Data-driven Windows: The Theory and Practice of Frames

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ABSTRACT
Abstract.

1. INTRODUCTION
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2. USE CASES
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3. FRAME SPECIFICATION
To give a formal specification of frames, we first define the framing of a data stream and then specify the functions that can be used to define a framing. We also describe how a framing can be used to fill frames with tuples from a stream. Finally, we introduce example of commonly used framings and describe how they can be expressed based on the given specification.

Definition 1: A *data stream S* is defined as an infinite sequence of tuples $S = [t_1, t_2, t_3, \dots]$. All tuples of a data stream have the same schema. One attribute of the schema, the *progressing attribute*, is distinguished as is defines the logical order of the tuples. The stream progresses in this attribute, i.e. if A is this attribute, then for any n, there is an i s.t. $t_i.A > n$. Note that while the presence of a progressing attribute implies a logical ordering, it does not require that the tuples within the stream are physically ordered.

3.1 Framing of a Data Stream
For the purpose of this paper, we define the framing of a data stream incrementally by introducing the set of possible frames that is then restricted through local and global conditions to obtain the set of candidate and final frames, respectively.

Definition 2: The *possible frames $F_p(S)$* of a data stream S are given by the infinite set of intervals (or framing) $F_p(S) = \{[s_1, e_1], [s_2, e_2], [s_3, e_3], \dots\}$, such that $\forall [s, e] \in F_p(S) : s, e \in dom(A)$, if A is the progressing attribute and $\forall i < j: s_i \leq s_j \land s_i = s_j \Rightarrow e_i \neq e_j$.[1] For an interval $[s, e] \in F_p(S)$, we define an $extent([s, e])$ as the set of tuples $\{t | t \in S \land s \leq t.A < e\}$, where A is the progressing attribute.

Theoretically, all set of intervals that satisfy the conditions given in the definition are valid framings of a stream. In practice, however, it is useful to further constrain framings. We distinguish *local* and *global conditions* that can be applied to restrict which intervals are contained in a framing.

A local condition p_l is a (conjunction of) predicates that can be individually checked for each interval extent contained in the set of possible frames F_p. We distinguish data-dependent and data-independent predicates. For *data-dependent predicates*, expressions of the form $lhs\ \theta\ rhs$ can be used, where θ is a comparison operator, rhs is a constant, and lhs is a sub-expression built from arithmetic operators, aggregates, and universal quantification. The predicate $t.X > c$ for instance restricts the framing to intervals where the value of attribute X of all contained tuples t is consistently larger than a constant c.

A *data-independent predicate*, guarantees the minimum (or maximum) duration of the interval. Duration can be expressed either in terms of the progressing attribute A or the number of tuples contained in the $extent([s, e])$. In the former case, the second condition is given by $e.A - s.A \geq n$ (or $e.A - s.A \leq n$), while in the latter case, it is given by $|extent([s.e])| \geq n$ (or $|extent([s, e])| \leq n$), where $|\cdot|$ denotes set cardinality. The two conditions are used in conjunction to form the local condition p_l in the following definition.

Definition 3: The *candidate frames $F_c(S)$* of a data stream S are those possible frames for which the local condition p_l is true, i.e., $F_c(S) = \{[s, e] | [s, e] \in F_p(S) \land p_l([s, e])\}$.

Global conditions p_g apply to all intervals in the set of candidate frames F_c, rather than to an individual interval. As a global condition, we can require that all intervals are either *minimal* or *maximal*. For example, a set of candidate frames obtained by the threshold predicate above is not guaranteed to report a unique set of intervals as for every interval that satisfies the predicate all sub-intervals down to individual tuples could be reported. In this case, requiring the framing to be maximal ensures that only non-overlapping intervals of maximal length are reported.

Another global condition that guides the selection of candidate frames is whether a set of intervals is *saturated* or *drained*. A set of frames is saturated if it satisfies all conditions and there is no candidate frame that can be added to it without violating a condition (set maximality). A final framing is drained if it satisfies all conditions and there is no frame that can be removed from it without violating a condition (set minimality).

