Quantitative Macroeconomics w/ AI and ML
Lec. 3: Programming Basics for Economists

Zhigang Feng

Dec., 2025

Overview

Today's Goal

By the end of this lecture, you should be able to:

- Understand the **economist's tech stack**: OS, Python, IDEs, libraries, and AI assistants (Cursor).
- Read and write basic **Python** code:
  - data types, lists, dictionaries, loops, functions, classes.
- Follow a typical **data science workflow**:
  - download, clean, save, and visualize data (e.g., FRED GDP series).
- Get a **first flavor** of **PyTorch** and the ML workflow:
  - tiny neural net: predict next-quarter GDP growth from last 4 quarters.
  - ML theory is next lecture; today is about *how the code fits together*.

The Economist's Tech Stack

How the Pieces Fit Together

- **1. Operating System (OS)**
  - Windows, macOS, Linux.
  - Manages hardware (CPU, RAM, file system).
  - Python and all tools run *on top* of this.
- **2. Python**
  - High-level programming language for data analysis, simulations, and ML.
  - You install it (e.g., via **Anaconda** or `python.org`).
- **3. IDE / Notebook**
  - Where you edit and run code:
  - **Jupyter**, **VS Code/Cursor**, or **PyCharm**.

Jupyter, VS Code/Cursor, and PyCharm

Jupyter (Notebooks)

- Run code **cell-by-cell**.
- Great for:
  - exploration,
  - data cleaning,
  - plotting.
- Immediate feedback: results appear under each cell.
- Comes with Anaconda as **JupyterLab**.
- Recommended for:
  - homework,
  - small experiments,
  - demonstrations in this course.

VS Code/Cursor and PyCharm

- **VS Code/Cursor**:
  - general-purpose editor/IDE,
  - becomes a full Python IDE with the Python extension,
  - excellent for both **small** and **large** projects.
- **PyCharm**:
  - dedicated **Python IDE**,
  - more Python-specific tools out of the box (refactoring, inspections),
  - great for bigger research codebases.
- Both can handle complex projects. Choice is about personal taste and features.

Python, PyTorch, and AI: How They Relate

- **Python**:
  - General-purpose language.
  - You use it for **data cleaning, regression, simulations, plotting**.
- **PyTorch**:
  - A **Python library** specialized for:
    - tensors (multi-dimensional arrays),
    - automatic differentiation (autograd),
    - neural networks (deep learning).
- **AI / ML Models**:
  - Built **in PyTorch using Python**.
  - Examples:
    - time series forecasters,
    - macro-finance deep learning models,
    - text models for central bank communications.

Takeaway
Python is the language. PyTorch is the toolbox. AI / ML models are what you *build* with that toolbox.

AI Assistants in Your Stack (Cursor, Copilot, . . .)

- **AI Coding Tools**:
  - Cursor, GitHub Copilot, ChatGPT-style tools.
  - Think of them as **supercharged TAs**:
    - complete boilerplate code,
    - explain error messages,
    - suggest better structure,
    - translate math into code.
- Use them especially when:
  - installation / environment is broken,
  - you see a mysterious error,
  - you are implementing a new algorithm from a paper.

Using Cursor Effectively for This Class

- **Cursor** = VS Code-like editor with AI deeply integrated.
- Helpful modes:
  - **Inline suggestions**: completes loops, function definitions.
  - **Chat panel**: ask questions with your code context.
  - **Explain / Fix**: highlight code → ask "Explain this" or "Fix this error".

Example Prompts in Cursor

Debugging:

```
I'm trying to run this PyTorch training loop, but I get a shape mismatch error.
Here is the full code and error.  Explain what's wrong and show a fixed version.
```

Code comprehension:

```
Explain this class in simple terms as if I were an economics student.
What are the inputs, outputs, and what does forward() do?
```

Environment help:

```
My Python environment has both conda and pip.  How should I install pandas and torch
correctly on macOS?
```

Installing Python and Tools

Anaconda, Python, and Editors: Who Does What?

- **Anaconda**:
  - Distribution that installs:
    - Python interpreter,
    - many scientific packages (NumPy, pandas, etc.),
    - environment manager (`conda`),
    - **JupyterLab** as a notebook interface.
  - It does *not* replace an editor: you still need a place to write code.
- **Editors/IDEs**:
  - **JupyterLab** (browser) — comes with Anaconda.
  - **VS Code/Cursor** — external editor; can use Anaconda's Python.
  - **PyCharm** — external Python IDE; can also use Anaconda envs.

Mental model
Anaconda = **Python + packages + env manager**.
VS Code/Cursor/PyCharm = **where you write, run, and debug your code**.

Installing Python (Practical Version)

- **Easiest path (recommended): Anaconda**
  - Download from `https://www.anaconda.com/download`
  - Includes Python + many scientific packages (NumPy, pandas, etc.).
- **Alternative: python.org**
  - Download from `https://www.python.org/downloads/`
  - On Windows: check "`Add Python to PATH`".
- **Verify installation** in terminal / command prompt:

```
python --version      # or python3 --version
```

- If this fails: **ask AI (Cursor / ChatGPT) for help** using a clear prompt and include the full error.

