

# Genome Graphs and BWT-based Data Structures

Jouni Sirén  
UCSC Genomics Institute

# Variation graph toolkit VG

- Most of this talk is based on my work on the **VG toolkit** (Garrison et al, 2018), available at <https://github.com/vgteam/vg>.
- In addition to the published work, the codebase contains **prototype implementations** of many genome graph algorithms, data structures, and workflows.
- We are in the process of moving the good parts into **reusable modules** outside the main VG codebase.

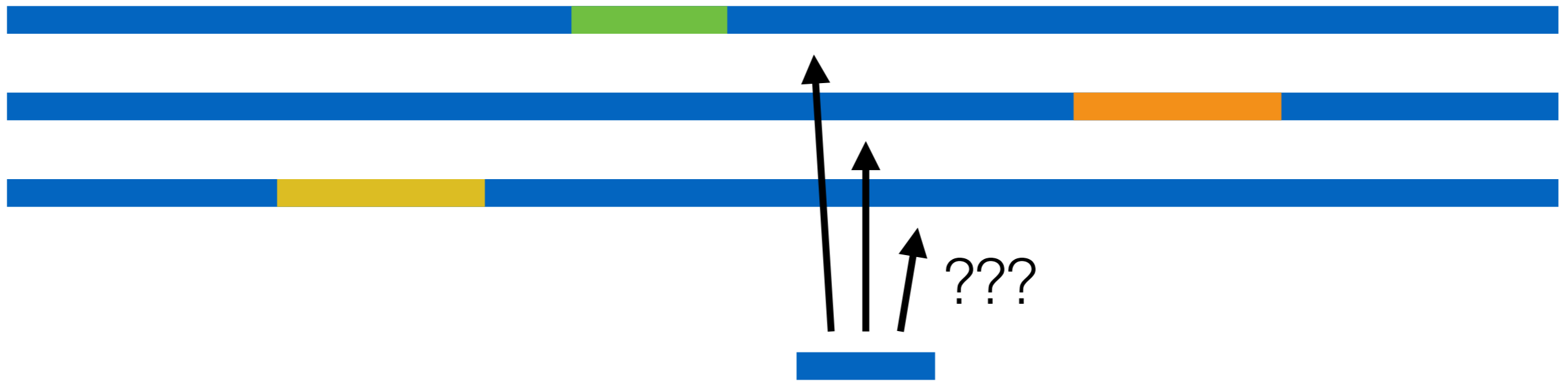
Why genome graphs?

# Reference bias



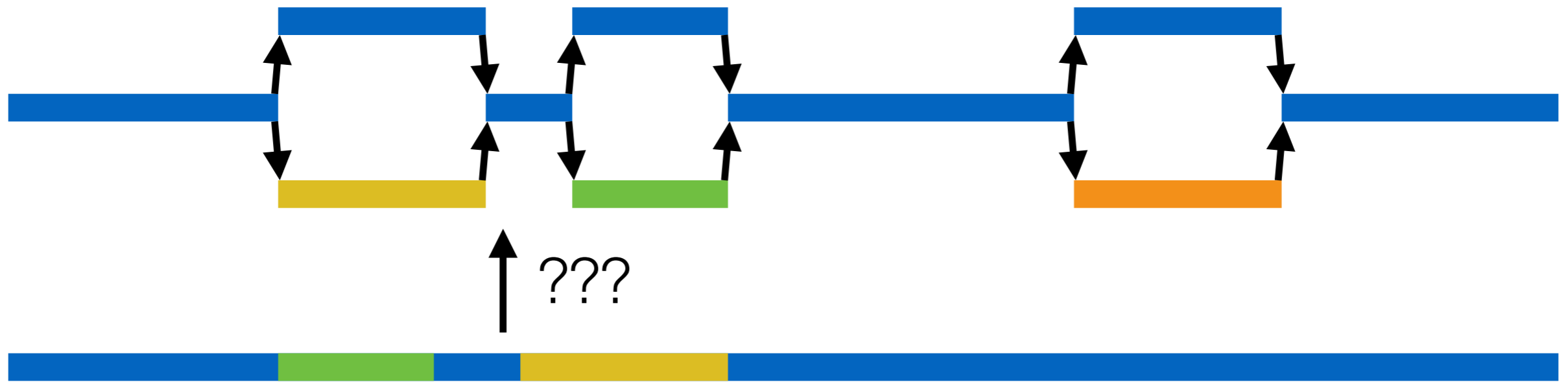
- **Reference sequences** are easy to work with.
- When the sequenced sample **diverges** from the reference, using the reference may **bias** our results.

