ComStreamClust: a Communicative Multi-Agent Approach to Text Clustering in Streaming Data

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Abstract
Topic detection is the task of determining and tracking hot topics in social media. Twitter is arguably the most popular platform for people to share their ideas with others about different issues. One such prevalent issue is the COVID-19 pandemic. Detecting and tracking topics on these kinds of issues would help governments and healthcare companies deal with this phenomenon. In this paper, we propose a novel, multi-agent, communicative clustering approach, so-called ComStreamClust for clustering sub-topics inside a broader topic, e.g., the COVID-19 and the FA CUP. The proposed approach is parallelizable, and can simultaneously handle several data-point. The LaBSE sentence embedding is used to measure the semantic similarity between two tweets. ComStreamClust has been evaluated by several metrics such as keyword precision, keyword recall, and topic recall. Based on topic recall on different number
of keywords, ComStreamClust obtains superior results when compared to the existing methods.

**Keywords**  Data stream · LaBSE · Semantic similarity · Stream clustering · Topic detection

### 1 Introduction

The utilization of learning in finding patterns from big data is an emerging field that has attracted many researchers and yielded various techniques for diverse problems [1–3]. Moreover, different modalities of data have been an aspect of this research, and recent advancements in this area are creating methods to address pattern findings from unstructured modalities [4, 5].

Social media, which has achieved growing popularity in recent decades, provides the opportunity for people to share their ideas with an enormous number of users worldwide. As a micro-blogging platform, Twitter allows its users to write short text messages regarding various issues ranging from politics, economy, and healthcare to routine tasks of people’s daily lives. One such issue, the COVID-19 pandemic, has had a profound impact on people’s social lives since the beginning of 2020.

Determining and tracking health issues such as COVID-19 on Twitter would help governments and healthcare companies better handle the impact of those diseases on societies. Concretely, assembling tweets on this topic and analyzing them may result in invaluable information for those companies. From the healthcare perspective, crawling tweets related to COVID-19 as a pandemic issue might help in finding a remedy for it. As manual processing of such information is prohibitively expensive, automatic or semi-automatic methods are thus needed; however, assembling and distilling such data is a challenging task.

Previous works have tackled this problem by streaming and grouping tweets into various categories by using supervised [6] or unsupervised [7] methods. Unsupervised methods, however, could gain greater popularity. These methods collect streaming tweets in a time interval and assign them to clusters based on their topics.

Clustering has already been used for topic detection in the literature. In stream data clustering, a two-phase task is accomplished. In the first phase, data are captured from a data stream; and in the second phase, clusters are created and (in this paper) re-organized to constitute denser clusters. The ultimate goal is to increase the intra-cluster similarities and decrease the inter-cluster similarities.

Two issues make clustering on streaming data a challenging task: 1) Concept drifting occurs over time and makes the clusters impure. Through constant communication with other agents, ComStreamClust prevents clusters from diverging and snowballing, and 2) The continuously increasing number of clusters would drastically increase the time-complexity; We used parallelization techniques to overcome this challenge. To the best of the authors’ knowledge, the existing methods in the literature do not address both problems simultaneously. The proposed approach as a multi-agent communicative algorithm addresses both problems and provides a viable solution.
To tackle the aforementioned problem, we propose a novel, communicative, multi-agent, parallelizable text clustering approach for tweet clustering, experimented on the COVID-19 and the FA CUP datasets, which is described with greater details in Sect. 3. The key aspect of this work is its multi-agent and communicative structure. The difference between this work and the existing ones is in the second phase (as mentioned above). In the communication step of the proposed approach, existing clusters may export data to and/or import data from other clusters. At the same time, the proposed approach can also distinguish outlier data and exclude them from their current clusters. All these tasks can be (and have been) accomplished in a parallel setting. The contributions of the proposed approach can be summarized as follows.

- ComStreamClust updates clusters by detecting outliers and distributing them among other clusters in streaming, parallel, and multi-agent setting. This setting is being used for the first time in the literature on topic detection problems.
- The proposed approach could achieve promising results when applied to the FA CUP dataset. We applied our approach also to this dataset for the sake of fair comparison. Obtained results were as good as or superior to the existing approaches such as LDA, SFPM, and BNgram.
- ComStreamClust benefits from a state-of-the-art sentence embedding model, the LaBSE, for measuring the semantic similarity between tweets.
- A comprehensive experimental evaluation of the proposed approach on two datasets with different parameter values, such as the number of topics per time slot and the number of keywords per topic, have been conducted.

