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Detecting Rumours with Latency Guarantees using Massive Streaming Data

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Abstract Today’s social networks continuously generate massive streams of data, which provide a valuable starting point for the detection of rumours as soon as they start to propagate. However, rumour detection faces tight latency bounds, which cannot be met by contemporary algorithms, given the sheer volume of high-velocity streaming data emitted by social networks. Hence, in this paper, we argue for best-effort rumour detection that detects most rumours quickly rather than all rumours with a high delay. To this end, we combine techniques for efficient, graph-based matching of rumour patterns with effective load shedding that discards some of the input data while minimizing the loss in accuracy. Experiments with large-scale real-world datasets illustrate the robustness of our approach in terms of runtime performance and detection accuracy under diverse streaming conditions.

1 Introduction

Social networks such as Twitter, Facebook, and Yelp produce data streams at an unprecedented rate. For instance, half a billion tweets are generated every day [6]. However, social networks are known to be susceptible to the spread of false information and rumours [36]. The inherent openness of social platforms enables users to produce and propagate content without authentication and verification, which has been exploited for massive rumour propagation. Reports show that three-quarters of online news consumers say they encounter one or more instances of rumours every day [21].

The high velocity and low veracity of data streams emitted by social networks render rumour detection extremely challenging. Beyond the sheer volume of data to process, the challenges stem from the fact that a rumour detection model needs to be continuously retrained to cope with concept drift. Especially in case of short bursts, which frequently happen during the propagation of rumours [34], the data volume exceeds processing limits, and the latency of rumour detection becomes unacceptably high. The latter is of utmost importance since rumours often cause devastating socio-economic damage before being effectively corrected [36]. The reason being that innocent users, without proper alerts from algorithmic models, tend to spread false information accidentally, thereby creating an exponentially growing amount of rumour representations. Hence, rumour detection for social platforms needs to meet tight latency bounds in order to enable mainstream media, governments, legal agencies, and public organisations to react immediately on emerging rumours, false stories, and misinformation [33, 8].

In this paper, we argue for best-effort rumour detection that aims to maximise the number of rumours de-
tected under a given latency constraint. To this end, we propose a load shedding framework that discards some streaming data. However, shedding might compromise detection accuracy, so that rumours could be missed or falsely detected. Thus, it is important to discard only data that has a small impact on rumour detection accuracy; and ideally, none at all. Selecting data for shedding raises several research questions, though: i) How to quantify the importance of data for rumour detection; ii) How to calculate the amount of data to shed in order to maintain a latency bound; and iii) How to shed data efficiently to avoid additional overhead. However, it is not straightforward to answer these questions. Skipping some inputs might make the system get out of overload in a short-term but does not change the efficiency nature of rumour detection, while incurring information loss and making the detection performance worse. Therefore, a good solution requires changing the nature of rumour detection algorithms from offline to online and designing a load shedding mechanism that takes into account these online information to retain only significant data elements. Moreover, these questions shall be addressed for data streams with unstable and fluctuating rates, which render traditional parallelization and distribution schemes insufficient [30].

Addressing the above questions, our contributions and the paper structure, following some background on anomaly-based rumour detection in §2, are summarised as follows:

- **Model and Architecture for efficient streaming rumour detection:** In §3, we propose a general framework that enables efficient rumour detection on high-velocity streams. At its core, this framework includes a load shedding strategy to guarantee latency constraints by discarding some of the input data. Using the remaining data, rumours are detected online by graph-based matching of propagation patterns and an anomaly scoring mechanism.
- **Streaming rumour detection:** In §4, we provide techniques for pattern matching and anomaly scoring in our framework. Based on existing mechanisms for static data, we present online algorithms that enable efficient rumour detection over data streams.
- **Coefficient-based load shedding:** In §5, we design a statistical model to capture the importance of social data for rumour detection. It assesses the correlation between data types and their ordering, and the patterns hinting at rumours. Based thereon, we present a load shedding algorithm that balances the trade-off between detection accuracy and latency.

We report on an experimental evaluation in §6. Then, §7 reviews our contributions in the light of related work, before §8 concludes the paper.

2 Background

This section provides background for our work. We first discuss how the spread of rumours in social networks is manifested in patterns in the respective data (§2.1). Subsequently, we summarise how these patterns form the basis for anomaly-based rumour detection (§2.2).

2.1 Rumour patterns in social network data

Considering the data emitted by a social network, a rumour is a rooted sub-graph of a graph spanned by its entities [36]. Taking the case of Twitter as an example, Fig. 1, illustrates entities such as users, tweets, links, and hashtags, along with their relations. Assuming that the visualised subgraph denotes a rumour, the root entity models the user who first published the rumour as part of a tweet. The subgraph further indicates other related entities, such as involved hashtags and links, as well as the propagation of the rumour through forwarding and reposting by another user. Monitoring the relations between entities, most of which are timestamped, reveals the propagation structures of rumours [34].

While different characteristics of social networks are linked to rumours, graph-based patterns of the propagation structure are known to be most relevant to detect rumours [36,37]. Using data on the relations between the network’s entities, rumours can be detected based on patterns, so-called rumour patterns, dozens of which have been identified for diverse domains [8,21].

*Example 1* Fig. 2 illustrates rumour patterns for the case of Twitter. In pattern $p_1$, a tweet that initiates a rumour contains a link, a hashtag, and a mention of a famous person. Pattern $p_2$ reflects a cascade of retweets by users. Pattern $p_3$ captures that a rumour often originates from a hot topic, which is captured by a hashtag that is used frequently.
Fig. 2: Typical rumour patterns in social networks.

Contemporary approaches to rumour detection use the matches of such rumour patterns as part of a learning process. That is, the matches are used as indicators of potential rumours rather than immediate characterizations of rumours. They are fed into a rumour detector, which then decides whether a pattern match shall be considered a rumour, or not. Note that a match also include node and edge features of the subgraph, which help a rumour detector to separate rumours from other social events. While most existing proposals for rumour detection consider the subgraph structure, some techniques also consider only the set of entities of a subgraph and their associated features to classify rumours [2, 41, 48]. Nevertheless, matching of rumour patterns is required to identify the sets of entities to feed into a rumour detector.

The exact definition of rumour patterns induces a trade-off: The more complex the patterns, the better they are correlated to rumours, separating them from other social phenomena [34]. Yet, faced with high volumes of data as emitted by social networks, matching complex patterns potentially exceeds processing limits. Against this background, several collections of patterns that proved useful have been presented in recent years, see [34, 39].

In our work, we largely abstract from the details of existing proposals for rumour detection. Rather, we focus on the efficiency of the first step of rumour detection, which is the matching of rumour patterns under latency bounds. As such, we rely on existing collections of rumour patterns rather than designing new ones, while our contributions are independent of the exact choice of a pattern collection. Moreover, we change the nature of rumour detection from offline to online by proposing streaming pattern matching via a pattern index and streaming anomaly computation via sketch structures.

In the remainder, we use Twitter as an example of a social network. Note though that our approach adopts a generic graph-based model that is applicable also to other social networks [28].

2.2 Anomaly-based rumour detection

While rumour patterns capture common propagation structures of rumours, not all of their matches denote actual rumours [17]. Rather, state-of-the-art approaches use these matches to extract features of entities and relations, and learn a model to classify matches as rumours or other types of social phenomena [49, 36]. Specifically, this classification is based on inconsistencies in the propagation structure described by pattern matches. In a first step, this involves the identification local anomalies related to the features of the entities and relations in the pattern matches. Since such local anomalies, typically, do not represent reliable signals, a second step is the identification of global anomalies that comprise connected entities for which local anomalies have been observed. Below, we exemplify this general approach.

Example 2 Consider the Twitter social network in Fig. 3. Here, entities have features, e.g., a user has a registration date and a number of followers. Also, relations are annotated with attributes, e.g., the tweet-article relation is annotated with the difference between the publication dates of the tweet and the article. Fig. 3 illustrates how rumours are manifested in local anomalies: The highlighted user has a registration date that is significantly newer than those of related users and the number of retweets of the highlighted tweet is suddenly very high. Using these local anomalies, a global anomaly is identified: The highlighted subgraph in the social network comprises a user, a tweet, a hashtag, and a linked article that all show local anomalies. In addition, some of the relations in the subgraph provide evidence for a rumour, such as the time difference between the highlighted tweet and linked article.

In the remainder of this section, we illustrate in more detail the features used for rumour detection along with the respective scoring mechanisms.

2.2.1 Features to identify rumours

While the definition of meaningful features is specific to the domain of the considered social network, we discuss some of the features defined in [34] for the case of Twitter as illustrative examples. Considering the entities, for instance, the registration age and a credibility score are used to identify rumours. Also, sudden changes in the number of followers of a user or the frequency with which a user publishes status updates potentially indicate anomalous behaviour. For articles linked in tweets, the linguistic style as well as the number of mentions over time are incorporated. Turning to the relations in a social network, for instance, differences in the time
and location of a tweet and a linked article serve as features. Another example is the relation between users and hashtags, for which the fact that the user has not used the hashtag before represents a feature.

The combination of a large number of diverse features ensures a certain robustness of rumour detection.

2.2.2 Local and global anomaly computation

Using sets of features as discussed above, rumour detection first identifies local anomalies related to individual entities and relations, before aggregating them to identify global anomalies, i.e., in terms of a subgraph in the social network [34].