# Collection of haplotypes



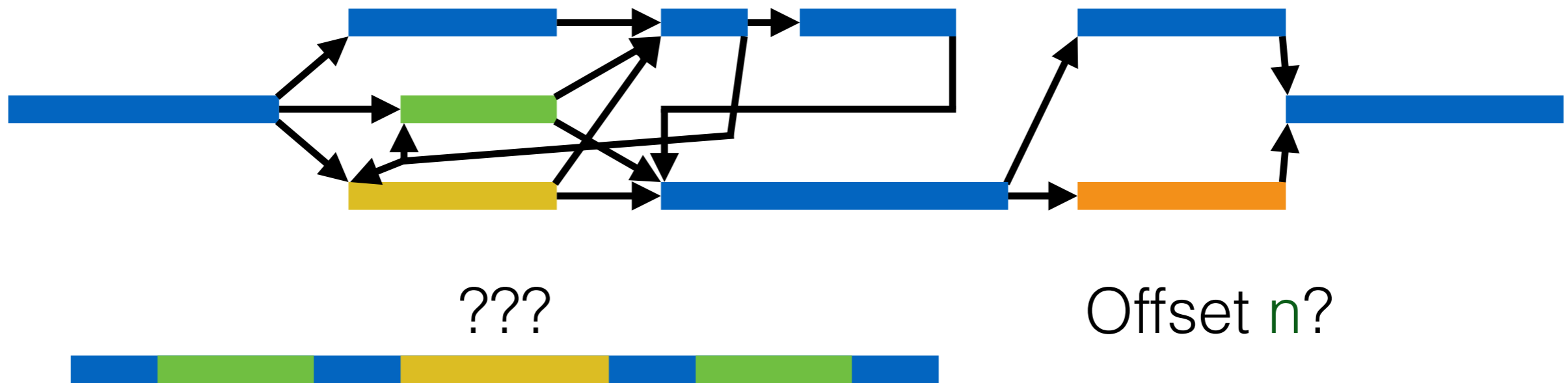
- We can try to reduce the reference bias by using a collection of **haplotypes** as the reference.
- Multiple hits: Same position in several haplotypes (useful) or several different positions (less useful)?

# Global alignment / DAG



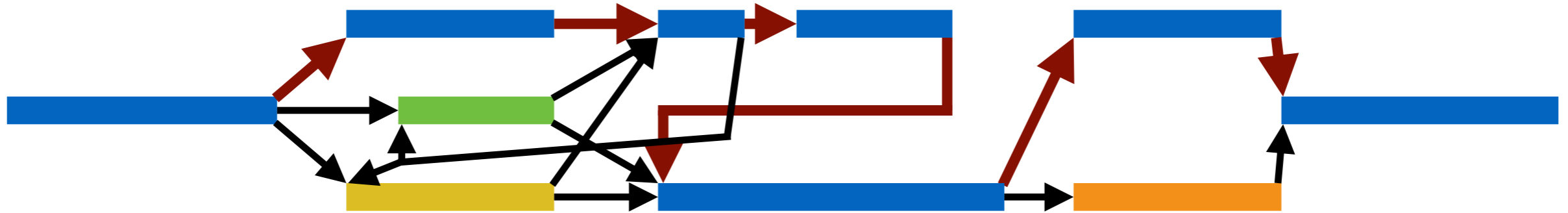
- A **global alignment** helps with reads mapping to multiple haplotypes. If we collapse shared regions, we get a **directed acyclic graph**.
- How to deal with **structural variation**?

# Local alignments



- If we use **local alignments** instead, we get **assembly graphs** that can handle structural variation.
- They contain **nonsensical paths** and lack a global coordinate system.