2 Related Work

Ibrahim et. al. [8] divides the topic detection techniques into five groups: clustering, frequent pattern mining, Exemplar-based, matrix factorization, and probabilistic models. The current research falls into the clustering-based models. Stream clustering is a type of clustering in which, data are continuously fed to a clustering system. Given this sequence of data, the goal is to group them in clusters, the elements of which are similar to each other but different from the elements of other clusters. In [9], the authors propose a two-level clustering method based on a document-pivot algorithm to detect topics in Twitter streaming data.

Some previous work relies on word frequency for topic detection and topic categorization on Twitter data. Using the “aging” theory for modeling the term life-cycle has experimented in [7]. In this work, Cataldi et al., defines a term as emerging, if it was rare in the past but frequent in a specified time interval. The authors benefit from emerging terms to detect emergent topics. In [6], and [10], the authors propose approaches that detect topics in Twitter, based on their word frequency, and categorize tweets into sentiment classes.

Unlike traditional clustering approaches that rely on a fixed set of input data, stream clustering assumes that input data are in a stream with an unknown number of usually unlabelled data. Along with the fast growth of social media such as Twitter, stream text clustering has gained growing popularity in recent decades. Several researchers
have tackled this problem with different approaches. The proposed method in [11] incrementally builds micro-clusters, which are later re-clustered to assemble final clusters. The idea of micro-clusters was earlier used in [12], in which, the first micro-cluster-based online clustering algorithm, so-called DBSCAN, was introduced. Hasler and Bolanos in this work, took into account the density of area between the micro-clusters, for the first time in the literature.

In another perspective, Fang et al., [13] categorize topic detection methods in Twitter into two main groups: traditional and new topic detection methods. In the traditional side, some research works [14] use an extension of LDA [15] for solving the topic detection problems. Some others tackle this problem by constructing a term co-occurrence network of keywords [16] and single-pass clustering along with a new threshold method [17].

Although traditional methods work well for long texts, they do not portray high performance on short texts such as tweets. Therefore, in new topic detection methods, traditional approaches have been extended to deal with new data types. In [13], the authors propose a new topic detection framework based on multi-view clustering. The Gradient Boosted Decision Trees is another method for detecting controversial events from Twitter which has been used in [18]. Computational cost is one of the major challenges in the real-time topic- or event-detection on Twitter. Hasan et al. [19] deal with this issue by proposing an event-detection system called TwitterNews+, which utilizes inverted indices and an incremental clustering approach with a low computational cost. Asgari et. al [20] propose a model based on the universal sentence encoder [21] and transformers [22] to detect main topics on Twitter regarding the COVID-19 pandemic.

Early detection of bursty topics is one of the most challenging problems in this era. TopicSkech [23] deals with this problem on Twitter. Similarly, PoliTwi [24], also has been proposed for early detection of emerging political events. Other approaches use different methods such as Formal Concept Analysis [25], clustering based on n-grams, and named entity boosting [26], and combination of singular value decomposition and K-means clustering methods [27]. More information and related work on topic detection on Twitter can be found in [28, 29].

Zhang et al. [30], employed an ensemble of models for data stream classification, and used an R-tree like height-balanced structure. Due to the high time constraint in the streaming data, this work focused on improving the prediction efficiency and reduced the expected prediction time from linear to sub-linear complexity in the ensemble models.. In another research work [31], the authors combined online learning [32, 33] and streaming feature selection [34, 35] to enable learning from trapezoidal data streams – where both data volume and feature space increase over time – with infinite training instances and features. This work could manage both data volume and data dimension simultaneously.

Despite a good deal of research work proposed for topic detection on Twitter, none of them is communicative, multi-agent, and parallelizable at the same time. The proposed approach can improve the purity of its clusters by communicating among clusters.
3 Proposed approach

Twitter streaming data is a sequence of data in which, data-points appear during the time. The problem tackled in this paper can be formally defined as follows: Each data-point is assumed as a quadruple \((id, t, ts, s)\), such that \(id\) is a unique value as the identification number; \(t\) is the text with at most 280 characters; \(ts\) is the timestamp of the tweet including its arrival date and time; \(s\) is the subject of the tweet which is not known in advance. Once the subject \(s\) is determined, the tweet can be assigned to one of the existing clusters. Having a set of topic clusters, the task is to assign a newly arrived tweet to one of the clusters. After this assignment, the attribute \(s\) of the tweet will be initialized, which can be updated later.

