ABSTRACT
Crowdsourced stream processing (CSP) is crowdsourcing applied to the processing of data streams. This can be seen as enabling crowdsourcing work to be applied to large-scale data at high speed, or equivalently, enabling stream processing to employ human intelligence. Independently of the perspective one adopts, this entails a substantial expansion of the capabilities of computer systems. Engineering a CSP system requires combining human and machine computation elements. From a general systems theory perspective, this implies taking into account inherited as well as emerging properties from such elements. In this paper, we define and position CSP systems within a broader taxonomy, introduce a series of design principles and evaluation metrics, present an extensible design framework, and describe several design patterns. We also perform a case study applying this framework to the design and analysis of a real system in the humanitarian computing domain.

Categories and Subject Descriptors
H.4 [Information Systems Applications]: Miscellaneous; D.2.2 [Software Engineering]: Design Tools and Techniques

General Terms
Design, Measurement

Keywords
Stream processing, Crowdsourcing

1. INTRODUCTION
In this article we study the design of a nascent class of hybrid human-machine systems that allow human intelligence to be applied to large-scale data at high speed. These systems are born at the intersection of stream processing and crowdsourcing and have characteristics inherited from them, as well as emerging properties that make them unique. Stream processing or streaming computation is a computation performed on an unbounded, high-speed, continuous, and time-varying set of events [49]. Streams often cannot be stored for offline analysis and need to be processed online. If analyzed timely and effectively, stream processing can play a vital role supporting decision making in real-time. Due to their continuous, unpredictable, and time-varying nature, data streams often require specially-designed algorithms, platforms (e.g. [45, 51]) and/or data management systems (e.g. [11, 12]). A drawback of traditional stream processing systems is that they are limited to tasks that can be performed entirely by automated means.

Crowdsourcing [31] describes the practice of obtaining a service from a large online community instead of from company employees or suppliers. It has been applied successfully in a variety of scenarios for many applications [18, 72]. Crowdsourced stream processing involves crowdsourced processing elements in combination with automatic processing elements. The amount of automation depends on the design of each system. It can be just the minimum automation required to pass data/events among pools of workers, up to complex architectures where crowdsourced and automatic processing elements are designed to interact and work together in complex ways. Crowd processing [27], which involves processing a large amount of homogeneous external stimuli (e.g. [3, 42, 70]), as well as real-time crowdsourcing [38] often resemble or are actual instantiations of what we refer to as crowdsourced stream processing (CSP). We give several examples of existing CSP applications. To the best of our knowledge this is the first work attempting to systematize the design and engineering of such applications. This formalization is necessary as it can lead to better designs and performance improvements in current systems and guide the development of new ones.

Contribution and organization of this paper. In this work, we propose a general framework for the design and analysis of crowdsourced stream processing systems. Our contribution begins in Section 2 by positioning CSPs into a broader taxonomy of systems. In Section 3 we describe design objectives, principles and quantifiable evaluation criteria. In Section 4 we introduce a generic application design framework in terms of composable elements and communication channels. In Section 5 we present a series of design patterns to solve specific design problems. Section 6 shows a case study in which we design and analyze a CSP system using our framework. Finally, Section 7 outlines related works and Section 8 summarizes our main conclusions.
2. TAXONOMY OF CROWDSOURCED STREAM PROCESSING SYSTEMS

In this section we position crowdsourced stream processing systems (CSPs) into a wider taxonomy of systems. Our goal is to provide a conceptual framework to understand the inter-connections of CSPs with other systems and their environment, and to specify the properties CSPs inherit from systems in their super-hierarchy.

We follow a relaxed systemic-modeling approach [50], which borrows explanatory elements from systems science and General Systems Theory [5]. According to this theory, a system is a set of interacting elements that has emerging properties which are richer than the sum of the properties of its parts. A system can be examined from two main perspectives [17]: (i) a behavioral or teleological perspective, where the system’s behavior and goals are examined, and (ii) a structural perspective, where the system’s structure, architecture and operations are considered.

2.1 Hierarchical CSPs taxonomy

We begin with a hierarchical taxonomy to explain the behavior of CSPs through the elements and properties that they inherit from their predecessors.

**System.** In addition to the concept of system defined earlier, there are supporting notions that include environment, objective, function, element and interface [2]. Environment is anything outside the system’s boundaries. Objective is the system’s finality at a given time, a notion that directly influences the system’s structure and functionality. Function is the set of actions the system can execute in order to realize its objective. Element is a component of a system, which can itself be a system. Finally, interface is the element through which the system establishes connections with its environment.

Environment, objective and function provide the behavioral perspective of the system, i.e. they denote the way that the system acts and reacts. Element and interface provide the structural perspective of the system, i.e. they materialize the internal organization and architecture of the system.

**Stream processing system (SPs).** From a behavioral perspective, the objective of an SP is to process data streams. Example applications include data mining [63], clustering [1, 74], classification [73], time series analysis [40, 75] and burst detection [64], among many others.

From a structural perspective, an SP is a composition of processing elements that read an input data stream and write an output data stream. Typically, each processing element performs a fairly simple task and is thus easy to implement, debug and maintain. The data passed between elements are data streams as well. Apart from handling a particular type of data (data streams) and employing single-pass processing, another emerging property of SP systems is that, in a structural level, each processing element is assumed to have limited memory/storage, i.e. the amount of data it can store is small in comparison to the total amount of data that passes through it [49]. Additional SPs properties, important because they are passed on to CSPs, are their evaluation metrics, including latency, throughput and load adaptability. These will be further discussed in Section 3.

