# Supplementary Information: Versatile genome assembly evaluation with QUAST-LG

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### Supplementary Tables

Supplementary Table 1: QUAST and QUAST-LG performance. The four compared modes are: QUAST (the default QUAST v4.5 distribution),  $adj. QUAST$  (QUAST v4.5 with the adjusted parameters, so the tool uses the same minimal contig, minimal alignment, and extensive misassembly thresholds as in QUAST-LG), QLG-NUCmer (QUAST-LG with Minimap2 [1] aligner replaced by NUCmer aligner from MUMmer v3.23 [2] which was used in all versions of QUAST before v5.0),  $QUAST-LG$  (the default QUAST-LG v5.0 distribution). The running time for the latter is given separately for *Old stats* (quality metrics available both in QUAST and QUAST-LG), New stats (novel features and quality metrics added in QUAST-LG, that is, k-mer-based statistics and upper bound assembly generation), and BUSCO (search for conservative single-copy orthologs using BUSCO [3]); the rest three modes include only *Old stats* for a fair comparison with conventional QUAST software. BUSCO is shown separately since this module is intended for reference-free evaluation and should not be normally run with referenced-based *Old* and *New stats. Num* stands for the number of assemblies being processed. Note, that in addition to input assemblies QUAST-LG computes and evaluates the upper bound assembly which was provided to QUAST as one more input assembly for a fair comparison. All running times are in hh:mm format, maximal  $RAM$  consumption is in GB (computed for three modes only), "—" indicates the fact that the NUCmer-based tools were not able to process the human datasets in a reasonable time. All benchmarking was done on a server with Intel Xeon X7560 2.27GHz CPUs using 8 threads.



Supplementary Table 2: Comparison of QUAST-LG alignment metrics computed using Minimap2 and NUCmer. Each cell represents the average value of the corresponding alignment metric among all input assemblies (upper bound assembly is not counted). GF  $(\%)$  stands for Genome fraction in percents, Dupl. is for Duplication ratio, *Largest al.* and Total len. are for the largest alignment length and the total number of aligned bases, respectively.  $\#$  mis. ( $\#$  local mis.) is for the number of extensive (local) misassemblies. Mis. len. stands for the total length of the contigs containing at least one extensive misassembly.  $# \, TEs$  is the number of misassembly events probably caused by transposable elements (not counted against  $# mis$ .). MM and IND stand for the number of mismatches and indels per 100 kb, respectively.  $\#$  unal. and Unal. len. is the number of contigs that have no alignment to the reference sequence and their total length, respectively.

Dataset	$\text{Yeast}_{PB}$		$\text{Yeast}_{NP}$		$W \text{orm}_{PB}$	
Aligner	Minimap2	NUC <sub>mer</sub>	Minimap2	NUCmer	Minimap2	NUCmer
GF(%)	97.52	97.50	98.58	98.63	99.22	99.34
Dupl.	1.033	1.036	1.008	1.009	1.016	1.022
Largest al. $(kb)$	1256	1265	1162	1200	3032	3181
Total len. (Mb)	12.385	12.385	12.134	11.985	105.959	105.959
NGA50 (kb)	610	644	685	670	1201	1160
NGA75 (kb)	370	420	457	451	718	681
LGA50	8.4	8.2	8.25	7.5	28.6	30.2
LGA75	15.6	14.4	12.75	13.0	55.8	58.8
$# \text{ mis.}$	34.6	28.4	9.5	9.25	152.6	238.0
$#$ local mis.	48	65.6	14.25	27.5	423.2	1045.4
Mis. len. $(Mb)$	6263	5654	2871	2973	81315	83207
$#$ TEs	8.8	21	3.5	2.3	80.0	136.0
ΜМ	344	252	172	142	43	26
IND	65	64	377	361	66	58
$#$ unal.	2.0	2.4	1.0	$1.5\,$	24.8	21.2
Unal. len. $(Mb)$	147	109	55	39	4872	4170

Supplementary Table 3: QUAST-LG report on the Yeast<sub>PB</sub> dataset. All statistics are given for scaffolds  $\geq 3$  kb. The best value for each column is indicated in bold.



