Crowdsourcing Salient Information from Tweets and News

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Abstract

The increasing streams of information pose challenges to both humans and machines. On the one hand, humans need to identify relevant information and consume only the information that lies at their interests. On the other hand, machines need to understand the information that is published in online data streams and generate concise and meaningful overviews. We consider events as prime factors to query for information and generate meaningful context. The focus of this paper is to acquire empirical insights for identifying salience features in tweets and news about a target event, *i.e.*, the event of "whaling". We first derive a methodology to identify such features by building up a knowledge space of the event enriched with relevant phrases, sentiments and ranked by their novelty. We applied this methodology on tweets and we have performed preliminary work towards adapting it to news articles. Our results show that crowdsourcing text relevance, sentiments and novelty *(1)* can be a main step in identifying salient information, and *(2)* provides a deeper and more precise understanding of the data at hand compared to state-of-the-art approaches.

Keywords: crowdsourcing, event salience, event topic space

1. Introduction

The key feature of the current information age is the continuously growing stream of information of various types, *e.g.*, news, tweets, videos, and across various distribution channels, *e.g.*, social, traditional media, personal blogs, information portals. All this results in an inconceivable amount of information redundancy, *i.e.*, the same item is re-shared across different channels in identical or similar forms. This poses challenges both for humans and machines. Humans need to reduce the information overload and to be able to identify the truly novel and relevant information items. Machines need to generate meaningful news clusters (by means of news aggregation systems[1,2]) by identifying the novel information items that are relevant to target stories.

Notions like novelty, relevance, and salience play a central role when dealing with such huge and continuous information streams. Defining these notions is not a trivial task as they are deeply interconnected. We consider salience, or information salience, in the context of relevance and novelty and we adopt the following definitions:

- *novelty*: corresponds to any bit of (relationally) new information. From this point of view, we follow the TREC definition of novelty, that is something which is presented as new with respect to a given context, which corresponds to the known information.
- *relevance*: identifies "something important". Importance can be determined only in relation with something (*e.g.*, an object, a topic, an event, among others) and in a context of occurrence. Subjectivity and intentionality play an important role in determining the relevance of an information item.
- *salience*: combination of novel and relevant information, seen as an incremental and gradable notion: first, relevant information is identified, then, on top of new data, novel information is identified.

Our approach uses relevant information to guide the identification of novel information, where not all relevant information is necessarily novel. Thus, novelty and relevance are strictly linked to time and can be seen as a by-product of the incremental processing of a discourse. Furthermore, they are connected to target discourse elements, *e.g.*, event mentions, entities, topics, which aim to reduce the search space for novel and relevant information. The combination of novelty and relevance can be used to assign salience scores to these elements up to a so-called "saturation" point. This paper describes our methodology to identify salient features in online data streams together with preliminary experimental results. Our approach is based on the novel combination of Natural Language Processing (NLP) and crowdsourcing. It harnesses the unique ability of the crowd to identify a wide range of features (Inel et al., 2013) potentially influencing the information salience of online data with respect to a specific central (linguistic) element. This builds the basis of salience understanding by example and can allow for training machine learning tools for salience detection. Our goal is to identify novel and relevant information which contribute to the assignment of salience scores to a given target event in tweets and news. As a guiding example we use the event "whaling"[3]. Our main findings show that through the crowd we are able to *(1)* first dissect and then recompose the problem in a time stamped collection of salience features of a given event; *(2)* enrich textual information with relevance, novelty, sentiment and intensity values, tasks where automated tools typically under-perform.

The paper is structured as follows. Section 2. describes the methodology for understanding salience and Section 3. introduces the use case and the datasets. Sections 4. and 5. report on the crowdsourcing experiments and the analysis of the results. Section 6. presents state-of-the-art approaches for relevance, novelty and sentiment analysis. Finally, Section 7. presents our conclusions and future work.

[1] Google News, `https://news.google.com`
[2] European Media Monitor, `http://emm.newsexplorer.eu/NewsExplorer/home/en/latest.html`
[3] `https://en.wikipedia.org/wiki/Whaling`

2. Methodology

This section describes the methodological framework that was applied to derive salient features in continuous online data streams. We have applied this methodology for tweets, *i.e.*, very short and concise pieces of information, and we chose to recreate it for news articles, *i.e.*, long and extensive pieces of information. We derive salience from relevant pieces of textual information that bring in new information (*i.e.*, new locations, organizations or word phrases) or new perspectives (*i.e.*, subjective information such as new sentiments or sentiment magnitudes). These two aspects help us to generate and extend the topic space of events.

The methodology is based on machine-generated and crowd-driven understanding of salient features. We use both state-of-the-art approaches and crowdsourcing to:

- build up a set of relevant texts for a given event;
- rank the relevant pieces of information based on the amount of new information they contain, *i.e.*, ranking based on novelty;
- build up a set of subjective perspectives triggered by relevant texts, word phrases or entities participating in the given event.

