In [1]:

```python
#Base Imports
import string
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#Pre Processing Imports
import re
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')
nltk.download('wordnet')
from nltk.stem import WordNetLemmatizer , SnowballStemmer
stop_words = set(stopwords.words("english"))
lemmatizer= WordNetLemmatizer()
stemmer = SnowballStemmer("english")
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
#Model Building Imports
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.layers import Dense, SimpleRNN ,LSTM, Embedding, Dropout, GRU , Bi
#Model Evaluation imports
from sklearn import metrics
from sklearn.metrics import (classification_report,confusion_matrix ,
                             precision_recall_curve ,precision_score,recall_score , accu
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

In [2]:

```python
df = pd.read_csv('emotions_preprocessed.csv')
```

In [3]:

```python
def stemming(text):
    text = text.split()
    text = [stemmer.stem(y)  for y in text]

    return " ".join(text)


def lemmatization(text):
     text = text.split()
     text=[lemmatizer.lemmatize(y)  for y in text]

     return " " .join(text)

def remove_stop_words(text):

    Text=[i for i in str(text).split() if i not in stop_words]
    return " ".join(Text)

def remove_numbers(text):
    text=''.join([i for i in text if not i.isdigit()])
    return text
```

```
def lower_case(text):

    text = text.split()

    text=[y.lower() for y in text]

    return " " .join(text)

def remove_punctuations(text):
    ## Remove punctuations
    text = re.sub('[%s]' % re.escape("""!"#$%&'()*+,،-./:;<=>؟?@[\]^_`{|}~"""), ' ', tex
    text = text.replace('؛',"", )

    ## remove extra whitespace
    text = re.sub('\s+', ' ', text)
    text =  " ".join(text.split())
    return text.strip()

def remove_urls(text):
    url = re.compile(r'https?://\S+|www\.\S+')
    return url.sub(r'', text)

def clean_stopwords_removed_lemma(df):

    df.text=df.text.apply(lambda text : remove_stop_words(text))
    df.text=df.text.apply(lambda text : remove_numbers(text))
    df.text=df.text.apply(lambda text : remove_punctuations(text))
    df.text=df.text.apply(lambda text : remove_urls(text))
    df.text=df.text.apply(lambda text : lower_case(text))
    df.text=df.text.apply(lambda text : lemmatization(text))
    return df

def clean_stopwords_removed_stemming(df):

    df.text=df.text.apply(lambda text : remove_stop_words(text))
    df.text=df.text.apply(lambda text : remove_numbers(text))
    df.text=df.text.apply(lambda text : remove_punctuations(text))
    df.text=df.text.apply(lambda text : remove_urls(text))
    df.text=df.text.apply(lambda text : lower_case(text))
    df.text=df.text.apply(lambda text : stemming(text))
    return df

def clean_stopwords_present_stemming(df):

    df.text=df.text.apply(lambda text : remove_numbers(text))
    df.text=df.text.apply(lambda text : remove_punctuations(text))
    df.text=df.text.apply(lambda text : remove_urls(text))
    df.text=df.text.apply(lambda text : lower_case(text))
    df.text=df.text.apply(lambda text : stemming(text))
    return df

def clean_stopwords_present_lemma(df):
    df.text=df.text.apply(lambda text : remove_numbers(text))
    df.text=df.text.apply(lambda text : remove_punctuations(text))
    df.text=df.text.apply(lambda text : remove_urls(text))
    df.text=df.text.apply(lambda text : lower_case(text))
    df.text=df.text.apply(lambda text : lemmatization(text))
    return df
```

In [4]:

```
df_clean_stopwords_removed_stemming = clean_stopwords_removed_stemming(df)
```

```
df_clean_stopwords_present_stemming =  clean_stopwords_present_stemming(df)
df_clean_stopwords_present_lemma = clean_stopwords_present_lemma(df)
```

Stemming With Stop Words Removed

In [5]:

```
X= df_clean_stopwords_removed_stemming.text
y= df_clean_stopwords_removed_stemming.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.1, random_state=
X_val,X_test,y_val,y_test= train_test_split(X_other,y_other,test_size=0.5,random_state=7
```

In [6]:

```
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
y_val = le.transform(y_val)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
y_val = to_categorical(y_val)
# Tokenize words
tokenizer = Tokenizer(oov_token='UNK')
tokenizer.fit_on_texts(pd.concat([X_train], axis=0))
sequences_train = tokenizer.texts_to_sequences(X_train)
sequences_test = tokenizer.texts_to_sequences(X_test)
sequences_val = tokenizer.texts_to_sequences(X_val)
max_len = max([len(t) for t in X_train])
X_train = pad_sequences(sequences_train, maxlen=max_len, truncating='pre')
X_test = pad_sequences(sequences_test, maxlen=max_len, truncating='pre')
X_val = pad_sequences(sequences_val, maxlen=max_len, truncating='pre')
vocabSize = len(tokenizer.index_word) + 1

#Text Representation Using Glove Embedding
path_to_glove_file = 'glove.6B.300d.txt'
num_tokens = vocabSize
embedding_dim = 300
embeddings_index = {}
misses=0
hits=0
with open(path_to_glove_file) as f:
    for line in f:
        word, coefs = line.split(maxsplit=1)
        coefs = np.fromstring(coefs, "f", sep=" ")
        embeddings_index[word] = coefs
print("Found %s word vectors." % len(embeddings_index))


embedding_matrix = np.zeros((num_tokens, embedding_dim))
for word, i in tokenizer.word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
        hits += 1
    else:
        misses += 1
print("Converted %d words (%d misses)" % (hits, misses))

#define early stopping to control overfitting
callback = EarlyStopping(
    monitor="val_loss",
    patience=3,
    restore_best_weights=True,
)
```

```
Found 23858 word vectors.
```

```
Converted 5468 words (13865 misses)
```

In [7]:
```python
gru_model = Sequential()
gru_model.add(Embedding(vocabSize, 300, input_length=X_train.shape[1], weights=[embeddin
gru_model.add(GRU(units=64, return_sequences=True))
gru_model.add(Dropout(0.5))
gru_model.add(GRU(units=32))
gru_model.add(Dropout(0.5))
gru_model.add(Dense(14, activation='softmax'))
gru_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 526, 300)          5800200

 gru (GRU)                   (None, 526, 64)           70272

 dropout (Dropout)           (None, 526, 64)           0

 gru_1 (GRU)                 (None, 32)                9408

 dropout_1 (Dropout)         (None, 32)                0

 dense (Dense)               (None, 14)                462

=================================================================
Total params: 5,880,342
Trainable params: 80,142
Non-trainable params: 5,800,200
_________________________________________________________________
```

In [8]:
```python
gru_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accuracy
```

In [9]:
```python
# Fit model
history_gru=gru_model.fit(X_train,
            y_train,
            validation_data=(X_val, y_val),
            verbose=1,
            batch_size=256,
            epochs=30,
            callbacks=[callback]
        )
```

