AutoFlow: Hotspot-Aware, Dynamic Load Balancing for Distributed Stream Processing

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Abstract—Stream applications are widely deployed on the cloud. While modern distributed streaming systems like Flink and Spark Streaming can schedule and execute them efficiently, streaming dataflows are often dynamically changing, which may cause computation imbalance and backpressure.

We introduce AutoFlow, an automatic, hotspot-aware dynamic load balance system for streaming dataflows. It incorporates a centralized scheduler which monitors the load balance in the entire dataflow dynamically and implements state migrations correspondingly. The scheduler achieves these two tasks using a simple asynchronous distributed control message mechanism and a hotspot-diminishing algorithm. The timing mechanism supports implicit barriers and a highly efficient state-migration without global barriers or pauses to operators. It also supports a time-window based load-balance measurement and feeds them to the hotspot-diminishing algorithm without user interference. We implemented AutoFlow on top of Ray, an actor-based distributed execution framework. Our evaluation based on various streaming benchmark dataset shows that AutoFlow achieves good load-balance and incurs a low latency overhead in highly data-skew workload.

Index Terms—Stream processing, Big data, Data skewness, Control message, Load balance

I. INTRODUCTION

Streaming dataflows are widely used ranging from AI applications [18] to website unique visitors (UV) counting nowadays. These streaming jobs are generally formed as directed acyclic graphs (DAGs) by modern streaming systems to be deployed on clusters, each node in the graph represents a streaming operator defined by users. Streaming framework then wraps them in each task [7] or actor [18], and initializes network channels, in-memory key-value store, and other components, and schedules them to physical nodes.

Streaming systems are designed to achieve both low latency and high throughput, while latency and throughput can be affected in different ways. An unexpectedly high input source rate that exceeds the processing capacity of a physical node in the graph will cause latency spikes [15]. Some physical nodes in the graph may become bottlenecks when there are inappropriate settings of parallel instances to operators [13], which will cause backpressure. Different fault-tolerance mechanisms may affect the system’s throughput and latency in different ways [20]. The data-skewness caused by highly uneven access on a small portion of state will lead to a hotspot issue in the streaming job, which often can’t be solved well at runtime.

In this paper, we focus on the data-skewness issue in distributed streaming dataflows. There are two general techniques to handle hotspot issues statically. One is pre-aggregation (Figure 1), in which the map operators apply the same reduce logic as the downstream reduce operators on their portion of data before they send results to downstream. The pre-aggregation technique reduces pressure to access the state of reduce operator when there are hotspot issues, while it has obvious drawbacks. Firstly, pre-aggregation requires grouping a small batch of data, which will cause latency overhead. In some real-time applications, this overhead may not be acceptable. Secondly, pre-aggregation is only applicable to reduce operations (Count, Sum, Min, Max), and is not fit for other operations like Join and EventTimeWindow. The other technique is rehashing (Figure 1), which adds an extra layer of reduce operators to scatter out the potential hotspots and merge results in the second layer. The rehashing method has similar drawbacks to pre-aggregation because it aggregates data twice.

Pre-aggregation and rehashing are static methods that mitigate hotspots issues, which means the physical graph built at compile time cannot be changed at run time. While streaming dataflows are long-running jobs in general, and the access pattern of data to stateful operators is often unpredictable, the static method is inherently not the best choice to solve the problem. Flink [7] supports rescaling the streaming jobs, which can change the parallelism of the operator instances and redistribute the state of stateful operators. However, this requires manual operations such as discovering when and where the hotspot issues raise, and how many instances to rescale. And this isn’t over yet, Spark [22] and Flink [7] have to halt the whole job graph until the rescaling job finishes, which is the overhead users have to tolerate. SnailTrail [13] adopts Critical Path Analysis to successfully detect data-skewness issues and other computation imbalance problem,
A lightweight centralized timing mechanism that generates total ordered control messages and induces implicit barriers.

An efficient state-migration method that only buffers minimal data messages.

An effective metric-collection scheme and hotspot-diminishing algorithm to reduce the load-imbalance.

A prototype system AutoFlow integrating the above methods.