The information space is first semantically enriched with relevant entities, event mentions, locations, participants, and times, characterized by different relevance scores. Filtering out information pieces that are not relevant for the event at hand optimizes the annotation workflow by focusing the other tasks only on the essential and important data. Furthermore, relevant information can be further analyzed in terms of information novelty. We consider novelty at the content level, *i.e.*, new information contained in the tweets or news article, and at the context level, *i.e.*, sentiments and sentiment magnitudes triggered by the tweet, news snippet and relevant event mentions. Given this, salient features are extracted as a result of relevance and novelty in terms of content and perspectives. Section 5. presents the results of this methodology on a dataset of tweets and introduces first insights on a news article dataset. In addition to this, we show comparative results between state-of-the-art approaches for relevance and sentiment assessment and our crowdsourcing experiments for the same tasks.

3. Use case: Whaling Event

We focus our analysis and experiments on the event instance of "whaling". Table 1 provides an overview of the three datasets used in the experiments presented in this paper. Social Sciences domain experts identified 36 seed words relevant to the event instance of "whaling" distributed in terms of types as follows: 9 seeds denoting locations (*e.g.*, "North Pacific Ocean", "factory ship vessels"), 5 seeds denoting related events(*e.g.*, "hunting", "commercial whaling"), 18 seeds denoting persons or organizations (*e.g.*, "Institute of Cetacean Research", "pro-whaling countries ", "Greenpeace") and 4 seeds denoting miscellaneous types (*e.g.*, "harpoon", "whale meats"). These seed words were used to build the $NewsDS3$ and $Tweet2015DS2$ datasets by querying the NewsReader WikiNews Corpus[4], and by mining the Twitter streaming API[5], respectively.

[4] `http://www.newsreader-project.eu/results/data/`
[5] `https://dev.twitter.com/docs/streaming-apis`

Dataset	Type	Source	Period	Units
Tweet2014DS1	Tweets	Twitter	2014	566
Tweet2015DS2	Tweets	Twitter	2015	430
NewsDS3	News	WikiNews	2005-2010	29

Table 1: Overview of the Whaling Event Datasets.

$Tweet2014DS1$ contains 566 English-language tweets relevant to the event of "whaling" (published in 2014) by querying a Twitter dataset from 2014 with the phrase "Whaling Hunting".

$Tweet2015DS2$ contains 430 English-language tweets relevant to the event of "whaling" (published between March-May 2015). The dataset was obtained by querying the Twitter API with combinations of domain experts' seed words (*e.g.*, event and location, event and organization).

$NewsDS3$ contains 29 English-language news articles from the WikiNews corpus (published between 2005 - 2010) with a total of 14537 tokens.

4. Deriving an Experimental Methodology

We apply the methodology described in Section 2. on the tweets datasets, $Tweet2014DS1$ and $Tweet2015DS2$. Part of the methodology is also applied on the news articles dataset, $NewsDS3$, as preliminary experiments for acquiring salience understanding in broader and lengthier information streams. We target the identification of salient information in the context of "whaling" event by identifying *(1)* relevant pieces of information, *(2)* novel pieces of information contained in the relevant information, and *(3)* sentiments triggered by the relevant pieces of information.

Dataset	Task	Judg/ Unit	Units/ Task	Tasks/ Worker	$/ Task
Tweet2014DS1 Tweet2015DS2	Relevance Analysis	7	1	10	$0.02
NewsDS3	Relevance Analysis	15	1	10	$0.02
Tweet2014DS1 Tweet2015DS2 NewsDS3	Sentiment Analysis	10	1	10	$0.01 - $0.02
Tweet2014DS1 Tweet2015DS2	Novelty Ranking	15	2	20	$0.03

Table 2: Crowdsourcing Tasks Settings.

A cascade of three different crowdsourcing experiments are performed. Table 2 shows the settings of each crowdsourcing task for each dataset. The overall workflow consists of: *(1) "Relevance Analysis"* task: the crowd is asked to identify relevant news snippets, tweets and highlight relevant event mentions in those; *(2) "Sentiment Analysis"* task: the crowd is asked to identify the sentiment of each relevant news snippet, tweet and relevant event mention from the data obtained from the "Relevance Analysis" task; and *(3) "Novelty Ranking"* task: the crowd is asked to rank the relevant tweets from the "Relevance Analysis" according to how much new information they bring in.

4.1. CrowdTruth Approach

We used the CrowdFlower[6] marketplace for running all the crowdsourcing experiments. The results were analyzed in the CrowdTruth framework (Inel et al., 2014) by applying the CrowdTruth metrics and methodology (Aroyo and Welty, 2014; Aroyo and Welty, 2014). These metrics are the basis for assessing the crowd workers, *i.e.*, identifying the quality and low-quality workers, and the probability of the input data to express a given annotation, *e.g.*, the relevance score of the positive sentiment. We introduce here the main components of the CrowdTruth methodology that guide us in analyzing the crowdsourcing experiments described in Sections 4.2., 4.3. and 4.4..

