News Article Teaser Tweets and How to Generate Them

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Abstract

We define the task of teaser generation and provide an evaluation benchmark and baseline systems for it. A teaser is a short reading suggestion for an article that is illustrative and includes curiosity-arousing elements to entice potential readers to read the news item. Teasers are one of the main vehicles for transmitting news to social media users. We compile a novel dataset of teasers by systematically accumulating tweets and selecting ones that conform to the teaser definition. We compare a number of neural abstractive architectures on the task of teaser generation and the overall best performing system is See et al. (2017)’s seq2seq with pointer network.

1 Introduction

A considerable number of people get the news in some digital format \textsuperscript{1}. The trend has made many publishers and editors shift their focus towards the web and experiment with new techniques to lure an Internet-savvy generation of readers to read their stories, as a result, there has been a noticeable increase in sharing of short illustrative piece of texts about the news on social media.

We define a ShortText as a short text (about 15 words or less) describing and pointing to a news article and whose purpose is to invite the recipient to read the article. A headline is a ShortText that optimizes relevance of the story to its reader by including interesting and high news value content from the article (Dor, 2003). Click-bait is a pejorative term for web content whose main goal is to make a user click an adjoining link by exploiting the information-gap. According to the definition, a principal part of the headline is an extract of the article, thereby creating an impression of the upcoming story. However, click-bait, a ShortText, contains mostly elements creating anticipation, thereby making a reader click, and eventually regret as the story doesn’t match the click-bait’s impression (Blom and Hansen, 2015). Thus, click-baits provides false impression (non-bona-fide) and has insufficient information (highly abstractive).

|     | bona-fide | teasing | abstractive |
|-----|-----------|---------|-------------|
| headline | yes | no | no |
| clickbait | no | yes | yes |
| teaser | yes | yes | yes |

Table 1: Categories of ShortTexts.

We introduce a new concept of a teaser and define it as a ShortText devised by fusing curiosity-arousing elements with interesting facts from the article in a manner that they create a valid impression of an upcoming story and a sense of incompleteness concurrently. A teaser is one of the main vehicles for transmitting news on a social media. Table 2 shows some teasers from a popular newswire.

We also introduce properties like bona-fide, teasing, and abstractive, that not only differentiate teasers from other ShortTexts but also help in compiling a dataset for the study. Teasing indicates whether curiosity-arousing elements are included in the ShortText. Abstractive indicates whether a fair proportion of the ShortText is distilled out of the news article. Bona-fide answers whether the news story matches the impression created by the ShortText. Table 1 lists the common forms of the ShortTexts along with the presence or absence of the above-mentioned properties.

In this study, we focus on teasers shared on Twitter\textsuperscript{2}, a social media platform whose role as a news conduit is rapidly increasing. An indica-
Global trade is in trouble, and investors don’t seem to care.
One of the ironies of the election of a fierce nationalist in
the U.S. .

Steel Yourself for Trump’s Anti-Trade Moves
Investors don’t seem worried about a trade war. Could
tariffs by Trump start one?

The U.S. Supreme Court on Monday partially revived
President Donald Trump’s executive order suspending
trade from six countries

High Court Says Travel Ban Not For Those With Bona
Fide Relationships
In a ‘bona fide’ relationship? You can visit the U.S.

Gan Liping pumped her bike across a busy street, racing to
beat a crossing light before it turned red. She didn’t make
it.

China’s All-Seeing Surveillance State Is Reading Its Citi-
zens Faces
China is monitoring its citizens very closely. Just ask jay-
walkers.

Table 2: The table contains tuples of news arti-
cles and their ShortTexts: Headline and Teaser. These tuples are from a popular newswire, The
Wall Street Journal.

tive tweet is a Twitter post containing a link to
an external web page that is primarily composed
of text. The presence of the URL in an indicative
tweet signals that it is functioning to help
users decide whether to read the article, and the
short length confirms it as a ShortText such as
as a headline, lead sentence or teaser. Lloret and
Palomar (2013) made an early attempt at generat-
ing indicative tweets using off-the-shelf extractive
summarization models and graded the gener-
ated texts as informative but uninteresting. Sid-
haye and Cheung (2015) showed extractive sum-
marization as an inappropriate method for generat-
ing such tweets as the overlaps between the tweets
and the corresponding articles in their collection
are low. We show indicative tweets, teasers, with
above-defined properties exhibit significant over-
laps, however, not full, and therefore are more ap-
propriate for abstractive study than extractive.