Supplementary Table 4: QUAST-LG report on the Yeast<sub>NP</sub> dataset. All statistics are given for scaffolds  $\geq 3$  kb. The best value for each column is indicated in bold.

Assembly	UpperBound	$\overline{\text{C}}$ anu	Flye	MaSuRCA	Miniasm
$#$ contigs	42	35	29	24	31
Largest contig	1524479	1090297	1080635	1546094	1056583
Total length	12170018	12264084	11963777	12324198	11985552
Reference length	12157105	12157105	12157105	12157105	12157105
GC(%)	38.15	38.31	38.33	38.14	38.61
Reference GC $(\%)$	38.15	38.15	38.15	38.15	38.15
$\overline{N50}$	776910	783642	782882	813521	659164
$\overline{\text{NG50}}$	776910	783642	782882	813521	659164
$\overline{N75}$	564006	449401	463994	541850	451115
$\overline{\text{NG75}}$	564006	449401	463994	541850	451115
L50	6	7	$\overline{7}$	$\boldsymbol{6}$	8
LG50	$\boldsymbol{6}$	$\overline{7}$	$\overline{7}$	$\boldsymbol{6}$	8
L75	11	$\overline{12}$	12	10	$\overline{13}$
LG75	$\overline{11}$	12	12	10	$13\,$
$#$ misassemblies	$\bf{0}$	12	$\bf 5$	14	7
$#$ misassembled contigs	$\bf{0}$	$\overline{10}$	$\overline{3}$	8	$\overline{5}$
Misassembled contigs len	$\bf{0}$	2037150	1834995	5269173	2344082
$# local \text{ missesembles}$	$\bf{0}$	22	9	10	16
$#$ scaffold gap size mis.	$\boldsymbol{0}$	$\overline{0}$	$\overline{0}$	$\overline{0}$	$\theta$
$#$ possible MGEs	$\boldsymbol{0}$	4	$\overline{2}$	4	4
$#$ unaligned mis. contigs	$\bf{0}$	$\bf{0}$	1	$\bf{0}$	1
$#$ unaligned contigs	$\overline{0+0}p$	$1+14p$	$1+14p$	$2+2p$	$\overline{0+12p}$
Unaligned length	$\bf{0}$	56584	66963	60723	34934
Genome fraction $(\%)$	99.869	98.843	97.708	99.518	98.261
Duplication ratio	1.002	1.016	$1.002\,$	1.014	1.000
$#$ N's per 100 kbp	$\overline{0.00}$	0.00	1.67	$\overline{0.00}$	0.00
# mm per 100 kbp	$\overline{0.00}$	565.83	56.14	12.39	52.60
$#$ indels per 100 kbp	$\overline{0.00}$	101.41	649.09	2.87	754.08
Complete BUSCO $(\%)$	99.31	97.93	34.14	99.31	34.48
Partial BUSCO $(\%)$	0.00	$\overline{1.03}$	33.79	0.00	32.41
Largest alignment	1524479	1089592	1080623	1521997	1056509
Total aligned len	12170018	12183658	11879194	12244032	11936970
$N_A50$	776910	657536	663200	740331	638568
$\overline{\text{NGA}50}$	776910	657536	663200	782448	638568
NA75	564006	447675	461922	459637	441933
NGA75	564006	447675	461922	478274	441933
LA50	6	7	8	7	8
LGA50	6	$\overline{7}$	8	6	8
LA75	11	13	13	12	14
LGA75	11	13	13	11	14
K-mer-based compl.	99.94	62.04	52.09	99.12	48.08
K-mer-based cor. len $(\%)$	99.26	96.44	85.41	74.93	94.49
K-mer-based mis. len $(\%)$	0.00	2.73	14.56	24.61	5.09
$#$ k-mer-based misjoins	$\bf{0}$	1	$\overline{3}$	5	1

Supplementary Table 5: QUAST-LG report on the  $Worm_{PB}$  dataset. All statistics are given for scaffolds  $\geq$  3 kb. The best value for each column is indicated in bold.



