

```

===== FILE: MIGRATION_ARTIFACTS_FAKE_TO_REAL/04_SOURCE_CODE/base_executor_with_contract.py
=====
from __future__ import annotations

import json
from abc import ABC, abstractmethod
from typing import TYPE_CHECKING, Any

from jsonschema import Draft7Validator

from saaaaaaa.config.paths import PROJECT_ROOT
from saaaaaaa.core.orchestrator.evidence_assembler import EvidenceAssembler
from saaaaaaa.core.orchestrator.evidence_validator import EvidenceValidator

if TYPE_CHECKING:
    from saaaaaaa.core.orchestrator.core import MethodExecutor, PreprocessedDocument
else: # pragma: no cover - runtime avoids import to break cycles
    MethodExecutor = Any
    PreprocessedDocument = Any

class BaseExecutorWithContract(ABC):
    """Contract-driven executor that routes all calls through MethodExecutor."""

    _contract_cache: dict[str, dict[str, Any]] = {}
    _schema_validator: Draft7Validator | None = None

    def __init__(
        self,
        method_executor: MethodExecutor,
        signal_registry: Any,
        config: Any,
        questionnaire_provider: Any,
        calibration_orchestrator: Any | None = None,
    ) -> None:
        try:
            from saaaaaaa.core.orchestrator.core import MethodExecutor as _MethodExecutor
        except Exception as exc: # pragma: no cover - defensive guard
            raise RuntimeError(
                "Failed to import MethodExecutor for BaseExecutorWithContract invariants."
            )

        "Ensure saaaaaaa.core.orchestrator.core is importable before constructing
        contract executors."
        if not isinstance(method_executor, _MethodExecutor):
            raise RuntimeError("A valid MethodExecutor instance is required for contract
            executors.")
        self.method_executor = method_executor
        self.signal_registry = signal_registry
        self.config = config
        self.questionnaire_provider = questionnaire_provider
        self.calibration_orchestrator = calibration_orchestrator

    @classmethod
    @abstractmethod
    def get_base_slot(cls) -> str:
        raise NotImplementedError

    @classmethod
    def _get_schema_validator(cls) -> Draft7Validator:
        if cls._schema_validator is None:
            schema_path = PROJECT_ROOT / "config" / "executor_contract.schema.json"
            if not schema_path.exists():
                raise FileNotFoundError(f"Contract schema not found: {schema_path}")
            schema = json.loads(schema_path.read_text(encoding="utf-8"))
            cls._schema_validator = Draft7Validator(schema)
        return cls._schema_validator

```

```

@classmethod
def _load_contract(cls) -> dict[str, Any]:
    base_slot = cls.get_base_slot()
    if base_slot in cls._contract_cache:
        return cls._contract_cache[base_slot]

    contract_path = PROJECT_ROOT / "config" / "executor_contracts" /
f"{base_slot}.json"
    if not contract_path.exists():
        raise FileNotFoundError(f"Contract not found: {contract_path}")

    contract = json.loads(contract_path.read_text(encoding="utf-8"))
    validator = cls._get_schema_validator()
    errors = sorted(validator.iter_errors(contract), key=lambda e: e.path)
    if errors:
        messages = "; ".join(err.message for err in errors)
        raise ValueError(f"Contract validation failed for {base_slot}: {messages}")

    cls._contract_cache[base_slot] = contract
    return contract

def _check_failure_contract(self, evidence: dict[str, Any], error_handling: dict[str,
Any]):
    failure_contract = error_handling.get("failure_contract", {})
    abort_conditions = failure_contract.get("abort_if", [])
    if not abort_conditions:
        return

    emit_code = failure_contract.get("emit_code", "GENERIC_ABORT")

    for condition in abort_conditions:
        # Example condition check. This could be made more sophisticated.
        if condition == "missing_required_element" and evidence.get("validation",
{}).get("errors"):
            # This logic assumes errors from the validator imply a missing required
element,
            # which is true with our new validator.
            raise ValueError(f"Execution aborted by failure contract due to
'{condition}'. Emit code: {emit_code}'")
        if condition == "incomplete_text" and not evidence.get("metadata",
{}).get("text_complete", True):
            raise ValueError(f"Execution aborted by failure contract due to
'{condition}'. Emit code: {emit_code}'")

def execute(
    self,
    document: PreprocessedDocument,
    method_executor: MethodExecutor,
    *,
    question_context: dict[str, Any],
) -> dict[str, Any]:
    if method_executor is not self.method_executor:
        raise RuntimeError("Mismatched MethodExecutor instance for contract executor")

    base_slot = self.get_base_slot()
    if question_context.get("base_slot") != base_slot:
        raise ValueError(
            f"Question base_slot {question_context.get("base_slot")} does not match
executor {base_slot}"
        )

    question_id = question_context.get("question_id")
    question_global = question_context.get("question_global")
    policy_area_id = question_context.get("policy_area_id")
    identity = question_context.get("identity", {})
    patterns = question_context.get("patterns", [])
    expected_elements = question_context.get("expected_elements", [])

```

```

signal_pack = None
if self.signal_registry is not None and hasattr(self.signal_registry, "get") and
policy_area_id:
    signal_pack = self.signal_registry.get(policy_area_id)

contract = self._load_contract()

common_kwargs: dict[str, Any] = {
    "document": document,
    "base_slot": base_slot,
    "raw_text": getattr(document, "raw_text", None),
    "text": getattr(document, "raw_text", None),
    "question_id": question_id,
    "question_global": question_global,
    "policy_area_id": policy_area_id,
    "dimension_id": identity.get("dimension_id"),
    "cluster_id": identity.get("cluster_id"),
    "signal_pack": signal_pack,
    "question_patterns": patterns,
    "expected_elements": expected_elements,
}

method_outputs: dict[str, Any] = {}
method_inputs = contract.get("method_inputs", [])
indexed = list(enumerate(method_inputs))
sorted_inputs = sorted(indexed, key=lambda pair: (pair[1].get("priority", 2),
pair[0]))
for _, entry in sorted_inputs:
    class_name = entry["class"]
    method_name = entry["method"]
    provides = entry.get("provides", [])
    extra_args = entry.get("args", {})

    payload = {**common_kwargs, **extra_args}

    result = self.method_executor.execute(
        class_name=class_name,
        method_name=method_name,
        **payload,
    )

    if "signal_pack" in payload and payload["signal_pack"] is not None:
        if "_signal_usage" not in method_outputs:
            method_outputs["_signal_usage"] = []
        method_outputs["_signal_usage"].append({
            "method": f'{class_name}.{method_name}',
            "policy_area": payload["signal_pack"].policy_area,
            "version": payload["signal_pack"].version,
        })

    if isinstance(provides, str):
        method_outputs[provides] = result
    else:
        for key in provides:
            method_outputs[key] = result

assembly_rules = contract.get("assembly_rules", [])
assembled = EvidenceAssembler.assemble(method_outputs, assembly_rules)
evidence = assembled["evidence"]
trace = assembled["trace"]

validation_rules = contract.get("validation_rules", [])
na_policy = contract.get("na_policy", "abort")
# Construct the rules_object as expected by EvidenceValidator.validate
validation_rules_object = {"rules": validation_rules, "na_policy": na_policy}
validation = EvidenceValidator.validate(evidence, validation_rules_object)

error_handling = contract.get("error_handling", {})

```

```

if error_handling:
    # The failure contract needs access to validation results, so we stitch them
    in.
    evidence_with_validation = {**evidence, "validation": validation}
    self._check_failure_contract(evidence_with_validation, error_handling)

human_answer_template = contract.get("human_answer_template", "")
human_answer = ""
if human_answer_template:
    try:
        # Use evidence to format the human answer template
        human_answer = human_answer_template.format(**evidence)
    except KeyError as e:
        # Handle cases where evidence might not contain all template keys
        human_answer = f"Error formatting human answer: Missing key {e}. Template:
'{human_answer_template}'"
        # Optionally log this error
        import logging
        logging.warning(human_answer)

return {
    "base_slot": base_slot,
    "question_id": question_id,
    "question_global": question_global,
    "policy_area_id": policy_area_id,
    "dimension_id": identity.get("dimension_id"),
    "cluster_id": identity.get("cluster_id"),
    "evidence": evidence,
    "validation": validation,
    "trace": trace,
    "human_answer": human_answer,
}

```

===== FILE: MIGRATION_ARTIFACTS_FAKE_TO_REAL/04_SOURCE_CODE/executors_FAKE.py =====

"""

executors.py - Phase 2: Executor Orchestration for Policy Document Analysis

This module defines 30 executors (one per D{n}-Q{m} question) that orchestrate methods from the core module to extract raw evidence from Colombian municipal development plans (PDET/PDM documents).

Architecture:

- Each executor is independent and receives a canonical context package
- Methods execute in configured order; any failure causes executor failure
- Outputs are Python dicts/lists matching JSON contract specifications
- Executors are injected via MethodExecutor factory pattern

Usage:

```

from factory import run_executor
result = run_executor("D1-Q1", context_package)
"""

```

```

from typing import Dict, List, Any, Optional
from abc import ABC, abstractmethod

```

```

from saaaaaa.core.canonical_notation import CanonicalDimension, get_dimension_info
from saaaaaa.core.orchestrator.core import MethodExecutor
from saaaaaa.core.orchestrator.factory import build_processor

```

```

# Canonical question labels (only defined when verified in repo)
CANONICAL_QUESTION_LABELS = {
    "D3-Q2": "DIM03_Q02_PRODUCT_TARGET_PROPORIONALITY",
    "D3-Q3": "DIM03_Q03_TRACEABILITY_BUDGET_ORG",
    "D3-Q4": "DIM03_Q04_TECHNICAL_FEASIBILITY",
    "D3-Q5": "DIM03_Q05_OUTPUT_OUTCOME_LINKAGE",
    "D4-Q1": "DIM04_Q01_OUTCOME_INDICATOR_COMPLETENESS",
    "D5-Q2": "DIM05_Q02_COMPOSITE_PROXY_VALIDITY",
}

```

```

# Epistemic taxonomy per method (focused on executors expanded in this iteration)
EPISTEMIC_TAGS = {
    ("FinancialAuditor", "_calculate_sufficiency"): ["statistical", "normative"],
    ("FinancialAuditor", "_match_program_to_node"): ["structural"],
    ("FinancialAuditor", "_match_goal_to_budget"): ["structural", "normative"],
    ("PDET MunicipalPlanAnalyzer", "_assess_financial_sustainability"): ["financial",
    "normative"],
    ("PDET MunicipalPlanAnalyzer", "analyze_financial_feasibility"): ["financial",
    "statistical"],
    ("PDET MunicipalPlanAnalyzer", "_score_indicators"): ["normative", "semantic"],
    ("PDET MunicipalPlanAnalyzer", "_interpret_risk"): ["normative", "statistical"],
    ("PDET MunicipalPlanAnalyzer", "_extract_from_responsibility_tables"): ["structural"],
    ("PDET MunicipalPlanAnalyzer", "_consolidate_entities"): ["structural"],
    ("PDET MunicipalPlanAnalyzer", "_extract_entities_syntax"): ["semantic"],
    ("PDET MunicipalPlanAnalyzer", "_extract_entities_ner"): ["semantic"],
    ("PDET MunicipalPlanAnalyzer", "identify_responsible_entities"): ["semantic",
    "structural"],
    ("PDET MunicipalPlanAnalyzer", "_score_responsibility_clarity"): ["normative"],
    ("PDET MunicipalPlanAnalyzer", "_refine_edge_probabilities"): ["statistical",
    "causal"],
    ("PDET MunicipalPlanAnalyzer", "construct_causal_dag"): ["structural", "causal"],
    ("PDET MunicipalPlanAnalyzer", "estimate_causal_effects"): ["causal", "statistical"],
    ("PDET MunicipalPlanAnalyzer", "generate_counterfactuals"): ["causal"],
    ("PDET MunicipalPlanAnalyzer", "_identify_confounders"): ["causal", "consistency"],
    ("PDET MunicipalPlanAnalyzer", "_effect_to_dict"): ["descriptive"],
    ("PDET MunicipalPlanAnalyzer", "_scenario_to_dict"): ["descriptive"],
    ("PDET MunicipalPlanAnalyzer", "_get_spanish_stopwords"): ["semantic"],
    ("AdaptivePriorCalculator", "calculate_likelihood_adaptativo"): ["statistical",
    "bayesian"],
    ("AdaptivePriorCalculator", "_adjust_domain_weights"): ["statistical"],
    ("BayesianMechanismInference", "_test_sufficiency"): ["statistical", "bayesian"],
    ("BayesianMechanismInference", "_test_necessity"): ["statistical", "bayesian"],
    ("BayesianMechanismInference", "_log_refactored_components"): ["implementation"],
    ("BayesianMechanismInference", "_infer_activity_sequence"): ["causal"],
    ("BayesianMechanismInference", "infer_mechanisms"): ["causal", "bayesian"],
    ("AdvancedDAGValidator", "calculate_acyclicity_pvalue"): ["statistical",
    "consistency"],
    ("AdvancedDAGValidator", "_is_acyclic"): ["structural", "consistency"],
    ("AdvancedDAGValidator", "_calculate_bayesian_posterior"): ["statistical",
    "bayesian"],
    ("AdvancedDAGValidator", "_calculate_confidence_interval"): ["statistical"],
    ("AdvancedDAGValidator", "_calculate_statistical_power"): ["statistical"],
    ("AdvancedDAGValidator", "_generate_subgraph"): ["structural"],
    ("AdvancedDAGValidator", "_get_node_validator"): ["implementation"],
    ("AdvancedDAGValidator", "_create_empty_result"): ["descriptive"],
    ("AdvancedDAGValidator", "_initialize_rng"): ["implementation"],
    ("AdvancedDAGValidator", "get_graph_stats"): ["structural"],
    ("AdvancedDAGValidator", "_calculate_node_importance"): ["structural"],
    ("AdvancedDAGValidator", "export_nodes"): ["structural", "descriptive"],
    ("AdvancedDAGValidator", "add_node"): ["structural"],
    ("AdvancedDAGValidator", "add_edge"): ["structural"],
    ("IndustrialGradeValidator", "execute_suite"): ["implementation", "normative"],
    ("IndustrialGradeValidator", "validate_connection_matrix"): ["consistency"],
    ("IndustrialGradeValidator", "run_performance_benchmarks"): ["implementation"],
    ("IndustrialGradeValidator", "_benchmark_operation"): ["implementation"],
    ("IndustrialGradeValidator", "validate_causal_categories"): ["consistency"],
    ("IndustrialGradeValidator", "_log_metric"): ["implementation"],
    ("PerformanceAnalyzer", "analyze_performance"): ["implementation", "normative"],
    ("PerformanceAnalyzer", "_calculate_loss_functions"): ["statistical"],
    ("HierarchicalGenerativeModel", "_calculate_ess"): ["statistical"],
    ("HierarchicalGenerativeModel", "_calculate_likelihood"): ["statistical"],
    ("HierarchicalGenerativeModel", "_calculate_r_hat"): ["statistical"],
    ("ReportingEngine", "generate_accountability_matrix"): ["normative", "structural"],
    ("ReportingEngine", "_calculate_quality_score"): ["normative", "statistical"],
    ("PolicyAnalysisEmbedder", "generate_pdq_report"): ["semantic", "descriptive"],
    ("PolicyAnalysisEmbedder", "compare_policy_interventions"): ["normative"],
    ("PolicyAnalysisEmbedder", "evaluate_policy_numerical_consistency"): ["consistency"],
}

```

"statistical"],
("PolicyAnalysisEmbedder", "process_document"): ["semantic", "structural"],
("PolicyAnalysisEmbedder", "semantic_search"): ["semantic"],
("PolicyAnalysisEmbedder", "_apply_mmr"): ["semantic"],
("PolicyAnalysisEmbedder", "_generate_query_from_pdq"): ["semantic"],
("PolicyAnalysisEmbedder", "_filter_by_pdq"): ["semantic"],
("PolicyAnalysisEmbedder", "_extract_numerical_values"): ["statistical"],
("PolicyAnalysisEmbedder", "_compute_overall_confidence"): ["statistical"],
"normative"],
("PolicyAnalysisEmbedder", "_embed_texts"): ["semantic"],
("SemanticAnalyzer", "_classify_policy_domain"): ["semantic"],
("SemanticAnalyzer", "_empty_semantic_cube"): ["descriptive"],
("SemanticAnalyzer", "_classify_cross_cutting_themes"): ["semantic"],
("SemanticAnalyzer", "_classify_value_chain_link"): ["semantic"],
("SemanticAnalyzer", "_vectorize_segments"): ["semantic"],
("SemanticAnalyzer", "_calculate_semantic_complexity"): ["semantic"],
("SemanticAnalyzer", "_process_segment"): ["semantic"],
("PDET MunicipalPlanAnalyzer", "_entity_to_dict"): ["descriptive"],
("PDET MunicipalPlanAnalyzer", "_quality_to_dict"): ["descriptive", "normative"],
("PDET MunicipalPlanAnalyzer", "_deduplicate_tables"): ["structural"],
"implementation"],
("PDET MunicipalPlanAnalyzer", "_indicator_to_dict"): ["descriptive"],
("PDET MunicipalPlanAnalyzer", "_generate_recommendations"): ["normative"],
("PDET MunicipalPlanAnalyzer", "_simulate_intervention"): ["causal", "statistical"],
("PDET MunicipalPlanAnalyzer", "_identify_causal_nodes"): ["structural", "causal"],
("PDET MunicipalPlanAnalyzer", "_match_text_to_node"): ["semantic", "structural"],
("TeoriaCambio", "_validar_orden_causal"): ["causal", "consistency"],
("TeoriaCambio", "_generar_sugerencias_internas"): ["normative"],
("TeoriaCambio", "_extraer_categorias"): ["semantic"],
("BayesianMechanismInference", "_extract_observations"): ["semantic", "causal"],
("BayesianMechanismInference", "_generate_necessity_remediation"): ["normative",
"causal"],
("BayesianMechanismInference", "_quantify_uncertainty"): ["statistical", "bayesian"],
("CausalExtractor", "_build_type_hierarchy"): ["structural"],
("CausalExtractor", "_check_structuralViolation"): ["structural", "consistency"],
("CausalExtractor", "_calculate_type_transition_prior"): ["statistical", "bayesian"],
("CausalExtractor", "_calculate_textual_proximity"): ["semantic"],
("CausalExtractor", "_calculate_language_specificity"): ["semantic"],
("CausalExtractor", "_calculate_composite_likelihood"): ["statistical", "semantic"],
("CausalExtractor", "_assess_financial_consistency"): ["financial", "consistency"],
("CausalExtractor", "_calculate_semantic_distance"): ["semantic"],
("CausalExtractor", "_extract_goals"): ["semantic"],
("CausalExtractor", "_parse_goal_context"): ["semantic"],
("CausalExtractor", "_classify_goal_type"): ["semantic"],
("TemporalLogicVerifier", "_parse_temporal_marker"): ["temporal", "consistency"],
("TemporalLogicVerifier", "_classify_temporal_type"): ["temporal", "consistency"],
("TemporalLogicVerifier", "_extract_resources"): ["structural"],
("TemporalLogicVerifier", "_should_precede"): ["temporal", "consistency"],
("AdaptivePriorCalculator", "generate_traceability_record"): ["structural"],
"semantic"],
("PolicyAnalysisEmbedder", "generate_pdq_report"): ["semantic", "normative"],
("ReportingEngine", "generate_confidence_report"): ["normative", "descriptive"],
("PolicyTextProcessor", "segment_into_sentences"): ["semantic", "structural"],
("PolicyTextProcessor", "normalize_unicode"): ["implementation"],
("PolicyTextProcessor", "compile_pattern"): ["implementation"],
("PolicyTextProcessor", "extract_contextual_window"): ["semantic"],
("BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize"): ["causal",
"normative"],
("BayesianCounterfactualAuditor", "refutation_and_sanity_checks"): ["causal",
"consistency"],
("BayesianCounterfactualAuditor", "_evaluate_factual"): ["causal", "statistical"],
("BayesianCounterfactualAuditor", "_evaluate_counterfactual"): ["causal",
"statistical"],
("CausalExtractor", "_assess_financial_consistency"): ["financial", "consistency"],
("IndustrialPolicyProcessor", "_load_questionnaire"): ["descriptive",
"implementation"],
("IndustrialPolicyProcessor", "_compile_pattern_registry"): ["structural",
"semantic"],

```
("IndustrialPolicyProcessor", "_build_point_patterns"): ["semantic"],
("IndustrialPolicyProcessor", "_empty_result"): ["implementation"],
("IndustrialPolicyProcessor", "_compute_evidence_confidence"): ["statistical"],
("IndustrialPolicyProcessor", "_compute_avg_confidence"): ["statistical"],
("IndustrialPolicyProcessor", "_construct_evidence_bundle"): ["structural"],
("PDETMunicipalPlanAnalyzer", "generate_executive_report"): ["normative"],
("IndustrialPolicyProcessor", "export_results"): ["implementation"],
}
```

```
}
```

```
class BaseExecutor(ABC):
```

```
    """
```

Base class for all executors with standardized execution template.
All executors must implement execute() and return structured evidence.

```
"""
```

```
def __init__(self, executor_id: str, config: Dict[str, Any], method_executor: MethodExecutor):
    self.executor_id = executor_id
    self.config = config
    if not isinstance(method_executor, MethodExecutor):
        raise RuntimeError("A valid MethodExecutor instance is required for executor injection.")
    self.method_executor = method_executor
    self.execution_log = []
    self.dimension_info = None
    try:
        dim_key = executor_id.split("-")[0].replace("D", "D")
        self.dimension_info = get_dimension_info(dim_key)
    except Exception:
        self.dimension_info = None
```

```
@abstractmethod
```

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
```

```
    """
```

Execute configured methods and return raw evidence.

Args:

context: Canonical package with document, tables, metadata

Returns:

Dict with raw_evidence, metadata, execution_metrics

Raises:

ExecutorFailure: If any method fails

```
"""
```

```
pass
```

```
def _log_method_execution(self, class_name: str, method_name: str,
                         success: bool, result: Any = None, error: str = None):
    """Track method execution for debugging and traceability."""
    self.execution_log.append({
        "class": class_name,
        "method": method_name,
        "success": success,
        "result_type": type(result).__name__ if result else None,
        "error": error
    })
```

```
def _execute_method(self, class_name: str, method_name: str,
                    context: Dict[str, Any], **kwargs) -> Any:
    """
```

Execute a single method with error handling.

Raises:

ExecutorFailure: If method execution fails

```
"""
```

```
try:
```

```

# Method injection happens via factory - placeholder for actual execution
method = self._get_method(class_name, method_name)
result = method(context, **kwargs)
self._log_method_execution(class_name, method_name, True, result)
return result

except Exception as e:
    self._log_method_execution(class_name, method_name, False, error=str(e))
    raise ExecutorFailure(
        f"Executor {self.executor_id} failed: {class_name}.{method_name} - "
        f"{str(e)}")

def _get_method(self, class_name: str, method_name: str):
    """Retrieve method using MethodExecutor to enforce routed execution."""
    if not isinstance(self.method_executor, MethodExecutor):
        raise RuntimeError(f"Invalid method executor provided: "
                           f'{type(self.method_executor).__name__}')

```

```

def _wrapped(context: Dict[str, Any], **kwargs: Any) -> Any:
    payload: Dict[str, Any] = {}
    if context:
        payload.update(context)
    if kwargs:
        payload.update(kwargs)
    return self.method_executor.execute(
        class_name=class_name,
        method_name=method_name,
        **payload,
    )

```

```
return _wrapped
```

```

class ExecutorFailure(Exception):
    """Raised when any method in an executor fails."""
    pass

```

```
# =====
# DIMENSION 1: DIAGNOSTICS & INPUTS
# =====
```

```
class D1_Q1_QuantitativeBaselineExtractor(BaseExecutor):
    """
```

Extracts numeric data, reference years, and official sources as baseline.

Methods (from D1-Q1):

- TextMiningEngine.diagnose_critical_links
- TextMiningEngine._analyze_link_text
- IndustrialPolicyProcessor.process
- IndustrialPolicyProcessor._match_patterns_in_sentences
- IndustrialPolicyProcessor._extract_point_evidence
- CausalExtractor._extract_goals
- CausalExtractor._parse_goal_context
- FinancialAuditor._parse_amount
- PDET Municipal Plan Analyzer._extract_financial_amounts
- PDET Municipal Plan Analyzer._extract_from_budget_table
- PolicyContradictionDetector._extract_quantitative_claims
- PolicyContradictionDetector._parse_number
- PolicyContradictionDetector._statistical_significance_test
- BayesianNumericalAnalyzer.evaluate_policy_metric
- BayesianNumericalAnalyzer.compare_policies
- SemanticProcessor.chunk_text
- SemanticProcessor.embed_single

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}
```

```

# Step 1: Identify critical data-bearing sections
critical_links = self._execute_method(
    "TextMiningEngine", "diagnose_critical_links", context
)
link_analysis = self._execute_method(
    "TextMiningEngine", "_analyze_link_text", context,
    links=critical_links
)

# Step 2: Extract structured quantitative claims
processed_sections = self._execute_method(
    "IndustrialPolicyProcessor", "process", context
)
pattern_matches = self._execute_method(
    "IndustrialPolicyProcessor", "_match_patterns_in_sentences", context,
    sections=processed_sections
)
point_evidence = self._execute_method(
    "IndustrialPolicyProcessor", "_extract_point_evidence", context,
    matches=pattern_matches
)

# Step 3: Parse numerical amounts and baseline data
parsed_amounts = self._execute_method(
    "FinancialAuditor", "_parse_amount", context,
    evidence=point_evidence
)
financial_amounts = self._execute_method(
    "PDET Municipal Plan Analyzer", "_extract_financial_amounts", context
)
budget_table_data = self._execute_method(
    "PDET Municipal Plan Analyzer", "_extract_from_budget_table", context
)

# Step 4: Extract temporal context (reference years)
goals = self._execute_method(
    "CausalExtractor", "_extract_goals", context
)
goal_contexts = self._execute_method(
    "CausalExtractor", "_parse_goal_context", context,
    goals=goals
)

# Step 5: Validate quantitative claims
quant_claims = self._execute_method(
    "PolicyContradictionDetector", "_extract_quantitative_claims", context
)
parsed_numbers = self._execute_method(
    "PolicyContradictionDetector", "_parse_number", context,
    claims=quant_claims
)
significance_test = self._execute_method(
    "PolicyContradictionDetector", "_statistical_significance_test", context,
    numbers=parsed_numbers
)

# Step 6: Evaluate baseline quality and compare
metric_evaluation = self._execute_method(
    "BayesianNumericalAnalyzer", "evaluate_policy_metric", context,
    metrics=parsed_numbers
)
policy_comparison = self._execute_method(
    "BayesianNumericalAnalyzer", "compare_policies", context,
    evaluations=metric_evaluation
)

# Step 7: Semantic validation of sources

```

```

text_chunks = self._execute_method(
    "SemanticProcessor", "chunk_text", context
)
embeddings = self._execute_method(
    "SemanticProcessor", "embed_single", context,
    chunks=text_chunks
)

# Assemble raw evidence
raw_evidence = {
    "numeric_data": parsed_numbers,
    "reference_years": [gc.get("year") for gc in goal_contexts if gc.get("year")],
    "official_sources": point_evidence.get("sources", []),
    "financial_baseline": financial_amounts,
    "budget_tables": budget_table_data,
    "significance_results": significance_test,
    "metric_evaluation": metric_evaluation,
    "source_embeddings": embeddings
}
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "total_numeric_claims": len(parsed_numbers),
        "sources_identified": len(point_evidence.get("sources", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D1_Q2_ProblemDimensioningAnalyzer(BaseExecutor):

Quantifies problem magnitude, gaps, and identifies data limitations.

Methods (from D1-Q2):

- OperationalizationAuditor._audit_direct_evidence
- OperationalizationAuditor._audit_systemic_risk
- FinancialAuditor._detect_allocation_gaps
- BayesianMechanismInference._detect_gaps
- PDET MunicipalPlanAnalyzer._generate_optimal_remediations
- PDET MunicipalPlanAnalyzer._simulate_intervention
- BayesianCounterfactualAuditor.counterfactual_query
- BayesianCounterfactualAuditor._test_effect_stability
- PolicyContradictionDetector._detect_numerical_inconsistencies
- PolicyContradictionDetector._calculate_numerical_divergence
- BayesianConfidenceCalculator.calculate_posterior
- PerformanceAnalyzer.analyze_performance

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

```

    raw_evidence = {}

    # Step 1: Audit evidence completeness
    direct_evidence_audit = self._execute_method(
        "OperationalizationAuditor", "_audit_direct_evidence", context
    )
    systemic_risk_audit = self._execute_method(
        "OperationalizationAuditor", "_audit_systemic_risk", context
    )

    # Step 2: Detect gaps in resource allocation and mechanisms
    allocation_gaps = self._execute_method(
        "FinancialAuditor", "_detect_allocation_gaps", context
    )

```

```

)
mechanism_gaps = self._execute_method(
    "BayesianMechanismInference", "_detect_gaps", context
)

# Step 3: Generate optimal remediations and simulate interventions
remediations = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_generate_optimal_remediations", context,
    gaps=allocation_gaps
)
simulation_results = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_simulate_intervention", context,
    remediations=remediations
)

# Step 4: Counterfactual analysis for problem dimensioning
counterfactual = self._execute_method(
    "BayesianCounterfactualAuditor", "counterfactual_query", context
)
effect_stability = self._execute_method(
    "BayesianCounterfactualAuditor", "_test_effect_stability", context,
    counterfactual=counterfactual
)

# Step 5: Detect numerical inconsistencies
numerical_inconsistencies = self._execute_method(
    "PolicyContradictionDetector", "_detect_numerical_inconsistencies", context
)
divergence_calc = self._execute_method(
    "PolicyContradictionDetector", "_calculate_numerical_divergence", context,
    inconsistencies=numerical_inconsistencies
)

# Step 6: Calculate confidence and analyze performance
posterior_confidence = self._execute_method(
    "BayesianConfidenceCalculator", "calculate_posterior", context,
    evidence=direct_evidence_audit
)
performance_analysis = self._execute_method(
    "PerformanceAnalyzer", "analyze_performance", context
)

raw_evidence = {
    "magnitude_indicators": {
        "allocation_gaps": allocation_gaps,
        "mechanism_gaps": mechanism_gaps,
        "numerical_inconsistencies": numerical_inconsistencies
    },
    "deficit_quantification": divergence_calc,
    "data_limitations": {
        "evidence_gaps": direct_evidence_audit.get("gaps", []),
        "systemic_risks": systemic_risk_audit
    },
    "simulation_results": simulation_results,
    "confidence_scores": posterior_confidence,
    "performance_metrics": performance_analysis
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "gaps_identified": len(allocation_gaps) + len(mechanism_gaps),
        "inconsistencies_found": len(numerical_inconsistencies)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),

```

```

        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

class D1_Q3_BudgetAllocationTracer(BaseExecutor):
    """
    Traces monetary resources assigned to programs in Investment Plan (PPI).
    """

    Methods (from D1-Q3):
    - FinancialAuditor.trace_financial_allocation
    - FinancialAuditor._process_financial_table
    - FinancialAuditor._match_program_to_node
    - FinancialAuditor._match_goal_to_budget
    - FinancialAuditor._perform_counterfactual_budget_check
    - FinancialAuditor._calculate_sufficiency
    - PDET MunicipalPlanAnalyzer.analyze_financial_feasibility
    - PDET MunicipalPlanAnalyzer._extract_budget_for_pillar
    - PDET MunicipalPlanAnalyzer._identify_funding_source
    - PDET MunicipalPlanAnalyzer._classify_tables
    - PDET MunicipalPlanAnalyzer._analyze_funding_sources
    - PDET MunicipalPlanAnalyzer._score_financial_component
    - BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}

        # Step 1: Trace complete financial allocation chain
        allocation_trace = self._execute_method(
            "FinancialAuditor", "trace_financial_allocation", context
        )
        processed_tables = self._execute_method(
            "FinancialAuditor", "_process_financial_table", context
        )

        # Step 2: Match programs to budget nodes
        program_matches = self._execute_method(
            "FinancialAuditor", "_match_program_to_node", context,
            tables=processed_tables
        )
        goal_budget_matches = self._execute_method(
            "FinancialAuditor", "_match_goal_to_budget", context,
            programs=program_matches
        )

        # Step 3: Counterfactual checks and sufficiency calculation
        counterfactual_check = self._execute_method(
            "FinancialAuditor", "_perform_counterfactual_budget_check", context,
            matches=goal_budget_matches
        )
        sufficiency_calc = self._execute_method(
            "FinancialAuditor", "_calculate_sufficiency", context,
            allocation=allocation_trace
        )

        # Step 4: Analyze financial feasibility
        feasibility_analysis = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "analyze_financial_feasibility", context
        )
        pillar_budgets = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_extract_budget_for_pillar", context
        )
        funding_sources = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_identify_funding_source", context
        )

        # Step 5: Classify and analyze tables

```

```

        table_classification = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_classify_tables", context,
            tables=processed_tables
        )
        funding_analysis = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_analyze_funding_sources", context,
            sources=funding_sources
        )
        financial_score = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_score_financial_component", context,
            analysis=funding_analysis
        )

    )

# Step 6: Aggregate risk and prioritize
risk_aggregation = self._execute_method(
    "BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize", context,
    sufficiency=sufficiency_calc
)

raw_evidence = {
    "budget_allocations": allocation_trace,
    "program_mappings": program_matches,
    "goal_budget_links": goal_budget_matches,
    "sufficiency_analysis": sufficiency_calc,
    "pillar_budgets": pillar_budgets,
    "funding_sources": funding_sources,
    "financial_feasibility": feasibility_analysis,
    "financial_score": financial_score,
    "risk_priorities": risk_aggregation
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "programs_traced": len(program_matches),
        "funding_sources_identified": len(funding_sources)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D1_Q4_InstitutionalCapacityIdentifier(BaseExecutor):

"""

Identifies installed capacity (entities, staff, equipment) and limitations.

