## Bioinformatics and Data analysis Software used List of software used... (html link if no citation available) FastQC v0.11.7 bbmap v38.05 STAR-2.5.2b bowtie2 v2.2.9 magicblast v1.3.0 SPAdes v3.13.1ncbi-blast v2.7.1 10 SegKit v0.11.0 11 Samtools v1.8 12 minimap2 v2.1 https://github.com/lh3/minimap2 13 sdust Release 0.1-r2 https://github.com/lh3/sdust LAST http://home.cc.umanitoba.ca/psgendb/doc/last/last.html 15 In Python v3.7.1 16 1. pandas v0.25.1 2. seaborn v0.9.0 18 3. matplotlib v2.2.3 4. matplotlib-venn v0.11.5 5. statsmodels v0.12.0 In R v4.05 1. polyester v1.26.0 Mystery Miner is available at is available at... https://github.com/senorelegans/MysteryMiner Layout of analysis This supplemental will follow closely along with the nextflow pipeline, subsequent filtering scripts, and the github

README. Inside of the main nextflow folder we have added a folder called RunFirst which should help building the various blast databases and indexes. All custom python scripts used in the pipeline are located under bin/src. Jupyter

script1.ipynb makes nb\_script1.py) using notebook2script.py. This provides a nice test driven environment to develop in

notebooks (.ipynb) in the src folder were used to generate python scripts with the correspond name (example:

For the explanations below we are assuming the nextflow out folder is called NF\_OUT

jupyter notebooks and is inspired by the fastai library https://www.fast.ai/

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1 Nextflow Pipeline	34
FastQC and Trimming	35
Reads were verified for quality using FastQC, over-represented sequences and adapter contamination were trimmed using bbduk and then rechecked with FastQC. The adapter file (adapters.fa) is located in the nextflow bin bbduk.sh in=R1.fastq.gz in2=R2.fastq.gz out=R1.trim.fastq.gz out=R1.trim.fastq.gz ref=bbmap_adapters	g 36 37 38 39 40 41 42
ktrim=r qtrim=10 k=23 mink=11 hdist=1	44
nullifybrokenquality=t maq=10 minlen=25	45 46
tpe tbo	47
literal=AAAAAAAAAAAAAAAAAAAA	48
Unmapped reads from target organisms (Human, Mice, Rat, etc)	49
Reads were aligned against the target organism using the following commands	50
STAR –genomeDir genome	51
-readFilesIn R1.trim.fastq.gz R2.trim.fastq.gz	52
-readFilesCommand zcat	53
-runThreadN 20	54
-runMode alignReads -outReadsUnmapped Fastx	55
outseasomapped rasix outseasomapped rasix	56
-outSAMtype SAM	57
-outFileNamePrefix name	58
-quantMode GeneCounts	59
-outFilterMultimapNmax 100	60
-outr intermunimapivimax 100	61
bowtie2	62
-q	63
-p 20	64
-x bowtie2_index	65
-1 Unmapped.out.mate1	66
-2 Unmapped.out.mate2	67
-S bowtie2.sam	68
-un-conc unmapped.fastq	69
magicblast	70
-query unmapped.1.fastq	71
-query_mate unmapped.2.fastq	72
-db magicblastDB	73
-infmt fastq	74
-outfmt tabular	75
-num_threads 20	76
-no_unaligned	77
-out blast.tsv	78

After magiculast, sequit is used to remove reads that match hits from magiculast. Additionally we have taken 400 reads out before magiculast, and add them back in after so that the assembly with spades won't fail.

Assembly

At this point we have unmapped reads ready for assembly. We assemble the samples as seperate single files, as well as concatenated by each condition (Control, Treatment1, Treatment2, etc), and all samples concatenated together (all). This gives us the different heirarchies of single, group, all. The concatenation step is important for the preprocessing for the LastALL step. It should be noted that spades can fail if you do not set the read orientation properly (=or in the nextflow pipeline). It might also fail if you put in too large of a kmer size (=kmer\_size in the nextflow pipeline). A general rule is to go a little under half your read length and set it to an odd number (Example: 75bp reads set kmer\_size to 35).

spades
--rna
--pel-or
--k kmer\_size
--pel-1 R1
--pel-2 R2
-o name\_spades
mv name\_spades/transcripts.fasta name\_spades.fasta

Nucelotide Blast

At this point we have contigs ready for nucleotide blast. This will give us taxid numbers we can query jgi with. We also add in fake/dummy contigs at this point as well so downstream processes won't fail. These sequences are located in dummysequences.fa in the bin. This will not be counted in the dataframe output but it is important to be aware of the dummy sequences so you do not mistake them as valid dark biome hits. This is also the point where any contigs not identified by BLAST are put into the darkbiome section of the pipeline.

