Clickbait Spoiler Generation

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Abstract

In the paper, we focus on the generation of the spoilers for the clickbait posts given the article content. We have explored the seq2seq models for generation of spoiler with model tuning via prompting techniques. With clickbaits framed as questions with Vicuna 13B model and the article, the seq2seq models are tuned with to generate the spoilers. Spoiler type information is exploited for generating seperate prompts for each type.

1. Introduction

Clickbait posts in the social media entice the users to generate clicks. They generate a curiosity gap to the users for trivial content in the article. In the SemEval 2023 Clickbait Challenge, for clickbait spoling share subtasks of spoiler type classification and spoiler generation are performed. In our paper, we priority focus on the task of spoiler generation. Spoilers generation from the article for a given clickbait is considered as a task of question answering. This approach is direct for generation of phrase type spoilers of a very short length. However, the main challenge in the task lies in generation of spoilers of passage type and multi type.

Spoilers for the Clickbait Posts are generated with a transformer model trained for the Question-Answering task and a task-specific post-processing step. The models, DeBERTa-large and RoBERTa-large are most effective for phrase type spoiler generation where as for the passage type spoiler generation MonoT5 and MonoBert have outperformed other models. For multi-type, the enumeration of spoiler types, identified with SpaCy, is included in the spoiler generation input. With enumeration, the DeBERTa outperformed the existing models. The use of transformer-based models proved to be beneficial for this task.

The TohokuNLP team utilized a straightforward seq2seq model for generating non-clickbait headlines from clickbait ones. Furthur incorporated a post-hoc ensemble of models leading to enhanced performance over a single model. The system generates spoilers in two steps. A multiseed seq2seq models generate spoilers, which are then post-processively ensembled using a similarity based ensemble approach. Results demonstrate that the T5 seq2seq model generates spoilers extractively rather than abstractively, indicating that seq2seq models can learn to identify spoilers from given contexts. They also discovered that the setting with the oracle classifier outperformed the setting without type information, indicating that spoiler type information can boost the performance of spoiler generation.

2. Clickbait Dataset

The dataset mostly collects clickbait postings from social media networks such as Facebook, Reddit, and Twitter. The main objective is to find spoilers in the article that disclose the substance of the clickbait piece. Spoilers are divided into three categories : single word or phrase spoilers, continuous sentence spoilers, and discontinuous word or sentence spoilers. The training set consists of 3200 examples, with roughly 43% for single-word or phrase spoilers, 40% for continuous phrases, and 17% for several discontinuous words or sentences.

3. System Overview

3.1. Question Generation from clickbait

For task of spoiler generation with question answering models, the clickbait is given as question and the article as context. Nevertheless, the clickbait are assertive sentences. Therefore, to better exploit the QA models, the clickbaits are converted to the question format. We have generated questions from the clickbait sentences with zero-shot learning. The LLMs employed are vicuna-13b-1.1 and Meta-Llama-3-70B-Instruct.

The LLMs are prompted to generated interrogative questions with the prompt, "For the below clickbait sentence from which write a interrogative questions to extract answer from the news article, Sentence:clickbait, Question:". The guestion generated, along with context, are utilized by the QA models for spoiler generation

3.2. Model tuning with Prompts

For spoiler generation as a downstream task of question answering, we have explored inference and finetuning with various transformer models. We further progressed to the Model tuning via prompts technique, for the spoiler generation. Rather than giving the clickbait and the article as question and context, they are included in the prompt template which completed with prompt infilling technique.

We have exploited the spoiler type information and have separately constructed the prompt template according to the spoiler type. Rather than tuning the model to generated the spoiler, alternatively the model is tuned to complete the masked part of the prompt template.

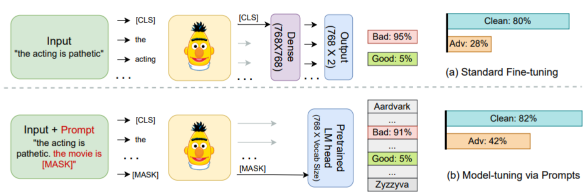

Figure 1: An example of standard fine-tuning and model-tuning using prompts.

The prompt templates for the phrase, passage and multi type spoiler generation are,

1. **Phrase**: Below is an question paired with a context for which generate answer. Write an answer as short as possible (max 5 words). Use only words from context. The clickbait Question:{question}. The article Context:{context}. The spoiler of the clickbait is [MASK]

2. **Passage**: Below is an question paired with a context for which generate a answer. Write a complete answer which will be from one to three sentences. Complete the answer properly. Use only words from context. The clickbait Question:{question}. The article Context:{context}. The spoiler of the clickbait is [MASK]"

3. **Multi**: Below is an question paired with a context for which generate answer.Write the spoiler which is multi part that means it contains multiple phrase or sentences as spoilers from given text. The spoilers are spanned through paragraphs, check for all spoilers. Use only words from context. The clickbait Question:{question} The article Context:{context}. The spoiler of the clickbait is [MASK]"

4. Experiments and Results

In our experiments, we have experimented various techniques with seq2seq models. We have fine-tuned the models for the spoiler generation with the clickbait generated questions as the question and the articles as the context.

