TwoPaCo

An efficient algorithm to build the compacted de Bruijn graph from many complete genomes

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Part I

Introduction

A pan-genomic algorithm

From the greek word *pan* (everything)

Given a series of complete genomes

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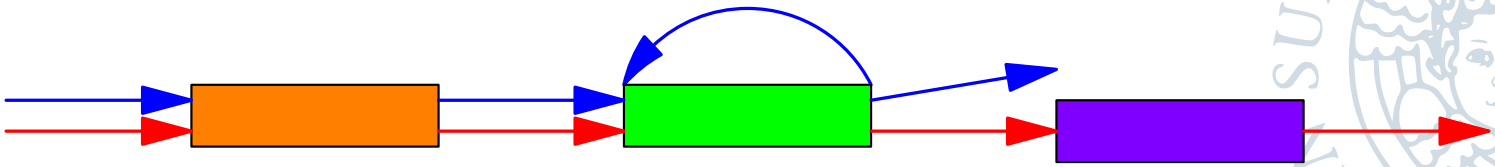
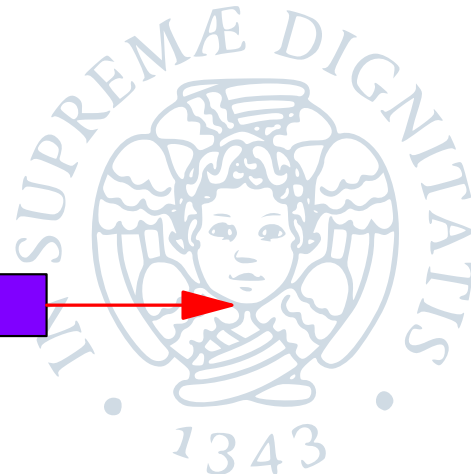
From the greek word *pan* (everything)

Given a series of complete genomes

What we want to see:

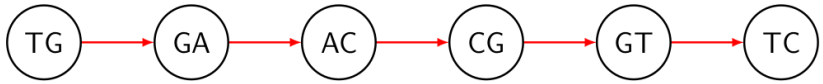
- Similarities
- Differences
- Duplications





de Bruijn graph

Sequence #1: TGACGTC (2-mers: TG GA AC CG GT TC)



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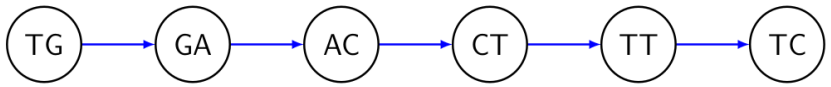

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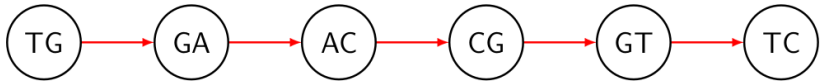

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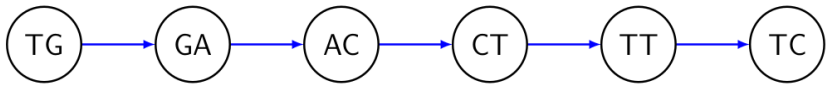
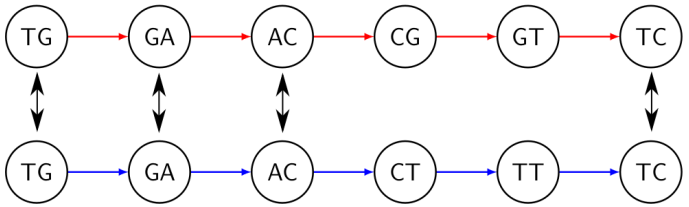


Find common vertices



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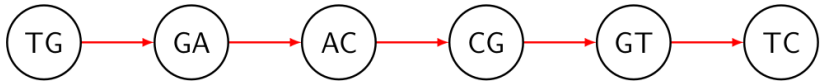

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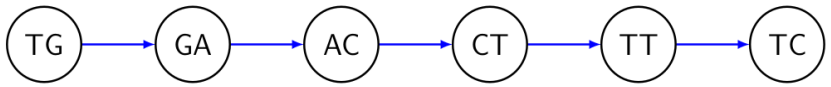

