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
stop_words = set(stopwords.words("english"))
lemmatizer= WordNetLemmatizer()
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  #Ac
#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')
```

Data Preprocessing

In [3]:
```python
def lemmatization(text):
    lemmatizer= WordNetLemmatizer()

    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(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
```

In [4]:

```
df = clean(df)
```

In [5]:

```
X= df.text
y= df.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.4, random_state=
X_val,X_test,y_val,y_test= train_test_split(X_other,y_other,test_size=0.5,random_state=7
#60/20/20 split used
```

In [6]:

```
X_train.head()
```

Out[6]:

```
31795                  there's lot u lady here unfortunately 😔
6383                     i surprised see name towing line show
20664                  name worse he's thing plus took boi name
23929     probably would tell worry much wait bit try fe...
6505                                            you nailed it
Name: text, dtype: object
```

In [7]:

```
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)
```

In [8]:

```
# Tokenize words
tokenizer = Tokenizer(oov_token='UNK')
```

```
tokenizer.fit_on_texts(X_train)
#tokenizer.fit_on_texts(pd.concat([X_train], axis=0))
```

In [9]:
```
X_train
```

Out[9]:
```
31795              there’s lot u lady here unfortunately 😔
6383                 i surprised see name towing line show
20664             name worse he’s thing plus took boi name
23929    probably would tell worry much wait bit try fe...
6505                                          you nailed it
                               ...
21563    how supposed get link first place site trustwo...
25916                                          ooo i go far
44824             at job i can do get laid lot second one
21618                               what word i m confused
23886              honestly that’s wife material get that
Name: text, Length: 32396, dtype: object
```

In [10]:
```
sequences_train = tokenizer.texts_to_sequences(X_train)
sequences_test = tokenizer.texts_to_sequences(X_test)
sequences_val = tokenizer.texts_to_sequences(X_val)
```

In [11]:
```
max_len = max([len(t) for t in X_train])
max_len
```

Out[11]:
```
155
```

In [12]:
```
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
print(f"Vocabulary size = {vocabSize}")
```

```
Vocabulary size = 20642
```

In [13]:
```
np.unique(X_train)
```

Out[13]:
```
array([    0,      2,      3, ..., 20639, 20640, 20641], dtype=int32)
```

Text Representation Using Glove Embedding

In [14]:
```
path_to_glove_file = 'glove.6B.300d.txt'
num_tokens = vocabSize
embedding_dim = 300
embeddings_index = {}
misses=0
hits=0
```

In [15]:
```
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))
```

```
Found 8074 word vectors.
Converted 5106 words (15535 misses)
```

In [16]:
```
X_train.shape
```

Out[16]:
```
(32396, 155)
```

In [17]:
```
y_train.shape
```

Out[17]:
```
(32396, 14)
```

In [18]:
```
#use early stopping to control overfitting
callback = EarlyStopping(
    monitor="val_loss",
    patience=3,
    restore_best_weights=True,
)
```

Simple RNN

In [19]:
```
rnn_model = Sequential()
rnn_model.add(Embedding(vocabSize, 300, input_length=X_train.shape[1], weights=[embeddin
rnn_model.add(SimpleRNN(units=64, return_sequences=True))
rnn_model.add(Dropout(0.5))
rnn_model.add(SimpleRNN(units=32))
rnn_model.add(Dropout(0.5))
rnn_model.add(Dense(14, activation='softmax'))
rnn_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)        (None, 155, 300)          6192600

 simple_rnn (SimpleRNN)       (None, 155, 64)           23360

 dropout (Dropout)            (None, 155, 64)           0

 simple_rnn_1 (SimpleRNN)     (None, 32)                3104

 dropout_1 (Dropout)          (None, 32)                0

 dense (Dense)                (None, 14)                462

=================================================================
Total params: 6,219,526
Trainable params: 26,926
Non-trainable params: 6,192,600
_________________________________________________________________
```

In [20]:
```
rnn_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accuracy
```

In [21]:
```
# Fit model
history_rnn=rnn_model.fit(X_train,
            y_train,
            validation_data=(X_val, y_val),
```

```python
                verbose=1,
                batch_size=256,
                epochs=30,
                callbacks=[callback]
        )
```

```
Epoch 1/30
127/127 [==============================] - 49s 306ms/step - loss: 2.6291 - accuracy: 0.2
060 - val_loss: 2.2951 - val_accuracy: 0.2997
Epoch 2/30
127/127 [==============================] - 40s 315ms/step - loss: 2.3864 - accuracy: 0.2
828 - val_loss: 2.1779 - val_accuracy: 0.3385
Epoch 3/30
127/127 [==============================] - 39s 304ms/step - loss: 2.2217 - accuracy: 0.3
418 - val_loss: 2.0948 - val_accuracy: 0.3589
Epoch 4/30
127/127 [==============================] - 38s 299ms/step - loss: 2.1477 - accuracy: 0.3
633 - val_loss: 2.0946 - val_accuracy: 0.3596
Epoch 5/30
127/127 [==============================] - 39s 309ms/step - loss: 2.1129 - accuracy: 0.3
725 - val_loss: 2.0740 - val_accuracy: 0.3717
Epoch 6/30
127/127 [==============================] - 39s 305ms/step - loss: 2.0665 - accuracy: 0.3
860 - val_loss: 2.0155 - val_accuracy: 0.3946
Epoch 7/30
127/127 [==============================] - 38s 299ms/step - loss: 2.0528 - accuracy: 0.3
939 - val_loss: 1.9979 - val_accuracy: 0.4032
Epoch 8/30
127/127 [==============================] - 38s 301ms/step - loss: 2.0210 - accuracy: 0.4
030 - val_loss: 1.9862 - val_accuracy: 0.4084
Epoch 9/30
127/127 [==============================] - 38s 299ms/step - loss: 1.9980 - accuracy: 0.4
148 - val_loss: 1.9640 - val_accuracy: 0.4124
Epoch 10/30
127/127 [==============================] - 38s 302ms/step - loss: 1.9859 - accuracy: 0.4
146 - val_loss: 1.9599 - val_accuracy: 0.4156
Epoch 11/30
127/127 [==============================] - 40s 312ms/step - loss: 1.9712 - accuracy: 0.4
201 - val_loss: 1.9569 - val_accuracy: 0.4191
Epoch 12/30
127/127 [==============================] - 39s 309ms/step - loss: 1.9637 - accuracy: 0.4
239 - val_loss: 1.9496 - val_accuracy: 0.4160
Epoch 13/30
127/127 [==============================] - 40s 319ms/step - loss: 1.9584 - accuracy: 0.4
250 - val_loss: 1.9402 - val_accuracy: 0.4194
Epoch 14/30
127/127 [==============================] - 40s 317ms/step - loss: 2.1714 - accuracy: 0.3
585 - val_loss: 2.5909 - val_accuracy: 0.1667
Epoch 15/30
127/127 [==============================] - 38s 301ms/step - loss: 2.1547 - accuracy: 0.3
527 - val_loss: 2.0482 - val_accuracy: 0.3835
Epoch 16/30
127/127 [==============================] - 39s 310ms/step - loss: 2.0694 - accuracy: 0.3
870 - val_loss: 2.0175 - val_accuracy: 0.3926
```

In [22]:

