GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception

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Abstract

Most research on emotion analysis from text focuses on the task of emotion classification or emotion intensity regression. Fewer works address emotions as a phenomenon to be tackled with structured learning, which can be explained by the lack of relevant datasets. We fill this gap by releasing a dataset of 5000 English news headlines annotated via crowdsourcing with their associated emotions, the corresponding emotion experiencers and textual cues, related emotion causes and targets, as well as the reader’s perception of the emotion of the headline. This annotation task is comparably challenging, given the large number of classes and roles to be identified. We therefore propose a multiphase annotation procedure in which we first find relevant instances with emotional content and then annotate the more fine-grained aspects. Finally, we develop a baseline for the task of automatic prediction of semantic role structures and discuss the results. The corpus we release enables further research on emotion classification, emotion intensity prediction, emotion cause detection, and supports further qualitative studies.

Keywords: emotion, structured learning, role labeling

1. Introduction

Research in emotion analysis from text focuses on mapping words, sentences, or documents to emotion categories based on the models of Ekman (1992) or Plutchik (2001), which propose the emotion classes of joy, sadness, anger, fear, trust, disgust, anticipation and surprise. Emotion analysis has been applied to a variety of tasks including large scale social media mining (Stieglitz and Dang-Xuan, 2013), literature analysis (Reagan et al., 2016; Kim and Klinger, 2019), lyrics and music analysis (Mihalcea and Strapparava, 2012; Dodds and Danforth, 2010), and the analysis of the development of emotions over time (Hellrich et al., 2019).

There are at least two types of questions that cannot yet be answered by these emotion analysis systems. Firstly, such systems do not often explicitly model the perspective of understanding the written discourse (reader, writer, or the text’s point of view). For example, the headline “Djokovic happy to carry on cruising” (Herman, 2019) contains an explicit mention of joy carried by the word “happy”. However, it may evoke different emotions in a reader (e.g., when the reader is a supporter of Roger Federer), and the same applies to the author of the headline. To the best of our knowledge, only one work considers this point (Buechel and Hahn, 2017c). Secondly, the structure that can be associated with the emotion description in text is not uncovered. Questions like “Who feels a particular emotion?” or “What causes that emotion?” remain unaddressed. There has been almost no work in this direction, with only a few exceptions in English (Kim and Klinger, 2018; Mohammad et al., 2014) and Mandarin (Xu et al., 2019; Ding et al., 2019).

With this work, we argue that emotion analysis would benefit from a more fine-grained analysis that considers the full structure of an emotion, similar to the research in aspect-based sentiment analysis (Wang et al., 2016; Ma et al., 2018; Xue and Li, 2018; Sun et al., 2019). Consider the headline: “A couple infuriated officials by landing their helicopter in the middle of a nature reserve” (Kenton, 2019) depicted in Figure 1. One could mark “officials” as the experiencer, “a couple” as the target, and “landing their helicopter in the middle of a nature reserve” as the cause of anger. Now let us imagine that the headline starts with “A cheerful couple” instead of “A couple”. A simple approach to emotion detection based on cue words will capture that this sentence contains descriptions of anger (“infuriated”) and joy (“cheerful”). It would, however, fail in attributing correct roles to the couple and the officials. Thus, the distinction between their emotional experiences would remain hidden from us.

In this study, we focus on an annotation task to develop a dataset that would enable addressing the issues raised above. Specifically, we introduce the corpus GoodNewsEveryone, a novel dataset of English news headlines collected from 82 different sources most of which are analyzed in the Media Bias Chart (Otero, 2018) annotated for emotion class, emotion intensity, semantic roles (experiencer, cause, target, cue), and reader perspective. We use semantic roles, since identifying who feels what and why is essentially a semantic role labeling task (Gildea and Jurafsky, 2000). The roles we consider are a subset of those defined for the semantic frame for “Emotion” in FrameNet (Baker et al., 1998).

We focus on news headlines due to their brevity and density of contained information. Headlines often appeal to a reader’s emotions and hence are a potentially good source for emotion analysis. Besides, news headlines are easy-to-obtain data across many languages, void of data privacy issues associated with social media and microblogging. Further, we opt for a crowdsourcing setting in contrast to an expert-based setting to obtain data annotated that is to a lesser extend influenced by individual opinions of a low number of annotators. Besides, our previous work showed that it is comparably hard to reach an acceptable agreement in such tasks even under close supervision (Kim and Klinger, 2018).

