MacroBase: Prioritizing Attention in Fast Data

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ABSTRACT

As data volumes continue to rise, manual inspection is becoming increasingly untenable. In response, we present MacroBase, a data analytics engine that prioritizes end-user attention in high-volume *fast data* streams. MacroBase enables efficient, accurate, and modular analyses that highlight and aggregate important and unusual behavior, acting as a search engine for fast data. MacroBase is able to deliver order-of-magnitude speedups over alternatives by optimizing the combination of explanation and classification tasks and by leveraging a new reservoir sampler and heavy-hitters sketch specialized for fast data streams. As a result, MacroBase delivers accurate results at speeds of up to 2M events per second per query on a single core. The system has delivered meaningful results in production, including at a telematics company monitoring hundreds of thousands of vehicles.

1. INTRODUCTION

Data volumes are quickly outpacing human abilities to process them. Today, Twitter, LinkedIn, and Facebook each record over 12M events per second [10, 63, 79]. These volumes are growing and are becoming more common: machine-generated data sources such as sensors, processes, and automated systems are projected to increase data volumes by 40% each year [50]. However, human attention remains limited; it is becoming increasingly impossible to rely on manual inspection and analysis of these large data volumes. They are simply too large. Due to this combination of immense data volumes and limited human attention, today's best-of-class application operators anecdotally report accessing less than 6% of data they collect [11], primarily in reactive root-cause analyses.

While humans cannot manually inspect these *fast data* streams, machines can [11]. Machines can filter, highlight, and aggregate fast data, winnowing and summarizing data before it reaches a user. As each result shown to the end-user consumes their attention [74], we can help prioritize this attention by leveraging computational resources to maximize the utility of each result shown. That is, fast data necessitates a search engine to help identify the most relevant data and trends (and to allow non-expert users to issue queries). The increased availability of elastic computation as well as advances in machine learning and statistics suggest that the construction of such an engine is possible.

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SIGMOD'17, May 14 - 19, 2017, Chicago, Illinois, USA

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ISBN 978-1-4503-4197-4/17/05. . . $15.00

DOI: http://dx.doi.org/10.1145/3035918.3035928

However, the design and implementation of this infrastructure is challenging; current analytics deployments are a far cry from this potential. Today, application developers and analysts can employ a range of scalable dataflow processing engines to compute over fast data (over 20 in the Apache Software Foundation alone). However, these engines leave the actual implementation of scalable analysis operators that prioritize attention (e.g., highlighting, grouping, and contextualizing important behaviors within fast data) up to the application developer. This development is hard: fast data analyses must *i.*) determine the few results to return to end users (to avoid overwhelming their attention) while *ii.*) executing quickly to keep up with immense data volumes and *iii.*) adapting to changes within the data stream itself. Thus, designing and implementing these analytics operators requires a combination of domain expertise, statistics and machine learning, and dataflow processing. This combination is rare. Instead, today's high-end industrial deployments overwhelmingly rely on a combination of static rules and thresholds that analysts report are computationally efficient but brittle and error-prone; manual analysis is typically limited to reactive, post-hoc error diagnosis that can take hours to days.

To bridge this gap between the availability of low-level dataflow processing engines and the need for efficient, accurate analytics engines that prioritize attention in fast data, we have begun the development of MacroBase, a fast data analysis system. The core concept behind MacroBase is simple: to prioritize attention, an analytics engine should provide analytics operators that automatically classify and explain fast data volumes to users. MacroBase executes extensible streaming dataflow pipelines that contain operators for both *classifying* individual data points and *explaining* groups of points by aggregating them and highlighting commonalities of interest. Combined, these operators ensure that a few returned results capture the most important properties of data. Much as in conventional relational analytics, when designed for reuse and composition, a small core set of efficient fast data operators allows portability across application domains.

The resulting research challenge is to determine this efficient, accurate, and modular set of core classification and explanation operators for prioritizing attention in fast data. The statistics and machine learning literature is replete with candidate algorithms, but it is unclear which can execute online at fast data volumes, and, more importantly, how these operators can be composed in an end-to-end system. Thus, in this paper, we both introduce the core MacroBase architecture—which combines domain-specific feature extraction with streaming classification and explanation operators—and present the design and implemention of MacroBase's default streaming classification and explanation operators. In the absence of labeled training data, MacroBase executes operators for unsupervised, density-based classification that highlight points lying far from the overall population according to user-specified *metrics* of interest (e.g., power drain). MacroBase subsequently executes sketch-based explanation operators, which highlight correlations that most differentiate outlying data points according to their *attributes* (e.g., firmware version, device ID).

Users of the open source MacroBase prototype[1] have utilized MacroBase's classification and explanation operators to find unusual and previously unknown behaviors in fast data from mobile devices, datacenter telemetry, automotives, and manufacturing processes, such as in the following example.

EXAMPLE. *A mobile application manufacturer issues a MacroBase query to monitor power drain readings (i.e.,* metrics*) across devices and application versions (i.e.,* attributes*). MacroBase's default operator pipeline reports that devices of type B264 running application version 2.26.3 are sixty times more likely to experience abnormally high power drain than the rest of the stream, indicating a potential problem with the interaction between devices of type B264 and application version 2.26.3.*

Beyond this basic default functionality, MacroBase allows users to tune their queries by *i*.) adding domain-specific feature transformations (e.g., time-series operations such as Fourier transform and autocorrelation) to their pipelines—without modifying the rest of the pipeline, *ii*.) providing supervised classification rules (or labels) to complement or replace unsupervised classifiers and *iii*.) authoring custom streaming transformation, classification, and explanation operators, whose interoperability is enforced by MacroBase's type system and can be combined with relational operators.

EXAMPLE. *The mobile application developer also wishes to find time-varying power spikes within the stream, so she reconfigures her pipeline by adding a time-series feature transformation to identify time periods with abnormal time-varying frequencies. She later adds a manual rule to capture all readings with power drain greater than* $100W$ *and a custom time-series explanation operator [55]—all without modifying the remainder of the operator pipeline.*

Developing these operators necessitated several algorithmic advances, which we address as core research challenges in this paper:

To provide responsive analyses over dynamic data sources, MacroBase's default operators are designed to adapt to shifts in data. MacroBase leverages a novel stream sampler, called the *Adaptable Damped Reservoir* (ADR), which performs sampling over arbitrarily-sized, exponentially damped windows. MacroBase uses the ADR to incrementally train unsupervised classifiers based on statistical density estimation that can reliably identify typical behavioral modes despite large numbers of extreme data points [46]. MacroBase also adopts exponentially weighted sketching and streaming data structures [27, 76] to track correlations between attribute-value pairs, improving responsiveness and accuracy in explanation.

To provide interpretable explanations of often relatively rare behaviors in streams, MacroBase adopts a metric from statistical epidemiology called the *relative risk ratio* that describes the relative occurrence of key attributes (e.g., age, sex) among infected and healthy populations. In computing this statistic, MacroBase employs two new optimizations. First, MacroBase exploits the cardinality imbalance between classified points to accelerate explanation generation, an optimization enabled by the combination of detection and explanation. Instead of inspecting "outliers" and "inliers" separately, MacroBase first examines the small set of outliers, then aggressively prunes its search over the much larger set of inliers. Second, MacroBase exploits the fact that many fast data streams contain repeated measurements from devices with similar attributes (e.g., firmware version) during risk ratio computation, reducing data structure maintenance overhead via a new counting sketch, the *Amortized Maintenance Counter* (AMC). These optimizations improve performance while highlighting the often small subset of attributes that matter most.

[1] https://github.com/stanford-futuredata/macrobase

We report on early production experiences and quantitatively evaluate MacroBase's performance and accuracy on both production telematics data as well as a range of publicly available real-world datasets. MacroBase's optimized operators exhibit order-of-magnitude performance improvements over existing operators at rates of up to 2M events per second per query while delivering accurate results in controlled studies using both synthetic and real-world data. As we discuss, this ability to quickly process large data volumes can also improve result quality: large numbers of samples combat statistical bias due to the multiple testing problem [70], thereby improving result significance. We also demonstrate MacroBase's extensibility via case studies in mobile telematics, electricity metering, and video-based surveillance, and via integration with several existing analytics frameworks.

We make the following contributions in this paper:

- MacroBase, an analytics engine and architecture for analyzing fast data streams that is the first to combine streaming outlier detection and streaming data explanation.
- The Adaptable Damped Reservoir, the first exponentially damped reservoir sample to operate over arbitrary windows, which MacroBase leverages in online classifier training.
- An optimization for improving the efficiency of combined detection and explanation by exploiting cardinality imbalance between classes in streams.
- The Amortized Maintenance Counter, a new heavy-hitters sketch that allows fast updates by amortizing sketch pruning across multiple observations of the same item.

The remainder of this paper proceeds as follows. Section 2 describes our target environment by presenting motivating use cases. Section 3 presents the MacroBase's interaction model and primary default analysis pipeline (which we denote MDP). Section 4 describes MacroBase's default streaming classification operators and presents the ADR sampler. Section 5 describes MacroBase's default streaming explanation operator, including its cardinality-aware optimization and the AMC sketch. We experimentally evaluate MacroBase's accuracy and runtime, report on experiences in production, and demonstrate extensibility via case studies in Section 6. Section 7 discusses related work, and Section 8 concludes.

2. TARGET ENVIRONMENT

MacroBase provides application writers and system analysts an end-to-end analytics engine capable of classifying data within high-volume streams while highlighting important properties of the data within each class. As examples of the types of workloads we seek to support, we draw on three motivating use cases from industry.

Mobile applications. Cambridge Mobile Telematics (CMT) is a five-year-old telematics company whose mission is to make roads safer by making drivers more aware of their driving habits. CMT provides drivers with a smartphone application and mobile sensor for their vehicles, and collects and analyzes data from many hundreds of thousands of vehicles at rates of tens of Hz. CMT uses this data to provide users with feedback about their driving.

CMT's engineers report that monitoring their application has proven especially challenging. CMT's operators, who include database and systems research veterans, report difficulty in answering several questions: is the CMT application behaving as expected? Are all users able to upload and view their trips? Are sensors operating at a sufficiently granular rate and in a power-efficient manner?

The most severe problems in the CMT application are caught by quality assurance and customer service, but many behaviors are more pernicious. For example, Apple iOS 9.0 beta 1 introduced a buggy Bluetooth stack that prevented iOS devices from connecting to CMT's sensors. Few devices ran these versions, so the overall failure rate was low; as a result, CMT's data volume and heterogeneous install base (which includes the 24K distinct device types in the Android ecosystem) obscured a potentially serious widespread issue in later releases of the application. Given low storage costs, CMT records all of the data required to perform analytic monitoring to detect such behaviors, yet CMT's engineers report they have lacked a solution for doing so in a timely and efficient manner.

In this paper, we report on our experiences deploying MacroBase at CMT, where the system has highlighted interesting behaviors such as those above, in production.

Datacenter operation. Datacenter and server operation represents one of the highest-volume data sources today. In addition to the billion-plus events per minute volumes reported at Twitter and LinkedIn, engineers reported a similar need to quickly identify misbehaving servers, applications, and virtual machines.

For example, Amazon AWS recently suffered a failure in its DynamoDB service, resulting in outages at sites including Netflix and Reddit. The Amazon engineers reported that "after we addressed the key issue...we were left with a low overall error rate, hovering between 0.15-0.25%. We knew there would be some cleanup to do after the event," and therefore the engineers deferred maintenance. However, the engineers "did not realize soon enough that this low overall error rate was giving some customers disproportionately high error rates" due to a misbehaving server partition [3].