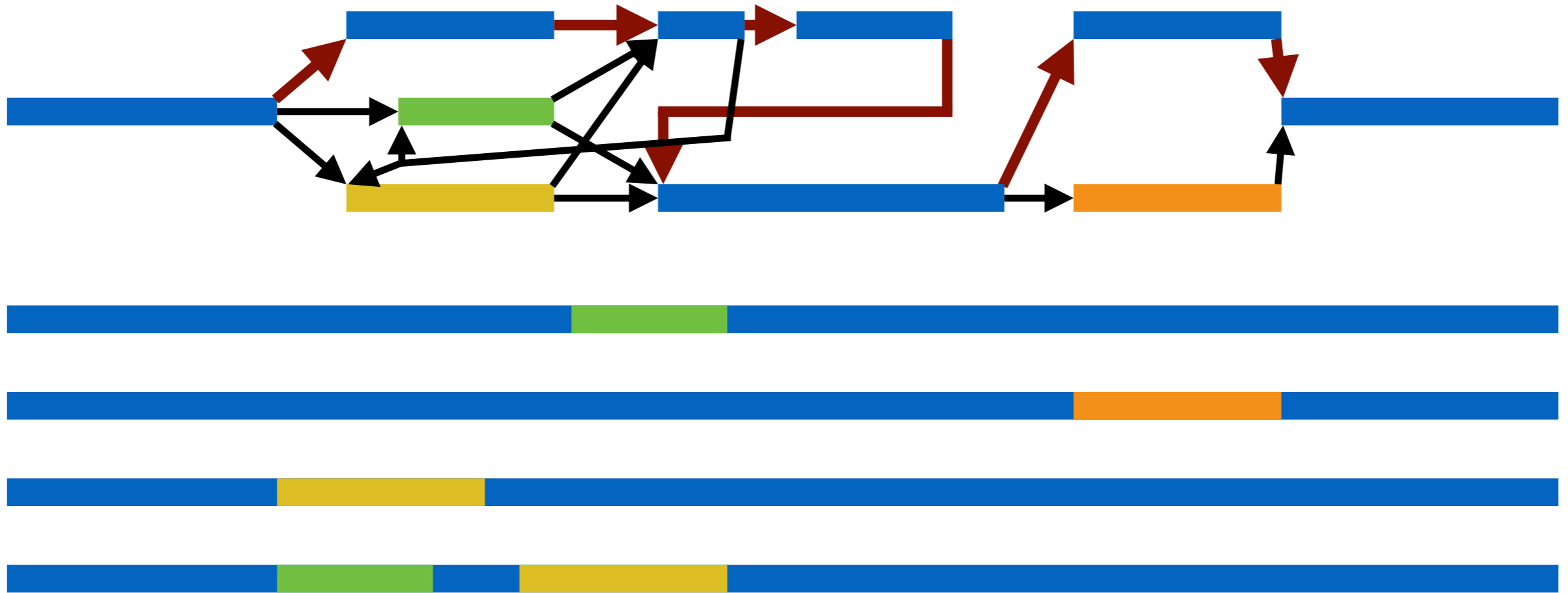
# Graph + path



- A **primary path** can provide a coordinate system.
- We still cannot deal with **structural variation** in DAGs or with **nonsensical paths** in assembly graphs.
- This was the initial **VG model**.



# Graph + path + haplotypes



Graph: These **positions** are equivalent.

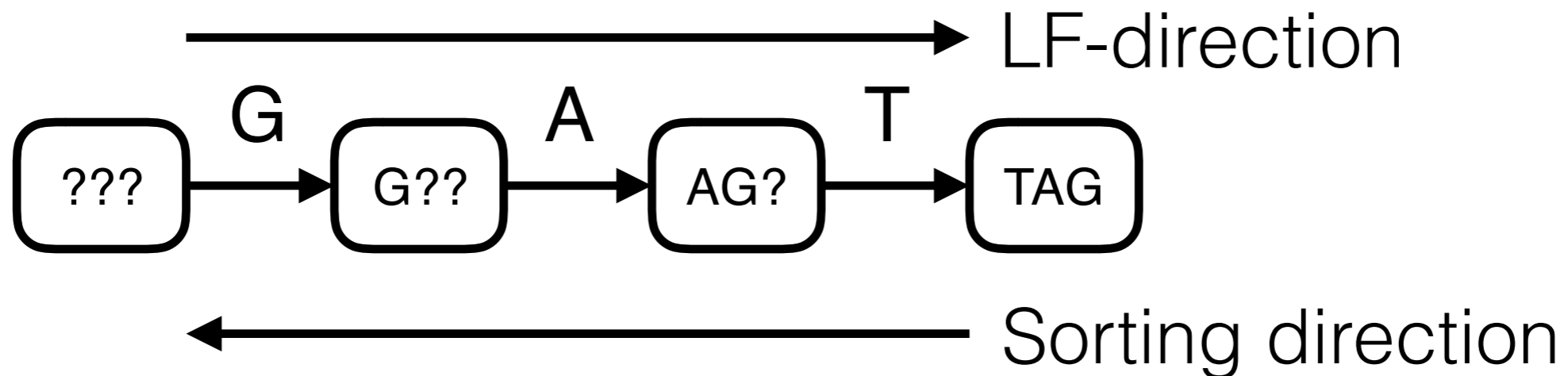
Haplotypes: These **paths** make sense.

Indexing graphs

# Wheeler graphs

- **Wheeler graphs** (Gagie et al, 2017) are edge-labeled directed graphs, where the nodes are ordered by a generalization of the **lexicographic order**.
- Node rank is determined by sorting by:
  1. **Incoming edge** labels (the first character)
  2. **Predecessor node** ranks (the following suffix)
- Useful subclass (generalizes de Bruijn graphs):
  - Nodes are a **prefix-free** set of strings.
  - Node order is the **lexicographic order** of the strings.
  - **Path labels** start with the string corresponding to the **initial node** (in the sorting direction).

