From Correct to Communicable: Code Quality & Documentation

AM215 - LECTURE 7

The AM215 Team

Today's Roadmap

▓▓▓ 1. Why Code Quality Matters

Moving beyond correctness to build trust and reduce cognitive load.

▓▓▓ 2. Static Assurance

Using tools like linters and type checkers to find bugs before running code.

▓▓▓ 3. Communicating Through Documentation

Writing effective docstrings that serve as contracts and user guides.

▓▓▓ 4. Automation & Integration

Embedding quality standards into our workflow with `pyproject.toml` and CI.

Part 1: Why Code Quality Matters

Beyond Correctness

In previous lectures, we've focused on making our code work correctly and reproducibly.

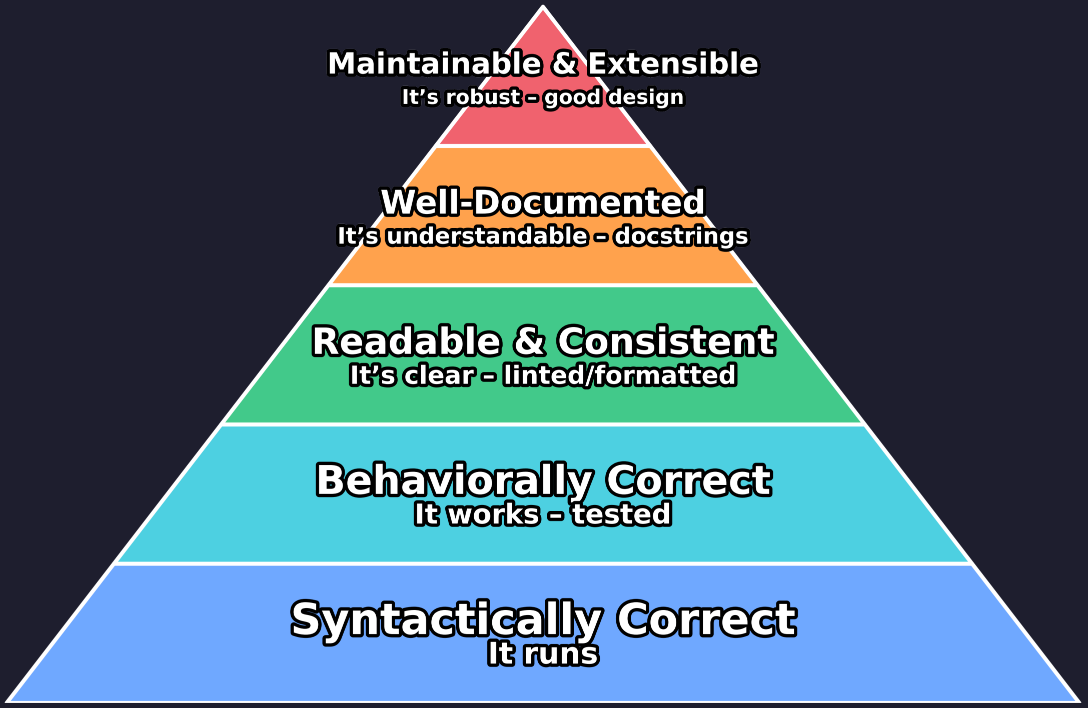
- **Lec 3 (Reproducibility):** Ensured our environment and results are deterministic.
- **Lec 6 (Testing):** Verified that our code's *behavior* is correct.

> But code that is correct is not necessarily code that is **usable**, **maintainable**, or **trustworthy**.

Passing tests doesn't mean the code is easy to understand, review, or extend.

The Code Quality Pyramid

We can think of code quality as a hierarchy of needs.



> Today, we focus on climbing from Level 2 to Level 5. The goal is to reduce **cognitive load** for our collaborators and our future selves.

The Problem: Inconsistent Style

Which of these is "correct"?

Developer A:

```
def process_data(data,
                 threshold=0.5):
    if (len(data) > 0):
        return [x for x in data if x >
threshold]
    else:
        return []
```

Developer B:

```
def process_data(data, threshold=0.5):
    if len(data) == 0:
        return []
    return [
        x for x in data
        if x > threshold
    ]
```

> Both run, but inconsistent style makes code harder to read and code reviews noisy. We waste cognitive energy on trivialities.

Format Example: The "Noisy" Diff

Imagine a code review. The only logical change was adding new_param. The rest is just style noise.

```
- def process_data(data, threshold=0.5, old_param=True):
+ def process_data(
+     data, threshold=0.5, old_param=True, new_param=False
+ ):
      # ...
-     result = [item for item in data if item > threshold]
+     result = [
+         item for item in data if item > threshold
+     ]
      return result
```

> **Problem:** It's hard to spot the meaningful change. The reviewer has to work harder to separate style from substance. An auto-formatter prevents this by ensuring a consistent style *before* the code is committed.

Format Example: Quotes and Spacing

This code is functionally correct, but visually jarring and inconsistent.

Before Formatting:

```
my_dict = {'key1':"value1",
    'key2' : "value2"}

x=1+2
y = 3  *  4
```

After Formatting (`ruff format .`):

```
my_dict = {"key1": "value1", "key2": "value2"}

x = 1 + 2
y = 3 * 4
```

> A formatter enforces consistent use of quotes (e.g., double quotes) and spacing around operators, making the code easier to parse visually.

Format Example: Line Breaks & Trailing Commas

Long lines are hard to read and cause horizontal scrolling.

