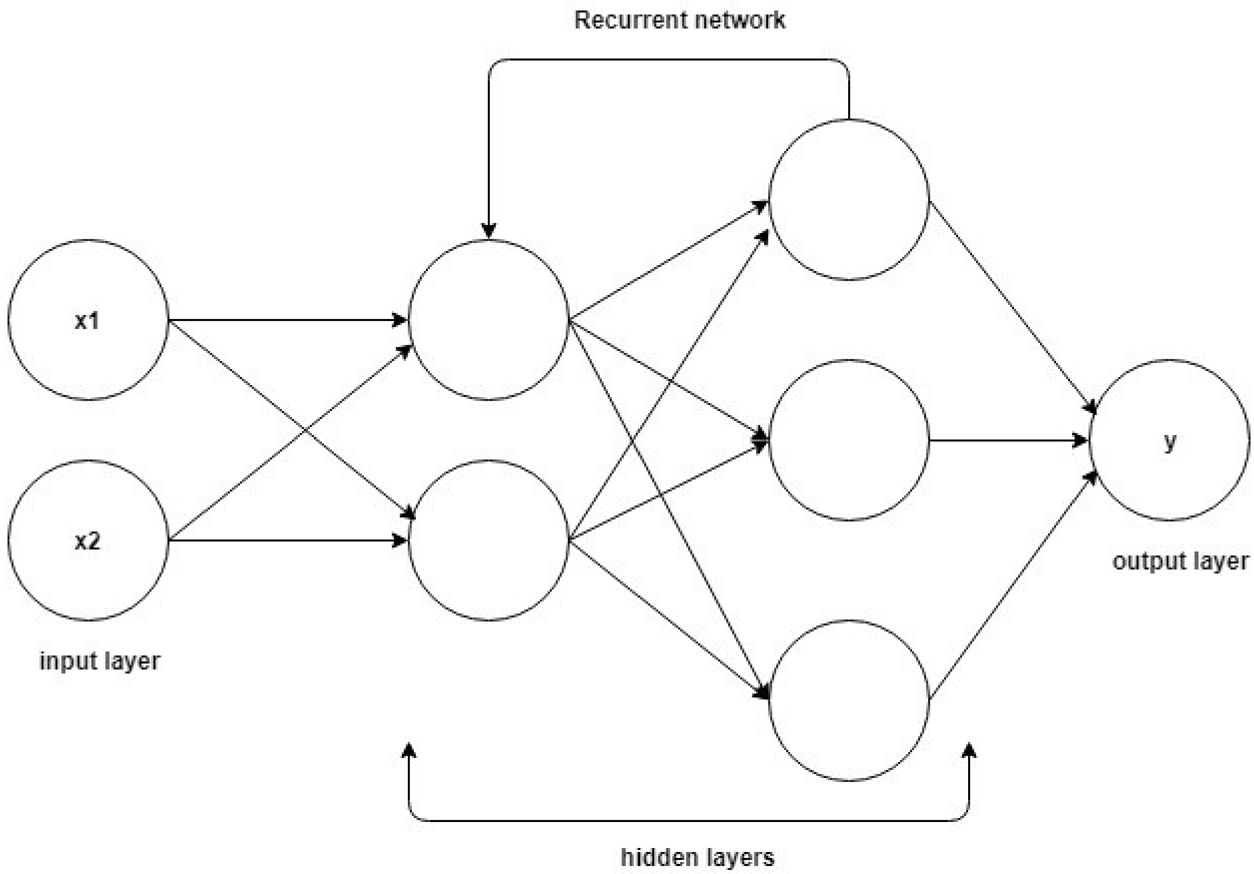
Deep Learning Text Emotion Analyzer

Implementing the Deep Learning Recurrent Neural Network Algorithm by PyTorch and tools to identify the different emotions in the text and paragraphs i.e. training and predicting accurately the emotions of anger, fear, joy, surprise and sadness by using the model.



In [2]:
```
#Install PyTorch
!pip3 install http://download.pytorch.org/whl/cu80/torch-0.4.1-cp36-cp36m-linux_x86_64.whl
```

