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Prediction:

- How should this model be used?
- What are the limitations?
- Where is the model/data/code?

Shallow vs deep learning

Shallow ML \Rightarrow we know the features (structured)

Deep ML \Rightarrow we learn the features (unstructured)

Similar concepts apply
 \Rightarrow requires a lot of data
($10^4 +$)

\hookrightarrow validation

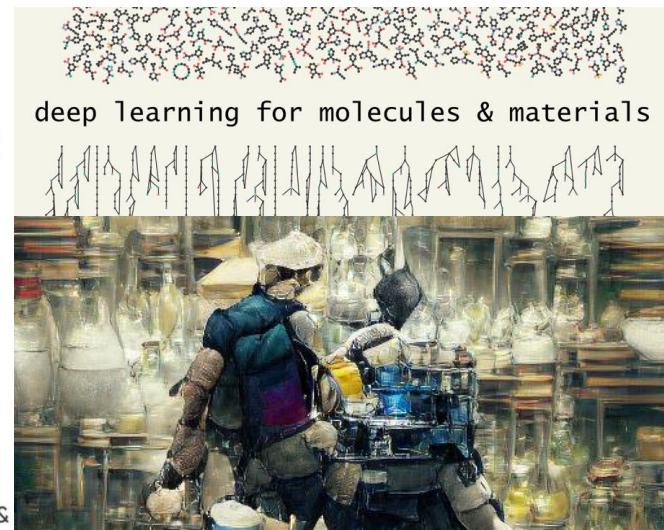
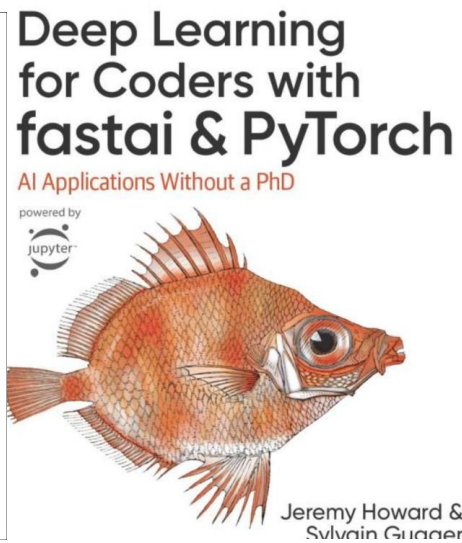
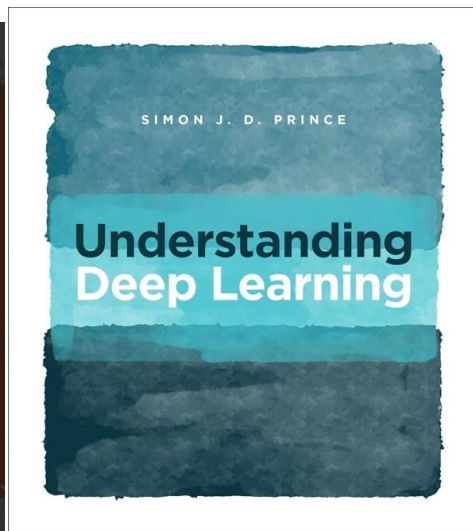
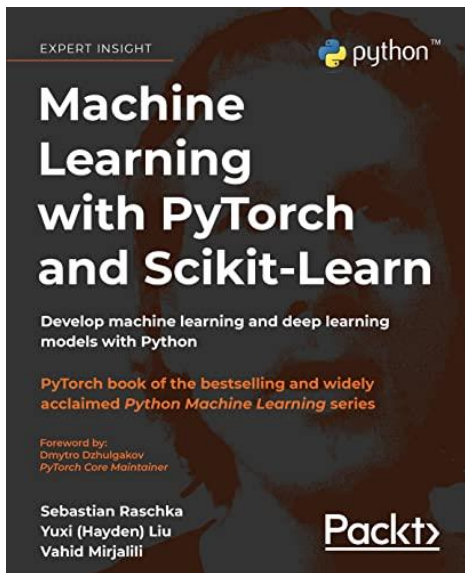
\hookrightarrow defining success

\hookrightarrow understanding features/representation

New challenge \Rightarrow training takes a long time
($10^6 - 10^{12}$ weights)

\hookrightarrow transfer learning
can help.

Where to go next



CS231n: Deep Learning for Computer Vision



Stanford - Spring 2023

DEEP LEARNING

DS-GA 1008 · FALL 2022 · NYU CENTER FOR DATA SCIENCE

INSTRUCTOR

Alfredo Canziani, Yann LeCun



Some quick advice on coding

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- Build classes to collect related functions/properties
- Use an IDE + AI assistant (e.g., VSCode+CoPilot)
- **Make sure your work is reproducible (track experiments, build python packages, use environments)**

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- 2) You are (probably) not going to invent a new ML method from scratch
- 3) **Still, your domain knowledge can lead to creative data-driven solutions and solve your problems!**

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- 3) Does my validation/testing scheme align with how the model will be used in practice?
- 4) Do my results pass a sanity check?!**