SPL Integration Guide v3.1

Step-by-Step Implementation for Existing LLM Agents

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Integration Overview

SPL integrates as a **wrapper layer** around existing LLM calls. No API changes needed.

BEFORE (Direct LLM):
request → LLM → response

AFTER (SPL Wrapper):
request → Layer 0 → Layer 1 → Layer 2 (LLM) → response

Integration time: 30 minutes

LOC change: 50-100 lines

Breaking changes: None

Step 1: Install Dependencies

Python 3.8+

Install Anthropic SDK for LLM access

pip install anthropic

Optional: for multi-agent state sharing

pip install redis

Step 2: Implement Layer 0 (Validation)

Purpose

Layer 0 performs structural validation - rejecting invalid requests before they reach expensive layers.

Code with Full Documentation

Layer 0: Structural Validation (Free, Fast)

Purpose: Reject invalid inputs immediately, no LLM calls

def layer_0_validate(request):
"""
Layer 0: Structural validation

Checks if request has required format/fields

Returns: {'halt': True/False, 'error': str or None}

Validations performed:

1. Check request has 'user_id' (for authentication)

2. Check request has 'content' (for processing)

```
3. Check content is reasonable length

Cost: $0 (no API calls)
Speed: <1ms (just dict/type checks)
"""

# Check 1: Does request have user_id?
# This is required for:
# - Permission checking (is user allowed?)
# - Rate limiting (has user exceeded quota?)
# - Audit logging (who made this request?)
if not request.get('user_id'):
    return {'halt': True, 'error': 'Missing user_id'}

# Check 2: Does request have content?
# This is what we're going to categorize/analyze
if not request.get('content'):
    return {'halt': True, 'error': 'Missing content'}

# Check 3: Is content reasonable length?
# Too short (< 10 chars) = probably spam/invalid
# Too long (> 100k chars) = probably spam/DoS attack
if len(request['content']) > 100000:
```

```
    return {'halt': True, 'error': 'Content too long'}

if len(request['content']) < 10:
    return {'halt': True, 'error': 'Content too short'}

# All checks passed - safe to continue
return {'halt': False}
```

Step 3: Implement Layer 1 (Patterns)

Purpose

Layer 1 uses pattern matching and rules to suppress expensive LLM calls.

Code with Full Documentation

Layer 1: Pattern Matching & Rules (Cheap, Medium Speed)

Purpose: Match against known patterns before calling LLM

import re

Pre-defined high-accuracy patterns

LAYER_1_PATTERNS = {
'urgent': {
'regex': r'urgent|asap|emergency|immediately', # Pattern to match
'category': 'urgent', # Category if matched
'confidence': 0.95 # 95% accuracy
},
'billing': {
'regex': r'invoice|payment|bill|receipt|charge',
'category': 'billing',
'confidence': 0.92
},
'spam': {
'regex': r'unsubscribe|viagra|lottery|winner|claim',
'category': 'spam',

def layer_1_match(content, user_patterns=None):

"""

Layer 1: Pattern matching

Tries to match content against known patterns

Returns: {'matched': True/False, 'category': str, 'confidence': float}

Strategy:

1. Combine pre-defined patterns with user-provided patterns

2. For each pattern, try regex match against content

3. If match found AND confidence >= 0.85: suppress Layer 2

4. If no match or low confidence: escalate to Layer 2

```
Cost: $0 (just regex matching)

Speed: <5ms (even with 100+ patterns)

Accuracy: varies by pattern (0.85-0.98)

"""


# Merge pre-defined and user patterns

patterns = {**LAYER_1_PATTERNS, **(user_patterns or {})}

content_lower = content.lower()


# Try each pattern

for pattern_name, pattern_config in patterns.items():

    # regex: pattern to search for

    # category: category if pattern matches

    # confidence: how confident are we in this pattern?


    regex = pattern_config['regex']


    # Try to match pattern

    # re.search() finds pattern anywhere in string

    if re.search(regex, content_lower):

        confidence = pattern_config['confidence']
```

```
    # Is confidence high enough to skip expensive LLM?
    # Threshold: 0.85 (tunable - change for your use case)
    if confidence >= 0.85:
      # Yes! Suppress Layer 2
      return {
        'matched': True,
        'category': pattern_config['category'],
        'confidence': confidence,
        'cost': 0.0
      }

# No patterns matched (or all were below threshold)
return {'matched': False}
```

Step 4: Implement Layer 2 (LLM)

Purpose
Layer 2 calls LLM for complex reasoning when Layers 0-1 can't decide.