The remainder of this paper is organized as follows. Section II provides the background. The AutoFlow is described in Section III. We present the performance results in Section IV. Section V overviews related work and Section VI concludes the paper.

II. BACKGROUND AND MOTIVATION

Modern big data systems can be divided into two categories, one of them is MapReduce [10], Hadoop [21], and Spark [22] that treat the input data as batches of records, while the other are Flink [7], Structured Streaming [5], Google Dataflow [4] and others [3], [16], [19] that treat the data as infinite data streams. A key difference between streaming and batch processing is that the streaming systems support event-time operation and watermarks. Most of the streaming systems focus on how to parallelize the operators to physical nodes in the clusters and schedule the tasks efficiently. This work focuses on hotspot issues, which are often less concerned or well handled in existing streaming systems.

A. Background

Modern streaming systems are more and more deployed on clusters, their goals of design first look at the ease of use, performance, scalability and fault tolerance. Therefore most of their dataflow architectures are often static, that is, they can act in streaming mode when processing data but act discretely when reconfiguring the dataflow graphs. Currently streaming systems, like Flink can only redistribute state by halting the whole dataflow graphs, which is a discrete way that incurs latency overhead and opposite to its streaming nature.

Furthermore, existing methods often consider a wide range of areas such as rescaling, checkpointing and other user-defined functions. Therefore, current profiling tools in streaming systems, like Flink [7] requires human efforts. Users may be required to monitor the screen and adjust it when they detect a data-skewness issue, thus an inevitable latency comes between the detection and repair.

Asynchronous Barrier Snapshot [6] is another technique that has been successfully applied to Flink [7] as a checkpointing mechanism. Its core concept has also been used by Chi [17] as distributed control messages to coordinate the reconfiguration stage in stream processing systems. Distributed control messages act like an asynchronous barrier that coordinate the reconfiguration process, there may just be a few of the operators are halting at the same time and other operators work as usual like Chi [17]. In the case of checkpointing and rescaling, if without the control messages, we will have to halt all the physical nodes in the dataflow and resume the work as usual like Chi [17]. The case of checkpointing and rescaling, if without the control messages, we will have to halt all the physical nodes in the dataflow and resume the work as usual like Chi [17].

B. Motivation

For the data skewness issue in stream processing, it’s desirable to design a lightweight adjusting scheme that only requires buffering the related data. The challenges are how to detect and react to data-skewness issues efficiently, and how to migrate state between straggler and non-straggler without a large overhead. The key idea is to combine data-skewness detecting and reacting as components embedded in the systems without user interference. For detecting the data-skewness issues, we adopt a scheduler to continuously collecting metrics from stateful operators. For reacting to the data-skewness issues, we let the scheduler to send distributed control messages to start a state-migration between operators. These two tasks adopt a control message mechanism in our AutoFlow to determine and adjust the state migration behaviours between the stragglers and non-stragglers efficiently.
III. AUTOFLOW DESIGN

A. Overview

AutoFlow’s dataflow model is similar to most of the streaming systems like Flink [7], Spark Streaming [23] and Google Dataflow [4]. It consists of two categories of operators. The first one is stateless operators such as map, flatmap, and filter, which does not hold any local mutable state. The second is stateful operators such as join, reduce, time-window. The stateful operator is one of the core concepts in streaming systems because many functionalities like checkpointing, state management is built for it.

The AutoFlow model is depicted in Figure 2. It abstracts the dataflow model as a DAG graph. The major part is a centralized lightweight scheduler that is embedded in the dataflow graph as a new operator. The scheduler is connected to all source operators and all stateful operators. The scheduler carries out two tasks: dynamically monitor the load balance in the entire dataflow and implement state migrations correspondingly. To achieve these goals, the scheduler incorporates a simple timing mechanism and a hotspot diminishing algorithm.

B. Timing Mechanism

The scheduler performs as a timer. It periodically generates empty control messages (the square items Figure 2) that are sent to all downstream operators, in particular, all source operators. Each message is attached with a timestamp. After receiving a control message, the source operator inserts it in its dataflow (circle items). The messages spread over the entire dataflow graph in a similar way and finally, return back to the scheduler.

