# Appendices

This appendix includes the following sections.

- 1 Implementation details of the break point finding algorithm
- 2 Data analysis of the Breaker and Merger
- 3 Feasibility of Breaker to recover consistent contigs
- 4 More information on the EM algorithm and the MSA
- 5 Commands used to run various tools
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# Appendix A: Implementation details of the break point finding algorithm

In forming a De Bruijn graph, we use the following method. First, we fill in the hidden end points by inspecting any inconsistent number of end points between repeat copies. In our example of  $x_1 = a[b(c]d)e, x_2 = f[bc]g, x_3 = h(cd)i$ , we have [()] as the long( $\geq 2L$ ) repeat end points. We fill in the hidden end points  $x_1 = a[b(c]d)e, x_2 = f[b|c]g, x_3 = h(c|d)i$  because between [] there should be a ), and between (), there should be a After filling in the hidden end points, we label and cluster the end points. At first, two end points have the same label if they correspond to the same side of the same repeat. Then, we cluster end points that are close to each other to have the same label. With the relabelled end points along each contig, we form a graph. Note that the end points correspond to edges of the graph. In the previous example, let the label of end point of [(]) be 1, 2, 3, 4 respectively, we have the edge sequences of  $x_1, x_2, x_3$  being (1, 2, 3, 4), (1, 2, 3), (2, 3, 4). And we will append beginning and ending edge to the sequences, so the actual edge sequences of  $x_1, x_2, x_3$  are  $(b_1, 1, 2, 3, 4, e_1), (b_2, 1, 2, 3, e_2), (b_3, 2, 3, 4, e_3)$ . Next, we need to find the nodes. This can be done by scannig for successive end points in the edge sequences. Any two successive end points define a node. And if they do not correspond to a closed end point followed by an open end point, it is considered as a repeat node. For example, (1,2) is a repeat node node, and  $(b_1,1)$  is a non-repeat node. Now we note that from the repeat nodes, we can gather together the edges to form the graph. For example, the incoming edges of node (1,2) are the two end points corresponding to 1 and outgoing edges of the node (1,2) are the two end points corresponding to 2. In order to handle double stranded nature of the genome, when scanning the edge sequences, we search both forward and backward to identify the nodes. The approximate nature of matching is handled when we cluster end points close to each other.

### Appendix B: Data analysis of the Breaker and Merger

We perform independent data analysis of the performance of Breaker and Merger of BIGMAC. We note that we both use QUAST and an independent evaluation(which is implemented by us) from QUAST. Users can use our evaluation scripts to evaluate the performance of their own improvement as well. We note that the dataset 1,2,3 are those studied in the experiment section and the dataset 0 is the synthetic dataset.

### B.1 Quast reports

The Breaker only and BIGMAC end-to-end results are tabulated as follows. We note that Breaker can decrease the number of contigs because it remove redundant contigs after breaking at potentially mis-assembled points. The are located at the QUAST report section.

#### B.2 Data anaysis on Breaker

We measure mis-assemblies fixing capability of Breaker. Specifically, we study the performance of ChimericContigFixing(Palindrome) and the combination of LocatePotentialMisassemblies and ConfirmBreakPoints (Repeat&Coverage). We map the contigs back to the ground truth to see if the segments mapped to different locations. We note that our method is more stringent that QUAST. Even in the cases of repeat, we only map the segment to the best matched location. Thus, occasionally, a FP may not be a real false positive. The script can be run as python -m srcRefactor.evalmfixer foldername mummerpath The precision and recall on the subcompoents are as follows.

Dataset	Break point detector	Precision	Recall	Number of TP	Number of FP
0	Palindrome	1	0	0	0
0	Repeat&Coverage	1	1	2	0
1	Palindrome	1	0	0	0
1	Repeat&Coverage	0.102041	0.483871	15	132
2	Palindrome	0.605556	0.246606	109	71
2	Repeat&Coverage	0.021898	0.032967	9	402
3	Palindrome	0.818182	0.157895	9	2
3	Repeat&Coverage	0.142857	0.113636	5	30

Table 4: Breaker Evaluation

### B.3 Data anaysis on Merger

To evaluation, we collect data from graphsurgery merges(when condensing edges), BRepeat merges(when repeat node is not a separte node) and XRepeat merges(when repeat node is a separate node). We map back to reference to identify correct successors. Then we report the percentage left. The scripts can be run as python -m srcRefactor.evalasplitter foldername mummerpath The precision and recall on the subcompoents are as follows. Note that we are more stringent than QUAST, because if two are not immediate successors then we report as FP here. Also, we use best match on the reference, meaning that repeat can be mapped to more than one location, thus a FP may not really be a FP. So, the number reported only serves as an approximation here. We note that we have duplicated tje contigs to handle reverse complements, so all numbers are approximately double of the actual number, with some offset due to slight variation due to tie-breaking in the alignment tool.

