1 BugSeq 16S: NanoCLUST with Improved Consensus Sequence Classification

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11 Abstract

- 12 NanoCLUST has enabled species-level taxonomic classification from noisy nanopore 16S
- 13 sequencing data for BugSeq's users and the broader nanopore sequencing community. We
- 14 noticed a high misclassification rate of NanoCLUST-derived consensus 16S sequences due to
- 15 its use of BLAST top hit taxonomy assignment. We replaced the consensus sequence classifier
- 16 of NanoCLUST with QIIME2's VSEARCH-based classifier to enable greater accuracy. We use
- 17 mock microbial community and clinical 16S sequencing data to show that this replacement
- 18 results in significantly improved nanopore 16S accuracy (over 5% recall and 19% precision),
- 19 and make this new tool (BugSeq 16S) freely available for academic use at BugSeq.com/free.

We read with great interest the recent publication of NanoCLUST, a species-level analysis of 16S rRNA nanopore sequencing data (Rodríguez-Pérez *et al.*, 2020). NanoCLUST brings a novel, unsupervised read clustering approach to identify groups of similar reads, and corrects the errors within each cluster to identify a highly accurate amplicon sequence variant (ASV). This approach reduces the typically high (>5%) nanopore sequencing error rate, enabling species-level identification from nanopore 16S sequencing data.

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After its release, we rapidly integrated NanoCLUST into BugSeq, our democratized online bioinformatics platform, to provide leading accuracy in 16S nanopore analysis for the academic community, free of charge (Fan *et al.*, 2020). While BugSeq users have reaped significant benefits from the development and online deployment of NanoCLUST, we have also noted significant differences from its published accuracy on real world data. Here we report on a frequent discrepancy between NanoCLUST and ground truth data, our solution, and a benchmark of our new classification accuracy.

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35 When designing NanoCLUST, Rodríguez-Pérez et al. used BLAST to classify ASVs (Camacho 36 et al., 2009). Specifically, corrected consensus sequences from clusters are BLASTed against 37 the NCBI 16S BLAST database, and the sequence is assigned to the taxonomy of the top hit. 38 This approach leads to a high misclassification rate for several reasons. First, some bacteria 39 have nearly identical 16S sequences, such that only a 100% sequence identity between query 40 and reference sequence is appropriate to assign a sequence to the reference's species (Edgar, 41 2018). No such safeguards are taken with the NanoCLUST approach - an ASV may have 80% 42 sequence identity to the top BLAST hit yet be assigned to that species. Second, NanoCLUST 43 accepts a BLAST hit of any length, as long as the expectation value of the alignment is less 44 than 11; that is, for any ASV classification, there may be up to 11 hits found just by chance.

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46 We sought to replace the ASV classification mechanism of NanoCLUST with a more accurate 47 16S classifier. We tried IDTAXA and a naive Bayes classifier, but settled on the QIIME2 48 VSEARCH consensus classifier as the former classifiers did not provide species-level 49 classification or could not be tuned to NanoCLUST data qualities (Murali et al., 2018; Bokulich 50 et al., 2018). The VSEARCH classifier sets default identity (80%) and alignment length (80%) 51 thresholds, ensuring that only high quality alignments are retained. Additionally, it collapses the 52 top search hits by lowest common ancestor to ensure precision when closely related sequences 53 exist in the reference database. We deviate in one other way from NanoCLUST: the minimum 54 cluster size for HDBSCAN was recently decreased from 200 to 50 in NanoCLUST (as of 55 February 15, 2021); BugSeq has yet to follow suit (as of March 5, 2021). 56 57 We evaluated our novel 16S analysis pipeline, BugSeq 16S, with publicly available full-length 58 16S sequencing data of known mock microbial communities. Cusco et al. sequenced the 59 ZymoBIOMICS mock microbial community, containing eight bacteria in even abundance, in 60 duplicate (Cuscó et al., 2019). Using NanoCLUST, there were 6 and 5 species correctly 61 identified in the samples, with 4 and 2 false positive species, respectively (average precision 62 66%, average recall 69%). Using BugSeq 16S, we identify 7 bacterial species correctly in each 63 sample, with 1 false positive in both (average precision 88%, average recall 88%). Specifically, 64 NanoCLUST classified the Listeria monocytogenes sequences as Listeria innocua, the Bacillus 65 subtilis sequences as Bacillus halotolerans and Bacillus tequilensis, and the Escherichia coli 66 sequences as Shigella flexneri. BugSeq 16S identified the Bacillus subtilis sequences to the 67 correct genus (without classifying to species level), and falsely identified an uncultured 68 bacterium from the Escherichia/Shigella genus, in addition to the present E. coli. Revising the 69 NanoCLUST minimum cluster size to 200 reads did not affect conclusions: there was still 70 misidentification of the B. subtilis and L. monocytogenes reads, with E. coli no longer detected.

