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On Characterization and Schedule Formation for Transformative tweet streams

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Abstract: Brief-textual content messages which include tweets are being created and shared at an unheard of charge. Tweets, in their uncooked form, whilst being informative, can also be overwhelming. For each give up-users and facts analysts, it's far a nightmare to plow through thousands and thousands of tweets which include great quantity of noise and redundancy. On this paper, we advocate a unique continuous summarization framework referred to as Sumblr to relieve the hassle. In contrast to the traditional file summarization methods which attention on static and small-scale records set, Sumblr is designed to cope with dynamic, rapid arriving, and massive-scale tweet streams. Our proposed framework includes three important additives. First, we advocate an online tweet move clustering algorithm to cluster tweets and hold distilled data in a information structure called tweet cluster vector (TCV). Second, we increase a TCV-Rank summarization technique for generating online summaries and historic summaries of arbitrary time periods. 1/3, we layout an effective subject matter evolution detection technique, which monitors summary-based totally/extent-based totally versions to provide timelines routinely from tweet streams. Our experiments on huge-scale real tweets exhibit the performance and effectiveness of our framework.

Index terms—Tweet move, continuous summarization, summary, timeline

Advent: Growing recognition of micro blogging offerings along with Twitter, Weibo, and Tumblr has resulted inside the explosion of the amount of brief-textual content messages. Twitter, as an example, which gets over four hundred million tweets in line with day1 has emerged as an invaluable source of news, blogs, opinions, and more. Tweets, of their raw shape, even as being informative, also can be overwhelming. as an example, search for a warm subject matter in Twitter can also yield thousands and thousands of tweets, spanning weeks. Despite the fact that filtering is authorized, plowing through so many tweets for vital contents might be a nightmare, not to say the massive amount of noise and redundancy that one might come across. To make matters worse, new tweets gratifying the filtering standards may additionally arrive continuously, at an unpredictable charge. One feasible strategy to facts overload hassle is summarization. Summarization represents a set of documents by way of a precis

including numerous sentences. Intuitively, a terrific summary need to cowl the principle subjects (or subtopics) and feature variety a few of the sentences to reduce redundancy. Summarization is extensively utilized in content material presentation, specifically while customers surf the internet with their mobile devices that have tons smaller monitors than computers. conventional record summarization techniques, but, aren't as effective within the context of tweets given each the huge extent of tweets as well as the quick and non-stop nature of their arrival. Tweet summarization, therefore, calls for functionalities which appreciably differ from traditional summarization. In fashionable, tweet summarization has to take into consideration the temporal function of the arrival tweets. let us illustrate the desired houses of a tweet summarization device the use of an illustrative instance of a usage of such a machine. bear in mind a consumer interested by a subject-associated tweet stream, for example, tweets about "Apple". A tweet summarization system will continuously monitor "Apple" associated tweets generating a real-time timeline of the tweet circulation. As illustrated in Fig. 1, a consumer might also discover tweets based on a timeline (e.g., "Apple" tweets posted among October 22nd, 2012 to November 11th, 2012). Given a timeline range, the summarization system may additionally produce a collection of timestamped summaries to highlight factors in which the subject/subtopics developed within the movement. any such machine will efficaciously enable the consumer to analyze fundamental news/ dialogue related to "Apple" while not having to study via the entire tweet circulate. Given the huge photograph approximately subject matter evolution approximately "Apple", a consumer may additionally decide to zoom in to get a greater targeted file for a smaller duration (e.g., from eight am to 11 pm on November 5th). The device may additionally provide a drill-down summary of the duration that allows the person to get extra information for that duration. A user, perusing a drill-down summary, can also alternatively zoom out to a coarser variety (e.g., October 21st to October 30th) to attain a roll-up precis of tweets. in order to support such drill-down and roll-up operations, the summarization system ought to help the subsequent queries: summaries of arbitrary time intervals and real-time/range timelines. Such utility might no longer best facilitate clean navigation in topic-applicable tweets, however additionally help various information evaluation duties consisting of immediate reviews or ancient survey. To this end, in this paper, we propose a brand new summarization technique, continuous summarization, for tweet streams. imposing non-stop tweet move summarization is however not an smooth assignment, when you consider that a large range of tweets are meaningless, irrelevant and noisy in nature, because of the social nature of tweeting. in addition, tweets are strongly correlated with their posted time and new tweets tend to reach at a completely rapid fee. consequently, an amazing solution for non-stop summarization has to deal with the subsequent 3 issues: (1) performance—tweet streams are always very huge in scale, therefore the summarization set of rules have to be relatively efficient; (2) flexibility—it must provide tweet summaries of arbitrary time durations. (three) topic evolution—it need to automatically stumble on sub-topic adjustments and the moments that they occur. lamentably, existing summarization techniques can not fulfill the above 3 requirements because: (1) they specially consciousness on static and small-sized records units, and hence aren't efficient and scalable for huge

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information sets and records streams. (2) to offer summaries of arbitrary intervals, they will must carry out iterative/recursive summarization for every viable time period, that's unacceptable. (3) their summary consequences are insensitive to time. for that reason it is hard for them to stumble on subject matter evolution . in this paper, we introduce a novel summarization framework referred to as sumblr (non-stop summarization by means of circulation clustering). to the first-rate of our expertise, our work is the first to study continuous tweet move summarization. the general framework is depicted in fig. 2. the framework includes 3 foremost additives, specifically the tweet flow clustering module, the high-level summarization module and the timeline technology module. within the tweet movement clustering module, we design an green tweet flow clustering algorithm, an online set of rules taking into account powerful clustering of tweets with only one skip over the records. this algorithm employs two information systems to keep critical tweet facts in clusters. the primary one is a novel compressed shape referred to as the tweet cluster vector (tcv). tcvs are taken into consideration as potential sub-subject matter delegates and maintained dynamically in reminiscence at some stage in flow processing. the second one shape is the pyramidal time body (ptf), which is used to shop and organize cluster snapshots at distinctive moments, accordingly permitting ancient tweet facts to be retrieved by means of any arbitrary time intervals. the high-level summarization module helps era of forms of summaries: on-line and historic summaries. (1) to generate on-line summaries, we advise a tcv-rank summarization set of rules through regarding the cutting-edge clusters maintained in reminiscence. this set of rules first computes centrality rankings for tweets kept in tcvs, and selects the top-ranked ones in terms of content material coverage and novelty. (2) to compute a historical summary in which the consumer specifies an arbitrary

