Efficient Time-Evolving Stream Processing at Scale

Yu Huang

Abstract—Time-evolving stream datasets exist ubiquitously in many real-world applications where their inherent hot keys often evolve over times. Nevertheless, few existing solutions can provide efficient load balance on these time-evolving datasets while preserving low memory overhead. In this paper, we present a novel grouping approach (named FISH), which can provide the efficient time-evolving stream processing at scale. The key insight of this work is that the keys of time-evolving stream data can have a skewed distribution within any bounded distance of time interval. This enables to accurately identify the recent hot keys for the real-time load balance within a bounded scope. We therefore propose an epoch-based recent hot key identification with specialized intra-epoch frequency counting (for maintaining low memory overhead) and inter-epoch hotness decaying (for suppressing superfluous computation). We also propose to heuristically infer the accurate information of remote workers through computation rather than communication for cost-efficient worker assignment. We have integrated our approach into Apache Storm. Our results on a cluster of 128 nodes for both synthetic and real-world stream datasets show that FISH significantly outperforms state-of-the-art with the average and the 99th percentile latency reduction by 87.12% and 76.34% (vs. W-Choices), and memory overhead reduction by 99.96% (vs. Shuffle Grouping).

Index Terms—Stream processing, streaming partition, load balance, efficiency, scalability

1 INTRODUCTION

Streaming processing has an important role in solving many real-world problems. From fraud detection (e.g., real-time financial activity [1]) to real-time recommendations (e.g., analytics over microblogs [2], [3] and live streaming [4]), applications that generate stream data are ubiquitous. Unlike structured stream data in which hot keys are relatively evenly distributed during the whole lifetime [5], real-world stream datasets often exhibit the unique feature that their inherent hot keys often evolve over times. One key is hot in some interval may be non-hot in the next interval. A typical example includes twitter dataset where its catchword may vary frequently for different instants of time. At present, it also becomes greatly necessary and important to efficiently process these time-evolving stream datasets.

Reasonably distributing time-evolving stream datasets on a cluster of machines can provide the beneficial businesses with the cost-effective services. In an effort to exploit maximum benefits, time-evolving stream processing systems need to do the best at two aspects at least. First, all loads for time-evolving stream datasets must be balanced to a maximum extent. This indicates whether each worker is fully mobilized. It also directly affects the overall latency and throughput of stream processing. Second, considering the state of the stream data is backed up on multiple workers, the combined memory overhead on all machines should be controlled with a minimum of duplicates. This indicates how much memory is stored redundantly, which directly influences the scalability of stream processing systems.

Unfortunately, few existing solutions can meet all these two hard requirements. Fields Grouping utilizes key-based routing, which is prone to load imbalance across multiple workers [6]. Shuffle Grouping [6] uses round-robin manner to assign the loads. However, it potentially replicates the states associated with keys on each worker with a linear proportion of the memory overhead. Other solutions attempt to balance the loads by leveraging operator migration [7], [8], [9], [10], [11], [12], [13]. A part of the keys are allowed to be rebalanced when load imbalance is detected. A number of studies [14], [15] also aim to reduce the rebalancing overhead by identifying hot key and further assigning more workers. These earlier efforts on structured stream processing make a significant progress on getting a reasonable tradeoff, which, however, is far unsatisfactory from practical use for time-evolving stream processing. This is particularly true when the number of machines is scaled (as discussed in Section 2.3). In this paper, we are addressing whether and how we can build such an efficient and scalable time-evolving stream processing system.

Nevertheless, there remains tremendously challenging to build a time-evolving stream processing system with all the desired properties satisfied. First, since time-evolving stream processing often involves a large number of recent hot key identification operations, it should be not only accurate but also efficient, which is notoriously difficult. In order to track most recently-occurred keys, it necessarily has to preserve a large amount of key-related information. Although existing approaches make a great progress on accuracy, the expense is that a substantial amount of computation [16], [17], [18] or memory overhead [19], [20], [21], [22], [23] has occurred.

Second, handling time-evolving stream dataset may also need a timely adjustment for load balance at every moment, which is also difficult. Even worse, heterogeneous resources may further exacerbate this problem. To assign the appropri-
ate workers for load balance, the servers have to frequently collect the state information from workers with considerable communication overhead [24], [25]. It remains challenging to make an efficient decision of worker assignment for preserving the real-time load balance.

In this paper, we propose an efficient grouping approach (named FISH) to process time-evolving streaming data at scale. Interestingly, we observe that, no matter how large a time interval is, the keys of time-evolving stream dataset within this bounded scope have a skewed power-law distribution where a small fraction of keys dominate most loads. This therefore allows to achieve real-time load balance within a bounded time interval by using hierarchical treatment [26]. We present an epoch-based approach to accurately identify recent hot key. Each epoch can be a customized key sequence. Intra-epoch identification counts the occurrence number of the key, which only stores the number of most frequent keys [27], [28] for preserving the low memory overhead. Inter-epoch identification uses time-aware approach [15], [17], [18], which adopts epoch-level (rather than tuple-level) update for reducing the superfluous computation. To ensure the efficiency of worker assignment, we also recognize the simplicity of operations and the similarity of keys. We further propose a heuristic approach to infer (rather than prohibitively communicate) the information of remote worker in a more efficient manner.

This paper makes the following contributions:

- We make a comprehensive study on the deficiencies of state-of-the-art grouping schemes for time-evolving stream datasets in terms of load balance and scalability.
- We present an efficient and scalable grouping scheme with epoch-based hot key identification and heuristic worker assignment, which can provide low-latency and high-throughput time-evolving stream processing.
- We evaluate our approach on both synthetic and real-world stream datasets. Experimental results show that our approach significantly outperforms state-of-the-art grouping schemes for time-evolving stream datasets in terms of load balance and scalability.

The rest of this paper is organized as follows. We first give the background and motivation in Section 2. Section 3 provides the overview of our approach. Section 4 elaborates the design of FISH. Section 5 describes the extension for handling dynamic scenario with worker variation. Section 6 discusses the results. We survey the related work in Section 7 and conclude this work in Section 8.

2 BACKGROUND AND MOTIVATION

In this section, we first briefly review the background of distributed stream processing and existing stream partitioning schemes. We next investigate the potential inefficiency of existing solutions towards time-evolving stream dataset through a comprehensive motivating study, finally followed by several challenges for coping with the problem.

2.1 Distributed Stream Processing

Distributed stream processing engine (DSPE) [6], [29], [30], [31], [32] often runs on a cluster of machines that can communicate with each other via messages. The target stream applications are processed under these DSPEs in the form of a directed acyclic graph (DAG). Figure 1 depicts a typical workflow of DSPE for the top-k word count stream application based on DAG where the vertex represents the operator of the stream engine that is applied on an incoming data stream for the data transformation. The directed edge represents data channel that points from an upstream operator (also called source for short) to a downstream operator (called worker for short). The data flow along these edges, representing a series of tuples, each associated with a key.

