Understanding Effects of Editing Tweets for News Sharing by Media Accounts through a Causal Inference Framework

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Abstract
To reach a broader audience and optimize traffic toward news articles, media outlets commonly run social media accounts and share their content with a short text summary. Despite its importance of writing a compelling message in sharing articles, research community does not own a sufficient level of understanding of what kinds of editing strategies are effective in promoting audience engagement. In this study, we aim to fill the gap by analyzing the current practices of media outlets using a data-driven approach. We first build a parallel corpus of original news articles and their corresponding tweets that were shared by eight media outlets. Then, we explore how those media edited tweets against original headlines, and the effects would be. To estimate the effects of editing news headlines for social media sharing in audience engagement, we present a systematic analysis that incorporates a causal inference technique with deep learning; using propensity score matching, it allows for estimating potential (dis-)advantages of an editing style compared to counterfactual cases where a similar news article is shared with a different style. According to the analyses of various editing styles, we report common and differing effects of the styles across the outlets. To understand the effects of various editing styles, media outlets could apply our easy-to-use tool by themselves.

1 Introduction
People prefer to read their news online rather than newspapers these days (Mitchell 2018). This paradigm shift has brought both good and bad influences on the news industry. The bad is that the competition among news organizations has become intense. Since the distribution costs of news content is far less expensive than it used to be in the pre-digital news era, many online news media have newly appeared, and the amount of news stories published in a day has been soaring (Atlantic 2016). The good, on the other hand, is that it enables media to get direct feedback from their audience; it further makes it easier to quantitatively measure the level of engagement on each news article. News organizations are increasingly adopting data-driven methods to understand their audience preferences, decide the coverage, predict article shelf-life, or recommend next articles to read (Castillo et al. 2014) [Kuiken et al. 2017]. Data-driven methods have also increased the understanding of effective news headlines that boost traffic (Kuiken et al. 2017) [Hagar and Diakopoulos 2019] while some headlines could undermine the credibility of news organizations in return for increased traffic (Chen, Conroy, and Rubin 2015a).

Pretty people have all the luck. Even Airbnb is a beauty contest, a new paper says

Figure 1: An example of news article shared by a media account on Twitter.

Sharing news articles on social media is a well-known strategy for boosting traffic to online news outlets. As shown in Figure 1, news outlets run an official account (we call media account for the rest of this paper) and share their articles with a short text. There are various ways for writing the social media posts. One could mirror news headlines without any modification or add clickbait-style phrases (e.g., “Even Airbnb is a beauty contest” in the figure). Social media managers at the newsroom face such a challenging task every day about how to write a short message to share a given news article (Aldous, An, and Jansen 2019b). In spite of its importance, they depend on their experience and make educated guesses to maximize audience engagement. As a result, they sometimes fail. Also, the research community is aware of different practices of using social media across media outlets (Russell 2019) [Welbers and Opgenhaffen 2019] yet does not own a sufficient level of understanding on which strategies lead to increased engagement.

In this work, we aim to fill this gap by analyzing news articles that are shared on Twitter by eight news media outlets, which vary publication channels and political leaning. In particular, we tackle the following research questions to deepen our understanding of editing practices of media accounts and their effects:

RQ1. How do news media edit text messages when sharing news articles on social media?
RQ2. Which kind of editing style leads to more audience engagement on social media?

We characterize how media accounts edit a tweet message against its original news headline and evaluate its effectiveness on the amount of audience engagement, such as the number of retweets or likes, by using the systematic analysis framework that incorporates propensity score analysis with deep learning.

The main contributions of this paper are as follows:

1. We build a parallel text corpus of news articles and social media posts (tweets in this work), written by eight hybrid and online-only media accounts, and make it publicly available to a wider community. From the dataset, we characterize patterns on how media outlets edit tweet messages when sharing news articles on Twitter.

2. To estimate the effects of editing news headlines on audience engagement, we utilize a systematic analysis framework that uses a deep learning-based model for propensity score analysis: it compares the level of engagements for a style with counterfactual cases where similar news articles are shared with a different editing style. This framework can be applied to any paired dataset of news article and its social media message that is shared by a media account, which will give a practical contribution to news media outlets for evaluating whether or not their strategy of publishing social media messages is effective.

3. Using the analysis framework on the dataset of the eight news outlets, we test which kind of editing strategy is effective in audience engagement. For example, we observed that writing a tweet message with the ‘clickbait’ style achieved a larger amount of engagement compared to its estimated counterfactual cases for half of the target media outlets.

2 Related works

2.1 News Media in the Era of Social Media

There has been a line of research on how news organizations use social media in terms of content and interaction. News organizations use Twitter as a promotional tool and write a tweet of headlines of news articles with a corresponding URL (Armstrong and Gao 2010) [Holcomb, Gross, and Mitchell 2011]. Another study pointed out that news media employ their accounts as a mere news dissemination tool without much interaction with audience (Malik and Pi effer 2016). However, the current practices on using social media vary across the news media and countries (Russell 2019) [Welbers and Opgenorth 2019].

The emergence of social media also brings changes in news writing (Dick 2011) [Tandoc Jr 2014], particularly in news headlines. In traditional newspapers, news headlines are expected to provide a clear understanding of what the news article is about (Van Dijk 2015) for helping those who read a newspaper while scanning headlines. Hence, headlines have functioned as a summary of the key points of the full article (Bell 1991) [Nir 1993]. As social media become popular (Hermida et al. 2012), headlines are also required to attract readers’ attention to increase traffic to their websites (Chen, Conroy, and Rubin 2015b). Accordingly, editors and journalists have adjusted the way they write headlines (Dick 2011). The characteristics of headlines in online news have been studied across the platforms, styles, sentiments, and news media (Kuiken et al. 2017) [Dos Reis et al. 2015] [Scacco and Muddiman 2019] [Piotrkowicz et al. 2017].

