Comments Radar: Dive into Unique Data on All Comments on the Web

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ABSTRACT

We introduce an entity-centric search engine CommentsRadar that pairs entity queries with articles and user opinions covering a wide range of topics from top commented sites. The engine aggregates articles and comments for these articles, extracts named entities, links them together and with knowledge base entries, performs sentiment analysis, and aggregates the results, aiming to mine for temporal trends and other insights. In this work, we present the general engine, discuss the models used for all steps of this pipeline, and introduce several case studies that discover important insights from online commenting data.

CCS CONCEPTS

•Computing methodologies → Natural language processing; Information extraction; Neural networks; •Applied computing \rightarrow IT architectures;

KEYWORDS

opinion mining, user-generated texts, named entity recognition, sentiment analysis, web mining

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1 INTRODUCTION

The amount of text data being produced is overwhelming; over 3 million blog posts are published on the Internet every day [35]. Hundreds of million people comment, reply to comments, and participate in online discussions. There is no question in the immense potential value of user comments, but retrieving and analyzing this valuable information presents a formidable challenge.

In this work, we present a comment search, user preference discovery, and recommendation engine CommentsRadar [6] that continuously scans the Internet and indexes all comments from select Web sites in order to identify trending topics and influencers. The main goal is to provide information retrieval services above and beyond simple search over the comments. We would like to be able to find main topics of discussion, identify trends, extract entities that the texts discuss, link them between articles and comments, find out the general sentiment of user comments towards an entity or an article, find which topics a user is interested in, discover correlations between trending topics, advise online media which topics are likely to become popular, and so on. For this purpose, CommentsRadar combines modern NLP approaches based on deep neural networks to index and analyze the text of online articles along with user comments from top commenting Web sites. Articles and comments cover a wide range of topics, and we discover interesting correlations between different types of articles and entities, finding most influential users and sentiment of user opinions. As a result, our system can be and has been adopted for practical sentiment evaluation of user comments by property/publication over time; Fig. 1 shows a provisional interface of the system.

The paper is organized as follows. In Section 2 we show the methods used in CommentsRadar, including a general system pipeline (Section 2.1), named entity recognition and linking models (Section 2.2), and sentiment analysis (Section 2.3). Section 3 presents our qualitative results in the form of three sample case studies made possible with the CommentsRadar system, and Section 4 concludes the paper.



Figure 1: Sentiment evaluation of comments about the *Tesla* entity by the *CommentsRadar* engine. Given an entity-centric query, the NLP engine retrieves articles and aggregate sentiment of user comments for them. Colored circles represent websites, their size corresponds to the number of articles and comments about this entity, and the horizontal axis shows sentiment.

2 NLP MODELS IN COMMENTSRADAR

2.1 Engine Overview

In this section, we present the pipeline of our engine named *CommentsRadar* that automatically indexes and analyzes all comments written by users on the Web for a wide selection of websites. First, the system collects unstructured texts from top commenting sites in order to identify trending topics and influencers. The system obtains articles from different categories of websites, including:

- (1) "News and Media" sites, e.g., Fox News, Breitbart News, The Guardian;
- (2) "Government and Politics" sites, e.g., The Daily Wire, The Hill, Wonkette;
- (3) "Arts and Entertainment" sites, e.g., TMZ, the Daily Express, The Avocado, and others.

There are two basic strategies to aggregate online comments: querying social media such as *Twitter* with entities extracted from articles or simply collecting all comments under a specific article. Many studies have used Twitter [2, 12, 18, 20], but we believe that the second strategy results in a less noisy dataset, aggregates more opinions, and makes it easier to connect opinions with sources. We crawl commenting sections of tens of thousands of Web sites and aggregate the comment texts. Supported commenting systems include Facebook, Disqus, Viafoura, Spot.IM, and others. All comments are linked to articles they relate to. This pipeline produces a large dataset of user comments linked to the corresponding articles.