The main component of the CrowdTruth metrics is the *annotation vector*, which enables the comparison of results using cosine similarity measures. For each worker i annotating an input unit u, the vector $W_{u,i}$ records the answer. The length of the vector depends on the number of possible answers in a question, while the number of such vectors depends on the number of questions contained in the task. If the worker selects a particular answer, its corresponding component is marked with 1, and 0 otherwise. Similarly, we compute an *input unit vector* $V_u = \sum_i W_{u,i}$ by adding up all the worker vectors for the given u.

We apply *worker metrics* in order to differentiate between quality and low-quality workers. These metrics, computed using cosine similarity as well, measure *(1)* the pairwise agreement between two workers across all u they annotated in common and *(2)* the similarity between the annotations of a worker and the aggregated annotations of the rest (subtracting the worker vector) of the workers. These measures show us how much a worker disagree with the rest of workers and thus, they identify the low-quality workers. The annotations of the workers that are under-performing are filtered out from the final results. To further verify the accuracy of the CrowdTruth quality metrics we also perform manual evaluation of the results. The *input unit-annotation score* is the core CrowdTruth metric to measure the probability of u to express a given annotation. It is measured for each possible annotation on each u as the cosine between V_u and the unit vector for that annotation.

4.2. Relevance Analysis

The tweet length is suitable for typical crowdsourcing tasks, thus, there is no need for pre-processing of $Tweet2014DS1$ and $Tweet2015DS2$ datasets. On the contrary, to optimize the length of the news articles for the crowdsourcing task, each news article was split into text snippets, *i.e.*, sentences. We obtained between 4 and 38 text snippets per article. The first sentence of each article has been removed as it is just a rephrasing of the title. In total, we extracted 394 snippets: 244 text snippets with overlapping tokens with the title and 150 text snippets without any overlapping tokens.

Next, we performed crowdsourcing experiments on all three datasets. For the news articles dataset, $NewsDS3$, we created 90 crowdsourcing input units containing *(i)* the title of the article (*i.e.*, a mention related to the event "whaling") and *(ii)* up to 5 randomly chosen text snippets. For the tweet datasets, $Tweet2014DS1$ and $Tweet2015DS2$, each tweet represents a crowdsourcing input unit.

During the *"Relevance Analysis"* task, for $NewsDS3$, the crowd is first asked to select all the text snippets which are relevant with respect to the article title and then highlight in them all the relevant event mentions. If none of the text snippets was relevant for the title of the news article, the workers were guided to choose the option "NONE". Based on the annotations gathered during these crowdsourcing experiments, we compose for each news article a set of relevant text snippets and a set of relevant event mentions. Following the CrowdTruth approach, a relevance score is assigned to each text snippet and event mention.

For $Tweet2014DS1$ and $Tweet2015DS2$, the crowd is asked to assign each tweet to the relevant instance from a list of 9 predefined events including the event "whaling" and highlight all the relevant event mentions in it. This results in a set of relevant tweets for each event instance. In this paper we report only on the tweets that are relevant for the event "whaling". The CrowdTruth cosine similarity metric is used to assign a relevance score, *i.e.*, a probability for a tweet to be relevant, with respect to the event instance "whaling" to each tweet and event mention.

4.3. Novelty Ranking

The *"Novelty Ranking"* task was performed only on the tweet datasets, $Tweet2014DS1$ and $Tweet2015DS2$. We first pre-processed the relevant tweets by ordering them in chronological order and computing the similarity of a tweet content (*i.e.*, we removed the (short) links, RT, user/author mentions from the tweet) with all the previous tweets' content in each dataset. We aimed at filtering out all the relevant tweets with a lot of redundant information, which are very unlikely to bring in new information.

This crowdsourcing task consists of a pair-wise comparison of the tweets with the following approach: all the tweets of a particular day are compared to each other, *i.e.*, each tweet is compared with each following tweet in time, resulting in a number of $\frac{n!}{k!*(n-k)!} = \frac{n*(n-1)}{2}$ pairs per day, where n is the total number of unique tweets in a day and k is the number of tweets compared at a time, *i.e.*, $k = 2$. The crowd receives the name of the "whaling" event, a summary of the event, *i.e.*, the top novel tweets from the previous day, and a pair of two tweets. Given the summary, for each pair of tweets the crowd needs to indicate which tweet provides more new information about whaling. The crowd can choose one of the 6 options: *(1)* $Tweet1$ provides more new information than $Tweet2$; *(2)* $Tweet1$ provides less new information than $Tweet2$; *(3)* Both tweets provide equally new information; *(4)* $Tweet1$ is relevant and $Tweet2$ is irrelevant; *(5)* $Tweet1$ is irrelevant and $Tweet2$ is relevant; *(6)* Both tweets are irrelevant. Next, the crowd has to to highlight the words in the tweet that point to new or known information. Given the task setup, we can rank the tweets per day, based on how much new information they bring in with respect to the rest of the tweets in each dataset. The CrowdTruth cosine measure, in this case, provides for each tweet a relevance score and a novelty score.

