OptiFit: a fast method for fitting amplicon sequences to existing OTUs

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Abstract

Assigning amplicon sequences to Operational Taxonomic Units (OTUs) is an important step in characterizing the composition of microbial communities across large datasets. OptiClust, a *de novo* OTU clustering method in the mothur program, has been shown to produce higher quality OTU assignments than other methods and at comparable or faster speeds (1, 2). A notable difference between *de novo* clustering and database-dependent methods is that OTU assignments clustered with *de novo* methods are not stable when new sequences are added to a dataset (3). However, in some cases one may wish to incorporate new samples into a previously clustered dataset without performing clustering again on all sequences, such as when deploying a machine learning model where OTUs are features (4). To provide an efficient and robust method to fit amplicon sequence data to existing OTUs, we developed the OptiFit algorithm as a new component of the mothur program.

- **TODO: summarize results & conclusion**

Importance

TODO

Introduction

Amplicon sequencing has become a mainstay of microbial ecology and host-associated microbiome research. Researchers can affordably generate millions of sequences to characterize the composition of hundreds of samples from culture-independent microbial communities. In a typical analysis pipeline, 16S rRNA gene sequences are assigned to Operational Taxonomic Units (OTUs) to facilitate comparison of taxonomic composition between communities. A distance threshold of 3% (or sequence similarity of 97%) is commonly used to cluster sequences into OTUs based on either a reference database or pairwise comparisons of the sequences within the dataset. The method chosen for clustering affects the quality of OTU assignments and thus may impact downstream analyses of community composition (1, 3, 5).

There are three main categories of OTU clustering algorithms: closed reference, open reference, and *de novo* clustering. Closed reference methods assign sequences to a set of pre-made OTUs generated from reference sequences. If a query sequence is not within the distance threshold to any of the reference sequences, it is discarded. While reference-based clustering is generally fast, it is limited by the diversity represented in the reference database. *De novo* methods cluster sequences based on their distance to each other, without the use of an external reference. open reference methods first perform closed reference clustering, then any sequences that cannot be assigned to reference OTUs are clustered *de novo* to create additional OTUs. *De novo* clustering overcomes the limitations of reference databases by considering only sequences in the dataset, but is more computationally intensive and generates different OTU assignments when new sequences are introduced. Previous studies found that *de novo* clustering created the highest quality OTU assignments based on the Matthews correlation coefficient (MCC) (3, 5).

- **TODO: clustering methods. describe reference vs de novo clustering.**

trade-offs. machine learning use-case.

- **TODO: mention OptiClust and vsearch.**
- **TODO:** gap in knowledge/ problem statement. acknowledge knock against OTUs, that they're not reproducible across studies. idea of ref-clustering is you can use existing OTUs to compare data across studies. can we make a ref-based method that's as good as *de novo*.
- **TODO:** in this study, we fix that problem.

Results

OptiFit algorithm

OptiFit leverages the method employed by OptiClust of iteratively assigning sequences to OTUs to produce the highest quality OTUs possible, and extends this method for reference-based clustering.

- **TODO: brief description of OptiFit algorithm**
- **TODO: open & closed reference modes**
- **TODO: MCC score; only considers query sequences (when printref=f)**

To evaluate the OptiFit algorithm and compare to existing methods, we used four published datasets isolated from soil (6), marine (7), mouse gut (8), and human gut (9) samples. There are two strategies for generating OTUs with OptiFit: 1) fit sequences to reference OTUs of an independent database, or 2) split the dataset into a reference and query fraction, then fit the query sequences to OTUs generated by clustering the reference sequences *de novo*. For each dataset repeated with 100 random seeds, we generated OTUs with OptiFit using both strategies, and also clustered *de novo* OTUs with OptiClust for comparison. All clustering was performed at a sequence dissimilarity threshold of 0.03 and OTU quality was evaluated using the Matthews Correlation Coefficient (MCC) as

described previously (3, 5). We calculated the fraction of query sequences that were fit to existing OTUs in closed reference mode as an additional measure of quality for this mode.

Reference clustering with public databases

- TODO: separate paragraphs for closed & open reference clustering. weave in vsearch within those paragraphs. mention median MCC values.
- TODO: avoid slightly/much – use numbers, e.g. X% better/worse.
- TODO: put the comparison at the beginning of the sentence, so you don't have to know what it is at the end.

To evaluate reference-based clustering with independent databases, we fit each dataset to reference OTUs generated by *de novo* clustering the Greengenes database (v13_8_99), Silva non-redundant database (v132), and the Ribosomal Database Project (RDP; v16). In open reference mode, OTU quality was similar between fitting the datasets to reference OTUs with OptiFit and clustering the datasets *de novo* with OptiClust. This held true for all datasets and reference databases. However, in closed reference mode, OTU quality was slightly worse when fitting to Greengenes and Silva, and much worse when fitting to RDP as compared to OptiClust. No more than half of query sequences were fit to reference OTUs in closed reference mode across any dataset/database combination. **TODO: specify exact numbers for fraction mapped.** OptiFit was able to fit more query sequences to reference OTUs created with the Greengenes and Silva databases than with RDP. In terms of run time, closed reference OptiFit outperformed OptiClust, while OptiClust outperformed open reference OptiFit.

