CHENNAI INSTITUTE OF TECHNOLOGY
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AD4305 PARALLEL PROGRAMMING THROUGH PYTHON

UNIT V – IMPLEMENTATION OF PARALLELISM IN PYTHON WITHOUT LIBRARIES

Python's multiprocessing module- Python's threading module- Python's asyncio module- POSIX threads- extensions in C or Cython to leverage low-level parallelism features - integration of C or Cython into Python code.

- **Introduction to Parallelism in Python**
  - Overview of parallel computing and its significance.
  - Types of parallelism: Data parallelism vs Task parallelism.
- **Python's multiprocessing Module**
  - How the multiprocessing module enables concurrent execution in Python.
  - Creating and managing processes using Process, Queue, and Pool.
  - Inter-process communication and synchronization using Pipe and Manager.
- **Python's threading Module**
  - Thread-based parallelism using the threading module.
  - Creating and managing threads using Thread.
  - Synchronization mechanisms: Lock, RLock, Semaphore, Event, and Condition.
- **Python's asyncio Module**
  - Asynchronous programming with the asyncio module.
  - Tasks, event loops, and coroutines.
  - Concurrency vs Parallelism: How asyncio handles non-blocking I/O operations.
- **POSIX Threads**
  - Understanding POSIX threads and their role in parallel programming.
  - Thread creation and management in Python through the ctypes or cffi modules.
  - Interaction between Python's threading model and POSIX threads.
- **Using the concurrent.futures Module**
  - Implementing parallelism with ThreadPoolExecutor and ProcessPoolExecutor.
  - Handling parallel tasks using submit() and map() functions.

- Futures and result collection in parallel execution.

 Extensions in C or Cython to Leverage Low-level Parallelism Features

- Writing parallelized code in C or Cython for performance improvements.
- Using Cython to write parallel C extensions that integrate with Python.
- Benefits of low-level parallelism for computational-heavy tasks.

 Integration of C or Cython into Python Code

- How to embed C or Cython extensions into Python scripts to speed up parallel execution.
- Using the ctypes or cffi library for interfacing with C code.
- Compiling and using Cython extensions for performance-critical code sections.

 Challenges and Best Practices in Parallelism with Python

- Limitations of Python's Global Interpreter Lock (GIL) in multithreading.
- Identifying performance bottlenecks and optimizing parallel execution.
- Thread safety, race conditions, and debugging parallel Python programs.

Introduction to Parallelism in Python

Parallel computing is a programming paradigm where multiple tasks or computations are executed simultaneously, leveraging the capabilities of multi-core processors or distributed systems. It is crucial for improving the efficiency, performance, and scalability of applications, especially when handling large datasets, complex computations, or real-time processing.

Python supports parallelism through various libraries and tools like multiprocessing, concurrent.futures, and threading. These help developers harness multi-core systems and maximize computational power.

Types of Parallelism

1. **Data Parallelism**
    - Focuses on distributing subsets of the same data across multiple processors.
    - Each processor performs the same operation on its respective subset of data in parallel.
    - Example: Applying the same filter to slices of an image or running the same function across chunks of a dataset.
    - Ideal for repetitive computations on large-scale data.

Data Parallelism Example

This program applies a mathematical operation (squaring numbers) to different parts of a dataset in parallel.

```
from concurrent.futures import ProcessPoolExecutor


# Function to square a number
 def square_number(number):
     return number * number


# Data: List of numbers
data = [1, 2, 3, 4, 5, 6, 7, 8, 9]


# Using ProcessPoolExecutor for parallel processing
with ProcessPoolExecutor() as executor:
    # Distributing the square_number function across the data
    results = list(executor.map(square_number, data))


print("Original Data:", data)
print("Squared Data:", results)
```

Output:

```
Original Data: [1, 2, 3, 4, 5, 6, 7, 8, 9]
Squared Data: [1, 4, 9, 16, 25, 36, 49, 64, 81]
```

Explanation:
Each number in the data list is processed independently in parallel by squaring it.

2. **Task Parallelism**

- Involves distributing different tasks (functions or computations) across multiple processors.
- Each processor executes a distinct task in parallel, which may or may not operate on the same data.

- Example: One task compresses a video while another encodes audio.
- Useful when tasks are independent but computationally intensive.

Task Parallelism Example

This program performs two different tasks in parallel: squaring numbers and cubing numbers.

```
from concurrent.futures import ThreadPoolExecutor


# Function to square a number
def square_number(number):
    return f"Square of {number}: {number * number}"


# Function to cube a number
def cube_number(number):
    return f"Cube of {number}: {number * number * number}"


# Input number
number = 4


# Using ThreadPoolExecutor for parallel task execution
with ThreadPoolExecutor() as executor:
    # Submitting two different tasks for parallel execution
    future_square = executor.submit(square_number, number)
    future_cube = executor.submit(cube_number, number)


    # Retrieving results
    result_square = future_square.result()
    result_cube = future_cube.result()


print(result_square)
print(result_cube)
```

Output:

```
Square of 4: 16

Cube of 4: 64
```

Explanation:
Two independent tasks (squaring and cubing a number) are executed simultaneously.

Key Difference in the Examples

- **Data Parallelism** distributes **the same task** across different parts of the data.
- **Task Parallelism** executes **different tasks** independently in parallel.

Both approaches help optimize computational resources based on the nature of the workload.

Python's multiprocessing Module

The multiprocessing module in Python allows programs to create multiple processes, enabling true parallelism by taking advantage of multiple CPU cores. Unlike threads, which share the same memory space, processes run in separate memory spaces, avoiding the Global Interpreter Lock (GIL) and enhancing performance for CPU-bound tasks.

1. Creating and Managing Processes

Using Process:

The Process class is used to create and manage individual processes.

Sample Program:

```
from multiprocessing import Process


# Function to be executed in a new process

def print_numbers():

    for i in range(5):

        print(f"Number: {i}")


# Create and start a new process

process = Process(target=print_numbers)

process.start()
```

```
# Wait for the process to complete
process.join()


print("Process finished!")
```

Explanation:

- The Process object runs print_numbers() in a separate process.
- start() begins execution, and join() ensures the main program waits for the process to finish.

