

# Computational Economics Workshop

The University of Melbourne

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# Topics

## Part 1: Workshop

- Background on scientific computing
- Current and future trends: AI-driven scientific computing
- Applications (hands on, using Python)

## Part 2: Computational economics in action

- Joint with James Hansen and Yong Song

Key questions:

- What computational skills should economists learn in 2024?
- What are some interesting applications?

Please feel free to question / debate / share your experiences

## Flow

- 1:00 – 2:30 Lecture 1
- 2:30 – 3:00 afternoon tea (staff lounge)
- 3:00 – 4:00 Lecture 2
- 4:00 – 4:15 break
- 4:15 – 5:00 Computational Economics in Action

Slides, code:

[https://github.com/QuantEcon/melbourne\\_2024](https://github.com/QuantEcon/melbourne_2024)

Quick poll:

- Python programmers?
  - NumPy? Numba? PyTorch? JAX?
- Julia?
- MATLAB?
- C?
- Fortran?

Regular GPU users?

# Prelude: AI-driven scientific computing

AI is changing the world

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

Plus killer drones, skynet, etc....

# Prelude: AI-driven scientific computing

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Projected spending on AI in 2024:

- Google: \$48 billion
- Microsoft: \$60 billion
- Meta: \$40 billion
- etc.

What kinds of problems are they solving?



# Deep learning in two slides

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

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

## 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  $y_{n+1} \approx f(x_{n+1})$

Training: 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  $f_{\theta}$  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
- $\sigma$  is a nonlinear “activation” function

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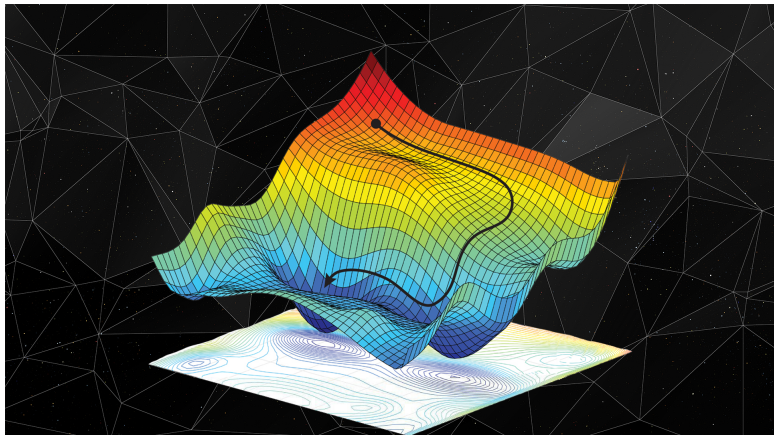
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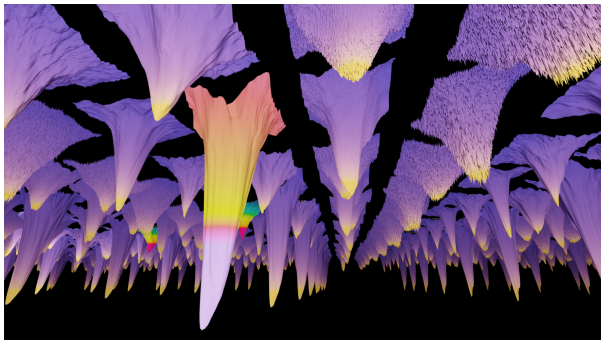
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Minimizing a smooth loss functions – what algorithm?



Source: <https://danielkhv.com/>

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



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

# Hardware



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



# Software

## Core elements

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

Crucially, these components must be well integrated

## Popular platforms with these features

- Pytorch
- Google JAX (with Python)

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

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

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

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

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Source: JAX readthedocs

# Summary

We can't afford the same hardware as OpenAI but we do have access to cheaper versions

And most of the relevant code is open source

Thus, AI-driven scientific computing is giving us many exciting and powerful new tools

- ▷ for deep learning and other kinds of mathematical modeling

Let's use them!