Buffered Streaming Edge Partitioning

Adil Chhabra ✉ 🄯
Heidelberg University, Germany

Marcelo Fonseca Faraj ✉ 🄯
Heidelberg University, Germany

Christian Schulz ✉ 🄯
Heidelberg University, Germany

Daniel Seemaier ✉ 🄯
Karlsruhe Institute of Technology, Germany

─── **Abstract** ───

Addressing the challenges of processing massive graphs, which are prevalent in diverse fields such as social, biological, and technical networks, we introduce `HeiStreamE` and `FreightE`, two innovative (buffered) streaming algorithms designed for efficient edge partitioning of large-scale graphs. `HeiStreamE` utilizes an adapted Split-and-Connect graph model and a Fennel-based multilevel partitioning scheme, while `FreightE` partitions a hypergraph representation of the input graph. Besides ensuring superior solution quality, these approaches also overcome the limitations of existing algorithms by maintaining linear dependency on the graph size in both time and memory complexity with no dependence on the number of blocks of partition. Our comprehensive experimental analysis demonstrates that `HeiStreamE` outperforms current streaming algorithms and the re-streaming algorithm `2PS` in partitioning quality (replication factor), and is more memory-efficient for real-world networks where the number of edges is far greater than the number of vertices. Further, `FreightE` is shown to produce fast and efficient partitions, particularly for higher numbers of partition blocks.

1 Introduction

Complex, large graphs, often composed of billions of entities, are employed across multiple fields to model social, biological, navigational, and technical networks. However, processing huge graphs requires extensive computational resources, necessitating the parallel computation of graphs on distributed systems. Large graphs are partitioned into sub-graphs distributed among k processing elements (PEs). PEs perform computations on a portion of the graph, and communicate with each other through message-passing. *Graph partitioning* models the distribution of graphs across PEs such that each PE receives approximately the same number of components (vertices) and communication between PEs (via edges between them) is minimized. Edge partitioning, which outperforms traditional vertex partitioning on real-world power-law graphs [22, 32, 34], partitions edges into k blocks such that vertex replication

is minimized, hence minimizing the communication needed to synchronize vertex copies. *Graph vertex and edge partitioning* are NP-hard [8, 21] and there can be no approximation algorithm with a constant ratio factor for general graphs unless P = NP [10]. Thus, heuristic algorithms are used in practice. Further, due to data proliferation, streaming algorithms are increasingly being used to partition huge graphs quickly with low computational resources [1, 3, 17, 18, 19, 24, 25, 35, 50, 51].

Streaming edge partitioning entails the sequential loading of edges for immediate assignment to blocks. One-pass streaming edge partitioners permanently assign edges to blocks during a single sequential pass over the graph's data stream [41, 53]. Alternatively, buffered streaming algorithms receive and store a buffer of vertices along with their edges before making assignment decisions, thus providing information about future vertices [18, 35], and re-streaming algorithms gather information about the global graph structure [36, 37]. With a few exceptions [37, 53] most streaming edge partitioners have a high time complexity due to a linear dependency on the number of blocks k. However, in recent years, high k values are frequently used in graph partitioning due to the increasing size of graphs, complexity of computations, and availability of processors. An existing re-streaming edge partitioner, `2PS-L` [37], achieves a linear runtime independent of k, but produces lower solution quality than state-of-the-art partitioners and has a linear memory dependence on k. Thus, there remains potential to explore high-quality streaming edge partitioners without a runtime and memory dependency on k.

Contribution. We propose `HeiStreamE`, a buffered streaming algorithm for edge partitioning that leverages the performance efficacy of multilevel algorithms. By employing an adapted version of the SPlit-And-Connect (SPAC) model [33] and solving it with a Fennel-based multilevel scheme [18], our algorithm produces superior solution quality while maintaining time and memory complexities that are linearly dependent on the size of the graph and independent of k. Our results establish the superiority of `HeiStreamE` over all current streaming algorithms, and even the re-streaming algorithm `2PS` [36, 37], in replication factor. These outcomes highlight the considerable potential of our algorithm, positioning it as a promising tool for edge partitioning. We additionally provide an implementation of an efficient streaming edge partitioner, `FreightE`, which uses streaming hypergraph partitioning [17] to partition edges on the fly. Our experiments demonstrate that `FreightE` is significantly faster than all competing algorithms, especially for high k values.

2 Preliminaries

2.1 Basic Concepts

(Hyper)Graphs. Let $G = (V = \{0, \ldots, n-1\}, E)$ be an *undirected graph* with no multiple or self-edges, such that $n = |V|$, $m = |E|$. Let $c : V \to \mathbb{R}_{\geq 0}$ be a vertex-weight function, and let $\omega : E \to \mathbb{R}_{>0}$ be an edge-weight function. We generalize c and ω functions to sets, such that $c(V') = \sum_{v \in V'} c(v)$ and $\omega(E') = \sum_{e \in E'} \omega(e)$. An edge $e = (u, v)$ is said to be *incident* on vertices u and v. Let $N(v) = \{u : (v, u) \in E\}$ denote the neighbors of v. A graph $S = (V', E')$ is said to be a *subgraph* of $G = (V, E)$ if $V' \subseteq V$ and $E' \subseteq E \cap (V' \times V')$. If $E' = E \cap (V' \times V')$, S is an *induced* subgraph. Let $d(v)$ be the degree of vertex v and Δ be the maximum degree of G. Let $H = (V, E)$ be an *undirected hypergraph* with $n = |V|$ vertices, $m = |E|$ hyperedges or nets. A net, unlike an edge of a graph, may consist of more than two vertices, and is defined as a subset of V.

Partitioning. Given a number of *blocks* $k \in \mathbb{N}_{\geq 1}$, and an undirected (hyper)graph with *positive* edge weights, the *(hyper)graph partitioning* problem pertains to the partitioning of a (hyper)graph into k smaller (hyper)graphs by assigning the vertices (*vertex partitioning*) or (hyper)edges (*edge partitioning*) of the graph to k mutually exclusive blocks, such that the blocks have roughly the same size and the particular objective function is minimized or maximized. More precisely, a *k-vertex partition* of a (hyper)graph partitions V into k blocks $V_1, \ldots, V_k$ such that $V_1 \cup \cdots \cup V_k = V$ and $V_i \cap V_j = \emptyset$ for $i \neq j$. The *edge-cut* (resp. *cut net*) of a k-partition consists of the total weight of the *cut edges* (resp. *cut nets*), i.e., (hyper)edges crossing blocks. More formally, let the edge-cut (resp. *cut net*) be $\sum_{i<j} \omega(E')$, in which $E' := \{e \in E, \exists (u,v) \subseteq e : u \in V_i, v \in V_j, i \neq j\}$ is the *cut-set*, i.e., the set of all *cut edges* (resp. *cut nets*). The *balancing constraint* demands that the sum of vertex weights in each block does not exceed a threshold associated with some allowed *imbalance* ε. More specifically, $\forall i \in \{1, \ldots, k\} : c(V_i) \leq L_{\max} := \lceil (1 + \varepsilon) \frac{c(V)}{k} \rceil$. For each net e of a hypergraph, $\Lambda(e) := \{V_i \mid V_i \cap e \neq \emptyset\}$ denotes the *connectivity set* of e. Further, the *connectivity* $\lambda(e)$ of a net e is the cardinality of its connectivity set, i.e., $\lambda(e) := |\Lambda(e)|$. The so-called *connectivity* metric $(\lambda - 1)$ is computed as $\sum_{e \in E'} (\lambda(e) - 1) \omega(e)$, where E' is the cut-set.

Similarly, a *k-edge partition* of a graph partitions the edge set E into k blocks $E_1, \ldots, E_k$ such that $E_1 \cup \cdots \cup E_k = E$ and $E_i \cap E_j = \emptyset$ for $i \neq j$. In edge partitioning, a common objective function is the minimization of the *replication factor*, which is defined as the number of replicated vertices divided by the total number of vertices in the graph. Formally, we define the set $V(E_i) = \{v \in V \mid \exists u \in V : (u,v) \in E_i\}$ for each partition E_i as the number of vertices in V that have at least one edge incident on them that was assigned to block E_i. Taking the sum of $|V(E_i)|$ over all k gives us the total number of vertex replicas generated by the partition. *Replication factor* is then defined as $RF(E_1, E_2, \ldots, E_k) = \frac{1}{n} \sum_{i=1,\ldots,k} |V(E_i)|$. Intuitively, a minimized *replication factor* suggests that vertices are replicated in minimum blocks. Minimum vertex replication, in turn, results in lower synchronization overhead in distributed graph processing due to reduced exchange of vertex state across blocks.