Using `Pool`:

The `Pool` class simplifies managing a group of worker processes to execute tasks in parallel.

Sample Program:

```
from multiprocessing import Pool


# Function to square a number
def square(num):
    return num * num


# List of numbers
data = [1, 2, 3, 4, 5]


# Create a pool of workers and map the task
with Pool(processes=3) as pool:
    results = pool.map(square, data)


print("Squared results:", results)
```

Explanation:

- map() distributes the square function across the data list using a pool of processes.
- The number of processes can be specified (processes=3 in this example).

2. Inter-Process Communication

Using `Queue`:

`Queue` allows processes to communicate by passing messages between them.

Sample Program:

```
from multiprocessing import Process, Queue


# Function to put data into the queue
def producer(q):
    for i in range(5):
        q.put(i)
    q.put(None)  # Signal the consumer to stop


# Function to get data from the queue
def consumer(q):
    while True:
        item = q.get()
        if item is None:  # Stop when producer signals
            break
        print(f"Consumed: {item}")


# Create a shared queue
q = Queue()


# Create and start producer and consumer processes
producer_process = Process(target=producer, args=(q,))
consumer_process = Process(target=consumer, args=(q,))
producer_process.start()
consumer_process.start()
```

```
# Wait for both processes to finish
producer_process.join()
consumer_process.join()
```

Explanation:

- The Queue object acts as a shared communication channel between producer and consumer.

3. Synchronization and Shared State

Using `Pipe`:

`Pipe` is used for communication between two processes.

Sample Program:

```
from multiprocessing import Process, Pipe


# Function to send data through the pipe
def sender(conn):
    conn.send("Hello from sender!")
    conn.close()


# Function to receive data through the pipe
def receiver(conn):
    message = conn.recv()
    print(f"Received: {message}")


# Create a pipe
parent_conn, child_conn = Pipe()


# Create and start sender and receiver processes
sender_process = Process(target=sender, args=(parent_conn,))
```

```
receiver_process = Process(target=receiver, args=(child_conn,))
sender_process.start()
receiver_process.start()

# Wait for both processes to complete
sender_process.join()
receiver_process.join()
```

Explanation:

- A Pipe connects two processes, enabling them to send and receive messages.

Using `Manager`:

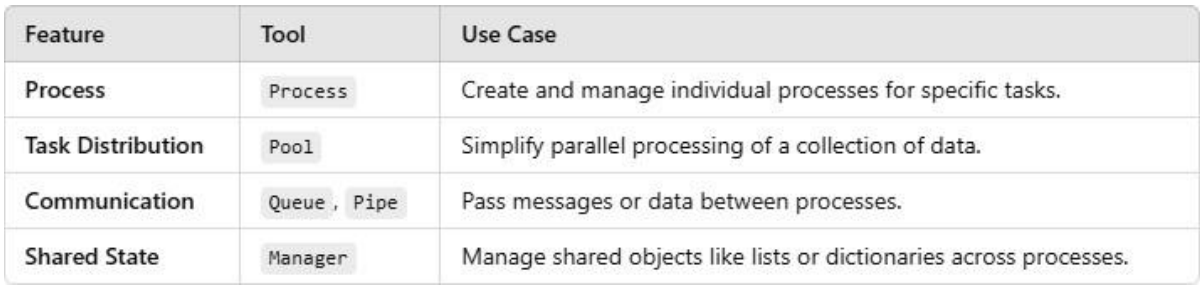
`Manager` provides shared data structures like lists and dictionaries for multiple processes.

Sample Program:

```
from multiprocessing import Process, Manager

# Function to update a shared list
def update_shared_list(shared_list):
    for i in range(5):
        shared_list.append(i)

# Create a manager to manage shared data
with Manager() as manager:
    shared_list = manager.list()  # Shared list
    process1 = Process(target=update_shared_list, args=(shared_list,))
    process2 = Process(target=update_shared_list, args=(shared_list,))

    # Start and join processes
    process1.start()
    process2.start()
    process1.join()

    process2.join()


    print("Shared List:", shared_list)
```

Explanation:

- Manager provides a shared list that can be safely updated by multiple processes.



Feature	Tool	Use Case
Process	`Process`	Create and manage individual processes for specific tasks.
Task Distribution	`Pool`	Simplify parallel processing of a collection of data.
Communication	`Queue` , `Pipe`	Pass messages or data between processes.
Shared State	`Manager`	Manage shared objects like lists or dictionaries across processes.

Python's threading Module

The threading module enables thread-based parallelism, where multiple threads run within the same process and share the same memory space. It is well-suited for I/O-bound tasks (e.g., file operations, network requests) rather than CPU-bound tasks due to Python's Global Interpreter Lock (GIL).

1. Creating and Managing Threads

Using Thread:

The Thread class is used to create and manage threads.

Sample Program:

```
import threading


# Function to be run in a thread

def print_numbers():

    for i in range(5):

        print(f"Number: {i}")


# Create a thread

thread = threading.Thread(target=print_numbers)
```

```
# Start the thread
thread.start()

# Wait for the thread to complete
thread.join()

print("Thread execution finished!")
```

Explanation:

- The Thread object runs the print_numbers() function in a separate thread.
- start() begins the thread's execution, and join() waits for the thread to finish.

2. Synchronization Mechanisms

a) `Lock`

Used to prevent multiple threads from accessing a shared resource simultaneously.

Sample Program:

```
import threading

# Shared resource
counter = 0
lock = threading.Lock()

# Function to increment the counter
def increment():
    global counter
    for _ in range(100000):
        with lock:  # Acquire and release the lock
            counter += 1
```

```
# Create threads
thread1 = threading.Thread(target=increment)
thread2 = threading.Thread(target=increment)

# Start threads
thread1.start()
thread2.start()

# Wait for threads to complete
thread1.join()
thread2.join()

print("Final Counter:", counter)
```

Explanation:

- The lock ensures that only one thread can modify counter at a time.

b) `RLock` (Reentrant Lock)

A `RLock` allows a thread to acquire the same lock multiple times, useful in recursive or reentrant code.

