The Python Data Model: Building Intuitive Scientific Tools

AM215 - LECTURE 4

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From Functions to Frameworks

So far, we've written scripts and functions. But as our models grow, we need a better way to organize our code.

The Challenge: How do we bundle related data and behavior together into logical, reusable, and intuitive components?

Today's Goal: Move from writing standalone functions to designing robust, class-based APIs for scientific computing.

Today's Roadmap

We will build our understanding of object-oriented design by example:

1. **A `Vector` Class**: Learn how operator overloading (`__add__`, `__mul__`) and properties (`@property`) create intuitive APIs.

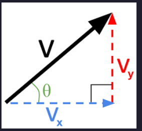
2. **Decorators Deep Dive**: Demystify decorators by building a `@time_it` function wrapper from scratch.

3. **A `Deck` of Cards**: See how implementing a simple protocol (`__len__`, `__getitem__`) enables powerful "duck typing."

4. **A Particle Simulation**: Synthesize all concepts to build a flexible simulation framework with inheritance and metaprogramming.

The Basics – A Vector Class

We'll start with a simple mathematical object to explore how Python's core features allow us to build intuitive tools.



The Simplest Possible Class

Let's start with an empty class. We can create an instance and then manually assign attributes to it.

```python
class Vector:
    pass

v = Vector()
v.x = 3
v.y = 4

print(v.x, v.y)
```

[finished]

```
3 4
```

> This works, but it's tedious and error-prone. There's no guarantee that every `Vector` instance will have an `x` and a `y`.

A Proper Constructor with __init__

The __init__ method is our first "dunder" method. It's a constructor that runs when an object is created, ensuring every instance is properly initialized.

```python
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y

v = Vector(3, 4)
print(v)
```

[finished]

```
<__main__.Vector object at 0x7f87b9bff350>
```

> We've solved the initialization problem, but now printing the object is useless. It doesn't show the vector's state.

A Developer-Friendly Representation (__repr__)

The __repr__ method provides the **official** string representation of an object. It should be unambiguous and, ideally, allow you to recreate the object.

```python
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y

    def __repr__(self):
        return f"Vector({self.x}, {self.y})"

v = Vector(3, 4)
print(v)

# The repr is valid Python code!
v2 = eval(repr(v))
print(v2)
```

——————————— [finished] ———————————

```
Vector(3, 4)
Vector(3, 4)
```

> The goal of `__repr__` is to be informative for the developer. If `__str__` is not defined, `print()` falls back to using `__repr__`.

A User-Friendly Representation (__str__)

The __str__ method provides a "pretty" or user-friendly string representation. It's what print() and str() use.

```
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y

    def __repr__(self):
        return f"Vector({self.x}, {self.y})"

    def __str__(self):
        return f"({self.x}, {self.y})"

v = Vector(3, 4)
print(v)
print(repr(v))
```

[finished]

```
(3, 4)
Vector(3, 4)
```

> **Rule:** Implement __repr__ for your developers (and your future self). Implement __str__ for your users.

Making Vectors Addable

What happens when we try to add two vectors?

```python
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y
    def __repr__(self):
        return f"Vector({self.x}, {self.y})"

v1 = Vector(2, 3)
v2 = Vector(10, 20)
v1 + v2
```

——————————— [finished with error] ———————————

```
Traceback (most recent call last):
  File "/tmp/.presentermec6C8G/snippet.py", line 10, in
<module>
    v1 + v2
    ~~~^~~~
TypeError: unsupported operand type(s) for +: 'Vector' and
'Vector'
```

> Python doesn't know what `+` means for our new type. We have to teach it by implementing the `__add__` dunder method.

Implementing __add__

When Python sees v1 + v2, it calls v1.__add__(v2).

```
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y
    def __repr__(self):
        return f"Vector({self.x}, {self.y})"
    def __add__(self, other):
        if not isinstance(other, Vector):
            return NotImplemented
        return Vector(self.x + other.x, self.y + other.y)

v1 = Vector(2, 3)
v2 = Vector(10, 20)
print(v1 + v2)
```

[finished]

```
Vector(12, 23)
```

> The special value NotImplemented signals that our method can't handle the operation for the given type, allowing Python to try other options.

Unary vs. Binary Operators: __neg__ and __sub__

The - symbol is overloaded: it can be a *unary* operator (negation) or a *binary* operator (subtraction). We must implement both.

```python
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y
    def __repr__(self):
        return f"Vector({self.x}, {self.y})"
    def __neg__(self):
        return Vector(-self.x, -self.y)

v = Vector(3, 4)
print(-v)
```

[finished]

```
Vector(-3, -4)
```

> __neg__ handles the unary case. But v1 - v2 will still fail.