ComStreamClust consists of three main steps: (1) Data streaming, in which, data points, i.e., tweets, are fetched from Twitter streaming data, (2) Data assignment, where the newly arrived tweet is assigned to an existing or a new cluster, and (3) Data exchange, which is a communicative step to exchange data among clusters to build denser clusters. The initialization phase is not assumed as the main step because it is accomplished once at the beginning of the whole process. Different steps of the proposed approach are described in greater detail in their respective subsections.

![The proposed approach as a flowchart](image-url)
The proposed approach is illustrated in Fig. 1 as a flowchart. The reference implementation of the proposed approach is also released under the MIT license.\footnote{1}

### 3.1 Initialization

The initialization phase receives and handles the first \( k \) tweets; we set \( k \) to 10. The first \( k \) tweets are randomly assigned to one of the initial agents. This phase will be finished when all initial agents are filled. The initial number of agents, identified by the `init-agents` parameter, and the initial capacity of these agents indicated by `init-agent-cap` are respectively set to 5 and 2 for both datasets (\( 5 \times 2 = 10 \)). In other words, the first ten tweets would be randomly assigned to five agents.

### 3.2 Data streaming

In this step, data are fetched from a data stream, e.g., Twitter. Such data sources have unique characteristics; in contrast to batch data sources, access to the dataset is limited by time—the whole data do not exist in advance. In other words, the system receives one data point at a time. This paper uses two streaming data sources for topic detection: the COVID-19 dataset and the FA CUP dataset. These datasets have been explained in Sect. 4.1. The streaming step fetches tweets from the data stream, and after passing a tweet through a preprocessing channel, assigns it to one of the agents (clusters).

#### 3.2.1 Data pre-processing

Because of the short length of tweets, Twitter users usually prefer to use informal language. Due to this informality, tweets should be first preprocessed to be prepared for further processing. In this phase, several subtasks are applied to the newly-arrived tweet before passing it to the next step (Data assignment).

- **URL removal**: In this subtask, hyperlinks to various webpages are removed, as they generally do not contribute to the topic.
- **Hashtag tokenization**: Hashtags are words or phrases starting with a `#` character. Hashtags may contribute to the tweet’s topic as they carry contextual information. A hashtag semantically links a tweet to all other tweets, including it. As a hashtag usually consists of several words, it is separated into its constituting words in this subtask.
- **Mention removal**: Twitter users might be mentioned in a tweet with an `@` character followed by their username. These names are also removed from tweets as they usually do not contain useful information for topic detection.
- **Tweet cleaning**: As explained above, Informal language is often preferred in Twitter, which tends to include digits or special characters such as “[]()!?.”. Such characters are also removed in this subtask.

1 The Python and Elixir implementation of the proposed approach is publicly available at https://github.com/AliNajafi1998/ComStream.
Tweet tokenization: Finally, the cleaned tweets are tokenized using the whitespace character. Bigrams and trigrams, including a hyphen between words are unchanged as they usually convey a non-compositional phrase, e.g., “brother-in-law” or “chronicle-independent”. Moreover, all capital words are lowered.

3.3 Data assignment

In this step, the coordinator receives a tweet and assigns it to one of the existing clusters, semantically the most similar to it. The coordinator is a component for monitoring the system and collaborating with agents (clusters). The similarity between a tweet and a cluster is measured by the similarity of topics covered by them. This similarity is being measured according to a state-of-the-art sentence embedding model. More specifically, we first compute the sentence embedding vector of a given tweet based on the Language Agnostic Bert Sentence Embedding (LaBSE) model [36], which generates similar embeddings for bilingual or monolingual sentence pairs that are semantically similar. We then measure the cosine similarity of this vector with centroids of the existing clusters—the average sentence embedding vector of each cluster—to find the most similar cluster to the given tweet. The LaBSE\(^2\) is a recently proposed multilingual sentence encoding model based on BERT [37], and its architecture is based on Bidirectional Dual-Encoder [38] with Additive Margin Softmax [39]. It has been trained on 17 billion monolingual sentences and 6 billion bilingual sentence pairs. It is the state of the art model for measuring the semantic similarity between two documents/sentences, and can measure the semantic similarity of two sentences/documents even if they do not share any word. Moreover, this model takes the whole message conveyed by a tweet instead of taking the constituting words of a tweet in isolation. Note that if the semantic distance of the newly arrived tweet from the most similar cluster to it is greater than a given threshold parameter, namely, assign radius, a new cluster including only the new tweet will be generated. The cosine similarity measure in equation 1 is used to compute

