PREPRINT
Full paper DOI: https://doi.org/10.2312/evs.20211063



# A Multilevel Approach for Event-Based Dynamic Graph Drawing

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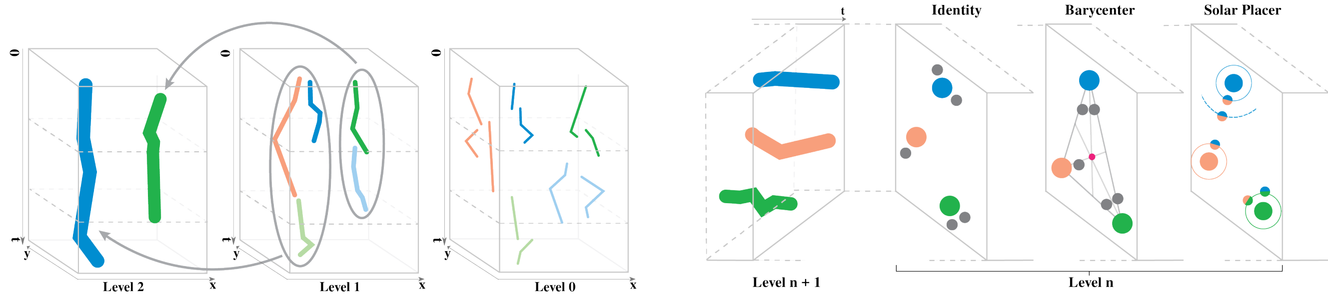


(a) Example of the coarsening process. When two or more nodes are merged together, their presence intervals are merged as well.

(b) Placement strategies for the three `MultiDynNoS` variants.

Figure 1: Multilevel strategies have two important stages: coarsening and placement. In this event-based multilevel approach, we coarsen and place trajectories. An example of the coarsening (a) and placement (b) stages used by the approach.

**Abstract**

*The timeslice is the predominant method for drawing and visualizing dynamic graphs. However, when nodes and edges have real coordinates along the time axis, it becomes difficult to organize them into discrete timeslices, without a loss of temporal information due to projection. Event-based dynamic graph drawing rejects the notion of a timeslice and allows each node and edge to have its own real-valued time coordinate. Nodes are represented as trajectories of adaptive complexity that are drawn directly in the three-dimensional space-time cube (2D + t). Existing work has demonstrated clear advantages for this approach, but these advantages come at a running time cost. In response to this scalability issue, we present **`MultiDynNoS`**, the first multilevel approach for event-based dynamic graph drawing. We consider three operators for coarsening and placement, inspired by Walshaw, GRIP, and FM$^3$, which we couple with an event-based graph drawing algorithm. We evaluate our approach on a selection of real graphs, showing that it outperforms timeslice-based and existing event-based techniques.*

## 1. Introduction

Usually, a dynamic graph is defined as a succession of individual static graphs [BBDW17], each one representing the state of the graph at a specific time instant (also known as a *timeslice*). This definition has two advantages: it works well when the time interval is clearly defined (e.g., yearly, monthly, etc.), and allows for existing static layout algorithms to be used directly for visualization. When nodes and edges present real time coordinates however, projecting onto the nearest timeslice results in a quantization error, potentially producing dynamic drawings of lower quality (see this video). *Event-based* networks (also known as *temporal networks* [HS12]) do not suffer of quantization problems since they specify real-valued time coordinates for each node and edge. Event-based drawing algorithms were introduced to exploit the full time resolution of the data and proved to outperform, in terms of drawing quality, timesliced drawing techniques on event-based graphs [SAK17, SAK20]. However, they have to optimize the *trajectory* of the nodes in the *space-time cube* (2D + $t$), with significant costs in terms of running time.

The higher complexity limited the use of event-based graph drawing, despite being able to provide more readable visualizations of event-based graphs than timesliced techniques. In this paper, we present `MultiDynNoS`: the first multilevel event-based graph drawing algorithm, capable of bringing the time to draw event-based networks comparable to timeslice-based approaches. Similar

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to standard multilevel techniques for static graphs, `MultiDynNoS` follows a *coarsening-refinement* strategy. We adapt the coarsening and placement strategies of Walshaw [Wal03], GRIP [GK00], and FM$^3$ [HJ04], designed for static graphs, to operate on node trajectories for drawing temporal graphs in the space-time cube. Our experiments show that drawing quality, in terms of stress, is comparable event-based approaches [SAK17, SAK20] but with significant running time improvements, making them comparable to timeslice-based approaches [BM11] but with improved quality.

