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Give me your Intentions, I’ll Predict Our Actions: A Two-level Classification of Speech Acts for Crisis Management in Social Media

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Abstract
Discovered by (Austin, 1962) and extensively promoted by (Searle, 1975), speech acts (SA) have been the object of extensive discussion in the philosophical and the linguistic literature, as well as in computational linguistics where the detection of SA have shown to be an important step in many down stream NLP applications. In this paper, we attempt to measure for the first time the role of SA on urgency detection in tweets, focusing on natural disasters. Indeed, SA are particularly relevant to identify intentions, desires, plans and preferences towards action, providing therefore actionable information that will help to set priorities for the human teams and decide appropriate rescue actions. To this end, we come up here with four main contributions: (1) A two-layer annotation scheme of SA both at the tweet and subtweet levels, (2) A new French dataset of 6,669 tweets annotated for both urgency and SA, (3) An in-depth analysis of the annotation campaign, highlighting the correlation between SA and urgency categories, and (4) A set of deep learning experiments to detect SA in a crisis corpus. Our results show that SA are correlated with urgency which is a first important step towards SA-aware NLP-based crisis management on social media.

Keywords: Speech acts, Crisis events, Social Media

1. Introduction
The use of social networks is pervasive in our daily life. All areas are concerned, including civil security and crisis management. Recently, Twitter has been widely used to generate valuable information in crisis situations, showing that traditional means of communication between population and rescue departments (e.g., phone calls) are clearly suboptimal (Vieweg et al., 2014; Olteanu et al., 2015). For example, more than 20 million tweets were posted during the super-storm Sandy in 2012 (Castillo, 2016) and the hashtag #NotreDame relatif to the the Notre Dame fire that occurred in France has been the most used in Twitter in 2019.

One crucial aspect of tweets posted during crisis events pertains to the fact that people express their intentions, desires, plans, goals and preferences towards action, providing therefore actionable information that will help to set priorities for the human teams and decide appropriate rescue actions. For example, in the tweet (1a) [the writer publicly expresses an explicit commitment to provide help after the Irma hurricane tragedy, using an explicit action verb (“to help”) which is under the scope of an explicit attitude verb (“want”).] (1b) on the other hand expresses an intention to complain about the absence of assistance without using any explicit intent keywords. Intention to advise, evacuate (cf. (1c)) are other types of actions expressed in crisis situations.

It is important to note that such useful messages do not always require an urgent and rapid action from rescue teams: messages like (1c), about affected people, or infrastructure damages can be seen as more urgent compared to other types of intention to act (cf. (1a-b)).

(1) a. #Irma Hurricane: “I want to go there to help.”
   b. Irma hurricane: where is disaster assistance one month later?
   c. Emergency heritage at Bordeaux. After the flood, the archaeology lab is looking for volunteers to evacuate collections.

Our work focuses on the impact of speech acts on emergency detection during crises. Discovered by (Austin, 1962) and extensively promoted by (Searle, 1975), speech acts (henceforth SA) have been the object of extensive discussion in the philosophical and the linguistic literature (Hamblin, 1970; Brandom, 1994; Sadock, 2004; Asher and Lascarides, 2008; Portner, 2018) to mention just a few. According to the Austman initial view, SA are to achieve action rather than conveying information. When uttering I now pronounce you man and wife, the priest accomplishes the action of marrying rather than just stating a proposition. Beyond these prototypical cases, the literature has quickly broadened the understanding of the notion of SA as a special type of linguistic object that encompasses questions, orders and assertions and transcends propositional content revealing communicative intentions on the part of the speaker (Bach and Harnish, 1979; Gunlogson, 2008; Asher and Lascarides, 2008; Giannakidou and Mari, 2021). Speech acts can in-


These are examples taken from our French corpus translated into English.
deed be understood as **attitudes** towards propositional content: by asserting the speaker presents the propositional content as true, by questioning the speaker reveals uncertainty towards propositional content, by ordering the propositional content is asked to be realized and with exclamatives, the speaker reveals some type of subjective evaluation towards propositional content. SA have received an extensive body of work in the computational linguistics literature (Stolcke et al., 2000; Keizer et al., 2002; Carvalho and Cohen, 2005; Joty and Mohiuddin, 2018) and have shown to be an important step in many down stream NLP applications such as dialogues summarization (Goo and Chen, 2018) and conversational systems (Higashimaka et al., 2014). In this paper we attempt to measure for the first time the role of SA on urgency detection in tweets, focusing on natural disasters.