The fields of the control messages are listed in Table III-B which are all immutable. If the scheduler operator sends an empty control message, the fields of migration, send, receiver and slot ids in the message are all empty, but the rest of the fields are required because it indicates a boundary of a period of datastream for further use. The field ‘migration’ indicates whether we perform state-migration or not.

The function of these messages is three-fold. First, previous schemes often utilize partially ordered timestamps. On the contrary, control messages are launched by a centralized scheduler in AutoFlow and totally ordered. This feature serve as a base of the following functions.

Second, control messages indicate implicit barriers. Control messages come from all upstream operators that have an equal timestamp identify an implicit control barrier. Specifically, when the downstream operator reducer-0 receive a control message from one of its input channels that has the content (event_time=200, sender=reducer-0, receiver=reducer-1, slot_id=2). The control message implies that: (1) there will be no data events with timestamps $t<200$ coming from this channel, and reducing-0 can safely migrate the state of the 2nd slot to reducing-1 after it receives the same control messages from all its input channel. (2) the data events with timestamps $t>200$ will be routed according to the update routing table in the map operators, the reducing-0 doesn’t have to worry if it will receive coming data events that are routed to the migrated slot it has sent. These two implications are critical to designing an efficient state-migration scheme. The detailed description is presented in Section III-C.

Third, a control message associated with a timestamp indicates a boundary of data records in a period of time. The source operator simply injects the control message in the data message flow and send it to all downstream operators. It is equal to group the data messages between two continuous control messages to an atomic data set that is processed identically. Since a control barrier message will be eventually broadcasted to all stateful operators, this property provides an implication for measuring the load-imbalance. Specifically, each stateful operator keeps collecting statistics data such as processing counts of each key slot. When a stateful operator receives all the empty control messages that carry the same timestamp from upstream, it will attach statistics results to the control message and send it back to the scheduler for further analysis. The scheduler keeps collecting metrics from stateful operators, analyzes the collected profiling data and employs an algorithm to optimize the load-balancing dynamically. It attaches a state-migration instruction to the next control message when detecting a hotspot issue. The detailed description is presented in Section III-D.

Another significant difference between AutoFlow and other systems is that we do not necessitate a timestamp associated with the data message. The reason is that AutoFlow only models a DAG graph without loops and assumes a FIFO communication channel. However, we can extend the timing scheme and support complex scenarios like dataflow graphs with loops. Specifically, we can utilize a simple logical timestamp scheme which is coordinated between the control messages and data messages. When a source operator receives an empty control message from the scheduler, it will continuously send data events that have smaller timestamps than that of the control message to downstream operators. When the data is sent in the source have timestamps that are larger than that of the control message, the source operator will propagate the control message to downstream and fetch another control message that has a larger timestamp. Other operators can be augmented in a similar way. We leave this extension as future work.

![Fig. 2. AutoFlow model. The scheduler is embedded as an operator in the dataflow graph, and continuously broadcasts control messages with increasing timestamps to source operators. The source operators flush data events until their timestamps exceeds the control event, and then propagate the control message indicated a data boundary.](image)
C. State Migration

We now present an efficient state-migration implementation with the assistance of the timing mechanism. When an operator receives a control message with a state-migration instruction from one of its input channels, it can expect the same control messages from all other channels. With the implicit barrier induced by the timing mechanism, it just needs to buffer subsequent data messages which are routed to the migrated slot indicated by the state-migration instruction and from the same channel. Other data messages can be immediately processed as usual. Moreover, we can process multiple state-migration control messages at the same time. Autoflow does not need to stop the data input channel or require global barriers. The implementation details for stateless and stateful operators are discussed in the following two parts respectively.

1) Stateless operator: Although stateless operators like map, filter do not hold any state of the dataflow, it’s their job to decide which downstream stateful operator to send when they processed a data record. There are often many parallel instances of operators in a streaming job for horizontal scalability, so it’s a common way that each map operator has the same immutable hashing function that acts as a static routing table shared across a cluster of workers. We split the distribution of state into many slots like the virtual nodes in consistency-hashing and each slot has a unique id. The slot is the atomic unit in our state-migration process. We only migrate slots between stateful operators when doing state-migration.