Supplementary Table 6: QUAST-LG report on the Fly<sub>MP</sub> dataset. All statistics are given for scaffolds  $\geq 3$  kb. The best value for each column is indicated in bold. This report was adjusted to fit the page: Total, Reference, and Total aligned lengths were converted from bp to Mb, few assembler and metric names were abbreviated.



Supplementary Table 7: QUAST-LG report on the  $\text{Human}_{MP}$  dataset. All statistics are given for scaffolds  $\geq$  3 kb. The best value for each column is indicated in bold.







## Supplementary Figures



Supplementary Figure 1: Assemblers performance on six benchmark datasets. Datasets are indicated by color, assemblers are shown by shape. Relative NGA50 is the scaffold NGA50 divided by UpperBound NGA50 for a given dataset. The x-axis ( $# \text{ misassemblies}$ ) is in a logarithmic scale.



Supplementary Figure 2: Circular alignment viewer for the Yeast<sub>PB</sub> dataset. The outer circle represents reference chromosomes with GC (%) heatmap (white for GC-poor and black for GC-rich regions). The inner circles are assemblies with green for correct contigs and red for contigs containing at least one misassembly breakpoint. The figure is generated using Icarus [4] and Circos [5] software.



Supplementary Figure 3: Circular alignment viewer for the Yeast<sub>NP</sub> dataset. The outer circle represents reference chromosomes with GC (%) heatmap (white for GC-poor and black for GC-rich regions). The inner circles are assemblies with green for correct contigs and red for contigs containing at least one misassembly breakpoint. The figure is generated using Icarus [4] and Circos [5] software.



Supplementary Figure 4: Circular alignment viewer for the  $\mathbf{Worm}_{PB}$  dataset. The outer circle represents reference chromosomes with GC (%) heatmap (white for GC-poor and black for GC-rich regions). The inner circles are assemblies with green for correct contigs and red for contigs containing at least one misassembly breakpoint. The figure is generated using Icarus [4] and Circos [5] software.



Supplementary Figure 5: Circular alignment viewer for the  $Fly_{MP}$  dataset. The outer circle represents reference chromosomes with GC (%) heatmap (white for GC-poor and black for GC-rich regions). The inner circles are assemblies with green for correct contigs and red for contigs containing at least one misassembly breakpoint. The figure is generated using Icarus [4] and Circos [5] software.



Supplementary Figure 6: Circular alignment viewer for the  $\text{Human}_{MP}$  dataset. The outer circle represents annotated reference chromosomes where centromeres are indicated with red color and all other regions are in gray scale. The inner circles are assemblies with green for correct contigs and red for contigs containing at least one misassembly breakpoint. The figure is generated using Icarus [4] and Circos [5] software.



Supplementary Figure 7: Circular alignment viewer for the  $\text{Human}_{NP}$  dataset. The outer circle represents annotated reference chromosomes where centromeres are indicated with red color and all other regions are in gray scale. The inner circles are assemblies with green for correct contigs and red for contigs containing at least one misassembly breakpoint. Note that the vast majority of the misassembled contigs are located in the centromeres regions which is visible especially in the MaSuRCA track. The figure is generated using Icarus [4] and Circos [5] software.

