# Project Report : Identify a clickbait and Un-clickbait it

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## Abstract

*This document describes the Final report for the term project as part of the Social Computing course. In this work, We tried to solve the problem of identifying clickbaits and to un-clickbait them.*

## 1 Code, Demo, and Presentation

The code is made public at this. The Demo video and the final presentation are also present in the github repository but you can also click on the link to get redirected.

## 2 Introduction

Clickbait is any content whose main purpose is to attract attention and encourage users to click on a link to a particular web page. These headlines exploit a user's curiosity gap and lure them to click on links that often disappoint them. So, by creating a curiosity gap, a clickbait teases a reader with a hint of what's to come without really giving away all the answers.

Common characteristics of a clickbait are:

- Content that inspires social sharing
- Content that is easy to skim
- Funny or memorable images/video.
- Headlines that grab your attention and leave you wanting more information
- Headlines that strongly appeal to specific and strong emotions, like humor or outrage

Clickbaits have been increasingly trending in most of the networking sites. So it becomes really important for us to detect and notify users regarding clickbaits as it helps us to give a good user experience preventing users from spending extended time on social media and the digital world.

## 3 Problem Statement

To shield the users from inappropriate content present in the articles which most of times is quite different from what was expected from the headline, we propose a model to a identify clickbaits. An extension to this work is to finally come up with an un-clickbaity headline for the corresponding detected clickbaity headline.

## 4 Relevant Work

### 4.1 Clickbait Detection

There has been a lot of work done on predicting click baits using NLP techniques.

One of the first studies regarding clickbait dealt with analysing the linguistics aspects of the clickbait (Rowe, 2011; Blom and Hansen, 2015), then features like textual similarity features between the headline and the body, informality and forward reference features, sentence structure features, word pattern features were extracted from the text and were used for classifications (Chakraborty et al., 2016). Nowadays due to the advancements in NLP, RNNs (Anand et al., 2016) and transformer architecture (Indurthi et al., 2020) models are popular. Studies were also done on predicting the intensity of clickbait rather than simple binary classification.

Most of the techniques involves training and validating a model on a given dataset comprising of clickbaits and unclickbaits. Clickbait16K was one of the first dataset which contained equal distribution of clickbaits and unclickbaits.

- The data is collected from various news sites.The clickbait headlines are collected from sites such as 'BuzzFeed', 'Upworthy', 'ViralNova', and 'Scoopwhoop'.

- The relevant or non-clickbait headlines are collected from many trustworthy news sites

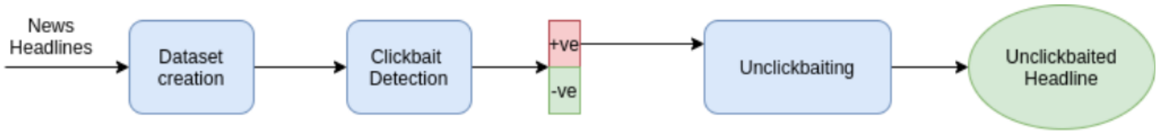


Figure 1: Overview of our method

such as 'WikiNews', 'New York Times', 'The Guardian', and 'The Hindu'.

### 4.2 Un-clickbait a Clickbait title

Unfortunately, all the previous works have focused only on the "detection" part of the clickbait. There also have been some works for predicting the strength of the clickbait. To the best of our knowledge, there have been no attempts yet to unclickbait the titles.

## 5 Our Approach

According to our approach, our task was divided into two parts:

- **Clickbait Prediction:** To predict whether a given headline is a clickbait or not.
- **Headline Generation:** On finding that a particular headline is a clickbait, task was to generate a new headline for the corresponding article.

The pipeline of our approach is represented in figure 1. We'll go through work done by us for each of these tasks in detail in the following sub-sections.

### 5.1 Clickbait Detection

The task is to classify a given headline as a clickbait or non clickbait.

The state-of-the-art transformer models improved the standard rnns with non-sequential nature, longer dependencies(using self attention) and use of positional embeddings. So, we use transformer models in our approach.

To increase the amount of dataset and update it to current style of clickbaits, we **added clickbait headlines** from the **past recent years** and for the non-clickbaity headlines were added from **abc-news** creating a dataset of **15 Lakhs** with equal proportion of both the types. A pretrained BERT and RoBERTa models were individually finetuned on our created dataset to serve as the "ground-truth model" to predict the clickbait. We used a max length of the sequence as 64(considering avg length of the title), batch size as 256(based on computational power) and learning rate at 2e-5. We used Cross Entropy Loss(since binary classification) function with AdamW Optimizer(better performance and faster convergence) for learning.

The RoBERTa model owing to better performance we thought would serve as the "**groundtruth model**" to identify the clickbait for us to unclickbait.