To summarize, our main contributions in this paper are, (1),
that we present the first resource of news headlines annotated for emotions, cues, intensities, experiencers, causes, targets, and reader emotion, (2), design a two-phase annotation procedure for emotion structures via crowdsourcing, and, (3), provide results of a baseline model to predict such roles in a sequence labeling setting. We provide our annotation guidelines and annotations at http://www.ims.uni-stuttgart.de/data/goodnewseveryone.

2. Related Work
Our annotation and modelling project is inspired by emotion classification and intensity prediction as well as role labeling and resources which were prepared for these tasks. We therefore look into each of these subtasks and explain how they are related to our new corpus.

2.1. Emotion Classification
Emotion classification deals with mapping words, sentences, or documents to a set of emotions following psychological models such as those proposed by Ekman (1992) (anger, disgust, fear, joy, sadness, and surprise) or Plutchik (2001); or continuous values of valence, arousal, and dominance (Russell, 1980).

Datasets for those tasks can be created in different ways. One way to create annotated datasets is via expert annotation (Aman and Szpakowicz, 2007; Strapparava and Mihalcea, 2007; Ghazi et al., 2015; Schuff et al., 2017; Buechel and Hahn, 2017c). A special case of this procedure has been proposed by the creators of the ISEAR dataset who make use of self-reporting instead, where subjects are asked to describe situations associated with a specific emotion (Scherer and Wallbott, 1994).

Crowdsourcing is another popular way to acquire human judgments (Mohammad, 2012; Mohammad et al., 2014; Mohammad et al., 2014; Abdul-Mageed and Ungar, 2017; Mohammad et al., 2018), for instance on Amazon Mechanical Turk or Figure Eight (previously known as Crowdflower). Troiano et al. (2019) recently published a data set which combines the idea of requesting self-reports (by experts in a lab setting) with the idea of using crowdsourcing. They extend their data to German reports (next to English) and validate each instance, again, via crowdsourcing.

Lastly, social network platforms play a central role in data acquisition with distant supervision, because they provide a cheap way to obtain large amounts of noisy data (Mohammad, 2012; Mohammad et al., 2014; Mohammad and Kiritchenko, 2015; Liu et al., 2017).

We show an overview of available resources in Table 1. Further, more details on previous work can for instance be found in Bostan and Klinger (2018).
2.2. Emotion Intensity

In emotion intensity prediction, the term intensity refers to the degree an emotion is experienced. For this task, there are only a few datasets available. To our knowledge, the first dataset annotated for emotion intensity is by Aman and Szpakowicz (2007), who ask experts to map textual spans to a set of predefined categories of emotion intensity (high, moderate, and low). Recently, new datasets were released for the EmoInt shared tasks (Mohammad and Bravo-Martinez, 2017; Mohammad et al., 2018), both annotated via crowdsourcing through best-worst scaling.

2.3. Cue or Trigger Words

The task of finding a function that segments a textual input and finds the span indicating an emotion category is less researched. First work that annotated cues was done manually by one expert and three annotators on the domain of blog posts (Aman and Szpakowicz, 2007). Mohammad et al. (2014) annotate the cues of emotions in a corpus of 4,058 electoral tweets from the US via crowdsourcing. Similar in annotation procedure, Liew et al. (2016) curate a corpus of 15,553 tweets and annotate it with 28 emotion categories, valence, arousal, and cues.

To the best of our knowledge, there is only one work (Kim and Klinger, 2018) that leverages the annotations for cues and considers the task of emotion detection where the exact spans that represent the cues need to be predicted.

