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On Explanation and Timeline Production for Development Tweet Torrents

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Summary: Short-textual content messages which include tweets are being created and shared at an unparalleled fee. Tweets, in their uncooked shape, while being informative, also can be overwhelming. For each quit-customers and data analysts, it's miles a nightmare to plow through tens of millions of tweets which incorporate great amount of noise and redundancy. On this project, we advise a unique continuous summarization framework referred to as sumblr to relieve the hassle. In assessment to the conventional record summarization methods which attention on static and small-scale statistics set, sumblr is designed to deal with dynamic, rapid arriving, and huge-scale tweet streams. Our proposed framework consists of 3 essential components. First, we propose a web tweet circulate clustering set of rules to cluster tweets and hold distilled data in a facts structure known as tweet cluster vector (tcv). 2nd, we develop a tcv-rank summarization approach for generating on line summaries and historical summaries of arbitrary time intervals. 0.33, we layout an effective subject matter evolution detection technique, which video display units precis-primarily based/volume-based totally variations to supply timelines robotically from tweet streams. Our experiments on huge-scale real tweets reveal the efficiency and effectiveness of our framework.

Index terms: tweet stream, continuous summarization, summary, timeline

1 CREATION

Growing popularity of microblogging services which include twitter, weibo, and tumblr has resulted inside the explosion of the amount of brief-textual content messages. Twitter, for example, which receives over four hundred million tweets according to day1 has emerged as an invaluable source of news, blogs, evaluations, and more. Tweets, of their uncooked form, at the same time as being informative, also can be overwhelming. As an instance, look for a warm topic in twitter may additionally yield hundreds of thousands of tweets, spanning weeks. Even though filtering is allowed, plowing via so many tweets for critical contents would be a nightmare, now not to say the tremendous amount of noise and redundancy that one may come across. To make things worse, new tweets satisfying the

filtering standards may also arrive continuously, at an unpredictable fee.

One feasible method to statistics overload hassle is summarization. Summarization represents a hard and fast of files via a precis consisting of numerous sentences. Intuitively, a terrific precis should cowl the principle topics (or subtopics) and have range the various sentences to reduce redundancy. Summarization is drastically utilized in content material presentation, specifically whilst customers surf the net with their cell devices which have a whole lot smaller monitors than pcs. Conventional record summarization techniques, but, are not as effective inside the context of tweets given each the huge quantity of tweets as well as the quick and continuous nature of their arrival. Tweet summarization, consequently, requires functionalities which notably differ from traditional summarization. In fashionable, tweet summarization has to take into attention the temporal function of the arrival tweets. Allow us to illustrate the preferred residences of a tweet summarization system the usage of an illustrative example of a usage of the sort of device. Consider a user interested in a subject-related tweet move, for instance, tweets approximately "apple". A tweet summarization gadget will continuously screen "apple" related tweets producing a actual-time timeline of the tweet movement. As illustrated in fig. 1, a consumer may explore tweets based totally on a timeline (e.g., "apple" tweets posted between october twenty second, 2012 to november 11th, 2012). Given a timeline range, the summarization gadget may additionally produce a sequence of timestamped summaries to highlight factors where the subject/subtopics evolved inside the stream. Any such system will effectively allow the person to analyze fundamental news/ dialogue associated with "apple" without having to read via the complete tweet circulate. Given the massive photograph about subject matter evolution about "apple", a person may also determine to zoom in to get a extra particular record for a smaller duration (e.g., from 8 am to 11 pm on november 5th). The device may also offer a drill-down summary of the duration that enables the user to get extra information for that length. Inside the tweet flow clustering module, we design an efficient tweet move clustering set of rules, an online set of rules making an allowance for effective clustering of tweets with best one pass over the statistics. This algorithm employs records structures to hold important tweet data in clusters. The primary one is a novel compressed structure known as the tweet cluster vector (tcv). Tcvs are taken into consideration as capacity sub-topic delegates and maintained dynamically in reminiscence in the course of flow processing. The second one shape is the pyramidal time frame (ptf) [1], that is used to keep and organize cluster snapshots at exclusive moments, accordingly permitting historic tweet statistics to be retrieved through any arbitrary time durations. The high-stage summarization module helps generation of two sorts of summaries: on-line and historic summaries. (1) to generate on line summaries, we suggest a tcv-rank summarization algorithm with the aid of relating to the present day clusters maintained in memory. This algorithm first computes centrality scores for tweets saved in tcvs, and selects the pinnacle-ranked ones in terms of content material insurance and novelty. (2) to compute a historical summary wherein the consumer specifies an arbitrary time duration, we first retrieve two historical cluster snapshots from the ptf with respect to the 2 endpoints (the beginning and finishing factors) of the duration. Then, based at the distinction among the two cluster snapshots, the tcv-rank summarization set of rules is applied to generate summaries. The middle of the

