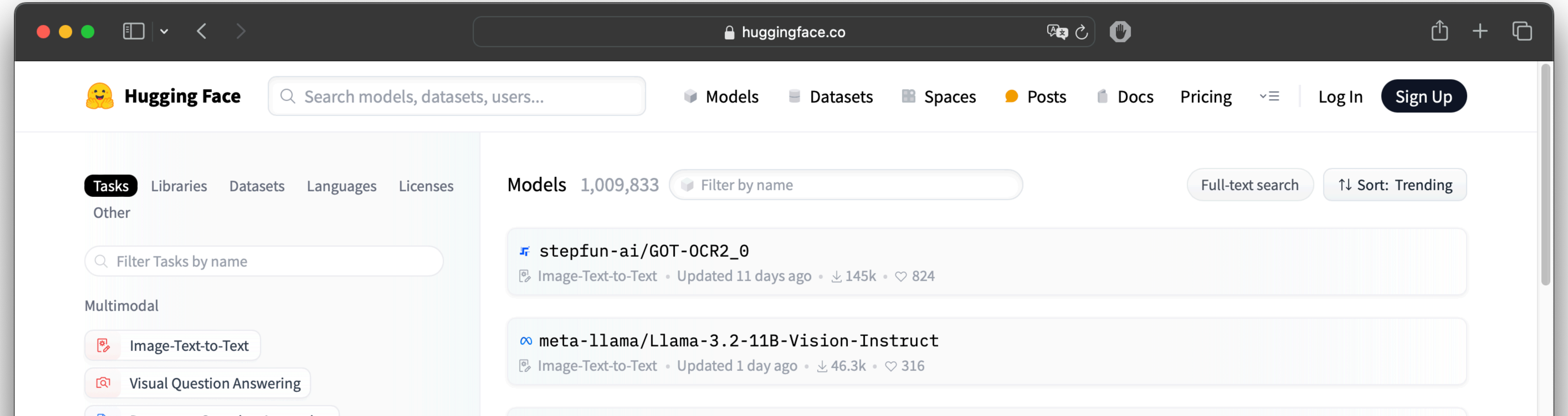
Optimizing PyTorch

Accelerating Training and Inference with Compilation, Custom Kernels, and Beyond

Alvaro Moran - Hugging Face - 2024-10-03

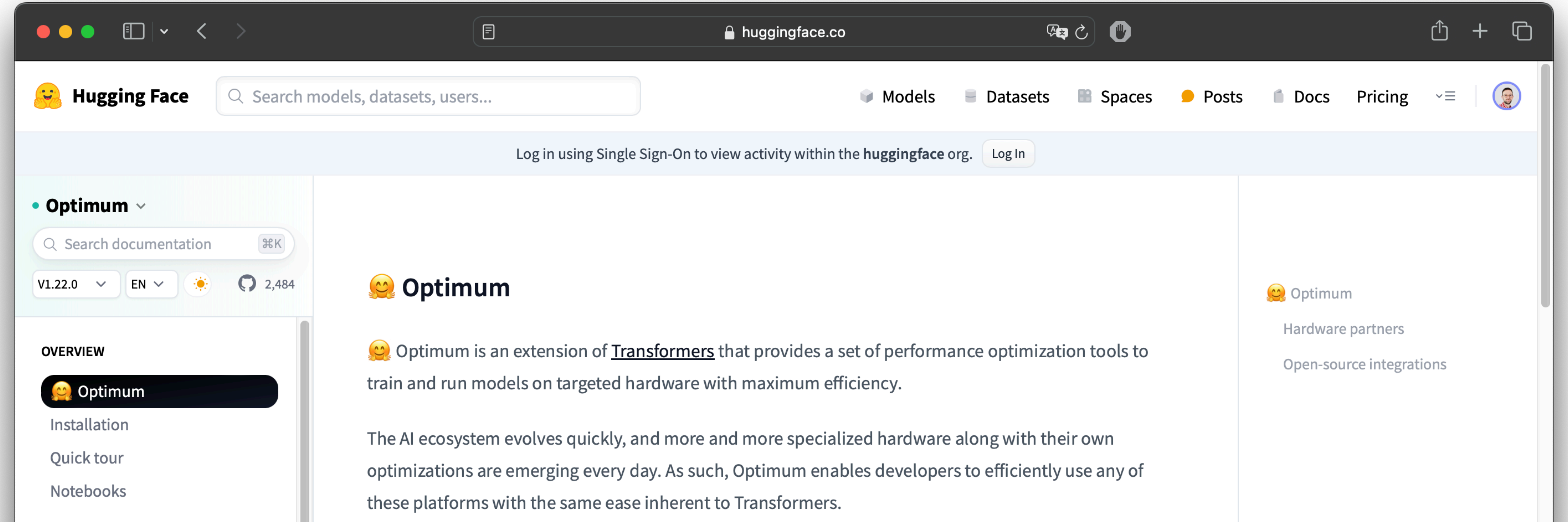
What is Hugging Face?

