# Distributed Memory Partitioning of High-Throughput Sequencing Datasets for Enabling Parallel Genomics Analyses 

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Outline

- Introduction
- Background
- Methods
- Results


## Introduction

- Large volume of short biological sequence data
- Construction of long sequences from short is time consuming
- Use existing sequence for reference
- Compare short sequences to each other
- Distributed computing is a promising direction for speed up
- Can intelligent partitioning benefit sequence construction?


## Introduction - Case 1: Alignment

- Assuming a copy of a reference exists in each partition
- Partitioning dataset is simply balancing partition sizes (always true?)
- Reference acts as global coordinate system
- Position on reference will infer relations across partitions



## Introduction - Case 2: Assembly

- Ideally, group reads with greatest relation
- How can we calculate overlap quickly?



## Introduction - Motivation

- Intelligently partitioning entire dataset can be time consuming (depending on method)
- Partitioning a graph that represents the dataset is a good partition of the dataset as well
- Related works:
- Pairwise similarity - very time consuming
- Hash partition of graph - destroys data locality


## Background - de Bruijn Graph

- Used to bring down number of comparisons in assembly
- Captures connection and frequency of common subsequences
- Tracing paths through graph recreate sequence dataset


## Background - de Bruijn Graph

Input Sequences, $\mathrm{k}=3$
AABCDD

## AABCED

Graph

A A B

## Background - de Bruijn Graph

Input Sequences, $\mathrm{k}=3$
$A \triangle B C D D$
$A \triangle B C D$

Graph
$A A B A$

## Background - de Bruijn Graph

Input Sequences, $\mathrm{k}=3$
$A A B C D D$
$A A B C E D$

Graph


## Background - de Bruijn Graph

Input Sequences, $\mathrm{k}=3$
$A A B C D D$
AABCED

Graph


## Methods

- Construction
- Compaction
- Graph Partition
- Dataset Partition


## Methods - Construction

- Each vertex has at most 8 neighbors
- Alphabet of size 4 for DNA
- 4 edges in, 4 out
- 2 Classes of vertex:
- Vertices that branch ( >1 in/out edges)
- Vertices in a chain



## Methods - Construction

- Build hash table of all subsequence of size $k$ in dataset
- For each subsequence check the 8 possible neighbors
- Add 1 to weight of edge for each occurrence
- Trim edges below some threshold



## Methods - Compaction

- Essentially connected components
- Combine chain vertices into single node
- Concatenate labels (subsequences) and sum edge weights



## Methods - Graph Partition

- Optimize two parameters - min cut and balance
- Cut defined as weight of edges between partitions
- Bound the balance of partitions by some threshold $(1+\varepsilon)$

$$
\begin{gathered}
\max _{1 \leq i \leq m} C\left(V_{i}\right) \\
\sum_{1 \leq i \leq m} C\left(V_{i}\right) / m \\
\text { Balance function } \\
\mathrm{C}_{\mathrm{V}}\left(\mathrm{~V}_{\mathrm{i}}\right)=\text { sum of weights of vertices in } \mathrm{V}_{\mathrm{i}} \\
\mathrm{~m}=\text { total number of partitions }
\end{gathered}
$$

## Methods - Graph Partition

- Recursively coarsen graph
- Partition coarsest graph
- Recursively un-coarsen graph, refining cut after each iteration



## Methods - Dataset Partitioning

- Map partition id to each subsequence of length $k$
- Chains will contain multiple subsequences that will need to map
- Build distributed index from mapping
- Assign sequence $r$ to partition id most frequently assigned
- Sequence $r$ will contain $|r|-k+1$ subsequences


## Results - Test Environment

- 32 nodes
- 16 cores
- 128GB memory
- OpenMPI 1.8.6

Table 1: Datasets used for experimental evaluation

| Dataset | Genome length <br> (Giga base-pairs) | Dataset size <br> (Giga bases) | Read length <br> (Bases) |
| :--- | ---: | ---: | ---: |
| Fish | 1.0 Gbp | 52.7 Gb | 101 |
| Bird | 1.2 Gbp | 70.7 Gb | 101 |
| Snake | 1.6 Gbp | 84.1 Gb | 121 |

## Results - Compaction

Table 2: Reduction in the size of the DBG due to compaction

| Dataset | Plain graph <br> (No. of vertices) | Compacted graph <br> (No. of vertices) | Compaction <br> ratio |
| :--- | ---: | ---: | ---: |
| Fish | $733,774,187$ | $16,672,988$ | 44 |
| Bird | $1,208,521,390$ | $25,740,770$ | 47 |
| Snake | $1,361,026,568$ | $27,199,895$ | 50 |

## Results - Graph Partitioning

Table 3: Quality of de Bruijn graph partitioning

| Dataset | Sum of weights of all <br> edges in the graph | Sum of weights <br> of edges cut | Cut <br> ratio |
| :--- | ---: | ---: | ---: |
| Fish | $13,593,910,042$ | $19,252,245$ | $1.42 \times 10^{-3}$ |
| Bird | $22,462,771,436$ | $22,337,839$ | $0.99 \times 10^{-3}$ |
| Snake | $29,754,489,857$ | $47,197,297$ | $1.59 \times 10^{-3}$ |

## Results - Graph Runtimes

Table 4: Runtime in seconds for the Bird dataset for de Bruijn graph construction (Algorithm 1), chain labeling (Algorithm 2) and compaction (Algorithm 3).

| No. of <br> cores | Algorithm 1 <br> Algorithm 2 | Algorithm 3 | Total <br> $(\mathrm{s})$ |  |
| :--- | ---: | ---: | ---: | ---: |
| 64 | 391 | 790 | 33 | 1214 |
| 128 | 159 | 309 | 11 | 479 |
| 256 | 76 | 180 | 6 | 262 |
| 512 | 45 | 115 | 3 | 163 |

## Results - Dataset Quality

Table 5: Read partitioning quality evaluation for all datasets

| Dataset | No. overlapping <br> read pairs | inter-pairs | Cut <br> ratio |
| :--- | ---: | ---: | ---: |
| Fish | $20,930,646,131$ | $193,013,621$ | $0.92 \times 10^{-2}$ |
| Bird | $14,302,047,674$ | $304,849,664$ | $2.13 \times 10^{-2}$ |
| Snake | $6,728,041,314$ | $263,882,542$ | $3.92 \times 10^{-2}$ |

## Results - Dataset Runtimes

Table 6: Runtime in seconds for the Bird dataset for computing read partitioning from de Bruijn graph partitioning.

| No. of cores | 64 | 128 | 256 | 512 |
| :--- | ---: | ---: | ---: | ---: |
| Runtime (s) | 2090 | 950 | 456 | 226 |

Total runtime for Bird dataset on 512 cores: 11 min

## References

[1] Henning Meyerhenke, Peter Sanders, and Christian Schulz. 2015. Parallel Graph Partitioning for Complex Networks. In Proceedings of the 2015 IEEE International Parallel and Distributed Processing Symposium. 1055-1064.