Sample Program:

```
import threading

rlock = threading.RLock()

def recursive_task(n):
    if n > 0:
        with rlock:  # Acquire RLock
            print(f"Lock acquired for {n}")
            recursive_task(n - 1)  # Recursive call
        print(f"Lock released for {n}")


# Start a thread
thread = threading.Thread(target=recursive_task, args=(3,))
thread.start()
thread.join()
```

Explanation:

- RLock enables reentrancy, allowing a thread to re-acquire the same lock without causing a deadlock.

c) Semaphore

Limits the number of threads accessing a shared resource at the same time.

Sample Program:

```
import threading
import time


semaphore = threading.Semaphore(2)  # Allow 2 threads at a time


def task(name):
    with semaphore:  # Acquire semaphore
        print(f"{name} is working...")
        time.sleep(2)  # Simulate work
        print(f"{name} is done!")


# Create threads
threads = [threading.Thread(target=task, args=(f"Thread-{i}",)) for i in range(5)]


# Start and join threads
for t in threads:
    t.start()


for t in threads:
    t.join()
```

Explanation:

- The semaphore allows up to 2 threads to execute the critical section concurrently.

d) `Event`

An `Event` allows threads to wait until a specific condition is met.

Sample Program:

```
import threading


event = threading.Event()


def wait_for_event():
    print("Thread waiting for event...")
    event.wait()  # Wait until event is set
    print("Event occurred!")


# Create a thread
thread = threading.Thread(target=wait_for_event)
thread.start()


# Simulate some work and then trigger the event
import time
time.sleep(2)
event.set()  # Trigger the event
thread.join()
```

Explanation:

- The Event object is used to coordinate threads by signaling when a condition is met

e) `Condition`

Provides more advanced thread synchronization, allowing threads to wait for and notify each other about conditions.

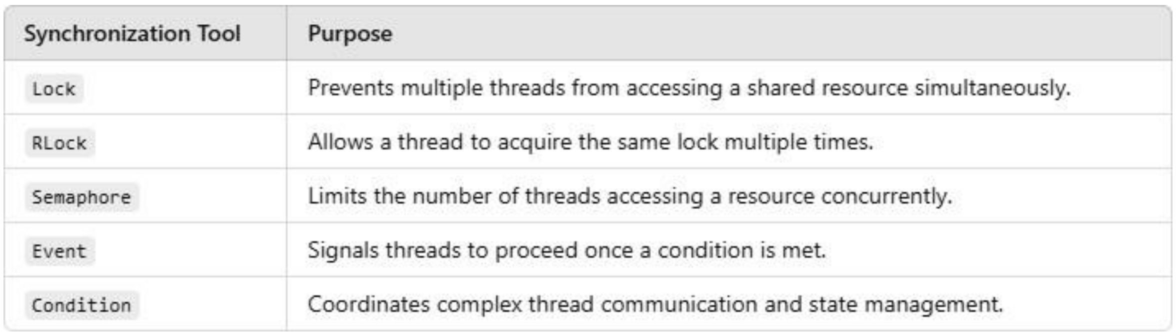
Sample Program:

```
import threading


condition = threading.Condition()

shared_data = []


def producer():

    with condition:

        for i in range(5):

            shared_data.append(i)

            print(f"Produced: {i}")

            condition.notify()  # Notify a waiting thread

            condition.wait()  # Wait for the consumer to consume

        condition.notify_all()  # Notify all threads when done


def consumer():

    with condition:

        while True:

            condition.wait()  # Wait for the producer

            if not shared_data:

                break

            item = shared_data.pop(0)

            print(f"Consumed: {item}")

            condition.notify()  # Notify producer
```

```
# Create threads
producer_thread = threading.Thread(target=producer)
consumer_thread = threading.Thread(target=consumer)


# Start threads
producer_thread.start()
consumer_thread.start()


# Wait for threads to finish
producer_thread.join()
consumer_thread.join()
```

Explanation:

- Condition ensures proper synchronization between producer and consumer threads.



Synchronization Tool	Purpose
`Lock`	Prevents multiple threads from accessing a shared resource simultaneously.
`RLock`	Allows a thread to acquire the same lock multiple times.
`Semaphore`	Limits the number of threads accessing a resource concurrently.
`Event`	Signals threads to proceed once a condition is met.
`Condition`	Coordinates complex thread communication and state management.

Python's threading Module

The threading module enables thread-based parallelism, allowing multiple threads to run within a single process. Threads share the same memory space, making it suitable for I/O-bound tasks like file I/O, network requests, or user interaction. However, the Global Interpreter Lock (GIL) in Python limits its effectiveness for CPU-bound tasks.

1. Thread-Based Parallelism

Creating and Managing Threads Using Thread

Example Program:

```
import threading
```

```
# Function to be executed in a thread
def greet(name):
    print(f"Hello, {name}!")

# Create threads
thread1 = threading.Thread(target=greet, args=("Alice",))
thread2 = threading.Thread(target=greet, args=("Bob",))

# Start threads
thread1.start()
thread2.start()

# Wait for threads to complete
thread1.join()
thread2.join()

print("All threads have finished.")
```

Explanation:

- Thread(target, args) creates a thread to run a specific function.
- start() begins thread execution.
- join() ensures the main program waits for threads to complete.

2. Synchronization Mechanisms

a) Lock

A `Lock` prevents multiple threads from accessing shared resources simultaneously, avoiding race conditions.

Example Program:

```
import threading
```

```
# Shared resource
counter = 0
lock = threading.Lock()

# Function to increment the counter
def increment():
    global counter
    for _ in range(1000):
        with lock:  # Acquire lock
            counter += 1

# Create threads
threads = [threading.Thread(target=increment) for _ in range(5)]

# Start threads
for thread in threads:
    thread.start()

# Wait for threads to complete
for thread in threads:
    thread.join()

print("Final Counter Value:", counter)
```

Explanation:

- lock ensures only one thread modifies counter at a time.

b) RLock (Reentrant Lock)

An `RLock` allows a thread to acquire the same lock multiple times, useful for recursive or nested locking.