### Appendix C: Feasbility of Breaker to recover consistent contigs

In this section, we study why Breaker can recover contigs by modelling the misassemblies formed by an upstream assembler

We define the ground truth to be  $S_0 = \{s_1, s_2, ..., s_n\}$  which is a set of strings with alphabets taken from  $\Sigma = \{A, C, G, T\}$ . Now we specify their repeat structures as follows. Let x, y be length L substrings of  $s_i, s_j$  respectively, where  $i \neq j$  and

0							
Dataset	Merger subroutine	precision	recall	TP₋num	FP₋num		
0	GraphSurgery	1	0	0	0		
0	BResolve	1	1	4	0		
0	XResolve	1	0	0	0		
1	GraphSurgery	0.829268	0.164251	68	14		
1	BResolve	0.745455	0.099034	41	14		
1	XResolve	0.823529	0.033816	14	3		
2	GraphSurgery	0.741379	0.076512	43	15		
2	BResolve	0.384615	0.008897	5	8		
2	XResolve	0.250000	0.001779	1	3		
3	GraphSurgery	0.235294	0.090909	4	13		
3	BResolve	0.333333	0.045455	2	4		
3	XResolve	1.000000	0.022727	1	0		

Table 5: Merger Evaluation

L > 2. If  $\forall 1 < k < L, x[k] = y[k]$  and  $x[1] \neq y[1], x[L] \neq y[L]$ , then we call (x, y) be a maximal exact repeat of length L - 2. Although this notion of maximal exact repeat can be generalized to the same string, for simplicity of discussion, we assume they are extracted from different strings. We fix  $K_0$  to be a large constant which is related to the length of the reads and assume that there are only r maximal exact repeats of length  $> K_0$ .

Next, we model the upstream assembler's mis-assembly formation process by the following sequence of operations of strings. Let  $\{T_j\}_{1 \le j \le m}$  be a sequence of operations that act on strings  $S_0$  and form  $\{S^{(j)}\}_{1 \le j \le m}$  successively. That is,  $S^{(0)} = S_0$  and  $1 \le j \le m, S^{(j)} = T_j(S^{(j-1)})$ . Now, we specify the action of  $T_j$ . It picks two arbitrary strings with a maximal repeat of length j,  $K_0$ . Then, it breaks at the start of the repeat and joins the corresponding string at the breakpoint. Symbolically, let T operate on two strings s = axb, t = cxd, where the common segment is x and the breakpoint is the position immediately before x. The resultant strings are s' = axd, t' = cxb. We further assume that each string under the operations does not have repeat within itself of length  $> K_0$ .

Under this setting, we prove the following theorem.

**Theorem C.1** Given  $S^{(m)}$  generated from  $S_0 = \{s_i\}_{1 \le i \le n}$  after successive operations by  $\{T_j\}_{1 \le j \le m}$ , we can recover a set of strings W of cardinality at most n + 4rsuch that W is consistent with  $S_0$  (i.e. for each string  $w \in W$ , w is a substring of some string  $s \in S_0$ ).

*Proof* The way to construct the set W is as follows. We first identify all maximal exact repeats across the strings in  $S^{(m)}$ . We then break the strings at every endpoints of each of these maximal exact repeats. Now, it remains to show that 1) there are at most n + 4r strings in W and 2) they are consistent with the ground truth.

To show them, we use the following bookkeeping method. Let us assign a unique label to each position at each string in the ground truth  $S_0$ . Let the set of all the labels be B and the mapping from B to string index and offset be  $f_0$ . At the beginning, we define  $\Phi_0$  as the labels that are the endpoints of any maximal exact repeat of length  $> K_0$ . That is,  $\Phi_0 = \{a \in$  $B \mid a$  corresponds to an endpoint of some maximal exact repeat of of length  $> K_0$  in  $S^{(0)}\}$ . When we apply  $T_j$  on the strings, let x be the repeat. We move both the segment and the associated labels to the other string starting at the left endpoint of x. The exceptions are the labels within the repeat xwhich are associated with some right endpoints of another repeat x' that has left endpoint before x. We keep those labels at the original positions. Since the set of labels remains invariant, and they correspond to a bijection,  $f_j$ , from B to string position at each stage after  $T_j$ , we can define  $\Phi_j = \{a \in$  $B \mid a$  corresponds to an endpoint of some maximal exact repeat of of length > $K_0$  in  $S^{(j)}\}$ 

