	(None, 75, 100)	100400
bidirectional_1 (Bidirectional)	(None, 75, 100)	60400
time_distributed (TimeDistributed)	(None, 75, 23)	2323
crf (CRF)	[(None, 75), (None, 75, 23), (None,), (23, 23)]	1127
=====		
Total params: 2281650 (8.70 MB)		
Trainable params: 2281650 (8.70 MB)		
Non-trainable params: 0 (0.00 Byte)		

Layer (type)	Output Shape	Param #
=====		
input_layer (InputLayer)	[(None, 75)]	0
embedding (Embedding)	(None, 75, 200)	2117400
bidirectional (Bidirectional)	(None, 75, 100)	100400
bidirectional_1 (Bidirectional)	(None, 75, 100)	60400
time_distributed (TimeDistributed)	(None, 75, 23)	2323
crf (CRF)	[(None, 75), (None, 75, 23), (None,), (23, 23)]	1127
=====		
Total params: 2281650 (8.70 MB)		
Trainable params: 2281650 (8.70 MB)		
Non-trainable params: 0 (0.00 Byte)		

Model Training

In [45]:

```
model.fit(
    X_tr, y_tr,
    validation_data = (X_te, y_te),
    batch_size=BATCH_SIZE,
    epochs=10,
    shuffle = True)
```

Epoch 1/10
WARNING:tensorflow:Gradients do not exist for variables ['chain_kernel:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `loss` argument?
WARNING:tensorflow:Gradients do not exist for variables ['chain_kernel:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `loss` argument?
155/155 [=====] - 18s 73ms/step - loss: 0.5703 - accuracy: 0.9442 - val_loss: 0.3207 - val_accuracy: 0.9696
Epoch 2/10
155/155 [=====] - 7s 48ms/step - loss: 0.2253 - accuracy: 0.9699 - val_loss: 0.1554 - val_accuracy: 0.9696
Epoch 3/10
155/155 [=====] - 7s 46ms/step - loss: 0.1176 - accuracy: 0.9713 - val_loss: 0.0919 - val_accuracy: 0.9734
Epoch 4/10
155/155 [=====] - 7s 45ms/step - loss: 0.0719 - accuracy: 0.9803 - val_loss: 0.0676 - val_accuracy: 0.9857
Epoch 5/10
155/155 [=====] - 7s 46ms/step - loss: 0.0505 - accuracy: 0.9903 - val_loss: 0.0548 - val_accuracy: 0.9921
Epoch 6/10
155/155 [=====] - 7s 46ms/step - loss: 0.0393 - accuracy: 0.9945 - val_loss: 0.0524 - val_accuracy: 0.9931
Epoch 7/10
155/155 [=====] - 7s 46ms/step - loss: 0.0317 - accuracy: 0.9973 - val_loss: 0.0494 - val_accuracy: 0.9952
Epoch 8/10
155/155 [=====] - 7s 47ms/step - loss: 0.0268 - accuracy: 0.9983 - val_loss: 0.0509 - val_accuracy: 0.9954
Epoch 9/10
155/155 [=====] - 7s 46ms/step - loss: 0.0233 - accuracy: 0.9989 - val_loss: 0.0495 - val_accuracy: 0.9954
Epoch 10/10
155/155 [=====] - 8s 49ms/step - loss: 0.0206 - accuracy: 0.9990 - val_loss: 0.0491 - val_accuracy: 0.9956

Out[45]: <keras.src.callbacks.History at 0x740288d4c1d0>

Validation Data Evaluation

In [46]:

```
# Flatten the sequences and exclude padding tokens
def filter_padding(y_pred, y_true, pad_token=0):
    filtered_pred = []
    filtered_true = []
    for pred_seq, true_seq in zip(y_pred, y_true):
        for pred_label, true_label in zip(pred_seq, true_seq):
            if true_label != pad_token and pred_label != pad_token and true_label != 21 and pred_label != 21 and true_label != 8 and pred_label != 8: # Ignore padding tokens
                filtered_pred.append(pred_label)
                filtered_true.append(true_label)
    return np.array(filtered_pred), np.array(filtered_true)
```

In [47]:

```
# Predict probabilities
y_val_pred_prob = model.predict(X_te)
```

18/18 [=====] - 3s 11ms/step

In [48]:

```
y_val_pred = np.argmax(y_val_pred_prob, axis=2)
np.argmax(y_te, axis=2)[0]
```

Out[48]: array([[16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 22, 16, 16, 16, 16, 16, 16,
16, 16, 0,
0, 0,
0, 0,
0, 0, 0, 0, 0, 0, 0, 0])

In [49]:

```
# Convert predictions and true labels, ignoring padding tokens
y_pred_flat, y_true_flat = filter_padding(y_val_pred, np.argmax(y_te, axis=2))

# Calculate metrics
accuracy = accuracy_score(y_true_flat, y_pred_flat)
print(f"Accuracy: {accuracy}")
```