Reusing Logic for __sub__

We can implement subtraction by elegantly reusing the logic we've already built for addition and negation.

```
class Vector:
    def __init__(self, x, y): self.x=x; self.y=y
    def __repr__(self): return f"Vector({self.x}, {self.y})"
    def __add__(self, other):
        if not isinstance(other, Vector): return NotImplemented
        return Vector(self.x + other.x, self.y + other.y)
    def __neg__(self): return Vector(-self.x, -self.y)
    def __sub__(self, other):
        if not isinstance(other, Vector): return NotImplemented
        return self + (-other)

v1 = Vector(10, 20)
v2 = Vector(3, 4)
print(v1 - v2)
```

[finished]

```
Vector(7, 16)
```

> `v1 - v2` becomes `v1.__sub__(v2)`, which we've defined as `v1 + (-v2)`. This calls `v1.__add__(v2.__neg__())`.

Scalar Multiplication

What about v * 2? And more trickily, 2 * v?

```python
class Vector:
    def __init__(self, x, y): self.x=x; self.y=y
    def __repr__(self): return f"Vector({self.x}, {self.y})"
    def __mul__(self, scalar):
        return Vector(self.x * scalar, self.y * scalar)

v = Vector(3, 4)
print(v * 2)

# This will raise a TypeError
print(2 * v)
```

[finished with error]

```
Vector(6, 8)
Traceback (most recent call last):
  File "/tmp/.presenterm4xSVTb/snippet.py", line 11, in
<module>
    print(2 * v)
          ~~^~~
TypeError: unsupported operand type(s) for *: 'int' and
'Vector'
```

> `v * 2` works, but `2 * v` fails. Why? Because `(2).__mul__(v)` is called first, and the `int` type doesn't know how to multiply by a `Vector`.

How Operators *Really* Work: The Dispatch Protocol

When Python sees `x * y`, it follows a precise protocol:

1. It calls `x.__mul__(y)`.
2. If that method doesn't exist, or if it returns `NotImplemented`, Python tries the reverse: `y.__rmul__(x)`.
3. If that also fails, it raises a `TypeError`.

> This two-step protocol is the core mechanism that makes Python's operators so flexible. It gives both operands a chance to handle the operation.

The Dispatch Protocol in Action: `__rmul__`

To handle `2 * v`, we implement the "right-multiply" method, `__rmul__`.

1. Python tries `(2).__mul__(v)`. This returns `NotImplemented`.
2. Python tries the reverse: `v.__rmul__(2)`.
3. Our class implements this, so the call succeeds.

```python
class Vector:
    def __init__(self, x, y): self.x=x; self.y=y
    def __repr__(self): return f"Vector({self.x}, {self.y})"
    def __mul__(self, scalar):
        return Vector(self.x * scalar, self.y * scalar)
    def __rmul__(self, scalar):
        return self.__mul__(scalar)

v = Vector(3, 4)
print(2 * v)
```

[finished]

```
Vector(6, 8)
```

> Implementing `__rmul__` makes our class a good citizen that can participate in operations even when it's on the right-hand side.

A Dynamic Attribute (@property)

We want a magnitude attribute. A naive approach is to calculate it in __init__.

```
class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y
        # This is calculated once and never updated!
        self.magnitude = (x**2 + y**2)**0.5

v = Vector(3, 4)
print(f"Initial magnitude: {v.magnitude}")
v.x = 0
print(f"Magnitude after change: {v.magnitude}")
```

[finished]

```
Initial magnitude: 5.0
Magnitude after change: 5.0
```

> The magnitude is now out of sync with the components. It should be computed dynamically.

The Solution: @property

A method is one option (v.magnitude()), but it feels like an attribute. The @property decorator gives us the best of both worlds.

```python
import math

class Vector:
    def __init__(self, x, y):
        self.x = x
        self.y = y

    @property
    def magnitude(self):
        """A read-only computed property."""
        return math.sqrt(self.x**2 + self.y**2)

v = Vector(3, 4)
print(f"Initial magnitude: {v.magnitude}")
v.x = 0
print(f"Magnitude after change: {v.magnitude}")
```

[finished]

```
Initial magnitude: 5.0
Magnitude after change: 4.0
```

> The @property decorator lets us expose a computed value as a clean, read-only attribute, creating a robust and intuitive API.