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timeline era module is a subject evolution detection set of rules, which consumes online/ancient summaries to provide actual-time/range timelines. The set of rules video display units quantified variation for the duration of the route of stream processing. A large variation at a particular moment implies a sub-subject matter alternate, leading to the addition of a new node at the timeline. In our layout, we bear in mind three different factors respectively in the set of rules. First, we keep in mind variant within the essential contents discussed in tweets (within the form of summary). To quantify the summary based variation (sum), we use the jensen-shannon divergence (jsd) to measure the space between two word distributions in two successive summaries. 2nd, we display the quantity-based variation (vol) which displays the importance of sub-topic adjustments, to discover fast increases (or "spikes") in the quantity of tweets over the years. 0.33, we outline the sum-vol version (sv) by combining each results of summary content material and significance, and come across subject matter evolution on every occasion there's a burst in the unified variation. The main contributions of this work are as follows:

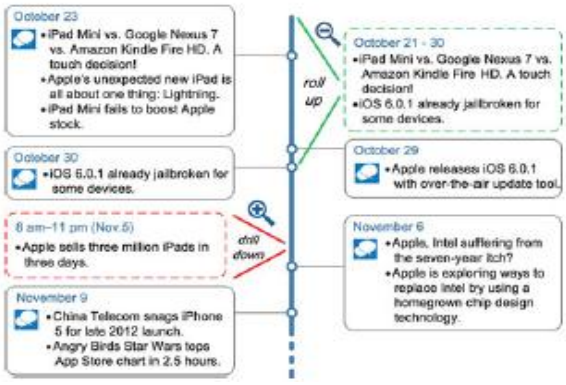

Fig. 1. A timeline example for topic "Apple".

we advise a continuous tweet move summarization framework, particularly sumblr, to generate summaries and timelines inside the context of streams. We design a novel facts shape referred to as tcv for stream processing, and endorse the tcv-rank algorithm for on line and historical summarization. We advocate a subject evolution detection algorithm which produces timelines with the aid of tracking three types of variations. Vast experiments on real twitter records units show the performance and effectiveness of our framework.

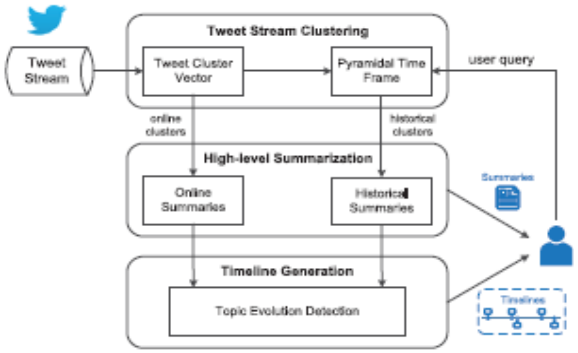

Fig. 2. The framework of Sumblr.

2 ASSOCIATED PAINTINGS

On this phase, we assess the related paintings which include move information clustering, file/micro blog summarization, timeline detection, and different micro blog mining tasks.

