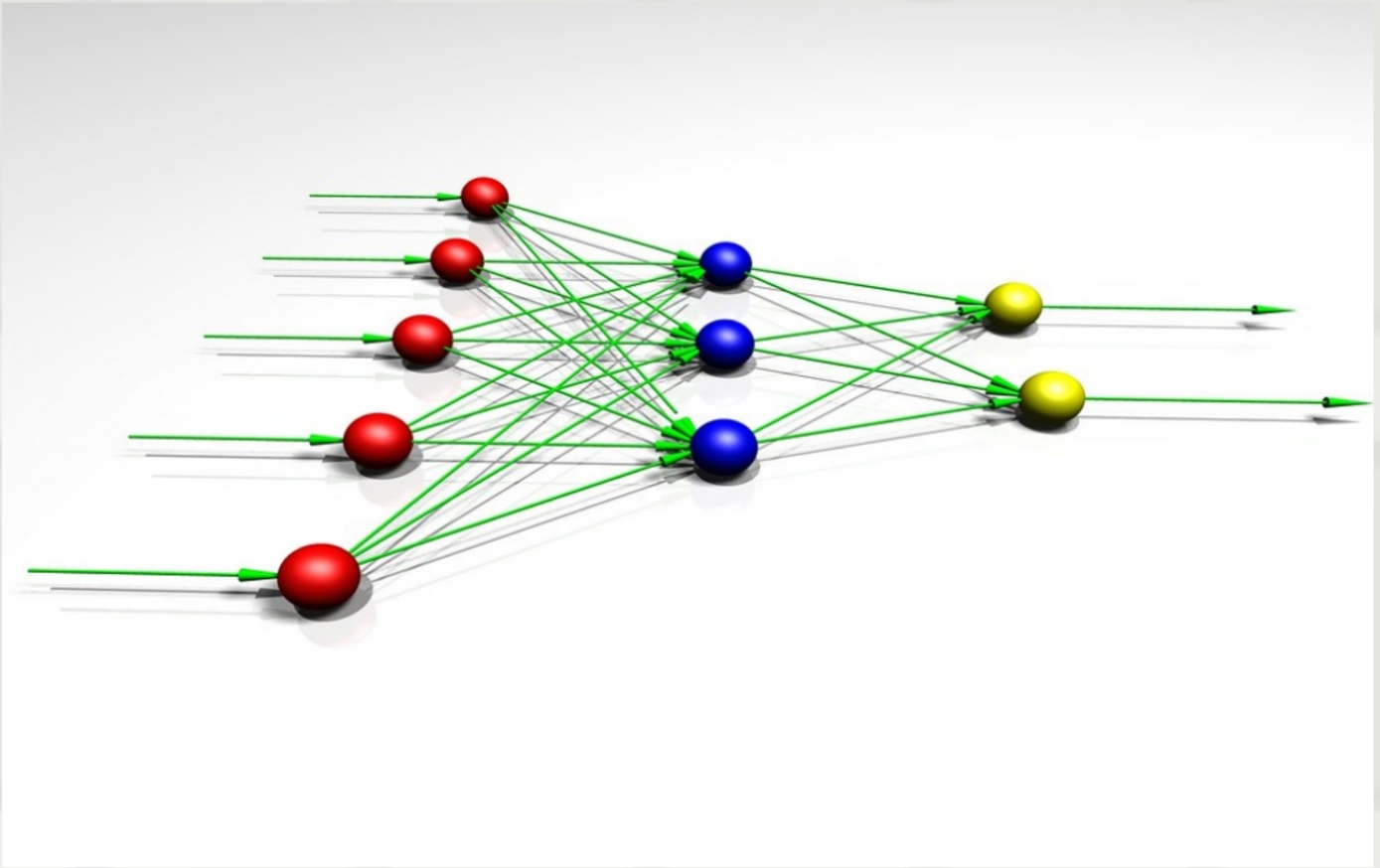
Sentiment Analyses Experiance



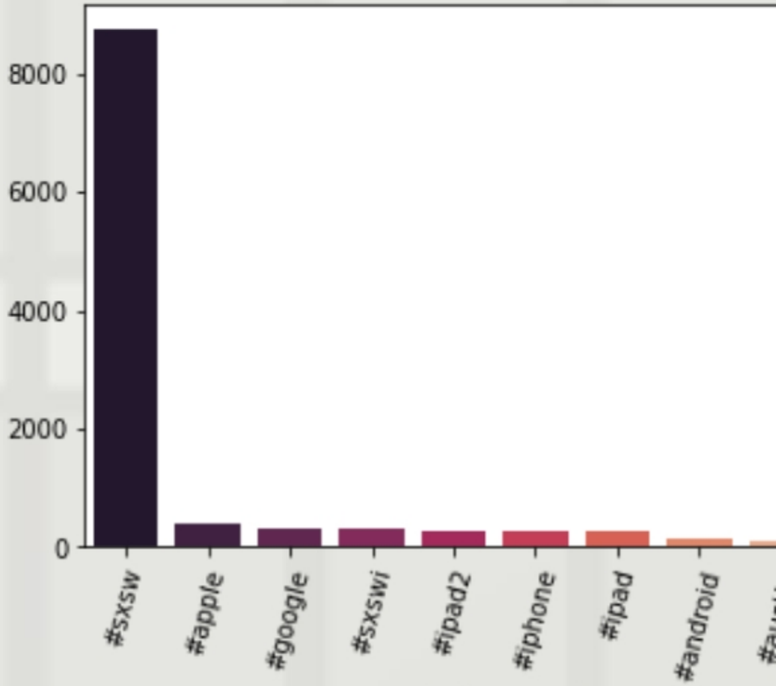
The goal

1. Find the best hyperparameters for training a neural network for Sentiment Analysis.

2. Use Machine Learning to classify tweets better than random guessing

THE DATASET

I used a dataset of 9,000 tweets provided by data.world provided by Crowdflower. The tweets are mainly public opinions of tech company's products such as Apple's iPad.