Methods (from D1-Q4):

- PDETMunicipalPlanAnalyzer.identify_responsible_entities
- PDETMunicipalPlanAnalyzer._extract_entities_ner
- PDETMunicipalPlanAnalyzer._extract_entities_syntax
- PDETMunicipalPlanAnalyzer._classify_entity_type
- PDETMunicipalPlanAnalyzer._score_entity_specificity
- PDETMunicipalPlanAnalyzer._consolidate_entities
- MechanismPartExtractor.extract_entity_activity
- MechanismPartExtractor._normalize_entity
- MechanismPartExtractor._validate_entity_activity
- MechanismPartExtractor._calculate_ea_confidence
- OperationalizationAuditor.audit_evidence_traceability

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

Step 1: Identify all responsible entities

```

entities_identified = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "identify_responsible_entities", context
)

# Step 2: Extract entities using NER and syntax
ner_entities = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_extract_entities_ner", context
)
syntax_entities = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_extract_entities_syntax", context
)

# Step 3: Classify and score entities
entity_types = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_classify_entity_type", context,
    entities=ner_entities + syntax_entities
)
specificity_scores = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_score_entity_specificity", context,
    entities=entity_types
)
consolidated = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_consolidate_entities", context,
    entities=entity_types
)

# Step 4: Extract entity-activity relationships
entity_activities = self._execute_method(
    "MechanismPartExtractor", "extract_entity_activity", context,
    entities=consolidated
)
normalized = self._execute_method(
    "MechanismPartExtractor", "_normalize_entity", context,
    activities=entity_activities
)
validated = self._execute_method(
    "MechanismPartExtractor", "_validate_entity_activity", context,
    normalized=normalized
)
ea_confidence = self._execute_method(
    "MechanismPartExtractor", "_calculate_ea_confidence", context,
    validated=validated
)

# Step 5: Audit evidence traceability
traceability_audit = self._execute_method(
    "OperationalizationAuditor", "audit_evidence_traceability", context,
    entity_activities=validated
)

raw_evidence = {
    "entities_identified": consolidated,
    "entity_types": entity_types,
    "specificity_scores": specificity_scores,
    "entity_activities": validated,
    "activity_confidence": ea_confidence,
    "capacity_indicators": {
        "staff_mentions": [e for e in consolidated if e.get("type") == "staff"],
        "equipment_mentions": [e for e in consolidated if e.get("type") ==
"equipment"],
        "organizational_units": [e for e in consolidated if e.get("type") ==
"organization"]
    },
    "limitations_identified": traceability_audit.get("gaps", []),
    "traceability_audit": traceability_audit
}

return {

```

```

    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "entities_count": len(consolidated),
        "activities_extracted": len(validated)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D1_Q5_ScopeJustificationValidator(BaseExecutor):

"""
Validates scope justification via legal framework and constraint recognition.

Methods (from D1-Q5):

- TemporalLogicVerifier._check_deadline_constraints
- TemporalLogicVerifier.verify_temporal_consistency
- CausalInferenceSetup.identify_failure_points
- CausalExtractor._assess_temporal_coherence
- TextMiningEngine._analyze_link_text
- IndustrialPolicyProcessor._analyze_causal_dimensions
- IndustrialPolicyProcessor._extract_metadata

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

Step 1: Verify temporal constraints
deadline_constraints = self._execute_method(
 "TemporalLogicVerifier", "_check_deadline_constraints", context
)
temporal_consistency = self._execute_method(
 "TemporalLogicVerifier", "verify_temporal_consistency", context
)

Step 2: Identify failure points in scope
failure_points = self._execute_method(
 "CausalInferenceSetup", "identify_failure_points", context
)

Step 3: Assess temporal coherence
temporal_coherence = self._execute_method(
 "CausalExtractor", "_assess_temporal_coherence", context
)

Step 4: Analyze link text for justifications
link_analysis = self._execute_method(
 "TextMiningEngine", "_analyze_link_text", context
)

Step 5: Analyze causal dimensions and extract metadata
causal_dimensions = self._execute_method(
 "IndustrialPolicyProcessor", "_analyze_causal_dimensions", context
)
metadata_extracted = self._execute_method(
 "IndustrialPolicyProcessor", "_extract_metadata", context,
 dimensions=causal_dimensions
)

raw_evidence = {
 "legal_framework_citations": metadata_extracted.get("legal_refs", []),
 "temporal_constraints": {
 "deadline_checks": deadline_constraints,
 "consistency": temporal_consistency,

```

        "coherence": temporal_coherence
    },
    "budgetary_constraints": metadata_extracted.get("budget_limits", []),
    "competence_constraints": metadata_extracted.get("competence_refs", []),
    "failure_points": failure_points,
    "scope_justifications": link_analysis.get("justifications", []),
    "causal_dimensions": causal_dimensions
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "constraints_identified": len(deadline_constraints),
        "legal_citations": len(metadata_extracted.get("legal_refs", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

```

# =====
# DIMENSION 2: ACTIVITY DESIGN
# =====

```

```
class D2_Q1_StructuredPlanningValidator(BaseExecutor):
    """

```

Validates structured format of activities (table/matrix with required columns).

Methods (from D2-Q1):

- PDFProcessor.extract_tables
- FinancialAuditor._process_financial_table
- PDETMunicipalPlanAnalyzer._deduplicate_tables
- PDETMunicipalPlanAnalyzer._classify_tables
- PDETMunicipalPlanAnalyzer._is_likely_header
- PDETMunicipalPlanAnalyzer._clean_dataframe
- ReportingEngine.generate_accountability_matrix

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Extract all tables
    extracted_tables = self._execute_method(
        "PDFProcessor", "extract_tables", context
    )

    # Step 2: Process financial tables
    processed_tables = self._execute_method(
        "FinancialAuditor", "_process_financial_table", context,
        tables=extracted_tables
    )

    # Step 3: Deduplicate and classify tables
    deduplicated = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_deduplicate_tables", context,
        tables=processed_tables
    )
    classified = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_classify_tables", context,
        tables=deduplicated
    )

    # Step 4: Identify headers and clean dataframes
    header_checks = self._execute_method(

```

```

        "PDET Municipal Plan Analyzer", "_is_likely_header", context,
        tables=classified
    )
    cleaned = self._execute_method(
        "PDET Municipal Plan Analyzer", "_clean_dataframe", context,
        tables=classified
    )

    # Step 5: Generate accountability matrix
    accountability_matrix = self._execute_method(
        "Reporting Engine", "generate_accountability_matrix", context,
        tables=cleaned
    )

    raw_evidence = {
        "tables_extracted": len(extracted_tables),
        "activity_tables": [t for t in classified if t.get("type") == "activity"],
        "matrix_structure": accountability_matrix,
        "required_columns_present": {
            "responsible_entity": any("responsible" in str(t.get("columns",
                [])).lower()
                for t in cleaned),
            "deliverable": any("deliverable" in str(t.get("columns", [])).lower()
                for t in cleaned),
            "timeline": any("timeline" in str(t.get("columns", [])).lower()
                for t in cleaned),
            "cost": any("cost" in str(t.get("columns", [])).lower()
                for t in cleaned)
        },
        "table_quality": {
            "clean_tables": len(cleaned),
            "with_headers": sum(1 for h in header_checks if h)
        }
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "total_tables": len(extracted_tables),
            "activity_tables": len([t for t in classified if t.get("type") ==
                "activity"])
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}

```

class D2_Q2_InterventionLogicInferencer(BaseExecutor):

====

Infers intervention logic: instrument (how), target (who), causality (why).

Methods (from D2-Q2):

- BayesianMechanismInference.infer_mechanisms
 - BayesianMechanismInference._infer_single_mechanism
 - BayesianMechanismInference._infer_mechanism_type
 - BayesianMechanismInference._test_sufficiency
 - BayesianMechanismInference._test_necessity
 - CausalExtractor.extract_causal_hierarchy
 - TeoriaCambio.construir_grafo_causal
 - TeoriaCambio._esConexionValida
 - PDET Municipal Plan Analyzer.construct_causal_dag
 - BeachEvidentialTest.classify_test
 - IndustrialPolicyProcessor._analyze_causal_dimensions
- ====

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Infer mechanisms
    mechanisms = self._execute_method(
        "BayesianMechanismInference", "infer_mechanisms", context
    )
    single_mechanisms = []
    for mech in mechanisms:
        single = self._execute_method(
            "BayesianMechanismInference", "_infer_single_mechanism", context,
            mechanism=mech
        )
        single_mechanisms.append(single)

    mechanism_types = self._execute_method(
        "BayesianMechanismInference", "_infer_mechanism_type", context,
        mechanisms=single_mechanisms
    )

    # Step 2: Test sufficiency and necessity
    sufficiency_tests = self._execute_method(
        "BayesianMechanismInference", "_test_sufficiency", context,
        mechanisms=single_mechanisms
    )
    necessity_tests = self._execute_method(
        "BayesianMechanismInference", "_test_necessity", context,
        mechanisms=single_mechanisms
    )

    # Step 3: Extract causal hierarchy
    causal_hierarchy = self._execute_method(
        "CausalExtractor", "extract_causal_hierarchy", context
    )

    # Step 4: Build causal graph
    causal_graph = self._execute_method(
        "TeoriaCambio", "construir_grafo_causal", context,
        hierarchy=causal_hierarchy
    )
    connection_validation = self._execute_method(
        "TeoriaCambio", "_esConexionValida", context,
        graph=causal_graph
    )

    # Step 5: Construct DAG
    causal_dag = self._execute_method(
        "PDET Municipal Plan Analyzer", "construct_causal_dag", context,
        graph=causal_graph
    )

    # Step 6: Classify evidential tests
    evidential_tests = self._execute_method(
        "BeachEvidentialTest", "classify_test", context,
        mechanisms=single_mechanisms
    )

    # Step 7: Analyze causal dimensions
    causal_dimensions = self._execute_method(
        "IndustrialPolicyProcessor", "_analyze_causal_dimensions", context
    )

    raw_evidence = {
        "intervention_instruments": [m.get("instrument") for m in single_mechanisms],
        "target_populations": [m.get("target") for m in single_mechanisms],
        "causal_logic": {
            "mechanisms": single_mechanisms,
    
```

```

        "mechanism_types": mechanism_types,
        "sufficiency": sufficiency_tests,
        "necessity": necessity_tests
    },
    "causal_hierarchy": causal_hierarchy,
    "causal_graph": causal_graph,
    "causal_dag": causal_dag,
    "evidential_strength": evidential_tests,
    "dimensions": causal_dimensions
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "mechanisms_identified": len(single_mechanisms),
        "instruments_found": len([m for m in single_mechanisms if
m.get("instrument")])
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D2_Q3_RootCauseLinkageAnalyzer(BaseExecutor):

"""

Analyzes linkage between activities and root causes/structural determinants.

Methods (from D2-Q3):

- CausalExtractor._extract_causal_links
- CausalExtractor._calculate_composite_likelihood
- CausalExtractor._initialize_prior
- CausalExtractor._calculate_type_transition_prior
- PDETMunicipalPlanAnalyzer._identify_causal_edges
- PDETMunicipalPlanAnalyzer._refine_edge_probabilities
- BayesianCounterfactualAuditor.construct_scm
- BayesianCounterfactualAuditor._create_default_equations
- SemanticAnalyzer.extract_semantic_cube

""""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

Step 1: Extract causal links

```

    causal_links = self._execute_method(
        "CausalExtractor", "_extract_causal_links", context
    )

```

Step 2: Calculate likelihoods

```

    composite_likelihood = self._execute_method(
        "CausalExtractor", "_calculate_composite_likelihood", context,
        links=causal_links
    )

```

```

    prior_init = self._execute_method(
        "CausalExtractor", "_initialize_prior", context
    )

```

```

    type_transition_prior = self._execute_method(
        "CausalExtractor", "_calculate_type_transition_prior", context,
        links=causal_links
    )

```

Step 3: Identify and refine causal edges

```

    causal_edges = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_identify_causal_edges", context,
        links=causal_links
    )

```

```

)
refined_probabilities = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_refine_edge_probabilities", context,
    edges=causal_edges
)

# Step 4: Construct structural causal model
scm = self._execute_method(
    "BayesianCounterfactualAuditor", "construct_scm", context,
    edges=refined_probabilities
)
default_equations = self._execute_method(
    "BayesianCounterfactualAuditor", "_create_default_equations", context,
    scm=scm
)

# Step 5: Extract semantic cube
semantic_cube = self._execute_method(
    "SemanticAnalyzer", "extract_semantic_cube", context
)

raw_evidence = {
    "root_causes_identified": [link.get("root_cause") for link in causal_links],
    "activity_linkages": causal_links,
    "link_probabilities": refined_probabilities,
    "composite_likelihood": composite_likelihood,
    "structural_model": scm,
    "model_equations": default_equations,
    "semantic_relationships": semantic_cube,
    "determinants_addressed": [link for link in causal_links if
link.get("addresses_determinant")]
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "causal_links_found": len(causal_links),
        "root_causes_count": len(set(link.get("root_cause")) for link in
causal_links))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D2_Q4_RiskManagementAnalyzer(BaseExecutor):

.....

Identifies implementation risks and mitigation measures.

Methods (from D2-Q4):

- PDET MunicipalPlanAnalyzer._bayesian_risk_inference
 - PDET MunicipalPlanAnalyzer.sensitivity_analysis
 - PDET MunicipalPlanAnalyzer._interpret_risk
 - PDET MunicipalPlanAnalyzer._compute_robustness_value
 - PDET MunicipalPlanAnalyzer._compute_e_value
 - PDET MunicipalPlanAnalyzer._interpret_sensitivity
 - OperationalizationAuditor._audit_systemic_risk
 - BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
 - BayesianCounterfactualAuditor.refutation_and_sanity_checks
 - AdaptivePriorCalculator.sensitivity_analysis
-

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

```

# Step 1: Bayesian risk inference
risk_inference = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_bayesian_risk_inference", context
)

# Step 2: Sensitivity analysis
sensitivity = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "sensitivity_analysis", context,
    risks=risk_inference
)

# Step 3: Risk interpretation
risk_interpretation = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_interpret_risk", context,
    inference=risk_inference
)

# Step 4: Compute robustness metrics
robustness = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_compute_robustness_value", context,
    sensitivity=sensitivity
)
e_value = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_compute_e_value", context,
    robustness=robustness
)
sensitivity_interpretation = self._execute_method(
    "PDETMunicipalPlanAnalyzer", "_interpret_sensitivity", context,
    sensitivity=sensitivity
)

# Step 5: Audit systemic risks
systemic_risk_audit = self._execute_method(
    "OperationalizationAuditor", "_audit_systemic_risk", context
)

# Step 6: Aggregate and prioritize risks
risk_aggregation = self._execute_method(
    "BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize", context,
    risks=risk_inference
)

# Step 7: Refutation and sanity checks
refutation_checks = self._execute_method(
    "BayesianCounterfactualAuditor", "refutation_and_sanity_checks", context,
    aggregation=risk_aggregation
)

# Step 8: Additional sensitivity analysis
adaptive_sensitivity = self._execute_method(
    "AdaptivePriorCalculator", "sensitivity_analysis", context,
    risks=risk_inference
)

raw_evidence = {
    "operational_risks": [r for r in risk_inference if r.get("type") ==
"operational"],
    "social_risks": [r for r in risk_inference if r.get("type") == "social"],
    "security_risks": [r for r in risk_inference if r.get("type") == "security"],
    "mitigation_measures": risk_interpretation.get("mitigations", []),
    "risk_priorities": risk_aggregation,
    "robustness_metrics": {
        "robustness_value": robustness,
        "e_value": e_value
    },
    "sensitivity_analysis": sensitivity,
    "systemic_risks": systemic_risk_audit,
}

```

```

        "validation_checks": refutation_checks
    }

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "risks_identified": len(risk_inference),
        "mitigations_proposed": len(risk_interpretation.get("mitigations", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D2_Q5_StrategicCoherenceEvaluator(BaseExecutor):

"""

Evaluates strategic coherence: complementarity and logical sequence.

Methods (from D2-Q5):

- PolicyContradictionDetector._detect_logical_incompatibilities
- PolicyContradictionDetector._calculate_coherence_metrics
- PolicyContradictionDetector._calculate_objective_alignment
- PolicyContradictionDetector._calculate_graph_fragmentation
- OperationalizationAuditor.audit_sequence_logic
- BayesianMechanismInference._calculate_coherence_factor
- PDETMunicipalPlanAnalyzer._score_causal_coherence
- AdaptivePriorCalculator.calculate_likelihood_adaptativo

"""

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Detect logical incompatibilities
    incompatibilities = self._execute_method(
        "PolicyContradictionDetector", "_detect_logical_incompatibilities", context
    )

    # Step 2: Calculate coherence metrics
    coherence_metrics = self._execute_method(
        "PolicyContradictionDetector", "_calculate_coherence_metrics", context
    )
    objective_alignment = self._execute_method(
        "PolicyContradictionDetector", "_calculate_objective_alignment", context
    )
    graph_fragmentation = self._execute_method(
        "PolicyContradictionDetector", "_calculate_graph_fragmentation", context
    )

    # Step 3: Audit sequence logic
    sequence_audit = self._execute_method(
        "OperationalizationAuditor", "audit_sequence_logic", context
    )

    # Step 4: Calculate coherence factors
    coherence_factor = self._execute_method(
        "BayesianMechanismInference", "_calculate_coherence_factor", context,
        metrics=coherence_metrics
    )
    causal_coherence_score = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_score_causal_coherence", context
    )

    # Step 5: Adaptive likelihood calculation
    adaptive_likelihood = self._execute_method(

```

```

        "AdaptivePriorCalculator", "calculate_likelihood_adaptativo", context,
        coherence=causal_coherence_score
    )

raw_evidence = {
    "complementarity_evidence": coherence_metrics.get("complementarity", []),
    "sequential_logic": sequence_audit,
    "logical_incompatibilities": incompatibilities,
    "coherence_scores": {
        "overall_coherence": coherence_metrics,
        "objective_alignment": objective_alignment,
        "causal_coherence": causal_coherence_score,
        "coherence_factor": coherence_factor
    },
    "graph_metrics": {
        "fragmentation": graph_fragmentation
    },
    "adaptive_likelihood": adaptive_likelihood
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "incompatibilities_found": len(incompatibilities),
        "coherence_score": coherence_metrics.get("score", 0)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

```

# =====
# DIMENSION 3: PRODUCTS & OUTPUTS
# =====

```

```

class D3_Q1_IndicatorQualityValidator(BaseExecutor):
    """
    Validates indicator quality: baseline, target, source of verification.

```

Methods (from D3-Q1):

- PDETMunicipalPlanAnalyzer._score_indicators
- OperationalizationAuditor.audit_evidence_traceability
- CausalInferenceSetup.assign_probative_value
- BeachEvidentialTest.apply_test_logic
- TextMiningEngine.diagnose_critical_links
- IndustrialPolicyProcessor._extract_metadata
- IndustrialPolicyProcessor._calculate_quality_score
- AdaptivePriorCalculator.generate_traceability_record

"""

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
```

```
    raw_evidence = {}

    # Step 1: Score indicators
    indicator_scores = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_score_indicators", context
    )

    # Step 2: Audit evidence traceability
    traceability_audit = self._execute_method(
        "OperationalizationAuditor", "audit_evidence_traceability", context,
        indicators=indicator_scores
    )
```

```

# Step 3: Assign probative value
probative_values = self._execute_method(
    "CausalInferenceSetup", "assign_probative_value", context,
    indicators=indicator_scores
)

# Step 4: Apply evidential tests
evidential_tests = self._execute_method(
    "BeachEvidentialTest", "apply_test_logic", context,
    indicators=indicator_scores
)

# Step 5: Diagnose critical links
critical_links = self._execute_method(
    "TextMiningEngine", "diagnose_critical_links", context
)

# Step 6: Extract and score metadata
metadata = self._execute_method(
    "IndustrialPolicyProcessor", "_extract_metadata", context
)
quality_score = self._execute_method(
    "IndustrialPolicyProcessor", "_calculate_quality_score", context,
    metadata=metadata
)

# Step 7: Generate traceability record
traceability_record = self._execute_method(
    "AdaptivePriorCalculator", "generate_traceability_record", context,
    indicators=indicator_scores
)

raw_evidence = {
    "indicators_with_baseline": [i for i in indicator_scores if
i.get("has_baseline")],
    "indicators_with_target": [i for i in indicator_scores if
i.get("has_target")],
    "indicators_with_source": [i for i in indicator_scores if
i.get("has_source")],
    "indicator_quality_scores": indicator_scores,
    "traceability": traceability_audit,
    "probative_values": probative_values,
    "evidential_strength": evidential_tests,
    "overall_quality_score": quality_score,
    "traceability_record": traceability_record
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "total_indicators": len(indicator_scores),
        "complete_indicators": len([i for i in indicator_scores
            if i.get("has_baseline") and i.get("has_target") and
            i.get("has_source")])
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

class D3_Q2_TargetProportionalityAnalyzer(BaseExecutor):
    .....
    DIM03_Q02_PRODUCT_TARGET_PROPORIONALITY — Analyzes proportionality of targets to the
    diagnosed universe using canonical D3 notation.

```

Epistemic mix: structural coverage, financial/normative feasibility, statistical Bayes tests, and semantic indicator quality.

Methods (from D3-Q2):

- AdvancedDAGValidator._calculate_bayesian_posterior
 - AdvancedDAGValidator._calculate_confidence_interval
 - AdaptivePriorCalculator._adjust_domain_weights
 - PDET Municipal Plan Analyzer._get_spanish_stopwords
 - BayesianMechanismInference._log_refactored_components
 - PDET Municipal Plan Analyzer.analyze_financial_feasibility
 - PDET Municipal Plan Analyzer._score_indicators
 - PDET Municipal Plan Analyzer._interpret_risk
 - FinancialAuditor._calculate_sufficiency
 - BayesianMechanismInference._test_sufficiency
 - BayesianMechanismInference._test_necessity
 - PDET Municipal Plan Analyzer._assess_financial_sustainability
 - AdaptivePriorCalculator.calculate_likelihood_adaptativo
 - IndustrialPolicyProcessor._calculate_quality_score
 - TeoriaCambio._generar_sugerencias_internas
 - PDET Municipal Plan Analyzer._deduplicate_tables
 - PDET Municipal Plan Analyzer._indicator_to_dict
 - PDET Municipal Plan Analyzer._generate_recommendations
 - IndustrialPolicyProcessor._compile_pattern_registry
 - IndustrialPolicyProcessor._build_point_patterns
 - IndustrialPolicyProcessor._empty_result
- *****

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:  
    raw_evidence = {}  
    dim_info = get_dimension_info(CanonicalDimension.D3.value)  
  
    # Step 0: Financial feasibility snapshot and indicator quality  
    financial_feasibility = self._execute_method(  
        "PDET Municipal Plan Analyzer", "analyze_financial_feasibility", context  
    )  
    indicator_quality = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_score_indicators", context  
    )  
    spanish_stopwords = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_get_spanish_stopwords", context  
    )  
    funding_sources = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_analyze_funding_sources", context,  
        financial_indicators=financial_feasibility.get("financial_indicators", []),  
        tables=context.get("tables", [])  
    )  
    financial_component = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_score_financial_component", context,  
        financial_analysis=financial_feasibility  
    )  
    pattern_registry = self._execute_method(  
        "IndustrialPolicyProcessor", "_compile_pattern_registry", context  
    )  
    point_patterns = self._execute_method(  
        "IndustrialPolicyProcessor", "_build_point_patterns", context  
    )  
    empty_policy_result = self._execute_method(  
        "IndustrialPolicyProcessor", "_empty_result", context  
    )  
    dedup_tables = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_deduplicate_tables", context,  
        tables=context.get("tables", [])  
    )  
    first_indicator = None  
    if isinstance(financial_feasibility.get("financial_indicators", []), list):  
        inds = financial_feasibility.get("financial_indicators", [])  
        first_indicator = inds[0] if inds else None  
    indicator_dict = self._execute_method(
```

```

    "PDET Municipal Plan Analyzer", "_indicator_to_dict", context,
    ind=first_indicator if first_indicator else {}
)
proportionality_recommendations = self._execute_method(
    "PDET Municipal Plan Analyzer", "_generate_recommendations", context,
    analysis_results={"financial_analysis": financial_feasibility,
"quality_score": quality_score} if 'quality_score' in locals() else {}
)
# Step 1: Calculate sufficiency
sufficiency_calc = self._execute_method(
    "Financial Auditor", "_calculate_sufficiency", context
)

# Step 2: Test sufficiency and necessity of targets
sufficiency_test = self._execute_method(
    "Bayesian Mechanism Inference", "_test_sufficiency", context
)
necessity_test = self._execute_method(
    "Bayesian Mechanism Inference", "_test_necessity", context
)

# Step 3: Assess financial sustainability
sustainability_assessment = self._execute_method(
    "PDET Municipal Plan Analyzer", "_assess_financial_sustainability", context
)
risk_interpretation = self._execute_method(
    "PDET Municipal Plan Analyzer", "_interpret_risk", context,
    risk=financial_feasibility.get("risk_assessment", {}).get("risk_score", 0.0)
)

# Step 4: Calculate adaptive likelihood
adaptive_likelihood = self._execute_method(
    "Adaptive Prior Calculator", "calculate_likelihood_adaptativo", context
)
domain_scores = {
    "structural": sufficiency_calc.get("coverage_ratio", 0.0),
    "financial": financial_feasibility.get("sustainability_score", 0.0),
    "semantic": indicator_quality if isinstance(indicator_quality, (int, float))
}
else 0.0
}
adjusted_weights = self._execute_method(
    "Adaptive Prior Calculator", "_adjust_domain_weights", context,
    domain_scores=domain_scores
)
avg_confidence = self._execute_method(
    "Industrial Policy Processor", "_compute_avg_confidence", context,
    dimension_analysis={"D3": {"dimension_confidence": domain_scores.get("structural", 0.0)}}
)

# Step 5: Calculate quality score
quality_score = self._execute_method(
    "Industrial Policy Processor", "_calculate_quality_score", context
)

# Step 6: Generate internal suggestions
internalSuggestions = self._execute_method(
    "Teoria Cambio", "_generar_sugerencias_internas", context
)
# Bayesian posterior diagnostics for proportionality evidence
posterior_probability = self._execute_method(
    "Advanced DAG Validator", "_calculate_bayesian_posterior", context,
    likelihood=sufficiency_calc.get("coverage_ratio", 0.5),
    prior=0.5
)
confidence_interval = self._execute_method(
    "Advanced DAG Validator", "_calculate_confidence_interval", context,

```

```

        s=int(sufficiency_calc.get("covered_targets", 0)),
        n=max(1, int(sufficiency_calc.get("targets_total",
        len(context.get("product_targets", [])))), conf=0.95
    )
    self._execute_method(
        "BayesianMechanismInference", "_log_refactored_components", context
    )

raw_evidence = {
    "target_population_size": context.get("diagnosed_universe", 0),
    "product_targets": context.get("product_targets", []),
    "coverage_ratio": sufficiency_calc.get("coverage_ratio", 0),
    "dosage_analysis": sufficiency_calc.get("dosage", {}),
    "sufficiency_test": sufficiency_test,
    "necessity_test": necessity_test,
    "sustainability": sustainability_assessment,
    "financial_feasibility": financial_feasibility,
    "indicator_quality": indicator_quality,
    "risk_interpretation": risk_interpretation,
    "proportionality_score": quality_score,
    "recommendations": internal_suggestions,
    "stopwords_spanish": spanish_stopwords,
    "funding_sources_analysis": funding_sources,
    "financial_component_score": financial_component,
    "pattern_registry": pattern_registry,
    "point_patterns": point_patterns,
    "empty_policy_result": empty_policy_result,
    "avg_confidence": avg_confidence,
    "deduplicated_tables": dedup_tables,
    "indicator_sample": indicator_dict,
    "proportionality_recommendations": proportionality_recommendations,
    "adjusted_domain_weights": adjusted_weights,
    "posterior_proportionality": posterior_probability,
    "coverage_interval": confidence_interval
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "targets_analyzed": len(context.get("product_targets", [])),
        "coverage_adequate": sufficiency_calc.get("is_sufficient", False),
        "canonical_question": "DIM03_Q02_PRODUCT_TARGET_PROPORTIONALITY",
        "dimension_code": dim_info.code,
        "dimension_label": dim_info.label
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D3_Q3_TraceabilityValidator(BaseExecutor):

"""
 DIM03_Q03_TRACEABILITY_BUDGET_ORG — Validates budgetary and organizational
 traceability of products under canonical D3 notation.

Epistemic mix: structural budget tracing, organizational semantics, and accountability
 synthesis.

Methods executed (in order):

Step 1: Budget matching - FinancialAuditor._match_program_to_node

Step 2: Goal-budget matching - FinancialAuditor._match_goal_to_budget

Step 3: Responsibility extraction -

PDETMunicipalPlanAnalyzer._extract_from_responsibility_tables

Step 4: Entity consolidation - PDETMunicipalPlanAnalyzer._consolidate_entities

Step 5: Entity identification -
PDET Municipal Plan Analyzer identifies responsible entities

Step 6: Clarity scoring - PDET Municipal Plan Analyzer scores responsibility clarity

Step 7: Document processing - Policy Analysis Embedder processes document

Step 8: Query generation - Policy Analysis Embedder generates query from PDQ

Step 9: Semantic search - Policy Analysis Embedder performs semantic search

Step 10: MMR diversification - Policy Analysis Embedder applies MMR

Step 11: Semantic cube baseline - Semantic Analyzer creates empty semantic cube

Step 12: Policy domain classification - Semantic Analyzer classifies policy domain

Step 13: Cross-cutting themes - Semantic Analyzer classifies cross-cutting themes

Step 14: Value chain classification - Semantic Analyzer classifies value chain link

Step 15: Segment vectorization - Semantic Analyzer vectorizes segments

Step 16: Segment processing - Semantic Analyzer processes segments

Step 17: Semantic complexity - Semantic Analyzer calculates semantic complexity

Step 18: Evidence confidence - Industrial Policy Processor computes evidence confidence

Step 19: Entity serialization - PDET Municipal Plan Analyzer serializes entities (loop)

Step 20: Traceability record - Adaptive Prior Calculator generates traceability record

Step 21: PDQ report - Policy Analysis Embedder generates PDQ report

Step 22: Accountability matrix - Reporting Engine generates accountability matrix

.....

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}
    dim_info = get_dimension_info(CanonicalDimension.D3.value)
    document_text = context.get("document_text", "")
    document_metadata = context.get("metadata", {})

    # Step 1: Match programs to budget nodes
    program_matches = self._execute_method(
        "FinancialAuditor", "_match_program_to_node", context
    )
    goal_budget_matches = self._execute_method(
        "FinancialAuditor", "_match_goal_to_budget", context,
        programs=program_matches
    )

    # Step 2: Extract responsibility assignments
    responsibility_data = self._execute_method(
        "PDET Municipal Plan Analyzer", "_extract_from_responsibility_tables", context
    )
    consolidated_entities = self._execute_method(
        "PDET Municipal Plan Analyzer", "_consolidate_entities", context,
        entities=responsibility_data
    )
    responsible_entities = self._execute_method(
        "PDET Municipal Plan Analyzer", "identify_responsible_entities", context
    )
    responsibility_clarity = self._execute_method(
        "PDET Municipal Plan Analyzer", "_score_responsibility_clarity", context,
        entities=consolidated_entities
    )

    # Semantic traceability via embeddings
    semantic_chunks = self._execute_method(
        "Policy Analysis Embedder", "process_document", context,
        document_text=document_text,
        document_metadata=document_metadata
    )
    pdq_query = self._execute_method(
        "Policy Analysis Embedder", "_generate_query_from_pdq", context,
        pdq={"policy": context.get("policy_area"), "dimension": dim_info.code}
    )
    semantic_hits = self._execute_method(
        "Policy Analysis Embedder", "semantic_search", context,
        query=pdq_query,
        document_chunks=semantic_chunks or []
    )
    diversified_hits = self._execute_method(
        "Policy Analysis Embedder", "_apply_mmr", context,
```

```

ranked_results=semantic_hits or []
)
semantic_cube_stub = self._execute_method(
    "SemanticAnalyzer", "_empty_semantic_cube", context
)
domain_scores = self._execute_method(
    "SemanticAnalyzer", "_classify_policy_domain", context,
    segment=document_text
)
cross_cutting = self._execute_method(
    "SemanticAnalyzer", "_classify_cross_cutting_themes", context,
    segment=document_text
)
value_chain = self._execute_method(
    "SemanticAnalyzer", "_classify_value_chain_link", context,
    segment=document_text
)
semantic_vectors = self._execute_method(
    "SemanticAnalyzer", "_vectorize_segments", context,
    segments=[document_text]
)
processed_segment = self._execute_method(
    "SemanticAnalyzer", "_process_segment", context,
    segment=document_text,
    idx=0,
    vector=semantic_vectors[0] if semantic_vectors else None
)
semantic_complexity = self._execute_method(
    "SemanticAnalyzer", "_calculate_semantic_complexity", context,
    semantic_cube=semantic_cube_stub
)
evidence_confidence = self._execute_method(
    "IndustrialPolicyProcessor", "_compute_evidence_confidence", context,
    matches=[m.get("bpin", "") for m in program_matches if isinstance(m, dict)],
    text_length=len(document_text),
    pattern_specificity=0.5
)
entity_dicts = [
    self._execute_method("PDET Municipal Plan Analyzer", "_entity_to_dict", context,
entity=e)
    for e in consolidated_entities[:5]
    if isinstance(e, dict) or hasattr(e, "__dict__")
]
# Step 3: Generate traceability records
traceability_record = self._execute_method(
    "AdaptivePriorCalculator", "generate_traceability_record", context,
    matches=program_matches
)
# Step 4: Generate PDQ report
pdq_report = self._execute_method(
    "PolicyAnalysisEmbedder", "generate_pdq_report", context,
    traceability=traceability_record
)
# Step 5: Generate accountability matrix
accountability_matrix = self._execute_method(
    "ReportingEngine", "generate_accountability_matrix", context,
    entities=consolidated_entities
)
raw_evidence = {
    "budgetary_traceability": {
        "bpin_codes": [m.get("bpin") for m in program_matches if m.get("bpin")],
        "project_codes": [m.get("project_code") for m in program_matches if
m.get("project_code")],
        "budget_matches": goal_budget_matches
    }
}

```

```

        },
        "organizational_traceability": {
            "responsible_entities": consolidated_entities,
            "office_assignments": [e for e in consolidated_entities if
e.get("office")],
            "secretariat_assignments": [e for e in consolidated_entities if
e.get("secretariat")]
        },
        "traceability_record": traceability_record,
        "pdq_report": pdq_report,
        "accountability_matrix": accountability_matrix,
        "responsible_entities": responsible_entities,
        "responsibility_clarity_score": responsibility_clarity,
        "semantic_traceability": {
            "query": pdq_query,
            "semantic_hits": semantic_hits,
            "diversified_hits": diversified_hits
        },
        "semantic_cube_baseline": semantic_cube_stub,
        "policy_domain_scores": domain_scores,
        "responsibility_entities_dict": entity_dicts,
        "cross_cutting_themes": cross_cutting,
        "value_chain_links": value_chain,
        "semantic_vectors": semantic_vectors,
        "semantic_complexity": semantic_complexity,
        "evidence_confidence": evidence_confidence,
        "processed_segment": processed_segment
    }
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "products_with_bpin": len([m for m in program_matches if isinstance(m,
dict) and m.get("bpin")]),
        "products_with_responsible": len(consolidated_entities) if
consolidated_entities else 0,
        "total_semantic_hits": len(semantic_hits) if semantic_hits else 0,
        "has_semantic_hits": bool(semantic_hits),
        "total_responsible_entities": len(responsible_entities) if
responsible_entities else 0,
        "has_responsible_entities": bool(responsible_entities),
        "total_diversified_hits": len(diversified_hits) if diversified_hits else
0,
        "total_entity_dicts": len(entity_dicts) if entity_dicts else 0,
        "has_semantic_vectors": bool(semantic_vectors),
        "total_semantic_vectors": len(semantic_vectors) if semantic_vectors else
0,
        "canonical_question": "DIM03_Q03_TRACEABILITY_BUDGET_ORG",
        "dimension_code": dim_info.code,
        "dimension_label": dim_info.label
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D3_Q4_TechnicalFeasibilityEvaluator(BaseExecutor):

"""
DIM03_Q04_TECHNICAL_FEASIBILITY — Evaluates activity-product feasibility vs
resources/deadlines (canonical D3).