Element-level scoring. An anomaly score is derived based on the differences between the current and past values of a feature vector assigned to an entity or a relation. To this end, an anomaly score is first derived per feature. Using historic data, this score is computed as a non-parametric statistical measure, an empirical p-value, that quantifies the number of past feature values that differ from the current observation. These anomaly scores per feature are then aggregated for each entity and relation, respectively. It was argued that such aggregation shall be guided by the minimum values over all features [34]. This way, false positives that stem from a few features that indicate anomalies, whereas other features do not, shall be avoided.

Subgraph scoring. Using the local anomaly scores per entity and relation, a global anomaly score is computed for connected subgraphs to identify those that represent a rumour. To this end, scan statistics [16] that assess the statistical significance of a subgraph being anomalous can be leveraged. In essence, it considers all elements (entities and relations) with anomaly scores that are significant at a given confidence level. To capture the propagation of rumours, the employed detection mechanism is commonly designed such that elements that have insignificant scores may be added to the subgraph as long as they are connected with a sufficiently large number of elements with significant scores.

3 Efficient Streaming Rumour Detection

This section introduces a general framework for efficient rumour detection on high-velocity streams. We argue that a good solution requires changing the nature of rumour detection algorithms from offline to online and designing a load shedding mechanism that takes into account these online information to retain only significant data elements. In §3.1, we first present a respective architecture. Subsequently, §3.2 defines a formal model that captures the most important notions needed to instantiate this architecture in the remainder of the paper.

3.1 Architecture

In Fig. 4, we outline a general architecture for streaming rumour detection. Ignoring load shedding for the time being, streaming data emitted by a social network are pushed to an input buffer. They are then processed by pattern matching, which is based on a predefined collection of patterns, as exemplified in the previous section. The matches are used by a rumour detector to identify rumours. Here, we abstract from the internals of the detector, such as the exact set of employed features. Instead, we focus on the algorithms used to compute anomaly scores online based on some set of features and the matches of rumour patterns.

This general approach is extended with functionality for load shedding in order to achieve efficient processing of the stream. Aiming to meet tight latency bounds, the respective component needs to assess whether the rumour detector is overloaded, which is operationalised by checking the input buffer size periodically. If an overload situation is detected, load shedding discards some input data before it is considered for pattern matching, thereby preventing that a latency threshold is violated.

Coefficient modelling, in turn, uses the results of the rumour detector to guide load shedding. Here, the goal is to minimise the loss in detection accuracy implied by the discarded data. To this end, a model of coefficients is maintained that captures the importance of particular types of data in the input buffer for rumour detection.
In sum, our approach is to monitor the processing rate (via waiting time of data in the buffer) and the utility of data (via statistics) to shed some data elements in the buffer when the system is overloaded (the latency threshold is violated). Intuitively, if we shed important data elements (high utility), it would harm the rumour detection accuracy as the detector will not have sufficient information. However, if less important data is kept, the system may become overloaded. This issue is addressed in our approach with statistical coefficients to capture the utility in the long run and to estimate the utility of any new data element.

Both, load shedding and maintenance of coefficients are time-critical tasks, as they shall ensure efficient processing in an overload situation. Hence, they must not induce a notable overhead, since this would thwart any performance benefit resulting from the discarded data.

3.2 Model

We capture the setting of rumour detection over streaming data with the following notions and notations. An overview is provided in Table 1.

**Multi-modal social graph.** Let $\mathcal{M}$ be a set of modalities and $\mathcal{U}$ be a set of entities. Then, a multi-modal social graph at a specific time point $t$ is an annotated graph $G(t) = (V(t), E(t), M(t))$, where vertices $V(t) \subseteq \mathcal{U}$ denote a set of entities, edges $E(t) \subseteq V(t) \times V(t)$ denote a set of relations, and $M(t) : V(t) \rightarrow \mathcal{M}$ is a function that assigns a modality to each entity. Note that the latter induces a second-order modality for each relation, i.e., the pair of modalities of the source and target entities. The notion of a social graph enables us to address rumour detection in a very generic setting [10].

**Example 3** We construct a multi-modal social graph from the example given in Fig. 1 as follows. The example comprises four modalities, which are given as $\mathcal{M} = \{\text{user, tweet, hashtag, link}\}$. Then, at time point 5, the set of entities can be denoted by $V(5) = \{v_1, v_2, \ldots, v_7\}$, where, for instance, $M(5)(v_1) = \text{user}$ and $M(5)(v_2) = \text{tweet}$. The set of relations is $E(5) = \{e_1, \ldots, e_6\}$. Moreover, as an example, the second-order modality of relation $e_1$ is $(\text{user, tweet})$.

**Data stream.** We model the stream of data emitted by a social network by an infinite set of timestamped stream elements $S = \{s_1, s_2, \ldots\}$. Each such element $s_i = (u, u', m, m', t)$ contains two entities, $u, u' \in \mathcal{U}$, of modalities $m, m' \in \mathcal{M}$, respectively, while $t$ is an occurrence timestamp. The occurrence timestamps of elements in a stream increase monotonically, which is denoted by their subscript. With the arrival of $s_i$, $u$ and $u'$ become vertices of $G$, if they are not already part of the graph, while $(u, u')$ becomes an edge. This way, both, new entities and new relations between them are modelled as part of the stream. By $S(t) = \{(u, u', m, m', t') \in S \mid t' \leq t\}$, we denote the stream prefix up to time $t$.

The data emitted by social networks is typically partitioned into windows (e.g., as extracted from the Twitter Streaming API). Here, we consider windows of a fixed size (count-based windows), even though our approach can also be applied for time-based windows, predicate-based windows, and hybrid windows [32]. That is, a window is a set $w = \{s_1, \ldots, s_w\}$ of $|w|$ elements of the stream, $s_i \in S$, $1 \leq i \leq |w|$. For the sake of brevity, we consider windows to be disjoint. However, we note that overlapping windows could be handled as well once a hashing mechanism would be in place to avoid duplicates.

**Rumour patterns.** As detailed above, contemporary approaches to rumour detection exploit collections of rumour patterns. With $\mathcal{M}$ as a set of modalities, we formalise a rumour pattern as an annotated graph $p = (V_p, E_p, M_p)$, where $V_p$ is a set of entity variables, edges $E_p \subseteq V_p \times V_p$ denote relation variables, and $M_p : V_p \rightarrow \mathcal{M}$ is a function that assigns a modality to each entity variable. A rumour detection technique processes the relations given in a data stream and matches a set of such patterns $P = \{p_1, \ldots, p_9\}$.

Let $G(t) = (V(t), E(t), M(t))$ be a multi-modal social graph at time point $t$. Then, a match of a pattern $p = (V_p, E_p, M_p)$ is given as an isomorphic subgraph of $G(t)$. That is, a match is characterised by a bijection $\lambda : V_p \rightarrow V(t)$, such that $(v, v') \in E_p \Leftrightarrow (\lambda(v), \lambda(v')) \in E(t)$ and for all $v \in V_p$ it holds that $M_p(v) = M(t)(\lambda(v))$.

**Example 4** Consider rumour pattern $p_2$ from Fig. 2, which models a cascade of retweets. We formalise this pattern as $p_2 = (V_{p_2}, E_{p_2}, M_{p_2})$, where the entity variables are given as $V_{p_2} = \{v_1', \ldots, v_4'\}$, edges are defined as $E_{p_2} = \{(v_1, v_2), (v_2, v_3), (v_3, v_4)\}$, and the modalities are given as $M_{p_2}(v_1) = M_{p_2}(v_3) = \text{user}$ and $M_{p_2}(v_2) = \text{tweet}$. Evaluating this pattern over the multi-modal social graph from Fig. 1, we derive a match based
Table 1: Overview of notions and notations.

| Notation           | Meaning                                                                 |
|--------------------|-------------------------------------------------------------------------|
| $\mathcal{M}$      | Set of modalities                                                       |
| $\mathcal{U}$      | Set of entities                                                         |
| $G(t) = (V(t), E(t), M(t))$ | Social graph at time $t$: Entities $V(t)$, relations $E(t) \subseteq V(t) \times V(t)$, and modalities $M(t) : V(t) \rightarrow \mathcal{M}$ |
| $S = \{s_1, s_2, \ldots\}$ | Stream of timestamped elements $s_i = (u, u', m, m', t)$ with $u, u' \in \mathcal{U}$ and $m, m' \in \mathcal{M}$ |
| $S(t)$             | Prefix of the stream up to time $t$                                      |
| $w = \{s_1, \ldots, s_{|w|}\}$ | Window of $|w|$ stream elements, $s_i \in S$, $1 \leq i \leq |w|$ |
| $p = (V_p, E_p, M_p)$ | Rumour pattern: Entity variables $V_p$, relation variables $E_p \subseteq V_p \times V_p$, and modalities $M_p : V_p \rightarrow \mathcal{M}$ |
| $P = \{p_1, \ldots, p_k\}$ | Set of rumour patterns                                                  |
| $\lambda : V_p \rightarrow V(t)$ | Bijection capturing a match of pattern $p = (V_p, E_p, M_p)$ over $G(t) = (V(t), E(t), M(t))$, such that $(v, v') \in E_p \Rightarrow (\lambda(v), \lambda(v')) \in E(t)$ and $\forall v \in V_p : M_p(v) = M(t)(\lambda(v))$ |
| $\Gamma$           | Rumour detector                                                         |
| $f(\Gamma, P, S(t))$ | Detection coefficient: $\#$ rumours detected by $\Gamma$ over stream prefix $S(t)$ based on patterns $P$ |
| $\rho : S \rightarrow [0, 1]$ | Load shedding function: Indicates which stream elements to discard (0) or process (1) |
| $S'(t) = \rho(S(t))$ | Stream prefix after load shedding                                         |

on the following bijection, $\lambda(v'_1) = v_1$, $\lambda(v'_2) = v_3$, $\lambda(v'_3) = v_6$, and $\lambda(v'_4) = v_7$.