[6] http://www.crowdflower.com/

4.4. Sentiment Analysis

In the *"Sentiment Analysis"* task we gather from the crowd the sentiment (positive, neutral, negative) and its magnitude (high, medium, low) for *(1)* each relevant tweet and text snippet and *(2)* all the relevant event mentions in those, gathered in the *"Relevance Analysis"* task (Section 4.2.). This task was performed both on the news articles dataset ($NewsDS3$) and on the tweet datasets ($Tweet2014DS1$, $Tweet2015DS2$). We use the CrowdTruth cosine metric to compute sentiment and magnitude scores for each relevant event mention, tweet and text snippet.

To compute the sentiment and sentiment magnitude scores for each event mention, relevant text snippet, and tweet we compute the cosine between the aggregated annotation vector and the unit vector for each label. For example, in order to see what is the probability for a tweet to express a positive sentiment we compute the cosine between the aggregated sentiment vector of the tweet and the unit vector for the positive sentiment.

5. Results

In this section we report on the results[7] of the crowdsourcing tasks. To outline the advantages of using our crowdsourcing approach, we compare the crowdsourcing results with existing, state-of-the-art approaches for relevance and sentiment analysis.

5.1. Crowdsourcing Relevance - Tweets & News

In the *"Relevance Analysis"* task on $Tweet2014DS1$, the crowd identified 476 out of 566 (88%) tweets as being relevant for "whaling", where the relevance score is higher than 0.2. Similarly, on $Tweet2015DS2$ 341 out of 430 (80%) tweets received a relevance score higher than 0.2. In Figure 1a we plot the relevance distribution histogram on the aggregation of the two datasets. More than 55% of the tweets have a high relevance score, above 0.9, while only 10% of the tweets are found at the bottom with a relevance score smaller than 0.5.

Figure 1b shows the distribution of the relevance scores for the tweets. The fact that about 84% of the total amount of tweets are considered relevant, out of which about 90% could indicate highly relevant tweets, shows that retrieving tweets based on relevant keywords or domain experts' seed words returns acceptable results. However, there is still room for improvement, *i.e.*, assessing the relevance of the tweets with regard to the event "whaling" is still necessary.

In Figure 1c we look at the distribution of the total number of relevant event mentions identified by the crowd in each relevant tweet. We observe that less relevant tweets tend to have less relevant mentions, while, the tweets with relevance score between 1 and 0.70 have a tendency to contain approximately equal amount of relevant event mentions.

From the *"Relevance Analysis"* task on $NewsDS3$ we gathered 284 relevant text snippets (205 texts snippets with overlapping tokens with the title and 79 text snippets without overlapping tokens with the title) and 1139 relevant whaling event mentions. The plot in Figure 2a shows the relevance score of the text snippets (those overlapping with the title in blue, those non-overlapping with the title in red) in $NewsDS3$. It confirms the intuition that the overlapping snippets contain more relevant information, with a larger distribution of scores. Relevant information can also be spotted in the non-overlapping snippets, though the distribution of scores and the number of snippets is lower. If we assume the score of 0.5 as a threshold for highly relevant information in a snippet, *i.e.*, every snippet above 0.5 is more prone to contain relevant information, we observe that 79.69% (314 out of 394) of the snippets has obtained scores below the threshold, while only 20.31% (81 snippets) are above the 0.5 value. Furthermore, 70 of the candidate relevant snippets have overlapping tokens while only 11 have non-overlapping tokens. A similar trend is observed for the number of relevant event mentions extracted by the crowd from the snippets, *i.e.*, the more relevant the snippet, the more relevant the event mentions identified by the crowd as shown in Figure 2b.

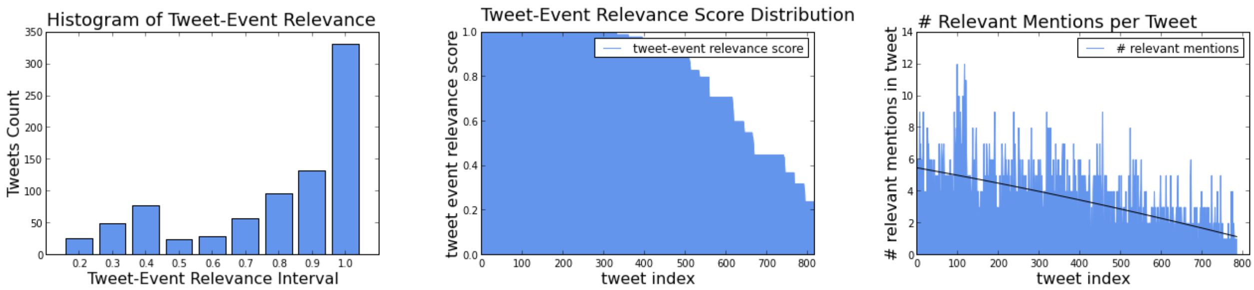
We also investigate whether there is a tendency between the position of snippets in an article and their relevance. We split each article in three sections (beginning, middle and end) and compute the average relevance score for each section. Snippets with the highest average score (0.34) appear in the beginning, followed by snippets in the middle (0.26) and then by those at the end (0.20). Things are similar when we look at the distribution of the text snippets with maximum relevance score per article: 12 snippets occur in the beginning, 9 in the middle and 9 at the end. There is a slightly difference when taking into account the average score of the snippets with maximum score: for the sentences in the beginning the average maximum score is 0.79, for those at the end 0.8 while for those in the middle is 0.73.

