```
================================================================================
F.A.R.F.A.N PIPELINE CODE AUDIT - BATCH 12
================================================================================
Generated: 2025-12-07T06:17:19.681422
Files in this batch: 17
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================================================================================
FILE: src/farfan_pipeline/core/calibration/data_structures-2.py
================================================================================

"""
Calibration system data structures.

These dataclasses define the EXACT structure of calibration outputs.
NO fields should be added or removed without updating this spec.

Design Principles:
1. Immutability: All dataclasses are frozen
2. Validation: __post_init__ checks invariants
3. Type Safety: Use type hints everywhere
4. Serializability: Support to_dict() for JSON export
"""
from dataclasses import dataclass, field
from typing import Any
from enum import Enum


class LayerID(str, Enum):
    """
    Exact identifier for each calibration layer.

    These correspond to the 7 layers in the theoretical model.
    """
    BASE = "b"          # @b - Intrinsic quality (COMPLETE)
    UNIT = "u"          # @u - PDT quality
    QUESTION = "q"      # @q - Question compatibility
    DIMENSION = "d"     # @d - Dimension compatibility
    POLICY = "p"        # @p - Policy area compatibility
    CONGRUENCE = "C"    # @C - Ensemble validity
    CHAIN = "chain"     # @chain - Data flow integrity
    META = "m"          # @m - Governance


@dataclass(frozen=True)
class LayerScore:
    """
    Single layer evaluation result.

    This represents the output of evaluating ONE layer for ONE subject.

    Attributes:
        layer: Which layer this score belongs to
        score: Numerical score in [0.0, 1.0]
        components: Breakdown of sub-scores (e.g., for @u: {S, M, I, P})
```

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        rationale: Human-readable explanation of the score
        metadata: Additional debug/audit information

    Example:
        LayerScore(
            layer=LayerID.UNIT,
            score=0.75,
            components={"S": 0.8, "M": 0.7, "I": 0.75, "P": 0.75},
            rationale="Unit quality: robusto (S=0.80, M=0.70, I=0.75, P=0.75)",
            metadata={"aggregation_method": "geometric_mean"}
        )
    """
    layer: LayerID
    score: float  # MUST be in [0.0, 1.0]
    components: dict[str, float] = field(default_factory=dict)
    rationale: str = ""
    metadata: dict[str, Any] = field(default_factory=dict)

    def __post_init__(self):
        """Validate score is in valid range."""
        if not 0.0 <= self.score <= 1.0:
            raise ValueError(
                f"Layer {self.layer.value} score {self.score} out of range [0.0, 1.0]"
            )

    def to_dict(self) -> dict:
        """Export as dictionary for JSON serialization."""
        return {
            "layer": self.layer.value,
            "score": self.score,
            "components": self.components,
            "rationale": self.rationale,
            "metadata": self.metadata,
        }


@dataclass(frozen=True)
class ContextTuple:
    """
    Execution context for a micro-question: ctx = (Q, D, P, U).

    This is the (Q, D, P, U) tuple that defines WHERE a method is being used.
    The context determines which compatibility scores apply.

    Attributes:
        question_id: e.g., "Q001", "Q031" (from questionnaire monolith)
        dimension: e.g., "DIM01" (canonical code, not "D1")
        policy_area: e.g., "PA01" (canonical code, not "P1")
        unit_quality: Pre-computed U score from PDT analysis, range [0.0, 1.0]

    Example:
        ContextTuple(
            question_id="Q001",
            dimension="DIM01",
            policy_area="PA01",
            unit_quality=0.75
```

```
        )
    """
    question_id: str
    dimension: str
    policy_area: str
    unit_quality: float

    def __post_init__(self):
        """Validate canonical notation and ranges."""
        # Validate dimension uses canonical notation
        if not self.dimension.startswith("DIM"):
            raise ValueError(
                f"Dimension must use canonical code (DIM01-DIM06), got {self.dimension}"
            )

        # Validate policy area uses canonical notation
        if not self.policy_area.startswith("PA"):
            raise ValueError(
                f"Policy must use canonical code (PA01-PA10), got {self.policy_area}"
            )

        # Validate question ID format
        if not self.question_id.startswith("Q"):
            raise ValueError(
                f"Question ID must start with 'Q', got {self.question_id}"
            )

        # Validate unit quality range
        if not 0.0 <= self.unit_quality <= 1.0:
            raise ValueError(
                f"Unit quality must be in [0.0, 1.0], got {self.unit_quality}"
            )

    def to_dict(self) -> dict:
        """Export as dictionary."""
        return {
            "question_id": self.question_id,
            "dimension": self.dimension,
            "policy_area": self.policy_area,
            "unit_quality": self.unit_quality,
        }


@dataclass(frozen=True)
class CalibrationSubject:
    """
    Subject of calibration I = (M, v, Î\223, G, ctx).

    This represents ONE method being evaluated in ONE context.

    From theoretical model:
    - M: Method artifact (code)
    - v: Version
    - Î\223: Computational graph (how methods connect)
    - G: Interplay subgraph (methods working together)
    - ctx: Context tuple (Q, D, P, U)
```

```

    Attributes:
        method_id: e.g., "pattern_extractor_v2"
        method_version: e.g., "v2.1.0"
        graph_config: Hash of the computational graph Î\223
        subgraph_id: Identifier for the interplay subgraph G
        context: The (Q, D, P, U) context

    Example:
        CalibrationSubject(
            method_id="pattern_extractor_v2",
            method_version="v2.1.0",
            graph_config="abc123def456",
            subgraph_id="Q001_analyzer_validator",
            context=ContextTuple(...)
        )
    """
    method_id: str
    method_version: str
    graph_config: str
    subgraph_id: str
    context: ContextTuple

    def to_dict(self) -> dict:
        """Export as dictionary."""
        return {
            "method_id": self.method_id,
            "method_version": self.method_version,
            "graph_config": self.graph_config,
            "subgraph_id": self.subgraph_id,
            "context": self.context.to_dict(),
        }


@dataclass(frozen=True)
class CompatibilityMapping:
    """
    Defines how compatible a method is with questions/dimensions/policies.

    This implements the Q_f, D_f, P_f functions from the theoretical model.

    Compatibility Scores (from theoretical model):
        1.0 = Primary (designed specifically for this context)
        0.7 = Secondary (works well, but not optimal)
        0.3 = Compatible (can work, limited effectiveness)
        0.1 = Undeclared (penalty, not validated for this context)

    Example:
        CompatibilityMapping(
            method_id="pattern_extractor_v2",
            questions={"Q001": 1.0, "Q031": 0.7, "Q091": 0.3},
            dimensions={"DIM01": 1.0, "DIM03": 0.7},
            policies={"PA01": 1.0, "PA10": 0.7}
        )
    """
    method_id: str
```

```
    questions: dict[str, float]   # question_id -> score â\210\210 {1.0, 0.7, 0.3, 0.1}
    dimensions: dict[str, float]  # dimension_code -> score
    policies: dict[str, float]    # policy_code -> score

    def get_question_score(self, question_id: str) -> float:
        """
        Get compatibility score for a question.

        Returns 0.1 (penalty) if question not declared.
        """
        return self.questions.get(question_id, 0.1)

    def get_dimension_score(self, dimension: str) -> float:
        """
        Get compatibility score for a dimension.

        Returns 0.1 (penalty) if dimension not declared.
        """
        return self.dimensions.get(dimension, 0.1)

    def get_policy_score(self, policy: str) -> float:
        """
        Get compatibility score for a policy area.

        Returns 0.1 (penalty) if policy not declared.
        """
        return self.policies.get(policy, 0.1)

    def check_anti_universality(self, threshold: float = 0.9) -> bool:
        """
        Check Anti-Universality Theorem compliance.

        The theorem states: NO method can have average compatibility â\211¥ 0.9
        across ALL questions, dimensions, AND policies simultaneously.

        Returns:
            True if compliant (method is NOT universal)
            False if violation detected
        """
        if not self.questions or not self.dimensions or not self.policies:
            return True  # Incomplete mapping, cannot be universal

        avg_q = sum(self.questions.values()) / len(self.questions)
        avg_d = sum(self.dimensions.values()) / len(self.dimensions)
        avg_p = sum(self.policies.values()) / len(self.policies)

        is_universal = (avg_q >= threshold and
                        avg_d >= threshold and
                        avg_p >= threshold)

        return not is_universal

    def to_dict(self) -> dict:
        """Export as dictionary."""
        return {
            "method_id": self.method_id,
```

```
            "questions": self.questions,
            "dimensions": self.dimensions,
            "policies": self.policies,
        }


@dataclass(frozen=True)
class InteractionTerm:
    """
    Represents a synergy between two layers in Choquet aggregation.

    Formula: a_â\204\223k Â• min(x_â\204\223, x_k)

    This captures the "weakest link" principle: the contribution of the
    interaction is limited by whichever layer scored lower.

    Standard Interactions (from theoretical model):
        (@u, @chain): weight=0.15, "Plan quality only matters with sound wiring"
        (@chain, @C): weight=0.12, "Ensemble validity requires chain integrity"
        (@q, @d): weight=0.08, "Question-dimension alignment synergy"
        (@d, @p): weight=0.05, "Dimension-policy coherence synergy"

    Example:
        InteractionTerm(
            layer_1=LayerID.UNIT,
            layer_2=LayerID.CHAIN,
            weight=0.15,
            rationale="Plan quality only matters with sound wiring"
        )
    """
    layer_1: LayerID
    layer_2: LayerID
    weight: float  # a_â\204\223k coefficient
    rationale: str  # Why this interaction exists

    def compute(self, scores: dict[LayerID, float]) -> float:
        """
        Compute interaction contribution.

        Formula: a_â\204\223k Â• min(x_â\204\223, x_k)

        Args:
            scores: Dictionary mapping LayerID to score

        Returns:
            Interaction contribution (can be 0 if layer missing)
        """
        score_1 = scores.get(self.layer_1, 0.0)
        score_2 = scores.get(self.layer_2, 0.0)
        return self.weight * min(score_1, score_2)

    def to_dict(self) -> dict:
        """Export as dictionary."""
        return {
            "layer_1": self.layer_1.value,
            "layer_2": self.layer_2.value,
```

```
            "weight": self.weight,
            "rationale": self.rationale,
        }


@dataclass(frozen=True)
class CalibrationResult:
    """
    Complete calibration output for a subject I.

    This is the FINAL result of the calibration pipeline.

    Formula: Cal(I) = Î£ a_â\204\223Â•x_â\204\223 + Î£ a_â\204\223kÂ•min(x_â\204\223, x_k)

    Attributes:
        subject: The calibration subject I = (M, v, Î\223, G, ctx)
        layer_scores: Individual scores for each layer
        linear_contribution: Î£ a_â\204\223 Â• x_â\204\223
        interaction_contribution: Î£ a_â\204\223k Â• min(x_â\204\223, x_k)
        final_score: Cal(I) = linear + interaction â\210\210 [0.0, 1.0]
        computation_metadata: Timestamps, hashes, config_hash, etc.

    Example:
        CalibrationResult(
            subject=CalibrationSubject(...),
            layer_scores={
                LayerID.BASE: LayerScore(..., score=0.9),
                LayerID.UNIT: LayerScore(..., score=0.75),
                ...
            },
            linear_contribution=0.65,
            interaction_contribution=0.15,
            final_score=0.80,
            computation_metadata={
                "config_hash": "abc123",
                "timestamp": "2025-11-11T10:30:00Z"
            }
        )
    """
    subject: CalibrationSubject
    layer_scores: dict[LayerID, LayerScore]
    linear_contribution: float
    interaction_contribution: float
    final_score: float
    computation_metadata: dict[str, Any] = field(default_factory=dict)

    def __post_init__(self):
        """Validate calibration result integrity."""
        # Validate final score range
        if not 0.0 <= self.final_score <= 1.0:
            raise ValueError(
                f"Final calibration score {self.final_score} out of range [0.0, 1.0]"
            )

        # Verify linear + interaction = final (within numerical tolerance)
        computed = self.linear_contribution + self.interaction_contribution
```

```
        if abs(computed - self.final_score) > 1e-6:
            raise ValueError(
                f"Final score {self.final_score} != "
                f"linear {self.linear_contribution} + "
                f"interaction {self.interaction_contribution} = {computed}"
            )

        # Verify all layer scores are in valid range
        for layer_id, layer_score in self.layer_scores.items():
            if not 0.0 <= layer_score.score <= 1.0:
                raise ValueError(
                    f"Layer {layer_id.value} score {layer_score.score} out of range"
                )

    def to_certificate_dict(self) -> dict:
        """
        Export as a calibration certificate for auditing.

        This is the format that gets saved to audit logs and can be
        used to reproduce the calibration result.
        """
        return {
            "certificate_version": "1.0",
            "method": {
                "id": self.subject.method_id,
                "version": self.subject.method_version,
                "graph_config": self.subject.graph_config,
                "subgraph_id": self.subject.subgraph_id,
            },
            "context": self.subject.context.to_dict(),
            "layer_scores": {
                layer_id.value: layer_score.to_dict()
                for layer_id, layer_score in self.layer_scores.items()
            },
            "aggregation": {
                "linear_contribution": self.linear_contribution,
                "interaction_contribution": self.interaction_contribution,
                "final_score": self.final_score,
                "formula": "Cal(I) = Î£ a_â\204\223Â•x_â\204\223 + Î£ a_â\204\223kÂ•min(x_â\204\223, x_k)",
            },
            "metadata": self.computation_metadata,
        }

    def to_dict(self) -> dict:
        """Export as dictionary."""
        return self.to_certificate_dict()



================================================================================
FILE: src/farfan_pipeline/core/calibration/data_structures.py
================================================================================

"""
Three-Pillar Calibration System - Core Data Structures

```

```
This module defines the fundamental data structures for the calibration system
as specified in the SUPERPROMPT Three-Pillar Calibration System.

Spec compliance: Section 1 (Core Objects), Section 7 (Certificates)
"""

from dataclasses import dataclass, field
from typing import Dict, Any, Optional, List, Set, Tuple
from enum import Enum


class CalibrationConfigError(Exception):
    """
    Raised when calibration configuration violates mathematical constraints.

    This error indicates:
    - Fusion weights don’t sum to valid range
    - Weight constraints violated (must be â\211¥ 0)
    - Invalid layer configuration
    - Misconfigured calibration parameters

    SIN_CARRETA Policy: Fail loudly on misconfiguration, never silently clamp.
    """
    pass


class LayerType(Enum):
    """Eight fixed calibration layers - NO RENAMING ALLOWED"""
    BASE = "@b"                   # Intrinsic quality
    CHAIN = "@chain"              # Chain compatibility
    UNIT = "@u"                   # Unit-of-analysis sensitivity
    QUESTION = "@q"               # Question compatibility
    DIMENSION = "@d"              # Dimension compatibility
    POLICY = "@p"                 # Policy compatibility
    INTERPLAY = "@C"              # Interplay congruence
    META = "@m"                   # Meta/governance


class MethodRole(Enum):
    """Method roles with fixed required layer sets"""
    INGEST_PDM = "INGEST_PDM"
    STRUCTURE = "STRUCTURE"
    EXTRACT = "EXTRACT"
    SCORE_Q = "SCORE_Q"
    AGGREGATE = "AGGREGATE"
    REPORT = "REPORT"
    META_TOOL = "META_TOOL"
    TRANSFORM = "TRANSFORM"


# Role-based required layers (L_* from spec Section 4)
REQUIRED_LAYERS: Dict[MethodRole, Set[LayerType]] = {
    MethodRole.INGEST_PDM: {LayerType.BASE, LayerType.CHAIN, LayerType.UNIT, LayerType.META},
    MethodRole.STRUCTURE: {LayerType.BASE, LayerType.CHAIN, LayerType.UNIT, LayerType.META},
    MethodRole.EXTRACT: {LayerType.BASE, LayerType.CHAIN, LayerType.UNIT, LayerType.META},
    MethodRole.SCORE_Q: {LayerType.BASE, LayerType.CHAIN, LayerType.QUESTION, LayerType.DIMENSION,
```

```
                         LayerType.POLICY, LayerType.INTERPLAY, LayerType.UNIT, LayerType.META},
    MethodRole.AGGREGATE: {LayerType.BASE, LayerType.CHAIN, LayerType.DIMENSION, LayerType.POLICY,
                           LayerType.INTERPLAY, LayerType.META},
    MethodRole.REPORT: {LayerType.BASE, LayerType.CHAIN, LayerType.INTERPLAY, LayerType.META},
    MethodRole.META_TOOL: {LayerType.BASE, LayerType.CHAIN, LayerType.META},
    MethodRole.TRANSFORM: {LayerType.BASE, LayerType.CHAIN, LayerType.META},
}


@dataclass(frozen=True)
class Context:
    """
    Execution context: ctx = (Q, D, P, U)

    Spec compliance: Definition 1.2

    Q: Question ID or None
    D: Dimension ID (DIM01-DIM06)
    P: Policy area ID (PA01-PA10)
    U: Unit-of-analysis quality [0,1]
    """
    question_id: Optional[str] = None  # Q â\210\210 Questions â\210ª {â\212¥}
    dimension_id: str = "DIM01"          # D â\210\210 Dimensions
    policy_id: str = "PA01"              # P â\210\210 Policies
    unit_quality: float = 0.85          # U â\210\210 [0,1]

    def __post_init__(self):
        """Validate context constraints"""
        if self.unit_quality < 0.0 or self.unit_quality > 1.0:
            raise ValueError(f"unit_quality must be in [0,1], got {self.unit_quality}")

        if self.dimension_id and not self.dimension_id.startswith("DIM"):
            raise ValueError(f"dimension_id must match DIM* pattern, got {self.dimension_id}")

        if self.policy_id and not self.policy_id.startswith("PA"):
            raise ValueError(f"policy_id must match PA* pattern, got {self.policy_id}")


@dataclass
class ComputationGraph:
    """
    Computation graph: Î\223 = (V, E, T, S)

    Spec compliance: Definition 1.1

    V: finite set of method instance nodes
    E: directed edges (must be DAG)
    T: edge typing function
    S: node signature function
    """
    nodes: Set[str] = field(default_factory=set)  # V
    edges: List[Tuple[str, str]] = field(default_factory=list)  # E â\212\206 V Ã\227 V
    edge_types: Dict[Tuple[str, str], Dict[str, Any]] = field(default_factory=dict)  # T
    node_signatures: Dict[str, Dict[str, Any]] = field(default_factory=dict)  # S

    def validate_dag(self) -> bool:
```

```
        """Axiom 1.1: Graph must be acyclic"""
        # Simple cycle detection via DFS
        visited = set()
        rec_stack = set()

        def has_cycle(node: str) -> bool:
            visited.add(node)
            rec_stack.add(node)

            for edge in self.edges:
                if edge[0] == node:
                    neighbor = edge[1]
                    if neighbor not in visited:
                        if has_cycle(neighbor):
                            return True
                    elif neighbor in rec_stack:
                        return True

            rec_stack.remove(node)
            return False

        for node in self.nodes:
            if node not in visited:
                if has_cycle(node):
                    return False
        return True


@dataclass
class InterplaySubgraph:
    """
    Valid interplay: G = (V_G, E_G) â\212\206 Î\223

    Spec compliance: Definition 2.1

    Must satisfy:
    1. Single target property
    2. Declared fusion rule
    3. Type compatibility
    """
    nodes: Set[str]
    edges: List[Tuple[str, str]]
    target_output: str
    fusion_rule: str
    compatible: bool = True


@dataclass(frozen=True)
class CalibrationCertificate:
    """
    Complete calibration certificate with audit trail.

    Spec compliance: Section 7 (Definition 7.1)

    MUST allow exact reconstruction of Cal(I) from contents.
    Property 7.1: No hidden behavior - all computations must appear here.
```

```
    """
    # Identity
    instance_id: str
    method_id: str
    node_id: str
    context: Context

    # Scores
    intrinsic_score: float  # x_@b
    layer_scores: Dict[str, float]  # All x_â\204\223(I)
    calibrated_score: float  # Cal(I)

    # Transparency
    fusion_formula: Dict[str, Any]  # symbolic, expanded, computation_trace
    parameter_provenance: Dict[str, Dict[str, Any]]  # Where each parameter came from
    evidence_trail: Dict[str, Any]  # Evidence used for layer computations

    # Integrity
    config_hash: str  # SHA256 of all config files
    graph_hash: str   # SHA256 of computation graph

    # Validation
    validation_checks: Dict[str, Any] = field(default_factory=dict)
    sensitivity_analysis: Dict[str, Any] = field(default_factory=dict)

    # Audit
    timestamp: str = ""
    validator_version: str = "1.0.0"

    def __post_init__(self):
        """Validate certificate constraints"""
        # Boundedness check
        if not (0.0 <= self.calibrated_score <= 1.0):
            raise ValueError(f"calibrated_score must be in [0,1], got {self.calibrated_score}")

        if not (0.0 <= self.intrinsic_score <= 1.0):
            raise ValueError(f"intrinsic_score must be in [0,1], got {self.intrinsic_score}")

        for layer, score in self.layer_scores.items():
            if not (0.0 <= score <= 1.0):
                raise ValueError(f"layer_scores[{layer}] must be in [0,1], got {score}")


@dataclass
class CalibrationSubject:
    """
    Calibration subject: I = (M, v, Î\223, G, ctx)

    Spec compliance: Definition 1.3

    M: method artifact
    v: node instance
    Î\223: containing graph
    G: interplay subgraph (or None)
    ctx: execution context
    """
```

```
    method_id: str  # M (canonical method ID)
    node_id: str    # v â\210\210 V
    graph: ComputationGraph  # Î\223
    interplay: Optional[InterplaySubgraph]  # G
    context: Context  # ctx

    # Additional metadata
    role: Optional[MethodRole] = None
    active_layers: Set[LayerType] = field(default_factory=set)


@dataclass
class EvidenceStore:
    """
    Storage for evidence used in calibration computations.
    All evidence must be traceable and auditable.
    """
    pdt_structure: Dict[str, Any] = field(default_factory=dict)
    pdm_metrics: Dict[str, Any] = field(default_factory=dict)
    runtime_metrics: Dict[str, Any] = field(default_factory=dict)
    test_results: Dict[str, Any] = field(default_factory=dict)
    deployment_history: Dict[str, Any] = field(default_factory=dict)

    def get_evidence(self, key: str, default: Any = None) -> Any:
        """Retrieve evidence by key"""
        for store in [self.pdt_structure, self.pdm_metrics, self.runtime_metrics,
                      self.test_results, self.deployment_history]:
            if key in store:
                return store[key]
        return default



================================================================================
FILE: src/farfan_pipeline/core/calibration/decorators.py
================================================================================

"""Calibration decorators using centralized ParameterLoaderV2."""

import functools
import logging
from collections.abc import Callable
from typing import Any

from farfan_pipeline.core.parameters import ParameterLoaderV2

logger = logging.getLogger(__name__)


def calibrated_method(method_id: str) -> Callable:
    """
    Decorator to apply calibration to a method using centralized ParameterLoaderV2.

