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 series of data transformations /
 operations (e.g. joining paired-end reads,
 assembling reads into longer sequences, aligning
 sequences to a reference genome, calling variants etc.)





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 or multiple samples / input files

steps

execution





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- to be run **sequentially** or **in parallel** on one or **multiple samples** / input files

steps

execution



this calls for a **structured** / organized **pipeline** / workflow of analysis





- large datasets
- embarrassing parallelization (hundreds of jobs)
- many different tools, scripts, languages (dependencies) → difficult to maintain and to update, almost impossible to make it portable



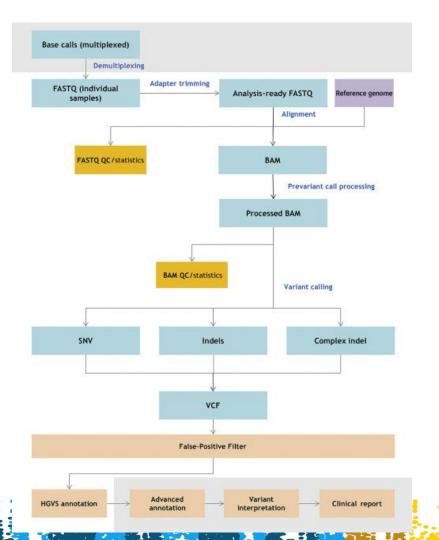
this calls for a **structured** / organized **pipeline** / workflow of analysis





bioinformatic pipelines

 chaining together multiple consecutive steps (processes) of a data analysis problem/project





bioinformatic pipelines

(Roy et al, 2018)



bioinformatic pipelines

- chaining together multiple consecutive steps of a data analysis problem/project
- advantages:
 - reproducibility
 - modularity
 - parallelization
 - scalability
 - portability
 - usability
 - automation



bioinformatic pipelines - reproducibility

Reproducibility: quantum mechanics (probabilistic world) \rightarrow average (statistical) reproducibility (besides, different environments / different labs \rightarrow different results are expected); this is true also in bioinformatics (same pipeline, same data, different machines \rightarrow different results are possible: underlying variance in the libraries, floats, machines -e,g, Mac cs Linux- and so on ...)

- https://journals.plos.org/plosone/article?id=10.1371/journal.pone.008
 0278;
- https://www.nature.com/articles/nbt.3820



- stand-alone **scripts**: e.g. Unix shell, Python etc.
 - features: variables, conditional logic
 - limitations: no support for dependencies and reentrancy (e.g. concatenated steps, adding input samples, updating parameters/resources, recovering from local failures, run/start intermediate steps etc.)



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- Make: compilation / build automation tool [Stallman and McGrath, 2020]
 - wse an instruction file (Makefile) to generate a target (e.g. compiled software)
 - features: wildcards, dependency tree



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- Make: compilation / build automation tool
 - use an instruction file (Makefile) to generate a target (e.g. compiled software)
 - wildcards = "card" (string) used to represent any other "card" (string),
 - e.g. ls -alt *.map (lists all map files in folder)
 - * stands for any prefix before .map (it is a wildcard)



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- Make: compilation / build automation tool
 - wse an instruction file (Makefile) to generate a target (e.g. compiled software)
 - dependency tree: file modification datetimes are used to determine which steps are required to generate the target



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- Make: compilation / build automation tool
 - use an instruction file (Makefile) to generate a target (e.g. compiled software)
 - features: wildcards, dependency tree
 - limitations: not designed for scientific pipelines, no direct support for distributed/parallel computing, insufficient flexibility for complex parameters, input data, execution logic etc.



bioinformatic pipelines - available frameworks

- pipeline execution engines / workflow management systems
 - Snakemake: https://snakemake.readthedocs.io/en/stable/
 - Nextflow: https://www.nextflow.io/
 - Pipeline for GWAS? (<u>under construction</u>)
 - BigDataScript: https://pcinqola.github.io/BigDataScript/
 - Pipengine: https://github.com/fstrozzi/bioruby-pipengine



bioinformatic pipelines - reading a bit more



Briefings in Bioinformatics, 18(3), 2017, 530-536

doi: 10.1093/bib/bbw020 Advance Access Publication Date: 24 March 2016 Paper

A review of bioinformatic pipeline frameworks

Jeremy Leipzig

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Abstract

High-throughput bioinformatic analyses increasingly rely on pipeline frameworks to process sequence and metadata. Modern implementations of these frameworks differ on three key dimensions: using an implicit or explicit syntax, using a configuration, convention or class-based design paradigm and offering a command line or workbench interface. Here I survey and compare the design philosophies of several current pipeline frameworks. I provide practical recommendations based on analysis requirements and the user base.