## 2. Related Work

The visualization of dynamic graphs has received a lot of attention over the years [BBDW17] with animated techniques [APP10, AP16, FQ11, BPF14] and representing time as a spatial dimension [APP10, SA06, BVB*11, LHS*15, AB20] receiving considerable attention. We focus on other related work in this section.

**Multilevel Graph Drawing.** In the 2000s, multilevel graph drawing algorithms [Wal03, AMA07, GK00, HJ04, BGKM10] were devised to scale to larger static graphs. These algorithms construct a hierarchy of coarse graphs and exploit this hierarchy to accelerate the drawing. Multilevel graph drawing approaches have been adapted to an online dynamic setting [CCM17, Vel07, Cra16]. Multi-*layer* networks, where several node and edge layers have different meaning [MGM*19], have been used for visualization.

**Temporal Networks and Event-Based Visualization.** Temporal and event-based networks [HS12, LVM18] have have been studied extensively for automatic graph analysis. For most of the past two decades, visualization of temporal networks has focused on drawing a series of timeslices in a way that encourages a stable drawing [BBDW17] – the position of nodes and edges should change as little as possible when a change is made to the graph [CP96] so that nodes and edges can be easily identified [AP12, AP16]. Algorithms have been explored to optimize the simultaneous drawing of timeslices in offline [DG02, DGK01, EHK*03, BM11] and online [MELS95, GDBG12, FT08] scenarios. Event-based visualization techniques [DSP*17, MLMdO*13, MLL*13] consider visualizing sequences of events with real time coordinates for each data point. Event-based dynamic graph drawing algorithms have been recently created to directly draw these graphs in the space-time cube [SAK17, SAK20]. Other techniques, such as HOTVis [PS21], exploit the temporal ordering of the edges (the *causal paths*) to influence the layout. However, they focus on 2D visualizations and do not optimize the drawing across the space-time cube.

**Contribution.** From our survey of the related literature, it clearly emerges a growing interest in event-based visualizations of networks for visual analytics applications. Drawing such graphs at full temporal resolution can help improve the quality of the representation. This motivates our research for a more scalable solution for embedding temporal networks in the space-time cube.

## 3. `MultiDynNoS` Pipeline

Consider a temporal network $D = (V, E)$ where each node and edge possesses *attributes* which are functions of time. Within this setting, two of them are of particular importance. The *appearance* of a node is defined as $A_v : V \times T \rightarrow [true, false]$ (edge appearance is defined similarly) which maps to node/edge insertion and deletion in the event-based graphs. $A_v$ defines a series of intervals in $T$ (time) in which the node/edge is present. The *position* of a node $n \in V$ in the plane over time is defined as $P_v : V \times T \rightarrow R^2$. Such function determines its coordinates at every time $t \in T$. When defined in this way, the appearance and position of the nodes are represented as a series of trajectories through time embedded in the space-time cube (e.g., Fig. 1a): lines that define node movement in the two dimensional plane as time passes downwards in the cube. We also define a *flattened* graph as the weighted static counterpart of a temporal graph where node and edge weights represent the cumulative duration of the time intervals in which their appearance attribute function yields true.

**Layout Process.** First, a *coarsening* operator is applied on $D$ to generate a *coarse hierarchy* of the graph, i.e. a series of graphs made up by increasingly simpler and smaller versions of the original. Subsequently, starting from the coarsest graph in this hierarchy, each single level gets *refined*: its drawing is computed and its coordinates are used to *place* (i.e. assign the initial coordinates) the vertices to the level below. This initial placement in turn provides quicker convergence in the following refinement cycle. Refinement ends when the final layout for the input graph is computed.