    Future: Will invoke CalibrationOrchestrator.calibrate(method_id, context) when available.

    Args:
```

```
        method_id: Fully qualified method identifier for parameter lookup

    Returns:
        Decorated function with calibration applied
    """

    def decorator(func: Callable) -> Callable:
        @functools.wraps(func)
        def wrapper(*args: Any, **kwargs: Any) -> Any:
            calibration_params = ParameterLoaderV2.get_all(method_id)

            logger.debug(
                f"Calling calibrated method '{method_id}' with {len(calibration_params)} parameters"
            )

            # Future: CalibrationOrchestrator.calibrate(method_id, context={
            #     "args": args,
            #     "kwargs": kwargs,
            #     "params": calibration_params
            # })

            return func(*args, **kwargs)

        return wrapper

    return decorator



================================================================================
FILE: src/farfan_pipeline/core/calibration/engine.py
================================================================================

"""
Three-Pillar Calibration System - Main Calibration Engine

This module implements the main calibrate() function and fusion operator
as specified in the SUPERPROMPT Three-Pillar Calibration System.

Spec compliance: Section 5 (Fusion Operator), Section 6 (Runtime Engine)
SIN_CARRETA Compliance: Pure fusion operator, fail-loudly on misconfiguration
"""

import json
import hashlib
from datetime import datetime, timezone
from pathlib import Path
from typing import Dict, Any, Optional
from farfan_pipeline.core.calibration.data_structures import (
    CalibrationCertificate, CalibrationSubject, Context,
    ComputationGraph, EvidenceStore, LayerType, MethodRole, REQUIRED_LAYERS,
    CalibrationConfigError
)
from farfan_pipeline.core.calibration.layer_computers import (
    compute_base_layer, compute_chain_layer, compute_unit_layer,
    compute_question_layer, compute_dimension_layer, compute_policy_layer,
```

```
    compute_interplay_layer, compute_meta_layer
)


class CalibrationEngine:
    """
    Main calibration engine implementing the three-pillar system.

    Spec compliance: Section 7 (Runtime Engine & Certificate)
    """

    def __init__(self, config_dir: str = None, monolith_path: str = None, catalog_path: str = None):
        """
        Initialize calibration engine and load configs.

        SIN_CARRETA: Validates fusion weights at load time to fail fast.
        Three-Pillar System: Loads from intrinsic, contextual, and fusion configs.

        Args:
            config_dir: Path to config directory (defaults to ../config)
            monolith_path: Path to questionnaire_monolith.json (defaults to ../data/questionnaire_monolith.json)
            catalog_path: Path to canonical_method_catalog.json (defaults to ../config/canonical_method_catalog.json)

        Raises:
            CalibrationConfigError: If fusion weights violate constraints
        """
        if config_dir is None:
            config_dir = Path(__file__).parent.parent / "config"
        else:
            config_dir = Path(config_dir)

        self.config_dir = config_dir
        self.intrinsic_config = self._load_json(config_dir / "intrinsic_calibration.json")
        self.contextual_config = self._load_json(config_dir / "contextual_parametrization.json")
        self.fusion_config = self._load_json(config_dir / "fusion_specification.json")

        # Load canonical method catalog for role determination
        if catalog_path is None:
            catalog_path = config_dir / "canonical_method_catalog.json"
        else:
            catalog_path = Path(catalog_path)
        self.catalog = self._load_json(catalog_path)
        self._build_method_index()

        # SIN_CARRETA: Validate fusion weights at load time
        self._validate_fusion_weights()

        # Load questionnaire monolith using canonical loader
        # This ensures hash verification and immutability
        from saaaaaa.core.orchestrator.factory import load_questionnaire

        if monolith_path is None:
            # Use default path from factory
            canonical_q = load_questionnaire()
        else:
            # Use specified path
```

```
            canonical_q = load_questionnaire(Path(monolith_path))

        # Convert to dict for backward compatibility with calibration system
        # (CalibrationEngine expects dict, not CanonicalQuestionnaire)
        self.monolith = dict(canonical_q.data)
        self._questionnaire_hash = canonical_q.sha256  # Store for verification

        # Compute config hash
        self.config_hash = self._compute_config_hash()

    @staticmethod
    def _load_json(path: Path) -> Dict[str, Any]:
        """Load JSON file"""
        with open(path, 'r') as f:
            return json.load(f)

    def _build_method_index(self) -> None:
        """
        Build index of methods from canonical catalog for fast role lookup.

        Three-Pillar System: Uses canonical_method_catalog.json as single source.
        """
        self.method_index = {}

        for layer_name, methods in self.catalog.get("layers", {}).items():
            for method_info in methods:
                canonical_name = method_info.get("canonical_name", "")
                method_name = method_info.get("method_name", "")
                class_name = method_info.get("class_name", "")
                layer = method_info.get("layer", "unknown")

                # Store method info with multiple lookup keys
                for key in [canonical_name, method_name, f"{class_name}.{method_name}"]:
                    if key:
                        self.method_index[key] = {
                            "canonical_name": canonical_name,
                            "method_name": method_name,
                            "class_name": class_name,
                            "layer": layer,
                            "metadata": method_info
                        }

    def _validate_fusion_weights(self) -> None:
        """
        Validate fusion weight constraints at config load time.

        Per canonic_calibration_methods.md specification.

        Constraints:
        1. All weights must be non-negative: a_â\204\223 â\211¥ 0, a_â\204\223k â\211¥ 0
        2. Total weight sum MUST equal 1: Î£(a_â\204\223) + Î£(a_â\204\223k) = 1 (tolerance 1e-9)

        Raises:
            CalibrationConfigError: If any weight constraint is violated
        """
        role_params_dict = self.fusion_config.get("role_fusion_parameters", {})
```

```
        TOLERANCE = 1e-9

        for role_name, role_params in role_params_dict.items():
            linear_weights = role_params.get("linear_weights", {})
            interaction_weights = role_params.get("interaction_weights", {})

            # Constraint 1: Non-negativity
            for layer, weight in linear_weights.items():
                if weight < 0:
                    raise CalibrationConfigError(
                        f"Negative weight for role={role_name}, layer={layer}: "
                        f"weight={weight}. All weights must be â\211¥ 0."
                    )

            for pair, weight in interaction_weights.items():
                if weight < 0:
                    raise CalibrationConfigError(
                        f"Negative interaction weight for role={role_name}, pair={pair}: "
                        f"weight={weight}. All weights must be â\211¥ 0."
                    )

            # Constraint 2: Must sum to exactly 1.0
            total_weight = sum(linear_weights.values()) + sum(interaction_weights.values())
            if abs(total_weight - 1.0) > TOLERANCE:
                raise CalibrationConfigError(
                    f"Weight sum must equal 1.0 for role={role_name}: "
                    f"total_weight={total_weight:.15f} (deviation: {abs(total_weight - 1.0):.15f}). "
                    f"Constraint: Î£(a_â\204\223) + Î£(a_â\204\223k) = 1.0 (tolerance {TOLERANCE})."
                )

    def _compute_config_hash(self) -> str:
        """
        Compute SHA256 hash of all config files.

        Spec compliance: Section 7 (audit_trail.config_hash)
        """
        hasher = hashlib.sha256()

        # Hash all three pillar configs in sorted order
        for config in sorted([
            json.dumps(self.intrinsic_config, sort_keys=True),
            json.dumps(self.contextual_config, sort_keys=True),
            json.dumps(self.fusion_config, sort_keys=True),
        ]):
            hasher.update(config.encode('utf-8'))

        return f"sha256:{hasher.hexdigest()}"

    @staticmethod
    def _compute_graph_hash(graph: ComputationGraph) -> str:
        """
        Compute SHA256 hash of computation graph.

        Spec compliance: Section 7 (audit_trail.graph_hash)
        """
        hasher = hashlib.sha256()
```

```

        # Hash nodes and edges
        graph_repr = json.dumps({
            "nodes": sorted(list(graph.nodes)),
            "edges": sorted([list(e) for e in graph.edges])
        }, sort_keys=True)

        hasher.update(graph_repr.encode('utf-8'))
        return f"sha256:{hasher.hexdigest()}"

    def _determine_role(self, method_id: str) -> MethodRole:
        """
        Determine method role from method ID using canonical catalog metadata.

        Three-Pillar System: Uses canonical_method_catalog.json for role inference.
        Mapping from catalog layer + method patterns to MethodRole enum.

        Args:
            method_id: Method identifier (canonical_name, method_name, or Class.method format)

        Returns:
            MethodRole enum value

        Raises:
            CalibrationConfigError: If method not found in catalog or role cannot be determined
        """
        # Look up method in catalog index
        method_info = self.method_index.get(method_id)

        if not method_info:
            # Try fallback patterns
            for key, info in self.method_index.items():
                if method_id in key or key in method_id:
                    method_info = info
                    break

        if not method_info:
            # Cannot calibrate unknown methods - fail loudly
            raise CalibrationConfigError(
                f"Method '{method_id}' not found in canonical_method_catalog.json. "
                f"Cannot determine role for calibration. "
                f"All calibrated methods must be registered in catalog.\n"
                f"To resolve:\n"
                f"  1. Add method to config/canonical_method_catalog.json with proper metadata\n"
                f"  2. Run scripts/rigorous_calibration_triage.py to generate intrinsic calibration\n"
                f"  3. Ensure method has correct layer, role, and signature information"
            )

        # Determine role from layer + method name patterns (per canonic_calibration_methods.md)
        layer = method_info.get("layer", "unknown")
        method_name = method_info.get("method_name", "").lower()

        # Role mapping based on layer and method semantics
        # Per L_* specification in canonic_calibration_methods.md
        if layer == "ingestion" or "ingest" in method_name or "pdm" in method_name:
            return MethodRole.INGEST_PDM
```

```
        elif "structure" in method_name or "parse" in method_name:
            return MethodRole.STRUCTURE
        elif "extract" in method_name:
            return MethodRole.EXTRACT
        elif "score" in method_name or "question" in method_name or layer == "analyzer":
            return MethodRole.SCORE_Q
        elif "aggregate" in method_name or "combine" in method_name:
            return MethodRole.AGGREGATE
        elif "report" in method_name or "format" in method_name:
            return MethodRole.REPORT
        elif "transform" in method_name or "normalize" in method_name or "convert" in method_name:
            return MethodRole.TRANSFORM
        else:
            # Default to META_TOOL for utility/orchestrator methods
            return MethodRole.META_TOOL

    def _detect_interplay(self, graph: ComputationGraph, node_id: str) -> Optional[Any]:
        """
        Detect interplay patterns from computation graph.

        Three-Pillar System: Interplays are DECLARED in config, not auto-detected.

        Per canonic_calibration_methods.md Section 1.3:
        - "An interplay G is valid only if all nodes share a single declared target output"
        - "A fusion rule is declared in config"
        - "Do not infer ensembles implicitly"

        This method checks if the node participates in any declared interplay
        from the contextual config.

        Args:
            graph: Computation graph
            node_id: Node identifier

        Returns:
            Interplay subgraph if node participates in one, None otherwise
        """
        # Per specification: interplays are declared in contextual config, not inferred
        # Check contextual_parametrization.json for declared interplays
        interplay_defs = self.contextual_config.get("interplay_definitions", {})

        for interplay_id, interplay_spec in interplay_defs.items():
            # Check if node_id is in this interplay's participant list
            participants = interplay_spec.get("participants", [])
            if node_id in participants:
                # Node participates in this declared interplay
                # Return interplay specification
                return {
                    "interplay_id": interplay_id,
                    "participants": participants,
                    "target_output": interplay_spec.get("target_output"),
                    "fusion_rule": interplay_spec.get("fusion_rule"),
                    "declared": True
                }

        # Node does not participate in any declared interplay
```

```
        # This is normal - most nodes don't participate in interplays
        return None

    def _compute_layer_scores(
        self,
        subject: CalibrationSubject,
        evidence: EvidenceStore
    ) -> Dict[str, float]:
        """
        Compute all layer scores for calibration subject.

        Spec compliance: Section 3 (all layers)
        """
        ctx = subject.context
        scores = {}

        # @b: Base layer (always required)
        scores[LayerType.BASE.value] = compute_base_layer(
            subject.method_id, self.intrinsic_config
        )

        # @chain: Chain compatibility (always required for non-META roles)
        scores[LayerType.CHAIN.value] = compute_chain_layer(
            subject.node_id, subject.graph, self.contextual_config
        )

        # @u: Unit-of-analysis
        if subject.role:
            scores[LayerType.UNIT.value] = compute_unit_layer(
                subject.method_id, subject.role, ctx.unit_quality, self.contextual_config
            )

        # @q: Question compatibility
        scores[LayerType.QUESTION.value] = compute_question_layer(
            subject.method_id, ctx.question_id, self.monolith, self.contextual_config
        )

        # @d: Dimension compatibility
        scores[LayerType.DIMENSION.value] = compute_dimension_layer(
            subject.method_id, ctx.dimension_id, self.contextual_config
        )

        # @p: Policy compatibility
        scores[LayerType.POLICY.value] = compute_policy_layer(
            subject.method_id, ctx.policy_id, self.contextual_config
        )

        # @C: Interplay congruence
        scores[LayerType.INTERPLAY.value] = compute_interplay_layer(
            subject.interplay, self.contextual_config
        )

        # @m: Meta/governance
        meta_evidence = {
            "formula_export_valid": True,
            "trace_complete": True,
```

```
                "logs_conform_schema": True,
                "version_tagged": True,
                "config_hash_matches": True,
                "signature_valid": True,
                "runtime_ms": evidence.runtime_metrics.get("runtime_ms", 100)
            }
            scores[LayerType.META.value] = compute_meta_layer(
                meta_evidence, self.contextual_config
            )

            return scores

        def _apply_fusion(
            self,
            role: MethodRole,
            layer_scores: Dict[str, float]
        ) -> tuple[float, Dict[str, Any]]:
            """
            Apply pure fusion operator to combine layer scores.

            Spec compliance: Section 5 (Fusion Operator)
            SIN_CARRETA Compliance: Pure mathematical formula, no clamping/normalization

            Formula: Cal(I) = Î£(a_â\204\223 Â• x_â\204\223) + Î£(a_â\204\223k Â• min(x_â\204\223, x_k))

            Weight constraints (enforced at load time):
            - All weights a_â\204\223, a_â\204\223k â\211¥ 0
            - Î£(a_â\204\223) + Î£(a_â\204\223k) â\211¤ 1 (ensures boundedness)

            Returns:
                (calibrated_score, fusion_details)

            Raises:
                CalibrationConfigError: If score violates [0,1] bounds (weight misconfiguration)
            """
            role_params = self.fusion_config["role_fusion_parameters"].get(
                role.value,
                self.fusion_config["default_fallback"]
            )

            linear_weights = role_params["linear_weights"]
            interaction_weights = role_params.get("interaction_weights", {})

            # Compute linear terms
            linear_sum = 0.0
            linear_trace = []

            for layer_key, weight in linear_weights.items():
                if layer_key in layer_scores:
                    contribution = weight * layer_scores[layer_key]
                    linear_sum += contribution
                    linear_trace.append({
                        "layer": layer_key,
                        "weight": weight,
                        "score": layer_scores[layer_key],
                        "contribution": contribution
```

```
                })

        # Compute interaction terms
        interaction_sum = 0.0
        interaction_trace = []

        for pair_key, weight in interaction_weights.items():
            # Parse "(layer1, layer2)" format
            pair_str = pair_key.strip("()")
            layer1, layer2 = [l.strip() for l in pair_str.split(",")]

            if layer1 in layer_scores and layer2 in layer_scores:
                min_score = min(layer_scores[layer1], layer_scores[layer2])
                contribution = weight * min_score
                interaction_sum += contribution
                interaction_trace.append({
                    "pair": pair_key,
                    "weight": weight,
                    "layer1_score": layer_scores[layer1],
                    "layer2_score": layer_scores[layer2],
                    "min_score": min_score,
                    "contribution": contribution
                })

        # Total calibrated score (PURE FUSION - no clamping or normalization)
        calibrated_score = linear_sum + interaction_sum

        # SIN_CARRETA: Fail loudly on weight misconfiguration
        # NEVER clamp or normalize - that would hide misconfiguration
        if calibrated_score < 0.0 or calibrated_score > 1.0:
            total_weight = sum(linear_weights.values()) + sum(interaction_weights.values())
            raise CalibrationConfigError(
                f"Fusion weights misconfigured for role {role.value}: "
                f"total_weight={total_weight:.6f} produced calibrated_score={calibrated_score:.6f}. "
                f"Score must be in [0,1]. Weight constraints violated. "
                f"Check fusion_specification.json and ensure Î£(a_â\204\223) + Î£(a_â\204\223k) â\211¤ 1."
            )

        fusion_details = {
            "symbolic": "Î£(a_â\204\223Â•x_â\204\223) + Î£(a_â\204\223kÂ•min(x_â\204\223,x_k))",
            "linear_terms": linear_trace,
            "interaction_terms": interaction_trace,
            "linear_sum": linear_sum,
            "interaction_sum": interaction_sum,
            "total": calibrated_score
        }

        return calibrated_score, fusion_details

    def calibrate(
        self,
        method_id: str,
        node_id: str,
        graph: ComputationGraph,
        context: Context,
        evidence_store: EvidenceStore
```

```
    ) -> CalibrationCertificate:
        """
        Main calibration function.

        Spec compliance: Section 7 (Runtime Engine)

        Args:
            method_id: Canonical method ID
            node_id: Node identifier in graph
            graph: Computation graph
            context: Execution context
            evidence_store: Evidence for calibration

        Returns:
            CalibrationCertificate with complete audit trail

        Raises:
            ValueError: If validation fails
        """
        # Validate graph is DAG
        if not graph.validate_dag():
            raise ValueError("Graph contains cycles - must be DAG")

        # Determine role
        role = self._determine_role(method_id)

        # SIN_CARRETA: Detect interplay from graph (fail if not implemented)
        interplay = self._detect_interplay(graph, node_id)

        # Create calibration subject
        subject = CalibrationSubject(
            method_id=method_id,
            node_id=node_id,
            graph=graph,
            interplay=interplay,
            context=context,
            role=role
        )

        # Validate layer completeness
        required = REQUIRED_LAYERS.get(role, set())

        # Compute layer scores
        layer_scores = self._compute_layer_scores(subject, evidence_store)

        # Check all required layers are present
        missing_layers = [layer for layer in required if layer.value not in layer_scores]
        if missing_layers:
            raise ValueError(
                f"Missing required layers for role {role.value}: "
                f"{[layer.value for layer in missing_layers]}"
            )

        # Apply fusion
        calibrated_score, fusion_details = self._apply_fusion(role, layer_scores)

```

```
        # Build parameter provenance
        role_params = self.fusion_config["role_fusion_parameters"].get(
            role.value,
            self.fusion_config["default_fallback"]
        )

        parameter_provenance = {
            "fusion_weights": {
                "source": "fusion_specification.json",
                "role": role.value,
                "linear_weights": role_params["linear_weights"],
                "interaction_weights": role_params.get("interaction_weights", {})
            },
            "intrinsic_calibration": {
                "source": "intrinsic_calibration.json",
                "method_id": method_id
            }
        }

        # Build evidence trail
        evidence_trail = {
            "pdt_metrics": evidence_store.pdt_structure,
            "runtime_metrics": evidence_store.runtime_metrics,
            "layer_computations": layer_scores
        }

        # Create certificate
        certificate = CalibrationCertificate(
            instance_id=f"{method_id}@{node_id}",
            method_id=method_id,
            node_id=node_id,
            context=context,
            intrinsic_score=layer_scores.get(LayerType.BASE.value, 0.0),
            layer_scores=layer_scores,
            calibrated_score=calibrated_score,
            fusion_formula=fusion_details,
            parameter_provenance=parameter_provenance,
            evidence_trail=evidence_trail,
            config_hash=self.config_hash,
            graph_hash=self._compute_graph_hash(graph),
            timestamp=datetime.now(timezone.utc).isoformat().replace('+00:00', 'Z'),
            validator_version="1.0.0"
        )

        return certificate


# Convenience function
def calibrate(
    method_id: str,
    node_id: str,
    graph: ComputationGraph,
    context: Context,
    evidence_store: EvidenceStore,
    config_dir: Optional[str] = None,
    monolith_path: Optional[str] = None
```

```
) -> CalibrationCertificate:
    """
    Calibrate a method instance.

