CS6005-DEEP LEARNING MINI PROJECT-NATURAL LANGUAGE PROCESSING DOCUMENT

Natural Language Processing for Automated Hate Speech and Offensive Language Detection

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Problem statement:

- Hate speech is currently of broad and current interest in the domain of social media. The anonymity and flexibility afforded by the Internet has made it easy for users to communicate in an aggressive manner. And as the amount of online hate speech is increasing, methods that automatically detect hate speech are very much required. Therefore, the goal of this project is to look at how Natural Language Processing applies in detecting hate-speech and offensive language. The task of the classifier is to assign each tweet to one of the categories of a Twitter dataset: *hate, offensive language*, and *neither*.

Data Description:

Name: HATE SPEECH AND OFFENSIVE LANGUAGE

Source: https://www.kaggle.com/mrmorj/hate-speech-and-offensive-language-dataset

Description:

Dataset using Twitter data, is used to research hate-speech detection. The text is classified as: hate-speech, offensive language, and neither. Due to the nature of the study, it's important to note that this dataset contains text that can be considered racist, sexist, homophobic, or generally offensive.

- 24k tweets labelled as hate speech, offensive language, or neither.
- **Attributes:**
    - **Count**
        - Number of CrowdFlower users who coded each tweet (min is 3, sometimes more users coded a tweet when judgments were determined to be unreliable by CF).
    - **Hate_speech**
        - Number of CF users who judged the tweet to be hate speech.

- **Offensive_language**
    - Number of CF users who judged the tweet to be offensive.
- **Neither**
    - Number of CF users who judged the tweet to be neither offensive nor non-offensive.
- **Class**
    - Class label for majority of CF users.
        - 0 - hate speech,
        - 1 - offensive language,
        - 2 – neither
- **Tweet**
    - Text tweets, including numericals and special characters. All tweets are unique and valid without any mismatched and missing values.

Class Split up:

- 1430 tweets are classified as hate speech
- 19190 tweets as offensive language
- 4163 tweets as normal language.

Module Description:

- **Loading Dataset**
  - The Dataset is imported and the necessary libraries are imported which are used for pre-processing of text data, building the LSTM model like Keras, Sequential, Dense, Dropout, Flatten, NLTK etc are imported.
  - The dataset is loaded and then set for visualization.
- **Data Preprocessing**
  - The data is pre-processed in various methods:
    - Removing Blank spaces
    - Removing Special Characters (include @, #, $)
    - Removing url
    - Removing punctuations
    - Removing Capitalization
  - **Tokenizing**
    - A token is a piece of a whole, so a word is a token in a sentence is a token in a paragraph. Tokenization is the process of splitting a string into a list of tokens.
  - **Removal of Stopwords**
    - They are words which are filtered out before or after processing of natural language data (text)
  - **Stemming**
    - It is a process where words are reduced to a root by removing inflection through dropping unnecessary characters, usually a suffix.
- **Feature Extraction**
  - The Features are extracted for the pre-processed data by the following techniques:

        - Word Level One Hot Encoding
        - TFIDF Vectorizer
        - Bag of Words [COUNT Vectorizer]
    - **Word Level One Hot Encoding**
        - Keras has built-in utilities for doing one-hot encoding text at the word level or character level, starting from raw text data. It takes care of a number of important features, such as stripping special characters from strings, or only taking into the top N most common words in your dataset (a common restriction to avoid dealing with huge input vector spaces).
    - **TFIDF Vectorizer**
        - It is an inbuilt library in python which converts a collection of raw documents to a matrix of TF-IDF (Term Frequency – Inverse Document Frequency) features. It uses two statistical methods and they are:
            - **Term Frequency** – It refers to the total number of times a given term t appears in the document doc against (per) the total number of all words in the document.
            - **Inverse Document Frequency** – It is a measure of how much information the word provides and it measures the weight of the given word in the entire document. It shows how common or rare a given word is across all documents.
    - **Bag of Words [COUNT Vectorizer]**
        - The bag-of-words model is a way of representing text data when modeling text with machine learning and deep learning algorithms. The bag-of-words model is simple to understand and implement and has seen great success in problems such as language modeling and document classification.

- **Building a Long Short-Term Memory (LSTM) model**
  - The LSTM model consists of various layers:
    - **Embedding Layer:**
      - It is one of the available layers in Keras. It can be used for neural networks on text data. This is mainly used in Natural Language Processing related applications such as language modeling, but it can also be used with other tasks that involve neural networks. An embedded layer with input length as 5000 and output dimension 20 is used.
    - **LSTM Layer:**
      - Based on available runtime hardware and constraints, this layer will choose different implementations (cuDNN-based or pure-TensorFlow) to maximize the performance. If a GPU is available and all the arguments to the layer meet the requirement of the CuDNN kernel (see below for details), the layer will use a fast cuDNN implementation. LSTM Layer with 15 units and dropout 50% is added.
    - **Flatten Layer**:
      - Transforms the format of the images from a 2d-array to a 1d-array
    - **Regularization function**:
      - I used Dropout technique to regularize which specifies the percentage of neurons to be dropped at each iteration.
    - **Dense Layer:**
      - The dense layer is a fully connected layer, meaning all the neurons in a layer are connected to those in the next layer. Two dense layers are used, one with 512 neurons and other with 3 neurons.
  - **Activation function**:

        - Dense Layer 1- **Relu**: given a value x, returns max(x, 0).
        - Output layer (Dense Layer 2) - **Softmax:** 3 neurons, probability that the tweet belongs to one of the classes.
        - The model built is compiled is compiled with parameters such as:
            - **Optimizer**: **adam** = RMSProp + Momentum.
            - **Momentum** = takes into account past gradients to have a better update. o RMSProp = exponentially weighted average of the squares of past gradients.
            - **Loss function**: I used categorical_crossentropy for classification, each tweet belongs to one class only.

- **Model Evaluation**
    - The model is evaluated by plotting Accuracy and loss curves
    - The model is also evaluated by constructing Confusion Matrix
    - Test score is obtained

Code Snapshots:

Module 1: Importing Libraries:

```
In [1]: import pandas as panda
        from nltk.tokenize import word_tokenize
        from nltk.corpus import stopwords
        from nltk.stem.porter import *
        import string
        import nltk

        from sklearn.preprocessing import OneHotEncoder
        import numpy as np
        from nltk.tokenize.treebank import TreebankWordDetokenizer

        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.model_selection import train_test_split

        from keras.models import Sequential
        from keras import layers
        from keras.optimizers import RMSprop,Adam
        from keras.preprocessing.text import Tokenizer
        from keras.preprocessing.sequence import pad_sequences
        from keras import regularizers
        from keras import backend as K
        from keras.callbacks import ModelCheckpoint
        import matplotlib.pyplot as plt
```

Loading Dataset:

```
In [2]: data = panda.read_csv("labeled_data.csv")
        data
```

Out[2]:

