Catching Attention with Automatic Pull Quote Selection

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Abstract

Pull quotes are an effective component of a captivating news article. These spans of text are selected from an article and provided with more salient presentation, with the aim of attracting readers with intriguing phrases and making the article more visually interesting. In this paper, we introduce the novel task of automatic pull quote selection, construct a dataset, and benchmark the performance of a number of approaches ranging from hand-crafted features to state-of-the-art sentence embeddings to cross-task models. We show that pre-trained Sentence-BERT embeddings outperform all other approaches, however the benefit over n-gram models is marginal. By closely examining the results of simple models, we also uncover many unexpected properties of pull quotes that should serve as inspiration for future approaches. We believe the benefits of exploring this problem further are clear: pull quotes have been found to increase enjoyment and readability, shape reader perceptions, and facilitate learning.

1 Introduction

In this paper, we introduce the novel problem of automated pull quote (PQ) selection and analyze several approaches. Ideally thought provoking and succinct, PQs are graphical elements of articles with spans of text pulled from an article by a writer or copy editor to be presented on the page in a more salient manner (French, 2018).

Following the 15 year period between 1965 and 1980 where many newspapers experimented with their design (having previously been graphically similar) (Utt and Pasternack, 1985), some newspapers adopted a more modern design. Supported by preference from readers, aspects of this newer design include a more horizontal or modular layout, the six-column format, additional whitespace around heads, fewer stories, larger photographs, more colour, and more pull quotes (Stone, 1987; Wanta and Gao, 1994; Click and Stempel, 1974).

PQs have been found to serve many purposes, including temptation (with unusual or intriguing phrases, they make strong entrypoints for a browsing reader), emphasis (by reinforcing particular aspects of the article), and improving overall visual balance and excitement (Stovall, 1997; Holmes, 2015). PQ frequency in reading material has also shown to be significantly related to information recall and student ratings of enjoyment, readability, attractiveness (Wanta and Gao, 1994; Wanta and Remy, 1994).

The problem in this work of automatically selecting PQs is distinct from, but related to previously studied problems of headline success prediction (Piotrkowicz et al., 2017; Lamprinidis et al., 2018), clickbait identification (Potthast et al., 2016; Chakraborty et al., 2016; Venneti and Alam, 2018), as well as key phrase extraction (Hasan and Ng, 2014) and document summarization (Nenkova and McKeown, 2012). In the context of convincing a reader to engage in a text, the title tells the reader what the article is about and sets the tone, clickbait makes (often unwarranted) lofty promises of what the article is about, and key phrases and summaries indicate whether the topic or constituent components are of interest to the user. In contrast PQs can provide specific intriguing entrypoints for the reader and maintain interest once reading has begun by providing glimpses of interesting things to come.

In this work we interpret PQ selection as a sentence classification task and create a dataset of news article and their human-selected PQs from a variety of news sources. We consider a wide variety of
approaches to solve this task: (1) handcrafted features, (2) n-gram encodings, (3) pre-trained sentence embeddings (specifically Sentence-BERT \cite{reimers-gurevych-2019-sentence} and predicted position distributions \cite{bohn-etal-2019-modeling}), and (4) cross-task models.

We find that on this dataset, pre-trained Sentence-BERT embeddings work best, with n-grams models close behind. Among the hand-crafted features, we found that reading difficulty, preposition density, and concreteness were the most informative. Motivated by the observation that PQs are not uniformly spread throughout news articles, we also demonstrate that using the predicted position distributions as sentence embeddings performs surprisingly well. Finally, as suggested by cross-task performance, we find that PQ selection is most similar to the task of clickbait identification, with models for headline popularity and summarization performing more poorly.

In summary, the main contributions of this work are as follows:

1. We describe several motivated approaches for PQ selection (Sec. 3).
2. We construct a dataset for training and evaluation of automated PQ selection (Sec. 4).
3. We thoroughly examine the performance of our approaches to gain a deeper understanding of PQs and their relation to other tasks (Sec. 5).