Managing Packages

- Use `pip` (or `conda` if using Anaconda) to install libraries:

```
# Using pip
pip install pandas pandas-datareader matplotlib seaborn torch

# Using conda (Anaconda)
conda install pandas matplotlib seaborn
conda install -c pytorch pytorch
```

- You install each package **once per environment**, not every time you run the code.
- If installation errors appear, copy the error text and ask:
  - a classmate,
  - AI (with full error),
  - or the instructor.

Python Basics: Data Types & Structures

Atomic Data Types

Smallest units of data in Python:

- **Integers (`int`)**: whole numbers.

```
year = 2025
```

- **Floats (`float`)**: real numbers (decimals).

```
inflation_rate = 0.035
```

- **Strings (`str`)**: text.

```
country = "United States"
```

- **Booleans (`bool`)**: logical truth values.

```
is_recession = False
```

Working with Text (Strings)

Economists often clean country names, tickers, etc.

```
country_raw = "  united states  "
gdp = 23.5

# f-strings: modern way to format text
print(f"The GDP of {country_raw} is {gdp} trillion.")
# Output: "The GDP of   united states   is 23.5 trillion."

# Cleaning methods
country_clean = country_raw.strip().title()
print(country_clean)
# Output: "United States"
```

Lists: Ordered Collections

Lists behave like columns of numbers in Excel.

```
# Quarterly GDP growth (%)
gdp_growth = [1.2, 2.5, 3.1, -0.5]

# Indexing (starts at 0)
first = gdp_growth[0]       # 1.2

# Slicing
subset = gdp_growth[1:3]    # [2.5, 3.1]

# Modifying
gdp_growth[3] = 0.1         # replace -0.5 with 0.1
```

Warning: Reference vs Copy

Important: variable names are just *labels*, not boxes.

```
a = [1, 2, 3]
b = a           # b points to the SAME list
b[0] = 99

print(a)        # [99, 2, 3]
```

To make an independent copy:

```
c = a.copy()    # now c is separate
```

This idea (sharing vs copying) also appears with **NumPy arrays** and **PyTorch tensors**.

Dictionaries: Key-Value Data

Dictionaries map **keys** to **values**, like labeled columns.

```
country_data = {
    "name": "Japan",
    "gdp": 4.2,            # trillion USD
    "population": 125,     # million
    "currency": "Yen"
}

print(country_data["gdp"])         # 4.2
country_data["income_per_cap"] = (
    country_data["gdp"] * 1e12 / (125e6)
)
```

Think of this as a tiny JSON object. Pandas DataFrames are like **tables of dictionaries**.

Tuples and Sets

- **Tuples** `()`: like lists, but **immutable**.

```
coords = (41.25, -95.93)    # (lat, lon)
```

Useful for fixed data (e.g., parameters, coordinates, (year, quarter)).

- **Sets** {}: unordered collection of **unique** items.

```
industry_codes = ["A", "B", "A", "C"]
unique_codes = set(industry_codes)    # {"A", "B", "C"}
```

Great for removing duplicates or checking membership.

Python Basics: Logic, Functions, Modules

Operators

- **Arithmetic**: `+`, `-`, `*`, `/`
- Power: `**` (e.g., `2**3 = 8`)
- Modulo: `%` (remainder, e.g., `17%4 = 1`)
- **Comparison**: `==`, `!=`, `>`, `<`, `>=`, `<=`
- **Logical**: `and`, `or`, `not`

Conditionals and Loops

If / Elif / Else

```
x = -1

if x > 0:
    print("Positive")
elif x < 0:
    print("Negative")
else:
    print("Zero")
```

For Loop

```
gdp_growth = [1.2, 2.5, -0.5]

for g in gdp_growth:
    if g < 0:
        print("Recession quarter!")
```

While Loop

```
count = 0
while count < 3:
    print(count)
    count += 1
```

List Comprehensions

Compact way to create lists. Like set-builder notation.

- Math: $S = \{x^2 \mid x \in \mathbb{N}, x > 0\}$
- Python:

```
data = [1, 2, 3, 4, 5]

# Old way
squares = []
for x in data:
    squares.append(x**2)

# Pythonic way
squares = [x**2 for x in data]

# Filter + transform
gdp_growth = [1.2, 2.5, -0.5, 0.3]
positive_growth = [g for g in gdp_growth if g > 0]
```

Error Handling: try / except

Economic data is messy. Use `try/except` to avoid crashes.

```
values = [100, 200, 0, 300]

for v in values:
    try:
        ratio = 10 / v
        print(f"Ratio: {ratio}")
    except ZeroDivisionError:
        print("Error: Division by zero, skipping...")
```

You can also catch `ValueError` when parsing strings from CSV files.

Functions: Reusable Blocks of Logic

```python
def cobb_douglas(k, l, alpha=0.3):
    """Output Y = K^alpha * L^(1-alpha)"""
    y = k**alpha * l**(1 - alpha)
    return y

# Usage
output = cobb_douglas(k=100, l=50)
print(output)
```

- **Inputs** are arguments (`k, l, alpha`).
- **Outputs** come from `return`.
- Docstring `"""..."""` explains the function.

Modules and Imports

- **Module**: a `.py` file containing Python code.
- **Package**: collection of modules (e.g., `pandas`, `torch`).

```python
import math
print(math.sqrt(16))    # 4.0

import numpy as np
import pandas as pd
```

Custom module example:

```python
# my_module.py
def square(x):
    return x * x

# main.py
import my_module
print(my_module.square(5))  # 25
```

Organization: Classes and Objects

Why Economists Need OOP

- **State management**:
  - An agent has wealth, age, employment status, expectations.
  - A class bundles these attributes together.
- **Behavior**:
  - Agent can consume, work, update beliefs, etc.
  - Methods define these behaviors.
- **PyTorch models are classes**:
  - A neural network is a class with:
    - attributes: layers (parameters),
    - methods: `forward` (how to compute outputs).