We consider the simple case when initially no two pairs of repeat copies overlap at exactly one point(otherwise, we just need to generalize our book keeping scheme by introducing multiple labels at those points). In that case, it turns out that  $\Phi_j$ is invariant(i.e.  $\Phi_j = \Phi_0$  for all j), which we will prove in a separate Lemma. With this Lemma, then we can show the theorem follows.

We first show that W is consistent with  $S_0$ . We note that for each  $T_j$ , if we mark the label of the junction as  $b_j$  and break them, then the resulting set of string will be consistent throughout. But since  $b_j \in \Phi_j$  and  $\bigcup_j \{b_j\} \subset \bigcup_j \Phi_j = \Phi_m = \Phi_0$ , it suffices to break at every position corresponding to  $\Phi_m$  in  $S^{(m)}$  to obtain consistent strings. Moreover,  $|\Phi_m| = |\Phi_0| \leq 4r$ . So, if we break at every position corresponding to  $\Phi_m$  in  $S^{(m)}$ , we have at most n + 4r resultant strings. This gives,  $|W| \leq n + 4r$ .

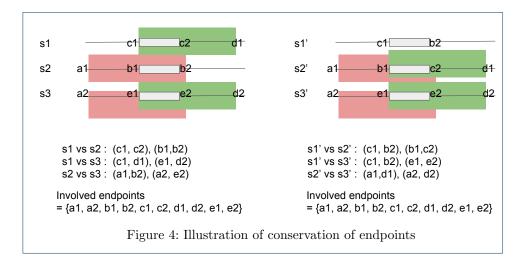
### **Lemma C.2** If $0 \le j \le m$ , we have $\Phi_j = \Phi_0$ .

*Proof* We consider j = 1 and inductively, the lemma follows. Without loss of generality, we assume  $s_1, s_2$  are the strings that  $T_1$  acts on and the associated repeat is x.

If  $T_1$  can cause an element  $b \in B$  to enter or leave  $\Phi_1$ , it could only belong to a maximal repeat that includes a copy of x. Otherwise the labels and the moving segment, which include that potential repeat segment, are moved together. Thus, there cannot be any creation/destruction of maximal exact repeats. We will show that, even for those repeats that include a copy of x, their endpoints are still invariant. Without loss of generality, we take the suspicious repeat to end at the right endpoint of  $s_1$ . There are two cases that can cause changes in  $\Phi_1$  upon  $T_1$ . These include getting a bigger maximal repeat or getting a big repeat separated into smaller pieces with a third string. Since we assume that we cannot have a repeat of length  $\zeta$   $K_0$  on the same string in the sequence of operations, the third string cannot be  $s_1$  or  $s_2$ . They correspond to a  $T_1$  that goes either from left to right or right to left in Fig 4. We enumerate the pairwise maximal repeats as shown in Fig 4. It turns out that in both cases, the set of associated repeat endpoints is invariant. This concludes the proof that  $\Phi_1 = \Phi_0$ 

# Appendix D: More information on the EM algorithm and the MSA

In this section, we discuss about the details of the EM algorithm used and related materials.



### D.1 Derivation of the EM algorithm

$$\begin{split} &\log P_{\theta}(X, Z) \\ &= \log \Pi_{1 \leq i \leq n} P_{\theta}(R_{i}, Z_{i}) \\ &= \sum_{1 \leq i \leq n} \log P_{\theta}(R_{i}, Z_{i}) \\ &= \sum_{1 \leq i \leq n} \log \Pi_{1 \leq j \leq k} (\lambda_{j} P(R_{i} \mid Z_{i} = j))^{1_{Z_{i} = j}} \\ &= \sum_{1 \leq i \leq n} \sum_{1 \leq j \leq k} 1_{Z_{i} = j} [\log \lambda_{j} - \log \ell_{j} + \log(q^{d(R_{i}, I_{j})}(1 - 2q)^{L - d(R_{i}, I_{j})})] \\ &= \sum_{1 \leq i \leq n} \sum_{1 \leq j \leq k} 1_{Z_{i} = j} [\log \lambda_{j} - \log \ell_{j} + d(R_{i}, I_{j}) \log \frac{q}{1 - 2q} + L \log(1 - 2q)] \end{split}$$

Thus, after taking expectation, we get  $E_{q(z|x,\theta^t)}[\ell(x,Z,\theta^{t+1})]$  as desired.