Previous works on communicative intentions during emergency crises has focused on the correlation between specific topics and SA (Zhang et al., 2011; Vosoughi, 2015; Elmadany et al., 2018a; Saha et al., 2020). As discussed below, it has been observed that people globally tend to react to natural disasters with SA distinct from those used in other contexts (e.g. celebrities): we might hypothesize that this is because all SA are not suited to constitute a pertinent reaction to emergency. Here, we explore the further hypothesis that SA can moreover be used as a sorting key between urgent and non-urgent utterances made in the same context of reaction to a natural disaster.

Before moving to real scenarios that rely on SA-aware automatic detection of urgency (this is left for future work), we first want to (1) measure the impact of SA in detecting intentions during crisis events in manually annotated data, and (2) explore the feasibility of SA automatic detection in crisis corpora. To this end, we present here an annotation schema for tweets using speech acts that (i) takes into account the variety of linguistic means whereby speech acts are expressed (including lexical items, punctuation, etc.), both at the message and sub-message level, (ii) newly uses a two-level classification of speech acts, and (iii) intersects a classification of urgency where messages are annotated according to three classes (non useful vs. urgent vs. non urgent). Our contributions are:

- A new annotation scheme of speech acts in tweets at two levels of granularity (message and sub-message levels) that goes beyond flat classification of SA used in related work.
- A new French dataset of 6,669 tweets annotated for both urgency and SA, extending a first layer of urgency annotations initially proposed by Koźlowski et al. (2020).[^4]

[See https://crisisnlp.qcri.org/ for an overview.]

[^4]: If accepted, the dataset will be publicly available.

This paper is organized as follows. Section 2 presents related work in SA detection in social media as well as main existing crisis datasets. Section 3 provides the classification of SA we propose and the annotation guidelines to annotate them. Section 4 details the dataset we relied on and the results of the annotation campaign. Section 5 focuses on the experiments we carried out to detect SA automatically. We end by some perspectives for future work.

## 2. Related Work

### 2.1. Crisis Datasets

The literature on emergencies detection has been growing fast in the recent years and several datasets (mainly tweets) have been proposed to account for crisis related phenomena[^3]. Messages are annotated according to relevant categories that are deemed to fit the information needs of various stakeholders like humanitarian organizations, local police and firefighters. Well known dimensions include relatedness (also known as usefulness or informativeness) to identify whether the message content is useful (Jensen, 2012), situation awareness (also known as urgency, criticality or priority) to filter out on-topic relevant (e.g., immediate post-impact help) vs. on-topic irrelevant information (e.g. supports and solicitations for donations) (Imran et al., 2013; McCreadie et al., 2019; Sarioglu Kayi et al., 2020; Koźlowski et al., 2020), and eyewitnesses types to identify direct and indirect eyewitnesses (Zahra et al., 2020). Annotations in most existing datasets are usually done at the text level. Some studies propose to additionally annotate images within the tweets (see for example Alam et al., 2018).

The question of how speakers convey emergency at the sentence level, has nonetheless be only tangentially addressed in a literature that has considered the correlation between specific speech acts and specific topics, without overtly addressing what the speech act shape of urgent messages is (see below).

### 2.2. Speech Acts in Social Media

Some amount of attention has been indeed devoted to understanding how speech acts (as used on Twitter) vary qualitatively according to the topic discussed or topic. In this line of questioning, SA have been studied as filters for new topics.

[^3]: A qualitative and quantitative analysis of the annotation campaign, highlighting the correlation between SA and urgency categories.

[^4]: A set of deep learning experiments to detect SA in social media content relying on transformer architectures coupled with relevant linguistic features about how SA are linguistically expressed.

[^4]: An overview.
Zhang et al. (2011) in particular, resorts to a Searlian typology of SA that distinguishes between assertive statements (description of the world) and expressive comments (expression of a mental state of the speaker). Zhang et al. (2011) also distinguish between interrogative questions and imperative suggestions. Finally, a category miscellaneous brings together the Searlian declaratives and the commissives, used to make promises. Concerning the question of emergency, Zhang et al. (2011) showed that the SA’s distribution on Twitter in the context of a natural disaster (e.g. earthquake in Japan) is distinctive: it is essentially composed by statements, associated to comments and suggestions/orders. In this context new information or ideas on how to (re)act are indeed expected and assertions are the most suitable to this aim. By contrast, discussion over a celebrity will mostly generate comments and almost no order or suggestion. Indeed, in this context, subjectivity matters more than immediate action.