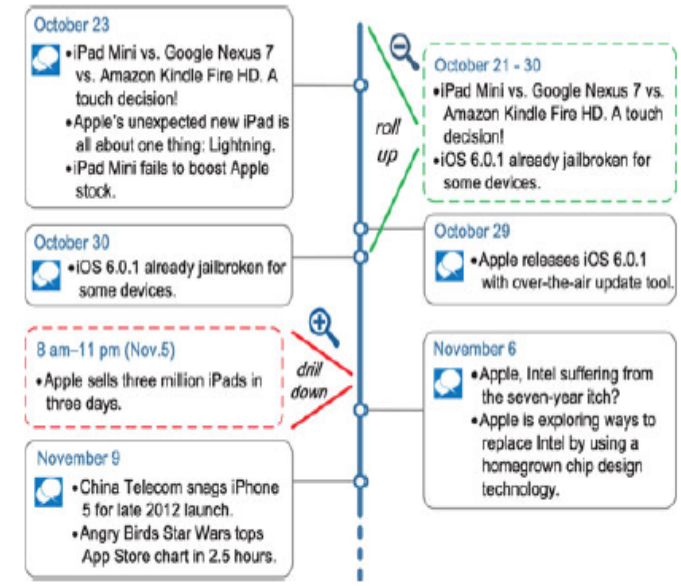

Fig. 1. A timeline example for topic "Apple".

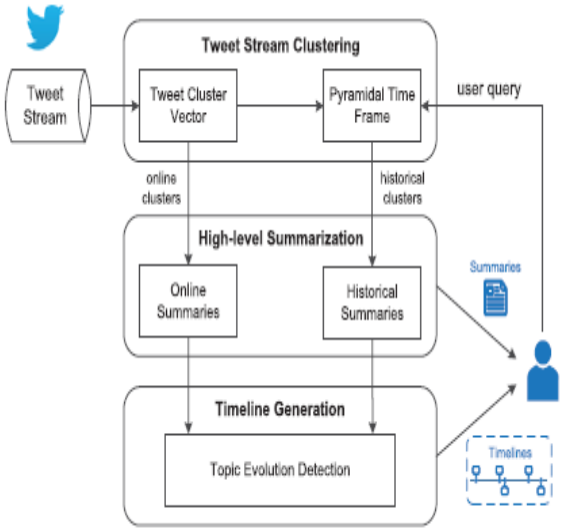

Fig. 2. The framework of Sumblr.

time duration, we first retrieve two historic cluster snapshots from the ptf with admire to the two endpoints (the start and ending points) of the duration. then, based totally at the distinction among the two cluster

snapshots, the tcv-rank summarization algorithm is carried out to generate summaries. the core of the timeline technology module is a topic evolution detection algorithm, which consumes on line/ancient summaries to provide real-time/variety timelines. The set of rules video display units quantified version all through the direction of circulation processing. a large variant at a selected second implies a sub-subject matter alternate, leading to the addition of a brand new node on the timeline. in our layout, we don't forget 3 various factors respectively within the set of rules. first, we don't forget variation inside the primary contents discussed in tweets (inside the shape of precis). to quantify the summarybased version (sum), we use the jensen-shannon divergence (jsd) to measure the gap between two word distributions in two successive summaries. 2nd, we reveal the volume-based totally variation (vol) which reflects the significance of sub-topic adjustments, to find out rapid will increase (or "spikes") in the extent of tweets over the years. third, we define the sum-vol variant (sv) by way of combining each results of summary content material and significance, and come across topic evolution each time there is a burst in the unified variant. the main contributions of this work are as follows: we endorse a non-stop tweet circulation summarization framework, namely sumblr, to generate summaries and timelines inside the context of streams. we design a unique records structure referred to as tcv for flow processing, and advise the tcv-rank set of rules for on-line and historical summarization. we endorse a topic evolution detection set of rules which produces timelines by means of tracking three types of versions. Big experiments on actual twitter statistics sets show the efficiency and effectiveness of our framework.

2 RELATED WORK:

In this section, we review the related work including stream data clustering, document/microblog summarization, timeline detection, and other microblog mining tasks.

Circulate facts Clustering:

Flow records clustering has been widely studied inside the literature. BIRCH clusters the information primarily based on an in-reminiscence shape called CF-tree as opposed to the unique big information set. Bradley et al. proposed a scalable clustering framework which selectively stores critical quantities of the records, and compresses or discards different portions. CluStream is one of the most conventional movement clustering methods. It includes an internet micro-clustering component and an offline macro-clustering element. The pyramidal time body was also proposed in to recall historical microclusters for exclusive time durations. a variety of offerings at the web such as news filtering, textual content crawling, and subject matter detecting and so on. have posed necessities for text flow clustering. some algorithms have been proposed to address the hassle. Maximum of those techniques undertake partition-based techniques to permit online clustering of flow statistics. therefore, those strategies fail to offer powerful evaluation on clusters formed over exceptional time periods. The authors prolonged CluStream to generate period- based totally clustering outcomes for text and specific records streams. however, this set of rules relies on a web phase to generate a large wide variety of "micro-clusters" and an offline segment to re-cluster them. In evaluation, our

tweet stream clustering algorithm is an online procedure without greater offline clustering. And inside the context of tweet summarization, we adapt the web clustering segment by way of incorporating the brand new structure TCV, and proscribing the number of clusters to assure performance and the high-quality of TCVs.