Before Formatting:

```
# This line is > 100 characters long
important_settings = {"user": "admin", "permissions": ["read", "write", "execute"], "
retries": 3, "timeout": 60, "log_level": "info"}
```

After Formatting:

```
important_settings = {
    "user": "admin",
    "permissions": ["read", "write", "execute"],
    "retries": 3,
    "timeout": 60,
    "log_level": "info", # <-- Trailing comma!
}
```

> The formatter breaks the dictionary into multiple lines. The trailing comma makes it so adding a new key-value pair only changes one line in a `git diff`.

Another Problem: Hidden Bugs

This code runs without error. But can you spot the problems?

```python
import sys
import numpy
import os # Unused import

def calculate_mean(data):
    # This works, but what if `data` is empty?
    # It will raise a `RuntimeWarning`.
    return numpy.mean(data)

def process_file(path):
    # This shadows the built-in `open`
    open = get_custom_opener()
    with open(path, "r") as f:
        return f.read()
```

> Relying on human memory to spot these issues is unreliable and doesn't scale.

Lint Example: Unused Imports

This code runs, but it's confusing.

```python
import sys
import numpy
import os # <-- Linter warning: Unused import `os`

def get_platform():
    # This function only uses the `sys` module.
    return sys.platform
```

> **Why it's a problem:**
>
> * **Cognitive Load:** A reader might wonder, "Where is `os` used? Am I missing something?"
> * **Maintenance:** It pollutes the namespace and can hide dependencies that are no longer needed.
>
> A linter automatically detects and can even remove this dead code.

Lint Example: Shadowing Built-ins

This is a very common and dangerous mistake.

```python
# The developer wants a list of numbers
list = [1, 2, 3]
print(list)

# Later, they try to convert a tuple to a list...
my_tuple = (4, 5, 6)
# This will fail! `list` is no longer the type, it's the variable.
new_list = list(my_tuple) # <-- TypeError: 'list' object is not callable
```

> A linter will immediately flag `list = [1, 2, 3]` with a warning like: `Redefinition of built-in 'list'`. This prevents the downstream `TypeError`.

Lint Example: Mutable Default Arguments

This is one of the most infamous "gotchas" in Python.

```python
def add_item(item, target_list=[]):
    target_list.append(item)
    return target_list

# First call seems to work
l1 = add_item("a") # -> ["a"]
print(f"l1: {l1}")

# Second call has a surprising result!
l2 = add_item("b") # -> ["a", "b"]
print(f"l2: {l2}")
```

> **The Bug:** The default list `[]` is created *once*, when the function is defined, not each time it's called. A linter detects this pattern and suggests the correct idiom: `target_list=None` and creating a new list inside the function.

Part 2: Static Assurance

The Goal: Static Assurance

> Let the computer find and fix predictable errors, so human reviewers can focus on what matters: **design, intent, and scientific validity.**

Static analysis tools read your code without executing it. This allows them to catch entire classes of bugs and style issues automatically, *before* your code runs.

We'll look at two main categories:

1. **Linting & Formatting:** Enforcing consistency and finding hidden bugs.

2. **Type Checking:** Verifying the "shapes" of your data match your intent.

The Standard: PEP 8

This problem is so common that the Python community created **PEP 8**, the official style guide for Python code.

It provides conventions for:

- **Line length:** Max 79 characters for code, 72 for docstrings.
- **Indentation:** 4 spaces per indentation level.
- **Imports:** Should be at the top of the file, grouped in a standard order.
- **Whitespace:** Around operators and after commas.
- **Naming:** `snake_case` for functions and variables, `PascalCase` for classes.

> Following a consistent style guide is more important than any single rule. An auto-formatter makes this effortless.

The Historical Formatter: black

To solve the problem of inconsistent style, the community developed opinionated auto-formatters. The most influential was black.

- **Philosophy:** "The Uncompromising Code Formatter."
- **Goal:** End debates over style by providing one single, deterministic style. It is not configurable.
- **Impact:** black popularized the idea of handing over all style decisions to an automated tool, enforcing a strict subset of PEP 8.

> black was a game-changer, but it only solved formatting. Developers still needed other tools to find bugs.

The Historical Linter Ecosystem

For finding bugs (linting), developers had to combine several different tools:

- `flake8`: A popular wrapper that bundled basic style checks (`pycodestyle`) and simple bug detection (`pyflakes`).
- `pylint`: A much more powerful (and often slower and "noisier") linter that performs deeper code analysis.
- `isort`: A specialized tool that did only one thing: sort import statements alphabetically and into sections.

> **The Problem:** Managing, configuring, and running this collection of separate, slow tools was complex and a common source of friction for projects.

The Modern, Unified Tool: ruff

ruff is an extremely fast, all-in-one tool written in Rust that replaces the entire historical ecosystem.

It is a formatter: Replaces black and isort.

```
# Format code
ruff format .
```

It is a linter: Replaces flake8, pylint, and many other plugins.

```
# Find and fix issues
ruff check --fix .
```

Why ruff?

- **Speed:** It is 10-100x faster than the tools it replaces.
- **Simplicity:** One tool to install, configure, and run.
- **Compatibility:** It can be configured to be a drop-in replacement for black and flake8.