Also inspired by Searle’s typology, Vosoughi (2015) and Vosoughi and Roy (2016) distinguish six categories: Assertions, Recommendations, Expressions, Question Requests and Miscellaneous. The authors use the definitions of Zhang et al. (2011), by distinguishing the topic discussed in the tweets, from the type of topic (Entity-oriented, Event-oriented topics, or Long-standing topics). 6 topics were then selected (2 of each type): for entity-oriented, they are interested in Ashton Kusher and the Red Sox; for event-oriented, they study the Boston bombings in 2013 and the Ferguson demonstrations in 2014; for Longstanding topics, they consider cooking and travel. The distribution of speech acts that the authors obtain allows them to show that there is a greater similarity of distribution between topics of the same type than between topics of different types. On the other hand, the entity-oriented and event-oriented types are closer to each other, with a majority of assertions and expressions, whereas for the long-standing types, assertions are less abundant and recommendations well represented.

In this same perspective of topic identification, Elmadany et al. (2018b) classify 21,000 tweets in Arabic according to their topic type and distinguish events (for example, in our case, natural disasters), entities (especially people) and various issues such as travel or cooking. Each tweet is associated to a pair of speech act/sentiment according to the following classification: Assertions, Recommendations, Expressions and Requests, and among Sentiments, the standard Positive, Negative, Mixed and Neutral categories. Their study makes emerge a salient association between assertions and people/events and neutrality on the one hand and an association between expressivity long-standing topics and negativity on the other.

For completeness, we note that SA have been studied in the context of political campaigns, notably by Subramanian et al. (2019) (The 2016 Australian “federal election cycle”), with a corpus composed of official statements/tweets/press clippings, where each statement is associated with a SA and a target party (liberal or conservative). The categorization envisioned by the authors articulates Assertives, Commissives-action-specific, Commissives-action-vague, Commissives-outcome (about a future reality state), Directives, Expressives, Past-actions and Verdictives (an assessment on prospective or retrospective actions). They observe an over-representation of assertives (40%), followed by verdictives (25%) and specific action (12%). The other categories represent less than 10% of the annotations. It is interesting to note that if we remove their precise characterization, commissives represent a little less than a quarter of the assigned speech acts, whereas they are almost absent from our corpus whose topic is emergency.

As far as we are aware, communicative intentions have never been explored in the context of urgency detection. This paper fills this gap by crossing the urgency classification and the SA classification in order to elucidate the interactions between speaker’s attitudes and urgency categories (and their associated actions). To achieve this, and as never previously undertaken, we propose a two-level typology of speech acts that allows us to characterize both the message as a whole and its parts providing multiple handles to study the correlation between emergency and speakers intentions.

3. Classification and annotations

We developed two sets of annotations: (i) one level classification including four distinct categories to label the tweet as an atomic unit, and (ii) a two-level annotation including the first four level categories and 8 second level categories. The second-level categories are used to annotate tweets at the subtweet level as opposed to the tweet as a whole. The goal of this double annotation both at the level of the tweet and at the level of the subtweet allows us to gather data to understand which part of the tweets determines the speech act at the holistic level.

3.1. Tweet level

Our classification of SA elaborates on the fundational Austrian and later Searlian distinction by (i) relying on propositional content and lexical clues such as modals (should, must, can, ...), evaluative adjectives, attitude verbs (think, believe, want, hope ...); (ii) introducing the category ‘subjectives’, which reshuffles some of the earlier classifications (‘wishes’, for instance are ‘subjectives’ rather than ‘jussives’ in our classification (e.g. Condoravdi and Lauer, 2012)); (iii) considering presuppositional content as well (see Mari, 2016 on French).

We distinguish four first-level categories which are mutually exclusive and define tweets as wholes, at a holistic level, as shown in Figure 1.