2.2 News Popularity and Audience Engagement

A significant amount of work has attempted to predict the popularity of news articles on web environments by modeling content features of news articles and user reactions on news websites and social media. Various studies have concluded that early user reactions on social media have a strong predictive power for the long-term popularity of news articles (Lerman and Hogg 2010) [Castillo et al. 2014] [Keneshloo et al. 2016]. Another study tackled a more challenging problem in forecasting the popularity (mainly view counts) of news articles even before its publication, which known as ‘cold start’ prediction (Bandari, Asur, and Huber man 2012). Applying the popularity prediction models relying only on news content, however, was not successful for the cold-start prediction in practice (Arapakis, Cambazoglou, and Lalmas 2014). A more recent study noted the importance of delivering fresh news earlier than competitors to attract readers (Rajapaksha, Farahbaksh, and Crespi 2019). In addition to views, various dimensions of audience engagements have been studied. A study that compared the most-clicked items with the most-commented items found that 40-59% of the items are different (Tenenboim and Cohen 2015). A more recent study observed that topics affect the level of engagement (Aldous, An, and Jansen 2019b), but the effects turned out to vary across engagement types: views, likes, and comments.

A recent study investigated the impact of editing a news headline with clickbait-style on view counts (Kuiken et al. 2017), which is a specific type of news headlines that is designed to attract users’ attention with a catchy text (Chen, Conroy, and Rubin 2015a) or by referring content that is not exposed in a headline (Blom and Hansen 2015). Using the dataset of one Dutch news aggregator, Blendle, Kuiken et al. (2017) examined 1.828 pairs of the original news headline and the rewritten title by Blendle editors. They found that rewriting a headline with clickbait-style is likely to increase the number of views.

Another line of research examined the role of posting time for the popularity of news articles. According to regression analyses for predicting view counts of the Washington Post articles, (Keneshloo et al. 2016) showed that the posting time was not an important factor for audience engagement. Another study investigated social media messages shared by Twitter accounts of 200 Irish journalists (Orellana-Rodriguez, Greene, and Keane 2016) and suggests that there is no best time of the day for engagements; they only found out a slight increase in audience engagement after 5 pm.

In the subsequent sections, we will first investigate how media accounts edit messages for sharing news articles on social media. Then, to estimate the effects of editing styles (e.g., sharing news with clickbait messages), we will apply
a systematic framework that controls for the effects of confounding variables on engagement. Following the literature on news popularity and audience engagement, we decide to control for the effects of news content as a major confounding variable in the following analyses.

3 Data Collection

To answer our research questions, we first build a parallel text corpus of news articles and social media posts. For covering diverse posting styles, we consider two types of news media in terms of channels for publishing news: hybrid news media and online-only news media. Hybrid news media (e.g., CNN) are the news outlets that have both conventional mass media channels, such as newspapers and television, and online channels. By contrast, online-only news media (e.g., HuffPost) are emerging media that publish content through online channels only.

| Type     | Media          | Followers | Tweets |
|----------|----------------|-----------|--------|
| Hybrid   | New York Times | 43.7M     | 143,011|
|          | The Economist  | 23.8M     | 30,200 |
|          | CNN            | 42.2M     | 50,841 |
|          | Fox News       | 18.5M     | 34,245 |
| Online-only| HuffPost     | 11.4M     | 23,712 |
|          | ClickHole      | 487K      | 5,535  |
|          | Upworthy       | 516K      | 168    |
|          | BuzzFeed       | 6.56M     | 18,862 |

Table 1: Descriptive data statistics

For hybrid news media, we collect a list of reliable news media and their political leaning from Media Bias/Fact Check, which is widely used in large-scale news media analysis (Media Bias Fact Check 2015). We also manually compile their social media accounts and their number of followers on social media. We then choose four most popular news media to cover different political leanings in our dataset: The New York Times (@nytimes, left-center), The Economist (@TheEconomist, least-biased), CNN (@CNN, left), and Fox News (@FoxNews, right). The popularity is measured based on the number of followers. For online-only news media, we choose four news media: HuffPost (@HuffPost), ClickHole (@ClickHole), Upworthy (@Upworthy), and BuzzFeed (@BuzzFeed) based on the previous literature (Chakraborty et al. 2016) and their popularity. For these eight media outlets, our data collection pipeline consists of four steps:

1. We collect tweets written by each media account. Using twint1, a third party library for Twitter data collections, we collect all available tweets but not mentions nor retweets. We also exclude tweets that contain an URL only.

2. We extract an embedded URL from each tweet. As it is typically shortened (e.g., http://nyti.ms/2hKFRv1) and sometimes shortened multiple times, we expand it until it reaches at the final destination. If the expanded URL points to other sites, such as YouTube, we exclude it.

3. We retrieve the HTML document of expanded URLs pointing to news articles. Our crawler sends requests with generous intervals.