**Detection coefficient.** Following the architecture outlined in Fig. 4, a rumour detector derives the matches of rumour patterns and, based thereon, distinguishes rumours from other phenomena commonly observed in social networks [40]. Let $\Gamma$ be the rumour detector, $S(t)$ be a stream prefix, and $P$ a set of rumour patterns. Then, we denote by $f(\Gamma, P, S(t))$ the detection coefficient, which is defined as the number of rumours detected by the rumour detector $\Gamma$ over stream prefix $S(t)$ based on the set of rumour patterns $P$.

**Load shedding.** Finally, we clarify, in abstract terms, how to incorporate load shedding in our model. It is captured by an indicator function $\rho : S \rightarrow \{0, 1\}$ over the stream elements, specifying whether they are discarded (0) or processed (1). Applying such a function to the data stream yields a projection of the original stream, i.e., all elements for which $\rho$ signals that they shall be discarded are removed from the stream. Overloading notation, we denote this application by $S'(t) = \rho(S(t))$ for a stream prefix $S(t)$ and by $w' = \rho(w)$ for a window over the stream $S$, where $S'(t) \subseteq S(t)$ and $w' \subseteq w$, respectively.

### 4.1 Streaming Pattern Matching

**Initial social graph.** The evolution of a social network is captured by a stream, an infinite set of timestamped relations, as introduced in §3.2. However, rumour detection typically does not start from scratch, i.e., without any information about the considered social network. Rather, rumour detection typically incorporates a snapshot of the network at a certain point in time. This model then serves as the basis for the construction of the features as well as the local and global anomaly scoring, as detailed in §3.2.

To capture this setting in our model, an initial social graph is derived from historic data of the social network. This data is analysed syntactically to extract different types of entities (e.g., the posts, links, hashtags, and users in case of Twitter) and relations (e.g., retweets, mentions, links, or hashtags). As such, the data stream that is actually processed for rumour detection captures the evolution of this initial social graph.

**Pattern index (P-index).** To enable efficient rumour detection, we introduce a data structure, coined P-index. It captures for each specific entity, how many entities of a particular modality are connected to it. Put differently, it captures the in-degree and the out-degree of an entity in the social graph $G(t) = (V(t), E(t), M(t))$, grouped per modality. We model the P-index as two functions $I_{in}^{(t)} : V^{(t)} \times M \rightarrow \mathbb{N}_0$ and $I_{out}^{(t)} : V^{(t)} \times M \rightarrow \mathbb{N}_0$, so that, at time point $t$, $I_{in}^{(t)}(v, m) = k$ captures that there are $k$ entities of modality $m$ connected to entity $v$, while $I_{out}^{(t)}(v, m) = k$ means that $k$ entities of modality
m are connected from it. By maintaining these structural dependencies between entities, our index supports streaming pattern discovery as it tracks partial matches of each pattern, as discussed next.

Example 5 Let us illustrate the use of the P-index with the example network in Fig. 1. At time $t = 3$, the P-index of entity $v_3$ contains the following entries:

\[
I_{in}^{(t)}(v_3, \text{user}) = 1, \quad I_{in}^{(t)}(v_3, \text{tweet}) = 0,
\]

\[
I_{in}^{(t)}(v_3, \text{hashtag}) = 0, \quad I_{in}^{(t)}(v_3, \text{link}) = 0,
\]

\[
I_{out}^{(t)}(v_3, \text{user}) = 0, \quad I_{out}^{(t)}(v_3, \text{tweet}) = 0,
\]

\[
I_{out}^{(t)}(v_3, \text{hashtag}) = 1, \quad I_{out}^{(t)}(v_3, \text{link}) = 1.
\]

Using this index, we know that $v_3$ does not yet belong to a match of $p_1$ in Fig. 2, as this would require:

\[
I_{out}^{(t)}(v_3, \text{user}) = 1,
\]

\[
I_{out}^{(t)}(v_3, \text{hashtag}) = 1,
\]

\[
I_{out}^{(t)}(v_3, \text{link}) = 1.
\]

Therefore, although we do not save all partial matches for an entity or relation, we may conclude that it is not yet part of a match. Once the necessary condition for a match is satisfied, we only need to conduct an additional breadth-first search to actually check for a match, as will be clarified next.

Matching algorithm. Given a data stream and a set of rumour patterns, the procedure to derive the pattern matches is formalised in Alg. 1. As discussed in §2.1, the set of rumour patterns is pre-defined and taken from existing work [34,38]. First, the social graph is initialsed as discussed above (line 1). Then, for each element $s$ of the stream arriving at time $t$, the entities, the relation, and the modalities are added to the social $G^{(t)}$ (line 6 to line 9). The P-index is updated for both entities, increasing the in- and out-degrees for the respective modalities (line 10 and line 11). Next, we iterate over the set of patterns $P$ to identify the matches. To this end, we first assess whether the edge created in the social graph by the current stream element $s$ matches one of the relation variables of pattern $p$, which is a necessary condition for further matching (line 13). If this condition is satisfied, function BFS-match returns any new matches, or the empty set if there are none (line 14). Since the P-index maintains all previous connection-related information of the entities in the social graph, the index is sufficient to check whether there exists a match. That is, using a guided breadth-first search (BFS) [12] from $(u, u')$ using the P-index and pattern $p$ as pivot, potential matches are derived efficiently. This is due to the fact that the BFS can stop early, if the P-index of an entity does not have sufficient in- and out-degrees for a given pattern to match. Moreover, the search also stops when a match is found. Therefore, the expansion is never larger than the pattern itself.

Example 6 Let us continue with Ex. 5 and consider the time that $e_5$ is inserted into the social graph as an element of data stream. Then, the P-index of entity $v_3$ will contain the following non-zero entries (the entries with a value of zero are not shown for brevity):

\[
I_{in}^{(t)}(v_3, \text{user}) = 1,
\]

\[
I_{in}^{(t)}(v_3, \text{link}) = 1,
\]

\[
I_{out}^{(t)}(v_3, \text{hashtag}) = 1,
\]

\[
I_{out}^{(t)}(v_3, \text{link}) = 1.
\]

The P-index of entity $v_5$ will be $I_{in}^{(t)}(v_5, \text{tweet}) = 1$ (again, zero-value indexes are not listed for brevity). As can be seen in Fig. 2, $e_5$ is a part of pattern $p_1$ (the relation from a tweet to a user). Our algorithm will perform a BFS starting from $e_5$. First, it will verify the P-index of $v_3$, i.e., it will check whether it is already connected to a link and a hashtag, which is true at that time. Then, the BFS will consider $e_3$ and $e_4$, before it stops, as the pattern $p_1$ does not expand beyond that.

Similarly, according to Fig. 2, $e_5$ is also a part of pattern $p_2$. However, since $v_3$ is not connected to another tweet yet, as indicated by the P-index, the BFS stops early and an empty match is returned.

Complexity. For each stream element $s \in S$, the most time-consuming operation of the above matching algorithm is the function BFS-match(). It takes $O(|p|_{\text{max}} \cdot d_{\text{max}})$ time, where

\[
|p|_{\text{max}} = \max_{(V_p, E_p, M_p) \in P} |V_p| \tag{1}
\]

is the size of the largest pattern in $P$, and

\[
d_{\text{max}} = \max_{v \in V^{(t)}} \{|v' \in V^{(t)} \mid (v, v') \in E^{(t)}\} \tag{2}
\]

is the maximum degree over all entities in the social graph. Processing $s$ thus takes $O(|P| \cdot |p|_{\text{max}} \cdot d_{\text{max}})$ time in total. Since these parameters are comparatively small, the runtime of Alg. 1 is asymptotically constant and can be estimated empirically.

Note that a stream element $s$ is unique (i.e., there cannot be more than one relation between two entities) and timestamped at $t$. Therefore, at time $t$, it can generate at most one new match for one specific pattern.
Algorithm 1: Matching of rumour patterns.

\[ \text{input : A data stream } S; \]
\[ \text{a set of rumour patterns } P; \]
\[ \text{output: Matches } A \text{ of query patterns.} \]
\[ \begin{align*}
1 & \text{ Initialise social graph } G^{(0)} = (V^{(0)}, E^{(0)}, M^{(0)}); \\
2 & t_{in}^{(0)}, t_{out}^{(0)} \gets \emptyset; \quad \text{// Initialise empty graph} \\
3 & A \gets \emptyset; \quad \text{// Initialise empty set of matches} \\
4 & t' \gets 0; \quad \text{// Initialise current time} \\
5 & \text{for } s = (u, u', m, m', t) \in S \text{ do} \\
6 & \quad V^{(t)} \leftarrow V^{(t')} \cup \{u, u'\}; \quad \text{// Add entities} \\
7 & \quad E^{(t)} \leftarrow E^{(t')} \cup \{(u, u')\}; \quad \text{// Add relation} \\
8 & \quad M^{(t)}(v) \leftarrow \\
9 & \quad \begin{cases}
   m & \text{if } v = u \\
   m' & \text{if } v = u' \\
   M^{(t)}(v) & \text{otherwise}
\end{cases} \\
10 & \quad G^{(t)} \leftarrow (V^{(t)}, E^{(t)}, M^{(t)}); \quad \text{// Update pattern index} \\
11 & \quad \text{for each pattern } p = (V_p, E_p, M_p) \in P \text{ do} \\
12 & \quad \quad \text{// If it defines a relation variable} \\
13 & \quad \quad \text{matched by the current stream element} \\
14 & \quad \quad \text{if } \exists (v, v') \in E_p : M_p(v) = m \land M_p(v') = m' \text{ then} \\
15 & \quad \quad \quad A \leftarrow A \cup \text{BFSmatch}(G^{(t)}, t_{in}^{(t)}, t_{out}^{(t)}; P, s); \\
16 & \quad \text{return } A;
\end{align*} \]

4.2 Streaming Anomaly Computation

Recall that anomaly-based rumour detection as discussed in §2.2 relies on the matches of rumour patterns and a predefined set of features. Based thereon, local anomalies related to individual entities and relations are derived, before they are aggregated to global anomalies that span a whole subgraph. Having discussed how pattern matching is conducted in an online manner, we now present a streaming approach for the computation of local, element-level anomaly scores as well as of global, subgraph-level anomaly scores.