**Crowdsourcing system (Cs).** From a behavioral perspective, the objective of a crowdsourcing system is to apply human intelligence to tasks that cannot be performed effectively by fully automated means. This is done by involving large numbers of workers, who perform small portions of a larger task, improving the efficiency of more traditional ways of work organization by reducing completion time and cost.

From a structural perspective, crowdsourcing systems vary significantly (for comprehensive surveys see [18, 72]). These variations depend on the application (knowledge or creativity-intensive or more mechanistic), type of input data (homogeneous or heterogeneous), type of task (open- or close-ended), and coordination mode (independent workers, collaboration, competition, mixed). Most real-time crowdsourcing applications (e.g. [3, 27]) are designed to respond with low latency (within seconds). This type of crowdsourcing, referred to as crowd processing [27], relies on homogeneous input data, highly decomposable and self-contained tasks, parallelizable task handing and centralized work coordination.

Other key properties passed on to CSPs are the innate uncertainty of human work (e.g. workers might leave unexpectedly and their skills might vary [57]), and the fact that crowdsourcing is in general slower and more costly per item than fully automatic processing. Important evaluation metrics, also passed on, include: quality, cost and their trade-off.

**Crowdsourced stream processing system (CSPs).** From a behavioral perspective the objective of CSPs is to process data streams. From a structural perspective CSPs involve both human and machine elements into their structure. CSPs lie in the junction between automated stream processing systems and crowd processing systems. They inherit behaviors and structural elements from both, while demonstrating their own emerging properties.

What CSPs inherit from SPs is their general objective: to process input streams efficiently. What differentiates them is the class of problems that CSPs can handle. From crowdsourcing systems, they inherit the capability of executing data processing tasks that require human intelligence, in contrast to the tasks traditional SPs execute, which can be done by computer algorithms alone. Also from crowdsourcing systems, CSPs inherit the uncertainty/variability introduced by human work, which necessitates methods and design choices to mitigate it.

2.2 Faceted CSPs taxonomy

We can also categorize CSPs based on three facets: (i) the role of the crowdsourced processing, (ii) the role of the auto-

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Figure 1: A taxonomy of crowdsourced stream processing systems. Top: hierarchical taxonomy (Section 2.1). Bottom: faceted taxonomy (Section 2.2).
matic processing, and (iii) the composition of crowdsourced and automatic processing elements.

2.2.1 By the role of crowdsourced processing

Human intelligence, provided by crowdsourcing workers, is used for tasks that can not be automated. Among the tasks workers can execute we may find: providing input to other processing elements, correcting an element’s output, validating that an element performed as expected, and training the automated processing elements so that they can learn to perform a task. As to the way that these functionalities are realized through tasks, there are at least three broad classes: binary classification, n-ary classification, and open-ended contributions. In binary classification, workers are asked to give a “yes/no” answer to a given question: “do these suspicious activities constitute an attack?” [14], “does this entity correspond to this word in this context?” [15], “do these two records correspond to the same person?” [70]. In n-ary classification, we can include determining if a word in a sentence represents a person, a place, or an organization [20], determining if an emergency-related tweet describes infrastructure damage, casualties, injuries, needs, etc. [33], determining which emotion corresponds to a tweet [42], etc. In open-ended contributions, workers are asked to perform an open-ended task such as: “rewrite this sentence in a shorter way” [3], “fill-in the missing fields in this record” [22], “make a drawing of an articulated figure” [15], etc. This list is not comprehensive as new task types emerge as crowdsourcing systems (and CSPs) mature.

2.2.2 By the role of the automatic processing

Whereas crowdsourced processing elements deal with high-difficulty tasks, automatic processing elements are employed for efficiency. First, and perhaps most frequently, automatic elements can be used to perform arbitrary computations over the data (transform, sort, join, etc. [48]). Secondly, automatic elements can be used for task filtering: performing sampling to reduce the number of elements that need to be processed. This may help to reduce the number of crowdsourcing calls by selectively using crowdsourcing only for difficult items (e.g. [15, 35]). Third, automatic elements can be used for automatic task generation, as for example in the case of systems that need to convert input streams into questions for humans (e.g. graph searching in [54], crowd-assisted data joins in [22]). Fourth, automatic elements can be used for task assignment purposes, e.g., with the online algorithm described in [29]. Finally, automatic elements can be used for aggregation of the output of other processing elements, in order to ensure output quality, as in the “get-another-label” system [34].

2.2.3 By the crowdsourced/automatic composition

In regards to the connections between crowdsourced and automatic processing elements, we may distinguish two prototypical connection topologies.

Parallel. In parallel connections, both automatic and crowdsourced processing elements function on the same type of task and layer of data stream processing, therefore on tasks that have no dependencies one from the other.

Serial. In serial connections, tasks have dependencies among them, requiring a certain degree of serialization in their processing.

| Table 1: Indicative examples of CSPs categorized on the facetted taxonomy. |
|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| Example CSPs | Crowdsourced processing | Automatic processing | Dominant composition |
| Intrusion detection [53] | input; binary classification | filter | serial |
| Entity resolution [70] | training; n-ary classification | task | complex |
| Text processing [3] | input, correcting, and validating; open-ended | aggregation | complex |

We remark that in general for solving real-world problems, complex topologies are used, involving a combination of parallel and serial connections.