    Spec compliance: Section 7

    This is the single authoritative calibration entry point.
    """
    engine = CalibrationEngine(config_dir=config_dir, monolith_path=monolith_path)
    return engine.calibrate(method_id, node_id, graph, context, evidence_store)



================================================================================
FILE: src/farfan_pipeline/core/calibration/intrinsic_calibration_loader.py
================================================================================

"""
intrinsic_calibration_loader.py - Single source loader for @b-layer intrinsic calibration

This module provides the ONLY interface for loading intrinsic calibration data.
Enforces strict @b-only access with fallback behavior:
- pending â\206\222 @b = 0.5 (neutral baseline)
- excluded â\206\222 @b = None (causes method skip)
- none â\206\222 @b = 0.3 (low confidence with warning)
- computed â\206\222 actual @b values from JSON

CRITICAL: This is the single source of truth for intrinsic calibration.
"""
import json
import logging
from dataclasses import dataclass
from pathlib import Path

logger = logging.getLogger(__name__)


@dataclass
class IntrinsicCalibration:
    """Intrinsic calibration data for a single method."""
    method_id: str
    intrinsic_score: tuple[float, float]
    b_theory: float
    b_impl: float
    b_deploy: float
    calibration_status: str
    layer: str
    last_updated: str

    def get_composite_b(self) -> float:
        """Calculate composite @b score from theory, impl, deploy."""
        return (self.b_theory + self.b_impl + self.b_deploy) / 3.0


class IntrinsicCalibrationLoader:
    """
```

```
    Single source loader for intrinsic calibration with fallback behavior.

    Fallback rules:
    - computed: Use actual values from JSON
    - pending: b_theory=0.5, b_impl=0.5, b_deploy=0.5 (neutral baseline)
    - excluded: Return None (signals method should be skipped)
    - none: b_theory=0.3, b_impl=0.3, b_deploy=0.3 (low confidence + warning)
    """

    def __init__(self, config_path: str = "config/intrinsic_calibration.json") -> None:
        self.config_path = Path(config_path)
        self._data: dict = {}
        self._load()

    def _load(self) -> None:
        """Load calibration data from JSON."""
        if not self.config_path.exists():
            raise FileNotFoundError(
                f"Intrinsic calibration file not found: {self.config_path}. "
                "Intrinsic calibration incomplete or contaminated."
            )

        with open(self.config_path) as f:
            self._data = json.load(f)

        metadata = self._data.get("_metadata", {})
        coverage = metadata.get("coverage_percent", 0)

        if coverage < 25.0:
            raise ValueError(
                f"Intrinsic calibration coverage {coverage}% < 25%. "
                "Intrinsic calibration incomplete or contaminated."
            )

        logger.info(
            f"Loaded intrinsic calibration: {metadata.get('computed_methods')} methods, "
            f"{coverage}% coverage"
        )

    def get_calibration(self, method_id: str) -> IntrinsicCalibration | None:
        """
        Get intrinsic calibration for a method with fallback behavior.

        Args:
            method_id: Method identifier (e.g., "ClassName.method_name")

        Returns:
            IntrinsicCalibration object or None if method is excluded

        Raises:
            ValueError: If calibration data is contaminated
        """
        if method_id not in self._data:
            logger.warning(
                f"Method '{method_id}' not in calibration registry. "
                f"Applying fallback: status='none', @b=0.3"
```

```
            )
            return IntrinsicCalibration(
                method_id=method_id,
                intrinsic_score=(0.28, 0.32),
                b_theory=0.3,
                b_impl=0.3,
                b_deploy=0.3,
                calibration_status="none",
                layer="utility",
                last_updated="unknown"
            )

        method_data = self._data[method_id]

        # Verify no contamination
        allowed_keys = {"intrinsic_score", "b_theory", "b_impl", "b_deploy",
                       "calibration_status", "layer", "last_updated"}
        extra_keys = set(method_data.keys()) - allowed_keys
        if extra_keys:
            raise ValueError(
                f"CONTAMINATION DETECTED in method '{method_id}': {extra_keys}. "
                "Intrinsic calibration incomplete or contaminated."
            )

        status = method_data["calibration_status"]

        # Handle fallback cases
        if status == "excluded":
            logger.info(f"Method '{method_id}' is excluded, returning None (skip method)")
            return None

        if status == "pending":
            logger.info(f"Method '{method_id}' is pending, applying fallback @b=0.5")
            return IntrinsicCalibration(
                method_id=method_id,
                intrinsic_score=(0.48, 0.52),
                b_theory=0.5,
                b_impl=0.5,
                b_deploy=0.5,
                calibration_status=status,
                layer=method_data["layer"],
                last_updated=method_data["last_updated"]
            )

        if status == "none":
            logger.warning(
                f"Method '{method_id}' has status='none', applying fallback @b=0.3"
            )
            return IntrinsicCalibration(
                method_id=method_id,
                intrinsic_score=(0.28, 0.32),
                b_theory=0.3,
                b_impl=0.3,
                b_deploy=0.3,
                calibration_status=status,
                layer=method_data["layer"],
```

```
                last_updated=method_data["last_updated"]
            )

        # status == "computed": return actual values
        return IntrinsicCalibration(
            method_id=method_id,
            intrinsic_score=tuple(method_data["intrinsic_score"]),
            b_theory=method_data["b_theory"],
            b_impl=method_data["b_impl"],
            b_deploy=method_data["b_deploy"],
            calibration_status=status,
            layer=method_data["layer"],
            last_updated=method_data["last_updated"]
        )

    def get_metadata(self) -> dict:
        """Get calibration metadata."""
        return self._data.get("_metadata", {})

    def verify_purity(self) -> bool:
        """
        Verify no contamination from other calibration layers.

        Returns:
            True if pure @b-only data

        Raises:
            ValueError: If contamination detected
        """
        forbidden_patterns = ["@chain", "@q", "@d", "@p", "@C", "@u", "@m",
                              "final_score", "layer_scores", "chain_", "queue_"]

        for method_id, method_data in self._data.items():
            if method_id == "_metadata":
                continue

            for key in method_data:
                for pattern in forbidden_patterns:
                    if pattern in key.lower():
                        raise ValueError(
                            f"CONTAMINATION DETECTED: method '{method_id}' contains "
                            f"forbidden key '{key}' matching pattern '{pattern}'. "
                            "Intrinsic calibration incomplete or contaminated."
                        )

        return True


# Singleton instance
_loader: IntrinsicCalibrationLoader | None = None


def get_intrinsic_calibration_loader(
    config_path: str = "config/intrinsic_calibration.json"
) -> IntrinsicCalibrationLoader:
    """Get singleton instance of intrinsic calibration loader."""
```

```
    global _loader
    if _loader is None:
        _loader = IntrinsicCalibrationLoader(config_path)
        _loader.verify_purity()
    return _loader


def get_method_calibration(method_id: str) -> IntrinsicCalibration | None:
    """
    Convenience function to get calibration for a method.

    Args:
        method_id: Method identifier (e.g., "ClassName.method_name")

    Returns:
        IntrinsicCalibration object or None if excluded
    """
    loader = get_intrinsic_calibration_loader()
    return loader.get_calibration(method_id)



================================================================================
FILE: src/farfan_pipeline/core/calibration/layer_assignment.py
================================================================================

"""
Layer Assignment System for Calibration

This module defines the canonical layer requirements for all method roles
and provides layer assignment with Choquet integral weights for executors.

Layers:
- @b: Code quality (base theory)
- @chain: Method wiring/orchestration
- @q: Question appropriateness
- @d: Dimension alignment
- @p: Policy area fit
- @C: Contract compliance
- @u: Document quality
- @m: Governance maturity
"""

import re
from typing import Any

LAYER_REQUIREMENTS: dict[str, list[str]] = {
    "ingest": ["@b", "@chain", "@u", "@m"],
    "processor": ["@b", "@chain", "@u", "@m"],
    "analyzer": ["@b", "@chain", "@q", "@d", "@p", "@C", "@u", "@m"],
    "score": ["@b", "@chain", "@q", "@d", "@p", "@C", "@u", "@m"],
    "executor": ["@b", "@chain", "@q", "@d", "@p", "@C", "@u", "@m"],
    "utility": ["@b", "@chain", "@m"],
    "orchestrator": ["@b", "@chain", "@m"],
    "core": ["@b", "@chain", "@q", "@d", "@p", "@C", "@u", "@m"],
    "extractor": ["@b", "@chain", "@u", "@m"],
```

```
}

CHOQUET_WEIGHTS: dict[str, float] = {
    "@b": 0.17,
    "@chain": 0.13,
    "@q": 0.08,
    "@d": 0.07,
    "@p": 0.06,
    "@C": 0.08,
    "@u": 0.04,
    "@m": 0.04,
}

CHOQUET_INTERACTION_WEIGHTS: dict[tuple[str, str], float] = {
    ("@u", "@chain"): 0.13,
    ("@chain", "@C"): 0.10,
    ("@q", "@d"): 0.10,
}


def identify_executors(executors_file_path: str) -> list[dict[str, Any]]:
    """
    Identify all D[1-6]Q[1-5] executors from the executors.py file.

    Args:
        executors_file_path: Path to executors.py

    Returns:
        List of executor metadata dicts with method_id, role, dimension, question

    Raises:
        RuntimeError: If <30 executors found
    """
    with open(executors_file_path) as f:
        content = f.read()

    pattern = re.compile(r"class (D([1-6])_Q([1-5])_\w+)\(")
    matches = pattern.findall(content)

    executors = []
    for class_name, dim, question in matches:
        method_id = f"farfan_pipeline.core.orchestrator.executors.{class_name}"
        executors.append(
            {
                "method_id": method_id,
                "class_name": class_name,
                "dimension": f"D{dim}",
                "question": f"Q{question}",
                "role": "executor",
                "type": "analyzer",
            }
        )

    if len(executors) < 30:
        raise RuntimeError(
            f"layer assignment corrupted: Found {len(executors)} executors, expected 30"
```

```
        )

    return executors


def assign_layers_and_weights(
    method_id: str, role: str, dimension: str = None, question: str = None
) -> dict[str, Any]:
    """
    Assign layers and Choquet weights to a method based on its role.

    Args:
        method_id: Fully qualified method identifier
        role: Method role (ingest, processor, analyzer, etc.)
        dimension: Dimension ID (D1-D6) for executors
        question: Question ID (Q1-Q5) for executors

    Returns:
        Dict with layers, weights, and aggregator_type

    Raises:
        ValueError: If role not found in LAYER_REQUIREMENTS
    """
    if role not in LAYER_REQUIREMENTS:
        raise ValueError(f"Unknown role: {role}")

    layers = LAYER_REQUIREMENTS[role]

    weights = {layer: CHOQUET_WEIGHTS[layer] for layer in layers}

    interaction_weights = {}
    for (l1, l2), weight in CHOQUET_INTERACTION_WEIGHTS.items():
        if l1 in layers and l2 in layers:
            interaction_weights[f"{l1},{l2}"] = weight

    sum_linear = sum(weights.values())
    sum_interaction = sum(interaction_weights.values())
    total = sum_linear + sum_interaction

    if abs(total - 1.0) > 0.01:
        scale = 1.0 / total
        weights = {k: v * scale for k, v in weights.items()}
        interaction_weights = {k: v * scale for k, v in interaction_weights.items()}

    return {
        "method_id": method_id,
        "role": role,
        "dimension": dimension,
        "question": question,
        "layers": layers,
        "weights": weights,
        "interaction_weights": interaction_weights,
        "aggregator_type": "choquet",
    }
```

```
def generate_canonical_inventory(executors_file_path: str) -> dict[str, Any]:
    """
    Generate the canonical inventory of methods with layer assignments.

    Args:
        executors_file_path: Path to executors.py

    Returns:
        Dict with metadata for all methods (NO SCORES)

    Raises:
        RuntimeError: If any validation fails
    """
    executors = identify_executors(executors_file_path)

    inventory = {
        "_metadata": {
            "version": "1.0.0",
            "description": "Canonical layer assignments for F.A.R.F.A.N. calibration system",
            "total_executors": len(executors),
            "layer_system": {
                "@b": "Code quality (base theory)",
                "@chain": "Method wiring/orchestration",
                "@q": "Question appropriateness",
                "@d": "Dimension alignment",
                "@p": "Policy area fit",
                "@C": "Contract compliance",
                "@u": "Document quality",
                "@m": "Governance maturity",
            },
        },
        "methods": {},
    }

    for executor in executors:
        assignment = assign_layers_and_weights(
            method_id=executor["method_id"],
            role=executor["role"],
            dimension=executor["dimension"],
            question=executor["question"],
        )

        if len(assignment["layers"]) < 8:
            raise RuntimeError(
                f"layer assignment corrupted: Executor {executor['method_id']} "
                f"has {len(assignment['layers'])} layers, expected 8"
            )

        weights_sum = sum(assignment["weights"].values()) + sum(
            assignment["interaction_weights"].values()
        )
        if abs(weights_sum - 1.0) > 0.01:
            raise RuntimeError(
                f"layer assignment corrupted: Weights for {executor['method_id']} "
                f"sum to {weights_sum}, expected 1.0"
            )
```

```

        inventory["methods"][executor["method_id"]] = {
            "method_id": assignment["method_id"],
            "role": assignment["role"],
            "dimension": assignment["dimension"],
            "question": assignment["question"],
            "layers": assignment["layers"],
            "weights": assignment["weights"],
            "interaction_weights": assignment["interaction_weights"],
            "aggregator_type": assignment["aggregator_type"],
        }

    return inventory



================================================================================
FILE: src/farfan_pipeline/core/calibration/layer_coexistence.py
================================================================================

"""
Layer Coexistence and Influence Framework

Formal mathematical framework for method calibration based on layer-specific
evidence aggregation with theoretically grounded fusion operators.

Theoretical Foundations:
- Bayesian inference (Pearl, 1988; Jaynes, 2003)
- Multi-criteria decision analysis (Keeney & Raiffa, 1976)
- Policy coherence structures (Nilsson et al., 2012)
- Ensemble learning (Dietterich, 2000; Wolpert, 1992)
- Fuzzy measures and aggregation (Yager, 1988; Beliakov et al., 2007)

Canonical Layer Notation (from questionnaire_monolith.json):
- @q: Question Layer (300 questions: Q001-Q300)
- @d: Dimension Layer (6 dimensions: DIM01-DIM06)
- @p: Policy Area Layer (10 areas: PA01-PA10)
- @C: Congruence Layer (ensemble compatibility)
- @m: Meta Layer (cross-layer aggregation)
"""

from dataclasses import dataclass, field
from typing import Dict, List, Set, Optional
from enum import Enum


class Layer(Enum):
    """
    Canonical layer identifiers.

    Source: questionnaire_monolith.json and theoretical framework specification.
    These are the ONLY valid layer identifiers in the system.
    """
    QUESTION = "@q"      # Evidence-weighted Bayesian scoring
    DIMENSION = "@d"     # Multi-criteria value functions
    POLICY_AREA = "@p"   # Policy coherence structures
```

```
    CONGRUENCE = "@C"    # Ensemble compatibility
    META = "@m"          # Generalized aggregation


@dataclass(frozen=True)
class LayerScore:
    """
    Score from a single layer for a method.

    Attributes:
        layer: The layer identifier
        value: Numerical score in [0, 1]
        weight: Importance weight in [0, 1]
        metadata: Additional layer-specific information
    """
    layer: Layer
    value: float
    weight: float = 1.0
    metadata: Dict = field(default_factory=dict)

    def __new__(cls, layer: Layer, value: float, weight: float = 1.0, metadata: Dict = None):
        """Validate score bounds before instance creation"""
        if not 0 <= value <= 1:
            raise ValueError(f"Layer score must be in [0,1], got {value}")
        if not 0 <= weight <= 1:
            raise ValueError(f"Layer weight must be in [0,1], got {weight}")
        if metadata is None:
            metadata = {}
        return super().__new__(cls)

    def __init__(self, layer: Layer, value: float, weight: float = 1.0, metadata: Dict = None):
        # dataclass will set fields, but we need to ensure metadata is not None
        if metadata is None:
            object.__setattr__(self, 'metadata', {})
@dataclass
class MethodSignature:
    """
    Complete signature for a method under Layer Coexistence framework.

    This is the canonical method notation that every calibrated method must expose.

    Attributes:
        method_id: Unique identifier (ClassName.method_name)
        active_layers: Set of layers relevant to this method (L(M))
        input_schema: Dict describing required inputs
        output_schema: Dict describing output space
        fusion_operator_name: Name of the fusion operator F_M
        fusion_parameters: Parameters for F_M
        calibration_rule: Human-readable calibration rule description
    """
    method_id: str
    active_layers: Set[Layer]
    input_schema: Dict
    output_schema: Dict
    fusion_operator_name: str
    fusion_parameters: Dict
```

```
    calibration_rule: str

    def to_dict(self) -> Dict:
        """Export to dictionary for serialization"""
        return {
            'method_id': self.method_id,
            'active_layers': [layer.value for layer in self.active_layers],
            'input_schema': self.input_schema,
            'output_schema': self.output_schema,
            'fusion_operator_name': self.fusion_operator_name,
            'fusion_parameters': self.fusion_parameters,
            'calibration_rule': self.calibration_rule
        }

    @classmethod
    def from_dict(cls, data: Dict) -> 'MethodSignature':
        """Load from dictionary"""
        return cls(
            method_id=data['method_id'],
            active_layers={Layer(layer_str) for layer_str in data['active_layers']},
            input_schema=data['input_schema'],
            output_schema=data['output_schema'],
            fusion_operator_name=data['fusion_operator_name'],
            fusion_parameters=data['fusion_parameters'],
            calibration_rule=data['calibration_rule']
        )


class FusionOperator:
    """
    Abstract base class for fusion operators F_M.

    All fusion operators must satisfy:
    - Monotonicity: â\210\202F/â\210\202x_â\204\223 â\211¥ 0 for all layers â\204\223
    - Boundedness: F: [0,1]^n â\206\222 [0,1]
    - Interpretability: Clear semantic meaning of output

    Subclasses must implement:
    - fuse(scores: List[LayerScore]) -> float
    - verify_properties() -> Dict[str, bool]
    - get_formula() -> str
    """

    def __init__(self, name: str, parameters: Dict):
        self.name = name
        self.parameters = parameters

    def fuse(self, scores: List[LayerScore]) -> float:
        """
        Aggregate layer scores into calibrated output.

        Args:
            scores: List of LayerScore objects

        Returns:
            Calibrated score in [0, 1]
```

```
        """
        raise NotImplementedError("Subclasses must implement fuse()")

    def verify_properties(self) -> Dict[str, bool]:
        """
        Verify mathematical properties (monotonicity, boundedness, etc.)

        Returns:
            Dict mapping property name to verification result
        """
        raise NotImplementedError("Subclasses must implement verify_properties()")

    def get_formula(self) -> str:
        """
        Return explicit mathematical formula in canonical notation.

        Returns:
            LaTeX-style formula string
        """
        raise NotImplementedError("Subclasses must implement get_formula()")

    def get_trace(self, scores: List[LayerScore]) -> List[str]:
        """
        Generate step-by-step arithmetic trace.

        Args:
            scores: List of LayerScore objects

        Returns:
            List of computation steps as strings
        """
        raise NotImplementedError("Subclasses must implement get_trace()")


class WeightedAverageFusion(FusionOperator):
    """
    Weighted average fusion operator.

    Formula: F_M(x) = Î£(w_â\204\223 Â• x_â\204\223) / Î£(w_â\204\223)

    Properties:
    - Monotonic: Yes (â\210\202F/â\210\202x_â\204\223 = w_â\204\223/Î£w > 0)
    - Bounded: Yes (min(x) â\211¤ F â\211¤ max(x))
    - Idempotent: Yes (F(c, c, ..., c) = c)
    - Compensatory: Full (low scores can be compensated by high scores)

    Reference: Standard weighted mean in MCDA (Keeney & Raiffa, 1976, Ch. 3)
    """

    def __init__(self, parameters: Optional[Dict] = None):
        super().__init__("WeightedAverage", parameters or {})
        self.normalize_weights = parameters.get('normalize_weights', True) if parameters else True

    def fuse(self, scores: List[LayerScore]) -> float:
        """Compute weighted average"""
        if not scores:
```

```
                return 0.0

            weighted_sum = sum(score.value * score.weight for score in scores)
            weight_sum = sum(score.weight for score in scores)

            if weight_sum == 0:
                return 0.0

            return weighted_sum / weight_sum

        def verify_properties(self) -> Dict[str, bool]:
            """Verify mathematical properties"""
            # Test monotonicity with sample inputs
            test_scores_low = [LayerScore(Layer.QUESTION, 0.3, 1.0)]
            test_scores_high = [LayerScore(Layer.QUESTION, 0.7, 1.0)]

            result_low = self.fuse(test_scores_low)
            result_high = self.fuse(test_scores_high)

            return {
                'monotonic': result_high >= result_low,
                'bounded': 0 <= result_low <= 1 and 0 <= result_high <= 1,
                'idempotent': abs(self.fuse([LayerScore(Layer.QUESTION, 0.5, 1.0)]) - 0.5) < 1e-10
            }

        def get_formula(self) -> str:
            """Return LaTeX formula"""
            return r"F_{WA}(x) = \frac{\sum_{\ell \in L(M)} w_\ell \cdot x_\ell}{\sum_{\ell \in L(M)} w_\ell}"

        def get_trace(self, scores: List[LayerScore]) -> List[str]:
            """Generate computation trace"""
            trace = []
            trace.append(f"Weighted Average Fusion: {len(scores)} layers")

            for i, score in enumerate(scores):
                trace.append(f"  Layer {score.layer.value}: x = {score.value:.4f}, w = {score.weight:.4f}")

            weighted_sum = sum(s.value * s.weight for s in scores)
            weight_sum = sum(s.weight for s in scores)

            trace.append(f"Weighted sum: Î£(wÂ•x) = {weighted_sum:.4f}")
            trace.append(f"Weight sum: Î£(w) = {weight_sum:.4f}")
            if weight_sum == 0:
                trace.append(f"Result: No valid weights, returning 0.0")
            else:
                trace.append(f"Result: {weighted_sum:.4f} / {weight_sum:.4f} = {weighted_sum/weight_sum:.4f}")

            return trace


class OWAFusion(FusionOperator):
    """
    Ordered Weighted Averaging (OWA) fusion operator.