# LF/sorting directions

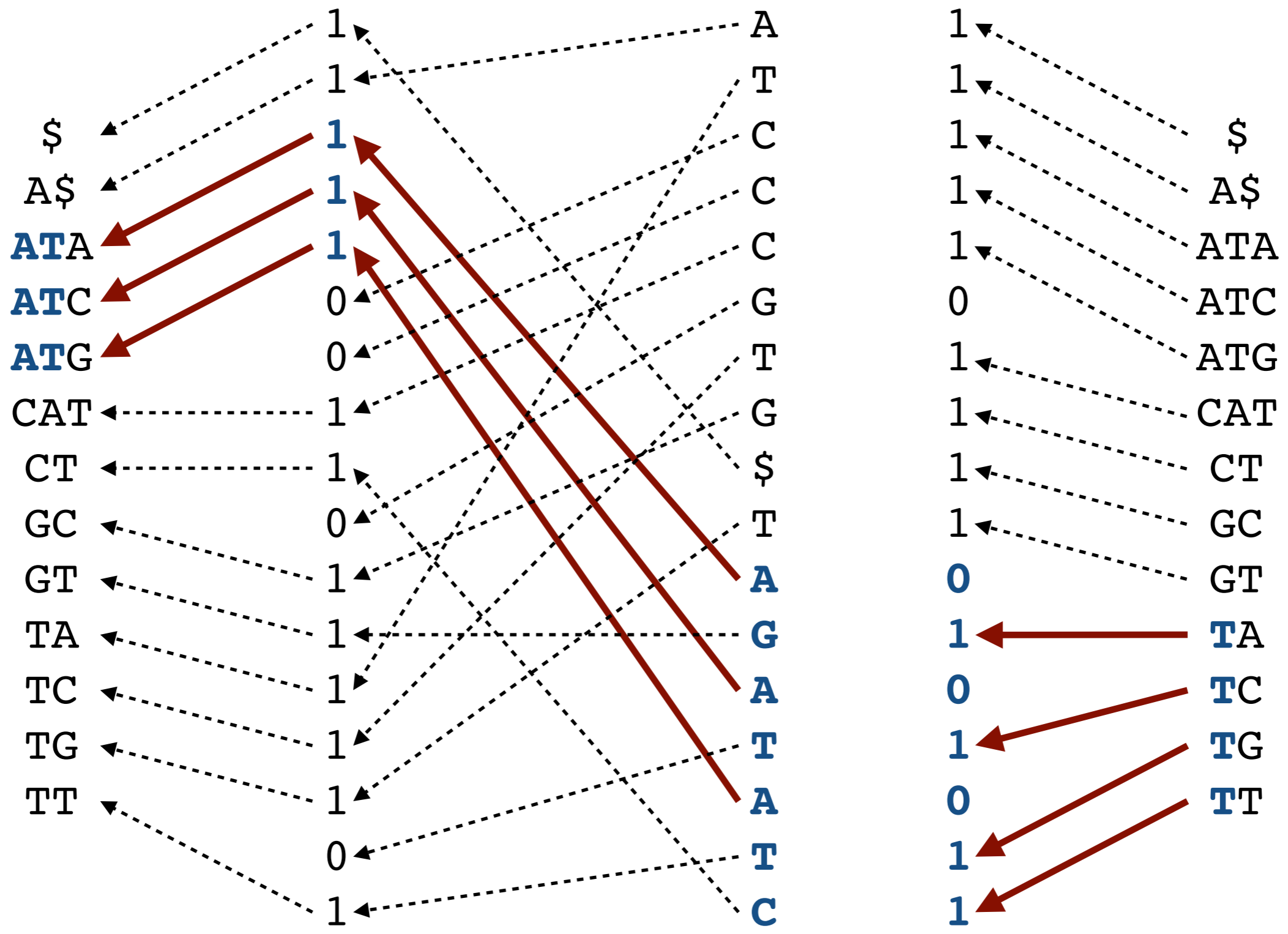


- **LF-direction:** LF-mapping moves **forward**; node order is based on **reverse prefixes**; and `locate()` returns the **endpoint** of the match.
- **Sorting direction:** LF-mapping moves **backward**; node order is based on **suffixes**; and `locate()` returns the **starting point** of the match.

# Indexing Wheeler graphs

- As the node order is based to the **lexicographic order**, we can use a generalization of the **FM-index**.
- One search step (in LF-direction):
  - Map the range of **nodes** into a range of **outgoing edges** using **select()** queries on a bitvector.
  - **Edge labels** form the **BWT**. Transform the range of **outgoing edges** into a range of **incoming edges** using LF-mapping.
  - Map the range of **incoming edges** into a range of **nodes** using **rank()** queries on a bitvector.
- Based on **GCSA** (Sirén et al, 2014) and the **succinct de Bruijn graph** (Bowe et al, 2012).

**Nodes**                      **Incoming**                      **BWT**                      **Outgoing**                      **Nodes**



rank()

LF()

select()

# Faster searching

- If the Wheeler graph is **deterministic**, we can avoid the **select()** queries by using **indicator bitvectors**.
- $B_c[i] = 1$ , if the node with rank  $i$  has an outgoing edge with label  $c$ .
- LF-mapping is just two **rank()** queries on a bitvector, making the index almost **as fast as any FM-index**.
- **GCSA2** (Sirén, 2017) can find **MEMs** between short reads and a 1000GP graph at **3 Mbps** and locate **200,000 occurrences/second**.

# More functionality

- Assume that the nodes of the Wheeler graph are a prefix-free **set of strings**.
- We can use **CST techniques** to represent the **trie** of the strings.
- **shorter()** and **longer()** in the **variable-order de Bruijn graph** (Boucher et al, 2015).
- **parent()**, **depth()**, and **count()** in **GCSA2**.



# Graph transformations

# Indexing general graphs

- We want to index **alignment graphs**, but we can only index **Wheeler graphs**. The intersection of these two classes consists of **de Bruijn graphs**.
- In order to index a **general graph**, we must **transform** into an (almost) equivalent Wheeler graph.
- As we want to align reads to the original graph, we index the **transformed graph** but make the index map to the **original graph**.

