Abstract—Modern Question-Answering websites, such as StackOverflow and Quora, have specific user rules to maintain their content quality. These systems rely on user reports for accessing new contents, which has serious problems including the slow handling of violations, the loss of normal and experienced users’ time, the low quality of some reports, and discouraging feedback to new users. Therefore, with the overall goal of providing solutions for automating moderation actions in Q&A websites, we aim to provide a model to predict 20 quality or subjective aspects of questions in QA websites. To this end, we used data gathered by the CrowdSource team at Google Research in 2019 and fine-tuned pre-trained BERT model on our problem. Model achieves 95.4% accuracy after 2 epochs of training and did not improve substantially in the next ones. Results confirm that by simple fine-tuning, we can achieve accurate models, in little time, and on less amount of data.

Keywords—Q&A websites; Subjective features; Quality prediction; Transfer learning; BERT; NLP

I. INTRODUCTION

In recent years, online Q&A websites have attracted many users and are turned into reliable references among experts from various fields. These systems, in addition to general user rules, have specific rules to maintain their content quality. Due to the vast expanse of some of these systems in terms of the number of users, manual check and verification of new contents by the administrators and official moderators are not feasible, and these systems require scalable solutions. In major Q&A networks, such as Stack Exchange websites\(^1\), the current strategy is to use crowdsourcing and reliance on user reports. This strategy has serious problems, including the slow handling of violations, the loss of normal and experienced users' time, the low quality of user reports, and discouraging feedback to new users.

With the overall goal of providing solutions for automating moderation actions in Q&A websites, in this research, we plan to provide a model that could predict 20 quality or subjective aspects of questions. Since these aspects include questions about opinions, recommendations, or personal experiences, they are harder to answer by computer than questions with single, verifiable answers [1].

Given the need to maintain quality standards for the contents of online Q&A communities and the significant problems of crowdsourcing, providing solutions and models for automatically detecting user violations can bring upon faster detection of user violations (such as detection of spam, advertisement, grammar faults, etc) and therefore, saving users time and improve the quality of the contents.

Unfortunately, it’s hard to build subjective question-answering algorithms, because of a lack of data and predictive models. In this article, we use data gathered by the CrowdSource team at Google Research, a group dedicated to advancing NLP and other types of ML science via crowdsourcing [1-3]. We used this new data set to build predictive algorithms for different subjective aspects of question quality.

Transfer Learning allowed researchers to smash multiple benchmarks with minimal task-specific fine-tuning and provided the rest of the NLP community with pre-trained models that could easily with less data and less compute time be fine-tuned to produce state of the art results [4]. Google’s BERT is one of these models that theoretically allows us to smash multiple benchmarks with minimal task-specific fine-tuning [5].

Therefore, this paper aims at predicting different subjective aspects of questions in question-answering websites using BERT. Since the task is to predict target values of 20 labels for each question and our selected target labels are all related to the question title and body, therefore, those that relate to the answer feature are excluded from this research.

The structure of this article is as follows: Section 2 reviews past works on quality prediction of questions in QA websites and latest NLP models. Section 3 explains the data and section 4 elaborates on the methodology. In Section 5, evaluation of the experiment is presented, and Section 6 is the concluding remarks.

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\(^1\) A group of more than 170 QA websites in diverse fields covering specific topics, such as Stackoverflow.com, Askubuntu.com and Superuser.com.
II. LITERATURE REVIEW

Transfer learning, particularly models like ULMFiT, Allen AI’s ELMo, and Google’s BERT, focuses on storing knowledge gained from training on one problem and applying it to a different but related problem (usually after simple fine-tuning on small amount of data).

The first transfer learning method in Natural Language Processing (NLP) was Universal Language Model Fine-tuning for Text Classification (ULMFiT) method [6] that fine tunes the language model on a new data set after training a language model on a preliminary data set, such as Wikitext. Finally, the resulting fine-tuned language model can be used in a classification task for the new data set. The model, besides significantly outperforming many state-of-the-art tasks, was done by training on only 100 labeled examples, that matched performances equivalent to old models trained on 100x more data.

ELMo is another related study that includes task-specific architectures and uses the pre-trained representations as additional features [7]. It is a deep contextualized word representation that represented complex characteristics of word use (e.g., syntax and semantics).

The BERT language model consists of several transformer encoders stacked together and is designed from unlabeled text to pretrain deep bidirectional representations by jointly conditioning on left and right context in all layers [5]. They presented two general types which are named include the BERT-base and the BERT-large. The characteristics of these models are shown below, where L is the number of stacked encoders, H the hidden layer size, and A the number of self-attention heads:

1. BERT-base: L:12, H: 768, A:12, Parameters: 110M
2. BERT-large: L:24, H:1024, A:16, Parameters: 340M

For the pre-training corpus, [5] used the BooksCorpus with 800M words [8] for the BERT-base and English Wikipedia with 2,500M words with BERT-large [9].

III. DATA

In this section, we will briefly explain our used data set, alongside some general statistics on the data set.

A. Data

The CrowdSource team at Google Research, a group dedicated to advancing NLP and other types of ML science via crowdsourcing, has collected data on a number of quality scoring aspects of questions and answers from QA websites. The questions consists of 5 categories: "Technology", "Stackoverflow", "Culture", "Science", "Life arts" and was collected from nearly 70 different stack exchange websites. Reportedly, raters received minimal guidance and training, and relied largely on their subjective interpretation of the prompts. As such, each prompt was crafted in the most intuitive fashion so that raters could simply use their common-sense to complete the task [1].