To compare to existing software, vsearch was used to cluster OTUs *de novo* or with reference-based clustering to the greengenes database. For all datasets and clustering methods (*de novo*, open reference, and closed reference), mothur's clustering algorithms produced higher quality OTUs than vsearch. When closed reference clustering against the

greengenes database, vsearch was able to map more query sequences to the reference than mothur's OptiFit algorithm. In terms of runtime, OptiFit generally performed faster than vsearch when reference clustering, while vsearch *de novo* clustering outperformed OptiClust.

Reference clustering with split datasets

Datasets were randomly split into a reference fraction and a query fraction. Reference sizes from 10% to 80% of the sequences were created, with the remaining sequences used for the query. Reference sequences were clustered *de novo* with OptiClust, then query sequences were fit to the *de novo* OTUs with OptiFit.

OTU quality from the split dataset strategy with OptiFit was highly similar to that from *de novo* clustering the whole dataset with OptiClust regardless of mode. OTU quality was remarkably stable across 100 different random seeds. In terms of runtime, closed reference OptiFit performed faster than OptiClust on whole datasets. In open reference mode, OptiClust performed faster than OptiFit only when the OptiFit reference fraction was 30% or less. The split dataset strategy performed just as well as the database strategy in open reference mode regardless of database used, and outperformed the database strategy in closed reference mode.

We also tested three methods for selecting the sequences to be used as the reference; a simple random sample, weighting sequences by relative abundance, and weighting by similarity to other sequences in the dataset. OTU quality was similar with the simple and abundance-weighted sampling, but slightly worse with similarity-weighted sampling. In closed reference mode, The fraction of query sequences that can be fit to the reference OTUs decreases as the reference fraction increases.

Discussion

- **TODO:** for these data, we don't see a compelling reason to use reference-based clustering over *de novo*. it was supposed to speed things up. the reason to do reference-based is if you like the ref OTUs – e.g. for ML or downstream tools e.g. PiCrust?
- **TODO:** highlight difference between what we're doing and what previously was done. others use single ref seq to define an OTU, while we use all the ref & query seqs to define an otu. highlight why ours is better than previous methods.

We developed a new algorithm for fitting sequences to existing OTUs and have demonstrated its suitability for reference-based clustering. OptiFit makes the iterative method employed by OptiClust available for tasks where reference-based clustering is required. We have shown that OTU quality is similar between OptiClust and OptiFit in open reference mode, regardless of strategy employed. open reference OptiFit does perform slower than OptiClust due to the additional *de novo* clustering step, so users may prefer OptiClust for tasks that do not require reference OTUs.

When fitting to public databases, OTU quality dropped in closed reference mode to different degrees depending on the database and dataset source, and no more than half of query sequences were able to be fit to OTUs across any dataset/database combination. This may reflect limitations of reference databases, which are unlikely to contain sequences from rare and novel microbes. This drop in quality was most notable with RDP. We recommend users who require an independent reference database opt for Greengenes or Silva instead. Since OptiClust performs faster than open reference OptiFit and creates higher quality OTUs than closed reference OptiFit with the database strategy, we recommend using OptiClust rather than fitting to a database where possible. (**TODO: "if you don't have breadth, closed ref will suck." - Pat**)

The mothur algorithms produced higher quality OTUs than vsearch in open reference, closed reference, or *de novo* modes. However, vsearch was able to fit more sequence into OTUs than OptiFit in closed reference mode. While both mothur and vsearch use a dissimilarity threshold for determining how to assign sequences into OTUs, vsearch is more permissive than mothur. Mothur requires that all pairs of sequences in an OTU are within the dissimilarity threshold without penalizing the MCC, while vsearch only requires sequences to be similar to one other sequence in the OTU. In this way, vsearch sacrifices OTU quality in order to allow more sequences to fit to OTUs. Users who require closed reference clustering may prefer to use vsearch if they wish to maximize the fraction of sequences that can be fit at the cost of OTU quality. However, mothur's OptiClust or OptiFit are preferred for *de novo* or open reference clustering.

When fitting with the split dataset strategy, OTU quality was remarkably similar when reference sequences were selected by a simple random sample or weighted by abundance, but quality was slightly worse when sequences were weighted by similarity. We recommend using a simple random sample since the more sophisticated reference selection methods do not offer any benefit. The similarity in OTU quality between OptiClust and OptiFit with this strategy demonstrates the suitability of using OptiFit to fit sequences to existing OTUs, such as when using already-trained machine learning models to make predictions on new data.

- **TODO: big picture concluding paragraph**

Materials and Methods

Data Processing Steps

Benchmarking

Data and Code Availability

We implemented the analysis workflow in Snakemake (10) and relied on Python (11), R (12), and GNU bash. Software used includes mothur v1.45.0 (2), vsearch v2.13.3 (13), numpy (14), the Tidyverse metapackage (15), R Markdown (16), and the conda environment manager (17). The complete workflow, manuscript, and conda environment are available at **TODO: UPDATED REPO LINK**.

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Author Contributions

KLS wrote the analysis code, evaluated the algorithm, and wrote the original draft of the manuscript. SLW designed and implemented the OptiFit algorithm and assisted in debugging the analysis code. MBM and GAD contributed analysis code. PDS conceived the study, supervised the project, and assisted in debugging the analysis code. All authors reviewed and edited the manuscript.

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