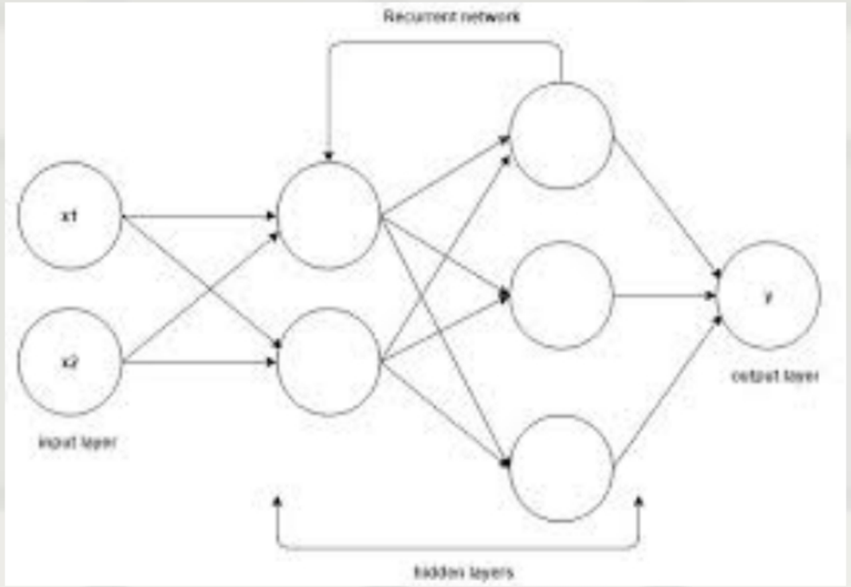


Top 10 most used hashtags within the dataset ^^

Deep Learning

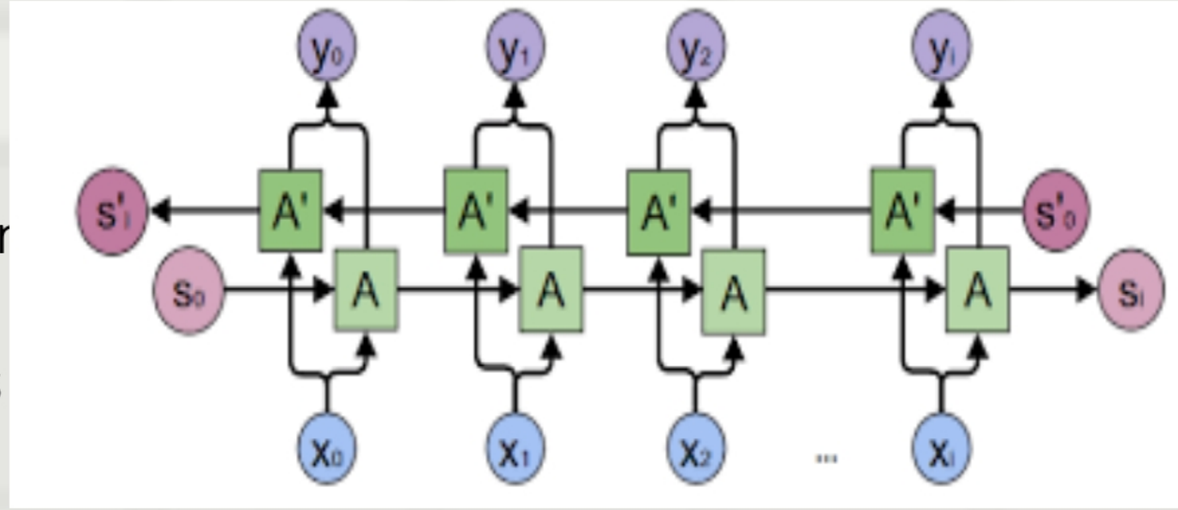
I tried 4 different approaches, the last one preformed the best

1. FeedForward, a very simple fully connected neural network
2. LSTM
3. GRU
4. Bidirectional LSTM



Bidirectional LSTM

Uses an LSTM Architecture, which is great for modeling sequential data. The reason for this is that the model can control what it 'remembers' and forgets what is seen as less important. This makes it great for NLP tasks such as sentiment analyses.