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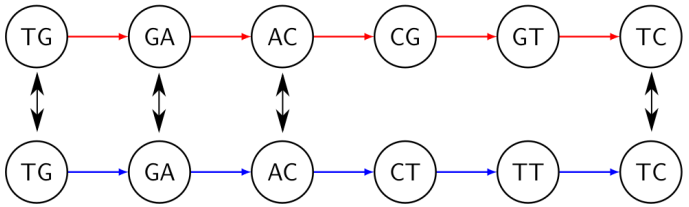
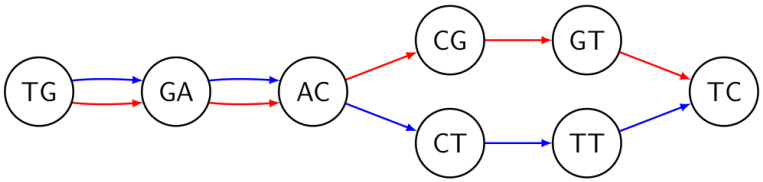


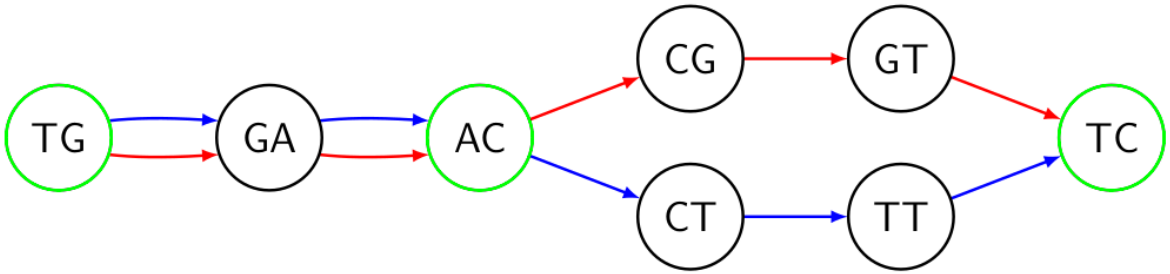
Merge them



Compacted de Bruijn graph

To compact the de Bruijn graph we need to find the junctions

A vertex is a junction if :
Is the initial or final part of some sequence
Has more than 1 in-edge or more than 1 out-edge



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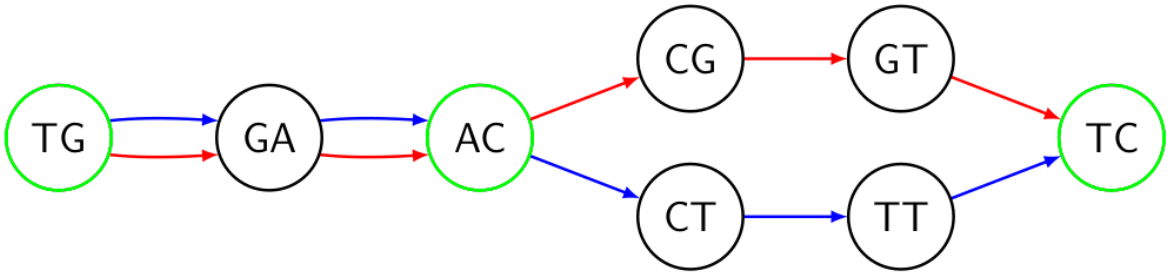
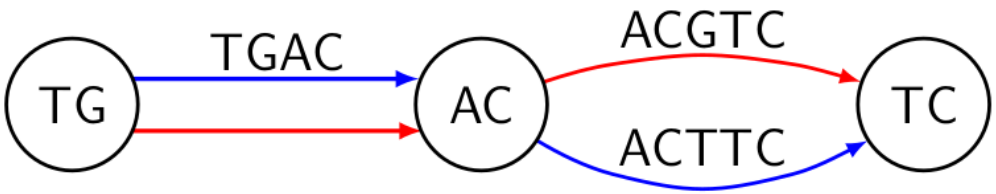