```python
rnn_y_pred = rnn_model.predict(X_test)
rnn_y_pred_labels = np.argmax(rnn_y_pred, axis=1)
rnn_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(rnn_y_test_labels, rnn_y_pred_labels))
```

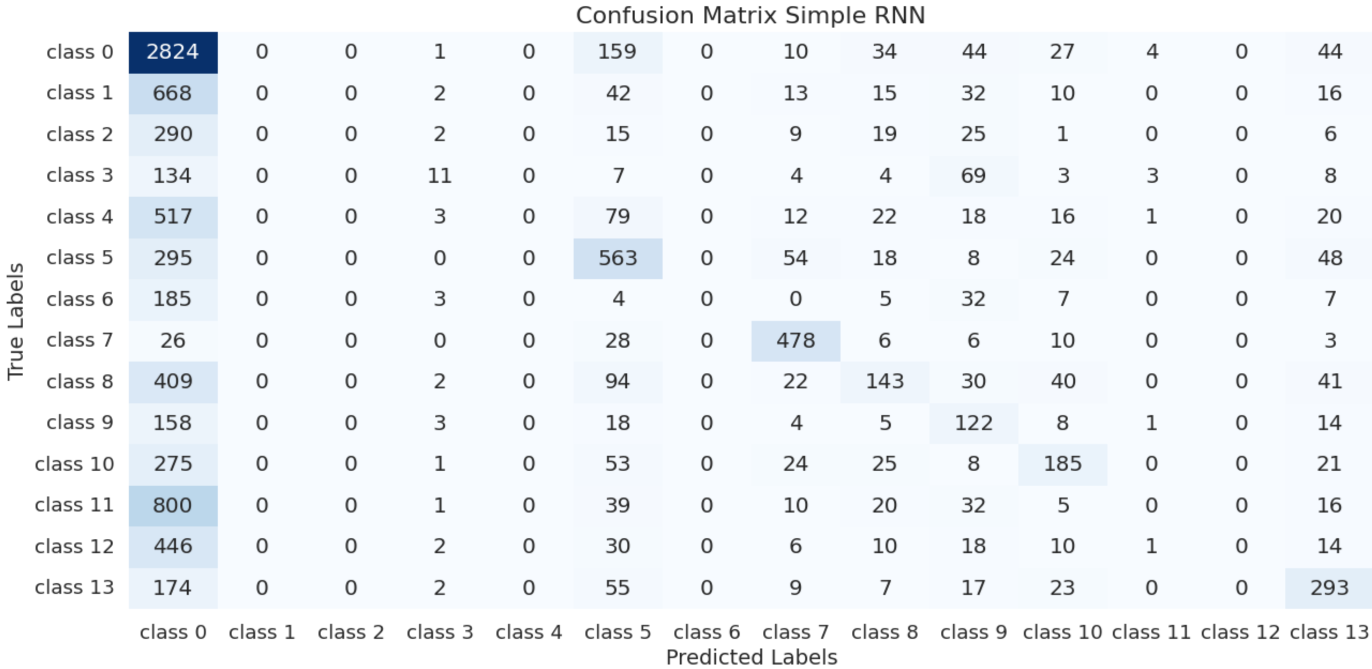
```
338/338 [==============================] - 10s 28ms/step
              precision    recall  f1-score   support

           0       0.39      0.90      0.55      3147
           1       0.00      0.00      0.00       798
           2       0.00      0.00      0.00       367
```

```
           3       0.33      0.05      0.08       243
           4       0.00      0.00      0.00       688
           5       0.47      0.56      0.51      1010
           6       0.00      0.00      0.00       243
           7       0.73      0.86      0.79       557
           8       0.43      0.18      0.26       781
           9       0.26      0.37      0.31       333
          10       0.50      0.31      0.39       592
          11       0.00      0.00      0.00       923
          12       0.00      0.00      0.00       537
          13       0.53      0.51      0.52       580

    accuracy                           0.43     10799
   macro avg       0.26      0.27      0.24     10799
weighted avg       0.30      0.43      0.33     10799
```

```
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: Undefine
dMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels wit
h no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: Undefine
dMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels wit
h no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.9/dist-packages/sklearn/metrics/_classification.py:1344: Undefine
dMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels wit
h no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

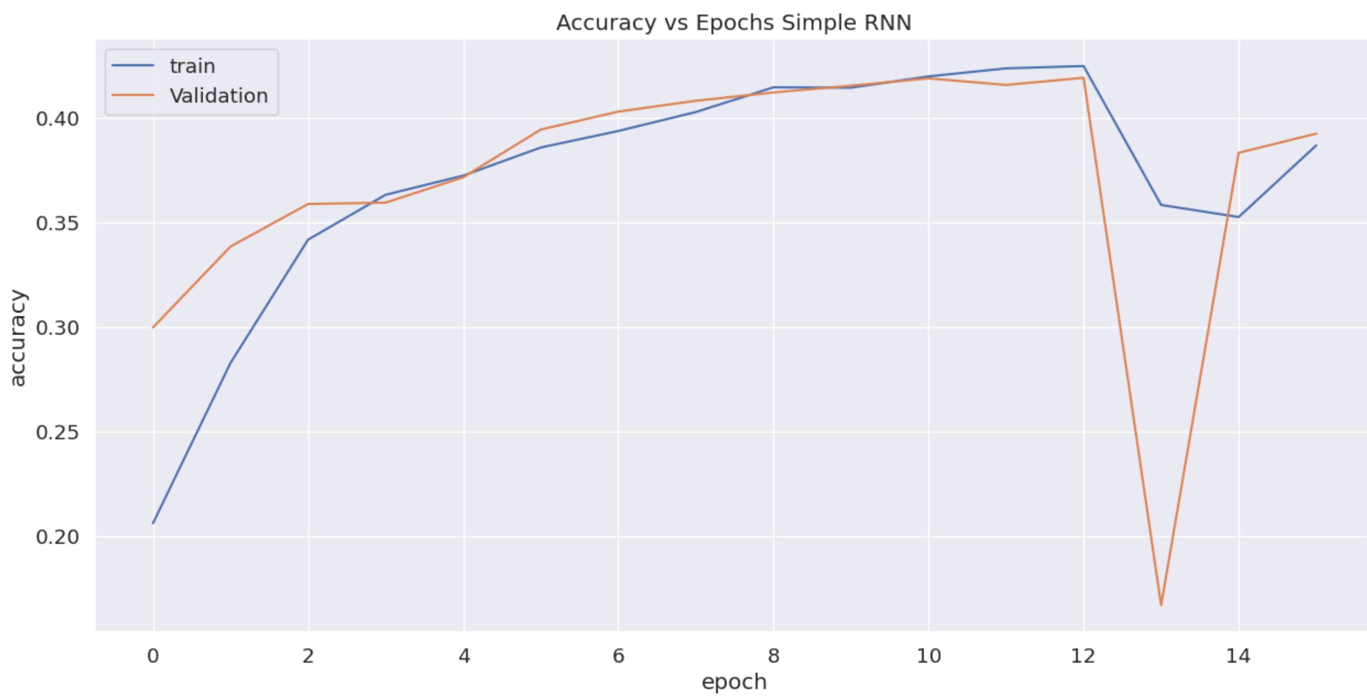
In [23]:

```
conf_mat_rnn = confusion_matrix(rnn_y_test_labels, rnn_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_rnn, 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 Simple RNN', fontsize=16)
plt.show()
```