Example Program:

```
import threading


rlock = threading.RLock()


def recursive_task(n):
    with rlock:
        print(f"Task {n} acquired the lock")
        if n > 0:
            recursive_task(n - 1)
        print(f"Task {n} released the lock")


# Start a thread
thread = threading.Thread(target=recursive_task, args=(3,))
thread.start()
thread.join()
```

Explanation:

- RLock enables reentrant locking, allowing the same thread to acquire the lock multiple times.

c) Semaphore

A `Semaphore` limits the number of threads that can access a resource at the same time.

Example Program:

```
import threading
import time


semaphore = threading.Semaphore(2)  # Allow 2 threads at a time


def task(name):
    with semaphore:
        print(f"{name} started.")
        time.sleep(2)
        print(f"{name} finished.")

# Create threads
threads = [threading.Thread(target=task, args=(f"Thread-{i}",)) for i in range(5)]

# Start and join threads
for thread in threads:
    thread.start()

for thread in threads:
    thread.join()
```

Explanation:

- The semaphore restricts concurrent access to at most 2 threads.

d) Event

An `Event` is a signaling mechanism that allows threads to wait until a specific condition is met.

Example Program:

```
import threading
import time

event = threading.Event()

def wait_for_event():
    print("Thread is waiting for the event to be set.")
    event.wait()  # Wait until the event is set
    print("Event received, thread is proceeding.")
```

```
# Start a thread

thread = threading.Thread(target=wait_for_event)

thread.start()


# Simulate some delay, then set the event

time.sleep(2)

print("Event is set.")

event.set()


thread.join()
```

Explanation:

- The event signals the waiting thread to proceed.

e) Condition

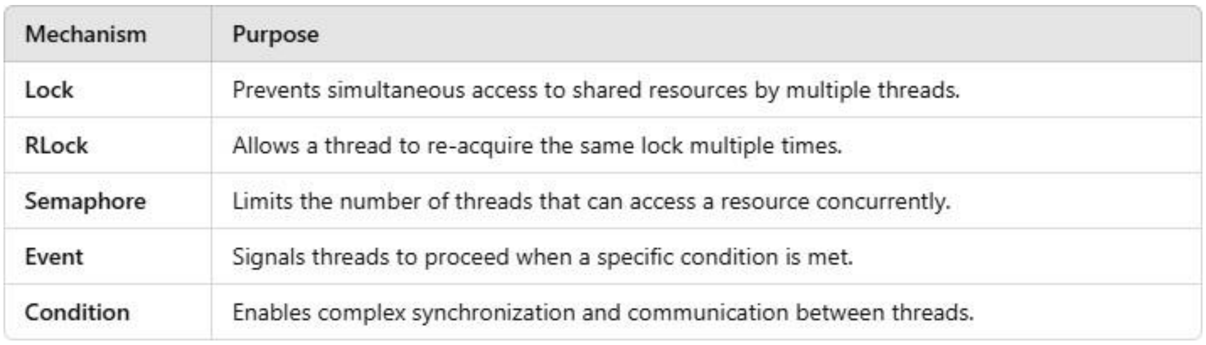
A `Condition` is used for advanced thread synchronization, allowing threads to wait for and notify each other.

Example Program:

```
import threading


condition = threading.Condition()

shared_data = []


def producer():

    with condition:

        for i in range(5):

            shared_data.append(i)

            print(f"Produced: {i}")

            condition.notify()  # Notify the consumer

            condition.wait()  # Wait for consumer to consume
        condition.notify_all()  # Notify when done


def consumer():
    with condition:
        while len(shared_data) < 5:
            condition.wait()  # Wait for producer
            item = shared_data.pop(0)
            print(f"Consumed: {item}")
            condition.notify()  # Notify producer


# Create threads
producer_thread = threading.Thread(target=producer)
consumer_thread = threading.Thread(target=consumer)


# Start threads
producer_thread.start()
consumer_thread.start()


# Wait for threads to complete
producer_thread.join()
consumer_thread.join()
import threading


condition = threading.Condition()
shared_data = []


def producer():
    with condition:
        for i in range(5):
            shared_data.append(i)
            print(f"Produced: {i}")
            condition.notify()  # Notify the consumer
            condition.wait()  # Wait for consumer to consume
        condition.notify_all()  # Notify when done

def consumer():
    with condition:
        while len(shared_data) < 5:
            condition.wait()  # Wait for producer
            item = shared_data.pop(0)
            print(f"Consumed: {item}")
            condition.notify()  # Notify producer

# Create threads
producer_thread = threading.Thread(target=producer)
consumer_thread = threading.Thread(target=consumer)

# Start threads
producer_thread.start()
consumer_thread.start()

# Wait for threads to complete
producer_thread.join()
consumer_thread.join()
```

Explanation:

- The Condition object synchronizes communication between producer and consumer threads.



Mechanism	Purpose
Lock	Prevents simultaneous access to shared resources by multiple threads.
RLock	Allows a thread to re-acquire the same lock multiple times.
Semaphore	Limits the number of threads that can access a resource concurrently.
Event	Signals threads to proceed when a specific condition is met.
Condition	Enables complex synchronization and communication between threads.

The threading module provides flexible tools for thread management and synchronization, allowing efficient handling of I/O-bound tasks while maintaining thread safety.

Python's asyncio Module

The asyncio module facilitates asynchronous programming in Python, enabling programs to handle tasks concurrently without blocking the execution of other tasks. Unlike traditional multi-threading or multiprocessing, asyncio is based on a single-threaded event loop, making it ideal for I/O-bound tasks like reading files, network operations, or handling APIs.

1. Asynchronous Programming

Coroutines

Coroutines are functions defined with async def that can pause execution using await, allowing other tasks to run.