Algorithm 1 shows how to process control messages in map operators. When the "migration" field is None, we just record it in the marker and continue to process data, and when the map operator receives all the same control messages from its upstream channels (L15), it will broadcast it to all its downstream operators. Thus, if there’s no migration event happens, the map operator does nothing different from when there’s no control message mechanism.

Algorithm 1 registers the migrated slots (L6) when there’s a state-migration event comes. It then buffers records from channels that have already received the control message if the corresponding slot will be migrated (L27). Finally, when the map operator receives control messages from all its input channels, it means an implicit barrier, and all data events in the buffer should be routed with respect to the updated routing table. So it is safe to change the routed table, broadcast the control messages to all its downstream reducers, and flush all records in the event buffer (L13-18). In summary, we only have to buffer data events that are routed to the migrated slot temporarily.

We demonstrate an example shown in Figure 3 where the map operator receives state-migration events interleaved with other data events from three input channels. The slot named

```
Algorithm 1 Control Operation in Map Operator
1: function PROCESS(event)
2:     if event["event_type"] is "ControlMsg" then
3:         event_time = event["event_time"]
4:         if marker.get(event_time) is None then
5:             marker[event_time] = 1
6:             if event["migration"] is not None then
7:                 Init(migrated_slot, event_buffer)
8:         end if
9:     else
10:         marker[event_time] += 1
11:     end if
12:     if marker[event_time] == num_input then
13:         if event["migration"] is not None then
14:             slot_ids = event[slot_ids]
15:             for slot_id in slot_ids do
16:                 receiver = event["receiver"]
17:                 routing_table.set(slot_id, receiver)
18:                 flush(slot_id, receiver)
19:             end for
20:         end if
21:         broadcast_control_msg(event)
22:     end if
23:     else if event["event_type"] == "DataMsg" then
24:         slot_id = event["slot_id"]
25:         event_time = event["event_time"]
26:         if slot_id is in migrated_slot && event_time > marker[event_time] then
27:             self.event_buffer.append(event)
28:         else
29:             process_data(event)
30:         end if
31:     end if
32: end function
```

| Field       | Type   | Description                                    |
|-------------|--------|-----------------------------------------------|
| event_type  | string | data record or control event                  |
| event_time  | long   | the logical timestamp                         |
| migration   | bool   | trigger state-migration or not                |
| sender      | string | the sender name of the state                  |
| receiver    | string | the receiver name of the state                |
| slot_ids    | list of strings | which state slots to send                  |

**Table I**

**Control Messages sent by the Scheduler Operator**

We demonstrate an example shown in Figure 3 where the map operator receives a control message from channel 1. It then buffers records from channel 2 that have already received the control message if the corresponding slot will be migrated. Finally, when the map operator receives control messages from all its input channels, it means an implicit barrier, and all data events in the buffer should be routed with respect to the updated routing table. So it is safe to change the routed table, broadcast the control messages to all its downstream reducers, and flush all records in the event buffer (L13-18). In summary, we only have to buffer data events that are routed to the migrated slot temporarily.

```
Fig. 3. Processing procedure of control operations in the map operator. (i) map operator receives a control message from uppermost channel (ii) mapper buffers the data events following the control message (iii) mapper finishes processing control messages and broadcast it to downstream.
```
"r_{x_{-}y}" means the y-th slot of reducer-x. The bottom of the figure is the hashing results of all data events and the routing table tells the slots owned by which reducer instance. In Figure 3(i), when the map operator receives a square control message with timestamp "8" from one uppermost channel, it parses the message and gets the name of the migrated slot "r_{0_{-}3}", which will be migrated from reducer-0 to reducer-1. Then the map operator writes down the slot id on its migrated slot list to indicate which data events need to be buffered. The map operator buffers the circle data event from the uppermost channel in Figure 3(ii) according to the migration instruction. The data event hashed to the slot "r_{0_{-}3}" in the middle input channel is sent to reducer-0 as usual since the map operator has not received the control. Figure 3(iii) illustrates that after the map operator receives the control messages with timestamp "8" from all its input channels, it changes the routed table, broadcast the control messages and flush all records in the event buffer to reducer-1.