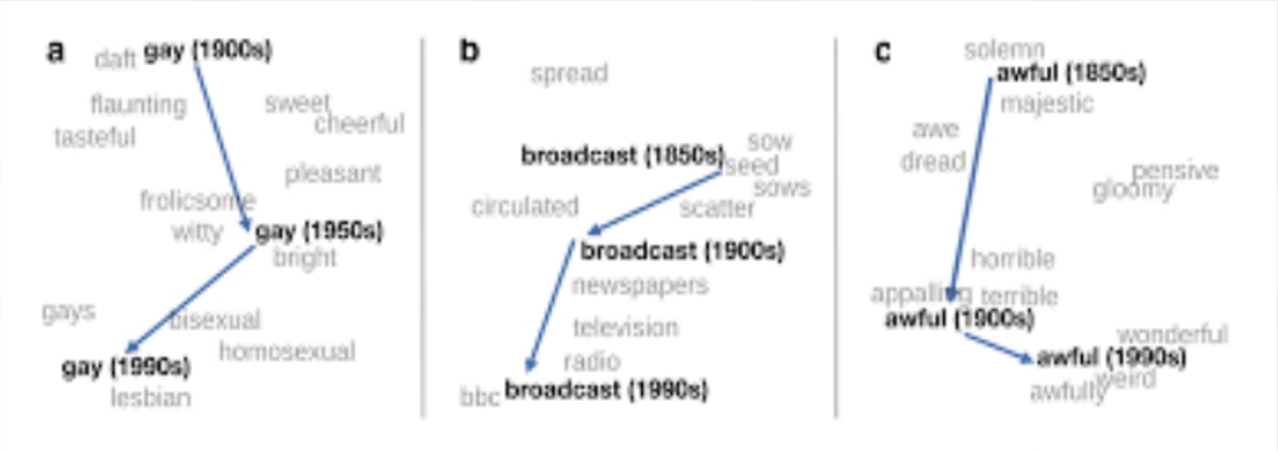


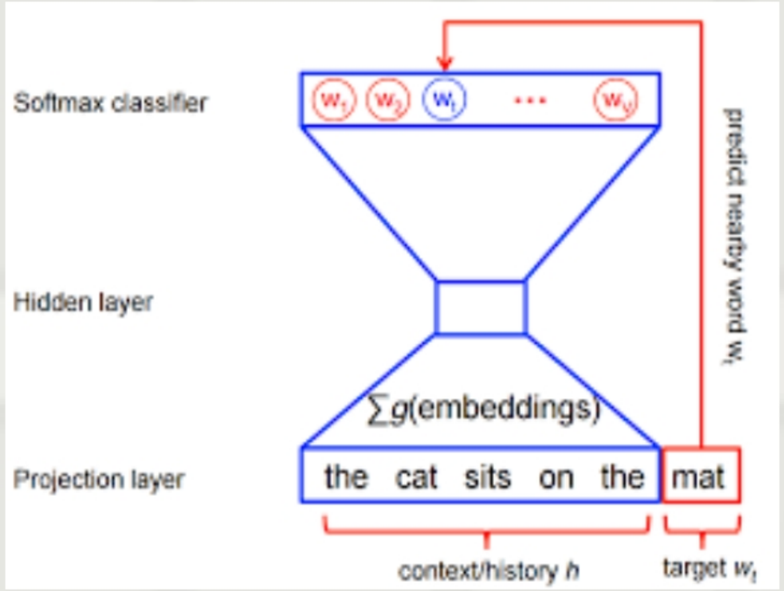

```
Model: "sequential_100"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_100 (Embedding)    (None, None, 128)         1600000
_________________________________________________________________
bidirectional_100 (Bidirecti (None, 256)               263168
_________________________________________________________________
dense_300 (Dense)            (None, 64)                16448
_________________________________________________________________
dense_301 (Dense)            (None, 32)                2080
_________________________________________________________________
dense_302 (Dense)            (None, 3)                 99
=================================================================
Total params: 1,881,795
Trainable params: 1,881,795
Non-trainable params: 0
_________________________________________________________________
```

'Reads' text in both directions to gain a deeper intuition for how each word is used, as well as how it's used in relation to the words surrounding it.

Word embeddings

Word embeddings serve as a 'lookup table' for the Neural Network. Each unique word in the text corpus has vector of numbers representing how similar that word is to all the other words.





How to make word Embeddings

```
model2 = models.Sequential()
model2.add(layers.Embedding(12500, 128))