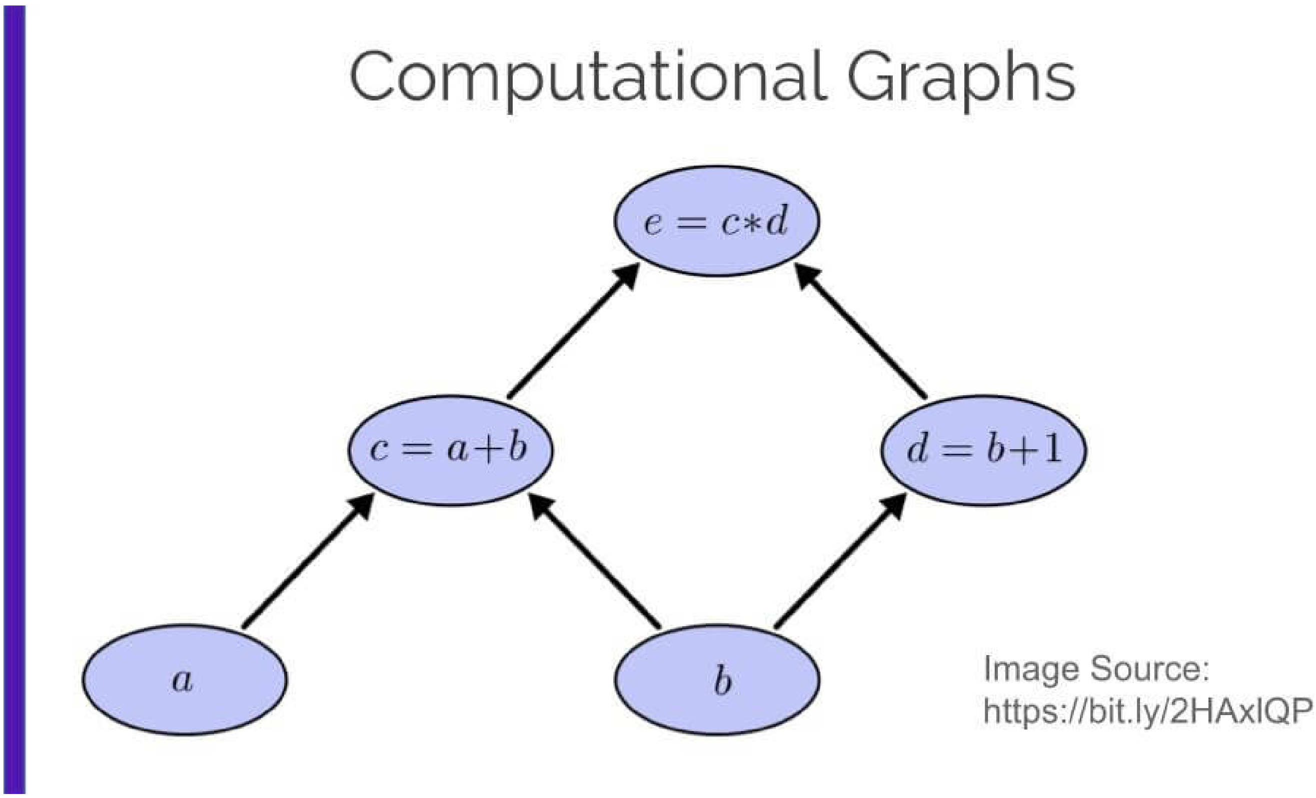
```
Collecting torch==0.4.1
  Downloading http://download.pytorch.org/whl/cu80/torch-0.4.1-cp36-cp36m-linux_x86_64.whl (483.0MB)
     |████████████████████████████████| 483.0MB 1.3MB/s
ERROR: torchvision 0.6.0+cu101 has requirement torch==1.5.0, but you'll have torch 0.4.1 which is incompatible.
ERROR: fastai 1.0.61 has requirement torch>=1.0.0, but you'll have torch 0.4.1 which is incompatible.
Installing collected packages: torch
  Found existing installation: torch 1.5.0+cu101
    Uninstalling torch-1.5.0+cu101:
      Successfully uninstalled torch-1.5.0+cu101
Successfully installed torch-0.4.1
```

Eager Execution

Eager execution allows us to operate on the computation graph dynamically, also known as imperative programming. TensorFlow requires that you manually set this mode, while PyTorch comes with this mode by default. Below we import the necessary libraries to use PyTorch.

In [3]:
```
import torch
import torch.functional as F
import torch.nn as nn
import torch.optim as optim
from torch.nn.utils.rnn import pack_padded_sequence, pad_packed_sequence
```

Computational Graph

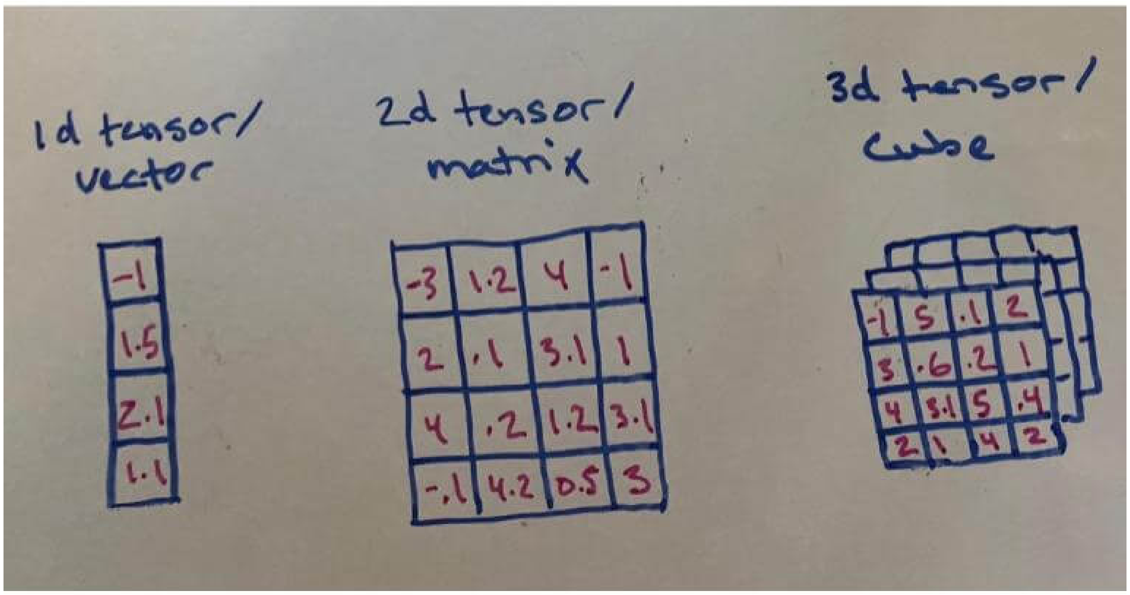


Math and Transformation of Tensors

In [4]:
```python
c = torch.tensor([[1.0, 2.0], [3.0, 4.0]])
d = torch.tensor([[1.0, 1.0], [0.0, 1.0]])
e = torch.matmul(c, d)
print(e)
print(c.size())
```

```
tensor([[1., 3.],
        [3., 7.]])
torch.Size([2, 2])
```

Tensor Basics



In [5]:
```python
### Automatic differentiation with PyTorch
x = torch.ones(2, 2, requires_grad=True)

# an operation of tensor
y = x + 2 # y inherits grad_fn

# apply operations on y
z = y * y * 3
out = z.mean()

print(out)

out.backward()

print(x.grad) # d(out)/dx
```

```
tensor(27., grad_fn=<MeanBackward1>)
tensor([[4.5000, 4.5000],
        [4.5000, 4.5000]])
```