2.1 Stream Information Clustering

Stream information clustering has been extensively studied inside the literature. Birch clusters the information primarily based on an in-memory shape known as cf-tree as opposed to the original large records set. Bradley et al. proposed a scalable clustering framework which selectively stores crucial portions of the statistics, and compresses or discards different portions. Clustream is one of the most conventional circulate clustering methods. It consists of a web micro-clustering aspect and an offline macro-clustering component. The pyramidal time body

became also proposed to keep in mind ancient micro clusters for extraordinary time durations. A diffusion of services on the web inclusive of information filtering, text crawling, and subject matter detecting and so forth. Have posed requirements for text circulation clustering. Some algorithms have been proposed to tackle the problem. Maximum of these techniques adopt partition-primarily based methods to allow on-line clustering of circulation facts. For this reason, those techniques fail to provide effective evaluation on clusters fashioned over unique time periods.

2.2 Document/micro blog summarization

Record summarization can be categorised as extractive and abstractive. The former selects sentences from the documents, at the same time as the latter might also generate terms and sentences that don't appear inside the authentic documents. On this project, we recognition on extractive summarization. Extractive document summarization has received a whole lot of latest interest. Maximum of them assign salient scores to sentences of the documents, and pick out the pinnacle-ranked sentences. A few works try and extract summaries without such salient ratings. Wang et al. Used the symmetric non-negative matrix factorization to cluster sentences and pick sentences in each cluster for summarization. He et al. Proposed to summarize documents from the attitude of statistics reconstruction, and pick sentences that can nice reconstruct the original files. In [14], xu et al. Modeled documents (inn evaluations) as multi-characteristic unsure statistics and optimized a probabilistic insurance hassle of the summary. At the same time as record summarization has been studied for years, microblog summarization remains in its infancy. Sharifi et al. Proposed the word reinforcement algorithm to summarize tweet posts using a unmarried tweet. Later, inouye and kalita proposed a hybrid tf-idf set of rules and a cluster-based algorithm to generate multiple publish summaries. Harabagiu and hickl leveraged two relevance models for micro blog summarization: an event structure model and a user conduct version.

2.3 Timeline detection

The demand for studying big contents in social medias fuels the developments in visualization techniques. Timeline is this type of strategies that may make evaluation duties simpler and faster. Diakopoulos and shamma made early efforts on this place, the use of timelines to explore the 2008 presidential debates with the aid of twitter sentiment. Dork et al. Provided a timeline-based totally backchannel for conversations around activities. Yan et al. Proposed the evolutionary timeline summarization (ets) to compute evolution timelines similar to ours, which includes a chain of time-stamped summaries. But, in [24], the dates of summaries are determined by using a pre-defined timestamp set. In assessment, our technique discovers the changing dates and generates timelines dynamically all through the procedure of non-stop summarization. Furthermore, ets does now not focus on performance and scalability problems, that are very essential in our streaming context.

2.4 Different micro blog mining obligations

The emergence of micro blogs has engendered researches on many different mining obligations, along with subject matter modeling, storyline technology and event exploration. Most of those researches focus on static records sets instead of information streams. For twitter circulation evaluation, yang et al. [29] studied common sample mining and compression. Van durme

aimed at discourse members type and used gender prediction as the instance project, which is likewise a distinct problem from ours. To sum up, in this paintings, we recommend a brand new problem known as non-stop tweet summarization. Special from preceding research, we aim to summarize big-scale and evolutionary tweet streams, producing summaries and timelines in an internet style.

3 PRELIMINARIES

On this segment, we first gift a facts model for tweets, then introduce essential records systems: the tweet cluster vector and the pyramidal time frame.

3.1 Tweet representation

Normally, a report is represented as a textual vector, in which the fee of every measurement is the tf-idf rating of a word. But, tweets are not handiest textual, however also have temporal nature—a tweet is strongly correlated with its published time. Similarly, the significance of a tweet is suffering from the writer's social impact. To estimate the user impact, we build a matrix based totally on social relationships among customers, and compute the userrank. As a end result, we outline a tweet ti as a tuple: (tvi; tsi; wi), where tvi is the textual vector, tsi is the posted timestamp and wi is the userrank fee of the tweet's creator.

