I Couldn’t Find a Therapist so I tried to Build One - Part II.

Capstone 2 Milestone Report

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Springboard

Table of Contents

Problem Statement & Project Proposal

Introduction

In my previous Capstone project, I identified three core limitations of my study. The following are those three limitations:

- Imbalanced classes & lack of data
- Lack of computation power to try out other hyperparameter settings
- Absence of comparative metrics -- currently only using BERT

For this portion of the Capstone, I will attempt to overcome these limitations in four ways:

1. Web scrape data from mental health support forums for all six classes to obtain more samples.
2. Move the computing environment to a Surface Studio equipped with a cuda GPU unit.
3. Compare results from 8 different non-deep learning models, and apply dimension reduction and two random sampling methods to normalize the data.
4. Fine tune BERT by training an attention head and running predictions.

After these four steps, I will compare all of the prediction results to determine which model performs the most reliably, and also determine which of the models is the most scalable for continued training and deployment.

Scope

This paper will compare several non-deep learning models and determine their efficacy as a multiclass text classifier. After running the initial comparisons, I choose one classifier to tune via grid searching and re-run the predictions. The goal of this process is to identify the best non-deep learning classifier for my dataset and compare its performance against the initial results from Capstone I.

Milestones

I have clearly defined in the above the limitations I must overcome to make this study more robust. The first and foremost milestone is to find and successfully scrape text data from mental health support forums, and preprocess it for exploratory analysis.

Once I have successfully obtained the data, I explore it in the same manner as I have previously in Capstone I, then I utilize slightly more advanced techniques to explore the feature space. The second milestone is achieved after the completion of this EDA.

The third milestone of this portion of the project is the comparison of the different classifiers, and to determine the best non-deep learning classifier for the dataset I introduced.

Metrics

I will leverage Scikit-Learn's classification report to obtain a high-level view of the results for each iteration. Since this is a multiclass classification task, observing the f1 score will be particularly helpful. The other metrics provided by the report will also serve as a good measure for selecting the classifier to tune. Then, I will employ a more visual approach by plotting the ROC AUC curve, as well as the confusion matrix to identify signs of performance issues and overfitting.

Data Wrangling Report

Sourcing Data

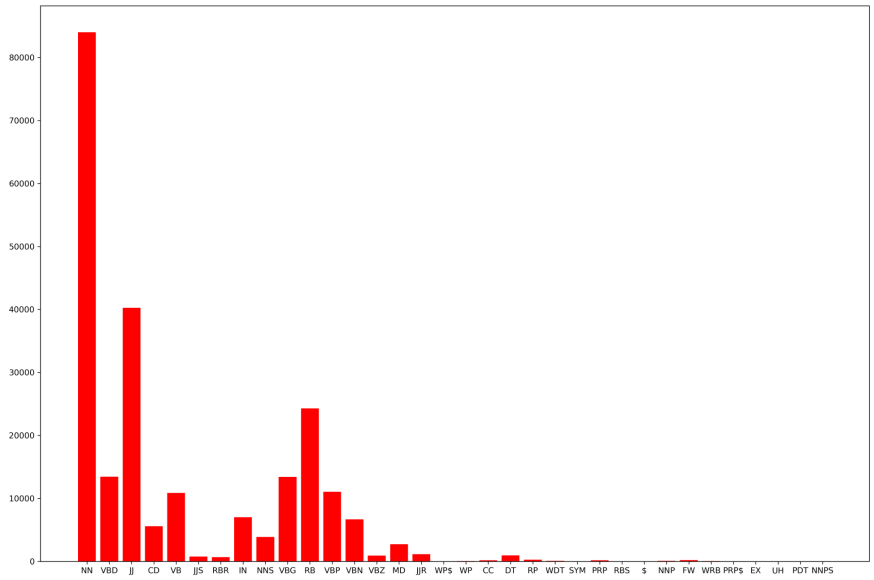
I identified a large mental health support forum called “mentalhealthforum”, which had groups for a variety of mental health conditions. The site was relatively easy to navigate, and it had groups for all six of my classes which I could not find elsewhere. A quick eye scan over the content seemed to be very rich in content; however, the number of available documents differed from one another significantly.