To the best of our knowledge, this is the first at-
tempt at comparing different types of ShortTexts
associated with a news article. We introduce a
novel concept of a teaser, an amalgamation of arti-
cle content and curiosity-arousing elements, used
for broadcasting news on a social media by a news
publisher.

We compiled a novel dataset to address the task
of teaser generation. The dataset is a collection of
news articles and their story-highlights and Short-
Texts: teaser and headline. Unlike ShortText, a
story-highlight is brief and self-contained sen-
tences (about 25-40 words) that allows the recip-
ient to quickly gather information on news sto-
ries (Woodsend and Lapata, 2010). As the dataset
assembles ShortTexts and story highlights, it will
provide NLP community a unique opportunity for
a joint study in generating such short texts.

We illustrate techniques like domain relevance
and unigram overlaps to manage interestingness
and abstractivity in the teasers. We compare head-
line and teasers by separately computing over-
laps between headlines and articles, and between
teasers and articles, and then plotting such over-
laps ratios. Interestingly, the plots show headlines
are near to extractive while teasers are largely ab-
stractive.

High abstractivity make teaser generation a
tougher task, however, seq2seq methods trained on
such corpus are effective in it. Our quantitative
results show a seq2seq assembling teasers from
both the source tokens and the vocabulary are bet-
ter than one with the only vocabulary. Therefore,
we set a strong baseline on the task of teaser gen-
eration with a pointer-based seq2seq model of See
et al. (2017).

2 Teaser Dataset

Linguistically, there are several patterns that can
invoke curiosity, e.g., provocative question, com-
paring extremes, short punchy statement, direct-
appeal, and important quotes; however, comput-
tationally defining an exhaustive set of rules for
all these patterns is a difficult task because often
such patterns involve many marker words and cor-
respondingly many grammar rules. An alterna-
tive and computationally feasible approach will be
compiling circulations from bona-fide agents that
are involved in luring business on a social media
and filtering those circulations that don’t comply
with the principal characteristics of the teaser. We
followed this approach in our study and choose
Twitter to conduct the study.

2.1 Dataset Collection

We identified official Twitter accounts of English-
language news publications that had tweeted a
substantial number of times before the collection
began; this removes a potential source of noise,
namely indicative tweets by third-party accounts
referencing the articles via their URL. We down-
loaded each new tweet from the accounts via Twit-
ter’s live streaming API. We limited the collection
to indicative tweets and extracted the article text
and associated metadata from the webpage using
2.2 Analysis

Through analyses, we recognize methods that verify interestingness and abstractivity in the teasers and then combine them to devise a teaser recognition algorithm. Analyses are performed on lower-cased and stopwords pruned texts.

2.2.1 Domain Level

Interestingness implies that a portion of the teaser must be a novel or interesting fact; therefore, one or more words in it must be a rare item in the vocabulary of the medium generating it.

Pareto principle or law of the vital few, also known as the 80/20 rule, states that the 2,000 most frequently-used words in a domain cover about 80% of usual conversation texts, even in complex reading materials like economics textbooks and academic articles (Nation, 2001). Therefore, filtering teasers constituted with only frequent-words should intuitively prune ordinary and uninteresting ones; however, a closer look at the filtered teasers show several interesting teasers with just out-of-place frequent-words in them, e.g., Las Vegas gunman Stephen bought nearly %%% guns legally. But none of the purchases set off any red flags. has only frequent-words of the corpus in it; however, the second part of the teaser, a sentence fragment, makes the teaser interesting by using a metaphorical phrase, red flag. This suggests that the methodology that uses plain frequency of words is not sufficient for determining interesting information.

Thus, we rely on domain relevance (**dr**) (Schulder and Hovy, 2014), an adapted TF-IDF (term frequency inverse document frequency) metric that measures the impact of a word in a domain rather than a document and is computed using Eq. 1. A word is assigned a low score if the word is either non-frequent in the domain or otherwise too frequent among other domains. We save teasers with at least a word with a low score. This score-based filtering is a threshold-based classification, and therefore, requires a threshold-value to classify a score either as a relevant or not. We use an unsupervised method to determine it; the details are described below.