### Supplementary Methods

#### Choice of the breakpoint threshold

QUAST-LG procedure for transposable elements (TEs) identification critically depends on the size of the breakpoint threshold  $X$ . This threshold should ideally fit the length of the largest TE in the genome. To find the optimal value for  $X$ , we measured the number of misassemblies and the number of possible TEs identified by our procedure in all assemblies of the six benchmark datasets for various  $X$  in a range of 1-10 kb with a step of 1 kb (Supplementary Figure 8). The figure demonstrates that the number of misassemblies drops significantly with increase of X until a certain point  $X = X_c$  where the curve nearly flattens. Likewise, the number of possible TEs quickly goes up from an almost zero value at  $X = 1$  kb and eventually reaches plateau. We can see that the value of  $X_c$  varies among genomes: for the two yeast datasets it is clearly close to  $X_c = 6$  kb; the worm dataset reaches it at approximately 2-3 kb; and the fruit fly, as well as human datasets' critical points seem to be around 6-7 kb. In fact,  $X_c$  strongly correlates with the largest TE among the most common TEs in the corresponding organisms. Indeed, Ty1-like retrotransposons in the yeast genome are up to 5.9 kb long [6], Tc5 transposon in the worm genome is 3.2 kb long [7], TEs of LTR families in the fruit fly genome are up to 7.5 kb [8], and the most widespread active TEs in the human genome, LINE-1, are approximately 6 kb long [9, 10]. For the sake of consistency, we used the same  $X = 7$  kb in all benchmark experiments and it is the default value in QUAST-LG. A user may use "–extensive-mis-size" option to force QUAST-LG to use a different X value.



Supplementary Figure 8: The number of misassemblies and possible TEs at different breakpoint thresholds X. The x-axis indicate X value in kb. The y-axis displays the number of misassemblies (blue solid lines) and possible TEs (red dashed lines). Each line corresponds to an assembly of a corresponding dataset; upper bound assemblies are not shown. Note that SOAPdenovo assembly of  $\text{Human}_{MP}$  (e) and MaSuRCA assembly of Human<sub>NP</sub> (f) have too many misassemblies to fit these scaled plots, so SOAPdenovo values are shown only with  $X \geq 6$  kb, and MaSuRCA values are divided by ten and plotted using a green dotted line.

#### Best set of alignments selection

Long contigs are rarely mapped to the reference genome perfectly as a single unambiguous alignment. An alignment software typically reports multiple alignment fragments  $A = (a_1, \ldots, a_n)$  mapped to the different ps of the genome. Note, that some of the alignments may correspond to the same contig fragment mapped to distinct genomic positions. This may happen due to the presence of genomic repeats and transposable elements (TEs) in the reference genome and in some cases — algorithmic issues in the assembly and alignment software. QUAST-LG attempts to accurately assess each contig and select the set of non-overlapping alignments  $A' \subseteq A$ , which maximizes the total alignment score  $Score(A')$  (described below). To solve this problem, we implement a dynamic programming algorithm called  $BestSetSelection$  (see Algorithm 1). This algorithm is conceptually similar to the algorithm described in ref. [11] for selecting the best spliced alignment for a mapped transcript but includes a significant speed up which allows to apply it for evaluation of large genome assemblies. The BestSetSelection algorithm takes as input the list of contig alignments A sorted according to the position in the contig of right-most base of each aligned fragment.

Algorithm 1 Best Set Selection

1: procedure BESTSETSELECTION(Sorted list of alignments A) 2:  $BestSets \leftarrow \{(Emptyalignment, 0)\}$ 3: for all  $a_i \in A$  do 4:  $best_i \leftarrow argmax_{B \in BestSets} Score(B \cup a_i)$ 5: BestSets ← BestSets  $\cup$   $(best_i, Score(best_i))$ return  $argmax_{B \in BestSets}Score(B)$ 

The scoring function depends on the *alignment score* of every individual alignment and *locality score* between adjacent alignments. Score of a single alignment a is defined as  $AlignmentScore(a) = Length(a) * Identity(a)$ , where Identity(a) is reported by the alignment software  $(100\%$  for a perfect match and decreases with the number of short indels and mismatches). Given a scored set of alignments  $A = (a_1, \ldots, a_{k-1})$ , the score of  $A \cup a_k$  is computed as following:

 $Score(A\cup a_k) = Score(A) + AlignmentScore(a_k) - Penalty(a_{k-1}, a_k) - OverlapLength(a_{k-1}, a_k) * Identity(a_k),$ (1)

where Penalty( $a_{k-1}, a_k$ ) depends on the inconsistency between  $a_{k-1}$  and  $a_k$  in the genome. Higher penalty values are given for the extensive misassembly events and smaller coefficient for long indels or short local errors. The last term in equation (1) guarantees that the extension of the set with an alignment fully overlapping in contig with another alignment from the set is unprofitable. The described function satisfies the conditions for the scoring functions compatible with the  $BestSetSelection$  algorithm deduced in ref. [11].