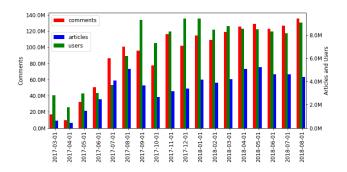


Figure 2: Dataset statistics over time.

Fig. 2 shows the statistics over time; over 2017 and the first half of 2018 we have collected more than 1.67B comments for more than 63.1M articles.

As for now, *CommentsRadar* is in the final stages of the beta—testing the system stability, speed capability, and the overall performance of the NLP pipeline described further. This product helps to deliver unique insight into the types of content consumed online, what online audiences care about. That's powerful information that can be leveraged by both Social Media Influencers, as well as the Agencies and Brand Advertisers that partner with them for greater ROI on their advertising campaigns with precision targeting.

The NLP problem here is to scan and categorize all this information. In the rest of this section, we describe in detail our NLP framework that: (1) extracts from the content of each article the named entities that describe parties, facts, events, and people involved in discussions; (2) performs entity linking between extracted entities and comments; (3) performs sentiment analysis on the comments; (4) aggregates and analyzes the results. In the rest of this section, we describe the architectures used for each NLP component in detail.

2.2 Named Entity Recognition and Linking

In order to select texts about a particular topic, we represent articles by named entities (NE) listing parties, facts, events, and people that come up in discussions. Entities are central to many web search queries; e.g., Lin et al. [24] found that 57% of queries have entities or entity categories and 28% queries contain a reference to a website as an entity, while Guo et al. [13] demonstrated that 71% of search queries contained named entities.

Named Entity Linking (NEL) is the task of assigning entity mentions in a text to corresponding entries in a knowledge base (KB). For example, the entity "Barcelona" in a sentence "They have not lifted a European Trophy since 1991 when they beat Barcelona" should refer to a knowledge base entity FC_Barcelona (the football club) rather than the city. NEL is often regarded as crucial for natural language understanding and commonly used as preprocessing for tasks such as question answering [37] and semantic search [4].

Given a text, the CommentsRadar engine performs NER and NEL. For each article, first a NE recognizer extracts a set of entities: companies, people, products, buildings, location, date, and others. Then an entity linking model labels the entity mentions and provides unambiguous pointers to entities in a knowledge graph (KG) such as Wikipedia. For the first task, we examine several models, including a production-ready pre-trained NER model en_core_web_md from the spaCy library [33] and our implementations of several LSTM-CRF models trained on OntoNotes 5.0 [36]. OntoNotes 5.0 contains a variety of text domains including newswire, broadcast news, broadcast conversation, telephone conversation, and web data. The English newswire portion includes 300K of English Wall Street Journal newswire. Following recent state-of-the-art models [22, 29], our NER models utilize pre-trained word embeddings, two bidirectional LSTM layers, and a conditional random field (CRF) loss [21]. We also experimented with ELMo (Embeddings from Language Models) representations derived from a bidirectional LSTM trained with a coupled language model (LM) objective [30].

The *spaCy* model is based on context-sensitive embeddings and residual convolutional neural networks (CNN) [33]. The NER model from the spaCy library was trained using multi-task learning. Aside from the NER task, the model learned on POS-tagging and dependency parsing tasks. It is reported to achieve F1 measure of 85.9% on the OntoNotes corpus. We have attempted to reproduce this result on several subsets of OntoNotes 5.0 and seen some results differ from the reported.

Table 1 presents the macro-averaged precision (P), recall (R), and F_1 -measure (F) of the spaCy model evaluated on various OntoNotes domains. SpaCy shows high performance on Newswire and Broadcast news types but performs poorly on other types. Following

Table 1: SpaCy evaluation on the OntoNotes dataset.

Document type	Prec.	Rec.	F
Broadcast Conversations	76.33	77.55	76.94
Broadcast News	87.90	88.46	88.18
Magazine Genre	76.92	81.08	78.95
Newswire	87.51	88.61	88.05
Telephone conversations	68.75	69.47	69.11
Web Data	74.47	73.79	73.63

Table 2: Experimental results on the Newswire subset of OntoNotes; 3-layer BiLSTM with char-level embeddings; other models, with GoogleNews embeddings and 512 hidden units.

