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, Embedding, Dropout, GRU #Activation, Flatten,
#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 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()
```

```python
    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]:

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

Out[4]:

	text	labels
0	my favourite food anything i cook myself	1
1	now himself everyone think he laugh screwing p...	1
2	why the fuck is bayless isoing	12
3	to make feel threatened	7
4	dirty southern wanker	12
...	...	...
53989	it s pretty dangerous state decides fictional ...	7
53990	i filed divorce morning hoping move next day so	11
53991	the last time happened i said no closed door	13
53992	i can't stand arrogant prick he's better thenf...	12
53993	but i like baby bang tiny voice	14

53994 rows × 2 columns

1ST SPLIT 90/5/5

In [5]:

```python
X= df.text
```

```
y= df.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 37231 word vectors.
Converted 13684 words (11651 misses)
```

In [7]:
```
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, 531, 300)          7600800

 gru (GRU)                   (None, 531, 64)           70272

 dropout (Dropout)           (None, 531, 64)           0

 gru_1 (GRU)                 (None, 32)                9408

 dropout_1 (Dropout)         (None, 32)                0

 dense (Dense)               (None, 14)                462

=================================================================
Total params: 7,680,942
Trainable params: 80,142
Non-trainable params: 7,600,800
_________________________________________________________________
```

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

In [9]:
```
# 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 60ms/step - loss: 2.2238 - accuracy: 0.33
97 - val_loss: 1.8817 - val_accuracy: 0.4407
Epoch 2/30
190/190 [==============================] - 11s 56ms/step - loss: 1.9140 - accuracy: 0.43
24 - val_loss: 1.7627 - val_accuracy: 0.4830
Epoch 3/30
190/190 [==============================] - 11s 56ms/step - loss: 1.8275 - accuracy: 0.45
91 - val_loss: 1.6942 - val_accuracy: 0.4952
Epoch 4/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7689 - accuracy: 0.47
40 - val_loss: 1.6619 - val_accuracy: 0.5056
Epoch 5/30
190/190 [==============================] - 11s 57ms/step - loss: 1.7325 - accuracy: 0.48
48 - val_loss: 1.6335 - val_accuracy: 0.5104
Epoch 6/30
190/190 [==============================] - 11s 58ms/step - loss: 1.7006 - accuracy: 0.49
27 - val_loss: 1.6126 - val_accuracy: 0.5107
Epoch 7/30
190/190 [==============================] - 11s 58ms/step - loss: 1.6774 - accuracy: 0.49
82 - val_loss: 1.6014 - val_accuracy: 0.5152
Epoch 8/30
190/190 [==============================] - 11s 60ms/step - loss: 1.6532 - accuracy: 0.50
55 - val_loss: 1.5893 - val_accuracy: 0.5207
Epoch 9/30
190/190 [==============================] - 12s 61ms/step - loss: 1.6384 - accuracy: 0.51
```

```
06 - val_loss: 1.5857 - val_accuracy: 0.5222
Epoch 10/30
190/190 [==============================] - 11s 60ms/step - loss: 1.6175 - accuracy: 0.51
65 - val_loss: 1.5754 - val_accuracy: 0.5222
Epoch 11/30
190/190 [==============================] - 11s 58ms/step - loss: 1.6098 - accuracy: 0.51
74 - val_loss: 1.5781 - val_accuracy: 0.5237
Epoch 12/30
190/190 [==============================] - 11s 58ms/step - loss: 1.5930 - accuracy: 0.52
26 - val_loss: 1.5721 - val_accuracy: 0.5189
Epoch 13/30
190/190 [==============================] - 11s 58ms/step - loss: 1.5753 - accuracy: 0.52
58 - val_loss: 1.5781 - val_accuracy: 0.5252
Epoch 14/30
190/190 [==============================] - 11s 58ms/step - loss: 1.5648 - accuracy: 0.52
83 - val_loss: 1.5731 - val_accuracy: 0.5252
Epoch 15/30
190/190 [==============================] - 11s 58ms/step - loss: 1.5533 - accuracy: 0.53
14 - val_loss: 1.5718 - val_accuracy: 0.5215
Epoch 16/30
190/190 [==============================] - 11s 58ms/step - loss: 1.5429 - accuracy: 0.53
41 - val_loss: 1.5792 - val_accuracy: 0.5252
Epoch 17/30
190/190 [==============================] - 11s 59ms/step - loss: 1.5348 - accuracy: 0.53
58 - val_loss: 1.5831 - val_accuracy: 0.5189
Epoch 18/30
190/190 [==============================] - 11s 59ms/step - loss: 1.5180 - accuracy: 0.54
17 - val_loss: 1.5860 - val_accuracy: 0.5248
```

In [10]:

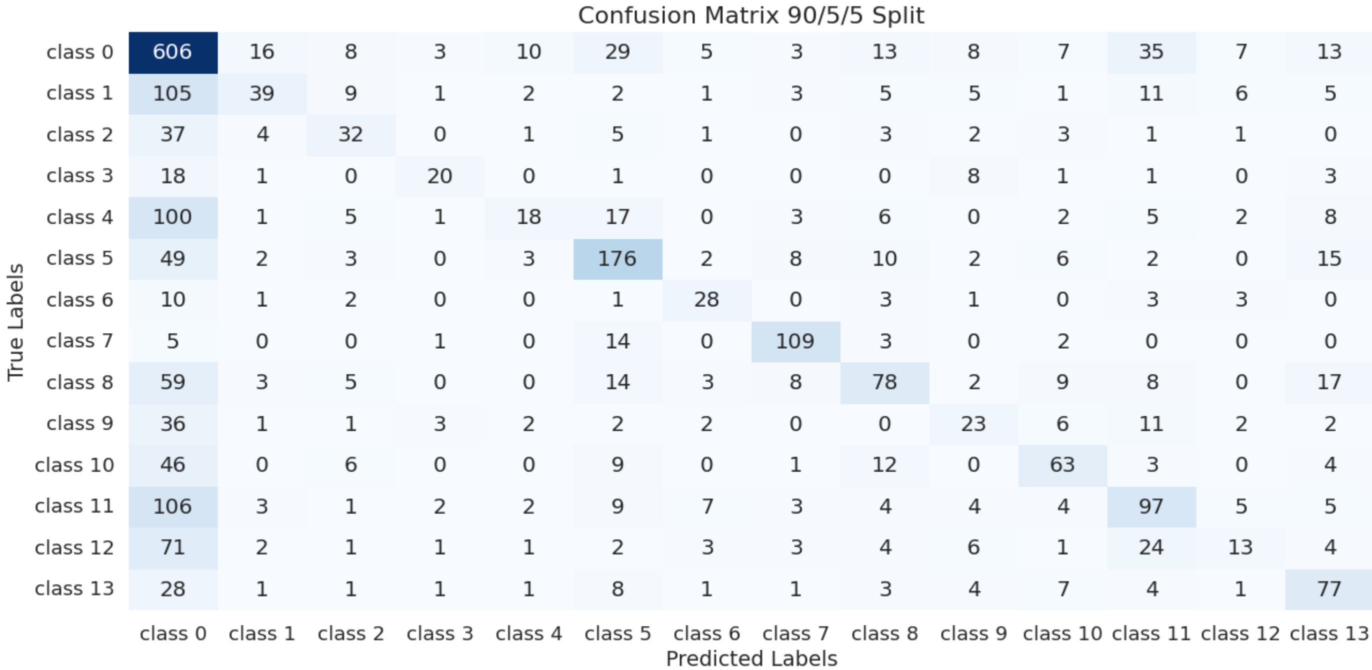
```
gru_y_pred = gru_model.predict(X_test)
gru_y_pred_labels = np.argmax(gru_y_pred, axis=1)
gru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(gru_y_test_labels, gru_y_pred_labels))
```

```
85/85 [==============================] - 2s 14ms/step
              precision    recall  f1-score   support

           0       0.47      0.79      0.59       763
           1       0.53      0.20      0.29       195
           2       0.43      0.36      0.39        90
           3       0.61      0.38      0.47        53
           4       0.45      0.11      0.17       168
           5       0.61      0.63      0.62       278
           6       0.53      0.54      0.53        52
           7       0.77      0.81      0.79       134
           8       0.54      0.38      0.45       206
           9       0.35      0.25      0.29        91
          10       0.56      0.44      0.49       144
          11       0.47      0.38      0.42       252
          12       0.33      0.10      0.15       136
          13       0.50      0.56      0.53       138

    accuracy                           0.51      2700
   macro avg       0.51      0.42      0.44      2700
weighted avg       0.51      0.51      0.48      2700
```