I used BeautifulSoup and requests to obtain the datasets. By iterating over the page count available in each of the forum groups (each group had a different number of pages available) I was able to create a nested for loop which clicked in each page and grab all of the specified text documents within that page. The biggest challenge of this phase was going through the html scripts to identify classes that indicated the correct documents on the web page.

Wrangling Data

I followed the same recipe to prepare the data for exploratory analysis. The steps involved tokenization, removing stopwords, and lemmatization. Once the data had been preprocessed, I proceeded to take a quick look into the corpus for visual insights.

I generated a count of the 20 most frequent words that showed up, searched for concordances with the word “want”, then found quadgram collocations. I also POS tagged every document to visualize choices in diction, and how they vary by class, by plotting each tags’ frequency throughout the dataset. The below are the outputs for the depression forum.



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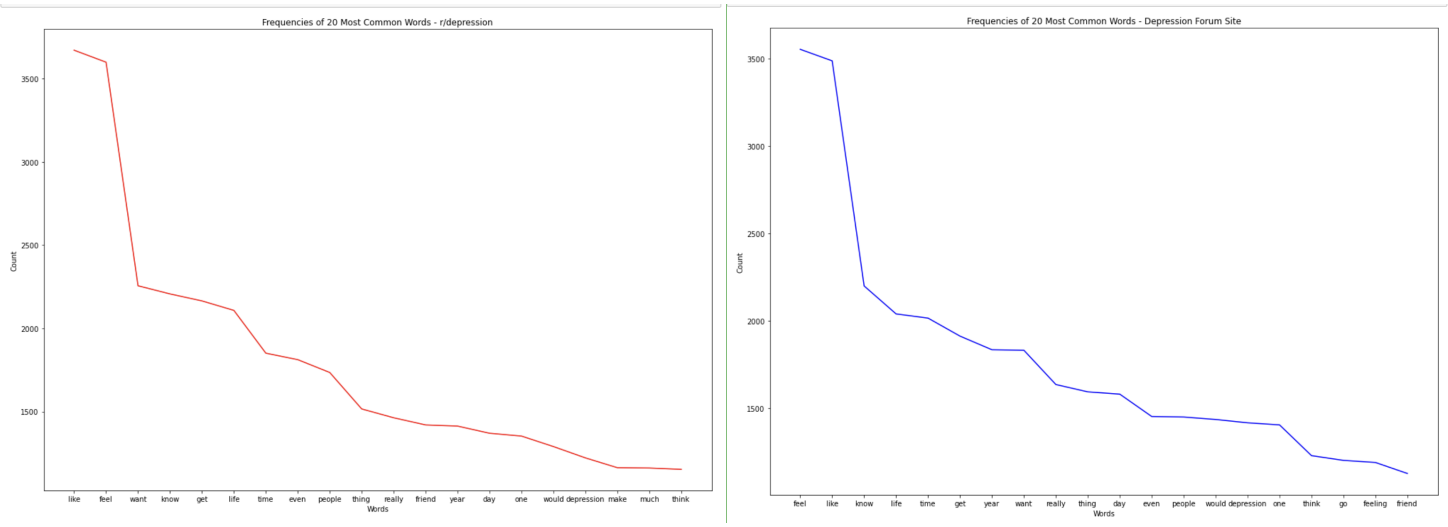
[('feel', 3555), ('like', 3489), ('know', 2201), ('life', 2041), ('time', 2017), ('get', 1914), ('year', 1836), ('want', 183
3), ('really', 1637), ('thing', 1595), ('day', 1582), ('even', 1454), ('people', 1451), ('would', 1437), ('depression', 141
8), ('one', 1406), ('think', 1230), ('go', 1203), ('feeling', 1191), ('friend', 1128)]
ing seems easier way much doubt ever want share experience read lot topic time
l think ruined honor locking 3 month want go back work living house live diffe