File/Microblog Summarization: file summarization may be classified as extractive and abstractive. the previous selects sentences from the files, even as the latter may also generate terms and sentences that don't appear in the unique files. in this paper, we consciousness on extractive summarization. Extractive record summarization has acquired a lot of current attention. maximum of them assign salient scores to sentences of the documents, and pick the top-ranked sentences. a few works attempt to extract summaries without such salient scores. Wang et al. used the symmetric non-bad matrix factorization to cluster sentences and pick out sentences in each cluster for summarization. He et al. proposed to summarize documents from the attitude of data reconstruction, and pick sentences that can excellent reconstruct the authentic files. Xu et al. modeled documents (resort critiques) as multi-characteristic uncertain records and optimized a probabilistic coverage trouble of the precis. at the same time as record summarization has been studied for years, microblog summarization is still in its infancy. Sharifi et al. proposed the phrase Reinforcement algorithm to summarize tweet posts the use of a single tweet. Later, Inouye and Kalita proposed a Hybrid TF-IDF algorithm and a Cluster- primarily based set of rules to generate more than one post summaries. Harabagiu and Hickl leveraged two relevance models for microblog summarization: an occasion structure version and a person behavior version. Takamura et al. proposed a microblog summarization method primarily based on the pmedian problem, which takes posted time of microblogs into consideration. lamentably, nearly all current document/ microblog summarization methods specifically cope with small and static records sets, and rarely pay attention to performance and evolution issues.

There have additionally been researched on summarizing microblogs for a few specific kinds of activities, e.g., sports events. Shen et al. proposed to become aware of the members of occasions, and generate summaries based totally on sub-activities detected from every participant. Chakrabarti and Punera introduced a solution by learning the underlying hidden nation representation of the occasion, which wishes to examine from previous activities (football video games) with similar shape. Kubo et al. summarized activities by means of exploiting “excellent journalists”, depending on event-unique key phrases which want to take delivery of in enhance. In contrast, we intention to address fashionable subject matter-relevant tweet streams with out such earlier understanding. Furthermore, their technique shops all the tweets in every phase and selects a unmarried tweet as the precis, even as our technique maintains distilled data in TCVs to lessen garage/ computation value, and generates more than one tweet summaries in phrases of content coverage and novelty. further to on line summarization, our method additionally supports ancient summarization by way of retaining TCV snapshots.

Timeline Detection:

The demand for studying massive contents in social medias fuels the trends in visualization strategies. Timeline is this type of techniques which can make analysis responsibilities less complicated and faster. Diakopoulos and Shamma made early efforts in this place, the usage of timelines to explore the 2008 Presidential Debates through Twitter sentiment. Dork et al. supplied a timeline-based totally backchannel for conversations around events.

Yan et al. proposed the evolutionary timeline summarization (ETS) to compute evolution timelines similar to ours, which includes a series of time-stamped summaries. However, the dates of summaries are decided through a pre-defined timestamp set. In contrast, our approach discovers the converting dates and generates timelines dynamically all through the process of non-stop summarization. Furthermore, ETS does not focus on efficiency and scalability problems, which are very essential in our streaming context. Several systems hit upon important moments when rapid increases or "spikes" in status update quantity show up. TwitInfo evolved an set of rules based on TCP congestion detection, even as Nichols et al. employed a slope-based totally approach to locate spikes. After that, tweets from each moment are recognized, and word clouds or summaries are decided on. Special from this two-step technique, our approach detects subject matter evolution and produces summaries/timelines in an on line style.

Different Microblog Mining obligations: The emergence of microblogs has engendered researches on many different mining obligations, together with topic modeling, storyline era and occasion exploration. most of these researches focus on static facts units alternatively of statistics streams. For twitter move evaluation, Yang et al. studied frequent pattern mining and compression. Van Durme aimed at discourse contributors type and used gender prediction as the example mission, which is also a one-of-a-kind trouble from ours. To sum up, on this work, we advocate a brand new problem referred to as continuous tweet summarization. Exclusive from preceding research, we aim to summarize massive-scale and evolutionary tweet streams, generating summaries and timelines in an online fashion.

$$\mathbf{cv} = \left(\sum_{i=1}^{n} w_i \cdot \mathbf{tv_i}\right) \Big/ n = \mathbf{wsum\_v}/n. \quad (1)$$

3 PRELIMINARIES:

In this phase, we first present a statistics model for tweets, then introduce two crucial information structures: the tweet cluster vector and the pyramidal time body.

Tweet representation: normally, a document is represented as a textual vector, where the fee of every measurement is the TF-IDF rating of a phrase. but, tweets are not best textual, but also have temporal nature—a tweet is strongly correlated with its published time. further, the importance of a tweet is tormented by the writer's social impact. To estimate the

Definition 2. *A pyramidal time frame stores snapshots at differing levels of granularity depending on the recency. Snapshots are stored into different* orders *varying from 0 to* $\lfloor \log_\alpha(T) \rfloor$ *, where T is the time elapsed since the beginning of the stream and* α *is an integer* $(\alpha > 1)$ *. A particular order of snapshots defines the level of granularity in time at which the snapshots are maintained. The snapshots of different orders are maintained as follows:*

- *Snapshots of the ith order occur at time intervals of* α^i*. Specifically, each snapshot of the ith order is taken at a moment in time when the timestamp from the beginning of the stream is exactly divisible by* α^i*.*
- *At any given moment in time, only the last* $\alpha^l + 1 (l \geq 1)$ *snapshots of order i are stored.*

Definition 1. *For a cluster C containing tweets* $t_1, t_2, \ldots, t_n$*, its* tweet cluster vector *is defined as a tuple:* $TCV(C) = (\mathbf{sum\_v}, \mathbf{wsum\_v}, ts1, ts2, n, ft\_set)$*, where*