5.1.1. Automated Relevance for Tweets and News

We assume that a good method to automatically derive relevance in our three datasets is text similarity: the more similar a text snippet is to the title or a tweet to the seed words, the more relevant the text fragments with respect to the target event. We thus applied an off-the-shelf tool based on a hybrid approach that combines distributional similarity and Latent Semantic Analysis (LSA) with semantic relations from WordNet (Han et al., 2013).

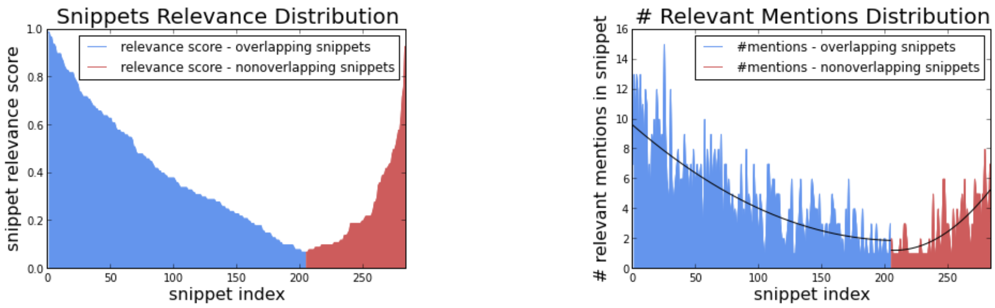
On $Tweet2014DS1$ and $Tweet2015DS2$ we computed the semantic similarity between the tweets and each seed word from the domain experts and then averaged these numbers and computed an overall similarity of the tweet with respect to "whaling". We performed this comparison on each of the datasets, separately. The reason for this was driven by the fact that the two datasets were collected in different ways. The automated similarity approach for tweets returned very low values: between 0 and 0.24 and an average of 0.11 on the $Tweet2014DS1$ dataset, where the crowd average is 0.84. The top scored tweet in this dataset is $TWEET1$ in Example 1, with reference to 3 seed words. Similarly, on $Tweet2015DS2$ the similarity scores range from 0 to 0.23, with even a lower average of 0.09. On $Tweet2015DS2$ dataset, the crowd average score is 0.78. The average values on the two datasets correlate with each other, as the tweets from the second dataset seem to be slightly less relevant with respect to "whaling". On

[7] available at data.crowdtruth.org/salience-news-tweets



(a) Histogram of Relevance Scores in $Tweet2014DS1$ & $Tweet2015DS2$ (b) Distribution of Tweets Relevance in $Tweet2014DS1$ & $Tweet2015DS2$ (c) Distribution of # Relevant Mentions in $Tweet2014DS1$ & $Tweet2015DS2$

Figure 1: Relevance Analysis - $Tweet2014DS1$ & $Tweet2015DS2$



(a) Distribution of Snippets Relevance in $NewsDS3$ (b) Distribution of # Relevant Mentions in $NewsDS3$

Figure 2: Relevance Analysis - $NewsDS3$

$Tweet2014DS1$ we get a positive Spearman correlation of 0.41, while on $Tweet2015DS2$ the correlation is 0.26.
By performing this comparison we can state that usually, non-expert people have different ways to express or refer to a given event, in contrast to domain experts that have very specific terms to compose the space of an event. However, this difference does not prove that the tweets can not contain useful information, *e.g.*, $TWEET2$ in Example 2, but it gives meaningful insights that the topic space given by the experts can be further enriched.

1. *World court orders Japan to stop whaling in Antarctic waters - Christian Science Monitor* [TWEET1]
   Crowd Relevance Score: 1 - **Similarity Score**: 0.24
2. *In a Major Victory, Court Orders a Halt on Japanese Whaling - Slate Magazine (blog)* [TWEET2]
   Crowd Relevance Score: 1 - **Similarity Score**: 0.13

On $NewsDS3$, we computed the semantic similarity between the article title *i.e.*, the event of whaling, and each text snippet from the article. As a general trend, we observed that overlapping text snippets usually have higher similarity scores, while the non-overlapping text snippets have lower scores. However, the relevance scores provided by the automated method have a much smaller interval, between 0 and 0.66. We computed the Spearman correlation between the two relevance values, from the crowd and machine. For the entire set of overlapping and non-overlapping sentences we got a positive Spearman correlation of 0.53. A manual exploration of the differences between the automatically assigned similarity scores and the crowd relevance score shows there is still room for improvement for the automatic methods and that news systems, more oriented to capturing relevance rather than similarity, need to be developed. Below we illustrate some examples where the use of similarity is not always the best choice to compute relevance. In particular, in Example 3 we notice that machines are not aware of the fact that Japan's scientific research program is called JARPA II, while in Example 4 machines do not understand that the "rescued whales" were stranded about 200 meters from the shore.