afraid tired everyday like nightmare want lose life person fell love know plea
en week really struggling experience want come home feel like need stay longer
ng promoted afford monthly rent plus want emergency saving fund live mother cl
ybody relate advice thanks nan hi dr want sign two week go ahead go work dr gi
ress let honest get lot stress would want come home hurt see depression suicid
ul dreamy 3 hour ever rare feel like want want wake much better time asleep sa
eamy 3 hour ever rare feel like want want wake much better time asleep sad dep
e name know others similar situation want tell last spend sunny day loved one
losing mom one trust world feel like want die hopeless starting get anger issu
onfident sexy hate negative attitude want stop therapy support group gonna get
d air forcing pretend happy positive want throw hand say amazing instead looke
ed got mad said really uncomfortable want talk immature attitude therapist alw
esteem hard hidradenitis suppuritiva want negative hi taken day today really s
ontact therapist reach fucking sleep want die though want hurt lovely boyfrien
 reach fucking sleep want die though want hurt lovely boyfriend really want di
gh want hurt lovely boyfriend really want die live like anymore either please
k long time figure never wanting man want woman suck social expectation abuse
 wanting easy time think lot anymore want die intend anything speed process wa
<nltk.collocations.QuadgramCollocationFinder object at 0x000001C26DF9EC48>
[(('faint', 'faint', 'faint', 'faint'), 11), (('anyone', 'else', 'feel', 'like'), 9), (('make', 'feel', 'even', 'worse'),
6), (('diagnosed', 'major', 'depressive', 'disorder'), 5), (('cut', 'long', 'story', 'short'), 5), (('nothing', 'make', 'hap
