

# Managing the Execution of Project Workflows

Snakemake

Programming Practices for Research in Economics

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# Some Reflection

What have we done so far:

- ① Use the command line to pass instructions to computer as text
- ② Version control with git
- ③ Programming and Data Analysis with Python and R

That is essentially **all** the ingredients we need to do the coding tasks within a paper or research project

How do we manage the workflow of the project?

- ▶ What code is executed when?
- ▶ What inputs does a given script need to run?

# Exhibit A

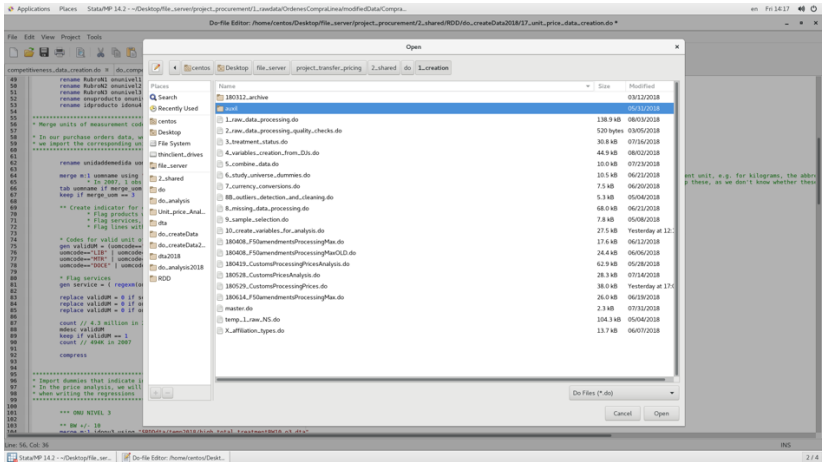
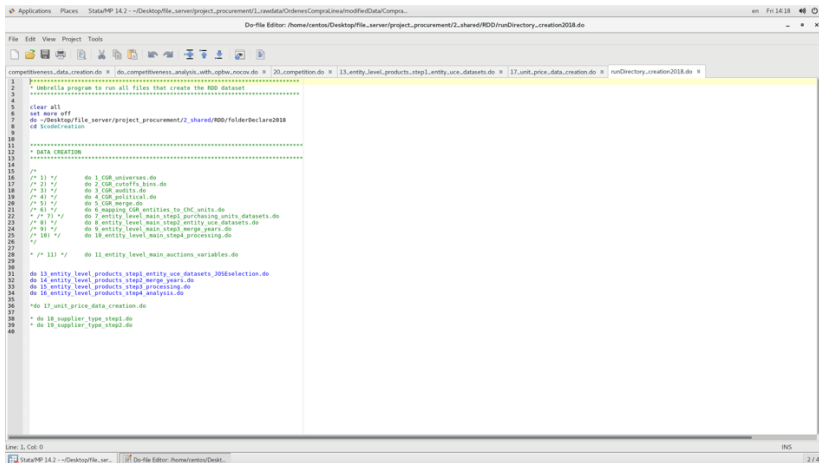


Figure 1: A typical research project

# Exhibit B



The screenshot shows a Do-file Editor window titled "Do-file Editor: /home/centos/Desktop/file\_server/project\_procurement/2\_shared/RD0/runDirectory\_creation2018.do". The editor contains a series of commands for data processing and analysis, including clearing all, setting more off, and running various data creation and analysis scripts. The commands are organized into sections, with some commented out. The status bar at the bottom indicates "Line: 1, Col: 0" and "INS".

```
1 *****
2 Umbrella program to run all files that create the RD0 dataset
3 *****
4
5 clear all
6 set more off
7 do ../Desktop/file_server/project_procurement/2_shared/RD0/folderDeclare2018
8 cd $codeCreation
9
10
11 *****
12 * DATA CREATION
13 *****
14
15 /*
16 /* 1) */ do 1_CGR_universes.do
17 /* 2) */ do 2_CGR_cutoffs_bins.do
18 /* 3) */ do 3_CGR_audit.do
19 /* 4) */ do 4_CGR_political.do
20 /* 5) */ do 5_CGR_merge.do
21 /* 6) */ do 6_mapping_CGR_entities_to_CHC_units.do
22 /* 7) */ do 7_entity_level_main_step1_purchasing_units_datasets.do
23 /* 8) */ do 8_entity_level_main_step1_entity_use_datasets.do
24 /* 9) */ do 9_entity_level_main_step3_merge_years.do
25 /* 10) */ do 10_entity_level_main_step4_processing.do
26 /*
27
28 /* 11) */ do 11_entity_level_main_auctions_variables.do
29
30 do 13_entity_level_products_step1_entity_use_datasets_30SEselection.do
31 do 14_entity_level_products_step2_merge_years.do
32 do 15_entity_level_products_step3_processing.do
33 do 16_entity_level_products_step4_analysis.do
34
35
36 *do 17_unit_price_data_creation.do
37
38 * do 18_supplier_type_step1.do
39 * do 19_supplier_type_step2.do
40
```