Anatomy of a Class

```python
class Agent:
    def __init__(self, wealth, age):
        # self = "this instance"
        self.wealth = wealth   # attribute
        self.age    = age      # attribute

    def consume(self, amount):
        # method (behavior)
        self.wealth -= amount

    def birthday(self):
        self.age += 1

# Instantiate (create objects)
a1 = Agent(wealth=1000, age=30)
a2 = Agent(wealth=500,  age=25)

# Call methods
a1.consume(100)
a1.birthday()
```

Without Classes vs With Classes

Without classes (state scattered):

```
# Separate variables
wealth_1 = 1000
age_1    = 30

wealth_2 = 500
age_2    = 25

def consume(wealth, amount):
    return wealth - amount

wealth_1 = consume(wealth_1, 100)
age_1    = age_1 + 1
```

With classes (state + behavior bundled):

```
class Agent:
    def __init__(self, wealth, age):
        self.wealth = wealth
        self.age    = age
```

Inheritance and Why PyTorch Uses It

```python
# Parent class
class GenericModel:
    def predict(self, x):
        print("Predicting...")

# Child class inherits from parent
class MyModel(GenericModel):
    pass

m = MyModel()
m.predict()  # "Predicting..."
```

- In PyTorch, your model will inherit from `nn.Module`:
  - registers parameters automatically,
  - integrates with optimizers and device management,
  - provides `model.parameters()`, `model.to(device)`, etc.

Data Science for Economists

The Data Workflow

Typical pipeline in an empirical macro project:

1. **Acquire** data (FRED, World Bank, CSVs).
2. **Clean**:
   - handle missing values, correct types, adjust dates.
3. **Persist**:
   - save clean data (CSV / pickle) so you do not redo steps 1–2.
4. **Analyze / Visualize**:
   - regressions, summary statistics, plots.
5. **Export**:
   - figures and tables for your LaTeX paper.

Acquire: FRED GDP Data

```
import pandas_datareader.data as web
import datetime

start = datetime.datetime(1990, 1, 1)
end   = datetime.datetime(2025, 1, 1)

# 'GDP' is the FRED series ID for real GDP (quarterly)
gdp_data = web.DataReader('GDP', 'fred', start, end)

print(gdp_data.head())
```

- `pandas_datareader` sends a web request to the FRED API.
- FRED identifies each series by its **series ID** (here: `'GDP'`).
- The response (dates + values) is converted into a **pandas DataFrame**.
- Requires an internet connection. For heavy use, you can obtain an API key from FRED, but many simple calls work without.

Clean: Compute Growth and Filter

```python
import pandas as pd
import numpy as np

# Compute quarterly growth rate
gdp_data['growth'] = gdp_data['GDP'].pct_change()

# Drop missing values from the first difference
clean = gdp_data.dropna()

# Example: post-2000
post_2000 = clean[clean.index >= '2000-01-01']

print(post_2000[['GDP', 'growth']].head())
```

Example: HP Filter (Trend and Cycle)

```
import numpy as np
from statsmodels.tsa.filters.hp_filter import hpfilter

# Log GDP
gdp_log = np.log(df['GDP'])

# HP filter with lambda=1600 for quarterly data
cycle, trend = hpfilter(gdp_log, lamb=1600)

df['gdp_trend'] = trend
df['gdp_cycle'] = cycle
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
plt.plot(df.index, gdp_log, label="log GDP", alpha=0.5)
plt.plot(df.index, df['gdp_trend'], label="HP trend", linewidth=2)
plt.title("HP Filter: log GDP and Trend")
plt.xlabel("Year")
plt.legend()
```

Persist: Saving Clean Data

```
# Save to CSV for sharing or inspection
post_2000.to_csv("gdp_post2000.csv")

# Save to pickle (Python-specific, preserves types)
post_2000.to_pickle("gdp_post2000.pkl")

# Later: load from CSV
df = pd.read_csv("gdp_post2000.csv",
                 index_col='DATE', parse_dates=True)
```

Visualize: GDP Growth

```python
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_theme(style="whitegrid")

x = df.index
y = df['growth'] * 100  # to percent

plt.figure(figsize=(10, 5))
plt.plot(x, y, label="Quarterly growth (%)")
plt.axhline(0, linestyle='--')
plt.title("US Real GDP Growth")
plt.xlabel("Year")
plt.ylabel("Growth (%)")
plt.legend()
plt.tight_layout()
```

Export: High-Quality Figures

```
# Save for your paper
plt.savefig("gdp_growth.png", dpi=300,
            bbox_inches='tight')

# Vector graphics (good for LaTeX)
plt.savefig("gdp_growth.pdf", bbox_inches='tight')

plt.show()
```

PyTorch Basics

What is PyTorch?

- **Open-source deep learning library** in Python.
- Key components:
  - **Tensors**: multi-dimensional arrays (like NumPy arrays).
  - **Autograd**: automatic differentiation.
  - **nn.Module**: building neural networks.
  - **optim**: optimizers (SGD, Adam, etc.).
- Widely used for:
  - time series forecasting,
  - macro / finance ML,
  - text and image models.