In [6]:
```
x = torch.tensor([[1, 2, 3], [4, 5, 6]])
print("X shape: ", x.size())

# add dimension
print(x.unsqueeze(1).size())

# transpose
torch.transpose(x, 0,1)
```

```
X shape:  torch.Size([2, 3])
torch.Size([2, 1, 3])
```

Out[6]:
```
tensor([[1, 4],
        [2, 5],
        [3, 6]])
```

Emotion Dataset

An Emotion Dataset containing of tweets labelled into six categories is used in the model

In [51]:
```
import re
import numpy as np
import time
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
%matplotlib inline

import itertools
import pandas as pd
from scipy import stats
from sklearn import metrics
from sklearn.preprocessing import LabelEncoder
```

In [10]:
```
### Helper functions
import pickle

def convert_to_pickle(item, directory):
    pickle.dump(item, open(directory,"wb"))


def load_from_pickle(directory):
    return pickle.load(open(directory,"rb"))
```

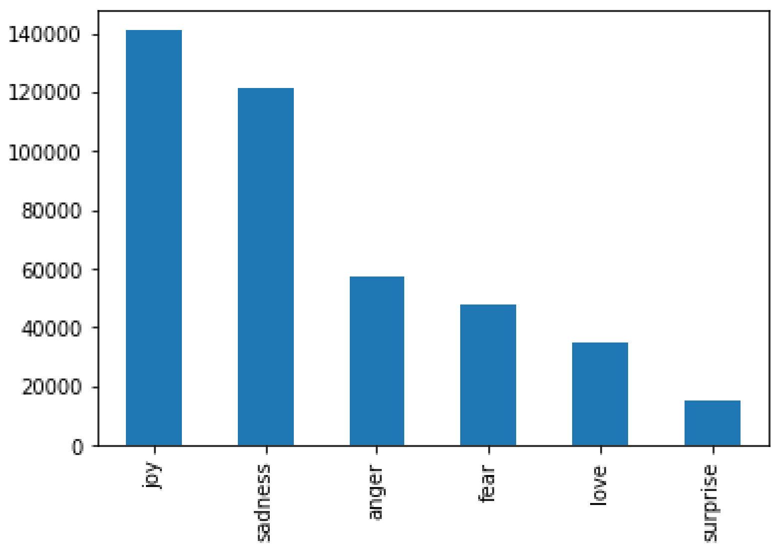
In [13]:
```
### read data from your Google Drive
from google.colab import drive
drive.mount('/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
··········
Mounted at /gdrive
```

In [15]:
```
# load data
data = load_from_pickle(directory="/gdrive/My Drive/Projects/Codes/Text Emotional Analyzer/emotion_text.pkl")
data.emotions.value_counts().plot.bar()
```

Out[15]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1798b6e80>
```



In [16]:
```
data.head(10)
```

Out[16]:

	text	emotions
27383	i feel awful about it too because it s my job ...	sadness
110083	im alone i feel awful	sadness
140764	ive probably mentioned this before but i reall...	joy
100071	i was feeling a little low few days back	sadness
2837	i beleive that i am much more sensitive to oth...	love
18231	i find myself frustrated with christians becau...	love
10714	i am one of those people who feels like going ...	joy
35177	i feel especially pleased about this as this h...	joy
122177	i was struggling with these awful feelings and...	joy
26723	i feel so enraged but helpless at the same time	anger

Preprocessing Data

1) Tokenization and Sampling

In [18]:
```
# retain only text that contain less that 70 tokens to avoid too much pad
ding
data["token_size"] = data["text"].apply(lambda x: len(x.split(' ')))
data = data.loc[data['token_size'] < 70].copy()

# sampling
data = data.sample(n=50000);
```

2) Constructing Vocabulary and Index-Word Mapping

In [19]:
```python
class ConstructVocab():
    def __init__(self, sentences):
        self.sentences = sentences
        self.word2idx = {}
        self.idx2word = {}
        self.vocab = set()
        self.create_index()

    def create_index(self):
        for s in self.sentences:
            # update with individual tokens
            self.vocab.update(s.split(' '))

        # sort the vocab
        self.vocab = sorted(self.vocab)

        # add a padding token with index 0
        self.word2idx['<pad>'] = 0

        # word to index mapping
        for index, word in enumerate(self.vocab):
            self.word2idx[word] = index + 1 # +1 because of pad token

        # index to word mapping
        for word, index in self.word2idx.items():
            self.idx2word[index] = word
```

In [20]:
```python
# construct vocab and indexing
inputs = ConstructVocab(data["text"].values.tolist())

# examples of what is in the vocab
inputs.vocab[0:10]
```

Out[20]:
```
['a',
 'aa',
 'aaaaaaaall',
 'aaaaah',
 'aab',
 'aabsolutely',
 'aaliyah',
 'aaradhya',
 'aardvark',
 'aaron']
```

Converting Data into Tensors

In [21]:
```python
# vectorize to tensor
input_tensor = [[inputs.word2idx[s] for s in es.split(' ')]  for es in da
ta["text"].values.tolist()]
```

In [23]:
```
# examples of what is in the input tensors
input_tensor[0:4]
```

```
Out[23]: [[11761, 781, 8899, 15738, 13123, 504],
          [11761,
           27215,
           10858,
           1473,
           16517,
           18611,
           1473,
           17743,
           16426,
           14968,
           11579,
           23431,
           11761,
           8887,
           72,
           860,
           12769,
           2105,
           11761,
           13529,
           12774,
           14652,
           24459,
           8887,
           20207,
           899,
           13146,
           899,
           13879,
           24459,
           26630,
           24788,
           24082,
           24788,
           22575,
           7742],
          [11761,
           8887,
           16426,
           16180,
           24788,
           16784,
           12774,
           24562,
           11761,
           6995,
           8887,
           1,
           2440,
           23836,
           12036,
           24436,
           1215,
           16773,
           12737,
           21693,
```