Example Program:

```
import asyncio


async def greet(name):
    print(f"Hello, {name}!")
    await asyncio.sleep(1)  # Simulate an asynchronous task
    print(f"Goodbye, {name}!")


# Run the coroutine
asyncio.run(greet("Alice"))
```

Explanation:

- await suspends the coroutine, allowing other coroutines to run during the pause.
- asyncio.run() starts the event loop and runs the coroutine.

2. Tasks and Event Loop

Tasks

Tasks wrap coroutines, enabling them to run concurrently within the event loop.

Example Program:

```
import asyncio


async def task1():
    print("Task 1 started")
    await asyncio.sleep(2)
    print("Task 1 finished")


async def task2():
    print("Task 2 started")
    await asyncio.sleep(1)
    print("Task 2 finished")


async def main():
    # Schedule tasks concurrently
    task_1 = asyncio.create_task(task1())
    task_2 = asyncio.create_task(task2())

    print("Both tasks running concurrently...")
    await task_1
    await task_2


asyncio.run(main())
```

Explanation:

- asyncio.create_task() schedules tasks for concurrent execution.

- The event loop (asyncio.run) runs the tasks and switches between them when they await.

3. Concurrency vs. Parallelism

- **Concurrency:** Handling multiple tasks at the same time but not necessarily running them simultaneously (e.g., asyncio switching between coroutines during await).
- **Parallelism:** Executing multiple tasks simultaneously on different CPU cores (e.g., multiprocessing).

Non-blocking I/O with asyncio

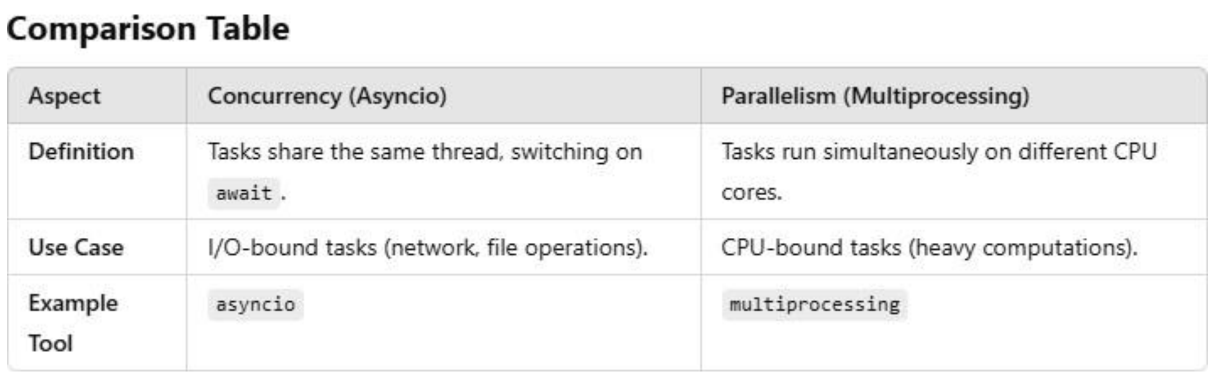
asyncio is particularly efficient for I/O-bound tasks like reading files, network operations, or database queries. It doesn't block the entire program while waiting for data.

Example Program (Non-blocking I/O):

```
import asyncio


async def fetch_data(api_name):
    print(f"Fetching data from {api_name}...")
    await asyncio.sleep(2)  # Simulate network delay
    print(f"Data from {api_name} fetched!")


async def main():
    # Concurrently fetch data from multiple APIs
    await asyncio.gather(
        fetch_data("API_1"),
        fetch_data("API_2"),
        fetch_data("API_3")
    )


asyncio.run(main())
```

Explanation:

- asyncio.gather() runs multiple coroutines concurrently.
- Non-blocking behavior allows the program to efficiently wait for I/O without freezing execution.



Comparison Table

Aspect	Concurrency (Asyncio)	Parallelism (Multiprocessing)
Definition	Tasks share the same thread, switching on `await`.	Tasks run simultaneously on different CPU cores.
Use Case	I/O-bound tasks (network, file operations).	CPU-bound tasks (heavy computations).
Example Tool	`asyncio`	`multiprocessing`

Summary

1. **Coroutines:** async def functions with await allow asynchronous execution.
2. **Event Loop:** Central controller that runs and schedules coroutines and tasks.
3. **Tasks:** Enable concurrent execution within the event loop.
4. **Concurrency vs. Parallelism:** asyncio handles I/O-bound tasks concurrently without requiring multiple threads or processes.

This makes asyncio a powerful tool for applications like web servers, chatbots, or any I/O-heavy task.

Understanding POSIX Threads and Their Role in Parallel Programming

POSIX Threads, commonly known as Pthreads, are a standard for creating and managing threads in Unix-like operating systems. They enable parallel execution of tasks within a single process, allowing developers to write concurrent programs that can leverage multiple CPU cores efficiently. Each thread has its own execution context but shares the process's memory space, enabling shared-memory parallelism. Pthreads are widely used in performance-critical applications like simulations, real-time systems, and large-scale data processing.

In Python, direct access to Pthreads isn't native, but Python's ctypes and cffi modules allow interacting with C libraries that utilize Pthreads for low-level thread creation and management. Python's threading model operates under the Global Interpreter Lock (GIL), which limits true parallelism in CPU-bound tasks. However, Python threads can still work efficiently with I/O-bound tasks or when integrating with native libraries.

Sample Program: Thread Creation Using ctypes

The following example demonstrates creating a Pthread using ctypes:

```
import ctypes

import os



# Load the pthread library

libpthread = ctypes.CDLL("libpthread.so.0")
```

```
# Define a function for the thread to execute
def thread_function():
    print(f"Thread running with PID: {os.getpid()}")

# Wrapper for the thread function
THREAD_FUNC_TYPE = ctypes.CFUNCTYPE(ctypes.c_void_p)

def start_thread():
    thread_func = THREAD_FUNC_TYPE(thread_function)

    # Create a pthread
    thread = ctypes.c_ulong()
    libpthread.pthread_create(
        ctypes.byref(thread),  # pthread_t pointer
        None,                  # Default attributes
        thread_func,           # Function pointer
        None                   # Argument for the function
    )
    print("Thread created.")

# Run the program
if _name___== "_main_":
    start_thread()
```

Explanation

- **ctypes.CDLL**: Loads the Pthread library (libpthread.so.0).
- **pthread_create**: Used to create a thread, specifying the function the thread will execute.