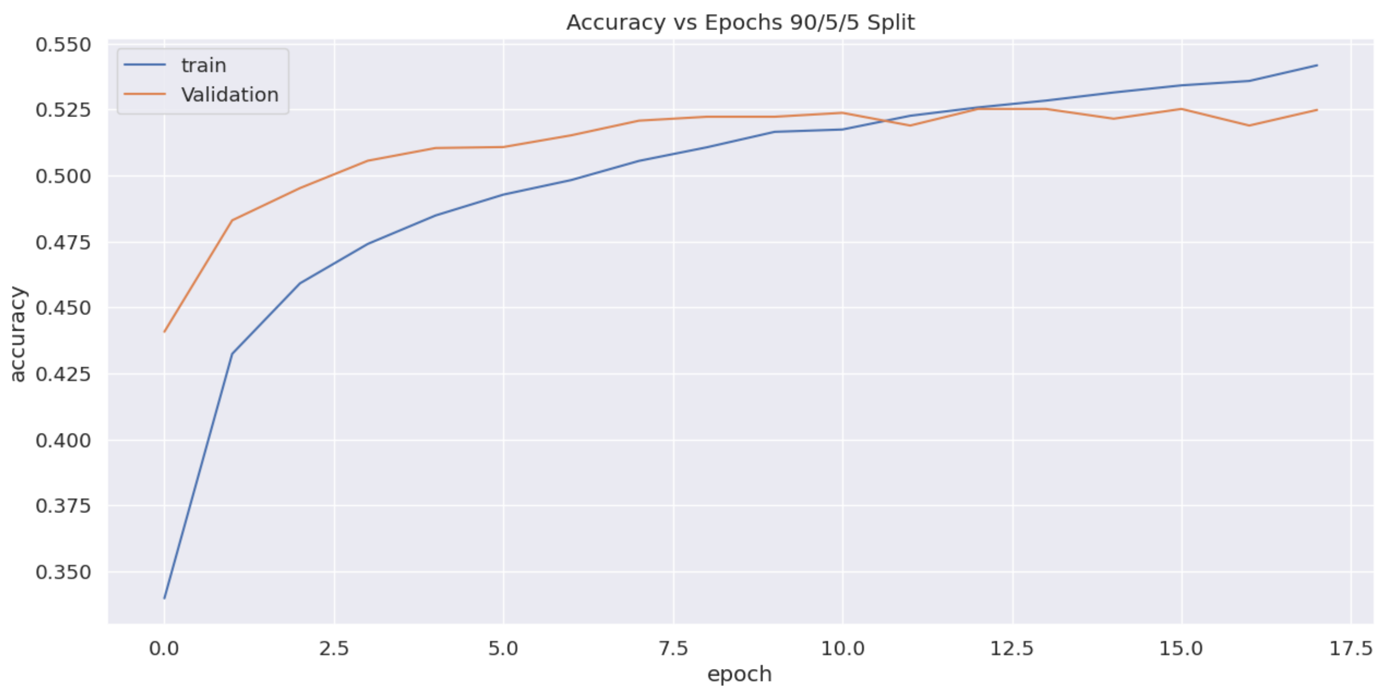
In [11]:

```
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 90/5/5 Split', fontsize=16)
plt.show()
```

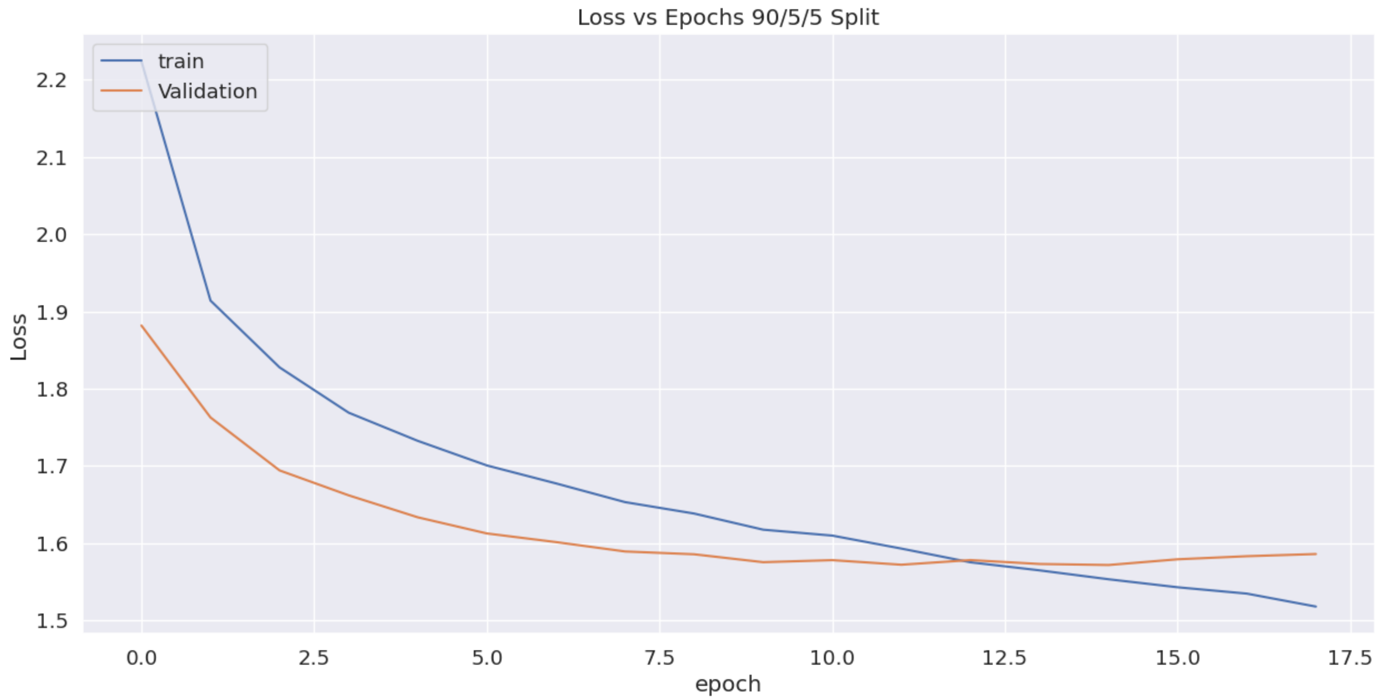


In [12]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs 90/5/5 Split')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [13]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs 90/5/5 Split')
```