Data is relatively small, only made of 6079 rows. It originally contains 40 columns, of which 10 are given as basic features (question title, body, answer …) and the rest are target quality labels. Of the 10 feature columns, we only used ‘question_title’ and ‘question_body’ for the purposes of this study and the rest is excluded. From the 30 target columns, 21 are related to the question and the remaining 9 columns are related to answer quality. Thus, we excluded columns related to answer from the data set. Finally, we removed ‘question_body_critical’, as its intent and meaning was not clear to us and no definition was given.

Table 1 gives the name and description of the selected target columns that we focus in this research. As we said earlier, target labels are aggregated from multiple raters and have continuous values in the range [0,1].

B. General Statistics and EDA

In this section, we introduce a few general statistics on the data set.

Figure 1 depicts distribution of the selected target values. Since the values are real values, we used ‘numpy.linspace’ to create 10 sub-ranges (0.1 each) for the purposes of this depiction. We can see that most of the columns, such as ‘question_asker_intent_understanding’ and ‘question_conversational’, are unevenly distributed and aggregated in one side value (0 or 1).

Figure 2 depicts correlation heat-map for the values of the target columns. We can barely view any strong correlation (lighter color) between the values of these columns. However, we can see a few anti-correlations (dark colors), such as conversation vs. fact, conversational vs. has commonly accepted answer, and fact-seeking vs. opinion-seeking.

Even though, because of our pre-trained model we do not require to perform feature extraction/engineering, we extracted a few simple features and depicted their correlation with target values. This was done to better understand the underlying latent relationships in data. To this end, we extracted character count and word count on question title and body, punctuations count in question body, and number of duplicate words, duplication rate, and number of sentences in question body. Correlation of these extracted features with target columns are depicted in Figure 3. We can see that the extracted features are not strongly correlated with the target values (coefficient between -0.17 to +0.25).

Finally, we performed sentiment analysis on the question body to extract polarity and subjectivity of texts. The mean for polarity is positive, while the questions are prone to be objective. Scatter plot for this analysis is depicted in Figure 4.
When using pre-trained BERT model, the steps are: (1) plug in the task specific inputs and outputs into BERT and (2) fine-tune all the parameters end-to-end. Therefore, we can get away with traditional training by fine-tuning pre-trained BERT model. Our instance loops over the folds in GroupKFold and trains each fold for 5 epochs with a batch_size of 6. A binary crossentropy is used as the objective loss function. We did not alter any of the BERT default parameters; however we did perform the fine-tuning on our data for learning rate values between 1e-5 to 9e-5.

We used ‘tensorflow’ and ‘huggingface’ transformers libraries in python for our base model, and sklearn, pandas, numpy, matplotlib and math libraries for data loading, additional preprocessing, and evaluation metrics.

HuggingFace created the well-known transformers library, formerly known as ‘pytorch-transformers’ or ‘pytorch-pretrained-BERT’, it brings together over 40 state-of-the-art pre-trained NLP models (BERT, GPT-2, RoBERTa, CTRL…) [10]. The implementation gives interesting additional utilities like tokenizer, optimizer or scheduler that we utilized in the implementation of this paper. While the transformers library can be self-sufficient, but incorporating it within the ‘fastai’ library provides simpler implementation compatible with powerful fastai tools like Discriminate Learning Rate, Gradual Unfreezing or Slanted Triangular Learning Rates.

A. Preprocessing

We performed the default model specific tokenizers provided by ‘huggingface’. For target variables, first we applied rank transform method (values are replaced with their corresponding ranks) and then, we continued with min-max scaling. This made the target values evenly distributed between 0 and 1.

We defined the maximum sequence length that will be used for the input to BERT (maximum is usually 512 tokens). Due to the 2 x 512 input, it will require significantly more memory when fine-tuning BERT.

V. Evaluation

We used 80% of data for training and 20% (1216 rows) for validation. Mean squared error was utilized on the validation set to gain the accuracy of the model. Based on our results on one epoch of training on 4864 rows, we achieved the accuracy of 94.9% almost in all of learning rate values. After three epochs of training, we achieved 95.1% to 95.2% accuracy which did not improve in the next iterations and in fact, it reduced or stabilized after three epochs. Our best results came from the second iteration with LR=3e-5 and LR=5e-5, where the model achieved the accuracy of 95.4%. Generally we can say that epochs of training did not improve our accuracy and one epoch of training is enough to achieve an accurate model.

In average, it took 8.76 minutes for each epoch on a computer with 16GB RAM and Intel(R) Xeon(R) CPU 2.00GHz.
In this study, we experiment the BERT model to solve a part of the problem of moderation actions in QA websites. To be specific, we used BERT to predict 20 quality or subjective aspects of questions in QA websites. Predicting subjective aspects is a hard problem with computers and we showed that it could benefit from transfer learning from pre-trained transformers.

Our model achieved 95.4% accuracy in predicting target values. Results confirm that by simple fine-tuning pre-trained BERT model, we can achieve high accuracy, in little time, and on less amount of data.

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Figure 1 Distribution of 21 target values. Values between 0 and 1; total sample size=6079.
Figure 2 Correlation heat-map for the target columns

Figure 3 Correlation heat-map between extracted sample features and target values

Figure 4 Results of sentiment analysis on question body