py', 'anymore'), 4), (('want', 'get', 'better', 'want'), 4), (('every', 'day', 'feel', 'like'), 4), (('feel', 'like', 'stayi
ng', 'bed'), 4), (('feel', 'like', 'good', 'enough'), 4), (('want', 'go', 'back', 'work'), 3), (('wish', 'could', 'go', 'bac
k'), 3), (('also', 'feel', 'like', 'im'), 3), (('thank', 'taking', 'time', 'read'), 3), (('say', 'something', 'along', 'lin
e'), 3), (('really', 'want', 'go', 'back'), 3), (('feel', 'like', 'want', 'exist'), 3), (('many', 'people', 'around', 'worl
d'), 3), (('1', '5', 'year', 'ago'), 3), (('time', 'playing', 'video', 'game'), 3)]
```

One interesting discovery is the similarity between the reddit data and the forum site's data. When I compared word clouds, the outputs were nearly identical!

A side-by-side comparison of word clouds from two depression data sources.

Down to word choice and term frequency ratios, the corpuses' resemblance to each other are uncanny even to the naked eye. I also plotted and compared the top 20 word frequencies from both the subreddits and the forum sites. The below were the results:



The left image is the word frequency from r/depression subreddit, and the right is from the forum site. I repeated this comparison for each of the classes and found similar results.

I then combined the two datasets into a master dataset, called "master_rf.csv". This helped to nearly double the amount of examples available for training, thus taking care of the first of the three limitations.

Exploratory Analysis

Procedures

In this EDA, I will examine model comparisons on three datasets: master - subreddit, master - forum, and master - combined. Then, I explore the feature space of the combined data to understand the effects of dimensionality reduction.