**Coarsening.** Coarsening yields a hierarchy of coarse node trajectories $D_H = \{D_w, D_1, ..., D_k\}$, with “depth” $k$, to be used by the refinement stage. $D_w$ is obtained by flattening $D$ into $D_f$ and then transferring the node and edge weights to $D$ as an attribute constant function. For each level $D_n = (V_n, E_n)$, we order the vertices of $V_n$ by their weight and put them on a stack. We pop the stack and get the heaviest vertex $v_n$: its copy $v_{n+1}$ is then assigned to $V_{n+1}$. At this point, we select some or all of the neighbors of $v_n$, depending on the coarsening strategy, summing their weights and merging their appearance intervals with $v_{n+1}$. We refer to $v_n$ as the “representative” in $V_{n+1}$ of the vertices merged with it in $V_n$. We refer to the set of representatives of level $n$ as $\overline{V}_n$. Once complete, $v_n$ and the vertices merged with it are removed from the stack. This process is repeated until the stack is empty. Coarsening stops at the coarsest hierarchy level $D_k$ when the node count falls below a threshold or it is $\geq 95\%$ the size of level $D_{k-1}$. The latter condition is introduced to avoid a long sequence of levels with very similar sizes, which would slow down drawing significantly. We implemented three different coarsening strategies, each one inspired by existing multilevel algorithms. First, we implemented the *Maximal Matching*, found in the multilevel approach by Walshaw [Wal03], where pairs of vertices connected by an edge belonging to the graph maximal matching are merged together in each level. Second, we implemented the *Maximal Independent Set* coarsening, used by *GRIP* [GK00]. Once a vertex is selected to be part of the new level, it is merged together with all of its neighbors. Finally, we implemented the *Solar Merger* algorithm, used by *FM*$^3$ [HJ04]. Each selected vertex is merged together with its neighbors up to distance 2, creating a “Solar System Partitioning” of the graph. Once the vertex set for the new level is created, we generate $E_{n+1}$: for each edge $e_n = (v_n, w_n)$, we create an edge $e_{n+1} = (v_{n+1}, w_{n+1})$ such that $v_n$ and $w_n$ were merged in $v_{n+1}$ and $w_{n+1}$ respectively. If that edge already exists, its presence is merged with the one of $e_n$.

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**Coarsest Level Placement.** Although we have a hierarchy of trajectories, we now need to embed them into the space-time cube. Initial placement assigns coordinates of vertices in $D_k$ as follows: we flatten $D_k$ to obtain $D'_k$, which is drawn using a static force-directed graph layout algorithm, either single or multilevel. This initial placement provides a reasonably good initial guess for trajectory locations. The algorithm extrudes these trajectories vertically downwards across time intially. Subsequent steps with an event-based dynamic graph drawing algorithm [SAK20] allow these trajectories to bend and change direction accross time. A good initial placement is expected to yield smoother trajectories with few bends, which in the end resolves in nodes with reduced movement.

**Refinement.** During each refinement iteration, `DynNoSlice` [SAK20] is run on $D_n$. One of the key points of the multilevel strategy is that more quality-oriented layout parameters can be used on coarse graphs, since they are smaller in size and therefore quicker to draw. As the size of the graph to layout increases, speed can be emphasized. In our approach, we tune two parameters: the maximum node mobility and the number of layout algorithm iterations. Coarser levels will benefit from more flexible trajectories, while finer levels are more conservative with reduced iterations and movement. The parameters decrease linearly by 7% at each level. This value was obtained empirically when the considering quality/running time trade off. Time trajectory post-processing of `DynNoSlice` [SAK17, SAK20] runs once every two layout iterations in the coarser levels and the interval grows by 2 with each new level. Once the layout for $D_n$ is computed (and $D_n \neq D_w$), the final coordinates are used to *place* the node trajectories in level $D_{n-1}$. First, each representative $v_{n-1} \in \overline{V}_{n-1}$ is placed at the coordinates of the corresponding vertex in $V_n$. We compute the initial coordinates of the remaining vertices based on the new coordinates of their representative . We implemented three placement operators (Fig. 1b) inspired by Walshaw [Wal03], *GRIP* [GK00], and *FM*$^3$ [HJ04]. The first strategy is the *identity placer*: the nodes are placed in the same position as their representative. The second strategy places the trajectories close to the *barycenter* of the coordinates of the representative's neighbors at level $n+1$. The final position of the node is skewed towards its own representative by a fixed rate. The third strategy is similar to barycenter but changes the attraction of the representative cluster. Specifically, given any two neighboring nodes $v_{n+1}, w_{n+1} \in V_{n+1}$, the solar system partitioning guarantees that representatives at level $n$, $v_n$ and $w_n$, are at most distance 5 from each other. Since $v_n$ and $w_n$ neighbors up to distance 2 are merged together in the *FM*$^3$ coarsening, with this information it is possible to reconstruct the relative position of any of the merged trajectories in the paths between $v_n$ and $w_n$, and place them accordingly. When the path position is not known it uses the barycenter placement strategy. For all approaches, randomness is added to the final coordinates to avoid possible accidental coordinate overlaps.