```
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



2ND SPLIT 10/45/45

In [14]:
```
X= df.text
y= df.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.9, 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
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 61159 word vectors.
Converted 6259 words (1483 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()
gru_model.compile(loss='categorical_crossentropy', optimizer= 'adam', metrics=['accuracy
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 140, 300)          2322900

 gru_2 (GRU)                 (None, 140, 64)           70272

 dropout_2 (Dropout)         (None, 140, 64)           0

 gru_3 (GRU)                 (None, 32)                9408

 dropout_3 (Dropout)         (None, 32)                0

 dense_1 (Dense)             (None, 14)                462

=================================================================
Total params: 2,403,042
Trainable params: 80,142
Non-trainable params: 2,322,900
_________________________________________________________________
```

In [17]:

```
# 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
22/22 [==============================] - 6s 87ms/step - loss: 2.4794 - accuracy: 0.2493
- val_loss: 2.3368 - val_accuracy: 0.3081
Epoch 2/30
22/22 [==============================] - 2s 78ms/step - loss: 2.3570 - accuracy: 0.2949
- val_loss: 2.2740 - val_accuracy: 0.3264
Epoch 3/30
22/22 [==============================] - 1s 53ms/step - loss: 2.2868 - accuracy: 0.3239
- val_loss: 2.2061 - val_accuracy: 0.3490
Epoch 4/30
22/22 [==============================] - 2s 80ms/step - loss: 2.2142 - accuracy: 0.3449
- val_loss: 2.1364 - val_accuracy: 0.3639
Epoch 5/30
22/22 [==============================] - 1s 50ms/step - loss: 2.1558 - accuracy: 0.3571
- val_loss: 2.0823 - val_accuracy: 0.3780
Epoch 6/30
22/22 [==============================] - 1s 50ms/step - loss: 2.0834 - accuracy: 0.3780
- val_loss: 2.0186 - val_accuracy: 0.4003
Epoch 7/30
22/22 [==============================] - 1s 50ms/step - loss: 2.0293 - accuracy: 0.3991
- val_loss: 1.9718 - val_accuracy: 0.4116
Epoch 8/30
22/22 [==============================] - 2s 77ms/step - loss: 1.9875 - accuracy: 0.4067
- val_loss: 1.9521 - val_accuracy: 0.4166
Epoch 9/30
22/22 [==============================] - 1s 51ms/step - loss: 1.9456 - accuracy: 0.4225
- val_loss: 1.9108 - val_accuracy: 0.4338
Epoch 10/30
22/22 [==============================] - 2s 78ms/step - loss: 1.9091 - accuracy: 0.4382
- val_loss: 1.8975 - val_accuracy: 0.4378
Epoch 11/30
22/22 [==============================] - 2s 78ms/step - loss: 1.8758 - accuracy: 0.4395
- val_loss: 1.8878 - val_accuracy: 0.4405
Epoch 12/30
22/22 [==============================] - 2s 89ms/step - loss: 1.8507 - accuracy: 0.4519
- val_loss: 1.8760 - val_accuracy: 0.4453
Epoch 13/30
22/22 [==============================] - 1s 57ms/step - loss: 1.8215 - accuracy: 0.4580
- val_loss: 1.8672 - val_accuracy: 0.4487
Epoch 14/30
22/22 [==============================] - 1s 51ms/step - loss: 1.7969 - accuracy: 0.4619
- val_loss: 1.8670 - val_accuracy: 0.4497
Epoch 15/30
22/22 [==============================] - 1s 50ms/step - loss: 1.7848 - accuracy: 0.4745
- val_loss: 1.8521 - val_accuracy: 0.4525
Epoch 16/30
22/22 [==============================] - 2s 78ms/step - loss: 1.7413 - accuracy: 0.4764
- val_loss: 1.8530 - val_accuracy: 0.4532
Epoch 17/30
22/22 [==============================] - 1s 52ms/step - loss: 1.7263 - accuracy: 0.4862
- val_loss: 1.8679 - val_accuracy: 0.4546
Epoch 18/30
22/22 [==============================] - 2s 78ms/step - loss: 1.7154 - accuracy: 0.4866
- val_loss: 1.8508 - val_accuracy: 0.4555
Epoch 19/30
22/22 [==============================] - 1s 56ms/step - loss: 1.6827 - accuracy: 0.4879
- val_loss: 1.8429 - val_accuracy: 0.4593
Epoch 20/30
22/22 [==============================] - 1s 55ms/step - loss: 1.6665 - accuracy: 0.4981
- val_loss: 1.8631 - val_accuracy: 0.4578
```

```
Epoch 21/30
22/22 [==============================] - 1s 51ms/step - loss: 1.6361 - accuracy: 0.5044
- val_loss: 1.8546 - val_accuracy: 0.4524
Epoch 22/30
22/22 [==============================] - 2s 80ms/step - loss: 1.6085 - accuracy: 0.5116
- val_loss: 1.8519 - val_accuracy: 0.4539
```

In [18]:

```
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))
```

```
760/760 [==============================] - 4s 5ms/step
              precision    recall  f1-score   support

           0       0.43      0.83      0.57      7134
           1       0.34      0.01      0.02      1683
           2       0.25      0.00      0.00       813
           3       0.42      0.03      0.05       512
           4       0.13      0.00      0.01      1516
           5       0.52      0.63      0.57      2338
           6       0.30      0.10      0.15       476
           7       0.75      0.80      0.77      1206
           8       0.44      0.29      0.35      1799
           9       0.36      0.27      0.31       834
          10       0.51      0.31      0.38      1264
          11       0.36      0.39      0.38      2035
          12       0.16      0.02      0.03      1330
          13       0.54      0.45      0.49      1358

    accuracy                           0.46     24298
   macro avg       0.39      0.30      0.29     24298
weighted avg       0.41      0.46      0.38     24298
```

