Trevor: Automatic configuration and scaling of stream processing pipelines

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Abstract
Operating a distributed data stream processing workload efficiently at scale is hard. The operator of the workload must parallelize and lay out tasks of the workload with resources that match the requirement of target data rate. The challenge is that neither the operator nor the programmer is typically aware of the scaling behavior of the workload as a function of resources. An operator manually searches for a safe operating point that can handle predicted peak load and deploys with ample headroom for absorbing unpredictable spikes. Such empirical, static over-provisioning is wasteful of both compute and human resources.

We show that precise performance models can be automatically learned for distributed stream processing systems that can predict the execution performance of a job even before deployment. Further, those models can be used to optimally schedule logically specified jobs onto available physical hardware. Finally, those models and the derived execution schedules can be refined online to dynamically adapt to unpredictable changes in the runtime environment or auto-scale with variations in job load.

1 Introduction
Real-time streaming workloads drive our favorite cloud services like Twitter feed, LinkedIn profiles, Netflix personalized recommendations, Redfin real-estate listings and mobile network control planes. However, those workloads frequently run over-provisioned. They process millions of events per minute with sub-second latency. In addition, they handle daily peak loads up to 3-5× the average load and up to 20× in case of special events like a FIFA World Cup [23, 14]. Insufficient processing capacity causes queue buildup and violation of the latency requirements. To guarantee SLAs, operators generally deploy such workloads with fixed configurations for peak load with headroom to absorb spikes [25] or machine failures. An enterprise datacenter like that of Netflix can have 200 different streaming applications active over thousands of machines. At such scale, fixed provisioning for peak-load can be extremely wasteful of resources.

The configuration problem: Real-time streaming workloads run over-provisioned due to the complexity of configuration - setting all the parallelism and physical resource allocation parameters to guarantee processing of a certain target data rate efficiently. For reference, we show a comparison with configuration parameters of cloud web servers in fig. [1]

(a) Configuring and scaling a webserver (b) Configuring and scaling a stream processing pipeline

Figure 1: Configuring and scaling web servers vs. stream processing pipelines

A webserver can be configured for a certain query rate by setting virtual machine dimensions D (CPU, memory and networking) and the number of virtual machines M. A search over M is usually enough to find an efficient configuration for a certain performance target. In contrast, configuring a streaming workload DAG requires searching over a much larger space. We must set parallelism for each individual DAG node ($n_X$), machine dimensions, and count. Then, we must pack DAG node instances onto the cluster of machines. Configuring the parallelism of a simple 3-stage DAG on a 100-machine cluster...
cluster results in a search space of more than \(7 \times 10^8\) combinations.

In many cases, streaming applications are generated with higher-level DSLs like Summingbird \(\mathcal{O}\). Lack of direct access to the runtime streaming workload makes configuration even harder. Moreover, the configuration must be re-optimized as code changes or deployment datacenter changes because the performance depends on both the application logic and the underlying infrastructure.

The scaling problem: Another related but distinct problem in operating streaming workloads efficiently is the complexity of scaling existing configurations to higher loads. Unlike webservers, performance of a streaming workload does not always grow with more parallelism, bigger containers, or more containers. Replicating an existing configuration may even cause performance to drop due to increase in communication overhead, as we show in sec. \(\mathcal{O}\). Further, bottlenecks in the DAG shift as configurations are changed, requiring relative parallelism of nodes to be adjusted for best performance. Those dependencies require re-optimization of configuration every time target load changes.

Reactive auto-scaling as in Dhalion \(\mathcal{O}\) can be used to find bottlenecks empirically and make point modifications to scale iteratively. However, such a process can take hours to converge even for small DAGs, making it impractical for responding to load spikes lasting few minutes \(\mathcal{O}\). Moreover, the resulting configuration can be inefficient due to limits on the extent of search space that can be explored empirically.

In this paper, we present Trevor, a model-based solution to auto-configure and auto-scale real-time streaming workloads. Trevor replaces the tedious manual workflow of a hit-and-trial search process with an automated, single-shot workflow as shown in fig. \(\mathcal{O}\). The core component of Trevor is an allocator that takes in a target data processing rate and outputs a configuration that will process the data rate efficiently. The allocator functions by training models that predict a workload’s performance under any given configuration. We train those models as a one-time exercise for any given workload. Models can be using runtime metrics collected from production settings or test deployments. Once trained, the allocator can be used to configure a workload for a fixed data rate or to repeatedly find new configurations quickly to scale the workload as load changes.

We solve the challenge of modeling complex performance dependencies in the DAG with the following insight: we can accurately predict the performance of a configuration if we explicitly account for the cost of data communication between DAG nodes in addition to the resource requirements (CPU, memory) for each node. We build on this insight to first develop prediction models and then using them to design an allocator.

In designing Trevor, we make the following concrete contributions:

- we show that a typical manually-tuned streaming workload configuration can be 2-3\(\times\) less resource-efficient than the optimal configuration for a target data processing rate,
- we design a performance model that can accurately predict the data rate that a parallelized stream processing DAG configuration can process, and
- we present an allocation algorithm that quickly finds efficient physical configurations for target data processing rates to auto-configure and auto-scale real-time streaming workloads.