model2.add(layers.Bidirectional(layers.LSTM(128)))
model2.add(layers.Dense(64, activation='relu'))
model2.add(layers.Dense(32, activation='relu'))
model2.add(layers.Dense(3, activation='softmax'))
```

```
[44]: from gensim.models import Word2Vec, keyedvectors

      W = Word2Vec(tokens, size=33, window=3, min_count=1, workers=4)
      W.train(sentences=tokens, total_examples=W.corpus_count, epochs=10)
      wv = W.wv

[45]: e = W.wv.get_keras_embedding(train_embeddings=False)

[46]: from keras.metrics import Recall #the model did better with accurac
      from keras.metrics import  Precision

      model3 = models.Sequential()
      model3.add(e)
```

```
glove = {}
with open('glove.6B.50d.txt', 'rb') as f:
    for line in f:
        parts = line.split()
        word = parts[0].decode('utf-8')
        if word in total_vocabulary:
            vector = np.array(parts[1:], dtype=np.float32)
            glove[word] = vector
```

Make it yourself with Keras

- This method worked the best for me
- it is very simple and can be done in Keras with one line of code
- the only downside it that it is very blackbox in the sense that you can't see the embeddings.

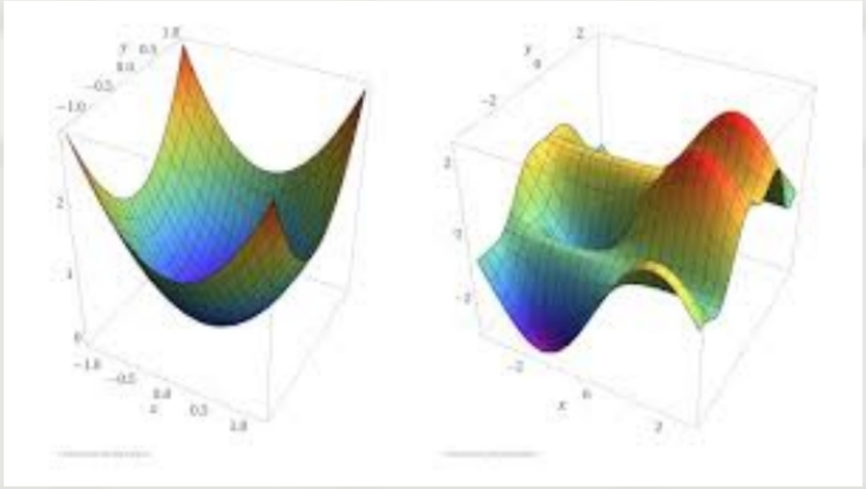
Use the Gensim Library

- This method didn't do too well in my experience, for this use case.
- However I still recommend it because you can see the results and get a feel for what words some words are similar to or the opposite of