#### 5.1.1 Comparing with Previous Methods

We compare our model performance on Clickbait16k dataset with previous studies in table 1. Our model was able to improve marginally improve the performance.

On our created dataset also we got similar results.

Due to wide range of news articles, our model predicts **clickbaits better than non-clickbaits** i.e some of the non-clickbaits are treated as clickbaits on real world examples and will go through the process of unclickbaitness. The non-clickbait news headlines of various different sources(other than which we trained on) had inconsistencies because of varying linguistics styles. For Example Inshorts(whose headlines are attractive but not clickbaity). There is no harm in that process as our task of identifying the **clickbaits are preserved** and our model seldom predicts a clickbaity title as non-clickbait.

### 5.2 Un-clickbaiting

We propose that the unclickbaity headline has the following characteristics:-

- Non-Persuasive. - Should not persuade the user to click on it because of attraction.
- Unsensationalized/Non-exaggerated. -

| Model | Accuracy | Precision | Recall | F1 macro |
|---|---|---|---|---|
| Chakraborty et al. (2016) (SVM) | 93 | 95 | 90 | 93 |
| Chakraborty et al. (2016) (Decision Tree) | 90 | 91 | 89 | 90 |
| Chakraborty et al. (2016) (Random Forest) | 92 | 94 | 91 | 92 |
| BiLSTM(CE+WE) | 98 | 98 | 98 | 98 |
| BERT | **98.125** | **98.074** | **98.125** | **98.099** |
| RoBERTa | **98.406** | **98.425** | **98.392** | **98.405** |

Table 1: Results for Clickbait Detection

Should not be sensationalizing a small headline.

- Capture the content of the article. - Should have the gist of the content.

### 5.2.1 Style Transfer

Language being very rich and powerful a similar meaning can be expressed in many ways. **Text Style Transfer(TST)** task, which aims to change the stylistic properties of the text while retaining its style-independent content.Style transfer is used for tasks like sentiment transfer, Story-level text generation, Shakespeare, negative to positive.

Style transfer can be done using both supervised an non-supervised methods.

**Supervised techniques** requires parallel data that contains a collection of original texts for the task and their corresponding expected set of outputs. For example, in a style transfer task, parallel data contains a collection of original texts in Style 1 and their corresponding texts in Style 2.

**Unsupervised techniques** do work with Non-parallel data. A non-parallel data is a data that contains a collection of original texts for our task and their corresponding expected set of outputs aren't available. Most of the real life data we encounter falls under the category of non-paralle data. Similar is our case, we have clickbaity tiles to which don't have the corresponding non-clickbaity titles. Generating such a data is a tedious task. So, it our approach we will use non-parallel data.

To our knowledge, no attempts have been made so far to unclickbait a clickbaity title. Whereas, attempts other way around has been made (Jin et al., 2020). We use a better approach (Tian et al., 2018) than used in (Jin et al., 2020) for doing style transfer from clickbaity to non-clickbaity. The approach uses auto encoder and binary style transfer for generating the sentence in target style. It enforces the decoder to generate sentences that have similar nouns.

**Drawbacks**: It doesn't preserve the content of the article and also was not performing well on our non-parallel data(buzzfeed and abcnews). From the previous research work it was evident that approaches worked other was around. A possible inference which we could draw is that non-clickbaity titles which are used as input in the previous model had a pattern, which was absent in our click-baits data. Also there was lot of difference in the vocabulary of non-parallel data leading to misplacing nouns in the transferred text.

### 5.2.2 Summarization

Another approach we tried was headline generation using summarization. The main intuition behind this was that since we need a headline that is not clickbait, and it should also preserve content from the article, it means that we need a good title for the article. This is where summarization comes in. We use state-of-the-art models of abstractive summarization and we feed them the content of the article and ask them to generate a one-sentence headline for the article. The idea was that the metrics for summarization models are ROUGE scores, and hence content preservation won't be a problem. We can also say that the headlines generated would be non-clickbait because those summarization models are good summarization models and they have been known to produce very good summaries of the article.

We used the following two datasets to train all of our models, except T5 whose reasons are described later:

- Gigaword Corpus (Graff et al., 2003; Rush et al., 2015):
  This corpus consists of article pairs from Gigaword consisting of around 4 million articles along with their headlines.

- Extreme Summarization (XSum) Dataset. (Narayan et al., 2018):

This corpus consists of articles from BBC consisting of around 200 thousand million articles along with their headlines.

For this task of headline generation using summarization, we experiment with the following models:

- **T5** (Raffel et al., 2019)
  T5 is a unified Text-to-Text Transfer Transformer. T5 is a model which is not only limited to summarization but it can perform any sequence-to-sequence task using just one trained model by the use of prompts. If the prompt is say "Summarize: ", then it will summarize the input, if it is "Translate to French: ", then it will translate the input to French, etc.