### D.2 Feasibility of MSA in our setting

Note that when we only have substitution noise and if all the  $R_i$  originates from the same genomic location, the problem of  $min_x \sum d(x, R_i)$  can be readily solved by a majority vote. We expect similar results regarding indel noise. However, we need to pre-process with an alignment phase before the majority vote. We thus introduce Algorithm majority-consensus-star-alignment.

- 1 Compute alignment of  $R_1$  and  $R_j$  where  $j \ge 2$
- 2 for j = 2 to n, use the alignment of  $R_1$  and  $R_j$  to form introduce gaps to previous alignment with the principle of "once a gap always a gap"
- 3 Take column-wise majority to form  $x^*$
- 4 return  $x^*$

We note that in the alignment, we use the scoring scheme of (1, -1, -1, -10) for match, insertion, deletion, substitution. It is because pure substitution noise is rare in current long read technology. We also note that when there is a run of alphabet, we will push the gap towards the end of the alignment. For example CCAAATT is aligned to CCAA\_TT.

**Theorem D.1** Let  $\{R_i\}_{1 \le i \le n}$  be a set of string with alphabets in  $\{A, C, G, T\}$  of length  $\{\ell(R_i)\}_{1 \le i \le n}$  where  $\ell(R_i) > n > 5$ . If  $\forall i \ne j, d(R_i, R_j) = 2$  and  $\exists x^*$  such that  $\forall i, d(x^*, R_i) = 1$  then the majority-consensus-star-alignment can find the optimizer of  $\min_x \sum d(x, R_i)$ .

*Proof* We can break it down into the following three steps. A high level intuition is that we are randomly placing an error on  $R_i$  generated from the same source, so, a simple majority vote should just work after doing an initial alignment.

- 1 Note that  $x^*$  is the optimizer. If we define  $R_{n+1} = R_1$ , we have,  $\forall x, \sum_{1 \le i \le n} d(x, R_i) = \frac{1}{2} \sum_{1 \le i \le n} [d(x, R_i) + d(x, R_{i+1})] \ge \frac{1}{2} \sum_{1 \le i \le n} d(R_i, R_{i+1}) = n$  But since  $\sum_{1 \le i \le n} d(x^*, R_i) = \sum_{1 \le i \le n} 1 = n$ , we know that  $x^*$  is the optimizer.
- 2 Second, we assume we input the ground truth  $x^*$  as a read, we will find that the algorithm give  $x^*$  as the output. The reason is as follows. Let  $e_i$  be the edit introduced by  $R_i$  when aligned to

*x*\*. Note that  $e_i \neq e_j$  if  $i \neq j$  otherwise,  $d(R_i, R_j) = 0$ . So, it means that  $e_i$  cannot win the majority vote at the end because  $n \geq 6$  and  $|\{A, C, G, T, -\}| = 5$ , so entry at *x*\* will be voted instead.

3 Finally, we find that the alignment with  $x^*$  is the same as that without it as input.

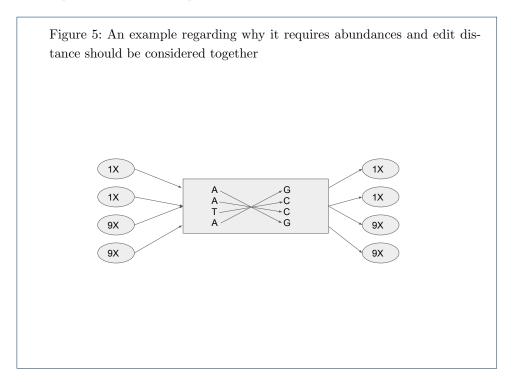
The reason is as follows. We have the notation of M(A, B) as the alignment of A and B when  $x^*$  is the first input, and  $M_S(A, B)$  as the alignment of A and B when  $x^*$  is the input. We claim that a small lemma, which says that  $\forall j, M(R_1, R_j) = M_S(R_1, R_j)$ . Note that it suffices because no gaps are introduced without conflicting some  $R_i$ . Then with the lemma, we have alignment of every reads be identical with and without  $x^*$ , and by step 1 and 2, we know that the algorithm will output the right optimizer. Now we proceed to show the lemma. First note  $e_i$  corresponds to edit on  $x^*$  for  $R_i$ . Recall that,  $e_i$  has to be distinct due to  $d(R_i, R_j) = 2$ . Now consider , without loss of generality,  $e_1, e_2$  and their corresponding location when  $x^*$  is the input. We define runs of alphabets that  $e_i$  lands on under  $M_S$  as  $r_i$ . Now, we exhaust the cases on  $r_i$ .