In order to achieve high performance, DSPE usually exploits data parallelism by running many instances of these operators. Each operator is responsible for handling a set of partitioned input sub-stream data, which relies on the creation of a particular grouping scheme (as will be discussed in Section 2.2). In this case, a well-known problem for DSPE is load imbalance. For the example in Figure 1, the key for each tuple is the word itself. Sources distribute tuples to workers based on a specific grouping scheme. Workers count the occurrence number of each word. The hot-key $F$ in this time-evolving stream data may be identified as non-hot potentially, leading to imbalanced tuple assignment. Also note that keys often have been duplicated in different workers with proportional memory overhead to the number of word types. The inefficiency of these aspects will be extensively investigated in Section 2.3.

2.2 Existing Stream Grouping Schemes

The input stream is composed of a sequence of tuples, each of which is associated with a key. As shown in Figure 1, different colored tuples correspond to different keys. Grouping scheme assigns each tuple to a worker by key. Different grouping schemes may make different decisions for this key assignment, with a summary as follow:

- **Shuffle Grouping (SG)** [6]: This scheme sends each tuple from the source to a round-robin selected worker, ensuring that each worker can evenly have the tuples.

1. Word count is a simple program that counts the number of occurrences of each word in a given input stream data
• Field Grouping (FG) [6]: This scheme ensures that the same key is always sent to the same worker via hashing.

• Partial Key Grouping (PKG) [14]: This scheme can be treated as a bounded FG. A given key for the PKG is allowed to be processed by two workers at most.

• D-Choices (D-C) [15]: This scheme is an improved PKG, which allows that frequent keys can be processed by d workers at most where d is determined by the distribution of key. Other keys continue using PKG.

• W-Choices (W-C) [15]: This scheme is similar to D-C, and the only difference is that it allows frequent keys can be processed on the entire set of workers instead of d ones.

2.3 Issues with Existing Grouping Schemes on Time-evolving Stream Datasets: A Motivating Study

These previous efforts [14], [15] have made a significant advance for the load balance problem of DSPEs, particularly for skewed stream data. By considering the hotness of keys from the entire processing lifetime, their original key identification and assignment, however, are in essential unaware of the frequency variation of hot key within a bounded time interval. As a result, existing grouping schemes may result in the potential issues for the time-evolving stream processing with either load imbalance or prohibitive memory overhead, which can be much serious at scale (with a large number of workers).

To investigate this problem, we have conducted a set of experiments on the real-world time-evolving Amazon Movie Review stream dataset with different machine scales (16, 32, 64 and 128 workers) for word count application based on different grouping schemes discussed in Section 2.1. Note that we test D-C and W-C schemes by considering top-100 and top-1000 keys in this motivating study.

Load Imbalance Issue Figure 2 depicts the results of latency, which is widely used for representing the load balance of the DSPEs [9], [14], [15]. The lower the latency is, the more balanced the system is. The 99th percentile latency of FG and PKG is up to 3,945 and 2,808 milliseconds, respectively. Both FG and PKG have high latency because of assigning only one or two workers to each key. The skew distribution of the key results in extreme load imbalance of each worker. The latency of W-C and D-C is related to the number of statistical keys. If there are 1000 keys, latency of both W-C1000 and D-C1000 is almost the same as the PKG. The increase of workers, the latency has a significant increase. This is due to inaccurate identification in the sense that some hot keys are detected as non-hot. If 100 keys are involved, the latency of D-C100 and W-C100 can have a part of improvement, but scalability issue below arises.

Scalability Issue Figure 3 depicts the results of memory overhead. FG assigns only one worker per key, and hence, it has little memory overhead as can be seen in Figure 3. In contrast, we can see that SG has the highest memory overhead by up to 23.16x in the case of 128 workers since many states have been replicated. The D-C100 and W-C100 are similar to the SG. When the number of workers increases, the memory overhead increase significantly. This is due to inaccurate identification in the sense that some non-hot keys are detected as hot. Therefore, SG, D-C100, and W-C100 may suffer from scalability problems. To ensure system scalability, we set the maximum set of keys by 1000 for the following experiment.

Summary It can be seen that neither of existing grouping schemes can perform well in both load balance and scalability. Although state-of-the-art D-C and W-C schemes have made the advance for a relatively good tradeoff, they may be still far from the ideal situations (where SG scheme shows the optimal case for latency criteria while FG scheme represents the optimal case for memory overhead criteria). More importantly, their tradeoff gradually underperforms as the number of workers is increasing. There still lacks effective grouping scheme for efficiently processing these time-evolving stream data at scale.

2.4 Challenges of Balancing Time-evolving Streaming Processing at Scale

Time-evolving stream data has a significant feature with the significant frequency variation of keys within different time intervals. Not only with the global load balance for the final state during the entire lifetime, time-evolving stream processing but also needs to additionally consider the local real-time load balance within some time interval at every moment, arising several unique challenges.

First, by considering the time-evolving factor, the identification scope for the hot keys has been consequently changed from the entire processing to a large number of short time intervals. The problem of identifying recent hot keys within a time interval has been extensively studied in the Data Mining field, which can fall into two broad categories. Sliding-window based approach [19], [20], [21], [22], [23] uses window threshold for bounding recent key counting. To get the accurate results, they have to use a large window size at the cost of potentially prohibitive memory overhead. Time-aware based approach [16], [17], [18] proposes that recent items have more weights so that a stale item is more likely to be pruned than a recent one. This approach uses a replacement strategy to reduce memory overhead, but each update for all items requires a time weight modification, leading to a large amount of computation.

Nevertheless, we should note that time-evolving stream processing often involves a large number of recent hot key identification operations, which can be easily more than millions for the real-world stream dataset. Technically, each of these operations is supposed to be efficient and lightweight so that the whole DSPE system can spread their superiority for load balance and scalability. There still lacks an effective technique to accurately identify the recent hot keys while preserving the low overhead in both computation and memory consumption.

Second, after the hot key identification, we have to assign an appropriate worker for each identified recent hot key. As discussed previously, the traditional stream processing only considers the global load balance for the final states. Thus, they simplify the work assignment problem by evenly assigning all tuples to the given workers. Nevertheless, the reality is that the processing capability between workers is often different for many reasons, e.g., heterogeneous
devices or network delays. As a consequence, it is likely for existing approaches to assign the keys for a busy worker in some time interval, leading to the local imbalance. An ideal method for work assignment is to select the optimal candidate worker according to the number of unprocessed tuples and processing capacity of workers.

Nevertheless, it is extremely difficult, if not impossible, to make efficient worker assignment. The unprocessed tuples information of workers is usually located in remote with respect to the source. Frequently requesting the queue states from workers may lead to a large amount of communication overhead between sources and workers. More serious is that this requested information may be quickly out of data since the state of workers is often changing dramatically. There remain tremendously challenging for developing such an efficient worker assignment for time-evolving stream processing.

3 OVERVIEW

To cope with the aforementioned challenges, we design our grouping approach in accordance with the following interesting observations for time-evolving stream processing.

Observation 1: The occurrence frequency between the recent hot keys and non-hot keys in the time-evolving stream data remains a large difference with a skewed distribution.

One typical example accounting for the above observation is twitter dataset. Although its catchword may change from one to the other over time, the occurrence frequency of these catchwords can be still significantly higher than the non-hot ones (within a short interval).