Our Workflow:

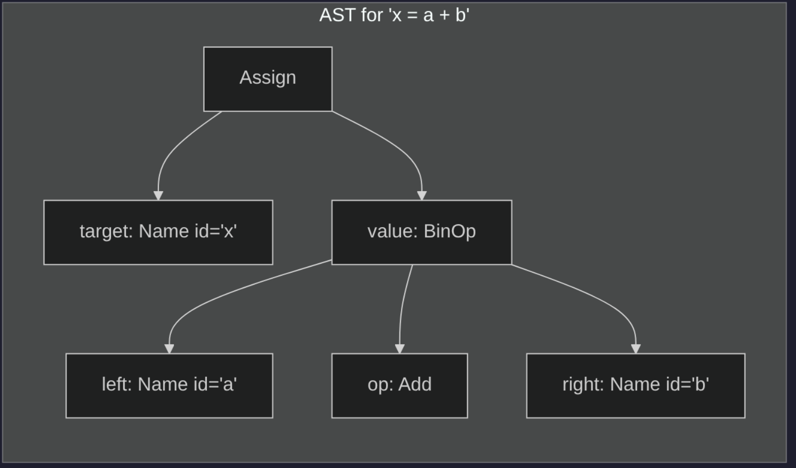
```
# 1. Format the codebase
ruff format .

# 2. Find and fix issues
ruff check --fix .
```

> This unified workflow is fast, simple, and makes code reviews easier because diffs are minimal and focused on logic, not style.

How Static Analysis Works: The AST

Tools like ruff don't just read text; they parse your code into an **Abstract Syntax Tree (AST)**. This tree represents the code's grammatical structure.



By "walking" this tree, a tool can understand the code's structure and enforce rules.

Inspecting the AST with ast.dump

The ast.dump() function gives a detailed, unambiguous view of the tree's structure. It's more verbose than a diagram but essential for debugging.

Source:

```python
import ast

code = "x = a + b"
tree = ast.parse(code)

# Get a developer-friendly view of the tree
print(ast.dump(tree, indent=4))
```

Output:

```
Module(
    body=[
        Assign(
            targets=[
                Name(id='x', ctx=Store())],
            value=BinOp(
                left=Name(id='a', ctx=Load()),
                op=Add(),
                right=Name(id='b',
ctx=Load())))],
    type_ignores=[])
```

> This detailed output shows every node and its attributes, like `ctx=Store()` (for assignment) vs. `ctx=Load()` (for usage).

Analyzing with `ast.NodeVisitor`

The `ast.NodeVisitor` class provides a way to walk the AST and execute code for every node of a certain type. It's perfect for collecting information without changing the code.

Example: Find all imported modules.

```python
import ast

class ImportCollector(ast.NodeVisitor):
    def __init__(self):
        self.imports = set()

    def visit_Import(self, node):
        for alias in node.names:
            self.imports.add(alias.name)
        self.generic_visit(node)

source = "import numpy as np\nimport os"
tree = ast.parse(source)
collector = ImportCollector()
collector.visit(tree)
print(collector.imports) # -> {'numpy', 'os'}
```

> The visitor pattern lets you write clean, targeted functions (`visit_Import`, `visit_FunctionDef`, etc.) that operate on specific parts of your code's structure.

Modifying the AST with ast.NodeTransformer

To change the code, we use ast.NodeTransformer. It's similar to NodeVisitor, but its visit_* methods can **return a new node** to replace the original one.

- **Return a new node:** Replaces the original node in the tree.
- **Return None:** Removes the node from the tree.
- **Return the original node:** The tree remains unchanged.

This allows for powerful, programmatic refactoring of source code.

> The key difference: NodeVisitor is for *reading*, NodeTransformer is for *writing*.

Example: Replacing a node

```
# Before: 2 + 3
# Transformer replaces `Add` with `Sub`
def visit_Add(self, node):
    return ast.Sub()
# After: 2 - 3
```

Example: Removing a node

```
# Before: pass
# Transformer removes `Pass` nodes
def visit_Pass(self, node):
    return None
# After: (empty line)
```

AST Example: A Simple Code Transformer

Let's write a transformer that finds all string literals and converts them to uppercase.

```python
import ast

class UppercaseStrings(ast.NodeTransformer):
    def visit_Constant(self, node):
        # In modern Python, strings are `Constant` nodes.
        # In older Python, they were `Str` nodes.
        if isinstance(node.value, str):
            # Create a new node with the modified value
            return ast.Constant(value=node.value.upper())
        return node

source = 'print("Hello, world!")'
tree = ast.parse(source)

transformer = UppercaseStrings()
new_tree = transformer.visit(tree)
```

> After this runs, `new_tree` represents the code `print("HELLO, WORLD!")`. But it's still a tree object. How do we get back to source code?

AST Example: A Mini-Linter

Let's write a tiny linter that flags functions with too many parameters, a common sign of poor design.

```python
# mini_linter.py
import ast
import sys

class FuncVisitor(ast.NodeVisitor):
    def visit_FunctionDef(self, node):
        # Rule: A function should not have more than 5 parameters.
        if len(node.args.args) > 5:
            print(
                f"Linter Warning: {node.name} at line {node.lineno} "
                f"has {len(node.args.args)} parameters (> 5)."
            )
        self.generic_visit(node) # Continue visiting child nodes

# Read a file, parse it into an AST, and visit the nodes.
source_code = open(sys.argv[1]).read()
tree = ast.parse(source_code)
FuncVisitor().visit(tree)
```

> This is the core principle behind all static analysis tools. They define rules by inspecting the structure of the code's AST.