**Obtaining Domains**

Computing a **dr** of a word in the teaser requires its domain information and to determine it, we make use of articles and articles keywords. Keywords are meta-information available for a subset of corpus instances. We cluster representations of the articles by K-Means clustering (Hartigan and Wong, 1979) and manually verify the correctness of the clustering by checking the uniformity among the 100 most-frequent keywords in each cluster. We rely on Doc2vec (Le and Mikolov, 2014) for obtaining the representations for the articles. Clustering the corpus into 8 domains resulted in uniformly distributed keywords sets; See Table 3 for domain-wise keywords and Figure 1 for distribution of domain-wise articles. Additionally, Table 4 provides the domain-wise statistics of the corpus.

![tSNE of doc2vec of articles in domains.](image)

### Selecting Threshold

To determine an appropriate threshold, we design an unsupervised methodology based on the cue that a right threshold will filter teasers that have only non-relevant words in them and these non-relevant words are very likely to be part of frequent used words, and therefore, the corpora filtered by the right threshold and frequent-words should exhibit a maximum overlap between them.

Thus, we compile a corpus with teasers constituting only most-frequent words (∼ 20004), and corpora by selecting different values for the

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3https://github.com/codelucas/newspaper/

4covers 80% of the total words occurrences.
Table 3: The table shows clusters of domains and the frequent-keywords in them.

| Domains                        | Instances | avg. article size (words) |
|-------------------------------|-----------|---------------------------|
| Cluster 0 (sports)            | 17,667    | 607.06                    |
| Cluster 1 (economy)           | 22,473    | 574.62                    |
| Cluster 2 (politics)          | 33,073    | 709.73                    |
| Cluster 3 (world)             | 33,073    | 695.48                    |
| Cluster 4 (entertainment)     | 16,603    | 498.65                    |
| Cluster 5 (crime & law)       | 16,603    | 498.65                    |
| Cluster 6 (climate & disasters)| 16,603    | 544.68                    |
| Cluster 7 (health & lifestyle)| 43,505    | 631.17                    |

Table 4: The table shows contributions of each domain in the corpus.

| Threshold | Overlap-Ratio |
|-----------|---------------|
| 0.001     | 0.67          |
| 0.002     | 0.59          |
| 0.003     | 0.51          |
| 0.004     | 0.43          |
| 0.005     | 0.35          |

Figure 2: Overlap-ratio of frequency-based and threshold-based filtered teasers for domains (c#).

We select 0.003 as the final threshold value as it filters most number teasers and show maximum overlap for all domains; see Table 5 for examples.

2.2.2 Document Level

Abstractive, the other principle characteristic of the teaser, implies that the teaser should exhibit content overlap with its source, but not a full overlap. A full-overlap is likely to be a case where a teaser is a substring of the lead sentence of the article while a non-overlap is likely to be a click-bait. Further, a quote teaser will exhibit a high degree of overlap while a short punchy statement will exhibit a low degree overlap.

We rely on Sidhaye and Cheung (2015)’s method of computing the percentage match between two stemmed texts for grading the abstractive ness. We obtain unigrams of first, $t_1$, and second text, $t_2$, using function $\text{uni}(x)$ and compute the percentage match using Eq. 2:

$$\text{perc_match}(t_1, t_2) = \frac{|\text{uni}(t_1) \cap \text{uni}(t_2)|}{|\text{uni}(t_1)|}$$

Given a data instance, the $\text{perc_match}$ scores between the teaser and windows of the article sentences are computed and the highest score window is selected as the prominent section that the teaser indicates of. We filter out instances where the match score between the teaser and its prominent section is above 80% or below 20%. The intuition behind the approach is that the curiosity arousing words are likely to be absent from the prominent section than the whole article and an absence of minimum 2-3 words (often 20%) is the easiest way to ascertain this fact. Analogously, a presence of minimum 2-3 words from source asserts that it is not a click-bait.

Comparing ShortTexts

The two ShortTexts, headline and teaser, have their distinct conveyance mediums and therefore
designed differently, e.g., mean lengths of 10 and 14 respectively. However, abstractivity is also presumed for the headline. So, we conduct additional overlap based studies to understand the differences in the abstractive property between them. We compute and plot the distribution of the overlaps between teasers ($t_1$) and articles ($t_2$), and one between headlines ($t_1$) and articles ($t_2$); see Figure 3a and Figure 3b for respective plot. Clearly, compared to the teaser, headline distribution is left-skewed (mean 77% and std 20%), and thereby implying headlines being a lesser abstractive than teasers. Further, a review of few instances of headline-article instances with lesser than 60% overlap reveals cases of noisy headlines or HTML parse failures; therefore, in a typical scenario a headline with a size of 10 words takes nearly all of its content (≈80%) from the source while a teaser of size 14 has sufficient non-extractive contents (≈32%).