A Deeper Look at Decorators

We just used `@property`. But what *is* a decorator?

Decorators are Python's most common tool for **metaprogramming**—the idea of writing code that operates on other code. They allow us to modify or extend the behavior of functions and classes dynamically.

Why is this useful?

- **Reduces boilerplate**: Apply common logic (like timing or logging) to many functions without rewriting it.
- **Increases flexibility**: Allows a framework to automatically discover and register components, like the different `Walker` types we'll build for our diffusion simulation.

> In short, decorators let us add behavior to functions or classes in a clean, reusable way.

Decorators as Closures

A decorator is a higher-order function that takes another function as input and returns a *new* function that wraps the original. The `@` syntax is just "syntactic sugar" for this:

```
# This syntax...
@time_it
def my_function():
    # ... do work ...

# ...is equivalent to this:
def my_function():
    # ... do work ...
my_function = time_it(my_function)
```

The returned wrapper is a **closure**: it's an inner function that "remembers" the original `my_function` from its enclosing scope, even after the outer function (`time_it`) has finished executing.

Example: A Timing Decorator

Let's build a simple decorator to time how long a function takes to run.

```python
import time

def time_it(func):
    """A decorator that prints the execution time of a function."""
    def wrapper(*args, **kwargs):
        """The wrapper function that adds timing behavior."""
        start = time.perf_counter()
        result = func(*args, **kwargs)
        end = time.perf_counter()
        print(f"'{func.__name__}' took {end - start:.4f}s to execute.")
        return result
    return wrapper

@time_it
def do_work(duration):
    """A simple function that simulates work by sleeping."""
    time.sleep(duration)

do_work(0.1)
```

[finished]

```
'do_work' took 0.1001s to execute.
```

> This pattern (a function that defines and returns an inner `wrapper` function) is the standard way to build decorators. But it has a hidden problem.

The Problem: Lost Metadata

Our decorator works, but it obscures the identity of the original function. Introspection tools now see the wrapper, not do_work.

```python
import time

def time_it(func):
    def wrapper(*args, **kwargs):
        """I am the wrapper function."""
        # ...
        return func(*args, **kwargs)
    return wrapper

@time_it
def do_work(duration):
    """I am the original do_work function."""
    time.sleep(duration)

print(f"Function name: {do_work.__name__}")
print(f"Docstring: {do_work.__doc__}")
```

[finished]

```
Function name: wrapper
Docstring: I am the wrapper function.
```

> This is bad for debugging and breaks tools that rely on introspection. The original function's metadata has been replaced by the wrapper's.

The Solution: functools.wraps

The functools module provides a decorator specifically to solve this problem.

```python
import time
import functools

def time_it(func):
    @functools.wraps(func)
    def wrapper(*args, **kwargs):
        """I am the wrapper function."""
        # ...
        return func(*args, **kwargs)
    return wrapper

@time_it
def do_work(duration):
    """I am the original do_work function."""
    time.sleep(duration)

print(f"Function name: {do_work.__name__}")
print(f"Docstring: {do_work.__doc__}")
```

[finished]

```
Function name: do_work
Docstring: I am the original do_work function.
```

> `@functools.wraps` is itself a decorator that copies the name, docstring, and other metadata from the original function to the wrapper. **Always use it.**

Custom Containers — A Deck of Cards

Let's model something more complex: a deck of cards. This will force us to think about how to create our own **container** objects and manage different kinds of behavior.

The Motivation: We want to build components for a card game simulation, like Blackjack. This requires a deck that can be shuffled, drawn from, and even constructed in special ways for game variants.

The Basic Card and Deck

A Card is a simple data object. A Deck is a **container** that holds and manages Card objects.

```
class Card:
    def __init__(self, rank, suit):
        self.rank = rank
        self.suit = suit
    def __repr__(self):
        return f"Card('{self.rank}', '{self.suit}')"

class Deck:
    def __init__(self):
        # This is an "internal" attribute
        self._cards = [...]
```

> We use a single underscore prefix (`_cards`) to signal that this attribute is for the class's internal use and not part of its public API. This is a key convention for **encapsulation**.

Python's "Private" Attributes

Python doesn't have true private variables. The underscore is a convention.