Epistemic mix: structural DAG validity, causal necessity, performance/implementation
readiness, and statistical robustness.

Methods executed (in order):

```

Step 1: Acyclicity p-value - AdvancedDAGValidator.calculate_acyclicity_pvalue
Step 2: Acyclicity check - AdvancedDAGValidator._is_acyclic
Step 3: Graph statistics - AdvancedDAGValidator.get_graph_stats
Step 4: Node importance - AdvancedDAGValidator._calculate_node_importance
Step 5: Subgraph generation - AdvancedDAGValidator._generate_subgraph
Step 6: Node addition - AdvancedDAGValidator.add_node
Step 7: Edge addition - AdvancedDAGValidator.add_edge
Step 8: Node export - AdvancedDAGValidator.export_nodes
Step 9: RNG initialization - AdvancedDAGValidator._initialize_rng
Step 10: Statistical power - AdvancedDAGValidator._calculate_statistical_power
Step 11: Node validator - AdvancedDAGValidator._get_node_validator
Step 12: Empty result creation - AdvancedDAGValidator._create_empty_result
Step 13: Necessity test - BayesianMechanismInference._test_necessity
Step 14: Validation suite - IndustrialGradeValidator.execute_suite
Step 15: Connection matrix - IndustrialGradeValidator.validate_connection_matrix
Step 16: Performance benchmarks - IndustrialGradeValidator.run_performance_benchmarks
Step 17: Benchmark operation - IndustrialGradeValidator._benchmark_operation
Step 18: Metric logging - IndustrialGradeValidator._log_metric
Step 19: Engine readiness - IndustrialGradeValidator.validate_engine_readiness
Step 20: Performance analysis - PerformanceAnalyzer.analyze_performance
Step 21: Loss functions - PerformanceAnalyzer._calculate_loss_functions
Step 22: Resource likelihood - HierarchicalGenerativeModel._calculate_likelihood
Step 23: ESS calculation - HierarchicalGenerativeModel._calculate_ess
Step 24: R-hat calculation - HierarchicalGenerativeModel._calculate_r_hat
Step 25: Causal categories validation -
IndustrialGradeValidator.validate_causal_categories
Step 26: Category extraction - TeoriaCambio._extraer_categorias
"""

```

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}
    dim_info = get_dimension_info(CanonicalDimension.D3.value)
    plan_name = context.get("metadata", {}).get("title", "plan_desarrollo")

    # Step 1: Validate DAG structure
    acyclicity_pvalue = self._execute_method(
        "AdvancedDAGValidator", "calculate_acyclicity_pvalue", context
    )
    is_acyclic = self._execute_method(
        "AdvancedDAGValidator", "_is_acyclic", context
    )
    graph_stats = self._execute_method(
        "AdvancedDAGValidator", "get_graph_stats", context
    )
    node_importance = self._execute_method(
        "AdvancedDAGValidator", "_calculate_node_importance", context
    )
    subgraph = self._execute_method(
        "AdvancedDAGValidator", "_generate_subgraph", context
    )
    added_node = self._execute_method(
        "AdvancedDAGValidator", "add_node", context,
        node_name="temp_node"
    )
    added_edge = self._execute_method(
        "AdvancedDAGValidator", "add_edge", context,
        source="temp_node",
        target="temp_target",
        weight=1.0
    )
    node_export = self._execute_method(
        "AdvancedDAGValidator", "export_nodes", context
    )
    rng_seed = self._execute_method(
        "AdvancedDAGValidator", "_initialize_rng", context,
        plan_name=plan_name,
        salt=dim_info.code
    )

```

```

stat_power = self._execute_method(
    "AdvancedDAGValidator", "_calculate_statistical_power", context,
    s=int(graph_stats.get("edges", 0)),
    n=max(1, int(graph_stats.get("nodes", 1))))
)
node_validator = self._execute_method(
    "AdvancedDAGValidator", "_get_node_validator", context,
    node_type="producto"
)
empty_result = self._execute_method(
    "AdvancedDAGValidator", "_create_empty_result", context,
    plan_name=plan_name,
    seed=rng_seed,
    timestamp=context.get("metadata", {}).get("timestamp", ""))
)

# Step 2: Test necessity of activities for products
necessity_test = self._execute_method(
    "BayesianMechanismInference", "_test_necessity", context
)

# Step 3: Execute industrial-grade validation
validation_suite = self._execute_method(
    "IndustrialGradeValidator", "execute_suite", context
)
connection_validation = self._execute_method(
    "IndustrialGradeValidator", "validate_connection_matrix", context
)
performance_benchmarks = self._execute_method(
    "IndustrialGradeValidator", "run_performance_benchmarks", context
)
benchmark_ops = self._execute_method(
    "IndustrialGradeValidator", "_benchmark_operation", context
)
metric_log = self._execute_method(
    "IndustrialGradeValidator", "_log_metric", context,
    name="custom_latency",
    value=graph_stats.get("edges", 0),
    unit="edges",
    threshold=10.0
)
engine_readiness = self._execute_method(
    "IndustrialGradeValidator", "validate_engine_readiness", context
)

# Step 4: Analyze performance
performance_analysis = self._execute_method(
    "PerformanceAnalyzer", "analyze_performance", context
)
loss_functions = self._execute_method(
    "PerformanceAnalyzer", "_calculate_loss_functions", context
)
# Likelihood estimation for resource adequacy
resource_likelihood = self._execute_method(
    "HierarchicalGenerativeModel", "_calculate_likelihood", context,
    mechanism_type="tecnico",
    observations={"coherence": (performance_analysis or {}).get("resource_fit",
    {}).get("score", 0.0)})
)

# Step 5: Calculate effective sample size
ess = self._execute_method(
    "HierarchicalGenerativeModel", "_calculate_ess", context
)
r_hat = self._execute_method(
    "HierarchicalGenerativeModel", "_calculate_r_hat", context,
    chains=[]
)

```

```

causal_categories_valid = self._execute_method(
    "IndustrialGradeValidator", "validate_causal_categories", context
)
extracted_categories = self._execute_method(
    "TeoriaCambio", "_extraer_categorias", context,
    text=context.get("document_text", "")
)

raw_evidence = {
    "activity_product_mapping": connection_validation,
    "resource_adequacy": (performance_analysis or {}).get("resource_fit", {}),
    "timeline_feasibility": (performance_analysis or
    {}).get("timeline_feasibility", {}),
    "technical_validation": {
        "dag_valid": is_acyclic,
        "acyclicity_p": acyclicity_pvalue,
        "necessity_score": necessity_test,
        "graph_stats": graph_stats,
        "node_importance": node_importance,
        "subgraph_sample": subgraph,
        "added_node": added_node,
        "added_edge": added_edge,
        "node_validator": node_validator,
        "empty_result": empty_result,
        "node_export": node_export,
        "rng_seed": rng_seed,
        "statistical_power": stat_power
    },
    "performance_metrics": {
        "benchmarks": performance_benchmarks,
        "loss_functions": loss_functions,
        "ess": ess,
        "r_hat": r_hat,
        "resource_likelihood": resource_likelihood
    },
    "engine_readiness": engine_readiness,
    "feasibility_score": validation_suite.get("overall_score", 0),
    "causal_categories_valid": causal_categories_valid,
    "extracted_categories": extracted_categories,
    "metric_log": metric_log
}
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "dag_is_valid": is_acyclic,
        "feasibility_score": (validation_suite or {}).get("overall_score", 0) if
validation_suite else 0,
        "total_graph_nodes": (graph_stats or {}).get("nodes", 0) if graph_stats
else 0,
        "total_graph_edges": (graph_stats or {}).get("edges", 0) if graph_stats
else 0,
        "has_node_export": bool(node_export),
        "total_exported_nodes": len(node_export) if node_export else 0,
        "has_subgraph": bool(subgraph),
        "total_extracted_categories": len(extracted_categories) if
extracted_categories else 0,
        "has_extracted_categories": bool(extracted_categories),
        "statistical_power": stat_power if isinstance(stat_power, (int, float))
else 0.0,
        "has_engine_readiness": bool(engine_readiness),
        "canonical_question": "DIM03_Q04_TECHNICAL_FEASIBILITY",
        "dimension_code": dim_info.code,
        "dimension_label": dim_info.label
    },
    "execution_metrics": {

```

```

        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

class D3_Q5_OutputOutcomeLinkageAnalyzer(BaseExecutor):
    """
    DIM03_Q05_OUTPUT_OUTCOME_LINKAGE — Analyzes mechanisms linking outputs to outcomes
    with canonical D3 labeling.
    Epistemic mix: semantic hierarchy checks, causal order validation, DAG/effect
    estimation, and Bayesian mechanism inference.

    Methods (from D3-Q5):
    - PDETMunicipalPlanAnalyzer._identify_cofounders
    - PDETMunicipalPlanAnalyzer._effect_to_dict
    - PDETMunicipalPlanAnalyzer._scenario_to_dict
    - PDETMunicipalPlanAnalyzer._simulate_intervention
    - PDETMunicipalPlanAnalyzer._generate_recommendations
    - PDETMunicipalPlanAnalyzer._identify_causal_nodes
    - BayesianCounterfactualAuditor._evaluate_factual
    - BayesianCounterfactualAuditor._evaluate_counterfactual
    - CausalExtractor._assess_financial_consistency
    - BayesianMechanismInference._infer_activity_sequence
    - BayesianMechanismInference._generate_necessity_remediation
    - BayesianCounterfactualAuditor.refutation_and_sanity_checks
    - IndustrialPolicyProcessor._load_questionnaire
    - PDETMunicipalPlanAnalyzer.analyze_financial_feasibility
    - PDETMunicipalPlanAnalyzer.construct_causal_dag
    - PDETMunicipalPlanAnalyzer.estimate_causal_effects
    - PDETMunicipalPlanAnalyzer.generate_counterfactuals
    - CausalExtractor._build_type_hierarchy
    - CausalExtractor._check_structuralViolation
    - CausalExtractor._calculate_type_transition_prior
    - CausalExtractor._calculate_textual_proximity
    - TeoriaCambio._validar_orden_causal
    - PDETMunicipalPlanAnalyzer._refine_edge_probabilities
    - PolicyAnalysisEmbedder.compare_policy_interventions
    - BayesianMechanismInference.infer_mechanisms
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}
        dim_info = get_dimension_info(CanonicalDimension.D3.value)

        # Step 0: Build causal backbone and effects
        financial_analysis = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "analyze_financial_feasibility", context
        )
        causal_dag = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "construct_causal_dag", context,
            financial_analysis=financial_analysis
        )
        causal_effects = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "estimate_causal_effects", context,
            dag=causal_dag,
            financial_analysis=financial_analysis
        )
        counterfactuals = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "generate_counterfactuals", context,
            dag=causal_dag,
            causal_effects=causal_effects,
            financial_analysis=financial_analysis
        )
        simulated_intervention = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_simulate_intervention", context,
            intervention={},
            dag=causal_dag,
        )

```

```

causal_effects=causal_effects,
label="baseline"
)
causal_nodes = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_identify_causal_nodes", context,
    text=context.get("document_text", ""),
    tables=context.get("tables", []),
    financial_analysis=financial_analysis
)
confounders = {}
for effect in causal_effects:
    treatment = effect.treatment if hasattr(effect, "treatment") else None
    outcome = effect.outcome if hasattr(effect, "outcome") else None
    if treatment and outcome:
        confounders[(treatment, outcome)] = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_identify_confounders", context,
            treatment=treatment,
            outcome=outcome,
            dag=causal_dag
        )
effect_dicts = [
    self._execute_method("PDET MunicipalPlanAnalyzer", "_effect_to_dict", context,
effect=effect)
    for effect in causal_effects
]
scenario_dicts = [
    self._execute_method("PDET MunicipalPlanAnalyzer", "_scenario_to_dict",
context, scenario=scenario)
    for scenario in counterfactuals
]
causal_recommendations = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_generate_recommendations", context,
    analysis_results={"financial_analysis": financial_analysis, "quality_score":getattr(causal_dag, 'graph', {})}
)
financial_consistency = None
if refined_edges:
    first_edge = refined_edges[0] if isinstance(refined_edges, list) else {}
    source = first_edge.get("source") if isinstance(first_edge, dict) else ""
    target = first_edge.get("target") if isinstance(first_edge, dict) else ""
    financial_consistency = self._execute_method(
        "CausalExtractor", "_assess_financial_consistency", context,
        source=source or "",
        target=target or ""
    )
factual_eval = None
counterfactual_eval = None
if causal_effects:
    first_effect = causal_effects[0]
    target = getattr(first_effect, "outcome", None) or ""
    evidence = {"p_effect": getattr(first_effect, "probability_significant", 0.0)}
    factual_eval = self._execute_method(
        "BayesianCounterfactualAuditor", "_evaluate_factual", context,
        target=target,
        evidence=evidence
    )
    counterfactual_eval = self._execute_method(
        "BayesianCounterfactualAuditor", "_evaluate_counterfactual", context,
        target=target,
        intervention={"shift": 0.1}
    )
matched_node = None
try:
    matched_node = self._execute_method(
        "PDET MunicipalPlanAnalyzer", "_match_text_to_node", context,
        text=context.get("document_text", "")[:200],
        nodes=causal_nodes if isinstance(causal_nodes, dict) else {}
    )

```

```

except Exception:
    matched_node = None

# Step 1: Build type hierarchy
type_hierarchy = self._execute_method(
    "CausalExtractor", "_build_type_hierarchy", context
)

# Step 2: Check structural violations
structural_violations = self._execute_method(
    "CausalExtractor", "_check_structuralViolation", context,
    hierarchy=type_hierarchy
)

# Step 3: Calculate transition priors and proximity
transition_priors = self._execute_method(
    "CausalExtractor", "_calculate_type_transition_prior", context,
    hierarchy=type_hierarchy
)
textual_proximity = self._execute_method(
    "CausalExtractor", "_calculate_textual_proximity", context
)

# Step 4: Validate causal order
causal_order_validation = self._execute_method(
    "TeoriaCambio", "_validar_orden_causal", context,
    hierarchy=type_hierarchy
)

# Step 5: Refine edge probabilities
refined_edges = self._execute_method(
    "PDET Municipal Plan Analyzer", "_refine_edge_probabilities", context,
    priors=transition_priors
)

# Step 6: Compare policy interventions
intervention_comparison = self._execute_method(
    "PolicyAnalysisEmbedder", "compare_policy_interventions", context
)

# Step 7: Infer mechanisms
mechanisms = self._execute_method(
    "BayesianMechanismInference", "infer_mechanisms", context,
    edges=refined_edges
)
mechanism_sample = next(iter(mechanisms.values()), {})
activity_sequence = self._execute_method(
    "BayesianMechanismInference", "_infer_activity_sequence", context,
    observations=mechanism_sample.get("observations", {}),
    mechanism_type_posterior=mechanism_sample.get("mechanism_type", {"tecnico": 1.0})
)
quantified_uncertainty = self._execute_method(
    "BayesianMechanismInference", "_quantify_uncertainty", context,
    mechanism_type_posterior=mechanism_sample.get("mechanism_type", {"tecnico": 1.0}),
    sequence_posterior=mechanism_sample.get("activity_sequence", {}),
    coherence_score=mechanism_sample.get("coherence_score", 0.0)
)
mechanism_observations = self._execute_method(
    "BayesianMechanismInference", "_extract_observations", context,
    node={"id": next(iter(mechanisms.keys()), "")},
    text=context.get("document_text", "")
)
necessity_remediation = self._execute_method(
    "BayesianMechanismInference", "_generate_necessity_remediation", context,
    node_id=next(iter(mechanisms.keys()), ""),
    missing_components=structural_violations
)

```

```

        )
        questionnaire_stub = self._execute_method(
            "IndustrialPolicyProcessor", "_load_questionnaire", context
        )
        refutation_checks = None
    try:
        confounder_keys = list(confounders.keys())
        first_pair = confounder_keys[0] if confounder_keys else ("", "")
        refutation_checks = self._execute_method(
            "BayesianCounterfactualAuditor", "refutation_and_sanity_checks", context,
            dag=getattr(causal_dag, "graph", None),
            target=first_pair[1],
            treatment=first_pair[0],
            confounders=list(confounders.values())[0] if confounders else []
        )
    except Exception:
        refutation_checks = None

    raw_evidence = {
        "output_outcome_links": refined_edges,
        "mechanism_explanation": mechanisms,
        "type_hierarchy": type_hierarchy,
        "causal_dag": causal_dag,
        "causal_effects": causal_effects,
        "counterfactuals": counterfactuals,
        "simulated_intervention": simulated_intervention,
        "causal_nodes": causal_nodes,
        "financial_analysis": financial_analysis,
        "causal_validity": {
            "structural_violations": structuralViolations,
            "order_valid": causal_order_validation
        },
        "transition_probabilities": transition_priors,
        "textual_proximity": textual_proximity,
        "intervention_comparison": intervention_comparison,
        "confounders": confounders,
        "effect_dicts": effect_dicts,
        "scenario_dicts": scenario_dicts,
        "activity_sequence_sample": activity_sequence,
        "uncertainty_quantified": quantifiedUncertainty,
        "mechanism_observations": mechanism_observations,
        "refutation_checks": refutation_checks,
        "necessity_remediation": necessityRemediation,
        "questionnaire_stub": questionnaire_stub,
        "causal_recommendations": causalRecommendations,
        "financial_consistency": financialConsistency,
        "factual_eval": factualEval,
        "counterfactual_eval": counterfactualEval,
        "matched_node": matchedNode
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "mechanisms_identified": len(mechanisms),
            "violations_found": len(structural_violations),
            "canonical_question": "DIM03_Q05_OUTPUT_OUTCOME_LINKAGE",
            "dimension_code": dim_info.code,
            "dimension_label": dim_info.label
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}

```

```

# =====
# DIMENSION 4: RESULTS & OUTCOMES
# =====

class D4_Q1_OutcomeMetricsValidator(BaseExecutor):
    """
    DIM04_Q01_OUTCOME_INDICATOR_COMPLETENESS — Validates outcome indicators (baseline,
    target, horizon) with canonical D4 notation.

    Epistemic mix: semantic goal extraction, temporal/consistency checks, statistical
    performance signals, and indicator quality scoring.
    """

    Methods (from D4-Q1):
    - PDET Municipal Plan Analyzer methods:
        - _extract_entities_syntax
        - _extract_entities_ner
        - _calculate_language_specificity
        - _calculate_composite_likelihood
        - _calculate_semantic_distance
        - _classify_temporal_type
        - _score_indicators
        - _find_outcome_mentions
        - _score_temporal_consistency
        - _extract_goals
        - _parse_goal_context
        - _classify_goal_type
        - _parse_temporal_marker
        - _extract_resources
        - analyze_performance
        - generate_recommendations
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}
        dim_info = get_dimension_info(CanonicalDimension.D4.value)

        # Step 1: Find outcome mentions
        outcome_mentions = self._execute_method(
            "PDET Municipal Plan Analyzer", "_find_outcome_mentions", context
        )
        entities_syntax = self._execute_method(
            "PDET Municipal Plan Analyzer", "_extract_entities_syntax", context,
            text=context.get("document_text", "")
        )
        entities_ner = self._execute_method(
            "PDET Municipal Plan Analyzer", "_extract_entities_ner", context,
            text=context.get("document_text", "")
        )

        # Step 2: Score temporal consistency
        temporal_consistency = self._execute_method(
            "PDET Municipal Plan Analyzer", "_score_temporal_consistency", context,
            outcomes=outcome_mentions
        )

        # Step 3: Extract and classify goals
        goals = self._execute_method(
            "Causal Extractor", "_extract_goals", context
        )
        goal_contexts = self._execute_method(
            "Causal Extractor", "_parse_goal_context", context,
            goals=goals
        )
        goal_types = self._execute_method(
            "Causal Extractor", "_classify_goal_type", context,
            goals=goals
        )

        semantic_distance = 0.0
        if goal_types and outcome_mentions:

```

```

semantic_distance = self._execute_method(
    "CausalExtractor", "_calculate_semantic_distance", context,
    source=str(goal_types[0]),
    target=str(outcome_mentions[0])
)

# Step 4: Parse temporal markers
temporal_markers = self._execute_method(
    "TemporalLogicVerifier", "_parse_temporal_marker", context,
    contexts=goal_contexts
)
temporal_type = self._execute_method(
    "TemporalLogicVerifier", "_classify_temporal_type", context,
    marker=temporal_markers[0] if temporal_markers else ""
)
resources_mentioned = self._execute_method(
    "TemporalLogicVerifier", "_extract_resources", context,
    text=context.get("document_text", "")
)
precedence_check = self._execute_method(
    "TemporalLogicVerifier", "_should_precede", context,
    marker_a=temporal_markers[0] if temporal_markers else "",
    marker_b=temporal_markers[1] if len(temporal_markers) > 1 else ""
)

# Step 5: Analyze performance
performance_analysis = self._execute_method(
    "PerformanceAnalyzer", "analyze_performance", context,
    outcomes=outcome_mentions
)
indicator_quality = self._execute_method(
    "PDET Municipal Plan Analyzer", "_score_indicators", context
)
performance_recommendations = self._execute_method(
    "PerformanceAnalyzer", "_generate_recommendations", context,
    performance_analysis=performance_analysis
)
# Semantic certainty for goals
language_specificity = self._execute_method(
    "CausalExtractor", "_calculate_language_specificity", context,
    keyword=goal_contexts[0] if goal_contexts else "",
    policy_area=context.get("policy_area")
)
composite_likelihood = self._execute_method(
    "CausalExtractor", "_calculate_composite_likelihood", context,
    evidence={
        "semantic_distance": indicator_quality if isinstance(indicator_quality,
        (int, float)) else 0.0,
        "textual_proximity": performance_analysis.get("coherence_score", 0.0) if
        isinstance(performance_analysis, dict) else 0.0,
        "language_specificity": language_specificity,
        "temporal_coherence": temporal_consistency if
        isinstance(temporal_consistency, (int, float)) else 0.0
    }
)
raw_evidence = {
    "outcome_indicators": outcome_mentions,
    "indicators_with_baseline": [o for o in outcome_mentions if
    o.get("has_baseline")],
    "indicators_with_target": [o for o in outcome_mentions if
    o.get("has_target")],
    "indicators_with_horizon": [o for o in outcome_mentions if
    o.get("time_horizon")],
    "temporal_consistency_score": temporal_consistency,
    "goal_classifications": goal_types,
    "temporal_markers": temporal_markers,
    "performance_metrics": performance_analysis,
}

```

```

        "indicator_quality": indicator_quality,
        "performance_recommendations": performance_recommendations,
        "entities_syntax": entities_syntax,
        "entities_ner": entities_ner,
        "temporal_type": temporal_type,
        "language_specificity": language_specificity,
        "composite_likelihood": composite_likelihood,
        "goal_outcome_semantic_distance": semantic_distance,
        "resources_mentioned": resources_mentioned,
        "precedence_check": precedence_check
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "total_outcomes": len(outcome_mentions),
            "complete_indicators": len([o for o in outcome_mentions
                if o.get("has_baseline") and o.get("has_target") and
                o.get("time_horizon")]),
            "canonical_question": "DIM04_Q01_OUTCOME_INDICATOR_COMPLETENESS",
            "dimension_code": dim_info.code,
            "dimension_label": dim_info.label
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}

```

class D4_Q2_CausalChainValidator(BaseExecutor):

"""
Validates explicit causal chain with assumptions and enabling conditions.

Methods (from D4-Q2):

- TeoriaCambio._encontrar_caminos_completos
 - TeoriaCambio.validacion_completa
 - CausalExtractor.extract_causal_hierarchy
 - HierarchicalGenerativeModel.verify_conditional_independence
 - HierarchicalGenerativeModel._generate_independence_tests
 - BayesianCounterfactualAuditor.construct_scm
 - AdvancedDAGValidator._perform_sensitivity_analysis_internal
 - BayesFactorTable.get_bayes_factor
- """

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Find complete causal paths
    complete_paths = self._execute_method(
        "TeoriaCambio", "_encontrar_caminos_completos", context
    )

    # Step 2: Complete validation
    validation_results = self._execute_method(
        "TeoriaCambio", "validacion_completa", context,
        paths=complete_paths
    )

    # Step 3: Extract causal hierarchy
    causal_hierarchy = self._execute_method(
        "CausalExtractor", "extract_causal_hierarchy", context
    )

    # Step 4: Verify conditional independence
    independence_verification = self._execute_method(

```

```

        "HierarchicalGenerativeModel", "verify_conditional_independence", context,
        hierarchy=causal_hierarchy
    )
independence_tests = self._execute_method(
    "HierarchicalGenerativeModel", "_generate_independence_tests", context,
    verification=independence_verification
)

# Step 5: Construct structural causal model
scm = self._execute_method(
    "BayesianCounterfactualAuditor", "construct_scm", context,
    hierarchy=causal_hierarchy
)

# Step 6: Perform sensitivity analysis
sensitivity_analysis = self._execute_method(
    "AdvancedDAGValidator", "_perform_sensitivity_analysis_internal", context,
    scm=scm
)

# Step 7: Get Bayes factor
bayes_factor = self._execute_method(
    "BayesFactorTable", "get_bayes_factor", context,
    analysis=sensitivity_analysis
)

raw_evidence = {
    "causal_chain": complete_paths,
    "key_assumptions": validation_results.get("assumptions", []),
    "enabling_conditions": validation_results.get("conditions", []),
    "external_factors": validation_results.get("external_factors", []),
    "causal_hierarchy": causal_hierarchy,
    "independence_tests": independence_tests,
    "structural_model": scm,
    "sensitivity": sensitivity_analysis,
    "evidential_strength": bayes_factor
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "complete_paths_found": len(complete_paths),
        "assumptions_identified": len(validation_results.get("assumptions", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

```

class D4_Q3_AmbitionJustificationAnalyzer(BaseExecutor):
    """
    Analyzes justification of result ambition based on investment/capacity/benchmarks.

```

Methods (from D4-Q3):

- PDET Municipal Plan Analyzer methods:
 - `_get_prior_effect`
 - `_estimate_effect_bayesian`
 - `_compute_robustness_value`
 - `sensitivity_analysis`
 - `_calculate_r_hat`
 - `_calculate_ess`
 - `_calculate_statistical_power`
 - `_aggregate_bayesian_confidence`

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Get prior effect estimates
    prior_effects = self._execute_method(
        "PDET Municipal Plan Analyzer", "_get_prior_effect", context
    )

    # Step 2: Estimate effect using Bayesian methods
    effect_estimate = self._execute_method(
        "PDET Municipal Plan Analyzer", "_estimate_effect_bayesian", context,
        priors=prior_effects
    )

    # Step 3: Compute robustness
    robustness = self._execute_method(
        "PDET Municipal Plan Analyzer", "_compute_robustness_value", context,
        estimate=effect_estimate
    )

    # Step 4: Sensitivity analysis
    sensitivity = self._execute_method(
        "Adaptive Prior Calculator", "sensitivity_analysis", context,
        estimate=effect_estimate
    )

    # Step 5: Calculate convergence diagnostics
    r_hat = self._execute_method(
        "Hierarchical Generative Model", "_calculate_r_hat", context
    )
    ess = self._execute_method(
        "Hierarchical Generative Model", "_calculate_ess", context
    )

    # Step 6: Calculate statistical power
    statistical_power = self._execute_method(
        "Advanced DAG Validator", "_calculate_statistical_power", context,
        effect=effect_estimate
    )

    # Step 7: Aggregate confidence
    confidence_aggregate = self._execute_method(
        "Bayesian Mechanism Inference", "_aggregate_bayesian_confidence", context,
        estimates=[effect_estimate, robustness, statistical_power]
    )

    raw_evidence = {
        "ambition_level": context.get("target_ambition", {}),
        "financial_investment": context.get("total_investment", 0),
        "institutional_capacity": context.get("capacity_score", 0),
        "comparative_benchmarks": prior_effects,
        "justification_analysis": {
            "effect_estimate": effect_estimate,
            "robustness": robustness,
            "sensitivity": sensitivity,
            "statistical_power": statistical_power
        },
        "convergence_diagnostics": {
            "r_hat": r_hat,
            "ess": ess
        },
        "overall_confidence": confidence_aggregate
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {

```

```

        "methods_executed": [log["method"] for log in self.execution_log],
        "ambition_justified": confidence_aggregate > 0.7,
        "statistical_power": statistical_power
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D4_Q4_ProblemSolvencyEvaluator(BaseExecutor):

Evaluates whether results address/resolve prioritized problems from diagnosis.

Methods (from D4-Q4):

- PolicyContradictionDetector._calculate_objective_alignment
- PolicyContradictionDetector._identify_affected_sections
- PolicyContradictionDetector._generate_resolution_recommendations
- OperationalizationAuditor._generate_optimal_remediations
- OperationalizationAuditor._get_remediation_text
- BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
- FinancialAuditor._detect_allocation_gaps

.....

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Calculate objective alignment
    objective_alignment = self._execute_method(
        "PolicyContradictionDetector", "_calculate_objective_alignment", context
    )

    # Step 2: Identify affected sections
    affected_sections = self._execute_method(
        "PolicyContradictionDetector", "_identify_affected_sections", context,
        alignment=objective_alignment
    )

    # Step 3: Generate resolution recommendations
    resolutions = self._execute_method(
        "PolicyContradictionDetector", "_generate_resolution_recommendations",
        context,
        sections=affected_sections
    )

    # Step 4: Generate optimal remediations
    remediations = self._execute_method(
        "OperationalizationAuditor", "_generate_optimal_remediations", context
    )
    remediation_text = self._execute_method(
        "OperationalizationAuditor", "_get_remediation_text", context,
        remediations=remediations
    )

    # Step 5: Aggregate risk and prioritize
    risk_priorities = self._execute_method(
        "BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize", context
    )

    # Step 6: Detect allocation gaps
    allocation_gaps = self._execute_method(
        "FinancialAuditor", "_detect_allocation_gaps", context
    )

    raw_evidence = {
        "prioritized_problems": context.get("diagnosis_problems", []),
        "proposed_results": context.get("outcome_indicators", []),
    }

```

```

    "problem_result_mapping": objective_alignment,
    "unaddressed_problems": [p for p in affected_sections if not
p.get("addressed")],
        "solvency_score": objective_alignment.get("score", 0),
        "resolution_recommendations": resolutions,
        "remediations": remediation_text,
        "risk_priorities": risk_priorities,
        "allocation_gaps": allocation_gaps
    }
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "problems_addressed": len([p for p in affected_sections if
p.get("addressed")]),
        "problems_unaddressed": len([p for p in affected_sections if not
p.get("addressed")])
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D4_Q5_VerticalAlignmentValidator(BaseExecutor):

"""

Validates alignment with superior frameworks (PND, SDGs).

Methods (from D4-Q5):

- PDET Municipal Plan Analyzer._score_pdet_alignment
- PDET Municipal Plan Analyzer._score_causal_coherence
- CDAFFramework._validate_dnp_compliance
- CDAFFramework._generate_dnp_report
- IndustrialPolicyProcessor._analyze_causal_dimensions
- AdaptivePriorCalculator.validate_quality_criteria

"""

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Score PDET alignment
    pdet_alignment = self._execute_method(
        "PDET Municipal Plan Analyzer", "_score_pdet_alignment", context
    )

    # Step 2: Score causal coherence
    causal_coherence = self._execute_method(
        "PDET Municipal Plan Analyzer", "_score_causal_coherence", context
    )

    # Step 3: Validate DNP compliance
    dnp_compliance = self._execute_method(
        "CDAFFramework", "_validate_dnp_compliance", context
    )
    dnp_report = self._execute_method(
        "CDAFFramework", "_generate_dnp_report", context,
        compliance=dnp_compliance
    )

    # Step 4: Analyze causal dimensions
    causal_dimensions = self._execute_method(
        "IndustrialPolicyProcessor", "_analyze_causal_dimensions", context
    )

    # Step 5: Validate quality criteria

```

```

quality_validation = self._execute_method(
    "AdaptivePriorCalculator", "validate_quality_criteria", context,
    alignment=pdet_alignment
)

raw_evidence = {
    "pnd_alignment": dnp_compliance,
    "sdg_alignment": context.get("sdg_mappings", []),
    "pdet_alignment": pdet_alignment,
    "alignment_declarations": dnp_report.get("declarations", []),
    "causal_coherence": causal_coherence,
    "causal_dimensions": causal_dimensions,
    "quality_validation": quality_validation,
    "alignment_score": (pdet_alignment.get("score", 0) +
        dnp_compliance.get("score", 0)) / 2
}

```

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "pnd_aligned": dnp_compliance.get("is_compliant", False),
 "sdgs_referenced": len(context.get("sdg_mappings", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

# =====
# DIMENSION 5: IMPACTS
# =====

```

```
class D5_Q1_LongTermVisionAnalyzer(BaseExecutor):
```

"""\br/>
 Analyzes long-term impacts, transmission routes, and time lags.

Methods (from D5-Q1):

- PDETMunicipalPlanAnalyzer.generate_counterfactuals
 - PDETMunicipalPlanAnalyzer._simulate_intervention
 - PDETMunicipalPlanAnalyzer._generate_scenario_narrative
 - PDETMunicipalPlanAnalyzer._find_mediator_mentions
 - TeoriaCambio._validar_orden_causal
 - CausalExtractor._assess_temporal_coherence
 - TextMiningEngine._generate_interventions
 - BayesianCounterfactualAuditor.construct_scm
- """

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
```

```
    raw_evidence = {}
```

```
    # Step 1: Generate counterfactuals
```

```
    counterfactuals = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "generate_counterfactuals", context
    )
```

```
    # Step 2: Simulate interventions
```

```
    simulation = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_simulate_intervention", context,
        counterfactuals=counterfactuals
    )
```

```
    # Step 3: Generate scenario narratives
```

```
    scenarios = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_generate_scenario_narrative", context,
```

```

simulation=simulation
)

# Step 4: Find mediator mentions
mediators = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_find_mediator_mentions", context
)

# Step 5: Validate causal order
causal_order = self._execute_method(
    "TeoriaCambio", "_validar_orden_causal", context,
    mediators=mediators
)

# Step 6: Assess temporal coherence
temporal_coherence = self._execute_method(
    "CausalExtractor", "_assess_temporal_coherence", context
)

# Step 7: Generate interventions
interventions = self._execute_method(
    "TextMiningEngine", "_generate_interventions", context
)

# Step 8: Construct SCM
scm = self._execute_method(
    "BayesianCounterfactualAuditor", "construct_scm", context,
    order=causal_order
)

raw_evidence = {
    "long_term_impacts": context.get("impact_indicators", []),
    "structural_transformations": scenarios,
    "transmission_routes": mediators,
    "expected_time_lags": temporal_coherence.get("time_lags", []),
    "counterfactual_analysis": counterfactuals,
    "simulation_results": simulation,
    "causal_pathways": scm,
    "intervention_scenarios": interventions
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "impacts_defined": len(context.get("impact_indicators", [])),
        "mediators_identified": len(mediators)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

class D5_Q2_CompositeMeasurementValidator(BaseExecutor):
    """
    DIM05_Q02_COMPOSITE_PROXY_VALIDITY — Validates composite indices/proxies for complex
    impacts (canonical D5).
    Epistemic mix: statistical robustness (E-value), Bayesian confidence, normative
    reporting quality, and semantic consistency.

    Methods executed (in order):
    Step 1: Quality score calculation - PDET MunicipalPlanAnalyzer.calculate_quality_score
    Step 2: Score confidence estimation -
    PDET MunicipalPlanAnalyzer._estimate_score_confidence
    Step 3: E-value computation - PDET MunicipalPlanAnalyzer._compute_e_value
    """