(1) **JUSSIVES**, as defined by Zanuttini et al., 2012, enhance commitment to take action, as in (2)

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4335
(2) #Inondation Si vous êtes en zone inondable, découvrez comment préparer un kit de survie (#Flooding If you are in an area at risk of flooding, discover how to prepare a survival kit).

In our classification we distinguish: *commissives* (i.e. the speaker commits himself or herself), *exhortatives* (i.e. the speaker commits some relevant individuals), *orders* (i.e. the speaker commits the addressee, in the case of authority relations), and *open-options* (i.e. the speaker describes the existence of a possibility).

(2) **ASSERTIVES.** Assertions are considered to convey objective truth (as opposed to subjective truth (Giannakidou and Mari, 2021)). With assertives, the speaker is committed toward the truthfulness of the proposition that is being uttered (Portner, 2018) and require their interlocutor to update the common ground (Ginzburg, 2012).

(3) Inondations dans l’Aude : la région débloque 25M€, le président Macron sur place lundi (Flooding in Aude: the region unlocks 25M€, the president Macron on the spot on Monday).

(3) **INTERROGATIVES.** This category is dedicated to a variety of questions including both those that require an informative answer and those that, besides triggering an answer, reveal bias and expectations on the part of the speaker (see (Ladd, 1981)).

(4) Salut Chelsea, comment ça va, la tempête, par chez vous? (Hi Chelsea, how is the storm at your place?).

(4) **SUBJECTIVES.** Finally, with subjectives, the speaker shares a mental state that can be either a personal evaluation or preference (see among many others (Lasersohn, 2005)) or an expressive state (an emotion or a feeling). The interlocutor is asked to update the common ground not just with the content of the evaluation but with the evaluation itself (see (Simons, 2007), and for recent discussion on French (Mari and Portner, 2021)). In our classification, ‘wishes’, for instance are ‘subjectives’ rather than ‘jussives’ as they do not trigger any commitment to act so to make the content of the wish true.

(5) Grosse pensée à ma Laure qui est en Martinique avec l’ouragan (My thoughts are with my Laure, who is in Martinique with the hurricane.)

Finally, **OTHERS** is added to the classification, for uncertain or unclassifiable cases.

(6) Simulation #3D d’une #inondation à Issy-les-Moulineaux merci à @Ubick3D pour le prêt #ortho3D #InterAtlas (3D simulation of a flood in Issy-les-Moulineaux thanks to @Ubick3D for the loan #ortho3D #InterAtlas).

Figure 1: A classification for tweets that makes use of four illocutionary categories.

### 3.2. Segment level

The two-level annotation considers that each tweet is a small discourse composed of one or more statements, so that it can not only be classified at the holistic level but also at the level of its segments (we identify them between ‘[ ... ]’). In order to achieve this, we have maintained the classification above at the holistic level, and we have elaborated each of the four categories to annotate the tweets at the segment level. At the segment level we use eight categories (see Figure 2), some of them are inspired by (Core et al., 1998) (e.g. the open-options).

From **JUSSIVES**, the annotation makes the distinction between (a) **OPEN-OPTIONS** – the speaker puts forward a possibility and leaves the addressee free to realize it or not (cf. (7)) –, and (b) utterances that enhance a direct commitment on the part of a discourse participant, *ie. COMMISSIVES, EXHORTATIVES, ORDERS AND INTERDICTIONS*, that are called **OTHER-JUSSIVES** (cf. (8)).

(7) Ouragan #Irma : victime des intempéries? [OPEN-OPTION Conseils déclaration de sinistre par téléphone et en ligne @MAIF] (Hurricane #Irma : victim of the bad weather? [OPEN-OPTION Claim reporting tips by phone and online @MAIF])

(8) Une grosse pensée pour les familles des victimes. [OTHER-JUSSIVE Taxons le carbone dès maintenant pour éviter que les choses empirent dans le futur.] (A big thought for the families of the victims. [OTHER-JUSSIVE Let’s tax the carbon now to prevent things from getting worse in the future.])

In **ASSERTIONS**, both second-level categories are deter-
Figure 2: Two-layers annotation for tweets and inner segments.

minded by the source of knowledge that the speaker relies upon, i.e. the evidentiality condition as defined by (Saurí and Pustejovsky, 2009). If the speaker grounds their utterance on a third-party source, the assertive utterance is (a) a REPORTED ASSERTION, whereas if there is no such explicit source, it is a (b) PROPER ASSERTION, see [(9)] and [(10)] respectively.