- **Single Underscore (`_name`):** A convention that means "this is for internal use." You can still access it, but you shouldn't. We can see it with `vars()`:

```
>>> deck = Deck()
>>> vars(deck)
{'_cards': [Card('2', '♠'), ...]}
```

- **Double Underscore (`__name`):** Triggers **name mangling**. Python renames the attribute to `_ClassName__name`. This isn't for privacy; it's to avoid naming conflicts in subclasses during inheritance (which will be covered shortly).

> The goal is to design a clean public API. The underscore conventions help communicate that intent.

The Container "Contract"

To make our Deck behave like a Python sequence (like a list), we need to implement the container **protocol**—an implicit contract.

```
# In the Deck class...
def __len__(self):
    """Enables the `len()` built-in function."""
    return len(self._cards)

def __getitem__(self, position):
    """Enables indexing and slicing (`deck[i]`, `deck[i:j]`)."""
    return self._cards[position]
```

> By implementing just these two dunder methods, we get a huge amount of functionality for free.

The Payoff: Duck Typing

Because our `Deck` object now "walks and talks" like a sequence, Python's built-in functions know how to work with it.

```
>>> import random
>>> from code.deck import Deck
>>> deck = Deck()

>>> len(deck)
52

>>> deck[0]  # First card
Card('2', '♠')

>>> random.choice(deck) # Works because deck has __len__ and __getitem__
Card('K', '♡')
```

> This is **Duck Typing**: "If it walks like a duck and quacks like a duck, then it must be a duck." We didn't have to register our class or inherit from `list`; we just implemented the right methods.

Instance Methods

Methods that modify the state of a *specific* object are called **instance methods**. They always take `self` as their first argument.

```python
# In the Deck class...
import random

def shuffle(self):
    """Shuffles the cards in this deck."""
    random.shuffle(self._cards)

def draw(self):
    """Removes and returns the top card from this deck."""
    return self._cards.pop()
```

> They need `self` to access `self._cards`. Calling `deck.shuffle()` modifies that specific `deck` object. This is the default and most common method type.

Building a Blackjack Game

Where should the rules for Blackjack live? Inside the `Deck` class?

> No. A `Deck` should manage cards; it shouldn't know the rules of every possible game. This is the principle of **separation of concerns**. We'll create a new `BlackjackGame` class to encapsulate the rules.

```
class BlackjackGame:
    # Game logic will go here...
    pass
```

Static Methods for Utility Logic

To play Blackjack, we need to calculate a hand's value. This logic is related to the game, but it doesn't depend on the state of a specific game instance.

> This is a self-contained utility function. It belongs in the `BlackjackGame` class for organization, but it doesn't need access to any state. This is the job of a `@staticmethod`.

```python
# In the BlackjackGame class...
@staticmethod
def get_hand_value(hand):
    """Calculates the Blackjack value of a hand of cards."""
    # ... logic to handle aces and face cards ...
    return value
```

Extending the Framework

What if we want to play "Joker Blackjack," where the deck has a Joker and any hand with it is an automatic 21?

This requires two changes:

1. A different kind of deck.

2. A different set of rules.

> A good design should allow us to add this new functionality without rewriting existing code. This is the **Open/Closed Principle**: open for extension, closed for modification.

Class Methods for Alternative Construction

To create our special deck, we can add a **factory** to the Deck class. This is the perfect use case for a @classmethod.

```
# In the Deck class...
@classmethod
def create_deck_with_joker(cls):
    """A factory method to create a 53-card deck with a Joker."""
    deck = cls()  # Creates a new standard deck instance
    deck._cards.append(Card('Joker', '🃏'))
    return deck
```

> A class method receives the class (`cls`) as its first argument, not the instance (`self`). This allows it to call the constructor (`cls()`) to create a new instance in a special configuration.

Extending Game Logic with Inheritance

To handle the new rules, we create a `JokerBlackjackGame` class that **inherits** from `BlackjackGame`. We override `get_hand_value` to add the new logic.

```python
class JokerBlackjackGame(BlackjackGame):
    @staticmethod
    def get_hand_value(hand):
        """Overrides the base method to handle the Joker rule."""
        if any(card.rank == 'Joker' for card in hand):
            return 21
        # Fall back to the original logic for hands without a Joker
        return super().get_hand_value(hand)
```

> We use `super()` to call the parent's version of the method. This lets us **extend** the original logic rather than completely replacing it, keeping our design clean and avoiding code duplication.

Running the Simulations

Our flexible design allows us to easily swap components to run different scenarios and compare the outcomes. The `simulation.py` script does exactly this, running simulations for:

1. **Standard Game** vs. **Joker Game**
2. **Blind Player Strategy** (stands on 17+) vs. **Informed Player Strategy** (also considers dealer's card)

The script generates a plot comparing the player's wealth trajectories across these four scenarios, allowing us to analyze the impact of game rules and player strategy.