Remove simple paths by connect junctions



The problem

How to construct the compacted de Bruijn graph,
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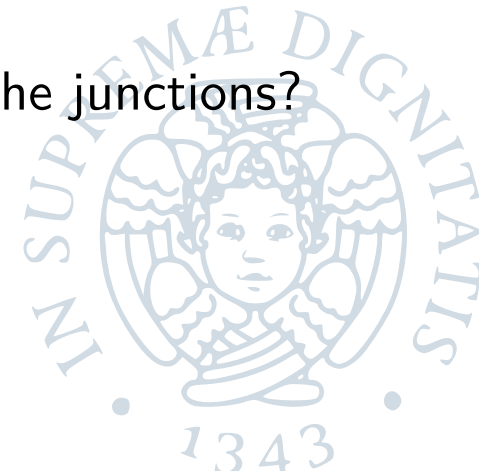
$\downarrow$

Which k-mers are junctions?

$+$

How to construct the compacted de Bruijn graph given the junctions?



Part II

The algorithm

Naive algorithm

- Store all $(k+1)$-mers in a hash table
- For each k-mers query the possible edges
- If only 1 in and 1 out edge, unmark as a junction

Algorithm 1: FILTER-JUNCTIONS

Input : $S = \{s_1, ..., s_m\}$ genoma sequences
k integer, size of k-mers
E empty set data structure
C Candidate set of junctions (**naively all positions are marked**)

Output: A reduce candidate set of junctions C

```
1  foreach s ∈ S do
2      for 1 ≤ i < |s| − k do
3          if C[s, i] = marked then
4              E ← E ∪ s[i..i + k] ∪ s[i − 1..i + k − 1]      ▷ Store all (k + 1)-mers

5  foreach s ∈ S do
6      for 1 ≤ i < |s| − k do
7          if C[s, i] = marked then
8              (in, out) ← (0, 0)                              ▷ Count in/out edges
9              foreach c ∈ {A, C, G, T} do
10                 if v · c ∈ E then
11                     in ← in + 1
12                 if c · v ∈ E then
13                     out ← out + 1
14             if (in, out) = (1, 1) then
15                 C[s, i] = unmarked                          ▷ Not a junction
16 return C
```

The memory issue

First part of the naive algorithm:

foreach $s \in S$ **do**
  for $1 \leq i < |s| - k$ **do**
    if $C[s, i] = marked$ **then**
      $E \leftarrow E \cup s[i..i + k] \cup s[i - 1..i + k - 1]$

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We don't really need and, in almost all pratical cases, we can't store all the possible $(k + 1)$-mers.

Mainly because **only a little percentual** of them are junction in the de Bruijn graph.

