How I Learned to Stop Worrying and Love Raw Events

Event Sourcing & CQRS with FastAPI and Celery

PyCon Athens 2025

Who Am I?

- **Staff Engineer** with 10+ years in Python
- Studied **Physics** → **Computational Physics** → **Software Engineering**
  - *"I went from calculating planet trajectories to debugging production systems. Turns out, both involve a lot of uncertainty!"*
- **Passionate about building systems** with quality

What We'll Discuss

Core Principles

- **Event Sourcing**: Store every change as an immutable event
- **CQRS**: Separate read and write concerns

Python Ecosystem Examples

- **FastAPI**: API surface for commands and queries
- **Celery**: Async event processing
- **Pydantic**: Data validation and modeling

The Aftermath

- **Real-world patterns** and gotchas
- **Performance considerations**
- **Debugging and testing** in an immutable world

The Nightmare: "Who Deleted My User?"

A real debugging story:

```python
# Traditional approach - we only store current state
def delete_user(user_id: int):
    user = db.get_user(user_id)
    db.delete(user)  # Gone forever!
```

The problem:

Monday 3:47 PM: "Sarah's account is missing!"

Tuesday 9:15 AM: "When was it deleted? Who did it? Why?"

What we can't answer:

- ❌ **When** was the user deleted?
- ❌ **Who** deleted the user?
- ❌ **Why** was it deleted?

Enter Event Sourcing: The System That Remembers

We store every change as an immutable event:

```
# Instead of deleting, we record what happened
UserDeleted(
    event_id=uuid4(),
    aggregate_id="user_123",
    timestamp=datetime.now(),
    event_type="USER_DELETED",
    data={
        "deleted_by": "admin_456",
        "reason": "Account closure request",
        "previous_state": {...}  # What was lost
    }
)
```

Now we can answer everything:

- ✅ **When**: March 15, 3:47 PM
- ✅ **Who**: Admin ID 456

The Journey: From Chaos to Clarity

What we just saw:

- **Traditional systems**: Lose history, can't explain themselves
- **Event Sourcing**: Every change is recorded, complete audit trail

Now let's understand the building blocks:

- **Events**: The immutable facts of what happened
- **Event Streams**: How we organize and order these facts
- **CQRS**: How we separate reading from writing
- **The Python Way**: FastAPI + Celery implementation

The goal: Build systems that can explain themselves

Core Concepts: The Building Blocks

1. Events: Immutable Facts

```
# Every change becomes an event
UserCreated(
    event_id=uuid4(),
    aggregate_id="user_123",
    timestamp=datetime.now(),
    event_type="USER_CREATED",
    data={"name": "Sarah", "email": "sarah@example.com"}
)
```

Key principle: **Events are immutable facts** - they never change

2. Event Streams: The Story of an Entity

Events belong to ordered sequences:

```
# A user's complete story
user_stream = [
    UserCreated(...),           # Version 1
    UserNameChanged(...),       # Version 2
    UserEmailChanged(...),      # Version 3
    UserStatusChanged(...),     # Version 4
    UserDeleted(...)            # Version 5
]
```

The stream is the source of truth - rebuild any point in time

3. CQRS: Separate Reading from Writing

The problem with traditional systems:

```
# Everything mixed together
class UserService:
    def update_user(self, user_id, data):  # Write
        # Complex business logic
        pass

    def get_user(self, user_id):           # Read
        # Simple data retrieval
        pass
```

The solution: Different models for different purposes

CQRS: Commands vs Queries

Commands (Write Model):

- **Command Handlers** - Process commands, call aggregates
- **Aggregates** - Apply business logic, create events
- **Event Store** - Persist events (source of truth)