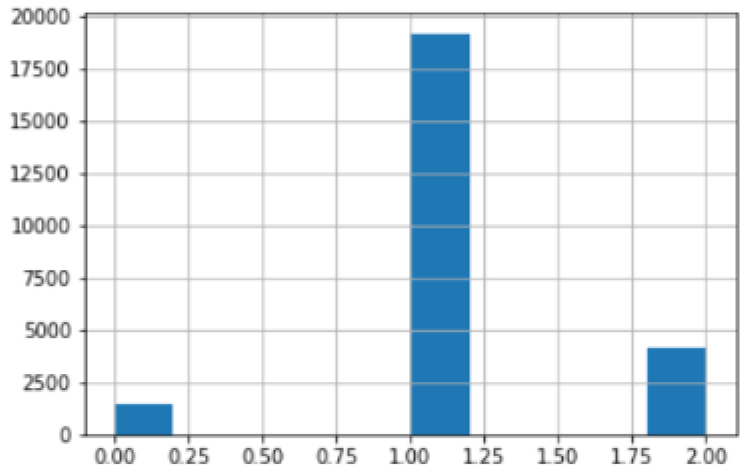
	index	count	hate_speech	offensive_language	neither	class	tweet
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...
...	...	...	...	...	...	...	...
24778	25291	3	0	2	1	1	you's a muthaf***in lie “@LifeAsKing: @2...
24779	25292	3	0	1	2	2	you've gone and broke the wrong heart baby, an...
24780	25294	3	0	3	0	1	young buck wanna eat!!.. dat nigguh like I ain...
24781	25295	6	0	6	0	1	youu got wild bitches tellin you lies
24782	25296	3	0	0	3	2	~~Ruffled | Ntac Eileen Dahlia - Beautiful col...

24783 rows × 7 columns

Visualizing data types of attributes and target class split up:

```
In [3]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 24783 entries, 0 to 24782
Data columns (total 7 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   index               24783 non-null  int64
 1   count               24783 non-null  int64
 2   hate_speech         24783 non-null  int64
 3   offensive_language  24783 non-null  int64
 4   neither             24783 non-null  int64
 5   class               24783 non-null  int64
 6   tweet               24783 non-null  object
dtypes: int64(6), object(1)
memory usage: 1.3+ MB
```

In [4]:
```
data['class'].hist()
```
Out[4]: <AxesSubplot:>



Module 2: Data Preprocessing:

Defining Remove space function

In [5]:
```
tweet=data.tweet
```

In [6]:
```
def remove_space(tweet):

    # removal of extra spaces
    regex_pat = re.compile(r'\s+')
    tweet_space = tweet.str.replace(regex_pat, ' ')
    # remove whitespace with a single space
    newtweet=tweet.str.replace(r'\s+', ' ')
    # remove leading and trailing whitespace
    newtweet=newtweet.str.replace(r'^\s+|\s+?$','')
    # replace normal numbers with numbr
    newtweet=newtweet.str.replace(r'\d+(\.\d+)?','numbr')
    # removal of capitalization
    tweet_lower = newtweet.str.lower()

    return tweet_lower
```

In [7]:
```
tweets_space= remove_space(tweet)
data["tweets_w/o_space"]=tweets_space
data.head()
```

Out[7]:

	index	count	hate_speech	offensive_language	neither	class	tweet	tweets_w/o_space
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	!!!!! rt @mleewnumbr: boy dats cold...tyga dwn...
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	!!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...

Defining Remove url function

In [8]:
```
def remove_urls(tweet):
    url_pattern = re.compile(r'https?://\S+|www\.\S+')
    return url_pattern.sub(r'', tweet)

data["tweet_w/o_url"] = data["tweets_w/o_space"].apply(lambda tweet: remove_urls(tweet))
```

Removing Special Characters using Wordnet Lemmatizer

In [10]:
```
from nltk.stem import WordNetLemmatizer

data['tweet_lem'] = [''.join([WordNetLemmatizer().lemmatize(re.sub('[^A-Za-z]',' ',tweet)) for tweet in lis]) for lis i
```

Tokenization

```
In [11]: data["tokenized_tweet"] = data["tweet_lem"].apply(lambda x: x.split())
```

```
In [12]: data.head()
```

Out[12]:

	index	count	hate_speech	offensive_language	neither	class	tweet	tweets_w/o_space	tweet_w/o_url	tweet_lem	tokenized_tweet
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...	rt mayasolovely as a woman you shouldn t...	[rt, mayasolovely, as, a, woman, you, shouldn,...
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	!!!! rt @mleewnumbr: boy dats cold...tyga dwn...	!!!! rt @mleewnumbr: boy dats cold...tyga dwn...	rt mleewnumbr boy dats cold tyga dwn...	[rt, mleewnumbr, boy, dats, cold, tyga, dwn, b...
2	2	3	0	3	0	1	!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...	!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...	rt urkindofbrand dawg rt numbrsb...	[rt, urkindofbrand, dawg, rt, numbrsbabynumbrl...
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...	rt c g anderson viva based she lo...	[rt, c, g, anderson, viva, based, she, look, l...
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...	rt shenikaroberts the shit you...	[rt, shenikaroberts, the, shit, you, hear, abo...

Removing Stop Words

```
In [14]: stopwords = nltk.corpus.stopwords.words("english")

         #extending the stopwords to include other words used in twitter such as retweet(rt) etc.
         other_exclusions = ["#ff", "ff", "rt"]
         stopwords.extend(other_exclusions)
         stemmer = PorterStemmer()
```

```
In [15]: data["tweet_w/o_stop"] = data["tokenized_tweet"].apply(lambda x: [item for item in x if item not in stopwords])
         data.head()
```

Out[15]:

	index	count	hate_speech	offensive_language	neither	class	tweet	tweets_w/o_space	tweet_w/o_url	tweet_lem	tokenized_tweet	
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...	rt mayasolovely as a woman you shouldn t...	[rt, mayasolovely, as, a, woman, you, shouldn,...	
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	!!!! rt @mleewnumbr: boy dats cold...tyga dwn...	!!!! rt @mleewnumbr: boy dats cold...tyga dwn...	rt mleewnumbr boy dats cold tyga dwn...	[rt, mleewnumbr, boy, dats, cold, tyga, dwn, b...	[dat
2	2	3	0	3	0	1	!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...	!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...	rt urkindofbrand dawg rt numbrsb...	[rt, urkindofbrand, dawg, rt, numbrsbabynumbrl...	[urk num
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...	rt c g anderson viva based she lo...	[rt, c, g, anderson, viva, based, she, look, l...	[c,
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...	rt shenikaroberts the shit you...	[rt, shenikaroberts, the, shit, you, hear, abo...	[sh

Stemming

In [16]:
```
processed_tweet = data["tweet_w/o_stop"].apply(lambda x: [stemmer.stem(i) for i in x])
```

In [17]:
```
 for i in range(len(processed_tweet)):
        processed_tweet[i] = ' '.join(processed_tweet[i])
        tweets_p= processed_tweet
```