Additionally, we also plot the density of the overlap scores between the two ShortTexts; see Figure 4. Evidently, a large group of teasers is distinct from headlines. However, as they often have some prominent section, they also exhibit a range of overlaps. A closer look at the full overlap cases of Figure 4 reveals teaser either a reformatted, extract, or social media themes adorn form of the headline. These cases are difficult to separate, so we filter out all the full-overlap cases.

We combine the domain and document levels methodologies to devise a pipeline for recognizing a teaser. We use notations like uppercase bold text for matrix, lowercase bold for vector or array, and lowercase normal for scalar. Data denotes an instance of the corpus. Algorithm 1 describes the teaser recognition algorithm.

Algorithm 1 Teaser Recognition
1: global
2: DOMAIN_TFIDF ← Domain_Relevance(corpus)
3: end global
4: procedure IS_TEASER(Data)
5: tfidf ← DOMAIN_TFIDF[Data.domain;]
6: dr_scores ← tfidf[Data.tweet]
7: if all (dr_scores > 0.003) then
8: return False
9: for s in Data_ARTICLE do
10: if (Data.tweet in s) Or (s in Data.tweet) then
11: return False ⊳ sub-string match
12: if Overlap(Data.tweet, Data.headline) > 0.8 then
13: return False ⊳ Overlap procedure uses Eq. 2
14: v ← Array()
15: for W in Window(Data_ARTICLE, 5) do
16: w ← Flatten(W)
17: v.add(Overlap(w, Data.tweet))
18: if 0.2 < Max(v) < 0.8 then:
19: return True
20: return False

3 Experiments
3.1 Models
We experiment with two state-of-the-art neural abstractive summarization techniques, attentive seq2seq (Bahdanau et al., 2014) and pointer seq2seq (See et al., 2017), for the teaser generation. Attentive seq2seq learns to generate a target with words from a fixed vocabulary while pointer seq2seq uses a flexible vocabulary which
Table 6: Rouge Recalls on the standard task of Headline Generation (Gigaword). seq2seq and seq2seq_point are reimplementations of Bahdanau et al. (2014) and See et al. (2017) respectively.

Table 7: Rouge F1-Score for seq2seq model and seq2seq_point models on the teaser task.

a final teaser corpus obtained using Algorithm. 1 that has 140k teaser instances. The corpus is split into non-overlapping 136k, 2k and 2k sets for training, validation, and testing respectively. Validation and test data are confirmed to include events exclusive from the train and to have equal representations of all eight domains. Hyper-parameters are tuned on the validation set. Table 7 shows the models performance on validation and test sets. Clearly, seq2seq_point performs better than seq2seq due to the boost in the recall gained by copying source words through the pointer network. However, compared to headline generation, the scores are lower due to comparably smaller training data and much tougher task.

3.3 Impact of Domain Relevance

We performed additional experiments to study the impact that can be generated using the domain relevance. Although in a baseline experiment a model determines the prominent section and generates the teaser using initial 100 words of the articles, we unburden the model of determining the prominent section by using the window of the prominent sentences instead of initial words, this minimizes the computation iterations. Also, we reduce the vocabulary to 10k. All the other settings are kept intact except the training corpus; this is changed by increasing the proportion of relevance terms in the teasers. New models are trained using equal size training instances sampled out of the revised corpora.

A bucketing of domain relevance percentages into [0%, 40%), [40%, 55%), [55%, 70%), and [70%, 100%) divides the corpus into equal sizes. We evaluate the recalls of the models as it estimates the system recovering of the reference contents, thereby signifying whether model is exposed to rare vocabularies. Figure 5 shows the change in the ROUGE-1 recall. Clearly, increasing the proportion of relevant terms introduces more UNK, a rare word representation, into
• pres. trump lashed out on twitter at the hosts of “ msnbc’s morning ”
• migration agency says more than %% people drowned and presumed dead in myanmar to bangladesh
• computer glitch led to google to be dramatically under-valued this morning
• alt-right activist jason kessler says he was swarmed by a group of charlottesville
• of identical triplets who beat the incredible odds of %%% million to survive

Table 8: Seq2seq_point generated teasers used in the survey-based study.

|                   | On Twitter | Stimulating |
|-------------------|------------|-------------|
|                   | Mean   | Std | Mean   | Std |
| ground-truth      | 0.660  | 0.064 | 0.621  | 0.079 |
| seq2seq_point teaser | 0.588  | 0.078 | 0.559  | 0.089 |
| baseline          | 0.476  | 0.127 | 0.501  | 0.111 |

Table 9: Mean and standard deviation of likelihood of being social-media text and stimulating user to read.