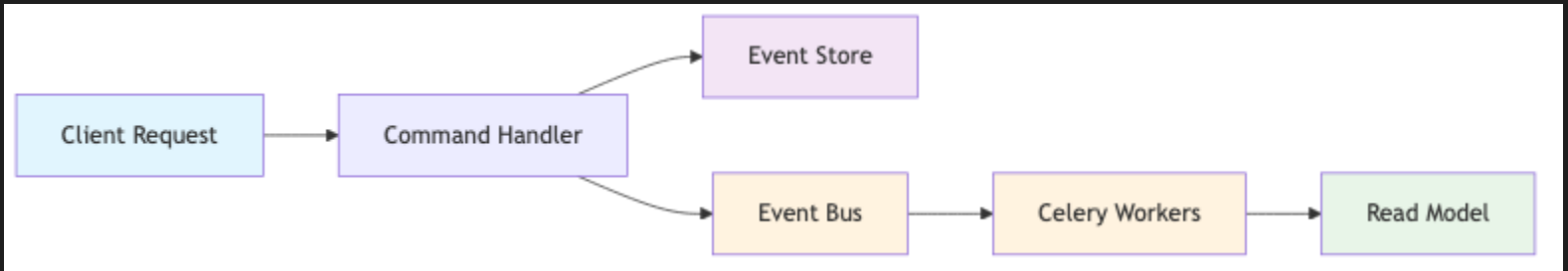
Queries (Read Model):

- **Query Handlers** - Process queries, return data
- **Read Models** - Optimized for fast reads
- **Separate database** - No business logic

Different databases for different purposes

The Complete Picture: How Everything Connects

A real-world example: "User changes their email"



Every change flows through this pattern

The Python Way: FastAPI + Celery

How we implement this in Python:

```
External Request → FastAPI → Command Handler → Aggregate → Event → Event Store
                                                                        ↓
Read Model ← Event Bus ← Celery Workers ← Projections ← Event
```

Python tools:

- **FastAPI**: API surface for commands/queries
- **Celery**: Async task runner, scalable workers
- **Event Store**: PostgreSQL, EventStoreDB, DynamoDB (with stream support)
- **Event Bus**: RabbitMQ, Kafka, EventBridge, SNS

Mapping: Theory to Python Implementation

Core Entities → Python Implementation:

Theory	Python Implementation
Events	Pydantic models with validation
Event Streams	PostgreSQL tables with versioning
Aggregates	Domain classes with apply() methods
Command Handlers	FastAPI dependency injection
Event Store	Repository pattern with async/await
Projections	Celery tasks with event handlers
Read Models	Optimized database views

Python ecosystem provides excellent tools for each concept

FastAPI: The Command Interface

Real implementation with Pydantic:

```python
@router.post("/users")
async def create_user(
    user_data: dict,
    infrastructure_factory: InfrastructureFactoryDep = None
):
    # Create command with validation
    command = CreateUserCommand(
        name=user_data["name"],
        email=user_data["email"]
    )

    # Get handler and process
    handler = infrastructure_factory.create_create_user_command_handler()
    await handler.handle(command)

    # Return immediately (async processing)
    return {"status": "accepted", "user_id": command.user_id}
```

Command Handlers: Business Logic

How we structure command processing:

```python
class CreateUserCommandHandler:
    async def handle(self, command: CreateUserCommand) -> None:
        # Load existing aggregate from stream (if exists)
        stream_id = command.user_id
        events = await self.event_store.get_stream(stream_id)
        user = UserAggregate(stream_id)

        # Reconstruct state from events
        for event in events:
            user.apply(event)

        # Call domain method (validates and creates event)
        event = user.create_user(command.name, command.email)

        # Append to stream with version check
        await self.event_store.append_to_stream(stream_id, len(events), [event])

        # Publish to event bus
        await self.event_bus.publish(event)
```

Celery: Async Task Runner & Scalable Workers

Event processing tasks:

```python
@app.task(name="process_user_event")
def process_user_event_task(event_data: Dict[str, Any]) -> None:
    """Process user event via Celery task."""
    process_user_event_async_sync = async_to_sync(process_user_event_async)
    process_user_event_async_sync(event_data=event_data)

async def process_user_event_async(event_data: Dict[str, Any]) -> None:
    # Business logic
    event = Event(**event_data)
    handler = infrastructure_factory.create_user_event_handler()
    await handler.handle(event)
```

Projections: Event-Driven Read Models

How projections build read models:

```
class UserProjection:
    async def handle_user_created(self, event: Event) -> None:
        # Build read model from event
        user_data = {
            "aggregate_id": event.aggregate_id,
            "name": event.data.get("name"),
            "email": event.data.get("email"),
            "status": event.data.get("status"),
            "created_at": event.timestamp,
        }

        # Save to read model
        await self.read_model.save_user(user_data)
```