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\(^2\) https://tfhub.dev/google/LaBSE/1.
the semantic similarity of two tweets, which are represented by two \( n \)-dimensional vectors. \( \mathbf{tw} \) and \( \mathbf{cl} \) respectively represent the tweet and cluster vectors.

\[
\text{cos}(\mathbf{tw}, \mathbf{cl}) = \frac{\mathbf{tw} \cdot \mathbf{cl}}{\|\mathbf{tw}\| \|\mathbf{cl}\|} = \frac{\sum_{i=1}^{n} t_{wi} c_{li}}{\sqrt{\sum_{i=1}^{n} (t_{wi})^2} \sqrt{\sum_{i=1}^{n} (c_{li})^2}} \tag{1}
\]

To prevent overflow in agents, we use a sliding window method. This window, indicated by a parameter named \textit{slid-win-init}, is set to twenty-four hours and 1 minute, respectively in the COVID-19 and the FA CUP datasets’ evaluations. This parameter differs from the \textit{timeslot} parameter that indicates a time interval, after which, the output of the system is stored and evaluated. In other words, topics and their keywords are separately extracted for each day in the COVID-19 and each minute in the FA CUP datasets. After each timeslot, a constant number of topics and a constant number of keywords per topic are stored. These constant numbers are represented by two parameters: \textit{no-topics} and \textit{no-keywords}. The \textit{no-topics} parameter varies in different experiments, whereas the \textit{no-keywords} is set to 5 and 9, respectively, in the COVID-19 and the FA CUP datasets.

### 3.4 Data exchange

After assigning the tweets to existing clusters in the data assignment step, a multi-agent communication-based data exchange occurs periodically among agents under the supervision of the coordinator. This period is a parameter in our approach, named \textit{comm-int}. In this step, the coordinator redistributes outlier tweets among clusters to achieve higher cluster density. Concretely, in each timeslot, the agents determine their outlier tweets and return them back to the coordinator. A tweet is assumed an outlier in a cluster if its cosine similarity from the cluster centroid is lower than a given threshold. This threshold, named \textit{outlier-threshold} is another parameter, which is set to 0.78 and 0.73 respectively in the COVID-19 and the FA CUP datasets. Then, the coordinator redistributes these outliers among existing clusters (agents), again based on the cosine similarity. The intuition behind this communication is that due to the automatic update in cluster centroids caused by the newly-added tweets, some tweets inside clusters gradually become an outlier. In other words, the topic carried by an outlier gradually gets away from the overall topic of the cluster including it. At the end of each communication phase, the weight of each agent is reduced by a parameter named \textit{agent-fading-rate}. After this update, if the weight of any agent is lower than a threshold, \textit{del-agent-weight}, it will be faded. This weight is incrementally by each data point’s arrival to an agent but not decremented by each outlier’s removal from that agent.
As mentioned already, the proposed methodology includes several parameters, which have been initialized by the try-and-test method. The complete list of parameters, as well as their values separately for two datasets, are listed in Table 1. The proposed approach has two versions: ComStreamClust1 and ComStreamClust2. The difference between these two versions is in parameters assign-radius and outlier-threshold. The value of assign-radius and outlier-threshold are 0.25 and 0.27 in ComStreamClust1 and 0.27 and 0.29 in ComStreamClust2 respectively.

4 Experimental Evaluation

In this section, we evaluate the proposed approach on two datasets, the COVID-19 and the FA CUP. Evaluation metrics, ground-truth, datasets, and obtained results have been explained with details in the following subsections.

Evaluation metrics: We use topic recall, keyword recall, and keyword precision for evaluation. F-score is also used for keyword evaluation as the harmonic mean of precision and recall. These metrics are calculated according to Eqs. 2 through 5.
Table 1  The parameters used in the proposed methodology. cc, dp, ts, and kw respectively stand for cluster-center, data-point, time-slot and keyword. Values inside parantheses have been used in two versions of the proposed approach

| Parameter name     | COVID-19 | FA CUP | Explanation                                      |
|--------------------|----------|--------|--------------------------------------------------|
| init-agents        | 5        | 2      | Initial number of agents                         |
| init-agent-cap     | 5        | 2      | Initial # of dps per agents                      |
| timeslot           | 24h      | 1m     | Time-interval to store the output               |
| comm-int           | 1.5h     | 1m     | Time-interval to repeat comm. phase              |
| slid-win-int       | 24h      | 1m     | Time-interval for naming a dp is as old          |
| assign-radius      | 0.2      | (0.25,0.27) | Max distance for assigning a dp to an agent |
| outlier-threshold  | 0.22     | (0.27,0.29) | Min dist. from cc for a dp to be an outlier |
| no-topics          | 2-20     | 2-20   | # of topics stored in each ts                    |
| no-keywords        | 5        | 9      | # of kws per topic stored in each ts             |
| agent-fading-rate  | 0.5      | 0      | Percentile of agents faded in comm. phase        |
| del-agent-weight-threshold | 0.4 | 0 | Weight threshold for deleting agents            |