We implement Trevor as a stand-alone auto-configuration and auto-scaling agent on top of the industry-standard Twitter Heron \(\mathcal{O}\) stream processing engine. We evaluate Trevor on a sample Word Count application, a Yahoo Ad Analytics benchmark \(\mathcal{O}\) and a production mobile network log processing pipeline. Our performance models are able to predict workload data rates to within 10% of measured rates for any configuration. Our allocator is able to produce efficient configurations for given target rates that operate within 10% of the estimated optimal efficiency.

2 Background, Motivation and Insights

Distributed stream processing systems like Twitter Heron \(\mathcal{O}\), Apache Samza \(\mathcal{O}\), and Spark Streaming \(\mathcal{O}\) provide map-reduce APIs similar to batch processing systems like Hadoop and Spark. However, instead of processing static batches of data, they operate continuously on unbounded streams of data such as live Tweets, ad impressions and click events, real-estate listings, or mobile user session events. The primary performance
metric of interest is the data rate (key-value tuples/sec or events/sec) that a workload can process in real-time without building up queues or dropping data. Typical applications expect sub-second processing delay per event. To understand the need for and challenge in auto-configuration and auto-scaling, we summarize the architecture of Twitter Heron as a reference stream processing system and explore its performance sensitivity to varying configurations.

2.1 Stream systems primer

Programming model: The basic structure of a Heron or Spark Streaming distributed stream processing application is a directed acyclic graph (DAG) of user-defined operations stitched together with map-reduce function calls and connected with data grouping operators. DAG nodes run as parallel instances over a set of physical machines, virtual machines, or containers with fixed resources functioning as sandboxes in a framework like Mesos [17].

A sample Heron WordCount application is shown in fig. 3a with two operations in the DAG. In this example, we are configuring the workload with 2 parallel instances of each DAG node, as shown in fig. 3b. The first node is a word-producer that emits 2-tuples with key being random words drawn from a finite vocabulary and value being 1. The second node is a counting-consumer that maintains running counts of word occurrences as a key-value store by adding up values of incoming tuples grouped by key.

Heron provides default implementations of 3 data grouping operators, which use different mapping functions to decide the downstream instance(s) for each tuple: fields-grouping(hash function), shuffle-grouping(random instance) and all-grouping(all instances). In this scenario, the fields-grouping operator is used to ensure that all occurrences of a specific word are routed to the same instance of the counting-consumer.

Physical deployment: A parallelized Heron DAG is deployed on physical infrastructure using containers in a framework like Mesos. Containers are sandboxed runtime environments that act as lightweight virtual machines. Each container has a specific set of CPU and memory resources dedicated to it. Containers are finally deployed onto physical or virtual machines in a datacenter or cloud by a cluster scheduling framework such as Aurora or Marathon. In the example shown, we are deploying the WordCount workload on 2 containers each with 3 CPUs and 4GB of memory packing DAG node instances into the containers in a round-robin manner.

The Heron runtime system sets up each container with a process called the stream manager, shown as S in fig. 3b. Instances packed into a container communicate with each other and remote instances through the stream manager. The stream manager is the single point of data entry and exit for any container. In general, a cluster of containers is a fully-connected graph with edges between stream managers. Stream managers also consume compute resources on containers.

**Configuration:** Operators of a Heron or Spark streaming workload must configure a set of runtime parameters before deploying it: 1) parallelism of each DAG node (P), 2) dimensions (CPU and memory) (D) of containers, 3) count of containers (M), and 4) packing of instances onto containers (tab. 1). For best performance, parallelism is configured for each DAG node separately. Similar to virtual machines, containers are units of physical resources, however, they can be sized on continuous axes. For example, it is possible to deploy containers with 2.5 CPUs and 3.1GB of memory. Packing of node instances onto containers affects data locality and the overhead of data shuffling.

| Heron     | Spark | Role                     |
|-----------|-------|--------------------------|
| parallelism (P) | partitions | degree of DAG node parallelism |
| container dimension (D) | executor dimension | unit of resource allocation |
| container count (M) | executor count | scaling of resource allocation |
| packing algorithm | locality wait | exploiting data locality |

Table 1: Key configuration parameters affecting distributed streaming workload performance in Heron and Spark.

As we show next, the performance of streaming workloads is very sensitive to configuration. However, finding the right configuration is challenging. A simple 3-node application can be parallelized and packed onto a cluster of 100 virtual machines in more than 700 million combinations[^3]. The space becomes even bigger if we permit container dimensions to vary from full machine size to a third-of-a-machine. In typical enterprise data-centers, smaller containers get scheduled faster due to more available slots, making container dimensions an important parameter to search over. While both Heron and Spark provide default configurations, they can be off by up to 3×
from ideal configurations.

2.2 Performance sensitivity & need for auto-configuring

WordCount workload: We studied the performance sensitivity of Heron workloads to configuration using the WordCount application in toy setups. The most insightful results are listed in tab. 2. A configuration is specified by parallelism of the word-producer (#W), parallelism of the counting-consumer (#C), number of containers (M), and the packing plan. We fixed container dimensions to 3 CPUs and 4GB memory. For each configuration, we measured the achieved tuple-rate expressed in kilotuples-per-second (ktps). A packing (w,c) represents two containers, each with an instance of each DAG node.