2.4. Emotion Cause Detection

Detecting the cause of an expressed emotion in text received relatively little attention, compared to emotion detection. There are only few works on English that focus on creating resources to tackle this task (Ghazi et al., 2015; Mohammad et al., 2014; Kim and Klinger, 2018; Gao et al., 2015). The task can be formulated in different ways. One is to define a closed set of potential causes after annotation. Then, cause detection is a classification task (Mohammad et al., 2014). Another setting is to find the cause in the text without sticking to clause boundaries. This is formulated as segmentation or clause classification on the token level (Ghazi et al., 2015; Mohammad et al., 2018). Finding the cause of an emotion is widely researched on Mandarin in both resource creation and methods. Early works build on rule-based systems (Lee et al., 2010; Lee et al., 2010; Chen et al., 2010), which examine correlations between emotions and cause events in terms of linguistic cues. The works that follow up focus on both methods and corpus construction, showing large improvements over the early works (Li and Xu, 2014; Gui et al., 2014; Gao et al., 2015; Gui et al., 2016; Gui et al., 2017; Xu et al., 2017; Cheng et al., 2017; Chen et al., 2018; Ding et al., 2019). The most recent work on cause extraction is being done on Mandarin and formulates the task jointly with emotion detection (Xu et al., 2019; Xia and Ding, 2019; Xia et al., 2019). With the exception of Mohammad et al. (2014) who are annotating via crowdsourcing, all other datasets are manually labeled by experts, usually using the W3C Emotion Markup Language¹.

2.5. Semantic Role Labeling of Emotions

Semantic role labeling in the context of emotion analysis deals with extracting who feels (experiencer) which emotion (cue, class), towards whom the emotion is directed (target), and what is the event that caused the emotion (stimulus). The relations are defined akin to FrameNet’s Emotion frame (Baker et al., 1998).

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¹https://www.w3.org/TR/emotionml/, last accessed Nov 27 2019
2.6. Reader vs. Writer vs. Text Perspective
Studying the impact of different annotation perspectives is another little explored area. There are few exceptions in sentiment analysis which investigate the relation between sentiment of a blog post and the sentiment of its comments (Tang and Chen, 2012) or model the emotion of a news reader jointly with the emotion of a comment writer (Liu et al., 2013).

Yang et al. (2009) deal with writer’s and reader’s emotions on online blogs and find that positive reader emotions tend to be linked to positive writer emotions. Buechel and Hahn (2017a) and Buechel and Hahn (2017b) look into the effects of different perspectives on annotation quality and find that the reader perspective yields better inter-annotator agreement values.

Haider et al. (2020) create an annotated corpus of poetry, in which they make the task explicit that they care about the emotion perceived by the reader, and not an emotion that is expressed by the author or a character. They further propose that for the perception of art, the commonly used set of fundamental emotions is not appropriate but should be extended to a set of aesthetic emotions.

3. Data Collection & Annotation
We gather the data in three steps: (1) collecting the news and the reactions they elicit in social media, (2) filtering the resulting set to retain relevant items, and (3) sampling the final selection using various metrics.

The headlines are then annotated via crowdsourcing in two phases by three annotators each in the first phase and by five annotators each in the second phase. As a last step, the annotations are adjudicated to form the gold standard. We describe each step in detail below.

3.1. Collecting Headlines
The first step consists of retrieving news headlines from the news publishers. We further retrieve content related to a news item from social media: tweets mentioning the headlines together with replies and Reddit posts that link to the headlines. We use this additional information for subsampling described later.

| Emotion       | Random | Entities | NRC | ReddIt | Twitter | Total |
|---------------|--------|----------|-----|--------|---------|-------|
| Anger         | 257    | 350      | 377 | 150    | 144     | 1278  |
| Annoyance     | 94     | 752      | 228 | 2      | 42      | 1118  |
| Disgust       | 125    | 98       | 89  | 31     | 50      | 392   |
| Fear          | 255    | 251      | 255 | 100    | 149     | 1010  |
| Guilt         | 218    | 221      | 188 | 51     | 83      | 761   |
| Joy           | 122    | 104      | 95  | 70     | 68      | 459   |
| Love          | 6      | 51       | 20  | 0      | 4       | 81    |
| Pessimism     | 29     | 79       | 67  | 20     | 58      | 253   |
| Neg. Surprise | 351    | 352      | 412 | 216    | 367     | 1698  |
| Optimism      | 38     | 196      | 114 | 36     | 47      | 431   |
| Pos. Surprise | 179    | 332      | 276 | 103    | 83      | 973   |
| Pride         | 17     | 111      | 42  | 12     | 17      | 199   |
| Sadness       | 186    | 251      | 281 | 203    | 158     | 1079  |
| Shame         | 112    | 154      | 140 | 44     | 114     | 564   |
| Trust         | 32     | 97       | 42  | 2      | 6       | 179   |
| Total         | 2021   | 3399     | 2626| 1040   | 1390    | 10470 |

Table 2: Sampling methods counts per adjudicated emotion.

