Structuring a DS Project

Lecture 3, DSC 180A

Announcements

Assignment 1 Comments: Comment on Grading; Code Review Friday.

Working on projects:

- Work a little every day (things always go wrong!)
- Work in parallel on multiple pieces
- Don't let a single step be a 'blocker'.

Data Ingestion

- Task: get data from internet to computer.
- Make it easy to (incrementally) change data ingested.
- Rerun to 'refresh' with new data.
- Run data pull on different servers to reproduce results

Data (DB)

Ingestion

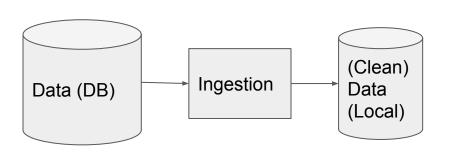
(Clean)

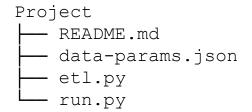
Data
(Local)

How to organize code to achieve this?

Data Ingestion: etl.py

- Library code: contains functions for importing by other processes.
- Good for interactive use; reusable.
- Written as generically as practicable.
- Contains logic not necessary for a consumer of the project to know.
- Contains data collection logic other developers might want to expand on, when forking a project.
- Library code know nothing of what calls it!





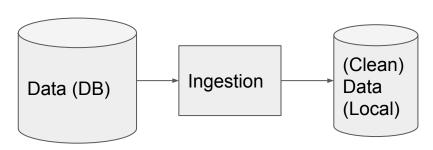
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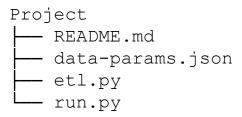
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```
111
etl.py contains functions used to download tables for different
teams and vears.
def get season(team, year):
    return a table of season statistics for a
    given team and year.
    return ...
def get data(years, teams, outdir):
    downloads and saves tables at the specified output
directory
    for the given years and teams.
    :param: years: a list of seasons to collect
    :param: teams: a list of teams to collect
    :param: outpath: the directory to which to save the data.
    return
```

Data Ingestion: data-params.json

- Configuration: parameters for different investigations and experiments.
- E.g. Parameterize across time/space.
- Used by the consumer of the project.
 Shouldn't require a knowledge of the source code!
- Helps log the results of different experiments.





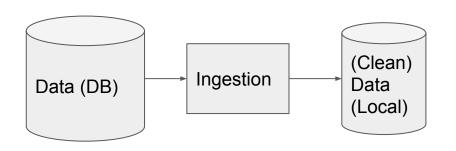
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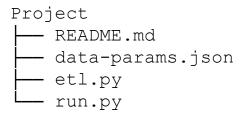
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```
"years": [2015, 2016, 2017, 2018, 2019],
"teams": ["sfo", "gnb"],
"outpath": "data/raw"
```

Data Ingestion: run.py

- Script: Builds (common portions of) the project.
- Imports and runs library code: gives examples of code usage.
- Current: hand-made run.py
- Also possible to use specialized tools: python CLI (e.g. argparse), Makefiles, Maven, etc...





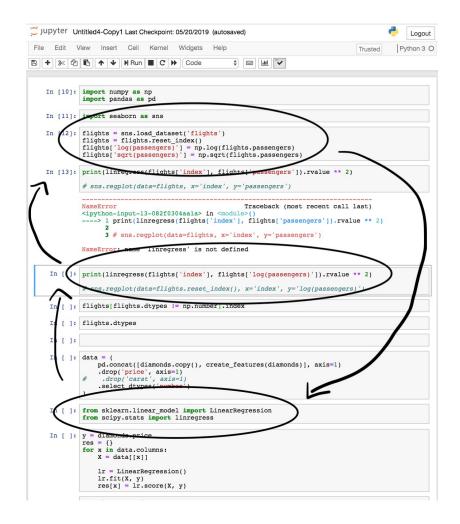
Data Ingestion: run.py

- Imports library code (get_data)
- Run as a script:
 - o python run.py data
- Shebang: #!/usr/bin/env python
 - Specifies which python interpreter to use.
- main function strings together library functions with parameters in config.
- __name__ == '__main__'... returns true only when file is run as a script.
 Should only have minimal code inside.

```
#!/usr/bin/env python
import sys
import json
from etl import get data
def main(targets):
    if 'data' in targets:
        with open('data-params.json') as fh:
            data cfg = json.load(fh)
        # make the data target
        get data(**data cfg)
    return
if name == ' main ':
    targets = sys.argv[1:]
    main(targets)
```

Project Structure:

- As project grows, so does code complexity!
- As a project grows, it becomes unclear:
 - how code should be run...
 - what the code does...
 - if the code is correct...



Why Care About Project Structure?

We're not talking about bikeshedding the indentation aesthetics or pedantic formatting standards — ultimately, data science code quality is about correctness and reproducibility.

Cookie Cutter Data Science

- Clear and consistent project organization encourages software development best-practices and readable code.
- Such habits yield more consistently correct code that's more easily fixed and adapted to other tasks.

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Cookie Cutter Data Science

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- Such habits yield more consistently correct code that's more easily fixed and adapted to other tasks.
- We will follow the opinions of <u>Cookie Cutter Data Science</u>

An Example Project Template

```
- .gitignore <- files to keep out of version control (e.g. data/binaries)</pre>
— README.md <- The top-level README for developers using this project.</p>
— data
  temp <- Intermediate data that has been transformed.

out <- The final, canonical data sets for modeling.

raw <- The original, immutable data dump.
- references <- Data dictionaries, explanatory materials.</pre>
— requirements.txt <- For reproducing the analysis environment, e.q.</p>
generated with `pip freeze > requirer
— src <- Source code for use in this project.
                     generated with `pip freeze > requirements.txt`
   - make dataset.pv
    - features <- Scripts to turn raw data into features for modeling</p>
      build features.pv
    — models <- Scripts to train models and make predictions</p>
      - predict model.py
      train model.py
  └─ visualization <- Scripts to create exploratory and results oriented viz
      — visualize.pv
```

Results are Derived from Immutable Raw Data

- Data is immutable: never edit raw data
 - Raw data is always (re)ingested from elsewhere.
 - File-path may be a symbolic link (shortcut), if stored locally.
 - Raw data never changes => doesn't need version control! (.gitignore)
- Final data is always reproducible from raw data (with run.py)
- Temp data holds data 'useful to keep around' for development, analysis, debugging, etc...

```
data

temp

- Intermediate data that has been transformed.

- Out

- The final, canonical data sets for modeling.

- The original, immutable data dump.
```

Notebooks are for Analysis and Communication

- Notebooks are great for communication, analysis, and initial development.
 - Use to create up-to-date, reproducible, static HTML reports.
- Complicated code in notebooks are hard to understand and don't work well with version control and collaboration.
- Notebooks should:
 - Mostly call library functions in src, with very simple code logic.
 - Never "copy-paste" code between notebooks -- if it's reusable, put it in a library function.
 - Name it something descriptive: 03-fraenkel-prelim-EDA.ipynb

```
notebooks <- Jupyter notebooks (presentation only).
```

Build from the Environment Up

- To reproduce a project from scratch, must also reproduce the computational environment on which it was run.
- requirements.txt contains all python libraries needed for running the project.
- git clone project => mk virtualenv => pip install requirements.txt
- When a project has more complicated requirements, may need to use container approach (e.g. Docker or Vagrant).

```
--- requirements.txt <- For reproducing the analysis environment, e.g. generated with `pip freeze > requirements.txt`
```