Master - Subreddit

The master dataset is the final dataset with two columns, text and label. Documents present in this dataset are exclusively collected and processed from subreddits for each of the classes. I constructed a dictionary of 9 models I wanted to compare against each other with default parameter settings. The tuning will come later. The 9 models are as follows:

- MultinomialNB()
- SGDClassifier()
- LogisticRegression()
- RandomForestClassifier()
- AdaBoostClassifier()
- GaussianNB()
- DecisionTreeClassifier()
- KNeighborsClassifier()
- DummyClassifier()

By iterating through each fit and using scikit-learn's classification_report, I was able to identify SGDClassifier(), LogisticRegression(), and RandomForestClassifier() as the three best performers for this dataset, as well as the others..

SGD - Classification Report

Classes	Precision	Recall	f1-score
0	.78	.80	.79
1	.84	.77	.80
2	.79	.74	.76
3	.88	.79	.83
4	.67	.92	.78
5	.87	.78	.82

Accuracy = 80%

LOG - Classification Report

Classes	Precision	Recall	f1-score
0	.74	.77	.76
1	.81	.73	.77
2	.74	.70	.72
3	.83	.76	.79
4	.69	.89	.78
5	.81	.76	.78

Accuracy = 77%

RF - Classification Report

Classes	Precision	Recall	f1-score
0	.69	.85	.76
1	.88	.79	.83
2	.84	.77	.80
3	.85	.83	.84
4	.77	.90	.83
5	.93	.78	.85

Accuracy = 82%

Master - Forum

SGD - Classification Report

Classes	Precision	Recall	f1-score
0	.63	.74	.68
1	.73	.58	.65
2	.74	.81	.77
3	.65	.68	.66
4	.79	.65	.71
5	.62	.57	.59

Accuracy = 68%

LOG - Classification Report

Classes	Precision	Recall	f1-score
0	.61	.74	.67