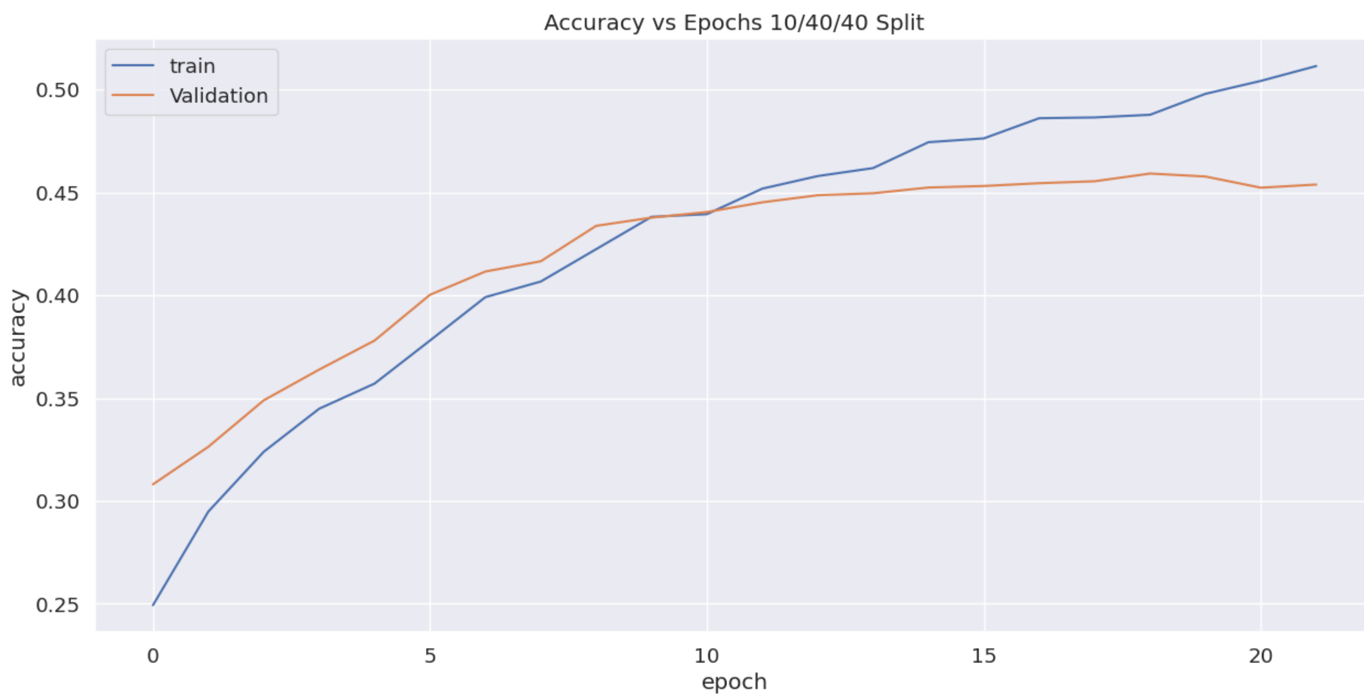
In [19]:

```
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 10/40/40 Split', fontsize=16)
plt.show()
```

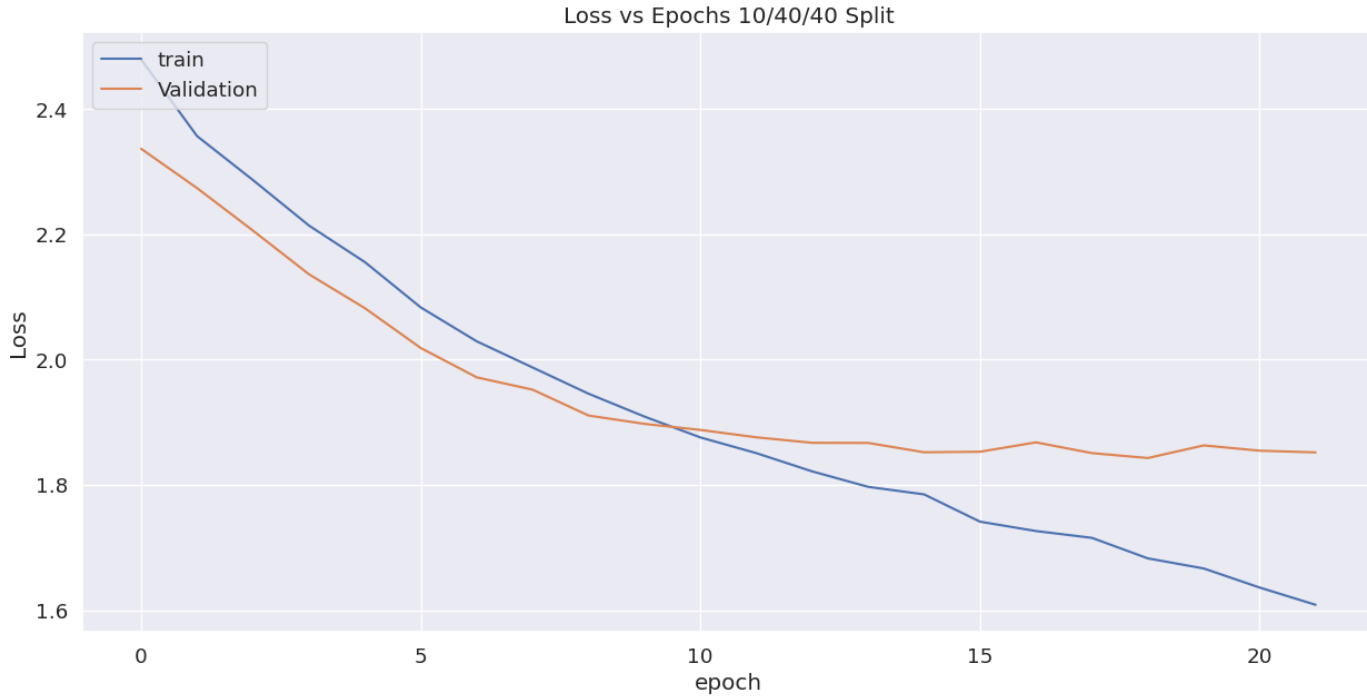
Confusion Matrix 10/40/40 Split

True Labels \ Predicted Labels	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
class 0	5955	6	1	2	4	305	12	23	144	46	56	445	24	111
class 1	1311	19	1	1	4	70	12	27	44	30	23	101	10	30
class 2	591	5	2	1	8	52	11	2	29	16	29	46	10	11
class 3	242	1	0	13	1	23	23	7	17	92	9	67	4	13
class 4	1048	3	0	0	4	143	5	33	69	30	39	74	10	58
class 5	501	3	0	1	3	1483	1	73	79	1	47	46	11	89
class 6	210	4	1	1	0	9	49	3	18	51	5	100	11	14
class 7	76	0	0	0	1	84	1	962	31	22	11	4	0	14
class 8	770	3	1	0	0	181	3	59	529	32	52	98	3	68
class 9	369	2	0	6	1	50	10	5	28	225	29	86	14	9
class 10	523	0	0	2	1	147	2	31	79	9	389	30	0	51
class 11	983	3	0	0	3	74	14	19	54	29	15	795	13	33
class 12	830	7	2	0	0	76	16	12	51	23	17	251	21	24
class 13	452	0	0	4	1	134	6	21	28	18	40	39	3	612

In [20]:
```python
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs 10/40/40 Split')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [21]:
```python
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs 10/40/40 Split')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