3.2 Tweet cluster vector

For the duration of tweet flow clustering, it is essential to hold information for tweets to facilitate precis technology. On this section, we endorse a brand new records shape referred to as tweet cluster vector, which continues statistics of tweet cluster. The definition of tcv is an extension of the cluster characteristic vector proposed. Besides information of information factors (textual vectors), tcv includes temporal statistics and representative unique tweets. Our tcv shape also can be updated in an incremental manner when new tweets arrive. We will talk information on tcv updating in segment four.1.2.

3.3 Pyramidal time body

To guide summarization over person-described time durations, it's far important to store the maintained tcvs at unique moments, which are known as snapshots. While storing snapshots at every moment is impractical due to large storage overhead, insufficient snapshots make it hard to recall historic information for specific periods. This dilemma results in the incorporation of the pyramidal time frame.

4 THE SUMBLR FRAMEWORK

As shown in fig. 2, our framework consists of three predominant modules: the tweet movement clustering module, the high-stage summarization module and the timeline generation module. In this segment, we shall gift each of them in detail.

4.1 Tweet flow clustering

The tweet move clustering module keeps the net statistical statistics. Given a topic-primarily based tweet circulation, it's miles in a position to efficiently cluster the tweets and keep compact cluster records.

4.1.1 Initialization

On the start of the stream, we acquire a small wide variety of tweets and use a okay-manner clustering set of rules to create the initial clusters. The corresponding tcvs are initialized in line with definition 1. Subsequent, the move clustering procedure starts off evolved to incrementally replace the tcvs each time a new tweet arrives.

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4.1.2 Incremental clustering

Suppose a tweet t arrives at time ts, and there are n active clusters at that point. The important thing problem is to decide whether to absorb t into one of the present day clusters or upgrade t as a new cluster. We first locate the cluster whose centroid is the closest to t. Mainly, we get the centroid of each cluster based on equation, compute its cosine similarity to t, and discover the cluster cp with the biggest similarity (denoted as maxsim(t)). Notice that although cp is the nearest to t, it does no longer suggest t clearly belongs to cp. The cause is that t may also still be very distant from cp. In such case, a brand new cluster should be created . The selection of whether to create a new cluster can be made with the subsequent heuristic. The above updating procedure is executed upon the arrival of every new tweet. Meanwhile, whilst the present day timestamp is divisible via ai for any integer i, we store the photograph of the contemporary tcvs into disk and index it through ptf. Set of rules 1 describes the overview of our incremental clustering process. Given the above analysis, we need to restriction the variety of active clusters. We acquire this aim through two operations: deleting old clusters and merging similar clusters. Due to the fact the computational complexity of deletion is o(n) and that of merging is $o(n^2)$, we use the former technique for periodical exam and use the latter technique only when memory restriction is reached.

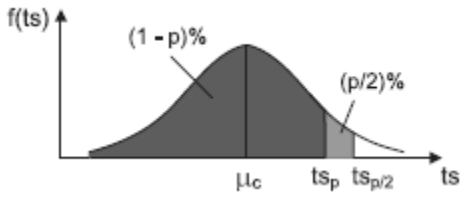

Fig. 3. Probability density function of timestamp

4.1.3 Deleting old clusters

For maximum events (including news, football matches and concerts) in tweet streams, timeliness is vital because they typically do not closing for a long time. Therefore it's miles safe to delete the clusters representing these sub-topics after they are rarely mentioned. To find out such clusters, an intuitive way is to estimate the average arrival time (denoted as a_{vgp}) of the remaining p percent of tweets in a cluster. But, storing p percent of tweets for each cluster will growth reminiscence costs, in particular whilst clusters grow big. For this reason, we employ an approximate technique to get a_{vgp}.