4. As the last step, we extract a pair of headline and body text from each HTML file we collected.

Table 1 is the summary statistics of our dataset used in this work. Our dataset consists of the pairs of news articles and their tweets that were published in 2018. For the New York Times, we utilize a publicly available dataset (Szpakowski 2017) in Step (3) to match news articles with their tweets in 2018. We also note that Upworthy actively tweeted only in the last two months of 2018. Due to the copyright issues, we only share news headlines accompanied with its corresponding tweet ids at the following repository2. One can easily retrieve the paired dataset used for the following analyses by downloading the tweets using the official Twitter API or twint with the provided tweet ids.

4 How the News Media Edited Tweets

To understand how media accounts edit tweet messages when sharing news articles on social media (RQ1), we characterize media accounts from the perspectives of headline mirroring (§4.1), content change in lexicons and semantics (§4.2), and clickbaitness of headlines and tweets (§4.3).

4.1 Do media accounts mirror headlines?

| Media     | NYTimes | TheEconomist | CNN  | FoxNews |
|-----------|---------|--------------|------|---------|
| Hybrid    | 0.123   | 0.124        | 0.075| 0.397   |
| Online-only| Huffman | 0.0001       | 0.809| 0.714   |
|           | ClickHole| 0.0014       | 0.294|         |
|           | Upworthy | 0.018        | 0.012|         |
|           | BuzzFeed | 0.0014       | 0.012|         |

Table 2: Fraction of the tweets with the mirroring headlines

Considering that the mainstream news media outlets publish about 150 to 500 news stories per day (Atlantic 2016), it may be challenging for news outlets to write new social media text for all their news stories. We first examine whether the media accounts use the original headline without modifications (mirroring) or edit the headline to better appeal to social media users. Table 2 presents the proportion of the mirrored tweets across the media outlets. Of the 8 news media, HuffPost is the most active in editing headlines for social media; only 0.01% of the tweets contain the original headlines. By contrast, ClickHole mirrors the original headlines in 80.9% of their tweets. Then, when a change happens, how much content of the headline is preserved in the tweet?
4.2 How much is the content preserved?

To examine how media accounts preserve original content when editing tweet messages, we use two measures that quantify similarity between news headlines and tweet texts: Levenshtein distance (edit distance) and Cosine similarity over an embedding space (embedding similarity). First, edit distance is utilized to quantify how many edits (deletion, insertion, and substitution) are required to transform a news headline to a tweet text. We normalize edit distance by the longer length of the two texts, which ranges from 0 (identical) to 1 (no character overlap). Second, to know whether how much semantics are preserved, we measure embedding similarity by utilizing a pre-trained fastText word embedding (fastText 2018). We map a headline and its corresponding tweet into 300d vectors using the embedding and measure the cosine similarity between the two vectors, which ranges from -1.0 (dissimilar) to 1.0 (identical). Contrary to edit distance, a higher score indicates that the two texts are more similar to one another.

Figure 2 shows the degree of content preservation of the eight news outlets, which is measured by edit distance and embedding similarity. Not surprisingly, most media accounts tend to make a small amount of change for posting tweets against its original news headline, which are represented as a high value of embedding similarity and a low value of edit distance. However, some outlets exhibit distinct patterns; for example, in HuffPost, the median value of embedding similarity is only 0.619, which is significantly lower than the overall median value of 0.835. We further investigate the media-level difference by employing a Mann-Whitney’s U test between each pair of the 8 outlets on edit distance and embedding similarity, respectively. All of the pairwise relationships show statistically significant differences ($p<0.001$) except one pair of ClickHole and Upworthy ($p=0.554$). Taken together, above observations suggest that the media outlets have different editing patterns for sharing news articles on social media.

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Edit distance and embedding similarity together describe how much the content of a news title is preserved in its corresponding tweet. For example, if edit distance is low and embedding similarity is high, the tweet should be almost identical to the headline. By contrast, if both edit distance and embedding similarity are high, the tweet may preserve the meaning but is written very differently against the headline, which corresponds to a paraphrase of the headline.

Table 3 demonstrates the fraction of headline-tweet pairs that belongs to each cluster. Cluster 0 represents the pairs of which the tweet is similar or identical to the news headline, which are of low edit distances and high embedding similarities. In Cluster 1, a larger amount of lexical changes are made, but the semantics of a tweet is still similar to the corresponding news headline, as represented by high edit distances and high embedding similarities. This pattern suggests that Cluster 2 may indicate paraphrasing. Cluster 3 demonstrates the highest edit distance and the lowest embedding similarity, which suggests that a tweet may be re-
written with less similar semantics for sharing news articles on Twitter.

Here, we make observations on common patterns against the type of media. Cluster 0 is the most frequent group for those online-only media except for Huffpost. Incorporated with the observation in Table 3, the online-only media tend to share news headlines with a marginal amount of change. On the other hand, Cluster 0 is the least frequent group for the hybrid media except for FoxNews; Cluster 1 is the most frequent for TheEconomist and CNN while NYTimes shows a balanced distribution over the clusters. This suggests that the hybrid media outlets actively rewrite messages specifically designed for sharing news articles on social media, as represented by the high frequencies in Cluster 1 and 2.

### 4.3 How differently do news outlets use clickbait for news titles and tweets?

As the news industry becomes competitive, news outlets have published articles with headlines of a specific style that makes the audience click to read more by stimulating psychological perspectives, which is known as clickbait (Kilgo and Sinta 2016; Molek-Kozakowska 2013; Stroud 2017). While the credibility of media outlets can be undermined when news outlets exploit clickbait too often in their websites, this practices might be acceptable on social media where people write casual expressions (e.g., Figure 1). To investigate how the usages of clickbait varies across the news outlets, we utilize a deep learning classifier to examine the headline-tweet pairs in our dataset.