PyTorch: Applications and Advantages

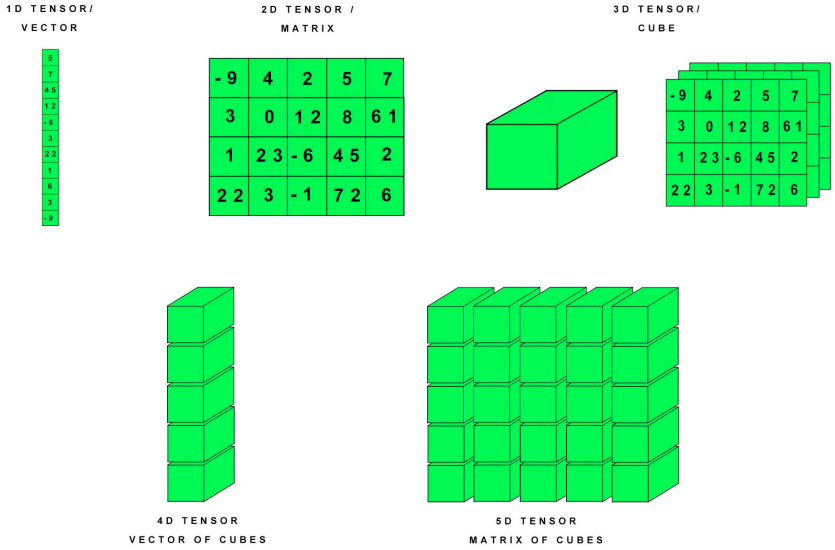
- **Applications**:
  - Computer vision: image classification, object detection.
  - NLP: text classification, language models, machine translation.
  - Reinforcement learning: training agents to interact with environments.
  - Economics: forecasting, structural models with neural nets, text analysis of policy statements.
- **Advantages**:
  - **Dynamic computation graph**:
    - Graph is built at runtime, easy to debug and modify.
  - **GPU acceleration**:
    - seamless move between CPU and GPU for speed.
  - **Active community**:
    - many tutorials, extensions, and research codebases.

Tensors: Like NumPy, but GPU-Ready

```python
import torch

# 1D tensor (vector)
t1 = torch.tensor([1, 2, 3, 4, 5])
print(t1)

# 2D tensor (matrix)
t2 = torch.tensor([[1, 2, 3],
                   [4, 5, 6]])
print(t2)

# Specify dtype
t_float = torch.tensor([1.0, 2.0, 3.0],
                       dtype=torch.float32)

# Zeros
t_zeros = torch.zeros((3, 4))
```

Tensors and NumPy arrays can be converted back and forth.

Tensors (Visual)



Tensors: Summary

- Multi-dimensional arrays with a uniform data type:
  - e.g., all `float32` or all `int64`.
- Similar to NumPy arrays:
  - support element-wise operations, reshaping, indexing, slicing.
  - can be moved between CPU and GPU memory.
- Designed for efficient numerical computation:
  - can handle large matrices and high-dimensional data.

Basic Tensor Operations

```
x = torch.tensor([1, 2, 3])
y = torch.tensor([4, 5, 6])

sum_result     = x + y   # [5, 7, 9]
product_result = x * y   # [4, 10, 18]

# Matrix-style operations
A = torch.tensor([[1.0, 2.0],
                  [3.0, 4.0]])
B = torch.tensor([[5.0, 6.0],
                  [7.0, 8.0]])

C = A @ B  # matrix multiplication
```

Reshaping: view() vs reshape()

```
x = torch.arange(1, 10)     # [1, 2, ..., 9]

# Want 3x3
y = x.view(3, 3)            # requires x to be contiguous
z = x.reshape(3, 3)         # more flexible

print(y)
# tensor([[1, 2, 3],
#         [4, 5, 6],
#         [7, 8, 9]])
```

- `view`: returns a new tensor that shares memory, but only works if memory layout is contiguous (otherwise you may need `x = x.contiguous().view(...)`).
- `reshape`: tries to return a view; if that fails, it creates a copy.
- In most beginner code, `reshape` is a safe default.

Concatenation and Transpose

```
x = torch.tensor([[1, 2],
                  [3, 4]])
y = torch.tensor([[5, 6],
                  [7, 8]])

# Concatenate vertically (rows)
cat_rows = torch.cat((x, y), dim=0)

# Concatenate horizontally (cols)
cat_cols = torch.cat((x, y), dim=1)

# Transpose
xt = x.T   # or torch.transpose(x, 0, 1)
```