Multilevel Scheme. A successful heuristic for *vertex partitioning* is the *multilevel* [14] approach. It recursively computes a clustering and *contracts* it to *coarsen* the graph into smaller graphs that maintain the same basic structure as the input graph. An *initial partitioning* algorithm is applied to the smallest (*coarsest*) graph and then the contraction is undone. At each level, a *local search* method is used to improve the partitioning induced by the coarser level. *Contracting* a cluster of vertices $C = \{u_1, \ldots, u_\ell\}$ involves replacing them with a new vertex v whose weight is the sum of the weights of the clustered vertices and is connected to all elements $w \in \bigcup_{i=1}^{\ell} N(u_i)$, such that $w \notin C$, with edge weight $\omega(\{v, w\}) = \sum_{i=1}^{\ell} \omega(\{u_i, w\})$. This ensures that the transfer of partitions from a coarser to a finer level maintains the edge-cut. The *uncontraction* of a vertex undoes the contraction. Local search moves vertices between blocks to reduce the objective.

SPAC Transformation. The SPAC transformation [33] provides a means to employ a vertex partitioning tool on a transformed graph G', which is derived from the original graph G, and subsequently apply the derived vertex partition to establish an edge partition for G. The transformation assumes an undirected, unweighted graph $G = (V, E)$ as input. The SPAC graph $G' = (V', E')$ is then constructed in two phases: In the *split* phase, each vertex $v \in V$ generates $d(v)$ split vertices $S_v := \{v'_1, \ldots, v'_{d(v)}\} \subseteq V'$. The *connect* phase introduces two kinds of edges in E', *dominant* edges and *auxiliary* edges. First, it assigns a *dominant* edge $e' = (u'_i, v'_j)$ in G' for each edge $e = (u, v)$ in G. Dominant edges are created with

infinite weight $\omega(e') = \infty$. Second, it introduces as many *auxiliary* edges e'' as necessary to create a path connecting the vertices in the set S_v for each vertex $v \in V$. Auxiliary edges are created with unitary weight $\omega(e'') = 1$. A visual representation of the SPAC transformation is provided in Figure 2. Due to the infinite weight of dominant edges, vertex partitioning tools usually refrain from splitting them, causing both endpoints of a dominant edge to be grouped in the same block (alternatively, straightforward heuristics can compel both endpoints of dominant edges to belong to the same block). Next, the block assigned to both endpoints of each dominant edge is assigned to the edge in G that induced the corresponding dominant edge, thereby resulting in an edge partition of G. The SPAC method is particularly effective in practical scenarios and yields a sound, provable approximation factor under specific balance constraints. Specifically, it approximates the balanced edge partitioning problem within $\mathcal{O}(\Delta\sqrt{\log n \log k})$, where Δ is the maximum degree of G [33].

Buffered Streaming. In the buffered streaming model, which is an extended version of the one-pass model, we load a δ-sized buffer or batch of input vertices along with their edges. We make block assignment decisions only after the entire batch has been loaded. In practice, the parameter δ can be chosen in accordance with memory available on the machine. In our contribution, we use a fixed δ throughout the algorithm. For a predefined batch size of δ, we load and repeatedly partition $\lceil n/\delta \rceil$ batches.

2.2   Related Work

We refer the reader to recent surveys on (hyper)graph partitioning for relevant literature [11, 14, 47]. Here, we focus on the research on streaming vertex and edge partitioning. Most high-quality vertex partitioners for real-world graphs use a multilevel scheme, including KaHIP [44], METIS [28], Scotch [40], and (mt)-KaHyPar [23, 45]. Edge partitioning has been solved directly with multilevel hypergraph partitioners, including PaToH [13], hMETIS [29], KaHyPar [46], Mondriaan [52], MLPart [2], Zoltan [15], SHP [27], UMPa [12], and kPaToH [13].

Streaming (Hyper)Graph Vertex Partitioning. Tsourakakis et al. [51] introduce Fennel, a one-pass partitioning heuristic adapted from the clustering objective *modularity* [9]. Fennel minimizes edge-cuts by placing vertices in partitions with more neighboring vertices. Fennel assigns a vertex v to the block V_i that maximizes the Fennel gain function $|V_i \cap N(v)| - f(|V_i|)$, where $f(|V_i|)$ is a penalty function to respect a balancing threshold. The authors define the Fennel objective with $f(|V_i|) = \alpha\gamma \cdot |V_i|^{\gamma-1}$, in which γ is a free parameter and $\alpha = m\frac{k^{\gamma-1}}{n^\gamma}$. After parameter tuning, the authors define $\gamma = \frac{3}{2}$ and $\alpha = \sqrt{k}\frac{m}{n^{3/2}}$. The time complexity of the algorithm depends on k and is given by $\mathcal{O}(nk + m)$. Stanton and Kliot [48] propose LDG, a greedy heuristic for streaming vertex partitioning. ReLDG and ReFennel are re-streaming versions of LDG and Fennel [39]. Prioritized re-streaming optimizes the ordering of the streaming process [3]. Faraj and Schulz [18] propose HeiStream, which uses a generalized weighted version of the Fennel gain function in a buffered streaming approach. Eyubov et al. [17] introduce FREIGHT, a streaming hypergraph partitioner that adapts the Fennel objective function to partition vertices of a hypergraph on the fly.

Streaming Edge Partitioning. One-pass streaming edge partitioners include hashing-based partitioners like DBH [53], constrained partitioners like Grid and PDS [26], and HDRF, proposed by Petroni et al. [41]. HDRF exploits the skewed degree distribution of real-world graphs by prioritizing vertex replicas of high-degree vertices. HDRF outperforms DBH, Grid and PDS in solution quality, but has a longer runtime. Zhang et al. [54] introduced SNE, a streaming

version of the in-memory edge partitioner `NE` that utilizes sampling methods. `SNE` produces better solution quality than `HDRF`, but with increased memory consumption and runtime [37]. In contrast to one-pass streaming models, `RBSEP` uses a buffered approach to postpone assignment decisions for edges with limited neighborhood partitioning information available during streaming [49]. Additionally, Mayer et al. [35] introduce `ADWISE`, a window-based streaming edge partitioner, which uses a dynamic window size that adapts to runtime constraints.

Mayer et al. [36] subsequently propose `2PS-HDRF`, a two-phase re-streaming algorithm for edge partitioning, using `HDRF` as the scoring function in its final partitioning step. The first phase uses a streaming clustering algorithm to gather information about the global graph structure; in the second phase, the graph is re-streamed and partitioned, using information obtained from clustering to make edge partitioning decisions. Mayer et al. [37] modify `2PS-HDRF` to propose `2PS-L`, which runs in time independent of k. `2PS-L` switches from `HDRF` to a new scoring function in the final partitioning step to remove its dependency on k, and thus achieves a time complexity of $\mathcal{O}(|E|)$. `2PS-L` outperforms `ADWISE`; it is faster than `HDRF` and `2PS-HDRF`, particularly at large k values, but has lower solution quality. `2PS-HDRF` achieves 50% better solution quality than `2PS-L` [37].

Sajjad et al. [43] propose `HoVerCut`, a platform for streaming edge partitioners, which can scale in multi-threaded and distributed systems by decoupling the state from the partitioner. Hoang et al. [24] propose `CuSP`, a distributed and parallel streaming framework to partition edges based on user-defined policies. `CuSP` is programmable and can express common streaming edge partitioning strategies from the literature.

3 Buffered Streaming Edge Partitioning

In this section, we present our algorithms, `HeiStreamE` and `FreightE`. First, we provide an overview of `HeiStreamE`'s iterative structure. Subsequently, we detail its input format and buffered graph model, and describe how it uses multilevel vertex partitioning to solve this model. Lastly, we discuss how `FreightE` builds a hypergraph representation to partition edges using a streaming hypergraph partitioner.

3.1 Overall Algorithm

Our framework draws inspiration from `HeiStream` [18]. We slide through the input graph G by iteratively performing the following series of operations until all the edges of G are assigned to blocks. First, we load a batch composed of δ vertices and their associated neighborhood, thereby obtaining a subgraph G_b contained within the graph G. This operation yields edges connecting vertices within the current batch, and edges connecting vertices in the current batch to vertices streamed in previous batches. Second, we build a model β_b corresponding to G_b, where the edges of G_b are transformed into vertices. Additionally, we incorporate a representation of block assignments from previous batches into β_b. Third, we partition

Algorithm 1 Overall Structure of `HeiStreamE`.