```
  7034,
  24543,
  13203,
  24788,
  25269,
  899,
  14479,
  694,
  24436,
  17743,
  26942,
  10963,
  2824,
  24788,
  1225,
  4538,
  27104,
  11162,
  12036,
  27104,
  24436,
  27161,
  10947,
  15505],
 [11761,
  8887,
  7928,
  6438,
  9344,
  899,
  19586,
  9411,
  24436,
  9060,
  26780,
  16773,
  27215,
  899,
  27228,
  12036]]
```

Padding of data

In [24]:
```
def max_length(tensor):
    return max(len(t) for t in tensor)
```

In [25]:
```
# calculate the max_length of input tensor
max_length_inp = max_length(input_tensor)
print(max_length_inp)
```

```
68
```

In [26]:
```
def pad_sequences(x, max_len):
    padded = np.zeros((max_len), dtype=np.int64)
    if len(x) > max_len: padded[:] = x[:max_len]
    else: padded[:len(x)] = x
    return padded
```

In [27]:
```
# inplace padding
input_tensor = [pad_sequences(x, max_length_inp) for x in input_tensor]
```

In [28]:
```
input_tensor[0:4]
```

Out[28]:
```
[array([11761,   781,  8899, 15738, 13123,   504,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0]),
 array([11761, 27215, 10858,  1473, 16517, 18611,  1473, 17743, 16426,
        14968, 11579, 23431, 11761,  8887,    72,   860, 12769,  2105,
        11761, 13529, 12774, 14652, 24459,  8887, 20207,   899, 13146,
          899, 13879, 24459, 26630, 24788, 24082, 24788, 22575,  7742,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0]),
 array([11761,  8887, 16426, 16180, 24788, 16784, 12774, 24562, 11761,
         6995,  8887,     1,  2440, 23836, 12036, 24436,  1215, 16773,
        12737, 21693,  7034, 24543, 13203, 24788, 25269,   899, 14479,
          694, 24436, 17743, 26942, 10963,  2824, 24788,  1225,  4538,
        27104, 11162, 12036, 27104, 24436, 27161, 10947, 15505,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0]),
 array([11761,  8887,  7928,  6438,  9344,   899, 19586,  9411, 24436,
         9060, 26780, 16773, 27215,   899, 27228, 12036,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0])]
```

Binarization

In [29]:
```
### convert targets to one-hot encoding vectors
emotions = list(set(data.emotions.unique()))
num_emotions = len(emotions)
# binarizer
mlb = preprocessing.MultiLabelBinarizer()
data_labels =  [set(emos) & set(emotions) for emos in data[['emotions']].
values]
bin_emotions = mlb.fit_transform(data_labels)
target_tensor = np.array(bin_emotions.tolist())
```

In [30]:
```
target_tensor[0:4]
```

Out[30]:
```
array([[0, 0, 1, 0, 0, 0],
       [1, 0, 0, 0, 0, 0],
       [0, 1, 0, 0, 0, 0],
       [0, 0, 1, 0, 0, 0]])
```

In [31]:
```
data[0:4]
```

Out[31]:

	text	emotions	token_size
6722	i am feeling more joyful again	joy	6
50713	i work hard at not preaching at people no matt...	anger	36
17473	i feel no need to offer it though i do feel a ...	fear	44
35005	i feel energetic determined focused and ready ...	joy	16

In [32]:
```
get_emotion = lambda t: np.argmax(t)
```

In [33]:
```
get_emotion(target_tensor[0])
```

Out[33]:
```
2
```

In [34]:
```
emotion_dict = {0: 'anger', 1: 'fear', 2: 'joy', 3: 'love', 4: 'sadness',
5: 'surprise'}
```

In [35]:
```
emotion_dict[get_emotion(target_tensor[3])]
```

Out[35]:
```
'joy'
```

Spliting data

In [36]:
```
# Creating training and validation sets using an 80-20 split
input_tensor_train, input_tensor_val, target_tensor_train, target_tensor_
val = train_test_split(input_tensor, target_tensor, test_size=0.2)

# Split the validataion further to obtain a holdout dataset (for testing)
-- split 50:50
input_tensor_val, input_tensor_test, target_tensor_val, target_tensor_tes
t = train_test_split(input_tensor_val, target_tensor_val, test_size=0.5)

# Show length
len(input_tensor_train), len(target_tensor_train), len(input_tensor_val),
len(target_tensor_val), len(input_tensor_test), len(target_tensor_test)
```

Out[36]:
```
(40000, 40000, 5000, 5000, 5000, 5000)
```

Data Loader and Batch Processing

In [37]:
```
TRAIN_BUFFER_SIZE = len(input_tensor_train)
VAL_BUFFER_SIZE = len(input_tensor_val)
TEST_BUFFER_SIZE = len(input_tensor_test)
BATCH_SIZE = 64
TRAIN_N_BATCH = TRAIN_BUFFER_SIZE // BATCH_SIZE
VAL_N_BATCH = VAL_BUFFER_SIZE // BATCH_SIZE
TEST_N_BATCH = TEST_BUFFER_SIZE // BATCH_SIZE

embedding_dim = 256
units = 1024
vocab_inp_size = len(inputs.word2idx)
target_size = num_emotions
```

In [38]:
```
from torch.utils.data import Dataset, DataLoader
```

In [39]:
```
# convert the data to tensors and pass to the Dataloader
# to create an batch iterator

class MyData(Dataset):
    def __init__(self, X, y):
        self.data = X
        self.target = y
        self.length = [ np.sum(1 - np.equal(x, 0)) for x in X]

    def __getitem__(self, index):
        x = self.data[index]
        y = self.target[index]
        x_len = self.length[index]
        return x, y, x_len

    def __len__(self):
        return len(self.data)
```

In [40]:
```
train_dataset = MyData(input_tensor_train, target_tensor_train)
val_dataset = MyData(input_tensor_val, target_tensor_val)
test_dataset = MyData(input_tensor_test, target_tensor_test)

train_dataset = DataLoader(train_dataset, batch_size = BATCH_SIZE,
                     drop_last=True,
                     shuffle=True)
val_dataset = DataLoader(val_dataset, batch_size = BATCH_SIZE,
                     drop_last=True,
                     shuffle=True)
test_dataset = DataLoader(test_dataset, batch_size = BATCH_SIZE,
                     drop_last=True,
                     shuffle=True)
```

In [41]:
```
val_dataset.batch_size
```

Out[41]:
```
64
```

Model

1) Constructing the Model

In [42]:
```
class EmoGRU(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_units, batch_sz,
output_size):
        super(EmoGRU, self).__init__()
        self.batch_sz = batch_sz
        self.hidden_units = hidden_units
        self.embedding_dim = embedding_dim
        self.vocab_size = vocab_size
        self.output_size = output_size