📅 Founded in 2016
🏢 HQ'd in New York, offices in Paris and few other cities.
🌟 A Hub with over 1 000 000 models available.
👉 Focused on having a positive impact on the AI field.



Who am I?

👋 ML Engineer, member of the *Optimization Team*.



Agenda

- Overview of PyTorch.
- Why optimization is useful.
- Key techniques: hardware usage, `torch.compile`, custom kernels, and mixed precision and distributed processing.

Pytorch Overview

- One of the most popular machine learning libraries.
- Accelerated tensor computing for CPUs, GPUs, etc.
- Deep neural library built on automatic differentiation system.
- Used in science to create and use models for complex tasks.

PyTorch

Why Do We Need Optimization

- 🏃 Faster inference and training.
- 🗜️ Compress data and information, avoid out-of-memory errors.
- 🪡 Tailor a model for constrained hardware environments.

Use the Hardware

Pytorch can be accelerated on different hardware.

```
a = torch.tensor([1, 2, 3]).to("cuda")

model.cuda()

pipe = pipeline("image-segmentation",
                device="cuda",
                framework="pt")
```

torch.compile

It makes code faster when running several times on a given hardware.

```
@torch.compile
def foo(x, y):
    a = torch.sin(x)
    b = torch.cos(y)
    return a + b

outputs = foo(x, y)
```

NOTE: *torch.compile* can give massive speed-up, but it can be hard to use it on a whole model. Try using it on smaller code blocks.

Custom Kernels

Some operations can be optimized to be even more efficient on a given hardware. To do that it's possible to use custom kernels:

- XLA and Pallas - easy, only on GPU and TPU
- Triton - somewhat hard, GPU
- CUDA (and C++ extensions) - hard, GPU

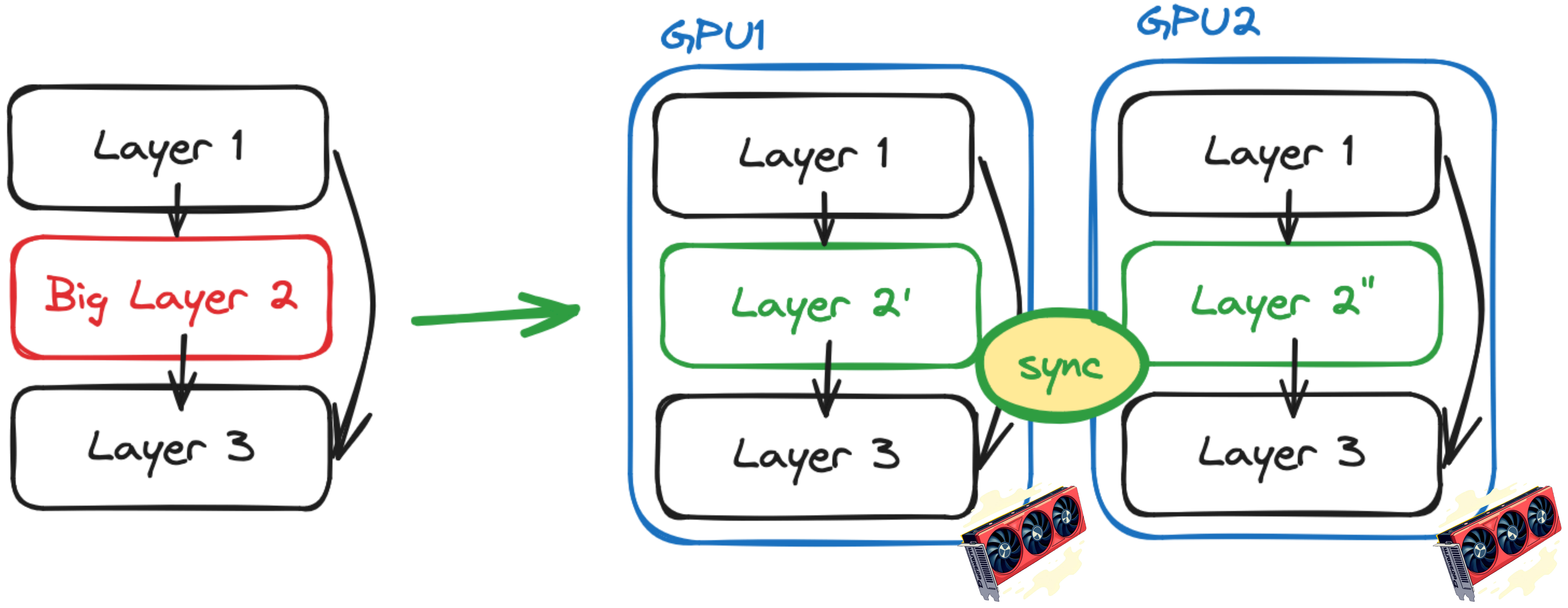
Half and Mixed Precision, Quantization

- Use `torch.float16`, `torch.bfloat16` if the hardware you use allows it. ➡️ Better performance, lower memory, similar accuracy.
- Quantize your model: use `bitsandbytes`, `optimum-quanto`, `marlin` or others. Mostly for matrix multiplication. ➡️ Much lower memory, lower accuracy, but usually slower.