1: **for** $b \in \{1, \ldots, \lceil \frac{n}{\delta} \rceil\}$ **do**
2:     Load subgraph G_b from input graph G
3:     Build model β_b from G_b
4:     Run multilevel vertex partitioning on β_b
5:     Permanently assign corresponding edges of G in G_b to blocks

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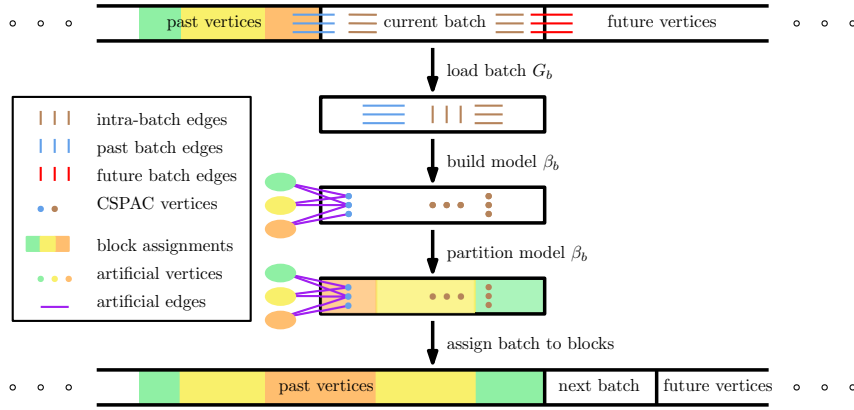
Figure 1 Detailed structure of `HeiStreamE`. The algorithm starts by loading a batch graph G_b consisting of vertices and their edges to the current batch and previous batches. Subsequently, it builds a meaningful model β_b from the batch graph, transforming edges into vertices, and incorporating a synthetic representation of the assignments made in previous batches. This model is then partitioned using a multilevel algorithm. Lastly, the edges from the loaded batch, which correspond to vertices in the partitioned batch model, are permanently assigned to blocks. This process is repeated for subsequent batches until the entire graph has been partitioned.

β_b using a multilevel vertex partitioning algorithm that has been shown to be effective in the context of buffered streaming [18]. We conclude by permanently assigning the edges in G that correspond to vertices in our model β_b to their respective blocks. Algorithm 1 summarizes the general structure of `HeiStreamE`, which is illustrated in Figure 1.

3.2 Input and Batch Format

`HeiStreamE` uses a vertex-centric input format and a buffered streaming approach, which refers to the sequential process of loading and handling the input graph in batches. Within each batch, it loads δ vertices one at a time along with their neighborhood, where δ is a parameter that defines the buffer size. Similar input formats are commonly used in streaming algorithms for vertex partitioning [3, 17, 18, 19, 25, 51] and are consistent with graph formats commonly found in publicly available real-world graph datasets, such as the METIS format. Each batch $b \in \{1, \ldots, \lceil \frac{n}{\delta} \rceil\}$ corresponds to a subgraph denoted as $G_b = (V_b, E_b)$ within the graph G. This subgraph is constructed as follows. Its vertex set V_b includes the δ vertices from the current batch, labeled within the domain $[0, \delta - 1]$, as well as the p vertices from past batches that share at least one edge with vertices in the current batch, labeled within the domain $[\delta, \delta + p - 1]$. Similarly, its edge set E_b comprises of edges with one endpoint in the current batch and the other endpoint in either the current batch or previous batches, expressed as $E_b = \{(u, v) \in E \mid \text{Batch}(u) = b \wedge \text{Batch}(v) \le b\}$. Edges with an endpoint in future batches are discarded, ensuring that each edge belongs exclusively to a unique batch graph G_b across all batches.

3.3 Model Construction

Our model construction consists of two steps, detailed in this section. First, using the batch graph G_b, we create a corresponding *Contracted SPlit-And-Connect* (CSPAC) graph, denoted as S_b^*. In S_b^*, edges from G_b are directly represented as vertices, while vertices from G_b are indirectly represented as edges. Subsequently, we create a graph model β_b based on S_b^*, which incorporates a representation of block assignments from prior batches.
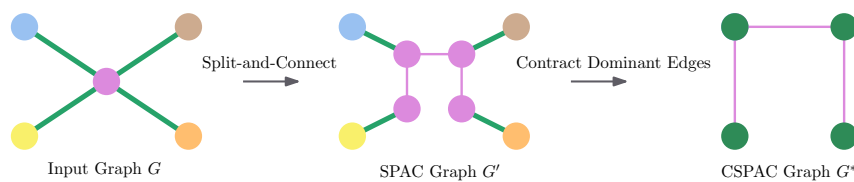
Figure 2 Building SPAC and CSPAC Graphs: The SPAC graph, denoted as G', features $d(v)$ split vertices for every vertex v in the original graph G. These split vertices are represented in the same color as the vertex they originate from. Every (thick green) edge from G is directly converted into a distinct dominant (thick green) edge in G' that connects corresponding split vertices. The auxiliary (thin) edges in G', which create a path between split vertices, are depicted in the same color as the split vertices they link. The CSPAC graph G^* is formed by contracting the dominant edges of G'. The vertices in G^* represent the edges in G, while the edges in G^* mirror the auxiliary edges in G'.

CSPAC Transformation. The CSPAC transformation is a faster and more condensed variant of the SPAC transformation conceived by Li et al. [33], as described in Section 2.1. Below we explain how the SPAC transformation evolves into the CSPAC transformation, and how this transformation is applied to G_b to yield the CSPAC graph S_b^*.

The SPAC graph G' of a graph G consists of dominant edges, i.e., edges with a weight of infinity that have a one-to-one correspondence with edges of the original graph, and auxiliary edges, which define a path between vertices of the SPAC graph. The CSPAC transformation is derived from the SPAC graph by contracting the dominant edges into vertices. Due to construction, the dominant edges in G' do not share any endpoints; they effectively form a matching, ensuring a consistent contraction. Further, each endpoint of the auxiliary edges is incident to a single dominant edge. Thus, the contraction of all dominant edges produces a coarser graph, in which every vertex represents a unique edge in the original graph G, and their connections correspond to the auxiliary edges in graph G'. The CSPAC transformation is illustrated in Figure 2.

In `HeiStreamE`, we derive the CSPAC graph S_b^* directly from the batch graph G_b, bypassing the construction of the intermediary SPAC graph. The procedure for this direct transformation is as follows. For each vertex $u \in V_b$, each of its outgoing edges $e = (u, v) \in E_b$ induces a vertex u^* in S_b^*, if $u < v$ to avoid redundancy. As each vertex is constructed, it is connected to at most two other vertices in S_b^* that are induced by other outgoing edges of u in G_b to form a path. This way, each undirected edge $e \in E_b$, which would have induced a dominant edge in the SPAC graph, is represented as a vertex in S_b^*. Further, each auxiliary edge of the SPAC graph is directly integrated into S_b^* to form paths between vertices in S_b^*. The direct construction of the CSPAC graph maintains the same computational complexity as the SPAC construction alone, specifically $\mathcal{O}(|V_b| + |E_b|)$, where $|V_b|$ and $|E_b|$ are the number of vertices and edges of G_b respectively. In practice, building S_b^* directly from G_b offers a time-saving advantage compared to the alternative method of building the SPAC graph and then contracting the dominant edges.

In each batch, S_b^* has $|E_b|$ vertices and $2|E_b| - |V_b|$ edges, i.e., it is linear in the size of the batch graph G_b. In contrast to the SPAC graph, the CSPAC graph has fewer vertices and edges. Further, where a vertex partitioner might cut a dominant edge of the SPAC graph, every vertex partition of the CSPAC graph corresponds to a valid edge partition of the original graph. Thus, there is no need for a verification step to transform a vertex partition of S_b^* into an edge partition of G_b.
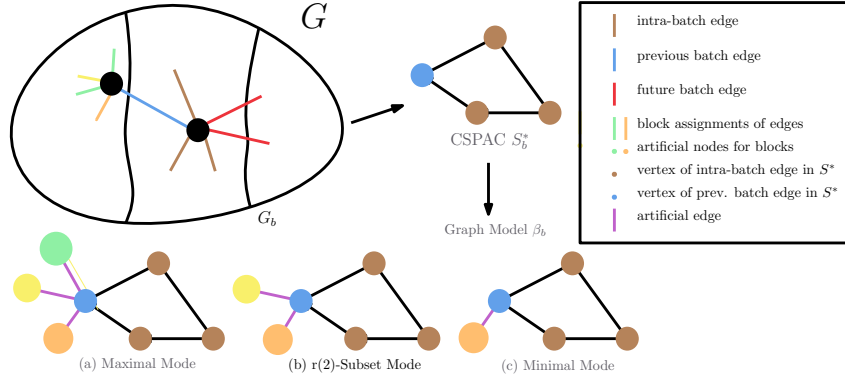
Figure 3 Graph model β_b construction. β_b is obtained by appending past assignment decisions to S_b^*. If a vertex of the current batch graph $u \in G_b$ has an edge $e = (u, v)$ to a previous batch (colored blue), we connect the CSPAC vertex u^* induced by e to artificial vertices representing blocks assigned to edges incident on v as follows: (a) *Maximal* Mode: u^* connects to all blocks incident on v (b) *r-Subset* Mode: u^* connects to r random blocks incident on v (c) *Minimal* Mode: u^* connects to the block assigned to the most recently partitioned edge incident on v.

Theorem 1 shows that when computing a vertex partition of S_b^* to minimize the edge-cut, the corresponding edge partition of G_b will also have a minimized number of vertex replicas. The SPAC approximation factor shown by Li et al. [33] is also directly valid for S_b^*.

