

(Consolidated)

SPL Multi-Agent Guide v3.1 (Consolidated)

****State-Grounded Coordination & Agent-to-Agent Communication****

****Author:**** Pamela Cuce

****Email:**** pamela@dasein.works

****Phone:**** 914-240-3564

****Version:**** 3.1 (Consolidated & Corrected)

****Date:**** December 3, 2025

Overview

SPL isn't just for single agents. The real power emerges when multiple SPL agents communicate and coordinate using:

1. ****State-grounded control:**** Agents share explicit world state (no guessing)
2. ****Cross-agent suppression:**** Lower-layer agents can suppress upper-layer operations network-wide
3. ****Pattern sharing:**** Learn once, reuse across entire agent team
4. ****Network-wide safety:**** Single violation halts all agents immediately

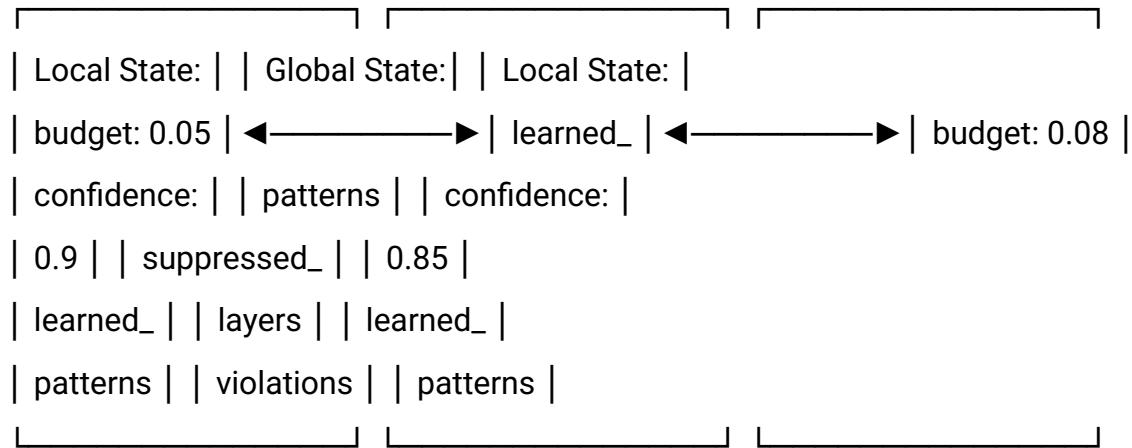
****Result:**** Single-agent SPL achieves 5-15x cost reduction.
Multi-agent SPL achieves 10-50x reduction through network effects.

Part 1: State-Grounded Coordination

Core Concept

With state-grounded control, multiple agents coordinate by sharing explicit world state. Agents don't guess what others know—they read state directly.

Agent A Shared State Agent B



Pattern Sharing Protocol

****Agent A Learns Pattern:****

1. Agent A processes 5 emails
2. Learns: "urgent_emails → high_priority" (0.95 confidence)
3. Publishes to shared state: `learned_patterns["urgent"] = 0.95`

****Agent B Uses Shared Patterns:****

1. Agent B receives email
2. Reads shared state: `learned_patterns["urgent"] = 0.95`
3. Checks: "Is this email urgent?" → YES
4. **STATE SUPPRESSES Layer 2** (LLM call)
5. Uses cached result from Agent A's learning
6. **Cost: \$0** (vs \$0.01 for LLM)

Part 2: Shared State Architecture

What Lives in Shared State?

Shared state structure

```
shared_state = {

    # Patterns learned by any agent

    'learned_patterns': {

        'urgent': {'confidence': 0.95, 'learned_by': 'agent_a', 'learned_at': '2025-12-03T17:00:00'},
        'billing': {'confidence': 0.92, 'learned_by': 'agent_c', 'learned_at': '2025-12-03T17:05:00'}
    },

    text

    # Which layers are currently suppressed?

    'suppressed_layers': {

        'agent_a':,  # Agent A's Layer 2 is suppressed[1]
        'agent_b': [],  # Agent B has no suppressions
        'agent_c':    # Agent C's Layers 1 & 2 are suppressed[2][1]
    },
}

# Safety violations detected

'violations': [
    {'agent': 'agent_b', 'violation': 'budget_exceeded',
     'timestamp': '2025-12-03T17:10:00'}
],


# Network-wide cost tracking

'cost_tracking': {

    'total_network_cost': 15.50,
    'total_suppressions': 450,
    'total_llm_calls': 50,
}
```

```
'cost_by_agent': {  
    'agent_a': 5.00,  
    'agent_b': 5.25,  
    'agent_c': 5.25  
}  
}  
}
```

```
### Reading Shared State
```

Pattern reading

```
agent_b_patterns = shared_state['learned_patterns']
```

Result: {'urgent': {...}, 'billing': {...}}

Suppression status

```
agent_a_suppressed = shared_state['suppressed_layers'].get('agent_a', [])
```