Reconstructing Code with ast.unparse

The ast.unparse() function (available in Python 3.9+) takes a modified AST and converts it back into valid Python source code.

Completing our example:

```python
# (continued from previous slide)
import ast

# ... UppercaseStrings transformer definition ...

source = 'print("Hello, world!")'
tree = ast.parse(source)
transformer = UppercaseStrings()
new_tree = transformer.visit(tree)

# Convert the new tree back to a string
new_code = ast.unparse(new_tree)
print(new_code)
```

Output:

```python
print('HELLO, WORLD!')
```

> This completes the cycle: code -> AST -> modified AST -> new code. This is the foundation of tools like ruff, which not only find issues but can also automatically fix them.

The Problem: Dynamic Type Errors

Python is **dynamically typed**: type errors are only caught when the code is executed.

The Code:

```python
def get_final_items(items):
    # The author assumes `items`
    # is a list of numbers.
    print(f"Processing {len(items)} items")
    return items[-1]

# This works
get_final_items([10, 20, 30])

# This fails at runtime!
get_final_items(123)
```

The Runtime Error:

```
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
  File "<stdin>", line 3, in get_final_items
TypeError: object of type 'int' has no len()
```

> We want to find these bugs *statically*—before we run a long simulation. In contrast, **statically-typed** languages (like C++ or Rust) would catch this before the program even runs.

The Solution: Type Hints & Checkers

Step 1: Add Type Hints We annotate our code to declare our intent. This is a form of documentation.

```python
def get_final_items(items: list[int]) -> int:
    print(f"Processing {len(items)} items")
    return items[-1]
```

Step 2: Run a Type Checker A static analysis tool reads the hints and validates them. Python itself does *not* enforce them at runtime.

```
# ty is a modern, fast type checker
# mypy is another popular choice
ty .
```

```
error: Argument 1 to "get_final_items" has incompatible type "int"; expected
"list[int]"
```

> Type hints + a checker turn runtime errors into static analysis errors.

The typing Module: A Vocabulary for Types

For more complex types, Python provides the typing module.

Common Primitives:

```python
from typing import List, Dict, Tuple,
Optional, Union

# Python 3.9+
ids: List[int]
scores: Dict[str, float]
# Python 3.10+ allows | syntax
ids: list[int]
scores: dict[str, float]
```

Composing Types:

```python
# A value that can be a string or None
user_id: Optional[str]
# Same as:
user_id: str | None

# A value that is an int or a float
value: Union[int, float]
# Same as:
value: int | float
```

> This vocabulary allows us to precisely describe the data our functions expect and return.

Advanced Types: Protocol

How do you type-hint an object that needs to behave a certain way (e.g., have `.fit()` and `.predict()` methods) without forcing it to inherit from a specific base class?

Use `typing.Protocol` to define an interface based on **behavior (duck typing)**, not inheritance.

```
from typing import Protocol
import numpy as np

class TrainableModel(Protocol):
    """A protocol for objects that can be trained and used for prediction."""
    def fit(self, X: np.ndarray, y: np.ndarray) -> None:
        ... # The "..." is a literal part of the syntax
    def predict(self, X: np.ndarray) -> np.ndarray:
        ...

def evaluate_model(model: TrainableModel, X_test, y_test):
    # The type checker now knows `model` has .fit and .predict methods.
    predictions = model.predict(X_test)
    # ... calculate accuracy ...
```

> This decouples your functions from specific implementations, making your code more flexible and reusable—perfect for comparing different scientific models.

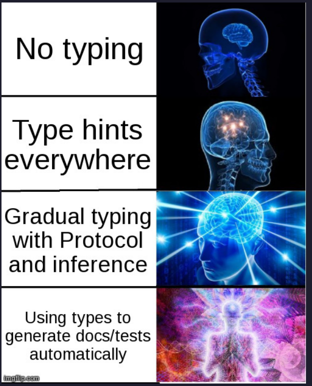
From Types to Tests

If you know the *shape* of your data, you can make the computer test it for you.

```
from hypothesis import given
from hypothesis.strategies import floats, lists
from typing import Sequence

def mean(xs: Sequence[float]) -> float:
    return sum(xs) / len(xs)

@given(lists(floats(min_value=0, max_value=1), min_size=1))
def test_mean(xs):
    y = mean(xs)
    assert 0 <= y <= 1
```



> Property-based testing tools like `Hypothesis` can use type hints to automatically infer test inputs. Future tools (like `pytest-typegen` or `pyright` plugins) will go even further — automatically generating tests directly from your type annotations and docstrings.

Part 3: Communicating Through Documentation

Docstrings vs. Comments

They serve different purposes and audiences.

- **Comments (`#`):** For the **maintainer** of the code.
  - Explain *how* a tricky piece of code works or *why* a specific implementation choice was made.
  - They live alongside the code they describe.
- **Docstrings (`"""..."""`):** For the **user** of the code.
  - Explain *what* a function/class does, its parameters, and what it returns.
  - They are part of the object's definition and can be accessed at runtime with `help()` or `__doc__`.

> **Rule:** Comments explain the implementation; docstrings explain the API.

Writing a Docstring

A good docstring is a user manual. For scientific code, it must be precise. We will build one piece by piece.

Part 1: Summary & Description

Start with a concise one-line summary, followed by a more detailed paragraph.

