Classification of Reddit Text Posts

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ABSTRACT

We work on a large text classification problem, specifically the Reddit Self-Post Classification Task (RSPCT). RSPCT is a dataset with around 1000 classes ("subreddits") with around 1000 examples per class, which is unique because most text classification datasets have sparse labels. We use two traditional machine learning algorithms and one deep learning algorithm to learn to predict the class (i.e., the subreddit) given the title and body of a post. We evaluate the performance of each model using the Precision-at-K metric and gain insight into the models and the dataset by using experiments on the title and body of the posts and by feature analysis.

Keywords

NLP; large text classification; multi-class classification

1. INTRODUCTION

Text classification with few classes, such as in sentiment analysis, has been well-studied [2] with state-of-the-art techniques like LSTM. However, those techniques do not always work as well in scenarios with many classes [3]. Another issue with training on many-class datasets is that they have a very large number of labels (such as WikiLSHTC-325K dataset [5], which has 325K labels) and are sparse - most labels in the above dataset have less than 100 examples [4].

We want to study this problem by using a dataset that has a large number of classes but also a large number of examples per class. To this end, we use the Reddit Self-Post Classification Task (RSPCT) dataset and trained three models and evaluated their performance.

We think this is a useful problem to solve because it has not been adequately studied, to the best of our knowledge, and because this could pave the way to future work on such many-class datasets.

2. DATASET

Reddit is a popular social link aggregation, web content rating, and discussion website. The content on Reddit is organized into "subreddits", which are sub-forums on Reddit dedicated to a specific topic, for example, r/geography, r/gameofthrones, r/MachineLearning.

There are two main types of posts a user can submit on Reddit: a simple URL link and a self-post. A self-post consists of a topic and a body of text and is generally much longer in length, thereby, providing more information to Redditors. Moreover, most of the self-posts talk closely about the subreddit that they were posted in, which makes for a good classification task.

The Reddit Self-Post Classification Task (RSPCT) dataset [1] is a text corpus containing such self-posts (i.e., text posts) from Reddit. RSPCT was collected to help spur research on models that could tackle a large number of classes by ensuring a large population of examples for each class. The data consists of 1.013M self-posts, posted from 1013 subreddits (1000 examples per class). For each post, its title, body and the subreddit that it belongs to are provided.

The aim is to allow for a situation comparable to that in the computer vision community, which was helped by the famous ILSRVC competition (ImageNet [7]) with 1000 classes and around 1400 examples per class. This potential is what made us find this project interesting.

3. PREPROCESSING

Since the RSPCT dataset contains real self-posts from Reddit, the text in these posts do not always conform to the grammar, spelling, vocabulary and other nuances of the English language. For this reason, we carried out a series of preprocessing steps.

Because this is a text classification problem and most of our models used the bag-of-words approach, we first lowercase all the text in the subreddit, title and body of each post. We noticed that many of the posts contained special HTML encoded text and tags like &gt, &amp, &lt, <lb>, <tab> etc. We used regular expression matching to replace these tags with a blank space. We also removed punctuation characters like !, ", #, $, %, &, (, [, *, + etc. such that we were only left with words at the end of this step.

Finally, we used Python's NLTK's PorterScanner to replace all words with their stem words. This resulted in words like "extremely" and "extreme" to be replaced with "extrem". ***Figure __ shows the whole process for preprocessing one self-post*** (TODO)

4. EXPLORATORY DATA ANALYSIS

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4.1 Distribution of Characters in Post and Title

We first explore the dataset by looking at the histogram of the post titles (figure TODO). We find that most titles are shorter than 100 characters in length, with a median of 35 characters and 7 words.

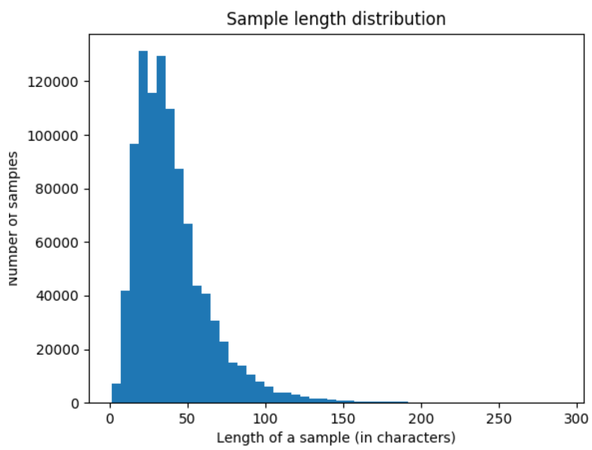

Figure 1: Sample Distribution for Length of Post's Title (in characters)

Similarly, the histogram for the post bodies (figure TODO) shows that most posts are shorter than 1000 characters in length, with a median of 500 characters and 105 words.