**Conceptually**, we divide the historic values of a feature into two classes: those of the current time \(t\) and those of earlier points in time \((<t)\). Practically, we maintain two Count-Min-Sketch (CMS) [4] data structures to capture the evolution of the values of a feature \(f\) for an element (entity or relation) \(x\) of the social graph. The first CMS shall approximate the sum of the feature values up to the current time, denoted by \(s^{(t)}\). At any time, the approximation of this sum, denoted by \(\hat{s}^{(t)}\), can be obtained in constant time and memory. The second CMS is used to capture the feature value at the current time, denoted by \(f^{(t)}\), while the approximated value is \(\hat{f}^{(t)}\). Here, the existence of the second CMS is motivated by the fact that many features lend themselves for online computation. For example, to compute the number of retweets of the tweet represented by entity \(v_3\) in Fig. 1, all paths of from \(v_3\) to a user entity and, subsequently, to a tweet entity must be identified. Instead of counting all these paths repeatedly, at any time instant, it is more efficient to maintain the CMS and rely on the approximated value.

As a result, the local anomaly score, i.e., the empirical p-value, that quantifies the number of past values that differ from the current observation, is computed as the chi-square statistic, capturing the difference be-
between the observed \((obs)\) and expected values \((exp)\), of the two classes:

\[
\hat{p}(f, x)^{(t)} = X^2 = \frac{(obs(t) - exp(t))^2}{exp(t)} + \frac{(obs(<t) - exp(<t))^2}{exp(<t)}
\]

\[
= \left( \frac{\hat{f}(t) - \hat{g}(t)/t}{\hat{g}(t)/t} \right)^2 + \left( \frac{\hat{g}(t) - \hat{f}(t) - \hat{g}(t)(t-1)/t}{\hat{g}(t)(t-1)/t} \right)^2
\]

\[
= \left( \frac{\hat{f}(t) - \hat{g}(t)}{t} \right)^2 \frac{t^2}{\hat{g}(t)(t-1)}
\]

(3)

The above formulation enables us to derive a bound for the approximation of the anomaly score, as follows.

**Proposition 1** (Confidence of streaming p-value). *If a feature value with \(\hat{p} < \alpha\), with \(0 < \alpha < 1\), is declared to be an anomaly, the confidence level of this conclusion is \(1 - \alpha\).*

**Proof.** We first recall the guarantees given by the CMS. Given specific values for \(\alpha\) and \(\epsilon\), for appropriately selected data structure sizes, with probability at least \(1 - \alpha/2\), the approximation by the CMS satisfies: \(\hat{f}(t) \leq f(t) + \epsilon N(t)\), where \(N(t)\) is the number of feature values up to time \(t\), and \(\hat{g}(t) \leq \hat{g}(t)\). Now we want to prove that:

\[
P\left( X^2 > X_{1-\alpha/2}^2(1) \right) < \alpha
\]

where

\[
X^2 = \left( \frac{\hat{f}(t) - \epsilon N(t) - \hat{g}(t)}{t} \right)^2 \frac{t^2}{\hat{g}(t)(t-1)}
\]

(5)

and \(X_{1-\alpha/2}^2(1)\) is the \(1 - \alpha/2\) quantitile of a chi-squared random variable with 1 degree of freedom. In other words, using \(X^2\) as our p-value and threshold \(X_{1-\alpha/2}^2(1)\) results in an incorrect anomaly score of at most \(\alpha\).

Since

\[
P(X^2 \leq X_{1-\alpha/2}^2(1)) = 1 - \alpha/2
\]

due to the chi-squared property, and

\[
P(\hat{f}(t) \leq f(t) + \epsilon N(t)) \geq 1 - \alpha/2
\]

(7)

due to the CMS property, we have the following union bound with probability at least \(1 - \epsilon\):

\[
X^2 = \left( \frac{\hat{f}(t) - \epsilon N(t) - \hat{g}(t)}{t} \right)^2 \frac{t^2}{\hat{g}(t)(t-1)}
\]

\[
\leq \left( \frac{f(t) - \hat{g}(t)}{t} \right)^2 \frac{t^2}{\hat{g}(t)(t-1)} = X^2
\]

(9)

\[
\leq X_{1-\alpha/2}^2(1)
\]

(10)

While the above p-value is computed for each feature of an element (entity or relation) of a social graph, the anomaly score of the element is derived by:

\[
p(x)^{(t)} = \frac{1}{t-1} \sum_{t'=1}^{t-1} I_{p_{\min}(x)^{(t')}} \leq p_{\min}(x)^{(t)}
\]

(11)

where \(I(.)\) equals to one if the condition \(.(.)\) is satisfied, and zero otherwise. And \(p_{\min}(x)^{(t')} = \min_f p(f, x)^{(t')}\) is the minimum p-value across all features of \(x\). Following [34], \(\min\) is used as an aggregation function to avoid false positives, where some features indicate an anomaly, whereas other do not. Moreover, we do not consider the minimum p-value over all features at a single timestamp directly, since elements can have different numbers of features. Rather, our idea is to cross-check the scores between different timestamps across features, so that our aggregation yields uniform scores over all entities and relations, regardless of their modality.

Again, we adopt CMS data structures and chi-square statistics to compute \(p(x)^{(t)}\) efficiently. Instead of maintaining the value \(p_{\min}(x)\) at all time points, we consider the p-value for each feature of \(x\) (Eq. 3) as streaming input. Using a similar mechanism as above, we obtain the approximate p-value, denoted by \(\hat{p}(x)^{(t)}\). To derive a bound for this approximation, we can use the union bound (Boole’s inequality) on Eq. 11, resulting in a \(1 - \alpha/(t-1)\) confidence. In other words, the more historical data we have, the more confidence one may put in our anomaly scores.

**Streaming subgraph scoring.** Based on the local anomaly scores per element (entities and relations) of a social graph, global anomaly scores are computed for connected subgraphs. To this end, it was suggested to rely on scan statistics [16] that incorporates all elements with anomaly scores that are significant at a specific confidence level. As detailed in [34], such an approach leads directly to an online procedure to approximate the respective subgraphs. In essence, it leverages the fact that newly added nodes may directly be characterised as being rumour related, either due to being connected to an existing rumour in the social graph or due to inducing a new rumour subgraph.

4.3 Complete View on Streaming Rumour Detection

Finally, we discuss how pattern matching and anomaly scoring as introduced above are combined for streaming rumour detection. Considering Alg. 1, the anomaly scoring is incorporated as follows. First, the element-level scoring is conducted immediately once a new stream element \(s = (u, u', m, m', t) \in S\) is received (line 5).

\[
\]
That is, the p-value is computed for each feature of entity \( u \), entity \( u' \), and relation \((u, u')\) (using Eq. 3). Second, the matches of query patterns are only collected if their anomaly scores have a confidence value above of specific threshold (typically 95%). That is, for each pattern match obtained by \( BFSmatch(G^{(t)}, I_{in}^{(t)}, I_{out}^{(t)}, p, s) \) (line 14) the global anomaly score is computed and used to decide whether the respective subgraph shall be added to the result set \( \Lambda \). This way, only the pattern matches that denote actual rumours are returned by the algorithm.

5 Load Shedding

Next, we turn to the load shedding mechanism in our framework for efficient stream rumour detection, see Fig. 4. However, doing so is not straight-forward as rumour detection is now streaming. Seemingly unimportant data elements might turn out to be important later and vice-versa. We first formulate the goal of load shedding as an optimization problem, i.e., we aim at guaranteeing a specific latency of processing while minimising the loss in the detection coefficient (§5.1). To address this problem, we introduce a coefficient model to capture the importance of data elements in the input buffer (§5.2). Then, we present strategies to decide when, how much, and what to shed based on this model (§5.3). Finally, we discuss extensions of this general approach that cope with more complex application scenarios (§5.4).

5.1 Problem Formulation

When a streaming system becomes overloaded, i.e., the input rate is larger than the processing rate, load shedding is needed to keep the processing latency low [11]. Shedding of elements of a data stream is particularly useful in rumour detection: Dropping data about entities and relations that have a low probability of being part of a match of a rumour pattern paves the way for the detection of actual rumours, which can be mitigated when detected early.

However, load shedding potentially leads to a loss of matches of rumour patterns and, hence, may lower the detection coefficient. Depending on the actual approach employed to detect rumours based on pattern matches, the consequence of load shedding may be both, false negatives, i.e., missed rumours, as well as false positives, i.e., falsely detected rumours. We illustrate this aspect with the following example.