Distributed Inference and Training

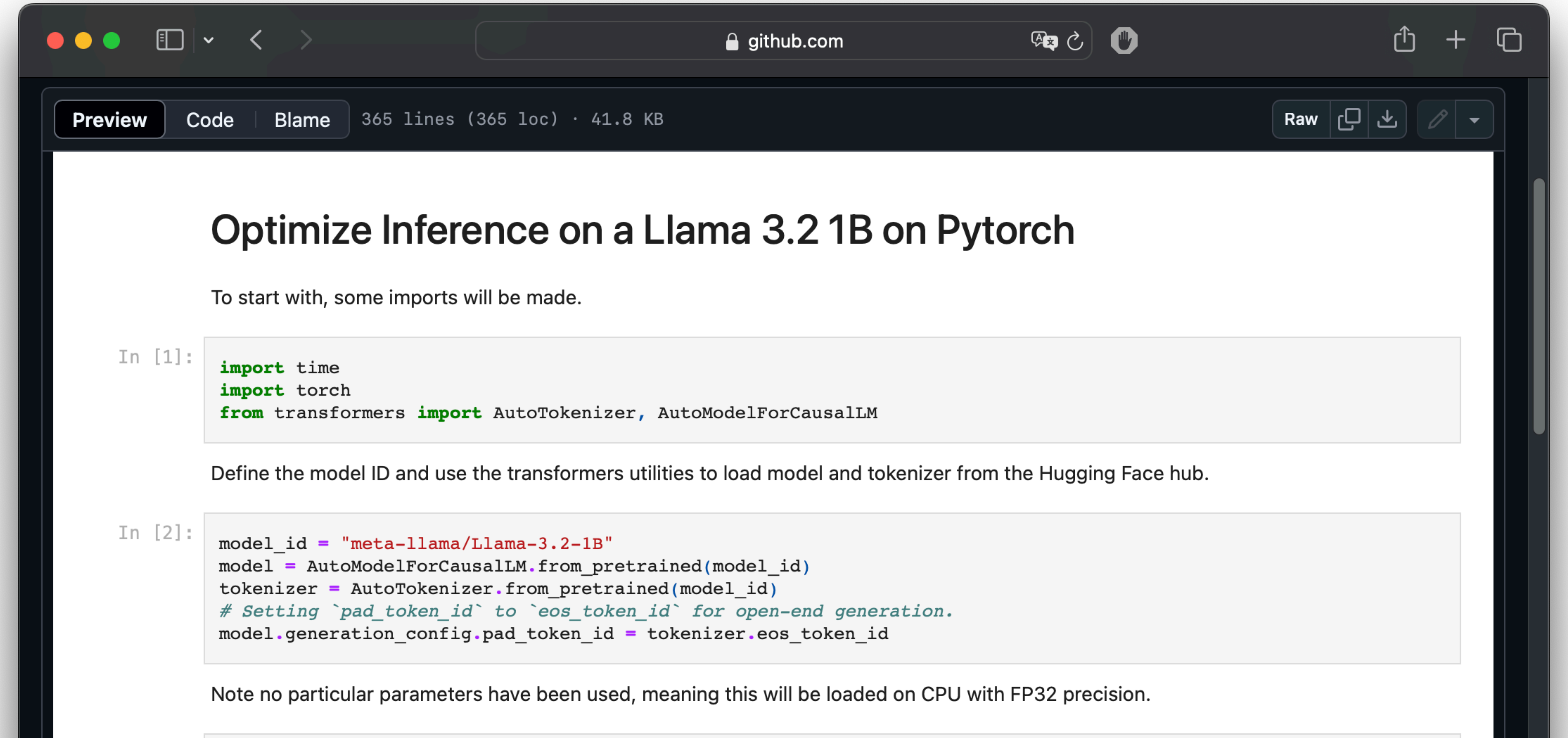
Model too big? Distribute!

- Inference ➡️ `torch.distributed`, difficult.
- Training, ➡️ Fully Sharded Data Parallel (FSDP), DeepZero.
- Use HuggingFace's `accelerate` library to simplify these scenarios.



Practical Example

A [Jupyter notebook] is available to walk through some of the mentioned techniques, and it is possible to run it on a common laptop.



Thank You!

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