Autograd: Conceptual View

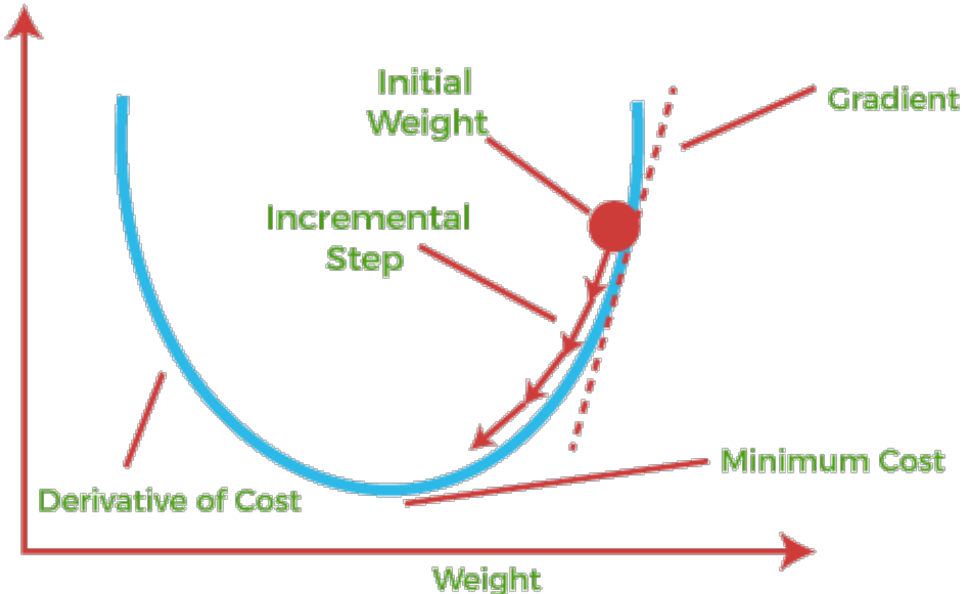
- PyTorch has an **automatic differentiation** engine: `autograd`.
- When you operate on tensors with `requires_grad=True`:
  - PyTorch builds a **computation graph** where:
    - nodes = tensors,
    - edges = operations.
- When you call `backward()` on a scalar output (typically a loss):
  - PyTorch traverses the graph backward,
  - applies the chain rule,
  - computes gradients for all tensors that require them.
- These gradients are stored in the `.grad` attribute of tensors (e.g., model parameters).

Autograd: Simple Example

```
import torch

x = torch.tensor(2.0, requires_grad=True)
y = x * x              # y = x^2

y.backward()           # dy/dx at x=2
print(x.grad)          # tensor(4.)
```

- Here, `y` is the **loss** (a scalar).
- `backward()` computes $\frac{dy}{dx}$.
- In neural nets, parameters (weights, biases) play the role of `x`.

Neural Networks and Gradient Descent (Visual)



Autograd: Steps for Optimization

1. **Enable gradient tracking**: create tensors with `requires_grad=True` (PyTorch does this for parameters in `nn.Module`).
2. **Forward pass**: compute model output and loss.
3. **Backward pass**: call `loss.backward()` to compute gradients.
4. **Update parameters**: use optimizer (e.g., `optimizer.step()`).
5. **Zero gradients**: call `optimizer.zero_grad()` before the next iteration.

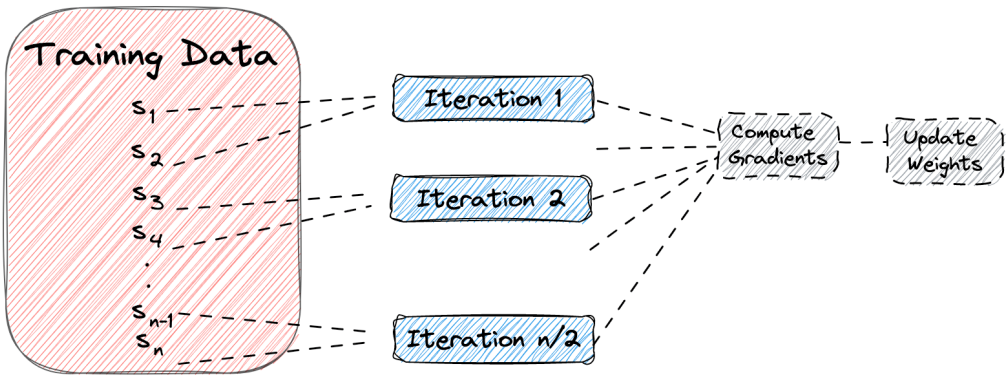
Optimizers and Training Loop Template

```python
import torch.nn as nn
import torch.optim as optim

model = nn.Linear(4, 1)         # simple linear model
optimizer = optim.SGD(model.parameters(), lr=0.01)
loss_fn = nn.MSELoss()

num_epochs = 10
for epoch in range(num_epochs):
    # x_batch, y_batch = ...
    optimizer.zero_grad()       # 1. clear old gradients
    preds = model(x_batch)      # 2. forward
    loss = loss_fn(preds, y_batch)  # 3. loss
    loss.backward()             # 4. backprop
    optimizer.step()            # 5. update params

    print(f"Epoch {epoch+1}, loss = {loss.item():.4f}")
```

Steps of a DNN Training Workflow (Reference)

1. Import libraries: `torch`, `torch.nn`, `torch.optim`, datasets.
2. Prepare data:
   - load or generate `x` and `y`,
   - convert to PyTorch tensors.
3. Build a dataset class (optional) and wrap with `DataLoader`.
4. Define the neural network as a class inheriting from `nn.Module`.
5. Choose loss function (e.g., MSE) and optimizer (e.g., Adam).
6. Train:
   - loop over epochs and batches,
   - forward $\rightarrow$ loss $\rightarrow$ backward $\rightarrow$ step.
7. Evaluate on validation/test data and visualize results.

Mini-batches and DataLoader (Visual)



DataLoader handles batching, shuffling, and iteration over the dataset.