3RD SPLIT 25/25/50

In [22]:
```
X= df.text
y= df.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.75, random_state
X_val,X_test,y_val,y_test= train_test_split(X_other,y_other,test_size=0.33,random_state=
```

In [23]:
```
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 65215 word vectors.
Converted 9880 words (3161 misses)
```

In [24]:

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

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_2 (Embedding)     (None, 145, 300)          3912600   
                                                                 
 gru_4 (GRU)                 (None, 145, 64)           70272     
                                                                 
 dropout_4 (Dropout)         (None, 145, 64)           0         
                                                                 
 gru_5 (GRU)                 (None, 32)                9408      
                                                                 
 dropout_5 (Dropout)         (None, 32)                0         
                                                                 
 dense_2 (Dense)             (None, 14)                462       
                                                                 
=================================================================
Total params: 3,992,742
Trainable params: 80,142
Non-trainable params: 3,912,600
_________________________________________________________________
```

In [25]:

```
# 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
53/53 [==============================] - 6s 48ms/step - loss: 2.4337 - accuracy: 0.2614
- val_loss: 2.2699 - val_accuracy: 0.3338
Epoch 2/30
53/53 [==============================] - 2s 32ms/step - loss: 2.2260 - accuracy: 0.3412
- val_loss: 2.0427 - val_accuracy: 0.3881
Epoch 3/30
53/53 [==============================] - 2s 42ms/step - loss: 2.0578 - accuracy: 0.3868
- val_loss: 1.9234 - val_accuracy: 0.4231
Epoch 4/30
53/53 [==============================] - 2s 43ms/step - loss: 1.9803 - accuracy: 0.4136
- val_loss: 1.8669 - val_accuracy: 0.4399
Epoch 5/30
53/53 [==============================] - 2s 42ms/step - loss: 1.9113 - accuracy: 0.4327
- val_loss: 1.8265 - val_accuracy: 0.4543
Epoch 6/30
53/53 [==============================] - 2s 32ms/step - loss: 1.8709 - accuracy: 0.4500
- val_loss: 1.8102 - val_accuracy: 0.4587
Epoch 7/30
53/53 [==============================] - 2s 33ms/step - loss: 1.8305 - accuracy: 0.4580
- val_loss: 1.7662 - val_accuracy: 0.4705
Epoch 8/30
53/53 [==============================] - 2s 42ms/step - loss: 1.8009 - accuracy: 0.4695
- val_loss: 1.7462 - val_accuracy: 0.4759
Epoch 9/30
53/53 [==============================] - 2s 34ms/step - loss: 1.7579 - accuracy: 0.4804
- val_loss: 1.7385 - val_accuracy: 0.4800
Epoch 10/30
53/53 [==============================] - 2s 44ms/step - loss: 1.7389 - accuracy: 0.4801
- val_loss: 1.7224 - val_accuracy: 0.4815
Epoch 11/30
53/53 [==============================] - 2s 33ms/step - loss: 1.7089 - accuracy: 0.4901
- val_loss: 1.7201 - val_accuracy: 0.4846
Epoch 12/30
53/53 [==============================] - 2s 33ms/step - loss: 1.6862 - accuracy: 0.4973
- val_loss: 1.7129 - val_accuracy: 0.4864
Epoch 13/30
53/53 [==============================] - 2s 33ms/step - loss: 1.6593 - accuracy: 0.5000
- val_loss: 1.7059 - val_accuracy: 0.4864
Epoch 14/30
53/53 [==============================] - 2s 42ms/step - loss: 1.6410 - accuracy: 0.5106
- val_loss: 1.7275 - val_accuracy: 0.4858
Epoch 15/30
53/53 [==============================] - 2s 33ms/step - loss: 1.6233 - accuracy: 0.5128
- val_loss: 1.7008 - val_accuracy: 0.4895
Epoch 16/30
53/53 [==============================] - 2s 34ms/step - loss: 1.5957 - accuracy: 0.5192
- val_loss: 1.7043 - val_accuracy: 0.4898
Epoch 17/30
53/53 [==============================] - 2s 34ms/step - loss: 1.5802 - accuracy: 0.5244
- val_loss: 1.7120 - val_accuracy: 0.4898
Epoch 18/30
53/53 [==============================] - 2s 42ms/step - loss: 1.5532 - accuracy: 0.5301
- val_loss: 1.7133 - val_accuracy: 0.4850
```

In [26]:

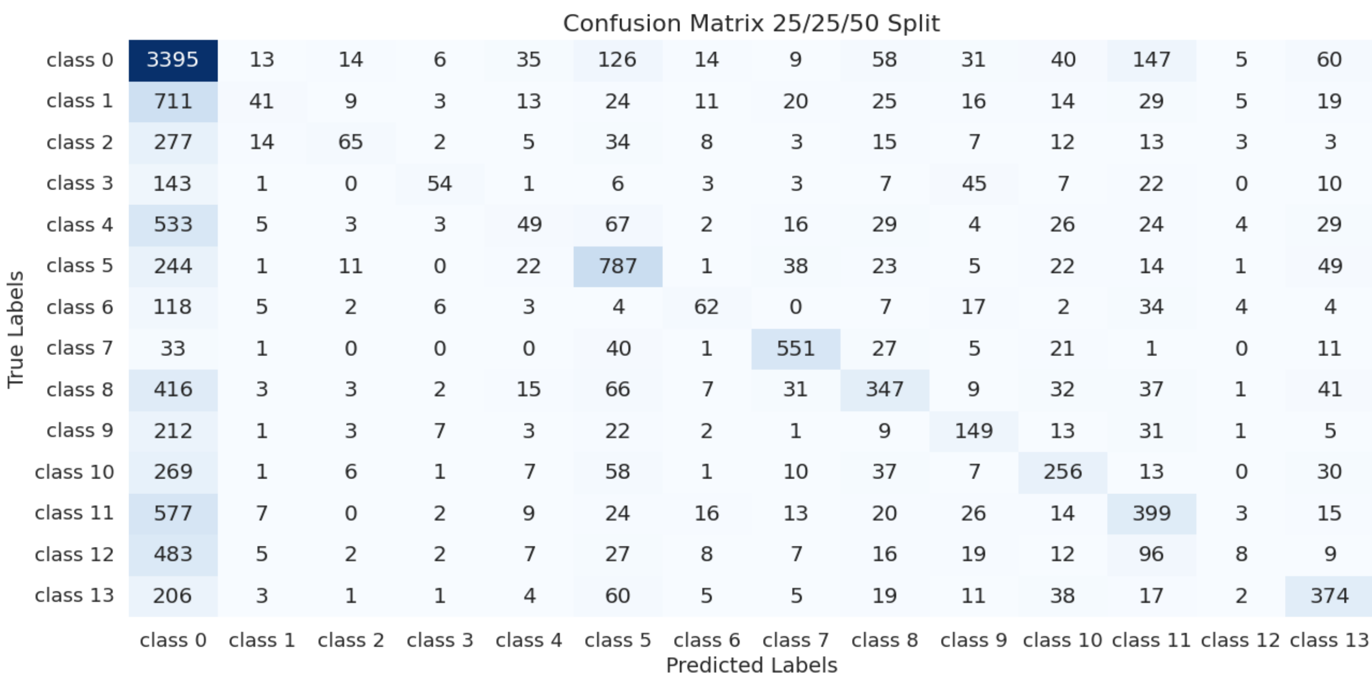
```
gru_y_pred = gru_model.predict(X_test)
gru_y_pred_labels = np.argmax(gru_y_pred, axis=1)
gru_y_test_labels = np.argmax(y_test, axis=1)
print(classification_report(gru_y_test_labels, gru_y_pred_labels))
```