In [18]:
```
data['processed_tweet'] = tweets_p
```

In [19]:
```
data.head()
```

Out[19]:

	index	count	hate_speech	offensive_language	neither	class	tweet	tweets_w/o_space	tweet_w/o_url	tweet_lem	tokenized_tweet	
0	0	3	0	0	3	2	!!! RT @mayasolovely: As a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...	!!! rt @mayasolovely: as a woman you shouldn't...	rt mayasolovely as a woman you shouldn t...	[rt, mayasolovely, as, a, woman, you, shouldn,...	
1	1	3	0	3	0	1	!!!!! RT @mleew17: boy dats cold...tyga dwn ba...	!!!!! rt @mleewnumbr: boy dats cold...tyga dwn...	!!!!! rt @mleewnumbr: boy dats cold...tyga dwn...	rt mleewnumbr boy dats cold tyga dwn...	[rt, mleewnumbr, boy, dats, cold, tyga, dwn, b...	[dat
2	2	3	0	3	0	1	!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...	!!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...	!!!!!!! rt @urkindofbrand dawg!!!! rt @numbrsb...	rt urkindofbrand dawg rt numbrsb...	[rt, urkindofbrand, dawg, rt, numbrsbabynumbrl...	[urk num
3	3	3	0	2	1	1	!!!!!!!!! RT @C_G_Anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...	!!!!!!!!! rt @c_g_anderson: @viva_based she lo...	rt c g anderson viva based she lo...	[rt, c, g, anderson, viva, based, she, look, l...	[c,
4	4	6	0	6	0	1	!!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...	!!!!!!!!!!!!! rt @shenikaroberts: the shit you...	rt shenikaroberts the shit you...	[rt, shenikaroberts, the, shit, you, hear, abo...	[sh

Displaying tweets and processed tweets

In [20]:
```
data.tweet
```

Out[20]:
```
0             !!! RT @mayasolovely: As a woman you shouldn't...
1             !!!!! RT @mleew17: boy dats cold...tyga dwn ba...
2             !!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
3             !!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
4             !!!!!!!!!!!!! RT @ShenikaRoberts: The shit you...
                                    ...
24778    you's a muthaf***in lie &#8220;@LifeAsKing: @2...
24779    you've gone and broke the wrong heart baby, an...
24780    young buck wanna eat!!.. dat nigguh like I ain...
24781                 youu got wild bitches tellin you lies
24782    ~~Ruffled | Ntac Eileen Dahlia - Beautiful col...
Name: tweet, Length: 24783, dtype: object
```

In [21]:
```
data.processed_tweet
```

Out[21]:
```
0        mayasolov woman complain clean hous amp man al...
1        mleewnumbr boy dat cold tyga dwn bad cuffin da...
2        urkindofbrand dawg numbrsbabynumbrlif ever fuc...
3                     c g anderson viva base look like tranni
4        shenikarobert shit hear might true might faker...
                                    ...
24778    muthaf lie numbr lifeask numbr pearl corey ema...
24779      gone broke wrong heart babi drove redneck crazi
24780    young buck wanna eat dat nigguh like aint fuck...
24781                       youu got wild bitch tellin lie
24782    ruffl ntac eileen dahlia beauti color combin p...
Name: processed_tweet, Length: 24783, dtype: object
```

One Hot Encoding of Target Label

In [23]:
```
labels = data['class']
```

In [24]:
```
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(sparse=False)

labels = encoder.fit_transform(np.array(labels).reshape(-1, 1))
```

Module 3: Feature Extraction:

Word Level One Hot Encoding

```
In [25]: from nltk.tokenize.treebank import TreebankWordDetokenizer
         def detokenize(text):
             return TreebankWordDetokenizer().detokenize(text)
```

```
In [26]: data1 = []

         for i in range(len(tweetstop)):
             data1.append(detokenize(tweetstop[i]))
         print(data1[:5])

         ['mayasolovely woman complain cleaning house amp man always take trash', 'mleewnumbr boy dats cold tyga dwn bad cuffi
         n dat hoe numbrst place', 'urkindofbrand dawg numbrsbabynumbrlife ever fuck bitch start cry confused shit', 'c g ande
         rson viva based look like tranny', 'shenikaroberts shit hear might true might faker bitch told ya numbr']
```

```
In [27]: data1 = np.array(data1)
```

```
In [28]: max_words = 5000
         max_len = 200

         tokenizer = Tokenizer(num_words=max_words)
         tokenizer.fit_on_texts(data1)
         sequences = tokenizer.texts_to_sequences(data1)
         tweets_in = pad_sequences(sequences, maxlen=max_len)
         print(tweets_in)

         [[   0    0    0 ...   83   76   15]
          [   0    0    0 ...    7  605  414]
          [   0    0    0 ...  470  900   12]
          ...
          [   0    0    0 ...   96   95  246]
          [   0    0    0 ...    3 1826 1247]
          [   0    0    0 ...   94   17   48]]
```

Using TFIDF Technique

```
In [38]: tfidf_vectorizer = TfidfVectorizer(ngram_range=(1, 2),max_df=0.75, min_df=5, max_features=1000)
         tfidf = tfidf_vectorizer.fit_transform(data['processed_tweet'] ).toarray()
         tfidf

Out[38]: array([[0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                ...,
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.]])
```

```
In [39]: tfidf.shape

Out[39]: (24783, 1000)
```

Using Bag of Words Technique [COUNTVectorizer]

```
In [47]: bow_vectorizer = CountVectorizer( max_features=100, stop_words='english', ngram_range=(2,2))
         bagofwords=bow_vectorizer.fit_transform(data['processed_tweet'] ).toarray()
         bagofwords

Out[47]: array([[0, 0, 0, ..., 0, 0, 0],
                [0, 0, 0, ..., 0, 0, 0],
                [0, 0, 0, ..., 0, 0, 0],
                ...,
                [0, 0, 0, ..., 0, 0, 0],
                [0, 0, 0, ..., 0, 0, 0],
                [0, 0, 0, ..., 0, 0, 0]], dtype=int64)

In [48]: bagofwords.shape

Out[48]: (24783, 100)
```

Combining all the Three Features [F1 + F2 + F3]

```
In [48]: modelling_features = np.concatenate([tfidf,bagofwords,tweets_in],axis=1)
         modelling_features.shape

Out[48]: (24783, 1300)
```

Module 4: Building a Long Short-Term Memory (LSTM) model:

```
In [30]: model = Sequential()

         model.add(layers.Embedding(max_words, 20))

         model.add(layers.LSTM(15,dropout=0.5))

         model.add(layers.Flatten())
         model.add(layers.Dropout(0.25))

         model.add(layers.Dense(512,activation='relu'))
         model.add(layers.Dense(3,activation='softmax'))

         model.compile(optimizer='adam',loss='categorical_crossentropy', metrics=['accuracy'])

In [31]: checkpoint = ModelCheckpoint("best_model.hdf5", monitor='val_accuracy', verbose=1,save_best_only=True, mode='auto',
                                      period=1,save_weights_only=False)

         WARNING:tensorflow:`period` argument is deprecated. Please use `save_freq` to specify the frequency in number of batches seen.
```

The LSTM Model is trained in the following features:

- Word level One Hot Encoding (F1).
- TFIDF (F2) Features.
- Bag of Words (F3).
- Combining all features (F1 + F2 + F3).