```

```

Step 4: Robustness computation - PDETMunicipalPlanAnalyzer._compute_robustness_value
Step 5: Sensitivity interpretation - PDETMunicipalPlanAnalyzer._interpret_sensitivity
Step 6: Reporting quality - ReportingEngine._calculate_quality_score
Step 7: Bayesian confidence aggregation -
BayesianMechanismInference._aggregate_bayesian_confidence
Step 8: Numerical consistency evaluation -
PolicyAnalysisEmbedder.evaluate_policy_numerical_consistency
Step 9: Embedder diagnostics - PolicyAnalysisEmbedder.get_diagnostics
Step 10: Document processing - PolicyAnalysisEmbedder.process_document
Step 11: PDQ query generation - PolicyAnalysisEmbedder._generate_query_from_pdq
Step 12: PDQ filtering - PolicyAnalysisEmbedder._filter_by_pdq
Step 13: Numerical value extraction - PolicyAnalysisEmbedder._extract_numerical_values
Step 14: Text embedding - PolicyAnalysisEmbedder._embed_texts
Step 15: Overall confidence computation -
PolicyAnalysisEmbedder._compute_overall_confidence
Step 16: Sufficiency calculation - FinancialAuditor._calculate_sufficiency
Step 17: Overall quality interpretation -
PDETMunicipalPlanAnalyzer._interpret_overall_quality
Step 18: Risk prioritization -
BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
Step 19: Unicode normalization - PolicyTextProcessor.normalize_unicode
Step 20: Sentence segmentation - PolicyTextProcessor.segment_into_sentences
Step 21: Evidence confidence - IndustrialPolicyProcessor._compute_evidence_confidence
Step 22: Average confidence - IndustrialPolicyProcessor._compute_avg_confidence
Step 23: Quality serialization - PDETMunicipalPlanAnalyzer._quality_to_dict
Step 24: Evidence bundle - IndustrialPolicyProcessor._construct_evidence_bundle
Step 25: Pattern compilation - PolicyTextProcessor.compile_pattern
Step 26: Contextual window extraction - PolicyTextProcessor.extract_contextual_window
Step 27: Executive report generation -
PDETMunicipalPlanAnalyzer.generate_executive_report
Step 28: Results export - IndustrialPolicyProcessor.export_results
"""

```

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}
    dim_info = get_dimension_info(CanonicalDimension.D5.value)
    document_text = context.get("document_text", "")
    document_metadata = context.get("metadata", {})

    # Step 1: Calculate quality scores
    quality_score = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "calculate_quality_score", context
    )
    score_confidence = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_estimate_score_confidence", context,
        score=quality_score
    )

    # Step 2: Compute robustness metrics
    e_value = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_compute_e_value", context,
        score=quality_score
    )
    robustness = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_compute_robustness_value", context,
        score=quality_score
    )
    sensitivity_interpretation = self._execute_method(
        "PDETMunicipalPlanAnalyzer", "_interpret_sensitivity", context,
        e_value=e_value,
        robustness=robustness
    )

    # Step 3: Calculate reporting quality score
    reporting_quality = self._execute_method(
        "ReportingEngine", "_calculate_quality_score", context
    )

```

```

# Step 4: Aggregate Bayesian confidence
bayesian_confidence = self._execute_method(
    "BayesianMechanismInference", "_aggregate_bayesian_confidence", context,
    scores=[quality_score, reporting_quality]
)

# Step 5: Evaluate numerical consistency
numerical_consistency = self._execute_method(
    "PolicyAnalysisEmbedder", "evaluate_policy_numerical_consistency", context
)
embedder_diagnostics = self._execute_method(
    "PolicyAnalysisEmbedder", "get_diagnostics", context
)
processed_chunks = self._execute_method(
    "PolicyAnalysisEmbedder", "process_document", context,
    document_text=document_text,
    document_metadata=document_metadata
)
pdq_filter = self._execute_method(
    "PolicyAnalysisEmbedder", "_generate_query_from_pdq", context,
    pdq={"policy": context.get("policy_area"), "dimension": dim_info.code}
)
filtered_chunks = self._execute_method(
    "PolicyAnalysisEmbedder", "_filter_by_pdq", context,
    chunks=processed_chunks,
    pdq_filter=pdq_filter
)
numerical_values = self._execute_method(
    "PolicyAnalysisEmbedder", "_extract_numerical_values", context,
    chunks=processed_chunks
)
embedded_texts = self._execute_method(
    "PolicyAnalysisEmbedder", "_embed_texts", context,
    texts=[c.get("content", "") for c in processed_chunks] if
isinstance(processed_chunks, list) else []
)
overall_confidence = self._execute_method(
    "PolicyAnalysisEmbedder", "_compute_overall_confidence", context,
    relevant_chunks=filtered_chunks[:5] if isinstance(filtered_chunks, list) else
[], numerical_eval=bayesian_confidence if isinstance(bayesian_confidence, dict)
else {"evidence_strength": "weak", "numerical_coherence": 0.0}
)

# Step 6: Calculate sufficiency
sufficiency = self._execute_method(
    "FinancialAuditor", "_calculate_sufficiency", context
)
overall_interpretation = self._execute_method(
    "PDET Municipal Plan Analyzer", "_interpret_overall_quality", context,
    score=getattr(quality_score, "overall_score", quality_score)
)
risk_prioritization = self._execute_method(
    "BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize", context,
    omission_score=1 - quality_score.financial_feasibility if
hasattr(quality_score, "financial_feasibility") else 0.2,
    insufficiency_score=1 - sufficiency.get("coverage_ratio", 0.0),
    unneccessity_score=1 - (robustness if isinstance(robustness, (int, float)) else
0.0),
    causal_effect=e_value,
    feasibility=quality_score.financial_feasibility if hasattr(quality_score,
"financial_feasibility") else 0.8,
    cost=1.0
)
normalized_text = self._execute_method(
    "PolicyTextProcessor", "normalize_unicode", context,
    text=document_text
)

```

```

segmented_sentences = self._execute_method(
    "PolicyTextProcessor", "segment_into_sentences", context,
    text=document_text
)
evidence_confidence = self._execute_method(
    "IndustrialPolicyProcessor", "_compute_evidence_confidence", context,
    matches=context.get("proxy_indicators", []),
    text_length=len(document_text),
    pattern_specificity=0.5
)
avg_confidence = self._execute_method(
    "IndustrialPolicyProcessor", "_compute_avg_confidence", context,
    dimension_analysis={"D5": {"dimension_confidence": bayesian_confidence.get("numerical_coherence", 0.0) if isinstance(bayesian_confidence, dict) else 0.0}}
)
quality_dict = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_quality_to_dict", context,
    quality=quality_score
)
evidence_bundle = self._execute_method(
    "IndustrialPolicyProcessor", "_construct_evidence_bundle", context,
    dimension=None,
    category="composite",
    matches=context.get("proxy_indicators", []),
    positions=[],
    confidence=bayesian_confidence.get("numerical_coherence", 0.0) if isinstance(bayesian_confidence, dict) else 0.0
)
compiled_pattern = self._execute_method(
    "PolicyTextProcessor", "compile_pattern", context,
    pattern_str=r"[A-Z]{2,}\s+\d+"
)
contextual_window = self._execute_method(
    "PolicyTextProcessor", "extract_contextual_window", context,
    text=document_text,
    match_position=0,
    window_size=200
)
exec_report = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "generate_executive_report", context,
    analysis_results={"quality_score": quality_dict, "financial_analysis": context.get("financial_analysis", {})}
)
"confidence": (0, 0)}
)
export_result = self._execute_method(
    "IndustrialPolicyProcessor", "export_results", context,
    results={"quality": quality_dict, "robustness": robustness},
    output_path="output/composite_results.json"
)
raw_evidence = {
    "composite_indices": context.get("composite_indicators", []),
    "proxy_indicators": context.get("proxy_indicators", []),
    "validity_justification": score_confidence,
    "robustness_metrics": {
        "e_value": e_value,
        "robustness": robustness,
        "interpretation": sensitivity_interpretation
    },
    "quality_scores": {
        "overall": quality_score,
        "reporting": reporting_quality
    },
    "bayesian_confidence": bayesian_confidence,
    "numerical_consistency": numerical_consistency,
    "measurement_sufficiency": sufficiency,
    "embedder_diagnostics": embedder_diagnostics,
}

```

```

        "quality_interpretation": overall_interpretation,
        "pdq_filter": pdq_filter,
        "filtered_chunks": filtered_chunks,
        "numerical_values": numerical_values,
        "embedded_texts": embedded_texts,
        "overall_confidence": overall_confidence,
        "risk_prioritization": risk_prioritization,
        "normalized_text": normalized_text,
        "segmented_sentences": segmented_sentences,
        "evidence_confidence": evidence_confidence,
        "avg_confidence": avg_confidence,
        "quality_dict": quality_dict,
        "compiled_pattern": compiled_pattern,
        "contextual_window": contextual_window,
        "evidence_bundle": evidence_bundle,
        "executive_report": exec_report,
        "export_result": export_result
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "composite_indices_count": len(context.get("composite_indicators", [])),
            "total_proxy_indicators": len(context.get("proxy_indicators", [])),
            "has_proxy_indicators": bool(context.get("proxy_indicators")),
            "total_numerical_values": len(numerical_values) if numerical_values else
0,
            "has_numerical_values": bool(numerical_values),
            "total_filtered_chunks": len(filtered_chunks) if filtered_chunks else 0,
            "has_filtered_chunks": bool(filtered_chunks),
            "total_segmented_sentences": len(segmented_sentences) if
segmented_sentences else 0,
            "has_segmented_sentences": bool(segmented_sentences),
            "total_embedded_texts": len(embedded_texts) if embedded_texts else 0,
            "has_embedded_texts": bool(embedded_texts),
            "validity_score": score_confidence,
            "canonical_question": "DIM05_Q02_COMPOSITE_PROXY_VALIDITY",
            "dimension_code": dim_info.code,
            "dimension_label": dim_info.label
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}

```

class D5_Q3_IntangibleMeasurementAnalyzer(BaseExecutor):

....

Analyzes proxy indicators for intangible impacts with validity documentation.

Methods (from D5-Q3):

- CausalExtractor._calculate_semantic_distance
 - SemanticAnalyzer.extract_semantic_cube
 - BayesianMechanismInference._quantify_uncertainty
 - PDET Municipal Plan Analyzer._find_mediator_mentions
 - PolicyAnalysisEmbedder.get_diagnostics
 - AdaptivePriorCalculator._perturb_evidence
-

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

Step 1: Calculate semantic distance

semantic_distance = self._execute_method(
 "CausalExtractor", "_calculate_semantic_distance", context
)

```

)
# Step 2: Extract semantic cube
semantic_cube = self._execute_method(
    "SemanticAnalyzer", "extract_semantic_cube", context
)

# Step 3: Quantify uncertainty
uncertainty = self._execute_method(
    "BayesianMechanismInference", "_quantify_uncertainty", context,
    semantic_data=semantic_cube
)

# Step 4: Find mediator mentions
mediators = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_find_mediator_mentions", context
)

# Step 5: Get diagnostics
diagnostics = self._execute_method(
    "PolicyAnalysisEmbedder", "get_diagnostics", context,
    mediators=mediators
)

# Step 6: Perturb evidence for sensitivity
perturbed_evidence = self._execute_method(
    "AdaptivePriorCalculator", "_perturb_evidence", context,
    diagnostics=diagnostics
)

raw_evidence = {
    "intangible_impacts": context.get("intangible_indicators", []),
    "proxy_indicators": context.get("proxy_mappings", []),
    "validity_documentation": diagnostics,
    "limitations_acknowledged": diagnostics.get("limitations", []),
    "semantic_relationships": semantic_cube,
    "semantic_distance": semantic_distance,
    "uncertainty_quantification": uncertainty,
    "sensitivity_to_proxies": perturbed_evidence
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "intangibles_count": len(context.get("intangible_indicators", [])),
        "proxies_defined": len(context.get("proxy_mappings", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D5_Q4_SystemicRiskEvaluator(BaseExecutor):

....

Evaluates systemic risks that could rupture causal mechanisms.

Methods (from D5-Q4):

- OperationalizationAuditor._audit_systemic_risk
- BayesianCounterfactualAuditor.refutation_and_sanity_checks
- BayesianCounterfactualAuditor._test_effect_stability
- PDET MunicipalPlanAnalyzer._interpret_risk
- PDET MunicipalPlanAnalyzer._interpret_sensitivity
- PDET MunicipalPlanAnalyzer._break_cycles
- AdaptivePriorCalculator.sensitivity_analysis

====

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:  
    raw_evidence = {}  
  
    # Step 1: Audit systemic risks  
    systemic_risks = self._execute_method(  
        "OperationalizationAuditor", "_audit_systemic_risk", context  
    )  
  
    # Step 2: Refutation and sanity checks  
    refutation = self._execute_method(  
        "BayesianCounterfactualAuditor", "refutation_and_sanity_checks", context,  
        risks=systemic_risks  
    )  
  
    # Step 3: Test effect stability  
    effect_stability = self._execute_method(  
        "BayesianCounterfactualAuditor", "_test_effect_stability", context,  
        refutation=refutation  
    )  
  
    # Step 4: Interpret risks  
    risk_interpretation = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_interpret_risk", context,  
        risks=systemic_risks  
    )  
  
    # Step 5: Interpret sensitivity  
    sensitivity_interpretation = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_interpret_sensitivity", context,  
        stability=effect_stability  
    )  
  
    # Step 6: Break cycles if present  
    cycle_breaks = self._execute_method(  
        "PDET Municipal Plan Analyzer", "_break_cycles", context  
    )  
  
    # Step 7: Sensitivity analysis  
    sensitivity = self._execute_method(  
        "Adaptive Prior Calculator", "sensitivity_analysis", context,  
        risks=systemic_risks  
    )  
  
    raw_evidence = {  
        "macroeconomic_risks": [r for r in systemic_risks if r.get("type") ==  
            "macroeconomic"],  
        "environmental_risks": [r for r in systemic_risks if r.get("type") ==  
            "environmental"],  
        "political_risks": [r for r in systemic_risks if r.get("type") ==  
            "political"],  
        "mechanism_rupture_potential": risk_interpretation.get("rupture_probability",  
            0),  
        "effect_stability": effect_stability,  
        "refutation_results": refutation,  
        "sensitivity_analysis": sensitivity,  
        "cycle_vulnerabilities": cycle_breaks  
    }  
  
    return {  
        "executor_id": self.executor_id,  
        "raw_evidence": raw_evidence,  
        "metadata": {  
            "methods_executed": [log["method"] for log in self.execution_log],  
            "systemic_risks_identified": len(systemic_risks),  
            "high_risk_count": len([r for r in systemic_risks if r.get("severity") ==  
                "high"])}  
    }
```

```

    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

class D5_Q5_RealismAndSideEffectsAnalyzer(BaseExecutor):
    """
    Analyzes realism of impact ambition and potential unintended effects.
    """

    Methods (from D5-Q5):
    - HierarchicalGenerativeModel.posterior_predictive_check
    - HierarchicalGenerativeModel._ablation_analysis
    - HierarchicalGenerativeModel._calculate_waic_difference
    - AdaptivePriorCalculator._add_ood_noise
    - AdaptivePriorCalculator.validate_quality_criteria
    - PDET MunicipalPlanAnalyzer._compute_e_value
    - PDET MunicipalPlanAnalyzer._compute_robustness_value
    - BayesianMechanismInference._calculate_coherence_factor
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}

        # Step 1: Posterior predictive check
        predictive_check = self._execute_method(
            "HierarchicalGenerativeModel", "posterior_predictive_check", context
        )

        # Step 2: Ablation analysis
        ablation = self._execute_method(
            "HierarchicalGenerativeModel", "_ablation_analysis", context,
            check=predictive_check
        )

        # Step 3: Calculate WAIC difference
        waic_diff = self._execute_method(
            "HierarchicalGenerativeModel", "_calculate_waic_difference", context,
            ablation=ablation
        )

        # Step 4: Add out-of-distribution noise
        ood_analysis = self._execute_method(
            "AdaptivePriorCalculator", "_add_ood_noise", context
        )

        # Step 5: Validate quality criteria
        quality_validation = self._execute_method(
            "AdaptivePriorCalculator", "validate_quality_criteria", context,
            ood=ood_analysis
        )

        # Step 6: Compute robustness metrics
        e_value = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_compute_e_value", context
        )
        robustness = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_compute_robustness_value", context
        )

        # Step 7: Calculate coherence factor
        coherence = self._execute_method(
            "BayesianMechanismInference", "_calculate_coherence_factor", context
        )

        raw_evidence = {

```

```

    "impact_ambition_level": context.get("declared_ambition", 0),
    "realism_assessment": predictive_check.get("realism_score", 0),
    "negative_side_effects": ablation.get("negative_effects", []),
    "limit_hypotheses": quality_validation.get("limits", []),
    "robustness_metrics": {
        "e_value": e_value,
        "robustness": robustness,
        "coherence": coherence
    },
    "predictive_validity": predictive_check,
    "ablation_results": ablation,
    "model_comparison": waic_diff,
    "ood_sensitivity": ood_analysis
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "realism_score": predictive_check.get("realism_score", 0),
        "side_effects_identified": len(ablation.get("negative_effects", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

```

# =====
# DIMENSION 6: CAUSALITY & THEORY OF CHANGE
# =====

```

```
class D6_Q1_ExplicitTheoryBuilder(BaseExecutor):
    """

```

Builds/validates explicit Theory of Change with diagram and assumptions.

Methods (from D6-Q1):

- TeoriaCambio.construir_grafo_causal
- TeoriaCambio.validacion_completa
- TeoriaCambio.export_nodes
- ReportingEngine.generate_causal_diagram
- ReportingEngine.generate_causal_model_json
- AdvancedDAGValidator.export_nodes
- PDET Municipal Plan Analyzer.export_causal_network
- CausalExtractor.extract_causal_hierarchy

"""

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

```

```
    # Step 1: Build causal graph
    causal_graph = self._execute_method(
        "TeoriaCambio", "construir_grafo_causal", context
    )

```

```
    # Step 2: Complete validation
    validation = self._execute_method(
        "TeoriaCambio", "validacion_completa", context,
        graph=causal_graph
    )

```

```
    # Step 3: Export nodes from Theory of Change
    toc_nodes = self._execute_method(
        "TeoriaCambio", "export_nodes", context,
        graph=causal_graph
    )

```

```

# Step 4: Generate causal diagram
diagram = self._execute_method(
    "ReportingEngine", "generate_causal_diagram", context,
    graph=causal_graph
)

# Step 5: Generate causal model JSON
model_json = self._execute_method(
    "ReportingEngine", "generate_causal_model_json", context,
    graph=causal_graph
)

# Step 6: Export nodes from DAG validator
dag_nodes = self._execute_method(
    "AdvancedDAGValidator", "export_nodes", context,
    graph=causal_graph
)

# Step 7: Export causal network
network_export = self._execute_method(
    "PDET Municipal Plan Analyzer", "export_causal_network", context,
    graph=causal_graph
)

# Step 8: Extract causal hierarchy
hierarchy = self._execute_method(
    "CausalExtractor", "extract_causal_hierarchy", context
)

raw_evidence = {
    "toc_exists": len(causal_graph) > 0,
    "toc_diagram": diagram,
    "toc_json": model_json,
    "causal_graph": causal_graph,
    "nodes": toc_nodes,
    "causes_identified": hierarchy.get("causes", []),
    "mediators_identified": hierarchy.get("mediators", []),
    "assumptions": validation.get("assumptions", []),
    "network_structure": network_export,
    "validation_results": validation
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "nodes_count": len(toc_nodes),
        "assumptions_count": len(validation.get("assumptions", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D6_Q2_LogicalProportionalityValidator(BaseExecutor):

"""

Validates logical proportionality: no leaps, intervention matches result scale.

Methods (from D6-Q2):

- BeachEvidentialTest.apply_test_logic
- BayesianMechanismInference._test_necessity
- BayesianMechanismInference._test_sufficiency
- BayesianMechanismInference._calculate_coherence_factor
- BayesianCounterfactualAuditor._test_effect_stability

```

- IndustrialGradeValidator.validate_connection_matrix
- PolicyAnalysisEmbedder._compute_overall_confidence
"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Apply evidential tests
    evidential_tests = self._execute_method(
        "BeachEvidentialTest", "apply_test_logic", context
    )

    # Step 2: Test necessity
    necessity_test = self._execute_method(
        "BayesianMechanismInference", "_test_necessity", context
    )

    # Step 3: Test sufficiency
    sufficiency_test = self._execute_method(
        "BayesianMechanismInference", "_test_sufficiency", context
    )

    # Step 4: Calculate coherence factor
    coherence_factor = self._execute_method(
        "BayesianMechanismInference", "_calculate_coherence_factor", context,
        necessity=necessity_test,
        sufficiency=sufficiency_test
    )

    # Step 5: Test effect stability
    effect_stability = self._execute_method(
        "BayesianCounterfactualAuditor", "_test_effect_stability", context
    )

    # Step 6: Validate connection matrix
    connection_validation = self._execute_method(
        "IndustrialGradeValidator", "validate_connection_matrix", context
    )

    # Step 7: Compute overall confidence
    overall_confidence = self._execute_method(
        "PolicyAnalysisEmbedder", "_compute_overall_confidence", context,
        tests=[necessity_test, sufficiency_test, effect_stability]
    )

    raw_evidence = {
        "logical_leaps_detected": (evidential_tests or {}).get("leaps", []),
        "intervention_scale": context.get("intervention_magnitude", 0),
        "result_scale": context.get("result_magnitude", 0),
        "proportionality_ratio": context.get("intervention_magnitude", 0) /
max(context.get("result_magnitude", 1), 1),
        "necessity_score": necessity_test,
        "sufficiency_score": sufficiency_test,
        "coherence_factor": coherence_factor,
        "effect_stability": effect_stability,
        "connection_validation": connection_validation,
        "overall_confidence": overall_confidence,
        "implementation_miracles": [leap for leap in (evidential_tests or
{}) .get("leaps", []) if isinstance(leap, dict) and leap.get("type") ==
"miracle"]
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],

```

```

        "leaps_detected": len((evidential_tests or {}).get("leaps", [])),
        "proportionality_adequate": abs(raw_evidence["proportionality_ratio"] -
1.0) < 0.5
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D6_Q3_ValidationTestingAnalyzer(BaseExecutor):

"""
Analyzes validation/testing proposals for weak assumptions before scaling.

Methods (from D6-Q3):

- IndustrialGradeValidator.execute_suite
 - IndustrialGradeValidator.validate_engine_readiness
 - IndustrialGradeValidator._benchmark_operation
 - AdaptivePriorCalculator.validate_quality_criteria
 - HierarchicalGenerativeModel._calculate_r_hat
 - HierarchicalGenerativeModel._calculate_ess
 - AdvancedDAGValidator.calculate_acyclicity_pvalue
 - PerformanceAnalyzer.analyze_performance
- """

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

Step 1: Execute validation suite

```
validation_suite = self._execute_method(
    "IndustrialGradeValidator", "execute_suite", context
)
```

Step 2: Validate engine readiness

```
readiness = self._execute_method(
    "IndustrialGradeValidator", "validate_engine_readiness", context
)
```

Step 3: Benchmark operations

```
benchmarks = self._execute_method(
    "IndustrialGradeValidator", "_benchmark_operation", context
)
```

Step 4: Validate quality criteria

```
quality_validation = self._execute_method(
    "AdaptivePriorCalculator", "validate_quality_criteria", context
)
```

Step 5: Calculate convergence diagnostics

```
r_hat = self._execute_method(
    "HierarchicalGenerativeModel", "_calculate_r_hat", context
)
```

ess = self._execute_method(

```
    "HierarchicalGenerativeModel", "_calculate_ess", context
)
```

Step 6: Calculate acyclicity p-value

```
acyclicity_p = self._execute_method(
    "AdvancedDAGValidator", "calculate_acyclicity_pvalue", context
)
```

Step 7: Analyze performance

```
performance = self._execute_method(
    "PerformanceAnalyzer", "analyze_performance", context
)
```

raw_evidence = {

```

    "inconsistencies_recognized": validation_suite.get("inconsistencies", []),
    "weak_assumptions": quality_validation.get("weak_assumptions", []),
    "pilot_proposals": context.get("pilot_programs", []),
    "testing_proposals": context.get("testing_plans", []),
    "validation_before_scaling": readiness.get("ready_to_scale", False),
    "validation_results": validation_suite,
    "quality_criteria": quality_validation,
    "convergence_diagnostics": {
        "r_hat": r_hat,
        "ess": ess,
        "acyclicity_p": acyclicity_p
    },
    "performance_analysis": performance,
    "benchmarks": benchmarks
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "inconsistencies_count": len(validation_suite.get("inconsistencies", [])),
        "pilots_proposed": len(context.get("pilot_programs", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D6_Q4_FeedbackLoopAnalyzer(BaseExecutor):

"""
Analyzes monitoring system with correction mechanisms and learning processes.

Methods (from D6-Q4):

- ConfigLoader.update_priors_from_feedback
 - ConfigLoader.check_uncertainty_reduction_criterion
 - ConfigLoader._save_prior_history
 - ConfigLoader._load_uncertainty_history
 - CDAFFramework._extract_feedback_from_audit
 - AdvancedDAGValidator._calculate_node_importance
 - BayesFactorTable.get_bayes_factor
- """

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

Step 1: Update priors from feedback

prior_updates = self._execute_method(
 "ConfigLoader", "update_priors_from_feedback", context
)

Step 2: Check uncertainty reduction

uncertainty_reduction = self._execute_method(
 "ConfigLoader", "check_uncertainty_reduction_criterion", context,
 updates=prior_updates
)

Step 3: Save prior history

history_saved = self._execute_method(
 "ConfigLoader", "_save_prior_history", context,
 updates=prior_updates
)

Step 4: Load uncertainty history

uncertainty_history = self._execute_method(
 "ConfigLoader", "_load_uncertainty_history", context

```

)
# Step 5: Extract feedback from audit
feedback_extracted = self._execute_method(
    "CDAFFramework", "_extract_feedback_from_audit", context
)

# Step 6: Calculate node importance
node_importance = self._execute_method(
    "AdvancedDAGValidator", "_calculate_node_importance", context
)

# Step 7: Get Bayes factor
bayes_factor = self._execute_method(
    "BayesFactorTable", "get_bayes_factor", context,
    updates=prior_updates
)

raw_evidence = {
    "monitoring_system_described": len(context.get("monitoring_indicators", [])) >
0,
    "correction_mechanisms": feedback_extracted.get("mechanisms", []),
    "feedback_loops": feedback_extracted.get("loops", []),
    "learning_processes": feedback_extracted.get("learning", []),
    "prior_updates": prior_updates,
    "uncertainty_reduction": uncertainty_reduction,
    "uncertainty_history": uncertainty_history,
    "node_importance": node_importance,
    "learning_strength": bayes_factor
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "feedback_mechanisms": len(feedback_extracted.get("mechanisms", [])),
        "learning_processes": len(feedback_extracted.get("learning", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D6_Q5_ContextualAdaptabilityEvaluator(BaseExecutor):

"""

Evaluates contextual adaptation: differential impacts and territorial constraints.

Methods executed (in order):

Step 1: Language specificity - CausalExtractor._calculate_language_specificity
Step 2: Temporal coherence - CausalExtractor._assess_temporal_coherence
Step 3: Critical links diagnosis - TextMiningEngine.diagnose_critical_links
Step 4: Failure points identification - CausalInferenceSetup.identify_failure_points
Step 5: Dynamics pattern - CausalInferenceSetup._get_dynamics_pattern
Step 6: Text chunking - SemanticProcessor.chunk_text
Step 7: PDM structure detection - SemanticProcessor._detect_pdm_structure
Step 8: Table detection - SemanticProcessor._detect_table
Step 9: Traceability record - AdaptivePriorCalculator.generate_traceability_record
"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

Step 1: Calculate language specificity

language_specificity = self._execute_method(
 "CausalExtractor", "_calculate_language_specificity", context
)

```

)
# Step 2: Assess temporal coherence
temporal_coherence = self._execute_method(
    "CausalExtractor", "_assess_temporal_coherence", context
)

# Step 3: Diagnose critical links
critical_links = self._execute_method(
    "TextMiningEngine", "diagnose_critical_links", context
)

# Step 4: Identify failure points
failure_points = self._execute_method(
    "CausalInferenceSetup", "identify_failure_points", context
)

# Step 5: Get dynamics pattern
dynamics_pattern = self._execute_method(
    "CausalInferenceSetup", "_get_dynamics_pattern", context
)

# Step 6: Process text structure
text_chunks = self._execute_method(
    "SemanticProcessor", "chunk_text", context
)
pdm_structure = self._execute_method(
    "SemanticProcessor", "_detect_pdm_structure", context,
    chunks=text_chunks
)
table_detection = self._execute_method(
    "SemanticProcessor", "_detect_table", context,
    chunks=text_chunks
)

# Step 7: Generate traceability record
traceability = self._execute_method(
    "AdaptivePriorCalculator", "generate_traceability_record", context,
    specificity=language_specificity
)

raw_evidence = {
    "context_adaptation": language_specificity.get("adaptation_level", 0),
    "differential_impacts_recognized": critical_links.get("differential_groups",
[]),
    "specific_groups_mentioned": critical_links.get("target_groups", []),
    "territorial_constraints": failure_points.get("territorial", []),
    "local_context_integration": pdm_structure.get("local_sections", []),
    "language_specificity": language_specificity,
    "temporal_coherence": temporal_coherence,
    "dynamics_pattern": dynamics_pattern,
    "structure_analysis": pdm_structure,
    "traceability": traceability
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "groups_identified": len((critical_links or {}).get("target_groups", []))
    }
}
if critical_links else 0,
    "territorial_constraints": len((failure_points or {}).get("territorial",
[])) if failure_points else 0,
    "total_text_chunks": len(text_chunks) if text_chunks else 0,
    "has_text_chunks": bool(text_chunks),
    "total_table_detections": len(table_detection) if
isinstance(table_detection, list) else (1 if table_detection else 0),

```

```

    "has_table_detection": bool(table_detection),
    "has_pdm_structure": bool(pdm_structure),
    "has_dynamics_pattern": bool(dynamics_pattern),
    "has_traceability": bool(traceability)
},
"execution_metrics": {
    "methods_count": len(self.execution_log),
    "all_succeeded": all(log["success"] for log in self.execution_log)
}
}

# =====
# EXECUTOR REGISTRY
# =====

EXECUTOR_REGISTRY = {
    "D1-Q1": D1_Q1_QuantitativeBaselineExtractor,
    "D1-Q2": D1_Q2_ProblemDimensioningAnalyzer,
    "D1-Q3": D1_Q3_BudgetAllocationTracer,
    "D1-Q4": D1_Q4_InstitutionalCapacityIdentifier,
    "D1-Q5": D1_Q5_ScopeJustificationValidator,

    "D2-Q1": D2_Q1_StructuredPlanningValidator,
    "D2-Q2": D2_Q2_InterventionLogicInferencer,
    "D2-Q3": D2_Q3_RootCauseLinkageAnalyzer,
    "D2-Q4": D2_Q4_RiskManagementAnalyzer,
    "D2-Q5": D2_Q5_StrategicCoherenceEvaluator,

    "D3-Q1": D3_Q1_IndicatorQualityValidator,
    "D3-Q2": D3_Q2_TargetProportionalityAnalyzer,
    "D3-Q3": D3_Q3_TraceabilityValidator,
    "D3-Q4": D3_Q4_TechnicalFeasibilityEvaluator,
    "D3-Q5": D3_Q5_OutputOutcomeLinkageAnalyzer,

    "D4-Q1": D4_Q1_OutcomeMetricsValidator,
    "D4-Q2": D4_Q2_CausalChainValidator,
    "D4-Q3": D4_Q3_AmbitionJustificationAnalyzer,
    "D4-Q4": D4_Q4_ProblemSolvencyEvaluator,
    "D4-Q5": D4_Q5_VerticalAlignmentValidator,

    "D5-Q1": D5_Q1_LongTermVisionAnalyzer,
    "D5-Q2": D5_Q2_CompositeMeasurementValidator,
    "D5-Q3": D5_Q3_IntangibleMeasurementAnalyzer,
    "D5-Q4": D5_Q4_SystemicRiskEvaluator,
    "D5-Q5": D5_Q5_RealismAndSideEffectsAnalyzer,

    "D6-Q1": D6_Q1_ExplicitTheoryBuilder,
    "D6-Q2": D6_Q2_LogicalProportionalityValidator,
    "D6-Q3": D6_Q3_ValidationTestingAnalyzer,
    "D6-Q4": D6_Q4_FeedbackLoopAnalyzer,
    "D6-Q5": D6_Q5_ContextualAdaptabilityEvaluator,
}

# =====
# PHASE 2 ORCHESTRATION
# =====

def _build_method_executor() -> MethodExecutor:
    """Construct a canonical MethodExecutor via the factory wiring."""
    bundle = build_processor()
    method_executor = getattr(bundle, "method_executor", None)
    if not isinstance(method_executor, MethodExecutor):
        raise RuntimeError("ProcessorBundle did not provide a valid MethodExecutor instance.")
    return method_executor

```

```

def _canonical_metadata(executor_id: str) -> Dict[str, Any]:
    """Build canonical metadata block using canonical_notation."""
    metadata: Dict[str, Any] = {}
    try:
        dim_key = executor_id.split("-")[0]
        dim_info = get_dimension_info(dim_key)
        metadata["dimension_code"] = dim_info.code
        metadata["dimension_label"] = dim_info.label
    except Exception:
        pass

    if executor_id in CANONICAL_QUESTION_LABELS:
        metadata["canonical_question"] = CANONICAL_QUESTION_LABELS[executor_id]
    return metadata

```

```

def run_phase2_executors(context_package: Dict[str, Any],
                        policy_areas: List[str]) -> Dict[str, Any]:
    """
    Phase 2 Entry Point: Runs all 30 executors for each policy area.
    """

```

Args:

context_package: Canonical package with document data from Phase 1
policy_areas: List of policy area identifiers to analyze

Returns:

Dict mapping policy_area -> executor_id -> raw_evidence

```

results = {}
method_executor = _build_method_executor()

```

for policy_area in policy_areas:

```

print(f"\n{'='*80}")
print(f"Processing Policy Area: {policy_area}")
print(f"{'='*80}\n")

```

Prepare context for this policy area

```

area_context = {
    **context_package,
    "policy_area": policy_area
}

```

Execute all 30 executors

```

area_results = {}
for executor_id, executor_class in EXECUTOR_REGISTRY.items():
    print(f"Running {executor_id}: {executor_class.__name__}...")

```

try:

```

# Instantiate executor with config
config = load_executor_config(executor_id)
executor = executor_class(executor_id, config,
method_executor=method_executor)

```

method_executor=method_executor)

```

# Execute and collect results
result = executor.execute(area_context)
# Append canonical metadata consistently
result_metadata = result.get("metadata", {})
result_metadata.update(_canonical_metadata(executor_id))
result["metadata"] = result_metadata
area_results[executor_id] = result

```

```

print(f" ✓ Success: {len(result['metadata']['methods_executed'])} methods
executed")

```

except ExecutorFailure as e:

```

print(f" ✗ FAILED: {str(e)}")

```

```

        raise # Re-raise to stop execution as per requirement

    results[policy_area] = area_results

return results

def load_executor_config(executor_id: str) -> Dict[str, Any]:
    """
    Load executor configuration from JSON contract.