▶ **Theorem 1.** *For any vertex partition $vp(S_b^*)$ of the CSPAC graph S_b^* with edge-cut cost $(vp(S_b^*))$, there exists a corresponding edge partition $ep(G_b)$ of the batch graph G_b with a number of vertex replicas cost $(ep(G_b))$, satisfying cost $(ep(G_b)) \leq$ cost $(vp(S_b^*))$, which establishes a lower bound spanning the set of possible CSPAC graphs S_b^* associated with G_b.*

Proof. See Appendix B.   ◀

Integrating Connectivity Information.   Directly partitioning the CSPAC graph S_b^* limits the partitioner's view to the current batch, as S_b^* does not take into account block assignments from previous batches. Specifically, when assigning a block to a vertex $u^* \in S_b^*$ induced by an edge $e = (u, v) \in E_b$, where u is a vertex of the current batch and v is a vertex of some previous batch, the partitioner might replicate v into a new block in the absence of global information. To solve this, we extend the CSPAC graph S_b^* with connectivity information derived from previous batch assignments to obtain the graph model β_b. We construct β_b by augmenting S_b^* with k artificial vertices representing the k partition blocks.

Each artificial vertex i corresponds to an existing partition block E_i in its current state, i.e., the weight of each artificial vertex i is the weight of its corresponding block E_i filled with edges that have been assigned to it from previous batches. An edge $e = (u, v) \in E_b$ of the current batch is represented in our model β_b as a vertex that connects to an artificial vertex i if v is a vertex of a previous batch and an edge incident to v has already been assigned to block E_i. However, in a streaming setting, there is limited knowledge of edge connectivity, i.e., it is not possible to directly determine which edges from previous batches are adjacent to edges from the current batch. To overcome this constraint, we maintain an array B of size n throughout the streaming process. This array records, for each vertex $u \in V$, block(s) assigned to edges incident on it. Then, in β_b, a vertex $u^* \in S_b^*$ induced by an edge $e = (u, v) \in E_b$ is connected to any artificial vertices i representing blocks recorded in $B[v]$. An added benefit of this model construction is that we do not need to maintain a data structure of size m in our algorithm.

We propose three configurations for β_b, which vary in how they use B, that we name, in decreasing level of exactness, *maximal*, *r-Subset*, and *minimal*. Each configuration has a runtime, memory and solution-quality trade-off. Let u^* be a vertex in S_b^* induced by an edge $e = (u, v) \in E_b$. In the *maximal* model β_b, u^* is connected to *all* artificial vertices i representing blocks recorded in $B[v]$. The memory required to store the array B in the *maximal* setup is $\mathcal{O}(nk)$. Theorem 2 demonstrates that computing a vertex partition of the *maximal* model β_b to minimize edge-cut corresponds to an edge partition of G_b that contributes a minimized number of new vertex replicas to the overall edge partition of the input graph G. In the *r-Subset* model, u^* is connected to *a sample of r* artificial vertices i representing blocks recorded in $B[v]$, where r is a parameter. Here, B is identical as in the *maximal* setup, but the model β_b is more concise, allowing for a faster partitioning phase. In the *minimal* model, u^* is connected to a single artificial vertex i representing *the most recent block* assigned to v in a previous batch. We only store the latest assignment per vertex in B, thus the memory requirement is $\mathcal{O}(n)$, and the model β_b is also more concise than in the other two setups. We illustrate the various configurations in Figure 3.

▶ **Theorem 2.** *For any vertex partition $vp(\beta_b)$ of the* maximal *model β_b with edge-cut $cost(vp(\beta_b))$, there exists a corresponding edge partition $ep(G_b)$ of the batch graph G_b that, when incorporated into the already partitioned section of the input graph G, introduces a number γ of new vertex replicas, satisfying $\gamma \leq cost(vp(\beta_b))$.*

Proof. See Appendix B. ◀

3.4 Partitioning

In this section, we describe how we partition our model β_b. We employ a vertex partitioning algorithm on β_b, specifically an adapted version of the multilevel weighted Fennel algorithm utilized in `HeiStream` [18]. We describe this algorithm and then present a modification to the initial partitioning phase to enhance our runtime performance. Lastly, we discuss possible adaptations to the Fennel parameter α.

Multilevel Fennel. Each per-batch graph model β_b is partitioned using a multilevel partitioning scheme consisting of three successive phases, coarsening, initial partitioning, and uncoarsening.

In the coarsening phase, the algorithm computes a clustering and contracts the graph at each level until it is smaller than a specified threshold. These clusters are computed with label propagation while adhering to size constraints [38]. The clustering algorithm ignores artificial vertices and edges during the coarsening phase, to ensure that they are never contracted and that previous block assignment decisions are available at the coarsest level. For a graph with n vertices and m edges, a single round of size-constrained label propagation can be executed in $\mathcal{O}(n + m)$ time. Initially, each vertex is placed in its own cluster, and in subsequent rounds vertices move to the cluster with the strongest connection, with a maximum of L rounds, where L is a tuning parameter. The coarsening phase ends as soon as the graph has fewer vertices than a threshold of $\mathcal{O}(\max(|\beta_b|/k, k))$, where $|\beta_b|$ is the number of vertices of β_b. For large buffer sizes this threshold simplifies to $\mathcal{O}(|\beta_b|/k)$, while for small buffer sizes, it becomes $\mathcal{O}(k)$.

Following the coarsening phase, an initial partitioning assigns all non-artificial vertices to blocks using the generalized Fennel algorithm [18] with a strict balancing constraint $L_{\max}$. After initial partitioning, the current solution is transferred to the next finer level by mapping the block assignment of each coarse vertex to its constituent vertices at the

finer level. Subsequently, a local search algorithm is applied at each level, which utilizes the size-constrained label propagation approach employed in the contraction phase but with a modified objective function. Specifically, when visiting a non-artificial vertex, we reassign it to a neighboring block to maximize the generalized Fennel gain function while strictly adhering to the balancing constraint $L_{\max}$, considering only adjacent blocks in contrast to the initial partitioning which considers all blocks. This ensures that a single algorithm round remains linear in the current level's size. Artificial vertices remain stationary during the process, but unlike during coarsening, they are not excluded from label propagation, as they contribute to the generalized Fennel gain function.

Faster Initial Partitioning. We adopt a modified Fennel function to enhance the initial partitioning step in `HeiStreamE` and demonstrate that this approach produces a better runtime without a decrease in solution quality.

For small buffer sizes, `HeiStream` has a linear dependency on k for overall partitioning time, as during initial partitioning each vertex $u \in \beta_b$ is assigned to the block with the highest score among all k blocks. To address this dependency, we adopt Eyubov et al.'s strategy [17] from streaming hypergraph partitioning to evaluate scores more efficiently, removing the runtime dependency on k. For the current vertex $u \in \beta_b$, we categorize k blocks V_i into two sets, S_1 and S_2, where $V_i \in S_1$ if a neighbor of u was assigned to it, and $V_i \in S_2$ otherwise. This allows us to determine the blocks V_{max} and V'_{max} that respectively maximize Equation (1) and Equation (2). Then, the block that maximizes the generalized Fennel function is $\max(V_{max}, V'_{max})$ where

$$V_{max} = \underset{i \in S_1}{\operatorname{argmax}} \left\{ \sum_{v \in V_i \cap N(u)} \omega(u, v) - c(u) f(c(V_i)) \right\} \tag{1}$$

$$V'_{max} = \underset{i \in S_2}{\operatorname{argmax}} \left\{ -c(u) f(c(V_i)) \right\} . \tag{2}$$

As $c(u)$ remains constant, determining the block $V_i \in S_2$ that maximizes Equation (2) is equivalent to finding the block V_i minimizing $f(c(V_i)) = \alpha * \gamma * c(V_i)^{\gamma-1}$, specifically, the $V_i \in S_2$ with the lowest block weight $c(V_i)$. In our scheme, $c(V_i) = c(E_i)$, that is, the number of edges assigned to block E_i of the overall edge partition. This optimized process, facilitated by a priority queue, reduces the evaluation of blocks for each vertex to those assigned to its neighbors and the minimum weight block overall. It results in an optimal block V_i for maximizing the generalized Fennel gain function in $\mathcal{O}(d(u) + \log(k))$ time using a binary heap priority queue or $\mathcal{O}(d(u))$ with a bucket priority queue, as suggested in [17], ultimately yielding an overall linear time complexity. With this enhanced approach, the runtime becomes independent of the parameter k.

The Parameter α. The authors of `Fennel` [51], define the parameter $\alpha = \sqrt{k} \frac{m}{n^{3/2}}$ for vertex partitioning of an input graph $G = (V, E)$ with n vertices and m edges. However this choice of α is not directly applicable for edge partitioning in our CSPAC-based model. If we built a single model β_b for the whole graph G at once, it would have $n^* = m$ vertices and a number m^* of edges equal to the number of auxiliary edges in β_b. While we know n^* immediately, we cannot directly obtain m^* without visiting all vertices of the whole graph. Thus, we need to estimate m^*.