Using a public dataset of clickbait and non-clickbait headlines that were manually annotated in a previous study (Chakraborty et al. 2016), we first train an attention-based bidirectional recurrent neural network (RNN) classifier. The gated recurrent unit (Cho et al. 2014) is used as a basic unit, and an attention mechanism is, in turn, applied to the hidden units of RNN. We train the network to minimize the cross-entropy loss using Adam optimizer with gradient clipping. On a separate test set of 90:10 split, the model realizes an F1-score of 0.994, which outperforms the initial performance of 0.934 using SVM (Chakraborty et al. 2016).

To understand to what extent each media uses clickbait on their headlines and tweets, we estimate their clickbait scores by using the sigmoid output between 0 and 1 from the RNN classifier, which marks the high performance in the separate test set.

Table 3: Fraction of the clusters determined by edit distance and embedding similarity between headline and tweet

| Media     | Cluster 0 (Marginal change) | Cluster 1 (Paraphrasing) | Cluster 2 (Semantic change) |
|-----------|-----------------------------|--------------------------|-----------------------------|
| NYTimes   | 0.3173                      | 0.3246                   | 0.3581                      |
| TheEconomist | 0.1332                     | 0.6095                   | 0.2572                      |
| CNN       | 0.2236                      | 0.6864                   | 0.0900                      |
| FoxNews   | 0.6478                      | 0.2866                   | 0.0656                      |
| Huffpost  | 0.0987                      | 0.1064                   | 0.7949                      |
| ClickHole | 0.8499                      | 0.0694                   | 0.1407                      |
| Upworthy  | 0.8929                      | 0.0952                   | 0.0119                      |
| BuzzFeed  | 0.5132                      | 0.1787                   | 0.3081                      |

Table 4: P(Tweet\_class | Headline\_class) for hybrid and online-only media (C=Clickbait, NC=Non-clickbait).

| Hybrid          | P(Headline\_class=NC | P(Headline\_class=C) | P(Tweet\_class=NC | P(Tweet\_class=C) |
|-----------------|----------------------|----------------------|-------------------|-------------------|
| NYTimes         | 0.188                | 0.226                | 0.106             | 0.474             |
| TheEconomist    | 0.381                | 0.333                | 0.222             | 0.133             |
| CNN             | 0.222                | 0.301                | 0.016             | 0.103             |
| FoxNews         | 0.20                 | 0.156                | 0.020             | 0.333             |
| Average         | 0.248                | 0.254                | 0.068             | 0.261             |

To better understand how each outlet exploits the clickbait style when sharing a news article on Twitter, we compute the probability of shifting the clickbait style of news article when sharing it on social media: P(Tweet\_class | Headline\_class). Table 4 reports the conditional probabilities of the tweet to be clickbait or non-clickbait given the headline is clickbait or non-clickbait. For example, for NYTimes, when sharing a clickbait news headline on Twitter, the probability of its corresponding tweet to be non-clickbait is 0.188. There are different trends against the media type. Given a non-clickbait news headline, the probability of its tweet to be clickbait is similar across the hybrid and the online-only media (0.254 and 0.261, respectively). On the other hand, given a clickbait news headline, the hybrid and online-only media accounts shift the style with a huge difference. In the hybrid media, on average,
the probability of controlling the clickbait style remains to be similar when non-clickbait news headlines are given (0.248); on the contrary, the online-only media become less likely to flip the style when clickbait-style headlines are given (0.068). This observation implies the difference of editing styles against whether a given news is clickbait across the media type: while the online-only outlets prefer to use clickbait-style tweets in any cases, the hybrid media tend to keep the original styles of news headlines.

5 Effects of Editing Styles for News Sharing on Audience Engagement

In the previous section, we present that the eight news media outlets employ various strategies in editing tweets when sharing their news articles on Twitter. While the simplest tactic of the media accounts is to mirror the original headline of news articles to social media (§4.1), they also make a significant amount of edits with changes of content and text styles (§4.2-4.3). Then, which strategies would be more effective for audience engagement on social media? How should media accounts write a tweet message? Based on the observation of content changes and prevalent usage of clickbait when shared on Twitter, we aim at estimating the effects of editing tweet messages on audience engagement by using the paired dataset of the eight news media (RQ2).

![Figure 5: User reactions on the tweets published by the media accounts (w/o outliers)](image)

We use the number of replies, retweets, and likes as a proxy of audience engagement. Figure 5 shows the distribution of the three metrics. Among the eight media outlets, FoxNews garnered the highest amount of user engagement across the three variables. ClickHole harvested the equivalent amount of likes to that of FoxNews but got lower number of retweets and replies. This finding suggests that each of the three measures reflects a different aspect of audience engagement on Twitter and thus the effects of editing tweets should be analyzed separately for each of the engagement measures and the news outlets.

5.1 Analysis framework

We utilize a systemic framework that incorporates propensity score analysis (Rosenbaum and Rubin 1983) with deep learning. The propensity analysis framework is widely used for estimating a causal effect of having a treatment condition from an observational dataset. To test whether a certain causal relationship exists from a treatment variable to an outcome variable, researchers generally conduct a controlled trial on human or animal subjects, for example, the effects of taking a pill on reducing the headache symptom. Since the casual relationship can be confounded by certain variables called covariates, such as gender and age, researchers randomly assign subjects into one of treatment group (taking a real pill) and control group (taking a placebo).