- (a) There exists at least one other run between  $r_1$  and  $r_2$ . For example, AAAA-CCCTTT vs AAA-CCCTT- Since putting  $e_1, e_2$  on  $M_S$  gives two edits between  $r_1, r_2$ , we cannot shift the alphabets at the middle to give the same edit distance. This means that the same alignment shows up under M so as to conserve the same edit distance. Moreover, as the is always put to the end of run, we will have that consistent under both  $M_S$  and M too.
- (b)  $r_1, r_2$  are neighboring runs. For example, CCC-TTT vs CCCCTT-. Shifting of run at  $r_1, r_2$  will cause substitution error, so it is not used under  $M_S$ . Thus,  $r_1, r_2$  will have the same alignment too under M to conserve the edit distance of 2.
- (c)  $r_1, r_2$  are on the same run. For example, CCCC– vs CCCCC while  $x^*$  gives CCCC- Since the is always put at the end of the run, we have the alignment conserved under M and  $M_S$ .

We note that, in our implementation of BIGMAC, we use ClustalW2[16] to do the core of multiple sequence alignment. We first use MUMmer to get a rough anchors of the reads and then we chop up the reads into smaller Kmers. Then, we group the related Kmers together use ClustalW2 to do the multiple sequence alignment.

### D.3 An interesting repeat

There is an interesting case which can justify why we need the EM algorithm for some tough cases. Consider the situation in Fig 5. The correct matching is the one that follows row by row. However, there exists matching at the interior such that the polymorphic sites are still consistent (as shown in the figure). Moreover, if we only consider abundance information alone, this repeat cannot be resolved as well (in the sense that we cannot find the correct matching). However, if we consider both the abundances and the polymorphism together during the decision making, we can identify the correct linkage. That is why we introduce the parameter formulation to incorporate both of these quantities.



# Appendix E: Commands for datasets

Commands for using BIGMAC on synthetic data and real data are all based on the following commands.

```
$ python -m srcRefactor.misassemblyFixerLib.mFixer destF mPath
$ python -m srcRefactor.repeatPhaserLib.aSplitter destF mPath
```

FinisherSC, SSPACE\_LongRead and PBJelly are run at their default settings. In particular, the commands used to run them are as follows.

```
FinisherSC :
$ python finisherSC.py dest mPath
PBJelly :
$ Jelly.py setup Protocol.xml
$ Jelly.py mapping Protocol.xml
$ Jelly.py support Protocol.xml
$ Jelly.py extraction Protocol.xml
$ Jelly.py assembly Protocol.xml
$ Jelly.py output Protocol.xml
$ Jelly.py output Protocol.xml
```

The protocol.xml has the following setting for BLASR, <blasr>-minMatch 8 -minPctIdentity 70 -bestn 1 -nCandidates 20 -maxScore -500 -nproc 20 -noSplitSubreads</blasr>

Moreover, we note that you can reproduce results regarding BIGMAC by running python reproduce.py to download data, dependencies and run the tools. The results is saved in allinone.txt

### Appendix F: Detailed Quast reports

The Quast reports for various comparison for synthetic data and dataset 1,2,3 are in the following tables.

# Appendix G: Future work

It would be interesting to apply similar ideas to hybrid data. Moreover, it would also be interesting to investigate the optimal way to use abundance information.

Table 6: Synthetic data (Comparison with Breaker only and HGAP results). All statistics are based on contigs of size  $\geq 500$  bp, unless otherwise noted (e.g., "# contigs ( $\geq 0$  bp)" and "Total length ( $\geq 0$  bp)" include all contigs).