(9) [REPORTED] Des patrouilles de police mises en place pour dissuader les cambrioleurs, via @franceinfo

(10) [PROPER] Au printemps, la fonte rapide de la neige peut provoquer une inondation. Votre famille est-elle prête?

In SUBJECTIVES, the distinction was made between (a) EXPRESSIONS/EVALUATIVES whereby the speaker describes a personal evaluation or an expressive state that it is not deemed to become common ground or truth (cf. [(11)]) and (b) OTHER SUBJECTIVE for utterances that do not explicitly fall in the previous category (eg: puns, greetings...).

(11) [EXP/EVAL. Penseés pour les saint Martinois et particulièrement pour ma famille installée la bas]

(12) [OTHER-SUBJECTIVE] Bonjour de la Guadeloupe ! Oui effectivement la situation ici est dramatique.

In INTERROGATIVES, the distinction was made between (a) INFORMATIVE questions to which the speaker cannot answer, and the ones that are (b) UNINFORMATIVE when the speaker is biased towards an answer, as in [(13)] and [(14)] respectively.

(13) @EmmanuelMacron Où sont les renforts censés arriver à Saint-Martin et [INFORMATIVE que comptez-vous faire] (@EmmanuelMacron Where are the reinforcements that are supposed to arrive in St. Martin and [INFORMATIVE what are you going to do])

(14) seisme ressenti en guadeloupe [UNINFORMATIVE pouvez vous confirmer svp] (earthquake felt in guadeloupe [UNINFORMATIVE could you please confirm])

A single message can be annotated with several labels at the segment level, with each segment being annotated by only one tag, as shown in [(15)]. Here an INTERROGATIVE tweet composed of two segments: a PROPER assertion followed by an UNINFORMATIVE question.

(15) [INTERR., [PROPER seisme ressenti en guadeloupe] [UNINF. pouvez vous confirmer svp]] ([INTERR., [PROPER earthquake felt in guadeloupe] [UNINF. could you please confirm]])

4. Data and Annotation

4.1. Dataset

Since our focus is on crises that occur in metropolitan France and its overseas departments, we rely on the only available corpus of French tweets by (Kozlowski et al., 2020) composed of 12,826 tweets collected using dedicated keywords about ecological crises that occurred in France from 2016 to 2019 and posted 24h before, during (48h) and 72h after the crisis: 2 floods that occurred in Aude and Corsica regions, 10 storms (Béryl, Berguitta, Fionn, Eleanor, Bruno, Egon, Ulrika, Susanna, Fakir and Ana), 2 hurricanes (Irma and Harvey), and 1 sudden crisis (Marseille building collapse).

The dataset comes with additional metadata including: number of likes and retweets of the tweet, and number of likes, followers, following of the user.

In this dataset, each tweet is annotated according to an urgency classification composed of three categories: URGENT that applies to messages mentioning human/infrastructure damages as well as security instructions to limit these damages during crisis events, NOT URGENT that groups support messages to the victims, critics or any other messages that do not have an immediate impact on actionability but contribute in raising situational awareness, and finally NOT USEFUL for messages that are not related to the targeted crisis or information pertaining to events occurring outside the French territories.

The collection is extremely imbalanced with 1,442 (11.24%) useful but NOT URGENT, 2,147 (16.74%) URGENT and 9,237 (72.02%) NOT USEFUL messages, which is in line with the proportions reported in other crisis corpora (see Section 2.1).

4.2. Results of the Annotation Campaign

A subset of this dataset composed of 6,669 tweets has been selected for SA annotations, so that almost all URGENT (2,080) and NON URGENT (1,401) messages have been annotated. Only 3,188 NOT USEFUL tweets have been selected in order to reduce the size of this class but keep it majority. Note that pre-existing urgency tags and metadata information have been removed, this will prevent annotators to get biased by specific urgency-SA pairs.