Keyword precision is the ratio of correctly extracted keywords of a topic over the total number of extracted keywords for that topic. The topic recall is the ratio of correctly extracted topics over the total number of topics. Keyword recall is the ratio of correctly extracted keywords of a topic over the total number of keywords of that topic. The correct topics and their keywords have been collected in a ground-truth set. Note that we did not use topic precision because there exist hot topics in the datasets which might not be in the ground-truth set. For example, daily events such as dying someone’s cat might be extracted as a hot topic, where it is not relevant to any topic in the ground-truth. $P_{kw}$, $R_{kw}$, and $R_{tp}$ respectively stand for keyword precision, keyword recall and topic recall.

$$P_{kw} = \frac{\text{# of estimated kws for } T_i}{\text{# of kws for } T_i \text{ in ground-truth}}$$  \hfill (2)

$$R_{tp} = \frac{\text{# of correctly extracted topics}}{\text{# of topics in ground-truth}}$$  \hfill (3)

$$R_{kw} = \frac{\text{# of correctly extracted kws for } T_i}{\text{# of kws for } T_i \text{ in ground-truth}}$$  \hfill (4)

$$F_{score_{P,R}} = \frac{2 * P * R}{P + R}$$  \hfill (5)

**Ground-truth:** The ground-truth data are available for the FA CUP dataset, which have been explained with details in [40]. However, to the authors’ best knowledge, there is no ground-truth publicly available for the COVID-19 dataset. To generate a ground-truth for this dataset, we manually extracted the hot topics and their associated keywords from online media and search engines, separately for each day from March 29 to April 30. We have made these ground-truth data publicly available.3

3 https://www.kaggle.com/thelonecoder/labelled-1000k-covid19-dataset.
4.1 Dataset

As already mentioned, two datasets have been used in this paper. The Football Association Challenge Cup, FA CUP, was compiled during a football game between Chelsea and Liverpool, on May 05, 2012, from 16:00:00 to 18:30:00. The data have been crawled using key hashtags such as the event name and the name of teams and key players. The set of hot topics in this dataset is comprised of 13 special times, including the start and the end of the match, the goal times, penalizing the players, and so on. This dataset includes about 113 thousand English tweets already labeled in [40].

The COVID-19 dataset is a collection of tweets compiled from Twitter from March 29 to April 30, 2020. This dataset has been assembled by crawling tweets, including the hashtag #COVID19. The total number of tweets in this dataset is about 9 million, but we randomly chose 1 million tweets and manually identified thirty topics in them as our ground-truth. We have made this subset publicly available for other researchers’ use. The number of tweets in each timeslot for both datasets has been illustrated as a histogram in Figs. 2 and 3. Both datasets have been automatically collected by using hashtags; therefore, irrelevant (outlier) tweets might exist in them, which would lead to challenges in topic detection. This issue was the reason for neglecting topic precision as an evaluation metric.

4.2 Results

The evaluation metrics include topic and keyword recall, keyword precision, and F-score (for keyword evaluation). We used micro-averaging for computing the final

![Fig. 2 Daily distribution of COVID-19 tweets in a 31-day interval](image-url)
value of evaluation metrics both for the topic and keyword evaluation (Fig. 4). We conducted several experiments, the results of which are portrayed in Fig. 5. These results have been obtained when topic-number-per-timeslot is 2 to 20 (for both datasets) and keyword-number-per-topic is 5 for the covid-19 and 9 for the FA CUP datasets. The exact values of topic recalls have also been provided in Table 2.

It can be concluded from this table and figure that a higher number of topics would result in a higher topic recall, especially in the COVID-19 dataset. The intuition behind the harsh slope of the line (from 0 to 3) in the COVID-19 is that the number of hot topics per timeslot ranges from 0 to 3, and therefore increasing the number of estimated hot topics would increase topic recall until 3, but after 3, due to the lower number of topics per timeslot in the ground-truth, the line rises with a lower slope. However, increasing this number does not affect other metrics (Keyword precision and recall) much because having more topics would require estimating more topic keywords, whereas our estimation would not always be correct (Fig. 6).