2.3 Examples

We look at three indicative CSPs examples, categorized according to the above-proposed taxonomy (Table 1).

Intrusion detection. Automatic processing elements monitor network or system logs, to detect candidate malicious activities and generate alarm reports about possible attacks [53]. Human input is then needed to manually verify candidate alarms and take further action (perform remedy, re-tune the system) in response. Processing composition in this example is serial, with the automated element performing the filtering part (detect) and the human element performing binary classification (verified attack or not).

Entity resolution. Crowdsourced processing elements are asked to correct n-ary classification of entities into semantic clusters, helping at the same time to train the automated element of the CSP into performing more accurate automatic classifications [70]. The processing composition in this system is complex (namely, a loop), with the automated element generating entity resolution questions, humans answering them and then these answers being sent back to the automated elements for training and decision purposes.

Text processing. Crowdsourced processing elements are orchestrated to improve a document’s writing, by detecting errors or shortening text passages [3]. This involves a complex topology in which passages are processed in parallel but each one passes through a series of sequential steps: first crowdsourced processing element finds problems, a second one proposes a fix, and a third one validates the solution.

3. DESIGN OBJECTIVES, PRINCIPLES AND METRICS

In the previous section we presented a taxonomy of crowdsourced stream processing systems. In this section we introduce measurable criteria for their design, and translate them into a series of design principles.

Each design objective is quantifiable through a certain metric, and trade-offs among different objectives may occur, as summarized on Table 2. The first three objectives (latency, throughput and adaptability) are common in the stream processing literature (e.g. [48, 66]), and here we adapt them to the crowdsourced stream processing setting. The last two objectives (cost and quality) are a consequence of the presence of humans as part of the system.
Throughput can be measured as the throughput of its components. The throughput of a system is a function of its design and potentially larger group of crowdsourcing workers. Individual task can be answered faster and/or by a potentially low-latency crowdsourcing stream processing systems.

Measuring latency. A typical measure for the latency of a system is the average latency of the items traversing through it. The latency of an item is trivial to compute if the mapping from input to output items is one-to-one. If that is not the case, for each input item that contributed to one or more output items, its latency can be measured as the time it took for the first such output item to be produced.

3.1 Low Latency

Latency is the time it takes for an item to be processed. Real-time crowdsourcing systems (e.g. [4, 38]), are basically low-latency crowdsourcing stream processing systems.

3.1.1 Automatic components: keep data moving

Automatic components should avoid unnecessary latencies due to network delays, storage operations, or other causes. Input items may be out-of-order, missing or delayed. Automatic processing elements should use non-blocking operations, never waiting indefinitely for some data items to arrive before continuing processing [62].

3.1.2 Crowdsourced components: trivial tasks

Task design depends on many aspects that include incentives, interface, task description, and more importantly the task itself [21, 38]. Research and practice suggest to decompose complex tasks into simple subtasks, where each task is designed to be trivial and follow specific requirements. This can not be understated, as it helps both to reduce the cost and to increase the quality of work. Simpler tasks are completed earlier [30], not only because each task is completed faster, but because the pool of people with the skills required to complete a task is larger if the task is simpler. A difficult task may introduce latency, and it may also reduce output quality [36].

Task decomposition helps reduce individual task complexity. The latency of the decomposed task may be lower if each individual task can be answered faster and/or by a potentially larger group of crowdsourcing workers.

3.2 High Throughput

Throughput is the speed at which items are processed. The throughput of a system is a function of its design and of the throughput of its components.

Measuring throughput. Throughput can be measured as output items per unit of time, e.g. items/second.

3.2.1 Automatic components: high performance

A stream processing system should process and accommodate long-running analysis requirements almost in real-time [66]. Each automatic processing element must be implemented to have high performance, and the application infrastructure including communication channels must be able to have a high throughput.

3.2.2 Crowdsourced components: task automation

In a crowdsourced stream processing system, in general the throughput of the crowdsourced processing components is lower than that of the crowdsourced processing components. Crowdsourced components may become a bottleneck.

Automating as much work as possible is a way of maintaining a high throughput: any aspect that can be automated should be not passed to a crowd. For instance in binary classification if we are searching for items belonging to a positive class, if an item can be automatically classified into the negative class, it does not need to be given to crowdsourcing workers.

3.3 Load Adaptability

The rate of input data may experience sudden changes including significant bursts. Adaptability is the capacity of the system to respond to a surge in demand.

Measuring load adaptability. Adaptability can be measured as the response function of throughput and latency vs input load. Ideally, these variables should not be strongly affected by increases in input load. In other words, we should not observe a significant reduction in throughput, or a significant increase in latency.

3.3.1 Automatic components: load shedding/queuing

Surges in input rate may require to use load shedding, this is, completely ignoring data items that are beyond the processing capabilities of a processing element at a given time [65]. Buffering may prevent shedding by allowing load queuing, using a bounded-size queue.