To evaluate the performance of the models, the metrics that we have used are BLEU score, BERT score, METEOR score.

BLEU score. measures the overlap of n-grams between the generated texts and reference text.
BERT score. evaluates the similarity between two text sequences using contextual embeddings.
METEOR score. assesses the quality of machine generated text based on precision, recall, and alignment with human reference summaries.

4.1. Fine tuning T5 base and flan T5 base

We have fine tuned the T5 and flan T5 models for generation of the clickbait. Here the clickbait question generated from Vicuna 13B, along with the article context are given as input. We have observed a good extraction of phrase type spoiler generation but the models weren't able to perform the same for the passage type and multi type spoilers.

In order to generate the spoiler from the generated questions, we have also attempted fine-tuning the flan-T5 model using the same parameters as the T5 model. Although the performance hasn't improved, we anticipate that parameter adjustment will produce better outcomes.

4.2. Fine tuning passage type spoilers.

Since the performance of T5 model is low on passage type spoilers compared to phrase type. We have performed error analysis and observed that spoiler output doesn't contain the entire expected passage. This could be because we are training the model with data containing both phrase type and passage type data.

So, we used the spoiler type information to fine-tune a new T5 model based solely on the passage type spoiler. We saw enhanced performance for the same. Further, since the monoT5 model gave enhanced performace for passage type spoiler generation, we have tuned the monoT5 model trained on MS MACRO dataset for generating passage type. The results comparision can be observed below,

Training data type	Bert Score	Bleu Score
All	85.63	12.8
Passage type - t5	88.91	16.56
Passage type - monot5-base-msmarco-10k	86.84	14.6

4.3. Paragraph level fine tuning for multi type

While the precision is rather high for multi-type spoiler generation, the recall numbers are low due to the model's inability to predict every answer in the spoiler. So we have performed paragraph level fine tuning of T5 model for only multi type spoilers. Here, the context is a paragraph and the corresponding answer is the spoiler in that paragraph (extracted with spoiler positions). We train the model by giving every paragraph and its corresponding spoiler (empty string if there is no spoiler in that paragraph) as the input. As most of the paragraphs of the article do not contain an answer, the model is biased towards giving empty strings as answers thus dropping the evaluation metrics.

4.4. Model Tuning with Prompts

We have exploited the model tuning with prompts for generating the spoiler. The prompts are manually improved for better performance. With MVP technique we have observed an improved performance for all the spoiler types. With separate prompts for each spoiler type, the model is able to generalize well and generate better spoilers.

The results are as follows.

Model	Spoiler	BLEU	BERT	METEOR
t5-base-model	All	33.8	90.77	41.56
	Phrase	51.6	92.10	53.34
	Passage	12.8	85.63	21.07
	Multi	20.20	91.4	34.55
t5 with prompts	All	37.87	90.58	39.66
	Phrase	63.21	94.66	60.07
	Passage	15.5	86.69	25.10
	Multi	13.41	89.56	34.45
t5-base (paper)	All	37.68	91.35	39.90

5. Conclusions and Future work

The model tuning via prompting technique with spoiler-type based prompts have improved the performance of the seq2seq models. In comparison of results for t5-base model the model with model tuning with prompts have showed an improved performance. We expect the same improved performance for flan-t5 large, the best performing seq2seq model but weren't able to produce the results due to compute issues.
In future work, we plan to incorporate more information in the prompts, like enumeration in the multi type, for enhanced spoiler generation.

References

[1] Clickbait Spoiling via Question Answering and Passage Retrieval. Matthias Hagen. Maik Fröbe. Artur Jurk. Martin Potthast.

[2] Generating clickbait spoilers with an ensemble of large language models. Mateusz Wozny. Mateusz Lango.

[3] Clickbait Spoiling via Simple Seq2seq Generation and Ensembling .Hiroto Kurita. Ikumi Ito. Hiroaki Funayama. Shota Sasaki. Shoji Moriya. Ye Mengyu. Kazuma Kokuta. Ryujin Hatakeyama. Shusaku Sone. Kentaro Inui.

[4] Comparing Dataset Expansion Techniques for Non-Transformer and Transformer Models: Improving Model Performance through Data Augmentation. Christian Falkenberg. Erik Schönwälder. Tom Rietzke. Chris-Andris Görner. Robert Walther. Julius Gonsior. Anja Reusch.

[5] Clickbait Spoiling. Maik Fröbe. Tim Gollub. Benno Stein. Matthias Hagen

[6] Discover the Shocking Truth Behind this Composite Approach to Clickbait Spoiling! Simon Birkenheuer. Jonathan Drechsel. Paul Justen. Jimmy Pöhlmann. Julius Gonsior. Anja Reusch.