Noisy Text Data: Achilles’ Heel of popular transformer based NLP models

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Abstract

In the last few years, the ML community has created a number of new NLP models based on transformer architecture. These models have shown great performance for various NLP tasks on benchmark datasets, often surpassing SOTA results. Buoyed with this success, one often finds industry practitioners actively experimenting with fine-tuning these models to build NLP applications for industry use cases. However, for most datasets that are used by practitioners to build industrial NLP applications, it is hard to guarantee the presence of any noise in the data. While most transformer based NLP models have performed exceedingly well in transferring the learnings from one dataset to another, it remains unclear how these models perform when fine-tuned on noisy text.

We address the open question by Kumar et al. (2020) to explore the sensitivity of popular transformer based NLP models to noise in the text data. We continue working with the noise as defined by them - spelling mistakes & typos (which are the most commonly occurring noise). We show (via experimental results) that these models perform badly on most common NLP tasks namely text classification, textual similarity, NER, question answering, text summarization on benchmark datasets. We further show that as the noise in data increases, the performance degrades. Our findings suggest that one must be vary of the presence of noise in their datasets while fine-tuning popular transformer based NLP models.

1 Introduction

It is a well known fact that pre-trained contextualized language models such as BERT (Bidirectional Encoder Representations from Transformers) Devlin et al. (2018), BART (Bidirectional and Auto-Regressive Transformer) Lewis et al. (2019), RoBERTa (robustly optimized BERT pretraining approach) Liu et al. (2019), ALBERT (A Lite BERT) Lan et al. (2019), XLNet (Generalized autoregressive pretraining for language understanding) Yang et al. (2019), T5 (Text-to-Text Transfer Transformer) Raffel et al. (2019) have shown remarkable gains in performance for various Natural Language Processing (NLP) tasks. This includes most common downstream tasks such as Text Classification, Textual Similarity, Summarization, Name-Entity Recognition, Question Answering, Machine Translation etc.

Given this fantastic progress, machine learning teams in the industry are actively experimenting with fine-tuning these models on their data to solve industry use cases. These include applications such as chatbots, sentiment analysis systems, intelligent ticketing systems, entity recognition systems, machine translation systems etc. To building these applications practitioners often assemble the required dataset by collecting text data from data sources & applications such as chats, emails, discussions from user forums, social media conversations, output of machine translation systems, automatically transcribing text from speech data, automatically recognized text from printed or handwritten material, etc. The text data from such applications is often noisy (The amount of noise may differ depending on the source). For example, the data coming from discussions on user forums & social media conversations, the noise in the text data can be significantly high.

Kumar et al. (2020) shows that the performance of pre-trained BERT degrades significantly when fine-tuned on noisy text data. We extend their work to show this holds true for most popular transformer based NLP models, namely BERT, BART, RoBERTa, ALBERT, XLNet and T5. To be precise Kumar et. al () benchmarked the performance of BERT when fine tuned on noisy text data for 2 tasks - text classification and textual similarity using 3 datasets - IMDB, SST-2 and STS-B. The main contributions of this paper are three fold:

• We extend the work of Kumar et al. (2020) to benchmark the performance of BERT when fine tuned on noisy text data for other fundamental NLP tasks - Question Answering, NER and Summarization using SQUAD, CoNLL and Billsum datasets respectively.

• We benchmark the performance of other popular transformer based NLP models - BART, RoBERTa, ALBERT, XLNet and T5 on fundamental NLP tasks - text classification, textual simi-
larity, Question Answering, NER and Summarization on noisy text data\(^1\).

- We show that all the above mentioned models perform badly when fine-tuned on noisy text data. Further, as the noise increases, performance becomes worse.

This work is motivated from a business use case where we built a conversational system over WhatsApp to screen job seekers for blue collar jobs. The candidates often are not even college graduates. This paired with the fat finger problem\(^2\) over a smartphone keypad often results in many typos and spelling mistakes in the responses job seekers send to our conversational system. Though this work is inspired from our business use case, our findings are applicable to other use cases that deal with noisy text data.