3.3.2 Crowdsourced components: task prioritization

The system should prevent crowdsourcing from becoming a bottleneck. This can be done by having a method for prioritizing tasks, in such a way that during periods of increased input rate, more tasks are taken by automatic parts of the system than normally. This may come with a cost in terms of quality.

For instance, Demartini et al. [15] pass to the crowd only tasks (in their case, entity linking tasks) for which an automatic system is uncertain, i.e. it has not given with high-confidence a positive or a negative answer. The thresholds of what constitute a high-confidence answer could be tuned to be able to handle more input items per unit of time.

3.4 Cost effectiveness

Given that crowdsourcing work is neither unlimited in supply nor free (even when done by volunteers, their time and motivation are precious resources), a principle of task frugality needs to be applied.

Crowdsourcing is usually compensated in proportion to the time spent by workers. Cost is therefore a function of
(i) the payment per unit of time, (ii) of the number of items to process, (iii) the time needed by each worker to complete one item, and (iv) the plurality of workers per item. Effort is also a parameter, eventually translatable to cost as well.

Increasing the payment per unit of time seems to have little effect in work quality, but can help reduce its latency [47].

The number of items to process is related to task automation—replacing crowd processing by automatic processing when possible— but also to the way processing elements are composed. Similarly to query planning in traditional database systems, heuristics or optimization methods can be used to determine the order in which automatic and crowdsourcing operations need to be done [22]. Task workflow design can be optimized through automatic processing elements, as described by Dai et al. [13].

The time and effort needed by each worker to complete one item can be decreased by decreasing task subjectivity and difficulty, for instance by decomposing into smaller sub-tasks, which may also lead to lower latency (Section 3.1.2). Task completion time can also be reduced by using more efficient worker-to-task allocation schemas, e.g., based on the average completion time and skills of each worker [8].

The plurality of workers per item reduces the effect of cheaters/spammers by using aggregated labels. This can be optimized by using a cost-sensitive objective, e.g., combining cost with quality as in [24].

Measuring cost effectiveness. This can be done in comparison with other aspects, e.g. cost/latency, cost/quality, etc. For instance, in [19] it is shown how larger budgets (in their case, fraction of items that are crowdsourced) yield better overall accuracy. The time to complete a task is also reduced when payment is increased [28, 47].

3.5 Quality

The addition of human elements makes crowdsourcing stream processing non-deterministic. Crowds vary in their composition and individual workers may provide varying levels of quality.

Output quality can be maintained by the interaction between automatic and crowdsourced components through operations such as aggregation, quality management and cheating detection (as mentioned e.g., in [72] and others). Section 5.1 describes a design pattern (“quality assurance loop”) based on this type of interaction. Furthermore, the automated elements can play an important role in regards to incentives engineering, for example in diversifying task recommendations (bored workers perform worse than interested ones [37]), as well as in allocating incentives to tasks [71], with an aim to attract qualitative worker contributions and thus increase overall task quality.

Measuring quality. Quality should be measured in an application-dependent manner. The metric may be binary (correct item vs. incorrect item) or continuous, and it may not be a single scalar but comprise several aspects.

4. GENERAL CSP FRAMEWORK

Taking into account the characteristics of CSPs and the design principles presented, in this section we describe an extensible framework for their design. We follow a model-driven design approach, where a model represents an abstract view of a system. This model is meant to be extended to incorporate new requirements as needed.

![Figure 2: Meta-model of a CSP application. The diagram depicts the model of processing elements (left side) and communication flows (right side).](image-url)

Our framework includes CSP applications (Section 4.1) made of composable processing elements (Section 4.2) and flexible communication flows (Section 4.3). The aim of this framework is to standardize the specification of elements and flows in a way that allows to easily created various kinds of topologies and to modify them when required.

4.1 Application-level

Well-defined software components are the basic building blocks of stream processing systems (e.g. [25, 51]). These components perform various kinds of jobs, and can be connected/composed together. Figure 2 depicts the generic meta-model of a CSP application.

According to the meta-model, a crowdsourced stream processing system may consists of one or more processing elements. A processing element can be of type crowdsourced (human-driven) or automatic (computer-driven). Processing elements perform dedicated tasks, and may depend on other processing elements in terms of their data requirements. To allow data flows among processing elements, the meta-model manifests such flow as data connections. Data connections tie input ports and output ports where the source emits data items through its (usually single) output port, and the target ingests the data items through (possibly multiple) input ports. Section 4.3 explains this asymmetry. Processing elements can also coordinate their behavior by establishing control connections among pairs of them using (possibly multiple) configuration ports.

4.2 Processing elements

A processing element consumes data items and control flow signals through input ports, implements an application-specific requirement, and emits the processed data items through an output port.

4.2.1 Automatic Processing Elements

An automatic processing element (APE) is a standard component in stream processing systems, e.g. in [25, 51]. It executes a set of operations in a fully-automated manner on its input stream. Following the streaming computation model [49], we assume APEs do not have memory to hold all the items that go through them.

4.2.2 Crowdsourced Processing Elements

A crowdsourced processing element (CPE) employs a large group of people (i.e. a crowd) to process data. The processing of items in CPEs is assumed to be more expensive and
slow than in APEs. This can be described as a constraint in the system by means of a budget of calls assumed to have equal cost (e.g. the whole application can not process more than k data items through CPEs in total), or through a cost function that varies according to the task.