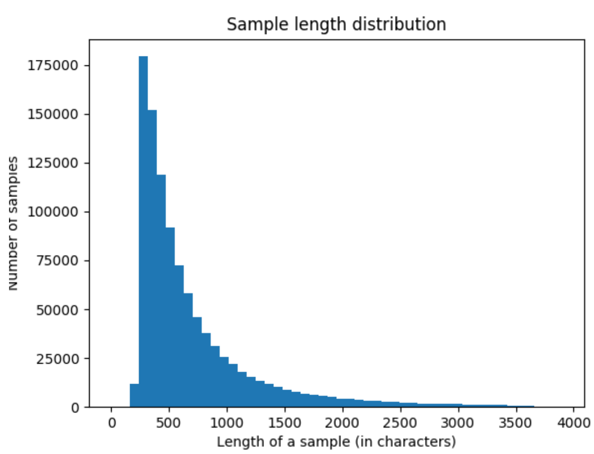

Figure 2: Sample Distribution for Length of Post's Body (in characters)

The t-SNE plot for the subreddits (figure TODO) shows that the subreddits seem to be well-separated by topic. For example, we can see clusters of subreddits for gaming, cryptocurrency, and diseases.

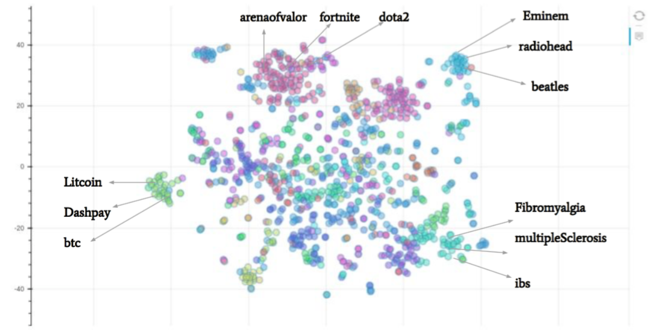

Figure 3: TSNE Plot of All the Self-Posts

5. ALGORITHMS IMPLEMENTED

5.1 Data Preparation

For the two traditional algorithms, we used a label encoder to transform each output label (subreddit name) into a number from 0 to 1012. Then, we used a TF-IDF vectorizer to get 30,000 top words, while excluding stop words and choosing only words that appeared in at least 5 documents and appeared in a maximum of 50% of the documents. For all three algorithms, we combined the title and body of the posts into one field.

5.2 Naive Bayes Classifier (NBC)

The first algorithm we looked at was the Naive Bayes Classifier because of its long use in text classification tasks (TODO). Specifically, we used `MultinomialNB` from **`sklearn`** with the hyperparameter **`alpha`**.

This model was the fastest to train among the three and gave us a quick baseline with which to compare the others. We also extended the maximum number of feature words to be 100,000 since it did not impact the training time too much. The training curve can be seen in figure TODO. We tried the following values of **`alpha`**: 0.1, 0.5, 0.9, 1.0, and found the best validation accuracy at 0.1.

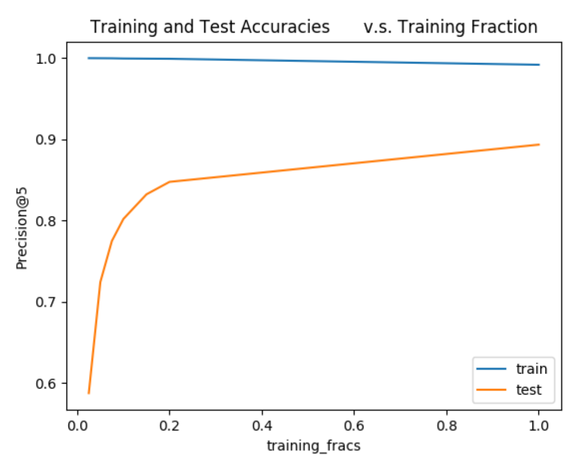

Figure 4: Learning Curve for Naive Bayes Classifier

5.3 Logistic Regression (LR)

The next traditional algorithm we wanted to consider was

Logistic Regression. We used `LogisticRegression` from `sklearn.linear_model` with the hyperparameter C.