Use a pretrained model such as GloVe

Setting Parameters

I strongly advise using a grid search to hypertune your model, I especially reccomend experimenting with:
- number of nodes in each layer -
- activation function; relu and tanh
- optimization function; adam and rmsprop



```
def TestDL(self, params, func, task, X, y, X_val=None, y_val=None, batch_size=64, epochs=50):
  early_stopping = [EarlyStopping(patience=10), ModelCheckpoint(filepath='model.{epoch:02d}-{val
  if task == 'classification':
    k = KerasClassifier(func)
  if task == 'regression':
    k = KerasRegressor(func)
  grid = GridSearchCV(k, params, cv=3)
  if type(X_val) != np.ndarray:
    grid.fit(X, y, batch_size=batch_size, epochs=epochs, validation_split=0.2)
  else:
    grid.fit(X, y, batch_size=batch_size, epochs=epochs, validation_data=(X_val, y_val), callbac
  return grid
```

Simple Machine Learning

Basic Machine learning strategies can work just as well as Deep Learning!

However, I tried a very strange approach that didn't work very well!

If you want to use basic ML, I would advise using a Gradient Boosted Random Forest, feed it the word embeddings, technically this part is deep learning.

What I Tried

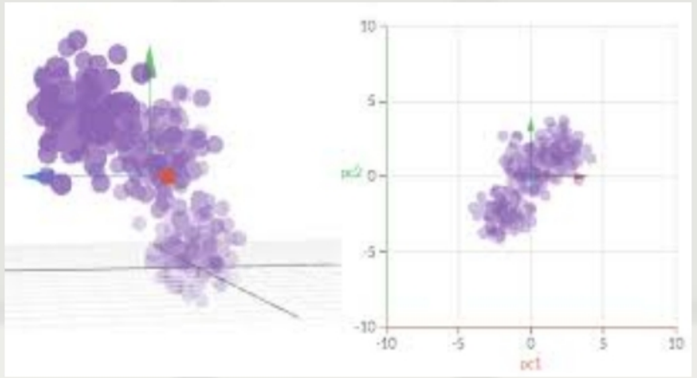
1. Rather than using word embeddings
I decided to One Hot Encode each tweet!
This means that each tweet was represented
by a vector of 1's and 0's, a 1 for each word
in the vocab that was used and a 0 for each
word that wasn't

2. Next, I compressed the data to make
it less sparse, each vector had 12,500
numbers
of which, about 12,470 were 0's. I used
PCA to compress
each vector to a length of 300

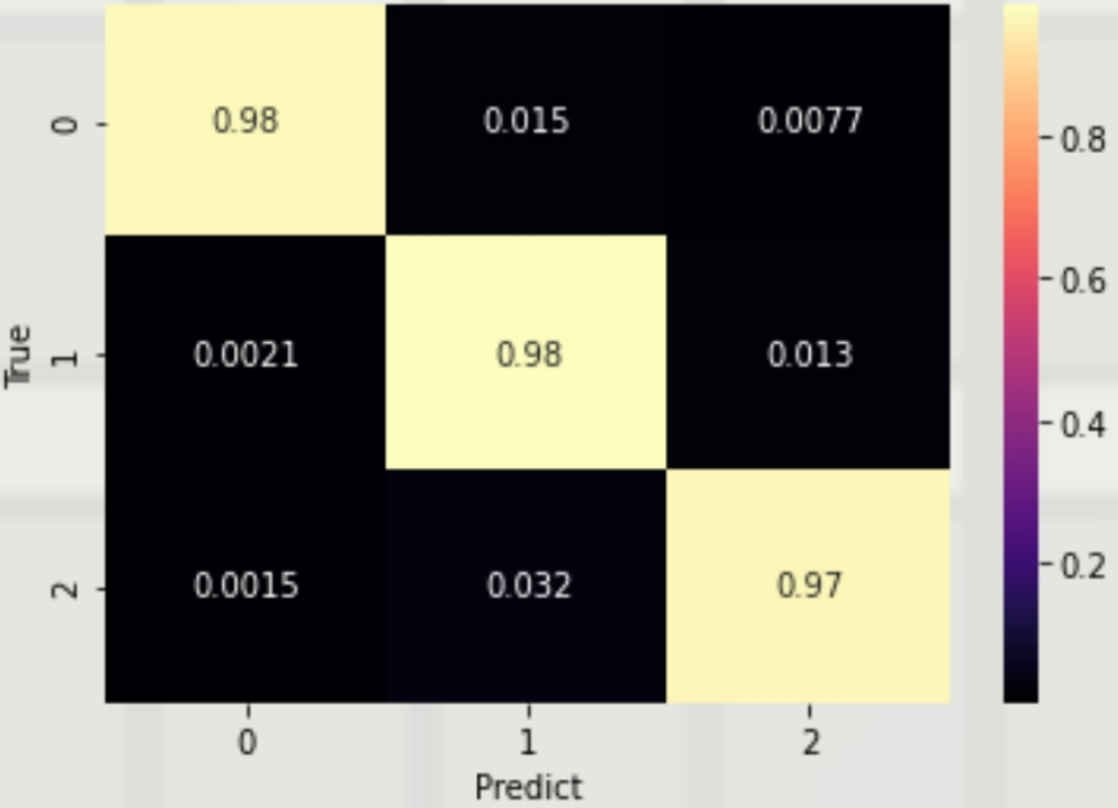
3. Lastly, I fit the
data to a
Gradient Boosted
Random Forrest...