Result: - Layer 2 is suppressed for Agent A

Safety check

```
violations = shared_state['violations']
```

Result: [...] - All violations on network

text

```
## Part 3: Cross-Agent Suppression
```

```
### Scenario: Budget Alert Triggers Network Suppression
```

Situation: Agent B's budget exceeded (\$100/day limit reached)

Response:

Agent B detects budget exceeded

```
if agent_b.total_cost > 100.0:  
    # Publish violation to shared state  
    shared_state['violations'].append({  
        'agent': 'agent_b',  
        'violation': 'budget_exceeded',  
        'timestamp': now()  
    })
```

text

```
# Signal all agents to suppress Layer 2
shared_state['suppressed_layers'][agent_b] =[1]

# All agents check shared state
# Agent A: "Agent B's Layer 2 is suppressed"
# Agent C: "Agent B's Layer 2 is suppressed"
# → No more expensive LLM calls for Agent B
```

text

Broadcasting Layer Suppressions

In main loop for each agent

```
def check_network_suppressions(agent_id, shared_state):
```

....

Check if this agent should suppress any layers

text

Args:

agent_id: this agent's ID (e.g., 'agent_a')

shared_state: network-wide state

Returns:

list: layers to suppress (,, or []) [2][1]

Logic:

1. Check violation list
2. If violation affects this agent, suppress that layer
3. Return list of suppressed layers

"""

```
suppressed_layers = []
```

```
# Check all violations
```

```
for violation in shared_state['violations']:
```

```
    if violation['agent'] == agent_id:
```

```
        # This violation affects us!
```

```
        if violation['violation'] == 'budget_exceeded':
```

```
            # Budget exceeded - suppress expensive Layer 2
```

```
            suppressed_layers.append(2)
```

```
        elif violation['violation'] == 'safety_concern':
```

```
            # Safety issue - suppress everything
```

```
            suppressed_layers.extend([2][1])
```

```
# Update shared state
```

```
shared_state['suppressed_layers'][agent_id] = suppressed_layers
```

```
return suppressed_layers
```

text

```
## Part 4: Pattern Learning & Sharing
```

```
### Individual Agent Learning
```

****Agent A's Learning Process:****

Iteration 1: Email "URGENT: Meeting" → Call LLM → Learns "urgent" pattern

Iteration 2: Email "URGENT: Budget" → Pattern matches → SUPPRESS Layer 2

...

Iteration 10: Email "URGENT: Hiring" → Pattern matches → SUPPRESS Layer 2

Cost: 1 LLM call (Iteration 1) + 9 cached (Iterations 2-10) = \$0.01

Savings: 90%

text

```
### Network Pattern Learning
```

****Multi-Agent Learning Process:****

Agent A processes emails 1-100

→ Learns 10 patterns (costs: \$0.10)

→ Publishes to shared state

Agent B processes emails 101-200

- Uses Agent A's 10 patterns
- Learns 5 new patterns
- Publishes to shared state
- Cost: \$0.05

Agent C processes emails 201-300

- Uses patterns from Agents A & B
- Learns 2 new patterns
- Cost: \$0.02

Total network cost: \$0.17

Per-email cost: \$0.00057 (vs \$0.01 baseline)

Cost reduction: 17.6x

Part 5: Multi-Agent Execution Example

Email Processing Pipeline

****Initial State:****

Agent A: budget=\$0.05, confidence=0.0

Agent B: budget=\$0.10, confidence=0.0

Agent C: budget=\$0.08, confidence=0.0

Global: learned_patterns={}

****Iteration 1 (Agent A):****

Processes: "URGENT: Meeting moved"

Layer 0: Valid ✓

Layer 1: No learned patterns → Escalate

Layer 2: LLM categorizes → "urgent"

→ Publishes: global_patterns["urgent"] = 0.92

→ Cost: \$0.01

****Iteration 2 (Agent B):****

Processes: "URGENT: Budget review"

Layer 0: Valid ✓

Layer 1: Checks global patterns → "URGENT" matches!

Reads: learned_patterns["urgent"] = 0.92

→ STATE SUPPRESSES Layer 2

→ Uses cached pattern (no LLM call)

→ Cost: \$0 (saved \$0.01)

Iteration 3 (Agent C):

Processes: "URGENT: Hiring decision"

Layer 0: Valid ✓

Layer 1: Checks global patterns → "URGENT" matches

Reads: learned_patterns["urgent"] = 0.92

→ STATE SUPPRESSES Layer 2

→ Uses cached pattern (no LLM call)

→ Cost: \$0 (saved \$0.01)

****Final State:****

Total emails: 3

LLM calls: 1 (only Agent A)

Cached calls: 2 (Agents B, C used Agent A's learning)

Total cost: \$0.01 (vs \$0.03 if all used LLM)