    Formula: F_OWA(x) = Î£(v_i Â• x_(i))
    where x_(i) is the i-th largest value and v_i are position weights
```

```

    Properties:
    - Monotonic: Yes (if all v_i â\211¥ 0)
    - Bounded: Yes
    - Allows modeling of optimism/pessimism (andness/orness)

    Reference: Yager (1988) "On ordered weighted averaging aggregation operators"
               Int. J. General Systems, 14(3), 183-194

    Parameters:
        weights: Position-based weights [v_1, v_2, ..., v_n]
        Should sum to 1 for proper normalization
    """

    def __init__(self, parameters: Dict):
        super().__init__("OWA", parameters)
        self.position_weights = parameters.get('weights', [])

        if len(self.position_weights) == 0:
            raise ValueError("OWA requires position weights")

    def fuse(self, scores: List[LayerScore]) -> float:
        """Compute OWA aggregation"""
        if not scores:
            return 0.0

        # Sort scores in descending order
        values = [score.value for score in scores]
        sorted_values = sorted(values, reverse=True)

        # Pad or truncate weights if necessary
        n = len(sorted_values)
        if len(self.position_weights) < n:
            # Extend with equal weights
            extended_weights = list(self.position_weights) + [1.0/n] * (n - len(self.position_weights))
        else:
            extended_weights = self.position_weights[:n]

        # Normalize weights
        weight_sum = sum(extended_weights)
        if weight_sum > 0:
            extended_weights = [w / weight_sum for w in extended_weights]

        # Compute weighted sum
        result = sum(w * v for w, v in zip(extended_weights, sorted_values))
        return float(result)

    def verify_properties(self) -> Dict[str, bool]:
        """Verify OWA properties"""
        # Check monotonicity, boundedness
        test_scores = [
            LayerScore(Layer.QUESTION, 0.2, 1.0),
            LayerScore(Layer.DIMENSION, 0.5, 1.0),
            LayerScore(Layer.POLICY_AREA, 0.8, 1.0)
        ]

```

```
        result = self.fuse(test_scores)
        weight_sum = sum(self.position_weights)

        return {
            'monotonic': True,  # Always true if weights are non-negative
            'bounded': 0 <= result <= 1,
            'weights_sum_to_one': abs(weight_sum - 1.0) < 1e-6
        }

    def get_formula(self) -> str:
        """Return LaTeX formula"""
        return r"F_{OWA}(x) = \sum_{i=1}^{n} v_i \cdot x_{(i)} \text{ where } x_{(i)} \text{ is i-th largest}"

    def get_trace(self, scores: List[LayerScore]) -> List[str]:
        """Generate computation trace"""
        trace = []
        trace.append(f"OWA Fusion: {len(scores)} layers")

        values = [(score.layer.value, score.value) for score in scores]
        values_sorted = sorted(values, key=lambda x: x[1], reverse=True)

        trace.append("Sorted values (descending):")
        for i, (layer, val) in enumerate(values_sorted):
            weight_idx = min(i, len(self.position_weights) - 1)
            weight = self.position_weights[weight_idx]
            trace.append(f"  Position {i+1}: {layer} = {val:.4f}, weight = {weight:.4f}")

        result = self.fuse(scores)
        trace.append(f"Result: {result:.4f}")

        return trace


# Registry of available fusion operators
FUSION_OPERATORS = {
    'WeightedAverage': WeightedAverageFusion,
    'OWA': OWAFusion,
}


def create_fusion_operator(name: str, parameters: Optional[Dict] = None) -> FusionOperator:
    """
    Factory function to create fusion operators.

    Args:
        name: Operator name from FUSION_OPERATORS
        parameters: Operator-specific parameters

    Returns:
        Configured FusionOperator instance
    """
    if name not in FUSION_OPERATORS:
        raise ValueError(f"Unknown fusion operator: {name}. Available: {list(FUSION_OPERATORS.keys())}")

    operator_class = FUSION_OPERATORS[name]
    return operator_class(parameters or {})
```

```



================================================================================
FILE: src/farfan_pipeline/core/calibration/layer_computers.py
================================================================================

"""
Three-Pillar Calibration System - Layer Computation Functions

This module implements the 8 layer score computation functions as specified
in the SUPERPROMPT Three-Pillar Calibration System.

Spec compliance: Section 3 (Layer Architecture)
"""

import json
import math
from pathlib import Path
from typing import Any

from farfan_pipeline.core.calibration.data_structures import (
    CalibrationConfigError,
    ComputationGraph,
    InterplaySubgraph,
    MethodRole,
)

_unit_transforms_config: dict[str, Any] | None = None


def _load_unit_transforms_config() -> dict[str, Any]:
    """Load unit transforms configuration from system/config/calibration/unit_transforms.json."""
    global _unit_transforms_config

    if _unit_transforms_config is not None:
        return _unit_transforms_config

    config_path = Path("system/config/calibration/unit_transforms.json")
    if not config_path.exists():
        raise FileNotFoundError(f"Unit transforms config not found: {config_path}")

    with open(config_path, encoding='utf-8') as f:
        _unit_transforms_config = json.load(f)

    return _unit_transforms_config


def compute_base_layer(method_id: str, intrinsic_config: dict[str, Any]) -> float:
    """
    Compute base layer score (@b): Intrinsic quality

    Spec compliance: Section 3.1
    Formula: x_@b = w_th Â• b_theory + w_imp Â• b_impl + w_dep Â• b_deploy

    Args:
```

```
        method_id: Canonical method ID
        intrinsic_config: Loaded intrinsic_calibration.json

    Returns:
        Score in [0,1]

    Raises:
        ValueError: If method not found or scores invalid
    """
    if method_id not in intrinsic_config.get("methods", {}):
        raise ValueError(f"Method {method_id} not found in intrinsic_calibration.json")

    method_data = intrinsic_config["methods"][method_id]
    weights = intrinsic_config["_base_weights"]

    b_theory = method_data["b_theory"]
    b_impl = method_data["b_impl"]
    b_deploy = method_data["b_deploy"]

    # Validate bounds
    for name, value in [("b_theory", b_theory), ("b_impl", b_impl), ("b_deploy", b_deploy)]:
        if not (0.0 <= value <= 1.0):
            raise ValueError(f"{name} must be in [0,1], got {value}")

    # Compute weighted sum
    score = (weights["w_th"] * b_theory +
             weights["w_imp"] * b_impl +
             weights["w_dep"] * b_deploy)

    return score


def compute_chain_layer(node_id: str, graph: ComputationGraph,
                       contextual_config: dict[str, Any]) -> float:
    """
    Compute chain compatibility layer (@chain)

    Spec compliance: Section 3.2
    Rule-based discrete mapping

    Args:
        node_id: Node identifier
        graph: Computation graph containing node
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    if node_id not in graph.nodes:
        raise ValueError(f"Node {node_id} not in graph")

    config = _load_unit_transforms_config()
    mappings = config.get("chain_layer", {}).get("discrete_mappings", {})

    if not mappings:
        mappings = contextual_config.get("layer_chain", {}).get("discrete_mappings", {})
```

```
    signature = graph.node_signatures.get(node_id, {})
    required_inputs = signature.get("required_inputs", [])

    has_hard_mismatch = False

    incoming_edges = [e for e in graph.edges if e[1] == node_id]

    if not incoming_edges and required_inputs:
        has_hard_mismatch = True

    if has_hard_mismatch:
        return mappings.get("hard_mismatch", 0.0)
    else:
        return mappings.get("all_contracts_pass_no_warnings", 1.0)


def compute_unit_layer(method_id: str, role: MethodRole, unit_quality: float,
                       contextual_config: dict[str, Any]) -> float:
    """
    Compute unit-of-analysis sensitivity layer (@u)

    Spec compliance: Section 3.3
    Formula: x_@u = g_M(U) if M is U-sensitive, else 1.0

    Args:
        method_id: Canonical method ID
        role: Method role
        unit_quality: U in [0,1]
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    if not (0.0 <= unit_quality <= 1.0):
        raise ValueError(f"unit_quality must be in [0,1], got {unit_quality}")

    config = _load_unit_transforms_config()
    g_functions_config = config.get("g_functions", {})

    role_name = role.value

    g_spec = None
    for g_name, g_def in g_functions_config.items():
        if role_name in g_def.get("applicable_roles", []):
            g_spec = g_def
            break

    if g_spec is None:
        return 1.0

    g_type = g_spec["type"]

    if g_type == "identity":
        return unit_quality

```

```
    elif g_type == "constant":
        return g_spec.get("value", 1.0)

    elif g_type == "piecewise_linear":
        abort_threshold = g_spec.get("abort_threshold", 0.3)
        if unit_quality < abort_threshold:
            return 0.0
        slope = g_spec.get("slope", 2.0)
        offset = g_spec.get("offset", -0.6)
        score = slope * unit_quality + offset

        if score < 0.0 or score > 1.0:
            raise CalibrationConfigError(
                f"Unit layer g_function produced out-of-range score: {score} "
                f"for unit_quality={unit_quality}. Config must be adjusted to ensure [0,1] output."
            )
        return score

    elif g_type == "sigmoidal":
        k = g_spec.get("k", 5.0)
        x0 = g_spec.get("x0", 0.5)
        score = 1.0 - math.exp(-k * (unit_quality - x0))

        if score < 0.0 or score > 1.0:
            raise CalibrationConfigError(
                f"Unit layer g_function produced out-of-range score: {score} "
                f"for unit_quality={unit_quality}, k={k}, x0={x0}. "
                f"Config must be adjusted to ensure [0,1] output."
            )
        return score

    else:
        raise ValueError(f"Unknown g_function type: {g_type}")


def compute_question_layer(method_id: str, question_id: str | None,
                           monolith: dict[str, Any],
                           contextual_config: dict[str, Any]) -> float:
    """
    Compute question compatibility layer (@q)

    Spec compliance: Section 3.4
    Formula: x_@q = Q_f(M | Q)

    Args:
        method_id: Canonical method ID
        question_id: Question ID (or None)
        monolith: Loaded questionnaire_monolith.json
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    config = _load_unit_transforms_config()
    levels = config.get("question_layer", {}).get("compatibility_levels", {})

```

```
    if not levels:
        levels = contextual_config.get("layer_question", {}).get("compatibility_levels", {})

    if question_id is None:
        return levels.get("undeclared", 0.6)

    micro_questions = monolith.get("blocks", {}).get("micro_questions", [])
    question = None
    for q in micro_questions:
        if q.get("question_id") == question_id:
            question = q
            break

    if not question:
        return levels.get("undeclared", 0.6)

    method_sets = question.get("method_sets", [])

    for method_spec in method_sets:
        if (method_id.endswith(f".{method_spec.get('function', '')}") or
            method_spec.get('class', '') in method_id):

            method_type = method_spec.get("method_type", "")
            priority = method_spec.get("priority", 99)

            if method_type == "extraction" or priority == 1:
                return levels.get("primary", 1.0)
            elif priority == 2:
                return levels.get("secondary", 0.8)
            elif method_type == "validation":
                return levels.get("validator", 0.9)

    return levels.get("undeclared", 0.6)


def compute_dimension_layer(method_id: str, dimension_id: str,
                            contextual_config: dict[str, Any]) -> float:
    """
    Compute dimension compatibility layer (@d)

    Spec compliance: Section 3.5
    Formula: x_@d = D_f(M | D)

    Args:
        method_id: Canonical method ID
        dimension_id: Dimension ID (DIM01-DIM06)
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    config = _load_unit_transforms_config()
    alignment = config.get("dimension_layer", {}).get("alignment_matrix", {})

    if not alignment:
        alignment = contextual_config.get("layer_dimension", {}).get("alignment_matrix", {})
```

```

    if dimension_id not in alignment:
        raise ValueError(f"Unknown dimension: {dimension_id}")

    dim_spec = alignment[dimension_id]

    return dim_spec.get("default_score", 1.0)


def compute_policy_layer(method_id: str, policy_id: str,
                         contextual_config: dict[str, Any]) -> float:
    """
    Compute policy area compatibility layer (@p)

    Spec compliance: Section 3.6
    Formula: x_@p = P_f(M | P)

    Args:
        method_id: Canonical method ID
        policy_id: Policy area ID (PA01-PA10)
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    config = _load_unit_transforms_config()
    policies = config.get("policy_layer", {}).get("policy_areas", {})

    if not policies:
        policies = contextual_config.get("layer_policy", {}).get("policy_areas", {})

    if policy_id not in policies:
        raise ValueError(f"Unknown policy area: {policy_id}")

    policy_spec = policies[policy_id]

    return policy_spec.get("default_score", 0.9)


def compute_interplay_layer(interplay: InterplaySubgraph | None,
                            contextual_config: dict[str, Any]) -> float:
    """
    Compute interplay congruence layer (@C)

    Spec compliance: Section 3.7
    Formula: C_play(G | ctx) = c_scale Â• c_sem Â• c_fusion

    Args:
        interplay: Interplay subgraph (or None)
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    config = _load_unit_transforms_config()
    interplay_config = config.get("interplay_layer", {})
```

```

    if not interplay_config:
        interplay_config = contextual_config.get("layer_interplay", {})

    if interplay is None:
        return interplay_config.get("default_when_not_in_interplay", 1.0)

    components = interplay_config.get("components", {})

    c_scale = components.get("c_scale", {}).get("same_range", 1.0)
    c_sem = 1.0
    c_fusion = components.get("c_fusion", {}).get("declared_and_satisfied", 1.0)

    return c_scale * c_sem * c_fusion


def compute_meta_layer(evidence: dict[str, Any],
                       contextual_config: dict[str, Any]) -> float:
    """
    Compute meta/governance layer (@m)

    Spec compliance: Section 3.8
    Formula: x_@m = 0.5 Â• m_transp + 0.4 Â• m_gov + 0.1 Â• m_cost

    Args:
        evidence: Evidence dictionary with metrics
        contextual_config: Loaded contextual_parametrization.json (deprecated, use unit_transforms.json)

    Returns:
        Score in [0,1]
    """
    config = _load_unit_transforms_config()
    meta_spec = config.get("meta_layer", {})

    if not meta_spec:
        meta_spec = contextual_config.get("layer_meta", {})

    transp_conditions = [
        evidence.get("formula_export_valid", False),
        evidence.get("trace_complete", False),
        evidence.get("logs_conform_schema", False)
    ]
    transp_count = sum(transp_conditions)

    transp_values = meta_spec.get("components", {}).get("m_transp", {})
    if transp_count == 3:
        m_transp = transp_values.get("all_three_conditions", 1.0)
    elif transp_count == 2:
        m_transp = transp_values.get("two_of_three", 0.8)
    elif transp_count == 1:
        m_transp = transp_values.get("one_of_three", 0.5)
    else:
        m_transp = transp_values.get("none", 0.0)

    gov_conditions = [
        evidence.get("version_tagged", False),
```

```
        evidence.get("config_hash_matches", False),
        evidence.get("signature_valid", False)
    ]
    gov_count = sum(gov_conditions)

    gov_values = meta_spec.get("components", {}).get("m_gov", {})
    if gov_count == 3:
        m_gov = gov_values.get("all_three_conditions", 1.0)
    elif gov_count == 2:
        m_gov = gov_values.get("two_of_three", 0.8)
    elif gov_count == 1:
        m_gov = gov_values.get("one_of_three", 0.5)
    else:
        m_gov = gov_values.get("none", 0.0)

    runtime_ms = evidence.get("runtime_ms", 100)
    thresholds = meta_spec.get("components", {}).get("m_cost", {}).get("thresholds", {})

    fast_threshold = thresholds.get("fast_runtime_ms", 50)
    acceptable_threshold = thresholds.get("acceptable_runtime_ms", 200)

    cost_values = meta_spec.get("components", {}).get("m_cost", {})
    if runtime_ms < fast_threshold:
        m_cost = cost_values.get("fast", 1.0)
    elif runtime_ms < acceptable_threshold:
        m_cost = cost_values.get("acceptable", 0.8)
    else:
        m_cost = cost_values.get("slow", 0.5)

    weights = meta_spec.get("aggregation", {}).get("weights", {})
    score = (weights.get("transparency", 0.5) * m_transp +
             weights.get("governance", 0.4) * m_gov +
             weights.get("cost", 0.1) * m_cost)

    return score



================================================================================
FILE: src/farfan_pipeline/core/calibration/layer_influence_model.py
================================================================================

"""
Layer Coexistence and Influence Model - Formal Specification

This module encodes the mathematical relationships between layers,
including:
- Conditional activation rules (when a layer becomes relevant)
- Influence relationships (how layers weight/transform each other)
- Coexistence constraints (compatibility requirements)

All rules are explicit, verifiable, and derived from theoretical foundations.

References:
- Pearl (1988): Probabilistic Reasoning in Intelligent Systems (conditional independence)
- Keeney & Raiffa (1976): Decisions with Multiple Objectives (preference independence)
```

```
- Grabisch (1997): k-order additive discrete fuzzy measures (interaction indices)
"""

from dataclasses import dataclass, field
from typing import Dict, List, Set, Optional, Callable, Tuple
from enum import Enum
import json

from farfan_pipeline.core.calibration.layer_coexistence import Layer, LayerScore


class LayerInfluenceType(Enum):
    """Types of influence one layer can have on another."""
    WEIGHTING = "weighting"          # Layer A modifies weight of Layer B
    TRANSFORMATION = "transformation"  # Layer A transforms values from Layer B
    ACTIVATION = "activation"          # Layer A determines if Layer B is active
    CONSTRAINT = "constraint"          # Layer A constrains valid values of Layer B


@dataclass
class LayerInfluence:
    """
    Formal specification of how one layer influences another.

    Attributes:
        source_layer: The influencing layer
        target_layer: The influenced layer
        influence_type: Type of influence relationship
        strength: Strength of influence in [0, 1]
        functional_form: Mathematical description of influence
        conditions: When this influence applies
    """
    source_layer: Layer
    target_layer: Layer
    influence_type: LayerInfluenceType
    strength: float
    functional_form: str
    conditions: Dict = field(default_factory=dict)

    def __post_init__(self):
        """Validate influence specification"""
        if not 0 <= self.strength <= 1:
            raise ValueError(f"Influence strength must be in [0,1], got {self.strength}")
        if self.source_layer == self.target_layer:
            raise ValueError("Self-influence not permitted in current model")


@dataclass
class LayerActivationRule:
    """
    Rule determining when a layer becomes active for a method.

    This encodes the endogenous determination of L(M) from method characteristics.

    Attributes:
        layer: The layer this rule applies to
```

```
        triggers: Conditions that activate this layer
        prerequisites: Other layers that must be active first
        priority: Activation priority (higher = checked first)
    """
    layer: Layer
    triggers: List[Callable]  # Functions that return bool
    prerequisites: Set[Layer] = field(default_factory=set)
    priority: int = 0

    def check_activation(self, method_characteristics: Dict) -> bool:
        """
        Check if this layer should be active given method characteristics.

        Args:
            method_characteristics: Dict describing method properties

        Returns:
            True if layer should be active
        """
        return any(trigger(method_characteristics) for trigger in self.triggers)


class LayerCoexistenceModel:
    """
    Formal model of layer interactions and dependencies.

    This encodes the complete "Layer Coexistence and Influence" system,
    including:
    - How to determine L(M) from method properties
    - How layers influence each other
    - Valid coexistence patterns
    - Composition rules for multi-layer fusion

    Design Principle: All layer interactions are explicit, not implicit.
    No hidden dependencies or undocumented couplings permitted.
    """

    def __init__(self):
        self.influences: List[LayerInfluence] = []
        self.activation_rules: Dict[Layer, LayerActivationRule] = {}
        self.compatibility_matrix: Dict[Tuple[Layer, Layer], float] = {}

        # Initialize canonical layer relationships
        self._initialize_canonical_relationships()

    def _initialize_canonical_relationships(self):
        """
        Define canonical layer relationships based on theoretical model.

        Canonical Relationships:

        1. @q â\206\222 @d (WEIGHTING): Question-level evidence weights dimension scores
           - High certainty at @q increases weight of @d
           - Functional form: w_d' = w_d Â• (1 + Î±Â•certainty_q)

        2. @d â\206\222 @p (ACTIVATION): Dimensions determine relevant policy areas
```

```
           - If dimension scores exist, policy coherence becomes relevant
           - Functional form: active(@p) â\237º |scored_dimensions| â\211¥ threshold

        3. @p â\206\222 @C (CONSTRAINT): Policy areas constrain ensemble methods
           - Policy structure limits valid ensemble combinations
           - Functional form: valid_ensembles â\212\206 compatible_with_policy_structure

        4. {@q, @d, @p} â\206\222 @m (TRANSFORMATION): Base layers feed meta-aggregation
           - Meta layer synthesizes across evidence levels
           - Functional form: x_m = g(x_q, x_d, x_p) where g is aggregation

        5. @C â\206\222 @m (WEIGHTING): Congruence modulates meta-layer confidence
           - Ensemble agreement increases meta-layer weight
           - Functional form: w_m' = w_m Â• congruence_score
        """

        # @q â\206\222 @d influence
        self.add_influence(LayerInfluence(
            source_layer=Layer.QUESTION,
            target_layer=Layer.DIMENSION,
            influence_type=LayerInfluenceType.WEIGHTING,
            strength=0.5,
            functional_form="w_d' = w_d * (1 + 0.5 * certainty_q)",
            conditions={'requires': 'question_certainty_available'}
        ))

        # @d â\206\222 @p influence
        self.add_influence(LayerInfluence(
            source_layer=Layer.DIMENSION,
            target_layer=Layer.POLICY_AREA,
            influence_type=LayerInfluenceType.ACTIVATION,
            strength=1.0,
            functional_form="active(@p) â\237º |scored_dimensions| â\211¥ 3",
            conditions={'threshold': 3}
        ))

        # @p â\206\222 @C influence
        self.add_influence(LayerInfluence(
            source_layer=Layer.POLICY_AREA,
            target_layer=Layer.CONGRUENCE,
            influence_type=LayerInfluenceType.CONSTRAINT,
            strength=0.7,
            functional_form="valid_ensembles â\212\206 policy_compatible_ensembles",
            conditions={'requires': 'policy_structure_defined'}
        ))

        # Base layers â\206\222 @m influence
        for base_layer in [Layer.QUESTION, Layer.DIMENSION, Layer.POLICY_AREA]:
            self.add_influence(LayerInfluence(
                source_layer=base_layer,
                target_layer=Layer.META,
                influence_type=LayerInfluenceType.TRANSFORMATION,
                strength=0.33,
                functional_form="x_m = weighted_mean(x_q, x_d, x_p)",
                conditions={'aggregation_type': 'weighted_mean'}
            ))
```

```
        # @C â\206\222 @m influence
        self.add_influence(LayerInfluence(
            source_layer=Layer.CONGRUENCE,
            target_layer=Layer.META,
            influence_type=LayerInfluenceType.WEIGHTING,
            strength=0.6,
            functional_form="w_m’ = w_m * congruence_score",
            conditions={’requires’: ’ensemble_agreement’}
        ))

        # Initialize compatibility matrix (all pairs compatible by default)
        for layer1 in Layer:
            for layer2 in Layer:
                # Diagonal: perfect self-compatibility
                if layer1 == layer2:
                    self.compatibility_matrix[(layer1, layer2)] = 1.0
                # Off-diagonal: initialize to compatible
                else:
                    self.compatibility_matrix[(layer1, layer2)] = 0.8

        # Adjust specific incompatibilities if any
        # (Currently all layers are mutually compatible)

    def add_influence(self, influence: LayerInfluence):
        """Register a layer influence relationship."""
        self.influences.append(influence)

    def add_activation_rule(self, rule: LayerActivationRule):
        """Register a layer activation rule."""
        self.activation_rules[rule.layer] = rule

    def determine_active_layers(
        self,
        method_characteristics: Dict
    ) -> Set[Layer]:
        """
        Determine L(M) endogenously from method characteristics.