- $\mathbf{sum\_v} = \sum_{i=1}^{n} \mathbf{tv_i} / \|\mathbf{tv_i}\|$ *is the sum of normalized textual vectors,*
- $\mathbf{wsum\_v} = \sum_{i=1}^{n} w_i \cdot \mathbf{tv_i}$ *is the sum of weighted textual vectors,*
- $ts1 = \sum_{i=1}^{n} ts_i$ *is the sum of timestamps,*
- $ts2 = \sum_{i=1}^{n} (ts_i)^2$ *is the quadratic sum of timestamps,*
- *n is the number of tweets in the cluster, and*
- *ft_set is a* focus tweet set *of size m, consisting of the closest m tweets to the cluster centroid.*

user have an impact on, we construct a matrix based on social relationships among users, and compute the UserRank. As a end result, we outline a tweet ti as a tuple: ðtvi; tsi; wiÞ, where tvi is the textual vector, tsi is the published timestamp and wi is the UserRank price of the tweet's writer.

Tweet Cluster Vector:

All through tweet circulation clustering, it's miles necessary to keep facts for tweets to facilitate summary generation. In this segment, we endorse a new statistics shape referred to as tweet cluster vector, which keeps information of tweet cluster.

From the definition, we can derive the vector of cluster centroid (denoted as cv)

Pyramidal Time Frame:

To support summarization over user-defined time durations, it is crucial to store the maintained TCVs at particular moments, which are called snapshots. While storing snapshots at every moment is impractical due to huge storage overhead, insufficient snapshots make it hard to recall historical information for different durations. This dilemma leads to the incorporation of the pyramidal time frame:

To clarify how snapshots are stored, we give an example here. Let α=3 and l = 2, then there are at most 32 snapshots in each order. Suppose the stream starts at timestamp1 and the current timestamp is 86. The stored snapshots are illustrated in Table 1. Redundancy is removed by storing each snapshot only in its highest possible order.

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TABLE 1
Example of PTF with $\alpha = 3$ and $l = 2$

Order	Timestamps of snapshots in the same order
4	81
3	54 27
2	72 63 45 36 18 9
1	84 78 75 69 66 60 57 51 48 42
0	86 85 83 82 80 79 77 76 74 73

4 THE SUMBLR FRAMEWORK:

As proven in Fig. 2, our framework consists of 3 predominant modules: the tweet circulate clustering module, the high-level summarization module and the timeline era module. on this segment, we shall present every of them in detail.

Tweet Circulate Clustering:

The tweet move clustering module maintains the online statistical statistics. Given a subject-based totally tweet circulation, it is able to effectively cluster the tweets and maintain compact cluster statistics.

Initialization: On the begin of the movement, we accumulate a small range of tweets and use a k-means clustering algorithm to create the initial clusters. The corresponding TCVs are initialized according to Definition 1. subsequent, the movement clustering manner starts to incrementally update the TCVs whenever a new tweet arrives.

Incremental Clustering: Suppose a tweet t arrives at time ts, and there are N energetic clusters at that point. the important thing trouble is to decide whether or not to absorb t into one of the present day clusters or improve t as a new cluster. We first locate the cluster whose centroid is the closest to t. particularly, we get the centroid of each cluster based totally on Equation (1), compute its cosine similarity to t, and locate the cluster Cp with the largest similarity (denoted as MaxSim (t). note that although Cp is the closest to t, it does not suggest t certainly belongs to Cp. The purpose is that t may additionally still be very distant from Cp. In such case, a brand new cluster need to be created. The decision of whether to create a new cluster can be made with the following heuristic.

Heuristic 1. The *minimum bounding similarity* (MBS) measures the average closeness between the centroid and the tweets included in the cluster C_p. MBS is used to decide whether t is close enough to C_p: if $MaxSim(t)$ is smaller than it, then t is upgraded to a new cluster; Otherwise, t is added to C_p.

Algorithm 1. Incremental Tweet Stream Clustering

```
Input: a cluster set C_set
1  while !stream.end() do
2    Tweet t = stream.next();
3    choose C_p in C_set whose centroid is the closest
     to t;
4    if MaxSim(t) < MBS then
5      create a new cluster C_new = {t};
6      C_set.add(C_new);
7    else
8      update C_p with t;
9    if TS_current %(α^i) == 0 then
10     store C_set into PTF;
```

During incremental clustering, assume there are N active clusters, the computational cost of finding the closest cluster for every new tweet is $O(N^2)$, where d is the vocabulary size. In addition, the complexity of computing Heuristic 1 and updating TCV is O(d) and O(md) respectively, where m is the size of focus set.

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Then the total cost is $O(N^2)$ m(d). Because m and d are static, the computational cost depends on N. Similarly, the storage costs in disk (TCV snapshots) and memory (current TCVs) also depend on N.

Given the above analysis, we need to restrict the number of active clusters. We achieve this goal via two operations: deleting outdated clusters and merging similar clusters. Since the computational complexity of deletion is O(N) and that of merging is $O(N^2)$, we use the former method for periodical examination and use the latter method only when memory limit is reached.

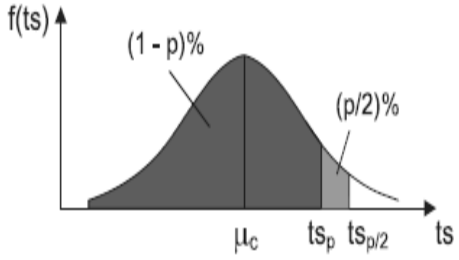

Fig. 3. Probability density function of timestamp.