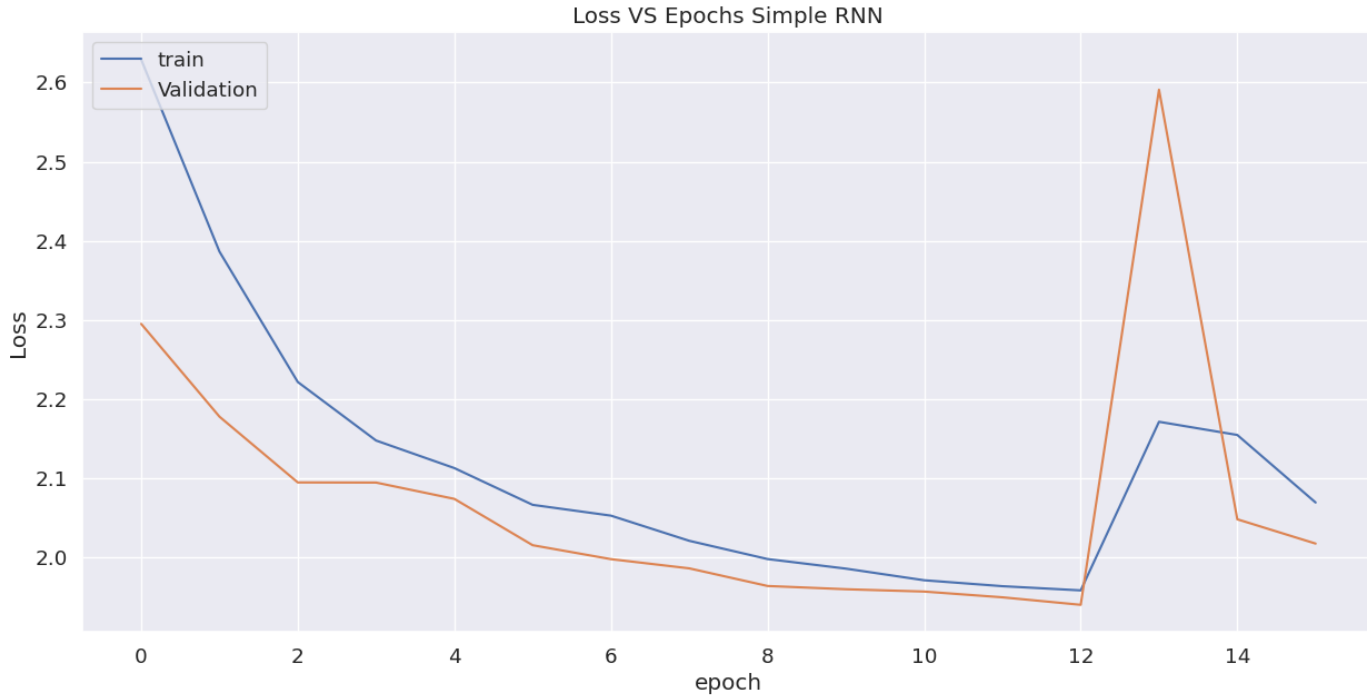
In [24]:

```python
plt.figure(figsize=(15,7))
plt.plot(history_rnn.history['accuracy'])
plt.plot(history_rnn.history['val_accuracy'])
plt.title('Accuracy vs Epochs Simple RNN')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [25]:

```python
plt.figure(figsize=(15,7))
plt.plot(history_rnn.history['loss'])
plt.plot(history_rnn.history['val_loss'])
plt.title('Loss VS Epochs Simple RNN')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



LSTM MODEL

In [26]:
```
lstm_model = Sequential()
lstm_model.add(Embedding(vocabSize, 300, input_length=X_train.shape[1], weights=[embeddi
lstm_model.add(LSTM(units=64, return_sequences=True))
lstm_model.add(Dropout(0.5))
lstm_model.add(LSTM(units=32))
lstm_model.add(Dropout(0.5))
lstm_model.add(Dense(14, activation='softmax'))
lstm_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)      (None, 155, 300)          6192600

 lstm (LSTM)                  (None, 155, 64)           93440

 dropout_2 (Dropout)          (None, 155, 64)           0

 lstm_1 (LSTM)                (None, 32)                12416

 dropout_3 (Dropout)          (None, 32)                0

 dense_1 (Dense)              (None, 14)                462

=================================================================
Total params: 6,298,918
Trainable params: 106,318
Non-trainable params: 6,192,600
_________________________________________________________________
```

In [27]:
```
lstm_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accurac
```

In [28]:
```
# Fit model
history_lstm=lstm_model.fit(X_train,
            y_train,
            validation_data=(X_val, y_val),
            verbose=1,
```

```
                batch_size=256,
                epochs=30,
                callbacks=[callback]
        )
```

```
Epoch 1/30
127/127 [==============================] - 9s 31ms/step - loss: 2.3150 - accuracy: 0.309
1 - val_loss: 2.1228 - val_accuracy: 0.3640
Epoch 2/30
127/127 [==============================] - 3s 24ms/step - loss: 2.0699 - accuracy: 0.393
3 - val_loss: 1.9659 - val_accuracy: 0.4116
Epoch 3/30
127/127 [==============================] - 3s 24ms/step - loss: 1.9727 - accuracy: 0.422
8 - val_loss: 1.9121 - val_accuracy: 0.4241
Epoch 4/30
127/127 [==============================] - 3s 22ms/step - loss: 1.9249 - accuracy: 0.434
3 - val_loss: 1.8773 - val_accuracy: 0.4299
Epoch 5/30
127/127 [==============================] - 3s 24ms/step - loss: 1.8906 - accuracy: 0.443
9 - val_loss: 1.8493 - val_accuracy: 0.4415
Epoch 6/30
127/127 [==============================] - 3s 24ms/step - loss: 1.8615 - accuracy: 0.450
7 - val_loss: 1.8398 - val_accuracy: 0.4420
Epoch 7/30
127/127 [==============================] - 3s 25ms/step - loss: 1.8404 - accuracy: 0.454
2 - val_loss: 1.8177 - val_accuracy: 0.4503
Epoch 8/30
127/127 [==============================] - 3s 22ms/step - loss: 1.8192 - accuracy: 0.458
5 - val_loss: 1.8074 - val_accuracy: 0.4525
Epoch 9/30
127/127 [==============================] - 3s 24ms/step - loss: 1.7998 - accuracy: 0.465
8 - val_loss: 1.7956 - val_accuracy: 0.4574
Epoch 10/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7881 - accuracy: 0.468
1 - val_loss: 1.8050 - val_accuracy: 0.4541
Epoch 11/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7740 - accuracy: 0.470
9 - val_loss: 1.7804 - val_accuracy: 0.4617
Epoch 12/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7537 - accuracy: 0.476
7 - val_loss: 1.7804 - val_accuracy: 0.4638
Epoch 13/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7424 - accuracy: 0.479
3 - val_loss: 1.7813 - val_accuracy: 0.4630
Epoch 14/30
127/127 [==============================] - 3s 24ms/step - loss: 1.7239 - accuracy: 0.486
6 - val_loss: 1.7776 - val_accuracy: 0.4641
Epoch 15/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7140 - accuracy: 0.485
9 - val_loss: 1.7715 - val_accuracy: 0.4639
Epoch 16/30
127/127 [==============================] - 3s 22ms/step - loss: 1.6969 - accuracy: 0.488
9 - val_loss: 1.7796 - val_accuracy: 0.4630
Epoch 17/30
127/127 [==============================] - 3s 22ms/step - loss: 1.6865 - accuracy: 0.493
5 - val_loss: 1.7780 - val_accuracy: 0.4617
Epoch 18/30
127/127 [==============================] - 3s 24ms/step - loss: 1.6736 - accuracy: 0.499
0 - val_loss: 1.7856 - val_accuracy: 0.4619
```

In [29]:

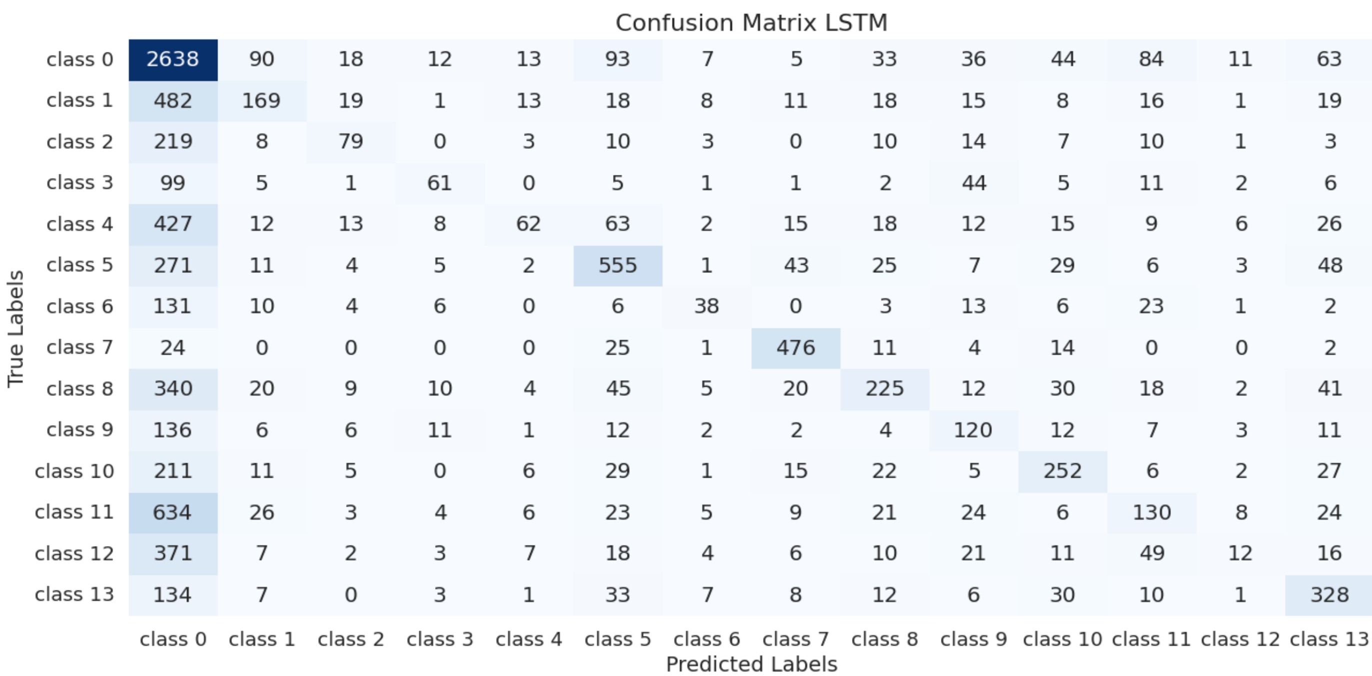
```
lstm_y_pred = lstm_model.predict(X_test)
lstm_y_pred_labels = np.argmax(lstm_y_pred, axis=1)
lstm_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(lstm_y_test_labels, lstm_y_pred_labels))
```

```
338/338 [==============================] - 3s 6ms/step
```

```
              precision    recall  f1-score   support

           0       0.43      0.84      0.57      3147
           1       0.44      0.21      0.29       798
           2       0.48      0.22      0.30       367
           3       0.49      0.25      0.33       243
           4       0.53      0.09      0.15       688
           5       0.59      0.55      0.57      1010
           6       0.45      0.16      0.23       243
           7       0.78      0.85      0.82       557
           8       0.54      0.29      0.38       781
           9       0.36      0.36      0.36       333
          10       0.54      0.43      0.48       592
          11       0.34      0.14      0.20       923
          12       0.23      0.02      0.04       537
          13       0.53      0.57      0.55       580

    accuracy                           0.48     10799
   macro avg       0.48      0.35      0.38     10799
weighted avg       0.47      0.48      0.43     10799
```

In [30]:

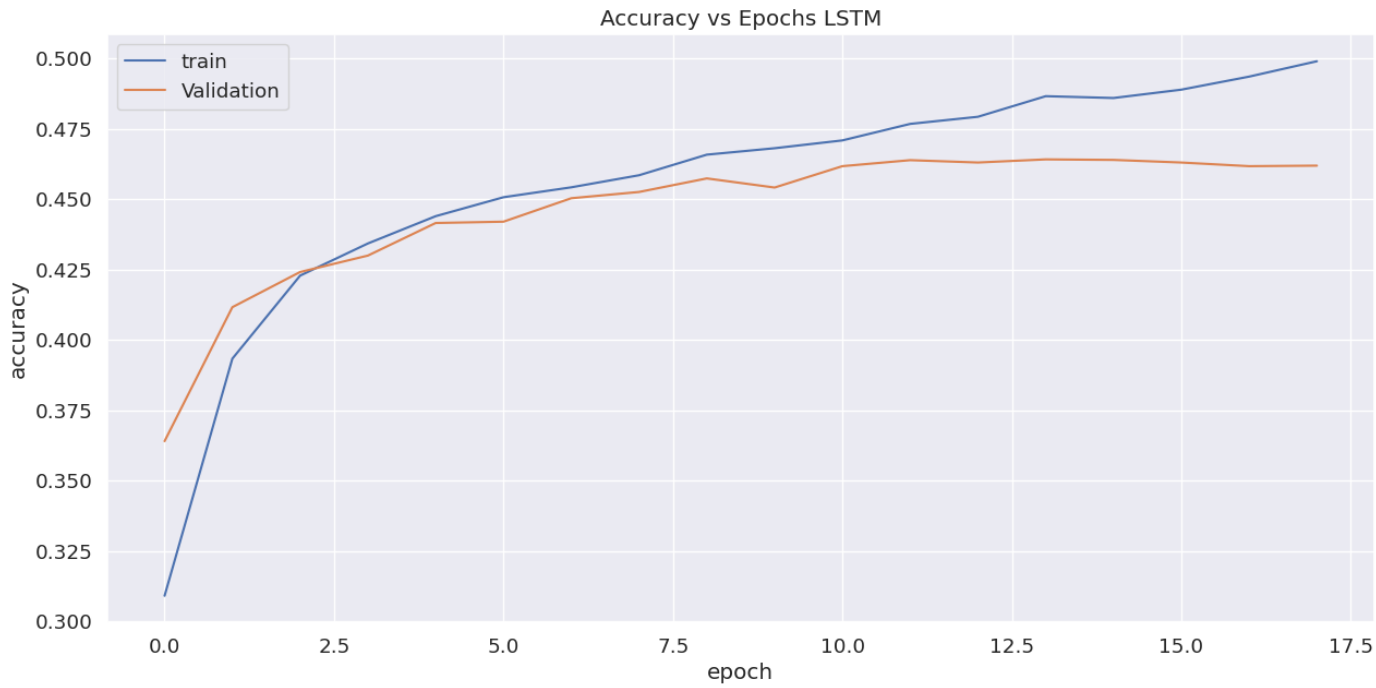
```python
conf_mat_lstm = confusion_matrix(lstm_y_test_labels, lstm_y_pred_labels)
plt.figure(figsize=(15,7))
# create a heatmap of the confusion matrix
sns.set(font_scale=1.2)
sns.heatmap(conf_mat_lstm, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['class 0', 'class 1', 'class 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 LSTM', fontsize=16)
plt.show()
```



