ABSTRACT

In the past, we presented a first approach for stream reasoning using Answer Set Programming (ASP). At the time, we implemented an exhaustive wrapper for our underlying ASP system, clingo, to enable reasoning over continuous data streams. Nowadays, clingo natively supports multi-shot solving: a technique for processing continuously changing logic programs. In the context of stream reasoning, this allows us to directly implement seamless sliding-window-based reasoning over emerging data. In this paper, we hence present an exhaustive update to our stream reasoning approach that leverages multi-shot solving. We describe the implementation of the stream reasoner’s architecture, and illustrate its workflow via job shop scheduling as a running example.

1 INTRODUCTION

Stream Reasoning [6, 7] has become a major subject of research in the last years. Some approaches rely on Answer Set Programming (ASP; [18, 2]), a well-established paradigm to declarative problem solving. Rather than solving a problem by telling a computer how to solve the problem, the idea is to simply describe what the problem is and leave its solution to the computer.

Several years ago, we proposed one of the first stream reasoning approaches [10, 9, 8] with ASP. At that time, we had to implement an exhaustive wrapper for our underlying ASP system, clingo [12, 13, 11], to enable reasoning over continuous data streams. Nowadays, clingo natively offers multi-shot solving [14]: a set of functionalities to support operative processing of streams. With that, instead of restarting the solver whenever an update arrives, we reuse the running clingo process by directly updating its internal knowledge base accordingly. Furthermore, users can define custom stream reasoning workflows with minimal effort via clingo’s API, available for programming languages C, Lua, and Python.

In this paper, we will detail a barebones approach to leverage clingo’s multi-shot solving capabilities for stream reasoning. Particularly, we will give a brief introduction to multi-shot solving; devise a basic stream reasoner based on multi-shot solving using clingo’s Python API; and showcase our stream reasoner’s workflow via job shop scheduling as a running example.

2 JOB SHOP SCHEDULING WITH ANSWER SET PROGRAMMING

For better illustration, we introduce a running example, job shop scheduling (JSP) that we solve first with regular
(single-shot) ASP. We consider a variant of JSP where jobs are pre-assigned to machines. The problem is the following: given $m$ jobs each with a specific duration and pre-assigned to one of $n$ available machines, what is a suitable schedule? Typically, we also assume $m > n$ to eliminate trivial problem instances.

The basic idea of ASP is to declaratively describe a problem by a logic program and feed it into an ASP solver to retrieve the program’s stable models, which correspond to the solutions of the original problem. For example, consider a JSP instance consisting of jobs 1, 2 and 3 with respective durations of 4, 2, and 2 minutes, assigned to machines 1, 2 and 3, respectively. In ASP, this can be represented by the facts

$$\text{job}(1,1,4). \text{job}(2,2,2). \text{job}(3,2,2).$$

where the first argument of job/3 is the job’s ID, the second its assigned machine, and the third its duration. The general JSP problem can represented as follows:\footnote{Full source code available at \url{https://github.com/potassco/aspStream/blob/master/aspStream/job.lp}.}

1: \texttt{#const horizon = 4.}


Line 1 sets the constant for the planning horizon to 4. The next rule (Line 3) chooses for each job $J$ a single starting time point $T$ stated as $\texttt{start}(J,T)$. Line 5 and 7 define when a machine is occupied by a job: when a job is started on a machine (Line 5), and when it is still running (Line 7). The constraint in the last line makes sure that at no point two jobs occupy the same machine. When we evaluate this encoding with the instance above, we retrieve two stable models: the first model, $\{\texttt{start}(1,1),\texttt{start}(2,3),\texttt{start}(3,1)\}$, schedules both job 1 and 3 at time point 1 and job 2 at 3; the second model, $\{\texttt{start}(1,1),\texttt{start}(2,1),\texttt{start}(3,3)\}$, schedules both job 1 and 2 at time point 1 and job 3 at 3.

3 \textbf{Multi-Shot Stream Reasoning}

In this section, we first give a brief conceptual overview of our stream reasoning approach. Afterwards, we informally explain how to leverage multi-shot solving in this context. Eventually, we give a technical description of our software architecture and its workflow.

In essence, our approach continuously evaluates an ASP problem over a \textit{stream}, a finite sequence of sets of ASP atoms. The domain of the sequence, i.e., natural numbers 1, 2, 3, 4, \ldots represents time steps. We employ a \textit{tuple-based sliding window} \cite{16} of fixed size to limit the scope of data to consider. To implement this mechanism in ASP, we leverage multi-shot solving \cite{12,15,17} to seamlessly add new and remove outdated information from the window over time. Formally, this portrays an alternative operational characterization for solving time-decaying logic programs\cite{10} with fixed expiration time. We leave the proof of this claim for the full paper.