Finally, we provide the t-distributed stochastic neighbor embedding (tSNE) diagrams for both datasets in a specific timeslot in Fig. 7. Each agent in this diagram represents a cluster including similar datapoints, i.e., tweets sharing a topic.

4.3 Discussion and comparison

We obtained different topic recall values for different values for topic-number-per-timeslot, which have been provided in Table 3. This table also compares the obtained values with other approaches applied to the FA CUP dataset for topic detection. The intuition behind applying the proposed approach on the FA CUP dataset is a fair com-
Fig. 4  TRec, KWRRec and KWPrec for different number of topics per timeslot in the COVID-19 dataset

Fig. 5  TRec, KWRRec and KWPrec for different number of topics per timeslot in the FA CUP dataset
Table 2  Topic recalls for both datasets obtained by the proposed approach

|      | 2   | 4   | 6   | 8   | 10  | 12  | 14  | 16  | 18  | 20  |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| COVID-19 | 0.361 | 0.500 | 0.611 | 0.667 | 0.722 | 0.833 | 0.861 | 0.861 | 0.917 |
| FA CUP   | 0.692 | 0.840 | 0.923 | 1    | 1    | 1    | 1    | 1    | 1    | 1    |

Fig. 6  The t-distributed stochastic neighbor embedding (tSNE) diagrams for a specific timeslot in the FA CUP datasets

Fig. 7  The t-distributed stochastic neighbor embedding (tSNE) diagrams for a specific timeslot in the COVID-19 datasets
### Table 3

The topic recalls of the proposed approach and its comparison with other methods when applying on the FA CUP dataset with different topic numbers. TR stands for Topic Recall. The maximum value in each column is in bold.

| Method          | TR@2 | TR@4 | TR@6 | TR@8 | TR@10 | TR@12 | TR@14 | TR@16 | TR@18 | TR@20 |
|-----------------|------|------|------|------|-------|-------|-------|-------|-------|-------|
| FA CUP          |      |      |      |      |       |       |       |       |       |       |
| Gfeat-P         | 0.000| 0.308| 0.308| 0.375| 0.375 | 0.375 | 0.375 | 0.375 | 0.375 | 0.375 |
| SNMF-Orig [41]  | 0.113| 0.180| 0.257| 0.334| 0.411 | 0.411 | 0.411 | 0.411 | 0.411 | 0.411 |
| SNMF-KL [41]    | 0.180| 0.334| 0.497| 0.651| 0.840 | 0.840 | 0.840 | 0.840 | 0.840 | 0.923 |
| SVD-Kmean [41]  | 0.473| 0.615| 0.692| 0.840| 0.923 | 0.961 | 0.961 | 0.961 | 0.961 | 0.961 |
| WDHG [41]       | 0.473| 0.615| 0.692| 0.718| 0.718 | 0.840 | 0.879 | 0.879 | 0.961 |       |
| LDA             | 0.692| 0.692| 0.840| 0.840| 0.923 | 0.923 | 0.840 | 0.840 | 0.840 | 0.750 |
| Exemplar [41]   | 0.802| 0.840| 0.879| 0.899| 0.923 | 0.923 | 0.923 | 0.923 |       | 0.923 |
| BNgram          | 0.769| 0.923| 0.923| 0.923| 0.923 | 0.923 | 0.923 | 0.923 |       | 0.923 |
| Doc-P           | 0.769| 0.840| 0.923| 0.923| 1     | 1     | 1     | 1     | 1     |       |
| SFPM            | 0.615| 0.840| 0.840| 1     | 1     | 1     | 1     | 1     | 1     |       |
| ComStreamClust1 | 0.692| 0.840| 0.923| 1     | 1     | 1     | 1     | 1     | 1     |       |
| ComStreamClust2 | 0.840| 0.923| 0.923| 0.923| 0.923 | 0.923 | 0.923 | 0.923 | 1     | 1     |

Comparison with the existing methods because the same datapoints in the FACUP dataset are used by other research works in the literature; However, in the case of COVID-19, a different subset of tweets are usually used in each work. Moreover, people usually do not make their dataset publicly available. We implemented most of the approaches shown in this table on the FA CUP and reported the results of a few recent works without re-implementing them – rows with citations. We applied also two versions of the proposed approach on this dataset. The difference between ComStreamClust 1 and 2 relies on two parameters: assign-radius, and outlier-threshold. ComStreamClust1 with lower values for these parameters starts not very well but fastly obtains the best result. On the other hand, ComStreamClust2 with higher values for these parameters starts well, but accelerates slowly. The intuition behind this issue is that the lower radius causes a higher number of agents, and a higher number of agents would make them more specific. But when the radius is higher, a lower number of agents with more generality would be generated.