In observational studies where data is given, however, researchers cannot control the process of data generation; therefore, observing correlations between a treatment variable and an outcome variable can be confounded by covariates. In this study, for example, we aim at measuring the effects of a certain editing style for news sharing on audience engagement on Twitter; however, merely observing how the two variables are associated can be confounded by other factors such as topics, which might affect the probability of that news media employ the editing style (Covariates→Treatment) as well as the expected amount of engagement independent of editing styles (Covariates→Outcome).

Propensity score matching (PSM) is proposed to address the issue and widely applied to observational studies on social media (De Choudhury and Kiciman 2017; Olteanu, Varol, and Kiciman 2017; Park et al. 2020). PSM first models a probability of having a treatment condition from given covariates (i.e., \( P(\text{Treatment}|\text{Covariate}) \)). Next, PSM ’matches’ the instances of the corresponding control group to each treatment unit that have a propensity score similar to that of the treatment unit. This process approximates randomized controlled trials in which the analysis units are randomly assigned into either treatment or control group, and thus, the risks of confounding effects due to covariates are minimized. For more details of PSM, please refer to (Guo and Fraser 2014).

**Modeling propensity scores** As discussed in related studies (Tenenboim and Cohen 2015; Mummolo 2016), the probability of selecting news items gets increased when a news article covers the topics of a reader’s interest, and so does the likelihood of audience engagement on social media. Therefore, we aim at reducing the confounding effects of topics on audience engagement by modeling a deep-learning-based propensity model that takes as input the body text of news articles. While social media engagements are also subject to who the posters are, we do not include it as one of the covariates because the analysis framework is applied to each news outlet separately; that is, the effects of the posters are naturally controlled.

To model the propensity score, we employ deep learning techniques that have shown state-of-the-art performances in text classification tasks in recent studies. In particular, we first transform a sequence of words in body text into a 300-dimensional vector by averaging word vectors that were pre-trained using fastText (Joulin et al. 2016) on news dataset (fastText 2018). The sentence vectors are fed into the three-layer fully-connected neural networks. For the activation of hidden layers, we use the ReLU non-linearity. The neural network is trained to minimize the cross-entropy of the labels on a treatment condition and the predicted value.
between 0 and 1, and the L2 regularization is applied to the last hidden layer ($\lambda=0.001$).

**Propensity score matching**  The next step is to match each treatment unit to the control units based on the propensity score. To put it differently, we prune instances that are too different from treatment groups in terms of the propensity score. We apply the $k$-nearest neighbor algorithm ($k=5$) to each treatment unit. After the matching process is done, the general PSM framework requires to check balances between a treatment group and its matched controls by the standardized mean difference of each covariate between the treatment group and the matched control group (Guo and Fraser 2014); If the two groups are not balanced, we cannot proceed the rest step since they cannot satisfy the conditional independence assumption, which is required to estimate a causal effect. In our experiments of which the text feature is represented by a 300-d latent vector, it is non-trivial to check whether the two groups cover similar content using the same metric. Alternatively, we use the cosine similarity between the embedding vectors of the treatment and control units, which is widely used to measure the similarity between two documents in the NLP community (Manning, Manning, and Schütze 1999). We formalize the condition of the successful matching as follows:

$$
\frac{1}{k} \sum_{t} \sum_{m} \text{Similarity}(t, m) \geq \max(\mu+\alpha \times \sigma, \text{threshold})
$$

where $T$ is a set of treatment units and $M_t$ is a set of control units matched to treatment unit $t$. $\alpha$ is a hyperparameter that controls the sensitivity of deciding whether a matching is successful, and $k$ is a hyperparameter of the nearest neighbor algorithm. $\mu$ and $\sigma$ are the mean and standard deviation of embedding similarity between all the pairs of documents from the original dataset before the matching is done. The *threshold* is to cope with the distribution where similarities are on average low. In the following experiments, we set $\alpha$ to be 1.5, which lets $\mu+\alpha \times \sigma$ corresponds to the 86th percentile of the similarity value, and threshold to be 0.8.

**Estimating treatment effects**  For the treatment groups with successfully matched instances, we measure the effect of having a treatment condition on a variable of audience engagement. The Estimated Average Treatment Effect (EATE) on an outcome variable is measured as follows:

$$EATE = \frac{1}{N_T} \sum_{t} \sum_{m} \left( \frac{y_t - y_m}{k} \right)$$

where $y_t$ and $y_m$ are the outcomes measured for $t$ and $m$, respectively. $N_T$ is the number of treatment units, and the meaning of other symbols is the same as those in Equation (1). EATE quantifies the potential (dis-)advantage of audience engagement by sharing a news article with a certain style (treatment) compared to another (control).

**Robustness check using cross-validation**  As discussed in (Kiciman and Sharma 2019), it is crucial to conduct a sensitivity analysis for conducting propensity score analysis because the matching process can lead to a biased result. As a step for a robustness check, we repeat the above process using 10-fold cross-validation. In particular, for every iteration, we make use of 90% of the dataset for training a propensity score model, matching, and measuring EATE. As the last step, we compute the 95% confidence interval by averaging the 10 EATEs and discard the cases where the interval includes zero. The reported EATE is the average of the 10 EATEs measured on the splits.

### 5.2 Results

Using the analysis framework, we investigate what effects are brought into audience engagement on Twitter by editing tweets for sharing news articles. Note that the analysis framework is applied to each scenario that tests an effect of style $A$ (e.g., editing) compared to style $B$ (e.g., mirroring) for $K$ outlet (e.g., NYT times): a propensity model is trained only on a dataset, control groups are matched for each treatment unit, and semantic balance and robustness are checked between the two groups. If a scenario does not pass the balance check or the robustness check, we are not able to measure the EATE, which is therefore omitted.