We hired two native French speaking annotators, both master’s degree students in Linguistics in order to annotate the tweets. We performed a two-step annotation with an intermediate analysis of agreement and disagreement between the annotators. 448 tweets have been annotated in the first step by both annotators so that the inter-annotator agreement could be computed (Cohen’s Kappa=0.62). Most cases of disagreement come from the difficulty of disentangling SUBJECTIVES from ASSERTIVES, in particular when attitudes and modal expressions are used such as believe, think that, etc. Indeed, both the subjective expressions (think, believe, or even more complex modal-tense-aspect combinations as fallait (which translates as ‘should have been’ with an additional implication of preference in [16])) or its content can be targeted, according to their contextual relevance. This delicate distinction is often resolved in different manners by annotators.

(16) Et maintenant il n’y a presque plus de fumée... Il fallait arrêter le trafic ce matin et pas au milieu de la journée.
(And now there is almost no more smoke... Traffic should have been stopped this morning and not in the middle of the day).

The final distribution of annotated tweets is 59.8%, 22.3%, 10%, 4.5% and 3.3% for ASSERTIVE, SUBJECTIVE, JUSSIVE, OTHER and INTERROGATIVE respectively. Table 1 details the frequency of the first layer SA tags (i.e., tweet level) when paired with the original urgency annotations. Concerning the two most frequent SA (ASSERTIVE and SUBJECTIVE), two observations emerge: (1) Among URGENT messages (resp. NON URGENT), 86.6% (resp. 48.7%) are ASSERTIVE; and (2) Only 5% of URGENT messages are SUBJECTIVE while 29% of NON URGENT messages are. Similarly, we observe that 7% of JUSSIVE are URGENT vs. 14% NON URGENT. All these frequencies are statistically significant using the χ² test (χ² = 1, 1011.62, df = 8, p < 0.01). When measuring the dependency strength between urgency and SA categories using the Cramer’s V, we get (V = .28, df = 2) which confirms the statistical correlation between these two classifications.

<table>
<thead>
<tr>
<th></th>
<th>URG</th>
<th>NON URG</th>
<th>NON USEF</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASSERT</td>
<td>1,802</td>
<td>682</td>
<td>1,506</td>
<td>3,990</td>
</tr>
<tr>
<td>JUSS</td>
<td>145</td>
<td>203</td>
<td>321</td>
<td>669</td>
</tr>
<tr>
<td>SUBJ</td>
<td>106</td>
<td>406</td>
<td>976</td>
<td>1,488</td>
</tr>
<tr>
<td>INTERR</td>
<td>20</td>
<td>58</td>
<td>145</td>
<td>223</td>
</tr>
<tr>
<td>OTHER</td>
<td>7</td>
<td>52</td>
<td>240</td>
<td>299</td>
</tr>
<tr>
<td>Total</td>
<td>2,080</td>
<td>1,401</td>
<td>3,188</td>
<td>6,669</td>
</tr>
</tbody>
</table>

Table 1: Urgency- First layer SA annotation pairs statistics.

Table 2 further details the SA distribution for each crisis. We can see that ASSERTIVE messages are the most frequent ones regardless of the crisis. Another interesting finding concerns the distribution of SA in sudden crises. Indeed, SA frequencies are relatively similar in natural disaster crises (flood, storms and hurricane) with about 60% of ASSERTIVE and 20% of SUBJECTIVE. However in the Marseille building collapse, we observe a higher proportion of SUBJECTIVE (35% vs. 49% for ASSERTIVE) showing that people tend to express fewer messages of warning-advice but many critics denouncing the lack of effectiveness of government social action.

Table 3 presents the percentage of the second layer SA tags when paired with urgency label. While Table 4 gives the distribution of the most frequent sequences showing that the most frequent single tags are also the most frequent when in first position of a sequence. This suggests that relying only on the first tag of a multi-label sequence can be relevant.

An in-depth analysis of the distribution of frequencies in these tables reveals that assertivity — and most prominently proper assertions — is an indication of urgency. This means that speakers privilege (what they consider) truthful information over orders and commands to enhance action (on the part of the rescuing teams, for instance). Indeed, in our classification ASSERTIONS do not include subjective evaluations, and thus convey content informationally reliable.
and objectively veridical (i.e. conform to the outer reality and not a mental state) (Giannakidou and Mari, 2017; Giannakidou and Mari, 2018; Giannakidou and Mari, 2021) and thus ready for uptake and endorsement (e.g. (Ginzburg, 2008), (Mari and Portner, 2021)) and be ready for uptake on the part of the helpers. Second-level SA