Definition 4: The *final frames $F_f(S)$* of a data stream S are the candidate frames for which all global conditions $p_g^1, \dots, p_g^n$ are true, i.e., $F_f(S) = \{[s, e] | [s, e] \in F_c(S) \Leftrightarrow \bigwedge_{1 \leq i \leq n} p_g([s, e])\}$.

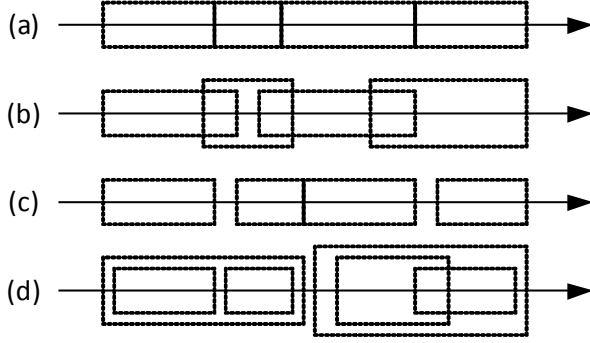[1] The names s_i and e_i stand for start and end point, respectively.

Figure 2: Different types of framings.

3.2 Properties of Framings

Depending on the local and global conditions chosen for a framing, we can observe different *framing schemes* that describe how a stream is segmented. **Error! Reference source not found.** summarizes important framing schemes.

a) **Partition.** Each interval $[s_i, e_i]$ begins where the previous frame $[s_{i-1}, e_{i-1}]$ ended, i.e. $s_i = e_{i-1}$. Note that this segmentation of the stream is similar to tumbling windows. However, intervals still vary in length, whereas windows are of fixed length, either in terms of time or tuples.

b) **Cover.** $\forall\, a \in dom(A): \exists\, [s_i, e_i] \in F: s_i < a \leq e_i$, where A is the progressing attribute, i.e. $s_i \leq e_{i-1}$. Note that this segmentation of the stream is similar to sliding windows. However, neither the slide offset nor the interval length is fixed. A special case of this segmentation is the case where intervals overlap by fixed value c, i.e. $s_i = e_{i-1} - c$. We will refer to this stream segmentation as **adjacent**. Another special case are **advancing** intervals, where we require that $b_i < b_{i+1} \wedge e_i < e_{i+1}$.

c) **Disjoint.** $\forall\, [s_i, e_i] \in F: \nexists\, [s_j, e_j] \in F: s_j \leq s_i \leq e_j \vee s_j \leq e_i \leq e_j$, i.e. $s_i \geq e_{i-1}$. Note that with this segmentation it is possible that some values $a \in domain(A)$, where A is the progressing attribute, are not contained in any intervals.

d) **Unconstrained.**

3.3 Examples

Coming back to the use cases presented in Section 2, we now describe a series of types of frames that address the requirements outlined earlier. We also discuss how each of these types can be specified within the framework introduced in this section.

Threshold Frames: This type of frame reports periods of the stream where the value of a user-defined attribute a is greater (or smaller) than a given threshold value x. As a consequence, this type of frame does not partition or cover the stream. It is defined by the frame predicate $a > x$ (or $a < x$) as a local condition. Global conditions that apply to this type of frame are maximal and drained to restrict the final frames to only include contiguous episodes of maximal length. An example of use for this type of frame is to report high-loss periods.

Boundary Frames: Boundary frames segment the stream whenever the value of a user-specified attribute crosses a (multiple of) a given boundary x. This type of frames partitions the stream: any tuple is contained in some candidate frame and
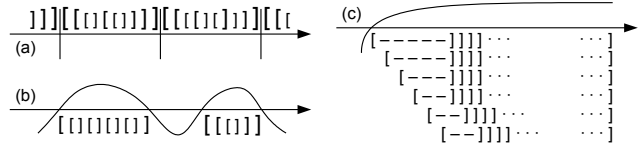

Figure 1: Boundary (a), threshold (b), and delta/aggregate (c) frames.

full coverage is given by the fact that any single tuple frame satisfies the predicate. The local condition is given by frame predicate for the nth frame as $(n - 1)x < a \leq nx$. Global conditions maximal and drained can be used in conjunction with this type of frame. Note that if attribute a is a progressing attribute, this equivalent to windows.