2 Related Work

In this section, we look at three areas of work related to PQ selection: (1) headline quality prediction, (2) clickbait identification, and (3) summarization and keyphrase extraction. These topics also motivates cross-task models whose performance on PQ selection is reported in Section 5.4.

2.1 Headline Quality Prediction

When a reader comes across a news article, the headline is often the first thing given a chance to catch their attention. Once they decide to check out the article, it is up to the content (including PQs) to maintain their engagement. A wide variety of research exists on attracting user attention, one of the core purposes of a pull quote. Understanding and predicting what we find interesting, attention-grabbing, and appealing has been studied for domains such as music \cite{lee-lee-2018-segmenting}, images and video \cite{dhar-rayatdoost-soleymani-2016-exploring}, web-page aesthetics \cite{reinecke-etal-2013-web}, as well as online news article content \cite{lagun-lalmas-2016-readability,davoudi-etal-2019-news}.

Predicting the success of headlines is a strongly motivated and well studied task. The features found to be useful have been relatively consistent. In \cite{piotrkowicz-etal-2017-predicting}, the authors experimented with two sets of features: journalism-inspired (which aim to measure how news-worthy the topic itself is), and linguistic style features (reflecting properties such as length, readability, and parts-of-speech). They found that overall the simpler style features work better than the more complex journalism-inspired features at predicting social media popularity of news articles. The success of simple features is also reflected in \cite{lamprinidis-etal-2018-modeling}, which proposed multi-task training of a recurrent neural network to not only predict headline popularity given pre-trained word embeddings, but also predict its topic and parts-of-speech tags. They found that while the multi-task learning helped, it performed only as well as a logistic regression model using character n-grams. A unique approach to predicting headline performance is taken in \cite{kim-etal-2016-detecting}, where the authors propose a method to model the click-value of individual words given current news trend information.

2.2 Clickbait Identification

The detection of a certain type of headline – clickbait – has been a recently popular task of study. Clickbait is a particularly catchy headline used by news outlets which lure potential readers but usually fail to meet expectations and leave readers disappointed \cite{potthast-etal-2016-clickbait}. We suspect that the task of distinguishing between clickbait and non-clickbait headlines is related to pull quote extraction because both tasks may rely on identifying the catchiness of a span of text. In \cite{venneti-alam-2018-clickbait}, the authors found that measures of topic novelty (estimated using LDA) and surprise (based on word bigram frequency) were strong features for detecting clickbait. A set of 215 features were considered
in (Potthast et al., 2016) including sentiment, length statistics, and many features based on specialized dictionary-based word occurrences, but the authors found that the most successful features were character and word n-grams. The strength of n-gram features at this task is also supported by (Chakraborty et al., 2016). In our work we also demonstrate that n-gram features work well (Sec. 5.2), nearly as effective as state-of-the-art deep pre-trained sentence embeddings.

2.3 Summarization and Keyphrase Extraction

Summarization and keyphrase extraction are two well-studied tasks in natural language processing with the goals of capturing and conveying the main topics and key information discussed in a body of text (Turney, 1999; Nenkova and McKeown, 2012). Keyphrase extraction is concerned with doing this at the level of individual phrases, while extractive document summarization (which is just one type of summarization (Nenkova et al., 2011)) aims to do this at the sentence level. We believe (and provide some evidence in Sec. 5) that the difference between these tasks and PQ selection comes down to their interpretations of importance: while summarization and keyphrase extraction defines importance as the ability to convey representative information, PQs define importance as the ability to intrigue the reader. With this view, PQs and summaries may overlap where the central information of a document is itself intriguing.

Along with their overlapping purposes are related applications. Where keyphrases can be applied to facilitate skimming through highlighting (Turney, 1999) to help find specific information of interest, PQs may facilitate skimming to help find more generally interesting reading material. Where summarization has found applications in education through automated evaluation of summary quality (Sung et al., 2016), PQs have found application here by being able to improve student reading comprehension and recall (Wanta and Gao, 1994; Wanta and Remy, 1994).