Feature 1:

Training the Model using Word level One Hot Encoding (F1) Features

Initializing X_train, X_test, y_train & y_test for F1

```
In [29]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(tweets_in,labels, random_state=0)
         print (len(X_train),len(X_test),len(y_train),len(y_test))

18587 6196 18587 6196
```

```
In [32]: history1 = model1.fit(X_train, y_train, epochs=10,validation_data=(X_test, y_test),callbacks=[checkpoint1])
```

```
Epoch 1/10
581/581 [==============================] - ETA: 0s - loss: 0.4937 - accuracy: 0.8260
Epoch 00001: val_accuracy improved from -inf to 0.88073, saving model to best_model1.hdf5
581/581 [==============================] - 33s 57ms/step - loss: 0.4937 - accuracy: 0.8260 - val_loss: 0.3475 - val_a
ccuracy: 0.8807
Epoch 2/10
581/581 [==============================] - ETA: 0s - loss: 0.3371 - accuracy: 0.8872
Epoch 00002: val_accuracy improved from 0.88073 to 0.89106, saving model to best_model1.hdf5
581/581 [==============================] - 36s 61ms/step - loss: 0.3371 - accuracy: 0.8872 - val_loss: 0.3234 - val_a
ccuracy: 0.8911
Epoch 3/10
581/581 [==============================] - ETA: 0s - loss: 0.3175 - accuracy: 0.8945
Epoch 00003: val_accuracy improved from 0.89106 to 0.89251, saving model to best_model1.hdf5
581/581 [==============================] - 36s 61ms/step - loss: 0.3175 - accuracy: 0.8945 - val_loss: 0.3189 - val_a
ccuracy: 0.8925
Epoch 4/10
581/581 [==============================] - ETA: 0s - loss: 0.3050 - accuracy: 0.8980
Epoch 00004: val_accuracy did not improve from 0.89251
581/581 [==============================] - 37s 64ms/step - loss: 0.3050 - accuracy: 0.8980 - val_loss: 0.3115 - val_a
ccuracy: 0.8904
Epoch 5/10
581/581 [==============================] - ETA: 0s - loss: 0.2908 - accuracy: 0.9029
Epoch 00005: val_accuracy improved from 0.89251 to 0.89703, saving model to best_model1.hdf5
581/581 [==============================] - 39s 66ms/step - loss: 0.2908 - accuracy: 0.9029 - val_loss: 0.2964 - val_a
ccuracy: 0.8970
Epoch 6/10
581/581 [==============================] - ETA: 0s - loss: 0.2782 - accuracy: 0.9046
Epoch 00006: val_accuracy improved from 0.89703 to 0.89800, saving model to best_model1.hdf5
581/581 [==============================] - 39s 67ms/step - loss: 0.2782 - accuracy: 0.9046 - val_loss: 0.2946 - val_a
ccuracy: 0.8980
Epoch 7/10
581/581 [==============================] - ETA: 0s - loss: 0.2645 - accuracy: 0.9100
Epoch 00007: val_accuracy improved from 0.89800 to 0.89832, saving model to best_model1.hdf5
581/581 [==============================] - 39s 67ms/step - loss: 0.2645 - accuracy: 0.9100 - val_loss: 0.2843 - val_a
ccuracy: 0.8983
```

ccuracy: 0.8983

```
Epoch 8/10
581/581 [==============================] - ETA: 0s - loss: 0.2585 - accuracy: 0.9122
Epoch 00008: val_accuracy improved from 0.89832 to 0.90219, saving model to best_model1.hdf5
581/581 [==============================] - 39s 66ms/step - loss: 0.2585 - accuracy: 0.9122 - val_loss: 0.2841 - val_a
ccuracy: 0.9022
Epoch 9/10
581/581 [==============================] - ETA: 0s - loss: 0.2491 - accuracy: 0.9157
Epoch 00009: val_accuracy did not improve from 0.90219
581/581 [==============================] - 36s 62ms/step - loss: 0.2491 - accuracy: 0.9157 - val_loss: 0.2792 - val_a
ccuracy: 0.9009
Epoch 10/10
581/581 [==============================] - ETA: 0s - loss: 0.2441 - accuracy: 0.9167
Epoch 00010: val_accuracy improved from 0.90219 to 0.90284, saving model to best_model1.hdf5
581/581 [==============================] - 39s 67ms/step - loss: 0.2441 - accuracy: 0.9167 - val_loss: 0.2779 - val_a
ccuracy: 0.9028
```

Feature 2:

Training the Model using TFIDF (F2) Features

Initializing X_train, X_test, y_train & y_test for F1

```
In [42]: from sklearn.model_selection import train_test_split
         X = tfidf
         X_train1, X_test1, y_train1, y_test1 = train_test_split(X, labels, random_state=42, test_size=0.2)
```

```
In [44]: history2 = model2.fit(X_train1, y_train1, epochs=10,  validation_data=(X_test, y_test),callbacks=[checkpoint2])
```

```
Epoch 1/10
620/620 [==============================] - ETA: 0s - loss: 0.6751 - accuracy: 0.7727
Epoch 00001: val_accuracy improved from -inf to 0.77469, saving model to best_model2.hdf5
620/620 [==============================] - 197s 318ms/step - loss: 0.6751 - accuracy: 0.7727 - val_loss: 0.6653 - val
_accuracy: 0.7747
Epoch 2/10
620/620 [==============================] - ETA: 0s - loss: 0.6627 - accuracy: 0.7746
Epoch 00002: val_accuracy did not improve from 0.77469
620/620 [==============================] - 197s 318ms/step - loss: 0.6627 - accuracy: 0.7746 - val_loss: 0.6686 - val
_accuracy: 0.7747
Epoch 3/10
620/620 [==============================] - ETA: 0s - loss: 0.6630 - accuracy: 0.7746
Epoch 00003: val_accuracy did not improve from 0.77469
620/620 [==============================] - 196s 317ms/step - loss: 0.6630 - accuracy: 0.7746 - val_loss: 0.6654 - val
_accuracy: 0.7747
Epoch 4/10
620/620 [==============================] - ETA: 0s - loss: 0.6626 - accuracy: 0.7746
Epoch 00004: val_accuracy did not improve from 0.77469
620/620 [==============================] - 196s 316ms/step - loss: 0.6626 - accuracy: 0.7746 - val_loss: 0.6702 - val
_accuracy: 0.7747
Epoch 5/10
620/620 [==============================] - ETA: 0s - loss: 0.6623 - accuracy: 0.7746
Epoch 00005: val_accuracy did not improve from 0.77469
620/620 [==============================] - 195s 315ms/step - loss: 0.6623 - accuracy: 0.7746 - val_loss: 0.6639 - val
_accuracy: 0.7747
Epoch 6/10
620/620 [==============================] - ETA: 0s - loss: 0.6624 - accuracy: 0.7746
Epoch 00006: val_accuracy did not improve from 0.77469
620/620 [==============================] - 196s 316ms/step - loss: 0.6624 - accuracy: 0.7746 - val_loss: 0.6642 - val
_accuracy: 0.7747
Epoch 7/10
620/620 [==============================] - ETA: 0s - loss: 0.6627 - accuracy: 0.7746
Epoch 00007: val_accuracy did not improve from 0.77469
620/620 [==============================] - 196s 316ms/step - loss: 0.6627 - accuracy: 0.7746 - val_loss: 0.6646 - val
_accuracy: 0.7747
Epoch 8/10
620/620 [==============================] - ETA: 0s - loss: 0.6625 - accuracy: 0.7746
Epoch 00008: val_accuracy did not improve from 0.77469
```

```
Epoch 8/10
620/620 [==============================] - ETA: 0s - loss: 0.6625 - accuracy: 0.7746
Epoch 00008: val_accuracy did not improve from 0.77469
620/620 [==============================] - 197s 318ms/step - loss: 0.6625 - accuracy: 0.7746 - val_loss: 0.6645 - val
_accuracy: 0.7747
Epoch 9/10
620/620 [==============================] - ETA: 0s - loss: 0.6622 - accuracy: 0.7746
Epoch 00009: val_accuracy did not improve from 0.77469
620/620 [==============================] - 197s 318ms/step - loss: 0.6622 - accuracy: 0.7746 - val_loss: 0.6645 - val
_accuracy: 0.7747
Epoch 10/10
620/620 [==============================] - ETA: 0s - loss: 0.6623 - accuracy: 0.7746
Epoch 00010: val_accuracy did not improve from 0.77469
620/620 [==============================] - 196s 316ms/step - loss: 0.6623 - accuracy: 0.7746 - val_loss: 0.6654 - val
_accuracy: 0.7747
```