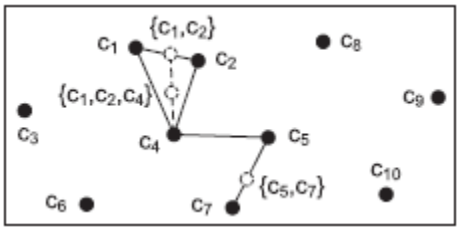

Fig. 4. A running example of cluster merging.

4.1.4 Merging clusters

If the wide variety of clusters keeps growing with few deletions, machine memory might be exhausted. To keep away from this, we specify an higher restriction for the range of clusters as nmax. When the restriction is reached, a merging process starts off evolved. The method merges clusters in a greedy manner. First, we sort all cluster pairs via their centroid similarities in a descending order. Then, starting with the most similar pair, we strive to merge clusters in it. When both clusters are single clusters that have now not been merged with other clusters, they're merged into a brand new composite cluster. While one of them belongs to a composite cluster (it has been merged with others earlier than), the opposite is also merged into that composite cluster. Whilst each of them had been merged, if they belong to the identical composite cluster,

this pair is skipped; otherwise, the two composite clusters are merged collectively. This procedure continues till there are only mc percent of the original clusters left (mc is a merging coefficient which provides a balance among to be had reminiscence space and the first-class of ultimate clusters).

4.2 Excessive-degree summarization

The excessive-stage summarization module presents forms of summaries: on line and historical summaries. An on line precis describes what is currently discussed some of the public. For this reason, enter for generating on-line summaries is retrieved at once from the modern clusters maintained in memory. Then again, a historic summary enables human beings recognize the primary happenings throughout a specific duration, which means that we want to put off the impact of tweet contents from the out of doors of that length. As a result, retrieval of the desired information for generating historical summaries is greater complicated, and this will be our cognizance within the following discussion.

The motivation of equation (2) is similar to that of maximal marginal relevance (mmr). In query-orientated summarization, mmr combines question relevance and facts novelty. Here, we combine coverage and novelty as our criterion: the primary element on the right facet of the equation favors tweets which have high scores and belong to big clusters (content coverage); the second one factor penalizes redundant tweets with comparable contents to those already selected (novelty). After the primary round choices, if the precis period is still now not reached, then we strive to select tweets globally (ti 2 t s) primarily based on equation (2) (traces 10-14).

4.3 Timeline era

The middle of the timeline era module is a subject evolution detection set of rules which produces actual-time and variety timelines in a similar manner. We will best describe the real-time case here. The algorithm discovers sub-subject matter adjustments via monitoring quantified variations throughout the path of movement processing. A large variant at a specific moment implies a sub-subject matter alternate, that is a brand new node at the timeline. The primary technique is described in set of rules three. We first bin the tweets by time (e.g., by day) because the stream proceeds. This sequenced binning is used as input of the set of rules. Then, we loop thru the bins and append new timeline nodes every time huge versions are detected.

4.3.1 Precis-based variant

As tweets arrive from the move, on-line summaries are produced constantly via making use of on line cluster information in tcvs. This lets in for technology of a real-time timeline. Generally, whilst an obvious version happens inside the fundamental contents mentioned in tweets (inside the shape of summary), we can anticipate a change of sub-topic (i.e., a time node at the timeline). To quantify the variant, we use the jensen-shannon divergence to degree the distance between two phrase distributions in successive summaries sc and sp (sc is the distribution of the modern summary and sp is that of the previous one)

4.3.2 Quantity-based totally variation

Even though the summary-primarily based variation can replicate sub-topic modifications, some of them might not be influential enough. Seeing that many tweets are associated with

customers' daily lifestyles or trivial events, a sub-subject matter exchange detected from textual contents won't be tremendous sufficient. To this cease, we keep in mind the usage of rapid will increase (or "spikes") within the quantity of tweets over time, which is a commonplace method in existing on line event detection structures. A spike shows that something crucial just occurred due to the fact many people determined the need to touch upon it.