This public postmortem is representative of many scenarios described by system operators in interviews. At a major social network, engineers reported that the challenge of identifying transient slowdowns and failures across hosts and containers is exacerbated by the heterogeneity of workload tasks. Failure postmortems can take hours to days, and, due to the labor-intensive nature of manual analysis, engineers report an inability to efficiently and reliably identify slowdowns, leading to suspected inefficiency.

Unlike the CMT use case, we do not directly present results over production data from these scenarios. However, datacenter telemetry is an area of ongoing activity within the MacroBase project.

Industrial monitoring. Increased sensor availability has spurred interest in and collection of fast data in industrial deployments. While many industrial systems already rely on legacy analytics systems, several industrial application operators we encountered reported a desire for analytics and alerting that can adapt to new sensors and changing conditions. These industrial scenarios can have important consequences. For example, an explosion and fire in July 2010 killed two workers at Horsehead Holding Corp.'s Monaca, PA, zinc manufacturing plant. The US Chemical Safety board's postmortem revealed that "the high rate-of-change alarm warned that the [plant] was in imminent danger 10 minutes before it exploded, but there appears to have been no specific alarm to draw attention of the operator to the subtle but dangerous temperature changes that were taking place much (i.e. hours) earlier." The auditor noted that "it should be possible to design a more modern control system that could draw attention to trends that are potentially hazardous" [48].

In this paper, we illustrate the potential to draw attention to unusual behaviors within electrical utilities.

3. MacroBase ARCHITECTURE AND APIS

As a fast data analytics engine, MacroBase filters and aggregates large, high-volume streams of potentially heterogeous data. As a result, MacroBase's architecture is designed for high-performance execution as well as flexible operation across domains using an array of classification and explanation operators. In this section, we describe MacroBase's query processing architecture, approach to extensibility, and interaction modes.

DATA TYPES
Point := (array<double> metrics, array<varchar> attributes)
Explanation := (array<varchar> attributes, *stats* statistics)

OPERATOR INTERFACE	
Operator	*Type Signature*
Ingestor	external data source(s) → stream<*Point*>
Transformer	stream<*Point*> → stream<*Point*>
Classifier	stream<*Point*> → stream<(label, *Point*)>
Explainer	stream<(label, *Point*)> → stream<*Explanation*>
Pipeline	Ingestor → stream<*Explanation*>

Table 1: MacroBase's core data and operator types. Each operator implements a strongly typed, stream-oriented dataflow interface specific to a given pipeline stage. A pipeline can utilize multiple operators of each type via transformations, such as group-by and one-to-many stream replication, as long as the pipeline ultimately returns a single stream of explanations.

3.1 Core Concepts

To prioritize attention, MacroBase executes streaming analytics operators that help filter and aggregate the stream. To do so, it combines two classes of operators:

Classification. Classification operators examine individual data points and label them according to user-specified classes. For example, MacroBase can classify an input stream of power drain readings into two classes: points representing statistically "normal" readings and abnormal "outlying" readings.

At scale, surfacing even a handful of raw data points per second can overwhelm end users, especially if each data point contains multi-dimensional and/or categorical information. As a result, MacroBase employs a second type of operator:

Explanation. Explanation operators group and aggregate multiple data points. For example, MacroBase can describe commonalities among points in a class, as well as differences between classes. Each result returned by an explanation operator can represent many individual classification outputs, further prioritizing attention.

As we discuss in Section 7, classification and explanation are core topics in several communities including statistics and machine learning. Our goal in MacroBase is to develop core operators for each task that are able to execute quickly over streaming data that may change over time and can be composed as part of end-to-end pipelines. Conventional relational analytics have a well-defined set of composable, reusable operators; despite pressing application demands at scale, the same cannot be said of classification and explanation today. Identifying these operators and combining them with appropriate domain-specific feature extraction operators enables reuse beyond one-off, ad-hoc analyses.

Thematically, our focus is on developing operators that deliver more information using less output. This score-and-aggregate strategy is reminiscent of many data-intensive domains, including search. However, as we show, adapting these operators for use in efficient, extensible fast data pipelines requires design modifications and even enables new optimizations. When employed in a system designed for extensibility, a small number of optimized, composable operators can execute across domains.

3.2 System Architecture

Query pipelines. MacroBase executes pipelines of specialized dataflow operators over input data streams. Each MacroBase *query* specifies a set of input data sources as well as a logical query plan, or *pipeline* of streaming operators, that describes the analysis.

MacroBase's pipeline architecture is guided by two principles. First, all operators operate over streams. Batch execution is supported by streaming over stored data. Second, MacroBase uses the compiler's type system to enforce interoperability. Each operator must implement one of several type signatures (shown in Table 1). In turn, the compiler enforces that all pipelines composed of these operators will adhere to the common structure we describe below.

This *architecture via typing* strikes a balance between the elegance of more declarative but often less flexible interfaces and the expressiveness of more imperative but often less composable interfaces. More specifically, this use of the type system facilitates three important kinds of interoperability. First, users can substitute streaming detection and explanation operators without concern for their interoperability. Early versions of the MacroBase prototype that lacked this modularity were hard to adapt. Second, users can write a range of domain-specific feature transformation operators to perform advanced processing (e.g., time-series operations) without requiring expertise in classification or explanation. Third, MacroBase's operators preserve compatibility with dataflow operators found in traditional stream processing engines. For example, a MacroBase pipeline can contain standard selection, project, join, windowing, aggregation, and group-by operators.

A MacroBase pipeline is structured as follows:

1.) Ingestion. MacroBase ingests data streams for analysis from a number of external data sources. For example, MacroBase's JDBC interface allows users to specify columns of interest from a base view defined by a SQL query. MacroBase subsequently reads the result-set from the JDBC connector, and constructs the set of data points to process, with one point per row in the view. MacroBase currently requires that any necessary stream ordering and joins be performed by this initial ingestion operator.

Each data point contains a set of *metrics*, corresponding to key measurements (e.g., trip time, battery drain), and *attributes*, corresponding to associated metadata (e.g., user ID and device ID). MacroBase uses metrics to detect abnormal or unusual events, and attributes to explain behaviors. In this paper, we consider real-valued metrics and categorical attributes.[2]

As an example, to detect the OS version problem at CMT, trip times could be used as a metric, and device and OS type as attributes. To detect the outages at DynamoDB, error rates could be used as a metric, and server or IP address as an attribute. To detect the Horsehead pressure losses, pressure gauge readings could be used as metrics and their locations as attributes, as part of an autocorrelation-enabled time-series pipeline (Section 6.4). Today, selecting attributes, metrics, and a pipeline is a user-initiated process; ongoing extensions (Section 8) seek to automate this.

2.) Feature Transformation. Following ingestion, MacroBase executes an optional series of domain-specific data transformations over the stream, which could include time-series specific operations (e.g., windowing, seasonality removal, autocorrelation, frequency analysis), statistical operations (e.g., normalization, dimensionality reduction), and datatype specific operations (e.g., hue extraction for images, optical flow for video). For example, in Section 6.4, execute a pipeline containing a grouped Fourier transform operator that aggregates the stream into hour-long windows, then outputs a stream containing the twenty lowest Fourier coefficients for each window as metrics and properties of the window time (hour of day, month) as attributes. Placing this feature transformation functionality at the start of the pipeline allows users to encode domain-specific analyses without modifying later stages. The base type of the stream is unchanged (*Point* → *Point*), allowing transforms to be chained. For specialized data types like video frames, operators can subclass *Point* to further increase the specificity of types (e.g., *VideoFramePoint*).

3.) Classification. Following ingestion, MacroBase performs classification, labeling each *Point* according to its input metrics. Both training and evaluating classifiers on the metrics in the incoming data stream occur in this stage. MacroBase supports a range of models, which we describe in Section 6. The simplest include rule-based models, which check specific metrics for particular values (e.g., if the `Point` metric's L2-norm is greater than a fixed constant). In Section 4, we describe MacroBase's default unsupervised models, which perform density-based classification into "outlier" and "inlier" classes. Users can also use operators that make use of supervised and pre-trained models. Independent of model type, each classifier returns a stream of labeled *Point* outputs (*Point* → `(label,` *Point*`)`).

4.) Explanation. Rather than returning all labeled data points, MacroBase aggregates the stream of labeled data points by generating *explanations*. As we describe in detail in Section 5, MacroBase's default pipeline returns explanations in the form of attribute-value combinations (e.g., device ID 5052) that are common among outlier points but uncommon among inlier points. For example, at CMT, MacroBase could highlight devices that were found in at least 0.1% of outlier trips and were at least 3 times more common among outliers than inliers. Each explanation operator returns a stream of these aggregates (`(label,` *Point*`)`→*Explanation*), and explanation operators can subclass *Explanation* to provide additional information, such as statistics about the explanation or representative sequences of points to contextualize time-series outliers.

Because MacroBase processes streaming data, explanation operators continuously summarize the stream. However, continuously emitting explanations may be wasteful if users only need explanations at the granularity of seconds, minutes, or longer. As a result, MacroBase's explanation operators are designed to emit explanations on demand, either in response to a user request, or in response to a periodic timer. In this way, explanation operators act as streaming view maintainers.

5.) Presentation. The number of output explanations may still be large. As a result, most pipelines rank explanations by statistics specific to the explanations before presentation. For example, by default, MacroBase delivers a ranked list of explanations—sorted by their degree of outlier—occurrence to downstream consumers. MacroBase's default presentation mode is a static report rendered via a REST API or GUI. In the former, programmatic consumers (e.g., reporting tools such as PagerDuty) can automatically forward explanations to downstream reporting or operational systems. In the GUI, users can interactively inspect explanations and iteratively define their MacroBase queries. In practice, we have found that GUI-based exploration is an important first step in formulating standing MacroBase queries that can later be used in production.

Extensibility. As we discussed in Section 1 and demonstrate in Section 6.4, MacroBase's pipeline architecture lends itself to three major means of extensibility. First, users can add new domain-specific feature transformations to the start of a pipeline without modifying the rest of the pipeline. Second, users can input rules and/or labels to MacroBase to perform supervised classification.

[2] We discretize continuous attributes (e.g., see [81]) and provide two examples of discretization in Section 6.4.

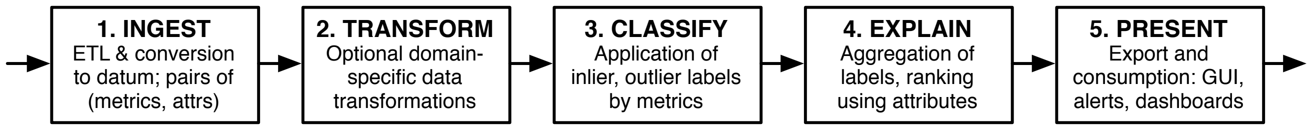


Figure 1: MacroBase's default analytics pipeline: MacroBase ingests streaming data as a series of points, which are scored and classified, aggregated by an explanation operator, then ranked and presented to end users.

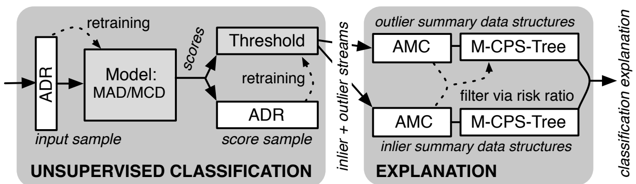


Figure 2: MDP: MacroBase's default streaming classification (Section 4) and explanation (Section 5) operators.