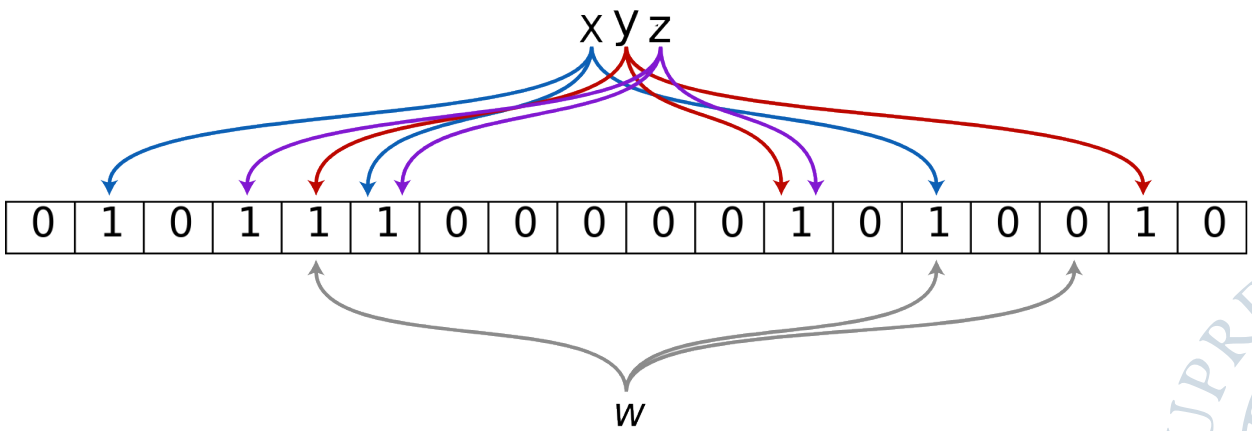
Bloom filter

A space-efficient probabilistic hash table

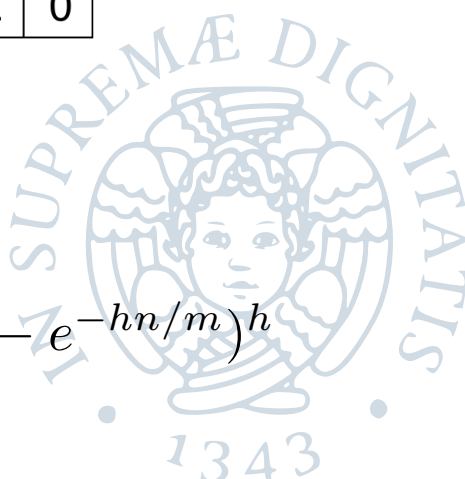
Bitmap V of size b, h hash functions $f_0, f_1, ..., f_{h-1} : U \rightarrow [0, b-1]$

insertion$(x) \rightarrow V[f_i(x)] = 1, \forall\ 0 \leq i < h$

contains$(x) \rightarrow$ **probably yes** if $V[f_i(x)] == 1, \forall\ 0 \leq i < h$



Probability of false positive, after n insertion: $p_{FP} \simeq (1 - e^{-hn/m})^h$



Two Pass version

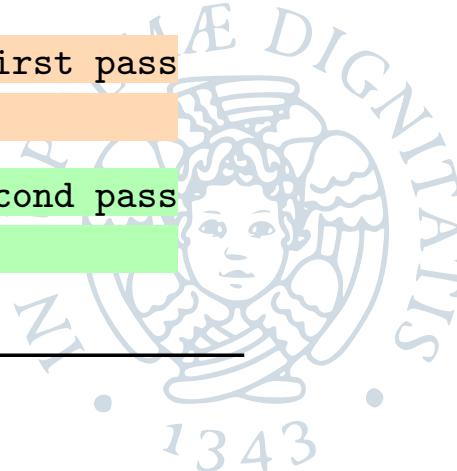
- First pass: Select a set of junction candidates by insert all the $(k+1)$-mers in a bloom filter of choosing size
- Second pass: Filter out the false positive by storing the reduce sets of $(k+1)$-mers in an hash table

Algorithm 2: FILTER-JUNCTIONS-TWO-PASS

Input : strings $S = \{s_1, ..., s_m\}$ genoma sequences
integer k, size of k-mers
integer b, size of bloom filter
Candidate set of junctions C_{in} (**naively all positions are marked**)

Output: A reduce candidate set of junctions C_{out}

1 $F \leftarrow$ empty bloom filter of size b ▷ First pass
2 $C_{temp} \leftarrow$ FILTER-JUNCTIONS(S, k, F, C_{in})
3 $H \leftarrow$ empty hash table ▷ Second pass
4 $C_{out} \leftarrow$ FILTER-JUNCTIONS(S, k, H, C_{in})
5 **return** C_{out}



The memory issue[2]

How much memory do we use now?

- First pass: Bloom filter of size b (of our decision)
- Second pass: Hash table containing $(k+1)$-mers of junction candidates

We don't know the possible size of the hash table in the second pass.
What if the hash table is not small enough?

The memory issue[2]

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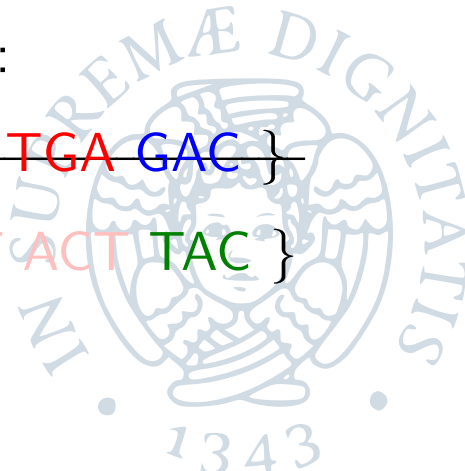
We don't know the possible size of the hash table in the second pass.
What if the hash table is not small enough?