Approaches to summarization have roughly evolved from unsupervised extractive heuristic-based methods (Luhn, 1958; Mihalcea and Tarau, 2004; Erkan and Radev, 2004; Nenkova and Vanderwende, 2005; Haghighi and Vanderwende, 2009), to supervised and often abstractive deep-learning approaches (Nallapati et al., 2016b; Nallapati et al., 2016a; Nallapati et al., 2017; Zhang et al., 2019). Approaches to keyphrase extraction fall into similar groups, with unsupervised approaches including (Tomokiyo and Hurst, 2003; Mihalcea and Tarau, 2004; Liu et al., 2009), and supervised approaches including (Turney, 1999; Medelyan et al., 2009; Romary, 2010).

3 Models

We consider four types of approaches for the task of PQ selection: (1) hand-crafted features either motivated by literature or otherwise interesting to study (Sec. 3.1), (2) n-gram features (Sec. 3.2), (3) pre-trained sentence embeddings (Sec. 3.3), and (4) cross-task models (Sec. 3.4). The aim of these approaches, as discussed further in Section 4.2, is to determine the probability that a given article sentence is part of the source text for a pull quote.

3.1 Handcrafted Features

Our handcrafted features can be loosely grouped into three categories: surface, parts-of-speech, and affective. For the classifier we will use AdaBoost (Hastie et al., 2009) with a decision tree base estimator.

3.1.1 Surface Features

- **Length**: Including length of the sentence is motivated by the preference by writers to choose PQs which are concise. To measure length, we will use the total character length, as this more accurately reflects the space used by the text than the number of words.

- **Sentence position**: We consider the location of the sentence in the document (from 0 to 1). This is motivated by the finding in summarization that summary-suitable sentences tend to occur near the beginning (Braddock, 1974) – perhaps a similar trend exists for PQs.

- **Readability**: Motivated by the assumption that a writer will not purposefully choose PQs which are difficult to read, we consider a few readability metric features:
– **Flesch Reading Ease**: This measure defines reading ease in terms of the number of words per sentence and the number of syllables per word (Flesch, 1979):

\[
R_{\text{Flesch}}(\text{text}) = 206.835 - 1.015 \left( \frac{\# \text{words}}{\# \text{sentences}} \right) - 84.6 \left( \frac{\# \text{syllables}}{\# \text{words}} \right) \tag{1}
\]

– **Coleman-Liau Index**: This measure, introduced in (Coleman and Liau, 1975), is designed to be easy to calculate automatically by not requiring syllable counting and is scaled to provide the approximate U.S. grade level necessary to comprehend the text. It considers the average number of letters per word, and average number of sentences per word:

\[
R_{\text{CLI}}(\text{text}) = 5.88 \left( \frac{\# \text{letters}}{\# \text{words}} \right) - 29.6 \left( \frac{\# \text{sentences}}{\# \text{words}} \right) - 15.8 \tag{2}
\]

– **Difficult words**: This measure, \( R_{\text{difficult}} \), simply computes the percentage of unique words which are considered difficult, where “difficult” is defined as being at least six characters long and not in a list of \( \sim 3000 \) words that are easy to understand. The source of the easy words list is given in Section 4.3.

– **Average word length**: While average word length, \( R_{\text{avg. word len}} \), in number of characters, is correlated with reading difficulty, it is conceivable that PQs could have higher average word length than average. The reasoning behind this is that authors can use relatively longer words (e.g. superlatives) to emphasize a passage.

### 3.1.2 Part-of-Speech Features

Part-of-speech (POS) features have appeared in many previous related works on headline popularity and clickbait (Piotrkowicz et al., 2017; Lamprinidis et al., 2018; Kim et al., 2016; Chakraborty et al., 2016). Here, we include the word density of a given POS tag in a sentence as a feature. As suggested by (Piotrkowicz et al., 2017) with respect to guidelines for writing good headlines, we suspect that verbs and adverbs will perform well.

