

WHY WILL MY QUESTION BE CLOSED? NLP-BASED PRE-SUBMISSION PREDICTIONS OF QUESTION CLOSING REASONS ON STACK OVERFLOW

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ABSTRACT

Stack Overflow is a popular Community-based Question Answer website focused on software programming and has attracted more and more users in recent years. As of October 2021, Stack Overflow had more than 22 million questions. Although the posting ethics were guided in detail, the quality of many posted questions is poor [1]. A question on SO is closed if it doesn't follow guidelines from SO. But often reason for closing particular question is blurred to user, which leads to debates and occasional negative behavior in answers or comments. With the aim of helping the users compose good quality questions, Toth et al proposed [2] a set of classifiers for the categorization of Stack Overflow posts prior to their actual submission. In this work, I have implemented their [2] **architecture from scratch** and tried to **replicate their results**. I have also provided additional visualizations of **intermediate representations** of architecture to verify if architecture is learning correct representation of Stack Overflow posts. I have also tried various types of BERT Embeddings to check if it improves model performance. Finally applied classical machine learning techniques on learnt embeddings for the given task which lead to **5% increase** in performance of binary classification task while approx **10% increase** in multi-class classification accuracy given in paper.

1. INTRODUCTION

Stack overflow is a huge community driven question answering website. As of October 2021, It has 22 million questions, 32 million answers, 83 million comments and 62 thousand tags. Whether you are professional or enthusiast programmer certainly Stack Overflow is a very popular platform. SO's immense popularity clearly shows the ever-growing impact of social media in Software Engineering, which, however, has its certain drawbacks. In particular, the competition between quantity and quality of questions is increasing as the number of posts rises, which leads to issues in maintaining the professionalism of the site. Given the extreme posting frequency, moderator work is undoubtedly an elaborate and laborious task. At the same time, moderation is the key to avoid the issue of quality decline, which is highly important for the sustainability of the service SO provides. In order to maintain a reasonable level of quality, supporting poor questions should be avoided, and closing or deleting them is often inevitable. Nevertheless, the definite reason for closing a particular post is often unclear to the users, which in frequent cases leads to heated debates. Essentially anyone with any experience level can ask a question on SO but there are a few community-established rules for posting. Questions not satisfying these requirements will be closed or deleted by moderators or privileged users. Currently, there are five reasons for closing a question:

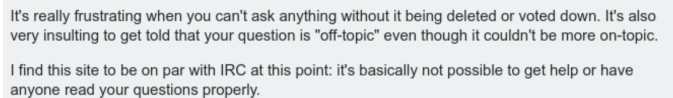
- Due to duplication.
- The question is off-topic.
- Unclear what the user is asking.
- The question is too broad and cannot be answered straightforwardly.
- The question is primarily opinion-based leading to subjective discussions.

The closing procedure is a manual task relying on a voting system. Moderators or privileged users can cast a vote if they find a question inappropriate, and five such votes would end up in closing the question. Previous studies in this topic essentially focused on the classification of SO questions according to their quality relying on features extracted primarily from **user data or post-submission** information available only after community feedback. The most important feature among those is reputation / experience of user because more reputed question posters are least likely to post question that may be closed because of their experience.

On contrast authors of this architecture wants to classify questions into the existing closed categories of SO prior to submission, that is, in a form visible only for the posting user. This pre-evaluation tool would assist the users in composing a question, which will very likely remain open and receive responses.

In order to solve this problem authors tried to implement **Gated-Recurrent-Unit-based (GRU)** classifier augmented with Natural Language Processing (NLP) tools capable of predicting whether a question will be closed by relying only on the textual features of the post. This is the first work to classify SO questions and also classify exact reason for closing of the questions.

Many times its not clear by which reason question was closed hence we can see following comments discussions regularly.¹



It's really frustrating when you can't ask anything without it being deleted or voted down. It's also very insulting to get told that your question is "off-topic" even though it couldn't be more on-topic.

I find this site to be on par with IRC at this point: it's basically not possible to get help or have anyone read your questions properly.