Table 2: WordCount performance under different configurations

| ID | #W | #C | M | packing | rate(ktps) | bound |
|----|----|----|---|---------|------------|-------|
| 1  | 1  | 1  | 2 | (w) → (c) | 658        | ሄR_c ሄ |
| 2  | 2  | 2  | 2 | (w,c) ↔ (w,c) | 965        | comm  |
| 3  | 2  | 2  | 2 | (w,w) → (c,c) | 648        | comm  |
| 4  | 1  | -1 | 2 | (w) → (0)    | 839        | ሄR_a ሄ |
| 5  | 1  | 2  | 3 | (w) → (c)×2 | 899        | ሄR_a ሄ |
| 6  | 2  | 2  | 4 | (w)×2 → (c)×2| 1319       | 2 × R_c |
| 7  | 2  | 3  | 5 | (w)×2 → (c)×3| 1779       | 2 × R_c |
| 8  | 2  | 4  | 6 | (w)×2 → (c)×4| 1847       | 2 × R_c |
| 9  | 2  | 5  | 7 | (w)×2 → (c)×5| 1582       | drop   |

We first tried to double the performance from a base configuration of one instance each (ID=1) to two instances of each node (ID=2,3), also doubling containers. Any DAG instance could use only 1 CPU at the most due to single-threaded implementation. With at most three instances per container (count stream manager) in any configuration, we expected our configuration switch to double performance. However, we only saw a 1.5× increase from 658ktps to 965ktps.

To isolate the performance bottleneck, we replaced the counting-consumer node C with a null operation that would simply drop all incoming tuples. This resulted in 839ktps (ID=4), higher than the base configuration. This indicated that C was the slower node with peak processing rate $R_c$. Of 658ktps and W had a peak rate $R_w$ of 839ktps. With those numbers, we expected the ID=2 configuration to process at $2 \times R_c$, or twice the rate of ID=1; however, we realized that the ID=2 configuration was bottlenecked on data shuffling. The permuted configuration of ID=3 was even more shuffling limited due to all data crossing containers. Inspecting resource utilization revealed that shuffling performance was CPU-limited at stream managers in those configurations.

The next set of experiments were focused on effects of shuffling overhead. We successively increased the parallelism of the slower node C while adding containers in proportion. Packing only one instance per container gave us the most number of stream managers per instance and thus most shuffling capacity in the configuration. As expected, this shifted the bottleneck from shuffling to computation within a DAG node (ID=6,7,8). This exploration revealed another effect – over-parallelization (ID=9) – where excess instances of a non-bottleneck node caused performance to drop.

AdAnalytics workload: We further analyzed performance sensitivity on a 6-node Yahoo ad-analytics pipeline \cite{9} that serves as a real-world stream application benchmark (fig. 5). Similar to WordCount, it showed counter-intuitive performance sensitivity to configuration.

In fig. 4a\cite{9}, we show a heatmap of the tuple rate under different mixes of parallelism and number of containers. Parallel instances were packed into containers in a round robin fashion. For a few tuple-rates, we highlight the optimal configurations out of the explored space with rectangles.

We can see that performance varies non-monotonically in the configuration space. There is no clear path through the space we can traverse greedily to reach the optimal configuration for a given target tuple rate. In fact, for the specific target rate of 500ktps, even in this small subspace of configurations that an operator might manually explore, the poorest configuration uses 30 containers as opposed to 12 in the best configuration (blue arrows). This amounts to a 2.5× efficiency cost of incomplete exploration.

In fig. 4b\cite{9}, we show that simply adding machines while fixing the parallelism will have limited benefit since we might become bottlenecked on one of the replications of the nodes. P denotes the per-node parallelism while M denotes container multiplicity which is the number of containers per virtual machine. Higher multiplicity implies smaller containers. In fig. 4c\cite{9}, we show that simply increasing the number of instances also can lead to performance degradation, this is because adding replications also increases the shuffling of tuples in the topology which adds communication overhead. C denotes the number of total containers in the configuration.

Insights: Based on the preceding sensitivity exploration, we draw following insights that are key to the design of Trevor:

- Workloads can become shuffling-limited in certain cases.

\footnote{The results in fig. 4b\cite{9} were generated by analyzing data flow through candidate configurations. Actual measurements for a subset of those configurations showed even steeper performance drop as parallelism was increased. We suspect that to be due to instance execution interference caused by effects like excess context switching.}
configurations. Shuffling limits could be hit due to CPU overhead, not just network resources.

- Under-parallelization of DAG nodes can cause computation bottlenecks while over-parallelization can cause excess data shuffling overhead.
- Using few big containers can cause communication bottlenecks while using many small containers can force excess parallelism and data shuffling overhead.

In summary, it is essential to analyze the data shuffling overhead in addition to DAG node computation cost to accurately predict the performance of a given configuration.