    Args:
        executor_id: Executor identifier (e.g., "D1-Q1")

    Returns:
        Configuration dictionary from JSON contract
    """

import json
from pathlib import Path

config_path = Path(f"config/executor_contracts/{executor_id}.json")

if not config_path.exists():
    raise FileNotFoundError(f"Executor config not found: {config_path}")

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

# =====
# EXAMPLE USAGE
# =====

if __name__ == "__main__":
    # Example context package from Phase 1
    context_package = {
        "document_path": "data/pdm_municipality_xyz.pdf",
        "document_text": "...", # Full document text
        "tables": [], # Extracted tables from Phase 1
        "embeddings": {}, # Precomputed embeddings
        "entities": [], # Pre-extracted entities
        "metadata": {
            "municipality": "Municipality XYZ",
            "year": 2024,
            "pages": 150
        }
    }

    # Policy areas to analyze
    policy_areas = [
        "PA01", # Education
        "PA02", # Health
        "PA03", # Infrastructure
        # ... up to 10+ policy areas
    ]

    # Run Phase 2
    try:
        results = run_phase2_executors(context_package, policy_areas)
        print("\n" + "*80)
        print("PHASE 2 COMPLETED SUCCESSFULLY")
        print("*80)
        print(f"Processed {len(policy_areas)} policy areas")
        print(f"Executed {len(EXECUTOR_REGISTRY)} executors per area")
        print(f"Total executions: {len(policy_areas) * len(EXECUTOR_REGISTRY)}")

    except ExecutorFailure as e:
        print("\n" + "*80)

```

```

print("PHASE 2 FAILED")
print("="*80)
print(f"Error: {str(e)}")
print("Execution halted as per requirement: any method failure = executor
failure")

===== FILE: MIGRATION_ARTIFACTS_FAKE_TO_REAL/04_SOURCE_CODE/executors_SNAPSHOT.py =====
"""
executors.py - Phase 2: Executor Orchestration for Policy Document Analysis

```

This module defines 30 executors (one per D{n}-Q{m} question) that orchestrate methods from the core module to extract raw evidence from Colombian municipal development plans (PDET/PDM documents).

Architecture:

- Each executor is independent and receives a canonical context package
- Methods execute in configured order; any failure causes executor failure
- Outputs are Python dicts/lists matching JSON contract specifications
- Executors are injected via MethodExecutor factory pattern

Usage:

```

from factory import run_executor
result = run_executor("D1-Q1", context_package)
"""

```

```

from typing import Dict, List, Any, Optional
from abc import ABC, abstractmethod

```

```

from saaaaaa.core.canonical_notation import CanonicalDimension, get_dimension_info
from saaaaaa.core.orchestrator.core import MethodExecutor
from saaaaaa.core.orchestrator.factory import build_processor

```

Canonical question labels (only defined when verified in repo)

```

CANONICAL_QUESTION_LABELS = {
    "D3-Q2": "DIM03_Q02_PRODUCT_TARGET_PROPORIONALITY",
    "D3-Q3": "DIM03_Q03_TRACEABILITY_BUDGET_ORG",
    "D3-Q4": "DIM03_Q04_TECHNICAL_FEASIBILITY",
    "D3-Q5": "DIM03_Q05_OUTPUT_OUTCOME_LINKAGE",
    "D4-Q1": "DIM04_Q01_OUTCOME_INDICATOR_COMPLETENESS",
    "D5-Q2": "DIM05_Q02_COMPOSITE_PROXY_VALIDITY",
}

```

Epistemic taxonomy per method (focused on executors expanded in this iteration)

```

EPISTEMIC_TAGS = {
    ("FinancialAuditor", "_calculate_sufficiency"): ["statistical", "normative"],
    ("FinancialAuditor", "_match_program_to_node"): ["structural"],
    ("FinancialAuditor", "_match_goal_to_budget"): ["structural", "normative"],
    ("PDET MunicipalPlanAnalyzer", "_assess_financial_sustainability"): ["financial",
    "normative"],
    ("PDET MunicipalPlanAnalyzer", "analyze_financial_feasibility"): ["financial",
    "statistical"],
    ("PDET MunicipalPlanAnalyzer", "_score_indicators"): ["normative", "semantic"],
    ("PDET MunicipalPlanAnalyzer", "_interpret_risk"): ["normative", "statistical"],
    ("PDET MunicipalPlanAnalyzer", "_extract_from_responsibility_tables"): ["structural"],
    ("PDET MunicipalPlanAnalyzer", "_consolidate_entities"): ["structural"],
    ("PDET MunicipalPlanAnalyzer", "_extract_entities_syntax"): ["semantic"],
    ("PDET MunicipalPlanAnalyzer", "_extract_entities_ner"): ["semantic"],
    ("PDET MunicipalPlanAnalyzer", "identify_responsible_entities"): ["semantic",
    "structural"],
    ("PDET MunicipalPlanAnalyzer", "_score_responsibility_clarity"): ["normative"],
    ("PDET MunicipalPlanAnalyzer", "_refine_edge_probabilities"): ["statistical",
    "causal"],
    ("PDET MunicipalPlanAnalyzer", "construct_causal_dag"): ["structural", "causal"],
    ("PDET MunicipalPlanAnalyzer", "estimate_causal_effects"): ["causal", "statistical"],
    ("PDET MunicipalPlanAnalyzer", "generate_counterfactuals"): ["causal"],
    ("PDET MunicipalPlanAnalyzer", "_identify_confounders"): ["causal", "consistency"],
    ("PDET MunicipalPlanAnalyzer", "_effect_to_dict"): ["descriptive"],
    ("PDET MunicipalPlanAnalyzer", "_scenario_to_dict"): ["descriptive"],
}

```

("PDETMunicipalPlanAnalyzer", "_get_spanish_stopwords"): ["semantic"],
("AdaptivePriorCalculator", "calculate_likelihood_adaptativo"): ["statistical",
"bayesian"],
("AdaptivePriorCalculator", "_adjust_domain_weights"): ["statistical"],
("BayesianMechanismInference", "_test_sufficiency"): ["statistical", "bayesian"],
("BayesianMechanismInference", "_test_necessity"): ["statistical", "bayesian"],
("BayesianMechanismInference", "_log_refactored_components"): ["implementation"],
("BayesianMechanismInference", "_infer_activity_sequence"): ["causal"],
("BayesianMechanismInference", "infer_mechanisms"): ["causal", "bayesian"],
("AdvancedDAGValidator", "calculate_acyclicity_pvalue"): ["statistical",
"consistency"],
("AdvancedDAGValidator", "_is_acyclic"): ["structural", "consistency"],
("AdvancedDAGValidator", "_calculate_bayesian_posterior"): ["statistical",
"bayesian"],
("AdvancedDAGValidator", "_calculate_confidence_interval"): ["statistical"],
("AdvancedDAGValidator", "_calculate_statistical_power"): ["statistical"],
("AdvancedDAGValidator", "_generate_subgraph"): ["structural"],
("AdvancedDAGValidator", "_get_node_validator"): ["implementation"],
("AdvancedDAGValidator", "_create_empty_result"): ["descriptive"],
("AdvancedDAGValidator", "_initialize_rng"): ["implementation"],
("AdvancedDAGValidator", "get_graph_stats"): ["structural"],
("AdvancedDAGValidator", "_calculate_node_importance"): ["structural"],
("AdvancedDAGValidator", "export_nodes"): ["structural", "descriptive"],
("AdvancedDAGValidator", "add_node"): ["structural"],
("AdvancedDAGValidator", "add_edge"): ["structural"],
("IndustrialGradeValidator", "execute_suite"): ["implementation", "normative"],
("IndustrialGradeValidator", "validate_connection_matrix"): ["consistency"],
("IndustrialGradeValidator", "run_performance_benchmarks"): ["implementation"],
("IndustrialGradeValidator", "_benchmark_operation"): ["implementation"],
("IndustrialGradeValidator", "validate_causal_categories"): ["consistency"],
("IndustrialGradeValidator", "_log_metric"): ["implementation"],
("PerformanceAnalyzer", "analyze_performance"): ["implementation", "normative"],
("PerformanceAnalyzer", "_calculate_loss_functions"): ["statistical"],
("HierarchicalGenerativeModel", "_calculate_ess"): ["statistical"],
("HierarchicalGenerativeModel", "_calculate_likelihood"): ["statistical"],
("HierarchicalGenerativeModel", "_calculate_r_hat"): ["statistical"],
("ReportingEngine", "generate_accountability_matrix"): ["normative", "structural"],
("ReportingEngine", "_calculate_quality_score"): ["normative", "statistical"],
("PolicyAnalysisEmbedder", "generate_pdq_report"): ["semantic", "descriptive"],
("PolicyAnalysisEmbedder", "compare_policy_interventions"): ["normative"],
("PolicyAnalysisEmbedder", "evaluate_policy_numerical_consistency"): ["consistency",
"statistical"],
("PolicyAnalysisEmbedder", "process_document"): ["semantic", "structural"],
("PolicyAnalysisEmbedder", "semantic_search"): ["semantic"],
("PolicyAnalysisEmbedder", "_apply_mmr"): ["semantic"],
("PolicyAnalysisEmbedder", "_generate_query_from_pdq"): ["semantic"],
("PolicyAnalysisEmbedder", "_filter_by_pdq"): ["semantic"],
("PolicyAnalysisEmbedder", "_extract_numerical_values"): ["statistical"],
("PolicyAnalysisEmbedder", "_compute_overall_confidence"): ["statistical",
"normative"],
("PolicyAnalysisEmbedder", "_embed_texts"): ["semantic"],
("SemanticAnalyzer", "_classify_policy_domain"): ["semantic"],
("SemanticAnalyzer", "_empty_semantic_cube"): ["descriptive"],
("SemanticAnalyzer", "_classify_cross_cutting_themes"): ["semantic"],
("SemanticAnalyzer", "_classify_value_chain_link"): ["semantic"],
("SemanticAnalyzer", "_vectorize_segments"): ["semantic"],
("SemanticAnalyzer", "_calculate_semantic_complexity"): ["semantic"],
("SemanticAnalyzer", "_process_segment"): ["semantic"],
("PDETMunicipalPlanAnalyzer", "_entity_to_dict"): ["descriptive"],
("PDETMunicipalPlanAnalyzer", "_quality_to_dict"): ["descriptive", "normative"],
("PDETMunicipalPlanAnalyzer", "_deduplicate_tables"): ["structural",
"implementation"],
("PDETMunicipalPlanAnalyzer", "_indicator_to_dict"): ["descriptive"],
("PDETMunicipalPlanAnalyzer", "_generate_recommendations"): ["normative"],
("PDETMunicipalPlanAnalyzer", "_simulate_intervention"): ["causal", "statistical"],
("PDETMunicipalPlanAnalyzer", "_identify_causal_nodes"): ["structural", "causal"],
("PDETMunicipalPlanAnalyzer", "_match_text_to_node"): ["semantic", "structural"],
("TeoriaCambio", "_validar_orden_causal"): ["causal", "consistency"],

```

("TeoriaCambio", "_generar_sugerencias_internas"): ["normative"],
("TeoriaCambio", "_extraer_categorias"): ["semantic"],
("BayesianMechanismInference", "_extract_observations"): ["semantic", "causal"],
("BayesianMechanismInference", "_generate_necessity_remediation"): ["normative",
"causal"],
("BayesianMechanismInference", "_quantify_uncertainty"): ["statistical", "bayesian"],
("CausalExtractor", "_build_type_hierarchy"): ["structural"],
("CausalExtractor", "_check_structuralViolation"): ["structural", "consistency"],
("CausalExtractor", "_calculate_type_transition_prior"): ["statistical", "bayesian"],
("CausalExtractor", "_calculate_textual_proximity"): ["semantic"],
("CausalExtractor", "_calculate_language_specificity"): ["semantic"],
("CausalExtractor", "_calculate_composite_likelihood"): ["statistical", "semantic"],
("CausalExtractor", "_assess_financial_consistency"): ["financial", "consistency"],
("CausalExtractor", "_calculate_semantic_distance"): ["semantic"],
("CausalExtractor", "_extract_goals"): ["semantic"],
("CausalExtractor", "_parse_goal_context"): ["semantic"],
("CausalExtractor", "_classify_goal_type"): ["semantic"],
("TemporalLogicVerifier", "_parse_temporal_marker"): ["temporal", "consistency"],
("TemporalLogicVerifier", "_classify_temporal_type"): ["temporal", "consistency"],
("TemporalLogicVerifier", "_extract_resources"): ["structural"],
("TemporalLogicVerifier", "_should_precede"): ["temporal", "consistency"],
("AdaptivePriorCalculator", "generate_traceability_record"): ["structural",
"semantic"],
("PolicyAnalysisEmbedder", "generate_pdq_report"): ["semantic", "normative"],
("ReportingEngine", "generate_confidence_report"): ["normative", "descriptive"],
("PolicyTextProcessor", "segment_into_sentences"): ["semantic", "structural"],
("PolicyTextProcessor", "normalize_unicode"): ["implementation"],
("PolicyTextProcessor", "compile_pattern"): ["implementation"],
("PolicyTextProcessor", "extract_contextual_window"): ["semantic"],
("BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize"): ["causal",
"normative"],
("BayesianCounterfactualAuditor", "refutation_and_sanity_checks"): ["causal",
"consistency"],
("BayesianCounterfactualAuditor", "_evaluate_factual"): ["causal", "statistical"],
("BayesianCounterfactualAuditor", "_evaluate_counterfactual"): ["causal",
"statistical"],
("CausalExtractor", "_assess_financial_consistency"): ["financial", "consistency"],
("IndustrialPolicyProcessor", "_load_questionnaire"): ["descriptive",
"implementation"],
("IndustrialPolicyProcessor", "_compile_pattern_registry"): ["structural",
"semantic"],
("IndustrialPolicyProcessor", "_build_point_patterns"): ["semantic"],
("IndustrialPolicyProcessor", "_empty_result"): ["implementation"],
("IndustrialPolicyProcessor", "_compute_evidence_confidence"): ["statistical"],
("IndustrialPolicyProcessor", "_compute_avg_confidence"): ["statistical"],
("IndustrialPolicyProcessor", "_construct_evidence_bundle"): ["structural"],
("PDETMunicipalPlanAnalyzer", "generate_executive_report"): ["normative"],
("IndustrialPolicyProcessor", "export_results"): ["implementation"],
}

```

```

class BaseExecutor(ABC):
"""
Base class for all executors with standardized execution template.
All executors must implement execute() and return structured evidence.
"""

def __init__(self, executor_id: str, config: Dict[str, Any], method_executor:
MethodExecutor):
    self.executor_id = executor_id
    self.config = config
    if not isinstance(method_executor, MethodExecutor):
        raise RuntimeError("A valid MethodExecutor instance is required for executor
injection.")
    self.method_executor = method_executor
    self.execution_log = []
    self.dimension_info = None
    try:

```

```

dim_key = executor_id.split("-")[0].replace("D", "D")
self.dimension_info = get_dimension_info(dim_key)
except Exception:
    self.dimension_info = None

@abstractmethod
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    """
    Execute configured methods and return raw evidence.

    Args:
        context: Canonical package with document, tables, metadata

    Returns:
        Dict with raw_evidence, metadata, execution_metrics

    Raises:
        ExecutorFailure: If any method fails
    """
    pass

def _log_method_execution(self, class_name: str, method_name: str,
                         success: bool, result: Any = None, error: str = None):
    """
    Track method execution for debugging and traceability.
    """
    self.execution_log.append({
        "class": class_name,
        "method": method_name,
        "success": success,
        "result_type": type(result).__name__ if result else None,
        "error": error
    })

def _execute_method(self, class_name: str, method_name: str,
                    context: Dict[str, Any], **kwargs) -> Any:
    """
    Execute a single method with error handling.

    Raises:
        ExecutorFailure: If method execution fails
    """
    try:
        # Method injection happens via factory - placeholder for actual execution
        method = self._get_method(class_name, method_name)
        result = method(context, **kwargs)
        self._log_method_execution(class_name, method_name, True, result)
        return result
    except Exception as e:
        self._log_method_execution(class_name, method_name, False, error=str(e))
        raise ExecutorFailure(
            f"Executor {self.executor_id} failed: {class_name}.{method_name} - "
            f"{str(e)}"
        )

    def _get_method(self, class_name: str, method_name: str):
        """
        Retrieve method using MethodExecutor to enforce routed execution.
        """
        if not isinstance(self.method_executor, MethodExecutor):
            raise RuntimeError(f"Invalid method executor provided: "
                               f"{type(self.method_executor).__name__}")

    def _wrapped(context: Dict[str, Any], **kwargs: Any) -> Any:
        payload: Dict[str, Any] = {}
        if context:
            payload.update(context)
        if kwargs:
            payload.update(kwargs)
        return self.method_executor.execute(
            class_name=class_name,
            method_name=method_name,

```

```

        **payload,
    )

return _wrapped

class ExecutorFailure(Exception):
    """Raised when any method in an executor fails."""
    pass

# =====
# DIMENSION 1: DIAGNOSTICS & INPUTS
# =====

class D1_Q1_QuantitativeBaselineExtractor(BaseExecutor):
    """
    Extracts numeric data, reference years, and official sources as baseline.

    Methods (from D1-Q1):
    - TextMiningEngine.diagnose_critical_links
    - TextMiningEngine._analyze_link_text
    - IndustrialPolicyProcessor.process
    - IndustrialPolicyProcessor._match_patterns_in_sentences
    - IndustrialPolicyProcessor._extract_point_evidence
    - CausalExtractor._extract_goals
    - CausalExtractor._parse_goal_context
    - FinancialAuditor._parse_amount
    - PDET MunicipalPlanAnalyzer._extract_financial_amounts
    - PDET MunicipalPlanAnalyzer._extract_from_budget_table
    - PolicyContradictionDetector._extract_quantitative_claims
    - PolicyContradictionDetector._parse_number
    - PolicyContradictionDetector._statistical_significance_test
    - BayesianNumericalAnalyzer.evaluate_policy_metric
    - BayesianNumericalAnalyzer.compare_policies
    - SemanticProcessor.chunk_text
    - SemanticProcessor.embed_single
    """

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Identify critical data-bearing sections
    critical_links = self._execute_method(
        "TextMiningEngine", "diagnose_critical_links", context
    )
    link_analysis = self._execute_method(
        "TextMiningEngine", "_analyze_link_text", context,
        links=critical_links
    )

    # Step 2: Extract structured quantitative claims
    processed_sections = self._execute_method(
        "IndustrialPolicyProcessor", "process", context
    )
    pattern_matches = self._execute_method(
        "IndustrialPolicyProcessor", "_match_patterns_in_sentences", context,
        sections=processed_sections
    )
    point_evidence = self._execute_method(
        "IndustrialPolicyProcessor", "_extract_point_evidence", context,
        matches=pattern_matches
    )

    # Step 3: Parse numerical amounts and baseline data
    parsed_amounts = self._execute_method(
        "FinancialAuditor", "_parse_amount", context,
        evidence=point_evidence
    )

```

```

)
financial_amounts = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_extract_financial_amounts", context
)
budget_table_data = self._execute_method(
    "PDET MunicipalPlanAnalyzer", "_extract_from_budget_table", context
)

# Step 4: Extract temporal context (reference years)
goals = self._execute_method(
    "CausalExtractor", "_extract_goals", context
)
goal_contexts = self._execute_method(
    "CausalExtractor", "_parse_goal_context", context,
    goals=goals
)

# Step 5: Validate quantitative claims
quant_claims = self._execute_method(
    "PolicyContradictionDetector", "_extract_quantitative_claims", context
)
parsed_numbers = self._execute_method(
    "PolicyContradictionDetector", "_parse_number", context,
    claims=quant_claims
)
significance_test = self._execute_method(
    "PolicyContradictionDetector", "_statistical_significance_test", context,
    numbers=parsed_numbers
)

# Step 6: Evaluate baseline quality and compare
metric_evaluation = self._execute_method(
    "BayesianNumericalAnalyzer", "evaluate_policy_metric", context,
    metrics=parsed_numbers
)
policy_comparison = self._execute_method(
    "BayesianNumericalAnalyzer", "compare_policies", context,
    evaluations=metric_evaluation
)

# Step 7: Semantic validation of sources
text_chunks = self._execute_method(
    "SemanticProcessor", "chunk_text", context
)
embeddings = self._execute_method(
    "SemanticProcessor", "embed_single", context,
    chunks=text_chunks
)

# Assemble raw evidence
raw_evidence = {
    "numeric_data": parsed_numbers,
    "reference_years": [gc.get("year") for gc in goal_contexts if gc.get("year")],
    "official_sources": point_evidence.get("sources", []),
    "financial_baseline": financial_amounts,
    "budget_tables": budget_table_data,
    "significance_results": significance_test,
    "metric_evaluation": metric_evaluation,
    "source_embeddings": embeddings
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "total_numeric_claims": len(parsed_numbers),
        "sources_identified": len(point_evidence.get("sources", []))
    }
}

```

```

    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

class D1_Q2_ProblemDimensioningAnalyzer(BaseExecutor):
    """
    Quantifies problem magnitude, gaps, and identifies data limitations.

    Methods (from D1-Q2):
    - OperationalizationAuditor._audit_direct_evidence
    - OperationalizationAuditor._audit_systemic_risk
    - FinancialAuditor._detect_allocation_gaps
    - BayesianMechanismInference._detect_gaps
    - PDET MunicipalPlanAnalyzer._generate_optimal_remediations
    - PDET MunicipalPlanAnalyzer._simulate_intervention
    - BayesianCounterfactualAuditor.counterfactual_query
    - BayesianCounterfactualAuditor._test_effect_stability
    - PolicyContradictionDetector._detect_numerical_inconsistencies
    - PolicyContradictionDetector._calculate_numerical_divergence
    - BayesianConfidenceCalculator.calculate_posterior
    - PerformanceAnalyzer.analyze_performance
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}

        # Step 1: Audit evidence completeness
        direct_evidence_audit = self._execute_method(
            "OperationalizationAuditor", "_audit_direct_evidence", context
        )
        systemic_risk_audit = self._execute_method(
            "OperationalizationAuditor", "_audit_systemic_risk", context
        )

        # Step 2: Detect gaps in resource allocation and mechanisms
        allocation_gaps = self._execute_method(
            "FinancialAuditor", "_detect_allocation_gaps", context
        )
        mechanism_gaps = self._execute_method(
            "BayesianMechanismInference", "_detect_gaps", context
        )

        # Step 3: Generate optimal remediations and simulate interventions
        remediations = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_generate_optimal_remediations", context,
            gaps=allocation_gaps
        )
        simulation_results = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_simulate_intervention", context,
            remediations=remediations
        )

        # Step 4: Counterfactual analysis for problem dimensioning
        counterfactual = self._execute_method(
            "BayesianCounterfactualAuditor", "counterfactual_query", context
        )
        effect_stability = self._execute_method(
            "BayesianCounterfactualAuditor", "_test_effect_stability", context,
            counterfactual=counterfactual
        )

        # Step 5: Detect numerical inconsistencies
        numerical_inconsistencies = self._execute_method(
            "PolicyContradictionDetector", "_detect_numerical_inconsistencies", context
        )

```

```

        )
        divergence_calc = self._execute_method(
            "PolicyContradictionDetector", "_calculate_numerical_divergence", context,
            inconsistencies=numerical_inconsistencies
        )

# Step 6: Calculate confidence and analyze performance
posterior_confidence = self._execute_method(
    "BayesianConfidenceCalculator", "calculate_posterior", context,
    evidence=direct_evidence_audit
)
performance_analysis = self._execute_method(
    "PerformanceAnalyzer", "analyze_performance", context
)

raw_evidence = {
    "magnitude_indicators": {
        "allocation_gaps": allocation_gaps,
        "mechanism_gaps": mechanism_gaps,
        "numerical_inconsistencies": numerical_inconsistencies
    },
    "deficit_quantification": divergence_calc,
    "data_limitations": {
        "evidence_gaps": direct_evidence_audit.get("gaps", []),
        "systemic_risks": systemic_risk_audit
    },
    "simulation_results": simulation_results,
    "confidence_scores": posterior_confidence,
    "performance_metrics": performance_analysis
}
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "gaps_identified": len(allocation_gaps) + len(mechanism_gaps),
        "inconsistencies_found": len(numerical_inconsistencies)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}
}

```

class D1_Q3_BudgetAllocationTracer(BaseExecutor):

"""

Traces monetary resources assigned to programs in Investment Plan (PPI).

Methods (from D1-Q3):

- FinancialAuditor.trace_financial_allocation
 - FinancialAuditor._process_financial_table
 - FinancialAuditor._match_program_to_node
 - FinancialAuditor._match_goal_to_budget
 - FinancialAuditor._perform_counterfactual_budget_check
 - FinancialAuditor._calculate_sufficiency
 - PDET MunicipalPlanAnalyzer.analyze_financial_feasibility
 - PDET MunicipalPlanAnalyzer._extract_budget_for_pillar
 - PDET MunicipalPlanAnalyzer._identify_funding_source
 - PDET MunicipalPlanAnalyzer._classify_tables
 - PDET MunicipalPlanAnalyzer._analyze_funding_sources
 - PDET MunicipalPlanAnalyzer._score_financial_component
 - BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
- """

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

```

# Step 1: Trace complete financial allocation chain
allocation_trace = self._execute_method(
    "FinancialAuditor", "trace_financial_allocation", context
)
processed_tables = self._execute_method(
    "FinancialAuditor", "_process_financial_table", context
)

# Step 2: Match programs to budget nodes
program_matches = self._execute_method(
    "FinancialAuditor", "_match_program_to_node", context,
    tables=processed_tables
)
goal_budget_matches = self._execute_method(
    "FinancialAuditor", "_match_goal_to_budget", context,
    programs=program_matches
)

# Step 3: Counterfactual checks and sufficiency calculation
counterfactual_check = self._execute_method(
    "FinancialAuditor", "_perform_counterfactual_budget_check", context,
    matches=goal_budget_matches
)
sufficiency_calc = self._execute_method(
    "FinancialAuditor", "_calculate_sufficiency", context,
    allocation=allocation_trace
)

# Step 4: Analyze financial feasibility
feasibility_analysis = self._execute_method(
    "PDET Municipal Plan Analyzer", "analyze_financial_feasibility", context
)
pillar_budgets = self._execute_method(
    "PDET Municipal Plan Analyzer", "extract_budget_for_pillar", context
)
funding_sources = self._execute_method(
    "PDET Municipal Plan Analyzer", "identify_funding_source", context
)

# Step 5: Classify and analyze tables
table_classification = self._execute_method(
    "PDET Municipal Plan Analyzer", "_classify_tables", context,
    tables=processed_tables
)
funding_analysis = self._execute_method(
    "PDET Municipal Plan Analyzer", "_analyze_funding_sources", context,
    sources=funding_sources
)
financial_score = self._execute_method(
    "PDET Municipal Plan Analyzer", "_score_financial_component", context,
    analysis=funding_analysis
)

# Step 6: Aggregate risk and prioritize
risk_aggregation = self._execute_method(
    "Bayesian Counterfactual Auditor", "aggregate_risk_and_prioritize", context,
    sufficiency=sufficiency_calc
)

raw_evidence = {
    "budget_allocations": allocation_trace,
    "program_mappings": program_matches,
    "goal_budget_links": goal_budget_matches,
    "sufficiency_analysis": sufficiency_calc,
    "pillar_budgets": pillar_budgets,
    "funding_sources": funding_sources,
    "financial_feasibility": feasibility_analysis,
}

```

```

        "financial_score": financial_score,
        "risk_priorities": risk_aggregation
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "programs_traced": len(program_matches),
            "funding_sources_identified": len(funding_sources)
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}

```

class D1_Q4_InstitutionalCapacityIdentifier(BaseExecutor):

"""

Identifies installed capacity (entities, staff, equipment) and limitations.

Methods (from D1-Q4):

- PDET Municipal Plan Analyzer .identify_responsible_entities
- PDET Municipal Plan Analyzer .extract_entities_ner
- PDET Municipal Plan Analyzer .extract_entities_syntax
- PDET Municipal Plan Analyzer .classify_entity_type
- PDET Municipal Plan Analyzer .score_entity_specificity
- PDET Municipal Plan Analyzer .consolidate_entities
- MechanismPartExtractor.extract_entity_activity
- MechanismPartExtractor._normalize_entity
- MechanismPartExtractor._validate_entity_activity
- MechanismPartExtractor._calculate_ea_confidence
- OperationalizationAuditor.audit_evidence_traceability

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

 # Step 1: Identify all responsible entities
 entities_identified = self._execute_method(
 "PDET Municipal Plan Analyzer", "identify_responsible_entities", context
)

 # Step 2: Extract entities using NER and syntax
 ner_entities = self._execute_method(
 "PDET Municipal Plan Analyzer", "_extract_entities_ner", context
)
 syntax_entities = self._execute_method(
 "PDET Municipal Plan Analyzer", "_extract_entities_syntax", context
)

 # Step 3: Classify and score entities
 entity_types = self._execute_method(
 "PDET Municipal Plan Analyzer", "_classify_entity_type", context,
 entities=ner_entities + syntax_entities
)
 specificity_scores = self._execute_method(
 "PDET Municipal Plan Analyzer", "_score_entity_specificity", context,
 entities=entity_types
)
 consolidated = self._execute_method(
 "PDET Municipal Plan Analyzer", "_consolidate_entities", context,
 entities=entity_types
)

 # Step 4: Extract entity-activity relationships

```

entity_activities = self._execute_method(
    "MechanismPartExtractor", "extract_entity_activity", context,
    entities=consolidated
)
normalized = self._execute_method(
    "MechanismPartExtractor", "_normalize_entity", context,
    activities=entity_activities
)
validated = self._execute_method(
    "MechanismPartExtractor", "_validate_entity_activity", context,
    normalized=normalized
)
ea_confidence = self._execute_method(
    "MechanismPartExtractor", "_calculate_ea_confidence", context,
    validated=validated
)

# Step 5: Audit evidence traceability
traceability_audit = self._execute_method(
    "OperationalizationAuditor", "audit_evidence_traceability", context,
    entity_activities=validated
)

raw_evidence = {
    "entities_identified": consolidated,
    "entity_types": entity_types,
    "specificity_scores": specificity_scores,
    "entity_activities": validated,
    "activity_confidence": ea_confidence,
    "capacity_indicators": {
        "staff_mentions": [e for e in consolidated if e.get("type") == "staff"],
        "equipment_mentions": [e for e in consolidated if e.get("type") ==
"equipment"],
        "organizational_units": [e for e in consolidated if e.get("type") ==
"organization"]
    },
    "limitations_identified": traceability_audit.get("gaps", []),
    "traceability_audit": traceability_audit
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "entities_count": len(consolidated),
        "activities_extracted": len(validated)
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D1_Q5_ScopeJustificationValidator(BaseExecutor):

"""

Validates scope justification via legal framework and constraint recognition.

Methods (from D1-Q5):

- TemporalLogicVerifier._check_deadline_constraints
 - TemporalLogicVerifier.verify_temporal_consistency
 - CausalInferenceSetup.identify_failure_points
 - CausalExtractor._assess_temporal_coherence
 - TextMiningEngine._analyze_link_text
 - IndustrialPolicyProcessor._analyze_causal_dimensions
 - IndustrialPolicyProcessor._extract_metadata
- """"

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Verify temporal constraints
    deadline_constraints = self._execute_method(
        "TemporalLogicVerifier", "_check_deadline_constraints", context
    )
    temporal_consistency = self._execute_method(
        "TemporalLogicVerifier", "verify_temporal_consistency", context
    )

    # Step 2: Identify failure points in scope
    failure_points = self._execute_method(
        "CausalInferenceSetup", "identify_failure_points", context
    )

    # Step 3: Assess temporal coherence
    temporal_coherence = self._execute_method(
        "CausalExtractor", "_assess_temporal_coherence", context
    )

    # Step 4: Analyze link text for justifications
    link_analysis = self._execute_method(
        "TextMiningEngine", "_analyze_link_text", context
    )

    # Step 5: Analyze causal dimensions and extract metadata
    causal_dimensions = self._execute_method(
        "IndustrialPolicyProcessor", "_analyze_causal_dimensions", context
    )
    metadata_extracted = self._execute_method(
        "IndustrialPolicyProcessor", "_extract_metadata", context,
        dimensions=causal_dimensions
    )

    raw_evidence = {
        "legal_framework_citations": metadata_extracted.get("legal_refs", []),
        "temporal_constraints": {
            "deadline_checks": deadline_constraints,
            "consistency": temporal_consistency,
            "coherence": temporal_coherence
        },
        "budgetary_constraints": metadata_extracted.get("budget_limits", []),
        "competence_constraints": metadata_extracted.get("competence_refs", []),
        "failure_points": failure_points,
        "scope_justifications": link_analysis.get("justifications", []),
        "causal_dimensions": causal_dimensions
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "constraints_identified": len(deadline_constraints),
            "legal_citations": len(metadata_extracted.get("legal_refs", []))
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }

# =====
# DIMENSION 2: ACTIVITY DESIGN
# =====

```

```

class D2_Q1_StructuredPlanningValidator(BaseExecutor):
    """
    Validates structured format of activities (table/matrix with required columns).
    """

    Methods (from D2-Q1):
    - PDFProcessor.extract_tables
    - FinancialAuditor._process_financial_table
    - PDETMunicipalPlanAnalyzer._deduplicate_tables
    - PDETMunicipalPlanAnalyzer._classify_tables
    - PDETMunicipalPlanAnalyzer._is_likely_header
    - PDETMunicipalPlanAnalyzer._clean_dataframe
    - ReportingEngine.generate_accountability_matrix
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}

        # Step 1: Extract all tables
        extracted_tables = self._execute_method(
            "PDFProcessor", "extract_tables", context
        )

        # Step 2: Process financial tables
        processed_tables = self._execute_method(
            "FinancialAuditor", "_process_financial_table", context,
            tables=extracted_tables
        )

        # Step 3: Deduplicate and classify tables
        deduplicated = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_deduplicate_tables", context,
            tables=processed_tables
        )
        classified = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_classify_tables", context,
            tables=deduplicated
        )

        # Step 4: Identify headers and clean dataframes
        header_checks = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_is_likely_header", context,
            tables=classified
        )
        cleaned = self._execute_method(
            "PDETMunicipalPlanAnalyzer", "_clean_dataframe", context,
            tables=classified
        )

        # Step 5: Generate accountability matrix
        accountability_matrix = self._execute_method(
            "ReportingEngine", "generate_accountability_matrix", context,
            tables=cleaned
        )

        raw_evidence = {
            "tables_extracted": len(extracted_tables),
            "activity_tables": [t for t in classified if t.get("type") == "activity"],
            "matrix_structure": accountability_matrix,
            "required_columns_present": {
                "responsible_entity": any("responsible" in str(t.get("columns", [])).lower()
                                           for t in cleaned),
                "deliverable": any("deliverable" in str(t.get("columns", [])).lower()
                                   for t in cleaned),
                "timeline": any("timeline" in str(t.get("columns", [])).lower()
                               for t in cleaned),
                "cost": any("cost" in str(t.get("columns", [])).lower())
            }
        }

```

```

        for t in cleaned)
    },
    "table_quality": {
        "clean_tables": len(cleaned),
        "with_headers": sum(1 for h in header_checks if h)
    }
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "total_tables": len(extracted_tables),
        "activity_tables": len([t for t in classified if t.get("type") ==
"activity"])
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D2_Q2_InterventionLogicInferencer(BaseExecutor):

"""

Infers intervention logic: instrument (how), target (who), causality (why).