Delta Frames: This type of frame monitors a user-specified attribute a of the tuples in the data stream. A frame is emitted whenever the delta between the minimum and maximum value of this attribute becomes greater than a predefined value x. The frame predicate is therefore given by $\max(a) - \min(a)\, \theta\, x$ as the local condition, θ is a comparison operator. Depending on the comparison operator, these framings are typically required to be minimal or maximal at the global level. For example, if the delta is required to be smaller than the constant x, it can make sense to only report maximal frames, whereas minimal frames are useful if the delta is required to be larger than the constant x. Depending on whether the framing is set to be drained or saturated, this type of frame produces non-overlapping and overlapping sets of intervals.

Aggregate Frames: This type of frames monitor a predicate over an aggregation of an attribute and reports a new frame if the aggregate value becomes greater than a given constant. The frame predicate is therefore given by $f_{aggr}(a)\, \theta\, x$, where f_{aggr} is an aggregation function and θ is a comparison operator. In terms of global conditions, the same observations as for delta frames apply to aggregate frames. An example of this type of frame is segmenting on the sum of dye mass.

3.4 "Lemmas and Proofs"

Definition 5: A framing has *union closure*, if the union of overlapping candidate frames is also a candidate frame. Note that this is the case for threshold and boundary frames. A framing has *super-interval closure*, if any frame that (fully) contains a candidate frame is also a candidate frame. Vice-versa, it has *sub-interval closure*, if any frame that is fully contained in a candidate frame is also a candidate frame.

Lemma 1: If a framing has union closure and the set of final frames is drained, maximal, and has coverage of candidate frames, then the final framing is unique.

Proof (by contradiction): If we assume that the framing is not unique then there are at least two different framings. Without loss of generality, we assume that these two framings differ for the interval $[i, j]$, which satisfies the local conditions. The first framing contains the intervals $[i, k]$ and $[k + 1, j]$, while the second contains $[i, l]$ and $[l + 1, j]$, where $k \neq l$. However, this is in contradiction to the lemma as these two framings are not drained and maximal. Because of candidate frame coverage, both framings can be drained further by substituting $[i, j]$ for the two intervals in each framing. ∎

Lemma 2: If a framing has super-interval closure (or sub-interval closure) and the set of final frames is drained, minimal (or

maximal), and has coverage of the candidate frames, then the final framing is unique.

Proof: Given that the framing has super-interval closure (or sub-interval closure), a minimal (or maximal) frame with starting point T_1 cannot properly contain a minimal (or maximal) frame with starting point T_2, where $T_2 > T_1$. Since the framing has coverage of the candidate frames and is drained, it is therefore unique as the first possible frame needs to be picked which then defines the starting point of the next frame, etc. ∎

3.5 Framing Function

A framing as defined in the previous section is a function that returns a sequence of frame intervals for a given data stream. However, in order to process the data stream as it progresses, we require that this function can be computed incrementally, based on the previously computed frame intervals and the next tuple of the stream.

Definition 6: A *framing function* $f(F_{i-1}, C_{i-1}, t_i) \rightarrow (F_i, C_i)$ applies the ith tuple to the current framing F_{i-1} and returns a new framing F_i. The framing F_i is an extension of the framing F_{i+1}, i.e. $F_{i+1} \subseteq F_i$. C_{i-1} and C_i denote the respective state before and after application of f for the ith tuple.

C manages both the internal state of the framing function and the list of frames that are currently being processed, i.e. the *open* frames. For every arriving tuple, the framing function needs to decide whether (a) to open a new frame, (b) update an existing frame, or (c) close and emit a frame. In the latter case, the frame is removed from state C and inserted into the framing F. Depending on the framing scheme, all of these actions can be applied once or multiple times. In order to control the behavior of a framing function, we have identified the following frame properties.

We conclude this subsection by outlining an example template of a framing function that generates partitioning frames.

