CodeForTheChange at SemEval-2019 Task 8: Skip-Thoughts for Fact Checking in Community Question Answering

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Abstract

Community Question Answering (cQA) is one of the popular Natural Language Processing (NLP) problems being targeted by researchers across the globe. Couple of the unanswered questions in the domain of cQA are ‘can we label the questions/answers as factual or not?’ and ‘Is the given answer by the user to a particular factual question correct and if it is correct, can we measure the correctness and factuality of the given answer?’. We have participated in SemEval-2019 Task 8 which deals with these questions. In this paper, we present the features used, approaches followed for feature engineering, models experimented with and finally the results. Our primary submission with accuracy (official metric for SemEval Task 8) of 0.65 in Subtask B (Answer Classification) and 0.63 in Subtask A (Question Classification) stood at 6\textsuperscript{th} and 16\textsuperscript{th} places respectively.

1 Introduction

Community Question Answering (cQA) forums such as Quora, StackOverflow, Yahoo! Answers, Qatar Living etc., now-a-days are fast and effective means of getting answers for any question. But the answers may or may not be correct and factual always. The focus of cQA research, for the last few couple of years, is revolving around determining the model which predicts the best answer for the question, given a question and a number of answers (might be hundreds or even thousands in number).

cQA is one of the popular problems being constantly in focus of SemEval organizers since 2015. The subtasks that were targeted earlier include (i) classifying the answer to a particular question as good or potentially good or bad in 2015\textsuperscript{1}, (ii) three reranking subtasks i.e., Question-Comment Similarity, Question-Question Similarity and Question-External Comment Similarity in 2016\textsuperscript{2} and (iii) Question Similarity (QS) to detect duplicate questions and Relevance Classification (RC) in 2017\textsuperscript{3}. Contrary to earlier tasks of SemEval focusing mainly on classification and similarity of questions and/or answers and/or comments, SemEval-2019 targets the factuality of the questions (whether the question is factual or not) and the factuality of the answers (whether the answers provided to the factual questions are factual or not). The tasks become more challenging as data have noisy (like !!!!), and unstructured (like Oh...) words.

SemEval-2019 Task 8 features the following two subtasks:

Subtask A (Question Classification) - determine whether a question asks for a factual information, an opinion/advice or is just socializing. Example from the “Qatar Living” forum given in competition page\textsuperscript{4} for this subtask is as follows:

Q: I have heard its not possible to extend visit visa more than 6 months? Can U please answer me.. Thankzzz...

answer 1: Maximum period is 9 Months....

answer 2: 6 months maximum

answer 3: This has been answered in QL so many times. Please do search for information regarding this. BTW answer is 6 months.

This subtask aims at building models to detect true factual information in cQA forums.

Subtask B (Answer Classification) - determine whether an answer to a factual question is true, false, or does not constitute a proper answer. 

This subtask aims at building models that classify the answers into the following three categories, given a factual question: a) Fact-
1) Factual - True b) Factual - False and c) Non-Factual. The examples for each of them are as follows:

- **Factual - True:**
  Q: I wanted to know if there were any specific shots and vaccinations I should get before coming over [to Doha].
  A: Yes there are; though it varies depending on which country you come from. In the UK; the doctor has a list of all countries and the vaccinations needed for each.

- **Factual - False:**
  Q: Can I bring my pitbulls to Qatar?
  A: Yes you can bring it but be careful this kind of dog is very dangerous.

- **Non-Factual:**
  Q: Which is suggested - buy a new car or an used one?
  A: Its better to buy a new one.

We participated in both the subtasks of SemEval-2019 Task 8. For detailed description of the task, different approaches used by other participants and results obtained by all the participants, please refer the task description paper (Mihaylova et al., 2019).

The rest of the paper is organized as follows: Section 2 describes the related work. Section 3 describes the data used for this SemEval task. Sections 4 and 5 elucidate the system architecture (feature extraction and model building) and experimentation details (along with the results) respectively. Section 6 concludes the paper with focus on future research on this task.