4.3.3 Unified variant

The above spike-locating method may fit nicely for short term activities together with soccer matches, however it might be hard for them to address long-term subject matter-associated streams, because of some time-conscious human behaviors in social media. For example, the variety of tweet posts2 and public engagement rate3 will fluctuate in day of week or time of day. Moreover, breaking information or rumors normally draw huge attention and create massive spikes in tweet volumes. These spikes will considerably growth the mean and suggest deviation values, reducing the chance for subsequent sub-topic changes being detected (equation (6)).

4.4 Dialogue

Dealing with noises. The impact of clusters of noises may be dwindled by using two means in sumblr. First, in tweet movement clustering, noise clusters which are not up to date frequently will be deleted as old clusters. 2nd, inside the summarization step, tweets from noise clusters are a ways less probable to be decided on into summary, due to their small lexrank ratings and cluster sizes. Extension to multi-subject matter streams. So far we've assumed a tweet movement of simplest one subject matter because the enter to sumblr. However, we must note that sumblr may be without problems prolonged for multi-subject matter streams. For example, while a brand new tweet arrives, we first decide its associated topics with the aid of key-word matching. Then it's miles added into distinct companies of clusters. Clusters are grouped through their corresponding topical ids. Consequently, sumblr is applied within every cluster institution. It is important to notice that this mechanism permits for distributed device implementation.

5 EXPERIMENTS

On this phase, we evaluate the performance of sumblr. We present the experiments for summarization and timeline generation respectively.

5.1 Experiments for summarization

5.1.1 Setup

Facts units: we construct five facts units to assess summarization. One is obtained by undertaking key-word filtering on a huge twitter records set used. The other four encompass tweets obtained during one month in 2012 through twitter's keyword tracking api.four as we do now not have get admission to to the respective customers' social networks for those four, we set their weights of tweets wi to the default fee of 1. Details of the information sets are listed in table 2. Floor reality for summaries. As no preceding work has carried out similar take a look at on non-stop summarization, we must construct our own floor truth (reference summaries). But, guide introduction of these summaries is apparently impractical due to the huge size of the facts units. Hence, we employ a two-step method to obtain fair-first-class reference summaries:

1) Given a time length, we first retrieve the corresponding tweet subset, and use the

subsequent 3 nicely-recognized summarization algorithms to get three candidate summaries. Clustersum clusters the tweets and alternatives the maximum weighted tweet from every cluster to shape precis. Lexrank first builds a sentence similarity graph, and then selects vital sentences based totally at the concept of eigenvector centrality. Dsdr models the connection among sentences using linear reconstruction, and reveals an most advantageous set of sentences to approximate the unique files, by means of minimizing the reconstruction mistakes.

2) Next, for each subset, the very last reference precis is extracted from 3 candidate summaries by using using a vote casting scheme. The instinct is if a specific tweet and its comparable tweets appear regularly within the candidate summaries, they are able to constitute crucial content material and need to be selected into the very last summary. Specially, for every tweet in every candidate summary, we compute its similarities to the tweets from the opposite two candidate summaries. Then, the tweet votes to its most similar one and these two tweets form a "pair". After processing all of the tweets in candidate summaries, we sort them in descending order of their overall votes. We delete the ones tweets whose pair members already exist at better ranks. At remaining, the pinnacle ranking tweets are introduced into the final reference precis till the summary duration is reached. Baseline strategies. Present summarization techniques have now not been designed to address non-stop summarization. But, they may be adapted to streaming data via using a sliding window scheme. As illustrated in fig. 5, each window contains a positive quantity (window size) of tweets which might be summarized as a report. After that, the window actions forward by way of a step size, in order that the oldest tweets are discarded and the brand new ones are delivered into the window. In this manner, we implement the sliding window version of the above 3 algorithms, namely clustersum, lexrank, and dsdr. The home windows are dimensioned via quantity of tweets as opposed to time period, due to the fact the wide variety of tweets may vary dramatically across fixed length durations, leading to very bad performance of the baseline algorithms. Evaluation approach. We follow the popular rouge toolkit for assessment. Amongst supported metrics, rouge-1 has been tested to be the maximum consistent with human judgement [37]. Considering the short and casual nature of the tweet contents, we determine that rouge-1 is appropriate for measuring the nice of tweet summaries.

