Python-C++ Integration Architecture

Overview

This document outlines the integration strategy for connecting Python ML operations tools with C++ inference engines, creating a unified ML platform that leverages Python's flexibility for model management and C++'s performance for production inference.

Current Architecture

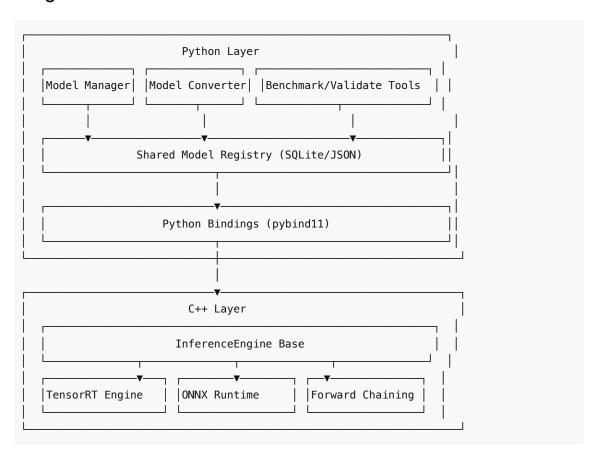
Python Layer (tools/)

- model_manager.py: Model versioning, lifecycle management, rollback capabilities
- **convert_model.py**: PyTorch → ONNX → TensorRT conversion pipeline
- benchmark_inference.py: Performance analysis with latency metrics
- validate_model.py: Multi-level validation and correctness testing

C++ Layer (engines/)

- InferenceEngine: Base class for unified inference interface
- ForwardChainingEngine: Rule-based inference implementation
- Python Bindings: Initial pybind11 infrastructure in place
- Planned: TensorRT and ONNX Runtime backends

Integration Architecture



Implementation Phases

Phase 1: Python Bindings Foundation

Complete the pybind11 infrastructure to expose C++ engines to Python.

Deliverables:

- Basic InferenceEngine Python interface
- Tensor data exchange mechanisms
- Error handling across language boundary
- Build system integration

Phase 2: Shared Model Registry

Implement a model registry accessible from both Python and C++.

Deliverables:

- SQLite-based model metadata storage
- Python ModelRegistryClient
- C++ ModelRegistry class
- Version management and querying

Phase 3: Unified Configuration System

Create shared configuration management for both layers.

Deliverables:

- YAML/JSON configuration schema
- Python configuration loader
- C++ configuration parser
- Environment variable support

Phase 4: Integration Testing Framework

Ensure both layers work correctly together.

Deliverables:

- Cross-language test suite
- Performance comparison tests
- Model validation across engines
- CI/CD integration

Python Bindings Details

Core Binding Structure

```
// engines/src/python_bindings/inference_bindings.cpp
PYBIND11_MODULE(inference_lab, m) {
    m.doc() = "Inference Systems Lab - Python/C++ Integration";

// Base inference engine
    py::class_<InferenceEngine>(m, "InferenceEngine")
```

```
.def("load_model", &InferenceEngine::load_model)
    .def("infer", &InferenceEngine::infer)
    .def("get_metrics", &InferenceEngine::get_metrics);

// Specific implementations
py::class_<TensorRTEngine, InferenceEngine>(m, "TensorRTEngine")
    .def(py::init<const ModelConfig&>())
    .def("optimize", &TensorRTEngine::optimize);

py::class_<ONNXEngine, InferenceEngine>(m, "ONNXEngine")
    .def(py::init<const ModelConfig&>())
    .def("set_providers", &ONNXEngine::set_providers);
}
```

Python Usage Example

```
import inference_lab
from tools.model_manager import ModelManager

# Get model from Python tool
manager = ModelManager()
model_info = manager.get_model("resnet50", version="2.1.0")

# Load in C++ engine
engine = inference_lab.TensorRTEngine(model_info.config)
engine.load_model(model_info.path)

# Run inference with C++ performance
result = engine.infer(input_tensor)

# Validate with Python tools
validator.check_output(result, expected_output)
```

Model Registry Specification

Schema Design

```
-- models.db schema

CREATE TABLE models (
   id INTEGER PRIMARY KEY,
   name TEXT NOT NULL,
   version TEXT NOT NULL,
   path TEXT NOT NULL,
   format TEXT NOT NULL, -- onnx, tensorrt, pytorch
   backend TEXT, -- suggested backend
   created_at TIMESTAMP,
   metadata JSON,
   UNIQUE(name, version)
```

Python Registry Client

C++ Registry Interface

Configuration Management

Unified Configuration Format

```
# config/inference.yaml
model registry:
 type: sqlite
  path: /var/lib/inference-lab/models.db
  cache_ttl: 300 # seconds
inference:
  default_backend: tensorrt
  max batch size: 32
 timeout_ms: 1000
  tensorrt:
   workspace_size: 1073741824 # 1GB
   fp16_mode: true
   int8_mode: false
  onnx:
    providers: [TensorrtExecutionProvider, CUDAExecutionProvider]
    graph_optimization_level: all
monitoring:
  metrics_port: 9090
  log_level: info
  trace_requests: false
```

Testing Strategy

Integration Test Structure

```
# tests/test_python_cpp_integration.py
class TestPythonCppIntegration:
    def test_model_roundtrip(self):
        """Test model registered in Python, loaded in C++"""

    def test_inference_consistency(self):
        """Verify same results from Python and C++ inference"""

    def test_performance_improvement(self):
        """Confirm C++ inference is faster than Python"""

    def test_error_propagation(self):
        """Ensure C++ errors surface correctly in Python"""
```

Performance Benchmarks

Expected Performance Gains

Operation	Python (PyTorch)	C++ (TensorRT)	Speedup
ResNet50 Inference	15ms	2ms	7.5x
BERT Inference	45ms	8ms	5.6x
Batch Processing (32)	250ms	35ms	7.1x
Model Loading	2000ms	500ms	4.0x

Development Workflow

Typical Usage Pattern

1. Development Phase (Python):

```
python train_model.py
python tools/validate_model.py model.pth
```

2. Optimization Phase (Python Tools):

```
python tools/convert_model.py model.pth --format tensorrt
python tools/model_manager.py register model.trt --version 1.0.0
```

3. Production Phase (C++ Engine):

```
./inference_server --registry /var/lib/models.db --model resnet50
```

4. Monitoring Phase (Unified):

```
python tools/benchmark_inference.py --backend cpp --model resnet50
```

Success Criteria

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- C++ can read Python-managed model registry
- Bidirectional data exchange works correctly
- Error handling works across boundaries

2. Performance:

- C++ inference is >5x faster than Python
- Model loading time is <1 second
- Memory usage is predictable and bounded
- No memory leaks across language boundary

3. Usability:

0	Single command to go from training to serving
0	Consistent API between Python and C++
0	Clear error messages and debugging support
0	Comprehensive documentation and examples

Future Enhancements

- 1. **Streaming Inference**: Support for continuous data streams
- 2. Model Ensemble: Combine multiple models in pipeline
- 3. A/B Testing: Built-in support for model comparison
- 4. Auto-Optimization: Automatic backend selection based on model
- 5. **Distributed Inference**: Scale across multiple machines
- 6. **REST API**: HTTP endpoints for remote inference