Several erroneous cases were causing lower topic recall in both datasets, such as the overshadowing phenomenon. For instance, in the FA CUP, a goal was achieved by Drogba in the 24th minute, which is a hot topic in timeslot 24. There is another hot topic in the 25th minute that discusses passing the ball to Drogba before achieving the goal. The latter topic was overshadowed by the first one, i.e., the latter was lost in minute 25 among tweets issued in minute 24.

**Keyword analysis:** We tested the proposed approach with different values for the parameter, *no-keywords* (per topic), and concluded that 5 and 9 keywords per topic respectively in the FACUP and COVID-19 datasets achieve the best results. A lower number of keywords would result in lower topic-recall due to detecting fewer topics, but higher topic precision. A greater number of keywords, on the other hand, would...
detect more topics causing higher topic recall and lower topic precision. At the end of all timeslots in each dataset, some keywords have been labeled as most frequent, which have been illustrated as boxplots in Figs. 8 and 9.

As can be seen in COVID-19’s boxplot, the most frequent words are "stay", "pandemic", "home" and "people", which may imply that due to the COVID-19 pandemic, people suggest each other to "stay at home". We observed in this dataset that the majority of tweets include the hashtag #StayAtHome. Note that obvious frequent keywords such as "COVID19", "coronavirus", "corona", and "virus" have been treated as stopwords, as they appear in almost all tweets. We chose a few sample tweets from each dataset, including a hot topic in its timeslot. Table 4 lists these sample tweets.
Table 4  Sample tweets including hot topics for each dataset

| Text                                                                 | Date-time | Keywords     |
|---------------------------------------------------------------------|-----------|--------------|
| COVID-19                                                            |           |              |
| #BREAKING The #UK #PrimeMinister @BorisJohnson has been moved to #ICU "#BorisJohnson moved to intensive care after being admitted to hospital with #coronavirus symptoms" #COVID19 https://t.co/mq4gDedDGx | 19:25:28  | Icu hospital |
| It’s #EarthDay2020. It’s ironic that the #COVID19 crisis has made us think more about how vulnerable we are on this fragile earth. Maybe now our governments will rethink their intransigence on climate change action. | 03:18:01  | Earth change |
| FA CUP                                                              |           |              |
| 44” Daniel Agger made a hard tackle to Mikel. And shown yellow card by the referee. #FAcup | 17:01:34  | Mikel daniel |
| Ø/ Yay Chelsea! RT @itvfootball: Congrats to #CFC on beating #LFC 2-1 and winning the 2012 #FAcupFinal | 18:09:52  | Cup chelsea  |
|                                                                      | 2020-04-22| Climate      |
|                                                                      | 2020-04-06| Boris johnson|
|                                                                      | 2020-04-22| Climate      |
Multi-agent setup: The proposed approach is capable of being parallelized. In order to prove this claim, we implemented it in the elixir language using a multi-processor system, after running the implemented system in python on a single-processor system. The CPU Specifications for this system is 4x i7 6700 HQ @3.8GHz, and its RAM is 16 GB. We conducted this experiment to see if the proposed approach can be executed in a multi-agent system and also how much time can be saved in a parallel setting compared to the sequential case. More specifically, we used a multi-agent system including eight processors, each of which handles one cluster. If the number of clusters is more than eight (which is the case in some time intervals), the parallel system will transform to an eight-processor pipeline—the ninth and other clusters will be concurrently processed. The time intervals spent for the sequential and parallel cases are respectively 5 minutes and 14 seconds and 4 minutes and 40 seconds. Note that sequential processing in python takes advantage of the optimal implementation of libraries such as NumPy which drastically decreases the execution time, whereas elixir lacks such optimality. Every process in this language has to be executed in parallel; no sequential execution is allowed in it. In conclusion, due to the facts discussed above, the improvement in the execution time is not substantial. This improvement could be greater with higher-speed processors.

The space complexity of ComStreamClust is: \( O(dp \times \text{sentence length} + \text{agents} \times \text{embedding dim}) \), where \( dp \) is the number of data-points, sentence length is the number of its characters, and agents are the number of clusters. The space depends on two factors: (1) The input data we receive through streaming, and (2) The number of agents and the embedding dimensionality they store. Since we have the embedding model and the content of each data-point, those data-points can be converted to embeddings, therefore, the embeddings of each data-point does not have to be stored. For the sake of lower space complexity, as the proposed system stores the existent data in the sliding window intervals, it frees up the memory by deleting older data-points as the time passes.