3. *Japan to hunt 950 whales for "scientific research"* [TITLE]
   Japan plans to kill over 900 minke whales and ten fin whales during the next six months as part of its whaling program, JAPRA II, marking a sharp escalation in Japan's whaling activities. [TEXT SNIPPET]
   Crowd Relevance: 0.9 - **Similarity Score**: 0.16
4. *500 stranded melon-headed whales rescued in Philippine bay* [TITLE]
   The whales were about 200 meters from the shore. [TEXT SNIPPET]
   Crowd Relevance: 0.73 - **Similarity Score**: 0.11

5.1.2. Crowd Mentions vs. Experts' Seed Words

We evaluated the relevant news snippets, tweets and crowd event mentions with respect to the domain experts' seed words. Only 17/36 seed words are found in the relevant news snippets, with a total of 249 occurrences. The event mentions highlighted by the crowd identified only 12/36 seed words, with a total of 366 and other 773 mentions that do not contain seed words. However, we need to keep in mind here that we asked the crowd to highlight relevant mentions with respect to the news article titles, *i.e.*, news snippets containing domain experts' seed words may not be relevant for the news article title. The tweets datasets however, had a smaller overlap with the seed words, only 14/36, with a total of 835 occurrences. The seed words covered by the crowd annotations is 11/36, with a total of 1860 occurrences. In addition, we gathered other 1239 mentions that the crowd consider relevant for the whaling event. Among the seed words not identified by the crowd we find some generic words *e.g.*, "shops" and "scientists". We also find words that overlap partially, *e.g*, "Sea Shepherd Conservation Society" (provided by the experts) and "Sea Shepherd" or "Sea Shepherd Conservation" (provided by the crowd).

5.2. Crowdsourcing Tweets Novelty

From the *"Novelty Ranking"* crowdsourcing task we obtain a comparison of each tweet with the rest of the tweets published on the same day. Thus, for each tweet we derive an aggregated novelty score in comparison with the rest, by using a weighted schema: weight 1 if the tweet is more novel, weight 0.5 if the tweets are equally novel and weight -1 if the tweet if less novel. Tweets contain a lot of redundant information. Out of 966 tweets, more than 70% were recurring tweets. Even though we conducted the experiments independently on the two tweet datasets, we observed that the content overlap between the two years is also considerable. For these initial experiments we chose to remove the tweets' short links because it is very difficult to analyze if they point to new or redundant information.

The results of the *"Novelty Ranking"* task show that the tweets that were published earlier are more prone to be novel. As an example, $TWEET5$ in Example 7 is considered less novel that a similar tweet published before, $TWEET4$ from Example 6. At the beginning of the period of time in analysis, there were more unique tweets but also more tweets that contain new information, while the end of the period of time contained less unique tweets but also less novel tweets. In short, the amount of novel tweets decreases significantly day by day. The relevance score of the tweets with respect to the event of "whaling" shows to influence the novelty ranking as well. This means that the crowd is also able to distinguish between tweets that have qualitative mentions of the whaling event (*e.g.*, $TWEET3$ in Example 5) and tweets that do not contain highly relevant information, (*e.g.*, $TWEET6$ shown in Example 8).

Sample of tweets and their novelty score on the same day:

5. *Japanese whaling fleet leaves port weeks after International court delivers ban verdict - WDC: http://t.co/BeuDUh5NO8* [TWEET3]
   Crowd Novelty Score: 1
6. *Denounce Japan 4 Whale Slaughter - ForceChange #Japanpoli #STOPkillingwhales obey the law #barbaricJapan stop lying!* [TWEET4]
   Crowd Novelty Score: 0.62
7. *Denounce Japan for Resuming Whale Slaughter - ForceChange* [TWEET5]
   Crowd Novelty Score: 0.30
8. *becook1964 fella may be into whaling even it small bait i tried to use a minnow could it be this 100 million for shark and tunna - oh ok* [TWEET6]
   Crowd Novelty Score: -0.45

5.3. Crowdsourcing Sentiments - Tweets & News

The last part of our methodology focuses on the sentiment and magnitude analysis. In Figure 3 we extracted from $Tweet2014DS1$ and $Tweet2015DS2$ a subset of relevant tweets that contain relevant event mentions about "whaling ban". There is a strong positive sentiment about the decision to ban whaling in Japan. However, this drastically transforms into a negative sentiment immediately after facts such as Japan plans to continue whaling are published. An overall overview of the sentiment distribution on the $Tweet2014DS1$ and $Tweet2015DS2$ is shown in Figure 4a. Similarly, in Figure 4c we see the sentiment distribution across the $NewsDS3$ dataset. We observe a similar trend across datasets, both the tweets and the text snippets are well distinguished as either positive or negative, while only a small portion clearly identifies as being neutral.