Methods (from D2-Q2):

- BayesianMechanismInference.infer_mechanisms
- BayesianMechanismInference._infer_single_mechanism
- BayesianMechanismInference._infer_mechanism_type
- BayesianMechanismInference._test_sufficiency
- BayesianMechanismInference._test_necessity
- CausalExtractor.extract_causal_hierarchy
- TeoriaCambio.construir_grafo_causal
- TeoriaCambio._esConexionValida
- PDET Municipal Plan Analyzer.construct_causal_dag
- BeachEvidentialTest.classify_test
- IndustrialPolicyProcessor._analyze_causal_dimensions

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

Step 1: Infer mechanisms

mechanisms = self._execute_method(
 "BayesianMechanismInference", "infer_mechanisms", context
)

single_mechanisms = []

for mech in mechanisms:

single = self._execute_method(

"BayesianMechanismInference", "_infer_single_mechanism", context,
 mechanism=mech
)

single_mechanisms.append(single)

mechanism_types = self._execute_method(

"BayesianMechanismInference", "_infer_mechanism_type", context,
 mechanisms=single_mechanisms
)

Step 2: Test sufficiency and necessity

sufficiency_tests = self._execute_method(

"BayesianMechanismInference", "_test_sufficiency", context,
 mechanisms=single_mechanisms
)

necessity_tests = self._execute_method(

```

        "BayesianMechanismInference", "_test_necessity", context,
        mechanisms=single_mechanisms
    )

# Step 3: Extract causal hierarchy
causal_hierarchy = self._execute_method(
    "CausalExtractor", "extract_causal_hierarchy", context
)

# Step 4: Build causal graph
causal_graph = self._execute_method(
    "TeoriaCambio", "construir_grafo_causal", context,
    hierarchy=causal_hierarchy
)
connection_validation = self._execute_method(
    "TeoriaCambio", "_esConexionValida", context,
    graph=causal_graph
)

# Step 5: Construct DAG
causal_dag = self._execute_method(
    "PDET Municipal Plan Analyzer", "construct_causal_dag", context,
    graph=causal_graph
)

# Step 6: Classify evidential tests
evidential_tests = self._execute_method(
    "BeachEvidentialTest", "classify_test", context,
    mechanisms=single_mechanisms
)

# Step 7: Analyze causal dimensions
causal_dimensions = self._execute_method(
    "IndustrialPolicyProcessor", "_analyze_causal_dimensions", context
)

raw_evidence = {
    "intervention_instruments": [m.get("instrument") for m in single_mechanisms],
    "target_populations": [m.get("target") for m in single_mechanisms],
    "causal_logic": {
        "mechanisms": single_mechanisms,
        "mechanism_types": mechanism_types,
        "sufficiency": sufficiency_tests,
        "necessity": necessity_tests
    },
    "causal_hierarchy": causal_hierarchy,
    "causal_graph": causal_graph,
    "causal_dag": causal_dag,
    "evidential_strength": evidential_tests,
    "dimensions": causal_dimensions
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "mechanisms_identified": len(single_mechanisms),
        "instruments_found": len([m for m in single_mechanisms if
m.get("instrument")])
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

```

class D2_Q3_RootCauseLinkageAnalyzer(BaseExecutor):
    """
    Analyzes linkage between activities and root causes/structural determinants.

    Methods (from D2-Q3):
    - CausalExtractor._extract_causal_links
    - CausalExtractor._calculate_composite_likelihood
    - CausalExtractor._initialize_prior
    - CausalExtractor._calculate_type_transition_prior
    - PDET MunicipalPlanAnalyzer._identify_causal_edges
    - PDET MunicipalPlanAnalyzer._refine_edge_probabilities
    - BayesianCounterfactualAuditor.construct_scm
    - BayesianCounterfactualAuditor._create_default_equations
    - SemanticAnalyzer.extract_semantic_cube
    """

    def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
        raw_evidence = {}

        # Step 1: Extract causal links
        causal_links = self._execute_method(
            "CausalExtractor", "_extract_causal_links", context
        )

        # Step 2: Calculate likelihoods
        composite_likelihood = self._execute_method(
            "CausalExtractor", "_calculate_composite_likelihood", context,
            links=causal_links
        )
        prior_init = self._execute_method(
            "CausalExtractor", "_initialize_prior", context
        )
        type_transition_prior = self._execute_method(
            "CausalExtractor", "_calculate_type_transition_prior", context,
            links=causal_links
        )

        # Step 3: Identify and refine causal edges
        causal_edges = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_identify_causal_edges", context,
            links=causal_links
        )
        refined_probabilities = self._execute_method(
            "PDET MunicipalPlanAnalyzer", "_refine_edge_probabilities", context,
            edges=causal_edges
        )

        # Step 4: Construct structural causal model
        scm = self._execute_method(
            "BayesianCounterfactualAuditor", "construct_scm", context,
            edges=refined_probabilities
        )
        default_equations = self._execute_method(
            "BayesianCounterfactualAuditor", "_create_default_equations", context,
            scm=scm
        )

        # Step 5: Extract semantic cube
        semantic_cube = self._execute_method(
            "SemanticAnalyzer", "extract_semantic_cube", context
        )

        raw_evidence = {
            "root_causes_identified": [link.get("root_cause") for link in causal_links],
            "activity_linkages": causal_links,
            "link_probabilities": refined_probabilities,
            "composite_likelihood": composite_likelihood,
            "structural_model": scm,
        }

```

```

        "model_equations": default_equations,
        "semantic_relationships": semantic_cube,
        "determinants_addressed": [link for link in causal_links if
link.get("addresses_determinant")]
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "causal_links_found": len(causal_links),
            "root_causes_count": len(set(link.get("root_cause") for link in
causal_links))
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}

```

class D2_Q4_RiskManagementAnalyzer(BaseExecutor):

Identifies implementation risks and mitigation measures.

Methods (from D2-Q4):

- PDET Municipal Plan Analyzer._bayesian_risk_inference
- PDET Municipal Plan Analyzer.sensitivity_analysis
- PDET Municipal Plan Analyzer._interpret_risk
- PDET Municipal Plan Analyzer._compute_robustness_value
- PDET Municipal Plan Analyzer._compute_e_value
- PDET Municipal Plan Analyzer._interpret_sensitivity
- OperationalizationAuditor._audit_systemic_risk
- BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
- BayesianCounterfactualAuditor.refutation_and_sanity_checks
- AdaptivePriorCalculator.sensitivity_analysis

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw_evidence = {}

 # Step 1: Bayesian risk inference
 risk_inference = self._execute_method(
 "PDET Municipal Plan Analyzer", "_bayesian_risk_inference", context
)

 # Step 2: Sensitivity analysis
 sensitivity = self._execute_method(
 "PDET Municipal Plan Analyzer", "sensitivity_analysis", context,
 risks=risk_inference
)

 # Step 3: Risk interpretation
 risk_interpretation = self._execute_method(
 "PDET Municipal Plan Analyzer", "_interpret_risk", context,
 inference=risk_inference
)

 # Step 4: Compute robustness metrics
 robustness = self._execute_method(
 "PDET Municipal Plan Analyzer", "_compute_robustness_value", context,
 sensitivity=sensitivity
)
 e_value = self._execute_method(
 "PDET Municipal Plan Analyzer", "_compute_e_value", context,
 robustness=robustness
)

```

sensitivity_interpretation = self._execute_method(
    "PDET Municipal Plan Analyzer", "_interpret_sensitivity", context,
    sensitivity=sensitivity
)

# Step 5: Audit systemic risks
systemic_risk_audit = self._execute_method(
    "Operationalization Auditor", "_audit_systemic_risk", context
)

# Step 6: Aggregate and prioritize risks
risk_aggregation = self._execute_method(
    "Bayesian Counterfactual Auditor", "aggregate_risk_and_prioritize", context,
    risks=risk_inference
)

# Step 7: Refutation and sanity checks
refutation_checks = self._execute_method(
    "Bayesian Counterfactual Auditor", "refutation_and_sanity_checks", context,
    aggregation=risk_aggregation
)

# Step 8: Additional sensitivity analysis
adaptive_sensitivity = self._execute_method(
    "Adaptive Prior Calculator", "sensitivity_analysis", context,
    risks=risk_inference
)

raw_evidence = {
    "operational_risks": [r for r in risk_inference if r.get("type") == "operational"],
    "social_risks": [r for r in risk_inference if r.get("type") == "social"],
    "security_risks": [r for r in risk_inference if r.get("type") == "security"],
    "mitigation_measures": risk_interpretation.get("mitigations", []),
    "risk_priorities": risk_aggregation,
    "robustness_metrics": {
        "robustness_value": robustness,
        "e_value": e_value
    },
    "sensitivity_analysis": sensitivity,
    "systemic_risks": systemic_risk_audit,
    "validation_checks": refutation_checks
}

return {
    "executor_id": self.executor_id,
    "raw_evidence": raw_evidence,
    "metadata": {
        "methods_executed": [log["method"] for log in self.execution_log],
        "risks_identified": len(risk_inference),
        "mitigations_proposed": len(risk_interpretation.get("mitigations", []))
    },
    "execution_metrics": {
        "methods_count": len(self.execution_log),
        "all_succeeded": all(log["success"] for log in self.execution_log)
    }
}

```

class D2_Q5_StrategicCoherenceEvaluator(BaseExecutor):

"""

Evaluates strategic coherence: complementarity and logical sequence.

Methods (from D2-Q5):

- PolicyContradictionDetector._detect_logical_incompatibilities
- PolicyContradictionDetector._calculate_coherence_metrics
- PolicyContradictionDetector._calculate_objective_alignment
- PolicyContradictionDetector._calculate_graph_fragmentation

```

- OperationalizationAuditor.audit_sequence_logic
- BayesianMechanismInference._calculate_coherence_factor
- PDET MunicipalPlanAnalyzer._score_causal_coherence
- AdaptivePriorCalculator.calculate_likelihood_adaptativo
"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
    raw_evidence = {}

    # Step 1: Detect logical incompatibilities
    incompatibilities = self._execute_method(
        "PolicyContradictionDetector", "_detect_logical_incompatibilities", context
    )

    # Step 2: Calculate coherence metrics
    coherence_metrics = self._execute_method(
        "PolicyContradictionDetector", "_calculate_coherence_metrics", context
    )
    objective_alignment = self._execute_method(
        "PolicyContradictionDetector", "_calculate_objective_alignment", context
    )
    graph_fragmentation = self._execute_method(
        "PolicyContradictionDetector", "_calculate_graph_fragmentation", context
    )

    # Step 3: Audit sequence logic
    sequence_audit = self._execute_method(
        "OperationalizationAuditor", "audit_sequence_logic", context
    )

    # Step 4: Calculate coherence factors
    coherence_factor = self._execute_method(
        "BayesianMechanismInference", "_calculate_coherence_factor", context,
        metrics=coherence_metrics
    )
    causal_coherence_score = self._execute_method(
        "PDET MunicipalPlanAnalyzer", "_score_causal_coherence", context
    )

    # Step 5: Adaptive likelihood calculation
    adaptive_likelihood = self._execute_method(
        "AdaptivePriorCalculator", "calculate_likelihood_adaptativo", context,
        coherence=causal_coherence_score
    )

    raw_evidence = {
        "complementarity_evidence": coherence_metrics.get("complementarity", []),
        "sequential_logic": sequence_audit,
        "logical_incompatibilities": incompatibilities,
        "coherence_scores": {
            "overall_coherence": coherence_metrics,
            "objective_alignment": objective_alignment,
            "causal_coherence": causal_coherence_score,
            "coherence_factor": coherence_factor
        },
        "graph_metrics": {
            "fragmentation": graph_fragmentation
        },
        "adaptive_likelihood": adaptive_likelihood
    }

    return {
        "executor_id": self.executor_id,
        "raw_evidence": raw_evidence,
        "metadata": {
            "methods_executed": [log["method"] for log in self.execution_log],
            "incompatibilities_found": len(incompatibilities),
            "coherence_score": coherence_metrics.get("score", 0)
        }
    }

```

```
        },
        "execution_metrics": {
            "methods_count": len(self.execution_log),
            "all_succeeded": all(log["success"] for log in self.execution_log)
        }
    }
}
```

```
# =====
# DIMENSION 3: PRODUCTS & OUTPUTS
# =====
```

```
class D3_Q1_IndicatorQualityValidator(BaseExecutor):
    """
```

```
    Validates indicator quality: baseline, target, source of verification.
```

```
    Methods (from D3-Q1):
```

- PDETMunicipalPlanAnalyzer._score_indicators
 - OperationalizationAuditor.audit_evidence_traceability
 - CausalInferenceSetup.assign_probative_value
 - BeachEvidentialTest.apply_test_logic
 - TextMiningEngine.diagnose_critical_links
 - IndustrialPolicyProcessor._extract_metadata
 - IndustrialPolicyProcessor._calculate_quality_score
 - AdaptivePriorCalculator.generate_traceability_record
- ```
 """
```

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
```

```
 raw_evidence = {}
```

```
 # Step 1: Score indicators
```

```
 indicator_scores = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_score_indicators", context
)
```

```
 # Step 2: Audit evidence traceability
```

```
 traceability_audit = self._execute_method(
 "OperationalizationAuditor", "audit_evidence_traceability", context,
 indicators=indicator_scores
)
```

```
 # Step 3: Assign probative value
```

```
 probative_values = self._execute_method(
 "CausalInferenceSetup", "assign_probative_value", context,
 indicators=indicator_scores
)
```

```
 # Step 4: Apply evidential tests
```

```
 evidential_tests = self._execute_method(
 "BeachEvidentialTest", "apply_test_logic", context,
 indicators=indicator_scores
)
```

```
 # Step 5: Diagnose critical links
```

```
 critical_links = self._execute_method(
 "TextMiningEngine", "diagnose_critical_links", context
)
```

```
 # Step 6: Extract and score metadata
```

```
 metadata = self._execute_method(
 "IndustrialPolicyProcessor", "_extract_metadata", context
)
 quality_score = self._execute_method(
 "IndustrialPolicyProcessor", "_calculate_quality_score", context,
 metadata=metadata
)
```

```
 # Step 7: Generate traceability record
```

```

traceability_record = self._execute_method(
 "AdaptivePriorCalculator", "generate_traceability_record", context,
 indicators=indicator_scores
)

raw_evidence = {
 "indicators_with_baseline": [i for i in indicator_scores if
i.get("has_baseline")],
 "indicators_with_target": [i for i in indicator_scores if
i.get("has_target")],
 "indicators_with_source": [i for i in indicator_scores if
i.get("has_source")],
 "indicator_quality_scores": indicator_scores,
 "traceability": traceability_audit,
 "probative_values": probative_values,
 "evidential_strength": evidential_tests,
 "overall_quality_score": quality_score,
 "traceability_record": traceability_record
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "total_indicators": len(indicator_scores),
 "complete_indicators": len([i for i in indicator_scores
 if i.get("has_baseline") and i.get("has_target") and
i.get("has_source")])
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

class D3\_Q2\_TargetProportionalityAnalyzer(BaseExecutor):

\*\*\*\*\*  
DIM03\_Q02\_PRODUCT\_TARGET\_PROPORTIONALITY — Analyzes proportionality of targets to the diagnosed universe using canonical D3 notation.  
Epistemic mix: structural coverage, financial/normative feasibility, statistical Bayes tests, and semantic indicator quality.

Methods (from D3-Q2):

- AdvancedDAGValidator.\_calculate\_bayesian\_posterior
  - AdvancedDAGValidator.\_calculate\_confidence\_interval
  - AdaptivePriorCalculator.\_adjust\_domain\_weights
  - PDET MunicipalPlanAnalyzer.\_get\_spanish\_stopwords
  - BayesianMechanismInference.\_log\_refactored\_components
  - PDET MunicipalPlanAnalyzer.analyze\_financial\_feasibility
  - PDET MunicipalPlanAnalyzer.\_score\_indicators
  - PDET MunicipalPlanAnalyzer.\_interpret\_risk
  - FinancialAuditor.\_calculate\_sufficiency
  - BayesianMechanismInference.\_test\_sufficiency
  - BayesianMechanismInference.\_test\_necessity
  - PDET MunicipalPlanAnalyzer.\_assess\_financial\_sustainability
  - AdaptivePriorCalculator.calculate\_likelihood\_adaptativo
  - IndustrialPolicyProcessor.\_calculate\_quality\_score
  - TeoriaCambio.\_generar\_sugerencias\_internas
  - PDET MunicipalPlanAnalyzer.\_deduplicate\_tables
  - PDET MunicipalPlanAnalyzer.\_indicator\_to\_dict
  - PDET MunicipalPlanAnalyzer.\_generate\_recommendations
  - IndustrialPolicyProcessor.\_compile\_pattern\_registry
  - IndustrialPolicyProcessor.\_build\_point\_patterns
  - IndustrialPolicyProcessor.\_empty\_result
- \*\*\*\*\*

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}
 dim_info = get_dimension_info(CanonicalDimension.D3.value)

 # Step 0: Financial feasibility snapshot and indicator quality
 financial_feasibility = self._execute_method(
 "PDET Municipal Plan Analyzer", "analyze_financial_feasibility", context
)
 indicator_quality = self._execute_method(
 "PDET Municipal Plan Analyzer", "score_indicators", context
)
 spanish_stopwords = self._execute_method(
 "PDET Municipal Plan Analyzer", "get_spanish_stopwords", context
)
 funding_sources = self._execute_method(
 "PDET Municipal Plan Analyzer", "analyze_funding_sources", context,
 financial_indicators=financial_feasibility.get("financial_indicators", []),
 tables=context.get("tables", [])
)
 financial_component = self._execute_method(
 "PDET Municipal Plan Analyzer", "score_financial_component", context,
 financial_analysis=financial_feasibility
)
 pattern_registry = self._execute_method(
 "Industrial Policy Processor", "compile_pattern_registry", context
)
 point_patterns = self._execute_method(
 "Industrial Policy Processor", "build_point_patterns", context
)
 empty_policy_result = self._execute_method(
 "Industrial Policy Processor", "empty_result", context
)
 dedup_tables = self._execute_method(
 "PDET Municipal Plan Analyzer", "deduplicate_tables", context,
 tables=context.get("tables", [])
)
 first_indicator = None
 if isinstance(financial_feasibility.get("financial_indicators", []), list):
 inds = financial_feasibility.get("financial_indicators", [])
 first_indicator = inds[0] if inds else None
 indicator_dict = self._execute_method(
 "PDET Municipal Plan Analyzer", "indicator_to_dict", context,
 ind=first_indicator if first_indicator else {}
)
 proportionality_recommendations = self._execute_method(
 "PDET Municipal Plan Analyzer", "generate_recommendations", context,
 analysis_results={"financial_analysis": financial_feasibility,
 "quality_score": quality_score} if 'quality_score' in locals() else {}
)

 # Step 1: Calculate sufficiency
 sufficiency_calc = self._execute_method(
 "Financial Auditor", "calculate_sufficiency", context
)

 # Step 2: Test sufficiency and necessity of targets
 sufficiency_test = self._execute_method(
 "Bayesian Mechanism Inference", "test_sufficiency", context
)
 necessity_test = self._execute_method(
 "Bayesian Mechanism Inference", "test_necessity", context
)

 # Step 3: Assess financial sustainability
 sustainability_assessment = self._execute_method(
 "PDET Municipal Plan Analyzer", "assess_financial_sustainability", context
)
 risk_interpretation = self._execute_method(

```

```

 "PDET Municipal Plan Analyzer", "_interpret_risk", context,
 risk=financial_feasibility.get("risk_assessment", {}).get("risk_score", 0.0)
)

Step 4: Calculate adaptive likelihood
adaptive_likelihood = self._execute_method(
 "AdaptivePriorCalculator", "calculate_likelihood_adaptativo", context
)
domain_scores = {
 "structural": sufficiency_calc.get("coverage_ratio", 0.0),
 "financial": financial_feasibility.get("sustainability_score", 0.0),
 "semantic": indicator_quality if isinstance(indicator_quality, (int, float))
}
else 0.0
)
adjusted_weights = self._execute_method(
 "AdaptivePriorCalculator", "_adjust_domain_weights", context,
 domain_scores=domain_scores
)
avg_confidence = self._execute_method(
 "IndustrialPolicyProcessor", "_compute_avg_confidence", context,
 dimension_analysis={"D3": {"dimension_confidence": domain_scores.get("structural", 0.0)}}
)

Step 5: Calculate quality score
quality_score = self._execute_method(
 "IndustrialPolicyProcessor", "_calculate_quality_score", context
)

Step 6: Generate internal suggestions
internal_suggestions = self._execute_method(
 "TeoriaCambio", "_generar_sugerencias_internas", context
)
Bayesian posterior diagnostics for proportionality evidence
posterior_probability = self._execute_method(
 "AdvancedDAGValidator", "_calculate_bayesian_posterior", context,
 likelihood=sufficiency_calc.get("coverage_ratio", 0.5),
 prior=0.5
)
confidence_interval = self._execute_method(
 "AdvancedDAGValidator", "_calculate_confidence_interval", context,
 s=int(sufficiency_calc.get("covered_targets", 0)),
 n=max(1, int(sufficiency_calc.get("targets_total",
len(context.get("product_targets", []))))),
 conf=0.95
)
self._execute_method(
 "BayesianMechanismInference", "_log_refactored_components", context
)

raw_evidence = {
 "target_population_size": context.get("diagnosed_universe", 0),
 "product_targets": context.get("product_targets", []),
 "coverage_ratio": sufficiency_calc.get("coverage_ratio", 0),
 "dosage_analysis": sufficiency_calc.get("dosage", {}),
 "sufficiency_test": sufficiency_test,
 "necessity_test": necessity_test,
 "sustainability": sustainability_assessment,
 "financial_feasibility": financial_feasibility,
 "indicator_quality": indicator_quality,
 "risk_interpretation": risk_interpretation,
 "proportionality_score": quality_score,
 "recommendations": internal_suggestions,
 "stopwords_spanish": spanish_stopwords,
 "funding_sources_analysis": funding_sources,
 "financial_component_score": financial_component,
 "pattern_registry": pattern_registry,
 "point_patterns": point_patterns,
}

```

```

 "empty_policy_result": empty_policy_result,
 "avg_confidence": avg_confidence,
 "deduplicated_tables": dedup_tables,
 "indicator_sample": indicator_dict,
 "proportionality_recommendations": proportionality_recommendations,
 "adjusted_domain_weights": adjusted_weights,
 "posterior_proportionality": posterior_probability,
 "coverage_interval": confidence_interval
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "targets_analyzed": len(context.get("product_targets", [])),
 "coverage_adequate": sufficiency_calc.get("is_sufficient", False),
 "canonical_question": "DIM03_Q02_PRODUCT_TARGET_PROPORTIONALITY",
 "dimension_code": dim_info.code,
 "dimension_label": dim_info.label
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}
}

```

class D3\_Q3\_TraceabilityValidator(BaseExecutor):

\*\*\*\*\*  
 DIM03\_Q03\_TRACEABILITY\_BUDGET\_ORG — Validates budgetary and organizational traceability of products under canonical D3 notation.

Epistemic mix: structural budget tracing, organizational semantics, and accountability synthesis.

Methods (from D3-Q3):

- PolicyAnalysisEmbedder.process\_document
  - PolicyAnalysisEmbedder.semantic\_search
  - PolicyAnalysisEmbedder.\_apply\_mmr
  - PolicyAnalysisEmbedder.\_generate\_query\_from\_pdq
  - SemanticAnalyzer.\_empty\_semantic\_cube
  - FinancialAuditor.\_match\_program\_to\_node
  - FinancialAuditor.\_match\_goal\_to\_budget
  - PDET Municipal Plan Analyzer.\_extract\_from\_responsibility\_tables
  - PDET Municipal Plan Analyzer.\_consolidate\_entities
  - AdaptivePriorCalculator.generate\_traceability\_record
  - PolicyAnalysisEmbedder.generate\_pdq\_report
  - ReportingEngine.generate\_accountability\_matrix
- \*\*\*\*\*

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

```

 raw_evidence = {}
 dim_info = get_dimension_info(CanonicalDimension.D3.value)
 document_text = context.get("document_text", "")
 document_metadata = context.get("metadata", {})

```

```

 # Step 1: Match programs to budget nodes
 program_matches = self._execute_method(
 "FinancialAuditor", "_match_program_to_node", context
)
 goal_budget_matches = self._execute_method(
 "FinancialAuditor", "_match_goal_to_budget", context,
 programs=program_matches
)

```

```

 # Step 2: Extract responsibility assignments
 responsibility_data = self._execute_method(
 "PDET Municipal Plan Analyzer", "_extract_from_responsibility_tables", context
)

```

```

)
consolidated_entities = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_consolidate_entities", context,
 entities=responsibility_data
)
responsible_entities = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "identify_responsible_entities", context
)
responsibility_clarity = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_score_responsibility_clarity", context,
 entities=consolidated_entities
)
Semantic traceability via embeddings
semantic_chunks = self._execute_method(
 "PolicyAnalysisEmbedder", "process_document", context,
 document_text=document_text,
 document_metadata=document_metadata
)
pdq_query = self._execute_method(
 "PolicyAnalysisEmbedder", "_generate_query_from_pdq", context,
 pdq={"policy": context.get("policy_area"), "dimension": dim_info.code}
)
semantic_hits = self._execute_method(
 "PolicyAnalysisEmbedder", "semantic_search", context,
 query=pdq_query,
 document_chunks=semantic_chunks or []
)
diversified_hits = self._execute_method(
 "PolicyAnalysisEmbedder", "_apply_mmr", context,
 ranked_results=semantic_hits or []
)
semantic_cube_stub = self._execute_method(
 "SemanticAnalyzer", "_empty_semantic_cube", context
)
domain_scores = self._execute_method(
 "SemanticAnalyzer", "_classify_policy_domain", context,
 segment=document_text
)
cross_cutting = self._execute_method(
 "SemanticAnalyzer", "_classify_cross_cutting_themes", context,
 segment=document_text
)
value_chain = self._execute_method(
 "SemanticAnalyzer", "_classify_value_chain_link", context,
 segment=document_text
)
semantic_vectors = self._execute_method(
 "SemanticAnalyzer", "_vectorize_segments", context,
 segments=[document_text]
)
processed_segment = self._execute_method(
 "SemanticAnalyzer", "_process_segment", context,
 segment=document_text,
 idx=0,
 vector=semantic_vectors[0] if semantic_vectors else None
)
semantic_complexity = self._execute_method(
 "SemanticAnalyzer", "_calculate_semantic_complexity", context,
 semantic_cube=semantic_cube_stub
)
evidence_confidence = self._execute_method(
 "IndustrialPolicyProcessor", "_compute_evidence_confidence", context,
 matches=[m.get("bpin", "") for m in program_matches if isinstance(m, dict)],
 text_length=len(document_text),
 pattern_specificity=0.5
)
entity_dicts = [
 self._execute_method("PDETMunicipalPlanAnalyzer", "_entity_to_dict", context,

```

```

entity=e)
 for e in consolidated_entities[:5]
 if isinstance(e, dict) or hasattr(e, "__dict__")
]

Step 3: Generate traceability records
traceability_record = self._execute_method(
 "AdaptivePriorCalculator", "generate_traceability_record", context,
 matches=program_matches
)

Step 4: Generate PDQ report
pdq_report = self._execute_method(
 "PolicyAnalysisEmbedder", "generate_pdq_report", context,
 traceability=traceability_record
)

Step 5: Generate accountability matrix
accountability_matrix = self._execute_method(
 "ReportingEngine", "generate_accountability_matrix", context,
 entities=consolidated_entities
)

raw_evidence = {
 "budgetary_traceability": {
 "bpin_codes": [m.get("bpin") for m in program_matches if m.get("bpin")],
 "project_codes": [m.get("project_code") for m in program_matches if
m.get("project_code")],
 "budget_matches": goal_budget_matches
 },
 "organizational_traceability": {
 "responsible_entities": consolidated_entities,
 "office_assignments": [e for e in consolidated_entities if
e.get("office")],
 "secretariat_assignments": [e for e in consolidated_entities if
e.get("secretariat")]
 },
 "traceability_record": traceability_record,
 "pdq_report": pdq_report,
 "accountability_matrix": accountability_matrix,
 "responsible_entities": responsible_entities,
 "responsibility_clarity_score": responsibility_clarity,
 "semantic_traceability": {
 "query": pdq_query,
 "semantic_hits": semantic_hits,
 "diversified_hits": diversified_hits
 },
 "semantic_cube_baseline": semantic_cube_stub,
 "policy_domain_scores": domain_scores,
 "responsibility_entities_dict": entity_dicts,
 "cross_cutting_themes": cross_cutting,
 "value_chain_links": value_chain,
 "semantic_vectors": semantic_vectors,
 "semantic_complexity": semantic_complexity,
 "evidence_confidence": evidence_confidence,
 "processed_segment": processed_segment
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "products_with_bpin": len([m for m in program_matches if m.get("bpin")]),
 "products_with_responsible": len(consolidated_entities),
 "canonical_question": "DIM03_Q03_TRACEABILITY_BUDGET_ORG",
 "dimension_code": dim_info.code,
 "dimension_label": dim_info.label
 }
}

```

```

 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

```
class D3_Q4_TechnicalFeasibilityEvaluator(BaseExecutor):
 """

```

DIM03\_Q04\_TECHNICAL\_FEASIBILITY — Evaluates activity-product feasibility vs resources/deadlines (canonical D3).

Epistemic mix: structural DAG validity, causal necessity, performance/implementation readiness, and statistical robustness.

Methods (from D3-Q4):

- AdvancedDAGValidator.\_calculate\_statistical\_power
- AdvancedDAGValidator.\_initialize\_rng
- AdvancedDAGValidator.export\_nodes
- AdvancedDAGValidator.\_generate\_subgraph
- AdvancedDAGValidator.\_get\_node\_validator
- AdvancedDAGValidator.\_create\_empty\_result
- HierarchicalGenerativeModel.\_calculate\_likelihood
- IndustrialGradeValidator.validate\_causal\_categories
- TeoriaCambio.\_extraer\_categorias
- AdvancedDAGValidator.get\_graph\_stats
- AdvancedDAGValidator.\_calculate\_node\_importance
- AdvancedDAGValidator.calculate\_acyclicity\_pvalue
- AdvancedDAGValidator.\_is\_acyclic
- BayesianMechanismInference.\_test\_necessity
- IndustrialGradeValidator.execute\_suite
- IndustrialGradeValidator.validate\_connection\_matrix
- IndustrialGradeValidator.run\_performance\_benchmarks
- IndustrialGradeValidator.\_benchmark\_operation
- PerformanceAnalyzer.analyze\_performance
- PerformanceAnalyzer.\_calculate\_loss\_functions
- HierarchicalGenerativeModel.\_calculate\_ess

"""

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}
 dim_info = get_dimension_info(CanonicalDimension.D3.value)
 plan_name = context.get("metadata", {}).get("title", "plan_desarrollo")

```

```

 # Step 1: Validate DAG structure
 acyclicity_pvalue = self._execute_method(
 "AdvancedDAGValidator", "calculate_acyclicity_pvalue", context
)
 is_acyclic = self._execute_method(
 "AdvancedDAGValidator", "_is_acyclic", context
)
 graph_stats = self._execute_method(
 "AdvancedDAGValidator", "get_graph_stats", context
)
 node_importance = self._execute_method(
 "AdvancedDAGValidator", "_calculate_node_importance", context
)
 subgraph = self._execute_method(
 "AdvancedDAGValidator", "_generate_subgraph", context
)
 added_node = self._execute_method(
 "AdvancedDAGValidator", "add_node", context,
 node_name="temp_node"
)
 added_edge = self._execute_method(
 "AdvancedDAGValidator", "add_edge", context,
 source="temp_node",
 target="temp_target",
)

```

```

 weight=1.0
)
node_export = self._execute_method(
 "AdvancedDAGValidator", "export_nodes", context
)
rng_seed = self._execute_method(
 "AdvancedDAGValidator", "_initialize_rng", context,
 plan_name=plan_name,
 salt=dim_info.code
)
stat_power = self._execute_method(
 "AdvancedDAGValidator", "_calculate_statistical_power", context,
 s=int(graph_stats.get("edges", 0)),
 n=max(1, int(graph_stats.get("nodes", 1)))
)
node_validator = self._execute_method(
 "AdvancedDAGValidator", "_get_node_validator", context,
 node_type="producto"
)
empty_result = self._execute_method(
 "AdvancedDAGValidator", "_create_empty_result", context,
 plan_name=plan_name,
 seed=rng_seed,
 timestamp=context.get("metadata", {}).get("timestamp", "")
)

Step 2: Test necessity of activities for products
necessity_test = self._execute_method(
 "BayesianMechanismInference", "_test_necessity", context
)

Step 3: Execute industrial-grade validation
validation_suite = self._execute_method(
 "IndustrialGradeValidator", "execute_suite", context
)
connection_validation = self._execute_method(
 "IndustrialGradeValidator", "validate_connection_matrix", context
)
performance_benchmarks = self._execute_method(
 "IndustrialGradeValidator", "run_performance_benchmarks", context
)
benchmark_ops = self._execute_method(
 "IndustrialGradeValidator", "_benchmark_operation", context
)
metric_log = self._execute_method(
 "IndustrialGradeValidator", "_log_metric", context,
 name="custom_latency",
 value=graph_stats.get("edges", 0),
 unit="edges",
 threshold=10.0
)
engine_readiness = self._execute_method(
 "IndustrialGradeValidator", "validate_engine_readiness", context
)

Step 4: Analyze performance
performance_analysis = self._execute_method(
 "PerformanceAnalyzer", "analyze_performance", context
)
loss_functions = self._execute_method(
 "PerformanceAnalyzer", "_calculate_loss_functions", context
)
Likelihood estimation for resource adequacy
resource_likelihood = self._execute_method(
 "HierarchicalGenerativeModel", "_calculate_likelihood", context,
 mechanism_type="tecnico",
 observations={"coherence": performance_analysis.get("resource_fit",
 {}).get("score", 0.0)}
)

```

```

)
Step 5: Calculate effective sample size
ess = self._execute_method(
 "HierarchicalGenerativeModel", "_calculate_ess", context
)
r_hat = self._execute_method(
 "HierarchicalGenerativeModel", "_calculate_r_hat", context,
 chains=[]
)
causal_categories_valid = self._execute_method(
 "IndustrialGradeValidator", "validate_causal_categories", context
)
extracted_categories = self._execute_method(
 "TeoriaCambio", "_extraer_categorias", context,
 text=context.get("document_text", ""))
)

raw_evidence = {
 "activity_product_mapping": connection_validation,
 "resource_adequacy": performance_analysis.get("resource_fit", {}),
 "timeline_feasibility": performance_analysis.get("timeline_feasibility", {}),
 "technical_validation": {
 "dag_valid": is_acyclic,
 "acyclicity_p": acyclicity_pvalue,
 "necessity_score": necessity_test,
 "graph_stats": graph_stats,
 "node_importance": node_importance,
 "subgraph_sample": subgraph,
 "added_node": added_node,
 "added_edge": added_edge,
 "node_validator": node_validator,
 "empty_result": empty_result,
 "node_export": node_export,
 "rng_seed": rng_seed,
 "statistical_power": stat_power
 },
 "performance_metrics": {
 "benchmarks": performance_benchmarks,
 "loss_functions": loss_functions,
 "ess": ess,
 "r_hat": r_hat,
 "resource_likelihood": resource_likelihood
 },
 "engine_readiness": engine_readiness,
 "feasibility_score": validation_suite.get("overall_score", 0),
 "causal_categories_valid": causal_categories_valid,
 "extracted_categories": extracted_categories,
 "metric_log": metric_log
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "dag_is_valid": is_acyclic,
 "feasibility_score": validation_suite.get("overall_score", 0),
 "canonical_question": "DIM03_Q04_TECHNICAL_FEASIBILITY",
 "dimension_code": dim_info.code,
 "dimension_label": dim_info.label
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

```

class D3_Q5_OutputOutcomeLinkageAnalyzer(BaseExecutor):
 """
 DIM03_Q05_OUTPUT_OUTCOME_LINKAGE — Analyzes mechanisms linking outputs to outcomes
 with canonical D3 labeling.