### 2.3 Load variation & need for auto-scaling

Streaming applications processing social networks or mobile networks need to deal with significant load variations. LinkedIn processes 12.7 mil-events/s on average over 24 hours with 18 mil-events/s at peak load; Netflix processes 4.6 mil-events/s daily average with peak of 8 mil-events/s [18]. A mobile network with 3000 cells processes 1.6k events/s to 83k events/s over a week. In addition to diurnal and weekly variations, those services must handle transient load peaks sometimes lasting only a few minutes with up to $25 \times$ higher load than average [24].

Static configurations to accommodate such variations are extremely wasteful of resources. Dynamic auto-scaling using a system like Dhalian [11] can potentially improve efficiency. However, using such a reactive system for scaling complex DAGs can be too slow. Even for a simple 3-node WordCount DAG, scaling the configuration from 1 mil-tuples/min to 4 mil-tuples/min took the system more than 30 minutes. This convergence time becomes higher with more DAG nodes.

To deal with transient load peaks over a high dynamic range, our goal in designing Trevor is to enable computing efficient configurations for target performance without requiring any manual intervention or hit-and-trial feedback loops.

### 3 Design

Trevor meets the objective of auto-configuring and auto-scaling streaming workloads by providing a declarative allocator. With Trevor, an operator can simply declare a target tuple-rate of processing. In return, the allocator will output an efficient configuration capable of sustaining the target performance. This eliminates the need for a reactive, tedious and slow process for finding efficient configurations empirically. While the reactive process can take multiple iterations of tuning and deployment to hit a target performance goal, the Trevor allocator finds the right configuration instantly. This enables Trevor to auto-configure complex workloads over large clusters and auto-scale them in response to load changes every minute. Trevor workflow and system architecture are shown in fig. 6.

In designing Trevor, we solve two key challenges. First, each workload has different performance sensitivities to configuration parameters, specific to the workload. The ideal configuration for a target rate depends on the computational load of user-defined DAG nodes. To find efficient configurations for arbitrary workloads, we need to model workload-specific performance behavior. Second, the configuration search space grows exponentially with DAG size and deployment scale. We need a computationally efficient way to translate workload per-
Per-node models $M$ completely characterize the computational footprint of user-defined operations in the workload. In addition, output-to-input ratios specify the change to flow rate as data passes through user-defined operations like aggregation, filter and map functions that can decrease or increase the rate for downstream nodes.

Figure 7: Basic DAG node model

We solve the design challenges with two key components: a modeling component and a workload allocator. The modeling component uses runtime metrics data for a workload to learn its application-specific performance behavior. Once trained, the workload model can accurately predict the tuple-rate that the workload will sustain under a given configuration. The models are used as input to a workload allocation algorithm that produces an efficient configuration for a declared performance target. The allocator sets DAG node parallelism, container dimensions, container count and packing of instances to containers. It functions by analyzing the DAG structure together with workload models to compute efficient configurations without needing to search over the space of configurations. The main insight that enables Trevor’s design is that computation and communication cost of data flow through a configuration must be precisely accounted for. Both the modeling and the allocator components are designed based on this insight.

### 3.1 Workload models

#### 3.1.1 DAG node models

The basic unit for application-specific resource modeling in Trevor is a DAG node. For each DAG node, we learn 1) a relation $M$ between CPU utilization (cputil) and input tuple rate, and 2) the output-to-input ratio ($\gamma$) of data rate for each DAG node, as shown in fig. 7. Per-node models $M$ completely characterize the computational footprint of user-defined operations in the workload. In addition, output-to-input ratios specify the change to flow rate as data passes through user-defined operations like aggregation, filter and map functions that can decrease or increase the rate for downstream nodes.

We train for the models $M$ using runtime CPU utilization and data flow rate metrics. As the load varies naturally in the workload due to diurnal patterns or spikes, metric timeseries span a range of operational loads that expose the performance sensitivity. With this data, we fit linear models to node CPU utilization. Examples of datasets and linear models for the WordCount application are shown in fig. 8a for emulated load variation. We obtained a fit of $R^2 = 0.7036$, $0.7434$, $0.7712$ for the three components W, S and C respectively. (Both W and C are single-threaded implementations but CPU utilizations exceed 1.0. This can happen due to additional supporting threads from the Heron runtime system.)

Node CPU utilization is not guaranteed to be a linear function of the input data rate in general. However, we expect most design patterns to follow close-to-linear relations. For example, a random number or string generator is doing constant amount of work per input (or output) data tuple. Similarly, a filter operation is usually evaluating a fixed-cost comparator per data tuple. The stream manager as a node generally showed higher variance in CPU utilization than user-defined operations, likely due to network interaction and buffering effects. However, the predominant relation in the data showed a good linear fit. Our modeling of nodes does not require linear kernels but we have found this to be a good approximation in practice. We evaluate the effects of this choice in more detail later.

We train for $\gamma$ also using a linear model. Assuming $\gamma$ is a constant factor, we can recover it as the slope of a linear model between the output data rate and the input data rate of the node under different loads. An example of learning $\gamma$‘s is shown in fig. 8c. It shows two nodes taken from the Yahoo AdAnalytics DAG. The event_projection node takes in a stream of ad events and emits each event after modifying the data representation. As expected, we

Models for DAG nodes capture the user-defined compute operations, however, we also need to model the data shuffling cost. Our performance sensitivity exploration in sec. 2 showed that workloads can become performance limited due to the computation burden of data shuffling. Recall that all data communication in Heron passes through the stream manager that is inserted by the Heron runtime system on each container. We exploit this runtime structure to model the compute cost of communication by treating the stream manager as another node in the DAG that splits each edge in the DAG. With this transformation, the original WordCount DAG $W \rightarrow C$ becomes $W \rightarrow S \rightarrow C$, where S is a stream manager node. Then, its compute cost can be modeled in the same way as user-defined nodes.