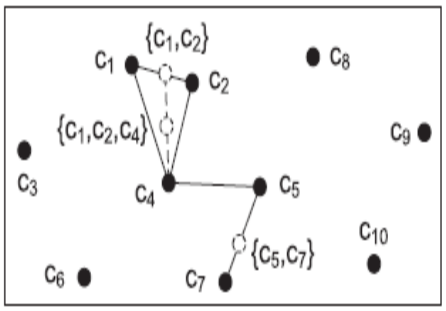

Fig. 4. A running example of cluster merging.

Deleting old Clusters: For maximum occasions (such as information, soccer fits and live shows) in tweet streams, timeliness is critical due to the fact they typically do no longer last for a long term. therefore it is safe to delete the clusters representing these sub-subjects after they

are rarely mentioned. To find out such clusters, an intuitive manner is to estimate the average arrival time (denoted as A_{vgp}) of the closing p percentage of tweets in a cluster. but, storing p percent of tweets for every

$$F(x) = \Phi\left(\frac{x-\mu_c}{\sigma_c}\right) = p'$$
$$x = \mu_c + \sigma_c \Phi^{-1}(p')$$
$$= \mu_c + \sigma_c \cdot \sqrt{2} erf^{-1}(2p' - 1),$$

cluster will increase reminiscence fees, in particular while clusters develop big. for that reason, we appoint an approximate approach to get Avgp.

Merging Clusters:

If the number of clusters keeps increasing with few deletions, system memory will be exhausted. To avoid this, we specify an upper limit for the number of clusters as Nmax. When the limit is reached, a merging process starts.

Fig. 4 shows a running example of the process. For ease of presentation, we use cluster centroids (the black solid points) to represent clusters and use euclidean distance instead of cosine distance.

High-Level Summarization:

Definition 3 (Aggregation Operation). *Let C_1 and C_2 be two clusters, and their TCVs be $TCV(C_1)$ and $TCV(C_2)$. When C_1 and C_2 are merged together, the composite cluster's $TCV(C_1 \cup C_2)$ is given by*

- $\mathbf{sum\_v} = \mathbf{sum\_v_1} + \mathbf{sum\_v_2}$
- $\mathbf{wsum\_v} = \mathbf{wsum\_v_1} + \mathbf{wsum\_v_2}$
- $ts1 = ts1_1 + ts1_2$
- $ts2 = ts2_1 + ts2_2$
- $n = n_1 + n_2$
- *ft_set consists of the first m tweets in $ft\_set_1 \cup ft\_set_2$, sorted by distance to the centroid of the newly merged cluster.*

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The high-level summarization module provides two types of summaries: online and historical summaries.

Definition 4 (Subtraction Operation). *Given a cluster C_1 in $S(ts_1)$ and its corresponding cluster C_2 in $S(ts_2)$, when C_2 is subtracted from C_1, their difference $TCV(C_1 - C_2)$ is given by*

- $sum\_v = sum\_v_1 - sum\_v_2$
- $wsum\_v = wsum\_v_1 - wsum\_v_2$
- $ts1 = ts1_1 - ts1_2$
- $ts2 = ts2_1 - ts2_2$
- $n = n_1 - n_2$
- *ft_set consists of tweets which exist in ft_set_1 but not in ft_set_2.*

An online summary describes what is currently discussed among the public. Thus, the input for generating online summaries is retrieved directly from the current clusters maintained in memory.

TCV−Rank Summarization Algorithm:

Given an input cluster set, we denote its corresponding TCV set as D(c). A tweet set T consists of all the tweets in the ft sets in D(c). The tweet summarization problem is to extract k tweets from T, so that they can cover as many tweet contents as possible.

From the geometric interpretation, our summarization tends to select tweets that span the intrinsic subspace of candidate tweet space, such that it can cover most information of the whole tweet set.

However, a potential problem of LexRank is that some top-ranked tweets may have similar contents. Fortunately, since the tweets are retrieved from TCVs, they have got inherent cluster information. Hence, we choose one tweet with the highest LexRank score from each TCV, and add tweet t into the summary (lines 4-9) according to:

$$t = \arg\max_{t_i} \left[\lambda \frac{n_{t_i}}{n_{max}} LR(t_i) - (1-\lambda) \operatorname{avg}_{t_j \in S} Sim(t_i, t_j) \right], \quad (2)$$

Timeline Generation:

The core of the timeline generation module is a topic evolution detection algorithm which produces real-time and range timelines in a similar way. We shall only describe the real-time case here.

Algorithm 2. TCV-Rank Summarization

```
Input: a cluster set D(c)
Output: a summary set S
1  S = ∅, T = {all the tweets in ft_sets of D(c)};
2  Build a similarity graph on T;
3  Compute LexRank scores LR;
4  T_c = {tweets with the highest LR in each cluster};
5  while |S| < L do
6    foreach tweet t_i in T_c − S do
7      calculate v_i according to Equation (2);
8    select t_max with the highest v_i;
9    S.add(t_max);
10 while |S| < L do
11   foreach tweet t'_i in T − S do
12     calculate v'_i according to Equation (2);
13   select t'_max with the highest v'_i;
14   S.add(t'_max);
15 return S;
```

The algorithm discovers sub-topic changes by monitoring quantified variations during the course of stream processing. A large variation at a particular

Algorithm 3. Topic Evolution Detection

```
Input: a tweet stream binned by time units
Output: a timeline node set TN
1: TN = ∅;
2: while !stream.end() do
3:    Bin C_i = stream.next();
4:    if hasLargeVariation() then
5:       TN.add(i);
6: return TN;
```

moment implies a sub-topic change, which is a new node on the timeline.