Model	Prec.	Rec.	F
3-layer BiLSTM(+ELMo)-CRF	86.38	90.40	88.34
1-layer BiLSTM-CRF	83.88	86.92	85.37
2-layer BiLSTM-CRF	85.24	89.62	87.33
2-layer BiGRU-CRF	87.51	88.61	88.05

recent state-of-the-art models [22, 29], we trained our own NER model with ELMo (Embeddings from Language Models) representations [30], bidirectional LSTM layers, and a conditional random field (CRF) loss [21], getting 76.94% F_1 on the Newswire subset of OntoNotes (see Table 2. The results are comparable, and Newswire and Broadcast news are exactly the type of text (and, more importantly, type of entities) we encounter most in *CommentsRadar*, so in the system we used spaCy since its license, unlike the OntoNotes corpus license, allows for commercial use.

For entity linking, we have compared two state of the art models: the TAGME system [9] and a recently proposed multi-relational neural model [23]. TAGME is designed specifically for annotating "on-the-fly" short texts and queries with respect to Wikipedia. TAGME exploits the structure of the Wikipedia graph, scoring all possible relations between mentions and entities and then applying a voting scheme. We adopted the re-implementation of TAGME presented in [14]. Hasibi et al. [14] conclude that there are some technical challenges involved in the TAGME approach and some of the results did not reproduce even with the API provided by TAGME authors. Le and Titov [23] used relations between entities as latent variables in a neural model, training it end-to-end and using CRF to assign the corresponding knowledge base entry to every mention. The authors made the code and pre-trained models publicly available.

AIDA-CoNLL is manually annotated gold standard NEL dataset [16] that contains news from Reuters Corpus V1 used for the CoNLL 2003 NER task. TAGME achieved 58.3% micro-F1 measure on AIDA-CoNLL [7], and the multi-relational neural model achieved 93.07% [23]. In our experiments with the *Daily Mail* dataset (see Section 3), TagMe mapped 54.14% of entity mentions to *Wikipedia* pages, while the multi-relational neural model mapped 70.77%. Thus, we have compared two models—state of the art from the "pre-deep-learning" era and current state of the art—and found considerable advantages of the latter, which we use in the system. Still,

we believe that entity linking for *CommentsRadar* can be further improved, and it is an important direction for further work.

2.3 Sentiment Analysis

The goal of sentiment analysis is to identify and categorize the opinions or feelings expressed in a a piece of text, specifically to determine whether the writer's attitude in general or toward a specific topic is positive, negative, or neutral (as shown in the dashboard of CommentsRadar on Fig. 1). A topic can be anything that users express opinions about: a celebrity (e.g., Taylor Swift), a policy (e.g., Obamacare), a product (e.g., Tesla Model S), an event (e.g., Formula 1 2018 VTB Russian Grand Prix), and so on. Numerous research studies develop sentiment models for a variety of domains and problem settings, ranging from very specific analysis of stance (e.g., whether the author of a text is in favor of or against a given target such as a political candidate [26]) to general (e.g., SemEval 2016/2017 task 4 [27, 31]). Practical applications, however, are usually not as interested in the sentiment of a specific text as in averaged estimates of sentiment scores about mentioned entities in a set of articles and/or their comments over some time interval.

For CommentsRadar, we have developed a sentiment model that classifies user opinions in general regardless of the topic. The neural network used for sentiment analysis consists of an embedding layer followed by CNNs with multiple filters of different lengths [19]. To obtain local features from a text with CNNs, we used multiple filters of different lengths [19], replicating each filter on a hidden layer across the entire input vector, learning the same localized features in every part of the input and subsampling them, as usual for one-dimensional CNNs, with max-over-time pooling layers that output the maximal value of a feature map over a time window. We used filters with window sizes $h \in \{3, 4, 5\}$ and 64 feature maps each. Pooled features were fed to a fully connected layer with softmax activation. We also enhanced this model with pre-trained ELMo word representations [30]. We present an evaluation of our models on the SemEval 2017 Task 4 Subtask A dataset [31] which is publicly available; results are shown in Table 3. SemEval's primary measure was recall averaged across classes, and the DataStories model ranked first in Subtask A with average recall of 68.1% [3]. We see that our best model obtains average recall of 67.98% on the same dataset, and has the advantage of being generic and applicable to CommentsRadar data.

