between values of a parameter in two consecutive messages, e.g. speed of an object to detect if it is accelerating or slowing down.

Another direction of extension is the improvement of the measurement methodology. So far we have used the system-level measures which are just aggregations and do not help much in the identification of weak points of each solution. In the future, we plan to use the built-in solutions available via additional monitoring API. Both Flink and Spark offer their own interface for monitoring various additional parameters, like for example heap size or separation of CPU usage between manager and workers. We will look for a common denominator to compare Spark and Flink in greater detail. The ultimate goal of the next paper will be confronting the capabilities of the tools with specific algorithms according to requirements to determine architecture choice.

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