Since our approach uses ASP multi-shot solving \cite{12} as semantic foundation, we subsequently give an informal introduction to the features we used, mostly borrowed from the material in \cite{15,17}. In general, \textit{clingo} offers several high-level constructs to realize reasoning processes that tolerate evolving problem specifications to enable the dynamic addition and removal of rules and data over time. This type of continuous solving interleaved with data manipulation is also known as Multi-Shot Solving. For our implementation, we heavily rely on the \texttt{#external} directive that allows to declare input atoms that may be instantiated by rules added later on. To this end, a directive like '\texttt{#external} \texttt{p(X,Y)} : \texttt{q(X,Z)}, \texttt{r(Z,Y)}.\texttt{'} is treated similar to a rule \texttt{p(X,Y) :- q(X,Z), r(Z,Y)}. during grounding. However, the head atoms of the resulting ground instances are merely collected as inputs, whereas the ground rules as such are discarded. Once grounded, the truth value of external atoms can be changed via \textit{clingo}'s API. By default, the initial truth value of external atoms is set to false. Then, for example, with \textit{clingo}'s Python API, function call \texttt{assign_external(clingo.parse_term('p(a,b)'),True)} can be used to set the truth value of the external atom $p(a,b)$ to true.

With the \texttt{#external} directive, we can also declare input atoms to resemble a sliding window, e.g. via

\begin{verbatim}
#external window(A,WT) : WT=1-wsize..0, watom(A).
\end{verbatim}

Intuitively, the atoms in the sliding window are represented as external atoms over predicate \texttt{window/2} where $A$ is an atom occurring in the stream at the current time step offset by $WT$. Further, \texttt{wsize} denotes the window size and $WT=1$-\texttt{wsize}..0 states the domain of $WT$ ranging from 1-\texttt{wsize} to 0, i.e, the time steps covered by the window relative to the current time step. To advance the window by one time step, we can toggle the truth values of the \texttt{window/2} atoms via \textit{clingo}'s python API accordingly, as detailed above.

At its core, our technical implementation\footnote{Source code available at \url{https://github.com/potassco/aspStream}.} relies on a \texttt{controller} module for the overall workflow shown in Listing 1. Its main function in Line 30-45 expects a \textit{streamed program} as input derived from abstract class \texttt{AbstractStreamedProgram} in Line 20-27. A streamed program is custom to a problem and constitutes 1) the
ASP problem encoding to apply, 2) the sliding window size, and 3) a function \texttt{next} that returns and afterwards removes the first element in the stream. With this setup, the \texttt{main} function is able to evaluate the problem encoding on the stream in a sliding window fashion. More precisely, in Line 33, the clingo control object gets initialized with the window size passed as a constant. Afterwards, in Line 34-35, the problem encoding provided by the streamed program and the declaration of external \texttt{window} in line 6 are grounded. As described previously, \texttt{window} represents the atoms of the current window and will be used in sequel to dynamically update those according to the current time step. Line 40-45 facilitate a loop that iteratively solves the problem for the atoms in the current window until the end of the stream. That is, Line 41-42 update the current window’s atoms by calling function \texttt{set_externals} to set newly added and expired atoms of external \texttt{window/2} to true or false, respectively. With the updated ground program, the solve method of clingo is called in line 44 utilizing our custom \texttt{on_model} method in line 9-11 to print the solve result to the standard output. Eventually, the sliding window is advanced by one time step by calling \texttt{next} in Line 45. In general, this loop can also be re-designed to advance the window more than one time step per cycle by adding the result of multiple \texttt{sp.next()} calls to the currently considered window atoms.

At this juncture, we apply our devised concepts to the job shop scheduling problem from Section 2. Since we intend to reuse our existing JSP encoding, we introduce a new predicate \texttt{request/3} that has the same signature as \texttt{jobs/3} but captures the notion of dynamically arriving job requests from the stream. For instance, consider a stream of length 2 where at time step 1 two job requests arrive: request 1 for machine 1 of duration 4, and request 2 for machine 2 of duration 2. Further, at time step 2 a single request arrives: request 1 for machine 2 of duration 3. With \texttt{request/3}, we can express this as a stream of ASP atoms as follows

<table>
<thead>
<tr>
<th>time step</th>
<th>window atoms</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>request(1,1,4), request(2,2,2). request(1,2,3).</td>
</tr>
<tr>
<td>2</td>
<td>request(1,1,4). request(2,2,2). request(1,2,3).</td>
</tr>
</tbody>
</table>

where \{ request(1,1,4), request(2,2,2) \} and \{ request(1,2,3) \} are the set of arriving ASP atoms for time steps 1 and 2, respectively. Then, processed by the controller function \texttt{set_externals} (Listing 1, Line 13-17) at time point 1, the following atoms of the sliding window \texttt{external window} would hold:

\[
\text{window(request(1,1,4),0)},
\text{window(request(2,2,2),0)}
\]

Processed again for time point 2 and assuming that the window size is at least 2 time steps, \texttt{set_externals} would change the true atoms of external \texttt{window} to

\[
\text{window(request(1,1,4),-1)},
\text{window(request(2,2,2),-1)},
\text{window(request(1,2,3),0)}.
\]