FastAPI: Query Interface

How we expose read models:

```python
@users_router.get("/{user_id}")
async def get_user(
    user_id: str,
    infrastructure_factory: InfrastructureFactoryDep = None
) -> Dict[str, Any]:
    # Create query handler
    query_handler = infrastructure_factory.create_get_user_query_handler()
    query = GetUserQuery(user_id=user_id)
    user = await query_handler.handle(query)
    return {"status": "success", "user": user.dict()}

@users_router.get("/{user_id}/history")
async def get_user_history(user_id: str, from_date: Optional[str] = None):
    # Get event history from event store
    query_handler = infrastructure_factory.create_get_user_history_query_handler()
    query = GetUserHistoryQuery(user_id=user_id, from_date=from_date)
    events = await query_handler.handle(query)
    return {"status": "success", "events": [event.dict() for event in events]}
```

The Aftermath: Real-World Patterns & Gotchas

What happens when you actually build this?

- **Eventual consistency**: Why it's a feature, not a bug
- **Performance challenges**: When replaying becomes slow
- **Debugging superpowers**: What debugging looks like in an immutable world
- **The dark side**: When NOT to use event sourcing

Let's talk about the real challenges

Eventual Consistency: The Feature Nobody Talks About

The story: "Why isn't my data updated?"

```
User creates account → Event stored → API returns success ✅
                            ↓
                    Event processing (async) ⏳
                            ↓
                    Read model updated (eventually) ✅
```

The reality:

- **User sees success immediately** - great UX
- **Data appears in UI within seconds** - acceptable
- **Processing can retry on failure** - resilient

Eventual consistency is a feature, not a bug

When Event Sourcing Goes Wrong

The performance nightmare:

```
# The problem: Replaying 10,000 events
def get_user_state(user_id: str):
    events = event_store.get_stream(user_id)  # 10,000 events!
    return replay_events(events)  # Takes 5 seconds 😱
```

The solution: Snapshots

```
# The fix: Start from a snapshot
def get_user_state(user_id: str):
    snapshot = get_latest_snapshot(user_id)  # Current state
    recent_events = get_events_since_snapshot(user_id, snapshot.version)
    return replay_from_snapshot(snapshot, recent_events)  # 50ms ✅
```

Performance is a feature you have to design for

Debugging Superpowers: The Immutable World

The story: "Something broke at 3:47 PM"

```
# Traditional debugging: "I don't know what happened"
def debug_issue():
    # Check logs... maybe?
    # Check database... current state only
    # Ask users... unreliable
    pass

# Event sourcing debugging: "I can see exactly what happened"
def debug_issue(user_id: str, timestamp: datetime):
    events = event_store.get_events(user_id, around=timestamp)

    print(f"User {user_id} at {timestamp}:")
    for event in events:
        print(f"  {event.timestamp}: {event.type} - {event.data}")

    # Replay to see exact state
    state = replay_events(events)
    print(f"State: {state}")
```

The Dark Side: When NOT to Use Event Sourcing

Event sourcing is NOT for:

- **Simple CRUD applications** - overkill
- **Teams new to distributed systems** - steep learning curve
- **Systems with simple audit requirements** - traditional logging suffices
- **Performance-critical reads** - eventual consistency overhead

Event sourcing is for systems that need to explain themselves

Real-World Trade-offs

What you gain:

- ✅ **Complete audit trail** - every change recorded
- ✅ **Time travel** - see any point in history
- ✅ **Debugging superpowers** - trace every decision
- ✅ **Scalability** - separate read/write concerns

What you lose:

- ❌ **Simplicity** - more complex than CRUD
- ❌ **Immediate consistency** - eventual consistency
- ❌ **Storage overhead** - events take more space
- ❌ **Learning curve** - new patterns to master

Event sourcing is a trade-off, not a silver bullet

Key Takeaways

What we learned:

1. Event sourcing is about building systems that can explain themselves
2. Python + FastAPI + Celery are more than capable for serious architecture
3. Eventual consistency is a feature, not a bug
4. Performance requires design - snapshots, indexing, caching
5. Event sourcing is not for every system - know when to use it

The goal: Build systems that can explain themselves 6 months from now

Thank You!

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Questions? Let's discuss!