2 Previous Work

Modern communication mediums such as SMS, chats, twitter, messaging apps encourage brevity and informalism, leading to non-canonical text. This presents significant challenges to the known NLP techniques. Research community has done a lot of work on validating various transformer based language models in the presence of noisy text. The NLP community has done a lot of work on understanding the effects of noise on the performance of NLP models. Taghva et al. (2000) evaluate the effect of OCR errors on text categorization. Wu et al. (2016) introduced ISSAC, a system to clean dirty text from online sources. Belinkov and Bisk (2017) show that character based neural machine translation (NMT) models are also prone to synthetic and natural noise even though these model do better job to handle out-of-vocabulary issues and learn better morphological representation.

Aspillaga et al. (2020) evaluated RoBERTa, XLNet, and BERT in Natural Language Inference (NLI) and Question Answering (QA) tasks. They used BiDAF (Seo et al., 2016) and Match-LSTM (Wang and Jiang, 2016) as baselines to compare stress tests against Transformer-based models. They did two type of tests - distraction test and noise test(spelling errors). They show that RoBERTa, XLNet and BERT are more robust in stress tests than recurrent neural network models. Ravichander et al. (2021) describes a real world scenario where question answering system can be affected by different types of noise such as keyboard errors and ASR errors. They evaluate SOTA methods on natural and synthetic noisy data and demonstrate that the performance of QA systems is impacted by the real world noise. They further analyze synthetic noise and its impact on the downstream question answering system and presented an initial exploration of mitigation strategies for real world noise. Alshemali and Kalita (2020) test DNN models on different NLP tasks like Classification, Machine Translation, Question Answering, Textual Entailment, Tagging etc. They illustrate the vulnerability of DNNs to adversarial examples — inputs modified by introducing small perturbations to deliberately fool the target model into giving incorrect results. Agarwal et al. (2007) study the effect of different kinds of noise on automatic Text Classification. They present detailed experimental results with simulated noise on the Reuters21578 and 20-newsgroups benchmark datasets; also with results on real-life noisy datasets from various CRM domains. They use spelling errors to generate synthetic dataset and show the effect of noise on final accuracy of text classification task. Subramaniam et al. (2009) present a survey on the types of text noise and techniques to handle it. Belinkov and Bisk (2017) show that character based neural machine translation (NMT) models are prone to synthetic and natural noise even though these model do better job to handle out-of-vocabulary issues and learn better morphological representation.

2.1 Sentiment Analysis [IMDB movie reviews (SST-2) (Socher et al., 2013)]

3 Experiments

We evaluate the 6 transformer based NLP models - BERT\(^3\), BART, RoBERTa, ALBERT, XLNet and T5. For this evaluation we use the following tasks [and corresponding datasets]:

1. Sentiment Analysis [IMDB movie reviews (Maas et al., 2011) and Stanford Sentiment Treebank (SST-2) (Socher et al., 2013)]

\(^1\)Certain models are not applicable for certain tasks. We skip those tasks

\(^2\)https://en.wikipedia.org/wiki/Fat-finger_error

\(^3\)BERT\(_{Base}\) uncased model
2. Textual similarity [Semantic Textual Similarity (STS-B) (Cer et al., 2017)]

3. Question Answering [SQuAD2.0 (Rajpurkar et al., 2016)]

4. Named Entity Recognition [CoNLL (Sang and De Meulder, 2003)]

5. Text summarization [Billsum (Kornilova and Eidelman, 2019)]

On each of these 6 datasets, we report the performance of each of the 6 models\(^4\), both with and without noise.

### 3.1 Noise

We directly borrow the notion of noise as defined by (Kumar et al., 2020). They focus on the noise introduced by spelling mistakes and typos. All the benchmark datasets used consist of examples \(X \rightarrow Y\) where \(X\) is the text input and \(Y\) is the corresponding label. They call the original dataset as \(D_0\). From \(D_0\) they create new datasets \(D_5, D_{10}, D_{15}, D_{20}\) and \(D_{25}\). \(D_k\) is a variant of \(D_0\) with \(k\%\) noise in each datapoint in \(D_0\).