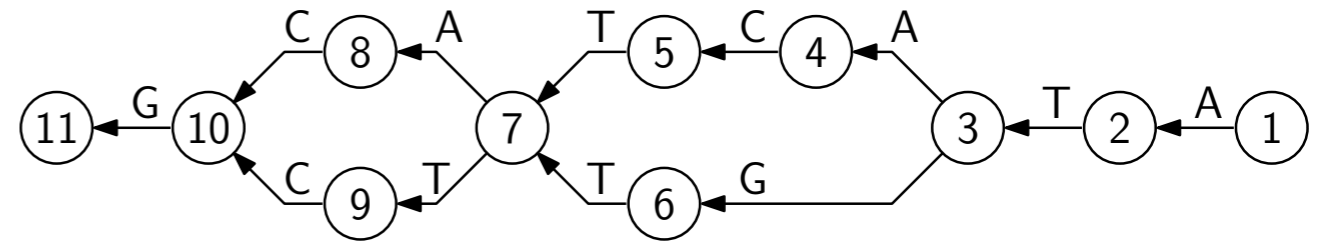
# Transforming DAGs

- We can transform a **DAG** into an equivalent (but potentially much larger) **Wheeler graph** using **prefix-doubling**.
- The **nodes** of intermediate graphs correspond to **paths** of length  $k$  in the original graph.
- Prefix-doubling: **Extend** paths of length  $k$  into paths of length  $2k$ . If all paths in a **lexicographic range** start from the same **original node**, **merge** them.
- Used in **GCSA**.

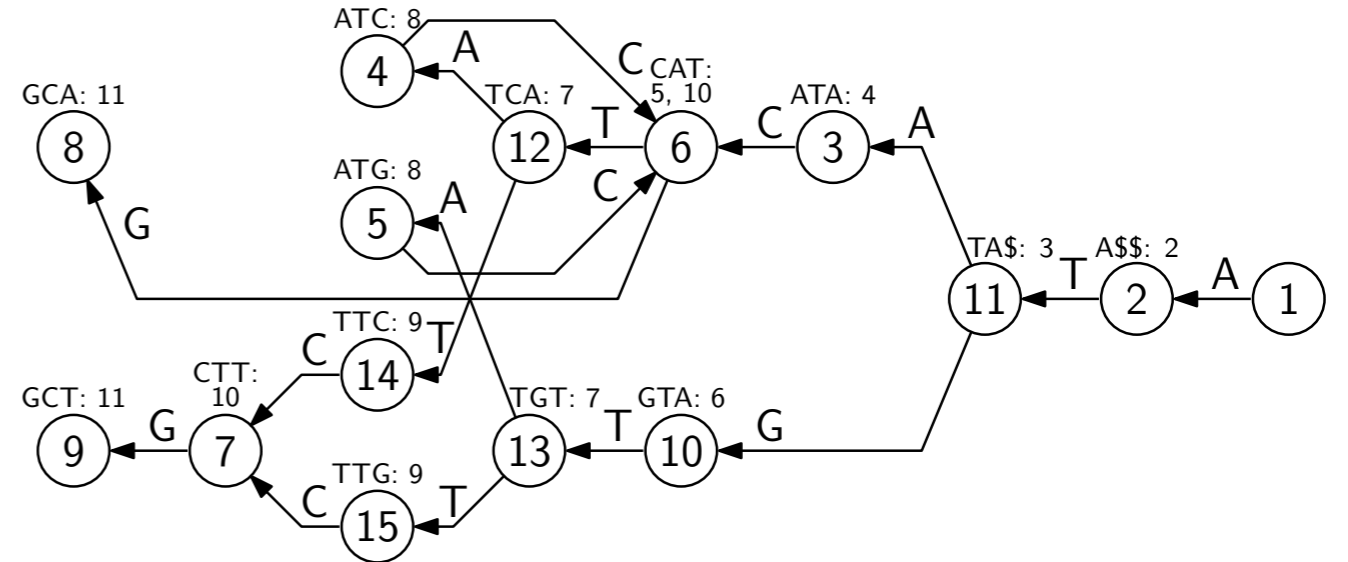
# Approximating general graphs

- Graphs with **cycles** may not have equivalent Wheeler graphs.
- If we **stop** the prefix-doubling at length  $k$  and merge only ranges corresponding to a shared prefix, the graph is equivalent to an order- $k$  **de Bruijn graph**.
- All **original paths** exist in the Wheeler graph, and all **Wheeler graph paths** of length  $\leq k$  exist in the original graph.
- Used in **GCSA2**.