We manually select all news sources available as RSS feeds (82 out of 124) from the Media Bias Chart (Otero, 2019), a project that analyzes reliability (from original fact reporting to containing inaccurate/fabricated information) and political bias (from most extreme left to most extreme right) of U.S. news sources. To have a source with a focus on more positive emotions, we include Positive. News in addition.

Our news crawler retrieved daily headlines from the feeds, together with the attached metadata (title, link, and summary of the news article) from March 2019 until October 2019. Every day, after the news collection finished, Twitter was queried for 50 valid tweets for each headline. In addition to that, for each collected tweet, we collect all valid replies and counts of being favorited, retweeted and replied to in the first 24 hours after its publication.

The last step in the pipeline is acquiring the top (“hot”) submissions in the /r/news4, /r/worldnews4 subreddits, and their metadata, including the number of up- and down-votes, upvote ratio, number of comments, and the comments themselves.

3.2. Filtering & Postprocessing
We remove headlines that have less than 6 tokens (e.g., “Small or nothing”, “But Her Emails”, “Red for Higher Ed”), as well as those starting with certain phrases, such as “E.,” “Watch Live,” “Playlist,” “Guide to,” and “Ten Things”. We also filter-out headlines that contain a date (e.g., “Headlines for March 15, 2019”) and words from the headlines which refer to visual content (e.g. “video”, “photo”, “image”, “graphic”, “watch”).

3.3. Sampling Headlines
To acquire data across a wide political and stylistic spectrum, we stratify the remaining headlines by source (150 headlines...
4) select the headlines with high impact on social media.

Table 2 on the previous page shows how many headlines are retweeted on Twitter, as well as most upvoted and most commented on posts on Reddit.

Sampling based on Reddit & Twitter. The last sampling strategy involves Twitter and Reddit metadata. This enables us to select and sample headlines based on their impact on social media (under the assumption that this correlates with the emotional connotation of the headline). This strategy chooses them equally from the most favorited tweets, most retweeted headlines on Twitter, most replied to tweets on Twitter, as well as most upvoted and most commented on posts on Reddit.

Table 2 on the previous page shows how many headlines are selected by each sampling method in relation to the most dominant emotion, which is the first of our annotation steps described in Section 3.4.1.

3.4. Annotation Procedure

Using these sampling and filtering methods, we select 9,932 headlines. Next, we set up two questionnaires (see Table 3) for the two annotation phases that we describe below. We use Figure Eight.

3.4.1. Phase 1: Selecting Emotional Headlines

The first questionnaire is meant to determine the dominant emotion of a headline if that exists, and whether the headline triggers an emotion in a reader. We hypothesize that these two questions help us to retain only relevant headlines for the next, more expensive, annotation phase.

During this phase, 9,932 headlines were annotated each by three annotators. The first question of the first phase (P1Q1) is: “Which emotion is most dominant in the given headline?” and annotators are provided a closed list of 15 emotion categories to which the category No emotion was added. The second question (P1Q2) aims to answer whether a given headline would stir up an emotion in most readers. The annotators could choose one from only two possible answers (yes or no, see Table 3 and Figure 1 for details).

Our set of 15 emotion categories is an extended set over Plutchik’s emotion classes and comprises anger, annoyance, disgust, fear, guilt, joy, love, pessimism, negative surprise, optimism, positive surprise, pride, sadness, shame, and trust. Such a diverse set of emotion labels is meant to provide a more fine-grained analysis and equip the annotators with a wider range of answer choices.

3.4.2. Phase 2: Emotion and Role Annotation

The annotations collected during the first phase are automatically ranked, and the ranking is used to decide which headlines are further annotated in the second phase. Ranking consists of sorting by agreement on P1Q1, considering P1Q2 in the case of ties. The top 5,000 ranked headlines are annotated by five annotators for emotion class, intensity, reader emotion, and other emotions in case there is not only one emotion. Along with these closed annotation tasks, the annotators are asked to answer several open questions, namely (1) who is the...
We test the annotators on a set of 1,100 test questions for which the annotator agrees with the response chosen (total $2,720.00). After we collected all annotations, we found unreliable annotations. The first step was to discard wrong annotations for open questions, such as annotations in languages other than English, or annotations of spans that were not part of the headline. In the next step, we incrementally apply a set of rules to the annotated instances in a one-or-nothing fashion. Specifically, we incrementally test each instance for several criteria in such a way that if at least one criterion is satisfied, the instance is accepted and its adjudication is finalized. Instances that do not satisfy at least one criterion are adjudicated manually by us.