At the same time, there is still plenty of work left for on-going studies since user comments cover many different domains about various entities. Sentiment classification remains challenging: it is difficult to gather annotated training data for all of them. The current experiments are carried out on (i) our in-house annotated data about politicians and electronics, (ii) general 30M user-generated texts annotated with a distant supervision technique [11], and (iii) publicly available datasets such as SemEval data, the Kaggle's toxic comment dataset [17], and the Yahoo news annotated comments corpus [28]. The neural architecture utilizes the multi-domain framework [5, 10, 25] to learn general features that are invariant across domains. Our extensive experiments have also shown that CNN is both efficient and effective over LSTM. An important future extension would be to extract not only the overall sentiment of a post but also stance towards specific mentioned entities.

Table 3: Sentiment classification on SemEval 2017 Task 4 Subtask A; ELMO+CNN and CNN with 64 feature maps; CNN, BiGRU, and BiLSTM with GoogleNews embeddings.

Model	Prec.	Rec.	F
ELMO + CNN	67.07	67.98	67.44
CNN	63.28	64.14	62.64
BiGRU	62.54	60.07	61.21
BiLSTM	61.3	59.75	60.47

3 EXPERIMENTAL RESULTS

In this section, we illustrate the operation of *CommentsRadar* with both qualitative and quantitative results. We present two types of results: analyzing a website to figure out what readers like to discuss the most and find influential commenters and studying the discussions about a particular event in order to understand user sentiment regarding it.

We present three case studies: a middle-market tabloid newspaper (Daily Mail¹), an important political event (Brexit), and an Instagram celebrity (Kendall Jenner). Daily Mail, a top selling newspaper with approximately 14.3 million readers per month in the UK from October 2016 to September 2017 [34], covers a wide range of topics including politics, sports, celebrity news, science, and health stories. The United Kingdom EU membership referendum, also known as Brexit, was held in the UK on June 23, 2016. British Prime Minister Theresa May signed an official letter invoking Article 50 on March 28, 2017 and thus making the UK's intention to leave the EU official. Finally, Kendall Jenner was one of the most popular figures on Instagram and also the subject of a media scandal during the period in question.

We explore *Daily Mail* articles collected by *CommentsRadar* from February 20 to August 8, 2017, linked with user comments from February 20 to June 20, 2017, with 29,101 articles and 2,150,178 comments in total, for a density (mean number of comments per article) of 74, very high for an average over a large website. We ran our entire pipeline, including sentiment analysis, on Brexit-related posts published on the *Daily Mail* website between February and June 2017.

3.1 Daily Mail readership, topics, and influencers

The primary goal of *CommentsRadar* is to aggregate publisher- and user-generated content in order to identify trending topics and influencers. After named entity recognition and linking step, we have found that in the *Daily Mail* dataset the average number of articles per entity was 3.2, while the mean number of comments per entity was 477.33.

Table 4 shows basic statistics: most commented entities sorted by the mean number of comments per article. The most engaging entities are related to the most common news sources in the scope of the data, e.g., Donald Trump. *Instagram* is an anchor entity for many celebrity-related news. City and country names are obviously related to policial centers, and the *Facebook* entity is very popular for two reasons: Facebook also appears as an anchor entity since

¹ http://www.dailymail.co.uk

Table 4: Top entities w.r.t. mean number of comments per article (density).

