# Al is Driving a Revolution in Scientific Computing

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## **Topics**

#### Part 1: Slides

- Al-driven scientific computing
- Applications

## Part 2: Hands on coding

https://github.com/QuantEcon/rba workshop 2024

# Al-driven scientific computing

### Al is changing the world

- image processing / computer vision
- speech recognition, translation
- scientific knowledge discovery
- forecasting and prediction
- generative AI

Plus killer drones, skynet, etc...

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## Projected spending on AI in 2024:

Google: \$50 billion

Microsoft: \$60 billion

Meta: \$40 billion

etc.

What kinds of problems are they solving?

# Deep learning in two slides

Aim: approximate an unknown functional relationship

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

### Examples.

- x = cross section of returns, y = return on oil futures tomorrow
- 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: choose model  $\{f_\theta\}_{\theta\in\Theta}$  and minimize the empirical loss

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

In the case of ANNs, we consider all  $f_{\theta}$  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
  - output = dot(kernel, input) + bias
- $\sigma$  is a nonlinear "activation" function

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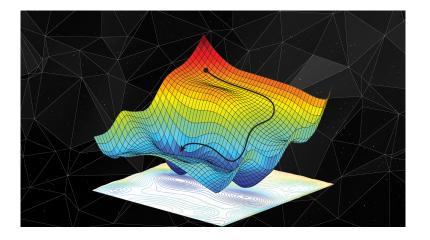
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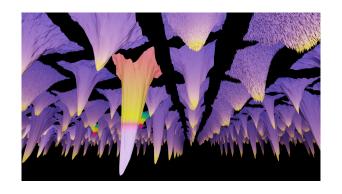
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### Minimizing a smooth loss functions – what algorithm?



Source: https://danielkhv.com/

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



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

## How does it work?

Why is it possible to minimize over  $\theta \in \mathbb{R}^d$  when  $d=10^{12}$  ?!?

#### Core elements

- automatic differentiation (for gradient descent)
- parallelization (GPUs or TPUs)
- Compilers / JIT-compilers

## How does it work?

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### Automatic differentiation

"Exact numerical" differentiation

```
def loss(θ, x, y):
    return jnp.sum((y - f(θ, x))**2)
loss_gradient = grad(loss))
```

Now use gradient descent...

### **Parallelization**

```
outputs = pmap(f, data)
```

- multithreading over GPU cores (how many?)
- multiprocessing over accelerators in a GPU farm (how many?)



## Just-in-time compilers

```
@jit
def f(x):
    return jnp.sin(x) - jnp.cos(x**2)
```

### Advantages:

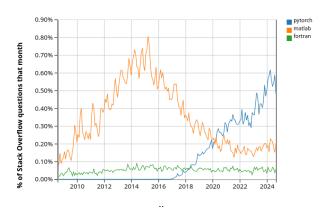
- compiler needs less type information
- can specialize based on parameter types / shapes
- can automatically specialize to CPU / GPU / TPU

### **Platforms**

Platforms that support AI / deep learning:

- PyTorch (Llama, ChatGPT)
- Google JAX (Gemini, DeepMind)
- Keras (backends = JAX, PyTorch)
- Mojo? (Modular (Python))

## Popularity



### Focus on JAX

- Just-in-time compilation
- Automatic differentiation
- Xccelerated linear algebra

### Advantages for economists:

- exposes low level functions
- elegant functional programming style close to maths

```
import jax.numpy as jnp
from jax import grad, jit
def f(\theta, x):
  for W, b in \theta:
    w = W \otimes x + b
    x = jnp.tanh(w)
  return x
def loss(\theta, x, y):
  return jnp.sum((y - f(\theta, x))**2)
grad loss = jit(grad(loss)) # Now use gradient descent
```

Example. AlphaFold3 (Google JAX)

## Highly accurate protein structure prediction with AlphaFold

John Jumper, Richard Evans, Alexander Pritzel, Tim Green, Michael Figurnov, Olaf Ronneberger, Kathryn Tunyasuvunakool,...

Nature Vol. 596 (2021)

- Citation count = 30K
- Nobel Prize in Chemistry 2024

# Al tools for economic modeling

Al-driven scientific computing provides many powerful new tools

And most of the relevent code is open source

Can be used for deep learning or mathematical modeling

In particular, can be used to accelerate macro models

# Case Study

The CBC uses the "overborrowing" model of Bianchi (2011)

- credit constraint loosens during booms
- bad shocks → sudden stops

### CBC implementation in MATLAB

- runs on \$10K mainframe with 356 CPUs and 1TB RAM
- runtime = 12 hours

## Rewrite in Python JAX

- runs on \$400 gaming GPU
- runtime = 4.17 seconds