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the training, thereby making the seq2seq generate more of them and therefore reduction in the recall; however, seq2seq_point learns to replace UNK with source words using its pointer network and therefore initially it gains with better exposure of UNK; however later with excessive of UNK it fails to use the pointer network efficiently, thereby reducing the recalls.

4 Human Evaluation

The quantitative evaluations show state-of-the-art models on headline generation task perform moderately on the novel task. This is mostly due to smaller training corpus and deficiency of the quantitative evaluation which is based on percentage overlap between system and reference for computing the score, which fails in case of non-extractive contents as they are heterogeneous in nature. The corpus is small despite several months of collections because the number of articles from the recognized organizations are small or not shared with teasers. Furthermore, we took a closer look at some of the generated examples, see Table 8, and observed frequent cases where generation suffered from typical problems, e.g. repetition of words, occurrences of UNK; however, there are also cases where generation are distinctive than ground-truth and are well formed too. Thus, we carried out a small survey to understand the quality of the generated teasers; however, we only selected non-repeating and non-UNK generations in order to anonymize the generation source for the survey.

We assembled a set of texts by randomly sampling 40 seq2seq_point teasers, 40 ground-truth teasers, and 40 lead sentences (baseline), and also established equal representations of the domains. We then assigned 72 sentences (3 per domain per category) to ten participants and asked them to rate for two questions: how likely is the text shared on Twitter for a news story by a news organization and how likely is the text to make a reader want to read the story. The first question helps us recognize participant’s understanding of the teasers, as an informed reader will rate a ground-truth significantly higher than the baseline, and 8 of them recognized it correctly, and their ratings are selected for the evaluation. The second question provides cue on the model capacity in generating inciting texts by learning interesting aspects present in the teaser corpus.

The annotators rated on a scale of 1 to 5; however, we normalized them to avoid the influence of annotators different rating personalities. The results, summarized in Table 9, show that the human written teasers are most likely to be a recognized as a social media text due to its distinct style from the lead sentence, and the model trained on such teasers closely follows it. Similarly, human written teasers are good at stimulating readers to read story compared to the lead sentence and the generated teasers.

5 Related Work

There are studies in utilizing cross-media correlation like coupling newswire with microblogs;
however, most of them involve improving tasks on newswire by utilizing complementary information from microblogs, e.g., improving news article summarization using tweets (Gao et al., 2012; Wei and Gao, 2014), generating event summaries through comments (Wang et al., 2015), etc. There are very limited works on using newswire and generating microblogs, e.g., article tweet generation (Lloret and Palomar, 2013), indicative tweet generation (Sidhaye and Cheung, 2015).

Twitter is a platform for news usability and the posts with URLs, indicative tweets, serve as pitches by the news publishers. Lloret and Palomar (2013) observed a simple executing of off-the-shelf extractive models result in summaries with high quantitative scores but not interesting enough. It suggests that extraction is not only the strategy employed by the author of the teaser. Similarly, Sidhaye and Cheung (2015) analyses of indicative tweets show the narrow overlaps between such tweets and their source limits the application of an extractive method for generating them. However, our controlled compilation of such tweets after a series of filtering show a mean percentage match of 68.3% (std: 16%) with its source; therefore, the mixture nature of such texts suggests for an abstractive study rather than extractive.

Text summarization can be extractive or abstractive. Extractive involve selecting the right set of phrases from the source text. However, unlike simplification by deletion, abstractive involves rewriting, such as reordering, substitution, and insertion. Banko et al. (2000) were the first to formulate the summarization as an abstractive procedure and used statistical machine translation methods for it. The task of short summarization was standardized with the task of short summary generation in the DUC-2003 and DUC-2004 competitions (Over et al., 2007).

