Real-Time Stream Mining: Online Knowledge Extraction Using Classifier Networks

Luca Canzian and Mihaela van der Schaar

The world is increasingly information-driven. Vast amounts of data are being produced by different sources and in diverse formats. It is becoming critical to endow assessment systems with the ability to process streaming information from sensors in real time in order to better manage physical systems, derive informed decisions, tweak production processes, and optimize logistics choices. This article first surveys the works dealing with building, adapting, and managing networks of classifiers, then describes the challenges and limitations of the current approaches, discusses possible directions to deal with these limitations, and presents some open research questions that need to be investigated.

The world is increasingly information-driven. Vast amounts of data are being produced by different sources and in diverse formats, including physiological measurements [1], tweets [2], and multimedia files [3]. Many businesses and government institutions are also embracing automation, and relying on a variety of sensors and infrastructure to collect, store, and analyze data on a continuous basis. It is becoming critical to endow assessment systems with the ability to process *streaming* information from sensors in real time in order to better manage physical systems, derive informed decisions, tweak production processes, and optimize logistics choices.

Stream mining refers to the broad class of techniques that can be used in *sense-and-respond* systems that *continuously* receive data streams from multiple sources and employ *analytics* aimed at detecting multiple concepts and turning the data into actionable information. An example of a stream mining application (SMA) is the surveillance application represented in Fig. 1, which is adopted as a case study throughout the article. In this application, multiple aerial and ground reconnaissance videos are collected by different cameras and processed in real time by a *network of classifiers* that are trained to detect different high-level semantic features. In practice, the classifiers are localized across distributed and interconnected processing nodes. Figure 2 shows a specific classifier network for a video stream acquired by a single camera, whereas Fig. 3 shows an example of how the classifiers are localized across distributed and interconnected processing nodes. The configu-

ration of each classifier and the network topology (i.e., how classifiers are interconnected) must adapt to both the characteristics of the video streams and to the currently available system resources (e.g., CPU, memory, I/O bandwidth). The results of the processing are finally used to take informed actions (e.g., to turn cameras on or off, to dynamically open or close some roads, and to provide evacuation paths).

The development of efficient stream mining mechanisms to extract the relevant knowledge from the data streams and make timely decisions based on this knowledge will benefit from the confluence of two major scientific and technological shifts:
• Advances in basic techniques in learning, data mining, and real-time data analytics
• Advances in building, adapting, and managing networks of classifiers.

Currently, the focus of the learning and data mining communities has been on the former research agenda, but with the emergence of applications relying on runtime decisions based on high-rate data streams that are analyzed multiple times (in multiple locations and with different analytics), the latter research area is becoming increasingly important.

This magazine article first surveys the works dealing with building, adapting, and managing networks of classifiers, then escribes the challenges and limitations of the current approaches, discusses possible directions to deal with these limitations, and presents some open research questions that need to be investigated

Network of Classifiers

An SMA can be viewed as a processing pipeline that analyzes streaming data from a set of raw data sources to extract valuable information in real time. Due to the naturally distributed set of data sources and classification tasks, as well as the high computational complexity of the analytics, distributed stream mining systems have been developed recently [4]. These systems leverage computational resources from a set of heteroge-
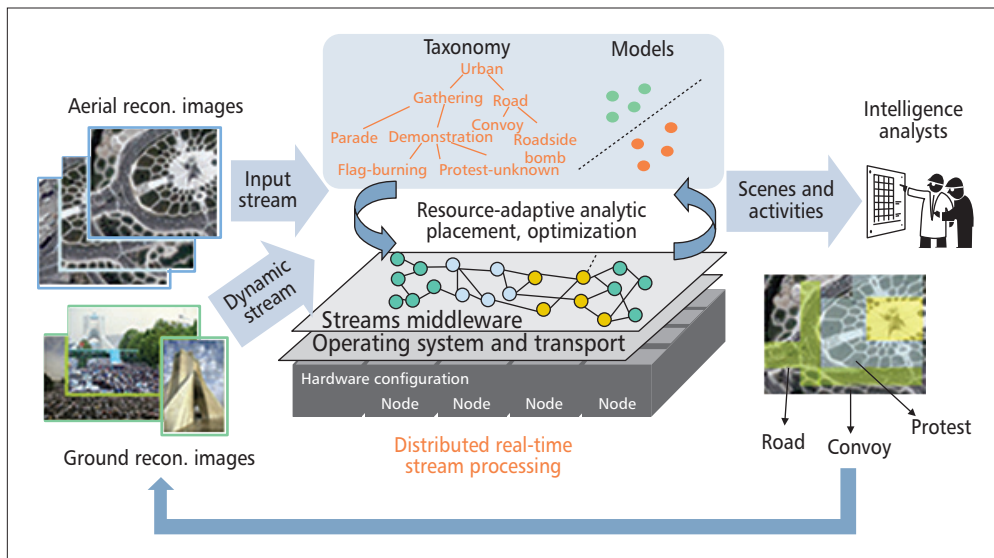
Figure 1. A hierarchical classifier system for surveillance applications. The acquired data is analyzed by multiple classifiers trained to detect different high-level semantic features. The order in which classifiers are invoked depends on the network topology and the intermediate processing results.