A CPE may be implemented through the API of a local crowdsourcing platform (e.g. PyBossa1) or through the API of a remote crowdsourcing application (e.g. Amazon’s Mechanical Turk2, CrowdFlower3, or others).

4.3 Communication flows

We aim for generality in this framework so we include three communication modalities among processing elements (point-to-point, distributed and broadcasted), and two types of flows (data flows and control flows). In this section we describe these types conceptually, but first we specify their general behavior through channels and ports.

4.3.1 Channels and ports

Communication is done through generic channels (sometimes referred to as streams). The concrete implementations of channels may vary. In case buffering is required, communication channels may be implemented using bounded-memory queues. If buffering is not required, other message-passing patterns can be used.

Processing elements have multiple input and output ports. A processing element can act either as information source, processor, or as consumer. Elements with no input ports are called information source elements, and perform edge adaptation [60]: converting external stimuli into data to be consumed by the CSP system. Elements with no output ports are called information consumers, and elements with both input and output ports are called information processors.4

A single output port for data is all that is needed in most applications, as the complexity of determining the destination for each message can be assumed by the communication modalities described next.

4.3.2 Communication modalities

Point-to-point. Point-to-point communications are the simplest case and have a single processing element as producer and a single processing element as consumer.

Distributed. In the distributed communication model, multiple processing elements are subscribed to the same channel, possibly filtering data according to certain criteria or keys (as in e.g. [51]). Data items are distributed to multiple consumers.

Broadcasted. To cope with the requirements when multiple processing elements can process same data items at the same time. The broadcasting communication model duplicates data items to all consumers that are subscribed to a channel.

4.3.3 Data and control flows

Data flows pass data items among processing elements. Data flows should use high-bandwidth channels with some amount of buffering, to provide better load adaptability.

Control flows allows a processing element to query or control the behavior of another processing element [7]. This can be used, for instance, to modify a parameter or a set of parameters in the operation of a processing element. Control flows should use low-latency channels with little or no buffering for faster response. Additionally, control flows should typically be used in point-to-point modality as control signals may depend on the target processing element being addressed.

5. DESIGN PATTERNS

The design framework we presented in the previous section provides generic design components. In this section we introduce specific design components as patterns of connections of automatic and crowdsourced processing elements. The idea of design patterns has been pivotal to software engineering since the work of Gamma et al. [23]. By its nature a list of design patterns is always open, as new problems and new solutions to existing problems can be incorporated.

In the remainder of this paper, we make use of the following notation: rectangles represent automatic processing elements, rounded rectangles are crowdsourced processing elements, solid lines are data flows, and dashed lines are control flows.

5.1 Quality assurance loop

Schematic structure:

Problem. The quality of work varies across workers, and/or the redundancy level required varies across tasks. We want per-task guarantees on a minimum number of trusted workers per each task, and/or a minimum level of agreeing labels. In this and similar cases, we need to continue asking for more labels for a task until certain criteria are satisfied. For instance, [24] stops asking the crowd when the marginal returns (in terms of accuracy) are smaller than the costs.

Solution. Use an automatic quality assurance loop to aggregate and evaluate crowdsourcing work, keeping a model of the trustworthiness of each worker, as in e.g. [34].

Applicability. This pattern is applicable when the quality of the crowdsourcing work can be evaluated automatically by checking labels from different workers, or when the data must comply with some constraint that can not be checked at a task level (e.g. transitivity on a relationship).

5.2 Task assignment

Schematic structure:

Problem. The crowd members are heterogeneous in their capacity to perform tasks. Assigning the “right” task to a worker leads to a reliable output, but failing to do so leads to an unreliable one.

Solution. An automatic processing element maintains a model of the skill of workers for different tasks. When feeding a task to a crowd, it indicates what is the specific worker-id that must perform each task. This design pattern should be combined with a quality assurance loop.

Applicability. This pattern is applicable when it is possible to automatically compute an estimation of the quality of the output of a worker performing a certain task.
5.3 Process automatically, verify manually

Schematic structure:

Problem. The input throughput vastly exceeds the budget of crowdsourcing calls, so the data needs to be reduced before being crowdsourced.

Solution. An automatic processing element operating as a “detector” can act as a filter, and pass only the elements that pass a certain criterion to a “verifier” crowdsourced processing element. For instance, crowdsourced content moderation (for profanity or hate speech) could pass only suspicious messages, containing certain keywords, to a crowd of workers.

Applicability. In the context of binary classification tasks (other cases can be dealt with in a similar manner), this pattern is useful when there are methods to filter-out true negatives deterministically or with high precision. In this case, the number of crowdsourcing calls can be reduced by passing to the crowd only the examples that have a sufficient probability of being positive.

5.4 Supervised learning

Schematic structure:

Problem. The input throughput vastly exceeds the budget of crowdsourcing calls, so an automatic system needs to learn to mimic the process crowdsourced workers perform.

Solution. An automatic processing element runs a parametrized machine-learned model. Its output is sampled according to a certain criterion, and sent to a crowdsourced processing element to provide training labels. These labels are used to learn a new model, which is sent through a control signal to the main processing element. The sampling can be done uniformly at random, or following the idea of active learning to maximize the gains in accuracy for every extra label. An example of this solution is Kamar et al. [35], who use machine vision to identify galaxies based on models learnt from human labels.