Example 7 Two patterns from Fig. 2 yield matches for the social graph constructed for Fig. 1 at time point 5. That is, for pattern \( p_1 \), we observe a match in which the entity variables of \( p_1 \) are mapped to the entities \( v_3, v_4, v_5, \) and \( v_6 \). Moreover, for pattern \( p_2 \), there is a match that maps the entity variables to entities \( v_1, v_2, v_6, \) and \( v_7 \), as discussed already in Ex. 4. Dropping information about the relation modelled by edge \( e_5 = (v_3, v_6) \) would eliminate these two matches, which may lead to false negatives: Rumours identified based on these patterns could be missed. On the other hand, the loss of edge \( e_6 = (v_5, v_7) \) might lead to false positives. That is, if the user modelled by the entity \( v_6 \) creates another tweet at a later point in time (\( t_5 \)), a match of \( p_2 \) would be induced. As such, a rumour may falsely be identified based on the later tweet.

Effective load shedding shall drop the elements of the data stream with the least impact on the detection coefficient. As such, our objective is to minimise the relative difference in the detection coefficient between rumour detection with and without load shedding, while satisfying a latency bound in the case of shedding.

Problem 1 (Load Shedding in Streaming Rumour Detection). Given a stream prefix \( S(t) \), a set of patterns \( P \), and a rumour detector \( \Gamma \), the problem of load shedding in streaming rumour detection is to design a shedding function \( \rho \), such that the latency of processing any stream element \( s \in S(t) \) stays below a threshold \( \theta \) and the following coefficient loss is minimal:

\[
\frac{f(\Gamma, P, S(t)) - f(\Gamma, P, \rho(S(t)))}{f(\Gamma, P, S(t))} \leq \theta
\]

where \( f(\Gamma, P, S(t)) \) is the detection coefficient, which is defined as the number of rumours detected by the rumour detector \( \Gamma \) over stream prefix \( S(t) \) based on the set of rumour patterns \( P \).

In general, Eq. 12 represents the degradation of rumour detection performance due to load shedding to preserve the processing latency. The above problem becomes more challenging when \( t \) is not fixed to a single time point, but considered over a large time interval. Since real-world rumours are dynamic and have different characteristics over time, rumour detection faces concept drift. As a consequence, a shedding strategy that was effective in the past may become obsolete in the future.

5.2 Coefficient Modelling

To avoid shedding elements of a data stream that contribute significantly to matches of rumour patterns, we assess the contribution of stream elements using a coefficient model. The model is based on the modalities
defined by the stream element for a pair of entities (and, hence, a relation), as well as their relative position within the windows in which the data is emitted by a social network, see §3.2. These choices are motivated by the following considerations: (i) the model shall be lightweight, i.e., it should comprise only relatively primitive information of the stream; (ii) the modalities determine to which extent entities and, hence, relations participate in matches of rumour patterns; (iii) the closer entities and, hence, relations, that are part of pattern matches in a stream, the more likely the matches denote actual rumours, since it is well-known that rumours propagate fast [36].

Statistical coefficient. Based on the above considerations, we build a statistical model for the detection coefficient. That is, we count the number of occurrences of each second-order modality of the relation described by a stream element (which implicitly covers the entities) that contribute to the detected rumours per position in a window. We tune the granularity of this model by normalizing these counts to a predefined interval, given as [0, 100] in the remainder. The coefficient values are stored in a coefficient matrix $II_{|M^2| \times |w|}$, where $|M^2|$ is the number of second-order modalities and $|w|$ is the window size. A cell $II((m, m'), i)$ of the matrix captures the coefficient value, normalized to $[0, 100]$, for a stream element $s = (u, u', m, m', t) \in S$ at the position $i$ of a window defined over the stream.

Shedding by coefficient thresholding. Load shedding shall drop the $k$ relations with the lowest coefficient values in a window (we later discuss how to choose a value of $k$). Yet, a naïve realisation of such a shedding function would have several drawbacks. It would require to wait until the window is fully available (which implies a $O(|w|)$ wait time), to then sort the relations (in $O(|w| \log k)$, e.g., by heap sort), while the overhead would be induced for each window.

Against this background, we consider a more efficient approach that relies on a coefficient threshold, denoted by $\pi_{\text{min}}$, to drop the desired number of relations on-the-fly. Here, the challenge is, given a value for $k$, to set $\pi_{\text{min}}$ accordingly, so that exactly $k$ relations are actually dropped. We address this challenge based on the properties of cumulative distribution functions. That is, for a given window $w$, we define the number of occurrences of a second-order modality, for which the coefficient is less or equal to a certain value $\pi$ as follows:

$$\Omega(\pi) = \{(m, m') \in M^2 | \sum_{1 \leq i \leq |w|} II((m, m'), i) \leq \pi\}. \quad (13)$$

We refer to $\Omega$ as the cumulative coefficient occurrence (CCO). Based thereon, the coefficient threshold $\pi_{\text{min}}$ is derived using the inverse function of CCO for a given the number of relations $k$, i.e., $\pi_{\text{min}} = \Omega^{-1}(k)$.

The CCO $\Omega$ can be derived from the coefficient matrix $II$ using dynamic programming, as shown in Alg. 2. Here, based on each window position and each second-order modality, we first compute $\omega_{\pi}$, the number of occurrences of each individual coefficient value $\pi \in [0, 100]$. Here, the division by $|M^2|$ (line 4) is explained by the fact that a single window position $i$ leads to incremented occurrences of coefficients of multiple second-order modalities; and hence, $\omega_{\pi}$ is shared by $|M^2|$ second-order modalities. Subsequently, the CCO is constructed by accumulating the respective numbers of occurrences of individual coefficient values $\omega_{\pi}$. Alg. 2 has a runtime complexity of $O(|M^2| \times |w| + 100)$, which can be considered as a constant update time.

Handling concept drift. The distribution of streaming data may show concept drift, i.e., it may be non-stationary [45,15]. In social networks, the propagation structure of rumours may change over time, which affects the coefficient distribution of second-order modalities, i.e., the coefficient matrix. As such, the model may become outdated and needs to be retrained.

To determine the need for retraining, we monitor changes to the coefficient matrix and recompute the CCO once a drift is detected. Specifically, we rely on the mean relative error (MRE) [26] to compare the current coefficient matrix with the one used to derive the CCO. Using the MRE has the advantage that the measure can be updated online upon the arrival of a new stream element in $O(1)$. Once the current coefficient matrix deviates by certain percentage from the one used to derive the current CCO, the model is recomputed using Alg. 2.

5.3 Load Shedding

We are now ready to answer three fundamental questions for the design of a load shedding mechanism: **When to shed.** Upon the arrival of a stream element, the matching of rumour patterns needs to consider all
stream elements that are currently in the input buffer, which are potentially part of multiple windows. As such, the latency of processing an arriving stream element is given as \( t_{\text{match}} \times b \), where \( b \) is the number of stream elements currently in the buffer and \( t_{\text{match}} \) is the delay induced per element. According to Problem 1, we must ensure that \( t_{\text{match}} \times b \leq \theta \). Hence, we monitor the input queue size and perform load shedding when:

\[
b > \alpha \times \frac{\theta}{t_{\text{match}}}
\]  

(14)

where \( \alpha \in [0, 1] \) is a trade-off factor. If we perform load shedding too early (i.e., a small value for \( \alpha \)), new stream elements are more likely to be dropped, especially in case of bursts that increase the latency for a short time period. If we perform load shedding relatively late (a large value for \( \alpha \)), elements with high utility are more likely to be shed as the coefficient threshold would be higher. Therefore, we update \( \alpha \) dynamically according to the current distribution of coefficients. The value of \( \alpha \) is selected such that a new window \( w \) is likely to have at least \( k \) elements with low utility, i.e., \( \alpha = k/|w| \).

**How much to shed.** A system is overloaded if the input rate \( r \) (which is dynamic) is strictly larger than the processing rate \( r_{\text{match}} \) (which is static). Moreover, a rumour detector \( I \) can be assumed to have a constant update time \( t_{\text{update}} \). In an overload situation, there will be an extra \( r - r_{\text{match}} \) number of stream elements in the input buffer per second, which increases the latency of processing a new element. Therefore, we must drop \( k \) elements in the current window to compensate for the additional elements. With \( b \) as the number of elements currently in the buffer and \( b_{\text{max}} \) as its size, we derive the number of elements to shed, \( k \), as follows:

\[
k = \max \left( \left\lceil \frac{r - r_{\text{match}}}{r} \times |w|, b - b_{\text{max}} + |w| \right\rceil \right).
\]  

(15)

The second term of the max function is explained by the fact that when pushing the remaining stream elements of a window to the input buffer, its size must not be exceeded. That is, we need to ensure that the condition \( b + |w| - k \leq b_{\text{max}} \) is satisfied.

**What to shed.** As mentioned, we drop stream elements with coefficients smaller than or equal to a coefficient threshold \( \pi_{\text{min}} \). To set \( \pi_{\text{min}} \), we iterate over an array representation of the cumulative coefficient occurrence \( \Omega \) (which is sorted by design) and define \( \pi_{\text{min}} \) based on the index of the first element with \( \Omega[\pi] \geq k \):

\[
\pi_{\text{min}} = \arg \min_{\pi \in [0, 100]} \{ \Omega(\pi) | \Omega(\pi) \geq k \}
\]  

(16)

Alg. 3 formalises the load shedding procedure, which encapsulates the actual pattern matching and rumour detection. It takes as input a data stream \( S \) over which (non-overlapping) windows of size \( |w| \) have been defined, along with information on the size of the input buffer, \( b_{\text{max}} \). The algorithm first initialises several auxiliary variables (lines 1-4), i.e., the current window (\( w_{\text{current}} \)), a flag that indicates whether load shedding has been activated (\( \text{shedding} \in \{T, L\} \)), the coefficient threshold (\( \pi_{\text{min}} \)), and the result stream without the elements that have been shed (\( S' \)).