Key words: pipeline; workflow; framework



Snakemake



bioinformatic pipelines - Snakemake

BIOINFORMATICS APPLICATION NOTE

Vol. 28 no. 19 2012, pages 2520–2522 doi:10.1093/bioinformatics/bts480

Genome analysis

Advance Access publication August 20, 2012

Snakemake—a scalable bioinformatics workflow engine

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¹Genome Informatics, Institute of Human Genetics, University of Duisburg-Essen and ²Paediatric Oncology, University Childrens Hospital, 45147 Essen, Germany

Associate Editor: Alfonso Valencia

- Pythonic variant of GNU Make
- Makefile → Snakefile





bioinformatic pipelines - Snakemake

- pipelines are defined in terms of **rules** that define how to create output files from input files:

input \rightarrow [rule] \rightarrow output

 dependencies between the rules are determined automatically, creating a DAG (directed acyclic graph) of jobs that can be automatically parallelized



Snakemake - the snakefile

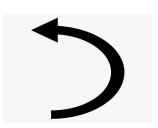


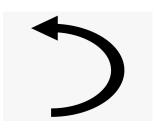
```
## target rule: files that we want to generate
## as final output of the pipeline
rule targets:
    input:
       "snp sorted.map.gz"
## step 2
## rule to compress the sorted map file
rule gzip:
    input:
       "snp sorted.map"
    output:
       "snp sorted.map.gz"
    shell:
        "gzip {input}"
## step 1
## rule to sort the map file
rule sort:
    input:
       "snp.map"
    output:
        "snp sorted.map"
    shell:
        "sort -n -k1 {input} > {output}"
```

Snakemake - the snakefile

```
Poysalia Courses
```

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```





[if exists(snp_sorted.map.gz)] else:

[if snp_sorted.map.gz > snp_sorted.map] else:

[if snp_sorted.map > snp.map] else:



Snakemake - the snakefile



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```

keywords: rule, input, output, shell

wildcards: {}, {input}, {output}



Snakemake - execution

snakemake --help

snakemake --dryrun --snakefile example snakefile



Snakemake - execution

```
snakemake --help
snakemake --dryrun --snakefile example snakefile
snakemake -n -s example snakefile
[have a look at the log from the dry run]
                                                short option
```

names



Snakemake - the DAG

```
snakemake --dag --dryrun --snakefile
example snakefile | dot -Tsvg > dag example.svg
```





Snakemake - execution

snakemake --snakefile example_snakefile --cores 1

- true run
- check output



Snakemake - execution

snakemake --snakefile example snakefile -c 1

- actual run
- check output
- 4

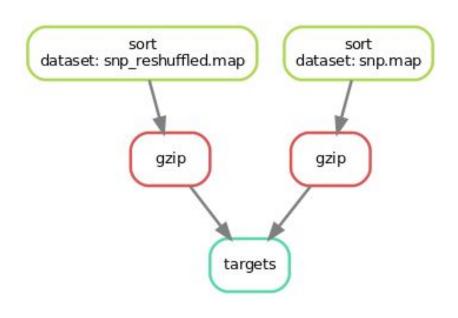
what happens if you unzip the sorted file? (try first the dry run, then the actual run)



Snakemake - multiple samples



```
## samples
DATASETS = ['snp.map', 'snp reshuffled.map']
## target rule: files that we want to generate
rule targets:
    input:
        expand("{dataset}.sorted.gz", dataset=DATASETS)
## step 2 - rule to compress the sorted map file
rule gzip:
    input:
        "{dataset}.sorted"
    output:
        "{dataset}.sorted.gz"
    shell:
        "gzip {input}"
## step 1 - rule to sort the map file
rule sort:
    input:
        "{dataset}"
    output:
        "{dataset}.sorted"
    shell:
        "sort -n -k1 {input} > {output}"
```





Snakemake - multiple samples

```
snakemake -n --snakefile example_snakefile_2 | dot -Tsvg >
dag_example.svg
```

snakemake --snakefile example_snakefile_2 --cores 1

- dry run
- actual run



The GWAS pipeline



GWAS pipeline - the atomized steps

- 1. download and prepare the data
- 2. data preprocessing and filtering
- 3. imputation of missing genotypes
- 4. GWAS



GWAS pipeline - the atomized steps

- 1. download and prepare the data
- 2. data preprocessing and filtering
- 3. imputation of missing genotypes
- 4. GWAS
- each folder contains a bash script to remove intermediate and output files (reset the step): clean_folder.sh
- set the correct paths to resources in the bash scripts (e.g. Plink, Beagle etc.)