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4$R^2$ describes the portion of variance of the dependent variable (CPU) that is explained by the dependent variable (tuplerate), high $R^2$ means better model fit
recover $\gamma = 1.0$ for this node. The event_filter node passes about a third of the ad events coming in. Again, we correctly recover $\gamma = 0.32$. For the stream manager, $\gamma = 1$ by definition as it is simply a router of data.

Our node models by themselves, are not sufficient to predict the performance of a workload configuration. As a case study, we tried to predict the tuple rate of a base configuration of WordCount. The configuration used 2 instances each of W and C deployed on 2 containers with 3 CPUs each. The packing was $(w, c) \leftrightarrow (w, c)$. We first predicted the tuple rate to be 1320ktps by saturating CPU utilization of W and C instances, however, the measured performance was 965ktps. Next, we factored in the CPU utilization of S too, however, we still predicted the same value which was 37% higher than the true value. This gap was due to inaccurate predictions of data rate being processed by each node, including the stream manager. Next, we present the design of a data flow solver that accurately predicts workload performance using node models, thus also proving that our node models accurately capture application specifics.

### 3.1.2 Data flow solver

The steady state data flow in a workload configuration depends on DAG node CPU models, DAG edge structure, data shuffling operators on the edges and the packing plan of node instances onto containers. Completely modeling a streaming workload requires the ability to analyze and predict the data flow in a given configuration. This is a necessary step in designing an allocator.

Our design of the data flow solver is based on the observation that a deployed configuration can be seen as a physical network of DAG node instances with resource constraints. Then, data flow can be analyzed by solving a network flow problem. Node resource models and packing plan imply CPU and memory constraints on node instances. Shuffling operators like fields-grouping or shuffle-grouping and link capacities of container imply constraints on edges in the network. An example of such modeling for WordCount is shown in fig. 9a.

We model the network flow problem as a linear program with edge flow rates as variables. Node CPU models, container dimensions and link capacities are expressed as linear constraints with a fairly standard formulation. Two sets of constraints are unique to Heron configurations and critical for accurately modeling the data flow: 1) data grouping constraints, and 2) stream manager constraints. Both of those constraint sets encode the shuffling behavior of edge operators connecting DAG nodes.

To understand the shuffling behavior and its translation into linear-program constraints, consider the example of a WordCount configuration as shown in fig. 9a. The DAG uses a fields-grouping shuffle operator on the edge connecting the producer W to the consumer C. This shuffle operator is applied by the stream managers. Let us assume that a producer instance outputs tuples at rate $r$ in steady state into the hosting stream manager with uniform distribution over the key space. Then, the stream manager will split the data equally among the two consumers, passing $r/2$ to the local consumer and remaining $r/2$ to the other container. The other stream manager splits its producer’s output rate $s$ similarly. Thus, in the resulting data flow, while the configuration is processing a total of $r + s$, the stream managers together are passing $1.5(r + s)$ in and out! The insight is that any data tuple that crosses a container boundary passes through two stream managers, thus costing twice the CPU resources for communication than a locally routed tuple. Accounting for intra- and inter-container data flow is the key to modeling communication cost and data flow correctly.

We encode data grouping behavior by constraining the edge set $(u, v)$ for all $v$ for any given node $u$. For example, in the network in fig. we would write a constraint like $r_{11} = r_{12}$. To encode stream manager constraints and correctly account for CPU costs of intra- and inter-container tuples, we insert additional nodes in the network by un-
(a) Modeling shuffle data rates  
(b) Modeling data grouping constraints  
(c) Modeling stream manager constraints

Figure 9: Modeling data flow constraints to solve for processing rate of a configuration

folding each stream manager into a left node that ingests local tuples (e.g., S1L) and a right node (e.g., S1R) that emits local tuples. We also add internal routing nodes (e.g., I1) for each container and a single switching node X for the network, as shown in fig. 9c. Data routing locally from S1L to S1R passes through I1. Data traversing container boundaries passes from S1L to SjL (i ≠ j) through X. This bifurcation of intra- and inter-container data correctly accounts for the true CPU cost of communication.

Our linear-program based data flow solver acts as a complete performance model for streaming workloads. It enables us to feed in an arbitrary configuration and get an accurate prediction of tuple rate performance. In doing so, it is able to precisely predict the flow rates within and across a configuration using only DAG node models as application-specific input. As a by-product, it also pin-points the rate-limiting parts of a configuration. This gives the operator visibility into the specific configuration parameters to tune in adjusting the target performance; it also gives the programmer visibility into specific DAG nodes to optimize for most gain in performance. For the case study of WordCount, the solver predicted 1050ktps for the true value of 965ktps, amounting to less than 10% of error. We evaluate the prediction performance in more detail later.