This finding has two implications at least for the recent hot-key identification. First, in spite of the frequent variation of hot keys, a small fraction of these keys can still dominate most loads during the whole stream processing. This allows to continue using “eighty-two” golden rule by handling these few critical keys for the balance of most loads. Since only a few keys are saved in multiple workers, a large amount of memory overhead can be saved. Second, hot keys are subject to change over time. The potentially hot keys may be inaccurately identified as non-hot ones from a global perspective in prior work [15]. Considering the skewed distribution of hot keys in a short interval, this implies that it is supposed to identify recent hot keys accurately in a locally-bounded (instead of global) manner.

Observation 2: Considering the operation type of stream processing are usually simplex, the processing time for the same batch of tuples under the same given worker can be considered same with a negligible performance difference.

Figure 4 illustrates the performance results of processing every 50,000 tuples 12 times for 10 randomly-selected workers. We can see that the performance fluctuation range can be on average as small as 4.37%, which can be often considered reasonable and negligible in practice [33].

This finding gives us an important implication for assigning an appropriate worker among all workers. The
premise is that we have to know which worker has the fewest tasks unprocessed, which are generally unavailable at the source end. The intuitive method obtains this information via the considerable communication between workers. In contrast, this observation allows us to infer (rather than communicate) the unprocessed computation amount of all workers in a more efficient manner.

According to these implications, we propose a custom-made grouping approach with the specially-designed key identification and work assignment. Figure 5 illustrates the overview of our approach (named FISH), consisting of two major components as follows.

**Accurate Recent Hot Key Identification** (Section 4.1): This part aims at accurately identifying the recent hot key for the time-evolving stream data. Although there exist a vast body of previous studies on recent hot key identification, these approaches are originally designed for mining the accurate data in data-mining applications, not yet satisfying the efficient requirement in the sense of low overhead in computation amount and memory consumption for stream processing applications. We present a specialized recent hot key identification approach that can accurately identify hot keys for a recent time interval with low computational and memory overhead.

**Heuristic Work Assignment** (Section 4.2): Given a set of workers, this part aims at assigning the identified hot keys to the appropriate workers for load balance. Unlike the previous studies that simply consider the global load balance at the final state (as discussed in Section 2.4), we additionally consider the local load balance at every time interval. This is particularly important for time-evolving stream processing. In contrast to communication-based worker assignment approach with heavy communication overhead, we propose a heuristic worker assignment, which can precisely infer the worker processing capacity based on the history information for worker assignment in a more efficient manner.

Note that this work focuses on addressing the common case where each tuple is associated with a single key. For the scenario where each tuple is allowed to carry multiple keys, we can still extend FISH to combine specific applications by prioritizing or synthesizing multiple keys. This is out of our scope, which can be interesting future work.

4 FISH

This section elaborates the design of the recent hot key identification and heuristic work assignment. For facilitating the descriptions, we define several notations used in this work. Table 1 lists the details regarding notations.

**4.1 Epoch-based Recent Hot-key Identification**

People often treat the hot key identification in the whole lifetime of stream processing. We either use a time-aware factor to compute the frequency of all keys [16, 17, 18] with a large amount of computation, or use the additional storage to memorize the history frequency of all keys in the cost of memory overhead [19, 20, 21, 22, 23].

Motivated by observation 1, the core idea of our recent hot key identification is an epoch-based approach, which divides the entire lifetime of stream processing into many epochs. *Epoch* is a collection of sequential tuples. The intra-epoch counts the occurrence number of the key, which only stores the number of most frequent keys [27, 28] for reducing the prohibitive memory overhead. The inter-epoch frequency counting of keys uses a time-aware [16, 17, 18] approach which adopts epoch-level (rather than tuple-level) update for reducing the superfluous amount of computation. Based on the frequency results, these keys are finally classified into hot and non-hot ones.

4.1 Key Frequency Statistics

In the following, we next introduce how we obtain the frequency of keys based on an epoch-driven approach.

**Intra-epoch Frequency Counting** The intra-epoch counting aims to count the occurrence number of the key in each individual epoch. To reduce memory overhead, we continue to only store the most frequent $K_{\text{max}}$ keys [28]. The related descriptions are located between Lines 8-17 in Algorithm 1. When a new key appears, if the current number of keys stored in $K$ is less than the maximum capacity, this key will be merged into the $K$ set, and its occurrence number is incremented. If $K$ is full, we use a replacement strategy to replace the least counted key from $K$. Note that its occurrence number is set to that of replaced keys plus 1 rather than 1 (as shown in ReplaceMin). The
Algorithm 1: Epoch-based Key Frequency Statistics

Input: $\alpha$ – time decaying factor
$D$ – input stream data
$N_{epoch}$ – the size of epoch
$K_{max}$ – maximum capacity of the set $K$

1. $K \leftarrow \emptyset$
2. $counter \leftarrow 0$
3. foreach $k \in D$ do
   4. /* Inter-epoch decaying */
   5. if $counter = N_{epoch}$ then
      6. TimeDecayingUpdate($K$)
      7. $counter \leftarrow 0$
   8. /* Intra-epoch counter */
   9. if $k \in K$ then
      10. $c_{k} \leftarrow c_{k} + 1$
   11. else
      12. /* Insert or replace the key */
      13. if $|K| < K_{max}$ then
         14. $K \leftarrow K \cup \{k\}$
         15. $c_{k} \leftarrow 1$
      16. else
      17. ReplaceMin($K, k$)
      18. $counter \leftarrow counter + 1$
   19. Subroutine ReplaceMin($K, k$)
   20. $k_{min} \leftarrow \min_{v \in K \cap \{k\}} c_{v}$
   21. $K \leftarrow K \setminus \{k_{min}\} \cup \{k\}$
   22. $c_{k} \leftarrow c_{min} + 1$
   23. Subroutine TimeDecayingUpdate($K$)
   24. /* Update counters according to the $\alpha$ */
   25. foreach $v \in K$ do
      26. $c_{v} \leftarrow c_{v} \times \alpha$

Algorithm 2: Classification of Hot Key (CHK)

Input: $d_{min}$ – minimal number of workers for hot key
$f_{top}$ – the highest frequency
$f_{k}$ – the frequency of the key $k$

Output: $d$ – number of candidate workers

1. if $f_{k} > \theta$ then
   2. /* Assign the number of candidate workers to the key */
   3. $index \leftarrow \lfloor \log_{2}(f_{top} / f_{k}) \rfloor$
   4. $d \leftarrow W_{num} / 2^{index}$
   5. if $d < d_{min}$ then
      6. $d \leftarrow d_{min}$
   7. if $M_{k} < d$ then
      8. $M_{k} \leftarrow d$
   9. else
      10. $d \leftarrow M_{k}$
   11. else
      12. $d \leftarrow 2$
   13. return $d$.

major reason is just for avoiding the unreasonable replacement of new keys [28]. To be more specific, if it is set to 1, once a new key comes, we will always replace this key until the occurrence number of this key exceeds others. This is unreasonable since the previous key is replaced and its valuable information is not reusable for the memory saving.