Algorithm 2 Process Operation in Stateful Operator

```
1: function PROCESS(event)
2:    if event["event_type"] is "ControlMsg" then
3:        event_time = event["event_time"]
4:        if marker.get(event_time) is None then
5:            marker[event_time] = 1
6:        if event["migration"] is not None then
7:            if event["receiver"] == my_id then
8:                Init(migrated_slot, event_buffer)
9:            end if
10:        end if
11:    else
12:        marker[event_time] += 1
13:    end if
14:    if marker[event_time] == num_input then
15:        if event["migration"] is not None then
16:            if event["sender"] == my_id then
17:                send_migration(event)
18:            else if event["receiver"] == my_id then
19:                async_recv(event["sender"])
20:            end if
21:        end if
22:        broadcast_control_msg(event)
23:    end if
24:    else if event["event_type"] == "DataMsg" then
25:        slot_id = event["slot_id"]
26:        if slot_id is in migrated_slot then
27:            self.event_buffer.append(event)
28:        else
29:            process_data(event)
30:        end if
31:    end if
32: end function
```

2) Stateful operator: Many core concepts in streaming systems like state-management, flow-control, and checkpointing are highly related to stateful operators that hold local mutable state in a key-value store. Unlike stateless operator where we barely encounter a hotspot issue because we can easily adapt schemes like random shuffle, round-robin and rebalance between operators to ensure load-balance, stateful operators often face the data-skewness problem that requires state-migration.

Cooperated with the stateless operator, specifically Algorithm 1 we know that (1) if a stateful operator has received a migrated control message, it will not receive the following event that routed to the slot. Our mechanism ensures the upstream stateless operators will route the event to the new operator. (2) the stateful operator will trigger a state-migration process after it receives all the control messages. With these two features, we present a similar algorithm for stateful operators (Algorithm 2) and describe it with an example in Figure 4.

In Figure 4(i) the left reducer firstly receives a control event "6" from the uppermost channel and record it in the marker (L4). Although the data event "4" from the middle channel is routed to the migrated slot is "r_{0_{-}1}", the reducer has not receive the control event from it yet, so it will process the event as usual and change the state in "r_{0_{-}1}". In the meantime, the right reducer receives the same control event and initializes buffer and migrated-slot list (L6-12), when there comes a data event "8" right after the control event that routed to slot "r_{0_{-}1}”, the reducer just buffers it. In Figure 4(ii) when the left reducer receives all control events, it will starts migration and send slot data “r_{0_{-}1}” to the received reducer (L19-25). In Figure 4 when the right reducer receives the slot (L27), it will merge the data events in the buffer to the slot. It’s worth mentioning that the migration process is asynchronous which means that the reducers are processing other data events concurrently.

D. Hotspot-diminishing

An external controller that widely used in big data systems is for task scheduling, resource management, and monitoring runtime status of the cluster. It’s a centralized way that can coordinates the tasks in a cluster directly. In AutoFlow we use scheduler as an operator in a more fine-grained way to tackle the data-skewness issue. Specifically, in the scheduler operator, we integrate monitoring of the runtime status in stateful operators with a feedback control component that reacts to the dataflow efficiently.

There are lots of ways to monitor a streaming system such as collecting the throughput and latency, monitoring the queue size of the input channels, and probing the data input or output rates of operators. Some of them either do not reflect the situation accurately [13] or are not efficient due to the natures of distributed systems such as network latency. As the control messages act like watermarks, we let the stateful operators send metrics such as the processing counts of each slot, and the total processing count to the scheduler operator when they reach an implicit barrier triggered by the empty control messages.
Common monitoring systems collect metrics such as memory consumption in each task, throughput and latency per record in each operator, size of the network buffers and so on. These collected metrics are often shown in the dashboard for users. When we build an integrated monitoring and feedback control component tackling the data-skewness, there’re three questions we need to consider:

**What information should we get?** When there’s a data-skewness issue, we will know that a large amount of data requests are routing to a few of the stateful operators. Throughput and latency are the two common metrics in streaming systems. Throughout represents the data output rates of an operator, which will reach a nearly constant when the data input rate exceeds or just reached its processing capacity. That is, we can hardly tell the difference between stragglers and non-stragglers just according to their throughputs. The latency of the stragglers will grow high beyond the non-stragglers. But these metrics are not enough for a feedback algorithm to make decisions of state-migration. In AutoFlow we collect the number of processing records of each slot in a period of time from every stateful operator.

