Karp: Accurate and fast taxonomic classification using pseudoalignment



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Software available at https://github.com/mreppell/Karp



Introduction and Background

- Pooled DNA samples arise in many contexts, i.e. microbiome or artificial selection experiments
- Accurately classifying the frequencies of contributors is critical for finding factors associated with pool composition
- Karp is a novel method for classifying the relative frequencies of organisms in a pooled DNA sample that combines pseudoalignment with likelihood-based estimation
- Karp builds on Kessner et al (2013) which introduced a likelihood-based inference procedure for estimating sample composition, and Bray et al's (2016) pseudoalignment, an efficient alignment-free classification method

Overview of Karp (1) Pseudoalign reads to full reference database Query Read AAT - ATG - TGC - GCA - CAT - ATG GCA - CAT - ATG AAT - ATG - TGC GCA - CAT - ATG Reference 2 AAT - ATG - TGC GCA - CAT - ATG (2) Locally align reads Reference 4 AAT - ATG - TGC GCA - CAA - AAG to pseudoaligned references Reference Haplotypes (3) Calculate likelihood that read originated from Local specific reference Alignments Read ATGCGGCTATCG Log-likelihood of Base quality scores 810=G+FDFG#B Reference 1 ATGCGACTATCG -20.70 Reference 2 ATGCGACTACCG -29.21 Reference 3 ATGCGGCTTTCG -19.43 (4) Likelihood based filter removes reads unlikely to have originated from any reference in database (5a) Estimate individual reference Actinobacteria frequencies using EM algorithm Clostridia (Karp - Full) -or-Bacilli (5b) Aggregate counts of references with identical taxonomic labels before estimating frequencies using Flavobacterii Acidobacterii EM algorithm (Karp - Collapse)

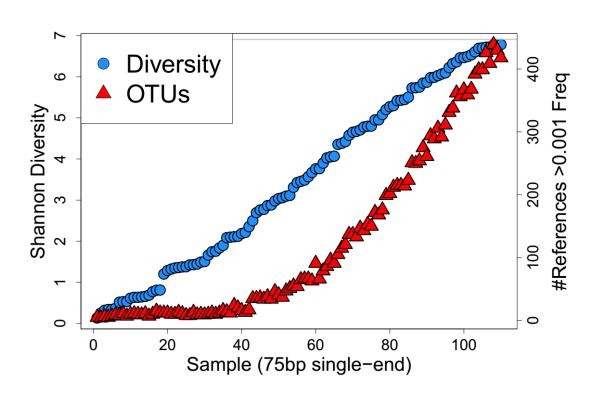
16S rRNA Simulations

- We simulate samples comprised of 1,000,000 total reads drawn from 1,000 different GreenGenes v13.8 references
- Each read is a partial copy of a reference haplotype with errors introduced according to base quality scores
- 3 scenerios with different empirical error distributions: 75bp single-end samples, 151bp paired-end samples, and 301bp paired-end samples
- Frequency of references in each sample chosen to vary across range of possible Shannon diversities (entropies)

Simulation Results

Erro. 1000-

250



— SortMeRNA

— USEARCH

Karp Full

— UCLUST

• Error metric = scaled summed absolute difference between true and estimated counts for each reference