Solution: Split the input k-mers in chunks and analyze them in multiple rounds.

Split *TGACTACTGAC* in 3 chunks of 3-mers:

~~Wrong: { TGA GAC ACT }, { CTA TAC ACT }, { CTG TGA GAC }~~

Correct: { TGA TGA CTG }, { GAC GAC CTA }, { ACT ACT TAC }



k-mers splitting

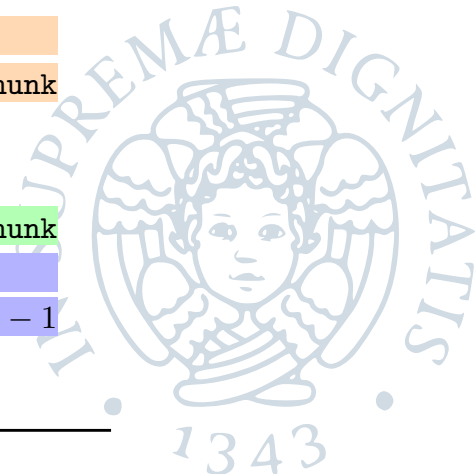
- Count how many k-mers are mapped in each of the c hash value ($c = 2^l$)
- Iterate over all the hash value and insert them in the current chunk
- If the size of current chunks exceeds the average pass to the next chunk

Algorithm 3: ROUND-SPLITTING

Input : strings $S = \{s_1, ..., s_m\}$ genoma sequences
integer k, size of k-mers
integer b, size of bloom filter
integer l, number of rounds
function $f(x)$, from k-mers to integers

Output: $(V_0, V_1, \ldots, V_{l-1})$ chunks of k-mers

1 $V_0 \leftarrow \emptyset, V_1 \leftarrow \emptyset, \ldots, V_{l-1} \leftarrow \emptyset$ ▷ Chunks, initially empty
2 $c_0 \leftarrow 0, c_1 \leftarrow 0, \ldots, c_{q-1} \leftarrow 0$ ▷ Counters, for balancing k-mers
3 $c_i \leftarrow |\{\ k\text{-mer } x \mid f(x) = i\ \}|$
4 $T \leftarrow \sum_{0 \le t < q} c_t / l$ ▷ Average size of a chunk
5 $idx \leftarrow 0$
6 **for** $0 \le i < q$ **do**
7 $V_{idx} = V_{idx} \cup \{i\}$ ▷ Add i to the current chunk
8 **if** $|V_{idx}| \ge T$ **then**
9 $idx \leftarrow \min(idx + 1, l - 1)$ ▷ Next chunk, until reach $l - 1$
10 **return** $(V_0, V_1, \ldots, V_{l-1})$



Multiple rounds: dealing with memory restrictions

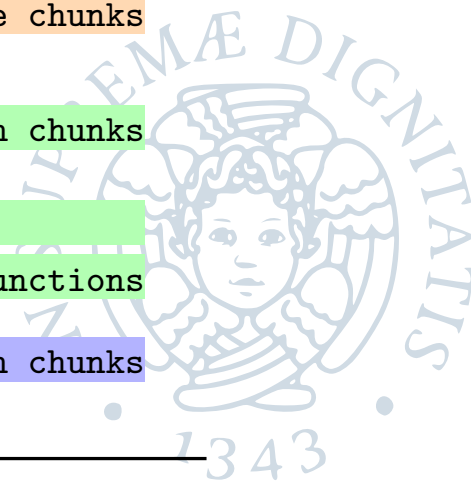
- Partitionate the input with ROUND-SPLITTING
- Analyse each partition with FILTER-JUNCTIONS-TWO-PASS
- Merge the results of each rounds and output the real junctions

Algorithm 4: TWOPACO

Input : strings $S = \{s_1, ..., s_m\}$ genoma sequences
integer k, size of k-mers
integer b, size of bloom filter
integer l, number of rounds
function $f(x)$, from k-mers to integers