<table>
<thead>
<tr>
<th></th>
<th>URG</th>
<th>NON URG</th>
<th>NON USEF</th>
</tr>
</thead>
<tbody>
<tr>
<td>JUSSIVE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>open-opt.</td>
<td>5.79</td>
<td>8.78</td>
<td>8.41</td>
</tr>
<tr>
<td>other.</td>
<td>7.85</td>
<td>6.96</td>
<td>5.31</td>
</tr>
<tr>
<td>ASSERTIVE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>report.</td>
<td><strong>15.41</strong></td>
<td>7.84</td>
<td>7.81</td>
</tr>
<tr>
<td>proper.</td>
<td><strong>60.80</strong></td>
<td>39.63</td>
<td>45.01</td>
</tr>
<tr>
<td>INTERROGATIVE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>infor.</td>
<td>0.22</td>
<td>1.66</td>
<td>2.42</td>
</tr>
<tr>
<td>uninfor.</td>
<td>1.23</td>
<td>3.90</td>
<td>4.90</td>
</tr>
<tr>
<td>SUBJECTIVE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>eval/exp.</td>
<td>6.89</td>
<td><strong>28.36</strong></td>
<td>19.14</td>
</tr>
<tr>
<td>other.</td>
<td>1.80</td>
<td>2.85</td>
<td>7.00</td>
</tr>
</tbody>
</table>

Table 3: Urgency- Second layer SA annotation pairs in percentage.

5. Automatic Detection of SA

Now the dataset has been annotated, the next step is to automatically detect SA. We explore here the detection at the tweet level, leaving the second level for future work. Most state of the art approaches make use of feature-based machine learning algorithms (SVM, Naïve Bayse) relying on various surface, lexical and syntactic features such as unigrams, punctuations, POS, emoticons and sentiment words (Vosoughi and Roy, 2016; Zhang et al., 2011; Algotiml et al., 2019). Deep learning architectures have also been explored, mainly for Arabic SA detection (Elmadany et al., 2018) and English tweets relative to political campaigns (Subramanian et al., 2019) or topic oriented events (Saha et al., 2020). As far as we know, this is the first attempt to detection SA in a French crisis dataset. To this end, we train different classifiers on 80% of the instances of our dataset and test them on 20%. Note that the OTHER instances (around 300 tweets) have been removed from the dataset for the experiments as attributes, whereby truth is also relativized to a particular mental state and cannot (without further negotiation) immediately become common ground (e.g. (Giannakidou and Mari, 2017; Giannakidou and Mari, 2018; Giannakidou and Mari, 2021) and be ready for uptake on the part of the helpers.

Second-level SA

<table>
<thead>
<tr>
<th></th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PROPER ASSERTION</td>
<td>20.69</td>
</tr>
<tr>
<td>PROPER ASSERTION + other(s) SA</td>
<td>21.78</td>
</tr>
<tr>
<td>EVAL./EXPR.</td>
<td>21.36</td>
</tr>
<tr>
<td>EVAL./EXPR. + other(s) SA</td>
<td>13.12</td>
</tr>
<tr>
<td>REPORTED ASSERTION</td>
<td>5.22</td>
</tr>
<tr>
<td>REPORTED ASSERTION + other(s) SA</td>
<td>2.46</td>
</tr>
<tr>
<td>OPEN-OPTION</td>
<td>5.04</td>
</tr>
<tr>
<td>OPEN-OPTION + other(s) SA</td>
<td>7.68</td>
</tr>
</tbody>
</table>

Table 4: Distribution of most frequent second-level SA.

Now the dataset has been annotated, the next step is to automatically detect SA. We explore here the detection at the tweet level, leaving the second level for future work. Most state of the art approaches make use of feature-based machine learning algorithms (SVM, Naïve Bayse) relying on various surface, lexical and syntactic features such as unigrams, punctuations, POS, emoticons and sentiment words (Vosoughi and Roy, 2016; Zhang et al., 2011; Algotiml et al., 2019). Deep learning architectures have also been explored, mainly for Arabic SA detection (Elmadany et al., 2018) and English tweets relative to political campaigns (Subramanian et al., 2019) or topic oriented events (Saha et al., 2020). As far as we know, this is the first attempt to detection SA in a French crisis dataset. To this end, we train different classifiers on 80% of the instances of our dataset and test them on 20%. Note that the OTHER instances (around 300 tweets) have been removed from the dataset for the experiments as attributes, whereby truth is also relativized to a particular mental state and cannot (without further negotiation) immediately become common ground (e.g. (Giannakidou and Mari, 2008) and be ready for uptake on the part of the helpers.