Inter-epoch Hotness Decaying Instead of performing a time decaying update when each tuple arrives (as described between Line 5-7 in Algorithm 1), we adopt a time-aware decaying approach in the epoch granularity. After tuple statistics in each epoch is completed, we multiply the counters of all the stored keys by $\alpha (0 < \alpha < 1)$ so that the time decaying effect can be taken. Hence, the counter is not only related to the number of occurrence number of the key but also the time decaying factor.

It is worth noting that the size of the epoch directly determines the computational overhead of the recent hot-key identification. The larger the epoch size is, the lower the computational overhead is, and vice versa. Nevertheless, large epoch size may also affect the accuracy of the hot key identification. We conduct our experiments with the empirical epoch size of 1000 by default. It is revealed that this result can cover almost all datasets (as will be discussed in Section 6) without compromising identification accuracy, and also can reduce the computational complexity of decaying updates by three orders of magnitude.

4.1.2 Hot Key Classification

We next introduce to classify recent hot keys based on the frequency results. Algorithm 2 describes the procedure of hot key classification (denoted as CHK). To determine the number of workers to which each key can be assigned, we use the set $M$ to hold the number of the candidate workers for each hot key. We are based on the idea that the higher the frequency is, the more workers assigned. First, we get the number of arithmetic assignment workers for the hot key through the formula from line 1 to 4 in Algorithm 2. Second, if the value of $d$ obtained is less than the minimum value of $d_{min}$, we directly assign $d$ to $d_{min}$. The $d_{min}$ is related to the sum of the frequency of all hot keys. Then, considering that the frequency of the key changes, $M_{k}$ saves the number of workers previously assigned to key $k$. If $d$ is greater than the $M_{k}$, $M_{k}$ is updated to $d$ and $d$ workers are assigned to the key. Otherwise, we assign $M_{k}$ workers to the hot key. It is worth noting that we assign workers for each key through a consistent hash so that we can deal with the dynamic workers. The detailed contents will be introduced in Section 5.

4.2 Heuristic Worker Assignment

This section introduces how to assign the identified hot keys to $d$ or 2 workers by CHK. Choosing a light-load worker from $d$ or 2 candidate workers is the next question that has to address. We present a heuristic method to efficiently estimate (rather than communicate in prior efforts) the runtime states of workers in a fine-grained time interval.

4.2.1 Worker State Estimation

In order to fully mobilize each worker, each tuple is expected to be processed as soon as possible. The selection of the light load worker usually depends on two states of the worker: the number of unprocessed tuples and processing
Algorithm 3: Heuristic Worker Assignment

```
Input: A – set of candidate worker  
      T – time interval 
Output: appro – number of selected worker.
1 /* Estimate the current status of each worker */
2 t_cur ← GetNowTime() 
3 if t_cur − t_pos > T then 
4     foreach w ∈ W do 
5         if (C_w + N_w) × P_w > T then 
6             C_w ← (C_w + N_w) × P_w − T)/P_w 
7         else 
8             C_w ← 0 
9     t_pos ← t_cur 
10 /* Select the appropriate load worker */
11 foreach w ∈ A do 
12     if appro = −1 then 
13         appro ← w 
14     else 
15         if C_appro × P_appro > C_w × P_w then 
16             appro ← w 
17     C_appro ← C_appro + 1
18 return appro
```

capacity. Unfortunately, obtaining this information from all workers can cause prohibitively communication overhead. We observe that stream processing usually takes the same kind of operation for processing each tuple. Therefore, we obtain the processing capacity (the average processing time of a tuple) of workers by a periodic sampling. Since the number of tuples for each worker can be directly obtained at the source end, we estimate that the number of unprocessed tuples of workers is as follow:

\[ C_w = \frac{(C_w + N_w) \times P_w - T}{P_w} \]  

(1)

where \(N_w\) is the number of assigned tuples from sources, \(P_w\) is the processing capacity of the worker \(w\) and \(T\) is the fixed time interval (10s). As shown in Figure 4, there is little difference in the processing time for the same batch of tuples under the same worker. We set the default time interval to 10 seconds. We thus can estimate the number of unprocessed tuples \(C_w\) for the worker \(w\).

4.2.2 Candidate Worker Selection

We estimate the number of unprocessed tuples in a heuristic fashion. Each tuple is expected to be processed as quickly as possible to fully squeeze each worker for load balance. Considering potentially-different processing capability of different workers, we select the worker with the shortest waiting time as shown between Line 12 to 18 in Algorithm 3. The estimated waiting time can be expressed as follow:

\[ T_w = C_w \times P_w \]  

(2)

where \(T_w\) is to estimate the waiting time for the worker \(w\). Considering the similarity of stream processing, capture the states of workers using a sampling technique [34].

5 Extension: Dynamic Change of Workers

There remains the fact that the number of workers may be dynamically changing in a practical deployment. For example, a worker might be shut down or failed. Alternatively, the new worker is put into operation.
A typical approach for adapting the dynamic scenario is to use a hashing algorithm [35]. By using a hash function \( F = \text{HASH}(k) \mod n \) where \( k \) is the key and \( n \) is the number of workers, keys can be mapped to different workers. Nevertheless, the overhead of this simple mapping is subject to the number of workers. When a worker is removed or added, all keys have to be remapped to all workers, resulting in considerable memory overhead.

An alternative approach is that we can create a virtual ID mapping table for the workers based on a maximum number of supported workers, and make the assignments based on virtual IDs [36]. However, this approach suffers from two defects at least. First, modifications to the virtual ID mapping table may introduce a large amount of synchronization overhead for the consistency across all sub-streams. Second, the assignment of workers is not random, resulting in the key not being evenly distributed to workers. It directly affects the balanced distribution of the load.

Let us reconsider this problem, which can be abstracted to map a batch of keys to \( n \) workers and need to meet two requirements. First, all keys are supposed to be randomly and mapped evenly to workers. Second, the addition or reduction of workers does not cause a large number of key-to-worker re-mappings with monotonicity. We therefore propose to use consistent hash [37], [38] for reducing the unnecessary key-to-worker mappings.

Figure 8 shows a case of consistent hashing algorithm. Each key can be hashed to a space with \( 2^{32} \) buckets. We connect these numbers to form a hash ring. The data is mapped to the ring through the hash algorithm. Now we hash \( key1, key2, key3, \) and \( key4 \) to the hash ring through a specific hash function. The worker is also mapped to the ring by using the same hash algorithm as key. In a clockwise direction, all the keys stored in their nearest worker. In Figure 8(a), the current state should be that \( key1 \) is stored in worker1, \( key3 \) in worker2, \( key2 \) and \( key4 \) in worker3.

**Worker Removal and Addition** Suppose the worker2 is crashed. As shown in Figure 8(b), we have to remove it from the hash ring. According to the clockwise rule, \( key3 \) is then mapped to worker3. No changes for all other keys have happened. Alternatively, suppose a new worker is added. Figure 8(c) illustrates the way for this case where \( key4 \) is added. By the clockwise shift rule, \( key2 \) is originally mapped to worker3 and will now be remapped to worker4 as worker4 is closer to \( key2 \) than worker3 on the ring. The other key still maintains the original mapping relationship with only change for the \( key2 \) mapping. In summary, the addition or removal of workers only affects the mapping of keys with a few steps (by just only changing worker to adjacent worker) on the hash ring. Correspondingly, a small portion of the keys in the ring space need to be remapped.