blastn -db ntblastDB
-query fa\_withdummy
-max\_target\_seqs 1
-max\_hsps 1
-outfmt "6 qseqid sseqid pident evalue staxids sscinames scomnames sskingdoms stitle"
-out name\_unmapped.tsv
-num\_threads 30

### Joint Genome Institute (JGI) Query

At this point we can query the jgi server using the taxids identified by BLAST. Contigs matching Human, Mouse, Vertebrate, Viridiplantae, Artificial (synth or vector or Vector or artificial in the name) are removed and placed into the NF\_OUT/unmapped/final/filter/contigs/blast/. In this folder you will also find the initial contigs that were made using spades. This step corresponds to the jgiJSON.ipynb and nb\_jgiJSON.py scripts in the bin.

#### concat fasta for Bowtie2Index

At this step we will take all of the contigs that spade assembled and build bowtie2 indexes out of them so we can map reads to them. It is important that we are taking all of the contigs used in spades so reads that want to map back to "junk" contigs have the opportunity. Additionally, since we get counts for all of the contigs we can use these in subsequent normal and dark biome calculations.

bowtie2-build -threads 20 condition fasta condition

## Map with bowtie2 and run mpileup

Now that we have indexes we can map using bowtie2. After mapping we sort and index these bams then run mpileup to get read counts for each basepair.

bowtie2 -q

- -p 20
- -x condition
- -1 R1.fastq
- -2 fin\_R2.fastq
- -S fout\_condition.sam

samtools view -@ 20 -bS -o fout\_conditiontmp fout\_condition.sam

samtools sort -@ 20 fout\_conditiontmp ; fout\_condition.bam

 $samtools index fout\_condition.bam$ 

samtools mpileup -f fa fout\_condition.bam ; fout\_condition\_pileup.txt

#### Dark Biome Dust Filter

At this point we have finished the normal biome. At the start of the Dark Biome we get all of the contigs that do not have a BLAST hit. Next, we run a dust filter from minimap2 that identifies repetitive regions, and use the created bed file to remove these contigs using seqkit.

sdust fa\_withdummy > name\_dust\_mask.bed

## 2 Post Nextflow Scripts

After the nextflow pipeline run the bash script 2.0\_MysteryMiner\_Filter.sh to run all of the python scripts below

### Filter darkGenome using LASTDB and BLASTX

Now that we have dark biome contigs free of overly repetitive sequences we can use the different levels/heirarchies of assembly (single sample, group/condition concatenated) to filter contigs found when all samples are assembled together. The logic here is that we want retain contigs that have a greater than %60 identitiy between assembled heirarchies. Briefly, this consist of making indexes out of the contigs in each heirarchy, then doing pairwise alignment between heirarchies. We use the single and group contigs to create a set of group contigs that are filtered by singles (Group\_FS), then use the Group\_FS contigs to filter the set of contigs made from all of the samples concatenated together. This gives you All\_FG (All filtered by Group\_FS). Finally, we protein BLAST (BLASTX) All\_FG.

Contigs that have a BLASTX hit are identified with JGI similar and filtered similar to the normal biome, and can be located in the NF\_OUT/unmapped/final/darkbiome/lastdb/FINAL\_Tophits.

Contigs with no hits can be located in the NF\_OUT/unmapped/final/darkbiome/lastdb/FINAL\_Nohits folder. This step was too complicated to execute in the nextflow pipeline and can be found in the 1.0-FilterDarkGenome.py and nb\_1.0-FilterDarkGenome.py script in the bin.

## Pileup coverage and normalization

In order to normalize samples by library size, we use the total mapped reads to the target genome from STAR to create a normalization factor for each sample. Normalization factors for each sample are calculated by finding the samples with the fewest mapped reads (norm\_min), and dividing all of the other samples by the norm\_min. We make the assumption that we can scale samples by the number of reads mapping to target genome and any unmapped reads that are not used in this calculation will have a negligible effect on normalization factors.

Next, using the mpileup output we calculate coverage for each contig by summing all of the counts for each base pair in a contig and dividing by the length of the contig.

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Finally, we library normalize each contig coverage number in a sample by multiplying by the appropriate normalization factor of that sample.

This is done using the nb\_2.0-PileupNormalize and nb\_3.0-PileupDataFrame scripts in the bin.

### Fastq and contig counting

Now we count all of the Fastq reads and contigs and create dataframes showing the amount. This is done in the nb\_4.0-CountContigs scripts.

