TwoPaCo

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

Gaspare Ferraro

University of Pisa
Department of Computer Science

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Parte I

Introduction

A pan-genomic algorithm

De Bruijn graph

Compacted de Bruijn graph

Junctions

The problem

Parte II

The algorithm

Naive algorithm

- Store all $(k+1)$-mers in a hash table
- For each k-mers query the possible edge
- 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                          ▷ surely 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**
      $E \leftarrow E \cup s[i..i + k] \cup s[i - 1..i + k - 1]$

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.

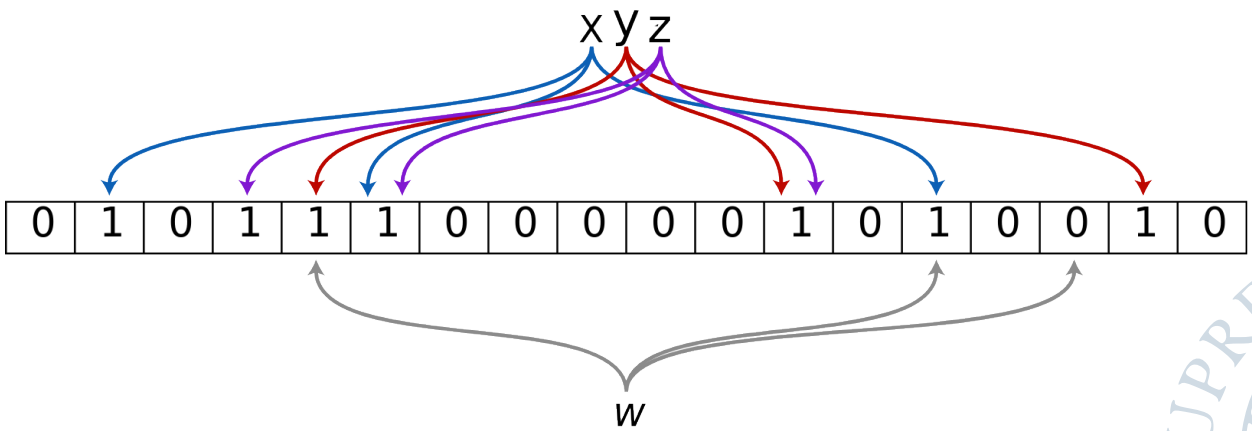
Bloom filter

A space-efficient probabilistic hash table

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

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

contains$(x) \to$ **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

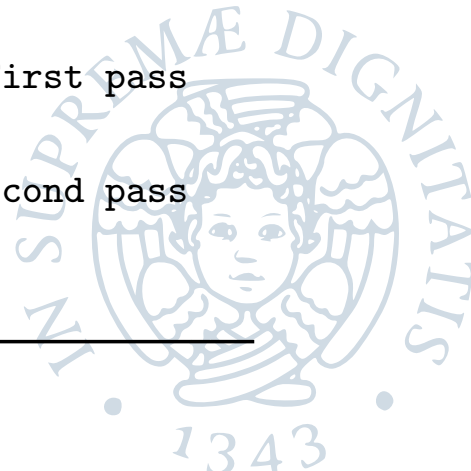
- First pass: Select a set of junction candidates by insert all the $(k+1)$-mers in a bloom filter of choosing size
- Second pass: Filter out the false positive by storing the reduce sets of $(k+1)$-mers in an hash table

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:
- Second pass:

What if the hash table in the second pass

Multiple rounds: dealing with memory restrictions

- Partitionate input k-mers in
- ciao

Algorithm 3: 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
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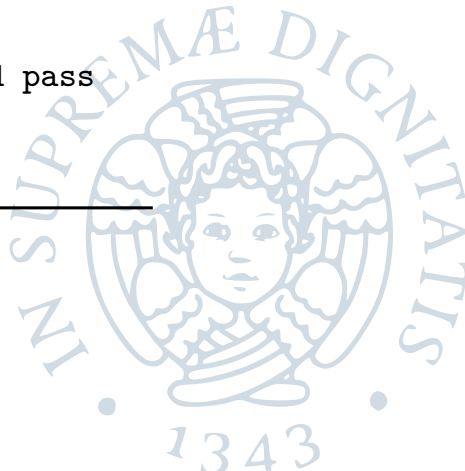
Output: C_{out} all the junctions in the compacted de Bruijn graph

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}



Parallelization scheme

Parte III

Results

Source code & Dataset

Original source code by medvedev group available on:

https://github.com/medvedevgroup/TwoPaCo

Personal implementation available on:

https://github.com/GaspareG/TwoPaCo

Dataset for experiments:

5 humans (from human reference genome)
8 primates (from ...)
62 Escherichia coli (from ...)
100 simulated human (from ...)

Memory complexity

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

- First pass: insert all k-mers in a bloom filter of size b
- Second pass: store all **junction candidates** in a hash table

How many junction candidates?

- Real junction, J
- False positive induced from the bloom filter, FP

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

Time complexity

The memory complexity is the sum
between the first and the second pass of TwoPaCo

- First pass: insert all k-mers in a bloom filter of size b using h hash functions
- Second pass: store all **junction candidates** in a hash table

How many k-mers?
$\mathcal{O}(m)$, where $m = \Sigma_{s \in S}|s|$ is the total input size

How many junction candidates?