        # layers
        self.embedding = nn.Embedding(self.vocab_size, self.embedding_dim
)
        self.dropout = nn.Dropout(p=0.5)
        self.gru = nn.GRU(self.embedding_dim, self.hidden_units)
        self.fc = nn.Linear(self.hidden_units, self.output_size)

    def initialize_hidden_state(self, device):
        return torch.zeros((1, self.batch_sz, self.hidden_units)).to(devi
ce)

    def forward(self, x, lens, device):
        x = self.embedding(x)
        self.hidden = self.initialize_hidden_state(device)
        output, self.hidden = self.gru(x, self.hidden) # max_len X batch_
size X hidden_units
        out = output[-1, :, :]
        out = self.dropout(out)
        out = self.fc(out)
        return out, self.hidden
```

2) Pretesting the model

In [43]:
```
### sort batch function to be able to use with pad_packed_sequence
def sort_batch(X, y, lengths):
    lengths, indx = lengths.sort(dim=0, descending=True)
    X = X[indx]
    y = y[indx]
    return X.transpose(0,1), y, lengths # transpose (batch x seq) to (seq
x batch)
```

In [44]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
model = EmoGRU(vocab_inp_size, embedding_dim, units, BATCH_SIZE, target_s
ize)
model.to(device)

# obtain one sample from the data iterator
it = iter(train_dataset)
x, y, x_len = next(it)

# sort the batch first to be able to use with pac_pack sequence
xs, ys, lens = sort_batch(x, y, x_len)

print("Input size: ", xs.size())

output, _ = model(xs.to(device), lens, device)
print(output.size())
```

```
Input size:  torch.Size([68, 64])
torch.Size([64, 6])
```

Training the Model

In [45]:
```
### Enabling cuda
use_cuda = True if torch.cuda.is_available() else False
device = torch.device("cuda" if use_cuda else "cpu")
model = EmoGRU(vocab_inp_size, embedding_dim, units, BATCH_SIZE, target_s
ize)
model.to(device)

### loss criterion and optimizer for training
criterion = nn.CrossEntropyLoss() # the same as log_softmax + NLLLoss
optimizer = torch.optim.Adam(model.parameters())

def loss_function(y, prediction):
    """ CrossEntropyLoss expects outputs and class indices as target """
    # convert from one-hot encoding to class indices
    target = torch.max(y, 1)[1]
    loss = criterion(prediction, target)
    return loss   #TODO: refer the parameter of these functions as the sa
me

def accuracy(target, logit):
    ''' Obtain accuracy for training round '''
    target = torch.max(target, 1)[1] # convert from one-hot encoding to c
lass indices
    corrects = (torch.max(logit, 1)[1].data == target).sum()
    accuracy = 100.0 * corrects / len(logit)
    return accuracy
```