Figure 2: Another typical research project

# Solutions for Managing Project Workflows

- ❶ Keep it all in your head
  - ▶ **a bad idea!**
- ❷ Writing a long README detailing your workflow
  - ▶ painful! rarely maintained simultaneously with code
- ❸ A “master file”
  - ▶ potentially keeps track of the order things should run
  - ▶ executes everything... might be very slow
  - ▶ might not be re-run often
- ❹ A bash script
  - ▶ order of execution will matter, dependencies must be specified
  - ▶ always executes everything
    - ▶ inefficient and slow!
- ❺ A build tool, like Snakemake
  - ▶ Keeps track of order of execution
  - ▶ understands which steps depends on which previous step
  - ▶ re-runs steps only if upstream scripts or data has been updated

# Today's plan

Build up our familiarity with Snakemake

- ▶ We will start simple . . .
- ▶ . . . at the end we will run a whole term paper typing just **two words**

## Aside - Directory structure

- ▶ Keep inputs and outputs separate
- ▶ Separate codes and data into logical subdirectories
- ▶ Call scripts from main directory

```
| - project-folder, `.`  
|   | - input  
|       | - code  
|       | - latex  
|       | - raw-data  
|   | - output  
|       | - data  
|       | - graphs  
|       | - tables
```

# Aside - Setting Up Packages

We want our code to run on anyone's machine

- ▶ Now, and in months, years after it is hopefully published.

One way to ensure this?

- ▶ Set up an 'environment' that freezes our packages (Python)
- ▶ Use packrat for R
- ▶ Stata - *harder to do*, have to install all ssc installed packages to a library inside our ROOT and ensure these are used.

Alternative? check out Docker, but we don't know how to use it



# Aside - Windows Users

- ▶ We have tried to get many different workflow management tools to work inside Cygwin or other Unix emulators
  - ▶ It usually breaks something
- ▶ We will use Powershell which is the native windows command line interface
  - ▶ Main differences:
    - ▶ Replace / with \\ everywhere
    - ▶ `rm filename` is a longer line

# Project Structure

# Hands on

## Example Project: Testing Zipf's Law

# Project: Zipf's Law

- ▶ **Zipf's Law:** The most frequently-occurring word occurs approximately twice as often as the second most frequent word.
- ▶ Our workflow:
  - ① Count occurrence of words in multiple texts
  - ② Plot the most occurring words for each text in a histogram
  - ③ 'Test' Zipf's Law
  - ④ Integrate results into a manuscript

# A Simple Directory Structure

```
| - src
|   | - data
|       |- abyss.txt
|       |- isles.txt
|       |- last.txt
|       |- LICENSE_TEXTS.md
|       |- sierra.txt
|   | - analysis
|       |- plotcount.py
|       |- wordcount.py
|       |- zipf_test.py
```

- Ignore (4) - integrating into a paper for now...

# What the Scripts Do

- ▶ `wordcount.py` counts the occurrence of words in a text

```
$ python src/analysis/wordcount.py src/data/isles.txt \
    out/analysis/isles.dat
```

- ▶ `plotcount.py` plots a histogram of the word occurrences

```
$ python src/analysis/plotcount.py out/analysis/isles.dat \
    out/figures/isles.png
```

- ▶ `zipf_test.py` tests Zipf's Law on for a set of texts

```
$ python src/analysis/zipf_test.py \
    out/analysis/abyss.dat \
    out/analysis/isles.dat \
    > out/final/results.txt
```

# A Bad Workflow Management Technique

## It's (probably) all in the mind

Logic:

- ① We know what the scripts do
- ② We remember what our data looks like and what we have
- ③ Manually invoke these scripts as we need them

**seems inefficient. . .**



# Shell Scripting

# Managing a Workflow with a Shell Script

## It's (almost) all written down

Logic:

- ① We know what the scripts do
- ② Write down all the commands we need to execute in a single script
- ③ Call shell script to execute entire workflow each time we change something

**we are making progress. . .**

# Writing a Shell Script

```
# runPipeline.sh
# Contributor: Lachlan Deer (@ldeer)
# See 'README.md' for explanation of
#   what this file does.
# Expected Usage:
#   $ bash runPipeline.sh

## Count Words of texts
python src/analysis/wordcount.py src/data/isles.txt \
    out/analysis/isles.dat
<...>

## Plot word count distributions
python src/analysis/plotcount.py out/analysis/isles.dat \
    out/figures/isles.png
<...>
```

# Writing a Shell Script (cont.)

```
## Test Zip's Law
python src/analysis/zipf_test.py \
    out/analysis/abyss.dat \
    out/analysis/isles.dat \
    > out/final/results.txt
```

Execute the script with

```
$ bash runPipeline.sh
```

# Advantages of a Shell script

This shell script solves several problems in computational reproducibility:

- 1 It explicitly documents our pipeline, making communication with colleagues (and our future selves) more efficient.
- 2 It allows us to type a single command, `bash runPipeline.sh`, to reproduce the full analysis.
- 3 It prevents us from *repeating* typos or mistakes. You might not get it right the first time, but once you fix something it'll stay fixed.

# Disadvantages of a Shell script

- ▶ We shouldn't need to recreate all the files each time - only the ones that would be updated / created with our changes
- ▶ Commenting out lines, and subsequently uncommenting them, can be a hassle and source of errors in complicated pipelines.

Want an executable *description* of our pipeline that allows software to do the tricky part for us: figuring out what steps need to be rerun.

# Workflow Management with Snakemake

# What we need

We want to be able to

- 1 Keep track of our analysis pipeline
- 2 Specify inputs and outputs explicitly
- 3 Keep track of complicated file dependencies
- 4 Only execute code that will update/create new outputs when scripts are modified
- 5 Be concise, without resorting to over abstraction
- 6 Not have to learn *yet another faddish programming language*
- 7 Use a tool designed to manage research workflows, not adapted from other purposes
- 8 Interface with (some types of) computing clusters and cloud computing environments



## Snakemake—a scalable bioinformatics workflow engine

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### ABSTRACT

**Summary:** Snakemake is a workflow engine that provides a readable Python-based workflow definition language and a powerful execution environment that scales from single-core workstations to compute clusters without modifying the workflow. It is the first system to support the use of automatically inferred multiple named wildcards (or variables) in input and output filenames.

**Availability:** <http://snakemake.googlecode.com>.

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### 1 INTRODUCTION

custom server processes running on the cluster nodes. Finally, Snakemake is the first system to support file name inference with multiple named wildcards in rules.

### 2 SNAKEMAKE LANGUAGE

A workflow is defined in a 'Snakefile' through a domain-specific language that is close to standard Python syntax. It consists of rules that denote how to create output files from input files. The workflow is implied by dependencies between the rules that arise from one rule needing an output file of another as an input file.

A rule definition specifies (i) a name, (ii) any number of input and output files and (iii) either a shell command or Python code that creates the output from the input. Input and output files

**Figure 3: Snakemake**

# Key Ideas of Snakemake

- ① Define rules that ultimately execute a script from a shell
- ② Within a rule specify (multiple) inputs and outputs
- ③ Only execute a rule if an input (i.e a dependency) changes
- ④ Encapsulates DRY principle - one rule can be used to run a single script on multiple input combinations

Let's see it in action...

# Our First SnakeFile

- ▶ Want to count words from the text `abyss.txt`, save output in `abyss.dat`
- ▶ Create a file `Snakefile` in our working directory and enter the following:

```
rule abyss:
    input: "src/data/abyss.txt"
    output:
        "out/analysis/abyss.dat"
    shell:
        "python src/analysis/wordcount.py \
         src/data/abyss.txt \
         out/analysis/abyss.dat"
```

- ▶ Execute by typing `snakemake` into your terminal and pressing Return

# Dependencies and Updating Output I

- ▶ Try and re-run our Snakefile, we get the following:

```
Nothing to be done.
```

- ▶ Why?