### 3.4.3 Quality Control and Results

To control the quality, we ensured that a single annotator annotates a maximum of 120 headlines (this protects the annotators from reading too many news headlines and from dominating the annotations). Secondly, we let only annotators who geographically reside in the U.S. contribute to the task.

We test the annotators on a set of 1,100 test questions for the first phase (about 10% of the data) and 500 for the second phase. Annotators were required to pass 95%. The questions were generated based on hand-picked non-ambiguous real headlines through swapping out relevant words from the headline in order to obtain a different annotation, for instance, for “Djokovic happy to carry on cruising”, we would swap “Djokovic” with a different entity, the cue “happy” to a different emotion expression.

Further, we exclude Phase 1 annotations that were done in less than 10 seconds and Phase 2 annotations that were done in less than 70 seconds.

After we collected all annotations, we found unreliable annotators for both phases in the following way: for each annotator and for each question, we compute the probability with which the annotator agrees with the response chosen by the majority. If the computed probability is more than two standard deviations away from the mean, we discard all annotations done by that annotator.

On average, 310 distinct annotators needed 15 seconds in the first phase. We followed the guidelines of the platform regarding payment and decided to pay for each judgment $0.02 for Phase 1 (total of $816.00). For the second phase, 331 distinct annotators needed on average ≈1:17 minutes to perform one judgment. Each judgment was paid with $0.08 (total $2,720.00).

### 3.5 Adjudication of Annotations

In this section, we describe the adjudication process we undertook to create the gold dataset and the difficulties we faced in creating a gold set out of the collected annotations. The first step was to discard wrong annotations for open questions, such as annotations in languages other than English, or annotations of spans that were not part of the headline. In the next step, we incrementally apply a set of rules to the annotated instances in a one-or-nothing fashion. Specifically, we incrementally test each instance for several criteria in such a way that if at least one criterion is satisfied, the instance is accepted and its adjudication is finalized. Instances that do not satisfy at least one criterion are adjudicated manually by us.

**Relative Majority Rule.** This filter is applied to all questions regardless of their type. Effectively, whenever an entire annotation is agreed upon by at least two annotators, we use all parts of this annotation as the gold annotation. Given the headline depicted in Figure 1 with the following target role annotations by different annotators: “A couple”, “None”, “A couple”, “officials”, “their helicopter”. The resulting gold annotation is “A couple” and the adjudication process for the target ends.

**Most Common Subsequence Rule.** This rule is only applied to open text questions. It takes the most common subsequence of all annotations. In the headline above, the experiencer annotations “A couple”, “infuriated officials”, “officials”, “officials”, “infuriated officials” would lead to “officials”.

**Longest Common Subsequence Rule.** This rule is only applied if two different intersections are the most common (previous rule), and these two intersect. We then accept the longest common subsequence. Revisiting the example for deciding on the cause role with the annotations “by landing their helicopter in the nature reserve”, “by landing their helicopter”, “landing their helicopter in the nature reserve”, “a couple infuriated officials”, “infuriated” the adjudicated gold is “landing their helicopter in the nature reserve”.

Table 4 shows through examples of how each rule works and how many instances are “solved” by each adjudication rule.

| Rule                          | Cue         | Exp. | Cause | Target |
|-------------------------------|-------------|------|-------|--------|
| 1. Majority                   | 3,872       | 4,820| 3,678 | 3,308  |
| 2. Most common subsequence    | 163         | 70   | 1,144 | 1,163  |
| 3. Longest common subseq.     | 349         | 74   | 170   | 419    |
| 4. Noun Chunks                | 0           | 11   | 0     | 0      |
| 5. Manual                     | 611         | 25   | 38    | 110    |

Table 4: Heuristics used in adjudicating gold corpus in the order of application on the questions of the type open and their counts. \( w_i \) refers to the word with the index \( i \) in the headline, each set of words represents an annotation.

**Noun Chunks** For the role of experiencer, we accept only the most-common noun-chunk(s).  

The annotations that are left after being processed by all the rules described above are being adjudicated manually by the authors of the paper. We show examples for all roles in Table 5.