	е (	p) menude a	<i></i> ,
Assembly	Original	Breaker only	BIGMAC end-to-end
# contigs ( $\geq 0$ bp)	2	4	2
# contigs ( $\geq$ 1000 bp)	2	4	2
Total length ( $\geq$ 0 bp)	1000000	1000000	9999992
Total length ( $\geq$ 1000 bp)	1000000	1000000	9999992
# contigs	2	4	2
Largest contig	5000000	2512000	4999998
Total length	1000000	1000000	9999992
Reference length	1000000	1000000	1000000
GC (%)	50.01	50.01	50.01
Reference GC (%)	50.01	50.01	50.01
N50	5000000	2512000	4999998
NG50	5000000	2512000	4999994
N75	5000000	2488000	4999994
NG75	5000000	2488000	4999994
L50	1	2	1
LG50	1	2	2
L75	2	3	2
LG75	2	3	2
# misassemblies	2	0	0
# misassembled contigs	2	0	0
Misassembled contigs length	1000000	0	0
# local misassemblies	0	0	0
# unaligned contigs	0 + 0 part	0 + 0 part	0+0 part
Unaligned length	0	0	0
Genome fraction (%)	100.000	100.000	100.000
Duplication ratio	1.000	1.000	1.000
# N's per 100 kbp	0.00	0.00	0.00
# mismatches per 100 kbp	0.00	0.00	0.05
# indels per 100 kbp	0.00	0.00	2.38
Largest alignment	2512000	2512000	4999998
NA50	2512000	2512000	4999998
NGA50	2512000	2512000	4999994
NA75	2488000	2488000	4999994
NGA75	2488000	2488000	4999994
LA50	2	2	1
LGA50	2	2	2
LA75	3	3	2
LGA75	3	3	2

Assembly	Original	Breaker only	BIGMAC end-to-end
# contigs ( $\geq 0$ bp)	130	199	131
# contigs ( $\geq$ 1000 bp)	130	197	129
Total length ( $\geq 0$ bp)	30499818	29452892	29273543
Total length ( $\geq$ 1000 bp)	30499818	29452752	29273403
# contigs	130	197	129
Largest contig	8887616	8615553	8615553
Total length	30499818	29452752	29273403
Reference length	30128987	30128987	30128987
GC (%)	56.54	57.45	57.68
Reference GC (%)	56.98	56.98	56.98
N50	818655	758280	4352719
NG50	1595590	567256	4352719
N75	274801	157172	274801
NG75	277114	132279	256020
L50	4	4	3
LG50	3	5	3
L75	23	28	14
LG75	22	32	16
# misassemblies	18	4	7
# misassembled contigs	15	4	7
Misassembled contigs length	16357196	536534	1785642
# local misassemblies	6	6	9
# unaligned contigs	0 + 0 part	0 + 0 part	0 + 0 part
Unaligned length	0	0	0
Genome fraction (%)	98.189	96.217	96.325
Duplication ratio	1.033	1.016	1.010
# N's per 100 kbp	0.00	0.00	0.00
# mismatches per 100 kbp	33.76	22.38	44.80
# indels per 100 kbp	7.13	5.40	63.44
Largest alignment	8631596	8615553	8615553
NA50	758280	758280	4351628
NGA50	758280	567256	4351628
NA75	227835	148337	262515
NGA75	254545	132279	181075
LA50	5	4	3
LGA50	5	5	3
LA75	26	29	14
LGA75	25	32	17

Table 7: Dataset 1 (Comparison with Breaker only and HGAP results): All statistics are based on contigs of size  $\geq 500$  bp, unless otherwise noted (e.g., "# contigs ( $\geq 0$  bp)" and "Total length ( $\geq 0$  bp)" include all contigs).

Table 8: Dataset 2 (Comparison with Breaker only and HGAP results). All statistics are based on contigs of size  $\geq 500$  bp, unless otherwise noted (e.g., "# contigs ( $\geq 0$  bp)" and "Total length ( $\geq 0$  bp)" include all contigs).

and Total length ( $\geq 0$ )	op) include	an contigs).	
Assembly	Original	Breaker only	BIGMAC end-to-end
# contigs ( $\geq$ 0 bp)	477	382	351
# contigs ( $\geq 1000$ bp)	477	371	341
Total length ( $\geq 0$ bp)	32897488	29572416	29605579
Total length ( $\geq$ 1000 bp)	32897488	29569477	29603092
# contigs	477	374	344
Largest contig	4673711	4673711	4673711
Total length	32897488	29571716	29605331
Reference length	66662626	66662626	66662626
GC (%)	47.38	48.81	48.80
Reference GC (%)	46.01	46.01	46.01
N50	397611	354308	397611
N75	38471	59190	75666
L50	9	13	12
L75	101	70	57
# misassemblies	187	25	28
# misassembled contigs	176	21	22
Misassembled contigs length	18192123	8079336	8582043
# local misassemblies	22	18	19
# unaligned contigs	39 + 7 part	30 + 7 part	29 + 8 part
Unaligned length	1646412	982915	993710
Genome fraction (%)	41.946	41.941	41.995
Duplication ratio	1.118	1.023	1.022
# N's per 100 kbp	0.00	0.00	0.00
# mismatches per 100 kbp	1.58	1.97	8.68
# indels per 100 kbp	8.63	9.02	37.15
Largest alignment	4547258	4547258	4547258
NA50	369454	333580	369454
NA75	32926	47209	56711
LA50	12	15	14
LA75	123	81	68