5.3.1. Automated Tweets Sentiment Detection

We compared our crowdsourcing results for the sentiments expressed in the tweets using an existing approach[8]. The choice of using this tool was made based on the fact that the tool returns, for a text, a vector space of sentiments, *i.e.*, each sentiment type gets a score, similarly as in CrowdTruth. Tools that focus specifically on tweets, tend to return only the primary sentiment type with/out the score. Computing the Pearson and Spearman correlations, however, between each sentiment type score of the crowd and the automated measure, showed a very weak to no correlation: positive sentiment - 0.026 and 0.014, negative sentiment - 0.15 and 0.12, neutral sentiment - -0.16 and -0.15. In Figure 4b we plotted the sentiment scores across all the tweets. Comparing this outcome with the one provided by the crowd, in Figure 4a, we observe this tool gives very ambiguous score, and for the majority of the tweets the scores are almost evenly distributed across sentiment types.

5.4. Discussion

The methodology performed in this research aims at understanding event salience from two perspectives:

1. "centrality": "central" discourse elements are the targets of the information flow and those more prone to be associated with novel and relevant information.

In this respect we assessed the relevance of tweets and news snippets and the novelty of tweets with regard to a target event, "whaling". Using automated semantic similarity measures instead of relevance, however, proved to be inaccurate as such methods have a poor performance when dealing with language ambiguity. The low semantic similarity correlation between domain experts "whaling" seed words and non-experts' tweets showed that the way people address/refer to a given event is broad *i.e.*, the crowd found a large set of relevant event mentions in all dataset, without using many domain-specific keywords.

2. "saturation": discourse elements ultimately reach a point when no new and relevant information is expressed, *i.e.*, an information saturation level.

This level can be investigated and identified by means of linguistic data which combines "objective information" (*e.g.*, the events an entity is involved as a participant), and

[8] http://text-processing.com/docs/sentiment.html

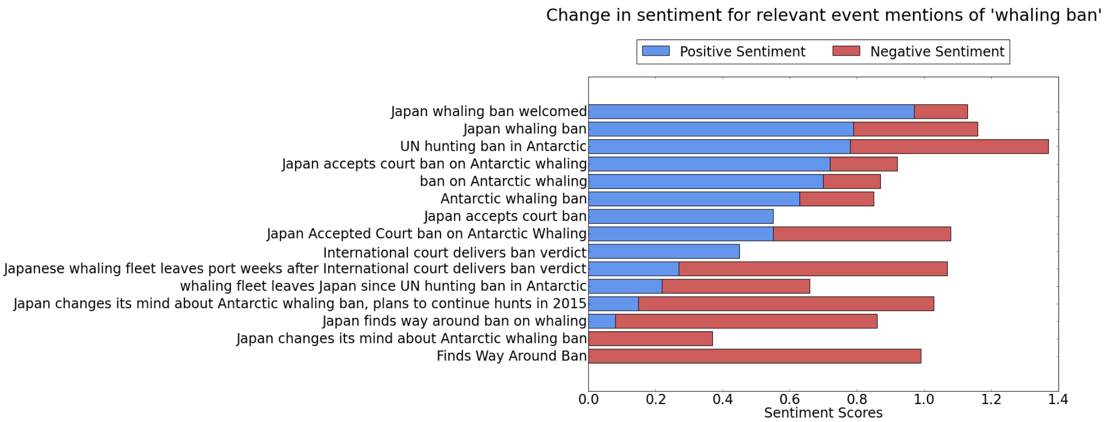
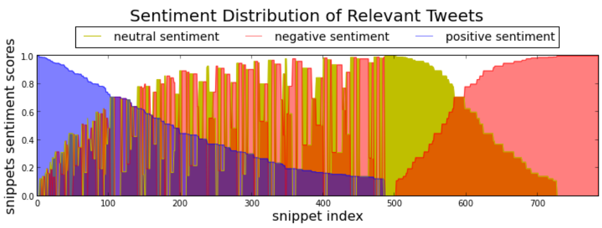
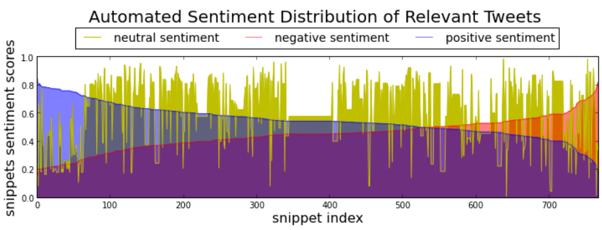


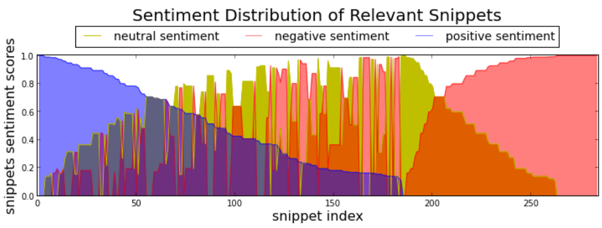
Figure 3: Sentiment Distribution "Whaling ban" Use Case



