

Editorial: Special Issue on Stream Reasoning

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Abstract. This editorial introduces the Special Issue on Stream Reasoning, part of the Semantic Web Journal.

Keywords: Stream reasoning, Data streams, Continuous queries

In the recent years, there has been an increasing speed and volume of data production in several domains, such as Internet of Things, Social Networks and Smart Cities. An interesting feature of such data is that its utility is often related to time: the sooner the data is processed, the higher is the value. Consequently, techniques to process huge amounts of heterogeneous streaming data in a continuous fashion are getting more and more important.

Data Stream Management Systems and Complex Event Processing [1] provide foundations for continuously querying and monitoring data streams. However, other kinds of processing are desired, such as deductive and inductive inference, where domain models provide background knowledge and context.

With Stream Reasoning we refer to a research trend that aims at studying how to introduce reasoning processes in scenarios involving streams. Up to now, we have seen two types of stream reasoning: reasoning over streams and reasoning about streams. Reasoning over streams is the incremental reasoning over information that is continuously produced and made available, typically in the context of a static domain model. Reasoning about streams is the reasoning with streams as first class entities. Stream Reasoning introduces new challenges with regard to traditional reasoning over static or slowly changing data: the data is

made available in a continuous way, possibly from different sources; time is a first-class citizen; responsiveness is a key requirement; and deletion mechanisms are often required in order to satisfy performance and space constraints.

The term *Stream Reasoning* emerged a decade ago [2], and developed as a trend involving different areas of computer science, such as semantic web, databases, robotics and knowledge representation. The multidisciplinary nature of Stream Reasoning offers an ideal setting for exchanging ideas and expertise. To push this process, community members contributed to tutorials, summer schools and workshops in important and prestigious venue. Additionally, in the last five years we have organised four invitation-based events to let the community meet and discuss. We observed an increasing trend in terms of attendance and advances in the research. So far, the majority of workshop presentations focused on logic-based reasoning. However, we observe an increasing number of studies focusing on the combination of logic-based reasoning with statistics-based inference techniques to create data processing pipelines. For example, in computer vision, tasks such as object detection, semantic segmentation, and image understanding get advantage of knowledge graphs to improve the quality of the results. In the database and knowledge management commu-

1 nities, the process of creating and enriching knowl-
 2 edge graphs uses statistics-based inference techniques,
 3 e.g. deep convolutional or recurrent neural networks,
 4 and Markov logic networks, in conjunction with logic
 5 reasoners, e.g. Datalog and first-order logic reasoners.
 6 To integrate uncertainty coming from learning models
 7 with logic reasoning processes, approaches such as
 8 Softlogic [3] or extensions of Answer Set Program-
 9 ming (ASP) [4, 5] have been proposed to make the best
 10 of both worlds. One approach is to compute probabil-
 11 ity distributions over MTL-formulas as a result of in-
 12 complete information [6] and another is to integrate
 13 probabilistic inference more directly by extending the
 14 syntax of MTL with probabilistic statements that are
 15 computed through probabilistic inference outside the
 16 logic [7]. While most of these studies focused on pro-
 17 cessing static data, we envision that the development of
 18 new methods and techniques based on statistics-based
 19 inference techniques and logic-based reasoning will be
 20 a driving force in stream reasoning in years to come.

21 Stream reasoning research should also look at dis-
 22 tribution. Most big data stream processing platforms,
 23 such as Apache Flink and Apache Spark, achieve scal-
 24 ability by supporting parallelization of complex it-
 25 erative computing workflows and execution on clus-
 26 ter or cloud platforms. Edge computing is pushing
 27 the computation closer to the data sources, e.g. a
 28 resource-constrained edge device can efficiently store
 29 and process 30 million of RDF triples with 80MB
 30 of RAM [8]. Since stream data is often generated in
 31 a distributed fashion, these decentralized computing
 32 paradigms are suitable and desirable choices to de-
 33 velop stream reasoning solutions. This is not straight-
 34 forward, since there are several theoretical and techni-
 35 cal challenges to build scalable and robust distributed
 36 stream reasoning systems. For example, [9] proposes
 37 to use ASP to formalise distributed reasoning work-
 38 flows (including data stream), by representing the fed-
 39 eration among heterogeneous reasoners. Systems able
 40 to perform reasoning—both logic-based and statistics-
 41 based—on streams may find application in a wide ar-
 42 e of use cases, including Internet of Things, autonomous
 43 driving and personalized medicine.

44 We ran this this special issue to collect the most re-
 45 cent and advanced research on stream reasoning. We
 46 received eight submissions, and after the review pro-
 47 cess, we selected two contributions.

48 In "Enhancing the Scalability of Expressive Stream
 49 Reasoning via input-driven Parallelization", the au-
 50 thors study how to let stream reasoning scale. The
 51 problem they focus on how to parallelise the execution

1 of non-monotonic rules expressed in a subset of ASP.
 2 As a solution, they propose a novel input splitting tech-
 3 nique based on the analysis of the relation between in-
 4 put data streams and ASP rules registered into the sys-
 5 tem. Extensive experiments analyse the performance
 6 of the proposed technique while considering different
 7 class of rules, including recursive and negation rules.

8 In "Ontology-mediated query answering over tem-
 9 poral and inconsistent data", the authors investigate
 10 how to cope with temporal and insistent data in stream
 11 reasoning. The paper considers a temporal query lan-
 12 guage that combines conjunctive queries with opera-
 13 tors of propositional linear temporal logic (LTL) un-
 14 der three consistency-tolerant semantics introduced in
 15 query consistent description logic knowledge bases.
 16 The key contributions of the authors are complexity
 17 analysis of an extensive number of cases of \mathcal{EL}_{\perp} and
 18 DL-Lite $_{\mathcal{R}}$. Also, another interesting contribution of the
 19 paper is its proposal for practical implementations.

20 We would like to thank all the people that contribute
 21 to this special issue. We thank all the authors that sub-
 22 mitted contributions, showing another time that there
 23 is an ongoing active and passionate research on stream
 24 reasoning. We thank the Editors-in-Chief, Pascal Hit-
 25 zler and Krzysztof Janowicz, which gave us the op-
 26 portunity to run this special issue and supported us
 27 in the whole process. Finally, we are very grateful to
 28 the reviewers, whose effort produced valuable insights:
 29 Eva Blomqvist, David Bowden, Jean Paul Calbimonte,
 30 Daniel de Leng, Ali Intizar, Robin Keskisärkkä, Thu
 31 Le-Pham, Alessandro Margara, Alessandra Mileo,
 32 Boris Motik, Özgür Özçep, Josiane Parreira, Kon-
 33 stantin Schekotihin, Patrik Schneider, Veronika Thost,
 34 Jacopo Urbani and Guohui Xiao.

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