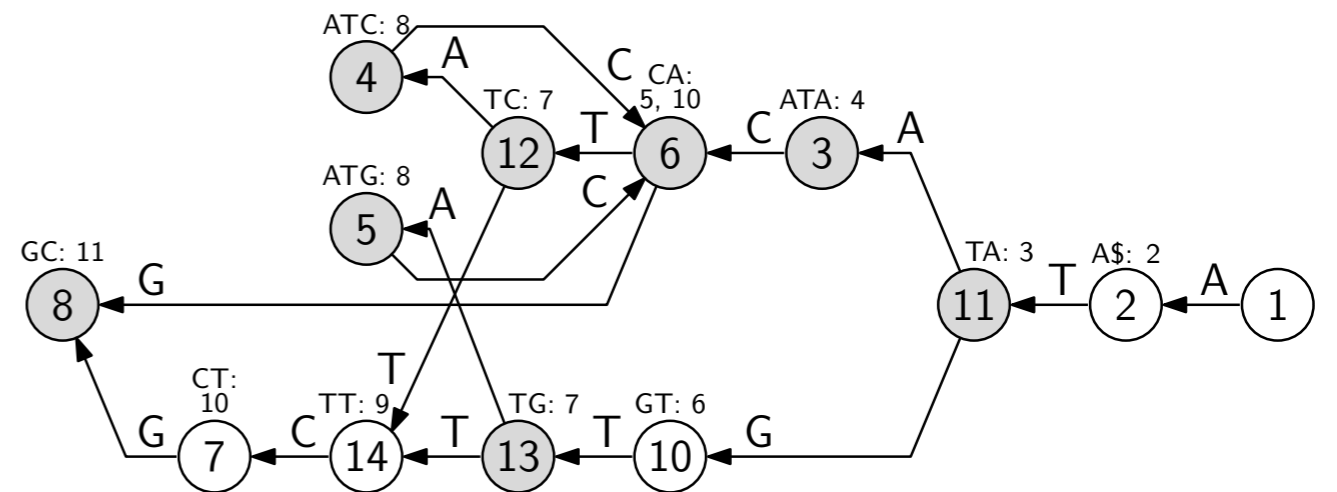
Original graph



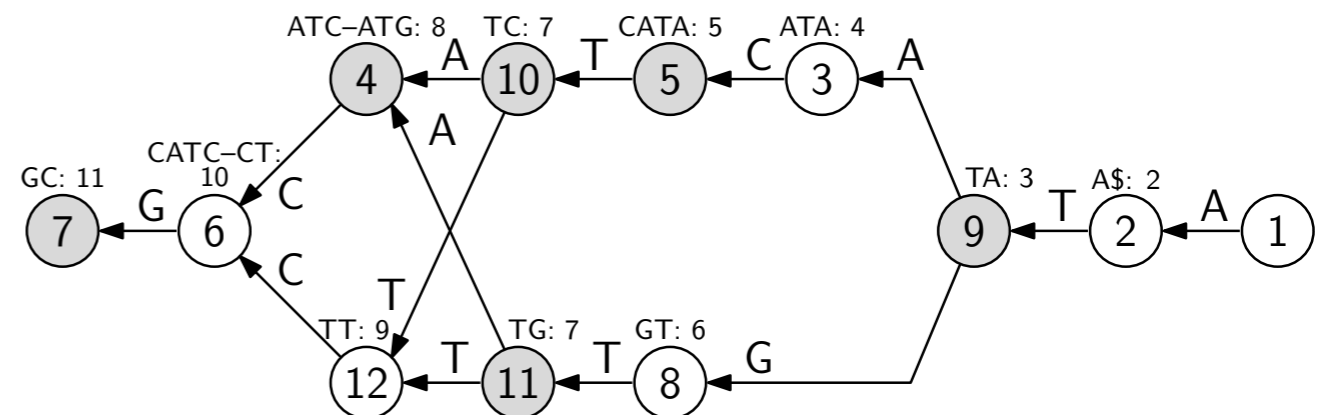
Order-3 de Bruijn graph



Order-3 pruned de Bruijn graph (GCSA2)



Prefix-range-sorted graph (GCSA)

