Punctuation Restoration

Viet Dac Lai, Amir Pouran Ben Veyseh, Franck Dernoncourt, Thien Huu Nguyen
1 University of Oregon, Eugene, Oregon, USA
2 Adobe Research, San Jose, CA, USA
{vietl, apouranb, thien} @uoregon.edu, dernonco@adobe.com

Abstract

Given the increasing number of livestreaming videos, automatic speech recognition and post-processing for livestreaming video transcripts are crucial for efficient data management as well as knowledge mining. A key step in this process is punctuation restoration which restores fundamental text structures such as phrase and sentence boundaries from the video transcripts. This work presents a new human-annotated corpus, called BehancePR, for punctuation restoration in livestreaming video transcripts. Our experiments on BehancePR demonstrate the challenges of punctuation restoration for this domain. Furthermore, we show that popular natural language processing toolkits are incapable of detecting sentence boundary on non-punctuated transcripts of livestreaming videos, calling for more research effort to develop robust models for this area.

Keywords: Livestreaming Video Transcripts, Punctuation Restoration, Datasets

1. Introduction

Livestreaming is a powerful broadcasting medium that catches attention of millions of users. Many video-sharing platforms have supported livestreaming for a wide range of topics such as Twitch for gaming, TikTok for short entertainment videos, Behance for visual creative work, and Youtube/Facebook Live accepting any topics. Among these videos, there are a substantially high number of videos that provide useful knowledge with exceptional visual demonstration. To this end, livestreaming videos are becoming a potential knowledge base waiting for being explored.

Mining videos on video/audio format directly is extremely hard and expensive because of their high data load and complexity in processing images and audio signals. Instead, mining video transcripts, transcribed by either human or machine, is much easier with the existing hardware and software. As such, livestreaming videos should be transcribed at high quality to facilitate future data mining research. As video transcription can be done using existing automatic speech recognition (ASR) systems, a reasonable step to improve the quality of transcribed texts for livestreaming videos involves post-processing produces to remove noises and restore correct language structures and texts from ASR-generated texts.

In this paper, we are particularly interested in punctuation restoration (PR) for livestreaming video transcripts. Punctuation restoration is the task to restore fundamental text structures such as sentences and phrases by inserting punctuation marks into non-punctuated text, e.g. text generated by an automatic speech recognition system for livestreaming videos in our paper. Punctuation restoration is an important post-processing step to improve the readability of ASR texts. Moreover, in natural language processing (NLP), PR is even more important as it enables the use of advanced techniques to process texts at sentence level to achieve optimal performance for various tasks, e.g., part-of-speech tagging and dependency parsing. Prior studies have shown that with proper sentence split and punctuation, a downstream application can tolerate the word error rate of 25% ( ), which is extremely high compared to the current state-of-the-art ASR. Figure [1] demonstrates how punctuation restoration improves the readability of ASR-generated texts.

In the literature, punctuation restoration is considered as a subtask of ASR, in which PR annotation is done as part of the ASR datasets such as the AMI [McCowan et al., 2005] and TED corpus [Federico et al., 2012]. However, the speeches recorded in these audios are multi-speaker meetings, as in AMI corpus, or single-speaker talks, as in TED corpus. Our work is different from this work in that we consider livestreaming videos that feature many
distinctive characteristics that are essential to study. In particular, the number of speakers in livestreaming videos varies greatly ranging from 1 to a few main speakers together with up to thousands of audiences. The audiences might participate in question-answering and commenting during the whole duration of the video, hence, changing the topic of the video. Furthermore, the speech in livestreaming is much more spontaneous than those in meetings in AMI corpus and the well-scripted TED talk. An issue with the research of punctuation restoration for livestreaming videos is the lack of a human-annotated dataset for model development and evaluation. This is even more critical when livestreaming has become one of the most powerful communication mediums for not only entertainment but also education purpose. Toward this end, we introduce a new dataset for Behance Livestreaming Video Punctuation Restoration, called BehancePR. The dataset was annotated by skilled transcription annotators for 4 types of punctuation. Our experiments reveal the challenges of the BehancePR dataset that the performance of the existing state-of-the-art models for punctuation restoration on BehancePR lags far behind one on the TED dataset. Our further experiment of cross-domain punctuation shows that models that are trained on a PR dataset of a different speech scenario perform much worse than those trained on the BehancePR dataset even with a much larger training set.