Accuracy: 0.9878571428571429

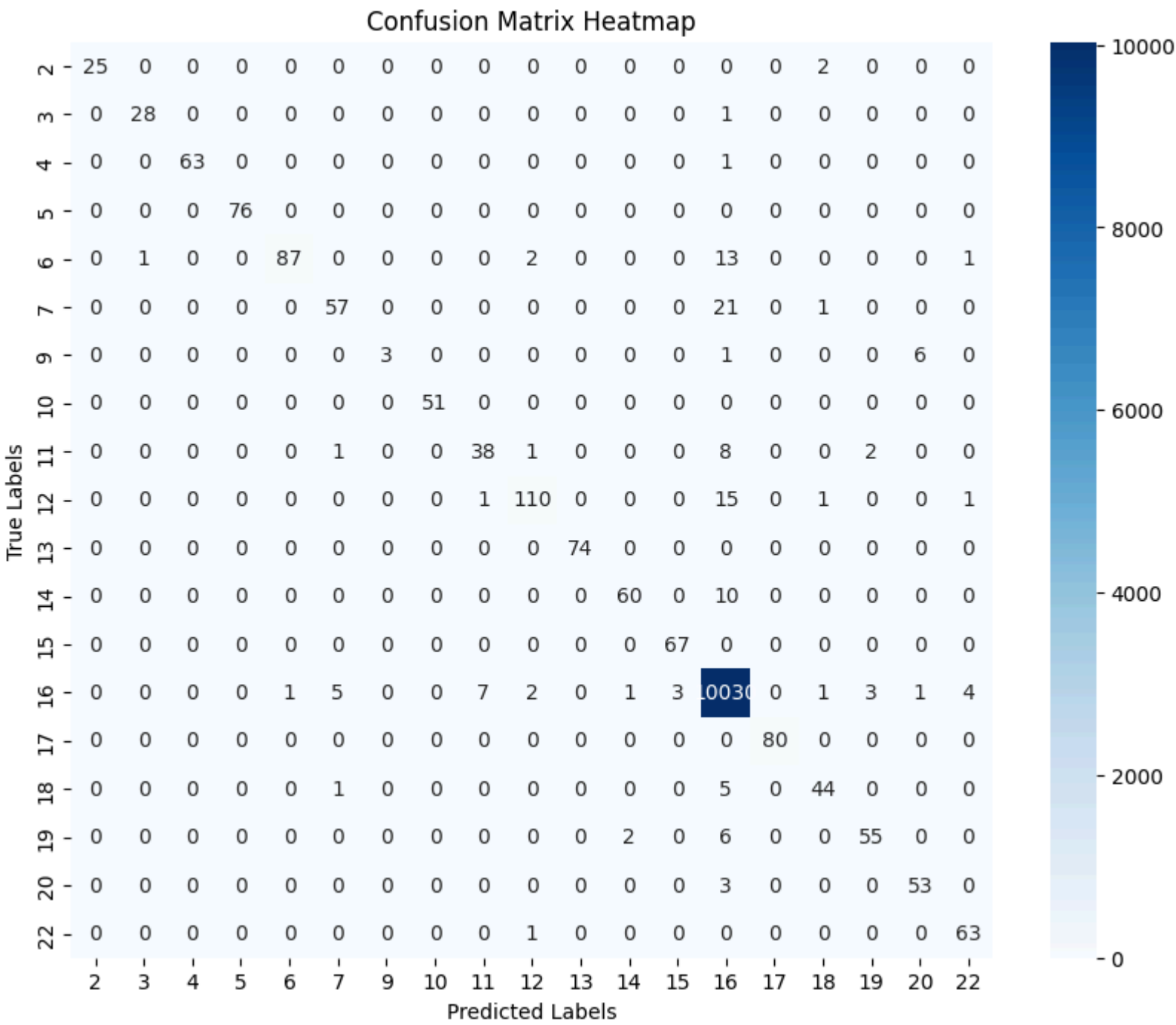
```
In [50]: # Classification report
print("Classification Report:")
print(classification_report(y_true_flat, y_pred_flat))
```

Classification Report:					
	precision	recall	f1-score	support	
2	1.00	0.93	0.96	27	
3	0.97	0.97	0.97	29	
4	1.00	0.98	0.99	64	
5	1.00	1.00	1.00	76	
6	0.99	0.84	0.91	104	
7	0.89	0.72	0.80	79	
9	1.00	0.30	0.46	10	
10	1.00	1.00	1.00	51	
11	0.83	0.76	0.79	50	
12	0.95	0.86	0.90	128	
13	1.00	1.00	1.00	74	
14	0.95	0.86	0.90	70	
15	0.96	1.00	0.98	67	
16	0.99	1.00	0.99	10058	
17	1.00	1.00	1.00	80	
18	0.90	0.88	0.89	50	
19	0.92	0.87	0.89	63	
20	0.88	0.95	0.91	56	
22	0.91	0.98	0.95	64	
accuracy			0.99	11200	
macro avg	0.95	0.89	0.91	11200	
weighted avg	0.99	0.99	0.99	11200	

```
In [51]: # Compute the confusion matrix
conf_matrix = confusion_matrix(y_true_flat, y_pred_flat)

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y_true_flat), yticklabels=np.unique(y_true_flat))

# Labels and title
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



```
In [52]: tag2idx
```

```
Out[52]: {'I-sportsteam': 2,
'I-geo-loc': 3,
'I-musicartist': 4,
'B-tvshow': 5,
'B-geo-loc': 6,
'I-other': 7,
'I-product': 8,
'I-company': 9,
'B-product': 10,
'B-other': 11,
'B-person': 12,
'I-tvshow': 13,
'I-facility': 14,
'B-movie': 15,
'O': 16,
'I-movie': 17,
'I-person': 18,
'B-facility': 19,
'B-company': 20,
'B-musicartist': 21,
'B-sportsteam': 22,
'PAD': 0,
'UNK': 1}
```

Testing: Dataset Evaluation and Creation

```
In [53]: file_path = "dataset/wnut_16test.txt.conll"
test_data = read_conll(file_path)
```

```
In [54]: len(test_data)
```

```
Out[54]: 3849
```

```
In [55]: print(test_data[0])
```



```
[('New', 'B-other'), ('Orleans', 'I-other'), ('Mother', 'I-other'), (''s', 'I-other'), ('Day', 'I-other'), ('Parade', 'I-other'), ('shooting', '0'), ('.', '0'), ('One', '0'), ('of', '0'), ('the', '0'), ('people', '0'), ('hurt', '0'), ('was', '0'), ('a', '0'), ('10-year-old', '0'), ('girl', '0'), ('.', '0'), ('WHAT', '0'), ('THE', '0'), ('HELL', '0'), ('IS', '0'), ('WRONG', '0'), ('WITH', '0'), ('PEOPLE', '0'), ('?', '0')]
```

```
In [56]: # Convert to a DataFrame if needed
test_df = pd.DataFrame([(token, tag) for value in test_data for token, tag in value], columns=['Token', 'Tag'])
print(test_df.head())
```