```
Epoch 1/30
190/190 [==============================] - 21s 61ms/step - loss: 2.2498 - accuracy: 0.33
64 - val_loss: 1.9976 - val_accuracy: 0.4100
Epoch 2/30
190/190 [==============================] - 10s 55ms/step - loss: 2.0251 - accuracy: 0.40
78 - val_loss: 1.8992 - val_accuracy: 0.4315
Epoch 3/30
190/190 [==============================] - 10s 55ms/step - loss: 1.9526 - accuracy: 0.42
60 - val_loss: 1.8548 - val_accuracy: 0.4426
Epoch 4/30
190/190 [==============================] - 11s 55ms/step - loss: 1.9143 - accuracy: 0.43
44 - val_loss: 1.8205 - val_accuracy: 0.4500
Epoch 5/30
190/190 [==============================] - 12s 63ms/step - loss: 1.8822 - accuracy: 0.44
15 - val_loss: 1.8025 - val_accuracy: 0.4563
Epoch 6/30
190/190 [==============================] - 11s 57ms/step - loss: 1.8621 - accuracy: 0.44
67 - val_loss: 1.7843 - val_accuracy: 0.4607
Epoch 7/30
190/190 [==============================] - 11s 56ms/step - loss: 1.8450 - accuracy: 0.44
97 - val_loss: 1.7732 - val_accuracy: 0.4593
```

```
Epoch 8/30
190/190 [==============================] - 11s 57ms/step - loss: 1.8236 - accuracy: 0.45
63 - val_loss: 1.7645 - val_accuracy: 0.4622
Epoch 9/30
190/190 [==============================] - 11s 57ms/step - loss: 1.8112 - accuracy: 0.45
81 - val_loss: 1.7564 - val_accuracy: 0.4637
Epoch 10/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7981 - accuracy: 0.46
39 - val_loss: 1.7595 - val_accuracy: 0.4648
Epoch 11/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7848 - accuracy: 0.46
36 - val_loss: 1.7495 - val_accuracy: 0.4641
Epoch 12/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7688 - accuracy: 0.46
84 - val_loss: 1.7565 - val_accuracy: 0.4667
Epoch 13/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7605 - accuracy: 0.46
91 - val_loss: 1.7496 - val_accuracy: 0.4667
Epoch 14/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7468 - accuracy: 0.47
14 - val_loss: 1.7517 - val_accuracy: 0.4711
```

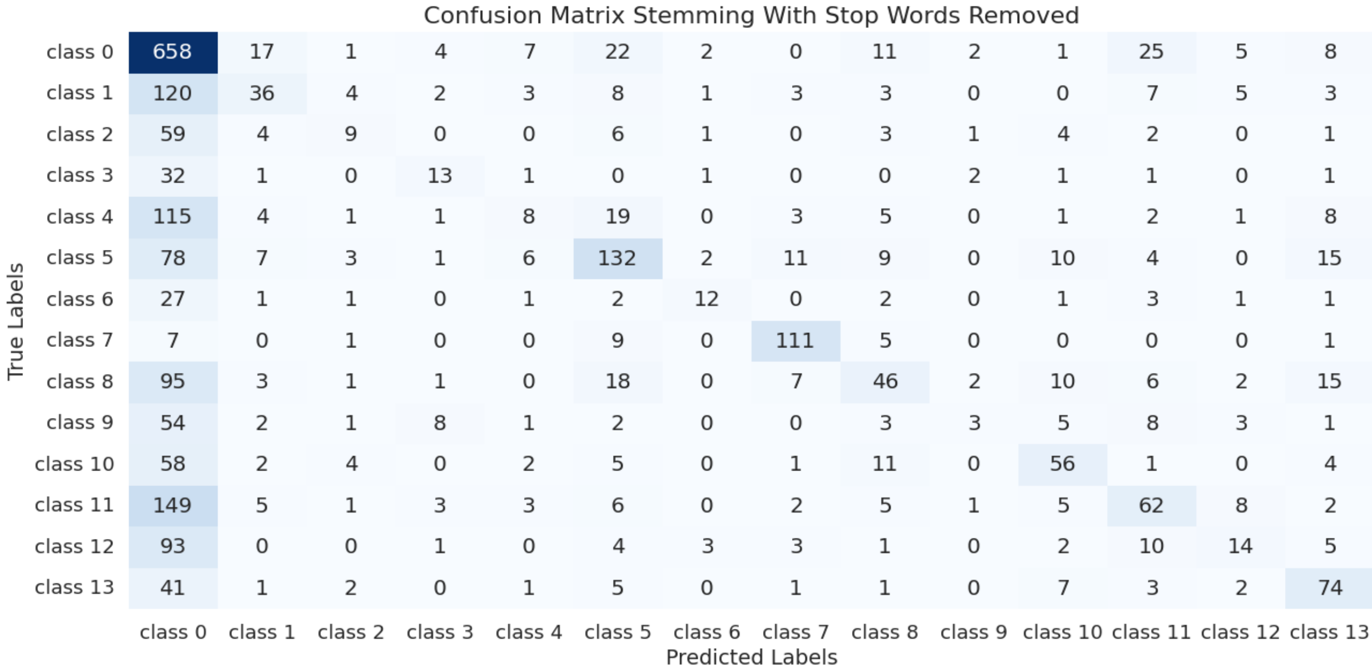
In [10]:

```
gru_y_pred = gru_model.predict(X_test)
gru_y_pred_labels = np.argmax(gru_y_pred, axis=1)
gru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(gru_y_test_labels, gru_y_pred_labels))
```

```
85/85 [==============================] - 2s 17ms/step
              precision    recall  f1-score   support

           0       0.41      0.86      0.56       763
           1       0.43      0.18      0.26       195
           2       0.31      0.10      0.15        90
           3       0.38      0.25      0.30        53
           4       0.24      0.05      0.08       168
           5       0.55      0.47      0.51       278
           6       0.55      0.23      0.32        52
           7       0.78      0.83      0.80       134
           8       0.44      0.22      0.30       206
           9       0.27      0.03      0.06        91
          10       0.54      0.39      0.45       144
          11       0.46      0.25      0.32       252
          12       0.34      0.10      0.16       136
          13       0.53      0.54      0.53       138