We thus have three distinct approaches for determining the Fennel parameter α. In the *static* α method, we keep α constant across all batches, setting it to $\alpha = \sqrt{k}\frac{m_{approx}}{n^{3/2}}$, where $n^* = m/2$, $m_{approx} = y*n^*$, and y is a tuning parameter. For the *batch* α approach, we update α for each batch, calculating it as $\alpha = \sqrt{k}\frac{m_s}{n_s^{3/2}}$, where n_s and m_s are the number of vertices and edges of each CSPAC graph S_b^* respectively. The *dynamic* α method also updates α per batch. It begins with the *static* α setting and refines m_{approx} in each batch by computing the number of auxiliary edges, determined through counting vertices of degree less than or equal to 2.

3.5 FreightE

In addition to `HeiStreamE`, we present `FreightE`, a fast streaming edge partitioner that uses streaming hypergraph partitioning to assign blocks to edges on the fly. In general, a hypergraph vertex partitioner can partition edges of an input graph G by first transforming it into its dual hypergraph representation H, where each edge of G is a hypervertex, and each vertex of G induces a hyperedge spanning its incident edges. Then, a hypergraph vertex partitioner that assigns the hypervertices of H into k blocks, while optimizing for the connectivity metric, directly provides an edge partition of G. The intuition behind this approach is that a hypergraph vertex partitioner that optimizes for the connectivity metric directly optimizes the replication factor of the underlying edge partition [14]. In `FreightE`, we perform the transformation of G into H on the fly as follows. At a given step, we read a vertex of the input graph (METIS format) along with its neighborhood. Each undirected edge in the neighborhood is treated as a unique hypervertex of the hypergraph, and permanently assigned to a block using the `FREIGHT` streaming hypergraph partitioner [17]. This process is repeated until all vertices along with their neighborhoods are visited, at which point each edge of the input graph is assigned to a block. Following the `FREIGHT` partitioner, the overall runtime of `FreightE` is $\mathcal{O}(n+m)$, and memory complexity is $\mathcal{O}(m+k)$. In comparison to `HeiStreamE`, `FreightE` is faster, as it does not require the construction of an equivalent CSPAC graph, and requires less memory unless $m \gg n$.

4 Experimental Evaluation

Setup. We implemented `HeiStreamE` and `FreightE` inside the `KaHIP` framework (using C++) and compiled it using gcc 9.3 with full optimization enabled (-O3 flag). Except for the largest graph instance `gsh-2015`, all experiments were performed on a single core of a machine consisting of a sixteen-core Intel Xeon Silver 4216 processor running at 2.1 GHz, 100 GB of main memory, 16 MB of L2-Cache, and 22 MB of L3-Cache running Ubuntu 20.04.1. To facilitate algorithms that required greater memory, `gsh-2015` was run on a single core of an alternate machine, consisting of a 64-core AMD EPYC 7702P Processor containing 1 TB of main memory.

Baselines. We compare `HeiStreamE` and `FreightE` against the state-of-the-art streaming algorithm `HDRF`, as well as the re-streaming algorithms `2PS-HDRF` [36] and `2PS-L` [37], which require three passes over the input graph. We exclude the following algorithms: `SNE` [54], as it fails to execute for $k > 127$ and is outperformed by `2PS-HDRF` [36]; `DBH` [53], as it ignores past partition assignments and thus has poor solution quality; `ADWISE` and `RBSEP` as they have limited global information during streaming, and `2PS-L` outperforms them [37].

For comparison with competitors, we obtained implementations of `2PS-HDRF` and `2PS-L` from their official repository, which also provides an implementation of `HDRF`. We configure all competitor algorithms with the optimal settings provided by the authors. `2PS-HDRF`,

`2PS-L` and `HDRF` require a vertex-to-partition table of size $\mathcal{O}(n*k)$, which stores the blocks that each vertex was replicated on. To optimize memory usage, these partitioners can be built with the number of partitions at compile time to only allocate the required amount of memory. Thus, we re-compile them with the CMake flag for the number of blocks for each k value in our experiments. We set the `HDRF` scoring function parameter $\lambda = 1.1$, similar to the authors of `2PS` [36]. The provided codes for `2PS-HDRF`, `2PS-L`, and `HDRF` in their official repositories set a hard-coded soft limit on the number of partitions to 256, which we override to test the algorithms with larger k values.

All competitors read a binary edge list format with 32-bit vertex IDs. This allows for faster IO during program execution. Additionally, all competitor programs offer a converter which can load a graph in the standard edge list format, convert it into the binary edge list format, and write it to memory before proceeding. For a fair comparison with `HeiStreamE` and `FreightE`, which are capable of reading both text-based (METIS) and binary (adjacency) graphs, we perform experiments with binary graph formats only. Further, we exclude the IO time since the objective of the experiments is to measure the performance of the partitioners and not IO efficiency. Similarly, we exclude the time it takes to convert the graphs into the binary format for all partitioners.

Instances.   Our graph instances for experiments are shown in Appendix Table 2 and are sourced from Ref. [4, 5, 6, 7, 20, 31, 42]. All instances evaluated have been used for benchmarking in previous works on graph partitioning. From these graph instances, we construct three disjoint sets: a tuning set for parameter study experiments, a test set for comparison against state-of-the-art and a set of huge graphs, for which in-memory partitioners ran out of memory on our machine. We set the number of blocks to $k = \{2^1, 2^2, \ldots, 2^{14}\}$ for all experiments except those on huge graphs, for which k values are shown in Table 1. We allow an imbalance of $\varepsilon = 3\%$ for all partitioners. While streaming, we use the natural order of the vertices in these graphs.

Methodology.   We measure running time, replication factor and memory consumption, i.e., the maximum resident set size for the executed process. When averaging over all instances, we use the geometric mean to give every instance the same influence on the final score. Further, we average all results of each algorithm grouped by k, to explore performance with increasing k values. Let the runtime, replication factor or memory consumption be denoted by the score σ_A for some k-partition generated by an algorithm A. We express this score relative to others using the following tools: *improvement* over an algorithm B, computed as a percentage $(\frac{\sigma_A}{\sigma_B} - 1) * 100\%$ and *relative* value over an algorithm B, computed as $\frac{\sigma_A}{\sigma_B}$. Additionally, we present performance profiles by Dolan and Moré [16] to benchmark our algorithms. These profiles relate the running time (resp. solution quality, memory) of the slower (resp. worse) algorithms to the fastest (resp. best) one on a per-instance basis, rather than grouped by k. Their x-axis shows a factor τ while their y-axis shows the percentage of instances for which an algorithm has up to τ times the running time (resp. solution quality, memory) of the fastest (resp. best) algorithm.

Parameter Tuning.   We tuned the parameters used by `HeiStreamE`, namely the selection of the batch graph model β_b mode and the choice of Fennel α, through experiments run on the Tuning Set (see Appendix Table 2). Due to space constraints we only give a short summary. Our results support the use of the *minimal* mode for β_b and batch α for Fennel's α parameter for subsequent experiments. Other parameters for the multilevel partitioning
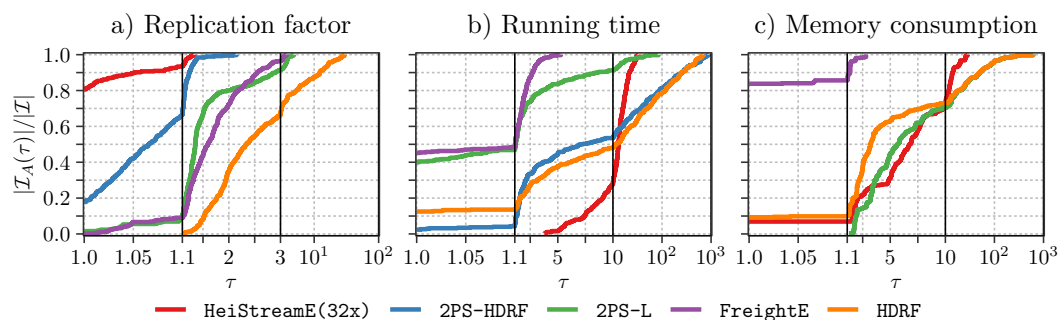
Figure 4 Comparison of `HeiStreamE` and `FreightE` with `2PS-HDRF`, `2PS-L` and `HDRF` on the Test Set in Appendix Table 2 using performance profiles. Let $\mathcal{A}$ be the set of all algorithms, $\mathcal{I}$ the set of instances, and $q_A(I)$ the quality of algorithm $A \in \mathcal{A}$ on instance $I \in \mathcal{I}$. For each algorithm A, we plot the fraction of instances $\frac{|\mathcal{I}_A(\tau)|}{|\mathcal{I}|}$ (y-axis) where $\mathcal{I}_A(\tau) := \{I \in \mathcal{I} | q_A \le \tau \cdot min_{A' \in \mathcal{A}} q_{A'}(I)\}$ and τ is on the x-axis. Includes all k values. Note the logarithmic scale in the final third of the plots. Memory consumption is measured as the maximum resident set size of the program execution. `2PS-HDRF` and `2PS-L` have the same memory consumption.

scheme align with optimal values from `HeiStream` [18]. The *minimal* model mode produces a solution quality improvement of 11.73% over the baseline of using no graph model, which is comparable to the 12.8% increase achieved by the *maximal* mode, while being $1.41\times$ and $1.29\times$ faster than the *maximal* and *r-Subset* mode respectively. On average, across all instances and all k values, batch α produces 0.86% and 3.27% better solution quality than static and dynamic α respectively. For $k > 32$, these averages increase to 2.1% and 5.2%, respectively.