neous and distributed processing nodes (ranging from personal computers and residential gateways to large-scale data centers), and provide the framework to deploy and run different SMAs on various network topologies. In such systems, complex jobs are decomposed into a network of operators in order to enhance scalability and reliability, and allow cost-performance trade-offs.

In this article, we focus on SMAs that are built using a network topology of low-complexity *binary classifiers*. Binary classifiers are processing elements that partition their input data into two classes of interest. These may be used to filter out irrelevant information or annotate multimedia data with different attributes relevant to the mining task.

Figure 2 represents a specific network of classifiers that processes the video acquired by a single camera for a surveillance application. Different classifiers are trained to detect different high-level semantic features. For example, the Gathering classifier is used to filter the incoming data into two streams, thereby shedding a significant volume of data before passing it to the downstream classifiers: positively identified data is forwarded to the Demonstration classifier, and the remaining data is forwarded to the Suspicious person classifier. Classifiers can be located at the same processing node or across different nodes. For instance, in Fig. 3 the Gathering classifier is located in the same node (i.e., processing node 1) of the camera, whereas the Suspicious person and Crime classifiers, which are specialized to detect situations involving a single individual, are located in processing node 4.

Deploying a network of classifiers in this manner enables successive identification of multiple features in the data, and provides significant advantages in terms of deployment costs and processing delays. Indeed, fewer computing resources are required because data is dynamically filtered through the network, and the analysis of multiple data can be carried on in parallel (e.g., while the current data is analyzed by the Demonstration classifier, other data can be acquired and analyzed by the Gathering classifier.

This article does not focus on classifier design, for which many solutions already exist; instead, it describes configuring networks of distributed classifiers while trading off the processing accuracy against the available processing resources or the incurred processing delays. There are two types of config-

uration choices we discuss: the ordering of networked classifiers into processing topologies and the local operating points at each classifier. As is made clear later, this problem can be formulated as a network optimization problem (NOP) [5]. In fact, the classifiers in Fig. 2 act as routers that forward the data to other classifiers. However, different from traditional NOPs, the classifiers not only route or discard data based on the current network condition; they also need to process the data and make routing decisions based on both the network conditions and the results of such processing. Importantly, the operating point of one classifier influences the distribution of input data to downstream classifiers; therefore, the configuration of the network and the operating points of *all* the classifiers are coupled in the optimization problem, making it significantly more complex than traditional NOPs.

Challenges for Stream Mining Applications

There is a unique combination of multiple features that distinguishes SMAs from traditional data analysis paradigms. We summarize these features in the following.