We consider the densities of an extensive set of POS tags\(^1\) and report results on the interesting set described in Table 1.

### 3.1.3 Affective Features

Events or images that are shocking, filled with emotion, or otherwise exciting will attract attention (Schupp et al., 2007). However, this does not necessarily mean that text describing these things will catch a readers interest as reliably (Aquino and Arnell, 2007). Like any other text, a reader must go through the process of decoding its meaning before becoming aware of its interesting qualities. Where individual words are involved, this may be a very fast involuntary process (McCandliss et al., 2003), perhaps behind the success of good headlines and clickbait.

To answer the question of how predictive sentence affective properties are of being part of a PQ, we include the following features:

- **Positive sentiment** \( (A_{\text{pos}}) \) and **negative sentiment** \( (A_{\text{neg}}) \).

- **Compound sentiment** \( (A_{\text{compound}}) \), which combines the positive and negative sentiments to represent overall sentiment between -1 and 1.

\(^1\)The full list of considered POS tags is here: [https://pythonprogramming.net/natural-language-toolkit-nltk-part-speech-tagging/](https://pythonprogramming.net/natural-language-toolkit-nltk-part-speech-tagging/)
- **Valence** \((A_{valence})\) and **arousal** \((A_{arousal})\): Valence refers to the pleasantness of a stimulus and arousal refers to the intensity of emotion provoked by a stimulus (Warriner et al., 2013). In (Aquino and Arnell, 2007), the authors specifically note that it is the arousal level of words, and not valence which is predictive of their effect on attention (measured via reaction time). Measuring early cortical responses and recall, (Kissler et al., 2007) observed that words of greater valence were both more salient and memorable. To measure valence and arousal of a passage, we use the average score for each word using a database of word ratings (Warriner et al., 2013). Stop words are removed and when a word rating cannot be found, a value of 5 is used for valence and 4 for arousal (the mean word ratings).

- **Concreteness** \((A_{concreteness})\): this is “the degree to which the concept denoted by a word refers to a perceptible entity” (Brysbaert et al., 2014). As demonstrated by (Sadoski et al., 2000), concrete texts are better recalled than abstract ones and concreteness is a strong predictor of text comprehensibility, interest, and recall. A concreteness score is computed similar to valence and arousal, with a mean concreteness word rating of 5 used when no value for a word is available.

### 3.2 N-Gram Features

We consider three types of n-gram text representations: character-level, word-level, and POS-tag level. A passage of text is then represented by a vector of the counts of the individual n-grams it contains.

### 3.3 Pre-trained Sentence Embeddings

Distributed word and sentence representations have proven their value at many NLP tasks in recent years (Kiros et al., 2015; Joulin et al., 2016; Cer et al., 2018; Devlin et al., 2018; Reimers and Gurevych, 2019). We evaluate two interesting sentence embedding techniques in this work:

- **Sentence-BERT**: based off the BERT (Bidirectional Encoder Representations from Transformers) language representation model (Devlin et al., 2018). Sentence-BERT is a modification designed to more efficiently produce directly semantically meaningful sentence embeddings (Reimers and Gurevych, 2019). Following (Reimers and Gurevych, 2019) we combine these embeddings with a logistic regression classifier for predicting PQ probability.

- **Predicted position distributions** (PPDs): Described by (Bohn et al., 2019). PPDs are a self-supervised sentence embedding technique where the embedding represents a discrete distribution over \(Q\) quantiles of a document (Eqn. [3]).

\[
PPD_Q(sentence) = (p_1, ..., p_Q), \text{ where } p_i = P(sentence \in \text{quantile } i/Q)
\]  

Our use of this self-supervised embedding technique is motivated by the observation that PQ source sentences do not occur uniformly throughout articles (discussed in Sec. 5.1). As demonstrated by (Bohn et al., 2019) in the context of extractive summarization, using the probability that a sentence occurs at the beginning significantly outperforms other unsupervised summarization algorithms. We use the entire predicted position distribution as a sentence encoding combined with a logistic regression classifier.