3.2 Model-based edge allocator

We now present the design of an allocator that can produce efficient configurations of a workload for any target data rate. A brute-force approach is to use a workload’s performance model as a blackbox to enumerate the performance of all possible configurations and then pick the best one. However, as our previous discussion showed (sec. 2), this approach is prohibitive due to the sheer size of the configuration space. Instead, we use the insights gained from designing the data flow solver to design a closed-form algorithm using DAG node models with linear time-complexity in the DAG size (nodes + edges).

Our allocation algorithm is based on the insight that a configuration is most efficient for a certain data rate when all DAG nodes are rate matched, i.e., they are operating at their full capacity, including the stream managers. Rate-matching DAG nodes to stream managers ensures that computation and communication are also rate-matched. Further, out of all rate-matched configurations, the one with most data locality, i.e., least cross-container data flow, will likely be the most efficient because it will impose the least compute overhead of data communication.

We exploit the rate-matching and data-locality insights by allocating balanced edge containers as basic units in the configuration. Consider the example of the 6-node AdAnalytics DAG shown in fig. 10. We first group nodes by edges alternate edges. Then, we compose a balanced container configuration for each edge, thus co-locating communicating nodes for data locality. For an edge P → Q, a balanced container has nP and nQ instances of P and Q such that the combined processing rates of those instances match up to each other and to the processing rate of the stream manager, based on DAG node models. Further, in this rate-matched configuration, we require that the stream manager is operating at peak capacity by using a full CPU, so that the container is fully utilized.

5 Another equivalent formulation is to cast the network flow problem as an integer linear program (ILP) with binary assignment variables. With this formulation, even solving WordCount over a few machines takes a few days.
Rate-matching instances P and Q in a balanced container to stream manager S poses a challenge: if P and Q are being allocated to process a rate R, then S will be processing a rate more than R that depends on the final configuration. The more the number of containers, the more S will be processing. We solve this cyclic dependency by assuming the worst-case for S. We can show that as containers increase in a configuration, S will need to pass a rate 4R in the limit.

After composing balanced containers, the allocator configures the required number of containers for each edge. Containers are replicated so that the configuration can process the target rate at the input and the corresponding rates (based on γ’s) on subsequent edges. Additionally, the allocator exposes a policy parameter for preferred container dimensions like half-a-machine or third-of-a-machine. If the parameter is set, the allocator scales down each balanced container before allocating copies of it. In the AdAnalytics example, the balanced container for edge P → Q adds up to a requirement of 3 CPUs at the rate-matching point. We emulate a scenario of allocation half-sized containers that use 2 CPUs each. We scale each balanced container with a factor α ≤ 1 to match this dimension. Finally, we replicate α-balanced-containers to the required count for target rate. Optionally, container dimensions can also be searched over by passing in a set of candidate container dimensions.

In the case of a general DAG with node degrees of more than 1, we generalize edge allocation using a topological sorting of the DAG and successively allocating critical paths based on compute cost. The time complexity of the algorithm is $O(|V| + |E|)$ for nodes V and edges E in the DAG. We omit the details for brevity.

4 Implementation

Prototype and execution speed: We prototype Trevor as a stand-alone auto-configuration and auto-scaling engine on top of Twitter Heron [20]. Our implementation can use metrics from production workloads or test deployments. Training Trevor models does not require any code changes to workloads or to the Heron runtime system. Once trained, models can predict performance of a configuration in [10][msec] to [100][msec] time and the allocator can produce a configuration for a target performance in [0.78][sec] on average.

Metrics: The Heron runtime system provides a rich collection of monitoring metrics for each node and stream manager in the topology. The main load metrics we use are tuple rates on each edge in a deployed configuration. The performance metrics per node instance we use are backpressure, capacityutil, cputil, memutil and gctime. Backpressure is a measure of time a node instance spends backlogged on data and slowing down upstream components. Capacityutil is defined by the fraction of time the node spent processing data as opposed to passively waiting for data. Cputil and memutil are traditional measures of CPU and memory utilization. Gctime is a measure of time spent in Java garbage collection.

Modeling of CPU, I/O, memory, link, and node model drift detection: We have described Trevor node models in terms of CPU utilization, however, nodes may not always be CPU-bound. For example, Kafka data ingestion nodes in our workloads make network calls to Kafka message brokers repeatedly, spending significant time in network I/O. Modeling them purely through cputil mispredicts their peak performance. We classify and train models for general nodes using the decision criteria in tab. 3.

If we detect backpressure in an instance at runtime, we treat it as a sign of performance saturation. We learn the saturation points for different resources for that node and include that as part of the node model. If backpressure is caused in a Trevor allocation, it signals node model error either due to noise or model drift. In either case, we trigger re-training of that node’s model.

If we classify a node to be I/O-bound, we normalize its CPU model such that cputil saturates with capacityutil. This hides some inefficiency in terms of CPU allocation to the node but ensures that the resulting configuration is feasible.