Large-Scale System of Autonomous Nodes
SMAs need the development of frameworks for knowledge extraction from the high volume of distributed data streams. As a consequence, SMAs need decentralized approaches. Indeed, in the surveillance application it would be infeasible, requiring the cameras to acquire images on a continuous basis with the highest resolution and send them to a central processing unit for complex data analytics; this approach would require huge communication bandwidth and energy consumption, and long transmission and processing delays. In practice, classifiers need to be distributed over a set of processing nodes, which can exchange only limited and/or costly messages and make decisions autonomously, based on the information available to them. This involves formally defining local objectives and associated inter-node message exchanges that enable the decomposition of the application into a set of autonomously operating nodes, while ensuring global performance. Moreover, since the autonomous classifiers need to interact to fulfill the demands of an application, the nodes need to learn online the effect of both their experienced
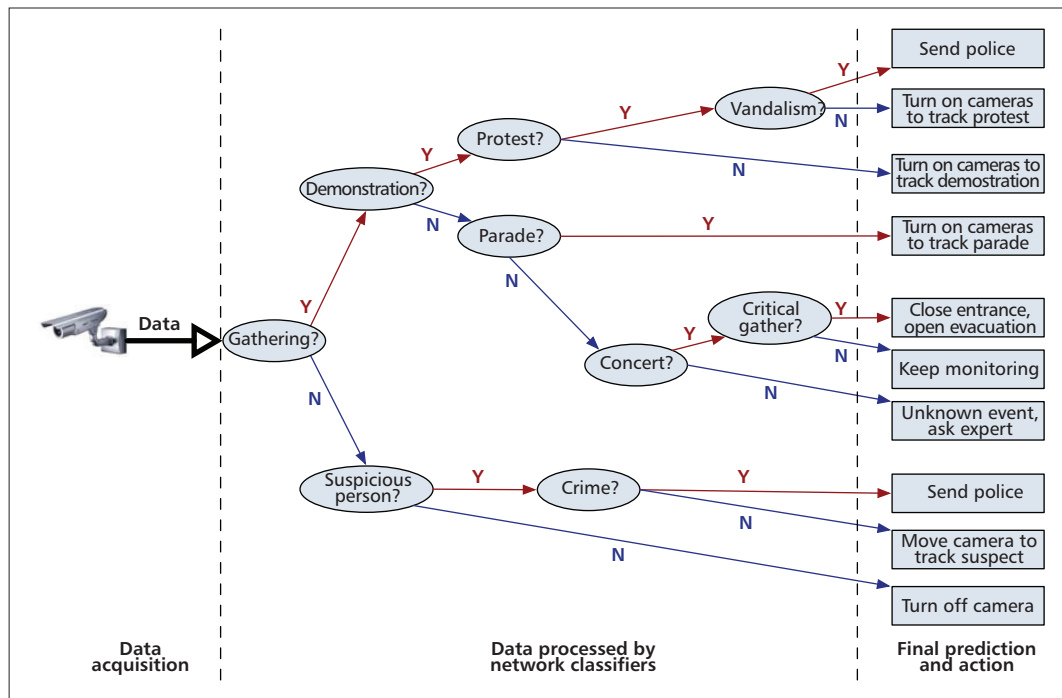
Figure 2. A hierarchical classifier system for surveillance applications. The acquired data is analyzed by multiple classifiers trained to detect different high-level semantic features. The order in which classifiers are invoked depends on the network topology and the intermediate processing results.

dynamics as well as the coupling with the other classifiers with which they interact in meeting the demands of an SMA.

Timing Issues

For many SMAs, high-volume data streams (e.g., video data streams) must be processed in real time. For example, a surveillance application needs to detect with low latency a crime in order to inform the police and catch the criminal before he/she escapes, and it must foresee situations such as a high and increasing density of people in order to open evacuation paths before the density level becomes critical. SMAs need to meet the desired delay requirements while minimizing misclassification and other costs. This is all the more challenging in a distributed environment, where the synchronization among nodes may not be possible or may lead to sub-optimal designs, as various nodes may experience different environmental dynamics and demands.

Resource Constraints

A key challenge in distributed real-time stream mining systems arises from the need to cope effectively with system overload, due to large data volumes and limited system resources (e.g., CPU, memory, I/O bandwidth). In fact, the computational cost incurred by a classifier limits the amount of input data that the classifier can handle. For example, detecting suspicious actions in crowded places may require a processing time that is longer than the acquisition time, which means that the acquired video must be filtered by other low-complexity classifiers before invoking the classifier that is responsible for detecting suspicious actions.

Learning and Adaptation to Dynamics

SMAs naturally evolve over time due to:
• Heterogeneous and dynamic data stream characteristics
• Classifier dependencies
• Congestion at shared processing nodes
• Communication delays between processing nodes
For example, the detection of criminal activities during excep-

tional events (e.g., concerts) may be more complex — in terms of both accuracy and resource requirements — than during a normal day. Additionally, several different queries may need to be satisfied by the system, requiring reconfiguration as queries change dynamically. Hence, the proposed solutions must employ online learning algorithms to learn how to adapt the classifier network topology and the classifier operating points in order to cope with all of these experienced dynamics.

Current Approaches for Stream Mining

In this section, we describe the traditional approaches that have been considered to deal with stream mining systems, and we discuss some limitations associated with such approaches. We divide the literature into two parts: we first review works dealing with the construction of the classifier topology, and then review works dealing with the adaptation of stream mining systems to resource constraints.

Building a Network of Classifiers

Stream mining systems build on distributed mining systems and query optimization research [6]. In such systems, stream processing jobs are built as topologies of distributed operators performing feature extraction, classification, aggregation, and correlation [4, 7].