**Small-scale Worker Deployment** Note that in the case that the number of workers is small, consistent hashing algorithm prone to causing the uneven distribution of keys for each worker. As shown in Figure 8(b), when worker2 is removed with only two workers, \( key2, key3, \) and \( key4 \) will be mapped to worker3. Only \( key1 \) will be mapped to worker1.

3. The size of the bucket space is determined by the hash algorithm. The hashing algorithm [35] is used in our method to return 32-bit integer data. The maximum value of unsigned integer data is \( 2^{32} - 1 \), we thus use \( 2^{32} \) for bucket space.

We complement to use a virtual node mechanism [38], [39], which calculates multiple hash values for each worker. By this means, each worker has multiple virtual nodes, which are further mapped onto the hash ring. Figure 8(d) shows an example with two virtual nodes for each worker. There thus have four virtual nodes, denoted as \( worker1-1, worker1-2, worker3-1, \) and \( worker3-2 \), respectively. The new key-to-worker mapping relationship in Figure 8(d) (i.e., \( key1 \) and \( key2 \) are mapped to \( worker1 \); \( key3 \) and \( key4 \) are mapped to \( worker3 \)) demonstrates that the distribution of keys is more balanced than otherwise.

### 6 Evaluation

In this section, we evaluate the efficiency and effectiveness of FISH by answering five research questions:

- **RQ1**: How efficient is FISH compared to existing state-of-the-art grouping schemes? (Section 6.2)
- **RQ2**: How to decide the internal parameters of FISH for load balance? (Section 6.3)
- **RQ3**: How effective is each part of FISH? (Section 6.4)
- **RQ4**: How effective is consistent hashing algorithm for dynamic extension of worker variation? (Section 6.5)
- **RQ5**: How is overall effect of FISH for a practical deployment on Apache Storm? (Section 6.6)

#### 6.1 Experimental Setup

**Simulation Settings** We process the stream dataset by simulating the basic DAG in Figure 1. Sources extract the data and the workers perform the data aggregation. The input stream data is received by sources through shuffle grouping. Each data consists of a timestamp and a corresponding key. We assign each tuple to the specified worker based on the grouping scheme we desire to evaluate.

**Datasets** We evaluate FISH on both real-world and synthetic stream datasets, as shown in Table 2. We use two real-world datasets, including MemeTracker (MT) [40] and Amazon Movie Review (AM) [41]. MT provides quotes and phrases from blogs and news media. We consider a keyword stream, which consists of words in the quotes and phrases where 571 stopwords provided in [42] are excluded. AM provides user reviews with product identification, which is used as the key for the tuples.

As for synthetic Zipf (ZF) dataset, we generate 50M tuples with \( 10^5 \) unique keys. Considering the skewness of stream data, the generated time-evolving ZF dataset has the following distribution with the exponent in the range \( z \in \{1.0, 1.1, \ldots, 2.0\} \). 1) For the first \( 0.8 \times N \) tuples, the occurrence probability of a given key \( i \) obeys \( Pr\{i\} \propto i^{-2} \); 2) For the last \( (1-0.8) \times N \) tuples, the occurrence probability of a given key \( i \) obeys \( Pr\{i\} \propto (k-i+1)^{-z} \) where \( k=10^4 \) and \( N=50M \). To simulate the feature of time-evolving data, the algorithms have been run 10 times with a different seed for the pseudo-random number generator.
assigns two workers for each key without considering the worst among all of four grouping schemes. The effect of increasing with the number of workers increases. PKG is Overall, the gap between the four grouping schemes is data is not taken into consideration, resulting in inaccurate to the fact that the feature of the time-evolving of the stream improvement than D-C and W-C respectively. This is due because that PKG only assign two workers for all keys. The effect for both MT and AM datasets. The execution time of load balancing but also memory overhead must be taken into consideration. We use the memory overhead of FG as a balance to normalize the results of other grouping schemes. FG assigns only one worker per key without any extra memory overhead. Thanks to the special assignment for a small fraction of keys, which dominate most loads in stream data. Even with the extended number of workers, the memory overhead of FISH is comparable (from 1.11x to 2.61x) to FG with 128 workers. Although SG is able to balance the load well with the increasing number of workers, the memory overhead has increased significantly (from 15.52x to 88.32x). Compared to FG, the memory overhead of PKG, D-C, and W-C schemes is close. Yet, they suffer from the problem of load imbalance, as depicted in Figure 9 and Figure 10. In summary, compared to all of existing grouping schemes, FISH showcases the best results in load balance and memory overhead for time-evolving stream data.

6.2 RQ1: Overall Evaluation

We investigate overall load balance and memory overhead of FISH against state-of-the-art PKG, D-C, and W-C grouping schemes on both synthetic and real-world datasets. For the load balance, we use the SG as the baseline, which is a well-known grouping scheme with an ideal load balancing effect. For memory overhead, we use FG as a baseline since it does not generate any extra memory overhead.

Load Imbalance Figure 9 illustrates the results on the real-world AM and MT datasets. We use the SG as the baseline. The lower the execution time is, the better the load balancing effect is. Compared to four tested grouping schemes, we can see that FISH has the best load balance effect for both MT and AM datasets. The execution time of FISH is almost same as the SG with the worst case of 1.07x. Compared to PKG, as the number of workers increases, the effect of FISH increases more significantly (from 1.19x to 8.32x for MT and from 1.12x to 7.31x for AM). This is because that PKG only assign two workers for all keys. The skew distribution of keys causes the tuples to be unevenly distributed among workers, resulting in load imbalance. Although W-C and D-C take into account the skew distribution of keys, its effect is still limited as the number of workers increases. Overall, FISH has up 7.44x and 6.95x improvement than D-C and W-C respectively. This is due to the fact that the feature of the time-evolving of the stream data is not taken into consideration, resulting in inaccurate hot key identification and inappropriate assignment.

Figure 10 further investigates the load balance of FISH on synthetic ZF dataset with the different skew factor. Overall, the gap between the four grouping schemes is increasing with the number of workers increases. PKG is worst among all of four grouping schemes. The effect of PKG becomes worse with the skew increases because it only assigns two workers for each key without considering the case of skewed data. The execution time of D-C and W-C becomes longer with the skew increases, although the skewed data feature is considered. Particularly with the increasing number of workers, the effect would become worse. FISH is up to 13.57x and 12.05x improvement than D-C and W-C respectively. This is because that time-evolving feature is not considered in D-C and W-C. As a result, they may lead to the fact that hot keys cannot be accurately identified and assigned. We also note that as the number of workers is scaling, FISH can always have the comparable load balance effect to SG with the worst case of 1.32x.

Memory Overhead Figure 11 shows the memory overhead of FISH compared to existing grouping scheme FG, SG, PKG, D-C, and W-C. For system scalability, not only load balancing but also memory overhead must be taken into consideration. We use the memory overhead of FG as a baseline to normalize the results of other grouping schemes. FG assigns only one worker per key without any extra memory overhead. Thanks to the special assignment for a small fraction of keys, which dominate most loads in stream data.