The number of feature words used in this bag-of-words approach affected the training time a lot. Similarly, when hyperparameter tuning, we found that while values of C like 0.0001 and 0.01 led to very short training time, they also led to poor validation accuracy. On the other hand, C = 100 (i.e., not penalizing large weight values) led to better validation accuracy but at the cost of orders of magnitude longer training time. The training curve can be seen in figure TODO (TODO: need to add training fraction 0.20).

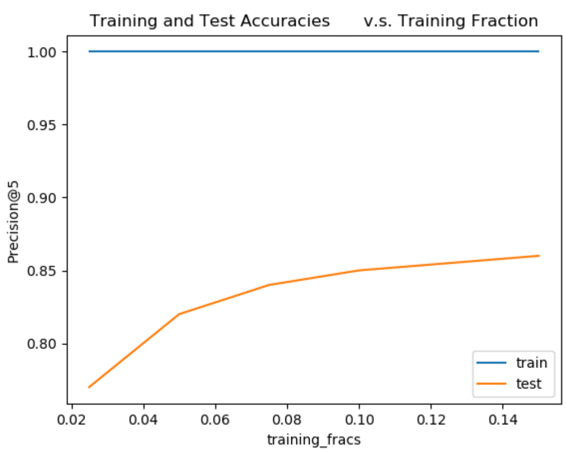

Figure 5: Learning Curve for Logistic Regression

5.4 Convolutional Neural Network (CNN)

Finally, we wanted to test a deep learning model on this dataset. We chose to use a Convolutional Neural Network because of its better average accuracy across different tasks and shorter training time then Recurrent Neural Networks.

To embed the words in the post, we used the GloVe (Global Vectors for Word Representation) embedding [6]. We tried a version with 100 embedding dimensions for each word and another version with 300 embedding dimensions and found the later to give quite a boost in overall accuracy.

We considered two architectures for the CNN, one with three successive layers of filters of size 5 and one with a multi-channel model of filters of sizes 2, 3, and 5. Upon testing, we found that the latter gave much higher accuracy even after a few epochs whereas the former seemed to overfit after a few epochs (TODO: maybe show the training curve for the old architecture). So, our multi-channel approach would consider two words at a time, three words at a time, and five words at a time. The later layers use max-pooling and softmax to predict one class label out of 1013 labels. Finally, we use dropout with probability 0.3. The optimizer we use is Adam because of its adaptive learning rate and the loss is categorical cross-entropy.

We trained the CNN for a maximum of 10 epochs over several days and obtained the following learning curve (figure TODO).

5.4.1 Performance

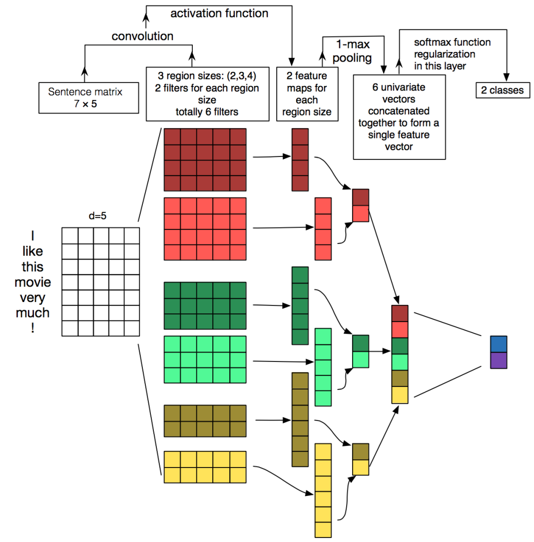

Figure 6: CNN Architecture

5.5 Performance Comparison

TODO

6. FURTHER EXPERIMENTS

6.1 Confusion Matrix

To analyze which subreddits are frequently mispredicted, we look at the confusion matrix. As the 1000x1000 matrix for all the labels was hard to read, we have zoomed in on the subreddits that were most frequently confused.

Figure TODO shows the top 40 most-confused subreddits, where we can see the characteristic diagonal of dark squares along with a few lighter squares denoting the mispredicted labels.