Fig. 1. Frustration for closing and deleting a question

The objective of authors work is to provide the user with a practical tool capable of pre-evaluating the questions to be posted on SO, and determining whether the question will be marked for closure by the community after submission. With these goals in mind, contribution contains three essential ideas:

¹<https://meta.stackoverflow.com/questions/388076/is-this-how-we-want-to-treat-newcomers>

- Classifiers relying exclusively on the textual properties of a question: its title, body
- Not using any post-submission information, such as number of answers, scores, or user reputation.
- Directly predict the exact closing reason of a question.

2. METHODS

Figure 2 shows overview of architecture that author has used. Details will be explained later.]

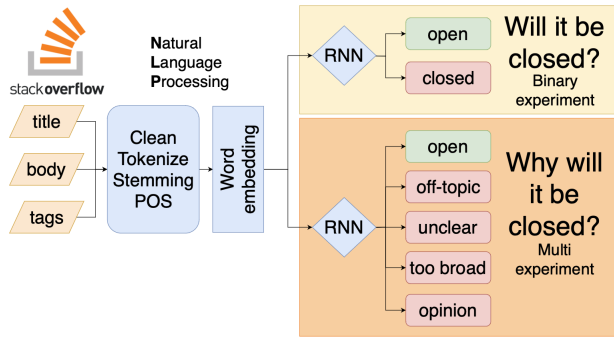


Fig. 2. Model Architecture

Code for this work can be viewed in Github repository ²

2.1. Dataset Preparation:

The dataset used is Stackoverflow data dump till Sept 2021 ³. Removed questions posted before June 2013 because after that current question closing policy was introduced. Questions closed due to duplication were also excluded from our dataset because of two reasons: i) this problem has already been well examined previously [3]; and ii) finding a duplicate would imply the knowledge of the previously posted questions, which is the opposite of the purpose of using only pre-submission information.

Stackoverflow has humongous dataset - 5.5 crore posts. There are around 1 million closed posts. In compressed format its around 30GB and expands to 401 GB SQL server database.

Following steps were used to prepare Dataset for computationally feasible data set:

- `Posts.xml` from SO data dump contains all the posts from Stack Overflow in XML format. (around 18 GB)
- Using XML parsing libraries converted this XML Dataset to required CSV format with the help of streaming API's because its difficult to load complete `Posts.xml` once in memory - `stackexchangeparser` folder in Repository
- Questions which are closed have `ClosedDate` attribute as non null.
- Sampled all Closed questions and sampled 2% of Open questions: which have nearly same number as total Closed questions - `sample.ipynb` Notebook

- Performed EDA and segregated Open and Closed questions from CSV - `EDA.py`
- To obtain reason for Closing Question there is another XML file in Stackoverflow Data dump : `PostHistory.xml` which records every event on posts.
- Stack Exchange networks have Data Explorer⁴ which is web interface of SQL Server of every Stack Exchange data dump. Queries can be fired and statistics can be calculated on real SE dataset. If results are small we can download them in CSV file hence I downloaded all the closed questions and their reason of closing questions using this method instead of downloading complete `PostHistory.xml` (27GBs!).
- Performed joins on tables from previous step and set of all closed questions obtained from `Posts.xml` to get reasons for closing that questions - `EDA.py`
- Removed Duplicate questions - `EDA.py`

These were the steps performed to provide to obtain SO dataset. In final dataset there are 584051 posts among which 265163 are closed. Class distributions are as follows, Open: 54.5%, Off-Topic: 20.7%, unclear: 10.7% , Too-broad: 10.11% and Opinion: 3%.

2.2. Input preparation for Model:

After removing Nulls and replacing NaNs with empty strings. I concatenated Title, Body of SO post to form a single a column of `title_body`. Using `BertTokenizer`⁵ converted text data into tokens and which in turn are converted to tensors in `csv2tensor.py`

2.3. Model:

In `models` directory there are `GRU.py` and `Bi_GRU.py` two files which contains code for models. First one uses unidirectional GRU layer while second one uses bidirectional GRU layer. In both the models first layer is Embedding layer then GRU layer and finally output from each time step of GRU layer is concatenated and passed it to fully connected layer for classification task. I have added 2 layers (stack) of RNN's in this task. Simple GRU layered model has around **10 million** parameters.

2.4. Hyper Parameters of model:

`Modules.py` contains list of all the parameters and their values at one place.