6.3 RQ2: Internal Parameter Decision

We next investigate how to decide the appropriate internal parameters of FISH for better effect. Two major parameters include the decaying factor $\alpha$ in Algorithm 1 and the hot key threshold $\theta$ in Algorithm 2.

Setting Decaying Factor $\alpha$ Our goal is to find an appropriate $\alpha$ so that more stream data can be processed. Figure 12 shows the impact of $\alpha$ value, ranging from 0 to 1, with different number of workers and skew.

Overall, the large $\alpha$ value can lead to the long execution time. Note that, when $\alpha$ is with 1, this shows the special case that does not consider the time-evolving feature. We thus can see that the execution time grows significantly (up to 12.14x compared to $\alpha$ of 0.2) as the skew increases. When $\alpha$ is with 0, all previous data for each update will be abandoned, although the execution time has a relatively-low level. An amount of memory overhead will be incurred, especially for low skew stream data (with 2.65x compared to $\alpha$ of 0.2). The reason is that abandoning previous data may mis-lead to many false non-hot keys that are supposed to be hot. Among all possible values, we can see that $\alpha$ with 0.2 has the best effect on load balance and memory overhead for many cases with different workers and skew.

Setting Hot Key Threshold $\theta$ As discussed in the previous study [15], if $\theta$ is greater than $2/n$ where $n$ is the number of workers, the DSPE can definitely suffer from load imbalance. If it is less than $1/5n$, the probability of load imbalance generated by PKG is bounded by $1 - 1/n$ at least.
An appropriate threshold $\theta$ often lies in the range of from $2/n$ down to $1/8n$. Figure 13 shows the potential impact with different $\theta$ thresholds.

In theory, the small threshold often results in the better load balance. The large threshold often results in the lower memory overhead. However, in practice, we can find in Figure 13 that significant load imbalance occurs only in the case of $\theta = 2/n$. For other thresholds, the result has almost no difference especially for the large number of workers. As for the memory overhead, we find that memory overhead has little change as $\theta$ is changing. We conservatively choose a threshold as $1/4n$ for two reasons.

First, its execution time is similar to the threshold of $1/8n$ which reflects the similar effect of load balancing. Second, as for memory overhead, it is almost no difference compared to the threshold of $2/n$. However, the threshold with $1/8n$ produces more memory overhead for the large number of workers and low skewed data. A compromised threshold with $1/4n$ can provide the reasonable results on both load balance and memory overhead.

6.4 RQ3: Breakdown

We next break down the effectiveness of FISH, including recent hot-key identification, hot-key classification and heuristic worker assignment.

**Effectiveness of Epoch-based Hot Key Identification**

Figure 14 shows the effectiveness of our epoch-based hot key identification compared to the entire lifetime counting-based approach in D-C and W-C. We can see that the execution time has been greatly improved. Especially when the number of workers and the skew increase, the effect becomes more pronounced (up to 11.91x). The main reason accounting for this is that hot key identification in D-C and W-C may potentially lead to inaccurate hot-keys. They monitor the entire lifetime of all keys, thereby resulting in the situation that the most recent hot keys are difficult to capture. This can thus lead to load imbalance among workers. More workers and larger skew can further aggravate the problem of load balance.

**Effectiveness of Hot Key Classification**

Figure 15 illustrates the memory overhead of FISH with and without CHK. FISH without using CHK includes two cases of hot-key processing approaches that are used in W-C (written as w/ W-C) and D-C (w/ D-C), respectively.

As shown in Figure 15, we can see that CHK can greatly reduce the memory overhead in comparison to the one of W-C. This benefit can be more significant as the number of workers increases. Compared to the method used in W-
C. FISH can save up to 25.23% and 45.34% of memory costs for 64 and 128 workers respectively. Although the method used in D-C has the less memory overhead than CHK in some cases, it may suffer from longer execution time and more serious load imbalance problems than CHK. Due to the skew distribution of keys, the frequency of hot keys usually varies dramatically. Simply treating all hot keys equally often results in load imbalance (for D-C) or unnecessary memory overhead (for W-C).

**Effectiveness of Heuristic Worker Assignment**

In order to verify the effectiveness of heuristic worker assignment (hwa), we assume that half of the worker’s processing capability is twice than the others.

Figure 16 plots the results. We can see that FISH can provide up to 2.61x improvement on the execution time compared to the traditional worker assignment in previous studies [14], [15] which assigns the keys according to the amount of worker’s load. The main reason accounting for this is that simply ensuring each worker has the same number of tuples in the final state may assign a busy worker for a tuple in some time interval, particularly true for the situation where workers have different processing capacity. In contrast, our approach is able to cope with scenarios where workers are heterogeneous and dynamically changing by inferring the status of workers.

**6.5 RQ4: Effectiveness of Consistent Hashing**

In order to investigate the effectiveness of consistent hashing (CH), we create the dynamic scenario by randomly adding or removing a worker instance during the processing.
Figure 17 illustrates the memory overhead of FISH with and without CH with different skewed stream data. As we can see, for stream data with low skew, FISH without CH almost has memory overhead twice than FISH with CH no matter the workers are increased or decreased. This is because that the previous key and worker mappings rely heavily on the number of workers. The variation of worker number just means that almost all possible mappings need to be changed, leading to twice memory overhead. Stream processing on highly-skewed dataset has less increase of memory overhead. The reason for this is that the hot keys for stream dataset with high skewness need to be re-mapped to new workers. Considering a part of new workers have already reserved the corresponding data of these hot keys. As a result, this can save an amount of memory overhead so that not too much remapping has occurred when the number of workers is changing.

6.6 RQ5: Practical Deployment on Apache Storm

To quantify the impact of FISH, we have integrated it into Apache Storm and deployed it on a cluster with 8 compute nodes, each of which has 20 available ports. We build a DAG topology configured with 32 sources and 128 workers. We compared FISH with state-of-the-art FG, SG, PKG, D-C and W-C grouping schemes.

Latency Figure 18 shows the results regarding end-to-end latency. The plot reports the average latency with the 50th, 95th, and 99th percentiles across all workers, respectively. Thanks to the accurate hot key identification and heuristic worker assignment. The 50th (median) and 99th percentiles in FISH have the geometric mean of latency with only 7 and 562 milliseconds (for MT), as well as 9 and 640 milliseconds (for AM), respectively. These results are almost the ideal latency provided by SG. In summary, FISH significantly outperform FG, W-C, D-C, and PKG. FISH can reduce the average and 99th percentile latency of state-of-the-art W-C by 87.12% and 76.34%, respectively.

Throughput Figure 19 shows the results regarding throughput. Overall, FG has the lowest throughput (with

7 RELATED WORK

A large number of previous studies leverage operator migration for load balance in DSPEs. Once a situation of load imbalance is detected, the system activates a rebalancing routine that moves some keys and their associated states away from an overloaded server.