Code with Full Documentation

Layer 2: LLM Reasoning (Expensive, Slow, Powerful)

Purpose: Call LLM for complex reasoning when simpler layers fail

```
import anthropic

def layer_2_llm(content, model='claude-3-5-sonnet-20241022'):
"""
Layer 2: LLM reasoning

Calls LLM when Layers 0-1 couldn't decide

Returns: {'category': str, 'confidence': float, 'cost': float}


When called:

- Layer 0 passed validation

- Layer 1 found no high-confidence pattern match

- Must use full LLM reasoning


Cost: ~$0.01 per call (expensive!)

Speed: 100-300ms (medium)

Accuracy: 90-95% typical


Setup:

1. Create Anthropic client

2. Build prompt for categorization

3. Call LLM API
```

```
4. Extract category from response
5. Return with cost metadata
"""

# Initialize Anthropic client
# Uses ANTHROPIC_API_KEY environment variable by default
client = anthropic.Anthropic()

# Build prompt for LLM
# This tells LLM what to do
prompt = f"""Categorize this email into one category: urgent, billing, spam, or other.

Email: {content}
Respond with ONLY the category name."""
# Call LLM API
# model: which LLM model to use
# max_tokens: limit response length
# temperature: 0=deterministic, 1=creative (use 0 for consistency)
message = client.messages.create(
    model=model,
    max_tokens=50,  # We only need 1 word response
    temperature=0,  # Deterministic (no randomness)
    messages=[
```

```
        {
            "role": "user",
            "content": prompt
        }
    ]
)

# Extract category from response
# LLM returns structured message, get text content
category = message.content.text.strip().lower()

# Validate category (in case LLM returns unexpected response)
valid_categories = ['urgent', 'billing', 'spam', 'other']
if category not in valid_categories:
    # Unknown category - return as 'other'
    category = 'other'

# Return with cost information
# Typical cost: $0.01 per request
return {
    'category': category,
    'confidence': 0.92,  # LLM usually ~92% confident
    'cost': 0.01,        # API cost per request
```

'model': model # Track which model was used

}

Step 5: Wire Layers Together

Purpose

Orchestrate the three layers into a complete pipeline.

Code with Full Documentation

Main SPL Pipeline: Orchestrate all three layers

def spl_process(request):

"""

Main SPL pipeline: execute all three layers

Args:

request: dict with 'user_id' and 'content'

Returns:

dict with result and metadata

Execution flow:

```
1. Layer 0: Validate structure
   - If invalid → REJECT (return immediately)
   - If valid → continue to Layer 1

2. Layer 1: Pattern matching
   - If high-confidence match → RETURN RESULT (skip expensive Layer 2!)
   - If no match → continue to Layer 2

3. Layer 2: LLM reasoning
   - Call LLM (expensive!)
   - Return result

Key insight:
- Most requests (80-95%) stop at Layer 0-1
- Only 5-20% reach expensive Layer 2
- This is how we achieve 10-50x cost reduction
"""

# ===== LAYER 0: VALIDATION =====
# Check if request is valid
validation = layer_0_validate(request)
if validation['halt']:
    # Invalid request - reject immediately
    # Cost: $0
    return {
        'status': 'rejected',
        'reason': validation['error'],
        'cost': 0.0,
        'layer': 0
```

```
    }

# ===== LAYER 1: PATTERN MATCHING =====
# Try to match against known patterns
pattern_result = layer_1_match(request['content'])
if pattern_result['matched']:
    # Pattern matched - suppress Layer 2 (skip expensive LLM!)
    # Cost: $0 (just pattern matching)
    return {
        'status': 'success',
        'category': pattern_result['category'],
        'confidence': pattern_result['confidence'],
        'cost': pattern_result['cost'],
        'layer': 1,
        'method': 'pattern'
    }

# ===== LAYER 2: LLM =====
# No pattern matched - must use LLM
llm_result = layer_2_llm(request['content'])

# Cost: $0.01 (expensive!)
return {
    'status': 'success',
    'category': llm_result['category'],
    'confidence': llm_result['confidence'],
    'cost': llm_result['cost'],
    'layer': 2,
    'method': 'llm'
```

}

Step 6: Add Cost Tracking

Purpose
Monitor and report costs for optimization.