Precise-primarily based variant:

As tweets arrive from the move, online summaries are produced continuously by way of making use of online cluster information in tcvs. this permits for generation of a actual-time timeline. usually, while an apparent variant occurs within the main contents discussed in tweets (inside the shape of precis), we
can assume a change of sub-topic (i.e., a time node at the timeline).

$$D_{JS}(S_c, S_p) = \frac{1}{2}(D_{KL}(S_c||M) + D_{KL}(S_p||M)). \quad (3)$$

$$D_{KL}(S||M) = \sum_{w \in V} p(w|S) log \frac{p(w|S)}{p(w|M)}. \quad (4)$$

In step with this summary-based totally variation, we determine whether or not the modern time is a sub-subject matter changing node by way of

$$\frac{D_{cur}}{D_{avg}} > \tau_s, \quad (5)$$

that is, we hit upon sub-topic modifications every time there's a burst in distances between successive summaries.

Extent-primarily based version:

Though the summary-primarily based variant can reflect sub-topic modifications, a number of them may not be influential enough. when you consider that many tweets are related to customers' daily life or trivial activities, a sub-subject matter exchange detected from textual contents might not be sizable sufficient. to this cease, we consider using fast increases (or "spikes") within the volume of tweets over time, that is a common method in current online event detection structures. A spike indicates that something crucial simply happened due to the fact many humans determined the want to comment on it.

in this element, we increase a spike-locating approach. As the enter, the binning method in algorithm three wishes to rely the tweet arrival quantity in each time unit. all through the flow generation, the main spike detection logic is:

Heuristic 2. If the tweet volume (C_i) is more than τ_v mean deviations from the mean value, we say that the current moment has a large *volume-based variation*, and identify it as a spike.

$$\frac{C_i - mean}{meandev} > \tau_v. \quad (6)$$

then suggest and mean deviation are up to date with each new bin remember. to alter to changing tweet frequency traits in a streaming context, we preserve exponentially weighted shifting imply and mean deviation (we set g = zero:125 as in [25]):

Unified variation:

$$meandev = \gamma * |C_i - mean| + (1 - \gamma) * meandev,$$
$$mean = \gamma * C_i + (1 - \gamma) * mean. \quad (7)$$

Algorithm 3. Topic Evolution Detection

Input: a tweet stream binned by time units
Output: a timeline node set TN
1: $TN = \emptyset$;
2: while !*stream.end()* do
3: *Bin* C_i = *stream.next()*;
4: if *hasLargeVariation()* then
5: *TN.add(i)*;
6: return TN;

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The above spike-finding approach may match properly for short term events inclusive of football fits, but it might be difficult for them to handle lengthy-time period subject matter-associated streams, due to a

$$SV_i = \eta * D^i_{JS}(S_c, S_p) + (1-\eta) * D^i_{vol}, \quad (8)$$

$$D^i_{vol} = \begin{cases} 1 - \dfrac{mean}{C_i}, & C_i > mean, \\ 0, & C_i \le mean. \end{cases}$$

while-aware human behaviors in social media. For example, the quantity of tweet posts2 and public engagement rate3 will fluctuate in day of week or time of day. moreover, breaking news or rumors commonly draw huge interest and create big spikes in tweet volumes. these spikes will extensively growth the suggest and suggest deviation values, decreasing the chance for subsequent sub-topic adjustments being detected (equation (6)).

$$\frac{SV_{cur}}{SV_{avg}} > \tau_{sv}, \quad (9)$$

Now we are able to decide whether or not the modern-day time is a subtopic changing node by

DISCUSSION:

Coping with noises. the impact of clusters of noises may be dwindled by using manner in sumblr. first, in tweet stream clustering, noise clusters which are not updated regularly will be deleted as previous clusters. 2nd, inside the summarization step, tweets from noise clusters are a long way much less probably to be decided on into summary, due to their small lexrank scores and cluster sizes.

TABLE 2
Basic Information of Data Sets

Topics (filtering keywords)	#Tweets	Time Span
Obama	95,055	2009.02 - 2009.10
Chelsea	438,884	2012.11 - 2012.12
Arsenal Arsene Wenger	323,555	2012.11 - 2012.12
Tablet Smartphone Cellphone	231,011	2012.11 - 2012.12
Black Friday	124,684	2012.11 - 2012.12

5 EXPERIMENTS:

In this segment, we examine the overall performance of Sumblr. We gift the experiments for summarization and timeline generation respectively.

5.1 Experiments for Summarization:

Setup: Information sets. We assemble five information sets to evaluate summarization. One is obtained by engaging in keyword filtering on a massive Twitter facts are set to be used. The alternative 4 include tweets obtained at some point of one month in 2012 via Twitter's key-word tracking API.four As we do not have get admission to to the respective users'

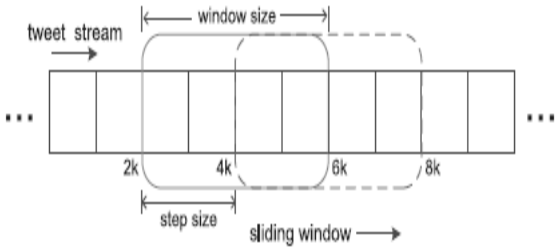

Fig. 5. The sliding window mechanism.

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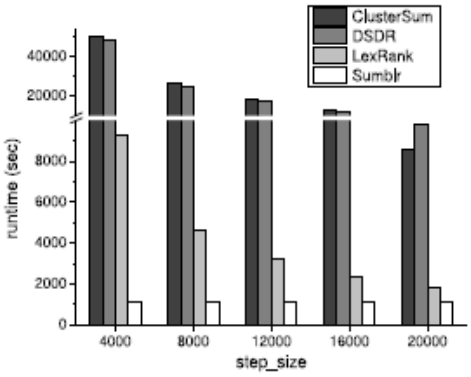
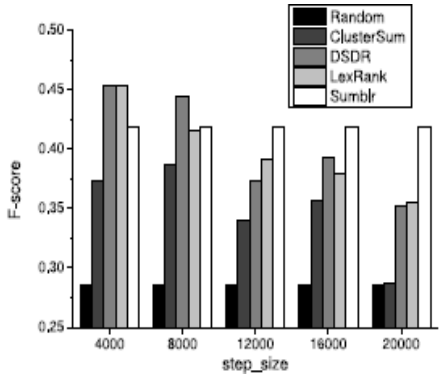
social networks for these 4, we set their weights of tweets wi to the default price of one. Information of the statistics units are indexed.