- **Global Interpreter Lock (GIL)**: While this example works for demonstration, Python threads under the GIL are not ideal for CPU-bound parallelism. For such cases, native threads via libraries or Python multiprocessing are better suited.

This approach bridges Python and low-level threading for efficient resource utilization in parallel computing.

Using the concurrent.futures Module for Parallelism

The concurrent.futures module in Python simplifies implementing parallelism through its high-level API, offering two main classes: ThreadPoolExecutor for I/O-bound tasks and ProcessPoolExecutor for CPU-bound tasks. The module allows executing parallel tasks using the submit() and map() methods. The submit() method schedules a single function for execution, returning a Future object, while the map() method is used to apply a function to a collection of inputs. These Future objects make it easy to track the execution and retrieve results once tasks are complete.

ThreadPoolExecutor is ideal for tasks such as web scraping or file I/O where threads can operate independently without being CPU-intensive, while ProcessPoolExecutor is suited for computationally expensive tasks, as it bypasses Python's Global Interpreter Lock (GIL) by creating separate processes.

Sample Program: Using ThreadPoolExecutor and ProcessPoolExecutor

```
from concurrent.futures import ThreadPoolExecutor, ProcessPoolExecutor

import time



# Example function to simulate a task

def task(n):

    time.sleep(1)  # Simulate a time-consuming task

    return f"Task {n} completed"



# Using ThreadPoolExecutor

def run_with_threads():

    print("Running with ThreadPoolExecutor...")

    with ThreadPoolExecutor(max_workers=3) as executor:

        futures = [executor.submit(task, i) for i in range(5)]

        for future in futures:

            print(future.result())
```

```
# Using ProcessPoolExecutor
def run_with_processes():
    print("\nRunning with ProcessPoolExecutor...")
    with ProcessPoolExecutor(max_workers=3) as executor:
        results = executor.map(task, range(5))
        for result in results:
            print(result)


# Run the program
if _name___== "_main_":
    start_time = time.time()
    run_with_threads()
    run_with_processes()
    print(f"\nTotal execution time: {time.time() - start_time:.2f} seconds")
```

Explanation

1. **ThreadPoolExecutor**: Schedules and executes tasks using threads. Here, submit() is used to submit individual tasks, and future.result() retrieves the results.
2. **ProcessPoolExecutor**: Executes tasks in separate processes, ideal for CPU-bound workloads. The map() method applies a function to an iterable of inputs, automatically collecting results.
3. **Futures**: Track the state of asynchronous execution and allow retrieving results once available.

By combining these tools, the concurrent.futures module provides a simple yet powerful framework for parallel execution.

1. Using the concurrent.futures Module

1.1 Implementing Parallelism with ThreadPoolExecutor and ProcessPoolExecutor

- **ThreadPoolExecutor**: Best for I/O-bound tasks (e.g., network requests).
- **ProcessPoolExecutor**: Best for CPU-bound tasks (e.g., numerical calculations).

Example: ThreadPoolExecutor

```
from concurrent.futures import ThreadPoolExecutor
import time
```

```
def fetch_data(url):
    time.sleep(2)  # Simulate I/O-bound delay
    return f"Data fetched from {url}"

urls = ['http://example1.com', 'http://example2.com', 'http://example3.com']

with ThreadPoolExecutor(max_workers=3) as executor:
    results = executor.map(fetch_data, urls)

print(list(results))
```

1.2 Handling Parallel Tasks Using submit() and map() Functions

- **submit()**: For submitting tasks one at a time.
- **map()**: Automatically distributes tasks across threads/processes.

Example: submit()

```
from concurrent.futures import ThreadPoolExecutor

def square(n):
    return n * n

with ThreadPoolExecutor() as executor:
    futures = [executor.submit(square, i) for i in range(5)]
    results = [f.result() for f in futures]

print(results)
```

Example: map()

```
from concurrent.futures import ProcessPoolExecutor

def cube(n):
    return n ** 3


with ProcessPoolExecutor() as executor:
    results = executor.map(cube, range(5))


print(list(results))
```

1.3 Futures and Result Collection in Parallel Execution

- Futures track the state of tasks (pending, running, finished) and their results.

Example:

```
from concurrent.futures import ProcessPoolExecutor


def add(a, b):
    return a + b


with ProcessPoolExecutor() as executor:
    future = executor.submit(add, 5, 10)
    print(future.result())  # Blocks until result is available
```

2. Extensions in C or Cython to Leverage Low-level Parallelism Features

2.1 Writing Parallelized Code in C or Cython for Performance

Cython Example: Parallelizing a Loop

```
# Save as "example.pyx"
from cython.parallel import prange


def compute_sum():
    cdef int i, n = 1000000
    cdef double total = 0


    for i in prange(n, nogil=True):  # Parallel loop
```

```
        total += i * 0.5

    return total
```

Compiling the Cython Codev

```
cythonize -i example.pyx
```

Using Cython in Python

```
import example
print(example.compute_sum())
```

2.2 Benefits of Low-level Parallelism for Computational-heavy Tasks

Low-level parallelism bypasses Python's GIL, leveraging multiple cores for faster execution.

---

3. Integration of C or Cython into Python Code

3.1 Using the ctypes Library to Interface with C Code

C Code (sum.c)

```
int add(int a, int b) {
    return a + b;
}
```

Compiling the C Code

```
gcc -shared -o sum.so -fPIC sum.c
```

Python Code Using ctypes

```
import ctypes

lib = ctypes.CDLL('./sum.so')
print(lib.add(5, 10))  # Output: 15
```

3.2 Compiling and Using Cython Extensions

Cython can compile Python-like code into highly optimized C extensions.