Third, users can write their own feature transformation, classification, and explanation operators, as well as new pipelines. This third option is the most labor-intensive, but is also the interface with which MacroBase's maintainers author new pipelines. These interfaces have proven useful to non-experts: a master's student at Stanford and a master's student at MIT each implemented and tested a new outlier detector operator in less than a week of part-time work, and MacroBase's core maintainers currently require less than an afternoon of work to author and test a new pipeline.

By providing a set of interfaces with which to extend pipelines (with varying expertise required), MacroBase places emphasis on "pay as you go" deployment [11]. MacroBase's Default Pipeline (MDP, which we illustrate in Figure 2 and describe in the following two sections) is optimized for efficient, accurate execution over a variety of data types without relying on labeled data or rules. It foregoes domain-specific feature extraction and instead operates directly on raw input metrics. However, as we illustrate in Section 6.4, this interface design enables users to incorporate more sophisticated features such as domain-specific feature transformation, time-series analysis, and supervised models.

In this paper, we present MacroBase's interfaces using an object-oriented interface, reflecting their current implementation. However, each of MacroBase's operator types is compatible with existing stream-to-relation semantics [9], theoretically allowing additional relational and stream-based processing between stages. Realizing this mapping and the potential for higher-level declarative interfaces above MacroBase's pipelines are promising areas for future work.

Operating modes. MacroBase supports three operating modes. First, MacroBase's graphical front-end allows users to interactively explore their data by configuring different inputs and selecting different combinations of metrics and attributes. This is typically the first step in interacting with the engine. Second, MacroBase can execute one-shot queries that can be run programmatically in a single pass over the data. Third, MacroBase can execute streaming queries that can be run programmatically over a potentially infinite stream of data. In streaming mode, MacroBase continuously ingests data points and supports exponentially decaying averages that give precedence to more recent points (e.g., decreasing the importance of points at a rate of 50% every hour). MacroBase continuously re-renders query results, and if desired, triggers automated alerting for downstream consumers.

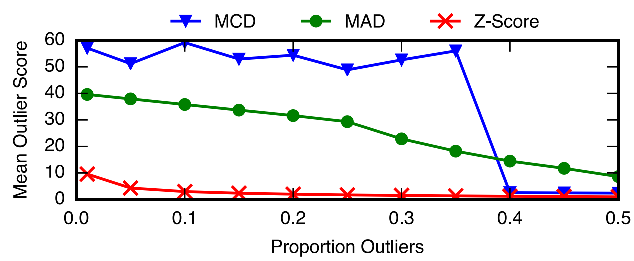


Figure 3: Discriminative power of estimators under contamination by outliers (high scores better). Robust methods (MCD, MAD) outperform the Z-score-based approach.

4. MDP CLASSIFICATION

MacroBase's classification operators label input data points, and, by default, identify data points that exhibit deviant behavior. While MacroBase allows users to configure their own operators, in this section, we focus on the design of MacroBase's default classification operators in MDP, which use robust estimation procedures to fit a distribution to data streams and identify the least likely points with the distribution using quantile estimation. To enable streaming execution, we introduce the Adaptable Damped Reservoir, which MacroBase uses for model retraining and quantile estimation.

4.1 Robust Distribution Estimation

MDP relies on unsupervised density-based classification to identify points that are abnormal relative to a population. However, a small number of anomalous points can have a large impact on density estimation. As an example, consider the *Z-Score* of a point drawn from a univariate sample, which measures the number of standard deviations that the point lies away from the sample mean. This provides a normalized way to measure the "outlying"-ness of a point (e.g., a Z-Score of three indicates the point lies three standard deviations from the mean). However, the Z-Score is not robust to outliers: a single outlying value can skew the mean and standard deviation by an unbounded amount, limiting its utility.

To address this challenge, MacroBase's MDP pipeline leverages robust statistical estimation [46], a branch of statistics that pertains to finding statistical distributions for data that is mostly well-behaved but may contain a number of ill-behaved data points. Given a distribution that reliably fits most of the data, we can measure each point's distance from this distribution in order to find outliers [57].

For univariate data, a robust variant of the Z-Score is to use the median and the Median Absolute Deviation (MAD), in place of mean and standard deviation, as measures of the location and scatter of the distribution. The MAD measures the median of the absolute distance from each point in the sample to the sample median. Since the median itself is resistant to outliers, each outlying data point has limited impact on the MAD score of all other points in the sample.

For multivariate data, the Minimum Covariance Determinant (MCD) provides similar robust estimates for location and spread [47]. The MCD estimator finds the tightest group of points that best represents a sample, and summarizes the set of points according to its location μ and scatter C (i.e., covariance) in metric space. Given these estimates, we can compute the distance between a point x and the distribution via the *Mahalanobis distance* $\sqrt{(x-\mu)^T C^{-1}(x-\mu)}$; intuitively, the Mahalanobis distance normalizes (or warps) the metric space via the scatter and then measures the distance to the center of the transformed space using the mean (see also Appendix A).

As Figure 3 empirically demonstrates, MAD and MCD reliably identify points in outlier clusters despite increasing outlier contamination (experimental setup in Appendix A). Whereas MAD and MCD are resilient to contamination up to 50%, the Z-Score is unable to distinguish inliers and outliers under even modest contamination.

Classifying outliers. Given a query with a single, univariate metric, MDP uses a MAD-based detector, and, given a query with multiple metrics, MacroBase computes the MCD via an iterative approximation called FastMCD [67]. These unsupervised models allow MDP to score points without requiring labels or rules from users. Subsequently, MDP uses a percentile-based cutoff over scores to identify the most extreme points in the sample. Points with scores above the percentile-based cutoff are classified as outliers, reflecting their distance from the body of the distribution.

As a notable caveat, MAD and MCD are parametric estimators, assigning scores based on an assumption that data is normally distributed. While extending these estimators to multi-modal behavior is straightforward [41] and MacroBase allows substitution of more sophisticated detectors (e.g., Appendix D), we do not consider them here. Instead, we have found that looking for far away points using these parametric estimators yields useful results: as we empirically demonstrate, many interesting behaviors manifest as extreme deviations from the overall population. Robustly locating the center of a population—while ignoring local, small-scale deviations in the body of the distribution—suffices to identify many important classes of outliers in the applications we study (cf. [42]).

4.2 MDP Streaming Execution

Despite their utility, we are not aware of an existing algorithm for training MAD or MCD in a streaming context.[3] This is especially problematic because, as the distributions within data streams change over time, MDP's estimators should be updated to reflect the change.

ADR: Adaptable Damped Reservoir. MDP's solution to the retraining problem is a novel adaptation of reservoir sampling over streams, which we call the Adaptable Damped Reservoir (ADR). The ADR maintains a sample of input data that is exponentially weighted towards more recent points; the key difference from traditional reservoir sampling is that the ADR operates over *arbitrary* window sizes, allowing greater flexibility than existing damped samplers. As Figure 2 illustrates, MDP maintains an ADR sample of the input to periodically recompute its robust estimator and a second ADR sample of the outlier scores to periodically recompute its quantile threshold.

The classic reservoir sampling technique can be used to select a uniform sample over a set of data using finite space and one pass [77]. The probability of insertion into the sample, or "reservoir," is inversely proportional to the number of points observed thus far. In the context of stream sampling, we can treat the stream as an infinitely long set of points and the reservoir as a uniform sample over the data observed so far.

In MacroBase, we wish to promptly reflect changes in the underlying data stream, and therefore we adapt a *weighted* sampling approach, in which the probability of data retention decays over time. The literature contains several existing algorithms for weighted reservoir sampling [5,22,29]. Most recently, Aggarwal described how to perform exponentially weighted sampling on a per-record basis: that is, the probability of insertion is an exponentially weighted function of the number of points observed so far [5]. While this is useful, as we demonstrate in Section 6, under workloads with variable arrival rates, we may wish to employ a decay policy that decays in *time*, not in number of tuples; specifically, tuple-at-a-time decay may skew the reservoir towards periods of high stream volume.

Algorithm 1 ADR: Adaptable Damped Reservoir

given: k: reservoir size $\in \mathbb{N}$; r: decay rate $\in (0,1)$
initialization: reservoir $R \leftarrow \{\}$; current weight $c_w \leftarrow 0$
function OBSERVE(x: point, w: weight)
    $c_w \leftarrow c_w + w$
    if $|R| < k$ **then**
        $R \leftarrow R \cup \{x\}$
    else with probability $\frac{k}{c_w}$
        remove random element from R and add x to R
function DECAY( )
    $c_w \leftarrow r \cdot c_w$

To support more flexible reservoir behavior, MacroBase adapts an earlier variant of weighted reservoir sampling due to Chao [22,29] to provide the first exponentially decayed reservoir sampler that decays over arbitrary decay intervals. We call this variant the *Adaptable Damped Reservoir*, or ADR (Algorithm 1). In contrast with existing approaches that decay on a per-tuple basis, the ADR separates the insertion process from the decay decision, allowing both time-based and tuple-based decay policies. Specifically, the ADR maintains a running count c_w of items inserted into the reservoir (of size k) so far. When an item is inserted, c_w is incremented by one (or an arbitrary weight, if desired). With probability $\frac{k}{c_w}$, the item is placed into the reservoir and a random item is evicted from the reservoir. When the ADR is decayed (e.g., via a periodic timer or tuple count), its running count is multiplied by a decay factor (i.e., $c_w := (1-\alpha)c_w$).

MacroBase currently supports two decay policies: time-based decay, which decays the reservoir at a pre-specified rate measured according to real time, and batch-based decay, which decays the reservoir at a pre-specified rate measured by arbitrarily-sized batches of data points (Appendix A). The validity of this procedure follows from Chao's sampler, which otherwise requires the user to manually manage weights and decay. As in Chao's sampler, in the event of extreme decay, "overweight" items with relative insertion probability $\frac{k}{c_w} > 1$ are always retained in the reservoir until their insertion probability falls below 1, at which point they are inserted normally.

MacroBase's MDP uses the ADR to solve the model retraining and quantile estimations problems:

Maintaining training inputs. Either on a tuple-based or time-based interval, MDP retrains models using the contents of an ADR that samples the input data stream. This streaming robust estimator maintenance and evaluation strategy is the first of which we are aware. We discuss this procedure's statistical impact in Appendix D.

Maintaining percentile thresholds. While streaming quantile estimation is well studied, we were not able to find many computationally inexpensive options for an exponentially damped model with arbitrary window sizes. Thus, instead, MacroBase uses an ADR to sample the outlier scores produced by MAD and MCD. The ADR maintains an exponentially damped sample of the scores, which it uses to periodically compute the appropriate score quantile value

[3] Specifically, MAD requires computing the median of median distances, meaning streaming quantile estimation alone is insufficient. FastMCD is an inherently iterative algorithm that iteratively re-sorts data.

(e.g., 99th percentile of scores).[4] A sample of size $O(\frac{1}{\varepsilon^2}\log(\frac{1}{\delta}))$ yields an ε-approximation of an arbitrary quantile with probability $1-\delta$ [15], so a ADR of size 20K provides an $\varepsilon = 1\%$ approximation with 99% probability ($\delta = 1\%$).

5. MDP EXPLANATION

MDP's explanation operators produce explanations to contextualize and differentiate inliers and outliers according to their attributes. In this section, we discuss how MacroBase performs this task by using a metric from epidemiology, the *relative risk ratio* (risk ratio), using a range of data structures. We again begin with a discussion of MDP's batch-oriented operation and introduce a cardinality-based optimization, then discuss how MacroBase executes streaming explanation via the Amortized Maintenance Counter sketch.