- 1. download and prepare the data
 - a. 1.get_data.sh → get_rice_data.sh, get_dog_data.sh
- 2. data preprocessing and filtering
 - a. 01_data_handling_and_eda.sh [optional]
 - b. 2.steps_filtering.sh
- 3. imputation of missing genotypes
 - a. 3.step_imputation.sh
- 4. GWAS
 - a. 4.gwas.sh



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- data preprocessing and filtering
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 - b. 2.steps_filtering.sh → rule filter_genotypes

```
plink --ped rice.ped --map rice.map --geno 0.05 --mind 0.2 --maf
0.05 --recode --out rice filtered
```

- 3. imputation of missing genotypes
 - a. 3.step_imputation.sh
- 4. GWAS
 - a. 4.gwas.sh



- 1. download and prepare the data
 - a. 1.get_data.sh → get_rice_data.sh, get_dog_data.sh
- 2. data preprocessing and filtering
 - a. 01_data_handling_and_eda.sh [optional]
 - b. 2.steps_filtering.sh → rule filter_genotypes
- 3. imputation of missing genotypes
 - a. $3.imputation.sh \rightarrow rule impute_genotypes$

```
beagle gt=rice filtered.vcf out=rice imputed
```

- 4. GWAS
 - a. 4.gwas.sh





- 1. download and prepare the data
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- 2. data preprocessing and filtering
 - a. 01_data_handling_and_eda.sh [optional]
 - b. 2.steps_filtering.sh → rule filter_genotypes
- 3. imputation of missing genotypes
 - a. 3.step_imputation.sh → rule impute_genotypes
- 4. GWAS
 - a. 4.gwas.sh → rule gwas_kinship

```
Rscript --vanilla gwas_rrblup.R genotype_file=rice_imputed.raw
snp_map=rice_imputed.map phenotype_file=rice_phenotypes.txt trait=PH
trait label=plant height
```





Let's assemble our GWAS pipeline with Snakemake!

- Begin with the rice dataset (continuous phenotype)



The GWAS pipeline for rice plant height



Prepare the environment:

```
mkdir data
mkdir steps
cp -r ../software .
cp ../4.gwas/gwas_rrblup.R software
cp ../4.gwas/gwas_statgengwas.R software
cp ../1.preparatory_steps/prep_rice_data_pipeline.R software
cp ../cross_reference/rice_group.reference_software
```



The GWAS pipeline for rice plant height

- The Snakemake pipeline file: Snakefile_GWAS.continuous
 - i. get data
 - ii. filter genotypes
 - iii. ped2vcf
 - iv. impute genotypes
 - v. vcf2ped
 - vi. plink recodeA
 - vii. gwas_kinship



The GWAS pipeline for rice plant height

The Snakemake pipeline file: Snakefile_GWAS.continuous

snakemake -n -p -s Snakefile_GWAS.continuous snakemake --dag -n -s Snakefile_GWAS.continuous | dot -Tsvg > dag_rice.svg



The GWAS pipeline for rice plant height

The Snakemake pipeline file: Snakefile_GWAS.continuous

snakemake -n -p -s Snakefile_GWAS.continuous snakemake --dag -n -s Snakefile_GWAS.continuous | dot -Tsvg > dag_rice.svg snakemake -s Snakefile_GWAS.continuous --cores 1





The GWAS pipeline for dogs cleft lip (binary phenotype)



The Snakemake pipeline file: Snakefile_GWAS.binary



include preparatory steps in a bash script

bash snakefile command line binary.sh



The GWAS pipeline for dogs cleft lip (binary phenotype)



The Snakemake pipeline file: Snakefile_GWAS.binary



include preparatory steps in a bash script

bash snakefile_command_line_binary.sh bash snakefile_command_line_knni.sh





MOLECULAR ECOLOGY

Molecular Ecology (2013) 22, 3949-3962

doi: 10.1111/mec.12376

Genomic dissection of variation in clutch size and egg mass in a wild great tit (*Parus major*) population

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data from a paper on genetic analysis of clutch size and egg mass in Parus major







Phenotypes

- egg numbers (clutch size)
- egg mass





- repository: https://datadryad.org/resource/doi:10.5061/dryad.ck1rg
- article: https://onlinelibrary.wiley.com/doi/pdf/10.1111/mec.12376

focus on:

- 1. understand the data and the problem/project at hand
- 2. manipulate the data to get them in the same format as the dogs and rice data before the filtering/imputation steps

challenges:

- multiple phenotypes per individual (over time)
- errors/missing values in the genotype data





Alternatively, you could use another phenotype from the rice dataset. File plantgrainPhenotypes.txt

- Panicle length (PL)
- Length of the flag leaf (FLL)
- Width of the flag leaf (FLW)
- Length of the seed (SL)
- Seed width (SW)
- Seed length/width ratio (SR)

you can also consider "binarising" a trait



- 1. Get and prepare the data
- 2. Explore and filter the data
- 3. Impute missing genotypes
- 4. GWAS
- Make a R Markdown report or slides with steps, results and interpretation

optional

- add extra steps: e.g. get genes from SNPs
- make a step in the pipeline to prepare the environment (folder to make, files to copy etc.)



GWAS pipeline - collaborative exercise

- Build your own pipeline!
 - a. Download the data
 - b. Prepare the data (look at the phenotypes!)
 - c. Filter the data
 - d. Impute missing genotypes
 - e. Run the GWAS
- Data on stump tail sperm defect of Swiss Large White boars (https://zenodo.org/record/4081475#.YKPfmnUzZhE)
- 1. Try on your own (individually, groups)
- 2. Let's do it all together!



NEXT LECTURE

Introduction to GWAS: collaborative exercise