Applicability. This pattern can be applied when it is possible to learn an automatic model of the process the crowd performs.

5.5 Crowwork sub-task chaining

Schematic structure:

Problem. A complex task generates high latency and low quality output, and needs to be divided into separate parts.

Solution. Two or more crowdsourced processing elements can be composed on a serial, parallel, or complex circuit. The output from one task is post-processed and sent to another task (that can also be post-processed automatically). This is related to the now-centenarian paradigm of scientific management/Taylorism/Fordism. One example can be the decomposition of the task of counting calories in pictures of meals described in [52], or the detect-fix-verify paradigm in [3], or a secondary grading task to control the quality of a primary task [61].

Applicability. This pattern can be applied when the task can be divided in advance into discrete sub-units. If not, this pattern can be extended by following an approach similar to [39]. In this case, control flows need to connect the different crowdsourced processing elements, indicating changes in the tasks performed in them.

5.6 Humans are not a bottleneck

Problem. A minimum throughput needs to be guaranteed, but crowdsourced stream processing elements can not guarantee that same throughput.

Solution. There should be a path of data flows between the application’s input and output needs to pass through any crowdsourced stream processing element. This means patterns such as supervised learning or other types of parallel connections need to be part of the design.

Applicability. This pattern can be applied when the minimum number of crowdsourcing calls needed in steady state for the application to function is zero.

5.7 Humans review every output element

Problem. A minimum quality, which can only be attained through human oversight, needs to be attained. This could be the case of a credit card fraud detection system, in which e.g., stop payment orders can only be authorized by a human operator.

Solution. Every path of data flows between the application’s input and output needs to pass through a crowdsourced stream processing element. Additionally, a minimum level of redundancy can be applied in all such elements if multiple paths exist.

Applicability. This pattern can be applied when low latency does not need to be guaranteed. Enforcing that every data element that will be written in the output needs to pass through a crowdsourced component may introduce latency in the system.

6. CASE STUDY: CLASSIFICATION OF CRISIS MESSAGES IN SOCIAL MEDIA

This section studies a concrete stream processing application, showing how this framework can guide the design of the application and serve as an analytical tool for its evaluation.

6.1 The Application: AIDR

The purpose of AIDR (Artificial Intelligence for Disaster Response), is to filter and classify in real-time messages posted in social media during humanitarian crises, such as natural or man-made disasters. Specifically, AIDR collects crisis-related messages from Twitter (‘tweets’), asks a crowd to label a sub-set of those messages, and learns an automatic classifier based on those labels. It also improves the classifier as more labels become available.

During a disaster, social media messages provide real-time or low-latency situational awareness information that enables responders to be more effective in their relief efforts [67]. Different emergency response agencies are interested in different types of messages. For instance, reports of damage to infrastructures should be directed to some agen-
cies, while reports about shortages of water and/or food should be directed to others. 7 Manual classification of messages is not possible given the scale of information that flows on Twitter. The largest documented peak during a natural disaster that we are aware of is 16,000 tweets per minute. 8 Automatic classification using pre-existing training data is not a satisfactory solution because although crises have elements in common, they also have specific elements which make domain adaptation difficult. Crisis-specific labels lead to higher accuracy than labels from past disasters [32].

AIDR users begin by creating a collection process by entering a set of keywords that will be used to filter the Twitter stream. Next, they define the ontologies to be used to classify messages, selecting them from a set of pre-existing ones, or creating them from scratch. AIDR then instantiates an ongoing crowdsourcing task to collect training labels, which are used to train an automatic classifier that runs over the input data. Finally, an output of messages sorted into categories is generated, which can be collected and used to create crisis maps and other types of reports.

6.2 Design overview

The design of AIDR follows the meta-model described in Section 4. At a high-level, the application uses the design pattern humans are not a bottleneck (Section 5.6), where items are able to traverse the application independently of the availability of crowdsourcing workers.

The processing elements of the application are composed following the diagram in Figure 3. Automatic processing elements include a Twitter collector, feature extractor, task generator, learner and classifier. A crowdsourcing processing element, the annotator, gathers human-provided labels.

The collector is an information source automatic processing element that performs edge adaptation [66] to consume tweets using the Twitter streaming API. The feature extractor is an information process automatic processing element that prepares the messages by converting them to a set of textual features using standard text operations (extraction of unigrams, bigrams, part of speech classes, etc.).

The classifier, task generator, annotator and learner processing elements interact following the supervised learning design pattern (Section 5.4). The task generator samples the input stream, optionally performing de-duplication (to diversify the elements to label) and active learning (selecting elements for which the classification confidence with the current model is low). Both operations are implemented in a stream-aware way, in which the search for near-duplicates or low-confidence elements is done on a bounded-size buffer containing only the latest tweets consumed by the system. The learner keeps 20% of the labels it receives as a test set, and uses the remaining 80% for training, allowing it to report to the user the quality of the current classifier. The learner creates a new classification model (random forest in this case) every 50 training labels and transfers it to the classifier processing element using control signals.

The composition of the processing elements is done through publish/subscribe channels and queues. The former are able to broadcast and distribute data items, as well as performing load shedding - discard elements in order to maintain throughput. The latter are capable of buffering data items.

Implementation. The implementation is done using Java and the Springs 3.0 framework for the main application logic, PyBossa for the crowdsourcing processing element, and REDIS 9 for the communication flows.