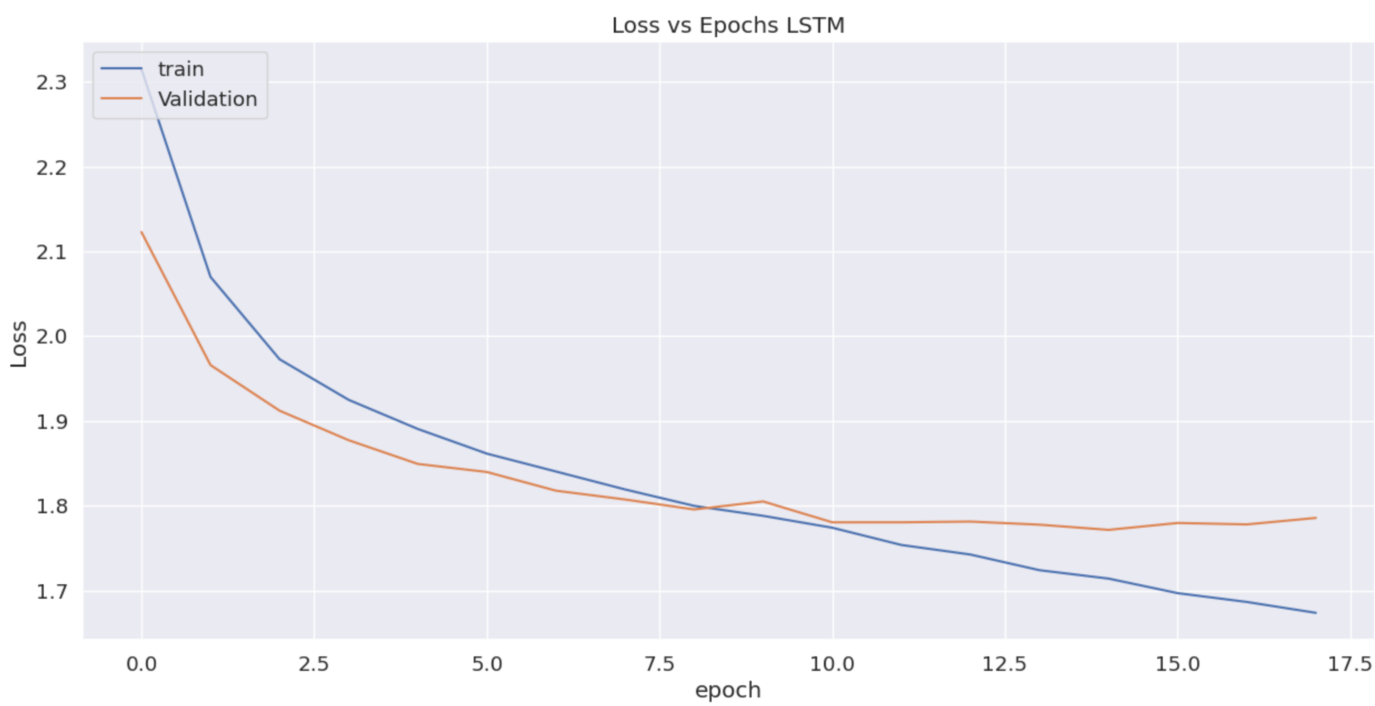
In [31]:

```python
plt.figure(figsize=(15,7))
plt.plot(history_lstm.history['accuracy'])
plt.plot(history_lstm.history['val_accuracy'])
plt.title('Accuracy vs Epochs LSTM')
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_lstm.history['loss'])
plt.plot(history_lstm.history['val_loss'])
plt.title('Loss vs Epochs LSTM')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



Gated Recurrent Unit (GRU)

In [33]:
```
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, 155, 300)          6192600

 gru (GRU)                   (None, 155, 64)           70272

 dropout_4 (Dropout)         (None, 155, 64)           0

 gru_1 (GRU)                 (None, 32)                9408

 dropout_5 (Dropout)         (None, 32)                0

 dense_2 (Dense)             (None, 14)                462

=================================================================
Total params: 6,272,742
Trainable params: 80,142
Non-trainable params: 6,192,600
_________________________________________________________________
```

In [34]:
```
gru_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accuracy
```

In [35]:
```
# 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
127/127 [==============================] - 7s 27ms/step - loss: 2.2912 - accuracy: 0.323
8 - val_loss: 2.0435 - val_accuracy: 0.3900
Epoch 2/30
127/127 [==============================] - 3s 24ms/step - loss: 2.0358 - accuracy: 0.403
0 - val_loss: 1.9425 - val_accuracy: 0.4211
Epoch 3/30
127/127 [==============================] - 3s 23ms/step - loss: 1.9559 - accuracy: 0.426
4 - val_loss: 1.8913 - val_accuracy: 0.4349
Epoch 4/30
127/127 [==============================] - 3s 21ms/step - loss: 1.9136 - accuracy: 0.441
4 - val_loss: 1.8558 - val_accuracy: 0.4448
Epoch 5/30
127/127 [==============================] - 3s 21ms/step - loss: 1.8843 - accuracy: 0.448
1 - val_loss: 1.8324 - val_accuracy: 0.4526
Epoch 6/30
127/127 [==============================] - 3s 23ms/step - loss: 1.8520 - accuracy: 0.452
3 - val_loss: 1.8050 - val_accuracy: 0.4554
Epoch 7/30
127/127 [==============================] - 3s 21ms/step - loss: 1.8272 - accuracy: 0.459
1 - val_loss: 1.7996 - val_accuracy: 0.4567
Epoch 8/30
127/127 [==============================] - 3s 23ms/step - loss: 1.8118 - accuracy: 0.463
1 - val_loss: 1.7818 - val_accuracy: 0.4618
Epoch 9/30
127/127 [==============================] - 3s 21ms/step - loss: 1.7986 - accuracy: 0.467
```

```
3 - val_loss: 1.7753 - val_accuracy: 0.4624
Epoch 10/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7790 - accuracy: 0.472
1 - val_loss: 1.7660 - val_accuracy: 0.4687
Epoch 11/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7682 - accuracy: 0.475
1 - val_loss: 1.7601 - val_accuracy: 0.4698
Epoch 12/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7499 - accuracy: 0.479
9 - val_loss: 1.7649 - val_accuracy: 0.4664
Epoch 13/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7412 - accuracy: 0.481
6 - val_loss: 1.7620 - val_accuracy: 0.4669
Epoch 14/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7237 - accuracy: 0.485
2 - val_loss: 1.7526 - val_accuracy: 0.4696
Epoch 15/30
127/127 [==============================] - 3s 24ms/step - loss: 1.7153 - accuracy: 0.486
9 - val_loss: 1.7490 - val_accuracy: 0.4729
Epoch 16/30
127/127 [==============================] - 3s 21ms/step - loss: 1.7050 - accuracy: 0.488
0 - val_loss: 1.7485 - val_accuracy: 0.4746
Epoch 17/30
127/127 [==============================] - 3s 21ms/step - loss: 1.6905 - accuracy: 0.490
5 - val_loss: 1.7522 - val_accuracy: 0.4708
Epoch 18/30
127/127 [==============================] - 3s 23ms/step - loss: 1.6818 - accuracy: 0.493
8 - val_loss: 1.7602 - val_accuracy: 0.4702
Epoch 19/30
127/127 [==============================] - 3s 24ms/step - loss: 1.6669 - accuracy: 0.497
9 - val_loss: 1.7660 - val_accuracy: 0.4696
```

In [36]:

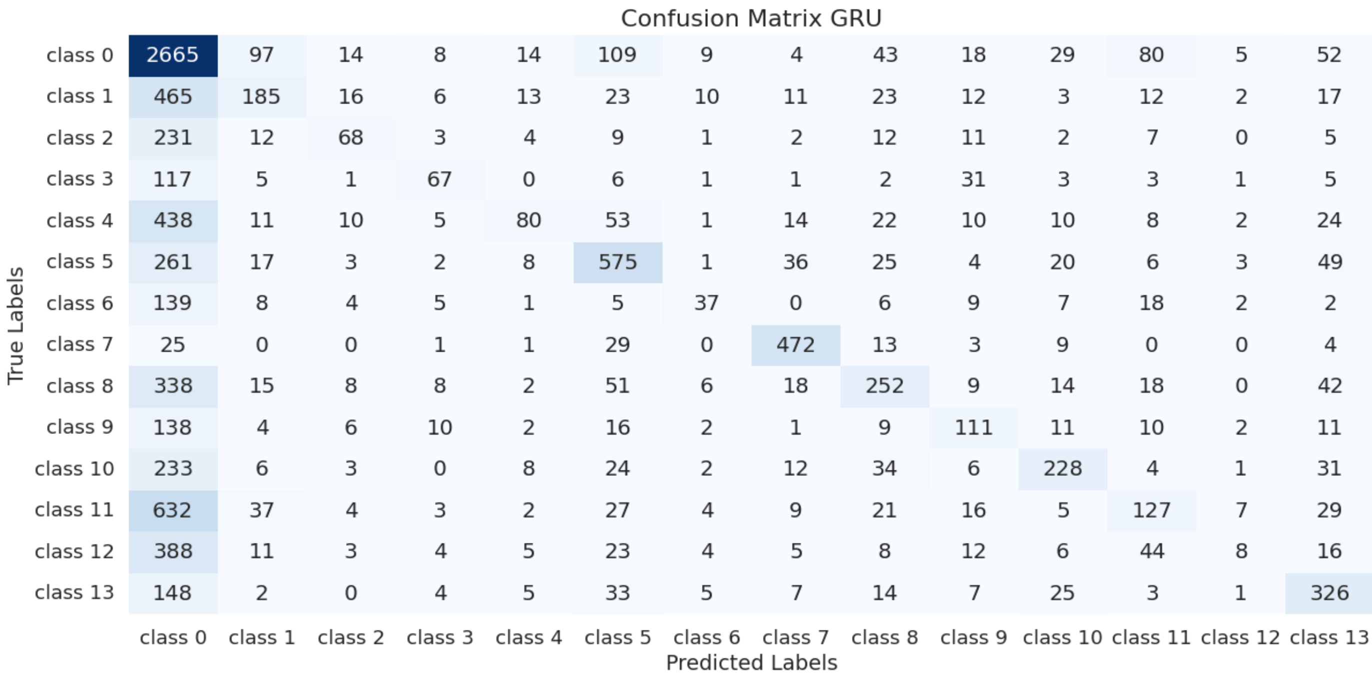
```python
gru_y_pred = gru_model.predict(X_test)
gru_y_pred_labels = np.argmax(gru_y_pred, axis=1)
gru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(gru_y_test_labels, gru_y_pred_labels))
```