To effectively support the scheduling of streamed requests, we still have to supplement our encoding in Section 2, e.g. with the rules in Listing 2. The overall idea of this addition is the mapping of arriving \texttt{request/3} atoms to \texttt{job/3} atoms such that our previous encoding can be reused for solving. Specifically, in Line 1 constants \texttt{jobs} and \texttt{requests} state the maximum number of streamed requests and processing jobs per time step, respectively, and \texttt{machines} states the number of available machines. The assignment of requests to jobs is accomplished by Line 3-7: the cardinality rule in Line 3 assigns each request \texttt{R} within the scope of the sliding window at relative time point \texttt{WT} to a job expressed by the implied \texttt{assign/2} atom. To ensure that different requests cannot be assigned to the same job, we add the constraint in Line 5. For every assigned request, we yield the respective \texttt{job/3} atom in Line 7. Recalling our declaration of external \texttt{window/2} from above, we must also define the domain of possible atoms occurring in the sliding window via \texttt{watom/1} in Line 9. The \#show statement in Line 11 formats the solution as \texttt{wstart/4} terms which state for each request \texttt{request(R,M,D)} in the window at relative time point \texttt{WT} its absolute starting time point \texttt{T}.

By setting up a custom streamed program\footnote{Full source code available at \url{https://github.com/potassco/aspStream/blob/master/aspStream/stream_controller.py}} with window size of at least 2 and our extended encoding, we can use the controller to schedule the request in the example stream above: after the first time step we retrieved stable model

\[
\text{wstart(request(1,1,4),0,1)},
\text{wstart(request(2,2,2),0,3)}
\]

which suggest to schedule request 1 and 2 at time point 1 and 3, respectively. After solving again at time point 2, we get stable model

\[
\text{wstart(request(1,1,4),-1,1)},
\text{wstart(request(2,2,2),-1,1)},
\text{wstart(request(1,2,3),0,3)}
\]

which suggest to schedule request 1 and 2 arrived at relative time point -1 both to absolute time point 1, and request 1 arrived at relative time point 0 to absolute time point 3. A notable drawback of this approach is that we

\footnote{Full source code available at \url{https://github.com/potassco/aspStream/blob/master/aspStream/stream.lp}}
def on_model(m):
    show = \n        \n        \n        print("Answer:
        \nListing 1: Controller module of the stream reasoner written in Python

Listing 2: Complementary ASP encoding to enable streamed JSP planning

reschedule all previously submitted jobs. Specifically, jobs that were started before the current timepoint may be reassigned to another start time. As a remedy, we developed an extended variant that considers already running jobs and occupied machines. For reasons of space, we skip a detailed explanation here and refer to our encoding.


4 DISCUSSION

There have been a host of logic and ASP-based approaches in recent years. For ontological knowledge bases, [3] proposes a stream reasoner with time-annotated RDF data that may expire. To bridge the gap between purely event-driven systems and rule-based reasoning, the first-order language ETALIS [1] was developed. The ASP-based language LARS [4] adds language primitives for time and data-based window operators as well as temporal modalities to compare streams and windows. An implementation of LARS based on clingo is presented in [5]. In a broader sense, clingo by itself can be seen as a general toolkit to facilitate dynamic workflows based on external updates. Our work in [12, 13, 11] presented a first concept for incremental stream reasoning with ASP.
In conclusion, we laid out a pragmatic approach to leverage clingo’s multi-shot solving capabilities for stream reasoning. To this end, we presented a basic implementation of a stream reasoner and showcased how to realize a sliding window using clingo’s Python API. Moreover, we demonstrated our devised concepts by applying them to an online-version of job shop scheduling. For the future, we aim to elaborate more advanced design patterns from a implementation point of view. In terms of theoretical conception, we plan to particularize the link to time-decay logic programs and potentially expand their semantics.

ACKNOWLEDGMENTS

This work was partially supported by DFG grant SCHA 550/9.

REFERENCES


**Author Biographies**

**Philipp Obermeier** is a doctoral student in the Knowledge-Based Systems group at the University of Potsdam, Germany since fall 2012. His scientific interests are centered around Answer Set Programming (ASP) and declarative languages for dynamic domains. Specifically, he co-developed new concepts to efficiently utilize ASP as integrated representation and reasoning layer for streamed data (e.g. sensor data, Web-based streams) and static background knowledge. Moreover, he co-designed best-practice design patterns for implementing sliding windows with finite logic programs. More recently, he began to explore design patterns and techniques for ASP to address dynamic application on a real-world scale. As a first step, he identified robotic intra-logistics as representative scenario and based on this, co-developed a standardized benchmark framework, ASPRIL. Closely related to that, he further co-developed a scalable ASP-based approach for a generalization of Target Assignment and Path Finding, and he participated in an project on routing automated transport vehicles in car assembly at Mercedes-Benz.

**Javier Romero** is a researcher at the University of Potsdam, Germany. He received a MSc. in Computer Science from the University of Corunna in 2006, and in Philosophy from the University of Santiago de Compostela in 2008, both in Spain. His research interests are knowledge representation and logic programming, and his research focuses in extensions of ASP for declarative heuristics and preference reasoning. He is a member of the open source project potassco.org developed at Potsdam, and the main developer of ASPRIN, a system for preferences in ASP.

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