75bp Single-end Reads

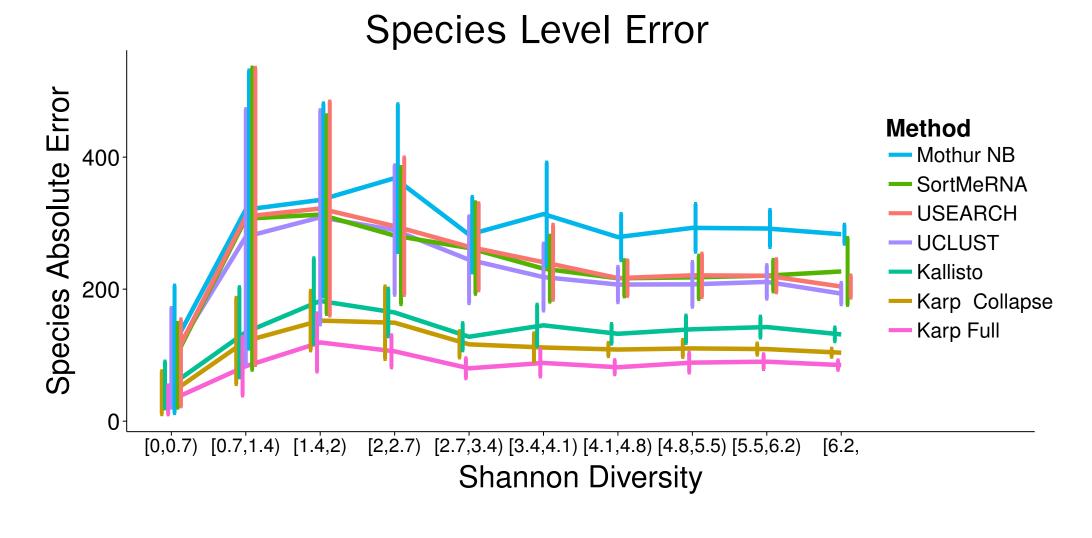
Method — SortMeRNA - USEARCH - UCLUST Kallisto [0,0.7) [0.7,1.4) [1.4,2) [2,2.7) [2.7,3.4) [3.4,4.1) [4.1,4.8) [4.8,5.5) [5.5,6.2) [6.2, **Shannon Diversity** 151bp Paired-end Reads Method <u>Е</u> Ш 1000-— SortMeRNA - USEARCH - UCLUST - Karp Full [0,0.7) [0.7,1.4) [1.4,2) [2,2.7) [2.7,3.4) [3.4,4.1) [4.1,4.8) [4.8,5.5) [5.5,6.2) [6.2,**Shannon Diversity** 301bp Paired-end Reads

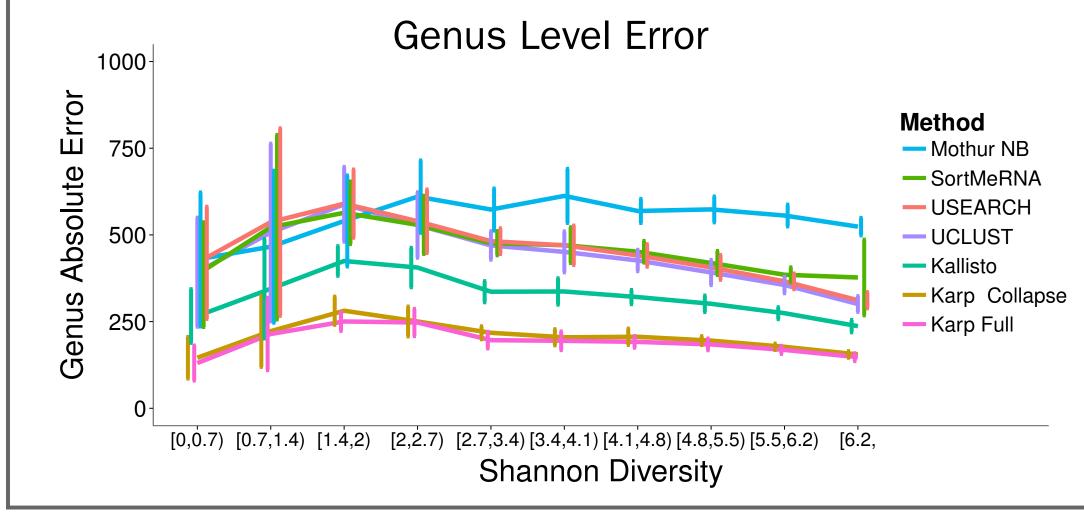
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Shannon Diversity

Higher Order Taxonomy

- Often researchers are interested in sample composition at the level of species, genus, or other higher order taxonomic classification, rather than individual reference sequences.
- Below we compare the accuracy of competing methods at higher orders in 75bp single-end read samples





