The Machine Learning Angle for Open Source Science

Linux Foundation Member Summit 2023

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PURDUE UNIVERSITY

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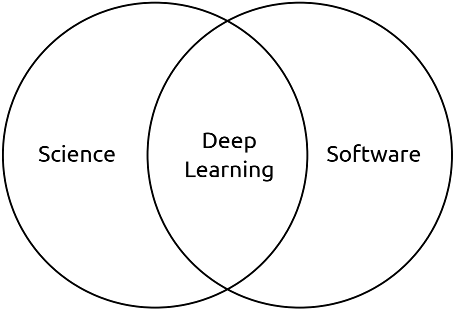

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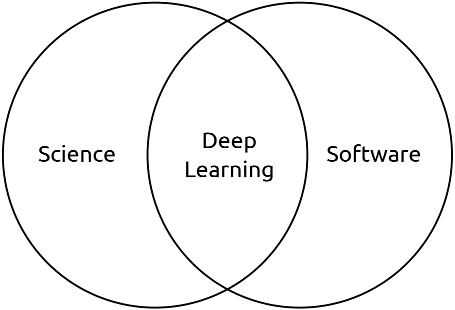

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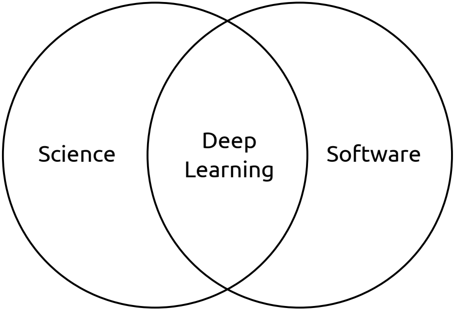

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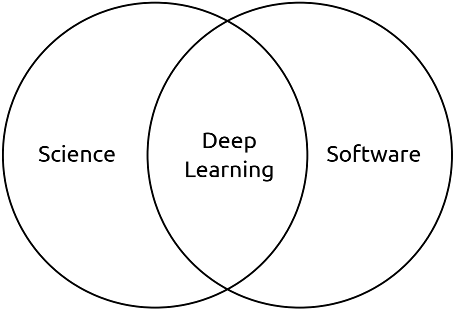

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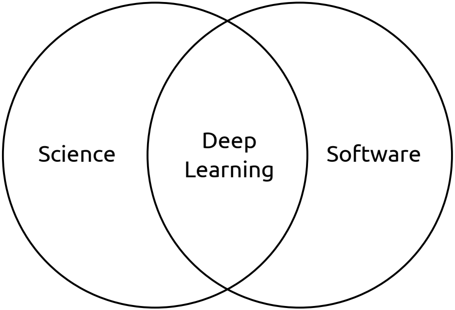

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Let's talk about it.

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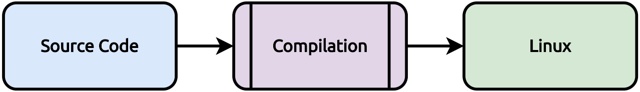

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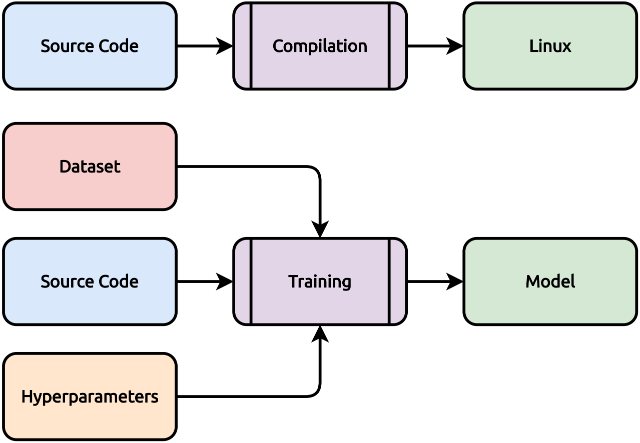