6.3 Evaluation

We apply the evaluation metrics described in Section 3. We remark that there are application-specific evaluation criteria that are outside the scope of our generic framework, e.g., user satisfaction in the case of interactive applications.

We simulate the operation of AIDR with a fixed input stream under a varying set of conditions. For the purposes of this simulation, the application is instrumented to provide detailed information about data passing through it. Mock objects are also created to simulate data input (from Twitter's API) and data labeling (from a crowd).

We use a dataset of 206,764 tweets containing the hashtag #joplin and posted during the tornado that struck Joplin, Missouri in 2011 [32]. We also use 4,000 human-provided labels obtained via CrowdFlower. The specific crowdsourcing task was to indicate if a message is informative with respect to the disaster and of interest to a broad audience, or if it is either entirely of a personal nature or irrelevant for the disaster (the two latter classes are merged into a single class not informative).

6.3.1 Throughput, latency and load adaptability

We first measure the attributes that AIDR inherits from being a stream processing application. To evaluate these variables, its classifier is trained using all the available labeled data, and then varying input loads are applied. Figure 4 shows the results. In addition to end-to-end throughput and latency, we include a breakdown for each of the two main automatic processing elements of the system: the feature extractor and the classifier.

The system is designed following the principles of keep data moving, high performance, task automation, and load shedding, outlined in Section 3. The results indicate that the system is able to maintain a high throughput (500 items/second or more) above the observed peak rates in real disasters (>270 items/second). Because some of the items are dropped, the latency is kept in the order of tens of milliseconds, even when the input load exceeds the maximum output throughput. For the purposes of this application, this is acceptable given the large amount of redundancy in Twitter messages.

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9 http://redis.io/
Throughputs: features extractor, classifier, system.

Latencies: features extractor, classifier, system.

Figure 4: Response of AIDR to varying input loads, in terms of throughput and latency. The vertical line corresponds to the highest peak rate documented for a natural disaster to date: 270 items/second during Hurricane Sandy in late 2012.

(a) Quality vs. number of labels, using passive learning.
(b) Quality vs. number of labels, using active learning.

Figure 5: Area under the ROC curve (AUC) vs. number of training labels. The plots on the left side are obtained without de-duplication, while the plots on the right include it.

– about 1/3 are re-tweets in this dataset, and about half of the remainder are near-duplicates of another message.

6.3.2 Quality and cost

We next measure the attributes that AIDR inherits from being a crowdsourcing application, specifically, the relationship between quality and cost. Quality is measured using the area under the ROC curve (AUC); higher values are best and 0.5 indicates a random classifier. Cost is directly mapped to the number of human labels used. We tested four configurations of the task generator: (1) passive learning, equivalent to uniform random sampling in this case, (2) passive learning removing near-duplicate elements, (3) active learning, and (4) active learning removing near-duplicate elements.

Results are shown in Figure 5 where we plot output quality vs. number of labels used by the classifier for training.

The system is designed following the principles of triial tasks and task prioritization. The test shows that even under conditions of task frugality the output quality is acceptable. After enough training data has been collected (≈1,000 labels), AUC fluctuations stabilize and the system performs at an AUC of above 0.70. This point is reached with about half the labels if de-duplication is done. Further labels continue to increase the quality of the classifier, with diminishing returns. Active learning as implemented in this setting (over a bounded-size buffer) does not seem to yield significant improvements.

We remark that in Figure 5 every point represents a different (growing) testing set, a consequence of the online nature of this process. An offline analysis where the testing set is fixed to 1/3 of the labeled elements is in general consistent with the evaluation in the online setting. In the best case and using de-duplication, we obtain a maximum AUC of 0.64 for passive learning (after ≈270 labels) and an AUC of 0.66 (after ≈200 labels) for active learning. The offline analysis also shows that more labeled items further improve the results: after using 2,600 labels we reach an AUC of 0.76.

In summary, this design enables human intelligence to be applied to a data intensive application. As a stream processing system, it is able to keep up with the input loads of even large-scale disasters; and as a crowdsourcing application, it is able to use crowdsourcing work in an effective manner.

7. RELATED WORK

Stream processing and crowdsourcing are vast research areas, so we focus on connecting our research to previous works covering topics closely related to ours. This includes engineering principles, frameworks, and taxonomies for the predecessors of CSPs, as well as example systems describing key design choices and best practices.

7.1 Data stream processing

Stream processing research covers many disparate fields (e.g., stock market data analysis [16], fraud detection system [60], intrusion detection systems [14], disaster prediction systems [10]), and has passed through a number of stages. Real-time stream processing systems perform data mining [63], clustering [1, 74], classification, time series analysis [40], and other decision support tasks [75]. Furthermore, to support the development of application-specific stream processing systems, there are general-purpose platforms such as S4 [51] and STORM [45] supporting scalable real-time processing. These systems are designed for high-speed continuous data ingestion, uninterrupted long-running processing, high-throughput, and low-latency.

We have incorporated key performance indicators from the above works into our evaluation metrics (Section 3), while our application design framework has been also inspired to some extent by the design of existing general-purpose stream platforms (Section 4).

