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BaitBuster: A Clickbait Identification Framework

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Abstract

The use of tempting and often misleading headlines (clickbait) to allure readers has become a growing practice nowadays among the media outlets. The widespread use of clickbait risks the reader's trust in media. In this paper, we present BaitBuster, a browser extension and social bot based framework, that detects clickbaits floating on the web, provides brief explanation behind its decision, and regularly makes users aware of potential clickbaits.

Introduction

Facebook engineers panic, pull plug on AI after bots develop their own language[1]– this headline and its similar versions, suggesting an apocalyptic situation, have misrepresented the true facts but, nonetheless, disrupted (shared more than $300K$ times[2] on Facebook alone) the social media by exploiting a technique called as *Clickbait*. The term *clickbait* refers to a form of web content that employs writing formulas and linguistic techniques in headlines to trick readers into clicking links (Palau-Sampio 2016; Chakraborty et al. 2016), but does not deliver on promises[3]. Examples of clickbait are– *You Won't Believe What These Dogs Are Doing!*, *What OJ's Daughter Looks Like Now is Incredible!* and so on. According to a study performed by Facebook[4], 80% users "preferred headlines that helped them decide if they wanted to read the full article before they had to click through". (M. Scacco and Muddiman 2016) shows that clickbait headlines lead to negative reactions among media users. In this paper, we describe a novel approach to identify clickbaits, and present BaitBuster, a browser extension and social bot based solution framework.

Clickbait Detection

We define the clickbait detection task as a supervised binary classification problem. We use distributed subword embeddings as features instead of applying *bag-of-words* (BOW) model. Specifically, we use Skip-Gram$_{sw}$, an extension of the continuous *skip-gram* model (Mikolov et al. 2013), which leverages subwords (substring of a word) to compute word embeddings (Bojanowski et al. 2016). Rather than treating each word as a unit like *skip-gram*, Skip-Gram$_{sw}$ breaks down words into subwords ($length = 3$) and wants to correctly predict the context subwords of a given subword. Then, the learned subword embeddings are aggregated to form the embedding of a word. This extension allows sharing of the subword embeddings across different words, thus allowing to learn reliable representations for rare words. We average the embeddings of words present in a sentence to form the hidden representation of it. These sentence representations are used to train a softmax classifier. Further technical details can be found in (Rony, Hassan, and Yousuf 2017).

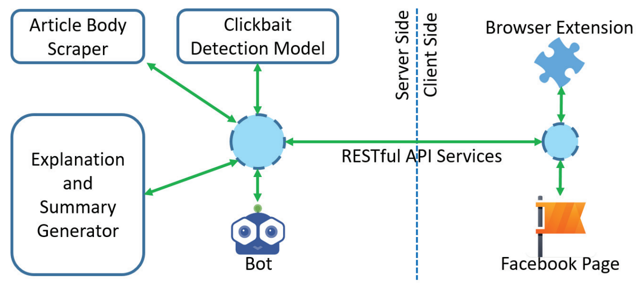
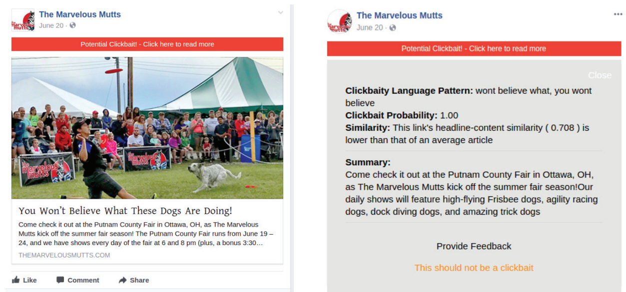


Figure 1: System architecture of BaitBuster

Dataset: Using Facebook Graph API, we accumulated all the Facebook posts created within January 1^{st}, 2014 and December 31^{st}, 2016 by 153 U.S. based media outlets. By considering only the link and video type posts, we had about 1.67 million Facebook posts (details in (Rony, Hassan, and Yousuf 2017)). We use this dataset to learn the subword embeddings. A collection of $32,000$ manually labeled news headlines ($15,999$ clickbait and $16,001$ non-clickbait), curated by (Chakraborty et al. 2016), was used to train a softmax classifier.

Evaluation: We performed 10-fold cross-validation and repeated each experiment 5 times to avoid any random behavior. We proposed 5 different models and the best model achieved an accuracy of 98.3% which is significantly better than the accuracy (93%) reported in (Chakraborty et al.