```
   Token  Tag
0    New B-other
1 Orleans I-other
2  Mother I-other
3     's I-other
4    Day I-other
```

```
In [57]: test_df["Tag"].value_counts(), len(test_df["Tag"].value_counts())
```

```
Out[57]: (Tag
0          55941
B-geo-loc    882
B-company    621
B-other      584
I-other      556
I-product    500
B-person     482
I-facility   366
I-person     300
I-company    265
B-facility   253
B-product    246
I-geo-loc    219
B-musicartist 191
B-sportsteam 147
I-musicartist 140
I-movie       48
I-sportsteam  48
I-tvshow      40
B-movie       34
B-tvshow      33
Name: count, dtype: int64,
21)
```

```
In [58]: df["Tag"].value_counts(), len(df["Tag"].value_counts())
```

```
Out[58]: (Tag
0          44000
B-person    449
I-other     320
B-geo-loc   276
B-other     225
I-person    215
B-company   171
I-facility  105
B-facility  104
B-product   97
I-product   80
I-musicartist 61
B-musicartist 55
B-sportsteam 51
I-geo-loc   49
I-movie     46
I-company   36
B-movie     34
B-tvshow    34
I-tvshow    31
I-sportsteam 23
Name: count, dtype: int64,
21)
```

```
In [59]: X_test = [[word2idx.get(ele[0], word2idx["UNK"]) for ele in sentence] for sentence in test_data]
```

```
# pad the sequences, to have same length
X_test = pad_sequences(
    maxlen = MAX_LEN,
    sequences = X_test,
    padding = "post",
    value = word2idx["PAD"]
)

# Convert my Tag/Label to tag_index
y_test = [[tag2idx.get(ele[1], tag2idx["UNK"]) for ele in sentence] for sentence in test_data]

# Padding each label to have same length
y_test = pad_sequences(
    maxlen = MAX_LEN,
    sequences = y_test,
    padding = "post",
    value = tag2idx["PAD"]
)

print(test_data[0])
print("Testing Sample input", X_test[0])
print("Testing Label", y_test[0])
```

```
[('New', 'B-other'), ('Orleans', 'I-other'), ('Mother', 'I-other'), (''s', 'I-other'), ('Day', 'I-other'), ('Parade', 'I-other'), ('shooting', '0'), ('.', '0'), ('One', '0'), ('of', '0'), ('the', '0'), ('people', '0'), ('hurt', '0'), ('was', '0'), ('a', '0'), ('10-year-old', '0'), ('girl', '0'), ('.', '0'), ('WHAT', '0'), ('THE', '0'), ('HELL', '0'), ('IS', '0'), ('WRONG', '0'), ('WITH', '0'), ('PEOPLE', '0'), ('?', '0')]
Testing Sample input [3905 1 1 5355 7041 5173 8278 9446 2388 5684 1030 2973 7381 1263
732 1 3766 9446 1543 1468 1 4078 1 4599 1 9231 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0]
Testing Label [11 7 7 7 7 7 16 16 16 16 16 16 16 16 16 16 16 16 16 16 16 16 16
16 16 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0]
```

```
In [60]: # Predict probabilities
y_test_pred_prob = model.predict(X_test)
```

```
121/121 [=====] - 1s 10ms/step
```

```
In [61]: y_test_pred_prob[0], len(y_test_pred_prob[0]), y_test_pred_prob.shape
```

```
Out[61]: (array([[ -0.5374383,  -0.39767364, -0.6336614 , ..., -0.14264779,
                -0.5366934 , -0.13972142],
                [ -0.39867145, -0.5109673 , -0.43382266, ..., -0.24962191,
                -0.7885021 , -0.2850893 ],
                [ -0.72724974, -0.56613266, -0.5574774 , ..., -0.24428938,
                -0.77247155, -0.35224035],
                ...,
                [  0.57631516, -0.02783631,  0.0026499 , ..., -0.01858024,
                -0.01993683, -0.02573788],
                [  0.57631516, -0.02783631,  0.0026499 , ..., -0.01858024,
                -0.01993683, -0.02573788],
                [  0.57631516, -0.02783631,  0.0026499 , ..., -0.01858024,
                -0.01993683, -0.02573788]], dtype=float32),
75,
(3849, 75, 23))
```

```
In [62]: ## Convert probabilities to class predictions (for multi-class classification)
y_val_pred = np.argmax(y_test_pred_prob, axis=2)
```

```
In [63]: y_val_pred[0], len(y_val_pred[0]), y_test[0], len(y_test[0])
```

```
Out[63]: (array([16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16,
                16, 16, 16, 16, 16, 16, 16, 16, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0]),
75,
array([11,  7,  7,  7,  7,  7, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16,
                16, 16, 16, 16, 16, 16, 16, 16, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0], dtype=int32),
75)
```

```
In [64]: y_val_pred[1], len(y_val_pred[1]), y_test[1], len(y_test[1])
```

```
Out[64]: (array([16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0]),
75,
array([16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 16, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 0, 0], dtype=int32),
75)
```

```
In [65]: # Convert predictions and true labels, ignoring padding tokens
y_pred_flat, y_true_flat = filter_padding(y_val_pred, y_test)

# Calculate metrics
accuracy = accuracy_score(y_true_flat, y_pred_flat)
print(f"Accuracy: {accuracy}")
```

Accuracy: 0.9170409051348999

```
In [66]: # Classification report
print("Classification Report:")
print(classification_report(y_true_flat, y_pred_flat))
```

Classification Report:					
	precision	recall	f1-score	support	
2	0.00	0.00	0.00	44	
3	0.06	0.02	0.03	192	
4	0.06	0.01	0.01	127	
5	0.00	0.00	0.00	31	
6	0.58	0.15	0.24	804	
7	0.24	0.04	0.07	512	
9	0.43	0.01	0.02	236	
10	0.21	0.02	0.03	220	
11	0.10	0.04	0.06	546	
12	0.31	0.15	0.20	454	
13	0.00	0.00	0.00	34	
14	0.44	0.08	0.13	324	
15	0.00	0.00	0.00	31	
16	0.93	0.99	0.96	52673	
17	0.00	0.00	0.00	44	
18	0.17	0.03	0.05	278	
19	0.09	0.03	0.05	230	
20	0.48	0.04	0.07	528	
22	0.20	0.01	0.01	142	
accuracy			0.92	57450	
macro avg	0.23	0.09	0.10	57450	
weighted avg	0.88	0.92	0.89	57450	