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\( ^7 \) We used spaCy’s named entity recognition model: https://spacy.io/api/annotation\#named-entities, last accessed Nov 25, 2019
We use Fleiss’ Kappa ($\kappa$) to measure the inter-annotator agreement for closed questions (Artstein and Poesio, 2008; Fleiss et al., 2013). Besides, we report the average percentage of overlaps between all pairs of annotators (%) and the mean entropy of annotations in bits. Higher agreement correlates with lower entropy. As Table 6 shows, the agreement on the question whether a headline is emotional or not obtains the highest agreement (.34), followed by the question on intensity (.22). The lowest agreement is on the question to find the most dominant emotion (.09).

### 4. Analysis

#### 4.1. Inter-Annotator Agreement

We calculate the agreement on the full set of annotations from each phase for the two question types, namely open vs. closed, where the first deal with emotion classification and second with the roles cue, experiencer, cause, and target.

##### 4.1.1. Emotion

We use Fleiss’ Kappa ($\kappa$) to measure the inter-annotator agreement for closed questions (Artstein and Poesio, 2008; Fleiss et al., 2013). Besides, we report the average percentage of overlaps between all pairs of annotators (%) and the mean entropy of annotations in bits. Higher agreement correlates with lower entropy. As Table 6 shows, the agreement on the question whether a headline is emotional or not obtains the highest agreement (.34), followed by the question on intensity (.22). The lowest agreement is on the question to find the most dominant emotion (.09).

#### Table 5: Example of linguistic realizations of the different roles.

| Role   | Chunk | Examples                                                                 |
|--------|-------|--------------------------------------------------------------------------|
| Exp    | NP    | cops, David Beckham, Florida National Park, Democrats, El Salvador’s President, former Trump associate illegal immigrant, muslim women from Sri Lanka, indian farmers, syrian woman, western media, dutch doctor |
| AdjP   | NP    | life lessons, scandal, no plans to stop, rebellion, record, sex assault   |
| Cue    | NP    | infuriates, fires, blasts, pushing, doing drugs, will shock              |
| Cause  | VP    | escaping the dictatorship of the dollar, giving birth in the wake of a storm |
| Clause | NP    | pensioners being forced to sell their home to pay for care               |
| Target | AdvP  | lazy students                                                           |
|        | NP    | nebraska flood victims, immigrant detention centers, measles crisis      |

#### Table 6: Agreement statistics on closed questions. Comparing with the questions in Table 3, Emotional/Non-Emotional uses the annotations of Phase 1 Question 1 (P1Q1). In the same way, Reader perception refers to P1Q2. Dominant Emotion is P2Q1, Intensity is linked to P2Q2, Other Emotions to P2Q8, and Reader Emotions to P2Q9.

| Emot./Non-Emot. | Reader Percep. | Dom. Emot. | Other Emotions | Reader Emotions |
|-----------------|----------------|------------|----------------|-----------------|
| Agreement       |                |            |                |                 |
| $\kappa$        | 0.34           | 0.09       | 0.09           | 0.22            |
| %               | 0.71           | 0.69       | 0.17           | 0.92            |
| H (in bits)     | 0.40           | 0.42       | 1.74           | 0.13            |

#### Table 7: Percentage agreement per emotion category on most dominant emotion (second phase). Each column shows the percentage of emotions for which the # of annotators agreeing is greater than 2, 3, 4, and 5

| Type          | $\kappa$ | $F_1$ | % Tok. | MASI | H   |
|---------------|----------|-------|--------|------|-----|
| Experiencer   | .40      | .43   | .36    | .56  | .35 | .72 |
| Cue           | .31      | .39   | .30    | .73  | .55 | .94 |
| Cause         | .28      | .60   | .16    | .58  | .47 | .58 |
| Target        | .15      | .36   | .12    | .45  | .54 | .04 |

#### Table 8: Pairwise inter-annotator agreement (mean) for the open questions annotations. We report for each role the following scores: Fleiss’s $\kappa$, Accuracy, $F_1$ score, Proportional Token Overlap, MASI and Entropy

All metrics show comparably low agreement on the closed questions, especially on the question of the most dominant emotion. This is reasonable, given that emotion annotation is an ambiguous, subjective, and difficult task. This aspect lead to the decision of not purely calculating a majority vote label but to consider the diversity in human interpretation of emotion categories and publish the annotations by all annotators.

Table 7 shows the counts of annotators agreeing on a particular emotion. We observe that Love, Pride, and Sadness show highest intersubjectivity followed closely by Fear and Joy. Anger and Annoyance show, given their similarity, lower scores. Note that the micro average of the basic emotions (+ love) is .21 for when more than five annotators agree.