The topology construction problem has been studied as part of the broader pipeline ordering problem [8, 9] as well as the classical set-cover problem [10] in query optimization. To minimize the end-to-end processing time, these approaches design low-complexity algorithms to order a set of filters applied to streaming data. They use centralized greedy optimization techniques to derive the appropriate order, and develop bounds on performance in terms of approximation factors to the utility of the optimal solution.

However, the focus of the above works has been on simple and deterministic operators. For instance, they only consider perfect classifiers (i.e., classifiers that make no mistakes). The
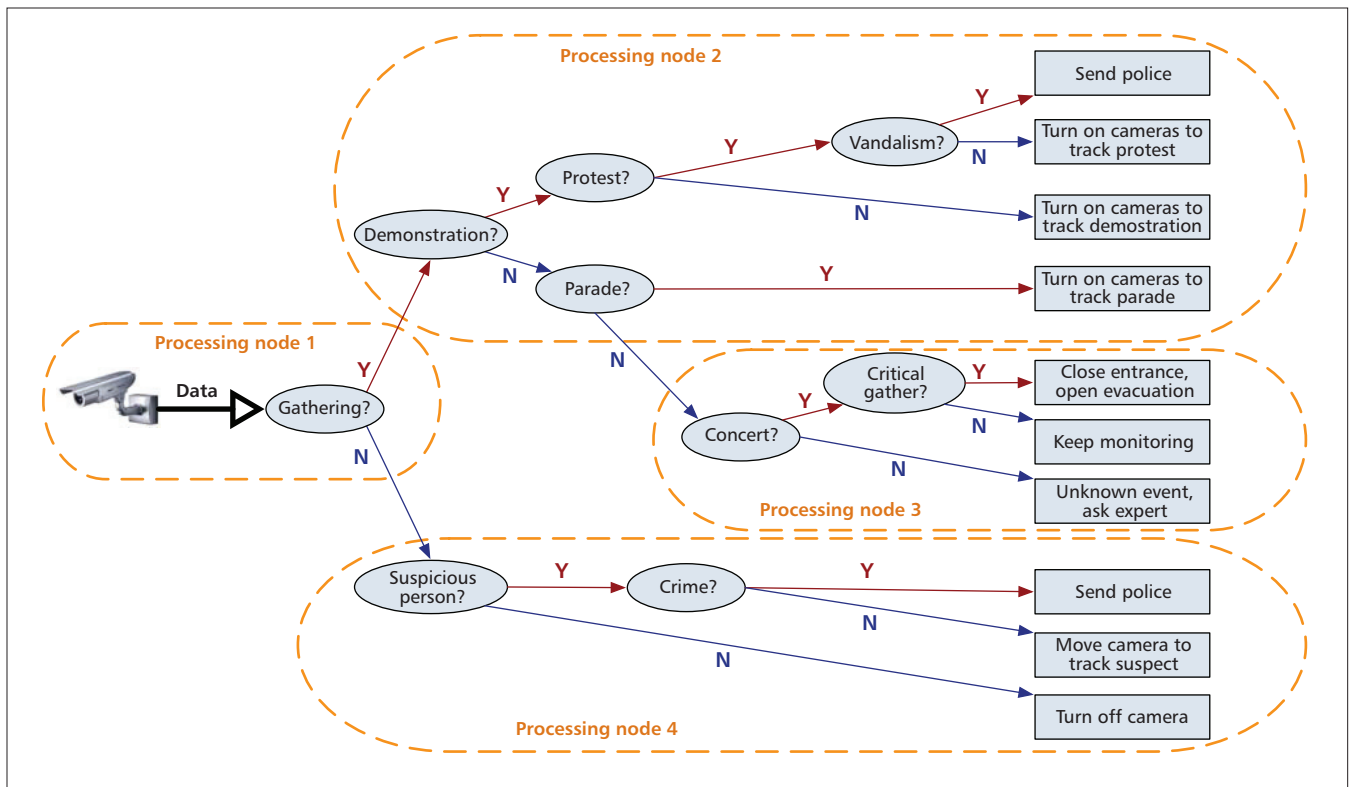
Figure 3. Classifiers are localized across different autonomous processing nodes.

extension of such approaches to real classifiers, which are subject to mistakes, is not trivial for a number of reasons. First, a classifier mistake can have repercussions on the rest of the network, causing either an increase in the end-to-end processing time or mistakes in the final results of the stream mining system. As a consequence, the system accuracy and the end-to-end processing time must be jointly optimized. Second, classifiers can operate in different configurations in order to trade off among different types of errors, and the performance of an individual classifier is coupled to the performance of the other classifiers to which it is connected. As a consequence, the optimal topology also depends on the configurations of all the classifiers, and the optimal system design involves a joint optimization over the topology and the classifier configurations.