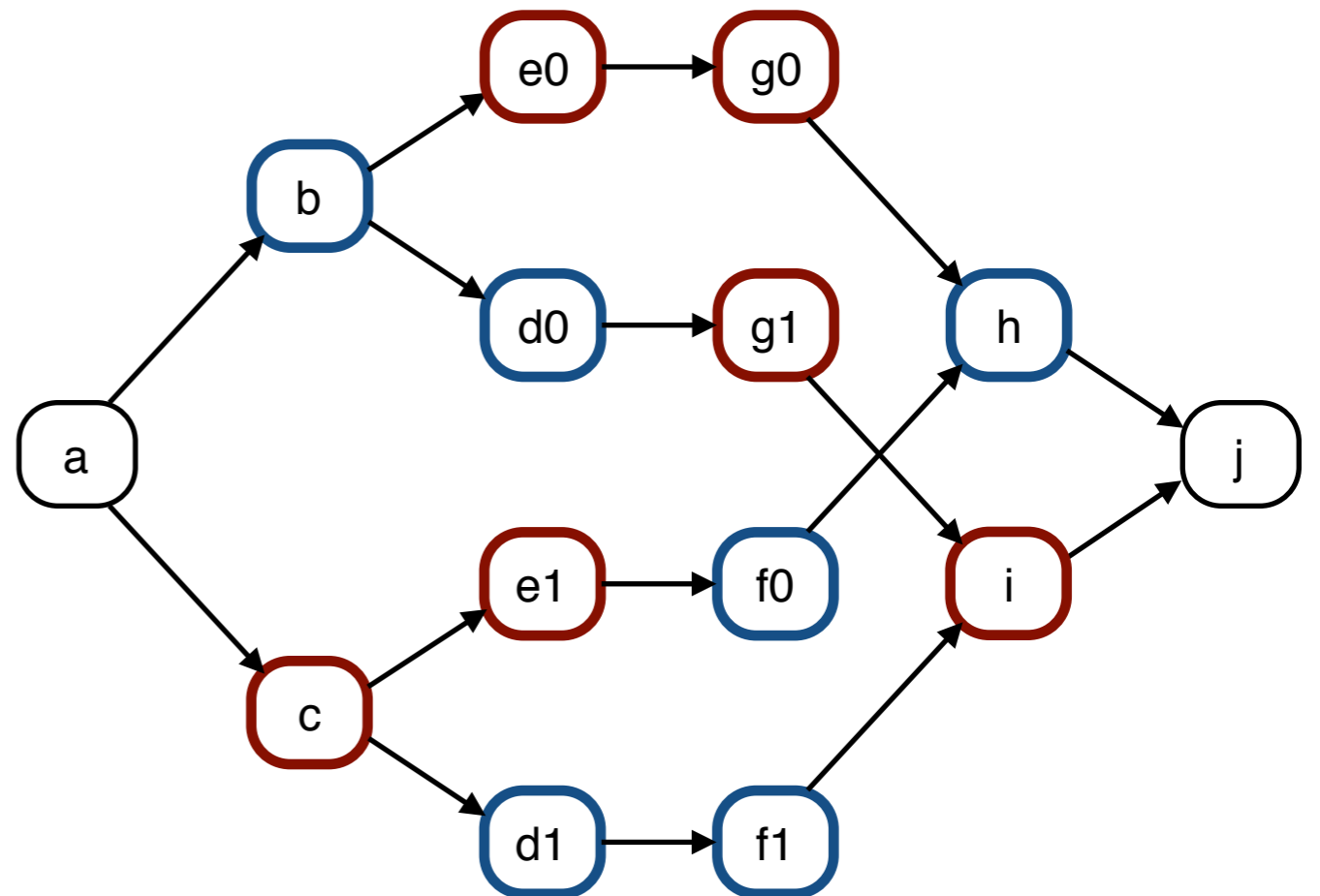
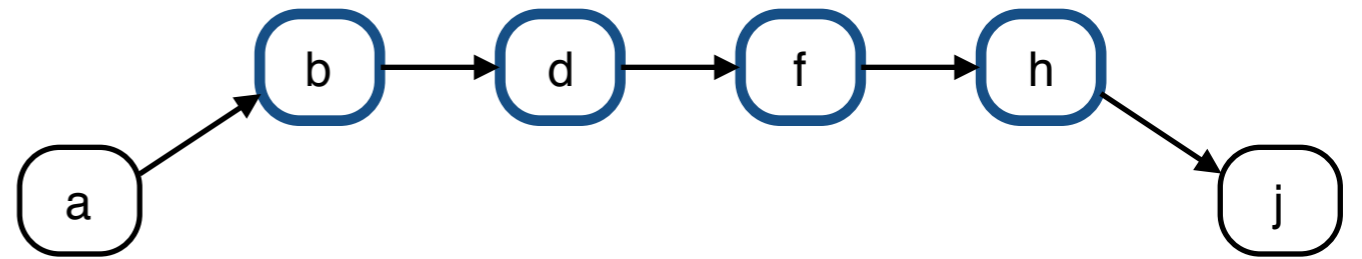
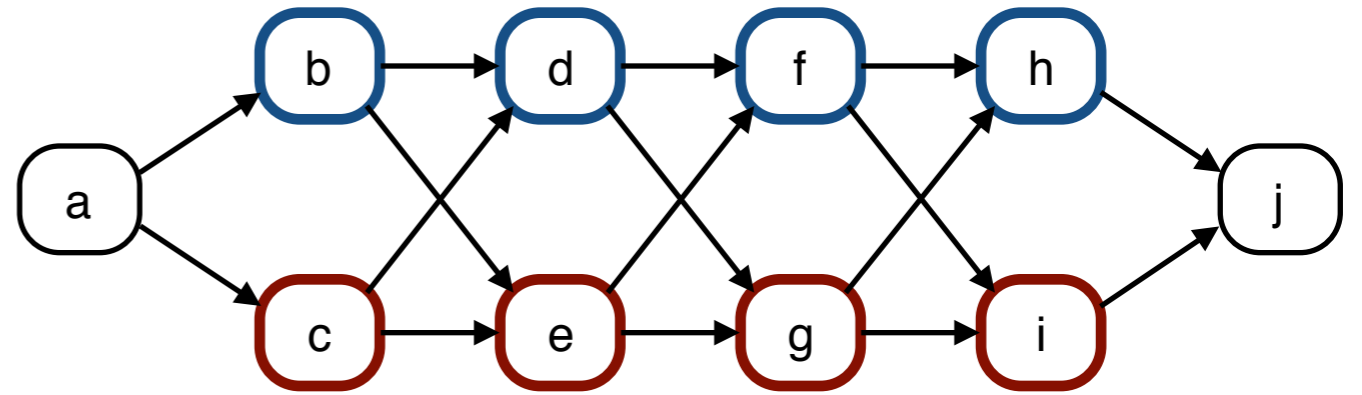


# Graph simplification

Complex graph regions cannot be indexed using Wheeler graph-based methods, because they contain too many paths of length  $k$ .

**VG** removes regions with too many paths in a **short window** and replaces them with the reference sequence.

If we have the original **haplotypes**, we can **unfold** them in the complex region (Sirén et al, 2018).