5.1 Semantics: Support and Risk Ratio

MacroBase produces explanations that describe attributes common to outliers but relatively uncommon to inliers. To identify combinations of attribute values that are relatively common in outliers, MDP finds combinations with high *risk ratio (or relative risk ratio)*. This ratio is a standard diagnostic measure used in epidemiology, and is used to determine potential causes for disease [60]. Formally, given an attribute combination appearing a_o times in the outliers and a_i times in the inliers, where there are b_o other outliers and b_i other inliers, the risk ratio is defined as:

$$\text{risk ratio} = \frac{a_o/(a_o+a_i)}{b_o/(b_o+b_i)}$$

Intuitively, the risk ratio quantifies how much more likely a data point is to be an outlier if it is of a specific attribute combination, as opposed to the general population. To eliminate explanations corresponding to rare but non-systemic combinations, MDP finds combinations with high *support*, or occurrence (by relative count) in outliers. To facilitate these two tests, MDP accepts a minimum risk ratio and level of outlier support as input parameters. As an example, *MDP* may find that 500 of 890 records flagged as outliers correspond to iPhone 6 devices (outlier support of 56.2%), but, if 80191 of 90922 records flagged as inliers also correspond to iPhone 6 devices (inlier support of 88.2%), we are likely uninterested in iPhone 6 as it has a low risk ratio of 0.1767. MDP reports explanations in the form of combinations of attributes, each subset of which has risk ratio and support above threshold.

5.2 Basic Explanation Strategy

A naïve solution to computing the risk ratio for various attribute sets is to search twice, once over all inlier points and once over all outlier points, and then look for differences between the inlier and outlier sets. As we experimentally demonstrate in Section 6, this is inefficient as it wastes times searching over attributes in inliers that are eventually filtered due to insufficient outlier support. Moreover, the number of outliers is much smaller than the inliers, so processing the two sets independently ignores the possibility of additional pruning. To reduce this wasted effort, MacroBase takes advantage of both the cardinality imbalance between inliers and outliers as well as the joint explanation of each set.

Optimization: Exploit cardinality imbalance. The cardinality of the outlier set is by definition much smaller than that of the inlier set. Therefore, instead of searching the outlier supports and the inlier supports separately, MDP first finds outlier attribute sets with minimum support and subsequently searches the inlier attributes, while only searching for attributes that were supported in the outliers. This reduces the space of inlier attributes to explore.

[4]This enables a simple mechanism for detecting quantile drift: if the proportion of outlier points significantly deviates from the target percentile (i.e., via application of a binomial proportion confidence interval), MDP should recompute the quantile.

Algorithm 2 MDP's Outlier-Aware Explanation Strategy

given: minimum risk ratio r, minimum support s, set of outliers O, set of inliers I

1: find attributes w/ support $\geq s$ in O and risk ratio $\geq r$ in O, I
2: mine FP-tree over O using only attributes from (1)
3: filter (2) by removing patterns w/ risk ratio $< r$ in I; return

Optimization: Individual item ratios are cheap. We have found that many important attribute combinations (i.e., with high risk ratio) can be explained by a small number of attributes (typically, one or two, which can be tested inexpensively). Moreover, while computing risk ratios for all attribute combinations is expensive (combinatorial), computing risk ratios for single attributes is inexpensive: we can compute support counts over both inliers and outliers via a single pass over the attributes. Accordingly, MDP first computes risk ratios for single attribute values, then computes support of combinations whose members have sufficient risk ratios.

In contrast with [54], this optimization for risk ratio computation is enabled by the fact that we wish to find *combinations* of attributes whose subsets are each supported and have minimum risk ratio. If a set of attributes is correlated, reporting them as a group helps avoid overwhelming the user with explanations.

Algorithms and Data Structures. In the one-pass batch setting, single attribute value counting is straightforward, requiring a single pass over the data; the streaming setting below is more interesting. We experimented with several itemset mining techniques that use dynamic programming to prune the search over attribute combinations with sufficient support and ultimately decided on prefix-tree-based approaches inspired by FPGrowth [40]. In brief, the FPGrowth algorithm maintains a frequency-descending prefix tree of attributes that can subsequently be mined by recursively generating a set of "conditional" trees. Corroborating recent benchmarks [34], the FPGrowth algorithm was fast and proved extensible in our streaming implementation below.

End result. The result is a three-stage process (Algorithm 2). MDP first calculates the attribute values with minimum risk ratio (support counting, followed by a filtering pass based on risk ratio). From the first stage's outlier attribute values, MDP then computes supported outlier attribute combinations. Finally, MDP computes the risk ratio for each attribute combination based on their support in the inliers (support counting, followed by a filtering pass to exclude any attribute combinations with insufficient risk ratio).

Significance. We discuss confidence intervals on MDP explanations as well as quality improvements achievable by processing large data volumes in Appendix B.

5.3 Streaming Explanation

As in MDP detection, streaming explanation generation is more challenging. We present the MDP implementation of single-attribute streaming explanation then extend the approach to multi-attribute streaming explanation.

Implementation: Single Attribute Summarization. To begin, we find individual attributes with sufficient support and risk ratio while respecting both changes in the stream and limiting the overall amount of memory required to store support counts. The problem of maintaining a count of frequent items (i.e., *heavy hitters*, or

Algorithm 3 AMC: Amortized Maintenance Counter

given: $\varepsilon \in (0,1)$; r: decay rate $\in (0,1)$
initialization: C (item $\rightarrow$ count) $\leftarrow\{\}$; weight $w_i \leftarrow 0$
function OBSERVE(i: item, c: count)
  $C[i] \leftarrow w_i + c$ if $i \notin C$ else $C[i] + c$
function MAINTAIN( )
  remove all but the $\frac{1}{\varepsilon}$ largest entries from C
  $w_i \leftarrow$ the largest value just removed, or, if none removed, 0
function DECAY( )
  decay the value of all entries of C by r
  call MAINTAIN( )

attributes with top k occurrence) in data streams is well studied [25]. Given a heavy-hitters sketch over the inlier and outlier stream, we can compute an approximate support and risk ratio for each attribute by comparing the contents of the sketches at any time.

Initially, we implemented the MDP item counter using the SpaceSaving algorithm [59], which provides empirically good performance [26] and has extensions in the exponentially decayed setting [27]. However, like many of the sketches in the literature, SpaceSaving was designed to strike a balance between sketch size and performance, with a strong emphasis on limited size. For example, in its heap-based variant, SpaceSaving maintains $\frac{1}{k}$-approximate counts for the top k item counts by maintaining a heap of the items. For a stream of size n, this requires $O(n\log(k))$ update time. (In the case of exponential decay, the linked-list variant can require $O(n^2)$ processing time.)

While logarithmic update time is modest for small sketches, given only two heavy-hitters sketches per MacroBase query, MDP can expend more memory on its sketches to improve accuracy; for example, 1M items require four megabytes of memory for float-encoded counts, which is small relative to modern server memory sizes. As a result, we developed a heavy-hitters sketch, called the *Amortized Maintenance Counter* (AMC, Algorithm 3), that occupies the opposite end of the design spectrum: the AMC uses a much greater amount of memory for a given accuracy level, but is faster to update and still limits total space utilization. The key insight behind the AMC is that if we observe even a single item in the stream more than once, we can amortize the overhead of maintaining the sketch across multiple observations of the same item. In contrast, SpaceSaving maintains the sketch for every observation but in turn ensures a smaller sketch size.

AMC provides the same counting functionality as a traditional heavy-hitters sketch but exposes a second method, *maintain*, that is called to periodically prune the sketch size. AMC allows the sketch size to increase between calls to *maintain*, and, during maintenance, the sketch size is reduced to a desired stable size, which is specified as an input parameter. Therefore, the maximum size of the sketch is controlled by the period between calls to *maintain*: as in SpaceSaving, a stable size of $\frac{1}{\varepsilon}$ yields an $n\varepsilon$ approximation of the count of n points, but the size of the sketch may grow within a period. This separation of insertion and maintenance has two implications. First, it allows constant-time insertion, which we describe below. Second, it allows a range of maintenance policies, including a sized-based policy, which performs maintenance once the sketch reaches a pre-specified upper bound, as well as a variable period policy, which operates over real-time and tuple-based windows (similar to ADR).

To implement this functionality, AMC maintains a set of approximate counts for all items that were among the most common in the previous period along with approximate counts for all other items that observed in the current period. During maintenance, AMC prunes all but the $\frac{1}{\varepsilon}$ items with highest counts and records the maximum count that is discarded (w_i). Upon insertion, AMC checks to see if the item is already stored. If so, the item's count is incremented. If not, AMC stores the item count plus w_i. If an item is not stored in the current window, the item must have had count less than or equal to w_i at the end of the previous period.

AMC has three major differences compared to SpaceSaving. First, AMC updates are constant time (hash table insertion) compared to $O(\log(\frac{1}{\varepsilon}))$ for SpaceSaving. Second, AMC has an additional maintenance step, which is amortized across all items seen in a window. Using a min-heap, with I items in the sketch, maintenance requires $O(I \cdot \log(\frac{1}{\varepsilon}))$ time. If we observe even one item more than once, this is faster than performing maintenance on every observation. Third, AMC has higher space overhead; in the limit, it must maintain all items it has seen between maintenance intervals.

Implementation: Streaming Combinations. While AMC tracks single items, MDP also needs to track combinations of attributes. As such, we sought a tree-based technique that would admit exponentially damped arbitrary windows but eliminate the requirement that each attribute be stored in the tree, as in recent proposals such as the CPS-tree [76]. As a result, MDP adapts a combination of two data structures: AMC for the frequent attributes, and an adaptation of the CPS-Tree data structure to store frequent attributes. We present algorithms for maintaining the adapted CPS-tree in Appendix B.

Summary. MDP's streaming explanation operator consists of two primary parts: maintenance and querying. When a new data point arrives at the summarization operator, MacroBase inserts each of the point's attributes into an AMC sketch. MacroBase then inserts a subset of the point's attributes into a prefix tree that maintains an approximate, frequency descending order. When a window has elapsed, MacroBase decays the counts of the items and the counts in each node of the prefix tree. MacroBase removes any attributes that are no longer above the support threshold and rearranges the prefix tree in frequency-descending order. To produce explanations, MacroBase runs FPGrowth on the prefix tree.

6. EVALUATION

In this section, we evaluate the accuracy, efficiency, and flexibility of MacroBase and the MDP operators. We wish to demonstrate that:

- MacroBase is accurate: on controlled, synthetic data, under changes in stream behavior and over real-world workloads from the literature and in production (Section 6.1).
- MacroBase can process up to 2M points per second per query on a range of real-world datasets (Section 6.2).
- MacroBase's cardinality-aware explanation strategy produces meaningful speedups (average: 3.2× speedup; Section 6.3).
- MacroBase's use of AMC is up to 500× faster than existing sketches on production data (Section 6.3).
- MacroBase's architecture is extensible, which we illustrate via three case studies (Section 6.4).

Experimental environment. We report results from deploying the MacroBase prototype on a server with four Intel Xeon E5-4657L 2.40GHz CPUs containing 12 cores per CPU and 1TB of RAM. To isolate the effects of pipeline processing, we exclude loading time from our results. By default, we issue MDP queries with a minimum support of 0.1% and minimum risk ratio of 3, a target outlier percentile of 1%, ADR and AMC sizes of 10K, a decay rate of 0.01 every 100K points, and report the average of at least three runs per experiment. We vary these parameters in subsequent experiments in this section and the Appendix.