```
/home/varun/Documents/MS/Business Cases/Twitter NER NLP/.twitter_venv/lib/python3.11/site-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/varun/Documents/MS/Business Cases/Twitter NER NLP/.twitter_venv/lib/python3.11/site-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/home/varun/Documents/MS/Business Cases/Twitter NER NLP/.twitter_venv/lib/python3.11/site-packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

```
In [67]: np.unique(y_true_flat)
```

```
Out[67]: array([ 2,  3,  4,  5,  6,  7,  9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
                20, 22], dtype=int32)
```

```
In [68]: np.unique(y_pred_flat)
```

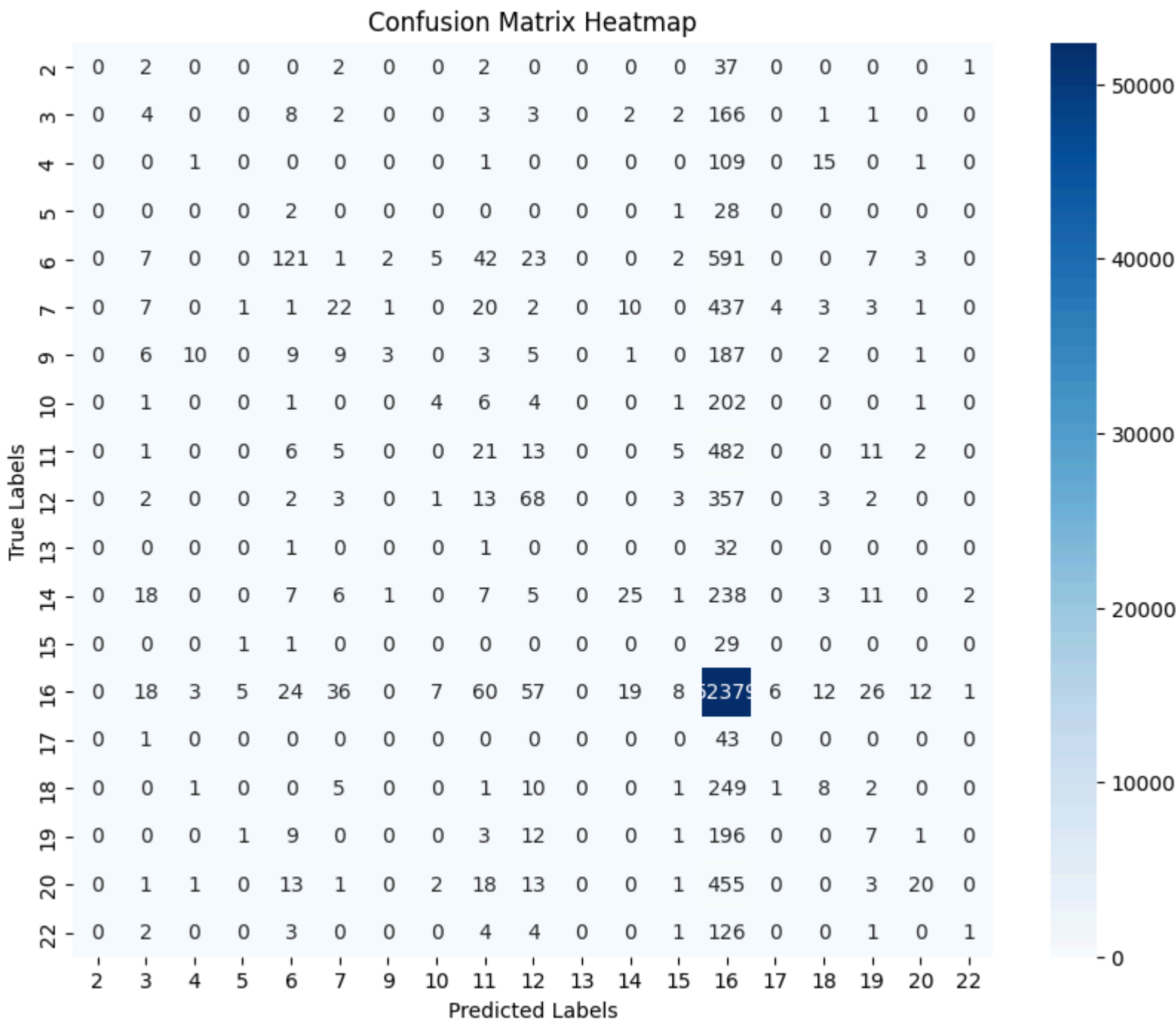
```
Out[68]: array([ 3,  4,  5,  6,  7,  9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 22])
```

```
In [69]: # Flatten the sequences and exclude padding tokens (filter padding as before)
y_pred_flat, y_true_flat = filter_padding(y_val_pred, y_test)

# Compute the confusion matrix
conf_matrix = confusion_matrix(y_true_flat, y_pred_flat)

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y_true_flat), yticklabels=np.unique(y_true_flat))

# Labels and title
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix Heatmap')
plt.show()
```