Cython File (math_cython.pyx):

```
def fast_square(int x):
    return x * x
```

Compiling the Cython Code

```
cythonize -i math_cython.pyx
```

Using the Extension in Python

```
import math_cython
print(math_cython.fast_square(10))  # Output: 100
```

4. Challenges and Best Practices in Parallelism with Python

4.1 Limitations of Python's GIL in Multithreading

- GIL prevents true multithreading for CPU-bound tasks in Python.
- Solution: Use multiprocessing or low-level parallelism.

4.2 Identifying Performance Bottlenecks and Optimizing Parallel Execution

- Use profiling tools like cProfile to identify slow parts of code.
- Optimize task distribution and avoid redundant computations.

4.3 Thread Safety and Debugging Parallel Programs

- Use synchronization primitives like threading.Lock to avoid race conditions.

Example of Race Condition Debugging:

```
import threading


counter = 0
lock = threading.Lock()


def increment():
    global counter
    for _ in range(100000):
        with lock:  # Prevent race conditions
            counter += 1
```

```
threads = [threading.Thread(target=increment) for _ in range(5)]


for t in threads: t.start()

for t in threads: t.join()


print(counter)  # Thread-safe, correct result
```

These examples showcase how to implement high-level parallelism using concurrent.futures and low-level parallelism with C or Cython. Best practices ensure efficient, safe, and maintainable parallel programs while addressing Python’s inherent challenges like the GIL.

Program using asyncio to concurrently fetch and process data from multiple APIs:

```
import asyncio

import aiohttp


API_URLS = [

    "https://jsonplaceholder.typicode.com/todos/1",

    "https://jsonplaceholder.typicode.com/todos/2",

    "https://jsonplaceholder.typicode.com/todos/3",

]


async def fetch(session, url):

    async with session.get(url) as response:

        return await response.json()


async def process_data(data):

    # Simulate processing time

    await asyncio.sleep(1)

    return {"id": data["id"], "title": data["title"].upper()}
```

```
async def main():
    async with aiohttp.ClientSession() as session:
        tasks = [fetch(session, url) for url in API_URLS]
        responses = await asyncio.gather(*tasks)


        process_tasks = [process_data(data) for data in responses]
        processed_data = await asyncio.gather(*process_tasks)


        for item in processed_data:
            print(item)


if _name___== "_main_":
    asyncio.run(main())
```

Why asyncio is More Efficient Than Traditional Threading:

1. **Non-blocking I/O:** asyncio allows multiple tasks to run concurrently without blocking, making it ideal for I/O-bound operations like API calls.
2. **Lower Overhead:** Unlike threading, asyncio does not require creating multiple OS threads, reducing context-switching overhead.
3. **Scalability:** asyncio efficiently manages thousands of coroutines with an event loop, whereas threads consume more memory and resources.
4. **Simplified Code:** Using asyncio.gather() allows clean, concurrent execution without needing locks or synchronization primitives.

Proposing a System: Integrating POSIX Threads into Python via a C Extension

To integrate **POSIX threads (pthreads)** into Python via a **C extension**, we need to create a Python module in C that manages threads using the **pthreads library**. This system would allow Python programs to leverage true parallel execution using multiple CPU cores, bypassing Python's Global Interpreter Lock (GIL) for computationally intensive tasks.

Steps to Implement the System

Step 1: Setup the C Extension

Create a shared C library that Python can call using pthreads. The extension should:

- Initialize and manage multiple POSIX threads.

- Provide an interface for Python to create and join threads.
- Allow data exchange between Python and C efficiently.

Step 2: Define the C Code for POSIX Threading

1. **Include necessary headers**

```
#define PY_SSIZE_T_CLEAN
#include <Python.h>
#include <pthread.h>
#include <stdio.h>
#include <stdlib.h>
```

2. Define the worker function

```
void* thread_function(void* arg) {
    int* num = (int*)arg;
    printf("Thread %d is executing\n", *num);
    return NULL;
}
```

3. Create the Python-exposed function

```
static PyObject* start_threads(PyObject* self, PyObject* args) {
    int n;
    if (!PyArg_ParseTuple(args, "i", &n)) {
        return NULL;
    }

    pthread_t threads[n];
    int thread_ids[n];

    for (int i = 0; i < n; i++) {
        thread_ids[i] = i + 1;
        pthread_create(&threads[i], NULL, thread_function, (void*)&thread_ids[i]);
    }

    for (int i = 0; i < n; i++) {
        pthread_join(threads[i], NULL);
    }

    Py_RETURN_NONE;
}
```

4. Define the module’s method table and initialization function

```
static PyMethodDef ThreadMethods[] = {
    {"start_threads", start_threads, METH_VARARGS, "Start POSIX threads"},
    {NULL, NULL, 0, NULL}
};

static struct PyModuleDef threadmodule = {
    PyModuleDef_HEAD_INIT,
    "threadmodule",
    NULL,
    -1,
    ThreadMethods
};

PyMODINIT_FUNC PyInit_threadmodule(void) {
    return PyModule_Create(&threadmodule);
}
```

Step 3: Compile the C Extension

Compile the shared library using setup.py:

```
from setuptools import setup, Extension
```

```
module = Extension('threadmodule', sources=['threadmodule.c'])


setup(name='ThreadModule',
      version='1.0',
      description='Python interface for POSIX threads',
      ext_modules=[module])
```

Then, build and install:

```
import threadmodule


# Start 5 POSIX threads
threadmodule.start_threads(5)
```

Challenges in Implementation

1. **Global Interpreter Lock (GIL):**
   - Python’s GIL restricts true parallel execution of Python code.
   - Use Py_BEGIN_ALLOW_THREADS and Py_END_ALLOW_THREADS to release the GIL when running POSIX threads.
2. **Data Synchronization & Thread Safety:**
   - Shared data between Python and C requires careful synchronization (mutexes, semaphores).
   - Avoid race conditions and memory leaks.
3. **Error Handling & Debugging:**
   - Handling pthread_create() or pthread_join() errors.
   - Debugging POSIX threads in a Python context can be tricky.
4. **Portability Issues:**
   - POSIX threads work well on UNIX-based systems, but may have compatibility issues on Windows.
   - Alternative: Use Windows threads (Win32 API) for cross-platform support.