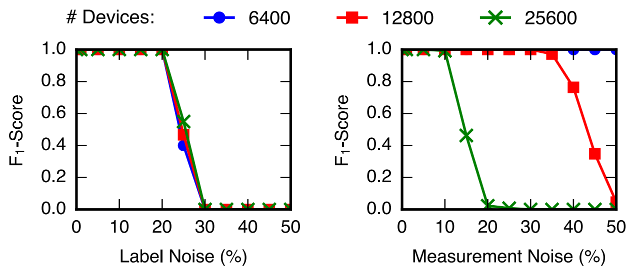


Figure 4: Precision-recall of explanations. Without noise, MDP exactly identifies misbehaving devices. MDP's use of risk ratio improves resiliency to both label and measurement noise.

Implementation. We describe MacroBase's implementation, dataflow runtime, and approach to parallelism in Appendix C.

Large-scale datasets. To compare the efficiency of MacroBase and related techniques, we compiled a set of large-scale real-world datasets (Table 2) for evaluation (descriptions in Appendix D).

6.1 Result Quality

In this section, we focus on MacroBase's statistical result quality. We evaluate precision/recall on synthetic and real-world data, demonstrate adaptivity to changes in data streams, and report on experiences from production usage.

Synthetic dataset accuracy. We ran MDP over a synthetic dataset generated in line with those used to evaluate recent anomaly detection systems [68, 80]. The generated dataset contains 1M data points from a number of synthetic devices. Each device in the dataset has a unique device ID attribute and metrics which are drawn from either an inlier distribution ($\mathcal{N}(10,10)$) or outlier distribution ($\mathcal{N}(70,10)$). We subsequently evaluated MacroBase's ability to automatically determine the device IDs corresponding to the outlying distribution. We report the F_1-score $\left(2 \cdot \frac{precision \cdot recall}{precision + recall}\right)$ for the set of device IDs identified as outliers metric for explanation quality.

Since MDP's statistical techniques are a natural match for this experimental setup, we also perturbed the base experiment to understand when MDP might underperform. We introduced two types of noise into the measurements to quantify their effects on MDP's performance. First, we introduced *label noise* by randomly assigning readings from the outlier distribution to inlying devices and vice-versa. Second, we introduced *measurement noise* by randomly assigning a proportion of both outlying and inlying points to a third, uniform distribution over the interval $[0, 80]$.

Figure 4 illustrates the results. In the the noiseless regions of Figure 4, MDP correctly identified 100% of the outlying devices. As the outlying devices are solely drawn from the outlier distribution, constructing outlier explanations via the risk ratio enables MacroBase to perfectly recover the outlying device IDs. In contrast, techniques that rely solely on individual outlier classification deliver less accurate results on this workload (cf. [68, 80]). Under label noise, MacroBase robustly identified the outlying devices until approximately 25% noise, which corresponds a $3:1$ ratio of correct to incorrect labels. As our risk ratio threshold is set to 3, exceeding this threshold causes rapid performance degradation. Under measurement noise, accuracy degrades linearly with the amount of noise. MDP is more robust to this type of noise when fewer devices are present; its accuracy suffers with a larger number of devices, as each device type is subject to more noisy readings.

In summary, MDP is able to accurately identify correlated causes of outlying data for noise of 20% or more. The noise threshold is improved by both MDP's use of robust methods as well as the use of risk ratio to prune irrelevant summaries. Noise of this magnitude is likely rare in practice, and, if such noise exists, is possibly of another interesting behavior in the data.

Real-world dataset accuracy. In addition to synthetic data, we also performed experiments to determine MacroBase's ability to accurately identify systemic abnormalities in real-world data. We evaluated MacroBase's ability to distinguish abnormally-behaving OLTP servers within a cluster, as defined according to data and manual labels collected in a recent study [81] to diagnose performance issues within a single host. We performed a set of experiments, each corresponding to a distinct type of performance degradation within MySQL on a particular OLTP workload (TPC-C and TPC-E). For each experiment, we consider a cluster of eleven servers, where a single server exhibits the degradation. Using over 200 operating systems and database performance counters, we ran MDP to identify the anomalous server.

We ran MDP with two sets of queries. In the former set, QS, MDP executed a query to find abnormal hosts (with hostname attributes) using a single set of 15 metrics identified via feature selection techniques on a holdout of 2 clusters per experiment (i.e., one query for all anomalies). As Table 4 (Appendix D) shows, under QS, MDP achieves top-1 accuracy of 86.1% on the holdout set across all forms of anomalies (top-3: 88.8%). For eight of nine anomalies, MDP's top-1 accuracy is higher: 93.8%. However, for the ninth anomaly, which corresponds to a poorly written query, the metrics correlated with the anomalous behavior are substantially different.

In the second set of experiments, QE, MDP executed a slow-hosts query using a set of metrics for each distinct anomaly type (e.g., network contention), again using a holdout of 2 clusters per experiment (i.e., one query per anomaly type). In contrast with QS, because QE targets each type of performance degradation with a custom set of metrics, it is able to identify behaviors more reliably, leading to perfect top-3 accuracy.

These results show that with proper feature selection, MacroBase accurately recovers systemic causes even in unsupervised settings.

Adaptivity. While the previous set of experiments operated over data with a static underlying distribution, we sought to understand the benefit of MDP's ability to adapt to changes in the input distribution via the exponential decay of ADR and AMC. We performed a controlled experiment over two types of time-varying behavior: changing underlying data distribution, and variable data arrival rate. We then compared the accuracy of MDP outlier detection across three sampling techniques: a uniform reservoir sample, a per-tuple exponentially decaying reservoir sample, and our proposed ADR.

Figure 5c displays the time-evolving stream representing 100 devices over which MDP operates. To begin, all devices produce readings drawn from a Gaussian $\mathcal{N}(10,10)$ distribution. After 50 seconds, a single device, $D0$, produces readings from $\mathcal{N}(70,10)$ before returning to the original distribution at 100 seconds. The second period (150s to 300s) is similar to the first, except we also introduce a shift in all devices' metrics: after 150 seconds, all devices produce readings from $\mathcal{N}(40,10)$, and, after 225 seconds, $D0$ produces readings from $\mathcal{N}(-10,10)$, returning to $\mathcal{N}(40,10)$ after 250 seconds. Finally from 300s to 400s, all devices experience a spike in data arrival rate. We introduce a four-second noise spike in the sensor readings at 320 seconds: the arrival rate rises by ten-fold, to over 200k points per second, with corresponding values drawn from a $\mathcal{N}(85,15)$ distribution (Figure 5d).

In the first time period, all three strategies detect $D0$ as an outlier, as reflected in the computed risk ratios in Figure 5a. After 100 seconds, when $D0$ returns to the inlier distribution, its risk ratio

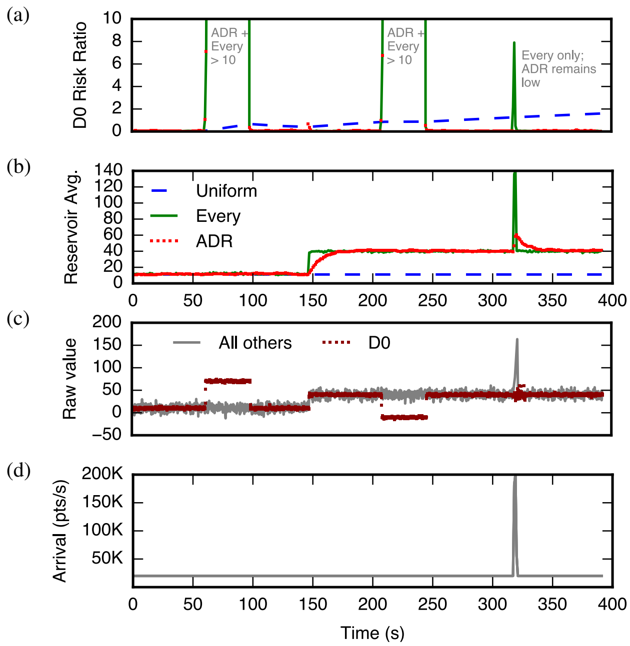


Figure 5: ADR provides greater adaptivity compared to tuple-at-a-time reservoir sampling and is more resilient to spikes in data volume (see text for details).

drops. The reservoir averages remain unchanged in all strategies (Figure 5b). In the second time period, both adaptive reservoirs adjust to the new distribution by 170 seconds, while the uniform reservoir fails to adapt quickly (Figure 5b). As such, when $D0$ drops to $\mathcal{N}(-10,10)$ from time 225 through 250, only the two adaptive strategies track the change (Figure 5a). At time 300, the short noise spike appears in the sensor readings. The per-tuple reservoir is forced to absorb this noise, and the distribution in this reservoir spikes precipitously. As a result, $D0$, which remains at $\mathcal{N}(40,10)$ is falsely suspected as outlying. In contrast, the ADR average value rises slightly but never suspects $D0$ as an outlier. This illustrates the value of MDP's adaptivity to distribution changes and resilience to variable arrival rates.

Production results. MacroBase currently operates over a range of production data and external users report the prototype has discovered previously unknown and sometimes serious behaviors in several domains. Here, we report on our experiences deploying MacroBase at CMT, where it identified several previously unknown behaviors. In one case, MacroBase highlighted a small number of users who experienced issues with their trip detection. In another case, MacroBase discovered a rare issue with the CMT application and a device-specific battery problem. Consultation and investigation with the CMT team confirmed these issues as previously unknown, and have since been addressed. These experiences and others [11] have proven a useful demonstration of MacroBase's ability to prioritize attention in production environments and inspired several ongoing extensions (Section 8).

6.2 End-to-End Performance

In this section, we evaluate MacroBase's end-to-end performance on real-world datasets. For each dataset X, we execute two MacroBase queries: a simple query, with a single attribute and metric (denoted XS), and a complex query, with a larger set of attributes and, when available, multiple metrics (denoted XC). We then report throughput for two system configurations: one-shot batch execution that processes each stage in sequence and exponentially-weighted streaming execution (EWS) that processes points continuously. One-shot and EWS have different semantics, as reflected in the explanations they produce. One-shot execution examines the entire dataset at once. Exponentially weighted streaming prioritizes recent points. Therefore, for datasets with few distinct attribute values (e.g., Accidents contains only nine types of weather conditions), the explanations will have high similarity. However, explanations differ in datasets with many distinct attribute values (typically the complex queries with hundreds of thousands of possible combinations—e.g., Disburse has 138,338 different disbursement recipients). For this reason, we provide throughput results both with and without explanations, as well as the number of explanations generated by the simple (XS) and complex (XC) queries and their Jaccard similarity.

Table 2 displays results across all queries. Throughput varied from 147K points per second (on MC with explanation) to over 2.5M points per second (on TS without explanation); the average throughput for one-shot execution was 1.39M points per second, and the average throughput for EWS was 599K points per second. The better-performing mode depended heavily on the particular data set and characteristics. In general, queries with multiple metrics were slower in one-shot than queries with single metrics (due to increased training time, as streaming trains over samples), and EWS typically returned fewer explanations due to its temporal bias. Generating each explanation at the end of the query incurred an approximately 22% overhead. In all cases, these queries far exceed the current arrival rate of data for each dataset. In practice, users tune their decay on a per-application basis (e.g., at CMT, streaming queries may prioritize trips from the last hour to catch errors arising from the most recent deployment). These throughputs exceed those of related techniques we have encountered in the literature (by up to three orders of magnitude); we examine specific factors that contribute to this performance in the next section.