![Figure 11: A typical memory sawtooth with garbage collection spikes](image)

We learn the memory requirement of a node by combining memutil and gctime metrics. We notice a typical sawtooth memory utilization pattern as shown in fig. 11. A node instance continues to draw memory until the JVM environment has used up all available memory. At that point, the garbage collector (GC) is triggered, immediately bringing down memory usage substantially. This usage pattern results in memutil being an oscillating timeseries that can lead to over-estimation of average memory requirement. We filter down the memutil timeseries to samples right after GC trigger points to glean the true memory requirement of a node. Further, with this filtered data, we model memory as a function of tuple rate, much like CPU. The intuition is that many streaming operations maintain key-value windowed data-structures like hashmaps that grow in proportion to the key-space mapped to a node instance. As a node is parallelized...
Table 3: Decision criteria for training CPU-bound and I/O bound node models

| Metric combination          | Implication                               | Treatment                                      |
|----------------------------|-------------------------------------------|------------------------------------------------|
| backpressure > 0           | node saturated, miscalibrated             | use caputil, cputil as saturating thresholds   |
| caputil > 90%, cputil < 80%| node saturated, I/O-bound                 | normalize CPU model                            |
| caputil > 90%, cputil ≥ 80%| node saturated, memory-bound              | allocate more memory and retrain               |
| caputil > 90%, cputil ≥ 80%, gctime high | node saturated, CPU-bound                 | use default CPU model                          |

more, it receives a smaller subspace of keys on any instance and therefore consumes less memory per instance. The memory-scaling model is incorporated into the allocator as a resource constraint when composing a balanced container. This modeling allows us to find configurations that can work with tight memory bounds.

Network utilization is modeled by simply using bytes accounting metrics and using them as scaling factors on tuple rates. Link rates are resource constraints on containers similar to memory.

**End-to-end model calibration, noise margin and drift detection:** Some noise is inherent in the models due to variations in performance caused by system effects like kernel scheduling, caching and I/O. In addition, there is a systematic sampling bias effect that can cause errors in the models. Any node is sampled for CPU $\sim$ tuple-rate relation in a limited dynamic range of CPU utilization depending on the configuration and the load range. For example, if a configuration over-provisions a node, each instance might only operate up to a peak cputil of 20%. Using a model from this data in predicting the tuple-rate at cputil of 80% succumbs to errors.

We handle the sampling bias problem with two safeguards. First, we use the trained model to predict back the performance of sampled configurations to compute the training error. We use this feedback loop to tune an internal over-provisioning factor to eliminate training error. For example, if we predict 1050ktps for a configuration measuring to 965ktps, we know we are over-predicting performance by 9%. Then, we set the over-provisioning factor to 1.09, so that the allocator produces configurations for 1.09 * target-rate. Second, as we deploy Trevor-generated configurations, we keep pooling metrics and improve model performance. The reason is that Trevor configurations deploy all nodes with rate-matching, so they operate close to their capacity. This pushes node instances into higher and more important ranges of resource utilization, providing us better sampling.

Finally, when the training error becomes bigger than a certain threshold, we declare model drift and trigger retraining.

Figure 12: A mobile network user-analytics logical DAG

5 Evaluation

In this section, we evaluate two aspects of Trevor’s performance: (1) its predictive models for components in a DAG, and (2) its allocator algorithm that returns an optimal allocation for a target input rate.

5.1 Workloads and test setup

We evaluate Trevor on three workloads: the WordCount workload in fig. 3a, the AdAnalytics workload [9] in fig. 5, and a mobile network user-analytics workload in fig. 12. All three workloads represent real world topologies with increasing degrees of complexity.

For our experiments, we use clusters with 4-CPU VMs, and deploy them on Heron 0.14.3. At the source of the DAG we deploy a cluster running Kafka [19] as input. To sweep over a range of input rates, we run a ConsoleProducer throttled to the specified rates, with appropriate hold times for each rate. We set our sampling interval to 10 seconds, swept over a wide range of inputs so the models generalize, and profiled the system over a span of 20 minutes. In a production setting, a profiling over the course of day should be sufficient to capture natural variation in load patterns; the models can then be refined in subsequent days, with no change to the deployment setup.

5.2 Model Accuracy

We first demonstrate the accuracy of our instance modeling techniques on the AdAnalytics DAG in fig. 8b, a more complex DAG than WordCount. The $R^2$ numbers for both the CPU and capacity linear models, shown in tab. 4 indicate that CPU utilization and DAG node capacity have a strong linear relationship with input rate.
Figure 13: Trevor prediction performance for AdAnalytics and WordCount

(a) Ad analytics performance using Trevor allocator
(b) WordCount pipeline CPU usage for different configurations
(c) Ad analytics pipeline CPU usage for different configurations

We demonstrate Trevor’s predictive ability under different scaling behaviors with the WordCount workload. In the first test, we begin with a container of one producer and one consumer, and incrementally scale the number of containers and machines. We compare the measured performance with our predicted performance, as shown in fig. 13a. Trevor accurately predicts the performance with an error of at most 10% of the measured result.

In the second test we evaluate an allocation in which we have 64 instances of either the producer or the consumer. We start with 2 producer and 62 consumers and incrementally shift producers to consumers until we have 62 producers and 2 consumer. The results are presented in fig. 13b. Trevor correctly predicts the performance as we change the ratio of parallelism between producers and consumers. We see that Trevor predicts the optimal configuration to be very close to the true optimal configuration.