**How do we get?** A stateful operator sends messages with the timestamps each time when it has received control messages from all channels. In the scheduler operator, we start a thread that keeps listening from stateful operators asynchronously. When the scheduler receives messages from all stateful operators, it indicates a boundary of time. It then feeds those metrics to our hotspot-diminishing algorithm.

**How to analyze the metrics?** As discussed above, the scheduler operator receives the processing count of each slot in every interval. While the dataflows are often changing dynamically. The current metrics data it receives might not always predict the situation in the next second correctly. For example, in a flash-sale activity online there might just be a latency spike in a task and vanished in a few seconds, while in other case the stragglers might last for a long time. Setting a better window-length parameter can help to predict the situation more accurately. For a wider range of application, we adopt a time-window based feedback algorithm in AutoFlow.

In a time-window scheme, the algorithm can combine the information in a long time or in a short period of time.

**Algorithm 3** Main Part of the Control Algorithm

**Input:** `total_count : {"worker_id" : count}` indicates processing count of each stateful operator respectively

**Output:** `migrate_slot` : a list of slot_ids that will be migrated

1: function `PROCESS_WINDOW(total_count, slot_count)`
2: max_id = max(total_count)
3: min_id = min(total_count)
4: migrated_slot = []
5: diff = total_count[max_id] - total_count[min_id]
6: if `diff / total_count[max_id] >= factor` then
7: `gap = diff / 2`
8: while `gap > 0` && `slot_count` is not None do
9: `slot_id = max(slot_count[max_id])`
10: `num = slot_count[max_id][slot_id]`
11: if `gap >= num` then
12: `migrated_slot.append(slot_id)`
13: `gap = gap - num`
14: end if
15: `slot_count[max_id].pop(slot_id)`
16: end while
17: end if
18: return `migrated_slot`
19: end function

**How to react?** For static workloads, it is often satisfied to shuffle the state between all workers with a global barrier to reach a perfectly load-balance. However, this scheme will
incur a large overhead for long-running and dynamically changing dataflows. In AutoFlow, we tend to act dynamically and continuously that we do not need to migrate a large amount of state.

Our hotspot-diminishing algorithm is presented in Algorithm 3. It only adjusts the workloads between the operators with the maximum and minimum metric, in particular, the total number of processing records in a time-window. Specifically, when the gap between the max-operator and the min-operator exceeds a predefined value (L6), we utilize the first-fit heuristic (L8-14) of the knapsack problem to pack slots whose total size approximately equals to half of the gap. Finally, the scheduler operator will serialize the migration meta-info in the control event and propagate it in the dataflow. Although we illustrate one algorithm implemented in AutoFlow, there are also many other load-balance schemes that can be adopted in our framework. Introducing user-defined function as a load-balance API is one of its future work.

E. Implementation

AutoFlow is built on top of Ray—an actor-based distributed execution framework. We implemented the core logic of operators and transform the logical dataflow graph to a physical graph through Ray’s Python bindings, in which each operator is wrapped in an actor. Each actor is connecting with each other through gRPC in Ray, when an operator sends a message to its downstream channel, a remote function will be called through the backend of Ray. Each operator in the logic graph of dataflow will be deployed in a cluster combined with a Python process. Currently, we implemented the (de)serialization of data events, and the state of stateful operators in Python’s standard library. Moving them to a more efficient programming language’s backend and adopting a high-performance key-value store are in our future work. In AutoFlow we bypassed the scheduling process of Ray’s backend by turning on the direct_call mode in the remote function’s API. In direct_call mode, Each remote function call is a Remote Procedure Call (RPC) to another process. At the start of the deployment, Ray will connect each actor through gRPC.