Output: C_{final} all the junctions in the compacted de Bruijn graph

1 $(V_0, V_1, \ldots, V_{l-1}) \leftarrow$ ROUND-SPLITTING(S, k, b, l, f) ▷ Create chunks
2 $C_{init} \leftarrow$ Boolean array with every position unmarked
3 **for** $0 \leq i < l$ ▷ For each chunks
4 **do**
5 $C_i \leftarrow$ mark every position of C_{init} that starts a k-mer with hash in V_i
6 $C_i \leftarrow$ FILTER-JUNCTIONS-TWO-PASS(S, k, b, C_i) ▷ Find junctions
7 $C_{final} = \bigcup C_i$ ▷ Merge junctions of each chunks
8 **return** C_{final}



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TwoPaCo can be easily parallelizable:

- Parallel for loops (OpenMP, TBB, ...)
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We made a clever usage of the concurrent data structs:

- Only insertion in the first part
- Only query in the second part (static table, no race conditions)

Part III

Results

Source code & Dataset

Original source code by medvedev group available on:

https://github.com/medvedevgroup/TwoPaCo

Personal implementation and presentation available on:

https://github.com/GaspareG/TwoPaCo

https://github.com/GaspareG/TwoPaCoPresentation

Dataset for experiments:

62 Escherichia coli (∼300Mb)
5 humans (∼21Gb)
8 primates (∼23Gb)
100 simulated human (∼400Gb)

Memory complexity

The memory complexity is the maximum
among the first and the second pass of TwoPaCo

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Result: $\mathcal{O}(\max\{b, (J + FP)k\})$

Time complexity

The time complexity is the sum
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- First pass: **insert all k-mers** in a bloom filter using h hash functions
- Second pass: iterate over all **candidate positions** and query the hash table

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Result: $\mathcal{O}(mh + (|G_c| + FP)k)$

Complexity comparison

State of the art for compacted de Bruijn graph construction:

- Sibelia (Minkin, Patel, Kolmogorov, Vyahhi, Pham, 2013)
- SplitMEM (Marcus, Lee, Schatz, 2014)
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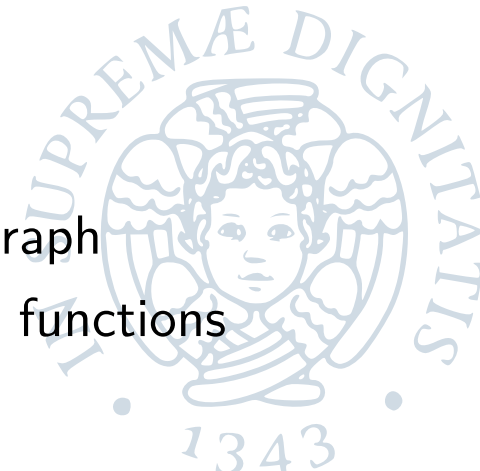
Algorithm	Time complexity	Memory complexity
Sibelia	$\mathcal{O}(m)$	$\mathcal{O}(m)$
SplitMEM	$\mathcal{O}(m \log g)$	$\mathcal{O}(\lvert G_c \rvert + m)$
bwt-based	$\mathcal{O}(m)$	$\mathcal{O}(m)$
TwoPaCo	$\mathcal{O}(mh + (\lvert G_c \rvert + FP)k)$	$\mathcal{O}(\max\{b, (J + FP)k\})$

- $m = \Sigma_{s \in S} \lvert s \rvert$, total input size
- $g = \max_{s \in S} \lvert s \rvert$, size of the biggest genoma
- J and $\lvert G_c \rvert$, number of vertex and edge in the de Bruijn Graph
- b and h, size of the bloom filter table and number of hash functions
- FP, number of false positives in first pass



Benchmark

What are the practical performances of TwoPaCo against the state of the art?