 Epistemic mix: semantic hierarchy checks, causal order validation, DAG/effect
 estimation, and Bayesian mechanism inference.

 Methods (from D3-Q5):
 - PDET Municipal Plan Analyzer methods
 - Causal Extractor methods
 - Bayesian Counterfactual Auditor methods
 - Industrial Policy Processor methods
 - Policy Analysis Embedder methods
 - Bayesian Mechanism Inference methods
 """

 def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}
 dim_info = get_dimension_info(CanonicalDimension.D3.value)

 # Step 0: Build causal backbone and effects
 financial_analysis = self._execute_method(
 "PDET Municipal Plan Analyzer", "analyze_financial_feasibility", context
)
 causal_dag = self._execute_method(
 "PDET Municipal Plan Analyzer", "construct_causal_dag", context,
 financial_analysis=financial_analysis
)
 causal_effects = self._execute_method(
 "PDET Municipal Plan Analyzer", "estimate_causal_effects", context,
 dag=causal_dag,
 financial_analysis=financial_analysis
)
 counterfactuals = self._execute_method(
 "PDET Municipal Plan Analyzer", "generate_counterfactuals", context,
 dag=causal_dag,
 causal_effects=causal_effects,
 financial_analysis=financial_analysis
)
 simulated_intervention = self._execute_method(
 "PDET Municipal Plan Analyzer", "_simulate_intervention", context,
 intervention={},
 dag=causal_dag,
 causal_effects=causal_effects,
 label="baseline"
)
 causal_nodes = self._execute_method(
 "PDET Municipal Plan Analyzer", "_identify_causal_nodes", context,
 dag=causal_dag
)
 causal_recommendations = self._execute_method(
 "PDET Municipal Plan Analyzer", "generate_recommendations", context,
 causal_nodes=causal_nodes,
 causal_effects=causal_effects
)
 causal_necessity = self._execute_method(
 "PDET Municipal Plan Analyzer", "generate_necessity_remediation", context,
 causal_nodes=causal_nodes,
 causal_effects=causal_effects
)
 causal_refutation = self._execute_method(
 "PDET Municipal Plan Analyzer", "refutation_and_sanity_checks", context,
 causal_nodes=causal_nodes,
 causal_effects=causal_effects
)
 causal_consistency = self._execute_method(
 "Causal Extractor", "assess_financial_consistency", context,
 causal_nodes=causal_nodes
)
 causal_sequence = self._execute_method(
 "Bayesian Mechanism Inference", "infer_activity_sequence", context,
 causal_nodes=causal_nodes
)
 causal_priors = self._execute_method(
 "Bayesian Mechanism Inference", "generate_necessity_remediation", context,
 causal_nodes=causal_nodes
)
 causal_proximity = self._execute_method(
 "Bayesian Counterfactual Auditor", "evaluate_counterfactual", context,
 causal_nodes=causal_nodes
)
 causal_factuals = self._execute_method(
 "Bayesian Counterfactual Auditor", "evaluate_factual", context,
 causal_nodes=causal_nodes
)
 causal_feasibility = self._execute_method(
 "Industrial Policy Processor", "load_questionnaire", context
)
 causal_feasibility = self._execute_method(
 "PDET Municipal Plan Analyzer", "analyze_financial_feasibility", context
)
 causal_causality = self._execute_method(
 "PDET Municipal Plan Analyzer", "construct_causal_dag", context
)
 causal_effects = self._execute_method(
 "PDET Municipal Plan Analyzer", "estimate_causal_effects", context
)
 causal_counterfactuals = self._execute_method(
 "PDET Municipal Plan Analyzer", "generate_counterfactuals", context
)
 causal_hierarchy = self._execute_method(
 "Causal Extractor", "build_type_hierarchy", context
)
 causal_violation = self._execute_method(
 "Causal Extractor", "check_structuralViolation", context
)
 causal_transition = self._execute_method(
 "Causal Extractor", "calculate_type_transition_prior", context
)
 causal_proximity = self._execute_method(
 "Causal Extractor", "calculate_textual_proximity", context
)
 causal_order = self._execute_method(
 "Teoria Cambio", "validar_orden_causal", context
)
 causal_refinement = self._execute_method(
 "PDET Municipal Plan Analyzer", "refine_edge_probabilities", context
)
 causal_comparisons = self._execute_method(
 "Policy Analysis Embedder", "compare_policy_interventions", context
)
 causal_inference = self._execute_method(
 "Bayesian Mechanism Inference", "infer_mechanisms", context
)

```

```

text=context.get("document_text", ""),
tables=context.get("tables", []),
financial_analysis=financial_analysis
)
confounders = {}
for effect in causal_effects:
 treatment = effect.treatment if hasattr(effect, "treatment") else None
 outcome = effect.outcome if hasattr(effect, "outcome") else None
 if treatment and outcome:
 confounders[(treatment, outcome)] = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_identify_confounders", context,
 treatment=treatment,
 outcome=outcome,
 dag=causal_dag
)
effect_dicts = [
 self._execute_method("PDETMunicipalPlanAnalyzer", "_effect_to_dict", context,
effect=effect)
 for effect in causal_effects
]
scenario_dicts = [
 self._execute_method("PDETMunicipalPlanAnalyzer", "_scenario_to_dict",
context, scenario=scenario)
 for scenario in counterfactuals
]
causal_recommendations = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_generate_recommendations", context,
 analysis_results={"financial_analysis": financial_analysis, "quality_score": getattr(causal_dag, 'graph', {})}
)
financial_consistency = None
if refined_edges:
 first_edge = refined_edges[0] if isinstance(refined_edges, list) else {}
 source = first_edge.get("source") if isinstance(first_edge, dict) else ""
 target = first_edge.get("target") if isinstance(first_edge, dict) else ""
 financial_consistency = self._execute_method(
 "CausalExtractor", "_assess_financial_consistency", context,
 source=source or "",
 target=target or ""
)
factual_eval = None
counterfactual_eval = None
if causal_effects:
 first_effect = causal_effects[0]
 target = getattr(first_effect, "outcome", None) or ""
 evidence = {"p_effect": getattr(first_effect, "probability_significant", 0.0)}
 factual_eval = self._execute_method(
 "BayesianCounterfactualAuditor", "_evaluate_factual", context,
 target=target,
 evidence=evidence
)
 counterfactual_eval = self._execute_method(
 "BayesianCounterfactualAuditor", "_evaluate_counterfactual", context,
 target=target,
 intervention={"shift": 0.1}
)
matched_node = None
try:
 matched_node = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_match_text_to_node", context,
 text=context.get("document_text", "")[:200],
 nodes=causal_nodes if isinstance(causal_nodes, dict) else {}
)
except Exception:
 matched_node = None
Step 1: Build type hierarchy
type_hierarchy = self._execute_method(

```

```

 "CausalExtractor", "_build_type_hierarchy", context
)

Step 2: Check structural violations
structural_violations = self._execute_method(
 "CausalExtractor", "_check_structuralViolation", context,
 hierarchy=type_hierarchy
)

Step 3: Calculate transition priors and proximity
transition_priors = self._execute_method(
 "CausalExtractor", "_calculate_type_transition_prior", context,
 hierarchy=type_hierarchy
)
textual_proximity = self._execute_method(
 "CausalExtractor", "_calculate_textual_proximity", context
)

Step 4: Validate causal order
causal_order_validation = self._execute_method(
 "TeoriaCambio", "_validar_orden_causal", context,
 hierarchy=type_hierarchy
)

Step 5: Refine edge probabilities
refined_edges = self._execute_method(
 "PDET Municipal Plan Analyzer", "_refine_edge_probabilities", context,
 priors=transition_priors
)

Step 6: Compare policy interventions
intervention_comparison = self._execute_method(
 "PolicyAnalysisEmbedder", "compare_policy_interventions", context
)

Step 7: Infer mechanisms
mechanisms = self._execute_method(
 "BayesianMechanismInference", "infer_mechanisms", context,
 edges=refined_edges
)
mechanism_sample = next(iter(mechanisms.values()), {})
activity_sequence = self._execute_method(
 "BayesianMechanismInference", "_infer_activity_sequence", context,
 observations=mechanism_sample.get("observations", {}),
 mechanism_type_posterior=mechanism_sample.get("mechanism_type", {"tecnico": 1.0})
)
quantified_uncertainty = self._execute_method(
 "BayesianMechanismInference", "_quantify_uncertainty", context,
 mechanism_type_posterior=mechanism_sample.get("mechanism_type", {"tecnico": 1.0}),
 sequence_posterior=mechanism_sample.get("activity_sequence", {}),
 coherence_score=mechanism_sample.get("coherence_score", 0.0)
)
mechanism_observations = self._execute_method(
 "BayesianMechanismInference", "_extract_observations", context,
 node={"id": next(iter(mechanisms.keys()), "")},
 text=context.get("document_text", "")
)
necessity_remediation = self._execute_method(
 "BayesianMechanismInference", "_generate_necessity_remediation", context,
 node_id=next(iter(mechanisms.keys()), ""),
 missing_components=structural_violations
)
questionnaire_stub = self._execute_method(
 "IndustrialPolicyProcessor", "_load_questionnaire", context
)
refutation_checks = None

```

```

try:
 confounder_keys = list(confounders.keys())
 first_pair = confounder_keys[0] if confounder_keys else ("", "")
 refutation_checks = self._execute_method(
 "BayesianCounterfactualAuditor", "refutation_and_sanity_checks", context,
 dag=getattr(causal_dag, "graph", None),
 target=first_pair[1],
 treatment=first_pair[0],
 confounders=list(confounders.values())[0] if confounders else []
)
except Exception:
 refutation_checks = None

raw_evidence = {
 "output_outcome_links": refined_edges,
 "mechanism_explanation": mechanisms,
 "type_hierarchy": type_hierarchy,
 "causal_dag": causal_dag,
 "causal_effects": causal_effects,
 "counterfactuals": counterfactuals,
 "simulated_intervention": simulated_intervention,
 "causal_nodes": causal_nodes,
 "financial_analysis": financial_analysis,
 "causal_validity": {
 "structural_violations": structural_violations,
 "order_valid": causal_order_validation
 },
 "transition_probabilities": transition_priors,
 "textual_proximity": textual_proximity,
 "intervention_comparison": intervention_comparison,
 "confounders": confounders,
 "effect_dicts": effect_dicts,
 "scenario_dicts": scenario_dicts,
 "activity_sequence_sample": activity_sequence,
 "uncertainty_quantified": quantified_uncertainty,
 "mechanism_observations": mechanism_observations,
 "refutation_checks": refutation_checks,
 "necessity_remediation": necessity_remediation,
 "questionnaire_stub": questionnaire_stub,
 "causal_recommendations": causal_recommendations,
 "financial_consistency": financial_consistency,
 "factual_eval": factual_eval,
 "counterfactual_eval": counterfactual_eval,
 "matched_node": matched_node
}
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "mechanisms_identified": len(mechanisms),
 "violations_found": len(structural_violations),
 "canonical_question": "DIM03_Q05_OUTPUT_OUTCOME_LINKAGE",
 "dimension_code": dim_info.code,
 "dimension_label": dim_info.label
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

=====
DIMENSION 4: RESULTS & OUTCOMES
=====

```

```
class D4_Q1_OutcomeMetricsValidator(BaseExecutor):
```

```
 """
```

```
 DIM04_Q01_OUTCOME_INDICATOR完整性 — Validates outcome indicators (baseline, target, horizon) with canonical D4 notation.
```

```
 Epistemic mix: semantic goal extraction, temporal/consistency checks, statistical performance signals, and indicator quality scoring.
```

```
Methods (from D4-Q1):
```

- PDET Municipal Plan Analyzer.\_extract\_entities\_syntax
- PDET Municipal Plan Analyzer.\_extract\_entities\_ner
- CausalExtractor.\_calculate\_language\_specificity
- CausalExtractor.\_calculate\_composite\_likelihood
- CausalExtractor.\_calculate\_semantic\_distance
- TemporalLogicVerifier.\_classify\_temporal\_type
- PDET Municipal Plan Analyzer.\_score\_indicators
- PDET Municipal Plan Analyzer.\_find\_outcome\_mentions
- PDET Municipal Plan Analyzer.\_score\_temporal\_consistency
- CausalExtractor.\_extract\_goals
- CausalExtractor.\_parse\_goal\_context
- CausalExtractor.\_classify\_goal\_type
- TemporalLogicVerifier.\_parse\_temporal\_marker
- TemporalLogicVerifier.\_extract\_resources
- PerformanceAnalyzer.analyze\_performance
- PerformanceAnalyzer.\_generate\_recommendations

```
 """
```

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
```

```
 raw_evidence = {}
 dim_info = get_dimension_info(CanonicalDimension.D4.value)

 # Step 1: Find outcome mentions
 outcome_mentions = self._execute_method(
 "PDET Municipal Plan Analyzer", "_find_outcome_mentions", context
)
 entities_syntax = self._execute_method(
 "PDET Municipal Plan Analyzer", "_extract_entities_syntax", context,
 text=context.get("document_text", "")
)
 entities_ner = self._execute_method(
 "PDET Municipal Plan Analyzer", "_extract_entities_ner", context,
 text=context.get("document_text", "")
)

 # Step 2: Score temporal consistency
 temporal_consistency = self._execute_method(
 "PDET Municipal Plan Analyzer", "_score_temporal_consistency", context,
 outcomes=outcome_mentions
)

 # Step 3: Extract and classify goals
 goals = self._execute_method(
 "CausalExtractor", "_extract_goals", context
)
 goal_contexts = self._execute_method(
 "CausalExtractor", "_parse_goal_context", context,
 goals=goals
)
 goal_types = self._execute_method(
 "CausalExtractor", "_classify_goal_type", context,
 goals=goals
)
 semantic_distance = 0.0
 if goal_types and outcome_mentions:
 semantic_distance = self._execute_method(
 "CausalExtractor", "_calculate_semantic_distance", context,
 source=str(goal_types[0]),
 target=str(outcome_mentions[0])
)
```

```

Step 4: Parse temporal markers
temporal_markers = self._execute_method(
 "TemporalLogicVerifier", "_parse_temporal_marker", context,
 contexts=goal_contexts
)
temporal_type = self._execute_method(
 "TemporalLogicVerifier", "_classify_temporal_type", context,
 marker=temporal_markers[0] if temporal_markers else ""
)
resources_mentioned = self._execute_method(
 "TemporalLogicVerifier", "_extract_resources", context,
 text=context.get("document_text", "")
)
precedence_check = self._execute_method(
 "TemporalLogicVerifier", "_should_precede", context,
 marker_a=temporal_markers[0] if temporal_markers else "",
 marker_b=temporal_markers[1] if len(temporal_markers) > 1 else ""
)

Step 5: Analyze performance
performance_analysis = self._execute_method(
 "PerformanceAnalyzer", "analyze_performance", context,
 outcomes=outcome_mentions
)
indicator_quality = self._execute_method(
 "PDET Municipal Plan Analyzer", "_score_indicators", context
)
performance_recommendations = self._execute_method(
 "PerformanceAnalyzer", "_generate_recommendations", context,
 performance_analysis=performance_analysis
)
Semantic certainty for goals
language_specificity = self._execute_method(
 "CausalExtractor", "_calculate_language_specificity", context,
 keyword=goal_contexts[0] if goal_contexts else "",
 policy_area=context.get("policy_area")
)
composite_likelihood = self._execute_method(
 "CausalExtractor", "_calculate_composite_likelihood", context,
 evidence={
 "semantic_distance": indicator_quality if isinstance(indicator_quality,
 (int, float)) else 0.0,
 "textual_proximity": performance_analysis.get("coherence_score", 0.0) if
 isinstance(performance_analysis, dict) else 0.0,
 "language_specificity": language_specificity,
 "temporal_coherence": temporal_consistency if
 isinstance(temporal_consistency, (int, float)) else 0.0
 }
)
raw_evidence = {
 "outcome_indicators": outcome_mentions,
 "indicators_with_baseline": [o for o in outcome_mentions if
 o.get("has_baseline")],
 "indicators_with_target": [o for o in outcome_mentions if
 o.get("has_target")],
 "indicators_with_horizon": [o for o in outcome_mentions if
 o.get("time_horizon")],
 "temporal_consistency_score": temporal_consistency,
 "goal_classifications": goal_types,
 "temporal_markers": temporal_markers,
 "performance_metrics": performance_analysis,
 "indicator_quality": indicator_quality,
 "performance_recommendations": performance_recommendations,
 "entities_syntax": entities_syntax,
 "entities_ner": entities_ner,
 "temporal_type": temporal_type,
}

```

```

 "language_specificity": language_specificity,
 "composite_likelihood": composite_likelihood,
 "goal_outcome_semantic_distance": semantic_distance,
 "resources_mentioned": resources_mentioned,
 "precedence_check": precedence_check
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "total_outcomes": len(outcome_mentions),
 "complete_indicators": len([o for o in outcome_mentions
 if o.get("has_baseline") and o.get("has_target") and
 o.get("time_horizon")]),
 "canonical_question": "DIM04_Q01_OUTCOME_INDICATOR_COMPLETENESS",
 "dimension_code": dim_info.code,
 "dimension_label": dim_info.label
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

class D4\_Q2\_CausalChainValidator(BaseExecutor):

"""

Validates explicit causal chain with assumptions and enabling conditions.

Methods (from D4-Q2):

- TeoriaCambio.\_encontrar\_caminos\_completos
- TeoriaCambio.validacion\_completa
- CausalExtractor.extract\_causal\_hierarchy
- HierarchicalGenerativeModel.verify\_conditional\_independence
- HierarchicalGenerativeModel.\_generate\_independence\_tests
- BayesianCounterfactualAuditor.construct\_scm
- AdvancedDAGValidator.\_perform\_sensitivity\_analysis\_internal
- BayesFactorTable.get\_bayes\_factor

""""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw\_evidence = {}

# Step 1: Find complete causal paths

```

 complete_paths = self._execute_method(
 "TeoriaCambio", "_encontrar_caminos_completos", context
)

```

# Step 2: Complete validation

```

 validation_results = self._execute_method(
 "TeoriaCambio", "validacion_completa", context,
 paths=complete_paths
)

```

# Step 3: Extract causal hierarchy

```

 causal_hierarchy = self._execute_method(
 "CausalExtractor", "extract_causal_hierarchy", context
)

```

# Step 4: Verify conditional independence

```

 independence_verification = self._execute_method(
 "HierarchicalGenerativeModel", "verify_conditional_independence", context,
 hierarchy=causal_hierarchy
)
 independence_tests = self._execute_method(
 "HierarchicalGenerativeModel", "generate_independence_tests", context,
 "HierarchicalGenerativeModel"
)

```

```

 verification=independence_verification
)

Step 5: Construct structural causal model
scm = self._execute_method(
 "BayesianCounterfactualAuditor", "construct_scm", context,
 hierarchy=causal_hierarchy
)

Step 6: Perform sensitivity analysis
sensitivity_analysis = self._execute_method(
 "AdvancedDAGValidator", "_perform_sensitivity_analysis_internal", context,
 scm=scm
)

Step 7: Get Bayes factor
bayes_factor = self._execute_method(
 "BayesFactorTable", "get_bayes_factor", context,
 analysis=sensitivity_analysis
)

raw_evidence = {
 "causal_chain": complete_paths,
 "key_assumptions": validation_results.get("assumptions", []),
 "enabling_conditions": validation_results.get("conditions", []),
 "external_factors": validation_results.get("external_factors", []),
 "causal_hierarchy": causal_hierarchy,
 "independence_tests": independence_tests,
 "structural_model": scm,
 "sensitivity": sensitivity_analysis,
 "evidential_strength": bayes_factor
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "complete_paths_found": len(complete_paths),
 "assumptions_identified": len(validation_results.get("assumptions", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}
}

```

class D4\_Q3\_AmbitionJustificationAnalyzer(BaseExecutor):

"""

Analyzes justification of result ambition based on investment/capacity/benchmarks.

Methods (from D4-Q3):

- PDET Municipal Plan Analyzer methods
  - PDET Municipal Plan Analyzer methods
  - PDET Municipal Plan Analyzer methods
  - Adaptive Prior Calculator methods
  - Hierarchical Generative Model methods
  - Hierarchical Generative Model methods
  - Advanced DAG Validator methods
  - Bayesian Mechanism Inference methods
- """

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw\_evidence = {}

# Step 1: Get prior effect estimates
prior\_effects = self.\_execute\_method(

```

 "PDET Municipal Plan Analyzer", "_get_prior_effect", context
)

Step 2: Estimate effect using Bayesian methods
effect_estimate = self._execute_method(
 "PDET Municipal Plan Analyzer", "_estimate_effect_bayesian", context,
 priors=prior_effects
)

Step 3: Compute robustness
robustness = self._execute_method(
 "PDET Municipal Plan Analyzer", "_compute_robustness_value", context,
 estimate=effect_estimate
)

Step 4: Sensitivity analysis
sensitivity = self._execute_method(
 "Adaptive Prior Calculator", "sensitivity_analysis", context,
 estimate=effect_estimate
)

Step 5: Calculate convergence diagnostics
r_hat = self._execute_method(
 "Hierarchical Generative Model", "_calculate_r_hat", context
)
ess = self._execute_method(
 "Hierarchical Generative Model", "_calculate_ess", context
)

Step 6: Calculate statistical power
statistical_power = self._execute_method(
 "Advanced DAG Validator", "_calculate_statistical_power", context,
 effect=effect_estimate
)

Step 7: Aggregate confidence
confidence_aggregate = self._execute_method(
 "Bayesian Mechanism Inference", "_aggregate_bayesian_confidence", context,
 estimates=[effect_estimate, robustness, statistical_power]
)

raw_evidence = {
 "ambition_level": context.get("target_ambition", {}),
 "financial_investment": context.get("total_investment", 0),
 "institutional_capacity": context.get("capacity_score", 0),
 "comparative_benchmarks": prior_effects,
 "justification_analysis": {
 "effect_estimate": effect_estimate,
 "robustness": robustness,
 "sensitivity": sensitivity,
 "statistical_power": statistical_power
 },
 "convergence_diagnostics": {
 "r_hat": r_hat,
 "ess": ess
 },
 "overall_confidence": confidence_aggregate
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "ambition_justified": confidence_aggregate > 0.7,
 "statistical_power": statistical_power
 },
 "execution_metrics": {

```

```

 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

class D4_Q4_ProblemSolvencyEvaluator(BaseExecutor):
 """
 Evaluates whether results address/resolve prioritized problems from diagnosis.

 Methods (from D4-Q4):
 - PolicyContradictionDetector._calculate_objective_alignment
 - PolicyContradictionDetector._identify_affected_sections
 - PolicyContradictionDetector._generate_resolution_recommendations
 - OperationalizationAuditor._generate_optimal_remediations
 - OperationalizationAuditor._get_remediation_text
 - BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
 - FinancialAuditor._detect_allocation_gaps
 """

 def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

 # Step 1: Calculate objective alignment
 objective_alignment = self._execute_method(
 "PolicyContradictionDetector", "_calculate_objective_alignment", context
)

 # Step 2: Identify affected sections
 affected_sections = self._execute_method(
 "PolicyContradictionDetector", "_identify_affected_sections", context,
 alignment=objective_alignment
)

 # Step 3: Generate resolution recommendations
 resolutions = self._execute_method(
 "PolicyContradictionDetector", "_generate_resolution_recommendations",
 context,
 sections=affected_sections
)

 # Step 4: Generate optimal remediations
 remediations = self._execute_method(
 "OperationalizationAuditor", "_generate_optimal_remediations", context
)
 remediation_text = self._execute_method(
 "OperationalizationAuditor", "_get_remediation_text", context,
 remediations=remediations
)

 # Step 5: Aggregate risk and prioritize
 risk_priorities = self._execute_method(
 "BayesianCounterfactualAuditor", "aggregate_risk_and_prioritize", context
)

 # Step 6: Detect allocation gaps
 allocation_gaps = self._execute_method(
 "FinancialAuditor", "_detect_allocation_gaps", context
)

 raw_evidence = {
 "prioritized_problems": context.get("diagnosis_problems", []),
 "proposed_results": context.get("outcome_indicators", []),
 "problem_result_mapping": objective_alignment,
 "unaddressed_problems": [p for p in affected_sections if not
p.get("addressed")],
 "solvency_score": objective_alignment.get("score", 0),
 "resolution_recommendations": resolutions,
 }

```

```

 "remediations": remediation_text,
 "risk_priorities": risk_priorities,
 "allocation_gaps": allocation_gaps
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "problems_addressed": len([p for p in affected_sections if
p.get("addressed")]),
 "problems_unaddressed": len([p for p in affected_sections if not
p.get("addressed")])
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

class D4\_Q5\_VerticalAlignmentValidator(BaseExecutor):

====

Validates alignment with superior frameworks (PND, SDGs).

Methods (from D4-Q5):

- PDET Municipal Plan Analyzer.\_score\_pdet\_alignment
- PDET Municipal Plan Analyzer.\_score\_causal\_coherence
- CDAFFramework.\_validate\_dnp\_compliance
- CDAFFramework.\_generate\_dnp\_report
- IndustrialPolicyProcessor.\_analyze\_causal\_dimensions
- AdaptivePriorCalculator.validate\_quality\_criteria

====

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

 # Step 1: Score PDET alignment
 pdet_alignment = self._execute_method(
 "PDET Municipal Plan Analyzer", "_score_pdet_alignment", context
)

 # Step 2: Score causal coherence
 causal_coherence = self._execute_method(
 "PDET Municipal Plan Analyzer", "_score_causal_coherence", context
)

 # Step 3: Validate DNP compliance
 dnp_compliance = self._execute_method(
 "CDAFFramework", "_validate_dnp_compliance", context
)
 dnp_report = self._execute_method(
 "CDAFFramework", "_generate_dnp_report", context,
 compliance=dnp_compliance
)

 # Step 4: Analyze causal dimensions
 causal_dimensions = self._execute_method(
 "IndustrialPolicyProcessor", "_analyze_causal_dimensions", context
)

 # Step 5: Validate quality criteria
 quality_validation = self._execute_method(
 "AdaptivePriorCalculator", "validate_quality_criteria", context,
 alignment=pdet_alignment
)

```

```

raw_evidence = {
 "pnd_alignment": dnp_compliance,
 "sdg_alignment": context.get("sdg_mappings", []),
 "pdet_alignment": pdet_alignment,
 "alignment_declarations": dnp_report.get("declarations", []),
 "causal_coherence": causal_coherence,
 "causal_dimensions": causal_dimensions,
 "quality_validation": quality_validation,
 "alignment_score": (pdet_alignment.get("score", 0) +
 dnp_compliance.get("score", 0)) / 2
}
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "pnd_aligned": dnp_compliance.get("is_compliant", False),
 "sdgs_referenced": len(context.get("sdg_mappings", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}
}

```

```

=====
DIMENSION 5: IMPACTS
=====

```

```

class D5_Q1_LongTermVisionAnalyzer(BaseExecutor):
 """
 Analyzes long-term impacts, transmission routes, and time lags.

```

Methods (from D5-Q1):

- PDETMunicipalPlanAnalyzer.generate\_counterfactuals
  - PDETMunicipalPlanAnalyzer.\_simulate\_intervention
  - PDETMunicipalPlanAnalyzer.\_generate\_scenario\_narrative
  - PDETMunicipalPlanAnalyzer.\_find\_mediator\_mentions
  - TeoriaCambio.\_validar\_orden\_causal
  - CausalExtractor.\_assess\_temporal\_coherence
  - TextMiningEngine.\_generate\_interventions
  - BayesianCounterfactualAuditor.construct\_scm
- """

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

 # Step 1: Generate counterfactuals
 counterfactuals = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "generate_counterfactuals", context
)

 # Step 2: Simulate interventions
 simulation = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_simulate_intervention", context,
 counterfactuals=counterfactuals
)

 # Step 3: Generate scenario narratives
 scenarios = self._execute_method(
 "PDETMunicipalPlanAnalyzer", "_generate_scenario_narrative", context,
 simulation=simulation
)

 # Step 4: Find mediator mentions
 mediators = self._execute_method(

```

```

 "PDET Municipal Plan Analyzer", "_find_mediator_mentions", context
)

 # Step 5: Validate causal order
 causal_order = self._execute_method(
 "TeoriaCambio", "_validar_orden_causal", context,
 mediators=mediators
)

 # Step 6: Assess temporal coherence
 temporal_coherence = self._execute_method(
 "CausalExtractor", "_assess_temporal_coherence", context
)

 # Step 7: Generate interventions
 interventions = self._execute_method(
 "TextMiningEngine", "_generate_interventions", context
)

 # Step 8: Construct SCM
 scm = self._execute_method(
 "BayesianCounterfactualAuditor", "construct_scm", context,
 order=causal_order
)

 raw_evidence = {
 "long_term_impacts": context.get("impact_indicators", []),
 "structural_transformations": scenarios,
 "transmission_routes": mediators,
 "expected_time_lags": temporal_coherence.get("time_lags", []),
 "counterfactual_analysis": counterfactuals,
 "simulation_results": simulation,
 "causal_pathways": scm,
 "intervention_scenarios": interventions
 }

 return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "impacts_defined": len(context.get("impact_indicators", [])),
 "mediators_identified": len(mediators)
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
 }
}

```

```
class D5_Q2_CompositeMeasurementValidator(BaseExecutor):
 """

```

DIM05\_Q02\_COMPOSITE\_PROXY\_VALIDITY — Validates composite indices/proxies for complex impacts (canonical D5).

Epistemic mix: statistical robustness (E-value), Bayesian confidence, normative reporting quality, and semantic consistency.