**Effects of modifying original content**  First, we investigate whether mirroring a news title to social media is a good strategy or not for each of the eight outlets. We consider the treatment group of headline-tweet pairs of which the tweet is different from the headline, and the control group is the pairs of which the original headline is identical to the tweet text. Because the distribution of audience engagement varies across those outlets as shown in Figure 5, we apply the propensity score matching to the headline-tweet pairs of each media separately.

Table 3 presents the EATE on the three variables of audience engagement, measured across the eight outlets. According to the results of balance check and robustness analysis, we exclude the results for CNN and Upworthy. Understanding which factors lead to a failure of matching would be an interesting research direction, but we leave it for future works.

There are three main observations. First, results show that editing tweet messages is more likely to increase the amount of engagement for the hybrid news media than mirroring headlines. For example, for NYT times, the tweets edited from news titles are on average more retweeted (+56.34) and liked (+77.90) than the tweets identical to news titles. While the positive effect is similarly observed for TheEconomist, FoxNews exhibits a different pattern; the number of retweets and likes increased, but that of replies decreased. Second, for the four online-only new outlets, editing tweets makes diverse effects. While BuzzFeed enjoys the positive effects of editing like the hybrid news media, for HuffPost and ClickHole, editing tweet messages does not help, but lower audience engagement. Interestingly, HuffPost and ClickHole are media that changed the news titles the most and least (95% and 19%). Third, there is a common trend across all the media; the magnitude on the number of likes is always bigger than that on retweet counts with the same direction, indicat-
Table 5: Effects of editing tweets against news headlines on the amount of audience engagement on Twitter. The blue background indicates a positive effect, and the red indicates a negative one. (RT: retweets, LK: likes, RP: replies)

| Media                  | EATE |     |   |
|------------------------|------|-----|---|
|                        | RT   | LK  | RP|
| NYTimes                | 56.34| 77.90| 9.33|
| TheEconomist           | 13.38| 17.33| 0.60|
| CNN                    | -    | -   | -  |
| FoxNews                | 25.57| 77.92| -49.26|
| HuffPost              | -11.88| -24.46| -  |
| ClickHole              | -103.63| -480.52| -5.64|
| Upworthy               | -    | -   | -  |
| BuzzFeed               | 13.57| 49.98| 0.47|
| NYTimes (Politics)     | 104.74| 149.32| 23.60|
| NYTimes (Entertainment)| 34.40| 65.23| 3.79|
| FoxNews (Politics)     | 21.97| 69.88| -46.21|
| FoxNews (Entertainment)| -    | -   | -  |
| NYTimes (00:00-08:59)  | 43.32| 60.75| 6.85|
| NYTimes (09:00-16:59)  | 64.02| 92.91| 13.11|
| NYTimes (17:00-23:59)  | 58.06| 75.38| 8.47|
| FoxNews (00:00-08:59)  | 20.19| 71.03| -37.76|
| FoxNews (09:00-16:59)  | -    | -   | -43.49|
| FoxNews (17:00-23:59)  | 47.69| 180.88| -54.23|

Table 5: Effects of editing tweets against news headlines on the amount of audience engagement on Twitter. The blue background indicates a positive effect, and the red indicates a negative one. (RT: retweets, LK: likes, RP: replies)
Table 6: Effects of the amount of content change in editing tweet messages against news headlines on audience engagement on Twitter. Unsuccessfully matched entries are omitted. (T: cluster index of treatment group, C: cluster index of control group, RT: retweets, LK: likes, RP: replies)

| Treatment (HL→TwT) | NYTimes | TheEconomist | FoxNews | Huffpost | Upworthy | BuzzFeed |
|---------------------|---------|--------------|---------|----------|----------|-----------|
| RT LK RP            | RT LK RP| RT LK RP     | RT LK RP| RT LK RP| RT LK RP| RT LK RP  |
| 1 0                 | 48.22 63.14 7.17 | 12.60 16.07 0.28 | 16.68 39.04 -49.46 | - 37.34 8.47 | 3.26 -0.31 | - - 0.56 |
| 2 0                 | 61.77 92.12 10.44 | 17.12 23.20 1.33 | -82.38 -226.03 -94.19 | -4.43 - | -4.30 -26.07 -1.85 | 12.58 50.91 - |
| 2 1                 | 15.38 34.45 4.37 | 14.14 22.83 1.56 | -12.85 - | -16.70 -11.23 -31.69 -5.65 | -8.32 -23.50 -0.72 | 11.10 48.23 -1.24 |

Table 7: Effects of controlling clickbait styles of news headlines (HL) into sharing tweets (TwT). Unsuccessfully matched entries are omitted. (RT: retweets, LK: likes, RP: replies, C: Clickbait, NC: Non-clickbait)

| Treatment (HL→TwT) | Control (HL→TwT) | NYTimes | TheEconomist | FoxNews | Huffpost | ClickHole |
|---------------------|------------------|---------|--------------|---------|----------|-----------|
| RT LK RP            | RT LK RP         | RT LK RP| RT LK RP     | RT LK RP| RT LK RP| RT LK RP  |
| C → NC              | C → C            | -5.23 -31.39 -1.77 | 9.20 8.20 - | - - - | - - - | - - -     |
| NC → C              | NC → NC          | 32.34 69.69 6.80 | 6.75 7.72 - | 15.12 87.88 -30.97 | 4.80 26.69 1.58 | -16.96 -93.65 - |

Effective strategy to increase audience engagement on Twitter. In other words, the editors of both news media could understand who are their audiences on Twitter and write tailored tweets that were often quite different from the original headlines. Second, Cluster 1 (Paraphrasing) leads to positive EATEs in Huffpost in comparison to the other clusters. Third, BuzzFeed tends to show the positive EATE for Cluster 2 and FoxNews tends to exhibit the positive EATE for Cluster 1; yet, the two media have the opposite effect for replies, suggesting that replies have a different characteristics compared to the other two engagement measures.