```
418/418 [==============================] - 3s 5ms/step
              precision    recall  f1-score   support

           0       0.45      0.86      0.59      3953
           1       0.41      0.04      0.08       940
           2       0.55      0.14      0.22       461
```

```
           3       0.61      0.18      0.28       302
           4       0.28      0.06      0.10       794
           5       0.59      0.65      0.61      1218
           6       0.44      0.23      0.30       268
           7       0.78      0.80      0.79       691
           8       0.54      0.34      0.42      1010
           9       0.42      0.32      0.37       459
          10       0.50      0.37      0.42       696
          11       0.45      0.35      0.40      1125
          12       0.22      0.01      0.02       701
          13       0.57      0.50      0.53       746

    accuracy                           0.49     13364
   macro avg       0.49      0.35      0.37     13364
weighted avg       0.48      0.49      0.43     13364
```

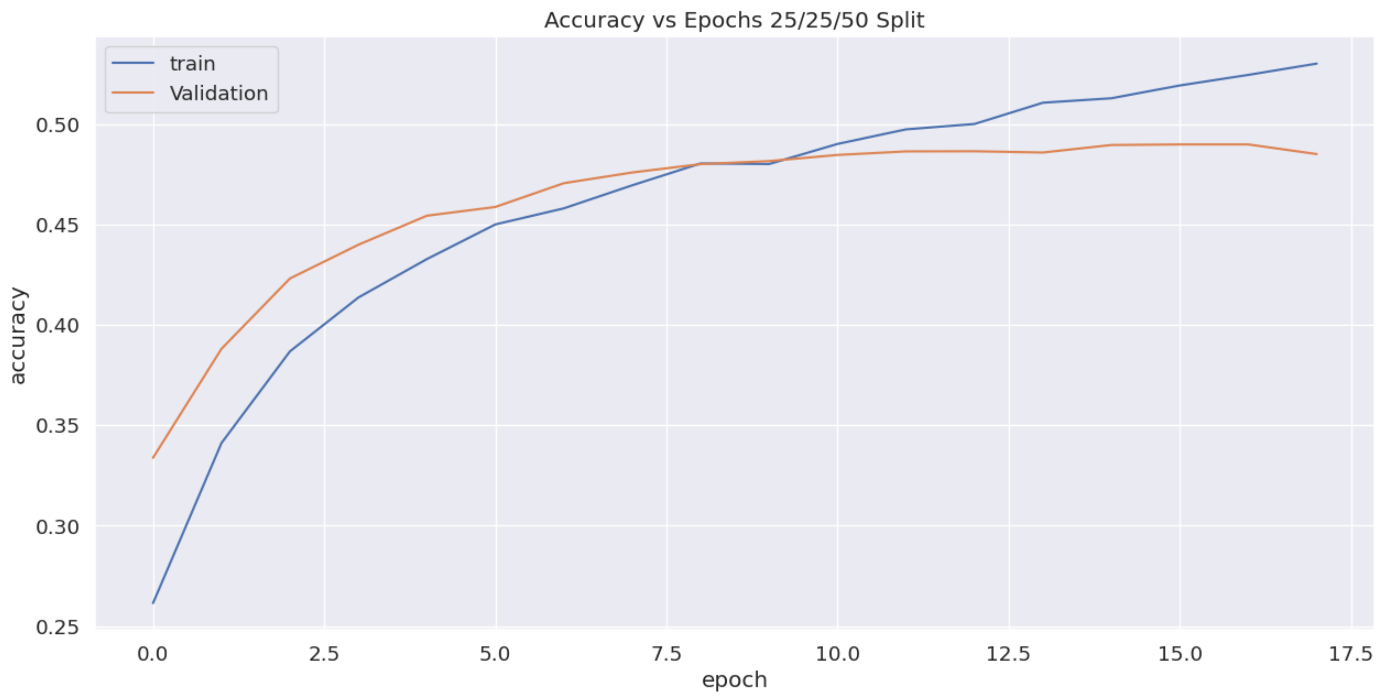
In [27]:

```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 25/25/50 Split', fontsize=16)
plt.show()
```

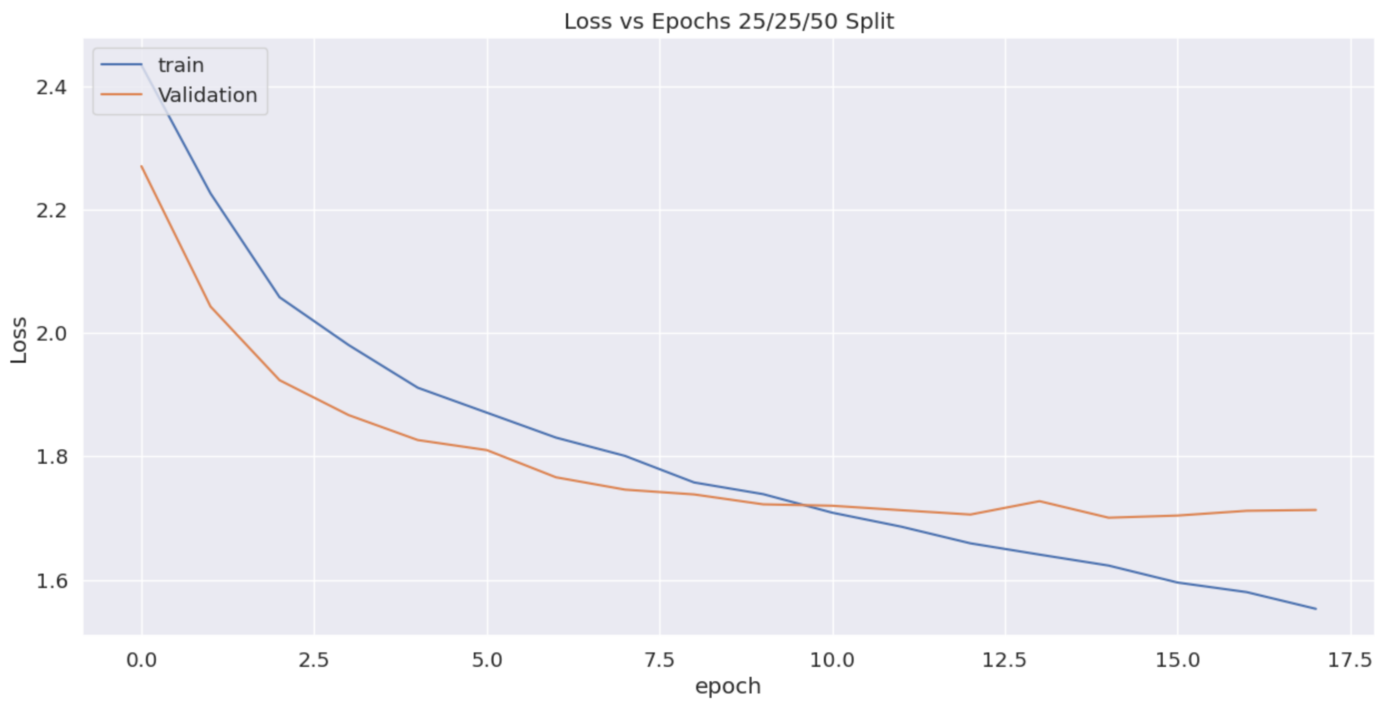


In [28]:

```python
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs 25/25/50 Split')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [29]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs 25/25/50 Split')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



4TH SPLIT 25/50/25

In [30]:
```
X= df.text
y= df.labels
X_train, X_other, y_train, y_other = train_test_split(X, y, test_size=0.75, random_state
X_val,X_test,y_val,y_test= train_test_split(X_other,y_other,test_size=0.67,random_state=
```

In [31]:
```
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
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 69272 word vectors.
Converted 9970 words (3071 misses)
```

In [32]:

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

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_3 (Embedding)     (None, 145, 300)          3912600

 gru_6 (GRU)                 (None, 145, 64)           70272

 dropout_6 (Dropout)         (None, 145, 64)           0

 gru_7 (GRU)                 (None, 32)                9408

 dropout_7 (Dropout)         (None, 32)                0

 dense_3 (Dense)             (None, 14)                462

=================================================================
Total params: 3,992,742
Trainable params: 80,142
Non-trainable params: 3,912,600
_________________________________________________________________
```

In [33]:
```
# 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
53/53 [==============================] - 6s 45ms/step - loss: 2.4354 - accuracy: 0.2721
- val_loss: 2.2576 - val_accuracy: 0.3222
Epoch 2/30
53/53 [==============================] - 1s 25ms/step - loss: 2.2312 - accuracy: 0.3353
- val_loss: 2.0779 - val_accuracy: 0.3623
Epoch 3/30
53/53 [==============================] - 2s 30ms/step - loss: 2.0886 - accuracy: 0.3777
- val_loss: 1.9588 - val_accuracy: 0.4100
Epoch 4/30
53/53 [==============================] - 1s 27ms/step - loss: 1.9850 - accuracy: 0.4132
- val_loss: 1.8693 - val_accuracy: 0.4432
Epoch 5/30
53/53 [==============================] - 1s 26ms/step - loss: 1.9139 - accuracy: 0.4347
- val_loss: 1.8175 - val_accuracy: 0.4607
Epoch 6/30
53/53 [==============================] - 1s 25ms/step - loss: 1.8628 - accuracy: 0.4495
- val_loss: 1.7857 - val_accuracy: 0.4682
Epoch 7/30
53/53 [==============================] - 2s 30ms/step - loss: 1.8301 - accuracy: 0.4612
- val_loss: 1.7681 - val_accuracy: 0.4726
Epoch 8/30
53/53 [==============================] - 1s 25ms/step - loss: 1.7834 - accuracy: 0.4696
- val_loss: 1.7476 - val_accuracy: 0.4739
Epoch 9/30
53/53 [==============================] - 2s 30ms/step - loss: 1.7671 - accuracy: 0.4747
- val_loss: 1.7354 - val_accuracy: 0.4771
Epoch 10/30
53/53 [==============================] - 2s 30ms/step - loss: 1.7407 - accuracy: 0.4790
- val_loss: 1.7237 - val_accuracy: 0.4804
Epoch 11/30
53/53 [==============================] - 2s 30ms/step - loss: 1.7130 - accuracy: 0.4911
- val_loss: 1.7150 - val_accuracy: 0.4846
```

```
Epoch 12/30
53/53 [==============================] - 2s 30ms/step - loss: 1.6855 - accuracy: 0.4951
- val_loss: 1.7113 - val_accuracy: 0.4835
Epoch 13/30
53/53 [==============================] - 2s 31ms/step - loss: 1.6634 - accuracy: 0.4980
- val_loss: 1.7086 - val_accuracy: 0.4863
Epoch 14/30
53/53 [==============================] - 1s 26ms/step - loss: 1.6429 - accuracy: 0.5070
- val_loss: 1.7076 - val_accuracy: 0.4860
Epoch 15/30
53/53 [==============================] - 1s 25ms/step - loss: 1.6293 - accuracy: 0.5087
- val_loss: 1.7023 - val_accuracy: 0.4883
Epoch 16/30
53/53 [==============================] - 1s 25ms/step - loss: 1.6111 - accuracy: 0.5121
- val_loss: 1.7070 - val_accuracy: 0.4873
Epoch 17/30
53/53 [==============================] - 1s 25ms/step - loss: 1.5717 - accuracy: 0.5251
- val_loss: 1.7156 - val_accuracy: 0.4884
Epoch 18/30
53/53 [==============================] - 1s 26ms/step - loss: 1.5629 - accuracy: 0.5281
- val_loss: 1.7172 - val_accuracy: 0.4890
```

In [34]:

```
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))
```

```
848/848 [==============================] - 5s 6ms/step
              precision    recall  f1-score   support

           0       0.46      0.81      0.59      8047
           1       0.44      0.07      0.12      1879
           2       0.47      0.15      0.23       908
           3       0.46      0.20      0.28       581
           4       0.32      0.01      0.02      1635
           5       0.61      0.62      0.62      2597
           6       0.47      0.30      0.37       562
           7       0.77      0.83      0.80      1382
           8       0.51      0.38      0.43      2015
           9       0.34      0.35      0.34       871
          10       0.51      0.39      0.44      1418
          11       0.40      0.44      0.42      2286
          12       0.36      0.03      0.05      1455
          13       0.51      0.56      0.53      1497