It then processes each element of the stream (line 5). The initial shedding parameters, i.e., \( k \), the number of elements to shed and \( \alpha \), the trade-off factor, capture the absence of shedding (line 6). Upon some time-based trigger, these parameters are updated dynamically (lines 7-9). That is, \( k \) is determined based on the input rate, the processing rate, and the current number of elements in the input buffer (see Eq. 15), while \( \alpha \) is derived from \( k \) and the window size \( |w| \).

If load shedding is active (line 10), the algorithm checks based on the coefficient matrix whether the current element shall either be shed or kept and, hence, added to the result stream (lines 11-12). We thereby implicitly realise the load shedding function \( \rho \), as defined in Problem 1.

In any case, the current element is recorded as part of the current window (line 13). If it was the last el-
tement of the window (line 14), the window is reset (line 15) and the status of the system is assessed (line 16). If the system is overloaded, the coefficient threshold $\tau_{\text{min}}$ is computed (line 17) and load shedding is activated (line 18). Otherwise, load shedding is deactivated (line 19). Finally, pattern matching and rumour detection are conducted based on the result stream $S_t$, from which some elements may have been shed (line 20).

5.4 Extensions

Having introduced our general approach to load shedding in stream rumour detection, we discuss how to cope with more complex application scenarios.

Variable window sizes. We lift our approach to windows of variable sizes, see [32], through two adaptations:

- Coefficient Modelling: If windows have variable size, $|w|$ no longer serves as the number of columns for the coefficient matrix. However, in practice, differences in window sizes can be expected to be relatively modest. Therefore, we consider an estimated window size $\hat{|w|}$, which, for instance, corresponds to the maximal size of windows seen so far. Then, the relative position of a stream element in a window $w_i$ is scaled by a factor of $|w_i|/\hat{|w|}$ to the coefficient matrix $H_{|\mathcal{M}_F|\times|\mathcal{G}|}$.

- Load Shedding: With variable window sizes, the size of the current window may be unknown until its end. Consequently, we cannot use Eq. 15 to compute how many stream elements shall be dropped. Again, the solution is to rely on an estimated window size $\hat{|w|}$. However, more precise methods to derive the number of elements to shed based on window size prediction can be found in [32].

Variable shedding intervals. Once shedding is triggered according to Eq. 14, it may be reasonable not to drop stream elements immediately. The reason being that the coefficient values may not be evenly distributed, e.g., elements with high utility may all be located in a certain range of the stream. Hence, dropping many stream elements consecutively potentially amplifies the coefficient loss, although it reduces the processing latency.

Against this background, we observe that the input buffer, in general, has spare space of size $z = \frac{\theta}{t_{\text{match}}} - \alpha \frac{\theta}{t_{\text{match}}}$. If the current window is smaller than that, $|w_{\text{current}}| \leq z$, one may wait for the next window to fill up before taking any shedding decision. However, if $|w_{\text{current}}| > z$, there is a risk of a latency violation if high-utility stream elements arrive consecutively, which means that more than $z$ elements can be pushed to the input buffer before the window ends. To handle this situation, we divide the current window into smaller parts of size $v = \lfloor z \rfloor$ and perform load shedding for these parts, using $|v|$ instead of the window size $|w|$ in Eq. 15.

6 Empirical Evaluation

We evaluated our approach with a dataset of rumours on Twitter. We first discuss the experimental setup (§6.1), before turning to an evaluation of the following aspects of our approach:

- The effectiveness of our shedding strategies (§6.2).
- The effectiveness of our approach to streaming rumour detection (§6.3).
- The efficiency of our shedding strategies (§6.4).
- The efficiency of streaming rumour detection (§6.5).
- The robustness of the presented techniques (§6.6).
- The end-to-end performance of our framework based on ablation tests (§6.7).

6.1 Experimental Setup

Datasets. We collected data comprising 4 million tweets, 3 million users, 28893 hashtags, and 305115 linked articles, including around 1022 rumours [34]. The data spans several domains, each of which is a separate dataset:

- Politics: rumours related to political issues.
- Crime: rumours related to incidents such as the 2017 Las Vegas shooting.
- SciTech: rumours related to scientific myths and exaggerated technological inventions.

Rumour detection. We consider various techniques for rumour detection:

- Ground: The rumour detector is simulated by the ground-truth itself.
- Decision [2]: A decision tree classifier that is based on the Twitter information credibility model. The decision tree is constructed based on several hand-crafted features.
- Nonlinear [41]: An SVM-based approach that uses a set of hand-crafted features, selected for the tweets to classify.
- Rank [48]: A rank-based classifier that aims to identify rumours based on enquiry tweets.
- Static [34]: A static version of anomaly-based rumour detection, which is based on 45 rumour patterns. Instead of using the presented mechanisms for online anomaly computation (§4.2), it derives the anomaly scores from the raw historical data. d
- Dynamic: The streaming version of anomaly-based rumour detection, as presented in this paper.
Note that further, similar rumour detection techniques have been proposed in the literature, see [19]. Most of them are not applicable in our context, which prevents a fair comparison. The reasons for that are (i) that they require large domain-specific training data [22, 1]; (ii) that they employ domain-specific pre-processing steps (e.g., they segment the data according to some domain-specific heuristics [49]); and (iii) that they are often intractable in a streaming setting [24].

**Metrics.** We complement common metrics for data streams [11], such as throughput, latency, shedding ratio with the following evaluation measures:

- **Shedding coefficient**: the ratio of detected rumours with shedding and without shedding.
- **F3-score**: a weighted combination of true positives, false negatives, and false positives [13]. It measures accuracy in the presence of imbalanced distributions. In our case, the ratio of stream elements participating in a rumour and the total number of elements is less than one. The weight \( \beta \) is set to this ratio for each dataset.
- **Error rate**: the ratio of the stream elements that are part of rumours and are shed, and their total number.

**Shedding baselines.** We compare our approach with several baseline techniques for load shedding:

- **Random shedding**: this strategy sheds \( k \) random elements of the current window, if the current input buffer satisfies \( b > \frac{\theta}{\text{match}} + 1 \) (the latter term ensures that processing of the last stream element in the buffer will have a latency \( \leq \theta \)).
- **Weighted shedding**: instead of uniform sampling \( k \) stream elements to shed, this strategy weights the sampling probability of each element proportional to its coefficient.

**Environment.** All results have been obtained on an Intel i7 2.8GHz system (4 cores, 16GB RAM). We report 10-run averages to mitigate randomness. The default window size is \( |w| = 100 \).

### 6.2 Effectiveness of Shedding Strategies

We first evaluate the effectiveness of our shedding strategy, in the light of the aforementioned baseline techniques.

**Accuracy.** We assess the accuracy of event detection, in terms of the F3-score, for our shedding strategy in comparison to the baseline techniques, i.e., random shedding and weighted shedding.

Fig. 5 shows the results for each dataset. Here, the X-axis varies the latency threshold from 1s to \( 10^3 \)s (≈ 17min), while the Y-axis reports the accuracy. We observe that our method outperforms the baseline strategies. Also, when varying the latency threshold, better accuracy is obtained with larger bounds. This is expected since larger thresholds imply less shedding of stream elements. Yet, the difference between the methods is also smaller with larger thresholds, as the shedding decisions are less critical once the overall amount of elements to shed is reduced.

Note that the weighted baseline performs worse than our method, even though both rely on the same coefficient information. The reason being that even elements with high coefficient values may be chosen by sampling.

**Shedding Coefficient.** Fig. 6 complements the above results with an experiment on the shedding coefficient for the individual datasets, for a latency threshold of \( \theta = 10ms \) (similar trends are observed for other \( \theta \) values). Again, load shedding based on coefficient modelling yields the best results. In comparison, the stream elements shed by our method do not introduce as many false negatives and false positives as shedding with the baseline techniques. The largest difference is observed for the Politics dataset, which features rumours with a complex propagation structure.

**Error Rate.** We study the effects of data arrival (in % on the x-axis) on the error rate induced by load shedding. Fig. 7, Fig. 8, and Fig. 9 illustrates the results for the Politics dataset, the Crime dataset, and the SciTech dataset, respectively. The error rate is high initially as the coefficient model is not yet stable. Later, the error rate is reduced significantly, which emphasises the correctness of our coefficient model.
6.3 Effectiveness of Rumour Detection

Having evaluated the effectiveness of different shedding strategies, we now turn to the evaluation of the approaches to rumour detection. That is, we compare our approach for streaming rumour detection against the ground truth as well as the state-of-the-art techniques mentioned in 6.1. In any case, rumour detection is conducted with our strategy for load shedding, since the

superiority of this strategy has been demonstrated in the previous experiments.

Accuracy. Fig. 10 compares the performance of different rumour detection techniques under various latency constraints, for each dataset. In general, streaming rumour detection as proposed in this paper (dynamic) outperforms the baseline techniques, and is closest to the actual ground truth.

We further note that the static version of anomaly-based rumour detection yields the next best results. Moreover, the results, in general, become better with higher latency thresholds. This may be explained by less aggressive load shedding.

Shedding Coefficient. Similar to the previous experiment, we compare the shedding coefficient for different datasets for various rumour detection strategies. Fig. 11 reports the results.