2.5. Evaluation and Metrics:

`evaluate.py` contains code for model evaluations where predictions are generated and saved. Later `metrics.py` is used to generated various metrics from these predictions like precision, recall and accuracy.

²<https://github.com/Kadam-Tushar/Why-Will-My-Question-Be-Closed>

³<https://archive.org/details/stackexchange>

⁴<https://data.stackexchange.com/>

⁵https://huggingface.co/transformers/fast_tokenizers.html

3. EXPERIMENTS:

Binary classification and Multi class classification experiments were conducted on SO datasets in this work. The second one is a five-class classification predicting the different closing reasons (off-topic, unclear, too broad, opinion-based) versus the open state. topic, unclear, too broad, opinion-based) versus the open state. Two different recurrent neural network (RNN) models denoted as UNI, BI GRU's representing Unidirectional and Bidirectional GRU were employed for this task. All networks apply the Adam optimizer together with cross-entropy as loss function. For the evaluation metrics, we applied micro and macro averages of the precision and recall pairs;

The input data was split into train and test sets applying the stratified k-fold cross-validation strategy with $k = 30$ yielding 30 different models. Here K-fold cross validation value of k is larger than usual because author argued it will help to evaluate variance in model performance.

In the models described in paper, author have used only learnt word-embeddings with GRU model. In this work I tried to use various embed-dings to improve performance of this model. I tried following different embed-dings.

- Learnable Word Embeddings
- Vanilla BERT [4]
- BERTOverflow [5] - Trained on StackOverflow Corpus
- BERTOverflow + POS
- BERTOverflow + Sliding Window

Here **BERTOverflow + POS** (Part of speech) tags means along with words from title and body of SO question I concatenated POS tags and get embeddings of that word too from BERT model. **BERTOverflow + Sliding window** means to capture long term dependencies (75% SO posts have less than 1700 words) in BERT embeddings. I hovered BERT input window of 512 length over 1700 sentence length with stride length of 400.

In these set of experiments I observed and also authors pointed in original paper most simple embeddings i.e **Learnable embed-dings with GRU model** is giving at-par performance compared to other SOTA models.

Finally to exploit and check usefulness of those learnt embed-dings from final hidden layer of GRU I used these embeddings to classical ML models: **Logistic Regression, Support Vector Classifier, KNN and Random forest.**

4. RESULTS:

Here are the results:

The evaluation metrics of the binary classification experiment are shown in above figure.

The number of related studies in the literature is scarce which uses only textual information of stack overflow questions. There is a recently published study that also used textual information exclusively, however, the classification task was different from that of this work. Tóth and co-workers[6] focused on question quality and obtained an accuracy of 74% for classifying SO posts in good versus bad categories using a deep neural network approach.

Table 1. Avg performance for the binary classification experiment

	Author's model	GRU	BERT	BERTOverflow
Micro precision	71.87	68.90	69.65	69.32
Micro recall	71.87	68.90	69.65	69.32
Micro F1	71.87	68.90	69.65	69.32
Macro precision	73.78	69.85	71.82	69.35
Macro recall	71.87	68.62	69.69	69.32
Macro F1	72.81	68.73	68.90	69.31
Accuracy	71.87	68.90	69.65	69.32

To visualise the effectiveness of learned SO post embedding, PCA and t-SNE plots are generated with different coloring for each class of post.

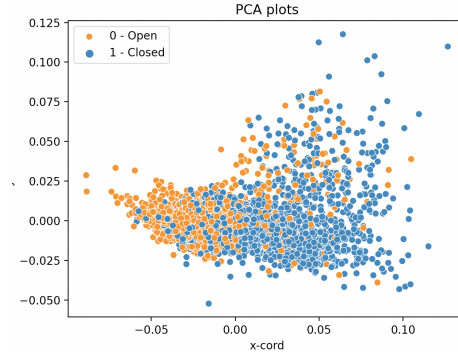


Fig. 3. PCA plot

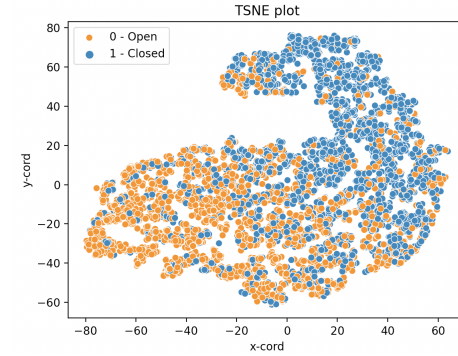


Fig. 4. t-SNE plot

From the plots we can observe for the binary classification problem these two classes are separable in 2 dimensions.