DataLoader: Mini-batches (Concept)

- `torch.utils.data.DataLoader`:
  - splits data into mini-batches,
  - can shuffle each epoch,
  - can load data in parallel (via `num_workers`).
- Properties:
  - Each epoch: all data points used once (unless `drop_last=True`).
  - `batch_size`: trade-off between speed and stability.
  - `shuffle=True`: helpful for training neural nets.

DataLoader Example

```
from torch.utils.data import Dataset, DataLoader
import torch

class CustomDataset(Dataset):
    def __init__(self, data, labels):
        self.data   = data
        self.labels = labels

    def __len__(self):
        return len(self.data)

    def __getitem__(self, idx):
        return self.data[idx], self.labels[idx]

dataset = CustomDataset(torch.randn(1000, 10),
                        torch.randint(0, 2, (1000,)))
loader = DataLoader(dataset, batch_size=32,
                    shuffle=True)

for batch_x, batch_y in loader:
```

Monitoring Progress with tqdm

```python
from tqdm import tqdm

for epoch in range(num_epochs):
    progress = tqdm(loader,
                    desc=f"Epoch {epoch+1}/{num_epochs}")
    for batch_x, batch_y in progress:
        optimizer.zero_grad()
        preds = model(batch_x)
        loss = loss_fn(preds, batch_y)
        loss.backward()
        optimizer.step()
        progress.set_postfix({"loss": loss.item()})
```

`tqdm` provides a progress bar and live loss updates.

GPU Acceleration (Optional for This Class)

```
device = torch.device("cuda" if torch.cuda.is_available()
                      else "cpu")

model = model.to(device)

for batch_x, batch_y in loader:
    batch_x = batch_x.to(device)
    batch_y = batch_y.to(device)
    # training steps...
```

- For this course, **CPU is fine** for small examples.
- GPU becomes important for:
  - large datasets,
  - big neural networks.

Reference: A Deeper MLP with Dropout

```python
import torch.nn as nn

class EqumNN(nn.Module):
    def __init__(self, n1, n2, dropout_prob=0.0):
        super().__init__()
        self.fc1 = nn.Linear(n1, 64)
        self.dropout1 = nn.Dropout(p=dropout_prob)
        self.fc2 = nn.Linear(64, 32)
        self.dropout2 = nn.Dropout(p=dropout_prob)
        self.fc3 = nn.Linear(32, n2)

    def forward(self, x):
        x = nn.functional.relu(self.fc1(x))
        x = self.dropout1(x)
        x = nn.functional.relu(self.fc2(x))
        x = self.dropout2(x)
        x = self.fc3(x)
        return x
```

EqumNN: Mathematical Representation

Let $x \in \mathbb{R}^{n_1}$ be the input and $y_3 \in \mathbb{R}^{n_2}$ the output.

- First layer:
$$y_1 = \mathrm{ReLU}(W_1 x + b_1), \quad W_1 \in \mathbb{R}^{64 \times n_1},\ b_1 \in \mathbb{R}^{64}.$$
- Second layer:
$$y_2 = \mathrm{ReLU}(W_2 y_1 + b_2), \quad W_2 \in \mathbb{R}^{32 \times 64},\ b_2 \in \mathbb{R}^{32}.$$
- Third layer:
$$y_3 = W_3 y_2 + b_3, \quad W_3 \in \mathbb{R}^{n_2 \times 32},\ b_3 \in \mathbb{R}^{n_2}.$$
- Dropout is used during training between layers as a regularization technique (randomly zeroes some components of y_1 and y_2).

In summary:
$$y_3 = W_3\,\mathrm{ReLU}(W_2\,\mathrm{ReLU}(W_1 x + b_1) + b_2) + b_3.$$

Mini Example: Predict GDP Growth with a Tiny MLP

Problem Setup

Goal: Use a small neural network to predict **next-quarter GDP growth** from the **last 4 quarters**.

- Input features at time t:

$$x_t = (\text{growth}_{t-4}, \text{growth}_{t-3}, \text{growth}_{t-2}, \text{growth}_{t-1})$$

- Target:

$$y_t = \text{growth}_t.$$

- Model:
  - small MLP with 1 hidden layer,
  - trained with MSE loss and Adam optimizer.
- This is **not** a sophisticated macro model — just a **simple demo** of the ML **workflow**.

Building Features from Cleaned Data

Assume we already have `df` with a `growth` column (from earlier).

```
import numpy as np
import torch
from torch.utils.data import TensorDataset, DataLoader

# 1. Get growth as NumPy array
g = df['growth'].values.astype(np.float32)

# 2. Build (X, y) where each X has last 4 quarters
X_list = []
y_list = []

for t in range(4, len(g)):
    X_list.append(g[t-4:t])  # last 4 quarters
    y_list.append(g[t])      # next quarter

X = np.stack(X_list)           # shape: [N, 4]
y = np.array(y_list)[:, None]  # shape: [N, 1]

# 3. Convert to tensors
```

Train / Test Split and DataLoader

```
N = X_tensor.shape[0]
train_size = int(0.8 * N)

X_train = X_tensor[:train_size]
y_train = y_tensor[:train_size]
X_test  = X_tensor[train_size:]
y_test  = y_tensor[train_size:]

train_ds = TensorDataset(X_train, y_train)
test_ds  = TensorDataset(X_test, y_test)

train_loader = DataLoader(train_ds, batch_size=32,
                          shuffle=True)
test_loader  = DataLoader(test_ds, batch_size=32,
                          shuffle=False)
```