## 4. Experimental Evaluation

We conduct an evaluation where we repeat the experiment performed in `DynNoSlice` [SAK20] to compare `MultiDynNoS` to state-of-the-art dynamic graph layout algorithms on known metrics. Differently from the previous experiment, we also include a static layout strategy as a baseline. Our *research question* can be formulated as follows: "Is `MultiDynNoS` faster than `DynNoSlice`, while providing layouts with comparable drawing quality?".

**Metrics and Strategies.** We evaluate the layouts using quality and readability metrics. We include: (i) the **time**, drawing time in seconds; (ii) **Movement**, the average distance travelled by a node during graph evolution [BM11, SAK20]; (iii) **Crowding**: the number of times nodes pass close to each other in the animation of the dynamic graph [SAK20]; (iv) **Depth**: coarsening depth (multilevel strategies only); (v) ***StressOn*** and (vi) ***StressOff***, which are the layout stress computed on a per-timesliced or between timeslices, respectively, with optimal scaling [SAK20] applied.
We test three `MultiDynNoS` variants: `MultiDynNoS wi_id` is the Walshaw variant of `MultiDynNoS` with maximal matching of trajectories and identity placement; `MultiDynNoS is_gr` is the GRIP variant of `MultiDynNoS` with maximal independent set coarsening of trajectories and barycenter placement; `MultiDynNoS sm_sp` is the FM$^3$ variant of `MultiDynNoS` with the FM$^3$ coarsening and placement strategy. Each variant is tested alternating the drawing algorithm for the coarsest level placement between `sfdp` [Hu05] and `fdp` [FR91]. The variants of `MultiDynNoS` are tested against `Visone` [BW04], a state-of-the-art timeslice-based dynamic graph drawing algorithm, and `DynNoSlice` [SAK17, SAK20]. `sfdp flat` flattens the entire event-based data and draws it once as a static graph using `sfdp` [Hu05], and is our baseline.

**Results.** Table 1 shows the results of our experiments. In terms of running time, on all the experiment instances `MultiDynNoS` is competitive with `Visone` and can be an order of magnitude faster than `DynNoSlice`. This represents a leap forward than previous studies [SAK17,SAK20] (whose results have been replicated here), where `Visone` always had the best performance when compared to `DynNoSlice` on this same set of graphs. In terms of drawing quality, `MultiDynNoS` approaches have competitive or lower levels of stress and crowding than `DynNoSlice`, thus confirming our research hypothesis, with smaller amounts of movement due to the initial placement. In timesliced graphs, `Visone` had unsurprisingly the least stress, with the notable exception of **`InfoVis`**, where `MultiDynNoS` and `DynNoSlice` perform better in terms of both types of stress and crowding. As previously discussed [SAK17], **`InfoVis`** is very similar to an event-based data, since there are drastic changes between timeslices as author sets rarely remain stable across consecutive years. On the event-based data, `MultiDynNoS` and `DynNoSlice` outperform or match `Visone` in terms of stress, movement, and crowding. `Visone` cannot optimize for stress between the timeslices imposed on this naturally expressed event-based data. The video in the supplementary material demonstrates these improvements. The *sfdp flat*, our baseline, is not able to perform very well in terms of stress on these smaller datasets. However, it is a multilevel algorithm and its strengths are in terms of scalability.