# What's Happening?

When asked to build a target:

- ① Snakemake checks the 'last modification time' of both the target and its dependencies.
  - ② If any dependency has been updated since the target, then the actions are re-run to update the target.
- ▶ Snakemake knows to only rebuild the files that, either directly or indirectly, depend on the file that changed.
  - ▶ This is called an **incremental build**

# What's Going On

- ▶ Snakemake has an option `summary` that documents important information for us:

```
$ snakemake --summary
```

```
output_file          date
out/analysis/abyss.dat Thu May 18 09:36:50 2017
```

```
rule    version log-file(s) status  plan
abyss    -                ok      no update
```

# What's Going On II

- Now let's remove `abyss.dat`, and check the summary output

```
$ rm -rf out/analysis/abyss.dat  
$ snakemake --summary
```

```
output_file          date  
out/analysis/abyss.dat -
```

```
rule  version  log-file(s)  status  plan  
abyss  -              missing update pending
```

# Looking at Snakemake's Execution Plan

- ▶ Snakemake has a dry-run option that allows us to see what operations it will perform without executing them

```
$ snakemake -n

rule abyss:
  input: src/data/abyss.txt
  output: out/analysis/abyss.dat
  jobid: 1

Job counts:
count  jobs
1      abyss
```

- ▶ Re-run snakemake



# What's Going On III

- Now let's update an input `abyss.txt`, and check the summary output

```
$ touch src/data/abyss.txt
$ snakemake --summary

output_file date
out/analysis/abyss.dat Thu May 18 09:52:20 2017

rule      version log-file(s) status
abyss     -                updated input files

plan
update pending
```

## Challenge: Create a New Rule

- ▶ Construct a rule, called 'isles' that counts the words from `isles.txt` and saves the output in `isles.dat`
- ▶ Place the rule above the one we made for `abyss`
- ▶ Time: 5 mins

# Creating a 'Clean' Rule

- ▶ Sometimes we want to clean out files that were generated by scripts.

```
rule clean:  
    shell:  
        "rm -f out/analysis/*.dat"
```

- ▶ Execute the rule with `snakemake clean`
- ▶ Try and re-run our analysis with the command `snakemake`

# Creating 'Target Rules'

- ▶ At the top of our Snakefile we can write a rule that will ensure all our outputs are created
- ▶ How?
  - ▶ Rule with no outputs or shell commands
  - ▶ Inputs are the files we want created.

```
rule processedData:  
    input:  
        isles = "out/analysis/isles.dat"
```

## Challenge: Update our Target Rule

- ▶ Update the target rule so that all our outputs can be constructed with one call to `snakemake`
- ▶ Time: 5 mins

# Automatic Variables

# Where we are now

- ▶ Snakefile has a lot of duplication.
- ▶ For example, the names of text files and data files are repeated in the input and output as well as the call to the shell.
- ▶ Snakefiles are a form of code and, in any code, repeated content can lead to problems
  - ▶ e.g. we rename a data file in one part of the Snakefile but forget to rename it elsewhere.
- ▶ Violates one of our early stated principles: DRY!
- ▶ Let us set about removing some of the repetition from our Snakefile.

# Automatic Variables

- ▶ Snakemake has 'macros' that allow us to directly use the inputs and outputs we specify in the shell command
- ▶ Unsurprisingly, they are called {input} and {output}

```
rule abyss:
    input: "src/data/abyss.txt"
    output:
        "out/analysis/abyss.dat"
    shell:
        "python src/analysis/wordcount.py \
         {input} {output}"
```



## Challenge: Update our Target Rule

- ▶ Update the rule `isles` using the input and output macros
- ▶ Create a new rule `last` that counts the words of the text `last.txt` using input and output macros
- ▶ Time: 5 mins

# The expand Function

- ▶ The processedData rule also has some duplication, all the inputs follow a similar pattern
- ▶ We can remove duplication by using snakemake's expand function to reduce this

```
TEXTS = ["abyss", "isles", "last"]

rule processedData:
    input: expand("out/analysis/{iText}.dat",
                 iText = TEXTS)
```