### 4.1.2. Roles

Table 8 presents the mean of pair-wise inter-annotator agreement for each role. We report average pair-wise Fleiss’ $\kappa$, span-based exact $F_1$ over the annotated spans, accuracy, proportional token overlap, and the measure of agreement on set-valued items, MASI (Passonneau, 2004). We observe a fair agreement on the open annotation tasks. The highest agreement is for the role of the Experiencer, followed by Cue, Cause, and Target.

This seems to correlate with the length of the annotated
spans (see Table 9). This finding is consistent with Kim and Klinger (2018). Presumably, Experiencers are easier to annotate as they often are noun phrases whereas causes can be convoluted relative clauses.

### 4.2. General Corpus Statistics

In the following, we report numbers of the adjudicated data set for simplicity of discussion. Please note that we publish all annotations by all annotators and suggest that computational models should consider the distribution of annotations instead of one adjudicated gold. The latter would be a simplification which we consider to not be appropriate. GoodNewsEveryone contains 5,000 headlines from various news sources. Overall, the corpus is composed of 56,612 words (354,173 characters), out of which 17,513 are unique. The headline length is short, with 11 words on average. The shortest headline contains six words, while the longest headline contains 32 words. The length of a headline in characters ranges from 24 the shortest to 199 the longest.

Table 9 presents the total number of adjudicated annotations for each role in relation to the dominant emotion. GoodNewsEveryone consists of 5,000 headlines, 3,312 of which have an annotated dominant emotion via majority vote. The rest of the 1,688 headlines (up to 5,000) ended in ties for the most dominant emotion category and were adjudicated manually. The emotion category Negative Surprise has the highest number of annotations, while Love has the lowest number of annotations. In most cases, Cues are single tokens (e.g., “infuriates”, “slams”). Causes have the largest proportion of annotations that span more than seven tokens on average (65% out of all annotations in this category).

For the role of Experiencer, we see the lowest number of annotations (19%), which is a very different result to the one presented by Kim and Klinger (2018), where the role Experiencer was the most annotated. We hypothesize that this is the effect of the domain we annotated; it is more likely to encounter explicit experiencers in literature (as literary characters) than in news headlines. As we can see, the Cue and the Cause relations dominate the dataset (27% each), followed by Target (25%) relations.

Table 9 also shows how many times each emotion triggered a certain relation. In this sense, Negative Surprise and Positive Surprise has triggered the most Experiencer, and Cause and Target relations, which due to the prevalence of the annotations for this emotion in the dataset.

Further, Figure 2, shows the distances of the different roles from the cue. The causes and targets are predominantly realized right of the cue, while the experiencer occurs more often left of the cue.

### 4.3. Emotions across News Sources

Table 10 shows the top three media sources for each emotion that has been annotated to be the dominating one and the respective sources for the reader’s emotion. Unsurprisingly for the positive emotions, Joy, Love, Positive Surprise, and Pride there is one common source, namely Positive.News. For strong negative emotions such as Anger and Disgust the top three across the different emotions vary. Though the annotated data for each of the sources is comparably limited, there are a set of interesting findings. Infowars, which the Media Bias Chart categorizes as most right wing and least reliable is found in the list of most frequently being associated with Fear in the reader. Breitbart is found to be associated with Negative Surprise in the reader. However, both these sources are not in the list of the text-level emotion annotation. Surprisingly, BBC and LA Times are in the list of the most associated with fear on the text-level, despite of both sources being relatively neutral and moderately factual. Further, it is noteworthy that Reuters, ABC News, as being categorized as maximally reliable, are not in the top emotion list at all.

This analysis regarding emotions and media sources is also interesting the other way round, namely to check which.
emotions are dominating which source. From all sources we have in our corpus, nearly all of them have their headlines predominantly annotated with surprise, either negative or positive. That could be expected, given that news headlines often communicate something that has not been known. Exceptions are BuzzFeed and The Hill, which are dominated by disgust, CNN, Fox News, Washington Post, The Advocate, all dominated by Sadness, and Economist, Financial Times, MotherJones, all dominated either by Positive or Negative Anticipation. Only Time has most headlines annotated as Joy.