Entity	# comm.	# art.	Density	Sentiment
United Kingdom	152,613	581	262.67	-0.06
Barack Obama	123,019	474	259.54	-0.22
Donald Trump	379,461	1,593	243.27	-0.22
Washington	1,121,08	478	234.54	-0.14
White House	191,989	836	229.65	-0.20
Facebook	177,019	788	224.64	-0.12
United States	215,350	1203	179.01	-0.10
Russia	120,042	634	189.34	-0.15
Europe	102,889	601	171.96	0.02
Manchester	116,317	701	165.93	0.05
London	236,784	1,510	156.81	0.05
New York	100,434	845	118.85	0.003
Instagram	165,703	1,859	89.14	0.11

Table 5: Entities with highest positive or negative scores mentioned in more than average number of articles (≥ 4).

Entity	Sentiment	# comm.	# art.				
Entities with highest positive sentiment scores							
Dusty Springfield	0.75	40	4				
La Masia	0.72	154	4				
Michael Polish	0.72	58	4				
Federico Fernandez	0.67	11	4				
Banqueting House	0.67	90	4				
Entities with highest negative sentiment scores							
New Jersey State Police	-0.8	7	4				
Vladikavkaz	-0.73	33	4				
Bureau of Consumer Protec-	-0.64	568	4				
tion							
Georgia Diagnostic and Clas-	-0.63	1,528	4				
sification State Prison							
Broadstairs	-0.63	3,174	6				

many news originate there, and also *Facebook Inc.* itself was a subject of political scandals during the spring and summer of 2017.

It is worth noting that many of the most commented entities have an overall neutral or only very slightly polarized sentiment among *Daily Mail* readership. And vice versa, Web sites where entities are mentioned the most usually keep a neutral or at most slightly positive or negative sentiment. For example, on Fig. 1 the largest circles tend to be in the middle. This could be due to the averaging effect over time: Web sites that mention a given entity a lot publish news with different sentiment, about positive and negative events, so the sentiment cancels out over time. This also implies that entities mentioned in fewer articles will be more polarized since the sentiment will be more likely due to only a few newsworthy events; results shown in Table 5 indeed confirm this hypothesis. This leads to the idea of time series sentiment analysis that could be performed by combining NLP and time series analysis techniques.

One important task for a media outlet is to find and analyze its *influencers*; an entire field of influencer marketing focuses on influential people rather than on target markets. For this purpose, we compare different measures of influence: total number of comments, number of replies, combined number of likes for all comments, number of dislikes, and three adaptations of the Hirsch index (h-index) [15], a well-known bibliometric score designed to characterize the scientific output of a researcher by jointly measuring the author's productivity (number of papers) and impact of the author's work (number of citations). Following Grčar et al. [12], we define a user with an index of h as a user that has posted h comments each of which has received a given interaction mark (reply, like, or dislike) at least h times.

So which measures are most suitable for identifying influencers? We considered top 500 users with respect to the number of comments written. Table 6 presents the statistics for this set of users and, for comparison, for the entire dataset. We note that the names and locations of users are gathered manually for this table using the publicly available data from the Daily Mail user profiles. Top 500 users wrote 13.1% of all comments and received 11.8% and 13% of likes and dislikes, respectively. To identify similarities between measures of influence, Fig. 3 reports Pearson correlation coefficients between them: (1) comments_count has, naturally, a high correlation (>0.80) with replies_count, likes_count, and dislikes_count; (2) correlations between h-index-replies and all other measures do not exceed 0.6, also expected since comments get less than 3 replies on average; (3) there is a high correlation (0.81) between h-index-likes and likes_count, while correlation between h-index-likes and comments_count is only 0.53, and a similar effect also holds for dislikes. In general, our experiments show that measures based on likes and dislikes are substantially different from measures based on counting comments or replies.