> This is the power of a good API: the final application code is a simple script that combines our components to answer interesting questions.

Alternative Design Questions

Our design works, but it's not the only way. Good design involves trade-offs.

- Should `Hand` be its own class? If so, adding a card could be `hand += card` by implementing `__iadd__`.

```python
# In a hypothetical Hand class...
def __iadd__(self, card):
    self._cards.append(card)
    return self
```

- Should `Player` and `Dealer` be classes with `wealth` and `strategy` attributes?
- For games like Poker, comparing hands is key. This would require **rich comparison methods** like `__eq__` and `__lt__` on a `Hand` class.

```python
# In a hypothetical Hand class...
def __lt__(self, other):
    return self.value < other.value
```

Modeling Questions and Insights

These simulations are not just toy examples; they are tools for generating insight. We can use our framework to answer real modeling questions:

- What is the optimal player strategy given the dealer's fixed rules?
- How does the player's long-term expected wealth (the drift of the random walk) change if we use six decks instead of one?
- Can we quantify the exact advantage the player gains in the Joker variant?

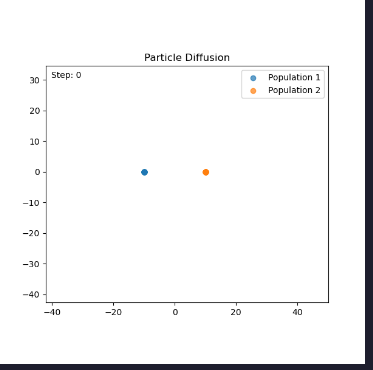
> By building flexible, class-based models, we can run computational experiments to understand and make predictions about complex systems.

Building an Extensible Simulation Framework

Let's synthesize our concepts to build a simulation of diffusing particles. Our goal is to create a flexible API that allows us to easily define and run different types of random walks.

- **Standard Walk**: $\vec{x}_{t+1} = \vec{x}_t + \vec{\delta}_t$, where $\vec{\delta}_t \sim \text{Uniform}(-1, 1)$
- **Biased Walk**: $\vec{x}_{t+1} = \vec{x}_t + \vec{\delta}_t + \vec{c}$, where $\vec{c}$ is a constant drift vector.

We'll model this system by creating `Particle` objects and different `Walker` classes that control their movement.



Controlling State with Setters

Our `Particle` will store its position in Cartesian coordinates (`x`, `y`), but what if we want to interact with it using polar coordinates (`r`, `theta`)?

```python
# code/diffusion/particle.py
class Particle:
    def __init__(self, x, y):
        self.x = x
        self.y = y

    @property
    def r(self):
        return math.sqrt(self.x**2 + self.y**2)

    @r.setter
    def r(self, new_r):
        """Scales the particle's position to a new radius."""
        if self.r == 0: return
        ratio = new_r / self.r
        self.x *= ratio
        self.y *= ratio
```

> A **setter** provides a controlled way to modify an object's internal state through a clean, attribute-based API.

Using the Setter Property

The setter allows us to interact with the particle using an intuitive polar coordinate API, while the object handles the complexity of keeping the underlying Cartesian coordinates consistent.

```
# Assume Particle class from previous slide
import math
class Particle:
    def __init__(self, x, y): self.x = x; self.y = y
    @property
    def r(self): return math.sqrt(self.x**2 + self.y**2)
    @r.setter
    def r(self, new_r):
        if self.r == 0: return
        ratio = new_r / self.r
        self.x *= ratio; self.y *= ratio

p = Particle(3, 4)
print(f"Initial: x={p.x:.2f}, y={p.y:.2f}, r={p.r:.2f}")

# Use the setter to change the radius
p.r = 10
print(f"After p.r = 10: x={p.x:.2f}, y={p.y:.2f}, r={p.r:.2f}")
```

[finished]

```
Initial: x=3.00, y=4.00, r=5.00
After p.r = 10: x=6.00, y=8.00, r=10.00
```

> The benefit is a cleaner, more intuitive interface. The user can think in terms of radius and angle, and the object guarantees its internal `x` and `y` state is always valid.