```
338/338 [==============================] - 2s 5ms/step
              precision    recall  f1-score   support

           0       0.43      0.85      0.57      3147
           1       0.45      0.23      0.31       798
           2       0.49      0.19      0.27       367
           3       0.53      0.28      0.36       243
           4       0.55      0.12      0.19       688
           5       0.58      0.57      0.58      1010
           6       0.45      0.15      0.23       243
           7       0.80      0.85      0.82       557
           8       0.52      0.32      0.40       781
           9       0.43      0.33      0.38       333
          10       0.61      0.39      0.47       592
          11       0.37      0.14      0.20       923
          12       0.24      0.01      0.03       537
          13       0.53      0.56      0.55       580

    accuracy                           0.48     10799
   macro avg       0.50      0.36      0.38     10799
weighted avg       0.48      0.48      0.43     10799
```

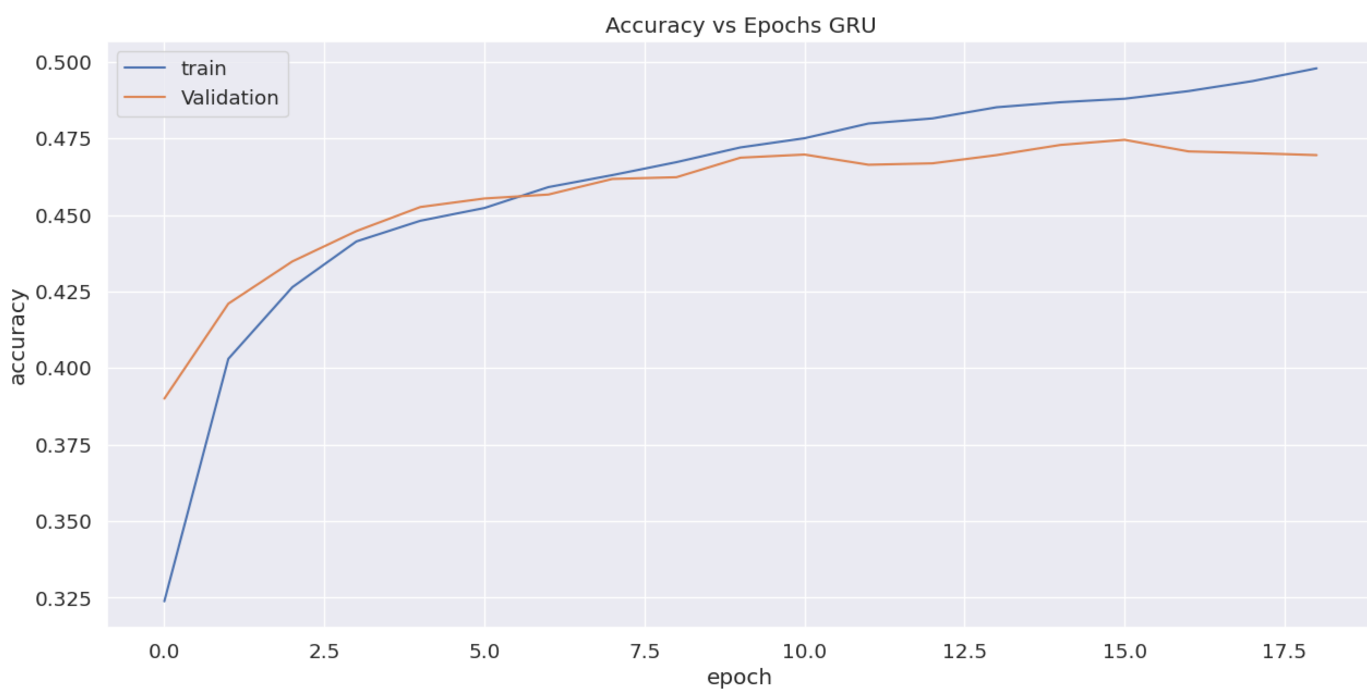
In [37]:

```python
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 GRU', fontsize=16)
plt.show()
```

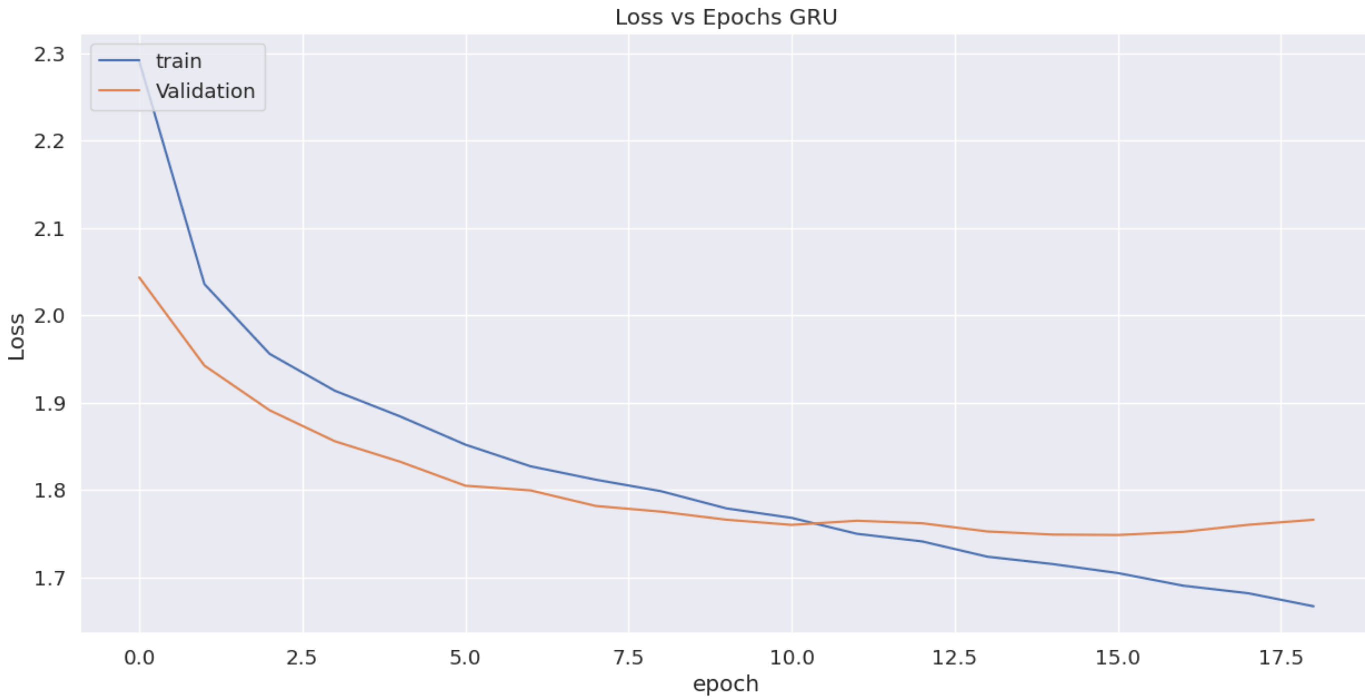


In [38]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs GRU')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [39]:
```
plt.figure(figsize=(15,7))
```