Additionally, the above approaches do not support dynamic adaptation to environment characteristics, and neglect computational and network resource constraints (e.g., CPU, memory, I/O bandwidth). Indeed, they are based on centralized algorithms, which require information about each classifier operating point to be available at one node, and for that node to manage the entire classifier network. Centralized approaches are limited in their scalability and adaptivity to dynamics, are subject to a single point of failure, and require exchange of information among the nodes of the distributed stream mining system. A key research challenge in distributed stream mining systems is the management of limited network resources while providing the desired application performance.

Adaptation to Resource Constraints

A significant body of work exists discussing how to adapt stream mining systems to resource constraints [6, 11, 12]. The majority of these approaches are based on load-shedding algorithms, which determine when, where, what, and how much data to discard given the observed data characteristics, quality of service requirements, available resources, and delay constraints.

Naive load shedding performs well for simple data management jobs such as windowing or aggregation, for which the quality of job results depends only on the sample size. However, such simple relationships between quality and sample size do not hold for more complex data classification tasks, where results depend on dynamic statistical properties of the data, semantic relationships between the concepts of interest, underlying features extracted, and selected classification algorithms.

There is also work on intelligent load shedding [13], where a load shedder attempts to maximize a quality of decision measure based on the predicted distribution of temporally correlated feature values. However, the approach in [13] considers information pertaining to only a single classifier. Without jointly considering the resource constraints at possibly multiple downstream classifiers in the network, the joint classification performance can be highly suboptimal, and the end-to-end processing delay for a cascade of classifiers can become intolerable for real-time applications.

Other proposed solutions include using an ensemble of classifiers with adjustable operating points (e.g., detection thresholds) to enable joint optimization of the quality of classification and resource requirements [14]. However, [14] imposes subset relationships between filters, which may not hold when the classification task aims to find data at the intersection of different high-level semantic features for which no subset relationship exists.

Finally, as for the literature dealing with topology construction, the majority of approaches to adapting the classifier operating points to resource constraints are based on centralized algorithms, and suffer from the drawbacks discussed earlier.

Advanced Techniques for Stream Mining

In this section, we describe frameworks to deal with the SMA features discussed earlier, and we review relevant works that consider and analyze similar frameworks. Specifically, our focus will be on constructing, managing, and adapting topolo-
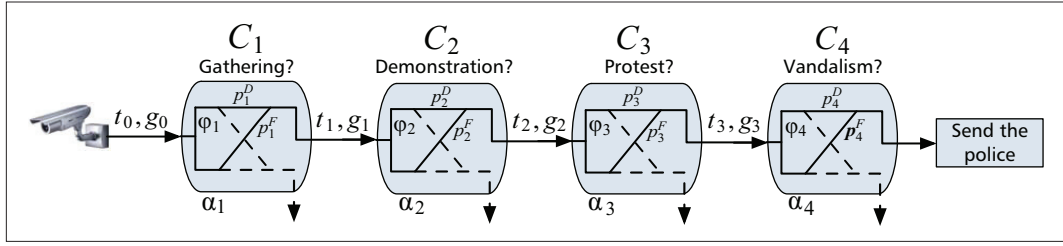
Figure 4. A chain of classifiers to detect vandalism acts during protests.

gies of distributed classifiers deployed on a set of resource constrained and heterogeneous processing nodes. The final goal is to develop learning and adaptive schemes that guarantee the quality of the decisions for the queries, have low delay, are able to adapt to the stream and application dynamics, and gracefully scale to the number of queries and processing nodes.

Building the Classifier Topology: A Network Optimization Problem

SMAs pose queries on data that require multiple concepts to be identified. More specifically, a query is answered as a conjunction of a set of N classifiers $\mathcal{C} = \{C_1, ..., C_N\}$, each associated with a concept to be identified. For example, the 10 different queries represented in Fig. 2 (protests with vandalism acts, civil protests, parades, etc.) are answered as a conjunction of nine classifiers specialized to detect concepts ranging from a group of individuals who are gathering in a place to a single individual who is committing a criminal action. By partitioning the problem into this ensemble of classifiers and filtering data successively, the amount of resources consumed by each classifier in the ensemble can be controlled. This justifies using a network of classifiers, where the output of one classifier is passed to subsequent classifiers. For simplicity of exposition, in this subsection we focus on chains of classifiers (Fig. 4), but the discussion is equally applicable to a general network topology.