Enforcing a Contract: Abstract Base Classes

Our simulation needs to work with any object that can "walk". How do we formalize what "can walk" means?

```python
# code/diffusion/walkers.py
from abc import ABC, abstractmethod

class RandomWalker(ABC):
    """An abstract base class defining the walker API contract."""

    @abstractmethod
    def move(self, particle):
        """Move the particle according to the walker's rules."""
        pass
```

> An **Abstract Base Class (ABC)** defines an interface. Any concrete class that inherits from `RandomWalker` *must* provide an implementation for the `move` method, or Python will raise a `TypeError`.

Specializing Behavior: Inheritance

As with our JokerBlackjackGame, we use inheritance to create specialized behavior. Here, we create concrete Walker classes that fulfill the RandomWalker contract.

```
# code/diffusion/walkers.py
import random
class StandardWalker(RandomWalker):
    """A simple walker that takes a random step."""
    def move(self, particle):
        particle.x += random.uniform(-1, 1)
        particle.y += random.uniform(-1, 1)

class BiasedWalker(RandomWalker):
    """A walker that tends to move to the right."""
    def move(self, particle):
        particle.x += random.uniform(0, 2) # Biased step
        particle.y += random.uniform(-1, 1)
```

> Here, inheritance isn't about reusing parent code (the ABC is empty). It's about **conforming to a contract**. This guarantees that any `RandomWalker` subclass will have a `move` method, allowing our simulation to treat all walkers polymorphically, knowing they will have the required functionality.

Automating Extensibility with Metaprogramming

Just as decorators let us modify functions, other metaprogramming tools let us modify classes. How can our simulation *automatically discover* all the `Walker` types we've defined?

We can use `__init_subclass__` to create a self-registering system.

```
# In the RandomWalker base class...
class RandomWalker(ABC):
    WALKER_REGISTRY = {}

    def __init_subclass__(cls, **kwargs):
        super().__init_subclass__(**kwargs)
        # Register the new subclass by its name, but not the ABC itself
        if cls.__name__ != "RandomWalker":
            RandomWalker.WALKER_REGISTRY[cls.__name__] = cls
        print(f"Registered walker: {cls.__name__}")
```

> **Why do this?** This makes the framework truly plug-and-play. The main simulation script can now select a walker by name (`"BiasedWalker"`) without ever having to import it explicitly. To add a new walker type, you just create a new file with a new class; the framework finds it automatically.

Diffusion Demonstration

We've built a flexible framework. Now let's use it.

The run_simulation.py script uses our components:

1. It creates two populations of Particle objects.
2. It looks up a Walker class from the registry by name.
3. It loops through time, calling walker.move(particle) for each particle.
4. It uses an animate module to generate a visualization.

```
# To run directly (from the code/ directory):
python diffusion/run_simulation.py

# Or, to run inside a container (from the code/ directory):
cd diffusion
./docker_build.sh
./docker_run.sh
```

> By designing our components with clean, class-based APIs, the final application code becomes simple, readable, and easy to extend.

Summary: Building Better Tools

We've built a powerful mental model for structuring code by leveraging Python's data model.

- **Dunder Methods**: Implement protocols (`__add__`, `__len__`) to enable operator overloading and achieve **duck typing**.
- **Properties & Method Types**: Use `@property` for controlled attribute access, `@staticmethod` for utility functions, and `@classmethod` for alternative constructors.
- **Decorators**: Create wrappers (like `@time_it`) to add behavior to functions in a clean, reusable way.
- **Inheritance & ABCs**: Extend functionality (`JokerGame`) and define formal API contracts (`RandomWalker`) for reliable, polymorphic code.
- **Metaprogramming**: Automate framework behavior, like the self-registering `Walker` classes, to create plug-and-play systems.

> The goal is to design APIs that are **intuitive, predictable, and extensible**.

Resources

Course Materials

- All lecture materials & code: `https://code.harvard.edu/AM215/main_2025/tree/main/am215_lectures/lec04`

Further Reading

- **Python's Data Model** (*https://docs.python.org/3/reference/datamodel.html*) (The official reference)
- **Fluent Python** (*https://www.oreilly.com/library/view/fluent-python-2nd/9781492056348/*) by Luciano Ramalho (The definitive guide to this topic)
- **Primer on Python Decorators** (*https://realpython.com/primer-on-python-decorators/*)
- **Python's `super()`: An In-Depth Guide** (*https://realpython.com/python-super/*)
- **Python Descriptors: An Introduction** (*https://realpython.com/python-descriptors/*) (The mechanism behind `@property`)
- **A Guide to Python Metaclasses** (*https://realpython.com/python-metaclasses/*) (Related to `__init_subclass__`)