(a) Crowd Sentiment on $Tweet2014DS1$ & $Tweet2015DS2$



(b) Automated Sentiment on $Tweet2014DS1$ & $Tweet2015DS2$



(c) Crowd Sentiment on $NewsDS3$

Figure 4: Sentiment Analysis

"subjective information" (*e.g.*, the sentiment and intensity reactions an entity or an event can trigger). We addressed the "subjective information" by crowdsourcing sentiments of tweets and news snippets. Using existing tools prove to be difficult, as current methods either give a single classification of the text, without addressing difference in opinions or give an inconclusive sentiment space, where clear decisions over the sentiment prove to be difficult to take.

6. Related Work

The definition of salience is not trivial and different disciplines such as Linguistics, Computational Linguistics, Information Extraction have used this notion and declined it in different ways. Notwithstanding the differences with respect to the cues which signal salience and the way to identify it, salience is best describes as something which is notable or prominent.

Current approaches use a similar workflow: select relevant text snippets for a given event and then rank them based on novelty, (Fernández and Losada, 2007; Zhao et al., 2006). Deciding whether a document is relevant for a given event ensures the fact that the novelty score is computed based on related documents and is not tainted by irrelevant documents (Zhao et al., 2006). Various approaches have been developed to compute how relevant two texts are for each other: Local Context Analysis (LCA) (Fernández and Losada, 2007), word similarity feature combined with part-of-speech (POS) tagging, Latent Semantic Analysis (LSA) and enrichment with semantic relations from WordNet (Han et al., 2013) among others. Crowdsourcing proved to be a cheap, quick, and reliable alternative for assessing relevance for the data used in the TREC Novelty Task (Alonso and Mizzaro, 2009; Grady and Lease, 2010). Although the approaches yield good results, their crowdsourcing approaches lack a well defined methodology to assess crowd workers and the inherent language ambiguity.

For novelty detection in texts, an extensive literature study of automated methods is presented in (Verheij et al., 2012). As another perspective of novelty, in (Wei and Gao, 2014), the authors perform single document summarization for creating news highlights. Their approach combines news articles with tweets in order to extract a set of relevant and novel text snippets from a document. However, the limit of this method is the use of a very restrictive set of tweets that are considered relevant, *i.e.*, the tweets that are linked to the news article. Although the cosine distance proved to be an optimal method to detect novel texts (Kumaran and Allan, 2004), it fails to output fair results on short texts (Sahami and Heilman, 2006), such as tweets. As we mentioned in our methodology, novelty can be also expressed through sentiments. Although crowdsourcing methods for tweets and news novelty detection are still under-developed, research has been done on crowdsourcing sentiments from news or microblogs (Balahur et al., 2010; Rao et al., 2014). Recently (Dunietz and Gillick, 2014) have proposed a new task, *entity salience*, which merges notions of centrality and referential salience. The task aims at assigning a salience score to each entity in a document. The authors define salience on the line of (Boguraev and Kennedy, 1999), *i.e.*, as those discourse objects which have a prominent position in the focus of attention of the speaker/hearer[9]. Salience labels are automatically generated by exploiting summary pairs from the annotated New York Times corpus (Sandhaus, 2008), containing 1.8 millions of news articles accompanied by a summary written by an expert.

7. Conclusion and Future Work

Current state-of-the-art approaches for relevance or similarity assessment, novelty or salience detection and sentiment analysis need large amounts of ground truth data that are typically difficult to acquire. Given the overwhelming load of information people are surrounded by, such systems are essential in order to get a relevant and concise overview. The results that we obtained from the current crowdsourcing experiments give us input for the challenge of identifying the topic space of the "whaling" event by obtaining a diverse set of entities and features that can be associated with salient information. We derived a methodology to obtain such features from streams of tweets and we have performed initial steps to apply it on news streams. First, there is little information known about a given topic, *i.e.*, domain experts' seed words. We extent this space with relevant tweets and news snippets and relevant event mentions in those. However, relevant information can be redundant as well. Thus, we search for novel information in terms of new content and new subjective perspectives such as sentiments in order to track the way the sentiment changes across a given mention. We compared the crowd results for relevance assessment with state-of-the-art approaches for similarity assessment which strengthen our insight that semantic similarity does not always perform well when dealing with ambiguous data or everyday people conversations.

As future work, we plan to *(1)* build a salience event-timeline by employing the relevant, novel and subjective features identifying in the current research, *(2)* deduce how every event mention influences the big picture of the event in terms of salient information or change in sentiment and intensity, and *(3)* identify when the event space gets saturated. Furthermore, using the lessons learnt from the tweets streams, we plan to conduct more experiments on news streams to identify novel information at the document level but also across news articles collections. Next step is to compare our results with more state-of-the-art NLP approaches and provide a set of salient features of online data streams to help training salience detection tools.

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