Runtime breakdown. To further understand how each pipeline operator contributed to overall performance, we profiled MacroBase's one-shot execution (EWS was challenging to instrument accurately due to its streaming execution). On MC, MacroBase spent approximately 52% of its execution training MCD, 21% scoring points, and 26% generating explanations. On MS, MacroBase spent approximately 54% of its execution training MAD, 16% scoring points, and 29% generating explanations. In contrast, on FC, which returned over 1000 explanations, MacroBase spent 31% of its execution training MAD, 4% scoring points, and 65% generating explanations. Thus, the overhead of each component is data- and query-dependent.

6.3 Microbenchmarks and Comparison

In this section, we explore two key aspects of MacroBase's design: cardinality-aware explanation and use of AMC sketches.

Cardinality-aware explanation. We evaluated the efficiency of MacroBase's cardinality-aware pruning compared to traditional FP-Growth. MacroBase leverages a unique pruning strategy that exploits the low cardinality of outliers, which delivers large speedups—on average, over 3× compared to unoptimized FPGrowth. Specifically, MacroBase's produced a summary of each dataset's inliers and outliers in 0.22–1.4 seconds. In contrast, running FPGrowth separately on inliers and outliers was, on average, 3.2× slower; compared to MacroBase's joint explanation according to support and risk ratio, much of the time spent mining inliers (with insufficient risk ratio) in FPGrowth is wasted. However, both MacroBase and FPGrowth must perform a linear pass over all of the inliers, which places a lower bound on the running time. The benefit of this optimization depends on the risk ratio, which we vary in Appendix D.

	Queries				Thru w/o Explain (pts/s)		Thru w/ Explain (pts/s)		# Explanations		Jaccard
Dataset	Name	Metrics	Attrs	Points	One-shot	EWS	One-shot	EWS	One-shot	EWS	Similarity
Liquor	LS	1	1	3.05M	1549.7K	967.6K	1053.3K	966.5K	28	33	0.74
	LC	2	4		385.9K	504.5K	270.3K	500.9K	500	334	0.35
Telecom	TS	1	1	10M	2317.9K	698.5K	360.7K	698.0K	469	1	0.00
	TC	5	2		208.2K	380.9K	178.3K	380.8K	675	1	0.00
Campaign	ES	1	1	10M	2579.0K	778.8K	1784.6K	778.6K	2	2	0.67
	EC	1	5		2426.9K	252.5K	618.5K	252.1K	22	19	0.17
Accidents	AS	1	1	430K	998.1K	786.0K	729.8K	784.3K	2	2	1.00
	AC	3	3		349.9K	417.8K	259.0K	413.4K	25	20	0.55
Disburse	FS	1	1	3.48M	1879.6K	1209.9K	1325.8K	1207.8K	41	38	0.84
	FC	1	6		1843.4K	346.7K	565.3K	344.9K	1710	153	0.05
CMT	MS	1	1	10M	1958.6K	564.7K	354.7K	562.6K	46	53	0.63
	MC	7	6		182.6K	278.3K	147.9K	278.1K	255	98	0.29

Table 2: Datasets and query names, throughput, and explanations produced under one-shot and exponentially weighted streaming (EWS) execution. MacroBase sustains throughput of several hundred thousand (and up to 2.5M) points per second.

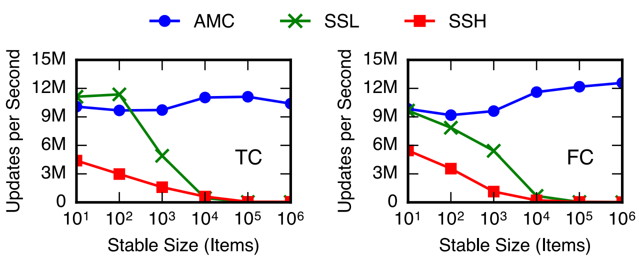


Figure 6: Streaming heavy hitters sketch comparison. AMC: Amortized Maintenance Counter with maintenance every 10K items; SSL: Space Saving List; SSH: Space Saving Hash. All share the same accuracy bound. Varying the AMC maintenance period produced similar results.

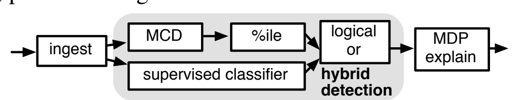
AMC Comparison. We also compared the performance of AMC with existing heavy-hitters sketches (Figure 6). AMC outperformed both implementations of SpaceSaving in all configurations by a margin of up to 500× for sketch sizes exceeding 100 items. This is because the SpaceSaving overhead (heap maintenance on every operation is expensive with even modestly-sized sketches or list traversal is costly for decayed, non-integer counts) is costly. In contrast, with an update period of 10K points, AMC sustained over 10M updates per second. The primary cost of these performance improvements is additional space: for example, with a minimum sketch size of 10 items and update period of 10K points, AMC retained up to 10,010 items while each SpaceSaving sketch retained only 10. As a result, when memory sizes are especially constrained, SpaceSaving may be preferable, at a measurable cost to performance.

Additional results. In Appendix D, we provide additional results examining the distribution of outlier scores, the effect of varying support and risk ratio, the effect of training over samples and operating over varying metric dimensions, the behavior of the M-CPS tree, preliminary scale-out behavior, comparing the runtime of MDP explanation to both existing batch explanation procedures, and MDP detection and explanation to operators from frameworks including Weka, Elki, and RapidMiner.

6.4 Case Studies and Extensibility

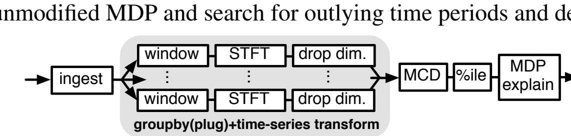
MacroBase is designed for extensibility, as we highlight via case studies in three separate domains. We describe the pipeline structures, performance, and interesting explanations from applying MacroBase over supervised, time-series, and video surveillance data.

Hybrid Supervision. We demonstrate MacroBase's ability to combine supervised and unsupervised classification models via a use case from CMT. Each trip in the CMT dataset is accompanied by a supervised diagnostic score representing the trip quality. While MDP's unsupervised operators can use this score as an input, CMT also wishes to capture low-quality scores independent of their distribution in the population. Accordingly, we authored a new MacroBase pipeline that feeds some metrics (e.g. trip length, battery drain) to the MDP MCD operator and also feeds the diagnostic metric (trip quality score) to a special rule-based operator that flags low quality scores as anomalies. The pipeline, which we depict below, performs a logical *or* over the two classification results:

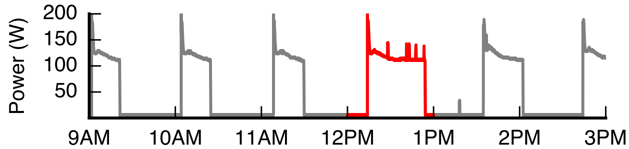


With this hybrid supervision strategy, MacroBase identified additional behaviors within the CMT dataset. Since the quality scores were generated external to MacroBase and the supervision rule in MacroBase was lightweight, runtime was unaffected. This kind of pipeline can easily be extended to more complex supervised models.

Time-series. MacroBase can also detect temporal behaviors via feature transformation, which we demonstrate using a dataset of 16M points capturing a month of electricity usage from devices within a household [12]. We augment MDP by adding a sequence of feature transforms that *i.*) partition the stream by device ID, *ii.*) window the stream into hourly intervals, with attributes according to hour of day, day of week, and date, then *iii.*) apply a Discrete-Time Short-Term Fourier Transform (STFT) to each window, and truncate the transformed data to a fixed number of dimensions. As the diagram below shows, we feed the transformed stream into an unmodified MDP and search for outlying time periods and devices:

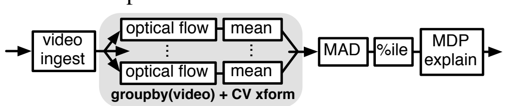


With this custom time-series pipeline, MacroBase detected several systemic periods of abnormal device behavior. For example, the following dataset of power usage by a household refrigerator spiked on an hourly basis (possibly corresponding to compressor activity); instead of highlighting the hourly power spikes, MacroBase was able to detect that the refrigerator consistently behaved abnormally compared to other devices in the household and to other time periods between the hours of 12PM and 1PM—presumably, lunchtime—as highlighted in the excerpt below:



Without feature transformation, the entire MDP pipeline completed in 158ms. Feature transformation dominated the runtime, utilizing 516 seconds to transform the 16M points via unoptimized STFT.

Video Surveillance. We further highlight MacroBase's ability to easily operate over a wide array of data sources and domains by searching for interesting patterns in the CAVIAR video surveillance dataset [1]. Using OpenCV 3.1.0, we add a custom feature transform that computes the average optical flow velocity between video frames, a technique that has been successfully applied in human action detection [30]. Each transformed frame is tagged with a time interval attribute, which we use to identify interesting video segments and, as depicted below, the remainder of the pipeline executes the standard MDP operators:



Using this pipeline, MacroBase detected periods of abnormal motion in the video dataset. For example, the MacroBase pipeline highlighted a three-second period in which two people fought:

Like our STFT pipeline, feature transformation via optical flow dominated runtime (22s vs. 34ms for MDP); this is unsurprising given our CPU-based implementation of an expensive transform but nevertheless illustrates MDP's ability to process video streams.

7. RELATED WORK

In this section, we discuss related techniques and systems.

Streaming and Specialized Analytics. MacroBase is a data analysis system specialized for prioritizing attention in fast data streams. In its architecture, MacroBase builds upon a long history of systems for streaming data and specialized, advanced analytics tasks. A range of systems from both academia [4, 21] and industry (e.g., Storm, StreamBase, IBM Oracle Streams) provide infrastructure for executing streaming queries. MacroBase adopts dataflow as its execution substrate, but its goal is to provide a set of high-level analytic monitoring operators; in MacroBase, dataflow is a means to an end rather than an end in itself. In designing a specialized engine, we were inspired by several past projects, including Gigascope (specialized for network monitoring) [28], WaveScope (specialized for signal processing) [36], MCDB (specialized for Monte Carlo-based operators) [52], and Bismarck (providing extensible aggregation for gradient-based optimization) [33]. In addition, a range of commercially-available analytics packages provide advanced analytics functionality—but, to the best of our knowledge, not the streaming explanation operations we seek here. MacroBase continues this tradition by providing a specialized set of operators for classification and explanation of fast data, which in turn allows new optimizations. We further discuss this design philosophy in [11].

Classification. Classification and outlier detection have an extensive history; the literature contains thousands of techniques from communities including statistics, machine learning, data mining, and information theory [7, 19, 44]. Outlier detection techniques have seen major success in several domains including network intrusion detection [32, 61], fraud detection (leveraging a variety of classifiers and techniques) [14, 64], and industrial automation and predictive maintenance [8, 56]. A considerable subset of these techniques operates over data streams [6, 18, 65, 75].

At stream volumes in the hundreds of thousands or more events per second, statistical outlier detection techniques will (by nature) produce a large stream of outlying data points. As a result, while outlier detection forms a core component of a fast data analytics engine, it must be coupled with streaming explanation. In the design of MacroBase, we treat the array of classification techniques as inspiration for a modular architecture. In MacroBase's default pipeline, we leverage detectors based on robust statistics [46, 57], adapted to the streaming context. However, in this paper, we also demonstrate compatibility with detectors from Elki [72], Weka [38], RapidMiner [45], and OpenGamma [2].