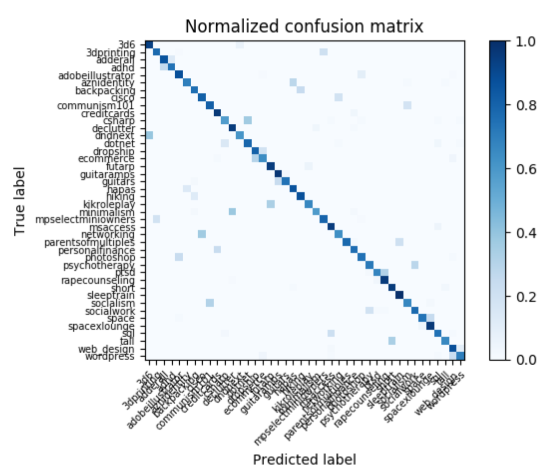

Figure 7

Another version is in figure TODO where we can see that r/Adderall and r/ADHD are often confused.

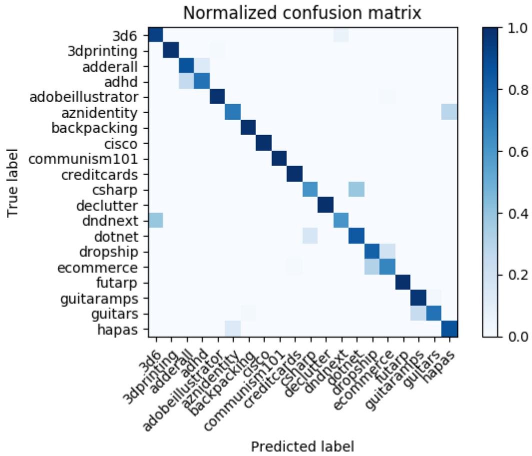

Figure 8

Again, since the matrix is quite sparse it is hard to show them on the same plot, so we decided to visualize the true label along with its most-confused label in the same plot (figure TODO). We see that posts from r/hiking are attributed to r/backpacking, posts from r/cisco are attributed to r/networking, and, for some reason, posts from r/short are attributed to r/tall (probably because both talk about height).

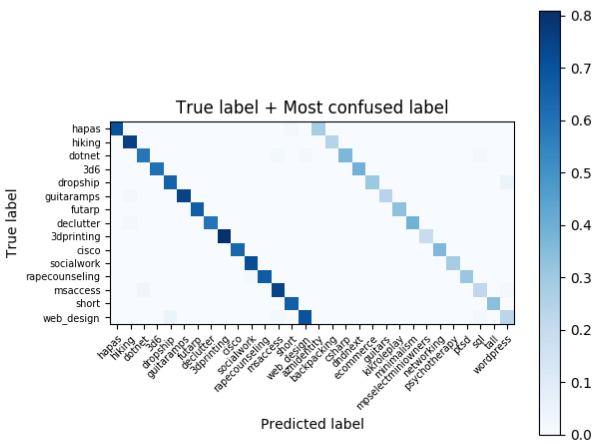

Figure 9

6.2 Toggle Title and Body

TODO: explain the table precision at 1 for cnn cuz not able to learn the exact label precision at 5 same for all implies some limit of the dataset which needs further experientaiotn

	Precision@1	Precision@3	Precision@5
NBC	0.74	0.86	0.89
LR	0.71	0.84	0.89
CNN	0.56	-	0.89