## Challenge: Create a results rule

- ▶ Create a rule `results` at the top of the Snakefile, that takes all data we have produced as inputs and tests Zipf's Law, producing the output `out/final/results.txt`
- ▶ Your rule should use everything we have learned so far:
  - ▶ `{input}`, `{output}`, `expand(<...>)`
- ▶ Time: 10 mins

# Dependencies

# Getting Dependencies Right

- ▶ Our data files are a product not only of our text files but the script, `wordcount.py`, that processes the text files and creates the data files.
- ▶ A change to `wordcount.py` (e.g. to add a new column of summary data or remove an existing one) results in changes to the `.dat` files it outputs.
- ▶ So, let's pretend to edit `wordcount.py`, and re-run Snakemake:

```
$ touch ./src/analysis/wordcount.py  
$ snakemake
```

# Getting Dependencies Right

```
Nothing to be done.
```

- ▶ We need to add `wordcount.py` as a dependency of each of our data files

# Specifying Multiple Inputs or Outputs:

```
rule abyss:
    input:
        data = "src/data/abyss.txt",
        script = "src/analysis/wordcount.py"
    output:
        "out/analysis/abyss.dat"
    shell:
        "python {input.script} {input.data} {output}"
```

# Getting Dependencies Right!

- ▶ Intuitively, we want to add `wordcount.py` as dependency for `results`,
  - ▶ as the final table should be rebuilt as we remake the `.dat` files.
- ▶ However, it turns out we don't have to!
  - ▶ Let's see what happens to `results` when we update `wordcount.py`...



# Getting Dependencies Right!

- ▶ The whole pipeline is triggered, even the creation of the `results` file!
- ▶ Why?
  - ▶ `results` depends on the `.dat` files.
  - ▶ The update of `wordcount.py` triggers an update of the `*.dat` files.
  - ▶ Thus, `snakemake` sees that the dependencies (the `.dat` files) are newer than the target file (`results.txt`) and thus it recreates `results.txt`.
- ▶ This is an example of the power of `snakemake`: updating a subset of the files in the pipeline triggers re-running the appropriate downstream steps.

## Challenge: Specifying Correct Dependencies

- ▶ Go through all of our rules and correctly identify all inputs
- ▶ Time: 10 mins

# Pattern Rules

# Motivation: DRY Principle Redux

- ▶ Our Snakefile still has repeated content.
- ▶ The rules for each .dat file are identical apart from the text and data file names.
- ▶ We can replace these rules with a single **pattern rule**
  - ▶ can be used to build any .dat file from a .txt file
- ▶ We might also want to replace our TEXTS dictionary with a short piece of python code to automatically detect all texts in our data directory
  - ▶ Then, when more data are added, analysis workflows immediately extend.

# Pattern Rules

- Let's create a rule `countWords` that will take any dataset with a given file extension, count the words inside it, and return the result:

```
rule countWords:
    input:
        data = "src/data/{dataset}.txt",
        script = "src/analysis/wordcount.py"
    output:
        "out/analysis/{dataset}.dat"
    shell:
        "python {input.script} {input.data} {output}"
```

# Pattern Rules

- ▶ The important point here is that `input` and `output` are both using the same macro, `{dataset}`
- ▶ Intuitively, this says
  - ▶ find any dataset in the data directory ...
  - ▶ I want to create an output, using it ...
  - ▶ according to the specified `shell` command

# Executing the Pattern Rule

- ▶ Intuitively, one would think this is the right call to execute our pattern rule:

```
$ snakemake countWords
```

```
WorkflowError:
```

```
Target rules may not contain wildcards.  
Please specify concrete files or a rule  
without wildcards.
```

What's going wrong?

# Executing the Pattern Rule

- ▶ Snakemake doesn't know how to fill the {dataset} wildcard
  - ▶ What datasets do you want to run?
- ▶ The Target Rule, processedData specifies these data sets:

```
$ snakemake processedData
```

```
Provided cores: 1
```

```
Rules claiming more threads will be scaled down.
```

```
Job counts:
```

```
count    jobs
```

```
4    countWords
```

```
1    processedData
```

```
5
```



# Executing the Pattern Rule

- ▶ Alternatively, calling another rule, which uses the outputs of your pattern rule as inputs will do the job

```
$ snakemake
```

```
Provided cores: 1
```

```
Rules claiming more threads will be scaled down.
```

```
Job counts:
```

```
count  jobs
```

```
4      countWords
```

```
1      results
```

```
5
```