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72 On a more complex mock microbial community containing 20 bacteria spanning a 1000-fold 73 concentration range (BEI HM-783D), NanoCLUST detected 5 species correctly with 8 false 74 positive species; BugSeq 16S detected 6 species correctly with 1 false positive species (Cuscó 75 et al., 2019). Recall was therefore 30% for BugSeq as compared to 25% for NanoCLUST, with 76 precision of 85.7% for BugSeq and 38% for NanoCLUST. Full results are available in Table 1. 77 78 We next compared BugSeq 16S with NanoCLUST on publicly available full-length 16S 79 sequencing data from patients with ventilator associated pneumonia (Maes et al., 2021). 80 Twenty-nine bronchoalveolar lavage samples from 24 patients underwent microbial culture, 81 multi-pathogen TagMan array and nanopore 16S sequencing as previously described (Maes et 82 al., 2021). We used a combination of culture and TaqMan array results as the gold standard. As 83 TaqMan and culture results were censored by the original authors at a cycle threshold value of 32 and 10^4 colony forming units per milliliter, respectively, only sensitivity of 16S sequencing 84 85 could be calculated. Full data is available in the supplementary material. 86 87 At the species level, BugSeg 16S achieved better sensitivity (n=28/35, 80%) as compared to 88 NanoCLUST (n=26/35, 74%). Specifically, patient 16 had an *E. coli* detected by culture and 89 BugSeg 16S but NanoCLUST detected a mix of Escherichia fergusonii, Shigella flexneri and 90 Shigella sonnei. Patient 17 has a Serratia marcescens detected by culture, TaqMan and 91 BugSeg 16S, while NanoCLUST detected a Serratia nematodiphila and Serratia 92 surfactantfaciens. BugSeq 16S achieved this greater species-level sensitivity while predicting 93 fewer total species present in each sample. BugSeg 16S predicted a median of 13 (IQR=8) 94 fewer species present in each sample as compared with NanoCLUST. 95 96 As BugSeq 16S collapsed results based on sequence similarity, it also correctly detected a

97 Stenotrophomonas spp. in patient 1 (sample 2) which NanoCLUST mislabelled as

- 98 Stenotrophomonas pavanii (ground truth: Stenotrophomonas maltophilia) and a Haemophilus
- 99 spp. in patient 21 which NanoCLUST mislabelled as Haemophilus parahaemolytics (ground
- 100 truth: *Haemophils influenzae*). Accounting for these confidence-aware classifications increases
- 101 BugSeq 16S's sensitivity to 85.7%.
- 102
- 103 In conclusion, BugSeq 16S builds on NanoCLUST to improve nanopore 16S sequencing
- 104 analysis using a popular, highly accurate sequence classifier. This change results in significantly
- 105 improved analysis accuracy on both mock microbial communities and real patient samples, and
- 106 is free for academic use at <u>bugseq.com/free</u>.

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	Theoretical		
	Operon Copies (x		
	10 ³) in the	BugSeq 16S	NanoCLUST
Species	Community	Abundance	Abundance
Streptococcus mutans	1000	42.34%	51.76%
Eschericia coli	1000	19.41%	0.00%
Staphylococcus epidermidis	1000	1.88%	22.78%
Rhodobacter sphaeroides	1000	1.10%	0.37%
Streptococcus agalactiae	100	1.59%	2.51%
Pseudomonas aeruginosa	100	0.78%	0.57%
Bacillus cereus	100	0.00%	0.00%
Clostridium beijerinkii	100	0.00%	0.00%
Staphylococcus aureus	100	0.00%	0.00%
Acinetobacter baumannii	10	0.00%	0.00%
Helicobacter pylori	10	0.00%	0.00%
Lactobacillus gasseri	10	0.00%	0.00%
Listeria monocytogenes	10	0.00%	0.00%
Neisseria meningitidis	10	0.00%	0.00%
Propionibacterium acnes	10	0.00%	0.00%
Actinomyces odontolyticus	1	0.00%	0.00%
Bacteroides vulgatus	1	0.00%	0.00%
Deinococcus radiodurans	1	0.00%	0.00%
Enterococcus faecalis	1	0.00%	0.00%
Streptococcus pneumoniae	1	0.00%	0.00%
Uncultured Escherichia/Shigella	0	6.82%	0.00%
Escherichia fergusonii	0	0.00%	10.11%
Shigella sonnei	0	0.00%	4.01%
Citrobacter rodentium	0	0.00%	2.25%
Staphylococcus caprae	0	0.00%	1.73%
Bacillus tropicus	0	0.00%	1.68%
Shigella flexneri	0	0.00%	1.08%
Bacillus badius	0	0.00%	0.58%
Shigella boydii	0	0.00%	0.57%

107 **Table 1:** Species-level abundance in the HM-783D mock microbial community using BugSeq

108 16S and NanoCLUST. Green rows reflect species actually present in the sample, red rows

109 reflect false positive species.