Each binary classifier C_i labels input data into two classes $\mathcal{H}_i$ and $\overline{\mathcal{H}_i}$. The class $\mathcal{H}_i$ is considered, without loss of generality, as the class of interest. Data labeled as belonging to $\mathcal{H}_i$ is forwarded, while data labeled as belonging to $\overline{\mathcal{H}_i}$ is dropped. For example, in the classifier chain represented in Fig. 4, the goal of which is to detect whether a protest with vandalism is going on, classifier C_1 has the role of detecting whether people are gathering in a place. If C_1 labels the data as belonging to $\overline{\mathcal{H}_1}$ (i.e., people are not gathering), we can conclude that there is no protest, so to avoid the unnecessary waste of bandwidth and computational resources, data can be immediately dropped.

Let X denote the input data of a generic classifier. Each classifier has an *a priori conditional selectivity* $\phi_i = \Pr(X \in \mathcal{H}_i | X \in \bigcap_{k=1}^{i-1} \mathcal{H}_k)$ corresponding to the conditional probability of data belonging to classifier C_i's class of interest, given that it belongs to the class of interest of the previous $i - 1$ classifiers. For example, with reference to Fig. 4, ϕ_2 is the probability that a group of people gathered in one place is a demonstration. Similarly, we define the *negative a priori selectivity* as $\overline{\phi}_i = \Pr(X \in \mathcal{H}_i | X \notin \bigcap_{k=1}^{i-1} \mathcal{H}_k)$. Note that these a priori selectivities are inherent to the data features and the relationships between concepts; thus, they do not depend on the operating points of individual classifiers.

The *detection probability* p_i^D of classifier C_i is the probability that data entering classifier C_i and belonging to class $\mathcal{H}_i$ is labeled correctly by classifier C_i. For example, with reference to Fig. 4, p_2^D is the probability that a demonstration correctly labeled by C_1 is correctly labeled by C_2 as well. Similarly, the

false alarm probability p_i^F is the probability that data entering C_i and belonging to class $\overline{\mathcal{H}_1}$ is labeled (erroneously) as belonging to class $\mathcal{H}_1$.

The performance of classifier C_i is characterized by its detection error trade-off (DET) curve, which represents the trade-offs between the detection probability and the false alarm probability. The DET curve can be represented as a function $p_i^D = f_i(p_i^F)$ that is increasing and concave [8]. As a consequence, an operating point on this curve is parameterized uniquely by its false alarm probability p_i^F.

The data that classifier C_i forwards to classifier C_{i+1} consists of correctly labeled data from class $\mathcal{H}_i$ as well as false alarms from class $\overline{\mathcal{H}_i}$. We refer to this quantity as the *throughput* t_i of classifier i. For example, in Fig. 4 the throughput t_2 is the amount of demonstrations that are correctly classified by both C_1 and C_2, plus the amount of non-demonstrations that are classified (either correctly or erroneously) by C_1 as "people are gathering" and classified (erroneously) by C_2 as "demonstrations."

We also define the *goodput* g_i of classifier i as the portion of data correctly labeled. Throughput and goodput are linked to each other, and given the DET curve of each classifier they can be derived recursively [8].

Another important metric is the average time α_i needed for classifier C_i to process a stream tuple. The order of magnitude of α_i depends on the data characteristics, as well as the classification algorithm, and can vary from microseconds (screening text) to multiple seconds (complex image or video classification).

The global utility function of the stream mining system can be expressed as a function of misclassification and delay cost, under resource constraints. Indeed, in practice the N classifiers are instantiated on M processing nodes, each of which has limited resources (bandwidth, memory, and computational resources). The resources consumed by each classifier are proportional to the throughput t_{i-1} (i.e., to the quantity of information it needs to process). Given a topology, the resource-constrained optimization problem can be formulated as a NOP [5]. In this context, instead of deciding *what fraction* of the data to process, as in load-shedding-based approaches, it is fundamental to develop approaches to determine *how* the available data should be processed. Specifically, each individual classifier in the ensemble must select its operating point in order to maximize the global end-to-end performance while meeting system resource constraints. This simultaneous selection of the network topology and the classifier configurations makes the problem significantly more complex than traditional NOPs.