Defining a Tiny MLP in PyTorch

```
import torch.nn as nn
import torch.optim as optim

class GrowthMLP(nn.Module):
    def __init__(self):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(4, 16),
            nn.ReLU(),
            nn.Linear(16, 1)
        )

    def forward(self, x):
        return self.net(x)

model = GrowthMLP()
optimizer = optim.Adam(model.parameters(), lr=0.01)
loss_fn = nn.MSELoss()
```

Training Loop

```python
num_epochs = 50

for epoch in range(num_epochs):
    model.train()
    epoch_loss = 0.0

    for batch_X, batch_y in train_loader:
        optimizer.zero_grad()
        preds = model(batch_X)
        loss = loss_fn(preds, batch_y)
        loss.backward()
        optimizer.step()

        epoch_loss += loss.item() * batch_X.size(0)

    epoch_loss /= len(train_loader.dataset)
    print(f"Epoch {epoch+1:03d} | Train MSE: {epoch_loss:.6f}")
```

Evaluating and Plotting Predictions

```
model.eval()
with torch.no_grad():
    y_pred_list = []
    y_true_list = []
    for batch_X, batch_y in test_loader:
        preds = model(batch_X)
        y_pred_list.append(preds.numpy())
        y_true_list.append(batch_y.numpy())

y_pred = np.vstack(y_pred_list).flatten()
y_true = np.vstack(y_true_list).flatten()

import matplotlib.pyplot as plt

plt.figure(figsize=(10, 4))
plt.plot(y_true, label="True growth")
plt.plot(y_pred, label="Predicted growth")
plt.title("Next-quarter GDP growth: true vs predicted")
plt.xlabel("Test observation index")
plt.ylabel("Growth")
```

Wrap-Up

What You Should Take Away

- **Tech stack**: OS → Python → Jupyter/VS Code/Cursor/PyCharm → libraries → AI assistants.
- **Python basics**: data types, lists, dictionaries, loops, functions, classes (attributes, methods, `self`).
- **Data workflow**: acquire, clean, HP-filter, persist, visualize.
- **PyTorch flavor**:
  - tensors, autograd, models as classes, optimizers, DataLoader.
  - tiny MLP predicting GDP growth from past values.
- Next lecture: **AI and ML theory for economists**:
  - loss functions, overfitting, regularization, evaluation, etc.

AI-Assisted Coding: The Research Architect Approach

The AI Era Challenge

What's changing?

AI tools can now write code, debug algorithms, and translate math into implementations.

Question: If AI can code, what's left for economists?

The Shift
Your **attention** shifts from **how to code** to **what to code and why**.

From Coder to Research Architect

Traditional

- Write every line
- Debug syntax errors
- Focus: **how**

Research Architect

- Design algorithms
- Validate economics
- Focus: **what & why**

Three core skills:

1. **Algorithm Design**: Translate theory into computational steps
2. **Strategic Direction**: Guide AI from simple to complex
3. **Critical Validation**: Verify technical + economic correctness

AI Coding Tools: Three Categories

Chatbox	**IDE-Integrated**	**Autonomous**
ChatGPT, Claude	Cursor, Copilot	Claude Code, Aider
Algorithm design	Real-time coding	Multi-file projects
Debugging	Inline suggestions	Refactoring
Theory questions	File awareness	Autonomous debug

Recommendation
Primary: Cursor (IDE) + Claude (chatbox)
Advanced: Claude Code (autonomous)

Tool 1: Cursor

VS Code + AI Integration

Key features:

- **Inline completion**: Tab to accept AI suggestions
- **Chat** (Cmd/Ctrl+L): Ask questions with file context
- **Composer** (Cmd/Ctrl+I): Multi-file edits

Use for: Day-to-day coding, quick iterations, debugging

Tool 2: Claude

Conversational AI for Research

Strengths:

- Long context ($\sim$200k tokens) — upload papers + code
- Strong economic reasoning
- Interactive artifacts

Use for:

- Algorithm design: "How to discretize state space?"
- Literature: Upload PDF, ask "Implement Section 3"
- Deep debugging with economic interpretation

Best practice: Provide economic context, not just code

Tool 3: Claude Code

Autonomous Terminal-Based Agent

What it does:

- Reads/writes multiple files
- Runs code, observes errors, debugs autonomously
- Works across entire projects

Use for:

- Large refactoring
- MATLAB $\rightarrow$ Python conversion
- Implementing full algorithms from papers

Key difference: Cursor assists you; Claude Code works autonomously

The Iterative Development Method

Core Idea:

Start simple. Grow complexity systematically.

Mathematical analogy: Homotopy continuation

- Solve easy problem $F_0(x) = 0$
- Define path: $H(x, t) = (1 - t)F_0(x) + tF_1(x)$
- Track solution as $t \to 1$ to reach hard problem $F_1(x) = 0$

Here: Start with simple model, incrementally add features

Pattern: Algorithm → Extensibility check → Code with diagnostics → Validate → Extend → Repeat

Why This Works

Benefits:

1. **Validation at each step**
   - Know exactly where bugs come from
   - Clear success criteria
2. **AI succeeds on simple problems**
   - Build confidence incrementally
   - Good starting point for complex versions
3. **Extensible by design**
   - Check algorithm accommodates future features
   - Avoid major refactoring later

Key Insight
Design for extensibility from the start, validate continuously

Example: RBC Model Development

Goal: Build stochastic RBC model

Don't start with full model!