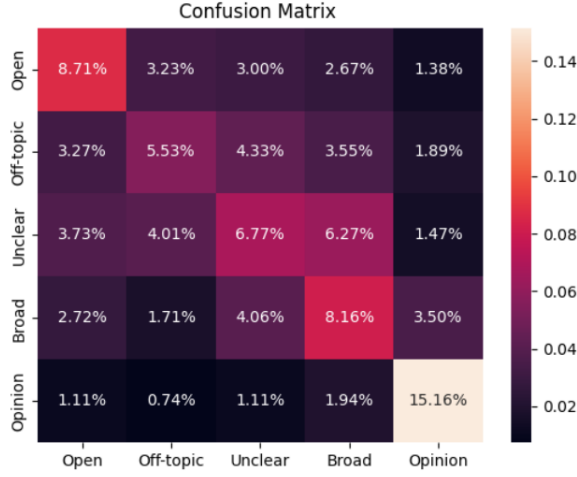
In this second experiment we try to answer why the stack overflow question was closed. So basically this five-class classifier using the same pre-submission textual information as the binary model above is designed with the labels off-topic, unclear, too-broad, opinion-based, and open. The original dataset is imbalanced in terms of these 5 classes.

The confusion matrix of test set is as follows:

As we can see from confusion matrix this 5-class classifier is much better than random guessing. Here classes are equally balanced and from confusion matrix we can see model most of the examples from opinion based closed question are correctly classified. While its becoming difficult for model to classify off-topic

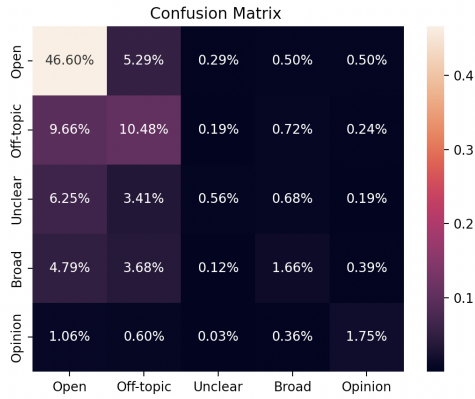
Table 2. Performance for the five-class experiment

	Author's model	GRU	BO	BO + POS	BO + Win
Micro precision	48.55	45.51	40.25	39.32	44.45
Micro recall	48.55	45.51	40.25	39.32	44.45
Micro F1	48.55	45.51	40.25	39.32	44.45
Macro precision	50.42	45.03	38.42	39.25	45.41
Macro recall	48.55	44.87	40.01	39.17	44.18
Macro F1	49.47	44.37	34.86	36.19	42.12
Accuracy	48.55	45.51	40.25	39.32	44.45