  Like mentioned before, we don't train T5 on the Gigaword or the x-sum datasets. This is because T5 was trained on the CNN/Dailymail Dataset. We tried to train it ourselves on Gigaword and x-sum, but we weren't able to do so as we didn't have that much compute power and we always ran out of memory. Hence we took one of the pretrained T5 models and asked it to generate summaries. The problem with T5 was that since it was trained on the CNN/Dailymail dataset, it was trained to produce long summaries rather than headlines.

  To counter that, we modified the model and penalized large summaries and limited the maximum length of output to 40. But, still the model didn't generate good headlines. It was trying to summarize, and not generate a headline. Outputs were not very human-like.

- **RoBERTa2RoBERTa** (Liu et al., 2019; Rothe et al., 2019)
  This was a fun model to experiment with. RoBERTa2RoBERTa is an encoder-decoder model that was initialized on the roberta-large checkpoints for both the encoder and decoder, and later fine-tuned on the x-sum dataset and the Gigaword corpus each separately. The idea looked good on paper but the results were not that good. We observed that the model hallucinated a lot and produced headlines unrelated to the article.

- **BART** (Lewis et al., 2019)
  BART uses a standard seq2seq/machine translation architecture with a bidirectional encoder (like BERT) and a left-to-right decoder (like GPT). The pretraining task involves randomly shuffling the order of the original sentences and a novel in-filling scheme, where spans of text are replaced with a single mask token. BART is particularly effective when fine tuned for text generation and Summarization is a text generation task, hence we used it for headline generation. The pretrained model was fine-tuned on the x-sum dataset and the Gigaword corpus each for 3 epochs, and the models with the highest ROUGE-1 score on the training set batches was kept and used. The model produced decent results and even outperformed PEGASUS on the Gigaword corpus in terms of ROUGE scores!

- **PEGASUS** (Zhang et al., 2019)
  Pegasus is a model proposed by Google whose pretraining task is intentionally similar to summarization: important sentences are removed/masked from an input document and are generated together as one output sequence from the remaining sentences, similar to an extractive summary. Pegasus achieves state-of-the-art summarization performance on all 12 downstream tasks, as measured by ROUGE and human evaluation.

  It produced the best results among the four models that we used according to ROUGE scores (almost) and according to human observations (by a significant margin!).

## 6 Browser Extension

A **Browser extension** is a small unit of software also referred to as a 'plug in' where the software executes code that performs various filters and controls to change the way a user might visit a web page or view information emanating from a web service.

For our requirement we made a web extension that identifies whether the title of the web-page is a Clickbaity or nor. If the title is clickbaity we provide the user with non-clickbaity title.

We integrated back-end with flask. **Best performing models** of identification of clickbait and unclickbaity them are integrated with the backend.

Owing to the generation if title and content of the webpage followed by the execution of the both the models repose time for the user us approximately **40 seconds**. In our future work we would like to

| Model | ROUGE-1 | ROUGE-2 | ROUGE-L |
|---|---|---|---|
| RoBERTa2RoBERTa | 38.62 | 19.78 | 35.94 |
| BART | **40.45** | **20.69** | **36.56** |
| PEGASUS | 39.15 | 19.86 | 36.24 |

Table 2: ROUGE Scores on Gigaword Corpus

| Model | ROUGE-1 | ROUGE-2 | ROUGE-L |
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Table 3: ROUGE Scores on Gigaword Corpus

reduce the response time by deploying the system in **GPUs**.

## 7 Conclusion

In this work, we implemented an end to end full pipeline for detecting a clickbait and to finally generating an un-clickbaity headline for the content. The first model trained for a classification task on the dataset containing both clickbaity and non-clickbaity news headline. We explore that the state-of-the-art transformer model produced better result for this task when compared to previous works. Further if a this model predicts a headline as clickbaity, a summarizer is used to generate a un-clickbaity headline for the content corresponding to that clickbaity headline. A browser extension is made as a final product that would act as a frontend for both the tasks. The work may be improved by exploring style transfer methods by creating a dataset for parallel style transfer and also with content of the article results may be better for style transfer.

## References


Ankesh Anand, Tanmoy Chakraborty, and Noseong Park. 2016. We used neural networks to detect clickbaits: You won't believe what happened next! *CoRR*, abs/1612.01340.

Jonas Nygaard Blom and Kenneth Reinecke Hansen. 2015. Click bait: Forward-reference as lure in online news headlines. *Journal of Pragmatics*, 76:87–100.

Abhijnan Chakraborty, Bhargavi Paranjape, Sourya Kakarla, and Niloy Ganguly. 2016. Stop clickbait: Detecting and preventing clickbaits in online news media. In *Advances in Social Networks Analysis and Mining (ASONAM), 2016 IEEE/ACM International Conference on*, pages 9–16. IEEE.