The algorithm  $BestSetSelection$  takes  $O(n^2)$  time, where n is the total number of alignments in A. This number is usually small since the short alignments are filtered out prior to running the algorithm. However, contigs in large eukaryotic assemblies may contain up to dozens of thousands alignments. To prevent the performance drop in this case, we implemented a speed up heuristic if the size of A exceeds threshold N (the default value is 100).

To construct  $best_i$  (the best alignment set ending at  $a_i$ ) the algorithm iterates through all already computed alignment sets  $B \in BestSets$  and chooses the one that gives the best score for  $B \cup a_i$  (line 4 of the algorithm 1). However, it appears that the distance between the majority of the alignment sets  $B \in BestSets$  and  $a_i$  is large, which makes  $Score(B \cup a_i)$  too small to add  $B \cup a_i$  to BestSets. Below we suggest an heuristics that allows to iterate only through a small subset of BestSets and thus reduce the running time.

We define a as a solid alignment if  $Score(A' \cup a) > Score(A')$  for any  $A' \subset A \setminus a$ , i.e. if it its addition to any subset of alignments  $A \setminus a$  improves its *Score*. By the definition, all solid alignments from A are included in the resulting best set of alignments (it would be possible to create a set with a higher score otherwise). Inpicular,  $best_i$  includes all solid alignments located to the left of  $a_i$  in the contig. Thus, the algorithm can only iterate though those sets  $B \in BestSets$  that include the right-most solid alignment before  $a_i$ . Since the  $BestSets$  is constructed iteratively, these sets will include all solid alignments to the left of  $a_i$ . This speed-up resulted in up to 10x drop of the running time on the fruit fly assemblies evaluation and allowed us to complete quality assessment for the human assemblies (Supplementary Table 1).

The criteria for choosing solid alignments can be deduced from equation  $(1)$ . An alignment a is guaranteed to be solid if

$$
UniqueLength(a) * Identity(a) > m * MaxPenalty,
$$
\n(2)

where  $Uniquelength(a)$  is the length of a without overlaps with all other alignments,  $MaxPenalty$  is the maximal penalty value, and  $m = 1$  if a is located on the start/end of the contig and  $m = 2$  otherwise. Supplementary Figure 9 shows an example of the best alignment set and solid alignments.



Supplementary Figure 9: Solid alignments detection. A contig (gray line at the top) has multiple alignments (dark and light green and pink bars in the middle) to the reference genome (gray line at the bottom), the alignments positions are visualized (with blue color in the contig and green/pink in the reference). Alignments A and C (dark green) are solid since they are sufficiently long and do not have large overlaps with other alignments. Alignments  $B, E$  and F have significant overlaps, so their UniqueLength is not enough to mark them solid. Alignments  $D_1$  and  $D_2$  are ambiguous and thus cannot be solid (their UniqueLength is equal to 0). Alignments for the best set are colored green (dark green for solid alignments and light green for the rest), the unused alignments are colored light pink.

The described heuristic always identifies the alignment set with the maximal alignment score by design. However, it could in theory produce zero speed up or even small slowdown if the input set contains no or very few solid alignments or, on the contrary, if all or almost all alignments in the set are solid. Nevertheless, our benchmark experiments on various real datasets demonstrate that such cases are almost impossible in practice and the heuristic always works sufficiently well. Note that there are alternative theoretical sub-quadratic algorithms for the best set selection problem [12] but they are always associated with a large constant which makes them impractical comparing to our heuristic approach.

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