- **One-line summary:** Used by automated tools for quick reports. Imperative mood ("Do this," not "Does this").
- **Extended description:** Provides context, explains the "why."

```python
def run_monte_carlo(n_samples: int, rng: np.random.Generator):
    """Run a Monte Carlo simulation to estimate particle distances.

    This function simulates multiple random walks and returns the final
    Euclidean distance of each walk from the origin.
    """
    # ... implementation ...
```

Part 2: Describing Parameters

The Parameters section describes each argument. For scientific code, this is non-negotiable.

For each parameter, specify:

- name : type
- Description
- Units, constraints, or expected shape.

```python
def run_monte_carlo(n_samples: int, rng: np.random.Generator):
    """...

    Parameters
    ----------
    n_samples : int
        The number of random walks to simulate. Must be positive.
    rng : np.random.Generator
        A seeded random number generator for reproducibility.
    """
    # ... implementation ...
```

Part 3: Describing Returns

The Returns section describes the output of the function.

For each returned value, specify:

- name : type
- Description
- Units and shape.

```
def run_monte_carlo(n_samples: int, rng: np.random.Generator) -> np.ndarray:
    """...

    Returns
    -------
    distances : np.ndarray, shape (n_samples,)
        An array containing the final distance for each simulated walk,
        measured in meters.
    """
    # ... implementation ...
```

Part 4: Assumptions & Side Effects

Use sections like Notes, Raises, or Warns to communicate non-obvious behavior.

- **Assumptions:** What must be true for the function to work? (e.g., "Input must be sorted.")
- **Side Effects:** Does the function modify inputs in-place? Does it write a file?
- **Errors:** What exceptions does it explicitly raise?

```python
def run_monte_carlo(n_samples: int, rng: np.random.Generator) -> np.ndarray:
    """...

    Raises
    ------
    ValueError
        If `n_samples` is not a positive integer.
    """
    # ... implementation ...
```

Part 5: Providing Examples

The Examples section provides a minimal, runnable example of how to use the function.

- This is often the first thing a user looks for.
- It serves as a quickstart guide.
- It can be automatically tested with doctest.

```python
def run_monte_carlo(n_samples: int, rng: np.random.Generator) -> np.ndarray:
    """...

    Examples
    --------
    >>> import numpy as np
    >>> rng = np.random.default_rng(42)
    >>> distances = run_monte_carlo(n_samples=5, rng=rng)
    >>> distances.shape
    (5,)
    """
    # ... implementation ...
```

Putting It All Together: A Full Scientific Docstring

This brings all the pieces together into a compact, readable, and machine-parseable format.

```python
import numpy as np

def run_monte_carlo(n_samples: int, rng:
np.random.Generator) -> np.ndarray:
    """Run a Monte Carlo simulation.

    Simulates random walks and returns final
distances.

    Parameters
    ----------
    n_samples : int
        Number of walks to simulate.
    rng : np.random.Generator
        Seeded random number generator.

    Returns
    -------
    distances : np.ndarray
        Final distance for each walk (meters).

    Examples
    --------
    >>> rng = np.random.default_rng(42)
    >>> run_monte_carlo(5, rng).shape
    (5,)
    """
    # ... implementation ...
```

Anatomy of the Docstring:

- **1. Summary:** A concise one-liner.
- **2. Description:** More context.
- **3. Parameters:** Inputs with types and descriptions.
- **4. Returns:** Outputs with types and descriptions.
- **5. Examples:** A runnable doctest.

Doctests: Executable Documentation

The `Examples` section of our docstring contains **doctests**. They are a simple way to demonstrate usage and provide a basic sanity check.

`pytest` can discover and run them automatically.

```
pytest --doctest-modules
```

> Doctests turn your examples into verifiable tests, ensuring your documentation never goes out of date.

Doctest Example: Where They Shine

Doctests are perfect for pure, deterministic functions with simple inputs and outputs.

```python
def factorial(n):
    """
    Computes the factorial of a non-negative integer.

    Examples
    --------
    >>> factorial(5)
    120
    >>> factorial(0)
    1
    """
    if n < 0:
        raise ValueError("Factorial not defined for negative numbers")
    if n == 0:
        return 1
    return n * factorial(n - 1)
```

> This is a perfect use case: the example is clear, easy to verify, and effectively documents the function's primary behavior.

Doctest Example: Where They Fail

Doctests are brittle and poorly suited for code with side effects, randomness, or complex output.

```
from datetime import datetime

def log_event(message):
    """
    Logs a message with a timestamp to a file.

    Examples
    --------
    >>> log_event("System start")
    # How do you test this?
    # 1. The return value is None.
    # 2. It writes to a file (a side effect).
    # 3. The log includes a timestamp, so the output is never the same.
    """
    with open("events.log", "a") as f:
        f.write(f"{datetime.now()}: {message}\n")
```

> This is a job for `pytest`, where you can use fixtures to create a temporary file and mock the `datetime` module.
>
> **Rule:** Use doctests to prove your *examples* are correct. Use `pytest` to prove your code is robust.