Comparison with State-of-the-Art

We now provide experiments in which we compare `HeiStreamE` and `FreightE` against the current state-of-the-art algorithms for (re)streaming edge partitioning, namely, `HDRF`, `2PS-HDRF` and `2PS-L`. These experiments were performed on the Test Set and the Huge Set of graphs in Appendix Table 2. Figure 4 gives performance profiles for the Test Set and Table 1 gives detailed per instance results for instances of the Huge Set. We distinguish between buffer sizes by defining, for example, `HeiStreamE(32x)` as `HeiStreamE` with a buffer size of $32\,768 = 32x$ vertices, where $x = 1\,024$.

Replication Factor. `HeiStreamE(32x)` produces better solution quality than state-of-the-art (re)streaming edge partitioners for all k values. The results from our Test Set demonstrate that `HeiStreamE(32x)` achieves an average improvement in solution quality of 7.56% (or 13.69% when using `HeiStreamE(256x)`) compared to `2PS-HDRF`, which produces the next best solution quality. As displayed in Figure 4a, `HeiStreamE(32x)` produces better solution quality than `2PS-HDRF` in approximately 80% of all Test Set instances. The largest improvement in replication factor that we observed for `HeiStreamE(32x)` over `2PS-HDRF` is of $\approx 53\%$ on graph `circuit5M` for $k \ge 8192$. Further, `HeiStreamE(32x)` achieves an average improvement in solution quality of 51.84% percent over `2PS-L`, and an average improvement of 202.86% over `HDRF`, the only other on-the-fly streaming algorithm presented here. These results from the Test Set are reflected in our experiments on huge graphs, shown in Table 1: `HeiStreamE(32x)` and `HeiStreamE(256x)` produce the best solution quality in most instances, providing the best solution quality for all k values for five of the six huge graphs. While `FreightE` produces
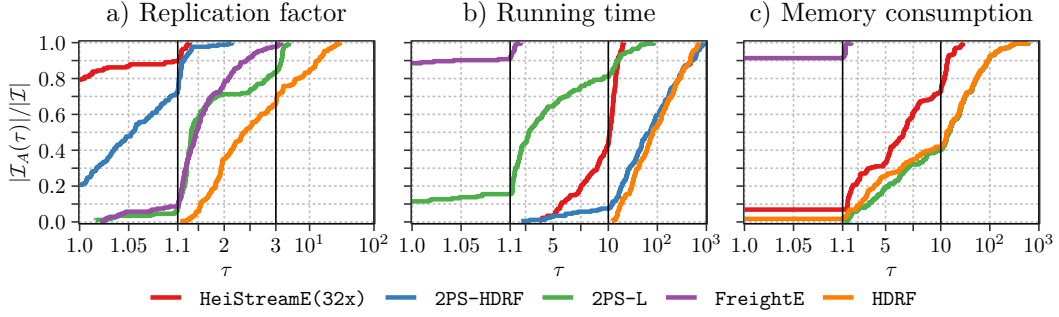
Figure 5 Comparison of `HeiStreamE` and `FreightE` with `2PS-HDRF`, `2PS-L` and `HDRF` on the Test Set in Appendix Table 2 using performance profiles (see Figure 4 caption for detailed description). Only includes runs with $k \geq 512$. Note the logarithmic scale in the final third of the plots. Memory consumption is measured as the maximum resident set size of the program execution. `2PS-HDRF` and `2PS-L` have the same memory consumption.

lower solution quality than `2PS-L` and `2PS-HDRF` on most Test Set instances, for $k \geq 512$, `FreightE`, produces 9.88% higher solution quality than `2PS-L` on average. `FreightE` produces 87.28% better solution quality than `HDRF` on average across all Test Set instances and k values. The same trends for `FreightE` are reflected in our results on huge graphs.

Runtime. `HeiStreamE(32x)` is on average slower than `2PS-HDRF` and `HDRF` for $k \leq 256$; however, since its runtime is not linearly dependent on k, `HeiStreamE` is substantially faster than `2PS-HDRF` and `HDRF` for higher k values (Figure 5b). On the Test Set, `HeiStreamE(32x)` is on average $6.7\times$ faster than `2PS-HDRF` and $8.7\times$ faster than `HDRF` for $k \geq 512$. Compared to `2PS-L`, whose time complexity is also independent of k, `HeiStreamE(32x)` is on average slower across all instances. Similarly, in our experiments on huge graphs, `HeiStreamE(32x)` and `HeiStreamE(256x)` are faster than `2PS-HDRF` and `HDRF` for high k values, but slower than `2PS-L`. On the Test Set, `FreightE` is the fastest algorithm among competitors; it is $1.3\times$ faster than `2PS-L` which is the next fastest algorithm. Additionally, it is $9.9\times$ faster than `HDRF` and $8\times$ faster than `2PS-HDRF` on average across all Test Set instances. In our experiments on huge graphs, `FreightE` is faster than `HDRF` and `2PS-HDRF` on average across all instances, and the fastest algorithm for $k \geq 2\,048$.

Memory Consumption. Since `HeiStreamE(32x)` uses a buffered streaming approach, it consumes on average more memory than `2PS-HDRF`, `2PS-L` and `HDRF` for $k \leq 256$ on the Test Set; however, since its memory consumption is not asymptotically dependent on m or k, `HeiStreamE(32x)` consumes significantly less memory than `2PS-HDRF`, `2PS-L`, and `HDRF` for higher k values. On average, for $k \geq 512$, `2PS-HDRF` and `2PS-L` use $3.0\times$ more memory than `HeiStreamE(32x)`, and `HDRF` uses $2.7\times$ more memory than `HeiStreamE(32x)`. Notably, while `HeiStreamE(32x)` consumes $1.46\times$ more memory on average than `2PS-HDRF` and `2PS-L` for $k \leq 256$ on the Test Set, in three out of six of the huge graphs, it is more memory efficient than them across all k values. On the Test Set, `FreightE` consumes significantly less memory than all competitors as shown in Figure 4c. It consumes $4.9\times$ less memory than `HDRF` and $7.2\times$ less memory than `2PS-L` and `2PS-HDRF` on average across all instances and all k values. Further, on average, `FreightE` consumes $16\times$ less memory than `2PS-L` and `2PS-HDRF` for $k \geq 512$ (Figure 5c). Since `FreightE`'s memory consumption is linearly dependent on m, it is less memory efficient on the huge graphs, which, like other real-world graphs, tend to have many more edges than vertices. `FreightE` uses more memory than competitors for $k \leq 256$ in five out of six of the huge graphs, but is more memory efficient at

high k due to its memory being asymptotically independent of k. In our experiments on huge graphs, `2PS-HDRF`, `2PS-L` and `HDRF` exceed the available memory on the machine at $k \geq 4\,096$ for uk-2007-05 and webbase-2001, and at $k \geq 8\,192$ for com-friendster. At $k \geq 16\,384$ they exceed the available memory for all graphs, while `HeiStreamE` and `FreightE`'s memory consumption is predictable and consistent across k.

■ **Table 1** Results of experiments on the Huge Set in Appendix Table 2. Here, we compare `HeiStreamE(32x)`, i.e., `HeiStreamE` with a buffer size of $32 \cdot 1\,024$ (resp. `HeiStreamE(256x)`), and `FreightE` with state-of-the-art (re)streaming edge partitioners on huge graph instances, displaying the Replication Factor *RF*, Running Time *RT* [s] and Memory Consumption *Mem* [GB]. The best solution quality for each instance is **emboldened**. The missing values indicate when an algorithm exceeded the memory of the machine for all graphs except `gsh-2015`, where the missing value indicates a timeout, i.e., the algorithm exceeded a runtime limit of 24 hours.