Moreover, different measures can be indicative of real influence in different domains; e.g., in politics people want to state their opinions and thus write comments, while in celebrity news a like usually suffices. To see that, Table 7 shows some top users ranked by four different metrics. Top users ranked by comments_count and replies_count discuss articles about politicians and international news (the most discussed entities in Table 4 are also mostly political). Top users ranked by h-index-likes are discussing popular celebrities. The case of h-index-dislikes is of separate interest because we see the most controversial topics rising to the top, such as Northern Ireland issues or supporting sports teams, where the body of commenters is naturally divided. Note, however, that the top Daily Mail commenters are typically not the most influential by h-index metrics.

3.2 Sentiment Evaluation of Brexit

For this case study, we evaluated 87,904 user comments linked to 200 articles about Brexit, the British referendum to leave the EU, with 439.52 comments per article on average. We computed the average sentiment of comments for each article. Cumulative sentiment distributions of *Daily Mail* users regarding Brexit are presented on Figs. 4 and 5 show the results. Fig. 5 shows sentiment scores for each day as average sentiment score across all articles published on this day (blue dots). To reduce random fluctuations and see sentiment trends through time, we applied linear interpolation to augment the number of available data points for smoothing and a smoothing

User, City			Num	ber of			Most discussed entities	
	comm.	repl.	likes	h-lk.	dislikes	h-dis.		
Users ranked by comments_count								
Dave, Gosport	3,475	2,932	203,519	136	62,931	72	Donald Trump, United States, United Kingdom, Russia, Paris	
David, Dunmow	2,838	1,829	162,833	132	46,068	69	London, Donald Trump, United States, Chelsea, United Kingdom	
John, Hong Kong	2,296	1,633	177,209	140	36,524	62	Donald Trump, United States, London, United Kingdom, North Korea	
					Users	ranked l	py replies_count	
Dave, Gosport	3,475	2,932	203,519	136	62,931	72	Donald Trump, United States, United Kingdom, Russia, Paris	
Type O Neg, Cheshire	1,394	2,221	62,470	90	14,489	42	London, Catherine Middleton, Martin McGuinness, France, Paris	
Adam March, Kingston	1,513	2,185	62,085	85	14,916	36	London, Manchester, United Kingdom, Instagram, Catherine Middleton	
					Users	ranked l	y h-index-likes	
Bighoss, London	729	20	129,292	175	13,908	46	Kendall Jenner, Instagram, Kourtney Kardashian, Barcelona	
Paul, Lansdale	1,986	942	182,944	157	27,060	55	Kim Kardashian, Donald Trump, North Korea, London, Britain	
JennyO82, NYC	632	29	95,950	151	16,611	56	Instagram, Ivanka Trump, Los Angeles, Bella Hadid, Oscar, Cannes	
Users ranked by h-index-dislikes								
JayR_, Monaco	433	74	20,341	60	50,364	99	Barcelona, Dortmund, Madrid, Cristiano Ronaldo, Liverpool, NHS	
LordBrendan, England	167	15	24,314	56	40,264	94	Martin McGuinness, IRA, Barack Obama, Northern Ireland	
LucidLucinda, Kensington	353	20	101,978	29	24,796	78	London, Donald Trump, Manchester, Jeremy Corbyn, Brexit	

Table 7: The most influential Daily Mail users.

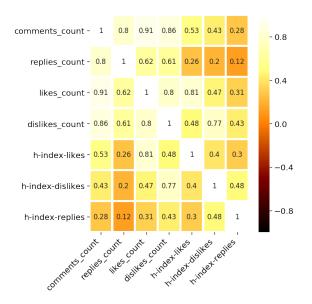


Figure 3: Correlation Matrix.

Table 6: Stats for all and top 500 Daily Mail commenters.

	All	Top 500
# users	54,024	500
# comments	2,150,178	281,019
# replies	1,563,267	233,805
# likes	145,800,587	17,147,338
# dislikes	37,550,303	4,891,883
mean # comments	40	562
mean # replies	29	468
mean # likes	2,699	34,295
mean # dislikes	695	9,784
mean h-index-likes	19.1	66.5
mean h-index-dislikes	9.7	35.9
mean h-index-replies	1.5	2.4

filter by Savitzky and Golay [32]. The smoothed sentiment score is shown with the red line; we also show standard deviations for the smoothed line (light blue area).