Similar to Banko et al. (2000), Cohn and Lapata (2008) used a translation based method of synchronous tree substitution grammar (Eisner, 2003)) for modeling consistent syntactic effects like reordering or lexical substitution. Woodsend et al. (2010) argued quasi-synchronous grammars (QG) are sufficient for mapping a document to its summaries and used an efficient search through the space of QGs to form optimal target summaries. Recently, there has been a significant surge in the data-driven neural networks for NLP tasks (Collobert et al., 2011). The success of seq2seq based architecture (Cho et al., 2014; Sutskever et al., 2014) in machine translation (Sutskever et al., 2014), question answering (Hermann et al., 2015) and many more has popularized it application in text mapping paradigms. The introduction of attention to seq2seq models by Bahdanau et al. (2014) provides generator with the additional source information and in a way addresses longterm dependency issues. In Rush et al. (2015) proposed attentive seq2seq neural network (ABS) for abstractive summarization, the OOV problem was handled by combining local conditional probability with additional features. Chopra et al. (2016) outperformed enhanced ABS with an enhanced encoder and a recurrent decoder, but without handling UNKs. Recently, (Vinyals et al., 2015) showed the target vocabulary for any decoder can be replaced with source items using their pointer network. Gülçehre et al. (2016) introduced a switching network into the attention based seq2seq model for switching the generator between extractive and abstractive modes. Nallapati et al. (2016); See et al. (2017) included this switching network for abstractive summarization and achieved state-of-the-art results on multiple summarization tasks.

6 Conclusion

We defined a novel concept of a teaser, a ShortText amalgamating interesting facts from the news article and curiosity-arousing elements, which is shared on social media to entice broader audiences who get their news on social media. We identified properties like abstractive, teasing, and bona-fide that assist in comparing a teaser with other forms of ShortTexts associated with a news article. Additionally, we compiled a novel dataset of teasers by identifying credible news organization handles on a popular social media, Twitter, collecting their indicative tweets, and selecting those that uphold the teaser properties. We illustrated techniques to control these properties in teasers and verified their impact through experiments. An overlap based comparative study of headlines and teasers shows teasers as abstractive ShortText while headlines as extractive. Thus, we performed neural abstractive summarization studies on teasers and set a strong benchmark on the novel task of teaser generation.
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7 Supplementary Material

7.1 List of Twitter accounts

The following is the list of Twitter accounts from which data was collected.

| Account ID | Account name   |
|------------|----------------|
| 759251     | CNN            |
| 807095     | nytimes        |
| 35773039   | theatlantic    |
| 14677919   | newyorker      |
| 14511951   | HuffingtonPost |
| 1367531    | FoxNews        |
| 28785486   | ABC            |
| 14173315   | NBCNews        |
| 2467791    | washingtonpost |
| 14293310   | TIME           |
| 2884771    | Newsweek       |
| 15754281   | USATODAY       |
| 16273831   | VOAnews        |
| 3108351    | WSJ            |
| 14192680   | NOLAnews       |
| 15012486   | CBSNews        |
| 12811952   | Suntimes       |
| 14304462   | TB_Times       |
| 8940342    | HoustonChron  |
| 16664681   | latimes        |
| 14221917   | phillydotcom   |
| 14179819   | njdotcom       |
| 15679641   | dallasnews     |
| 4170491    | ajc            |
| 6577642    | usnews         |
| 1652541    | reuters        |
| 12811952   | Suntimes       |
| 7313362    | chicagotribune |
| 8861182    | newsday        |
| 17820493   | ocregister     |
| 11877492   | starledger     |
| 14267944   | clevelanddotcom|
| 14495726   | phillyinquirer |
| 17348525   | starttribune   |
| 87818409   | guardian       |
| 15084853   | IrishTimes     |
| 15438913   | mailonline     |
| 5098062    | theeconomist   |
| 17680050   | thescotsman    |
| 16973333   | independent    |
| 4970411    | ajenglish      |

7.2 Parameter Settings

We initialized all weights, including word embeddings, with a random uniform distribution with mean 0 and standard deviation 0.1. The embedding vectors are of dimension 100. All hidden states of encoder and decoder in the seq2seq models are set to dimension 100. We pad short sequences with a special, \( \langle PAD \rangle \). We use Adam with initial learning rate .001 and batch size 32 for training. Texts are lowercased and numbers are replaced by the special symbol %. The token length for the source is limited to 100 and target sequence to 25. The teaser baseline experiments and headline generation use vocabulary size of 30000.