Word2Vec Word Embeddings with Bi-LSTM

Embeddings

```
In [70]: len(data)

Out[70]: 2393

In [71]: data[0]

Out[71]: [('@SammieLynnsMom', '0'),
          ('@tg10781', '0'),
          ('they', '0'),
          ('will', '0'),
          ('be', '0'),
          ('all', '0'),
          ('done', '0'),
          ('by', '0'),
          ('Sunday', '0'),
          ('trust', '0'),
          ('me', '0'),
          ('*wink*', '0')]

In [72]: for _ in range(10):
          print(data[_])

[('@SammieLynnsMom', '0'), ('@tg10781', '0'), ('they', '0'), ('will', '0'), ('be', '0'), ('all', '0'), ('done', '0'), ('by', '0'), ('Sunday', '0'), ('trust', '0'), ('me', '0'), ('*wink*', '0')]
[('Made', '0'), ('it', '0'), ('back', '0'), ('home', '0'), ('to', '0'), ('GA', 'B-geo-loc'), (',', '0'), ('It', '0'), ('sucks', '0'), ('not', '0'), ('to', '0'), ('be', '0'), ('at', '0'), ('Disney', 'B-facility'), ('world', 'I-facility'), ('', '0'), ('but', '0'), ('its', '0'), ('good', '0'), ('to', '0'), ('be', '0'), ('home', '0'), (',', '0'), ('T ime', '0'), ('to', '0'), ('start', '0'), ('planning', '0'), ('the', '0'), ('next', '0'), ('Disney', 'B-facility'), ('World', 'I-facility'), ('trip', '0'), (',', '0')]
[('', '0'), ('Breaking', 'B-movie'), ('Dawn', 'I-movie'), ('', '0'), ('Returns', '0'), ('to', '0'), ('Vancouver', 'B-geo-loc'), ('on', '0'), ('January', '0'), ('11th', '0'), ('http://bit.ly/dbdMs8', '0')]
[('@ls_n', '0'), ('perhaps', '0'), (',', '0'), ('but', '0'), ('folks', '0'), ('may', '0'), ('find', '0'), ('something', '0'), ('in', '0'), ('the', '0'), ('gallery', '0'), ('th at', '0'), ('is', '0'), ('helpful', '0'), ('in', '0'), ('their', '0'), ('day-to-day', '0'), ('work', '0'), ('as', '0'), ('well', '0'), (',', '0'), ('Even', '0'), ('just', '0'), ('to', '0'), ('use', '0'), ('it', '0'), (',', '0')]
[('@Carr0t', '0'), ('aye', '0'), ('been', '0'), ('tonight', '0'), ('-', '0'), ('excellent', '0')]
[('RT', '0'), (',', '0'), ('RT', '0'), ('this', '0'), ('if', '0'), ('you', '0'), ('want', '0'), ('me', '0'), ('to', '0'), ('go', '0'), ('back', '0'), ('live', '0'), ('on', '0'), ('Ustream', 'B-company'), ('later', '0'), ('tonight', '0')]
[('@Hollly_', '0'), ('16', '0'), ('b', '0'), ('17', '0'), ('in', '0'), ('feb', '0')]
[('RT', '0'), ('@obsidianchao', '0'), (',', '0'), ('OF', '0'), ('FUCKING', '0'), ('COURSE', '0'), (',', '0'), ('I', '0'), ('GET', '0'), ('HOME', '0'), ('AND', '0'), ('MY', '0'), ('BROTHER', '0'), ('IS', '0'), ('ON', '0'), ('THE', '0'), ('FUCKING', '0'), ('XBOX', 'B-product'), (',', '0'), ('Worst', '0'), ('fucking', '0'), ('day', '0'), ('ever', '0'), (',', '0')]
[('I', '0'), ('haven't', '0'), ('driven', '0'), ('to', '0'), ('bc', 'B-geo-loc'), ('in', '0'), ('years', '0'), (',', '0'), ('and', '0'), ('I', '0'), ('am', '0'), ('just', '0'), ('stunned', '0'), ('by', '0'), ('how', '0'), ('beautiful', '0'), ('the', '0'), ('drive', '0'), ('is', '0'), (',', '0')]
[('@daraobriain', '0'), ('hmmm', '0'), (',', '0'), ('Cant', '0'), ('wait', '0'), (',', '0'), ('Comin', '0'), ('on', '0'), ('Thursday', '0'), (',', '0'), ('First', '0'), ('tim e', '0'), ('to', '0'), ('the', 'B-facility'), ('Apollo', 'I-facility'), (',', '0')]

In [73]: # Step 1: Preprocess the data to remove tags and extract tokens
          sentences = [[word for word, tag in sentence] for sentence in data]

# Step 2: Train Word2Vec model
embedding_size = 150
word2vec_model = Word2Vec(
    sentences,
    vector_size=embedding_size,
    window=5, # Context window size
    min_count=1, # Include all words
    workers=4, # Number of threads
    sg=1, # Skip-gram model
    epochs=50 # Number of training epochs
)

# Step 3: Access word embeddings
word_embeddings = word2vec_model.wv
print(f"Vector for 'Disney': {word_embeddings['Disney']}")
```