- Real junction, J
- False positive induced from the bloom filter, FP

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

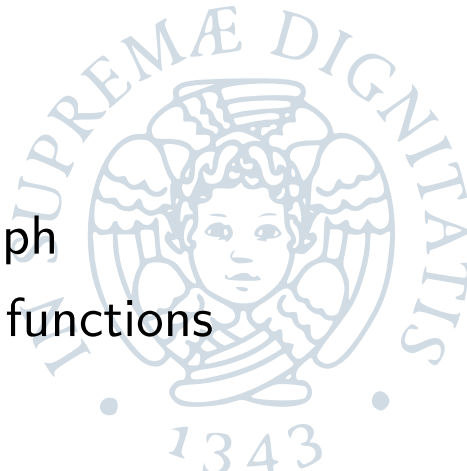
Complexity comparison

State of the art for compressed de Bruijn graph construction:

- Sibelia (Minkin, Patel, Kolmogorov, Vyahhi, Pham, 2013)
- SplitMEM (Marcus, Lee, Schatz, 2014)
- bwt-based (Baier, Beller, Ohlebusch, 2015)

Algorithm	Time complexity	Memory complexity
Sibelia	$\mathcal{O}(m)$	$\mathcal{O}(m)$
SplitMEM	$\mathcal{O}(m \log g)$	$\mathcal{O}(m + \|G_c\|)$
bwt-based	$\mathcal{O}(m)$	$\mathcal{O}(m)$
TwoPaCo	$\mathcal{O}(mh + (\|G_c\| + FP)k)$	$\mathcal{O}(\max\{b, (J + FP)k\})$

- $m = \Sigma_{s \in S}|s|$, total input size
- $g = \max_{s \in S}|s|$, size of the biggest genoma
- J and G_c, 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



Running time comparison

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

Dataset	Sibelia	SplitMEM	bwt-based	TwoPaCo	
				1 thread	15 thread
62 E.coli (k=25)	0 (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

How many rounds do we need to compress the graph without exceeding a given memory threshold?

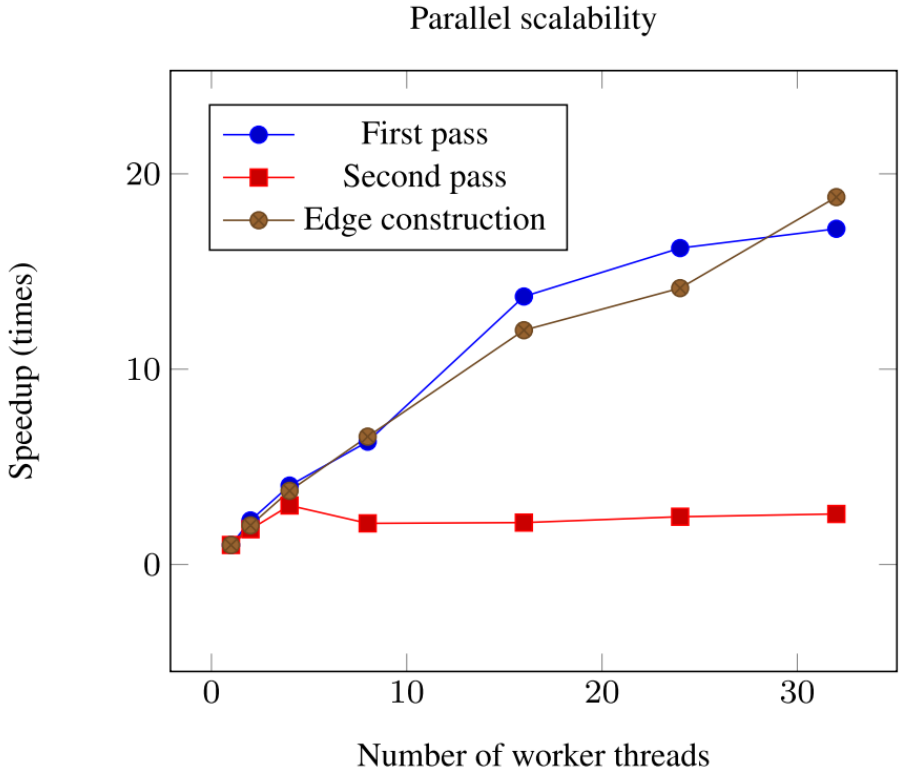
Threshold	Used memory	Bloom filter size	Running time	Rounds
10GB	8.62GB	8.59GB (2^{33})	4h	1
8GB	6.73GB	4.29GB (2^{32})	7h	3
6GB	5.98GB	4.29GB (2^{32})	9h	4
4GB	3.51GB	2.14GB (2^{31})	11h	6

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

Result: we can trade-off memory for time.

Parallel scalability

How does the performance of TwoPaCo improve to the increasing of working threads?



- First pass: great improvement thanks to concurrent bloom filter
- Second pass: slight improvement due to race-conditions on the hash table
- Edge construction: great improvement thanks to k-mers independency

Bloom Filter false positive

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

Thanks for your attention!