### 3.4 Cross-Task Models

In order to test the similarity of the PQ selection task with the related tasks of headline popularity prediction, clickbait identification, and summarization, we use the following models:

- **Headline popularity**: Using Sentence-BERT embeddings and linear regression, we train a model to predict the popularity of a headline. We then apply this model to PQ selection by predicting the popularity of each sentence, scaling the predictions for each article to lie in \([0, 1]\) and interpreting these values as PQ probability.
Clickbait identification: Using Sentence-BERT embeddings and logistic regression, we train a model to discriminate between clickbait and non-clickbait headlines. Clickbait probability is then used as a proxy for PQ probability.

Summarization: Using multiple extractive summarization algorithms, we score each sentence in an article, scale the values to lie in [0, 1], and interpret these values as PQ probability.

4 Experimental Setup

4.1 Dataset Construction

To conduct our experiments, we created a pull quote dataset using articles from several online news outlets: National Post, The Intercept, Ottawa Citizen, and Cosmopolitan. For each news outlet we obtain a list of articles and identify those containing at least one pull quote. From these articles, we extract the following pieces of information were extracted:

- The body: the full list of sentences composing the body of the article.
- The edited PQs: the pulled texts as they appear after being augmented by the editor to appear as pull quotes. This can include replacing pronouns such as “she”, “they”, “it”, with the more precise nouns or proper nouns, or shortening sentences by removing individual words or clauses, or even replacing words with ones of a similar meaning but different length in order to achieve a clean text rag.
- The PQ source sentences: the article sentences from which the edited pull quotes came. In this work, we aim to determine whether a given article sentence belongs to this group or not.

Statistics of the dataset are provided in Table 2. Notably, the total number of articles in the dataset is near 15,000, with a majority coming from National Post. It is also interesting to note that the number of PQ/article varies widely across news outlets, ranging from 1.02/article for Ottawa Citizen, to 2.26/article for The Intercept. Overall, our dataset contains ~26,500 positive samples (sentences in PQs) and ~680,000 negative samples (all non-PQ sentences), for a positive to negative ratio of 1:25. For all experiments, we use the same training/validation/test split of the articles (70/10/20).

|                      | nationalpost | theintercept | ottawacitizen | cosmopolitan | train | val | test | all   |
|----------------------|--------------|--------------|---------------|--------------|-------|-----|------|-------|
| # articles           | 11080        | 1183         | 1082          | 1272         | 10217 | 1459| 2921 | 14597 |
| # PQ                 | 16211        | 2670         | 1083          | 2374         | 15611 | 2207| 4520 | 22338 |
| # PQ/article         | 1.46         | 2.26         | 1.02          | 1.87         | 1.53  | 1.51| 1.55 | 1.53  |
| # sentences/PQ       | 1.17         | 1.23         | 1.32          | 1.24         | 1.19  | 1.18| 1.2  | 1.19  |
| # sentences/article  | 40.48        | 97.93        | 38.34         | 79.01        | 48.38 | 47.65| 48.54 | 48.34 |
| # pos samples        | 18879        | 3277         | 1431          | 2925         | 18504 | 2595| 5413 | 26512 |
| # neg samples        | 429681       | 112572       | 39285         | 97582        | 475829| 66927| 136364| 679120|

Table 2: Statistics of our PQ dataset, composed of articles from four different news outlets. Only articles with at least one PQ are included in the dataset.