1	.80	.46	.58
2	.81	.74	.77
3	.57	.72	.64
4	.71	.67	.59
5	.75	.40	.52

Accuracy = 66%

RF - Classification Report

Classes	Precision	Recall	f1-score
0	.58	.75	.66
1	.73	.52	.61
2	.77	.68	.72
3	.55	.65	.59
4	.73	.69	.71
5	.64	.24	.35

Accuracy = 64%

Master - Combined

SGD - Classification Report

Classes	Precision	Recall	f1-score
0	.72	.74	.73
1	.76	.71	.73
2	.72	.72	.72
3	.71	.74	.73
4	.76	.79	.77
5	.79	.72	.75

Accuracy = 74%

LOG - Classification Report

Classes	Precision	Recall	f1-score
0	.68	.76	.72
1	.79	.63	.70
2	.71	.66	.69
3	.74	.71	.73

4	.65	.80	.72
5	.79	.69	.74

Accuracy = 72%

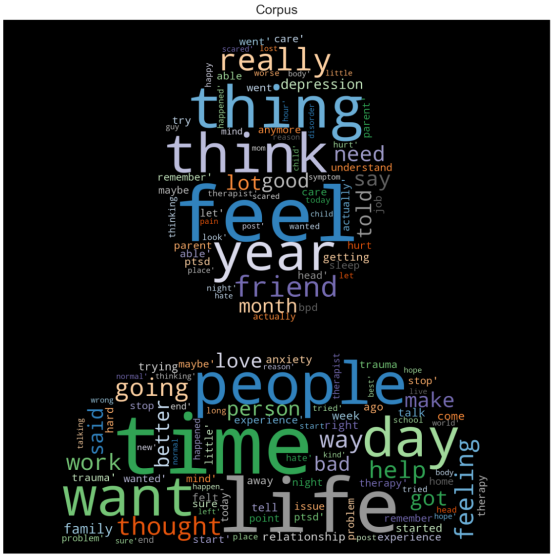
RF - Classification Report

Classes	Precision	Recall	f1-score
0	.60	.81	.69
1	.84	.69	.76
2	.80	.64	.71
3	.66	.76	.70
4	.76	.77	.76
5	.89	.61	.73

Accuracy = 72%

The Analysis

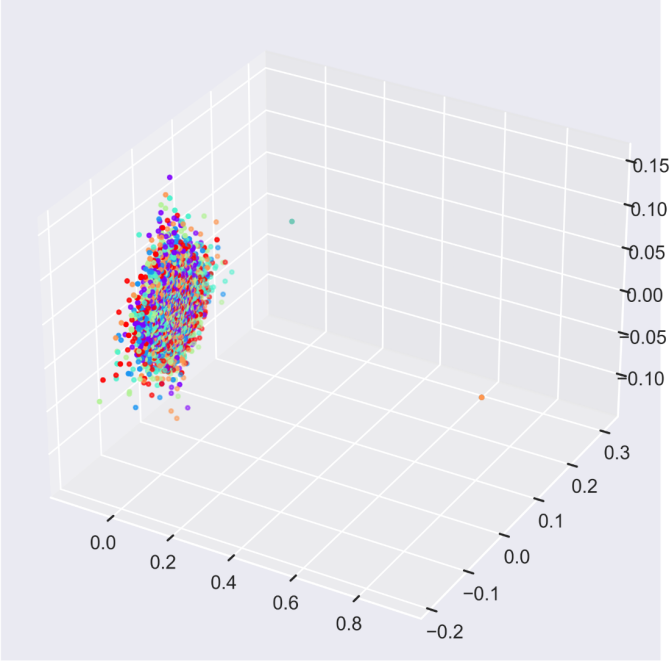
Apart from repeating the steps I followed in Capstone 1, I wanted to observe the embedding of my dataset in a more visual way. I introduce in this project, two dimensionality reduction techniques: Principal Components Analysis, and UMAP-learn.



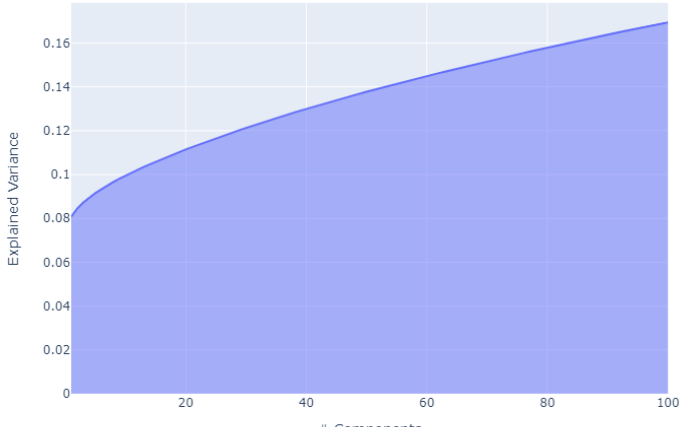
First, I vectorized the entire dataset setting limits on the maximum amount of documents a term can show up before it is removed from the vectorization. By doing so, I am able to reduce the dimensions from being hundreds of thousands of features to humble tens of thousands.

Because the dataset is so sparse [X.shape = (27151, 65595)], I expected PCA to perform poorly when it comes to evaluating the models. The question for me was, which model performs the best when the data is projected into a lower dimension?