Ground facts for summaries: As no previous paintings has carried out comparable examine on non-stop summarization, we need to build our very own ground truth (reference summaries). but, guide introduction of these summaries is seemingly impractical due to the massive size of the information sets. For this reason, we appoint a -step method to acquire fair-first-rate reference summaries: 1) Given a time length, we first retrieve the corresponding tweet subset, and use the following three properly-recognized summarization algorithms to get three candidate

Summaries: Cluster Sum clusters the tweets and alternatives the most weighted tweet from every cluster to shape precis. LexRank first builds a sentence similarity graph, and then selects crucial sentences based on the concept of eigenvector centrality. DSDR fashions the relationship among sentences using linear reconstruction, and finds an foremost set of sentences to approximate the original documents, by minimizing the reconstruction error





To evaluate the metric on a continuous time period [T0; T], we need to calculate the indispensable of the metric over the length, that is given through

$$\int_{T_0}^{T} metric(t)\, dt. \qquad (10)$$

In our experiments, we discover similar trends in the assessment of precision, keep in mind and F-rating among the proposed technique and the baseline

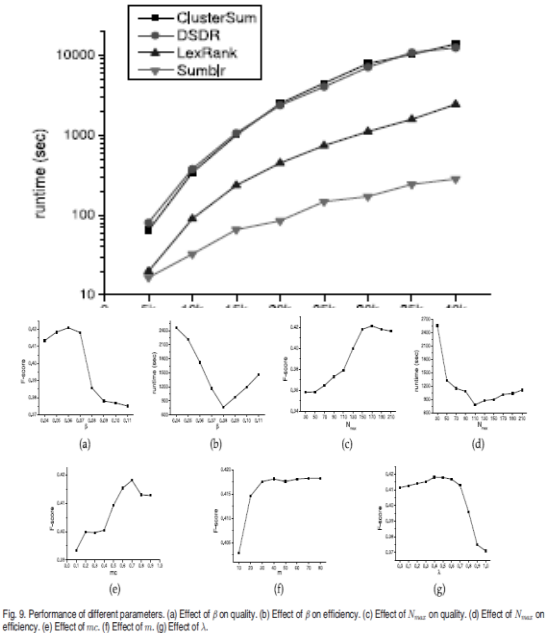


Fig. 9. Performance of different parameters. (a) Effect of β on quality. (b) Effect of β on efficiency. (c) Effect of N_{max} on quality. (d) Effect of N_{max} on efficiency. (e) Effect of m. (f) Effect of m. (g) Effect of λ.

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strategies. therefore, we will simplest report the F-score outcomes to shop area. The F-rating effects provided are averaged on all 5 data units.

Ordinary performance comparison:

In this segment, we compare the F-scores and runtime costs between Sumblr and three baseline algorithms (sliding window version). As tweets are often produced very fast and reach a massive extent in a quick whilst, it's far hardly ever meaningful to summarize a small number of tweets. Thus the window length ought to be a fantastically massive one. In this experiment, we set window length to 20,000 and sampling c programming language to 2,000. The step size varies from 4,000 to 20,000.

The metrics are averaged over the entire flow.

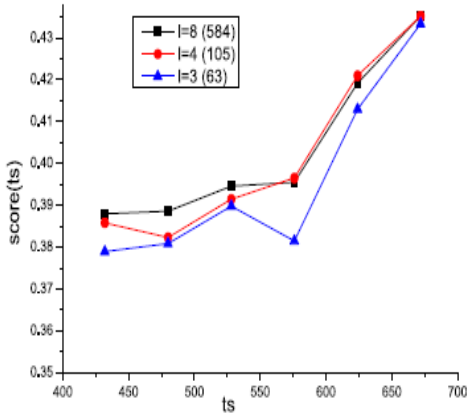

Fig. 10. Quality on time duration.

Scalability: The scalability test evaluates the efficiency results of a single window, even as various the window size. It simulates the case of a massive burst of tweets in a quick period. Fig. eight presents the scalability outcomes for distinct methods.

Parameter Tuning: On this segment, we song the parameters in our technique. In every of the following experiments, we range one parameter and keep the others fixed.

Flexibility

One distinguishing characteristic of Sumblr is the power to summarize tweets over arbitrary time intervals. this option is supplied with the aid of incorporating the PTF. The effectiveness of PTF depends on a and l (segment 3.3). We restore a at 2 and display the outcomes varying l. For consistency, we extract a subset of 1-month duration from each facts set because the enter circulate. The c program languageperiod between two successive snapshots (timestamp unit) is one hour. For a timestamp ts, we evaluate the effects for exclusive periods with duration len varying from 1 to 10 days.

TABLE 3
Results of Different Granularities ($\alpha = 2, l = 6$)

	24	72	144
Obama	0.4567	0.4867	0.4765
Chelsea	0.3089	0.3474	0.3019
Arsenal	0.4197	0.4116	0.3876
Smartphone	0.4214	0.3855	0.4017
Black Friday	0.3275	0.3613	0.3537

Fig. 10 gives the following observations:

There exists a commonplace trend: greater current time

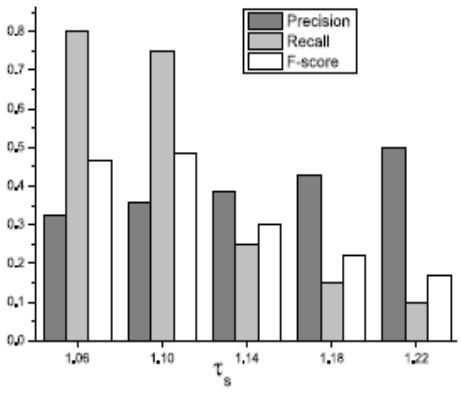

Fig. 11. Effect of τ_s (SUM).