5.1.2 Normal performance evaluation

On this phase, we evaluate the f-ratings and runtime costs among sumblr and 3 baseline algorithms (sliding window version). As tweets are regularly produced very quick and reach a large extent in a short even as, it's far hardly meaningful to summarize a small variety of tweets. Accordingly the window length must be a enormously huge one. In this experiment, we set window size to 20,000 and sampling interval to 2,000. The step length varies from 4,000 to 20,000. The metrics are averaged over the whole flow. Figs. 6 and 7 gift the outcomes for specific step sizes. In fig. 6, we also deliver a baseline random technique, which selects tweets randomly from every window. Be aware that sumblr is now not suffering from the step length, as it helps non-stop summarization inherently.

5.1.3 Parameter Tuning

On this phase, we song the parameters in our technique. In each of the subsequent experiments, we range one parameter and preserve the others fixed. Effect of b: In heuristic

1 we use b to determine whether or not to create a new cluster. Figs. 9a and 9b display its effect on summary nice and efficiency. When b is small, tweets related to distinct sub-topics can be absorbed into the equal clusters, so the enter of our summarization element is of low satisfactory. On the equal time, there are many awareness tweets in every cluster, therefore the time price of cluster updating and summarization is excessive. While b will increase, too many clusters are created, causing harm to both exceptional and performance. An amazing choice is b = 0.07 because it offers greater balanced effects.

Impact of n_{max}: figs. 9c and 9d depict the overall performance of n_{max}. For small nmaxs, many merging operations are carried out, which are time-eating and bring masses of low-exceptional clusters. For big values, circulation clustering is slow due to large range of clusters. Be aware that the garage overhead (each in reminiscence and disk) is likewise higher for larger nmaxs. A balanced fee for nmax is 150. Effect of mc. Some other parameter in cluster merging is mc ($0 < mc < 1$). It does not have substantial impact on performance, so we most effective gift its quality outcomes (fig. 9e). Small values of mc result in low-fine clusters, even as big ones cause many merging operations, which in flip lessen the best of clusters. A really perfect price for mc is zero.7.

5.1.4 Flexibility

One distinguishing feature of sumblr is the power to summarize tweets over arbitrary time periods. This selection is furnished through incorporating the ptf. The effectiveness of ptf relies upon on a and l (section 3.3). We restore a at 2 and display the outcomes varying l. For consistency, we extract a subset of one-month length from each records set because the input movement. The c program languageperiod between successive snapshots (timestamp unit) is one hour. For a timestamp ts, we evaluate the outcomes for unique intervals with duration len various from 1 to 10 days. We document the average f-score score(ts) by using c language of 48 hours. Due to space limit, we most effective there exists a not unusual fashion: extra latest time periods have higher precis quality. This is because ptf has finer granularity of snapshots for extra latest moments. As a end result, the queried periods may be higher approximated. A bigger l leads to better usual best. Because of large capacity of each order, ptf with a bigger l is capable of maintain greater snapshots, and thus produce extra accurate approximation for the queried intervals. Unfortunately, a bigger l additionally requires extra storage fee (the numbers within the parentheses represent the quantities of snapshots in ptf). This is apparent given that it permits ptf to save more snapshots, which ends in heavier storage burden. For extraordinary packages, sumblr may be customized with one-of-a-kind l values. For instance, for real-time summarization, a small l is enough; whilst for historical assessment, a massive l is wanted. Granularity. To further examine the power of sumblr, we also conduct a granularity take a look at. We partition the onemonth facts sets into time intervals with constant length (e.g., 24, seventy two, or one hundred forty four hours), then document the common f-rankings for those periods underneath one-of-a-kind stages of granularity. As proven in desk 3, precis fine does not have sizeable distinction among unique granularities. This is because the first-class of a historical summary particularly depends on two endpoints of the duration (i.e., the accuracy of duration approximation in ptf) rather than the length of the length.