Note that this analysis does not say a lot about what the media sources publish—it might also reflect on our sampling strategy and point out what is discussed in social media or which headlines contain emotion words from a dictionary.

5. Baseline

As an estimate for the difficulty of the task, we provide baseline results. We focus on the segmentation tasks as these form the main novel contribution of our data set. Therefore, we formulate the task as sequence labeling of emotion cues, mentions of experiencers, targets, and causes with a bidirectional long short-term memory network with a CRF layer (biLSTM-CRF) that uses ELMo embeddings (Peters et al., 2018) as input and an IOB alphabet as output.

The results are shown in Table 11. We observe that the results for the detection of emotion expressions perform best, with .48F₁, followed by the detection of causes with .37F₁. The recognition of causes and targets is more challenging, with .14F₁ and .09F₁. Given that these elements consist of longer spans, this is not too surprising. These results are in line with the findings by Kim and Klinger (2018), who report an acceptable result of .3F₁ for experiencers and a low .06F₁ for targets. They were not able achieve any correct segmentation prediction for causes, in contrast to our experiment.

6. Conclusion and Future Work

We introduce GoodNewsEveryone, a corpus of 5,000 headlines annotated for emotion categories, semantic roles, and reader perspective. Such a dataset enables answering instance-based questions, such as, “who is experiencing what emotion and why?” or more general questions, like “what are typical causes of joy in media?” To annotate the headlines, we employ a two-phase procedure and use crowdsourcing. To obtain a gold dataset, we aggregate the annotations through automatic heuristics.

As the evaluation of the inter-annotator agreement and the baseline model results show, the task of annotating structures encompassing emotions with the corresponding roles is a difficult one. We also note that developing such a resource via crowdsourcing has its limitations, due to the subjective nature of emotions, it is very challenging to come up with an annotation methodology that would ensure less dissenting annotations for the domain of headlines.

We release the raw dataset including all annotations by all annotators, the aggregated gold dataset, and the question-naire annotations through automatic heuristics. The released dataset will be useful for social science scholars, since it contains valuable information about the interactions of emotions in news headlines, and gives exciting insights into the language of emotion expression in media. Finally, we would like to note that this dataset is also useful to test structured prediction models in general.

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| Emotion | Dominant Emotion | Reader Emotions |
|---------|------------------|-----------------|
| Anger   | The Blaze, The Daily Wire, BuzzFeed | The Gateway Pundit, The Daily Mail, Talking Points Memo |
| Annoyance | Vice, NewsBusters, AlterNet | Vice, The Week, Business Insider |
| Disgust | BuzzFeed, The Hill, NewsBusters | Mother Jones, The Blaze, Daily Caller |
| Fear    | The Daily Mail, Los Angeles Times, BBC | Palmer Report, CNN, InfoWars |
| Guilt   | Fox News, The Daily Mail, Vice | The Washington Times, Reason, National Review |
| Joy     | Time, Positive.News, BBC | Positive.New, ThinkProgress, AlterNet |
| Love    | Positive.News, The New Yorker, BBC | Positive.New, AlterNet, Twitchy |
| Pessimism | MotherJones, Intercept, Financial Times | The Guardian, Truthout, The Washington Post |
| Neg. Surprise | The Daily Mail, MarketWatch, Vice | The Daily Mail, BBC, Breitbart |
| Optimism | Bussines Insider, The Week, The Fiscal Times | MarketWatch, Positive.New, The New Republic |
| Pos. Surprise | Positive.New, BBC, MarketWatch | Positive.New, The Washington Post, MotherJones |
| Pride   | Positive.New, The Guardian, The New Yorker | Daily Kos, NBC, The Guardian |
| Sadness | The Daily Mail, CNN, Daily Caller | The Daily Mail, CNN, The Washington Post |
| Shame   | The Daily Mail, The Guardian, The Daily Wire | Mother Jones, National Review, Fox News |
| Trust   | The Daily Signal, Fox News, Mother Jones | Economist, The Los Angeles Times, The Hill |

Table 10: Top three media sources in relation to the main emotion in the text and the reader’s emotion.

| Category | P  | R  | F₁ |
|----------|----|----|----|
| Experimenter | 0.44 | 0.53 | 0.48 |
| Cue | 0.39 | 0.35 | 0.37 |
| Cause | 0.19 | 0.11 | 0.14 |
| Target | 0.10 | 0.08 | 0.09 |

Table 11: Results for the baseline experiments.
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