## 5. Conclusion and Future Work

In this paper, we present `MultiDynNoS`: a multilevel approach for event-based dynamic graph drawing. Our experiment shows an improvement up to a order of magnitude in terms of running time

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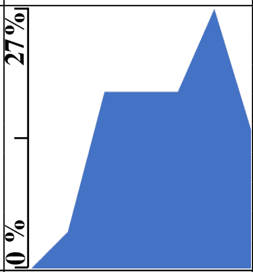
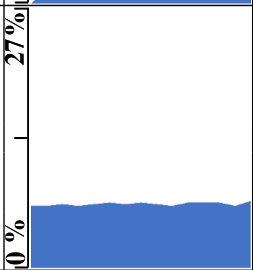
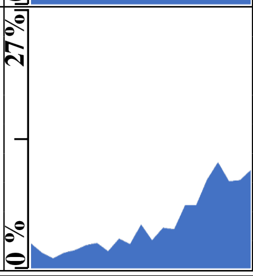
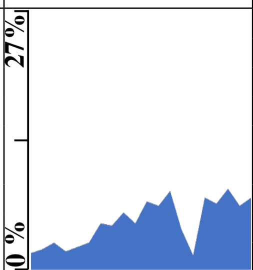
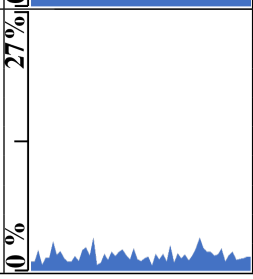
Table 1: Results of the experiment. $|V|$ and $|E|$ columns report the number of nodes and edges in the flattened graph. $|E_v|$ reports the number of events in thousands. The **Trend** column visualizes the number of events per timeslice on a scale from 0 to 27% of the total events of the graph. The number of timeslices is reported by the name of the graph in brackets. The **Type** column reports the tested algorithm. The `MultiDynNoS` variant used is presented as the combination of the initial placement layout (`fdp` or `sfdp`) and the coarsening/placement technique used. ***T*** column reports the algorithm running time in seconds. **Sc.(aling)** column reports the scaling value. Columns ***On*** and ***Off*** show the *StressOn* and *StressOff* values. Columns *M* and *C* represent Movement and Crowding respectively; *D* reports the depth of the coarsened hierarchy. `MultiDynNoS` is implemented in Java 14 and the experiments are run on an i7-8750H CPU with 16GB of RAM.

| Timesliced Graphs | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\|V\|$ | $\|E\|$ | $\|E_v\|$ | **Trend** | **Type** | ***T*** **(s)** | **Sc.** | ***On*** | ***Off*** | *M* | *C* | *D* |
| **VanDebunt** (7) | 39 | 32 | 0.1$k$ |  | Visone | **0.12** | 1 | 1.14 | 1.46 | 3.79 | 0 | - |
| | | | | | DynNoSlice | 5.04 | 0.62 | 1.23 | 1.21 | 3.92 | 0 | - |
| | | | | | sfdp flat | 0.14 | 1.61 | 2.77 | 2.81 | - | 0 | - |
| | | | | | fdp wi_id | 0.48 | 0.68 | 1.55 | 1.62 | 1.03 | 0 | 5 |
| | | | | | fdp is_gr | 0.47 | 0.75 | **1.03** | **1.06** | 0.99 | 0 | 3 |
| | | | | | fdp sm_sp | 0.46 | 0.75 | 1.05 | 1.08 | 1.00 | 0 | 3 |
| | | | | | sfdp wi_id | 0.56 | 0.68 | 1.37 | 1.39 | 0.98 | 0 | 6 |
| | | | | | sfdp is_gr | 0.58 | 0.75 | 1.09 | 1.12 | 0.97 | 0 | 3 |
| | | | | | sfdp sm_sp | 0.58 | 0.68 | 1.42 | 1.48 | **0.92** | 0 | 3 |
| **Newcomb** (15) | 17 | 93 | 0.6$k$ |  | Visone | 0.10 | 1 | **14.04** | **14.76** | 16.36 | 8 | - |
| | | | | | DynNoSlice | 7.58 | 0.68 | 16.60 | 16.57 | 13.44 | 1 | - |
| | | | | | sfdp flat | **0.15** | 1.33 | 26.54 | 26.52 | - | **0** | - |
| | | | | | fdp wi_id | 0.32 | 0.82 | 28.40 | 28.48 | 2.87 | 2 | 6 |
| | | | | | fdp is_gr | 0.31 | 0.82 | 21.01 | 20.86 | 2.95 | 4 | 3 |
| | | | | | fdp sm_sp | 0.32 | 0.82 | 22.55 | 22.39 | 2.87 | 1 | 3 |
| | | | | | sfdp wi_id | 0.42 | 0.82 | 27.05 | 26.94 | 2.89 | 2 | 6 |
| | | | | | sfdp is_gr | 0.38 | 0.82 | 20.89 | 20.70 | **2.82** | 1 | 3 |
| | | | | | sfdp sm_sp | 0.39 | 0.82 | 21.79 | 21.71 | 2.85 | 2 | 3 |
| **InfoVis** (21) | 1,136 | 2,506 | 2.8$k$ |  | Visone | 77.43 | 0.46 | 51.66 | 52.97 | 2.14 | 36 | - |
| | | | | | DynNoSlice | 224.93 | 0.56 | 30.14 | 30.19 | 2.03 | 2 | - |
| | | | | | sfdp flat | **0.55** | 1.33 | 105.29 | 102.87 | - | 1,253 | - |
| | | | | | fdp wi_id | 143.95 | 0.51 | 47.26 | 47.49 | 0.78 | 16 | 7 |
| | | | | | fdp is_gr | 87.79 | 0.56 | **28.08** | **27.79** | 1.50 | 4 | 4 |
| | | | | | fdp sm_sp | 138.95 | 0.56 | 28.88 | 28.65 | 1.51 | 4 | 3 |
| | | | | | sfdp wi_id | 110.00 | 0.46 | 51.03 | 50.97 | **0.70** | 36 | 7 |
| | | | | | sfdp is_gr | 83.00 | 0.62 | 28.69 | 28.59 | 1.62 | 2 | 4 |
| | | | | | sfdp sm_sp | 85.00 | 0.56 | 27.21 | 27.02 | 1.48 | **1** | 3 |