To create \(D_k\), they take \(i^{th}\) data point \(x_i \in D_k\), and introduce noise in it. They represent the modified datapoint by \(x_{i,k}^{\text{noise}}\). Then, \(D_k\) is simply the collection \((x_{i,k}^{\text{noise}}, y_i), \forall i\). To create \(x_{i,k}^{\text{noise}}\) from \(x_i\), they randomly choose \(k\%\) characters from the text of \(x_i\) and replace them with nearby characters in a qwerty keyboard. For example, if character \(d\) is chosen, then it is replaced by a character randomly chosen from \(e, s, x, c, f, or r\). This is because in a qwerty keyboard, these keys surround the key \(d\). They inject noise in the complete dataset. Once split \(D_i\) into \textit{train} and \textit{test} chunks.

### 3.2 Text Classification

For text classification we use IMDB movie reviews (Maas et al., 2011) and Stanford Sentiment Treebank (SST-2) (Socher et al., 2013) datasets in binary prediction settings. IMDB datasets consist of 25000 training and 25000 test sentences. We represent the original IMDB dataset (one with no noise) as IMDB\(_0\). Using the process of introducing noise (as described in section 3.1), we create 5 variants of IMDB\(_0\) namely IMDB\(_1\), ... , IMDB\(_{25}\) with varying degrees of noise.

SST-2 dataset consists of 67349 training and 872 test sentences. Here too we add noise as described in Section 3.1 to create 5 variants of SST-2\(_0\) - SST-2\(_5\). To measure the performance for text classification, we use F1 score.

### 3.3 Textual Similarity

For the textual similarity task, we use the Semantic Textual Similarity (STS-B) (Cer et al., 2017) dataset. The dataset consists of 5749 training and 1500 test data points. Each data point consists of 2 sentences and a score between 0-5 representing the similarity between the two sentences. We represent the original data set by STS-B\(_0\) and create 5 noisy variants. Here, we use Pearson-Spearman correlation to measure model’s performance.

### 3.4 Question Answering

For the question answering task, we use the Stanford Question Answering Dataset version 2.0 (SQUAD2.0) (Rajpurkar et al., 2016). This dataset has 129,941 training and 5915 test paragraph and question pairs. The evaluation metric we used is F1. F1 score takes each gold answer as bags of words and doesn’t require choosing the exact same span as a human’s, which is seen as more reliable.

### 3.5 Named Entity Recognition

We used the CoNLL-2003 (Sang and De Meulder, 2003) dataset for Named Entity Recognition. It consists of 22,137 sentences totally and is split into 14,987, and 3,684 sentences for the training and test sets, respectively. It is tagged with four linguistic entity types (PER, LOC, ORG, MISC). We used average F1 score as evaluation metric.

### 3.6 Text Summarization

For the text summarization task, we used the Billsum (Kornilova and Eidelman, 2019) dataset. It contains 23,000 US Congressional bills and human-written reference summaries from the 103rd-115th (1993-2018) sessions of Congress. We use ROUGE1-F1(ROUGE (2004)) metric for the summarization task.

### 3.7 Results

The results of various experiments are shown in Tables 1, 2, 3, 4, 5 and 6 respectively. Note that 0% error case represents a no noise scenario. Interestingly

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\(^4\)Certain models are not applicable for certain tasks. We skip those.
for most scenarios across tasks - RoBERTa consistently gives better performance as compared to other three models for same amount of noise. At the same time BERT and ALBERT show bad performance.

4 Conclusion and Future Work

In this work, we studied the effect of synthetic noise (spelling mistakes) in text data on the performance of popular transformer based language models. Our experiments show that as the noise in the data increases, model performance drops significantly. Our work shows that one must be cognizant of the presence of any noise in their text data if they are fine tuning NLP models on noisy text data. Further, if there is noise in text data, then either 1) one has to preprocess data until all noise is removed. This can become a full fledged project in its own. 2) make changes to the architecture of these models to make them robust to noise. We leave this as a future work.

It will also be interesting to see how these models perform in the presence of other types of noise. It also remains to be seen if the results will hold when the noise is restricted to only frequent misspellings. Also it remains to be seen why RoBERTa shows more stability to noise unlike BERT and ALBERT.

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