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Table 4: Distribution of most frequent second-level SA.
they are very less frequent in urgent tweets and have no regular linguistic patterns. The final dataset is therefore composed of 6,370 tweets. We experiment with several feature-based (SVM) and deep learning models (CNN, BiLSTM, transformers) but we only report here the models having the best results.

- **BERT** uses the pre-trained BERT multilingual cased model (Devlin et al., 2019). We used the HuggingFace’s PyTorch implementation of BERT (Wolf et al., 2019) that we trained for four epochs.

- **FlaubERT** and CamemBERT use respectively the FlaubERT (Le et al., 2019) and the CamemBERT base cased models (Martin et al., 2020), two pre-trained French contextual embeddings. We run them for four epochs and a learning rate of $2e^{-5}$.

- **CamemBERT** uses focal loss (Lin et al., 2017). Our aim here is to compare with one of the most effective approach for handling imbalanced data (Cui et al., 2019).

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Finally, we observed that the classifier is misguided by the interrogation mark. Indeed, 60% of the errors where INTERROGATIVE has been wrongly predicted include tweets containing at least one interrogation mark, as in the example below.

(18) Comment un avion peut atterrir dans une tempête qui empêche les bagages de sortir ? (How can a plane land in a storm that prevents the luggage from getting out? It is not possible xD)

GOLD = SUBJECTIVE, PREDICTED = INTERROGATIVE

Table 5: Overall SA classification results.

<table>
<thead>
<tr>
<th>Models</th>
<th>P</th>
<th>R</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT</td>
<td>64.81</td>
<td>58.00</td>
<td>60.80</td>
</tr>
<tr>
<td>FlaubERT</td>
<td>72.13</td>
<td>66.19</td>
<td>68.80</td>
</tr>
<tr>
<td>CamemBERT base</td>
<td>74.16</td>
<td>70.57</td>
<td>71.22</td>
</tr>
<tr>
<td>CamemBERT base+F</td>
<td>75.26</td>
<td>70.47</td>
<td>72.64</td>
</tr>
<tr>
<td>CamemBERT focal</td>
<td>75.23</td>
<td>71.62</td>
<td>72.22</td>
</tr>
<tr>
<td>CamemBERT focal+F</td>
<td>75.66</td>
<td>71.95</td>
<td>73.55</td>
</tr>
</tbody>
</table>

Table 6: Best model results per class.

<table>
<thead>
<tr>
<th></th>
<th>P</th>
<th>R</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assert.</td>
<td>87.06</td>
<td>88.72</td>
<td>87.89</td>
</tr>
<tr>
<td>Juss.</td>
<td>75.22</td>
<td>60.28</td>
<td>64.44</td>
</tr>
<tr>
<td>Subj.</td>
<td>72.93</td>
<td>77.10</td>
<td>66.93</td>
</tr>
<tr>
<td>Inter.</td>
<td>67.44</td>
<td>61.70</td>
<td>74.96</td>
</tr>
</tbody>
</table>

Accuracy=81.87

6. Conclusion

In this paper, we presented the first corpus-based study to measure the impact of speech acts in messages posted during crisis events in social media. We first proposed a new annotation guideline to annotate speech acts both at the tweet and subtweet levels, then a new dataset annotated for both speech acts and urgency categories in French. Our results show a strong correlation (i) between Assertive messages (in particular those that rely on first hand knowledge, i.e., PROPER ASSERTIONS) and urgency and (ii) Subjective messages and absence of urgency, with a high frequency of expressives and evaluatives. We finally conducted a set of experiments to detect SA at the tweet level relying on transformer architectures augmented with dedicated features. Our results are encouraging and constitute the first step towards SA-aware urgency detection in social media content.

Acknowledgment

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Mari gratefully acknowledges ANR-17-EURE-0017 FrontCog. The research of Farah Benamara and Véronique Moriceau is also partially supported by DesCartes: the National Research Foundation, Prime Minister’s Office, Singapore under its Campus for Research Excellence and Technological Enterprise (CREATE) program.

7. Bibliographical References


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