PARTITION$(F_{in}, C_{in}, t, p) \rightarrow (F_{out}, C_{out})$
1:   $f_{old} \leftarrow [s_{old}, e_{old}] \mid [s_{old}, e_{old}] \in C_{in}$
2:   **IF** $p(t, S_{in})$ **THEN**
3:       $F_{out} \leftarrow F_{in}$
4:       $f_{new} \leftarrow [s_{old}, ts(t)]$
5:   **ELSE**
6:       $F_{out} \leftarrow F_{in} \cup \{f_{old}\}$
7:       $f_{new} \leftarrow [ts(t), ts(t)]$
8:   **END**
9:   $C_{out} \leftarrow C_{in} \backslash f_{old} \cup \{f_{new}\}$
10: **RETURN** (F_{out}, C_{out})

The function template begins by extracting the current frame from the state C. Note that there is only one open frame in the state as this template follows the partition scheme. On line 2, the predicate is evaluated. If it still holds, the current frame is extended (lines 3 and 4). If not, the current frame is emitted (line 6) and a new
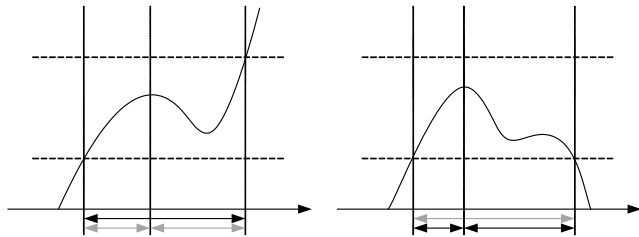

Figure 3: Boundary frames with multiple open frames.

frame is opened (line 7). Finally, the state is updated to reflect the updated or new frame (line 9). The function $ts(\cdot)$ is used to return the value of the progressing attribute of a tuple.

3.6 Filling Frames

Once a framing of a stream has been defined in terms of a sequence of intervals, it can be used to fill frames. A framing that has computed based on one stream can be used to produce frames of that stream or any other stream. A frame filling $\hat{F}$ is given as a set of tuple sequences $\hat{F} := \{\langle t_1, t_2, \dots t_i\rangle, \dots \langle t_{n-j}, \dots t_{n-1}, t_n\rangle\}$.

Definition 7: A *frame filling* is defined by a function $f := (S', g(F), Q) \rightarrow \hat{F}$, where S' is the data stream furnishing the tuples, F is the framing, and Q is a query.

The function $g(\cdot)$ allows intervals in the framing to be modified. For example, the function could be used to extend or reduce the lengths of intervals by a fixed amount. In particular, it can be used to produce adjacent frames. In contrast, the query Q defines a subset of the tuples that fall into the interval of the frame, or performs aggregation.

4. IMPLEMENTATION
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5. EVALUATION

We are primarily interested to evaluate frames using task-based performance metrics that quantify the value of frames as a technology to compute a specific data product. We compare the quality of frame-based data products to window-based and manually created data products. Finally, we evaluate the run-time performance overhead of frames with respect to windows.

All experiments were run in NiagaraST, using its existing window implementation and the frame implementation presented in ??. The figures reported in this section were measured on a Dell Optiplex 780 with a 3 GHz CPU and 4 GB of main memory.

The dataset used in the experiments contains measurements from dye track cruise W0908B, conducted by Oregon State University (OSU) in the Pacific Ocean off the coast near Newport from August 26 to September 2, 2009. Dye is measured with a photometer at a sub-second frequency.

5.1 Episode Detection

An important application for frames is the detection of so-called episodes in a stream. In Maier *et al.* [3], we exclusively focus on the use and the evaluation of threshold frames for this use-case. We will not repeat these results here and direct the interested reader to our previous publication.

5.2 Histogram Approximation

We evaluate the use of frames to compute specific data products in the setting of dye mass vs. depth histograms as used by oceanographers at OSU. As a baseline, we compute the exact histogram manually using the same technique as the oceanographers. We then compare this baseline to approximations based on frames and windows. Each of these histograms is computed based on a different technique to segment the data. To reduce noise, the average dye mass of each segment is calculated and multiplied by the Δdepth of the segment. Finally, this value is summed to the corresponding density bin of the histogram.