Color
Red
Red
Yellow
Green
Yellow

Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1



Final Test Results



Final Test Results: 99% train accuracy, 97% validation accuracy, 6
test accuracy
- The model's test results weren't great, however it was able to d
better than random guessing.
- I'm also pleased to see that the model didn't simply give everyt
the same label as the dominant class.

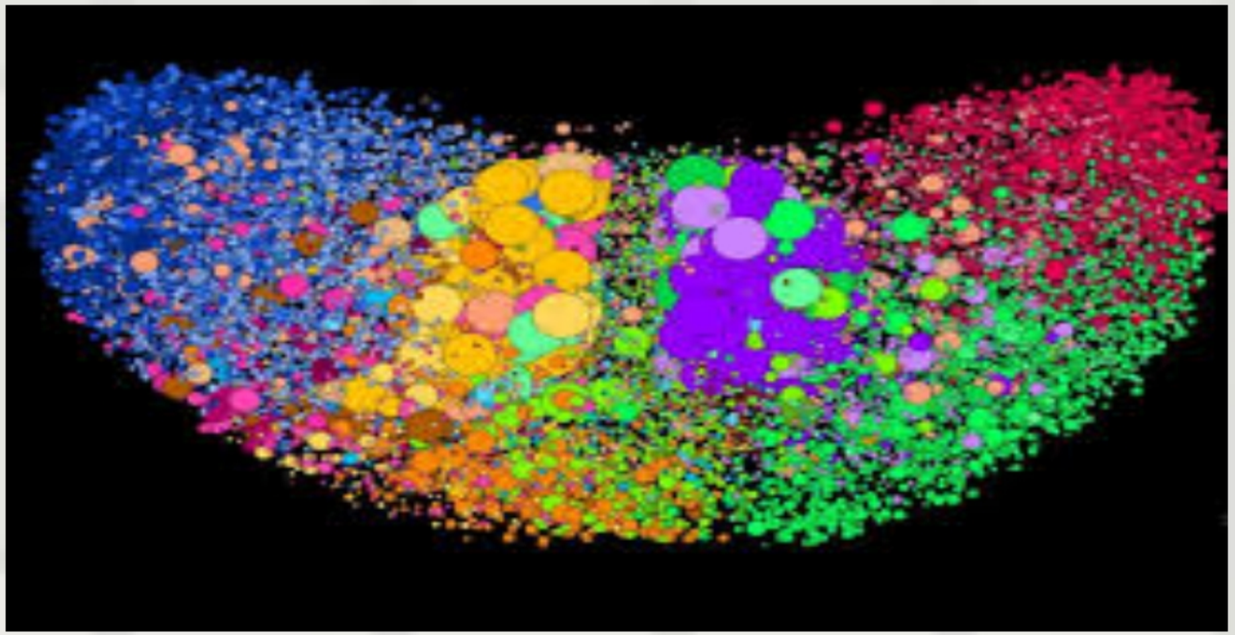
Conclusions

For Sentiment Analysis I recommend the following...

1. using a grid search to test out various hyperparameter combinations.
2. experiment with the number of nodes in each layer
3. for activation test between relu and tanh
4. for optimization test between adam and rmsprop

Future works

With more time to work on this project I would use my model to label tweets my their sentiment and use that feature alongside other features to create a polarity predictor!



Thank You