2. Annotation

2.1. Dataset preparation

The livestreaming videos that we annotate in this work are derived from Behance. Behance is an online platform to showcase and discover creative work such as digital drawing, graphic design, and photo/video editing. In those videos, one or a few creators stream their work on graphic design tools. The topics in the videos relate to design theories, graphical ideas, and tutorials to use those graphic design tools. The videos are split into shorter clips of approximately 5 minutes per clip. Then, the videos are transcribed by Microsoft Automatic Speech Recognition (ASR) system. The video and the aligned automatic-generated transcript are presented to the annotators. To prepare for the annotation, we also created a taxonomy for livestreaming video punctuation restoration. Similar to prior studies in punctuation restoration, we inherit the taxonomy of three most popular markers: period, comma, and question mark (Federico et al., 2012). However, as livestreaming videos of creative works involve a lot of emotional expressions such as excitement, we include exclamation mark to better present strong feelings and emphasis.

2.2. Annotation

We recruit 6 annotators from Upwork crowdsourcing platform. As Upwork allows the freelancers to submit their resumes, we can choose the most experienced annotators with prior practices with audio transcribing. A detailed annotation guideline with many examples is provided to the annotators. We developed a customized web-based annotation tool that allows the annotator to work most efficiently with the material. To make sure the annotators understand the task and be familiar with the annotation tool, they are further trained on 2 hours of audio on the Behance videos, equivalent to approximately 6 hours of training and practice. We group 6 annotators into 3 pairs of annotators that work together in the same set of documents. The inter-annotation Cohen-Kappa agreement scores for three pairs are 0.53, 0.58, and 0.65, which indicates a moderate to substantial agreement. Toward the end, the annotators are allowed to discuss to make the final version of the dataset. Table 1 shows the detailed statistics and label distribution of the BehancePR dataset.

| Statistics                      | Train | Dev  | Test |
|---------------------------------|-------|------|------|
| # Document                     | 2,174 | 60   | 80   |
| # Sent                         | 115,661 | 2,969 | 3,986 |
| # Token                       | 1,216,439 | 34,265 | 44,224 |

| Label distribution            | PERIOD | COMMA | QUESTION | EXCLAMATION |
|-------------------------------|--------|-------|----------|-------------|
|                               | 101,228 | 126,739 | 7,337 | 7,096 |
|                               | 2,583   | 3,986   | 175    | 211         |
|                               | 4,442   | 4,388   | 437    | 320         |

Table 1: Statistics and label distribution of the BehancePR dataset.

3. Dataset Challenges

Compare to existing punctuation restoration datasets, e.g., TED (Federico et al., 2012), AMI (McCowan et al., 2005), our dataset BehancePR features several unique challenges for punctuation restoration. First, as its documents are obtained from live streaming video on the Behance platform, it features unique characteristics of spontaneous speech. They are much different from TED talks, in which the talks were heavily scripted, and AMI meetings, where the talks were also well prepared. As such, the live streaming video transcript text has a much lower cohesion. As it might be presented in a sudden change of topic and incomplete syntax. Besides, they come with a substantially high-frequency verbal pause, repetition of words and phrases, which are the results of hesitation and stutter of the speakers. The following shows some examples:

- Second, as the documents in this dataset are generated from an automatic speech recognition system, it is ex-
Table 2: Examples of noisy text in transcript text of live streaming video.

Table 3: Examples of sentences with and without emotional words.

Table 4: Performance comparison of different models.

4. Experiments

4.1. Punctuation restoration

To reveal the complexity of the punctuation restoration for the livestreaming video, we evaluate the performance of the state-of-the-art model for punctuation restoration. Similar to prior work in this task, we model the task as a sequence labeling task on the token level. We investigate two major model architectures: neural-based model with Bi-Directional Long Short-Term Memory (BiLSTM) (Alam et al., 2020), and graphical-based model with Conditional Random Field (CRF) (Makhija et al., 2019). We also investigate the recent advance in data augmentation technique for punctuation restoration (Alam et al., 2020). These leave us four combinations of model and technique as presented in Table 4. All of these models leverage a pre-trained language model RoBERTa (Liu et al., 2019) to obtain representation vectors.

Table 4 presents the performance of four models on the development and the testing sets of the BehancePR dataset. First, the graphical-based models with CRF show a slight improvement over the neural-based models in case no data augmentation is applied. In contrast, the performance on the test set decreases. This result is consistent with the prior study in punctuation restoration (Alam et al., 2020) that performance gain is not significant when CRF is used, which is opposite to the Named Entity Recognition task that CRF works very well. We attribute this to the difference between the PR and the NER tasks. In punctuation restoration, an entity, which is a sentence, is much longer than an entity in the NER task. As such, it is harder to model the dependency between tokens in such a long sequence. Hence, CRF is incapable of producing significant improvement. Second, the data augmentation technique slightly improves the performance of the BiLSTM model but slightly decreases the performance of the CRF-based model. Importantly, we find that the performance of the PR models on Behance is far below on the TED talk dataset (F-score=84%) . This suggests
Table 4: Performance of the examined models on the Behance dataset.