IV. Evaluation

We evaluated the AutoFlow model on the generated Nexmark benchmark dataset. To measure the benefits of AutoFlow’s dynamic load-balance scheme, our evaluation falls into four categories. First, we ran a stateful query on various workloads with fixed skewness percentages to show the AutoFlow can achieve load-balance through our control message mechanism (Section IV-B). Second, we tested our model on workloads with a suddenly changed extent of skewness to show the reaction speed of our algorithm (Section IV-C). Third, To an unpredictable, rapidly changing workload, our algorithm can handle it to what extent? (Section IV-D)

A. Experimental setup

We run all our experiments on up to three machines on the Aliyun ECS cluster, each is an m5.2xlarge instance with 8 vCPUs and 32GB of RAM, running on Ubuntu 18.04. The schema in Nexmark benchmark is a model that consists of three entities: Person, Auction, Bid, which simulates a public auction. We generated the dataset according to the opened source code from [2]. There many standard queries in Nexmark benchmark, such as a simple map (Q1), a simple filter (Q2), an incremental join (Q3). We chose to test a source-map-reduce model on our workloads as the following stateful query:

```
stream = env.source(record)
    .map(record => bids)
    .keyby(bids.id)
    .reduce(state[bids.id] += bids.price)
```

And each operator has the same parallel instances in our settings.

B. Fixed skewness workload

We tested various workloads with different skewness percentages on AutoFlow, and compared the results between turning off and turning on the load-balance algorithms. The latency and throughput in each workload are shown in Figure 5. The latency is sampled once every 1000 records, and the throughput is recorded once every 1000 records.

Figure 5(a) shows an increasingly high latency overhead when 50% of data events were routed to one of the reducers, and Figure 5(b) shows the throughput in the hotspot worker is obviously higher than the others, the load-balance algorithm was not used in this workload. When we turned on the load-balance scheme in the scheduler operator, the data-skewness issue is alleviated according to Figure 5 (d). We detected a slightly latency spike and a throughput dropping down of reducer-1 (t=30s in Figure 5(c)(d)), this indicated state-migration between reducers has happened. Figure 5 (e) and Figure 5 (f) illustrate a high skewness workload that most of the data events were routed to one reducer, and the problem was solved well from the start. Although the migration overhead is hidden at the start of Figure 5 (g), we detected a slight latency overhead of state-migration happened at t=25 (Figure 5(h)).

The workloads depicted in Figure 5(i)-(o) is running on 5 workers of each operator. The x%-skewness in those workloads means that x% of the data events are routed two of the reducers. Figure 5(i) depicts the overhead caused in the 60% skewness workload, and the problem was solved through migration with some slight latency overhead (t=50 in Figure 5(k)). The rest of the figures also show the alleviation of data skewness in AutoFlow.

In the above workloads, we illustrate that the AutoFlow model reaches better a load-balance. While in the real-world applications the dataflows are often dynamically changing, we need to generalize our algorithm to fit in the unpredictable environment.
Fig. 5. (a)(b) 50% skewness in 3 reducers without dynamic load-balance. (c)(d) 50% skewness in 3 reducers with dynamic load-balance. (e)(f) 80% skewness in 3 reducers without dynamic load-balance. (g)(h) 80% skewness in 3 reducers with dynamic load-balance. (i)(j) 60% skewness in 5 reducers without dynamic load-balance. (k)(l) 60% skewness in 5 reducers with dynamic load-balance. (m)(n) 80% skewness in 5 reducers without dynamic load-balance. (o) 80% skewness in 5 reducers with dynamic load-balance.
C. Spikingly changing workloads

In real-world scenarios, we often encounter spiking events in which a large number of requests are flushed to servers for just a few seconds. These also cause hotspot issues in most of the time. Solving them requires a faster reactive method to detect the issues from the beginning.

The feedback control algorithm proposed in Section III-D has a window-length parameter exposed to users that can generalize to these spiking events. The window-length parameter indicates the duration the scheduler operator collects metrics for. When the dataflow is stable or slowly changing, we can collect the metrics from a broad range of time by setting the window-length parameter bigger, and the scheduler operator can make decisions better according to those metrics. However, when the dataflow has spiking events, the effective metrics are concentrated on a short range of time. In this case, it’s wise to set the window-length smaller to better suited to the fast-changing workloads.