Fig. 5 shows the probability density function of the sentiment distribution of posts, with scores from −1 (very negative) to 1 (very positive), with a slightly negative overall pattern, and sentiment changes over time. On March 28, 2017, Theresa May signed a letter invoking Article 50 that formally began the UK's departure from EU. At that day, overall sentiment was neutral. Starting from April 7, 2017, sentiment score tended to decrease from neutral (\approx 0.05) to slightly negative (\approx -0.2). We have also analyzed opinion polls on whether the UK was right to decide to leave the EU conducted by YouGov. Starting from April 26, 2017, it appears that more people thought the Brexit decision was wrong [1, 8], so sentiment changes found for Daily Mail comments do correlate with YouGov opinion polls. It would be interesting to undertake a larger study over a period of several years; previous studies analyzed relations between the mood on Twitter and the referendum outcome [2, 12], but the tweets they used date only from May-June 2016.

3.3 Sentiment Evaluation of an Influencer

In this case study, we investigate how negative comments are influenced by scandals and, generally, press surrounding the entity. We have investigated the case of Kendall Jenner, one of 2017's most popular Instagram influencers and thus a bankable bet for brands and marketers looking to leverage an influencer's following for engagement. We expanded the list of websites for this case study to collect opinions not only from Britain; in total, we found 115,582 user comments linked to 1,009 articles from 129 websites, dating from February 20 to May 25, 2017, with 115 comments per article on average.

Fig. 6 and 7 show the sentiment distribution of posts and its changes over time. There is a clear shift starting in the first week of April: on April 5, *Pepsi* released a commercial featuring Kendall Jenner in a multiracial protest. After massive reaction from groups such as *Black Lives Matter*, *Pepsi* apologized and pulled the advert less than 24 hours after its release. For several weeks, Jenner was a target of ridicule, and comments' sentiment decreased to negative (\approx -0.18); e.g., a *Daily Mail* comment "Clueless stupid girl makes clueless stupid commercial for clueless stupid company. Way to go, Pepsi" gathered 2826 likes and only 111 dislikes. By the end of the month the effect waned, and sentiment became neutral again.

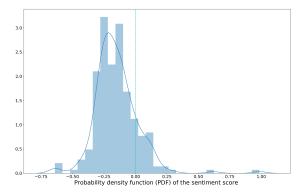


Figure 4: Probability density function (PDF) of the sentiment score.

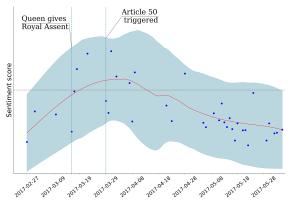


Figure 5: The sentiment evaluation of Brexit over time.

4 CONCLUSION

In this work, we have presented the *CommentsRadar* engine that collects articles and user comments from large Web sites, analyzes them with state of the art NLP models, and allows to draw important conclusions. With qualitative experiments shown in Section 3, we have confirmed that the *CommentsRadar* approach based on state of the art tools for named entity recognition, named entity linking, and sentiment analysis is already a suitable tool for discovering influencers in media outlets and analyzing sentiment over time for entities that appear in the news. Future directions for research include representing entities by both names and relations in category hierarchies, filtering offensive comments, detecting and tracking events over time, and clustering articles according to events.

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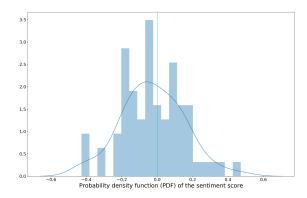


Figure 6: Probability density function (PDF) of the sentiment score.

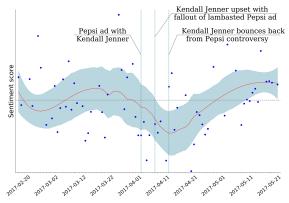


Figure 7: Sentiment evaluation of Kendall Jenner over time.

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