GBWT

# Are FM-indexes too slow?

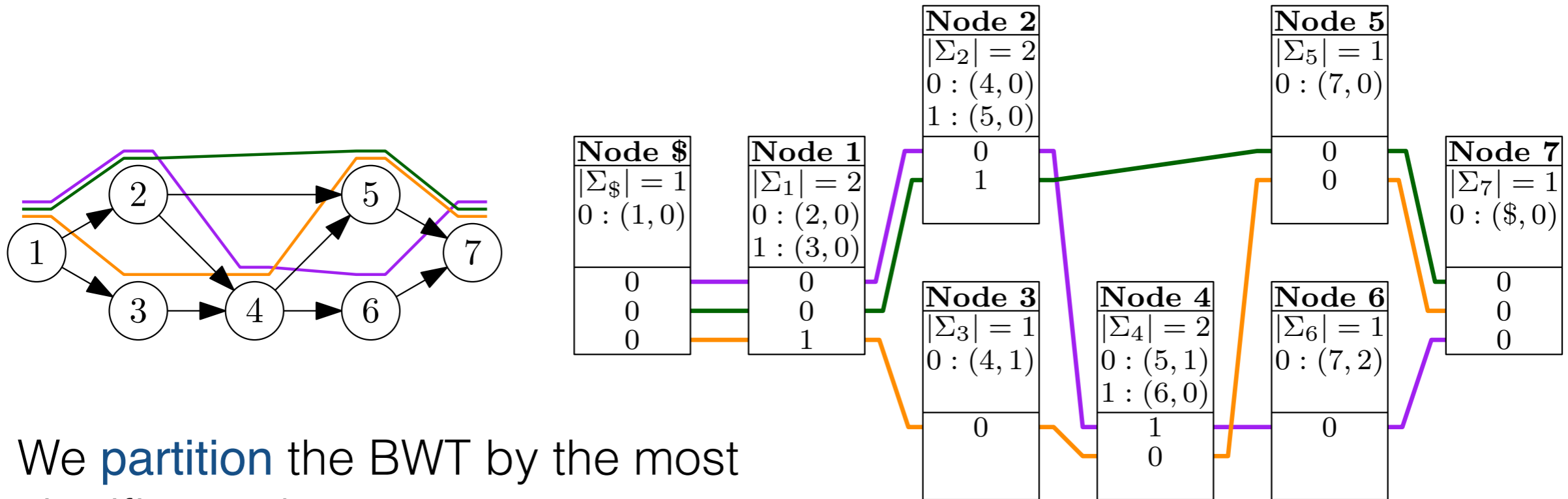
- Iterated LF-mapping jumps **randomly** around the BWT. We usually get **cache misses** for **each character** of the pattern.
- Once the pattern is **unique**, it should be faster to extend it in the **graph** than in the index.
- Do we need an FM-index if we only match **short patterns**?
- **Minimizer indexes** (sparse **k**-mer indexes) are 10x faster in 2x space.



# GBWT

- **GBWT** (Sirén et al, 2018) is the **haplotype index** used in VG. It is based on the graph extension (Novak et al, 2017) of the **PBWT** (Durbin, 2014).
- We represent the haplotypes as **paths** in the graph and store the node sequences in **RLBWT**.
- Index **construction** is straightforward at **1000GP** scale (5,000 human haplotypes,  $n \approx 2^{41}$ ).
- Indexing **100x larger datasets** ( $n \approx 2^{48}$ ) is feasible but expensive.

# GBWT details



- We **partition** the BWT by the most significant character.
- Each **node** contains the corresponding part of the BWT and a local **rank()** structure.
- If the graph layout is **cache-friendly**, iterated LF-mapping is also cache-friendly.
- One iteration of LF-mapping **per node** vs per character.

Node 4
Outdegree 2
0: node 5, offset 1
1: node 6, offset 0
10

# GBWT construction

- Basic construction is like in **RopeBWT2** (Li, 2014): We insert a **batch** of paths into a **dynamic FM-index** using the **BCR algorithm** (Bauer et al, 2013).
- When the basic algorithm is too slow, we can build **partial indexes** in parallel and merge them using **BWT-merge** (Sirén, 2016). (This is unnecessary at 1000GP scale.)
- Different **chromosomes** use different **node ids**, so we can index them in parallel and **merge** the indexes by **concatenating** the BWTs.

# GBWT benchmarks

**AWS i3.8xlarge instance:** 16 physical / 32 logical CPU cores, 244 GiB memory.

**1000GP haplotypes:** 240,232 paths of total length 2.19 trillion nodes in a graph with 612 million nodes.

**Index construction:** 17 hours.

**Index size:** 8.43 GiB for bidirectional GBWT, 8.17 GiB for DA samples ( $d = 1024$ ).

**Bidirectional search:** 2 million nodes/second (short patterns), 4 million nodes/second (long patterns).

# Some GBWT applications

- **Haplotype unfolding** for GCSA2 construction.
- **Minimizer index** construction: 10 minutes for 1000GP haplotypes (>30 hours with GCSA2).
- **Gapless seed extension**: Illumina sequencing errors are mostly substitutions, and most real indels are already in the haplotypes.

# Faster document listing?

- With the default **DA sample rate 1024**, GBWT can list the **matching haplotypes** at 10,000 (single positions) to 100,000 (ranges of positions) hits/second.
- It would be nice to use the fast **locate()** structure from the **r-index** (Gagie et al, 2018).
- Can we maintain the r-index **locate()** structure when **inserting/deleting** strings and **merging** indexes?