Vector for 'Disney': [-0.03401573 -0.07787138 0.05246223 -0.28506628 0.02353712 -0.1624959
-0.19079438 0.42354813 0.06821679 0.06068345 0.4157507 -0.29883167
-0.22237596 -0.10609876 0.11701673 0.20186906 0.5043893 -0.12632003
-0.18080994 0.04397307 -0.3651332 -0.13581058 -0.01587982 0.35307884
-0.5621385 0.39848664 -0.56236696 0.02754335 -0.07502747 -0.502823
-0.31107312 -0.0445449 0.03266294 -0.01730459 -0.2593072 0.2979832
0.36678627 0.37062788 -0.09166308 -0.1251839 -0.01594435 0.26690006
-0.21882516 -0.34856465 0.19949387 -0.07813776 0.13054474 -0.22594261
0.05825325 0.15789446 -0.58728904 0.33159664 -0.312625 0.37511227
0.33214206 0.05489832 0.2111212 0.29015055 -0.2504633 0.07771383
-0.2957542 -0.35381976 0.27779567 0.11154643 -0.07416416 -0.02981466
0.08412196 -0.44147018 -0.3652614 0.00863719 0.09326027 0.12367988
-0.16488908 -0.37062156 0.24497145 0.3576005 -0.041061 0.05594293
-0.11582067 -0.05303695 -0.09977928 -0.22775374 -0.2866275 0.6790525
-0.3457443 -0.20013179 -0.20358212 -0.22744489 -0.04371682 0.03106547
0.05175491 -0.32696563 0.09880885 -0.17706047 0.25957704 -0.01110298
0.23391901 -0.25427836 0.33221915 -0.01227436 0.16463201 0.09954442
0.04415408 0.3930667 -0.23338678 -0.55329627 0.24051702 0.18351263
-0.40197685 -0.0876613 -0.43153515 0.16051762 0.02845318 0.02999252
-0.2618869 0.24209966 -0.24726154 -0.16916844 0.1887627 -0.23513676
-0.29218438 0.43171975 0.14807948 -0.15444678 -0.01364498 -0.15573676
-0.11074308 0.22746444 -0.20232055 0.31982994 0.23498186 0.14990577
0.19201663 -0.3420321 -0.10932205 0.2855867 -0.29095507 0.15402879
-0.43093428 -0.05573097 0.43701807 -0.24090146 -0.40638244 -0.20283583
0.5939381 -0.01180765 -0.23240122 0.01146152 -0.03607401 -0.08186235]

```
In [74]: # Step 3: Access word embeddings
word_embeddings = word2vec_model.wv
print(f"Vector for 'home': {word_embeddings['home']}")

Vector for 'home': [-2.17520669e-02 -1.23522535e-01 4.03272778e-01 -9.50646847e-02
 2.09373888e-02 -1.03636181e+00 -7.77050614e-01 1.09794244e-01
-2.02605486e-01 -8.28408375e-02 5.37826061e-01 -2.85710692e-01
-4.91160899e-01 -2.24952340e-01 1.32991582e-01 -4.85456623e-02
-3.18757147e-01 -1.36877835e-01 6.68644488e-01 1.77497491e-01
2.53561795e-01 -3.23926061e-01 3.92769635e-01 3.52166742e-01
-2.00121135e-01 -6.99025718e-03 -3.03980082e-01 2.58893371e-01
-3.49489242e-01 -2.89208561e-01 -2.23292992e-01 -5.23376226e-01
2.73092419e-01 2.97249019e-01 -1.92513317e-01 1.22791104e-01
1.03366017e+00 2.55178511e-01 -3.76552403e-01 -1.05154049e+00
-5.47984801e-02 3.69442284e-01 -3.77792329e-01 -3.08469027e-01
5.65425694e-01 4.95817184e-01 4.84890461e-01 -3.94151517e-04
2.60794550e-01 1.27608806e-01 -6.75134480e-01 3.23139697e-01
-5.72929978e-01 -8.36640298e-02 8.04057240e-01 5.33819139e-01
3.55098784e-01 1.79456174e-02 1.68445989e-01 -7.64750957e-01
2.12430477e-01 -1.21459281e+00 -3.76641095e-01 -2.08619758e-01
1.11989588e-01 -3.76551926e-01 -1.77989945e-01 4.37731326e-01
-2.78139114e-01 -1.89304411e-01 -3.46914113e-01 2.04146504e-01
6.37338996e-01 -4.65905368e-01 5.44220626e-01 3.62667620e-01
2.61005610e-02 -2.52471387e-01 -2.94082522e-01 -2.98057020e-01
2.29056608e-02 -9.63223457e-01 8.95210952e-02 2.49305353e-01
-7.47928202e-01 6.55037105e-01 2.90195316e-01 -2.19683751e-01
1.09361100e+00 -5.15561439e-02 2.77381569e-01 -4.14447248e-01
2.40178972e-01 -2.64910072e-01 2.26422057e-01 7.82843232e-01
5.15844710e-02 -7.31627224e-03 3.54684174e-01 -5.12745142e-01
4.25068915e-01 2.33487904e-01 1.15283251e+00 1.10446155e-01
1.27067730e-01 -5.45828462e-01 1.62739426e-01 4.06471360e-03
-1.10352427e-01 6.96255624e-01 -6.61640048e-01 -2.21629709e-01
1.04710078e+00 2.70657212e-01 -2.12506369e-01 5.04333615e-01
-5.31772554e-01 2.78278738e-02 -7.33204544e-01 5.44545710e-01
-1.06133866e+00 7.08162546e-01 -2.66446061e-02 -3.89453650e-01
1.83967084e-01 5.09890556e-01 2.83497602e-01 1.29095033e-01
-1.94625571e-01 5.61425090e-01 4.15723830e-01 -8.67420852e-01
-1.36932865e-01 -1.29872561e-01 -4.41022992e-01 5.86374430e-03
-1.50379226e-01 -1.34648681e-01 -2.68392235e-01 -7.27117419e-01
9.77859274e-02 -5.11193216e-01 -5.09659588e-01 -1.31728634e-01
1.02307332e+00 -5.64503551e-01 -2.67847151e-01 -6.72695458e-01
5.25546789e-01 -1.08838582e+00]
```

In [75]: len(word_embeddings)

Out[75]: 10585

Features and Label, Data Splitting

```
In [76]: X = [[word_embeddings[word] for word,tag in sentence] for sentence in data]

# pad the sequences, to have same length
X = pad_sequences(
    maxlen = 100,
    sequences = X,
    padding = "post",
    dtype = "float32"
)

print('Raw Sample:\n ', ' '.join([w[0] for w in data[0]]))
print('\n ' )
print('After processing, sample:\n', X[0])
```

Raw Sample:
@SammieLynnsMom @tg10781 they will be all done by Sunday trust me *wink*

After processing, sample:
[[-0.03880797 0.05548448 -0.13441 ... 0.11422057 0.1480474
-0.09564422]
[-0.01246704 0.08164434 -0.17308524 ... 0.12239877 0.19282947
-0.12012949]
[-0.03163513 0.22668353 0.29047447 ... 0.50402355 -0.21388218
-0.37641183]
...
[0. 0. 0. ... 0. 0.
0.]
[0. 0. 0. ... 0. 0.
0.]
[0. 0. 0. ... 0. 0.
0.]]