In combination with the findings on the effects of the mirroring strategy in Table 6, the above results suggest that the optimal editing style varies across the news media outlets.

**Effects of using clickbait style**

Next, we estimate the effects of controlling clickbait styles of news titles for sharing on Twitter. Note that we exclude identical headline-tweet pairs for the subsequent analysis to capture a distinct pattern against the effects of editing. Table 7 shows the EATE on audience engagement by sharing non-clickbait headlines with clickbait tweets and those of sharing clickbait headlines with non-clickbait tweets. The clickbait label is annotated by the same process described in §4.3.

As shown in the second row in Table 7 compared to sharing non-clickbait headlines on Twitter, sharing those with clickbait-style tweets is likely to increase the number of retweets, likes and replies for NYTimes, TheEconomist, and Huffpost. In FoxNews, the positive EATEs are observed for retweets and likes but the opposite effect manifests for replies. The opposite trend of replies in FoxNews was repeatedly observed in the earlier analyses, including Tables 5 and 6.

From the experiments on the effects of sharing non-clickbait tweets for clickbait-style news titles, we achieve successful matching across the three engagement measures only for NYTimes; we observed negative effects of sharing non-clickbait tweets for clickbait news. Together with the positive effect for sharing clickbait tweets for non-clickbait news, the result implies that clickbait could boost audience engagement effectively; at least for NYTimes, it could be recommended to mirror a news title if the title is clickbait but to rewrite it with the clickbait style for non-clickbait news.

It is interesting to observe that TheEconomist shows the positive EATEs for both C → NC and NC → C. Given a news article, the editors may know what is a desirable style for being shared on social media. As there is no published report about their internal guideline on how to share news on Twitter, we cannot explain how they work, but the observed data describes the effective approach of TheEconomist toward clickbaits.

We further see whether the results hold the same in the politics and entertainment sections for NYTimes and FoxNews for generalizability. In the Entertainment section of NYTimes, the effects remain the same as those measured in the whole data, except for replies. On the contrary, in Politics, the effects become the opposite; sharing non-clickbait tweets for clickbait news in politics turns out to be beneficial for promoting engagement. The distinct direction of effects across the sections suggests there might exist desirable styles for different topics. In FoxNews, the section-level analysis also exhibits a different trend from that as a whole. In both sections, sharing clickbait tweets with non-clickbait news likely decreases the amount of engagement. This contradicting observation suggests that the audience of FoxNews on Twitter responds to clickbait tweets differently for Politics and Entertainment compared to news in other sections.

### 6 Discussion and Conclusion

Social media serve as places where people read and discuss news today (Mitchell 2018). News organizations have run their media accounts to share their own articles on social media. Unlike traditional newspapers that readers can see headlines and body text at the same time, on social media, the main content is not shown to the readers, but a short text (e.g., tweet) should attract readers to click the link to read more. Therefore, it is crucial to write an effective social media post for sharing news articles. The lack of available
dataset and analysis framework, however, makes it challenging to evaluate which editing strategy is more effective in garnering user attention on social media in a systemic manner.

As a first step to overcome such limitations, we built a parallel corpus of news articles and tweets that are shared by the eight news outlets and examined how they edit the tweet messages against the news headlines (RQ1). The findings show that the media outlets employed diverse strategies in writing the social media messages. While mirroring a news headline to Twitter was a common strategy, the outlets also made various levels of change on content; for example, more frequently for the online-only media, the news articles were shared more with clickbait tweets.

A natural following question is, which editing strategy is more effective in promoting audience engagement for sharing news articles on Twitter (RQ2). To answer the question in a data-driven way, we employed a systematic analysis framework that incorporates deep learning with propensity score analysis; in particular, we utilized a deep learning model for modeling the propensity of having a treatment condition. The propensity score analysis framework allows for estimating the effect of one editing style on audience engagement by matching counterfactual outcomes where the same article is shared with another editing style. The high performance of deep learning for text classification enables to mitigate the effects of covariates such as textual features more effectively in the matching process.

The findings of the RQ2 can be summarized as three: First, editing a news headline was likely to increase audience engagement on Twitter than mirroring the headline in the four hybrid news media, which publish news articles through both offline and online channels. By contrast, in the news media who only keep online channels, the estimated effects of editing tweets were generally negative except for BuzzFeed. Second, in terms of lexical and semantic changes, there were no universal best strategy applicable to different media outlets. For example, changing the original semantics of news headlines (Cluster 2) was estimated to be the best tactic for NYTimes, yet paraphrasing original headlines for sharing tweets (Cluster 1) was the best for HuffPost in terms of EATE. Third, sharing tweets with clickbait-style messages was likely to increase the amount of audience engagement in the four outlets. This finding is congruent with a previous study showing rewriting news headlines with a clickbait style increased the amount of engagement in a Dutch news service (Kuiken et al. 2017). Yet, the opposite direction of EATEs was also observed from the shared tweets of ClickHole. The differing trend across the media outlets might suggest that the level of audience engagement is not just a function of editing styles but also dependent on who their audiences are. To test the hypothesis, future studies could characterize audience types of news outlets (e.g., socioeconomic status) and investigate how different editing styles are preferred by each audience type.