| Event-Based Graphs | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\|V\|$ | $\|E\|$ | $\|E_v\|$ | **Trend** | **Type** | ***T*** **(s)** | **Sc.** | ***On*** | ***Off*** | *M* | *C* | *D* |
| **Rugby** (20) | 12 | 66 | 3.1$k$ |  | Visone | **0.07** | 0.68 | 3.08 | 2.70 | 25.46 | 6 | - |
| | | | | | DynNoSlice | 2.84 | 0.51 | 1.86 | **1.78** | 6.64 | 0 | - |
| | | | | | sfdp flat | 0.18 | 0.90 | 2.07 | 2.02 | - | 0 | - |
| | | | | | fdp wi_id | 0.75 | 0.56 | 2.18 | 2.01 | 1.74 | 1 | 5 |
| | | | | | fdp is_gr | 1.84 | 0.56 | **1.76** | 1.84 | 1.25 | 0 | 2 |
| | | | | | fdp sm_sp | 0.52 | 0.51 | 2.10 | 1.94 | 1.28 | 0 | 2 |
| | | | | | sfdp wi_id | 0.88 | 0.51 | 2.19 | 1.97 | 1.51 | 1 | 5 |
| | | | | | sfdp is_gr | 1.04 | 0.513 | 1.99 | 1.87 | **1.11** | 0 | 2 |
| | | | | | sfdp sm_sp | 0.77 | 0.56 | 2.03 | 1.95 | 1.41 | 0 | 2 |
| **Dialogs** (61) | 118 | 501 | 4.0$k$ |  | Visone | 3.39 | 0.17 | 0.62 | 0.87 | 5.44 | 682 | - |
| | | | | | DynNoSlice | 49.53 | 0.28 | 0.75 | 0.90 | 1.35 | 0 | - |
| | | | | | sfdp flat | **0.21** | 1 | 0.65 | 0.69 | - | 6 | - |
| | | | | | fdp wi_id | 1.53 | 0.42 | **0.53** | 0.60 | 0 | 711 | 14 |
| | | | | | fdp is_gr | 5.05 | 0.35 | 0.66 | 0.96 | 0.76 | 1 | 4 |
| | | | | | fdp sm_sp | 5.49 | 0.35 | 0.65 | 0.91 | 0.73 | 0 | 3 |
| | | | | | sfdp wi_id | 1.63 | 0.42 | 0.55 | **0.58** | 0 | 441 | 13 |
| | | | | | sfdp is_gr | 5.07 | 0.35 | 0.64 | 0.92 | 0.71 | 0 | 4 |
| | | | | | sfdp sm_sp | 5.96 | 0.31 | 0.74 | 0.88 | **0.64** | 0 | 3 |

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compared to `DynNoSlice` while retaining its advantages. Future work includes performing a new evaluation on larger datasets, that were inaccessible to event-based layout techniques - until now.

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