The amount of fastq reads removed at each step and for singles, groups, and all can be found in

NF\_OUT/unmapped/final/filter/fastq/fastq\_amount\_df.csv

The amount of regular biome contigs and amount removed at different filtering steps can be found in

NF\_OUT/unmapped/final/filter/contigs/blast/contigs\_amount\_df.txt'

The amount of dark biome contigs at each filtering step can be found in

NF\_OUT/unmapped/final/darkbiome/contigs\_amount\_dark\_afterblast.txt

### T-Test and quantification

In the script nb\_5FilterTtest.py a generic T-Test is ran for every permutation of conditions and ranks = ['superkingdom', 'kingdom', 'phylum', 'order', 'family', 'genus', 'species',"name"] and

superkingdoms = ['Bacteria', 'Viruses', 'Eukaryota', 'NA', 'Archaea']

After running this script you can look in NF\_OUT/FINAL\_OUT for the final output. As an example, if you wanted to look for bacteria reads binned by species for condition A and B you would go to the final output and open the folder A\_B\_Bacteria\_Bin\_species and look in A\_B\_Bacteria\_Bin\_species\_all\_pileupCoverageNormalizedMatched.txt for the regular biome or A\_B\_Bacteria\_Bin\_species\_dark\_all\_pileupCoverageNormalizedMatched.txt for the dark biome. There is also a folder for dark biome contigs in each comparison. The folder A\_B\_OUT\_ALL\_CONTIGS contains the individual contigs, fastas, and T-Test for that comparison.

Inside you will see output for doubledark

To create a custom query and T-Test open up the notebook 6.0-CustomTtest.ipynb once the other scripts are finished. This will allow you to create custom queries and remove taxonomies at different levels or select a particular taxonomy to look at. Detailed instructions are in the jupyter notebook.

A two-sided T-Test is ran using stats.ttest.ind from scipy and a padj value is calculated using the number of contigs or species in the dataframe using statsmodels.sandbox.stats.multicomp.fdrcorrection0 from statsmodels.

The significance threshold is set to 0.05 but can be changed inside the script.

# Synthetic minibiome

We first used Polyester set to 10 replicates with two groups, error rate set to 0.005, paired end = TRUE, readlen = 100, and seed = 12.

We then generated the chr22 fasta using the default command from polyester

fasta\_file = system.file('extdata', 'chr22.fa', package='polyester')

Next, we took the first 10 sequences from that and the first 10kb of the sequence. We then generated reads with no fold change difference and coverage set to 1000.

We next took the fastas of the sequences described in the paper and took the first 10kb from them. Next, we generated reads at multiple coverage levels from 1000 down to 0.01 in multiples of ten. We then combined these files.

We then used reformat.sh from bbmap to generate read quality scores from the output of polyester.

Finally, we combined the fastqs from human and minibiome using the "cat" command in bash and ran it through Mystery Miner.

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### Creating RDRP phylogeny tree

We first used BLASTX from the BLAST website on default settings on the contig to find similar hits. We then took the hits along with the RDRP contig performed multiple sequence alignment using CLUSTALW2 on default settings. https://www.ebi.ac.uk/Tools/msa/clustalo/. Next, we used the alignments to build the tree using Simple Phylogeny on default settings https://www.ebi.ac.uk/Tools/phylogeny/simple\_phylogeny/.

RDRP contig amino acid sequence used in BLASTX 208  ${\tt DEGSLESRGEDTKTRRSDQNPQGDIITDAEYAEVIHALKGYVWPDRSSNAELTSLLYQTGLGNTCTPECD}$ 209 IFVKTKFSTIVSTCTSLYPKSNCHEDKASDVAFIHDVIRSELYTHTSVWDASPGYPFQIVYPTLLDLVDS 210 EPSALITLTLLLILRWGLTPHSQVRLMTAAELFEAKLTFLVRLFVKQEPHPVQKALDGRWRLVSSVPSHV 211 NVAARVLLGPQHRLNIRSCDYISPSIGLGLSDPMIQTHIRKAAMVEDSFGLVSSDQSGFDWRFYLLWADV212 IAQVWVNLTCATGFWENAIRNYCYTMVFSYYVLSDGRIFGLLIPAARKSGDLDTGSGNSLHRIALNITIR 213 LWLKLERPSLVNRSVLPAMTMGDDCCESFGTRVDGPTLVEMFRQLGFKLTDVVIGSRNRFEFCSTRFEYD214 GSWTITPLSWPRMLFRLLSQEPKQEFLDQFKYELRNLTGVYGGVNLRMLCLFLDRVGWKVPFDSPTNL 215

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