        This is the key function that derives active layers from method
        properties rather than requiring manual specification.

        Args:
            method_characteristics: Dict with keys like:
                - ’operates_on_questions’: bool
                - ’aggregates_dimensions’: bool
                - ’addresses_policy_areas’: bool
                - ’uses_ensemble’: bool
                - ’performs_meta_aggregation’: bool
                - ’question_count’: int
                - ’dimension_count’: int
                - ’policy_area_count’: int

        Returns:
            Set of active layers for this method
        """
```

```
        active = set()

        # Sort rules by priority
        sorted_rules = sorted(
            self.activation_rules.items(),
            key=lambda x: x[1].priority,
            reverse=True
        )

        # Check each rule
        for layer, rule in sorted_rules:
            # Check prerequisites
            if not rule.prerequisites.issubset(active):
                continue

            # Check triggers
            if rule.check_activation(method_characteristics):
                active.add(layer)

        return active

    def get_layer_influences(
        self,
        target_layer: Layer,
        active_layers: Set[Layer]
    ) -> List[LayerInfluence]:
        """
        Get all influences affecting a target layer from active layers.

        Args:
            target_layer: Layer being influenced
            active_layers: Set of currently active layers

        Returns:
            List of applicable LayerInfluence objects
        """
        return [
            inf for inf in self.influences
            if inf.target_layer == target_layer
            and inf.source_layer in active_layers
        ]

    def compute_effective_weight(
        self,
        target_layer: Layer,
        base_weight: float,
        layer_scores: Dict[Layer, LayerScore],
        active_layers: Set[Layer]
    ) -> float:
        """
        Compute effective weight for a layer after applying influences.

        Args:
            target_layer: Layer whose weight is being computed
            base_weight: Initial weight
            layer_scores: Scores for all active layers
```

```
            active_layers: Set of active layers

        Returns:
            Effective weight after influence application
        """
        effective_weight = base_weight

        # Get weighting influences
        influences = [
            inf for inf in self.get_layer_influences(target_layer, active_layers)
            if inf.influence_type == LayerInfluenceType.WEIGHTING
        ]

        for influence in influences:
            source_score = layer_scores.get(influence.source_layer)
            if source_score:
                # Apply influence (simplified model)
                modifier = 1.0 + influence.strength * (source_score.value - 0.5)
                effective_weight *= modifier

        # Ensure weight stays in valid range
        return max(0.0, min(1.0, effective_weight))

    def check_compatibility(
        self,
        layer_set: Set[Layer]
    ) -> Tuple[bool, float]:
        """
        Check if a set of layers is compatible for coexistence.

        Args:
            layer_set: Set of layers to check

        Returns:
            (is_compatible, compatibility_score)
            where compatibility_score in [0, 1]
        """
        if len(layer_set) <= 1:
            return True, 1.0

        # Compute minimum pairwise compatibility
        min_compatibility = 1.0
        layer_list = list(layer_set)

        for i, layer1 in enumerate(layer_list):
            for layer2 in layer_list[i+1:]:
                compat = self.compatibility_matrix.get((layer1, layer2), 0.8)
                min_compatibility = min(min_compatibility, compat)

        # Compatible if minimum exceeds threshold
        is_compatible = min_compatibility >= 0.5
        return is_compatible, min_compatibility

    def export_model(self) -> Dict:
        """Export model to JSON-serializable format."""
        return {
```

```
            'influences': [
                {
                    'source': inf.source_layer.value,
                    'target': inf.target_layer.value,
                    'type': inf.influence_type.value,
                    'strength': inf.strength,
                    'formula': inf.functional_form,
                    'conditions': inf.conditions
                }
                for inf in self.influences
            ],
            'compatibility_matrix': {
                f"{l1.value},{l2.value}": score
                for (l1, l2), score in self.compatibility_matrix.items()
            }
        }


def initialize_canonical_activation_rules() -> Dict[Layer, LayerActivationRule]:
    """
    Initialize canonical activation rules for all layers.

    These rules encode when each layer becomes relevant based on
    method characteristics.

    Returns:
        Dict mapping Layer to LayerActivationRule
    """
    rules = {}

    # @q activation: Method operates on individual questions
    rules[Layer.QUESTION] = LayerActivationRule(
        layer=Layer.QUESTION,
        triggers=[
            lambda mc: mc.get('operates_on_questions', False),
            lambda mc: mc.get('question_count', 0) > 0,
        ],
        priority=100  # Highest priority - foundational layer
    )

    # @d activation: Method aggregates across dimensions
    rules[Layer.DIMENSION] = LayerActivationRule(
        layer=Layer.DIMENSION,
        triggers=[
            lambda mc: mc.get('aggregates_dimensions', False),
            lambda mc: mc.get('dimension_count', 0) > 0,
        ],
        prerequisites={Layer.QUESTION},  # Requires question layer
        priority=90
    )

    # @p activation: Method addresses policy areas
    rules[Layer.POLICY_AREA] = LayerActivationRule(
        layer=Layer.POLICY_AREA,
        triggers=[
            lambda mc: mc.get('addresses_policy_areas', False),
```

```
            lambda mc: mc.get('policy_area_count', 0) > 0,
            lambda mc: mc.get('dimension_count', 0) >= 3,  # @d â\206\222 @p influence
        ],
        prerequisites={Layer.DIMENSION},  # Requires dimension layer
        priority=80
    )

    # @C activation: Method uses ensemble techniques
    rules[Layer.CONGRUENCE] = LayerActivationRule(
        layer=Layer.CONGRUENCE,
        triggers=[
            lambda mc: mc.get('uses_ensemble', False),
            lambda mc: mc.get('ensemble_method_count', 0) > 1,
        ],
        priority=70
    )

    # @m activation: Method performs cross-layer meta-aggregation
    rules[Layer.META] = LayerActivationRule(
        layer=Layer.META,
        triggers=[
            lambda mc: mc.get('performs_meta_aggregation', False),
            lambda mc: len(mc.get('active_base_layers', set())) >= 2,
        ],
        priority=60  # Lowest priority - synthesizes other layers
    )

    return rules


# Global canonical model instance
CANONICAL_LAYER_MODEL = LayerCoexistenceModel()

# Register activation rules
for layer, rule in initialize_canonical_activation_rules().items():
    CANONICAL_LAYER_MODEL.add_activation_rule(rule)



================================================================================
FILE: src/farfan_pipeline/core/calibration/meta_layer.py
================================================================================

"""
Meta Layer (@m) - Full Implementation.

Evaluates governance compliance using weighted formula:
x_@m = 0.5Â•m_transp + 0.4Â•m_gov + 0.1Â•m_cost
"""
import logging
from typing import Optional
from farfan_pipeline.core.calibration.config import MetaLayerConfig

logger = logging.getLogger(__name__)

```

```
class MetaLayerEvaluator:
    """
    Evaluates governance and meta-properties of methods.

    Attributes:
        config: MetaLayerConfig with weights and thresholds
    """

    def __init__(self, config: MetaLayerConfig):
        """
        Initialize evaluator with meta layer config.

        Args:
            config: MetaLayerConfig instance
        """
        self.config = config
        logger.info(
            "meta_evaluator_initialized",
            extra={
                "w_transparency": config.w_transparency,
                "w_governance": config.w_governance,
                "w_cost": config.w_cost
            }
        )

    def evaluate(
        self,
        method_id: str,
        method_version: str,
        config_hash: str,
        formula_exported: bool = False,
        full_trace: bool = False,
        logs_conform: bool = False,
        signature_valid: bool = False,
        execution_time_s: Optional[float] = None
    ) -> float:
        """
        Compute the weighted score x_@m = w_transparencyÂ•m_transp + w_governanceÂ•m_gov + w_costÂ•m_cost,
        where `w_transparency`, `w_governance`, and `w_cost` come from the provided `config`.

        Args:
            method_id: Method identifier
            method_version: Method version string
            config_hash: Configuration hash
            formula_exported: Has formula been documented?
            full_trace: Is full execution trace available?
            logs_conform: Do logs conform to standard?
            signature_valid: Is cryptographic signature valid?
            execution_time_s: Runtime in seconds

        Returns:
            x_@m â\210\210 [0.0, 1.0]
        """
        logger.info(
            "meta_evaluation_start",
            extra={
```

```
                "method": method_id,
                "version": method_version
            }
        )

        # Component 1: Transparency (m_transp)
        m_transp = self._compute_transparency(
            formula_exported, full_trace, logs_conform
        )
        logger.debug("m_transp_computed", extra={"score": m_transp})

        # Component 2: Governance (m_gov)
        m_gov = self._compute_governance(
            method_version, config_hash, signature_valid
        )
        logger.debug("m_gov_computed", extra={"score": m_gov})

        # Component 3: Cost (m_cost)
        m_cost = self._compute_cost(execution_time_s)
        logger.debug("m_cost_computed", extra={"score": m_cost})

        # Weighted sum
        x_m = (
            self.config.w_transparency * m_transp +
            self.config.w_governance * m_gov +
            self.config.w_cost * m_cost
        )

        logger.info(
            "meta_computed",
            extra={
                "x_m": x_m,
                "m_transp": m_transp,
                "m_gov": m_gov,
                "m_cost": m_cost,
                "method": method_id
            }
        )

        return x_m

    def _compute_transparency(
        self,
        formula: bool,
        trace: bool,
        logs: bool
    ) -> float:
        """
        Compute m_transp based on observability.

        Scoring:
            1.0: All 3 conditions met
            0.7: 2/3 conditions met
            0.4: 1/3 conditions met
            0.0: 0/3 conditions met

```

```
        Returns:
            m_transp â\210\210 {0.0, 0.4, 0.7, 1.0}
        """
        count = sum([formula, trace, logs])

        if count == 3:
            return 1.0
        elif count == 2:
            return 0.7
        elif count == 1:
            return 0.4
        else:
            return 0.0

    def _compute_governance(
        self,
        version: str,
        config_hash: str,
        signature: bool
    ) -> float:
        """
        Compute m_gov based on governance compliance.

        Scoring:
            1.0: All 3 conditions met
            0.66: 2/3 conditions met
            0.33: 1/3 conditions met
            0.0: 0/3 conditions met

        Returns:
            m_gov â\210\210 {0.0, 0.33, 0.66, 1.0}
        """
        # Check version
        has_version = bool(version and version != "unknown" and version != "1.0")

        # Check config hash
        has_hash = bool(config_hash and len(config_hash) > 0)

        # Count conditions
        count = sum([has_version, has_hash, signature])

        if count == 3:
            return 1.0
        elif count == 2:
            return 0.66
        elif count == 1:
            return 0.33
        else:
            return 0.0

    def _compute_cost(self, execution_time_s: Optional[float] = None) -> float:
        """
        Compute m_cost based on runtime.

        Scoring:
            1.0: < threshold_fast (e.g., <1s)
```

```
            0.8: < threshold_acceptable (e.g., <5s)
            0.5: >= threshold_acceptable
            0.0: timeout/OOM (not provided)

        Returns:
            m_cost â\210\210 {0.0, 0.5, 0.8, 1.0}
        """
        if execution_time_s is None:
            logger.warning("meta_timing_not_available")
            return 0.5  # Default: acceptable

        if execution_time_s < 0:
            logger.error("meta_negative_time", extra={"time": execution_time_s})
            return 0.0

        if execution_time_s < self.config.threshold_fast:
            return 1.0  # Fast
        elif execution_time_s < self.config.threshold_acceptable:
            return 0.8  # Acceptable
        else:
            logger.warning(
                "meta_slow_execution",
                extra={
                    "runtime": execution_time_s,
                    "threshold": self.config.threshold_acceptable
                }
            )
            return 0.5  # Slow but usable



================================================================================
FILE: src/farfan_pipeline/core/calibration/orchestrator.py
================================================================================

"""Calibration Orchestrator - Mandatory Single Path Enforcement.

This module implements the ONLY allowed path for calibration scoring.
Any code that bypasses this orchestrator MUST be rejected.

Architecture:
- Singleton pattern enforces single entry point
- Loads intrinsic calibration (@b scores) from JSON
- Reads layer requirements from canonical inventory
- Computes runtime layers dynamically (@chain, @q, @d, @p, @C, @u, @m)
- Aggregates via choquet_integral or weighted_sum
- Applies threshold: â\211¥0.7 PASS, <0.7 FAIL

CRITICAL: This is the ONLY calibration path. All other calibration logic must be removed.
"""

from __future__ import annotations

import json
import logging
from pathlib import Path
```

```
from typing import TYPE_CHECKING

from farfan_pipeline.core.orchestrator.calibration_types import (
    IntrinsicScores,
    LayerRequirements,
    RuntimeLayers,
)

if TYPE_CHECKING:
    from farfan_pipeline.core.orchestrator.calibration_context import CalibrationContext

logger = logging.getLogger(__name__)

CALIBRATION_THRESHOLD = 0.7


class MissingIntrinsicCalibrationError(Exception):
    """Raised when intrinsic calibration (@b scores) are missing for a method."""

    def __init__(self, method_id: str) -> None:
        self.method_id = method_id
        super().__init__(
            f"Missing intrinsic calibration for method ’{method_id}’. "
            f"All methods must have @b scores in intrinsic_calibration.json"
        )


class InsufficientContextError(Exception):
    """Raised when context is required but not provided."""

    def __init__(self, method_id: str) -> None:
        self.method_id = method_id
        super().__init__(
            f"Insufficient context for method ’{method_id}’. "
            f"CalibrationContext is required for runtime layer evaluation."
        )


class MethodBelowThresholdError(Exception):
    """Raised when a method’s calibration score falls below threshold."""

    def __init__(self, method_id: str, score: float, threshold: float) -> None:
        self.method_id = method_id
        self.score = score
        self.threshold = threshold
        super().__init__(
            f"Method ’{method_id}’ calibration score {score:.3f} is below "
            f"threshold {threshold:.3f}. Method cannot be executed."
        )


class CalibrationOrchestrator:
    """Singleton orchestrator for all calibration operations.

    This is the MANDATORY and ONLY path for calibration scoring.
    """
```

```
    _instance: CalibrationOrchestrator | None = None
    _initialized: bool = False

    def __new__(cls) -> CalibrationOrchestrator:
        if cls._instance is None:
            cls._instance = super().__new__(cls)
        return cls._instance

    def __init__(self) -> None:
        if self._initialized:
            return

        self._intrinsic_scores: dict[str, IntrinsicScores] = {}
        self._layer_requirements: dict[str, LayerRequirements] = {}
        self._runtime_layer_config: dict = {}
        self._load_intrinsic_calibration()
        self._load_layer_requirements()
        self._load_runtime_layer_config()

        CalibrationOrchestrator._initialized = True
        logger.info("CalibrationOrchestrator initialized (singleton)")

    def _load_intrinsic_calibration(self) -> None:
        """Load intrinsic calibration using IntrinsicCalibrationLoader."""
        from farfan_pipeline.core.calibration.intrinsic_calibration_loader import get_intrinsic_calibration_loader

        loader = get_intrinsic_calibration_loader()

        # Get all methods from intrinsic calibration
        # Load the JSON directly to get all method IDs
        import json
        from pathlib import Path

        config_path = Path("config/intrinsic_calibration.json")
        if not config_path.exists():
            logger.warning(f"Intrinsic calibration file not found: {config_path}")
            return

        try:
            with open(config_path, encoding='utf-8') as f:
                data = json.load(f)

            for method_id in data.keys():
                if method_id == "_metadata":
                    continue

                calibration = loader.get_calibration(method_id)
                if calibration is not None:
                    self._intrinsic_scores[method_id] = IntrinsicScores(
                        b_theory=calibration.b_theory,
                        b_impl=calibration.b_impl,
                        b_deploy=calibration.b_deploy
                    )

            logger.info(f"Loaded intrinsic scores for {len(self._intrinsic_scores)} methods")
```

```
        except Exception as e:
            logger.error(f"Failed to load intrinsic calibration: {e}")
            raise

    def _load_layer_requirements(self) -> None:
        """Load layer requirements from layer_assignment module."""
        from farfan_pipeline.core.calibration.layer_assignment import LAYER_REQUIREMENTS, CHOQUET_WEIGHTS

        # For each method in intrinsic calibration, assign layers
        for method_id in self._intrinsic_scores.keys():
            # Determine role from method_id or from intrinsic calibration
            role = self._determine_role(method_id)

            if role in LAYER_REQUIREMENTS:
                required_layers = LAYER_REQUIREMENTS[role]

                # Build weights dict
                weights = {}
                for layer in required_layers:
                    if layer in CHOQUET_WEIGHTS:
                        weights[layer] = CHOQUET_WEIGHTS[layer]

                # Normalize weights
                total = sum(weights.values())
                if total > 0:
                    weights = {k: v/total for k, v in weights.items()}

                self._layer_requirements[method_id] = LayerRequirements(
                    required_layers=required_layers,
                    weights=weights,
                    aggregation_method='weighted_sum'
                )

        logger.info(f"Loaded layer requirements for {len(self._layer_requirements)} methods")

    def _determine_role(self, method_id: str) -> str:
        """Determine role from method_id or intrinsic calibration."""
        # If it's an executor (D1Q1, etc), it's 'executor'
        if 'D' in method_id and 'Q' in method_id:
            return 'executor'

        # Try to get from intrinsic calibration
        from farfan_pipeline.core.calibration.intrinsic_calibration_loader import get_intrinsic_calibration_loader
        loader = get_intrinsic_calibration_loader()
        calibration = loader.get_calibration(method_id)

        from farfan_pipeline.core.calibration.layer_assignment import LAYER_REQUIREMENTS
        if calibration and hasattr(calibration, 'layer') and calibration.layer in LAYER_REQUIREMENTS:
            return calibration.layer

        # Default to analyzer (safest - uses all layers)
        return 'analyzer'

    def _load_runtime_layer_config(self) -> None:
        """Load runtime layer configuration from system/config/calibration/runtime_layers.json."""
```

```
        config_path = Path("system/config/calibration/runtime_layers.json")
        if not config_path.exists():
            logger.warning(f"Runtime layer config not found: {config_path}, using defaults")
            return

        try:
            with open(config_path, encoding='utf-8') as f:
                self._runtime_layer_config = json.load(f)
            logger.info("Loaded runtime layer configuration")
        except Exception as e:
            logger.error(f"Failed to load runtime layer config: {e}")
            raise

    def evaluate_runtime_layers(
        self,
        method_id: str,
        context: CalibrationContext | None
    ) -> RuntimeLayers:
        """Evaluate runtime layers dynamically based on context.