| Model       | Dev  | Test |
|-------------|------|------|
|             | P    | R    | F   | P    | R    | F    |
| LSTM        | 63.6 | 63.1 | 63.4 | 62.0 | 61.4 | 61.7 |
| LSTM+aug    | 64.8 | 62.2 | 63.5 | 63.8 | 60.7 | 62.2 |
| LSTM+CRF    | 62.8 | 65.2 | 64.0 | 62.2 | 63.5 | 62.9 |
| LSTM+CRF+aug| 62.8 | 64.5 | 63.7 | 61.1 | 62.8 | 62.0 |

Table 5: Performance of domain adaptation with TED dataset as the source domain.

| Model       | Dev  | Test |
|-------------|------|------|
|             | P    | R    | F   | P    | R    | F    |
| LSTM        | 53.5 | 59.1 | 56.2 | 54.6 | 59.6 | 57.0 |
| LSTM+aug    | 55.8 | 58.0 | 56.9 | 55.7 | 58.5 | 57.1 |
| LSTM+CRF    | 52.7 | 60.4 | 56.3 | 53.2 | 60.3 | 56.5 |
| LSTM+CRF+aug| 56.5 | 57.3 | 56.9 | 57.0 | 57.8 | 57.4 |

Table 6: Performance of sentence split.

| Model       | P    | R    | F   |
|-------------|------|------|-----|
| Stanza      | 70.4 | 1.4  | 2.8 |
| Trankit     | 72.1 | 7.8  | 14.0|
| SpaCy       | 52.1 | 21.9 | 30.9|
| LSTM        | 70.3 | 75.6 | 72.8|
| LSTM+aug    | 71.5 | 72.8 | 72.1|
| LSTM+CRF    | 73.3 | 72.0 | 72.6|
| LSTM+CRF+aug| 71.6 | 73.0 | 72.3|

4.2. Domain adaptation

As punctuation restoration data is abundant, we further explore the cross-domain evaluation setting where the models are trained on a different source domain and evaluated on the BehancePR dataset. In particular, we choose the TED corpus as the source domain because TED talks are monologues, which is the closest to the Behance videos. Table 5 presents the out-of-domain performance of the models (in comparison with the in-domain performance presented in Table 4). It is clear from the table that the performances of all punctuation restoration models degrade significantly when they are trained on TED talk and evaluated on Behance. This demonstrates the considerable difference in domains even they are almost monologue.

4.3. Sentence split

In this experiment, we evaluate the performance of the models on the sentence splitting task. In this task, the model is trained and evaluated to predict where the sentence end. We trained the models presented in Section 4.1 on the same BehancePR dataset. We further examine the performance of existing NLP toolkit for this task including Stanford Stanza (Qi et al., 2020), SpaCy (Honnibal and Montani, 2017), and Trankit (Nguyen et al., 2021). The performance of the models and toolkits are presented in Table 6.

Several observations can be seen from the table. First, the published toolkits perform very poorly on this kind of text. Trankit and SpaCy are slightly better with higher recalls of 7.8% and 21.9%, respectively, because they employ a neural-based sentence splitter that can detect the context shift between sentences. Secondly, the models trained on the BehancePR dataset outperform the published toolkits with large margins at consistent F-1 score above 72%. This suggests the importance of the training data for even fundamental tasks like sentence splitting.

5. Related work

Early studies on the punctuation restoration task explored a wide range of features such as lexical, acoustic, prosodic, and their combination (Gravano et al., 2009; Levy et al., 2012; Xu et al., 2014; Che et al., 2016a; Szaszak and Tündik, 2019). Graphical model such as conditional random field has been widely used for this task (Lu and Ng, 2010; Zhang et al., 2013) before the emerging of neural network. Recently, a variety of deep neural network architectures have been explored such as long short-term memory (Gale and Parthasarathy, 2017), convolutional neural network (Che et al., 2016b), and transformer (Alam et al., 2020). Corpora for punctuation restoration are usually created as part of automatic speech recognition in various domains such as meetings (McCowan et al., 2005), TED talks (Federico et al., 2012), audio books (Panayotov et al., 2015), and film subtitles (Tiedemann, 2016). Among these, TED corpus is widely used as the benchmark corpus for punctuation restoration. However, livestreaming videos have not been explored for this task.

6. Conclusion

We presented BehancePR, the first dedicated corpus for punctuation restoration. BehancePR was manually annotated for 4 markers. The comprehensive experiments with state-of-the-art models show the challenges of the punctuation restoration for livestreaming video, as well as the poor performance of existing NLP toolkit for non-punctuated text.
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