The *oceanographer's histogram* (baseline) segments the dye dataset into predefined depth slices of a fixed size. The *windows-based approximation* segments the dye dataset based on its
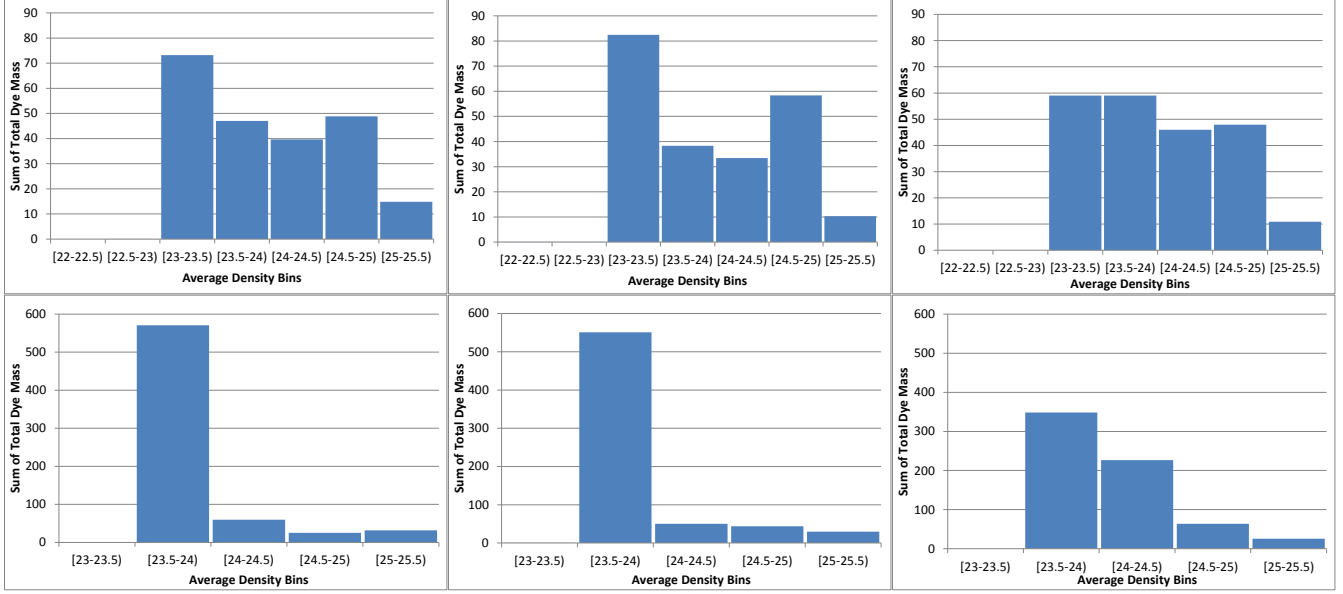
Figure 4: Baseline histogram, frame-based and window-based approximation for tow06 (top) and tow13 (bottom).

progressing attribute, i.e., the scan number into tuple-based windows of a fixed size. We compute *frame-based approximations* based on three types of delta-frames that each uses a different framing predicate. The first type of delta-frame starts a new frame whenever it has seen a shift in density (of the water). The second type uses the same approach to look for shifts in dye mass. Finally, the third type of delta-frame applies both predicates and starts a frame if either of them is true. In the last case, we have fixed the ratio between the two deltas to 1:2. Finally, we use dynamic programming to compute the *pair-wise constant optimal approximation* of the oceanographer's histogram in terms of partition boundaries, given a predefined number of partitions.

As a task-based metric to compare the histograms we compute, we use the so-called *earth-mover distance* (EMD). The earth-mover distance measures how many data units have been assigned to a wrong bin in the histogram in terms of how "far" they would have to be moved to be in the correct bin.

In Figure 4, we show the oceanographer's baseline histogram (left) together with the frame-based (center) and window-based (right) approximation. The top line of histograms is based on

tow06 from the dye dataset, whereas the bottom line visualizes tow13 from the same dataset. We have chosen these two tows as the relative task-based error of frames with respect to windows is worst on tow06 and best on tow13.

The tow06 data stream consists of a total of 519,998 tuples, which are segmented into 51,756 depth slices for the baseline histogram capturing a total of 225.6 dye units. The frame-based approximation is computed based on 897 frames and has earth-mover distance 19.3 with respect to the baseline histogram. The window-based approximation is computed using 897 windows but has earth-mover distance 23.7.