# Your turn

## Challenge: Creating a Pattern Rule

- ▶ Create a Pattern Rule, and a corresponding Target Rule to generate the .png plots we had in our bash pipeline.
- ▶ Time: 15 mins

# Using Patterns in File Names

- In our `snakemake` file we are explicitly writing down which files we want the programs to use as input data

```
TEXTS = ["abyss", "isles", "last"]
```

- But our texts all come from the same directory, and have the same line ending:

```
$ ls src/data/*.txt
```

```
src/data/abyss.txt  src/data/isles.txt  
src/data/last.txt  src/data/sierra.txt
```

# Using Patterns in File Names

- ▶ The python package `glob` can match patterns for us
- ▶ The python package `os` knows how to operate on our file system
- ▶ `Snakemake` is written in python
- ▶ A simple solution is apparent ...

# Using Patterns in File Names

- Replace our manually entered text dictionary with

```
import glob, os

# Get a list of all texts in the data folder
TEXTS = [os.path.splitext(
    os.path.basename(textNames)
)[0]
    for textNames
    in glob.glob('src/data/*.txt')]
```

- Try running `snakemake` again

# Building the Entire Workflow

# Where we are:

We have done quite a bit:

- ① How to create rules
- ② Using macros / wildcards
- ③ Correct specification of dependencies
- ④ Writing 'generalizable' rules

How do we ensure our entire workflow runs through from beginning to end?

- ▶ Some (all?) of us weren't getting the `.pngs` *and* `results.txt` built with one call to `snakemake`

# Adding an `all` Target

- ▶ Recall how we are using Pattern Rules?
  - ▶ build all inputs with a particular line ending
  - ▶ by specifying them as `inputs`
- ▶ Generalize this... specify all targets we want built as inputs to a rule,
  - ▶ call the rule `all` ...
  - ▶ could be anything, we are just following in the footsteps of others
  - ▶ place it at the beginning of your workflow



# Adding an all Target

```
rule all:
    input:
        table = "out/final/results.txt",
        figures = expand("out/figures/{iText}.png",
                        iText = TEXTS)
```

# Adding an all Target

- ▶ Examine the proposed workflow with
  - ▶ `snakemake --summary`
  - ▶ `snakemake -np`
- ▶ Build the workflow if we are happy with what we see

# Subworkflows

# Keeping Things Tidy

- ▶ Throughout the course we have emphasized that short scripts are the preferred way to work
- ▶ Our `snakemake` file is starting to get long
  - ▶ and in a full-blown research pipeline would be **much** longer
- ▶ **Solution:** divide our one `Snakefile` into multiple, separate ones that can talk to each other to construct the entire workflow
  - ▶ also means we can build a each subworkflow separately if we like

# Setting up a Subworkflow

- ▶ Let's take all the rules that do some kind of analysis, and separate them into their own Snakefile located in the `src/analysis` subdirectory

```
## Subworkflow: Analysis
<...>
# --- Build Rules --- ##

rule allAnalysis:
    <...>
rule results:
    <...>
<...>
rule countWords:
    <...>
```

# Setting up a Subworkflow

- ▶ In our Snakefile in the working directory we can now refer to the subworkflow:

```
<...>
# --- Sub Workflows --- #
subworkflow analysis:
    workdir: "."
    snakefile: "src/analysis/Snakefile"
# --- Build Rules --- #
rule all:
    input:
        table = analysis("out/final/results.txt"),
        figures = analysis(
            expand("out/figures/{iText}.png",
                iText = TEXTS)),
<...>
```

## Challenge: Creating a Subworkflow

- ▶ Create a new subworkflow called `manuscript` that compiles a short paper, `shortpaper.md`, to a pdf file `shortpaper.pdf`.
- ▶ The short paper takes as an input, the figure `abyss.png`
- ▶ The correct path to the figure is in the manuscript already, assuming your working directory is the project's root.
- ▶ The shell command to build the paper is `pandoc {input.manuscript} --latex-engine=pdflatex -o {output}`
- ▶ Add the output of the manuscript workflow
- ▶ Time: 15-20 mins

# Adding Useful Rules to Snakefile

- ▶ Now our main `Snakefile` looks quite short (tidy!)
- ▶ There are some other useful rules we can build to make our life a little easier
  - ▶ Some additional cleaning rules
  - ▶ A rule that prints out some help for the user when they forget which rule does what