Feature 3:

Training the Model using Bag of Words (F3) Features

Initializing X_train, X_test, y_train & y_test for F1

```
In [49]: X = bagofwords
         X_train2, X_test2, y_train2, y_test2 = train_test_split(X, labels, random_state=42, test_size=0.2)
```

```
In [52]: history3 = model3.fit(X_train2, y_train2, epochs=10, steps_per_epoch=20, validation_data=(X_test, y_test),callbacks=[ch
```

```
Epoch 1/10
20/20 [==============================] - ETA: 0s - loss: 0.8173 - accuracy: 0.7500
Epoch 00001: val_accuracy improved from -inf to 0.77469, saving model to best_model3.hdf5
20/20 [==============================] - 7s 327ms/step - loss: 0.8173 - accuracy: 0.7500 - val_loss: 0.6705 - val_acc
uracy: 0.7747
Epoch 2/10
20/20 [==============================] - ETA: 0s - loss: 0.6652 - accuracy: 0.7746
Epoch 00002: val_accuracy did not improve from 0.77469
20/20 [==============================] - 6s 278ms/step - loss: 0.6652 - accuracy: 0.7746 - val_loss: 0.6623 - val_acc
uracy: 0.7747
Epoch 3/10
20/20 [==============================] - ETA: 0s - loss: 0.6621 - accuracy: 0.7746
Epoch 00003: val_accuracy did not improve from 0.77469
20/20 [==============================] - 6s 305ms/step - loss: 0.6621 - accuracy: 0.7746 - val_loss: 0.6625 - val_acc
uracy: 0.7747
Epoch 4/10
20/20 [==============================] - ETA: 0s - loss: 0.6618 - accuracy: 0.7746
Epoch 00004: val_accuracy did not improve from 0.77469
20/20 [==============================] - 5s 273ms/step - loss: 0.6618 - accuracy: 0.7746 - val_loss: 0.6581 - val_acc
uracy: 0.7747
Epoch 5/10
20/20 [==============================] - ETA: 0s - loss: 0.6622 - accuracy: 0.7746
Epoch 00005: val_accuracy did not improve from 0.77469
20/20 [==============================] - 5s 272ms/step - loss: 0.6622 - accuracy: 0.7746 - val_loss: 0.6548 - val_acc
uracy: 0.7747
Epoch 6/10
20/20 [==============================] - ETA: 0s - loss: 0.6619 - accuracy: 0.7746
Epoch 00006: val_accuracy did not improve from 0.77469
20/20 [==============================] - 6s 288ms/step - loss: 0.6619 - accuracy: 0.7746 - val_loss: 0.6530 - val_acc
uracy: 0.7747
Epoch 7/10
20/20 [==============================] - ETA: 0s - loss: 0.6618 - accuracy: 0.7746
```

```
Epoch 8/10
20/20 [==============================] - ETA: 0s - loss: 0.6619 - accuracy: 0.7746
Epoch 00008: val_accuracy did not improve from 0.77469
20/20 [==============================] - 6s 282ms/step - loss: 0.6619 - accuracy: 0.7746 - val_loss: 0.6525 - val_acc
uracy: 0.7747
Epoch 9/10
20/20 [==============================] - ETA: 0s - loss: 0.6617 - accuracy: 0.7746
Epoch 00009: val_accuracy did not improve from 0.77469
20/20 [==============================] - 5s 256ms/step - loss: 0.6617 - accuracy: 0.7746 - val_loss: 0.6499 - val_acc
uracy: 0.7747
Epoch 10/10
20/20 [==============================] - ETA: 0s - loss: 0.6617 - accuracy: 0.7746
Epoch 00010: val_accuracy did not improve from 0.77469
20/20 [==============================] - 5s 272ms/step - loss: 0.6617 - accuracy: 0.7746 - val_loss: 0.6485 - val_acc
uracy: 0.7747
```

Feature 4:

Training the Model using (F1 + F2 + F3) Features

Initializing X_train, X_test, y_train & y_test for F1 + F2 + F3

```
In [49]: X = modelling_features
         X_train3, X_test3, y_train3, y_test3 = train_test_split(X, labels, random_state=42, test_size=0.2)
```

```
In [50]: history4= model.fit(X_train3, y_train3, epochs=10, steps_per_epoch=20, validation_data=(X_test3, y_test3),
                             callbacks=[checkpoint])
```

```
Epoch 1/10
20/20 [==============================] - ETA: 0s - loss: 0.3324 - accuracy: 0.8962
Epoch 00001: val_accuracy improved from 0.88202 to 0.90418, saving model to best_model.hdf5
20/20 [==============================] - 111s 6s/step - loss: 0.3324 - accuracy: 0.8962 - val_loss: 0.3003 - val_accuracy: 0.90
42
Epoch 2/10
20/20 [==============================] - ETA: 0s - loss: 0.2740 - accuracy: 0.9112
Epoch 00002: val_accuracy did not improve from 0.90418
20/20 [==============================] - 114s 6s/step - loss: 0.2740 - accuracy: 0.9112 - val_loss: 0.2939 - val_accuracy: 0.90
34
Epoch 3/10
20/20 [==============================] - ETA: 0s - loss: 0.2502 - accuracy: 0.9174
Epoch 00003: val_accuracy did not improve from 0.90418
20/20 [==============================] - 116s 6s/step - loss: 0.2502 - accuracy: 0.9174 - val_loss: 0.2961 - val_accuracy: 0.90
36
Epoch 4/10
20/20 [==============================] - ETA: 0s - loss: 0.2337 - accuracy: 0.9223
Epoch 00004: val_accuracy did not improve from 0.90418
20/20 [==============================] - 117s 6s/step - loss: 0.2337 - accuracy: 0.9223 - val_loss: 0.2931 - val_accuracy: 0.90
01
Epoch 5/10
20/20 [==============================] - ETA: 0s - loss: 0.2171 - accuracy: 0.9271
Epoch 00005: val_accuracy did not improve from 0.90418
20/20 [==============================] - 122s 6s/step - loss: 0.2171 - accuracy: 0.9271 - val_loss: 0.2966 - val_accuracy: 0.89
95
Epoch 6/10
20/20 [==============================] - ETA: 0s - loss: 0.2010 - accuracy: 0.9320
Epoch 00006: val_accuracy did not improve from 0.90418
20/20 [==============================] - 119s 6s/step - loss: 0.2010 - accuracy: 0.9320 - val_loss: 0.2953 - val_accuracy: 0.90
34
```

```
Epoch 7/10
20/20 [==============================] - ETA: 0s - loss: 0.1885 - accuracy: 0.9348
Epoch 00007: val_accuracy did not improve from 0.90418
20/20 [==============================] - 119s 6s/step - loss: 0.1885 - accuracy: 0.9348 - val_loss: 0.3046 - val_accuracy: 0.89
57
Epoch 8/10
20/20 [==============================] - ETA: 0s - loss: 0.1790 - accuracy: 0.9380
Epoch 00008: val_accuracy did not improve from 0.90418
20/20 [==============================] - 119s 6s/step - loss: 0.1790 - accuracy: 0.9380 - val_loss: 0.3067 - val_accuracy: 0.90
28
Epoch 9/10
20/20 [==============================] - ETA: 0s - loss: 0.1695 - accuracy: 0.9398
Epoch 00009: val_accuracy did not improve from 0.90418
20/20 [==============================] - 118s 6s/step - loss: 0.1695 - accuracy: 0.9398 - val_loss: 0.3173 - val_accuracy: 0.89
89
Epoch 10/10
20/20 [==============================] - ETA: 0s - loss: 0.1641 - accuracy: 0.9433
Epoch 00010: val_accuracy did not improve from 0.90418
20/20 [==============================] - 120s 6s/step - loss: 0.1641 - accuracy: 0.9433 - val_loss: 0.3369 - val_accuracy: 0.89
43
```

```
Epoch 7/10
20/20 [==============================] - ETA: 0s - loss: 0.1885 - accuracy: 0.9348
Epoch 00007: val_accuracy did not improve from 0.90418
20/20 [==============================] - 119s 6s/step - loss: 0.1885 - accuracy: 0.9348 - val_loss: 0.3046 - val_accuracy: 0.89
57
Epoch 8/10
20/20 [==============================] - ETA: 0s - loss: 0.1790 - accuracy: 0.9380
Epoch 00008: val_accuracy did not improve from 0.90418
20/20 [==============================] - 119s 6s/step - loss: 0.1790 - accuracy: 0.9380 - val_loss: 0.3067 - val_accuracy: 0.90
28
Epoch 9/10
20/20 [==============================] - ETA: 0s - loss: 0.1695 - accuracy: 0.9398
Epoch 00009: val_accuracy did not improve from 0.90418
20/20 [==============================] - 118s 6s/step - loss: 0.1695 - accuracy: 0.9398 - val_loss: 0.3173 - val_accuracy: 0.89
89
Epoch 10/10
20/20 [==============================] - ETA: 0s - loss: 0.1641 - accuracy: 0.9433
Epoch 00010: val_accuracy did not improve from 0.90418
20/20 [==============================] - 120s 6s/step - loss: 0.1641 - accuracy: 0.9433 - val_loss: 0.3369 - val_accuracy: 0.89
43
```

LSTM Model Summary

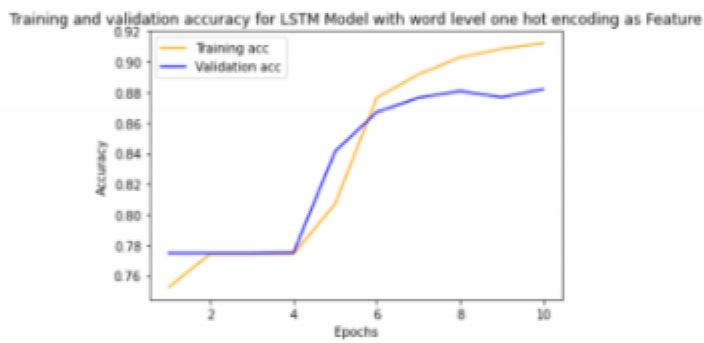
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 20)          100000
_________________________________________________________________
lstm (LSTM)                  (None, 15)                2160
_________________________________________________________________
flatten (Flatten)            (None, 15)                0
_________________________________________________________________
dropout (Dropout)            (None, 15)                0
_________________________________________________________________
dense (Dense)                (None, 512)               8192
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 1539
=================================================================
Total params: 111,891
Trainable params: 111,891
Non-trainable params: 0
_________________________________________________________________
```

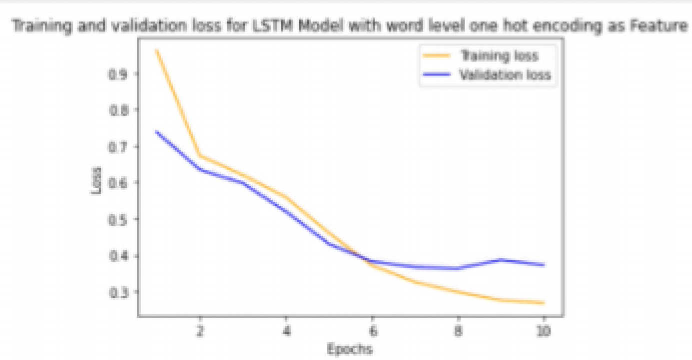
Module 5: Model Evaluation:

Accuracy and Loss curve for LSTM Model Trained using Feature 1

In [33]:
```
import matplotlib.pyplot as plt
acc = history1.history['accuracy']
val_acc = history1.history['val_accuracy']

epochs = range(1, 11)

plt.plot(epochs, acc, 'orange', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy for LSTM Model with word level one hot encoding as Feature')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.figure()
plt.show()
```

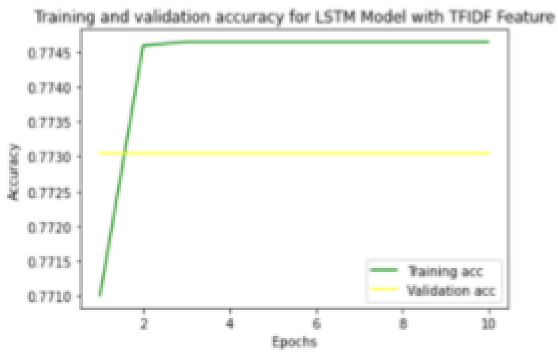


In [34]:
```
loss = history1.history['loss']
val_loss = history1.history['val_loss']

epochs = range(1, 11)

plt.plot(epochs, loss, 'orange', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss for LSTM Model with word level one hot encoding as Feature')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