        Args:
            method_id: Method identifier
            context: Calibration context (required for evaluation)

        Returns:
            RuntimeLayers with computed scores

        Raises:
            InsufficientContextError: If context is None
        """
        if context is None:
            raise InsufficientContextError(method_id)

        chain_score = self._compute_chain_score(context)
        quality_score = self._compute_quality_score(context)
        density_score = self._compute_density_score(context)
        provenance_score = self._compute_provenance_score(context)
        coverage_score = self._compute_coverage_score(context)
        uncertainty_score = self._compute_uncertainty_score(context)
        mechanism_score = self._compute_mechanism_score(context)

        layers = RuntimeLayers(
            chain=chain_score,
            quality=quality_score,
            density=density_score,
            provenance=provenance_score,
            coverage=coverage_score,
            uncertainty=uncertainty_score,
            mechanism=mechanism_score
        )

        logger.debug(
            f"Runtime layers for {method_id}: {layers.to_dict()}"
        )

        return layers
```

```
    def _compute_chain_score(self, context: CalibrationContext) -> float:
        """Compute chain of evidence score (@chain)."""
        config = self._runtime_layer_config.get('layers', {}).get('chain', {})
        base_score = config.get('base_score', 0.65)
        dimension_factor = config.get('dimension_factor', 0.15)
        dimension_max = config.get('dimension_max', 10.0)
        position_bonus = config.get('position_bonus', 0.1)
        position_threshold = config.get('position_threshold', 0.5)

        score = base_score
        if context.dimension > 0:
            score += dimension_factor * min(context.dimension / dimension_max, 1.0)
        if context.method_position < context.total_methods * position_threshold:
            score += position_bonus
        return min(score, 1.0)

    def _compute_quality_score(self, context: CalibrationContext) -> float:
        """Compute data quality score (@q)."""
        config = self._runtime_layer_config.get('layers', {}).get('quality', {})
        base_score = config.get('base_score', 0.70)
        question_factor = config.get('question_factor', 0.08)
        question_max = config.get('question_max', 20.0)

        score = base_score
        if context.question_num > 0:
            score += question_factor * min(context.question_num / question_max, 1.0)
        return min(score, 1.0)

    def _compute_density_score(self, context: CalibrationContext) -> float:
        """Compute data density score (@d)."""
        config = self._runtime_layer_config.get('layers', {}).get('density', {})
        base_score = config.get('base_score', 0.68)
        position_factor = config.get('position_factor', 0.15)
        optimal_position = config.get('optimal_position', 0.5)

        score = base_score
        if context.total_methods > 0:
            ratio = context.method_position / context.total_methods
            score += position_factor * (1.0 - abs(optimal_position - ratio))
        return min(score, 1.0)

    def _compute_provenance_score(self, context: CalibrationContext) -> float:
        """Compute provenance traceability score (@p)."""
        config = self._runtime_layer_config.get('layers', {}).get('provenance', {})
        return config.get('base_score', 0.75)

    def _compute_coverage_score(self, context: CalibrationContext) -> float:
        """Compute coverage completeness score (@C)."""
        config = self._runtime_layer_config.get('layers', {}).get('coverage', {})
        base_score = config.get('base_score', 0.72)
        bonus_dimensions = config.get('bonus_dimensions', [1, 2, 5, 10])
        dimension_bonus = config.get('dimension_bonus', 0.1)

        score = base_score
        if context.dimension in bonus_dimensions:
```

```
            score += dimension_bonus
        return min(score, 1.0)

    def _compute_uncertainty_score(self, context: CalibrationContext) -> float:
        """Compute uncertainty quantification score (@u)."""
        config = self._runtime_layer_config.get('layers', {}).get('uncertainty', {})
        return config.get('base_score', 0.68)

    def _compute_mechanism_score(self, context: CalibrationContext) -> float:
        """Compute mechanistic explanation score (@m)."""
        config = self._runtime_layer_config.get('layers', {}).get('mechanism', {})
        base_score = config.get('base_score', 0.65)
        dimension_threshold = config.get('dimension_threshold', 7)
        dimension_bonus = config.get('dimension_bonus', 0.15)

        score = base_score
        if context.dimension >= dimension_threshold:
            score += dimension_bonus
        return min(score, 1.0)

    def choquet_integral(
        self,
        layers: RuntimeLayers,
        weights: dict[str, float]
    ) -> float:
        """Aggregate layers using Choquet integral for executors.

        Simplified Choquet-like aggregation that weights higher-scoring layers more heavily.

        Args:
            layers: Runtime layer scores
            weights: Layer weights from requirements

        Returns:
            Aggregated score (0.0-1.0)
        """
        layer_dict = layers.to_dict()

        total_weight = sum(weights.values())
        if total_weight == 0:
            return 0.0

        weighted_total = sum(
            layer_dict.get(name, 0.0) * weight
            for name, weight in weights.items()
        )

        return min(max(weighted_total / total_weight, 0.0), 1.0)

    def weighted_sum(
        self,
        layers: RuntimeLayers,
        weights: dict[str, float]
    ) -> float:
        """Aggregate layers using weighted sum for non-executors.

```

```
        Args:
            layers: Runtime layer scores
            weights: Layer weights from requirements

        Returns:
            Aggregated score (0.0-1.0)
        """
        layer_dict = layers.to_dict()
        total_weight = sum(weights.values())

        if total_weight == 0:
            return 0.0

        weighted_total = sum(
            layer_dict.get(name, 0.0) * weight
            for name, weight in weights.items()
        )

        return min(max(weighted_total / total_weight, 0.0), 1.0)

    def calibrate_method(
        self,
        method_id: str,
        context: CalibrationContext | None = None,
        is_executor: bool = False
    ) -> float:
        """MANDATORY CALIBRATION PATH - This is the ONLY allowed entry point.

        Args:
            method_id: Method identifier
            context: Calibration context (required for runtime evaluation)
            is_executor: Whether this is an executor method (uses Choquet)

        Returns:
            Final calibration score (0.0-1.0)

        Raises:
            MissingIntrinsicCalibrationError: If @b scores missing
            InsufficientContextError: If context is None
            MethodBelowThresholdError: If score < threshold
        """
        if method_id not in self._intrinsic_scores:
            raise MissingIntrinsicCalibrationError(method_id)

        intrinsic = self._intrinsic_scores[method_id]
        intrinsic_score = intrinsic.average()

        logger.debug(
            f"Intrinsic score for {method_id}: {intrinsic_score:.3f} "
            f"(theory={intrinsic.b_theory:.3f}, impl={intrinsic.b_impl:.3f}, "
            f"deploy={intrinsic.b_deploy:.3f})"
        )

        runtime_layers = self.evaluate_runtime_layers(method_id, context)

        requirements = self._layer_requirements.get(method_id)
```

```
        if requirements is None:
            logger.warning(
                f"No layer requirements for {method_id}, using default weights"
            )
            requirements = LayerRequirements(
                required_layers=['quality', 'provenance'],
                weights={'quality': 0.5, 'provenance': 0.5},
                aggregation_method='weighted_sum'
            )

        if is_executor or requirements.aggregation_method == 'choquet_integral':
            runtime_score = self.choquet_integral(runtime_layers, requirements.weights)
        else:
            runtime_score = self.weighted_sum(runtime_layers, requirements.weights)

        final_score = (intrinsic_score + runtime_score) / 2.0

        logger.info(
            f"Calibration for {method_id}: intrinsic={intrinsic_score:.3f}, "
            f"runtime={runtime_score:.3f}, final={final_score:.3f}"
        )

        if final_score < CALIBRATION_THRESHOLD:
            raise MethodBelowThresholdError(method_id, final_score, CALIBRATION_THRESHOLD)

        return final_score

    @classmethod
    def get_instance(cls) -> CalibrationOrchestrator:
        """Get singleton instance."""
        if cls._instance is None:
            cls._instance = CalibrationOrchestrator()
        return cls._instance

    @classmethod
    def reset_instance(cls) -> None:
        """Reset singleton instance (for testing only)."""
        cls._instance = None
        cls._initialized = False


__all__ = [
    'CalibrationOrchestrator',
    'MissingIntrinsicCalibrationError',
    'InsufficientContextError',
    'MethodBelowThresholdError',
    'CALIBRATION_THRESHOLD'
]



================================================================================
FILE: src/farfan_pipeline/core/calibration/parameter_loader.py
================================================================================

"""Legacy parameter loader - now wraps ParameterLoaderV2."""
```

```

from typing import Any

from farfan_pipeline.core.parameters import ParameterLoaderV2


class ParameterLoader:
    """Stub parameter loader for backward compatibility.

    Legacy wrapper around ParameterLoaderV2 for backward compatibility.
    DEPRECATED: Use ParameterLoaderV2.get(method_id, param_name) directly.
    """

    def __init__(self) -> None:
        pass

    def load(self) -> None:
        """No-op: ParameterLoaderV2 auto-loads."""
        pass

    def get(
        self, method_id: str, default: dict[str, Any] | None = None
    ) -> dict[str, Any]:
        """
        Gets the parameters for a given method_id.
        Delegates to ParameterLoaderV2.
        """
        if default is None:
            default = {}

        params = ParameterLoaderV2.get_all(method_id)
        return params if params else default


_parameter_loader = ParameterLoader()


def get_parameter_loader() -> ParameterLoader:
    """Get the global parameter loader instance."""
    return _parameter_loader



================================================================================
FILE: src/farfan_pipeline/core/calibration/pdt_structure.py
================================================================================

"""
PDT (Plan de Desarrollo Territorial) structure definition.

This module defines the data structure that represents a parsed PDT.
The PDT is the INPUT to the Unit Layer evaluation.

The structure is populated by a separate PDT parser (not shown here),
which extracts:
- Text content and tokens
```

```
- Block structure (DiagnÃ³stico, EstratÃ©gica, PPI, Seguimiento)
- Section analysis (keywords, numbers, sources)
- Indicator matrix (if present)
- PPI matrix (if present)
"""
from dataclasses import dataclass, field
from typing import Any


@dataclass
class PDTStructure:
    """
    Extracted structure of a PDT.

    This is populated by the PDT parser and consumed by UnitLayerEvaluator.

    Attributes:
        full_text: Complete text of the PDT
        total_tokens: Total word/token count
        blocks_found: Detected structural blocks
        headers: List of headers with numbering validation
        block_sequence: Actual order of blocks (for checking sequence)
        sections_found: Analysis of mandatory sections
        indicator_matrix_present: Whether indicator table was found
        indicator_rows: Parsed indicator table rows
        ppi_matrix_present: Whether PPI table was found
        ppi_rows: Parsed PPI table rows
    """
    # Raw content
    full_text: str
    total_tokens: int

    # Block detection (for S - Structural compliance)
    blocks_found: dict[str, dict[str, Any]] = field(default_factory=dict)
    # Example: {
    #     "DiagnÃ³stico": {"text": "...", "tokens": 1500, "numbers_count": 25},
    #     "Parte EstratÃ©gica": {"text": "...", "tokens": 1200, "numbers_count": 15},
    # }

    headers: list[dict[str, Any]] = field(default_factory=list)
    # Example: [
    #     {"level": 1, "text": "1. DIAGNÃ\223STICO", "valid_numbering": True},
    #     {"level": 2, "text": "1.1 Contexto", "valid_numbering": True},
    # ]

    block_sequence: list[str] = field(default_factory=list)
    # Example: ["DiagnÃ³stico", "Parte EstratÃ©gica", "PPI", "Seguimiento"]

    # Section analysis (for M - Mandatory sections)
    sections_found: dict[str, dict[str, Any]] = field(default_factory=dict)
    # Example: {
    #     "DiagnÃ³stico": {
    #         "present": True,
    #         "token_count": 1500,
    #         "keyword_matches": 5,  # e.g., "brecha", "DANE", "lÃ-nea base"
    #         "number_count": 25,
```

```
    #         "sources_found": 3,  # e.g., "DANE", "Medicina Legal"
    #     }
    # }

    # Indicator matrix (for I - Indicator quality)
    indicator_matrix_present: bool = False
    indicator_rows: list[dict[str, Any]] = field(default_factory=list)
    # Example: [
    #     {
    #         "Tipo": "PRODUCTO",
    #         "LÃnea EstratÃ©gica": "Equidad de GÃ©nero",
    #         "Programa": "PrevenciÃ³n de VBG",
    #         "LÃnea Base": "120 casos",
    #         "AÃ±o LB": 2023,
    #         "Meta Cuatrienio": "80 casos",
    #         "Fuente": "ComisarÃa de Familia",
    #         "Unidad Medida": "Casos reportados",
    #         "CÃ³digo MGA": "1234567"
    #     }
    # ]

    # PPI matrix (for P - PPI completeness)
    ppi_matrix_present: bool = False
    ppi_rows: list[dict[str, Any]] = field(default_factory=list)
    # Example: [
    #     {
    #         "LÃnea EstratÃ©gica": "Equidad de GÃ©nero",
    #         "Programa": "PrevenciÃ³n de VBG",
    #         "Costo Total": 500000000,
    #         "2024": 100000000,
    #         "2025": 150000000,
    #         "2026": 150000000,
    #         "2027": 100000000,
    #         "SGP": 300000000,
    #         "SGR": 0,
    #         "Propios": 200000000,
    #         "Otras": 0
    #     }
    # ]



================================================================================
FILE: src/farfan_pipeline/core/calibration/rigorous_calibration_triage.py
================================================================================

#!/usr/bin/env python3
"""
Rigorous Intrinsic Calibration Triage - Method by Method Analysis

Per tesislizayjuan-debug requirements (comments 3512949686, 3513311176):
- Apply decision automaton to EVERY method in canonical_method_catalog.json
- Use machine-readable rubric from config/intrinsic_calibration_rubric.json
- Produce traceable, reproducible evidence for all scores

Pass 1: Determine if method requires calibration (3-question gate per rubric)
```

```
Pass 2: Compute evidence-based intrinsic scores using explicit rubric rules
Pass 3: Populate intrinsic_calibration.json with reproducible evidence

NO UNIFORM DEFAULTS. Each method analyzed individually.
ALL SCORES TRACEABLE. Evidence shows exact computation path.
"""

import json
import sys
import ast
import re
from pathlib import Path
from datetime import datetime, timezone
from typing import Dict, Any, Tuple, Optional, List


def load_json(path: Path) -> dict:
    """Load JSON file"""
    with open(path, 'r') as f:
        return json.load(f)


def save_json(path: Path, data: dict) -> None:
    """Save JSON file with formatting"""
    with open(path, 'w') as f:
        json.dump(data, f, indent=2, ensure_ascii=False)
        f.write('\n')


def triage_pass1_requires_calibration(method_info: Dict[str, Any], rubric: Dict[str, Any]) -> Tuple[bool, str, Dict[str, Any]]:
    """
    Pass 1: Does this method require intrinsic calibration?
    Determine if a method requires calibration based on the 3-question rubric.

    Returns: (requires_calibration, reason, evidence_dict)
    """
    method_name = method_info.get('method_name', '')
    docstring = method_info.get('docstring', '') or ''
    layer = method_info.get('layer', 'unknown')
    return_type = method_info.get('return_type', '')

    # Load decision rules from rubric
    triggers = rubric['calibration_triggers']
    exclusion_rules = rubric['exclusion_criteria']

    # Check explicit exclusion patterns first
    exclusion_patterns = exclusion_rules['patterns']
    for pattern_rule in exclusion_patterns:
        if pattern_rule['pattern'] in method_name:
            return False, pattern_rule['reason'], {
                "matched_exclusion_pattern": pattern_rule['pattern'],
                "exclusion_reason": pattern_rule['reason']
            }

    # Q1: Analytically active?
    q1_config = triggers['questions']['q1_analytically_active']
```

```
    primary_verbs = q1_config['indicators'].get('primary_analytical_verbs', [])
    etl_verbs = q1_config['indicators'].get('generative_etl_verbs', [])
    all_analytical_verbs = primary_verbs + etl_verbs

    q1_matches_name = [verb for verb in all_analytical_verbs if verb in method_name.lower()]
    q1_matches_doc = [verb for verb in all_analytical_verbs[:10] if verb in docstring.lower()]
    q1_analytical = len(q1_matches_name) > 0 or len(q1_matches_doc) > 0

    # Q2: Parametric?
    q2_config = triggers['questions']['q2_parametric']
    parametric_keywords = q2_config['indicators'].get('parametric_keywords', [])
    parametric_verbs = q2_config['indicators'].get('parametric_verbs', [])
    critical_layers = q2_config['indicators'].get('check_layer', [])

    q2_matches_kw = [kw for kw in parametric_keywords if kw in docstring.lower()]
    q2_matches_verb = [verb for verb in parametric_verbs if verb in method_name.lower()]
    q2_parametric = len(q2_matches_kw) > 0 or len(q2_matches_verb) > 0 or layer in critical_layers

    # Q3: Safety-critical?
    q3_config = triggers['questions']['q3_safety_critical']
    safety_verbs = q3_config['indicators'].get('safety_verbs', [])
    safety_layers = q3_config['indicators'].get('critical_layers', [])
    eval_types = q3_config['indicators'].get('evaluative_return_types', [])

    q3_matches_verb = [verb for verb in safety_verbs if verb in method_name.lower()]
    q3_safety_critical = (len(q3_matches_verb) > 0 or
                          layer in safety_layers or
                          return_type in eval_types)

    if q3_config['indicators'].get('exclude_simple_getters', False) and method_name.startswith('get_'):
        # Only exclude if it's NOT a safety verb (e.g. 'get_validation_status' might be critical, but 'get_name' is not)
        if not q3_matches_verb:
             q3_safety_critical = False

    # Additional exclusion rules
    is_private_utility = (method_name.startswith('_') and
                         not q1_analytical and
                         layer == 'utility')
    is_pure_getter = (method_name.startswith('get_') and
                      return_type in ['str', 'Path', 'bool'] and
                      not q1_analytical and not q3_safety_critical)

    # Build machine-readable evidence
    triage_evidence = {
        "q1_analytically_active": {
            "result": q1_analytical,
            "matched_verbs_in_name": q1_matches_name,
            "matched_verbs_in_doc": q1_matches_doc
        },
        "q2_parametric": {
            "result": q2_parametric,
            "matched_keywords": q2_matches_kw,
            "matched_verbs": q2_matches_verb,
            "layer_is_critical": layer in critical_layers
        },
        "q3_safety_critical": {
```

```
            "result": q3_safety_critical,
            "matched_safety_verbs": q3_matches_verb,
            "layer_is_critical": layer in safety_layers,
            "return_type_is_evaluative": return_type in eval_types
        },
        "decision_rule": "requires_calibration = (q1 OR q2 OR q3) AND NOT excluded"
    }

    # Decision per rubric
    if is_private_utility:
        return False, "Private utility function - non-analytical", triage_evidence

    if is_pure_getter:
        return False, "Simple getter with no analytical logic", triage_evidence

    if q1_analytical or q2_parametric or q3_safety_critical:
        reasons = []
        if q1_analytical:
            reasons.append("analytically active")
        if q2_parametric:
            reasons.append("encodes assumptions/knobs")
        if q3_safety_critical:
            reasons.append("safety-critical for evaluation")
        return True, f"Requires calibration: {', '.join(reasons)}", triage_evidence

    return False, "Non-analytical utility function", triage_evidence


def compute_b_theory(method_info: Dict[str, Any], repo_root: Path, rubric: Dict[str, Any]) -> Tuple[float, Dict]:
    """
    Compute b_theory: theoretical foundation quality

    Uses machine-readable rules from rubric config
    """
    docstring = method_info.get('docstring', '') or ''
    method_name = method_info.get('method_name', '')

    # Load rubric rules
    b_theory_config = rubric['b_theory']
    weights = b_theory_config['weights']
    rules = b_theory_config['rules']

    # Component 1: Statistical grounding
    stat_rules = rules['grounded_in_valid_statistics']['scoring']
    stat_keywords = stat_rules['has_bayesian_or_statistical_model']['keywords']
    stat_matches = [kw for kw in stat_keywords if kw in docstring.lower()]

    if len(stat_matches) >= stat_rules['has_bayesian_or_statistical_model']['threshold']:
        stat_score = stat_rules['has_bayesian_or_statistical_model']['score']
    elif len(stat_matches) >= stat_rules['has_some_statistical_grounding']['threshold']:
        stat_score = stat_rules['has_some_statistical_grounding']['score']
    else:
        stat_score = stat_rules['no_statistical_grounding']['score']

    # Component 2: Logical consistency
    logic_rules = rules['logical_consistency']['scoring']
```

```
    has_docstring_gt_50 = len(docstring) > 50
    has_docstring_gt_20 = len(docstring) > 20
    has_returns_doc = 'return' in docstring.lower()
    has_params_doc = 'param' in docstring.lower() or 'arg' in docstring.lower()

    if has_docstring_gt_50 and has_returns_doc and has_params_doc:
        logical_score = logic_rules['complete_documentation']['score']
    elif has_docstring_gt_20:
        logical_score = logic_rules['partial_documentation']['score']
    else:
        logical_score = logic_rules['minimal_documentation']['score']

    # Component 3: Appropriate assumptions
    assumption_rules = rules['appropriate_assumptions']['scoring']
    assumption_keywords = assumption_rules['assumptions_documented']['keywords']
    assumption_matches = [kw for kw in assumption_keywords if kw in docstring.lower()]

    if len(assumption_matches) > 0:
        assumptions_score = assumption_rules['assumptions_documented']['score']
    else:
        assumptions_score = assumption_rules['implicit_assumptions']['score']

    # Weighted combination per rubric
    b_theory = (
        weights['grounded_in_valid_statistics'] * stat_score +
        weights['logical_consistency'] * logical_score +
        weights['appropriate_assumptions'] * assumptions_score
    )

    # Machine-readable evidence
    evidence = {
        "formula": "b_theory = 0.4*stat + 0.3*logic + 0.3*assumptions",
        "components": {
            "grounded_in_valid_statistics": {
                "weight": weights['grounded_in_valid_statistics'],
                "score": stat_score,
                "matched_keywords": stat_matches,
                "keyword_count": len(stat_matches),
                "rule_applied": "has_bayesian_or_statistical_model" if len(stat_matches) >= 3
                               else "has_some_statistical_grounding" if len(stat_matches) >= 1
                               else "no_statistical_grounding"
            },
            "logical_consistency": {
                "weight": weights['logical_consistency'],
                "score": logical_score,
                "docstring_length": len(docstring),
                "has_returns_doc": has_returns_doc,
                "has_params_doc": has_params_doc,
                "rule_applied": "complete_documentation" if (has_docstring_gt_50 and has_returns_doc and has_params_doc)
                               else "partial_documentation" if has_docstring_gt_20
                               else "minimal_documentation"
            },
            "appropriate_assumptions": {
                "weight": weights['appropriate_assumptions'],
                "score": assumptions_score,
                "matched_keywords": assumption_matches,
```

```
                "rule_applied": "assumptions_documented" if assumption_matches else "implicit_assumptions"
            }
        },
        "final_score": round(b_theory, 3),
        "rubric_version": rubric['_metadata']['version']
    }

    return round(b_theory, 3), evidence


def get_method_source(repo_root: Path, file_path: str, start_line: int) -> str:
    """
    Attempt to read the source code of a method.
    This is a heuristic extraction based on indentation.
    """
    try:
        full_path = repo_root / "src" / file_path
        if not full_path.exists():
            return ""

        with open(full_path, 'r') as f:
            lines = f.readlines()

        if start_line < 1 or start_line > len(lines):
            return ""

        # Adjust for 0-indexing
        start_idx = start_line - 1
        method_def = lines[start_idx]

        # Determine indentation of the def line
        indentation = len(method_def) - len(method_def.lstrip())

        source_lines = [method_def]

        for i in range(start_idx + 1, len(lines)):
            line = lines[i]
            if not line.strip(): # Keep empty lines
                source_lines.append(line)
                continue

            current_indent = len(line) - len(line.lstrip())
            if current_indent <= indentation:
                break # End of method
            source_lines.append(line)

        return "".join(source_lines)
    except Exception:
        return ""

def compute_b_impl(method_info: Dict[str, Any], repo_root: Path, rubric: Dict[str, Any]) -> Tuple[float, Dict]:
    """
    Compute b_impl: implementation quality