In general, rumour detection with higher accuracy leads to larger shedding coefficients. This is explained
by the fact that accurate detection leads to stable coefficient modelling, which is the basis for our shedding strategy.

**Error Rate.** We compare the shedding error when using our strategy for streaming rumour detection (*dynamic*) and against the next-best approach, i.e., *static* rumour detection based on anomalies. Fig. 12, Fig. 13, and Fig. 14 illustrate the results for the Politics dataset, the Crime dataset, and the SciTech dataset, respectively. Here, we observe that our technique converges relatively quick to low errors, whereas the error stays at high values with the *static* strategy. This reason for this observation is the fact that the *static* strategy does not give a latency guarantee. Hence, the system may shed many stream elements that are important to reach stable coefficient modelling. Results with the other rumour detection strategies show a similar trend.

![Fig. 12: Error rate with different rumour detectors (Politics dataset).](image1)

![Fig. 13: Error rate with different rumour detectors (Crime dataset).](image2)

Fig. 14: Error rate with different rumour detectors (SciTech dataset).

**Shedding Ratio.** Fig. 16 presents the percentage of shed data (smaller is better), while varying the window size ($\theta = 1 ms$). The *sort* version of the load shedding procedure performs worst, due to the sorting overhead and the need to shed more data in the next window. Our actual method has similar performance as the *weighted* and random baselines since they use the same decision on when and how much data to shed. Our extension that includes a variable shedding interval (§5.4) performs best, as shedding is conducted at a more fine-grained level.

**6.5 Efficiency of Rumour Detection**

We complement the above results with experiments on the latency and shedding ratio of different strategies for rumour detection. As above, we combine these techniques with our approach to load shedding.

**Latency.** Fig. 17 illustrates the latency observed for different rumour detection strategies, under a latency
threshold of $\theta = 1s$. Again, the latency is considered relative to the elapsed time. It can be seen that our proposed dynamic strategy to rumour detection guarantees the latency constraint, while the other strategies violate it.

**Shedding Ratio.** Fig. 18 depicts the percentage of shed data (smaller is better) for different rumour detection strategies. We vary the window size, while fixing the latency threshold to $\theta = 1s$. In general, our proposed dynamic strategy outperforms the baseline techniques. This is because the other strategies violate the latency threshold and, hence, increase the amount of data that needs to be shed.

**Runtime.** Fig. 19 reports the runtime of streaming pattern matching (§4.1, namely i-PM) and streaming anomaly computation (§4.2, namely i-Anomaly) against their offline counterparts for different graph sizes. We use GraphGen,¹ to generate social graphs of different sizes and features. Here, static-PM is the offline counterpart of i-PM that uses SPMiner [42], a state-of-the-art method to find matches of subgraph patterns based on subgraph isomorphism. Moreover, static-Anomaly denotes the offline counterpart of i-Anomaly, which computes anomaly scores from raw historical data [34].

In general, the proposed streaming mechanisms outperform their offline counterparts from one to two orders of magnitude. The stacked bar chart in Fig. 19 further reveals that graph-based rumour detectors [34, 48] that use static-PM and static-Anomaly, in general, are much slower than the streaming approach presented in this work.

**6.6 Sensitivity Analysis**

**Coefficient distribution, input rate, and pattern size.** Table 2 illustrates the sensitivity of our approach against different data distributions (normal and skewed coefficient distributions), input rates (the delay between stream elements follows a normal or skewed distribution), and pattern sizes. Here, larger pattern sizes lead to better performance since the coefficient statistics are more accurate (their matches are more likely to become rumours). Skewed input rates lower the performance since more data is shed in case of short bursts. However, skewed coefficient distributions improve the results since low-coefficient data are more likely to be shed together in a window.

| Coefficient dist. | input rate | $|p| = 3$ | $|p| = 5$ | $|p| = 10$ |
|-------------------|------------|----------|----------|----------|
| normal            | normal     | 0.81     | 0.82     | 0.85     |
|                   | skewed     | 0.71     | 0.73     | 0.78     |
| skewed            | normal     | 0.84     | 0.83     | 0.86     |
|                   | skewed     | 0.75     | 0.78     | 0.85     |

¹https://cse.hkust.edu.hk/graphgen/
Table 3: Shedding coefficient with rumour detectors (θ = 10ms)

| window size | pattern size | f = 50% | f = 75% | f = 100% |
|-------------|--------------|---------|---------|---------|
| normal      | normal       | 0.63    | 0.91    | 0.95    |
|             | skewed       | 0.61    | 0.90    | 0.92    |
| skewed      | normal       | 0.59    | 0.89    | 0.93    |
|             | skewed       | 0.62    | 0.88    | 0.91    |

Effects of detection accuracy. Table 3 explores the impact of the quality of rumour detection, which is simulated by negating the ground-truth with different probabilities (f = 50%, 75%, 100%). We consider normal and skewed distributions for the pattern size and the window size, to also test our extension for variable window sizes (§5.4). Our approach turns out to be robust. Only for a random detector (f = 50%), the shedding coefficient is significantly reduced, as one cannot learn the correlation between data features and rumours.

6.7 End-to-end Evaluation

Finally, we report on an experiment that targets an end-to-end evaluation of our framework, under a latency threshold of θ = 1s, averaged over all datasets. Table 4 presents the result for four ablation settings, in which we identify the importance of our strategies for load shedding and rumour detector, respectively. In the first setting, we run our full approach with the proposed strategies for load shedding and rumour detection, achieving an accuracy value of 0.91 under a guaranteed latency value of 1s. The second setup comprises the static strategy for rumour detection without any shedding. This setup results in an accuracy value of 0.96 and a latency of 6720s, which violates the threshold. The third setup includes the dynamic strategy for rumour detection with random shedding. Here, the accuracy is 0.79, under a guaranteed latency of 1s. The last setting combines our shedding strategy with the static rumour detector, which yields an accuracy of 0.86, under a latency of 3617s.

Table 4: Ablation tests.

| Shedding Strategy | Rumour Detector | F3-score (Prec|Rec) | latency (s) |
|------------------|-----------------|---------|------------|
| Our              | Dynamic         | 0.91 (0.92/0.90) | ~1         |
| None             | Static          | 0.96 (0.95/0.97) | 6720       |
| Random           | Dynamic         | 0.79 (0.84/0.74) | ~1         |
| Our              | Static          | 0.86 (0.84/0.80) | 3617       |

In general, a good shedding strategy helps to achieve timely rumour detection, without sacrificing too much accuracy. Moreover, our proposed strategy for streaming rumour detection also improves the accuracy for streaming data. In Table 4, we also report the respective precision and recall values for reference.

7 Related Work

Multi-modal social graph. The content of social networks can be modelled by a multi-modal social graph aka heterogeneous information networks [28,7]. Some models capture real-world entities, such as users and posts, while others represent derived data elements, such as topics and communities [19]. Existing work on rumour detection in social networks focuses on propagation patterns of known phenomena [9,49] or known events [48]. This setting is orthogonal to our work, since we strive for the detection of rumour, a phenomenon that emerges on social networks but is not known a priori. Moreover, designing an algorithm that provides a latency guarantee for large-scale graphs is challenging [27,5], but is particularly necessary for applications in social networks.

Rumour Detection. Most means for rumour detection in social networks, surveyed in [49,31,29], are not suited for real-time applications. They rely on large training datasets and hence neglect evolving characteristics of rumours. Moreover, most traditional detection features emerge only after rumours affected many users. To overcome these limitations, methods for streaming rumour detection have been proposed [30,33,38,6], with most of them being based on pattern matching [39,48,20]. Yet, these approaches cannot give latency guarantees and may detect rumours solely with a significant delay [35]. Our approach works under latency constraints and sheds unimportant data that do not contribute to rumour detection, regardless of the specific technique for rumour detection. Moreover, we change the nature of pattern matching from offline to online to make the detection even more efficient.

Anomaly scoring. Anomaly scoring techniques can be divided into two categories: point-based or group-based [44,46]. Point-based methods work on individual data items to identify the signals that separate anomalies from the rest of the data [14]. Group-based techniques, in turn, identify subsets of individuals that collectively have different characteristics compared to any other subset [3,43,23]. Anomaly scoring is a reasonable strategy for rumour detection since rumours often propagate collectively over social networks. For example, [3] addresses a similar use case, but neglects anomalies related to feature differences between entities. Most similar to our work is [34], which identifies subgraphs of social networks that are deemed to be rumours. However, the approach requires memory that grows in the size of
the data to process, which is intractable in a streaming setting. Our work proposes a streaming anomaly computation via sketch structures while still guaranteeing a bounded quality.

**Load shedding.** In streaming processing, load shedding helps to cope with bursty input rates [25, 18]. While many approaches focus on queries for relational and sequential data stream processing [32, 11, 47], load shedding is also useful for social networks that generate enormous volumes of high-velocity streaming data. Our work is the first to propose a load shedding approach for rumour detection to provide latency guarantees. In particular, we design a coefficient modeling for each data element that is closely coupled with the proposed streaming pattern matching via occurrence utility.