The time complexity of ComStreamClust is: \( O(dp \times \text{agents} \times \text{embedding dim} / \# \text{of parallel cores}) \) which is mostly affected by the streaming step where the algorithm finds the distance between the streamed data-point and agents to find the most appropriate agent to assign the data-point. Note that the communication step has the same time complexity as the streaming step, so it does not change the overall time-complexity. For the sake of parallelism, ComstreamClust assigns agents to cores to independently manage them; therefore, the number of parallel cores is a factor that reduces the time-complexity.

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4 https://elixir-lang.org/docs.html.
| Table 5 | Sample tweets turned to normal data-points from outlier |
|---------|--------------------------------------------------------|
|         | Tweet | Tweet assumed as outlier | Tweet assumed as normal |
| COVID-19| british prime minister boris johnson moved intensive care | ['boris', 'johnson', 'pandemic', 'trump', 'news', 'care', 'social', 'lockdown', 'health'] | ['boris', 'johnson', 'care', 'intensive', 'stay', 'moved', 'prime', 'minister', 'icu', 'recovery'] |
| FACUP  | great save by cech from a low suarez shot. fa cup final | ['the', 'arsenal', 'you', 'goal', 'cfc', 'still', 'please', 'minutes', 'have', 'chelsea'] | ['cup', 'fa', 'final', 'wembley', 'cfc', 'sl', 'chelsea', 'cech', 'suarez', 'save'] |
Data-point tracking: For deeper analysis, we tracked some data-points during their life-cycle in our methodology. Some data-points might be assumed as an outlier in a cluster but after reassignment to another cluster, they turn to be a normal data-point. Two sample tweets have been tracked in Table 5. In this table, the COVID-19 tweet was first categorized in a general-concept cluster, but when it was identified as an outlier in that cluster, the coordinator re-assigned it to a more specific cluster; Therefore, a normal data-point could be kept among clustered data. In the FACUP tweet, the situation is also similar. Saving the shot of Suarez by Cech was supposed to be an outlier in a general tweet and then labeled as a normal data-point in a more specific one.

The strengths of the proposed approach include its dynamic, communicative, and parallelizable nature and keeping the detected topics (clusters) as pure as possible. ComStreamClust attempts to keep clusters fresh, by discarding older tweets and updating the clusters by adding newer ones, and also detecting and deleting the outliers. A tweet might gradually turn into an outlier due to the updates that happen to the cluster, including it. The weakness of this approach might be its need for parameter tuning, i.e., it requires adapting each parameter for the given dataset.

5 Conclusion and future work

This paper proposes a new topic detection approach using stream clustering on Twitter data. The proposed approach, named “ComStreamClust”, is unique in that it benefits from a communication phase, in which, clusters communicate with each other in
a multi-agent and parallelizable setting. ComStreamClust has been applied on two datasets, the COVID-19 and the FA CUP. When applied to the FA CUP dataset, it was shown that the proposed methodology provides superior or, in some cases, equal performance compared to other methodologies. The current analysis on the COVID-19 dataset approves the assumption that social media can help governments and health centers cure this pandemic more efficiently and rapidly. For example, almost all Twitter users have used #StayAtHome in their tweets, which would remind people that staying at home is the most efficient treatment for the COVID-19 pandemic. Our future works include exploiting images inside tweets to accomplish a multi-modal topic detection on Twitter.

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**Data Availability**  Two datasets used in this article are available online:
Covid Dataset: [https://www.kaggle.com/thelonecoder/labelled-1000k-covid19-dataset](https://www.kaggle.com/thelonecoder/labelled-1000k-covid19-dataset)
FA CUP Dataset: [https://ieeexplore.ieee.org/abstract/document/6525357](https://ieeexplore.ieee.org/abstract/document/6525357)

**Code Availability**  The code is available online and it is shared in the paper: [https://github.com/AliNajafi1998/ComStream](https://github.com/AliNajafi1998/ComStream)

**Conflicts of interest**  There is no conflict of Interest

**Ethical Statements**  We hereby declare this manuscript is the result of our independent creation under the reviewers’ comments. Except for the quoted contents, this manuscript does not contain any research achievements that have been published or written by other individuals or groups. We are the only authors of this manuscript. The legal responsibility of this statement shall be borne by us.

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