Table 9: Dataset 3 (Comparison with Breaker only and HGAP results). All statistics are based on contigs of size  $\geq 500$  bp, unless otherwise noted (e.g., "# contigs ( $\geq 0$  bp)" and "Total length ( $\geq 0$  bp)" include all contigs).

-end
145
140
2664
796
140
3563
796
3268
0.98
1.71
704
3563
878
/104
7
1
<b>27</b>
5
14
5
3506
2
bart
3281
.982
.060
0.00
2.30
3.60
9755
436
5251
/104
10
4
7

bb) and Total lengt	· - /		<i>• ,</i>		
Assembly	original	BIGMAC	finisherSC_e2e	jelly_e2e	SSPACE_e2e
# contigs ( $\geq 0$ bp)	130	131	53	100	86
$\# \text{ contigs } (\geq 1000 \text{ bp})$	130	129	53	100	86
Total length ( $\geq 0$ bp)	30499818	29273543	29883342	30619263	30589751
Total length ( $\geq$ 1000 bp)	30499818	29273403	29883342	30619263	30589751
# contigs	130	129	53	100	86
Largest contig	8887616	8615553	8887616	8889022	8887616
Total length	30499818	29273403	29883342	30619263	30589751
Reference length	30128987	30128987	30128987	30128987	30128987
GC (%)	56.54	57.68	57.14	56.54	56.54
Reference GC (%)	56.98	56.98	56.98	56.98	56.98
N50	818655	4352719	2531294	4642330	4657611
NG50	1595590	4352719	2531294	4642330	4657611
N75	274801	274801	415024	418480	493683
NG75	277114	256020	399053	818655	818655
L50	4	3	3	3	3
LG50	3	3	3	3	3
L75	23	14	12	6	6
LG75	22	16	13	5	5
# misassemblies	18	7	32	19	32
# misassembled contigs	15	7	23	16	20
Misassembled contigs length	16357196	1785642	20096169	21804531	17545253
# local misassemblies	6	9	11	9	36
# unaligned contigs	0 + 0 part	0 + 0 part	0 + 0 part	0+11 part	0 + 0 part
Unaligned length	0	0	0	33217	0
Genome fraction (%)	98.189	96.325	98.330	98.423	98.189
Duplication ratio	1.033	1.010	1.030	1.034	1.037
# N's per 100 kbp	0.00	0.00	0.00	0.00	294.00
# mismatches per 100 kbp	33.76	44.80	73.10	34.06	33.96
# indels per 100 kbp	7.13	63.44	23.53	9.39	6.69
Largest alignment	8631596	8615553	8631596	8631646	8631596
NA50	758280	4351628	2530093	3871007	3854031
NGA50	758280	4351628	1537643	3871007	3854031
NA75	227835	262515	304665	361412	361362
NGA75	254545	181075	304665	414429	414429
LA50	5	3	3	3	3
LGA50	5	3	4	3	3
LA75	26	14	16	8	8
	25	17	16	7	7

Table 10: Dataset 1 (Comparison with other tools) : All statistics are based on contigs of size  $\geq$  500 bp, unless otherwise noted (e.g., "# contigs ( $\geq$  0 bp)" and "Total length ( $\geq$  0 bp)" include all contigs).

Table 11: Dataset 2 (Comparison with other tools) : All statistics are based on contigs of size  $\geq$  500 bp, unless otherwise noted (e.g., "# contigs ( $\geq$  0 bp)" and "Total length ( $\geq$  0 bp)" include all contigs).