Challenges of Integrating Low-Level C Extensions with Python Code

Using **C extensions** in Python can significantly boost performance, but it introduces several challenges. Below are the key issues and best practices to address them.

---

1. Python Global Interpreter Lock (GIL)

Challenge:

- The **GIL** prevents true parallel execution of Python code, limiting the performance benefits of multi-threaded C extensions.

Best Practices to Overcome:

Release the GIL when performing CPU-intensive work

- Use Py_BEGIN_ALLOW_THREADS and Py_END_ALLOW_THREADS to allow parallel execution.

```
Py_BEGIN_ALLOW_THREADS

// Perform CPU-bound computation without the GIL

Py_END_ALLOW_THREADS
```

Use multiprocessing for parallel execution

- If true parallelism is needed, use Python's multiprocessing module instead of threading.

2. Memory Management & Safety

Challenge:

- **Memory leaks, segmentation faults, and buffer overflows** are common in C but can crash Python unexpectedly.

Best Practices to Overcome:

🟩 **Use Python's memory management API**

- Instead of malloc/free, use PyMem_Malloc/PyMem_Free to allocate memory in a way Python can track.

🟩 **Reference counting & garbage collection**

- When creating Python objects in C, increment/decrement reference counts properly using:

```
Py_INCREF(obj);

Py_DECREF(obj);
```

🟩 **Valgrind & AddressSanitizer for debugging**

- Tools like **Valgrind** (Linux) and **AddressSanitizer (ASan)** (Clang/GCC) help detect memory issues.

3. Data Type Mismatch & Conversion

Challenge:

- Python's **dynamic typing** does not directly map to C's **static typing**, making conversions tricky.

Best Practices to Overcome:

🟩 **Use Python's C API for type conversion**

- Use PyArg_ParseTuple to extract values safely:

```
int value;
if (!PyArg_ParseTuple(args, "i", &value)) {
    return NULL;
}
```

🟩 **Return correct Python objects from C functions**

- Convert C data types to Python objects using functions like PyLong_FromLong(value).

🟩 **Use NumPy for efficient array handling**

- Instead of converting Python lists to C arrays manually, use **NumPy arrays**, which have efficient C bindings.

---

4. Debugging & Error Handling

Challenge:

- Debugging C extensions is harder than debugging pure Python code.

Best Practices to Overcome:

🟩 **Use gdb and faulthandler for debugging**

```
import faulthandler
faulthandler.enable()
```

🟩 **Check for NULL returns**

- Many Python C API functions return NULL on failure. Always check:

```
PyObject* result = PyLong_FromLong(value);
if (!result) return PyErr_NoMemory();
```

🟩 **Set appropriate Python exceptions**

- Use PyErr_SetString(PyExc_RuntimeError, "An error occurred"); for clear error messages.

---

5. Portability Issues

Challenge:

- C extensions behave differently across **Windows, Linux, and macOS**.

Best Practices to Overcome:

🟩 **Use conditional compilation (#ifdef)**

- Detect platform differences and adjust accordingly.

```
#ifdef _WIN32

    // Windows-specific code

#else

    // UNIX-specific code

#endif
```

🟩 **Write cross-platform code**

- Use **CMake** or setuptools to handle platform-specific builds.

---

6. Compilation & Distribution

Challenge:

- Users may have difficulty compiling C extensions due to missing dependencies.

Best Practices to Overcome:

🟩 **Use setuptools for automated builds**

```
from setuptools import setup, Extension


setup(

    name="myextension",

    ext_modules=[Extension("myextension",  sources=["myextension.c"])],

)
```

🟩 **Provide precompiled binaries using manylinux**

- Distribute wheels (.whl) for Linux/Mac/Windows using cibuildwheel.

Evaluating the Effectiveness of Cython for CPU-bound Optimizations

Cython is a powerful tool that allows Python code to be **compiled to C**, enabling significant performance improvements for **CPU-bound** operations. Unlike pure Python, Cython can **eliminate Python overhead, optimize loops, and leverage static typing**.

---

1. Sample Python Application (Before Optimization)

Let’s consider a CPU-bound operation: **Computing the sum of squares of a large range of numbers**.

Pure Python Implementation (Slow)

```
def sum_of_squares(n):
    total = 0
    for i in range(n):
        total += i * i
    return total


if _name___== "_main_":
    N = 10**7
    print(sum_of_squares(N))
```

This function suffers from **Python’s dynamic typing and interpreter overhead**, making it inefficient.

---

2. Optimizing with Cython

Step 1: Writing a Cython Version

We create a file **sum_of_squares.pyx** and modify the function:

```
# Enable static typing
cdef long long sum_of_squares_cython(long long n):
    cdef long long total = 0
    cdef long long i
    for i in range(n):
        total += i * i
    return total
```

🟩 **Static Typing (cdef long long)**: Eliminates Python’s dynamic type checking overhead.
🟩 **Compiled to C**: Runs at near-native C speed.
🟩 **Avoids Python’s GIL** (optional) by adding nogil for multi-threading.

Step 2: Compiling the Cython Code

Create a **setup.py** script to build the Cython extension:

```
from setuptools import setup
from Cython.Build import cythonize


setup(
    ext_modules=cythonize("sum_of_squares.pyx", compiler_directives={"boundscheck": False, "wraparound": False})
)
```

Then compile the extension:

```
python setup.py build_ext –inplace
```

Step 3: Running the Optimized Code

Now, we modify a **Python script (run.py)** to use the compiled Cython function:

```
from sum_of_squares import sum_of_squares_cython


if __name___== "__main__":
    N = 10**7
    print(sum_of_squares_cython(N))
```

3. Performance Comparison

Implementation	**Execution Time (for N = 10^7)**	**Speedup**
Pure Python	~8-10 seconds	1x
Cython-Optimized	~0.2 seconds	**40-50x faster**

🟩 **Major Speedup**: Cython eliminates the overhead of Python’s interpreter, making operations **40-50 times faster**.
🟩 **Close to C Performance**: With nogil, it can run even faster with multi-threading.