G	k	HeiStreamE(32x)			HeiStreamE(256x)			FreightE			2PS-HDRF			2PS-L			HDRF		
		RF	RT	Mem	RF	RT	Mem	RF	RT	Mem	RF	RT	Mem	RF	RT	Mem	RF	RT	Mem
uk-2007-05	4	**1.05**	3385	15.35	**1.05**	3648	18.59	1.76	424	12.72	1.12	139	5.92	1.40	142	5.92	2.74	133	2.35
	32	1.05	3707	15.36	**1.04**	3610	18.54	3.03	427	12.72	1.16	283	5.92	2.05	149	5.92	8.30	718	2.35
	128	1.07	3411	15.37	**1.05**	3543	18.54	3.59	419	12.72	1.22	918	6.70	2.64	158	6.70	12.45	2589	3.92
	256	1.09	3642	15.37	**1.06**	3684	18.54	3.81	398	12.71	1.26	1725	8.27	3.06	170	8.27	14.76	4682	7.06
	512	1.10	3407	16.56	**1.06**	3718	18.35	4.01	373	12.72	1.30	3525	14.50	3.60	201	14.50	17.08	8714	13.32
	1024	1.13	3421	16.54	**1.08**	3685	18.54	4.18	371	12.72	1.38	7505	27.03	4.39	279	27.03	19.55	16753	25.86
	2048	1.18	3406	15.39	**1.11**	3551	18.54	4.34	371	12.72	1.51	17720	52.10	5.58	527	52.10	22.10	33302	50.93
	4096	1.24	3419	16.78	**1.16**	3538	18.54	4.53	370	12.73	-	-	-	-	-	-	-	-	-
	8192	1.33	3413	16.94	**1.23**	3580	18.54	4.72	384	12.73	-	-	-	-	-	-	-	-	-
	16384	1.50	3464	15.67	**1.32**	3577	18.54	4.97	509	12.73	-	-	-	-	-	-	-	-	-
com-friendster	4	**1.62**	3356	1.19	1.74	7230	7.08	2.83	357	6.98	1.88	423	3.72	2.08	394	3.72	2.35	251	1.47
	32	**4.90**	3410	1.22	4.94	7159	7.33	10.71	314	6.98	5.21	865	3.72	6.99	422	3.72	7.97	561	1.47
	128	10.00	3516	1.23	9.53	7370	7.60	18.47	311	6.98	**9.00**	2159	4.21	12.17	526	4.21	14.53	1523	2.45
	256	13.10	3585	1.26	**10.87**	7530	7.60	19.79	308	6.98	11.12	3633	5.18	15.05	557	5.18	18.00	2611	4.40
	512	15.92	3681	1.31	**11.98**	7688	7.59	22.68	306	6.98	13.19	6513	9.05	17.69	615	9.05	21.16	4743	8.31
	1024	18.05	3742	1.31	**12.90**	7828	7.76	24.89	312	6.98	15.16	12226	16.87	20.03	702	16.87	23.78	9173	16.14
	2048	19.00	3916	1.30	**13.91**	7929	7.73	25.97	339	6.98	16.95	23536	32.51	21.87	858	32.51	25.76	17678	31.78
	4096	19.77	4024	1.35	**15.35**	8243	7.84	26.56	358	6.98	18.52	45773	63.80	23.27	1161	63.80	27.15	33753	63.06
	8192	20.26	4154	1.36	**16.90**	8325	8.10	26.86	404	6.98	-	-	-	-	-	-	-	-	-
	16384	21.10	4339	1.33	**19.16**	8782	8.55	26.90	479	6.98	-	-	-	-	-	-	-	-	-
it-2004	4	**1.10**	999	11.65	**1.10**	1019	17.83	1.73	131	4.03	1.15	46	2.54	1.45	47	2.54	2.65	43	0.93
	32	**1.09**	1000	11.23	1.09	1021	17.70	2.74	116	4.03	1.21	91	2.54	2.12	49	2.54	7.75	229	0.93
	128	1.11	1006	11.22	**1.09**	1021	18.79	3.20	116	4.03	1.27	271	2.85	2.40	52	2.85	11.70	787	1.54
	256	1.12	1001	11.22	**1.09**	1021	18.01	3.38	117	4.03	1.31	514	3.47	2.52	55	3.47	13.85	1425	2.77
	512	1.14	1008	11.85	**1.10**	1007	17.90	3.53	117	4.03	1.35	1033	5.70	2.98	66	5.70	16.15	2684	5.23
	1024	1.17	1002	11.68	**1.12**	1013	17.57	3.67	117	4.03	1.39	2132	10.62	3.46	92	10.62	18.51	5237	10.16
	2048	1.21	1000	11.23	**1.16**	999	17.86	3.78	116	4.03	1.51	5127	20.46	4.33	157	20.46	20.82	10452	20.00
	4096	1.27	1013	11.87	**1.21**	1031	19.47	3.89	118	4.03	1.68	13010	40.15	5.89	356	40.15	22.94	20717	39.69
	8192	1.38	1020	11.88	**1.30**	1033	18.08	4.02	116	4.03	1.90	31776	79.53	7.44	817	79.53	24.80	40267	79.07
	16384	1.53	1032	11.99	**1.40**	1050	18.09	4.18	151	4.04	-	-	-	-	-	-	-	-	-
sk-2005	4	**1.14**	2041	12.97	1.16	2126	18.31	2.18	232	7.17	1.17	85	2.94	1.30	88	2.94	2.93	73	1.14
	32	1.25	2036	13.25	**1.18**	2143	18.32	4.11	236	7.17	1.25	194	2.94	3.06	91	2.94	9.78	391	1.14
	128	1.31	2028	13.02	**1.19**	2147	19.27	4.90	202	7.17	1.33	630	3.31	4.67	102	3.31	14.13	1459	1.89
	256	1.39	2047	13.10	**1.22**	2158	19.14	5.16	203	7.17	1.38	1254	4.07	5.65	120	4.07	16.20	2636	3.40
	512	1.46	2052	13.09	**1.27**	2140	18.35	5.42	203	7.17	1.51	2743	6.98	7.04	159	6.98	18.40	4836	6.42
	1024	1.55	2035	13.35	**1.33**	2153	18.35	5.64	203	7.17	1.72	6358	13.02	8.93	261	13.02	20.69	9226	12.45
	2048	1.63	2064	13.15	**1.42**	2145	18.43	5.89	205	7.17	1.99	14369	25.09	9.79	452	25.09	23.01	18224	24.53
	4096	1.75	2076	13.27	**1.51**	2168	18.37	6.22	207	7.17	2.31	31775	49.24	11.27	997	49.24	25.39	36426	48.67
	8192	1.86	2095	13.56	**1.62**	2159	18.38	6.64	211	7.17	2.67	70438	91.45	12.34	2051	91.46	27.95	72800	91.44
	16384	2.06	2155	13.09	**1.78**	2185	18.40	7.21	262	7.18	-	-	-	-	-	-	-	-	-
webbase-2001	4	1.06	770	1.33	**1.05**	782	2.20	1.44	140	3.65	1.10	51	6.32	1.34	50	6.32	2.17	42	2.59
	32	**1.08**	785	1.31	1.09	790	2.20	1.96	112	3.65	1.16	91	6.32	1.61	53	6.32	4.49	192	2.59
	128	**1.09**	774	1.31	1.09	789	2.25	2.13	113	3.65	1.20	245	7.18	1.68	57	7.18	5.96	610	4.31
	256	**1.09**	782	1.38	1.09	799	2.21	2.18	112	3.65	1.22	439	9.04	1.68	61	9.04	6.66	1113	7.75
	512	**1.09**	790	1.34	1.09	797	2.19	2.21	111	3.65	1.24	817	15.93	1.66	67	15.93	7.33	2117	14.64
	1024	1.10	751	1.41	**1.09**	798	2.23	2.24	109	3.65	1.26	1594	29.71	1.66	79	29.71	7.97	4126	28.42
	2048	1.11	760	1.34	**1.10**	798	2.20	2.26	108	3.65	1.27	3187	57.26	1.69	108	57.26	8.54	8123	55.97
	4096	1.13	763	1.46	**1.11**	798	2.27	2.27	107	3.65	-	-	-	-	-	-	-	-	-
	8192	1.15	776	1.33	**1.12**	810	2.16	2.28	107	3.66	-	-	-	-	-	-	-	-	-
	16384	1.17	797	1.46	**1.14**	818	2.16	2.30	109	3.66	-	-	-	-	-	-	-	-	-
gsh-2015	4	1.26	22797	45.57	**1.25**	25128	56.42	1.60	3178	100.49	1.30	2151	52.83	1.70	2149	52.83	3.59	1881	22.10
	32	1.33	22916	45.57	**1.32**	25522	59.00	2.58	3468	100.35	1.51	4194	52.83	2.74	2195	52.83	16.94	10216	22.10
	128	**1.39**	23275	46.24	**1.39**	25421	56.82	3.09	2268	100.49	1.65	11623	60.19	3.52	2393	60.19	26.99	38232	36.83
	256	1.42	23194	45.57	**1.41**	25403	59.94	3.28	2253	100.49	1.70	21482	77.33	3.87	2545	77.33	31.09	64247	66.29
	512	1.46	23299	45.57	**1.43**	25495	59.32	3.44	2264	100.49	1.77	41227	136.25	4.21	2751	136.25	-	-	-

5 Conclusion

In this work, we propose `HeiStreamE`, a buffered streaming edge partitioner that achieves state-of-the-art solution quality, and `FreightE`, a highly efficient streaming edge partitioner that uses streaming hypergraph partitioning to assign blocks to edges on the fly. `HeiStreamE` processes the input graph in batches, constructs a novel graph transformation on the per-batch graph model, extends it with global partitioning information, and partitions it with a multilevel scheme. Aside from hashing-based streaming partitioners, which have poor solution quality, `HeiStreamE` and `FreightE` are the only known streaming edge partitioners whose runtime and memory consumption are both linear and asymptotically independent of the number of blocks of partition k. Our experiments demonstrate that `HeiStreamE` and `FreightE` consistently outperform all existing (re)streaming edge partitioners with regard to vertex replication metrics and runtime respectively. Additionally, `HeiStreamE` uses less memory than high-quality (re)streaming edge partitioners at $k \geq 256$ or when the graph has far more edges than vertices, as is the case for most real-world networks. Our findings underscore `HeiStreamE` as a highly memory-efficient and effective solution for streaming edge partitioning of large-scale graphs.