The tow13 data stream contains 407,992 tuples in total, which require 38,172 depth slices for the baseline histogram capturing a total dye mass of 687.7 units. The frame-based approximation uses 4,217 frames and yields an error of earth-mover distance 60.5. Similarly, the window-based approximation needs 4,207 windows, but has earth-mover distance 294.6, i.e., almost 45% of the total dye mass.

Figure 6 plots the relative error of windows over frames for all six two data streams of the dye data set. The relative error is
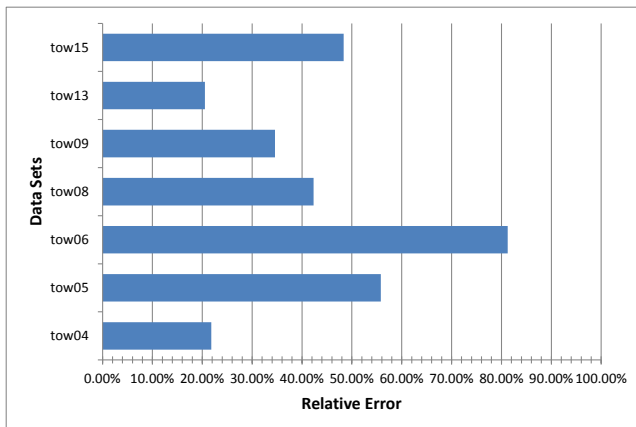

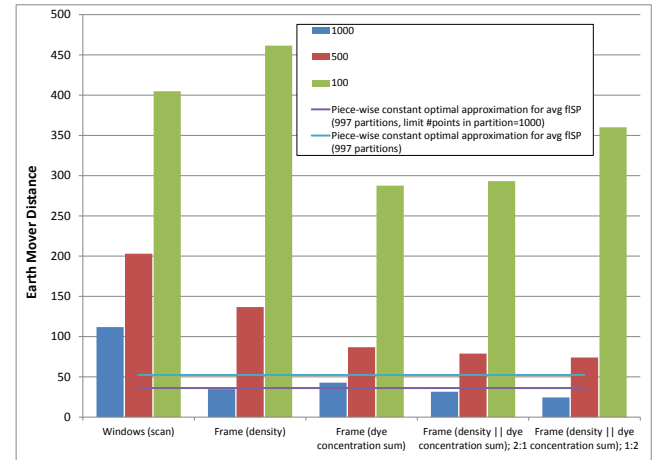**Figure 6: Relative error of windows and frames.**

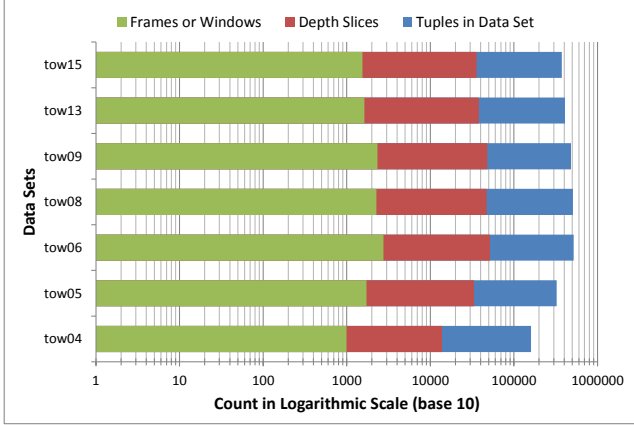**Figure 5: EMD for different frame and window sizes (tow04).**

Figure 7: Data points in computation.

calculated as $1 - EMD_{frame}/EMD_{window}$.

In Figure 5, we compare the earth-mover distance of histograms computed based on three different window sizes (100, 500, and 1000 tuples) to four different delta framings, which were tuned (by adjusting the delta constant) to yield the same (or a very close) number of frames. The first framing is segmented using dye density deltas, whereas the second frames on the delta of the sum of dye concentration. The third and the forth framing use a conjunction of the previous delta predicates, with the delta of the two predicates adjusted to 1:2 in the former case and 2:1 in the latter case. As a reference, we have also included the piece-wise constant optimal approximation that uses dynamic programming to find the boundaries of the partitions. We show the values for (about) 1000 partitions once with and once without a limit of 1000 points per partition. We note that the two framings that use a conjunction of predicate seem to perform "super-optimally". This is explained by the fact that the dynamic programming algorithm only considers average fluorescence (density), whereas these framings also factor in dye mass.