## 2 Related Work

Some of the earlier works on cQA include the use of classification models - Support Vector Machines(SVMs) (Šaina et al., 2017; Nandi et al., 2017; Xie et al., 2017; Mihaylova et al., 2016; Wang and Poupart, 2016; Balchev et al., 2016) for Similarity tasks; Convolutional Neural Networks (CNNs) for Similarity tasks (Šaina et al., 2017; Mohtarami et al., 2016) and for answer selection (Zhang et al., 2017); Long-Short Term Memory (LSTM) model for answer selection (Zhang et al., 2017; Feng et al., 2017; Mohtarami et al., 2016); Random Forests (Wang and Poupart, 2016); LDA topic language model to match the questions at both the term level and topic level (Zhang et al., 2014); translation based retrieval models (Jeon et al., 2005; Zhou et al., 2011); XgBoost (Feng et al., 2017) and Feedforward Neural Network (NN) (Wang and Poupart, 2016).

All of the above related works on cQA used the features such as Bag of Words (BoW) (Franco-Salvador et al., 2016), Bag of vectors (BoV) (Mohtarami et al., 2016), Lexical features (for example, Cosine Similarity, Word Overlap, Noun Overlap, N-gram Overlap, Longest Common Substring/Subsequence, Keyword and Named Entity features etc.) (Franco-Salvador et al., 2016; Mohtarami et al., 2016; Nandi et al., 2017); Semantic features (for eg, Distributed representations of text, Knowledge Graphs, Distributed word alignments, Word Cluster Similarity, etc.) (Franco-Salvador et al., 2016); Word Embedding Features (like Word2vec\(^5\) (Mikolov et al., 2013), GloVe\(^6\) (Pennington et al., 2014) etc.) (Wang and Poupart, 2016; Mohtarami et al., 2016; Nandi et al., 2017); Metadata-based features (like user information, answer length, question length, question marks in answer, question to comment length etc.) (Mohtarami et al., 2016; Mihaylova et al., 2016; Xie et al., 2017).

Another related task to cQA is Fact Checking in Community Forums (Mihaylova et al., 2018). This work doesn’t involve classification of questions/answers based on factuality but it determines the veracity of the answer given a particular question. This work is related to our task in a way that the data being used in our task is annotated and released to the research community by Tsvetomila Mihaylova and her team.

The fact that this research problem is relatively new, the strengths of the scalable gradient tree boosting algorithm, XGBoost (Chen and Guestrin, 2016) and distributed sentence encoder, Skip-Thought vectors (Kiros et al., 2015) are not explored yet. We tried to apply and combine these two effective methods for finding factual nature of the questions and answers.

## 3 Data Description

The data for both Question Classification - Subtask A and Answer Classification - Subtask B, is organized into train, dev and test sets. The number of samples in each of these datasets is shown in the Table 1.

\(^5\)https://code.google.com/archive/p/word2vec/  
\(^6\)http://nlp.stanford.edu/projects/glove/
4 System Description

4.1 Feature Extraction

4.1.1 Data pre-processing
We have applied some basic preprocessing tasks like removing URLs, converting text to lowercase along with removing stopwords.

4.1.2 Extract Skip-Thought vectors
We choose Skip-Thought Vectors as word embeddings for this task mainly because these are highly generic sentence representations unlike GloVe or Word2Vec which averages word embeddings of each individual word to calculate the word embedding for a complete sentence.

In subtask A, we have retrieved Skip-Thought vectors for question body and question subject. In subtask B, we extracted Skip-Thought vectors for question body, question subject and answer comment. For both the subtasks, we have used the code\(^7\) written by the Skip-Thought vectors’ authors.

4.2 Model Building
Once we have extracted Skip-Thought vectors, we used these vectors to train different models - AdaBoost Classifier (only in case of Subtask B), DecisionTree Classifier, RandomForest Classifier, ExtraTrees Classifier, XGBoost Classifier and Multi-layer Neural Network with dropout layers in between, Adam optimizer and softmax activation in the final layer. The hyper-parameters of all the models is determined by applying Grid-Search with 10-fold cross-validation. The hyper-parameters are shown in the Table 2.

| Classifier     | Hyper-parameters                                      |
|----------------|-------------------------------------------------------|
| Decision Tree  | min_samples_split = 2                                 |
| Random Forest  | n_estimators = 25                                      |
|                | min_samples_leaf = 1                                  |
|                | min_samples_split = 2                                 |
| Extra Trees    | n_estimators = 20                                     |
|                | max_features = 37                                     |
| XGBoost        | learning_rate = 0.1                                   |
|                | n_estimators = 100                                    |
|                | max_depth = 5                                         |
|                | objective = ’multi:softprob’                          |
| Adaboost       | n_estimators = 45                                     |
|                | learning_rate = 1.0                                   |