Formulations similar to the approach described above have been analyzed in [3, 8, 15] proposing algorithms to optimally configure networks of classifiers given system processing resource constraints. First, a global performance metric is defined for classifier networks by trading off the end-to-end probabilities of detection and false alarm; then centralized and distributed algorithms are designed to provide efficient and fair resource allocation among several classifier networks competing for system resources. In addition to constructing

	Topology/routing selection	Classifier configuration selection	Online learning
Traditional NOP [5]	Adapted dynamically based on network state (e.g., congestion experienced by nodes)	No	No
[8]	Adapted dynamically based on network state and results of local data processing	No	No
[3, 15]	Adapted dynamically based on network state and results of local data processing	Yes	No
[16, 18]	Fixed topology, classifiers can communicate with each other	Yes	Yes

Table 1. Comparison between traditional NOP and the schemes described earlier.

and adapting the networks of classifiers, [3] and [15] also analyze how to configure the individual classifiers in order to trade off the accuracy of feature identification with the filtering delay. Reference [15] first develops centralized algorithms for joint ordering and individual classifier operating point selection, and then proposes a decentralized learning approach to design a dynamic-routing-based order selection strategy. Different learning strategies that lead to rapid convergence, while requiring minimum coordination and message exchange, are investigated. Exploiting queuing theoretic models, [3] proposes a utility metric that captures both the performance and the delay of a binary filtering classifier system. Moreover, it introduces a low-complexity framework for estimating the system utility by observing, estimating, and/or exchanging parameters between the interrelated classifiers deployed across the system, provides distributed algorithms to reconfigure the system, and analyzes these algorithms based on their convergence properties, optimality, information exchange overhead, and rate of adaptation to non-stationary data sources.

Online Learning of the Classifier Operating Points

Earlier we discussed a framework to build an optimal network of classifiers given the a priori conditional selectivities and the DET curve of each classifier. However, in many SMAs these values are not known beforehand and/or can change in time because of the non-stationary environment. In these scenarios the relevant parameters must be *learned online*.

In the *supervised online learning* framework an entity, to which we refer as a *learner*, needs to receive feedback about its actions in order to learn which is the optimal way to behave. Such feedback can be received from a human expert (e.g., a technician that analyzes a subset of the data offline) or incorporated automatically in the system loop with delay (e.g., if the task is to predict the trend of the stock market in the next hour, the feedback is automatically received with a one hour delay after the real trend is observed).

The learning task of a classifier that is part of a classifier network is more challenging than in the traditional online learning framework for two reasons:
• The feedback represents global information about the behavior of the system; it does not provide direct information about the contribution of each individual classifier to the system performance.
• The contribution of each classifier is correlated with the network topology and the operating points of the other classifiers.
To learn the optimal configuration, the stream mining system must explore multiple configurations — different network topologies and classifier operating points. Whenever feedback is received, a comparison between the answer provided by the current configuration and the feedback gives an estimate of the performance of the current configuration. This

estimate can be exploited to decide whether to explore a new configuration and, in this case, how to compute the new configuration.

To improve the speed of learning of the system, it is possible to exploit any a priori information about the correlation among the classifiers in the current network topology and *parallelize* the learning. For example, consider the network topology represented in Fig. 2, and assume that the current stream of data passes through the Demonstration classifier. In this case, the final answer of the system is not affected by a change in the operating points of the Suspicious person and Crime classifiers or a swap in the positions of these classifiers. This means that a single classifier's feedback can simultaneously provide information about multiple network topologies and classifier operating points. By exploitating these considerations, the speed of learning can be considerably increased.

Online learning schemes to learn the optimal classifier operating points are proposed and analyzed in [16–18]. These works consider a network of processing nodes that observe distributed, heterogeneous, and dynamic data sources. These processing nodes preprocess the observed data locally and exchange information to generate a final global prediction. The network topology is not constrained to be a chain or tree of classifiers; hence, each processing node can simultaneously receive multiple correlated inputs — multiple source observations and/or multiple preprocessed outputs from other processing nodes — and need to learn online how to aggregate such information. Reference [16] focuses on regression problems and proposes an online learning scheme in which the amount of information exchanged depends on the estimated correlation among processing nodes; this allows trade-off of system performance and amount of exchanged information. Instead, [17] focuses on classification problems and proposes a learning scheme with the following features:
• It requires a minimal exchange of information.
• The observed data can be discarded after it is processed.
• It only requires basic operations such as add, multiply, and compare.
These features are extremely important when the available communication bandwidth is small, the processing nodes have very limited memory and computational capabilities, and the processing delay plays an important role (e.g., for real-time SMAs). In addition to it, [18] designs a scalable and efficient information dissemination protocol to spread the required information in the network, and applies the proposed scheme to some well-known real-world data sets showing gains ranging from 20 to 70 percent with respect to state-of-the-art solutions.