    accuracy                           0.46      2700
   macro avg       0.45      0.32      0.34      2700
weighted avg       0.45      0.46      0.41      2700
```

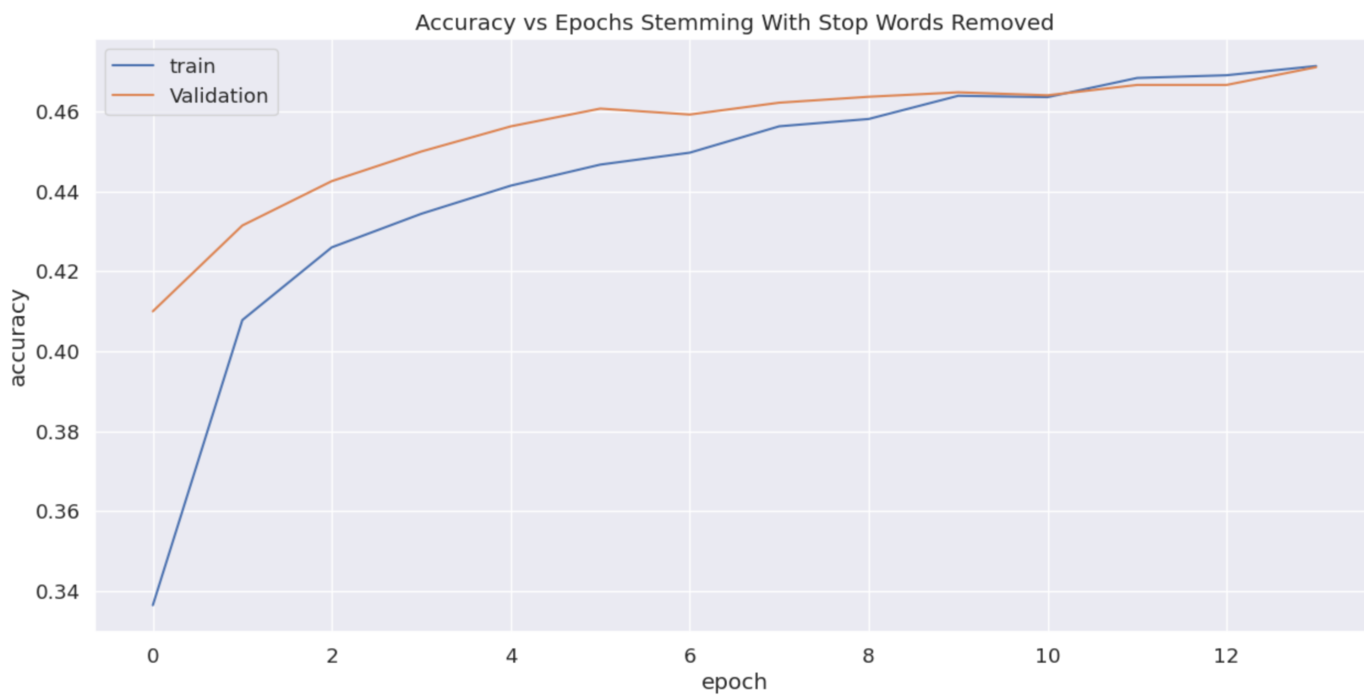
In [11]:

```
conf_mat_gru = confusion_matrix(gru_y_test_labels, gru_y_pred_labels)
plt.figure(figsize=(15,7))
# create a heatmap of the confusion matrix
sns.set(font_scale=1.2)
sns.heatmap(conf_mat_gru, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5
                         'class 6', 'class 7', 'class 8', 'class 9', 'class 10',
                         'class 11', 'class 12', 'class 13'],
            yticklabels=['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5
                         'class 6', 'class 7', 'class 8', 'class 9', 'class 10',
                         'class 11', 'class 12', 'class 13'])
plt.xlabel('Predicted Labels', fontsize=14)
plt.ylabel('True Labels', fontsize=14)
plt.title('Confusion Matrix Stemming With Stop Words Removed', fontsize=16)
plt.show()
```



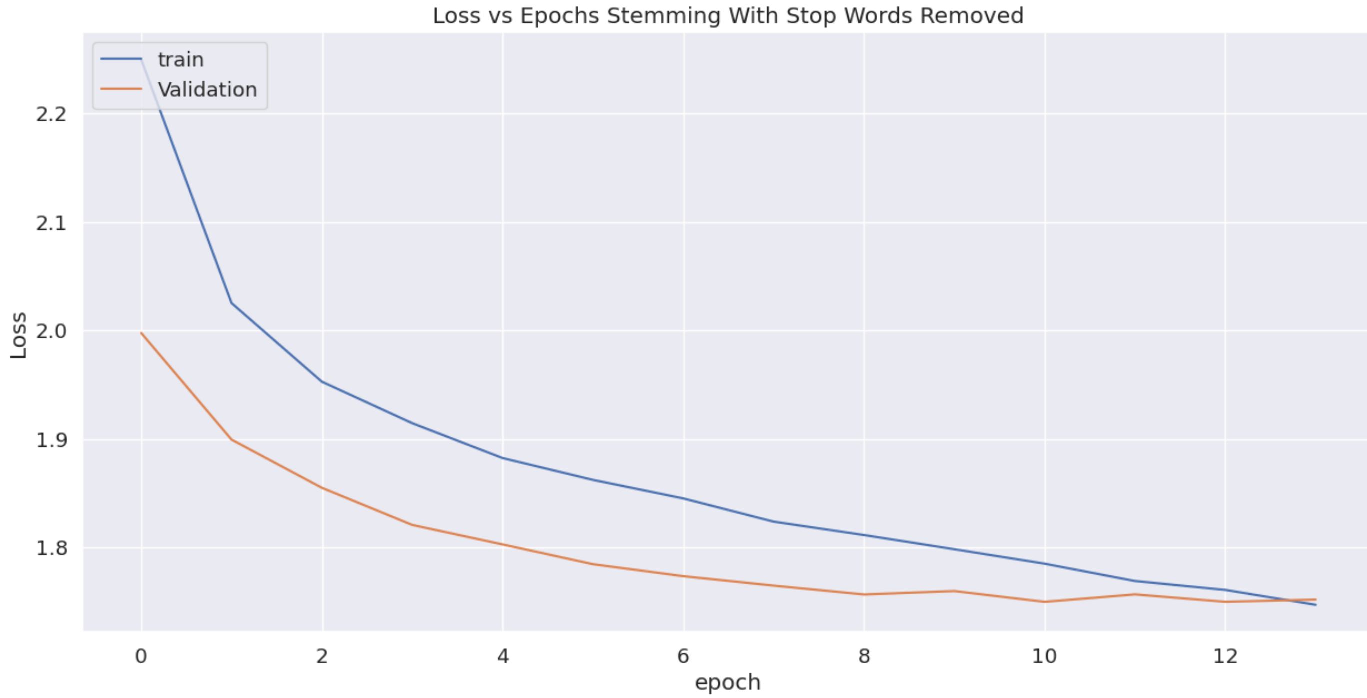
In [12]:

```python
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs Stemming With Stop Words Removed')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [13]:

```python
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs Stemming With Stop Words Removed')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



Stemming With Stop Words Present

In [14]:

```
X= df_clean_stopwords_present_stemming.text
y= df_clean_stopwords_present_stemming.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.1, random_state=
X_val,X_test,y_val,y_test= train_test_split(X_other,y_other,test_size=0.5,random_state=7
```

In [15]:

```
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
y_val = le.transform(y_val)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
y_val = to_categorical(y_val)
# Tokenize words
tokenizer = Tokenizer(oov_token='UNK')
tokenizer.fit_on_texts(pd.concat([X_train], axis=0))
sequences_train = tokenizer.texts_to_sequences(X_train)
sequences_test = tokenizer.texts_to_sequences(X_test)
sequences_val = tokenizer.texts_to_sequences(X_val)
max_len = max([len(t) for t in X_train])
X_train = pad_sequences(sequences_train, maxlen=max_len, truncating='pre')
X_test = pad_sequences(sequences_test, maxlen=max_len, truncating='pre')
X_val = pad_sequences(sequences_val, maxlen=max_len, truncating='pre')
vocabSize = len(tokenizer.index_word) + 1

#Text Representation Using Glove Embedding
num_tokens = vocabSize
embedding_dim = 300
embeddings_index = {}
misses=0
hits=0
with open(path_to_glove_file) as f:
    for line in f:
        word, coefs = line.split(maxsplit=1)
        coefs = np.fromstring(coefs, "f", sep=" ")
        embeddings_index[word] = coefs
print("Found %s word vectors." % len(embeddings_index))
```

```
embedding_matrix = np.zeros((num_tokens, embedding_dim))
for word, i in tokenizer.word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
        hits += 1
    else:
        misses += 1
print("Converted %d words (%d misses)" % (hits, misses))

#define early stopping to control overfitting
callback = EarlyStopping(
    monitor="val_loss",
    patience=3,
    restore_best_weights=True,
)
```

```
Found 41286 word vectors.
Converted 7014 words (12319 misses)
```

In [16]:

```
gru_model = Sequential()
gru_model.add(Embedding(vocabSize, 300, input_length=X_train.shape[1], weights=[embeddin
gru_model.add(GRU(units=64, return_sequences=True))
gru_model.add(Dropout(0.5))
gru_model.add(GRU(units=32))
gru_model.add(Dropout(0.5))
gru_model.add(Dense(14, activation='softmax'))
gru_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 526, 300)          5800200

 gru_2 (GRU)                 (None, 526, 64)           70272

 dropout_2 (Dropout)         (None, 526, 64)           0

 gru_3 (GRU)                 (None, 32)                9408

 dropout_3 (Dropout)         (None, 32)                0

 dense_1 (Dense)             (None, 14)                462

=================================================================
Total params: 5,880,342
Trainable params: 80,142
Non-trainable params: 5,800,200
_________________________________________________________________
```

In [17]:

```
gru_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accuracy
```

In [18]:

```
# Fit model
history_gru=gru_model.fit(X_train,
            y_train,
            validation_data=(X_val, y_val),
            verbose=1,
            batch_size=256,
            epochs=30,
            callbacks=[callback]
        )
```

```
Epoch 1/30
190/190 [==============================] - 16s 63ms/step - loss: 2.2322 - accuracy: 0.34
```

```
20 - val_loss: 1.9711 - val_accuracy: 0.4252
Epoch 2/30
190/190 [==============================] - 11s 59ms/step - loss: 2.0015 - accuracy: 0.41
58 - val_loss: 1.8875 - val_accuracy: 0.4437
Epoch 3/30
190/190 [==============================] - 11s 59ms/step - loss: 1.9343 - accuracy: 0.43
30 - val_loss: 1.8409 - val_accuracy: 0.4533
Epoch 4/30
190/190 [==============================] - 11s 59ms/step - loss: 1.8959 - accuracy: 0.44
40 - val_loss: 1.8103 - val_accuracy: 0.4611
Epoch 5/30
190/190 [==============================] - 11s 58ms/step - loss: 1.8645 - accuracy: 0.45
03 - val_loss: 1.7867 - val_accuracy: 0.4611
Epoch 6/30
190/190 [==============================] - 11s 58ms/step - loss: 1.8420 - accuracy: 0.45
54 - val_loss: 1.7674 - val_accuracy: 0.4685
Epoch 7/30
190/190 [==============================] - 11s 58ms/step - loss: 1.8225 - accuracy: 0.45
96 - val_loss: 1.7566 - val_accuracy: 0.4704
Epoch 8/30
190/190 [==============================] - 11s 57ms/step - loss: 1.8038 - accuracy: 0.46
32 - val_loss: 1.7538 - val_accuracy: 0.4678
Epoch 9/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7864 - accuracy: 0.46
92 - val_loss: 1.7485 - val_accuracy: 0.4689
Epoch 10/30
190/190 [==============================] - 11s 59ms/step - loss: 1.7734 - accuracy: 0.46
97 - val_loss: 1.7361 - val_accuracy: 0.4722
Epoch 11/30
190/190 [==============================] - 11s 60ms/step - loss: 1.7607 - accuracy: 0.47
31 - val_loss: 1.7337 - val_accuracy: 0.4726
Epoch 12/30
190/190 [==============================] - 11s 60ms/step - loss: 1.7480 - accuracy: 0.47
56 - val_loss: 1.7272 - val_accuracy: 0.4759
Epoch 13/30
190/190 [==============================] - 11s 60ms/step - loss: 1.7361 - accuracy: 0.47
98 - val_loss: 1.7410 - val_accuracy: 0.4670
Epoch 14/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7268 - accuracy: 0.48
14 - val_loss: 1.7313 - val_accuracy: 0.4752
Epoch 15/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7146 - accuracy: 0.48
54 - val_loss: 1.7258 - val_accuracy: 0.4785
Epoch 16/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7038 - accuracy: 0.48
77 - val_loss: 1.7296 - val_accuracy: 0.4744
Epoch 17/30
190/190 [==============================] - 11s 57ms/step - loss: 1.6901 - accuracy: 0.49
04 - val_loss: 1.7296 - val_accuracy: 0.4737
Epoch 18/30
190/190 [==============================] - 11s 57ms/step - loss: 1.6787 - accuracy: 0.49
27 - val_loss: 1.7308 - val_accuracy: 0.4737
```

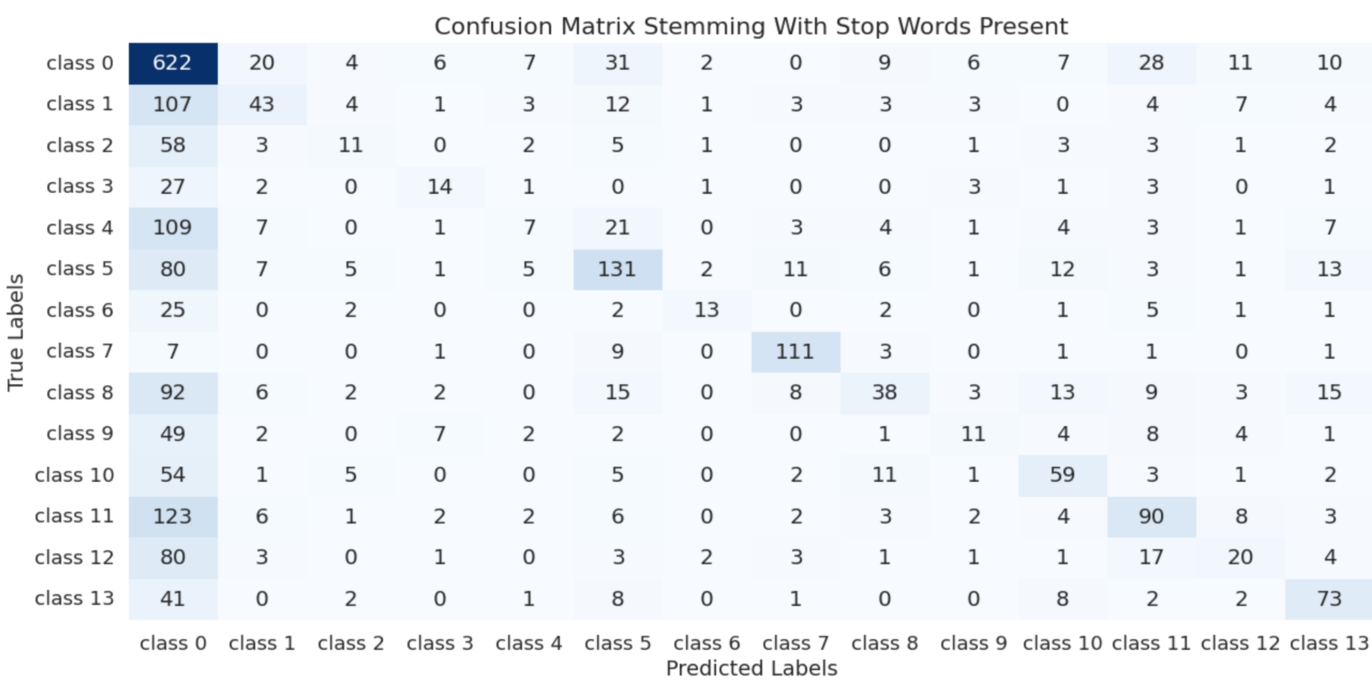
In [19]:

```python
gru_y_pred = gru_model.predict(X_test)
gru_y_pred_labels = np.argmax(gru_y_pred, axis=1)
gru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(gru_y_test_labels, gru_y_pred_labels))
```

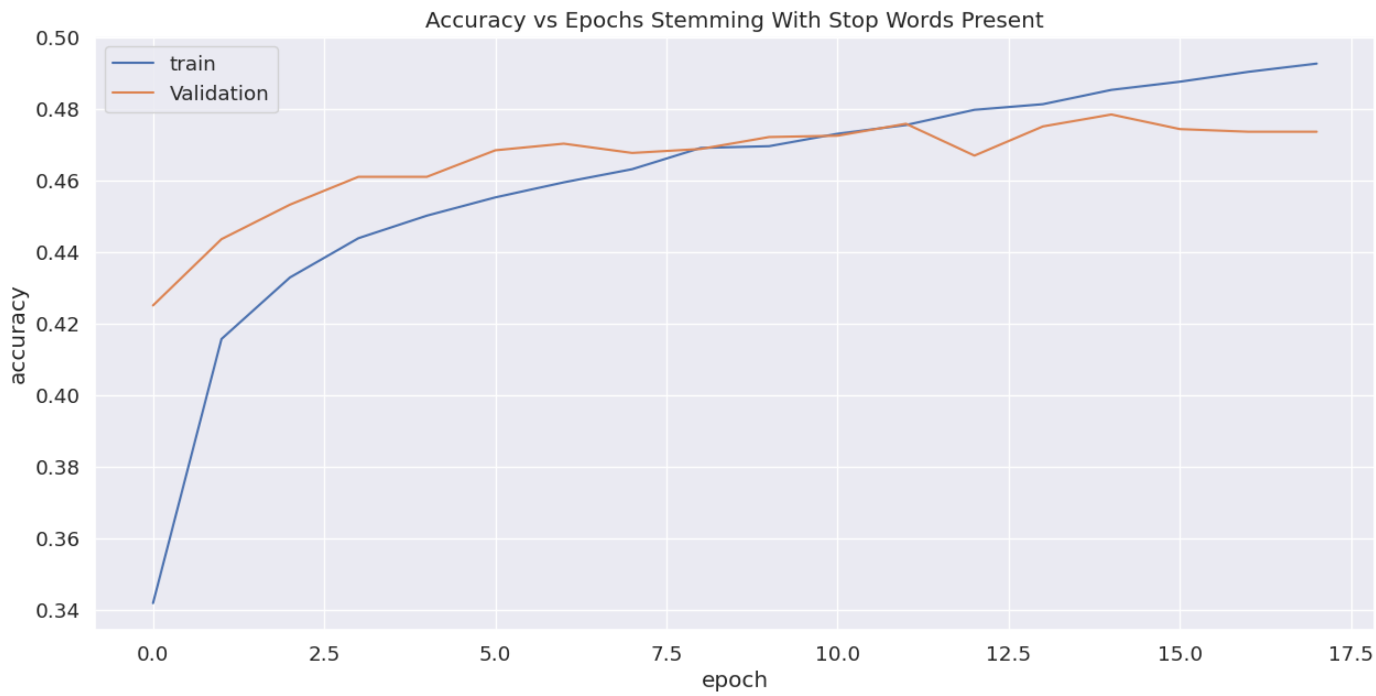
```
85/85 [==============================] - 2s 11ms/step
              precision    recall  f1-score   support

           0       0.42      0.82      0.56       763
           1       0.43      0.22      0.29       195
           2       0.31      0.12      0.17        90
           3       0.39      0.26      0.31        53
           4       0.23      0.04      0.07       168
```

```
           5       0.52      0.47      0.50       278
           6       0.59      0.25      0.35        52
           7       0.77      0.83      0.80       134
           8       0.47      0.18      0.26       206
           9       0.33      0.12      0.18        91
          10       0.50      0.41      0.45       144
          11       0.50      0.36      0.42       252
          12       0.33      0.15      0.20       136
          13       0.53      0.53      0.53       138