On top of the above observations on how the eight outlets edited tweets for news sharing and its effects on audience engagement, we believe the overall analysis framework, from how to process the data to how to conduct propensity score analysis, could benefit any media outlets in practice. In particular, similarly as we measured the effects of editing in Table 5, the media outlets would be able to evaluate how effectively they posted social media messages using their own headline-tweet pairs. To the end, we thus will release our systematic analysis framework as an easy-to-use toolkit.

### 6.1 Limitation and Future Direction

Although we consider diverse news media from hybrid to online-only and left to right in this study, additional studies with more number of media across multiple regions are essential for evaluating the generalizability of the observations. As we are sharing the entire analysis pipelines as an easy-to-use toolkit, we hope that it becomes an easy starting point for following studies on different datasets. Another weakness of this study is an inherent limitation of the propensity score analysis, which is the risk of unobserved covariates. Based on the findings of the literature on news engagement, we tried to minimize the risk through various comparisons. Last but not least, while we found that using a clickbait-style message increased audience engagement on tweets, it could make an adverse effect on media credibility simultaneously; the long-term effect of the clickbait usage on the perceived credibility should be carefully studied in the future.

Beyond the news domain, our analysis framework could be extended to other cross-platform sharing activities (Park et al. 2016). For example, how could researchers share their research papers on social media for effectively drawing attention and achieving more citations in the long run? Mirroring the paper title may not be the best strategy because a scientific paper is usually written in a formal language. Our framework can be used to quantify which messages would be effective. Another exciting research direction is to automatically generate a social media post when a news article is given. Training a naive sequence-to-sequence model might not work well as there exist diverse headline-to-tweet mappings as shown in this study. Future researchers could develop a controlled generation technique such as (Hu et al. 2017) for handling such diversity in the mappings.

### References

[Aldous, An, and Jansen 2019a] Aldous, K. K.; An, J.; and Jansen, B. J. 2019a. The challenges of creating engaging content: Results from a focus group study of a popular news media organization. In Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems, LBW2317. ACM.

[Aldous, An, and Jansen 2019b] Aldous, K. K.; An, J.; and Jansen, B. J. 2019b. View, like, comment, post: Analyzing user engagement by topic at 4 levels across 5 social media platforms for 53 news organizations. In ICWSM, volume 13, 47–57.

[Arapakis, Cambazoglu, and Lalmas 2014] Arapakis, I.; Cambazoglu, B. B.; and Lalmas, M. 2014. On the feasibility of predicting news popularity at cold start. In Proc. of the SocInfo, 290–299. Springer.
[Orellana-Rodriguez, Greene, and Keane 2016] Orellana-Rodriguez, C.; Greene, D.; and Keane, M. T. 2016. Spreading the news: how can journalists gain more engagement for their tweets? In Proc. of the Web Science, 107–116. ACM.

[Park et al. 2016] Park, K.; Weber, I.; Cha, M.; and Lee, C. 2016. Persistent sharing of fitness app status on twitter. In Proc. of the CSCW, 184–194.

[Park et al. 2020] Park, K.; Kwak, H.; Song, H.; and Cha, M. 2020. Trust Me, I Have a Ph. D.: A Propensity Score Analysis on the Halo Effect of Disclosing One’s Offline Social Status in Online Communities. In Proc. of the ICWSM, volume 14, 534–544.

[Piotrkowicz et al. 2017] Piotrkowicz, A.; Dimitrova, V.; Otterbacher, J.; and Markert, K. 2017. Headlines matter: Using headlines to predict the popularity of news articles on twitter and facebook. In Proc. of the ICWSM.

[Rajapaksha, Farahbakhsh, and Crespi 2019] Rajapaksha, P.; Farahbakhsh, R.; and Crespi, N. 2019. Scrutinizing news media cooperation in Facebook and Twitter. IEEE Access.

[Rosenbaum and Rubin 1983] Rosenbaum, P. R., and Rubin, D. B. 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70(1):41–55.

[Russell 2019] Russell, F. M. 2019. Twitter and news gatekeeping: Interactivity, reciprocity, and promotion in news organizations’ tweets. Digital Journalism 7(1):80–99.

[Scacco and Muddiman 2019] Scacco, J. M., and Muddiman, A. 2019. The curiosity effect: Information seeking in the contemporary news environment. New Media & Society.

[Stroud 2017] Stroud, N. J. 2017. Attention as a valuable resource. Political Communication 34(3):479–489.

[Szpakowski 2017] Szpakowski, M. 2017. Fake News Corpus. [Online; accessed 8-Aug-2020].

[Tandoc Jr 2014] Tandoc Jr, E. C. 2014. Journalism is twerking? how web analytics is changing the process of gatekeeping. New media & society 16(4):559–575.

[Tenenboim and Cohen 2015] Tenenboim, O., and Cohen, A. A. 2015. What prompts users to click and comment: A longitudinal study of online news. Journalism 16(2):198–217.

[Van Dijk 2013] Van Dijk, T. A. 2013. News as discourse. Routledge.

[Welbers and Opgenhaffen 2019] Welbers, K., and Opgenhaffen, M. 2019. Presenting news on social media: Media logic in the communication style of newspapers on facebook. Digital Journalism 7(1):45–62.