4.2 Evaluation

To evaluate PQ selection models, we will use the AUC averaged across articles, as described in Equation 4, where \( a_{\text{inclusions}} \) is the binary vector indicating whether each sentence of article \( a \) is used for a PQ, and \( \hat{a}_{\text{inclusions}} \) contains the corresponding predicted probabilities.

\[
AUC_{\text{avg}} = \frac{1}{\# \text{articles}} \sum_{a \in \text{articles}} AUC(a_{\text{inclusions}}, \hat{a}_{\text{inclusions}}) \tag{4}
\]

This has the following intuitive interpretation: it is the probability that a random true positive sample is ranked by the model above a random true negative sample. By averaging scores across sentences from
individual articles instead of calculating AUC over all sentences at the same time, the evaluation method is compatible with the observation that different articles may be more “pull-quotable” than others. If this observation is not taken into account and articles are combined with computing AUC, the average sentence from an interesting article may be ranked higher than the best sentence from a less interesting article.

4.3 Implementation Details

Here we outline the various tools, datasets, and other implementation details important to our experiments:

- To perform part-of-speech tagging for feature extraction, we use the NLTK 3.4.5 perceptron tagger (Bird et al., 2009).
- To compute sentiment, the VADER Sentiment Analysis tool is used (Hutto and Gilbert, 2014), accessed through the NLTK library.
- Implementations of the readability metrics $R_{\text{Flesch}}$ and $R_{\text{CLI}}$ are provided by the Textstat 0.6.0 Python package. The corpus of easy words for $R_{\text{difficulty}}$ is also made available by this package.
- Valence, arousal word ratings are obtained from the dataset described in (Warriner et al., 2013).
- Concreteness word ratings are obtained from the dataset described in (Brysbaert et al., 2014).
- The Sentence-BERT (Reimers and Gurevych, 2019) implementation and pre-trained models are used for text embedding.
- For PPD models, we use Sentence-BERT for the initial embeddings, and train a neural network with two hidden layers to predict the position distributions. We test a range of $Q$ values: 5, 10, 15, 20, 25, 30. For each $Q$, we use the validation performance averaged across 5 trials to select layer sizes (chosen from (128, 64), (256, 128), (512, 256)) and layer dropouts (chosen from (0.5, 0.5), (0.5, 0.25), (0.25, 0.1), (0, 0)). The Keras library (Chollet and others, 2015) is used to implement the network networks with the Adam optimizer (Kingma and Ba, 2014) (with default Keras settings) and categorical cross-entropy loss. We use selu activations (Klambauer et al., 2017), batch size of 128, and up to 30 epochs with early stopping done with the validation set.
- The clickbait identification dataset introduced by (Chakraborty et al., 2016) is used, which contains 16,000 clickbait samples and 16,000 non-clickbait headlines.
- The headline popularity dataset introduced by (Moniz and Torgo, 2018) is used, which includes feedback metrics for about 100,000 news articles from various social media platforms. For preprocessing, we remove those article where no popularity feedback data is available, and compute popularity by averaging percentiles across platforms. For example, if an article is in the 80th popularity percentile on Facebook and in the 90th percentile on LinkedIn, then it is given a popularity score of 0.85.
- We use the following summarizers: TextRank (Mihalcea and Tarau, 2004), SumBasic (Nenkova and Vanderwende, 2005), LexRank (Erkan and Radev, 2004), and KLSum (Haghighi and Vanderwende, 2009).

2 Available online here: https://github.com/shivam5992/textstat
3 Available online at http://crr.ugent.be/archives/1003
4 Available online at http://crr.ugent.be/archives/1330
5 Can be found online at https://github.com/UKPLab/sentence-transformers We use the bert-base-nli-mean-tokens pre-trained model.
6 Available online at https://github.com/bhargaviparanjape/clickbait/tree/master/dataset
7 Available online at https://archive.ics.uci.edu/ml/machine-learning-databases/00432/Data/
8 Implementations provided by Sumy library, available at https://pypi.python.org/pypi/sumy
• We used the Scikit-learn (Pedregosa et al., 2011) implementations of AdaBoost, decision trees, and logistic regression. To accommodate the imbalanced training data, balanced class weighting was used for the decision trees in AdaBoost and logistic regression.