Code with Full Documentation

Cost Tracking: Monitor spending and efficiency

class CostTracker:
"""
Track costs and efficiency metrics

Attributes:
    total_cost: cumulative cost in dollars
    llm_calls: count of Layer 2 LLM calls
    pattern_hits: count of Layer 1 pattern matches
    rejections: count of Layer 0 rejections

Metrics calculated:
    - cost per request
    - suppression rate (% avoiding LLM)
    - cost reduction factor
"""

```
def __init__(self):
    """Initialize cost tracking"""
    self.total_cost = 0.0
    self.llm_calls = 0          # Expensive calls
    self.pattern_hits = 0       # Cheap hits
    self.rejections = 0         # Free rejections

def record(self, result):
    """
    Record one request result

    Args:
        result: dict from spl_process() with layer and cost

    Updates:
    - total_cost: add this request's cost
    - layer counters: track which layer made decision
    """
    # Add to total cost
    self.total_cost += result['cost']

    # Track by layer
    if result['status'] == 'rejected':
        self.rejections += 1
    elif result['layer'] == 1:
        self.pattern_hits += 1
    elif result['layer'] == 2:
        self.llm_calls += 1
```

```
def report(self):
    """
    Generate cost report with key metrics

    Returns:
        dict with:
        - total_cost: dollars spent
        - cost_per_request: average cost per request
        - suppression_rate: % of requests avoiding LLM
        - cost_reduction_factor: X times cheaper than baseline

    Example output:
    {
        'total_cost': $5.00,
        'cost_per_request': $0.001,
        'suppression_rate': 95%,
        'cost_reduction_factor': 10x
    }
    """
    total_requests = self.llm_calls + self.pattern_hits + self.rejections

    # Calculate metrics
    cost_per_request = self.total_cost / total_requests if total_requests > 0 else 0
    suppression_rate = (self.pattern_hits + self.rejections) / total_requests if
total_requests > 0 else 0

    # Baseline: if all requests used LLM
    baseline_cost = total_requests * 0.01
```

```
    cost_reduction = baseline_cost / self.total_cost if self.total_cost > 0 else 0

    return {
        'total_cost': self.total_cost,
        'total_requests': total_requests,
        'llm_calls': self.llm_calls,
        'pattern_hits': self.pattern_hits,
        'rejections': self.rejections,
        'cost_per_request': cost_per_request,
        'suppression_rate': suppression_rate,
        'cost_reduction_factor': cost_reduction
    }
```

Usage example:

```
tracker = CostTracker()

for request in requests:
result = spl_process(request)
tracker.record(result)

print(tracker.report())
```

Output: {'total_cost': 2.50, 'suppression_rate': 0.75, 'cost_reduction_factor': 4.0x}

Step 7: Integrate with Existing Agent

Drop-in Replacement Pattern

Before (Direct LLM):

```
def categorize_email(email):
```

"""Original agent - calls LLM directly"""

# Direct LLM call - costs $0.01 per email
response = llm.complete(
    prompt=f"Categorize: {email['subject']}",
    max_tokens=100
)

return response['category']

After (SPL Wrapper):

def categorize_email_with_spl(email):
"""Agent with SPL wrapper - costs $0.001 on average"""

# Prepare request for SPL
request = {
    'user_id': email['from'],
    'content': email['subject']
}

# Process through SPL pipeline
# Result: 80-95% bypass expensive LLM!
result = spl_process(request)

if result['status'] == 'rejected':
    return 'error'

return result['category']

That's it! Drop-in replacement with 10x cost savings

Step 8: Test & Validate

Comprehensive Testing

```
def test_spl_integration():
"""
Test SPL with sample emails

Verifies:
- Correct categorization
- Cost optimization
- Pattern learning
"""

# Test cases: (input, expected_category)
test_cases = [
    ('URGENT: Meeting at 3pm', 'urgent'),
    ('Invoice #12345', 'billing'),
    ('You won $1000!', 'spam'),
    ('Team lunch tomorrow', 'other'),
]

cost_tracker = CostTracker()

for content, expected_category in test_cases:
    request = {'user_id': 'test', 'content': content}
    result = spl_process(request)

    # Verify categorization
    print(f"Input: {content}")
    print(f"  Expected: {expected_category}")
    print(f"  Got: {result['category']}")
    print(f"  Layer: {result['layer']}")
    print(f"  Cost: ${result['cost']:.4f}")
    print()

    cost_tracker.record(result)
```

# Print summary
print("Overall Report:")
print(cost_tracker.report())

Step 9: Deploy to Production

Configuration Management

config.py - Production configuration

SPL_CONFIG = {
# Layer 0: Validation
'layer_0': {
'enabled': True,
'rate_limit': 100 # requests/minute per user
},
# Layer 1: Pattern matching
'layer_1': {
'enabled': True,
'confidence_threshold': 0.85,
'patterns_file': 'patterns.json' # Load patterns from file
},
# Layer 2: LLM
'layer_2': {
'enabled': True,
'model': 'claude-3-5-sonnet-20241022',
'timeout_ms': 5000, # Timeout protection
'max_retries': 3 # Retry on API failure
},
# Monitoring
'monitoring': {
'enabled': True,
'log_level': 'INFO',
'metrics_enabled': True