**8 Conclusion**

In this paper, we proposed an approach for streaming rumour detection for social networks under latency constraints. In the presence of high-velocity data streams, we argue for best-effort processing: Our goal is to detect the majority of rumours quickly. To this end, we took existing ideas on anomaly-based rumour detection, which identify local and global anomalies for propagation structures as captured by rumour patterns, as a starting point. Specifically, we lifted these ideas from a static setting to a streaming setting. We presented an algorithm for matching graph-based patterns in asymptotically constant time via a pattern index, along with a model for streaming anomaly scoring of individual entities and whole subgraphs via sketch structures. Moreover, our load shedding goes beyond the state-of-the-art by developing a streaming model to capture the correlation between the coefficient of streaming data and rumours. Based thereon, we proposed a coefficient-based load shedding strategy to drop low-coefficient data when the system exceeds the latency threshold. Experiments on large-scale real-world data showed that our approach is more effective and more efficient than baseline strategies. Our approach also turned out to be robust over diverse application settings.

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**References**

1. Bian, T., Xiao, X., Xu, T., Zhao, P., Huang, W., Rong, Y., Huang, J.: Rumor detection on social media with bi-directional graph convolutional networks. In: AAAI, vol. 34, pp. 549–556 (2020)
2. Castillo, C., Mendoza, M., Poblete, B.: Information credibility on twitter. In: WWW, pp. 675–684 (2011)
3. Chen, F., Neill, D.B.: Non-parametric scan statistics for event detection and forecasting in heterogeneous social media graphs. In: KDD, pp. 1166–1175 (2014)
4. Cormode, G., Muthukrishnan, S.: An improved data stream summary: the count-min sketch and its applications. Journal of Algorithms 55(1), 58–75 (2005)
5. Das, A., Svendsen, M., Tirthapura, S.: Incremental maintenance of maximal cliques in a dynamic graph. The VLDB Journal 28(3), 351–375 (2019)
6. Ding, K., Li, J., Dhar, S., Devan, S., Liu, H.: Interspot: interactive spammer detection in social media. In: IJCAI, pp. 6509–6511 (2019)
7. Fang, Y., Huang, X., Qin, L., Zhang, Y., Zhang, W., Cheng, R., Lin, X: A survey of community search over big graphs. The VLDB Journal 29(1), 353–392 (2020)
8. Farajtabar, M., Yang, J., Ye, X., Xu, H., Trivedi, R., Khalil, E., Li, S., Song, L., Zha, H.: Fake news mitigation via point process based intervention. In: ICML, pp. 1097–1106 (2017)
9. Friggeri, A., Adamic, L.A., Eckles, D., Cheng, J.: Rumor cascades. In: ICWSM (2014)
10. Hao, T., Huang, L.: A social interaction activity based time-varying user vectorization method for online social networks. In: IJCAI, pp. 3790–3796 (2018)
11. He, Y., Barman, S., Naughton, J.F.: On load shedding in complex event processing. In: ICDT, pp. 213–224 (2014)
12. Hu, S., Sturtevant, N.R.: Direction-optimizing breadth-first search with external memory storage. In: IJCAI, pp. 1258–1264 (2019)
13. Huang, H., Zhang, Q., Huang, X., Huang, H., Zhang, Q., Huang, X.: Mention recommendation for twitter with end-to-end memory network. In: IJCAI, pp. 1872–1878 (2017)
14. Ihler, A., Hutchins, J., Smyth, P.: Adaptive event detection with time-varying poisson processes. In: KDD, pp. 207–216 (2006)
15. Knoblauch, J., Jewson, J.E., Damoulas, T.: Doubly robust bayesian inference for non-stationary streaming data with beta-divergences. In: NIPS, pp. 64–75 (2018)
16. Kullendorff, M.: A spatial scan statistic. Communications in Statistics-Theory and methods 26(6), 1481–1496 (1997)
17. Kwon, S., Cha, M., Jung, K.: Rumor detection over varying time windows. PLoS one 12(1) (2017)
18. Lee, J., Han, W.S., Na, H.J., Park, C.G., Kim, K.H., Kim, D.H., Lee, J.Y., Cha, S.K., Moon, S.: Parallel replication across formats for scaling out mixed oltp/olap workloads in main-memory databases. The VLDB Journal 27(3), 421–444 (2018)
19. Li, R.H., Qin, L., Yu, J.X., Mao, R.: Finding influential communities in massive networks. The VLDB Journal 26(6), 751–776 (2017)
20. Liu, G., Zheng, K., Wang, Y., Orgun, M.A., Liu, A., Zhao, L., Zhou, X.: Multi-constrained graph pattern matching in large-scale contextual social graphs. In: ICDE, pp. 351–362 (2015)
21. Ma, J., Gao, W., Mittra, P., Kwon, S., Jansen, B.J., Wong, K.F., Cha, M.: Detecting rumors from microblogs with recurrent neural networks. In: IJCAI, pp. 3818–3824 (2016)
22. Ma, J., Gao, W., Wong, K.F.: Detect rumors in microblog posts using propagation structure via kernel learning. In: ACL, vol. 1, pp. 708–717 (2017)
23. Muanedt, K., Schölkopf, B.: One-class support measure machines for group anomaly detection. arXiv preprint arXiv:1903.0309 (2019)
24. Nguyen, T.T., Nguyen, T.T., Nguyen, T.T., Vo, B., Jo, J., Nguyen, Q.V.H.: Judo: Just-in-time rumour detection in streaming social platforms. Information Sciences 570, 70–93 (2021)
25. Owususui, O.I., Malik, O., Zhang, J., Ramchurn, S.D., et al.: Algorithms for fair load shedding in developing countries. In: IJCAI, pp. 1590–1596 (2018)
26. Peierls, R.: Statistical error in counting experiments. Royal Society 149(868), 467–486 (1935)
27. Sahu, S., Mhedhbi, A., Salihoglu, S., Lin, J., Özsö, M.T.: The ubiquity of large graphs and surprising challenges of graph processing: extended survey. The VLDB Journal pp. 1–24 (2019)
28. Shi, C., Li, Y., Zhang, J., Sun, Y., Philip, S.Y.: A survey of heterogeneous information network analysis. TKDE 29(1), 17–37 (2017)
29. Shu, K., Liu, H.: Detecting fake news on social media. Synthesis Lectures on Data Mining and Knowledge Discovery 11(3), 1–129 (2019)
30. Shu, K., Mahudseswaran, D., Liu, H.: Fakenewstracker: a tool for fake news collection, detection, and visualization. Computational and Mathematical Organization Theory 25(1), 60–71 (2019)
31. Shu, K., Sliva, A., Wang, S., Tang, J., Liu, H.: Fake news detection on social media: A data mining perspective. SIGKDD Explorations Newsletter 19(1), 22–36 (2017)
32. Slo, A., Bhowmik, S., Rothermel, K.: espice: Probabilistic load shedding from input event streams in complex event processing. In: Middleware, pp. 215–227 (2019)
33. Srijith, P., Bepple, M., Bontcheva, K., Preotu-C-Pietro, D.: Sub-story detection in twitter with hierarchical dirichlet processes. IPM 53(4), 989–1003 (2017)
34. Tam, N.T., Weidlich, M., Zheng, B., Yin, H., Hung, N.Q.V., Stantic, B.: From anomaly detection to rumour detection using data streams of social platforms. PVLDB 12(9), 1016–1029 (2019)
35. To, Q.C., Soto, J., Markl, V.: A survey of state management in big data processing systems. The VLDB Journal 27(6), 847–872 (2018)
36. Vosoughi, S., Roy, D., Aral, S.: The spread of true and false news online. Science 359(6380), 1146–1151 (2018)
37. Wang, B., Chen, G., Fu, L., Song, L., Wang, X., Liu, X.: Drinux: Dynamic rumor influence minimization with user experience in social networks. In: AAAI, pp. 791–797 (2016)
38. Wang, S., Moise, I., Helbing, D., Terano, T.: Early signals of trending rumor event in streaming social media. In: COMPSAC, vol. 2, pp. 654–659 (2017)
39. Wang, S., Terano, T.: Detecting rumor patterns in streaming social media. In: Big Data, pp. 2709–2715 (2015)
40. Xing, C., Wang, Y., Liu, J., Huang, Y., Ma, W.Y.: Hashtag-based sub-event discovery using mutually generative lda in twitter. In: AAAI, pp. 2666–2672 (2016)
41. Yang, F., Liu, Y., Yu, X., Yang, M.: Automatic detection of rumor on sina weibo. In: Proceedings of the ACM SIGKDD Workshop on Mining Data Semantics, p. 13 (2012)
42. Ying, R., Wang, A., You, J., Leskovec, J.: Frequent subgraph mining by walking in order embedding space. In: ICML (2020)
43. Yu, R., He, X., Liu, Y.: Glad: group anomaly detection in social media analysis. TKDD 10(2), 18 (2015)
44. Yu, R., Qiu, H., Wen, Z., Lin, C., Liu, Y.: A survey on social media anomaly detection. ACM SIGKDD Explorations Newsletter 18(1), 1–14 (2016)
45. Yu, S., Wang, X., Principe, J.C.: Request-and-reverify: Hierarchical hypothesis testing for concept drift detection with expensive labels. In: IJCAI, p. 30333033 (2018)
46. Zellag, K., Kemme, B.: Consistency anomalies in multi-tier architectures: automatic detection and prevention. The VLDB Journal 23(1), 147–172 (2014)
47. Zhao, B., Hung, N.Q.V., Weidlich, M.: Load shedding for complex event processing: Input-based and state-based techniques. In: ICDE, pp. 1093–1104 (2020)
48. Zhao, Z., Resnick, P., Mei, Q.: Enquiring minds: Early detection of rumors in social media from enquiry posts. In: WWW, pp. 1395–1405 (2015)
49. Zubiaga, A., Aker, A., Bontcheva, K., Liakata, M., Procter, R.: Detection and resolution of rumours in social media: A survey. CSUR 51(2), 32 (2018)