5 Experimental Results

We present our experimental results for the four types of approaches: handcrafted features (Sec. 5.1), n-gram features (Sec. 5.2), pre-trained sentence embeddings (Sec. 5.3), and cross-task models (Sec. 5.4).

Additionally, in Table 3, we include the PQ sentences selected by several of the models discussed on two test articles.

| Article URL                                                                 | True PQ Source                                                                 |
|---------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| https://nationalpost.com/news/arizona-man-dies-after-taking-chloroquine-for-coronavirus | We will analyze any additional information as it becomes available, the company said in a statement. |

Table 3: The top sentence chosen for each of several models for two different test articles.

5.1 Handcrafted Features

The performance of each of our handcrafted features is provided in Figure 1. There are several interesting observations, including some that support and contradict hypotheses made in Section 3.1.

• Simply using the sentence location works better than random guessing. When we inspect the distribution of this feature value for PQ and non-PQ sentences in Figure 2h, we see that PQ sentences are not uniformly distributed throughout articles, but rather tend to occur slightly more often around a quarter of the way through the article.

• The proportion of difficult words is the second-best handcrafted feature, outperforming other reading difficulty metrics. As we suggested in Section 3.1.1 and reflected in Figure 2b, PQ sentences are indeed easier to read than non-PQ sentences.

• Of the POS tag densities, personal pronoun (PRP) and verb (VB) density are the most informative. Inspecting the feature distributions, we see that PQs tend to have slightly higher PRP density (Fig. 2c) as well as VB density – suggesting that sentences about people doing things are good candidates for PQs. In the following subsection we attempt to further investigate the importance of different POS tags.

• Affective features tended to performed poorer than expected, contradicting our (non-expert) intuition that more exciting or emotional sentences would be chosen for pull quotes. The exception to this is that concreteness is indeed an informative feature, as we can also see in Figure 2c. The improved memorability that comes with more concrete texts (Sadoski et al., 2000) may help explain the beneficial effects of PQ on learning outcomes (Wanta and Gao, 1994; Wanta and Remy, 1994).
The results for our n-gram models are provided in Table 4. Impressively, all n-gram models performed better than all handcrafted features, with the best model, character bi-grams, demonstrating an $AUC_{avg}$ of 76.0. When we inspect the learned logistic regression weights for the best variant of each model type (summarized in Table 5), we find a few interesting observations:

- The highest weighted character bi-grams exclusively aim to identify the beginnings of quotations, suggested that the presence of a quote is highly informative. Curiously, although not show in Tab. 5 due to space limitations, end-of-quotation indicators (i.e. ‘”’ ”) occur among the lowest weighted features. Additionally, presence of a quotation being present but not starting the sentence is a strong negative indicator (i.e. ‘”’ ”).

- Among the lowest weighted character bi-grams are also indicators of numbers, URLs, and possibly twitter handles (i.e. “@”).

- Although the highest weighted words are difficult to interpret together, among the lowest weighted words are those which indicate past tense: “called”, “declined”, “described”, “included”, “suggested”. This suggests a promising approach for PQ selection would include identification of the tense of each sentence.

- The perspective offered by POS tags appears even more difficult to determine. The single highest weighted POS tag sequence, “PDT-RB” (predeterminer-adverb) reflects such phrases as “...both
happily...” or “...all grimly...”. When inspecting the feature weighting of the less successful POS-based model with \( n = 1 \), we see that the EX (existential there) tag is weighted highest, used in such phrases as “There is a place” or “The man said that there are no jobs.”

| token  | \( n \) |
|--------|---------|
|        | 1       | 2       | 3       |
| char   | 71.9    | 76.0    | 74.6    |
| word   | 74.4    | 73.1    | 66.2    |
| pos    | 69.2    | 72.2    | 71.3    |

Table 4: Performance results of the n-gram models tested. Overall, the character-level n-grams worked best (especially with \( n = 2 \)), followed by the word and POS-tag n-grams. A vocabulary size of 1000 was used for all models, and lower-casing was applied for the character and word models.