5.2 Experiments for timeline era

5.2.1 Facts units and ground fact: In this section, we compare the effectiveness of subject matter evolution detection, i.e., timeline era. We use the "arsenal" and "chelsea" information sets in segment 5.1, and upload more current information units ("arsenal2013" and "chelsea2013"). We pick out these data units because reference timelines for game topics are fantastically less complicated to construct. For this test, the reference timelines are manually produced. Particularly, we read thru all the associated news at some point of the ones intervals of the corresponding information units from information web sites (yahoo!, espn, and so on.), and pick out the ones dates as nodes at the reference timelines whilst something important happen, e.g., soccer matches, gamers' signing of recent contracts, and so forth. The time unit of timelines is day. Facts of the facts sets and the reference timelines (numbers of timeline nodes) are indexed in table 4.

5.2.2 Results

Our objective is to detect nodes within the reference timeline as the flow proceeds. We compare performance of the topic evolution detection algorithm the use of 3 special versions in phase 4.3, i.e., summary-primarily based variant, volume based variant and sum-vol variation. We present precision, consider, and f-score of the timeline nodes detected by means of those strategies. When you consider that similar tendencies are observed in all 4 statistics sets, right here we handiest show results for the largest statistics set chelsea2013 to keep space. Effects for different data sets are also to be had. 5 figs. 11 and 12 display the effects of the decision threshold for sum (ts) and vol (television), respectively. In each figures, as the edge will increase, consider declines whilst precision increases. That is predicted seeing that better threshold might exclude extra promising candidate nodes, and people remaining nodes with large variations are much more likely to be the best ones.

6. END

We proposed a prototype referred to as sumblr which supported non-stop tweet movement summarization. Sumblr employs a tweet stream clustering set of rules to compress tweets into tcvs and continues them in an internet style. Then, it makes use of a tcv-rank summarization algorithm for generating on-line summaries and historic summaries with arbitrary time intervals. The subject evolution can be detected mechanically, allowing sumblr to produce dynamic timelines for tweet streams. The experimental outcomes display the performance and effectiveness of our method. For destiny paintings, we aim to expand a multi-topic version of sumblr in a dispensed system, and evaluate it on greater entire and massive-scale data units.

7. REFERENCES

[1] c. C. Aggarwal, j. Han, j. Wang, and p. S. Yu, "a framework for clustering evolving data streams," in proc. 29th int. Conf. Very large data bases, 2003, pp. 81–92.

[2] t. Zhang, r. Ramakrishnan, and m. Livny, "birch: an efficient data clustering method for very large databases," in proc. Acm sigmod int. Conf. Manage. Data, 1996, pp. 103–114.

[3] p. S. Bradley, u. M. Fayyad, and c. Reina, "scaling clustering algorithms to large databases," in proc. Knowl. Discovery data mining, 1998, pp. 9–15.

[4] l. Gong, j. Zeng, and s. Zhang, "text stream clustering algorithm based on adaptive feature

selection," expert syst. Appl., vol. 38, no. 3, pp. 1393–1399, 2011.

[5] q. He, k. Chang, e.-p. Lim, and j. Zhang, "bursty feature representation for clustering text streams," in proc. Siam int. Conf. Data mining, 2007, pp. 491–496.

[6] j. Zhang, z. Ghahramani, and y. Yang, "a probabilistic model for online document clustering with application to novelty detection," in proc. Adv. Neural inf. Process. Syst., 2004, pp. 1617–1624.

[7] s. Zhong, "efficient streaming text clustering," neural netw., vol. 18, nos. 5/6, pp. 790–798, 2005.

[8] c. C. Aggarwal and p. S. Yu, "on clustering massive text and categorical data streams," knowl. Inf. Syst., vol. 24, no. 2, pp. 171–196, 2010.

[9] r. Barzilay and m. Elhadad, "using lexical chains for text summarization," in proc. Acl workshop intell. Scalable text summarization, 1997, pp. 10–17.

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