One goal of the approaches using frames or windows is to reduce the number of data points in the computation. In Figure 7, we quantify this reduction by comparing the number of data points in the original data sets, to the number of depth slides, and to the number of frames or windows. As can be seen, the use of frames or windows reduces the number of data points that need to be processed by an order of magnitude with respect to the manual approach for all tow data streams.
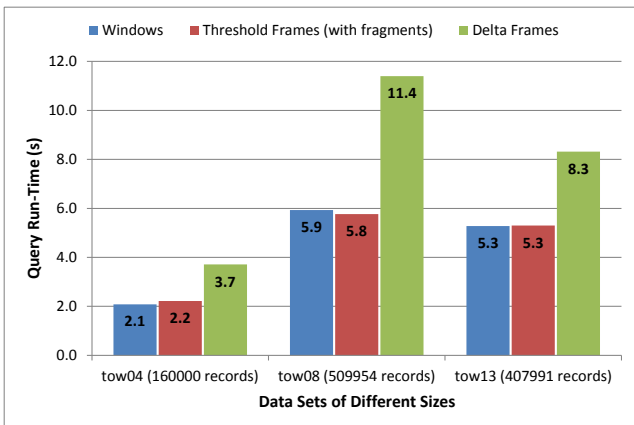

Figure 8: Comparison of run-time performance.

5.3 Dataset Summarization

6. RELATED WORK

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The proposal to extend XQuery with windows by Botan *et al.* [1] shares some similarities with frames. As frames, the proposed windows for XQuery are not tuple or time-based, but are specified using a mandatory start and end condition as well as an optional where predicate, which have the same effect as the local conditions in our approach. Additionally, the approach distinguishes tumbling, sliding, and landmark windows to control the behavior of the system. This is comparable to our notion of global conditions. We believe, however, that our separation of concerns into local and global conditions is conceptually superior as with XQuery windows there can be interference between window types and start conditions. Finally, the proposed windows for XQuery do not take disorder or very long windows into consideration. In our work on frames, we have addressed both issues with punctuation and frame fragments, respectively.

7. CONCLUSION

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8. ACKNOWLEDGMENTS

9. REFERENCES

[1] I. Botan, P. M. Fischer, D. Florescu, D. Kossmann, T. Kraska, and R. Tamosevicius. Extending XQuery with Window Functions. In *Proc. Intl. Conf. on Very Large Databases (VLDB)*, pages 75-86, 2007.

[2] P. M. Fischer, A. Garg, and K. S. Esmaili. Extending XQuery with a Pattern Matching Facility. In *Proc. Intl. XML Database Symposium (XSym)*, pages 48-57, 2010.

[3] D. Maier, M. Grossniklaus, S. Moorthy, and K. Tufte. Capturing Episodes: May the Frame Be with You (Invited Keynote). In *Proc. Intl. Conf. on Distributed Event-Based Systems (DEBS)*, pages ??-??, 2012.

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Note that some of the local properties imply global properties. For example, requiring intervals to be maximal at the local level will always lead to a disjoint framing scheme as overlapping intervals

can be combined into a single interval. Similarly, certain constraints on the starting points of interval will also directly yield a certain framing scheme. For example, to specify an adjacent segmentation, the starting point condition would be defined as $s_i = e_{i-1}$, while the condition $s_i = e_{i-1} + 1$ yields a partitioning of the stream. As a consequence, care has to be taken in order not to specify conflicting conditions.

Furthermore, we allowing multiple possible interval starting points using a complex expression together with a non-overlapping framing scheme, the situation may arise where a starting point occurs *before* the ending point of the preceding interval. We use policies to indicate which condition will be violated by the framing if such a situation arises. There are three possibilities.

a) **Close and report the preceding interval:** This policy will lead to a framing that possibly violates the local condition defined by the predicate.

b) **Drop and suppress the previous interval:** This policy possibly leads to false negatives in terms of the local condition defined by the predicate. It will also possibly violate the global condition of a covering (or partitioning) framing scheme.

Continue the previous interval: This policy does not violate any of the local conditions, but possibly violates a requirement to generate a non-overlapping framing scheme.

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