Savings: 67%

Part 6: Network-Wide Cost Tracking

```
class NetworkCostTracker:  
def init(self):  
  
    self.costs_by_agent = {}  
  
    self.costs_by_layer = {}  
  
    self.network_savings = 0.0  
  
def record_execution(self, agent_id, layer, cost, method):  
  
    """Record cost for one execution"""  
  
    if agent_id not in self.costs_by_agent:  
  
        self.costs_by_agent[agent_id] = 0.0  
  
  
  
  
    self.costs_by_agent[agent_id] += cost  
  
  
  
  
    if layer not in self.costs_by_layer:  
  
        self.costs_by_layer[layer] = 0.0  
  
  
  
  
    self.costs_by_layer[layer] += cost
```

```
def record_network_savings(self, saved_cost, reason):

    """Track network-wide savings"""

    self.network_savings += saved_cost


def report(self):

    """Generate comprehensive report"""

    total = sum(self.costs_by_agent.values())

    return {

        "costs_by_agent": self.costs_by_agent,

        "costs_by_layer": self.costs_by_layer,

        "total_network_savings": self.network_savings,

        "efficiency": self.network_savings / (total + self.network_savings) if total > 0 else 0

    }
```

Part 7: Multi-Agent Learning Rate

Single Agent:

100 emails

Learns: 10 patterns

Cost: \$0.50

Multi-Agent (5 agents, 100 emails each):

500 emails total

Shared: 15 patterns (network-wide learning)

Cost if isolated: $\$0.50 \times 5 = \2.50

Cost with sharing: $\$0.50$ (first agent) + $\$0.00 \times 4 = \0.50

Savings: \$2.00 (80% reduction)

Why Network Learning is 20x Faster:

- Agent A learns pattern in iteration 10
- Agents B, C, D, E use it immediately in iteration 11
- No redundant LLM calls for same pattern
- Pattern library grows 5x faster than single agent

Part 8: Failure Modes & Recovery

Failure Mode 1: Shared State Unavailable

Symptom: Redis/database goes down

Impact: Agents can't read shared patterns

Recovery:

Fallback to local patterns only

```
def execute_with_fallback(agent, request, shared_state):
    """Execute with graceful fallback"""

    try:
        # Try to use shared patterns
        shared_patterns = shared_state['learned_patterns']
    except Exception:
        # Shared state unavailable - use local only
        shared_patterns = {}

    # Combine local + shared patterns
    all_patterns = {**agent.local_patterns, **shared_patterns}

    # Continue processing
    return process_with_patterns(request, all_patterns)
```

Failure Mode 2: Inconsistent Pattern Confidence

****Symptom:**** Agent A learned pattern with 0.92 confidence, but it's wrong 20% of time

****Impact:**** Layer 1 makes incorrect decisions at scale

****Recovery:****

Confidence validation

```
def validate_pattern_confidence(pattern_name, pattern_info):
    """Validate pattern confidence"""

    confidence = pattern_info['confidence']
```

```
# If confidence dips below threshold, flag for review
if confidence < 0.85:
    # Alert: Pattern may be inaccurate
    # Option 1: Lower suppression (escalate to Layer 2 more often)
    # Option 2: Remove pattern entirely
    # Option 3: Retrain with more examples
    return False # Don't use this pattern

return True # Pattern is reliable
```

Failure Mode 3: Violation Broadcast Delays

Symptom: Budget exceeded but not all agents know yet

Impact: Some agents still calling expensive LLM

Recovery:

Aggressive violation checking

```
def critical_checkViolations(agent_id, shared_state):
```

....

Check for critical violations frequently

Run this every N requests (e.g., every 10 requests)

....

```
criticalViolations = [
    'budget_exceeded',
    'safety_concern',
```

```
'rate_limit_exceeded'  
]  
  
for violation in shared_state['violations']:  
    if violation['violation'] in critical_violations:  
        if violation['agent'] == agent_id:  
            # IMMEDIATE response  
            # Suppress all expensive operations now  
            return True # Should halt  
  
    return False # OK to continue
```

Conclusion

****Single-agent SPL:**** 5-15x cost reduction
****Multi-agent SPL:**** 10-50x cost reduction (80%+ for large networks)

This is the power of explicit state-grounded control: agents don't repeat learning; they build on each other's discoveries.

Key Benefits:

- ✓ ****Compositional agents**** (small, focused agents)
- ✓ ****Cross-agent optimization**** (suppress expensive agents)
- ✓ ****Hierarchical control**** (Layer 0 agents suppress higher layers globally)
- ✓ ****Unprecedented cost efficiency**** (10-50x reduction)
- ✓ ****MCP-native**** (agents discover & call each other via MCP)

Pamela Cuce | pamcuce@alum.vassar.edu | Version 3.1 (Consolidated & Corrected) | December 3, 2025