Teaching software engineering for AI-enabled systems

Filippo Lanubile
University of Bari, Italy

19th European Computer Science Science Summit (ECSS 2023)
AI and the Future of Informatics Education Workshop
Session 1: AI and the practice of teaching Software Engineering
25 October Edinburgh, UK
AI-enabled systems

• Software systems that use AI to provide value for users

• Most AI-enabled systems use data-driven AI
No standard terms

Al-enabled systems
• ML-enabled systems
• ML-based systems
• Production ML systems

How to build Al-enabled systems
• Software engineering for AI (SE4AI)
• Software engineering for ML (SE4ML)
• AI Engineering
• ML Engineering
• ML in Production
"Machine learning engineering is where we were in Software Engineering 20 years ago. A lot of things still need to be invented. We need to figure out what testing means, what CD (continuous delivery) means, we need to develop tools and environments..."
Academic AI courses tend to focus on ML model building

This is not enough!

The Big Challenge from a SE perspective:

• How to take an idea and a model developed by data scientists and deploy it as part of a scalable and maintainable system
Decomposing the big challenge: 
Reproducible and auditable process

- 1.4 million notebooks from GitHub: attempted to execute all 753,405 Python notebooks with unambiguous execution order

**RQ7. How reproducible are notebooks?**
**Answer:** We were able to successfully run 24.11% of the unambiguous execution order Python notebooks. This number is close to the results of a previous reproducibility study [32] about general computer systems research (24.9%). However, the rate is way smaller (4.03%) when we count only notebooks that produce the same results. The most common causes of failures were related to missing dependencies, the presence of hidden states and out-of-order executions, and data accessibility.

J. F. Pimentel, L. Murta, V. Braganholo and J. Freire. A Large-Scale Study About Quality and Reproducibility of Jupyter Notebooks. MSR 2019
Decomposing the big challenge: Unexpected complexity

- Only a small fraction of real-world ML systems is composed of the ML code
- The required surrounding infrastructure is vast and complex
- There is hidden technical debt

D. Sculley et al., "Hidden technical debt in machine learning systems" NIPS'15: Proc. of the 28th Int. Conf. on Neural Information Processing Systems - 2015
Decomposing the big challenge: Cross-functional teams

Different patterns around different organizations

- Lack of ML literacy leads to unrealistic requirements
- Product requirements are often not translated into clear model requirements
- ...

Decomposing the big challenge: Testing and quality

MLOps comes to help

A set of practices and tools to facilitate the creation of ML-based systems

• rooted in software engineering and inspired by DevOps
• emphasis on (full) automation

From Christian Kästner. *Machine Learning in Production: From Models to Products*. 2022
SE for AI-enabled systems: our course

- **Pre-requisite**: students already acquainted with ML techniques
- **Goal**: to teach how to put ML components into production and provide hands-on experience with MLOps tools
- **Method**: project-based learning working in teams of 3-5 people

<table>
<thead>
<tr>
<th>Since Fall 2021</th>
<th>Since Fall 2022</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>University of Bari</strong></td>
<td><strong>Universitat Politècnica de Catalunya</strong></td>
</tr>
<tr>
<td>Bari, Italy</td>
<td>Barcelona, Spain</td>
</tr>
<tr>
<td>Grad students (MSc in Computer Science)</td>
<td>Undergrads (BSc in Data Science)</td>
</tr>
</tbody>
</table>
Assignment

Turn a prototypical ML model into a production-ready ML component

• be the product of a reproducible build process
• have production-grade quality
• expose a cross-platform API
• be packaged in a portable way
Criteria for MLOps tool selection

• Preferably open source
• Popular in the MLOps community
• Well-documented
• Easy to learn
Project milestones

M1
Scoping an ML problem & coordinating teamwork
- Model & dataset cards
- Trello • Slack

M2
Ensuring ML pipeline reproducibility
- Cookiecutter DS
- Git • DVC • MLflow
Project milestones

M3

Fostering QA

Pylint • Pynblint • Pytest
Code Carbon • GE

M4

API development

FastAPI • OpenAPI

Express • Django
Project milestones

M5

Component delivery

Docker • Compose
GitHub Actions

docker

M6

Keeping the feedback loop

Better Uptime
Prometheus • Grafana
Retrospective based on anonymous survey

Appreciations

• Most of the students found the course useful
  – especially tools for reproducibility

  “I found it really useful. I think having this type of subject in our degree is crucial. I have used and I will use what I have learned.”

Suggestions for improvement

• Some students complained about the heavy workload of the course
  “Nowadays, ML-based systems are everywhere, and it is necessary to have this course. It would be great if it could be extended into a 9-credit course.”

• Some students not happy with recommended tools for data QA
  – Need to support image data
Conclusions

• Students familiar with ML are eager to know more about MLOps
• Core MLOps competencies can be successfully taught over the course of a semester

Credits

Luigi Quaranta
University of Bari

Silverio Martínez-Fernández
Universitat Politècnica de Catalunya
Reading pointers

- F. Lanubile, S. Martínez-Fernández and L. Quaranta, "Training future ML engineers: a project-based course on MLOps" in IEEE Software (Early Access),
Discussion points

• How much a course of SE for AI would have to change if it is aimed at students with no knowledge of SE or, conversely, students with no knowledge of AI? Which basic knowledge in SE or AI is required?
• How realistic should project work be to experience the challenges practitioners face in the workplace?
• How to cope with the choice between the many tools and the rapid changes in the offer? Should we favor commercial platforms with educational licenses or open source tools?