Table 1 summarizes the main differences between a traditional NOP and the stream mining schemes described in this section.

Open Research Questions

There are several open research problems that need to be investigated to support the deployment of large-scale distributed systems for SMAs. We describe these open research problems in the following.

Adaptation. There are several interesting topology configuration and adaptation problems that can be used to dynamically modify individual classifiers (e.g., change the model or thresholds for a classifier), automatically reorganize the topology to potentially increase parallelism, or use selectivity of individual operators to reduce workloads on downstream operators. The impact of different levels of adaptation needs to be investigated. Some examples of exploiting these trade-offs have been considered in [3, 8, 15], but this is a fertile space for future research.

Speed of learning. It is fundamental to derived analytics for SMAs that allow both *long-term* and *short-term* bounds on system performance to be determined with respect to a given metric. For example, there are preliminary results that characterize the classification accuracy of a data mining scheme in the long term [18]. However, it is vital for real-time SMAs to learn quickly, achieving high classification accuracy in the short term as well. Hence, it is important to determine bounds for the *speed of learning*, that is, the time required by the scheme to guarantee a minimum classification accuracy.

Optimize resources. There are several resource optimization problems related to taking a given processing topology and mapping it to physical processes that can be instantiated on a distributed computational platform. This requires multi-objective optimization where communication costs need to be traded off with memory and computational costs. Also, given the resource requirements, data characteristics may change over time, and as a consequence these optimization problems may need to be solved incrementally or periodically. The interaction between these resource optimizations and system classification accuracy also needs to be formally investigated.

Robustness to missing and delayed information. In distributed environments it is difficult to guarantee perfect synchronization and communication among processing nodes. Loss of synchronization may result in information that is received with delay, whereas communication errors or local failures may result in missing information. The robustness of different learning schemes and network topologies with respect to these issues needs to be investigated.

Acquisition rate. In some cases (e.g., sensor networks) the processing nodes can decide the acquisition rate to adopt to collect data. The impact of this additional degree of freedom on the system classification accuracy and the system resources must be investigated.

Privacy. When data streams include sensitive information, a stream mining system requires control over the privacy of the information, making sure that the analysis respects the desired anonymization, authorization, encryption, and authentication requirements. It is an open research question how these requirements translate into constraints of the network optimization problem and their impact on system performance.

Conflicting objectives. There are some scenarios in which the multiple processing nodes belong to different entities that have conflicting objectives. In these scenarios it is not plausible to assume that the nodes cooperate with each other. Non-cooperative game theoretic approaches must be adopted to analyze these distributed environments.

Unsupervised learning. While we have posed the problem of distributed learning in a supervised setting (i.e., with feedback that is eventually observed), there is also a need to build large-scale online algorithms for knowledge discovery in unsupervised settings. Constructing online ensemble methods for clustering, outlier detection, and frequent pattern estimation are all very interesting directions for more research.

Overall, we believe that the space of SMAs is extremely fertile for novel research and construction of real-world deployments which have the potential to accelerate our effective use of streaming data.

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Biographies

LUCA CANZIAN [M'13] received his B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the University of Padova, Italy, in 2005, 2007, and 2013, respectively. From 2007 to 2009 he worked in Venice, Italy, as an R&D engineer at Tecnomare, a company providing design and engineering services for the oil industry. From September 2011 to March 2012 he was on leave at the University of California, Los Angeles (UCLA). From January 2013 to April 2014 he was a postdoctoral researcher in the Electrical Engineering Department at UCLA. From April 2014 to April 2015 he was a postdoctoral researcher in the Computer Science Department at the University of Birmingham, United Kingdom. Since April 2015 he has been working in Bassano del Grappa, Italy, as an R&D engineer at Qascom, a company providing design and engineering services for the satellite communication and navigation industry.

MIHAELA VAN DER SCHAAR [F'10] is Chancellor's Professor of Electrical Engineering at UCLA. She has been a Distinguished Lecturer of the Communications Society and Editor in Chief of *IEEE Transactions on Multimedia*. She received an NSF CAREER Award, three IBM Faculty Awards, and several Best Paper Awards. She holds 33 granted U.S. patents. She is also the founding director of the UCLA Center for Engineering Economics, Learning, and Networks. Her research interests include engineering economics and game theory, network science, expert and social networks, online reputation and social media, dynamic multi-user networks and system designs, wireless networks, online and interactive learning, and real-time stream mining.