In fig. 13c we show that our predictions remain accurate on complex nonlinear DAGs, such as the mobile network user-analytics DAG. Trevor again predicts with a 10% error from the measured result.

The runtime of Trevor’s prediction system varies based on the size of the DAG. In our example topologies, predictions ran between 10 and 100 milliseconds.

5.3 Allocation Efficiency

We evaluate Trevor’s allocator algorithm by showing we can configure the AdAnalytics workload to hit an increasing range of tuple rates. As we saw in the previous section, we can correctly predict the performance of an allocation with an error rate of 10%. To account for the 10% error rate we overprovision our workload by 10%-20%. For instance, if we want to hit a rate of 1Mtps we run our allocator for 1.15Mtps.

The performance of our allocator’s configuration algorithm at different input rates is shown in fig. 14a. The predicted line shows the rate Trevor predicted for the optimal allocation generated, and the target line shows
the target rate we configured for. We can see that we can generally correctly configure using the allocator by maintaining the 10% over prediction rate.

To measure Trevor’s resource utilization, we compare its allocation with optimal resource utilizations and different paths of round robin allocation scaling in fig. 14b for WordCount and fig. 14c for AdAnalytics.

We calculate the optimal line by placing all instances of the DAG in a single container with unlimited resources, and we remove the resource limitation on the stream manager. We increase parallelism and see how many CPUs where required to hit a given tuple rate. For round robin allocation, we decide how many instances are placed in each container, and we scale by increasing the number of containers and instances while maintaining this ratio (donated by I in the graph).

In Figure 14b, we can see that round robin performs quite well for the simple WordCount DAG. But once we move to a more complex DAG such as AdAnalytics in Figure 14c, Trevor beats all round robin allocations in CPU and tracks the optimal CPU usage quite well, differing by 10% at most from the optimal.

Trevor’s allocator also perform well in terms of the run time required to calculate an allocation. The balanced container’s algorithm is a closed form algorithm dependent only on the graph complexity and not the target input rate. For AdAnalytics calculating an allocation took 0.7811 seconds on average across all rates.

| Instance           | CPU | CPU | Cap | Cap |
|--------------------|-----|-----|-----|-----|
|                    | R²  | Range | R²  | Range |
| ads                | 0.597 | 0.10-0.32 | 0.741 | 0.90-1.00 |
| event deserializer | 0.933 | 0.10-1.10 | 0.956 | 0.10-0.90 |
| campaign processor | 0.763 | 0.01-0.05 | 0.500 | 0.01-0.25 |
| event projection   | 0.715 | 0.03-0.13 | 0.998 | 0.01-0.15 |
| event filter       | 0.892 | 0.10-0.40 | 0.990 | 0.01-0.17 |
| redis join         | 0.758 | 0.01-0.16 | NA   | NA    |
| stream manager     | 0.797 | 0.01-0.26 | NA   | NA    |

Table 4: $R^2$ for Ad Analytics model fit

6 Related work

The work closest to ours that addresses auto-tuning and auto-scaling in stream processing systems is Dhalion[11]. Dhalion is a self-regulating system built on the Heron[20] platform, which enables auto-scaling and auto-tuning through a stepwise iteration over allocations during runtime, incrementally reacting to bottlenecks by adjusting parallelism until the topology is stable.

Trevor on the other hand requires no runtime iteration, and can reach a given target performance with a closed form algorithm, allowing for faster tuning and scaling than Dhalion. Additionally, Trevor achieves a CPU efficient allocation while Dhalion will maintain inefficiencies that are present in the initial allocation it is regulating.

Other works for auto-scaling for stream processing have previously been proposed, such as Elastic Auto-Parallelization[13] and DRS[12]. These methods, however, are not designed to scale and tune the topology based on the input rates, as with Trevor.

There has been a lot of prior work on auto-tuning in the batch processing world, such as Hemingway[22] and ROPE[1]. These works are based on multiple techniques including modeling compute and communication in relation to tuning parameters and identifying bottlenecks. Many of these works utilize learning techniques from past data [8, 7].

A few works such as Quasar[10], CherryPick[2], Throughput-Scheduler[15], Proactive ReOptimization[5] and Starfish[16], like Trevor, try to optimize for a goal, based on performance. Yet both papers are based on a black box model of the entire application, which requires a search involving many iterations over a large search space. As we have shown with Trevor, this might result in inefficient stream processing applications.

The techniques presented in the batch processing papers target a different set of applications than Trevor does, and are not directly applicable to stream processing. More over batch processing systems are rescheduled periodically, and can be modified between each run. Stream processing systems are scheduled once and then regulated.

7 Conclusion

In this paper, we introduced Trevor, an auto-tuning system for stream processing pipelines. We demonstrated the difficulty of tuning streaming pipelines to a given performance, and showed that this can result in both inefficiencies in resource utilization and over-provisioning. We demonstrated how Trevor uses effective node modeling to learn and predict the pipeline performance with a 10% error rate. We showed how Trevor’s predictive models can be used to design the Trevor allocator, which produces an optimal allocation for the topology, given a target rate. Additionally, we have shown that the Trevor allocator can—in less than 1 second—produce an allocation which achieves the desired target rate.
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