6.3 Performance Using Features for Sentiment Analysis and Readability Level

TODO: add graphs

6.4 Qualitative Analysis

TODO: talk about this

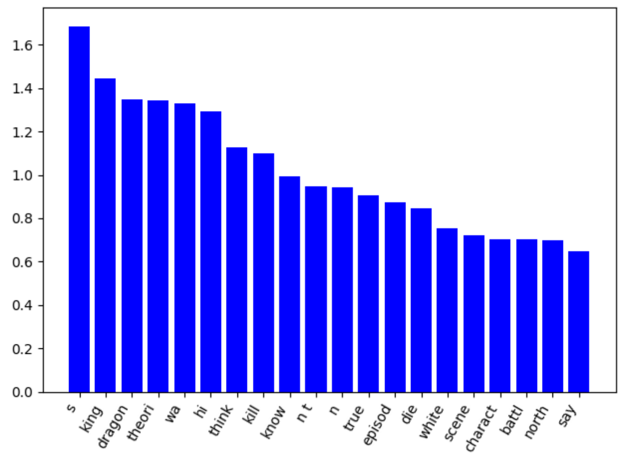

Figure 10: Important Features for subreddit r/gameofthrones

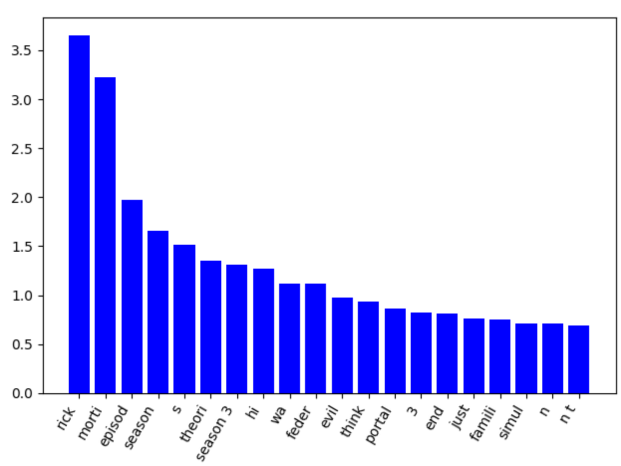

Figure 11: Important Features for subreddit r/rickandmorty

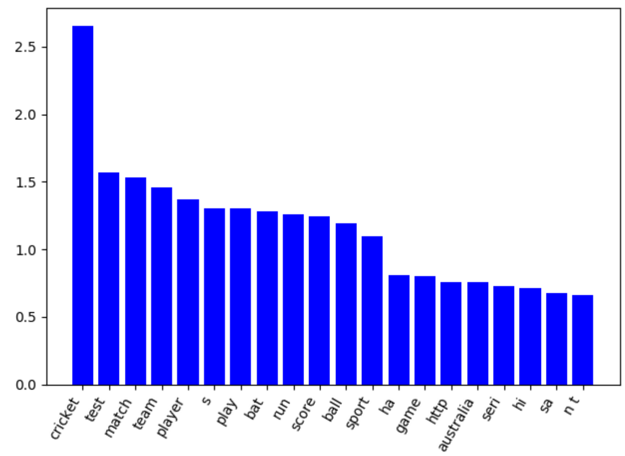

Figure 12: Important Features for subreddit r/cricket

7. EVALUATION OF PROJECT GOALS

Our project goals consisted of:

1. Preprocessing

   We preprocessed the data by converting it to lowercase, removing encoded HTML and other tags, removing punctuations and stemming the words.

2. Exploratory Data Analysis

   Exploratory Data Analysis was done by exploring the sample distribution length for the title and body of the posts and by plotting a TSNE plot to see if similar subreddits are clustered together.

3. Implementing algorithms

   We implemented two traditional learning algorithms (Naive Bayes Classifier and Logistic Regression) and a deep learning model (Convolutional Neural Network). We also tuned the hyper parameters of these algorithms to get the best possible performance on our dataset.

4. Toggling post's title and body

   To understand the impact of the title on classification, we measured the performance by training and testing on just the titles of the posts, just the bodies of the posts, and then with both title and body.

5. Experiment with adding new features

   In order to see if we can extract even more information from the data, we added features for the sentiment value and readability score of every post in the dataset.

In addition to the above, we also computed the confusion matrix and carried out qualitative analysis by computing the feature importance for our models.

We, therefore, have achieved our goals that we set in the project proposal.

8. CONCLUSIONS

Overall, we were able to get good results on the RSPCT dataset, which supports our hypothesis that one of the main bottlenecks in large text classification tasks is the sparsity of examples for labels. All three models were clearly able to learn over the dataset and curiously produced very similar results for the top-5 classification accuracy. Future work might focus on either increasing the accuracy on this dataset using better model and more tuning or aggregating such a large number of examples per label for other tasks (perhaps using Reddit itself). Another question to answer is whether adding more than 1000 examples per label might improve accuracy even further or whether the benefits would taper off.

Our experiments on the title and body showed us that as few as 7 words could allow a reasonably-high degree of accuracy even with 1000 labels. Our investigation of the feature importance shows us the strengths of the models and points to clear steps for future work. Finally, our analysis of the confusion matrix points to the most-confused subreddits, which could inform future work in this area.

TODO: Need at least as many citations as the proposal.

9. ACKNOWLEDGEMENTS

We would like to thank Professor Ming Yin for her suggestion about using a confusion matrix for pinpointing the subreddits that frequently confused our model.

10. TEAM MEMBER CONTRIBUTIONS

11. REFERENCES

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