    Uses machine-readable rules from rubric config
    """
```

```
    signature = method_info.get('signature', '')
    docstring = method_info.get('docstring', '') or ''
    input_params = method_info.get('input_parameters', [])
    return_type = method_info.get('return_type', None)
    file_path = method_info.get('file_path', '')
    line_number = method_info.get('line_number', 0)

    # Load rubric rules
    b_impl_config = rubric['b_impl']
    weights = b_impl_config['weights']
    rules = b_impl_config['rules']

    # Component 1: Test coverage (conservative default)
    test_rules = rules['test_coverage']['scoring']
    test_score = test_rules['no_test_evidence']['score']  # Conservative default

    # Component 2: Type annotations (use formula from rubric)
    params_with_types = sum(1 for p in input_params if p.get('type_hint'))
    total_params = max(len(input_params), 1)
    has_return_type = return_type is not None and return_type != ''
    # Formula: (typed_params / total_params) * 0.7 + (0.3 if has_return_type else 0)
    type_score = (params_with_types / total_params * 0.7) + (0.3 if has_return_type else 0)

    # Component 3: Error handling (detect try/except)
    error_rules = rules['error_handling']['scoring']

    # Try to read source to find try/except
    source_code = get_method_source(repo_root, file_path, line_number)
    has_try_except = "try:" in source_code and "except" in source_code

    if has_try_except:
        error_score = error_rules['comprehensive_handling']['score']
        error_rule = "comprehensive_handling"
    else:
        error_score = error_rules['minimal_handling']['score']
        error_rule = "minimal_handling"

    # Component 4: Documentation (use formula from rubric)
    doc_length = len(docstring)
    has_description = doc_length > 50
    has_params_doc = 'param' in docstring.lower() or 'arg' in docstring.lower()
    has_returns_doc = 'return' in docstring.lower()
    has_examples = 'example' in docstring.lower()
    # Formula: (0.4 if doc_length > 50 else 0.1) + (0.3 if has_params_doc else 0) + (0.2 if has_returns_doc else 0) + (0.1 if has_examples else 0)
    doc_score = (
        (0.4 if has_description else 0.1) +
        (0.3 if has_params_doc else 0) +
        (0.2 if has_returns_doc else 0) +
        (0.1 if has_examples else 0)
    )

    # Weighted combination per rubric
    b_impl = (
        weights['test_coverage'] * test_score +
        weights['type_annotations'] * type_score +
        weights['error_handling'] * error_score +
```

```
            weights['documentation'] * doc_score
    )

    # Machine-readable evidence
    evidence = {
        "formula": "b_impl = 0.35*test + 0.25*type + 0.25*error + 0.15*doc",
        "components": {
            "test_coverage": {
                "weight": weights['test_coverage'],
                "score": test_score,
                "rule_applied": "no_test_evidence",
                "note": "Conservative default until measured"
            },
            "type_annotations": {
                "weight": weights['type_annotations'],
                "score": round(type_score, 3),
                "formula": "(typed_params / total_params) * 0.7 + (0.3 if has_return_type else 0)",
                "details": {
                    "typed_params": params_with_types,
                    "total_params": total_params,
                    "has_return_type": has_return_type
                }
            },
            "error_handling": {
                "weight": weights['error_handling'],
                "score": error_score,
                "rule_applied": error_rule,
                "has_try_except": has_try_except
            },
            "documentation": {
                "weight": weights['documentation'],
                "score": round(doc_score, 3),
                "formula": "weighted_sum(desc, params, returns, examples)",
                "details": {
                    "doc_length": doc_length,
                    "has_params": has_params_doc,
                    "has_returns": has_returns_doc,
                    "has_examples": has_examples
                }
            }
        },
        "final_score": round(b_impl, 3),
        "rubric_version": rubric['_metadata']['version']
    }

    return round(b_impl, 3), evidence


def compute_b_deploy(method_info: Dict[str, Any], rubric: Dict[str, Any]) -> Tuple[float, Dict]:
    """
    Compute b_deploy: deployment maturity

    Uses machine-readable rules from rubric config
    """
    layer = method_info.get('layer', 'unknown')

```

```
    # Load rubric rules
    b_deploy_config = rubric['b_deploy']
    weights = b_deploy_config['weights']
    rules = b_deploy_config['rules']

    # Get layer maturity baseline from rubric
    layer_maturity_map = rules['layer_maturity_baseline']['scoring']
    base_maturity = layer_maturity_map.get(layer, layer_maturity_map['unknown'])

    # Apply formulas from rubric
    # validation_runs: layer_maturity_baseline * 0.8
    validation_score = base_maturity * 0.8

    # stability_coefficient: layer_maturity_baseline * 0.9
    stability_score = base_maturity * 0.9

    # failure_rate: layer_maturity_baseline * 0.85
    failure_score = base_maturity * 0.85

    # Weighted combination per rubric
    b_deploy = (
        weights['validation_runs'] * validation_score +
        weights['stability_coefficient'] * stability_score +
        weights['failure_rate'] * failure_score
    )

    # Machine-readable evidence
    evidence = {
        "formula": "b_deploy = 0.4*validation + 0.35*stability + 0.25*failure",
        "components": {
            "layer_maturity_baseline": {
                "layer": layer,
                "baseline_score": base_maturity,
                "source": "rubric layer_maturity_baseline mapping"
            },
            "validation_runs": {
                "weight": weights['validation_runs'],
                "score": round(validation_score, 3),
                "formula": "layer_maturity_baseline * 0.8",
                "computation": f"{base_maturity} * 0.8 = {round(validation_score, 3)}"
            },
            "stability_coefficient": {
                "weight": weights['stability_coefficient'],
                "score": round(stability_score, 3),
                "formula": "layer_maturity_baseline * 0.9",
                "computation": f"{base_maturity} * 0.9 = {round(stability_score, 3)}"
            },
            "failure_rate": {
                "weight": weights['failure_rate'],
                "score": round(failure_score, 3),
                "formula": "layer_maturity_baseline * 0.85",
                "computation": f"{base_maturity} * 0.85 = {round(failure_score, 3)}"
            }
        },
        "final_score": round(b_deploy, 3),
        "rubric_version": rubric['_metadata']['version']
```

```
    }

    return round(b_deploy, 3), evidence


def triage_and_calibrate_method(method_info: Dict[str, Any], repo_root: Path, rubric: Dict[str, Any]) -> Dict[str, Any]:
    """
    Full triage and calibration for one method using rubric.

    Returns calibration entry for intrinsic_calibration.json
    """
    canonical_name = method_info.get('canonical_name', '')

    # Pass 1: Requires calibration?
    requires_cal, reason, triage_evidence = triage_pass1_requires_calibration(method_info, rubric)

    if not requires_cal:
        # Excluded method
        return {
            "method_id": canonical_name,
            "calibration_status": "excluded",
            "reason": reason,
            "triage_evidence": triage_evidence,
            "layer": method_info.get('layer', 'unknown'),
            "last_updated": datetime.now(timezone.utc).isoformat(),
            "approved_by": "automated_triage",
            "rubric_version": rubric['_metadata']['version']
        }

    # Pass 2: Compute intrinsic calibration scores using rubric
    b_theory, theory_evidence = compute_b_theory(method_info, repo_root, rubric)
    b_impl, impl_evidence = compute_b_impl(method_info, repo_root, rubric)
    b_deploy, deploy_evidence = compute_b_deploy(method_info, rubric)

    # Pass 3: Create calibration profile with machine-readable evidence
    return {
        "method_id": canonical_name,
        "b_theory": b_theory,
        "b_impl": b_impl,
        "b_deploy": b_deploy,
        "evidence": {
            "triage_decision": triage_evidence,
            "triage_reason": reason,
            "b_theory_computation": theory_evidence,
            "b_impl_computation": impl_evidence,
            "b_deploy_computation": deploy_evidence
        },
        "calibration_status": "computed",
        "layer": method_info.get('layer', 'unknown'),
        "last_updated": datetime.now(timezone.utc).isoformat(),
        "approved_by": "automated_triage_with_rubric",
        "rubric_version": rubric['_metadata']['version']
    }


def main():
```

```
    """Execute rigorous method-by-method triage using machine-readable rubric"""
    repo_root = Path(__file__).resolve().parents[4]
    catalogue_path = repo_root / "config" / "canonical_method_catalogue_v2.json"
    rubric_path = Path(__file__).resolve().parent / "intrinsic_calibration_rubric.json"  # Same directory as script
    output_path = repo_root / "config" / "intrinsic_calibration.json"

    print("Loading machine-readable rubric...")
    rubric = load_json(rubric_path)
    print(f"  Rubric version: {rubric['_metadata']['version']}")

    print("Loading canonical method catalogue...")
    catalogue = load_json(catalogue_path)
    print(f"  Total methods in catalogue: {len(catalogue)}")

    print("Loading current intrinsic calibrations...")
    if output_path.exists():
        intrinsic = load_json(output_path)
    else:
        intrinsic = {}

    # Get existing calibrations (keep manually curated ones)
    existing_methods = {}
    for method_id, profile in intrinsic.items():
        if not method_id.startswith("_"):
            # Keep if approved_by indicates manual curation
            if "system_architect" in profile.get("approved_by", ""):
                existing_methods[method_id] = profile

    print(f"Preserving {len(existing_methods)} manually curated calibrations")

    #Process ALL catalogue methods (flat array structure)
    all_methods = {}
    for method_info in catalogue:
        unique_id = method_info.get("unique_id", "")
        if unique_id:
            # Add method_name field from canonical_name for compatibility
            method_info['method_name'] = method_info.get('canonical_name', '')
            all_methods[unique_id] = method_info

    print(f"\nProcessing {len(all_methods)} methods with rubric-based triage...")
    print("=" * 80)

    processed = 0
    calibrated = 0
    excluded = 0

    new_methods = {}

    for method_id, method_info in sorted(all_methods.items()):
        # Keep existing manual calibrations
        if method_id in existing_methods:
            new_methods[method_id] = existing_methods[method_id]
            calibrated += 1
        else:
            # Apply triage process with rubric
            calibration_entry = triage_and_calibrate_method(method_info, repo_root, rubric)
```

```
            new_methods[method_id] = calibration_entry

            if calibration_entry.get("calibration_status") == "excluded":
                excluded += 1
            else:
                calibrated += 1

        processed += 1
        if processed % 100 == 0:
            print(f"  Processed {processed}/{len(all_methods)} methods...")

    # Update intrinsic calibration file
    output_data = {
        "_metadata": {
            "version": "2.0.0",
            "generated": datetime.now(timezone.utc).isoformat(),
            "total_methods": len(all_methods),
            "computed_methods": calibrated,
            "excluded_methods": excluded,
            "coverage_percent": round((calibrated / len(all_methods)) * 100, 2),
            "rubric_version": rubric['_metadata']['version'],
            "rubric_reference": "src/farfan_pipeline/core/calibration/intrinsic_calibration_rubric.json",
            "methodology": "Machine-readable rubric with traceable evidence",
            "reproducibility": "All scores can be regenerated from rubric + catalogue"
        }
    }
    output_data.update(new_methods)

    print(f"\nSaving intrinsic_calibration.json...")
    save_json(output_path, output_data)

    print("\n" + "=" * 80)
    print("RIGOROUS TRIAGE COMPLETE")
    print("=" * 80)
    print(f"Total methods processed: {len(all_methods)}")
    print(f"Methods calibrated: {calibrated}")
    print(f"Methods excluded: {excluded}")
    print(f"Coverage: {calibrated/len(all_methods)*100:.2f}%")
    print(f"Rubric version: {rubric['_metadata']['version']}")
    print("\nâ\234\223 Every method analyzed using machine-readable rubric")
    print("â\234\223 All scores traceable with explicit formulas and evidence")
    print("â\234\223 Scores are reproducible from rubric + catalog")

    return 0


if __name__ == "__main__":
    sys.exit(main())



================================================================================
FILE: src/farfan_pipeline/core/calibration/unit_layer.py
================================================================================

"""
```

```
Unit Layer (@u) - PRODUCTION IMPLEMENTATION.

Evaluates PDT quality through 4 components: S, M, I, P.
"""
import logging
from farfan_pipeline.core.calibration.config import UnitLayerConfig
from farfan_pipeline.core.calibration.pdt_structure import PDTStructure
from farfan_pipeline.core.calibration.data_structures import LayerID, LayerScore

logger = logging.getLogger(__name__)


class UnitLayerEvaluator:
    """
    Evaluates Unit Layer (@u) - PDT quality.

    PRODUCTION IMPLEMENTATION - All scores are data-driven.
    """

    # Mandatory blocks required for PDT compliance
    MANDATORY_BLOCKS = ["DiagnÃ³stico", "Parte EstratÃ©gica", "PPI", "Seguimiento"]

    def __init__(self, config: UnitLayerConfig):
        self.config = config

    def evaluate(self, pdt: PDTStructure) -> LayerScore:
        """
        Production implementation - computes S, M, I, P from PDT data.

        THIS IS NOT A STUB - all scores are data-driven.
        """
        logger.info("unit_layer_evaluation_start", extra={"tokens": pdt.total_tokens})

        # Step 1: Compute S (Structural Compliance)
        S = self._compute_structural_compliance(pdt)
        logger.info("S_computed", extra={"S": S})

        # Step 2: Check hard gate for S
        if S < self.config.min_structural_compliance:
            return LayerScore(
                layer=LayerID.UNIT,
                score=0.0,
                components={"S": S, "gate_failure": "structural"},
                rationale=f"HARD GATE: S={S:.2f} < {self.config.min_structural_compliance}",
                metadata={"gate": "structural", "threshold": self.config.min_structural_compliance}
            )

        # Step 3: Compute M (Mandatory Sections)
        M = self._compute_mandatory_sections(pdt)
        logger.info("M_computed", extra={"M": M})

        # Step 4: Compute I (Indicator Quality)
        I_components = self._compute_indicator_quality(pdt)
        I = I_components["I_total"]
        logger.info("I_computed", extra={"I": I})

```

```
        # Step 5: Check hard gate for I_struct
        if I_components["I_struct"] < self.config.i_struct_hard_gate:
            return LayerScore(
                layer=LayerID.UNIT,
                score=0.0,
                components={"S": S, "M": M, "I_struct": I_components["I_struct"]},
                rationale=f"HARD GATE: I_struct={I_components['I_struct']:.2f} < {self.config.i_struct_hard_gate}",
                metadata={"gate": "indicator_structure"}
            )

        # Step 6: Compute P (PPI Completeness)
        P_components = self._compute_ppi_completeness(pdt)
        P = P_components["P_total"]
        logger.info("P_computed", extra={"P": P})

        # Step 7: Check hard gates for PPI
        if self.config.require_ppi_presence and not pdt.ppi_matrix_present:
            return LayerScore(
                layer=LayerID.UNIT,
                score=0.0,
                components={"S": S, "M": M, "I": I, "gate_failure": "ppi_presence"},
                rationale="HARD GATE: PPI required but not present",
                metadata={"gate": "ppi_presence"}
            )

        if self.config.require_indicator_matrix and not pdt.indicator_matrix_present:
            return LayerScore(
                layer=LayerID.UNIT,
                score=0.0,
                components={"S": S, "M": M, "I": I, "P": P, "gate_failure": "indicator_matrix"},
                rationale="HARD GATE: Indicator matrix required but not present",
                metadata={"gate": "indicator_matrix"}
            )

        # Step 8: Aggregate
        U_base = self._aggregate_components(S, M, I, P)
        logger.info("U_base_computed", extra={"U_base": U_base})

        # Step 9: Anti-gaming
        gaming_penalty = self._compute_gaming_penalty(pdt)
        U_final = max(0.0, U_base - gaming_penalty)

        # Step 10: Quality level
        if U_final >= 0.85:
            quality = "sobresaliente"
        elif U_final >= 0.7:
            quality = "robusto"
        elif U_final >= 0.5:
            quality = "mÃ-nimo"
        else:
            quality = "insuficiente"

        return LayerScore(
            layer=LayerID.UNIT,
            score=U_final,
            components={"S": S, "M": M, "I": I, "P": P, "U_base": U_base, "penalty": gaming_penalty},
```

```
            rationale=f"Unit quality: {quality} (S={S:.2f}, M={M:.2f}, I={I:.2f}, P={P:.2f})",
            metadata={"quality_level": quality, "aggregation": self.config.aggregation_type}
        )

    def _compute_structural_compliance(self, pdt: PDTStructure) -> float:
        """Compute S = w_blockÂ•B_cov + w_hierarchyÂ•H + w_orderÂ•O."""
        # Block coverage
        blocks_found = sum(
            1 for block in self.MANDATORY_BLOCKS
            if block in pdt.blocks_found
            and pdt.blocks_found[block].get("tokens", 0) >= self.config.min_block_tokens
            and pdt.blocks_found[block].get("numbers_count", 0) >= self.config.min_block_numbers
        )
        B_cov = blocks_found / len(self.MANDATORY_BLOCKS)

        # Hierarchy score
        if not pdt.headers:
            H = 0.0
        else:
            valid = sum(1 for h in pdt.headers if h.get("valid_numbering"))
            ratio = valid / len(pdt.headers)
            if ratio >= self.config.hierarchy_excellent_threshold:
                H = 1.0
            elif ratio >= self.config.hierarchy_acceptable_threshold:
                H = 0.5
            else:
                H = 0.0

        # Order score - count inversions in block_sequence vs expected
        expected = ["DiagnÃ³stico", "Parte EstratÃ©gica", "PPI", "Seguimiento"]
        inversions = 0
        if pdt.block_sequence:
            # Find positions of blocks in actual sequence
            positions = {}
            for i, block in enumerate(pdt.block_sequence):
                if block in expected:
                    positions[block] = i

            # Count inversions (pairs out of order)
            for i, block1 in enumerate(expected):
                if block1 not in positions:
                    continue
                for block2 in expected[i+1:]:
                    if block2 not in positions:
                        continue
                    if positions[block1] > positions[block2]:
                        inversions += 1

        O = 1.0 if inversions == 0 else (0.5 if inversions == 1 else 0.0)

        S = (self.config.w_block_coverage * B_cov +
             self.config.w_hierarchy * H +
             self.config.w_order * O)

        return S

```

```
    def _compute_mandatory_sections(self, pdt: PDTStructure) -> float:
        """Compute M = weighted average of section completeness."""
        # Section requirements (from config)
        requirements = {
            "DiagnÃ³stico": {
                "min_tokens": self.config.diagnostico_min_tokens,
                "min_keywords": self.config.diagnostico_min_keywords,
                "min_numbers": self.config.diagnostico_min_numbers,
                "min_sources": self.config.diagnostico_min_sources,
                "weight": self.config.critical_sections_weight,  # Critical section
            },
            "Parte EstratÃ©gica": {
                "min_tokens": self.config.estrategica_min_tokens,
                "min_keywords": self.config.estrategica_min_keywords,
                "min_numbers": self.config.estrategica_min_numbers,
                "weight": self.config.critical_sections_weight,  # Critical section
            },
            "PPI": {
                "min_tokens": self.config.ppi_section_min_tokens,
                "min_keywords": self.config.ppi_section_min_keywords,
                "min_numbers": self.config.ppi_section_min_numbers,
                "weight": self.config.critical_sections_weight,  # Critical section
            },
            "Seguimiento": {
                "min_tokens": self.config.seguimiento_min_tokens,
                "min_keywords": self.config.seguimiento_min_keywords,
                "min_numbers": self.config.seguimiento_min_numbers,
                "weight": 1.0,
            },
            "Marco Normativo": {
                "min_tokens": self.config.marco_normativo_min_tokens,
                "min_keywords": self.config.marco_normativo_min_keywords,
                "weight": 1.0,
            }
        }

        total_weight = 0.0
        weighted_score = 0.0

        for section_name, reqs in requirements.items():
            section_data = pdt.sections_found.get(section_name, {})

            if not section_data.get("present", False):
                # Missing section gets 0
                score = 0.0
            else:
                # Check all requirements
                checks_passed = 0
                checks_total = 0

                if "min_tokens" in reqs:
                    checks_total += 1
                    if section_data.get("token_count", 0) >= reqs["min_tokens"]:
                        checks_passed += 1

                if "min_keywords" in reqs:
```

```
                    checks_total += 1
                    if section_data.get("keyword_matches", 0) >= reqs["min_keywords"]:
                        checks_passed += 1

                if "min_numbers" in reqs:
                    checks_total += 1
                    if section_data.get("number_count", 0) >= reqs["min_numbers"]:
                        checks_passed += 1

                if "min_sources" in reqs:
                    checks_total += 1
                    if section_data.get("sources_found", 0) >= reqs["min_sources"]:
                        checks_passed += 1

                score = checks_passed / checks_total if checks_total > 0 else 0.0

            weight = reqs.get("weight", 1.0)
            weighted_score += score * weight
            total_weight += weight

        M = weighted_score / total_weight if total_weight > 0 else 0.0
        return M

    def _compute_indicator_quality(self, pdt: PDTStructure) -> dict:
        """Compute I = w_structÂ•I_struct + w_linkÂ•I_link + w_logicÂ•I_logic."""
        if not pdt.indicator_matrix_present or not pdt.indicator_rows:
            logger.warning("indicator_matrix_absent", extra={"I": 0.0})
            return {
                "I_struct": 0.0,
                "I_link": 0.0,
                "I_logic": 0.0,
                "I_total": 0.0
            }

        # I_struct: Field completeness
        critical_fields = ["Tipo", "LÃ-nea EstratÃ©gica", "Programa", "LÃ-nea Base",
                          "Meta Cuatrienio", "Fuente", "Unidad Medida"]
        optional_fields = ["AÃ±o LB", "CÃ³digo MGA"]

        total_struct_score = 0.0
        for row in pdt.indicator_rows:
            critical_present = sum(1 for f in critical_fields if row.get(f))
            optional_present = sum(1 for f in optional_fields if row.get(f))

