Python and the AI Revolution

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March 2024

Topics

We will discuss

- Deep learning and AI
- AI-driven scientific computing
- Where are we heading?
- How will that impact economic modeling for policy work?

AI-driven scientific computing

AI is changing the world

- LLMs
- image processing and computer vision
- speech recognition, translation
- scientific knowledge discovery
- forecasting and prediction

Plus killer drones, skynet, etc....

Key point: vast investment in AI is changing the choice set for **all** scientific coders

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Key players

- OpenAI / Microsoft
- Google (Google Research, Google DeepMind)
- Meta
- Anthropic, etc.

Platforms / libraries

- PyTorch (ChatGPT, Meta's LLaMA 2, Stable Diffusion)
- Google JAX (Google's Gemini)
- Tensorflow, Keras, Mojo?

Deep learning in two slides

Supervised deep learning: find a good approximation to an unknown functional relationship

$$y = f(x) \qquad (x \in \mathbb{R}^d,\ y \in \mathbb{R})$$

Examples.

- $x =$ sequence of words, $y =$ next word
- $x =$ weather sensor data, $y =$ max temp tomorrow

Problem:

- observe $(x_i, y_i)_{i=1}^n$ and seek f such that $y_{n+1} \approx f(x_{n+1})$

Nonlinear regression: minimize the empirical loss

$$\ell(\theta) := \sum_{i=1}^{n} (y_i - f_\theta(x_i))^2 \quad \text{s.t.} \quad \theta \in \Theta$$

But what is $\{f_\theta\}_{\theta \in \Theta}$?

In the case of ANNs, we consider all f_θ having the form

$$f_\theta = \sigma \circ A_1 \circ \cdots \circ \sigma \circ A_{k-1} \circ \sigma \circ A_k$$

where

- $A_i x = W_i x + b_i$ is an affine map
- σ is a nonlinear "activation" function

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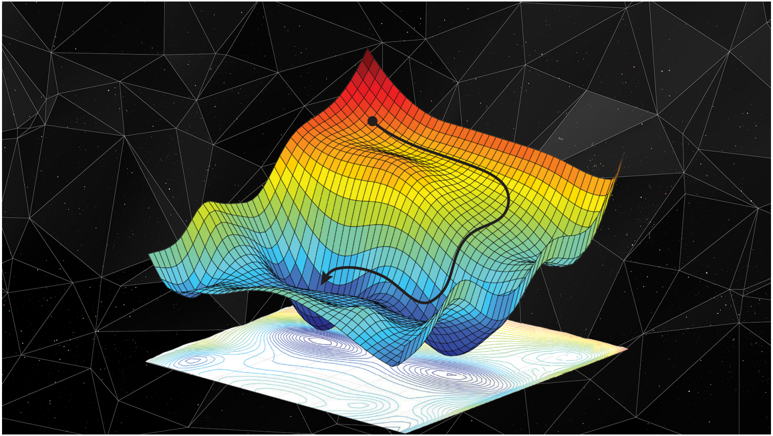
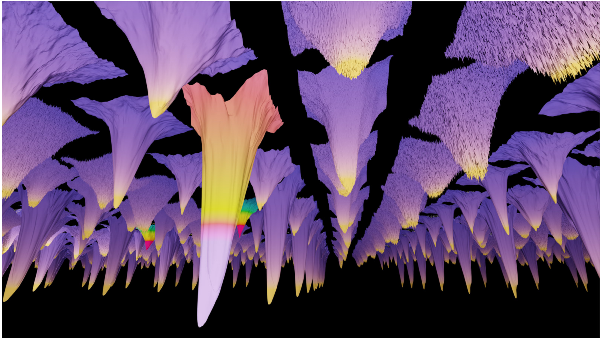
Minimizing a smooth loss functions – what algorithm?



Source: https://danielkhv.com/

Deep learning: $\theta \in \mathbb{R}^d$ where $d = ?$



Source: https://losslandscape.com/gallery/

But what about the curse of dimensionality!???

Software

Core elements

- automatic differentiation (for gradient descent)
- parallelization (GPUs! — how many?)
- Compilers / JIT-compilers

Crucially, these components are all integrated

- autodiff is JIT compiled
- JIT compiled functions are automatically parallelized
- etc.

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```python
import jax.numpy as jnp
from jax import grad, jit

def f(params, x):
  for W, b in params:
    y = W @ x + b
    x = jnp.tanh(y)
  return y

def loss(params, x, y):
  return jnp.sum((f(params, x) - y)**2)

grad_loss = jit(grad(loss))  # Now use gradient descent
```

Source: Google JAX readthedocs

Hardware

“NVIDIA today announced its next-generation AI supercomputer — the NVIDIA DGX SuperPOD powered by GB200 Grace Blackwell Superchips — for processing trillion-parameter models for superscale generative AI training and inference workloads.

Featuring a new, highly efficient, liquid-cooled rack-scale architecture, the DGX SuperPOD provides 11.5 exaflops of AI supercomputing and 240 terabytes of fast memory.”

“NVIDIA supercomputers are the factories of the AI industrial revolution.” – Jensen Huang

Example: Weather forecasting

"ECMWF's weather forecasting model is considered the gold standard for medium-term weather forecasting..."

Google DeepMind claims to now beat it 90% of the time...

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My view

- Policy-centric macroeconomic modeling will survive much longer than traditional weather forecasting
- Deep learning is yet to prove itself as a "better" approach to numerical methods

And yet,

- the AI computing revolution is generating tools that are enormously beneficial for macroeconomic modeling
  - autodiff, JIT compilers, parallelization, GPUs, etc.
- We can take full advantage of them right now

And that's exactly what we're going to do!

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