Table 5: The top ten highest and lowest weighted n-grams for the best character (2-char), word (1-word), and POS-tag (2-POS) models. Weights are the coefficients learned by the corresponding logistic regression model.

5.3 Pre-trained Sentence Embeddings

The results of the two deep pre-trained sentence embedding techniques we evaluate are included in Figure 3. We note the following interesting observations:

- The optimal number of PPD quantiles is around 20, with an \( AUC_{avg} \) of 69.7, below the simpler n-gram features, but still impressive given the low dimensionality and fact that the vectors only represent predicted position. Even with only 5 quantiles, the method outperforms all handcrafted features. The layer sizes for the best PPD model were found to be (128, 64) with dropout rates of (0.25, 0.1).

- If we instead use the true position distributions with the same number of quantiles (i.e. one-hot vectors), the performance is indeed much worse than using the PPD.

- The performance of the pre-trained Sentence-BERT embeddings performs the best out of all approaches tested. However, at 77.6, it is only marginally better than the best n-gram approach with \( AUC_{avg} \) of 76.0.

5.4 Cross-Task Models

The final set of models we consider provide insight into the cross-task performance of models built for the related problems of headline popularity prediction, clickbait identification, and summarization. The results for these models are shown in Table 6. We note the following interesting observations:

Considered holistically, the results suggest that PQs are not designed to inform the reader about what they are reading (the shared purpose of headlines and summaries), so much as they are designed to attract attention and motivate...
Figure 3: Performance results of the PPD models, Sentence-BERT, as well as true sentence quantile distributions. We see that using the predicted position distributions indeed works better than the true position distribution. However, the Sentence-BERT embeddings still considerably outperform the PPDs.

further engagement (the sole purpose of clickbait). However, the considerable performance gap between the clickbait model and PQ-specific models (such as character bi-grams and Sentence-BERT embeddings) suggest that this is only one aspect of choosing good pull quotes.

Another interesting observation is the variability in performance of summarizers at PQ selection with performance ranging from worse-than-random to slightly better than random. After considering the summarization performance of these models as reported together in (Chen et al., 2016), we see that PQ selection performance is not strongly correlated with their summarization performance.

6 Conclusion

In this paper we introduced the interesting task of automated pull quote selection, which has applications in education, writing assistance, and engagement maximization. To approach this problem, we created a PQ dataset with articles coming from a variety of online news outlets. We additionally describe and benchmark four groups of approaches: hand-crafted features inspired by related works and results from psychology and neuroscience, n-grams, deep pre-trained sentence embeddings, and cross-task models.

By closely examining the model results, we report many intriguing findings to inspire further research on PQ selection and related tasks. We find that contrary to our intuition, sentiment is not as an informative of a feature as reading difficulty, personal pronoun density, and concreteness. By examining the highest and lowest weighted n-grams, we also uncover specific non-trivial linguistic patterns found in PQs. We also find that sentences are not uniformly spread throughout articles, and using the predicted position distribution of a sentence leverages this to achieve good performance with very low dimensional sentence embeddings, but not quite as high as n-gram models or Sentence-BERT embeddings. Finally, by comparing to cross-task models we provide evidence suggesting PQs are chosen to catch interest, similar to clickbait, rather than let the reader know more generally what they are reading about.

There are many interesting avenues for future research with regard to pull quotes. While we assume in this work that all true PQs in our dataset are of equal quality, it would be valuable to know the quality of individual PQs. Additionally, the creation of a pull quote by a copy editor can be a complex and nuanced process, where beyond simply selecting the source sentences, they often undergo augmentation of abbreviating, paraphrasing, or replacing words. Thus, instead of PQ selection, future work could consider an editing process to turn the selected sentences into a final edited PQ.
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