The Problem: Documentation Doesn't Scale

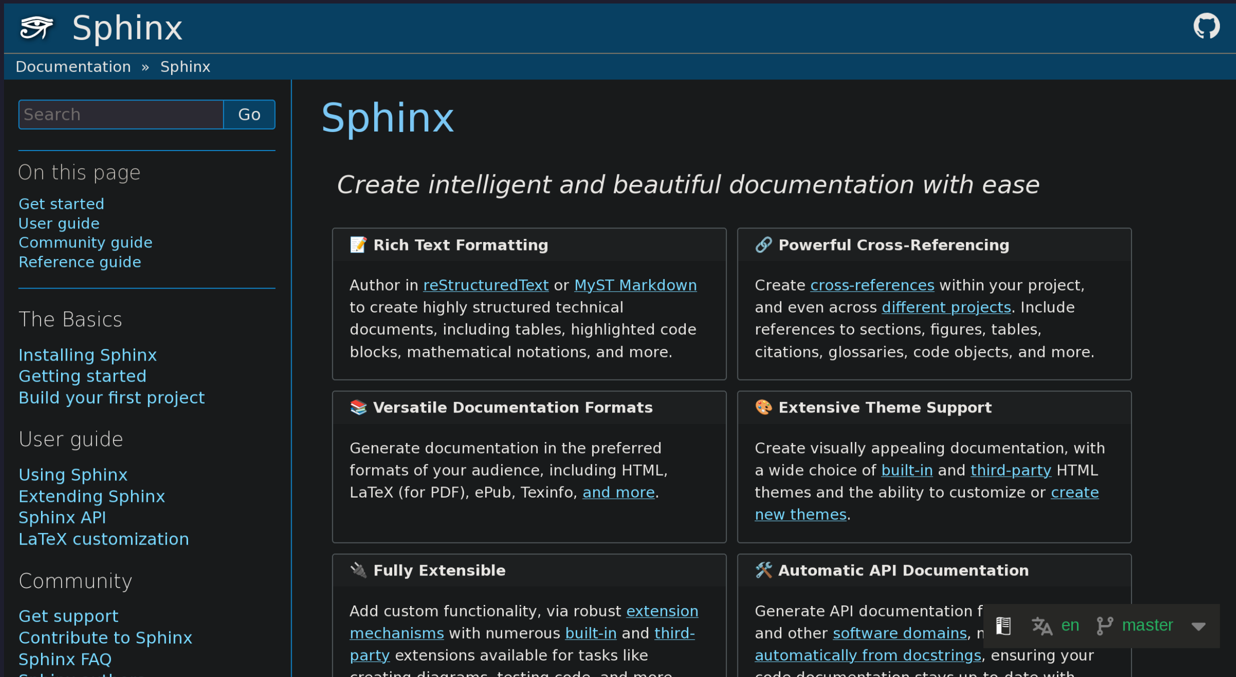
For a small project, reading source code or using `help(my_function)` might be enough. But as a project grows, this approach fails.

- **No Central Hub:** How do you get a high-level overview of the whole library?
- **Hard to Discover:** How do you find a function if you don't know its name?
- **Poorly Organized:** `help()` just dumps a wall of text. It's not browsable or searchable.

> We need a way to turn our docstrings into a centralized, cross-referenced, and searchable website.

The Solution: Sphinx

Sphinx is the de facto standard documentation generator for the Python ecosystem. It builds a professional website directly from your source code's docstrings.



> Sphinx turns your inline documentation into a first-class, user-facing product. It's what powers the documentation for NumPy, SciPy, Pandas, and thousands of other libraries.

Sphinx Workflow Step 1: Setup

First, you set up the documentation source directory.

```
# Install sphinx and a theme
pip install sphinx sphinx_rtd_theme numpydoc

# Create a docs directory
mkdir docs
cd docs

# Run the interactive setup wizard
sphinx-quickstart
```

This creates a `source` directory with key files:

- `conf.py`: The main configuration file for your documentation project.
- `index.rst`: The homepage of your documentation website.

> The `.rst` extension stands for reStructuredText, a markup language similar to Markdown.

Sphinx Workflow Step 2: Configuration

Next, you edit `docs/source/conf.py` to tell Sphinx how to find and interpret your code.

```python
# docs/source/conf.py

# ... other settings ...

# List of extensions to enable
extensions = [
    'sphinx.ext.autodoc',            # Core: pull documentation from docstrings
    'sphinx.ext.napoleon',           # To understand NumPy/Google style docstrings
    'sphinx.ext.viewcode',           # Add links to source code
    'sphinx_autodoc_typehints', # Render type hints in documentation
]

# Set the theme
html_theme = 'sphinx_rtd_theme'
```

> The `extensions` list is the most important part. It activates plugins that give Sphinx its power.

Sphinx Workflow Step 3: Connecting Code

Now, you tell Sphinx *which* modules to document. You do this in your `.rst` files using `autodoc` directives.

Example: `docs/source/api.rst`

```
API Reference
=============

.. automodule:: my_package.simulation
   :members:

.. automodule:: my_package.analysis
   :members:
```

- `.. automodule:: my_package.simulation`: Tells Sphinx to find the `simulation` module.
- `:members:`: Tells Sphinx to document all public functions, classes, and methods in that module.

> You can also use `autoclass` or `autofunction` for more granular control.

Sphinx Workflow Step 4: Building the Site

Finally, you install your package and run the build command.

```
# From the project root directory
# 1. Install the package in editable mode
pip install -e .

# 2. Build the documentation
sphinx-build -b html docs/source docs/build/html
```

- Installing the package makes it importable by Sphinx without `sys.path` hacks.
- `sphinx-build` then generates the HTML site into the `docs/build/html` directory.

> You can now open `docs/build/html/index.html` in a browser to see your documentation website.