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A   Instance Properties

■ **Table 2** Graphs used for experiments. The roadNet graphs, wiki graphs, web-Google, web-NotreDame, and all social, co-purchasing, and autonomous systems graphs were obtained from the publicly available SNAP dataset [31]. We also used graphs from the 10th DIMACS Implementation Challenge, namely eu-2005, in-2004 and uk-2007-05 [4]. Any remaining graphs are available on the network repository website [42] or on the Laboratory for Web Algorithmics website [5, 6, 7]. For our experiments, we converted these graphs to a vertex-stream format (METIS) while removing parallel edges, self-loops, and directions, and assigning unitary weight to all vertices and edges. If a graph was unavailable in an equivalent edge list format, we converted the METIS format into the edge list format while preserving edge order for fairness during streaming.

Graph	n	m	Type	Graph	n	m	Type
Tuning Set				Test Set			
hcircuit	105 676	203 734	Circuit	Dubcova1	16 129	118 440	Mesh
coAuthorsCiteseer	227 320	814 134	Citations	DBLP-2010	300 647	807 700	Citations
coAuthorsDBLP	299 067	977 676	Citations	com-Amazon	334 863	925 872	Social
com-DBLP	317 080	1 049 866	Social	web-NotreDame	325 729	1 090 108	Web
roadNet-PA	1 088 092	1 541 898	Roads	citationCiteseer	268 495	1 156 647	Citations
web-Google	356 648	2 093 324	Web	wiki-Talk	232 314	1 458 806	Web
amazon0601	403 394	2 443 408	Co-Purch.	roadNet-TX	1 379 917	1 921 660	Roads
com-Youtube	1 134 890	2 987 624	Social	amazon0312	400 727	2 349 869	Co-Purch.
Amazon-2008	735 323	3 523 472	Similarity	amazon0505	410 236	2 439 437	Co-Purch.
soc-lastfm	1 191 805	4 519 330	Social	roadNet-CA	1 965 206	2 766 607	Roads
as-Skitter	554 930	5 797 633	Aut. Syst.	G3_circuit	1 585 478	3 037 674	Circuit
italy-osm	6 686 493	7 013 978	Roads	soc-flixster	2 523 386	7 918 801	Social
in-2004	1 382 908	13 591 473	Web	great-britain-osm	7 733 822	8 156 517	Roads
ML_Laplace	377 002	13 656 485	Mesh	FullChip	2 986 999	11 817 567	Circuit
				coPapersDBLP	540 486	15 245 729	Citations
webbase-2001	118 142 155	854 809 761	Web	coPapersCiteseer	434 102	16 036 720	Citations
it-2004	41 291 594	1 027 474 947	Web	eu-2005	862 664	16 138 468	Web
com-friendster	65 608 366	1 806 067 135	Social	soc-pokec	1 632 803	22 301 964	Social
sk-2005	50 636 154	1 810 063 330	Web	wiki-topcats	1 791 489	25 444 207	Social
uk-2007-05	105 896 555	3 301 876 564	Web	circuit5M	5 558 311	26 983 926	Circuit
gsh-2015	988 490 691	25 690 705 118	Web	com-LJ	3 997 962	34 681 189	Social
				soc-LiveJournal1	4 846 609	42 851 237	Social
				Ljournal-2008	5 363 186	49 514 271	Social
				ca-hollywood-2009	1 069 126	56 306 653	Roads
				Flan_1565	1 564 794	57 920 625	Mesh
				Bump_2911	2 852 430	62 409 240	Mesh
				com-Orkut	3 072 441	117 185 083	Social
				HV15R	2 017 169	162 357 569	Mesh

B   Omitted Proofs

▶ **Theorem.** *For any vertex partition $vp(S_b^*)$ of the CSPAC graph S_b^* with edge-cut $cost(vp(S_b^*))$, there exists a corresponding edge partition $ep(G_b)$ of the batch graph G_b with a number of vertex replicas $cost(ep(G_b))$, satisfying $cost(ep(G_b)) \leq cost(vp(S_b^*))$, which establishes a lower bound spanning the set of possible CSPAC graphs S_b^* associated with G_b.*

Proof. Our proof can be delineated through three consecutive claims. (i) The existence of a singular edge partition $ep(G_b)$ that corresponds to a specified vertex partition $vp(S_b^*)$. (ii) The general validity of the inequality $cost(ep(G_b)) \leq cost(vp(S_b^*))$. (iii) The validity of the equality $cost(ep(G_b)) = cost(vp(S_b^*))$ for a specific CSPAC graph S_b^*.

Claim (i) trivially holds, as $ep(G_b)$ stems directly from $vp(S_b^*)$ by virtue of the one-to-one correspondence between edges in G_b and vertices in S_b^*. For the proof of assertions (ii) and (iii), consider the following. (a) There can be no replicas of vertices with degree lower than 2. (b) Vertices in G_b with a degree lower than 2 are not represented by any edges in S_b^*. (c) Vertices u in G_b that possess a degree $d(u) \geq 2$ are represented in S_b^* through unique, edge-disjoint paths, each connecting the $d(u)$ vertices in S_b^* corresponding to the edges incident to u in G_b.

To prove (ii), we show that the number of replicas of any vertex u in $ep(G_b)$ does not exceed the number of cut edges directly induced by u in $vp(S_b^*)$. From (a) and (b), it trivially holds for vertices with a degree lower than 2. Assuming there are $x > 0$ replicas of u in $ep(G_b)$, it implies that edges incident on u are distributed across $x + 1$ nonempty blocks. According to (c), u is uniquely represented by an edge-disjoint path connecting the vertices in S_b^* that correspond to the edges of u in G_b. When the vertices of a connected (sub)graph are partitioned into $x + 1$ blocks, these blocks themselves are interconnected. Therefore, the edge-cut directly attributable to vertex u is at least x, which completes the proof for (ii).

To prove (iii), we show how to build a valid CSPAC graph S_b^*, such that $cost(ep(G_b)) = cost(vp(S_b^*))$. For vertices of G_b with a degree lower than 2, the equality trivially holds based on (a) and (b). For a vertex u in $ep(G_b)$ with $x > 0$ replicas (edges distributed across $x + 1$ nonempty blocks), we create $x + 1$ independent paths connecting the vertices in S_b^* that represent the edges incident to u in G_b. Vertices in each path are then assigned to a common block. As these paths are between vertices of the same block, they have no cut edges. Subsequently, these paths are interlinked to form a unified path. This introduces exactly x cut edges directly associated with vertex u, thereby concluding the proof for condition (iii) and the overall proof. ◀

▶ **Theorem.** *For any vertex partition $vp(\beta_b)$ of the* maximal *model β_b with edge-cut $cost(vp(\beta_b))$, there exists a corresponding edge partition $ep(G_b)$ of the batch graph G_b that, when incorporated into the already partitioned section of the input graph G, introduces a number γ of new vertex replicas, satisfying $\gamma \leq cost(vp(\beta_b))$.*

Proof. The only disparity between the CSPAC graph S_b^* and the maximal model β_b is the presence of artificial vertices and edges in β_b. If there are no artificial edges in β_b, it implies that none of the edges in the batch graph G_b are adjacent to edges in G that have previously been assigned to blocks. In this scenario, Theorem 1 provides sufficient grounds to establish the claim. If β_b contains artificial edges, each artificial edge signifies a unique adjacency in G of an edge in the batch graph G_b to edges already assigned to blocks in previous batches. In this scenario, we complete the proof of the claim by noting that the number of cut artificial edges in $vp(\beta_b)$ cannot be less than the number of new replicas introduced exclusively for vertices contained in previous batches. ◀