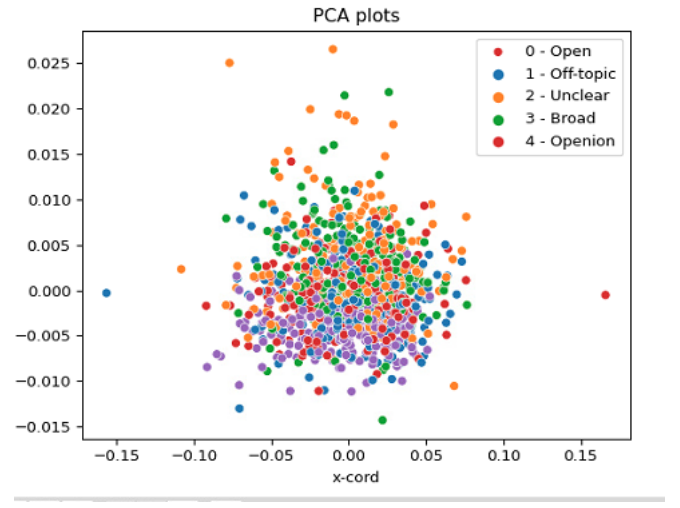
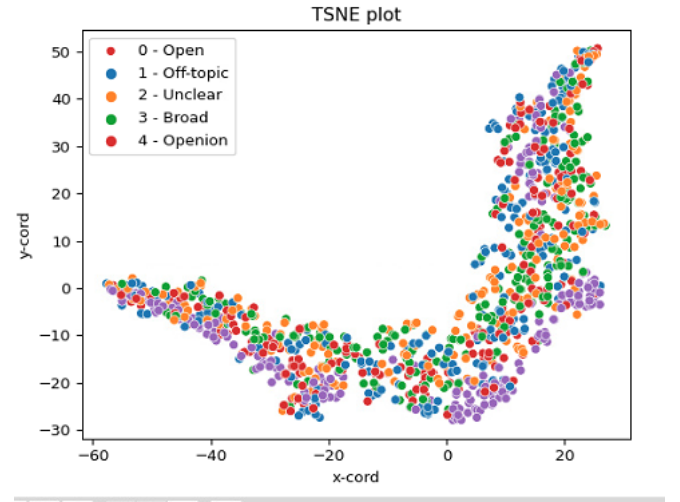
**Fig. 5.** Confusion matrix of Multi-class experiment

questions.

To demonstrate class imbalance we can see confusion matrix with their relative proportion. These observations hints us to apply class balancing techniques and re-train our model.

**Fig. 6.** Confusion matrix - Class proportion

To visualise the effectiveness of learned SO post embedding PCA and t-SNE plots for 5-class classification are as follows:

**Fig. 7.** PCA plot of 5-classes**Fig. 8.** t-SNE plot of 5-classes

Finally to fully utilise those embeddings I applied classical ML techniques over learnt embeddings of best performing model. Because of this I was able to produce 5% increase in accuracy of binary classification problems and 10% increase in accuracy of multi-class classification problem.

5. CONTRIBUTIONS

- **Pre-processing:** Tokenization, Sampling, Dataset generation.
- **Developing architecture from Scratch** Developed this GRU architecture to work with word embedding from scratch
- **Embeddings:** Tried various forms of BERT Embeddings.
- **Classical ML models:** Application of classical ML models on embeddings for performance gain.
- **Visualizations:** 2D plots of vector representation of SO questions using t-SNE and PCA.
- **Model Evaluation:** Tried precision, recall, F1-score.

Table 3. Performance on five-class problem

	Author's model	KNN	LR	RF	SVC
Micro precision	48.55	53.80	45.14	57.85	44.45
Micro recall	48.55	53.80	45.14	57.85	44.45
Micro F1	48.55	53.80	45.14	57.85	44.45
Macro precision	50.42	53.61	44.87	57.69	45.41
Macro recall	48.55	53.61	44.87	57.69	44.18
Macro F1	49.47	52.98	43.27	57.38	42.12
Accuracy	48.55	53.80	45.14	57.85	44.45

Table 4. Performance on Binary-class problem

	Author's model	KNN	LR	RF	SVC
Micro precision	71.87	76.04	75.59	76.58	75.90
Micro recall	71.87	76.04	75.59	76.58	75.90
Micro F1	71.87	76.04	75.59	76.58	75.90
Macro precision	73.78	76.05	75.60	76.58	75.91
Macro recall	71.87	76.05	75.60	76.58	75.91
Macro F1	72.81	76.04	75.56	76.58	75.88
Accuracy	71.87	76.04	75.59	76.58	75.90

6. DEVIATIONS FROM ORIGINAL WORK

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- Original work used dataset till 2019 but this work has considered dataset till Sept-2021.
- Used hidden states from all the timesteps to better capture long term dependency but on the other its not clear from paper what exactly they have used in their work for e.g only last timestep hidden state or every hidden state.
- Because of time required for training I was not able to train Composite model (3rd model) from paper. But author mentioned best results were only obtained from Unidirectional simple GRU model hence given priority to implement that.
- Author used 30-fold cross validation for more reliable statistical analysis but I used 3-fold and 6-fold because of interest of time.
- As for k-fold cross validation I used small k hence I was not able to run statistical tests like KS and ANOVA for proving statistical significance for results.

7. REFERENCES

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