Data explanation. Data explanation techniques assist in summarizing differences between datasets. The literature contains several recent explanation techniques leveraging decision-tree [23] and Apriori-like [39, 80] pruning, grid search [68, 82], data cubing [69], Bayesian statistics [78], visualization [17, 62], causal reasoning [81], and several others [31, 43, 51, 58]. While we are inspired by these results, none of these techniques executes over streaming data or at the scale we seek. Several exhibit runtime exponential in the number of attributes (which can number in the hundreds of thousands to millions in the fast data we examine) [69, 78] and, when reported, runtimes in the batch setting often vary from hundreds to approximately 10K points per second [68, 78, 80] (we also directly compare throughput with several techniques [23, 69, 78, 80] in Appendix D).

To address the demands of streaming operation and to scale to millions of events per second, MacroBase's explanation techniques draw on sketching and streaming data structures (specifically [22, 24, 25, 27, 29, 59, 71, 76]), adapted to the fast data setting. We view existing explanation techniques as a useful second step in analysis following the explanations generated by MacroBase, and we see promise in adapting these existing techniques to streaming execution at high volume. Given our goal of providing a generic architecture for analytic monitoring, future improvements in streaming explanation should be complementary to our results here.

8. CONCLUSIONS AND FUTURE WORK

We have presented MacroBase, a new analytics engine designed to prioritize attention in fast data streams. MacroBase provides a flexible architecture that combines streaming classification and data explanation techniques to deliver interpretable summaries of important behavior in fast data streams. MacroBase's default analytics operators, which include new sampling and sketching procedures, take advantage of this combination of detection and explanation and are specifically optimized for high-volume, time-sensitive, and heterogeneous data streams, resulting in improved performance and result quality. This emphasis on flexibility, accuracy, and speed has proven useful in several production deployments, where MacroBase has already identified previously unknown behaviors.

MacroBase is available as open source and is under active development. The system serves as the vehicle for a number of ongoing research efforts, including techniques for temporally-aware explanation, heterogeneous sensor data fusion, online non-parametric density estimation, and contextual outlier detection. Ongoing production use cases continue to stimulate the development of new functionality to expand the set of supported domains and leverage the flexibility provided by MacroBase's pipeline architecture.

Acknowledgments

We thank the many members of the Stanford InfoLab, our collaborators at MIT and Waterloo, Ali Ghodsi, Joe Hellerstein, Mark Phillips, Leif Walsh, and the early adopters of the MacroBase prototype for providing feedback on and inspiration for this work. This research was supported in part by Toyota Research Institute, Intel, the Army High Performance Computing Research Center, RWE AG, Visa, Keysight Technologies, Facebook, VMWare, and Philips Lighting, and by the NSF Graduate Research Fellowship under grants DGE-114747 and DGE-1656518. As MacroBase is open source and publicly available, there is no correspondence—either direct or implied—between the use cases described in this work and the above institutions that supported this research.

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APPENDIX

A. CLASSIFICATION

MCD. Computing the exact MCD requires examining all subsets of points to find the subset whose covariance matrix exhibits the minimum determinant. This is computationally intractable for even modestly-sized datasets. Instead, MacroBase adopts an iterative approximation called FastMCD [67]. In FastMCD, an initial subset of points S_0 is chosen from the input set of points P. FastMCD computes the covariance C_0 and mean μ_0 of S_0, then performs a "C-step" by finding the set S_1 of points in P that have the $|S_1|$ closest Mahalanobis distances (to C_0 and μ_0). FastMCD subsequently repeats C-steps (i.e., computes the covariance C_1 and mean μ_1 of S_1, selects a new subset S_2 of points in P, and repeats) until the change in the determinant of the sample covariance converges (i.e., $det(S_{i-1}) - det(S_i) < \varepsilon$, for small ε). To determine which dimensions are most anomalous in MCD, MacroBase uses the corr-max transformation [35].

Handling variable ADR arrival rates. We consider two policies for collecting samples using an ADR over real-time periods with variable tuple arrival rates. The first is to compute a uniform sample per decay period, with decay across periods. This can be achieved by maintaining an ADR for the stream contents from all prior periods and a regular, uniform reservoir sample for the current period. At the end of the period, the period sample can be inserted into the ADR. The second policy is to compute a uniform sample over time, with decay according to time. In this setting, given a sampling period (e.g., 1s), for each period, insert the average of all points.

Contamination plot details. In Figure 3, we examine a dataset of 10M points drawn from two distributions: a uniform *inlier* distribution, with radius 50 centered at the origin, and a uniform *outlier* distribution, with radius 50 centered at (1000, 1000). We varied the proportion of points in each to evaluate the effect of contamination on the Z-Score, MAD, and MCD (using univariate points for Z-Score and MAD).

B. EXPLANATION

Streaming combinations: CPS-tree adaptation. Given the set of recently frequent items, MDP monitors the attribute stream for frequent attribute combinations by maintaining a frequency-descending prefix tree of attribute values: the CPS-tree data structure [76], with several modifications, which we call the M-CPS-tree. Like the CPS-tree, the M-CPS-tree maintains both the basic FP-tree data structures as well as a set of leaf nodes in the tree. However, in an exponentially damped model, the CPS-tree stores at least one node for every item ever observed in the stream. This is infeasible at scale. As a compromise, the M-CPS-tree only stores items that were frequent in the previous window: at each window boundary, MacroBase updates the frequent item counts in the M-CPS-tree based on its AMC sketch. Any items that were frequent in the previous window but were not frequent in this window are removed from the tree. MacroBase then decays all frequency counts in the M-CPS-tree nodes and re-sorts the M-CPS-tree in frequency descending order (as in the CPS-tree, by traversing each path from leaf to root and re-inserting as needed). Subsequently, attribute insertion can continue as in the FP-tree.

Confidence. To provide confidence intervals on its output explanations and prevent false discoveries (type I errors, our focus here), MDP leverages existing results from the epidemiology literature, applied to the MDP data structures. For a given attribute combination appearing a_o times in the outliers and a_i times in the inliers, with a risk ratio of o, b_o other outlier points, and b_i other inlier points, we can compute a $1-p\%$ confidence interval as:

$$o \pm \exp\left(z_p\sqrt{\frac{1}{a_o} - \frac{1}{a_o+a_i} + \frac{1}{b_o} - \frac{1}{b_o+b_i}}\right)$$

where z_p is the z-score corresponding to the $1-\frac{p}{2}$ percentile [60]. For example, an attribute combination with risk ratio of 5 that appears in 1% of 10M points has a 95th percentile confidence interval of $(3.93, 6.07)$ (99th: $(3.91, 6.09)$). Given a risk ratio threshold of 3, MacroBase can return this explanation with confidence.

However, because MDP performs a repeated set of statistical tests to find attribute combinations with sufficient risk ratio, MDP subject to the multiple testing problem: large numbers of statistical tests are statistically likely to contain false positives. To address this problem, MDP can apply a correction to its intervals. For example, under the Bonferroni correction [70], if a user seeks a confidence of $1-p$ and MDP tests k attribute combinations, MDP should instead assess the confidence for z_p at $1-\frac{p}{k}$. We can compute k at explanation time by recording the number of support computations.

k is likely to be large as, in the limit, MDP may examine the power set of all attribute values in the outliers. However, with fast data, this is less problematic. First, the pruning power of MDP's explanation routine eliminates many tests, thus reducing type I errors. Second, empirically, many of MacroBase's explanations have very high risk ratio—often in the tens or hundreds. This is because many problematic behaviors are highly systemic, meaning large intervals may still be above the user-specified risk ratio threshold. Third, and perhaps most importantly, MacroBase analyzes large streams. In the above example, even with $k = 10M$, the 95th percentile confidence interval is still $(3.80, 6.20)$. Compared to medical studies with study sizes in the range of hundreds of samples, the large volume of data mitigates many of the problems associated with multiple testing. For example, the same $k = 10M$ yields a 95th percentile confidence interval of $(0, 106M)$ when applied to a dataset of only 1000 points, which is effectively meaningless. (This trend also applies to alternative corrective methods such as the Benjamini-Hochberg procedure [13].) Thus, while the volumes of fast data streams pose significant computational challenges, they can actually improve the statistical quality of analytics results.

C. IMPLEMENTATION

In this section, we describe the MacroBase prototype implementation and runtime. As of February 2017, MacroBase's core comprises approximately 9,400 lines of Java, over 7,000 of which are devoted to operator implementation, along with an additional 1,000 lines of Javascript and HTML for the front-end and 7,600 lines of Java for diagnostics and prototype pipelines.

	LS	TS	ES	AS	FS	MS
Throughput (points/sec)	7.86M	8.70M	9.35M	12.31M	7.05M	6.22M
Speedup over Java	7.46×	24.11×	5.24×	16.87×	5.32×	17.54×

Table 3: Speedups of hand-optimized C++ over Java MacroBase prototype for simple queries (queries from Section 6).

We chose Java due to its high productivity, support for higher-order functions, and popularity in open source. However, there is considerable performance overhead associated with the Java virtual machine (JVM). Despite interest in bytecode generation from high-level languages such as Scala and .NET [20, 53], we are unaware of any generally-available, production-strength operator generation tools for the JVM. As a result, MacroBase leaves performance on the table in exchange for programmer productivity. To understand the performance gap, we rewrote a simplified MDP pipeline in hand-optimized C++. As Table 3 shows, we measure an average throughput gap of 12.76× for simple queries. JVM code generation will reduce this gap.

MacroBase executes operator pipelines via a custom single-core dataflow execution engine. MacroBase's streaming dataflow decouples producers and consumers: each operator writes (i.e,. pushes) to an output stream but consumes tuples as they are pushed to the operator by the runtime (i.e., implements a `consume(OrderedList<Point>)` interface). This facilitates a range scheduling policies: operator execution can proceed sequentially, or by passing batches of tuples between operators. MacroBase supports several styles of pipeline construction, including a fluent, chained operator API. By default, MacroBase amortizes calls to `consume` across several thousand points, reducing function call overhead. This API also allows stream multiplexing and is compatible with a variety of existing dataflow execution engines, including Storm, Heron, and Amazon Streams, which could act as future execution substrates. We demonstrate interoperability with several existing data mining frameworks in Appendix D.

The MacroBase prototype does not currently implement fault tolerance, although classic techniques such as state-based checkpointing are applicable here [49], especially as MDP's operators contain modest state. The MacroBase prototype is also oriented towards single-core deployment. For parallelism, MacroBase currently runs one query per core (e.g., one query pipeline per application cluster in a datacenter). We report on preliminary multi-core scale-out results in Appendix D.

The MacroBase prototype and all code evaluated in this paper are available online under a permissive open source license.

D. EXPERIMENTAL RESULTS

Dataset descriptions. CMT contains user drives at CMT, including anonymized metadata such as phone model, drive length, and battery drain; Telecom contains aggregate internet, SMS, and telephone activity for a Milanese telecom; Accidents contains statistics about United Kingdom road accidents between 2012 and 2014, including road conditions, accident severity, and number of fatalities; Campaign contains all US Presidential campaign expenditures in election years between 2008 and 2016, including contributor name, occupation, and amount; Disburse contains all US House and Senate candidate disbursements in election years from 2010 through 2016, including candidate name, amount, and recipient name; and Liquor contains sales at liquor stores across the state of Iowa. All but CMT are *i.*) publicly accessible, allowing reproducibility, and *ii.*) representative of many challenges we have encountered in analyzing production data beyond CMT in both scale and behaviors. While none of these datasets contain ground-truth labels, we have verified several of the explanations from our queries over CMT.