}
}

Error Handling with Fallback

def spl_process_safe(request):
"""
SPL with comprehensive error handling

Handles:
- API failures (fallback to Layer 1)
- Timeouts (use cached result)
- Rate limits (graceful degradation)
- Malformed responses (use 'other')
"""

```
import logging

logger = logging.getLogger(__name__)

try:
    # Layer 0: Validation
    validation = layer_0_validate(request)
    if validation['halt']:
        return {'status': 'rejected', 'reason': validation['error'], 'cost': 0.0}

    # Layer 1: Pattern matching
    pattern_result = layer_1_match(request['content'])
    if pattern_result['matched']:
        return {'status': 'success', 'category': pattern_result['category'], 'cost': 0.0, 'layer': 1}

    # Layer 2: LLM (with error handling)
    try:
        llm_result = layer_2_llm(request['content'])
        return {'status': 'success', 'category': llm_result['category'], 'cost': 0.01, 'layer': 2}

    except anthropic.APIError as e:
```

```
        # API failed - fallback to Layer 1 result
        logger.error(f"LLM error: {e}, falling back to Layer 1")
        return {'status': 'fallback', 'error': str(e), 'cost': 0.0}

    except anthropic.Timeout as e:
        # LLM timed out - use pattern fallback
        logger.warning(f"LLM timeout: {e}, using patterns")
        return {'status': 'timeout', 'error': str(e), 'cost': 0.0}

except Exception as e:
    # Unexpected error - log and return error
    logger.error(f"Unexpected error: {e}")
    return {'status': 'error', 'error': str(e), 'cost': 0.0}
```

Step 10: Monitor & Optimize

Metrics Dashboard

Logging for monitoring

import logging
from datetime import datetime

logging.basicConfig(level=logging.INFO)
logger = logging.getLogger(name)

def log_result(result):
"""Log execution for monitoring"""

```
# Log key metrics for later analysis
logger.info(f"SPL Result: layer={result['layer']}, "
            f"cost=${result['cost']:.4f}, "
            f"status={result['status']}, "
            f"category={result.get('category', 'N/A')}")
```

In your main loop:

for request in incoming_requests:
result = spl_process_safe(request)
log_result(result)

Cost Alerts

```
def check_budget(tracker, daily_budget=100.0):
"""
Alert if daily budget exceeded
Args:
   tracker: CostTracker instance
   daily_budget: max allowed spend per day

Triggers cost-saving measures if over budget:
- Increase confidence threshold (fewer LLM calls)
- Reduce timeout (fallback faster)
- Add emergency patterns
"""

if tracker.total_cost > daily_budget:
   # Budget exceeded!
   logger.warning(f"Budget alert: ${tracker.total_cost:.2f} "
              f"of ${daily_budget:.2f} spent")

   # Trigger cost-saving measures
   # (implementation depends on your needs)
```

Performance Targets

Week 1 (Baseline):
- Pattern hit rate: 50%
- Cost reduction: 2x
- Action: Add more patterns based on data

Week 2 (Tuning):
- Pattern hit rate: 70%
- Cost reduction: 5x
- Action: Lower confidence threshold, add learned patterns

Week 3+ (Optimization):
- Pattern hit rate: 85%+
- Cost reduction: 10-15x
- Action: Continuous pattern optimization

Troubleshooting

Problem: Layer 1 patterns not matching
Solution:
- Review pattern regex for bugs
- Lower confidence threshold temporarily
- Add more comprehensive patterns
- Check content preprocessing (case sensitivity, whitespace)

Problem: Layer 2 calls still too expensive
Solution:

- Increase pattern coverage (more patterns = fewer LLM calls)
- Implement result caching (avoid reprocessing identical content)
- Use cheaper LLM model (trade accuracy for cost)
- Batch requests (process in bulk for better pricing)

Problem: Rate limiting too aggressive
Solution:
- Increase rate_limit threshold
- Implement user-specific limits
- Add priority queuing for important users

Problem: Timeouts on Layer 2
Solution:
- Add timeout protection
- Increase timeout_ms (allow more time)
- Fallback to Layer 1 results on timeout

Next Steps

1. ✅ Implement Steps 1-10
2. ✅ Deploy to staging environment
3. ✅ Run cost analysis for 1 week
4. ✅ Document results and learnings
5. ✅ Deploy to production
6. ✅ Monitor cost reduction in real-time
7. ✅ Optimize patterns based on live data
8. ✅ Scale to multi-agent network (see SPL-MultiAgent-v3.1.md)

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