David Graff, Junbo Kong, Ke Chen, and Kazuaki Maeda. 2003. English gigaword. *Linguistic Data Consortium, Philadelphia*, 4(1):34.

Vijayasaradhi Indurthi, Bakhtiyar Syed, Manish Gupta, and Vasudeva Varma. 2020. Predicting clickbait strength in online social media. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 4835–4846.

Di Jin, Zhijing Jin, Joey Tianyi Zhou, Lisa Orii, and Peter Szolovits. 2020. Hooks in the headline: Learning to generate headlines with controlled styles. *arXiv preprint arXiv:2004.01980*.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2019. BART: denoising sequence-to-sequence pretraining for natural language generation, translation, and comprehension. *CoRR*, abs/1910.13461.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692.

Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018. Don't give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. *ArXiv*, abs/1808.08745.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *CoRR*, abs/1910.10683.

Sascha Rothe, Shashi Narayan, and Aliaksei Severyn. 2019. Leveraging pre-trained checkpoints for sequence generation tasks. *CoRR*, abs/1907.12461.

David Rowe. 2011. Obituary for the newspaper? tracking the tabloid. *Journalism*, 12(4):449–466.

Alexander M. Rush, Sumit Chopra, and Jason Weston. 2015. A neural attention model for abstractive sentence summarization. *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*.

Youzhi Tian, Zhiting Hu, and Zhou Yu. 2018. Structured content preservation for unsupervised text style transfer. *arXiv preprint arXiv:1810.06526*.

Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter J. Liu. 2019. PEGASUS: pre-training with extracted gap-sentences for abstractive summarization. *CoRR*, abs/1912.08777.

## 8 Appendix

Below are some sample outputs produced by our summarization models which were used to produce unclickbaity titles using headline generation.

**Article**:
Little known secrets to finding coupons and discounts using search engines. Who doesn't like to save money? If you have an internet connection then you have access to the largest database of free coupons in the world.are hundreds of sites offering free coupons from everything to grocery stores and shopping malls. All you need to do is take advantage of these free coupons and I am going to show you how to get free coupons online.today's times when you are looking for coupons or bargains, where is the first place you visit? Yup, the search engines.often do you get less than what you are looking for when you are searching. Well by the time you read this article this will be a challenge of the past.of the time people are searching for bargains or looking to find coupons online they simply type in the term or terms and click the search button.The Right Coupon Databasesare free coupon databases that can be found online. These are basically websites that have lists of hundreds, or even thousands, of different coupons that you can get.offer the coupons for free, promo codes and some of them have a cost associated with it. Both can offer great savings at many stores. Find these databases and you will find a gold mine of savings.Competitions Offering Big Prizespays to enter the big competitions. You only need to win one major competition to save you a lot of money. Smaller competitions are great because it is more likely that you will win a prize, but large competitions offer bigger prizes and make it more worth your while.you are tired of finding expired or irrelevant deals, bargains and coupons online when using the search engines, this method will save you a lot of time and headache.

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**Clickbait Title**:
You won't believe this is the best way to save money

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**T5 Summary**:
there are hundreds of sites offering free coupons from everything to grocery stores and shopping malls.

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**RoBERTa2RoBERTa Summary**:
[”finding free coupons online”, ”Have you ever found a deal to find a discount on your supermarket or shop at a supermarket?”]

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**BART Summary**:
how to find coupons online

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**PEGASUS Summary**:
how to get free coupons on the internet step-by-step

**Article**:
CommunityMost Hated Man In UtahAugust 8th, new regulations that all began with this Utah State Representative, may have this man re-thinking his position and his story about electronic cigarettes. While he professes to be protecting the children and claims that nicotine causes cancer, This reporter has discovered that he has taken very significant donations from: Altria (Tobacco companies tobacco product sales), GLAXOSMITHKLINE (Pharmaceuticals Health Products Nicotine patch and nicotine gum), PFIZER (Pharmaceuticals Health Products Nicitrol Inhaler). By the end of the year with thousands of small businesses destroyed and tens of thousands of employees laid off. Along with over 4 million Vapers that all are forced to buy the inferior products that the tobacco companies want them to buy. This may very well be the most hated man in the United States. Dear Paul, my personal opinion is that you and your conspirators represent the biggest threat to Free Enterprise and the American way of life.

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**Clickbait Title**:
Here's who the most hated man in the United States

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**T5 Summary**:
by August 8, new regulations that began with Utah State Representative, may very well be the most

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**RoBERTa2RoBERTa Summary**:
Do you know the man who brought the ban on electronic cigarettes in the United States ?

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**BART Summary**:
utah 's most hated man in the united states

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**PEGASUS Summary**:
this is an open letter to the most hated man in the united states.