Flux encapsulates adaptive state partitioning and dataflow routing, migrates operators from the most loaded to the least loaded server. Xing et al. present a correlation based load distribution algorithm for dynamic load migration to adapt to changing loads. Fernandez et al. propose an integrated approach for scale-out and failure recovery through checkpointing and migration. Gedik propose partitioning functions for stream processing systems that employ stateful data parallelism to improve application throughput and control migration cost.

These rebalance-based approaches usually require setting a number of parameters, such as how often to check for imbalance. These parameters are typically application-specific with different tradeoff situations between imbalance and rebalance cost. Further, each sub-stream needs to maintain a routing table that maps the key to each PEs with prohibitive memory overhead. Also, modifying the routing table introduces additional consistency checking across all
sub-streams \cite{14}. In contrast, we consider operators replication which allows the key can be processed by multiple workers and show it is sufficient to balance the load without active monitoring of the load imbalance.

A wide spectrum of studies attempt to consider operator replication to prevent load imbalance \cite{14,15,45}. They allow that each key can be processed by multiple operator instances, and selects the minimum load of the two whenever a tuple for a given key must be processed. Nasir et al. \cite{15} propose a lightweight streaming grouping scheme which is based on the SpaceSaving \cite{28} algorithm and does not require training or monitoring to detect the heavy hitters. CG \cite{45} studied the load balancing problem for streaming engines running in a heterogeneous cluster. Our specialized approach differs from these replication-based approaches with the following significant innovation: 1) We first consider the feature of time-evolving stream data and investigate real-time load balance within same time interval; 2) We present a novel heuristic method to assess the state information of remote workers for efficient worker assignment.

There also involves much effort put into operator placement, which ensures load balance by exploiting computational resources. Xing et al. \cite{47} propose a correlation-based algorithm that strives to minimize operator movement overhead and support more resilient operator placement. \cite{48} deploys a topology via using both online and offline analyzing methods under the minimal network communication. Eidenbenz et al \cite{49} analyze the task allocation problem and propose an approximation algorithm to exploit optimal solution. In contrast to these studies with resource partition, our approach makes workload partition for load balance. Note that our approach is compatible with an integration of this type of approach with a hybrid partition, which can be interesting future work for achieving load balance with minimum computational resources.

8 Conclusion

In this work, we investigate the load balance problem for time-evolving stream processing with a large scale deployment. Our key innovation comes from two major technical advances. First, we present an epoch-based approach to identify recent hot keys efficiently by intra-epoch frequency counting and inter-epoch hotness decaying. Second, based on the similarity of operations in streaming processing, we further propose a heuristic approach to infer the state information of remote workers to make the efficient worker assignment. We evaluate our approach on a cluster of 128 nodes with both synthetic and real-world datasets. Our practical deployment on Apache Storm demonstrates that FISH significantly outperforms state-of-the-art with the average and 99th percentile latency reduction by up to 87.12% and 76.34% (vs. W-Choices), and 96.66% memory consumption reduction (vs. Shuffle Grouping).

References

\cite{11} N. Parikh and N. Sundaresan, “Scalable and near real-time burst detection from ecommerce queries,” in Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2008, pp. 972–980.

\cite{2} X. Wang, Y. Zhang, W. Zhang, and X. Lin, “Efficient identification of local keyword patterns in microblogging platforms,” IEEE Transactions on Knowledge and Data Engineering, vol. 28, no. 10, pp. 2621–2634, 2016.

\cite{3} A. Sharma, J. Jiang, P. Bommanna var, B. Larson, and J. Lin, “Graphjet: real-time content recommendations at twitter,” Proceedings of the VLDB Endowment, vol. 9, no. 13, pp. 1281–1292, 2016.

\cite{4} X. Liao, H. Jin, Y. Liu, L. M. Ni, and D. Deng, “Anysee: Peer-to-peer live streaming,” in Processing of IEEE International Conference on Computer Communications (INFOCOM), 2006, pp. 1–10.

\cite{5} Wikibench. [Online]. Available: http://www.wikibench.eu/

\cite{6} Apache Storm. [Online]. Available: http://storm.apache.org/

\cite{7} Z. Shao, J. M. Hellerstein, S. Chandrasekaran, and M. J. Franklin, “Flux: An adaptive partitioning operator for continuous query systems,” in Proceedings of the 19th IEEE International Conference on Data Engineering, 2003, pp. 25–36.

\cite{8} Y. Xing, S. Zdonik, and J.-H. Hwang, “Dynamic load distribution in the borealis stream processor,” in Proceedings of the 21st IEEE International Conference on Data Engineering, 2005, pp. 791–802.

\cite{9} B. Gedik, “Partitioning functions for stateful data parallelism in stream processing,” The International Journal on Very Large Data Bases, vol. 23, no. 4, pp. 517–539, 2014.

\cite{10} B. Gedik, S. Schneider, M. Hirzel, and K.-L. Wu, “Elastic scaling for data stream processing,” IEEE Transactions on Parallel and Distributed Systems, vol. 25, no. 6, pp. 1447–1463, 2014.

\cite{11} R. Castro Fernandez, E. Kahvianiaki, and P. Pietzuch, “Integrating scale out and fault tolerance in stream processing using operator state management,” in Proceedings of the ACM SIGMOD International Conference on Management of Data, 2013, pp. 725–736.

\cite{12} H. Chen, Z. Sun, F. Yi, and J. Su, “Bufferbank storage: an economic, scalable and universally usable in-network storage model for streaming data applications,” Science China Information Sciences, vol. 59, no. 1, pp. 1–15, 2016.

\cite{13} P. Basanta-Val, N. Fernández-García, L. Sánchez-Fernández, and J. Arias-Fisteus, “Patterns for distributed real-time stream processing,” IEEE Transactions on Parallel and Distributed Systems, vol. 28, no. 11, pp. 3243–3257, 2017.

\cite{14} A. M. Nasir, M. A. Us, G. D. F. Morales, D. García-Soriano, N. Kourtellis, and M. Serafini, “The power of both choices: Practical load balancing for distributed stream processing engines,” in Proceedings of 31st IEEE International Conference on Data Engineering, 2015, pp. 137–148.

\cite{15} A. M. Nasir, G. D. F. Morales, N. Kourtellis, and M. Serafini, “When two choices are not enough: Balancing at scale in distributed stream processing,” in Proceedings of 32nd IEEE International Conference on Data Engineering, 2016, pp. 589–600.

\cite{16} N. R. Mabrouk and C. I. Ezeife, “A taxonomy of sequential pattern mining algorithms,” ACM Computing Surveys, vol. 43, no. 3, pp. 1–41, 2010.

\cite{17} Z. Shan, C. Ling, and T. Li, “Frequent items mining on data stream using hash-table and heap,” in Proceedings of the IEEE Conference on Intelligent Computing and Intelligent Systems, 2009, pp. 141–145.

\cite{18} Y. Lim, J. Choi, and U. Kang, “Fast, accurate, and space-efficient tracking of time-weighted frequent items from data streams,” in Proceedings of the 23rd ACM International Conference on Information and Knowledge Management, 2014, pp. 1109–1118.