```
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs GRU')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



LSTM With GRU Layers

In [40]:

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

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_3 (Embedding)      (None, 155, 300)          6192600

 lstm_2 (LSTM)                (None, 155, 64)           93440

 dropout_6 (Dropout)          (None, 155, 64)           0

 gru_2 (GRU)                  (None, 32)                9408

 dropout_7 (Dropout)          (None, 32)                0

 dense_3 (Dense)              (None, 14)                462

=================================================================
Total params: 6,295,910
Trainable params: 103,310
Non-trainable params: 6,192,600
_________________________________________________________________
```

In [41]:
```
lstmgru_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accu
```

In [42]:
```
# Fit model
history_lstmgru=lstmgru_model.fit(X_train,
            y_train,
            validation_data=(X_val, y_val),
            verbose=1,
            batch_size=256,
            epochs=30,
            callbacks=[callback]
        )
```

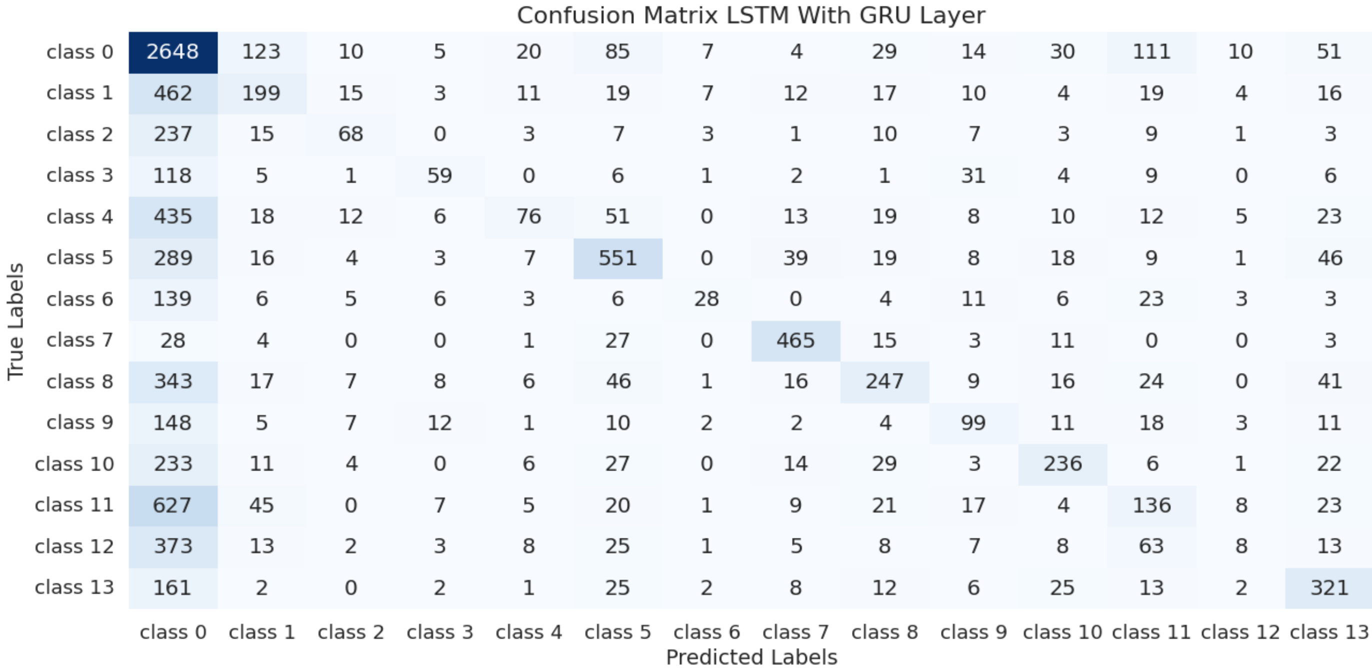
```
Epoch 1/30
127/127 [==============================] - 8s 32ms/step - loss: 2.2739 - accuracy: 0.329
4 - val_loss: 2.0342 - val_accuracy: 0.3887
Epoch 2/30
127/127 [==============================] - 3s 22ms/step - loss: 2.0292 - accuracy: 0.406
1 - val_loss: 1.9280 - val_accuracy: 0.4211
Epoch 3/30
127/127 [==============================] - 3s 25ms/step - loss: 1.9461 - accuracy: 0.428
9 - val_loss: 1.8883 - val_accuracy: 0.4370
Epoch 4/30
127/127 [==============================] - 3s 24ms/step - loss: 1.9063 - accuracy: 0.438
3 - val_loss: 1.8699 - val_accuracy: 0.4399
Epoch 5/30
127/127 [==============================] - 3s 25ms/step - loss: 1.8798 - accuracy: 0.442
0 - val_loss: 1.8395 - val_accuracy: 0.4452
Epoch 6/30
127/127 [==============================] - 3s 25ms/step - loss: 1.8534 - accuracy: 0.452
5 - val_loss: 1.8246 - val_accuracy: 0.4487
Epoch 7/30
127/127 [==============================] - 3s 22ms/step - loss: 1.8298 - accuracy: 0.458
2 - val_loss: 1.8083 - val_accuracy: 0.4518
Epoch 8/30
127/127 [==============================] - 3s 22ms/step - loss: 1.8126 - accuracy: 0.462
4 - val_loss: 1.7992 - val_accuracy: 0.4537
Epoch 9/30
127/127 [==============================] - 3s 25ms/step - loss: 1.7887 - accuracy: 0.465
0 - val_loss: 1.8018 - val_accuracy: 0.4554
Epoch 10/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7739 - accuracy: 0.470
2 - val_loss: 1.7894 - val_accuracy: 0.4546
Epoch 11/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7559 - accuracy: 0.477
2 - val_loss: 1.7914 - val_accuracy: 0.4557
Epoch 12/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7430 - accuracy: 0.478
4 - val_loss: 1.7811 - val_accuracy: 0.4605
Epoch 13/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7289 - accuracy: 0.481
8 - val_loss: 1.7874 - val_accuracy: 0.4608
Epoch 14/30
127/127 [==============================] - 3s 23ms/step - loss: 1.7181 - accuracy: 0.485
8 - val_loss: 1.7799 - val_accuracy: 0.4620
Epoch 15/30
127/127 [==============================] - 3s 22ms/step - loss: 1.7021 - accuracy: 0.488
5 - val_loss: 1.7781 - val_accuracy: 0.4626
Epoch 16/30
127/127 [==============================] - 3s 24ms/step - loss: 1.6842 - accuracy: 0.492
2 - val_loss: 1.7904 - val_accuracy: 0.4618
Epoch 17/30
127/127 [==============================] - 3s 25ms/step - loss: 1.6740 - accuracy: 0.495
8 - val_loss: 1.7796 - val_accuracy: 0.4628
Epoch 18/30
```