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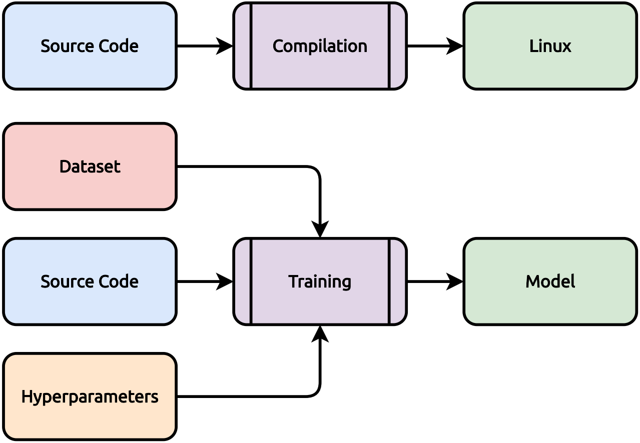

Key Difference: time(training) $>>$ time(compilation)

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Important Note

This still is a partial answer. The democratization of accelerated hardware is still a **significant challenge** we fail to address.

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So; where do we go from here?

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Despite being computationally inexpensive, and having open source {code, data, hyperparameters}, it's not *actually* helpful.

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Great Example: Ultralytics' YOLOv8.
Great Template: Cookie Cutter Data Science

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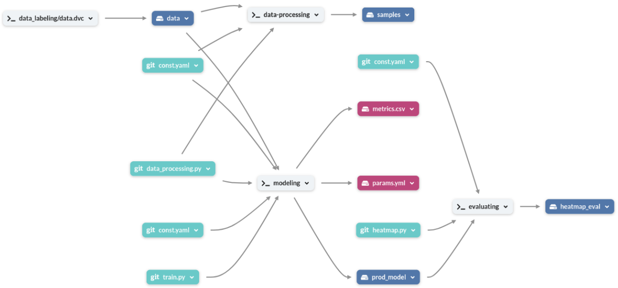
Consequence: Data is now tracked. It's associated with a specific commit, and can be diffed.

Directed Acyclic Graph for Execution

DVC also allows us to structure code execution as a **DAG** (Directed Acyclic Graph), elucidating code / data / hyperparameter relationships:



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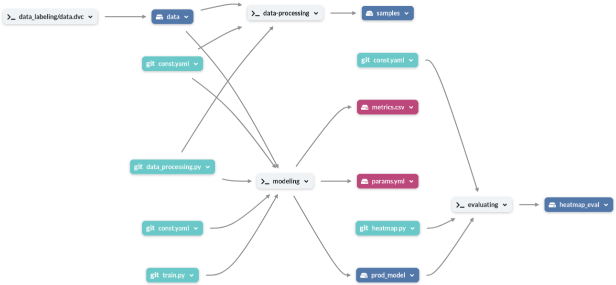

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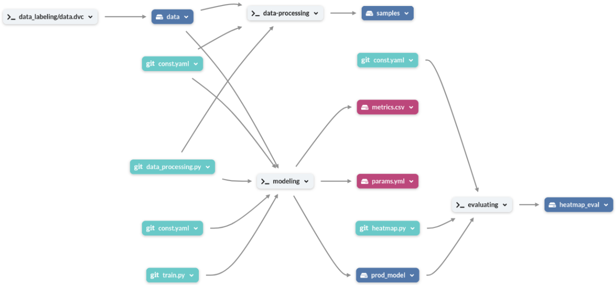

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Projects can be reproduced using: `$ dvc repro`

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This tool manages the experiment-model **lifecycle**.

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It also connects with **GitHub** and **Colaboratory**, and allows for big-picture view of the project.

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As a consequence, we can realistically evaluate the claims made by the paper's authors.

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b. Identify the parameters required to recreate the experimental setup.
c. Set hard / soft requirements based on criticality to replication & user privacy.

QA / Discussion

Questions for me?

Thank you!

Have an awesome rest of your day!

Slides: https://www.cs.purdue.edu/homes/jsetpal/slides/lfms.pdf

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