Start simple:

- Deterministic RBC
- Log utility, Cobb-Douglas production
- Fixed labor supply
- Has closed-form steady state for validation

Solve via VFI: Iterate on Bellman equation until convergence

Why VFI for deterministic case?

- Algorithm naturally extends to stochastic case
- Same code structure accommodates shocks later

Workflow Step 1: Design Algorithm

Your prompt to AI:

"Design a VFI algorithm for deterministic RBC:

- Production: $Y = AK^{\alpha}$
- Bellman: $V(k) = \max_{k'} \log(AK^{\alpha} - k') + \beta V(k')$
- Use grid search over k'

"

AI responds with algorithm

CRITICAL: Before implementing, ask AI:

"Can this algorithm extend to stochastic productivity? Where would shocks enter?"

Refine algorithm: Ensure state space structure accommodates (k, A) later

Workflow Step 2: Implement with Diagnostics

Your prompt to AI:

"Implement this algorithm. Include diagnostic checks:

1. Convergence plot (sup norm vs iteration)
2. Compare $V(k)$, $k'(k)$ to analytical steady state
3. Compute and plot Euler equation residuals

"

AI writes code with built-in validation

Your job:

- Run code
- Check plots: Does $k'(k)$ match steady state formula?
- Euler residuals near machine precision?

Workflow Step 3: Extend Algorithm

After validating deterministic version:

Your prompt to AI:

"Extend algorithm for stochastic productivity:

- AR(1): $\log A_{t+1} = \rho \log A_t + \epsilon_t$
- State space: (k, A) grid
- Bellman: $V(k, A) = \max_{k'} u(c) + \beta E[V(k', A')|A]$
- Discretize using Tauchen method

Show updated algorithm."

Review algorithm before coding

Workflow Step 4: Update Code

Your prompt to AI:

"Implement stochastic version. Add:

1. Simulation of $\{k_t, A_t, Y_t, C_t\}$ for $T = 1000$ periods
2. Impulse response to productivity shock
3. Report: $E[Y]$, $\sigma(Y)$, corr(Y_t, Y_{t-1})
4. Verify: Setting $\rho = 0, \sigma = 0$ recovers deterministic case

"

Validate:

- Check IRF shapes (positive shock $\rightarrow$ output rises)
- Verify moments make economic sense
- Confirm limiting case works

Workflow Step 5: Iterate

Next iteration: Add variable labor

Repeat the pattern:

1. Extend algorithm: Add labor choice, MRS = MPL
2. Check extensibility: Room for labor adjustment costs?
3. Implement with diagnostics: Plot labor supply, verify FOC
4. Validate: Does labor respond to shocks correctly?

Continue: Adjustment costs $\rightarrow$ Multiple sectors $\rightarrow$ Financial frictions $\rightarrow$ ...

The Progression
Each validated iteration becomes foundation for the next

Key Principles of Iteration

1. **Algorithm first, code second**
   - Design and refine algorithm before implementing
   - Cheaper to fix algorithm than code
2. **Check extensibility immediately**
   - "Can this accommodate feature X?"
   - Avoid painting yourself into a corner

Key Principles of Iteration

3. Build diagnostics into code

- Comparison plots, Euler residuals, limiting cases
- Code should validate itself

4. One feature at a time

- Know which change caused any bugs
- Clear attribution of results

Your Validation Checklist

At every iteration, verify:

Technical

- Convergence?
- NaNs/infinities?
- Grid adequate?

Economic

- Results sensible?
- Comparative statics correct?
- Limiting cases work?

Golden Rule
AI writes code. YOU validate economics.

Debugging with AI

When something goes wrong:

1. Provide full context: code + error + expected behavior
2. AI suggests diagnostics
3. You run diagnostics, report back
4. Iterate until resolved

AI catches:

- Indexing errors, broadcasting issues
- Numerical problems (overflow, underflow)
- Logic errors in algorithms

You catch:

- Nonsensical equilibria
- Wrong comparative statics
- Economic assumptions violated

Best Practices

1. **Always start simple**
   - Find analytically tractable special case
2. **Design for extensibility**
   - Check algorithm accommodates future features
3. **Build in validation**
   - Code should include diagnostic checks
4. **Use AI strategically**
   - AI handles implementation
   - You handle algorithm design and validation
5. **Validate incrementally**
   - Never move forward with unresolved issues

The Research Architect Mindset

Traditional	Research Architect
Writes every line	Designs algorithms
Debugs syntax	Validates economics
"How to code X?"	"Does X make sense?"
Bottleneck: coding	Bottleneck: understanding

Your edge:

- Economic theory expertise
- Spotting nonsensical results
- Knowing which simplifications preserve mechanisms

Core Takeaway

AI democratizes **implementation**.

Knowing what to implement and **validating correctness** remain your unique value.

The workflow:

1. Design algorithm (check extensibility)
2. Implement with diagnostics
3. Validate thoroughly
4. Extend algorithm
5. Repeat

Summary

AI tools: Cursor (IDE) + Claude (chatbox) + Claude Code (autonomous)

Iterative method:

- Start simple (analytical benchmark)
- Design extensible algorithms
- Code with built-in validation
- Add features incrementally

Your role: Algorithm architect + Economics validator

Next: We'll see Python basics and how this workflow looks in practice