Score distribution. We plot the CDF of scores in each of our real-world dataset queries in Figure 7. While many points have high outlier scores, the tail of the distribution (at the 99th percentile) is extreme: a very small proportion of points have outlier scores over over 150. Thus, by focusing on this small upper percentile, MDP highlights the most extreme behaviors.

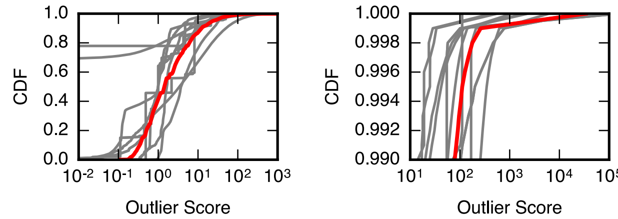

Figure 7: CDF of outlier scores for all datasets, with average in red; the datasets exhibit a long tail with extreme outlier scores at the 99th percentile and higher.

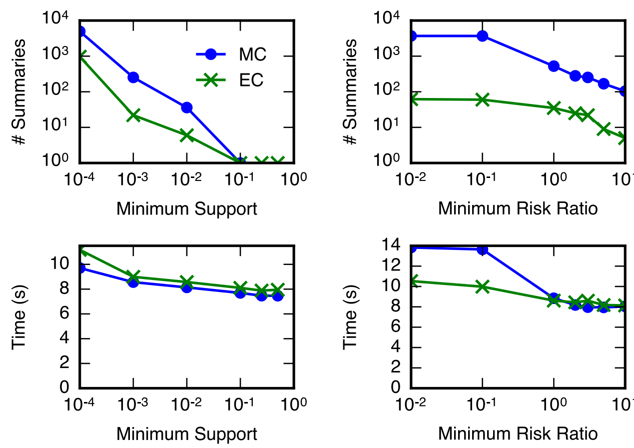

Figure 8: Number of summaries produced and summarization time under varying support (percentage) and risk ratio.

Varying support and risk ratio. To understand the effect of support and risk ratio threshold on explanation, we varied each and measured the resulting runtime and the number of summaries produced on the EC and MC datasets, which we plot in Figure 8. Each dataset has few attributes with outlier support greater than 10%, but each had over 1700 with support greater than 0.001%. Modifying the support threshold beyond 0.01% had limited impact on runtime; most time in explanation is spent in simply iterating over the inliers rather than maintaining tree structures. This effect is further visible when varying the risk ratio, which has less than 40% impact on runtime yet leads to an order of magnitude change in number of summaries. Our default setting of support and risk ratio yields a sensible trade-off between number of summaries produced and runtime.

Operating on samples. MDP periodically trains models using samples from the input distribution. The statistics literature offers confidence intervals on the MAD [73] and the Mahalanobis distance [66] (e.g., for a sample of size n, the confidence interval of MAD shrinks with $n^{1/2}$), while MCD converges at a rate of $n^{-1/2}$ [16]. To empirically evaluate these effects, we measured the accuracy and efficiency of training models on samples from a 10M point dataset. In Figure 9, we plot the outlier classification accuracy versus sample size for the CMT queries. MAD precision and recall are largely unaffected by sampling, allowing a two order-of-magnitude speedup without loss in accuracy. In contrast, MCD accuracy is slightly more sensitive due to variance in the sample selection. This variance is partially offset by the fact that models are retrained regularly under streaming execution, and the resulting speedups in both models are substantial.

Metric scalability. As Figure 10 demonstrates, MCD train and score throughput (here, over Gaussian data) is linearly affected by data dimensionality, encouraging the use of dimensionality reduction techniques for complex data.

M-CPS and CPS behavior. We also investigated the behavior of the M-CPS-tree compared to the generic CPS-tree. The two data structures

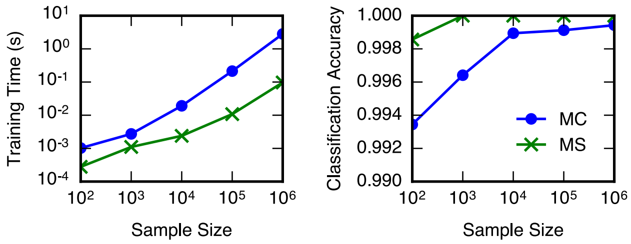

Figure 9: Behavior of MAD (MS) and MCD (MC) on samples.

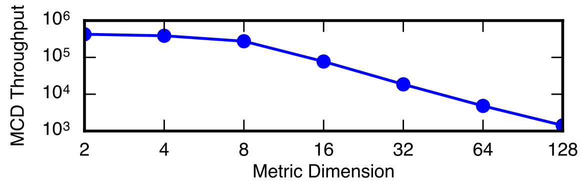

Figure 10: MCD throughput versus metric size.

have different behaviors and semantics: the M-CPS-tree captures only itemsets that are frequent for at least two windows by leveraging an AMC sketch. In contrast, CPS-tree captures all frequent combinations of attributes but must insert each point's attributes into the tree (whether supported or not) and, in the limit, stores (and re-sorts) all items ever observed in the stream. As a result, across all queries except ES and EC, the CPS-tree was on average 130x slower than the M-CPS-tree (std dev: 213x); on ES and EC, the CPS-tree was over 1000x slower. The exact speedup was influenced by the number of distinct attribute values in the dataset: Accidents had few values, incurring 1.3x and 1.7x slowdowns, while Campaign had many, incurring substantially greater slowdowns

Preliminary scale-out. As a preliminary assessment of MacroBase's potential for scale-out, we examined MDP behavior under a naïve, shared-nothing parallel execution strategy. We partitioned the data across a variable number of cores of a server containing four Intel Xeon E7-4830 2.13 GHz CPUs and processed each partition in parallel; upon completion, we return the union of each core's explanation. As Figure 11 shows, this strategy delivers excellent linear scalability. However, as each core processes a sample of the overall dataset, accuracy suffers due to both model drift (as in Figure 9) and lack of cross-partition cooperation in summarization. For example, with 32 partitions spanning 32 cores, FS achieves throughput nearing 29M points per second, with perfect recall, but only 12% accuracy. Improving accuracy while maintaining scalability is the subject of ongoing work.

Explanation runtime comparison. Following the large number of recent data explanation techniques (Section 7), we implemented several additional methods. The results of these methods are not comparable, and prior work has not evaluated these techniques with respect to one another in terms of semantics or performance. We do not attempt a full comparison based on semantics but do perform a comparison based on running time, which we depict in Table 5. We compared to a data cubing strategy suggested by Roy and Suciu [69], which generates counts for all possible combinations (21x slower), Apriori itemset mining [39] (over 43x slower), and Data X-Ray [78]. Cubing works better for data

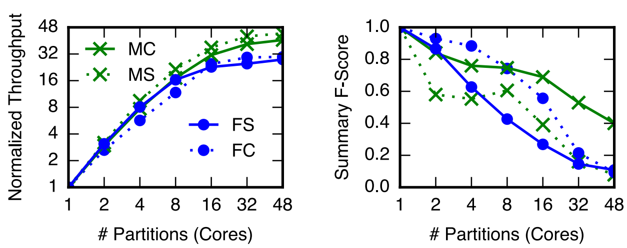

Figure 11: Behavior of naïve, shared-nothing scale-out.

TPC-C (QS: one MacroBase query per cluster): top-1: 88.8%, top-3: 88.8%									
	A1	A2	A3	A4	A5	A6	A7	A8	A9
Train top-1 correct (of 9)	9	9	9	9	9	8	9	9	8
Holdout top-1 correct (of 2)	2	2	2	2	2	2	2	2	0
TPC-C (QE: one MacroBase query per anomaly type): top-1: 83.3%, top-3: 100%									
	A1	A2	A3	A4	A5	A6	A7	A8	A9
Train top-1 correct (of 9)	9	9	9	9	9	8	9	9	7
Holdout top-1 correct (of 2)	2	2	2	2	2	1	2	2	0
TPC-E (QS: one MacroBase query per cluster): top-1: 83.3%, top-3: 88.8%									
	A1	A2	A3	A4	A5	A6	A7	A8	A9
Train top-1 correct (of 9)	9	9	9	9	9	8	9	9	0
Holdout top-1 correct (of 2)	2	2	2	2	2	1	2	2	0
TPC-E (QE: one MacroBase query per anomaly type): top-1: 94.4%, top-3: 100%									
	A1	A2	A3	A4	A5	A6	A7	A8	A9
Train top-1 correct (of 9)	9	9	9	9	9	8	9	9	6
Holdout top-1 correct (of 2)	2	2	2	2	2	1	2	2	2

Table 4: MDP accuracy on DBSherlock workload. A1: workload spike, A2: I/O stress, A3: DB backup, A4: table restore, A5: CPU stress, A6: flush log/table; A7: network congestion; A8: lock contention; A9: poorly written query. "Poor physical design" (from [81]) is excluded as the labeled anomalous regions did not exhibit significant correlations with any metrics.

Query	MB	FP	Cube	DT10	DT100	AP	XR
LC	1.01	4.64	DNF	7.21	77.00	DNF	DNF
TC	0.52	1.38	4.99	10.70	100.33	135.36	DNF
EC	0.95	2.82	16.63	16.19	145.75	50.08	DNF
AC	0.22	0.61	1.10	1.22	1.39	9.31	6.28
FC	1.40	3.96	71.82	15.11	126.31	76.54	DNF
MC	1.11	3.23	DNF	11.45	94.76	DNF	DNF

Table 5: Running time of explanation algorithms (s) for each complex query. MB: MacroBase, FP: FPGrowth, Cube: Data cubing; DTX: decision tree, maximum depth X; AP: A-Aprioi; XR: Data X-Ray. DNF: did not complete in 20 minutes.

with fewer attributes, while Data X-Ray is optimized for hierarchical data; we have verified with the authors of Data-XRay that, for MacroBase's flat attributes, Data X-Ray will consider all combinations unless stopping criteria are met. MacroBase's cardinality-aware explanation completes fastest for all queries.

Compatibility with existing frameworks. We implemented several additional MacroBase operators to validate interoperability with existing data mining packages. We were unable to find a single framework that implemented both unsupervised outlier detection and data explanation and had difficulty locating streaming implementations. Nevertheless, we implemented two MacroBase outlier detection operators using Weka 3.8.0's `KDTree` and Elki 0.7.0's `SmallMemoryKDTree`, an alternative FastMCD operator based on a recent RapidMiner extension (`CMGOSAnomalyDetection`) [37], an alternative MAD operator from the OpenGamma 2.31.0, and an alternative FPGrowth-based summarizer based on SPMF version v.0.99i. As none of these packages allowed streaming operation (e.g., Weka allows adding points to a `KDTree` but does not allow removals, while Elki's `SmallMemoryKDTree` does not allow modification), we implemented batch versions. We do not perform accuracy comparisons here but note that the kNN performance was substantially slower (>100x) than MDP's operators (in line with recent findings [37]) and, while SPMF's operators were faster than our generic FPGrowth implementation, SPMF was still 2.8× slower than MacroBase due to MDP's cardinality-aware optimizations. The primary engineering overheads came from adapting to each framework's data formats; however, with a small number of utility classes, we were able to easily compose operators from different frameworks and also from MacroBase, without modification. Should these frameworks begin to prioritize streaming execution and/or explanation, this interoperability may prove fruitful in the future.