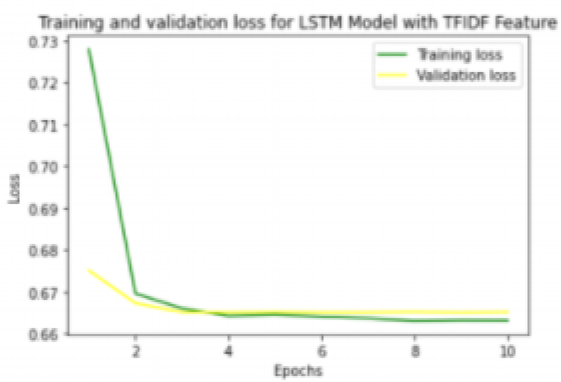


Accuracy and Loss curve for LSTM Model Trained using Feature 2

In [40]:
```
import matplotlib.pyplot as plt
acc = history2.history['accuracy']
val_acc = history2.history['val_accuracy']

epochs = range(1, 11)

plt.plot(epochs, acc, 'green', label='Training acc')
plt.plot(epochs, val_acc, 'yellow', label='Validation acc')
plt.title('Training and validation accuracy for LSTM Model with TFIDF Feature')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.figure()
plt.show()
```

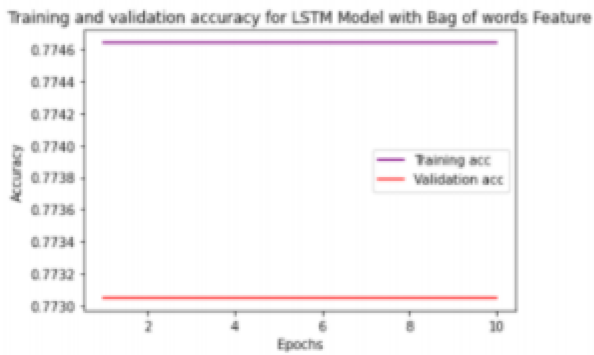


In [41]:
```
loss = history2.history['loss']
val_loss = history2.history['val_loss']

epochs = range(1, 11)

plt.plot(epochs, loss, 'green', label='Training loss')
plt.plot(epochs, val_loss, 'yellow', label='Validation loss')
plt.title('Training and validation loss for LSTM Model with TFIDF Feature')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

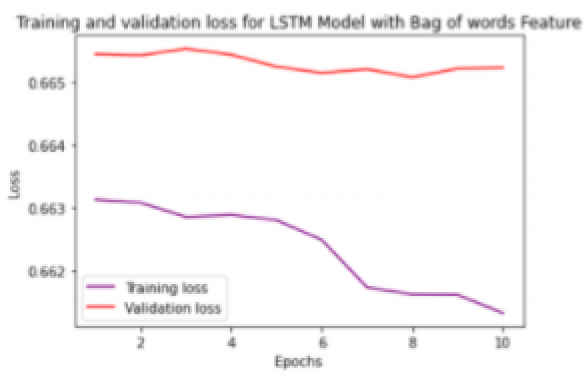


Accuracy and Loss curve for LSTM Model Trained using Feature 3

In [46]:
```
import matplotlib.pyplot as plt
acc = history3.history['accuracy']
val_acc = history3.history['val_accuracy']

epochs = range(1, 11)

plt.plot(epochs, acc, 'purple', label='Training acc')
plt.plot(epochs, val_acc, 'red', label='Validation acc')
plt.title('Training and validation accuracy for LSTM Model with Bag of words Feature')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.figure()
plt.show()
```



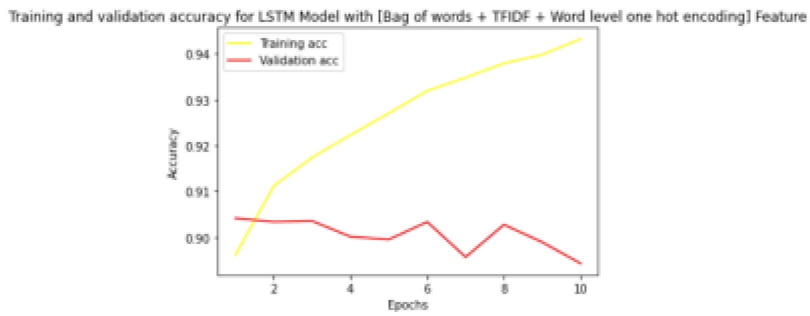
In [47]:
```
loss = history3.history['loss']
val_loss = history3.history['val_loss']

epochs = range(1, 11)

plt.plot(epochs, loss, 'purple', label='Training loss')
plt.plot(epochs, val_loss, 'red', label='Validation loss')
plt.title('Training and validation loss for LSTM Model with Bag of words Feature')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



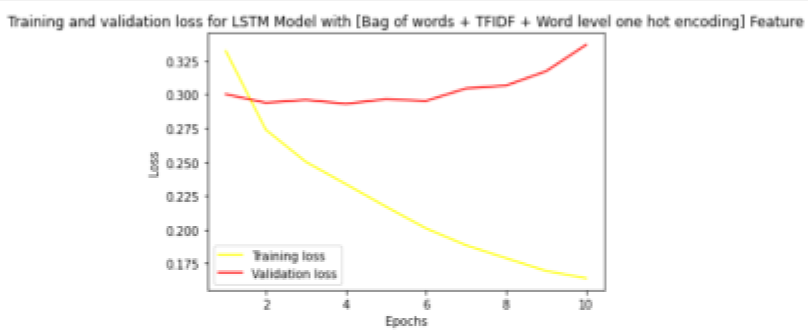
Accuracy and Loss curve for LSTM Model Trained using Feature 1+2+3

From Feature 4

In [51]:
```
acc = history4.history['accuracy']
val_acc = history4.history['val_accuracy']

epochs = range(1, 11)

plt.plot(epochs, acc, 'yellow', label='Training acc')
plt.plot(epochs, val_acc, 'red', label='Validation acc')
plt.title('Training and validation accuracy for LSTM Model with [Bag of words + TFIDF + Word level one hot encoding] Feature')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.figure()
plt.show()
```



In [52]:
```
loss = history4.history['loss']
val_loss = history4.history['val_loss']

epochs = range(1, 11)

plt.plot(epochs, loss, 'yellow', label='Training loss')
plt.plot(epochs, val_loss, 'red', label='Validation loss')
plt.title('Training and validation loss for LSTM Model with [Bag of words + TFIDF + Word level one hot encoding] Feature')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



Printing the Test Accuracy and Test Loss

```
In [53]: score1 = model.evaluate(X_test, y_test, verbose=0)
         print('Test loss:', score1[0])
         print('Test accuracy:', score1[1])

         Test loss: 0.20353253185749054
         Test accuracy: 0.9351194500923157

In [54]: score2 = model.evaluate(X_test1, y_test1, verbose=0)
         print('Test loss:', score2[0])
         print('Test accuracy:', score2[1])

         Test loss: 0.6697127819061279
         Test accuracy: 0.7730482220649719

In [55]: score3 = model.evaluate(X_test2, y_test2, verbose=0)
         print('Test loss:', score2[0])
         print('Test accuracy:', score2[1])

         Test loss: 0.6697127819061279
         Test accuracy: 0.7730482220649719

In [76]: score4 = model.evaluate(X_test3, y_test3, verbose=0)
         print('Test loss:', score4[0])
         print('Test accuracy:', score4[1])