- /	$(\geq 0 \text{ p})^{-1}$ and "lotal length ( $\geq 0 \text{ p}$ )" include all contigs).						
Assembly	original	BIGMAC	finisherSC_e2e	jelly_e2e	SSPACE_e2e		
$\# \text{ contigs } (\geq 0 \text{ bp})$	477	351	447	403	307		
# contigs ( $\geq 1000$ bp)	477	341	447	403	307		
Total length ( $\geq$ 0 bp)	32897488	29605579	32870423	34484366	33520228		
Total length ( $\geq 1000$ bp)	32897488	29603092	32870423	34484366	33520228		
# contigs	477	344	447	403	307		
Largest contig	4673711	4673711	4673711	4673711	4673711		
Total length	32897488	29605331	32870423	34484366	33520228		
Reference length	66662626	66662626	66662626	66662626	66662626		
GC (%)	47.38	48.80	47.40	46.90	47.38		
Reference GC (%)	46.01	46.01	46.01	46.01	46.01		
N50	397611	397611	654163	1585584	1568442		
NG50	-	-	-	17013	14909		
N75	38471	75666	43018	61775	95133		
L50	9	12	8	6	7		
LG50	-	-	-	329	294		
L75	101	57	89	65	45		
# misassemblies	187	28	192	271	255		
# misassembled contigs	176	22	168	246	165		
Misassembled contigs length	18192123	8582043	18393113	24250973	23415983		
# local misassemblies	22	19	22	37	101		
# unaligned contigs	39 + 7 part	29 + 8 part	34 + 7 part	38 + 23 part	17 + 5  part		
Unaligned length	1646412	993710	1594170	1760782	1479235		
Genome fraction (%)	41.946	41.995	41.999	43.521	41.946		
Duplication ratio	1.118	1.022	1.117	1.128	1.146		
# N's per 100 kbp	0.00	0.00	0.00	0.00	1857.80		
# mismatches per 100 kbp	1.58	8.68	4.39	15.40	1.58		
# indels per 100 kbp	8.63	37.15	16.06	71.69	8.49		
Largest alignment	4547258	4547258	4547258	4547258	4547258		
NA50	369454	369454	401563	742006	737193		
NA75	32926	56711	33995	46245	42004		
LA50	12	14	11	9	9		
LA75	123	68	113	90	82		

Table 12: Dataset 3 (Comparison with other tools) : All statistics are based on contigs of size  $\geq 500$  bp, unless otherwise noted (e.g., "# contigs ( $\geq 0$  bp)" and "Total length ( $\geq 0$  bp)" include all contigs).

Assembly	original	BIGMAC	finisherSC_e2e	jelly_e2e	SSPACE_e2e
# contigs ( $\geq 0$ bp)	185	145	162	133	97
#  contigs  (> 1000  bp)	185	140	162	133	97
Total length ( $> 0$ bp)	17393660	13912664	17391031	18003698	17738519
Total length ( $> 1000$ bp)	17393660	13911796	17391031	18003698	17738519
# contigs	185	140	162	133	97
Largest contig	3968563	3968563	3968563	3971059	4319145
Total length	17393660	13911796	17391031	18003698	17738519
Reference length	7883268	7883268	7883268	7883268	7883268
GC (%)	61.18	60.98	61.19	61.19	61.18
Reference GC (%)	61.71	61.71	61.71	61.71	61.71
N50	257044	359704	996532	1103847	1266912
NG50	3968563	3968563	3968563	3971059	4319145
N75	82370	99878	97964	128718	290104
NG75	3924590	517104	3924590	3927083	3985906
L50	5	7	3	3	3
LG50	1	1	1	1	1
L75	38	27	27	19	10
LG75	2	5	2	2	2
# misassemblies	26	14	25	27	43
# misassembled contigs	20	5	17	21	23
Misassembled contigs length	5470082	4328506	5465644	9434182	10736561
# local misassemblies	2	2	2	2	5
# unaligned contigs	118 + 0 part	115 + 2 part	99 + 0 part	66 + 14 part	50 + 0 part
Unaligned length	5585886	5553281	5602837	6149028	5791170
Genome fraction (%)	99.983	99.982	99.983	99.983	99.983
Duplication ratio	1.498	1.060	1.496	1.504	1.516
# N's per 100 kbp	0.00	0.00	0.00	0.00	1944.13
# mismatches per 100 kbp	0.18	2.30	0.16	0.60	0.18
# indels per 100 kbp	8.70	23.60	5.14	6.39	8.70
Largest alignment	3924590	1719755	3924590	3925633	3924590
NA50	137772	284436	152488	107893	126445
NGA50	1719755	576251	1719755	1719755	1719755
NGA75	1452284	517104	1452284	1453076	1452284
LA50	11	10	10	13	12
LGA50	2	4	2	2	2
LGA75	3	7	3	3	3