\cite{19} L. Golab, D. DeHaan, E. D. Demaine, A. Lopez-Ortiz, and J. I. Munro, “Identifying frequent items in sliding windows over online packet streams,” in Proceedings of the 3rd ACM SIGCOMM Conference on Internet Measurement, 2003, pp. 173–178.

\cite{20} J. H. Chang and W. S. Lee, “Finding recent frequent itemsets adaptively over online data streams,” in Proceedings of the 9th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2003, pp. 487–492.

\cite{21} A. Arasu and G. S. M. M. P. Majin, “Approximate counts and quantiles over sliding windows,” in Proceedings of the 23rd ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems, 2004, pp. 286–296.

\cite{22} J. Wang, J. Han, Y. Lu, and P. Tzevekov, “Tfp: An efficient algorithm for mining top-k frequent closed itemsets,” IEEE Transactions on Knowledge and Data Engineering, vol. 17, no. 5, pp. 652–663, 2005.

\cite{23} Z. Deng, Z. Wang, and H. Jiang, “A new algorithm for fast mining frequent itemsets using n-lists,” Science China Information Sciences, vol. 55, no. 9, pp. 2088–2093, 2012.

\cite{24} P. Pietzuch, J. Ledlie, J. Shneidman, M. Roussopoulos, M. Welsh, and M. Seltzer, “Network-aware operator placement for stream-
processing systems,” in Proceedings of the 22nd IEEE International Conference on Data Engineering, 2006, pp. 49–49.

[25] T. Buddhika, R. Stern, K. Lindburg, K. Ericson, and S. Pallickara, “Online scheduling and interference alleviation for low-latency, high-throughput processing of data streams,” IEEE Transactions on Parallel and Distributed Systems, vol. 28, no. 12, pp. 3553–3569, 2017.

[26] F. Tödtling and M. Trippl, “One size fits all?: Towards a differentiated regional innovation policy approach,” Elsevier Research Policy, vol. 34, no. 8, pp. 1203–1219, 2005.

[27] G. S. Manku and R. Motwani, “Approximate frequency counts over data streams,” in Proceedings of the 28th Elsevier International Conference on Very Large Data Bases, 2002, pp. 346–357.

[28] D. R. Karger and M. Ruhl, “Simple efficient load balancing algorithms for peer-to-peer systems,” in Proceedings of the 16th ACM Symposium on Parallelism in Algorithms and Architectures, 2004, pp. 36–43.

[29] Apache Flink. [Online]. Available: https://link.apache.org/

[30] L. Neumeyer, B. Robbins, A. Nair, and A. Kesari, “S4: Distributed stream computing platform,” in Proceedings of the 10th IEEE International Conference on Data Mining Workshops, 2010, pp. 170–177.

[31] D. Eastlake and P. Jones, “Us secure hash algorithm 1 (sha1),” IETF RFC 3174, Tech. Rep., 2001.

[32] R. Kapoor, L.-J. Chen, L. Lao, M. Gerla, and M. Y. Sanadidi, “Capprobe: A simple and accurate capacity estimation technique,” in Proceedings of the ACM SIGCOMM Conference on Applications, Technologies, Architectures, and Protocols for Computer Communication, 2004, pp. 67–78.

[33] D. P. Warwick and C. A. Lininge, The sample survey: Theory and practice. McGraw-Hill, 1975.

[34] D. Karger, A. Sherman, A. Berkheimer, B. Bogstad, R. Dhanidina, K. Iwamoto, B. Kim, L. Matkins, and Y. Yerushalmi, “Web caching with consistent hashing,” Elsevier Computer Networks, vol. 31, no. 11, pp. 1203–1213, 1999.

[35] I. Stoica, R. Morris, D. Liben-Nowell, D. R. Karger, M. F. Kaashoek, F. Dabek, and H. Balakrishnan, “Chord: a scalable peer-to-peer lookup protocol for internet applications,” IEEE/ACM Transactions on Networking, vol. 11, no. 1, pp. 17–32, 2003.

[36] J. Leskovec, L. Backstrom, and J. Kleinberg, “Meme-tracking and the dynamics of the news cycle,” in Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2009, pp. 497–506.

[37] J. J. McAuley and J. Leskovec, “From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews,” in Proceedings of the 22nd International Conference on World Wide Web, 2013, pp. 897–908.

[38] Y. Xing, J.-H. Hwang, U. Çetintemel, and S. Zdonik, “Providing resiliency to load variations in distributed stream processing,” in Proceedings of the 32nd International Conference on Very Large Data Bases, 2006, pp. 775–786.

[39] F. Tödtling and M. Trippl, “One size fits all?: Towards a differentiated regional innovation policy approach,” Elsevier Research Policy, vol. 34, no. 8, pp. 1203–1219, 2005.

[40] L. Aniello, R. Baldoni, and L. Querzoni, “Adaptive online scheduling in Storm,” in Proceedings of the 7th ACM International Conference on Distributed Event-Based Systems, 2013, pp. 207–218.

[41] D. Karger, A. Sherman, A. Berkheimer, B. Bogstad, R. Dhanidina, K. Iwamoto, B. Kim, L. Matkins, and Y. Yerushalmi, “Web caching with consistent hashing,” Elsevier Computer Networks, vol. 31, no. 11, pp. 1203–1213, 1999.

[42] D. Karger, E. Lehman, T. Leighton, R. Panigrahy, M. Levine, and D. Lewin, “Consistent hashing and random trees: Distributed caching protocols for relieving hot spots on the world wide web,” in Proceedings of the 29th ACM Symposium on Theory of Computing, 1997, pp. 654–663.

[43] D. Karger, A. Sherman, A. Berkheimer, B. Bogstad, R. Dhanidina, K. Iwamoto, B. Kim, L. Matkins, and Y. Yerushalmi, “Web caching with consistent hashing,” Elsevier Computer Networks, vol. 31, no. 11, pp. 1203–1213, 1999.

[44] I. Stoica, R. Morris, D. Liben-Nowell, D. R. Karger, M. F. Kaashoek, F. Dabek, and H. Balakrishnan, “Chord: a scalable peer-to-peer lookup protocol for internet applications,” IEEE/ACM Transactions on Networking, vol. 11, no. 1, pp. 17–32, 2003.

[45] J. Leskovec, L. Backstrom, and J. Kleinberg, “Meme-tracking and the dynamics of the news cycle,” in Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2009, pp. 497–506.

[46] J. J. McAuley and J. Leskovec, “From amateurs to connoisseurs: modeling the evolution of user expertise through online reviews,” in Proceedings of the 22nd International Conference on World Wide Web, 2013, pp. 897–908.

[47] Y. Xing, J.-H. Hwang, U. Çetintemel, and S. Zdonik, “Providing resiliency to load variations in distributed stream processing,” in Proceedings of the 32nd International Conference on Very Large Data Bases, 2006, pp. 775–786.

[48] L. Aniello, R. Baldoni, and L. Querzoni, “Adaptive online scheduling in Storm,” in Proceedings of the 7th ACM International Conference on Distributed Event-Based Systems, 2013, pp. 207–218.

[49] R. Eidenbenz and T. Locher, “Task allocation for distributed stream processing,” in Proceedings of the 35th IEEE International Conference on Computer Communications, 2016, pp. 1–9.