    accuracy                           0.46      2700
   macro avg       0.45      0.34      0.36      2700
weighted avg       0.45      0.46      0.42      2700
```

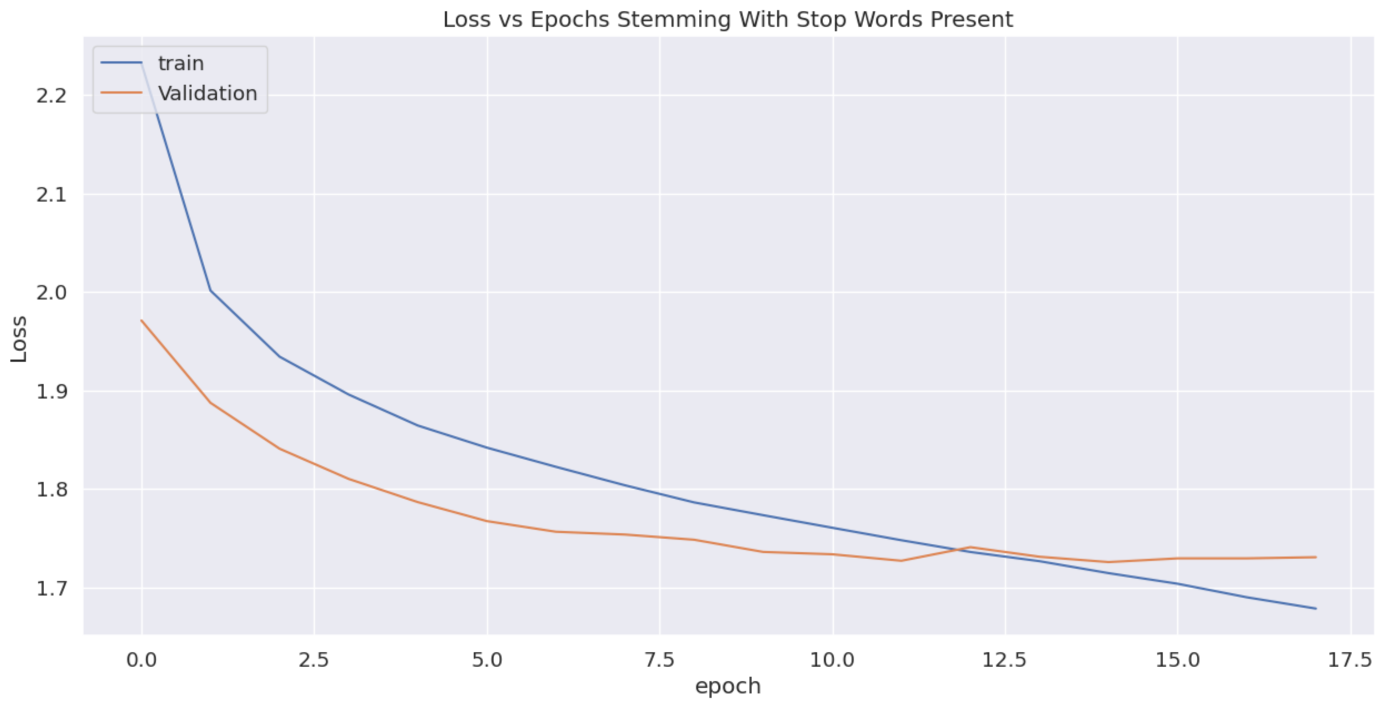
In [20]:
```
conf_mat_gru = confusion_matrix(gru_y_test_labels, gru_y_pred_labels)
plt.figure(figsize=(15,7))
# create a heatmap of the confusion matrix
sns.set(font_scale=1.2)
sns.heatmap(conf_mat_gru, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5
                         'class 6', 'class 7', 'class 8', 'class 9', 'class 10',
                         'class 11', 'class 12', 'class 13'],
            yticklabels=['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5
                         'class 6', 'class 7', 'class 8', 'class 9', 'class 10',
                         'class 11', 'class 12', 'class 13'])
plt.xlabel('Predicted Labels', fontsize=14)
plt.ylabel('True Labels', fontsize=14)
plt.title('Confusion Matrix Stemming With Stop Words Present', fontsize=16)
plt.show()
```



In [21]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs Stemming With Stop Words Present')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [22]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs Stemming With Stop Words Present')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



Lemmatization With Stop Words Present

In [23]:
```
X= df_clean_stopwords_present_lemma.text
y= df_clean_stopwords_present_lemma.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.1, random_state=
X_val,X_test,y_val,y_test= train_test_split(X_other,y_other,test_size=0.5,random_state=7
```

In [24]:
```
le = LabelEncoder()
```

```python
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
y_val = le.transform(y_val)

y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
y_val = to_categorical(y_val)
# Tokenize words
tokenizer = Tokenizer(oov_token='UNK')
tokenizer.fit_on_texts(pd.concat([X_train], axis=0))
sequences_train = tokenizer.texts_to_sequences(X_train)
sequences_test = tokenizer.texts_to_sequences(X_test)
sequences_val = tokenizer.texts_to_sequences(X_val)
max_len = max([len(t) for t in X_train])
X_train = pad_sequences(sequences_train, maxlen=max_len, truncating='pre')
X_test = pad_sequences(sequences_test, maxlen=max_len, truncating='pre')
X_val = pad_sequences(sequences_val, maxlen=max_len, truncating='pre')
vocabSize = len(tokenizer.index_word) + 1

#Text Representation Using Glove Embedding
num_tokens = vocabSize
embedding_dim = 300
embeddings_index = {}
misses=0
hits=0
with open(path_to_glove_file) as f:
    for line in f:
        word, coefs = line.split(maxsplit=1)
        coefs = np.fromstring(coefs, "f", sep=" ")
        embeddings_index[word] = coefs
print("Found %s word vectors." % len(embeddings_index))


embedding_matrix = np.zeros((num_tokens, embedding_dim))
for word, i in tokenizer.word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
        hits += 1
    else:
        misses += 1
print("Converted %d words (%d misses)" % (hits, misses))

#define early stopping to control overfitting
callback = EarlyStopping(
    monitor="val_loss",
    patience=3,
    restore_best_weights=True,
)
```

```
Found 59131 word vectors.
Converted 7936 words (11397 misses)
```

In [25]:

```python
gru_model = Sequential()
gru_model.add(Embedding(vocabSize, 300, input_length=X_train.shape[1], weights=[embeddin
gru_model.add(GRU(units=64, return_sequences=True))
gru_model.add(Dropout(0.5))
gru_model.add(GRU(units=32))
gru_model.add(Dropout(0.5))
gru_model.add(Dense(14, activation='softmax'))
gru_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 embedding_2 (Embedding)     (None, 526, 300)          5800200

 gru_4 (GRU)                 (None, 526, 64)           70272

 dropout_4 (Dropout)         (None, 526, 64)           0

 gru_5 (GRU)                 (None, 32)                9408

 dropout_5 (Dropout)         (None, 32)                0

 dense_2 (Dense)             (None, 14)                462

=================================================================
Total params: 5,880,342
Trainable params: 80,142
Non-trainable params: 5,800,200
_________________________________________________________________
```

In [26]:

```
gru_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accuracy
```

In [27]:

```
# Fit model
history_gru=gru_model.fit(X_train,
            y_train,
            validation_data=(X_val, y_val),
            verbose=1,
            batch_size=256,
            epochs=30,
            callbacks=[callback]
        )
```