The Sphinx Workflow: A Recap

1. **Setup (`sphinx-quickstart`):** Create the initial `docs/source` directory and configuration files.
2. **Configure (`conf.py`):** Point Sphinx to your source code and enable extensions like `autodoc` and `napoleon`.
3. **Connect (`.rst` files):** Use `automodule` directives to tell Sphinx which parts of your code to document.
4. **Build (`sphinx-build`):** Run the command to generate the final HTML website from your docstrings.

> This workflow seems complex at first, but it's a one-time setup. Once configured, you just write docstrings and run the build command.

Part 4: Automation & Integration

The Goal: Sustainable Quality

> Standards should live in configuration files and automated checks, not in people's heads or style guide documents.

This ensures that quality is maintained over time and across a team, without relying on manual effort or memory.

The central hub for this automation is `pyproject.toml`.

pyproject.toml: The Central Hub

As we saw in **Lecture 5**, pyproject.toml defines our package. It's also where we configure our quality tools.

```toml
# pyproject.toml

# Project metadata from Lec 5
[project]
name = "am215-demo"
version = "0.1.0"
requires-python = ">=3.11"

# Ruff configuration
[tool.ruff]
line-length = 88
select = [
    "E", "F", "I", # Base rules
    "UP",          # Pyupgrade
    "B",           # Bugbear
]
```

```toml
# (continued from left)

# Ty configuration
[tool.ty]
strict = true

# Pytest configuration from Lec 6
[tool.pytest.ini_options]
minversion = "6.0"
addopts = "-ra -q"
testpaths = [
    "tests",
    "src",
]
```

> Consolidating configuration makes the project's standards explicit and easy to manage.

What are Git Hooks?

Git hooks are scripts that run automatically at certain points in the `git` lifecycle.

- **Client-side hooks:** Triggered by local actions like committing (`pre-commit`) or pushing (`pre-push`).
- **Server-side hooks:** Run on the remote server, e.g., after a push is received.

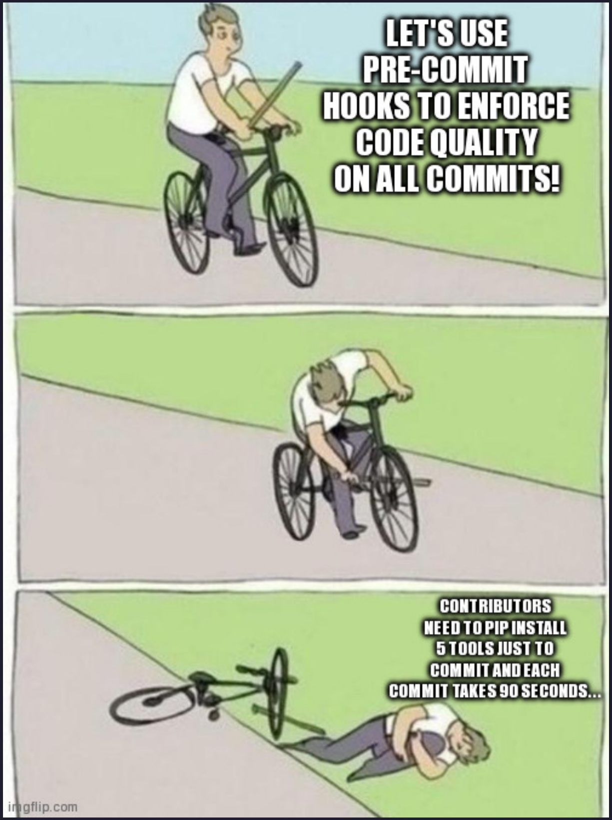
They live inside your local `.git/hooks` directory. When you run `git init`, Git populates this directory with example scripts.

```
$ ls .git/hooks
applypatch-msg.sample  pre-rebase.sample
commit-msg.sample      pre-push.sample
post-update.sample     prepare-commit-msg.sample
pre-applypatch.sample  update.sample
pre-commit.sample
```

> To enable a hook, you just remove the `.sample` extension and make the script executable.

The Allure of Pre-Commit Hooks

The most common use case is the `pre-commit` hook. The idea is to automatically run quality checks before a commit is even created.



The Perceived Benefit:

The Problem: Hooks are Local and Not Shared

The `.git` directory is **local to your machine**. It is not cloned, not version-controlled, and not shared with collaborators.

- This means every developer on a team must **manually install and manage their own hooks**.
- There is no guarantee that everyone has the same hooks, or any hooks at all.
- This makes them completely unreliable as a project-wide enforcement mechanism.

> A standard that relies on every single person opting in and correctly configuring their local environment is not a standard at all.

The Problem: Hooks Create Friction and Can Be Bypassed

Even if a developer has hooks installed, they are not a foolproof quality gate.

1. **They can be bypassed.** Any hook can be skipped with the `--no-verify` flag.

```
# This command skips all pre-commit and commit-msg hooks
git commit -m "I'm ignoring the rules" --no-verify
```

2. **They create friction.** Slow-running hooks can make committing a frustrating experience, encouraging developers to bypass them.

> Mandatory local checks create a poor developer experience and provide a false sense of security.

The Better Solution: CI as the Source of Truth

Quality enforcement belongs in a **centralized, non-bypassable CI pipeline**.

- **Centralized:** The rules are defined once in a version-controlled file (e.g., `.github/workflows/ci.yml`).
- **Consistent:** The same checks run in the same clean environment for every single commit and pull request.
- **Non-Bypassable:** Branch protection rules in GitHub can be configured to *require* the CI checks to pass before merging.

> Use local tools like `ruff` and `ty` for **developer convenience** to get fast feedback. Use a CI pipeline as the **authoritative quality gate** for enforcement.