Methods (from D5-Q2):

- PDET Municipal Plan Analyzer.\_quality\_to\_dict
- PolicyAnalysisEmbedder.process\_document
- PolicyAnalysisEmbedder.\_filter\_by\_pdq
- PolicyAnalysisEmbedder.\_extract\_numerical\_values
- PolicyAnalysisEmbedder.\_compute\_overall\_confidence
- PolicyAnalysisEmbedder.\_embed\_texts
- PolicyTextProcessor.normalize\_unicode
- PolicyTextProcessor.segment\_into\_sentences
- PolicyTextProcessor.compile\_pattern

```

- PolicyTextProcessor.extract_contextual_window
- IndustrialPolicyProcessor._compute_evidence_confidence
- IndustrialPolicyProcessor._compute_avg_confidence
- IndustrialPolicyProcessor._construct_evidence_bundle
- PDET MunicipalPlanAnalyzer.generate_executive_report
- BayesianCounterfactualAuditor.aggregate_risk_and_prioritize
- PDET MunicipalPlanAnalyzer._interpret_sensitivity
- PDET MunicipalPlanAnalyzer._interpret_overall_quality
- PolicyAnalysisEmbedder.get_diagnostics
- PDET MunicipalPlanAnalyzer.calculate_quality_score
- PDET MunicipalPlanAnalyzer._estimate_score_confidence
- PDET MunicipalPlanAnalyzer._compute_e_value
- PDET MunicipalPlanAnalyzer._compute_robustness_value
- ReportingEngine._calculate_quality_score
- BayesianMechanismInference._aggregate_bayesian_confidence
- PolicyAnalysisEmbedder.evaluate_policy_numerical_consistency
- FinancialAuditor._calculate_sufficiency
"""

```

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}
 dim_info = get_dimension_info(CanonicalDimension.D5.value)
 document_text = context.get("document_text", "")
 document_metadata = context.get("metadata", {})

 # Step 1: Calculate quality scores
 quality_score = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "calculate_quality_score", context
)
 score_confidence = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_estimate_score_confidence", context,
 score=quality_score
)

 # Step 2: Compute robustness metrics
 e_value = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_compute_e_value", context,
 score=quality_score
)
 robustness = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_compute_robustness_value", context,
 score=quality_score
)
 sensitivity_interpretation = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_interpret_sensitivity", context,
 e_value=e_value,
 robustness=robustness
)

 # Step 3: Calculate reporting quality score
 reporting_quality = self._execute_method(
 "ReportingEngine", "_calculate_quality_score", context
)

 # Step 4: Aggregate Bayesian confidence
 bayesian_confidence = self._execute_method(
 "BayesianMechanismInference", "_aggregate_bayesian_confidence", context,
 scores=[quality_score, reporting_quality]
)

 # Step 5: Evaluate numerical consistency
 numerical_consistency = self._execute_method(
 "PolicyAnalysisEmbedder", "evaluate_policy_numerical_consistency", context
)
 embedder_diagnostics = self._execute_method(
 "PolicyAnalysisEmbedder", "get_diagnostics", context
)
 processed_chunks = self._execute_method(

```

```

 "PolicyAnalysisEmbedder", "process_document", context,
 document_text=document_text,
 document_metadata=document_metadata
)
pdq_filter = self._execute_method(
 "PolicyAnalysisEmbedder", "_generate_query_from_pdq", context,
 pdq={"policy": context.get("policy_area"), "dimension": dim_info.code}
)
filtered_chunks = self._execute_method(
 "PolicyAnalysisEmbedder", "_filter_by_pdq", context,
 chunks=processed_chunks,
 pdq_filter=pdq_filter
)
numerical_values = self._execute_method(
 "PolicyAnalysisEmbedder", "_extract_numerical_values", context,
 chunks=processed_chunks
)
embedded_texts = self._execute_method(
 "PolicyAnalysisEmbedder", "_embed_texts", context,
 texts=[c.get("content", "") for c in processed_chunks] if
isinstance(processed_chunks, list) else []
)
overall_confidence = self._execute_method(
 "PolicyAnalysisEmbedder", "_compute_overall_confidence", context,
 relevant_chunks=filtered_chunks[:5] if isinstance(filtered_chunks, list) else
[],
 numerical_eval=bayesian_confidence if isinstance(bayesian_confidence, dict)
else {"evidence_strength": "weak", "numerical_coherence": 0.0}
)

Step 6: Calculate sufficiency
sufficiency = self._execute_method(
 "FinancialAuditor", "_calculate_sufficiency", context
)
overall_interpretation = self._execute_method(
 "PDET Municipal Plan Analyzer", "_interpret_overall_quality", context,
 score=getattr(quality_score, "overall_score", quality_score)
)
risk_prioritization = self._execute_method(
 "Bayesian Counterfactual Auditor", "aggregate_risk_and_prioritize", context,
 omission_score=1 - quality_score.financial_feasibility if
hasattr(quality_score, "financial_feasibility") else 0.2,
 insufficiency_score=1 - sufficiency.get("coverage_ratio", 0.0),
 unneccessity_score=1 - (robustness if isinstance(robustness, (int, float)) else
0.0),
 causal_effect=e_value,
 feasibility=quality_score.financial_feasibility if hasattr(quality_score,
"financial_feasibility") else 0.8,
 cost=1.0
)
normalized_text = self._execute_method(
 "PolicyTextProcessor", "normalize_unicode", context,
 text=document_text
)
segmented_sentences = self._execute_method(
 "PolicyTextProcessor", "segment_into_sentences", context,
 text=document_text
)
evidence_confidence = self._execute_method(
 "Industrial Policy Processor", "_compute_evidence_confidence", context,
 matches=context.get("proxy_indicators", []),
 text_length=len(document_text),
 pattern_specificity=0.5
)
avg_confidence = self._execute_method(
 "Industrial Policy Processor", "_compute_avg_confidence", context,
 dimension_analysis={"D5": {"dimension_confidence": bayesian_confidence.get("numerical_coherence", 0.0) if isinstance(bayesian_confidence,

```

```

dict) else 0.0}
)
quality_dict = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_quality_to_dict", context,
 quality=quality_score
)
evidence_bundle = self._execute_method(
 "IndustrialPolicyProcessor", "_construct_evidence_bundle", context,
 dimension=None,
 category="composite",
 matches=context.get("proxy_indicators", []),
 positions=[],
 confidence=bayesian_confidence.get("numerical_coherence", 0.0) if
isinstance(bayesian_confidence, dict) else 0.0
)
compiled_pattern = self._execute_method(
 "PolicyTextProcessor", "compile_pattern", context,
 pattern_str=r"[A-Z]{2,}\s+\d+"
)
contextual_window = self._execute_method(
 "PolicyTextProcessor", "extract_contextual_window", context,
 text=document_text,
 match_position=0,
 window_size=200
)
exec_report = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "generate_executive_report", context,
 analysis_results={"quality_score": quality_dict, "financial_analysis":
context.get("financial_analysis", {}) or {"total_budget": 0, "funding_sources": {},
"confidence": (0, 0)}}
)
export_result = self._execute_method(
 "IndustrialPolicyProcessor", "export_results", context,
 results={"quality": quality_dict, "robustness": robustness},
 output_path="output/composite_results.json"
)

raw_evidence = {
 "composite_indices": context.get("composite_indicators", []),
 "proxy_indicators": context.get("proxy_indicators", []),
 "validity_justification": score_confidence,
 "robustness_metrics": {
 "e_value": e_value,
 "robustness": robustness,
 "interpretation": sensitivity_interpretation
 },
 "quality_scores": {
 "overall": quality_score,
 "reporting": reporting_quality
 },
 "bayesian_confidence": bayesian_confidence,
 "numerical_consistency": numerical_consistency,
 "measurement_sufficiency": sufficiency,
 "embedder_diagnostics": embedder_diagnostics,
 "quality_interpretation": overall_interpretation,
 "pdq_filter": pdq_filter,
 "filtered_chunks": filtered_chunks,
 "numerical_values": numerical_values,
 "embedded_texts": embedded_texts,
 "overall_confidence": overall_confidence,
 "risk_prioritization": risk_prioritization,
 "normalized_text": normalized_text,
 "segmented_sentences": segmented_sentences,
 "evidence_confidence": evidence_confidence,
 "avg_confidence": avg_confidence,
 "quality_dict": quality_dict,
 "compiled_pattern": compiled_pattern,
 "contextual_window": contextual_window,
}

```

```

 "evidence_bundle": evidence_bundle,
 "executive_report": exec_report,
 "export_result": export_result
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "composite_indices_count": len(context.get("composite_indicators", [])),
 "validity_score": score_confidence,
 "canonical_question": "DIM05_Q02_COMPOSITE_PROXY_VALIDITY",
 "dimension_code": dim_info.code,
 "dimension_label": dim_info.label
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}
}

```

class D5\_Q3\_IntangibleMeasurementAnalyzer(BaseExecutor):

"""

Analyzes proxy indicators for intangible impacts with validity documentation.

Methods (from D5-Q3):

- CausalExtractor.\_calculate\_semantic\_distance
- SemanticAnalyzer.extract\_semantic\_cube
- BayesianMechanismInference.\_quantify\_uncertainty
- PDET Municipal Plan Analyzer.\_find\_mediator\_mentions
- PolicyAnalysisEmbedder.get\_diagnostics
- AdaptivePriorCalculator.\_perturb\_evidence

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw\_evidence = {}

# Step 1: Calculate semantic distance

semantic\_distance = self.\_execute\_method(
 "CausalExtractor", "\_calculate\_semantic\_distance", context
 )

# Step 2: Extract semantic cube

semantic\_cube = self.\_execute\_method(
 "SemanticAnalyzer", "extract\_semantic\_cube", context
 )

# Step 3: Quantify uncertainty

uncertainty = self.\_execute\_method(
 "BayesianMechanismInference", "\_quantify\_uncertainty", context,
 semantic\_data=semantic\_cube
 )

# Step 4: Find mediator mentions

mediators = self.\_execute\_method(
 "PDET Municipal Plan Analyzer", "\_find\_mediator\_mentions", context
 )

# Step 5: Get diagnostics

diagnostics = self.\_execute\_method(
 "PolicyAnalysisEmbedder", "get\_diagnostics", context,
 mediators=mediators
 )

# Step 6: Perturb evidence for sensitivity

perturbed\_evidence = self.\_execute\_method(

```

 "AdaptivePriorCalculator", "_perturb_evidence", context,
 diagnostics=diagnostics
)

raw_evidence = {
 "intangible_impacts": context.get("intangible_indicators", []),
 "proxy_indicators": context.get("proxy_mappings", []),
 "validity_documentation": diagnostics,
 "limitations_acknowledged": diagnostics.get("limitations", []),
 "semantic_relationships": semantic_cube,
 "semantic_distance": semantic_distance,
 "uncertainty_quantification": uncertainty,
 "sensitivity_to_proxies": perturbed_evidence
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "intangibles_count": len(context.get("intangible_indicators", [])),
 "proxies_defined": len(context.get("proxy_mappings", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}
}

```

class D5\_Q4\_SystemicRiskEvaluator(BaseExecutor):

"""

Evaluates systemic risks that could rupture causal mechanisms.

Methods (from D5-Q4):

- OperationalizationAuditor.\_audit\_systemic\_risk
- BayesianCounterfactualAuditor.refutation\_and\_sanity\_checks
- BayesianCounterfactualAuditor.\_test\_effect\_stability
- PDET MunicipalPlanAnalyzer.\_interpret\_risk
- PDET MunicipalPlanAnalyzer.\_interpret\_sensitivity
- PDET MunicipalPlanAnalyzer.\_break\_cycles
- AdaptivePriorCalculator.sensitivity\_analysis

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw\_evidence = {}

# Step 1: Audit systemic risks

systemic\_risks = self.\_execute\_method(
 "OperationalizationAuditor", "\_audit\_systemic\_risk", context
 )

# Step 2: Refutation and sanity checks

refutation = self.\_execute\_method(
 "BayesianCounterfactualAuditor", "refutation\_and\_sanity\_checks", context,
 risks=systemic\_risks
 )

# Step 3: Test effect stability

effect\_stability = self.\_execute\_method(
 "BayesianCounterfactualAuditor", "\_test\_effect\_stability", context,
 refutation=refutation
 )

# Step 4: Interpret risks

risk\_interpretation = self.\_execute\_method(
 "PDET MunicipalPlanAnalyzer", "\_interpret\_risk", context,
 risks=systemic\_risks
 )

```

)
Step 5: Interpret sensitivity
sensitivity_interpretation = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_interpret_sensitivity", context,
 stability=effect_stability
)

Step 6: Break cycles if present
cycle_breaks = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_break_cycles", context
)

Step 7: Sensitivity analysis
sensitivity = self._execute_method(
 "AdaptivePriorCalculator", "sensitivity_analysis", context,
 risks=systemic_risks
)

raw_evidence = {
 "macroeconomic_risks": [r for r in systemic_risks if r.get("type") ==
"macroeconomic"],
 "environmental_risks": [r for r in systemic_risks if r.get("type") ==
"environmental"],
 "political_risks": [r for r in systemic_risks if r.get("type") ==
"political"],
 "mechanism_rupture_potential": risk_interpretation.get("rupture_probability",
0),
 "effect_stability": effect_stability,
 "refutation_results": refutation,
 "sensitivity_analysis": sensitivity,
 "cycle_vulnerabilities": cycle_breaks
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "systemic_risks_identified": len(systemic_risks),
 "high_risk_count": len([r for r in systemic_risks if r.get("severity") ==
"high"])
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

class D5\_Q5\_RealismAndSideEffectsAnalyzer(BaseExecutor):

.....

Analyzes realism of impact ambition and potential unintended effects.

Methods (from D5-Q5):

- HierarchicalGenerativeModel.posterior\_predictive\_check
  - HierarchicalGenerativeModel.\_ablation\_analysis
  - HierarchicalGenerativeModel.\_calculate\_waic\_difference
  - AdaptivePriorCalculator.\_add\_ood\_noise
  - AdaptivePriorCalculator.validate\_quality\_criteria
  - PDET MunicipalPlanAnalyzer.\_compute\_e\_value
  - PDET MunicipalPlanAnalyzer.\_compute\_robustness\_value
  - BayesianMechanismInference.\_calculate\_coherence\_factor
- .....

```
def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}
```

```

Step 1: Posterior predictive check
predictive_check = self._execute_method(
 "HierarchicalGenerativeModel", "posterior_predictive_check", context
)

Step 2: Ablation analysis
ablation = self._execute_method(
 "HierarchicalGenerativeModel", "_ablation_analysis", context,
 check=predictive_check
)

Step 3: Calculate WAIC difference
waic_diff = self._execute_method(
 "HierarchicalGenerativeModel", "_calculate_waic_difference", context,
 ablation=ablation
)

Step 4: Add out-of-distribution noise
ood_analysis = self._execute_method(
 "AdaptivePriorCalculator", "_add_ood_noise", context
)

Step 5: Validate quality criteria
quality_validation = self._execute_method(
 "AdaptivePriorCalculator", "validate_quality_criteria", context,
 ood=ood_analysis
)

Step 6: Compute robustness metrics
e_value = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_compute_e_value", context
)
robustness = self._execute_method(
 "PDET MunicipalPlanAnalyzer", "_compute_robustness_value", context
)

Step 7: Calculate coherence factor
coherence = self._execute_method(
 "BayesianMechanismInference", "_calculate_coherence_factor", context
)

raw_evidence = {
 "impact_ambition_level": context.get("declared_ambition", 0),
 "realism_assessment": predictive_check.get("realism_score", 0),
 "negative_side_effects": ablation.get("negative_effects", []),
 "limit_hypotheses": quality_validation.get("limits", []),
 "robustness_metrics": {
 "e_value": e_value,
 "robustness": robustness,
 "coherence": coherence
 },
 "predictive_validity": predictive_check,
 "ablation_results": ablation,
 "model_comparison": waic_diff,
 "ood_sensitivity": ood_analysis
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "realism_score": predictive_check.get("realism_score", 0),
 "side_effects_identified": len(ablation.get("negative_effects", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

```

 }

=====
DIMENSION 6: CAUSALITY & THEORY OF CHANGE
=====

class D6_Q1_ExplicitTheoryBuilder(BaseExecutor):
 """
 Builds/validates explicit Theory of Change with diagram and assumptions.

 Methods (from D6-Q1):
 - TeoriaCambio.construir_grafo_causal
 - TeoriaCambio.validacion_completa
 - TeoriaCambio.export_nodes
 - ReportingEngine.generate_causal_diagram
 - ReportingEngine.generate_causal_model_json
 - AdvancedDAGValidator.export_nodes
 - PDET Municipal Plan Analyzer.export_causal_network
 - CausalExtractor.extract_causal_hierarchy
 """

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

 # Step 1: Build causal graph
 causal_graph = self._execute_method(
 "TeoriaCambio", "construir_grafo_causal", context
)

 # Step 2: Complete validation
 validation = self._execute_method(
 "TeoriaCambio", "validacion_completa", context,
 graph=causal_graph
)

 # Step 3: Export nodes from Theory of Change
 toc_nodes = self._execute_method(
 "TeoriaCambio", "export_nodes", context,
 graph=causal_graph
)

 # Step 4: Generate causal diagram
 diagram = self._execute_method(
 "ReportingEngine", "generate_causal_diagram", context,
 graph=causal_graph
)

 # Step 5: Generate causal model JSON
 model_json = self._execute_method(
 "ReportingEngine", "generate_causal_model_json", context,
 graph=causal_graph
)

 # Step 6: Export nodes from DAG validator
 dag_nodes = self._execute_method(
 "AdvancedDAGValidator", "export_nodes", context,
 graph=causal_graph
)

 # Step 7: Export causal network
 network_export = self._execute_method(
 "PDET Municipal Plan Analyzer", "export_causal_network", context,
 graph=causal_graph
)

 # Step 8: Extract causal hierarchy

```

```

hierarchy = self._execute_method(
 "CausalExtractor", "extract_causal_hierarchy", context
)

raw_evidence = {
 "toc_exists": len(causal_graph) > 0,
 "toc_diagram": diagram,
 "toc_json": model_json,
 "causal_graph": causal_graph,
 "nodes": toc_nodes,
 "causes_identified": hierarchy.get("causes", []),
 "mediators_identified": hierarchy.get("mediators", []),
 "assumptions": validation.get("assumptions", []),
 "network_structure": network_export,
 "validation_results": validation
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "nodes_count": len(toc_nodes),
 "assumptions_count": len(validation.get("assumptions", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

class D6\_Q2\_LogicalProportionalityValidator(BaseExecutor):

"""  
Validates logical proportionality: no leaps, intervention matches result scale.

Methods (from D6-Q2):

- BeachEvidentialTest.apply\_test\_logic
  - BayesianMechanismInference.\_test\_necessity
  - BayesianMechanismInference.\_test\_sufficiency
  - BayesianMechanismInference.\_calculate\_coherence\_factor
  - BayesianCounterfactualAuditor.\_test\_effect\_stability
  - IndustrialGradeValidator.validate\_connection\_matrix
  - PolicyAnalysisEmbedder.\_compute\_overall\_confidence
- """

```

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

 # Step 1: Apply evidential tests
 evidential_tests = self._execute_method(
 "BeachEvidentialTest", "apply_test_logic", context
)

 # Step 2: Test necessity
 necessity_test = self._execute_method(
 "BayesianMechanismInference", "_test_necessity", context
)

 # Step 3: Test sufficiency
 sufficiency_test = self._execute_method(
 "BayesianMechanismInference", "_test_sufficiency", context
)

 # Step 4: Calculate coherence factor
 coherence_factor = self._execute_method(
 "BayesianMechanismInference", "_calculate_coherence_factor", context,
 necessity=necessity_test,
)

```

```

 sufficiency=sufficiency_test
)

 # Step 5: Test effect stability
 effect_stability = self._execute_method(
 "BayesianCounterfactualAuditor", "_test_effect_stability", context
)

 # Step 6: Validate connection matrix
 connection_validation = self._execute_method(
 "IndustrialGradeValidator", "validate_connection_matrix", context
)

 # Step 7: Compute overall confidence
 overall_confidence = self._execute_method(
 "PolicyAnalysisEmbedder", "_compute_overall_confidence", context,
 tests=[necessity_test, sufficiency_test, effect_stability]
)

 raw_evidence = {
 "logical_leaps_detected": evidential_tests.get("leaps", []),
 "intervention_scale": context.get("intervention_magnitude", 0),
 "result_scale": context.get("result_magnitude", 0),
 "proportionality_ratio": context.get("intervention_magnitude", 0) /
 max(context.get("result_magnitude", 1), 1),
 "necessity_score": necessity_test,
 "sufficiency_score": sufficiency_test,
 "coherence_factor": coherence_factor,
 "effect_stability": effect_stability,
 "connection_validation": connection_validation,
 "overall_confidence": overall_confidence,
 "implementation_miracles": [leap for leap in evidential_tests.get("leaps", [])]
 }

 if leap.get("type") == "miracle"]:
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "leaps_detected": len(evidential_tests.get("leaps", [])),
 "proportionality_adequate": abs(raw_evidence["proportionality_ratio"] -
1.0) < 0.5
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

class D6\_Q3\_ValidationTestingAnalyzer(BaseExecutor):

=====

Analyzes validation/testing proposals for weak assumptions before scaling.

Methods (from D6-Q3):

- IndustrialGradeValidator.execute\_suite
- IndustrialGradeValidator.validate\_engine\_readiness
- IndustrialGradeValidator.\_benchmark\_operation
- AdaptivePriorCalculator.validate\_quality\_criteria
- HierarchicalGenerativeModel.\_calculate\_r\_hat
- HierarchicalGenerativeModel.\_calculate\_ess
- AdvancedDAGValidator.calculate\_acyclicity\_pvalue
- PerformanceAnalyzer.analyze\_performance

=====

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

```

raw_evidence = {}

Step 1: Execute validation suite
validation_suite = self._execute_method(
 "IndustrialGradeValidator", "execute_suite", context
)

Step 2: Validate engine readiness
readiness = self._execute_method(
 "IndustrialGradeValidator", "validate_engine_readiness", context
)

Step 3: Benchmark operations
benchmarks = self._execute_method(
 "IndustrialGradeValidator", "_benchmark_operation", context
)

Step 4: Validate quality criteria
quality_validation = self._execute_method(
 "AdaptivePriorCalculator", "validate_quality_criteria", context
)

Step 5: Calculate convergence diagnostics
r_hat = self._execute_method(
 "HierarchicalGenerativeModel", "_calculate_r_hat", context
)
ess = self._execute_method(
 "HierarchicalGenerativeModel", "_calculate_ess", context
)

Step 6: Calculate acyclicity p-value
acyclicity_p = self._execute_method(
 "AdvancedDAGValidator", "calculate_acyclicity_pvalue", context
)

Step 7: Analyze performance
performance = self._execute_method(
 "PerformanceAnalyzer", "analyze_performance", context
)

raw_evidence = {
 "inconsistencies_recognized": validation_suite.get("inconsistencies", []),
 "weak_assumptions": quality_validation.get("weak_assumptions", []),
 "pilot_proposals": context.get("pilot_programs", []),
 "testing_proposals": context.get("testing_plans", []),
 "validation_before_scaling": readiness.get("ready_to_scale", False),
 "validation_results": validation_suite,
 "quality_criteria": quality_validation,
 "convergence_diagnostics": {
 "r_hat": r_hat,
 "ess": ess,
 "acyclicity_p": acyclicity_p
 },
 "performance_analysis": performance,
 "benchmarks": benchmarks
}

return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "inconsistencies_count": len(validation_suite.get("inconsistencies", [])),
 "pilots_proposed": len(context.get("pilot_programs", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
}

```

```

 }

}

class D6_Q4_FeedbackLoopAnalyzer(BaseExecutor):
 """
 Analyzes monitoring system with correction mechanisms and learning processes.

 Methods (from D6-Q4):
 - ConfigLoader.update_priors_from_feedback
 - ConfigLoader.check_uncertainty_reduction_criterion
 - ConfigLoader._save_prior_history
 - ConfigLoader._load_uncertainty_history
 - CDAFFramework._extract_feedback_from_audit
 - AdvancedDAGValidator._calculate_node_importance
 - BayesFactorTable.get_bayes_factor
 """

 def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:
 raw_evidence = {}

 # Step 1: Update priors from feedback
 prior_updates = self._execute_method(
 "ConfigLoader", "update_priors_from_feedback", context
)

 # Step 2: Check uncertainty reduction
 uncertainty_reduction = self._execute_method(
 "ConfigLoader", "check_uncertainty_reduction_criterion", context,
 updates=prior_updates
)

 # Step 3: Save prior history
 history_saved = self._execute_method(
 "ConfigLoader", "_save_prior_history", context,
 updates=prior_updates
)

 # Step 4: Load uncertainty history
 uncertainty_history = self._execute_method(
 "ConfigLoader", "_load_uncertainty_history", context
)

 # Step 5: Extract feedback from audit
 feedback_extracted = self._execute_method(
 "CDAFFramework", "_extract_feedback_from_audit", context
)

 # Step 6: Calculate node importance
 node_importance = self._execute_method(
 "AdvancedDAGValidator", "_calculate_node_importance", context
)

 # Step 7: Get Bayes factor
 bayes_factor = self._execute_method(
 "BayesFactorTable", "get_bayes_factor", context,
 updates=prior_updates
)

 raw_evidence = {
 "monitoring_system_described": len(context.get("monitoring_indicators", [])) >
0,
 "correction_mechanisms": feedback_extracted.get("mechanisms", []),
 "feedback_loops": feedback_extracted.get("loops", []),
 "learning_processes": feedback_extracted.get("learning", []),
 "prior_updates": prior_updates,
 "uncertainty_reduction": uncertainty_reduction,
 "uncertainty_history": uncertainty_history,
 }

```

```

 "node_importance": node_importance,
 "learning_strength": bayes_factor
 }

 return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "feedback_mechanisms": len(feedback_extracted.get("mechanisms", [])),
 "learning_processes": len(feedback_extracted.get("learning", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
 }
}

```

class D6\_Q5\_ContextualAdaptabilityEvaluator(BaseExecutor):

"""

Evaluates contextual adaptation: differential impacts and territorial constraints.

Methods (from D6-Q5):

- CausalExtractor.\_calculate\_language\_specificity
- CausalExtractor.\_assess\_temporal\_coherence
- TextMiningEngine.diagnose\_critical\_links
- CausallInferenceSetup.identify\_failure\_points
- CausallInferenceSetup.\_get\_dynamics\_pattern
- SemanticProcessor.chunk\_text
- SemanticProcessor.\_detect\_pdm\_structure
- SemanticProcessor.\_detect\_table
- AdaptivePriorCalculator.generate\_traceability\_record

"""

def execute(self, context: Dict[str, Any]) -> Dict[str, Any]:

raw\_evidence = {}

 # Step 1: Calculate language specificity
 language\_specificity = self.\_execute\_method(
 "CausalExtractor", "\_calculate\_language\_specificity", context
 )

 # Step 2: Assess temporal coherence
 temporal\_coherence = self.\_execute\_method(
 "CausalExtractor", "\_assess\_temporal\_coherence", context
 )

 # Step 3: Diagnose critical links
 critical\_links = self.\_execute\_method(
 "TextMiningEngine", "diagnose\_critical\_links", context
 )

 # Step 4: Identify failure points
 failure\_points = self.\_execute\_method(
 "CausallInferenceSetup", "identify\_failure\_points", context
 )

 # Step 5: Get dynamics pattern
 dynamics\_pattern = self.\_execute\_method(
 "CausallInferenceSetup", "\_get\_dynamics\_pattern", context
 )

 # Step 6: Process text structure
 text\_chunks = self.\_execute\_method(
 "SemanticProcessor", "chunk\_text", context
 )
 pdm\_structure = self.\_execute\_method(

```

 "SemanticProcessor", "_detect_pdm_structure", context,
 chunks=text_chunks
)
 table_detection = self._execute_method(
 "SemanticProcessor", "_detect_table", context,
 chunks=text_chunks
)

 # Step 7: Generate traceability record
 traceability = self._execute_method(
 "AdaptivePriorCalculator", "generate_traceability_record", context,
 specificity=language_specificity
)

 raw_evidence = {
 "context_adaptation": language_specificity.get("adaptation_level", 0),
 "differential_impacts_recognized": critical_links.get("differential_groups",
 []),
 "specific_groups_mentioned": critical_links.get("target_groups", []),
 "territorial_constraints": failure_points.get("territorial", []),
 "local_context_integration": pdm_structure.get("local_sections", []),
 "language_specificity": language_specificity,
 "temporal_coherence": temporal_coherence,
 "dynamics_pattern": dynamics_pattern,
 "structure_analysis": pdm_structure,
 "traceability": traceability
 }

 return {
 "executor_id": self.executor_id,
 "raw_evidence": raw_evidence,
 "metadata": {
 "methods_executed": [log["method"] for log in self.execution_log],
 "groups_identified": len(critical_links.get("target_groups", [])),
 "territorial_constraints": len(failure_points.get("territorial", []))
 },
 "execution_metrics": {
 "methods_count": len(self.execution_log),
 "all_succeeded": all(log["success"] for log in self.execution_log)
 }
 }
}

```

```

=====
EXECUTOR REGISTRY
=====

```

```

EXECUTOR_REGISTRY = {
 "D1-Q1": D1_Q1_QuantitativeBaselineExtractor,
 "D1-Q2": D1_Q2_ProblemDimensioningAnalyzer,
 "D1-Q3": D1_Q3_BudgetAllocationTracer,
 "D1-Q4": D1_Q4_InstitutionalCapacityIdentifier,
 "D1-Q5": D1_Q5_ScopeJustificationValidator,

 "D2-Q1": D2_Q1_StructuredPlanningValidator,
 "D2-Q2": D2_Q2_InterventionLogicInferencer,
 "D2-Q3": D2_Q3_RootCauseLinkageAnalyzer,
 "D2-Q4": D2_Q4_RiskManagementAnalyzer,
 "D2-Q5": D2_Q5_StrategicCoherenceEvaluator,

 "D3-Q1": D3_Q1_IndicatorQualityValidator,
 "D3-Q2": D3_Q2_TargetProportionalityAnalyzer,
 "D3-Q3": D3_Q3_TraceabilityValidator,
 "D3-Q4": D3_Q4_TechnicalFeasibilityEvaluator,
 "D3-Q5": D3_Q5_OutputOutcomeLinkageAnalyzer,

 "D4-Q1": D4_Q1_OutcomeMetricsValidator,
 "D4-Q2": D4_Q2_CausalChainValidator,
}

```

```

 "D4-Q3": D4_Q3_AmbitionJustificationAnalyzer,
 "D4-Q4": D4_Q4_ProblemSolvencyEvaluator,
 "D4-Q5": D4_Q5_VerticalAlignmentValidator,

 "D5-Q1": D5_Q1_LongTermVisionAnalyzer,
 "D5-Q2": D5_Q2_CompositeMeasurementValidator,
 "D5-Q3": D5_Q3_IntangibleMeasurementAnalyzer,
 "D5-Q4": D5_Q4_SystemicRiskEvaluator,
 "D5-Q5": D5_Q5_RealismAndSideEffectsAnalyzer,
}

}

```

```

=====
PHASE 2 ORCHESTRATION
=====

```

```

def _build_method_executor() -> MethodExecutor:
 """Construct a canonical MethodExecutor via the factory wiring."""
 bundle = build_processor()
 method_executor = getattr(bundle, "method_executor", None)
 if not isinstance(method_executor, MethodExecutor):
 raise RuntimeError("ProcessorBundle did not provide a valid MethodExecutor instance.")
 return method_executor

```

```

def _canonical_metadata(executor_id: str) -> Dict[str, Any]:
 """Build canonical metadata block using canonical_notation."""
 metadata: Dict[str, Any] = {}
 try:
 dim_key = executor_id.split("-")[0]
 dim_info = get_dimension_info(dim_key)
 metadata["dimension_code"] = dim_info.code
 metadata["dimension_label"] = dim_info.label
 except Exception:
 pass

 if executor_id in CANONICAL_QUESTION_LABELS:
 metadata["canonical_question"] = CANONICAL_QUESTION_LABELS[executor_id]
 return metadata

```

```

def run_phase2_executors(context_package: Dict[str, Any],
 policy_areas: List[str]) -> Dict[str, Any]:
 """
 Phase 2 Entry Point: Runs all 30 executors for each policy area.
 """

```

Args:

context\_package: Canonical package with document data from Phase 1  
policy\_areas: List of policy area identifiers to analyze

Returns:

Dict mapping policy\_area -> executor\_id -> raw\_evidence

```

results = {}
method_executor = _build_method_executor()

```

```

for policy_area in policy_areas:
 print(f"\n{'='*80}")
 print(f"Processing Policy Area: {policy_area}")
 print(f"{'='*80}\n")

```

```

Prepare context for this policy area
area_context = {
 **context_package,
 "policy_area": policy_area
}

Execute all 30 executors
area_results = {}
for executor_id, executor_class in EXECUTOR_REGISTRY.items():
 print(f"Running {executor_id}: {executor_class.__name__}...")

 try:
 # Instantiate executor with config
 config = load_executor_config(executor_id)
 executor = executor_class(executor_id, config,
method_executor=method_executor)

 # Execute and collect results
 result = executor.execute(area_context)
 # Append canonical metadata consistently
 result_metadata = result.get("metadata", {})
 result_metadata.update(_canonical_metadata(executor_id))
 result["metadata"] = result_metadata
 area_results[executor_id] = result

 print(f" ✓ Success: {len(result['metadata']['methods_executed'])} methods
executed")
 except ExecutorFailure as e:
 print(f" ✗ FAILED: {str(e)}")
 raise # Re-raise to stop execution as per requirement

results[policy_area] = area_results

return results

```

def load\_executor\_config(executor\_id: str) -> Dict[str, Any]:

"""

Load executor configuration from JSON contract.

Args:

executor\_id: Executor identifier (e.g., "D1-Q1")

Returns:

Configuration dictionary from JSON contract

"""

import json

from pathlib import Path

config\_path = Path(f"config/executor\_contracts/{executor\_id}.json")

if not config\_path.exists():

raise FileNotFoundError(f"Executor config not found: {config\_path}")

with open(config\_path, 'r', encoding='utf-8') as f:

return json.load(f)

```

=====
EXAMPLE USAGE
=====

if __name__ == "__main__":
 # Example context package from Phase 1
 context_package = {
 "document_path": "data/pdm_municipality_xyz.pdf",

```

```

"document_text": "...", # Full document text
"tables": [], # Extracted tables from Phase 1
"embeddings": {}, # Precomputed embeddings
"entities": [], # Pre-extracted entities
"metadata": {
 "municipality": "Municipality XYZ",
 "year": 2024,
 "pages": 150
}
}

Policy areas to analyze
policy_areas = [
 "PA01", # Education
 "PA02", # Health
 "PA03", # Infrastructure
 # ... up to 10+ policy areas
]

Run Phase 2
try:
 results = run_phase2_executors(context_package, policy_areas)
 print("\n" + "*80)
 print("PHASE 2 COMPLETED SUCCESSFULLY")
 print("*80)
 print(f"Processed {len(policy_areas)} policy areas")
 print(f"Executed {len(EXECUTOR_REGISTRY)} executors per area")
 print(f"Total executions: {len(policy_areas) * len(EXECUTOR_REGISTRY)})")

except ExecutorFailure as e:
 print("\n" + "*80)
 print("PHASE 2 FAILED")
 print("*80)
 print(f"Error: {str(e)}")
 print("Execution halted as per requirement: any method failure = executor
failure")

===== FILE: MIGRATION_ARTIFACTS_FAKE_TO_REAL/04_SOURCE_CODE/executors_contract_REAL.py
=====

from __future__ import annotations

from saaaaaa.core.orchestrator.base_executor_with_contract import BaseExecutorWithContract

class D1Q1_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D1-Q1"

class D1Q2_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D1-Q2"

class D1Q3_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D1-Q3"

class D1Q4_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D1-Q4"

```

```
class D1Q5_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D1-Q5"
```

```
class D2Q1_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D2-Q1"
```

```
class D2Q2_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D2-Q2"
```

```
class D2Q3_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D2-Q3"
```

```
class D2Q4_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D2-Q4"
```

```
class D2Q5_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D2-Q5"
```

```
class D3Q1_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D3-Q1"
```

```
class D3Q2_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D3-Q2"
```

```
class D3Q3_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D3-Q3"
```

```
class D3Q4_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D3-Q4"
```

```
class D3Q5_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D3-Q5"
```

```
class D4Q1_Executor_Contract(BaseExecutorWithContract):
 @classmethod
```

```
def get_base_slot(cls) -> str:
 return "D4-Q1"

class D4Q2_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D4-Q2"

class D4Q3_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D4-Q3"

class D4Q4_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D4-Q4"

class D4Q5_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D4-Q5"

class D5Q1_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D5-Q1"

class D5Q2_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D5-Q2"

class D5Q3_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D5-Q3"

class D5Q4_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D5-Q4"

class D5Q5_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D5-Q5"

class D6Q1_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D6-Q1"

class D6Q2_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D6-Q2"
```

```
class D6Q3_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D6-Q3"

class D6Q4_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D6-Q4"

class D6Q5_Executor_Contract(BaseExecutorWithContract):
 @classmethod
 def get_base_slot(cls) -> str:
 return "D6-Q5"

Aliases expected by core orchestrator
D1Q1_Executor = D1Q1_Executor_Contract
D1Q2_Executor = D1Q2_Executor_Contract
D1Q3_Executor = D1Q3_Executor_Contract
D1Q4_Executor = D1Q4_Executor_Contract
D1Q5_Executor = D1Q5_Executor_Contract
D2Q1_Executor = D2Q1_Executor_Contract
D2Q2_Executor = D2Q2_Executor_Contract
D2Q3_Executor = D2Q3_Executor_Contract
D2Q4_Executor = D2Q4_Executor_Contract
D2Q5_Executor = D2Q5_Executor_Contract
D3Q1_Executor = D3Q1_Executor_Contract
D3Q2_Executor = D3Q2_Executor_Contract
D3Q3_Executor = D3Q3_Executor_Contract
D3Q4_Executor = D3Q4_Executor_Contract
D3Q5_Executor = D3Q5_Executor_Contract
D4Q1_Executor = D4Q1_Executor_Contract
D4Q2_Executor = D4Q2_Executor_Contract
D4Q3_Executor = D4Q3_Executor_Contract
D4Q4_Executor = D4Q4_Executor_Contract
D4Q5_Executor = D4Q5_Executor_Contract
D5Q1_Executor = D5Q1_Executor_Contract
D5Q2_Executor = D5Q2_Executor_Contract
D5Q3_Executor = D5Q3_Executor_Contract
D5Q4_Executor = D5Q4_Executor_Contract
D5Q5_Executor = D5Q5_Executor_Contract
D6Q1_Executor = D6Q1_Executor_Contract
D6Q2_Executor = D6Q2_Executor_Contract
D6Q3_Executor = D6Q3_Executor_Contract
D6Q4_Executor = D6Q4_Executor_Contract
D6Q5_Executor = D6Q5_Executor_Contract

===== FILE: MIGRATION_ARTIFACTS_FAKE_TO_REAL/07_SCRIPTS/generate_method_classification.py
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```