In [77]: len(X), X.shape

Out[77]: (2393, (2393, 100, 150))

```
In [78]: # Convert my Tag/Label to tag_index
y = [[tag2idx[ele[1]] for ele in sentence] for sentence in data]

# Padding each label to have same length
y = pad_sequences(
    maxlen = 100,
    sequences = y,
    padding = "post",
    value = tag2idx["PAD"]
)

# One-Hot encode
y = [to_categorical(i, num_classes=23) for i in y] # n_tags+1(PAD)
```



```
print('Raw Label:\n ', ' '.join([w[1] for w in data[0]))
print('\n ' )
print('After processing, labels:\n', y[0])
```

Raw Label:

0 0 0 0 0 0 0 0 0 0 0

After processing, labels:

```
[[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
[0. 0. 0. ... 0. 0. 0.]
...
[1. 0. 0. ... 0. 0. 0.]
[1. 0. 0. ... 0. 0. 0.]
[1. 0. 0. ... 0. 0. 0.]
```

In [79]: len(y), len(y[0])

Out[79]: (2393, 100)

In [80]: *# Data Splitting*

```
X_tr, X_te, y_tr, y_te = train_test_split(X, y, test_size=0.1)
```

```
y_tr = np.array(y_tr)
y_te = np.array(y_te)
```

Model Summary and Training

In [81]:

```
embedding_size = 150
def build_model(max_len=100, embedding_dim=embedding_size): # 10585 vocab size
    # Input layer to accept precomputed embeddings
    input_layer = Input(shape=(max_len, embedding_dim), name='input_layer')

    # BiLSTM layers
    lstm_output = Bidirectional(LSTM(units=50, return_sequences=True))(input_layer)
    lstm_output = Bidirectional(LSTM(units=50, return_sequences=True))(lstm_output)

    # Dense layer
    dense_output = TimeDistributed(Dense(64, activation="relu"))(lstm_output)

    # CRF layer
    crf = CRF(23, name='crf') # 21 classes
    predicted_sequence, potentials, sequence_length, crf_kernel = crf(dense_output)

    # Build the model
    model = Model(inputs=input_layer, outputs=potentials, name = "Twitter_NER_V1")

    # Compile the model
    model.compile(
        optimizer=AdamW(weight_decay=0.001 ,learning_rate=0.001),
        loss=SigmoidFocalCrossEntropy(), # Use CRF-specific loss
        # loss = custom_loss,
        metrics=["accuracy"] # Optional: Use CRF accuracy
    )

    return model

# Build and compile the model
wv_ner_model = build_model()

# Checkpointing
save_model = tf.keras.callbacks.ModelCheckpoint(filepath='wv_twitter_ner_crf.weights.h5',
    monitor='val_loss',
    save_weights_only=True,
    save_best_only=True,
    verbose=1
)

# Early stopping
es = tf.keras.callbacks.EarlyStopping(monitor='val_loss', verbose=1, patience=10)

callbacks = [save_model, es]

wv_ner_model.summary()
```


Model: "Twitter_NER_V1"

Layer (type)	Output Shape	Param #
=====		
input_layer (InputLayer)	[(None, 100, 150)]	0
bidirectional_2 (Bidirectional)	(None, 100, 100)	80400
bidirectional_3 (Bidirectional)	(None, 100, 100)	60400
time_distributed_1 (TimeDistributed)	(None, 100, 64)	6464
crf (CRF)	[(None, 100), (None, 100, 23), (None,), (23, 23)]	2070
=====		
Total params: 149334 (583.34 KB)		
Trainable params: 149334 (583.34 KB)		
Non-trainable params: 0 (0.00 Byte)		

Layer (type)	Output Shape	Param #
=====		
input_layer (InputLayer)	[(None, 100, 150)]	0
bidirectional_2 (Bidirectional)	(None, 100, 100)	80400
bidirectional_3 (Bidirectional)	(None, 100, 100)	60400
time_distributed_1 (TimeDistributed)	(None, 100, 64)	6464
crf (CRF)	[(None, 100), (None, 100, 23), (None,), (23, 23)]	2070
=====		
Total params: 149334 (583.34 KB)		
Trainable params: 149334 (583.34 KB)		
Non-trainable params: 0 (0.00 Byte)		

```
In [82]: ww_ner_model.fit(
        X_tr, y_tr,
        validation_data = (X_te, y_te),
        batch_size=BATCH_SIZE,
        epochs=10,
        shuffle = True)
```

Epoch 1/10
WARNING:tensorflow:Gradients do not exist for variables ['chain_kernel:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `loss` argument?
WARNING:tensorflow:Gradients do not exist for variables ['chain_kernel:0'] when minimizing the loss. If you're using `model.compile()`, did you forget to provide a `loss` argument?
68/68 [=====] - 7s 52ms/step - loss: 0.1648 - accuracy: 0.9618 - val_loss: 0.0194 - val_accuracy: 0.9872
Epoch 2/10
68/68 [=====] - 3s 40ms/step - loss: 0.0199 - accuracy: 0.9846 - val_loss: 0.0194 - val_accuracy: 0.9849
Epoch 3/10
68/68 [=====] - 3s 40ms/step - loss: 0.0154 - accuracy: 0.9874 - val_loss: 0.0147 - val_accuracy: 0.9881
Epoch 4/10
68/68 [=====] - 3s 39ms/step - loss: 0.0143 - accuracy: 0.9881 - val_loss: 0.0361 - val_accuracy: 0.9883
Epoch 5/10
68/68 [=====] - 3s 42ms/step - loss: 0.0168 - accuracy: 0.9878 - val_loss: 0.0135 - val_accuracy: 0.9887
Epoch 6/10
68/68 [=====] - 3s 40ms/step - loss: 0.0132 - accuracy: 0.9883 - val_loss: 0.0129 - val_accuracy: 0.9887
Epoch 7/10
68/68 [=====] - 3s 40ms/step - loss: 0.0128 - accuracy: 0.9885 - val_loss: 0.0131 - val_accuracy: 0.9891
Epoch 8/10
68/68 [=====] - 3s 40ms/step - loss: 0.0156 - accuracy: 0.9871 - val_loss: 0.0139 - val_accuracy: 0.9875
Epoch 9/10
68/68 [=====] - 3s 40ms/step - loss: 0.0127 - accuracy: 0.9885 - val_loss: 0.0125 - val_accuracy: 0.9890
Epoch 10/10
68/68 [=====] - 3s 38ms/step - loss: 0.0123 - accuracy: 0.9888 - val_loss: 0.0120 - val_accuracy: 0.9892