intervals have higher precis nice. this is due to the fact PTF has finer granularity of snapshots for more recent moments. As a result, the queried periods can be higher approximated. A bigger l ends in higher standard first-class. Due to large capacity of each order, PTF with a larger l is able to hold extra snapshots, and for this reason produce greater correct approximation for the queried intervals.

lamentably, a larger l additionally requires more garage value (the numbers inside the parentheses represent the

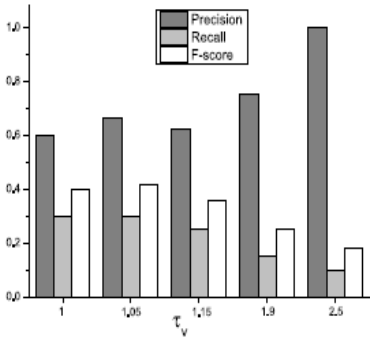

Fig. 12. Effect of τ_v (VOL).

amounts of snapshots in PTF). that is apparent on the grounds that it allows PTF to save more snapshots, which ends in heavier storage burden.

Results:

Our goal is to stumble on nodes within the reference timeline as the circulate proceeds. We compare performance of the topic evolution detection set of rules the usage of 3 one-of-a-kind versions in section 4.three, i.e., precis-primarily based variant, volume based variation and sum-vol version. We present precision, consider, and F-score of the timeline nodes detected by means of these methods. on account that similar developments are discovered in all 4 facts sets, right

TABLE 4
Statistics of Data Sets

Data Sets	#Tweets	Time Span	#Timeline Nodes
Arsenal2012	323,555	2012.11 - 2012.12	10
Chelsea2012	438,884	2012.11 - 2012.12	9
Arsenal2013	606,698	2013.03 - 2013.05	12

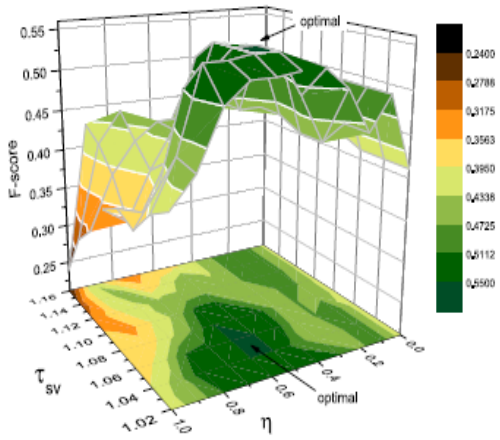

Fig. 14. Effect of τ_{sv} and η on F-score (SV).

here we most effective show consequences for the largest data set Chelsea 2013 to save area. outcomes for other facts sets are also available.

Finally, we present output timelines of the SV approach. Each timeline consists of five nodes, and each node contains a timestamp and a summary. The nodes whose timestamps are included in braces are contained in the reference timelines. Due to space limit, we only show five nodes of each timeline and two sentences in the summary of each node.

Arsenal2012	Chelsea2013
(12.09): 1. Arsenal 1-0 West Brom! Come on Arsenal! 2. Come on @Arsenal ‡MustWin	(03.15): 1. GOAL: CHELSEA 3-1 Steaua Bucharest - Torres (71) 2. Chelsea defeat Steaua Bucharest 3-1 to claim a 3-2 aggregate win and a last-eight place in the Europa League.
(12.12): 1. Yes Bradford! WENGER OUT. 2. And Arsene Wenger thinks this ‡Arsenal team can still win the league and or finish in the top 4!!! They can't even beat Bradford!!	03.17: 1. Chelsea v westham tomoz there are soo many players injured at westham :'(2. Chelsea vs West Ham! GO West Ham!!!
(12.18): 1. Arsenal vs Reading Come on arsenal ‡Arsenal 2. What a come back! Cazorla is a class! But I love how Wenger gave the right position for Walcott.	(03.18): 1. Lampard scores his 200th Chelsea goal. Chelsea 1-0 West Ham. 2. (Sky Sport) Zola quiet on Chelsea rumours.
(12.19): 1. Jack Wilshere, Alex Oxlade-Chamberlain, Aaron Ramsey, Kieran Gibbs and Carl Jenkinson sign long-term deals at Arsenal. No Theo though ‡afc 2. Arsenal vs West Ham Boxing Day match off due to Tube strike.	(03.31): 1. HT : Chelsea 1 - 2 Southampton Come On CHELSEA !!! 2. Southampton 2-1 CHELSEA... Southampton 3-1 City... Southampton 3-1 Liverpool... Southampton 2-3 MAN UNITED!! WE ARE UNITED!!
(12.20): 1. Champions League draw: Manchester United v Real Madrid, Arsenal v Bayern Munich, Celtic v Juventus. 2. Arsenal vs Bayern Munich gonna be a tough game.	(04.01): 1. Chelsea v Man u. No Manchester United please. Come on Chelsea! 2. Chelsea defeats Man United 1-0, stay alive in FA Cup. Chelsea haven't lost an FA Cup game at home in an incredible 10 YEARS.

TABLE 5 Selected Part of Timelines for "Arsenal2012" (Left) and "Chelsea2013" (Right)

6. CONCLUSION:

We proposed a prototype called Sumblr which supported continuous tweet stream summarization. Sumblr employs a tweet stream clustering algorithm to compress tweets into TCVs and maintains them in an online fashion. Then, it uses a TCV-Rank summarization algorithm for generating online summaries and historical summaries with arbitrary time durations. The topic evolution can be detected automatically, allowing Sumblr to produce dynamic timelines for tweet streams. The experimental results demonstrate the efficiency and effectiveness of our method. For future work, we aim to develop a multi-topic version of Sumblr in a distributed system, and evaluate it on more complete and large-scale data sets.

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