Technical Tricks

- Karp is >100x faster than Harp (Kessner 2013) while maintaining inference accuracy. To achieve this Karp uses:
- Pseudoaligning to avoid >99.9% of alignments
- Highly parallelized functions
- Sparse data structure for encoding likelihoodsSquareEM for faster EM convergence (Varadhan 2004)
- For taxonomic level estimation rather than individual references, Karp Collapse mode further improves speed

Computational Performance

**to keep memory <16GB limited to 4 cores

• Time and memory to classify 1,000,000 75bp single-end reads against full GreenGenes v13.8 database using 12 cores:

Method	Time (Minutes)	Maximum Memory (GB)
Karp Full	179.5	10
Karp Collapse	37.5	10
Kallisto	5.1	10
QIIME UCLUST	84.3	4
QIIME USEARCH	9.5	4
QIIME SortMeRNA	35.8	4
Mothur Naive Bayes**	502.4	16

We would like to thank the NIH, University of Chicago Resource Computing Center, and the Ober and Gilbert Labs for their support of this project

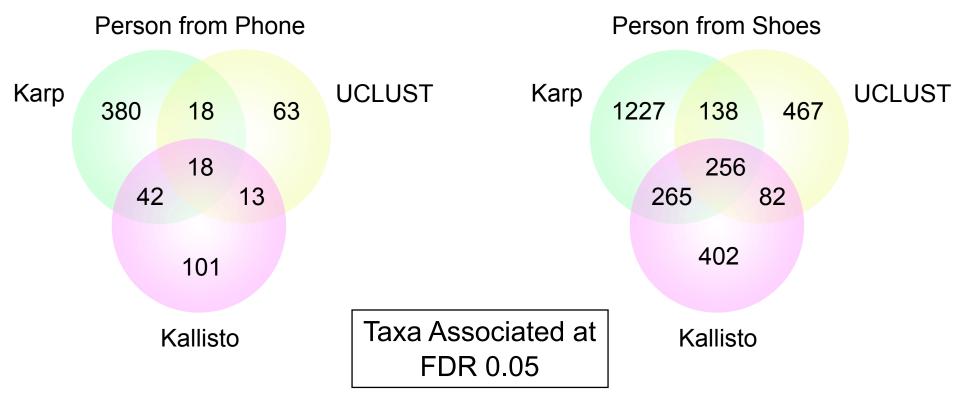
Real 16S Sequence Data

- From Lax et al (2015), samples collected from shoes and phones of two study participants every hour for two 12 hour periods
- V4 region of 16S rRNA gene amplified and sequenced, 151bp single-end reads
- We estimated sample composition with Karp, Kallisto and UCLUST, normalized to equal read depth, then used randomForest method to classify and measured error

	OTU Classification Error					
Method	Person from Phone	Person from Shoe	Phone Side from Person 1	Phone Side from Person 2		
Baseline	0.495	0.488	0.481	0.471		
Karp	0.029	0.001	0.292	0.245		
Kallisto	0.036	0.003	0.302	0.245		
UCLUST	0.04	0.004	0.398	0.278		

	Genus Classification Error					
Method	Person from Phone	Person from Shoe	Phone Side from Person 1	Phone Side from Person 2		
Baseline	0.495	0.488	0.481	0.471		
Karp – Full	0.048	0.005	0.371	0.321		
Karp – Collapse	0.046	0.004	0.363	0.287		
Kallisto	0.053	0.006	0.387	0.311		
UCLUST	0.044	0.002	0.392	0.3		

• In our classified samples we also tested for differences in the mean abundance of taxa between individuals



Conclusions

- In simulations Karp's estimated compositions are the closest to the true sample compositions across scenerios and taxa level
- In the real 16S data Karp's estimates often result in lower error when clustering samples, suggesting more power to detect important differences between samples
- While very fast, and nearly as accurate as Karp, Kallisto struggles with longer reads. Kallisto uses a stricter definition of pseuoaligning, leading to fewer matches and greater errors with longer reads