After I transformed the data using PCA, I plotted a scree plot to check the explained variance. Not

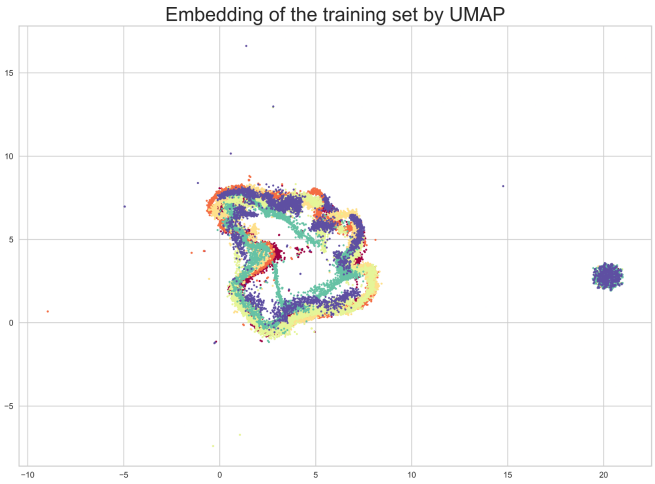


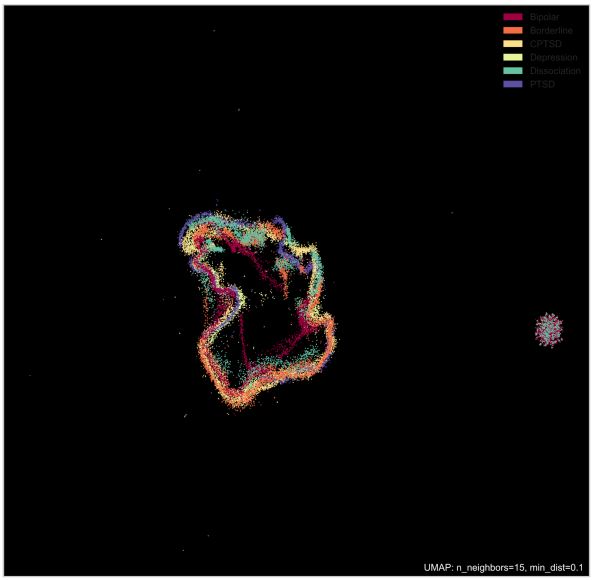
surprisingly, even at n_components = 100 the explained variance was at only 16.9%. The evaluation results gathered from the model dictionary from Capstone 1 yielded only slightly better results than



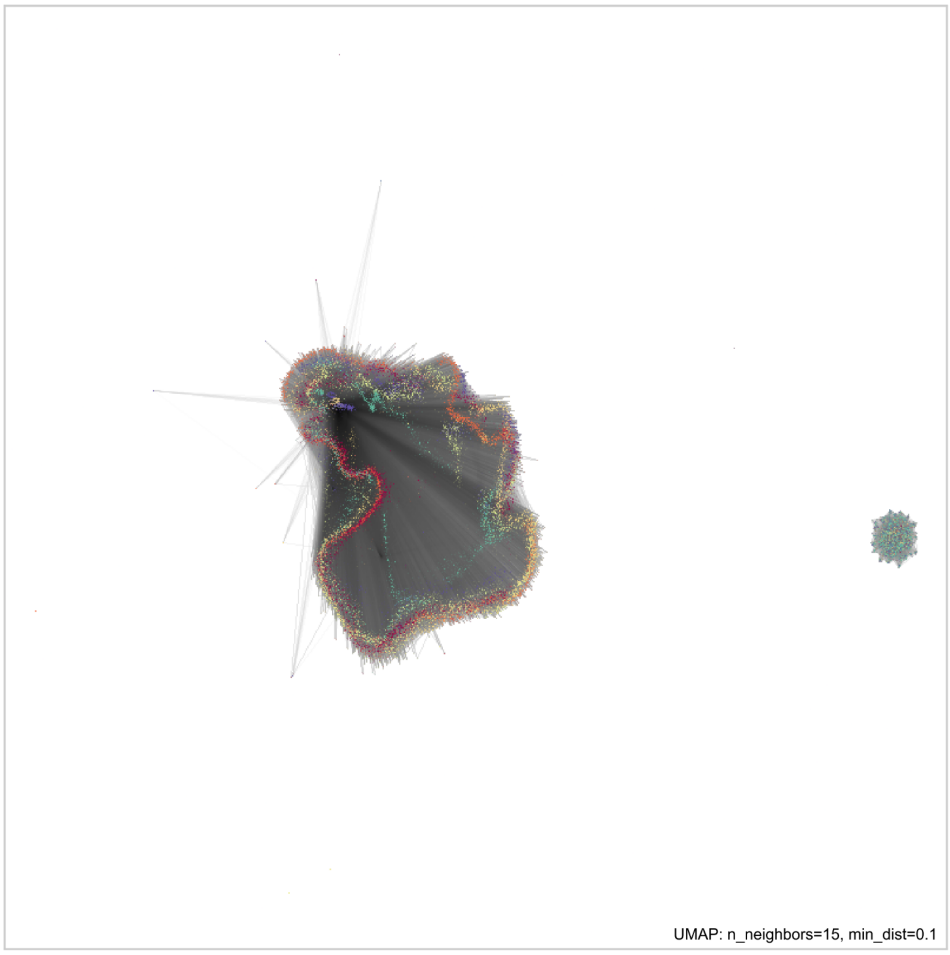
the dummy classifier. The best result was yielded by RandomForestClassifier(), with a prediction accuracy score of merely 30%.

UMAP-learn achieved slightly better results. Projected onto two dimensions, as I did before with PCA, the data transformer achieved 56% with the KNearestClassifier(). UMAP was also helpful for understanding the embedded space, as it allows users to plot interactive plots and visualize manifolds that respects the overall topology of the data. Its flexibility in reducing dimensions also allows for dynamic distributions making it easy for the naked eye to see class separations.

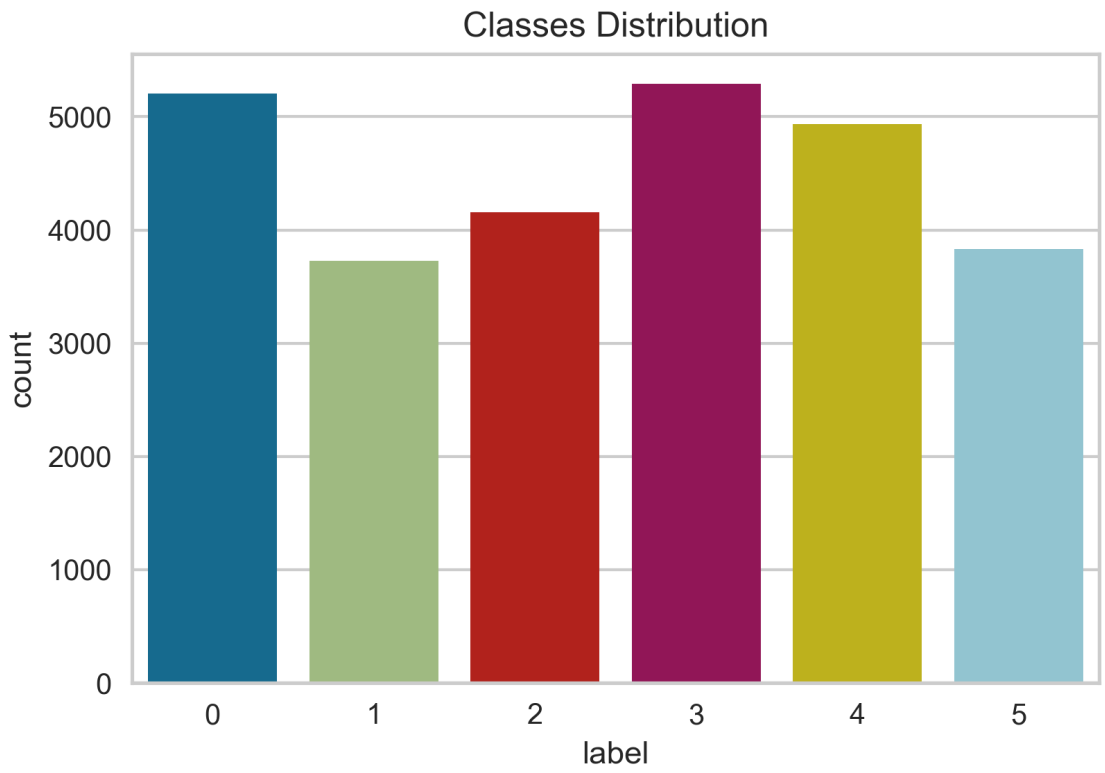




UMAP also supports visualizing connectivity plots which provides a view of the embeddings, and where it was sampled from. The graph below shows the embeddings converging to a single point, with the exception of a cluster of outliers.



Finally, I check the distribution of classes. Knowing that the imbalances in the classes affected the results in Capstone 1, I deliberately saved the step of balancing out classes for the next portion of the project which employs deep learning.



The imbalance slightly improved with the addition of the forum site data, but classes 0, 3, and 4 are still entire heads over the others.