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Dataset	Sibelia	SplitMEM	bwt-based	TwoPaCo	
				1 thread	15 thread
62 E.coli (k=25)	10 (12.2)	70 (178.0)	8 (0.85)	4 (0.16)	2 (0.39)
62 E.coli (k=100)	8 (7.6)	67 (178.0)	8 (0.50)	4 (0.19)	2 (0.39)
7 humans (k=25)	-	-	867 (100.30)	436 (4.40)	63 (4.84)
7 humans (k=100)	-	-	807 (46.02)	317 (8.42)	57 (8.75)
8 primates (k=25)	-	-	-	914 (34.36)	111 (34.36)
8 primates (k=100)	-	-	-	756 (56.06)	101 (61.68)
50 humans (k=25)	-	-	-	-	705 (69.77)
50 humans (k=100)	-	-	-	-	927 (70.21)

Running times in minutes and memory usage in gigabytes in parenthesis

- - on Sibelia = out of time
- - on SplitMEM = out of memory
- - on bwt-based = out of memory
- - on TwoPaCo = experiment not done

Fixed memory

In how many rounds do we need to split the input to not exceeding a given memory threshold?

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Threshold	Used memory	Bloom filter size	Running time	Rounds
10GB	8.62GB	8.59GB (2^{33})	4h	1
8GB	6.73GB	4.29GB (2^{32})	7h	3
6GB	5.98GB	4.29GB (2^{32})	9h	4
4GB	3.51GB	2.14GB (2^{31})	11h	6

Experiments on 5 simulated human genomes, $k = 25$, 8 threads

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Result: **we can trade-off memory for time**

Bloom Filter false positive

Is the Bloom Filter really efficient in reducing junction candidates?

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Is the Bloom Filter really efficient in reducing junction candidates?

		Junction candidates		
Dataset	k	Initial	First pass	Second pass
62 E.coli	25	310 157 564 (100%)	24 649 489 (7.94%)	24 572 562 (7.92%)
62 E.coli	100	310 157 489 (100%)	22 848 018 (7.36%)	9 492 091 (3.06%)
7 humans	25	21 201 290 922 (100%)	3 489 946 013 (16.46%)	2 974 098 154 (14.02%)
7 humans	100	21 201 290 847 (100%)	1 374 287 870 (6.48%)	188 224 214 (0.88%)
8 primates	25	24 540 556 921 (100%)	5 423 003 377 (22.09%)	5 401 587 503 (22.01%)
8 primates	100	24 540 556 846 (100%)	1 174 160 336 (4.78%)	502 441 107 (2.04%)

- Initial: total number of k-mers in dataset
- First pass: number of junction candidates (using a bloom filter)
- Second pass: real number of junction (using an hash table)

Conclusion

- Store in main memory only the necessary
- Lowest time/memory usage in the state of the art
- Highly scalable (best performance with multi-thread CPUs)
- Time/memory trade-off (suitable for small computer)
- Bloom filter perform very well in practice

References

[1] Minkin, I., Pham, S., Medvedev, P. (2016).
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Sibelia: a scalable and comprehensive synteny block generation tool for closely related microbial genomes.

[3] Marcus, S., Lee, H., Schatz, M. C. (2014).
SplitMEM: a graphical algorithm for pan-genome analysis with suffix skips.

[4] Baier, U., Beller, T., Ohlebusch, E. (2015).
Graphical pan-genome analysis with compressed suffix trees and the **Burrows-Wheeler transform**.

Questions

Thanks for your attention!

Questions?

My results

Source code:
https://github.com/GaspareG/TwoPaCo/blob/master/srcgas/twopaco.cpp

Dataset	k	Version	Time	Initial	First Pass	Second Pass
2 E.coli	25	BF+HT	18s	10.207.478	392.836	177.396
2 E.coli	25	BF	29s	10.207.478	-	177.396
4 E.coli	25	BF+HT	38s	20.301.208	1.261.345	676.686
4 E.coli	25	BF	64s	20.301.208	-	676.686
8 E.coli	25	BF+HT	87s	39.871.914	3.231.119	1.822.718
8 E.coli	25	BF	134s	39.871.914	-	1.822.718
16 E.coli	25	BF+HT	160s	77.848.026	7.076.460	4.046.561
16 E.coli	25	BF	280s	77.848.026	-	4.046.561

Running time and junctions candidate after each pass