In [46]:

```
EPOCHS = 10

for epoch in range(EPOCHS):
    start = time.time()

    ### Initialize hidden state
    # TODO: do initialization here.
    total_loss = 0
    train_accuracy, val_accuracy = 0, 0

    ### Training
    for (batch, (inp, targ, lens)) in enumerate(train_dataset):
        loss = 0
        predictions, _ = model(inp.permute(1 ,0).to(device), lens, device
) # TODO:don't need _

        loss += loss_function(targ.to(device), predictions)
        batch_loss = (loss / int(targ.shape[1]))
        total_loss += batch_loss

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        batch_accuracy = accuracy(targ.to(device), predictions)
        train_accuracy += batch_accuracy

        if batch % 100 == 0:
            print('Epoch {} Batch {} Val. Loss {:.4f}'.format(epoch + 1,
                                                             batch,
                                                             batch_loss.cpu()
.detach().numpy()))

    ### Validating
    for (batch, (inp, targ, lens)) in enumerate(val_dataset):
        predictions,_ = model(inp.permute(1, 0).to(device), lens, device)
        batch_accuracy = accuracy(targ.to(device), predictions)
        val_accuracy += batch_accuracy

    print('Epoch {} Loss {:.4f} -- Train Acc. {:.4f} -- Val Acc. {:.4f}'.
format(epoch + 1,
                                                                     total_loss /
TRAIN_N_BATCH,
                                                                     train_accura
cy / TRAIN_N_BATCH,
                                                                     val_accuracy
/ VAL_N_BATCH))
    print('Time taken for 1 epoch {} sec\n'.format(time.time() - start))
```

```
Epoch 1 Batch 0 Val. Loss 0.3045
Epoch 1 Batch 100 Val. Loss 0.2847
Epoch 1 Batch 200 Val. Loss 0.1997
Epoch 1 Batch 300 Val. Loss 0.0757
Epoch 1 Batch 400 Val. Loss 0.0338
Epoch 1 Batch 500 Val. Loss 0.0205
Epoch 1 Batch 600 Val. Loss 0.0450
Epoch 1 Loss 0.1401 -- Train Acc. 67.0000 -- Val Acc. 90.0000
Time taken for 1 epoch 60.36439299583435 sec

Epoch 2 Batch 0 Val. Loss 0.0306
Epoch 2 Batch 100 Val. Loss 0.0412
Epoch 2 Batch 200 Val. Loss 0.0385
Epoch 2 Batch 300 Val. Loss 0.0247
Epoch 2 Batch 400 Val. Loss 0.0147
Epoch 2 Batch 500 Val. Loss 0.0211
Epoch 2 Batch 600 Val. Loss 0.0294
Epoch 2 Loss 0.0264 -- Train Acc. 92.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 60.306763648986816 sec

Epoch 3 Batch 0 Val. Loss 0.0157
Epoch 3 Batch 100 Val. Loss 0.0210
Epoch 3 Batch 200 Val. Loss 0.0159
Epoch 3 Batch 300 Val. Loss 0.0218
Epoch 3 Batch 400 Val. Loss 0.0149
Epoch 3 Batch 500 Val. Loss 0.0102
Epoch 3 Batch 600 Val. Loss 0.0303
Epoch 3 Loss 0.0201 -- Train Acc. 93.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 59.07735061645508 sec

Epoch 4 Batch 0 Val. Loss 0.0348
Epoch 4 Batch 100 Val. Loss 0.0092
Epoch 4 Batch 200 Val. Loss 0.0160
Epoch 4 Batch 300 Val. Loss 0.0084
Epoch 4 Batch 400 Val. Loss 0.0214
Epoch 4 Batch 500 Val. Loss 0.0258
Epoch 4 Batch 600 Val. Loss 0.0258
Epoch 4 Loss 0.0182 -- Train Acc. 94.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 59.67210912704468 sec

Epoch 5 Batch 0 Val. Loss 0.0274
Epoch 5 Batch 100 Val. Loss 0.0507
Epoch 5 Batch 200 Val. Loss 0.0141
Epoch 5 Batch 300 Val. Loss 0.0143
Epoch 5 Batch 400 Val. Loss 0.0041
Epoch 5 Batch 500 Val. Loss 0.0276
Epoch 5 Batch 600 Val. Loss 0.0298
Epoch 5 Loss 0.0165 -- Train Acc. 94.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 60.10885834693909 sec

Epoch 6 Batch 0 Val. Loss 0.0172
Epoch 6 Batch 100 Val. Loss 0.0180
Epoch 6 Batch 200 Val. Loss 0.0227
Epoch 6 Batch 300 Val. Loss 0.0057
Epoch 6 Batch 400 Val. Loss 0.0053
Epoch 6 Batch 500 Val. Loss 0.0048
Epoch 6 Batch 600 Val. Loss 0.0222
```

```
Epoch 6 Loss 0.0150 -- Train Acc. 95.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 60.09766483306885 sec

Epoch 7 Batch 0 Val. Loss 0.0031
Epoch 7 Batch 100 Val. Loss 0.0160
Epoch 7 Batch 200 Val. Loss 0.0263
Epoch 7 Batch 300 Val. Loss 0.0124
Epoch 7 Batch 400 Val. Loss 0.0145
Epoch 7 Batch 500 Val. Loss 0.0047
Epoch 7 Batch 600 Val. Loss 0.0193
Epoch 7 Loss 0.0134 -- Train Acc. 96.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 59.763386249542236 sec

Epoch 8 Batch 0 Val. Loss 0.0054
Epoch 8 Batch 100 Val. Loss 0.0052
Epoch 8 Batch 200 Val. Loss 0.0201
Epoch 8 Batch 300 Val. Loss 0.0052
Epoch 8 Batch 400 Val. Loss 0.0062
Epoch 8 Batch 500 Val. Loss 0.0159
Epoch 8 Batch 600 Val. Loss 0.0133
Epoch 8 Loss 0.0112 -- Train Acc. 96.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 59.46015405654907 sec

Epoch 9 Batch 0 Val. Loss 0.0032
Epoch 9 Batch 100 Val. Loss 0.0005
Epoch 9 Batch 200 Val. Loss 0.0069
Epoch 9 Batch 300 Val. Loss 0.0024
Epoch 9 Batch 400 Val. Loss 0.0152
Epoch 9 Batch 500 Val. Loss 0.0080
Epoch 9 Batch 600 Val. Loss 0.0239
Epoch 9 Loss 0.0100 -- Train Acc. 97.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 60.02734041213989 sec

Epoch 10 Batch 0 Val. Loss 0.0021
Epoch 10 Batch 100 Val. Loss 0.0006
Epoch 10 Batch 200 Val. Loss 0.0000
Epoch 10 Batch 300 Val. Loss 0.0071
Epoch 10 Batch 400 Val. Loss 0.0085
Epoch 10 Batch 500 Val. Loss 0.0108
Epoch 10 Batch 600 Val. Loss 0.0104
Epoch 10 Loss 0.0087 -- Train Acc. 97.0000 -- Val Acc. 91.0000
Time taken for 1 epoch 59.33428716659546 sec
```

In [47]:

```
model.parameters
```

Out[47]:

```
<bound method Module.parameters of EmoGRU(
  (embedding): Embedding(27613, 256)
  (dropout): Dropout(p=0.5)
  (gru): GRU(256, 1024)
  (fc): Linear(in_features=1024, out_features=6, bias=True)
)>
```

Assessment of the Testing Data

In [48]:
```python
test_accuracy = 0
all_predictions = []
x_raw = []
y_raw = []

device = "cuda" # we don't need GPU to do testing
model.to("cuda")

for (batch, (inp, targ, lens)) in enumerate(test_dataset):
    predictions,_ = model(inp.permute(1, 0).to(device), lens, device)
    batch_accuracy = accuracy(targ.to(device), predictions)
    test_accuracy += batch_accuracy

    x_raw = x_raw + [x for x in inp]
    y_raw = y_raw + [y for y in targ]

    all_predictions.append(predictions)

print("Test Accuracy: ", test_accuracy.cpu().detach().numpy() / TEST_N_BA
TCH)
```

```
Test Accuracy:  91.6923076923077
```

Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a ML/DL model on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm.

```
In [52]: ### Class to Properly Evaluate our Models
class Evaluate():

    def va_dist(cls, prediction, target, va_df, binarizer, name='', silen
t=False):
        """ Computes distance between actual and prediction through cosin
e distance """
        va_matrix = va_df.loc[binarizer.classes_][['valence','arousal']].
values
        y_va = target.dot(va_matrix)
        F_va = prediction.dot(va_matrix)

        # dist is a one row vector with size of the test data passed(emot
ion)
        dist = metrics.pairwise.paired_cosine_distances(y_va, F_va)
        res = stats.describe(dist)

        # print by default (if silent=False)
        if not silent:
            print('%s\tmean: %f\tvariance: %f' % (name, res.mean, res.var
iance))

        return {
            'distances': dist,
            'dist_stat': res
        }

    def evaluate_class(cls, predictions, target, target2=None, silent=Fal
se):
        """ Compute only the predicted class """
        p_2_annotation = dict()

        precision_recall_fscore_support = [
            (pair[0], pair[1].mean()) for pair in zip(
                ['precision', 'recall', 'f1', 'support'],
                metrics.precision_recall_fscore_support(target, predictio
ns)
            )
        ]

        metrics.precision_recall_fscore_support(target, predictions)

        # confusion matrix
        le = LabelEncoder()
        target_le = le.fit_transform(target)
        predictions_le = le.transform(predictions)
        cm = metrics.confusion_matrix(target_le, predictions_le)

        # prediction if two annotations are given on test data
        if target2:
            p_2_annotation = pd.DataFrame(
                [(pred, pred in set([t1,t2])) for pred, t1, t2 in zip(pre
dictions, target, target2)],
                columns=['emo','success']
            ).groupby('emo').apply(lambda emo: emo.success.sum()/ len(emo
.success)).to_dict()
```

```
        if not silent:
            print("Default Classification report")
            print(metrics.classification_report(target, predictions))

            # print if target2 was provided
            if len(p_2_annotation) > 0:
                print('\nPrecision on 2 annotations:')
                for emo in p_2_annotation:
                    print("%s: %.2f" % (emo, p_2_annotation[emo]))

            # print accuracies, precision, recall, and f1
            print('\nAccuracy:')
            print(metrics.accuracy_score(target, predictions))
            print("Correct Predictions: ", metrics.accuracy_score(target,
predictions,normalize=False))
            for to_print in precision_recall_fscore_support[:3]:
                print( "%s: %.2f" % to_print )

            # normalizing the values of the consfusion matrix
            print('\nconfusion matrix\n %s' % cm)
            print('(row=expected, col=predicted)')
            cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.new
axis]
            cls.plot_confusion_matrix(cm_normalized, le.classes_, 'Confus
ion matrix Normalized')

        return {
            'precision_recall_fscore_support': precision_recall_fscore_su
pport,
            'accuracy': metrics.accuracy_score(target, predictions),
            'p_2_annotation': p_2_annotation,
            'confusion_matrix': cm
        }

    def predict_class(cls, X_train, y_train, X_test, y_test,
                      pipeline, silent=False, target2=None):
        """ Predicted class,then run some performance evaluation """
        pipeline.fit(X_train, y_train)
        predictions = pipeline.predict(X_test)
        print("predictions computed....")
        return cls.evaluate_class(predictions, y_test, target2, silent)

    def evaluate_prob(cls, prediction, target_rank, target_class, binariz
er, va_df, silent=False, target2=None):
        """ Evaluate through probability """
        # Run normal class evaluator
        predict_class = binarizer.classes_[prediction.argmax(axis=1)]
        class_eval = cls.evaluate_class(predict_class, target_class, targ
et2, silent)

        if not silent:
            print('\n - First Emotion Classification Metrics -')
            print('\n - Multiple Emotion rank Metrics -')
            print('VA Cosine Distance')

        classes_dist = [
```

```
            (
                emo,
                cls.va_dist(
                    prediction[np.array(target_class) == emo],
                    target_rank[np.array(target_class) == emo],
                    va_df,
                    binarizer,
                    emo,
                    silent)
                ) for emo in binarizer.classes_
        ]
        avg_dist = cls.va_dist(prediction, target_rank, va_df, binarizer,
'avg', silent)

        coverage_error = metrics.coverage_error(target_rank, prediction)
        average_precision_score = metrics.average_precision_score(target_
rank, prediction)
        label_ranking_average_precision_score = metrics.label_ranking_ave
rage_precision_score(target_rank, prediction)
        label_ranking_loss = metrics.label_ranking_loss(target_rank, pred
iction)

        # recall at 2
        # obtain top two predictions
        top2_pred = [set([binarizer.classes_[i[0]], binarizer.classes_[i[
1]]]) for i in (prediction.argsort(axis=1).T[-2:].T)]
        recall_at_2 = pd.DataFrame(
            [
            t in p for t, p in zip(target_class, top2_pred)
            ], index=target_class, columns=['recall@2']).groupby(level=0)
.apply(lambda emo: emo.sum()/len(emo))

        # combine target into sets
        if target2:
            union_target = [set(t) for t in zip(target_class, target2)]
        else:
            union_target = [set(t) for t in zip(target_class)]

        # precision at k
        top_k_pred = [
            [set([binarizer.classes_[i] for i in i_list]) for i_list in (
prediction.argsort(axis=1).T[-i:].T)]
            for i in range(2, len(binarizer.classes_)+1)]
        precision_at_k = [
            ('p@' + str(k+2), np.array([len(t & p)/(k+2) for t, p in zip(
union_target, top_k_pred[k])]).mean())
            for k in range(len(top_k_pred))]

        # do this if silent= False
        if not silent:
            print('\n')
            print(recall_at_2)
            print('\n')
            print('p@k')
            for pk in precision_at_k:
                print(pk[0] + ':\t' + str(pk[1]))
            print('\ncoverage_error: %f' % coverage_error)
```

```
            print('average_precision_score: %f' % average_precision_score
)
            print('label_ranking_average_precision_score: %f' % label_ran
king_average_precision_score)
            print('label_ranking_loss: %f' % label_ranking_loss)

        return {
            'class_eval': class_eval,
            'recall_at_2': recall_at_2.to_dict(),
            'precision_at_2': precision_at_k,
            'classes_dist': classes_dist,
            'avg_dist': avg_dist,
            'coverage_error': coverage_error,
            'average_precision_score': average_precision_score,
            'label_ranking_average_precision_score': label_ranking_averag
e_precision_score,
            'label_ranking_loss': label_ranking_loss
        }


    def predict_prob(cls, X_train, y_train, X_test, y_test, label_test, p
ipeline, binarizer, va_df, silent=False, target2=None):
        """ Output predcations based on training and labels """
        pipeline.fit(X_train, y_train)
        predictions = pipeline.predict_proba(X_test)
        pred_to_mlb = [np.where(pipeline.classes_ == emo)[0][0] for emo i
n binarizer.classes_.tolist()]
        return cls.evaluate_prob(predictions[:,pred_to_mlb], y_test, labe
l_test, binarizer, va_df, silent, target2)


    def plot_confusion_matrix(cls, cm, my_tags, title='Confusion matrix',
cmap=plt.cm.Blues):
        """ Plotting the confusion_matrix"""
        plt.rc('figure', figsize=(4, 4), dpi=100)
        plt.imshow(cm, interpolation='nearest', cmap=cmap)
        plt.title(title)
        plt.colorbar()
        tick_marks = np.arange(len(my_tags))
        target_names = my_tags
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

        # add normalized values inside the Confusion matrix
        fmt = '.2f'
        thresh = cm.max() / 2.
        for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[
1])):
            plt.text(j, i, format(cm[i, j], fmt), horizontalalignment="ce
nter", color="white" if cm[i, j] > thresh else "black")

        plt.tight_layout()
        plt.ylabel('True label')
        plt.xlabel('Predicted label')
```

