W01D4

Miniproject Introductions

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Outline for today

- Python/APIs review
- Value of miniprojects
- Strategies for miniprojects
- Project presentations

Python/APIs review

Value of miniprojects

Projects in data science

- Primary source of knowledge/experience
- Most important part of job interviews
- Benchmarking a new technique
 - Example: you develop a new classification algorithm and want to compare it to existing ones
 - Use popular publicly available benchmark datasets (e.g. from Kaggle)
- New use-case for existing technique
 - Example: you apply a product-recommendations algorithm to your business's order history

Projects at Lighthouse Labs

- Question/answer-based or open-ended
 - Come up with some of your own problem statements and goals to frame your work
 - Not limited to *just* answering the questions

Miniprojects

- APIs Python data structures (individual)
- Databases (SQL) Pandas (individual)
- Feature engineering Dimensionality reduction Unsupervised learning (pairs)
- Supervised learning Deployment (individual)
- Deep Learning NLP (individual)
- Open-ended final project

Individual and group work

- Two minds do not necessarily code twice as fast!
- Typical scenario: team of data scientists each with their own project
- Parallelization
 - Different sub-tasks
 - Different files
 - No pair-coding (unless to help someone)!
- Code reviews of each-other's work
- GitHub: push only at working milestones (no errors)

This week's miniproject

- Part 1: Transport of London API
 - Example: Plan the journey from Heathrow Airport to Tower Bridge using Public Transport, Taxi
 or Bike? Which way is the fastest?
- Part 2: The Movie Database API (stretch)
 - Example: Find top 5 trending movies
- Challenges:
 - Working with difficult documentation (poor descriptions of what input/return values are)
 - Parsing complex data structures (nested lists/dictionaries)
- 7 minute presentation (plus 1 minute feedback)

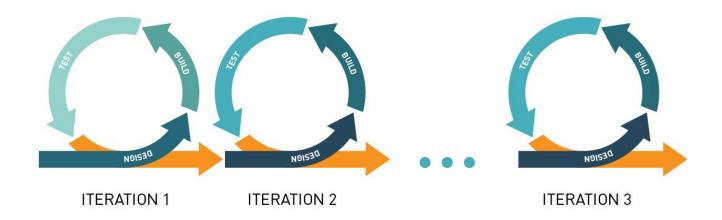
Strategies for miniprojects

Code

- Define functions and/or classes whenever possible (e.g. get_transit(url))
 - Any time you find yourself writing similar code again and again, make a function
- Save trained models and only retrain when needed
- Save GET request results and only fetch when needed (e.g. function that checks if data has been fetched, fetches data at a URL, then saves it)
- Jupyter code blocks should have a clearly defined goal.
- Periodically refactor code (i.e. clean up, reorganize, consolidate)

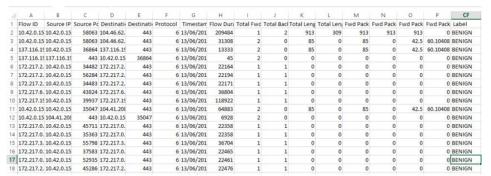
Iterative progress and difficulty

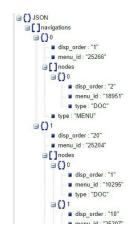
- Make a minimum viable product (MVP) early
- Dataset difficulty (e.g. one company's stock before arbitrary company)
- Model complexity (e.g. autoregressive before LSTM)
- Task complexity (e.g. past stock before adding sentiment)



Explore the dataset, API, and other tools

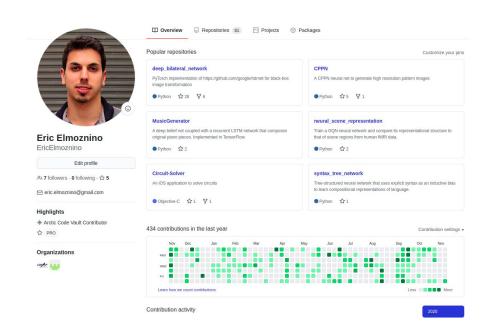
- Play with the dataset
 - What do the variables mean?
 - Which variables are categorical, ordinal, and continuous?
 - Range/variance of each variable?
 - Plot the dataset!!!
- Try out the API functions and explore the returned structure
 - For json, print using JSON(response)!





Why use git?

- Public: Employers can see all the projects you've worked on
- Versioned: You will have a history and can roll back to old commits
- Server deployment: Just git pull to any new machine
- Teamwork: Everyone can work on their own copy and working versions to the master copy



Important git commands

- `git init`: Create a local repository in the current folder
- `git remote add origin [GitHub repo URL]`: Connect your local repository to the remote on you created on GitHub
- `git add [filename]`: Add a file to the local repository
- `git commit -am [commit message]`: Store commits (i.e. changes) in the local repository
- `git push`: Send local changes to the remote repository

Project presentations

General pointers

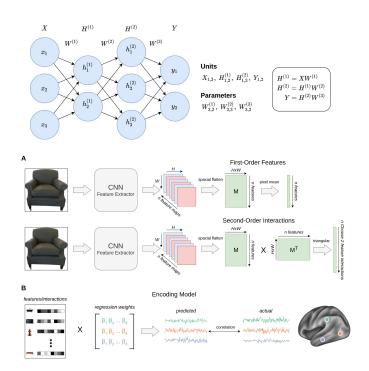
- Present as if to a client (who has some data science knowledge)
- Make it a story
 - What is the problem?
 - What is the dataset?
 - How did you analyze the dataset?
 - What were the findings?
- You can walk through code, but only as a chronological reference for explaining how you analyzed the data
 - However, I recommend having no code at all

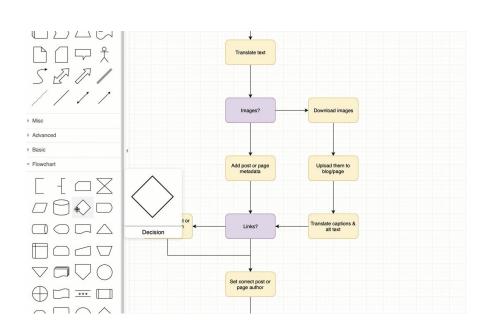
Presentation structure

- **Motivation**: What is the problem? Why is it important (either business, public good, or research perspective)?
- Task: Problem from a technical perspective. Description of the dataset,
 algorithm inputs/outputs, analyses done using model
- Modeling: Important aspects of your approach. How did you process the data or engineer features? What model did you use? Use schematics!
- Results: Visuals! Show metrics and experiments. Demo (if any)
- Conclusions: What worked? What didn't (and why)? How are we better off?
 Where could the project go next?

Figures: draw.io

- Good for schematics, model diagrams, shapes, math typesetting, etc.





Figures: python plotting libraries

- Good for displaying information about your dataset and results