7.2 Crowdsourcing

Two extensive crowdsourcing surveys can be found in [18, 72], which examine a variety of crowdsourcing systems – often under different names such as collective intelligence, human computation, or social systems.
7.2.1 Crowdsourcing system taxonomies

First, a number of works categorize crowdsourcing systems from an organizational theory point of view, classifying them according to their business model functionality. Geerts [26] performs a model-driven categorization, distinguishing the models of crowdcasting, crowdstorming, crowd production and crowdfunding. Vukovic [68] categorizes crowdsourcing systems by business-driven objectives, and further distinguish them in regards to their coordination model (marketplace or competitive-based). Lykourentzou et al. [43] distinguishes different user interaction modalities in crowdsourcing: collaborative, competitive, and hybrid. Saxton et al. [58] identify nine basic types which span from social financing to citizen media production models; one of their main conclusions is the need for crowd management which as we describe can be provided by a combination of processing elements, through certain design patterns.

Regarding type-based classification, crowdsourcing systems are classified per type of task (simple, complex, creative) in [59], while the different functions of the crowd (crowd rating, creation, processing and solving) are described in [27]. The first work covers "what" crowdsourcing workers do, and the second one covers "how" they do it, which is in line with the description of the role of humans in CSPs (Section 2.2).

There are other works that do not explicitly aim at a taxonomical ordering of crowdsourcing, but contain taxonomical and design elements. Quinn and Bederson [55] describe 3 dimensions related to our work: quality control, aggregation, and process order. The first is a design principle (Section 3.5). The second is an automatic element role (Section 2.2). The third describes interaction models between "computers, workers and requesters", and as such it is related to the design patterns that we propose (Section 5).

7.2.2 Crowdsourcing frameworks and modeling approaches

Certain studies propose frameworks and modeling approaches to improve the design of crowdsourcing systems. Bozzon et al. [9] introduce a reactive crowdsourcing modeling approach focusing on the dynamic control of the crowd, by transforming high-level specifications (e.g. regarding task planning or worker handling) into elementary task-type executions. Roy et al. [57] propose SmartCrowd, a framework to interactively optimize three crowdsourcing processes: task generation, worker-to-task assignments and task evaluation, by taking into account the uncertainties introduced by the human factor. A number of works provide goal-driven design principles, which focus on the optimization of crowdsourcing systems for a global-level performance target. In this line, Lykourentzou et al. [44] present a stepwise modeling approach for the design of corporate crowdsourcing systems, realized in five decision-making and application steps (define goals, characterize jobs, profile workers, identify constraints and design a crowdsourcing optimization algorithm). Finally, Boutsis and Kalogeraki [8] focus on the process of task-to-worker allocation, and present a framework comprising four components (task management, dynamic assignment, profiling and scheduling), which aims at guaranteeing efficient crowdsourcing system performance under dynamic conditions of the crowdsourcing environment.

These works basically describe methodologies to optimize specific objectives of crowdsourcing system design. In contrast, our work describes a broad set of objectives and principles in a top-down manner (Section 3), providing a framework against which specific design methodologies can be implemented by composing different elements (Section 4).

7.3 CSPs examples and best practices

To the best of our knowledge, no prior work attempts to provide a general framework for engineering CSPs. However, there are works that describe CSP applications or best practices in their design. We have already mentioned a number of these works in Section 2. Concrete examples include web table matching [19], entity resolution [70], or iterative text recognition [41]. A common element in them are high-throughput and low-latency requirements, which we capture in Section 3. There are also works describing real-time crowd-involving systems (“flash crowds” [38]), such as the system by Mashhadi and Capra [46] on quality control for user-contributed data in ubiquitous applications, the ones proposed by Bernstein et al. [3] and Bigham et al. [6], or the crisis response system described by Rogstadius et al. [56] (the latter has been recently adapted to operate with AIDR, the application we describe as a use case in Section 6).

An indicative example is CDAS [42], a CSP system for data analytics applied to tasks of sentiment analysis and image tagging. CDAS includes a quality assurance mechanism that takes into account the performance deviations of crowdsourced processing by monitoring historical performance data to estimate each element's accuracy (instantiation of the quality evaluation metric of Section 3.5), as well as an online strategy to reduce waiting time (latency evaluation metric in our framework). Finally, systems using a mix of crowdsourced and automatic elements to achieve more efficient treatment of homogeneous data have been described, with two key examples described in [22, 69].

Certain elements of our framework borrow notions from the success and limitations showcased in the above systems. As an example, the study of performance in terms of quality, cost and speed, mentioned in the above works, have been expanded into the evaluation metrics (Section 3). Furthermore, several of the best practices illustrated above have been converted into design patterns (Section 5).

8. CONCLUSIONS

Crowdsourced stream processing is a new computational frontier that combines high-speed processing with human intelligence. Its progress hinges upon the development of efficient algorithms, as well as on the design of software architectures that implement those algorithms into applications having impact on the real world.

This paper introduces a general framework covering system-level properties and behavior, design principles, structural elements, compositions and patterns, to enable better designs for future applications and to serve as a basis for the evaluation and re-engineering of existing ones.

Much remains to be done between the design of specific CSP applications solving concrete problems, and the development of general frameworks and best practices that can serve as a basis for those designs. This includes extending specialized taxonomies of CSPs, creating new metrics for their evaluation, expanding a catalog of design patterns, among many other tasks that remain open for future work.
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