            # Penalize placeholders
            placeholder_count = sum(
                1 for f in critical_fields
                if row.get(f) in ["S/D", "N/A", "TBD", ""]
            )

            critical_score = critical_present / len(critical_fields)
            optional_score = optional_present / len(optional_fields)
            placeholder_penalty = (placeholder_count / len(critical_fields)) * self.config.i_placeholder_penalty_multiplier

            row_score = (critical_score * self.config.i_critical_fields_weight + optional_score) / (self.config.i_critical_fields_weight + 1)
            row_score = max(0.0, row_score - placeholder_penalty)
```

```
            total_struct_score += row_score

        I_struct = total_struct_score / len(pdt.indicator_rows)

        # I_link: Traceability (fuzzy matching between indicators and strategic lines)
        linked_count = 0
        for row in pdt.indicator_rows:
            programa = row.get("Programa", "")
            linea = row.get("LÃ-nea EstratÃ©gica", "")
            if programa and linea:
                # Simplified: check if they share significant words
                prog_words = set(programa.lower().split())
                linea_words = set(linea.lower().split())
                if len(prog_words & linea_words) >= 2:  # At least 2 words in common
                    linked_count += 1

        I_link = linked_count / len(pdt.indicator_rows)

        # I_logic: Year coherence
        logic_violations = 0
        for row in pdt.indicator_rows:
            year_lb = row.get("AÃ±o LB")

            if year_lb is not None:
                try:
                    year_lb_int = int(year_lb)
                    if not (self.config.i_valid_lb_year_min <= year_lb_int <= self.config.i_valid_lb_year_max):
                        logic_violations += 1
                except (ValueError, TypeError):
                    # Invalid year format counts as violation
                    logic_violations += 1

        I_logic = 1.0 - (logic_violations / len(pdt.indicator_rows))

        # Aggregate
        I_total = (self.config.w_i_struct * I_struct +
                  self.config.w_i_link * I_link +
                  self.config.w_i_logic * I_logic)

        return {
            "I_struct": I_struct,
            "I_link": I_link,
            "I_logic": I_logic,
            "I_total": I_total
        }

    def _compute_ppi_completeness(self, pdt: PDTStructure) -> dict:
        """Compute P = w_presenceÂ•P_presence + w_structÂ•P_struct + w_consÂ•P_consistency."""
        # P_presence
        P_presence = 1.0 if pdt.ppi_matrix_present else 0.0

        if not pdt.ppi_matrix_present or not pdt.ppi_rows:
            return {
                "P_presence": P_presence,
                "P_struct": 0.0,
                "P_consistency": 0.0,
```

```
                "P_total": P_presence * self.config.w_p_presence
            }

        # P_struct: Non-zero rows
        nonzero_rows = sum(
            1 for row in pdt.ppi_rows
            if row.get("Costo Total", 0) > 0
        )
        P_struct = nonzero_rows / len(pdt.ppi_rows)

        # P_consistency: Accounting closure
        violations = 0
        for row in pdt.ppi_rows:
            costo_total = row.get("Costo Total", 0)

            # Check temporal sum
            temporal_sum = sum(row.get(str(year), 0) for year in range(2024, 2028))
            if abs(temporal_sum - costo_total) > costo_total * self.config.p_accounting_tolerance:
                violations += 1

            # Check source sum
            source_sum = (row.get("SGP", 0) + row.get("SGR", 0) +
                         row.get("Propios", 0) + row.get("Otras", 0))
            if abs(source_sum - costo_total) > costo_total * self.config.p_accounting_tolerance:
                violations += 1

        P_consistency = 1.0 - (violations / (len(pdt.ppi_rows) * 2))  # 2 checks per row

        # Aggregate
        P_total = (self.config.w_p_presence * P_presence +
                  self.config.w_p_structure * P_struct +
                  self.config.w_p_consistency * P_consistency)

        return {
            "P_presence": P_presence,
            "P_struct": P_struct,
            "P_consistency": P_consistency,
            "P_total": P_total
        }

    def _aggregate_components(self, S: float, M: float, I: float, P: float) -> float:
        """Aggregate S, M, I, P using configured method."""
        if self.config.aggregation_type == "geometric_mean":
            # Geometric mean: (SÂ•MÂ•IÂ•P)^(1/4)
            product = S * M * I * P
            return product ** 0.25
        elif self.config.aggregation_type == "harmonic_mean":
            # Harmonic mean: 4 / (1/S + 1/M + 1/I + 1/P)
            if S == 0 or M == 0 or I == 0 or P == 0:
                return 0.0
            return 4.0 / (1.0/S + 1.0/M + 1.0/I + 1.0/P)
        else:  # weighted_average
            return (self.config.w_S * S +
                   self.config.w_M * M +
                   self.config.w_I * I +
                   self.config.w_P * P)
```

```

    def _compute_gaming_penalty(self, pdt: PDTStructure) -> float:
        """Compute anti-gaming penalties."""
        penalties = []

        # Check placeholder ratio in indicators
        if pdt.indicator_matrix_present and pdt.indicator_rows:
            placeholder_count = 0
            total_fields = 0
            for row in pdt.indicator_rows:
                for key, value in row.items():
                    total_fields += 1
                    if value in ["S/D", "N/A", "TBD", ""]:
                        placeholder_count += 1

            placeholder_ratio = placeholder_count / total_fields if total_fields > 0 else 0
            if placeholder_ratio > self.config.max_placeholder_ratio:
                penalty = (placeholder_ratio - self.config.max_placeholder_ratio) * 0.5
                penalties.append(penalty)

        # Check unique values in PPI costs
        if pdt.ppi_matrix_present and pdt.ppi_rows:
            costs = [row.get("Costo Total", 0) for row in pdt.ppi_rows]
            unique_costs = len(set(costs))
            unique_ratio = unique_costs / len(costs) if costs else 0

            if unique_ratio < self.config.min_unique_values_ratio:
                penalty = (self.config.min_unique_values_ratio - unique_ratio) * 0.3
                penalties.append(penalty)

        # Check number density in critical sections
        critical_sections = ["DiagnÃ³stico", "Parte EstratÃ©gica", "PPI"]
        for section in critical_sections:
            section_data = pdt.sections_found.get(section, {})
            if section_data.get("present"):
                tokens = section_data.get("token_count", 0)
                numbers = section_data.get("number_count", 0)
                density = numbers / tokens if tokens > 0 else 0

                if density < self.config.min_number_density:
                    penalty = (self.config.min_number_density - density) * 0.2
                    penalties.append(penalty)

        total_penalty = sum(penalties)
        return min(total_penalty, self.config.gaming_penalty_cap)



================================================================================
FILE: src/farfan_pipeline/core/calibration/validators.py
================================================================================

"""
Three-Pillar Calibration System - Validation Functions

This module implements validation checks for the calibration system
```

```
as specified in the SUPERPROMPT Three-Pillar Calibration System.

Spec compliance: Section 8 (Validation & Governance)
"""

import json
from pathlib import Path
from typing import Dict, Any, Set, List, TYPE_CHECKING

if TYPE_CHECKING:
    from farfan_pipeline.core.calibration.data_structures import CalibrationCertificate

from farfan_pipeline.core.calibration.data_structures import MethodRole, LayerType, REQUIRED_LAYERS


class CalibrationValidator:
    """
    Validation system for calibration configs and runtime checks.

    Spec compliance: Section 8 (Validation & Governance)
    """

    def __init__(self, config_dir: str = None):
        """Initialize validator with config directory"""
        if config_dir is None:
            config_dir = Path(__file__).parent.parent / "config"
        else:
            config_dir = Path(config_dir)

        self.config_dir = config_dir

    def validate_layer_completeness(
        self,
        method_id: str,
        role: MethodRole,
        declared_layers: Set[LayerType]
    ) -> tuple[bool, List[str]]:
        """
        Validate that method declares all required layers for its role.

        Spec compliance: Section 4 (Theorem 4.1 - No Silent Defaults)

        Args:
            method_id: Canonical method ID
            role: Method role
            declared_layers: Set of layers method declares

        Returns:
            (is_valid, error_messages)
        """
        required = REQUIRED_LAYERS.get(role, set())
        missing = required - declared_layers

        if not missing:
            return True, []

```

```
        errors = [
            f"Method {method_id} (role={role.value}) missing required layers: "
            f"{[l.value for l in missing]}"
        ]
        return False, errors

    def validate_fusion_weights(
        self,
        role_params: Dict[str, Any],
        role_name: str
    ) -> tuple[bool, List[str]]:
        """
        Validate fusion weight normalization and constraints.

        Spec compliance: Section 5 (Fusion Operator Constraints)

        Constraints:
        1. a_â\204\223 â\211¥ 0 for all â\204\223
        2. a_â\204\223k â\211¥ 0 for all (â\204\223,k)
        3. Î£(a_â\204\223) + Î£(a_â\204\223k) = 1.0

        Args:
            role_params: Parameters from fusion_specification.json
            role_name: Role identifier

        Returns:
            (is_valid, error_messages)
        """
        errors = []

        linear_weights = role_params.get("linear_weights", {})
        interaction_weights = role_params.get("interaction_weights", {})

        # Check non-negativity
        for layer, weight in linear_weights.items():
            if weight < 0:
                errors.append(
                    f"Role {role_name}: linear weight for {layer} is negative: {weight}"
                )

        for pair, weight in interaction_weights.items():
            if weight < 0:
                errors.append(
                    f"Role {role_name}: interaction weight for {pair} is negative: {weight}"
                )

        # Check normalization
        linear_sum = sum(linear_weights.values())
        interaction_sum = sum(interaction_weights.values())
        total = linear_sum + interaction_sum

        tolerance = 1e-9
        if abs(total - 1.0) > tolerance:
            errors.append(
                f"Role {role_name}: weights do not sum to 1.0. "
                f"Linear={linear_sum:.6f}, Interaction={interaction_sum:.6f}, "
```

```
                f"Total={total:.6f}"
            )

        return len(errors) == 0, errors

    def validate_anti_universality(
        self,
        method_config: Dict[str, Any],
        method_id: str,
        contextual_config: Dict[str, Any],
        monolith: Dict[str, Any]
    ) -> tuple[bool, List[str]]:
        """
        Validate anti-universality constraint.

        Spec compliance: Section 3.4 (Anti-Universality Constraint)

        No method may have maximal compatibility (1.0) with ALL Q, D, and P.

        Args:
            method_config: Method configuration
            method_id: Canonical method ID
            contextual_config: Contextual parametrization config
            monolith: Questionnaire monolith

        Returns:
            (is_valid, error_messages)
        """
        errors = []

        # For now, ensure policy default is < 1.0 (we set it to 0.9 in config)
        policy_areas = contextual_config.get("layer_policy", {}).get("policy_areas", {})
        all_policies_maximal = True

        for policy_id, policy_spec in policy_areas.items():
            if policy_spec.get("default_score", 0.0) < 0.99:
                all_policies_maximal = False
                break

        if all_policies_maximal:
            errors.append(
                f"Method {method_id} violates anti-universality: "
                f"all policy areas have maximal (â\211¥0.99) compatibility"
            )

        return len(errors) == 0, errors

    def validate_intrinsic_calibration(
        self,
        config: Dict[str, Any]
    ) -> tuple[bool, List[str]]:
        """
        Validate intrinsic_calibration.json structure and values.

        Args:
            config: Loaded intrinsic_calibration.json
```

```

        Returns:
            (is_valid, error_messages)
        """
        errors = []

        # Check weights sum to 1.0
        weights = config.get("_base_weights", {})
        weight_sum = weights.get("w_th", 0) + weights.get("w_imp", 0) + weights.get("w_dep", 0)

        if abs(weight_sum - 1.0) > 1e-9:
            errors.append(f"Base weights do not sum to 1.0: {weight_sum}")

        # Check each method entry
        methods = config.get("methods", {})
        for method_id, method_data in methods.items():
            if method_id.startswith("_"):
                continue  # Skip metadata

            # Check required fields
            for field in ["b_theory", "b_impl", "b_deploy"]:
                if field not in method_data:
                    errors.append(f"Method {method_id} missing field: {field}")
                    continue

                value = method_data[field]
                if not (0.0 <= value <= 1.0):
                    errors.append(
                        f"Method {method_id} field {field} out of bounds: {value}"
                    )

        return len(errors) == 0, errors

    def validate_config_files(self) -> tuple[bool, List[str]]:
        """
        Validate all three pillar config files.

        Spec compliance: Section 8 (CI / QA Rules)

        This should be run in CI to ensure config integrity.

        Returns:
            (is_valid, error_messages)
        """
        all_errors = []

        # Load configs
        try:
            with open(self.config_dir / "intrinsic_calibration.json") as f:
                intrinsic = json.load(f)
        except Exception as e:
            all_errors.append(f"Failed to load intrinsic_calibration.json: {e}")
            intrinsic = {}

        # Validate contextual config exists (full validation TBD)
        try:
```

```
            contextual_path = self.config_dir / "contextual_parametrization.json"
            if not contextual_path.exists():
                all_errors.append("contextual_parametrization.json not found")
        except Exception as e:
            all_errors.append(f"Failed to check contextual_parametrization.json: {e}")

        try:
            with open(self.config_dir / "fusion_specification.json") as f:
                fusion = json.load(f)
        except Exception as e:
            all_errors.append(f"Failed to load fusion_specification.json: {e}")
            fusion = {}

        # Validate intrinsic calibration
        if intrinsic:
            valid, errors = self.validate_intrinsic_calibration(intrinsic)
            all_errors.extend(errors)

        # Validate fusion weights for each role
        if fusion:
            role_params = fusion.get("role_fusion_parameters", {})
            for role_name, params in role_params.items():
                valid, errors = self.validate_fusion_weights(params, role_name)
                all_errors.extend(errors)

        return len(all_errors) == 0, all_errors

    def validate_boundedness(
        self,
        layer_scores: Dict[str, float],
        calibrated_score: float
    ) -> tuple[bool, List[str]]:
        """
        Validate boundedness constraint: all scores in [0,1].

        Spec compliance: Section 8 (P1. Boundedness)

        Args:
            layer_scores: All layer scores
            calibrated_score: Final calibrated score

        Returns:
            (is_valid, error_messages)
        """
        errors = []

        # Check layer scores
        for layer, score in layer_scores.items():
            if not (0.0 <= score <= 1.0):
                errors.append(f"Layer {layer} score out of bounds: {score}")

        # Check calibrated score
        if not (0.0 <= calibrated_score <= 1.0):
            errors.append(f"Calibrated score out of bounds: {calibrated_score}")

        return len(errors) == 0, errors
```

```


# Convenience functions
def validate_config_files(config_dir: str = None) -> tuple[bool, List[str]]:
    """
    Validate all calibration config files.

    This should be called in CI/CD pipelines.
    """
    validator = CalibrationValidator(config_dir=config_dir)
    return validator.validate_config_files()


def validate_certificate(
    certificate: 'CalibrationCertificate'
) -> tuple[bool, List[str]]:
    """
    Validate a calibration certificate.

    Args:
        certificate: CalibrationCertificate to validate

    Returns:
        (is_valid, error_messages)
    """
    validator = CalibrationValidator()

    # Check boundedness
    valid, errors = validator.validate_boundedness(
        certificate.layer_scores,
        certificate.calibrated_score
    )

    return valid, errors



================================================================================
FILE: src/farfan_pipeline/core/dependency_lockdown.py
================================================================================

"""Dependency lockdown enforcement to prevent magic downloads and hidden behavior.

This module enforces explicit dependency management by:
1. Checking if online model downloads are allowed via HF_ONLINE env var
2. Setting HuggingFace offline mode when online access is disabled
3. Providing early failure for missing critical dependencies
4. Allowing explicit degraded mode marking for optional dependencies

No fallback logic, no "best effort" embeddings. Either dependencies are present
and configured correctly, or the system fails fast with clear error messages.
"""

import logging
import os

```

```
logger = logging.getLogger(__name__)


def _is_model_cached(model_name: str) -> bool:
    """Check if a HuggingFace model is cached locally.

    Uses a heuristic check of common cache locations to determine if a model
    is likely available offline. This is a best-effort check - false positives
    are acceptable (will fail later when model actually loads), but false negatives
    should be minimized to avoid blocking offline usage of cached models.

    Args:
        model_name: HuggingFace model name (e.g., "sentence-transformers/model")

    Returns:
        True if model appears to be cached locally, False otherwise
    """
    from pathlib import Path

    # Check common HuggingFace cache locations
    cache_dirs = [
        os.path.expanduser("~/.cache/huggingface/hub"),
        os.path.expanduser("~/.cache/torch/sentence_transformers"),
        os.getenv("HF_HOME"),
        os.getenv("TRANSFORMERS_CACHE"),
    ]

    # Convert model name to cache directory pattern
    # HF uses "models--org--name" format in cache
    model_slug = model_name.replace("/", "--")

    for cache_dir in cache_dirs:
        if cache_dir and os.path.exists(cache_dir):
            cache_path = Path(cache_dir)
            # Use glob with specific pattern instead of rglob for efficiency
            # Check just the top-level directories, not recursive
            if any(model_slug in p.name for p in cache_path.iterdir()):
                return True

    return False


class DependencyLockdownError(RuntimeError):
    """Raised when a dependency constraint is violated."""
    pass


class DependencyLockdown:
    """Enforces strict dependency controls to prevent hidden/magic behavior.

    This class ensures that:
    - Online model downloads are explicitly controlled via HF_ONLINE env var
    - HuggingFace models only download when explicitly allowed
    - Critical dependencies fail fast if missing
    - Optional dependencies are clearly marked as degraded when missing
    """
```

```

    def __init__(self) -> None:
        """Initialize dependency lockdown based on environment configuration."""
        self.hf_allowed = os.getenv("HF_ONLINE", "0") == "1"
        self._enforce_offline_mode()
        self._log_configuration()

    def _enforce_offline_mode(self) -> None:
        """Enforce HuggingFace offline mode if HF_ONLINE is not enabled."""
        if not self.hf_allowed:
            # Set HuggingFace environment variables to prevent downloads
            os.environ["HF_HUB_OFFLINE"] = "1"
            os.environ["TRANSFORMERS_OFFLINE"] = "1"
            logger.info(
                "Dependency lockdown: HuggingFace offline mode ENFORCED "
                "(HF_ONLINE=0 or not set)"
            )
        else:
            logger.warning(
                "Dependency lockdown: HuggingFace online mode ENABLED "
                "(HF_ONLINE=1). Models may be downloaded from HuggingFace Hub."
            )

    def _log_configuration(self) -> None:
        """Log current dependency lockdown configuration."""
        logger.info(
            f"Dependency lockdown initialized: "
            f"HF_ONLINE={self.hf_allowed}, "
            f"HF_HUB_OFFLINE={os.getenv('HF_HUB_OFFLINE', 'unset')}, "
            f"TRANSFORMERS_OFFLINE={os.getenv('TRANSFORMERS_OFFLINE', 'unset')}"
        )

    def check_online_model_access(
        self,
        model_name: str,
        operation: str = "model download"
    ) -> None:
        """Check if online model access is allowed, raise if not.

        Args:
            model_name: Name of the model being accessed
            operation: Description of the operation (for error message)

        Raises:
            DependencyLockdownError: If online access is not allowed
        """
        if not self.hf_allowed:
            raise DependencyLockdownError(
                f"Online model download disabled in this environment. "
                f"Attempted operation: {operation} for model '{model_name}'. "
                f"To enable online downloads, set HF_ONLINE=1 environment variable. "
                f"No fallback to degraded mode - this is a hard failure."
            )

    def check_critical_dependency(
        self,
```

```
        module_name: str,
        pip_package: str,
        phase: str | None = None
    ) -> None:
        """Check if a critical dependency is available, fail fast if not.

        Args:
            module_name: Python module name to import
            pip_package: pip package name for installation instructions
            phase: Optional phase name where dependency is required

        Raises:
            DependencyLockdownError: If critical dependency is missing
        """
        try:
            __import__(module_name)
        except ImportError as e:
            phase_info = f" for phase '{phase}'" if phase else ""
            raise DependencyLockdownError(
                f"Critical dependency '{module_name}' is missing{phase_info}. "
                f"Install it with: pip install {pip_package}. "
                f"No degraded mode available - this is a mandatory dependency. "
                f"Original error: {e}"
            ) from e

    def check_optional_dependency(
        self,
        module_name: str,
        pip_package: str,
        feature: str
    ) -> bool:
        """Check if an optional dependency is available.

        Args:
            module_name: Python module name to import
            pip_package: pip package name for installation instructions
            feature: Feature name that requires this dependency

        Returns:
            True if dependency is available, False otherwise

        Note:
            This does NOT raise an error, but logs a warning about degraded mode.
            Caller must explicitly handle degraded mode and log it clearly.
        """
        try:
            __import__(module_name)
            return True
        except ImportError:
            logger.warning(
                f"DEGRADED MODE: Optional dependency '{module_name}' not available. "
                f"Feature '{feature}' will be disabled. "
                f"Install with: pip install {pip_package}"
            )
            return False

```

```
    def get_mode_description(self) -> dict[str, str | bool]:
        """Get current dependency lockdown mode description.

        Returns:
            Dictionary with mode information for logging/debugging
        """
        return {
            "hf_online_allowed": self.hf_allowed,
            "hf_hub_offline": os.getenv("HF_HUB_OFFLINE", "unset"),
            "transformers_offline": os.getenv("TRANSFORMERS_OFFLINE", "unset"),
            "mode": "online" if self.hf_allowed else "offline_enforced",
        }


# Global singleton instance
_lockdown_instance: DependencyLockdown | None = None


def get_dependency_lockdown() -> DependencyLockdown:
    """Get or create the global dependency lockdown instance.

    Returns:
        Global DependencyLockdown instance
    """
    global _lockdown_instance
    if _lockdown_instance is None:
        _lockdown_instance = DependencyLockdown()
    return _lockdown_instance


def reset_dependency_lockdown() -> None:
    """Reset the global dependency lockdown instance (for testing)."""
    global _lockdown_instance
    _lockdown_instance = None
```