[1]http://bit.ly/facebookAIpanic
[2]http://bit.ly/FacebookAICount
[3]https://www.wired.com/2015/12/psychology-of-clickbait/
[4]http://bit.ly/FacebookClickbaitStudy



(a) BaitBuster identifies clickbait post

(b) Explanation behind the decision.

Figure 2

2016). We also compared our models with other works in terms of precision, recall, and other measures. More detailed evaluation can be found in (Rony, Hassan, and Yousuf 2017).

BaitBuster

BaitBuster consists of a browser extension that identifies clickbaits present in a Facebook timeline and a Facebook page. We choose Facebook because 44% of American adults get their news from Facebook[5].

System Overview: Figure 1 shows the architecture of the BaitBuster framework. The browser extension monitors a user's Facebook news feed and alerts her if a post (link) contains a clickbait headline. In addition, it provides a brief explanation behind the decision which includes- what language features present in a headline makes it a clickbait, whether the headline represents the corresponding body fairly, and a brief summary of the corresponding article so that the user can get the gist without leaving the current page.

Implementation: BaitBuster follows a client-server system architecture model where the client side has a JavaScript based browser extension and a bot powered BaitBuster Facebook page. The extension scans the Document Object Model (DOM) of the current page, identifies the anchor elements, and sends the data to the server side using POST request. The server processes the request and sends response back to the client. Then the extension creates a new DOM object with the clickbait decision for each anchor and inserts the object along the corresponding anchor element. Figure 2a and 2b show the graphical user interface (GUI) of the extension. The server side has several components. The *Article Body Scraper* component uses *Newspaper*[6] to extract the headline and the body of an article. We prepare a list of 1000 most frequent n-grams ($n = 3$) present in the $15,999$ clickbait headlines. The *Explanation and Summary Generator* component detects if any of the n-grams is present in the requested headline. It uses Gensim's [7] `TextRank` based summarizer to extract the summary of a body and cosine similarity to measure the similarity between the summary and the corresponding headline to give an idea of how fairly a headline represents its body. This component doesn't leverage the learnings from the detection phase as our detection model is non-interpretable. Activities of the browser extension are logged in a database. These data allows us to know, for any time interval, the most viewed clickbait posts and their source controversiality. The social bot automatically generates a small report (by filling up a template) with the most viewed clickbait posts on a day including their source identity and controversiality. Using Facebook API, it publishes the report to the client side page on a daily basis. As numerous malicious bots are spreading disinformation across the web (Woolley and Howard), we believe this is a small step towards fighting misinformation using benevolent bots. We have also released an API service [8] for third-party programs to use BaitBuster.

Related Work

There have been several attempts to limit clickbaits using browser extensions. For instance, *B.S. Detector* [9] and *Check This by MetaCert* maintain an aggregated list of sources and check web contents against the set of sources. One limitation of this approach is it doesn't allow checking content which hasn't already been checked by the aggregated list. *Stop Clickbait* (Chakraborty et al. 2016) uses supervised models to check clickbaits. However, they don't provide any explanation behind the model's decision. According to our knowledge, only BaitBuster provides deep learning powered classification and supplements it with explanation and summary by leveraging the headline-body relation.

References

Bojanowski, P.; Grave, E.; Joulin, A.; and Mikolov, T. 2016. Enriching word vectors with subword information. *arXiv preprint arXiv:1607.04606*.

Chakraborty, A.; Paranjape, B.; Kakarla, S.; and Ganguly, N. 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*, 9–16. IEEE.

M. Scacco, J., and Muddiman, A. 2016. Investigating the influence of "clickbait" news headlines. http://bit.ly/ClickbaitInfluence.

Mikolov, T.; Sutskever, I.; Chen, K.; Corrado, G. S.; and Dean, J. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, 3111–3119.

Palau-Sampio, D. 2016. Reference press metamorphosis in the digital context: clickbait and tabloid strategies in elpais. com. *Communication & Society* 29(2).

Rony, M. M. U.; Hassan, N.; and Yousuf, M. 2017. Diving deep into clickbaits: Who use them to what extents in which topics with what effects? In *2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM*.

Woolley, S. C., and Howard, P. N. Computational propaganda worldwide: Executive summary. Technical report.

[5]http://pewrsr.ch/2yzFfRr

[6]https://github.com/codelucas/newspaper

[7]https://radimrehurek.com/gensim/

[8]http://dear.cs.olemiss.edu/baitbuster

[9]http://bsdetector.tech/