Out[82]: <keras.src.callbacks.History at 0x74024437a510>

Validation Data : Evaluation

```
In [83]: # Predict probabilities
y_val_pred_prob = ww_ner_model.predict(X_te)

y_val_pred = np.argmax(y_val_pred_prob, axis=2)
```

8/8 [=====] - 1s 11ms/step

```
In [84]: # Convert predictions and true labels, ignoring padding tokens
y_pred_flat, y_true_flat = filter_padding(y_val_pred, np.argmax(y_te, axis=2))

# Calculate metrics
accuracy = accuracy_score(y_true_flat, y_pred_flat)
print(f"Accuracy: {accuracy}")
```

Accuracy: 0.9528099528099528

```
In [102]: ## Classification report
# print("Classification Report:")
# print(classification_report(y_true_flat, y_pred_flat))
```

```
In [101]: ## Compute the confusion matrix
# conf_matrix = confusion_matrix(y_true_flat, y_pred_flat)

# # Plot the heatmap
# plt.figure(figsize=(10, 8))
# sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y_true_flat), yticklabels=np.unique(y_true_flat))

# # Labels and title
# plt.xlabel('Predicted Labels')
# plt.ylabel('True Labels')
# plt.title('Confusion Matrix Heatmap')
# plt.show()
```

Testing Data: Evaluation

```
In [87]: # Define a default (zero) embedding for OOV words
unk_embedding = np.zeros(embedding_size)

# Function to get embeddings
```

Raw Sample:
New Orleans Mother 's Day Parade shooting . One of the people hurt was a 10-year-old girl . WHAT THE HELL IS WRONG WITH PEOPLE ?

```
In [88]: # Convert my Tag/Label to tag_index
y_test = [[tag2idx.get(ele[1], tag2idx["UNK"]) for ele in sentence] for sentence in test_data]

# Padding each label to have same length
y_test = pad_sequences(
    maxlen = 100,
    sequences = y_test,
    padding = "post",
    dtype = "float32"
)
```

121/121 [=====] - 1s 12ms/step

```
Out[90]: (3849, 100, 23)
```

[illegible][illegible][illegible][illegible]

```
Out[95]: (3849, 3849)
```

Accuracy: 0.9115562016547317

```
In [100...  ## Compute the confusion matrix
            # conf_matrix = confusion_matrix(y_true_flat, y_pred_flat)

            ## Plot the heatmap
            # plt.figure(figsize=(10, 8))
```

```
# sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y_true_flat), yticklabels=np.unique(y_true_flat))

# # Labels and title
# plt.xlabel('Predicted Labels')
# plt.ylabel('True Labels')
# plt.title('Confusion Matrix Heatmap')
# plt.show()
```

Conclusion

Key Observations

- Using **Bi-LSTM with CRF**:
 - Achieved **high accuracy** on the validation dataset.
 - Results showed close to **99% accuracy** with **good recall** and **precision values** for each entity.
- Comparison with Word2Vec Embeddings:
 - Directly using **pre-trained Word2Vec embeddings** in a neural network resulted in **lower accuracy**.
 - Incorporating a **custom embedding layer** and training on top of it yielded **better performance**.

Questions and Answers

Defining the problem statements, and where can this and modications of this be used?

- We've finalized NER for over 25 entities that help social networking giants like Twitter, Instagram, Reddit, Inc., Pinterest, LinkedIn (the usual suspects) gather insights and boost user engagement. Because, obviously, understanding what people are posting is important.

Explain the data format (CoNLL BIO format)

- The CoNLL BIO format is a common structure for annotating text data for NER tasks. Each token is assigned a label indicating whether it begins (B), is inside (I), or is outside (O) of a named entity. For example:
Barack B-PER
Obama I-PER
was O
born O
in O
Hawaii B-LOC
. O

What other NER data annotation formats are available and how are they different?

- IOB**: Similar to BIO but lacks the distinction between beginning (B) and inside (I) when there is no ambiguity.
- BIOES**: Extends BIO by adding labels for single-token entities (S) and the end of entities (E).
- BILOU**: Similar to BIOES, but uses "L" for the last token of an entity and "U" for unit-length entities.

Why do we need tokenization of the data in our case?

- Tokenization breaks text into manageable units (tokens) for processing. For NER, it ensures proper alignment of tokens with entity annotations, facilitating accurate tagging and model training.

What other models can you use for this task?

- Alternatives include spaCy, Flair, T5, GPT-4, and custom transformer-based models.

Did early stopping have any effect on the training and results?

- Early stopping prevents overfitting, especially when training on small datasets. It ensures the model generalizes better to unseen data.

How does the BERT model expect a pair of sentences to be processed?

- BERT concatenates sentences with a `[SEP]` token and prepends them with a `[CLS]` token. The input is tokenized and converted into embeddings.

Why choose attention-based models over recurrent-based ones? - Attention mechanisms process all tokens simultaneously, enabling better handling of long-range dependencies and faster training. RNNs process tokens sequentially, which can be slower and less effective for long texts.

Differentiate BERT and Simple Transformers. - **BERT**: A transformer-based model pre-trained on masked language modeling and next-sentence prediction. - **Simple Transformers**: A Python library that simplifies the training and fine-tuning of transformer models, including BERT, for various NLP tasks.