         Test loss: 0.33693215250968933
         Test accuracy: 0.8942909240722656
```

Inference

The test accuracy score is high when the LSTM Model is Trained using Features like

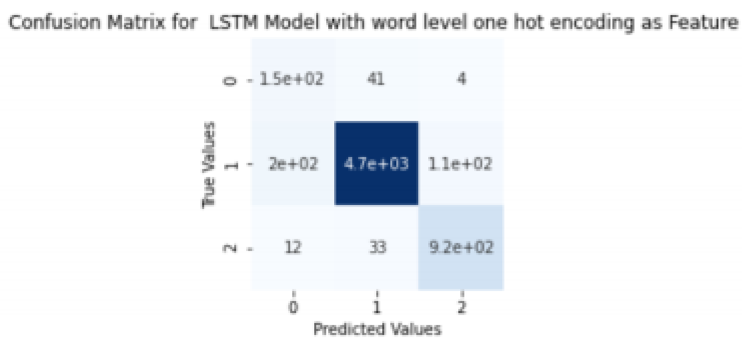
- Word Level One Hot Encoding (F1)
- Word Level One Hot Encoding + TFI DF + Bag of Words (F1 + F2 + F3)

Where as the test accuracy score is low for the LSTM Model Trained using features like:

- TFIDF (F2)
- Bag of Words (F3)

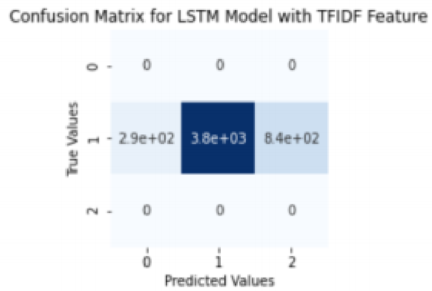
Printing Confusion Matrix for Feature 1:

```
In [57]: from sklearn.metrics import confusion_matrix
         import seaborn as sns
         fig = plt.figure(figsize=(3, 3))

         y_preds = model.predict(X_test)

         Y_pred = np.argmax(y_preds, 1)
         Y_test = np.argmax(y_test, 1)

         mat = confusion_matrix(Y_test, Y_pred)

         sns.heatmap(mat.T, square=True, annot=True, cbar=False, cmap=plt.cm.Blues)
         plt.title('Confusion Matrix for  LSTM Model with word level one hot encoding as Feature ')
         plt.xlabel('Predicted Values')
         plt.ylabel('True Values');
         plt.show();
```



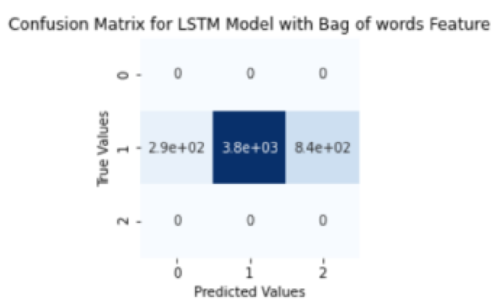
Printing Confusion Matrix for Feature 2:

In [58]:
```
fig = plt.figure(figsize=(3, 3))

y_preds = model.predict(X_test1)

Y_pred = np.argmax(y_preds, 1)
Y_test = np.argmax(y_test1, 1)

mat = confusion_matrix(Y_test, Y_pred)

sns.heatmap(mat.T, square=True, annot=True, cbar=False, cmap=plt.cm.Blues)
plt.title('Confusion Matrix for LSTM Model with TFIDF Feature')
plt.xlabel('Predicted Values')
plt.ylabel('True Values');
plt.show();
```



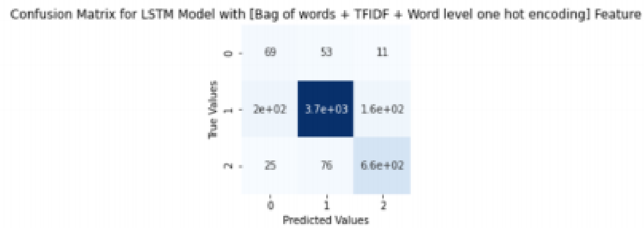
Printing Confusion Matrix for Feature 3:

In [59]:
```
fig = plt.figure(figsize=(3, 3))

y_preds = model.predict(X_test2)

Y_pred = np.argmax(y_preds, 1)
Y_test = np.argmax(y_test2, 1)

mat = confusion_matrix(Y_test, Y_pred)

sns.heatmap(mat.T, square=True, annot=True, cbar=False, cmap=plt.cm.Blues)
plt.title('Confusion Matrix for LSTM Model with Bag of words Feature')
plt.xlabel('Predicted Values')
plt.ylabel('True Values');
plt.show();
```



Printing Confusion Matrix for Feature 4:

```
In [60]: fig = plt.figure(figsize=(3, 3))

         y_preds = model.predict(X_test3)

         Y_pred = np.argmax(y_preds, 1)
         Y_test = np.argmax(y_test3, 1)

         mat = confusion_matrix(Y_test, Y_pred)

         sns.heatmap(mat.T, square=True, annot=True, cbar=False, cmap=plt.cm.Blues)
         plt.title('Confusion Matrix for LSTM Model with [Bag of words + TFIDF + Word level one hot encoding] Feature')
         plt.xlabel('Predicted Values')
         plt.ylabel('True Values');
         plt.show();
```



Prediction

```
In [63]: import keras
         best_model = keras.models.load_model("best_model.hdf5")

In [64]: sentiment = ['Hatespeech','Offensivelanguage','Neither']

In [65]: sequence = tokenizer.texts_to_sequences(['this experience has been the worst , want my money back'])
         test = pad_sequences(sequence, maxlen=max_len)
         sentiment[np.around(best_model.predict(test), decimals=0).argmax(axis=1)[0]]

Out[65]: 'Hatespeech'

In [66]: sequence = tokenizer.texts_to_sequences(['as a woman you should not complain about cleaning up your house'])
         test = pad_sequences(sequence, maxlen=max_len)
         sentiment[np.around(best_model.predict(test), decimals=0).argmax(axis=1)[0]]

Out[66]: 'Offensivelanguage'

In [67]: sequence = tokenizer.texts_to_sequences(['when twitter rappers dm me their trash links'])
         test = pad_sequences(sequence, maxlen=max_len)
         sentiment[np.around(best_model.predict(test), decimals=0).argmax(axis=1)[0]]

Out[67]: 'Neither'
```

Results

The LSTM Model is trained using four different features. Confusion matrices and accuracy for the models with different features are obtained.

Conclusion

A deep learning approach like LSTM (Long Short-Term Memory) Model has been used for creating a model for detecting hate speech and offensive language detection. The model is trained and tested with different features and it achieved good results compared to its simplicity.

References

1. https://github.com/sergiovirahonda/TweetsSentimentAnalysis/blob/main/TweetsSentimentPredictions.ipynb.
2. https://github.com/Sachin-Jain-98/Detection-And-Classification-Of-Hate-Speech-In-Social-Media-Using-Python/blob/master/Hate_speech_detection_Final_code.ipynb.
3. https://towardsdatascience.com/how-to-use-nlp-in-python-a-practical-step-by-step-example-bd82ca2d2e1e?gi=e6a4dc0f76ef.