# A Useful help rule

```
## help:           provide simple info about each rule
rule help:
    input:
        mainWorkflow = "Snakefile",
        analysisWorkflow = "src/analysis/Snakefile",
        manuscriptWorkflow = "src/paper/Snakefile"
    shell:
        "sed -n 's/^##//p' {input.mainWorkflow} \
          {input.analysisWorkflow} \
          {input.manuscriptWorkflow}"
```

# Configuration Files

# A Final Step

- ▶ Sometimes in our workflows there are some references that we are making all the time
  - ▶ Always true of calls to subdirectories
  - ▶ And these are easy to screw up and cause headaches
- ▶ We can set these references as a dictionary in a separate file `config.yaml`, and call them as we need them
  - ▶ can also be a `config.json` if you prefer
- ▶ Let's set one up!

# A Simple config.yaml

```
ROOT: "."
src: "src/"
src_analysis: "src/analysis/"
src_paper: "src/paper/"
src_data: "src/data/"

out_analysis: "out/analysis/"
out_figures: "out/figures/"
out_final: "out/final/"
out_paper: "out/paper/"
```

# Importing the config

- ▶ We need to import the config file into each Snakefile that we wish to use it.

```
<...>
# --- Importing Configuration Files --- #
configfile: "config.yaml"
<...>
```

- ▶ Reference objects in the dictionary using `config["someName"]`
  - ▶ Let's do this together in our main Snakefile in the working directory

# Referencing config

```
# --- Sub Workflows --- #
subworkflow analysis:
    workdir: config["ROOT"]
    snakefile: config["src_analysis"] + "Snakefile"
<...>
## All:      generate all outputs,
##          copy paper to root directory
rule all:
    input:
        table = analysis( config["out_final"]
                          + "results.txt"),
<...>
```

## Challenge: Using config files

- ▶ Import our `config.yaml` file into each of our subworkflows
- ▶ Replace directory references in each workflow with the corresponding reference to the config dictionary
- ▶ Time: 10-15 mins

# Summary



# What we argued

- ▶ Correctly specifying a correct workflow that manages an entire build of a research project is non-trivial
- ▶ The worst option (and most commonly used) is fatally flawed
- ▶ Build Tools can manage the entire workflow of large projects that resemble academic papers and research reports
  - ▶ particularly when there are computational steps involved
- ▶ Snakemake is a relatively easy toolbox to manage our workflow and track file dependencies

# What we did

Used Snakemake to:

- ▶ Divide a workflow into a set of individual rules that specify outputs and inputs
- ▶ Correctly specify file dependencies to generate partial builds
- ▶ Generalized rules to reduce repetition and minimize error
- ▶ Split a research project into manageable subworkflows that are easily combined
- ▶ Decorate our example to reflect a simple workflow that resembles how a full-blown project should be managed

# What we didn't do

- ▶ Examine how to use inputs from the Snakemake workflow inside our scripts
  - ▶ Specific to Python and R
- ▶ How to use Snakemake to manage jobs sent to computational clusters
- ▶ Examine and use more advanced features of Snakemake
  - ▶ That said, we have already built a pretty powerful set of tools in just a few hours
- ▶ Compare alternative build tools

Complete Documentation available:

[Snakemake Documentation](#)

but generally uses an unfamiliar to us example from Bioinformatics

# Acknowledgements

- ▶ This module is designed after and borrows a lot from:
  - ▶ Effective Programming Practices for Economists, a course by Hans-Martin von Gaudecker
  - ▶ Software Carpentry's Automation and Make lesson
- ▶ Snakemake is software made available under the MIT license and was created by Johannes Köster
- ▶ The example project from these slides utilizes python scripts and data originally designed for Software Carpentry's Automation and Make lesson
- ▶ The follow up exercise adapts the Schelling Model example from Hans-Martin's module on Waf, from which the python scripts were originally borrowed from QuantEcon.
- ▶ The material from above sources is made available under Attribution based Licenses, as is this course's material.

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- ▶ Suggested Citation:  
  
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Programming Practices for Research in Economics was created by

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- \* Adrian Etter
- \* Julian Langer
- \* Max Winkler

at the Department of Economics, University of Zurich in 2016.  
These slides are from the 2017 edition, conducted by the original  
course developers.