As depicted in Figure 6, we showed workloads that have spiking events lasted for 20 seconds (Figure 6(a)) and 10 seconds (Figure 6(c)). In Figure 6 (b), we set a smaller window-length and got better results compared to Figure 6 (a). The latency overhead is greatly reduced by our feedback control algorithm. However, to the workload with shorter reaction time in Figure 6(c), our algorithm can only relax it to some extent. There are some reasons for that: (1) our algorithm is not efficient enough for this workload, (2) there’s a delay from sending and receiving metrics, and a delay from sending control messages and performing state-migration. Building a more reactive scheme is in our future work.

D. Dynamically changing workloads

Streaming dataflows are long-running jobs and they often change dynamically. To see if our algorithm can fit into the dynamically changing environment, we generated the workloads that have hotspots in every moment and the location of the hotspot changed dynamically. At any time, there was a reducer that becomes the hotspot in the dataflow depicted in Figure 7 (a) and Figure 7 (c). It’s worth mentioning that the situation in Figure 7 (c) was far worse than that in Figure 7 (a), because the time when the latency overhead rises depends on both the skewness percentage and the source input rate. Figure 7 (b) shows fixed the hotspot issues but left for one, this may due to the efficiency of our algorithm. In Figure 7 (d), AutoFlow detected some of the hotspots and reduced the overhead greatly compared to Figure 7 (c), but some other hotspots still existed. Imagine a case, a straggler migrates state to a non-straggler for load-balance, after a while, the non-straggler becomes the hotspot, and the situation may become worse.

Although we might not meet the above extremely workloads in real-world applications, we shows the generality of our algorithm to some extent.

V. RELATED WORK

There are two types of work on building more reacting, more efficient streaming systems. One is building a monitoring system or algorithms that can detect issues or failures in the system faster and more accurately [9], [12], [13], [15], [19]. The other is finding a more efficient way of doing specific things like checkpointing, rescaling [6], [8], [11], [23].

Reconfiguration. Flink [7] currently only supports rescaling when the whole dataflow graph is stopped. Megaphone [14] employ a similar fluid-migration scheme but it lacks of a controller and needs to block more the data message, which
also incurs overhead. SEEP \cite{7} integrated a checkpointing mechanism that can act asynchronously with the rescaling operation to reduce the overhead. Dhalion \cite{11} provided a control policy mechanism that allows users to define their own policy and self-tunes a streaming job with their needs. Chi \cite{17} integrated control messages with data messages on a programmable control plane in distributed stream processing. However, our AutoFlow differs from the above methods in: 1. we focus on tackling the data-skewness issue through distributed control message mechanism, we use control message only for state-migration but the other control operations. 2. our AutoFlow only requires buffering the migrated part of the data events when doing the migration, other methods either require halting the whole dataflow graph or blocking channels of some operators.

**Monitoring.** DS2 \cite{15} provided an external controller that supports both automatic scaling and monitoring. SnailTrail \cite{13} adopted Critical Path Analysis (CPA) to analyze the bottleneck of the streaming dataflows. AutoFlow embedded a lightweight scheduler as an operator to continuously analyze hotspots in the dataflows and sends control messages to perform state-migration between stragglers and non-stragglers. Thus, our model is an integrated approach to tackling a specific problem.

## VI. Conclusion

In this paper, we proposed and evaluated AutoFlow, a hotspot-aware dataflow model that support dynamic load-balance in distributed stream processing. Our model integrated the distributed control message mechanism and a self-adapted scheduler operator to detect hotspot issues quickly and perform state-migration between operators efficiently. Experimental result shows that our model achieved better load balance on various data-skewness workloads, and the hotspot operator is diminished according to its latency and throughput. Our model also got better results under spikingly changing situation due to the elastic time-window based algorithm.

In future work, we seek to adapt our AutoFlow model to more scenarios like dynamic rescaling and automatic parallelization of dataflows.

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