A Minimal CI Pipeline

This GitHub Actions workflow automates our quality checks on every push and pull request, building on our CI knowledge from **Lecture 6**.

```yaml
# .github/workflows/ci.yml
name: Quality and Docs
on: [push, pull_request]
jobs:
  main:
    runs-on: ubuntu-latest
    steps:
      - uses: actions/checkout@v4
      - uses: actions/setup-python@v5
        with:
          python-version: '3.11'
      - name: Install dependencies
        run: |
          pip install ruff ty sphinx \
            sphinx-autodoc-typehints numpydoc
```

```yaml
# (continued from left)
      - name: Lint and Format Check
        run: |
          ruff check .
          ruff format --check .
      - name: Type Check
        run: ty .
      - name: Build Documentation
        run: sphinx-build -b html docs/source
docs/_build/html
      - name: Upload Docs Artifact
        uses: actions/upload-artifact@v4
        with:
          name: docs-html
          path: docs/_build/html
```

> This pipeline ensures that no code can be merged unless it passes all linting, formatting, type, and documentation build checks.

The Problem: Repetitive Local Commands

While CI provides enforcement, it's tedious to manually run all the checks locally before you push.

You might have a sequence of commands like this:

```
# Check for linting errors
ruff check .

# Check formatting
ruff format --check .

# Run the type checker
ty .

# Run the test suite
pytest
```

> This is hard to remember, easy to get wrong, and inconsistent across a team. We need a single, simple command to run all our local checks.

Solution 1: make - The Classic Task Runner

make is a classic, language-agnostic tool for automating command sequences, originating from the C/C++ world. It uses a Makefile to define "targets".

Example Makefile:

```
.PHONY: lint test docs

lint:
    ruff check .
    ruff format --check .

test:
    pytest

docs:
    sphinx-build -b html docs/source docs/build/html

all: lint test docs
```

To run:

```
make lint
make all
```

> make is simple and ubiquitous, but it's not Python-aware and doesn't manage environments.

Solution 2: `nox` - The Python-Native Approach

`nox` is a modern, Python-native task runner that uses a `noxfile.py` for configuration.

Key Advantages:

- **Configuration is Python:** Use the full power of Python to define your tasks.
- **Environment Isolation:** `nox` creates a clean, temporary virtual environment for each session. This ensures your checks run in a reproducible environment, separate from your local development setup.

> This isolation prevents issues where a check passes locally but fails in CI because of a missing or incorrect dependency.

Example: nox in Practice

A noxfile.py defines sessions, which are isolated environments for running commands.

```python
# noxfile.py
import nox

@nox.session
def lint(session):
    session.install("ruff")
    session.run("ruff", "check", ".")
    session.run("ruff", "format", "--check", ".")

@nox.session
def docs(session):
    session.install("sphinx", "numpydoc")
    session.run("sphinx-build", "-b", "html", "docs", "docs/_build")
```

To run:

```bash
# Run specific sessions
nox -s lint docs

# List all available sessions
nox -l
```

> This provides a consistent, convenient interface for developers without the friction of mandatory pre-commit hooks.

Other Modern Alternatives: `just`

`just` is another popular command runner that aims to be a simpler, cleaner alternative to `make`. It uses a `justfile`.

Example `justfile`:

```
# justfile
lint:
    ruff check .
    ruff format --check .

test:
    pytest

docs:
    sphinx-build -b html docs/source docs/build/html

all: lint test docs
```

To run:

```
just lint
just all
```

> `just` is a great choice if you want the simplicity of `make` with a more modern syntax and without the baggage of `make`'s file-dependency features.

Code Review as Social CI

Automation handles the objective details. Human review is for the subjective.

> A good code review is a dialogue about **design and intent**.

A Quick Review Checklist:

- **Naming:** Are variable and function names clear and unambiguous?
- **API Surface:** Is the public interface intuitive?
- **Invariants:** Does the code maintain important assumptions (e.g., "this array is always sorted")?
- **Data Contracts:** Are data shapes, units, and types handled correctly?
- **Testability:** Is the code structured in a way that is easy to test?

Lecture Recap

- **Code quality** is about communication and reducing cognitive load, not just correctness.
- **Static analysis** tools (`ruff`, `ty`) find bugs and enforce style automatically by analyzing the code's structure (AST).
- **Docstrings** are for users (the API), while **comments** are for maintainers (the implementation).
- **Automation is key:** Centralize configuration in `pyproject.toml` and run checks in CI to ensure quality is sustainable.
- **Human review** complements automation by focusing on high-level design and intent.

Summary: A Mental Map for Quality

Dimension	Toolchain	Purpose
Behavior	pytest, hypothesis	Does it *work correctly*?
Quality	ruff, ty	Is it *clear, consistent, and safe*?
Communication	Docstrings, Sphinx	Is it *understandable and verifiable*?
Sustainability	pyproject.toml, CI	Will it *stay that way*?
Collaboration	Code Review	Is the *design sound*?

> These dimensions are interconnected. Good documentation makes code more testable. Automated formatting makes code reviews more effective.

Next Steps

- Apply this template to your own projects.
- Start with a simple `pyproject.toml` configuration for `ruff`.
- Write one high-quality, NumPy-style docstring for a key function.
- Add a simple CI workflow to your repository to automate the checks.

> "Automation is kindness to your future collaborator." — and your future self is your most frequent collaborator.