Table 2: Hyper-parameters used for models

5 Evaluation and Results

5.1 Subtask A (Question Classification)
For this subtask, we extract Skip-Thought vectors as described in section 4.1.2. Once we get these two vectors, we generated four different combinations of vectors - (i) question body only, (ii) question subject only, (iii) concatenation vector of both question body and question subject and (iv) average vector of both question body and question subject. We trained all the models mentioned in the section 4.2 with each one of these vectors. The evaluation scores for these models on test data are shown in the Table 3.

5.2 Subtask B (Answer Classification)
For this subtask, we extract Skip-Thought vectors as described in section 4.1.2. Once we get these three vectors, we generated two different combinations of vectors - (i) concatenation vector of question body, question subject & answer and (ii) average vector of question body, question subject & answer. We trained all the models mentioned in the section 4.2 using each one of these embedding vectors. The evaluation scores for these models (except MAP scores) on test data are shown in the Table 4.

In both the tables 3 and 4, the column Vector represents Skip-Thought vector combination type (whether it is body only (in case of Subtask A) or subject only (in case of Subtask A) or

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\(^7\)https://github.com/ryankiros/Skip-Thoughts
| Model          | Vector | Accuracy | F-score | Avgrec |
|----------------|--------|----------|---------|--------|
| Decision Tree  | Bodies | 0.5728   | 0.3550  | 0.3893 |
|                | Subjects | 0.5567 | 0.3308  | 0.3626 |
|                | Avg     | 0.5966  | 0.3904  | 0.4277 |
|                | Concat  | 0.5691  | 0.3498  | 0.3909 |
| Extra Trees    | Bodies | 0.5406  | 0.3015  | 0.4075 |
|                | Subjects | 0.5329 | 0.2992  | 0.4002 |
|                | Avg     | 0.5315  | 0.2902  | 0.4015 |
|                | Concat  | 0.5509  | 0.3158  | 0.4180 |
| Random Forest  | Bodies | 0.5476  | 0.3119  | 0.4161 |
|                | Subjects | 0.5329 | 0.2971  | 0.3950 |
|                | Avg     | 0.5567  | 0.3275  | 0.4236 |
|                | Concat  | 0.5446  | 0.3153  | 0.4139 |
| Neural Network | Bodies | 0.6849  | 0.5118  | 0.5426 |
|                | Subjects | 0.6338 | 0.4404  | 0.4677 |
|                | Avg     | 0.6884  | 0.5228  | 0.5561 |
|                | Concat  | 0.6740  | 0.5007  | 0.5405 |
| XGBoost        | Bodies | 0.6268  | 0.4382  | 0.5194 |
|                | Subjects | 0.5959 | 0.4032  | 0.4646 |
|                | Avg**   | 0.6366  | 0.4474  | 0.5195 |
|                | Concat* | 0.6299  | 0.4416  | 0.5130 |

Table 3: Evaluation scores for Subtask A
* - marks the scores of our primary submission
** - marks the scores of our contrastive submission
Row in bold - post evaluation accuracy score (improved over actual submission)

Another interesting observation that we found is the models, surprisingly, performed better when URLs are kept in the text compared to when URLs were removed.

## 6 Conclusion

The earlier works on cQA didn’t use Skip-Thought vectors, to the best of our knowledge. Hence, we used these vectors for both subtasks. We also have tried unique combinations of Skip-Thought vectors of question body, question subject and comments/answers (only in case of Subtask B) - either concatenation or average of vectors with different models. Out of all the models, concatenated Skip-Thought vectors with XGBoost Classifier generated best result out of all the combinations; as a result of which we stood 6th in Subtask B and 16th in Subtask A. However, post-evaluation submission which used concatenated Skip-Thought vectors with Neural Network classifier produced better accuracy score of 0.6752 compared to 0.6537 (which is official best result for Task B) and 0.6884 compared to 0.6299 (which is official best result for Task A). However, in future we would like to extend our work with other word embeddings like Word2vec, GloVe and BERT (Devlin et al., 2018) features and compare the results with current work using Skip-Thought vectors.

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