    accuracy                           0.49     27133
   macro avg       0.47      0.37      0.37     27133
weighted avg       0.48      0.49      0.44     27133
```

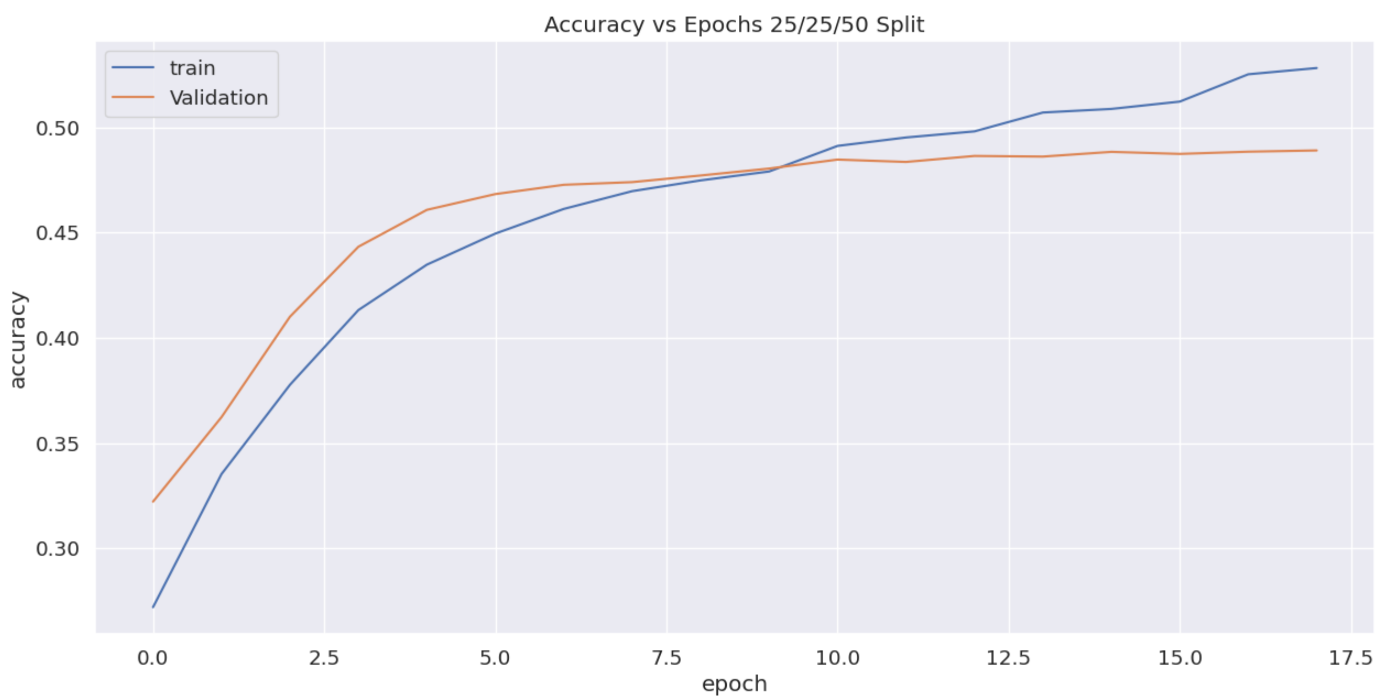
In [35]:

```
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 25/50/25 Split', fontsize=16)
plt.show()
```

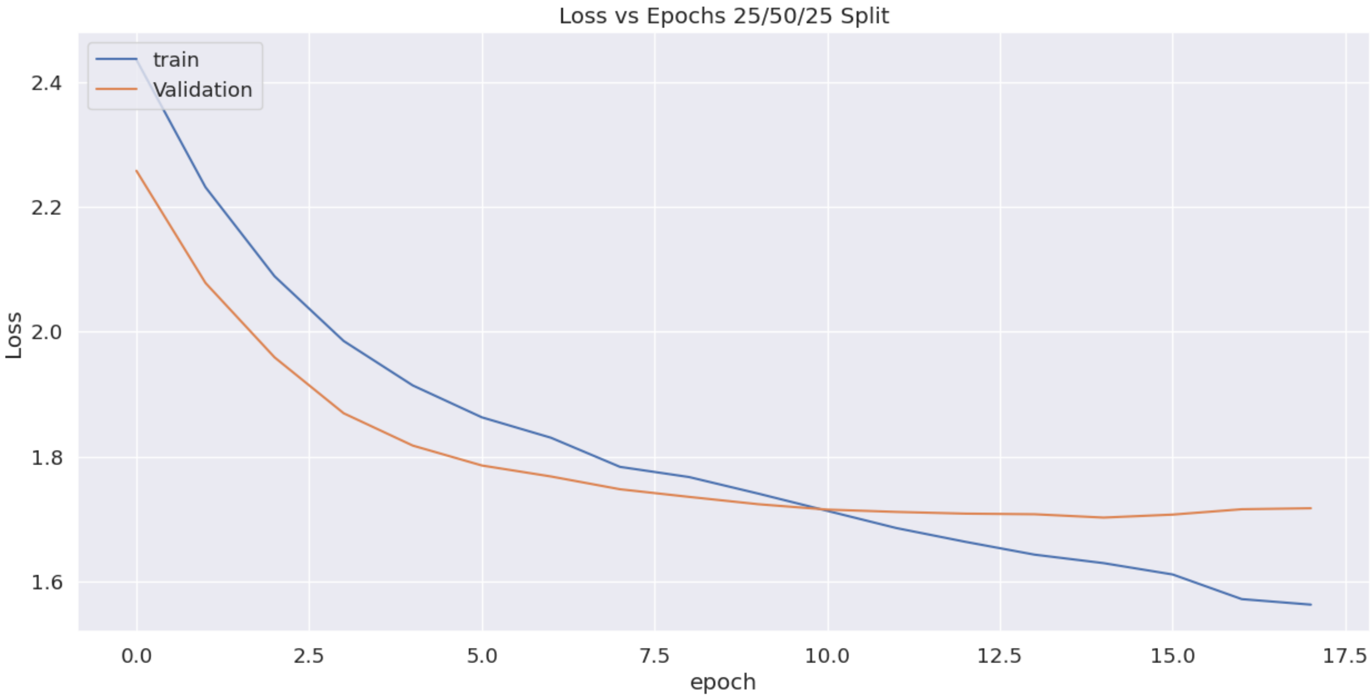
Confusion Matrix 25/50/25 Split

True Labels \ Predicted Labels	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
class 0	6489	50	40	24	13	266	27	20	171	87	103	552	14	191
class 1	1247	133	28	9	4	59	29	31	47	48	38	140	5	61
class 2	476	28	137	6	3	61	8	1	32	40	41	66	0	9
class 3	217	5	0	119	2	9	15	1	15	118	13	39	0	28
class 4	1086	14	13	8	21	131	6	36	65	34	54	77	12	78
class 5	495	2	22	5	11	1618	3	104	97	9	52	53	5	121
class 6	190	8	5	10	0	7	171	1	6	52	12	75	5	20
class 7	55	1	1	1	0	64	2	1142	55	13	24	5	0	19
class 8	759	10	13	11	0	118	10	51	758	29	59	85	3	109
class 9	335	7	3	31	1	25	15	4	20	303	26	76	7	18
class 10	472	9	18	7	3	101	4	30	96	15	547	39	2	75
class 11	950	17	1	9	3	48	32	25	45	59	19	1016	12	50
class 12	869	11	6	11	5	67	23	13	38	63	23	250	37	39
class 13	342	9	2	8	0	86	21	18	37	25	66	45	0	838

In [36]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['accuracy'])
plt.plot(history_gru.history['val_accuracy'])
plt.title('Accuracy vs Epochs 25/25/50 Split')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```



In [37]:
```
plt.figure(figsize=(15,7))
plt.plot(history_gru.history['loss'])
plt.plot(history_gru.history['val_loss'])
plt.title('Loss vs Epochs 25/50/25 Split')
plt.ylabel('Loss')
plt.xlabel('epoch')
plt.legend(['train', 'Validation'], loc='upper left')
plt.show()
```


Loss vs Epochs 25/50/25 Split
train
Validation
Loss
epoch
2.4
2.2
2.0
1.8
1.6
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5