In [53]:

```
evaluator = Evaluate()

final_predictions = []

for p in all_predictions:
    for sub_p in p:
        final_predictions.append(sub_p.cpu().detach().numpy())

predictions = [np.argmax(p).item() for p in final_predictions]
targets = [np.argmax(t).item() for t in y_raw]
correct_predictions = float(np.sum(predictions == targets))

# predictions
predictions_human_readable = ((x_raw, predictions))
# actual targets
target_human_readable = ((x_raw,  targets))

emotion_dict = {0: 'anger', 1: 'fear', 2: 'joy', 3: 'love', 4: 'sadness',
5: 'surprise'}

# convert results into dataframe
model_test_result = pd.DataFrame(predictions_human_readable[1],columns=[
"emotion"])
test = pd.DataFrame(target_human_readable[1], columns=["emotion"])

model_test_result.emotion = model_test_result.emotion.map(lambda x: emoti
on_dict[int(float(x))])
test.emotion = test.emotion.map(lambda x: emotion_dict[int(x)])

evaluator.evaluate_class(model_test_result.emotion, test.emotion );
```

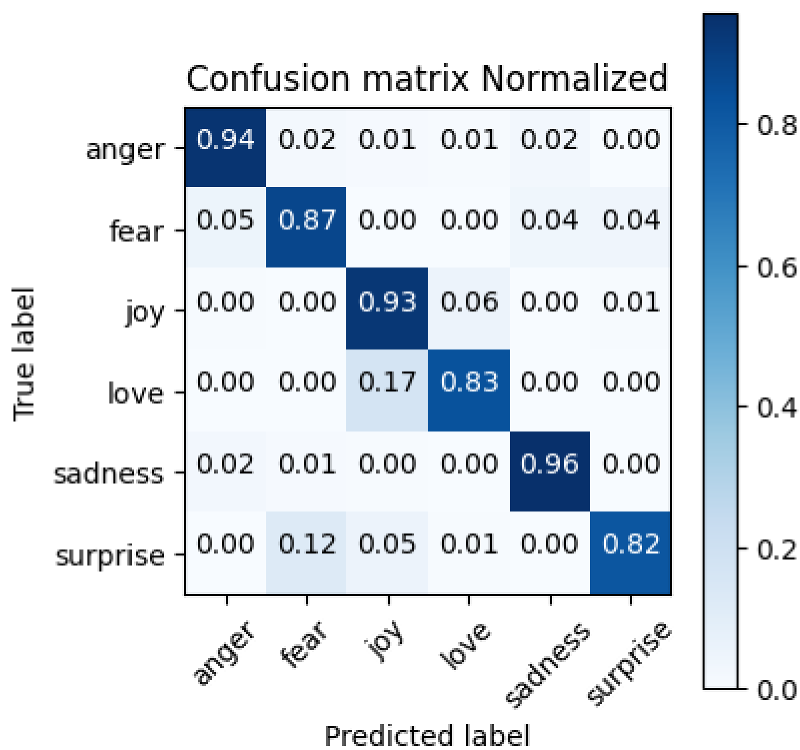
```
Default Classification report
              precision    recall  f1-score   support

       anger       0.91      0.94      0.92       703
        fear       0.90      0.87      0.89       543
         joy       0.95      0.93      0.94      1742
        love       0.76      0.83      0.79       398
     sadness       0.97      0.96      0.96      1436
    surprise       0.80      0.82      0.81       170

    accuracy                           0.92      4992
   macro avg       0.88      0.89      0.89      4992
weighted avg       0.92      0.92      0.92      4992


Accuracy:
0.9216746794871795
Correct Predictions:  4601
precision: 0.88
recall: 0.89
f1: 0.89

confusion matrix
 [[ 662   13    6    5   17    0]
 [  27  474    1    0   20   21]
 [   7    2 1620   96    5   12]
 [   0    0   67  331    0    0]
 [  33   16    7    3 1375    2]
 [   0   21    9    1    0  139]]
(row=expected, col=predicted)
```



Conclusion

Trained the Deep Learning model to predict accurately; the emotions of anger, fear, joy, surprise and sadness by the pickled Emotion-Text Dataset using Analysis & RNN model implemented by PyTorch and other tools and packages to evaluate above 91% accuracy in test. Also by implmenting the Confusion Matrix and Test Asssessment.

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