```
Epoch 1/30
190/190 [==============================] - 16s 61ms/step - loss: 2.2397 - accuracy: 0.33
60 - val_loss: 1.9760 - val_accuracy: 0.4070
Epoch 2/30
190/190 [==============================] - 11s 58ms/step - loss: 2.0059 - accuracy: 0.41
09 - val_loss: 1.8751 - val_accuracy: 0.4456
Epoch 3/30
190/190 [==============================] - 11s 58ms/step - loss: 1.9260 - accuracy: 0.43
40 - val_loss: 1.8204 - val_accuracy: 0.4559
Epoch 4/30
190/190 [==============================] - 11s 58ms/step - loss: 1.8873 - accuracy: 0.44
34 - val_loss: 1.7921 - val_accuracy: 0.4581
Epoch 5/30
190/190 [==============================] - 11s 57ms/step - loss: 1.8543 - accuracy: 0.45
04 - val_loss: 1.7654 - val_accuracy: 0.4667
Epoch 6/30
190/190 [==============================] - 11s 58ms/step - loss: 1.8298 - accuracy: 0.45
90 - val_loss: 1.7473 - val_accuracy: 0.4689
Epoch 7/30
190/190 [==============================] - 11s 57ms/step - loss: 1.8123 - accuracy: 0.46
56 - val_loss: 1.7426 - val_accuracy: 0.4730
Epoch 8/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7900 - accuracy: 0.46
90 - val_loss: 1.7332 - val_accuracy: 0.4711
Epoch 9/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7726 - accuracy: 0.47
27 - val_loss: 1.7261 - val_accuracy: 0.4748
Epoch 10/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7582 - accuracy: 0.47
67 - val_loss: 1.7153 - val_accuracy: 0.4737
Epoch 11/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7449 - accuracy: 0.48
02 - val_loss: 1.7160 - val_accuracy: 0.4737
Epoch 12/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7327 - accuracy: 0.48
```

```
05 - val_loss: 1.7082 - val_accuracy: 0.4733
Epoch 13/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7204 - accuracy: 0.48
59 - val_loss: 1.7174 - val_accuracy: 0.4807
Epoch 14/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7086 - accuracy: 0.48
79 - val_loss: 1.7040 - val_accuracy: 0.4811
Epoch 15/30
190/190 [==============================] - 11s 58ms/step - loss: 1.6982 - accuracy: 0.48
99 - val_loss: 1.7085 - val_accuracy: 0.4826
Epoch 16/30
190/190 [==============================] - 11s 58ms/step - loss: 1.6867 - accuracy: 0.49
28 - val_loss: 1.7160 - val_accuracy: 0.4819
Epoch 17/30
190/190 [==============================] - 11s 58ms/step - loss: 1.6732 - accuracy: 0.49
63 - val_loss: 1.7111 - val_accuracy: 0.4815
```

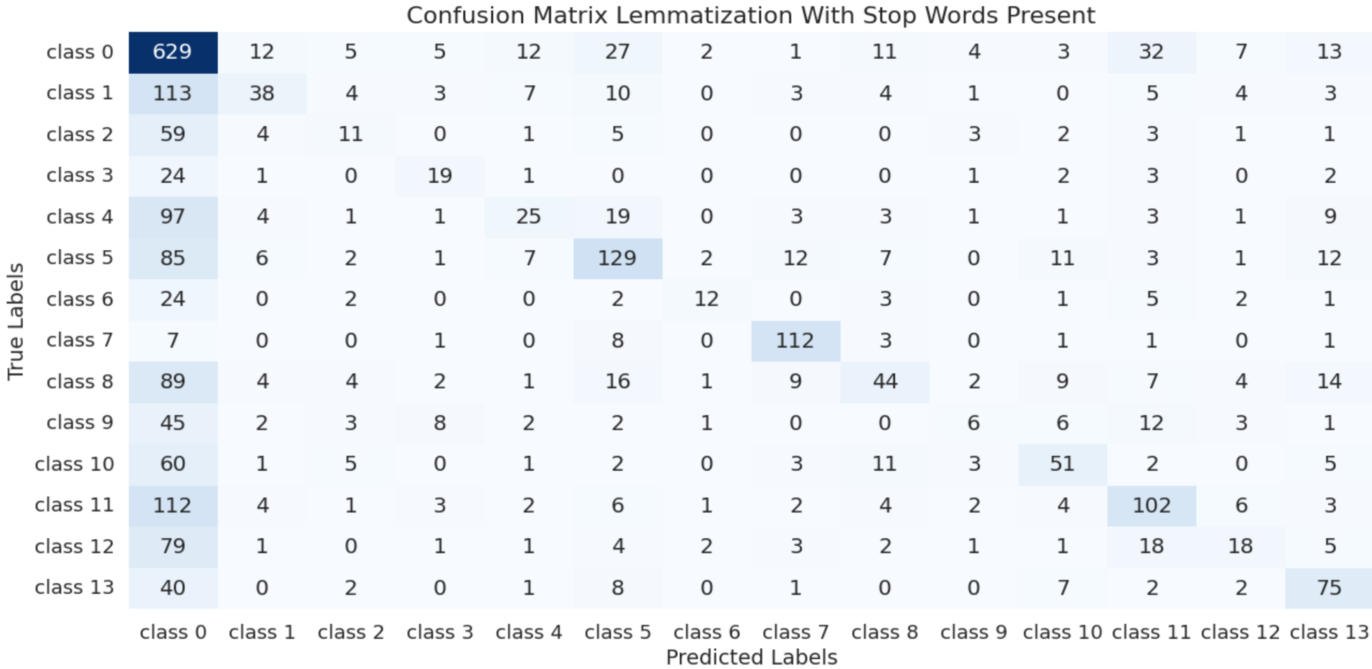
In [28]:

```
gru_y_pred = gru_model.predict(X_test)
gru_y_pred_labels = np.argmax(gru_y_pred, axis=1)
gru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(gru_y_test_labels, gru_y_pred_labels))
```

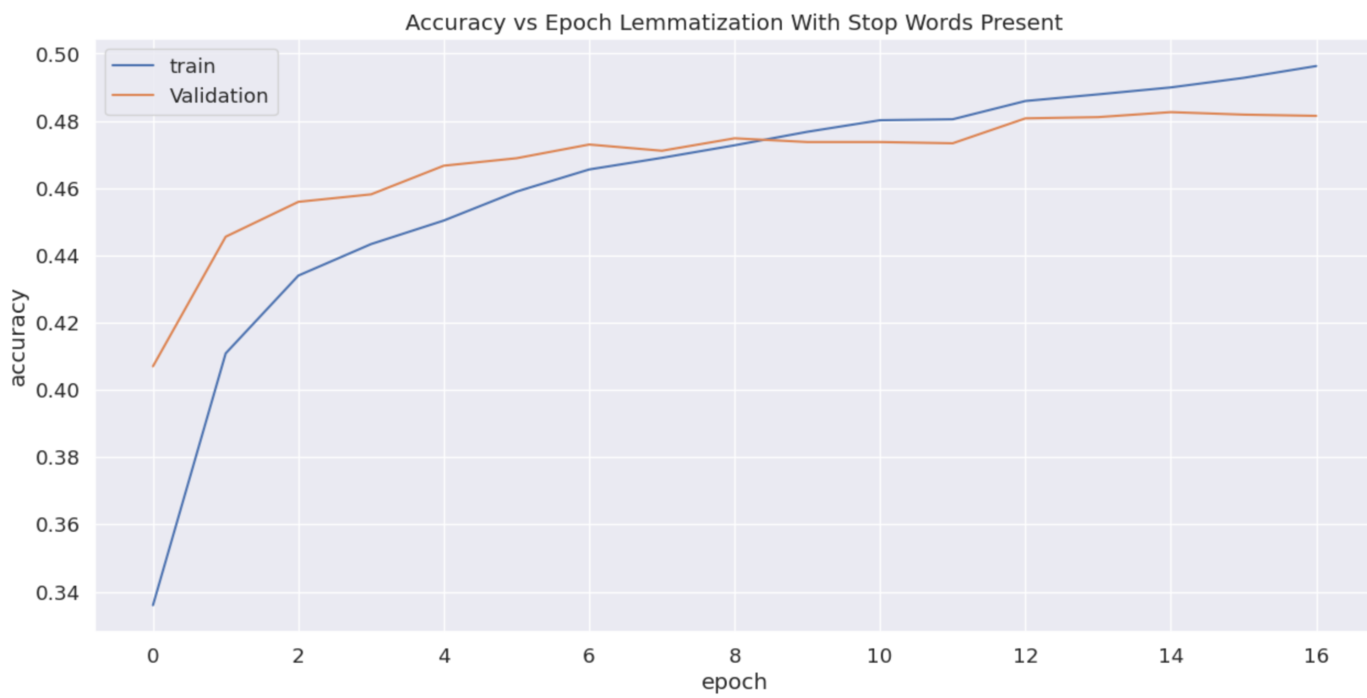
```
85/85 [==============================] - 2s 13ms/step
              precision    recall  f1-score   support

           0       0.43      0.82      0.57       763
           1       0.49      0.19      0.28       195
           2       0.28      0.12      0.17        90
           3       0.43      0.36      0.39        53
           4       0.41      0.15      0.22       168
           5       0.54      0.46      0.50       278
           6       0.57      0.23      0.33        52
           7       0.75      0.84      0.79       134
           8       0.48      0.21      0.30       206
           9       0.25      0.07      0.10        91
          10       0.52      0.35      0.42       144
          11       0.52      0.40      0.45       252
          12       0.37      0.13      0.19       136
          13       0.52      0.54      0.53       138

    accuracy                           0.47      2700
   macro avg       0.47      0.35      0.37      2700
weighted avg       0.47      0.47      0.43      2700
```

In [29]:

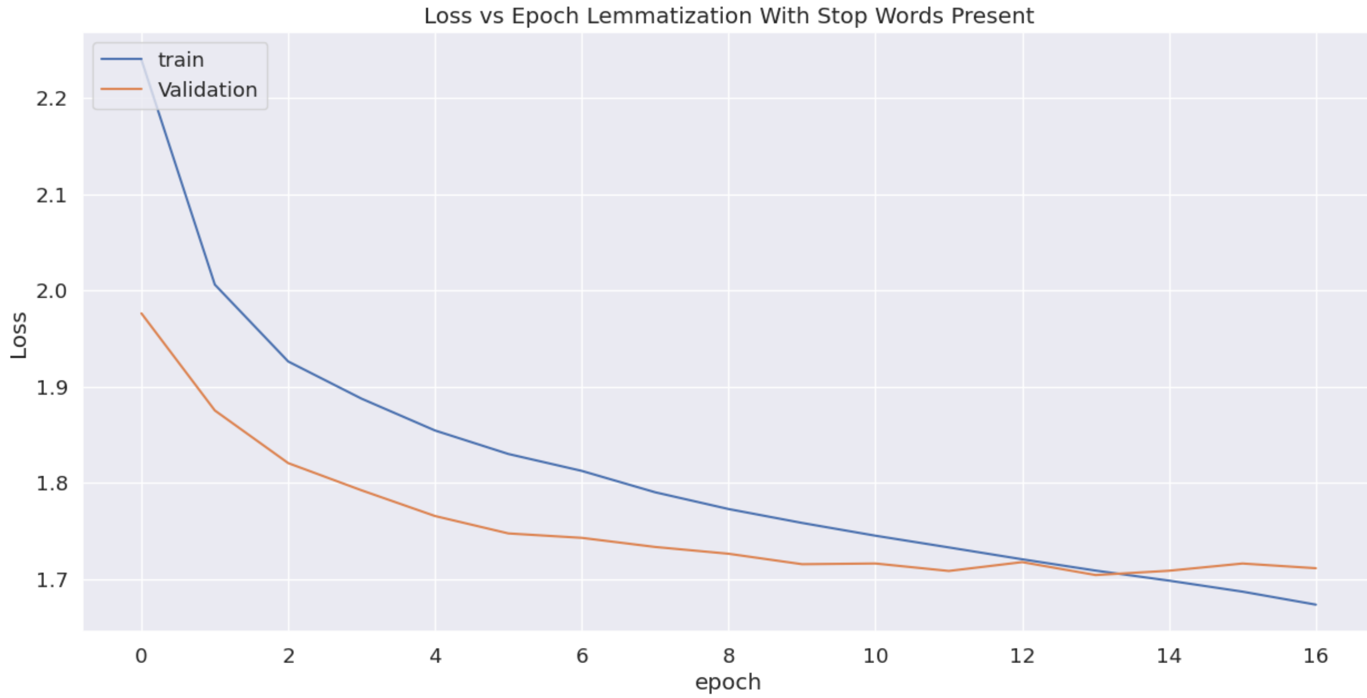
```
conf_mat_gru = confusion_matrix(gru_y_test_labels, gru_y_pred_labels)
plt.figure(figsize=(15,7))
# create a heatmap of the confusion matrix
sns.set(font_scale=1.2)
sns.heatmap(conf_mat_gru, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5
                         'class 6', 'class 7', 'class 8', 'class 9', 'class 10',
                         'class 11', 'class 12', 'class 13'],
            yticklabels=['class 0', 'class 1', 'class 2', 'class 3', 'class 4', 'class 5
                         'class 6', 'class 7', 'class 8', 'class 9', 'class 10',
                         'class 11', 'class 12', 'class 13'])
plt.xlabel('Predicted Labels', fontsize=14)
plt.ylabel('True Labels', fontsize=14)
plt.title('Confusion Matrix Lemmatization With Stop Words Present', fontsize=16)
plt.show()
```



In [31]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epoch Lemmatization With Stop Words Present')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [32]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epoch Lemmatization With Stop Words Present')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```


Loss vs Epoch Lemmatization With Stop Words Present
train
Validation
Loss
2.2
2.1
2.0
1.9
1.8
1.7
0
2
4
6
8
10
12
14
16
epoch