```
127/127 [==============================] - 3s 23ms/step - loss: 1.6545 - accuracy: 0.500
8 - val_loss: 1.7882 - val_accuracy: 0.4622
```

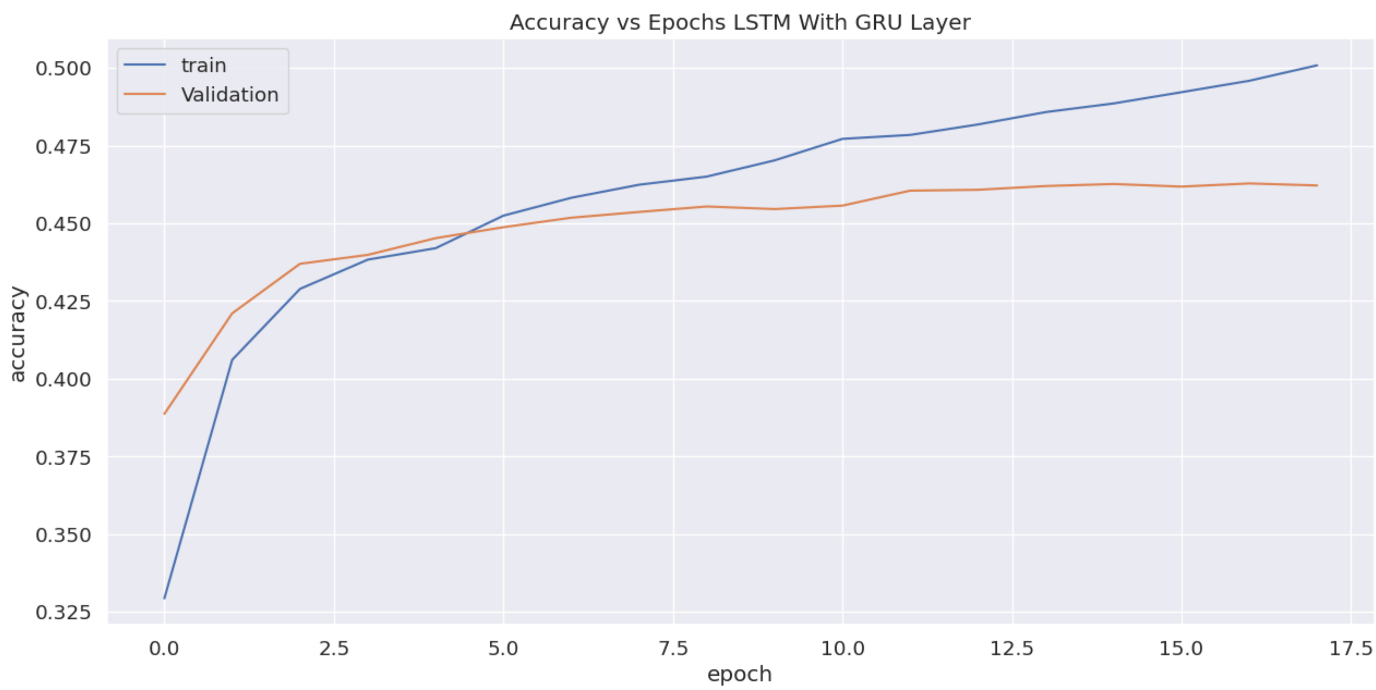
In [43]:
```
lstmgru_y_pred = lstmgru_model.predict(X_test)
lstmgru_y_pred_labels = np.argmax(lstmgru_y_pred, axis=1)
lstmgru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(lstmgru_y_test_labels, lstmgru_y_pred_labels))
```

```
338/338 [==============================] - 2s 5ms/step
              precision    recall  f1-score   support

           0       0.42      0.84      0.56      3147
           1       0.42      0.25      0.31       798
           2       0.50      0.19      0.27       367
           3       0.52      0.24      0.33       243
           4       0.51      0.11      0.18       688
           5       0.61      0.55      0.58      1010
           6       0.53      0.12      0.19       243
           7       0.79      0.83      0.81       557
           8       0.57      0.32      0.41       781
           9       0.42      0.30      0.35       333
          10       0.61      0.40      0.48       592
          11       0.30      0.15      0.20       923
          12       0.17      0.01      0.03       537
          13       0.55      0.55      0.55       580

    accuracy                           0.48     10799
   macro avg       0.50      0.35      0.38     10799
weighted avg       0.48      0.48      0.43     10799
```

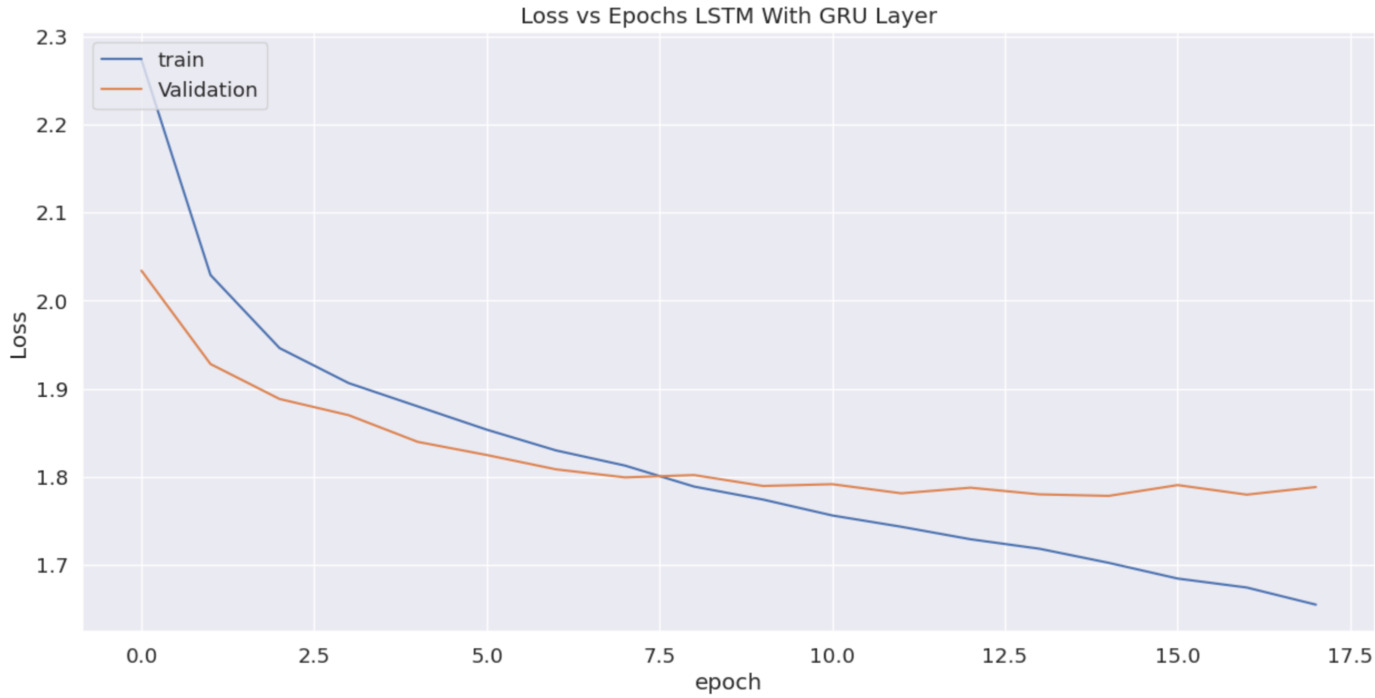
In [44]:
```
conf_mat_lstmgru = confusion_matrix(lstmgru_y_test_labels, lstmgru_y_pred_labels)
plt.figure(figsize=(15,7))
# create a heatmap of the confusion matrix
sns.set(font_scale=1.2)
sns.heatmap(conf_mat_lstmgru, annot=True, fmt='d', cmap='Blues', cbar=False,
            xticklabels=['class 0', '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 LSTM With GRU Layer', fontsize=16)
plt.show()
```



In [45]:
```
plt.figure(figsize=(15,7))
plt.plot(history_lstmgru.history['accuracy'])
plt.plot(history_lstmgru.history['val_accuracy'])
plt.title('Accuracy vs Epochs LSTM With GRU Layer')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [46]:
```
plt.figure(figsize=(15,7))
plt.plot(history_lstmgru.history['loss'])
plt.plot(history_lstmgru.history['val_loss'])
plt.title('Loss vs Epochs LSTM With GRU Layer')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```


Loss vs Epochs LSTM With GRU Layer
train
Validation
Loss
epoch
2.3
2.2
2.1
2.0
1.9
1.8
1.7
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

```
In [46]:
```